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Digital remotely-sensed data and their characteristics

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This chapter explores the nature and properties of digital remotely-sensed data. Rather than simply summarising the ever-growing range of airborne and satellite sensor systems, together with their technical characteristics, the chapter is divided into three distinct parts, namely: (a) the interaction of electromagnetic radiation with Earth surface materials, focusing on the physical, chemical, and biological properties that control their reflectance, emittance, and scattering characteristics; (b) the impact of sensor and platform design on the ability to record the surface-leaving radiation and the nature of the data that are produced; and (c) the production of data-processing algorithms to translate the recorded signals into estimates of the intrinsic properties of the observed surfaces.

1 PHYSICAL PRINCIPLES

1.1 Remote sensing: inference and estimation

Broadly speaking, the subject matter of terrestrial remote sensing encompasses the set of instruments (sensors), platforms, and data-processing techniques that are used to derive information about the physical, chemical, and biological properties of the Earth's surface (i.e. the land, atmosphere, and oceans) without recourse to direct physical contact. Information is derived from measurements of the amount of electromagnetic radiation reflected, emitted, or scattered from the Earth surface, and its variation as a function of wavelength, angle (direction), wave polarisation, phase, location, and time. A variety of sensors is commonly employed in this context – both passive (i.e. those reliant on reflected solar radiation or emitted terrestrial radiation) and active (i.e. those generating their own source of electromagnetic radiation) – operating throughout the electromagnetic spectrum from visible to microwave wavelengths (see also Dowman, Chapter 31). The platforms on which these instruments are mounted are similarly diverse: although Earth-orbiting satellites and fixed-wing aircraft are by far the most common, helicopters, balloons, masts, and booms are also used. Finally, a wide range of data-processing techniques has been developed, often in response to advances in sensor technology, but increasingly to meet the demands of a growing set of applications.

The problem with the definition of remote sensing outlined above is that it focuses on the *technology,* as opposed to the *science*, of remote sensing. In doing so, it obscures two fundamental aspects of the remote sensing process, namely *inference* and *estimation*. The role of inference becomes clear when it is understood that very few properties of interest to the environmental scientist can be measured directly by remote sensing. Instead, they must be inferred from measurements of reflected, emitted, or scattered radiation using some form of mathematical model, or via their relationship with a surrogate variable (e.g. land cover) that can be derived more readily from the remotely-sensed data (see also Bibby and Shepherd, Chapter 68; Fisher, (Chapter 13). The accuracy with which a given property can be inferred is therefore dependent on the quality (generality, applicability, reliability, etc.) of the model and algorithms used, or on the degree of correlation between the surrogate and target variables, together with the accuracy and suitability of any land-cover classification scheme involved and the classes that this defines. Unfortunately, our understanding of these relationships is, in many instances, still quite poor (see also Dowman, Chapter 31). Even where our knowledge is well developed, we may be forced to employ models involving a number of approximations or simplifications, perhaps to reduce the computational load in time-critical applications. As a consequence, the values inferred from remotely-sensed data are almost always estimates of the actual quantities of interest.

1.2 Sources of information

There are five main sources of information that can be exploited by remote sensing systems. These relate to variations in the recorded signal as a function of:

- wavelength ('spectral');
- angle ('directional');
- wave polarisation;
- location ('spatial');
- time ('temporal').

1.2.1 Inference and estimation from spectral variations

Most remote sensing studies attempt to exploit spectral (i.e. wavelength dependent) variations in the radiation emanating from the Earth's surface: these are controlled by the physical and chemical properties of Earth surface materials. In the case of healthy green leaves, for example, the principal controlling factors are plant pigments (e.g. chlorophyll, xanthophyl, and the carotenoids), lignin, cellulose, protein, and leaf-water content (Asrar 1989; Jacquemoud and Baret 1990). In the case of soils, the most important factors are the content of moisture, iron oxides, and organic matter, together with surface structure (Price 1990; Jacquemoud et al 1992).

There are two main ways in which the relationship between surface properties and spectral response can be exploited. At one level, the aim may be simply to distinguish different types of surface material. In this case, the objective is to identify those wavelengths at which the contrast between their reflectance, emittance, or scattering characteristics is maximised. Since not all surface materials can be distinguished at a given wavelength, it is common to record data in several parts of the electromagnetic spectrum (i.e. multispectral remote sensing). A subsequent aim may be to identify the nature of the surface materials; that is, to assign each a label from a set of pre-defined classes, typically expressed in terms of land cover.

The second major use of multispectral data is to estimate values for selected properties of the observed surface materials. For example, many studies have attempted to derive information on the above-ground biomass, leaf area index (LAI), and levels of photosynthetic activity of vegetation canopies. This is commonly based on linear combinations of data recorded in two or more spectral wavebands, generally centred on the visible red and near-infrared wavelengths (Myneni and Williams 1994). Use of this type of empirical model – referred to generically as vegetation indices – is widespread, despite their well-known limitations (Baret and Guyot 1991; Myneni et al 1995); indeed, new indices are continually being developed. The enduring attraction of vegetation indices lies in their conceptual and computational simplicity. This goes some way to explain the enduring popularity of the normalised difference vegetation index (NDVI), most recently for mapping and monitoring vegetation at regional and global scales (Townshend et al 1995).

Recent advances in sensor technology, specifically those relating to improvements in spectral resolution (Vane and Goetz 1993), have prompted more detailed studies of the relationships between spectral response and surface biochemical properties (Wessman et al 1988; Hunt 1991). Many of these studies continue to make use of simple empirical transformations (such as ratios) of data measured in a number of spectral wavebands (Danson et al 1992). Attention has also been focused on locating the so-called 'red edge' (the wavelength of maximum slope in the spectral response of vegetation between 690μm and 740μm; Figure 1), using this as an indicator of photosynthetic activity and leaf biochemistry (Boochs et al 1990; Filella and Peñuelas 1994; Curran et al 1995). More importantly, attempts have also been made to develop physically-based models to account for the optical properties of individual leaves in terms of their chemical and physical characteristics (Jacquemoud and Baret 1990). In principle, these models should be less data-dependent and site-specific than their empirical counterparts. It may also be possible to invert them, so that estimates of their parameters – and, hence, the surface biophysical properties to which they relate – can be derived from multispectral measurements made by remote sensing systems.

