An Expert System Classifies Eucalypt Forest Types Using Thematic Mapper Data and a Digital Terrain Model

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ABSTRACT: Landsat Thematic Mapper digital data were classified into seven native eucalypt forest type classes using a nonparametric classifier that also calculated the probability of correct classification for each pixel. A digital elevation model, spaced on a 30-m grid, was generated and used to derive terrain features of gradient, aspect, and topographic position, which were geometrically co-registered with the TM thematic images. Using the knowledge of local forest service personnel, the relationships between forest type classes and terrain (i.e., gradient, aspect, topographic position) were quantified. These relationships were used as rules in a rule-based expert system. The thematic maps of forest type, probability of correct classification, and terrain features provided data for the expert system to infer the most likely forest species occurring at any given pixel. In addition, a check of association was made between adjacent pixels to ensure that pixels were contextually correct in an ecological sense, with the classification being modified (where necessary) to improve this. The modified thematic map output by the expert system had a higher mapping accuracy than the thematic map produced by the supervised nonparametric, the maximum likelihood, and the Euclidean distance classifier.

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 labor 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.* (1988). Thematic maps at Anderson (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 percent (Nelson, 1981; Walsh, 1980), but where forest types have been discriminated (e.g., Anderson level III) mapping accuracies have been typically below 80 percent (Strahler *et al.*, 1978; Merola *et al.*, 1983; Hame, 1984). However, Skidmore (1987) mapped eight forest types (i.e., at Anderson level III) in central Pennsylvania with an accuracy of 90 percent, and Skidmore and Turner (1988) discriminated five age classes in coniferous (*Pinus radiata*) plantations in Australia with an 87 percent mapping accuracy using a supervised nonparametric classifier, where conventional supervised and unsupervised classification strategies had been unsuccessful, yielding less than 56 percent 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) co-registered SIR-B radar data with Landsat MSS data. 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.

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 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 with terrain features derived from elevation data 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 digitial 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, 1982), 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 favor 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 important environmental variable determining forest species distributions on a local to 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).

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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 percent for a deciduous and a coniferous class, respectively.

Tom and Miller (1982) 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 percent, but this figure may be inflated as the training area pixels were also used to test mapping accuracy (see Mead and Szajgin, 1982) and only 37 pixels were tested for accuracy over nine classes (i.e., approximately four 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 percent 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 percent accuracy. As with Tom and Miller (1980), 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 modeling 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.

In an attempt to integrate disparate data types, expert systems have been proposed (Lee *et al.*, 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, *viz.*:

- A "knowledge base" that contains the data pertaining to a system to be modeled, 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."
- 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 behavior in the Northern Territory of Australia (Davis *et al.*, 1986); identifying 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 using remotely sensed data (Goldberg *et al.*, 1985); despatch of forest fire control resources (Kourtz, 1987); proposing management strategies for aspen forests using information in a GIS (White and Morse, 1987); and selection and scheduling of cultural practices in forests (Rauscher and Cooney, 1986). Gray and Stokoe (1988) provide a summary 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 and aspect) 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 (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), Richards *et al.* (1982), 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.

The overall aim of the study 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 gradient, 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

- there is an ability to update class probabilities using more than two data (i.e., evidence) sources (compare with Strahler *et al.* (1978));
- a nonparametric classifier (Skidmore and Turner, 1988) is implemented which yields the probability of correct classification for a class and therefore avoids the assumption of normality in the class conditional probabilities (Lee *et al.*, 1987);
- ecological knowledge is incorporated into the expert system to improve forest type mapping; and
- a contextual check is made to ensure the classification is ecologically consistent.

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 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 color aerial photographs used in this study.

The study area is covered by mostly dry schlerophyll forest (Baur, 1965), where the overstory 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.

FIG. 1. Location of the study area.

One major paved 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). The activity of man has 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 classification (1965), 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 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).

DEFINITION OF THE EXPERT SYSTEM

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 $X_{i,j}$ being defined as the i^{th} row and j^{th} column position of a cell (or pixel) in a raster (gridded) GIS 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 $X_{i,j}$. Available at each grid cell location $X_{i,j}$ 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 2). In this study, the layers were comprised of

- the possible thematic classes (derived from the nonparametric classifier),
- the probability of correct classification for the classes (derived from the nonparametric classifier),
- gradient,
- aspect, and
- topographic position (i.e., 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* 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 the knowledge of experienced foresters.

