# Nonparametric Classifier for GIS Data Applied to Kangaroo Distribution Mapping

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## Abstract

*A supervised nonparametric classifier, previously applied to classify remotely sensed data, is used to classify GIS layers. The algorithm is trained using GIS data layers as the independent variables, and predicts the spatial distribution of a dependent variable using a nonparametric technique. A GIS database of kangaroo distribution in Australia tests the algorithm. Results are satisfactory, with the presence of kangaroos being mapped with a producers accuracy of 93 percent for the western grey, and 100 percent for the eastern grey and red kangaroo. The algorithm appears robust to variations in training sample size and* a priori *probabilities.*

## Introduction

The modeling capabilities of most geographic information systems (GIS) use a tool-box approach, where sophisticated models may be generated by combining simple commands, such as mathematical or Boolean operators. The "cartographic modeling" approach described by Tomlin (1987) is one of the best known approaches. Wildlife distribution has been mapped with GIS, using a number of alternative analysis techniques. Examples of using the "cartographic modeling" technique for wildlife mapping include characterizing suitable condor habitat using GIS (Scepan *et al.*, 1987), delineating Florida Scrub Jay habitat (Breininger *et al.*, 1991), and evaluating the preferred habitat of cranes (Herr and Queen, 1993). The main problem with conventional cartographic modeling is that rules and knowledge must be known before writing the GIS model.

A more sophisticated and automated method of using GIS to map wildlife involves the classification and regression tree (CART) software package (Brieman *et al.*, 1984) to develop rules for mapping the distribution of kangaroos (Walker and Moore, 1988). The rules are entered into the MAP GIS (Tomlin, 1987), and kangaroo distribution is predicted from climate and vegetation variables (Walker and Moore, 1988). Another technique proposed for wildlife habitat mapping uses regression analysis. For example, Periera and Itami (1991) mapped red squirrel habitat using regression techniques in combination with GIS. Wildlife has been modeled using a modified bioclimatic analysis and prediction system termed BIOCLIM (Busby, 1986; Richards *et al.*, 1990); this method interpolates climatic variables, and the bio-climatic envelope of a species can then be estimated and the distribution of the species mapped. Flather and King (1992) used discriminant function analysis to generate classification rules that predict deer and turkey abundance, as well as woodpecker presence/absence based on land-based predictor variables. Yet another method for classifying GIS data layers involves expert systems (Skidmore, 1989) where expert knowledge about the variable being modeled relates the GIS data layers to the variable, through a series of rules. Aspinall (1992) and Aspinall and Veitch (1993) mapped the extent of red deer in Scotland with a similar probability-based approach.

Regardless of the classification method used, an important issue in wildlife ecology is the scale chosen to describe the distribution of a species. For example, is it reasonable to describe the distribution of kangaroos on a continental scale, when an individual or small group of kangaroos interact with the environment at a local scale? As Van Horne (1983) points out, the inference of habitat quality is dependent on identifying the important independent factors which influence habitat quality. The climatic data used in this study were shown by Caughley *et al.* (1987) to be the major variables influencing the distribution of three kangaroo species across Australia. The study by Caughley *et al.* (1987) described the range of climate experienced by each kangaroo species, and determined the components of the climate that indexed the distributions most economically. They did not assume that precipitation and temperature alone determine whether a particular species occupies an area; rather, they used climatic variables as a rough index of attributes (such as land use, forage production, water supply, and habitat) which directly influence a species ability to survive and reproduce.

## Objectives

The aim of this study is to generalize a nonparametric classifier to work with GIS data and map the distribution of kangaroos across Australia; the supervised nonparametric classifier has been previously used with remotely sensed data (Skidmore and Turner, 1988; Dymond, 1993; Dymond and Luckman, 1994). A GIS database of kangaroo distribution in Australia was selected to test the algorithm as it has been reviewed in the ecological literature (Caughley *et al.*, 1987) as well as the GIS literature (Walker, 1990).

## Method

### Preparation of Data

The data set used to test the algorithm was initially developed to map the distribution of kangaroos using the BIOCLIM model (Caughley *et al.*, 1987). This data set comprises 12 climatic variables (Table 1) considered to represent the mean, seasonal, and extreme climatic variables for a species.

Caughley *et al.* (1987) aerially surveyed the distribution of the red kangaroo (*Macropus rufus*), the western grey kangaroo (*Macropus fuliginous*), and the eastern grey kangaroo (*Macropus giganteus*) by recording the presence or absence of each species along transects across Australia. A grid of 40

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by 33 cells was constructed, with each cell representing 1° longitude by 1° latitude. For each cell occurring over Australia (i.e., 686 cells), the presence of kangaroos was recorded (Table 2), as well as the 12 climatic variables. Note that some grid cells have more than one species of kangaroo present.

TABLE 2. NUMBER OF GRID CELLS WITH KANGAROOS PRESENT AND ABSENT IN EACH 1° LONGITUDE BY 1° LATITUDE GRID CELL

| Species | presence | absence |
|---|---|---|
| red | 331 | 355 |
| western grey | 142 | 544 |
| eastern grey | 183 | 503 |
| total | 656 | 1402 |

#### Definition of the Nonparametric Classifier

Data in a raster GIS may be viewed as a series of geometrically rectified layers. Each layer (notated as $E_i$, for $i = 1, ..., n$ layers) pertains to a variable (containing a set of values) and consists of co-registered grid cells that define the spatial position of each value in the layer. For example, four layers may exist such as precipitation, slope, elevation, and temperature. For the precipitation layer, an estimate of precipitation is recorded at each grid cell.

The layers may be mapped into an $n$-dimensional feature space, with each layer forming one dimension in the feature space. For two layers ($E_1$ and $E_2$), a frequency histogram may be constructed, using "F" as the notation for frequency (Figure 1).

The frequency histogram is built using known regions (or training areas) from the data layers. Grid cells of known classes are selected, and the values of each GIS layer are recorded. These independent environmental variables are then mapped into an $n$-dimensional feature space. If more that one grid cell occurs at a vector $\mathbf{E}$ in feature space (as in Figure 1), then the grid cells at that vector space are counted. The class with the largest sum at the vector space $\mathbf{E}$ "represents" the vector. Finally, each grid cell of unknown class is assigned to its vector in feature space based on the values in the GIS layers (i.e., $E_1$ and $E_2$), and is allocated to the class with the greatest probability of occurring at the vector position $\mathbf{E}$.

