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Remote Sensing Scale and Data Selection Issues

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INTRODUCTION

Remote sensing can be termed a mature discipline, in the sense that the underlying physical principles are well understood, and applications are beginning to appear in operational contexts spanning a diverse array of applications. In addition, the supporting technology has evolved to the extent that image acquisition, field work, and digital analysis are today much more sophisticated than in the early days of analog imaging, computer mainframe-based processing, and qualitative analysis. However, with the wide range of remotely sensed data that is now available, the rapid and continued advances in the power and storage capacity of modern desktop computers, and the sophistication of the many software packages available, remote sensing is far from a static field. Indeed, the last decade has seen the development of commercial fine resolution remote sensing from space (Toutin, in this volume), the exponential growth of lidar (also known as airborne laser scanning) (Hyyppä et al., in this volume), and the increasing sophistication and automation of image processing, to name just a few examples. This rapid evolution of remote sensing technology suggests that there is a need for a periodic and relatively comprehensive review of the field of remote sensing. This book is an attempt to address that need.

In this introductory chapter we lay the groundwork for a theme that is common throughout many of the chapters in this book, namely, the tradeoffs and issues that should be considered in selecting data for a specific problem. For example, in Chapter 25 Wulder et al. consider data selection within the context of vegetation characterization, and in Chapter 31, Crews and Walsh review data selection from the perspective of social scientists. This introductory chapter provides a broad perspective on this important topic.

Ironically, selecting data is today more challenging than in the past, a consequence of the wide range of data currently available. In the past, few remotely sensed data sets were available, and consequently the properties of the available data tended to determine the nature of the problems that could be addressed. Thus, an important part of early remote sensing research using the Earth Resources Technology Satellite (ERTS, later renamed Landsat) was simply to ask the question, “What can we do with these new data?” Today, we have a vast array of data to select from in remote sensing, and so a new problem has emerged – how do we optimize the data characteristics that we use, so that the data will most effectively address a particular application or research problem? It should thus be clear that the definition of an optimal data set is entirely dependent on the aims of the project for which the data are intended.

Adding to the complexity of choosing data attributes are three related issues. Firstly, there are fundamental physical and engineering trade-offs that limit the nature and detail of the data that can be collected using an imaging system (Kerekes, in this volume; Figure 1.1). These constraints help explain the design choices made in satellite-borne sensors, and likewise need to be considered by those planning their own custom acquisitions of aerial imagery (Stow, in this volume).

A second issue that makes selecting the appropriate data for a project complex is that, just as too little data will likely reduce quality of the analysis, data with too much detail may also have a negative effect (Latty et al. 1985). It is intuitive that too much spatial detail can be burdensome for a computer-based analysis, and the same principle applies to other components of imagine information, including the spectral, radiometric and temporal scales of the data. For example, Hughes (1968) showed that an excessive number of spectral bands can lead to lower classification accuracy, an observation that is known as the *Hughes phenomenon* (Swain and Davis 1978).

The last issue, perhaps the most important of the three, is the need to match the scale of the analysis to the scale of the phenomena under investigation (Wiens 1989). Inferences drawn from an analysis at one spatial scale are not necessarily valid at another scale, an issue known in ecology as *cross-level ecological fallacy* (Robinson 1950, Alker 1969). In geography, the dependence of observed patterns on how data are aggregated is known as *the modifiable areal unit problem* (MAUP, Openshaw and

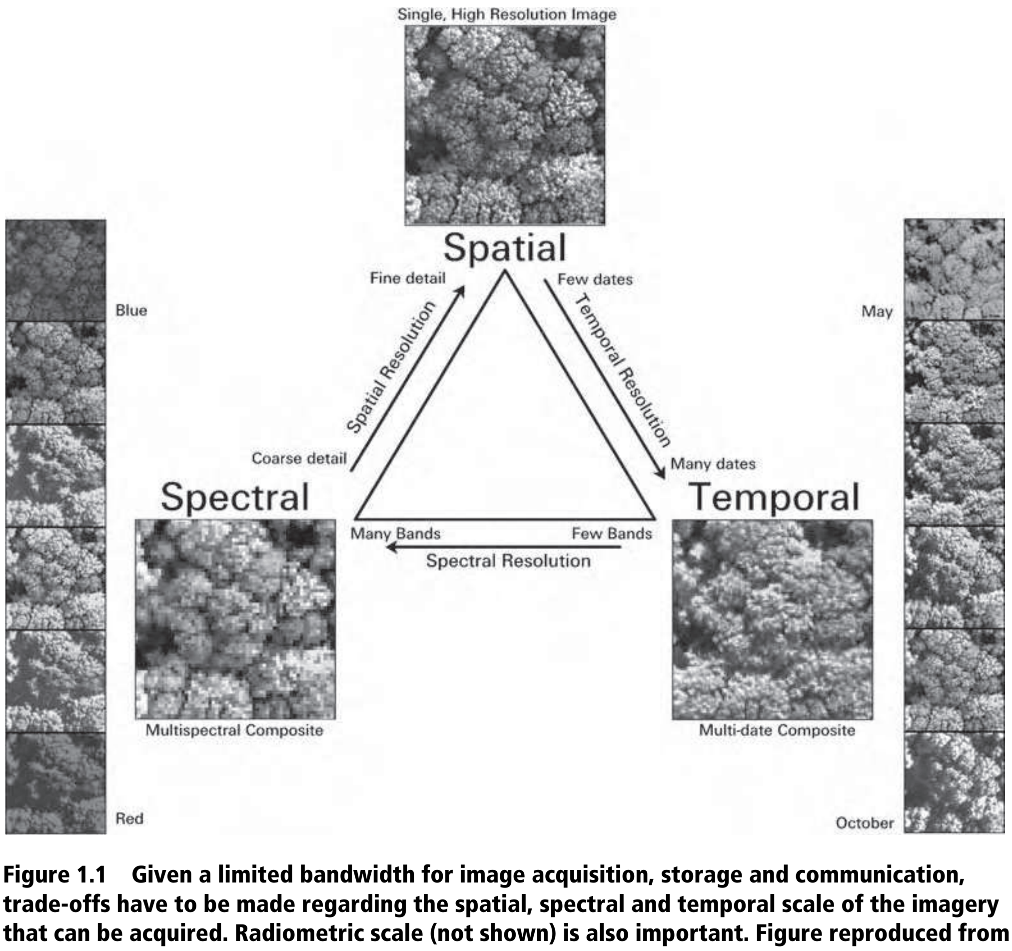

Figure 1.1 Given a limited bandwidth for image acquisition, storage and communication, trade-offs have to be made regarding the spatial, spectral and temporal scale of the imagery that can be acquired. Radiometric scale (not shown) is also important. Figure reproduced from T. Key, T. Warner, J. McGraw, and M. A. Fajvan, 2001. A comparison of multispectral and multitemporal imagery for tree species classification. *Remote Sensing of Environment* 75: 100–112.

Taylor 1979, Openshaw 1983, 1984). The MAUP has two components (Jelinsky and Wu 1996):

- The scale problem, which focuses on how results may vary as the size of the aggregation units (pixels, in the typical remote sensing analysis) varies.
- The zoning (or aggregation) problem, which focuses on how the results may vary as the shape, orientation and position of the units vary, even as the number of aggregation units is held constant.

In remote sensing, attention has usually focused on the MAUP scale problem, and less attention has been applied to the zoning problem (for an exception, see Jelinsky and Wu 1996), because most pixels are assumed to represent a similar, approximately square shape. However, NOAA Advanced Very High Resolution Radiometer (AVHRR) Global Area Coverage (GAC) data is produced by aggregating a linear-oriented subset of finer scale Local Area Coverage pixels (Justice and Tucker, in this volume), thus potentially opening the GAC data to zoning problems. Clearly, both scale and zoning MAUP problems are potentially present when ancillary vector-derived data are used in a remote sensing analysis (Merchant and Narumalani, in this volume).

