# GIS AND REMOTE SENSING

F W DAVIS AND D S SIMONETT

*This chapter briefly reviews remote sensing as both a data collection technology providing data for GIS and a user of spatially referenced data for scientific analysis. The discussion focuses on the importance of linking raster remote sensing systems with vector GIS to create Integrated GIS (IGIS). The use of IGIS is examined in applications such as image classification, calibration and environmental modelling. There is clearly great complementarity between remote sensing and GIS. Both areas developed independently to some extent, especially in the early days. By linking the technology, concepts and theories of both in IGIS, information systems considerably richer and more sophisticated can be created for use in substantive applications. Almost all projects currently employing satellite data or dealing with environmental data could potentially benefit from the development of truly integrated GIS.*

## INTRODUCTION

This chapter discusses the integration of digital remotely sensed data and cartographic information for GIS. Synergisms between remote sensing and GIS for land surface analysis are emphasized, specifically for surface classification, sensor calibration and physical modelling of earth surface processes.

There is a need to distinguish at the outset the difference between *measurements*, such as radiances obtained by a remote scanner system, and *geographical information*, that is knowledge of geographical phenomena obtained by the analysis of surface measurements or other geographical data. *Cartographic information* is geographical information obtained from maps. *Data* refers to measurements or information input to a geographical analysis. These distinctions are important in discussing the integration of remote sensing and GIS. Unquestionably, a large proportion of measurements of the earth's surface are now obtained from satellites and these provide an opportunity for greatly expanding and revising understanding of earth systems. To serve as input to GIS, satellite data must be well calibrated and in a suitable format and data structure. Also in the context of GIS, it is of paramount importance to know how best to use existing (and imperfect) geographical information to maximize the information potential of satellite measurements.

Early discussions of the relationship between digital remote sensing and GIS focused on the benefits of incorporating classified satellite imagery into land information systems for GIS-based analysis (e.g. Peplies and Keuper 1975). Treating the output of a remote sensing analysis as input to GIS tended to isolate the respective analysts and hindered the integration of remote sensing and GIS (Marble *et al.* 1983). The separation grew increasingly artificial as remote sensing analysts relied on ancillary geographical information to improve image classification (e.g. Hoffer *et al.* 1979; Strahler 1981; Mason *et al.* 1988) and as GIS analysts relied on satellite data for purposes such as cartographic rectification and map update (e.g. Hill and Kelly 1987).

Several recent papers have treated remote sensing and GIS in the more general framework of integrated spatial analysis, considering remotely sensed imagery as one element of a GIS for earth surface modelling (e.g. Marble *et al.* 1983; Jackson and Mason 1986; Ehlers, Edwards and Bedard 1989; Parker 1988; Star and Estes 1990). This has expanded the discussion of remote sensing and GIS from methods for improving image classification accuracy and data structure conversion, towards the more general problem of jointly representing and analysing disparate geographical data that can vary in structure, acquisition date, resolution, and level of pre-processing or human interpretation (e.g. Zhou 1989; Logan and Bryant 1987). The objective of this chapter is to extend this discussion in the light of recent advances in remote sensing theory and application. For a general review of remote sensing principles, the reader is referred to the *Manual of Remote Sensing* (Colwell 1983) and recent texts by Richards (1986), Elachi (1987) and Asrar (1989). The discussion focuses on the following issues:

- spatial resolution of digital satellite measurements, and the regularization of surface spatial variation by remote sensing systems;
- temporal resolution of satellite measurements and remote monitoring of earth surface dynamics;
- data structures for handling remotely sensed data and integrated geographical analysis;
- integrated GIS analysis for land surface classification, sensor calibration and physical modelling of surface properties.

There are other important aspects of the integration of remote sensing and GIS that will not be addressed because of space restrictions. The close links between aerial photointerpretation, existing map products and GIS will not be discussed explicitly. For example, since 1957 all operational maps produced by the US Government have used some form of remote sensing data as a base. Advances in production of digital orthophotography are especially significant in accelerating the integration of non-satellite remote sensing and GIS. The practical problems that hinder the integration of digital satellite data into existing land information systems for local planning are also not addressed, although many of the issues raised are germane to this important subject area.

Similarly, the significant fiscal and institutional impediments to integrating remote sensing and GIS technologies (Ehlers *et al.* 1989) are not considered. These issues are addressed in part by other authors in this volume. The discussion instead concentrates on some scientific issues that need to be considered in order to take fullest advantage of integrated GIS for research, resource analysis and management.

## REMOTE SENSING AS A SOURCE OF GEOGRAPHICAL DATA

*Remote sensing* is defined narrowly here as measurement of the electromagnetic properties of a surface or object without being in contact with it. The discussion here is limited to digital data collected by aircraft or satellite. While most local environmental surveys still depend on manual interpretation of aerial photography, the use of digital imagery for regional analysis is now commonplace and will undoubtedly increase in the future. As a source of geographical information, digital remote sensing represents more than a simple extension of conventional aerial photography, requiring fundamentally different approaches to the analysis of earth surfaces (Everett and Simonett 1976).

### Spatial characteristics of remotely sensed data

Remote sensing systems range from active microwave systems, which measure how a signal is scattered by the surface, to passive systems, which measure surface reflectance or emission. In a GIS context, especially important features of remotely sensed data are their sampling characteristics in the space and time domains.

The basic properties of a remote sensor can be summarized as:

- spectral coverage (spectral band locations);
- spectral resolution (spectral band width);
- spectral dimensionality (number of bands);
- radiometric resolution (quantization);
- instantaneous field of view (IFOV);
- angular field of view;
- point spread function (PSF);

- temporal response function (Strahler, Woodcock and Smith 1986).

Sensor *spatial resolution* has deliberately not been listed, as this term can be defined in several ways that give quite different values (Forshaw *et al.* 1983). Image resolution is the ground area covered by picture elements (pixels), which are themselves a function of the sensor IFOV, scene characteristics and data pre-processing. Even estimates of sensor IFOV can vary depending on the criteria that are used, and can change through time depending on the satellite orbital altitude. For example, estimates of the IFOV for the Landsat MSS have ranged from 73.4 to 81 metres (Simonett *et al.* 1983).

From a practical point of view, spatial resolution is defined by the size of the smallest object that can be reliably detected against a spectrally contrasting background, referred to as the effective resolution element (ERE). ERE is image specific, depending not only on the sensor IFOV, but on a host of other factors including the sensor PSF, surface–sensor geometry, atmospheric conditions, scene properties such as spectral contrast and object geometry, and data processing such as image rectification or enhancement (Billingsley *et al.* 1983; Duggin 1985; Strahler *et al.* 1986). Image dependencies become crucial as pixel size approaches the Nyquist limit for scene elements of interest (see below).

In a broader sense, the spatial resolution of a remote sensor varies with the task to which the data are applied, specifically: (1) *detection*, determining the presence of an object; (2) *identification* or labelling of an object; or (3) *analysis*, where information is obtained about an object beyond its initial detection and identification. Simonett *et al.* (1983) suggest that for low contrast targets the effective resolution of sensors required for analysis may be as much as 10 times less than that for identification and 30 times less than that for detection.

## Autocorrelation and regularization in satellite imagery

Spatial variation in a satellite image is produced by the convolution of intrinsic variation in surface electromagnetic properties with the sampling field of the sensor. Surface variation can be categorized as *continuous* (gradients), *discrete* (mosaics), *linear* or *localized* (e.g. intermittent extreme events, point processes and disc processes) (see also Getis and Boots 1978). It is also important to recognize whether the surface process being investigated is *stationary*, so that its statistical properties do not depend on absolute spatial location (Cliff and Ord 1981), and whether the pattern of surface variation is random, contagious or regular.

Statistical properties of environmental processes are typically highly *scale dependent*. Scale is the interval of space or time over which a measurement is made, so that *scale dependence* refers to the relationship between the magnitude or variability of a spatial process and the scale of measurement. Most natural surfaces are non-stationary over large areas, manifesting many different types of variation within and between different measurement scales. This renders satellite measurements highly sensitive to sensor IFOV, scan angle effects (e.g. National Oceanographic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) pixels range from 1.1 x 1.1 km at nadir to 4 x 1.1 km at 55.4° off-nadir) and pre-processing involving pixel resampling and interpolation. Multiple scales of surface variation also make it unreliable to calibrate sensors using ground measurements made over sample areas that depart significantly from sensor resolution.

Much research is needed on spatial variability of earth surfaces to utilize satellite data fully. Some recent studies have examined scale-dependent variation in terrain variables such as topography and radiation (e.g. Mark and Aronson 1984; Mulla 1988; Dubayah, Dozier and Davis 1990), and soils (Burrough 1983; Oliver and Webster 1986). Digital satellite data have been analysed to study scale dependence in vegetation patterns (e.g. Woodcock and Strahler 1987; Davis, Dubayah and Dozier 1989; Townshend and Justice 1990). Inferring surface variation from spatial variation in satellite data is not straightforward, however, because satellite radiances are affected by non-surface factors such as sun–earth–satellite geometry and atmospheric characteristics. Furthermore, as mentioned earlier, surface variation is filtered by the sensor in the process known as scene *regularization*. This is an important feature of satellite data that distinguishes them from most other sources of geographical information (Star and

Estes 1990). Recent work by Jupp, Walker and Penridge (1986) and Jupp, Strahler and Woodcock (1989) provides useful insight into how surface variability is regularized by satellites. Some of their results are summarized below.

The reflected radiance of a surface at location $x$ at time $t$ can be summarized as (Moik 1980):

$$f(x,\lambda,t,p) = r(x,\lambda,t,p)\ i(x,\lambda,t) \qquad [14.1]$$

where $r(x,\lambda,t,p)$ is the reflectance of the surface as a function of position $(x)$, wavelength $(\lambda)$, time $(t)$ and polarization $(p)$, and $i(x,\lambda,t)$ is the incident illumination. For simplicity, consider only the variation in reflectance with spatial position, $f(x)$. One important property of this variation is its *spatial autocorrelation* or *autocovariance*, which measures how $f(x)$ varies as a function of the distance and orientation between observations. Ignoring directional effects, spatial autocovariance in reflectance of a surface at points separated by distance $h$, denoted by $cov(h)$, can be described using the *isotropic variogram*, where

$$V(h) = cov(0) - cov(h) = 1/2\ E(f(x) - f(x + h))^2 \qquad [14.2]$$

In remote sensing, surface spatial variation is 'regularized' through the convolution of $f(x)$ with the sampling field of the sensor, **Z**. For intermittent surfaces, the regularization of $f(x)$ by **Z** leads to a new spatial function

$$f_Z(y) = 1/Mes(\mathbf{Z})\int_{Z_y} f(x)\ d|x| \qquad [14.3]$$

where $\mathbf{Z}_y$ is the sampling field (e.g. square pixel) centred at location $y$ and $Mes(\mathbf{Z})$ is the sample area. The variogram for the regularized image then becomes:

$$V_Z = (T*V)_h - (T*V)_0 \qquad [14.4]$$

where $T$ is the overlap function for **Z**,

$$T = I_Z * I_Z^* / Mes^2(\mathbf{Z}) \qquad [14.5]$$

where * is convolution and $I_Z$ is the indicator function ($I_Z(x) = 1$ for $\mathbf{x} \in \mathbf{Z}$, 0 else, and $I_Z^*(t) = I_Z(-t)$). Equation [14.4] states that the variogram that results from the regularization of a surface by a satellite sensor is related to the variogram of the surface convolved with the covariance function of the pixel.

