Monitoring Land Condition in the Upper Blackwood and Frankland-Gordon Catchments

A report from the LWRRDC project:

“Mapping and monitoring land condition in the Blackwood and Frankland-Gordon catchments using remotely sensed data”

April 1998

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Summary

This report summarises the work and findings to date of a project funded by the Land and Water Resources Research and Development Corporation on “Mapping and monitoring land condition in the Upper Blackwood and Frankland-Gordon catchments”.

The aims of the project are:

- to carry out integrated land condition mapping across the catchments using remotely sensed and related spatial data, looking simultaneously at salinity, remnant vegetation, waterlogging, on-farm productivity, and areas at risk from salinity; and
- to transfer the results (and the approaches used to derive the results) to catchment groups, project officers and landcare technicians.

The outputs from the project are:

- maps showing changes in salinity between 1989 and 1994 in the Upper Blackwood and Frankland-Gordon catchments;
- maps showing areas at risk from salinity;
- a simple decision-tree model for assessing salinity risk;
- maps showing remnant vegetation, clearing and re-vegetation;
- maps showing condition indices for remnant vegetation;
- a case-study on the use of Landsat imagery for mapping species composition in the Dongolocking reserves area; and
- a series of farm-scale studies to transfer the results of the project, and assess the usefulness of the maps at farm and catchment scales.

The results of the project show that salinity change and risk maps, remnant vegetation maps and waterlogging / productivity maps can be produced with sufficient accuracy for farm use, and that farmers are enthusiastic about their use at both farm and catchment scales.
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1 Introduction

The project “Mapping and Monitoring Land Condition in the Blackwood and Frankland-Gordon Catchments” is providing coordinated land condition mapping of salinity, remnant vegetation, wind erosion, waterlogging, on-farm productivity and areas at risk from salinity. This report describes the methods used to produce such maps, and the results achieved by the project.

1.1 Background

The Regional Landcare Strategy for the Blackwood Catchment identified dryland salinity, decline in remnant vegetation, wind erosion and waterlogging as particular issues of concern to landholders in the upper and middle Blackwood. A review of the Frankland-Gordon Catchment showed a similar suite of problems. The LWRRDC project on “Detecting and Monitoring Land Condition Through Time Using Remotely Sensed Data” (Project CDM 1) has shown that it is feasible, using sequences of calibrated TM data, to map salinity in the WA wheatbelt, to identify areas affected by waterlogging, to monitor wind erosion and to monitor the condition of remnant vegetation. The studies have proceeded in parallel, and have been carried out in different parts of the wheatbelt. This is partly because the various problems were considered more pressing in some parts of the landscape than others, and partly because of the interests of the collaborating agencies and their networks with landcare groups.

The Blackwood and Frankland-Gordon Catchments provide ideal test-beds to carry out coordinated land condition mapping, looking simultaneously at salinity, remnant vegetation, waterlogging and on-farm productivity. Moreover, the project was designed to provide timely input of information at regional, catchment and farm scales to the Blackwood Regional Initiative and the South Coast Regional Initiative. Transfer of the technology to the catchments is an important focus of the project.

1.2 Project objectives

- To carry out integrated land condition mapping across the catchments using remotely sensed and related spatial data, looking simultaneously at salinity, remnant vegetation, waterlogging, on-farm productivity, and areas at risk from salinity.

- To transfer the results (and the approaches used to derive the results) to catchment groups, project officers and landcare technicians.

1.3 Achievements

The project has integrated approaches from the two LWRRDC projects listed above in a semi-operational way to provide critical information for the Blackwood and South Coast regional Initiatives.

The project has provided maps of the current extent of dryland salinity in the Upper Blackwood and Frankland-Gordon Catchments, and documented the spread of salinity. Maps showing the areas of remnant vegetation have been produced, and changes in the area of remnant vegetation between 1990 and 1996 have been documented. This strategic information will form critical inputs to proposed NHT projects and provide a basis for helping the community develop salinity and nutrient action plans. In addition, a study on the feasibility of mapping species composition and condition in the Dongolocking reserves has been conducted.

The second phase of the project has focussed on operational use of this information at a local (catchment / farm) scale by providing information to farmers and catchment groups to help improve on-farm productivity. This included information on within-paddock variability, susceptibility to waterlogging,
and areas at risk from salinity. This has been done by providing detailed information products to
selected groups of farmers, and working with them to evaluate and modify the products. These
products will be available to farmers throughout the catchments as part of a fee-paying service
provided by the Department of Land Administration’s Satellite Remote Sensing Services in
collaboration with CSIRO.
2 Mapping, monitoring and predicting salinity

2.1 Introduction

Seventy percent of Australia’s dryland salinity is in Western Australia. It is estimated that 1.8 million hectares or 10% of WA land cleared for agriculture is affected by salinity, causing agricultural production losses of $64 million a year (State Action Salinity Plan, 1996). Studies conducted by CSIRO Mathematical and Information Sciences (CMIS) have shown that data from the Landsat Thematic Mapper satellite can be used to map areas affected by salinity (Wheaton et al., 1992, Wheaton et al. 1994, Furby et al., 1995). Landsat TM data are usually classified using traditional statistical methods, such as maximum likelihood classification.

Using Landsat TM images from several successive seasons and landform data, it is possible to make assumptions about how the data relate to salinity. For instance, if an area that shows poor productivity in one year yields a healthy crop the following year; it is unlikely that the area is salt-affected. However, if an area shows poor productivity for two years in a row, the probability that it is salt-affected is much higher. A conditional probability network, or CPN, (Neapolitan, 1990; Heckerman, 1996) has been investigated for combining individual-year maximum-likelihood classifications with landform data to produce salinity maps for each date. The advantage of using a conditional probability network is that it provides a framework for including prior knowledge about relationships between variables in the classification model. The network has been used to produce maps showing changes in salinity through time for the upper Blackwood and Frankland-Gordon catchments.

