16 An Introduction to Temporal-Geographic Information Systems (TGIS) for Assessing, Monitoring and Modelling Regional Water and Soil Processes

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Abstract

In this chapter we introduce the concept of temporal-geographic information systems (TGIS). We first describe some nontemporal concepts of GIS, consider the issues of scale and of continuous and discrete data, and give a brief background to the basis of remote sensing measurements. Using the concept of the 'data construct' as a tool for understanding TGIS data structures, we explain the relationship between characteristics (extent, resolution and density) and domains (attribute, spatial and temporal) of each dataset. Finally, we discuss two emerging issues in TGIS: the assessment of spatial–temporal accuracy and uncertainty, and the use of metadata systems.

我们在本章引入了时态地理信息系统（TGIS）的概念。首先解说 GIS 的非时间概念，考虑了尺度问题、连续数据与离散数据问题，简单介绍了遥感测量的物理背景。从数据构建概念入手，说明 TGIS 数据结构。阐明了每套数据特性（范围、精度和密度）与域性（属性、空间和时间信息）的关系。最后，探讨了 TGIS 中的两个议题：时间空间精度的评估和不确定性，标准格式的数据系统的应用。

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IN THIS CHAPTER we provide background information on some of the techniques that are used to assess the sustainability of regional agricultural systems that are described in subsequent papers in this section. We introduce the concept of temporal-geographic information systems (TGIS) and explain how remote sensing data can be used to generate information for GIS monitoring.

Most readers of this book will have already heard the term 'GIS', which usually connotes analysis in the spatial domain. However, to assess the sustainability of agricultural systems, the temporal domain is also needed; we use the term TGIS to describe this concept. The benefit of using this slightly nonstandard term is that the reader immediately contemplates both the spatial and temporal domains. The concept of adding a temporal element is essentially similar to the notion of integrating remote sensing into GIS (IGIS), proposed by Quattrochi (1993). Theoretical and technical aspects of data integration arising from the inclusion of time in GIS are discussed in detail by Langran (1992), Peuquet (1994, 1995) and Mitasova et al. (1995).

Scale, resolution and extent

Many different definitions of the term 'scale' are in common use in the TGIS community (Quattrochi 1993; Bian 1997; Cao and Lam 1997), and among other agricultural scientists and policy makers who use output from TGIS. The confusion that this situation creates can sometimes be overcome by using the terms 'resolution' or 'extent' rather than scale. Below, we describe some of the different ways in which the term 'scale' is used, and show why alternative terms may be preferable or qualify what is meant by 'scale'.

- 'Cartographic scale' or 'map scale' refers to the ratio first used in the production of paper maps. For example, a cartographic scale of 1:1000 means that 1 mm on the map represents 1 m (1000 mm) on the ground; whereas 1:1,000,000 means that 1 mm on the map represents 1 km (1,000,000 mm) on the ground.
- 'Geographic scale' is a term often used by noncartographic scientists to describe area. In this sense, a large study area is said to have a large scale. The term 'extent' is preferable to 'scale' for describing the size of a study area (which is sometimes referred to by ecologists as the 'spatial domain').
- A third meaning of scale is that of resolution — the smallest element (or grain) that can be distinguished. For example, the resolution of an electronic microscope is much finer than that of a traditional optical microscope, and one minute is a finer measure of time than one hour.
- Finally, and most applicable to TGIS analysis and modelling, there is 'operational scale' or 'process scale'. For example, a single wheat plant operates on a smaller spatial extent than a wheat field.

Time can also be the scalar; for example, a tree will usually have a longer temporal extent than an individual wheat plant. Hence, in a spatial–temporal construct, a tree occupies a larger volume than does a wheat plant. Put simply, trees usually live longer and are bigger than wheat plants. Obviously, in this tree–wheat example, the different life forms are operating at different spatial and temporal scales. Thus, a model generated at one scale may not be totally applicable at another scale (i.e. a model generated for trees may not be applicable to wheat plants). Although this may be obvious in the above example, in complex environmental modelling it is not always easy to determine whether scaling up or down from one extent–resolution domain to another is appropriate. For example, is the model developed for a single tree relevant for modelling a stand of trees or a forest? The answer to this question depends on which process is modelled (which in part determines the transferability of the model across scales) and on data availability. Many models developed for small spatial extents (usually short temporal extents) are 'data-hungry' and are not easily applied to larger spatial extents (usually longer temporal extents). Chapter 1 discusses the question of extrapolating from one scale to another with respect to water balance models.

An area of active research in the disciplines of pedology and hydrology is the aptness of 'upscaling' (going from small to large, in space and/or time, by crossing geographic scales) and 'downscaling' (from large to small). The terms 'upscaling' and 'downscaling' are not equivalent to the terms 'aggregating' or 'disaggregating', respectively (Bloschl and Sivapalan 1995). Upscaling and downscaling involve a fundamental change in approach in the TGIS modelling, whereas aggregating implies combining a scale of measurement and disaggregating implies splitting it. For example, crop yield can be aggregated from a district to a county level simply by adding the district level values together; this is routinely performed on the North China Plain (Chapter 18). Weekly rainfall totals can be disaggregated into daily values using some knowledge of rainfall patterns.

In the original definitions of scale relevant to TGIS (Lam and Quattrochi 1992), the concepts of resolution and extent were, by default, both included in 'geographic scale'. Later modifications (Bian 1997; Cao and Lam 1997) differentiated geographic scale into the related concepts of resolution and extent. To give a spatial example of the concept of extent, the whole of China is a large spatial extent (or 'patch of dirt'). The entire country could not be modelled using 10 m (fine resolution) grid data because the data volumes would be too large to store on current computing hardware and processing would take too long. It is more likely that China would be modelled with 1000 m (coarse resolution) grid data. In terms of temporal extent, processes of soil genesis, which occur over a long time (a large extent) obviously require coarser measurements and descriptions of temporal resolution than do within-season crop water-use processes, which occur over a period of a few months (a short extent).

In hierarchy theory — a type of multilevel modelling used in ecology and landscape ecology — temporal and spatial scales tend to covary in relation to one another. That is, processes that operate over large areas usually occur over long periods, and processes that operate over small areas usually do so over short periods (Bloschl and Sivapalan 1995), as in the tree–wheat example given above. However, this principle does not hold for all environmental sciences. For example, extreme climatic events such as hurricanes and typhoons occur over large areas and have a relatively short duration. Therefore, the cartographic notion of a minimum mapping unit, which is spatial, needs to be extended for TGIS to include a temporal component. The minimum element in TGIS, in both space and time, needs to be placed in the context of both the operational (or process) scale and the resolution (and hence extent) of the study. If the two are not matched, a trend may go undetected because any signal measured will be influenced by the overlay of processes occurring at different spatial and temporal resolutions (and hence extents). Thus, if the resolution in space or time is too small, the process studied will appear as noise and any trend in either time or space will not be evident. On the other hand, if the resolution is too large, an established process may only appear as a slowly varying trend.