Whichever methods are employed, it should be noted that vegetation canopies do not behave simply as 'big leaves', so that problems arise in attempting to apply the techniques described above directly to remotely-sensed images. More specifically, relationships determined *in vitro*, or *in vivo* at the scale of a single leaf, are complicated by differences in, among other things, the spatial and geometric structure of vegetation canopies and variations in the soil substrate (Goel 1989; Asrar 1989). For this reason, attempts to estimate biophysical or biochemical properties at the canopy scale require the use of coupled models of canopy and leaf reflectance (Jacquemoud 1993; Jacquemoud et al 1995).

1.2.2 Inference and estimation from directional variations

The detected reflectance of most Earth surface materials varies, sometimes considerably, as a function of the angles at which they are illuminated by the Sun and viewed by the sensor. The form and magnitude of this effect are controlled by:

- the optical properties of the component elements of the surface material (e.g. the spectral reflectance and transmittance of plant leaves, stems, tree crowns, and soil facets);
- the spatial and geometric arrangement of these elements;
- the spectral and angular distribution of the incident solar radiation (Goel 1989; Barnsley 1994).

The angular distribution of the reflected radiation is described by the bidirectional reflectance distribution function (BRDF). Research in this area has focused on the development and implementation of various mathematical models (Myneni et al 1990), ranging from simple empirical (e.g. Walthall et al 1985) and semi-empirical functions (e.g. Roujean et al 1992), to models with a more direct foundation in physical principles (e.g. Ahmad and Deering 1992; Kuusk 1994). Interest in these models arises from their potential to derive quantitative estimates of certain biophysical properties of the Earth surface (e.g. the LAI). This can be achieved by inverting the model against measurements of reflected radiation made at a number of different sensor view angles and solar illumination angles with respect to a fixed point on the Earth surface (Plate 21; Goel 1989; Barnsley et al 1994). Estimates of the surface albedo can also be obtained through numerical or analytical integration of the modelled BRDF (Kimes et al 1987; Barnsley et al 1997a).

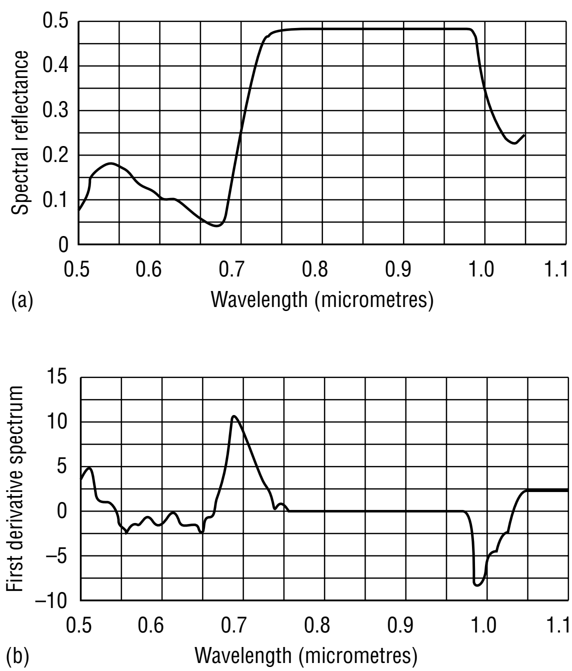
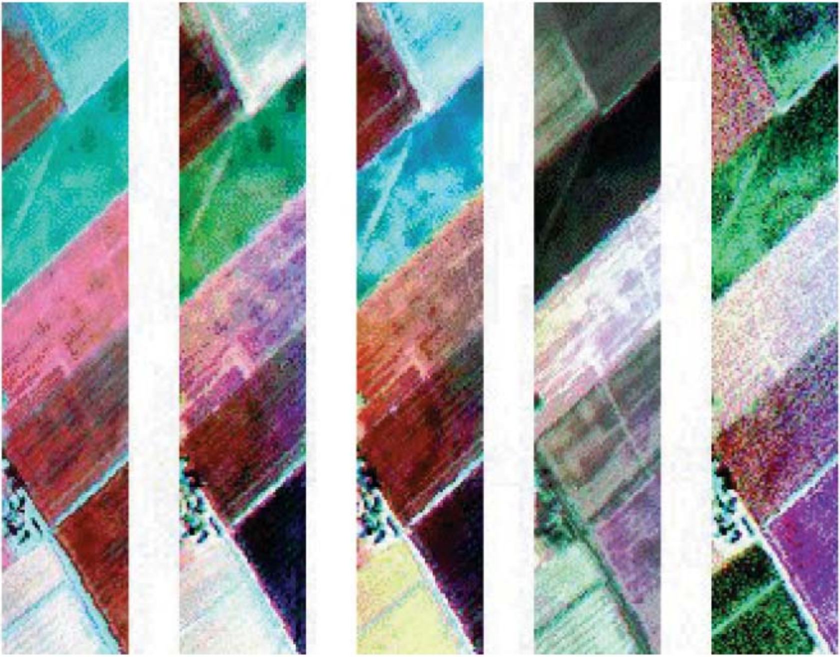


Fig 1. (a) Example leaf reflectance spectrum at visible and near-infrared wavelengths; (b) first derivative spectrum produced from Figure 1(a), showing position of the 'red-edge' (peak in derivative spectrum) at 0.693μm.

1.2.3 Inference and estimation from wave polarisation

Electromagnetic radiation considered in wave form has two fields (electric and magnetic) which are perpendicular both to one another and to the direction of propagation (Rees 1990). The orientation of these two fields, known as the wave polarisation of the radiation, has been observed to change as a result of scattering and reflection within the atmosphere and at the Earth surface. The majority of studies in this area have employed data from the microwave region of the electromagnetic spectrum. For example, polarimetric radar data have been used to distinguish different stands in coniferous forests (Grandi et al 1994) and to assess their biophysical characteristics (Baker et al 1994). A smaller number of studies has explored



(a) (b) (c) (d) (e)

Plate 21 (above)

Comparison between a standard (i.e. multi-spectral) false-colour composite covering an area of arable farmland (**a**), and four single-band, multiple view angle (MVA) false-colour composite images of the same site (**b–e**). The MVA composites have each been constructed using data acquired in a single spectral waveband – (**b**) green, (**c**) red, (**d**) near-infrared, (**e**) middle-infrared – but at three different sensor view angles (two opposing oblique angles, plus nadir). The images show the potential value of directional (angular) reflectance data for distinguishing Earth surface materials.

(*Source:* Barnsley et al 1997a)

polarisation characteristics of Earth surface materials at visible and infrared wavelengths (e.g. Vanderbilt et al 1991; Ghosh et al 1993). This is partly attributable to the paucity of appropriate airborne and satellite sensors, and partly because the polarisation signal is dominated by the atmosphere at these wavelengths.