Predicting areas at risk from salinity is important for land management, since it allows resources to be allocated to those areas in the most need of assistance. Making predictions is very difficult; in the past, reliable predictions could only be made using small-scale data-intensive process-based models or by hydrologists with extensive experience and local knowledge. A simple model is developed for predicting salinity risk using ground truth data provided by several experienced hydrologists.

The aims of this process are to:

1. develop a cost-effective method for predicting salinity risk over broad areas;

2. produce a simple model which can be easily understood and used to help understand the processes underlying salinity risk; and

3. determine whether simple rules can be developed for assessing salinity risk.

The salinity maps produced using the conditional probability network are used to derive a map showing the distance to known salinity which is used with DEM-derived landform data for making predictions about future salinity risk. A decision tree classifier (Quinlan, 1992) is used to predict salinity risk, since it provides a means for exploratory data analysis and an understanding of the relationships between the input attributes and salinity risk. The decision tree is used to produce maps showing areas at risk from salinity for the upper Blackwood and Frankland-Gordon catchments. Rules for assessing salinity risk are derived from the tree. The decision tree, and derived rules, might be refined using additional hydrogeological information, on-site management and other factors. This kind of information requires more detailed mapping than can be cost-effectively provided using broad-scale Landsat TM imagery and digital elevation models, and has been excluded from this work for these reasons.
2.2 The study areas

The Blackwood and Frankland-Gordon catchments study area covers the following region:
6380700N, 451250W, 6180000S, 652850E. The entire study area crosses the boundary of two Landsat TM scenes (Dumbleyung and Mt Barker). The scenes have been mosaicked, and neighbourhood-modified maximum likelihood classifications have been produced for each date. However, this area is too large to process using a CPN. It has been divided into several smaller study areas for the production of salinity maps.

The Upper Blackwood catchment study area consists of 6638 image lines, each containing 7488 pixels at 25m resolution. The geographic boundaries of the study area are: 6404150N, 453300W, 6238200S, 640500E.

The Frankland-Gordon catchment study area consists of 3264 image lines, each containing 4470 pixels at 25m resolution. The geographic boundaries of the study area are: 6264300N, 480800W, 6182700, 592550E.

2.3 The data

2.3.1 Landsat TM image data

A sequence of spring Landsat TM images has been assembled for the Blackwood and Frankland-Gordon catchments. The image dates used for this study are:

- August 1989
- September 1990
- September 1993
- August 1994

The images have been rectified to AMG coordinates at 25m pixel resolution, and then calibrated to like-values (Campbell et al., 1994).

2.3.2 Ground truth data

Training sites for the Landsat classification were digitised using the yearly images as bases. Only sites from the Blackwood catchment were used (note: this excludes the Ryan's Brook ground data, which were reserved for validation). The sites were selected to include the following ground cover types: water; healthy remnant vegetation; poor remnant vegetation; bare salt scalds; salt-affected land with ground cover (such as trees or other salt-tolerant species); bare soil; bright crops (such as canola or lupins); dark crops (such as wheat, oats or barley); good and poor pastures.

Ground truth data for salinity prediction were provided in the form of aerial photograph interpretations by Agriculture Western Australia hydrologists Ruhi Ferdowsian and Richard George.

2.3.3 Landform data

The major source of elevation data in WA is digitised contour levels obtained from stereoscopic aerial photographs. Digital contour data at ten and twenty metre contour intervals were obtained from the Department of Land Administration. The contour data were gridded using spline interpolation (Mitasova and Mitas, 1993; Mitasova and Hofierka, 1993) to form digital elevation models (DEMs) for the Upper Blackwood catchment and Frankland-Gordon study areas.
To obtain information about landform, water accumulation maps were produced from the DEMs. Water accumulation models work on the principle that water flows downhill. At the start of the computation, each pixel is given one unit of water. A pixel passes to each of its downhill neighbours a portion of its accumulated water, the portions being proportional to the slope from the pixel to the neighbour. This is in contrast to some implementations, which pass all the water to the neighbour which has the greatest downhill slope. As the terrain in WA is relatively flat, passing a fraction of the water to each downhill neighbour provides a better measure of water accumulation.

Because slopes in flat areas are poorly defined, the above algorithm performs badly in such areas. A flat-area classifier is used to separate and classify broad valley floors, using the proportion of pixels at the boundary of the feature draining into it as the selection criterion. Hilltops have a low proportion of inflow, while valley floors have a very high proportion of inflow. The map of broad valleys can then be combined with landform classes obtained by stratifying the water accumulation map.

The water accumulation map provides a continuous measure of landform since the values are low on hilltops and increase as they move into lower components of the landscape. Five landform classes were derived by stratifying the water accumulation: hilltops, upper slopes, lower slopes, valleys and broad valley systems.

The DEMs were also used to produce maps showing the steepest downhill slope from any pixel.

![Figure 1](image1)

**Figure 1** (i) Water accumulation and (ii) Downhill slope maps

Further details about the processing of contour data to form DEMs and derived data can be found in the task report “Blackwood and Frankland-Gordon catchment digital elevation models and derived data”.

### 2.4 Mapping and monitoring salinity

The methodology used to produce maps of salinity is:

1. rectify the images to a common map base - this allows ground sites to be traced through time and the satellite images can be compared with other map-based data sets;

2. calibrate the imagery to *like-values* so that the digital numbers from different dates can be compared;
3. locate sample sites of all the major cover types in the image, reserving a proportion of the sites for each cover type for validation of the results;

4. stratify the area into zones within which there are no marked regional differences in rainfall, crop types, geology, predominant soil types or visible patterns in the image - if there are strong spectral patterns in the image, the zones should be analysed separately;

5. apply maximum likelihood classification techniques to the image dates in each growing season; and

6. combine the cover class probabilities from two or more consecutive seasons with landform to calculate the probability of each pixel being salt-affected, using a conditional probability network (CPN) to implement the calculations.