Woodcock and Strahler (1987) provide a useful remote sensing conceptual framework that categorizes images based on the size of the pixels relative to objects in the scene. Thus an H-resolution image has pixels small enough to resolve objects or phenomena of interest in the scene. In contrast, in an L-resolution image, the pixels are too large to resolve the individual objects. However, most scenes have objects at a variety of scales, and therefore it may be more useful to refer to H- and L-resolution image elements, both of which are likely to be present in any one image (Ferro and Warner 2002).

Central to the ideas presented so far is the concept of scale (Quattrochi and Goodchild 1997, Walsh et al. 1997, 2003, Marceau and Hay 1999, Spiker and Warner 2007). Landscape ecology recognizes scale as having two attributes: grain and extent (Turner et al. 2001). Although there are numerous definitions of these terms, for our purposes we will define *grain* as the finest level of measurement, the degree of detail, or the sampling unit. An example of grain is the instantaneous field of view (IFOV) of the sensor, which in turn is related to the ground sampling distance or ground resolution element, depending on the context. (Although pixel size is not as precise a term, for simplicity we will use it to represent the concept of ground sampling distance in this chapter.) *Extent* can be defined as the range over which measurements are made, for example, the area represented in an imaged scene. Grain and extent tend to be inversely related, simply because the total amount of data that can be collected is usually constrained.

Even though the examples given here draw on image spatial properties, the term scale is often also applied to the three other attributes of image data already referred to, namely the spectral, radiometric and temporal properties. Although scale is a common thread in this chapter, it is important to note that it is not the only attribute that is important in selecting data to address a particular problem.

The remainder of this chapter is organized in seven major sections. Following this general introduction, we discuss factors that influence the optimal characteristics of each of the four major types of image properties: spatial, spectral, radiometric and temporal. We then present some examples of the interactions and tradeoffs between the individual types of major image properties, before considering some broader, more general issues. In the concluding sections, we look to the future to discuss challenges and opportunities on the horizon.

SELECTING IMAGES WITH OPTIMAL SPATIAL PROPERTIES

Scale and image spatial properties

The concept of scale is particularly useful for discussing image spatial properties (Cao and Lam 1997, Marceau and Hay 1999). For example, the section in this book on satellite-borne sensors is partly organized along the lines of pixel size. Thus, we have chapters on fine (Toutin, in this volume), moderate (Goward et al., in this volume), and coarse spatial resolution (Justice and Tucker, in this volume) sensors. However, the challenges that the authors of these chapters faced, both in arriving at these terms, and in using them consistently, suggests that meaning of scale varies greatly depending on the focus of the analysis, and perhaps also the historical context of the time. Thus, despite its name, the Advanced Very High Resolution Radiometer (AVHRR), with 1.1 km pixels, is grouped in this book with coarse resolution sensors. The Landsat Enhanced Thematic Mapper Plus (ETM+), which we treat as a moderate resolution sensor, has also been termed a fine spatial resolution sensor by some. Adding complexity is the fact that many satellite-borne sensors have bands of differing spatial resolution. For example ASTER acquires data in three bands with 15 m pixels, six bands with 30 m pixels, and five bands with 90 m pixels. It is apparent that spatial resolution of modern satellite sensors fall along a continuum, and therefore attempts to label sensors by

Table 1.1 Image spatial resolution categories

Pixel size (m)	*Spatial resolution*	*Example satellite-borne sensors*
<1	very fine	WorldView
1–10	Fine	IKONOS
10–100	Moderate	ASTER, AWIFS, ETM+, MSS, SPOT
100–1000	Coarse	MODIS, MERIS
>1000	Very coarse	AVHRR, GOES, METEOSAT

simple spatial resolution descriptors is inherently arbitrary. Nevertheless, to minimize confusion, we have attempted throughout this book to standardize as far as possible on the terms summarized in Table 1.1.

Although often used interchangeably, *spatial resolution* and *pixel size* are not strictly speaking equivalent. This is because pixel size refers to the sampling frequency, and not the ground resolution element or sampling area. Thus, for example, the Landsat MultiSpectral Scanner (MSS) oversampled data along the scan line, producing pixels that are smaller than the ground resolution element. In addition, spatial resolution is dependent on the spectral radiometric properties of both the object being resolved, and the background against which it is being resolved. Generally, a higher spectral radiometric contrast between an object and its background will result in a higher apparent spatial resolution. At the one extreme, an object with no contrast against the background is not resolvable, irrespective of its size. At the other extreme, it is potentially possible to detect the presence of a single, bright object that is much smaller than a pixel, as long as the object is surrounded by a much darker background. However, for this latter example, it is not normally possible to predict where in the pixel that object occurs, so in that sense, the resolution is ultimately limited by the pixel size. Nevertheless, because of mixed pixels, and the low contrast of most Earth scenes, objects generally need to be multiple times the size of a single pixel before they are large enough to be discerned as distinct spatial features.

A more precise way of specifying resolution is the modulation transfer function (MTF). This is a specification of how contrast in the scene is represented in ('transferred to') the image. To measure MTF, a test signal of multiple bars of defined contrast, and varying spatial frequency (width of the bars), is imaged, normally in a laboratory setting. The contrast in the resulting image, at each of the various spatial frequencies, is then measured as a proportion of the original contrast. A similar measure is the point spread function (PSF), which characterizes how a point signal is blurred when it is measured by the sensor (Huang et al. 2002). Blurring results from the effects of the atmosphere, the sensor optics and electronics, and image resampling. Because of blurring, the information in a pixel usually includes a component from neighboring pixels (Zhang et al. 2006). Huang et al. (2002) have shown how modeling of the PSF can be used to reduce this adjacency effect, and thus improve the overall fidelity of the image.

In real images, quantifying spatial resolution requires identification and exploitation of natural boundaries between features in the image. Tarnavsky et al. (2004) used the full-width-half-maximum (FWHM) of the line spread function (LSF), derived from the study of the edges of objects in the image, to compare the spatial fidelity of scanned aerial film, and digital aerial images.

Image spatial extent and pixel size are generally inversely related. Thus, spatial resolution generally limits the potential extent of the scene. For example, it is possible to collect a global set of near cloud-free Landsat 7 ETM+ imagery, with 30 m pixel size, on a seasonal basis (Goward et al., in this volume). However, MODIS with 250 m visible and near infrared (NIR) pixels, can provide weekly global composites of nearly cloud-free imagery (Justice et al. 2002). In contrast, despite almost a decade of data collection by multiple commercial companies, there is as yet no fine spatial resolution global data set.

Choosing an optimal spatial scale

What is the optimal spatial resolution for a particular project? As already mentioned, it is important to clarify the interpretation objective of a project, before this question can be addressed. If the aim is to map the location of discrete objects, or the overall spatial patterns in an image data set, then methods that estimate optimal resolution based on finding the pixel size with the maximum local variation have been shown to be very effective. For example, Woodcock and Strahler (1987) related the graph of local variation plotted against pixel size to the average size of objects in an image. Variograms, which characterize the variability between measurements as a function of distance between those measurements (Jupp et al. 1989), have a particularly rich theoretical underpinning (Matheron 1971, Journel and Huijbregts 1978, Jupp et al. 1988). Variograms have been used to identify optimal distances between field measurements and the optimal pixel size (Hyppänen 1996, Atkinson and Curran 1997). An alternative measure, lacunarity, which is based on fractal theory, is useful for identifying multiple scales in an image (Butson and King 2006).

If the aim is to map the size and spatial extent of individual objects or regions, then it is important to have a pixel size much smaller than the distance calculated for optimal sampling, as described above. However, if the resolution becomes too fine, unwanted spatial detail will likely be resolved in the image, and, at least using conventional image analysis techniques, classification accuracy may be lower (Latty et al. 1985). On this basis, the optimal resolution has been defined as the scale that minimizes variance within the classes to be mapped (Marceau et al. 1994). An important consequence of this definition is that the optimal scale is therefore likely to be class-dependent (Marceau et al. 1994).

Hengl (2006) provides a thorough overview of the issues associated with choosing an optimal scale. He recommends a scale that is a compromise between *the coarsest legible scale*, which respects the scale and properties of the dataset; and *the finest legible scale*, which preserves at least 95% of the object or scene variability (Hengl 2006). McCloy and Bøcher (2007) extend Woodcock and Strahler's (1987) local variance concept to show how a graph of average local variance (AVL) can help predict a scale that minimizes within class variance, and thus optimizes the accuracy of subsequent classifications.