1.2.4 Inference and estimation from spatial variations

The amount of radiation reflected, emitted, or scattered from the Earth's surface varies spatially in response to changes in the nature (type) and properties of the surface materials. These variations may be continuous, discrete, linear, or localised, depending on the controlling environmental processes (Davis and Simonett 1991). They may also be manifest at a variety of different spatial scales (Townshend and Justice 1990; Barnsley et al 1997b; Figure 2). The relationships between surface type, surface properties, and spatial variability in land-leaving radiance has been exploited using measures of:

- texture – the statistical variability of the detected signal, typically based on the grey-level co-occurrence matrix, measured at the level of individual pixels (Richards 1993);
- pattern – including the size and shape of discrete spatial entities (regions), typically land-cover parcels, identified within the scene, as well as the spatial relations between them (LaGro 1990; Lam 1990);
- context – referring to the structural and semantic relations between discrete spatial entities identified within the scene (Barr and Barnsley 1997).

1.2.5 Inference and estimation from temporal variations

The reflectance, emittance, and scattering properties of most Earth surface materials vary with respect to time. This may be in response to diurnal effects (e.g. changes in the leaf-angle distribution of vegetation canopies attributable to moisture deficiency or heliotropism), seasonal effects (e.g. phenology), episodic events (e.g. rainfall and fire), anthropogenic influences (e.g. deforestation), or long-term climate change. There are several ways in which these temporal variations can be exploited, namely:

- to assist in distinguishing surface materials, by selecting the time of day or year at which the contrast between their reflectance, emittance, or scattering properties is greatest;
- to detect a change in the dominant land-cover type or biophysical property of an area by measuring variations in the amount of surface-leaving radiation over time (known as change detection);
- to determine the physical, chemical, and biological properties of Earth surface materials.

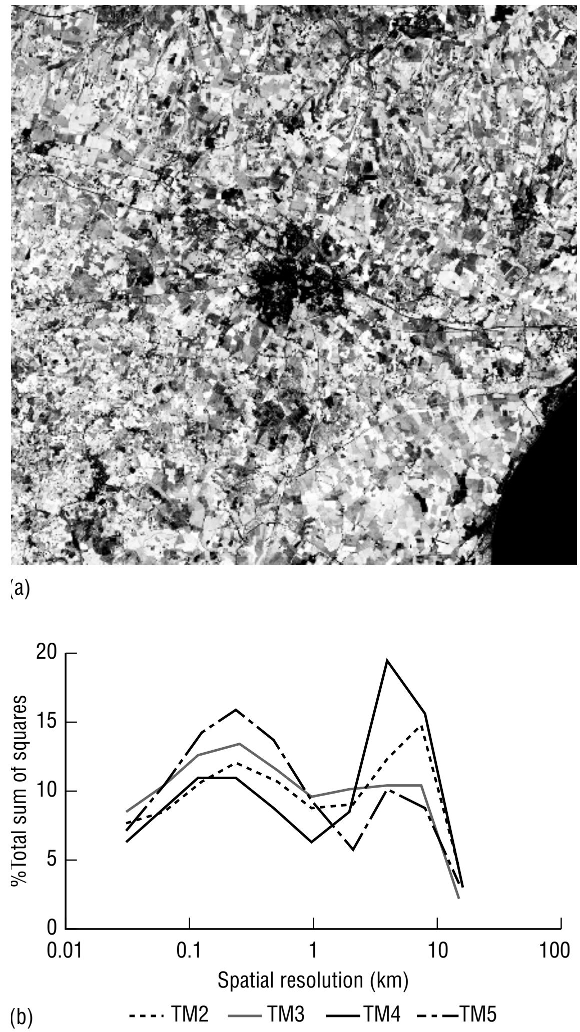


Fig 2. (a) LANDSAT-TM sub-scene (2048 by 2048 pixels; near-infrared waveband) covering part of southeast England; (b) Scale variance analysis (Townshend and Justice 1990) applied to the LANDSAT-TM sub-scene of southeast England (a). The diagram shows the different scales of spatial variability that occur in this scene, indicated by the two peaks in variance at approximately 250m and 5km, respectively. Barnsley et al (1977b) suggests that the first peak corresponds to variation in detected reflectance at the scale of individual field parcels, while the second peak relates to broader edaphic and geological differences across the scene.

For example, the third approach has been used to produce land cover maps at regional and global scales from coarse spatial resolution satellite sensor images (Lloyd 1990). Lloyd's approach is based on an analysis of the date-of-onset, duration, and amplitude of the 'greening-up' curve, derived from a time-series of NDVI values (Figure 3).

2 MEASURING THE SIGNAL

This section considers the impact of sensor and platform design on the ability to record surface-leaving radiation. While some space is dedicated to specific sensor systems and the characteristics of the data that they produce, the intention is not to provide a summary of current and future remote sensing devices. Rather, the aim is to examine the way in which their general design affects the ability to translate the recorded signals into estimates of the intrinsic properties of the Earth surface. Thus, the sensor system is viewed both as a measurement device and as 'filter' to the surface-leaving signal.

2.1 Spectral resolution and spectral coverage

Since most remote sensing studies – particularly those concerned with the use of optical instruments – exploit spectral variations in surface-leaving radiation, it seems appropriate to begin with a consideration of the spectral characteristics of remote sensing systems, namely:

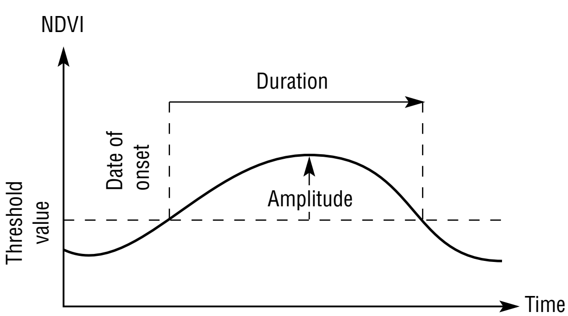


Fig 3. Diagrammatic representation of the variation in the normalised difference vegetation index (NDVI) for a vegetated surface over the growing season. The figure illustrates the concepts of the date-of-onset, the duration, and the amplitude of the 'greening-up' curve used by Lloyd (1990) to map land cover at the regional scale using coarse spatial resolution satellite sensor images.

- the number of spectral wavebands in which the sensor operates (see also Estes and Loveland, Chapter 48);
- the position of these spectral wavebands within the electromagnetic spectrum (spectral coverage);
- the range of wavelengths covered by each waveband (spectral bandwidth or spectral resolution) (Davis and Simonett 1991).

