Natural Resources and Water
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Development and application of remote sensing techniques for detecting and mapping a land management practice: contour banks

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EXECUTIVE SUMMARY

Land management practices have significant impacts on the condition of Australia's land, water and biodiversity resources and the profitability and sustainability of agriculture. Identifying patterns in the adoption of land management practices, and changes in practices over time can assist in monitoring and measuring natural resource condition and trend, and progress towards agricultural sustainability.

In this study we have investigated and developed semi-automated remote sensing classification techniques for a specific land management practice: contour banks. The semi-automated method applies image enhancement, segmentation and object-oriented classification technology to high-resolution satellite imagery (SPOT 5). Three classification methods were trialled on a subset of imagery from the Condamine catchment to separate contour bank features from other landscape features on the basis of shape characteristics: an unsupervised *k*-means classification; a hybrid decision tree/expert system classification; and, an ensemble learning (multiple classification tree) approach. Mapping results suggest that the decision tree and classification tree methods outperform the unsupervised method. Furthermore, the ensemble learning method performed better than the hybrid decision tree/expert system. An advantage of the decision tree and classification tree approaches is that they can be automated for wider application across regions and through time. However, whilst the semi-automated techniques captured many of the contour banks, supplementary manual mapping was required to ensure a complete and accurate coverage of contour banks in cropping areas in Queensland.

Despite some limitations, image segmentation and object-oriented classification has great potential for mapping of land management practices and natural resources, particularly as remotely sensed imagery becomes more affordable and is more readily available. Other land management practices which can potentially be mapped through this approach include strip cropping and controlled traffic farming.

1. INTRODUCTION

Land management practices have significant impacts on the condition of Australia's land, water and biodiversity resources and the profitability and sustainability of agriculture. There is also a strong linkage between changing patterns of land management practice and economic and social conditions in regional Australia. Improved land management practices have been identified by the National Land and Water Resources Audit as a major way forward for Australian agriculture to enhance on-farm productivity and off-farm natural resource benefits.

Identifying patterns in the adoption of land management practices, and changes in practices over time can assist in monitoring and measuring natural resource condition and trend and progress towards agricultural sustainability. Generally, the available information on agricultural land management practices is insufficient for the above described purposes. Remotely sensed information can provide a range of indicators and products that can be utilized to identify patterns in land management practices and therefore assist monitoring and inventory of the condition and extent of natural resources.

The purpose of this project is to use remotely sensed imagery to map selected land and crop management practices in Queensland, in particular contour banks. Spatial information on contour banks will improve soil erosion estimates and consequently water quality models which predict the quantity of sediments transported into our waterways. The information and techniques developed by this project will also provide a valuable baseline for future monitoring and further development of mapping techniques for other land management practices and natural resource applications.

This project is very timely, as substantial investments have recently been made in Australia in the capture of high-resolution satellite imagery. The primary driver for this purchase in Queensland is property planning with the majority of funding provided by regional NRM groups. This high resolution imagery offers considerable potential for monitoring natural resource condition through direct measurements of specific indicators, such as vegetation crown cover or water body extent and inundation frequency, or indirectly by detecting and mapping changes in land use and management. However, this potential will not be realised without investing in the development of appropriate methods for mapping and monitoring.

Many land management practices, including contour banks and controlled traffic farming (CTF), do not have spectral reflectance characteristics that allow them to be readily classified using traditional pixel-based classification methods. They vary greatly in their reflectance values both within scenes and between scenes. However, many land practices have other characteristics that make them distinct from other landscape features. These include spatial features such as size, shape, texture and relationships to surrounding features. Object-based classification enables greater utilisation of spectrally and spatially homogeneous regions within an image. Objects are defined as basic entities located within an image, where each pixel group is composed of similar digital values, and possesses an intrinsic size, shape, and geographic relationship with the real-world scene component it models (Hay et al., 2001).

In this project, we used the Definiens® Professional version 5 and Definiens® Developer version 7 software suites to create image-object sets (segmentations) that include features that approximate the specific spectral and spatial properties of contour banks. We then applied and evaluated three different classification techniques to separate the contours from surrounding landscape feature objects.

2. STUDY AREA

Contour banks occur in most of the major arable river catchments in Queensland (Fig. 1). These include the Condamine-Balonne, Moonie, and Border Rivers catchments of the Murray-Darling Basin drainage division, and the Fitzroy, Burdekin, Burnett, Barron, O'Connell and Pioneer catchments of the North-East Coast drainage division. Primary land uses in these catchments include production from natural environments (e.g. grazing) (88%), production from dryland agriculture (e.g. cropping) (6%) and nature conservation (4%) (Witte et al., 2006).

3. METHODS

3.1. Data

SPOT 5 was acquired by the NRM Regional Bodies for the major cropping areas of Queensland. The imagery was acquired for property planning and natural resource management activities in Queensland for single image dates during 2004, 2005 and 2006. The extent of the imagery is shown in Fig. 1. The SPOT 5 data were acquired orthorectified as three separate products: 10-m resolution multispectral 3 band (green, red, near infrared) or 4 band (green, red, near infrared, shortwave infrared); 2.5-m resolution greyscale panchromatic; 2.5-m resolution pan-sharpened multispectral 3 band (green, red, near infrared). Some issues exist with this imagery for remote sensing applications: the imagery has been georectified by inconsistent methods and none of the imagery has been radiometrically or atmospherically corrected. As a result comparisons between images and across regions and over time can be difficult.

Other supporting data available for this project includes *Soil Conservation Act 1996* notings and registered plans. The notings are a point location indicating that a soil conservation plan exists for a property or group of properties. Fig. 1 shows the density of notings in the catchments of Queensland. It provides an indication of where most contour banks occur in Queensland. Registered soil conservation plans are schematic diagrams of the layout of soil and land management works on a property or group of properties. They were originally created in hardcopy form but most have since been scanned to digital format (jpeg image).

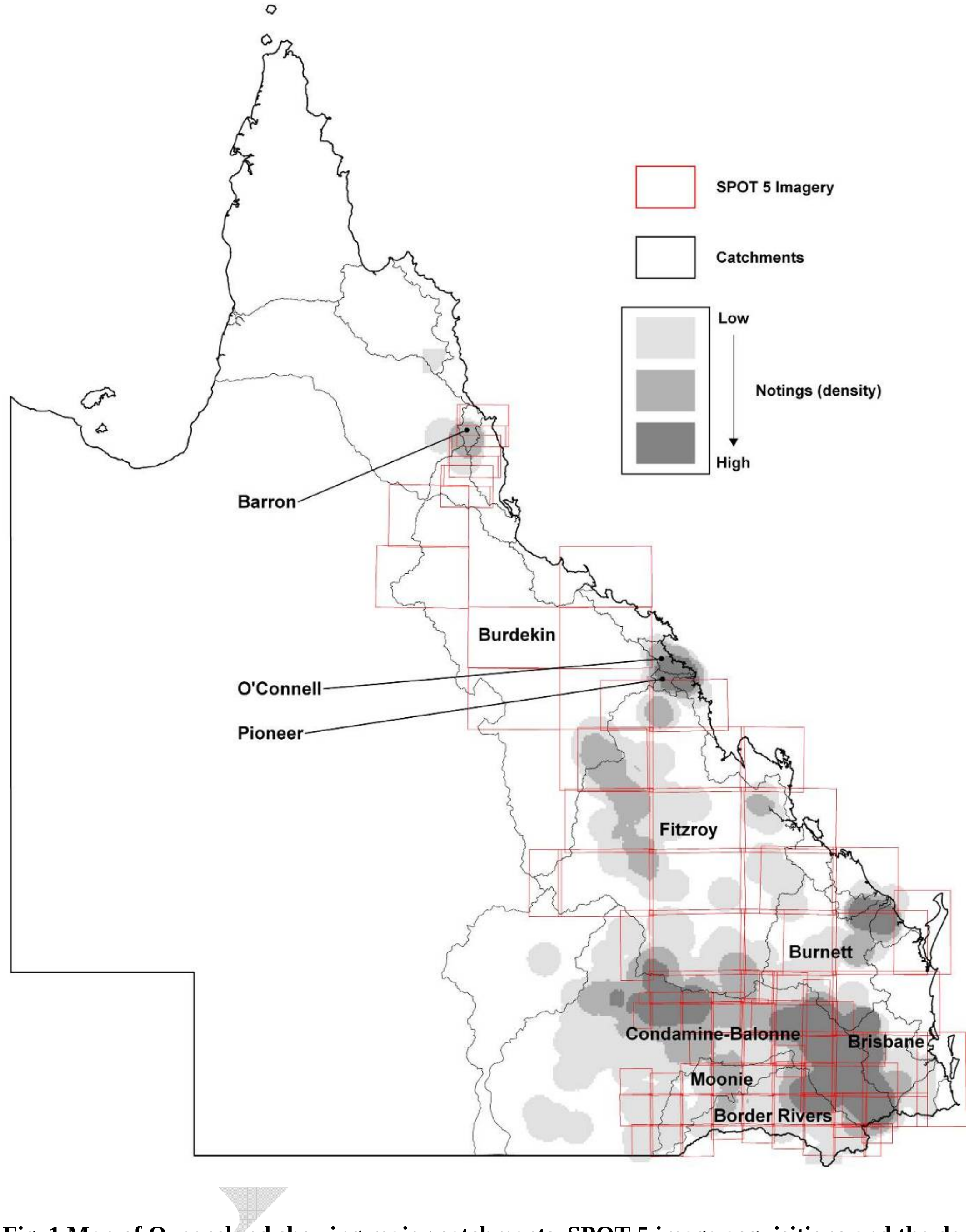


Fig. 1 Map of Queensland showing major catchments, SPOT 5 image acquisitions and the density of *Soil Conservation Act 1996* registered plan notings that indicate cropping areas of Queensland with contour banks.

3.2. Manual mapping of contour banks and CTF

Pan-sharpened 2.5-m colour SPOT 5 imagery provides sufficient resolution for visual interpretation of most contour banks and CTF practices. The additional spectral information obtained by merging the multispectral bands from the 10-m product with the 2.5-m resolution of the panchromatic product allows true colour images to be displayed in a Geographic Information System (GIS) at high resolution.

Contour banks and the approximate boundary of the land parcel (paddock) they occur in were interpreted from the pan-sharpened 2.5-m colour SPOT 5 imagery and digitised as line vector features in ArcGIS®. Ancillary information including aerial photography, survey notings and Soil Conservation Plans were used as supplementary data to assist interpretation. Metric classes relating to the approximate width of the bank, the data source and confidence in the location and interpretation of the bank were recorded (Table 1).

Table 1 Values and attributes for manual mapping

Value	Confidence	Source	Width (m)
1	High	Imagery	0-10
2	Medium	Registered plan/noting	10-20
3	Low	Other	>20

The line features delineating the land parcels containing contour banks were converted to polygon features. This enabled the area of land subject to contour bank cultivation practices, and other summary statistics, to be calculated for the catchments in which they occur. As the project nears completion, they will also provide a reference to test the efficacy of the semi-automated object-based techniques for mapping contour bank paddock boundaries.