The variograms that result as a surface is regularized to different pixel sizes can be predicted from the *point* variogram of the unregularized surface (Jupp *et al.* 1986). However, the unregularized variogram of natural surfaces is usually not known. Simulations based on the regularization of different surface types has proven useful. For example, Jupp *et al.* (1986) analyse binary surfaces covered by discs of different size and pattern, a simple analogy to scattered trees on uniform terrain, to relate image regularization to image texture, fractal behaviour and estimated cover (see also Goodchild 1980).

The semi-variogram of an image is closely related to image local variance, which is the average standard deviation of image brightness in a moving three-by-three window:

$$T_{i,j} = \left[ 1/8 \sum_{k=i-1}^{i+1} \sum_{l=j-1}^{j+1} (x_{k,l} - \bar{x}_{i,j})^2 \right]^{1/2} \qquad [14.6]$$

This measure, which is often used for edge detection and for image segmentation and classification, is the regularized value of the semi-variogram at a step size equal to or slightly greater than (for diagonals) image resolution or pixel size (Jupp *et al.* 1989).

Strahler *et al.* (1986) distinguish two fundamentally different models, the H-resolution model, in which scene elements are large compared to image resolution, and the L-resolution model, in which elements are smaller than the image resolution area and are not individually detectable. Image texture increases as image resolution approaches the dimensions of scene elements. Large local variance can be problematic in image classification using high resolution sensors such as Landsat Thematic Mapper (TM) and SPOT to map land cover types such as urban areas or woody vegetation, where sensor resolution approaches the size of individual buildings or clearings. Scene elements are often organized into larger features (e.g. buildings into blocks and trees into stands) that are manifested as additional peaks in image texture at larger pixel sizes. To the degree that different surface processes have characteristic scale dependencies, multi-resolution imagery (*image pyramids*) ranging from H- to L-resolution may be effective in surface recognition and classification (e.g. Wharton 1989).

The *regularization* of surface spatial variation by imaging systems means that information derived from analysis of satellite data differs fundamentally from most cartographic information, which usually derives from *generalization* of perceived spatial variation (e.g. in producing soils maps) or *interpolation* of point measurements of the surface (e.g. mapping of surface topography or climate data). The intermixing of regularized, generalized and interpolated surfaces in GIS convolves intrinsic surface variation with the effects of resolution and processing of the satellite data, map scale and generalization procedures, data structure and data conversion, modelling procedures, etc. The theory of GIS is still a long way from a formal decomposition of these effects. Special attention must be paid to non-linear scale dependencies of some surface types, because these surfaces will be highly sensitive to source image resolution (e.g. Lovejoy and Shertzer 1985).

## Temporal characteristics of remotely sensed data

Satellite sensors provide the opportunity for consistent multi-temporal measurements of large areas over time periods of days to decades. Sensor coverage and repeat interval are determined by platform altitude, angular velocity, orbital inclination relative to the Equator and orbital orientation relative to the vernal equinox (Elachi 1987). Many optical sensors are placed in sun-synchronous near-polar orbits to achieve global coverage and consistent illumination geometry (e.g. Landsat, AVHRR). The repeat interval varies among these sensors depending on their altitude and velocity. Others are placed in geosynchronous orbits to provide high frequency coverage of the same region (e.g. the GOES meteorological satellites).

The ability to detect changes in a surface imaged over time depends on the spatial (geometrical registration and resolution), spectral (band location and width), radiometric and temporal (imaging frequency) properties of the sensor system (Townshend and Justice 1988). The comparison of images acquired by the same sensor on different dates is complicated by any changes in instrument gain and offset as well as differences in atmospheric properties, notably in sub-pixel cloud cover. Change detection is considerably more complicated when more than one sensor system is used because of differences in sensor IFOV, PSF, bandwidths and spectral response properties (Duggin 1985).

Many techniques have been developed for atmospheric correction and radiometric calibration of satellite imagery for multi-temporal analysis (e.g. Holben and Fraser 1984; Hall and Badhwar 1987; Singh and Saull 1988; Schott, Salvaggio and Volchok 1988; Suits, Malila and Weller 1988). Less easily accounted for are changes in surface reflectance properties caused by illumination geometry. These are especially problematic because they can greatly affect the relationship between satellite radiances and surface properties (Deering 1989). Thus extracting detailed quantitative information from multi-date imagery requires sophisticated algorithms to correct for scene-specific illumination geometry, atmospheric effects and sensor characteristics.

Much of the previous discussion about spatial environmental variation applies to temporal variation as well. A process operating through time can be described as continuous, discrete or intermittent, as *stationary* or *non-stationary*, and as random, autocorrelated or regular (Jenkins and Watts 1968). For many applications, remote sensing can be treated as point sampling in the time domain (i.e. the time interval over which the image is acquired can be assumed negligibly short).

Equation [14.1] can be rewritten as a function of time:

$$f(t) = r(t)\, i(t) \qquad [14.7]$$

If $T$ is the time interval between successive samples, then a series of repeated satellite observations of a location can be considered the convolution of continuous spectral change in the environment by the temporal sampling filter $i(t)$, which can be modelled as a series of delta functions:

$$i(t) = \sum_{n=-\infty}^{\infty} \delta(t - n\mathbf{T}) \qquad [14.8]$$

Thus

$$f_T(t) = f(t) i(t) \qquad [14.9]$$

$f(t)$ can be recovered from $f_T(t)$ for temporal changes manifested over periods of $\geq 2\mathbf{T}$, or less than the Nyquist frequency of $1/2\mathbf{T}$. Processes that change at higher frequencies (shorter periods) will be aliased into $f_T(t)$.

Surface electromagnetic properties change over time scales from fractions of seconds to years. For example, vegetated surfaces change within seconds as a result of physiological adjustments of plant canopies and wind-driven changes in leaf orientation, whereas successional processes can operate over decades to centuries. The high frequency variation contributes unavoidable noise in multi-temporal imagery. Rapid atmospheric changes and surface reflectance changes with illumination also contribute noise, but it may be possible to remove these effects.

Despite considerable high frequency 'noise', satellite data have been used effectively to monitor surface processes that are continuous or persist over more than a few days and that can manifest detectable change within a few years. Detection of intermittent high magnitude events such as fires and floods is feasible but their short duration means that they can only be described probabilistically over large areas (Robinson 1987). Systems undergoing gradual directional change (e.g. expansion of urban areas) or more rapid but non-directional change (e.g. shifting cultivation of tropical forest lands where the proportions in different stages of use or recovery remain unchanged) are also problematic because the information about such surfaces is especially sensitive to both spatial and temporal sampling properties of the sensor system. Unfortunately, there is scant quantitative information on scale-dependent spatio-temporal variation of earth surfaces, though such analyses are now feasible over large areas using satellite data.

Townshend and Justice (1988) provide a useful example of space–time interactions in remote sensing in the context of monitoring changes in land cover over large regions. They note that most landscapes undergo a wide variety of changes through space and time at many different characteristic scales. The ability of sensor systems to monitor such state changes in a surface depends on the radiometric contrast between states and on how temporal change in states is distributed in space (e.g. uniform area changes uniformly through time, sharp extensive boundary between two states moves progressively, a state expands radially from a point through time). They conclude that high spatial resolution is especially critical for land surface monitoring. Presumably, an opposite conclusion would apply to ocean surface monitoring, where high temporal resolution is much more important than spatial resolution (Table 14.1).

### Operational and planned satellite remote sensors

The civilian satellite remote sensing programme in the United States has operated since the mid-1960s, providing global coverage by the Landsat series since 1972 and by the NOAA AVHRR series since 1978. Landsat 1,2 and 3 alone acquired more than 1 million images (Lauer 1990). Many other sensors have been launched subsequently, and a wide array of research instruments are expected to be launched over the next decade (Eos Science Steering Committee 1987).

In summarizing the information needs for a satellite-based Earth Observing System, Goddard Space Flight Center (1984) listed 30 major environmental parameters that could be measured with operational or planned sensors over time scales of $10^{-4}-10^{1}$ years and spatial scales of $10^{-4}-10^{3}$ km$^2$. Some surface parameters are listed in Table 14.1. Existing and planned sensor systems capable of providing such information are summarized in Table 14.2. Some examples of future research sensors, such as HIRIS and MODIS, have been included to show the remarkable capabilities expected from the next generation of research sensors, and to indicate the probable direction of future operational systems.

## INTEGRATING REMOTE SENSING AND GIS

Previous sections described the general features of remotely sensed data and alluded to some of the issues that must be addressed in integrating these data with other information sources for geographical analysis. In this section some technical and analytical concerns related to data integration and spatial modelling are considered. Three points are particularly emphasized:

1. Satellite data differ from nearly all other geographical data in their consistency, high positional accuracy, high spatial and temporal resolution, and low level of human abstraction or interpretation. GIS require raster capabilities to store and analyse large volumes of these data with minimum loss of resolution or radiometric precision.