The probability of class $i$ (for $i = 1, ..., k$ classes) occurring, given a vector position $\mathbf{E}$, is as follows (Skidmore and Turner, 1988; Gong and Dunlop, 1993):

$$P(i \mid \mathbf{E}) = \frac{\left(\frac{N}{N_i}\right) n_i(\mathbf{E}) P(i)}{\sum_{j=1}^{k} \left(\frac{N}{N_j}\right) n_j(\mathbf{E}) P(j)}. \quad (1)$$

Note that $N$ is the sum of all training area cells, $N_i$ is the sum of training area cells for class $i$, and $n_i(\mathbf{E})$ is the number of grid cells at vector position $\mathbf{E}$. The *a priori* probability of the class $P(i)$ may be estimated from the relative areal extent of the class: i.e.,

$$P(i) = \frac{A_a}{A_t} \quad (2)$$

where $A_a$ is the area extent of class "$a$" and $A_t$ is the total area. The kangaroo data were used to estimate the *a priori* probability for each species of kangaroo (Table 3), though these values could also be estimated by an experienced wildlife biologist.

For the kangaroo data set described above, the feature space of the data set has 12 dimensions (i.e., $i = 1, ..., 12$ for Equation 1). To reduce the number of dimensions of the data set while maintaining the information content of the kangaroo data set, principal components analysis was applied (Richards, 1986). The first four principal components were selected to predict the distribution of the kangaroos; these principal components explained 99.95 percent of the variance in the data.

Note that the supervised nonparametric classifier is trained using the presence data. The absence of a kangaroo at a grid cell cannot be differentiated from the grid cell being unclassified, because an unclassified grid cell will occur at an empty vector position $\mathbf{E}$ in the feature space (Figure 2).

The data were entered into the SPIRAL GIS (Myers, 1986) and linked to the algorithm. Map output was created using the ARC-INFO GIS software on a Sun SparcStation (ESRI, 1992) and the MAP II GIS software (Pazner *et al.*, 1989).

#### Testing the Performance of the Nonparametric Classifier

The performance of the algorithm as the number of training cells are varied was tested by randomly selecting a training sample of 5, 10, 25, 50, 75, and 100, as well as all data points, for each kangaroo species. The training data were input to the classifier and the effect on the accuracy of the output maps was calculated.

The *a priori* probabilities of the kangaroos were also varied to test the robustness of the classifier to changes in the user estimates for this parameter. The *a priori* probabilities were varied as shown in Table 3. The intermediate probabilities in Table 4 were interpolated by a linear stretch (Richards, 1986) between the *a priori* probabilities in Table 3 and equally probable (that is $p = 0.33$ for each species) *a priori* probabilities.

The accuracy of the maps was calculated by randomly selecting 30 grid cells from the "present" and "absent" strata defined by Caughley *et al.* (1987) (Figures 2, 3, and 4). These

TABLE 1. CLIMATIC VARIABLES (ACROSS AUSTRALIA) USED TO PREDICT THE KANGAROO DISTRIBUTION. TOTAL SAMPLE WAS 686 GRID CELLS

| BIOCLIM Variable | Mean | Standard Deviation | Median |
|---|---|---|---|
| Annual Mean Temperature (°C) | 21.59 | 4.06 | 21.86 |
| Minimum Temperature of the Coldest Month (°C) | 6.92 | 3.62 | 5.96 |
| Maximum Temperature of the Hottest Month (°C) | 35.54 | 3.91 | 36.64 |
| Annual Temperature Range (°C) | 28.62 | 3.78 | 29.42 |
| Mean Temperature of the Wettest Quarter (°C) | 24.88 | 7.27 | 27.99 |
| Mean Temperature of the Driest Quarter (°C) | 18.80 | 4.14 | 19.22 |
| Annual Mean Precipitation (mm) | 435.55 | 323.37 | 308.68 |
| Minimum Precipitation of the Wettest Month (mm) | 81.58 | 70.67 | 55.25 |
| Maximum Precipitation of the Driest Month (mm) | 11.19 | 13.51 | 6.94 |
| Annual Precipitation Range (mm) | 70.24 | 70.86 | 43.06 |
| Mean Precipitation of the Wettest Quarter (mm) | 214.73 | 185.54 | 145.42 |
| Mean Precipitation of the Driest Quarter (mm) | 40.56 | 47.21 | 25.22 |

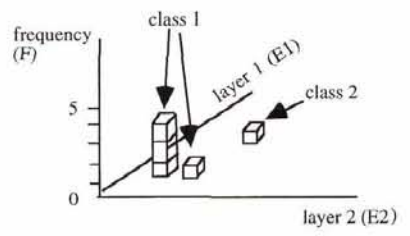

Figure 1. Frequency histogram of two GIS layers ($E_1$ and $E_2$).

TABLE 3. *A PRIORI* PROBABILITY FOR THE KANGAROO SPECIES

| Species | $P(i)$ | class |
|---|---|---|
| red | 0.505 | 1 |
| western grey | 0.216 | 2 |
| eastern grey | 0.278 | 3 |

Figure 2. Red kangaroo distribution data developed by Caughley *et al.* (1987).

points were used to calculate user and producer accuracy of the maps (Congalton, 1991). User accuracy is the total number of grid cells the classifier correctly attributes to the class divided by the total number of grid cells the classifier attributes to the class. The producer accuracy is the total number of grid cells the classifier correctly attributes to the class divided by the total number of ground truth (reference) grid cells for the class. As a consumer of a map classification, one is usually more interested in the user accuracy, because this shows the probability that the grid cell is truly the class labeled on the output map. Both the user and producer accuracies are plotted in the following Results section.

## Results

The original presence and absence data for the three kangaroo species are shown in Figures 2 to 4, (i.e., red kangaroo (Figure 2), eastern grey kangaroo (Figure 3), and western grey kangaroo (Figure 4)).

TABLE 4. INTERMEDIATE *A PRIORI* PROBABILITIES INTERPOLATED BETWEEN THE *A PRIORI* AND THE EQUALLY PROBABLE PROBABILITIES, AND USED TO TEST THE ROBUSTNESS OF THE CLASSIFIER

| species | *a priori* probabilities | intermediate probability 1 | intermediate probability 2 | intermediate probability 3 | equally probable |
|---|---|---|---|---|---|
| red | 0.505 | 0.463 | 0.420 | 0.377 | 0.333 |
| western grey | 0.216 | 0.290 | 0.306 | 0.319 | 0.333 |
| eastern grey | 0.278 | 0.243 | 0.273 | 0.303 | 0.333 |

Figure 3. Eastern grey kangaroo distribution data developed by Caughley *et al.* (1987).