Clearly, the specific configuration adopted for a given sensor is determined by the scientific objectives of the mission, but it is also conditioned by a number of fundamental technical constraints. The latter include the need to locate the wavebands within 'atmospheric windows', the total volume of data that must be handled (including telemetry to Earth, in the case of spaceborne sensors), and the need to achieve an acceptable signal-to-noise ratio (SNR).

2.1.1 Atmospheric windows

The atmosphere scatters and absorbs radiation during its passage from the Sun to the Earth's surface and from the Earth's surface to the sensor. In doing so, it attenuates the amount of radiation reaching the ground and, subsequently, the sensor. It also alters the spectral composition and the angular distribution of this radiation (Diner and Martonchik 1985; Kaufman 1988). The magnitude of these effects varies strongly with wavelength. Sensors designed to study either the land surface or the oceans operate in regions of the electromagnetic spectrum in which the transmission of radiation through the atmosphere is high – known as 'atmospheric windows'. Even so, solar radiation may be scattered within the atmosphere into the path of the sensor without interacting with the Earth surface. Among other things, this component of the signal detected by the sensor, known as path radiance, reduces the apparent contrast between surface materials within the resultant image (Kaufman 1993).

2.1.2 Data volumes and spectral redundancy

Over the last twenty years or so, there has been a continuing trend towards sensors that are able to record data in a greater number of (typically narrower) spectral wavebands, resulting in an increase in the total volume of data acquired. In general, however, the amount of useful information that can be extracted from these data does not increase linearly with the number of available spectral wavebands: there is often a strong statistical correlation between the data recorded in different parts of the electromagnetic spectrum, particularly those from adjacent spectral wavebands. As a result, the intrinsic dimensionality of a multispectral dataset may be very considerably smaller than the number of available wavebands. This is sometimes referred to as 'spectral redundancy'.

2.1.3 Imaging spectrometers and signal-to-noise ratio

Despite the observations made above, one of the major developments in optical sensor technology in recent years has been the advent of imaging spectrometers and imaging spectroradiometers – instruments capable of recording data in tens, or even hundreds, of very narrow (typically contiguous) spectral channels (Vane and Goetz 1993). The manner in which data from these sensors are generally employed differs from that of conventional multispectral scanners. Instead of focusing on the data simply as a set of 2-dimensional images, emphasis is placed on an analysis of the detailed spectral response recorded for each pixel. These can be compared against spectra for a range of different surface materials, drawn either from an on-line library or from representative pixels sampled within the image itself. In addition to the overall shape of the spectra, comparisons can be made in terms of the presence, depth, and width of absorption features associated with specific biochemical constituents. This may allow the analyst to derive detailed information on the nature, properties, and proportions of the different surface materials present in the corresponding area on the ground.

The Advanced Visible and Infrared Imaging Spectrometer (AVIRIS) instrument operated by NASA is one example of an imaging spectrometer (Vane et al 1993). This airborne sensor records data in approximately 200 narrow spectral channels in the region 0.4μm to 2.5μm. One of the penalties commonly associated with the use of narrow spectral wavebands is a reduction in the SNR of the sensor, because of the smaller number of photons admitted to the detector. This can be compensated for by increasing the sensor dwell-time (at the expense of a reduction in the effective sensor spatial resolution) or by combining images from several successive flights over the same target.

A spaceborne imaging spectrometer, known as HIRIS (High Resolution Imaging Spectrometer), was originally scheduled for launch at the end of the decade as part of NASA's 'Mission to Planet Earth' programme (Goetz and Herring 1989). The instrument was, however, de-selected at an early stage because of budgetary constraints. A second imaging spectrometer, known as MODIS (Moderate Resolution Imaging Spectrometer) is due to be launched in 1998/9, although this sensor has a much smaller number of spectral wavebands (30, cf. ~200 for HIRIS) and a considerably coarser spatial resolution (250m to 1 km, cf. 30m for HIRIS; Ardanuy et al 1991).

2.2 Radiometric resolution and radiometric calibration

2.2.1 Radiometric resolution

The radiometric resolution of a sensor can be thought of as its ability to distinguish different levels of reflected, emitted, or scattered radiation. Expressed more precisely, radiometric resolution involves three key concepts, namely:

- quantisation;
- signal-to-noise ratio;
- dynamic range.

A digital remote sensing device converts the radiation incident on its detectors initially into an analogue signal (i.e. an electrical voltage) and subsequently into a digital signal. After the analogue-to-digital (A-to-D) conversion, the detected signal is represented as a numerical value, referred to (somewhat tautologously) as a digital number (DN). The set of possible values for the DN is determined by the quantisation level: thus, if a sensor has 8-bit quantisation, it will record values in the range 0 to 255 (i.e. 2^8 or 256 different levels of incident radiation), where a value of 0 indicates the lowest level of detectable radiance and 255 the highest. The sensor designer must also decide how the range of DN are to be used to record incident radiation. It is possible, for example, to design an instrument that is capable of recording the full range of radiances expected under normal illumination conditions from surfaces with reflectances varying between 0 and 1. Alternatively, if the intention is primarily to observe relatively dark targets, such as the oceans, the dynamic range of the instrument might be limited accordingly. Thus, the set of available DNs would be optimised to distinguish surfaces in the desired range of reflectances, although the instrument response would saturate over brighter targets.

2.2.2 Radiometric calibration

One characteristic of some of the most recent and many of the proposed future satellite sensors is the greater attention that is being given to their absolute radiometric calibration. This ensures that the recorded DN can be related accurately to known levels of surface reflectance (or emittance) (Price 1987). This assists in the retrieval of datasets expressed in terms of standard geophysical units and ensures greater consistency between datasets generated by different sensors, or by the same sensor over a prolonged period of time (Hall et al 1991). The lack of accurate radiometric calibration in early satellite sensors has been one of the major hindrances to the use of these data for long-term regional and global-scale environmental monitoring (Hall et al 1995).

2.3 Spatial resolution

In simple terms, the spatial resolution of a sensor determines the level of spatial detail that it provides about features on the Earth's surface. Beyond this, spatial resolution can be defined in a number of different ways (Forshaw et al 1983). For example, the instantaneous field-of-view (IFOV) defines the (nominal) angle, subtended at the sensor, over which the instrument records radiation emanating from the Earth's surface at a given instant in time. The area on the Earth's surface to which this corresponds, known as the ground resolution element (GRE), is therefore controlled by the IFOV and the height of the sensor above the ground. The actual area of ground from which radiation is incident on the detector is, however, larger than this and is determined by the sensor's point spread function (PSF). Finally, 'pixel size' denotes the area of ground covered by a single pixel in the resultant image. This may differ from the GRE because of the effects of over-sampling, variations in the height of the terrain below the sensor, and variations in the attitude and altitude of the platform on which the sensor is mounted (Forshaw et al 1983).