**Table 14.1** Some important earth surface parameters that can be measured remotely, and required spatial and temporal sampling frequencies for various applications (modified and simplified Table 2 from Goddard Space Flight Center 1984). Spatial frequencies are expressed in terms of maximum pixel dimension germane to the application.

| Parameter | Application | Spatial frequency | Temporal frequency |
|---|---|---|---|
| Soil | | | |
| types | Geochemistry, agriculture, forestry | 30 m | Annual |
| moisture | Hydrology, geochemistry | 30 m–10 km | Weekly |
| erosion | Agriculture, geochemistry | 30 m | Annual |
| carbon, nitrogen | Geochemistry | 30 m | Monthly |
| permafrost | Bioclimatology | 30 m | Annual |
| Surface temperature | | | |
| land | Bioclimatology | 1 km | 12 h |
| inland waters | Pollution, climatology | 30 m | 12 h |
| ocean | Climatology | 1–4 km | 12 h |
| ice | Climatology | 1 km | Daily |
| Vegetation | | | |
| types | Resource analysis | 30 m | Annual |
| | Geochemistry, bioclimatology | 1 km | Weekly |
| composition | Resource analysis | 30 m | Weekly |
| condition | Geochemistry, bioclimatology | 1 km | Weekly |
| Land use | Demography, planning, Resource analysis | 10–30 m | Annual |
| Snow | Hydrology | 1 km | Weekly |
| Radiation (SW, LW) | Climatology, hydrology | 1 km | Daily |
| Precipitation | Climatology, hydrology | 1 km | Daily |
| Phytoplankton | Fisheries, biogeochemistry | 1–4 km | 2 days |
| Turbidity | Pollution, erosion, geochemistry | 30m–1 km | 2 days |
| Surface elevation | | | |
| land | Geomorphology, hydrology, ecology | 10–30 m | 10 years |
| ocean | Oceanography | 25 km | 2 days |
| Rock mineralogy | Geology, pedology | 30 m | 10 years |

2. Maps use points and lines to portray selected features of reality in a highly abstracted and generalized form. This information establishes a conceptual spatial context for the analysis of remotely sensed data. GIS require vector capabilities to store such information in a feature-oriented data model that minimizes feature distortion and loss of topological information.

3. Integrated geographical analysis will require multiple data structures and software that support a wide range of spatial queries and promote statistical and deterministic modelling. No existing GIS has all of these capabilities.

## Spatial data structures

*Spatial data structure* refers to the form in which geo-referenced data are represented and stored in a computer. Frank and Barrera (1990) list four major ways that spatial data structures can differ from one another:

1. Type of geometrical data (point versus region)

**Table 14.2** Some operational and research satellites for earth surface analysis (Goddard Space Flight Center 1984; Ehlers, Edwards and Bedard 1989).

| Platform | Sensor | Year | Bands | Spectral | IFOV | Repeat Cover | Country |
|---|---|---|---|---|---|---|---|
| Landsat | MSS | 1972– | 4 | VIS/NIR | 80 m | 16 d | USA |
| | TM4, 5 | 1982– | 7 | VIS/NIR/TIR | 30/120 m | 16 d | USA |
| | TM6 | 1992– | 8 | VIS/NIR/TIR | 20/30/120 m | 16 d | USA |
| NOAA | AVHRR | 1978– | 5 | VIS/NIR/TIR | 1–4 km | 12 h | USA |
| GOES | VISSR | 1975– | 2 | VIS/TIR | 0.9/8 km | 12 h | USA |
| NIMBUS-7 | CZCS | 1978– | 1 | VIS | 10 km | 27 d | USA |
| HCMM | HCMR | 1978–1980 | 2 | VIS/TIR | 500 m/600 m | 16 d | USA |
| Shuttle | LFC | 1984 | | Film | VIS/NIR | 10–20 m | USA |
| | SIR-A, B | 1981– | 1 | Radar | | 17–58 m | USA |
| | SIR-C | 1991– | 2 | Radar | | 10–60 m | USA |
| EOS-A | HIRIS | 1998– | 192 | VIS/TIR | 30 m | 4 d | USA |
| | MODIS-N | 1998– | 35+ | VIS/TIR | 250–1000 m | 2 d | |
| | MODIS-T | 1998– | 64 | VIS/TIR | 1 km | 2 d | |
| SPOT | HRV-P | 1986– | 1 | VIS | 10 m | 2.5 d | France |
| | HRV-XS | 1986– | 3 | VIS/NIR | 20 m | 2.5 d | |
| MOS/LOS | MESSR | 1987– | 4 | VIS/NIR | 50 m | 17 d | Japan |
| | VTIR | 1987– | 4 | VIS/TIR | 1–3 km | 17 d | |
| | MSR | 1987– | 1 | Radar | 25 m | 17 d | |
| ERS-1 | AMI | 1990– | 1 | Radar | 30 m | 3 d | EEC |
| | ASTR | 1990– | 3 | TIR | 1 km | 3 d | |
| RADARSAT | SAR | 1990– | 1 | Radar | 30 m | 3 d | Canada |

2. Object handling (non-fragmenting versus fragmenting)
3. Retrieval (direct versus hierarchical)
4. Subdivision of space (regular versus data determined).

Data are most commonly represented in GIS in either *grid raster* (region, fragmenting, direct, regular) or *vector* (region, non-fragmenting, direct, data determined) form. Satellite measurements are acquired in raster format, whereas much existing GIS software and many widely available databases are in vector format. The incompatibility of these data structures and the need for reconciling the raster/vector dichotomy is a pervasive theme in the literature on the integration of remote sensing and GIS (e.g. Logan and Bryant 1987; Archibald 1987; Smith *et al.* 1987a; Barker 1988; Peuquet 1988; Ehlers *et al.* 1989; Zhou 1989). The discussion here focuses on the use of one or both data structures for handling and analysing remotely sensed data and for integrated geographical analysis. (Technical features and relative merits of raster and vector representations are discussed in detail by Egenhofer and Herring 1991 in this volume and are only briefly discussed here.)

### Raster data structures

Raster data structures tessellate space and assign each spatial element a unique value, thus providing *explicit* information for each location (Burrough 1986). Raster structures include *regular* versus *irregular* tessellations, and *hierarchical* versus *non-hierarchical* models. They have been described as *field-based* (Ehlers *et al.* 1989), as opposed to *object-based* representations provided by vector structures, referring to the fact that fields are assigned object attributes in a raster model whereas objects are given locations and attributes in the latter model.

The most common raster structure is a square lattice whose values are stored as two-dimensional arrays in the computer. This structure is convenient for imaging systems such as satellite sensors or other digital scanning devices, and has many additional advantages including (Burrough 1986):

- simplicity;
- ease of image display and processing;
- ease of data aggregation and data overlay;
- uniform cell size and shape for multidimensional spatial analysis and spatial simulation modelling.

Also, the square grid is the only practical structure for maintaining full radiometric precision and spatial resolution of satellite data. This is because the advantages of other data structures such as hierarchical or vector structures depend on the presence of large fields of pixels with identical values. Such fields are uncommon in satellite data acquired over land, where much of the variation occurs at high spatial frequencies (e.g. Davis *et al.* 1989).

Although well suited to satellite data, the raster structure has many limitations:

1. Gridding of point and line features entails loss of locational precision.
2. Griding of uniform polygons leads to misclassification of perimeter areas and to areal estimation error, both of which depend on grid resolution and polygon shape (e.g. Switzer 1975; Muller 1977; Goodchild 1980; Crapper 1980; Crapper, Walker and Nanninga 1986).
3. Many surfaces are more naturally fitted with alternative shapes such as irregular triangles (see Weibel and Heller 1991 in this volume).
4. Local interactions are not easily modelled on a square lattice because of differences in the distance and degree of connectedness among vertical and horizontal versus diagonal neighbours. This is especially awkward in modelling contagious diffusion processes such as fire spread, which are better described using a hexagonal lattice.
5. Analyses requiring metric or topological information (e.g. the length of a linear feature, the size and shape of a patch, network relationships, degree of connectedness among patches) cannot be performed on raster data without first reassembling those objects.

The regular lattice can impose large data volumes because lattice resolution is generally selected to capture the smallest feature of interest. Raster data structures are often chosen specifically because of the desire to incorporate satellite data, and all other cartographic information is gridded to the resolution of those data. In practice, such databases rapidly grow very large because of the analyst's desire to use the highest resolution satellite data that can be obtained.

**Hierarchical raster data structures**

Several methods of data compaction have been developed to store raster data more efficiently, including different coding schemes (e.g. run-length or block coding) and hierarchical representations such as quadtrees, hextrees, R-trees and field trees (Samet 1984; Frank and Barrera 1990). Hierarchical data structures require tessellations that can be recursively decomposed into similar patterns of smaller size (Smith *et al.* 1987a). The square tessellation is used most commonly in constructing a hierarchy in which a cell at each level in the tree can be subdivided into four cells at the next sublevel, down to the level of individual pixels (Bell *et al.* 1983). Smith *et al.* (1987a) distinguish *image pyramids*, in which information for all levels is retained, from quadtree regionalizations in which information is stored to the level of a homogeneous subregion and no further. Similar hierarchies have been constructed for point and line data (Samet 1984).

Hierarchical data structures offer several advantages over raster structures for integrated analysis of satellite and map data (Jackson and Mason 1986). Data volume and processing time can be greatly reduced depending on image or map complexity. Spatial overlay and proximity analyses are facilitated by the more *object-like* representation of surface variation. Similarly, this representation makes it easier to incorporate information on size, shape and scale dependence into algorithms for pattern recognition and image classification, thus lending itself to knowledge-based GIS analyses (Chen 1987; Smith *et al.* 1987b; Menon 1989). Despite these substantial advantages, hierarchical data structures are still field based and can provide only limited and geometrically artificial information about objects. Similarly, although quadtrees may allow more precise representation of points and lines, their raster structure still imposes some loss of locational precision, and they are not easily adapted to handling network phenomena.

### Vector data structures

Vector data structures represent spatial variation using lines located in continuous coordinate space. Lines in the original analogue map are stored as strings of coordinates, and the spatial relationships among map entities are stored explicitly or are computed when needed (Peuquet 1988). Vector representations may be *unlinked*, in which object boundaries are encoded without reference to neighbours, or *topologically linked*, in which sections of boundary lines (arcs) are referenced by their endpoints, orientation and the attributes of adjoining regions (Peucker and Chrisman 1975). The identity of map entities is preserved by this data structure, which can thus to some extent be considered *object oriented*.

The vector data structure has some serious disadvantages for spatial analysis. Information is lost during data encoding due to line generalization and digitizing errors (see Veregin 1989 for review; Prisley, Gregoire and Smith 1989). The high data volume per element in a vector model makes storage costs prohibitive for dense maps or unprocessed satellite data. The data structure is more complex than raster or hierarchical structures, and operations such as overlay and display are more difficult (Burrough 1986). Spatial analyses involving spatial statistics or simulation are much less straightforward because each polygon has a unique size, shape and orientation.

The evolution of vector-based GIS software has been driven largely by the desire to encode and analyse existing mapped information. The vector model of points, lines and polygons in *continuous coordinate space* permits the closest approximation to the original map. Furthermore, implicit topological relationships in the original maps such as network linkages can be retained as attributes in vector data structures.