### 2.4.1 Canonical variate analyses

Canonical variate analyses were used to investigate the spectral separability of the training sites. Table 1 summarises the canonical roots.

<table>
<thead>
<tr>
<th>Year</th>
<th>1st Canonical Root</th>
<th>2nd Canonical Root</th>
<th>3rd Canonical Root</th>
<th>4th Canonical Root</th>
<th>5th Canonical Root</th>
<th>6th Canonical Root</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>35.03</td>
<td>11.11</td>
<td>3.173</td>
<td>0.5273</td>
<td>0.3596</td>
<td>0.1311</td>
</tr>
<tr>
<td>1990</td>
<td>42.85</td>
<td>21.16</td>
<td>13.96</td>
<td>1.718</td>
<td>1.191</td>
<td>0.6256</td>
</tr>
<tr>
<td>1993</td>
<td>42.67</td>
<td>26.80</td>
<td>6.788</td>
<td>4.337</td>
<td>2.391</td>
<td>1.592</td>
</tr>
<tr>
<td>1994</td>
<td>32.71</td>
<td>14.72</td>
<td>6.669</td>
<td>2.142</td>
<td>0.7373</td>
<td>0.4737</td>
</tr>
</tbody>
</table>

The canonical variate analyses showed a lack of separation between some saline, bare and poor pasture sites. Sites within the overlap area were checked in the images and their labels confirmed. In the western zone of the image (higher rainfall zone), some saline and bare soil sites could not be adequately separated. In the eastern zone (lower rainfall zone), some saline, bare and poor pasture sites could not be adequately separated. These sites were used to define a mixed class containing bare, salt-affected and poorly pastured areas.

The training sites were aggregated to form six classes: salt, mixed bare / salt / pasture, bare soil, remnant vegetation, crop / pasture and water.

### 2.4.2 Maximum likelihood classification

Each image was classified using maximum likelihood classification to produce a class label image and posterior probability images (ie. the probability of belonging to each class) for each of the six classes. The classification maps for August 1989 and September 1990 are shown in Figure 2. Visual examination shows that the 1989 classification tends to over-estimate salinity, frequently mapping agricultural areas with poor ground cover as salt-affected. The 1990 classification maps a much smaller proportion of the image as salt; this is possibly caused by the differences in scene brightness between the two years. This reflects seasonal differences: the rainfall data for the region show that 1989 was a wetter year than 1990.
Classification accuracies were calculated over the training data as well as over independent validation sites located in the Ryan’s Brook subcatchment. The resubstitution estimates are given in tables 2 to 5.

**Table 2  1989 resubstitution accuracies**

<table>
<thead>
<tr>
<th>Reference Label</th>
<th>Image Label</th>
<th>salt</th>
<th>mixed</th>
<th>bare soil</th>
<th>bush</th>
<th>crop / pasture</th>
<th>water</th>
<th>% accurate</th>
</tr>
</thead>
<tbody>
<tr>
<td>salt</td>
<td>salt</td>
<td>642</td>
<td>14</td>
<td>0</td>
<td>2</td>
<td>8</td>
<td>0</td>
<td>96.40</td>
</tr>
<tr>
<td>mixed</td>
<td>mixed</td>
<td>47</td>
<td>712</td>
<td>20</td>
<td>0</td>
<td>42</td>
<td>0</td>
<td>86.72</td>
</tr>
<tr>
<td>bare soil</td>
<td>bare soil</td>
<td>9</td>
<td>51</td>
<td>534</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>88.70</td>
</tr>
<tr>
<td>bush</td>
<td>bush</td>
<td>8</td>
<td>0</td>
<td>48</td>
<td>1148</td>
<td>0</td>
<td>0</td>
<td>95.53</td>
</tr>
<tr>
<td>crop/pasture</td>
<td>crop/pasture</td>
<td>5</td>
<td>42</td>
<td>14</td>
<td>36</td>
<td>2018</td>
<td>0</td>
<td>95.41</td>
</tr>
<tr>
<td>water</td>
<td>water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>56</td>
<td>96</td>
<td>63.16</td>
</tr>
</tbody>
</table>

**Table 3  1990 resubstitution accuracies**

<table>
<thead>
<tr>
<th>Reference Label</th>
<th>Image Label</th>
<th>salt</th>
<th>mixed</th>
<th>bare soil</th>
<th>bush</th>
<th>crop / pasture</th>
<th>water</th>
<th>% accurate</th>
</tr>
</thead>
<tbody>
<tr>
<td>salt</td>
<td>salt</td>
<td>912</td>
<td>33</td>
<td>0</td>
<td>1</td>
<td>47</td>
<td>0</td>
<td>91.84</td>
</tr>
<tr>
<td>mixed</td>
<td>mixed</td>
<td>36</td>
<td>1722</td>
<td>0</td>
<td>2</td>
<td>17</td>
<td>0</td>
<td>96.90</td>
</tr>
<tr>
<td>bare soil</td>
<td>bare soil</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>NA</td>
</tr>
<tr>
<td>bush</td>
<td>bush</td>
<td>11</td>
<td>11</td>
<td>0</td>
<td>1140</td>
<td>0</td>
<td>0</td>
<td>98.11</td>
</tr>
<tr>
<td>crop/pasture</td>
<td>crop/pasture</td>
<td>2</td>
<td>15</td>
<td>0</td>
<td>36</td>
<td>1495</td>
<td>0</td>
<td>96.58</td>
</tr>
<tr>
<td>water</td>
<td>water</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>53</td>
<td>96</td>
<td>60.38</td>
</tr>
</tbody>
</table>
Classification accuracies calculated over the validation sites are shown in Tables 6 to 9. The percentage of accurately classified sites for each class is shown in the final row of the tables. This value represents the proportion of each true class that was classified correctly.