2.3.1 Impacts of sensor spatial resolution

Images produced by digital sensors can be thought of as 2-dimensional grids or arrays of data cells ('picture elements' or pixels). The spatial resolution of the sensor defines the size of these cells, in terms of the area that they represent on the ground (Plate 22). Thus, a remotely-sensed image represents a spatial regularisation of the observed scene (Jupp et al 1988). One effect of this process is that two or more surface materials may fall within a single pixel, producing a 'mixed pixel' (or 'mixel'). The extent to which this occurs is, of course, dependent on the spatial resolution of the sensor and the spatial variability of the observed surface. The mixed pixel effect has a number of implications for information retrieval from remotely-sensed images. First, the detected spectral response of a mixel will be some composite of the individual spectral signals from the constituent surface materials (Smith et al 1985). Second, the size, shape, and spatial arrangement (pattern) of the major spatial entities present within the scene will be to some extent obscured (Woodcock and Strahler 1987). The first of these two problems has been addressed through the development of a number of techniques designed to 'un-mix' the component spectral responses contained in each pixel (Ichoku and Karnieli 1996). The most widely used of these is linear mixture modelling, in which the composite signal is assumed to be a linear summation of the spectral curves for the component land-cover types, weighted by their relative abundance (i.e. proportion of ground covered) within the pixel. The second problem has received rather less attention in the field of remote sensing, although it is the subject of detailed investigation by landscape ecologists (Barnsley et al 1997b).

2.3.2 Current and future directions

In recent years, there has been an intriguing bifurcation in the spatial resolution of spaceborne optical sensors. One element of this has been the widespread development of 'moderate' (or 'medium') resolution (~1km) devices (as is shown in Table 1 and Figure 4; see also Ardanuy et al 1991; Diner et al 1991; Prata et al 1990). The lineage of these sensors is simple to trace – deriving from the outstanding and, to a certain extent, unanticipated success of the current generation of NOAA's Advanced Very High Resolution (AVHRR) sensors in monitoring the land surface at continental and global scales.

Hand-in-hand with this, there is a continuing trend – initiated with LANDSAT-TM and SPOT-HRV during the mid 1980s – towards sensors with an increasingly fine spatial resolution. This trend has been extended through the availability of data from a range of Russian satellite sensors (e.g. KFA-1000 and KFA-3000), as well as the Panchromatic sensor on-board the Indian satellite IRS-1C, and is set to

Plate 22 (right)
Multi-spectral false-colour composite image comprising data from near-infrared, red and green wavebands. These data were acquired by an airborne scanner over Orpington in the London Borough of Bromley. The spatial resolution of these data is approximately 2 metres. The figure illustrates the type of data that will be available from the new generation of very high spatial resolution, commercial satellite sensors.

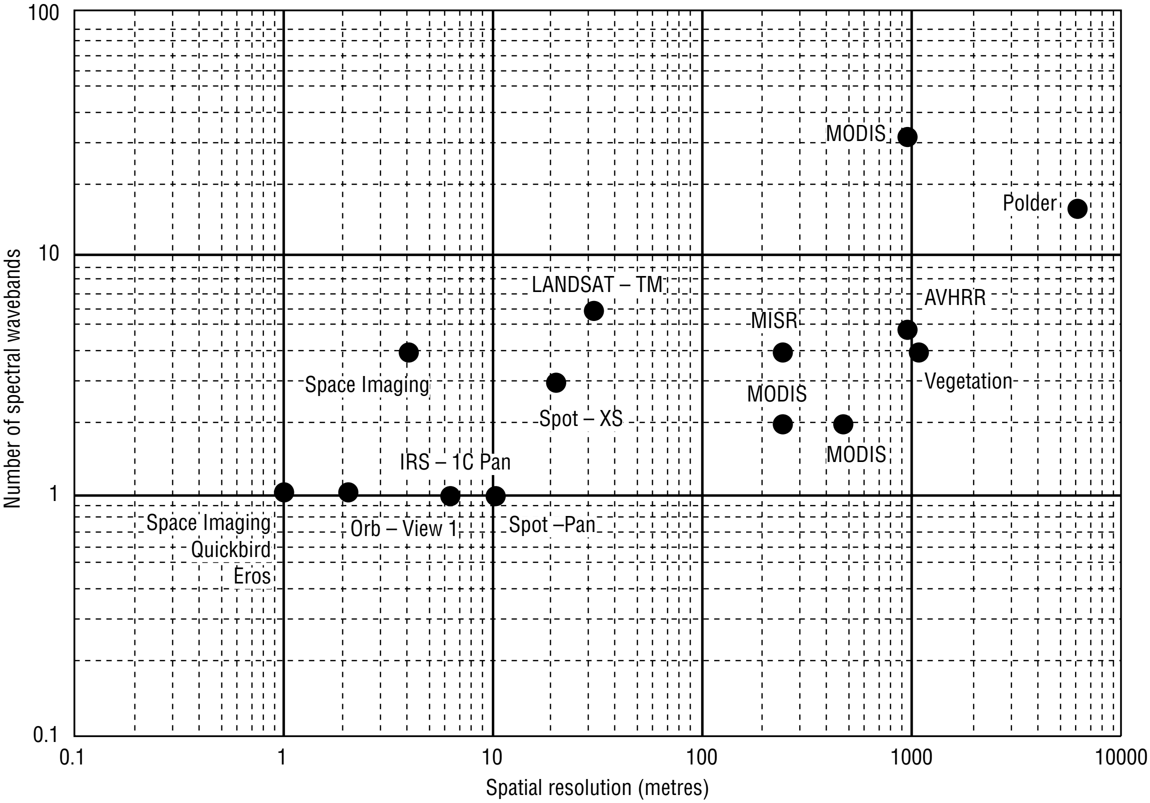


Fig 4. Diagrammatic representation of the range of current and proposed satellite sensors, together with their main spectral and spatial characteristics.

Table 1 Characteristics of a number of 'medium' or 'moderate' spatial resolution satellite sensors currently in operation or scheduled for launch in the next few years. Some other 'standard' remote sensing image sources are set out in Estes and Loveland (Chapter 48) and Dowman (Chapter 31 Table 1).

