

THE APPLICATION OF NEURAL NETWORKS TO THE FLORISTIC CLASSIFICATION OF REMOTE SENSING AND GIS DATA IN COMPLEX TERRAIN.

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ABSTRACT:

This study applies a Back-Propagation Neural Network to the task of floristic land cover classification. The input data consists of the three LANDSAT TM bands 2, 4 and 7 and the GIS based environmental variables Aspect, Elevation, Catchment, Geology and Slope. This dataset covers a 225 square-km sub scene centred near the town of Kioloa, South East, Australia.

The study area is complex comprising a mixture of disturbed and partially cleared sclerophyll forest and rainforest on rough terrain with variable geology. Rainforest gullies and coastal heath are found along the coastal fringe thus adding to the floristic complexity confronted by the neural network.

The resulting neural network classifications provide a realistic estimate of the distribution of floristic classes. The patterning is more sophisticated and less polygonal than that achieved using earlier models. The most awkward vegetation class, rainforest ecotone is handled effectively by the neural network. Misclassified pixels are allocated to either wet sclerophyll or rainforest.

KEY WORDS: neural network application, land cover classification, floristic classification, remote sensing application, GIS application.

I. INTRODUCTION

The resolution of available statistical techniques used to interpret remotely sensed data are not sufficient to differentiate the fine structure now required in forest management. Quicker, more efficient and accurate techniques for the classification of this data are required. A number of new techniques including decision trees and neural networks have been tested in the processing of remotely sensed data. These land cover classification techniques achieve accuracies of upto 60% (Benediktsson, 1989; Decatur (1989); Hepner, 1990; Key, 1990; Lees & Ritman, 1991; Heermann 1991; Yin 1991). Applying these techniques to remotely sensed and GIS data shows great promise over single data source techniques (Lees & Ritman, 1991; Benediktsson, 1989). Benediktsson (1989) has worked at the floristic classification level using remotely sensed and GIS data and as such is the most similar to this study. He achieved an overall classification accuracy comparable to the results achieved in this study (see Table III).

Decision trees have been successfully used on the Kioloa dataset by Moore et al. (1990) and Lees & Ritman (1991) which provide a valuable set of reference results to compare this study's neural network classification against. The two techniques are shown to produce similar overall classification results but differ at the class and spatial patterning level. This paper reports the results of applying a back-propagation neural network to a floristic classification in complex terrain. All previous cited authors (with the exception of Benediktsson (1991)) have applied neural

networks to the delineation of gross structural classifications such as forest, urban areas, water bodies and open paddocks.

II. STUDY SITE and DATA SOURCES

The terrain examined is a 225 km. square site located on the forested coastal ranges and plain in the south-east coastal region around Kioloa, New South Wales, Australia (Figure 1). The topography varies from vertical cliffs down through alluvial flats and coastal plains. The altitudinal variation is from sea level to 285 meters. The study area is extremely complex comprising a mixture of disturbed and partially cleared forest on rough terrain with variable geology.

The Kioloa GIS dataset consisted of 15 overlay files stored in IDRISI. The images include the core set of 7 LANDSAT TM bands. The GIS overlays comprised a set of environmental variables. Each overlay contained 501 rows and 600 columns making 300,600 pixels. Of these 15 potential overlays, 8 were selected following the decision tree analysis of Lees & Ritman (1991). The 8 overlays selected were: LANDSAT TM bands 2, 4 and 7, Aspect, Elevation, Catchment, Geology and Slope.

The training overlay LX9 contained 1117 terrestrial ground

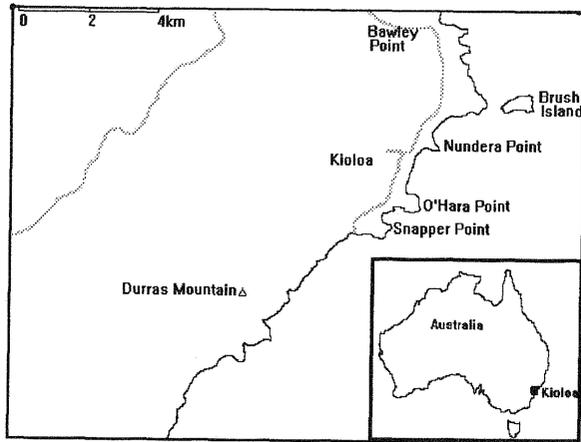


Figure 1: Location of the study area, Kioloa, N.S.W., Australia.

