Notes on mapping and monitoring forest change in Australia using remote sensing and other data

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Abstract - Landuse changes associated with agriculture and forestry are a significant component in Australia's carbon budget. To quantify the amount, the Australian Greenhouse Office has progressively developed the National Carbon Accounting System (NCAS) over the past 4 years. The NCAS provides an integrated and comprehensive greenhouse gas emissions reporting capability for land based emissions.

The NCAS uses calibrated models to estimate carbon gain/loss on areas of clearing and regrowth as identified from the analysis of time series Landsat data. This data currently consists of twelve continental coverages (approximately 4070 scenes) of geographically and spectrally calibrated data acquired between 1972 and 2002. The project responsible for the compilation and analysis of the remotely sensed data is referred to as the NCAS Landcover Change Project (LCP), which is the topic of this paper.

We provide an overview of the techniques that have been shown to be reliable for constructing a monitoring system of this size. We describe our methodology and some of the techniques and algorithms we employ, and how we have applied the approach in practice.

1. INTRODUCTION

In Australia, remotely sensed Landsat TM data is routinely used for mapping and monitoring the change in extent of woody perennial vegetation. Time series remotely sensed satellite imagery and ground information is used to form multi-temporal classifications of presence/absence of woody cover.

Current operational monitoring systems typically involve:

- registration of time series Landsat data
- calibration of Landsat data to a common reference
- processing of the calibrated data to remove `corrupted' data, which include dropouts, data affected by fire, smoke and cloud .
- stratification of the data into `zones', where landcover types within a zone have similar spectral properties.
- (if required) processing of the calibrated data to adjust for viewing geometry including differential terrain illumination
- analysis of ground data and spectral data to determine a single-date classifier and its parameters.

Greater classification accuracies can be obtained by including the following step

- specification of a joint model for multi-temporal classification.

The demands for the spatial and temporal resolution used here arose from the development of the reporting rules (Marrakech Accord) guiding the implementation of accounting procedures for the Kyoto Protocol. However the remote sensing program has many additional benefits for bodies interested in monitoring landuse change generally.

An overview of techniques used for the NCAS LCP are described in the ensuing sections.

2. MATERIALS AND METHODS

Our methods use:

- Long-term sequences of orthorectified and calibrated Landsat TM and MSS satellite data to provide observations relating to land use;
- Discriminant analysis techniques to (spectrally) separate classes of interest; in this case forest and non-forest;
- Human interpretation / opinion and function minimisation to specify / estimate classifier parameters; and
- Spatial/temporal models to reduce errors

Training and validation data is obtained from interpretation of stereo photography to identify samples of forest and non-forest. This is performed independently at the Royal Melbourne Institute of Technology.

The following methods are applied by the private sector to specifications audited by a Quality Assurance process.

2.2 Landsat data and preprocessing

An important step in the development of methods for detecting, measuring and monitoring change through time is the ability to compare images from different dates and sites in different scenes. These comparisons require the digital counts from each scene to be registered and calibrated to common reference values. For this purpose, scenes acquired in the dry season (when underlying grasses are cured) are optimal, however the process must be applicable and robust to data acquired on non-optimal dates.

Sequences of Landsat data are routinely radiometrically calibrated and co-registered as outlined in the following sections.

2.2.1 Image Rectification

The main steps in establishing a rectified sequence of MSS and TM imagery are:

1) establish an ortho-rectified base mosaic of TM data; and

2) register other images in the temporal sequence to the base mosaic.

PCI OrthoEngine software was used for this purpose.

Visual inspection and a numerical procedure based on cross-correlation feature matching (Campbell, 1999) are used in Quality Assurance to assess the accuracy of co-registration of the images in a sequence to the base.

2.2.2 Image calibration and mosaicing

Ideally, all images would be calibrated to standard reflectance units. However, when comparing images to detect change, it is sufficient to convert raw digital counts to be consistent with a chosen reference image.

Three calibration steps were considered in the radiometric correction procedure for Landsat imagery: 1) Gain and offset calibration; 2) Sun angle and distance correction; and 3) BRDF calibration. Each step is briefly described in the following subsections.

