6

Vegetation mapping and monitoring

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6.1 INTRODUCTION

The nature and properties of vegetation are fundamental attributes of landscapes. The nature of the vegetation in an area is determined by a complex combination of effects related to climate, soils, history, fire and human influences which can date back several millenia in some locations. People have been interested in understanding the distribution of vegetation types since the times of Theophrastus, with significant contributions coming from such noted historical figures as Alexander von Humboldt and Lord Alfred Wallace. When viewed from this historical perspective, vegetation mapping has a long history which includes a variety of contexts and a wide range of geographic scales.

From a more modern perspective, one common distinction in vegetation mapping separates attempts to map 'potential' and 'actual' vegetation. Maps of potential vegetation attempt to determine what the vegetation type would be in the absence of human influences (Box 1981; Kuchler and Zonneveld 1988).

Maps of 'actual' vegetation attempt to characterize the vegetation as it exists in an area. Different vegetation maps emphasize different attributes of the vegetation. Some are floristic in orientation and focus on taxonomic differences between places. Others are focussed on more structural attributes of the vegetation, emphasizing the basic lifeforms of the vegetation and the size and density of cover. The characteristics emphasized in vegetation maps and their scale are typically dependent on the needs and interests of the users of the maps. At one end of the spectrum are global vegetation maps which are often used to study the relationship between vegetation types and climate (Köppen 1931; Olson *et al.* 1983; also see Chapter 4).

More local scales of vegetation maps are often made to serve the needs of local land management. Vegetation can be viewed in a myriad of ways from the land management perspective, including as: a source of food and/or fiber; habitat for wildlife; protector of soils; a recreational resource; a regulator of the interactions between the surface and the atmosphere with respect to heat, gases, and moisture; or simply as a fundamental attribute and descriptor of landscapes. Thus, vegetation is fundamental to many environmental processes and as a result plays a central role for the focus of this book, or the use of GIS for environmental modelling.

The goal of this chapter is to provide some history and context to recent and current efforts to map and monitor vegetation, while providing some indications regarding the way vegetation maps are used in environmental modelling. Remote sensing has revolutionized vegetation mapping, as the synoptic perspective is ideal for mapping landscape attributes. The focus here will be on the use of satellite remote sensing for vegetation mapping and monitoring, and the discussion attempts to characterize the recent innovations and ongoing areas of active research. Please note that this chapter focuses on vegetation maps at local to regional scales. Discussion of the use of satellite imagery for continental to global scales is included in Chapters 4 and 5.

6.2 VEGETATION MAPPING

6.2.1 Historical overview

The first vegetation maps made with the help of remote sensing were based on the visual interpretation of aerial photographs. The basic mapping scenario involves delineation of homogeneous patches, or stands of vegetation, for which labels are provided concerning the properties of the vegetation within the polygon. Typical vegetation properties included are the overall lifeform of the vegetation, dominant species, height and density of the vegetation, and the presence and nature of understory vegetation. Some of these properties are measured using photogrammetric methods, such as vegetation height measurements using a parallax bar (Lillesand and Kiefer 2000). Other vegetation properties are inferred from the tone, color, shape, texture, pattern, site, context and association observed in the aerial photograph (Estes *et al.* 1983) based on the knowledge of the interpreter and augmented with field visits to the area being mapped.

With the advent of the Landsat programme in 1972, there was an immediate interest in the potential for mapping vegetation over larger areas in a more efficient manner than traditional air photo interpretation. The primary initial advantages derived from the digital format of the imagerywhich made it possible to use computers to do automated interpretation. The use of computers for analysis held great promise for reducing time and effort in vegetation mapping. Another immediate savings resulted from the digital format and geometric fidelity of the data which greatly facilitated integration of the resulting vegetation maps into GIS.

Vegetation mapping from satellite imagery has been dominated by use of data from the reflective wavelengths of the solar spectrum, primarily the visible, near-infrared and mid-infrared. The initial sensor used for vegetation mapping was the Landsat Multispectral Scanner (MSS) which has four broad spectral bands in the visible and near-infrared wavelengths. Landsat 4 included a new sensor called the Thematic Mapper, which has 6 reflective bands with 30 m spatial resolution and a thermal band. The SPOT HRV provides finer spatial resolution (20 m) than Landsat TM but fewer spectral bands and the images cover a smaller area (see Chapter 3 for a review of sensor characteristics). Landsat TM and SPOT HRV have been the most commonly used sensors for vegetation mapping and monitoring.

The strong reliance of air photo interpretation on the skill and experience of the interpreter is both the strength and weakness of this approach to vegetation mapping. In general, digital analysis of satellite imagery cannot match the quality of vegetation maps derived from outstanding air photo interpretation. Many vegetation maps are still made via air photo interpretation, particularly for areas small enough that the economies of scale associated with digital analysis of satellite imagery are unimportant, or where the requirements for spatial detail or accuracy of the vegetation maps are beyond those achievable with satellite remote sensing. Vegetation mapping was one of the first uses of satellite remote sensing imagery and has been one of the most common ever since (see for example Hoffer and Staff 1975).

There have been many approaches and developments involving vegetation mapping from satellite remote sensing. The discussion below is organized by the information sources exploited to map vegetation, presented in roughly the order in which they were pursued and developed.

6.2.2 Multispectral data and image classification

The first and most common approach used to map vegetation from satellite imagery is the use of multispectral data in image classification. In this approach patterns of spectral reflectance, or 'spectral signatures', are associated with different vegetation types. In the image classification step, each pixel in the image data is assigned to a particular vegetation type, resulting in a map. This paradigm has used data primarily from the solar reflective wavelengths, but other kinds of data were later included, such as texture data or other kinds of map data such as topographic variables.

Image classification algorithms can be sorted into those which are 'supervised' or 'unsupervised'. The supervised classification approaches require training sites as input prior to the image classification step which are used to characterize the spectral signatures of the vegetation types. Initially, parametric statistical classifiers such as maximum likelihood dominated (Swain and Davis 1978).

Unsupervised classification proceeds by allowing the computer to define spectral clusters of pixels, or groups of pixels in the image with similar spectral properties. Each pixel is then assigned to one such cluster. User input is necessary to associate vegetation types with spectral clusters. The primary difference between the supervised and unsupervised approaches is the timing of the user input relative to the classification step. When the input is provided ahead of classification, the approach is said to be supervized. Unsupervised approaches require user input after the classification step.

The maximum likelihood classifier assumes that the spectral signatures of vegetation types are distributed in a multivariate normal fashion, which is often not true. Vegetation classes often exhibit multimodal or non-normal shapes in their distributions, which is the result of the inherently complex nature of remote sensing images in the optical domain. Many factors influence the reflectance from vegetation canopies, some diagnostic of the vegetation types of interest in the mapping process and others unrelated. The vegetation factors known to influence the spectral reflectance of vegetation canopies include the overall life form of the vegetation, leaf properties (leaf area and leaf angle distribution and spectral reflectance properties), vegetation height or tree size, the fractional cover of vegetation, and the health and water content of leaves. In addition, the soil colour and wetness contribute to the spectral response at any given location in the image. The net effect is that the same vegetation type may have many spectral manifestations in the image, which significantly complicates the image classification process.

There have been many approaches proposed and tested to attempt to accommodate the complex nature of spectral signatures of vegetation types in the classification process. Unsupervised image classification can be formulated to include many more spectral clusters than the number of intended vegetation types, thus allowing many spectral clusters within each vegetation type. In supervised classification, many training sites can be used for single vegetation types, with individual training sites or small groups of training sites used separately through the image classification step to identify subpopulations of the intended vegetation types. These subpopulations can then be merged after the classification step to produce the final map.

There has also been significant innovations in image classifiers driven by the problems posed by vegetation mapping. For example, Skidmore and Turner (1988) developed nonparametric classification algorithms to accommodate the problems associated with non-normal distributions. More recently algorithms based on decision trees and artificial neural networks are proving to be more effective than traditional methods (Foody *et al.* 1995, Friedl and Brodley 1997, Carpenter *et al.* 1997). It should be noted that not all investigators are finding improvements with these algorithms (Skidmore *et al.* 1997), and they often are more difficult to implement as they require more training data and are not available in common image processing packages. The main strength of these algorithms with respect to vegetation mapping is to allow association of many spectral patterns to single vegetation types using a supervized approach without requiring separation of the training data into subpopulations.