3.3. Semi-automated object-based mapping of contour banks and CTF

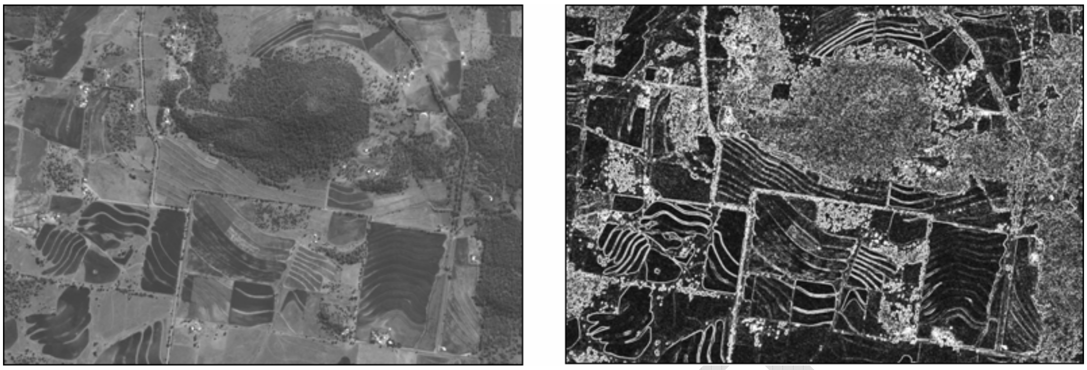
3.3.1. Imagery

Due to the limitations of the multispectral SPOT 5 data currently available (refer section 3.1) and following preliminary trials of the available SPOT 5 products for object-based analysis, the SPOT 5 2.5-m resolution panchromatic product was selected for use in this project. This was chosen over the pan-sharpened product as the primary focus for classification was spatial (e.g. size, shape) rather than spectral properties. Furthermore, pan-sharpening algorithms leave a 'halo' around image-objects as a result of non-linear mixing in the coarser resolution multispectral imagery (Definiens 2007a). This can adversely affect image segmentations by the creation of objects that represent 'halo'-affected areas, increasing the number uninformative objects, and significantly increasing processing time. Initial trial segmentations using both the panchromatic and pan-sharpened imagery showed that the additional spectral information contained in the pan-sharpened imagery did not yield objects that were more homogeneous or informative for the purpose of contour bank delineation. The SPOT 5 10-m resolution multispectral product was not considered for use as the resolution was not adequate for segmentation of objects that delineate contour banks that can be constructed with bank widths smaller than the resolution of the data.

3.3.2. Image pre-processing

3.3.2.1. Edge enhancement

An edge enhancement technique was applied to the SPOT 5 panchromatic image to minimise spatial and spectral heterogeneity of objects in the image domain. This results in a minimisation of image region heterogeneity and therefore more defined image-objects result from image segmentation procedures. Edge enhancement aims to highlight areas of contrast in an image by highlighting changes in spatial frequency of the data that correspond to edges (Fig. 2). This can lead to filtering and removal of unnecessary data while preserving the important structural properties in an image. In the SPOT 5 panchromatic imagery, contour banks generally have contrasting spatial properties to the surrounding landscape. Edge enhancement maximises this contrast.



(a) (b)

Fig. 2 (a) SPOT 5 panchromatic image from Condamine catchment showing contour banks; and (b) SPOT 5 panchromatic image with non-directional edge enhancement (Sobel) applied to enhance contour bank features

A non-directional edge detection with the two-dimensional Sobel filter was applied to the SPOT 5 panchromatic image using the Non-directional Edge function in Erdas Imagine® (Leica Geosystems 2005). The resultant non-directional edge enhanced image (the NDE image) was included as an image layer in the segmentation procedures outlined in section 3.3.4.

3.3.2.2. Image dicing

Multiresolution image segmentation algorithms require considerable processing time and computer memory allocation. The greater the minimisation of heterogeneity in the image-object domain (i.e. the smaller the size and greater the number of objects that are required), the greater the processing time and computer system requirements. This can be a major limitation in applying object-based techniques to high resolution imagery over large geographic areas.

To reduce processing time and to maximise the efficiency of the image segmentation procedures, the SPOT 5 panchromatic and NDE images were diced into eight equal parts (based on pixel width) using the Dice Image function in Erdas Imagine®.

3.3.3. Image masks

Cropping areas account for around 2% of the total area of Queensland (Witte et al., 2006). To reduce processing time and to target the cropping areas of interest, two image mask layers were derived: a slope mask and a woody vegetation mask. A third layer, the contour banks paddock polygon layer (refer to section 3.3.3.3), replaced the slope mask and woody vegetation mask in the processing as the manual mapping progressed and the data became available.

3.3.3.1. Slope mask

Contour banks are generally constructed on slopes exceeding 1–1.5% (~1°) (Department of Natural Resources and Water, 2004). A slope mask based on the Digital Elevation Model (SRTM-DEM) (approximate cell resolution 90-m) derived from the NASA Shuttle Radar Topography Mission, was created using a 1° threshold. This conservative threshold was used to ensure all slopes with the potential to have contour banks constructed on them were included in the image segmentation procedures. It was also intended to mask out significant areas of intensive agriculture (e.g. strip cropping, irrigation areas) on the alluvial flats and plains that do not have contour banks due to their small gradients.

A slope image was derived from the SRTM-DEM using the Surface Slope function in Erdas Imagine® with degrees specified as the output units. The slope image was then reclassified to a two-class image as follows:

[<1° = 0; ≥1° = 1].

A majority filter with four orthogonal neighbours and a majority replacement threshold setting was then applied using ArcGIS® to generalise the image and to remove isolated masked pixels within the areas of interest.

3.3.3.2. Woody vegetation mask

Given that contour banks are primarily within cleared, open cropping areas, a woody vegetation mask was created to eliminate wooded areas from the areas of interest.

The woody vegetation mask was derived from the NRW State Land and Tree Study (SLATS) Foliage Projective Cover (FPC) product (Armston et al., 2004) using a 12% FPC threshold. This threshold is equivalent to a basal area of approximately 4.5 which is the lower threshold for open woodlands. The SLATS FPC product is an interpreted/derived product based on Landsat imagery and occasionally misclassifies areas of crops as woody vegetation, particularly at the lower thresholds. As a result some cropping areas were removed from the contour mapping process. However, it is likely that any contour banks occurring in these cropping areas were captured in the final manual editing component of the methodology.

The SLATS FPC product was reclassified to produce a two-class FPC image mask (the FPC image) as follows:

[<12% FPC = 1; ≥12% FPC = 2].

3.3.3.3. Contour bank paddock layer

The contour bank paddocks polygon layer generated in the manual mapping was used as a replacement for the slope mask and woody vegetation mask where the data had been captured and completed. The polygon layer was converted to a two-class raster (image) mask as follows:

[contour bank paddock = 1; not contour bank paddock = 2]

3.3.4. Image segmentation and image-object generalisation

The process tree in Definiens® Professional and Definiens®Developer was used for image segmentation. Multiresolution segmentation with a composition of homogeneity criterion of 0.9 for colour and 0.1 for shape, 0.5 for compactness and smoothness, and a scale parameter of 10 was applied to the pan and NDE image layers with weightings of 1 and 2, respectively. These parameters were chosen following heuristic analysis of various combinations of multiresolution segmentation parameters and following visualisation of the image-objects that best approximated contour bank features. The scale parameter of 10 resulted in a large number of objects and hence processing time, however larger scale parameters did not delineate contour banks in sufficient detail for classification and mapping purposes. The NDE image was weighted greater than the pan image because it was determined that for the purposes of delineating contour banks, the reduced spatial frequencies in the NDE image resulted in more homogeneous image-objects. The image layer masking was applied by inclusion of the slope and FPC images in the multiresolution segmentation process and setting the No Data value for these layers to 0 and 2, respectively. These layers were replaced with the contour bank paddock image mask where it was available at the time of processing and the No Data value set to 2 for this layer.

A second process was added to the process tree to convert image-objects to polygons. This step was required to facilitate the image-object generalisation process and to create skeletons which describe the internal structure of image-objects. The Create Polygons function was used with a base threshold of 1.25 and the Remove Slivers function enabled. A third process was added to the process tree that applied a generalisation (merge) to the image-objects that did not correspond to contour bank features. Contour bank objects resulting from the image segmentation process are generally linear, narrow features. Image-objects were investigated for a general shape-based threshold that could be used in combination with the Merge Region function to merge larger, non-linear, robust objects to reduce processing and assist classification by reducing the number of potentially conflicting objects in the dataset. The Merge Region function was used with a condition setting of Compactness (polygon) feature greater than or equal to 0.25. Compactness is a measure of linearity and width and is defined as the ratio of the area of a polygon to the area of a circle of the same perimeter and is given by the formula (Definiens 2007a).

$$Compactness = \frac{4 \times \pi \times Area}{Perimeter^2}$$

A fourth and final process was added to the process tree to export the image-objects for classification. The Export Vector Layer function was used with No Condition to export a line shapefile of the image-objects (based on the main line of the polygon image-objects). This function allows the user to export an attribute table with the shapefile that includes features and their values for each object. The user can select as many features as they care to. The features can then be used as variables in classification algorithms to classify the objects of interest. Shape-based features were chosen for classification in this project as they are relatively generic and consistent for objects irrespective of the way in which they were originally segmented. In addition, the limitations and inconsistencies in the image data meant that it would be difficult to develop a technique that included reflectance-based features as it could not be consistently applied across a large geographic region. Thirty-six shape-based features (Table 2) were exported as attributes with the line shapefile.

Table 2 Shape-based features (variables) exported with line shapefile from Definiens® Developer*.

Shape	Feature (variable)	Alias
Generic	area	*Area*
	length	*Length*
	width	*Width*
	length/width	*LengWidt*
	border length	*BordLeng*
	asymmetry	*Asymmetr*
	main direction	*MainDire*
	density	*Density*
	shape index	*ShapInde*
	border index	*BordInde*
	compactness	*Compactn*
	roundness	*Roundnes*
	elliptic fit	*ElliFit*
	rectangular fit	*RectFit*
	radius of smallest enclosing eclipse	*RaSmEnEc*
	radius of largest enclosed eclipse	*RaLaEnEc*
Based on polygons	area (excluding inner polygons)	*ArExclP*
	area (including inner polygons)	*ArInclP*
	perimeter	*PerimetP*
	compactness	*CompactP*
	number of edges	*NumEdgeP*
	std deviation of length of edges	*StdLeEdP*
	average length of edges	*AvLeEdP*
	length of longest edge	*LeLoEdP*
	number of inner objects	*NumInnOP*
Based on skeletons	degree of skeleton branching	*DegBrSk*
	length/width (only main line)	*LenWidSk*
	length of main line (no cycles)	*LenMaSk*
	width (only main line)	*WidthSk*
	curvature/length (only main line)	*CurvLeSk*
	std deviation curvature (only main line)	*StdCurSk*
	number of segments	*NumSegS*
	std deviation of area represented by segments	*StArSeSk*
	length of main line (regarding cycles)	*LeMaCySk*
	maximum branch length	*MaxBrLSk*
	average branch length	*AvBrLSk*

* For full explanation of variables refer to Definiens 2007a.