Figure 4. Western grey kangaroo distribution data developed by Caughley *et al.* (1987).

The results from the classifier using equal probabilities are shown in Figure 5. The *a posteriori* probabilities for each species $P(i|\mathbf{E})$ are mapped into percentile ranges (Table 5) for ease of comparison. An interpretation of the likelihood of occurrences for the species, given the percentile range, is also indicated in Table 5. If a vector position is trained so that $P(i|\mathbf{E})$ is greater than 0.5 for a particular species, then it may be assumed that the species is most likely to occur, given two classes co-occurring in the vector space. For three or more classes, the percentile ranges may be considered conservative for mapping the occurrence of the three kangaroo species.

When the *a priori* probabilities listed in Table 1 are used, the resulting classifications are little changed, as shown in Figure 6, except that the probability of occurrence for the eastern grey and western grey kangaroos decreases relative to the red kangaroo. The effects of using only 50 sample points for each training area are shown in Figure 7, for a classification using the *a priori* probabilities (Table 1). When the *a priori* probabilities are assumed to be equal, the classification results are shown in Figure 8. There appears to be little change in the output maps as a result of varying the *a priori* probabilities, or the number of sample points used to train the classifier. The raw *a posteriori* probabilities for each species ($P(i|\mathbf{E})$), expressed as a percentage, may also be displayed. For example, Figure 8 is re-displayed showing the (percentage) *a posteriori* probabilities (Figure 9).

Table 5. Likelihood of Occurrence for a Species in Figures 6 through 9

| $P(i\|\mathbf{E})$ | Percentile Range | Interpretation of Likelihood |
|---|---|---|
| 0.5-1.0 | 50-100 | most likely |
| 0.01-0.49 | 1-49 | marginal |
| 0 | 0 | absent |

In order to test the robustness of the classifier to changes in the *a priori* probabilities, the *a priori* probabilities in Table 4 were input to the algorithm and the accuracy was calculated. Figures 10a and 10b show the user and producer accuracies for red kangaroos, Figures 11a and 11b for eastern grey kangaroos, and Figures 12a and 12b for western grey kangaroos. There is no change in accuracy (for either user or producer accuracy) for the three species (Figures 10, 11, and 12). Note that, in Figures 10, 11, and 12, "inter 1," "inter 2," and "inter 3" refer to the intermediate probability 1, 2, and 3, respectively, as defined in Table 4, while "equal" refers to the equal probabilities.

The accuracy of the maps output by the classifier changes as the sample size decreases below 50 samples per training area, but the classifier appears robust if the size of the sample is greater than 50 (Figures 13 to 15). The pro-

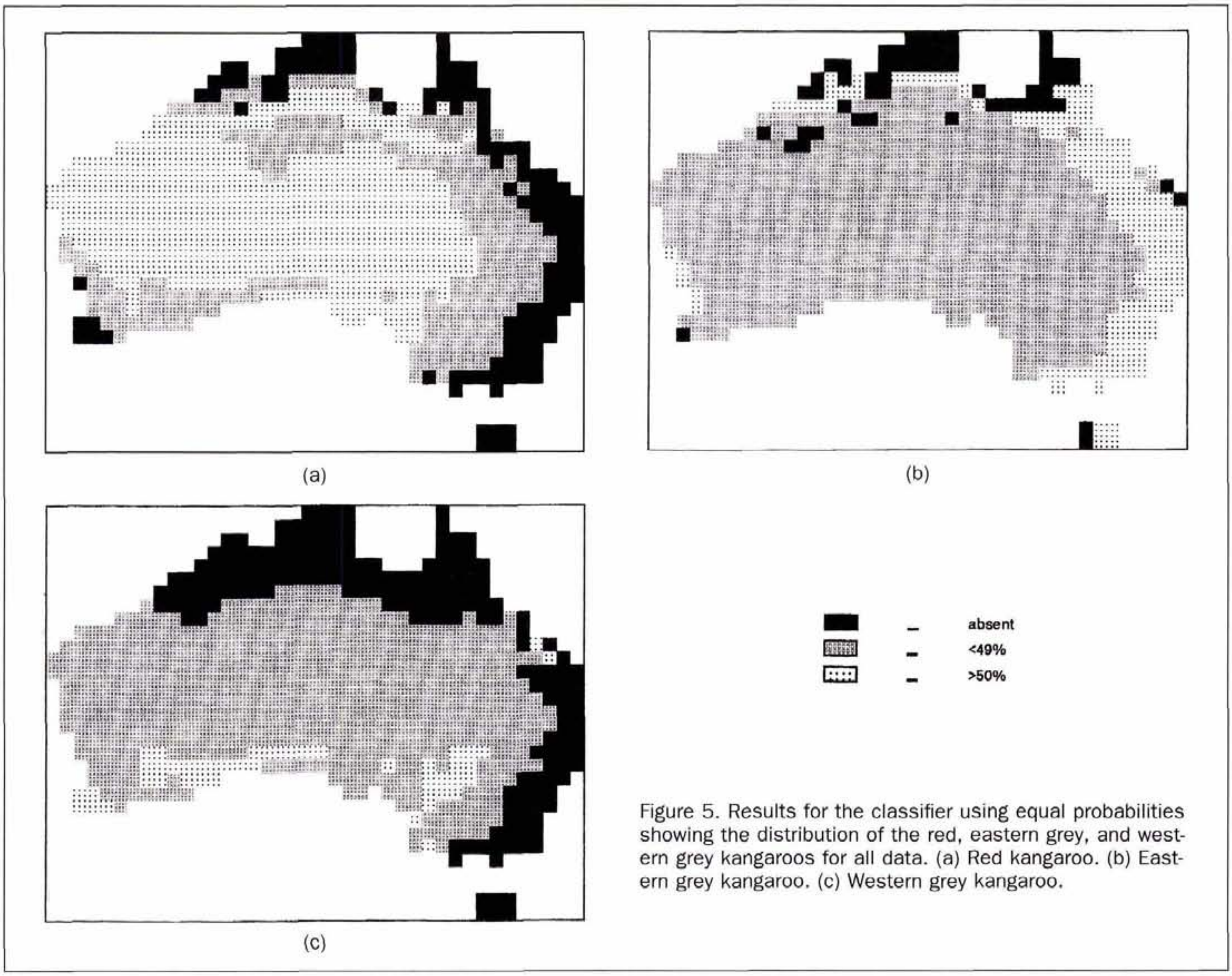


Figure 5. Results for the classifier using equal probabilities showing the distribution of the red, eastern grey, and western grey kangaroos for all data. (a) Red kangaroo. (b) Eastern grey kangaroo. (c) Western grey kangaroo.