The order in which hypotheses or evidence are considered

TABLE 1. FOREST TYPES AND SUB-TYPES RECOGNIZED IN THIS STUDY (AFTER BAUR, (1965) AND BOLAND ET AL. (1984)

Forest type and sub-type	F.C. N.S.W. Type No.*	Component forest species	
		Common name	Scientific name
Silvertop Ash	112	Silvertop Ash	*Eucalyptus sieberi*
Yertchuk	102	Yertchuk	*Eucalyptus consideniana*
Stringybark-Gum		Yellow stringybark	*Eucalyptus muelleriana*
		Mountain Grey Gum	*Eucalyptus cypellocarpa*
		White Stringybark	*Eucalyptus globoidea*
Blueleaved Stringybark	121	Blueleaved Stringybark	*Eucalyptus agglomerata*
Tea Tree		Tea Tree	*Leptospermum spp.*
Black Oak		Black Oak	*Allocasuarina littoralis*
Silvertop Ash-Gum		Silvertop Ash	*Eucalyptus sieberi*
		Mountain Grey Gum	*Eucalyptus cypellocarpa*

A nonforest class was also recognized that included quarry, road, and clearfallen areas.

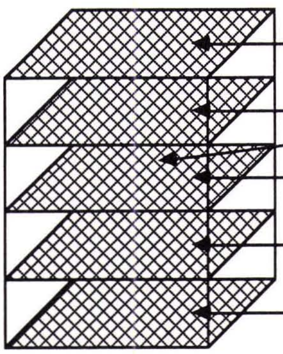

FIG. 2. Data layers used in the raster database.

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 concluded that they both require a method of deciding which piece of evidence, or wich 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 valid for the grid cell being considered. If the grid cell $X_{i,j}$ was not similar to the adjacent grid cells, then the cells adjacent to $X_{i,j}$ form weighting factors to recalculate $X_{i,j}$.

FORMAL STATEMENT DESCRIBING THE EXPERT ALGORITHM

Let S_a be the forest type class (for $a=1,\ldots,_n$ classes) occuring at location $X_{i,j}$. 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 $X_{i,j}$. 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 $X_{i,j}$ given a piece of evidence (E_b), i.e.,

$$P(H_a{:}E_b) = \frac{P(E_b{:}H_a)P(H_a)}{P(E_b)} \quad (1)$$

Note that $P(E_b{:}H_a)$ is the 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 $X_{i,j}$ (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 $X_{i,j}$. 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 $b=2,\ldots,k$) from the database, $P(H_a{:}E_b \mid b=1)$ (i.e., the *a posterior* probability of H_a given E_b, for $b=1$) replaces $P(H_a)$ in Equation 1. $P(E_b)$ 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 $P(E_b)$:i.e.,

$$P(E_b) = \sum_{a=1}^{n} P(E_b{:}H_a)P(H_a),$$

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 *a posterior* probabilities to be incorrect. In this case the evidence $\{E_b, b=1,\ldots,k\}$ was assumed to be statistically independent, as none of the evidence was obviously correlated. For example, the gradient of a pixel is not related to aspect. The most likely hypothesis (i.e., class) for a cell, is the hypothesis which has the maximum *a posterior* probability $\{\max P(H_a)|a=1,\ldots,n\}$ at $X_{i,j}$.

A contextual check is performed to ensure that the class $\{S_a\}$ selected at $X_{i,j}$ 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

TABLE 2. MATRIX SHOWING THE FOREST TYPES THAT MAY OCCUR ADJACENT TO THE CLASSIFIED FOREST TYPE

Forest types that may occur adjacent to the classified forest type	Forest type classified by the expert system: STA	Y	S/G	BLS	TT	ALT	SA/G	CC	Q
STA	X	X	X	X		X	X	X	X
Y		X		X		X		X	X
S/G			X	X	X	X	X	X	X
BLS				X		X	X	X	X
TT					X		X	X	X
ALT						X	X	X	X
SA/G							X	X	X
CC								X	X
Q									X

KEY

STA - Silvertop Ash
Y - Yurtchuk
S/G - Stringybark/Gum
BLS - Blueleafed Stringybark
Q - Quarry/road
TT - Tee Tree
ALT - Black Oak
SA/G - Silvertop Ash/Gum
CC - Clearcut forest

$\{T_a|a=1,\ldots,n\}$ that naturally occur adjacent to the most likely class $\{\max P(H_a)\}$ at $X_{i,j}$. The context of the eight cells adjacent to the central cell $X_{i,j}$ are checked in sequence, using the matrix (Table 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 2), then $\{P(H_a{:}E_b)\}$ is updated by assigning

$$P(E_b : H_a) = \{1/8^*T\}.$$

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 the next sections, and stored in the SPIRAL geographic information system (Myers, 1986), while the *a priori* data 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, 1987).

PREPARATION OF THE EVIDENCE AND *A PRIORI* PROBABILITIES FOR INPUT INTO THE EXPERT SYSTEM

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 1 October, 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-scale 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 ten ground control points located on the map and the TM image. The image was resampled to a 30-m square grid by nearest neighbor 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-scale black-and-white and 1:10,000-scale color 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, in order 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).

