EXTRACTING FOREST RESOURCE INFORMATION FROM REMOTELY SENSED AND ANCILLARY DATA: USE OF AN EXPERT SYSTEM

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Originality of Thesis
Except where specific acknowledgement is given, this thesis is my original work.

Andrew K. Skidmore
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A literature review of forest mapping from remotely sensed data showed map accuracies were at best moderate, and that high mapping accuracies were only obtained when broad or generalized classes were mapped. As there were inconsistencies and confusion in the reporting of map accuracies, a critical evaluation of the vexed issue of map accuracy was undertaken, and a novel method for assessing map accuracy based on line intersect sampling was developed and tested. In order to improve mapping accuracies, there has been a trend towards integrating remotely sensed data with other ancillary data such as elevation and geology. A forest model conceptualized the link between such spatial digital data and forest resource quantities (forest type and structure, soil, wildlife habitat etc.). New supervised and unsupervised algorithms for mapping forests from remotely sensed data were developed and tested over a variety of forests. Six methods for calculating gradient and aspect from a regular digital elevation model (DEM) were compared. A new method for calculating topographic position from a DEM was developed, and the DEM was also used to generate a soil wetness index. These diverse data types (including the analysed remotely sensed data, and terrain variables derived from the DEM) were input into a geographic information system (GIS). The GIS data, as well as knowledge about the forest (for instance, which sites were preferred by what tree species), were accessed and integrated using an expert system approach, and native forest types and forest soil were successfully mapped. As conceptualized in the forest system model, expert systems linked the spatial digital data and knowledge to produce maps of forest resources.
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1. INTRODUCTION

Who could fail to be moved by the dramatic photographs of the earth taken by the Apollo astronauts from the moon? The earth appeared as a tiny speck in space. Suddenly, our planet looked like a small and fragile place.

A growing world population combined with aspirations for greater material wealth, is placing unprecedented demands on natural resources worldwide. The pollution and environmental degradation resulting from industrial and agricultural activities supplying this demand is plainly visible. Many examples spring to mind including forest dieback in Europe and North America perhaps caused by airborne industrial pollutants reacting to cause acid rain; massive soil degradation and erosion worldwide; acidification of lakes in Scandinavia and Canada; pollution of rivers and coastal waters; destruction of forests, especially in the tropics; the increase in atmospheric carbon dioxide perhaps leading to the greenhouse effect; destruction of the ozone layer by chlorofluorocarbons; periodic mass starvation and chronic fuel wood shortages in many parts of Africa and Asia. The list is seemingly endless. However, what is disturbing is that these effects are not 'local', but regional or global in nature.

Balancing economic development with conservation of the earth's ecological processes is paramount to our survival, and the survival of other species. For many species, such concern is too late - they are extinct. However for others, there is still time. The first stage in predicting the environmental, economic and social consequences of development, is to inventory the type, quality and quantity of resources in the environment. The generation of natural resource inventories is critical for providing information to government, industry and any other interested organizations or individuals about both the positive and negative consequences of a development.

Models predicting changes in the environment, economy and society may be generated from these inventories. However, such models are time-consuming and expensive to create, especially when using traditional ground based and/or aerial photograph interpretation methods. Results are often biased due to inconsistent assessment practices between individuals, and changes in assessment practices by an individual over time. Results may also become dated, while decision makers frequently require new information at some future date, necessitating a fresh inventory.

The overall objective of this study was to develop techniques for generating an inventory of forest resource parameters from remotely sensed and other available ancillary information. A subsidiary aim was to frame the techniques and methodologies within a generalized model of the forest. The model of the forest illustrates the linkages between forest resource parameters. It also provides a mechanism for joining the socioeconomic and biogeophysical environment. The forest system model is described (Chapter 2). Chapter 3 provides a review of remotely sensed digital data and geographical information systems, and describes many of the computer algorithms used to analyze such data, and the results obtained using these techniques over forested country. Methods for assessing the accuracy of thematic maps are critically evaluated, and the problem of error accumulation in geographic information systems is examined (Chapter 4).
A new unsupervised classification strategy is proposed to aid in delineating training areas (Chapter 5). This classifier utilizes both the spatial and spectral patterns inherent in remotely sensed data. When the results are compared with conventional unsupervised classifiers it becomes obvious that the output from the unsupervised classifier assists in the definition of training areas. The unsupervised classifier was tested in *Pinus radiata* plantations of the Australian Capital Territory (A.C.T.), and in native eucalypt forests of southeast New South Wales (N.S.W.) using SPOT XS and Landsat Thematic Mapper (TM) imagery respectively.

The training area information can be used as input into a supervised nonparametric classifier that is described and tested in the mixed conifer/hardwood forests of Pennsylvania, in *Pinus radiata* plantations of the Australian Capital Territory (A.C.T.), and in native eucalypt forests of southeast N.S.W. using SPOT XS, Landsat MSS and Landsat TM imagery (Chapter 6 and part of Chapter 8). These forests were mapped at level III (Anderson, 1976), that is individual species or age classes were identified. The results from the supervised nonparametric classifier are compared with conventional supervised classifiers.

Other spatial information may be available for an area in the form of analogue maps, digitized data or aerial photographs, showing geology, soil, vegetation, elevation, etc. Digital elevation data can be readily generated in most areas of the world using existing contour maps, stereocorrelated aerial photographs or even stereocorrelated digital remotely sensed data. In Chapter 7, the creation of a digital elevation model over an area of native eucalypt forest in southeast N.S.W. is described and a number of algorithms for calculating slope and aspect are compared. A new algorithm for calculating position in the topography (for example ridge, midslope, gully) is proposed and contrasted with other algorithms.

In order to improve mapping accuracies by incorporating contextual and ecological information into the classification of remotely sensed and topographic data, an expert system classifier was developed, and tested in a native forest of southeastern N.S.W. (Chapter 8). The expert system operates on the output from the supervised nonparametric classifier (Chapter 6) and the digital terrain modelling (Chapter 7). The Forestry Commission of N.S.W. requested that the expert system approach be used to operationally map over 48 000 ha of forest for an environmental impact statement (EIS). The problems involved in converting the experimental GIS and expert system into an operational system are discussed (Chapter 8).

The forest system model and the expert system classifier are used to map forest soil types (Chapter 9). Concluding remarks form Chapter 10.

During the course of research towards this thesis, some of these chapters have been published at the date of submission of this thesis in refereed international journals (*viz.* Chapters 3, 5, 6 [two papers], 7 [two papers] and 8 [two papers]), while portions of Chapters 2, 4 and 7 have been accepted as conference papers. The published papers have been modified for presentation as this thesis to maintain continuity between chapters, and to include further information.
2. A FOREST SYSTEM MODEL FOR FOREST MANAGEMENT

2.1. Introduction

A forest system model that allows a forest to be described at a variety of spatial and temporal scales is proposed. Included in the model are techniques to link biogeophysical processes, that occur within the forest system, with the socioeconomic environment. The tools used to construct the forest system model include image processing of remotely sensed imagery and geographic information system (GIS) technology. These allow the rapid generation of forest resource data from available remotely sensed and other digital spatial data. The data can be used to map forest resources of interest to managers, improving the quality and quantity of information about the forest and providing a medium for communication between forest managers, conservationists, industry and political decision makers. The different values and interests of these groups can be incorporated into the model, allowing the effect of various management strategies on forest resource quantity and quality to be estimated.

2.2. The need to model forest systems

A model is an abstraction or simplification of reality (Odum, 1975). Three basic model types exist and include analogue models (e.g. a scale figure in clay), word models (i.e. a verbal description), and mathematical models (i.e. symbolic logic expressing relationships of a complex nature in a simple and parsimonious way [Jeffers, 1978]). Christiansen (1968) and Jeffers (1978) suggest the generation of models should pass through a series of chronological steps including recognition of the problem, bounding the problem, defining the goals of the investigation, gathering information, information storage and retrieval, generation of a possible set of solutions to the problem, evaluating the validity of the model, and implementing the result.

The objective of forest resource managers is to generate 'products' from the biogeophysical environment in order to supply the demand created by the socioeconomic system. At one extreme exists 'preservation' which is a theoretical concept implying the maintenance of the natural environment to supply products such as wildlife habitat and wilderness experience. Various organizations oriented towards park and wildlife management have been set up around the world to accomplish this. At the other extreme is clearfelling a forest (perhaps to supply pulpwood or sawlogs), followed by agricultural use, thereby removing a piece of land from active forest management, and turning the land over to agricultural activities. At varying intermediate levels of forest management activity, other products may be produced

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1 Note that part of this Chapter has been accepted as a contributed paper at the Institute of Foresters of Australia Conference 'Forests and People', held September 18-22, 1989, Leura, N.S.W.
including timber products, water (both quantity and quality may be considered), recreation, grazing, soil conservation, bee hive sites, game animals etc.

The model proposed here differentiates between forest resource quantities and the value that is placed on a unit of the resource. Any forest resource can be quantified: for example, number of species per unit area, timber volume per unit area, quality and quantity of water flowing from a given area\(^1\), number of people deriving pleasure from knowing that a wilderness area exists, aesthetic quality (Ribe, 1989) etc. The actual value that is placed on the resource is a result of the social\(^2\), economic and political interaction of a society; value will therefore change as the cultural and economic conditions which characterize a society also change. The political, economic and legal systems interact over environmental issues, and may be critical for natural resource management and planning (Harris, 1985; Lund, 1987). An example is property rights, where political influence and legislative control may be used to modify or change management. Value is in essence a measure of the human 'want' or desire to control or to use a resource (Fusfeld, 1982). Groups which value a particular forest resource may gain control or use of that resource through political decision, monetary exchange, or barter.

Ideally, managers, planners and/or political decision makers must be able to quantitatively assess the impact on the forest environment of either a particular forest management policy, or a change in policy or management objectives as a result of changing values in society. The aim of this chapter is to propose a forest system model that provides a framework for describing the total forest environment by incorporating biogeophysical knowledge with societal values. The total forest system includes the ecological, social, economic and political parameters which may impact on the forest. The forest model may be used to generate a knowledge base acceptable to all parties (for example a common map scale and common vegetation classification schemes) around which objective discussion can be held, and which may be used as a decision support system to assist decision makers.

The forest system model is structured to allow easy integration of readily available information such as remotely sensed data, digital terrain data, and any other spatially linked information stored in a digital form (for example soil, cadastral boundaries and forest inventory plots). In addition, knowledge about relationships within the forest system (for example the influence of topography on the occurrence of tree species, or the effect of international wood product prices on the viability of building a forest road) can be included in the model.

The model allows a truly geographic description of the forest. Forest management is inherently a spatially based science, with parameters of interest to forest managers and planners varying in both space and time. The ability to accurately model the spatial and temporal distribution of forest parameters is a feature of this forest model.

\(^1\)Criteria such as erosion (tonne/ha/year), flooding (m above datum) and sedimentation (tonne/km\(^2\)/year) may be evaluated (de Meijere and van de Putte, 1987).

\(^2\)Social conditions include the ethics and lifestyle of a society (Metcalf, 1977).
2.3. Problems with existing forest management planning

The proposed forest system model is a tool for assisting in forest management planning. The following critical evaluation of existing forest management planning techniques highlights the shortcomings of present methodologies.

The conventional definition of forest management planning as '...the integration and assessment of all biological, social, economic and other factors that affect management decisions about the forest...' is dismissed by Leuschner (1984) on the grounds that the required knowledge is impossible to obtain and that forest management decisions are not made in that way. He goes on to propose a definition of forest management as 'the study and application of analytical techniques to aid in choosing those management alternatives that contribute most to organizational attitudes'. The complicated interactions inherent in a forest system have been considered difficult to integrate in practice, as highlighted by Holling and Chambers (1973), who argued that a narrow approach to modelling the forest environment ensured the problem remained within bounds.

It is now practical to generate accurate biogeophysical spatial data over extensive areas. High quality spatial data and computer-based tools may be used to map and model forest biogeophysical and socio-economic processes. The spatial data allows a holistic view of the forest to be created, by highlighting the interconnections between the biological, social and economic factors affecting the forest environment. Such a holistic view is close to the original concept of forest management planning. The holistic view permits all the relevant information about a forest to be integrated and objectively assessed.

Long and medium term forest planning are usually formalized in a management plan. Originally, these plans tended to conform to a classical European structure of firstly describing what forest resources are present, and secondly listing a set of prescriptions and/or objectives for managing the forest. As the plan is implemented, increasingly specialized and detailed operational plans need to be devised. Such a prescriptive structure ensures the dogma of the authoring organization is perpetuated, as well as perpetuating the illusion within the organization that as the planning is structured and condoned by the organization, it can be safely and unquestioningly followed (Kennedy, 1988).

The early European management plans concentrated on the timber resource. A narrow emphasis on timber production is viewed with concern by some members of society, who feel the opportunity costs (i.e. the benefits or satisfactions that would have been obtained by choosing an alternative strategy) associated with logging (such as water sedimentation, wildlife habitat change, decreasing wilderness areas) outweigh any economic, environmental and social benefits which accrue. Other objections to timber production include, for instance, that the earth may become uninhabitable for human occupancy due to degradation of natural resources (Dasmann, 1973), and/or an ethical obligation to other species and future human generations to preserve representative and viable natural habitats (Mattern, 1966).
There is obviously a need to strike a balance between human (economic) activity and 'conservation', as these two objectives are essentially incompatible over a given forest area\(^1\) (Schumacher, 1974). In response to growing environmental awareness in the late 1960s and 1970s, an integrated approach to forest management was pioneered in North America, and was termed 'multiple use forestry' (Duerr et al., 1979; Lund, 1987). For example, United States legislation requires land to be managed for the sustained production of wood, forage, wildlife, wilderness, recreation, and water. In other words, the objectives of management became more numerous, highlighting inadequacies with the classical European forest management objectives of maximizing timber volume or financial return. The environmental conflicts of the 1970s and 1980s were in part due to the inability or unwillingness of forest management organizations to rapidly modify their forest management plans to reflect changing societal values.

One disadvantage with multiple use management of forests is that all outputs are produced in sub-optimal quantities. For example, Fox et al. (1989) modeled the effect of constraining timber production by the National Forest Management Act (1976) (constraints included wildlife habitat, aesthetics, riparian area protection, and soils and slope harvesting restrictions). The maximum timber harvest available was reduced by 58 per cent. The outputs from the forest fail to satisfy any one special interest group, even though the maximum combined benefit may be obtained. As Kirkland (1988) points out, this leads to a 'state of moderated dissatisfaction' amongst all client groups - and usually a final decision rests with politicians. (The legal system implements and interprets laws created by politicians). With politicians being the final arbitrator, political lobbying is often the critical factor deciding the outcome of a conflict. In other words, a group's motivation, articulateness, organization and political awareness are most important in pressuring politicians towards their value system. This does not give equal weight to all views within the multiple use management system, and the inherent conflict will often remain (Kirkland, 1988).

With such perceived shortcomings in the multiple use approach, the New Zealand Government has moved to segregate commercial timber production operations from preservation or conservation management within the New Zealand Forest Service (Kirkland, 1988). Three separate organizations have been created to manage conservation, timber production (inappropriately called the Ministry of Forestry) and harvesting/conversion operations respectively. Under such a strategy, the principle of maximum combined benefit is lost to a plethora of local 'solutions'. For example, a forest may be reserved for preservation, at a cost to local employment and social conditions, as well as to the local, regional and national economy. Conversely, an area designated for intensive harvesting activity has drastically reduced wildlife habitat potential, poorer quality of run-off water etc. Thus environmental, social, or economic resources may be optimised over a forest, but at a cost to the potential individuals or groups who miss out on using the forest for their purpose.

\(^1\)This is a controversial issue due to the ambiguous meanings assigned to the word 'conservation'. The main point is that dramatically changing the forest condition (for example flooding the Amazon rainforest to produce hydroelectricity in Brazil) is incompatible with conserving the flora and fauna of a forest. Subtle human activity in forests such as selective logging may conserve the structural and species integrity of a forest.
To successfully evolve and grow, an organization must be able to monitor public attitudes, and to respond with flexibility in its provision of goods and services. Hopkins (1980) makes the point that processes should be available within a forest management planning system that allow a rapid response to changing economic and social conditions. The response may involve modifying policy and objectives, introducing new technology, or changing management and production structures, so that the demand for the organization's goods and services are more efficiently satisfied. However, Florence (1984) warns against rapidly changing forest management strategy to appease a vocal group. Rather he emphasizes an attitude of 'potential for change' before, during and after the process of planning and negotiated consensus.

To ensure a balanced perspective in forest management planning, interested groups should be able to have input into, and make criticisms of, the plan at all stages of development and implementation. In the U.S.A., this opportunity is extended during the pre-planning process when management objectives are determined (Henderson, 1984). Using the forest system model, the consequences of a change in the plan would be quickly displayed on maps, graphs and tabular summaries. The information should be written in plain English (a requirement of U.S.A. management plans\(^1\)), or presented as easily understandable graphs and diagrams, to ensure non-specialists can understand the implications of the plan. Such a model would reduce criticism of forest management organizations by aiding communication between resource managers, research scientists, interested public organizations and individuals, and politicians. The resistance by forest services to change existing forest management methods has been fostered by an illusion of invulnerability and morality caused by a 'groupthink mentality\(^2\)' (Kennedy, 1988). As the need to modify management strategies is proposed (or demanded) by 'outsiders' in the form of protest or legislative action, groupthink behaviour may assert itself with 'surprise, alarm or reactionary response' (Kennedy, 1988).

The final problem with forest management planning is the inefficiencies inherent in the planning process. Much of the planning budget may be spent on highly paid professionals locating and sorting information to be used in the planning process. Sugarbaker (1987a) reports that 0.75 per cent of revenue for the Washington State Department of Natural Resources is spent on managing the data used for natural resource planning (using geographic information systems). He notes that this is considered a fairly large amount by many, but historical accounting records show that benefits have been greater than costs.

The forest system model proposed here is a powerful tool for balancing socio-economic and environmental considerations. It aids in the clarification of what quantity and quality of forest resources is present, in planning objectives for a forest, and in testing whether planning objectives have been

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\(^1\)Gallagher and Patrick-Riley (1989) point out that reading U.S. Forest Service management plans requires 3 to 6 years of college education when ranked using the Flesch Reading Ease Scale. This is despite a legislative requirement to have plain English management plans.

\(^2\)Groupthink, a term coined by Janis (1967), describing the 'tendency of an organization to become unduly proud, cohesive and confident', may be central to the inability of organizations to successfully adapt in a changing world. (Kennedy, 1988, cites the US Forest Services as an example of an organization that has suffered from groupthink). Characteristics of groupthink are an illusion of invulnerability and morality, shared stereotypes amongst staff groups, rationalization and justification of policy and management objectives, and 'mindguarding' leaders (i.e. agreeing with a superior's opinion) (Janis, 1967).
achieved. Using the proposed model, high quality spatial digital data of the biogeophysical characteristics of the forest can be modeled and linked to the socioeconomic and political influences which affect the forest system.

2.4. The stages in developing the forest system model

A method for rapidly generating information over large areas of forest in a cost effective manner is becoming increasingly important for management planning and the allocation of forest resources to various uses. The model requires a systematic approach in its development in order to ensure the integrity of the data input into, and output from, the model, as well as the full utilization of the available digital spatial data.

A number of stages are followed during the modelling process. The first stage is to set bounds to the problem (Jeffers, 1978). The physical area of the forest must be delineated and the 'resources' to be modeled defined (i.e. forest volume, soils, forest types, wildlife habitat etc.). Public concerns can be identified and the objectives of management initially defined (Henderson, 1984). According to Duerr et al. (1979), the complexity of the model must also be considered at this stage, as the model is a trade off between simplicity and precision. However, the proposed model is designed to incorporate increasing complexity as additional information becomes available, or additional resources require modelling.

The second stage in modelling the forest is to quantify what resources are present - that is make an inventory. The proposed model allows the quantity of a 'resource' to be easily incorporated as the resource becomes recognized or more clearly defined as 'important' by society or scientists. For example, knowledge about habitat requirements for arboreal mammals in Australia is becoming increasingly refined, with new criteria being continually added (compare Recher et al. [1980] with Kavanagh [1984 and 1987]). The rapid changes that occur in forests justify fairly frequent updating of inventories. In the U.S.A., legislation requires an assessment of renewable resources of all forests and rangelands every ten years (Lund, 1987). The model is flexible, permitting the information needs of forest managers to be generated as required: additional resource inventories may be generated as the managers become more sophisticated in using the tool, and new management problems arise.

The third stage in modelling a forest is to quantify the rate of change within the forest over time. A forest is dynamic with changes occurring at all time scales. For example, temperature profiles within the forest canopy vary over a period of hours (Holbo et al., 1989; Luvall and Holbo, 1989); forest and woodland productivity varies seasonally (Justice et al., 1985; Tucker et al., 1985); flood and drought periods are related to oceanic/atmospheric effects occurring over three to ten years such as El Nino (Skidmore, 1988); and long term climate variation over centuries can also alter vegetation patterns. Natural catastrophic events may dramatically alter the forest structure and dynamics, for example cyclones, wildfire and landslides. Human influence on forests may also alter the forest environment and these include logging and clearing.
Thus change in the forest may be abrupt or gradual. The ramifications of change on forest succession and stability need to be understood and modeled if forest management planning is to be effective. Sophisticated models have been proposed for modelling change in forests (Jeffer, 1978; Shugart et al., 1980; Shugart and Noble, 1981; Shugart, 1984) and in addition many techniques for analysing remotely sensed data collected on multiple dates have been developed (Skidmore et al., 1987; and see Chapter 3). This proposed forest system model permits change to be modeled.

The final part of the forest system model aims to allocate forest resources in order to satisfy the conflicting criteria imposed by interest groups and it achieves this by using the following methods singly or in combination:
1) valuing the resources to a common denominator such as monetary value;
2) constraining production from forests to yield a minimum or maximum quantity of particular resources; and
3) producing maps showing the distribution and areal extent of resources in the forest under different management strategies or policies.

The final stage also involves writing the management plans for operational use by the organization and for public scrutiny, implementing the plan, monitoring performance of the plan, and updating the plan as required (Henderson, 1984).

2.5. The forest system model

The aim of the forest system model is to provide a framework for describing a forest system applicable to forest management. The model characteristics include: the fact that it is general (it allows a description of the forest at any scale of time or space); input for the model can be easily generated from available information; and the model is designed using a structured analysis approach whereby an overall picture of the forest system model is initially obtained and increasing levels of detail and sophistication are added as required.

The model integrates diverse data types such as remotely sensed data (continuous data), elevation data (continuous data), geology (categorical data), forest plot data (discrete or point data) and even knowledge about the forest such as the tendency for species X to occur on a ridge or other environmental position (rule based data). High resolution satellite data are readily available over most parts of the world, in a wide range of spectral wavelengths (from visible through to infrared and microwave) and spatial resolutions (from approximately 1 m through to 1.1 km). Topographic information is also available in digital form from existing digital terrain models, automatic stereocorrelation of overlapping SPOT images, or by digitizing existing analogue contour maps (Skidmore, 1989c - also see Chapter 7). Spatial data allow large scale observation over areas of forest, which may be difficult and expensive to make an inventory of using ground based plots or conventional interpretation of aerial photographs (Bretherton, 1985).
Extracting information from remotely sensed data, combining diverse data types and modelling additional parameters of interest to the forest and natural resource manager receive the main emphasis here. However, these topics are framed within the context of the overall forest model described below.

2.5.1 Conceptual overview of the model

The model has no bounds either in area or in complexity of the forest parameters being modeled. It is designed using a structured analysis approach (Wigander et al., 1984). The model is created as a series of levels with each level becoming increasingly complex as the forest system is considered in greater detail. Input information may flow into the model and resources are predicted by the model.

The model is divided into components, with a component being defined as a sub-process of the model. That is, each component is itself a discrete model describing a smaller part of the system. Data flows into a component from a previous component or from an external source. The component may produce results which in turn are used by another component, or the results are output directly to the decision maker or manager.

Connectivity between components is the essence of the forest system model. Even though the aim of the forest system model is to create an ordered view of the forest by dividing the system into understandable parts, the connections between components reflect the wholeness of the forest system. A taxonomic (or divisive) approach to the problem of modelling the forest is convenient, but it should not obscure the overall picture of the forest system (Gould, 1982).

In an overall view of the model (Figure 2-1) each component or sub-process is represented as a rectangle. Six levels represent the changing data types as they flow through the model. The first three levels are considered in detail in this thesis viz. primary (or independent) variables, secondary (or dependent) variables, and tertiary variables (or predicted resource quantities). As shown (Figure 2-1), the model may be extended to assign value to the forest resources, and allocate resources to various uses based on the value. The valuation of resources and their allocation to uses are not addressed with specific examples here.

Note that the variables cited as examples in Figure 2-1 are not inclusive of all variables that are operating in the forest system. Rather, the selected examples are shown to elucidate the concepts behind the forest system model.

The four stages of model design and development (viz. bounding the problem, quantifying the resource, quantifying the rate of change, and allocating resources) are described in detail below.
2.5.2. Bounding the problem

The forest system model must be bounded (that is terms of reference defined) and criteria for bounding the forest system include:

1) defining the areal extent of the physical forest to be modeled;
2) identifying the data available for input into the model;
3) defining the resource parameters to be modeled; and
4) defining the extent and type of the social, economic and political influences on the forest.

2.5.3. Quantifying the resource

Using the structured analysis approach for model development allows the forest model to be considered in increasing detail up to the level required. Level 1 of the model includes inputs into and outputs from, the forest model (Figure 2-2). Obviously, inputs and outputs will be varied to suit the particular application.
Figure 2-2: Level 1 of the forest system model

At the second level of the forest model the primary components (or sub-processes) become apparent. The components are the derivation of secondary variables, quantifying resource amounts, and applying socio-political values to the resources (Figure 2-3).

Figure 2-3: Level 2 of the forest system model

The third level appears more complex due to the data flow between components (or sub-processes) being shown in greater detail. The derivation of secondary (dependent) and tertiary (resource quantity) variables becomes more intricate (Figure 2-4) and is illustrated in this case by the generation of soil and forest type.

\[\text{Note that the components or processes are annotated as rectangles, the flow of data as arrows, and the storage of data (i.e. both input and output) as circles.}\]
Figure 2-4: Level 3 of the forest system model

An illustration of level 4 of the model (Figure 2-5) shows how one sub-process from level 3 (i.e. generation of a forest type map) can be considered in detail. Complex relationships may exist between the secondary/tertiary variables and the primary variables and these require rules to describe them (Figure 2-5).
At the fifth level of the model, mathematical descriptions of the components (sub-processes) are made. Jeffers (1978) discussed the application of a number of mathematical models for predicting forest resources from existing plot data, including dynamic models, matrix models, stochastic models and multivariate models.

A mathematical tool suited to incorporating rules on relationships between components in the forest model, is the expert system. Expert systems have had limited application in conjunction with GISs (Skidmore, 1989b), though they are especially suited for use with the forest system model. The main advantage of an expert system is the ability to build models between primary and secondary (or tertiary) data that can include relationships which have uncertainty associated with them.

The computer programming required to automate the processing of the digital spatial data in the forest system model components may be detailed as a sixth level.

2.5.4. Derivation of primary (independent) variables

Digital spatial data are input into the forest system model as primary (independent) data. It should be noted that some of the primary data may not be statistically independent, for example some of the
remotely sensed channels may be correlated. Such redundant information should be reduced prior to inputting the data into the forest system model, for example by deleting correlated channels or preprocessing the remotely sensed data using feature reduction techniques such as principal components analysis.

Other primary data or information may not be geographically registered, but are nonetheless important for modelling. Expert system 'rules' are derived from research or field observation, and examples include habitat preferences for wildlife based on forest tree species mix and topographic data, or forest volume information generated from volume tables using structural attributes and forest type.

2.5.5. Derivation of secondary (dependent) variables

Secondary variables may include gradient, aspect, topographic position and forest type. These variables are generated from primary variables, often using simple models. For example, the derivation of gradient and aspect from a digital elevation model is described in Chapter 7.

2.5.6. Derivation of tertiary (resource quantity) variables

The secondary variables are in turn used to model tertiary variables such as biomass volume, wildlife habitat etc. (Figure 2-4). Numerous secondary variables (and even primary variables) may be included in a component modelling tertiary (resource quantity) variables. In addition, rules may be incorporated into tertiary components which describe the relationships between secondary and tertiary variables.

2.5.7. Dynamic processes in the model

Functions which model change in the forest over time\(^1\) may also be incorporated into the forest system model. The impact of change may flow through the system affecting many components, for example, a forest fire may change forest and understorey types, forest structure, forest growth, soil characteristics and faunal populations. In a similar way, logging will modify forest parameters by varying the species mix, altering forest structure, compacting soil, altering wildlife habitat, or changing chemical nutrient cycles. The effect of logging on the resources output from the forest can be followed in Figure 2-6, where water yield and quality, soil properties, quantities of different timber product types etc., will vary over time.

\(^1\)Such functions which model change have been suggested by Jeffers (1978), Shugart and Noble (1981), Shugart et al. (1980), Shugart (1984) and Barnard et al. (1985).
logging secondary variables including soil wetness index; gradient; aspect; topographic position; vegetation classes & probability of correct classification etc.

Figure 2-6 - A forest system model showing change of forest growth and composition

A change to the forest environment such as an 'opening' of the forest canopy may affect forest parameters differently depending upon the process used to open the canopy. This may require feedback to the forest parameters stored by the model. For example, logging may cause soil compaction and nutrient loss, thereby changing soil wetness patterns, reducing forest growth and/or altering seral progression in a native forest. In contrast, natural tree fall due to senescence or cyclone damage may cause less soil compaction and nutrient loss, and hence influence secondary and tertiary variables differently. Many native forest conflicts centre around the sustainability of timber production, and the length of rotations between harvesting operations. A thorough inventory of the present quality and quantity of forest resources, as well as predictive models of future resource developments, are precursors to an objective consensus being reached on the use of such resources.

2.6. Valuation and allocation of resources.

Chapman (1975) recognized three components in the man-dominated ecosystem, (these being economic, political and social forces), though he did not link them into an overall model. This part of the proposed forest system model is inherently subjective, being dependent upon the political, social and...
economic values that society places on the forest resource. If culture is considered the sum of political, social and economic values 'that includes thought, speech, action, institutions, and artefacts' (Longman, 1984), then recognition of a resource is dependent upon culture. In other words, a resource only becomes 'appreciated' as a result of cultural pressures (Zimmerman, 1951). For example, the increasing concern of people with conserving the forest environment contrasts with the previous laissez-faire attitude. Some quantitative analyses have been performed: for example Hofstede and Bond (1988) link national, cultural and philosophical characteristics with economic growth and wealth accumulation.

The study by Hofstede and Bond (1988) has implications for modelling the 'value' different nations place on the resources that may be extracted from a forest, and hence on international trade in forest products and international attitudes to forest conservation. Individualism is a measure of how loose the ties are between individuals: individualistic nations tend to have individuals who look after themselves and immediate families, while 'collective' nations have strong cohesive groups, which protect their members in return for unquestioning loyalty. (Note these terms refer to social phenomena, not political systems). Hofstede and Bond (1988) show that individualism is correlated with wealth, and that as nations become wealthier the people of the nation become more individualistic. Individualistic people may be more likely to challenge the accepted norms of society, and not be afraid to challenge government bureaucracies or private industry over environmental issues.

Other factors influence societal values and ethics. For example, poor people (or nations) will be more likely to develop natural resources with minimal environmental safeguards, as relief from poverty will be foremost in their minds. An example is the clearing of the tropical forests for timber and agricultural production in developing countries. In contrast, individuals within wealthy nations may feel more secure with their accumulated wealth, and be prepared to forego further material benefits to protect the environment (even though earlier in many wealthy nation's histories, individuals were ruthless in clearing land for agricultural production).

Economists and management experts have attempted to model the value that society places on forest resources using a variety of techniques. However, valuation becomes increasingly difficult for intangible resources such as wildlife habitat and recreation. Commonly used techniques include opportunity cost, time preference, shadow pricing, and indirect pricing (Gregory, 1972), though many other approaches have been tested as described by Sinden and Worrell (1979). The principal objection to these methods is that they are derived values which do not reflect a market value. For example, logging a forest will result in environmental 'costs' which can be quantified such as tonnes of soil eroded or number of fauna displaced. However using opportunity costs to estimate the value of displaced fauna can be criticized, as the fauna bear no relation to the value of logs extracted. In addition, the time preference of wilderness is a derived value, and we have no idea of a reasonable figure. We can surmise though that the future value of wilderness may be higher in an overcrowded world.

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1Opportunity cost is the revenue foregone by choosing to preserve a forest instead of logging it.
2Time preference is the rate of discounting future income to make it comparable with present income.
3Shadow pricing is artificially applying a price to a resource.
4An example of indirect pricing is how far are people prepared to drive for a recreation experience.
Commercial or accounting costs should be separated from ecological values, according to some ecologists (Harris, 1985). For example, 'deep ecologists' reject the notions of conventional economics, and claim that the natural environment has infinite value. Such a view effectively means the natural resources should be preserved untouched in a park.

Even though economists have only had partial success in placing a value on intangible resources within the forest, the fact that a large spatial database can be quickly and easily manipulated, ensures that decision makers can be presented with the forest resource information pertinent to a management decision. There is likely to be less subjective and emotive influence from self-interest groups, hence increasing the chance of a satisfactory consensus. The data output by the forest system and the decision maker's conclusions, could be scrutinized for bias by all concerned, ensuring a more balanced view.

The tools offered by the forest system model could be perceived as a threat by decision makers and/or lobby groups, as the derived resource information may not concur with the values of individuals or organizations. For example, a frequently cited reason for preserving a forest is 'uniqueness'. A proposal to create a park over an area of forest could be thwarted by the forest system model showing that the area has no unique features deserving preservation. Equally, the forest system model could highlight forested areas with 'special' attributes that should be preserved. Such attributes may include a combination of rare flora or fauna, aesthetics, water supply and large intact wilderness area.

The advantage of the forest system model approach is that it allows an objective overview to be made of the resources in a forest. Then, by applying different value systems to the forest, the model allows the implications of a particular strategy to be evaluated (e.g. increasing the value placed on wildlife habitat, while maintaining a constant timber value).

If a value could be placed on an intangible forest resource to bring all resources to a common denominator (e.g. monetary value), or constraints imposed stating a minimum or maximum level that a resource may fall or rise to in an area (i.e. the minimum number of possums in the forest that constitutes a viable breeding population), the allocation of resources may be made using an operations research tool (such as linear programming [Dallenbach and George, 1978]). Such a computer-based mathematical tool is objective and therefore even less susceptible to human bias and subjectivity.

2.7. Discussion

Though the forest system model described above is an abstraction of reality, it allows an overview of the forest system at any scale by considering the forest as a set of connected and interdependent resources. More detail can be easily and logically included in the model (take Figures 2-1 to 2-6 as an example). One advantage of the forest model is that it models resources using research plot results and digital spatial data, while another is the ability to study a wide range of management options for the forest, quickly modelling the effect of changing market conditions, societal attitudes or environmental fluctuations.

By considering the broader implications of different management strategies, the conflict between conservationists and industry may be resolved. All that is needed is a willingness by industry to develop
Conservation based strategies that ensure the long term environmental and economic sustentation of an operation (I.F.A., 1987), and a willingness by the conservation movement to acknowledge the importance of forest industries to the social and economic well being of a region, as well as providing a renewable timber and wood fibre resource. The forest system model helps achieve this by providing a forum for communication, which clearly shows the implications of different strategies.

The forest system model may potentially develop problems under a number of conditions. The first problem is in defining 'cause and effect' when modelling secondary and tertiary variables. This problem may be rephrased using the following example: should soil type be predicted from forest species, or are forest species an indicator of soil type? Daubenmire (1976) maintained that vegetation reflects the sum of all the elements of the environment which are important to plants, and that the species with the highest competitive powers are the best indicators of site conditions. In contrast Vanclay (1988) states that site productivity may be modeled from geological maps and Landsat TM data. In practice the method used to predict soil and vegetation will be determined by the data available. In this thesis vegetation was initially predicted because the remotely sensed data used records the reflectance from the vegetation canopy and not the soil. The derived vegetation map was then used to model soil types. The bottom line when considering the output of models is the accuracy of the predictions (Chapter 4).

Another problem with the forest system model is the incorporation of erratically prepared data sets or sub-processes during the construction of the model. Once the model is constructed, the output required by decision makers may vary dramatically and unpredictably with changing policy. The forest system model is designed to accommodate such change by flexibility in predicting new secondary and tertiary variables.

Care must be exercised during the creation of secondary and tertiary variables to ensure layers are not duplicated, to avoid storage expense, potential confusion and error duplication during modelling. In addition, the most efficient method of deriving new data layers must be carefully considered, especially with respect to the accumulation of error (Chapter 4).

The forest system model is viewed as an unified, interdependent system (compare with Lovelock's 'Gaia theory' [Lovelock, 1979]). A complete numerical model of the forest system may never be constructed, due in part to the mathematical relationships requiring substantiation from plot measurements and field observation. However, the attempt to view the forest in a holistic sense and to concentrate on the resources of the forest which forest managers are concerned with, may help an overall understanding of the forest ecosystem.

The practicality of deriving resource quantities (secondary and tertiary variables) using the forest system model is proven using technology developed in this thesis. The forest system model also provided a logical framework for planning the sequence of work that constitutes this thesis.

Although the forest system model is applied to the problem of forest management planning, the ideas encapsulated by the model are general and could equally be applied to other natural environments.

There are many possible areas in which the model can be further developed. Examples include calculation of mapping accuracies for derived maps (Chapter 4), integrating observation, lore and
knowledge into the model (Chapter 8), allocation of value to resources, and determining methodologies for assigning particular forest areas for production of the different resources sought from the forest. Austin and Cocks (1978) described a study undertaken on the south coast of New South Wales designed to understand regional land use problems, and to identify the available techniques for land use planning. Though their study considered all forms of land cover (including forests), many of the techniques described for allocation of value to resources and land use planning could be incorporated into further developments of the proposed forest system model.

2.8. Application of the forest system model

The forest system model provides a framework to link the results presented in this thesis. The model has been developed to serve the following roles:

1) to maintain an overall perspective of the study,
2) to provide a planning tool during the project,
3) to illustrate the interrelationships of data types in forests,
4) to highlight that a few input parameters can generate a lot of information,
5) to emphasize that the output generated by the study can be used by decision makers,
6) to illustrate that research results can be linked by such a model, and
7) to highlight the problem of allocating forest resources.

Duerr et al. (1979) states that building a model is easy, but the hard part is supplying the model with information, or a resource inventory. With the development of geographical information systems (Burrough, 1986; Marble et al., 1984) spatial information can be conveniently summarized and stored. The aim of this thesis is to prove that digital spatial data can be rapidly generated over a forest, then synthesized with forest plot data and the accumulated experience of foresters, and used to map forest resources.

The forest resource model has been applied to a native forest in southeast Australia. A number of new techniques are described in this thesis which have been developed to aid in the generation of the secondary (dependent) variables and tertiary (resource quantities) variables using the experience of foresters, remotely sensed data, and other digital spatial data. These techniques have been evaluated in two additional forest types to establish the generality of the techniques (these forest types being plantations in the Australian Capital Territory, and mixed forests in Pennsylvania).
3. LITERATURE REVIEW: THE USE OF REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEMS IN FORESTRY

3.1. Introduction

Landsat-1 was launched in 1972 by the National Aeronautical and Space Administration (N.A.S.A.) and was one of the first 'land satellites' designed and operated specifically for monitoring the earth's natural resources. The Landsat series of satellites was welcomed by some members of the forestry profession as a panacea for solving many monitoring and inventory problems not answered by aerial photographic techniques, as it provided frequent synoptic overviews over an extended spectral range, repetitive coverage every 18 days and automated processing of the imagery (by computer) (Latham and McCarty, 1972; Zsilinsky, 1973; Heath, 1974). This enthusiasm was partly due to a strong advertising campaign by N.A.S.A., who were keen to have the data from the newly launched satellite used by as many as possible of the agencies interested in monitoring and mapping the earth. However, interest from foresters in the new technology waned rapidly, when many alleged advantages were not realized. Note that this situation is synonymous with the introduction of aerial photographs by foresters at the beginning of the twentieth century. Initially a small group of foresters recognized aerial photographs as a valuable source of local information, though the majority of foresters were reluctant to absorb the new techniques, due to the resistance of older foresters to new technologies, and the expense involved in incorporating new technologies into existing organizations (Stellingwerf, 1986).

Over the following decade, remote sensing researchers sought to determine ways of using satellite-derived data to meet the needs of forest managers, and a large volume of literature was produced (for example the Manual of Remote Sensing edited by Colwell, 1983). Research progressed from detecting forest phenomena on early imagery, to identifying forest resources, and finally to monitoring forest change (Williams and Miller, 1979). By the late 1970s, it became apparent that forest types may be classified more accurately by combining Landsat data with other data sources such as digital topographic data, rather than Landsat data alone (see 3.8.6). Improved computer techniques for manipulating Landsat data and lower price/performance ratios for computers enhance the value of computer imagery because more efficient programs can be executed on cheaper but more powerful computers. In addition, currently operational and planned future satellites (Table 3-1) may increase the accuracy of forest classification due to improved spatial and spectral resolution.

In recent years, a renaissance of thought on the utility of remotely sensed data has overcome some of the pessimism. This has resulted from improved image processing techniques, increased spatial, spectral and temporal resolution and from linking remotely sensed data with GISs. Gwynne (1983)
emphasized the importance of remotely sensed data and GISs for global monitoring, while Swain (1985) discussed how combining GISs and remote sensing can amplify their respective practical utility.

In this chapter past, present and future remote sensing systems are reviewed. Data from the Landsat and SPOT series of satellites have been most widely used by the forestry profession, and results are critically analysed. The increasing importance of GIS for forest management is examined. A summary of the current usage of remotely sensed data and GIS for land management purposes in Australia is presented. A discussion of the radiometric response of vegetation follows in order to understand the physical relationship between forest cover and remote sensing systems. This assists in the development of image processing algorithms for using the remotely sensed data (Daughty et al., 1989), and may be used to design appropriate sensors (especially those proposed with increasingly finer spectral resolution). Note that the range of topics covered in this chapter is general: specialist reviews introduce the specific research detailed in later chapters.

3.2. Overview of remote sensing and remote sensing systems

3.2.1. Radiometric response of vegetation

Reflectance of electromagnetic radiation from vegetation is a complex interaction of the components of the environment. Factors affecting electromagnetic radiation reflectance include plant material, plant structure, soil and other inorganic and organic surfaces. Particular wavelengths of electromagnetic radiation are suited to remote sensing, as the atmosphere does not attenuate the electromagnetic radiation. These wavelengths are often called windows and are detailed by Suits (1983). Reflectance curves vary for different vegetative covers (Townshend, 1981); for example Billings and Morris (1951) found desert species have higher overall reflectivity compared with sub-alpine species.

Pigments in vegetation absorb electromagnetic radiation (photons) which excites electrons, allowing energy to be collected for plant use during the process of photosynthesis. 90 per cent of the blue and violet electromagnetic radiation (0.4-0.5 μm) and 80 to 90 per cent of the orange and red electromagnetic radiation (0.6-0.7 μm) is absorbed, while only 70 per cent of the green electromagnetic radiation is absorbed (Hoffer and Johannsen, 1969; Salisbury and Ross, 1978). Hence vegetation tends to be coloured green. At the red edge1 of the electromagnetic spectrum through to the near infrared, plants tend to reflect heavily. About 60 per cent of radiation is reflected at wavelengths of 0.7-1.3 μm (Hoffer and Johannsen, 1969). This effect is related to the moisture content of the vegetation and the mesophyll cell structure (McCloy, 1984). Decreased reflectivity in the near infrared plateau has been correlated with decreased health of vegetation (Rock et al., 1986). Feeney et al. (1982) found that the ultraviolet reflectivity of tamarack (Larix laricina) was higher than other species in the U.S.A. However, due to atmospheric attenuation, ultraviolet is not a suitable wavelength to sense forests from satellites or high altitude aircraft platforms (Suits, 1983).

---

1 The red edge is the sharp transition zone between the red and near infrared wavelengths.
The above ground structure and shape of the vegetation also influences reflectivity. North American hardwood forests have higher reflectivity than conifers because of canopy overlap and fewer shadows. Dottavio (1981) found that the percentage of crown cover and uniformity of the crowns was a most important variable in determining reflectivity in North American hardwood forests.

Some work on the reflective properties of eucalypts has been performed by Howard (1966) who found that the transmittance through one leaf was negligible. He also noted that eucalypt leaves hang vertically, and that leaf orientation is an important factor influencing reflectivity. Total reflectivity per unit area was considerably decreased when the radiation source was at 60°, compared with normal to the leaf. Howard (1966) concluded that an ability of the plant to alter the leaf orientation was a simple and efficient mechanism to adjust to prolonged or intense irradiation. Barber (1955) noticed increasing reflectivity with increased glaucousness on eucalypt leaves. Other factors which may be affecting the reflectivity of eucalypt forests include stocking, crown density, branch and stem geometry (important for radar responses; Richards, Sun and Simonett, 1987), bark types, and understorey species composition.

3.2.2. Remote sensing systems

Remote sensing can be defined as the acquisition of information about an object without physical contact with that object (Simonett et al., 1983). Techniques for extracting information about forests from aerial photographs were developed after the First World War (Simonett et al., 1983), and these techniques have continued to improve (e.g. B.J. Myers, 1974, 1983, 1984; Myers et al., 1984).

In the early 1960’s, N.A.S.A. began to launch various satellites and both manned and unmanned spacecraft. These carried conventional camera systems recording images on film as well as sensors which recorded images as digital data. The early images obtained indicated the potential of remote sensing for monitoring and mapping the earth’s surface and atmosphere. Since then, many nations other than the U.S.A. have launched a variety of satellites with sensors designed for different purposes. Table 3-1 summarizes the main remote sensing systems of the past, present and future. This information was obtained from Simonett et al., (1983), Duchossis (1984), Langham et al., (1984), Konijnenburg and Irysam (1984), and J.A. Richards1.

Table 3-1: Main Remote Sensing Systems

<table>
<thead>
<tr>
<th>Name of Satellite</th>
<th>Purpose</th>
<th>Date of launch</th>
<th>Country of origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOAA</td>
<td>Meteorological</td>
<td>1960-present</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Mercury-Atlas</td>
<td>Monitor spacecraft altitude</td>
<td>1960</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Gemini-Titan</td>
<td>Earth resource analysis</td>
<td>1965-1967</td>
<td>U.S.A.</td>
</tr>
</tbody>
</table>

1Richards, J.A., Department of Electrical Engineering, A.D.F.A., University of N.S.W., Campbell, A.C.T. 2601, Australia.
(Table 3-1 continued)

<table>
<thead>
<tr>
<th>Programme</th>
<th>Description</th>
<th>Dates</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apollo</td>
<td>Earth resource analysis</td>
<td>1967-1969</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Landsat (=ERTS)</td>
<td>Earth resource analysis</td>
<td>1972-present</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Skylab</td>
<td>General</td>
<td>1973</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>HCCM</td>
<td>Earth's surface cover and soil moisture (geology, hydrology, agriculture)</td>
<td>1978-1980</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Seasat</td>
<td>Oceanography</td>
<td>1978</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>Space Shuttle</td>
<td>Earth resource analysis</td>
<td>1981-present</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>SPOT</td>
<td>Earth's surface and earth resource analysis</td>
<td>1986-present</td>
<td>France</td>
</tr>
<tr>
<td>MOS-1</td>
<td>Marine observation</td>
<td>1987</td>
<td>Japan</td>
</tr>
<tr>
<td>Meteor</td>
<td>Various meteorological oceanographic and terrestrial monitoring satellites</td>
<td>late 1950's-present</td>
<td>U.S.A.S.R.</td>
</tr>
<tr>
<td>Chinasat</td>
<td>Terrestrial, ocean and meteorological monitoring</td>
<td>1975-present</td>
<td>China</td>
</tr>
<tr>
<td>Bhaskara</td>
<td>Terrestrial and ocean resource analysis</td>
<td>1982-present</td>
<td>India</td>
</tr>
<tr>
<td>ERS-1</td>
<td>Earth and ocean resource analysis</td>
<td>1990</td>
<td>European Space Agency</td>
</tr>
<tr>
<td>JERS</td>
<td>Earth resources</td>
<td>1992</td>
<td>Japan</td>
</tr>
<tr>
<td>Radarsat</td>
<td>Terrestrial and ocean resource analysis</td>
<td>1994</td>
<td>Canada</td>
</tr>
<tr>
<td>HIRIS</td>
<td>High spectral resolution scanning system</td>
<td>1995</td>
<td>U.S.A.</td>
</tr>
<tr>
<td>TERS</td>
<td>Meteorological and vegetation analysis in the tropics</td>
<td>Unknown</td>
<td>Indonesia</td>
</tr>
</tbody>
</table>

---

a - National Oceanic and Atmospheric Administration (NOAA)
b - Heat Capacity Mapping Mission (HCCM)
c - Système Probatoire d'Observation de la Terre (SPOT)
d - Marine Observation Satellite (MOS)
Landsat has been the satellite most used by the forestry profession to date, due to its relatively high spatial resolution and the ready availability of imagery compared with other imagery such as from the meteorological satellites. Usage on a global scale between 1979 and 1984 was 885,767 scenes, which generated a revenue of approximately 30 million U.S. dollars.

However, other remote sensing systems have proved useful to forestry as they offer even higher spatial resolution and more appropriate spectral ranges for sensing forested land. For example, SPOT has both a multispectral scanner (MSS) and a panchromatic scanner with resolutions of 20 m and 10 m respectively. The scanners can be turned to scan areas up to 475 km on either side of the satellite. This permits rescanning every one to two days, as well as providing stereoscopic images.

ERS-1 and Radarsat will carry microwave or radar sensors. The advantages of these sensors are that structural information about forest types is obtained, the microwaves are unaffected by cloud and the sensors can operate continuously. Aircraft borne lasers have been used to estimate forest biomass and volume. HIRIS, which is a high spectral resolution scanning system designed to record over 150 spectral channels, is a satellite system proposed for launch in the 1990s.

These systems are described in greater detail below. Slater (1980), Njoku (1982), Kairu (1982) and Colwell (1983) also provide general reviews of remote sensing programs.

3.2.3. Description of the Landsat system

The following information was sourced from the Landsat Data Users Handbook (1979), Landsat Data Users Notes (1986) and Colwell (1983). The first satellite designed specifically to collect data about the earth's resources was the Earth Resources Technology Satellite (ERTS-1) launched in 1972. In 1975 the second satellite in this series was launched and was named Landsat-2, changing the series name from ERTS to Landsat.

Features of the Landsat series of satellites are summarized in Table 3-2.

The Landsat satellites have a sun-synchronous near-polar orbit, which results in the satellite crossing the same point on the earth's surface every 16 days (see Table 3-2), and crossing the same latitude at the same time of day on each orbit (Figure 3-1). As the satellite overpasses all points on the earth's surface at approximately 9:30 am, sun angle varies according to the season, with a low sun angle in winter accentuating relief (as sunlit and shaded areas vary in reflectivity).
<table>
<thead>
<tr>
<th>Landsat 1</th>
<th>Landsat 2</th>
<th>Landsat 3</th>
<th>Landsat 4</th>
<th>Landsat 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Launch</td>
<td>23/7/72</td>
<td>22/1/75</td>
<td>5/3/78</td>
<td>16/7/82</td>
</tr>
<tr>
<td>Altitude</td>
<td>918 km</td>
<td>918 km</td>
<td>918 km</td>
<td>705 km</td>
</tr>
<tr>
<td>Repeat coverage</td>
<td>18 days</td>
<td>18 days</td>
<td>18 days</td>
<td>16 days</td>
</tr>
<tr>
<td>RBVa channel</td>
<td>1. 475-575b</td>
<td>475-575b</td>
<td>1500-700b</td>
<td>No RBVa</td>
</tr>
<tr>
<td></td>
<td>2. 580-680b</td>
<td>580-680b</td>
<td>panchromatic</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. 698-830b</td>
<td>698-830b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBVa resolution</td>
<td>80x80 m</td>
<td>80x80 m</td>
<td>40x40 m</td>
<td>-</td>
</tr>
<tr>
<td>MSSf channel</td>
<td>1. 500-600b (green)</td>
<td>as for Landsat 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. 600-700b (red)</td>
<td>as for Landsat 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. 700-800b (near IRc)</td>
<td>as for Landsat 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. 800-1100b (near IRc)</td>
<td>as for Landsat 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5. 10.4-10.6d (thermal IRc)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSSf resolution</td>
<td>79x79 m</td>
<td>79x79 m</td>
<td>79x79 m</td>
<td>79x79 m</td>
</tr>
<tr>
<td>Quantization levels</td>
<td>128</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>TMc channels</td>
<td>No TMc</td>
<td>No TMc</td>
<td>No TMc</td>
<td>1. 450-520b (blue/green)</td>
</tr>
<tr>
<td>on Landsats 4 and 5</td>
<td></td>
<td></td>
<td></td>
<td>2. 520-600b (green)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3. 630-690b (red)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4. 760-900b (near IRc)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5. 1550-1750b (mid IRc)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6. 10.4-12.5d (thermal IRc)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>7. 2.08-2.35d (mid-IRc)</td>
</tr>
<tr>
<td>TMc resolution</td>
<td>30x30 m for channels 1-5,7</td>
<td>120 m for channel 6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quantization levels</td>
<td>256</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repeat rate</td>
<td></td>
<td></td>
<td></td>
<td>16 days</td>
</tr>
</tbody>
</table>

a - return beam vidicon camera (RBV)
b - nanometers
c - infrared (IR)
d - micrometers
e - thematic mapper (TM)
f - multispectral scanner (MSS)

1 Richards, J.A., Department of Electrical Engineering, A.D.F.A., University of N.S.W., Campbell, A.C.T. 2601, Australia.
The first three Landsat satellites had two major sensing systems, viz. a multispectral scanner (MSS) and a return beam vidicon camera (RBV) (Landsat Data Users Handbook, 1986). Multispectral scanners were also included in the Landsat-4 and -5 payloads, but the RBV was replaced by a scanner similar to the MSS called a thematic mapper (TM).

The multispectral scanners are linescan devices which continually scan the earth in a 185 km swath nominally perpendicular to the Landsat orbital path. Reflected or reradiated electromagnetic radiation from the earth's surface is collected by electro-optical detectors. These detectors generate a variable voltage depending upon the radiant flux (i.e. the 'brightness' of the electromagnetic radiation detected) striking the detector surface. The analog signal (voltage) is then digitized and transmitted to earth or stored temporarily by on-board tape recorders.

The MSS consists of 24 detectors (Landsats-1 and -2) or 30 detectors (Landsats-3, -4 and -5). These are arranged as a 6 by 4 or 6 by 5 matrix respectively. Six lines are scanned simultaneously and for each line the radiant flux for four reflective bands is measured (named bands 4 to 7 respectively). The four bands are formed by filtering the incoming radiant flux. The position of each band in the electromagnetic spectrum is described in Table 3-2.

Each sample of electromagnetic radiation effectively represents 59 m by 79 m of land surface (i.e. 0.47 ha). Such a sample is called a pixel. Within a Landsat scene (185 km by 185 km) there are approximately 7.4 million pixels.

The TM was designed to provide improved spatial, spectral and radiometric information compared with the MSS. The spatial (linear geometric) resolution of the TM is approximately 2.6 times that of the MSS, with a pixel size of approximately 30 m by 30 m. Much more textural and contextual information is apparent on TM imagery compared with MSS imagery, though this additional information has not been fully utilized to date (Joyce and Sader, 1986). The TM has seven bands and the bands are narrower than in the MSS. This improves the sensitivity of the TM to spectral changes that result from different
ground cover types. The number of brightness values recorded per band is increased from 64 with the MSS to 256 for the TM.

Data from the RBV were never really researched or used operationally, due to technical problems with the sensor on Landsat-1 and -2 and to the RBV images appearing inferior to the excellent imagery produced by the MSS. As a consequence, this paper largely focuses on the results obtained using the MSS and TM. However, research results using other non-Landsat sensor systems are described where applicable. There are plans to launch a Landsat-6 in 1989 and Landsat-7 in 1993 to ensure continuity of the data.

3.2.4. Description of the SPOT system

The Système Probatoire d’Observation de la Terre (SPOT) satellite carries a ‘pushbroom’ sensor, which is a linear array of sensor cells individually recording electromagnetic radiation. The sensor operates in either a multispectral mode or a panchromatic mode, providing imagery with the characteristics as listed in Table 3-3.

Table 3-3: SPOT imagery characteristics (after Williams, 1983)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Multispectral mode</th>
<th>Panchromatic mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>spectral bands</td>
<td>0.50-0.59 μm</td>
<td>0.51-0.73 μm</td>
</tr>
<tr>
<td></td>
<td>0.61-0.68 μm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.79-0.89 μm</td>
<td></td>
</tr>
<tr>
<td>ground sampling area (nadir view)</td>
<td>20 by 20 m</td>
<td>10 by 10 m</td>
</tr>
<tr>
<td>number of pixels per line</td>
<td>3000</td>
<td>6000</td>
</tr>
<tr>
<td>ground swath width (nadir view)</td>
<td>60 km</td>
<td>60 km</td>
</tr>
<tr>
<td>altitude</td>
<td>830 km</td>
<td></td>
</tr>
<tr>
<td>repeat rate</td>
<td>(1-) 26 days</td>
<td></td>
</tr>
</tbody>
</table>

The field of view may be directed away from the nadir by up to ±27°, thereby allowing the same area to viewed on several consecutive days and also achieving stereoscopic coverage. Lillesand (1987) reports that the geometric accuracy of SPOT data (supplied at processing level 1B) was very high, obtaining a root mean square (RMS) error of ±0.48 pixel for the multispectral data and ±0.46 pixel for the panchromatic data (RMS is discussed in Chapter 8). The time of overpass is approximately 10:39 am Australian local time, which results in images with less shadowing compared with Landsat (which overpasses at approximately 9:30 am).

1SPOT imagery may be supplied at various levels of radiometric and geometric accuracy (ACRES, undated). Level 1A has no geometric correction, and the only radiometric processing is the equalization of the response of the detectors. Level 1B has radiometric and geometric error induced by the acquisition system with a locational accuracy of 1500 m (rms - see Chapter 4 for details). Level 2 has radiometric correction as for level 1B, though each scene is corrected into a cartographic projection using 6 to 9 ground control points. Locational accuracy is 50 m (rms). Level S involves registration with a reference scene, and locational accuracy is to within 0.5 of a pixel.
3.2.5. Description of microwave or radar systems

Radar is an acronym for radio detection and ranging: the interference pattern, or backscatter, of radio waves reflected from a target is (detected and) used to determine the target's position, or range. Three radar parameters may be modified in order to change backscatter characteristics viz. wavelength (or frequency), angle of incidence and polarization.

The wavelength of radar is considered to extend approximately from 1 mm to 0.8 m (i.e. 300 GHz to 0.375 GHz). Wavelength influences the depth of penetration into a target (the longer the wavelength, the deeper the penetration). Backscatter is influenced by the interaction between wavelength and the dielectric constant of the material. An increased dielectric constant is caused largely by raised moisture content of the target (Fung and Ulaby, 1983), though factors such as the row direction of crops may also effect the dielectric constant (Sieber and Trevett, 1983). As the dielectric constant (i.e. per cent moisture content) rises, the backscatter also increases.

The relationship between wavelength and surface roughness and angle of incidence is modeled using the Rayleigh criteria\(^1\). As the surface roughness \(H\) increases above \(H_R\), reflectance becomes more diffuse (i.e. electromagnetic radiation is reflected in all directions), while for smoother surfaces the reflectance becomes specular (i.e. the target acts as a 'mirror'). Angle of incidence will determine the amount of backscatter received at the sensor. A low angle of incidence over a smooth surface will result in very little backscatter, as Richards, Woodgate and Skidmore (1987) found for a flooded *Eucalyptus camaldulensis* forest in western N.S.W.

The microwave electromagnetic radiation (emr) may be polarized into a horizontal or vertical plane. When this polarized electromagnetic radiation interacts with the surface material, it is depolarized and rotated. The horizontal and vertical components of this backscattered electromagnetic radiation may be recorded by the microwave antennae, and yield interesting information on the characteristics of the surface material.

The main advantages of radar are its cloud penetrating capability, and ability to derive information on forest structure (Joyce and Sader, 1986). The main disadvantage of radar imagery is that the interference of the ground with the microwaves is not sensed by humans, and this lack of familiarity has contributed to the difficulty in understanding the microwave response (Kessler, 1987).

\[ H_R = \frac{\lambda}{8 \cos \theta} \]

where
\[ \lambda = \text{wavelength (cm)} \]
\[ H_R = \text{surface roughness threshold (cm)} \]
\[ \theta = \text{angle of incidence (degrees)} \]

3.2.6. Description of AVHRR systems

The advanced very high resolution radiometers (AVHRR) aboard the NOAA-series of environmental satellites provide four channels (Table 3-4) (Matson et al., 1984). Other characteristics of the AVHRR imagery are also shown in Table 3-4. The satellites are polar orbiting and offer twice daily
monitoring of the earth's surface, making the AVHRR imagery highly suitable for monitoring seasonal variation of vegetation (Joyce and Sader, 1986). The highest spatial resolution of 1.1 km is obtained at the nadir view of the satellite, while resolution degrades away from the centre of the image. This resolution has resulted in the sensor being used as the first stage in multistage sampling over regional to continental scales (Joyce and Sader, 1986).

Table 3-4: AVHRR imagery characteristics (after Matson et al., 1984)

<table>
<thead>
<tr>
<th>Image characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>spectral bands</td>
<td>0.58-0.68 µm</td>
</tr>
<tr>
<td></td>
<td>0.725-1.10 µm</td>
</tr>
<tr>
<td></td>
<td>3.55-3.93 µm</td>
</tr>
<tr>
<td></td>
<td>10.5-11.5 µm</td>
</tr>
<tr>
<td>ground sampling area (nadir view)</td>
<td>1.1 by 1.1 km</td>
</tr>
<tr>
<td>ground swath width (nadir view)</td>
<td>2600 km</td>
</tr>
</tbody>
</table>

3.2.7. Description of HIRIS systems

A number of high spectral resolution scanners including the high resolution imaging spectrometer (HIRIS) and the moderate resolution imaging spectrometer (MODIS) are intended for launch by the mid-1990s. These sensors will capture data simultaneously for 192 and 80 spectral bands respectively in the 0.4 to 2.5 µm wavelength region, at a spatial resolution of 30 m (Barnes, 1985; Goetz and Herring, 1987). The possibilities for spectral differentiation of forests are exciting, though high data volumes will be a problem, and Swain (1985) predicts that analysis of high-dimensional image data will regain its prominence in remote sensing research. Chen and Landgrebe (1988) discuss the problem of the high-dimensional data sets that will be produced by these sensors, and propose a feature reduction technique that may operate in real-time aboard the satellite.

