ASSIMILATION OF SPECTRAL INFORMATION AND TEMPORAL HISTORY INTO A STATEWIDE WOODY COVER CHANGE CLASSIFICATION

Peter Scarth

Sam Gillingham

Jasmine Muir

Joint Remote Sensing Research Program
Remote Sensing Centre, Department of Natural Resources and Water, Queensland Government, Climate Building, 80 Meiers Road, Indooroopilly, QLD 4068, Australia
Centre for Remote Sensing and Spatial Information Science, School of Geography, Planning and Architecture, The University of Queensland, Brisbane, QLD 4072, Australia
Ph: +61 7 3896 9627
Email: peter.scarth@qld.gov.au

Abstract

The Statewide Landcover and Trees Study (SLATS) is a major vegetation monitoring initiative of the Queensland Department of Natural Resources and Water (NRW). SLATS gathers accurate woody vegetation cover and land cover change information for vegetation management planning and compliance, and for greenhouse gas inventory purposes. The SLATS land cover change is produced annually over the state of Queensland and is required to map changes in woody vegetation at a sub-hectare scale. Detailed operational mapping of such a large area requires robust and automated methods wherever possible in the image processing chain.

The SLATS woody vegetation change classification relies on the analysis of Landsat TM and ETM+ satellite imagery but this imagery is limited in its ability to reliably detect minor clearing and more subtle changes in woody vegetation such as thinning and drought related death using only two image dates. However, by accessing the SLATS archive of Landsat imagery it is possible to develop change detection algorithms that account for the historical variability of woody cover to improve the classification estimator. This paper describes the development of the classifier, which uses the statewide change classification from previous eras as training data to derive both time series and spectrally based indices. The output from the classifier is a woody change probability and an interpretation image that is then checked by an operator before field validation.

Introduction

The Statewide Landcover and Trees Study (SLATS) maps and monitors Queensland's woody vegetation cover using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) satellite imagery. The imagery has been used to compare the vegetation cover and change from 1988 to 2007, including annual change assessment from 1999. Image analysis methods used to map woody vegetation and change have advanced significantly over this time, driven by the need to provide both a fast turnaround of mapping and a consistent classification across the 87 Landsat scenes used for analysis across Queensland (Goulevitch *et al.* 1999). Improvements in image rectification (Armston *et al.* 2002) and radiometric calibration (de Vries *et al.* 2007) have improved the foundation for assessing image differences by minimising the errors associated with misregistration (Igbokwe 1999; Phinn and Rowland 2001; Stow 1999) and sensor radiometric drift (Song *et al.* 2001; Vogelmann *et al.* 2001).

SLATS uses foliage projective cover (FPC) (Specht 1981, 1983) as a primary descriptor of vegetation cover. Recent improvements to the method used to map FPC from Landsat imagery has been undertaken using more than 2000 vegetation sites throughout Queensland (Danaher *et al.* 2004; Lucas *et al.* 2006). The SLATS FPC product is produced annually across Queensland and is available for most years from 1988 to present. This time series allows the monitoring of vegetation changes over time, which can be linked to indicators of condition. (Wallace *et al.* 2006). However, remotely sensed cover is not necessarily stable over time, with the varying contributions of perennial and herbaceous components at different times of the year (Lu *et al.* 2003) causing changes in the surface anisotropy (Armston *et al.* 2007) and hence on changes in remotely sensed FPC. Thus, a simple classifier based on FPC change alone will have high omission and commission errors.

There are many excellent reviews of remote sensing change detection methods (e.g. Coppin and Bauer 1996; Mouat *et al.* 1993). However, the difficulties in consistently and reliably detecting woody change across a wide range of vegetation types over a large geographical extent required the development of a change method that combined both the spectral changes from scene to scene and the historical variability in foliage cover. This combination of change detection methodologies was based on combining a modified form of image differencing (e.g. Mas 1999) with a statistical analysis of the FPC time series to detect true change (e.g. Nemani and Running 1997).

Methods

Calibration data was collected from an analysis of previous operator interpreted and field checked woody change data sets from previous years. Of the 87 Landsat scenes across Queensland, 48 were selected that had at least 0.1% cleared area per year. Each of these scenes had 14 images in the associated time series and was sampled on a regular 10 × 10 pixel grid. In all, 672 images were processed resulting in a calibration data set of almost 6,000,000 samples. Each sample had the FPC and reflective band time series for that pixel, along with the operator-interpreted change for each previous change epoch. These data were then used to develop both the spectral and temporal indices.