Image geometric properties

Another issue that should be considered in selecting data is the quality of the georeferencing to a cartographic projection. High quality georeferencing is generally expensive. For an image acquired from a nadir-viewing sensor, a simple polynomial warp that does not include terrain correction may be sufficient, and if local map control at a sufficient scale is available, can be applied routinely. Topographically induced image distortion increases with increasing angle away from nadir, as does the distortion of the shape and size of the pixel. Thus, with sensors that have a pointing capability, the view angle is an important variable to consider in selecting data. However, the increasing sophistication and availability of automated photogrammetric software makes it potentially possible for non-specialists to generate high quality orthorectifications, although the procedure remains relatively complex.

The quality of the image geometric properties is particularly important for multi-temporal analysis. Even a 0.2 pixel misregistration can cause as much as 10% error in the estimate of the change in spectral values, depending on the heterogeneity of the scene (Townshend et al. 1992). The quality of georeferencing is also important for change detection derived from object-based classification. In object-based classification, pixels are first grouped into so-called image objects, which are then classified as a single unit (Jensen et al., in this volume). In a series of experiments on the effects of misregistration on object-based change detection, Wang and Ellis (2005) found change detection error increased with increased positional error, increased landscape heterogeneity, and finer change detection resolution (the local region over which change is identified). The relationships between these variables were summarized using regression, and then used to calculate an optimal change detection resolution, based on a desired degree of accuracy (Wang and Ellis 2005).

SELECTING IMAGES WITH OPTIMAL SPECTRAL PROPERTIES

Scale and image spectral properties

When the concept of scale is applied to spectral properties, *spectral grain* can be used to refer to the wavelength interval, or width, of the spectral bands. Multispectral sensors, with a coarse spectral grain, have bands that span hundreds to thousands of nm. The *spectral extent* can be used to describe the spectral wavelength region encompassed by the bands (e.g., many optical sensors operate in the visible and near-infrared spectral region), and the total number of bands. The definition of hyperspectral data, which usually emphasizes the number, width and contiguity of the spectral bands (Schaepman, in this volume), thus encompasses the concepts of both spectral grain and extent.

The specific location and width of spectral bands can be very important for subsequent analysis. For example, Teillet et al. (1997) show that normalized difference vegetation index (NDVI) values are not necessarily comparable between satellites with different spectral properties, even if the data are atmospherically corrected and radiometrically calibrated. The width and location of the red band used in the NDVI calculation is particularly important, and should ideally be less than 50 nm wide (Teillet et al. 1997). Thus the spectral grain of Envisat Medium Resolution Imaging Spectrometer (MERIS) appears to be more appropriate for NDVI work than either the Landsat TM or SPOT HRV sensors (Teillet et al. 1997).

The choice between using multispectral and hyperspectral data has important ramifications for the range of information extraction routines that are appropriate for subsequent analysis. Multispectral analysis techniques tend to use data from within the scene to develop empirical models and classifications. Obtaining sufficient reliable within-scene training data can be a major challenge with multispectral analyses. In addition, the spectral separability of the classes of interest may be limited with multispectral data.

Hyperspectral analysis techniques often employ methods that are not premised on requiring in-scene knowledge. For example, hyperspectral methods may employ theoretical biophysical models, or draw on spectral libraries for classification (Chen and Campagna, in this volume). Spectral libraries consist of high quality spectra, usually acquired under laboratory conditions, which are assumed to represent material classes over wide areas. A number of extensive mineralogical spectral libraries are available in the public domain (for example, Clark et al. 2003); more recently an urban land cover library has been developed (Herold et al. 2003). The availability of spectral libraries for vegetation tends to be more limited, because of the phenological and environmental variation in vegetation properties limit the generalization that can be achieved. One of the difficulties in exploiting library spectra is that scaling from small laboratory samples and field spectrometer measurements to pixels, is complex (Baccini et al. 2007).

Choosing the optimal spectral bands

In the early days of digital image processing of remotely sensed data, limited computing power made it attractive to select only the most useful bands for classification. This constraint has largely fallen away with the steady improvement in computing power. Nevertheless band reduction is still often desirable, especially as advances in sensor technology enable data acquisition in more bands. The Hughes phenomenon (Hughes 1968, Warner and Nerry 2008), which has already been referred to above, is assumed to result from the increased number of parameters needed to characterize the distributions of training samples as the number of bands increases. The effect of the Hughes phenomenon is most likely classifier-dependent, and indeed, support vector machines are thought to be less susceptible to this problem (Melgani and Bruzzone 2004).

The simplest way of selecting bands is to use knowledge of the spectral properties of interest. For example, in a vegetation application one might select bands from the visible, NIR, and short wave infrared (SWIR) to sample spectral regions influenced by vegetation pigments, leaf structure, and moisture status, respectively (van Leeuwen, in this volume). In geological applications, one might use spectral libraries to identify the wavelengths associated with important diagnostic absorption features of the minerals and rocks of interest (Chen and Campagna, in this volume).

A variety of automated and statistical approaches have been proposed for selecting optimal subsets of image bands that carry the most information (Serpico and Moser 2007). One assumption common to many band selection methods is that highly correlated bands are redundant (Wiersma and Landgrebe 1980, Miao et al. 2007). Using the statistical method of principle component analysis (PCA) (Jensen 2005), the axes of multidimensional data can be rotated so that an *n*-band original data set is transformed to *n* new orthogonal and uncorrelated bands. The new bands are normally ordered according to the proportion of the original variance each new band explains. This strategy generally works very well, with the first few principle components carrying most of the information, and the remaining, low variance components generally dominated by noise. PCA is one of the most widely-used general image analysis techniques, having applications that go well beyond data compression and band selection. The minimum noise fraction (MNF) transformation (Green et al. 1988), typically applied to hyperspectral data, is a cascaded sequence of PCA transformations in which the noise is isolated and removed.

Despite the robustness of PCA, it is important to be aware that this method uses correlated variance as a surrogate measure for information. In situations where the signal of interest is not correlated across bands, but is instead isolated in a narrow spectral absorption feature, PCA will not be so useful. In addition, although highly correlated bands are likely somewhat redundant, they may nevertheless contain non-redundant information that can be very useful for separating subtle spectral differences (Warner and Shank 1997).

An alternative to this focus on covariance is data transformations and band selections that specifically enhance the spatial patterns in the resulting images. The spatial analog to PCA is multivariate spatial correlation (MSC) (Wartenberg 1985), which can be used to transform and compress image data (Warner 1999). Comparisons of the autocorrelation of ratios of image bands have also been used to select individual bands, and combinations of bands (Warner and Shank 1997). This autocorrelation-based method of selecting bands has been found not only to increase classification accuracy, but also to result in classifications that have higher autocorrelation, and thus potentially more clearly defined spatial patterns (Warner et al. 1999).

Data fusion

Data fusion has been defined as:

> a formal framework in which [there] are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application. (Wald 1999: 1191)

Pohl and Van Genderen (1998) note that data fusion can take place at three different levels in the image processing chain of analysis:

1 At the *pixel level*, by combining raw image bands of different sources.
2 At the *feature level*, by segmenting the images to identify image objects, and combining the different images in the context of each image object.
3 At the *decision level*, where each image is first analyzed separately, and then the derived information is combined.

The attributes of the data that are combined through data fusion could potentially cover any individual or combinations of the four attributes of scale: spatial, spectral, radiometric, and temporal, as well as a combination of imagery with ancillary data (Pohl and Van Genderen 1998). In this section, which focuses on image spectral properties, the discussion will be limited to attempts to increase the information content of a data set by combining images of disparate wavelengths at the pixel level (Briem et al. 2002). Subsequently, in the section on interactions between the different scale components, pan-sharpening using multi-spatial resolution data fusion will also be discussed.