TGIS has many different environmental applications. Recent reviews include urban systems (Mesev 1997), agrometeorology (Maracchi et al. 2000), rural land use and associated changes in soil condition (Sommer et al. 1998), drought (McVicar and Jupp 1998), aquatic botany (Lehmann and Lachavanne 1997), hydrologic processes (Gurnell and Montgomery 1998; Rango and Shalaby 1998), regional evapotranspiration (Kustas and Norman 1996), atmospheric processes (Bernard et al. 1998), geomorphology (Butler and Walsh 1998) and oceanographic fisheries (Santos 2000). A common feature of most reviews is the extensive use of remote sensing for what are often considered as two different tasks: monitoring the environment and updating GIS. Here, we consider these two tasks as identical operations.

Geographic Information Systems

Geographic location is a key component of GIS, which themselves are a subset of information systems. There are many information systems that make little or no use of geographic location. For example, in those used by banks and other financial institutions the quantity (i.e. how much money there is) is the main attribute of interest (pardon the pun). However, as such systems become more complex, the temporal components (e.g. calculating interest rates and compound returns on long-term investment strategies) become more important, because quantity depends on factors such as time since a deposit was made or when a loan was established.

Types of data

In GIS, map-type data can be stored digitally, displayed visually and integrated with other data sets. One way to visualise data is as vectors. Vector data are commonly points, lines or polygons, with one, or more, attribute(s) associated with the geographic feature of interest. Examples of point data are meteorological data measurements (e.g. air temperatures, rainfall and solar insolation) and soil pH at a location accurately determined using global positioning system (GPS) technology. Linear data include features such as road, rail and river networks. Attributes associated with a road could be whether it is paved or not and how wide it is. Polygon data are usually thematic maps that include attributes such as administrative boundaries, land use and land cover. Point-based measurements can be interpolated[1] to generate polygon data. For example, soil pH data recorded at many points can be spatially interpolated to produce a map of soil pH.

GIS data are either continuous or discrete (discontinuous). For example, pH units, (which are continuous from 1 to 14) may be stratified into several discrete pH ranges (e.g. $<$ 5.0, 5.0–8.0 and $>$ 8.0) in order to assess the land capability for potential agricultural uses. Although the extent of any of the three domains (attribute, spatial and temporal) may be equal, the continuous or discontinuous nature of the data needs to be known if it is to be used effectively in spatial–temporal analysis (Heuvelink and Huisman 2000).

Spatial analysis

In GIS, different attributes for the same geographic area are separated to allow for spatial analysis. For example, Figure 1 shows five different attributes of the landscape (or 'real world' in GIS terminology) — climate, vegetation, soil, geology and digital elevation. When these five attributes are overlaid, and the landscape stratified into unique combinations, 14 different hydrothermal regions are identified.

An important distinction in GIS is that between land cover and land use. For example, in an area designated 'State forest', the land use is forestry; however, the land cover, which in this case would be mainly forest, may vary from 100% (e.g. old-growth forest) to 0% (e.g. roads or areas which have been clear-felled), with a range in between. Many of the variables mapped in GIS are exclusive; that is, the data are thematic, with each area belonging to one class or another. However, there are several examples where spatial data are not exclusive but depend on the user's perspective. For example, the most valuable asset of a State forest could be its provision of clean water or maintenance of biodiversity (through providing a habitat for flora and fauna). Thematic maps, simulation outputs and all products generated from TGIS need to be

[1] In GIS, the term 'interpolation' refers to values of an attribute at unsampled points being estimated from measurements made at surrounding sites.