The distinction between the *map-oriented* vector structure and the *data-oriented* raster structure calls attention once more to the differences among cartographic *information*, remotely sensed *measurements* and information derived from those data (Maffini 1987). Maps represent surface variation in a highly generalized, selective and abstracted form (Ehlers *et al.* 1989), and the processes and data used to generate the cartographic information are usually unknown or irretrievable. For instance, boundary placement on a soils map can be driven as much by the analyst's purposes and underlying model of reality as by observed or measured patterns in surface variation. Conversely, satellite measurements involve little or no human interpretation other than for registration and calibration.

Conversion of satellite data to vector format generally requires classification (i.e. interpretation) of low-level information at the expense of measurement precision and spatial detail, whereas rasterizing a map to be conformal with satellite data means disaggregating and degrading high-level cartographic information. These are fundamental trade-offs that must be confronted in the integration of satellite and cartographic data into a single data structure.

## Integration of disparate data structures

There are case-dependent technical and analytical advantages and disadvantages to raster, hierarchical and vector data structures, and recent literature has tended to emphasize the use of more than one data model in geographical analyses (e.g. Haralick 1980; Logan and Bryant 1987; Rhind and Green 1988; Peuquet 1988; Simonett 1988; Ehlers *et al.* 1989; Zhou 1989). A recent survey noted that nearly half of all GIS packages now support both vector and raster structures, suggesting that the advantages of flexibility in choice of data structure outweigh the burden of additional processing software and analysis time (Parker 1989).

The term *Integrated Geographical Information Systems* (IGIS) has been coined to describe systems capable of processing both vector and raster data. The simplest kind of integrated system, what Ehlers *et al.* (1989) term the separate but equal strategy, provides for data conversion, data transfer between vector GIS and image processing software, and simultaneous display of raster and vector data. Examples of such systems are provided by Logan and Bryant (1987) and Goodenough (1988). Relational GIS have also been developed in which raster and vector data are linked through a relational database management system (RDBMS) (Zhou 1989). Cartographic information can be digitized in vector format but is converted and processed with satellite data in a raster environment. However, feature attributes that were encoded during vector processing are retained in non-spatial relational data structures and can be linked to the raster data for analysis. Such systems are useful, but it should be recognized that multiple conversions of vector and raster data carry with them the cost of data degradation through loss of precision and accuracy.

A somewhat fuller integration would allow tandem raster and vector processing, hierarchical representation and object-oriented handling of remote sensing data. Some quadtree-based GIS such as the Knowledge Based Geographical Information System (KBGIS) have many of these capabilities, including heuristic search procedures and learning capacities (Smith *et al.* 1987b). Ideally, a fully integrated GIS should be *seamless* in maintaining both object-oriented and field-oriented representations of geographical data, and should facilitate a wide range of spatial queries and analyses that would promote both statistical and deterministic modelling of earth surfaces (Ehlers *et al.* 1989). Much of the impetus for developing such a GIS has come from resource analysts trying to incorporate satellite data into land information systems, and from the scientific community concerned with modelling physical and biological systems at regional to global scales (e.g. Archibald 1987; Goodenough 1988; Estes and Bredekamp 1988). The remainder of this chapter is devoted to a fuller discussion of some model types that are specially suited to IGIS analysis, some of the issues that need to be addressed in applying such models, and some recent examples of IGIS analysis for modelling terrestrial ecosystems.

## INTEGRATED GIS MODELLING OF EARTH SURFACES

### Remote sensing models

Strahler *et al.* (1986) distinguish three basic model types in remote sensing: *sensor*, *atmosphere* and *scene*. In practice, the analysis of satellite imagery may incorporate one or more of these. Models are further divided into *empirical* versus *deterministic* and *invertible* versus *non-invertible*. Empirical models rely on the statistical association of sensor measurements and surface characteristics, whereas deterministic models rely on radiative and heat transfer theory. Invertible models are those in which unknown properties of the scene can be inferred from remote sensing measurements. Strahler *et al.* (1986) point out that these dichotomies are really endpoints in continua of model types. For example, deterministic models often have empirical components, and non-invertible models can sometimes be inverted under restricted conditions. Classification and calibration of satellite imagery both exemplify the empirical invertible modelling approach, while physical scene modelling represents the other extreme of deterministic (and often non-invertible) models. Each is discussed below in the context of IGIS analysis.

### Classification

Classification is the grouping of objects into classes based on their similarity with respect to one or more variables, whereas discrimination is the assigning of objects to pre-defined classes based on object properties. The objective of most remote sensing applications is to discriminate and map pre-determined ground information classes, usually with the aid of statistical clustering or discrimination methods. The literature on remote sensing often refers to cluster analysis as unsupervised classification and to discrimination as supervised classification or pattern recognition. This enormous literature cannot be reviewed here. Readers are referred to works by Moik (1980), Haralick and Fu (1983) and Richards (1986).

Unsupervised classification involves clustering individual pixels into spectral classes based on measured reflectance values in the original channels or transformations of those channels. The spectral classes are then assigned to ground information classes (e.g. land use/land cover categories) by an analyst based on field observations or interpretation of air photos.

In supervised classification, pixels are assigned to ground information classes through a discriminant function based on observed spectral properties of the information classes in a set of preselected training sites. Statistical discriminant functions include *maximum likelihood estimators*, where the spectral mean vector and covariance matrix of the training sites are taken to be those of the information class, and *Bayesian estimators*, where the Probability Density Function (PDF) of the information class is assumed to be known *a priori* and training samples are used to refine the PDF to obtain an *a posteriori* discriminant function. Another form of discrimination is *syntactic* pattern recognition, which uses hierarchical decision structures and grammar rules to recognize information classes based on a set of primitive features characteristic of each class (Haralick and Fu 1983).

Some classification approaches combine supervised and unsupervised methods, using unsupervised classification to generate training classes with multivariate normal probability density functions that are subsequently used in a supervised classification procedure (see Richards 1986). Another hybrid approach is *guided* clustering, which involves initial seeding of spectral clusters or pooling of spectral clusters based on training class statistics (Peterson and Running 1989).

**Problems in the statistical classification of satellite imagery**

In statistical classification and discrimination, objects are usually classified based on measurement variables relevant to the information classes. For example, plant species abundance data are used to classify vegetation samples into vegetation types. In remote sensing, however, surface electromagnetic properties are surrogates for relevant properties of the information classes such as land use, timber type, and so on (Robinove 1981). The strength of this surrogate relationship is strongly scene dependent because the information classes do not possess unique electromagnetic signals (Hoffer 1978). Usually the information class pertains to one feature of the environment, for example crop type. The spectral signature for that type will vary with changes in soil characteristics, stage of crop development, illumination, atmosphere and so forth. Atmospheric corrections and radiometric rectification to account for illumination changes reduce some of the unwanted signature variation. Band ratios and spectral transformations such as the Kauth–Thomas Tassled Cap Transformation help to isolate the reflectance variation related to plants (Kauth and Thomas 1976). Classification accuracy can also be improved by using multi-temporal imagery. For example, multi-temporal profiles have been used to improve crop recognition based on crop-specific phenology (Hall and Badhwar 1987). In the final analysis, however, local and regional variation in physical and biological processes and scene-specific radiative transfer conditions mean that there is always a strong local, empirical element to statistical classification of satellite imagery.

A second concern in satellite-based classification of earth surfaces relates to the earlier discussion of object-oriented versus data-oriented analysis. Classification systems evolve through the interaction of human needs and human capabilities to structure available information. Environmental classification systems in use today (e.g. Anderson, Hardy and Roach 1976) describe entities that have been abstracted by humans from ground observations and, more recently, from air photo data. Humans recognize these environmental entities in remotely sensed imagery based in part on local tone and colour, but principally on complex spatial attributes of pattern, size, shape, texture and context that are not involved in per-pixel classification or discrimination procedures (Estes, Hajic and Tinney 1983).

A number of digital processing procedures have been implemented that utilize local textural or temporal data in addition to per-pixel spectral data, image segmentation or expert system approaches to generate more object-like image classes (Haralick and Fu 1983; Wang *et al.* 1983; Goodenough *et al.* 1987; Wharton 1989; Bryant 1990). These methods tend to produce better results than per-pixel classifiers, and, because they rely on other information beyond absolute spectral reflectances, reduce reliance on scene-specific optimization of statistical classification parameters (Wharton 1989). Furthermore, because these procedures produce image classes with spatial properties closer to those of idealized ground information classes, they render satellite-based maps that are more compatible with the traditional needs of local and regional land planners and managers and are more readily incorporated into vector GIS.

**Errors in the classification of remotely sensed imagery**

Classification accuracies are now routinely reported for satellite classifications of land surfaces.

Misclassification of satellite imagery is usually measured using a *confusion matrix* or *contingency table* that compares image class to actual class for a sample of pixels from the image (Dozier and Strahler 1983). Actual class is determined by ground survey or from more reliable image or map data. The simplest statistic that can be derived from the table is the per cent correctly classified, although additional measures can be derived (Card 1982; Congalton, Oderwald and Mead 1983; see Veregin 1989 for a review). Image class and ground class may disagree for a variety of reasons, notably:

- misregistration of satellite data to cartographic coordinate system;
- misregistration of ground data to cartographic coordinate system;
- inadequate spectral separation of information classes;
- inappropriate statistical or contextual classifier;
- analyst misclassification of actual information class in test data;
- spatial disaggregation of a ground feature into several spectral classes;
- mixed pixel or boundary effects.

It should be noted that it is difficult to obtain a sufficiently large and unbiased sample of test sites to measure confidently thematic map accuracy (Congalton 1988a). Also, in many applications the classification bias (class-specific errors of omission versus commission) and spatial distribution of errors may be as important as overall accuracy. Experience shows that image classifications are often biased, that error rates nearly always differ systematically among information classes, and that errors are rarely (if ever) randomly distributed (e.g. Campbell 1981; Walsh, Lightfoot and Butler 1987; Congalton 1988b). Such error distributions may be difficult to model analytically and can have serious consequences in a decision or spatial modelling framework (Anselin 1989).