3.2.8. Analysis of remotely sensed data

Material in this section is drawn from Colwell (1983) and Richards (1986), as well as other cited references.

Remotely sensed images are not photographs, but are generated from digital data by computer programs. For example, a pixel in a Landsat MSS image has an assigned brightness value ranging from 0 to 64 (on a grey scale this range is from black to white respectively). Black and white images can be created by proportionally assigning the appropriate 'grey level' to the brightness values recorded for each pixel. Each pixel may have a number of spectral bands recorded, e.g. Landsat MSS data has four. Thus separate monochrome images of each band can be generated for each image. Alternatively, coloured images can be created by assigning a colour gun on a television monitor (i.e. either the red, green or blue gun) to each band, forming a 'colour composite'. When the bands are overlaid, the prime colours blend to form the colours of the visible spectrum. Such an image is one of the simplest and most common forms for presenting remotely sensed data as a 'picture'. Colour composites have been widely used for manual interpretation purposes. Smith (1973) used 1:1 000 000 Landsat MSS colour composites to map land
use, native forests, conifer plantations and burnt areas. Skidmore (1983) used a 1:250 000 Landsat MSS colour composite to differentiate Pinus radiata plantations into three age classes, and Smith and Woodgate (1985) indicated the extent of wildfires using 1:1 000 000 Landsat MSS colour composites.

Other forms of imagery are produced by using 'computer classification techniques'. Classification techniques include both supervised and unsupervised classification. Supervised classification involves collecting information on the brightness of known land cover types (such as forest or grass) in each of the bands. Such areas are called 'training areas'. Figure 3-2 shows training areas for four cover types and their stylized response in each Landsat band.

Figure 3-2: Stylized Landsat response for four cover types

BV = brightness value or digital number (DN)
4 = Landsat band 4
5 = Landsat band 5
6 = Landsat band 6
7 = Landsat band 7
The training area information can then be used as a template (by generating statistical parameters) against which unknown pixels are compared. If an unknown pixel has the same spectral response as the statistical parameters defining a given training area, the pixel is classified as belonging to that cover class type. Figure 3-3 shows an example of a *supervised* classification procedure. The statistical parameters describe decision boundaries used to classify unknown pixels (Swain and Davis, 1978). Supervised classifiers are reviewed in Chapter 6, and a novel supervised classification technique based on nonparametric statistics is presented.

![Figure 3-3: An example of a supervised classification procedure](image)

As shown on Figure 3-3, where objects of different brightness occur within or across a pixel, the brightness value of the pixel becomes an average, proportional by area. Mixed pixels lead to misclassified or unclassified pixels. Errors introduced by mixed pixels are discussed in detail in Chapter 4 in relation to map accuracy.

*Unsupervised* classification is an automatic computer procedure. Pixels with similar brightness values are automatically grouped according to preset rules (such as Euclidean distance clustering - Swain and Davis, 1978). The clusters formed are then related to land cover types. As with supervised classification, grouped brightness values are used to assign unknown pixels to land cover classes. The land cover class map is then displayed by assigning a particular colour to each class. Unsupervised classification is reviewed in detail in Chapter 5.

Many other computer-based image processing procedures are available to analyse and enhance remotely sensed images (Swain and Davis, 1978). Some of these include contrast stretching, which involves expanding the dynamic range of brightness values in each band to improve image contrast for
that band, and calculating ratios of two (or more) bands to highlight a particular feature (or features) on
the image (see 3.4). Boundaries between different cover types may be enhanced using a variety of edge
detection algorithms. Density slicing is a simple classification technique performed on individual bands
where pixels, which fall within a specified brightness value range, are assigned a particular colour or shade
of grey (Hathout, 1980; Befort and Evans, 1988). Numerous techniques for analysing texture and context
(or association) have been suggested, and are reviewed in Chapter 5. Swain (1985) reviews progress in
extracting temporal change, spatial and spectral information from remotely sensed data, and describes a
number of research problems that need to be addressed.

Techniques are available to geometrically correct remotely sensed images and to reduce distortions
introduced by spacecraft roll and yaw, earth curvature effects, and sensor inaccuracies. Radiometric errors,
due to atmospheric attenuation and other problems, may also be reduced. Geometric and radiometric errors
are discussed in Chapter 4.

From its inception, remotely sensed data was recognized to have certain advantages over
conventional aerial photography. It offers a synoptic view of the earth’s surface, with near orthographic
representation (Howard, 1976). Landsat MSS data have been readily available in the U.S.A. since 1972
and in Australia since 1979. Landsat TM has been available in limited quantities in Australia since 1986,
and with the present upgrade of the Australian Centre for Remote Sensing, the data will be fully
available. SPOT data is available over Australia. As the data are in digital form, geometric correction
during production is possible. Some authors claim that Landsat imagery is less expensive and more
efficient than conventional aerial photography for some inventory applications (Dodge and Bryant, 1976;
Hathout, 1980; LaPerriere et al., 1980; Myers, 1980). The advantages of computer classification
techniques over visual classification were quickly realized (Heller, 1976) and include ease in combining
and comparing Landsat imagery from different dates, and the rapid extraction of the maximum spectral and
spatial information from the Landsat data.

Proof of the usefulness of remote sensing technology for natural resource management is the
widespread use of remote sensing in many countries described below in 3.3. However, with the
commercialization of remote sensing, Mackenzie (1984) points out that Third World countries may not be
able to afford the technology, while Willard (1983) states that in Third World countries remote sensing
may be a worse option than employing cheap labour for ground reconnaissance. Morgan (1982) examines
international law relating to remote sensing and asks who actually owns the rights to the data.

3.3. Research results of interest to forestry

3.3.1. Introduction

Before citing specific examples of applying Landsat imagery to forestry, it is worth briefly
considering the difficulties in comparing the accuracy of forest maps produced by different workers¹. First,
the level of detail on maps varies considerably. Some workers conclude that forests can be mapped

¹The issue of map accuracy assessment is examined in detail in Chapter 4.
accurately, but they only map broad cover classes such as forest, agriculture and urban (Jupp et al., 1979). Other workers obtain poorer results, but do attempt to map 'forest' types within the broad forest category (Benning et al., 1981; Skidmore, 1983). The second difficulty in comparing accuracy of forest maps is that various methods for calculating map accuracy have been used which are not immediately comparable. A third problem is that most researchers do not indicate the reliability or confidence intervals of their results, although methods for doing this are available.

3.3.2. Forest mapping

Some of the earliest research using Landsat MSS data involved the visual detection of forests and stress within forests, on colour composite images (Latham and McCarty, 1972; Zsilinsky, 1973; Murtha, 1973). Killed and dying trees downwind of a factory producing SO$_2$ were identified. Good results have been reported with visual interpretation of Landsat imagery. Howard (1976), Jaakola (1976) and Jones (1976) successfully mapped forest and nonforest classes, while Hafker and Philipson (1982) discriminated hardwood clearcuts using Landsat MSS bands 5 and 7. However, Heath (1974) could not visually delineate forest type classes on Landsat MSS imagery.

A large number of studies have investigated the utility of supervised classification strategies for analysing Landsat MSS data. Dodge and Bryant (1976) used supervised computer classification to differentiate hardwood forest from softwood forest in the U.S.A., using summer Landsat imagery. These researchers obtained a 92 per cent accuracy in comparing the total area of hardwood and softwood on their classified Landsat map to the total area estimated by an intensive forest inventory. Thus, locational accuracy and confidence limits for the cover classes were not estimated. Bryant et al. (1980) obtained only 63 per cent accuracy when identifying similar forest associations, and again offered no estimation of confidence limits. Heath (1974) classified 14 classes in Texas including hardwood, cutover hardwood, regenerated pine and pine with a 74 per cent accuracy, though the number of samples used to calculate the mapping accuracy were not cited. Kalensky and Scherk (1975) classified Canadian forests into deciduous and coniferous types with an accuracy of 76 and 67 per cent respectively. The overall mapping accuracy (which included agricultural land and other categories) was 83 per cent. In another study in northern Saskatchewan, Kalensky et al. (1979) classified four forest classes (softwood, regeneration and brush, recent burn and unproductive land) with an overall mapping accuracy of greater than 90 per cent. They used imagery from two dates and a maximum likelihood classifier to achieve this result. The boreal forests of Canada were mapped at level III (Anderson et al., 1976) using Landsat MSS data and a maximum likelihood classifier (Dixon et al., 1985). An overall classification accuracy of 70 per cent was obtained.

Benning et al. (1981) had limited success at classifying exotic forest types into age classes in New Zealand using a maximum likelihood classification to analyse Landsat MSS data. Their classification accuracies ranged from 16-58 per cent with a 99.9 per cent confidence interval. Skidmore (1983) obtained a 69 per cent accuracy (with a 95 per cent confidence limit) in mapping Pinus radiata plantation age classes in the Tumut district, N.S.W. using a parallelepiped classifier. Shimabukura et al.
(1980) mapped four plantation classes in Brazil (viz. Pinus elliottii, other Pinus spp., Eucalyptus spp. 8 months to 2 years, and Eucalyptus spp. greater than 2 years of age) using a simple parallelepiped classifier, obtaining accuracies ranging from 56 per cent to 93 per cent. In South Africa, Van der Zel (1985) reported an attempt to map indigenous forests, pine plantations, eucalypt plantations and wattle plantations using maximum likelihood classification and Landsat MSS data. In mountainous areas sunlit pine plantations were confused with eucalypt plantations in the shade.

Adomeit et al. (1981) mapped five cover types (viz. forest, swamp, cleared water and agriculture) with 79 per cent accuracy on the south coast of N.S.W. They could not successfully separate native eucalypt forest density classes, partly cleared or woody regeneration areas.

Madhavan Unni et al. (1985) used maximum likelihood classification of Landsat imagery to map teak bearing forests in India, and reported an overall mapping accuracy of over 80 per cent, though the technique used to calculate mapping accuracy was not described. Sweet et al. (1980) used a supervised classification technique to classify six cover types (pine thicket, oak thicket, water, wooded areas, marshes and flatwoods) on Cape Canaveral. A mapping accuracy of 49 per cent was obtained; a low figure due to the complex distribution of the cover types.

A useful technique suggested by Rohde (1978), Hoffer and Bartolucci (1980), Sadowski and Danjoy (1980) and Roller and Visser (1980) involves visually stratifying a remotely sensed image into homogeneous areas prior to further analysis. Hoffer and Bartolucci (1980) recommended each stratum should have separate training area data and error accuracy assessment.

Unsupervised\(^1\) computer classification techniques have also been used to map forest types. Graetz et al. (1979), using the CSIRO-ORSER system, evaluated broad vegetation groups in South Australia. Accuracy was calculated by comparing area estimates of the various cover types prepared by the South Australian Department of Lands with the areas obtained on the classified Landsat map. In another study on the south coast of N.S.W., Jupp et al. (1979) also concluded that forest could only be mapped accurately at a broad level (for example forest land versus agricultural land, urban and built up land, water). Petersen et al. (1983) performed a statewide unsupervised classification of Californian forests, discriminating commercial timberlands from nonforest classes with a 75.1 per cent mapping accuracy, and mapping forest from nonforest with an 80 per cent mapping accuracy. Hoffer (1976) listed a number of problems with unsupervised classification including that the analyst may not know how many spectral classes are truly present. In addition, classes of interest may have subtle differences in spectral response which cannot be discriminated by unsupervised classification, while many of the other classes may be easily separable but contain little information. Swain (1985) noted that where there is spectral confusion between classes, it is difficult to assign a meaningful cover class name to the clusters produced by the unsupervised procedure.

\(^1\)Also termed nonsupervised classification and cluster analysis.
Combining supervised and unsupervised classification methods\(^1\) is claimed to be superior to either individual technique, and was described by Fleming et al. (1975) and Hoffer (1976). The technique has also been used with good results by Beaubien (1979), LaPerriere et al. (1980), Thompson et al. (1980) and Walsh (1980). It has a number of advantages, \textit{viz.} the capacity to extract and retain the main spectral information (by utilizing training areas to delineate areas of a known cover class and then performing unsupervised classifications to group those data); \textit{a priori} information can be included; computer costs are reduced; classification accuracy is superior to that obtained with either supervised or unsupervised classification; and the method can be implemented with existing software on general-purpose computer systems. Hoffer (1976) defined five major cover types (\textit{viz.} coniferous forest, deciduous forest, grassland, bare rock and water) with an overall mapping accuracy of 91.2 per cent in the San Juan Mountains of the U.S.A., while a 'regional' classification within those major cover types (for example pine, spruce/pine, oak and aspen) had an average accuracy of 77.2 per cent. He concluded this was a significant result in view of the vegetative and topographic complexity of the area. Walsh (1980) used a combined supervised-unsupervised method to classify twelve land cover types in the U.S.A., with an average accuracy of 88 per cent (range 84-95 per cent).

High forest mapping accuracies have been obtained using Landsat Thematic Mapper (TM) data. Lillesand et al. (1985) discriminated forest from nonforest classes with a 98 per cent mapping accuracy, while forest types (including hardwoods, jack pine, red pine, lowland conifers, lakes, clearcuts, roads, clouds and jack pine budworm defoliation) were mapped with a 93 per cent accuracy in Wisconsin. In a later study in Wisconsin, Hopkins et al. (1988) mapped nine forest type classes with an overall mapping accuracy of 85 per cent using a maximum likelihood classification of TM imagery. Lillesand et al. (1985) found that TM bands 4 and 5 yielded most information for discriminating forests, while bands 1, 2 and 3 offered less discrimination. Horler and Ahern (1985) found TM bands 3, 4 and 5 were useful for discriminating Canadian forest types. Nelson et al. (1984) analysed (simulated) TM data for Baxter State Park in Maine, and concluded most forest information was contained in bands 4, 5 and 1. The overall mapping accuracy was 57.7 per cent for 13 cover type classes that included conifer, hardwood, mixed hardwood/softwood, alder bog, and three conifer defoliation classes.

Satellites other than Landsat have been used for mapping forests. Remotely sensed imagery from NOAA meteorological satellites (in the visible and near infra-red parts of the electromagnetic spectrum) are used to generate global vegetation indices on a weekly basis at a resolution of approximately 20 km (Tarpley et al., 1984). A normalized vegetation index (NVI)\(^2\) is computed by ratioing the AVHRR channel 1 visible band (0.58-0.68 \(\mu\)m) and the AVHRR channel 2 near infrared band\(^3\) (0.73-1.1 \(\mu\)m) at a resolution of 4 km by 4 km. The higher NVI values on the image corresponded to greener vegetation on the ground. Thus, global biomass production was estimated.

\(^1\)Termed 'modified clustering' by Fleming (1974), Hoffer and staff (1975) and Hoffer (1976).
\(^2\)NVI = (near infrared - visible) / (near infrared + visible). This ratio has also been called the normalized difference index (NDI) (Miller \textit{et al.}, 1986).
\(^3\)A similar ratio of Landsat channels has also been significantly related the leaf area index of wheat (Wiegand \textit{et al.}, 1979).
Thermal scanners were used by Holbo and Luvall (1989) and Luvall and Holbo (1989) to calculate the thermal response number (TRN), which is a measure of the energy required to change the temperature of a cover type. TRN was shown to be useful for distinguishing forest and other cover types (barren surfaces had the lowest TRN while forests had the highest). They speculated that TRN may also be used to map precipitation, regional energy balance, impact of drought, cold air drainage patterns, and insect damage to forests.

Imagery from microwave (radar) sensors is unaffected by cloud cover and provides information on the structure of the forest. Side-looking airborne radar (SLAR) involves transmitting a pulse of microwave radiation perpendicular to the direction of travel of a plane. The microwave radiation is reflected by the terrain and objects on the ground, and the backscatter is recorded by the antenna on the plane. The difference between the incident and reflected radiation is used to construct an image of ground conditions. Reviews of radar systems are provided by Henderson and Merchant (1978), Slater (1980), Njoku (1981), Carver et al. (1985) and Ulaby (1982). Joyce and Sader (1986) discuss the relationship between forest structure and radar response caused by changing wavelength and polarization.

SLAR has been used for tropical forest inventory in various countries, including Nigeria, Brazil, Colombia (reported in Grainger, 1984); Ecuador, Indonesia, Nicaragua, Papua New Guinea and Panama (reported in Howard, 1976). Synthetic aperture radar (SAR) has been used more in recent years. At high altitudes, the resolution of radar images becomes very poor, but, as the resolution of radar is proportional to antenna size, a method for increasing resolution by synthetically enlarging the antenna (using the Doppler shift principle) has been developed.

Sicco Smit (1978) visually interpreted small-scale radar images of humid tropical rainforest regions in the Amazon. Forest and nonforest as well as dry and wetland forest types could be discriminated, with delineation of physiographic features being possible within the dryland type (e.g. drainage and topography). Mahogany bearing forests could not be identified.

Inkster et al. (1980) manually interpreted X-band radar images which ranged in spatial resolution from 2 to 20 m. They reported that forest areas in Canada were difficult to discriminate from grass and other land uses at resolutions coarser than 10 m. Forest operations and roads were identifiable at a resolution of 6 m. Tree species and age were difficult to distinguish at resolutions greater than 6 m.

Knowlton and Hoffer (1981) investigated the suitability of HH\textsuperscript{1} and HV\textsuperscript{2} polarization for identifying hardwood, softwood, mixed hardwood/softwood, clearfelled, pastures, emergent crops, water and bare soil cover types. The SAR was obtained from side looking airborne radar at an elevation of 18 000 m. Positive prints at a resolution of 15 m were manually interpreted. Tonal and textural characteristics for the imagery were examined, and it was concluded the overall tonal contrast was greater on the HH image, though neither polarization was consistently better for identifying the cover types. The authors suggest that a dual-polarized SAR is optimal for forestry applications.

\textsuperscript{1}Horizontal polarization is transmitted and recorded at the antenna.
\textsuperscript{2}Horizontal polarization is transmitted and vertical polarization is recorded at the antenna.
In Australia, Wyllie and Houghton (1984) and Milne (1984) studied SIR-A SAR imagery acquired over semi-arid agricultural and pastoral regions of southern Western Australia and south west New South Wales respectively. Wyllie and Houghton (1984) concluded that an ability to discriminate vegetation on the SIR-A imagery was related to moisture differences. The structural variation in forest and woodland in the area was not considered. Milne (1984) studied mallee (*Eucalyptus socialis* and *E. dumosa*) woodland cover growing on sandplains and dunefields, and concluded that much textural information was present in the imagery. Milne (1984) cautioned that cover types with similar texture, but different composition, may not be discriminated by this type of imagery. Skidmore *et al.* (1986) concluded that a SIR-B SAR image of the Riverina red gum forests of New South Wales improved forest classification when combined with Landsat data, and that stand structure was one factor affecting radar backscatter.

Engheta and Elachi (1982), Wu (1984) and Richards, Woodgate and Skidmore (1987) reported that standing water beneath forest stands may be detected by X-band SAR data, due to an increased backscatter effect. Richards, Woodgate and Skidmore (1987) went on to develop a model to explain this phenomena.

C-band radar has been proposed for ice mapping and measurement of wind. In order to calibrate C-band satellite radars, Birrer *et al.* (1982) and Bernard and Vidal-Madjar (1989) proposed that tropical rainforest would offer a homogeneous target. They successfully showed that C-band radar has a virtually constant response that varies smoothly as incidence angle changes. This indicates that C-band would not be a suitable wavelength for forest mapping.

Aircraft borne scanners recording digital data offer an alternative to conventional aerial photographs. Befort and Evans (1988) tested the forest mapping capability of imagery with a 5 by 5 feet resolution (1.6 m by 1.6 m) in the 0.4 to 0.8 μm wavelength range. Four forest types were recognized at three stocking levels (12 forest classes in all) and visually interpreted on the imagery. The overall mapping accuracy was 70.5 per cent.

3.3.3. Forest inventory and multistage sampling using remotely sensed data

Remotely sensed data has been used extensively for estimating the area of forest on earth. Lanly (1983) and Grainger (1984) provide reviews of this work for the tropical regions.

Hame (1981) reported the use of Landsat imagery for forest site quality mapping in Finnish spruce and pine forests. The Finnish Government taxes private forest owners on the potential productivity (or site quality) of their forests. Eight site quality classes were defined, and class mapping accuracies ranged from 0 to 100 per cent with an average of 59 per cent. Neither locational accuracy nor confidence limits were considered.

Singh (1987) found that two forest density classes (*viz.* a mixed broadleaf forest canopy cover of greater than 50 per cent and a mixed broadleaf forest canopy cover of 20 to 50 per cent) in India were significantly different when tested using a pairwise divergent analysis (Swain and Davis, 1978). A nonparametric test of overlap was proposed by Skidmore *et al.* (1988), who showed that *Pinus radiata* plantation stands of different ages (or density) were spectrally separate, and therefore could be potentially mapped using Landsat MSS data. Williams (1979) used a euclidean distance classifier to map crown
closure of plantations in North Carolina from Landsat MSS imagery. The crown closure information was
input to a forest inventory model. Roller and Visser (1980) concluded that crown cover was more
important than species in determining Landsat radiance.

Strahler and Li (1981; 1984) reported on a study using Landsat MSS data to estimate stocking
and height in sparse to moderately stocked ponderosa pine (Pinus ponderosa) forests. The proposed model
assumes trees are widely spaced cones, and that reflectance measured by the Landsat MSS sensor is a
mixture of shadow, understory and tree crown. Inverting the model allows tree density and height to be
predicted from Landsat radiometric responses. Mapping of tree size and density was 'within about 10 per
cent of the true values' for sparse pine forests in northern California. Franklin et al. (1986) modeled the
canopy reflectance of woodland and savannah in the Sudan and Sahel using a similar approach to Strahler
and Li (1981; 1984). Instead of assuming the trees were inverted cones, Franklin et al. (1986) modeled the
trees as hemispheres on sticks. Other assumptions were that the trees were sparsely spaced, the tree counts
varied from pixel to pixel (i.e. the spatial pattern is random), the size and shape of trees were known, and
that the spectral response of tree crowns and shadow was distinct from the understory. Results were again
encouraging, with the correlation between predicted and observed values having a $r^2$ value of greater than
0.85, though tree density was consistently overestimated and tree size underestimated. Walker et al. (1986)
and Jupp et al. (1986) discussed the relationship between eucalypt woodland structure and Landsat MSS
response. They reported that woodland structure is detectable on Landsat imagery, and that sun position
and season are also important factors in determining the spectral characteristics of woodlands. They
concluded that it should be possible to invert predictive models (as shown by Strahler and Li, 1981 and
1984) to calculate woodland cover and structure from Landsat MSS imagery. However, assumptions similar to the assumptions used in the models of Strahler and Li (1981; 1984) and Franklin
et al. (1986) would be required.

Multi-stage sampling using Landsat as the first stage was discussed by Aldrich (1971). Howard
(1976) and De Steigeur (1978) suggested the most effective use of Landsat-1, -2 and -3 imagery is as base
maps to which information from medium to large scale aerial photography and ground survey can be
added. Canadians have used Landsat to stratify the forest into cover types as a first stage during conifer
forests inventories (Kirby and Van Eck, 1977). The subsequent stratified sampling focused on timbered
areas and required only one third of the number of samples required for simple random sampling. Frayer
(1981) discussed a multilevel sampling design incorporating Landsat imagery which allowed the variance
of forest populations to be estimated. The advantage of multistage sampling is that estimated rather than
known stratum sizes may be used in the sampling procedure, thus increasing efficiency. Roller and
Colwell (1986) suggested that NOAA AVHRR data may be useful for stratifying broad land cover types
prior to sampling, as AVHRR data costs 0.1 per cent of Landsat MSS by area.

Kalensky et al. (1979) used supervised classification of two combined Landsat images to delineate
a remote forested area in Canada into nine cover classes (viz. softwood, softwood regeneration, hardwood
regeneration and brush, recent burn, treed muskeg, roads, rivers, lakes and clouds) so that efficient ground
sampling could be undertaken. Results indicated that accuracy of forest classification at the softwood-hardwood-mixedwood level ranged from 70-90 per cent, with 95 per cent confidence limits.

Poso et al. (1984) developed a two phase sampling method for estimating the age and volume of timber in Finnish forests. The first phase involved measuring stand characteristics over a systematic sample of forest plots. The second phase involved relating Landsat radiometric responses to the stand characteristics. The correlation between the first principal component and stand age was $r^2 = 0.82$, and between the first principal component and stand volume was $r^2 = 0.78$.

More unusual sensors have also been used to inventory forests. Nelson et al. (1988) used a laser to estimate forest biomass and volume along 20 m wide strips in the U.S.A. The laser measured tree height, from which the total tree volume was estimated and found to be within 2.6 per cent of the true value. Green biomass was within 2.0 per cent of the true value. Baker and Maggio (1986) also report a close correlation between laser and field measurements for total stand height, crown diameter and basal area in Western Louisiana\(^1\). Lasers appear to be particularly useful for strip sampling of forests.

Holbo and Luvall (1989) used a thermal infrared multispectral scanner (TIMS), with a pixel resolution of 0.1 ha, to map temperature for sites occurring over mature Douglas fir forest, natural regeneration with Douglas fir and maple, shelterwood, Douglas fir plantation, clearcut, and rock outcrop/quarry. The temperature was related to forest structure characteristics. The most striking result was that over forested sites, day time temperatures were lower and had a narrower range, while night time temperature variation was much higher for nonforest sites. Holbo and Luvall (1989) proposed these results may be used to classify forests on the basis of the thermal response; to interrelate thermal classifications with ecological processes; to evaluate alternative land management practices in microclimatic terms; and to predict the regional climatic impacts of change in forest structure.

The Dutch have been developing radar systems for use in the cloudy regions of Europe and the Tropics as part of a project named 'ROVE' (De Loor et al., 1982). As part of the ROVE project, Hoekman (1985) found that X-band SLAR backscatter increased in older (or denser) spruce plantations in Holland, indicating that forest structure can be mapped by radar.

Wu (1984) found SAR images taken during the SIR-A space shuttle flight had a radar return strength that was highly correlated with tree height or age in pine plantations. Crawford and Stutzman (1983) found radar backscatter was linearly related to the weight of herbaceous plants and woody shoots in spruce/fir and northern hardwood stands in the U.S.A. Richards, Sun and Simonett (1987) showed that four components effect radar backscatter from coniferous forest stands in the L band HH mode. These were volume scatter from foliage, direct backscatter from the ground surface, bistatic scatter from trunk to ground and then back to the radar, and scatter from foliage to ground and then back to the radar. Sun and Simonett (1988) further developed this model and showed that the trunk term is the dominant factor in determining backscatter from conifer stands when using L band radar in HH mode.

\(^1\)The field and laser measurements were averaged.
3.3.4. Mapping wildlife habitat

Landsat imagery has been used in North America to map forest habitat suitable for certain wildlife. Thompson et al. (1980) determined habitat suitable for caribou in a 90,000 km² area. The ecological requirements of caribou at different times of the year were established by ground survey (counting faecal pellets in eight different ecological types). Land ‘complexes’ were then defined by grouping training area statistics and determining the proportion of ecological types occurring in each complex. The ecological type map produced had 77 per cent of the area correctly mapped, though the method for estimating accuracy did not include locational accuracy. Also, as the sample used to estimate mapping accuracy was not random, statistical inferences could not be drawn. LaPerriere et al. (1980) used Landsat imagery to analyse moose habitat over 13 million ha in North America but offered no estimate of mapping accuracy.

The wildlife habitat value of an area of northern Australian eucalypt woodland was estimated from Landsat MSS data by Saxon and Dudzinski (1984). The variance was calculated for a three-by-three moving window on two scenes collected eight years apart. They defined the total environmental gradient as the sum of the variances from the two data sets, and the measure of persistence as the absolute difference of the variance between the two dates. Saxon and Dudzinski (1984) stated an ecocline would have a moderate total environmental gradient, while an ecotone and monotone would have a low and high measure of persistence respectively. They found that vulnerable animals were associated with gradual gradients (ecoclines). Potential pests and sites without fauna were associated with areas of little textural variation (i.e. monotones) and abrupt boundaries (i.e. ecotones). The information gained from the analysis of the remotely sensed data was used to order biological reserve priorities.

Deer were counted in real time after a heavy snowfall, using an aircraft borne multispectral scanner in the U.S.A. (Trivedi et al., 1984). A two stage thresholding approach was used to analyse channel ratios in real-time from the scanner. The number of deer were estimated with a claimed accuracy of 87.6 per cent.

Smith et al. (1981) modeled temperature profiles in conifer and hardwood canopies in the U.S.A. from canopy surface temperatures. They postulated that temperature profiles may be an important factor in modelling wildlife habitat suitability.

3.3.5. Mapping forest soils from remotely sensed data

Soil mapping accuracies from remotely sensed data have generally been poor due to vegetation and varying soil moisture conditions (Satterwhite et al., 1984). Any albeit limited success has occurred in

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1The variance calculated over a three-by-three moving window is a measure of texture - see Chapter 6 for details.
2An ecocline is a gradual transition between environmental gradients e.g. a wet-dry gradient caused by climatic conditions across a continent (Odum, 1975).
3An ecotone is an area of abrupt change between two (or more) homogeneous environmental areas (or monotones) e.g. a forest-grassland boundary (Odum, 1975).
4A monotone is a homogeneous area exhibiting similar environmental characteristics e.g. agricultural grassland (Odum, 1975).
semi-arid and arid regions, or over cleared or lightly vegetated agricultural fields. Soil mapping from remotely sensed data is reviewed in Chapter 9, where a technique for mapping forest soils using an expert system is described.

3.3.6. Derivation of elevation models from stereoscopic remotely sensed data

Capturing surface elevation information in a digital form suitable to input into a computer involves sampling x, y and z (i.e. easting, northing and elevation) points from a model representing the surface. Other surface attributes such as gradient and aspect may be derived from the digital elevation model (DEM) and stored in a computer as a 'digital terrain model' (DTM).

DEM's have been derived by using automatic stereocorrelation of overlapping remotely sensed digital images (Ehlers and Welch, 1987). With the increasing spatial accuracy of remotely sensed data, future DEMs will have increasingly higher spatial accuracies (Rodriguez et al., 1988); indeed Swann et al. (1988) state that DEM extraction with less than 10 m root mean square (RMS) error in all three planes is possible using SPOT data. Bloom et al. (1988) suggest that DEMs may be generated from overlapping SIR-B (radar) and Landsat TM data using stereophotogrammetry with an accuracy of between ± 30 m and ± 40 m.

3.4. Detecting change in the forest

3.4.1. Introduction

The potential for automatic update of land use surveys is one of the major advantages of satellite remote sensing (Estes, 1985). Various techniques using satellite imagery have been developed for detecting forest change. Examples of forest change include wildfire damage, insect attack, deforestation and seasonal changes in vegetation.

Howarth and Wickware (1981), Landgrebe (1981) and Swain (1985) noted that change detection methods can be categorized into two groups. The first is the 'stacked vector approach' where multiple data sets of different dates are overlaid and then analysed. The second group is 'post-classification updating', where a scene from one date is classified and then compared with a classified scene from a second date. Both techniques require the images collected on multiple dates to be geometrically registered.

The disadvantage with the stacked vector approach is the large number of features or spectral channels that can be generated in a multiple date comparison. As the number of features increases, mapping accuracy will eventually begin to fall as the training areas do not supply an adequate number of samples (Swain, 1985). This effect was noted by Kalensky and Scherk (1975), who found classification accuracies were consistently higher for single date compared with multi-date imagery. Principal components analyses have been used to reduce the number of features prior to change detection classification (Lapietra and Megier, 1976; Lichtenegger, 1981; Richards and Milne, 1984; Milne, 1986).

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1Principal components analysis is a transformation of the original Landsat data which generates a new set of 'spectral bands' called principal components. Using two date Landsat imagery (i.e. eight bands
A number of variations on the stacked vector approach have been suggested. A simple normalized ratio of Landsat bands 7 and 5, reduces topographic and seasonal deviations such as shadowing and changing seasonal illumination, thus permitting changes between dates to be emphasized. Holben and Justice (1981) found that ratios of spectral bands reduced the topographic effect by more than 83 per cent, though for this method to be successful, the variation in band 5 needs to be large. Justice et al. (1981) used a non-Lambertian model\(^1\) to successfully reduce the adverse effect of shadowing in Landsat data, and hence improved forest classification. Howarth and Wickware (1981) suggested dividing the reflected energy recorded in one band for the pixels of one scene by the intensities in the same band for the other scene. Howarth and Wickware (1981) then assigned the band 5 ratio to the red gun of a colour monitor and the band 7 ratio to the green gun. Areas of change were associated with red colouration on the image.

Another method for analysing stacked data involves calculating the difference in brightness of a channel on two dates; in other words channel 7 from a Landsat MSS image collected on date 1 is subtracted from the channel 7 image collected on date 2 (Williams and Stauffer, 1979; Olsson, 1984). If the difference is greater than a prespecified threshold then the area is considered to have changed. Lichtenegger (1981) calculated the principal components of images collected over an agricultural area at three dates. The first principal component of each date was used to construct a colour composite that indicated change. Frank (1984) took two Landsat MSS scenes from two dates, and regressed the band ratios. Areas with a greater than expected change in reflectance had increased vegetation from summer thunderstorms. Colwell and Weber (1981) described a change detection methodology they termed change vector analysis (CVA). CVA uses the Kauth-Thomas transform (Kauth and Thomas, 1976) to locate a pixel at two dates in the greenness and brightness space. The Euclidean distance between the two dates is used to calculate the magnitude of change, and the angle between the two dates is used to calculate the angle of change.

The post-classification updating technique involves classifying an area independently on two dates, and then locating areas of change by subtraction. For the post-classification updating technique and the stacked vector approach to be successful, radiometric errors need to be removed.

As discussed above, ratios of channels have been frequently used to reduce the seasonal, topographic and atmospheric attenuation effects present in remotely sensed data. In addition, Forster (1984) proposed methods of reducing atmospheric attenuation in remotely sensed imagery. With the reduction of atmospheric attenuation, Forster (1985) suggested that change detection is simplified over urban (and other) cover types, as aberrant results caused by atmospheric attenuation are less likely to occur.

\(^1\)A non-Lambertian model does not assume that the reflectance from a point spreads equally in all directions.
3.4.2. Mapping fire damage

Fire boundaries have been delineated, and the intensity of fires within the boundaries have been mapped into broad categories. Zsilinsky (1973) noted recently burnt areas and plumes of smoke on early ERTS-1 imagery over Canada. Heath (1974) noticed that burnt areas on ERTS-1 imagery appeared like 'a black smudge on an otherwise red colouration', and used this observation to successfully interpret the perimeter of a small (40 ha) light ground fire in the U.S.A. using a Landsat colour composite image. Tanaka and Kimura (1983) superimposed a classified Landsat image of a burnt island near Japan onto a topographic map and obtained a high correlation between the total area burnt estimated by visual interpretation of the Landsat imagery and that estimated from aerial photographs. Mapping accuracy was not calculated. Sayn-Wittgenstein and Wightman (1975) used individual black and white images of Landsat bands 5 and 7 to monitor smoke plumes and to delineate burnt areas in Canada. These techniques are used operationally in the more remote areas to assess fire damage at a fraction of the cost of conventional methods.

Benson and Briggs (1979) used unsupervised classification to map three intensities of wildfire in Victoria. They found that the possible range of overall mapping accuracy (including positional accuracy) was 45-56 per cent at the 95 per cent confidence interval. After the Warburton fire, Smith and Woodgate (1985) used a Landsat colour composite print (1:250 000 scale) to visually locate the most severely burnt mountain ash and mixed eucalypt species forests carrying sawlog sized trees.

Churchill et al. (1982) reported on experiments using a thermal infrared scanner which yielded information on the effect of rainfall events on canopy-soil temperatures for grassland and Pinus radiata plantations near Adelaide. From these data, evapotranspiration models were constructed and used to map evapotranspiration over the study area. Thus, digital image processing of high resolution satellite imagery may have real potential for mapping fuel moisture content.

Richards and Milne (1984) successfully used a principal components transformation of two Landsat images before and after a wildfire (i.e 8 bands in all) to examine changes in the Kuringai Chase National Park, Sydney. Milne (1986) discussed other analysis techniques for detecting change in land cover caused by bushfires. He stated that Landsat imagery is most useful for post-fire analysis in remote areas. Such imagery can indicate the point of ignition and the direction and movement of the fire, and can be used to establish a fire severity index. He reported that bushfires, depending on their severity, remove varying amounts of green and brown biomass from the forest. 'Greenness' and 'brownness' of the vegetation are correlated with Landsat bands 5 and 7 respectively. Thus, ratios of bands 5 and 7 indicate the proportion of brown and green components in the forest, and can be used as a measure of fire severity. Hathout (1980) used a simple density slice (see 3.2.6) to identify burnt areas on Landsat MSS imagery.

Imagery from airborne infrared multispectral scanners have been used by Forest Services in Australia during fire fighting operations to allow penetration of dense smoke, to define fire boundaries and hot spots, and to locate uncontrolled fire fronts (Green et al., 1984; Smith and Woodgate, 1985; R. Squires1, pers. comm.). Green et al. (1984) discussed the development of this technology in Australia for

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1Squires, R., Forestry Commission of N.S.W., Box 2667, G.P.O., Sydney, N.S.W. 2000, Australia.
a bushfire research program undertaken by the C.S.I.R.O. called Project Aquarius. The imagery obtained during Project Aquarius showed that fire behaviour models under extreme fire conditions underestimate the rate of spread by up to 10 times.

Potter (1984) developed a successful and novel method for monitoring atmospheric aerosol levels which he suggested could also be used to monitor smoke plumes. However, aerosols and smoke particles have quite different atmospheric attenuation effects, so his suggestion may not necessarily apply.

Isaacson et al. (1981) obtained Landsat imagery of an area prior to it being damaged by wildfire. This information was combined with high altitude infrared and conventional monochrome aerial photographs at scales of 1:130,000 and 1:32,000 respectively to map the distribution, abundance and condition of various indicator species before the burn. From this information, a plan for rehabilitation of the damaged area was produced and implemented.

Kourtz and Scott (1978) mapped new clearcut areas, deciduous and coniferous forests and small lakes by visual interpretation of a highly magnified Landsat band 5 image. This information was used by forest managers to help estimate forest fuel type and the location of water bodies in remote areas so that an appropriate fire suppression strategy could be organized. They also used unsupervised classification to map water, coniferous and deciduous forest, clearcut areas and major forest roads using Landsat imagery. These maps are used operationally for dispatching initial attack fire crews to fires, and are claimed to 'have paid for themselves many times' (Kourtz and Scott, 1978). No mapping accuracies were given for these maps.

Klock et al. (1984) mapped four classes of crown closure for conifers to 90 per cent accuracy and species distribution to 80 per cent accuracy, with 80 per cent confidence intervals. It was intended that this information be used in Washington State, U.S.A. to predict rates of spread of fires by compiling a fire pre-attack plan.

NOAA AVHRR data has been used to map and monitor wildfires. The coarser spatial resolution of the AVHRR data compared with the Landsat MSS data is offset by the twice daily repeat coverage, low cost, synoptic view and thermal infrared channel. Matson et al. (1984) showed that the thermal infrared channel may be used as an efficient and economical method for detecting and monitoring range, forest and tundra fires. The intensity of fire activity may also be estimated using the thermal infrared channel (Malingreau, 1984). Nelson et al. (1987) used this channel to count fires with a temperature greater than 310° K in the Brazilian Amazon. Malingreau et al. (1985) mapped smoke plumes over Borneo using AVHRR data, and then located the individual fires using the thermal infrared channel.

3.4.3. Mapping insect damage

The potential advantage of satellite imagery for monitoring insect attack is in repetitive coverage which permits change to be detected over a matter of weeks, or seasons.

Using Landsat imagery to assess insect damage to forests has had mixed success. Heath (1974), in the U.S.A., found damage to spruce by the spruce budworm too localized to register on Landsat imagery. Heath (1974) also noted that his research team failed to visually identify an outbreak of tussock
moth disease in the southern U.S.A. Damage to coniferous forests in the U.S.A. was visible if
defoliation was heavy and contrast with surrounding vegetation was high (Harris et al., 1977). However,
Harris et al. (1977) concluded that in most cases detection was not sufficiently accurate to be useful. In
Canada, Sayn-Wittgenstein and Wightman (1975) found it difficult to delineate spruce budworm attacks,
as the hardwood regrowth appearing under the dying pine resulted in a spectral response which was
confused with the spectral response of the mixed spruce/hardwood cover type.

Defoliation of deciduous forests in north-eastern U.S.A. by the gypsy moth caterpillar has been
mapped successfully to at least two levels of severity from Landsat data (Dottavio and Williams, 1983).
However, accuracy statements did not include positional accuracy or confidence limits. Williams and
Stauffer (1979) subtracted 'before' and 'after' Landsat images of defoliated oaks in Pennsylvania, and then
created colour composites of these 'difference' images. Williams and Stauffer (1979) also created a
forest/nonforest image (with a supervised classifier) and used this as a mask to eliminate all nonforest
cells from the 'difference images'. Landsat data have been used in Pennsylvania for statewide mapping of
defoliation by the gypsy moth caterpillar (Turner and Baumer, 1982). Williams et al. (1985) created a
Pennsylvania wide database for tracking the spread of gypsy moth infestations. A forest/nonforest map
was created by density slicing, and overlaid onto a Landsat image collected at a time of peak insect
defoliation. A ratio of Landsat MSS band 7 to Landsat MSS band 5 was used to map defoliation; low
ratio values indicated heavy defoliation, while high ratio values indicated healthy forests. In Idaho,
Brockhaus et al. (1985) used Landsat MSS data to map three damage classes in Lodgepole pine, caused by
the Lodgepole pine beetle. A supervised euclidean distance classifier yielded an overall mapping accuracy
of 76 per cent, from a sample of 29 plots.

Nelson et al. (1984) mapped three levels of spruce budworm infestation in Maine, obtaining
mapping accuracies of between 52.0 and 77.6 per cent. Lillesand et al. (1985) and Hopkins et al. (1988)
identified three jack pine budworm defoliation classes in Wisconsin with a 96, 98 and 79 per cent
accuracy respectively, using a supervised maximum likelihood classification algorithm to analyse Landsat
TM data.

Spruce budworm defoliation was mapped in New Brunswick, Canada, using an airborne electro-
optical pushbroom scanner (called a multi-detector electro-optical imaging scanner with the acronym
MEIS) (Ahern et al., 1985). Spruce budworm showed up as a brown discolouration on a green
background. In another study in British Columbia, the pushbroom scanner imagery was collected at two
resolutions (viz. 1.4 and 3.4 m) and compared with 230 mm normal colour aerial photographs (Kneppeck
and Ahern, 1989). The 1.4 m pushbroom scanner imagery was used to correctly detect the most number
of trees recently infected with mountain pine beetle. The success was attributed to the pixel size of 1.4 m
being smaller than the sunlit portion of tree crowns, allowing the infected trees to be easily detected.
Beaubien and Laframboise (1985) found a colour composite of the principal components of SPOT
multispectral (XS) simulated data gave the best discrimination of spruce budworm damage in Quebec,
compared with Landsat TM or SPOT panchromatic data.
In Australia, defoliation by insect attack (e.g. looper caterpillar) in *Pinus radiata* plantations has occurred but has not been heavy. Studies to assess the effectiveness of Landsat imagery for mapping insect attack have not yet been undertaken.

### 3.4.4. Mapping seasonal changes from remotely sensed data

Tucker *et al.* (1984) used NOAA-6 and NOAA-7 data to monitor vegetation change in the Nile Delta, Egypt. They found that the amount of green vegetation under irrigation increased in the delta as the summer progressed. The twice daily overpass of this satellite compensated somewhat for the poor spatial resolution of the data (1.1 km), by increasing the probability of obtaining cloud free scenes, as well as offering the possibility of early warning monitoring for drought and the prediction of seasonal vegetation dynamics at regional, or global, scales (Justice *et al.*, 1985; Tucker *et al.*, 1985).

McGuiness and Tarpley (1985) found that the ratio of the visible and infra-red bands from the NOAA satellites could be used to map changes in vegetation patterns quickly and routinely. Analysis of an area around Lake Chad in Africa clearly indicated changing native vegetation species in response to fluctuations in precipitation. Malingreau *et al.* (1985) monitored drought in Borneo using AVHRR ratio images. Seasonal variation of arid areas in Asia, as well as tropical forests in Borneo were successfully mapped by Malingreau (1986) with the normalized difference vegetation index (see 3.3.2) calculated for AVHRR data.

Olsson (1984) studied the change in growth of the Sahelian grasslands in Africa during the wet and dry seasons. He detected change by subtracting Landsat MSS channel 7 from two dates, as well as performing a parallelepiped classification of the two date Landsat MSS data.

### 3.4.5. Monitoring deforestation using remotely sensed data

Myers (1980) and N. Myers (1984) summarized the causes of, and environmental problems resulting from tropical deforestation, and emphasized the need to monitor the rate of deforestation and the occurrence of endangered species so that remedial action may be taken. Lanly (1983) and Grainger (1984) summarized a number of reports which estimated tropical deforestation rates by using, amongst other techniques, remotely sensed imagery. Park *et al.* (1983) and Grainger (1984) examined methods of monitoring global deforestation, and emphasized that remotely sensed imagery would be one of the main inputs. However, a problem using visible and near infrared remotely sensed data for these purposes (as Grainger [1984] points out) is the difficulty of obtaining cloud-free images. For example, 46 per cent of Landsat scenes collected during 1977-78 had more than 50 per cent cloud cover, and this percentage would undoubtedly be higher for tropical scenes (Landsat Data Users Notes, 1986). An alternative to visible and near infrared remotely sensed data is radar (microwave) imagery. The advantages of radar are that it penetrates cloud, the data can be collected at any time of day or night, and that radar sensors are to be included on most of the satellites to be launched later this decade.

Another exciting development is the proposed inclusion of a forward looking cloud detector on a satellite orbiting the equator (TERS) proposed by the Dutch and Indonesians (Konijnenburg and Irsyam,
1984). If the area required to be imaged is sensed to be cloud free, then an image is collected. As the satellite will be on an equatorial orbit, four overpasses per day would be possible.

Other work undertaken in the tropics to monitor deforestation rates included that by Lorenzo et al. (1979) who used a simple method of supervised classification on two Landsat scenes in the Philippines. The change in total area of mangrove forest between the two dates allowed an estimation of deforestation rates. Roy et al. (1985) used a supervised classification technique to map areas of shifting cultivation in India with an accuracy of 95 per cent, but no locational accuracy or confidence limits were given and the number of ground truth sample checks was small. Miller and Williams (1979) undertook a supervised classification of Landsat MSS imagery in Nigeria and found reserved tropical forests were being exploited. Miller et al. (1979) mapped the rate of slash and burn agriculture in the northern Thailand 'Golden Triangle' by finding the difference in Landsat MSS channel 7 reflectance between two dates. Ahmad (1986) concluded that due to lack of computing facilities and expertise, developing countries have largely used visual interpretation of Landsat imagery instead of computer aided analysis. However many developing countries have established and effectively utilized computing facilities for forestry applications (Umali, 1987). This trend will continue as computer equipment and image analysis software become cheaper and more available (see 3.6).

Tucker et al. (1984) used AVHRR data to monitor the rate of tropical clearing in Brazil, and concluded that previous estimates were too low. Nelson et al. (1987) used NOAA AVHRR imagery as the first stage in a multistage sample to estimate the rate of forest clearing in Brazil. The AVHRR imagery was used to identify fire activity (as reported in 3.4.2). Those images with a high fire activity were used to select Landsat MSS scenes, for which clearing rates were estimated. The rate of clearing was then applied to all the AVHRR imagery to estimate the total rate of forest clearing.

In temperate regions, remotely sensed data has been used extensively to map forest logging activities. Zsilinsky (1973), Lee (1974) and Oswald (1974) mapped and monitored clearcutting operations in Canada from visual interpretation of Landsat MSS imagery. Colwell and Weber (1981) compared two methods for detecting change (both deforestation and reforestation) in temperate forest cover in South Carolina. The first involved classifying Landsat scenes from two dates and comparing them to highlight where change had occurred. The second was the 'change vector analysis' technique described in 3.4.1. They concluded that the two methods indicated very different amounts of change, with the first method overestimating change by a factor of approximately 6.

In Canada, Kourtz and Scott (1978) used an unsupervised classification of summer and (snow-covered) winter images to detect windblown forest stands and clear cut areas in Canada. However, mapping accuracies were not calculated. Hafker and Philipson (1982) also successfully detected 74 per cent of clearcuts on winter Landsat images using bands 5 and 7. The best spectral discrimination occurred as a result of a ground snow cover in combination with leafless deciduous trees.
3.4.6. Monitoring forest die-back and pollution stress

Rock et al. (1986) and Vogelmann and Rock (1986) found ratios of Landsat TM bands ([band 6 + band 5] and [band 6 + band 4]) correlated well with dieback in high altitude spruce-fir forests, and also reduced variation caused by shadow and biomass quantity. Vogelmann and Rock (1988) found a ratio of Landsat TM channel 5 to Landsat TM channel 4 was strongly correlated with conifer forest damage in northeastern U.S.A. \((r^2 = 0.92)\). Defeo et al. (1987) reported a high visual correlation between TM ratio (band 5 + band 4) and spruce-fir dieback, though no quantitative check was made. Defeo et al. (1987) also reported a distinct regional pattern in northeast U.S.A., with heavy damage over Pennsylvania and New Jersey, decreasing into New England. Murtha (1973) visually delineated four damage classes in forests caused by sulphur dioxide emanating from a factory in Ontario. The downwind pattern of dieback from the point source gave a distinctive pattern compared to areas that had been clear cut, burnt or occurred over frozen lakes.

Heavy metals deposited by pollution have been shown to affect reflectivity. Sabins (1978) showed that increased copper and molybdenum lead to higher near infrared reflectance in balsam fir, and decreased reflectance in red spruce. Horler et al. (1983) found trace metal stress caused shifts in the position and slope of the red edge\(^1\). Collins et al. (1983) found the red edge shifted towards shorter wavelengths for various types of vegetation growing on soils with higher concentrations of zinc, lead, and copper. Rock et al. (1986) found that near infrared reflectance was reduced in plants growing on soils with increased levels of trace metals.

In Australia, pollution induced stress in forests has not been identified as a problem. There is noticeable dieback of large trees retained on agricultural land in some regions, possibly caused by a combination of factors including insect attack, stock compacting the soil, over fertilization, drought and fungal attack. As yet there are no studies using remotely sensed imagery to monitor this problem. Myers et al. (1984) studied die-back in southern Tasmanian 'tall wet forest' regrowth which is possibly attributable to drought and *Amillaria spp.* root rot. They noticed a slow decline affecting understorey rather than the overstorey, and stated that the dieback could be accurately assessed by aerial photograph interpretation. There was a significant difference between the mapping accuracy of individual interpreters.

3.5. Collateral data

Perhaps the most useful development in the assessment of natural resources, is the inclusion of data, other than remotely sensed data. Such data has been called 'ancillary', 'auxiliary' or 'collateral' by the remote sensing community. The difference between image processing (of remotely sensed data) and geographic information systems (discussed in 3.8) becomes blurred when remotely sensed and other geographically registered data are merged. Geographically referenced information, such as digital elevation data, ownership boundaries etc., may be registered to a common projection in a GIS data structure, and analysed using algorithms originally designed for image processing or GIS data. Analyses of non-

\(^1\)See 3.2.1 for details about the red edge.
remotely sensed data are considered in 3.8. Examples of remotely sensed data being used in combination with other spatial data are also considered in 3.8.

3.6. Use of remotely sensed imagery in Australian forestry

The Department of Conservation, Forests and Lands (formerly Forests Commission) of Victoria has been using Landsat imagery since 1973 when it undertook a program of evaluation in its role as official investigator reporting to N.A.S.A. (Smith, 1973). Following these exploratory studies, the Department now uses Landsat imagery for vegetation mapping, estimating rates of forest clearing (Woodgate and Black, 1988), and forest fire mapping and evaluation. In the semi-arid lands of northwestern Victoria the imagery is used in mapping the final boundaries of both wild fires and protective burns. This information provides an accurate record of fire history (which will be important in future ecological studies in this region) and a valuable basis for planning future fire protection and suppression. A 'microBrian' image processing system is installed with the Department of Conservation, Forests and Lands.

Landsat is also being used in several other regions of Victoria to map the pattern of spread of major fires as part of continuing studies of fire behaviour. Although the resolution of Landsat MSS imagery is coarse, the imagery has been used in the preparation of a vegetation map for Victoria showing forest, woodland, shrubland and grassland categories (Paine, 1982). Landsat imagery has also been used in preparing a forest type map at a scale of 1:1 000 000 (R.B. Smith, pers. comm.1). The Country Fire Authority in Victoria is developing techniques to gauge fire hazard from grass fuel build-up using satellite imagery (J.R. Barber, pers. comm.2). The Department of Conservation, Forests and Lands routinely maps recent fire scars in the mallee region of western Victoria using Landsat MSS prints (Woodgate, pers. comm.3).

The Forestry Commission of N.S.W. are currently evaluating image processing and GIS hardware and software. Various other N.S.W. departments are using imagery, and the Department of Lands has installed a Dipix image analysis system. This system is now being upgraded, and tenders have been called. The Department of Agriculture, Western Lands Commission, and the Forestry Commission of N.S.W. are using Landsat imagery to monitor land clearing in western N.S.W. and to identify valuable cypress pine stands on leasehold land (R. Squires, pers. comm.4). The Murray Darling Vegetation Monitoring Project is another inter-Departmental project with which the Forestry Commission

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collaborates. A committee with representatives from government, academic and business organizations oversees the use of remote sensing in N.S.W. A newsletter is published by this committee.

The Queensland Department of Forestry had undertaken occasional pilot studies involving satellite imagery (Department of Forestry, Queensland, 1985), and subsequently installed a DISIMP image processing system. Preston (1987) used Landsat MSS imagery to operationally map three classes of cyclone damage using a maximum likelihood classifier, with an accuracy of 77 per cent. The Queensland Department of Forestry participates in the Northern Rainforest Management Agency (NORMA, 1988), which is responsible for on-going land use planning for the wet tropics of Queensland.

The Woods and Forests Department of South Australia used Landsat MSS data, collected five days after the wild fires of 16th February 1983, to assess the extent of fires and also fire intensities within the plantation areas. The Landsat imagery was compared with maps prepared by ground survey and the correlation was very satisfactory. Further studies are being carried out by the Department in a major program to develop a fire hazard/fire risk capability in the Adelaide Hills area where agriculture, horticulture, urban development, native woodland and forest, and pine plantations are intermixed. Currently, the Remote Sensing Applications Branch (RSAB) of the Department of Environment and Planning in South Australia is using Landsat imagery for monitoring the clearing of vegetation as required by the state Vegetation Retention Act. They have also been surveying and mapping the vegetation in National Parks using Landsat imagery and aerial photography combined with ground verification. The South Australian Centre for Remote Sensing has installed a McDonald-Dettwiler image processing system. The Woods and Forests Department has been following these projects with interest (Keeves, pers. comm.).

Satellite images at a scale of 1:250 000 are being used in Western Australia to delineate the vegetation types within which sandalwood (*Santalum spicatum*) is likely to occur in the eastern and northeastern goldfields region. This has eliminated a great deal of field work in this area of nearly 20 million ha. Images have also been used to indicate areas mined for bauxite, coal, tin and mineral sands; areas cleared for pine forests, transmission lines and agriculture; and areas burnt in forest fires. Satellite imagery has not proved useful for detecting die-back and leaf miner damage.

In Tasmania, the Forests Commission, Associated Forest Holdings, Australian Newsprint Mills, and Forest Resources combined to fund a research project at the University of Tasmania to explore the possibilities of using Landsat spectral data to undertake basic forest inventory work in the northeastern section of the State (Scottsdale District) viz. forest type classification, crown density estimation and monitoring changes in land use. This work was undertaken by Ahmad (1987) using Landsat MSS imagery, and five broad forest classes (viz. pine plantation, rainforest, mixed forest wet sclerophyll forest and dry sclerophyll forest) were mapped with an overall mapping accuracy of 86 per cent.

Following the success of this first study, private forestry organizations again combined to fund a new project with the aims of mapping and monitoring temporal changes in private forest areas for
Tasmania (1980 to 1987), to develop uniform vegetation mapping of the State, and to incorporate satellite data in multi-stage forest inventories (Warner, 1988). It is proposed to perform this work using Landsat MSS imagery on a DISIMP image processing system installed at the University of Tasmania.

Limited use is being made of Landsat imagery by the Forestry Unit of the Conservation Commission of the Northern Territory. Usage is confined to monitoring the occurrence of fires in the Murganella Management Area in northwest Arnhem Land and on Melville Island (G. Davis, pers. comm.). Each year, the Bush Fire Council Section of the Commission prepares a fire history to assess the suitability of Landsat for estimating fuel status and grass curing rates in the Territory. In a collaborative project with the CSIRO Division of Wildlife and Range Management at Alice Springs, the Commission is investigating the suitability of Landsat and other remote sensing imagery for assessing fuel loads and forecasting fire behaviour (Allan, 1984; G.E. Allan, pers. comm.). The Australian National Parks and Wildlife Service at Kakadu National Park conducts regular monitoring of fire occurrence in the park using Landsat. In addition, wildlife habitat has been mapped, and refuges planned using Landsat MSS data (see 3.3.4 for details).

Environmental authorities in the Australian Capital Territory (A.C.T.) (Forests and Conservation Sections of the A.C.T. Administration) see little need for satellite imagery as a management tool because the Territory is so small and it is covered regularly by high quality aerial photography. However, most authorities acknowledge that the monitoring capability of satellite imagery may be utilized in the future.

The forestry remote sensing community in Australia occasionally meets as the forestry committee on remote sensing (FORCORS), with Dr B.J. Turner being the convener. A FORCORS newsletter is periodically published by Dr Turner.

3.7. Remote sensing - its future in Australia

An important development has been the commercial implementation of image processing systems on microcomputers. C.S.I.R.O. have developed a 'PC'-compatible based version of their BRIAN (Barrier Reef Image ANalysis) system (Jupp et al., 1985), which is now available commercially through Microprocessor Applications Pty Ltd of Melbourne (Bell, 1986). This system was designed for charting ocean reefs and islands, though it has been used for land use studies. The Great Barrier Reef Marine Authority recently used the BRIAN system to map the whole reef for a cost of $250 000 (Bell, 1986). The authority estimated that the cost of surveying the reef using conventional methods would have been $21 million!

Researchers at Stanford University U.S.A. have transferred an automatic computer classification system (named REMSEARCH) from a PDP 11/34 minicomputer to an IBM-PC microcomputer. Digital
data image processing costs on the new IBM-PC are only six per cent of the costs involved with the PDP 11/34. However, the available classification algorithm (parallelepiped) is rather simple, leading to rather coarse results (Lyon and Lanz, 1984; Littman and Friedland, 1984).

Another microcomputer based image analysis system is ERDAS (Earth Resources Data Analysis System) developed in the U.S.A., which runs on IBM compatible microcomputers as well as Unix based workstations. This product is sophisticated and offers many of the features normally found on the expensive minicomputer based image analysis systems. Other microcomputer based image processing systems have since been commercially released, and details can be found in publications such as the American Society of Photogrammetry and Remote Sensing directory of mapping services (ASPRS, 1989). Interestingly, some packages are available at little or no cost, including GRASS\(^1\) (ASPRS, 1989), ORSER (Turner \textit{et al.}, 1982), and SPIRAL (Myers, 1986).

The Commonwealth Government of Australia is funding the upgrade of the Australian Landsat Station so it can process Landsat TM and SPOT data. Forestry in Australia should benefit from the upgrade in facilities as much more detailed data will be available. The tragic loss of the Space Shuttle on 28 January, 1986, also destroyed a Tracking and Data Relay Satellite System (TDRSS) satellite which would have acted as a communications satellite relaying TM data collected over Australia to the U.S.A. A temporary receiving facility was constructed by C.S.I.R.O. and AMIRA Pty Ltd for Landsat TM data, and this facility was used to collect the TM data used in this thesis. A TDRSS replacement was recently launched by the shuttle.

In the next 5 years, the launching by various countries of numerous satellites for earth resource analysis may provide useful information about Australian forest resources and allow many problems to be solved cheaply and efficiently. Encouraging results from the use of microwave (radar) and higher resolution scanners in the visible and infrared parts of the electromagnetic spectrum support this view.

3.8. Geographic information systems in forestry

3.8.1. Introduction

Geographic information systems (GISs) are being increasingly utilized by forestry organizations around the world (Price \textit{et al.}, 1987). An outline of GIS data structures (viz. raster and vector) and GIS analysis procedures are presented, and applications relevant to forestry are summarized. Expert systems are now used to extract information from GISs, and a literature review of this work is included in Chapter 8 and Chapter 9. The development of GISs for modelling forest soils is discussed in Chapter 9.

The material presented in this section is drawn from Marble \textit{et al.} (1984), Burrough (1986) and other cited references.

\(^1\)GRASS runs on Apple Macintosh microcomputers as well as Sun workstations.
3.8.2. Raster data structure

A raster data structure is a two-dimensional array of rectangular cells, and is the data structure used in image processing of remotely sensed data. A family of regular data structures called 'tessellations' exist. Tessellations may be triangular, hexagonal, rectangular or square (Figure 3-4).

![Square or rectangular tessellation](image)

![Triangular tessellation](image)

![Hexagonal or rosette tessellation](image)

Figure 3-4: Tessellated data structures

The raster data structure has been widely adopted for use with GISs, because of its compatibility with programming languages such as FORTRAN, as well as with computer hardware, and was used as the main GIS data structure in this thesis. The advantage of the square grid is that it can be recursively subdivided, allowing a finer resolution mesh to retain the same shape and orientation. The advantage of the hexagonal data structure is that all neighbouring cells of a given cell are equidistant from that cell’s centre. Irregular triangular tessellations have been used in digital terrain modelling (see Chapter 7). Tessellated models are suited to GIS analysis operations such as overlaying, because the spatial relationship between cells is retained as a result of the implicit topology\(^1\) of the data structure. Thus map overlaying, spatial analysis, simulation and modelling may be performed rapidly and cheaply.