### Table 4 1993 resubstitution accuracies

<table>
<thead>
<tr>
<th>Reference Label</th>
<th>Image Label</th>
<th>salt</th>
<th>mixed</th>
<th>bare soil</th>
<th>bush</th>
<th>crop / pasture</th>
<th>water</th>
<th>% accurate</th>
</tr>
</thead>
<tbody>
<tr>
<td>salt</td>
<td></td>
<td>1084</td>
<td>41</td>
<td>11</td>
<td>5</td>
<td>35</td>
<td>0</td>
<td>92.18</td>
</tr>
<tr>
<td>mixed</td>
<td></td>
<td>53</td>
<td>820</td>
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<td>0</td>
<td>32</td>
<td>0</td>
<td>88.27</td>
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<tr>
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<td>79</td>
<td>619</td>
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<td>0</td>
<td>88.43</td>
</tr>
<tr>
<td>bush</td>
<td></td>
<td>14</td>
<td>0</td>
<td>64</td>
<td>1058</td>
<td>0</td>
<td>0</td>
<td>93.13</td>
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<tr>
<td>salt/pasture</td>
<td></td>
<td>8</td>
<td>10</td>
<td>0</td>
<td>120</td>
<td>1757</td>
<td>0</td>
<td>92.72</td>
</tr>
<tr>
<td>water</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>72</td>
<td>96</td>
<td>57.14</td>
</tr>
</tbody>
</table>

### Table 5 1994 resubstitution accuracies

<table>
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<th>Reference Label</th>
<th>Image Label</th>
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<th>mixed</th>
<th>bare soil</th>
<th>bush</th>
<th>crop / pasture</th>
<th>water</th>
<th>% accurate</th>
</tr>
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<tbody>
<tr>
<td>salt</td>
<td></td>
<td>826</td>
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<td>0</td>
<td>44</td>
<td>123</td>
<td>0</td>
<td>73.95</td>
</tr>
<tr>
<td>mixed</td>
<td></td>
<td>72</td>
<td>1621</td>
<td>6</td>
<td>0</td>
<td>53</td>
<td>0</td>
<td>92.52</td>
</tr>
<tr>
<td>bare soil</td>
<td></td>
<td>0</td>
<td>79</td>
<td>300</td>
<td>0</td>
<td>13</td>
<td>0</td>
<td>76.53</td>
</tr>
<tr>
<td>bush</td>
<td></td>
<td>18</td>
<td>5</td>
<td>58</td>
<td>1103</td>
<td>0</td>
<td>0</td>
<td>93.16</td>
</tr>
<tr>
<td>crop/pasture</td>
<td></td>
<td>2</td>
<td>23</td>
<td>4</td>
<td>121</td>
<td>1048</td>
<td>0</td>
<td>87.48</td>
</tr>
<tr>
<td>water</td>
<td></td>
<td>6</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>63</td>
<td>90</td>
<td>56.25</td>
</tr>
</tbody>
</table>

Each of the Landsat image classifications showed large errors of omission (35-50%) and errors of commission (26-35%) when mapping salinity. That is, 35-50% of the saline validation sites were mapped as non-saline and 26-35% of the non-saline sites were mapped as saline.
Examination of the classifications at the saline ground sites showed that none of the sites was entirely incorrectly classified - only pixels within the sites and on the edges of the saline sites were erroneously labelled as other than salt.

### 2.4.3 Salinity maps produced using conditional probability networks

Errors of omission and commission are high for the individual-year classifications. The use of several dates of imagery enables land that is bare because of seasonal management factors to be discriminated from land that is bare because of rising salinity. Errors can be further reduced by combining the multiple dates of imagery with landform information.

The method used to combine the land condition data from two seasons and landform is a conditional probability network. In its simplest form, this can be thought of as a series of rules that decide how to combine the classification maps with landform. For example, one rule might be \textit{if cover in year 1 is salt and cover in year 2 is salt and landform is local or broad valley, then condition at time 1 is salt-affected}. This very simple formulation, however, ignores some important sources of information.

One source of information is the probability of class membership. The classification procedure applied to the image data in each year calculates probabilities of belonging to a number of cover classes. The label assigned to each site is the cover class for which it has the highest probability. Consider two sites, both labelled as salt-affected by the classification, but the first has a probability of being salt-affected of 0.95 and a probability of being in poor condition of 0.05 and the second has a probability of being salt-affected of 0.6, a probability of being in poor condition of 0.3 and a probability of being in good condition of 0.1. We might have more confidence that the first site is salt-affected than the second and want to incorporate this into our rules. Our confidence in the label is incorporated into the network model by using the probabilities instead of the label.

A second source of information that is ignored is the accuracy of the classification. Ground reference sites can give an indication of the accuracy of the individual classifications. If it is found that the salt class correctly identifies salt-affected sites 80% of the time and misses 15% of all salt-affected sites, we want to modify our rules to reflect this. This is done by expressing the rules themselves as probabilities. For example, the new rule might \textit{be if label equals salt, then the cover is salt with probability 0.8}.

The final two sources of information that are ignored in the simple example above relate to terrain information. The first relates to the likely occurrence of salt on hilltops or slopes. Although poor-
condition land in these parts of the landscape are more likely to be caused by erosion, hillside seeps are an indication that while the probability of salinity is low, it is not zero. The rules are expressed in terms of the probabilities of the occurrence of salt-affected land on each landform unit. The landform units themselves are also subject to uncertainty. The units are derived from a digital elevation model calculated by gridding contour data. If the contours are widely spaced in the horizontal direction, the edges of valleys cannot be accurately defined. A site labelled as being in a valley may actually be on the slope at the edge of the valley. Instead of using a landform label, a landform probability is used.