The underlying rational for multi-wavelength data fusion is that different wavelength regions may respond to different physical phenomena. Thus, for example, a combined analysis of optical and synthetic aperture radar imagery potentially can provide information about vegetation type, biomass, structure, and water content (Hill et al. 2005).

Similarly, combining hyperspectral VNIR and SWIR with multispectral thermal infrared (TIR) data may allow the incorporation of temperature or emittance variations in discrimination between land cover units. For mineral mapping, SWIR bands often provide an ability to discriminate clays, whereas multispectral thermal bands are valuable for separating silicate minerals (Chen and Campagna, in this volume; Chen et al. 2007a). However, the benefits of combining these disparate wavelength regions varies greatly with classification method used (Chen et al. 2007b), and for some classifiers, the accuracy may actually decline when disparate data are combined. This suggests that a suitable approach for mineral discrimination may sometimes be an expert system that adapts to the spectral pattern of each pixel to draw on different classifiers, using different wavelength intervals, to classify each pixel independently.

The fusion of VNIR and SWIR data with multispectral thermal data also holds promise for classification in the urban environment, especially for the discrimination of different roof and road materials. In a study of Strasbourg, France, it was found that various combinations of four to six broad bands from the visible, NIR and SWIR, together with six multispectral TIR bands, resulted in higher classification accuracy than with using 71 hyperspectral visible, NIR, and SWIR bands (Warner and Nerry 2008). Unfortunately, there are currently no planned medium or high spatial resolution thermal satellite-based sensors, and therefore opportunities to exploit data fusion with TIR may remain limited.

SELECTING IMAGES WITH OPTIMAL RADIOMETRIC PROPERTIES

Scale and image radiometric properties

Radiometric resolution is arguably as important as spatial, spectral, and temporal resolution, yet does not seem to receive as much attention as the other image attributes. When scale is applied to radiometric properties, *grain* refers to the fineness of the division between successive brightness levels the sensor measures. *Extent* refers to the range of brightness levels over which the sensor can differentiate changes in radiance. A sensor with a rather unusual radiometric extent is the Operational Linescan System (OLS), which is flown aboard the Defense Meteorological Satellite Program (DSPM). The OLS is particularly sensitive to a range of low light levels, which makes it possible to detect illumination at night from street lights (Henderson et al. 2003) and other sources of illumination, such as fires and flares.

The number of bits over which the signal is quantized can serve as an indicator of the radiometric grain. An eight-bit resolution (2^8, or 0–255 DN values) has been until recently a common choice, partly because this data range corresponds to the underlying structure of computer data storage. Nevertheless, it is important to consider the range of radiometric values actually filled (Malila 1985), as well as the noise in the data. Thus, radiometric grain is perhaps more usefully characterized as the minimum radiance change that can be detected reliably. This change can be measured in radiance units, or as the signal-to-noise ratio. The latter measure is normally defined as the mean signal divided by the standard deviation of the noise. Atkinson et al. (2007) have demonstrated the utility of using land-cover-specific variograms to estimate the signal-to-noise ratio based on the relative variance of both the signal and noise. This land-cover specific measure of radiometric grain emphasizes the importance of the scene context in interpreting measures of noise.

Over time the radiometric range of data quantization from available sensors has increased notably. Tarnavsky et al. (2004) have shown that scanned color infrared aerial photographs have more noise than Airborne Data Acquisition and Registration (ADAR) 5500 multispectral images, which are acquired using digital cameras. The original Landsat MSS sensor recorded just six bits of data, although the data for the first three bands were scaled non-linearly to provide an effective seven-bit range (Goward et al., in this volume). In contrast, Landsat TM data is quantized over eight bits. Malila (1985) used an analysis of entropy to show the importance of this radiometric improvement in increasing the information content compared to the improvement in the number, width and location of the spectral bands. On the other hand, Narayanan et al. (2000) suggest that TM imagery can potentially be compressed to as few as only four bits per pixel, and still produce classifications that are similar in accuracy to the original eight-bit data.

The commercial high resolution sensors of IKONOS, Quickbird and OrbView are all quantized with 11-bit data (Toutin, this volume). Nevertheless, purchasers of these data sets are offered degraded 8-bit versions of the data, perhaps reflecting legacy software or limited hardware and software available to some purchasers. Based on the personal experience of the authors, one of the advantages of the higher radiometric resolution of the commercial sensors appears to be the increased information content in dark areas of the images, especially shadows.

Radiometric normalization and calibration

Many image analysis procedures can be undertaken with images in DN format. However, some change detection techniques and most biophysical transformations (e.g. vegetation indices) require normalization or calibration to radiance units or equivalent reflectance (Teillet et al. 1997, Song et al. 2001). For example, conversion to reflectance is particularly important for hyperspectral data, especially if the imagery is to be classified using spectral libraries (Chen and Campagna, this volume). In comparing radiance and reflectance measurements between sensors, and between field spectrometers and remote imaging devices, it is particularly important to define and consider the geometric arrangement of the illuminating energy and the observing sensor. Schaepman-Strub et al. (in this volume) provide a comprehensive review of the terminology and the relationships between different types of spectral measurements.

Conversion to reflectance requires information about the spectral sensitivity of the sensor, as well as both solar illumination and atmospheric transmission and scattering. The effect of topography on illumination may be calculated if a sufficiently detailed digital elevation model is available (Warner and Chen 2001). However, the bidirectional reflectance distribution function (BRDF), or dependence of reflectance on the geometry on the illumination and observation (Schaepman-Strub et al., in this volume), varies between different materials, and thus if a single BRDF model is used to normalize topographic variations in an area of varying land cover properties, the calculated reflectances may have cover-dependent errors.

SELECTING IMAGES WITH OPTIMAL TEMPORAL PROPERTIES

Scale and image temporal properties

The application of the concept of scale to image temporal properties is somewhat more complex than in the spatial and spectral domains. Normally, an image is acquired in a single, very short period of time, which might be referred to as the temporal scale extent. If only one image is considered, the grain and extent are identical. On the other hand, the concept of temporal scale is very useful for discussing multitemporal image archives, as well as for characterizing change detection and time series analyses. The temporal *extent* of an archive is quite straightforward, and is the overall period of time covered. However, the temporal *grain* can potentially refer to two different attributes. In the case of a series of individual images, the grain might be the period *between* the image acquisition dates. However, for coarse resolution data, single bands are often generated on a pixel by pixel basis from multiple sequential images, using algorithms that minimize the effects of cloud. For such data, the final image represents a multi-temporal composite, where each pixel has been individually selected from the images acquired during the compositing period (Holben 1986). Thus, at least for multitemporal composited data, grain could also refer to *the period of time over which the image data have been integrated.* For example, a compositing period of a week or a month is often used to generate some image data products (Justice et al. 2002).

Cloud-free multitemporal composites have been found to be particularly useful for characterizing the annual pattern of ecosystem response to annual weather patterns (Loveland et al. 1995). For example, the date of onset of greenness, total integrated greenness over time, and maximum greenness, have been used to classify different land cover classes. By extending such studies over multiple years, apparent changes in climate have been observed, including an earlier spring greenup at high latitudes (Myneni et al. 1997, Delbart et al. 2006). However, Schwartz et al. (2002) have cautioned that the integration of data over a week or longer periods can result in uncertainty and bias in the phenological trends identified.

For change detection studies, the temporal extent of the available image archive constrains the period over which change can be observed. Thus, the Landsat TM and ETM+ sensors provide a particularly important long term data set, with a temporal extent of over 25 years (Goward et al., in this volume). The temporal extent of change detection studies can be extended back to 1972 by using Landsat MSS imagery, and for some areas, to as early as 1960, by using declassified CORONA imagery, although the latter are mostly digitized black and white film. However, for change detection studies, images from different sensors should be used with caution, because it can be challenging to differentiate between real changes in the scene, and changes in the sensors.

The grain, or revisit period of the sensor, also constrains the potential differentiation of events within the period studied. However, the actual availability of cloud free imagery is usually some small fraction of what might be assumed based on only the sensor revisit time.