One issue that confronts the use of digital satellite images for mapping vegetation concerns scale, or the relationship between the size of individual pixels and the desired scale of the resulting map. Frequently, the pixels in satellite images are too small to be classified individually in the final map. For example, at map scales common for use in local land management, such as 1:25,000, minimum mapping units are typically on the order of 1–2 hectares, or 25–50 pixels in a SPOT HRV image or 11–22 pixels in a Landsat TM image. This issue remains one of active research, and several approaches exist for this situation, including: filtering of the images resulting from per-pixel classifiers (Kim 1996); using spatial or contextual information in the classification process (Kettig and Landgrebe 1976; Stuckens *et al.* 2000), and the segmentation of images into polygons in a step independent of image classification (Woodcock and Harward 1992).

6.2.3 Vegetation mapping, ancillary data and GIS

The relationship between vegetation mapping and GIS is mutually beneficial. On the one hand, vegetation maps are used extensively within GIS for the purposes of environmental modelling, as illustrated in many ways in this book. However, the integration of other kinds of map data with remote sensing images through the use of GIS has greatly improved the vegetation mapping process. It is this dimension of the relationship between vegetation mapping and GIS which is emphasized in this section.

Vegetation mapping based solely on image classification of multispectral data is limited with respect to the vegetation attributes that can be provided in a reliable manner. Particularly apparent in this regard is the difficulty of mapping vegetation at the level of detail of individual plant species. This problem arises because many species often have overlapping spectral signatures which makes their identification impossible or of poor accuracy.

The use of topographic data to improve or augment maps made using satellite imagery dates from some of the earliest attempts to use satellite remote sensing to make vegetation maps (Hoffer and staff 1975; Strahler *et al.* 1978). The primary intent of the use of topographic data was to capture the influence of climate on species distributions, with topographic variables of elevation, aspect and slope being used as surrogates for temperature and moisture conditions. Such approaches have proven highly successful and are used frequently in vegetation mapping efforts (Skidmore 1989; Woodcock *et al.* 1994).

The detailed example given below helps illustrate the ways in which ancillary data are being integrated with remote sensing in vegetation mapping efforts.

6.2.3.1 Modelling example: mapping Eucalyptus *species distribution using solar radiation data*

Introduction

A number of response models have been developed to investigate the relationships between different environmental factors and the distribution of forest species (e.g. McColl 1969; Austin *et al.* 1984; Austin *et al.* 1990; Moore *et al.* 1991). These models have included environmental variables such as nutrient availability, rainfall, temperature (Moore *et al.* 1991), topographic position (Austin *et al.* 1983; Austin *et al.* 1994), elevation, aspect, exposure to wind (Mosley 1989), slope position (Twery *et al.* 1991), soil structure (Florence 1981) and soil nutrients (Turner *et al.* 1978).

Some of these models have used a solar radiation index for vegetation mapping (Kirkpatrick and Nunez 1980; Austin *et al.* 1983; Moore *et al.* 1991; Ryan *et al.* 1995), with Kirkpatrick and Nunez (1980) reporting a strong correlation between solar radiation and the distribution of several species of eucalyptus along a single transect in the Risdon Hills in Tasmania. These models have calculated solar radiation over individual field plots through field measured parameters using the method suggested by Fleming (1971) or have used radiation measuring devices, such as pyranometers (Kirkpatrick and Nunez 1980). While solar radiation data collected in the field are generally the most reliable, it is very difficult to extrapolate these data to other sites or over a large area, especially in mountainous areas where solar radiation is strongly influenced by terrain. Such data, based on point samples measured in the field, are not suited to spatial modelling in a GIS.

Solar radiation indices based solely on slope aspect and slope gradient are crude estimates as they do not take into account shading by adjacent terrain. While such a method may be acceptable in flat areas, it will not work adequately in hilly regions where shading by topographic features can account for large differences in the radiation received at a site (Kumar *et al.* 1997). Simulations in a mountainous area by Hetrick *et al.* (1993) showed that topographic shading was more important than surface orientation. Simulations at different field sites have shown that when shading by topographic features is included, approximately 30 per cent of grid cells had their total radiation reduced by 10 per cent.

Previous research (e.g. Austin *et al.* 1984) showed the distribution of vegetation responding directly to environmental factors including temperature, moisture regime and nutrient availability; and since temperature and moisture regime may be linked to solar radiation (Ahrens 1982), it is hypothesized that the distribution of vegetation should be related to solar radiation. The aim of this study was to confirm whether the distribution of *Eucalyptus* species are related to differences in solar radiation incident at a grid cell.

Solar radiation data

Solar radiation for the study area was calculated using the method proposed by Kumar *et al.* (1997). In brief, solar radiation received at a site is dependent on the azimuth and elevation of the sun, surface gradient (slope) and orientation (aspect), as well as position relative to neighbouring surfaces. Variables such as solar azimuth and solar elevation angles change continuously throughout the day and so they have to be calculated every time the intensity of solar radiation is computed. Another important factor that needs to be calculated instantaneously is shading by topographic features. In contrast, solar declination may be calculated daily, as it varies more gradually.

Aspect and slope may be easily calculated from a DEM. The additional inputs required to derive solar radiation are the latitude of the site and the Julian date (note that if calculations are required for more than one day, the start and end day are needed). For integrating the total radiation over a period (i.e. days, weeks or months), the repeat period between the instantaneous calculation of solar flux must be specified by the user. While it would be ideal to have a very short time interval to obtain accurate results, this is not always feasible because of constraints such as computational expense and the availability of a fast computer. The time interval chosen can be larger for flat terrain but has to be smaller for mountainous regions as shadowing effects will be prominent in such environments (Kumar *et al.* 1997). The radiation flux is calculated at the mid-point of each time interval to reduce shadowing effects.

Due to the forest having a natural mix of species in each plot, the data were pre-processed before analyzing the relationship between species distribution and solar radiation. In order to generate an index of solar radiation adjusted for the species composition of the plot, the radiation values for each plot were normalized according to the number of trees of each species present. Thus, for a particular species (such as *Eucalyptus sieberi*), a 'weighted mean' of the radiation values was calculated by multiplying the radiation value of each plot by the number of trees of *Eucalyptus sieberi* in the plot, adding up these values, and then dividing by the total number of trees of *E.sieberi* in all the plots. The 'weighted mean' radiation value therefore represents the overall radiation zone in which species are located. This index emphasized the plots in which a particular species is located, as the frequency of occurrence gives an indication of the environment in which those species are located. If the plot data are not normalized by the number of trees, then a plot with say 100 trees of *E.sieberi* has the same weight as a plot which has only one tree of *E.seiberi*, and both will contribute equally to the analysis. The decision to normalize is based on the observation that the forest structure is composed of 'old growth' that is dominated by an overstorey of large and medium sized trees.

A research hypothesis that the 'mean weighted' radiation values differed between species was tested using the F-test. Stated formally, the null hypothesis is that the mean solar radiation for different species are equal, that is:

Ho: $\mu_{\text{species 1}} = \mu_{\text{species 2}}$

while the alternative hypothesis is that there is a difference in mean solar radiation between species 1 and species 2,

H1: $\mu_{\text{species 1}} \neq \mu_{\text{species 2}}$

for $\alpha' < 0.05$.

Species groupings were investigated using multivariate techniques such as cluster analysis. Due to the large number of cases the K-Means cluster analysis algorithm, based on the nearest centroid sorting (Anderberg 1973), was used for determining cluster membership.

Results

Figure 6.1 shows the variation in short wave solar radiation across the study area for the different seasons, ranging from 3600 to 11200 MJ/m^2/year. Exposed sites received almost 3 times as much solar radiation as shadowed sites.

The seasonal difference in the solar radiation is large, and as expected, the summer season receives more radiation than the winter season. The mean radiation is highest in summer, followed by spring, autumn and winter respectively, with the mean winter value being 60 per cent of the summer value. Many gully sites do not receive any direct radiation during winter as adjacent ridges continually shade them.