The process tree was saved as a Definiens® process (.dcp) file to enable the technique to be applied as a semi-automated process on the image dataset.

3.3.5. Image-object classification

To assess the most appropriate technique for operational application, three different classification techniques were trialled initially on a shapefile generated from an image-object subset from the Condamine catchment (total area approximately 15,000-ha; 20,106 image-objects). All three techniques used the exported line shapefile of image-objects with the attached attribute table containing the 36 shape-based features. The first technique was an unsupervised *k*-means classification. The other two techniques were based on different decision tree classification applications: the first, a hybrid decision tree/expert knowledge system, and the second, an ensemble learning system. In the decision tree techniques, the response variable is the contour bank image-objects and the predictor variables are the shape-based features (attributes).

3.3.5.1. k-means classification

An unsupervised *k*-means classification was trialled to investigate class membership of contour bank image-objects compared with other image-objects in the dataset. FuzME, a fuzzy *k*-means with extragrades program (Minasny and McBratney, 2002) was used to derive several classifications with a different number of classes specified for each classification. The basic premise of *k*-means classification is to minimise the within-class sum square errors such that members of one class have stronger membership in that class than they do in another. In FuzME, the strength of the membership is given by the degree of fuzziness in the final solution, that is, the degree of overlap between groups. This is determined by the fuzzy exponent value which ranges from $(1, \infty)$ where a value of 1 (or close to) results in a hard partition (Minasny and McBratney, 2002).

The matrix operations applied in the *k*-means classification process become ill-conditioned when variables have similar or equal values. To avoid this, only the 16 generic shape variables were used in the *k*-means classification process (refer to Table 2). Trials were run in FuzME for 5, 10, 15, 20, 30 and 50 classes using 300 iterations of the *k*-means algorithm, based on the Mahalanobis distance metric and a random start membership scatter value of 0.5. As contour banks are a categorical landscape feature, the fuzzy exponent was set at 1.01 to invoke a hard partition between classes in the results. FuzME output summaries were then examined to determine the optimum number of classes for the data. This was determined from the point at which the separate fuzzy validity value (*S*) is no further reduced by the addition of more classes. For the trial subset, this was determined to be about 17 to 18 classes. The 15-class trial was therefore used for the final classification.

The results of the 15-class classification were then attached to the line shapefile attribute table and the classes viewed in ArcGIS® to assess if any of the classes related mostly or wholly to contour banks. On initial inspection, it was obvious that the k-means classification had low discriminatory power and that significant manual editing would be required to accurately map contour banks. A decision was made early in this project not to apply the *k*-means classification beyond the trial area except where it was utilised in the development of the training data set for the decision tree classification techniques (refer to section 3.3.5.2).

3.3.5.2. Training data

A training data set was required for the decision tree classifications. This enabled the trees to predict which variables best define image-objects that were either contour banks or not contour banks. Image-objects were selected from parts of the Condamine and Fitzroy River catchments. This data set was considered to be representative of the variation in shape-based variables of image-objects delineating contour banks (and non-contour bank) features across the cropping areas of Queensland.

First, the results of the 15-class *k*-means classification were examined in ArcGIS® together with the panchromatic image, to determine if any of the classes were representative of contour bank features. Those classes that did not contain contour bank features were removed from view to minimise the number of image-objects that were available for selection in the next step. Next, a sample of image-objects that corresponded to a contour bank, as interpreted from the panchromatic image, was collected and labelled as 'contour'. Finally, all classes in the 15-class *k*-means classification were examined and a sample of image-objects that corresponded to landscape features that were not contour banks was collected and labelled as 'not contour'. All labelled image-objects were then exported to a separate file, converted to integers (by multiplying by a factor of 1000 and rounding) and given variable aliases (see Table 2). The final training data set contained 2642 objects that were selected as 'contour' and 5000 objects were selected as 'not contour'.

3.3.5.3. Hybrid decision tree/expert system classification

A hybrid decision tree/expert system classification technique (Keith and Bedward, 1999) was trialled to create a set of decision rules comprised of a series of quantitative statements about the shape-based variables, connected by conjunctions, that describe (classify) the distribution of image-objects that are either contour banks or not contour banks. Keith and Bedward (1999) comment that some of the benefits of this technique include that it is explicit and repeatable and is free from statistical constraints and assumptions about the structure of the data. They state that the major benefit of the technique is that it allows for intervention by experts in an explicit manner through the choice and design of decision rules, therefore providing a framework for the incorporation of non-formal expert knowledge into the classification.

Interactive modelling software (ALBERO) (Bedward, 1998) was used to develop a set of generic decision rules with the assumption that they could be applied to image-objects from different regions provided that they had been generated from consistent image segmentation procedures. ALBERO generates decision rules in the form of a tree by statistical induction and facilitates expert intervention at various stages of model development (Keith and Bedward 1999). At each node in the decision tree ALBERO uses chi-square probability (with a user-specified critical value) as a measure of informativeness of the significance of the predictor variables to discriminate the response variable classes. ALBERO then nominates appropriate thresholds for discrimination (Bedward, 1998; Keith and Bedward, 1999). The predictors and thresholds can then be examined and investigated by the user and the most appropriate split chosen for that node. Further explicit expert intervention is accommodated by facilitating exploration of alternative tree structures, forcing non-significant splits, and by permitting definition of data-free terminal nodes (Keith and Bedward, 1999).

A decision tree model of image-objects was developed using the training data set described above. The default critical value of 0.05 was used to define significant predictors at each node. Successive splits were chosen by examining significant predictors and selecting the shape-based variable that best resulted in the separation of 'contour' from 'not contour'. Decisions were made on the basis of meaningful shape-based features and by investigation of the characteristics and distribution of image-objects in a landscape context. This was done by visual interpretation in ArcGIS® or by feature calculation and investigation in Definiens® Professional and Definiens® Developer. Upper level splits were mainly based on general shape characteristics such as *Asymmetr*, *WidthSk* and *Compactn* (Table 2) while lower level splits were based on a range of variables including more specific features such *CurvLeSk* and *NumSegSk*. In some cases the tree structure was adjusted or a non-significant split was forced. Nodes were added to the decision tree until all image-objects in the training data had been assigned to a terminal node as either ‘contour’, ‘not contour’ or ‘undefined’.

ALBERO can export rules in three alternative formats: C/C++ IF-ELSE statements; C/C++ IF statements; ArcGRID® CON statements. To enable automated application of the rule set to the line shapefiles across regions, the rules were exported as C/C++ IF statements and then converted to the Python programming language (Python Software Foundation, 2007) using a purpose-designed script, *c2py.py* (Koders, 2007). Additional programming combined the rules with the Add Field and Calculate Field scripting functions in ArcGIS®. The result is the addition of a field to the attribute table of the line shapefile that attributes each individual object with either ‘contour’ or ‘not contour’ as defined by the rule set.

3.3.5.4. Ensemble learning classification

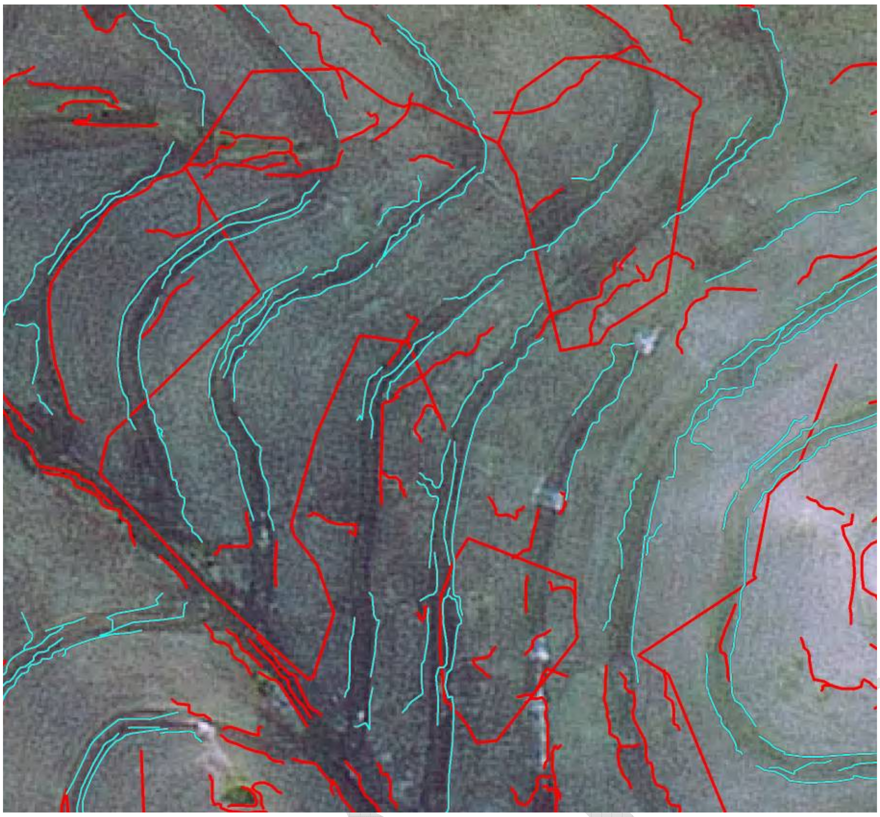
An ensemble learning classification technique was trialled to obtain predictive values of the probability that an image-object is a contour bank based on the shape-based predictor variables in the training data. The same training data can be used to predict across many data sets therefore providing a consistent prediction of contour banks across regions. This assumes that the data sets contain the same variables and have been created using standard image segmentation procedures, a difficult exercise, as will be discussed later.

The randomForest library was developed for the R statistical software package (Development Core Team, 2007) and provides an R interface to the Fortran programs originally written by Breiman and Cutler (Breiman, 2001; Liaw and Wiener, 2002). Random forests are essentially multiple classification trees with nodal splits defined by the best among a subset of predictors randomly chosen at each node. New data is predicted by aggregating the predictions, based on majority votes, of the n_{tree} trees in the forest (Liaw and Wiener, 2002). The use of majority votes in the prediction rule results in a categorical prediction of the response. If majority votes is not used, a probability estimate of the response is provided that can be thresholded to achieve a classification outcome. This more flexible approach can have benefits for choosing a classification outcome and can compensate for imbalance between classes in the training data. This is the approach we used here.