Image acquisition frequency

Finding recent imagery tends to be an important consideration for some applications. Procedures for satellite data collection vary greatly between the nadir viewing sensors, such as Landsat ETM+, and pointable satellites, a category which includes all fine resolution sensors, such as IKONOS and WorldView. For nadir-viewing sensors, the operators usually attempt to acquire and archive all images on a systematic basis, at least when the satellite is within sight of a receiving station. Landsat ETM+ is unique in that the operators have a policy of acquiring multiple global data sets on a regular basis (Goward et al., in this volume). For pointable satellites, image acquisition is prioritized based on requests from customers, who pay a premium for tasking the satellite. Thus, archive imagery is only available over limited areas, and new acquisitions may be delayed depending on the priorities of the operator. These same issues tend to apply to other sensors that have only a limited acquisition capability, such as ASTER and HYPERION.

Obtaining images of the appropriate season is also important. This is particularly true of vegetation studies, where the timing of phenological events such as leaf out and senescence may be as valuable as spectral information (Key et al. 2001).

Geostationary satellites, such as European EuMetSat's Meteosat Second Generation (MSG) satellites and the planned US National Polar-orbiting Operational Environmental Satellite System (NPOESS) satellites, offer the greatest potential for high frequency of coverage. For example METOSAT-9 acquires full disk images of Earth every 15 minutes, and in rapid scanning mode, where only part of the Earth disk is imaged, images can be acquired even more frequently. The tradeoff with geostationary sensors is the comparatively low spatial resolution, for example 1–3 km pixels at the sub-satellite point for the METEOSAT Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument. Nevertheless, this high temporal frequency of acquisition opens the possibility for completely new remote sensing applications associated with highly dynamic phenomena, such as modeling the growth and development of individual fires (Umamaheshwaran et al. 2007).

Airborne sensors (Stow et al., in this volume) can provide high spatial resolution as well as complete user-control of acquisition timing, including not just the date, but even time of day. In practice, however, mobilization and operational costs may limit the degree to which the user can achieve this flexibility.

Acquisitions for time-critical events

Time-critical applications of remote sensing include disaster response (Teeuw et al., in this volume) and precision agriculture (Nellis et al., in this volume) support. When timing is critical, pointable sensors clearly have advantage over nadir viewing sensors in that they have a shorter potential revisit period.

For disaster response, a rapid delivery of analyzed imagery requires a series of expedited responses, starting with emergency tasking of the satellite, pre-preprocessing by the satellite operator, and internet-based data delivery. Following receipt of the data, the analyst may need to perform additional georeferencing work before interpretation can be done. Because time is normally very limited, relatively routine or simple methods are necessary.

The fact that rapid response requires some advance planning and organization is demonstrated by the establishment of the International Charter on Space and Major Disasters (International Charter 2007, Harris, in this volume, Teeuw et al., in this volume). This agreement, initiated by the French, European and Canadian space agencies in 2000, now includes the space agencies of six other countries, and additional agreements with commercial satellite operators. The charter provides for 24-hour availability of a single point of contact for requesting emergency remote sensing support. In France, the organization Service Régional de Traitement d'Image et de Télédétection (SERTIT) has been contracted by the French space agency, CNES, to provide 24-hour availability of image analysts (SERTIT 2005). SERTIT places its image map products on a website, for free download (http://sertit.u-strasbg.fr/documents/RMS_page_garde/RMS_page_garde.htm).

Of course, data currency is a concern not just in disaster response, but in all applications studying dynamic phenomena. Satellite images typically require preprocessing by the data provider prior to being made available to the user. Additional bottlenecks may occur in the distribution, although internet access to the data can overcome this problem.

INTERACTIONS BETWEEN DIFFERENT COMPONENTS OF SCALE

So far, the discussion has been limited to each of the different components of scale: spatial, spectral, temporal, and radiometric. However, clearly, these components are linked. For example, if image acquisition is constrained by the rate at which data are stored and transmitted, then increasing one type of resolution (such as spectral resolution), will necessarily require changes to other types of resolution (such as spatial resolution) (Figure 1.1). The Compact Airborne Spectral Imager (CASI), manufactured by ITRES of Canada, is a good example of an instrument that is designed to have maximum flexibility within the constraints of data acquisition trade-offs. CASI is a programmable sensor, in which the operator chooses the number, width, and location of spectral bands prior to image acquisition. Because longer integration times are needed as the number of bands imaged increases, there is an inverse relationship between the number of bands and the spatial resolution for this sensor (ITRES 2007).

Alternatively, it is possible in some instances to overcome the spatial-spectral constraint described above by employing pan sharpening, in which data fusion is used to combine high spatial resolution, panchromatic (i.e., single band) images with comparatively low spatial resolution, multispectral images (Alparone et al. 2007). Pan sharpening has become increasingly important since the SPOT sensors popularized the concept of acquiring simultaneous high spatial resolution panchromatic data to complement a lower spatial resolution multispectral data set, and this design approach has been followed for a number of subsequent sensors, including ETM+ (Goward et al., in this volume), IKONOS, and QuickBird (Toutin, in this volume). The aim of pan sharpening is quite simple: to incorporate the spatial detail from the panchromatic image, and the spectral information from the multispectral images. The challenge, however, is to ensure that the combined data set maintains a spectral balance such that when the images are displayed as a color composite, the colors of the sharpened images are similar to the original, low spatial resolution multispectral data set (Alparone et al. 2007). This challenge is particularly great if the panchromatic band is poorly correlated with the individual multispectral bands (Gross and Schott 1998, Price 1999).

Pohl and Van Genderen (1998) provide a comprehensive review of pan sharpening methods. Alparone et al. (2007) empirically compared eight different methods, and found that multiresolution analysis, incorporating for example wavelets or Laplacian pyramids to characterize the spatial dependence of DN values on scale, generally outperformed component substitution, in which some transformed component of the multispectral data set, such as the first principal component, is replaced by the panchromatic data. In particular, the two methods found to have the best results both take into account physical models of the image formation, namely the modulation transfer function (Alparone et al. 2007). Wang et al. (2005) use a theoretical framework, which they term general image fusion, to compare the different methods, and conclude that the optimal method is multiresolution analysis-based intensity modulation. Pan sharpening using spectral mixture analysis also shows promise, especially for hyperspectral imagery (Gross and Schott 1998).

There are other complex interactions between the different types of resolution. Malila (1985) has found that, although the increased number and range of spectral bands of TM compared to MSS provide a great deal more information as indicated by studies of entropy, if both TM and MSS had been quantized at just five bits, the information content of the two sensors would have been approximately equal.

Key et al. (2001) compared the value of multiple spectral bands with multiple image dates for classifying individual deciduous trees species. Their study showed that a single, optimally chosen, multispectral image acquired during peak autumn colors resulted in relatively high classification accuracy. However, multiple dates of single band imagery could provide a similar high accuracy. This finding suggests that if the spatial resolution of multispectral imagery is too coarse, panchromatic imagery, which typically has a higher spatial resolution, may be substituted, if multiple dates can be obtained (Key et al. 2001). For example, the current highest spatial resolution from commercial satellites is provided by the WorldView-1 sensor, launched in 2007. Worldview-1 provides imagery with 0.5 m pixels, but only panchromatic data, with no multispectral bands (DigitalGlobe 2007).

OTHER ISSUES

Additional, broader issues should be considered in selecting image data sets. Data cost, particularly for the new commercial sensors, can be high. However, the commercial providers generally make a distinction between new acquisitions, which require tasking the satellite, and existing images in the companies' archives, charging a premium for the former. Commercial image licensing agreements may constrain sharing the data with others, even in the same organization. Thus purchasers should consider the long-term use of imagery, and consider paying extra to have more flexible use of the data. One of the major advantages of US government data, including Landsat TM, ETM+, and Terra and Aqua MODIS data, is not only the very economical price, but the absence of constraints on data sharing (Harris, in this volume). Indeed, large internet archives of US satellite imagery are available for free downloading (Table 1.2).

A second major issue relates to data volume. Large volumes of data can strain computer storage and processing capacity. Although this issue is far less significant today compared to when early sensing systems such as the Landsat MSS were launched, it is still important for projects that cover relatively large geographic areas, or use multiple dates of images.