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 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, the *a priori* probability "$P(i)$" (as notated by Skidmore and Turner (1988)) could be estimated.

A principal components analysis was performed on the seven TM bands, in order to reduce the number of features and thereby improve computational efficiency. The first two principal components, which accounted for 91 percent of the total scene variance, were classified by a supervised nonparametric strategy (Skidmore, 1987; Skidmore and Turner, 1988). The principal components were rescaled to range in brightness (i.e., DN values) from 0 to 63 in order to improve the computational efficiency of the supervised nonparametric classifier. The supervised nonparametric classifier generated a thematic image of the class with the highest probability of occurrence at each pixel. This program was modified so that all the classes (S_a) that occur at pixel location $X_{i,j}$ were output to a raster database, along with the probability of correct classification for each class.

Using notation from Skidmore and Turner (1988), all the classes (i.e., S_a) that occured at vector position ($\mathbf{X}$) in N-dimensional feature space were written into a lookup table. The vector position in N-dimensional feature space of the pixel being considered $\{\mathbf{X}_{i,j}\}$ was equated with the appropriate lookup table value $\{\mathbf{X}\}$. All the probabilities of correct classification and the classes that occured at $\mathbf{X}$ in the lookup table were written into the raster database location $X_{i,j}$.

The probability of correct classification for class 'a' is the class conditional probability $\{P(E_b{:}H_a)\}$, defined as the probability of the spectral response $\{\mathbf{X}\}$ occurring (where $\mathbf{X}$ is a vector position in N-dimensional feature space and is equivalent to a piece of evidence (E_b)) given class $\{H_a\}$.

TOPOGRAPHIC DATA

Topographic variables may be readily generated in digital form and merged with other digital data, such as remotely sensed data. Skidmore (1989c) described the method for generating the regular digital elevation grid that was used in this study. Streamlines and high points were digitized from the Mount Imlay map sheet (which 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 (1988) was used to calculate elevation values to 1 m on a regular 30-m grid. This program imposes a global drainage condition which automatically removes spurious "sinks." This ensures that all streams apparently flow downhill without ponding or damming, a reasonable assumption for the study area as no significant surface ponding occurs.

The modeling of topographic variables from a regular grid of digital elevation data was reviewed by Skidmore (1989b), who proposed that either the third-order finite difference method, or multiple linear regression models, were suitable for calculating gradient and aspect. Consequently, a third-order finite difference method was used to calculate gradient and aspect. The modeling of terrain position (i.e., ridge, upper midslope, midslope, lower midslope, and valley) from gridded digital elevation data, using an algorithm proposed by Skidmore (1989c), 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 ten ground control points and nearest neighbor interpolation (Turner *et al.*, 1982).

The remotely sensed thematic images and the topographic data (i.e., gradient, 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).

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., $\{P(E_b{:}H_a)\}$, must be ascertained in order to calculate Equation 1. In an ideal situation, $\{P(E_b{:}H_b)\}$ 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.

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* probabilities detailed in Table 3 were collated by averaging the probability responses of the various experienced foresters, observations from field plots, and the unpublished documents.

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 *a priori* probability of occurrence for a species at a position along an environmental gradient was not attempted by Whittaker. 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 a 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.* (1984) 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 require a large number of samples that are well distributed over all zones.

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 neighbor (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 (Skidmore and Turner, 1988). Principal component 3 was discarded as a result of inconsistencies in the image (see Discussion).

MAPPING ACCURACY ASSESSMENT

Mapping accuracies for the thematic maps output by the three supervised classification strategies and by the expert system were calculated. Eighty-four 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 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 percent 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 course 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 percent), Silvertop Ash (30 percent) and Blue-leaved Stringybark (20 percent), so the forest class name would be Yertchuk. Theoretically, a plot may have contained Blue-leaved Stringybark (52 percent) and Silvertop Ash (48 percent), and would be called Blue-leaved Stringybark, while an adjacent plot may have contained Blue-leaved Stringybark (48 percent) and Silvertop Ash (52 percent) and be called Silvertop Ash. Even though such situations were