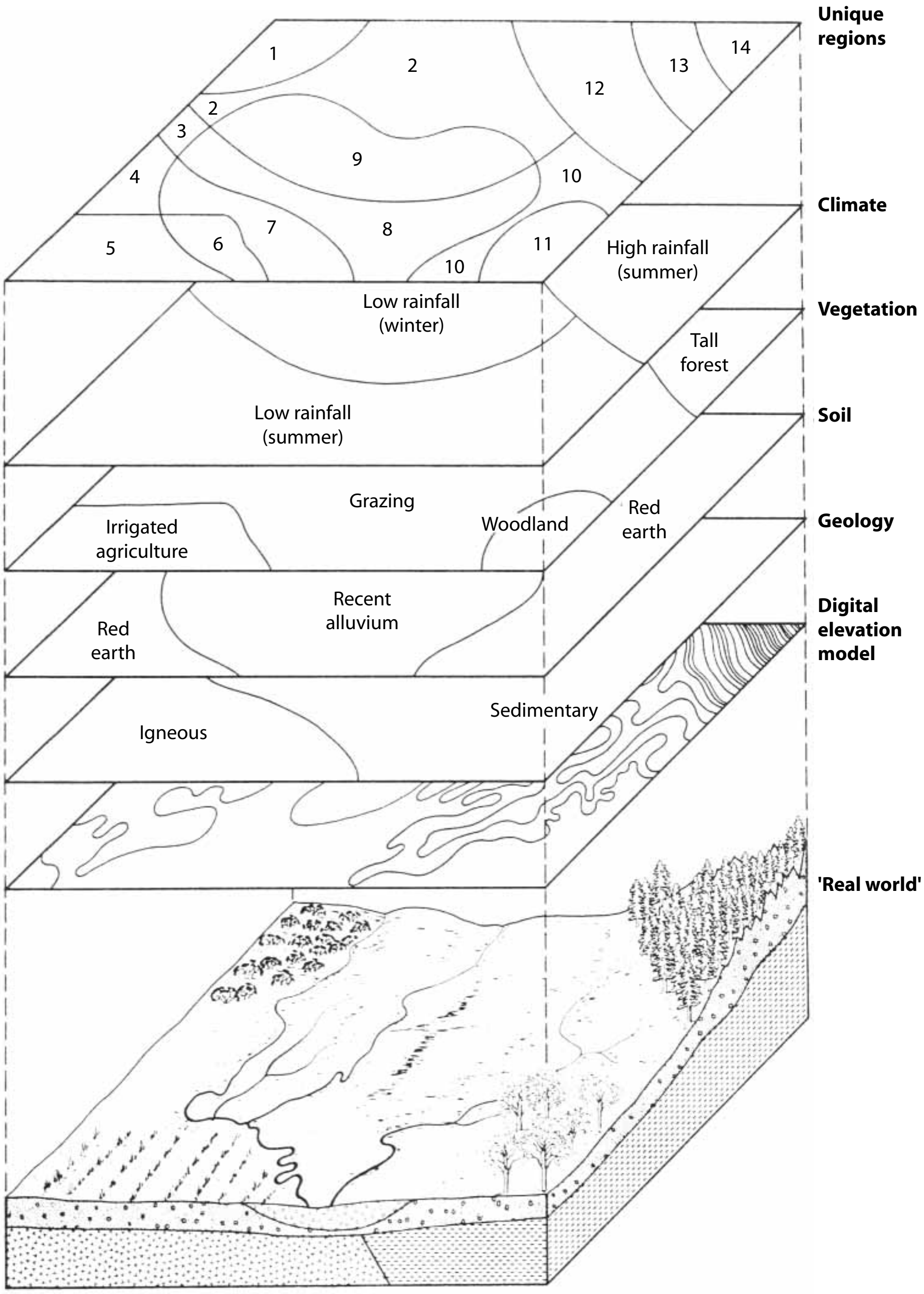

Figure 1. GIS landscape stratification of unique regions, based on five attributes (climate, vegetation, soil, geology and digital elevation model).

critically evaluated because the conclusions can be strongly influenced by the perspective of the user, the accuracy of the data and even the very nature of the data.

Currently, many researchers with point models wish to add a 'spatial dimension'. Three common ways to add a spatial dimension are described below.

- 'Area-weighting' (AW) was first used in the late 1960s and early 1970s; it is simply the multiplication of a response (e.g. crop yield), based on its proportion of a larger area, which is assumed to be homogeneous (Fig. 1).
- The 'interpolate then calculate' (IC) approach involves interpolating all driving parameters and variables, and simulating an output for an entire landscape by running the model at many points, with a given spatial resolution over a given spatial extent. This can be a daunting task given the resolution and extent of the study area, the time interval and length of simulation runs, and the number of parameters and variables.
- 'Calculate then interpolate' (CI) is a recent approach that is gaining popularity. Stein et al. (1991) introduced CI and found that it was preferable to the IC approach; Bosma et al. (1994) came to the same conclusion in the case of small samples. Bechini et al. (2000), estimating global solar radiation in northern Italy, reported that mean square errors using the CI approach were only about half those calculated using the IC method. Chapter 19 discusses the use of a CI approach to estimate moisture availability within the Murray–Darling Basin (MDB).

The AW approach allows remotely sensed data (discussed in detail below) to be classified to provide a potentially rich source of polygon data. Remotely sensed data are usually classified into discrete land-cover classes; these may be amalgamated to land-use classes and then integrated with other data layers in GIS. Remote sensing is stored in a raster (grid) data format; this type of format is most suited to spatially continuous data sets (where each grid cell can be thought of as a discrete element), such as those collected by remotely sensed data sources. Other interpolated data sets, such as digital elevation models (DEMs) or climate surfaces (e.g. monthly maximum and minimum air temperatures and rainfall), may also be stored as rasters.

Remote Sensing

'Remote sensing' is the term used for the acquisition of digital information describing characteristics of the Earth's surface. It involves measuring the electromagnetic spectrum (EMS) using satellite, aircraft or ground-based systems. Characteristically, the information is obtained at a distance (or 'remote') from the target — hence the name. Sensors on board numerous satellites and aircraft can be used in the assessment of sustainable agriculture. In this section we provide some general background information on remote sensing and describe different techniques involved, drawing heavily on material presented by McVicar and Jupp (1998).

Remote sensing data are obtained as digital recordings of the signal strength from specific portions (channels or bands) of the reflective, thermal or microwave portions of the EMS. Figure 2 shows how a satellite records such data. Some satellites orbit the Earth at approximately 700 km, while others are geostationary, located above the equator at some 36 000 km. Computer analysis of the digital images can highlight features of soils and vegetation. Each pixel (picture element) contributing to the image is a measurement of a particular wavelength of electromagnetic radiation at a particular spatial resolution for a particular location at a particular time (minute, hour, day, month and year).

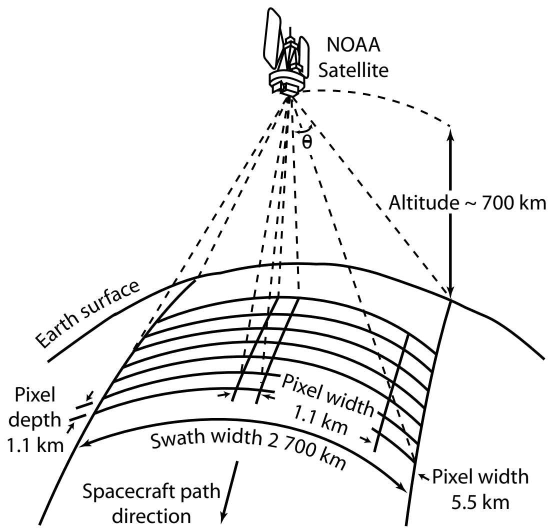

Figure 2. How satellites record data from the Earth's surface (adapted from Harrison and Jupp 1989), specifically NOAA-AVHRR, outlined in Table 1.

Remote sensors can distinguish different types of land cover (e.g. green grass, fine sandy loam and water) by their spectral properties, as shown in Figure 3. This allows the different land covers to be classified (i.e. mapped as separate classes). Remote sensing instruments vary in their ability to resolve the EMS signal. Figure 3 shows the spectral properties of different surfaces as measured by four different sensors. In two of the four cases (Hyperion and MSS) the attribute (spectral) response is continuous; however, because the resolution and extent of the data obtained are very different, the two sensors provide different attribute responses for any particular surface (Table 1). Hyperion, which records 196 calibrated channels, each with a 10 nm spectral resolution, is regarded as a hyperspectral sensor; while MSS is considered a broadband sensor.