The main disadvantage of regular tessellations is the potentially massive data storage they require. This is exacerbated over homogeneous areas, as each resolution element within the homogeneous area is assigned the same value. In other words, tessellated data structures are not very compact, and tend to store

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\(^1\) Topology is the branch of mathematics dealing with surfaces which are unaffected by deformations such as stretching and twisting. The spatial interrelationships between cells are "built-in".
redundant data values. A number of methods for compressing raster data have been proposed. These include Freeman chain codes (Freeman, 1974), run-length codes, block codes, quadtree and Fourier transforms. Unfortunately, analysis of some compressed tessellated data structures may be difficult without returning to the full grid representation. Another disadvantage with the raster data structure is that most of the well established commercially available GISs are vector based.

3.8.3. Vector data structure

The vector presentation of an object is an attempt to represent the object using nodes (points) and arcs (lines), so that it is represented as accurately as possible (see Figure 3-5 as an example of a vector representation of a forest compartment compared with a raster representation). The vector data structure can be used to store lines, points and arcs. In this thesis, vector data was obtained in point form, before being converted to a raster data structure for analysis (see Chapter 7).

![Diagram of vector and raster representations](image)

**Figure 3-5: A compartment map is compared with a vector and raster representation**

A number of vector data structures have been proposed and developed including spaghetti or simple polygon models, as well as models such as the GBF/DIME system (geographic base file/dual independent map encoding) and the POLYVRT model which contain implicit topological information (Peuquet, 1984; Burrough, 1986). The advantage of the topological models is that spatial relationships between objects are recorded, thus reducing computational expense during analysis. However, the cost of the additional topological information is increased data storage requirements. So the choice of data structure is a trade off between data storage and computational expense.

The advantage of vector data structures is that they are direct digital translations of cartographic line maps, and so are easily interpreted. The algorithms used to analyse this data also tend to be direct translations of traditional methods. Some aspects of vector data analysis, such as network analysis, are more efficiently executed using vector data structures compared with raster data structures (Lupien et al.,
Vector data structures and vector display methods yield the highest quality line drawing (even though the lines may be drawn in the wrong place!). The disadvantages with vector data are the computational expense of some algorithms such as overlaying, and the problem of spurious polygons created when two layers are overlaid and boundaries do not exactly match. The issue of error in geometrically rectified data layers is addressed further in Chapter 4.

In fact, the vector and raster data structures are logical duals, and algorithms have been developed to readily convert data between these two structures, albeit at a computational expense (Peuquet, 1981a; Peuquet, 1981b; Clarke, 1985). The Western Australian Department of Conservation and Land Management (CALM) decided to maintain data in both vector and raster format, to avoid the conversion expense (Pearce, 1988). However, the disadvantages of this strategy are a higher mass storage requirement, and problems with updating both data formats when a change is made. Hybrid models have been proposed which retain the advantages of the raster and vector data structures, while minimizing the disadvantages (Peuquet, 1983). However, working examples of these theoretical hybrid models have not been developed.

3.8.4. Attribute data

Attribute data is text information (for example owner, forest type, road name) which may be assigned to a cell in a raster data structure, or to a point, line or polygon in a vector data structure. A number of innovative methods have been devised to link attribute data to the spatial raster or vector data. Relational databases allow spatial or attribute data to be linked using a common primary key value (Codd, 1982). The relational database concept has been used by Dueker (1985) and Morehouse (1985) to relate attribute or text information to geographic (spatial) data.

3.8.5. Data modelling techniques

Two theoretical approaches for structuring and modelling GIS data have been proposed. One approach suggested by Bouillé (1978) has been termed 'phenomena-based'. This is an attempt to completely represent reality by recording all relevant geographically referenced information; as such it has been criticized as too complex by Mark (1978), causing a redundancy of information and excessive computational expense. In contrast, Mark (1978) suggested a 'minimalist' approach, where only the data and relationships, relevant for an application, are included in the GIS. However, the minimalist approach may be limiting if the GIS is to be used for purposes other than those for which it was originally developed. In practice, a 'middle ground' approach is usually taken, to maximize the benefits of the 'phenomena-based' and 'minimalist' approaches, while minimizing their disadvantages.

Hutchinson (1982) discussed the three possible situations for combining spectral data with other ancillary data viz. stratifying a remotely sensed image prior to classification; incorporating the ancillary data during the classification of the remotely sensed image; and post-classification, where a classified image is modified by the ancillary data, e.g. shadow reduction. The data modelling techniques now described may be categorized as belonging to one of these three data types.
Craig and Green (1984) overlaid topographic, geological, geochemical and remotely sensed data, and visually inspected and analysed the layers to extract regional geological information\(^1\). Remotely sensed data from different sensors, and at different resolutions, have been combined using the intensity, hue, and saturation (IHS) technique (Smith, 1978). For example, Lillesand (1987) and Essadiki (1987) and Turner et al. (1989) combined SPOT panchromatic data (10 m) with SPOT multispectral data (20 m), by considering the panchromatic band to be equivalent to the intensity component of the IHS transform.

Simply overlaying data planes (i.e. the two dimensional arrays) allows areas with a combination of features to be identified (Hart et al., 1985). For example, overlaying forest type with gradient allows areas of a particular forest type occurring on a gradient of, for example, 20° to be identified. Simple overlaying is equivalent to the Boolean ‘AND’ condition. Other Boolean operators including ‘OR’, ‘XOR’, and ‘AND NOT’ may be used to define overlay conditions. Arithmetic and mathematical operators may be used to model dependent, or higher-level, variables from a number of independent variable layers (Tomlin and Berry, 1979; Burrough, 1986). Such arithmetic and mathematical operators have been termed 'map algebra' by Tomlin and Berry (1979).

Strahler et al. (1978) mapped forests using remotely sensed and digital terrain data. They partitioned a Landsat scene into regions based on slope and aspect, and inferred the \textit{a priori} probabilities of forest types occurring in each region. The \textit{a priori} information for each region was then used to weight a Bayesian maximum likelihood classification of the remotely sensed data.

Richards et al. (1982) used supervised relaxation modelling to incorporate digital elevation data, and spatial context information into a remotely sensed image classified by the maximum likelihood classifier. This post-classification modification of a classified image involved two steps. The first step was termed 'probabilistic label relaxation', and exploits the fact that certain cover types are more likely to occur together over adjacent pixels in remotely sensed image data (Kettig, 1975). The user defines \textit{a priori} conditional probabilities that express the likelihood that pixel \(i\) (that is the pixel being updated by the relaxation method) is labeled as class \(\lambda\) given that adjacent pixel \(j\) is labeled as class \(\lambda'\) (i.e. \(P(\lambda|\lambda')\)). These \textit{a priori} conditional probabilities are used to describe the support from the neighbouring pixels for the labeling of pixel \(i\) as \(\lambda\). (Note that the pixels had already been classified by the supervised maximum likelihood classifier.) For example it may be known that the probability of adjacent pixels being wheat and pasture is very high, while the probability of neighbouring pixels being labeled wheat and urban is low. The second step in the supervised relaxation modelling technique is 'supervised relaxation labeling', and is similar to the method proposed by Strahler et al. (1978). This step assumes ancillary data is available which provides additional information with which to discriminate the cover classes classified by the supervised maximum likelihood classifier. Prior probabilities are generated to describe the relative likelihood of each of the pieces of ancillary data being the correct one for the pixel label. For example, it is highly likely that if the pixel is classified as a spruce-fir forest, then the elevation is around 3200 m. The \textit{a priori} probability would be set high (e.g. \(p = 0.95\)) for a pixel classified as spruce-fir forest and

\[^1\text{Using the above definitions proposed by Hutchinson (1982), this application would be classified as the (manual) incorporation of the ancillary data during the classification of the remotely sensed image.}\]
ancillary data showing elevation is 3500 m. Thus, if the currently favoured label on the pixel is strongly supported by the ancillary data, then the probability that the pixel is correctly classified is increased. Conversely, if the currently favoured class label is not strongly supported by the ancillary data then its probability is weakened.

3.8.6. GIS applications

3.8.6.1. Forest mapping

One of the earliest examples of remotely sensed imagery being used in combination with ancillary data was a study by Westby et al. (1968), where a radar altimeter was combined with aerial photographs to give higher accuracy ground measurements over forests.

Forested areas often occur over rugged terrain. In winter especially, shadowing effects are accentuated by the mid-morning overflight time (i.e. approximately 9:30 am) of the Landsat satellite. Shadowing is therefore a contributing factor to the relatively low forest mapping accuracies reported over rugged terrain. Inclusion of topographic information (elevation, aspect, slope) allows shadowing effects to be reduced, as well as providing additional information that may assist in discriminating between forest species. Hoffer and staff (1975) included elevation data with three selected Skylab-2 spectral bands, and input the resulting four band data set directly into a maximum likelihood classifier. Mapping accuracies were improved by 23 and 32 per cent for a deciduous and a coniferous class respectively. In southern France, Flouzet (1978) demonstrated that fir forest types vary consistently as slope, aspect and altitude change, and suggested that such a priori information could be used to aid classification of Landsat imagery.

Ancillary data may be used to stratify remotely sensed data before or after image analysis, in order to reduce confusion. For example, Fleming and Hoffer (1979) stratified Landsat MSS data using elevation, gradient and aspect prior to classifying forests. They improved overall mapping accuracies by 15 per cent. Hart et al. (1985) classified a Landsat scene and then post-stratified the image using terrain data (see 3.8.6.3 for details).

Strahler et al. (1978) combined remotely sensed imagery and topographic information using a priori probabilities as described above in 3.8.5. Overall classification accuracy for twelve forest types in south western Colorado, U.S.A. improved from 58 to 85 per cent when elevation and aspect were introduced. Strahler et al. (1980) developed a forest classification and inventory system (FOCIS) in a study of Californian forests. Unsupervised clustering was used to create a large number of potential classes, which were then grouped on the basis of their spectral similarity to other classes. This smaller number of classes (usually about 70) was viewed on an interactive screen by an operator, and adjacent classes were manually merged if aerial photographs indicated the forest had trees of similar size and spacing. Timber volume was estimated for the merged classes by sampling ground plots. Species typing was performed by using ecological relationships between topographic data (i.e. slope, aspect, elevation) and species occurrence. The proportions of species which occurred at a pixel was predicted from the pixel's
slope, aspect and elevation using trend surface analysis. Levitan and Bowlin (1986) described the operational use of the FOCIS system in California.

Tom and Miller (1980) combined elevation, gradient, aspect, photointerpreted vegetation cover, Landsat multispectral scanner (MSS) data and Landsat ratio bands, using a nonparametric linear discriminant function (described in Duda and Hart, 1973). They claimed a forest mapping accuracy of 97.3 per cent, but this figure may be inflated as the training area pixels (or picture elements) were also used to test mapping accuracy (see Mead and Szajgin, 1982) and only 37 pixels were tested for accuracy over 9 classes (approximately 4 samples per class) which would lead to a wide confidence interval around the mapping accuracy estimate (Hay, 1979). Using a virtually identical linear discriminant function procedure, Fox et al. (1985) obtained an overall mapping accuracy of 78.5 per cent when discriminating between two forest site quality classes and non-forest. Richards et al. (1982) used supervised relaxation labeling (see 3.8.5) to combine topographic information, spatial context data and a supervised classification of forests (into spruce-fir and other forest categories), and improved overall mapping accuracy from 68 to 81 per cent. Vanclay (1988) used an ad hoc linear regression equation to model growth indices for Queensland rainforests from parent material and Landsat TM data ratios. The most successful regression modeled 56 per cent of the total variance.

Cibula and Nyquist (1987) combined topographic, climatological and Landsat MSS data using simple Boolean operators to link the data layers, and distinguished vegetation and land cover classes with a 92 per cent accuracy. As noted for Tom and Miller (1980), many of the classes had a small number of pixels tested for mapping accuracy, so confidence intervals would be large.

Sugarbaker et al. (1980), cited by Klock et al. (1984), increased mapping accuracies of forest species and forest density by 29-52 per cent when digital topographic data were combined with MSS data to identify ecological sites in eastern Washington. Gum (1985) reported a supervised classification of Landsat MSS imagery for inventory of forest vegetation for fire pre-attack planning. Mapping accuracies of greater than 80 per cent with the confidence interval at 85 per cent were obtained. Once the type maps were generated, ecological information on the location of particular species was used to manually blank out cover types which occurred in the wrong ecological site. Such techniques can be performed automatically by a computer if digital terrain data are available for the site being mapped.

A number of studies have shown the utility of combining radar data with remotely sensed data collected in the visible and microwave portions of the electromagnetic spectrum. Yao and Gilbert (1984) describe the method of combining SAR imagery with Landsat TM data, and report geometric errors of less than one pixel (30 m). Welch and Ehlers (1988) coregistered Landsat TM data and SIR-B SAR at an accuracy of ± 20 m. Skidmore et al. (1986) combined SIR-B SAR radar data with Landsat MSS data and improved the mapping accuracy of six forest type classes (including three site quality classes) in the river red gum forests of New South Wales and Victoria by 10 to 15 per cent. The SIR-B and MSS data were treated as a five channel data set, and analysed using a supervised maximum likelihood classifier. Rebeillard and Nguyen (1982) increased the mapping accuracy of six cover classes in the northern Algerian Sahara when SIR-A SAR was included with Landsat MSS data, and analysed as a five channel
data set. Over agricultural crops, Rosenthal and Blanchard (1984) and Ulaby et al. (1982) found the addition of radar to Landsat MSS data improved overall mapping accuracies by 19 and 10 per cent respectively.

Soil information was used in combination with Landsat MSS data by Ernst and Hoffer (1979) to differentiate swamp hardwood and wetland from upland hardwood. A decision tree classifier was used; the first decision was whether soil was an upland or bottomland type (viz. swamp hardwood and wetland), and then the wetland types were mapped using the spectral information only. Overall classification accuracy improved from 71.7 to 84.3 per cent. Clerke et al. (1983) combined Landsat data with U.S.D.A. Soil Conservation data to predict the location and area of eight forest classes differentiated by site productivity in South Carolina. A GIS was developed in Senegal by Cisse et al. (1984) for estimating crop production and potential crop production per capita in administration areas. In this case layers included soils, land use (developed from Landsat), forest and pasture reserves and administration boundaries. The layers were analysed using simple overlaying.

Smith and Blackwell (1980) developed a GIS to monitor the effect of logging and clearing of forests for residential sites on water quality in Lake Tahoe. Sixty five drainage basins which form the catchment area for Lake Tahoe were digitized, and geometrically registered with a digital elevation model and three Landsat scenes of different dates. By analysing change in forest cover, the researchers hoped to identify nonpoint pollution sources.

Heller (1981) discussed the applicability of modelling the risk of insect attack using Landsat and ancillary data (such as elevation, aspect, gradient, topographic position, tree density, crown diameter, forest stand area, and species). High risk forests may be identified by modelling the relationships between susceptibility to insect attack and these data layers. Appropriate silvicultural techniques may then be applied to susceptible forest stands.

Some GISs have been constructed without the use of remotely sensed data. Maps were used by Myers and Kolenik (1984) to create data layers of cadastra, roads and trails, forest management areas, contours and forest types over the Pennsylvania State University Experimental Forest. This information is available for applied forest research projects. One use was as ground truth information for assessing the accuracy of forest type maps derived from remotely sensed data (Skidmore, 1987). Hoschke (1976) and Hoschke and Squire (1978) described the forest inventory system (FORINS) which was a systematic sample over the entire State of New South Wales at various scales. Systematic sampling plots were spaced at distances of 2743.2 m (eastern zone), 5486.4 m (middle zone) and 10972.8 m (western zone). Many environmental parameters were recorded for each point, and the database was used to solve a number of timber volume and allocation problems. There are obviously difficulties with the coarseness of the data collected in the FORINS system, as environmental conditions (such as forest type) would not remain constant between the widely spaced points. Maniere et al. (1984) developed a GIS for the Mercantour national park in France that assisted general planning and modelling. Layers included elevation, slope, vegetation, exposure, geomorphology and avalanche potential. Martin (1985) entered land ownership boundaries, roads and trails, a digital terrain model, photogrammetric control points and photointerpreted
forest stand boundaries into a GIS. Field plots were sampled, and timber volumes estimated for each forest stand type. Examining slope and stand type maps identified areas where skyline timber harvesting systems were required. The system was also used for forest road design. Johnston (1987) used simple overlaying, Boolean and arithmetic operators to produce a land use map for an area of unlogged (predominantly) conifer forest in New Brunswick. Six mathematical models were used to calculate visual quality, landscape ecology, potential natural vegetation, fire management, wind management and production of economics, from GIS layers that included topography, soils, glacial deposits, vegetation, windthrow affected areas, spruce-budworm affected areas, forest crown closure, forest development stage, deeryards, roads and water. The model outputs were ranked in importance by area. For example, a manager may wish to have 65 per cent of the forest retained for visual quality purposes, and 35 per cent for landscape ecology. The highest weighted cells for visual quality would then be selected over 65 per cent of the area.

3.8.6.2. Fire hazard mapping

Salazar (1982) used Landsat data and high altitude aerial photography to produce a GIS containing fire pre-attack information on fuel types, road systems and water resources. Fuel models combined with environmental variables provide the information necessary to determine rates of spread, fire line intensity and flame length. Salazar (1982) claimed such pre-attack plans are moderately reliable and easily updated. Petersen et al. (1983) reported on studies that combined cover classes derived from unsupervised classification of Landsat imagery with slope information, proximity to urban areas, and proximity to areas with a high incidence of fire ignitions. This data was used to calculate a fire danger rating for forested areas. The ratings were based on fuel loads and slope. The risk of fire was calculated from the proximity of fire fuel to urban areas, as well as the proximity to areas with a history of fire ignitions. Such risk modelling assumes that historical conditions will be indicators of future fires.

Miller et al. (1986) geometrically registered AVHRR data with political boundaries, roads, major water bodies, elevation, slope and aspect onto one km UTM grid, in order to predict fuel loads within political areas in northwestern U.S.A. The normalized vegetation index (NVI) (see 3.3.2) for the AVHRR data was calculated to estimate vegetation greenness. The NVI was calculated for four dates and merged with the visible and near infrared band from one date to form a six layer raster database. The principal components for this six channel data set were calculated. From the principal components, eleven fuel types were mapped with an overall accuracy of 92 per cent using a modified clustering approach. Miller et al. (1986) also monitored fuel build up rates over nine dates during 1982 and 1983. This fuel load information supported an initial attack management system (IAMS). Lightning strikes and weather conditions were automatically recorded in remote locations, and transmitted to a central computer facility. Here, the fuel load information was analysed in near real-time to compute the probability of fire ignition and spread.

The fire fuel maps generated using the methodology described above by Miller et al. (1986) were compared with fuel maps visually interpreted from 1:250 000 Landsat colour composites, by Miller and

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1The procedures followed in calculating fuel load rates were also discussed by McKinlay et al. (1985).
Johnston (1985). The overall mapping accuracy of the NOAA AVHRR derived fuel maps was 87 per cent, while the visually interpreted fuel map accuracy was 92 per cent. However, the AVHRR analysis cost one fifth of the Landsat MSS analysis. Computer analysis of Landsat MSS imagery using the same technique employed for the AVHRR data, would probably improve mapping accuracies further.

Landsat MSS data were classified into forest type classes (e.g. Douglas fir, subalpine fir, ponderosa pine) by Gum (1985) with an accuracy of 88 per cent, while crown closure classes were mapped at an accuracy of 85 per cent. Additional data layers, including current and potential timber productivity, land ownership, slope, aspect, elevation, deer habitat potential and transportation system, were geometrically registered to the classified MSS images. Fire control information that detailed the fire attack response under different fire intensity conditions was prepared for management areas over the forest.

Root et al. (1985) developed a GIS for predicting fire fuel quantities in a Washington State park. Five data layers were geometrically registered, viz. classified Landsat MSS imagery (classified using a modified clustering approach), precipitation, elevation, slope and aspect. A multivariate model was then developed and used to predict plant community types from the classified Landsat image, terrain and precipitation data. From the vegetation community type classes, forest fire fuel type maps were modeled, which were then verified by comparison with existing fire fuel models developed by the U.S.A. Forest Service.

3.8.6.3. Wildlife mapping

Turner and Baumer (1984) combined Landsat and digital elevation data in a multiple level database on the Isle Royale National Park, Lake Superior, U.S.A. Using these data, they mapped vegetation, slope, aspect, and proximity to Lake Superior on a 2.5 ha grid. Biologists then added relevant biological data to this base-grid and used the full data base for mapping wildlife habitat (B.J. Turner, pers. comm.1).

Hart et al. (1985) performed an unsupervised classification of Landsat MSS data in Montana and produced 99 classes. Some classes were confused, particularly shadow and water bodies, timber and shrubs, and natural and artificial grasslands. By combining the unsupervised image with elevation and aspect data, 3600 unique spectral-elevation-aspect categories were created. These categories were compared with ground conditions, and 189 final vegetation classes were recognized. Other data layers added to the GIS included timber harvest history, ownership, precipitation, drainage basins, roads, trails and hydrology. By overlaying these data, Hart et al. (1985) modeled suitable elk habitat, as well as which roads to close during elk calving periods.

Henderson (1984) geometrically registered land cover type classes (derived from a hybrid supervised/unsupervised classification of Landsat MSS imagery), slope, aspect, elevation, hydrology and human infrastructure in Alaska. Overlaying these data layers allowed wildlife refuges to be rapidly planned.

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3.8.7. Design of GISs for forest management

A few studies have examined the feasibility, design and evaluation of GISs. Many of the ideas expounded below come from general texts from the field of software engineering (e.g. Boehm, 1981; King, 1984; Yourdan, 1979). Some of the information discussed is anecdotal, sourced from a GIS workshop held in Manitoba, Winnipeg during 1987 (Price et al., 1987).

A decision to develop a GIS presumes that the advantages (benefits) of a GIS outweigh the disadvantages (costs). In other words, the GIS would have to be more cost effective, or more productive, or both, than an already existing or proposed manual method, for handling forest inventory and management planning (Tomlinson and Boyle, 1981). Tomlinson (1987) stated the main advantage of GIS is that computer power is used to replace the labourious manual job of data handling, analysis, and summary (which is frequently performed by highly paid professionals). Thus, time consuming manual methods may be performed in a shorter time, to meet tight deadlines.

The environmental legislation being implemented worldwide, and increasing public concern about forest management practices, necessitates that planning for timber and natural resource management be performed in a more complex way. More sophisticated and detailed planning requires more staff, or improved technology. GIS offers the technological fix. Tomlinson (1987) pointed out that GIS is a tool which allows one to look deeper into a problem, and may help researchers and forest managers identify deficiencies in the data, knowledge or management strategies for a forest.

Sugarbaker (1987a) stated that three types of benefits are recognized by the Washington State Department of Natural Resources, viz. (1) increased revenue from timber sales obtained by identifying the most profitable forests to thin, and increased revenue from leasing data; (2) cost avoidance (an example is eliminating lawsuits through better planning); (3) decreased costs (examples include the more efficient and cheaper stewardship\(^1\) of land thereby reducing resource management costs; more efficient map production; rapid information generation for lawsuits). Other nontangible benefits include political kudos as a result of presenting information in a succinct and easily comprehended form (i.e. maps, graphs and tables), and avoidance of mistakes.

Myers and Kolenik (1984) listed a number of advantages of automated GIS over manual map and file record systems. These include speed and cheapness compared with manual extraction of information from maps and files, easy access and full utilization of the available information (rather than relying on the memory of those acquainted with the forest), ease of integrating information from a multitude of maps and files, and obtaining a holistic view of the forest and the history of the forest.

A factor making GISs increasingly attractive is that hardware and software are dropping in price rapidly (Dangermond, 1987). Over the lifetime of a GIS, one GIS vendor estimated 20 per cent of cost is for technology (hardware and software) and 80 per cent for database design and construction (Dangermond, 1987). As hardware and software decline in relative price, the 'technology' is expected to be 2-3 per cent of

\(^{1}\)Stewardship may include planning of wildlife corridors, stream buffer placement, cross drain placement etc..
the total cost of the GIS, and the database design and construction will constitute 97-98 per cent of the
cost of the GIS (Dangermond, 1987). Tomlin (1987a) also predicted the increasing use of low cost 'PC
based' systems, as these systems now have the power of mid-range minicomputers of five years ago.
Most hardware manufacturers, and increasingly software engineers, are moving towards independent and
open (UNIX-type) operating systems. The advantage for the user is that an outdated GIS may be
transferred to a future GIS with minimal problems.

The obvious disadvantage of a GIS is the expense, especially during the early phases of
implementation when the system is becoming operational and no benefits are obvious. Sugarbaker
(1987b) discussed the Washington State Department of Natural Resource's GIS, which has been operating
for 20 years, and has involved four different systems. The current system includes a mainframe, five head
office workstations and digitizers, eight workstations and digitizers in remote sites, 60 dedicated lines, and
up to 100 users logging on sometimes. The budget for managing the information used for land
management in Washington is 0.75 per cent of the revenue of the organization. The breakdown of costs
shows 50 per cent goes on salaries (25 per cent of which is for data capture and 25 per cent for production
and maintenance of databases and report writing facilities); contract equipment and software maintenance
costs 11 per cent; software and hardware comprise 17.9 per cent; supplies make up 4 per cent of costs;
rental 2.7 per cent; and travel 0.9 per cent. As stated above, the system is considered cost effective.

All managers and researchers involved with designing and implementing GISs agree that a
structured, well planned approach is critical to the success of a GIS project. Good GIS design ensures the
system is properly utilized, data is efficiently processed, and that the life of the system is extended as far
as possible (Calkins, 1983). Numerous methods have been suggested for the design, implementation and
evaluation of a GIS, though they all generally follow four stages, viz. a functional requirements study
during which the goals and objectives\(^1\) of the GIS are stated and the needs of the users are
evaluated and a conceptual system\(^2\) is designed; a systems evaluation study that benchmarks the
performances of the various proposed systems relative to the stated functions; a system implementation plan which is a strategic plan detailing database design, input data flow, monitoring,
staffing, budgeting, site preparation, training, macro-writing for general users, procedure manuals etc.;
prototyping and piloting applications followed by monitoring, which is a continuing process
of designing new GIS components, integrating existing components into the system, and evaluating\(^3\) the
functions of the GIS (Calkins, 1984; Dangermond, 1987; Tomlinson, 1987).

Tomlinson and Boyle (1981), Manire (1984), Myers and Kolenik (1984), and Sugarbaker (1987a;
1987b) specified the functional requirements for natural resource GISs in Saskatchewan, Pennsylvania and
Washington respectively. In addition, Manire (1984) lists GIS vendors he was able to identify (current to
1984), as well as a number of organizations which had implemented GISs. Sugarbaker (1987a) suggested

\(^1\) Goals are the broad statements of what is intended, objectives are the specific statements of what is to
be accomplished.

\(^2\) A conceptual system is a general statement describing the major GIS components.

\(^3\) Evaluation involves testing the GIS under normal operating conditions, stress testing under extreme
condition, logical testing of the GIS components, and path testing functions for completeness.
buying a small system for use during a prototyping stage for a GIS, and then to go through a major system upgrade when ready.

3.9. Conclusions

Remotely sensed imagery from the Landsat MSS, Landsat TM, AVHRR, SPOT, and microwave satellite systems have been used extensively by the forestry profession to assess the species distribution in native forests, rates of forest clearing and reforestation, fire boundaries and intensities of fire damage, spread of major forest pests, areas and locations of private pine plantations and native forests, and changes in land use. The operational use of Landsat by public and private forest owners and managers will become more widespread as costs are reduced through the availability of cheaper and more efficient computers, as better sensors improve the resolution of the imagery, and as the advantages of combining remotely sensed data with other ancillary data in GISs are realized.

GISs are now used widely throughout Australia and the rest of the world for forest mapping and planning. The rapidly increasing use of GISs worldwide is testament to the potential for this forest management tool, and as computer hardware and software costs decrease relative to functionality, even greater use will be made of GISs. The potential of GISs is being realized with the development of more sophisticated modelling techniques for analysing the available spatial digital data in GISs (for example using artificial intelligence and expert systems - see Chapter 8 and Chapter 9), and the use of operations research tools such as linear programming for allocating forest areas to various uses based on available forest resources (for example the U.S.D.A. Forest Service FORPLAN model).

Finally, this review showed that remotely sensed data are but one type of spatial data that have been included in GISs. The power of GIS lies in its ability to integrate diverse spatial data types. In Chapters 8 and 9, (nonspatial) knowledge about the forest is also included during the analysis of GIS spatial data, through the use of an expert system.
4. ACCURACY ASSESSMENT OF MAPS IN GIS AND REMOTE SENSING

4.1. Introduction

The main function of a geographic information system (GIS) is the production of maps (or summary of information from the maps), and possibly the most important question to be asked by a user is 'how accurate are the maps produced by a GIS?'. Many articles have been written on the sources of error in the data layers that may be included in a GIS. The aim of this chapter is to review sources of error in GISs, to discuss methods of assessing mapping accuracy, and to critically evaluate the accumulation of thematic map errors in GISs. Two approaches for modelling error accumulation in a GIS are proposed, as well as a novel approach for assessing thematic map accuracy using line sampling theory.

4.2. Raster images

4.2.1. Introduction

Raster images may be obtained from remote sensing sensors carried by aircraft or spacecraft platforms, or by converting an existing vector data structure to a raster data structure (see 4.4). Two types of error are inherent in remotely sensed images, viz. geometric and radiometric. These error sources are addressed in detail in numerous monographs and papers including Colwell (1983) and Richards (1986). A brief outline of the inherent errors in remotely sensed data follows.

4.2.2. Raster image errors and their correction

A raster image is usually made up of a regular grid of adjacent rectangular cells or pixels (i.e. a rectangular tessellation), though a number of other tessellation structures have been proposed including hexagonal and triangular tessellations (see 3.8.2 for details). In this review, the tessellation is assumed to be rectangular, and the terms 'cell' and 'pixel' are used interchangeably.

Geometric error in a remotely sensed image is caused by 1) movement in the remote sensing platform, 2) distortion due to earth curvature and terrain, 3) different centrifugal forces from earth affecting spacecraft movement, 4) earth rotational skew, and 5) distortions introduced by the remote sensing device itself including systematic distortions caused by sampling sequentially from each detector, and nonlinear scanning (Adomeit et al., 1981; Richards, 1986). Geometric error causes a point on the remotely sensed image to occur in the wrong position relative to other points in the image.

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1This chapter is to be published in part as:
Correction of geometric errors in remotely sensed data is now a routine aspect of preprocessing remotely sensed data. One method of removing systematic errors such as earth rotation skew and scan line skew is to model sources of error mathematically (Richards, 1986). The more commonly used method for reducing geometric error is 'rubber sheet stretching', where a set of ground control points (GCPs) (i.e. easily recognizable points such as road intersections, river intersections, boundary fences etc.) are located on both the image and some cartographically correct reference, such as a map. A mathematical coordinate transform is then empirically determined from the GCPs and used to correct the geometry of the image (Ford and Zanelli, 1985). A triangulation method has been used in the U.S.A. (Saalfeld, 1985; Goshtasby, 1986). Triangles of connecting non-intersecting lines are formed between control points, and a localized linear transform is developed for each triangle. An overall mapping function is formed by piecing together the linear mapping functions.

The remotely sensed image is usually 'rubber sheet stretched' to an appropriate map projection. For example, Skidmore (1989b) removed geometric errors and co-registered a digital elevation model and remotely sensed data using a base map with a Universal Transverse Mercator (UTM) projection (see Chapter 8). Corrected images with geometric errors less than 0.5 pixel are obtainable and acceptable1 (Ford and Zanelli, 1985; Ehlers and Welch, 1987; Skidmore, 1989b [see Chapter 8]). However the base maps from which control point information is derived may be of poor quality. Bell (1986) reported that maps used to geometrically correct images of the Great Barrier Reef contained errors of up to 1 km. The accurate selection of control points is crucial to obtaining acceptable results.

Points within a rubber stretched image will no longer be on a regular grid as they have been warped to fit into the projection defined by the GCPs. To obtain a regular grid, an interpolation method is employed to nominate a value for a regular grid point which falls between the points in the rubber stretched image. Three main interpolation methods are used, viz. 1) nearest neighbour (the nearest point in the rubber stretched image to the regular grid point is used as the value for the regular grid point), 2) bilinear interpolation (two orthogonal linear regression functions create a surface, and regular points are selected from the surface), and 3) cubic convolution (a third order linear regression surface is fitted to the rubber stretched image, and regular points are selected from the surface) (Richards, 1986). More sophisticated interpolation methods have not been utilized in remote sensing, as they are considered an 'overkill'. Lam (1983) provides an excellent review of other interpolation methods including splines, finite difference and kriging.

The process of interpolation introduces errors, as the radiometric values at the regular grid points are being estimated. Forster and Trinder (1984) examined the effect of interpolation on mapping accuracy, 

\[ \text{rms}_x = \sqrt{\frac{D^2}{n}} \]

where

\[ D^2 = d_1^2 + d_2^2 + ... + d_n^2 \]

\[ d = \text{discrepancy in the X coordinate direction (i.e. } X_{\text{map}} - X_{\text{check}}) \]

\[ n = \text{total number of pixels checked on the map in the X coordinate direction.} \]

---

1Note that the accuracy of the geometric correction is sometimes expressed as 'root-mean-square' (rms) error, which is the standard error (of the difference between the transformed GCPs and the original GCPs) multiplied by the pixel size. Rms is defined by ASPRS (1988) as,
by comparing an image classified by a maximum likelihood classifier before, and after, interpolation. They found a significant number of pixels changed classes, especially along the boundaries between classes, and within classes of small area. Interestingly, the pixels which changed class tended to then reflect the true ground conditions.

Radiometric errors occur as a result of differential scattering of electromagnetic radiation at varying wavelengths, sensors that have poorly calibrated multiple detectors within a band, sensor calibration error, signal-digitization error, and scene specific error such as off-nadir viewing, irradiance variation, and terrain topography (Richards, 1986). Correction for band to band distortion is performed using image histograms (shifted to the origin to remove atmospheric scattering effects), while line striping effects are reduced by calibration of detectors, or by matching detector statistics during computer processing (Richards, 1986; Teillet, 1986).

A final type of error may be caused by a time-lag between ground truthing and image collection. In this case, pixels may be noted as incorrect in the error matrix (see 4.5.2), when actually correct.

4.2.3. Classification errors

Classification errors result from the poor spectral separation of classes by the classification decision rule being used (Skidmore et al., 1988). Spectrally discrete classes will yield images with a higher accuracy. The cause of poor spectral separation includes mixed pixels (i.e. a large pixel contains more than one cover class: in other words the spatial resolution of the image is greater than the variation of the cover class being mapped); insufficient ground truthing (i.e. the full spectral range of a class is not fully sampled); inaccurate ground truthing (i.e. the cover class name is not correct for the training area data); low spectral resolution (i.e. there is insufficient 'contrast' between cover types so classes co-occur in a common vector position); and poor delineation of classes in multispectral space due to inadequacies with the decision rule itself (Skidmore et al., 1988).

Two types of thematic mapping error are (1) locational, where a pixel is incorrectly classified according to some ground truth criteria, and (2) areal, where the area of a class on an image does not equal the area of the class according to the ground truth. Locational and areal mapping accuracy are correlated, so a high locational mapping accuracy equates with a high areal mapping accuracy (Skidmore and Turner, 1988) (see 6.6).

4.3. Vector image errors

4.3.1. Original errors

Vector 'images' have been traditionally recorded and stored as maps. Maps are subject to many errors. Some errors are introduced during the creation of the map, such as the original line smoothing by draughtsmen which may not follow the true isolines on the ground (Chrisman, 1984), the emphasis in cartography of 'slick graphic presentation that may obscure variations in our knowledge' (Chrisman, 1984), and the categorization of gradients (see 4.8.2 and Chapter 8) (Skidmore, 1989b). Other errors may
be associated with the physical medium used to 'store' the map (for example paper stretch and distortion) (Burrough, 1986).

Maps may be represented in computer GISs by a variation of the vector data structure (Peuquet, 1984; Burrough, 1986), or converted to a raster data structure (4.4). In its simplest form, the vector data structure has map lines approximated to a set of points (nodes), which are linked by lines (or arcs). Vector data may be obtained by digitization (see Chapter 7).

Digitization introduces a number of errors. Varying line thickness on the original map requires automatically scanned vector lines to be thinned (see 7.3.3.1 for a description of automatic scanning and a line thinning algorithm). During manual digitization the centre of the map line must be carefully followed if the map lines vary in thickness. Additional error may be introduced by the need to digitize at 0.001' (0.00254 cm) resolution to separate the distance between closely drawn lines (Peuquet and Boyle, 1984). This requires very careful hand digitizing, or high accuracy automatic scanners. The number of vertices (points) used to approximate a curve is also critical (Aldred, 1972). Too few vertices will result in the line appearing stepped, while too many vertices create large data volumes. Stepped lines can be smoothed using splines or some other interpolation technique, but obviously true 'deviations' must be included. Thus, even with extreme care, error is introduced during digitization (Burrough, 1986).

4.3.2. Corrections of the original vector data

As for raster images, the main method of correcting geometric error in vector images is by using ground control points from a cartographically correct map to transform the vector image to a known projection.

4.4. Vector-to-raster and raster-to-vector conversion

Converting a vector image into a raster image (and vice versa) is now routinely done, albeit at a computational expense (Peuquet, 1981b; Burrough, 1986). However, an artefact of the conversion in either direction is the introduction of error due to approximating positions in the alternative data structure.

Error is exacerbated by a number of factors during vector-to-raster conversion. The resolution and geometry of the raster grid will determine how closely the raster image approximates the original vector. Figure 4-1 shows the effect of doubling the pixel resolution in the x and y directions.

The sinuosity of the lines on the true map is approximated by the raster cells that cover the line. The similarity of the raster image to the true map will be determined by the resolution of the raster tessellation relative to the rate of change in the x and y directions of the arc. Obviously, small changes in the vector arc may not be apparent in a coarse raster grid.
Figure 4-1: Effect of raster resolution and geometry on the representation of a vector arc

Short vectors may be poorly transferred to a raster grid of coarse resolution during vector-to-raster conversion (Figure 4-2). The junctions of vectors may also be poorly mapped in the raster image (Figure 4-2).

The errors generated during raster-to-vector conversion are a corollary of the problems encountered during vector-to-raster conversion. The vector lines approximated by the raster cells in Figure 4-2 will need to be thinned. Short vertices and intersections may not be resolved, or inaccurately resolved on the raster image.
Switzer (1975) proposed a universal method for estimating the degree of mismatch between an ideal map (with infinitely narrow lines) and a raster image of the map, using a Taylor expansion (of the derivative) of a function describing the probability that a point representing class i occurs on the true map and the estimated map. Burrough (1986) empirically tested Switzer's (1975) method, and found that a fourfold increase in the number of grid cells is required to reduce the mismatch by one half.

4.5. Methods of quantifying errors in a raster data layer

4.5.1. Introduction

Methods for quantifying error in a raster data layer are based around the error matrix (also called a contingency table or confusion matrix) concept, first expounded for remotely sensed data in the 1970s (for example, Hoffer, 1975). A number of sophisticated measures of accuracy based on the error matrix have been proposed, including methods for approximating confidence in map accuracy statements.

For modelling error accumulation in a GIS, a map showing the error associated with each cell in each data layer would be most useful, rather than a general statement of accuracy based on error matrices. Some methods for achieving error or reliability maps for a data layer are now critically examined.

4.5.2. The error matrix (or confusion matrix)

The aim of the error matrix is to estimate the mapping accuracy (i.e. the number of correctly mapped pixels) within an image. An error matrix is constructed from points sampled from the image. The reference (or verification) data is normally represented along the columns of the matrix, and is compared with the classified (or image) data represented along the rows. The major diagonal of the matrix represents the agreement between the two data sets (Table 4-1).
Table 4-1: Typical error matrix

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>VI</th>
<th>V</th>
<th>VII</th>
<th>VIII</th>
<th>IX</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>14</td>
<td>3</td>
<td>7</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>1</td>
<td></td>
<td>38</td>
</tr>
<tr>
<td>II</td>
<td>14</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>III</td>
<td>1</td>
<td>16</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V</td>
<td>2</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VI</td>
<td>1</td>
<td>1</td>
<td>16</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VII</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIII</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IX</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Total no. of pixels**: 20 19 38 6 17 8 8 17 2 135

**Overall classification accuracy**: 50.4%

Table Legend:  
I = Yertchuk  
II = Gum/Stringybark  
III = Silvertop Ash  
IV = Blue-leaved Stringybark  
V = Clearcut/road  
VI = Tea Tree  
VII = Gum/Silvertop Ash  
VIII = Black Oak  
IX = unclassified

* Ratio of the sum of correctly classified pixels in all classes to the sum of the total number of pixels tested.

To check every image pixel for correctness would be impossible except for the smallest image area, so various sampling schemes have been proposed to select pixels to test. The design of the sampling strategy, the number of samples required, and the area of the samples have been debated by the remote sensing and cartographic community, and the suggested alternatives are discussed below.

4.5.2.1. **Sampling design**

As with any sampling problem, one is obviously trying to select the sampling design which gives the smallest variance and highest precision, for a given cost (Cochran, 1977). A number of alternative designs have been proposed for sampling the pixels to be used in constructing the error matrix. Berry and Baker (1968) commended the use of a stratified systematic sample\(^1\). The advantage of systematic sampling over random sampling is that sample units are distributed equitably over the area. The disadvantage is that the resulting sample is weighted in favour of the class covering the largest area, and that classes with a small area may not be sampled at all.

\(^1\)Each stratum has an unaligned systematic sample
Simple random sampling in land evaluation surveys emphasizes larger areas, and undersamples smaller areas (Zonneveld, 1974). Zonneveld (1974) suggested a stratified random sample was preferable, and Van Genderen et al. (1978) agreed that a stratified random sample is 'the most appropriate method of sampling in resource studies using remotely sensed data'. Hay (1979) proposed a slight modification, where a simple random sample is used to select samples until a stratum (of a class) contains a minimum specified number of samples. Additional random samples are then selected within those strata with fewer than the minimum specified number of samples. Stratification works well when cover type strata can be easily identified (e.g. Skidmore and Turner (1988) [see Chapter 6] could easily identify pine plantation age classes), but stratification prior to the classification is difficult in many natural areas such as native eucalypt forests. Indeed, stratification is often the reason for undertaking the analysis of the remotely sensed data in the first place!

Rosenfield et al. (1982) suggested a stratified systematic unaligned sampling procedure (i.e. an area weighted procedure) as a first stage sample to assist in identifying categories occupying a small area, followed by further stratified random sampling for those classes with fewer than the desired minimum number of points. Todd et al. (1980) argued that single stage cluster sampling is the cheapest sampling method, as multiple observations can be checked at each sample unit on the ground.

Congalton (1988) simulated five sampling strategies (viz. simple random sampling, stratified random sampling, cluster sampling, systematic sampling and stratified systematic unaligned sampling) using different number of samples over remotely sensed images of forest, rangeland and grassland. The aim of the study was to ascertain the effect of different sampling schemes on estimating map accuracies using error matrices. He concluded that great care should be taken in using systematic sampling and stratified systematic unaligned sampling because these methods could overestimate population parameters. The overestimation occurs due to a possible correlation between the spacing in the systematic sample with periodicity of erroneous pixels in the image. Congalton (1988) also stated that cluster sampling may be used, provided a small number of pixels per cluster are selected (he suggests a maximum of 10 sample pixels per cluster). Stratified random sampling worked well and may be used where small but important areas need to be included in the sample. However, simple random sampling may be used in all situations.

Upon further analysis of the results presented by Congalton (1988) for the cluster sampling method (see Figure 8 of Congalton (1988)), it can be noted that as the number of samples in the cluster increases, the average intra-cluster correlation decreases, thereby negating the benefit of low intra-cluster variation. It is the low intra-cluster variation which maximizes the benefits of single stage cluster sampling (Cochran, 1977). In fact, a cluster of about five samples in a forest has the same intra-cluster correlation as a cluster of about 30 samples in an agricultural area! Using relative cost and precision (Cochran, 1977) as the criteria for deciding the optimal sampling strategy, two conclusions can therefore be made, viz., 1) the cost increases and precision decreases for a greater number of pixels in each cluster, and 2) cluster sampling will give a higher precision and lower cost for agricultural cover types than for forest. Maxim and Harrington (1984) pointed out that spatial correlation between adjacent cells has the

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1After Berry and Baker (1968)
tendency of making large sub-cells inefficient in cluster sampling. For a forested area, a decision to use cluster sampling (Rohde, 1978; Roller and Visser, 1980; Todd et al., 1980) should be compared with other sampling techniques according to relative cost and precision criteria.

4.5.2.2. **Number of samples for accuracy statements**

The number of samples may be related to two factors in map accuracy assessment: (1) the number of samples that must be taken in order to reject a map as being inaccurate; and (2) the number of samples required to determine the true accuracy within some error bounds for a map.

Van Genderen et al. (1978) pointed out that we wish to know, for a given number of sample pixels, the probability of accepting an incorrect map. In other words, when a high mapping accuracy is obtained with a small sample (e.g. of size 10), there is a chance that no pixels which are in error may be sampled (i.e. a type II error\(^1\) is committed). The corollary as stated by Ginevan (1979) is also important, that is the probability of rejecting a correct map (i.e. committing a type I error) must also be determined.

The binomial probability function has been used by all authors debating the number of samples to be selected from an image. (The binomial distribution is used because a pixel is assumed to be correctly classified or incorrectly classified; the shortcomings of this assumption are discussed in 4.8.2). In some cases the normal approximation of the binomial probability function has been used (Hord and Brooner, 1976), though it is more convenient to use the exact values of the binomial probability function provided by Ginevan (1979). The following explanation of the use of binomial theory for estimating the number of samples comes from Ginevan (1979).

The binomial probability is calculated from:

\[
P(s) = \frac{N!}{(N-s)!s!} Q^s (1-Q)^{N-s} \quad \text{(1)}
\]

where

- \(P(s)\) = probability of obtaining \(s\) correctly classified points in the sample
- \(N\) = sample size
- \(Q\) = prespecified accuracy of the image/map
- \(s\) = number of correctly classified points in the sample.

A more convenient measure is the probability of obtaining \(Y\) misclassified or erroneous points\(^2\) (i.e. \(s = N - Y\)). Thus \(P(Y)\) is calculated from:

\[
P(Y) = \frac{N!}{Y!(N-Y)!} Q^Y (1-Q)^{N-Y} \quad \text{(2)}
\]

The aim is to find the sample size \(N\), and the number of incorrectly classified pixels \(Y\) needed to reject a null hypothesis that an image is inaccurate. The user prespecifies the level below which the image is considered inaccurate (Ginevan [1979] suggested the proportion that is correctly classified \([Q_2]\) could be set at 0.85 or less) at a confidence of, say, 95 per cent (that is \(\beta = 0.05\)). The user also specifies the

---

\(^1\)Type I errors have been termed "consumer's risk" and type II errors "producer's risk" by Aronoff (1982), Fung and LeDrew (1988), and others. These terms are taken from a branch of statistics called acceptance sampling. For consistency through this thesis, and in order to use conventional statistical terms, type I and type II errors will be used.

\(^2\)The same term "Y" has also been labeled as "X" by Aronoff (1979) and "E" by Van Genderen et al. (1978)
accuracy of the map that one does not wish to incorrectly reject as inaccurate (Ginevan [1979] suggests $Q_1 = 0.95$), again at, say, $\alpha = 0.05$. From the following equation:

$$\sum_{Y=0}^{X} P(Y|Q_2) = \beta$$

... (3)

the number of pixels ($N$) is given and the critical value $X$ calculated for $Q_2$. Similarly the critical region $N$ can be calculated for $Q_1$:

$$\sum_{Y=0}^{N} P(Y|Q_1) = \alpha$$

... (4)

For example, if the total number of samples selected is $N=93$, $\beta = 0.05$, $\alpha = 0.05$, $Q_1 = 0.95$, and $Q_2 = 0.85$, then if 8 or less (i.e. $Y = 8$) pixels are incorrect, the image is accepted as accurate.

Van Genderen and Lock (1977) and Van Genderen et al. (1978) argued that only those maps (at a predetermined accuracy ($Q_2$) of 90 per cent) with no errors ($X$) in a class with a sample size of 30, should be accepted as accurate within 95 per cent confidence intervals (i.e. $\beta = 0.05$). At a prespecified image accuracy of $Q_2 = 85$ per cent, Van Genderen et al. (1978) showed the number of samples required is 20, and as the image accuracy of the map falls to $Q_2 = 60$ per cent they indicated only 5 samples per strata are required (Table 1 in Van Genderen et al. [1978]). Ginevan (1979) pointed out there is no allowance made by Van Genderen et al. (1978) for incorrectly rejecting an accurate map. The trade-off one makes using the approach of Ginevan (1979) is to take a larger sample, but in so doing reduce the chance of rejecting an acceptable map: that is Ginevan (1979) proposed a more conservative approach. Hay (1979) concluded the minimum sample size should be 50. His minimum sample size is larger than that of Van Genderen and Lock (1977): he stated that 'any sample size of less than 50 will be an unsatisfactory guide to error rates'.

Rosenfield et al. (1982) also criticized Van Genderen et al. (1978) because they did not propose methods for estimating the maximum number of misclassified pixels (i.e. $Y$ in equation (4)) which may be sampled. Rosenfield et al. (1982) found 19 samples were required for an image with a prespecified accuracy of 85 per cent, which is the same result as obtained by Ginevan (1979) and very close to the 20 required by Van Genderen et al. (1978). However, at a prespecified accuracy of 60 per cent, Rosenfield et al. (1982) calculated that 60 samples would be required. This result is counter intuitive as well as contradicting the results of Van Genderen et al. (1978) and Ginevan (1979). When the image is less accurate (i.e. there is more error), the chance of a correct pixel being sampled would be less, thereby requiring fewer pixels in the sample.

Hord and Brooner (1976) were some of the first authors to describe the use of the binomial distribution to estimate sample sizes. Their approach has been criticized by Hay (1979), Ginevan (1979) and then Aronoff (1982) because Hord and Brooner (1976) assumed the errors would have a normal distribution. As Hay (1979) noted, this assumption is only acceptable when the number of samples is large.

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1 Hay (1979) noted the ideas expounded by Van Genderen and Lock (1977) were developed by himself.
Congalton (1988) empirically simulated the effect of varying sample size on the estimated population parameters. He found highly variable population estimates, which appeared to depend on sample method as much as number of samples. Generally simple random samples gave the best results, requiring between 50 and 100 samples per category in order to approximate sample parameters in a stable manner.

Todd et al. (1980) calculated that a total of 400 samples (ranging from 16 to 56 samples per class) would be necessary to estimate the accuracy of each class within 90 per cent confidence limits in a cluster sample, using formulae presented by Cochran (1977). The limitations of the cluster sampling design have been noted above.

The methods discussed above calculate sample size based on confidence limits or acceptance testing. Thomas and Allcock (1984) described a method for calculating the confidence intervals about a mapping accuracy statement, for a sample of a size specified by the user. Their technique is again based on using binomial distribution theory. An assumption is that the minimum number of samples should be greater than 50, with a sample in the hundreds being more acceptable. The lowest 99.9 per cent confidence level for a map's accuracy is calculated as follows:

\[
99.9 \% \text{ CL} = (m - 3e_m) - 3(s + 3e_s) \quad \ldots(5)
\]

where
\[
\begin{align*}
N &= \text{number of samples taken} \\
p &= \text{number of samples that have been correctly classified} \\
q &= 1-p \\
m &= Np \\
s &= \sqrt{Npq} \\
e_m &= s/\sqrt{N} \\
e_s &= s/\sqrt{2N}
\end{align*}
\]

To calculate the 99 and 95 per cent confidence levels, '3' in equation (5) can be replaced with '2.33' and '1.65' respectively. Note that this technique can be used on a class by class basis, or for the whole image. The technique was applied by Skidmore (1989b) (see Chapter 8) who concluded that he was 95 per cent confident that at least 68.6 per cent of the pixels classified by an expert system had been correctly classified, and 99.9 per cent confident that at least 61.3 per cent of the pixels were correctly classified.

A practical problem with utilizing the ideas of minimum sample size per category to achieve prespecified confidence levels, is the large number of samples which may be required to accept an image as having a statistically significant accuracy. For example, Skidmore (1989b) (see Chapter 8) found three of the cover type classes were relatively rare in his study area (viz. Tea Tree, Gum/Silvertop Ash, and Black Oak), and as a consequence were poorly represented in the error matrices because of the simple random sampling design. Information was not available to stratify the study area into forest type classes in order to improve sampling efficiency, nor could the information be rapidly generated within the time and cost constraints of the project. Therefore, procedures for generating confidence intervals for individual classes could not be used due to low sample numbers.
4.5.2.3. Sample unit area

The number of samples must be traded-off against the area covered by a sample unit, given a certain quantity of money to perform a sampling operation. 'Should many small-area samples or a few large-area samples be taken?' was a question posed by Curran and Williamson (1986). The answer is that it depends on the cover type being mapped - a highly variable cover type such as rainforest is better suited to many small-area samples, while for relatively homogeneous cover types it is more efficient to take fewer large area samples. The reasons for these conclusion are discussed below.

Woodcock and Strahler (1987) investigated inter-pixel variation in remotely sensed images. Their results are applicable to this discussion as an image pixel is conceptually a radiometric sample over a small area. If the spatial resolution of a sample pixel is considerably finer than the objects (or ground resolution elements) in the scene, then pixels will be highly correlated with their neighbours and inter-pixel variation will be low. However, the intra-pixel variance will be high, as multiple ground resolution elements occur within the pixel sample (a situation Cochran [1977] states will lead to a biased result). As the resolution of the ground objects become closer to the resolution of the pixels, the likelihood of neighbours being similar decreases, and inter-pixel variation becomes high. At the same time, intra-pixel variation will remain relatively low because there is is still less than one ground resolution element coinciding with the pixel sample. When the ground resolution elements are much smaller than the image pixel samples, the inter-pixel variance is low as many elements are averaged over one sample. However, intra-pixel (or within sample) variation would increase because many elements contribute to the variance of the pixel (De Vries, 1986). These relationships are generalized in Figure 4-3.

Figure 4-3: Change in intra-pixel and inter-pixel variance as the resolution of the ground elements decreases relative to the image pixel resolution
Woodcock and Strahler (1987) made two interesting observations applicable to the problem of determining sample size, when they degraded image (or sample) resolution for various scenes and noted change in inter-pixel (or local) variance within a three-by-three moving window. Firstly, the peak in inter-pixel variation occurred when the pixel (sample) resolution was 0.5 to 0.75 of the size of the ground resolution elements (note that there is no absolute scale on the x axis for Figure 4-3). When the ground resolution elements and image pixels (samples) are the same size, boundaries between ground resolution elements may fall within the pixels (samples), thereby creating boundary image pixels of mixed (but common) tone that as a consequence have less variation within the three-by-three window. With pixels (samples) of 0.5 to 0.75 the size of ground resolution elements, the propensity to form multiple mixed pixels is reduced, while the inter-pixel variation is yet to decrease as a result of many elements being found in one image pixel. Thus maximum inter-cell variation occurs around 0.5 to 0.75 of the ground resolution cell. A second observation by Woodcock and Strahler (1987) is related to the first: the scale of the ground resolution elements is important in determining the inter-pixel (sample) variation.

A number of case studies using remotely sensed data support these conclusions on inter-pixel (sample) variation. Generally, mapping of heterogeneous classes such as 'forest' and 'residential' is more accurate at 80 m resolution than at finer resolution such as 30 m (Toll, 1984); however more homogeneous classes such as agriculture and rangelands are more accurately mapped at 30 m than 80 m (Toll, 1984). The reason for this is the trade-off between ground element resolution and image pixel size. Agricultural fields are large, and the inter-pixel variation at 30 and 60-80 m resolution occurs on the left hand side of the curve in Figure 4-3. That is, the finer resolution results in decreasing inter-pixel variation. In contrast, forest element resolution is small, and the 30 and 60-80 m image resolution size occurs on the right hand side of the curve.

The effect of intra-pixel variation (i.e 'mixed pixels' or 'mixels') also needs to be considered. In one study, mixed Landsat MSS pixels (i.e. 79 by 79 m resolution) made up 54.9 per cent of an area where the ratio of the average polygon to map cell was 16 (Jupp et al., 1979). Sweet et al. (1980) field checked 800 Landsat MSS pixels and found that only 51 per cent occurred over one cover type. Crapper (1984) derived equations to predict the number of boundary cells between classes in remotely sensed images\(^1\). Over wheat fields (a very homogeneous cover type), 10.9 per cent of pixels were mixed when using Landsat MSS, 4.9 per cent for Landsat TM, 3.2 per cent for 20 m SPOT data and 1.6 per cent for

\[ N^B = \sum_{j=1}^{M} K_1 \sqrt{\pi A_j / L} \]

where:

- \( N^B \) = number of boundary cells
- \( K_1 \) = a shape factor
- \( L \) = average length of a random straight laid across a grid cell
- \( A_j \) = area of region \( j \)
- \( M \) = total number of regions
10 m SPOT data. Thus as the spatial resolution increases, the proportion of mixed pixels decreases. Irons et al. (1985) found that at a resolution of 28.5 m, between 29.6 and 71.6 per cent of pixels were mixed, while at a resolution of 57 m between 45.4 and 88.9 per cent of pixels were mixed, for classes including water, developed land, row crops, grass and forest. Toll (1984) also reported that the proportion of mixed pixels (that is intra-pixel variation) decreases as spatial resolution increases. Thus the proportion of mixed pixels, and by analogy intra-pixel variance, increase at coarser spatial resolutions.

In contrast to the agricultural studies cited above, Ahem et al. (1980) reported lower mapping accuracy of forests at 30 m compared with 80 m. According to the left hand side of the model depicted in Figure 4-3, the decreasing inter-pixel variance would be compensated by the increasing intra-pixel variance. In other words the shape and magnitude of the inter-pixel and intra-pixel variance curves in Figure 4-3 can counteract, and may produce an unexpected result. Markham and Townshend (1981) found a number of such apparent inconsistencies during an interesting study in which they spatially degraded remotely sensed data collected from an aircraft platform.

Markham and Townshend (1981) examined two sites at which inter-pixel variance and class mapping accuracies were measured as resolution was degraded from 5 m to 80 m. At another two sites the percentage of pure pixels (i.e. a measure of intra-pixel variance) and class mapping accuracies were measured at spatial resolutions also ranging from 5 to 80 m. Results appeared contradictory at first inspection. For example, as the spectral resolution was degraded, forest was more accurately classified for one site. At another site, forest had the highest mapping accuracy at a spatial resolution of 60 m and then mapping accuracy decreased. Another example was rangeland, where the highest mapping accuracy occurred at 10 m, and then decreased, while at another site the mapping accuracy of rangeland consistently decreased as the resolution became coarser. These apparent inconsistencies are now explained.

A cover type located at a particular location will have a unique pattern or arrangement. The components within the cover type (e.g. trees, understorey, soil, rocks etc. in a forest) and the boundaries between cover types (e.g. between grass and forest) will result in a different set of intra-pixel and inter-pixel variances at different resolutions. Intra-pixel and inter-pixel variances will also vary between different cover types. Markham and Townshend (1981) showed that forests generally have a decreasing inter-pixel variance, and an increasing intra-pixel variation, at coarser resolutions. The relative shape and magnitude of the variances determine the map accuracy. A subtle change in inter-pixel or intra-pixel variance will alter the forest class mapping accuracy. In Figure 4-4a (which occurs on the right hand side of the generalized Figure 4-3), forest mapping accuracy increases as ground element resolution increases (i.e. in agreement with results obtained by Markham and Townshend [1981], Toll [1984] etc.). The inter-pixel variance is dropping, while the intra-pixel variance is rising at a slower rate. In Figure 4-4b, a situation described by Markham and Townshend (1981) is modelled. Here forest mapping accuracy drops from a peak at about 60 m due to a faster increase in intra-pixel variance than in Figure 4-4a. In Figure 4-4c, the forest mapping accuracy is decreasing at coarser resolution, due to the intra-pixel variance increasing faster than the rate of decrease of inter-pixel variance.
In contrast, water classes would occur on the left hand side of Figure 4-3, because the resolution elements are smaller than the sample (pixel) resolution. In this case, both the inter-pixel and intra-pixel variances are increasing. This has the effect of a decreasing class mapping accuracy (Figure 4-5).
The results of Ahern et al. (1980) point to another factor in selecting an appropriate sample unit area: the changing scale of ground elements (Woodcock and Strahler, 1987). The influence of the scale factor is indicated schematically as broken lines on Figure 4-3. As the sample unit size is decreased over forests from 30 m to 5 m (i.e. on the left hand side of the curve in Figure 4-3), individual trees will be sampled rather than groups of trees. (The groups of trees constitute a stand or forest type of homogeneous structure and species [Skidmore, 1989b]). Thus at a sample resolution of 5 m, a new scale of ground resolution element is being considered for which the definition of ground resolution elements (i.e. groups of trees) is no longer applicable. A new curve of inter-pixel and intra-pixel variation therefore becomes applicable.

Assuming the inter-pixel and intra-pixel variances equally influence the mapping accuracy of an image, the theoretically optimal sample size may be at the point where the intra-pixel and inter-pixel variances are both minimum. If one variance has a greater effect on mapping accuracy than another, then the variances should be suitably weighted.

Curran and Williamson (1985) concluded that when considering large sample unit areas, the ground element data has more measurement error than the (averaged) sample data. In other words, the scale of the ground resolution elements may be 'inappropriate' for the sample size. The 'inappropriateness' may be due to the spatial variability of the ground resolution elements in the terrain; in other words the sample size should be varied according to the ground conditions. For example, agricultural fields tend to be large homogeneous areas which are therefore suitable for larger sample areas. However, patches of poor or failed crop will introduce measurement error into the ground element, depending upon the resolution. In contrast to agricultural fields, native forests (especially rainforest) will contain a heterogeneous mix of forest types requiring much smaller samples to enclose a homogeneous area of a single cover type (De Vries, 1986).

Barnard et al. (1985), considered that sampling intensities should be determined by the application, with low spatial densities and resolution over extensive zones, and high spatial density for location specific monitoring, such as management plans or environmental impact statements.