The variance in solar radiation is least during summer and largest in winter, especially for the south, southeast and southwest aspects (Note that the study site is located in the southern hemisphere). These aspects have the largest variation on their midslopes, caused by shading when the sun is lower in the winter sky.

North facing slopes receive far more radiation than the south facing slopes, with other aspects ranging between these two extremes. While the radiation values for north, north-east and north-west aspects stay almost constant with slope, those for south, south-east and south-west fall off fairly sharply as the slope increases. At low slopes, there is little difference in the radiation values for the different aspects, with the differences between aspects being least in the summer months.

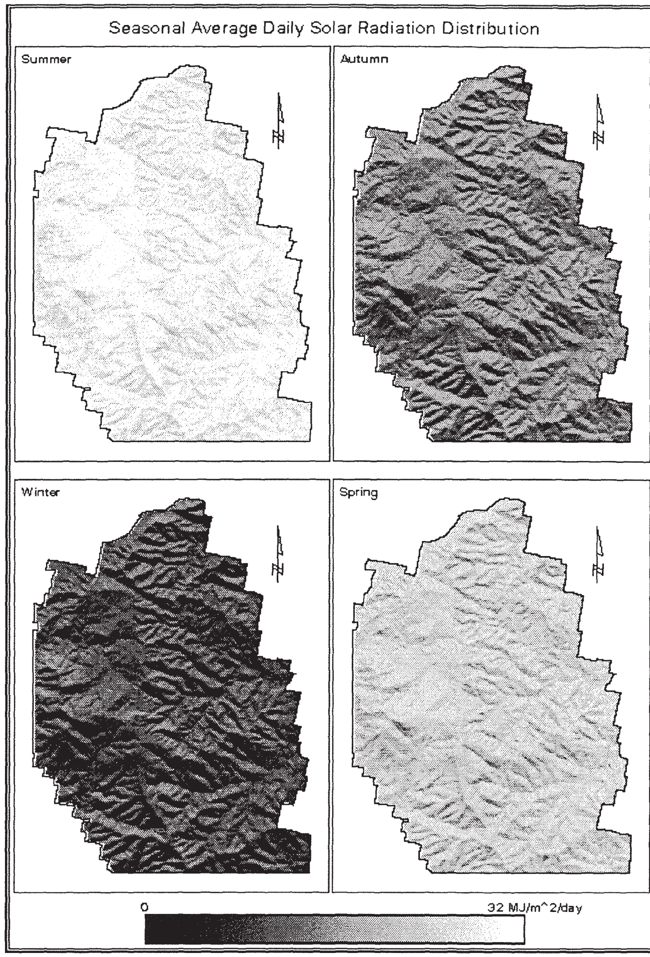

Figure 6.1: Solar radiation distribution for the different seasons.

Figure 6.2 shows that different species are located in certain radiation zones. Of the 12 species in this study, *E.smithii* and *E.consideniana* occur at sites with the lowest radiation values. *E.sieberi*, *E.globoidea* and *E.viminalis* are consistently placed at the high end of radiation values. Seasonal variation in solar radiation was also found to influence the occurrence of *Eucalyptus* species. Results of Student-Newman-Keuls Test showed that, for many of the species, the differences in the mean radiation were statistically significant. For example *E.consideniana* had insolation values which were significantly different from all species for all the seasons, except in spring and summer where *E.smithii* was an exception. Similarly *E.obliqua* was significantly different from all the species for all the seasons. Some other species that returned significance with many of the species were *E.agglomerata*, *E.bosistoana*, *E.cypellocarpa*, *E.globoidea* and *E.muellerana*.

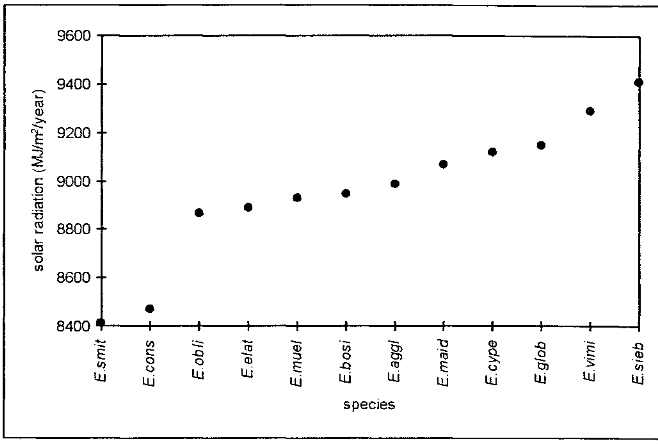

Figure 6.2: Relationship between the 'weighted mean' solar radiation and the different species.

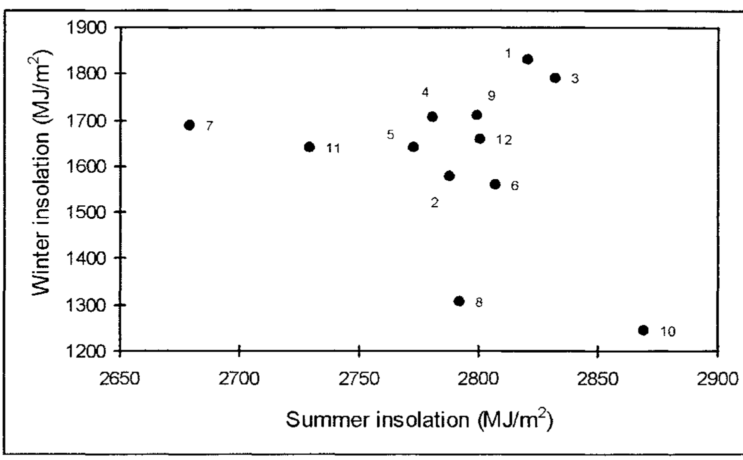

Figure 6.3: Species position in relation to their summer and winter radiation values.

[1. *E.agglomerata*, 2. *E.bosistoana*, 3. *E.consideniana*, 4. *E.cypellocarpa*, 5. *E.elata*, 6. *E.globoidea*, 7. *E.maidenii*, 8. *E.muellerana*, 9. *E.obliqua*, 10. *E.sieberi*, 11. *E.smithii*, 12. *E.viminalis*]

Another important aspect that was noted was that the confidence intervals shifted between seasons, indicating that seasonal differences in radiation may assist in characterizing species. For example *E.sieberi* had a confidence interval placed at the high end of radiation in summer and was at the upper end of the interval for *E.viminalis* but moved lower in autumn and winter seasons and, when compared to *E.viminalis*, was at the lower end of its confidence interval. Therefore, while the confidence intervals changed by seasons, much as expected, they also shifted position relative to other species by seasons (Kumar and Skidmore 2000). It is these changes in position relative to other species over different seasons that may be used to characterize species. The winter season showed the greatest variation in mean radiation and the confidence intervals were more separated. Figure 6.3 shows how species separate when winter insolation values for each species are plotted against their summer values.

Possible uses of insolation data in forestry modelling

Since many species show that their radiation regimes are significantly different from other species, this information can be utilized to delineate individual species or to find the most likely habitats of the species. The different seasonal confidence intervals of means for each species can be combined to make the selection criteria. For example, from the means tables, the conditions for the different species would be used to produce probability maps as given in Figure 6.4. Diagrams such as these can then be used for planning logging operations, habitat mapping, conservation work, etc. These figures do not confirm with 100 per cent certainty that the particular *Eucalyptus* species would be found at the mapped site, but they pinpoint the most probable sites of occurrence and hence a good starting point. The Australian Koala Foundation is already using the insolation model for the prediction of koala populations. Koalas feed on specific species of *Eucalyptus* and if the habitat of these species is mapped out then the possible locations of koalas can be predicted.