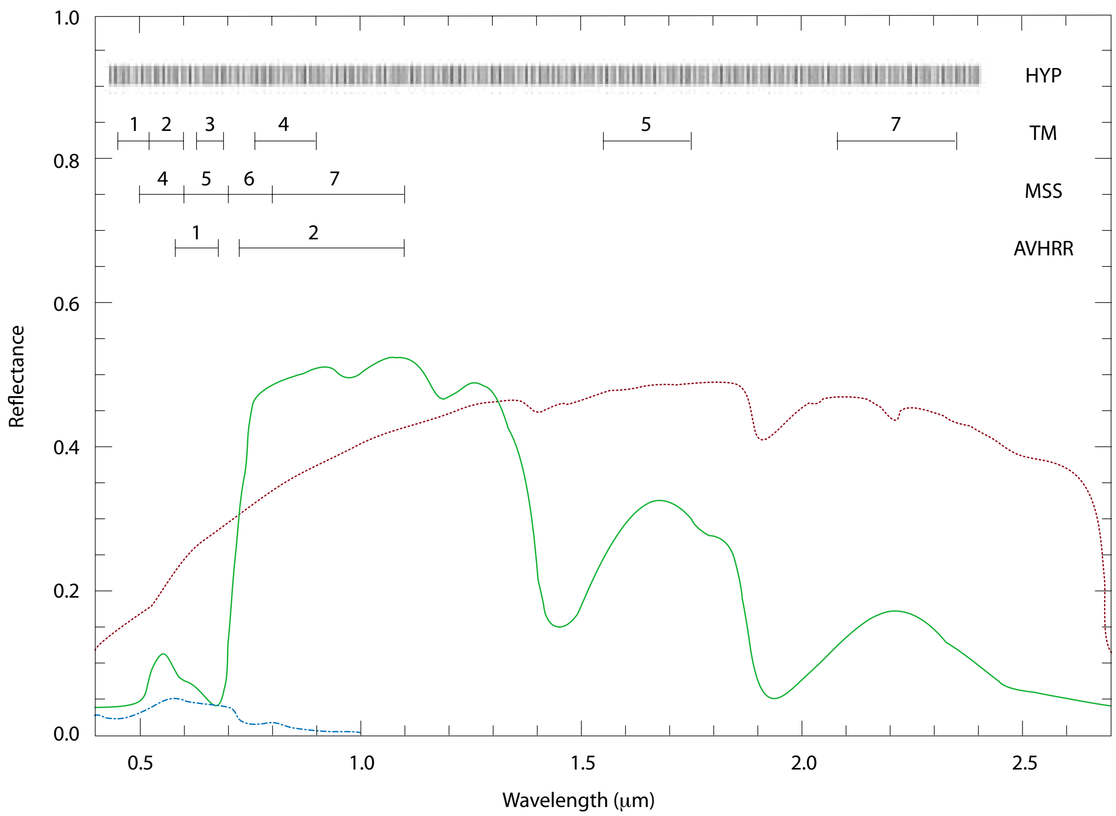

Figure 3. Idealised reflectance plots from 0.4 to 2.7 μm for green grass (solid line), fine sandy loam (dotted line), and water (dash-dot line). The figures show channel resolutions for some typical remote sensing instruments that are further discussed in Table 1. AVHRR = advanced very high resolution radiometer; Hyp = Hyperion; MSS = multispectral scanner; TM = Thematic mapper.

Table 1. General description of some current satellite optical remote sensing based sensors.

Satellite: sensor (quantisation)	Channel number	Spectral resolution	Spatial resolution (in m) at nadir	Sample swath	Repeat cycle	Lifetime
NOAA–AVHRR (10 bit)	1[a]	580–680 nm	1100	2700 km	Every 12 hours	1978 to present
	2	725–1100 nm				
	3	3.55–3.93 μm				
	4	10.5–11.3 μm				
	5	11.5–12.5 μm				
Landsat:MSS[b] (6 and 7 bit)	4	500–600 nm	80	185 km	Every 16 days[c]	1972 to present
	5	600–700 nm				
	6	700–800 nm				
	7	800–1100 nm				
Landsat:TM[d] (8 bit)	1	450–520 nm	30	185 km	Every 16 days	1983 to present
	2	520–600 nm				
	3	630–690 nm				
	4	769–900 nm				
	5	1.55–1.75 μm				
	7	2.08–2.35 μm				
	6	10.4–12.5 μm	120			
EO-1:Hyperion (12 bit)	242 in total	from 436 nm to 2405 nm	30	7.6 km	Every 16 days	Nov 2000 to Sept 2002

AVHRR = advanced very high resolution radiometer; EO = Earth observing; MSS = multispectral scanner; NOAA = National Oceanographic and Atmospheric Administration; TM = thematic mapper; Note 1000 nm = 1 μm.

a From 1978 to 1981 only the first four of these five channels were acquired.

b The Landsat:MSS is a multispectral sensor on board the Landsat satellites. Channels 4–6 are recorded as 7-bit and calibrated to 8-bit; channel 7 is recorded as 6-bit and calibrated to 8-bit.

c From 1972 to 1983, the repeat cycle for Landsat 1–3 was 18 days.

d Landsat:TM is the TM sensor on board Landsat 4 and 5. The channel numbers do not ascend in order of increasing wavelength due to the late inclusion of channel 7. The TM sensor was enhanced on Landsat 7, and is hence abbreviated as ETM. There is an additional 15 m panchromatic channel (520 to 900 nm), and the spatial resolution of the thermal channel (10.4-12.5 μm) has reduced from 120 m to 60 m. Landsat 7 was launched on 15 April 1999.

Remote sensing of the Earth's surface relies on the presence of atmospheric windows — wavelengths of the EMS where a signal generated from properties of the Earth's surface can pass with little, or no, interaction with the atmosphere. Certain areas of the EMS are not suitable for remote sensing because atmospheric constituents absorb all the electromagnetic radiation in particular wavelengths. For example, in Figure 3, Thematic mapper (TM) Channel 5 is in an atmospheric window that extends from around 1.5 to 1.7 μm. Either side of this window (1.45 and 1.95 μm) there is a relatively low reflectance for green grass due to a strong absorption of these wavelengths. Figure 4 shows the divisions of the EMS, some of which are discussed in more detail below.