Sensor	*Satellite*	*Spatial resolution (at nadir)*	*Number of spectral bands*	*Year of launch (actual or projected)*
ATSR-1	ERS-1	1km	4	1994
ATSR-2	ERS-2	1km	6	1995
POLDER	ADEOS-1	6km by 7km	16	1996
VEGETATION	SPOT-4	1.15km	4	1997/8
MODIS	EOS-1 AM	250m, 500m and 1km	30	1998/9
MERIS	ENVISAT-1	250m (land) and 1km (oceans)	15 (programmable in position and width)	1988
MISR	EOS-1 AM	250m and 1km	4	1998/9

continue with the launch of a number of new, commercially-operated satellite devices (Table 2). Each of these instruments will be capable of producing digital image data with a spatial resolution of between 1 and 5 metres (McDonald 1995; Fritz 1996).

2.4 Angular sampling

Interest in the directional reflectance properties of Earth surface materials has grown considerably in recent years, partly in response to the increasing availability of satellite sensors that can record data at several different angles with respect to the Earth surface. This can be achieved in a number of ways (Barnsley 1994), namely:

- by means of a very wide across-track field-of-view (e.g. NOAA's AVHRR sensors, and the proposed SPOT-4 VEGETATION, MODIS, and MERIS [Medium Resolution Imaging Spectrometer] instruments);
- through the use of a very wide field-of-view in both the along-track and across-track directions (e.g. the POLDER [polarisation and directionality of the Earth's reflectances] sensor on board the ADEOS-1 satellite);
- by pointing the sensor off-nadir in the across-track direction (e.g. the HRV [high resolution visible] instruments on the SPOT-series of satellites), the along-track direction, or both;
- through the use of multiple sensors pointed forward, nadir and aft of the platform (e.g. the multi-angle imaging Spectroradiometer [MISR] scheduled for launch as part of NASA's Earth Observing System); or
- through the use of a conical scanning motion (e.g. the Along-Track Scanning Radiometer ATSR on the European remote sensing [ERS] satellites).

The range of view angles and solar illumination angles over which a given instrument can acquire data is controlled not only by the geometry of the sensor, but also by the orbital characteristics of the satellite on which it is mounted (Barnsley et al 1994). In most cases, the actual number of angles at which

Table 2 Characteristics of a number of very high spatial resolution satellite sensors currently in operation or planned for launch in the near future (see also Dowman, Chapter 31 Table 1).

Sensor	*Year of launch (actual or projected)*	*Spatial resolution*		*Swath width*		*Stereoscopic viewing capability*
		Pan	*XS*	*Pan*	*XS*	
KFA-1000	1994	6m	—	80km	—	No
KFA-3000	1994	3m	—	27.5km	—	No
IRS-1C	1995	5.8m	—	70km	—	Yes
KVR-1000	1996*	2m	—	40km	—	No
Earlybird	1997	3m	15m	6km	30km	Yes
AVNIR	1997	8m	16m	80km	80km	Yes
EROS	1997	1m	1.5m	15km	15km	Yes
Quickbird	1997	1m	4m	6km	36km	Yes
Space Imaging	1997	1m	4m	11km	11km	Yes
Orbview-1	1998	1–2m	4m	8km	8km	Yes
GDE	1998	1m	—	15km	—	Yes

* digital format

reflectance data can be sampled is quite limited (Figure 5). Appropriate mathematical models are therefore required to interpolate between, and to extrapolate beyond, these sample measurements to describe and account for the full BRDF. If the models are also invertible, it may be possible to retrieve estimates of certain properties of the surface (e.g. LAI) from the sample directional reflectance data. Various BRDF models have been developed for this purpose, ranging from simple empirical formulations through to more complex, physically-based models. While the latter offer significant advantages in principle, inversion of such models typically demands the use of computationally-intensive numerical procedures. For this reason, attention is currently being focused on the use of so-called 'semi-empirical, kernel-driven' BRDF models, which can be inverted analytically (Wanner et al 1995; Barnsley et al 1997c). These models, however, tend not to be specified in terms of measurable biophysical properties of the land surface, so that further work is required to establish the relationships between such properties and the model parameters.