Curran and Williamson (1986) stated that it is preferable to have a few highly accurate ground measurements, rather than a greater number of less accurate measurements. In other words the quality of
the measurement at a sample point is more important than the quantity of samples collected. This conclusion was made after they found that the error in measuring a variable or class on the ground was much higher than the error in the remotely sensed data samples.

Sample unit area is related to sample design and number of samples. Precision and variation of population estimates are dependent on these three criteria, and must be balanced in any sampling strategy by the cost. An example of the interaction between sample design and area of samples is given by De Vries (1986), who showed that with cluster sampling in rainforest, the accuracy decreases once the area of clusters increases beyond the scale of the forest types in the image.

Poor geometric rectification of an image, will cause a correctly classified sample pixel to be in the wrong place in the image, and hence to be deemed incorrectly classified during the error analysis. Geometric rectification usually reduces geometric errors to less than ± 0.5 pixel. However, geometric error was the reason Todd et al. (1980) chose to increase the minimum mapping unit for accuracy assessment from a Landsat pixel of 0.64 hectares, to a five-by-five window of 16 hectares. They achieved this by naming the five-by-five window after the class which occurred most commonly in the window. However, they did not consider the problem of matching the spatial resolution of the image with the spatial variation of the ground resolution elements.

In conclusion: the ideal situation is to minimize intra-pixel and inter-pixel variation; however, the left and right hand sides of the curve in Figure 4-3 will pass to a new scale of ground element towards the extremes. The optimal sample size is determined by the ground resolution element, but should be designed to minimize inter-pixel and intra-pixel variances, or some weighting of these variances.

4.5.2.4. Accuracy estimates using correlation coefficients

Some authors calculated correlation coefficients as a measure of mapping accuracy. For example, Vogelmann and Rock (1988) found a ratio of Landsat TM channel 5 to Landsat TM channel 4 was strongly correlated with the per cent of damaged trees within conifer forests in northeastern U.S.A. ($r^2 = 0.92$). The main disadvantage with correlation coefficients is that it must be used with continuous variables. Map classes are discrete units, so it is inappropriate to use correlation coefficients.

4.5.2.5. Measures of mapping accuracy generated from an error matrix

A commonly cited measure of mapping accuracy is the 'overall accuracy' which is the number of correctly classified pixels (i.e. the sum of the major diagonal cells in the error matrix) divided by the total number of pixels checked (Table 4-1). Anderson et al. (1976) suggested the minimum level of interpretation accuracy in the identification of land-use and land-cover categories should be at least 85 per cent.

Overall classification accuracy is the ratio of the total number of correctly classified pixels to the total number of pixels in each class (Kalensky and Scherk, 1975). This only takes into account omissions. Stated mathematically:

$$M_i(\%) = \frac{N_i}{N_i + E_i} \times 100$$
where $M_i(\%) = \text{mapping accuracy of class } i$

$N_i = \text{number of correctly classified pixels in class } i$

$E_i = \text{number of erroneous pixels in class } i \text{ (i.e. sum of omissions and commissions).}$

Overall mapping accuracy takes into account both omission and commission errors, and as a consequence allows for positional accuracy (Kalensky and Scherk, 1975).

$$M\% = \frac{\sum_{i=1}^{n} P_iM_i}{\sum_{i=1}^{n} P_i}$$

where $M\% = \text{overall mapping accuracy}$

$M_i = \text{mapping accuracy class } i$

$n = \text{number of classes.}$

Note that:

$$P_i = \frac{T_i}{\sum_{i=1}^{n} T_i}$$

where $T_i = \text{correct number of pixels in class } i.$

Cohen (1960) and Bishop et al. (1975; P. 396-397) defined a measure of overall agreement between image data and the reference (ground truth) data called 'Kappa' or 'K':

$$K = \frac{\theta_1 - \theta_2}{1 - \theta_2}$$

where $\theta_1 = \sum_i p_{ii}$ and $\theta_2 = \sum_i p_{i+} p_{+i}$

Note that $p_{ii}$ is the sum of the ith row and $p_{i+}$ is the sum of the ith column. $p$ is the simple proportion obtained by dividing the observed counts in the error matrix by the total number of observations $N$.

They further defined the estimated asymptotic variance of $K$:

$$\sigma^2_{\text{approx}}[K] = \frac{1}{N} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(28\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(4\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4} \right\}$$

where $\theta_1$ and $\theta_2$ are as above and

$\theta_3 = \sum_i p_{ii}(P_{i+} P_{+i})$ and $\theta_4 = \sum_i p_{ii}(P_{i+} P_{+i})^2$.

'K' ranges in value from 0 (no association, that is any agreement between the two images equals chance agreement) through to 1 (full association, there is perfect agreement between the two images). 'K' can also be negative, which signifies a less than chance agreement. Rosenfield and Fitzpatrick-Lins (1986) made the point that values for 'K' (expressed as a percentage i.e. Kx100) are less than the values for total per cent correct (or mapping accuracy). A disadvantage with this measure of mapping accuracy is that
classes that are nearly correctly classified are considered in conjunction with classes which may have a low mapping accuracy, giving an average figure which does not reflect between class differences.

4.5.2.6. Mapping accuracy of individual classes

Kalensky and Scherk (1975) considered omission and commission errors using their measure of 'overall mapping accuracy' and 'class mapping accuracy' described above. Story and Congalton (1986) suggested that accuracy assessment should be expressed in terms of 'user' and 'producer' accuracy, which are actually accuracy measures related to those proposed by Kalensky and Scherk (1975). Story and Congalton (1986) proposed that user accuracy for a class is the reliability of a classified image to a user; that is how well the map represents what is actually on the ground. User accuracy can be defined as:

\[ U_i(\%) = \frac{N_i}{N_i + C_i} \]

where \( U_i(\%) \) = user accuracy for class \( i \)

\( C_i \) = number of commissions (i.e. total of row \( i \) in Table 4-1)

\( N_i \) = number of correctly classified pixels in class \( i \).

The producer accuracy is the probability that a reference (ground) pixel is correctly classified, that is it represents the probability that a pixel of class \( i \) is correctly classified on the map. Producer accuracy is defined as:

\[ P_i(\%) = \frac{N_i}{N_i + O_i} \]

where \( P_i(\%) \) = producer accuracy for class \( i \)

\( O_i \) = number of omissions for class \( i \) (i.e. total of column \( j \)).

Note that Kalensky and Scherk (1975) defined the total number of erroneous pixels to be \( E_i = O_i + C_i \), that is \( E_i \) is a measure of positional accuracy that includes both commission and omission errors.

Rosenfield and Fitzpatrick-Lins (1986) showed the \( K \) statistic discussed above can be used as an alternative measure of accuracy for a class. The conditional ' \( K \) ' value for the \( i \)th class is calculated thus:

\[ K_i = \frac{p_{ii} - p_{i*}p_{*i}}{p_{i*} - p_{i*}p_{*i}} \]

4.5.3. Testing for significant differences between image factors

4.5.3.1. A test for a significance difference between images

Testing for a significant difference between images is important when trying to analyse which factors may be causing a significant difference in the accuracy of images. For example, type of classifier (Rosenfield and Melley, 1980; Hudson, 1987; Skidmore, 1989b [see Chapter 8]), type of imagery (i.e. spatial or spectral resolution), date of imagery (Congalton et al. 1983), and film/filter combinations for photointerpretation (Congalton and Mead, 1983) may all be important factors in determining the utility of one remotely sensed product over another.
Congalton et al. (1983) and Skidmore (1989b) (see Chapter 8) applied discrete multivariate analysis techniques developed by Cohen (1960) and Bishop et al. (1975) to test whether two error matrices were significantly different. In these studies, the type of classifier was varied, while other factors such as date of image collection, training areas etc. were held constant.

To test for a statistically significant difference between two error matrices, Cohen (1960) proposed using the K values (e.g. \( K_1 \) and \( K_2 \) representing images 1 and 2 respectively) and their associated variance (described in 4.5.2.5) by evaluating the normal curve deviate:

\[
z = \frac{K_1 - K_2}{\sqrt{\sigma^2_{K_1} + \sigma^2_{K_2}}}
\]

This test statistic may be applied to paired combinations of error matrices, to ascertain whether the error matrices are significantly different. Obviously only one image factor should be changed at any time, such as classifier type or date of image collection. A null hypothesis can be set up to test whether the K values for the two images differ;

\[ H_0: K_1 = K_2 \]

versus

\[ H_a: K_1 \neq K_2. \]

The null hypothesis is rejected using the normal curve deviate statistic (z) for \( \alpha = 0.05 \) if \( z_t > 1.96 \) (i.e. \( z_{\alpha=0.05} = 1.96 \)). Note that any other rejection region can be used e.g. \( \alpha = 0.01 \) or \( \alpha = 0.001 \).

Examples of the K statistic applied to remote sensing problems can be found in Congalton and Mead (1983) and Skidmore (1989b) (see Chapter 8).

Rosenfield and Fitzpatrick-Lins (1986) discussed the Cohen (1960) 'K' coefficient as a relation to a family of coefficients which correct for chance agreement between two error matrices (or contingency tables). They commended the Cohen 'K' coefficient statistic because it considers within class correlation as well as overall image correlation: in other words all cells in the error matrix are considered (Fung and LeDrew, 1988).

Rosenfield and Melley (1980) compared mapping accuracy obtained from Landsat MSS imagery and high altitude aerial photographs using one-way statistical tests. Test sites were compared on both imagery types as being correctly or incorrectly classified. These test sites were paired, so a research hypothesis could be stated that there was no difference in the number of correctly classified sites for the two images. This hypothesis was tested using the Student t-test as well as the Sign and Wilcoxon tests, which are nonparametric tests. In addition, a two way analysis of variance was performed to test whether there was a significant difference between imagery as well as a significant difference between the mapping accuracies of the classes. Hixson et al. (1980) used analysis of variance to test whether a remotely sensed image classified by different classifiers had significantly different mapping accuracies. They used the Duncan multiple range test to identify which classifiers were significantly different.

A disadvantage of the technique described in Rosenfield and Melley (1980) and Hixson et al. (1980) is that the effect of omissions and commissions (i.e. intraclass variation) is not considered. In addition, an aberrant class(es) may cause a rejection of the null hypothesis. The use of parametric tests
(such as the Student 't' test and analysis of variance) are questionable, as it was assumed that the variable
being compared (i.e. mean number of correctly classified points) was normally distributed. These authors
applied a transformation to the data so it met the assumption of normality. However the transformation
will affect the analysis of variance result because the variable values were being modified. In contrast,
transformation of the ranked (nonparametric) data does not change the value (order) of the data. Therefore a
nonparametric two-way analysis would be more appropriate, such as the Friedman test (Noether, 1976).

Rosenfield (1986) analysed categorical data, such as the data found in error matrices, using linear
models developed by Grizzle et al. (1969) and Koch et al. (1977).

4.5.3.2. A test for a significant difference between classes

On occasions it may be desirable to test whether there is a statistically significant difference
between the accuracy obtained for class x versus class y. The importance of this test is in identifying
those classes with a low mapping accuracy (though that is often obvious from visual inspection of a
confusion matrix!). Rosenfield (1986) proposed a test for significant difference between classes, based on
the analysis of the error matrix using linear models. Given that there is a difference in mapping accuracy
between classes, pairs of classes are compared to ascertain whether there is a significant difference between
the accuracy of the two classes.

No test has been proposed to compare whether there is a significant difference between individual
classes using the Kappa or 'K' statistic described in 4.5.2.5.

4.6. Methods of quantifying errors in a vector data layer

4.6.1. Introduction

The methods discussed above for quantifying error in raster images are equally applicable to
quantifying error in vector polygons. Instead of checking whether an image pixel is correctly classified, a
point within the polygon is verified against the ground truth information. A specific problem encountered
with vector images are ground truth samples which occur across boundary lines; in this case the class
with the largest area within the sample area may be selected to represent the vector map image.

If the class represented by a polygon is homogeneous within the polygon (e.g. a local
government boundary) then any sample will have a 100 percent mapping accuracy, given that the
boundary is accurately mapped. Methods of estimating the error bands surrounding a boundary are
discussed in 4.6.2. Alternatively if the class within a polygon is heterogeneous or continuous (e.g. soil
type or elevation) then samples within the polygon will be associated with error. A number of methods
for estimating polygonal error are discussed in 4.6.3.

4.6.2. Error bands for boundaries

Cartographers have proposed a number of methods for measuring error around boundaries of
homogeneous polygons. Error bands are present as a result of inherent error of the original maps, and
error introduced during the digitizing process (Blakemore, 1984; Poiker, 1982). Cartographers have attempted to make maps aesthetically pleasing (as well as accurate), so that information can be easily extracted by users (Poiker, 1982). Chrisman (1984) pointed out that the emphasis on 'slick graphic presentation obscures the variation in our knowledge'. The emphasis on making maps aesthetic by the use of symbolism, colour, smooth line work, and good layout may hide deficiencies in the original information used to construct the map.

Blakemore (1984) used the concept of 'epsilon' distance developed by Perkal (1966) to describe the uncertainty associated with a line on a polygonal map. An epsilon distance is defined as the error band on either side of a polygon line. A point in the vicinity of the polygon has five states, viz. definitely in, possibly in, ambiguous (i.e. on the digitized border line), possibly out and definitely out (Figure 4-6). The area of the polygon that is definitely in the class is calculated, and represents the area of the map for which there is certainty as to the accuracy. Unfortunately the method described by Blakemore (1984) assumes a constant epsilon band for the map. This is an oversimplification for most environmental parameters, especially in the situation where environmental gradients are being mapped.

![Figure 4-6: Error zones as defined by Blakemore (1984)](image)

4.6.3. Polygonal error in vector maps

MacEachren (1985) suggested as a hypothesis that three factors were significant in determining map accuracy in vector maps, and include polygon size\(^1\), polygon compactness\(^2\), and variation within the polygon. It was assumed that the individual polygons are generalizations (i.e. average, median etc.) of continuous variables (e.g. elevation) or heterogeneous variables (such as soil or forest type).

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\(^1\)First suggested by Coulson (1978).
\(^2\)Polygonal compactness is the ratio of the boundary length of the polygon to the area of the polygon.
MacEachren (1985) tested his hypothesis by extracting a systematic sample of points from four different elevation surfaces (the systematic samples are gridded at the same scale over the four surfaces). The elevation surfaces vary from a simple inclined plane through to a deeply dissected and variable surface. Overlaid onto the elevation surfaces is a choropleth (i.e. a polygonal) vector map, with polygons varying in compactness and area. He calculated indices describing polygon compactness, size and variability. The coefficient of variance for the elevation values\(^1\) within each polygon were calculated for the four surfaces, and were compared with the indices using regression analysis.

Map accuracy decreases with increasing variation within a polygon, increasing polygon size and decreasing polygon compactness (MacEachren, 1985). MacEachren (1985) concluded that intrapolygon variation had the most deleterious effect on map accuracy, followed by polygon size\(^2\). The effect of within polygon variation on map accuracy concurs with the results in 4.5.2.3 for raster data (i.e. remotely sensed data), that the within cell variance must be viewed in conjunction with between cell variance. MacEachren (1985) also surmised that other unknown factors are affecting map accuracy.

In contrast to the conclusions of MacEachren (1985), Coulson (1978) suggested that polygon compactness and size are of equal importance in determining map accuracy, though he did not test this hypothesis experimentally.

4.7. Map accuracy assessment using line sampling

4.7.1. Introduction

A number of methods for estimating map accuracy have been reviewed above. A novel method of assessing map accuracy is now described and tested, based on line intersect sampling. Line intersect sampling has been applied to a number of forestry related problems including the assessment of logging waste (Warren and Olsen, 1964), the total length of roads and waterways (Matern, 1964) and forest fuel sampling (Van Wagner, 1968). Hildebrandt (1975; reported in De Vries, 1986) suggests line intersect sampling may be used for estimating the total length of border between different ecosystems.

Line intersect sampling is used to estimate the length of cover class boundaries on a map\(^3\) that coincide with the true boundaries of the cover classes on the ground. A ratio of coincident boundary to total boundary is proposed as a measure of map accuracy and this ratio is called the 'boundary error'. Though this technique has been developed for vector maps, it is equally applicable to raster maps.

As explained in 4.5, the conventional method of assessing map accuracy is to take a number of point samples, and to check whether the cover class predicted on the map being tested is the same as the actual cover class on the ground. Unfortunately the task of checking numerous point samples is extremely

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\(^1\)It was assumed that the coefficient of variation is a measure of polygonal precision - a reasonable assumption given that polygons are assumed to be homogeneous areas.

\(^2\)In other words, if the pixel resolution is larger than the ground unit resolution, variation within pixels will be larger. This has implications in selecting the appropriate remotely sensed data source for a given project.

\(^3\)The map may be generated from remotely sensed imagery, or from traditional cartographic methods such as aerial photograph interpretation.
time consuming. Instead line sampling is suggested: the advantages of this technique are that it is fast, cheap, and accurate compared with point sampling designs, for a given sampling cost.

A hypothesis that an estimate of total boundary length ($X_m$) obtained by line sampling equals the true boundary length ($X_m'$) was tested i.e.

$$\text{Ho: } X_m = X_m'$$

versus

$$\text{HA: } X_m \neq X_m'.$$

In addition, a hypothesis that an estimate of coincident boundary length ($X_r$) obtained by line sampling equals the true coincident boundary length ($X_r'$) was also tested i.e.

$$\text{Ho: } X_r = X_r'$$

versus

$$\text{HA: } X_r \neq X_r'.$$

If the above null hypotheses are correct, then the true boundary error ($X = X_r - X_m$) equals the estimated boundary error ($X' = X_r' - X_m'$).

4.7.2. Line intersect sampling theory

4.7.2.1. Introduction

It was assumed that a map showing cover classes is derived by conventional aerial photograph interpretation or satellite image analysis, and geometrically rectified to a cartographic projection. The cover classes have a fixed, unordered orientation.

Line transects are randomly placed onto the map, and a count is made of the number of times that the line transects intersect with the cover class boundaries. From this count, the length of boundary per unit area of map may be estimated (see 4.7.4 below).

4.7.2.2. Error bands

Experience with forest cover class maps has shown that boundaries between forest types are located on the map with some inaccuracy (Skidmore, 1989b) (see Chapter 8). Native forest types frequently exist along ecoclines (Whittaker, 1967). As the environmental conditions change (for example elevation, parent material, climate) the ability of a species to survive will be increased or decreased, and hence the composition of the forest will change. Thus there is a fuzziness introduced at the borders between cover types.

Another reason for inaccurate boundaries may be attributed to map lines having a finite thickness and hence an inherent 'width' that varies with the scale of the map (though the lines may be considered infinitely thin in some cases). Similarly a remotely sensed image will have boundary pixels that are a mixture of cover types, with the number of mixed pixels increasing as the pixel size becomes larger.

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1For example forest type classes or agricultural crop types
Boundaries will also vary due to operator error. Individuals will delineate boundaries slightly differently on the same aerial photographs. Transcribing forest type boundaries from aerial photographs to a cartographically correct map base will also involve operator error. Other errors may be associated with the physical medium used to 'store' the map (e.g. paper stretch and distortion) (Burrough, 1986). If map lines are digitized for input into a computer, the problem of spurious polygons may become important (Goodchild, 1978; Burrough, 1986) (see 4.9.3).

A boundary may be erroneous due to a cartographer smoothing a curve, in order to improve the aesthetic appearance of a map. That is, the smoothing on the map may not follow the true isolines on the ground (Chrisman, 1984).

Thus there is inherent uncertainty surrounding the physical depiction of map boundaries. The concept of epsilon distance developed by Perkal (1966) and Blakemore (1984) is used to describe the uncertainty associated with a map line. As stated in 4.6.2, Blakemore (1984) suggested a point can have five states in the vicinity of a polygon line, viz. definitely in, possibly in, ambiguous (i.e. on the line), possibly out and definitely out. Instead of the five states, it is suggested that only three states should be recognized, viz. definitely in, ambiguous and definitely out. The ambiguous class would be a merged class containing the possibly in, on-the-line and possibly out class. This is reasonable as the possibly in, on-the-line and possibly out categories are all ambiguous categories, with uncertainty as to the actual name which should be used to represent these categories.

4.7.2.3. Calculation of the boundary length and variance

The following formulae are taken from De Vries (1986).

The boundary length of polygons per unit area of the map can be estimated using the following formulae:

\[ \hat{X} = \frac{\pi \cdot m}{2L} \]

where

\( L \) = total length of the transect line(s)

\( m \) = the number of intersections of the transect line(s) with the polygon boundaries.

The estimated variance of the boundary length of polygons per unit area of the map is:

\[ \text{var} \hat{X} = \left( \frac{\pi}{2L} \right)^2 \cdot m \]

4.7.2.4. Number of samples

The estimated number of line samples (k) required to meet a prespecified precision can be calculated (after De Vries, 1986) as:

\[ \hat{k} = \left( \frac{0.975 \cdot \text{CV}(X)}{k \cdot \text{CV}(X)} \right)^2 \]

The value of \( \hat{k} \) that satisfies (6) is found as follows. Calculate
where the coefficient of variation is:

$$CV(X) = \frac{\hat{X}}{\hat{\text{var}}(X)}$$

and $E$ is the prespecified allowable error fraction.

The number of sample lines $n$ is found iteratively such that:

$$\frac{n}{\left( \frac{0.975}{t_{0.01}} \right)^2} < K$$

...(7)

Stauffer (1982) provides tables that detail $n$ for given values of $E$ and $CV(X)$.

4.7.3. Methods

4.7.3.1. Study area

The map of cover types generated from aerial photograph interpretation or image processing of remotely sensed data is geometrically rectified to a cartographically correct projection. An example of such generated boundaries are shown in Figure 4-7 for a hypothetical forest type map.

The error bands are represented as thick lines and describe the uncertainty associated with a line on a map. Error bands represent the maximum error introduced by a number of factors. For example, the geometric rectification of the image to the map projection being used may be ± 50 m (with a 95 per cent confidence), the ecotone width is less than 100 m for 95 per cent of the boundary lengths, and the map compilation error caused by operator errors and media distortion may be 30 m for 95 per cent of the boundary lengths. In this case, the error band should be approximately ± 180 m at scale of the map.

A map showing the true forest type boundaries overlaid onto the generated map is detailed as Figure 4-8. The true map has been used to calculate the actual (i.e. true) map accuracies.

---

1Note that the map has been reduced to permit inclusion in the thesis.
Figure 4-7: Hypothetical forest map.

Legend
•: pilot study transect line
<>: generated forest type boundaries
:—: true forest type boundaries
••••: incorrectly mapped strata

Figure 4-8: True location of forest types overlaid onto the generated map.
Note that when using the line transect sampling technique operationally, only the generated map would be available. Where the transect lines intersect with the generated map boundaries, the true boundaries would be located from air photographs or ground sampling, to ascertain whether the generated map boundaries coincide with the true map boundaries.

4.7.3.2. Pilot study

A pilot study was made to estimate the number of sample lines necessary to meet prespecified 95% confidence intervals. For the pilot study, one sampling line of length \( L = 12.5 \text{ cm} \) was randomly located on Figure 4-8. A length of 12.5 cm was chosen to obtain a sample of approximately 4 to 8 intersection points, thereby ensuring the variance of the pilot sample was not too high. The allowable error fraction (E) was set at 10 per cent.

The point of intersection of the true map boundary lines with the line samples were identified. If the true map line falls within the error bands of the generated map at the intersection with the line sample, then the true and generated map lines coincide (point 1 on Figure 4-8). If the true map line falls outside the error bands, the true and generated map lines do not coincide (point 2 on Figure 4-8).

In order to calculate the total length of boundaries per unit area of map, the total number of intersections of the line transect with the generated map boundaries are counted and notated as 'm'. If the true map boundary and generated error bands also coincide at this intersection point, the generated map boundary correctly intersects with the true map boundary. Such an intersection point is counted and notated as 'r'.

In practice, where the sampling line (L) intersects the error band on the generated map, a ground truth check would be made to determine whether the error band coincides with an actual boundary condition on the ground.

4.7.4. Results

4.7.4.1. Line sampling

Inspection of Figure 4-8 shows the pilot sample line intersects with \( m = 5 \) and \( r = 4 \) boundaries. Using equation (2), the total number of line samples necessary to obtain an estimate of boundary length per unit area within 95 per cent confidence intervals is obtained from tables prepared by Stauffer (1982).

Let

\[
\begin{align*}
L &= 12.5 \text{ cm} \\
 m &= 5 \\
 E &= 0.1
\end{align*}
\]

Therefore

\[
\begin{align*}
X &= 0.502 \\
 \text{var} \ X &= 0.063 \\
 \text{CV}(X) &= 0.125
\end{align*}
\]

From Stauffer (1982), the required number of transects is \( n = 9 \).
Note that \( r > m \), that is there are more line sample intersections with the true map boundaries than coincident true map and error band boundaries. Therefore, the nine transects lines can also be used to estimate the total boundary length of the generated map boundary at a confidence level of at least 95 per cent.

The nine transect lines were randomly distributed over the map and \( 'r' \) and \( 'm' \) were counted. The number of transect line intersections with the generated map boundaries was 43 (\( m = 43 \)). There were 28 points at which the true map boundary and generated error bands also coincided at these intersection points (\( r = 28 \)).

From these counts the estimated total length of generated boundary lines (\( X_m \)), and the estimated length of boundary line where the generated map boundary coincided with the true maps error bands (\( X_r \)) were calculated. The variance of \( X_r \) and \( X_m \) were also estimated.

\[
X_m = 0.600 \text{ cm cm}^{-2}
\]
\[
X_r = 0.390 \text{ cm cm}^{-2}
\]
\[
\text{var } X_m = 0.0084
\]
\[
\text{var } X_r = 0.0054
\]

A measure of map accuracy is the ratio of \( X_r \) to \( X_m \) i.e.

\[
X = \frac{X_r + X_m}{X_m} \times 100 = 65.1\%
\]

This ratio is interpreted below.

4.7.4.2. True boundary lengths

The true length of boundaries on the generated map (\( X_{m'} \)), and the true length of boundaries where the generated map and the true map coincided (\( X_{r'} \)) were directly measured using an electronic digitizer. The results were as follows:

Area of map = 260 cm\(^2\)

Length of true generated map boundary = 102.6 cm

Therefore \( X_{m'} = 0.394 \text{ cm cm}^{-2} \)

Length where maps are coincident = 160.0

Therefore \( X_{r'} = 0.615 \text{ cm cm}^{-2} \).

Thus \( X_t = X_{m'} + X_{r'} = 64\% \).

On inspection, the true lengths compared favourably with the sampling results. The research hypothesis of whether there was a significant difference between the true and estimated length of boundaries was tested, as discussed in the introduction (see 4.7.1). The confidence interval test was used, viz. reject \( H_0 \) and conclude there is a significant difference between the true and estimated length of boundaries if \( X_{m'} \) and \( X_{r'} \) occur outside the confidence intervals defined by

\[
X_m \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}
\]

and

\[
X_r \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}
\]

at \( \alpha' = 0.05 \).
Thus, the confidence limits for $X_m$ and $X_r$ at $\alpha' = 0.05$ and $n = 43$ (for $X_m$) and $n = 28$ (for $X_r$) are:

$$0.6 \pm 1.96 \left(0.092^{+6.56}_{-6.56}\right) = 0.6 \pm 0.0275$$

and

$$0.39 \pm 1.96 \left(0.074^{+5.29}_{-5.29}\right) = 0.39 \pm 0.0274$$

respectively.

As $X_r' = 0.615$, and $X_m' = 0.394$, we conclude that the estimated boundary length is not significantly different from the true boundary length at $\alpha' = 0.05$.

4.7.4.3. Area accuracy

Two strata were recognized on Figure 4-8, viz. correctly mapped and incorrectly mapped. The area of both strata were measured with an electronic digitizer. The total area of the map was 26 000 mm$^2$, and the area that was incorrectly mapped was 1 917 mm$^2$. The map accuracy by area was therefore 92.7 per cent.

4.7.5. Discussion

The true boundary lengths were not significantly different from the estimated boundary lengths sampled using line intersect sampling, with $\alpha' = 0.05$. The estimated boundary accuracy (64%) was extremely close to the true boundary accuracy (65.1%), and there was no significant difference between the true and estimated boundary accuracy.

Mapping accuracy expressed as boundary accuracy is a conservative measure of map accuracy: conservative because it measures coincident boundary length, and not the area of the map that is correctly classified. In other words, the boundary accuracy is a lower map accuracy estimate compared with an area accuracy statement, and would therefore give an increased probability that the map would not have an acceptable mapping accuracy (hence a conservative measure). However, accuracy estimates using the boundary length and area methods would be correlated: that is high accuracy calculated by boundary length would correlate with high accuracy by area estimates. Accuracy calculated by the two measures are not directly comparable. The disadvantage of the area map accuracy estimates is that it does not allow an estimate of how closely boundaries coincide.

Error bands are a successful mechanism for defining fuzziness or uncertainty around a polygonal boundary. It is reasonable that error bands were used to indicate the probable position of the generated line, within certain confidence limits.

A problem with line intersect sampling may occur with a map or image that has a systematic bias. For example, in landscapes such as the Allegheny Mountains of Pennsylvania, the ridge and valley lines run (approximately) parallel in a north-south direction. In such a case, a single sample line for estimating the number of line transects required to estimate boundary lengths, within specified confidence intervals, may give a biased result.

The advantages of the line intersect sampling technique are that it is fast, cheap, and simple compared with point sampling. Line transect sampling offers the possibility of yielding a higher
precision estimate of map accuracy for a given cost, as it is usually cheaper and simpler to traverse line transects using a compass bearing during ground truth operations, than identify numerous point sample locations in the field.

4.8. Complications in estimating accuracy in thematic data layers

4.8.1. Spatial resolution

A large grid cell will record smaller features of interest which fall within the large cell. A shortcoming with the accuracy assessment methods described in 4.5 and 4.6 is the assumption that the point (or pixel) being checked is either correctly or incorrectly classified (hence the overwhelming emphasis on the binomial distribution). However a pixel can be a mix of classes (or mixel) (Adomeit et al., 1981). For example, a cell can take the average value of elevation points occurring within it, a remote sensing device will average the radiometric response over the cell, or a cell may be represented by the largest class by area.

The ground resolution elements may vary over the scene at different scales. An agricultural field is more homogeneous than a native forest. Even within a forest, the heterogeneity of the forest types will vary considerably. For example, De Vries (1986) showed that tropical forest species vary from patches of pure species (Dipterocarps) through to individual trees (Ulin). It is assumed by the sampling techniques discussed in 4.5 and 4.6 that a constant sample unit size is used over the image or map being assessed for accuracy. The variability of ground resolution elements suggests that the sample unit size perhaps should be varied across strata to improve sampling efficiency.

4.8.2. Categorization of environmental gradients

For truly categorical data such as land tenure boundaries, a polygon will contain only one class if the boundary is correctly mapped. However, for classes which occur along a gradient, there may be great difficulty in deciding which class a given polygon or pixel should belong to. For example, two cover types may be recognized in an agricultural area, viz. cleared of trees or carrying a high proportion (by area) of trees. However, a gradient of tree cover may actually exist, with categories such as lightly timbered, moderately timbered etc. Definitions need to be made to characterize a pixel as being lightly timbered or moderately timbered, for example a lightly timbered pixel may have between 10 and 30 per cent of the pixel being covered by tree canopy, while moderately timbered pixel may have a cover of between 31 and 50 per cent. Such definitions are arbitrary, and the categories may have a large variation depending on the width of the class bands.

The classes on a map may be drawn with varying detail to reflect the different number of levels defined. For example, the agricultural area may be defined to consist of just two areas, viz., either cleared (0 to 40 per cent cover) or heavily timbered (40 to 80\(^1\) per cent covered in trees). The number of categories may be increased by reducing the percentile band width for each category. However, the

\(^{1}\)Note that at greater than 80 percent cover, the pixel may be defined as belonging to a forest class.
ludicrous end point would be an infinite number of 'classes' along the gradient of 0 to 100 per cent timber cover. The number of samples occurring in each class would be very low, so the confidence limits associated with the estimate of map accuracy would be wide (4.5). The problem of defining class names is discussed by Skidmore (1989b) (see Chapter 8) with reference to mixes of eucalypt forest species occurring along ecological gradients in southeast Australia. Whittaker (1967) discussed a number of ecological gradients, and their effect on species occurrence and growth.

The number of classes may be reduced by grouping the class types into broader categories. This grouping causes similar types previously confused in the error matrices to be generalized to one broad type name. Todd et al. (1980) and Skidmore (1989b) reported such an increase in forest mapping accuracy when forest type classes were aggregated.

4.8.3. 'Almost' correct map categories

Under the assumption of the binomial distribution, a class is either correctly classified or incorrectly classified. The reliance on the binomial distribution as the model for estimating map accuracy has excluded consideration of 'almost' correct classes. An 'almost' correct pixel may occur along an environmental gradient or in a mixed pixel. For example, using the example from 4.8.2, a pixel which has 32 per cent tree cover by area is very similar to a pixel with a 28 per cent cover, though the two pixels would fall in different classes due to the definition of a lightly timbered class having 10-30 per cent tree cover and a moderately timbered class having 30-50 per cent tree cover. Thus, a pixel may have been recorded in the error matrix as incorrect, when in fact the pixel being checked was 'almost' correct. Ideally, accuracy statements for an image should incorporate such 'almost' correct information.

The existence of 'almost correct' pixels has been acknowledged by Curran and Williamson (1985). They noted that when dealing with continuous variables, fewer than 50 samples per stratum\(^1\) may be required because a misclassified sample unit is likely to be classified into a similar class; in other words the misclassified pixel is almost correct.

4.8.4. Class names for unsupervised classification

Unsupervised classification\(^2\) of remotely sensed imagery is performed by a computer algorithm grouping the remotely sensed data into clusters based on spectral similarity (Turner, 1982), or a combination of textural and spectral similarity measures (Skidmore, 1989a) (see Chapter 5). After the spectral groups are formed, the analyst attempts to 'name' the spectral groups with appropriate cover types. However, the given name may not relate to the cover type being described by the class (Townshend and Justice, 1980). In addition, the given name may not be comparable between the various images produced by different algorithms. For example, the assignment of cover type names that would allow the classes formed by a nearest neighbour or spatial/nonparametric unsupervised classifiers to be quantitatively compared is obviously very difficult.

---

\(^1\)This is the suggested number of pixels per strata required to obtain a population estimate within 95 per cent confidence intervals (Hay, 1979).

\(^2\)See also 3.2.8.
Another problem is consistently defining the cover type on the ground or map. Band (1986) discussed the problem of quantitatively comparing algorithms which produced maps of ridge and stream networks from a digital elevation model, and concluded that objective criteria for the interpretation of streams and divides from the contour map must be first developed. To define what is a ridge, and what is a stream (or valley) on a contour map, would then allow an objective comparison of the different images produced by the algorithms modelling topographic position.

Roller and Visser (1980) pointed out that images classified using remotely sensed data may not be comparable with traditional forest cover type maps. Classes on the traditionally prepared maps may be drawn based on land use, rather than land cover. The remotely sensed classification may appear to be incorrectly identifying classes, when it is actually recognizing the components of the class.

4.8.5. Time lag between ground truth data and map

If the ground truth data and the map being tested for accuracy have a time lag, the conditions may have changed and an incorrectly classified sample may in fact be have been correctly classified at the time that the map was made. Adomeit et al. (1981) reported that this was an important source of error in a study of cover types on the south coast of N.S.W.

4.9. Error accumulation in GIS overlaying

4.9.1. Introduction

A number of maps of the same region (for example elevation, soils, ground cover and ownership) may be digitized and geographically rectified to a common projection in a GIS. Such maps may be stored as a series of layers in a GIS. Each point within a polygon, or each cell in a raster layer (where each raster-cell is assigned one value), takes the values of the layers directly above the point (Figure 4-9). Many questions may be asked about the point or cell, such as what is the slope or aspect at the point. In addition, an analyst may be interested in mapping areas with a slope greater than 30 degrees, with erodible soils, which occur on a southerly aspect. By overlaying the map layers, such simple queries may be answered. Overlaying vector data layers will create a large number of smaller polygons (McAlpine and Cook, 1971). For raster GISs, if the raster-cells in each layer are geographically referenced, then the number of cells in the overlay will not change.

GISs often contain nonspatial or text data which will contribute to error accumulation. Nonspatial data include knowledge or rules used by expert systems (see Chapter 8). The inaccuracies of polygon boundaries (4.7.2) and error in geometric rectification of data layers are also contributing factors to error accumulation when overlaying GIS data layers.

More complicated models have been developed to overlay and analyse map layers using Boolean and Bayesian logic, and arithmetic operators. These models have different effects on the way in which error is accumulated from each map layer into a final composite map. The various models are reviewed and their effect on error accumulation summarized.
4.9.2. Nonspatial data

Burrough (1986) claimed nonspatial data included attributes associated with a feature (for example a road may be linked with information including surface type or construction method). By definition, these data are associated with points or vectors in the GIS, so can be considered spatial.

Burrough (1986) also claimed nonspatial data included attributes of a polygon or cell which were, for example, averaged or counted over the polygon. Examples include number of supermarkets in a region of a city, number of farm buildings on a property, telephone lists for an area etc. Such data are associated with a region (polygon), but the actual location of the data is indefinite within the polygon. Data of this type can be considered to be homogeneous over a polygon, as at all points in the polygon the average or count is constant. Overlay operations become meaningless with such data when polygons are divided or segmented into smaller portions. The 'average' or 'count' within a smaller polygon created during overlay operations will change.

One method for analysing spatial data in a GIS uses an expert system approach based on Bayes' theorem (Skidmore, 1989b) (see Chapter 8). This type of analysis is described in detail in 4.10.5. An important data source is the knowledge obtained from experienced personnel (i.e. experts), which is used to define relationships modelled by the expert system. This 'knowledge' of the expert is then used to relate the evidence at the point to the hypothesis. This knowledge is truly nonspatial, as it is applied generally over the whole study area.

Nonspatial data used by expert systems will have error associated with them, but use of Bayesian probability theory allows an estimate of error accumulation to be made (4.9.4).
4.9.3. Geometric inaccuracies in overlaying

If the same polygonal boundaries occur on two (or more) maps, such as a local government boundary, the boundaries will not always coincide during overlaying. This is because digitizing introduces inherent errors and approximations to the boundary location. Overlaying such map boundaries will produce large numbers of small 'spurious' polygons (Goodchild, 1978). Goodchild (1978) showed that 75 percent of polygons were spurious when three layers of polygons were overlaid. Burrough (1986) pointed out that the spurious polygon phenomenon has two paradoxes. The first is that as the boundaries are more accurately digitized (i.e. line contains more digitized points) the number of spurious polygons increases. Secondly, subjective methods of map drawing (such as smoothing) designed to assist the map user, adds to the problem of trying to match boundaries when working with digital maps.

Methods for reducing or removing spurious polygons include removing one side of a spurious polygon after checking the polygon using a minimum area criteria (Burrough, 1986). An alternative strategy also suggested by Burrough (1986), is to consider all points within a given distance of the spurious polygon as estimates of the location of the new line, and then fit a new line by a polynomial or spline function.

4.9.4. Composite, Boolean and arithmetic overlaying

Composite overlaying is the simplest overlaying technique. Two (or more) layers are combined, and the raster location (or polygons formed) describe the union of the classes on the layers. The composite overlay is in effect a universal Boolean 'AND' operation over the whole map. That is, for a two layer data set comprising layer X and layer Y, we note \( X_i \cap Y_j \) (i.e. the intersection of X and Y for the n classes in map X and the m classes in map Y) at all points over the map.

Boolean operations may be used to specifically nominate a class (or classes) in one layer to be overlaid with a class (or classes) in another layer(s). The Boolean operators include 'AND', 'OR', 'NOT' and 'LOGICAL' (Mendenhall and Reinmuth, 1978). For example, we may wish to isolate those areas of a map which have a slope greater than 20 degrees and occur on erodible soils, but which are not on a northerly aspect. The Boolean operators to achieve this for three layers A, B, and C would be \( \{A_3 . \text{AND} . B_2 . \text{NOT} . C_4\} \), where A_3 are areas with a slope greater than 20 degrees, B_2 are areas with highly erodible soils, and C_4 are areas with a northerly aspect.

Arithmetic and mathematical operators that may be applied to two or more layers include addition, subtraction, multiplication, division, maximum, minimum, average, and exponent.

The method(s) by which error is accumulated during the overlaying process is important for modelling error in the final map products. The first necessity for modelling map error accumulation is to quantify the error in the individual layers being overlaid. As discussed above, there has been a lot of work expended on this problem, with some tangible results.

Newcomer and Szajgin (1984) used probability theory to calculate error accumulation through two map layers. Using their notation, the probability of an error occurring in layer 1 is \( P(E_1) \) and in
layer 2 is \(P(E_2')\), while the probability of layer 1 being correct is \(P(E_1)\) and layer 2 being correct is \(P(E_2)\).

Newcomer and Szajgin (1984) assumed that the two map layers were dependent; that is if we select a cell which is in error in layer 1 then that act reduces the probability of selecting an erroneous cell from layer 2. (Newcomer and Szajgin [1984] use the formulae \(P(E_1' \cap E_2') = P(E_1')P(E_2'|E_1')\)). If the data layers are independent, then an erroneous cell selected from layer 1, will not reduce the probability of selecting an incorrect cell from layer 2. The assumption of dependent layers by Newcomer and Szajgin (1984) is flawed, because if layers are truly related there is no benefit in combining the layers because additional information is not generated.

There are a number of other shortcomings with the approach of Newcomer and Szajgin (1984). Firstly, it was assumed the error rate is constant over the whole image: that is a pixel has a certain probability of being correct and a certain probability of being incorrect. This assumption ignores the differences in class mapping accuracies that typically occur over an image. For example, class X may be accurately mapped, but classes Y and Z are confused. Secondly, the probabilities are generated from samples, using the concept that the sample cell is either correctly or erroneously classified. There is no provision for incorporating the idea developed in 4.8.3 that a pixel can be almost correct. The third shortcoming of the approach is that it is limited to Boolean operators. Boolean operators create a new layer using the original layers. Using Boolean logic, \(A \text{ AND } B\) will create a third layer showing the locations where classes A and B coincide on the two layers, so if one (or both) of the cells are incorrect, the overlay layer will also be in error. In contrast, arithmetic operators compute a new value from the original layer values, and the new computed value may not be incorrect if the errors counteract each other. For example, expected revenues for sites of various productivity may be subtracted from transport costs to yield profit zones for growing coffee within a coffee growing region (Burrough, 1986). A potentially high revenue site that has expensive transport will yield the same profit as if the site was incorrectly labeled as a low revenue site with low cost transport.

Burrough (1986) discussed the modelling of error accumulation during GIS overlaying using statistics developed by Parratt (1961). It was assumed that each value in the GIS has a standard error \(\varepsilon\) associated with it that is random, independent and normally distributed. Then the value of an overlay cell \(u\) can be calculated from an arithmetic function

\[
u = f(x_1, x_2, x_3, ..., x_j),
\]

where \(x\) is the value in the jth layer. \(Su\), the standard deviation of \(u\) is calculated from:

\[
Su = \sqrt{\sum_{i=1}^{j} \left(\frac{\partial u}{\partial x_i}\right)^2 Sx_i^2}
\]

where \(Sx_i^2\) is the standard deviation of the xth term.

When the \(x_i\) terms are correlated, a correlation coefficient \(r_{XY}\) \((-1 \leq r_{XY} \leq 1\) is used to allow for the increase in error due to the correlation. Parratt (1961) described the correlation term only for a two layer case; obviously a measure of association can only be ascertained for two layers at one time. An
additional problem with using the 'Su' statistic is that standard deviation can not be calculated for ranked or categorical data (e.g. topographic position or soil type class).

Using the statistics of Parratt (1961) with empirical data, Burrough (1986) concluded from the above work that with two layers of continuous data, the addition operation is relatively unimportant in terms of error accumulation. The amount of error accumulated by the division and multiplication operations is much larger. The largest error accumulation occurs during subtraction operations. Correlated variables may have higher error accumulation rates compared with non-correlated data, because erroneous regions will tend to coincide, and concentrate error rates there (Burrough, 1986).

Burrough (1986) attempted to apply fuzzy set theory to error accumulation, following the reasoning of Salton and McGill (1983). Fuzzy set theory is a method of coping with uncertainty in mathematical decision making. The ideas of Salton and McGill (1983) are extended in 4.10 as a suitable method of mapping error accumulation through a GIS.

4.9.5. Bayesian overlaying

The use of Bayesian logic for GIS overlaying is explained in Skidmore (1989b) (see Chapter 8). As with Boolean, arithmetic and composite overlaying, there is inherent error in the individual data layers when overlaying using Bayesian logic. In addition, Bayesian overlaying uses rules to link the evidence to the hypotheses: the rules have an associated uncertainty and are an additional source of error.

4.10. Solutions for quantifying error accumulation

4.10.1. Introduction

A number of possible solutions are suggested for modelling accumulation of error in a GIS. These include reliability diagrams, a probabilistic approach, and a technique called cell similarity.

4.10.2. Reliability diagrams for each layer

Wright (1942) suggested that reliability diagrams should accompany all maps. Wright (1942) emphasized that the sources used to generate different regions of the map have varying accuracy, and these sources should be clearly stated on the map. For example, one region may have been mapped using low altitude aerial photography and controlled ground survey, and would therefore be more accurate than another region mapped using high altitude photography and only reconnaissance survey. This theme was taken up by Chrisman (1984) and MacEachren (1985), who suggested such a reliability diagram showing map pedigree should be included as an additional layer accompanying each map layer in a GIS. Chrisman (1984) further suggested that training area information and ground truth information obtained for supervised classification should also be included as layers to ensure potential error sources are retained for future checking. However, for the purposes of error accumulation modelling, reliability diagrams do not provide a quantitative statement about the accuracy (or error) of the map.

Kriging is a technique for interpolating values between irregularly spaced points (European Software Contractors, 1982; Lam, 1983; Burrough, 1986). It was developed by mining engineer D.G.
Kriging, to assist in interpolating between rock sample sites, but has also been used by soil scientists and hydrologists, to interpolate between sample points. The technique assumes that the distance between samples is related to the sample values: that is sample values are correlated and the dependence between sample values decreases with their distance apart. The Kriging technique is based on the 'semi-variogram', which is a plot of distance between sample points versus 'semi-variance' between the two samples calculated thus:

\[
\hat{\gamma}(h) = \frac{1}{2n} \sum_{i=1}^{n} (Z(x_i) - Z(x_i + h))^2
\]

where \( \gamma(h) \) = estimated variance at distance \( h \)
\( Z(x_i) \) = sample value at first sample \( x \)
\( Z(x_i + h) \) = sample value at second sample \( x \)
\( h \) = distance vector between first and second sample
\( n \) = total number of samples.

A semi-variogram has a number of characteristic features including the sill\(^1\), range\(^2\), nugget variance\(^3\) and spatially dependent structural variance\(^4\) (see Figure 4-10). A function is fitted to approximate the trend line between samples, and a theoretical trend line is shown in Figure 4-10.

![Semi-variogram Diagram](image)

**Figure 4-10**: An idealized semi-variogram showing sample points and the structural component. Note that lag(\( h \)) is the distance between samples expressed in multiples of distance \( h \), and \( \gamma(h) \) is the semi-variance.

Assuming that the samples from which the Kriging technique interpolates are correct, the spatial variance from the semi-variogram is used to weight the values of the nearest sample points according to

\(^1\)The sill is the maximum level of \( \gamma(h) \).
\(^2\)The range is the point on the x axis where \( \gamma(h) \) reaches a maximum. Points closer than the range are related, points further then the range are not (Curran, 1988).
\(^3\)Nugget variance represents the spatially independent variance (Curran, 1988).
\(^4\)Spatially dependent variance is the sill minus the nugget variance (Curran, 1988).
the distance the sample points are from the point to be interpolated. Thus a map of 'reliability' is
generated for the interpolated points, indicating the Kriging variance of the interpolated point.

Thus, given a set of irregularly spaced points, a regular grid can be interpolated, as well as the
'reliability' of the interpolated points. However, caution must be exercised in using the Kriging variance
map as a reliability map indicative of error. Interpolated points have a variance value calculated as a
weighted function of the distance from the nearest sample points, so this variance value represents
uncertainty in interpolation. The uncertainty in interpolation does not necessarily relate to error in
mapping, because the semi-variance does not model the error in a map layer.

The supervised nonparametric classifier described by Skidmore (1987) and Skidmore and Turner
(1988) classified remotely sensed digital data (see Chapter 6). The classifier outputs for all pixels a class
(i) and the empirical probability of correct classification for the ith class according to the training area
data. The value of the empirical probability of correct classification clearly differentiates classes which are
spectrally similar (low probability value) from classes which are spectrally discrete (high probability
value).

There may be difficulty in recognizing some cover types detailed on maps. This may be due to
multiple definitions of meanings associated with a cover type. An example cited in 4.8.4 was topographic
position maps detailing ridge, midslope and gully positions. Creating quantitative reliability maps for
such map layers is impossible, as there is uncertainty as to what cover type name the ground condition
should be given. Due to the variety of data types that may be geographically overlaid in a GIS (e.g.
continuous, categorical), a universal method of mapping error (or accuracy) for all points in a GIS
database has not been developed.

4.10.3. Modelling error accumulation

The few methods proposed for modelling error accumulation are limited in their application.
Working with ideal data, these methods do allow some conclusions to be drawn about error accumulation
during GIS overlay operations. However, the methods break down when used with map layers created
under different conditions than assumed by the methods.

Newcomer and Sjazgin (1984) used probability theory to model error accumulation. They defined
the probability of an error occurring in layer 1 at a cell as P(E1'), the probability of an error occurring in
layer 2 as P(E2'), the probability of no error occurring in layer 1 as P(E1), and the probability of no error
occurring in layer 2 as P(E2). However, Newcomer and Sjazgin (1984) incorrectly assumed the data layers
were dependent, as explained in 4.9.4. As this argument is flawed, let us instead assume the layers are
independent. Then the probability of error occurring in both layers 1 and 2 may be calculated as:

\[ P(E_1 \cap E_2') = P(E_1')P(E_2'). \]

The probability of error occurring in only one layer may be calculated as

\[ P(E_1' \cap E_2) = P(E_1')P(E_2) \]

and

\[ P(E_1 \cap E_2') = P(E_1)P(E_2). \]
The probability of no errors occurring in either layer is

\[ P(E_1 \cap E_2) = P(E_1)P(E_2) \]

or

\[ P(E_1 \cap E_2) = 1 - \left[ P(E_1)P(E_2') + P(E_1')P(E_2) + P(E_1')P(E_2') \right]. \]

This probabilistic approach may be used with specific error statements for a cell, or general accuracy statements for a class or layer. However, it is only suitable for composite and Boolean overlaying. The technique will not work with the Bayesian overlaying approach, as additional information is being input in the form of rules.

4.10.4. Modelling similarity of cells

Salton and McGill (1983) and Burrough (1986) developed theoretical ideas about the central concept. This is similar to supervised classification strategies in remote sensing. Their ideas are modified below to develop a universal approach for automatically generating an error map of an overlay.

A well-defined central point (such as a soils pit or a forest plot) is surrounded by a cloud of points that are not known with certainty (e.g., interpolated points). Let the 'central point' of the class from layer 1 at a cell (located at row i and column j in the map layer) be termed \( fA(i,j) \). In other words, \( fA(i,j) \) represents the known value of a class in layer 1 at cell \((i,j)\). Similarly, the central point of classes in the second (and subsequent) layers may be termed \( fB(i,j), fC(i,j), \ldots, fT(i,j) \), for T layers.

Some membership function \( DZ(i,j) \) can be developed for the known overlay result at cell \((i,j)\) with the dependent variables being the respective values of the T layers:

\[ DZ(i,j) = \langle fA(i,j), fB(i,j), fC(i,j), \ldots, fT(i,j) \rangle. \]

The Euclidean distance between two cells \( DZ(i,j) \) and \( U(i+1,j+1) \) may be calculated with respect to the T layers:

\[ d(DZ(i,j), U(i+1,j+1)) = \sqrt{\sum_{x=1}^{T} (fx(i,j) - fx(i+1,j+1))^2}. \]

The similarity of the \( DZ(i,j) \) cell to all other cells with the same dependent variable value \( U(i+1,j+1) \) in the overlay map may be calculated. A number of known cell locations with dependent variable value \( DZ(i,j) \) may be sampled and used to construct a cloud of known points belonging to \( DZ(i,j) \) in the T layers. The Euclidean distance from the known cell values to all other cells with the same dependent variable value in the overlay map may be calculated. The minimum Euclidean distance is used as a measure of similarity of cell \( U(i+1,j+1) \) to the known cell \( DZ(i,j) \) (Figure 4-11).
Other membership functions may be calculated at other known overlay results. That is $D_z(i,j)$ is calculated for $z=1, n$ known classes.

The euclidean distance between $D_z(i,j)$, for $z = 1, n$, and all other cells in the layer may be similarly calculated. The accuracy of cells in the overlay layer may then be ranked according to their similarity to the membership function $D_z(i,j)$.

Two potential difficulties are apparent with this method. The first is obtaining a representative sample of the known $D_z(i,j)$ cells. In remote sensing studies, a representative sample contains 30, and preferably greater than 50 points (4.5.2.2). The second difficulty is the different scales and data types of the various layers (axes). For example, a vegetation layer may contain 10 classes (i.e. a categorical data type), while an associated (geographically registered) layer may detail aspect ranging from 0 through 360 degrees (i.e. continuous data). However, by ranking the relative distances of the $U(i,j)$ cells from the $D_z(i,j)$ cells, the accuracy map would be scale independent, while still showing relative accuracy.

### 4.11. Conclusions

The errors inherent in raster and vector images have been well documented in the literature. Methods for summarizing the accuracy of raster and vector maps using point samples and error matrices are now widely used by the remote sensing community. The binomial distribution has been largely adopted as the parametric model to describe and test the error matrix statistics. However, standard techniques have not had universal acceptance for a number of reasons.

A plethora of methods have been proposed to estimate the number of points to sample in an image; from these methods there is a consensus that many sampling units increase the accuracy of the estimate of image correctness. A larger number of sampling units increases the confidence in the accuracy statement, but also raises the cost. Ginevan (1979) provided the most convincing and statistically sound arguments for calculating the number of sampling units required to achieve a given level of confidence in a map, using the binomial distribution theory. Ginevan (1979) included the error of rejecting an accurate
image as well as the error of accepting an inaccurate image in setting confidence limits for a statement of estimated accuracy. Thomas and Allcock (1984) developed a method for calculating confidence levels for an accuracy statement, given a certain number of sampling units. (This is an important result because the number of ground truth samples may be limited due to financial or labour constraints, but one still needs to know the confidence level of the estimate.) It is important images have an accuracy statement as well as a confidence limit for the accuracy statement.

A number of alternative sampling designs have been proposed for analysing the accuracy of imagery. The choice of a sampling design is often subject to the particular problems associated with the area to be ground truthed. However, a number of general trends are obvious from the literature. Firstly, random or stratified random sampling are acknowledged as methods that maximize precision and accuracy (albeit at a higher cost compared with cluster sampling or systematic sampling). It should be noted that in heterogeneous native forests (especially tropical forests), stratification is often too costly to consider. Cluster sampling offers reduced sampling costs, but is dependent upon low intracluster variance to be effective. Cluster sampling gives higher precision when performed over more homogeneous cover types (for example, agricultural fields are more homogeneous than forests). Precision will generally be lower using cluster sampling compared with simple random sampling (De Vries, 1986). Systematic sampling schemes may lead to bias in parameter estimation if periodic errors align with the sampling frame (for example as a result of image banding, or linear topographic features such as in the Allegheny Mountains of Pennsylvania).

The area of sampling units should be determined by offsetting intra-pixel variation against inter-pixel variation. As noted in 4.5.2.4, intra-pixel and inter-pixel variation may need to be weighted if one variance has a greater effect on mapping accuracy than another.

The aim during sampling is to maximize precision and accuracy for a given cost, or minimize cost for a given accuracy and precision. During all sampling, the sample parameters should be measured accurately.

It was noticed that relatively few methods of map accuracy assessment have been proposed for vector maps, so a novel method for assessing vector map accuracy was developed and tested, based on line intersect sampling. This technique may be also used for raster images.

GIS data layers contain numerous errors. A number of methods for analysing, overlaying and modelling GIS data have been proposed: each of these analysis techniques pose particular problems because they accumulate errors during the analysis process. Though modelling the accumulation of error during GIS overlay analysis is still in its infancy, two methods for measuring error accumulation during GIS analysis are discussed, and enhancements suggested.

Any procedure to reduce mapping error in individual layers in a GIS will improve the mapping accuracy of an overlay generated from the GIS. Until better error modelling techniques are developed for GIs, descriptive statistics should ideally be calculated for each layer in a GIS, as well as for each layer produced by a GIS. The descriptive statistics should include overall mapping accuracies as well as class mapping accuracies.
5. A NEW METHOD OF UNSUPERVISED TRAINING AREA SELECTION USING A NONPARAMETRIC DISTANCE MEASURE AND SPATIAL INFORMATION

5.1. Introduction

The delineation of training areas representative of a cover type is most effective when an image analyst has knowledge of the geography of a region, and experience with the spectral properties of the cover classes. In many parts of the world, including forested areas in Australia, this information is not available and creation of class spectral signatures to input into supervised classification strategies is difficult and time consuming, even if high quality ground truth reference sources are available (such as aerial photography and topographic maps). Manual delineation of training areas can be biased as only typical and homogeneous areas tend to be chosen to represent a cover type. As a consequence, the full spectral range of the cover type is not sampled. In remote areas the problems of accurately delineating training areas are compounded by difficulties with access for field checking.

Unsupervised clustering has been used to identify spectrally similar cover types (Townshend and Justice, 1980; Nelson, 1981; Kelly and Richards, 1984). However, results are generally less than satisfactory due to large homogeneous areas (such as wheat fields) being broken into subareas, giving the area a speckled appearance (Bryant, 1979). (Note that if a classification strategy invokes an unsupervised clustering to generate statistics which are subsequently input to a supervised classifier [e.g. Beaubien, 1979; Townshend and Justice, 1980; Walsh, 1980], the segmentation of large homogeneous fields may be desirable.) Other objections to unsupervised clustering are that it does not provide any more detailed information than can be obtained by visual interpretation of colour composite images (Howard, 1976), and that there is no provision for the introduction of a priori probabilities (Richards, 1986).

Unsupervised clustering does not utilize information on the spatial relationships of pixels. The principal techniques for quantitatively describing spatial relationships are context and textural measures based upon tone and texture. Context is the spatial position of a pixel (or group of pixels) with respect to the pixels or classes in the remainder of the scene (Townshend and Justice, 1980; Gurney, 1981). Haralick (1979) describes tone as a region of connected picture elements (pixels) exhibiting a similar spectral property (i.e. average, maximum or minimum tone), and texture as a description of the spatial organization of the tonal regions. Zucker (1976) views texture as a global pattern arising from the repetition, either deterministically or randomly, of local subpatterns. Statistical and structural approaches for the analysis of texture are reviewed by Haralick (1979), Van Gool et al. (1985) and Swain (1985). A

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2Techniques which incorporate spatial as well as spectral information have been termed 'per field' techniques (Lillesand, 1987). Algorithms which consider only spectral information have been termed 'per point' techniques (Lillesand, 1987).
statistical approach uses the individual grey tones (i.e. density number [DN] values for pixels) in an
image to describe texture, whilst a structural approach groups the grey tones into a number of composite
building blocks, and it is these building blocks that are used to describe texture (Haralick, 1979; Harris,
1980).

There have been attempts to use semi-variograms (see 4.10.2 for a description of
semi-variograms) in remote sensing to study the relationship between how far pixels are apart and
similarity of their spectral responses (Curran, 1988; Woodcock et al., 1988a and 1988b). These authors
showed such a relationships exists. Woodcock et al. (1988a and 1988b) concluded that semi-variograms
are useful for understanding the spatial variation in images: they showed the height of the sill (Figure
4-10) is related to the density of the objects\(^1\), the range of influence is related to the size of objects, and
that increased variance in in the size distributions of the objects is related to a more rounded shape in the
variogram near the sill. Increased pixel size causes a decrease in the height of the sill and an increase in
the 'range' of influence. Curran (1988) discussed the use of the semivariogram for designing ground
sampling schemes for map accuracy assessment, as well as for selecting a suitable image spatial
resolution for particular ground cover types.

Duda and Hart (1973) discuss the concept of 'region analysis', in which a digital image is
partitioned into disjoint regions. The criteria for partitioning is the maximum of the ratio of the common
length of two adjacent regions to the perimeters of the two regions; if this ratio is less than a predefined
threshold the two regions are merged into one. Such an approach does not utilize the spectral information
of remotely sensed data.

Davis and Mitiche (1980) describe the classical textural approach to edge detection, where the
difference in brightness value between adjacent pixels defines an edge, if it is greater than a predetermined
threshold. Rosenfeld (1981) outlines methods of edge detection, but notes that regions of similar tone
may not be discriminated from the defined edges, as the edges have gaps due to blur and noise. Townshend
and Justice (1981) point out that such gaps, which break a regional boundary, need to be closed by some
textural process. The method proposed here defines areas of similar tone using an algorithm based upon
textural properties.

Haralick (1980) argues that edge detection and region growing are essentially the same problem,
where region growing is the process of defining areas of similar grey tone values. He proposes a
theoretical 'slope facet' model that determines whether an edge exists between two regions. A slope is
fitted to each region using a least squares procedure. The difference between the values predicted by the
least square procedure and the original values in the region is used to compute a F statistic. The F statistic
tests a null hypothesis that there is not an edge between the two regions. This idea was not tested with
remotely sensed digital data.

Strahler et al. (1980) and Franklin et al. (1986) use a method of combining spectral and spatial
information involving the manual aggregation of classes which are spatially continuous as well as
spectrally similar. The disadvantage with this approach is the cost of an analyst's time.