A. Gain and Offset Calibration

The gain and offset for each image band are obtained from the ACRES report file associated with each Landsat scene, or estimated from the data.

When estimating gains and offsets from the data, we assume the existence of known locations (targets) in the images that have (near) constant reflectance through time. We refer to targets having constant reflectance through time as *invariant* and those having near constant reflectance as *pseudo-invariant*. Targets are selected to cover the range of data values within each band.

Calibrating a sequence of images to like-values consists of the following steps:

1) Select a reference image, to which other images will be corrected;

2) Select (pseudo) invariant targets;

3) Estimate calibration coefficients to calibrate each image to the reference image;

4) Examine the calibration curves and refine the target selection if necessary; and

5) Use the estimated coefficients to calibrate the image.

To minimise the influence of atypical pixels, and/or changing pixel values within otherwise invariant targets, (statistically) robust techniques are used to estimate the gains and offsets. The approach employed is based on S-estimation of the regression coefficients (Rousseeuw and Yohai, 1984). For more information, see (Furby and Campbell, 2000).

B. Sun Angle and Distance Correction

The sun zenith angle for each pixel and the distance from the scene centre to the sun are calculated, then the reflectance correction is calculated for each band as described in Vermote *et. al.* (1994).

C. BRDF Calibration

A two-kernel empirical BRDF model was used to correct the remaining scene-to-scene differences. Simple variations of Walthall's model, as described by Danaher *et. al.* (2001), were used in our BRDF calibration approach. The model is a three-parameter model (see Equation 3 in (Danaher *et. al.*, 2001)), where the three parameters were calculated by solving equations based on the image overlap areas, and the same parameters were applied to all scenes (see TABLE 1).

TABLE 1

THREE PARAMETERS FOR BRDF CORRECTION.

	a	*b*	*c*
Band 1	0.99707	0.009819	0.018906
Band 2	-0.53200	-0.005423	-0.006888
Band 3	-0.75085	-0.012555	-0.011285
Band 4	-1.00000	-0.006400	-0.008647
Band 5	0.99609	0.014900	0.006204
Band 7	-1.00000	-0.017147	-0.012555

The effects of using a common set of coefficients for all scenes, and of using varying coefficients for each scene were compared in (Danaher et. al., 2001). While using different coefficients for each scene seemed to produce good scene-to-scene matches, it did not remove the east-to-west illumination effect and in addition removed some real change. It was decided that a common set of coefficients should be used.

Danaher *et. al.* (2001) showed that there were considerable differences in BRDF caused by different land cover types in the landscape in question, however it is only possible to correct for these differences if each land cover type can be identified at the same resolution as the imagery. It would be desirable to use different kernel coefficients for each land cover type. However, the land cover data were not available for the continent so a generalised correction for all land cover types was applied.

Data for the year 2000 were chosen to form the calibration base mosaic (Wu et. al, 2001), and all other scenes from other dates calibrated to it.

The individual landsat scenes were mosaiced to form a coverage for a particular period / `year'. Coverages have been assembled for the years 1972, 1977, 1980, 1985, 1988, 1989, 1990, 1991, 1992, 1995, 1998, 2000 and 2002.

2.4 Classification of remotely sensed and other data

The aim of classification is to recognise the state of a physical process by using a set of measurements recorded on it. The method used for performing the classification is generally called the *classifier*, while the recorded measurements are referred to as *data.* The state of the process recognised by the classifier is labelled as belonging to a particular *class*. After this stage, the labelled data are called the *classification* and the data are said to have been *classified.*

The process of classification requires at least the following steps:

1) defining the number of possible classes;

2) choosing a model for assessing the information in the available data; and

3) deciding the class label after having assessed the information in the data.

Perhaps the most popular classifier for optical data is the Maximum Likelihood Classifier (MLC) (Rao, 1966). These classifiers generally assume that spectral descriptions for classes can be modelled using multivariate Gaussian densities.

Here we apply band reduction routines related to canonical variate analysis (CVA) to identify the important spectral band combinations for the questions of interest, and related routines (McKay & Campbell 1982) to smooth the band coefficients to derive simplified spectral indices. Instead of modelling the spectral data using multivariate Gaussian distributions, we derive index thresholds (for one or more indices) to produce single date classifications using intervals between thresholds to produce 'soft'classifications (initial interpretations – see sections 2.5).