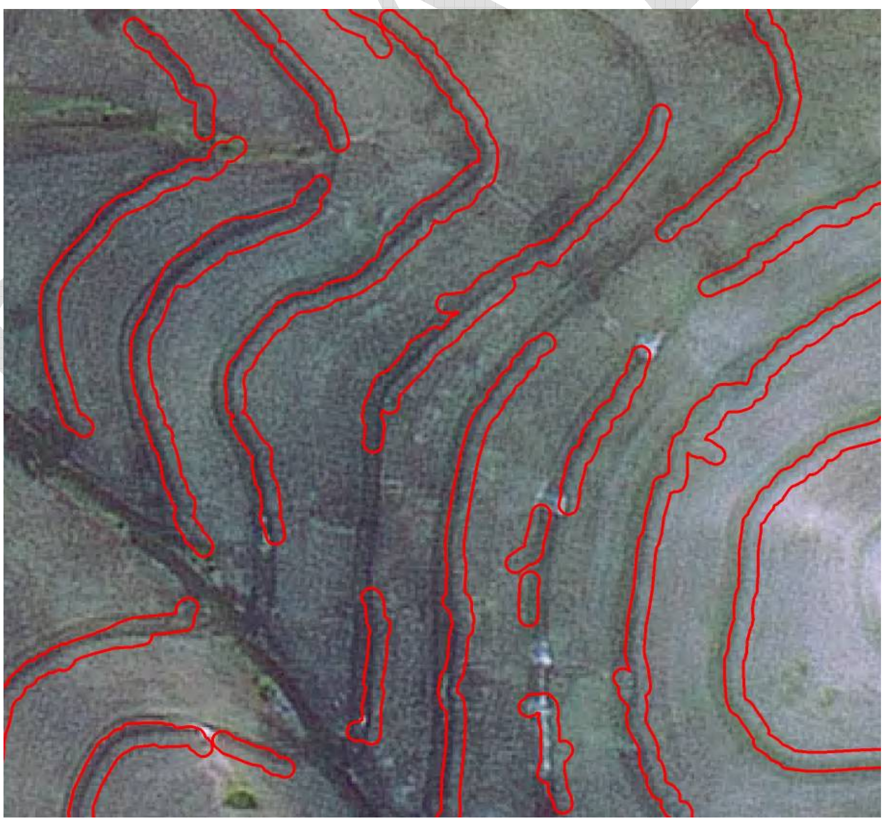
Using the training data, a random forest classification was constructed with n_{tree} = 750. Prediction in a new area was achieved by segmenting an area of interest to create a shapefile with the same attributes as for the training data. The attributes of this shapefile were read into R in dbf format. The random forest object with all variables was then used to predict the class (contour/not contour) for this new data set. Each line feature in the shapefile is thus given a probability that it is a contour. The classification of line features is then assessed by assigning probability thresholds in ArcGIS®.

3.3.6. Editing of classified image-objects

The classification processes are aimed at predicting which objects in the image-object data set are contour banks. This assumes that the image-objects adequately delineate contour bank features and that the objects share common shape-based characteristics. A further assumption is made for the decision tree techniques that these shape-based characteristics are represented in the training data. The processing parameters used for the image-object segmentation (refer to section 3.3.4) result in contour bank features that are rarely delineated by a single image-object. More commonly, they are represented by more than one, often discontinuous image-object (Fig. 3a). These generally have a similar narrow, linear shape to the single object contour banks. To simplify multiple classified image-objects that are delineating single contour banks, a 5–m buffer is applied to the image-objects in ArcGIS® using the Buffer function with the Dissolve All option (Fig. 3b). The resulting shapefile is then exploded into single part features using the Multipart To Single Part function.



(a)



(b)

Fig. 3 Segmentation results – image-objects (a) multiple, discontinuous image-objects delineate contour bank (b) result of buffering multiple image-objects to delineate contour bank. Imagery: SPOT 5 panchromatic 2.5-m resolution

4. RESULTS

4.1. Manual mapping

The location of contour banks (paddocks) has been mapped for the Condamine, upper Burnett and Fitzroy catchments by manual interpretation (Fig. 4). Contour bank features have been manually mapped for around half of each of these catchments with the remainder being supplemented by the semi-automated mapping products. Fig. 5 is an example of the product.

Table 3 presents the results for the manual mapping in the areas assessed to date. As it is a much larger catchment than the Condamine and upper Burnett combined, the Fitzroy has had a much greater area assessed. The Fitzroy has almost twice as much area subject to contour bank agricultural practices. This reflects the larger scale at which these practices are adopted in the Fitzroy. However, the Condamine and upper Burnett have a slightly higher density for contour banks per hectare due to generally greater slopes and smaller, more intensively managed areas subject to contour bank practices.

Table 3 Results to date for manual mapping of contour bank locations in the Condamine, upper Burnett and Fitzroy catchments.

Statistic	Condamine/upper Burnett	Fitzroy
Total area assessed (km^2)	49,100	159,300
Area of contour bank practices (paddocks) (ha)	334,563	604,354
Area of contour bank practices (paddocks) with contour bank features mapped to date (ha)	44,369	211,184
No. contour bank features mapped to date	2766	9423
Average density of contour banks (No./ha)	0.06	0.04

Most of the contour banks were able to be interpreted with confidence from the pan-sharpened SPOT 5 imagery. Those that were delineated with less confidence are generally older, eroded and poorly maintained, or under-utilised banks, or those that may be confused with tracks, fence lines or natural drainage lines. Field verification and ancillary data (e.g. stereoscopic interpretation of aerial photography) will be used to confirm these features. The majority of the contour banks mapped are likely to be narrow-based design with approximately 90% being categorised in the 0–10-m range.

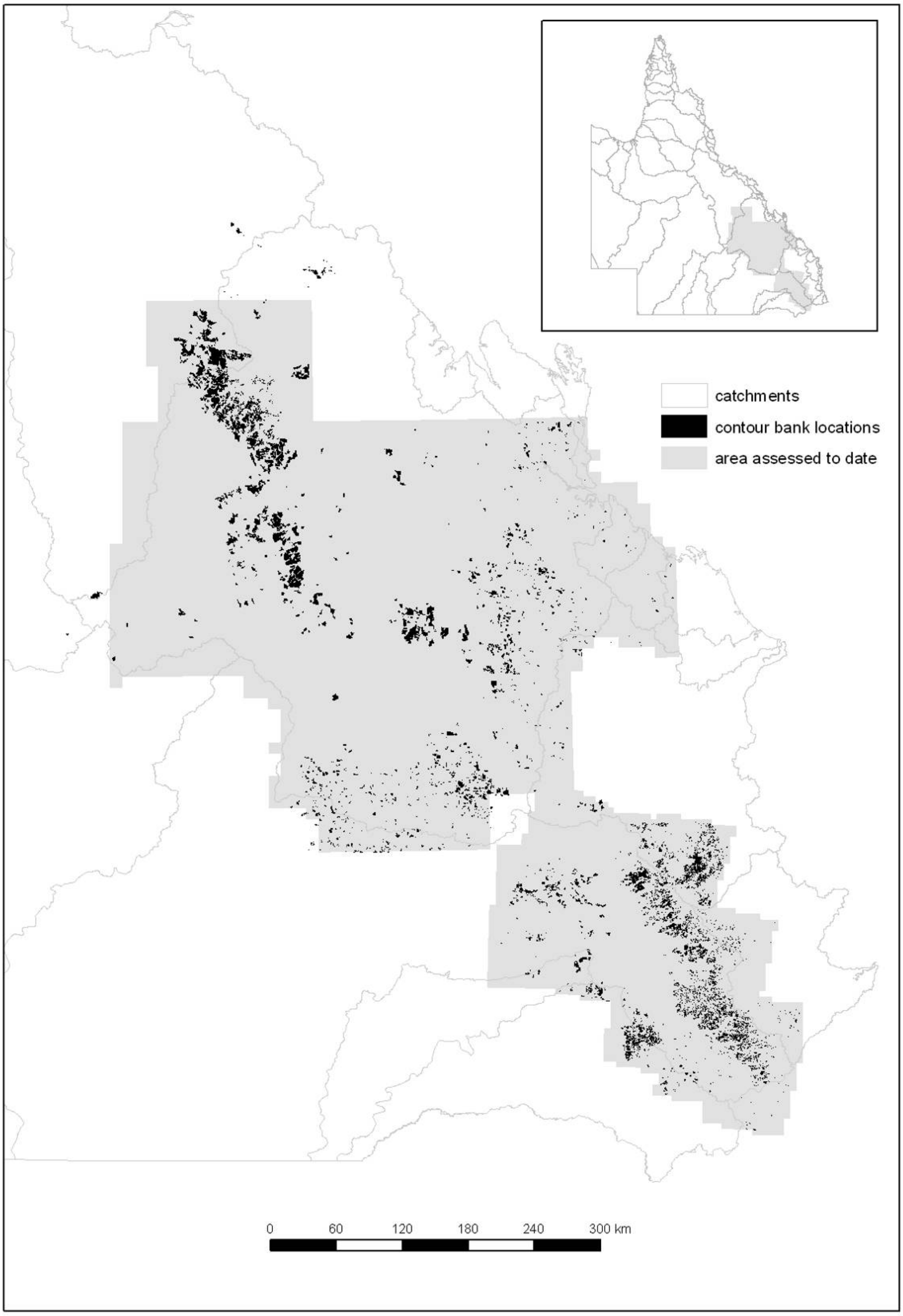


Fig. 4 Area assessed to date and location of contour banks (shown in black) in the Condamine, upper Burnett and Fitzroy catchments using the manual mapping technique.

(a)

(b)

Fig. 5 Example of manual mapping from Condamine catchment (a) contour banks paddocks are delineated (b) contour banks paddocks and contour banks are delineated. Imagery: SPOT 5 pan-sharpened 2.5-m resolution

4.2. Semi-automated object-based mapping

The semi-automated mapping and classification techniques have been trialled on a 15,000-ha subset of data from the Condamine catchments (refer to section 3.3.5). Further, operational application of the decision tree classification techniques has been implemented for the Condamine and Fitzroy River catchment areas. Results suggest that for the purposes of mapping contour banks the combination of image-object segmentation procedures and a classification technique could be used to map the majority of contour banks in cropping areas of Queensland. The decision tree classifiers outperform the *k*-means classification which is to be expected as they are supervised techniques and contour banks are a specific landscape feature with defined shape characteristics. To date, no formal testing of the completeness and accuracy of outputs has been conducted. As the project progresses and further areas are mapped, a more detailed account of results and statistical testing of the outputs will be conducted.

4.2.1. Image-object segmentation

4.2.1.1. Image-object segmentation - trial area

The initial segmentation of the trial area subset image created 58,413 image-objects. Generalisation (refer to section 3.3.4) reduced this to a final total of 20,106 image-objects. The final segmentation is shown in Fig. 6. On inspection, the segmentation appears to delineating the majority of contour bank features with varying success. Some contour banks have not been delineated due to masking but these are relatively few and were mapped by manual techniques.