\(^{1}\)An object is a discernible feature on the imagery, such as a tree.
Spatial information has been automatically linked with spectral classification algorithms in an attempt to weight spectrally similar pixels according to their spatial relationships (Kauth et al., 1977; Bryant, 1979; Landgrebe, 1980; Thomas, 1980; Gurney, 1981; Merembeck, 1982; Richards et al., 1982, Gordon and Philipson, 1986; He and Wang, 1987). The introduction of such spatial information appears to improve mapping accuracy, but may not effectively delineate regions bounding pixels of similar tone. For example, the method proposed by Kauth et al. (1977) breaks large areas of homogeneous tone into smaller multiple areas as a result of a distance weighting factor1. Thomas (1980), Gurney (1981), Irons and Petersen (1981), Landgrebe (1980), Richards et al. (1982), Saxon (1984), Strahler and Li (1984) and Gordon and Philipson (1986) use moving window techniques. For example, properties such as mean, variance, skewness, and kurtosis of grey levels within the moving window, or mean and maximum grey level differences between adjacent windows were calculated. Milgram (1979) lists a number of objections to moving windows. Firstly, where no object (i.e. cover type boundary) is present in the window, noise may produce probable 'objects'. Second, if more than one object is present in the window, then a single threshold will not suffice. Milgram (1979) goes on to propose a method which compares the result of multiple thresholding (i.e. level-slicing a binary image) with edge detection, thus isolating real objects from noise. Irons and Petersen (1981) found moving window transformations generally useful for edge detection and image enhancement, though moving window transformations were not useful as features for the thematic mapping of terrain categories.

Moving window techniques may be less effective in delineating irregularly shaped regions, such as along narrow meandering river valleys. A minimum number of adjacent pixels belonging to a class must occur within the window in order for the class to be preserved. For example, Bryant (1979) utilizes a contextual correction after a clustering algorithm, by declassifying any pixel which is unlike at least two of its (eight nearest) neighbours. The declassified pixels are then reclassified to the neighbouring pixel class if they fall within a rejection distance threshold. The technique developed by Bryant (1979) has been called AMEBA, and has been tested over agricultural areas with flat terrain and large homogeneous fields. The assumptions of the AMEBA technique make it unsuitable for forest inventory (Strahler, 1981).

Gurney (1981) also uses a moving window technique in a similar manner to Bryant (1979). Gurney (1981) firstly classifies an image into two classes (urban and non-urban) using a parallelepipiped classifier, and then changes any non-urban pixels to urban if a predetermined number of pixels in a moving window are urban. To avoid commission errors, urban areas of less than a predetermined number of pixels within a window were changed to non-urban. Gurney's (1981) contextual approach is based on the presumption that the outskirts of urban areas have low density housing which would tend to be misclassified as rural, and that farm houses and outbuildings in rural areas would be classified as urban.

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1This method has been termed the 'BLOB' technique by Kauth et al. (1977) and has been widely used in forestry applications (for example Cicone et al., 1977; Lyons, 1984). The BLOB technique includes x and y (line and sample) coordinate positions as an additional channel to the spectral channels. Intercluster distance is used to classify pixels; the user specifies weights for the spatial and spectral contribution to the intercluster distance. If the spectral component is given a low weight, the spatial channels are emphasized. This would increase the number of clusters, as spatially distant clusters must have very similar spectral characteristics to belong to the same cluster.
The utility of this approach in forested country with many cover classes may be limited. Firstly, the parallelepiped classifier has been shown to be extremely poor for discriminating age classes within a pine plantation (Skidmore et al., 1988). Secondly, the order in which the cover classes are smoothed, and the threshold number of pixels in the moving window would be difficult to elucidate.

Thomas (1980) applies a spatial correction to an image also classified by a parallelepiped algorithm. This technique reclassifies a central pixel (from a 3 by 3 moving window matrix) into another class if the central pixel has a high proximity to the other class. The proximity measure is based upon arbitrary weightings for the classes and the distance the pixels are apart (i.e. for Landsat data either 79 m or 59 m). Deciding upon the appropriate weightings for each class may be difficult. The algorithm proposed in this paper avoids the problems associated with moving windows and defining thresholds or weighting factors for classes. In addition, the algorithm processes the image in one pass, thereby not requiring the input of a pre-classified image which may be of a poor quality for the proposed use.

A feature of some spectral-spatial classification strategies is the use of 'least-squares' to calculate the covariance matrices and euclidean distances used for parametrizing the spectral clusters and measuring distance in multispectral space. A problem with the least-squares statistic used in covariance matrices is that the spectral group data are assumed to be normally distributed and independent. Inspection of histograms show the groups are frequently not normal and there is ample evidence that there is correlation between adjacent pixels (Kettig and Landgrebe, 1976). If data distributions are radiometrically transformed (e.g. histogram equalization), different covariance matrices and euclidean distances (or distances obtained by any other metric such as the Canberra metric) will be created and different thematic maps produced. A final problem with the use of the least-squares statistic in image classification is that pixels distant in multispectral space are over-emphasized as a result of squaring the difference between the distant pixel and the mean. A segmentation of a ground cover class into smaller components may result. The use of a nonparametric distance measure based on ordered statistics as described below avoids these problems.

Haralick (1979) describes the use of co-occurrence matrices to calculate seven common textural features, and reports high classification results (82 to 89 per cent mapping accuracies) using these features. In a combined spectral-spatial approach, He and Wang (1987) added two textural features (obtained from co-occurrence matrices using the methods described by Haralick, 1979) to six Landsat TM channels (or features) prior to attempting an unsupervised classification, and claim an improvement in classification accuracy, though a quantitative mapping accuracy was not attempted. A disadvantage with the co-occurrence matrix approach is that the co-occurrence probabilities are based on one spatial distance (i.e. one pixel), and that textural relationships between distant pixels are not considered (Haralick, 1979). The proposed algorithm assumes pixels may form a reasonably homogeneous region of tone regardless of the distance the pixels are apart.

Thus the aim of this chapter is to describe a new unsupervised technique that automatically delineates areas with a similar tone, for remotely sensed data comprised of multiple features.
5.2. Conceptual overview of the algorithm

An algorithm is proposed which automatically isolates areas with a homogeneous tone. According to the definitions proposed by Townshend and Justice (1981), the proposed algorithm is a 'context-free, tone-texture classifier'. The algorithm combines a nonparametric distance measure (based on ordered statistics) with a region-growing process (to include spatial proximity information).

A seed pixel is initially selected from the image. This seed pixel defines a spectral value in each feature (or spectral band) around which a spectral range is constructed using a nonparametric distance measure. A parallelepiped shaped decision volume is thus defined around the seed pixel. Pixels spatially adjacent to the seed pixel are tested for spectral similarity with the seed pixel using the parallelepiped shaped decision volume. If the adjacent pixels occur within the decision volume, they are assigned to the same class as the seed pixel, and form a new boundary for the region. In this way a region of similar tone is delineated by growing the region until it is surrounded by pixels which do not occur within the decision volume. At this stage a new seed pixel is selected and the algorithm is repeated, until all pixels are assigned to a class.

This algorithm differs from other reported unsupervised techniques in two ways. It firstly uses an ordered statistic to define the spectral ranges of the decision volume. The spatial distance in each feature or spectral channel is not fixed, but varies according to the frequency distribution of the feature and the position of the seed pixel in the frequency distribution. The nonparametric distance is independent of any radiometric transformations. The second difference is that information on the spectral adjacency of pixels is used to delineate regions around the seed pixel, resulting in homogeneous cover classes (or training areas) being formed.

The purpose of the classifier is to delineate areas of similar tone which correspond to a cover class type, and to use these areas to train a supervised classifier.

5.3. Construction of the algorithm

Let \( B_p(i,j) \) be the brightness at point \( i,j \) (where \( i \) is the row position and \( j \) is the column position) for spectral channel (or feature) \( p \) (\( p=1,2,\ldots,n \); where \( n \) is the number of channels).

Let \( P_{ij}(B_p) \) be a ranking of the brightness values (or digital numbers [DN]) for feature \( p \),
\[
P_{ij}(B_p) = (B_p(i-u,j-v) \mid u =1,N_i ; v =1,N_j),
\]
where \( N_i \) is the total number of rows and \( N_j \) is the total number of columns. The total number of pixels in the image is \( T = N_i \times N_j \).

The median is defined as \( M(i,j) = \beta \), where \( P_{ij}(\beta) = 0.5 \).

Any range of brightness values can be defined. A conventional measure is the interquartile distance (Q), defined as:
\[
Q_p(i,j) = \beta - \sigma, \text{ where } P_{ij}(\beta) = 0.75 \text{ and } P_{ij}(\sigma) = 0.25.
\]
Similarly any other distance can be defined.
Given a 'seed' pixel $B_p(i,j)$ located at position $i=1, j=1$, which is defined to be a member of class $m$ (where $m=1, 2, \ldots, z$ classes), a decision rule can be applied to adjacent pixels to test whether they are spectrally similar to $B_p(i,j)$. The similarity is defined by a nonparametric distance measure, in this case the interquartile distance. Let $B_p(i,j+1)$ be the brightness of an adjacent pixel. Now if the following decision rule:

$$P_{ij}(B_p) - Q_{ij}(i,j) < B_{p(i,j+1)} < P_{ij}(B_p) + Q_{ij}(i,j) \quad \text{for all } p,$$

is true, then $C(i,j) = C(i,j+1) = m$, where $C(i,j)$ is the classification of $B_p(i,j)$ to class $m=1$ at point $(i,j)$. Note that if $P_{ij}(B_p)-Q_{ij}(i,j) < 0$, then let $P_{ij}(B_p)-Q_{ij}(i,j) = 0$. Similarly if $P_{ij}(B_p)+Q_{ij}(i,j) > \text{(maximum value of all } B_p(i,j)}$, then let $P_{ij}(B_p)+Q_{ij}(i,j) = \text{(maximum value of all } B_p(i,j)}$.

The decision rule is similarly applied to all adjacent pixels in order to create a connected region which exhibits the same spectral characteristics as defined by the decision rule (2). Adjacent pixels are tested in a repetitive pattern. The search pattern examines all pixels in a horizontal direction (first right and then left from $B_p(i,j)$) for membership of class $m=1$. If an adjacent pixel is a member of class $m=1$ (as defined by decision rule (2)) it is assigned to class $m=1$. The pixels above and below this pixel are tested by the decision rule (2) and if either (or both) belong to class $m=1$, they are written to a temporary array. This process is continued until both horizontal directions (to the left and right of the seed pixel) are surrounded by (two) pixels which are not members of class $m=1$.

The algorithm then steps vertically down one pixel to $B_p(i+1,j)$ and searches horizontally for member pixels as described above. Again, any pixels above or below the horizontal line which are a member of class $m=1$ are written to the temporary array; however the same pixel is not written twice to the temporary array, nor is it written to the temporary array if the pixel is already assigned to class $m=1$. This process is continued until the region being formed is surrounded (below) by pixels not belonging to class $m=1$.

The algorithm then moves vertically up one pixel from the original starting pixel ($B_p(i-1,j)$) and again proceeds in a horizontal search pattern as detailed above. This process is continued until the patch is surrounded above by pixels not belonging to class $m=1$.

Once the patch is surrounded by nonmember pixels, the algorithm treats each pixel stored in the temporary array as a starting pixel from which to search for additional members of class $m=1$. The frequently occurring situation as depicted in Figure 5-1, necessitates the use of the temporary array. The temporary array pixel ('T' in Figure 5-1) acts as a 'bridge' between the members of class $m=1$ ('X' in Figure 5-1) and the unclassified pixels which belong to class $m=1$ ('1' in Figure 5-1). Note that blank cells in Figure 5-1 are not members of class $m=1$. The total number of pixels in region 1 is $T_1$. Region 1 is a region of homogeneous tone as defined by the nonparametric distance measure.

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Equation (1) may also be expressed as:

$$P_{ij}(B_p) = \Pr(B_p(k,l) < B_p(i,j)), \quad \text{where } (k,l) \text{ run over all pixels in the image}$$

Equation (2) may also be expressed for an interquartile distance as:

$$|P_{ij}(B_p) - P_{ij+1}(B_p)| \leq 0.25,$$

or for any other distance.
Figure 5-1: The temporary array stores pixel \( T \) which bridges between members of class \( m=1 \) (X) and unclassified pixels which also belong to class \( m=1 \) (1).

A pixel which has not yet been assigned to a class is selected at another point \( B_p(i,j) \) and defined to be a member of a different class; for example class \( m=2 \) (thus let \( C(i,j)=2 \)). The new seed pixel \( B_p(i,j) \) is located at the minimum of \( (i,j) \), where \( (i,j) \) cannot be a pixel location already classified as \( m=1 \). All pixels adjacent to region 2 are tested for membership of class \( m=2 \) by equation (2).

The process can be continued until all pixels are allocated to a class \( (m=1,2,\ldots,z) \). Note that if a patch has the same tonal properties as a preceding patch, it is assigned to the same class as the preceding patch (even though the regions are not connected).

If a pixel \( B_p(i,j) \) is classified as two classes (i.e. at a mixed pixel boundary between two classes), it is assigned to the class with the larger number of pixels (i.e. \( B_p(i,j) \) is assigned to class \( m \) if \( T_m > T_{m+1} \)).

5.4. Testing the algorithm

The algorithm was tested using a three channel (or feature) SPOT XS scene centred over Canberra, Australian Capital Territory, Australia, and obtained during 1986 as part of the PEPS investigation (Turner et al., 1989). A subscene of 150 by 150 pixels (3 by 3 km) was selected to include a portion of the Stromlo radiata pine plantations (Pinus radiata) west of Canberra. The plantations comprise even-aged stands, planted between 1928 and 1986, of similar spectral properties (Turner et al., 1989). The plantation is surrounded by grassland to the north and west, and by suburbs to the south. Available ground truth material included 1:10 000 black and white aerial photography and a forest compartment map showing the boundaries of the even-aged stands (Figure 5-2 is the 3 by 3 km subscene annotated from the forest compartment map).
The algorithm was executed using an interquartile distance (i.e. $P_{ij}(\beta)=0.75$ and $P_{ij}(\delta)=0.25$) and another distance of $P_{ij}(\beta)=0.66$ and $P_{ij}(\delta)=0.33$. In order to compare the effectiveness of the proposed algorithm for delineating training areas, a minimum euclidean distance clustering algorithm (Turner, 1982) was tested on the same data set with the number of clusters set to 10 and initial critical distances of 5 and 10. A moving window texture based algorithm (Borden, 1982) which assigns the maximum euclidean distance between (four or nine) adjacent pixels and the central pixel, to the central pixel, was also applied to the same subscene.

The three methods were executed on the VAX-cluster at the Australian National University Computer Services Centre. The ORSER package (Turner et al., 1982) contained the texture based (UMAP) and clustering (CLUS) algorithms. The proposed algorithm made use of the SPIRAL GIS system (Myers, 1986) for data storage and input/output operations. The UNIRAS (European Software Contractors, 1982) and MAP (Tomlin, 1987b) packages were used to drive Tektronix graphics hardware.
5.5. Results

The thematic images obtained using the two nonparametric distance measures are shown in Figures 5-3 and 5-4 respectively. As would be expected, the larger distance ($P_{ij}(\theta)=0.33$) led to fewer patches containing a greater number of pixels compared with the interquartile distance ($P_{ij}(\theta)=0.25$), due to the interquartile distance having a narrower spectral range in each feature. The number of classes generated by the proposed algorithm exceeded the fourteen colours available for display. Thus, only the largest classes were displayed.

Both Figures 5-3 and 5-4 are characterized by having relatively large and homogeneous areas corresponding to the ground cover classes. In contrast, the clustering algorithm developed by Turner (1982) resulted in a more heterogeneous pattern from which class boundaries could not be easily ascertained for the two different clustering distances viz. 5.0 and 20.0 units (see Figures 5-5 and 5-6 respectively).

The texture based algorithm did indicate some uniform areas, but as can be seen from Figure 5-7, the result was very heterogeneous. An area of uniform colour in Figure 5-7 indicates a similar maximum euclidean distance occurs between pixels.

---

1Note that Figures 5-3 through 5-7 are images that represent an area of 3 by 3 km.
Figure 5-3: Thematic image produced by the proposed algorithm at distance $P_{ij}(d)=0.33$

Figure 5-4: Thematic image produced by the proposed algorithm at distance $P_{ij}(d)=0.25$

Figure 5-5: Thematic image produced by a clustering algorithm, distance set at 5 units

Figure 5-6: Thematic image produced by a clustering algorithm, distance set at 10 units

Figure 5-7: Thematic image produced by a moving window texture based algorithm
5.6. Discussion

By inspection of Figure 5-2 it can be seen that the pine forest forms a distinctive area in the northeast triangle of the subscene. The pine forest contains clearfelled areas and recently established pines (planted 1982-1986), a large block of 1972 pine and a number of other compartments planted between 1940 and 1970. The other distinctive features on the subscene are the Molonglo River Valley which form a sharp right angle bend and areas of grassland. Roads can also be seen on Figure 5-2.

The algorithm proved effective in delineating established pine forest from other land covers when a large nonparametric distance was used \((P_{ij}(\delta) = 0.33, \text{ Figure 5-3})\). At this nonparametric distance, recently established pine was also distinguished from the other cover types. The smaller interquartile distance \((P_{ij}(\delta)=0.25)\) clearly delineated pine forest and was effective in subdividing the pine forest into its component age classes (Figure 5-4). Comparing Figure 5-4 with Figure 5-2 shows that the recently established pine areas, the 1970 to 1979 age class, the 1950 to 1959 age classes and the 1940 to 1949 age class are delineated as separate areas. There was some confusion within the 1940-1949 age class and inspection of the aerial photographs showed this was related to differences in stocking. Within the grassland class there was differentiation related to topography and grazing patterns. Thus in order to obtain finer segmentation of a cover class a smaller nonparametric distance must be used. Alternatively, for mapping principal cover types (for example agriculture, forest, water, rock) a large nonparametric distance is selected. As the nonparametric distance becomes smaller, the areal extent of individual patches decreases due to narrower spectral ranges in the decision volume. At very small distances, textural measures (i.e. the pattern of tone across the image) based on a structural approach (Haralick, 1979) would become important.

It is obvious from Figures 5-3 and 5-4 that the homogeneous classes delineated by the proposed classifier relate to real cover classes. In contrast, the minimum euclidean distance clustering classifier (Figure 5-5) did not delineate the 1970-1979 or the 1980-1985 age classes. The clustering classifier also merged the recently clearfelled and young pine into one class as well as classifying the Molonglo River's poplar-lined banks into the same class as young pine. The 1950-1959 and 1940-1949 age classes were treated as one class. The main differences between the two clustering distances (Figures 5-5 and 5-6) were that the smaller distance resulted in more unclassified pixels and the class areas were smaller in areal extent.

The texture-based classifier (Figure 5-7) (Borden, 1982) emphasizes edges between areas with a sharp contrast in brightness, for example rivers and roads. Cover types were poorly differentiated by the texture-based classifier, compared with the proposed classifier. This is due to the texture-based classifier considering the difference in brightness between adjacent pixels, whereas the proposed classifier uses the similarity in brightness.

Overall the proposed classifier (Figures 5-3 and 5-4) delineated the large homogeneous areas of even-aged pine and grassland more effectively than the other two methods tested, because spatial information on the adjacency of similar pixels was included during the formation of each class.
The seed pixel location for each class may affect the position of the class in the classified image, though the algorithm as implemented is simple and robust. An alternative strategy would be to randomly select from the image the seed pixel location for each class.

The computational requirements were similar for the clustering and texture based methods, though the proposed method took approximately double the cpu time for 22 500 pixels. Testing the algorithm with larger data sets indicated that the cpu requirements for the algorithm increase as the square of the number of pixels, due to the region-growing component of the algorithm. The other algorithms' cpu requirements increased at a rate slightly faster than linearly (possibly n.log(n), where n is the number of pixels).

It was debated whether mapping accuracies should be calculated using one of the numerous techniques proposed during the last 10 years (see Chapter 4 for details). To quantify the mapping accuracy of an unsupervised thematic image, a name must be given by the analyst to a class (or colour on the image). The given name may not relate to the cover type being described by the class (Townshend and Justice, 1980). In addition, the given name may not be comparable between the various images produced by different methods. For example, the assignment of cover type names that would allow the classes in Figures 5-3 and 5-5 to be quantitatively compared is obviously very difficult. Thus, it is possible to quantitatively assess the accuracy of unsupervised classifications, though it is not feasible to undertake quantitative comparative studies. For these reasons, mapping accuracies were not calculated.

5.7. Conclusions

A new technique combining spectral and spatial image attributes has been developed and implemented, that automatically delineates areas with a similar tone. The proposed algorithm 'grows' a region of homogeneous tone around a seed pixel; membership criteria for the region are based upon a nonparametric distance measure. The thematic image output can be used to define training areas for a supervised classifier and offers an alternative method for aiding in the selection of training areas. Images produced by uniform texture mapping and clustering were compared with the proposed algorithm using SPOT XS data collected over a multiaged forest plantation in south east Australia. The proposed algorithm yields a superior thematic image for the purpose of delineating training areas. The algorithm may alternatively be used as an unsupervised classifier. The algorithm was also successfully used to locate training areas in a native eucalypt forest of south east Australia, when tested with Landsat TM imagery (see Chapter 8 for details).
6. FOREST MAPPING ACCURACIES ARE IMPROVED USING A SUPERVISED NONPARAMETRIC CLASSIFIER

6.1. Introduction

In Chapter 3, reasons were outlined for the apparent reluctance of foresters to embrace remotely sensed data for operational use, with the major reasons cited being imagery of poor spatial resolution, and resultant maps having poor accuracy (Turner et al., 1989; Skidmore et al., 1987). Though spatial resolution is improving with the new generation of satellites such as SPOT, forest cover mapping accuracies using conventional classifiers have been generally low (typically less than 80 per cent mapping accuracy at 90 per cent confidence levels), especially where forest types are discriminated at Anderson et al. (1976) level III (e.g. Strahler et al., 1978; Merola et al., 1983; Hame, 1984). Only a few examples of high mapping accuracies have been reported. Nelson (1981) cited accuracies of 79 to 88 per cent, but only discriminated hardwood from conifer and grassland. Walsh (1980) claimed mapping accuracies of 88 per cent (ranging from 85 to 95 per cent per strata). However, at each random point within a strata, Walsh (1980) included the 25 (5 by 5) surrounding pixels into his calculation. This may have artificially increased mapping accuracy, as Kettig and Landgrebe (1976) showed that adjacent pixels are autocorrelated.

Classification strategies may be categorized into supervised or unsupervised methods (see Chapter 3). Both methods assume that the image data form separate groups in N-dimensional feature space (where N-dimensional feature space refers to the space created when N channels [or features] of data are each placed on an orthogonal axis) and these groups can be associated with observed ground cover types. The groups of data can be described by parametric or nonparametric techniques. Parametric classification strategies assume that each group can be enclosed by a boundary, such as defined by the hyper-ellipsoid shaped decision volume of the maximum likelihood classifier (Swain and Davis, 1978; Richards, 1986). Nonparametric classifiers make no assumptions about the shape of the data distributions, except that the groups of data can be separated by some discriminant function (Nilsson, 1965) such as the linear regression functions derived from logit modelling (Strahler et al., 1980; Maynard and Strahler, 1981) or decision trees such as the piecewise linear classifier developed by Lee and Richards (1985).

To improve the accuracy of forest maps derived from remotely sensed data, supervised and unsupervised techniques have been combined. One methodology involves delineating training areas

1This Chapter has been published as:
containing representative cover classes; the training area data are then clustered using an unsupervised strategy (Fleming, 1975; Beaubien, 1979; La Perriere et al., 1980; Thompson et al., 1980; Walsh, 1980). The unsupervised cluster strategy may produce a thematic map directly, or the algorithm can generate statistics which are input into a supervised parametric classifier. Another method to improve mapping accuracies is to include data ancillary to the remotely sensed data (Strahler et al., 1978; Tom and Miller, 1980; Hutchinson, 1982; Cibula and Nyquist, 1987). Hutchinson (1982) discussed the three methods of combining spectral data with other ancillary data viz., stratifying an image prior to classification; incorporating the ancillary data during the classification operation; and post-classification, where a classified image is modified by the ancillary data. These techniques use conventional parametric and nonparametric approaches for the classification of the data, and aim to improve map accuracy through the inclusion of additional input data. The proposed nonparametric classifier does not incorporate any additional information in order to improve mapping accuracies.

Skidmore et al. (1988) showed that (forest plantation) cover classes could not be successfully mapped from Landsat MSS data using parallelepiped or euclidean distance classifiers. Using a general nonparametric test, they quantified the co-occurrence (or spectral overlap) of training set data distributions at each vector point in N-dimensional feature space for a number of forest plantation spectral classes. The main conclusion was that training area data from some plantation age classes were not co-occurring in N-dimensional feature space, even though the classification strategies could not separate these classes. This apparent contradiction was explained by the observation that the distributions of training area data in two dimensional feature space (i.e. a 'scatter plot') are frequently observed to not have a shape that can be approximated by a parametric classifier (e.g. a rectangular shape for a parallelepiped classifier, or an ellipsoid shape for a maximum likelihood classifier). To improve the accuracy of the forest cover type map, a supervised nonparametric classifier based on these results has been developed.

Thus the aim of this Chapter was to develop and test a new supervised nonparametric classifier, that produces classified images of higher accuracy compared with conventional supervised classifiers. A subsidiary aim was to create an image showing the empirical probability of correct classification for each pixel.

6.2. Construction of the supervised nonparametric classifier

6.2.1. Introduction

The classifier can be generally described as follows. Training area data are collected for representative cover class areas. Each pixel for the first cover class is assigned to the cell (or vector position) in the N-dimensional feature space which equates with the brightness value of the pixel. The number of pixels (for the first class) that occur in each cell are summed. Similarly the pixels of the second cover class are summed into the cells of the N-dimensional feature space, but are stored as separate records (to the first class). This process is continued for all remaining cover classes.
Each cell in the N-dimensional feature space is now tested sequentially by the classifier. The classifier finds the class with the highest empirical probability in the cell and assigns that cover class identity to the cell. The empirical probability for the cell is calculated by dividing the number of pixels in the cell for that class by the total number of pixels tallied for all cover classes in the cell. The number of training area pixels in each land cover class are normalized.

Any unknown pixel is classified by matching its pixel brightness value in each feature with the equivalent cell in the N-dimensional feature space, and extracting the class and empirical probability from the cell. The class and empirical probability for each pixel can then be displayed as two images. Thus the classifier is not function based, but rather each cell in the N-dimensional feature space is considered as a separate decision rule.

6.2.2. Description of the algorithm

Let (X) describe the vector position of a pixel in N-dimensional feature space \((X_1, X_2, ..., X_N)\), where \(X_N\) is the brightness value in spectral band N. Training set data are generated for each \(i^{\text{th}}\) class, for \(i=1,2,...,j\) classes.

Let \(P(i | X)\) be the probability that class \(i\) occurs at vector position \(X\). Using Bayes' Theorem,

\[
P(i | X) = \frac{P(X | i) P(i)}{P(X)}
\]

An estimator of \(P(X | i)\) is,

\[
P(X | i) = \frac{F_i(X)}{F_i}
\]

where \(F_i(X)\) is the count of pixels from training sets of class \(i\) at \((X)\) and \(F_i = \sum F_i(X)\).

Now, \(P(X) = \sum P(X | j) P(j)\).

Therefore,

\[
P(i | X) = \frac{P(X | i) P(i)}{\sum_j P(X | j) P(j)}
\]

(see also Geisser, 1982)

\[
P(i | X) = \frac{\left(\frac{F_i(X)}{F_i}\right) P(i)}{\sum_j \left(\frac{F_j(X)}{F_j}\right) P(j)}
\]

... (1)

The total number of pixels in class \(i\) (i.e. \(F_i\)) may be normalized using the total number of pixels sampled (i.e. \(F_j\)).

\[
P(i | X) = \frac{\left(\frac{F_i}{F_j}\right) F_i(X) P(i)}{\sum_j \left(\frac{F_j}{F_j}\right) F_j(X) P(j)}
\]

... (2)

where \(P_i\) is the \textit{a priori} probability for class \(i\), in this case the relative areal extent of the classes in the image. \((F_j/F_i)\) is the sum of all training area pixels divided by the sum of pixels in class \(i\), that is a weighting factor to normalize training area fields of different size.

A decision rule can be generated for each vector position in feature space \((X)\) by allocating to the vector position \((X)\) the class \(i\) with the highest probability of occurrence, \(P(i | X)\). That is, if \( \{ P(i | X) > \)
P(i \!+\! 1 
\mid X) \), then the decision rule will allocate class i and probability P(i \!\mid X) to vector position (X). In this way, a two dimensional lookup table of vector position (X) against probability and class number can be generated for all (X). In the event of two (or more) classes having equal probabilities, the smallest class number is assigned to the class. Alternative strategies can include stating a priori which class should have preference, summing P_j(X) in the adjacent vector positions and selecting the class with the highest sum, or randomizing the selection (i.e. flip a coin).

An unknown pixel, which is located at vector position (X) in N-dimensional feature space, is assigned to the class and empirical probability value equated with (X) in the lookup table.

The training sets usually contain relatively few pixels with a considerable range in brightness values and many missing values. As unfilled feature vector spaces result in unclassified image pixels, the algorithm is obviously sensitive to the degree of sparseness. To overcome the problem of sparseness, the data distributions are collapsed into a smaller brightness value range by multiplying the pixel brightness value by a factor of less than one, and truncating the result to an integer (i.e. (X') = \{\text{integer of } (X.f)\}, where 0 < f < 1). The result is fewer vacant feature vector spaces and more classified pixels in the image. Substituting (X') into (2) yields P(i \!\mid X'). For example, if the original data was 8 bit (0-255 brightness levels) then a collapsing factor of 0.5 would reduce the radiometric sensitivity to 7 bit data (0-127), while a collapsing factor of 0.25 would result in a 6 bit (0-63) data set. Obviously, if \{\sum F_j(X') P(j)\} in equation (2) is 0, then P(i \!\mid X') will be undefined, and unknown pixels equated with the vector position (X) will be unclassified.

The algorithm was written in Fortran-77 and executed on the VAX-cluster at the Australian National University. The SPIRAL geographical information system (Myers, 1986) was used for data input/output. The UNIRAS software package (European Software Contractors, 1982) was used to display the thematic images on Tektronix graphics hardware.

6.2.3. Simple example of the algorithm

For a classification of two classes at vector position (X), let F_1(X) = 30, F_2(X) = 25 and \sum F_j(X) = 55. Also let P(1) = 0.75 and P(2) = 0.25. Assume there are 60 pixels in the training area for class 1 and 40 pixels in the training area for class 2.

Then P(X) = \frac{30}{55}(0.75)\frac{100}{60} + \frac{25}{55}(0.25)\frac{100}{40} = 0.965,
and P(1|X) = \frac{30}{55}(0.75)\frac{100}{60}P(X) = 0.71,
and P(2|X) = \frac{25}{55}(0.25)\frac{100}{40}P(X) = 0.29.

The decision rule is to allocate any unknown pixel which is located at vector position (X) to class 1, and to assign an empirical probability of 0.71 to the pixel.

Note that as would be expected, P(1|X) + P(2|X) = 1.0.
6.3. Evaluation of the algorithm

6.3.1. Landsat MSS data over mixed hardwood/conifer forests in Pennsylvania, U.S.A.

6.3.1.1. Introduction

The algorithm was tested over the Pennsylvania State University Experimental Forest located in the Allegheny Mountains of Central Pennsylvania. The forest is a complex mix of natural broadleaf and conifer stands, with some plantation areas. Terrain varies from undulating to steep. Eight cover types were recognized within the study area from existing forest type maps and aerial photographs, and these are listed in Table 6-1 along with the areal extent of each cover class over the study area. These areal extents were used as the initial \( a \text{ priori} \) probabilities in the classifier (i.e. \( P(i) \) in equation (2)).

<table>
<thead>
<tr>
<th>Cover type</th>
<th>Areal extent of cover type (percentage of study area)</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>2</td>
</tr>
<tr>
<td>pine plantation</td>
<td>12</td>
</tr>
<tr>
<td>white pine</td>
<td>2</td>
</tr>
<tr>
<td>mixed oak</td>
<td>30</td>
</tr>
<tr>
<td>natural pine</td>
<td>6</td>
</tr>
<tr>
<td>hemlock/hardwood</td>
<td>2</td>
</tr>
<tr>
<td>pine/hardwood</td>
<td>6</td>
</tr>
<tr>
<td>agricultural fields</td>
<td>40</td>
</tr>
</tbody>
</table>

The multispectral data source was a Landsat MSS scene recorded in the summer of 1979. At least two representative training sets were obtained for each cover class, and the pixel brightness values entered as a training set. The training data sets ranged in size from approximately 40 to 200 pixels. Another data set comprising the areal extent of the different cover types was also created. No attempt was made to interactively refine data sets based upon preceding classification results.

Various collapsing factors between 0.4 and 1 were tested. With a factor of 0.4, the training data sets tended to merge lowering the empirical probabilities that pixels were correctly classified, but increasing the number of classified image pixels. With no collapsing (factor equals 1), there were many unclassified image pixels, but empirical probability of a correct classification was higher. Though any collapsing factor can be used, a value between 0.5 and 0.8 ensures a reasonable compromise. For the Pennsylvania MSS data, a collapsing factor of 0.6 was chosen.

For comparative purposes, a maximum likelihood classification was made over the study area using the same training set data, with an ERDAS image processing system. In addition, an unsupervised euclidean distance classification using minimum distance criteria was performed, again using the ERDAS system. A simple (and preliminary) quantitative comparison of the supervised nonparametric classifier was performed as described below. No additional radiometric or geometric corrections were made to the Landsat MSS data set.
6.3.1.2. Results and discussion

A ground truth map showing a section of the study area is detailed in Figure 6-1. A 'colour' composite of the study area can be seen as Figure 6-2, where Landsat MSS band 7 was displayed on the red gun, band 5 on the green gun and band 4 on the blue gun. The results obtained by the nonparametric classifier are shown in Figure 6-3, and the empirical probabilities that pixels are correctly classified are shown in Figure 6-4. Classification results obtained by the maximum likelihood classifier, supervised euclidean distance classifier and the unsupervised euclidean distance classifier are detailed in Figures 6-5 to 6-7 respectively.

A subjective evaluation of the mapping accuracies of the three classification strategies showed that the nonparametric technique is significantly better than the other two (Myers\textsuperscript{1}, per. comm.). The unsupervised clustering was virtually useless, with a large proportion of forested country being misclassified as agriculture. Coniferous forests and plantations were reasonably delineated, though confused with the conifer/hardwood areas. The supervised maximum likelihood classifier yielded a better result than the supervised and unsupervised euclidean distance classifiers, especially within the forest area, though here confusion still existed with hardwoods being misclassified as conifers, and plantation areas being misclassified as natural forests. The major problem with the maximum likelihood classification was a large area in the north western section of the study area being classified as agriculture, though ground truthing shows it to be an easterly ridge covered by mixed oak, hemlock/hardwood and occasional grass patches.

In a preliminary attempt to quantify the superiority of the nonparametric classifier, 70 pixels were randomly selected from the classified image. Pixels were selected only if they had a 100 percent empirical probability of being correctly classified. These pixels were compared with ground truth information (derived from aerial photographs and stand type maps) and results entered into a confusion table (see Table 6-2) for the eight cover classes considered.

\textsuperscript{1}Myers, W.L., Manager, Pennsylvania State University Experimental Forest, Pennsylvania State University, University Park, PA 16802.
Figure 6-1: Map of the Pennsylvania State University Experimental Forest study area
Figure 6-2: Colour composite of the study area

Figure 6-3: Classified image produced by the supervised nonparametric classifier

Figure 6-4: Empirical probability of correct classification produced by the supervised nonparametric classifier

Figure 6-5: Image produced by the maximum likelihood classifier

Figure 6-6: Image produced by the supervised euclidean distance classifier

Figure 6-7: Image produced by the unsupervised euclidean distance classifier
Key to Figures 6-3 through to 6-7

Figure 6-2: Colour composite used for visual interpretation

Figure 6-3: Supervised nonparametric classification
purple - water
brown - pine plantation
green - mixed oak
yellow - agriculture
blue/green - natural pine
red - hemlock/hardwood
orange - mixed plantation
pink - pine/hardwood

Figure 6-4: Supervised nonparametric classification - empirical probability of correct classification
blue - 100% correct
green - 80-99% correct
yellow - 50-79% correct
red - less than 50% correct

Figures 6-5, 6-6: Maximum likelihood and supervised euclidean distance classifications
purple - water
brown - pine plantation
green - mixed oak
yellow - agriculture
pink - natural pine
dark green - hemlock/hardwood
light brown - mixed plantation
red - pine/hardwood

Figure 6-7: Unsupervised euclidean distance classification
Table 6-2: Confusion table for a random selection of pixels with 100% empirical probability (Pennsylvania)

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>II</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>Number III</td>
<td>5</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6</td>
</tr>
<tr>
<td>of pixels</td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>(map) V</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>16</td>
<td></td>
<td>16</td>
</tr>
<tr>
<td>VI</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>VII</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>VIII</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>1</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>22</td>
<td>17</td>
<td>6</td>
<td>9</td>
<td>70</td>
</tr>
</tbody>
</table>

Overall classification accuracy\(^1\) = 90%
Overall mapping accuracy\(^2\) = 88%

Key to abbreviations in Table 6-2: I - pine/hardwood; II - water; III - white pine; IV - hemlock/hardwood; V - mixed oak; VI - agriculture; VII - pine plantation; VIII - natural pine.

These results were biased in favour of accurately classified pixels, as only those pixels with a 100 percent empirical probability of correct classification were selected. However results were sufficiently encouraging to pursue testing of the supervised nonparametric classifier.

6.3.2. SPOT data over Australian Capital Territory pine plantations

6.3.2.1. Methods

A study area of 12 by 15 km was selected over a section of the Stromlo radiata (or Monterey) pine (*Pinus radiata*) plantations near Canberra, A.C.T., Australia (see Figure 6-8). The plantations are even-aged stands planted between 1930 and 1986. Eight cover types were identified (viz., pine older than 40 years, 30 to 40 year old pine, 20 to 30 year old pine, 10 to 20 year old pine, pine less than 10 years old, urban and water) and at least two training areas per class were delineated. The pine cover classes had experienced different silvicultural treatments (thinning, pruning etc.) but a history of treatments was not available, so the age cover classes could not be segmented by stand structure. The terrain varies from

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\(^1\) Overall classification accuracy is the ratio of the total number of correctly classified pixels to the total number of pixels in each class (Kalensky and Scherk, 1975). See 4.5.2.5 for further details.

\(^2\) Overall mapping accuracy takes into account both omission and commission errors, and consequently allows for positional accuracy (Kalensky and Scherk, 1975). See 4.5.2.5. for further details.
undulating (0 to 10 degrees) to moderately steep (approximately 25 degrees). Aerial photographs at a scale of 1:10 000 and compartment maps were available for ground truth reference.

Figure 6-8: Map of the Stromlo plantation study area near Canberra, A.C.T.

A SPOT XS scene (K386, J421) centred over Canberra, Australia, provided the three channel remotely sensed data (Turner et al., 1989). This cloud free scene was acquired on September 11th, 1986, which is late winter in southeast Australia. The view angle was from the right at 4.5 degrees.

A preliminary unsupervised clustering of the area using the CLUS algorithm (Turner et al., 1982) yielded the approximate areal extent of the eight cover classes. The land cover classes and their approximate areal extent are listed in Table 6-3.

<table>
<thead>
<tr>
<th>Class</th>
<th>Areal extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>5%</td>
</tr>
<tr>
<td>grassland</td>
<td>15%</td>
</tr>
<tr>
<td>urban</td>
<td>10%</td>
</tr>
<tr>
<td>before 1950</td>
<td>10%</td>
</tr>
<tr>
<td>1950-1959</td>
<td>10%</td>
</tr>
<tr>
<td>1960-1969</td>
<td>20%</td>
</tr>
<tr>
<td>1970-1979</td>
<td>20%</td>
</tr>
<tr>
<td>1980-1985</td>
<td>10%</td>
</tr>
</tbody>
</table>
These data were used as the initial \textit{a priori} probabilities in the classifier (i.e. $P(i)$ in equation (2)). These probabilities were modified empirically to improve the discrimination of cover type classes in the final thematic image.

The training area data were extracted and statistics (mean, covariance matrix, range) generated. In order to visually compare the locations of the training area data in N-dimensional feature space, boxplots (Minitab, 1986) of the DN (density number) values for each cover class in the three channels were drawn.

The proposed algorithm was tested with various collapsing factors ($f$) between 0.1 and 1. With a factor of $f = 0.1$, the training data sets tended to merge, lowering the empirical probabilities that pixels were correctly classified but increasing the number of classified image pixels. With no collapsing ($f = 1$), there were more unclassified image pixels but empirical probability of a correct classification was higher. Though any collapsing factor can be used, empirical testing using the SPOT data confirmed that a value between 0.5 and 0.8 (i.e. a dynamic range decrease from 256 DN to 128 and 205 DN respectively) ensures a reasonable compromise between reducing the number of unclassified pixels and increasing empirical probabilities\textsuperscript{1}. A collapsing factor of 0.5 was used in this case.

A maximum likelihood classifier (MAXCLASS) and a euclidean distance classifier (CLASS) contained in the ORSER package (Turner \textit{et al.}, 1982) were executed using the same image and training areas as used in testing the proposed classifier.

A quantitative analysis of mapping accuracy for the maximum likelihood, euclidean distance and supervised nonparametric classifiers was performed using the methodology proposed by Hay (1979). At least fifty pixels were randomly located within each cover class strata on a 1:25 000 scale compartment map that was geometrically rectified with the classified images. The large number of roads within and bounding the plantation area made it easy to locate the pixels to be tested. The mapping accuracies are summarized as error matrices (Kalensky and Scherk, 1975). A fourth error matrix was generated to include those pixels sampled from the supervised nonparametric classification that had an empirical probability of more than 75 per cent, to ascertain whether a relationship exists between empirical probability and overall mapping accuracy.

\textbf{6.3.2.2. Results}

The boxplots of the DN values for the training areas are presented in Figure 6-9. The boxplots visually indicate the spread of the data, the skewness of the distribution around the median, and the range within the data spread where most of the observations occur. The average number of pixels per training area class was approximately 900, and ranged from about 700 to 2000.

The thematic image produced by the nonparametric classifier is shown in Figure 6-10, and the empirical probability of correct classification is shown in Figure 6-11. The thematic maps output by the maximum likelihood and euclidean distance algorithms are included as Figures 6-12 and 6-13 respectively.

Error matrices for the three classification strategies, and also for pixels with a probability of more than 75 per cent correct classification, are detailed in Tables 6-4 to 6-7. Note that six classes were tested,

\textsuperscript{1}This is a similar result to that reported for Landsat MSS in 6.3.1.1.
comprising the five pine age classes and a 'non-pine' class which included the grass, water and urban classes. The overall classification mapping accuracies are summarized in Table 6-8.


Note: The median is represented by the cross-bars. The total range of the data is shown by the thin lines. The thick lines represent the range between "adjacent values" defined as:

\[ \{LQ - 1.5 \times S\} \text{ and } \{UQ + 1.5 \times S\}, \]

where

LQ = the lower quartile around the median

UQ = the upper quartile around the median

S = UQ - LQ. (See Minitab [1986] for details).

Figure 6-9: Boxplots of the DN values for the training areas selected over the Canberra scene
133

blue : 100%
green : 70-99%
yellow : 50-69%
red : less than 50%

classification produced by the supervised nonparametric classifier

Figure 6-11: Empirical probability of correct classification produced by the supervised nonparametric classifier

Figure 6-10: Classified image produced by the supervised nonparametric classifier

Legend for 6-10, 6-12 and 6-13
- dark blue : urban
- light green : grass
- purple : water
- red/dark green : 1980-1986
- light blue : 1960-1969
- pink : 1950-1959
- yellow : before 1950

Figure 6-12: Image produced by the maximum likelihood classifier

Figure 6-13: Image produced by the unsupervised euclidean distance classifier
Table 6-4: Error matrix for the supervised nonparametric classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>VI</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>Total</th>
<th>Omissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No. %</td>
</tr>
<tr>
<td>I</td>
<td>29</td>
<td>6</td>
<td>14</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td>55</td>
<td>26 47</td>
</tr>
<tr>
<td>II</td>
<td>5</td>
<td>22</td>
<td>14</td>
<td>8</td>
<td>1</td>
<td></td>
<td></td>
<td>50</td>
<td>28 56</td>
</tr>
<tr>
<td>of</td>
<td>III</td>
<td>1</td>
<td>41</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td>54</td>
<td>13 24</td>
</tr>
<tr>
<td>pixels</td>
<td>IV</td>
<td>4</td>
<td>43</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td>50</td>
<td>7 14</td>
</tr>
<tr>
<td>(map)</td>
<td>V</td>
<td>2</td>
<td>1</td>
<td>6</td>
<td>39</td>
<td>2</td>
<td></td>
<td>50</td>
<td>11 22</td>
</tr>
<tr>
<td></td>
<td>VI</td>
<td>1</td>
<td>9</td>
<td>46</td>
<td>1</td>
<td></td>
<td></td>
<td>57</td>
<td>11 19</td>
</tr>
<tr>
<td>Total no. of pixels</td>
<td>37</td>
<td>28</td>
<td>74</td>
<td>76</td>
<td>48</td>
<td>51</td>
<td>2</td>
<td>316</td>
<td>96</td>
</tr>
<tr>
<td>Overall classification accuracy*</td>
<td>70%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table Legend: I = greater than 40 year old pine
II = 30 to 40 year old pine
III = 20 to 30 year old pine
IV = 10 to 20 year old pine
V = pine younger than 10 years old
VI = non-pine (including water, grass and urban classes)
VII = unclassified

* Ratio of the sum of correctly classified pixels in all classes to the sum of the total number of pixels tested.

Table 6-5: Error matrix for the maximum likelihood classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>VI</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>Total</th>
<th>Omissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No. %</td>
</tr>
<tr>
<td>I</td>
<td>30</td>
<td>9</td>
<td>11</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td></td>
<td>55</td>
<td>25 45</td>
</tr>
<tr>
<td>II</td>
<td>9</td>
<td>9</td>
<td>16</td>
<td>10</td>
<td>6</td>
<td></td>
<td></td>
<td>50</td>
<td>41 82</td>
</tr>
<tr>
<td>of</td>
<td>III</td>
<td>19</td>
<td>10</td>
<td>11</td>
<td>2</td>
<td>1</td>
<td>7</td>
<td>54</td>
<td>43 79</td>
</tr>
<tr>
<td>pixels</td>
<td>IV</td>
<td>1</td>
<td>3</td>
<td>39</td>
<td>7</td>
<td></td>
<td></td>
<td>50</td>
<td>11 22</td>
</tr>
<tr>
<td>(map)</td>
<td>V</td>
<td>2</td>
<td>3</td>
<td>45</td>
<td></td>
<td></td>
<td></td>
<td>50</td>
<td>5 10</td>
</tr>
<tr>
<td></td>
<td>VI</td>
<td>1</td>
<td>14</td>
<td>42</td>
<td></td>
<td></td>
<td></td>
<td>57</td>
<td>15 26</td>
</tr>
<tr>
<td>Total no. of pixels</td>
<td>61</td>
<td>28</td>
<td>41</td>
<td>66</td>
<td>68</td>
<td>52</td>
<td>2</td>
<td>316</td>
<td>142</td>
</tr>
<tr>
<td>Overall classification accuracy</td>
<td>56%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6-6: Error matrix for the supervised euclidean distance classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>VI</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>Total</th>
<th>Omissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>No. %</td>
</tr>
<tr>
<td>I</td>
<td>26</td>
<td>6</td>
<td>16</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>55</td>
<td>29 53</td>
</tr>
<tr>
<td>II</td>
<td>5</td>
<td>8</td>
<td>15</td>
<td>16</td>
<td>5</td>
<td>1</td>
<td>1</td>
<td>50</td>
<td>42 84</td>
</tr>
<tr>
<td>of</td>
<td>III</td>
<td>23</td>
<td>19</td>
<td>11</td>
<td>1</td>
<td></td>
<td></td>
<td>54</td>
<td>35 64</td>
</tr>
<tr>
<td>pixels</td>
<td>IV</td>
<td>3</td>
<td>11</td>
<td>36</td>
<td>3</td>
<td></td>
<td></td>
<td>50</td>
<td>14 28</td>
</tr>
<tr>
<td>(map)</td>
<td>V</td>
<td>4</td>
<td>3</td>
<td>42</td>
<td>1</td>
<td></td>
<td></td>
<td>50</td>
<td>8 16</td>
</tr>
<tr>
<td></td>
<td>VI</td>
<td>1</td>
<td>14</td>
<td>27</td>
<td>15</td>
<td></td>
<td></td>
<td>57</td>
<td>30 53</td>
</tr>
<tr>
<td>Total no. of pixels</td>
<td>59</td>
<td>14</td>
<td>61</td>
<td>71</td>
<td>62</td>
<td>31</td>
<td>18</td>
<td>316</td>
<td>160</td>
</tr>
<tr>
<td>Overall classification accuracy</td>
<td>50%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6-7: Error matrix for pixels generated by the supervised nonparametric classifier with an empirical probability of greater than 75 per cent.

<table>
<thead>
<tr>
<th>Class</th>
<th>Number of pixels</th>
<th>Total</th>
<th>Omissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
<td>III</td>
</tr>
<tr>
<td>I</td>
<td>27</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>13</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>12</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>IV</td>
<td>1</td>
<td>13</td>
<td>1</td>
</tr>
<tr>
<td>V</td>
<td>2</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>VI</td>
<td>6</td>
<td>44</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>28</td>
<td>13</td>
<td>19</td>
</tr>
</tbody>
</table>

Overall classification accuracy 87%

Table 6-8: Summary of mapping accuracy results

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Overall mapping accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>supervised nonparametric</td>
<td>70</td>
</tr>
<tr>
<td>supervised nonparametric (&gt;75% empirical probability)</td>
<td>87</td>
</tr>
<tr>
<td>maximum likelihood</td>
<td>56</td>
</tr>
<tr>
<td>supervised euclidean distance</td>
<td>50</td>
</tr>
</tbody>
</table>

6.3.2.3. Discussion

The boxplots in Figure 6-9 show that the pine age classes are spectrally similar in all three channels, once the pine tree crowns have closed together. Pine trees greater than 10 years old had closed crowns (i.e. classes I to IV). The non-pine classes (urban, grass and water) differ spectrally from each other and from the pine, particularly in channels 2 and 3. The similar pattern of the boxplots in Figure 6-9 indicates that channels 1 and 2 are correlated, with channel 2 having lower DN values than channel 1. This was confirmed by inspecting the correlation matrices for the six classes, which showed a correlation coefficient between channels 1 and 2 of greater than 0.90 for every class except for the pine class less than 10 years old. The boxplots also show that the classes are skewed towards the lower values in channels 1 and 2. The high spectral variance is also obvious, especially for channel 3.

Given the spectral similarity of the cover classes to be discriminated, the utility of the proposed nonparametric classifier in improving mapping accuracies becomes apparent (Table 6-8). The nonparametric classifier yielded a higher mapping accuracy (70 per cent) than the maximum likelihood (56 per cent) or the euclidean distance (50 per cent) classifiers using identical training area data. Tables 6-4 to 6-6 show that the classifiers had the lowest mapping accuracies when discriminating between the older pine age classes (i.e. greater than 20 years old). Figure 6-9 shows that these classes were spectrally the most similar. Nevertheless the supervised nonparametric classifier achieves adequate class mapping accuracies for the 20 to 30 year old pine, and has a comparatively better class mapping accuracy for the 30 to 40 year old pine. The class mapping accuracies for the more than 40 year old pine was similar for all three classifiers.
As part of the mapping accuracy check, an error matrix was formed using only those pixels with an empirical probability greater than 75 per cent (Table 6-7). This threshold was chosen to provide a subsample of pixels with a high empirical probability. The resulting mapping accuracy was 87 per cent, which was better than any other classifier including the nonparametric classifier error matrix where the empirical probability ranged from 0 to 100 per cent (Table 6-4). However the smaller sample size (less than 50 pixel samples per cover type) means that the confidence (interval) for the accuracy figures was lower. (As a corollary, if a larger number of test pixels was utilized, the confidence in the accuracy estimate would be higher).

6.4. General Discussion of the Landsat MSS and SPOT experiments

The higher mapping accuracy obtained using pixels with an empirical probability of greater than 75 per cent is consistent with preliminary results presented in 6.3.1 for Landsat MSS data, where high mapping accuracies (90 per cent) were obtained while discriminating between six forest types in Pennsylvania, using pixels that had a 100 per cent empirical probability of correct classification. A benefit of the proposed nonparametric classifier is that the pixels which have a 100 percent empirical probability of being correctly classified (according to the training set data) have a high mapping accuracy at a level III classification (Anderson et al., 1976). This has important implications for multistage sampling (De Vries, 1986), as high mapping accuracy for the first stage sample (i.e. the forest typing at level III) can be obtained using the supervised nonparametric algorithm.

Those areas having a low empirical probability of correct classification can be visually isolated (Figures 6-4 and 6-11 for the Pennsylvania and Canberra scenes respectively). For example, in the SPOT experiment (Figure 6-11), pine older than 40 years and the 30 to 40 year old pine classes tended to have an empirical probability of correct classification of less than 50 per cent. To improve class mapping accuracy, new training areas may be selected, and old training areas checked for consistency in delineating the class. Then, if the empirical probability of correct classification stays low, it may be concluded that classes are spectrally similar, and could perhaps be merged into one class.

The superior mapping accuracy result obtained with the proposed classifier is due to the lack of assumptions concerning the shape or distribution of decision volumes which are implicit in other classification strategies. Each vector in N-dimensional intensity space is treated as a separate decision rule by the proposed classifier. The supervised nonparametric classifier requires \textit{a priori} probabilities as an integral part of the classification, and these prior probabilities can be modified easily to improve the thematic map. Although \textit{a priori} probabilities could be included in maximum likelihood and euclidean distance classifiers (Duda and Hart, 1973) it is not commonly done, so in this study, the \textit{a priori} probabilities were assumed to be constant.

Strahler et al., (1980) stated that an advantage with their proposed nonparametric logit classification model is that it can accept continuous data (e.g. Landsat data) or categorical data (e.g. a soil map) as independent variables to model (by regression) the probability that a pixel is a member of a given
class. The decision rule proposed for the nonparametric classifier is based upon ordered statistics, and so any data types (for example continuous or categorical data) may be included as features in the classification without violating statistical assumptions.

The algorithm required approximately four times the cpu-time compared with the maximum likelihood classifier, for 200 000 pixels. The cpu time requirements appeared to increase proportionally to n.log(n), where n is the number of pixels. As additional channels are added, the number of vector spaces (or bins) would increase. For example, using TM data, 256⁷ (7x10¹⁶) bins would be required, many of which would be empty. In this case some feature reduction technique, such as principal component analysis, could be used. The improved mapping accuracies obtained with the proposed classifier have to be offset against the higher computational expense.

The nonparametric classifier was developed to improve forest mapping accuracy, but it is a totally general algorithm which may be implemented in any land cover mapping exercise using remotely sensed data. In addition to the experiments conducted in Pennsylvania and Canberra, a modified version of the supervised nonparametric classifier was used to analyse Landsat TM data in an area of native eucalypt forest near Eden, New South Wales, Australia (Chapter 8). The modifications allowed the thematic images and empirical probabilities produced by the supervised nonparametric classifier to be utilized by the expert system described in Chapter 8.

6.5. Areal mapping accuracy cannot be correctly estimated using a modification of the supervised nonparametric classifier proposed by Lowell (1989)

This section is a response to a note by Dr K. Lowell of the University of Missouri-Columbia (Lowell's paper is included as Appendix 1) which appeared in *Photogrammetric Engineering and Remote Sensing* (Lowell, 1989). A succinct version of this section was also published in *Photogrammetric Engineering and Remote Sensing* (Skidmore and Turner, 1989).

Two types of thematic mapping error are (a) locational, where a pixel is incorrectly classified according to some ground truth criteria, and (b) areal, where the area of a class on an image does not equal the area of the class according to the ground truth.

The concern of Lowell (1989) is that areas for classes may be poorly estimated using the supervised nonparametric classifier. This problem is common to all probabilistic classifiers, including the maximum likelihood classifier.

At the outset, it should be emphasized that spectrally discrete classes will yield images with a higher spatial and areal accuracy, independent of the probabilistic classifier used. As discussed in 6.4, the images of the empirical probability (Figures 6-4 and 6-11) of correct classification (i.e. (P(i|X)) clearly differentiates classes which are spectrally similar from classes which are spectrally discrete. Thus, spectrally similar classes that will have low locational and areal accuracies can be identified. If there is co-occurrence at vector position (X) then information cannot be created from the confusion. The advantage of the supervised nonparametric classifier becomes apparent when two adjacent vector positions (X) each
contain a separate class. In such a situation, parametric classifiers (such as the maximum likelihood classifier) may parameterise the adjacent vector positions as having the two classes co-occurring, when in fact the classes do not co-occur.

Lowells' (1989) example of a binary data set with two features is unrealistic as it is not characteristic of remotely sensed data. As discussed in 6.3.1.1 and 6.3.2.1, data sets such as the one proposed by Lowell (1989) could be considered to be in a severe state of 'collapse' from the original 6 or 8 bit data. Using such a data set, a classifier will behave unpredictably due to classes being merged into (that is co-occurring in) a common vector position. High mapping accuracies are obtained when classes do not co-occur in vector positions, which is hopefully the situation when using a less severely collapsed data set. With more vector spaces, the area estimates of the supervised nonparametric classifier would be closer to the true values.

Furthermore, Lowell's (1989) modification will not correctly estimate the area of a class, where the estimated a priori probability for a class (over the area being classified) does not equal the true proportion of the class.

Following the notation of Skidmore and Turner (1988), the supervised nonparametric classifier is used to compute $P(i|X)$ for $i=1,2$, where $P(i|X)$ is the probability of class $i$ occurring at vector position $X$. Lowell's (1989) allocation of pixels to class 1 can be succinctly stated as follows:

$$S_1 = \sum_{X \in I} P(i|X) T(X)$$

where $S_1$ is the proportion of the image classified as class 1, $T(X)$ is the total number of image pixels occurring at vector space $(X)$, and $n$ is the total number of pixels in the image. Note that it is not necessary to perform list sampling or create a classified image as proposed by Lowell.

$P(i|X)$ may be calculated using Bayes' Theorem (equation (2) in 6.2.2). Using Lowell's (1989) example (Appendix 1), $P(1) = 0.5$, $P(2) = 0.5$, the area of class 1 is 500 pixels, the area of class 2 is 500 pixels, and there are two features. It is then simple to calculate $P(1|X)$, $P(2|X)$, $S_1$ and $S_2$ at each vector position in 2-dimensional feature space (see the 'Simple example of the algorithm' at 6.2.3. for details), as shown in Table 6-9 below.

| Vector position | $T(X)$ | $P(1|X)$ | $P(2|X)$ | $P(1|X)*T(X)$ | $P(2|X)*T(X)$ |
|-----------------|--------|---------|---------|---------------|---------------|
| 0,0             | 300    | 0.167   | 0.833   | 50.1          | 249.9         |
| 0,1             | 275    | 0.545   | 0.455   | 149.9         | 125.1         |
| 1,0             | 175    | 0.571   | 0.429   | 99.9          | 75.1          |
| 0,0             | 250    | 0.800   | 0.200   | 200.0         | 50.0          |

$S_1 = 500.0$, $S_2 = 500.0$

So when $P(1) = (S_1/n)$, Lowell's (1989) modification works. In other words, the modification works when the a priori probabilities equal the actual proportions of class areas in the image.
However, if the *a priori* probabilities are not known exactly and (as is usually the case) estimated incorrectly, then the areas of the classes are also incorrectly estimated. For example, the effect of changing $P(1)$ to 0.45 and $P(2)$ to 0.55 on the estimated areas can be seen in Table 6-10.

Table 6-10: Calculation of number of pixels in class 1 using Lowell's modification at $P(1) = 0.45$

| Vector position | $T(X)$ | $P(1|X)$ | $P(2|X)$ | $P(1|X) * T(X)$ | $P(2|X) * T(X)$ |
|-----------------|--------|----------|----------|----------------|----------------|
| 0,0             | 300    | 0.141    | 0.859    | 42.2           | 257.8          |
| 0,1             | 275    | 0.495    | 0.505    | 136.2          | 138.8          |
| 1,0             | 175    | 0.522    | 0.478    | 91.3           | 83.7           |
| 0,0             | 250    | 0.766    | 0.234    | 191.5          | 58.5           |

Therefore, using Lowell's (1989) modification the area of class 1 is incorrectly estimated as 461 and the area of class 2 is incorrectly estimated as 539. The areal accuracy (i.e. number of pixels correctly classified as class 1) is plotted below (Figure 6-14) for prior probabilities ranging from 0 through to 1.0, using both Lowell's modification and the original Skidmore decision rule proposed in 6.2.2.

![Figure 6-14: Areal accuracy for prior probabilities in the range 0 to 1.0 for Skidmore algorithm and Skidmore algorithm as modified by Lowell](image)

It can be seen from the figure that the errors in estimating class areas become larger as the estimate of the *a priori* probabilities deviates further from the true values, for both methods. For example, consider Lowell's (1989) modification. When $P(1) = 0.2$, $S_1 = 250$; and when $P(1) = 0.75$, $S_1 = 700$ (remember the true value should be 500). Also note that the graph of areal accuracy calculated from the
original decision rule is stepped, as a result of the data set having a radiometric accuracy of only 2 bits. If the radiometric resolution of the data set was increased from 2 bits to 7 or 8 bits, it is obvious that the steps would be smoothed into a curve more closely approximating the Lowell curve.

The following question then arises. If we know a priori the exact area of class 1 and class 2, then why are we bothering to calculate the areas? If we do not know the exact areas, then an incorrect estimation of the a priori probabilities will lead to an incorrect estimation of the class areas.

Even using Lowell’s (1989) pathological example, the supervised nonparametric classifier decision rule gives an equal or better estimate of area at some a priori probabilities (e.g. between P(1) = 0.75 and P(1) = 0.8), even though the spectral resolution (i.e. a binary two feature data set) has little similarity with remotely sensed data (which normally has 3 to 7 features and a spectral resolution per channel of 6 to 8 bits). Thus, the data set proposed by Lowell (1989) accentuates errors in the area estimates of the supervised nonparametric classifier because there are only four vector spaces at which the classifier makes a decision.

Lowell’s (1989) modification will increase locational errors in the classified image at all vector positions (X) by introducing noise through randomly allocating pixels to classes according to the proportions of P(1|X) and P(2|X) (see Lowell’s Figure 2 in Appendix 1). The only exceptions are when P(lX) is 1.0, 0.5 or 0.