**IGIS-based land surface classification**

Integration of cartographic and satellite data has proven an effective partial solution to many of the problems of satellite image classification, and the use of both data sources for land surface classification is now commonplace. Many different GIS variables and approaches have been used, for example:

- Use of digital elevation data to account for illumination effects in pixel radiance values (e.g. Hutchinson 1982; Franklin *et al.* 1986; Jones, Settle and Wyatt 1988).
- Use of digital elevation data to account for elevational zonation of environmental factors, plant species and vegetation types (e.g. Hoffer *et al.* 1979; Strahler 1981; Satterwhite, Rice and Shipman 1984; Cibula and Nyquist 1987).
- Use of map information to stratify a satellite scene into more homogeneous and statistically stationary subregions in which to apply statistical pattern recognition methods (e.g. Gaydos and Newland 1978; Hutchinson 1982).
- Use of map information as an aid to labelling spectral clusters in unsupervised classification (Hutchinson 1982; Ustin *et al.* 1986).
- Spectral/geomorphometric mapping of terrain features (Franklin, Peddle and Moulton 1989).
- Selection of training sites for supervised classification.
- Selection of scene-invariant targets for atmospheric correction.
- Location of field sites for map accuracy assessment.
- Aid in visual interpretation of image features (e.g. Harding and Forrest 1989).
- Knowledge-based image segmentation and classification (Estes, Sailer and Tinney 1986; Goodenough *et al.* 1987; Tong, Richards and Swain 1987; McKeown 1986; Mason *et al.* 1988).

In several of the applications listed above, map information provides a basis for segmenting the scene into regions that are physically, ecologically or spectrally more homogeneous. In this way, map data are used to constrain the classification of satellite reflectance measurements, to improve the surrogate relationship between satellite measurements and information classes, and to make the spatial attributes of spectral classes more consistent with those of other geographical data.

Integration of satellite and cartographic data for land surface classification introduces new sources of error into the classification product because of inaccuracies in the GIS data as well as imperfect specification of the relationship between ground information classes and GIS variables. GIS errors are treated by Chrisman (1991 in this volume), so only a few examples are cited here:

- GIS data may contain measurement or estimation errors that will lead to incorrect image segmentation or use of inappropriate prior classification probabilities. For instance, digital elevation data are prone to non-randomly distributed errors, and derivatives of elevation such as slope angle and aspect can be unreliable (Walsh *et al.* 1987; Weibel and Heller 1991 in this volume).
- Maps of hydrology, land use or land cover are rapidly outdated.
- Misregistration of satellite and GIS data can be problematic unless map features are much larger than pixel size [satellite data may often have higher positional accuracy than the base maps used for their rectification (Welch and Usery 1984)].
- Maps may be too generalized to be of much value for image segmentation (Rhind and Clark 1988).
- Use of geographical data to develop and apply weights or prior probabilities to image classification depends on a correctly specified statistical model as well as on accurate maps for applying the model.

In general, the gains in classification accuracy obtained by incorporating GIS data more than offset misclassification due to GIS errors. Because errors in image classification are often associated with changes in illumination and background, including information on these variables reduces map bias and non-random spatial pattern in classification errors. This underscores the notion that classification products produced by IGIS are not classified satellite imagery, as they are often called, but are a qualitatively different amalgam combining features of both satellite and cartographic data.

## Calibration models

As opposed to classification models, the term *calibration models* is used to refer to statistical models that relate satellite radiances or their derivatives to measured physical or biological surface properties. As pointed out by Deering (1989), calibration studies that compare surface properties to ground-based radiometers can be the first stage in the development of deterministic remote sensing models. Here the concern is with the calibration of satellite data using ground measurements. Such modelling is increasing as scientists attempt to take advantage of the spatial coverage and temporal resolution of satellite data to parameterize physically based ecological and climatological models (Hall, Strebel and Sellers 1988). Examples include the use of radiances or derived indices to predict surface radiation (Tarpley 1979), canopy leaf area index (LAI), photosynthesis or respiration (Sellers 1985), soil properties such as organic matter or moisture content (see Irons, Weismuller and Petersen, 1989, for review), snowpack condition (Dozier 1989) or surface mineralogy (Goetz 1989).

A basic problem in calibration modelling is obtaining sufficiently accurate and representative satellite and surface measurements (Curran and Hay 1986). Measurement accuracy can be reduced by errors in:

- measurement of remotely sensed variables;
- measurement of ground variables;
- physical correlation of ground variables and remotely sensed variables caused by spatial and temporal misregistration.

Error sources in remotely sensed variables were discussed earlier and can be summarized as variation in irradiance over the time interval of scene acquisition, sensor miscalibration, sensor radiometric resolution signal digitization, atmospheric attenuation and atmospheric path radiance (Curran and Hay 1986). These errors are non-trivial, but methods to minimize them continue to be refined. Ground measurement errors, on the other hand, can be substantial for the many biophysical variables that cannot be measured over the full IFOV of a sensor, but must instead be estimated by sub-sampling (Curran and Williamson 1986).

Curran and Hay (1986) discuss the problem of measurement error in the context of regression analysis, where remotely sensed radiance or reflectance data ($y$) are predicted by ground measurements of a surface variable ($x$) using the linear model:

$$y = \beta x + \alpha + \varepsilon \qquad [14.10]$$

$\alpha$ and $\beta$ are regression coefficients and $\varepsilon$ is an error term due to uncontrolled exogenous variables and errors in the measurement of $y$. If there are measurement errors in $x$, the estimate of $\beta$ will be biased, such that:

$$\hat{\beta}^* = \beta/(1 + \sigma^x{}_v/\sigma^2{}_x) \qquad [14.11]$$

where $\hat{\beta}^*$ is the estimate of $\beta$, $\sigma^x{}_v$ is variance from measurement errors in $x$ and $\sigma^2{}_x$ is variance due to 'true' variance in $x$. Thus large measurement errors in $x$ can result in substantially underestimating $\beta$.

A larger problem in calibration models could be described as *specification errors* that occur from using an inappropriate model form, incorrect variables or parameter values (Anselin 1989). Models fitted to a narrow region and/or time period may be mis-specified for other conditions. For example, Weiser *et al.* (1986) needed different regression coefficients to relate NDVI to LAI for burned versus unburned grasslands, and for the same grasslands in different years. Box, Holben and Kalb (1989) showed that the relationship between NDVI and variables such as annual evapotranspiration or net primary productivity depended on topographic conditions and varied systematically between different major vegetation types.

Careful field measurements of a wide variety of environments will be needed to calibrate remotely sensed measurements (Deering 1989). IGIS analysis of cartographic data and satellite data offers a means of reducing ground measurement errors during model development and minimizing mis-specification errors when applying these models over large heterogeneous surfaces. The applications of IGIS are similar to those listed in the previous section, and involve the delineation of homogeneous regions for stratified ground sampling and for model application. At present, the merits of different data types for scene segmentation are poorly understood. There are trade-offs between: depending solely on ground measurements and satellite data; combining ground, map and satellite data; and perhaps combining ground and satellite data with lower resolution satellite data.

An example of the use of IGIS capabilities for reducing errors in ground measurements is provided by FIFE, the First ISLSCP Field Experiment. The ISLSCP experiments are 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). The experiment was conducted between 1987 and 1989 over a 16 x 16 $km^2$ region near Manhattan, Kansas. FIFE's sampling approach was to acquire simultaneously ground measurements and remotely sensed data spanning a range of spatial scales throughout the growing season.

A major challenge in FIFE has been integrating local ground measurements of surface climate parameters such as leaf area, biomass and soil moisture to obtain statistically reliable estimates of these parameters over 1 $km^2$ or larger areas resolved by meteorological satellites. In an effort to reduce errors in ground-based estimates, a stratified sampling design was used based on topographic and land management characteristics. Digital maps of these variables are being used to derive site-wide estimates of variables such as biomass and soil moisture based on point measurements within the different strata.

A problem encountered in FIFE and likely to be encountered in all similar experiments was selecting a site stratification scheme that was appropriate for many different meteorological and biophysical variables. The stratification used in FIFE was based on previous research, but the criteria for determining the number and characteristics of strata were necessarily somewhat *ad hoc*. Davis *et al.* (1990) subsequently showed that an improved *a priori* stratification could be obtained based on the correspondence of digital terrain variables with TM imagery. Plate14.1 shows their results for the Konza Long Term Ecological Research (LTER) Area, which occupies the northwestern portion of the FIFE site. The new stratification, which was based on regression tree analysis of the image and map database, performed better that the initial stratification for integrating ground measurements of both soil moisture and total biomass. Davis and Dozier (1990) used a similar approach to develop a land classification system for a region in coastal California based on the association of vegetation patterns with maps of geology and seasonal insolation. In both studies, hierarchical land classifications were derived from joint analysis of satellite and digital terrain data. This is comparable to the production of index maps from GIS weighting and overlay maps (Burrough 1986), but here variable weights and nested combinations are constrained to have maximum correspondence with satellite measurements.

Much of the current effort to calibrate satellite measurements is directed towards coupling those measurements with physical and ecological process models for regional and global forecasting. This coupling, which has been made possible by the evolution of IGIS and by increasingly powerful computers, represents a significant departure from the early applications of remote sensing for classification and inventory. It is also a different application of many process models that were originally developed to improve understanding about the temporal dynamics of spatially homogeneous systems (Costanza, Sklar and White 1990). Implementing these models over large areas requires their re-formulation to account for spatial heterogeneity, spatial interactions and stochastic uncertainty.

Considerable progress has been made in spatial simulation modelling and in incorporating satellite data to parameterize models of processes such as crop growth (Kanemasu, Asrar and Fuchs 1985), forest photosynthesis and transpiration (Running *et al.* 1989), and surface mass and energy fluxes (Smith *et al.* 1990). GIS-based regionalizations have only recently been used to account for spatial heterogeneity in applying process models. Examples include drainage basin partitioning for modelling runoff (Band and Wood 1988), evapotranspiration and photosynthesis (Running *et al.* 1989). Davis and Dozier (1990) demonstrated the potential impact of cartographic errors on the information value of GIS-based regionalization, but to date there has been little progress in formally accounting for cartographic errors and their propagation in the development and application of physical and ecological models. Heuvelink, Burrough and Stein (1989) have developed a method for predicting error propagation that may occur when using continuously distributed random variables in the quantitative analysis of gridded data in a raster GIS. The method, which depends on approximating errors by Taylor expansion, can be applied to regression-type models. The authors applied the method to surfaces derived by semi-variogram analysis and Kriging of point measurements, but note that simpler surfaces may also be analysed. A great deal more research and technical development is needed to support process modelling efforts. Simonett (1988) suggests the following areas require attention:

- Research on space–time dynamics and scale dependence of surface processes.
- Additional investigations such as FIFE to determine the best mix of ground measurements, satellite measurements and existing cartographic information for parameterizing process models.
- Studies on the effects of satellite data preprocessing on model outputs.
- Theoretical and empirical studies on effects of data resolution and quality on error propagation in process modelling.
- Tests of the model sensitivities to missing data.
- Identification of appropriate spatial statistical models for calibration and verification.
- Development of fully integrated GIS; such an IGIS must provide for flexible handling of multiple data structures and multi-scale data, and must support complex spatial queries and spatio-temporal statistical analyses (Ehlers *et al.* 1989).