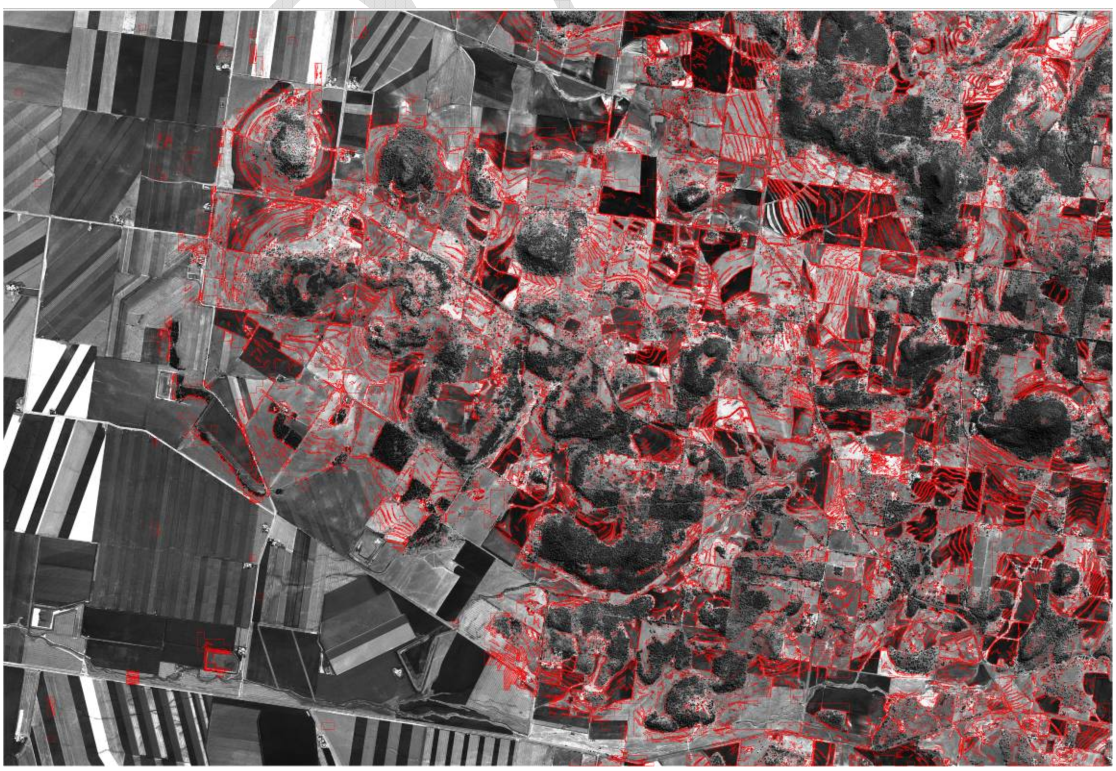


Fig. 6 SPOT 5 panchromatic image with segmentation results (20,106 image-objects) shown.

4.2.1.2. Image-object segmentation – operational application

Using the process outlined in section 3.3.4, a total area of 31,329-km^2 (~64% of total area assessed) and 22,948-km^2 (~14% of total area assessed) has been processed in the Condamine/upper Burnett and Fitzroy catchments, respectively (Fig. 7) (Table 6). For the Condamine/upper Burnett catchments this resulted in a total of 2,555,111 image-objects, and for the Fitzroy, 273,663 image-objects (Table 6).

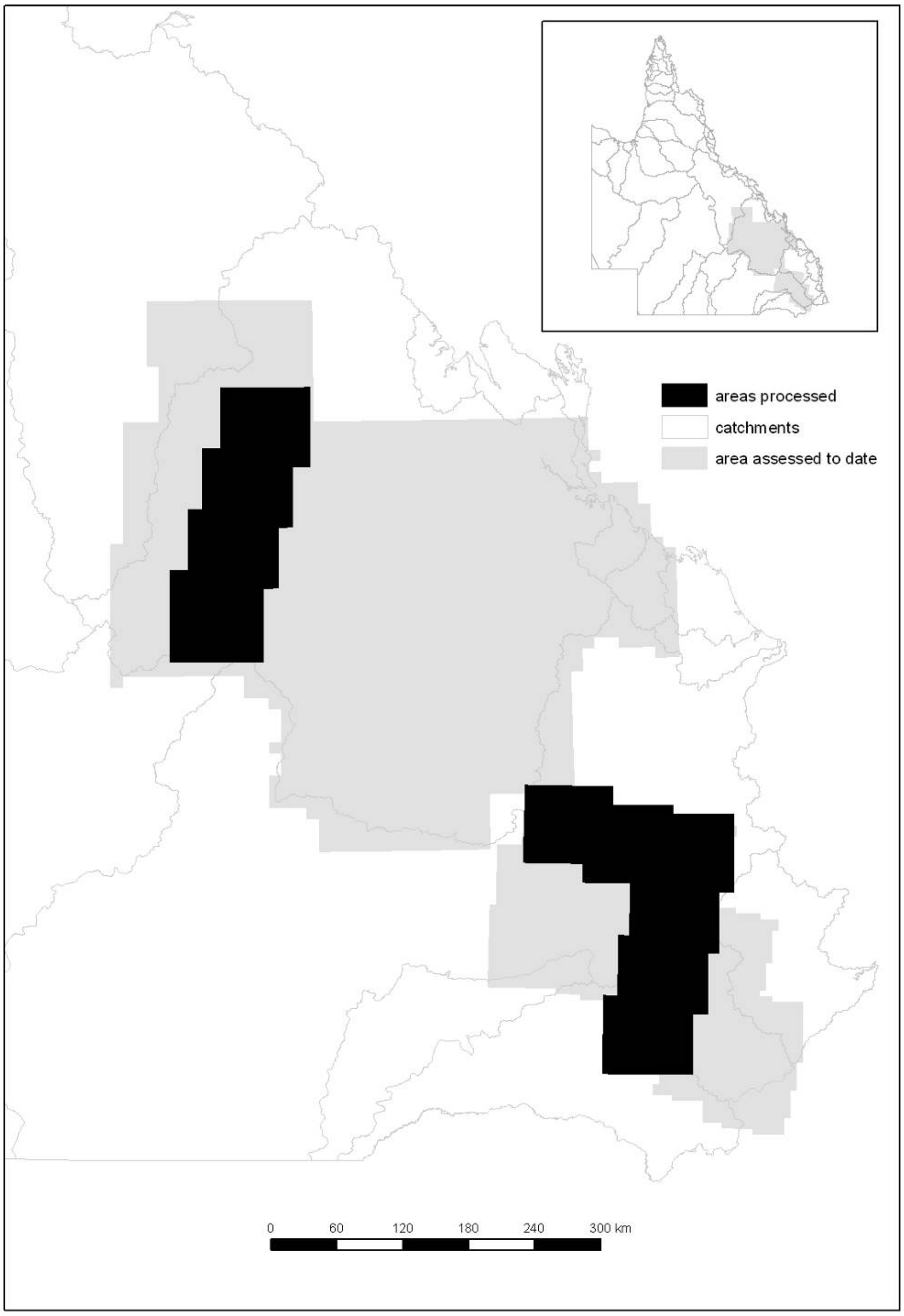


Fig. 7 Areas processed to date (shown in black) in the Condamine, upper Burnett and Fitzroy catchments.

4.2.2. *k*-means classification

Results of the 15-class *k*-means classification for the trial area subset image are shown in Fig. 8.

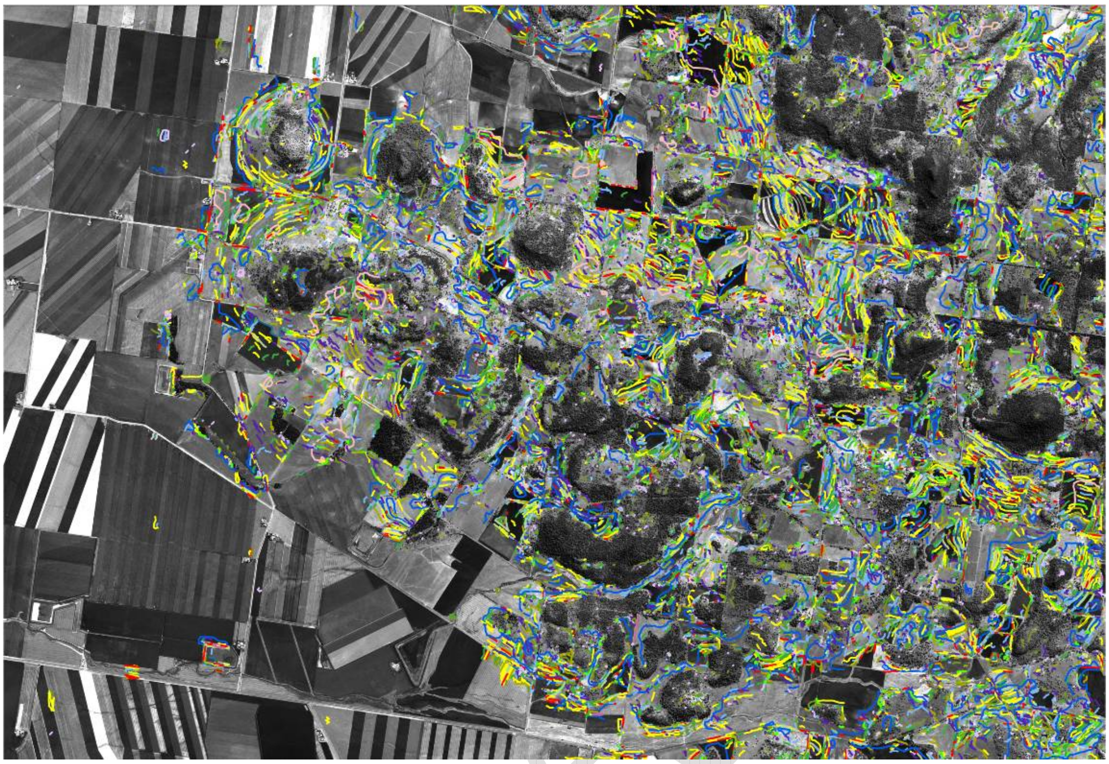


Fig. 8 SPOT 5 panchromatic image with results of 15 class fuzzy classification. Each colour represents a separate class.

Visual inspection of the classification shows that 3 or 4 of the 15 classes corresponded to most features that delineate contour banks. These classes also contained other landscape features that corresponded to other linear features such as road and riparian corridors and some areas of strip cropping that had not been masked out. The results of the fuzzy membership classification are likely to be comprised of classes that do not clearly discriminate between certain landscape features, including contour banks. It is expected that significant manual editing and interpretation would be required to separate the contour banks from other features. Due to these issues and as previously mentioned in section 3.3.5.1, the k-means classification was not considered further for operational application.

4.2.3. Hybrid decision tree/expert system classification

4.2.3.1. Trial area application

Based on the training data, a hierarchical set of 166 decision rules was developed iteratively to model, on the basis of shape characteristics, the distribution of image-object features that corresponded to contour banks in the image subset.

Asymmetr was the most frequently used shape variable in the decision tree (Table 4). Other frequently used variables included *Compactn, BordInde* and *WidthSk*. Seven variables were not used. Table 5 provides some examples of the decision rules used in the classification.