TABLE 3. TABLE SHOWING THE PRIOR PROBABILITIES OF THE EVIDENCE

ENVIRONMENTAL INFORMATION	FOREST TYPES									
	Q	Y	TT	YSM	BLS	STL	STD	CC	STM	ALL
N	0.4	0.4	0.3	0.4	0.4	0.4	0.3	0.3	0.2	0.2
W	0.4	0.5	0.4	0.5	0.4	0.3	0.4	0.3	0.4	0.3
S	0.4	0.4	0.4	0.5	0.5	0.4	0.4	0.3	0.4	0.3
E	0.4	0.4	0.3	0.5	0.5	0.4	0.3	0.3	0.3	0.3
F1	0.4	0.4	0.6	0.5	0.3	0.1	0.1	0.3	0.1	0.1
R	0.4	0.5	0.05	0.1	0.75	0.6	0.6	0.3	0.4	0.1
Um	0.4	0.5	0.08	0.2	0.6	0.5	0.5	0.3	0.5	0.1
M	0.4	0.5	0.1	0.3	0.5	0.3	0.5	0.3	0.6	0.2
Lm	0.4	0.3	0.2	0.7	0.4	0.2	0.2	0.3	0.6	0.3
G	0.4	0.1	0.6	0.8	0.1	0.01	0.01	0.3	0.5	0.3
<10	0.4	0.5	0.4	0.2	0.2	0.2	0.2	0.3	0.2	0.1
10-20	0.4	0.3	0.1	0.35	0.3	0.4	0.4	0.3	0.4	0.3
>20	0.4	0.2	0.01	0.3	0.2	0.4	0.4	0.3	0.4	0.3

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 then 10 degrees
10 - 20 - Slope 10 to 20 degrees
>20 - Slope greater than 20 degrees

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.

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 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 simple random selection of forest plot locations.

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 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 the 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 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 percent confidence intervals.

Congalton *et al.* (1983) applied discrete multivariate analysis techniques proposed by Cohen (1960) to test whether two error matrices were significantly different. In this study, the type of classifier was varied, while other factors such as date of image collection, training areas, etc., were held constant. Bishop *et al.* (1975; p. 396–397) express the ideas of Cohen (1960) as follows. They detail a measure of overall agreement between the image and the reference data called Kappa or "K": i.e.,

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

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

Note that p_{i+} 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 go on to detail the estimated asymptotic variance of K: i.e.,

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

where θ_1 and θ_2 are as above,

$$\theta_3 = \sum_i p_{ii}\,(p_{i+} + p_{+i}), \text{ and } \theta_4 = \sum_i p_{ij}\,(p_{i+} + p_{+j})^2.$$

To test for a statistically significant difference between two error matrices, Cohen (1960) proposed using K values (K_1 and K_2) and their associated variance by evaluating the normal curve deviate: i.e.,

$$z = \frac{K_1 - K_2}{\sqrt{\sigma^2_{K1} + \sigma^2_{K2}}}.$$

This test statistic was applied to the paired combinations of the four error matrices in order to ascertain whether any of the error matrices were significantly different.

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 could not be used due to low sample numbers (Rosenfield *et al.*, 1982).

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 ± 0.6 of a pixel from the true map value. The root-mean-square planimetric error ($RMSE_x$ and $RMSE_y$) 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 $RMSE_{xy}$ values being ± 10m and ± 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 (i.e., DN values) for each species (Figure 3) show that some cover type classes were spectrally different (e.g., 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.

Table 4 shows the eigenvector matrix generated by the principal components analysis, as well as the eigenvalues for each principal component.

A thematic map showing the output from the expert system is included as Figure 4. Figures 5 to 7 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 is a thematic map showing the probability of correct classification generated by the supervised nonparametric classifier (Skidmore and Turner, 1988).

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 5 to 8, respectively). In addition, the mapping accuracy was calculated at 95 and 99 percent confidence intervals. A summary of the mapping accuracy results are listed in Table 9. Table 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.

DISCUSSION

The geometric correction of the digital terrain model and the remotely sensed data was satisfactory, with an $RMSE_{xy}$ of approximately less than half a pixel. The sample plots 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 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 (Skidmore, 1989a) 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 demonstrated for plantation forests.

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 9, the first principal component was dominated by channels 5, 4, and 7 (i.e., near infrared and middle infrared) and represented 86 percent of the total scene variance. The second principal component was also dominated by channels 4, 5, and 7 and represented nearly 10 percent 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 percent 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 9). The robustness of the supervised nonparametric classifier for discriminating between spectrally similar classes had previously been demonstrated for a mixed broadleaf/conifer forest in Pennsylvania using Landsat MSS data (Skidmore, 1987) and for a number of age classes in *Pinus radiata* plantations in Australia using SPOT XS data (Skidmore and Turner, 1988). 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 5 to 8) were calculated. The first method was the overall mapping accuracy, which for the expert system was 76.2 percent (Table 9). The second measure of mapping accuracy cited was the mapping accuracy calculated within nominated confidence intervals (Thomas and Allcock, 1984). From Table 9 it can be seen that we are 95 percent confident that at least 68.6 percent of the pixels classified by the expert system had been correctly classified, and 99.9 percent confident that at least 61.3 percent 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.* (1982) to quantify the agreement between an image (or map) and ground truth reference data (Table 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 have a high mapping accuracy 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 9 and 10. Confirming previous studies, the supervised nonparametric classifier yielded the highest mapping accuracy, while the maximum likelihood classifier generated a thematic map of higher accu-