Remote sensing measurements

The following background provides some discussion of the physical basis of remotely sensed measurements and how the flux of photons is converted into a digital image. The terms and concepts may be somewhat daunting to those not actively involved in remote sensing, and it may help

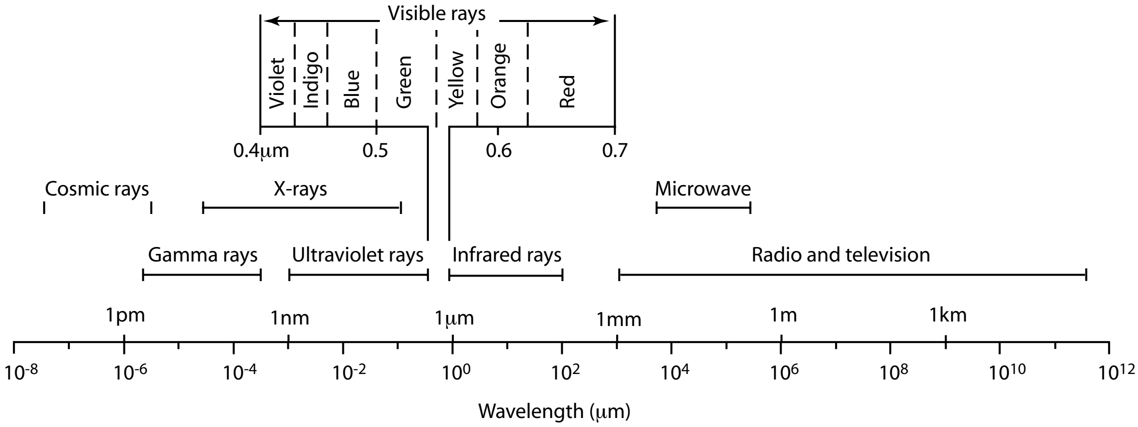

Figure 4. The parts of the electromagnetic spectrum (adapted from Harrison and Jupp 1989).

to think of remote sensing instruments as 'high-tech' cameras that record certain characteristics (extent, resolution and density) for each of the three domains (attribute, spatial and temporal).

Satellites and sensors

Table 1 gives characteristics for selected sensors and satellites on board a few of the Earth observing (EO) satellites used for assessing regional agricultural sustainability; these include NOAA (National Oceanographic and Atmospheric Administration), Landsat and EO satellites. The NOAA series of United States satellites carry the advanced very high resolution radiometer (AVHRR) sensor. The NOAA satellites orbit the poles at a height of some 700 km, similar to the height of the Landsat satellites. Data from NOAA are acquired over a large swath width when compared to the Landsat data; this is due to the wide scan angle (± 55°) of the AVHRR sensor. The local area coverage (LAC) pixel size is 1100 m at the subsatellite point, becoming 5400 m at the edge of the swath. The sensor also records global area coverage (GAC) data, which are a subset of the LAC data and nominally have a 5 km × 3 km resolution. GAC data are derived from LAC data on board the satellite and are recorded at the National Aeronautics and Space Agency (NASA) Goddard Space Flight Centre. Cracknell (1997) provides an extensive overview of the AVHRR sensor, the NOAA series of satellites and some applications of AVHRR data.

The Landsat series of satellites operate at a height of 700 km; they are polar-orbiting, sun-synchronous and pass a given latitude at the same solar time. Landsat 3 had a thermal channel. The main remote sensing system on Landsat 1–3 was the MSS sensor, while the TM sensor was included on Landsat 4.

EO-1 was launched on 21 November 2000 as part of NASA's 'New Millennium' program. One of the main aims of EO-1 is to demonstrate new technologies. The satellite carries three remote sensing instruments: Hyperion, Advanced Land Imager and Atmospheric Corrector. Hyperion is the first hyperspectral satellite-based sensor available for civilian applications; its spectral extent is from 436 nm to 2406 nm. The exact position of Hyperion's 7.6 km wide swath is determined by rolling the EO-1 spacecraft and pointing the instrument. Hyperion's ground resolution is nominally 30 m, similar to TM. To provide the opportunity to cross-validate with the enhanced TM carried by Landsat 7, EO-1 is in orbit one minute after Landsat 7.

Reflective remote sensing

The reflective portion of the EMS ranges nominally from 0.4 to 3.75 μm. Light of shorter wavelength than this is termed ultraviolet (UV). The reflective portion of the EMS can be further subdivided into the visible (0.4–0.7 μm), near-infrared (NIR) (0.7–1.1 μm), and shortwave-infrared (SWIR) (1.1–3.75 μm). Our remote sensing devices (eyes) allow us to see in the visible portion of the EMS, and to distinguish colours through different properties of reflective surfaces. However, there are differences in the way people see shades of certain colours. For example, some people cannot sense subtle changes in colours — things are black or white, there are no shades of grey — whereas more perceptive people sense different shades of grey. In remote sensing, this is akin to the idea of 'quantisation', the term used to refer to the number of possible levels of response. Remote sensing converts an analogue photon flux to digital images, where the number of quantisation levels is a function of the number of bits used to represent the photon flux. The number of quantisation levels equals two to the power of the number of bits. Thus, 7-bit data provide 128 (2^7) levels of quantisation, 8-bit data 256 (2^8), 10-bit data 1024 (2^{10}) and 12-bit data 4096 (2^{12}). The ability of remote sensing measurements to distinguish different properties of the Earth's surface in the EMS is partly determined by the level of quantisation.

Many remote sensing instruments have channels situated in the red and NIR parts of the spectrum (see Table 1). These two reflective bands are often combined to produce vegetation indexes. The most common linear combinations are the simple ratio (NIR/red) and normalised difference vegetation index (NDVI), which is derived from (NIR–red)/(NIR+red). Several publications (Tian 1989; Kaufman and Tanre 1992; Thenkabail et al. 1994; Leprieur et al. 1996) provide comprehensive listings of vegetation indexes.

Figure 5 shows how a typical green leaf reflects light. Chlorophyll pigments in the leaf absorb red light. Radiation in the NIR portion of the spectrum is scattered by the internal spongy mesophyll leaf structure, leading to higher values in the NIR channels. This interaction between leaves and the light that strikes them is one determinant of the different responses in the red and NIR portions of reflective light shown in Figure 5.

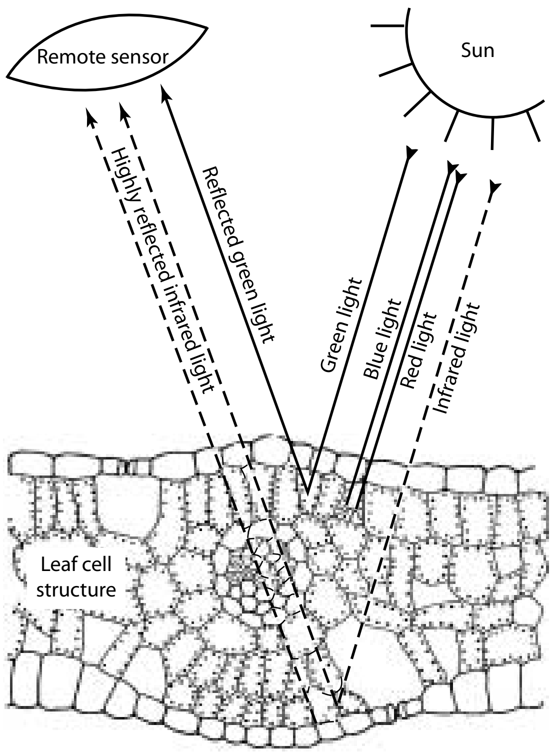

Figure 5. Reflectance of a typical green leaf in cross-section; chloroplasts reflect the green light and absorb red and blue light for photosynthesis. Near infrared light is highly scattered by water in the spongy mesophyll cells (adapted from Harrison and Jupp (1989).