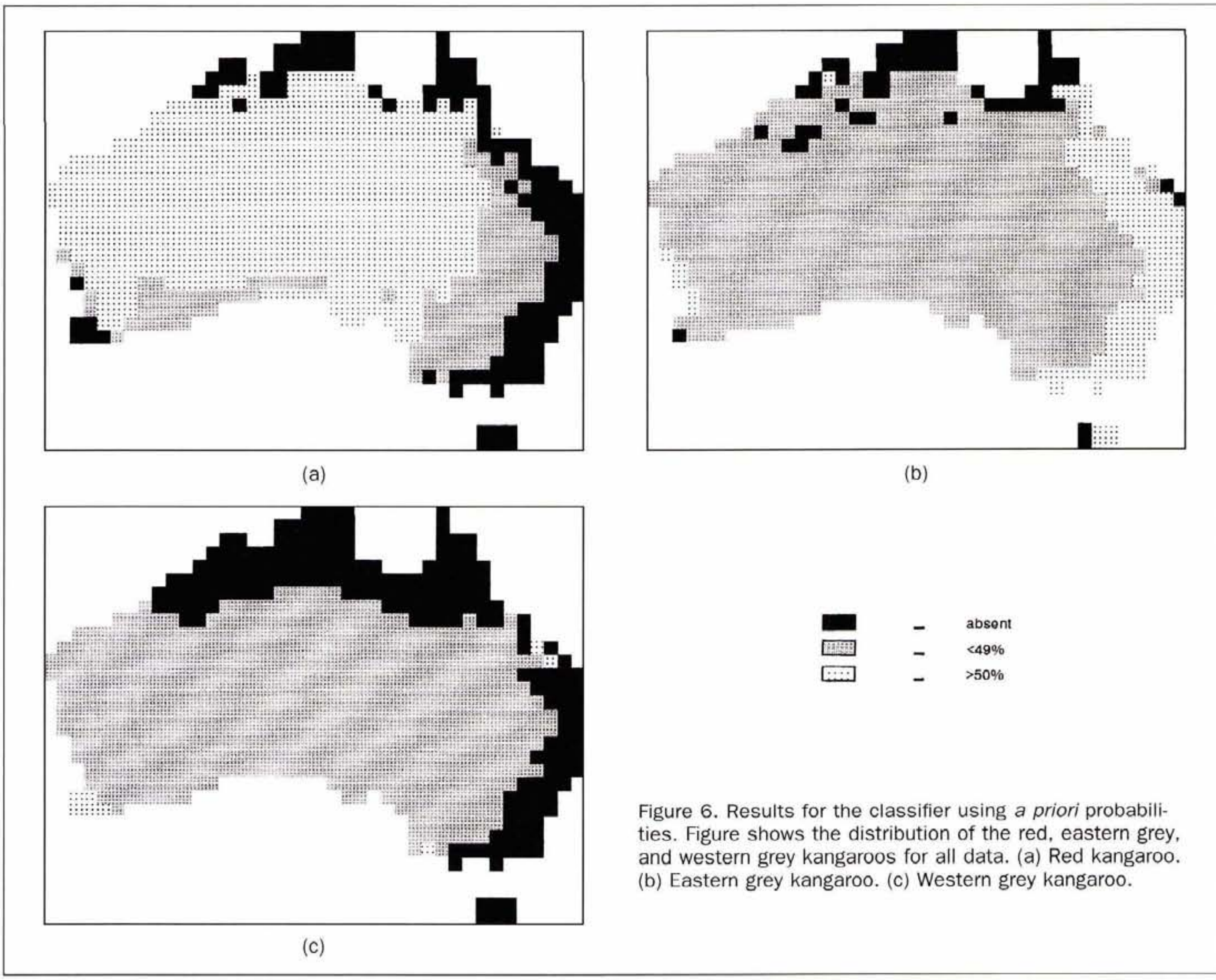


Figure 6. Results for the classifier using *a priori* probabilities. Figure shows the distribution of the red, eastern grey, and western grey kangaroos for all data. (a) Red kangaroo. (b) Eastern grey kangaroo. (c) Western grey kangaroo.

ducer accuracies for Figures 13 to 15 show that the percentage of grid cells that are absent and unclassified increases as the sample size decreases (remember that the absence of a kangaroo species at a grid cell cannot be differentiated from the grid cell remaining unclassified). The eastern grey kangaroo has the largest percentage of unclassified grid cells for low sample sizes (i.e., for 5 and 10 samples). The user accuracies for Figures 13 to 15 show that the presence of the kangaroo species appears to become more accurately mapped with fewer grid cells per training area. Some potential anomalies are apparent for the eastern grey kangaroo with a sample size of 5, 10, and all samples (Figure 14).

## Discussion

The generalized nonparametric classifier successfully classified the kangaroo data set prepared by Caughley *et al.* (1987). The predicted distribution of the kangaroos (Figure 3) visually matches the distribution of the kangaroos as recorded by Caughley *et al.* (1987) (Figures 2 to 4). This was confirmed in Figures 10 to 12, where the classifier predicts the presence of the red and eastern grey kangaroo species with a producer accuracy of 100 percent, and the western grey kangaroo presence with a producer accuracy of 94 percent. It is concluded that the generalized nonparametric classifier successfully predicts the presence of the kangaroo species.

The "absent and unclassified" class on the output maps is generally under-classified. In other words, few ground truth grid cells of the "present" class tend to occur over the "absent" areas on the classified map, because the map is mostly comprised of the "present" class. Consider, for example, the error matrix for the red kangaroo map generated by using all samples for the training data, and the *a priori* probabilities (Table 6). The user accuracy is 100 percent for the "absent" class, because no ground truth "present" class occurs on the "absent" areas on the classification. Table 6 also highlights and explains the different results in Figures 10 to 15 for user and producer accuracies; a high user accuracy for the absent class does not necessarily correspond to a high producer accuracy!