In addition to improvements in computer hardware, software has also advanced considerably since the early 1970s. Early programs, typically running on main-frame computers, often were based on command-line program initiation. Today, remote sensing packages typically have graphical user-interfaces, and even semi-automated 'wizards' that help guide the less sophisticated users. Furthermore, there are now specific programs for advanced analysis such as for photogrammetry and hyperspectral classification. On the other hand, the development of software that integrates remote sensing analysis and GIS analysis has been more mixed (Merchant and Narumalani, in this volume).

FUTURE CHALLENGES AND OPPORTUNITIES

It is evident that the number and diversity of satellite-borne sensors will only grow in future years, especially as the commercial satellite sector grows, and additional nations launch and operate their own satellite programs. Thus, the challenges, and opportunities, in selecting data to address specific problems, will also likely grow. Some specific trends can be observed with regards to image spatial and spectral properties, as well as the availability of relatively new types of image data.

With regards to spatial resolution, it appears for the moment that ~0.5 m is the smallest pixel size of space-borne imagery that will be available to non-government users, due to security issues. Thus, the operating licenses for both Worldview-1 (DigitalGlobe 2007) and the planned GEOEYE-1 (GeoEye 2007) limit the spatial resolution of imagery that is sold to the general public to 0.5 m.

In terms of spectral properties, one likely future development is finally to achieve operational hyperspectral imaging from space. For the user, space-based hyperspectral imagery should be more economical than contracting for airborne hyperspectral data. An operational satellite-borne hyperspectral system will also remove the geographical constraints of the narrow swath of the experimental satellite-based Hyperion hyperspectral sensor. Once these financial and geographical barriers are removed, hyperspectral analysis may enter the mainstream, especially if there is continued improvement in the ease of use of hyperspectral software analysis tools. Nevertheless, limits on the signal-to-noise and spatial resolution for space-based hyperspectral sensors may ensure that aerial hyperspectral imaging will continue to play an important role for some time to come.

Another area of likely future importance, and challenge to users, will be greater integration of diverse wavelength regions and characteristics, including hyperspectral VNIR and SWIR,

Table 1.2 ***Sources of free imagery***

Facility	*Example data*	*URL*[1]
Global Land Cover Facility, University of Maryland	TM, MSS, MODIS, ASTER	http://glcf.umiacs.umd.edu
AmericaView	Landsat	http://glovis.texasview.org
USGS EROS	Landsat	http://edc.usgs.gov/products/satellite/landsat_ortho.html
USGS-NASA DataPool	ASTER, MODIS	http://lpdaac.usgs.gov/datapool/datapool.asp
Boston University Climate and Vegetation Group	AVHRR, MODIS	http://cliveg.bu.edu/modismisr/products/products.html
Boston University Land Cover and Land Cover Dynamics	MODIS	http://duckwater.bu.edu/lc/datasets.html

[1] URLs current as of January 2008.

hyperspectral thermal, and multi-wavelength, fully polarimetric radar. The integration of lidar with multispectral and hyperspectral imagery seems a particularly promising area (Bork and Su 2007).

Relatively new types of data will also likely become more available, although once again the general exploitation of these data may be dependent on the development of easy to use software. Polarization information, currently used mainly with microwave wavelengths, holds promise for improved image analysis of optical wavelengths (Zallat et al. 2004). Multi-angular imaging, already available from the Multiangle Imaging SpectroRadiometer (MISR) experimental satellite, allows characterization and exploitation of BRDF information (Armston et al. 2007, Jovanovic et al. 2007). One particularly interesting application of BRDF information is for mapping wetlands by exploiting the distinctive and strong angular reflection signature of water compared to other surface types. This approach has been shown to be effective for discriminating inundated areas with emergent vegetation, open water, and non-inundated areas (Vanderbilt et al. 2002). One strength of this approach is that as the pixel size increases, the accuracy of unmixing the proportions of these cover types tends to increase (Vanderbilt et al. 2007), making the method particularly effective for global-scale hydrological modeling.

In conclusion, remote sensing has advanced greatly since the early 1970s and since the beginnings of regular satellite Earth observations with the ERTS/Landsat MSS sensor. The many advances in remote sensing technology have themselves brought new challenges, as exemplified by issues such as the Hughes Phenomenon (Hughes 1968). Although many of these challenges can be addressed through innovative research, one area outside the control of most individual scientists is the general area of remote sensing policy (Harris, in this volume). For example, despite the importance of data continuity in global change studies, there unfortunately seems to be a lack of political will, at least in the United States, to support an aggressive, long term strategy to ensure data continuity for moderate resolution imaging. This problem has recently been highlighted by the difficulties associated with the Landsat Data Continuity Mission (Goward et al., in this volume). Despite these difficulties, remote sensing offers a powerful, objective and consistent tool for studying the earth, from local to global scales. The value of remote sensing is demonstrated by the growing number of research studies, and the increasing use of remote sensing in operational environments. The chapters that follow give insight into the many facets and key issues of this rapidly developing subject.

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REFERENCES

Alker, H. R., 1969. A typology of ecological fallacies. In M. Dogan and S. Rokkan (eds), *Quantitative Ecological Analysis in the Social Sciences*. The MIT Press, Cambridge, MA, USA.

Alparone, L., L. Wald, J. Chanussot, C. Thomas, P. Gamba, and L. M. Bruce, 2007. Comparison of pansharpening algorithms: Outcome of the 2006 GRS-S data-fusion contest. *IEEE Transactions on Geoscience and Remote Sensing*, 45(10): 3012–3021, doi 10.1109/TGRS.2007.904923.

Armston, J. D., P. F. Scarth, S. R. Phinn, and T. J. Danaher, 2007. Analysis of multi-date MISR measurements for forest and woodland communities, Queensland, Australia. *Remote Sensing of Environment*, 107: 287–298.

Atkinson, P. M. and P. J. Curran, 1997. Choosing an appropriate spatial resolution for remote sensing investigations. *Photogrammetric Engineering and Remote Sensing*, 63(12): 1345–1351.

Atkinson, P. M., I. M. Sargent, G. M. Foody, and J. Williams, 2007. Exploring the geostatistical method for estimating the signal-to-noise ratio of images. *Photogrammetric Engineering and Remote Sensing*, 73(7): 841–850.

Baccini, A., M. A. Friedl, C. E. Woodcock, and Z. Zhu, 2007. Scaling field data to calibrate and validate moderate spatial resolution remote sensing models. *Photogrammetric Engineering and Remote Sensing*, 73(8): 945–954.

Bork E. W., and J. G. Su, 2007. Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis. *Remote Sensing of Environment*, 111: 11–24.

Briem, G. J., J. A. Benediktsson, and J. R. Sveinsson, 2002. Multiple classifiers applied to multisource remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing*, 40(10): 2291–2299.

Butson, C. R. and D. J. King, 2006. Lacunarity analysis to determine optimal extents for sample-based spatial information extraction from high-resolution forest imagery. *International Journal of Remote Sensing*, 27(1): 105–120.

Cao, C. and N. S.-N. Lam, 1997. Understanding the scale and resolution effects in remote sensing and GIS. In D. A. Quattrochi and M. F. Goodchild (eds), 1997. *Scale in Remote Sensing and GIS*. Lewis Publishers, Boca Roton, FL, USA, Chapter 3, pp. 57–72.

Chen, X., and D. Campagna, in this volume. Geological applications. Chapter 22.

Chen, X., T. A. Warner, and D. J. Campagna, 2007a. Integrating visible, near infrared and short wave infrared hyperspectral and multispectral thermal imagery for geologic mapping: simulated data. *International Journal of Remote Sensing*, 28(11): 2415–2430.

Chen, X., T. A. Warner, and D. J. Campagna, 2007b. Integrating visible, near-infrared and short-wave infrared hyperspectral and multispectral thermal imagery for geological mapping at Cuprite, Nevada. *Remote Sensing of Environment*.

Clark, R. N., G. A. Swayze, R. Wise, K. E. Livo, T. M. Hoefen, R. F. Kokaly, and S. J. Sutley, 2003. *USGS Digital Spectral Library splib05a*. U.S. Geological Survey, Open File Report 03-395. (http://pubs.usgs.gov/of/2003/ofr-03-395/ofr-03-395.html, last date accessed 24 September 2007).