There are positive correlations between NDVI and factors such as plant condition (Sellers 1985); foliage presence (including leaf area index (LAI)) (Curran et al. 1992; Tucker 1979; Nemani and Running 1989; McVicar et al. 1996a; McVicar et al. 1996b; McVicar et al. 1996c); and per cent foliage cover (Lu et al. 2001). Based on the relationship between LAI and NDVI, many previous studies have modelled crop yield by integrating the area under the NDVI curve (denoted ∫NDVI) for all or part of the growing season (Rasmussen 1998a; Rasmussen 1998b; McVicar et al. 2000; Honghui et al. 1999). Some researchers have used regression-based models developed from NDVI data acquired at specific times during the growing season (Maselli et al. 1992; Smith et al. 1995).

The amount of green leaf is one determinant of the signal strength in the reflective portion of the EMS. Several other important factors that affect the acquired value include soil colour and sun-target-sensor geometry.

The following discussion draws heavily on Roderick et al. (2000), whose work elegantly illustrated the effect of soil colour and quantisation on overall reflectance, and showed how change can be distinguished using remotely sensed measurements. The authors assumed a Lambertian surface (one that has no angular dependency), with no shade present and two soils, one dark (5% albedo[2]) and the other bright (30% albedo), with green grass (10% albedo) in the red portion of the EMS. Table 2 shows the simulated landscape's reflectance as the amount of simulated grass cover increases by 20% intervals from 0 to 100%.

On a dark soil, a 20% increase in green grass results in an overall 1% increase in albedo; on a bright soil it results in a 4% decrease. Hence, the albedo of the elements that make up the scene and their relative proportions are important to the overall albedo. We can invert this reasoning and ask 'How much change in green grass is needed to detect a change for different instrument quantisation?' Table 3 shows the results.

For dark soils sensed with a 7-bit instrument, a 15% change in cover is needed to change the recorded digital number by 1. This reduces to 0.5% for a 12-bit system. At the same level of quantisation, a larger relative difference between end-members requires a smaller change in per cent grass cover to detect change. This is because there is a greater difference in the albedo of the end-members when looking at bright soils (20% difference) than when considering the dark soil (5% difference) example.

Table 2. Overall reflectance (%) when the amount of green grass (10% albedo) increases by intervals of 20% cover over a dark (5% albedo) and bright (30% albedo) soil.

Green grass cover (%)	Overall reflectance (%) when on a dark soil	Overall reflectance (%) when on a bright soil
0	5	30
20	6	26
40	7	22
60	8	18
80	9	14
100	10	10

In reality, the land surface is not a perfect Lambertian reflector (Liang and Strahler 2000) — most surfaces in the optical (reflective and thermal) portions of the EMS are strongly anisotropic[3]. The geometry of sun, target and sensor, and the size, shape and spacing of elements (e.g. trees over bare ground) controls the amount of shadow contributing to the signal (Hall et al. 1995). This effect, termed the bidirectional reflectance distribution function (BRDF) (Burgess and Pairman 1997; Deering 1989), is characteristic of vegetation structure in reflective remotely sensed images. This means that in addition to the albedo of the scene elements and their relative proportions, the spatial distribution and the pixel size of observation affect the signal measured by remote sensing instruments (Jupp 1989ab; Woodcock and Strahler 1987; Walker et al. 1986; Jupp and Walker 1996). In addition, the match between the operational scale and the resolution partly controls the strength of relationships between surface properties and remote sensing (Friedl 1997). Image information content is minimal when the resolution is approximately equal to the operational scale (Woodcock et al. 1988ab). Other factors affecting

[2] Albedo is the fraction of light that is reflected by a body or surface.

[3] Anisotropic means having different physical properties in different directions.

Table 3. The change needed in amount of green grass to detect a change for different instrument quantisation levels.

Quantisation	Levels	Precision (1/level)	Change of green grass cover on dark soil (%)	Change of green grass cover on bright soil (%)
7-bit	128	0.007813	15.626	3.907
8-bit	256	0.003906	7.812	1.953
10-bit	1024	0.000977	1.954	0.489
12-bit	4096	0.000244	0.488	0.122

the reflective portion of the EMS include changes in the observed signal due to changes in the atmospheric component of the signal, including atmospheric precipitable water (Choudhury and DiGirolamo 1995; Hobbs 1997), and changes in the response of the sensor over time (Mitchell 1999).

Thermal remote sensing

The thermal portion of the EMS ranges nominally from 3.75 to 12.5 μm. The observed surface temperature is a function of the radiant energy emitted by the surface which is remotely sensed, be it land, ocean or cloud top. Models have been developed to allow surface temperature to be extracted from thermal remote sensing data. Prata et al. (1995) review the algorithms and issues, including land emissivity estimation, involved in the calculation of land-surface temperature, denoted T_s.

Thermal remote sensing is an observation of the status of the surface energy balance (SEB) at a specific time of day. The SEB is driven by the net radiation at the surface. During the daytime, the net radiation is usually dominated by incoming shortwave radiation from the sun, the amount reflected depending on the albedo of the surface. There are also longwave components that well up and down. At the ground surface, the net all-wave radiation is balanced between the sensible, latent and ground heat fluxes. The ground heat flux averages out over long periods of time; thus, the SEB represents the balance between the sensible and latent heat fluxes. During the day, T_s is partially dependent on the relative magnitude of the sensible and latent heat fluxes (Quattrochi and Luvall 1999; McVicar and Bierwirth 2001). This is exploited in the mapping of regional moisture availability for the MDB, as reported in Chapter 19.

Remotely sensed thermal data are also recorded at night. At this time, the SEB is dominated by the release from the ground of heat that was absorbed during daylight hours, which is governed by how much heat was absorbed during the day and the rate at which it is released after sunset. The environment's capacity to store heat depends on the amount of water it is storing.

Microwave remote sensing

The microwave portion of the EMS ranges nominally from 0.75 to 100 cm. Radio signals have wavelengths that are included in these bands. These systems can either be active (the sensor sends its own signal) or passive (the background signal from the Earth's surface is observed). This range of the EMS is further divided into five smaller sections that are used for remote sensing (Table 4).