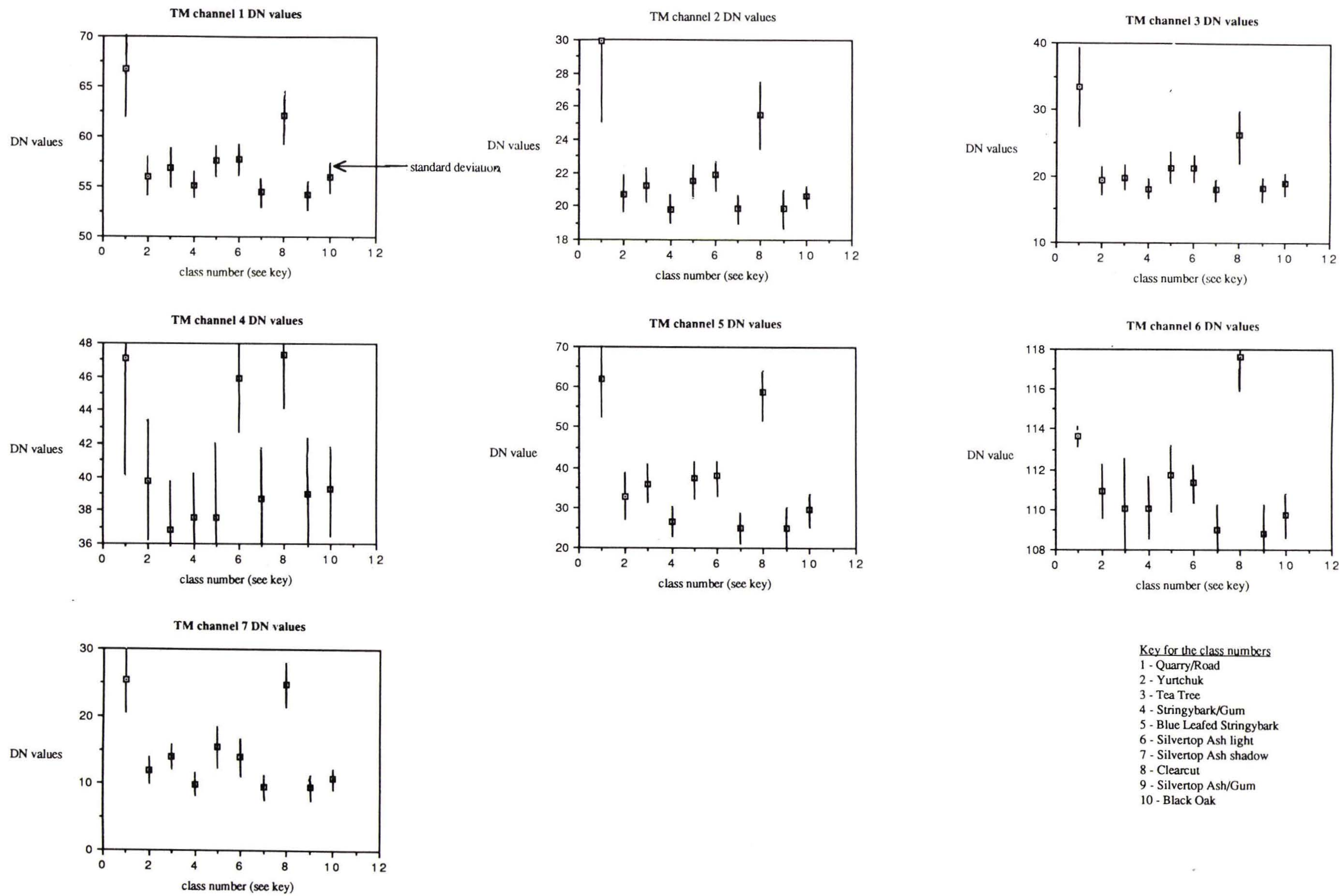

FIG. 3. Plots of the brightness level (DN value) for each forest type, by TM channels 1 to 7.