TABLE 6. ERROR MATRIX FOR THE RED KANGAROO MAP GENERATED BY USING ALL SAMPLES FOR THE TRAINING DATA, AND THE *A PRIORI* PROBABILITIES

| | | Reference ground truth class | | User |
|---|---|---|---|---|
| | | absent | present | accuracy |
| Class output | absent | 14 | 0 | 100% |
| from the classifier | present | 16 | 30 | 65% |
| Producer accuracy | | 47% | 100% | |

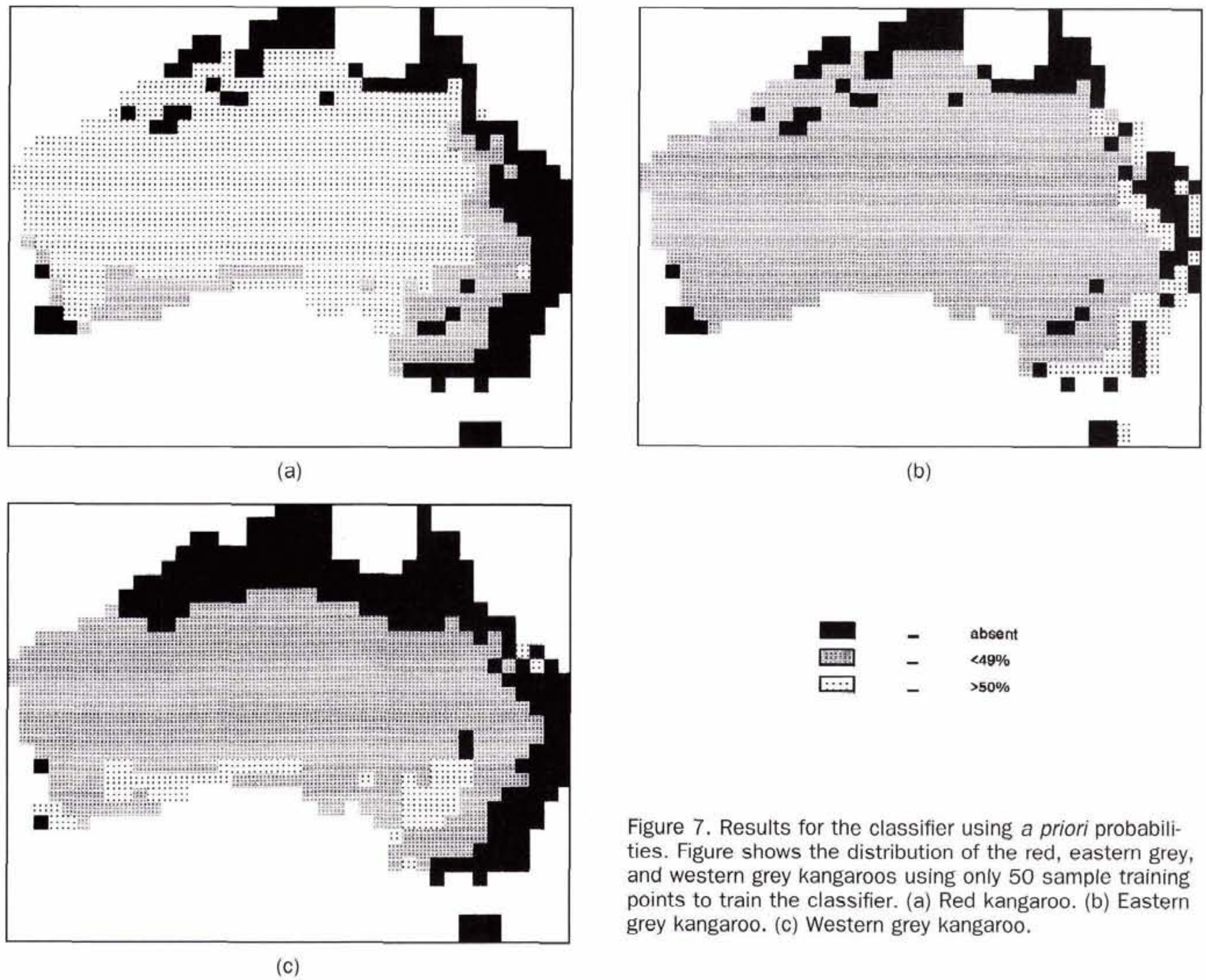


Figure 7. Results for the classifier using *a priori* probabilities. Figure shows the distribution of the red, eastern grey, and western grey kangaroos using only 50 sample training points to train the classifier. (a) Red kangaroo. (b) Eastern grey kangaroo. (c) Western grey kangaroo.

To ascertain the robustness of the algorithm, the equal probabilities (that is, for the three kangaroo species, $P(i|\mathbf{E}) = 0.33$) were replaced with the *a priori* probabilities in Table 1. As visually indicated in Figure 6, there were small visual differences; specifically, the probability of a cell being a western grey or an eastern grey decreases relative to the red kangaroo. To quantify this observation, a series of intermediate *a priori* probabilities was estimated (Table 4) between the equally probable $P(i|\mathbf{E}) = 0.33$ and the *a priori* probabilities in Table 1. The accuracy of maps (Figures 10 to 12) shows that there is no change in accuracy (i.e., both user and producer) for the three kangaroo species. It is concluded that the output from the classifier is not significantly altered by variations in the *a priori* probabilities.

Another test of robustness of the algorithm was to vary the number of training area samples for each species. The results shown in Figures 7 and 8 for 50 samples indicate that the algorithm is little changed by a reduction in training area number, but, as expected, the number of unclassified cells increases for 50 samples (Figures 7 and 8), compared with Figures 5 and 6 where all data are used to train the classifier. This may be explained by some vector positions remaining unfilled or partly filled (for one or all of the species). As a result, a grid cell may become "unclassified" because no training area samples have filled the vector space, or the *a posteriori* probability may change due to the varying numbers of training area grid cells contributing to the conditional probabilities calculated for the vector position. In order to quantify these observations, the classifier was executed with 5, 10, 25, 50, 75, and 100, as well as all data points, as training area data.

The producer accuracies for Figures 13 to 15 show that the percentage of "absent" grid cells increases as the sample size decreases. This is because the number of unclassified grid cells increases (remember that the absence of a kangaroo at a grid cell cannot be differentiated from the grid cell remaining unclassified). The user accuracies for Figures 13 to 15 show that the presence of the kangaroo species appear to become more accurately mapped as fewer grid cells train the classifier. This apparent contradiction is because both the user and producer accuracy are calculated. As the number of sample cells is reduced, the number of unclassified cells on the map increases. This decreases the overall number of correct and incorrect grid cells of the "present" class. Thus, the producer accuracy for the absent class increases (there are more correct "absent" cells), while the user accuracy for the "present" class also increases (there are fewer absent cells incorrectly classified as present). The behavior of the user and producer accuracy also explains the unusual values for the eastern grey kangaroo with small sample sizes (Figure 14).