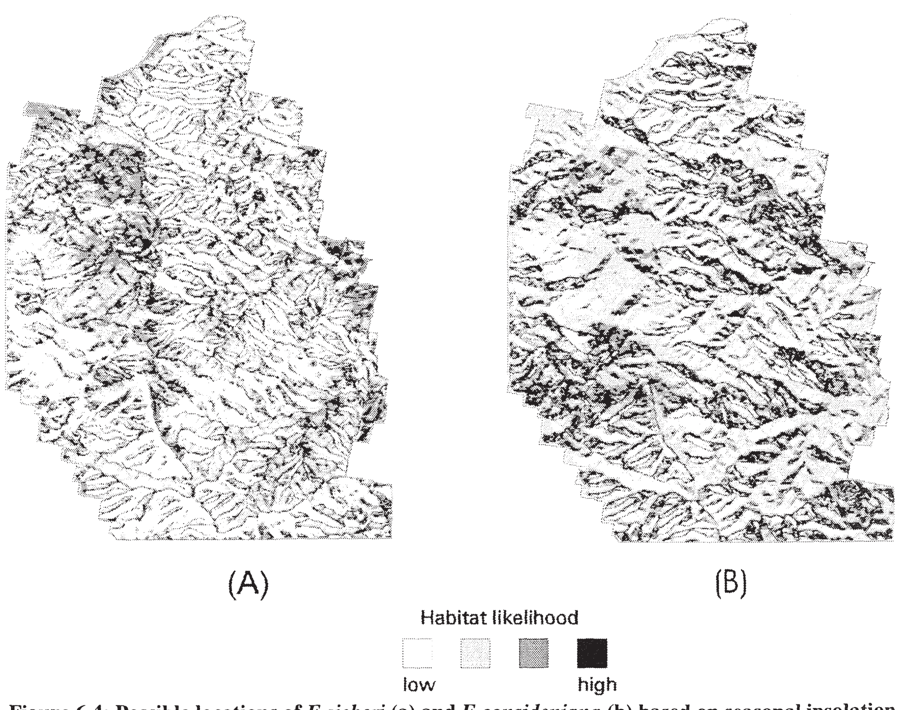

Figure 6.4: Possible locations of *E.sieberi* (a) and *E.consideniana* (b) based on seasonal insolation data.

Similar work can be extended to forest types as well. If a large number of plots are surveyed and confidence intervals of means are produced as done for the species distribution, then a similar set of conditions can be coded. This should show the most likely locations for the different forest types.

However the main use of solar radiation in modelling vegetation distribution would be as a value added layer in other environmental models (Figure 6.5). As mentioned before, solar radiation is one of a number of environmental factors that affect species distribution. Other researchers have shown the correlation between species and a number of other environmental factors. These factors can be combined with solar insolation to model the species more effectively. In a GIS, each of these factors can be stored as a different layer and Boolean conditions can be coded to model the different species. Solar radiation modelled in this manner can also be used as an input parameter in expert systems or neural networks.

6.2.4 Use of spatial and temporal patterns

Two additional kinds of information which have been used in vegetation mapping based on satellite imagery are spatial and temporal patterns. The use of spatial patterns, or texture, is based on the long recognized value of texture in air photo interpretation for differentiating vegetation types. To use texture in vegetation mapping using satellite imagery, a new texture band is created from one of the original spectral bands. The texture band (or bands) are then combined with the original spectral bands in the image classification process, increasing the number of input bands. It represents an attempt to exploit in automated image classification one kind of information which contributes greatly to visual interpretation of air photos. Several studies have shown the use of texture data to improve vegetation maps derived from satellite imagery (Franklin *et al.* 1986; Franklin and Peddle 1989; Jakubauskas 1997).

Temporal patterns, or the change in reflectance properties over time, have been used extensively for mapping vegetation at continental to global scales using NOAA AVHRR imagery (See Chapter 3). The NOAA imagery has coarse spatial resolution but high temporal resolution, so phenological patterns of vegetation can be captured using AVHRR imagery (DeFries and Townshend 1994). The basic approach is to use multiple dates of imagery as input bands to image classification procedures. More recently, several investigators have found that use of multitemporal imagery can improve vegetation mapping at local to regional scales using imagery such as Landsat TM or SPOT HRV (Wolter, *et al.* 1995; Mickelson *et al.* 1998). The use of multitemporal imagery appears most promising in environments with mixes of evergreen and deciduous species.

Model output as an input to other more sophisticated models

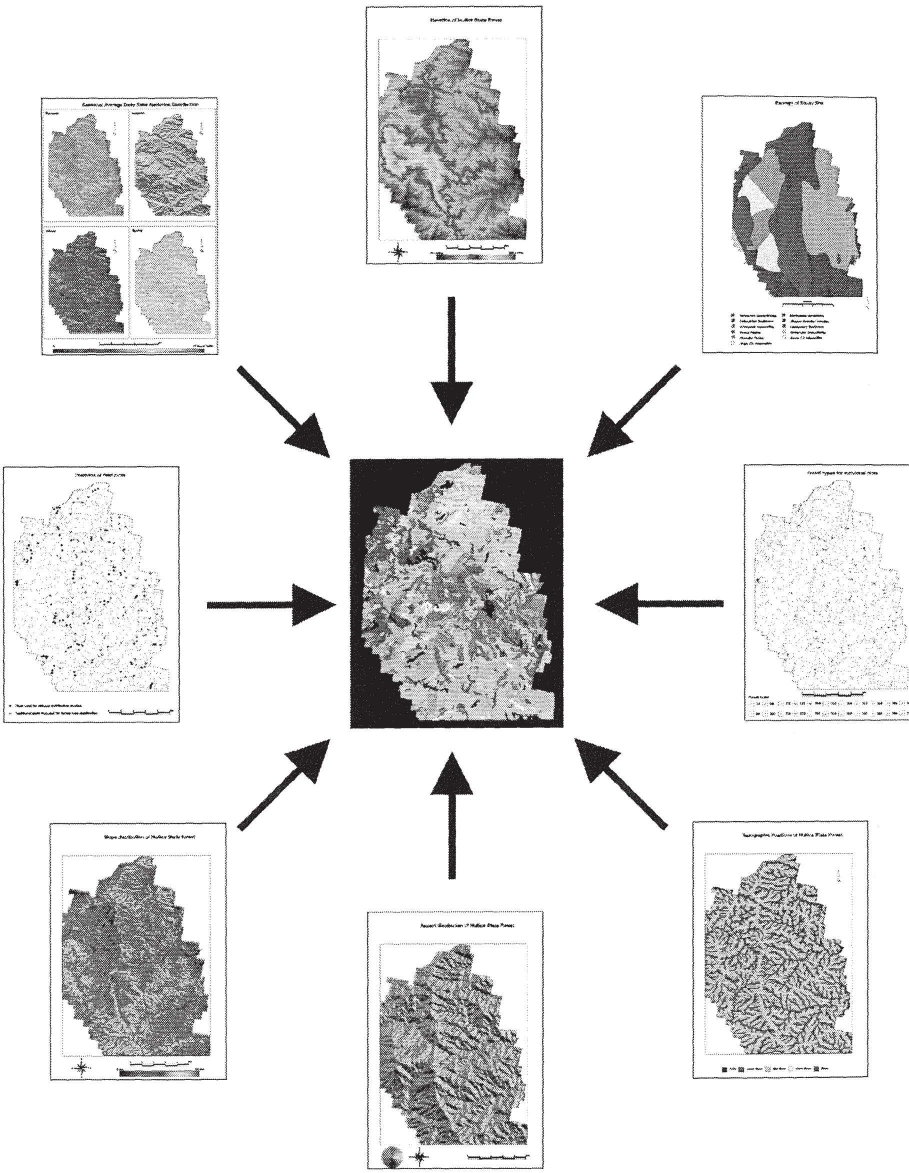

Figure 6.5: Solar radiation data form the GIS model as input into another larger GIS model.

6.2.5 New kinds of imagery

There are a variety of new kinds of imagery being used, or at least experimented with, for vegetation mapping. They hold great potential for improving the kinds of information that can be provided about vegetation via remote sensing in the future. These new types of imagery are described in detail in Chapter 3.

6.2.5.1 Hyperspectral imagery

While data obtained from broadband sensors (such as the Landsat TM and ETM+ and SPOT HRV) have been useful in many respects for vegetation mapping, they also have their limitations. Because of their limited number of channels and wide bandwidths, a lot of the data about plant reflectance is lost. Most natural objects have characteristic features in their spectral signatures which distinguish them from others and many of these characteristic features occur in very narrow wavelength regions (Figure 6.6).