Spectral Indices

A regression index based on truncated singular value decomposition was developed. This method was chosen since it offers greater numerical stability when working with near collinear data and it gives similar results to the often used partial least squares method (Kalivas 1999). The regression index was developed using the extracted training data, and was optimised such that the solution delivers an accurate prediction whilst being relatively insensitive to noise in the inputs. This was achieved by optimising the index to use bands and transforms that:

- minimised the RMSE between predictions and measured,
- minimised the sensitivity of the model to extreme values by calculating the mean and maximum of the partial derivatives of each band; and
- maximised the reduction in error variance per term added using the method of Elden (2004).

All processing was completed on Log transformed reflective bands to minimise the effect of illumination differences (Ahmad *et al.* 1989).

The final set of coefficients is shown in Table 1. Note that the blue and near infrared bands were not used in the change model. These coefficients were applied to the transformed Landsat bands and were summed to generate the regression model output.

	Band 2	Band 3	Band 5	Band 7
Date 1	1.0	0.4	4.1	0.5
Date 2	-0.5	0.6	-4.7	-1.4

Table 1 - Coefficients applied to Log transformed Landsat TM bands for mapping woody vegetation change

Temporal Indices

The initial step in processing the SLATS FPC product was to normalise the annual FPC estimates. Although the image data is selected to correspond with the local dry season, there is still significant interaction between the woody and herbaceous components of the FPC signal. A simple histogram normalisation method was applied on a scene-by-scene basis to account for these effects (Kautsky *et al.* 1984; Yang and Lo 2000), resulting in all image dates having a similar FPC histogram. An example of this normalisation is shown in Figure 1.

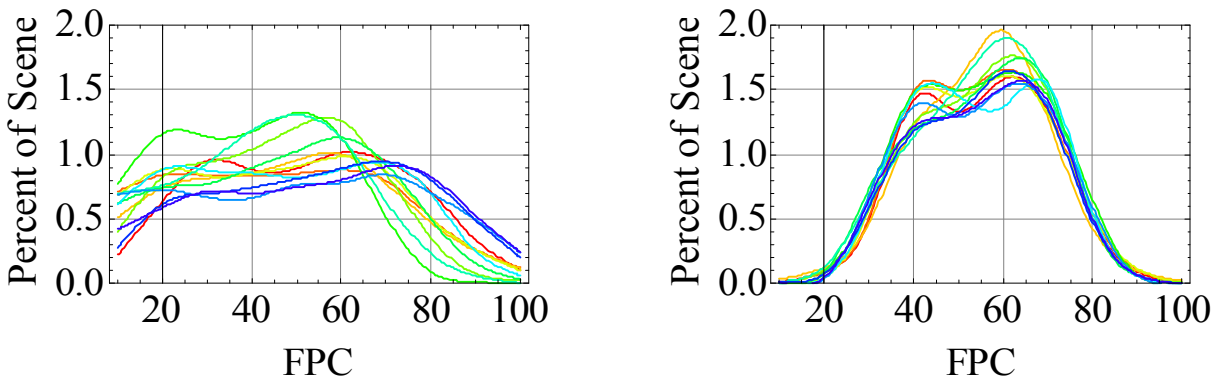

Figure 1- Multitemporal FPC Histograms from the Sunshine Coast Landsat scene. Each year is represented by a different colour. Left panel is original (uncorrected) histograms. Right panel is histograms corrected to a common mean and standard deviation.

The corrected FPC data were then used to build two change indices: the first is a simple difference of the corrected FPC over the change dates; and the second is a time series metric. The latter measures the variance around a line fitted to the FPC time series, and uses this variance in a difference test. The form of the test is given in (1):

$$t = \frac{fpc_{pred} - fpc_{meas}}{s} \tag{1}$$

Where fpc_{meas} is the FPC determined from the Landsat imagery at the change point, while the predicted FPC (fpc_{pred}) is the fit of the line through the FPC time series, extrapolated to the current year as shown in (2)

$$fpc_{pred} = a + bt_{n+1} \tag{2}$$

Where a and b are the intercept and slope of the linear regression of the Landsat FPC against time. s^2 is the estimate of the variance in the fitted FPC values and is calculated using (3):

$$s^2 = \frac{n\left(\sigma_{fpc} - \frac{\mathrm{cov}(t, fpc)^2}{\sigma_t}\right)}{n-2} \tag{3}$$

Where σ_{fpc} is the standard deviation of the FPC, σ_{time} is the standard deviation of time, n is the number of years in the time series before the change event and $cov(t,fpc)$ is the covariance between FPC and time.