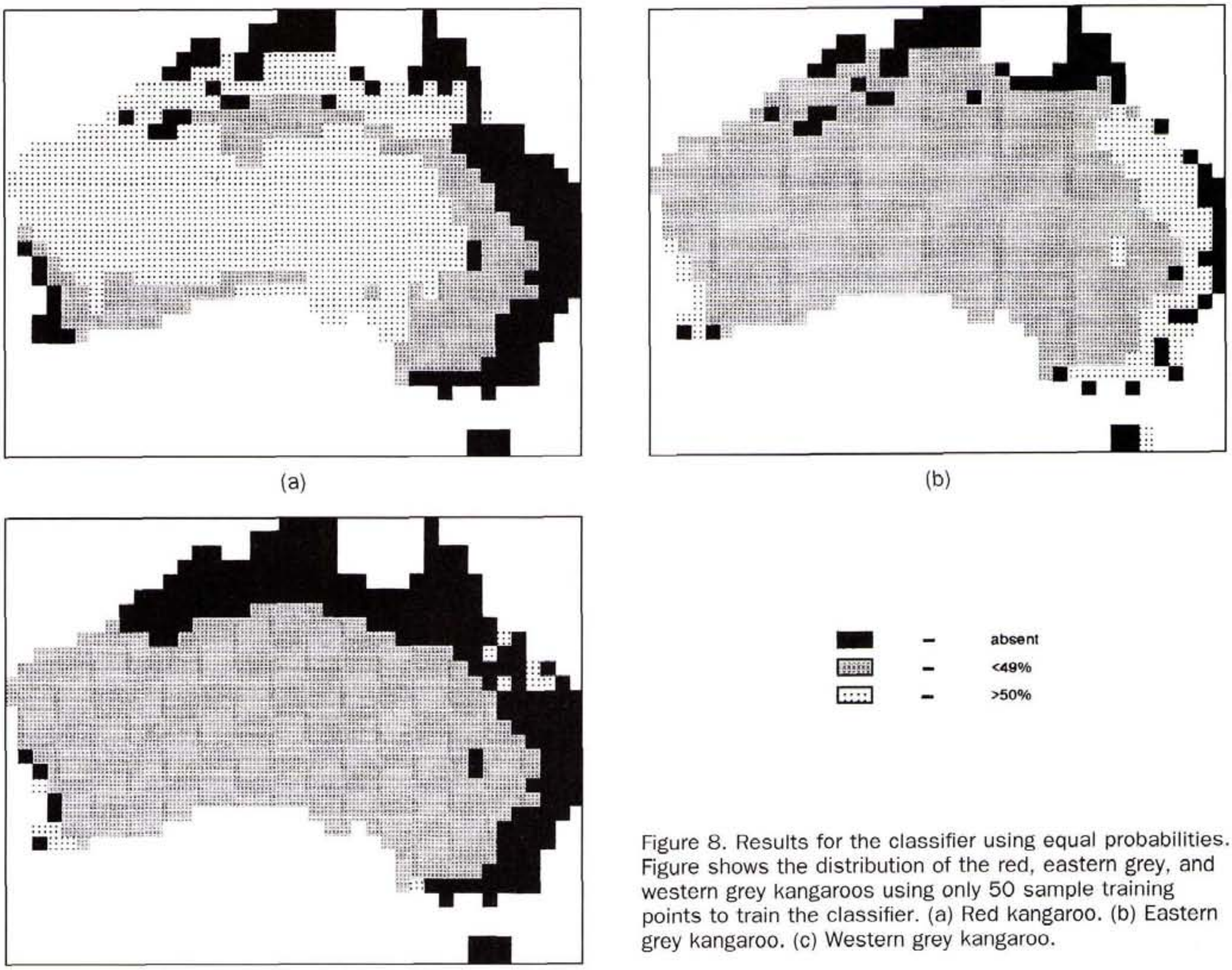


Figure 8. Results for the classifier using equal probabilities. Figure shows the distribution of the red, eastern grey, and western grey kangaroos using only 50 sample training points to train the classifier. (a) Red kangaroo. (b) Eastern grey kangaroo. (c) Western grey kangaroo.

Most of the variance (99.95 percent) in the kangaroo data is in the first four principal components because the climatic variables are interpolated from common data (i.e., DEM and weather records) and are, therefore, highly correlated. Feature reduction techniques, such as principal component analysis, are particularly useful when "independent" variables are partially correlated. An alternative strategy would be to directly remove climatic variables which are clearly dependent (for example, "precipitation" and "rainfall").

As the algorithm is based on nonparametric (ranked) statistics, it does not assume the training data or map data values are normally distributed. It is therefore possible to include diverse data sets into a classification problem. For example, it would be possible to incorporate remotely sensed data, digital elevation and terrain models, and classification (thematic) data such as a soil map without violating statistical assumptions. Parametric classifiers, such as maximum likelihood (Richards, 1986) and discriminant function analysis (Johnson and Wichern, 1984), are sensitive to the distribution of the input (training) data, particularly the assumption of normality, because they are based on covariance matrices and standard deviations, respectively.

It should be emphasized that the probability of correct classification (e.g., Figure 9) refers to the training area alone. It may be that the training area does not adequately sample the full environmental domain for a species; in this case, the probability of correct classification would be biased by the sample. However, this is also a problem for any supervised classifier, such as maximum likelihood.

There is no attempt here to consider density of kangaroos as an indicator of habitat quality, although density has been considered by others, as in the study by Short *et al.* (1983), who incorporated density indices of kangaroos in Western Australia. Indeed, as Van Horne (1983) points out, "*...we need to be much more careful in identifying high-quality or critical habitat and not assume simple density-habitat quality relationships without the demographic data to support them.*" Thus, the method proposed here does not attempt to model habitat quality *per se*. Rather, ecologists may consider using the model in the future for mapping wildlife habitat quality as additional field data and knowledge become available. It is, of course, possible to apply the technique at higher spatial resolutions and to incorporate additional independent variables, thereby exploring the habitat relationships of individual species at a particular site (Van Horne, 1983).