truth sites. A further 286 randomly selected pixels from the Tasman Sea portion (representing a proportional sample of 0.47% of the available sea pixels) of the sub scene were also included in the LX9 training overlay, thus bringing the training sample size to 1403 sites. The 1117 terrestrial ground truth pixels are part of the same 1257 ground truth sites reported in Moore et al. (1990) and Lees & Ritman (1991). Thus the results of the neural network classification in this study could be directly compared to the results achieved by these authors.

The training sites in the LX9 overlay were classified into 9 land use/ floristic classes. These classes were:

1. Dry Sclerophyll
2. Eucalyptus botroyoides
3. Lower slope wet
4. Wet E. maculata
5. Dry E. maculata
6. Rainforest ecotone
7. Rainforest
8. Paddocks/ cleared ground
9. Sea/ water body

III. PRE-PROCESSING of the MULTI-SOURCE KIOLOA GIS

The neural network simulation software used in this study was HNC Explorenet 3000 running under Microsoft Windows ver 3.0, all running on an Olivetti M380 386dx 20Mhz (4 mb of RAM) based PC. The IDRISI 8 bit unsigned integer binary format could be read directly by Explorenet 3000. However, the processing overheads of both Explorenet and Windows 3 were prohibitive and this data interface to the neural network software was quickly abandoned as impractical. The most expedient route to interfacing the Kioloa GIS dataset to the neural network software was to write a series of FORTRAN programs which extracted and pre processed the 8 input variables into a binary training vector ready for input into Explorenet 3000.

The training vector pre-processing was carried out in two stages. Firstly we read in the LX9 training site overlay and selected a 25% uniform sample of the training sites. The uniform sample selected equal numbers of training sites in

each of the 9 land cover classes. The output was a file containing the pixel addresses of the selected training sample. We then selected two 15% statistically independent random samples which were used for testing and validating the neural network training process. These two samples were statistically independent of each other and the 25% training sample. The output was two files containing the pixel addresses of the test and validation samples.

The second stage of the training vector pre-processing involved merging the 8 input overlays from IDRISI using the pixel addresses of the selected training, test and validation samples generated in the first stage. The 8 pixel values are then normalised to the range 0.05 to 0.95 to facilitate learning under the logistic activation function used by the back-propagation algorithm in the neural network. Simultaneously, the corresponding LX9 training site class value were converted to an output class vector of the form:

$$\begin{aligned} \text{LX9out}(i) &= 1 \text{ for } i = \text{LX9 class value index and} \\ \text{LX9out}(i) &= 0 \text{ elsewhere.} \end{aligned}$$

Examples of this coding scheme are:

$$\begin{aligned} \text{LX9} &= 1, & \text{LX9out} &= 1000000000 \\ \text{LX9} &= 2, & \text{LX9out} &= 0100000000 \\ \text{LX9} &= 9, & \text{LX9out} &= 0000000010 \end{aligned}$$

The last step in the pre-processing was to assemble these components together into a training vector ready for input into Explorenet 3000. The 8 normalised input variables along with the LX9out output vector for each sample training site were combined into a single 76 byte binary vector.

IV. TRAINING the NEURAL NETWORK and CLASSIFYING the ENTIRE KIOLOA SUB SCENE

The back-propagation network used in this study consisted of three layers, an input layer of 8 nodes (one for each input variable), a hidden processing layer of 24 nodes and an output layer of 10 nodes (one for each of the allowable floristic classes). Hepner (1990) and Benediktsson (1991) discuss the structure of neural networks in detail. The final structure of the neural network used in this study was arrived at by trial and error. Arriving at the final structure of a neural network seems to be a black art even in the computer science community (Caudill, 1991).