At all a priori probabilities the supervised nonparametric classifier has a higher locational mapping accuracy (except for P(1) = 0 or P(1) = 1.0), even when using Lowell’s (1989) pathological example. Locational mapping accuracy may be calculated for Lowell’s modification from the N-dimensional feature space containing P(l|X). Firstly calculate P(i|X) for all X and i, that is the probability that class i occurs given vector position X. Let P(i|X) be called Ti. Let the probability that an unknown pixel is truly class i be P(Ai); in other words P(Ai) is the proportion of pixels of class i from the whole image that occur at vector position (X). Four possible states exist for an unknown pixel when only two classes are classified viz.,

1) The unknown pixel is classified as class 1 (i.e. P(T1) > P(T2)) when the unknown pixel is actually class 2 (i.e. P(A1) < P(A2)).
2) The unknown pixel is classified as class 2 (i.e. P(T1) < P(T2)) when the unknown pixel is actually class 1 (i.e. P(A1) < P(A2)).
3) The unknown pixel is classified as class 2 (i.e. P(T1) < P(T2)) when the unknown pixel is actually class 2 (i.e. P(A1) < P(A2)).
4) The unknown pixel is classified as class 1 (i.e. P(T1) > P(T2)) when the unknown pixel is actually class 1 (i.e. P(A1) > P(A2)).

Assuming that the training area data truly represent the spectral distribution of the image population over all X, then P(T1) is (approximately) equal to P(A1), and P(T2) is (approximately) equal to P(A2), and,

\[ P(T_1 \cap A_1) = P(T_1) \cdot P(A_1) \]
\[ P(T_1 \cap A_2) = P(T_1) \cdot P(A_2) \]
\[ P(T_2 \cap A_1) = P(T_2) \cdot P(A_1) \]
\[ P(T_2 \cap A_2) = P(T_2) \times P(A_2). \]

\[ P(1|X) \text{ and } P(2|X) \] were calculated above for the example proposed by Lowell (1989) (Appendix 1), with \( P(1) = 0.5 \) at all \( X \) (Table 6-9). A 'confusion' matrix (see Chapter 4) for \( T_1, T_2, A_1, A_2 \) can then be constructed for all \( X \):

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>130</td>
<td>80</td>
<td>210</td>
</tr>
<tr>
<td>T2</td>
<td>80</td>
<td>112</td>
<td>192</td>
</tr>
<tr>
<td>column total</td>
<td>210</td>
<td>192</td>
<td>402</td>
</tr>
</tbody>
</table>

Overall mapping accuracy = \( \frac{242}{402} = 60.2\% \)

The mapping accuracy at other prior probabilities can be similarly calculated for Lowell's modification. Note that \( A_1 \) is the probability that an unknown pixel is truly class 1 at vector position \( X \), and \( T_1 \) is the probability that class 1 occurs given vector position \( X \).

Using the original (Skidmore) decision rule proposed in 6.2.2, locational mapping accuracy is simply calculated by allocating \( P(1|X) \) of the total (training area) pixels occurring at vector position \( X \) to cell \( T_1-A_1 \) (in the confusion matrix above) if \( P(1|X) > P(2|X) \). Then, \( P(2|X) \) of the total pixels in \( X \) must be also allocated to cell \( T_1-A_2 \). Similarly, if \( P(1|X) < P(2|X) \) then \( P(2|X) \) of the total pixels in \( X \) are allocated to cell \( T_2-A_2 \) in the confusion matrix, and \( P(1|X) \) of the total pixels in \( X \) are allocated to cell \( T_2-A_1 \).

Figure 6-15 is a plot of locational mapping accuracy calculated for the original decision rule and Lowell's proposed modification for \( P(1) \) ranging from 0 through to 1.
Figure 6-15: Locational mapping accuracy at different prior probabilities P(1)

It can be seen from this figure that the decision rule described in 6.2.2 has a higher locational mapping accuracy at all prior probabilities except 0 and 1.0, compared with the Lowell modification.

With real data, it is not safe to assume that P(T1) is (approximately) equal to P(A1) and P(T2) is (approximately) equal to P(A2), due to training areas not being representative of cover classes because of natural variability in cover classes or pixels containing more than one cover class (i.e. a mixed pixel). Then P(1|X) and P(2|X) calculated from the training areas would not equal the P(1|X) and P(2|X) for the whole image. When P(i|X) is not equal to the P(Ai), Lowell's (1989) modification will still give a poorer estimate of locational and areal mapping accuracy compared with the original algorithm, because it randomly allocates pixels to classes in the proportion that the ith class occurs at X.

Methods for improving mapping accuracies include merging similar classes into one class, selecting realistic training areas, introducing collateral data, considering the spatial context of features in the remotely sensed data, or improving the spatial, spectral and temporal resolution of the remotely sensed data. The information to improve the biases over the region can come from visual inspection of the image, or a confusion matrix.

Lowell's (1989) concern over area estimates using the supervised nonparametric classifier is valid. Therefore a procedure for calculating confidence intervals associated with area estimates is presented. Each vector position (X) can be considered to have a binomial distribution for class 1 and class 2. Using Lowell's (1989) example with P(1) = 0.5 and P(2) = 0.5, the number of training pixels falling in each vector position is:
Assume each vector position (X) has a binomial distribution with \( x = np \) and \( \sigma = npq \), where \( p = P(1|X) \) and \( q = 1-p \). Then the mean and standard deviation for class 1 and class 2 are:

![Class 1 and Class 2 Tables]

Note that the 95 per cent confidence intervals for a large sample are approximately \( x \pm 1.65 \sigma \). Then the 95 per cent confidence intervals for the number of training area pixels in class 1 are:

![Confidence Intervals for Class 1]

If the minimum values of the 95 per cent confidence intervals are considered, then 25 per cent (50/200) of the pixels will be assigned to class 1, while at the maximum values, 70 per cent (140/200) of the image pixels will be assigned to class 1. Therefore, we are at least 95 per cent confident that 50 per cent of the image area is class 1 (i.e. this is confirmation of the known areal extent of class 1).

When \( P(1) = 0.45 \) and \( P(2) = 0.55 \), the 95 per cent confidence interval ranges from 25 per cent to 70 per cent of the image. Again we are at least 95 per cent confident that 50 per cent of the image area is class 1.

It is important to note that if the number of pixels at a vector position is small, this binomial distribution technique for estimating confidence in mapping accuracy is inappropriate.
6.6. Conclusions

The supervised nonparametric classifier produced a thematic image as well as the empirical probability of correct classification, for SPOT XS data over a forest plantation in southeast Australia and for Landsat MSS data over a Pennsylvania mixed forest. This allows an analyst to visually locate those parts of the image where classification success can be improved. The classifier produced maps of higher accuracy than those from conventional supervised classifiers. A modification to the supervised nonparametric classifier proposed by Lowell (1989) was critically examined, and shown not to produce higher mapping accuracies, as claimed in that article. The thematic maps and images of empirical probability are suitable to input into the expert system developed to map native eucalypt forests in southeast Australia (Chapter 8).
7. TERRAIN FEATURE MODELLING FROM A GRIDDED DIGITAL ELEVATION MODEL

7.1. Introduction

Capturing surface elevation information in a digital form suitable to input into a computer involves sampling x, y and z (i.e. easting, northing and elevation) points from a model representing the surface, such as a contour map, stereocorrelated aerial photographs or other images. This sample of the terrain surface is usually called a digital elevation model (DEM). Other surface attributes such as terrain position (for example ridge, mid-slope, valley), gradient and aspect may be derived from the DEM and stored in a computer as a 'digital terrain model' (DTM). DTMs are potentially useful for modelling environmental parameters and processes using Geographic Information Systems (GISs).

DEMs may be sampled using a variety of techniques. Manual sampling of DEMs involves overlaying a grid onto a topographic map and manually coding the elevation values directly into each cell (Travis et al., 1975; Dangermond, 1983). However this is an extremely tedious and time consuming operation suitable only for small areas. Alternatively, elevation data may be sampled by direct quantitative photogrammetric measurement from aerial photographs on an analytical stereo-plotter. More commonly, digital elevation data are sampled from contour maps using a digitizing table which translates the x, y and z data values, nominated by the operator for a point on a contour map, into a digital signal. Cameron (1984) provides a review of this technology. Equipment for automatically scanning line maps have also been developed, based on either laser driven line following devices (Dangermond, 1983), or a raster scanning device, such as the drum scanner developed by I.B.M. for the Canadian Geographic Information System (Tomlinson et al., 1976). However, 'automatic' systems still require an operator to nominate the elevation values for contour lines, and to also manually remove errors in the contour data, caused by poor line work, the intrusion of non-contour lines (for example text or a cliff face) across the contour line being automatically scanned, or other inconsistencies (Peuquet and Boyle, 1984; Faust, 1987; Kubik and Frederiksen, 1987). The errors associated with rasterizing vector (i.e. contour) maps are examined by Burrough (1986).

DEMs may be derived from overlapping remotely sensed digital data using automatic stereocorrelation techniques, thereby permitting the fast and accurate derivation of DEMs (Ehlers and Welch, 1987). With the increasing spatial accuracy of remotely sensed data, future DEMs will have

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1This chapter has been published as:


2Raster scanning devices such as the drum scanner create large volumes of raster data which must be compressed prior to vectorization (Comeau and Holbaek-Hanssen, 1984). Comeau and Holbaek-Hanssen (1984) discuss a number of data compression techniques.
increasingly higher spatial accuracies (Rodriguez et al., 1988); indeed Swann et al. (1988) state that DEM extraction with less than 10 m root-mean-square (rms\(^1\)) error in all three planes is possible using SPOT data. Bloom et al. (1988) suggest that DEMs may be generated from overlapping SIR-B (radar) and Landsat TM data using stereophotogrammetry with an accuracy of between ±30 m and ± 40 m.

The majority of DEMs have an irregular spatial layout. Derivation of terrain attributes may be made from a Triangulated Irregular Network or TIN (Peucker et al., 1978) which involves connecting the irregularly spaced sample points to form triangular facets. Gold and Cormack (1987) describe the generation of contour maps from a TIN using Delauney Triangulation.

The irregularly spaced elevation points are more commonly interpolated to a regular tessellation spaced at a nominated distance. The tessellation may be triangular, as used by Palmer (1984) to extract terrain position features, though more commonly the tessellation is rectangular.

Hutchinson (1989) described an algorithm for generating a regular grided rectangular DEM from irregularly spaced elevation points. The interpolation algorithm is based on a finite difference technique, and imposes a global drainage condition to remove spurious sinks. Hutchinson's (1989) algorithm was used in this study to interpolate a regular grided rectangular DEM.

The major disadvantage with regularly tessellated DEMs is the large amount of data redundancy in areas of uniform terrain, and the subsequent inability to change grid sizes to reflect areas of different relief complexity (Burrough, 1986). However, various data compaction techniques have been proposed to reduce the severity of this problem including quadtrees, Freeman chaincodes, run-length codes, block codes, and vaster data structures. Peuquet (1983 and 1984) and Burrough (1986) provide a summary and critique of these various techniques. The advantages of a regularly grided DEM is its easy integration with raster databases and remotely sensed digital data, the smoother more natural appearance of contour maps and derived terrain features maps, and the ability to rapidly change the scale of the grid cells.

The first aim of this chapter is to produce a map showing the position in the terrain of each cell (i.e. ridge, upper midslope, midslope, lower midslope or gully) from a regularly grided rectangular DEM. Three previously published algorithms for calculating streams and ridges were compared with a new method proposed here. In addition, a novel method of mapping midslope position is proposed, based on a euclidean distance measure.

Another terrain feature useful for modelling environmental parameters and processes is slope. Slope is defined by a plane tangent to the surface, as modelled by the DEM at a point (Burrough, 1986). Slope has two components viz., gradient which is the maximum rate of change in altitude, and aspect which is the compass direction of this maximum rate of change.

Gradient and aspect are important environmental variables in many ecological models, as well as in the management of natural resources. In particular, these variables have been used extensively in combination with remotely sensed data for improving thematic image mapping accuracies (for example, Strahler et al., 1978; Fleming and Hoffer, 1979; Tom and Miller, 1980; Justice et al., 1981; Hutchinson, 1982; Franklin et al., 1986; Cibula and Nyquist, 1987; also see Chapter 3), as well as in geographic

\(^1\)See 4.2.2 for a definition of rms.
information systems (GISs) for modelling purposes (Johnston, 1987; Skidmore, 1989b; also see Chapters 8 and 9).

A number of methods for calculating gradient and aspect have been proposed for a DEM based on a regular grid. The second aim of this chapter is to quantitatively compare six methods which are commonly used to generate aspect and gradient from gridded DEMs.

7.2. Methodology

7.2.1. Introduction

Irregularly spaced elevation data were digitized over an area in southeast Australia using a Department of Lands 1:25 000 series map ('Mount Imlay' sheet [8823-IV-S]) which conforms to the Australian National Mapping Council standards of accuracy. Digitizing was performed on a Tektronix digitizing table, with the digital elevation data being input into a VAX-cluster using the DIG (A.N.U., 1988) software system. All streamlines were digitized (a total of 2115 points), except for first order streams that did not significantly effect topography (i.e. in situations where contour lines did not significantly deviate when crossed by a streamline). In addition, spot heights on hill tops and saddles were digitized. A selection of other irregularly spaced elevation points were also digitized, predominantly along the hundred metre contour lines (which were bolder and therefore quicker to manually follow with the digitizing puck). A total of 3306 elevation points and spot heights were recorded.

This irregular data set was input into a program which calculated elevation values to one metre contours, on a regular grid spaced at thirty metres (Hutchinson, 1989). The 30 m interval used in the DEM was selected as it matches Landsat Thematic Mapper pixels. The DEM and Landsat Thematic Mapper data were geometrically rectified and input into a geographic information system database at a grid spacing of 30 m. This database was accessed by an expert system, and forest cover types mapped (Skidmore, 1989b; also see Chapters 8 and 9).

Hutchinson's (1989) program imposes a global drainage condition which automatically removes spurious sinks; the degree of sink removal being dependent on three user defined thresholds. Data points which block drainage lines and are less than the first threshold above the drainage line are removed; with the DEM used in this study the first threshold was set to ten metres. The second threshold is the maximum difference in height of non-data (i.e. interpolated) point saddles (which may be considered as possible exits from the sink) and the sink. In this study the second threshold was set to twenty metres. The third threshold was set to fifty metres, and is the maximum (ridge or saddle) elevation that a sink can 'push' through to maintain a connected stream.

Three previously reported methods for calculating ridge and gully position in the terrain are described below, followed by the new algorithm proposed here. An algorithm for interpolating midslope positions between the ridge and gully lines is described. Note that terrain position was not calculated for the edge cells of the DEM, using any of the methods. Finally, six methods which are commonly used to generate aspect and gradient from gridded DEMs are compared.
The full (7.5 by 7.5 km) DEM was used in the experiment comparing the six methods of calculating aspect and gradient. A subset of this DEM (that measured 3 by 3 km) was used for the ridge and gully position work, so that better defined monochrome images could be produced.

7.2.2. Previously reported methods for calculating ridge and gully positions

7.2.2.1. Peucker and Douglas (1975) algorithm

Ridges and valleys were mapped by Peucker and Douglas (1975) using a simple moving window algorithm. The cell with the lowest elevation in a two by two moving window is flagged. Any unflagged cells remaining after the algorithm has passed over the DEM represent ridges. Similarly the highest cell in the window is flagged, with any unflagged cells in the DEM corresponding to valley lines.

7.2.2.2. O'Callaghan and Mark (1984) algorithm

O'Callaghan and Mark (1984) described an algorithm for extracting stream and ridge networks from a DEM. This algorithm was based on quantifying the drainage accumulation (which can be thought of as the approximate surface and subsurface water volume flow) at each cell in the DEM. Cells which had a drainage accumulation above a user-specified threshold were considered to be on a drainage channel. Ridges were defined as cells with no drainage accumulation (i.e. water only flows out from the cell).

The regular elevation matrix described in 7.2.1 (called ELEVN by O'Callaghan and Mark [1984]) contained \( N \) cells, and was arranged in a regular grid with \( n \) columns and \( r \) rows (i.e. \( N = nr \)). A drainage accumulation matrix (DAREA), also of size \( n \) columns and \( r \) rows was initialised to value one.

The number of drainage inputs to each grid cell was calculated and entered into a temporary matrix (TEMP), again of size \( n \) columns and \( r \) rows. TEMP was constructed by passing a three-by-three moving window over the digital elevation model (ELEVN), and adding one to the adjacent cell which had the steepest gradient from the central cell. (Note that where two (or more) adjacent cells have the same low value, the algorithm drains to the first cell encountered clockwise from the north.)

Each cell in the TEMP array with a zero value was then tested sequentially (and will be called the TEMP test-cell, and assumed to be located at column \( i \) and row \( j \)). The drainage accumulation value (from DAREA) at column \( i \) and row \( j \) was added to the drainage accumulation value of the neighbouring (DAREA) cell (located for instance at column \( i+1 \) and row \( j+1 \)) to which it drains. The TEMP test-cell was given a large value (to avoid reprocessing it) and the neighbouring TEMP cell (i.e. located at column \( i+1 \) and row \( j+1 \)) was decremented by one.

The TEMP matrix was then repeatedly tested until no cell with a value of zero remained. Ridges were then defined as being cells with no input drainage (i.e. when DAREA values equals 0). Streamlines were defined as cells with a value above a user specified threshold (i.e. when DAREA is greater than the threshold the cell is defined as a stream). O'Callaghan and Mark (1984) suggested thresholds of between 5 and 20 are appropriate, so three images were generated with threshold values of 5, 10 and 20.

In order to facilitate comparisons between the algorithms tested here, the ridge network was thinned to a final one cell-wide line representation.
7.2.2.3. **Band (1986) algorithm**

Band (1986) proposed a method of identifying stream lines from a DEM, based on the Peucker and Douglas (1975) algorithm which was enhanced by a method of joining 'broken' streamlines. Ridges and streamlines calculated using the Peucker and Douglas (1975) algorithm were thinned to one cell wide using the Rosenfeld and Kak (1982) thinning algorithm (described below in 7.2.3.1). The upstream and downstream nodes on each stream fragment were then flagged. Each downstream node was then 'drained' along the line of maximum descent until it connected with another streamline. The streams were again thinned to the final cell-wide line representation of the stream network.

Band (1986) did not calculate ridges, but rather 'drainage divide networks'. The divide network was generated by thinning the complement of the streams; that is the 'lines' defined by the nonstream cells in the stream image were thinned using the Rosenfeld and Kak (1982) algorithm, with the qualification that stream junctions were nonthinnable points (in order to anchor the divide graph to the stream network).

7.2.3. Proposed method for mapping ridge and gully position

7.2.3.1. **Gully position**

A cell can be defined as a gully if it has two opposite neighbours which are higher, and if the other two (orthogonal) neighbours have a lower and a higher elevation (see Figure 7-1).

![Figure 7-1: A streamline with raised channel sides and draining in a north-south direction](image)

The algorithm assumes there are eight directions the gully can drain to, viz., north to south, south to north, east to west, west to east, northwest to southeast, southeast to northwest, southwest to northeast and northeast to southwest. The north-south situation is described in detail below; it is then simple to extend the algorithm to the other directions.
Cells to the east and west of the cell being tested (hereafter called the test-cell) are checked to see whether they have a higher elevation than the test-cell. If they both have a higher elevation then the test-cell is assumed to be a 'potential gully' running in a north-south direction. If one or both of the adjacent cell's elevations are lower, then the test-cell is not a gully in a north-south direction, and the test-cell is checked in another direction: this allows stream curvature (i.e. curvature in plan) to be modelled. If one (or both) of the adjacent cells are equal in elevation to the test-cell, then the next adjacent cell outwards is checked (Figure 7-2), until adjacent cells which are higher, or lower, than the test-cell are found. There is no limit to the number of adjacent cells that are checked. However the maximum stream width in the analysis area may be noted and used to set the maximum number of outward iterations for a procedural programming language.

![Figure 7-2: Two cell wide streamline across and along the drainage channel](image)

If the test-cell is a 'potential gully' running in a north-south or a south-north direction, then the gully must drain in an orthogonal (north-south or a south-north) direction. A check is made that one of the adjacent (north-south) cells is higher and one is lower; then the cell is flagged as a gully and the algorithm passes to the next cell in the matrix. Again, if one (or both) of the cells is equal in elevation, the algorithm continues to search in a north or south direction until a higher or lower cell is found. If the adjacent cells are both lower, then the test-cell is not a gully (in fact it is a saddle) and the algorithm passes to the next direction. Note that all spurious sinks had been removed using Hutchinson's (1989) interpolation algorithm, so the situation where the adjacent cells are both higher in a north-south direction could not occur.

The algorithm was then repeated for the other directions until the cell is flagged as a streamline, and the algorithm passes onto the next cell in the DEM. If the cell was not on a streamline in any of the eight directions, the cell is not flagged, and the algorithm passes onto the next cell.
The streams were thinned to a width of one cell using the Rosenfeld and Kak (1982) line thinning algorithm. Using this algorithm, cells are deleted only if they are not end points, and if they will not disconnect a continuous streamline. The north border point (C3 in Figure 7-3) will be removed if

\[ \sum C_{i} = 0, \]

where \( \bar{C} \) is the binary inverse of \( C \) (i.e. \( 0 = 1 \) and \( 1 = 0 \)). End points (i.e. cells having exactly one neighbour in the three by three moving window) need to be tested for separately, as they should not be deleted.

![Figure 7-3: Numbering system for the three by three moving window](image)

After the first execution of the algorithm, it was noticed that some extraneous streamlines were being created due to noise in the DEM. Consider again Figure 7-1. 'False' streams of short length were being mapped in situations where the difference in elevation between the test-cell and the adjacent (east-west) cells was one metre, possibly due to noise in the DEM. A user-specified threshold was introduced, defining a test-cell as a neighbour only if the difference in elevation between the test-cell and the adjacent cells was more than or equal to the threshold.

One effect of the threshold on the streamline image was to break three previously connected streamlines, where valley sides were low at stream junctions on wide valley floors. To correct this problem, the user specifies the downstream node of the broken streamline. The specified downstream node was then connected to the nearest streamline using the line of maximum descent. In other words, for the three-by-three moving window shown in Figure 7-3, the next downstream cell chosen is:

\[ C_{i} \rightarrow \Delta C_{i} = \max(\Delta C_{1}, \Delta C_{2}, \Delta C_{3}, \Delta C_{4}, \Delta C_{5}, \Delta C_{6}, \Delta C_{7}, \Delta C_{8}) \]

where

\[ \Delta C_{i} = C_{0} - C_{i} \]

until connection with a streamline occurs. Note that \( \Delta C_{i} \) is the gradient of the central cell \( C_{0} \) to the adjacent cells \( C_{i} \) (for \( i = 1, \ldots, 8 \)), and is consequently adjusted by a factor of \( \sqrt{2} \) for the diagonals (i.e. for \( i = 2, 4, 6, \) and \( 8 \)).

The required threshold value will vary according to the nature of the DEM. A DEM interpolated to the nearest 10 m height contour will obviously require a larger threshold value than a DEM.
interpolated to the nearest 1 m. The reduction in spurious or false streams must be balanced against the breakage of significant streams, especially if the headwaters portion of the stream is removed as a result of the threshold. In practice, the user would know the approximate level of noise in the DEM, and an appropriate threshold value may be selected by iteratively testing alternative threshold values that lie around this approximate value. In this case the threshold was set to two metres.

7.2.3.2. **Ridge position**

Calculating ridge position is a corollary of calculating stream lines. A test-cell was defined as a ridge if it had two opposite neighbours which were lower, and two orthogonal neighbours which are both lower (see Figure 7-4a) or have a lower and a higher elevation. If the orthogonal neighbours have a lower and a higher elevation then the ridge must be at least two cells long in the orthogonal direction (see Figure 7-4b). Again, if one (or both) of the cells is equal in elevation, the algorithm continues to search until a higher or lower cell is found. The ridges were also thinned to a one cell wide line, using the algorithm proposed by Rosenfeld and Kak (1982).

![Diagram of ridge and lower cells](image)

*Figure 7-4a: Ridge (peak) surrounded by lower cells*
7.2.3.3. Interpolating midslope positions

To create a map of the topographic position of a cell in the terrain (e.g. upper mid-slope, mid-slope, or lower mid-slope), a euclidean distance algorithm was devised to interpolate between the ridge lines and valleys. Each cell is visited in turn. If the cell is not flagged as a valley or ridge, the euclidean distance from the cell to the nearest valley cell and the nearest ridge cell is calculated. These two euclidean distances are then summed and the ratio of the cell's distance from the ridge to the cell's distance from the valley is used to determine the relative position in the topography for the cell. The assignment of a name describing the topographic position is arbitrary, and dependent upon the actual topographic relief being considered and the number of mid-slope positions required.

The nearest ridge cell and nearest valley cell were initially sought in a zone one cell wide from the test-cell. Within this zone, the cells were checked in order of proximity to the test-cell to ascertain whether they were labeled as a ridge or a valley. If the cell was labeled, the euclidean distance from the test-cell to the cell was calculated. If a ridge or valley cell was not located in the first zone, a second zone, of two cells width from the test-cell, was selected. Again the algorithm searched the cells, in order of proximity to the test-cell, to elucidate whether any cell was a ridge or a valley. This process was iterated until the euclidean distances to the nearest ridge and to the nearest valley were obtained. The relative position \((P_{i,j})\) of the test-cell (that is not a ridge or a valley) in the terrain was calculated thus:

\[
P_{i,j} = \frac{\text{euclidean distance to the nearest valley}}{\text{euclidean distance to the nearest valley} + \text{euclidean distance to nearest ridge}}
\]

For the study area, the allocation of a name describing the topographic position of the test-cell was made as follows:

If \((P_{i,j} < 0.1)\), \(X_{i,j}\) is a valley;
If \(0.1 < P_{i,j} < 0.4\), \(X_{i,j}\) is a lower mid-slope;
If \(0.4 < P_{i,j} < 0.6\), \(X_{i,j}\) is a mid-slope;
If \(0.6 < P_{i,j} < 0.8\), \(X_{i,j}\) is an upper mid-slope;
If \(P_{i,j} \geq 0.8\), \(X_{i,j}\) is a ridge.

Such an allocation is obviously arbitrary, and can be adjusted according to the requirements of the user and the terrain being modelled. For example, more than three mid-slope positions may be modelled, or the threshold distances along \(P_{i,j}\) may be changed according to the terrain type (see 7.5.1 for details).

All the algorithms described above for calculating streams, ridges and terrain position were written in Fortran-77 and executed on a VAX-cluster at the Australian National University. Maps produced by the algorithms were displayed on Tektronix graphics hardware using the MAP software (Tomlin, 1987).

7.2.4. Six commonly used methods for calculating gradient and aspect are compared

Six different methods were tested to ascertain how effectively they calculated aspect and gradient from the regularly gridded DEM. All methods are based on a three-by-three moving window which traverses the DEM.

1) The first method defines aspect as the direction of the maximum drop (i.e. the maximum gradient) from the centre pixel to the eight nearest cells (Travis et al., 1975; EPPL7, 1987), that is:
\[
\text{gradient} = \max((z_{i,j} - z_{i-1,j-1}),(z_{i,j} - z_{i-1,j}),(z_{i,j} - z_{i-1,j+1}),(z_{i,j} - z_{i+1,j-1}),(z_{i,j} - z_{i+1,j}),(z_{i,j} - z_{i+1,j+1})).
\]
where \(z_{i,j}\) is the centre cell of the window located at the \(i^{th}\) row and \(j^{th}\) column. In other words, aspect is the direction (in \(45^\circ\) intervals) of the maximum gradient. For example, if the maximum gradient is in the direction of cell \(z_{i-1,j+1}\) then aspect = \(45^\circ\).

2) The second method of calculating gradient and aspect is similar to the first, with gradient being defined as either the maximum gradient of the steepest drop or the steepest rise. Aspect is then the direction of the maximum gradient (EPPL7, 1987).

3) The third method tested was a second-order finite difference method (also called numerical differentiation) described in Dozier and Strahler (1983) for a two by two moving window, and also used by Fleming and Hoffer (1979). The first step in the algorithm is to calculate:
\[
\frac{\delta z}{\delta x}_{i,j} = \frac{[z_{i+1,j} - z_{i-1,j}]}{2\Delta X}
\]
and
\[
\frac{\delta z}{\delta y}_{i,j} = \frac{[z_{i,j+1} - z_{i,j-1}]}{2\Delta Y},
\]
where \(\Delta X\) is the spacing between points in the horizontal direction, \(\Delta Y\) is the distance in the vertical direction, and \(i\) and \(j\) are not the peripheral rows or columns.

For points on the end of a row or column, calculate
\[
\left\{\frac{\delta z}{\delta x}_{i,j} \mid (u=1)\right\} = \frac{[-3z_{1,j} + 4z_{2,j} - z_{3,j}]}{2\Delta X}
\]
and
\[
\left\{\frac{\delta z}{\delta y}_{i,j} \mid (u=un)\right\} = \frac{[z_{n-2,j} - 4z_{n-1,j} + 3z_{n,j}]}{2\Delta Y},
\]
where \(u\) is the row and/or column number and \(n\) is the total number of rows and/or columns.
The gradient is then defined as:
\[\tan G = \sqrt{(\delta z/\delta x)^2 + (\delta z/\delta y)^2)},\]...(1)

while aspect is defined as:
\[\tan A = \frac{(\delta z/\delta x)}{(\delta z/\delta y)},\]...(2)

4) A third-order finite difference method for calculating gradient and aspect proposed by Horn (1981) was the fourth method used, where:
\[\frac{[\delta z/\delta x]_{i,j}}{\delta x} = \left[\left((z_{i+1,j+1}) + 2(z_{i+1,j}) + (z_{i+1,j-1})\right) - \left((z_{i-1,j+1}) + 2(z_{i-1,j}) + (z_{i-1,j-1})\right)\right] / 8\Delta X\]...(3)

and
\[\frac{[\delta z/\delta y]_{i,j}}{\delta y} = \left[\left((z_{i+1,j+1}) + 2(z_{i,j+1}) + (z_{i,j-1})\right) - \left((z_{i-1,j+1}) + 2(z_{i-1,j}) + (z_{i-1,j-1})\right)\right] / 8\Delta Y\]...(4)

Aspect and gradient are calculated for each cell as in (1) and (2). Sharpnack and Akin (1969) had earlier proposed a third-order finite difference method for calculating gradient and aspect that did not have a weighting factor for the non-diagonally adjacent cells. For the Sharpnack and Akin (1969) model, equation (3) would be rewritten as:
\[\frac{[\delta z/\delta x]_{i,j}}{\delta x} = \left[\left((z_{i+1,j+1}) + (z_{i+1,j}) + (z_{i+1,j-1})\right) - \left((z_{i-1,j+1}) + (z_{i-1,j}) + (z_{i-1,j-1})\right)\right] / 6\Delta X\]

and equation (4) as:
\[\frac{[\delta z/\delta y]_{i,j}}{\delta y} = \left[\left((z_{i+1,j+1}) + (z_{i,j+1}) + (z_{i,j-1})\right) - \left((z_{i-1,j+1}) + (z_{i-1,j}) + (z_{i-1,j-1})\right)\right] / 6\Delta Y.

In fact, any weighting scheme could be introduced into the third-order finite difference model, though the Horn (1981) model was used for comparative purposes in this study.

5) The fifth and sixth methods tested were multiple linear regression models proposed by Travis et al. (1975) and reported by Evans (1980), where a surface is fitted to the nine grid cells in a 3 by 3 window, using least squares (or orthogonal polynomials to improve computational efficiency) to minimize the sum of distances from the surface to the cells. The regression surface for the fifth model is:
\[Z = \beta_0 + \beta_1X + \beta_2Y + \epsilon_i\]...(5)
Assuming \(E(\epsilon_i) = 0\), the regression function for the model in (5) is:
\[E(Z) = \beta_0 + \beta_1X + \beta_2Y.\]...(6) (Neter and Wasserman, 1974)

Taking partial derivatives of (6) with respect to X and Y yields:
\((\delta E(Z)/\delta X) = \beta_1\) and \((\delta E(Z)/\delta Y) = \beta_2\).

Gradient and aspect are then calculated using (1) and (2), substituting \((\delta E(Z)/\delta X)\) for \((\delta z/\delta x)\) and \((\delta E(Z)/\delta Y)\) for \((\delta z/\delta y)\).

6) The surface modelled by the sixth method is:
\[Z = \beta_0 + \beta_1X + \beta_2Y + \beta_3X^2 + \beta_4Y^2 + \beta_5XY + \epsilon_i.\]...(7)
Again, assuming \(E(\epsilon_i) = 0\), the regression function for the model in (7) is:
\[E(Z) = \beta_0 + \beta_1X + \beta_2Y + \beta_3X^2 + \beta_4Y^2 + \beta_5XY.\]...(8) (Neter and Wasserman, 1974)

The partial derivatives of (8) with respect to X and Y are:
As for method 5, gradient and aspect are then calculated using (1) and (2), substituting \((\delta E(Z)/\delta X)\) for \((\delta z/\delta x)\) and \((\delta E(Z)/\delta Y)\) for \((\delta z/\delta y)\).

The linear multiple regression coefficients for methods 5 and 6 \((\beta_1, \beta_2, \beta_3, \beta_4, \text{ and } \beta_5)\) were calculated from covariance matrices (Neter and Wasserman, 1974), using Fortran subroutines provided by the IMSL (1987) suite of statistical routines.

These six methods were quantitatively compared by taking a subsample grid of three by three cells and recording the elevation of the cells. The grid was plotted on graph paper and the centre cell was connected to the adjacent positions (in the three by three matrix) that had the same elevation. The gradient and aspect were then manually calculated by drawing a tangent to the contour passing through the centre cell and graphing the perpendicular bisector of the tangent (Myers and Shelton, 1980). Aspect was calculated from the direction of the perpendicular bisector, and the gradient calculated by dividing the difference in height along the perpendicular bisector by the length of the perpendicular bisector. The manually calculated values of slope and aspect were taken as the true values.

In all, 50 samples were taken at random. One sample occurred on a saddle, and therefore had no gradient and an undefined aspect. This sample was rejected, and another sample was randomly selected to replace it. The differences between true aspect and the aspect calculated by methods 1 to 6 were calculated, and plotted as histograms. The mean and standard error of the mean for these histograms are also detailed on the Figures. The differences between true gradient and calculated gradient were similarly found, and plotted as histograms. The aim was to visually detect those methods which had the least deviation from the true values of aspect and gradient.

As the true gradient and aspect measurements were paired with the gradient and aspect values calculated by the six methods, Kendall’s tau measure of association test (Noether, 1976) was used to test a research hypothesis that the true gradient was positively correlated with the calculated gradient and the true aspect was positively correlated with the calculated aspect viz.,

\[ H_O : X, Y \text{ are independent versus } H_A : X, Y \text{ are positively correlated}, \quad \ldots (9) \]

where \(X\) is the true aspect of the cell and \(Y\) is aspect calculated by method 1. Note that the same null hypothesis was applied to the aspect values derived from methods 2, 3, 4, 5 and 6, and also to the gradient calculations using methods 1 to 6. The test was one-sided with \(\alpha' = 0.05\), and the test statistic \(z_{\alpha'} = 1.645\).

Spearman’s rank correlation coefficient (Noether, 1976) was used to measure the monotone relationship between the true values of aspect and the measured values of aspect, and the true values of gradient and the calculated values of gradient, for the six methods tested. Tests for significant positive association between the true and calculated aspect and gradient variables were calculated using the Spearman’s rank correlation coefficients. The same null and alternative hypotheses were used as described in (9). In this case, the test was one-sided with \(\alpha' = 0.05\), and \(H_O\) was rejected if:

\[ \sqrt{n-1} \ (r_s) > z_{\alpha'} \]

where \(n\) is the number of samples and \(r_s\) is the Spearman’s rank correlation coefficient.
7.3. Results

7.3.1. Terrain position algorithms

A map showing ridges and streams in the study area is presented as Figure 7-5. The Band (1986) algorithm generated the image shown in Figure 7-6, and though the streams are mostly connected, there are a number of extraneous streams in the northwest and north central sections of the image. Ridges (i.e. 'divide networks') were not plotted for reasons cited in the methods (7.2.2.3). Figures 7-7, 7-8 and 7-9 show the (thinned) ridge and streams produced using the O'Callaghan and Mark (1984) algorithm at thresholds of 5, 10 and 20. Note that at a threshold of 5, many cells are included as streams compared with a threshold of 20. Figure 7-10 shows that ridges and streams generated by the Peucker and Douglas (1975) algorithm are fragmented. A composite image showing ridges and streams (at a threshold of 20) calculated using the O'Callaghan and Mark (1984) algorithm is included (Figure 7-11).

Figure 7-12 shows the image of the valleys and ridges produced by the algorithm proposed here. Finally, the image of the midslope positions interpolated from Figure 7-12 is detailed as Figure 7-13.

![Figure 7-5: Map showing positions of the ridges and streams in the study area](image-url)
Figure 7-6: Image of the stream network as produced by the Band (1986) algorithm.

Figure 7-8: Image of streams produced using the O'Callaghan and Mark (1984) algorithm with a threshold of greater than or equal to 10.

Figure 7-9: Image of streams produced using the O'Callaghan and Mark (1984) algorithm with a threshold of greater than or equal to 20.
Figure 7-10: Image of the stream and ridge networks produced by the Peucker and Douglas (1975) algorithm.

Figure 7-11: Composite image of streams and ridges produced using the O'Callaghan and Mark (1984) algorithm with a threshold of greater than or equal to 20.

Figure 7-12: Image of the valley and ridges produced by the proposed Skidmore (1989) algorithm.

Figure 7-13: Image showing interpolated midslope positions between the valleys and ridges shown in Figure 7-12.
7.3.2. Gradient and aspect algorithms

The 7.5 by 7.5 km DEM used to test the gradient and aspect algorithms was digitized from the contour map shown in Figure 7-14. The contour map interpolated from the DEM (Figure 7-15) compares closely with the original contour map (Figure 7-14).

The six methods used to calculate gradient and aspect were quantitatively compared with the true values, using the Kendall tau test, and the resulting standardized 'tau' (τ) values are presented in Table 7-1. Aspect values calculated by methods 1 through 6 were significantly correlated with the true aspect at α* = 0.05. Figure 7-16 confirms diagrammatically the result from Table 7-1; that there is no significant deviation between true aspect and calculated aspect for any of the six methods.

Table 7-1: Comparison of the six methods used to calculate aspect and gradient with the true values of aspect and gradient using Kendall's tau test.

<table>
<thead>
<tr>
<th>Topographic position</th>
<th>Method number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect</td>
<td>1</td>
</tr>
</tbody>
</table>

* - Denotes that the standardized τ values were statistically significant at α* = 0.05. Consequently, reject the null hypothesis (9), and conclude that the true value is positively correlated with the calculated value.

The gradient values calculated by methods 1 to 6 were all significantly correlated with the true gradient (Table 1). Table 1 shows that the gradient values calculated by methods 5 and 6 have the highest correlation with the true values, and this is confirmed by Figure 7-17, where the deviation of the gradient values from the true values was smaller compared with methods 1, 2, 3 and 4.
Figure 7-14: Original contour map of the study area used to digitize the DEM

Figure 7-15: The contour map interpolated from the DEM by Hutchinson's (1989) SPLIN2H program
Figure 7-16: The difference between true aspect and calculated aspect (in degrees) for methods 1 to 6.
Figure 7-17: The difference between true gradient and calculated gradient (in degrees) for methods 1 to 6.
The Spearman's rank correlation coefficients are listed in Table 7-2, and confirm the observations made from Figures 7-16 and 7-17 and Table 7-1. The correlation between true gradient and calculated gradient and true aspect and calculated aspect was highest for methods 4, 5 and 6 and lowest for methods 1 and 2. The statistical significance of the $r_s$ values is summarized in Table 7-3. The results are similar to those presented in Table 7-1.

**Table 7-2: Spearman's rank correlation coefficients for gradient and aspect.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Gradient ($r_s$)</th>
<th>Aspect ($r_s$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.908</td>
<td>0.619</td>
</tr>
<tr>
<td>2</td>
<td>0.936</td>
<td>0.844</td>
</tr>
<tr>
<td>3</td>
<td>0.974</td>
<td>0.884</td>
</tr>
<tr>
<td>4</td>
<td>0.985</td>
<td>0.999</td>
</tr>
<tr>
<td>5</td>
<td>0.985</td>
<td>0.999</td>
</tr>
<tr>
<td>6</td>
<td>0.985</td>
<td>0.999</td>
</tr>
</tbody>
</table>

**Table 7-3: Comparison of the six methods used to calculate aspect and gradient with the true values of aspect and gradient using Spearman's rank correlation coefficient.**

<table>
<thead>
<tr>
<th>Topographic feature</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
</table>

* - Denotes that the Spearman's rank correlation coefficient values were statistically significant at $\alpha' = 0.05$. Consequently, reject the null hypothesis (9), and conclude that the true value is positively correlated with the calculated value.

### 7.4. Discussion

#### 7.4.1. Terrain position algorithms

The images of topographic position (Figures 7-12 and 7-13) generated using the new algorithms clearly match the streamlines within the study area (Figure 7-5). Note that the river valleys are clearly defined, and that the streamlines are unbroken, as would be expected in a valley network that drains. The mapped ridges generally follow the actual ridges (Figure 7-5). The midslope positions are realistically portrayed (Figure 7-13).

A problem with the proposed algorithm is that not all valleys are mapped (for example in the area of 50-53 and column 75-95 in Figure 7-12), and that some streams are joined across ridges (for example at row 23, column 14 in Figure 7-12). Some mapped ridges are not continuous, though the midslope interpolation algorithm successfully joined the broken ridges (for example in the area of rows 60-70 and columns 20-40 in Figure 7-13).
The interpolated midslope positions closely correspond with the original contour lines. The midslope interpolation algorithm models the valley and ridge width; for example a narrow valley, in the area of row positions 40-45 and column positions 40-45 in Figure 7-13, is modelled as a narrow strip of gully and lower midslope cells, while the wide valley bottom (at row positions 25-35 and column positions 50-60) is also successfully mapped.

The Peucker and Douglas (1975) algorithm produced an image (Figure 7-10) with streams and ridges in the correct locations, but the streams and ridges were fragmented. The resulting image is an unsatisfactory representation of the stream and ridge network. Breaks in the streamlines were caused by the valley floor being more than one cell wide; there is obviously not a lowest single cell in a two by two moving window in this case!

Band (1986) recognized the limitations of the Peucker and Douglas (1975) algorithm, and corrected the problem by joining the stream fragments together. The resulting image (Figure 7-6) had connected streams. However, in areas of flatter terrain (such as in the area of rows 65-95 and columns 5-35) there were a plethora of false cross-streams linking the true streams. This was caused by the downslope node of a stream fragment draining to nearest cell along the line of maximum descent. In some situations, two cells had an equally steep maximum descent from the downstream node, causing multiple connecting streams to form.

The drainage divide network calculated by Band (1986) was not comparable with the ridges generated by the other algorithms. This was because the divide networks were not specifically linked to the true ridges. The divide networks are actually the loci of the streams, and would therefore not correspond in places to the ridges. In addition, catchment boundaries descend to the stream junctions; in such a situation one would expect cells to be defined as valleys and not as a divide (or ridge). Finally, the Band (1986) algorithm will not isolate minor (or false) ridges which do not occur on the drainage divide.

The stream network produced by O'Callaghan and Mark's (1984) algorithm was not continuous, even at a threshold of 5 (Figure 7-7). Breaks in the streams occurred at flat sections of the stream, where multiple cells had the same elevation. In such situations, the stream flowed back on itself due to the arbitrary allocation of a cell to the next downstream point (i.e. where two [or more] adjacent cells have the same elevation, the algorithm drains to the first cell encountered clockwise from the north). Some streams with uniform slope had an adjacent parallel stream at a threshold of 10 (such as in the area of rows 35-50 and columns 15-30 in Figure 7-8), though this phenomena was noted and discussed by O'Callaghan and Mark (1984). The stream network produced at a threshold of 20 (Figure 7-9) was broken where streams had a slight gradient. The ridge network was well linked and generally followed the true ridges, as shown on Figure 7-11 which is a composite image showing ridges and streams at a threshold of 20.

The four algorithms were compared over one set of terrain conditions (i.e. an area of flat to moderate terrain in southeast Australia). An algorithm may produce a better map of stream and ridge networks under different terrain conditions (for example a flat floodplain, or steeply dissected alpine areas). O'Callaghan and Mark (1984) tested their algorithm over three different terrain types, and noted that extraction of terrain information is difficult over floodplains. Band (1986) noted that the Peucker and
Douglas (1975) algorithm will work well over 'rugged terrain with well-incised streams and sharp divides' (p. 17). Band (1986) tested his algorithm in an area of 'sharp-crested ridges and well-incised drainage lines' (p. 22). The confused stream network that Band's algorithm produced in the flatter areas of the present study area suggests the algorithm may be less suited to this terrain type. Indeed, Band (1986) acknowledged that other algorithms may have advantages in certain topographic situations.

In order to compare the efficiency of the four algorithms, the cpu time required to calculate the stream and ridge networks over the same DEM was measured. The Peucker and Douglas (1975) algorithm was the most efficient (6.81 cpu seconds), followed by the O'Callaghan and Mark (1984) algorithm (8.86 cpu seconds), and the algorithm proposed here (12.11 cpu seconds). The Band (1986) algorithm took 67.88 cpu seconds, due to the computational expense in locating the downstream nodes and then tracing the drainage lines from the downstream nodes.

Midslope positions were effectively interpolated using the proposed algorithm. Any number of midslope positions may be defined by an analyst, depending upon the particular application. In addition, the range of 'P_{ij}' assigned to a particular mid-slope position can be changed to reflect the topographic landscape being considered. For example, a youthful, steeply uplifted landscape will tend to have longer mid-slopes compared with an ancient rounded topography.

The success of any stream and ridge mapping algorithm is dependent on the accuracy of the gridded DEM. Fortunately, the program developed by Hutchinson (1989) creates a DEM that 'drains', by forcing any spurious 'sink' holes to drain downhill. This global drainage condition is valid for the study area as no surface ponds or lakes exist. The DEM used in this study had some small 'errors' where the streams on the DEM did not follow the actual streams (e.g. at row 69, columns 55-60). These errors may be due to poor input data. Interpolation algorithms such as the method described by Hutchinson (1989) do permit irregularly spaced environmental data captured by digitizing to be rapidly and accurately interpolated to a regular tesselation.

Regularly gridded DEMs can be easily incorporated into grid based GISs. For example, the algorithm described here was used to calculate terrain positions over an area of forest in southeast Australia, and the terrain information was geometrically rectified with remotely sensed data in a GIS (see Chapter 8 for details).

Band (1986) discussed the problem of quantitatively comparing algorithms which produce maps of ridge and stream networks, and concluded that objective criteria for the interpretation of streams and divides from contours must be developed, but that that was beyond the scope of his paper. To define what is a ridge, and what is a stream (or valley) on a contour map, would allow an objective comparison of the different images produced by the algorithms tested here.

7.4.2. Gradient and aspect algorithms

There was a statistically significant correlation between true gradient and calculated gradient for all six methods, when tested with the Kendall tau and Spearman rank correlation coefficient tests (Tables 7-1 and 7-3).
A statistically significant correlation was also apparent between true aspect and calculated aspect for all methods when using the Kendall tau and Spearman rank correlation coefficient tests (Tables 7-1 and 7-3).

Table 7-1 shows gradient calculated by method 6 had the highest tau value. Modelling the surface using linear regression models (methods 5 and 6) yielded slightly higher tau values than when using the finite difference methods (3 and 4). Interestingly the $r_s$ values were equal for the third order finite difference method and the regression methods (i.e. methods 4, 5 and 6 [Table 7-2]). As the difference in tau values for methods 4, 5 and 6 (Table 7-1) are small, it can be seen there is little difference between the the third order finite difference method and the regression methods.

There was no difference between true aspect and calculated aspect for the third order finite difference method and the regression methods (methods 4, 5 and 6) when tested with the Spearman rank correlation coefficient test (all three had a correlation of 0.999). The correlation between true aspect and calculated aspect was more accurately estimated by the surface modelled by third order linear regression surface (method 6) than the second order linear regression surface (method 5) according to the Kendall tau test. The subtle changes introduced by the quadratic terms in the linear regression model may have caused a slightly better estimate of elevation changes in the X and Y directions. The correlation between true aspect and calculated aspect is greater for the third order finite difference method (method 6) than the regression methods (methods 5 and 6). However, the difference in correlation values is small and it would be improper to conclude that method 6 is 'better'.

Gradient and aspect were calculated more accurately by the third order finite difference method (method 4) compared with the second order finite difference method (method 3). This may be due to a larger area being sampled by the adjacent diagonals used by the third order finite difference method (method 4). Gradient and aspect were more accurately estimated when the steepest rise or the steepest fall was considered (method 2) compared with steepest fall alone (method 1).

Methods 1 and 2 gave poorer estimates of gradient and aspect. This is due to aspect and gradient being calculated in the direction of steepest rise or fall (for the eight cells adjacent to the test cell). The direction is therefore truncated to $45^\circ$ intervals. In addition, in the event of two directions having an equal and maximum gradient, aspect calculated by methods 1 and 2 will be less accurate, as a choice about the 'correct' direction of maximum gradient will have to be made. The main reason for the third-order finite difference method (method 4) and the multiple linear regression methods (methods 5 and 6) more accurately calculating gradient and aspect compared with methods 1, 2 and 3, is that all cells adjacent to the centre cell contribute to the calculation.

Spurious gradient and aspect values may be generated over some terrain features regardless of the method used to calculate gradient and aspect. Examples of terrain features for which aspect and gradient may be difficult to define include saddles and areas of flat terrain. (It was noted in 7.2.4 that one sample occurred over a saddle and as a consequence was rejected.) In the forest type mapping study (see Chapter 8) for which gradient and aspect were included as data layers in a GIS, the effect of spurious gradient and
aspect values was minimized by the use of prior probabilities in the expert system, and inclusion of ecotonal information. These issues are discussed in detail in Chapter 9.

Evans (1980) reported correlation coefficients between true aspect and calculated aspect, and true gradient and calculated gradient, for a six-parameter linear regression model (equivalent to third order linear regression model [method 6] reported here). The \( r' \) values were similar to those reported for this study (i.e. Evans [1980] reported a \( r' \) value of 0.998 for aspect and 0.984 for gradient). Differences in reported \( r' \) values could be expected because as the grid spacing shortens, the gradient and aspect values will approach the true gradient and aspect values, for any of the methods tested. It is not apparent from Evans (1980) which correlation coefficient (i.e. Pearson product-moment coefficient of correlation or Spearman's correlation coefficient) was used.

The assumption of Hutchinson (1989), that all the streams drain, was valid in the study area, as no natural 'sinks' occurred (i.e. ponds or lakes). The irregular data interpolated by Hutchinson's (1989) program were digitized from a topographic map over a forested region. The contours drawn on the map were assumed to be accurate (the map stated it was prepared to conform with Australian Mapping Council standards of accuracy), though the map may have been another source of error in this study.

The assumption that the manually measured aspect and gradient are the 'true' aspect and gradient is obviously a debatable point! Manually fitting contour lines between elevation points permits the use of human 'intelligence' in drawing smoothly fitting contours that are 'sensible' in the context of the grid points. The disadvantage is that different operators may produce different results when they fit slightly different curves between a given set of points. In other words, the curve fitted between points by two operators will never be the same, so an exact mathematical model can not be developed even using higher order linear regression models. Another problem with estimating gradient and aspect is that they will vary at different scales in the topography. Anyone who has measured gradient and aspect in the field will appreciate that gradient and aspect vary according to whether one measures them over a length of one metre (rocks and boulders may influence the estimate) or over 100 metres (a change in grade and aspect may occur 30 m from the point being measured). The method used in this study follows the accepted field technique for recording gradient and aspect (Myers and Shelton, 1980), by calculating the average gradient along the perpendicular bisector of the tangent to the contour. The results obtained here indicate that the linear regression models and third order finite difference method have the best potential for estimating gradient and aspect.

7.5. Conclusions

The proposed terrain position modelling algorithm generates a satisfactory image of streams and ridges from a regularly gridded DEM by utilizing basic geographical principles. Streams and ridges closely followed the original contour map, and improved upon the results from three alternative algorithms. The Peucker and Douglas (1975) and O'Callaghan and Mark (1984) algorithms produced images with broken streams in areas of flat gradient. The image produced by the Band (1986) algorithm was similar to that of
the proposed algorithm, though it caused a plethora of streams to appear in the flatter parts of the study area. The Band (1986) algorithm was also computationally expensive. A realistic map showing midslopes was successfully interpolated between the calculated valleys and ridges, using a new algorithm based on euclidean distance interpolation.

There is little difference between the third order finite difference method (method 3) and the linear regression models (methods 5 and 6) for calculating aspect and gradient. The general linear regression models or the third order finite difference method (i.e. method 4) appear to be optimal for calculating gradient and aspect from a gridded DEM.

Terrain position, gradient and aspect are potentially useful variables with which to model environmental processes using geographical information systems (GISs). These terrain variables are now used by an expert system to model forest vegetation types and forest soils (Chapters 8 and 9).
8. AN EXPERT SYSTEM CLASSIFIES EUCALYPT FOREST TYPES USING THEMATIC MAPPER DATA AND A DIGITAL TERRAIN MODEL

8.1. Introduction

A forest type is an area of forest which exhibits a general similarity in tree species composition and character. Maps of native forest that detail the distribution of forest types have traditionally been made using aerial photographs supported by ground surveys. This method is labour intensive and subjective, and may result in inconsistencies in the assignment of forest type boundaries or names between different aerial photograph interpreters, and over time with individual interpreters.

The advantages emanating from the objectivity and speed of computer processing of digital remotely sensed imagery have been detailed by Hoffer (1981), Skidmore et al. (1986) and Turner et al. (1989) and in Chapter 3. Thematic maps at Anderson et al. (1976) level I and II (i.e. discriminating between deciduous and coniferous forests) from remotely sensed data have been produced with accuracies of greater than 80 per cent (Nelson, 1981; Walsh, 1980), but where forest types have been discriminated (e.g., Anderson level III) mapping accuracies have been typically below 80 per cent (Strahler et al., 1978; Merola et al., 1983; Hame, 1984). However, in Chapter 6 eight forest types (i.e. at Anderson level III) in central Pennsylvania were mapped with an accuracy of 90 per cent, and five age classes in coniferous (Pinus radiata) plantations in Australia were discriminated with an 87 per cent mapping accuracy, using a supervised nonparametric classifier. Conventional supervised and unsupervised classification strategies had been unsuccessful, yielding less than 56 per cent overall mapping accuracies.

Combined supervised and unsupervised classification strategies have produced higher mapping accuracies than using only one of these techniques (Fleming, 1975; Beaubien, 1979; La Perriere et al., 1980; Thompson et al., 1980; Walsh, 1980).

Different remotely sensed data types have been combined to improve mapping accuracies. Skidmore et al. (1986) coregistered SIR-B radar data with Landsat MSS data using various classifiers. Higher mapping accuracies were obtained using the combined data sources than with either data source individually. Richards et al. (1987) used this data set to show enhanced radar backscatter occurred over flooded forests. Refer to Chapter 3 for more details on this topic.

To further improve mapping accuracies, spatial information ancillary to the remotely sensed data have been vector-digitized from maps or aerial photographs, and geometrically rectified to overlay the

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1This chapter has been published as: Skidmore, A.K., 1989. A rule based expert system classifies native forest types using Landsat Thematic Mapper and a digital terrain model. *Photogrammetric Engineering and Remote Sensing* (in press).

remotely sensed data. In most applications, the vector data have been rasterized to form a grid of cells of the same size as the remotely sensed pixels.

Remotely sensed data have been frequently combined with digital elevation data, and terrain features derived from elevation such as gradient, aspect and topographic position. Digital elevation data can be readily generated in most parts of the world from contour maps or aerial photographs. Some countries, such as the U.S., have complete digital elevation data coverage at various scales. For areas without elevation information, the stereoscopic capabilities of the SPOT satellite may be used to automatically generate digital elevation data to within ±10 m accuracy for the x, y and z coordinates (Swann et al., 1988; Rodriguez et al., 1988).

Other data which have been included with remotely sensed data in multisource digital data analysis include aerial photograph interpreted forest types (Tom and Miller, 1980), forest volume estimates (Strahler et al., 1979), precipitation and temperature data (Cibula and Nyquist, 1987) and soils (Ernst and Hoffer, 1979). Such environmental factors are important in determining forest species distribution. Australian researchers have shown that parent material (Austin, 1978; Austin et al., 1983), soil chemistry and structure (Kelly and Turner, 1978; Turner et al., 1978), fire history (Gill et al., 1981) and climate (Austin et al., 1983; Margules et al., 1987; Booth et al., 1987; Booth et al., 1988) are factors affecting the distribution of native forest species. In combination, these environmental variables create site conditions which favour a particular suite of forest species.

The importance of ancillary data types in determining species distribution will vary according to the size of the area being considered. Topographic data improves mapping accuracies when combined with remotely sensed data on a local (i.e. tens of kilometres) to regional scale (Hoffer et al., 1975; Tom and Miller, 1982; Austin et al., 1983). Parent material has been shown to be an increasingly important environmental variable determining forest species distributions on a regional scale (Turner et al., 1978; Austin et al., 1983). On a regional and continental scale, climatic information becomes useful (Austin et al., 1983; Margules et al., 1987; Booth et al., 1987; Booth et al., 1988).

Following are some specific examples that illustrate the improvement in map accuracy made possible by integrating ancillary data with remotely sensed data. Hoffer et al. (1975) included elevation data with three selected Skylab-2 spectral bands, and input the resulting four band data set directly into a maximum likelihood classifier. Mapping accuracies were improved by 23 and 32 per cent for a deciduous and a coniferous class respectively.

Tom and Miller (1980) combined elevation, gradient, aspect, photointerpreted vegetation cover, Landsat multispectral scanner (MSS) data and Landsat ratio bands, using a nonparametric linear discriminant function (described in Duda and Hart, 1973). They claimed a forest mapping accuracy of 97.3 per cent. Using a virtually identical linear discriminant function procedure, Fox et al. (1985) obtained an overall mapping accuracy of 78.5 per cent when discriminating between two forest site quality classes and non-forest.

Cibula and Nyquist (1987) combined topographic, climatological and Landsat MSS data using simple Boolean operators to link the data layers, and distinguished vegetation and land cover classes with
a 92 per cent accuracy. Many of the classes had a small number of pixels tested for mapping accuracy, so confidence intervals would be large.

An alternative strategy for combining multiple data sources is to stratify a scene using an ancillary data source before or after classifying a remotely sensed image. For example, Strahler et al. (1978) initially pre-stratified a forested area into elevation ranges, and then classified Landsat MSS data within each stratum into land cover and forest type classes. In another study, Hutchinson (1982) classified an area of desert using Landsat MSS data, and proceeded to post-classify dark pixels into shadowed slope, basalt and desert varnish classes using ancillary topographic data. Bright dry lake beds (playa) were similarly discriminated from the steep sunny slopes of sand dunes, using this post-classification technique. Talbot and Markon (1986) also used this technique, and claimed an improvement in mapping accuracy when topographic data were used to post-classify a maximum likelihood classification through the incorporation of shadow information.

A number of approaches to remove the effect of shadow on remotely sensed data by directly combining digital terrain data and remotely sensed data have been attempted. Areas which are shadowed as a result of topography will have lower mean and variance brightness values compared with areas which are sunlit (Holben and Justice, 1980). Reduction of the shadow effect prior to classification will reduce the variation in brightness values within a cover type across the topography (Justice et al., 1981). Increasing the brightness of shadowed areas (that have a low variance) will not increase the amount of information content per se. The brighter class values may still not be discriminated, as the variance is unchanged. The position of the sun in relation to the aspect of a piece of land is obviously a major factor in determining the amount of reflectance. The extent of the shadow problem in remotely sensed data is in part determined by the steepness of the topography, as Hall-Könyves (1987) showed that for gentle terrain in Sweden, there is only a weak relationship between topography and Landsat MSS brightness values. Leprieur et al. (1988) also investigated the relationship between slope and reflectance, but found the relationship was confused by variations in the forest type cover (i.e. deciduous or coniferous forest). Reflectance also varies according to the wavelength band, with shorter wavelength bands exhibiting less variation in reflectance across the topography compared with longer wavelengths (Leprieur et al., 1988). Another compounding problem highlighted by Karaska et al. (1986) was the percentage of tree and shrub cover, which masked the effect of topographic variables on Landsat Thematic Mapper (TM) spectral responses. There has been some debate whether Lambertian (i.e. light is scattered equally in all directions from a surface) or non-Lambertian models are more suited for modelling topographic shadowing (Malila et al., 1978; Hoffer et al., 1979; Justice et al., 1981), although Smith et al. (1980) and Holben and Justice (1980) showed that ponderosa pine and sand will exhibit both Lambertian and non-Lambertian scattering at different sun incident angles. Therefore, reducing topographic effects in remotely sensed data is difficult (Justice et al., 1981), and much more work needs to be performed to establish it as a practical method of combining remotely sensed data and digital topographic data.

In a forest environment not appreciably modified by humans, a given species or forest type characteristically appears within a range of environmental variable values (Pryor, 1959; Whittaker, 1967;
Florence, 1981; Austin et al., 1983). Such *a priori* information may be exploited to improve the mapping accuracy of forested areas when using remotely sensed data. For example, Strahler et al. (1978) used *a priori* probabilities based on slope and aspect to weight forest class probabilities in a maximum likelihood classification, and improved mapping accuracies. However, the same sample plots were used for generating the *a priori* probabilities and calculating mapping accuracies. This would artificially improve the mapping accuracies as the *a priori* probabilities were directly matched to the pixels selected to test mapping accuracy. Other drawbacks with this approach are that only two *a priori* probabilities may be introduced into the maximum likelihood classification strategy (Bishop et al., 1975), and the *a priori* information should be normally distributed. Richards et al. (1982) used a 'supervised relaxation labeling' technique over a forested area to include topographic information with an already classified Landsat MSS data. Supervised relaxation labeling assumes ancillary information is available which provides additional information with which to discriminate the cover classes. Prior probabilities are generated describing the relative likelihood of each of the pieces of ancillary data being the correct one for the pixel label. If the currently favoured label on the pixel is strongly supported by the ancillary data, then the probability that the pixel is correctly classified is increased. Conversely, if the currently favoured class label is not strongly supported by the ancillary data then its probability is weakened.