Hence to sense these narrow features the use of narrow band sensors is required. Broadband sensors integrate the reflectance over a wide range and so the narrow spectral features are lost or masked by other stronger features surrounding them. For this reason hyperspectral remote sensing, often with bandwidths of only 5–10 nm, offers a powerful tool for significant advancement in the understanding of the Earth and its environment. A number of these narrow-band imaging spectrometers have been discussed in Chapter 3.

Figure 6.7 shows typical spectral reflectance data of vegetation as collected by a spectrometer (GER IRIS) and a simulated model of what the resulting signal would be from Landsat TM. Notice that the hyperspectral data includes detailed spectral features characteristic of vegetation which are lost in broadband sensors. Thus hyperspectral data holds the potential for providing more detailed information about vegetation than is possible with broadband sensors. While several hyperspectral sensors are planned for future satellites, current research is based on airborne systems, which are reviewed briefly in Chapter 3. Research has shown that hyperspectral remote sensing has a lot to offer with respect to species identification (Kumar and Skidmore 1998).

Also, data from airborne imaging spectrometers have been found to yield higher quality information about vegetation health and cover than those obtained from broadband sensors (Collins *et al.* 1983, Curran *et al.* 1992, Peuelas *et al.* 1993, Carter 1994, Carter *et al.* 1996, Kraft *et al.* 1996). Gamon *et al.* (1993) used the narrow AVIRIS spectral bands to evaluate the spatial patterns of vegetation type, productivity, and physiological activity in annual grasslands and the results showed the major vegetation types and fine scale patterns not discernible from broadband data.

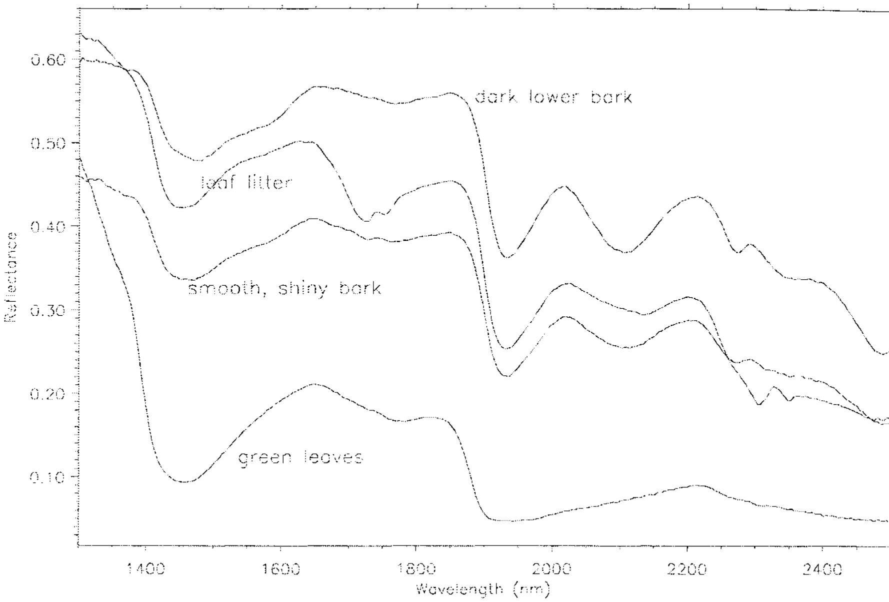

Figure 6.6: Hyperspectral data showing some spectral fine features in green leaves and different bark types in *Eucalyptus sieberi*. Note the features around 1750 nm, 2270 nm, 2300 nm and 2350 nm.

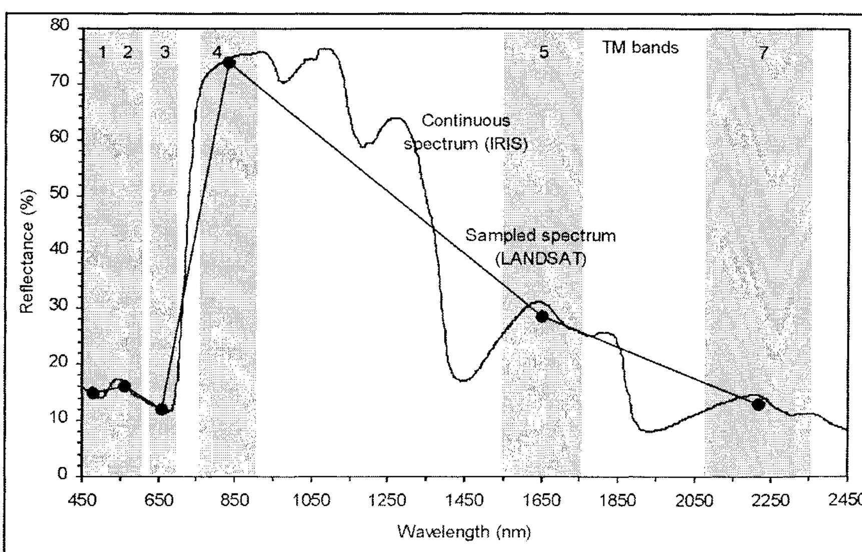

Figure 6.7: Data content of broadband (Landsat) and narrow-band (IRIS) sensors.

6.2.5.2 Radar imagery

Experiments with the use of radar for studying vegetation have demonstrated considerable promise. Research has found that radar can be sensitive to vegetation structure and biomass, particularly with multiband radar systems including lower frequencies (P- and L-band) with cross polarizations (Kasischke *et al.* 1997). There has also been progress on the use of radar imagery for general land cover mapping, which provides information on basic vegetation types. One of the main benefits of radar imagery is the independence of sensing from solar illumination, which allows for effective sensing during cloudy periods or even at night. This benefit is particularly valuable in areas characterized by high frequency of cloud cover, as is the case in many equatorial regions. Many new spaceborne radar systems have been launched recently, and a review of their characteristics has been provided in Chapter 3. The improving availability of radar imagery is destined to speed the pace with which radar imagery is adopted for vegetation mapping. The potential for combining radar and optical imagery to improve vegetation mapping is high and largely untapped at this point in time.

6.2.5.3 High spatial resolution imagery

One trend is toward the collection from satellites of imagery with high spatial resolution. Currently there is one operational satellite system, IKONOS, providing 1 m panchromatic and 4 m multispectral imagery. Other private sector systems are planned with similar spatial resolutions (see Chapter 3 for details). In anticipation of such capability, a number of airborne systems have been developed to allow for development of methods for analyzing high spatial resolution images (Franklin 1994).

Particularly in Canada there has been considerable effort devoted to learning how to use high spatial resolution imagery for vegetation mapping. The high resolution imagery contains effects associated with individual trees, and progress has been made on the problem of how to identify individual tree crowns and their size (Wulder *et al.*, 2000). Another area of active research is the estimation of tree size and cover from high resolution imagery through the analysis of observed spatial patterns in images (St Onge *et al.* 1997). The availability of satellite imagery with very high spatial resolution is destined to improve the quality of information about vegetation canopies, at least for selected areas.

6.2.6 Accuracy assessment

One important issue regarding the use of vegetation maps derived from remote sensing is accuracy. All vegetation maps contain errors, and the significance of those errors is dependent on the manner in which the vegetation maps are used. One result is that the accuracy requirements for the same map may vary between potential users of the map! Thus, careful characterization of the accuracy of vegetation maps is essential for their informed use. The most common approach used to determine the accuracy of vegetation maps is to conduct an accuracy assessment. While there are many ways to conduct an accuracy assessment, the most common is to populate an error matrix (also referred to as a confusion matrix) based on samples selected from the vegetation map. Such an approach allows estimation of the categorical nature of the errors and their overall frequency. Jensen (1996) provides a helpful discussion of the many issues and decisions involved in conducting an accuracy assessment.

Table 6.1 is an example of a hypothetical accuracy assessment for a vegetation map including four vegetation types. By convention, most confusion matrices are created with the map labels on the rows, and the reference data, or truth, down the columns. Below the confusion matrix, the Producer's and User's Accuracies are calculated for each class, as well as the overall accuracy and an accuracy estimate that removes the effect of random chance on accuracy, referred to as the Khat statistic (Skidmore 1999).