Table 4 Number of times variables were used in the decision rules

Feature (variable)	Alias	No. of times used
area	*Area*	0
length	*Length*	19
width	*Width*	0
length/width	*LengWidt*	23
border length	*BordLeng*	96
asymmetry	*Asymmetr*	334
main direction	*MainDire*	114
density	*Density*	39
shape index	*ShapInde*	13
border index	*BordInde*	174
compactness	*Compactn*	203
roundness	*Roundnes*	154
elliptic fit	*ElliFit*	19
rectangular fit	*RectFit*	29
radius of smallest enclosing eclipse	*RaSmEnEc*	39
radius of largest enclosed eclipse	*RaLaEnEc*	76
area (excluding inner polygons)	*ArExclP*	0
area (including inner polygons)	*ArInclP*	0
perimeter	*PerimetP*	23
compactness	*CompactP*	8
number of edges	*NumEdgeP*	0
std deviation of length of edges	*StdLeEdP*	6
average length of edges	*AvLeEdP*	8
length of longest edge	*LeLoEdP*	20
number of inner objects	*NumInnOP*	0
degree of skeleton branching	*DegBrSk*	26
length/width (only main line)	*LenWidSk*	5
length of main line (no cycles)	*LenMaSk*	5
width (only main line)	*WidthSk*	190
curvature/length (only main line)	*CurvLeSk*	25
std deviation curvature (only main line)	*StdCurSk*	44
number of segments	*NumSegS*	72
std deviation of area represented by segments	*StArSeSk*	6
length of main line (regarding cycles)	*LeMaCySk*	0
maximum branch length	*MaxBrLSk*	7
average branch length	*AvBrLSk*	28

Table 5 Example decision rules

IF Asymmetr > 885 AND
WidthSk <= 15595 AND
Compactn > 3225 AND
Roundnes <= 2335 AND
Asymmetr > 945 AND
StdCurSk <= 415 AND
MainDire <= 80820 AND
Asymmetr <= 985 AND
WidthSk > 9035 AND
WidthSk <= 10685
THEN class = 'contour'

IF Asymmetr > 885 AND
WidthSk <= 15595 AND
Compactn > 3225 AND
Roundnes <= 2335 AND
Asymmetr > 945 AND
StdCurSk <= 415 AND
MainDire <= 80820 AND
Asymmetr <= 985 AND
WidthSk > 9035 AND
WidthSk > 10685
THEN class = 'not_contour'

One thousand and sixty five image-objects were classified as contour banks. Nineteen thousand and forty one were classified as not contour banks. The results for the trial area are shown in Fig. 9.

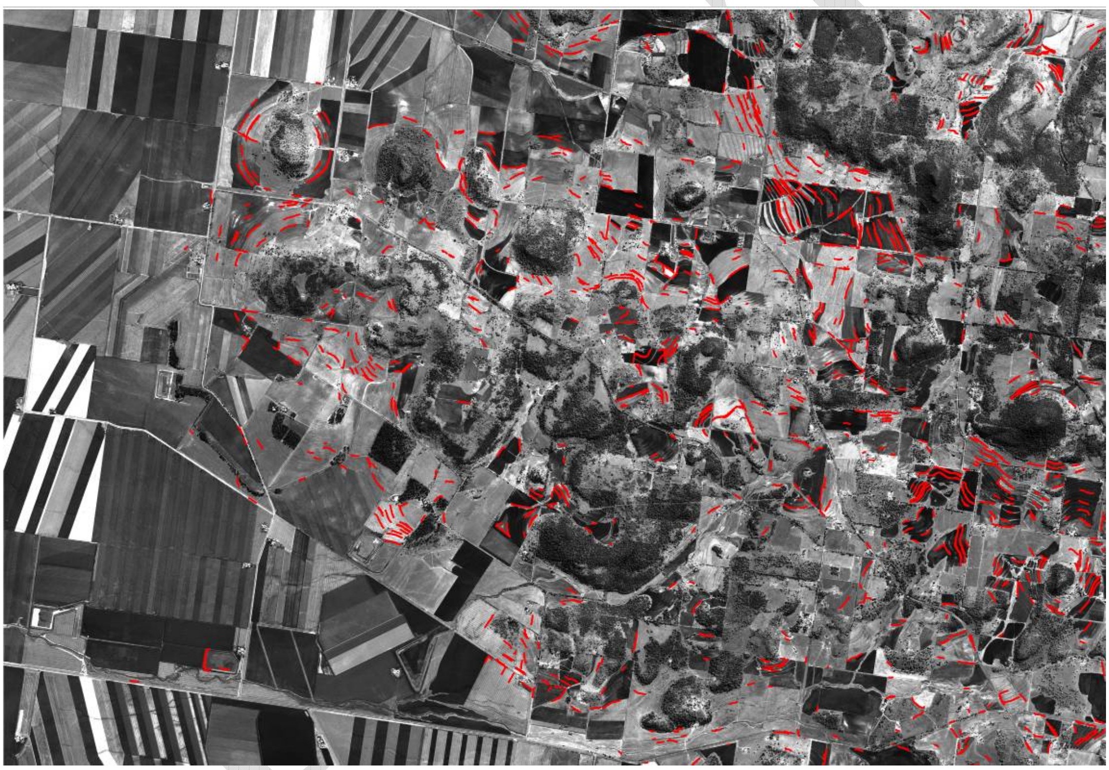


Fig. 9 SPOT 5 panchromatic image with results of hybrid decision tree/expert system classification.

Compared with the manual mapping which could be assumed to be a reference data set, the method appears to be accurate where contour banks have been mapped, although there is still significant omission error. Application of the decision rules to other areas in the Condamine and Fitzroy catchments suggest that the rules may be applied generically across other image-objects segmented using the same procedure. The results are presented in the following section.

4.2.3.2. Operational application

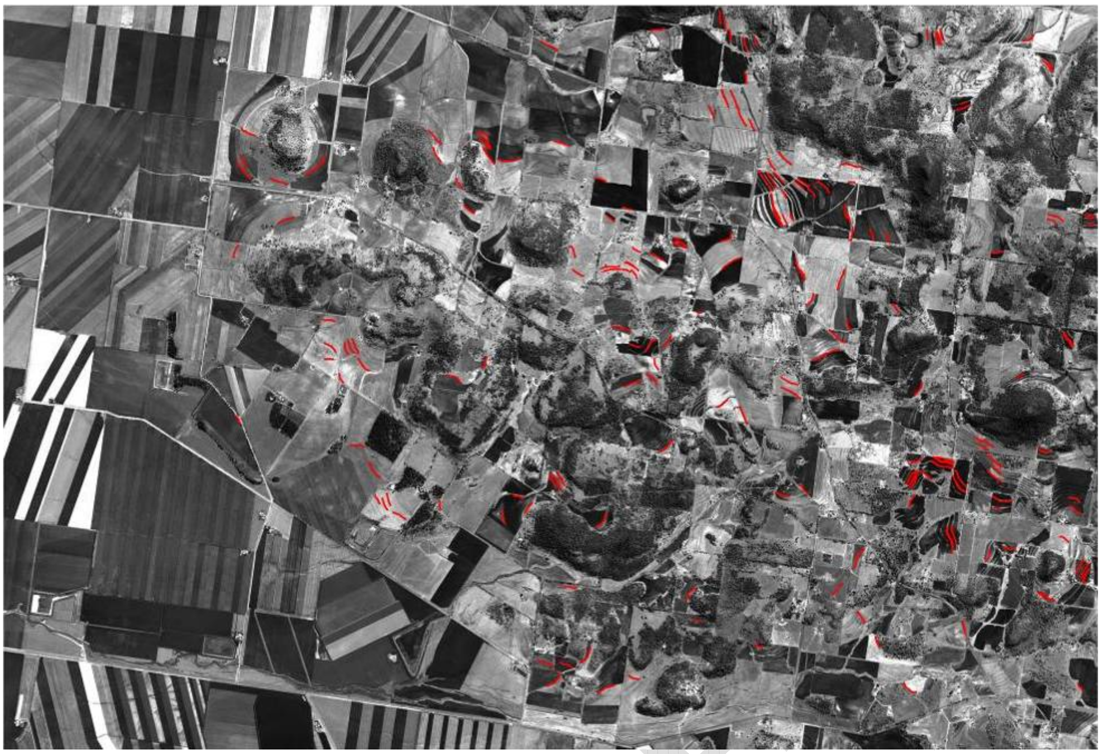
Operational application of the 166 decision rules to the 2,828,774 image-objects generated for the Condamine, upper Burnett and Fitzroy catchments (refer to section 4.2.1.2, Table 6) resulted in 37,813 being classified as contour bank features. As for the trial area, the method is accurate where contour banks are mapped but there remains significant omission error, particularly compared with the ensemble learning technique (refer to section 4.2.5). GIS-based buffering processes (refer to section 3.3.6) reduced the number of features to 29,827.

4.2.4. Ensemble learning classification

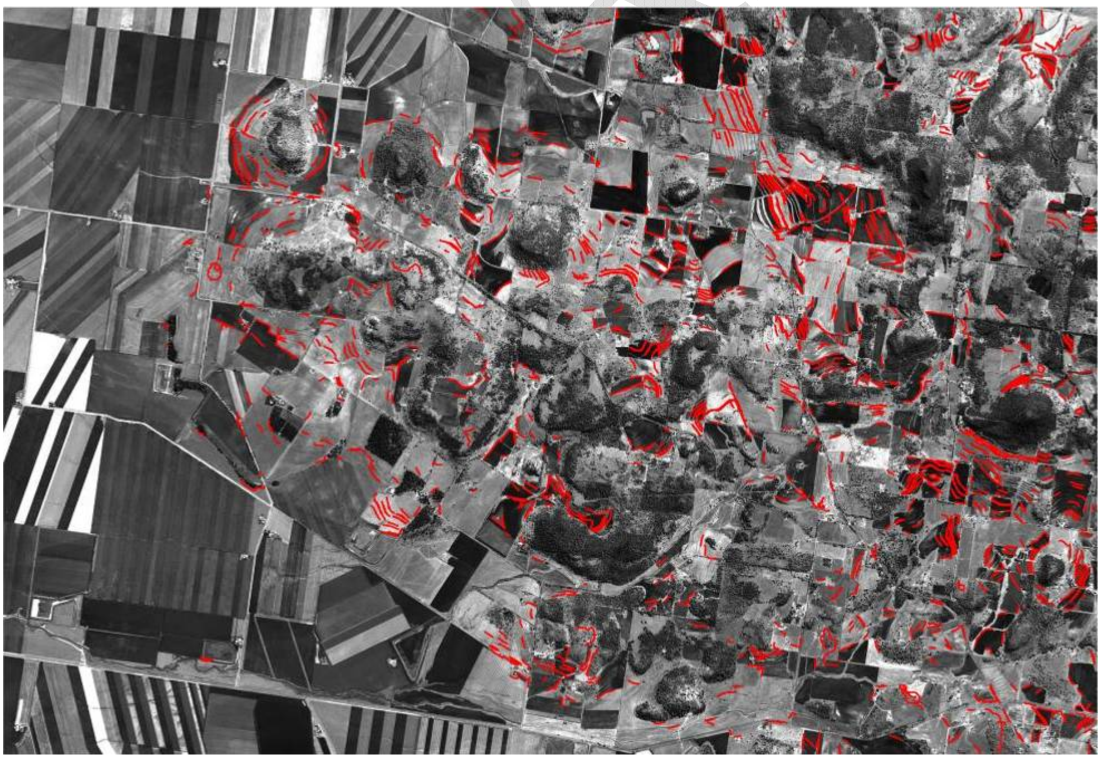
4.2.4.1. Trial area application

The randomForest predictions were provided for all image-objects in the subset image based on the training data. The out-of-bag (OOB) estimate of error for n_{tree} = 750 was approximately 4.8%. An examination of variable importance suggests that the variables *MainDire, Density* and *RaSmEnEc* (Table 2) are useful for prediction of contours. A reduced model, using just these three variables produced an OOB estimate of error of 5.1%, suggesting that the addition of more variables results in only a minor increase in accuracy.