The conditional probability network provides the framework for combining these probabilities. The same model is used to combine salinity probabilities from two-season time intervals.

The form of the networks used is shown in Figure 3. Input attributes are represented by boxes; nodes 5 to 8 represent the classified images and node 0 represents the landform type. The influence on any pixel of the labels of neighbouring pixels is represented by nodes 9 to 12; the effects are included in an iterative manner similar to the methods used in section 3. Output salinity maps are produced at nodes 1 to 4.

The probability tables were initialised using the error estimates from the neighbourhood-modified maximum likelihood classifications and best judgements of the probabilities of different cover types occurring in each landform type. Two areas were used to determine the final probabilities for the CPNs: the Broomehill study area and the Ryan’s Brook study area. Maps were produced for the two validation areas, and error estimates were calculated for salt and not salt classes. The error estimates and visual assessment of the salinity maps were used to refine the probability tables. This process was repeated through several iterations. The accuracies achieved are shown in Tables 10 and 11.
The Ryan’s Brook accuracies show a marked improvement on the results achieved using maximum likelihood techniques. Errors of omission have been reduced to between 19-22% and errors of commission have been reduced to 7-9%. Figure 4 shows the salinity maps produced using the CPN. Marked improvements can be seen over the previous maps. In particular:

- mapped saline areas are constrained to valleys and depressions thus eliminating noise in the form of saline patches mapped on slopes and hilltops; and
- salinity is mapped consistently through time - there are no significant changes in the areas mapped as saline within any single-year time interval.

![Maps of salinity](image)

Figure 4 Salinity maps produced using the CPN
2.5  Predicting salinity using decision trees

Predicting areas at risk from salinity is important for land management, since it allows resources to be allocated to those areas in the most need of assistance. Making predictions is very difficult; at present, reliable predictions can only be made using small-scale data-intensive process-based models or by hydrologists with extensive experience and local knowledge. This section develops a simple model for predicting salinity risk using ground truth data provided by several experienced hydrologists.

The aims of this process are to:

1. develop a cost-effective method for predicting salinity risk over broad areas;
2. produce a simple model which can be easily understood and used to help understand the processes underlying salinity risk; and
3. determine whether simple rules can be developed for assessing salinity risk.

The salinity maps produced using the conditional probability network are used to derive a map showing the distance to known salinity, which is used with DEM-derived landform data for making predictions about future salinity risk. A decision tree classifier is used to predict salinity risk since it provides a means for exploratory data analysis and an understanding of the relationships between the input attributes and salinity risk. Salinity predictions have been produced using the decision tree classifier c4.5

2.5.1 Attribute selection

The following sets of input attributes were assessed using the default parameter options

1. distance to mapped saline areas, water accumulation and downhill slope;
2. distance to mapped saline areas, water accumulation, downhill slope and Landsat TM band 4 (September 1993); and
3. distance to mapped saline areas, water accumulation, downhill slope and Landsat TM bands 2, 4, 5 and 7 (September 1993).

The landform attributes are identical to those used for mapping salinity. In addition, information provided by the salinity mapping is used by including the attribute distance to known salinity. The Landsat data are used to provide information about cover density for the last available date.

* The September 1993 image was chosen in preference to the August 1994 image because of its larger spectral range (the 1994 image was taken early in the growing season when crop growth was less developed).
Table 12  Accuracies for salinity risk prediction

<table>
<thead>
<tr>
<th>attribute set</th>
<th>not salt accuracy</th>
<th>salt accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7640</td>
<td>0.7722</td>
</tr>
<tr>
<td>2</td>
<td>0.8308</td>
<td>0.7399</td>
</tr>
<tr>
<td>3</td>
<td>0.8638</td>
<td>0.6869</td>
</tr>
</tbody>
</table>

Table 12 shows that the highest accuracies are achieved using the second set of input attributes (according to the kappa Value). For this reason, decision trees have been produced using the second set of attributes. Since the aim of this chapter is to produce a model that can be interpreted to give some insight into the process of salinisation, this attribute set is also preferable since it is smaller than the third attribute set.

### 2.5.2 Decision trees for predicting salinity risk

A requirement for predicting salinity risk is that the classifiers be simple and generalisable. Hence, the decision trees have been fitted with maximal pruning and with larger numbers of training sites required to be classified at each leaf of the tree. The results are shown in Table 13. Figure 5 shows the ground truth-data for a part of the Broomehill study area, and the predicted salinity maps produced using these decision trees.

Table 13  Accuracies for different parameter settings

<table>
<thead>
<tr>
<th>options</th>
<th>not salt accuracy</th>
<th>salt accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>-c1 -m200</td>
<td>0.8539</td>
<td>0.7243</td>
</tr>
<tr>
<td>-c1 -m100</td>
<td>0.8547</td>
<td>0.7224</td>
</tr>
<tr>
<td>-c1 -m50</td>
<td>0.8512</td>
<td>0.7398</td>
</tr>
<tr>
<td>-c1 -m20</td>
<td>0.8520</td>
<td>0.7363</td>
</tr>
<tr>
<td>-c5 -m200</td>
<td>0.8497</td>
<td>0.7323</td>
</tr>
<tr>
<td>-c5 -m100</td>
<td>0.8512</td>
<td>0.7287</td>
</tr>
<tr>
<td>-c5 -m50</td>
<td>0.8471</td>
<td>0.7462</td>
</tr>
<tr>
<td>-c5 -m20</td>
<td>0.8477</td>
<td>0.7462</td>
</tr>
<tr>
<td>-c10 -m200</td>
<td>0.8444</td>
<td>0.7297</td>
</tr>
<tr>
<td>-c10 -m100</td>
<td>0.8507</td>
<td>0.7308</td>
</tr>
<tr>
<td>-c10 -m50</td>
<td>0.8435</td>
<td>0.7487</td>
</tr>
<tr>
<td>-c10 -m20</td>
<td>0.8421</td>
<td>0.7491</td>
</tr>
</tbody>
</table>