Finally, even though more spatially detailed analyses are possible, the data used in this study record the presence and absence of kangaroos on a 1° longitude by 1° latitude grid. The application of site-level observations to regional models

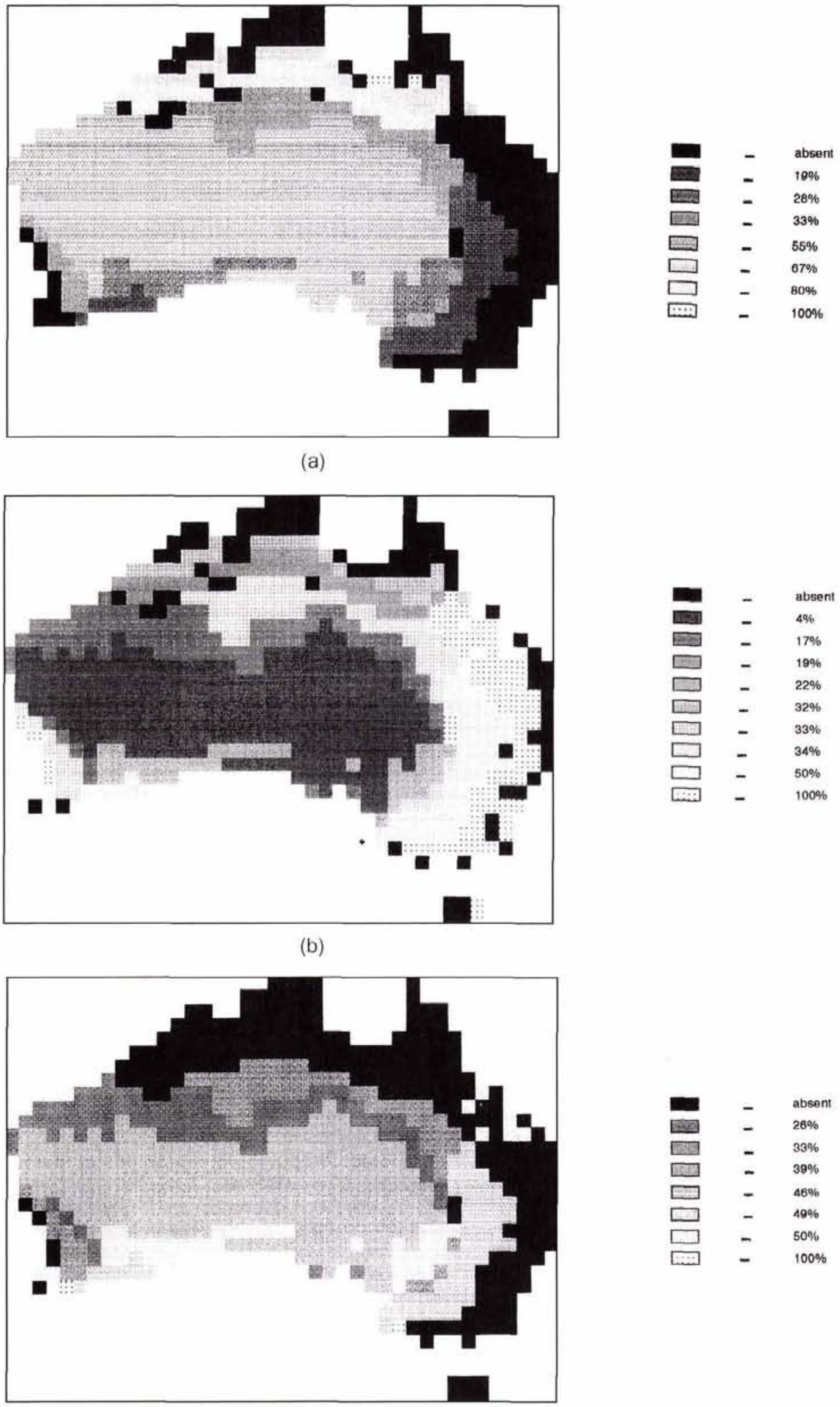


Figure 9. Results for the classifier using equal probabilities. Figure shows the distribution of the red, eastern grey, and western grey kangaroos using only 50 sample training points to train the classifier. The raw *a posteriori* probabilities, expressed as a percentage, are displayed. (a) Red kangaroo. (b) Eastern grey kangaroo. (c) Western grey kangaroo.

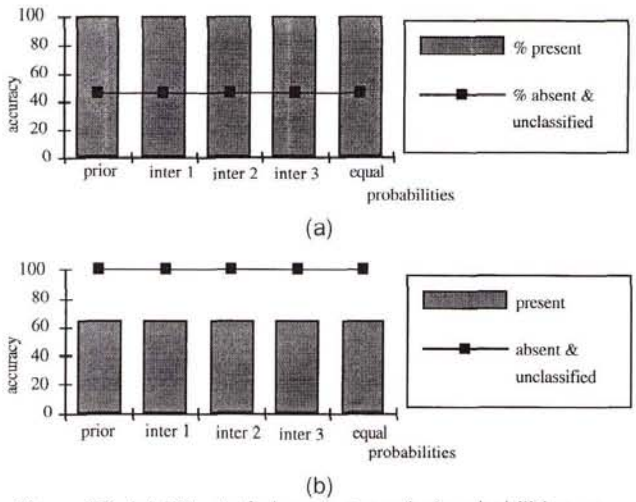


Figure 10. (a) Effect of changing *a priori* probabilities on the mapping accuracy of the red kangaroos for Producers accuracy. (b) Effect of changing *a priori* probabilities on the mapping accuracy of the red kangaroos for Users accuracy.

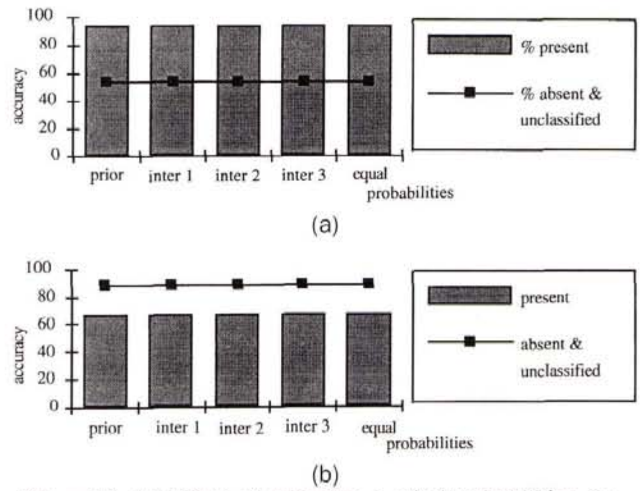


Figure 12. (a) Effect of changing *a priori* probabilities on the mapping accuracy of the western grey kangaroos for Producers accuracy. (b) Effect of changing *a priori* probabilities on the mapping accuracy of the western grey kangaroos for Users accuracy.

is not recommended, but reasonable models of empirically defined habitat relationships can be defined, and their use justified, if the accuracy of the models is evaluated (Flather and King, 1992).