Crews, K., and S. J. Walsh, in this volume. Remote sensing and the social sciences. Chapter 31.

Delbart, N., T. Le Toan, L. Kergoat, and V. Fedotova, 2006. Remote sensing of spring phenology in boreal regions: A free of snow-effect method using NOAA-AVHRR and SPOT-VGT data (1982–2004). *Remote Sensing of Environment*, 101: 52–62.

DigitalGlobe 2007. Worldview-1. http://www.digitalglobe.com/about/worldview1.html (last date accessed 14 October 2007).

Ferro, C. J. and T. A. Warner, 2002. Scale and texture in digital image classification. *Photogrammetric Engineering and Remote Sensing*, 68(1): 51–63.

GeoEye 2007. GeoEye imagery products: GEOEYE-1. http://www.digitalglobe.com/about/worldview1.html (last date accessed 14 October 2007).

Goward, S. N., T. Arvidson, D. L. Williams, R. Irish, and J. Irons, in this volume. Moderate spatial resolution optical sensors. Chapter 9.

Green, A. A., M. Berman, P. Switzer and M. D. Craig, 1988. A transformation for ordering multispectral data in terms of image quality with implications for noise removal. *IEEE Transactions on Geoscience and Remote Sensing*, 26: 65–74.

Gross, H. N., and J. R. Schott, 1998. Application of spectral mixture analysis and image fusion techniques for image sharpening. *Remote Sensing of Environment*, 63: 85–94.

Harris, R. in this volume. Remote sensing policy. Chapter 2.

Henderson, M., E. T. Yeh, P. Gong, C. Elvidge, and K. Baugh, 2003. Validation of urban boundaries derived from global night-time satellite imagery. *International Journal of Remote Sensing*, 24(3): 595–609.

Hengl, T., 2006. Finding the right pixel size. *Computers and Geosciences*, 32: 1283–1298. doi: 10.1016/j.cageo.2005.11.008

Herold, M., M. Gardner, and D. A. Roberts, 2003. Spectral resolution requirements for mapping urban areas. *IEEE Transactions on Geoscience and Remote Sensing*, 41(9): 1907–1919.

Hill, M. J., C. J. Ticehurst, J-S. Lee, M. R. Grunes, G. E. Donald, and D. Henry, 2005. Integration of optical and radar classifications for mapping pasture type in Western Australia. *IEEE Transactions on Geoscience and Remote Sensing*, 43(7): 1665–1681. doi 10.1109/TGRS.2005.846868.

Holben, B., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. *International Journal of Remote Sensing*, 7(11): 1417–1434.

Huang, C., J. R. G. Townshend, S. Liang, S. N. V. Kalluri, and R. S. DeFries, 2002. Impact of sensor's point spread function on land cover characterization: assessment and deconvolution. *Remote Sensing of Environment* 80(2) 203–212.

Hughes, G. F., 1968. On the mean accuracy of statistical pattern recognizers. *IEEE Transactions on Informational Theory*, IT-14: 55–63.

Hyyppä, J., W. Wagner, M. Hollaus, and H. Hyyppä, in this volume. Airborne laser scanning. Chapter 14.

Hyppänen, 1996. Spatial autocorrelation and optimal spatial resolution of optical remote sensing data in boreal forest environment. *International Journal of Remote Sensing*, 17(17): 3441–3452.

International Charter, 2007. International charter: Space and major disasters. http://www.disasterscharter.org (last date accessed: September 24, 2007).

ITRES, 2007. Flight planning flexibility. http://www.itres.com/Flight_Planning_Flexibility (last date accessed October 14, 2007).

Jelinsky, D. E., and J. Wu, 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11(3): 129–140.

Jensen, J. R., J. Im, P. Hardin, and R. R. Jensen, in this volume. Image classification. Chapter 19.

Jensen, J. R., 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice Hall, Upper Saddle River, NJ, USA.

Journel, A. G., and C. J. Huijbregsts, 1978. *Mining Geostatistics*. Academic Press, London.

Jovanovic, V., C. Moroney, and D. Nelson, 2007. Multi-angle geometric processing for globally geo-located and co-registered MISR image data. *Remote Sensing of Environment*, 107(1–2): 22–32.

Jupp, D. L. B., A. H. Strahler, and C. E. Woodcock, 1988. Autocorrelation and regularization in digital images. I. Basic theory. *IEEE Transactions on Geoscience and Remote Sensing*, 26(4): 463–473.

Jupp, D. L. B., A. H. Strahler, and C. E. Woodcock, 1989. Autocorrelation and regularization in digital images. II. Simple image models. *IEEE Transactions on Geoscience and Remote Sensing*, 27(3): 247–258.

Justice, C. O. and C. J. Tucker, in this volume. Coarse resolution optical sensors. Chapter 10.

Justice, C. O., J. R. G. Townshend, E. F. Vermote, E. Masuoka, R. E. Wolfe, N. Saleous, D. P. Roy, and J. T. Morisette, 2002. An overview of MODIS Land data processing and product status. *Remote Sensing of Environment*, 83: 3–15.

Kerekes, J. P., in this volume. Optical sensor technology. Chapter 7.

Key, T., T. Warner, J. McGraw, and M. A. Fajvan, 2001. A comparison of multispectral and multitemporal imagery for tree species classification. *Remote Sensing of Environment*, 75: 100–112.

Latty, R. S., R. Nelson, B. Markham, D. Williams, D. Toll, and J. Irons, 1985. Performance comparison between information extraction techniques using variable spatial resolution data. *Photogrammetric Engineering and Remote Sensing*, 51(9): 1459–1470.

Loveland, T. R., J. W. Merchant, J. F. Brown, D. O. Ohlen, B. C. Reed, P. Olson, and J. Hutchinson, 1995. Seasonal land-cover regions of the United States. *Annals of the Association of American Geographers*, 85(2): 339–355.

Malila, W. A., 1985. Comparison of the information contents of Landsat TM and MSS data. *Photogrammetric Engineering and Remote Sensing*, 51(9): 1449–1457.

Marceau, D. J. and G. J. Hay. 1999. Remote sensing contributions to the scale issue. *Canadian Journal of Remote Sensing,* 25(4): 357–366.

Marceau D. J., D. J, Gratton, R. A. Fournier, and J. P. Fortin, 1994. Remote-sensing and the measurement of geographical entities in a forested environment. 2. The optimal spatial-resolution. *Remote Sensing of Environment*, 49(2): 105–117.

Matheron, G., 1971. *The Theory of Regionalized Variables and its Applications*. Cahiers du Centre de Morphologie Mathematique de Fontainbleau, No. 5.

McCloy, K. R. and P. K. Bøcher, 2007. Optimizing image resolution to maximize the accuracy of hard classification. *Photogrammetric Engineering and Remote Sensing*, 73(8): 893–903.

Melgani, F. and L. Bruzzone, 2004. Classification of hyperspectral remote sensing images with support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42: 1778–1790.

Merchant, J. W. and S. Narumalani, in this volume. Integrating remote sensing and geographic information systems. Chapter 17.

Miao, X., P. Gong, S. Swope, R. Pu, R. Carruthers, and G. L. Anderson, 2007. Detection of yellow starthistle through band selection and feature extraction from hyperspectral imagery. *Photogrammetric Engineering and Remote Sensing*, 73(9): 1005–1015.

Myneni, R. B., C. D. Keeling, C. J. Tucker, G. Asrar, and R. R. Nemani, 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature*, 386: 698–702.

Narayanan, R. M., T. S. Sankaravadivelu, and S. E. Reichenbach, 2000. Dependence of information content on gray-scale resolution. *Geocarto International*, 15(4): 15–27.

Nellis, M. D., K. Price, and D. Rundquist, in this volume. Remote sensing of cropland agriculture. Chapter 25.

Openshaw, S. 1983. The modifiable areal unit problem. *Concepts and Techniques in Modern Geography* 38. Geo Books, Norwich, UK.