Since the accuracy over non-saline areas is low, it can be seen that each of the decision trees is over-estimating the areas at risk from salinity. The final map, Figure 5 (iv), was produced using option -m200, so that each leaf of the decision trees must classify at least 200 of the training sites. This has had the effect of smoothing the output classification map and removing some of the noise seen in the earlier two maps.
2.5.3 A simple decision tree for predicting salinity risk

The simplest decision tree in the previous section did not prove to be the most accurate. However, a simple model for salinity risk is preferable when trying to form an understanding of the concepts underlying salinity risk.

Figure 6 shows the salinity prediction produced using the simplest, maximally pruned decision tree (options -c1 -m200) which corresponds to the area shown in Figure 5.
The prediction map in Figure 6 can be compared to those produced using less-pruned decision tree which are shown in Figure 5. The smoothing effects noted in Figure 5 (iv) are further pronounced in the above map. Despite the lower accuracy, this map looks very similar to Figure 5 (iv), suggesting that the simpler decision tree is more generalisable.

The decision tree used to produce this classification of salinity risk areas is shown in Figure 8. Paths through the tree can be examined to assess whether they correspond with current opinions about salinity risk. For instance, one path might be:

flow $> 69 \rightarrow$ tm4 $> 107 \rightarrow$ dist $\leq 14 \rightarrow$ tm4 $\leq 115 \Rightarrow$ salinity risk.

This can be interpreted in the following way:

IF the water accumulation is moderately high (flow $> 69$), implying that the site is located in a valley system

AND IF the value of Landsat band 4 is high (tm4 $> 107$), implying that there is good vegetative cover at the site

AND IF the site is within 14 pixels (350m) of a known saline site (dist $\leq 14$)

AND IF the value of Landsat band 4 is not extremely high (tm4 $\leq 115$), implying less than dense vegetative cover

THEN there is a risk of future salinity.

This path obviously makes sense when considering salinity risk assessment. In effect, it is saying that sites located within valleys, close to known saline areas and with poor vegetative cover are likely to be at risk from salinity.

* Here and in Figure 7, flow = water accumulation, tm4 = September 1993 Landsat TM band 4 and dist = distance to known salinity.
It is possible to examine each path through the decision tree in such a manner. However, the following section uses derives rules for predicting salinity from the decision tree, using an algorithm available with the c4.5 decision tree software.

![Simple decision tree for predicting risk](image)

**Figure 7** Simple decision tree for predicting risk

### 2.5.4 Simple rules for predicting salinity risk

The decision tree shown in Figure 7 has been converted into rules for predicting salinity, using the c4.5 rules program (Quinlan, 1992). These rules can be converted into easily understood language to aid their interpretation, and summarised into seven simple rules for predicting salinity risk:

**Rule 1:** If the site is greater than 125m from known salinity, and on a hilltop, upper or lower slope with low to high vegetative cover (>15%), then there is no risk.

**Rule 2:** If the site is on a hilltop or upper slope and there is moderate to high vegetative cover (>50%), then there is no risk.

**Rule 3:** If the site is in a valley floor, with a catchment area greater than 4.5 ha, then there is a risk of future salinisation.

**Rule 4:** If there is very little (≤15%) vegetative cover, then there is a risk of salinisation.

**Rule 5:** If the site is within 250m of a known saline site, is not on a hilltop and has low to moderate (≤25%) vegetative cover, then there is a risk of salinisation.
Rule 6: If the site is within 200m of a known saline site and is in a valley, then there is a risk of salinisation.

Rule 7: If the site is within 100m of a known saline site and has low vegetative cover (\(\leq 38\%\)), then there is a risk of salinisation.

Rule 8: Otherwise, there is no risk.

2.6 Conclusions

This section has described the methods used to produce maps showing changes in salinity, and maps showing areas at risk from salinity for the Upper Blackwood and Frankland-Gordon catchments. A conditional probability network has been used combine individual-year landcover classifications with landform to produce salinity maps that are consistent through time. Using this method, prior knowledge about the relationships between the input attributes and their relationship with salinity can be used to improve the accuracy of the salinity maps.

This section has also shown that the decision tree classifier can be used to produce maps of salinity risk areas with an accuracy of 73% over risk areas and 84% over non-risk areas. In addition, the decision tree can be pruned, to produce a simple model for assessing salinity risk, without reducing the accuracy of the classifier by more than 2.5% for either class.

Rules for assessing salinity risk are derived from the decision tree. The decision tree, and derived rules, could be refined using additional hydrogeological information concerning the rate of watertable rise, location of underground hydrological structures, on-site management and other factors. These kinds of information require more detailed mapping than can be cost-effectively provided using broad-scale data like Landsat TM imagery and digital elevation models, and have been excluded from this work for these reasons. However, with additional information of these kinds, it might be possible to produce predictions of salinity risk, using decision tree classifiers, which can be time-stamped so that areas can be labelled according to when they are likely to become saline, given current on-ground conditions.

The risk assessment rules are simple and could be easily applied in the field by field officers and property owners with little background knowledge of the process of salinisation. It must be noted, however, that the simplicity of the rules means that on-site evaluation must be taken further than this simple step of determining whether an area is at risk of salinisation or not. If risk is determined using these rules, local knowledge about the site and its history will be required to further evaluate: (a) why the area is at risk; (b) when the risk may be realised; and (c) which management options could help alleviate the causes of risk.