In an attempt to integrate disparate data types, expert systems have been proposed (Lee et al., 1987; Ripple and Ulshoefer, 1987; Robinson and Frank, 1987). Expert systems have been defined as computer programs that handle complex, real-world problems and attempt to solve problems by reasoning like an expert (Forsyth, 1984, Weiss and Kulikowski, 1984). Expert systems should also reach the same conclusion as a human expert, given a similar problem (Weiss and Kulikowski, 1984). The structure of expert systems vary widely, and Stock (1987) and Goldberg et al. (1985) provide reviews. However, expert systems have been characterized by two components;

1. A 'knowledge base' that contains the data pertaining to a system to be modelled, as well as rules (or relationships) linking the data and the hypotheses (or classes) that are being solved. The data and the rules are often termed 'evidence'.

2. An algorithm (the 'inference engine') controlling the program flow, or inferencing, between the evidence and the hypotheses (or classes) that are to be solved. That is, the algorithm controls the order in which the rules and the data are considered.

Expert systems have been devised to perform various functions with respect to digital spatial data including predicting fire behaviour in the Northern Territory of Australia (Davis and Nanninga, 1985; Davis et al., 1986); the identification of objects from remotely sensed digital data (such as training areas [Goodenough et al., 1987] and buildings and monuments [McKeown, 1987]); interpreting airports from (digital) maps and aerial photographs (McKeown, 1987); planning helicopter routes (Garvey, 1987); updating forestry maps by using remotely sensed data for change detection (Goldberg et al., 1985); despatch of forest fire control resources (Kourtz, 1987); selection and scheduling of cultural practices in forests (Rauscher and Cooney, 1987); and aiding forest managers by linking rules about aspen silviculture and management with a GIS called MOSS (map overlay and statistical system) (White and Morse,
Gray and Stokoe (1988) and Robinson and Frank (1987) provide summaries of other expert systems that have been applied to environmental assessment and management problems. Forsyth (1984) discussed general concepts in Bayesian (statistical) updating of probabilities. Lee et al. (1987) combined the two visible Landsat MSS bands with the two MSS infrared bands using Bayesian updating. They obtained similar results by using evidential calculus (Shafer, 1979).

This paper describes a method for combining many diverse data sources (e.g. gradient, aspect and elevation) with remotely sensed thematic images in order to map forests. The expert system modifies a thematic map of forest types, by using Bayes' theorem to integrate the ancillary topographic information with remotely sensed digital data. The system essentially mimics an experienced ecologist, assigning the most likely forest type to an area, after considering the area's gradient, aspect, topographic position and remotely sensed data response. If more information about the area becomes available (e.g. the soil type or parent material) then that knowledge can be easily incorporated into the decision making process of the expert system. An additional feature of this expert system is the inclusion of spatial information (see Chapter 5 and Skidmore, 1989a). If an area (in the case of this expert system a pixel) is not surrounded by ecologically plausible forest classes, the forest type is recalculated for the pixel using a contextual weighting factor. In simpler executions of contextual classification, Thomas (1980), Landgrebe (1980), Gurney (1981), Saxon (1984), Strahler and Li (1984), and Gordon and Philipson (1986) have used various moving window techniques to correct an unlikely central pixel, based on a measure of homogeneity with adjacent pixels. The expert system can also report on the reasoning behind a particular forest species being assigned to a pixel.

Richards et al. (1982) used 'probabilistic label relaxation' to incorporate contextual information into a classified image. Probabilistic label relaxation exploits the fact that certain cover types are more likely to occur together over adjacent pixels in remotely sensed image data (Kettig, 1975). The user defines a priori conditional probabilities that express the likelihood that pixel i (i.e. the pixel being updated by the relaxation method) is labeled as class $\lambda$, given that adjacent pixel j is labeled as class $\lambda'$ (i.e. $P(\lambda|\lambda')$). These a priori conditional probabilities are then used to describe the support from the neighbouring pixels for the labeling of pixel i as $\lambda$.

The overall aim of this chapter was to automatically map forest types in a complex native eucalypt forest in southeast Australia, using available multisource data including Landsat TM digital data, and digital topographic data including slope, aspect and topographic position (i.e. ridge, midslope, valley). A priori knowledge about the environmental position in which particular forest types and species occur, and the forest types that occur adjacent to one another have been included as rules in this classification process. The main differences between this expert system approach and preceding studies are that:

(a) there is an ability to update class probabilities using more than two data (i.e. evidence) sources (compare with Strahler et al., 1978);

(b) a nonparametric classifier (Skidmore and Turner, 1988) is implemented which yields the probability of correct classification for a class (as detailed in Chapter 6) and therefore avoids the assumption of normality in the class conditional probabilities (Lee et al., 1987);
(c) ecological knowledge is incorporated into the expert system to improve forest type mapping;
(d) a contextual check is made to ensure the classification is ecologically consistent.

8.2. Description of the study area

A study area of approximately 7.5 km by 7.5 km situated approximately 40 km west of the coastal township of Eden in southeast Australia was selected (Figure 8-1). The study area was selected as a pilot project, from which it was planned to operationally map the adjacent forest region. Experiments concerned with the silviculture, hydrology and fire history of the forests have been established in the area by the Forestry Commission of New South Wales, yielding ground plot data and colour aerial photographs used in this study.

![Figure 8-1: Location of the study area.](image)

The study area is covered by mostly dry schlerophyll forest (Baur, 1965), where the overstorey tree canopy is totally dominated by *Eucalyptus spp*. In gullies, some wet schlerophyll forest appears (Baur, 1965). The parent material is Devonian granite, with soil formations being mostly podzolic, though gley soils form in areas of colluvial deposition. The topography is moderate, ranging in elevation from 150 to 600 m.

One major sealed road passes through the area, and a number of fire access trails exist. The area is subject to periodic wildfire, though the forest generally recovers rapidly (Gill *et al.*, 1981). Man's
activities have been limited to low intensity fires purposely lit to reduce fire fuel loads. In addition, some areas to the south of the study area have been harvested to produce sawlogs and woodchips for paper pulp manufacture. These areas have had a larger number of higher quality roads constructed for access.

According to Baur’s (1965) classification\(^1\), there are a number of forest types in this area. Baur (1965) defines a forest type as an assemblage of forest species that occur together over an appreciable land area. In this study, some sub-types have been recognized in order to examine the resolution with which the expert system can automatically delineate forest species. A sub-type is derived by splitting the types recognized by Baur (1965) into component species. A summary of the forest types and sub-types recognized in this study is presented in Table 8-1. The forest is a complex mix of forest species, with forest types and sub-types appearing over small areal extents. For an area to be recognized as a forest type or sub-type in this study, it had to have an areal extent of greater than 0.1 ha (i.e. approximately the size of a TM pixel).

Table 8-1: Forest types and sub-types recognized in this study (after Baur, 1965: and Boland et al., 1984)

<table>
<thead>
<tr>
<th>Forest type and sub-type</th>
<th>F.C. N.S.W. Type No.*</th>
<th>Component forest species</th>
<th>Common name</th>
<th>Scientific name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Silvertop Ash</td>
<td>112</td>
<td>Silvertop Ash</td>
<td>Eucalyptus sieberi</td>
<td></td>
</tr>
<tr>
<td>Yertchuk</td>
<td>102</td>
<td>Yertchuk</td>
<td>Eucalyptus consideniana</td>
<td></td>
</tr>
<tr>
<td>Stringybark/Gum</td>
<td></td>
<td>Yellow stringybark</td>
<td>Eucalyptus muellerana</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mountain Grey Gum</td>
<td>Eucalyptus cypellocarpa</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>White Stringybark</td>
<td>Eucalyptus globoidea</td>
<td></td>
</tr>
<tr>
<td>Blue-leaved Stringybark</td>
<td>121</td>
<td>Blue-leaved Stringybark</td>
<td>Eucalyptus agglomerata</td>
<td></td>
</tr>
<tr>
<td>Tea Tree</td>
<td></td>
<td>Tea Tree</td>
<td>Leptospermum spp.</td>
<td></td>
</tr>
<tr>
<td>Black Oak</td>
<td></td>
<td>Black Oak</td>
<td>Allocasuarina littoralis</td>
<td></td>
</tr>
<tr>
<td>Silvertop Ash/Gum</td>
<td></td>
<td>Silvertop Ash</td>
<td>Eucalyptus sieberi</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mountain Grey Gum</td>
<td>Eucalyptus cypellocarpa</td>
<td></td>
</tr>
</tbody>
</table>

A nonforest class was also recognized that included quarry, road and clearfallen areas.

8.3. Definition of the expert system

8.3.1. Conceptual overview of the expert system

The research question to be answered by the expert system is 'what species occurs at a given location in the forest?', with location \(X_{ij}\) being defined as the \(i^{th}\) row and \(j^{th}\) column position of a cell (or pixel) in a raster (gridded) database. This research question can be formalized as a research hypothesis that species \(S_a\) (for \(a=1,...,n\) species) occurs at grid cell location location \((i,j)\). Available at each grid cell location \((i,j)\) are multiple sources of evidence (or data) in a raster database to assist in testing the research hypothesis. The raster database can be conceived of as a stack of layers, with each layer pertaining to a type of evidence (Figure 8-2).

\(^1\)A number of alternative vegetation classification schemes could have been used. However, as this thesis emphasizes forestry applications, the 'forest type' vegetation classification scheme accepted as a standard by the Forestry Commission of N.S.W. was adopted.
In this study, the layers were comprised of:

(a) the possible thematic classes (derived from the nonparametric classifier);
(b) the probability of correct classification for the classes (derived from the nonparametric classifier);
(c) slope;
(d) aspect;
(e) topographic position (specifically ridge, upper midslope, midslope, lower midslope, valley).

Using this database, the expert system infers the most probable species that would occur at a given grid cell. *A priori* conditional probabilities for all the items of evidence were incorporated into the inferencing process using a Bayesian (statistical) rule-based approach. The *a priori* conditional probabilities relating to the evidence were generated from the knowledge of experienced foresters (see 8.4.3).

The order in which hypotheses or evidence are considered by an expert system has been used to characterize expert systems into two types (Naylor, 1984; Weiss and Kulikowski, 1984). The first is a bottom-up or backward chaining approach, where a hypothesis is considered to be true and the evidence (data) relating to the hypothesis are considered in turn. The second approach is top-down or forward chaining, which is essentially an evidence (data) driven process. A piece of evidence is selected and applied to each hypothesis in turn. In this study, a forward chaining strategy was used to schedule the sequence in which the evidence was combined with the research hypotheses.

Naylor (1984) reviews forward and backwards chaining strategies, and concludes that they both require a method of deciding which piece of evidence, or which hypothesis, will be sequenced next by the expert system. Without such a methodology, the expert system lacks direction in its search for a solution, as it glibly proceeds to sequentially evaluate all hypotheses or evidence. Deciding upon which piece of evidence or hypothesis to consider has been called sideways chaining. Naylor (1984) proposed a 'rule value' approach, while Shortcliffe (1976) developed a 'certainty factor' approach as sideways chaining solutions. Sideways chaining was not attempted in this study for reasons cited in the discussion.
The decision as to which species would represent the cell location was made by selecting the (research) hypothesis with the highest probability. A contextual check was then made to ascertain whether the adjacent pixels had been classified into forest types that were ecologically sensible for the grid cell being considered. If the grid cell $X_{ij}$ was not similar to the adjacent grid cells, then the cells adjacent to $X_{ij}$ form weighting factors with which to calculate $X_{ij}$ again (8.3.2).

8.3.2. Formal statement describing the expert algorithm

Let $S_a$ be the forest type class (for $a=1,...,n$ classes) occurring at location $(i,j)$. Let $E_b$ be an item of evidence (for $b=1,...,k$ items of evidence) known at location $(i,j)$. Set up a hypothesis ($H_a$) that class $S_a$ occurs at location $(i,j)$. A rule may be defined thus:

$$E_b \Rightarrow H_a,$$

that is, given a piece of evidence $E_b$, then infer $H_a$. However, there may be uncertainty associated with this rule, that is the probability of the rule may not be 0 (i.e. false) or 1 (i.e. true), but rather lie in the continuum $\{0 \rightarrow 1\}$, depending on how 'sure' we are that the rule is true (or false).

Bayes' Theorem may be used to update the probability of the rule that the hypothesis ($H_a$) occurs at location $(i,j)$ given a piece of evidence ($E_b$) i.e.

$$P(H_a|E_b) = \frac{P(E_b|H_a) P(H_a)}{P(E_b)}$$

...(1)

Note that $P(E_b|H_a)$ is the a priori conditional probability that there is a piece of evidence $E_b$ (e.g. a southerly aspect) given (a hypothesis $H_a$) that class $S_a$ occurs at location $(i,j)$ (also known as the class-conditional probability - see Duda and Hart, 1973). $P(H_a)$ is the probability for the hypothesis ($H_a$) that class $S_a$ occurs at location $(i,j)$. This probability is initially obtained from the probability of correct classification supplied by the nonparametric classifier. On iterating with further pieces of evidence $E_b$ (i.e. for $b=2,...,k$) from the database, $P(H_a|E_b ; b=1)$ (i.e. the posterior probability of $H_a$ given $E_b$; for $b=1$) replaces $P(H_a)$ in (1). $P(E_b)$ is the 'classical marginal probability', and is the probability of the evidence alone, or, the probability that any cell has an item of evidence $\{E_b\}$ such as a southerly aspect. Bayes' Theorem provides a formula to calculate $P(E_b)$:

$$P(E_b) = \sum_{a=1}^{n} P(E_b|H_a) P(H_a)$$

thereby allowing $P(E_b)$ to be continually updated at runtime as $P(H_a)$ is updated. Note that the evidence $\{E_b\}$ must be independent, otherwise $P(E_b)$ would become larger or smaller, thereby decrementing or incrementing $H_a$, causing the posterior probabilities to be incorrect. In this case the evidence $\{E_b, b=1,...,k\}$ was assumed to be statistically independent, as none of the evidence was obviously correlated. For example, the slope of a pixel is not related to aspect. The most likely hypothesis (i.e. class) for a cell, is that which has the maximum posterior probability $\{\text{max} P(H_a) \mid a=1,...,n\}$ at location $(i,j)$.

A contextual check is performed to ensure that the class $\{S_a\}$ selected at location $(i,j)$ is ecotonally similar to the adjacent cells, during a second pass through the image. A matrix (Table 2) is set up that provides contextual information about the species $\{T_a \mid a=1,...,n\}$ that naturally occur adjacent to
the most likely class \( \max P(H_a) \) at location \((i,j)\). The context of the eight cells adjacent to the central cell \( X_{i,j} \) are checked in sequence, using the matrix (Table 8-2). If, according to the matrix table, the adjacent cells can occur naturally alongside the central pixel \( X_{i,j} \), then the algorithm proceeds to the next cell. However, if one (or more) of the adjacent cells may not occur next to the central cell \( X_{i,j} \) (according to the matrix Table 8-2), then \( P(H_a|E_b) \) is updated by assigning:

\[
P(E_b|H_a) = \frac{1}{8} \times T.
\]

Note that \( T \) is the number of cells of species 'a' in the 3 by 3 matrix adjacent to \( X_{i,j} \) (i.e. \( T = \{ T_a \mid i=(i-1),i,(i+1); j=(j-1),j,(j+1); \text{ NOT } (i,j) \} \)).

The expert system was written in Fortran-77 and executed on a DEC VAX 8700 computer cluster at the Australian National University. The evidence was prepared as described in sections 4.1 and 4.2, and stored in the SPIRAL geographic information system (Myers, 1986), while the \textit{a priori} conditional probability data (8.4.3) were stored as an ASCII file. The thematic maps output from the various classification strategies were plotted on Tektronix hardware using Uniras software (European Software Contractors, 1982) and Map Analysis Package software (Tomlin, 1987b).
Table 8-2: Matrix showing the forest types (T_x) that may occur adjacent to the classified forest type (max P(H_x)).

<table>
<thead>
<tr>
<th>Forest type classified by the expert system</th>
<th>STA</th>
<th>Y</th>
<th>S/G</th>
<th>BLS</th>
<th>TT</th>
<th>ALL</th>
<th>SA/G</th>
<th>CC</th>
<th>Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>STA</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Y</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>S/G</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>BLS</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TT</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALL</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA/G</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CC</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>X</td>
<td>X</td>
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<td>Q</td>
<td></td>
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<td></td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>

**KEY**
- STA - Silvertop Ash
- Y - Yertchuk
- S/G - Stringybark/Gum
- BLS - Blueleafed Stringybark
- ALL - Black Oak
- SA/G - Silvertop Ash/Gum
- TT - Tea Tree
- CC - Regenerating forest
- Q - Quarry/road

8.4. Preparation of the evidence and a priori conditional probabilities for input into the expert system

8.4.1. Remotely sensed digital data

A Landsat Thematic Mapper image (path 90, row 86) was obtained for the study area. This cloud free scene was collected on October 1st, 1986. The analysis of the Landsat TM data began with the geometric rectification of the TM scene to a contour map. The contour map was a New South Wales
Department of Lands 1:25 000 series map with a 10 m contour interval ('Mount Imlay' sheet 8823-IV-S) which conforms to the Australian National Mapping Council standards of accuracy. A second order polynomial was calculated using 10 ground control points located on the map and the TM image. The image was resampled to a 30 m square grid by nearest neighbour interpolation, using program SUBGM in the ORSER image processing system (Turner et al., 1982), and the study area was subset to yield a grid of 239 rows by 239 columns.

Overlapping sets of 1:40 000 black and white and 1:10 000 colour aerial photographs, flown in 1977 and 1988 respectively, were obtained from the Forestry Commission of New South Wales. Extensive ground truth reconnaissance combined with interpretation from the aerial photographs, allowed three or more training areas representative of each forest type to be located in the study area. Mean and covariance matrices of the forest classes for all seven TM bands were extracted for these training areas using the STATS program in the ORSER system (Turner et al., 1982). From this information, plots of band brightness levels (i.e. DN values) were prepared for each class, to study the spectral distribution of the training area data sets. The mean and the standard deviation around the mean were plotted for each class.

Unsupervised classification strategies was used to isolate areas of spectral homogeneity in the image. These methods included a minimum distance clustering algorithm (program CLUS), and an algorithm that finds the norm of each observation and transforms the norm into a percentage of the maximum possible value for the norm (program NMAP) (see Turner et al., 1982). An unsupervised nonparametric strategy that incorporates contextual information was also used to delineate training areas (Skidmore, 1989a), as detailed in Chapter 5.

In an iterative process, the unsupervised classification results were compared with the aerial photographs and field notes, and the training area boundaries were adjusted to improve the homogeneity of the cover classes on the unsupervised thematic maps.

The approximate areal extent of each forest cover type was estimated by inspecting the unsupervised classification results, and from discussions with local forestry staff. Thus 'P(i)' (as notated in 6.2.2) could be estimated.

A principal components analysis was performed on the seven TM bands, in order to reduce the number of features and thereby improving computational efficiency. The first two principal components, which accounted for 91 per cent of the total scene variance, were classified by the supervised nonparametric strategy (see Chapter 6 for details). The principal components were rescaled to range in brightness (i.e. DN values) from 0-63 in order to improve the computational efficiency of the supervised nonparametric classifier. The supervised nonparametric classifier generates a thematic image of the class with the highest probability of occurrence at each pixel. This program was modified so that all the classes (Sa) that occur at pixel location X_{ij} were output to a raster database, along with the probability of correct classification for each class.

Using notation from Chapter 6, all the classes (i.e. Sa) that occur at vector position (X) in N-dimensional feature space are written into a lookup table. The vector position in N-dimensional feature
space of the pixel being considered \( X_{i,j} \) is equated with the appropriate lookup table value \( X \). All the probabilities of correct classification and the classes that occur at \( X \) in the lookup table are written into the raster database location \( X_{i,j} \).

The probability of correct classification for class 'a' is the class \textit{a priori} conditional probability \( P(E)^{Ha} \), defined as the probability of the spectral response \( X \) occurring (where \( X \) is a vector position in \( N \)-dimensional feature space and is equivalent to a piece of evidence \( E_{b} \)) given class \( H_{a} \).

8.4.2. Elevation and terrain data

Topographic variables can be readily generated in digital form and merged with other digital data, such as remotely sensed data. The method for generating the regular digital elevation grid used in this study is detailed in Chapter 7. Streamlines and high points were digitized from the Mount Imlay map sheet (that was also used to geometrically rectify the remotely sensed data). 3306 spot heights were selected, as well as 2115 points along streamlines. An interpolation program developed by Hutchinson (1989) was used to calculate elevation values to 1 m on a regular 30 m grid.

The modelling of topographic variables from a regular grid of digital elevation data was reviewed in Chapter 7 and it was proposed that the third order finite difference method and the linear regression models were optimal for calculating slope and aspect (Skidmore, 1989c). Consequently, a third-order finite difference method was used to calculate slope and aspect. The modelling of terrain position (i.e. ridge, upper mid-slope, mid-slope, lower mid-slope and valley) from gridded digital elevation data, proposed in Chapter 7 (see also Skidmore, 1989d), was also implemented.

The DTM (digital terrain model) data were geometrically corrected to the same geometric projection and scale as the remotely sensed data, using a second order polynomial with 10 ground control points and nearest neighbour interpolation (Turner \textit{et al.}, 1982).

The remotely sensed thematic images and the topographic data (i.e. slope, aspect, topographic position) were now geometrically corrected to the same map base and resampled to a regular 30 m grid. These data sets were input as separate layers into a raster database using the SPIRAL GIS system (Myers, 1986).

8.4.3. \textit{A priori} conditional probabilities of evidence

Assigning the \textit{a priori} conditional probability of occurrence for a piece of evidence is the most subjective aspect of an expert system (Forsyth, 1984). The probability of an item of evidence occurring, given a particular hypothesis (i.e. \( P(E_{b}|H_{a}) \)), must be ascertained to calculate Equation (1). In an ideal situation, \( P(E_{b}|H_{a}) \) may be derived statistically, though in most applications this is not possible, so \( P(E_{b}|H_{a}) \) is a heuristic, estimated from the 'feeling' or 'knowledge' of experts. In this study, \( P(E_{b}|H_{a}) \) was estimated by qualitative methods including interviewing experts, field observations, and a number of unpublished internal documents from the Forestry Commission of New South Wales.

\footnote{See 7 for detailed discussion of digital terrain models.}
Foresters and forest workers employed by the Forestry Commission of New South Wales in the Eden region have substantial local knowledge about the location of particular forest tree species in the environment, and have sound observations on the natural factors which influence the distribution of species. This knowledge was captured by a series of personal interviews and a written questionnaire designed to ascertain the probability of a particular species occurring given a piece of evidence. The a priori conditional probabilities detailed in Table 8-3 were collated by averaging the probability responses of the various experienced foresters, observations from field plots, and the unpublished documents.

Table 8-3: The a priori conditional probabilities of the evidence

<table>
<thead>
<tr>
<th>ENVIRONMENTAL INFORMATION</th>
<th>FOREST TYPES</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q</td>
</tr>
<tr>
<td>N</td>
<td>0.4</td>
</tr>
<tr>
<td>W</td>
<td>0.4</td>
</tr>
<tr>
<td>S</td>
<td>0.4</td>
</tr>
<tr>
<td>E</td>
<td>0.4</td>
</tr>
<tr>
<td>Fl</td>
<td>0.4</td>
</tr>
<tr>
<td>R</td>
<td>0.4</td>
</tr>
<tr>
<td>Um</td>
<td>0.4</td>
</tr>
<tr>
<td>M</td>
<td>0.4</td>
</tr>
<tr>
<td>Lm</td>
<td>0.4</td>
</tr>
<tr>
<td>G</td>
<td>0.4</td>
</tr>
<tr>
<td>&lt;10</td>
<td>0.4</td>
</tr>
<tr>
<td>10-20</td>
<td>0.4</td>
</tr>
<tr>
<td>&gt;20</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Key
N - North
W - West
S - South
E - East
Fl - Flat i.e. no aspect
R - Ridge
Um - Upper midslope
M - Midslope
Lm - Lower midslope
G - Gully
<10 - Slope less than 10 degrees
10 - 20 - Slope 10 to 20 degrees
>20 - Slope greater than 20 degrees
Q - quarry/road
Y - Yertchuk
TT - Tea Tree
YSM - Stringybark/Monkey Gum
BLS - Blue Leaved Stringybark
STL - Silvertop Ash (sunlit)
STD - Silvertop Ash (shadow)
CC - regenerating forest
STM - Silvertop Ash/Monkey Gum
ALL - Black Oak
The quantitative description of the position of a forest species in the environment was considered by Whittaker (1967), who described the concept of gradient analysis as the variation in the occurrence of a species along an environmental gradient (such as elevation or moisture availability). Occurrence of a species at different positions in the environment was measured in convenient units such as 'stems per hectare' or 'percentage of stand'. Generating the probability of occurrence for a species at a position along an environmental gradient was not attempted by Whittaker (1967). Austin et al. (1983) used a generalized linear model to predict the probability of eucalypt species occurrence. Their model required a number of dependent environmental parameters to successfully predict an eucalypt species. However, the expert system used Bayes' theorem which operates on the probability of a species occurring given a single piece of evidence (or environmental parameter) only. Austin et al. (1983) calculated the probability of occurrence for Eucalyptus species within environmental zones (that included 100 m altitude zones, and 100 mm rainfall estimate zones) based on the proportion of (sample) sites within each zone at which the species were found. Such probability estimates requires a large number of samples that are well distributed over all zones.

8.5. Conventional methods for classifying the remotely sensed data

In order to compare the expert system with conventional methods of analyzing remotely sensed data, maximum likelihood, nearest neighbour (based on euclidean distance) and supervised nonparametric classifications of the study area were performed using statistics from the same training area boundaries. Maximum likelihood and euclidean distance classifications were performed on the geometrically corrected seven channel TM data set. Apart from resampling, no additional radiometric corrections were made to the TM data. Only the first two principal components were utilized for the supervised nonparametric classifier as principal components 4 to 7 contained noise, and a reduced number of features increased the efficiency of computation (see Chapter 6 for details). Principal component 3 was discarded as a result of inconsistencies in the image (see 8.8).

8.6. Mapping accuracy assessment

Mapping accuracies were calculated for the thematic maps output by the three supervised classification strategies and by the expert system. A total of 84 field sample plots had been randomly located within the study area as part of a major research project undertaken by the Forestry Commission of New South Wales to study the effects of logging and fire on the forests of southeast Australia. A large number of variables were measured at each plot: information collected included the species of all trees greater than 10 cm diameter at 1.3 m above ground level, and the dominance of those trees (on a scale of 1 = trees that totally dominate other trees, through to 9 = trees that are totally suppressed). A Fortran-77 program was written to calculate the forest class name for each plot based on the definitions in Table 8-1.
All trees with a dominance of 1, 2 or 3 were included in the calculation, with the forest class name being determined by the species with the highest frequency in the plot.

The 'name' to be given to a particular mix of species in a natural forest is a perennial problem for ecologists and foresters. After discussing the problem with colleagues and local forestry staff, the following naming conventions were developed. For a species to contribute to the forest class name, it had to have a frequency of greater than 25 per cent within the plot. In some cases, the proportion of species in a plot did not equate with one of the forest type names. There were three options available to deal with this problem. The first option was to generate a large number of class names by creating names to represent each new species mix. This option could theoretically create an infinite range of forest type names along a forest gradient as the proportion of species changed (Whittaker, 1967). In addition, during the field checking of randomly selected plots for mapping accuracy, the rarer forest type classes would have relatively few samples collected, given limited resources (time and money) to undertake field checking. A second option was to broadly generalize the forest types into a few 'catch-all' groupings such as gully type, stringybark type etc. However, it was felt that such coarse mapping would not show the full potential of the method. As a compromise, the species name(s) with the highest frequency determined the forest class name for the plot. For example, a plot may have Yertchuk (50%), Silvertop Ash (30%) and Blue-leaved Stringybark (20%), so the forest class name would be Yertchuk. Theoretically, a plot may have contained Blue-leaved Stringybark (52 per cent) and Silvertop Ash (48 per cent), and would be called Blue-leaved Stringybark, while an adjacent plot may have contained Blue-leaved Stringybark (48 per cent) and Silvertop Ash (52 per cent) and be called Silvertop Ash. Even though such situations were not common in the actual field plot measurements, errors may have been recorded in the error matrix when in fact the pixel being checked was 'almost' correct (see also 4.8.3).

Additional randomly located plots were visited and the dominant forest type noted. In all, this yielded 135 field plots. The higher frequency of some forest types such as the Yertchuk and Gum/Stringybark classes in the study area is reflected in the higher numbers of those forest types in the error matrix due to the forest plots being selected randomly.

The field plots were manually located on the geometrically corrected thematic images using the road and stream networks as reference points. The class name associated with each plot was checked against the classes predicted on the thematic images produced by the four classifiers. The mapping accuracies were summarized as error matrices (Kalensky and Scherk, 1975) (see 4.5.2). Overall mapping accuracies were calculated for the thematic images produced by the four classifiers using the conventional measure of the number of correctly classified pixels divided by the total number of pixels checked.

Thomas and Allcock (1984) proposed a method for calculating the confidence intervals for a mapping accuracy statement using binomial distribution theory (see 4.5.2.2). An assumption is that the minimum number of samples should be greater than 50, with a sample in the hundreds being more acceptable. The total sample size in this study was 135. The mapping accuracies for the four classification strategies (i.e. euclidean distance, maximum likelihood, supervised nonparametric, and expert system) were calculated at the 95 and 99 per cent confidence intervals.
Congalton et al. (1983) applied discrete multivariate analysis techniques described by Bishop et al. (1975) to test whether two error matrices were significantly different (see 4.5.3.1). In this study, the type of classifier was varied, while other factors such as date of image collection, training areas etc. were held constant. The test statistic proposed by Cohen (1960) (see 4.5.3.1) was applied to the paired combinations of the error matrices, to ascertain whether any of the error matrices were significantly different, and hence whether there was a statistically significant difference between the mapping accuracies of the images.

Three of the cover type classes were relatively rare in the study area (viz., Tea Tree, Gum/Silvertop Ash, and Black Oak), and consequently were poorly represented in the error matrices as a result of the simple random sampling design. Information was not available to stratify the study area into forest type classes in order to improve sampling efficiency, nor could the information be rapidly generated within the time and cost constraints of the project. Therefore, procedures for generating confidence intervals for categories (see 4.5.3.2) could not be used due to low sample numbers (Rosenfield et al., 1982).

8.7. Results

The geometric correction of the remotely sensed data resulted in all TM pixel locations being fitted by the regression with an error of less than $\pm 0.6$ of a pixel from the true map value. The root-mean-square (rms) planimetric error values along the $x$ and $y$ axis ($\text{RMSE}_x$ and $\text{RMSE}_y$) were $\pm 13$ m and $\pm 15$ m respectively. Results for the geometric correction of the DTM data were better, with the maximum error being less than $\pm 0.4$ of a pixel and $\text{RMSE}_{xy}$ values being $\pm 10$ m and $\pm 11$ m respectively.

The number of pixels trained per class ranged from 32 (quarry/road) to 354 (Blue-leaved Stringybark), with an average number of pixels per class of 187 (i.e. approximately 17 hectares).

The plots of band brightness levels (DN values) for each species (Figure 8-3) show that some cover type classes were spectrally different (compare the clearfallen class with the Silvertop Ash/Gum class). Forest classes appeared to be mostly similar in all channels, though the sunlit Silvertop Ash class had higher DN values than the other forest classes in channel 4.

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1See 4.2.2 for a definition of rms.
Figure 8-3: Plots of the brightness level (DN value) for each species, by TM channels 1-7.
Table 8-4 shows the eigenvector matrix generated by the principal components analysis, as well as the eigenvalue for each principal component.

**Table 8-4: Eigenvectors and eigenvalues produced by the principal components analysis**

<table>
<thead>
<tr>
<th>Eigenvectors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1726</td>
<td>0.0831</td>
<td>0.3763</td>
<td>-0.4379</td>
<td>-0.4380</td>
<td>-0.6477</td>
<td>-0.1362</td>
</tr>
<tr>
<td>2</td>
<td>0.1479</td>
<td>0.0263</td>
<td>0.2711</td>
<td>-0.2255</td>
<td>-0.0970</td>
<td>0.2296</td>
<td>0.2296</td>
</tr>
<tr>
<td>TM Channel</td>
<td>0.1811</td>
<td>0.0538</td>
<td>0.4734</td>
<td>-0.3865</td>
<td>0.0698</td>
<td>0.6344</td>
<td>-0.4284</td>
</tr>
<tr>
<td>4</td>
<td>0.4134</td>
<td>-0.9068</td>
<td>0.0173</td>
<td>0.0345</td>
<td>0.0506</td>
<td>-0.0501</td>
<td>-0.0171</td>
</tr>
<tr>
<td>5</td>
<td>0.7942</td>
<td>0.3514</td>
<td>-0.1995</td>
<td>0.3446</td>
<td>-0.2733</td>
<td>0.1021</td>
<td>-0.0450</td>
</tr>
<tr>
<td>6</td>
<td>0.1588</td>
<td>0.0387</td>
<td>-0.6823</td>
<td>-0.6986</td>
<td>0.1368</td>
<td>0.0280</td>
<td>0.0120</td>
</tr>
<tr>
<td>7</td>
<td>0.3006</td>
<td>0.2057</td>
<td>0.2347</td>
<td>0.0016</td>
<td>0.8354</td>
<td>-0.3341</td>
<td>0.0521</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Principal component</th>
<th>Eigenvector</th>
<th>Percentage of the total variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>436.49</td>
<td>86.26</td>
</tr>
<tr>
<td>2</td>
<td>50.52</td>
<td>9.98</td>
</tr>
<tr>
<td>3</td>
<td>8.18</td>
<td>1.62</td>
</tr>
<tr>
<td>4</td>
<td>6.99</td>
<td>1.38</td>
</tr>
<tr>
<td>5</td>
<td>2.07</td>
<td>0.41</td>
</tr>
<tr>
<td>6</td>
<td>1.16</td>
<td>0.23</td>
</tr>
<tr>
<td>7</td>
<td>0.61</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Four of the forest 'types' occurring in the study area are shown (Figures 8-4 to 8-7). The Stringybark/Monkey Gum type (Figure 8-4) occurs in moist gullies, while the Blue-leaved Stringybark (Figure 8-5) grows on better drained sites. The Yertchuk type (Figure 8-6) typically occurs on poorer quality sites subject to waterlogging. The regenerating forest type (Figure 8-7) gives an impression of a typical logging operation occurring in the south of the study area.

Thematic maps showing the output of the three unsupervised strategies (viz., CLUS, NMAP and the unsupervised nonparametric classifier) are detailed as Figures 8-8 to 8-10 respectively. Figure 8-11 shows the digital elevation model data drawn with 67 m contours. Gradient, aspect and topographic position were generated from the digital elevation data and are included as Figures 8-12 to 8-14 respectively.

A thematic map showing the output from the expert system is included as Figure 8-15. Figures 8-16 to 8-18 are thematic maps produced by the three supervised strategies (viz., the maximum likelihood classifier, the euclidean distance classifier and the supervised nonparametric classifier). Figure 8-19 is a thematic map showing the probability of correct classification generated by the supervised nonparametric classifier (Chapter 6).

---

167 m contours were selected because a 67 m interval equally divided the total elevation range into the number of available colour display levels.
Figure 8-4: Stringybark/Gum forest type
Figure 8-5: Blue-leaved Stringybark forest type
Figure 8-6: Yerrabub forest type
Figure 8-7: 'Regenerating' forest class (includes roads, quarries, and regenerating areas)
Figure 8-8: Thematic map produced by the CLUS program

Figure 8-9: Thematic map produced by the NMAP program

Figure 8-10: Thematic map produced by the unsupervised nonparametric program
Figure 8-11: Digital elevation data with 67 m contours

Figure 8-12: Gradient calculated from the digital elevation data

Figure 8-13: Aspect calculated from the digital elevation data

Figure 8-14: Topographic position calculated from the digital elevation data
Figure 8-15: Thematic map of the output from the expert system

Figure 8-16: Thematic map produced by the maximum likelihood classifier

Figure 8-17: Thematic map produced by the euclidean distance classifier

Figure 8-18: Thematic map produced by the supervised nonparametric classifier

Figure 8-19: Thematic map showing the probability of correct classification produced by the nonparametric classifier
Error matrices detailing the quantitative overall mapping accuracy assessments for the euclidean distance classifier, the maximum likelihood classifier, the supervised nonparametric classifier, and the expert system were calculated (see Tables 8-5 to 8-8 respectively). In addition the mapping accuracy was calculated at 95 and 99 per cent confidence intervals. A summary of the mapping accuracy results are listed in Table 8-9. Table 8-10 lists the results for the pairwise comparisons between error matrices for the four classification strategies. Note that the shadowed and sunlit Silvertop Ash cover types were amalgamated into one class during the quantitative mapping accuracy assessment.

Table 8-5: Error matrix for the maximum likelihood classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>VI</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
<th>IX</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>14</td>
<td>3</td>
<td>7</td>
<td>2</td>
<td>5</td>
<td>7</td>
<td>38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>14</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of pixels</td>
<td>1</td>
<td>16</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of pixels (Map)</td>
<td>4</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>21</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>V</td>
<td>2</td>
<td>16</td>
<td>1</td>
<td>19</td>
<td></td>
<td></td>
<td>19</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VI</td>
<td>1</td>
<td>1</td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VII</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td></td>
<td></td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VIII</td>
<td>2</td>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IX</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total no. of pixels</td>
<td>20</td>
<td>19</td>
<td>38</td>
<td>17</td>
<td>8</td>
<td>17</td>
<td>2</td>
<td>135</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall classification accuracy*</td>
<td>50.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table Legend:  
I = Yertchuk  
II = Gum/Stringybark  
III = Silvertop Ash  
IV = Blue-leaved Stringybark  
V = Clearcut/road  
VI = Tea Tree  
VII = Gum/Silvertop Ash  
VIII = Black Oak  
IX = unclassified

* Ratio of the sum of correctly classified pixels in all classes to the sum of the total number of pixels tested.
Table 8-6: Error matrix for the euclidean distance classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>Number of pixels (Image)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>I</td>
<td>17</td>
<td>5</td>
</tr>
<tr>
<td>II</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Number of pixels</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>of V</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>(Map) VI</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>VII</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>VIII</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>IX</td>
<td>38</td>
<td></td>
</tr>
</tbody>
</table>

Total no. of pixels | 31 | 14 | 27 | 4 | 0 | 15 | 12 | 15 | 17 | 135
Overall classification accuracy | 31.1%

Table 8-7: Error matrix for the supervised nonparametric classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>Number of pixels (Image)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>I</td>
<td>27</td>
<td>6</td>
</tr>
<tr>
<td>II</td>
<td>3</td>
<td>20</td>
</tr>
<tr>
<td>Number of pixels</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>of V</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>(Map) VI</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>VII</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>VIII</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>IX</td>
<td>39</td>
<td></td>
</tr>
</tbody>
</table>

Total no. of pixels | 39 | 32 | 25 | 17 | 17 | 1 | 1 | 3 | 0 | 135
Overall classification accuracy | 66.7%

Table 8-8: Error matrix for the expert system classification of the TM data

<table>
<thead>
<tr>
<th>Class</th>
<th>Number of pixels (Image)</th>
<th>Total</th>
</tr>
</thead>
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<td></td>
<td>I</td>
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<td>II</td>
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<td>23</td>
</tr>
<tr>
<td>Number of pixels</td>
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<td>1</td>
</tr>
<tr>
<td>of IV</td>
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<td>1</td>
</tr>
<tr>
<td>pixels V</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>(Map) VI</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>VII</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>VIII</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>IX</td>
<td>39</td>
<td></td>
</tr>
</tbody>
</table>

Total no. of pixels | 39 | 32 | 25 | 17 | 17 | 1 | 1 | 3 | 0 | 135
Overall classification accuracy | 76.2%
Table 8-9: Summary of mapping accuracy results

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Overall mapping accuracy (%)</th>
<th>Mapping accuracy at:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>99.9% C.I.</td>
</tr>
<tr>
<td>expert system</td>
<td>76.2</td>
<td>61.3</td>
</tr>
<tr>
<td>supervised nonparametric</td>
<td>66.7</td>
<td>50.5</td>
</tr>
<tr>
<td>maximum likelihood</td>
<td>50.4</td>
<td>33.3</td>
</tr>
<tr>
<td>euclidean distance</td>
<td>31.1</td>
<td>15.2</td>
</tr>
</tbody>
</table>

Table 8-10: Results of the pairwise comparisons between error matrices for the four classification strategies

<table>
<thead>
<tr>
<th>Error matrix</th>
<th>'K' statistic</th>
<th>Variance of 'K'</th>
</tr>
</thead>
<tbody>
<tr>
<td>expert</td>
<td>0.705</td>
<td>0.00195</td>
</tr>
<tr>
<td>supervised nonparametric</td>
<td>0.587</td>
<td>0.00242</td>
</tr>
<tr>
<td>maximum likelihood</td>
<td>0.422</td>
<td>0.00236</td>
</tr>
<tr>
<td>euclidean distance</td>
<td>0.210</td>
<td>0.00181</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pairwise comparison</th>
<th>Z Statistic</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>expert &amp; sup. nonparametric</td>
<td>1.78</td>
<td>S* NS** NS</td>
</tr>
<tr>
<td>expert &amp; maximum likelihood</td>
<td>4.31</td>
<td>S S S</td>
</tr>
<tr>
<td>expert &amp; euclidean distance</td>
<td>8.07</td>
<td>S S S</td>
</tr>
<tr>
<td>sup. nonparametric &amp; maximal</td>
<td>2.39</td>
<td>S S NS</td>
</tr>
<tr>
<td>sup. nonparametric &amp; euclidean distance</td>
<td>5.80</td>
<td>S S S</td>
</tr>
<tr>
<td>maximum likelihood &amp; euclidean distance</td>
<td>3.28</td>
<td>S S S</td>
</tr>
</tbody>
</table>

* S - significant; ** NS - not significant

8.8. Discussion

The geometric correction of the digital terrain model and the remotely sensed data was satisfactory, with a RMSE_{xy} of approximately less than half a pixel. The sample plots (for map accuracy assessment) could be accurately located on high quality ink jet plots of the thematic maps, using an overlaid transparency of the stream and road networks.

The plots of band brightness levels (DN values) for each species (Figure 8-3) indicate that many of the forest types have similar spectral properties. For example, the Tea Tree and Blue-leaved Stringybark types exhibit close spectral characteristics.

The thematic maps resulting from the unsupervised classifications were useful as aids for delineating training areas. The unsupervised nonparametric classifier (Chapter 5) in particular produced a useful map with classes that were less heterogeneous compared with those produced by other methods. The utility of this algorithm for identifying suitable training areas had previously been tested for plantation forests (Chapter 5).

In order to improve the computational efficiency of the supervised nonparametric classifier, the seven feature thematic mapper data was reduced to two features, by taking the first two principal
components produced by a principal components analysis. As detailed in Table 8-9, the first principal component was dominated (in order of decreasing importance) by channels 5, 4 and 7 (i.e. near infrared and middle infrared), and represented 86 per cent of the total scene variance. The second principal component was also dominated by channels 4, 5 and 7, and represented nearly 10 per cent of the variance.

Displaying the seven principal components generated from the TM bands as separate images yielded an unusual result. The third principal component image had a north-south lineation running through the middle of the study area, with the western half being dark and the eastern half being light. The two weeks preceding the collection of the TM imagery were wet and cool with low evapotranspiration rates. The lineation may be related to different soil moisture levels on either side of the lineation, as the thermal band (channel 6) dominated the third principal component eigenvectors. The fourth principal component contained striping, while the last three principal components appeared to be noise and contained less than one per cent of the total variance.

The supervised nonparametric classifier used only the first two principal components, but still yielded a higher mapping accuracy than that of the euclidean distance and maximum likelihood classifiers that operated with the full seven TM channels (Table 8-9). The robustness of the supervised nonparametric classifier for discriminating between spectrally similar classes has been demonstrated in Chapter 6 for a mixed broadleaf/conifer forest in Pennsylvania using Landsat MSS data and for a number of age classes in *Pinus radiata* plantations in Australia using SPOT XS data. All available features had been used by the supervised nonparametric classifier in these two studies.

Three measures of mapping accuracy based on error matrices (Tables 8-5 to 8-8) were calculated. The first method was the overall mapping accuracy, which for the expert system was 76.2 per cent (Table 8-9). The second measure of mapping accuracy cited was the mapping accuracy calculated within nominated confidence intervals (Thomas and Allcock, 1984). From Table 8-9 it can be seen that we are 95 per cent confident that at least 68.6 per cent of the pixels classified by the expert system had been correctly classified, and 99.9 per cent confident that at least 61.3 per cent of the pixels were correctly classified. The third method of evaluating mapping accuracy was a measure of association termed 'K' (Cohen, 1960), and was used by Congalton *et al.* (1983) to quantify the agreement between an image (or map) and ground truth reference data (Table 8-10). 'K' ranges in value from 0 (no association) through to 1 (full association). A disadvantage with these measures of mapping accuracy is that classes that are nearly correctly classified are considered in conjunction with classes which may have a low mapping accuracy, giving an average figure which does not reflect between class differences.

The mapping accuracies and 'K' values for the three classification strategies that only used remotely sensed data (i.e. the supervised nonparametric, maximum likelihood and euclidean distance classifiers) are summarized in Tables 8-9 and 8-10. Confirming previous studies, the supervised nonparametric classifier yielded the highest mapping accuracy, while the maximum likelihood classifier generated a thematic map of higher accuracy than the euclidean distance classifier because the assumed Gaussian distribution more accurately parameterizes the forest class training areas in N-dimensional feature space (Estes *et al*., 1983; Skidmore *et al*., 1988). In contrast, Hudson (1987) and Ince (1987)
The forest is a complex mosaic of species grading together creating stands that merge continually. Large areas of homogeneous forest type of greater than 5 to 10 ha are uncommon in the study area. Figures 8-16 and 8-17 appear more spatially cohesive than Figure 8-15 and 8-18 (i.e. forest type stands appear as larger connected regions). The primary reason for the expert system and supervised nonparametric classifier having higher classification accuracies are that they better reflect the actual pattern of forest types in this complex forest (R. Bridges, per. comm.1). In other words, the forest types occur over small areas and these classifiers are better at differentiating between the small minimum typing areas. The minimum typing areas could be increased by aggregating similar classes or smoothing (for example by specifying that any cluster of pixels must have at least four pixels belonging to any one class) the expert and nonparametric classifiers - however this would result in a loss of accuracy. Thus the euclidean distance and maximum likelihood classifiers look more like a traditional aerial photograph interpretation of forest type, as the interpreter merges the types into (minimum-sized) management areas.

This phenomenon may be accentuated by the highly reduced images (Figures 8-15 through to 8-18). On inspecting a subset of Figure 8-15 used for the soil mapping work (Figure 9-6, page 217), it is apparent that the image is more cohesive at this enlargement. It should also be emphasized that this phenomenon was not apparent in the more homogeneous pine plantations (Figure 6-10, page 133). Another compounding reason for the apparently greater spatial cohesion of the maximum likelihood and euclidean distance classifiers, is the poor choice of colours in Figures 8-15 to 8-18. If similar class types (for example sunlit and shadowed Silvertop Ash and Blue Leaved Stringybark) had similar colours (for example shades of blue) the heterogeneity may be reduced.

The reason for the maximum likelihood and euclidean distance classifiers apparently having greater spatial cohesion over this particular forest may be due to their parametric decision boundaries. At the overlap or co-occurrence region between two (or more) forest classes, the parametric classifier assigns image pixels to a class based on the parameters of the particular classifier (Skidmore et al., 1988). Thus similar classes (such as Blue Leaved Stringybark and Silvertop Ash) will be consistently misclassified into one or another class. For example, in this case the Blue Leaved Stringybark was misclassified as Silvertop Ash. Further research is required to understand the cause of this phenomena.

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1 Bridges, R, Forestry Commission of NSW, GPO Box 2667, Sydney, NSW 2000, Australia.
claimed that the maximum likelihood classifier did not always produce the highest mapping accuracy; in fact they found little difference between maximum likelihood classification and nearest neighbour type classifiers. However, Ince (1987) and Hudson (1987) noted that a number of factors effect mapping accuracies of different classifiers including the quality and quantity of training area data and the composition and distribution of forests.

The expert system yielded a higher mapping accuracy than any of the three supervised classifiers (Table 8-9), while from Table 8-10, it can be seen that the expert system had the highest measure of association between the image and the ground truth information. This is not surprising as topographic and contextual information were being combined with the thematic information output from the nonparametric classifier, using a set of ecological rules. The ability to discriminate between spectrally similar forest cover types is therefore increased. The inclusion of the ecological rules in the expert system allows forest types classified incorrectly from the remotely sensed data, to be reclassified according to the environmental position supplied by the topographic information. For example, the Gum/Stringybark type is less likely to occur on ridges or midslope positions, so this information was included in the set of rules (see Table 8-3). The highest mapping accuracy obtained by the expert system was aided by the fact that its input thematic maps were produced using the nonparametric classifier, which itself has a higher mapping accuracy than the maximum likelihood and euclidean distance classifiers.

Cohen (1960) described a Z test based on 'K', that examined whether there was a statistically significant difference between two error matrices. The results in Table 8-10 show that at the 90 per cent confidence interval there is a statistically significant difference in mapping accuracies between all the classifiers. At the 95 per cent confidence interval there is a significant difference between all the classifiers, apart from the expert system and the supervised nonparametric classifier. In addition, there is a significant difference between the supervised nonparametric classifier and the maximum likelihood classifier at the 95 per cent confidence interval, but not at the 99 per cent confidence interval. In other words, we are 99 per cent certain that the the expert system and supervised nonparametric classifier have a different (higher) mapping accuracy than the maximum likelihood and euclidean distance classifiers, and we are 90 per cent confident that there is a statistically significant difference between the expert system and the supervised nonparametric classifier.

In an attempt to confirm that the qualitative a priori conditional probabilities used during the expert system classification were reasonable, a count of trees with a dominance of 1 to 3 was tallied by plot (from the set of 84 measured field plots - see 8.6 for details) for each species according to environmental (dependent) variables (for example, the number of Silvertop Ash [E. sieberi ] trees occurring on plot number 7 that had an easterly aspect was nine). The average number of trees over all plots was then calculated for each environmental variable (for example, the average number of Silvertop Ash trees on plots with an easterly aspect was 5) (Table 8-11). These calculations were performed after the mapping accuracy assessments, and were not used to modify the a priori conditional probabilities used during the expert system classification. Rather, the results were used to check that the a priori conditional probabilities proposed by the experienced foresters and ecologists were reasonable. The average number of
trees over all plots for each environmental variable was calculated in order to reduce the effect of differing sample sizes, caused by the random sampling scheme 'oversampling' the common species such as Yertchuk, and 'undersampling' the rarer species such as Messmate.

Table 8-11: The average number of trees (per species) over all plots calculated for each environmental variable

<table>
<thead>
<tr>
<th>Species</th>
<th>R</th>
<th>U</th>
<th>M</th>
<th>L</th>
<th>G</th>
<th>≤10</th>
<th>10-20</th>
<th>&gt;20</th>
<th>N</th>
<th>NE</th>
<th>E</th>
<th>SE</th>
<th>S</th>
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<td>0</td>
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<td>2</td>
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<td>Y</td>
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<td>17</td>
<td>20</td>
<td>8</td>
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<td>16</td>
<td>22</td>
<td>6</td>
<td>15</td>
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<td>10</td>
<td>21</td>
<td>16</td>
<td>23</td>
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<td>2</td>
<td>0</td>
<td>0</td>
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<td>3</td>
<td>1</td>
<td>0</td>
<td>5</td>
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<td>3</td>
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<td>1</td>
<td>9</td>
<td>9</td>
<td>7</td>
<td></td>
</tr>
</tbody>
</table>

Key to Table 8-11: R=ridge, U=upper midslope, M=midslope, L=lower midslope, G=gully, ≤10=slope less than or equal to 10°, 10-20=slope greater than 10° and less than 20°, >20=slope greater than or equal to 20°, N=north, NE=northeast, E=east, SE=southeast, S=south, SW=southwest, W=west, NW=northwest, A=Allocasuarina, BLS=Blue-leaved Stringybark, Y=Yertchuk, MG=Monkey Gum, WSB=White Stringybark, YSB=Yellow Stringybark, MM=Messmate, STA=Silvertop Ash.

The a priori conditional probabilities generated by the qualitative and quantitative methods were similar. There was general agreement between the qualitative and quantitative methods over the relative importance of the dependent variables in determining the occurrence of the species. For example, Silvertop Ash was more likely to occur on a ridge than in a gully. In addition, the likelihood of different species occurring given a particular dependent variable was similar between the qualitative and quantitative methods (for example Silvertop Ash was more likely to occur on a ridge than Monkey Gum).

It should be noted that the estimated areal extent of the forest type classes within the study area required as a priori evidence by the supervised nonparametric classifier (i.e. P(i) in 6.2.2) was not used again as evidence by the expert system, because the expert system evidence must be independent. In this case P(i) modified the supervised nonparametric classifier results that were subsequently input into the expert system. Therefore the direct use of P(i) as evidence in the expert system would contravene the assumption of independence.

The introduction of spatial information into the expert system meant that forest classes could be corrected in situations where the classes do not occur naturally adjacent to each other in the field, but were adjacent on the thematic map. This contextual approach is especially useful where it is known that the position of forest species in the topography is controlled by environmental variables.

For management purposes, such as an environmental impact statement (Forestry Commission of N.S.W., 1988), the number of forest types are often reduced by generalizing the class types into broader categories. In such a situation, one would expect the mapping accuracy to improve, because similar types previously confused in the error matrices would be generalized to one broad type name (see 4.8.2 for details). The error matrix for the expert system classification was recalculated for four classes. The classes
included gully (i.e. classes II and VII in Table 8-5 were combined), mixed eucalypt (classes I and III combined), stringybark (class IV) and nonforest/unclassified (classes V, VI, VIII and IX combined). The overall mapping accuracy for these four classes increased to 80 per cent. Using the methodology of Thomas and Allcock (1984), a mapping accuracy of 66.7 per cent was calculated for a 99.9 confidence interval, and a mapping accuracy of 73.3 per cent for a 95 per cent confidence interval. Todd et al. (1980) also reported an increase in forest mapping accuracy when similar forest type classes where aggregated.

As the size of the study area increases, data layers other than those used in this study may become important in determining the distribution of a forest species. Environmental variables such as parent material, soil type, elevation, latitude and longitude, climate, and soil moisture, may increasingly dominate on a regional or continental scale (see 8-1). The effective extrapolation of the expert system approach to a larger area or a different region, requires that the principal environmental factors affecting forest species distribution are recognized and modelled in a suitable format, such as Table 8-3.

The choice of auxiliary data sets to complement the classification of remotely sensed data is determined primarily by the availability of such data. Topographic data are especially useful, as they are readily available for most areas, or can be automatically generated if not readily available (see 8.1). Topographic data are also relatively constant factors in the environment over a time scale of hundreds of years in most parts of the world, so that once obtained the data can be repeatedly used over a number of decades for different applications. Similarly, parent material is another data type that is reasonably constant, though substantial field work by expert geologists is often needed to successfully map geological boundaries.

In contrast, other data layers such as vegetation structure, species composition, ease of harvesting the forest and wildlife habitat may change over a time scale of less than a year to several hundred years. These factors may be derived using an expert system, with topographic data, remotely sensed data and a set of rules as input. Indeed, a derived thematic product, such as the vegetation type map generated in this study, may be used as an input layer by the expert system to derive additional thematic maps showing factors such as soils or wildlife habitat potential.

Analyzing remotely sensed imagery from different dates may also increase mapping accuracies. Eucalyptus trees exhibit seasonal flowering (Kavanagh, 1984; Kavanagh, 1987). By obtaining a series of satellite images at the time of flowering of the different species, individual species may be able to be discriminated using the remotely sensed imagery alone. A number of techniques have been proposed for analyzing multivariate imagery (see Chapter 3 for details). For this application, a suitable approach may be to perform a separate feature reduction on each image, and then input the first two principal components of each image as features for the supervised nonparametric classifier to classify.

In the expert system developed for this study, forward chaining was used with a complete enumeration of the data (that is a blind search terminated by running out of evidence), because:

(a) Conventional expert systems undertake an interactive dialogue with a user to extract answers (i.e. evidence for the system). This dialogue would appear aimless to the user if there was no direction in the method of asking questions, because the expert system would sequentially process evidence or hypotheses
in the order that they occur in the expert system. In this study, the expert system produces a map showing forest types, from an existing raster database made up of multiple layers of evidence. It is therefore not necessary to have an interactive dialogue.

(b) The expert system as implemented (with 13 layers) required approximately three times the CPU of a maximum likelihood classification of the same area with seven layers. Thus, the computational requirements are feasible (see Naylor, 1984), and it is not necessary to introduce a 'rule value' approach to successfully calculate a solution. An area four times larger than the study area reported here has been analyzed, and the CPU requirement appears to increase proportionally to \( n \log(n) \), where \( n \) is the number of pixels.

(c) A complete enumeration of the data allows all the information available to the decision maker (i.e. the expert system) to be incorporated into the decision making process. The sideways chaining approach (i.e. 'certainty factor' or 'rule value') may stop the processing before all the evidence has been evaluated.

Expert systems offer many advantages and some disadvantages over conventional statistical approaches for the analysis of remotely sensed and other spatial digital data. The major advantage is that knowledge about the environment can be integrated into the classification process. In this study, the supervised nonparametric classifier yielded possible forest species which may be occurring at a pixel, as well as the probability of the species occurrence. Known ecological relationships between environmental parameters (slope, aspect, topographic position) and the location of forest species were then used to confirm the most likely forest species at each pixel. The expert system handles uncertainty in the relationships (e.g. it is fairly certain that Silvertop Ash occurs on ridges, but it may not always occur on a ridge) by use of probabilities. In contrast, previous studies tried to link environmental variables with vegetation cover used simple Boolean operators (Cibula and Nyquist, 1987). Such an approach required an unequivocal statement about whether the relationship was 'true' or 'false' (i.e. does Silvertop Ash occur on a ridge? Yes or no).

Another advantage of expert systems is that additional environmental parameters can be quickly incorporated into the expert system model as data layers are generated and the relationships between data layers and the dependent variable being modelled (in this case forest species) become known. Additional dependent variables can also be generated, assuming that the necessary environmental data are available, and the relationships between the environmental variables and dependent variable are known. Examples of dependent variables that may be generated using this technique include wildlife habitat suitability, forest harvesting and recreation potential. In Chapter 9 the technique is applied to forest soil mapping.

An obvious disadvantage with the expert system approach is that the answer the computer gives for a pixel may not be true. However, this would be highlighted during the mapping accuracy assessment. Poor mapping accuracy may be due to the rules for predicting the dependent variable (in this case forest type) being seriously incomplete (for example, a particular forest type was not known to occur within the region being considered, or the expert system is extrapolated to an area outside the region within which the expert system was developed). In such a situation, additional data layers (independent variables) may be required, and the relationships between the dependent variables and the independent variables defined.
Alternatively, the expert system may be incorrectly classifying a forest type in a consistent manner (i.e. gives a biased answer), in which case the probabilities associated with the rules can be adjusted to better reflect the opinion of the human expert.

A final disadvantage of expert systems is that experts may not agree amongst themselves about the category name for a particular set of observed ground conditions (for example, has an area a high recreation value?). The 'correctness' of a map generated by an expert system has to be gauged against the criteria defined by the expert(s) who provided the knowledge for the expert system, as well as by other experts who can validate the results.

The expert system approach for forest mapping is now discussed using the terminology and methodology of the forest system model. Three primary data sources were used viz., remotely sensed Landsat TM data, a digital elevation model and knowledge about the forest. A map detailing forest type was output from the forest model (Figure 8-20).

![Figure 8-20: Forest system model level 1 - forest type mapping.](image)

The remotely sensed data were analysed using the unsupervised nonparametric classifier (Chapter 5) and supervised nonparametric classifier (Chapter 6). The digital elevation model data were analysed using both the third-order finite difference method to model gradient and aspect and the topographic position modelling algorithm (Chapter 7). These processes are shown in Figure 8-21.

The forest system model has been used to plan and integrate the data and methodologies described in this Chapter. The basic premise of the forest system model has been satisfied viz., a few primary data sources may be used to generate a forest resource map. Another premise of the forest system model was that many different forest resource maps may be generated from a few primary data sources: in Chapter 9 the remotely sensed data and digital elevation model primary data sources are also used to map forest soils.
8.9. Converting the experimental GIS into an operational GIS

8.9.1. Introduction

Native eucalypt forest types were successfully mapped using the expert system approach described above. The Forestry Commission of New South Wales subsequently requested a forest type map to be produced over a larger area of 48,000 ha for inclusion in an environmental impact statement (EIS). The forest type map had to be produced in less than five weeks. Rapidly producing the map proved problematic; the solutions are discussed below.

8.9.2. Problems encountered with the Operational GIS

It became apparent that the program used to interpolate the regular DEM (Hutchinson, 1989) had a limiting memory requirement of 500 by 500 cells, due to memory and CPU time constraints. As a
consequence, the project area was segmented into smaller sub-areas which had a maximum grid size of 250 000 grid cells.

An unknown factor was the speed of digitizing stream lines and spot heights used as input into Hutchinson's interpolation program. Four 1:25 000 scale map sheets had to be digitized, as well as portions of a further five map sheets. A cartographer\(^1\) was temporarily transferred to assist with the manual digitizing. In general it took three to four days to digitize one map sheet. However the time taken to train a digitizer operator may be substantial, depending upon the ability of the operator. A problem developed of ensuring data captured was properly backed up; daily tape backups were instigated. An unforeseen difficulty were the idiosyncrasies of the digitizing software (Chapter 7). Examples included an inability to zoom onto areas being digitized, poor screen editing capabilities, and poor ergonomic layout of keyboard commands. The problems were not catastrophic so a decision was made not to fix them during the project.

The digitized spot heights and streamlines exhibited two errors that were not apparent during the earlier experimental stage of the GIS development. These errors were 'patched' around during the project; it is noteworthy that these errors passed rigorous system specification and testing, and only became apparent under operational conditions.