Many useful things can be learned from analysis of the accuracy assessment. The simplest statistic to derive is the overall accuracy. This is simply the sum of the diagonal elements divided by the total number of pixels (or sites) evaluated. In this case, the overall accuracy is moderate at 82 per cent, but the level of accuracy is highly variable between classes.

To better understand the variability of the accuracies of the different classes, one can also calculate the Producer's and User's accuracies. The Producer's accuracy is the number of correct elements for a class divided by the total number of pixels (or sites) given that map label (the row total). The User's accuracy is the number of correct elements divided by the total number of pixels that should truly have that label (the column total). In this context, analysts often discuss *errors of omission* and *errors of commission.* Errors of omission are those pixels which were missed by the Producer and thus are calculated as 100 minus the Producer's accuracy. By extension, errors of commission are the pixels wrongly assigned to a class and are calculated as 100 minus the User's accuracy. Thus, each error of omission from one class is also and error of commission for another class.

Table 6.1: A hypothetical result from an accuracy assessment, including a confusion matrix, and calculation of the Producer's, User's and overall accuracies (see Jensen 1996 for details).

Map	Reference Data				
Classification	A	B	C	D	Row Total
Map Class A	178	3	10	0	191
Map Class B	0	38	2	0	40
Map Class C	5	25	58	19	107
Map Class D	2	9	0	68	79
Column Total	185	75	70	87	417

Producer's Accuracy		User's Accuracy
Class A:	178/185 = 96%	178/191 = 93%
Class B:	38/75 = 51%	38/40 = 95%
Class C:	58/70 = 83%	58/107 = 54%
Class D:	68/87 = 78%	68/79 = 86%

Overall Accuracy 342/417 = 82% ; Khat Statistic = 74%

In the example, Class A is clearly the most accurately mapped, with high Producer's and User's accuracies (96 per cent and 93 per cent respectively). In contrast, Class B has a high User's accuracy (95 per cent), meaning you can be very confident of sites identified as Class B on the map, but the Producer's accuracy is very low (51 per cent) meaning the mapping process missed about half the area that is truly class B (49 per cent errors of omission).

Class C on the other hand has a high Producer's accuracy (83 per cent). The mapping process has found most of Class C, but a site on the map identified as Class C is only correct about half the time (54 per cent User's accuracy and 46 per cent errors of commission).

Finally, Class D is moderately accurate, but examination of the confusion matrix shows that most of the problems are errors of omission. The 78 per cent Producer's accuracy means 22 per cent errors of omission. Most of the errors of omission (19/30) are mislabelled as Class C. Thus, to improve the accuracy of class D, one might begin with reevaluation of the areas mapped as class C.

6.3 MONITORING VEGETATION CHANGE

Vegetation health, condition and change through time are of great interest from a variety of perspectives. Satellite imagery, primarily due to its synoptic views of landscapes and multitemporal sensing, is well suited for monitoring vegetation health and change through time. One of the benefits of continued collection of satellite imagery by programs like Landsat and SPOT is the ability to study changes in landscapes over time, with changes in vegetation being among the most common features studied. The historical archive of satellite imagery for studying landscape change continues to grow and its duration now covers more than a quarter of a century. While this chapter highlights many ways in which this imagery is being used to study vegetation change, it is noteworthy that recently there has been a dramatic increase in studies using the archive of historical satellite imagery. This trend indicates the growing value of this archive of imagery and points to a future where remote sensing data plays a key role in our understanding of how landscapes are changing and how humans are influencing the health of vegetation.

Like vegetation mapping, imagery from the optical domain (Landsat and SPOT) have dominated efforts to monitor vegetation change. Many kinds of vegetation changes have been monitored in many different contexts and regions of the world and using a wide variety of methods. The simple taxonomy presented below emphasizes the different kinds of vegetation change being monitored with remote sensing and the numbers of images being used. The examples mentioned are far from a complete inventory of the ways remote sensing is being used in this context, but they are intended to serve as representative of the kinds of problems and range of geographic locations being studied.

6.3.1 Monitoring vegetation condition and health

Many factors influence vegetation condition and health, ranging from drought and pests to acid rain and air pollution. While it is necessary to characterize the nature of the problem and the ranges of magnitude of effects on the vegetation through field samples, it is difficult to determine the geographic extent and locations of the areas affected using conventional field methods. Remote sensing offers an alternative approach whose strengths are in spatial coverage, which when merged with field samples has been shown to be extremely helpful for monitoring vegetation health.

6.3.1.1 Single date assessments

Damage from insects is a key concern for forest health monitoring. Information on the location of damage and its severity is essential to local resource management. Williams and Nelson (1986) report on the ability to use Landsat MSS data and ratios of NIR to red reflectance to map defoliation due to insects in the hardwood forests of the north-eastern USA. Ekstrand (1990) similarly found Landsat TM data useful for monitoring levels of insect damage in Swedish conifer forests using single dates of Landsat TM imagery in the late summer.

Some of the most dramatic anthropogenic effects on vegetation health arise from air pollution and associated acid rain. Vogelmann and Rock (1988) mapped forest damage in high elevation forests of the North-eastern US using Landsat imagery. They found that a ratio of the mid IR reflectance to near infrared reflectance was diagnostic of forest damage due to acid rain/air pollution in conifer forests. Ardo *et al.* (1997) were able to map three classes of forest damage, in the form of levels of needle loss, in spruce forests in the Czech Republic using Landsat data. The forest damage classes were defined on the basis of regressions between needle loss and TM spectral data. Their study helped quantify the magnitude of deforestation and forest damage resulting from extreme acid rain/air pollution problems in this region.

6.3.1.2 Multitemporal analysis

While there has been success at times using single acquisitions of satellite imagery to map the locations of vegetation affected by such factors as insects and air pollution/acid rain, it has been much more common to use multitemporal satellite imagery to monitor vegetation health. In this approach, images from different dates for the same location are coregistered such that spectral values from the two dates can be directly compared.

In several settings, analysis of multidate images has proven effective for monitoring defoliation of forests due to insects. Muchoney and Haack (1994) used multitemporal SPOT imagery for identifying changes in hardwood forest defoliation due to gypsy moths in the eastern US. They tested a variety of methods and found the best results using image differencing and principal components analysis. In a later study, Radeloff *et al.* (1999) used spectral mixture analysis to measure the magnitude of defoliation in pine forests in north-western Wisconsin, US. Their study illustrated the importance of controlling for factors like the presence of hardwoods within pine stands on the effectiveness of defoliation monitoring. In related studies, Macomber and Woodcock (1994) and Collins and Woodcock (1994) studied drought-induced mortality in conifer forests using multitemporal Landsat imagery. The vegetation change in this case is still caused by insects, but the insects kill the trees, which is measured as a change in canopy cover or basal area. They tested a variety of methods and found that many worked well for estimating mortality within forest stands, providing an encouraging indication of the ability to detect subtle changes in canopy cover over time with multispectral satellite imagery.

Coppin and Bauer (1994) report on development of methods for operational monitoring of forest change in Minnesota, US. Their methods identify changes in forest cover due to a variety of reasons, including storm damage. They used multitemporal images and found that changes in the overall brightness and greenness of forest stands were reliable indicators of forest change. Another cause of vegetation change is air pollution, which was found to significantly damage the forests in the Kola Peninsula of northern Russia (Rigina *et al.* 1999). The air pollution was the result of the smelting industry and caused extensive damage which was monitored using satellite imagery from 1978 and 1996. Analysis of the patterns of vegetation damage indicated the influence of the surrounding mountains on the location of areas protected from damage.

6.3.2 Vegetation conversion and change

Another kind of change in vegetation of great interest is wholesale conversion of vegetation types. The most obvious example of this kind of change is deforestation, which is one of the most significant forms of land-use change occurring on Earth. Whether deforestation is due to the harvest of wood products, conversion of land to other uses such as agriculture or urban uses, the result of forest fires, or some combination of the above, monitoring of deforestation is a concern in many regions of the world. Remote sensing has been the primary tool used for monitoring deforestation. Experience has shown that deforestation is best monitored using medium resolution sensors such as Landsat and SPOT, as coarse resolution sensors such as AVHRR often produce misleading estimates of the total area deforested.