The conditional probability network has been used to produce salinity maps for the upper Blackwood and Frankland-Gordon catchments. These maps have been distributed to catchment groups and Agriculture WA technical officers for use in management planning and for continuing on-ground validation. The decision tree classifier has been used to map areas at risk from salinity in the upper Blackwood and Frankland-Gordon catchments. The results will be validated on the ground by the Agriculture WA Catchment Hydrology Group.
3 Monitoring remnant vegetation

3.1 Introduction

The condition of remnant vegetation is increasingly recognised as a factor affecting land degradation and salinity risk. Effective assessment, planning and management of remnant vegetation depends on a sound knowledge of the distribution and condition of vegetation types at local and regional scales, and a capacity to detect changes over time.

Landsat TM satellite data have been shown to be useful for mapping remnant vegetation and changes in the condition of remnants through time (Wallace and Furby, 1995). As a part of this project, similar methods are applied in the Upper Blackwood and Frankland-Gordon catchments. In addition, a study is conducted in the Dongolocking area, which aims to determine whether species type and composition can be identified using Landsat imagery.

3.2 Mapping remnant vegetation

Maps showing vegetation, clearing and re-vegetation and maps showing vegetation condition indices have been prepared. The condition index maps have been distributed to the Blackwood Catchment Coordinating Group for validation. Further work will be completed as part of the Land Monitor project.

A portion of the map showing vegetation status for 1990-1996 is shown in Figure 8. In this map, green areas show remnant vegetation in 1996, red areas show clearing between 1990 and 1996, and blue areas show revegetation that has occurred during the same period.

![Figure 8 Remnant vegetation status map - 1990 to 1996](image)

3.3 Dongolocking case study - mapping species composition

A case study on mapping vegetation type, condition, and changes in condition through time is being performed in the Dongolocking Reserve area. The study forms part of a collaborative venture with the CSIRO Division of Wildlife and Ecology which provided ground data and is currently validating the results to date, and producing a ground-based species classification. This section describes the methodology used to map vegetation composition in the Dongolocking reserves, and to monitor the condition of the remnant vegetation through time using remotely sensed data.
The results of this study will be used as part of the *lighthouse project* “Planning Remnant Vegetation, Dongolocking Area”, which is a joint project involving the WA Department of Conservation and Land Management, Agriculture Western Australia, CSIRO and the community. The project aims to develop case studies for a regional management strategy.

### 3.3.1 The data

A sequence of summer Landsat TM images have been assembled for the Blackwood and Frankland-Gordon catchments. The entire study area crosses the boundary of two Landsat TM scenes (Dumbleyung and Mt Barker). However, the Dongolocking reserves are fully located within the Dumbleyung scene. The dates of imagery used for this study are:

- April 1990
- January 1994
- February 1996

The images have been rectified to AMG coordinates at 25m pixel resolution and been calibrated to *like values*.

Ground truth data for species composition were provided by CALM in the form of hand-drawn maps of remnants in the reserve, which show boundaries between vegetation types. The maps covered the reserves numbered 19089 and 19090 (Region 1). A further map (Region 2) was available in the report “Biological Survey of the Western Australian Wheatbelt. Part 5: Dongolocking Nature Reserve”, published in 1978. The maps were scanned in several parts, rectified to AMG coordinates, and mosaiced to form complete maps. The mosaiced composition maps for region 1 are shown in Figure 9.

![Figure 9 Mosaiced composition maps](image-url)
Stereoscopic aerial photographs were obtained from the Department of Land Administration. Photographs for the regions of interest were scanned and digitised.

### 3.3.2 Mapping species composition

Figures 10 and 11 show the mosaiced aerial photograph for Region 1, and a corresponding Landsat image for February 1996. These images both show differences in vegetation density and composition.

The February 1996 image was used to map species composition. Classification of the image into species type involved the following steps:

1. production of a remnant vegetation mask so that areas not of interest could be excluded from the analyses;
2. selection of training sites for each composition type;
3. examination of the spectral separability of the training sites using canonical variate analyses;
4. classification of the image using neighbour-modified maximum likelihood classification; and
5. accuracy assessment and field validation of the classification maps.

![Figure 10 1996 air-photo mosaic](image-url)
3.3.3 Selection of training sites

The scanned and rectified composition maps were used to select training sites for the major species types. Detailed descriptions for each site were recorded with the same level of detail provided by the maps. The species types were aggregated into the following classes: woodland, mallee, shrubland, heath and forest. The sites were selected so that each site was totally contained within boundaries specified on the composition map. The February 1996 Landsat TM image was used to guide the selection of sites; so that sites were selected so that they corresponded to the different colours in the image. If a region marked on the composition map showed more than one image colour, then sites were chosen from each colour in the region.

The aerial photographs were also used to guide the selection of training sites. This was required because of the age of the composition maps, and the manner in which they were produced. Some changes may have occurred since the maps were created. The possibility of human error in transcribing the maps is also likely.

Training sites numbering 105 were chosen from the reserves 19089 and 19090 (Regions 1). The Dongolocking reserve (Region 2) was retained as an independent area for validating the results of the classification, and for determining whether the spectral signatures appropriate for classifying the reserves 19089 and 19090 could be applied to the Dongolocking reserve.

3.3.4 Canonical variate analyses

Canonical variate analyses were conducted to examine whether the image data for different species types are sufficiently different for the types to be differentiated in the image.
Preliminary analyses examined whether the broader classes (woodland, mallee, shrubland, heath and forest) could be separated. Dark forest targets show some degree of separation. Similarly, some barer, bright woodland targets can also be separated. However, there is otherwise a large amount of overlap between the classes. This can be seen in the canonical variate plot, shown in Figure 12.