TABLE 4. EIGENVECTORS AND EIGENVALUES GENERATED BY THE PRINCIPAL COMPONENTS ANALYSIS

		Eigenvectors						
		1	2	3	4	5	6	7
TM Channel	1	0.1726	0.0831	0.3763	−0.4379	−0.4380	−0.6477	−0.1362
	2	0.1479	0.0263	0.2711	−0.2255	−0.0970	0.2296	0.8904
	3	0.1811	0.0538	0.4734	−0.3865	0.0698	0.6344	−0.4284
	4	0.4134	−0.9068	0.0173	0.0345	0.0506	−0.0501	−0.0171
	5	0.7942	0.3514	−0.1995	0.3446	−0.2733	0.1021	−0.0450
	6	0.1588	0.0387	−0.6823	−0.6986	0.1368	0.0280	0.0120
	7	0.3006	0.2057	0.2347	0.0016	0.8354	−0.3341	0.0521
Principal component		1	2	3	4	5	6	7
Eigenvalue		436.49	50.52	8.18	6.99	2.07	1.16	0.61
Percentage of the total variance		86.26	9.98	1.62	1.38	0.41	0.23	0.12

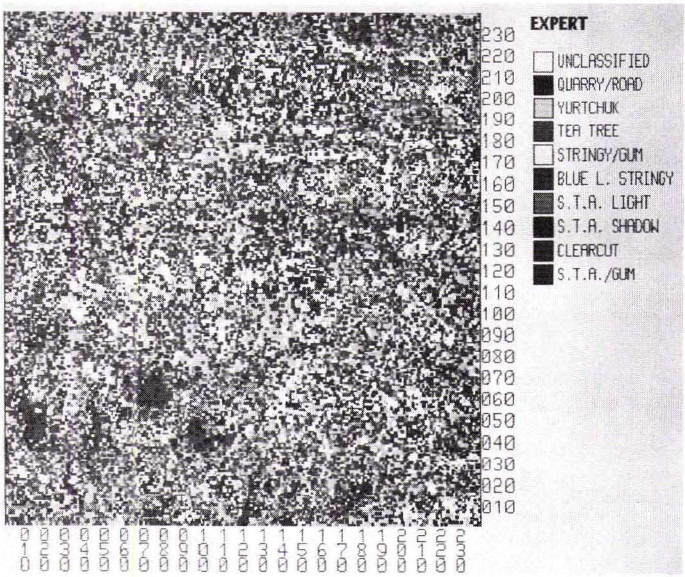

FIG. 4. Thematic map of the output from the expert system.

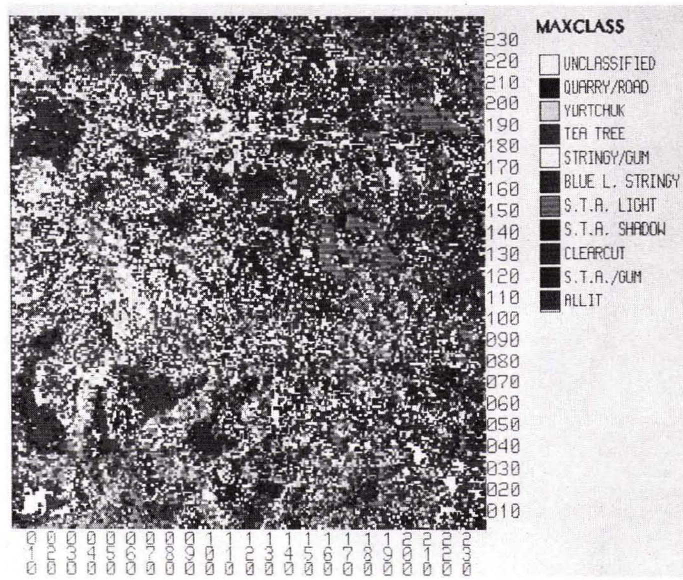

FIG. 5. Thematic map produced by the maximum likelihood classifier.

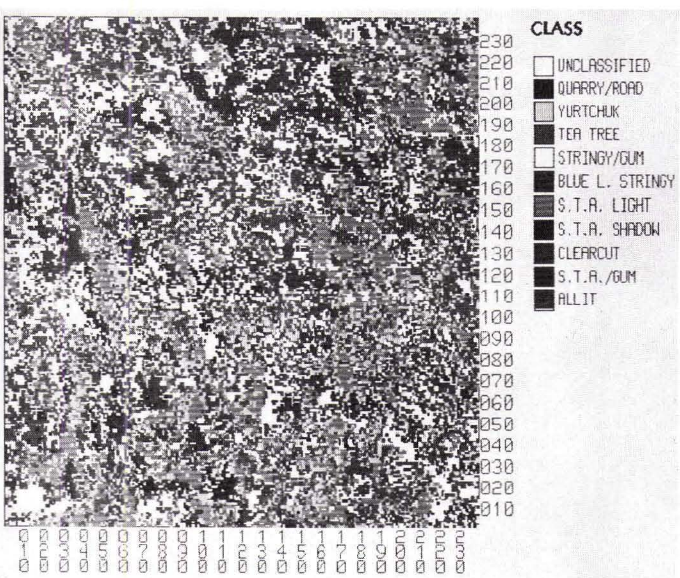

FIG. 6. Thematic map produced by the Euclidean distance classifier.