There are a variety of reasons for monitoring forest clearing, or deforestation. One reason is to understand the role of forest change in the global carbon budget, which requires data on deforestation over large areas. The best known example in this regard is the ongoing effort to monitor deforestation in Amazonia (Skole and Tucker 1993). Another reason for monitoring forest clearing is local land management. In Finland, where forests are actively managed for wood products, multitemporal Landsat TM images have been shown to be useful for providing timely information on rapid changes in forest cover (Varjo 1997). India is suffering from serious depletion of its forest cover, and remote sensing is playing a valuable role in providing information on the location and extent of forest clearing (Singh 1986; Jha and Unni 1994). Research continues with regard to how to best monitor forest clearing over large areas. Much of the initial deforestation work was based on visual interpretation of images, but recent efforts have indicated the viability of using automated analysis of multitemporal images to monitor forest change (Cohen *et al.* 1998).

6.4 CONCLUDING COMMENTS

Vegetation is a fundamental attribute of landscapes which influences a whole host of environmental processes. Mapping of vegetation via remote sensing is providing information on vegetation properties for large parts of the world in sufficient spatial detail to aid environmental modelling. Vegetation mapping at local to regional scales is currently dominated by imagery from the Landsat and SPOT satellites, but future vegetation mapping will be improved by use of hyperspectral imagery, radar imagery, and high spatial resolution imagery. Monitoring of vegetation change using remote sensing is providing an improved understanding of the health and condition of vegetation as well as rates of conversion of natural vegetation to other land uses. The value of the historical archive of satellite imagery is being repeatedly demonstrated in an increasing number of vegetation monitoring projects.

6.5 REFERENCES

Ahrens, C.D., 1982, *Meteorology Today*, St. Paul, MN, West Publishing Company.

Anderberg, M.R., 1973, *Cluster analysis for applications*. New York., Academic Press.

Aplin, P., Atkinson, P. and Curran, P., 1997, Fine spatial resolution satellite sensors for the next decade, *International Journal of Remote Sensing*, **18**, 3873–3881.

Ardo, J., Pilesjo, P. and Skidmore, A.K 1997, Neural networks, multitemporal Landsat Thematic Mapper data and topographic data to classify forest damages in the Czech Republic, *Canadian Journal of Remote Sensing*, **23**, 217–229.

Austin, M.P., Cunningham, R.B. and Fleming, M.P., 1984, New approaches to direct gradient analysis using environmental scalars and statistical curve-fitting procedures *Vegetatio*, **55**, 11–27.

Austin, M.P., Cunningham, R.B. and Good, R.B., 1983, Altitudinal distribution of several Eucalypt species in relation to other environmental factors in southern New South Wales. *Australian Journal of Ecology*, **8**, 169–180.

Austin, M.P., Nicholls, A.O., Doherty, M.D. and Meyers, J.A., 1994, Determining species, response functions to an environmental gradient by means of a ß-function. *Journal of Vegetation Science*, **5**, 215–228.

Austin, M.P., Nicholls, A.O. and Margules, C.R., 1990, Measurement of the realised qualitative niche: Environmental niches of five Eucalyptus Species. *Ecological Monographs*, **60**, 161–177.

Box, E.O., 1981, *Macroclimate and Plant Forms*. The Hague, Netherlands, Dr. W. Junk Publishers.

Carpenter, G.A., Gjaja, M.N., Gopal, S. and Woodcock, C.E., 1997, ART neural networks for remote sensing: Vegetation classification from Landsat TM and Terrain Data. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, 308–325.

Carter, G.A., 1994, Ratios of leaf reflectances in narrow wavebands as indicators of plant stress. *International Journal of Remote Sensing*, **15**, 697–703.

Carter, G.A., Cibula, W.G. and Miller, R.L., 1996, Narrow-band reflectance imagery compared with thermal imagery for early detection of plant stress. *Journal of Plant Physiology*, **148**, 515–522.

Cohen, W.B., Fiorella, M. and K. Anderson, 1998, An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, **64**, 293–300.

Collins, W., Chang, S.H., Raines, G., Canney, F. and Ashley, R., 1983, Airborne biogeophysical mapping of hidden mineral deposits. *Economic Geology and the Bulletin of the Society of Economic Geologists*, **78**, 737–749.

Collins, J.B. and Woodcock, C.E., 1994, Change detection using the Gramm-Schmidt transformation applied to mapping forest mortality. *Remote Sensing of Environment*, **50**, 267–279.

Congalton, R.G., Oderwald, R.G. and Mead, R.A., 1983, Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogrammetric Engineering and Remote Sensing*, **49**, 1671–1678.

Coppin, P.R. and Bauer, M.E., 1994, Processing of multitemporal Landsat TM Imagery to optimize extraction of forest cover change features. *IEEE Transactions on Geoscience and Remote Sensing*, **32**, 918–927.

Curran, P.J., Dungan, J.L., Macler, B.A., Plummer, S.E. and Peterson, D.L., 1992, Reflectance spectroscopy of fresh whole leaves for the estimation of chemical concentration. *Remote Sensing of Environment*, **39**, 153–166.

DeFries, R.S. and Townshend, J.R.G., 1994, NDVI-derived land cover classification at global scales. *International Journal of Remote Sensing*, **15**, 3567–3586.

Ekstrand, S., 1990, Detection of moderate damage on Norway Spruce using Landsat TM and digital stand data. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, 685–692.

Estes, J.E., Hajic, E.J. and Tinney, L.R., 1983, Fundamentals of Image Analysis: Analysis of Visible and Thermal Infrared Data. In: *The Manual of Remote Sensing, Second Edition*, R.N. Colwell, (ed.), American Society of Photogrammetry.

Fleming, P.M., 1971, The calculation of clear day solar radiation on any surface. Paper presented at *Aust. Inst. Refrig. Air. Cond. Heating Conference*, Perth, May 1971.

Florence, R.G., 1981, The biology of the eucalypt forest. *Biology of Native Australian Plants*. J. Pate and A. McComb, (eds.), University of W.A. Press, Perth, Australia.

Foody, G.M., Mcculloch, M.B. and Yates, W.B., 1995, Classification of remotely-sensed data by an artificial neural-network – Issues related to training data characteristics. *Photogrammetric Engineering and Remote Sensing*, **61**, 391–401.

Franklin, S., 1994, Discrimination of subalpine forest species and canopy density using digital casi, SPOT LA, and Landsat TM data. *Photogrammetric Engineering and Remote Sensing*, **60**, 1233–1241.

Franklin, J., Logan, T.L., Woodcock, C.E. and Strahler, A.H., 1986, Coniferous forest classification and inventory using Landsat and digital terrain data. *IEEE Transactions on Geoscience and Remote Sensing*, **GE-24**, 39–149.

Franklin, S.E. and Peddle, D.R., 1989, Spectral texture for improved class discrimination in complex terrain. *International Journal of Remote Sensing*, **8**, 310–314.

Friedl, M.A. and Brodley, C.E., 1997, Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, **61**, 399–409.

Gamon, J.A., Field, C.B., Roberts, D.A., Ustin, S.L. and Valentini, R., 1993, Functional patterns in an annual grassland during an AVIRIS overflight. *Remote Sensing of Environment*, **44**, 239–253.

Hetrick, W.A., Rich, P.M. and Weiss, S.B., 1993, Modelling isolation on complex surfaces. *Proceedings of the Thirteenth Annual ESRI User Conference* (Redlands: ESRI) 2, 447–458.

Hoffer, R.M. and Staff, 1975, *Natural resource mapping in mountainous terrain by computer-analysis of ERTS-1 satellite data, Research Bull 919*, Agricultural Experiment Station and Lab, for Applications of Remote Sensing, West Lafayette, IN. Purdue University.

Jha, C.S. and Unni, N.V.M., 1994, Digital change detection of forest conversion of a dry tropical Indian forest region. *International Journal of Remote Sensing*, **15**, 2543–2552.

Jakubauskas, M.E., 1997, Effects of forest succession on texture in Landsat Thematic Mapper imagery. *Canadian Journal of Remote Sensing*, **23**, 257–263.

Jensen, J.R., 1996, *Introductory Digital Image Processing: A Remote Sensing Perspective, Second Edition*, New Jersey, Prentice Hall, 318 pp.