An example of the application of this statistic can be seen in Figure 2. The combination of the magnitude of difference between the predicted FPC at the change point and the actual FPC normalised by the variance in the time series allows the same statistic to be used across many different vegetation types across Queensland since it takes into account both trend in cover and the variance of the cover type.

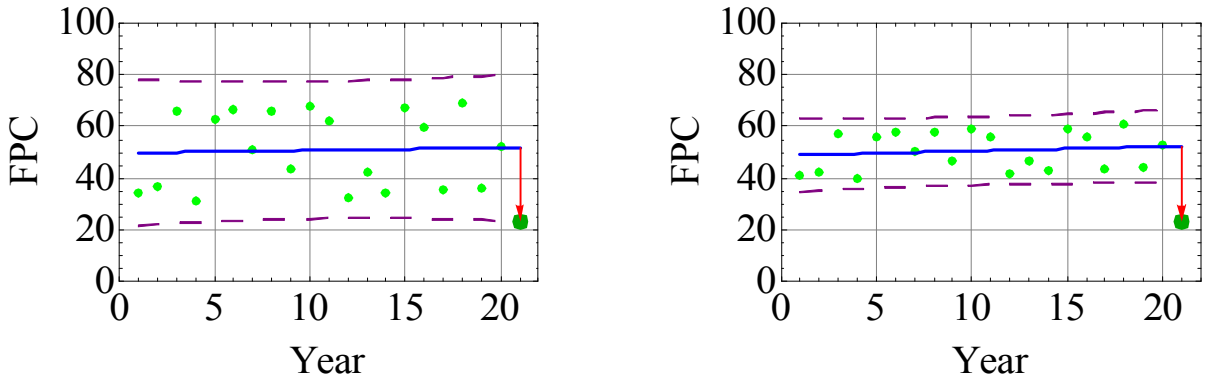

Figure 2 - Illustration of the time series change detection. Both left and right panels display a similar trend in FPC over time (green dots with fitted blue trend line). However, right hand series has a lesser variance in the time series, so the drop to the current year's value (dark green dot, red arrow) is more significant than the same magnitude of drop in the left hand series.

Classification

The final classifier was developed by training a linear combination of both the spectral and temporal indices against the calibration data. The final classifier displays a high degree of sensitivity to woody change although some confused pixels are also apparent as indicated in Figure 3. The final classifier sits within the SLATS operational python based processing framework and is run with minimal user intervention as a batch job across all the state scenes.