### Deterministic models

Physical scene models are deterministic models that use theories of radiative transfer or energy balance to derive quantitative estimates of surface reflectance or emission. This brief discussion is restricted to physical models that have been developed to describe the reflectance properties of plant canopies. A good review of current modelling approaches to other surface variables can be obtained in Asrar (1989).

Physical models are often not intended for application to satellite data, but are formulated to improve understanding of processes that contribute to the signal received by satellite sensors. Many of the models cannot be inverted, while inversion of others requires that they be coupled to atmospheric and sensor models and calibrated with detailed ground and atmospheric data. All models must make simplifying assumptions to account for spectral heterogeneity of the medium at practically all scales of measurement due to variations in composition, spatial arrangement and non-Lambertian bidirectional reflectance of constituent elements.

Among plant canopy models, for example, one model class (*geometrical models*; Goel 1989) treats individual plants as solid objects with prescribed shape and reflectance characteristics that are distributed in some statistical fashion across a ground surface possessing specified reflectance properties (Li and Strahler 1985; Richards, Sun and Simonett 1987). Another class of models (*turbid medium models*) treats plant canopies as homogeneous clouds of small particles with specified orientation, absorption and reflectance characteristics (Verhoef 1984; Norman 1979). Still another class of *hybrid* models has been developed that considers both the geometrical arrangement of plants and multiple scattering by plant canopy elements (Goel 1989).

Some canopy models are sufficiently simplified that they can be parameterized with field reflectance measurements to invert satellite data. These might be considered semi-empirical models, in that physical calculations are combined with statistical spectral mixture models to invert reflectance data (Pech, Graetz and Davis 1986; Jupp *et al.* 1986; Jasinski and Eagleson 1989).

Inversion of physically based canopy models over actual land surfaces is still in an early stage of development. To be made operational, these models need to be coupled to atmosphere and sensor models, parameterized for a representative set of conditions and validated empirically. In complex environments, the number of parameters needed to model the system accurately exceeds the dimensionality of satellite measurements (Goel 1989). Use of spatial measures such as local image variance, as well as multi-temporal and multi-view imagery, can provide additional dimensions (Kimes 1981; Li and Strahler 1985). Also, cartographic information can be used to segment the scene or add other variables so that the model inversion provides more realistic results. For example, Woodcock, Strahler and Jupp (1989) have used digital elevation data and forest stand maps to segment TM imagery into stand types before applying the Li–Strahler geometrical-optical canopy model to map timber volume in the Stanislaus National Forest in California.

For those models that cannot be implemented due to their complexity or to the lack of appropriate data, IGIS offer a powerful tool for conducting simulation and model sensitivity studies over realistic surfaces. For example, Generic Scene Simulation Software (GENESSIS) has been developed that combines physically based atmosphere and scene models to simulate spatially and radiometrically accurate visible and infrared imagery (Acquista 1986; Reeves, Anding and Mertz 1987). Model inputs include illumination geometry, atmospheric properties, surface topography and surface reflectance and emittance. Sub-pixel electromagnetic variation can also be specified. Scene simulation is performed by aggregating point-by-point ray calculations to produce apparent radiances for each pixel of specified spatial resolution. The model has performed well across a wide range of sensor and environmental parameters, and appears to offer many opportunities to investigate IGIS-based physical modelling of terrestrial phenomena. Computing demands are a practical concern in applying GENESSIS or many other spatial simulation models to realistically large and heterogeneous data sets, and may well require additional IGIS capabilities such as parallel processing (Costanza *et al.* 1990; Ehlers 1989).

## RESEARCH CHALLENGES IN THE INTEGRATION OF REMOTE SENSING AND GIS

This chapter has highlighted some of the technical and scientific challenges to fuller utilization of remote sensing and GIS. The coupling of satellite measurements with other spatial data has tremendous potential for characterization and analysis of earth surfaces, but the relationship between these hybrid products and the surfaces that they represent is still poorly understood on both physical and statistical grounds. Some of the recent research cited here has just begun to address the difficult issues of 'artifacting, indeterminacy, improper extrapolation between scales, and environmental modulation of spatial error budgets' (Simonett 1988:124) that were identified 15 years ago by Everett and Simonett (1976). However, such studies are few in number and have been nearly exclusively at local to regional scales.

In closing, the following list of general research topics, some repeated from earlier sections is offered. These must be given high priority in integrated analysis of geographical data:

- Characterize space-time interactions and scaling properties of terrain variables.
- Compile/create high quality, representative real and simulated data sets for IGIS model testing and validation.
- Develop appropriate sampling, measurement and modelling strategies for different environment types, including identification of the best mix of ground, satellite and map data for classification, calibration and process models.
- Improve methods for display and visualization of IGIS products.
- Determine the error properties of IGIS products and error propagation in modelling using those products.
- Identify appropriate methods to calibrate and test the performance of spatial models implemented over large regions (e.g. Turner, Costanza and Sklar 1989).
- Develop parallel processing capabilities to operate complex spatial models on large data sets.
- Improve software and hardware interfaces among existing data handling and analysis systems, notably image processing, GIS, database management, expert systems, and statistical packages.
- Identify appropriate data structures and data management strategies for processing large quantities of satellite data, including the use of GIS data to guide the timing and location of image acquisition (e.g. areas of change) and the choice of suitable image resolution, and spatial and non-spatial statistical packages.
- Develop specific technical and scientific guidelines and data standards for future IGIS hardware and software development.

## REFERENCES


**Acquista C** (1986) GENESSIS computer code reference manual. *Photon Research Associates Report R-135-86*. PRA Inc, La Jolla California

**Anderson J E, Hardy E E, Roach J T** (1976) A land use and land cover system for use with remote-sensor data. *US Geological Survey Professional Paper 964*: 28

**Anselin L** (1989) What is special about spatial data? Alternative perspectives on spatial data analysis. *Technical Paper 89–4*. National Center for Geographic Information and Analysis, Santa Barbara California

**Archibald P D** (1987) GIS and remote sensing data integration. *Geocarto International* **3**: 67–73

**Asrar G** (ed.) (1989) *Theory and Applications of Optical Remote Sensing*. Wiley, New York

**Band L E, Wood E F** (1988) Strategies for large-scale distributed hydrologic simulation. *Applied Mathematics and Computation* **27**: 23–37

**Barker G R** (1988) Remote sensing: the unheralded component of geographic information systems. *Photogrammetric Engineering and Remote Sensing* **54**: 195–9

**Bell S B M, Diaz B M, Holroyd F, Jackson M J** (1983) Spatially referenced methods of processing raster and vector data. *Image and Vision Computing* **1**: 211–20

**Billingsley F C, Anuta P E, Carr J L, McGillem C D, Smith D M, Strand T C** (1983) Data processing and reprocessing. In: Colwell R N (ed.) *Manual of Remote Sensing*. American Society of Photogrammetry, Falls Church Virginia, pp. 719–88

**Box E O, Holben B N, Kalb V** (1989) Accuracy of the AVHRR Vegetation Index as a predictor of biomass, primary productivity and net $CO_2$ flux. *Vegetatio* **80**: 71–89

**Bryant J** (1990) AMOEBA clustering revisited. *Photogrammetric Engineering and Remote Sensing* **56**: 41–7

**Burrough P A** (1983) Multiscale sources of spatial variation in soil. I. The application of fractal concepts to nested levels of soil variation. *Journal of Soil Science* **34**: 577–97

**Burrough P A** (1986) *Principles of Geographical Information Systems for Land Resource Assessment*. Clarendon Press, Oxford

**Campbell J B** (1981) Spatial correlation effects upon accuracy of supervised classification of land cover.

*Photogrammetric Engineering and Remote Sensing* **47**: 355–63

**Card D H** (1982) Using known map category marginal frequencies to improve estimates of thematic map accuracy. *Photogrammetric Engineering and Remote Sensing* **48**: 431–9

**Chen Z** (1987) *Quadtree and Quadtree Spatial Spectra in Large Geographic Information Systems: the hierarchical handling of spatial data*. Unpublished PhD dissertation, University of California, Santa Barbara California

**Chrisman N R** (1991) The error component in spatial data. In: Maguire D J, Goodchild M F, Rhind D W (eds.) *Geographical Information Systems: principles and applications*. Longman, London, pp. 165–74, Vol 1

**Cibula W G, Nyquist M O** (1987) Use of topographic and climatological models in a geographic database to improve Landsat MSS classification for Olympic National Park. *Photogrammetric Engineering and Remote Sensing* **53**: 67–75

**Cliff A D, Ord J K** (1981) *Spatial Processes: models and applications*. Pion, London

**Colwell R N** (1983) *Manual of Remote Sensing*. American Society of Photogrammetry, Falls Church Virginia

**Congalton R G** (1988a) A comparison of sampling schemes used in generating error matrices for assessing the accuracy of maps generated from remotely sensed data. *Photogrammetric Engineering and Remote Sensing* **54**: 593–600

**Congalton R G** (1988b) Using spatial autocorrelation analysis to explore the errors in maps generated from remotely sensed data. *Photogrammetric Engineering and Remote Sensing* **54**: 587–92

**Congalton R G, Odervwald R, Mead R** (1983) Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogrammetric Engineering and Remote Sensing* **6**: 169–73

**Costanza R, Sklar F H, White M L** (1990) Modeling coastal landscape dynamics. *Bioscience* **40**: 91–107

**Crapper P F** (1980) Errors incurred in estimating an area of uniform land cover using Landsat. *Photogrammetric Engineering and Remote Sensing* **10**: 1295–301

**Crapper P F, Walker P A, Nanninga P M** (1986) Theoretical prediction of the effect of aggregation on grid cell data sets. *Geo-processing* **3**: 155–66

**Curran P J, Hay A M** (1986) The importance of measurement error for certain procedures in remote sensing at optical wavelengths. *Photogrammetric Engineering and Remote Sensing* **52**: 229–41

**Curran P J, Williamson H D** (1986) Sample size for ground and remotely sensed data. *Remote Sensing of Environment* **20**: 31–41

**Davis F W, Dozier J** (1990) Information analysis of a spatial database for ecological land classification. *Photogrammetric Engineering and Remote Sensing* **56** (5): 605–13

**Davis F W, Dubayah R, Dozier J** (1989) Covariance of greenness and terrain variables over the Konza Prairie. *Proceedings of IGARRS 89*, pp. 1322–5