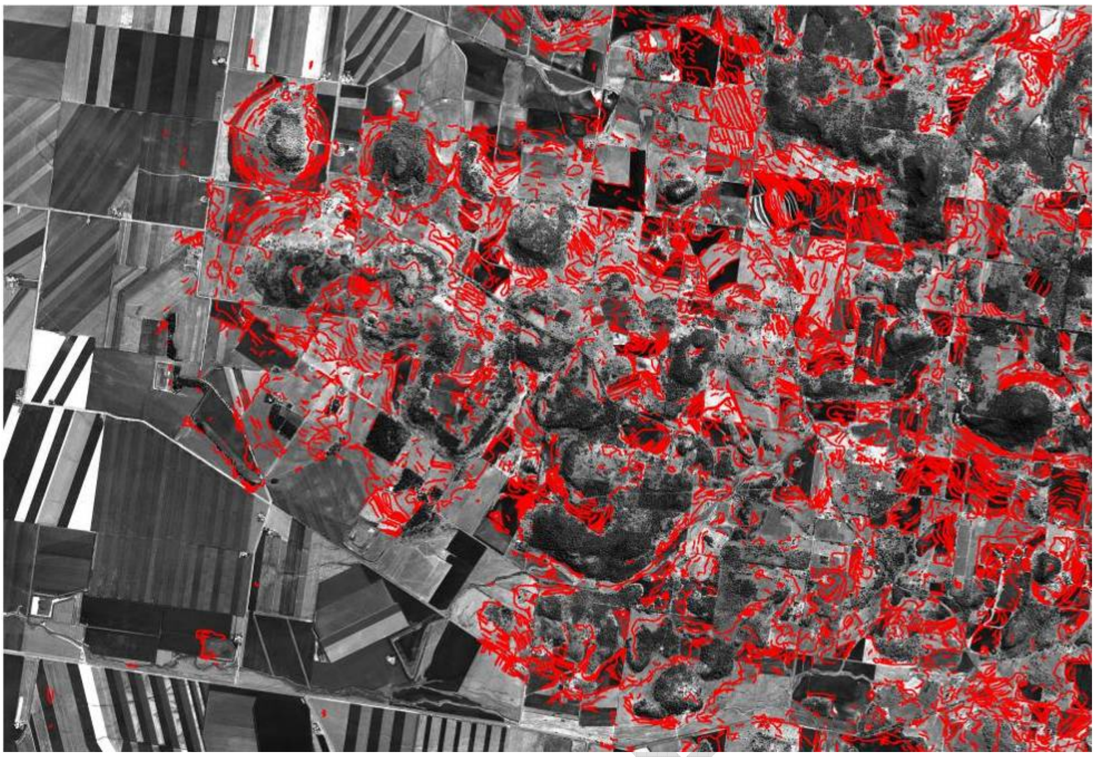
A number of predictive (probability) thresholds were investigated for the trial area. Fig. 10 shows the results of the application of three predictive threshold values applied to the image-objects. It was expected that a predictive threshold value that reflected the ratio of contour bank features to non-contour bank features in the training data would provide the best prediction of contour bank image-objects. At a predictive threshold of 0.5 (Fig. 10a), 204 image-objects were classified as contour banks. Visual inspection suggests that the majority of image-object features classified using this threshold are contour banks, but there is a large omission rate. A smaller threshold of 0.3 (Fig. 10b) classifies a greater number of features as contour banks (1588 image-objects) and these also seem to be accurate although there remains some omission. A threshold value of 0.2 (Fig. 10c) classifies 6657 image-objects with minimal omission but there also appears to be a number of commission errors. Therefore, for the operational application of the technique, the choice of a threshold will be defined by the balance between omission and commission and how much manual mapping and editing is required to amend the output.



(a)



(b)



(c)

Fig. 10 Random forest classification of the trial area subset image with three different predictive thresholds: (a) threshold value 0.5; (b) threshold value 0.3; and, (c) threshold value 0.2. Imagery: SPOT 5 panchromatic 2.5-m resolution.

4.2.4.2. Operational application

Using the training data (refer to section 3.3.5.2) for prediction of contour banks with the 2,828,774 image-objects generated for the Condamine, upper Burnett and Fitzroy catchments (refer to section 4.2.1.2, Table 6), 216,601 were classified as contour bank features at a predictive threshold value of 0.7. Post-processing (refer to section 3.3.6) reduced this to 89,620 features. The higher, more conservative predictive threshold value was chosen as it minimised commission error at minor expense to omission error, thus reducing the need for manual editing. The advantage of the technique is that the user can adjust this predictive threshold until a satisfactory output is achieved. In reality, this may vary from processed image to processed image and is a function of both the number of objects generated, the variables used for prediction, and the balance or ratio of the training data.

4.2.5. Comparison of decision tree classification techniques

Table 6 below provides a comparison of the results for the two classification techniques for the combined areas of the Condamine, upper Burnett and Fitzroy catchments. Fig. 11 shows the results for each technique for the same location in the Fitzroy catchment and compares them with outputs from the manual mapping.

Table 6 Comparison of results for the hybrid decision tree/expert systems and ensemble learning classification techniques for the areas processed to date

Statistic	Hybrid decision tree/expert system	ensemble learning*
No. objects (total)	2,828,774	2,828,774
No. objects predicted	37,813	216,601
No. features after buffer**	29,827	89,620

*predictive threshold value = 0.7
**refer to section 3.3.6

At a predictive threshold of 0.7, the ensemble learning technique predicts almost six times more objects as contour banks than the hybrid decision tree/expert system. Fig. 11 also shows that the objects that are predicted by the ensemble learning technique map contour banks with reasonable accuracy and minimal commission error. The hybrid decision tree/expert system technique also maps contour banks with reasonable accuracy and low commission error, but it also has significant error of omission. This is due to the strict conditions for class membership imposed by the ruleset for this technique. It also highlights the advantage of the ensemble learning technique as it allows greater flexibility through the selection of predictive thresholds and is robust against overfitting. Greater flexibility could also be built into the hybrid decision tree/expert system technique, but this requires the decision tree to be dismantled and recreated using a different hierarchy of rules. This takes some time, but as the project progresses to completion, we may construct alternative trees that are less conservative to allow further comparison of the techniques. Regardless of the technique chosen for classification, manual editing is still required to achieve a complete and accurate coverage of contour banks features.

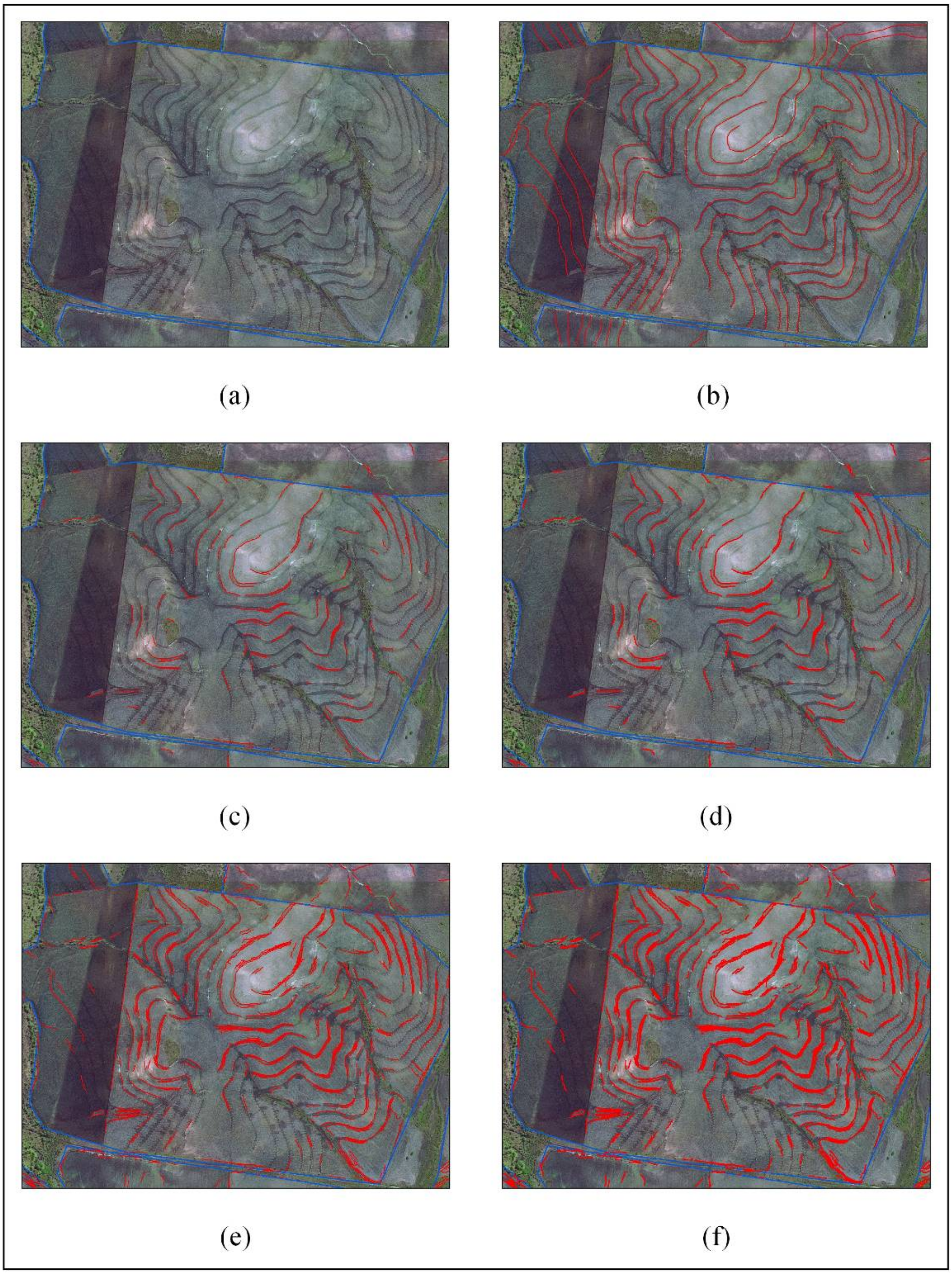


Fig. 11 Example output from mapping and classification techniques (a) Pan-sharpened SPOT 5 imagery showing contour banks in the Fitzroy catchment (b) Contour banks delineated by manual mapping (c) contour banks predicted by the hybrid decision tree/expert system classification (d) contour banks predicted by the hybrid decision tree/expert system classification and buffered by 5-m (e) contour banks predicted by the ensemble learning technique (f) contour banks predicted by the ensemble learning technique and buffered by 5-m.

5. DISCUSSION

Results from this project suggest that semi-automated object-based classification methods using high-resolution remotely sensed imagery have significant potential for mapping land management practices in Australian landscapes. For contour banks in Queensland, classification based on shape characteristics of image-objects derived from image segmentation procedures has been demonstrated using three different approaches. Of the three approaches, the decision tree methods yielded the best results, particularly the ensemble learning technique, based on visual verification.