## Conclusion

The generalized nonparametric classifier proposed by Skidmore and Turner (1988) is described. It is shown here that the classifier will successfully function with spatial data input from a GIS. The GIS analyst may delineate training areas, which in turn are used to predict dependent variables from the input spatial data. Spatial data, showing the distribution of kangaroos in Australia (Caughley *et al.*, 1987), were used to test the algorithm. The algorithm is robust to variations in sample size and *a priori* probabilities. Analysts may wish to consider this algorithm as another alternative model when classifying GIS data.

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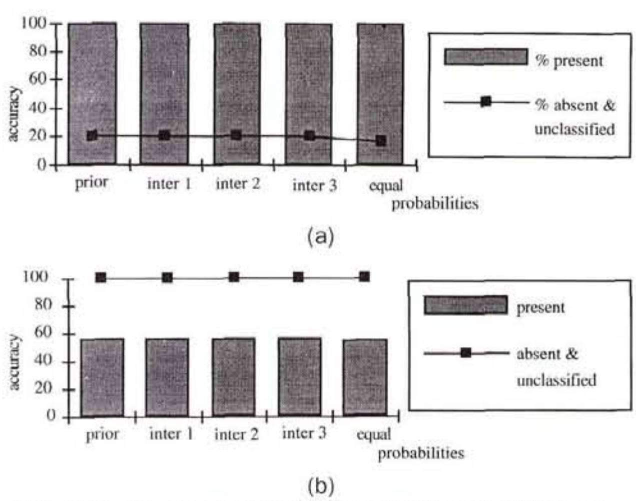


Figure 11. (a) Effect of changing *a priori* probabilities on the mapping accuracy of the eastern grey kangaroos for Producers accuracy. (b) Effect of changing *a priori* probabilities on the mapping accuracy of the eastern grey kangaroos for Users accuracy.

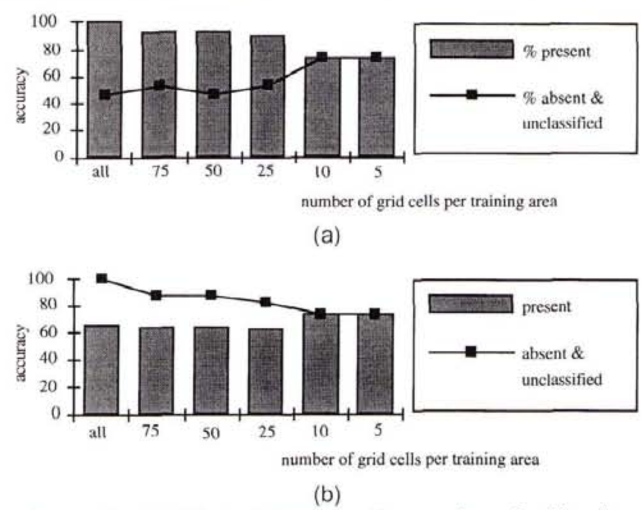


Figure 13. (a) Effect of changing the number of grid cells per training area on the mapping accuracy of the red kangaroos for producers accuracy. (b) Effect of changing the number of grid cells per training area on the mapping accuracy of the red kangaroos for users accuracy.

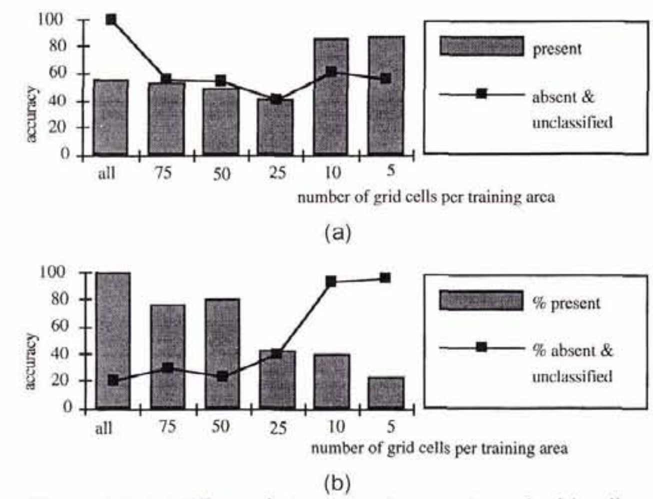

Figure 14. (a) Effect of changing the number of grid cells per training area on the mapping accuracy of the eastern grey kangaroos for producers accuracy. (b) Effect of changing the number of grid cells per training area on the mapping accuracy of the eastern grey kangaroos for users accuracy.

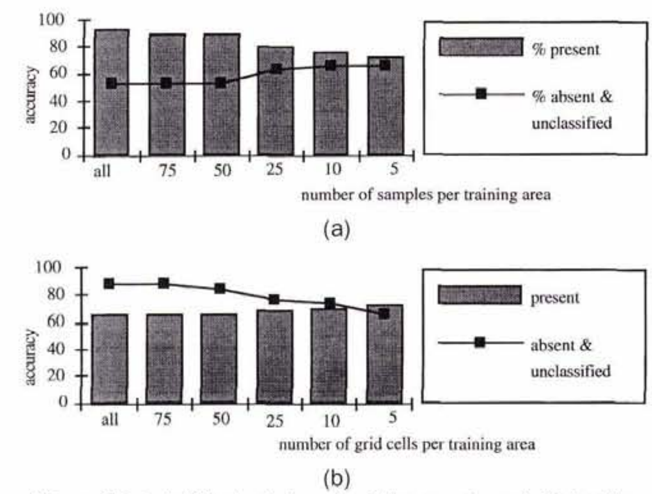

Figure 15. (a) Effect of changing the number of grid cells per training area on the mapping accuracy of the western grey kangaroos for producers accuracy. (b) Effect of changing the number of grid cells per training area on the mapping accuracy of the western grey kangaroos for users accuracy.


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