**Davis F W, Michaelsen J, Dubayah R, Dozier J** (1990). Optimal terrain stratification for integrating ground data from FIFE. *Proceedings of the AMS Symposium on the First ISLSCP Field Experiment (FIFE)*. American Meteorological Society, Boston Massachusetts, pp. 11–15

**Deering D** (1989) Field measurements of bidirectional reflectance. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 14–65

**Dozier J** (1989) Spectral signature of alpine snow cover from the Landsat Thematic Mapper. *Remote Sensing of Environment* **28**: 9–22

**Dozier J, Strahler A H** (1983) Ground investigations in support of remote sensing. In: Colwell R N (ed.) *Manual of Remote Sensing*. American Society of Photogrammetry, Falls Church Virginia, pp. 959–86

**Dubayah R, Dozier J, Davis F W** (1990) Topographic distribution of clear-sky radiation over the Konza Prairie, Kansas. *Water Resources Research* **26** (4): 679–90

**Duggin M J** (1985) Factors limiting the discrimination and quantification of terrestrial features using remotely sensed radiance. *International Journal of Remote Sensing* **6**: 3–27

**Egenhofer M J, Herring J R** (1991) High-level spatial data structures for GIS. In: Maguire D J, Goodchild M F, Rhind D W (eds.) *Geographical Information Systems: principles and applications*. Longman, London, pp. 227–37, Vol 1

**Ehlers M** (1989) Remote sensing and geographic information systems: towards integrated spatial information processing. *Proceedings of IGARRS 89*, pp. 63–6

**Ehlers M, Edwards G, Bedard Y** (1989) Integration of remote sensing with geographic information systems: a necessary evolution. *Photogrammetric Engineering and Remote Sensing* **55**: 1619–27

**Elachi C** (1987) *Introduction to the Physics and Techniques of Remote Sensing*. Wiley, New York

**Eos Science Steering Committee** (1987) *Earth Observing System Volume II. From pattern to process: the strategy of the Earth Observing System*. National Aeronautics and Space Administration, Washington DC

**Estes J E, Bredekamp J H** (1988) Activities associated with global databases in the National Aeronautics and Space Administration. In: Mounsey H M (ed.) *Building Databases for Global Science*. Taylor & Francis, London, pp. 251–69

**Estes J E, Hajic E J, Tinney L R** (1983) Manual and digital analysis in the visible and infrared regions. In: Simonett D S, Ulaby F T (eds.) *Manual of Remote Sensing*, 2nd edn. Vol. 1. American Society of Photogrammetry, Falls Church Virginia, 987–1123

**Estes J E, Sailer C, Tinney L R** (1986) Applications of artificial intelligence techniques to remote sensing. *Professional Geographer* **38**: 133–41

**Everett J, Simonett D S** (1976) Principles, concepts and philosophical problems. In: Lintz J L, Simonett D S (eds.) *Remote Sensing of Environment*. Addison-Wesley, Reading Massachusetts, pp. 85–127

**Forshaw M R B, Haskell A, Miller P F, Stanley D J,**

**Townshend J R G** (1983) Spatial resolution of remotely sensed imagery: a review paper. *International Journal of Remote Sensing* **4**: 497–520

**Frank A U, Barrera R** (1990) The fieldtree: a data structure for geographic information systems. In: Buchmann A, Gunther O, Smith T R, Wang Y-F (eds.) *Design and Implementation of Large Spatial Databases*. Springer-Verlag, New York, pp. 29–44

**Franklin J, Logan T L, Woodcock C E, Strahler A H** (1986) Coniferous forest classification and inventory using Landsat and digital terrain data. *IEEE Transactions on Geoscience and Remote Sensing* **GE-24**: 139–46

**Franklin S E, Peddle D R, Moulton J R** (1989) Spectral/ geomorphometric discrimination and mapping of terrain: a study in Gros Morne National Park. *Canadian Journal of Remote Sensing* **15**: 28–42

**Gaydos L, Newland W L** (1978) Inventory of land use and land cover of the Puget Sound region using Landsat digital data. *US Geological Survey Journal of Research* **6**: 807–14

**Getis A, Boots B** (1978) *Models of Spatial Processes* University Press, Cambridge

**Goddard Space Flight Center** (1984) Earth Observing System: Science and Mission Requirements, Working Group Report, Volume H 1. *NASA Goddard Space Flight Center Technical Memorandum 86129*. National Aeronautics and Space Administration, Greenbelt Maryland

**Goel N S** (1989) Inversion of canopy reflectance models for estimation of biophysical parameters from reflectance data. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 205–51

**Goetz A F H** (1989) Spectral remote sensing in geology. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 491–526

**Goodchild M F** (1980) The effects of generalization in geographical data encoding. In: Freeman H, Pieroni G (eds.) *Map Data Processing*. Academic Press, New York, pp. 191–205

**Goodenough D G** (1988) Thematic Mapper and SPOT integration with a geographic information system. *Photogrammetric Engineering and Remote Sensing* **54**: 167–76

**Goodenough D G, Goldberg M, Plunkett G, Zelek J** (1987) An expert system for remote sensing. *IEEE Transactions on Geoscience and Remote Sensing* **GE-25**: 349–59

**Hall F G, Badhwar G D** (1987) Signature-extendable technology: global space-based crop recognition. *IEEE Transactions on Geoscience and Remote Sensing* **GE-25**: 93–103

**Hall F G, Strebel D E, Sellers P J** (1988) Linking knowledge among spatial and temporal scales: vegetation, atmosphere, climate and remote sensing. *Landscape Ecology* **2**: 3–22

**Haralick R M** (1980) Edge and region analysis for digital image data. *Computer Graphics and Image Processing* **12**: 60–73

**Haralick R M, Fu K** (1983) Pattern recognition and classification. In: Colwell R N (ed.) *Manual of Remote Sensing*, 2nd edn. American Society of Photogrammetry, Falls Church Virginia, pp. 793–805

**Harding A E, Forrest M D** (1989) Analysis of multiple geological data sets from the English Lake District. *IEEE Transactions on Geoscience and Remote Sensing* **27**: 732–9

**Heuvelink G B M, Burrough P A, Stein A** (1989) Propagation of errors in spatial modelling with GIS. *International Journal of Geographical Information Systems* **3**: 303–22

**Hill G J E, Kelly G D** (1987) A comparison of existing map products and Landsat for land cover mapping. *Cartography* **16**: 51–7

**Hoffer R M** (1978) Biological and physical considerations in applying computer-aided analysis techniques to remote-sensor data. In: Swain P H, Davis S M (eds.) *Remote Sensing: the quantitative approach*. McGraw-Hill, New York, pp. 227–87

**Hoffer R M, Fleming M D, Bartolucci L A, Davis S M, Nelson R F** (1979) Digital processing of Landsat MSS and topographic data to improve capabilities for computerized mapping of forest cover types. *LARS Technical Report 011579*, p. 159

**Holben B N, Fraser R S** (1984) Red and near-infrared sensor response to off-nadir viewing. *International Journal of Remote Sensing* **5**: 145–60

**Hutchinson C F** (1982) Techniques for combining Landsat and ancillary data for digital classification improvement. *Photogrammetric Engineering and Remote Sensing* **48**: 123–30

**Irons J R, Weismuller R A, Petersen G W** (1989) Soil reflectance. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 66–106

**Jackson M J, Mason D C** (1986) The development of integrated geo-information systems. *International Journal of Remote Sensing* **7**: 723–40

**Jasinski M F, Eagleson P S** (1989) The structure of red-infrared scattergrams of semivegetated landscapes. *IEEE Transactions on Geoscience and Remote Sensing* **27**: 441–51

**Jenkins G M, Watts D G** (1968) *Spectral Analysis and Its Applications*. Holden-Day, Oakland California

**Jones A R, Settle J J, Wyatt B K** (1988) Use of digital terrain data in interpretation of SPOT HRV-1 multispectral imagery. *International Journal of Remote Sensing* **9**: 669–76

**Jupp D L B, Strahler A H, Woodcock C E** (1989) Autocorrelation and regularization in digital images: II. Simple image models. *IEEE Transactions on Geoscience and Remote Sensing* **27**: 247–56

**Jupp D L B, Walker J, Penridge L K** (1986) Interpretation of vegetation structure in Landsat MSS imagery: a case study in disturbed semi-arid Eucalypt woodlands. Part 2. Model-based analysis. *Journal of Environmental Management* **23**: 35–57

**Kanemasu E T, Asrar G, Fuchs M** (1985) Application of remotely sensed data in wheat growth modeling. In: Day

D W, Atkin R K (eds.) *Wheat Growth and Modelling*. Plenum, New York, pp. 407–25
**Kauth R J, Thomas G S** (1976) The tasselled cap: a graphic description of the spectral-temporal development of crops as seen by Landsat. *Proceedings of the 3rd Symposium on Machine Processing of Remotely Sensed Data*, Vol. 4B. Purdue University, West Lafayette Indiana, pp. 41–51
**Kimes D S** (1981) Remote sensing of temperature profiles in vegetation canopies using multiple view angles and inversion techniques. *IEEE Transactions on Geoscience and Remote Sensing* **GE-19**: 85–90

**Lauer D** (1990) *An Evaluation of National Policies Governing the United States Civilian Satellite Land Remote Sensing Program*. Unpublished PhD dissertation, Department of Geography, University of California, Santa Barbara California
**Li X, Strahler A H** (1985) Geometric-optical modeling of a conifer forest canopy. *IEEE Transactions on Geoscience and Remote Sensing* **GE-23**: 705–21
**Logan T L, Bryant N A** (1987) Spatial data software integration: merging CAD/CAM/mapping with GIS and image processing. *Photogrammetric Engineering and Remote Sensing* **53** (10): 1391–5
**Lovejoy S, Schertzer D** (1985) Generalised scale invariance in the atmosphere and fractal models of rain. *Water Resources Research* **21**: 1233–50