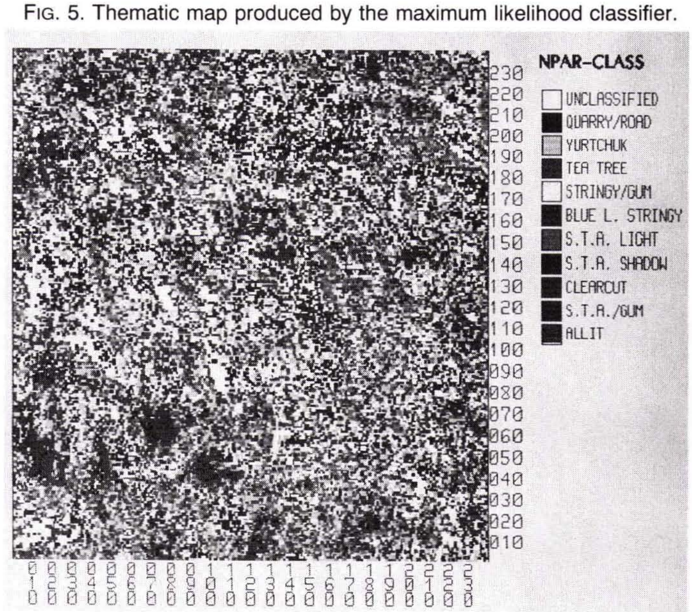

FIG. 7. Thematic map produced by the supervised nonparametric classifier.

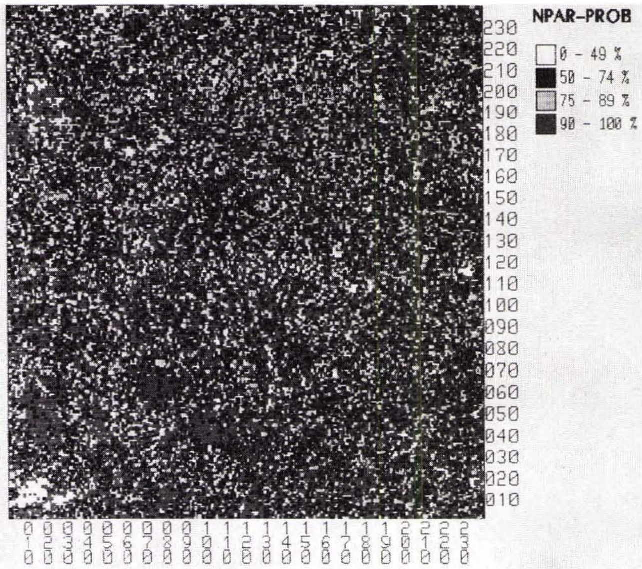

FIG. 8. Thematic map showing the probability of correct classification produced by the nonparametric classifier.

racy than the Euclidean distance classifier because the assumed Gaussian distribution more accurately parameterizes the class training areas in *N*-dimensional feature space (Estes *et al.*, 1983; Skidmore *et al.*, 1988). In contrast, Hudson (1987) and Ince (1987) 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 neighbor 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 other three supervised classifiers (Table 9), while from Table 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 that *a priori* information was included in the set of rules (see Table 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 10 show that at the 90 percent confidence interval there is a statistically significant difference in mapping accuracies between all the classifiers. At the 95 percent 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 percent confidence interval, but not at the 99 percent confidence interval. In other words, we are 99 percent certain that 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 percent confident that there is a statistically significant difference between the expert system and the supervised nonparametric classifier.

TABLE 5. ERROR MATRIX FOR THE MAXIMUM LIKELIHOOD CLASSIFER

		Number of pixels (Image)									
	Class	I	II	III	IV	V	VI	VII	VIII	IX	Total
Number of pixels (Reference)	I	14	3	7	2		5		7		38
	II		14	3				3	4	1	25
	III		1	16	1		1	1	1		21
	IV	4		8	3		2	1	3		21
	V	2				16				1	19
	VI			1		1					2
	VII		1	3				3			7
	VIII								2		2
	IX										
	Total no. of pixels	20	19	38	6	17	8	8	17	2	135
	Overall classifcation accuracy*	50.4%									

Table Legend: I = Yertchuk
II = Gum/Stringybark
III = Silvertop Ash
IV = Blueleafed 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 6. ERROR MATRIX FOR THE EUCLIDEAN DISTANCE CLASSIFIER