5.1. Image Segmentation

The accuracy of the final mapping products derived from the semi-automated mapping are a direct function of the initial image-object segmentation procedures applied. Many factors influence the outcome of an image segmentation including the type, area, resolution and weighting of the input imagery, the homogeneity criterion used and even the segmentation algorithm selected. A procedure employed for one image may not yield similar results for another. This has significant implications for the consistent application of any classification method that relies on image segmentation procedures. These factors can also significantly influence processing time and therefore further affect the application of any selected method over a large region.

SPOT 5 panchromatic and edge-enhanced panchromatic imagery were selected for this project as they had the appropriate spatial resolution for the segmentation of small landscape features such as contours and, have reduced spectral influence on the image segmentation. Using this imagery, image-objects are created on the basis of contrast, shape and texture differences rather than spectral characteristics. However, the relatively high resolution (2.5m) and use of a small scale parameter in the segmentation algorithm had significant computer memory requirements, and hence processing time and capability. This is mainly a function of the memory allocation of the 32 bit Windows operating system for software. For example, a test was conducted using a multiresolution segmentation of a complete SPOT 5 panchromatic image in Definiens® Professional 5 LDH (large data handling version). With a scale parameter of 50, the process took approximately 36 hours. Later versions (i.e. Definiens® Developer) have improvements that have resulted in increased processing capability and alternative ways of dealing with large data sets (e.g. tiling and stitching functions). In addition, the development of a 64 bit version in the near future, should greatly increase processing capability. For other landscape and land management features, medium resolution, multispectral imagery and larger scale parameters may be adequate. This would reduce processing time and memory requirements and can still provide accurate delineation of image-objects for classification. It is important to note that multispectral SPOT 5 imagery was available for this project. However, the lower spatial resolution (10m) limits its potential for identifying and mapping small landscape features such as contour banks. Currently, appropriate radiometric corrections have not been developed for this imagery which limits the value of the spectral information for pixel and also object-based classification. The appropriate radiometric corrections are particularly important for large-scale operational projects, such as this one, which require automated methods to be applied to a large number of images and potentially, through time.

Clearly, the selection of imagery and scale of segmentation would depend on the application. Definiens (2007a) recommend that a user should always aim to produce objects of the largest scale possible which still distinguishes different image regions for the given purpose. Another limitation of the software is the difficulty to investigate and statistically compare image-object features (e.g. shape-based features, reflectance features, texture features), and to determine which are the most appropriate for classification. As for the processing, improvements in more recent versions of the software have provided functions that can assist with these comparisons. However, these comparisons can still be very time consuming and in some cases, subjective. This is one of the main reasons for the investigation of classification techniques external to the software in this project. Automation remains the key limitation of the software for application across regions and repeatability through time. Semi-automation of the procedures is possible in Definiens® Developer but complete automation of a procedure is not possible, even when combined with external classification techniques. According to Definiens (2007b), the Enterprise version of the software is able to assist scientists, analysts and informaticians to extract information in fully automated and semi-automated modes. However, the Enterprise version is a complete integrated system and requires significant adaptation of hardware and large establishment expenses. Despite these limitations, image segmentation processes using Definiens® Developer remain a very powerful tool for mapping and classifying landscape features, particularly when compared with traditional pixel-based approaches (for example see Grounds, 2008). Other image segmentation packages are available, many of them developed for medical imaging applications. Testing of these packages is beyond the scope of this project however NRW's Remote Sensing Centre plans to investigate the application of some of them in the near future.

5.2. Object-based classification

5.2.1. *k*-means classification

The *k*-means classification was unable to provide classes with clear distinction for mapping contour banks. It was, however, useful for further generalising the image-object data for the purposes of creating training datasets. While this classification technique was not particularly successful or suitable for contour bank mapping it still has some distinct advantages that could make it particularly useful for classifying image-object data for natural resource applications where class distinction is less defined. By increasing the fuzzy exponent to values greater than 1.01, the relations between class memberships can be better understood. This is particularly useful for applications such as soil and vegetation mapping as it presents spatial variability as gradual instead of abrupt, disjointed classes that are poorly fit to reality (Minasny and McBratney, 2002). To apply this concept to image-objects derived from segmentation procedures, one would have to assume that the image-objects occur on a continuum. This assumption is somewhat counterintuitive to the principles of image segmentation which aims to produce objects with 'hard' boundaries based on homogeneous image regions. Larger segmentation parameters could be chosen that deliberately include a degree of fuzziness in the image-objects (through larger, more heterogeneous image-objects), and any number of continuous or categorical image layers could be included. Another advantage of *k*-means classification is that it may help to inform omission and commission errors for individual classes. By examining class memberships, it is possible to gain an understanding of which classes share strong relationships and therefore which features may be confused between classes. This may be useful for an application such as contour bank classification based on image-object features as it may help to determine which landscape features are confused with contour banks. The information can then assist decision tree development, particularly those that incorporate non-formal expert knowledge such as hybrid decision tree/expert system classifications.

5.2.2. Hybrid decision tree/expert systems classification

The hybrid decision tree/expert systems classification developed for the subset image was quite successful at classifying image-objects that corresponded to contour banks. In addition, the ruleset derived from the classification was automated for application across a wider region where image-objects have been derived using standard procedures. The main advantage of this approach is that the rules can be easily manipulated for wider application and the incorporation of expert knowledge helps the model to reflect the reality. However, as is the case for any supervised classification, the resultant model is only as good as the training data provided. In this project the training data was limited and should be expanded to ensure that the variability in shape-based features of contour banks is represented. Despite this, the ruleset developed for the image subset suggests that the variation of shape-based features of image-objects corresponding to contour banks can be explained mostly by a small number of feature types. This suggests that fewer, well chosen variables, possibly some other than shape-based features, may provide a better classification than a large number of variables that include uninformative feature types. This could also potentially decrease processing time in Definiens® Developer as fewer feature types would need to be exported. It may also assist for easier incorporation of expert knowledge as many shape-based and other features derived in Definiens® Developer are based on complex algorithms that are not readily visualised or conceptualised. In addition, the imbalance between contour features and not contour features in the training data may lead to overfitting of the contour classification. Keith and Bedward (1999) also highlight a further limitation of standard decision trees in that they utilise fewer and fewer samples as more variables are fitted leading to inadequate sampling of the multidimensional feature space. This is the reason for trialling the ensemble learning approach in this project as it utilises the best of several trees derived from random subsets (‘bootstraps’) of the training data. It therefore does not effectively diminish the multidimensional feature space as variables are progressively fitted in the way that a single decision tree does. For this project, it is planned that as more image-object data is produced, the training data set will be expanded and a rule set based on a sample of a larger, more representative region will be developed, applied and compared with the ensemble learning approach.

5.2.3. Ensemble learning classification

Depending on the threshold value used for prediction of contour banks, the random forest ensemble learning classification appears to outperform the other two classification techniques. As is the case with the hybrid decision tree/expert system classification, its predictive capability is limited by the training data. Although arguable, an advantage of the random forest approach is the objectivity and strength of the prediction as it is based on multiple trees rather than one single tree, independent of significant user intervention. While it may not directly allow for expert knowledge incorporation as the hybrid decision tree/expert system approach does, the random forest approach is robust against overfitting and extra information such as error estimates and variable importance can be obtained (Liaw and Wiener, 2002). For these reasons it may also be possible to incorporate a larger number of variables other than shape-based variables, but as discussed, many of these image-object variables are reliant on imagery that has been geometrically and radiometrically corrected.

Prediction from the random forest classifier was through a predictive threshold rather than majority vote (Liaw and Wiener, 2002). This provides the opportunity of adjusting the threshold to balance omission and commission errors. It was found that a threshold of 0.7 for the random forest resulted in a classification with six times as many image-objects labelled as contour banks than the hybrid decision tree/expert systems classification with only slightly greater commission error. At this stage, assessment of error was qualitative and based on visual assessment, but future accuracy assessments will allow us to quantify these errors.

The ability to adjust the threshold is important, since the classification that is most efficient for manual editing is not necessarily the one with the lowest overall error rate. It may, for example, be more efficient to knowingly under-predict and manually add missed contours than to spend time removing many objects incorrectly labeled as contours. For this reason, and for consistency in application across large geographic regions, a conservative threshold was chosen here that minimised commission error at minor expense to omission.

5.3. Application of techniques for mapping land management practices

The techniques used for this project have been developed with two main objectives. The first is to improve our ability to map contour banks using remote sensing data and to be able to apply the technique over regions and potentially over time. The second is to investigate the applicability of object-based techniques for mapping land management practices.

Some issues still remain that influence the achievement of both objectives. Radiometric and geometric corrections and consistency in segmentation results remain the primary issues for standard application of any object based classification of remotely sensed imagery. The other major limitation is the processing time and large data handling capability of image segmentation methods and software. For contour banks, this has been somewhat overcome by developing techniques that divide imagery into smaller files, and are based on single band, greyscale, shape-based analysis. The classification then reasonably assumes that contour banks have a relatively consistent shape across the landscape. This may not be a valid assumption for other land management applications where spectral or textural characteristics may provide more information than shape. The advantage of combining the image-object segmentation with the classification techniques trialled in this project is that the approaches are relatively objective, efficient in terms of time and effort, and are applicable to any number or type of variables or classes. This means that, given imagery of appropriate spectral and spatial resolution for the mapping objective, the techniques could be readily adapted to many other land management practices across Australia in a relatively standard manner.

Other classification techniques may also provide satisfactory results, although these have not been explored in detail for this project. Hierarchical classification in the Definiens® Developer software enables the user to define rules with either fuzzy or hard membership thresholds as well as the ability to use multi-level (i.e. multi-scale) relationships between image-objects created and classified at different levels of detail. This may be of particular benefit classifying the paddocks that contain contour banks and for CTF practices. Other classification techniques could be adapted. Some which have been used elsewhere for image-object classification include neural networks, and hierarchical and non-hierarchical clustering techniques.

For this project, the ensemble learning approaches, supplemented by manual mapping were used. Further statistical comparisons will be made of the accuracy and efficiency of the techniques and final dataset.

6. CONCLUSION

Of the three classification techniques compared in this study, the ensemble learning technique captured the majority of contour banks and did not classify many features incorrectly as contour banks. An advantage of the ensemble learning technique is the ability to use a probability threshold that enables the operator to further control omission and commission errors. However, considerable manual edits were still required to ensure the linework accurately represented the length and shape of the contour banks as seen on the SPOT 5 imagery. This was due to the way in which contour banks were represented by the objects derived from the image segmentation processes.

Despite some limitations, image-object segmentation and classification is an exciting new field of learning. It has great potential for mapping selected land management practices and landscape features with unique shapes, texture or patterns, particularly as remotely sensed imagery becomes more readily available. For example, the high resolution SPOT 5 imagery used in this project is now available for many areas in Australia. The advent of new, objective, multidimensional data exploration and classification techniques can further assist the development of standard mapping and classification methods using object-based information. The results suggest that the methods may be readily applied over large regions and a variety of landscapes.

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