Both passive and active microwave observations have been used to determine the near-surface soil moisture for a number of experimental field sites. Radar (radio detection and ranging), is an active system based upon sending a pulse of microwave energy and then recording the strength, and sometimes polarisation, of the return pulses. The way the signal is returned provides information to determine characteristics of the landscape. Radar has been used in the determination of near-surface soil moisture. Table 5 gives technical specifications of the current satellite radar systems — the Japanese

Earth Resources Satellite (JERS), the Earth Resource Satellite (ERS) and the RADARSAT. JERS observes the Earth's surface using eight spectral bands in the reflective portion of the EMS. ERS was launched and is operated by the European Space Agency. RADARSAT is a synthetic aperture RADAR (SAR) on board a Canadian satellite.

A 'Data Construct' Perspective

Within TGIS remotely sensed data, GIS data, point-based measurements and model outputs (either point and spatial) can all be integrated, as they all have spatial and temporal characteristics associated with the data attribute. Economic and social data can also be integrated as they too have temporal and (usually) spatial components. Some data used to assess regional agricultural sustainability are 'aspatial' in that they do not have a precise spatial reference (e.g. wool prices or interest rates), but the temporal nature of these variables can be incorporated into larger information systems.

The integration of several data types, usually with varying spatial–temporal characteristics, allows for more objective determination of agricultural sustainability. In the chapters in this section, the data used depend in part on the specific issue that is being modelled under the broad topic of 'regional agricultural sustainability'.

Temporal aspects of TGIS

Time plays a minimal part in some aspects of TGIS modelling. For example, in most environments there is little or no acknowledgment of the temporal attribute of DEMs — because it is generally temporally invariant, the time when the data was captured is of little relevance. However, in other aspects of TGIS modelling, time is an important component (e.g. in the case of active erosion, soil characteristics changing in response to changes in vegetation, soils becoming acidified, or crop water use and irrigation scheduling through the growing season).

Temporal component of DEM

Elevation varies with time in some circumstances; for example, in small, deep actively eroding gullies on the Loess Plateau (as described in Chapter 10). The DEM for these small parts of the plateau may need to be updated perhaps every two years, or possibly after heavy episodic rainfall events that instigate erosion. In contrast, the DEM for the entire plateau may be updated only when there are major technological and methodical advancements

Table 4. The parts of the microwave section of the electromagnetic spectrum used for remote sensing.

	Band				
	P	L	S	C	X
Wavelength (cm)	100–30	30–15	15–7.5	7.5–3.75	3.75–2.4

Table 5. Technical specifications of current satellite- based radar data.

Sensor	Wavelength	Pixel size (m^2)	Incidence angle	Polarisation	Swath width (km)	Recorded since	Current repeat cycle
JERS	L-band	18	35°	HH	75	June 1993	44 days
ERS	C-band	12.5	23°	VV	102.5	Sept 1991	35 days
RADARSAT	C-band	100	20–49°	HH	500[a]	Nov 1995	3 days

ERS = Earth Resource Satellite; JERS = Japanese Earth Resources Satellite; RADAR = radio detection and ranging
[a] The ScanSAR wide mode is reported here, as it has the largest swath width and therefore has the most potential for regional agricultural assessment through electrical conductivity. The large incidence angle means that the repeat cycle is only a few days. However, the entire 30º range may not be suitable for the accurate estimation of soil moisture.

in producing such measurements, perhaps every 20 years. The date when data are captured can be used to model rates of erosion (in units of cubic metres of soil lost per year) and to monitor the movement of gully fronts. On the Loess Plateau, authorities can use such data to ensure the long-term viability, based on geomorphic stability, of roads and rail networks. Massive expenditure is required to construct new highways and railways to support the increased transport of goods and services in China's rapidly developing economy. Therefore, it is important to ensure that transport pathways are not placed in positions where they will need constant maintenance (or even rebuilding) because of slump erosion in gullies after heavy rains.

Temporal components of soils

Temporal data can also be important for soils. Certain physical properties, such as water-holding capacity, may be considered temporally inert, and therefore may need to be mapped only once. However, TGIS scientists need to understand the processes that control the water-holding capacity of soils in order to take these processes into account. For example, there are plans to control erosion on the Loess Plateau and rising watertables in southeastern Australia by replanting vast tracks of land with deep-rooted perennial vegetation. This change in land use will have a range of effects (spatial and temporal) on the soil:

- The initial vegetation type replanted will depend on environmental considerations such as rainfall amount and seasonality, and may be a mix of trees, shrubs or grasses. The mix is likely to change with time, as soil conditions improve.
- Changing the land use from agricultural systems based on cropping or grazing to deeper-rooted perennial vegetation will usually, over time, result in increased levels of organic matter and nutrients (N, P and K) in the top layers of the soil.
- The changes to the top layers of soil are likely to change infiltration rates and soil water-holding capacity, especially for soils relatively close to the surface.
- If areas are replanted with shrubs, changes to the soil properties are unlikely to be constant because the plants will induce spatial variation: soil that is close to the shrub will be influenced more quickly and intensely than soil further away as a result of organic matter produced by the plant. This potential influence at the microscale will reduce with time, as the shrubs grow bigger and plant material is laterally distributed by water and wind flowing over the soil surface.

The concept of soils being in motion due to combinations of wind and water systems, operating at different space and time scales, with varying residence times between motions, can make it difficult to understand the origins of present-day soil properties (Gatehouse et al. 2001). TGIS can help to provide conceptual models of landscape evolution that can be used to assess the impact of possible management actions on a range of landscape functions.

A further example of the importance of time to soil spatial data is the identification and monitoring of soil degradation due to waterlogging, which in southeastern Australia leads to the development of acid sulfate soils. Knowing when data was captured allows scientists to assess the rate of change of acid sulfate scalds. More importantly, such monitoring will allow conceptual models of the processes governing the development of acid sulfate soils to be further refined.

Temporal components of water balance

Assessment of spatial–temporal patterns and trends in regional ecohydrology often involves the use of time-series data, such as in situ regional yield estimates, water use figures and remotely sensed data. Because it provides repeated measurements at a particular spatial resolution and electromagnetic wavelength, remote sensing makes it possible to monitor dynamic environmental conditions. This is illustrated in Chapter 19 for assessing moisture availability in the MDB and in Chapters 18 and 20 for vegetation cover.