Kasischke, Eric S., Melack, J.M. and Dobson, M.C., 1997, The use of imaging radars for ecological applications – A review. *Remote Sensing of Environment*, **59**, 41–156.

Kettig, R.L. and Landgrebe, D.A., 1976, Classification of multispectral iamge data by extraction and classification of homogeneous objects. *IEEE Transactions on Geoscience Electronics*, **14**, 19–26.

Kim, K.E., 1996, Adaptive majority filtering for contextual classification of remote sensing data. *International Journal of Remote Sensing*, **17**, 1083–1087.

Kirkpatrick, J.B. and Nunez, M., 1980, Vegetation-radiation relationships in mountainous terrain: Eucalypt dominated vegetation in the Risdon Hills, Tasmania. *Journal of Geography*, **7**, 197–208.

Köppen, V., 1931, *Grundriss der Klimakunde*. Berlin, Walter de Gruyter Verlag.

Kraft, M., Weigel, H., Mejer, G. and Brandes, F., 1996, Reflectance measurements of leaves for detecting visible and non-visible ozone damage to crops. *Journal of Plant Physiology*, **148**, 148–154.

Küchler, A.W. and Zonneveld, I.S., 1988, *Vegetation Mapping*. Kluwer Academic Publishers, Dordrecht, 635

Kumar, L. and Skidmore, A.K., 1998, Use of derivative spectroscopy to identify regions of differences between some Australian eucalypt species. *Proceedings 9th Australasian Remote Sensing and Photogrammetry Conference*, Sydney, Australia, July 20–24.

Kumar, L. and Skidmore, A.K., 2000, Radiation – vegetation relationships in an Eucalyptus forest. *Photogrammetric Engineering and Remote Sensing*, **66**, 193–204.

Kumar, L., Skidmore, A.K. and Knowles, E., 1997, Modelling topographic variation in solar radiation in a GIS environment. *International Journal of Geographical Information Science*, **11**, 475–497.

Lillesand, T.M. and Kiefer, R.W., 2000, *Remote Sensing and Image Interpretation, 4th edition*. New York, John Wiley and Sons, Inc., 724 pp.

Macomber, S. and Woodcock, C.E., 1994, Mapping and monitoring conifer mortality using remote sensing in the Lake Tahoe Basin. *Remote Sensing of Environment*, **50**, 255–266.

McColl, J.G., 1969, Soil-plant relationships in a Eucalyptus forest on the south coast of New South Wales. *Ecology*, **50**, 354–362.

Mickelson, John G., Jr., Civco, D.L. and Silander, J.A., Jr., 1998, Delineating forest canopy species in the Northeastern United States using multi-temporal TM imagery. *Photogrammetric Engineering and Remote Sensing*, **64**, 891–904.

Moore, D.M., Lees, B.G. and Davey, S.M., 1991, A new method for predicting vegetation distributions using decision tree analysis in a Geographic Information System. *Environmental Management*, **15**, 59–71.

Mosley, G., 1989, *Blue mountains for world heritage*. Colony Foundation for Wilderness, Sydney.

Muchoney, D.M. and Haack, B.N., 1994, Change detection for monitoring forest defoliation. *Photogrammetric Engineering and Remote Sensing*, **60**, 1243–1251.

Olson, J.S., Watts, J. and Allison, L., 1983, *Carbon in live vegetation of major world ecosystems*, W-7405-ENG-26, U.S. Department of Energy, Oak Ridge National Laboratory.

Peuelas, J., Filella, I., Biel, C., Serrano, L. and Save, R., 1993, The reflectance at the 950–970nm region as an indicator of plant water status. *International Journal of Remote Sensing*, **14**, 1887–1905.

Radeloff, V.C., Mladenoff, D.J. and Boyce, M., 1999, Detecting Jack Pine budworm defoliation using spectral mixture analysis: separating effects from determinants. *Remote Sensing of Environment*, **69**, 156–169.

Ryan, P., Coops, N., Austin, M. and Binns, D., 1995, Incorporating soil chemical data into environmental models for predicting forest species distribution in south-east NSW. *Institute of Foresters of Australia 16th Biennial Conference*, 18–21 April, Ballarat, Victoria.

Singh, A., 1986, Change detection in the tropical forest environment of northeastern India using Landsat. In *Remote Sensing and tropical land management*, Eden, M.J. and Parry, J.T. (eds), John Wiley and Sons, 237–254.

Skidmore, A.K., 1989, An expert system classifies eucalypt forest types using thematic mapper data and a digital terrain model. *Photogrammetric Engineering and Remote Sensing*, **55**, 1449–1464.

Skidmore, A.K. and Turner, B.J., 1988, Forest mapping accuracies are improved using a supervised nonparametric classifier with spot data. *Photogrammetric Engineering and Remote Sensing*, **54**, 1415–1421.

Skidmore, A.K., Turner, B.J., Brinkhof, W. and Knowles, E., 1997, Performance of a neural network: Mapping forests using GIS and remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, **63**, 501–514.

Skidmore, A.K., 1999, Accuracy assessment of spatial information. In: Stein, A., van der Meer, F., and Gorte, B. (ed.). *Spatial Statistics for Remote Sensing*, Dordrecht, Kluwer Academic Publishers. pp. 197-209.

Skole, D. and Tucker, C.J., 1993, Tropical deforestation and habitat fragmentation in the Amazon: Satellite data from 1978 to 1988. *Science*, **260**, 1905–1910.

St Onge, Benoit A. and Cavalais, F., 1997, Automated forest structure mapping from high resolution imagery based on directional semivariogram estimates. *Remote Sensing of Environment*, **61**, 82–95.

Strahler, A.H., Logan, T.L. and Bryant, N.A., 1978, Improving forest cover classification accuracy from Landsat by incorporating topographic information. *Proceedings of the 12th International Symposium on Remote Sensing of Environment*, Ann Arbor, MI, 1541–1557.

Stuckens, J., Coppin, P.R. and Bauer, M.E., 2000, Integrating contextual information with per-pixel classification for improved land cover classification. *Remote Sensing of Environment*, **71**, 282–296.

Swain, P.H. and Davis, S.M., 1978, *Remote Sensing: The quantitative approach*, New York, Mc-Graw-Hill Book Company, 396 pp.

Turner, J., Kelly, J. and Newman, L.A., 1978, Soil nutrient-vegetation relationships in the Eden area, NSW. II. Vegetation-soil associations. *Australian Forestry*, **41**, 223–231.

Twery, M., Elmes, G.A. and Yuill, C.B., 1991, Scientific exploration with an intelligent GIS: Predicting species composition from topography. *AI Applications*, **5**, 45–53.

Varjo, J., 1997, Change detection and controlling forest information using multi-temporal Landsat TM imagery. *Acta Forestalia Fennica*, 0001-5636, 258, 64

Vogelman, J.E. and Rock, B.N., 1988, Assessing forest damage in high-elevation coniferous forests in Vermont and New Hampshire using thematic mapper data. *Remote Sensing of Environment*, **24**, 227–246.

Williams, D.L. and Nelson, R.F., 1986, Use of remotely sensed data for assessing forest stand conditions in the eastern United States. *Transactions on Geoscience and Remote Sensing*, **GE-24**, 130–138.

W 'er, P.T., Mladenoff, D.J., Host, G.E. and Crow, T.R., 1995, Improved forest classification in the northern Lake States using multi-temporal Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, **61**, 1129–1143.

Woodcock, C.E. and Harward, V.J., 1992, Nested-hierarchical scene models and image segmentation. *International Journal of Remote Sensing*, **13**, 3167–3187.

Woodcock, C.E., Collins, J.B., Gopal, S., Jakabhazy, V.D., Li, X., Macomber, S., Ryherd, S., Wu, Y., Harward, V.J., Levitan, J. and Warbington, R., 1994, Mapping forest vegetation using Landsat TM imagery and a canopy reflectance model. *Remote Sensing of Environment*, **50**, 240–254.

Wulder, M., Nieman, K.O. and Goodenough, D.G., 2000, Local maximum filtering for the extraction of tree locations and basal area from high spatial resolution imagery. *Remote Sensing of Environment*, **73**, 103–114.