Geometrically correcting the Landsat TM imagery to the cartographically correct 1:25 000 topographic maps proved difficult, as ground control points could not be easily identified in areas of unroaded native eucalypt forest. Even where roads (such as fire trails) were present, discrepancies between the position of the roads on the 1:25 000 topographic maps and on the aerial photographs of the area were apparent. Obtaining valid control points was very time consuming, though eventually a good set of ground control points were located. A second order polynomial affine transformation generated a corrected image with a maximum error of less than one pixel width (30 m). The control points eventually selected were located at road and stream intersections on the 1:25 000 topographic maps; the position of the intersections were confirmed from aerial photographs. The accurate cartographic correction of the Landsat TM imagery minimized the geometric errors introduced during overlaying with the DEM (see Chapter 4 for details).

The training areas selected for the supervised classification of the Landsat TM data over the original study area also defined the classes used during the operational phase. The expert system rules were similarly extrapolated. It was assumed that conditions remained unchanged over the whole forest; this is probably an unrealistic assumption as parent material and elevation were known to vary. Ideally, additional training areas, rules and data layers would be included into the expert system approach, to improve mapping accuracy over the whole region.

Operational GISs require large amounts of mass storage. For example, in this project, 13 data layers were stored for 4 500 000 cells (i.e. 58 500 000 integers!). Mass storage requirements may be reduced by storing data in a compressed form (Chapter 3). Alternatively, the basic data may be stored (in

\(^1\)Mr C. Ferrugio, Forestry Commission of N.S.W., G.P.O. Box 2667, Sydney, N.S.W. 2000, Australia.
this case the DEM and Landsat TM) and the derived data layers (e.g. gradient, aspect, topographic position) may be generated as required by the expert system. This would reduce the memory requirement to 9,000,000 integers for this example (i.e. a reduction of 85 per cent).

An issue related to data storage requirements is cell size; obviously a larger cell size requires less mass storage. During the experimental mapping, the cell size was 30 m by 30 m (i.e. approximately 0.1 ha). This resulted in a high mapping accuracy (see 8.7), as the cell size approximately matched the forest stand size (see Chapter 4). At larger scales (such as the 1:100,000 scale map produced for the EIS), a larger pixel may more appropriately match the scale of the map. However, the larger pixels may reduce mapping accuracies, as forest types would be averaged over the larger pixel.

8.10. Conclusion

Forest type mapping has traditionally been a difficult and expensive task in Australian native forests, when using aerial photograph interpretation and ground reconnaissance. An expert system has been developed to map forest types in a complex eucalypt forest in south east Australia. The expert system successfully integrated disparate spatial data including remotely sensed data (Chapters 5 and 6), and a digital terrain model (Chapter 7). The expert system also incorporated ecological knowledge into the classification process. The knowledge encapsulated by the expert system included known relationships between forest type classes and environmental variables, and ecotonal associations between forest types. The utility of the supervised nonparametric classifier described in Chapter 6 for preprocessing remotely sensed data into a form suitable to input into the expert system has been demonstrated.

Mapping of forest types using the expert system approach was more accurate compared with classifying remotely sensed data alone. It was shown that the thematic image produced by the expert system had a significantly higher mapping accuracy compared with the maximum likelihood, the euclidean distance and the supervised nonparametric classifiers.

The potential for extending expert system techniques to map other forest attributes was discussed (in Chapter 9 soil types are mapped using these techniques). It is conceivable that expert systems will be increasingly used to manage and analyze the complex information contained in geographic information systems.
9. MAPPING FOREST SOILS FROM REMOTELY SENSED AND DIGITAL TERRAIN DATA USING AN EXPERT SYSTEM: A COMPARISON WITH CONVENTIONAL METHODS

9.1. Introduction

Maps of forest soils have traditionally been made using aerial photographs supported by ground surveys. This method is labour intensive and subjective, and may result in inconsistencies in the assignment of soil type boundaries or names between different aerial photograph interpreters, and over time with individual interpreters.

Soil-landscape mapping reduces some of the subjectivity of soil mapping, by including terrain as a factor influencing the classification of the soil map units. The relationships between soil, terrain and geology are used by an interpreter to delineate mapping unit boundaries on aerial photographs. The advantage of soil—landscape unit mapping is that it can be performed at smaller scales. For instance, the Soil Conservation Service of N.S.W. produces soil-landscape maps at the 1:100 000 and 1:250 000 scale.

There has been little success in mapping forest soils or estimating soil chemistry properties using remotely sensed data. This is due to vegetation cover obscuring the soil response in the visible, infrared and microwave portions of the electromagnetic spectrum (Tucker and Miller, 1977; Siegel and Goetz, 1977; Westin and Lemme, 1978; Thompson and Henderson, 1984; Musick and Pelletier, 1988). Taking an alternative viewpoint, Ezra et al. (1988) found agricultural crops mapped using remotely sensed data were confused by different underlying soil types!

Soil types have been visually delineated on Landsat photographic images. Lewis et al. (1975) visually interpreted Landsat bands and found that soil types could be discriminated in the sand hills of Nebraska. Westin and Frazee (1976) visually interpreted a Landsat colour composite as well as individual bands, and successfully mapped soils. Thompson et al. (1984) measured Landsat Thematic Mapper (TM) radiance values over two areas of soybeans; one area had varying soil types and the other area had constant soil type. They found that the area with different soil types had higher variation in its radiance values, and they concluded that Landsat TM data was producing information related to soil properties over soybean fields. Cipra et al. (1980) concluded that for fields without vegetation, soil colour was significantly correlated with Landsat MSS spectral reflectance. Horvath et al. (1984) used the ratio of Landsat bands 4 plus 5 to bands 6 plus 7 as a dependent variable against which were regressed a number of soil related independent parameters including per cent clay, per cent fragments greater then 2 mm, the sum of forest and brush crown densities, pH of the surface horizon, colour of the surface horizon, litter cover and aspect. They found 81 per cent of the variation in the remotely sensed data response was explained by these independent factors.

Attempts have been made to map soils using conventional computer pattern recognition techniques, though again, sites chosen generally had little or no vegetation cover. Kornblau and Cipra...
(1983) used a supervised maximum likelihood classification of Landsat multispectral scanner data to map soils under range conditions in Colorado with a 47 per cent mapping accuracy. They concluded that the map produced compared favourably with boundaries on soil maps made using conventional surveys. Thompson and Henderson (1984) used a supervised minimum distance classifier to map soils under fields of soybeans and corn. Results at the soil unit level of accuracy were disappointing; the best results were 55 per cent (corn) and 46 per cent (soybeans). At the coarser great soil group level, mapping accuracies were 92.9 per cent for corn and 75.6 per cent for soybeans. Lee et al. (1988) used unsupervised classification to map five soil groups in a Wisconsin agricultural area, using Landsat TM data combined with a digital terrain model of gradient and aspect. Lee et al. (1988) compared the classified image with a conventionally generated soil map and claimed a 72 per cent agreement between the two maps. Thompson et al. (1981) attempted to map soils under woodland in Texas using supervised classification of Landsat MSS imagery with limited success. They found that soils were correctly mapped only where they were correlated with different overstorey species discriminated by the Landsat MSS imagery.

There has been some success in correlating soil chemical properties with spectral reflectance measurements and mapping areas of mineralisation, especially in areas of sparse vegetation such as arid zones (Abrams, 1984; Kruse, 1988), cleared agricultural fields (Schrier, 1986), or mine tailings (Schrier, 1986); also Singh and Dwivedi (1989) reported that salt affected areas in India are operationally mapped by supervised maximum likelihood classification of Landsat MSS imagery. It should be noted that in addition to vegetation cover, spectral reflectance over soils is affected by varying soil moisture levels, especially in the infrared region (Orbukhov and Orlov, 1964; Slater and Jackson, 1982; Huete et al., 1985; Suzuki, 1989), atmospheric effects (Huete and Jackson, 1988; Cipra et al., 1980), physical soil characteristics including soil drainage (Myers, 1983; Fagbami, 1986), and observation conditions (for example illumination intensity and direction).

A relationship between soil zinc levels and Landsat MSS and TM response over a spruce forest was reported by Banninger (1986), though Banninger (1986) was no correlation with copper and lead levels at the same study site. Banninger (1986) attributes this to the ability of the spruce trees to translocate zinc to the canopy in proportion to soil zinc levels, with the spectral response of the canopy being effected by the concentration of zinc in the canopy. In contrast, lead and copper were not translocated to the canopy.

Microwave and thermal infrared data has yielded some information on soil moisture content, though again vegetation cover and soil type introduces noise, thereby reducing the accuracy of soil moisture estimates (Myers, 1983; Fung and Ulaby, 1983; Bruckler et al., 1988; Owe and Chang, 1988). In fact, Jackson et al. (1984) reported that forest cover totally attenuated microwave data at the K-, L- and C-bands (i.e. wavelengths of approximately 1 cm, 6 cm and 21 cm respectively), resulting in the radar system being unable to measure soil moisture. Microwave data has been combined with visible and infrared imagery to show enhanced radar backscatter occurred over flooded forests (Richards et al., 1987).

Mapping soils directly from remotely sensed data has been confounded by the complexity of environmental factors contributing to the spectral reflectance measured by a sensor. As forest vegetation
attenuates electromagnetic radiation at most wavelengths, there has been little success in directly mapping forest soils using remotely sensed data.

Expert systems have been proposed as a method of integrating various data types, and are defined and described in Chapter 8. The use of expert systems for forestry and natural resource management is rapidly increasing, and a number of examples are cited in Chapter 8. This chapter describes a method for assessing information from many diverse data sources (including gradient, aspect, vegetation cover, a soil wetness index, as well as knowledge about the position of soil units in the environment) in order to map forest soils. An expert system is used to integrate the data sources. The system essentially mimics an experienced soil scientist, assigning the most likely forest type to an area, after considering the area's gradient, topographic position, soil wetness and vegetation type.

Thus the overall aim was to automatically map forest soil units in a complex native eucalypt forest in southeast Australia, using available multisource data including Landsat TM digital data, a digital terrain model1, and a soil wetness index. A priori knowledge about the environmental position in which particular forest soil types occur were included as rules in this classification process.

9.2. Description of the study area

A study area of approximately 3 km by 3 km situated approximately 40 km west of the coastal township of Eden in southeast Australia was selected. Experiments concerned with the silviculture, hydrology and fire history of the forests have been established in the area by the Forestry Commission of New South Wales, yielding the ground plot data and colour aerial photographs used in this study. The 9 km² block used in this study was located within the larger experimental area named the 'Burning Study Area' that was described in Chapter 8.

The study area is covered by mostly dry sclerophyll forest (Baur, 1965), where the overstorey tree canopy is totally dominated by *Eucalyptus spp.* In gullies, some wet sclerophyll forest appears (Baur, 1965). The parent material was described by Beams (1980) as a coarse grained, felsic adamellite/granite, and it is an integral part of the larger Devonian Bega Batholith. Within the study area, the parent material is essentially homogeneous. The topography is moderate, ranging in elevation from 150 to 600 m.

9.3. Conventional soil mapping of the study area

The experimental forest area called the 'Burning Study Area' had 48 soil profiles described, and 21 of these profiles were located within the 9 km² block used in this study. These profiles were described using the terminology of McDonald *et al.* (1984) and classified using the great soil groups of Australia (Stace *et al.*, 1968) and *A Factual Key* (Northcote, 1979).

---

1The digital terrain model includes information describing gradient and topographic position (i.e. ridge, midslope, valley)
Soil development on the Wallagaraugh Adamellite has been studied in detail at the Yambulla research catchments, 15 km to the south of the study area. A soil-geomorphological model based on the terminology of Paton (1978) was devised to explain the variation in this coarse-grained granitic material. Five soil-landscape units were recognized by Ryan (in press), and are now described.

Residual crests and interfluves (RC). These are stable, flat and well drained soils having minimal erosional or depositional activity. Soil water movement is limited to vertical infiltration. Soil classifications include yellow to red podzolic great soil groups (Stace et al., 1968) or sandy mottled-yellow duplex soils (Dy5.41, Dy5.81) (Northcote, 1979). Increase in clay content and structure of the B horizons are features of this soil mapping unit, compared with the other soil types now described.

Degraded mid- to upper slopes (DS1). These soils are found on ridges and hillslopes where they are affected by the transportational geomorphic processes. That is, these soils are continually being stripped of surface material and are therefore geomorphically unstable or degraded (Paton, 1978). Slope gradients are at a maximum, so surface and subsurface lateral soil water flow play an important role in soil formation. Morphology of these soils is that of shallow, coarse sandy loams to sandy clay loams with minimum horizon and structural development, although deeper profiles can occur in colluvium dammed behind adamellite tors. Lithosols, brown and yellow earths are the most common great soil groups, while primary profile forms range from uniform coarse (Uc) through gradational (Gn) to duplex (Dy). Adamellite tors and surface rock outcrops are a common feature of this soil landscape type.

Degraded lower slopes (DS2). When gradient decreases, the transportational processes are not so severe. These soils tend to be deeper than DS1 soils, with development of distinctly coloured B2 horizons and often evidence of colluvial origin of the surface horizons. Surface and subsurface water flow are still the dominant geomorphic agents. Yellow earths and minimal yellow podzolics are the common great soil groups while principal profile forms include Gn2.21, Gn3.01 and Dy4.81.

Aggraded well drained slopes (AS1). Thick layers of coarse sandy alluvium can accumulate on lower slope positions. If these aggraded areas are well drained and relatively stable, then a podzol morphology can develop. These soils display a thick humic A1 horizon, a bleached A2 horizon, and an illuviated humic-sesquioxide B2hs horizon which can often be cemented. Soil textures are clayey coarse sand, to coarse sandy loams, reaching a depth of at least 1 m. These podzol soils (Uc2.31) are uncommon because the aggraded layers usually occur in drainage lines which have semi-permanent water tables.

Aggraded slopes with restricted drainage (AS2). The presence of fluctuating water tables in these thick layers of sandy colluvium limits the development of podzol soil morphology and produces more hydromorphic features. Thick humic A1 horizons and bleached A2 horizons still occur, but B2 horizons tend to be yellow mottled with pale or gleyed colours. These soils often display evidence of more than one depositional episode. Humic gleyed and gleyed podzolic great soil groups (Gn1.84, Uc4.24, Uc2.23) are the common classifications within this soil landscape unit.

The relative position of these five soil units in the landscape are shown in Figure 9-1.
Over 50 per cent of the profiles located in the study area were on DS1 sites. It is usually associated with Silvertop Ash (*Eucalyptus sieberi*) and the stringybarks. The next most important soil type is AS2 (25 per cent of the profiles) which has the characteristic vegetation association with thick *Melaleuca-Hakea-Leptospermum* swamps, with few eucalypts. Vegetation associations on DS2 sites were similar to those on the DS1 soil units, though there can be greater abundance of *Eucalyptus agglomerata*, *Eucalyptus consideniana* and *Eucalyptus cypellocarpa* reflecting the deeper soils and better water availability. Few distinguishing vegetation associations separate RC from DS1 sites, with *Eucalyptus sieberi* dominating both. AS1 soils were the least common (5 per cent of the study area) so few definitive statements can be made other than association with *Eucalyptus obliqua*, *Eucalyptus consideniana* and *Eucalyptus cypellocarpa*.

The study area was conventionally mapped by interpretation of 1:10 000 colour aerial photographs\(^1\). The aerial photograph interpretation utilized the relationships of the soil landscape model, plus the observed vegetation associations that were described above. This information, as well as the known areal extent of each soil unit, were utilized by the expert system to infer soil unit classes.

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\(^1\)The conventional soil mapping was performed by Dr P. Ryan, W.T.F.R.D., Forestry Commission of N.S.W., P.O. Box 100, Beecroft, N.S.W. 2119, Australia.
9.4. Definition of the expert system

9.4.1. Introduction

The expert system was described in detail in Chapter 8, and the same terminology is used here. In this case, the research question to be answered by the expert system is 'what soil type occurs at a given location in the forest?'. The raster database layers used for the forest soil mapping included:

- overstorey vegetation,
- gradient,
- topographic position (i.e. ridge, upper midslope, midslope, lower midslope, valley), and
- a soil wetness index.

The expert system infers the most probable soil type that would occur at a given grid cell using information from these data layers. *A priori* probabilities for all the items of evidence were incorporated into the inferencing process using a Bayesian (statistical) rule-based approach. The *a priori* probabilities relating to the evidence were generated from field work and the knowledge of an experienced soil scientist (see 9.1 and 9.3.4).

9.4.2. Formal statement describing the expert algorithm

In this case, let $S_a$ be the forest soil type class (for $a=1,\ldots,n$ classes) occurring at location $(i,j)$. Let $E_b$ be an item of evidence (for $b=1,\ldots,k$ items of evidence) known at location $X_{i,j}$. Set up a hypothesis ($H_a$) that class $S_a$ occurs at location $(i,j)$. A rule may be defined thus:

$$E_b \Rightarrow H_a,$$

that is, given a piece of evidence $E_b$, then infer $H_a$. The expert system then inferred the most likely soil type at a given cell using Bayes' Theory, as detailed in Chapter 8.

The expert system was written in Fortran-77 and executed on a DEC VAX 8700 computer cluster at the Australian National University. The evidence was prepared as described in 9.5 and stored in the SPIRAL geographic information system (Myers, 1986), while the *a priori* data (see 9.5.4) were stored as an ASCII file. The thematic maps output from the various classification strategies were plotted on Tektronix hardware using Uniras software (European Software Contractors, 1982) and Map Analysis Package (MAP) software (Tomlin, 1987b).

9.5. Preparation of the evidence and *a priori* probabilities for input into the expert system

9.5.1. Forest overstorey map

A vegetation map showing the forest overstorey of the study area was prepared from digital elevation data and remotely sensed data using a expert system (Skidmore, 1989b - see Chapter 8). The overstorey vegetation types recognized in this study are listed in Table 8-1. The methodology used to prepare the map of forest overstorey is now briefly described.
Landsat Thematic Mapper data were classified into forest types using a supervised nonparametric classifier (Skidmore and Turner, 1988). The supervised nonparametric classifier also yielded the empirical probability of correct classification for the forest type classified at each grid cell. The forest type and empirical probability information were geometrically co-registered with a digital terrain model of gradient, aspect and topographic position to a grid, spaced at 30 m intervals. This data set were accessed by the expert system described in Chapter 8, and a map of forest type produced.

9.5.2. Topographic data

Topographic variables can be readily generated in digital form and merged with other digital data, such as remotely sensed data. The method for generating the regular digital elevation grid used in this study was described in Chapter 7 (see also Skidmore, 1989d). Streamlines and high points were digitized from the Mount Imlay map sheet (that was also used to geometrically rectify the remotely sensed data). Within the study area, 346 spot heights were selected, as well as 322 points along streamlines. As described in Chapter 7, an interpolation program¹ developed by Hutchinson (1989) was used to calculate elevation values to 1 m on a regular 30 m grid.

The DEM (digital elevation model) was geometrically corrected to the same geometric projection and scale as the remotely sensed data, using a second order polynomial with 10 ground control points and nearest neighbour interpolation (Turner et al., 1982).

The modelling of topographic variables from a regular grid of digital elevation data was reviewed in Chapter 7 (also see Skidmore 1989c), and it was proposed that either the third order finite difference method, or multiple linear regression models, were suitable for calculating gradient and aspect. As a consequence, a third-order finite difference method was used to calculate gradient and aspect. The modelling of terrain position (i.e. ridge, upper midslope, midslope, lower midslope and valley) from gridded digital elevation data was also implemented using an algorithm proposed in Chapter 7 (see also Skidmore, 1989d).

9.5.3. Soil wetness index

The DEM (digital elevation model) used to produce estimates of gradient and topographic position at each 30 m grid cell (9.5.2) was also used to calculate a soil wetness index. The soil wetness index was used to test for conditions of local soil waterlogging, in addition to showing relative levels of wetness through the area being studied. The algorithm used here was described fully by O'Loughlin (1986).

O'Loughlin's (1986) model is based on contours calculated from the DEM described in 9.5.2. Partial catchment areas (A) are calculated upslope from contour segments (of length b), allowing the catchment area contributing to a point (P) in the catchment to be estimated (see Figure 9-2 taken from O'Loughlin, 1986). The net drainage flux (q) at the point (P) equals the net efflux Qₒ, so over the whole catchment (Aₒ) generating the outflow Qₒ, the relationship between q and Qₒ is:

¹The characteristics of Hutchinson's algorithm are described in 7.2.1.
Local saturation will occur when the drainage flux is greater than the efflux at a point (x,y). That is, the product of the upslope partial catchment A and drainage flux q is greater or equal to the local soil transmissivity T and the local surface gradient M:

\[ \frac{1}{A} \int q(x,y) \, d(A) \geq TM \]  

...(1)

Because the local drainage flux is difficult to measure, q is assumed to have a uniform distribution with an average value q. In addition, the mean catchment transmissivity T is estimated. If soil
transmissivity and drainage flux are uniform everywhere, then soil wetness at a point can be estimated from a topographic map alone. Normalizing equation (1) for mean transmissivity and mean drainage flux, the following estimate of wetness \( w(x,y) \) at a point in the catchment is obtained:

\[
w(x,y) = \frac{1}{M_b L} \left[ \frac{T}{T_1} \right] \int \left[ \frac{q}{Q} \right] d(A) \geq \frac{TA_1}{Q_0 L}
\]

The study area was located over Devonian granite parent material, and was considered to have a uniform transmissivity. Detailed hydrological experiments had been conducted in a similar catchment area to the south of the study area (Moore et al., 1986), so results could be used to estimate transmissivity and drainage flux.

The soil wetness model as currently implemented operates on only one catchment at a time. The study area was covered by 13 catchments (or parts thereof), so soil wetness was calculated for each individual catchment and then concatenated into one map showing soil wetness for the whole study area. In order for soil wetness to be derived, the whole catchment area must be available for the soil wetness model. The Wallagaraugh River flows through the southwest quadrant of the study area, though the watershed of this river does not occur within the study area. No accurate soil wetness information was therefore available for this portion of the study area.

The soil wetness index data was derived from the DEM (9.4.2), so it was geometrically corrected to the remotely sensed data. Thus the remotely sensed thematic images, the topographic data (i.e. gradient, aspect, topographic position), and the soil wetness index were now geometrically corrected to the same map base and resampled to a regular 30 m grid. These data sets were input as separate layers into a raster database using the SPIRAL geographic information system (GIS) system (Myers, 1986).

9.5.4. Combining soil wetness and topographic position

Combining soil wetness and topographic position allows the importance of the topographic feature in the landscape to be inferred. For example, a gully with a low soil wetness index will be found high in a catchment (i.e. it is a high order stream), while a gully with a high soil wetness index will have more catchment contributing to its flow and will therefore be a lower order stream. In a similar way, the importance of ridges and midslopes in the landscape may be ascertained from their soil wetness. A dry ridge will represent a watershed, while a wetter ridge indicates a false ridge occurring within a catchment area. A dry midslope will occur relatively high in the catchment, while a wet midslope will occur nearer the outflow of the catchment.

Four soil wetness states (i.e. very dry, dry, moist and wet) were overlaid onto the map showing the five topographic positions (i.e. ridge, upper midslope, midslope, lower midslope, gully) using the SPIRAL GIS. Thus 20 soil wetness/topographic position strata were created as shown in Table 9-1. The abbreviations used below for these strata are also shown in Table 9-1.
Table 9-1: The soil wetness/topographic position strata and their abbreviations

<table>
<thead>
<tr>
<th>Topographic position</th>
<th>Very Wet</th>
<th>Moist</th>
<th>Dry</th>
<th>Very Dry</th>
</tr>
</thead>
<tbody>
<tr>
<td>gully</td>
<td>gvd</td>
<td>gm</td>
<td>gd</td>
<td>drv</td>
</tr>
<tr>
<td>lower midslope</td>
<td>lvd</td>
<td>lm</td>
<td>ld</td>
<td>lvd</td>
</tr>
<tr>
<td>midslope</td>
<td>mvd</td>
<td>mm</td>
<td>md</td>
<td>mvd</td>
</tr>
<tr>
<td>upper midslope</td>
<td>uvd</td>
<td>um</td>
<td>ud</td>
<td>uvd</td>
</tr>
<tr>
<td>ridge</td>
<td>rvd</td>
<td>rw</td>
<td>rd</td>
<td>rvd</td>
</tr>
</tbody>
</table>

The soil wetness/topographic position strata increased the amount of expert knowledge recorded for each soil unit. This allowed better discrimination of the soil units by the expert system. For example, the DS2 type was considered to have a low probability of occurring on moist sites (p = 0.3), and a low probability of occurring on midslope sites (p = 0.3) over the whole study area. In other words, given that any of the topographic positions (i.e. ridge, upper midslope, midslope, lower midslope, gully) were moist, the chance that the soil was DS2 would be low. However, it was observed that sites occurring on moist midslopes had a moderate probability of being DS2. Such specific knowledge could be captured using the soil wetness/topographic position strata.

More generally, the soil wetness/topographic position strata offer a mechanism for automatically ranking the importance of the topographic features in the environment. For example, overlaying streams with soil wetness allows relative stream order to be inferred.

9.5.5. A priori probabilities of evidence

Assigning the a priori probability of occurrence for a piece of evidence is the most subjective aspect of an expert system (Forsyth, 1984). The probability of an item of evidence occurring, given a particular hypothesis (i.e. \(P(E|H_a)\)), must be ascertained to calculate Equation (1). In an ideal situation, \(P(E|H_a)\) may be derived statistically, though in most applications this is not possible, so \(P(E|H_a)\) is a heuristic, estimated from the 'feeling' or 'knowledge' of experts. In this study, \(P(E|H_a)\) was estimated by qualitative methods including interviewing experts, field observations, published material (Kelly and Turner, 1978; Turner et al., 1978) and results from a number of soil pits. The a priori probabilities detailed in Table 9-2 were collated by averaging the probability responses of an experienced soil scientist\(^1\) and observations from soil pits.

\(^1\)Dr P. Ryan.
### Table 9-2: Prior probabilities of the evidence

<table>
<thead>
<tr>
<th>Environmental Variable</th>
<th>Soil Landscape Unit</th>
<th>RC</th>
<th>DS1</th>
<th>DS2</th>
<th>AS1</th>
<th>AS2</th>
</tr>
</thead>
<tbody>
<tr>
<td>GVD</td>
<td></td>
<td>0.4</td>
<td>0.6</td>
<td>0.2</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>GD</td>
<td></td>
<td>0.3</td>
<td>0.5</td>
<td>0.5</td>
<td>0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>GM</td>
<td></td>
<td>0.2</td>
<td>0.4</td>
<td>0.6</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>GW</td>
<td></td>
<td>0.1</td>
<td>0.4</td>
<td>0.5</td>
<td>0.4</td>
<td>0.8</td>
</tr>
<tr>
<td>LVD</td>
<td></td>
<td>0.3</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>LD</td>
<td></td>
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<td>0.4</td>
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</tr>
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<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
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<td>0.6</td>
<td>0.3</td>
<td>0.3</td>
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</tr>
<tr>
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<td></td>
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<td>0.6</td>
<td>0.4</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
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<td>0.5</td>
<td>0.3</td>
<td>0.1</td>
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</tr>
<tr>
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<td>0.3</td>
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</tr>
<tr>
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<td>0.2</td>
</tr>
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<td>0.4</td>
<td>0.3</td>
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<tr>
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</tr>
<tr>
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<td>0.3</td>
<td>0.5</td>
<td>0.6</td>
<td>0.2</td>
</tr>
</tbody>
</table>

**Key to Table 9-2:**

See Table 9-1 for soil wetness/topographic position abbreviations

- <5 - less than 5° slope
- 6-10 - 6 to 10° slope
- 11-20 - 11 to 20° slope
- >21 - greater than 21° slope
- Q/R - quarry/road
- Y - yertchuk
- TT - Tea tree
- S/MG - stringybark/monkey gum
- BLS - blue leaved stringybark
- STA - silvertop ash
- REG - regenerating forest
- MG/STA - monkey gum/silvertop ash

### 9.6. Map accuracy assessment

Mapping accuracies for the thematic map output by the expert system were calculated. Randomly located soil pits were dug at 21 sites by the Forestry Commission of N.S.W. and the soil type was described. The higher frequency of some soil types such as the DS1 class in the study area was reflected in
the higher numbers of this soil type in the error matrix, due to the simple random selection of soil pit locations. In addition, a large number of forest overstorey and understorey variables were measured at each plot.

The field plots were manually located on the geometrically corrected thematic images using the road and stream networks as reference points. The class name associated with each plot was checked against the classes predicted on the thematic images produced by the four classifiers. The mapping accuracies were summarized as error matrices (Kalensky and Scherk, 1975). Overall mapping accuracy was calculated for the thematic images produced by the four classifiers using the conventional measure of the number of correctly classified pixels divided by the total number of pixels checked. More sophisticated map error analyses (such as those used in Chapter 8) were not attempted due to the low sample number.

9.7. Results

The geometric correction of the remotely sensed data resulted in all TM pixel locations being less than ±0.6 of a pixel from the true map value. The root-mean-square planimetric error (RMSEX and RMSEy) values were ±13 m and ±15 m respectively (i.e. the standard error multiplied by the pixel size of 30 m). Results for the geometric correction of the DTM data were better, with the maximum error being less than ±0.4 of a pixel and RMSExy values being ±10 m and ±11 m respectively.

The data layers integrated by the expert system were soil wetness (Figure 9-3), gradient (Figure 9-4), topographic position (Figure 9-5) and overstorey vegetation (Figure 9-6). A map of soil type boundaries derived using conventional methods is included as Figure 9-7. A thematic soil map generated by the expert system is included as Figure 9-8. Note that a soil wetness index value of greater than or equal to 10 on Figure 9-3 represents waterlogged conditions.

An error matrix (see 4.5.2) for the expert system map was calculated (Table 9-3).

Table 9-3: Error matrix for the expert system derived soil map

<table>
<thead>
<tr>
<th>Number of pixels (image)</th>
<th>RC</th>
<th>DS1</th>
<th>DS2</th>
<th>AS1</th>
<th>AS2</th>
<th>total</th>
<th>% correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of pixels</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DS1</td>
<td>1</td>
<td>10</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>100</td>
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<tr>
<td>DS2 (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AS1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>100</td>
</tr>
<tr>
<td>AS2</td>
<td></td>
<td></td>
<td>1</td>
<td></td>
<td>1</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>total</td>
<td>1</td>
<td>13</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td>% correct</td>
<td>100</td>
<td>77</td>
<td>33</td>
<td>-</td>
<td>100</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

overall mapping accuracy = 14 + 21 = 66.7 per cent

If one groups the soil units into the broader categories of stable, degraded and aggraded soils (see Figure 9-1) the overall mapping accuracy rises to 71.4 per cent

---

1 See 4.5.2 for a definition of overall mapping accuracy.
2 See 4.2.2 for a definition of root-mean-square error.
Figure 9-3: Soil wetness over the study area

Figure 9-4: Gradient over the study area

Figure 9-5: Topographic position over the study area

Figure 9-6: Vegetation derived (derived in Chapter 8)

Figure 9-7: Soil map interpreted by conventional methods

Figure 9-8: Soil map derived by the expert system
9.8. Discussion

The geometric correction of the digital terrain model and the remotely sensed data was satisfactory, with a $\text{RMSE}_{xy}$ of approximately less than half a pixel. The sample plots could be accurately located on high quality inkjet plots of the thematic maps.

Visual inspection of the soil type maps generated by conventional methods and the expert system showed that they compared well (Figures 9-7 and 9-8). Some areas of difference between the two maps were obvious, and were generally caused by inaccuracies in the GIS data layers. For example, in the centre of the southwest quadrant there was a large area of DS2 delineated on Figure 9-7, that did not appear on the expert system derived map (Figure 9-8). This was due to the soil underneath the Wallagaraugh River being modelled as dry (Figure 9-3), when in fact it should be wet. As explained in 9.4.3, the soil was dry because the catchment for the Wallagaraugh River did not occur within the study area. Another example of a discrepancy between the two maps occurred at the border between the southwest and west quadrants on Figure 9-7. The DS2 and AS2 were mapped using conventional methods, while RC was predicted by the expert system. This was caused by a ridge being incorrectly located in Figure 9-5 due to an error in the DEM. Thus errors in the GIS data layers accumulated, and caused errors in the soil map predicted by the expert system. There was some disagreement in the location of the AS2 soil unit, because a critical factor in the identification of this soil unit was the presence of *Melaleuca-Hakea-Leptospermum* swamp. In places, this swamp vegetation had a width of much less than the 30 m resolution of the Landsat TM imagery\(^1\), and consequently was not delineated on the vegetation layer in the GIS accessed by the expert system. As the narrow strips of swamp vegetation were missing, the AS2 soil type could not be mapped by the expert system.

Other errors in the expert system map were caused by ambiguity in the expert system rules. The ambiguity was due to not all the environmental variables which may be affecting the distribution of soil types being included in the GIS. For example, the RC soil unit occurred on wide and flat areas. However, there was no data layer in the GIS indicating the areal extent of flat regions, though such a data layer would be useful for improving the mapping accuracy of the RC soil unit.

The descriptions of the soil units (9.3) were somewhat vague. This is because soil is actually a continuum of different types (see Figure 9-1) which has been artificially split into units. The position of the soil unit boundaries are difficult to identify even in the field or on aerial photographs (4.8.2), because soils are hidden quantities which make them difficult to assess (Webster and Beckett, 1968). Thus the difficulty of defining soil type boundaries also effects the placement of boundaries on the conventional soil map (Figure 9-7). The boundaries on Figure 9-7 were subjectively delineated from aerial photographs, and were not field checked by soil pits. To assess the error of the conventional and expert maps in a statistically significant manner, additional soil pits must be sampled within the study area. As discussed in 4.5.2.2, a minimum of 30 soil pit samples per soil type is recommended (Van Genderen *et al.*, 1978),

\(^{1}\text{Note that swamp vegetation of less than approximately 5 m width could be delineated on the aerial photographs.}\)
with a preference for over 50 (Hay, 1979). Ginevan (1979) showed that 96 soil pit samples would be required in order to avoid committing type I and type II errors in accepting (or rejecting) a map as accurate. Unfortunately it was not feasible to dig and describe such a large number of soil pits.

Errors in the GIS data layers will reduce the mapping accuracy of the thematic images derived by the expert system (see 4.9 for details). The extent to which errors are accumulated from the GIS data layers to the final derived thematic image is uncertain, and requires further theoretical and empirical evaluation. However, in some instances the use of the expert system may reduce or even negate the error in the GIS data layers. As an example, consider the mapping accuracy of the vegetation layer used by the expert system, which was 69 per cent (within 95 per cent confidence intervals) (see 8.7). If a cell in the vegetation layer was incorrectly classified, the expert system may still yield the correct soil type for the following two reasons:

1) Even though the individual forest types were not always mapped with a high accuracy, the major forest associations (i.e. gully vegetation type versus ridge forest type) were classified to a higher accuracy (see 8.8). A number of forest types occurred within each forest association (for example, Yertchuk, Blue-leaved Stringybark and Silvertop Ash occurred within the ridge forest association). Now take the case where a Yertchuk cell was incorrectly mapped as a Silvertop Ash cell in the vegetation layer. The \textit{a priori} probabilities listed in Table 9-2 would still correctly map the DS1 soil type because of the high \textit{a priori} probabilities of occurrence of DS1 in association with Yertchuk or Silvertop Ash.

2) Other data layers in the GIS may have a high mapping accuracy, which offsets the effect a layer with lower mapping accuracy may have on the final classification of the soil type map. Using the above example, a cell in the vegetation layer may have a low classification accuracy (for example, the cell may be classified as Monkey Gum/Silvertop Ash when in fact it is Yertchuk), but the cell is correctly classified as occurring on a upper midslope. If the correct soil classification is RC, the fact that the topographic position (i.e. upper midslope) is accurately mapped will improve the probability of the cell being RC instead of one of the other soil type classes (see Table 9-2).

The use of the soil pit data to determine the \textit{a priori} probabilities for the expert system, as well as for assessing map accuracy, may have biased the mapping accuracy assessment (see Chapter 4). The mapping accuracy of the conventional soil map (Figure 9-7) was 100 per cent, as the soil pit data was used to guide the air photo interpretation. In other words the interpreter ensured that soil pits were correctly classified on the conventional soil map (Figure 9-7). Thus a direct comparison of the soil map with the manually derived map is not valid.

The overall mapping accuracy for the expert system map (Figure 9-8) was 66.7 per cent (Table 9-3), while mapping of the stable, degraded and aggraded soils was at an overall mapping accuracy of 71.4 per cent. Visual inspection showed the soil maps generated by the expert system and conventional methods compared well. These results may be improved as discussed now.

Data layers other than those used in this study may become important in determining the distribution of a forest soils over larger of smaller areas than the 9 square kilometre area studied here. Environmental variables such as parent material, elevation, latitude and longitude, climate and overstorey
vegetation may increasingly dominate soil type on a regional or continental scale (Jenny, 1941). The effective extrapolation of the expert system approach to a larger area or a different region, requires that the principal environmental factors affecting forest soil distribution are recognized and modelled in a suitable format, such as Table 9-2. The use of an expert system is one of the most effective ways of quantitatively applying Jenny's (1941) 'State Factor Model' of soil formation to an actual soil survey. Conventional soil survey mapping can only simulate this via the qualitative skill of the surveyor.

The choice of auxiliary data sets to use for forest soil mapping is determined primarily by the availability of such data. Various types of remotely sensed data are available over Australia and most parts of the earth. Topographic data are useful, as they are readily available for most areas, or can be automatically generated if not readily available (see 9.1). Topographic data are also relatively constant factors in the environment over a time scale of hundreds of years in most parts of the world, so that once obtained the data can be repeatedly used over a number of decades for different applications. Similarly, parent material is another data type that is reasonably constant, though substantial field work by expert geologists is often needed to successfully map geological boundaries.

In contrast, other data layers such as vegetation structure and species composition may change over a time scale of a year to several hundred years. As shown in Chapter 8, forest type may be derived using an expert system, with topographic data, remotely sensed data and a set of rules as input. A derived thematic product, such as the vegetation type map, may in turn be used as an input layer by the expert system to derive additional thematic maps showing factors such as soil type mapping, as demonstrated in this Chapter.

Expert systems offer many advantages and some disadvantages over conventional pattern recognition or statistical approaches for the analysis of remotely sensed and other spatial digital data. The advantages and disadvantages are discussed in Chapter 8.

In the expert system developed for this study, forward chaining was used with a complete enumeration of the data (i.e. a blind search terminated by running out of evidence). Reasons why this is an optimal strategy for geographic information system data are discussed in Chapter 8 (also see Skidmore, 1989b).

The expert system effectively mapped the boundaries of the soil types by using the information contained in four data layers (viz., soil wetness, topographic position, gradient and forest vegetation). This essentially mimicked the conventional soil-landscape interpretation methods that use aerial photograph interpretation and knowledge of the location of soil types in the environment. The speed, objectivity and cost effectiveness of the expert system approach means soil maps are not affected by individual bias, and that large areas could be systematically mapped compared with conventional methods. The costly and labour intensive manual interpolation of forest soil maps can be effectively automated, provided good ground truth knowledge is available that allows relationships to be developed between the readily available digital spatial data and the soil types. Inclusion of additional data layers, and more sophisticated rules, will further improve mapping accuracy.
The methodologies followed in this Chapter to map forest soils are now summarized using the concept of the forest system model. Three primary data types (viz., remotely sensed data, knowledge and a digital elevation model) were used to derive the soil type map (Figure 9-9).

![Forest System Model Diagram](image)

**Figure 9-9: Forest system model level 1 - forest soil mapping**

The remotely sensed data were analysed using the unsupervised nonparametric classifier (Chapter 5) and the supervised nonparametric classifier (Chapter 6) to form a secondary variable of forest cover. Four secondary variables were derived from the digital elevation model viz., topographic position, gradient, aspect and soil wetness. By combining the secondary variables of aspect, gradient, topographic position and soil wetness with the knowledge of experienced researchers (using an expert system) a forest soil map was produced (Figure 9-10).
Figure 9-10: Forest system model level 2 - forest soil mapping

The 'expert system' sub-process shown in Figure 9-10 is now described at a third level of the forest system model. A forest cover layer derived using the supervised nonparametric classifier (Chapter 6) was combined with aspect, gradient, topographic position and knowledge, and input to a (forest vegetation) expert system which generated a forest type map (as described in Chapter 8). This forest type map was then combined with aspect, topographic position, gradient, soil wetness and knowledge. Using
these variables, a second (forest soil) expert system produced the forest soil map included as Figure 9-8. The expert system sub-process is now detailed as a level 3 of the forest system model (Figure 9-11).

Figure 9-11: Forest system model level 3 - the expert system sub-process

The generality of the forest system model has now been shown for forest vegetation cover mapping (Chapter 8) as well as forest soil mapping (Chapter 9). It is obvious that the forest system model technique may be extended to the mapping of other forest resources (such as wildlife habitat or forest biomass mapping), provided that the necessary primary and secondary data layers are available (or can be generated) and that the relationships between the primary and secondary data layers and the forest resource are known.
9.9. Conclusion

A forest soil type map has been successfully generated using an expert system to integrate readily available digital spatial data including Landsat Thematic Mapper and a digital elevation model (DEM). From the DEM, three data layers important for determining soil type were calculated viz., topographic position, gradient and soil wetness (note that to calculate soil wetness ancillary information including average transmissivity and drainage flux had to be known). A map detailing overstorey vegetation was constructed from remotely sensed data and the DEM.

Knowledge about the relationship of soil types to environmental variables were encapsulated in a matrix of prior probabilities. This matrix was used by the expert system to link the digital terrain data layers (viz., gradient and topographic position), the soil wetness index and the overstorey vegetation, and to create a map showing the distribution of soil types in the study area.

The map generated by the expert system compared well with a map constructed by conventional means. The overall mapping accuracy of the soil map derived using the expert system was 66.7 per cent. However, additional soil pits would need to be dug to establish a statistically valid estimate of map accuracy for both the conventional and expert system soil maps.
10. CONCLUSIONS

A literature review indicated a wide variety of forest resources in many parts of the world have been mapped with moderate success, using remotely sensed imagery (Chapter 3). As there was confusion and contradiction in the methods to be used to calculate mapping accuracy, the techniques proposed for assessing map accuracy were reviewed (Chapter 4). In addition, a novel method of calculating map accuracy based on line intersect sampling was developed and discussed, as well as a number of methods for modelling the accumulation of error during the overlay of GIS layers.

In order to raise the accuracy of forest maps (produced from remotely sensed data) to an acceptable level for managers, forest classes are often generalized\(^1\) to a point that they are no longer useful. More specific forest mapping, such as at Anderson \textit{et al.} (1976) level III, was shown to be associated with a rapid decrease in mapping accuracy (Chapter 3). To improve mapping accuracies, there has been a trend to combine the remotely sensed imagery with ancillary data available over the forest, such as elevation. In all cases cited in the literature review (Chapter 3), the inclusion of ancillary data improved forest mapping accuracies, compared with using remotely sensed data alone.

However, the ancillary data may still be under-utilized, because of primitive data analysis techniques. A theoretical forest system model was developed (Chapter 2), which highlights the interrelationships between the available remotely sensed and ancillary data, and the forest resources. An important concept of the forest system model is that a few input data types can be used to generate a lot of information about forest resources.

As stated in Chapter 1, the aim of this study was to show that forest resource information may be generated from remotely sensed and ancillary data at an accuracy acceptable to forest managers. The remotely sensed imagery was initially investigated, as two problems with the use of image processing algorithms over forests had been identified viz.,

1. there were difficulties in identifying training areas over Australian eucalypt forests, especially for those forests with little or no ground truth information and poor access;
2. it had been previously shown that conventional classifiers were not extracting all the forest information available in remotely sensed data (Skidmore \textit{et al.}, 1988).

The solution to the first problem was to develop an unsupervised classification algorithm that included spatial as well as spectral information (Chapter 5). The spatial information assisted in delineating homogeneous areas. The unsupervised classification algorithm allowed homogeneous forest areas suitable as training areas to be more easily identified, compared with conventional unsupervised methods.

In order to solve the second problem, a supervised nonparametric classifier was developed to increase the amount of forest information extracted from remotely sensed data (Chapter 6). The supervised nonparametric classifier produced more accurate forest maps compared with conventional supervised techniques, as well as producing an additional map showing the probability of correct classification.

\(^1\)For example to Anderson \textit{et al.} (1976) level I or II.
A commonly available ancillary source of information over forests is elevation. For localized forest studies (for example over an area of five by five kilometres), elevation *per se* may not be too useful, but the derivatives of elevation such as gradient, aspect and topographic position may be critical in determining the occurrence of forest flora and fauna. Six algorithms proposed by various authors for calculating gradient and aspect were tested, and it was concluded that the general linear regression models and the third order finite difference method were most accurate (Chapter 7). A number of algorithms for calculating the position of streams and ridges from DEMs have been developed by different workers, but upon testing, none proved adequate. A new algorithm for calculating ridge and gully positions was therefore developed (Chapter 7). In addition, a midslope interpolation algorithm was developed and tested (Chapter 7). Finally, a soil wetness index was generated from the DEM (Chapter 9).

Other types of ancillary data may be available for a forest, for example geology and climatic information. This data may be digitized and entered into a geographical information system (GIS) (for a discussion on digitizing see Chapter 7). In addition, 'knowledge' about the forest may be available, for example that a tree species tends to occur at a particular position in the environment. Such 'knowledge' is obviously not spatially registered, and therefore has not been easily incorporated into traditional GIS modelling.

The registration and overlaying of these diverse *spatial data* types is usually accomplished in a GIS (Chapter 3). However, in order to access the potential information of the GIS, the data must be analysed. A number of methods have been proposed for the analysis of GIS data, and were reviewed in Chapter 3. None of these techniques allowed the spatial digital data in the GIS to be analysed in conjunction with the 'knowledge' about the forest. In order to incorporate knowledge about the forest, an expert system approach was developed. The expert system significantly improved forest mapping accuracies compared with analysis of remotely sensed data alone (Chapter 8). The accuracies obtained were considered acceptable for operational mapping. An expert system was also used to generate a forest soil map of acceptable accuracy (Chapter 9); a soil map could not be generated using remotely sensed data alone as the vegetation obscured the spectral response of the soil.

The expert system approach may be applied to the mapping of other forest resources, including biomass, wildlife habitat, recreation potential etc. The technique is only limited by the availability of the input data required to model the forest resource, and the knowledge of the specialist researcher or natural resource worker.

Thus the objective of successfully generating forest resource maps from available spatial digital data, and knowledge about the forest, has been met.

In terms of the forest system model proposed in Chapter 2, it has been shown that forest resource quantities may be derived from readily available primary data (Figure 2-1). Further work required for the development of the forest system model will include deriving methods for assessing the value of forest resource quantities (tertiary variables), and allocating resources to different uses.
11. REFERENCES


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APPENDIX 1
A Probabilistic Modification of the Decision Rule in the Skidmore/Turner Supervised Nonparametric Classifier

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ABSTRACT: Using a hypothetical example, the paper demonstrates how the original classification decision rule may cause the amount of land in each cover type to be misestimated. An alternative is proposed and discussed which should provide better area estimates for each type, though locational accuracy may be decreased. The aesthetic quality of the classified image is also reduced because of the "salt and peppering" that results from the use of the probabilistically based rule.

INTRODUCTION

Skidmore and Turner (1988) presented and discussed a supervised nonparametric classifier which was used with multispectral SPOT data to improve classification accuracy compared to either a maximum-likelihood classifier or a Euclidean distance classifier for Monterey pine (Pinus radiata D. Don) plantations in Canberra, Australia. To utilize the classifier, a training field is selected from an unclassified image for each land-cover type of interest. For each training sample extracted, a unique N-dimensional space is created in which each dimension represents one spectral band of data, and each "edge" of the space is dimensioned by the possible range of pixel brightness values. For example, 7-band 8-bit Thematic Mapper data would result in the creation of a series of seven-dimensional spaces with each dimension or "side" ranging from 0 to 255. (The space, therefore, would have a total of 256 raised to the 7th power, cells, a number which may be reduced by using a "collapsing factor." ) For each training sample, the number of pixels in each cell position of the appropriate N-dimensional space is tallied based on the brightness value of each band for each pixel. A probability is then assigned to each cell position in a particular N-dimensional space relative to the number of pixels tallied in that cell position over all N-dimensional spaces. The image is then classified by assigning each unknown pixel to the cover type for which the probability is the greatest at the appropriate cell position.

However, because unknown pixels are not distributed to each cover type in the same proportion as they occur in the training samples, this decision rule may cause the amount of land in a particular type to be misestimated. To demonstrate this and describe an alternative decision rule, an intentionally simplistic example will be utilized so that laborious computations are minimized. The simplicity of the example does not decrease the validity of the points discussed, however.

In this example, a tract of land of 1000 hectares is available on which it is known that two cover types exist, with each type comprising exactly half — 500 hectares — of the area. A cloud-free digital image of the area has been obtained using a sensor comprising exactly half — 500 hectares — of the area. A cloud-free digital image of the area has been obtained using a sensor comprised of two spectral bands using 1-bit data and a pixel size of 1 hectare. To classify this image using the nonparametric classifier, two training samples of 100 pixels each have been extracted from areas on the image which are known to be perfectly representative of Types 1 and 2, respectively. For each type, the pixels were tallied in two-dimensional space based on brightness values and spectral band numbers with the following results:

Using the original decision rule, the 700 pixels/hectare in cell positions (0,1), (1,0), and (1,1) are assigned to Type 1 due to a probability of 0.83 compared to 0.17 for Type 2. The 300 pixels/hectare in cell position (0,0) are assigned to Type 2 due to a probability of 0.80 compared to 0.20 for Type 1. However, it is known that 500 pixels/hectare are in each of Types 1 and 2. If 700 and 300 hectares of Types 1 and 2, respectively, are used as the estimates of the amount of each type in the area, then erroneous decisions having potentially severe consequences may be made by land managers. The degree of misestimation is dependent upon the highest type probability — as the highest probability decreases, the degree of misestimation increases (Figure 1). In case where the highest probability is 0.10 at a particular cell position, 10 times as much land would be estimated as exists.
as actually exists will be placed in a single type and zero area
will be estimated to occur for the remaining classes, even though
90 percent of the pixels at this cell position in the training samples
were not in this type. If accurate area estimates are to be obtained,
therefore, one must hope that the errors of under- and over­
estimation for each type will compensate – rather than com­
 pound – over all cell positions.

A possible alternative is a decision rule which would assign
unknown pixels to land types in an unbiased fashion so that
despite are distributed according to the calculated probabilities.
To do this, a range of values is associated with a particular type
proportional to its probability at a given cell position, and a
random number is generated to determine to which type the
pixel is assigned. For cell position (0,0) in the example pre­

tented, values 1 through 18 and 100 would be as­
sign to Types 1 and 2, respectively. For each unknown pixel
having brightness values of 0 for both Bands 1 and 2, a random
number between 1 and 100 inclusive would be generated with
a value less than 18 resulting in the classification of the pixel as
Type 1, and a larger random number resulting in the pixel being
assigned to Type 2. In this way, 17 percent of the pixels in this
cell position would be assigned to Type 1 and 83 percent would
be assigned to Type 2, as similar pixels were distributed in the
training samples. As a result, a better estimate of the amount
of land in each type should result. In this example, the proba­
bility for each cell position can be multiplied by the expected
number of pixels in each position for the entire scene to dem­
 onstrate that area estimates would better reflect true values:

<table>
<thead>
<tr>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>300</td>
<td>0.157</td>
</tr>
<tr>
<td>275</td>
<td>0.345</td>
</tr>
<tr>
<td>250</td>
<td>0.800</td>
</tr>
</tbody>
</table>

While this decision rule clearly provides better estimates of
the total area of each type, there are other factors that will affect
which rule is preferable in individual cases. The primary weak­
ness of the proposed rule is that of location. For example, if
there are only two types represented at a cell position for which
probabilities are 0.90 and 0.10, respectively, the original deci­
sion rule will assign 100 percent of the unknown pixels to Type
1. Though this means that 10 percent of the unknown pixels
(which are actually Type 2) will be incorrectly assigned to Type
1, and also that no pixels at this cell position will be correctly
located for Type 2, 90 percent of all pixels (or 100 percent of the
type 1 pixels) can be expected to be located correctly. Con­
versely, use of the proposed decision rule would result in 90
percent of the unknown pixels randomly placed in Type 1 being
classified correctly (or 81 percent of the total) and 10 percent of
these being classified incorrectly (9 percent of the total). For
Type 2, 10 percent of the pixels placed in Type 2 would be
classified correctly (1 percent of the total), but 90 percent of
those placed in Type 2 would be classified incorrectly (9 percent
of the total). Thus, the original rule could be expected to locate
90 percent of the unknown pixels correctly, whereas the pro­
posed rule would locate only 82 percent correctly.

The proposed rule is not inferior for locational purposes over
the entire probability range, however. In cases where the high­
est probability is near 1.0, and in cases where the probability
for a cell position is nearly equal over all types, the two rules
can be expected to locate approximately the same number of
pixels correctly (Figure 2). Thus, both rules perform similarly
when there is either near certainty, or great uncertainty, about
the true type of a pixel at a particular cell position.

Considering the trade-off between accuracy and location, the
choice of either decision rule depends on a number of factors.
In the original article, Skidmore and Turner used the classifier
to identify types – forest plantations of different ages – which
are known to occur in blocks, rather than in a distributed pat­
tern. In similar situations, the original decision rule is probably
preferable because it may be undesirable to have the inherent
"salt and peppering" which occurs if pixels are classified based
on a random number. However, area estimates may be slightly
incorrect using the original rule due to the mixed pixels which
would occur at the edges of different plantations.

This also leads to the suggestion that the probability matrices
should be examined for each type before selecting a decision
rule. Figure 2 demonstrates that the two decision rules perform
similarly for both area and location if great certainty or uncer­
tainty exists concerning the actual type of a pixel. Thus, to clas­
sify a scene where types are either spectrally very similar (e.g.,
soy beans and corn) or spectrally very different (e.g., roads and
forest), the choice of decision rule may make little difference.

Rarely, however, does a scene exist where all classes of in­
terest are either extremely similar or different. Therefore, the
selection of either decision rule must be based upon the in­
SKIDMORE/TURNER SUPERVISED NONPARAMETRIC CLASSIFIER

Why Areal Accuracy Is Not Correctly Estimated Using Lowell's Modification of the Supervised Nonparametric Classifier

Two types of thematic mapping error are (a) locational, where a pixel is incorrectly classified according to some ground truth criteria, and (b) areal, where the area of a class on an image does not equal the area of the class according to the ground truth.

The concern of Lowell is that areas for classes may be poorly estimated using the supervised nonparametric classifier. This problem is common to all probabilistic classifiers, including the maximum likelihood classifier.

At the outset, it should be emphasized that spectrally discrete classes will yield images with a higher spatial and areal accuracy, independent of the probabilistic classifier used. As discussed by Skidmore and Turner (1988), the image (Figure 4 on page 1418) of the empirical probability of correct classification (i.e., P(I|X)) clearly differentiates classes which are spectrally similar from classes which are spectrally discrete. Thus, spectrally similar classes that will have low locational and areal accuracies can be identified. If there is co-occurrence at vector position X then information cannot be created from the confusion. The advantage of the supervised nonparametric classifier becomes apparent when two adjacent vector positions (X) each contain a separate class. In such a situation, parametric classifiers (such as the maximum likelihood classifier) may parameterize the adjacent vector positions as having the two classes co-occurring, when in fact the classes do not co-occur.

Lowell's example of a binary data set with two features is unrealistic as it is not characteristic of remotely sensed data. As discussed by Skidmore and Turner (1988), data sets such as the one proposed by Lowell could be considered to be in a severe state of "collapse" from the original 6- or 8-bit data. Using such a data set, a classifier will behave unpredictably due to classes being merged into (i.e., co-occurring in) a common vector position. High mapping accuracies are obtained when classes do not co-occur in vector positions, which is hopefully the situation when using a less severely collapsed data set. With more vector spaces, the area estimates of the supervised nonparametric classifier would be closer to the true values.

Furthermore, Lowell's modification will not correctly estimate the area of a class, where the estimated a priori probability for a class (over the area being classified) does not equal the true proportion of the class.

Following the notation of Skidmore and Turner (1988), the supervised nonparametric classifier is used to compute P(I|X) for i = 0, 1, 2, where P(I|X) is the probability of class i occurring at vector position X. Lowell's allocation of pixels to class 1 can be succinctly stated as follows:

\[ S_i = \sum_{x} P(I|X) T(X) \]

where \( S_i \) is the proportion of the image classified as class 1, T(X) is the total number of image pixels occurring at vector space (X), and n is the total number of pixels in the image. Note that it is not necessary to perform list sampling or create a classified image as proposed by Lowell.

P(I|X) may be calculated using Bayes' Theorem (see Skidmore and Turner, 1988). Using Lowell's example, P(I) = 0.5, P(2) = 0.5, the area of class 1 is 500 pixels, the area of class 2 is 500 pixels, and there are two features. It is then simple to calculate P(I|X), P(2|X), S1, and S2 at each vector position in two-dimensional feature space, as shown in Table 1.

So when P(I) = (S1/n), Lowell's modification works. In other words, the modification works when the a priori probabilities equal the actual proportions of class areas in the image.

However, if the a priori probabilities are not known exactly and (as is usually the case) estimated incorrectly, then the areas of the classes are also incorrectly estimated. For example, the effect of changing P(I) to 0.45 and P(2) to 0.55 on the estimated areas can be seen in Table 2. Therefore, using Lowell's modi-

### Table 1.

| Vector position | T(X) | P(1|X) | P(2|X) | P(1|X)*T(X) | P(2|X)*T(X) |
|-----------------|------|--------|--------|-------------|-------------|
| 0,0             | 300  | 0.167  | 0.833  | 50.1        | 249.9       |
| 0,1             | 275  | 0.545  | 0.455  | 149.9       | 125.1       |
| 1,0             | 175  | 0.571  | 0.429  | 99.9        | 75.1        |
| 0,0             | 250  | 0.800  | 0.200  | 200.0       | 50.0        |

### Table 2.

| Vector position | T(X) | P(1|X) | P(2|X) | P(1|X)*T(X) | P(2|X)*T(X) |
|-----------------|------|--------|--------|-------------|-------------|
| 0,0             | 300  | 0.141  | 0.859  | 42.2        | 257.8       |
| 0,1             | 275  | 0.495  | 0.505  | 136.2       | 138.8       |
| 1,0             | 175  | 0.322  | 0.678  | 91.3        | 83.7        |
| 0,0             | 250  | 0.766  | 0.234  | 191.5       | 58.5        |

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The errors in estimating class areas become larger as the estimate of the a priori probabilities deviates further from the true values. For example, when P(1) = 0.2, S1 = 250; and when P(1) = 0.75, S1 = 700 (remember, the true value should be 500).

The following question then arises. If we know a priori the exact area of class 1 and class 2, then why are we bothering to calculate the areas? If we do not know the exact areas, then an incorrect estimation of the a priori probabilities will lead to an incorrect estimation of the class areas.

Even using Lowell's pathological example, the supervised nonparametric classifier decision rule gives an equal or better estimate of area at some a priori probabilities (e.g., between P(1) = 0.75 and P(1) = 0.8), even though the spectral resolution (i.e., a binary two-feature data set) has little similarity with remotely sensed data (which normally has three to seven features and a spectral resolution per channel of 6 to 8 bits), and such a discretised data set accentuates errors in the area estimates of the supervised nonparametric classifier because there are only four vector spaces at which the classifier makes a decision.

Lowell's modification will increase locational errors in the classified range at all a priori probabilities (except 1.0, 0.5, and 0) by introducing noise through randomly allocating pixels to classes according to the proportions of P(1|X) and P(2|X) (see Lowell's Figure 2).

A final problem not discussed by Lowell is that training areas may not be representative of cover classes, because of natural variability in cover classes or pixels containing more than one cover class (i.e., a mixed pixel). If it is assumed, for the example Lowell presents, that training areas are not representative of the classes, the areal (and of course locational) estimates would be incorrect. This is because the P(1|X), P(2|X), and T(X) calculated from the training areas would not equal to the P(1|X), P(2|X), and T(X) for the whole image.

Methods for improving mapping accuracies include merging similar classes into one class, selecting realistic training areas, introducing collateral data, considering the spatial context of features in the remotely sensed data, or improving the spatial, spectral, and temporal resolution of the remotely sensed data.

Acknowledgment

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REFERENCE


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In the paper, "Forest Mapping Accuracies Are Improved Using a Supervised Nonparametric Classifier with SPOT Data," by Andrew K. Skidmore and Brian J. Turner (PE&RS, October 1988, page 1416), Equation 2 should read as follows:

\[ P(X) = \frac{(F_1 f(X)/P(X))}{[G(F_1 f(X)/P(X))] + [G(F_2 f(X)/P(X))] - 1} \]

Erratum

New Sustaining Member

PCI Remote Sensing Corp.
2300 M Street, NW, Suite 130, Washington, DC 20037

PCI Remote Sensing Corp. develops and supports image analysis software and provides integrated computer workstations. Hundreds of PCI systems are used around the world to more effectively monitor and map crops, terrain, forests, oceans, and the atmosphere.

PCI's software, called EASI/PACE, converts remotely-sensed imagery and digitized aerial photography into vivid, color-enhanced images, allowing users to readily analyze and extract meaningful information. It's one of the most comprehensive and best-supported image analysis systems; users benefit from the flexibility of the software, as it was designed for easy networking and operates on a wide variety of hardware. The benefits of EASI/PACE continue to be discovered for use in resource management and conservation; exploration; teaching and research; mapping, charting, and geodesy (MC&G); and for intelligence data fusion.

The company was established in 1982 and is driven by one of Canada's leading founders of remote sensing, Dr. Murray Strome. Dr. Strome assisted in the design and implementation of the country's first Landsat processing system and now presides as Chairman of the Board.

The PCI team includes professionals with strong education and experience. One team member is a geologist with ten years' service with a large mining company; another member spent six years as a researcher and manager of a remote sensing research project with the Canadian Forestry Service. Others have university degrees in geophysics, geography, and engineering; several have backgrounds in computers and business. Because of the team's collective strengths, PCI is able to provide extensive education, system support, and consulting services.

EASI/PACE continues to be upgraded with new ideas and technology; this emphasis on software enhancements has contributed to the company's success, both at home and abroad. PCI's head office is located in Toronto, Canada; a network of representatives and distributors are located outside North America to help build PCI's leading reputation.

PCI