![CVA plot](image)

Figure 12  CVA plot: black=woodland, red=mallee, green=shrubland, blue=heath, yellow=forest

Each site was carefully examined to determine whether separable classes based on the vegetation structure or density could be created. The classes still proved to be inseparable.

### 3.3.5 The classification maps

The canonical variate analyses showed that the training sites were spectrally inseparable. This means that a classification into species type could not be performed. However, visual analysis of the Landsat images shows homogeneously-coloured regions that correspond with the regions shown in the composition maps (compare Figures 9 and 11). To use this information, the CV-space was divided into regions that correspond roughly to the colours in the enhanced image. A neighbourhood-modified first-pass classification was produced for regions 1, 2 and 3. Figure 13 shows the classification map.
Figure 13  14-class classification map of the reserves 19089 and 19090

Examination of the classification maps against the species composition maps shows broad correspondences. However, despite reasonable mapping of species boundaries, the image classification can not accurately map the species type within the boundaries since they are not spectrally separable (as shown in the canonical variate plot in figure 12).

The 14 classes were aggregated to form four broad classes. These are shown in Figure 14 (overleaf).
3.3.6 Results in the Dongolocking Reserve

The same procedure was used to map broad classes in the Dongolocking Reserve. The results are shown in Figures 15 and 16 (overleaf).

3.3.7 Accuracy assessment and field validation

The 14-class classification map and 4-class map will be ground-truthed by CSIRO Wildlife and Ecology. This ground validation aims to:

- determine which vegetation classes are required to complete the regional management strategy - these may be different to the composition classes outline in the CALM maps;
- ground-truth the CALM maps; and
- validate the classification maps derived from the satellite imagery.

The results will determine whether further analysis of the satellite imagery is required. Further collaborative work has been proposed.
3.4 Conclusions

This section has discussed the application of methodologies developed for vegetation monitoring to the upper Blackwood and Frankland-Gordon catchments. In addition, the use of Landsat imagery for identifying species composition is investigated in the Dongolocking reserve area. The results of this study have identified the need for accurate ground data, which will be provided by CSIRO Wildlife and Ecology.

Further work on mapping change in vegetation condition will be completed as part of the Land Monitor project.
4 Farm-scale mapping

4.1 Introduction

One of the objectives of this project was to transfer the results of the project to farmers, catchment groups, project officers and landcare technicians. This has been achieved by providing detailed information products (in the form of specifically enhanced images and classification maps) to selected groups of farmers, and working with them to evaluate and modify the products.

4.2 Farm-scale maps

Nineteen property-owners were selected from numerous volunteers: a group of eleven farmers from the western part of the study area and eight farmers from the eastern part of the study area were involved. The farmers have been provided with:

- enhanced image products showing the farm boundaries;
- maps showing changes in salinity and predicted risk areas; and
- maps showing waterlogging for two years (1990 and 1993).

Wind erosion maps were not produced, as most farmers reported that this was not a problem on their properties. Example maps are given in Figures 17 to 19.

![Enhanced image showing the property boundary](image_url)

Figure 17 Enhanced image showing the property boundary
4.3 Field visits

To obtain feedback on the accuracy and usefulness of the maps, and to create awareness of their availability, most farmers in the western group were visited individually in February 1998, and a workshop was held for the eastern group of farmers shortly after.

Farmers reported that overall the maps were accurate and confirmed their understanding of their properties and future risk areas. The small proportion of errors in the salinity maps included some incorrect mapping of dams, remnant vegetation, sandy and gravelly soils, waterlogging and bare ground as salt. Most errors can be understood by considering the method used to map salinity, since areas in valley floors with consistently poor productivity are assumed to be salt-affected. There were also a
small number of salt-affected areas that were not mapped as salt. These tended to be mapped as risk areas, but not in all cases.

The waterlogging maps accurately showed areas that experienced poor productivity in either of the two years that were mapped. However, they mapped all areas of low productivity including salt-affected areas, remnant vegetation, sandy and gravelly soils, rock outcrops and dams. Many of the errors could be easily fixed by overlaying the salinity and remnant vegetation maps.

Overall, farmers were supportive of the project and the information provided to them. They see the maps as useful tools for monitoring the effects of on-ground changes with respect to the types of problems they are aiming to alleviate. The farmers know their properties very well; whilst the maps are not showing them anything new, they do aid the decision-making process by supporting their judgements. Younger farmers believe that the maps will be particularly useful for those new to the land, or for those farming new properties. In many cases, they can be used to change perceptions about salinity change and salinity risk by identifying areas previously believed to be stable.

Several farmers expressed enthusiasm for being able to view their farms and paddocks in three-dimensional maps. In addition, it was widely felt that the maps will be useful for promoting decision-making at catchment scale because they provide a bird's eye view that shows how land condition on each property is affected by its neighbours.

4.4 Yield mapping

Paddock yield data were only available from six farmers; totalling twenty paddocks. Of the twenty paddocks, ten were planted to barley, six to oats and four to wheat. An attempt was made to relate yields to the mean Landsat TM band 4 response of the paddocks. The fitted regressions showed that the prediction of yields is not possible given the small size of this data set.

If further data were available, and if different fits were produced for each crop type, these analyses should perform better. This conclusion is supported by the work of the Department of Land Administration’s Satellite Remote Sensing Services.

4.5 Conclusions

This section has described the results of farm-scale mapping across nineteen properties in the upper Blackwood catchment. The aim of this study was to provide information to farmers about the availability and use of satellite imagery for farm management, and to evaluate the use of a suite of products at farm-scale.

The results showed that maps can be produced sufficient accuracy for farm use, and that farmers are enthusiastic about their use at both farm and catchment scales.
5 References


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