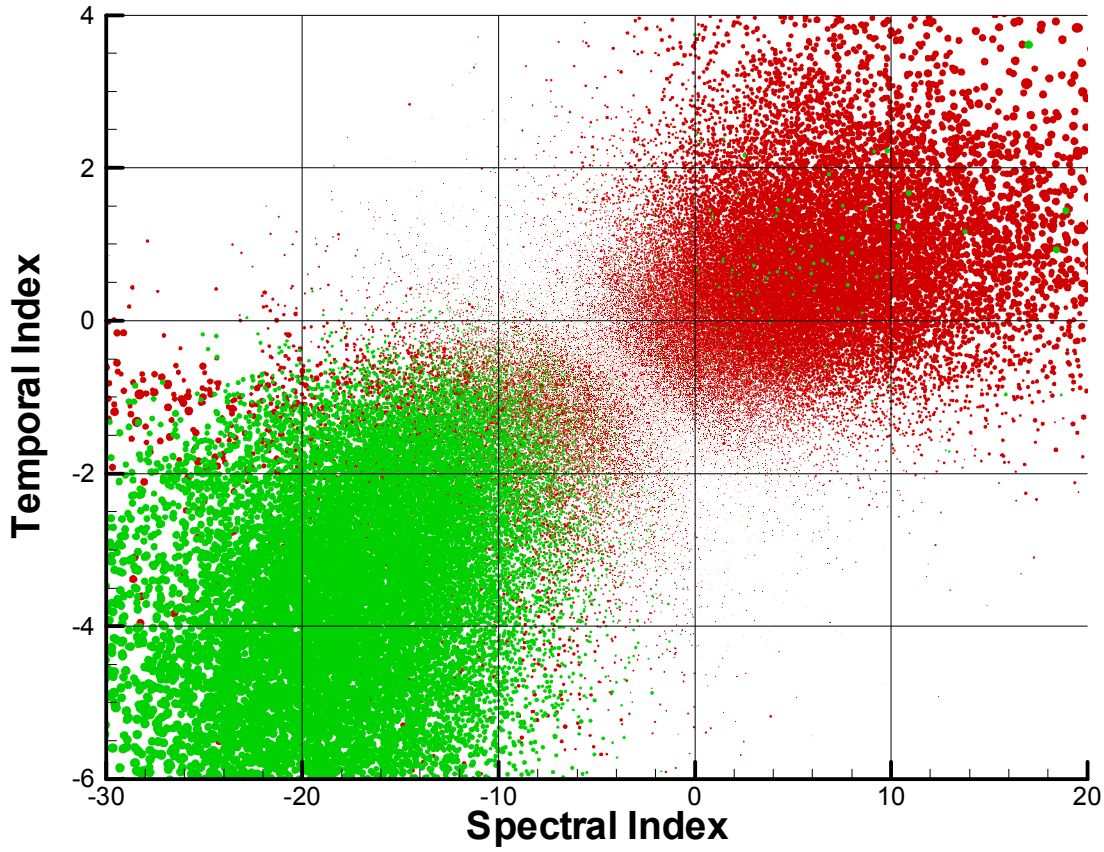

Figure 3 – Scatter plot demonstrating the class separability of the classifier on a state-wide data set Dots show the relationship between the spectral and temporal indices. Dot size is proportional to the magnitude of the combined index. Red dots are cleared points; green dots are no change points.

Results and Discussion

The effectiveness of both the individual and combined classifiers was evaluated using receiver operating curves (ROC) (Cheng *et al.* 1998). Figure 4 shows the ROC for the simple FPC difference approach as well as for the spectral, time series and combined classifier.