**Maffini G** (1987) Raster versus vector encoding and handling: a commentary. *Photogrammetric Engineering and Remote Sensing* **53**: 1397–8
**Marble D F, Peuquet D J, Boyle A R, Bryant N, Calkins H W, Johnson T** (1983) Geographic information systems and remote sensing. In: Colwell R N (ed.) *Manual of Remote Sensing*. American Society of Photogrammetry, Falls Church Virginia, pp. 923–57
**Mark D M, Aronson P B** (1984) Scale-dependent fractal dimensions of topographic surfaces: an empirical investigation, with applications in geomorphology and computer mapping. *Mathematical Geology* **16**: 671–83
**Mason D C, Corr D G, Cross A, Hoggs D C, Lawrence D H, Petrou M, Tailor A M** (1988) The use of digital map data in the segmentation and classification of remotely-sensed images. *International Journal of Geographical Information Systems* **2**: 195–215
**McKeown D M** (1986) The role of artificial intelligence in the integration of remotely sensed data with Geographic Information Systems. *Report CMU-CS-86-174*. Department of Computer Science, Carnegie-Mellon University, Pittsburgh Pennsylvania
**Menon S** (1989) *Spatial Search for Multi-component Objects in a Geographic Information System Using Symbolic Models and Hierarchical Data Structures*. Unpublished PhD dissertation, University of California, Santa Barbara California
**Moik J G** (1980) Digital processing of remotely sensed images. *NASA SP-431*. Scientific and Technical Information Branch National Aeronautics and Space Administration, Washington DC
**Mulla D M** (1988) Using geostatistics and spectral analysis to study spatial patterns in the topography of southeastern Washington State, USA. *Earth Surface Processes and Landforms* **13**: 389–405
**Muller J-C** (1977) Map griding and cartographic errors: a recurrent argument. *The Canadian Cartographer* **14**: 152–67

**Norman J** (1979) Modeling of complete crop canopy. In: Barfield B G, Gerber J F (eds.) *Modification of the Aerial Environment of Plants*. American Society of Agricultural Engineers, St Joseph Mississippi, pp. 249–77

**Oliver M A, Webster R** (1986) Semi-variograms for modelling the spatial pattern of landform and soil properties. *Earth Surface Processes and Landforms* **11**: 491–504

**Parker H D** (1988) The unique qualities of a geographic information system: a commentary. *Photogrammetric Engineering and Remote Sensing* **54**: 1547–9
**Parker H D** (1989) GIS software 1989: a survey and commentary. *Photogrammetric Engineering and Remote Sensing* **55**: 1589–91
**Pech R P, Graetz R D, Davis A W** (1986) Reflectance modelling and the derivation of vegetation indices for an Australian semi-arid shrubland. *International Journal of Remote Sensing* **7**: 389–403
**Peplies R W, Keuper H F** (1975) Regional analysis. In: Reeves R G, Anson A, Landen D (eds.) *Manual of Remote Sensing*, Vol. 2. American Society of Photogrammetry, Falls Church Virginia, pp. 1947–98
**Peterson D L, Running S W** (1989) Applications in forest science and management. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 429–73
**Peucker T K, Chrisman N R** (1975) Cartographic data structures. *The American Cartographer* **2**: 55–69
**Peuquet D J** (1988) Issues involved in selecting appropriate data models for global databases. In: Mounsey H M (ed.) *Building Databases for Global Science*. Taylor & Francis, London, pp. 66–78
**Prisley S P, Gregoire T G, Smith J L** (1989) The mean and variance of area estimates computed in an arc-node Geographic Information System. *Photogrammetric Engineering and Remote Sensing* **55**: 1601–12
**Reeves R, Anding D, Mertz F** (1987) First principles deterministic simulation of IR and visible imagery. *Photon Research Associates Report R-024-88*. PRA Inc., La Jolla California
**Rhind D, Clark P** (1988) Cartographic data inputs to global databases. In: Mounsey H (ed.) *Building Databases for Global Science*. Taylor & Francis, London, pp. 79–104
**Rhind D W, Green N P A** (1988) Design of a geographical information system for a heterogeneous scientific community. *International Journal of Geographical Information Systems* **2**: 171–89
**Richards J A** (1986) *Remote Sensing Digital Image Analysis: an introduction*. Springer-Verlag, New York
**Richards J A, Sun G Q, Simonett D S** (1987) L-band radar

backscatter modeling of forest stands. *IEEE Transactions on Geoscience and Remote Sensing* **GE-25**: 487–98
**Robinove C J** (1981) The logic of multispectral classification and mapping of land. *Remote Sensing of Environment* **11**: 231–44
**Robinson J** (1987) The role of fire on earth: a review of the state of knowledge and a systems framework for satellite and ground based observations. *NCAR Cooperative Thesis 112*. National Center for Atmospheric Research, Boulder Colorado
**Running S W, Nemani R R, Peterson D L, Band L E, Potts D F, Pierce L L, Spanner M A** (1989) Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation. *Ecology* **70**: 1090–101

**Samet H** (1984) The quadtree and related hierarchical data structures. *ACM Computing Surveys* **16**: 187–260
**Satterwhite M, Rice W, Shipman J** (1984) Using landform and vegetation factors to improve the interpretation of LANDSAT imagery. *Photogrammetric Engineering and Remote Sensing* **50**: 83–91
**Schott J R, Salvaggio C, Volchok W J** (1988) Radiometric scene normalization using pseudoinvariant features. *Remote Sensing of Environment* **26**: 1–16
**Sellers P J** (1985) Canopy reflectance, photosynthesis, and transpiration. *International Journal of Remote Sensing* **6**: 1335–72
**Sellers P J, Hall F G, Asrar G, Strebel D E, Murphy R E** (1988) The first ISLSCP field experiment (FIFE). *Bulletin of the American Meteorological Society* **69**: 22–7
**Simonett D S** (1988) Considerations on integrating remote sensing and Geographic Information Systems. In: Mounsey H (ed.) *Building Databases for Global Science*. Taylor & Francis, London, pp. 105–28
**Simonett D S, Reeves R G, Estes J E, Bertke S E, Sailer C T** (1983) The development and principles of remote sensing. In: Colwell R N (ed.) *Manual of Remote Sensing*. American Society of Photogrammetry, Falls Church Virginia, pp. 1–32
**Singh S M, Saull R J** (1988) The effect of atmospheric correction on the interpretation of multitemporal AVHRR-derived vegetation index dynamics. *International Journal of Remote Sensing* **25**: 37–51
**Smith E A, Crosson W L, Cooper H J, Weng H** (1990) Heat and moisture flux modeling of the FIFE grassland canopy aided by satellite derived canopy variables. *Proceedings of the Symposium on FIFE*. American Meteorological Society, Boston Massachusettes, pp. 154–62
**Smith T R, Menon S, Star J L, Estes J E** (1987a) Requirements and principles for the implementation and construction of large-scale geographic information systems. *International Journal of Geographical Information Systems* **1**: 13–31
**Smith T R, Peuquet D, Menon S, Agarwal P** (1987b) KBGIS-II. A knowledge-based geographical information system. *International Journal of Geographical Information Systems* **1**: 149–72
**Star J, Estes J E** (1990) *Geographic Information Systems: an introduction*. Prentice Hall, Englewood Cliffs New Jersey
**Strahler A H** (1981) Stratification of natural vegetation for forest and rangeland inventory using Landsat digital imagery and collateral data. *International Journal of Remote Sensing* **2**: 15–41
**Strahler A H, Woodcock C E, Smith J A** (1986) On the nature of models in remote sensing. *Remote Sensing of Environment* **20**: 121–39
**Suits G, Malila W, Weller T** (1988) Procedures for using signals from one sensor as substitutes for signals of another. *Remote Sensing of Environment* **25**: 395–408
**Switzer P** (1975) Estimation of the accuracy of qualitative maps. In: Davis J C, McCullagh M J (eds.) *Display and Analysis of Spatial Data*. Wiley, New York, pp. 1–13

**Tarpley J D** (1979) Estimating incident solar radiation at the earth's surface from geostationary satellite data. *Journal of Applied Meteorology* **18**: 1172–81
**Tong L, Richards J A, Swain P H** (1987) Probabilistic and evidential approaches for multisource data analysis. *IEEE Transactions on Geoscience and Remote Sensing* **GE-25**: 283–93
**Townshend J R G, Justice C O** (1988) Selecting the spatial resolution of satellite sensors required for global monitoring of land transformations. *International Journal of Remote Sensing* **9**: 187–236
**Townshend J R G, Justice C O** (1990) The spatial variation of vegetation at very coarse scales. *International Journal of Remote Sensing* **11**: 149–57
**Turner M G, Costanza R, Sklar F H** (1989) Methods to evaluate the performance of spatial simulation models. *Ecological Modelling* **48**: 1–18

**Ustin S L, Adams J B, Elvidge C D, Rejmanek M, Rock B N, Smith M O, Thomas R W, Woodward R A** (1986) Thematic Mapper studies of semiarid shrub communities. *Bioscience* **36**: 446–52

**Veregin H** (1989) A taxonomy of error in spatial databases. *Technical Paper 89–12*. National Center for Geographic Information and Analysis, Santa Barbara California
**Verhoef W** (1984) Light scattering by leaf layers with application to canopy reflectance modeling: the Sail model. *Remote Sensing of Environment* **16**: 125–41

**Walsh S J, Lightfoot D R, Butler D R** (1987) Recognition and assessment of error in geographic information systems. *Photogrammetric Engineering and Remote Sensing* **53**: 1423–30
**Wang S, Elliott D B, Campbell J B, Erich R W, Haralick R M** (1983) Spatial reasoning in remotely sensed data. *IEEE Transactions on Geoscience and Remote Sensing* **GE-21**: 94–101
**Weibel R, Heller M** (1991) Digital terrain modelling. In: Maguire D J, Goodchild M F, Rhind D W (eds.)

*Geographical Information Systems: principles and applications*. Longman, London, pp. 269–97, Vol 1
**Weiser R L, Asrar G, Miller G P, Kanemasu E T** (1986) Assessing grassland biophysical characteristics from spectral measurements. *Remote Sensing of Environment* **20**: 141–52
**Welch R, Usery E L** (1984) Cartographic accuracy of Landsat-4 MSS and TM image data. *IEEE Transactions on Geoscience and Remote Sensing* **GE-22**: 281–8
**Wharton S W** (1989) Knowledge-based spectral classification of remotely sensed image data. In: Asrar G (ed.) *Theory and Applications of Optical Remote Sensing*. Wiley, New York, pp. 548–77
**Woodcock C E, Strahler A H** (1987) The factor of scale in remote sensing. *Remote Sensing of Environment* **21**: 311–32
**Woodcock C E, Strahler A H, Jupp D L B** (1988) The use of variograms in remote sensing: I. Scene models and simulated images. *Remote Sensing of Environment* **25**: 323–48
**Woodcock C E, Strahler A H, Jupp D L B** (1989) Autocorrelation and regulatization in digital images: II. Simple image models. *IEEE Transactions on Geoscience and Remote Sensing* **27**: 247–56

**Zhou Q** (1989) A method for integrating remote sensing and geographic information systems. *Photogrammetric Engineering and Remote Sensing* **55**: 591–6