Here the classifier is constructed in two steps:

(i) derivation of linear combinations of bands (or *spectral indices*) which `best' separate the classes in spectral space.

(ii) specification of decision boundaries (or *thresholds*) mapping spectral space into the specified classes. Here we consider a two classes; *Forrest* and *non-Forrest*.

Typically a set of spectral indices is chosen once for each zone in an image, and the thresholds are adjusted year to year to account for seasonal variation and limitations in the accuracy of calibration.

This approach was taken for pragmatic reasons which include the need for many operators from diverse backgrounds and training performing initial interpretations (initial classifications) and the requirement to have a system where potential errors are easily understood and remedied.

The time series is composed of sources of data of varying quality and spectral discrimination. To improve classification accuracy, we use joint models which incorporate error rates of the initial interpretations as well as temporal and spatial rules.

2.5 Spatial temporal models for classification

In this section we describe the models we use for classification. To begin, we need to define some notation. For pixel k=1..m and time slice i=1..n we write y_{ik} , y'_{ik} , l_{ik}, l'_{ik} and z_{ik} to represent landsat coverage, index image, initial interpretation, `true' class label and stratification zone respectively. We use the notation r(k) to denote the 8 pixels adjacent to k.

The joint model for the observed and unobserved images can be written as

$$p(y'_{1k} .. y'_{nk} , l'_{1k} .. l'_{nk} , l_{1k} .. l_{nk} , l'_{1r(k)} .. l'_{nr(k)} , z_{1k} .. z_{nk}) =$$

$$\Pi_{i=1..n}\ p(y'_{ik} \mid z_{ik} , l_{ik})\ p(l_{ik} \mid z_{ik} , l'_{ik})\ p(l'_{ik} \mid l'_{i-1,k} , l'_{ir(k)})\ p(z_{ik}) \qquad (1)$$

where $p(l'_{1k} \mid l'_{0k} , l'_{ir(k)})$ is defined as $p(l'_{1k} \mid l'_{ir(k)})$.

The `true' class labels are obtained from the joint distribution of $l'_{1k} .. l'_{nk}$ given the observable images by a cyclic ascent algorithm as in (Caccetta, 1997 pp 187-192), (Kiiveri and Caccetta, 1998).

Useful properties of the approach include:

- propagation of *uncertainties* in inputs and calculation of uncertainties in outputs
- production of *hard* and *soft* maps
- handling of *missing data* by using all available information to make predictions
- existence of well-developed statistical tools for parameter estimation.

Results/conclusions

The approach has been implemented over the last 3 years to produce national coverages of forest change. In this period the project has:

a) Held a number of workshops and conducted pilot tests to established `best practice' for mapping and monitoring of forest in the Australian context (Suzanne and Woodgate, 2002)

b) Documented procedures to a level useful for outsourcing (Furby, 2002).

c) Established a continental Landsat rectification base

d) Established a continental Landsat calibration base (Wu *et. al.* , 2001).

e) Interpreted data from 1972-2000 to produce forest change coverages, and

f) Tested the system in `update' mode, by doing a second round of analysis/processing to incorporate data from the year 2002 into the time series

We make the following broad observations:

(i) For southern `agricultural' areas where change is due to land conversion and plantation management classification accuracies are typically high, with omission and commission error rates typically being less than 5%. Accuracies in other areas are typically less than this, with some of the reasons listed below.

(ii) Differential terrain illumination introduces errors. McDonald *et. al*. (2000) demonstrated that the effects of terrain could be reduced using a relatively accurate digital elevation model and a correction first published by Teillet *et al*, (1982) and referred to by Meyer *et al*, (1993) as the C-correction. However in many instances a digital elevation model or sufficient accuracy is not available or does not exist.

(iii) Steps to minimise operator variability are essential, and the Quality Assurance specifications were written with this in mind.

(iv) Sparse forests systems pose the greatest challenge both for the collection of training and validation data (as interpreted from the definition of "Forrest") as well as typically being areas that have the greatest seasonal variations for reasons other than management.

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