Data are usually integrated from several different sources, all with varying TGIS data constructs. In order to spatially monitor (or temporally map) an issue concerning regional agricultural sustainability, it is helpful to think of the data construct as a cube, in which two of the three dimensions are spatial (latitude and longitude) and one is temporal. To provide a culinary analogy, the data construct for monitoring moisture availability in a region (as in Chapter 19) could be thought of as pancakes of remotely sensed data intersected at right angles by skewers of point-based meteorological data. In some situations, more complex spatial–temporal data models are needed (e.g. event-driven and four–dimensional data models) (Peuquet 2001; Chen and Jiang 2000; Zhang and Hunter 2000). For example, in modelling the movement of pollutants in groundwater and the atmosphere, the extra dimension of elevation (or depth) must be included in the TGIS data construct. The most appropriate spatial–temporal data model to use will depend on the application, and there are subtle interactions between database design and utility that should be taken into account (Roddick et al. 2001; Abraham and Roddick 1999).

Linking remotely sensed data with meteorological data (as in Chapter 19) illustrates the concept of the ‘data construct’, as the two types of data have very different spatial, temporal and attribute characteristics. For example, cloud-free AVHRR data for the land surface may be available only weekly; whereas some meteorological variables are recorded as daily extremes (maximum and minimum air temperatures), daily averages (vapour pressure) or daily integrals (precipitation and solar radiation).

Spatial aspects of TGIS

Remotely sensed data are spatially dense because the image is a census at a particular spatial resolution and electromagnetic wavelength rather than a point sample. There is a contrast between spatial density of remote sensing and isolated meteorological stations or field sites. For example, meteorological stations may be 200 km apart but remotely sensed data might be measured at a spatial resolution of 1 km for each of those 200 km.

While GIS data may cover entire regions, they are often produced from the spatial interpolation (or extrapolation) of point samples; this is frequently the case for meteorological and soil data. In these instances, the spatial extent of the GIS data may appear to be complete, but in fact the spatial density of the input data is low. For example, a thematic map of soil classes may be developed from a series of observation points located every 5 km^2 for a 1000 km^2 area. The data from these 200 point samples are interpolated to characterise the soils for the larger area. Whether or not this is valid will depend on the spatial autocorrelation of the soil property being mapped. If the soil is uniform, only one observation may be needed to characterise the entire area, whereas if the soils vary considerably, the 200 observations may provide a poor representation. Soil maps are currently generated using stratified soil sampling based on continuous data sets. Where such data are radiometric or DEMs, they are usually obtained from interpolation of point or linear data, so it is important to track the density of the input data. Also, some error analysis of the interpolation process used to create the surface should be included in the associated metadata system.

To fully understand the data construct of all data sets being integrated in a TGIS for a specific application, it is useful to consider the characteristics of each data set in terms of a three-by-three matrix. The attribute (spectral), spatial and temporal characteristics can be defined in terms of the extent, resolution and density of the different data sets (Table 6). In order to use TGIS effectively to assess and monitor the agricultural sustainability of a region, all the elements that make up this matrix need to be taken into account.

Emerging Issues

Accuracy and uncertainty assessments

For geospatial simulation modelling, including AW, IC and CI approaches, sensitivity analysis is needed to determine the uncertainty of the final output (Mowrer and Congalton 2000). Sources of uncertainty include both input data and the model itself (Heuvelink and Pebesma 1999). Recently, Gahegan and Ehlers (2000) provided a framework to model uncertainty when linking remotely sensed and GIS data, but they assumed that remotely sensed data would be used only in a thematic (or discontinuous) way. In analysing uncertainty and error propagation in GIS, positional accuracy is often forgotten; this may become an issue for institutionally available GIS data in Australia (Van Niel and McVicar 2001; Van Niel and McVicar 2002). There are many methods for assessing the accuracy of thematic maps derived from the classification of remote sensing data (Fenstermaker 1994); these should be used to estimate overall accuracy, user and producer accuracy for the map, and how each class can best be used in TGIS analysis.

Metadata

Awareness of the importance of metadata (data about data) in TGIS is increasing. As monitoring frameworks extend, any changes in the measurement system or processing must be recorded, to allow those undertaking retrospective analysis of such data sets to understand the genesis of the data. This is also true for data collected over large areas, possibly by many individuals. Operational agencies that collect and disseminate data routinely (e.g. national meteorological and national mapping agencies) allocate many resources to ensuring that metadata are collected, updated and readily available. A metadata system to comprehensively study long-term, large-area environmental issues is becoming a central part of any TGIS. In short, the metadata are at least as important as the data. In TGIS, if there are no metadata, there may as well be no data. A crucial part of a comprehensive metadata system is keeping track of where data are stored and of their current backup status. Assessing the quality of data is also

Table 6. Matrix showing characteristics of remotely sensed data sets in terms of their domain.

	Characteristic		
Domain	Extent	Resolution	Density
Attribute (spectral)	Portion of the EMS being sampled	Bandwidth	Number of bands in a particular portion of the EMS (e.g. hyperspectral sensors have higher spectral density than broadband instruments)
Spatial	Area covered by the image	Smallest pixel or picture element acquired	Complete[a]
Temporal	Recording period over which the data are available[b]	Period of data acquisition[c]	Repeat characteristics of the satellite (and, for some applications, the availability of cloud-free data)

[a] This contrasts with the potentially lower spatial density of point observations
[b] For some remotely sensed systems (e.g. Landsat MSS) data have been recorded for 25 years
[c] For remotely sensed systems this is a matter of seconds, which contrasts with point data such as the daily rainfall totals recorded at meteorological stations

important in developing TGIS. This is easier in the case of data collected directly by the TGIS developer than it is for data that are collected by others or obtained remotely and then integrated into the system. The issues of metadata and the data life cycle (Goodchild 2000) need to be comprehensively addressed, especially for institutionally maintained and distributed data.

TGIS researchers working alone or in small groups may have no or little understanding of issues relating to metadata. However, if they wish to become part of interconnected TGIS studies, they must give due consideration and resources to this issue. During the course of this ACIAR project (July 1997 to June 2001), there was a rapid increase in the number of databases available from the internet for China, Australia and other countries. Evidently, global 'interconnectedness' is only beginning.

Conclusions

The spatial–temporal data construct of regional databases can be used to monitor and assess the sustainability of agricultural production within the broader environmental context. Data are integrated from a variety of sources, and information extracted by empirical relationships, 'data-mining' and spatial–temporal process models.

For all geographic regions, spatial and temporal trend analysis of regional agricultural sustainability (and other variables) must be based on data. Currently, there is a mismatch between the data that are available and what is required to infer causal relationships between measures of regional agricultural sustainability and agricultural practices for large areas over long periods. The collection of data and the quality and availability of databases are major issues facing organisations involved in research and policy of regional agriculture. These issues need to be addressed by those managing agricultural, water and land resources.

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