	Number of pixels (Image)									
Class	I	II	III	IV	V	VI	VII	VIII	IX	Total
Number of pixels (Reference) I	17	5	5	1		2	2	5	1	38
II	7	6	3			1	2	5	1	25
III	2	1	13				4		1	21
IV	4	2	1	3		5	2	3	1	21
V	1					7			11	19
VI							1	1		2
VII			5				1	1		7
VIII								2		2
IX										
Total no. of pixels	31	14	27	4	0	15	12	15	17	135
Overall classification accuracy	31.1%									

TABLE 7. ERROR MATRIX FOR THE SUPERVISED NONPARAMETRIC CLASSIFIER

	Number of pixels (Image)									
Class	I	II	III	IV	V	VI	VII	VIII	IX	Total
Number of Pixels (Reference) I	27	6	1	2	1		1			38
II	3	20	2							25
III	1	2	16	1		1				21
IV	3	2	3	12	1					21
V	3			1	15					19
VI	1	1								2
VII	1	1	2					3		7
VIII		1		1						2
IX										
Total no. of pixels	39	32	25	17	17	1	1	3	0	135
Overall classification accuracy	66.7%									

TABLE 8. ERROR MATRIX FOR THE EXPERT SYSTEM CLASSIFICATION OF THE TM DATA

	Number of pixels (Image)									
Class	I	II	III	VI	V	VI	VII	VIII	IX	Total
Number of pixels (Reference) I	35	2	1							38
II	1	23	1							25
III	4	1	15			1				21
IV	4	1	1	15						21
V	3			3	13					19
VI						2				2
VII		1						6		7
VIII		2								2
IX										
Total no. of pixels	39	32	25	17	17	1	1	3	0	135
Overall classification accuracy	76.2%									

In an attempt to confirm that the qualitative *a priori* 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 Mapping Accuracy Assessment section 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). These calculations were performed after the mapping accuracy as-

TABLE 9. SUMMARY OF MAPPING ACCURACY RESULTS

Classifier	Overall mapping accuracy (%)	Mapping accuracy at: 99.9% C.I.	95% C.I.
expert system	76.2	61.3	68.6
supervised nonparametric	66.7	50.5	58.0
maximum likelihood	50.4	33.3	41.9
euclidean distance	31.1	15.2	22.6

TABLE 10. RESULTS OF THE PAIRWISE COMPARISONS BETWEEN ERROR MATRICES FOR THE FOUR CLASSIFICATION STRATEGIES

Error matrix	"K" statistic	"Variance of "K"
expert	0.705	0.00195
supervised nonparametric	0.587	0.00242
maximum likelihood	0.422	0.00236
euclidean distance	0.210	0.00181

Pairwise comparison	Z Statistic	Results 90%	95%	99%
expert & sup. nonparametric	1.78	S[1]	NS	NS
expert & maximum likelihood	4.31	S	S	S
expert & euclidean distance	8.07	S	S	S
sup. nonparametric & maximum likelihood	2.39	S	S	NS
sup. nonparametric & euclidean distance	5.80	S	S	S
maximum likelihood & euclidean distance	3.28	S	S	S

[1]S - significant; NS - not significant

sessments, and were not used to modify the *a priori* probabilities used during the expert system classification. Rather, the results were used to check that the *a priori* probabilities proposed by the experienced foresters and ecologists were reasonable.

The *a priori* 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 (i.e., Silvertop Ash was more likely to occur on a ridge than a mix of Yellow Stringybark and Monkey Gum).

It should be noted that the estimated area of the forest type classes within the study area (i.e., *P(i)* required as *a priori* probabilities by the supervised nonparametric classifier) were 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 may 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 is 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. 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 7 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 percent. Using the methodology of Thomas and Allcock (1984), a mapping accuracy of 66.7 percent was calculated for a 99.9 percent confidence interval, and a mapping accuracy of 73.3 percent of for a 95 percent confidence interval. Todd *et al.* (1980) also reported an increase in forest mapping accuracy when 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, soil moisture, etc., may increasingly dominate on a regional or continental scale (see Introduction). 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 modeled in a suitable format, such as Table 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 they can be automatically generated if not readily available (see Introduction). 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 several decades 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.

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) because

- 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 were 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.
- The expert system as implemented (i.e., 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.
- 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 (gradient, 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 modeled (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, recreation potential, etc. The author is currently applying the technique 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 become obvious 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 for land classification and mapping is that experts may not agree among themselves about the category name for a particular set of observed ground conditions (e.g., 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.

CONCLUSION

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 and a digital terrain model. 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 (Skidmore and Turner, 1988) 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 is 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 (such as soil type, forest biomass, ease of harvesting the forest, etc.) is discussed. It is conceivable that expert systems will be increasingly used to manage and analyze the complex information contained in geographic information systems.

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