There are three steps in producing a successful neural network classifier - training, testing and validating. Training the neural network involves designing the neural network structure in Explorenet 3000 and then feeding the pre-processed training vector to it repeatedly until the overall classification accuracy has stabilised. Explorenet 3000 has a training facility called *fast_train* which allows a block of training vectors to be read into memory and then learned repeatedly by the network. This feature greatly expedites the training process. The final training cycle for the LX9 overlay (LX946a) took some 19 hours to stabilise at an overall classification accuracy of 61%.

Once the network has been trained, it must be tested on a

statistically independent set of training vectors to ensure that it has not simply memorised the training data. This process took some 9.5 hours. To finally accept the network as trained, a third statistically independent validation sample is run through the trained network (taking 10 hours) which produced an acceptable overall classification accuracy of 67%. The neural network was now ready to classify the entire Kioloa sub scene from the 8 input variables. This process took some 30 hours and resulted in the full sub scene classified image LX946a.

During the training process, two different training methods were tried. The first consisted of randomised replacement sampling from the training and test vectors. During each training cycle, a randomised 50% replacement sample of all available training vectors was selected and trained on by the network. In this way the neural network saw a large variety of training vector mixes. By comparison, the non replacement sequential training process selected progressive blocks of 400 training vectors for training. By either method, the networks converged on a minimum error level and achieved overall classification accuracies of 67% during validation. Lee (1990) is the only author cited who has investigated the effects of randomising the training vectors on classification accuracy.

V. RESULTS of the NEURAL NETWORK CLASSIFICATION

The sub scene image LX946a (see poster) was the final result of the application of our neural network to the classification of vegetation from the Kioloa GIS dataset. It represents the fusion of remote sensing and environmental variables by a trained neural network.

Table I represents the error matrix for the neural network classification in image LX946a. The overall classification accuracy for land and sea training sites was 98% and 51% for the land portion only (Table I). These percentages are lower than the training and validation results reported above because they are now based on all the training sites, not just the 25% training sample. The corresponding kappa agreement statistics are 0.62 and 0.40. These kappa values correspond to a good and poor level of agreement respectively. Congalton (1991) discusses the use of the kappa statistic and Fitzgerald & Lees (1992) have a detailed discussion of the application of the kappa statistic to this dataset.

As a means of comparing the relative performance of our neural network classification, we crosstabulated the LX946a neural network classified image with the corresponding image described by Lees & Ritman (1991) for the same training sites in the Kioloa area (see poster image LEERIT). The Lees & Ritman (1991) classification only applies to land pixels for which they obtained an overall classification rate and kappa statistic of 51% and 0.40 respectively, the same as the neural network.

At this gross classification level, the two classification methods performed equally. At the individual floristic class level, the two classification techniques differ substantially. Table II is a comparison of the diagonal elements (total class agreement) from the individual error matrices of the neural network classified image LX946a and the Lees & Ritman

(1991) decision tree classified image. The neural network's class classification accuracy is distinctly different to that of the decision tree model.

A more detailed analysis of the inter class differences between these two classification techniques using the kappa statistics is discussed in Fitzgerald & Lees (1992). This analysis also raises the question of the discreteness of the classification scheme and the appropriateness of the statistical analysis used to assess classification accuracy. These same issues are addressed by Congalton (1991).

The discussion above has compared the relative performance of two classifiers on the same Kioloa dataset. Table III compares the relative performance of our neural network classification against the five authors cited earlier who have used neural networks in land cover classification problems. The neural network classifier's performance compares well with all the other cited authors and especially Benediktsson's (1990). It's interesting to note that Decatur (1989) and Ritter & Hepner (1989), who both relied on remote sensing data only reported higher overall classification accuracies. However, they required training samples of the order of 10 and 78 times that used in this study to achieve these levels of accuracy. As Congalton (1991) points out, the statistical representativeness of the ground truth sampling is more important in its affects on classification accuracy than sheer sample size.

VI. CONCLUSION

The resulting classified image LX946a provides a realistic estimate of the distribution of floristic classes in the Kioloa study area. The floristic patterning is more sophisticated and less polygonal than that achieved using the decision trees of Lees & Ritman (1991). Despite this, the overall classification accuracies as assessed using percentages and the kappa statistic show that the two techniques are equivalent. The differences appear at the floristic class level. The classifier developed in this study compares favourably with other cited examples indicating that the technique is sound. The fusion of remotely sensed data and environmental variables from a GIS has contributed to the sophisticated classification result displayed in image LX946a. It has also compensated for the comparatively small number of ground truth sites.