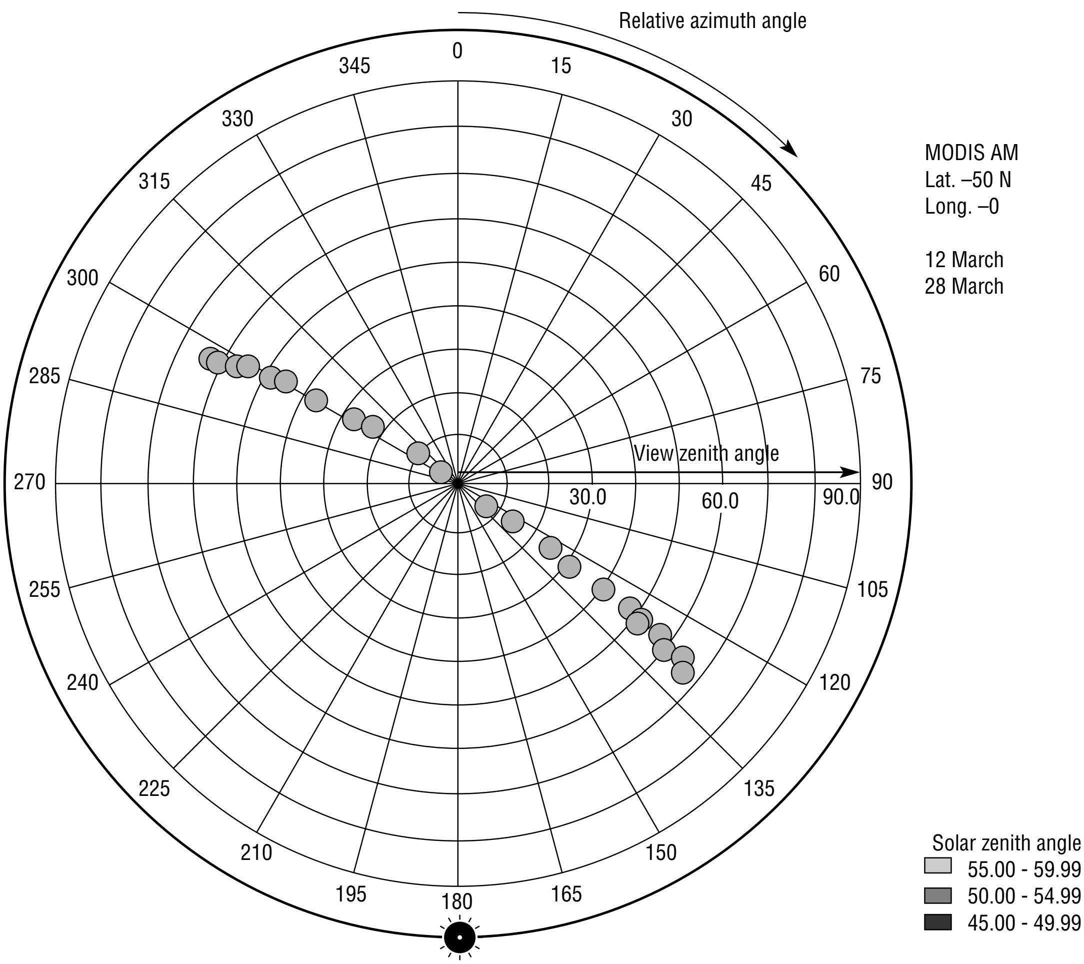


Fig 5. Angular (directional) sampling capability of NASA's proposed MODIS (moderate resolution imaging spectrometer) satellite sensor (in the form of a polar plot) for a fixed site at 50°N over a 16-day period around the vernal equinox (Barnsley et al 1994). Each dot indicates a single occasion on which the sensor is able to observe the target; the position of the dot in the plot indicates the angles at which this was achieved. The figure illustrates the comparatively sparse sample of directional reflectance data that can be acquired using this and other, similar sensors.

2.5 Wave polarisation

The majority of sensors able to measure the polarisation properties of Earth surface materials operate in the microwave region of the electromagnetic spectrum. Sensors such as these can transmit and receive (record) radiation in a given plane polarisation. Where the transmitted and received radiation have the same plane polarisation, the signal is referred to as being like-polarised; where they are of different polarisations, the signal is said to be cross-polarised (Rees 1990). Imaging radar polarimeters can derive a measure of backscattered radiation for any configuration of transmitted and received radiation using a process known as polarisation synthesis (Zyl et al 1987).

The POLDER instrument, launched on board the ADEOS-1 satellite in 1996, offers the capability to measure polarisation properties at visible and near-infrared wavelengths (Deschamps et al 1990). The primary use envisaged for these data is, however, to derive information on atmospheric aerosol properties, rather than the biophysical characteristics of land surface materials.

2.6 Temporal resolution

In simple terms, temporal resolution refers to the frequency with which repeat data can be acquired for a given area on the Earth's surface. This is controlled both by the geometry of the sensor and by the orbital characteristics of the satellite on which it is mounted. In terms of the latter, two main types of orbit are used by Earth-observing sensors, namely: (a) Sun-synchronous, near-polar; and (b) geo-stationary (or geo-synchronous).

Satellites in the first of these two orbits progress in a near-circular path at an altitude of between 500km and 1000km above the Earth's surface. The orbital plane is inclined, so that the satellite passes close to, but not over, the poles (hence 'near-polar'). By taking advantage of precession in the satellite's orbit, it is possible to ensure that the satellite crosses the equatorial plane at approximately the same local solar time on each orbit (hence 'Sun-synchronous'). The rotation of the Earth beneath the satellite means that successive orbits pass over different regions of the surface. Eventually the satellite will complete its sequence of orbits and begin to trace the path of the first orbit again. For a point on the equatorial plane, the period between two such orbits is known as the repeat cycle; LANDSAT-5, for example, has a repeat cycle of 16 days. It is possible to observe a given point on the Earth's surface more frequently than this, depending on the latitude of the site and the configuration of the sensor. Since the satellite's orbital paths converge towards the poles, there is increasing overlap between images acquired on different orbits at higher latitudes; such sites can therefore be imaged more frequently than those at lower latitudes. This effect is also controlled by the field-of-view and, hence, the swath width of the sensor: the wider the swath width, the greater the number of occasions on which a given point can be imaged during the nominal repeat cycle. Even so, key episodic and seasonal events may still be missed because of cloud cover or simply because the event took place while the satellite was tracing another orbit. The former is, of course, less of a problem for active microwave systems, since these can penetrate cloud. The latter can be offset, to a certain extent, by tilting (or pointing) the sensor away from the sub-satellite point (i.e. off-nadir). This allows the sensor to target an area for repeated imaging, even though the satellite is not directly overhead (Barnsley et al 1994).

The second major type of satellite orbit referred to above is the geo-stationary or geo-synchronous orbit. Here, the satellite maintains a fixed position above the Earth's surface, usually at an altitude of around 36 000 km. This orbit is generally reserved for operational meteorological satellites which require frequent coverage (i.e. once every 20 to 30 minutes) of very large areas at a comparatively low spatial resolution (1–5 km) (Kramer 1994).

3 SELECTED DEVELOPMENTS IN DATA PROCESSING

It is not possible, within the scope of this chapter, to provide a comprehensive review of the full range of techniques and algorithms that are used to derive useful information from digital remotely-sensed images; although some have already been mentioned briefly in the preceding sections. Rather, this section attempts to highlight just a few of the most important, recent developments in image data processing.

3.1 Modelling surface-radiation interactions and data assimilation

Perhaps the most significant developments in the processing of remotely-sensed data over recent years have been the increasing focus on converting the detected signals into estimates of key geophysical units and the assimilation of these data into numerical models of various environmental processes (Hall et al 1995; Townshend et al 1995). The first of these two elements is being achieved through the use of increasingly sophisticated, deterministic, radiative-transfer and energy-balance models, some of which have been alluded to in the preceding sections. This general approach is, for example, central to NASA's 'Mission to Planet Earth' programme, embodied in the Earth Observing System (EOS) and its constituent satellite sensors (Running et al 1994). The significance of this development cannot be overstated: it marks the continuing transition of digital remote sensing from being principally an instrument for large-scale (land cover) mapping, to a more comprehensive, robust, and effective scientific tool for environmental monitoring.

The second element – assimilation of remotely-sensed data products into models of, for example, the global carbon cycle, the surface energy balance, and the net primary productivity of the land surface and oceans – is also receiving widespread attention (Running et al 1994; Townshend et al 1995). It reflects the recognition among much of the remote sensing community that, in addition to developing the science and technology to underpin remote sensing *sensu stricto*, there is a need to generate data products that are both appropriate to, and immediately usable by, the broader community of environmental scientists: that the rationale for remote sensing lies not simply in the development of sensors and algorithms, but more importantly in addressing real environmental problems. The scientific challenges that this creates include the requirement (a) to handle very large volumes (i.e. Tera-bytes) of data, often acquired by more than one sensor and/or satellite; (b) to process these data using robust, computationally-efficient, and validated algorithms, based on methods acceptable to most, if not all, of the target community; and (c) to generate usable products at the appropriate spatial and temporal scales, often in near-real time. Ultimately, remote sensing will be measured against how successful it is in meeting these stringent challenges.