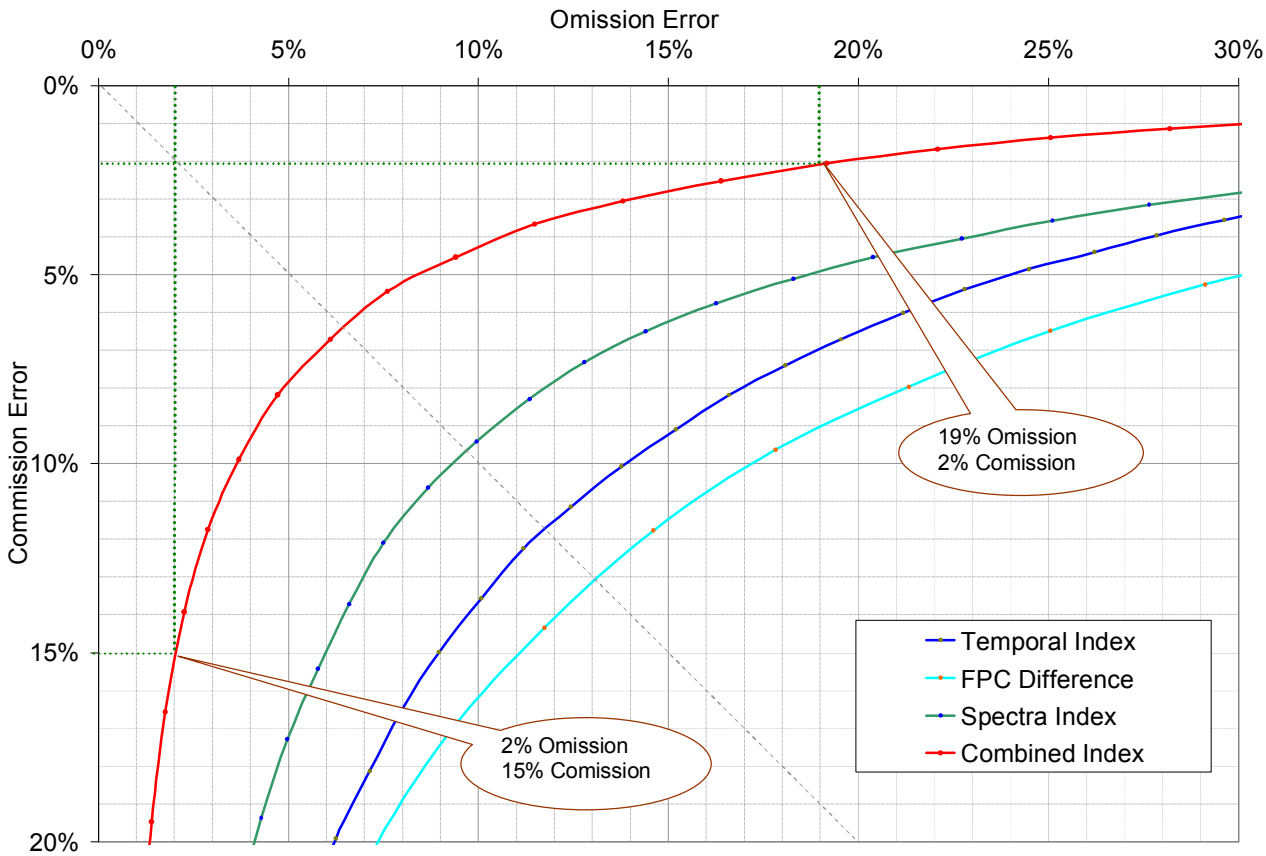

Figure 4 - Receiver Operator Curve for the change classifier. Performance of the individual classifiers and the combined index is shown, along with the selected classification levels for the final imagery.

If we balance the omission and commission error, then the "knee" of the combined ROC shows that the classifier is achieving 93.7% overall accuracy which is an excellent result given the large range of vegetation and change types across Queensland. It is notable that the FPC difference across the change period is the worst performing classifier, showing that it requires the additional information of variability in the time series to improve its efficacy. The spectral index on its own is the best performing single classifier with 90.4% overall accuracy. This classifier is primarily based on Landsat band 5 differences (Table 1) which is consistent with the observation that a clearing event often results in disturbed soil with a high reflectivity in band 5.

In order to use this classifier in an operational reporting environment, several levels of classification accuracy are used. The two primary levels (2% and 15% omission) are shown by balloons in Figure 4. This is used to produce a two level classification (Figure 5) which is then further interpreted, edited and field checked by an operator. This manual interpretation stage is used to check the output of the classifier and additionally to further improve the accuracy of the final product before it is used to produce the annual SLATS woody change figures and reports.

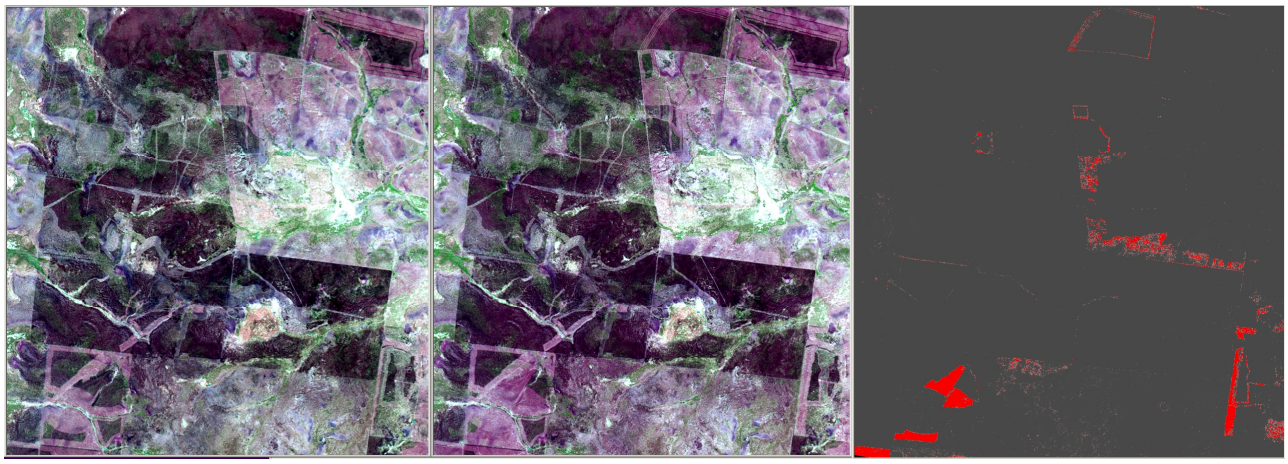

Figure 5 - Example output of the classifier on a portion of the Morven Landsat scene. Left panel is the 2005 Landsat image. Middle panel is the 2006 Landsat image. Right panel is the woody change classification showing areas with high and moderate change probabilities as red and pink respectively.

This change process is a significant improvement over the initial SLATS change process (Goulevitch *et al.* 1999) and has brought about a considerable improvement in the consistency of the classification along with a significant drop in manual operator processing. Since the SLATS operational processing system is fully automated and scriptable, it is possible to reprocess the entire archive when improved classifiers are developed. With ongoing improvements in processing capacity, future work will investigate machine learning algorithms as a way of further improving classifier performance (DeFries and Cheung Wai Chan 2000).

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