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Table I: Error matrix for the Neural network classifier

AGREEMENT analysis - Error matrix of Lx9 with Lx946a (NN classified image)

| NN classified | Lx9 Training sites | | | | | | | | | Marg pi. | Row n | |
|------------------|--------------------|-------|------|-------|------|------|------|------|------|----------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | | | |
| Dry Sclerophyll | 1 | 215 | 25 | 28 | 68 | 28 | 8 | 2 | 0 | 242 | .010 | 616 |
| E. botryoides | 2 | 24 | 36 | 12 | 3 | 3 | 2 | 11 | 0 | 29 | .002 | 120 |
| Lower slope wet | 3 | 1 | 1 | 4 | 0 | 0 | 1 | 0 | 0 | 148 | .002 | 155 |
| Wet E. maculata | 4 | 23 | 5 | 4 | 94 | 24 | 23 | 22 | 2 | 0 | .003 | 197 |
| Dry E. maculata | 5 | 49 | 1 | 3 | 67 | 124 | 13 | 18 | 0 | 0 | .004 | 275 |
| RF Ecotone | 6 | 3 | 0 | 0 | 2 | 1 | 16 | 5 | 0 | 0 | .000 | 27 |
| Rainforest | 7 | 1 | 0 | 1 | 17 | 2 | 40 | 31 | 0 | 0 | .001 | 92 |
| Paddocks | 8 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 50 | 59 | .002 | 112 |
| Sea | 9 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 61132 | .975 | 61133 |
| Marginal p.i | | .005 | .001 | .001 | .004 | .003 | .002 | .001 | .001 | .982 | 1.000 | |
| Column n | | 317 | 68 | 52 | 253 | 182 | 104 | 89 | 52 | 61610 | | 62727 |
| | | | | Kappa | | | | | | | | |
| Overall Accuracy | | 98.4% | | .617 | | | | | | | | |
| QA (Land) | | 51.1% | | .395 | | | | | | | | |

Source: xtab392, 13-Mar-92, ktab11.prn

Table II:

Comparison of the diagonals (total agreement) of the error matrices from the NN classification (Lx946a) and Lees & Ritman (1991).

| | Vegetation class ¹ | | | | | | | |
|-----------------|-------------------------------|----|----|----|----|----|----|----|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Neural Networks | 68 | 53 | 8 | 37 | 68 | 15 | 35 | 96 |
| Lees & Ritman | 70 | 31 | 19 | 49 | 40 | 40 | 38 | 88 |

Source: Neural network classified image Lx946a

Lees & Ritman (1991)

1 - 1, Dry Sclerophyll 2, E. Botryoides 3, Lower slope wet
 4, Wet E. Maculata 5, Dry E. Maculata 6, RF Ecotone
 7, Rainforest 8, Paddocks

Table III:

Comparative table of Neural Networks classification results between those achieved by this thesis and comparable cited authors.

| | Percent classification accuracy | | | Data source ⁶ | Sample size % |
|------------------------------|---------------------------------|-------|--------------------|--------------------------|---------------|
| | Overall | Water | Forest Paddocks | | |
| Lx946a ¹ | 51 | 100 | 40 ² 96 | ms | 0.5 |
| Benediktsson ³ | 52 | 98 | 43 ² 29 | ms | 11 |
| Ritter & Hepner ⁴ | 69 | 66 | 80 55 | rs | 39 |
| Decatur ⁵ | 76 | 92 | - 57 | rs | 5 |

Sources & notes:

- 1 - Neural network classified, 9 classes
- 2 - average of all forest sub classes.
- 3 - Benediktsson, 1990, table VI-B, pg549, model E
- 4 - Ritter & Hepner, 1989, table 2, pg 879
- 5 - Decatur, 1989, table 2.1, pg i-285
- 6 - Data source: rs = remote sensing only, ms = multi-sourced