3.2 Image classification and segmentation

At a somewhat different level, the production of thematic maps from digital, remotely-sensed images – commonly referred to as image classification – remains an area of considerable research interest. Attention is, however, shifting from the use of standard, statistical classification algorithms to the wider application of artificial neural network (ANN), fuzzy-set, knowledge-based and evidential reasoning techniques (Fischer, Chapter 19; Bezdek et al 1984; Mesev et al 1995; Schalkoff 1992; Wilkinson 1996). The attraction of ANNs, for instance, lies in their ability to 'learn' by example, as well as their relative freedom from assumptions about the statistical distributions of the candidate classes (cf. conventional statistical classifiers, such as the maximum likelihood algorithm; Foody 1992). Fuzzy-set techniques, on the other hand, move away from the notion that each pixel must be assigned a single label drawn from a set of discrete, mutually exclusive classes. In doing so, they provide another way to account for the mixed pixel ('mixel') effect in remotely-sensed images (Foody 1992; see also Fisher, Chapter 13). Finally, both knowledge-based and evidential reasoning approaches offer ways to incorporate ancillary data (e.g. digital map data exported from a GIS), heuristics, and facts or evidence into the classification process (Wilkinson 1996).

Despite these developments, the overwhelming majority of studies continue to use image-classification algorithms that operate at the level of the individual pixel; that is, algorithms in which each pixel is assigned a label solely on the basis of its multispectral response, without reference to those of neighbouring pixels or the context of that pixel within the scene as a whole. By comparison, relatively limited use has been made of syntactic (or structural) pattern-recognition techniques, which operate on discrete, multi-pixel regions (i.e. meaningful spatial entities or 'objects') to infer further, higher-level information about the scene (Schalkoff 1992). Notable exceptions include the studies by Moller-Jenson (1990) and Nichol (1990) – on the spatial generalisation of thematic maps derived from remotely-sensed data – and, more recently, by Barr and Barnsley (1997) – to infer information on land use in urban areas from satellite sensor images. The comparative lack of attention given to syntactic pattern-recognition techniques in remote sensing to date is probably because of the relatively coarse spatial resolution of the images acquired by the current generation of satellite sensors. This results in uncertainty, not only about the nature (i.e. land cover type) of the principal spatial entities present within the scene, but also their morphological properties (e.g. size, shape, and boundaries) and the spatial (e.g. adjacency, containment, distance, and direction) and structural (e.g. 'forms part of') relations between them. This situation is, however, likely to change with the advent of the new generation of very high spatial resolution (<5m), commercial satellite sensors (but see Smith and Rhind, Chapter 47, for a discussion of some residual limitations). Indeed, data acquired by these new sensors demand alternatives to the conventional, per-pixel classification algorithms, if we are to derive information other than simple land cover about the observed scenes. Syntactic pattern-recognition techniques offer considerable potential in this context.

3.3 Integration of GIS and remote sensing technologies

The relationship between remote sensing and GIS has received considerable attention in the literature and, indeed, remains the subject of continuing discussion (Hinton 1996; Wilkinson 1996). Much of this discussion revolves around the scientific and technical issues relating to 'integration' of the two technologies (Ehlers et al 1989, 1991), so that remotely-sensed images can be used both as a source of spatial data within GIS and to exploit the functionality of GIS in processing remotely-sensed data. Despite this, the actual progress towards the goal of full integration is surprisingly slow. While this is undoubtedly due to the very considerable technical challenge of accessing, manipulating, and visualising vector, raster, and tabular data simultaneously, it seems unlikely that technical constraints have been the sole barrier to achieving full integration. It might be argued that competing imperatives in both remote sensing and GIS have tended to draw attention away from the issue of integration. For instance, from a remote sensing perspective, the recent focus on monitoring global environmental change using coarse (~1km) spatial resolution sensors – and the assimilation of the data that they produce into various environmental simulation models – has deflected some of the attention away from the traditional issues of large-scale mapping, which are more closely allied to the concerns and use of GIS. Similarly, one can see a number of other developments – such as the emergence of GIS functionality (albeit fairly limited) within standard office software, the potential for wider access to GIS software via network/Web platforms, and the role and application of multimedia technology within GIS – that have consumed much of the research and development effort in the field of GIS.

Nevertheless, there are at least two reasons why the issue of integration is likely to receive fresh impetus in the near future. The first is the increasing availability of data from the very high spatial resolution, commercial satellite sensors that are scheduled for launch over the next few years. These will produce data appropriate to many of the large-scale mapping projects in which GIS have often been used, and are likely to compete directly with the traditional aerial photography market. The second is that these high resolution images require the development of new data processing algorithms, such as syntactic (or structural) pattern-recognition techniques, to extract the maximum amount of information about the observed scene. There is a considerable overlap between the objectives and functionality of these techniques and those used in mainstream GIS, at least in terms of their potential for spatial analysis, and this may also bring the two communities closer together. Estes and Loveland (Chapter 48) provide a more detailed overview of the management of the data products of new remote sensing technologies.

4 CONCLUSIONS

This chapter has attempted to provide a broad overview of the nature of digital remote sensing, including: (a) the physical, chemical, and biological properties that control the interaction of electromagnetic radiation with Earth surface materials; (b) the impact of sensor and platform design on the ability to record these signals and the nature of the data that are produced; and (c) the derivation of useful information from these data. The coverage has necessarily been brief and somewhat partial. It is impossible, within the scope of this chapter, to do justice to all aspects of the subject. For example, little has been mentioned of the development of remote sensing as it relates to the study of the Earth's oceans and atmosphere, or to the exciting advances that have been made in the application of interferometric synthetic aperture radar (SAR) to measure the morphology and deformation of the Earth's crust. Perhaps some of these aspects are of less relevance to the wider GIS community. What should be apparent, however, is the rapid developments taking place in – and the increasing breadth of – digital remote sensing at the present time. Thus, while remote sensing will continue to be an important source of spatial data that can be used within GIS, the nature of these data is set to change in terms of an increase in their diversity and an improvement in their utility, accuracy, and reliability.

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