Openshaw, S. 1984. Ecological fallacies and the analysis of areal census data. *Environment and Planning A*, 6: 17–31.

Openshaw, S. and P. J. Taylor. 1979. A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In: R. J. Bennett (ed.), *Statistical Applications in the Spatial Sciences*. Pion, London, UK.

Pohl, C. and J. L. Van Genderen, 1998. Multisensor image fusion in remote sensing: concepts, methods and applications. *International Journal of Remote Sensing*, 19(5): 823–854. doi: 10.1080/014311698215748.

Price, J. C. 1999. Combining multispectral data of differing spatial resolution. *IEEE Transactions on Geoscience and Remote Sensing*, 37(3): 1199–1203.

Quattrochi, D. A. and M. F. Goodchild (eds), 1997. *Scale in Remote Sensing and GIS*. Lewis Publishers, Boca Roton, FL, USA.

Robinson, W.S. 1950. Ecological correlations and the behavior of individuals. *American Sociological Review*, 15: 351–357.

Schaepman, M. E., in this volume. Imaging spectrometers. Chapter 12.

Schaepman-Strub, G., M. E. Schaepman, J. V. Martonchik, T. H. Painter, and S. Dangel, in this volume. Terminology of radiometry and reflectance – from concepts to measured quantities. Chapter 15.

Schwartz, M. D., B. C. Reed, and M. A. White, 2002. Assessing satellite-derived start-of-season measures in the conterminous USA. *International Journal of Climatology*, 22: 1793–1805. doi: 10.1002/joc.819.

Serpico, S. B. and G. Moser, 2007. Extraction of spectral channels from hyperspectral images for classification purposes. *IEEE Transactions on Geoscience and Remote Sensing*, 45(2): 484–495.

SERTIT 2005. SERTIT: Introduction. http://sertit.u-strasbg.fr/english/en_presentation.htm (last date accessed September 24 2007).

Song, C., C. E. Woodcock, K. C. Seto, M. Pax Lenney, and S. A. Macomber, 2001. Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment*, 75: 230–244.

Spiker, S. and T. A. Warner, 2007. Scale and spatial autocorrelation from a remote sensing perspective. In: J. Gattrell and R. Jensen (eds.), *Geo-Spatial Technologies in Urban Environments*. Springer-Verlag, Heidelberg, pp. 197–213.

Stow, D. A., L. L. Coulter, and C. A. Benkelman, in this volume. Airborne digital multispectral imaging. Chapter 11.

Swain, P. and S. M. Davis, 1978. *Remote Sensing: The Quantitative Approach*. McGraw Hill, New York.

Tarnavsky, E., D. Stow, L. Coulter, and A. Hope, 2004. Spatial and radiometric fidelity of airborne multispectral imagery in the context of land-cover change analyses. *GIScience and Remote Sensing*, 41(1): 62–80.

Teeuw, R., P Aplin, N. McWilliam, T. Wicks, K. Matthieu, and G. Ernst, in this volume. Hazard assessment and disaster management using remote sensing. Chapter 32.

Teillet, P. M., K. Staenz, and D. J. Williams, 1997. Effects of spectral, spatial and radiometric characteristics on remote sensing vegetation indices of forested regions. *Remote Sensing of Environment*, 61: 139–149.

Toutin, T., in this volume. Fine spatial resolution optical sensors. Chapter 8.

Townshend, J. R. G., C. O. Justice, C. Gurney, and J. McManus, 1992. The impact of misregistration on change detection. *IEEE Transactions on Geoscience and Remote Sensing*, 30(5): 1054–1060.

Turner, M. G., R. H. Gardner, and R. V. O'Neill, 2001. *Landscape Ecology in Theory and Practice: Pattern and Process*. Springer, New York, USA.

Umamaheshwaran, R., W. Bijker, and A. Stein, 2007. Image mining for modeling of forest fires from Meteosat images. *IEEE Transactions on Geoscience and Remote Sensing*, 45(1): 246–253. doi 10.1109/TGRS.2006.883460.

Vanderbilt, V. C., G. L. Perry, G. P. Livingston, S. L. Ustin, M. C. Diaz Barrios, F.-M. Bréon, M. M. Leroy, J.-Y. Balois, L. A. Morrissey, S. R. Shewchuk, J. A. Stearn, S. E. Zedler, J. L. Syder, S. Bouffies-Cloche, and M. Herman, 2002. Inundation discriminated using sun glint. *IEEE Transactions on Geoscience and Remote Sensing*, 40(6): 1279–1287.

Vanderbilt, V. C., S. Khanna, and S. L. Ustin, 2007. Impact of pixel size on mapping surface water in subsolar imagery. *Remote Sensing of Environment*, 109: 1–9.

van Leeeuwen, W. J. D., in this volume. Visible, near-IR and shortwave IR spectral characteristics of terrestrial surfaces. Chapter 3.

Wald, L., 1999. Some terms of reference in data fusion. *IEEE Transactions on Geoscience and Remote Sensing*, 37(3): 1190–1191.

Walsh, S. J., A. Moody, T. R. Allen and D. G. Brown, 1997. Scale dependence of NDVI and its relationship to mountainous terrain. In: D. A. Quattrochi and M. F. Goodchild (eds.), *Scale in Remote Sensing and GIS*. Lewis Publishers, Boca Raton, pp. 27–55.

Walsh, S. J., L. Bian, S. McKnight, D. G. Brown, and E. S. Hammer, 2003. Solifluction steps and risers, Lee Ridge, Glacier National Park, Montana, USA: a scale and pattern analysis. *Geomorphology*, 55: 381–398.

Wang, H. and E. C. Ellis, 2005. Image misregistration error in change measurements. *Photogrammetric Engineering and Remote Sensing*, 71(9): 1037–1044.

Wang, Z., D. Ziou, C. Armenakis, D. Li, and Q. Li, 2005. A comparative analysis of image fusion methods. *IEEE Transactions on Geoscience and Remote Sensing*, 43(6): 1391–1402. doi 10.1109/TGRS.2005.846874

Warner, T. A., 1999. Analysis of spatial patterns in remotely sensed data using multivariate spatial correlation. *Geocarto International*, 14(1): 59–65.

Warner, T. A. and M. Shank, 1997. An evaluation of the potential for fuzzy classification of multispectral data using artificial neural networks. *Photogrammetric Engineering and Remote Sensing*, 63(11): 1285–1294.

Warner, T. and X. Chen, 2001. Normalization of Landsat thermal imagery for the effects of solar heating and topography. *International Journal of Remote Sensing*, 22(5): 773–788.

Warner, T. A. and F. Nerry, 2008. Does a single broadband or multispectral thermal data add information for classification of visible, near- and shortwave infrared imagery of urban areas? *International Journal of Remote Sensing*, in press.

Warner, T. A., K. Steinmaus, and H. Foote, 1999. An evaluation of spatial autocorrelation-based feature selection. *International Journal of Remote Sensing*, 20(8): 1601–1616.

Wartenberg, D., 1985. Multivariate spatial correlation: a method for exploratory geographical analysis. *Geographical Analysis*, 17(4): 263–283.

Wiens, J.A. 1989. Spatial scaling in ecology. *Functional Ecology*, 3: 385–397.

Wiersma, D. J. and D. A. Landgrebe, 1980. Analytical design of multispectral sensors. *IEEE Transactions on Geoscience and Remote Sensing*, GE-18: 180–189.

Woodcock, C. E. and A. H. Strahler, 1987. The factor of scale in remote sensing. *Remote Sensing of Environment*, 21: 311–332.

Wulder, M., J. C. White, S. Ortlepp, and N. C. Coops, in this volume. Remote sensing for studies of vegetation condition: theory and application. Chapter 25.

Zallat, J., C. Collet, and Y. Takakura, 2004. Clustering of polarization-encoded images. *Applied Optics*, 43: 283–292.

Zhang, P., J. Li; E. Olson, T. J. Schmit, J. Li, and W. P. Menzel, 2006. Impact of point spread function on infrared radiances from geostationary satellite. *IEEE Transactions on Geoscience and Remote Sensing*, 44(8): 2176–2183.