Continental Scale Land Cover Change Monitoring in Australia using Landsat Imagery

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Abstract

Land use changes associated with agriculture and forestry are a significant component in Australia's carbon budget. In response to the need to quantify the resulting greenhouse gas emissions, the National Carbon Accounting System - Land Cover Change Project has developed the capability for continental monitoring of land cover change using Landsat imagery through collaboration between the Australian Greenhouse Office, the CSIRO and other partners. The initial implementation of the program was completed in 2002 producing forest extent and change products from 1972 to 2000. These products are regularly updated with more recent imagery, now on an annual basis. Subsequent to the initial mapping of forest presence/absence, the monitoring program is expanding to include the mapping of plantation type (softwood or hardwood) for both post-1990 Kyoto compliant plantings and pre-1990 forest inventory and monitoring of sparse woodland to meet both carbon accounting and natural resource management needs.

5000 Landsat MSS, TM and ETM+ images, from fifteen time periods since 1972, are now used to monitor land cover attributes at 25m resolution for the Australian continent. The original demands for the spatial and temporal resolution used 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 evolved to cover broader interests in natural resource management. This paper will present an overview of the program, the methodology and some recent results.

Keywords: Remote Sensing, Land Cover, Monitoring, Multi-temporal, Landsat, Forestry.

1. Introduction

Fundamental to the accounting for carbon change in forestry and agriculture is an understanding of the change in land cover to detect afforestation, reforestation and deforestation events. The impact of an event associated with land cover change may continue over many years and vary with time since the event took place. It is, therefore, necessary to be able to monitor change in land cover over extended periods of time. In response to the need to quantify the resulting greenhouse gas emissions, the National Carbon Accounting System - Land Cover Change Project (NCAS-LCCP) has developed the capability for continental monitoring of land cover change using Landsat imagery through collaboration between the Australian Greenhouse Office (AGO), the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and other partners.

The original demands for the spatial and temporal resolution used in the Program arose from the development of the Marrakech Accord (UNFCCC, 2002) reporting rules guiding the implementation of accounting procedures for the Kyoto Protocol, with particular emphasis on forest extent and changes. The system accounts for emissions from forest conversion since 1972, including emissions resulting from the loss of soil carbon and decay of vegetation that was deforested in previous years. The relevant decay cycle covers a period of 20 years. The amount of regrowth vegetation and removal of regrowth is also critical for determining net emissions. The development of the modelling components and data requirements for Australia's carbon accounting system is described by Brack *et.al.* (2006).

With its temporal coverage (15 epochs) and spatial resolution (25m) of the Australian continent, the NCAS-LCCP is one of the largest land cover monitoring programs in the world. Over a comparable spatial extent, the European CORINE and US national land cover datasets each consist of two epochs separated by a decade. Global monitoring programs tend to operate at coarser spatial resolution. The Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD), for example, plans to operate at 250m to 1km spatial scales for land cover change with periodic monitoring of regional areas at finer scales (20-30% of the forested areas per year).

The initial implementation of the program, which produced forest extent and change products over ten periods from 1972-2000, was completed in 2002. Since then, the remote sensing program has evolved to cover broader interests in natural resource management. Forest updates are now produced annually and a range of other products are being developed. This paper presents the key methodology elements for the operational and near-operational products from the program. The following section describes the forest extent and change methodology. The third section describes the mapping of plantation type (hardwood or softwood) for both post-1990 Kyoto plantings and pre-1990 forest inventory. The fourth section describes the development of a forest canopy density product. The fifth section describes the extension of the processing to sparse woody perennial vegetation. The final section discusses some likely future directions for the program.

2. Forest Extent and Change Methodology

To meet Australia's current definition of forest, a land cover must have 20% tree crown cover and the potential to reach greater than 2m in height. As well as according with accepted definitions this threshold corresponds, in many environments, to densities which can be reliably mapped from Landsat spectral bands. The stages in the forest extent and change mapping are:

1. Select and acquire relevant image and supporting spatial data
2. Ortho-rectify and calibrate the image data
3. Mosaic the individual images into 1:1,000,000 map sheet units for processing
4. Thresholding to produce single-date forest cover probability images
5. Multi-temporal refinement of the forest cover probabilities and change calculations
6. Manual attribution of the change layers

Each of these stages is performed independently. Most stages are outsourced by the AGO with commercial entities competing for allocations of work. Quality assurance procedures have been implemented so that the output of each stage is thoroughly checked against the agreed accuracy and/or consistency standards before the next stage of the processing is commenced. Key aspects of each of these stages are described below. The methodology and its evolution are described by Caccetta et al (2003, 2007) and fully detailed specifications for operational processing for the system are given in Furby (2002).

2.1 The data

Landsat MSS, TM and ETM+ imagery are the principal sources of remotely-sensed data used. Landsat MSS data are available from 1972. The higher spectral and spatial resolution Landsat TM data has been available since 1987 and Landsat ETM+ since 1999. Data sources such as radar and airborne scanner data were excluded because of their limited availability during the 1970-1990 period. Although aerial photographs cover most areas of Australia, coverages are sparse in time and have been irregularly acquired. In addition, they have not been considered as a primary data source because of the prohibitively high cost of analysis. However photographs and the high-resolution Ikonos satellite imagery have been used as ground-truth data for training and validation. NOAA AVHRR and equivalent imagery was not considered because the pixel size (250m to 1.1 km) is far too coarse for the detection of the majority of areas subject to change.

Dry season (summer) imagery with as little green vegetation cover as possible has been found to provide the best discrimination between forest and non-forest cover (Wallace and Furby, 1994). If images at the optimal dates appear to have a lot of green vegetation cover, consideration is given to less green images further from the optimal date. Consideration is also given to limiting other potential problems with the imagery. The most common of these problems include, but are not limited to, data errors (eg line drop-out), cloud, smoke, extensive flooding and wildfire damage. Preference in the image selections is given to same-date sequences along paths and to temporal consistency of the image dates selected.

2.2 Ortho-rectification and calibration

Change detection requires that the images be well registered to each other. In order to integrate the image data with other datasets, the images must be rectified to a map grid. Ortho-rectified base images for each 1:1,000,000 map sheet (from a mosaic of several path/rows) were created for a single time period using a viewing-geometry approach (Toutin, 1994, Cheng and Toutin, 1995) with ground control points. The

remaining images in the sequence were registered to the base mosaic. Cross-correlation feature matching techniques were used to increase the speed and accuracy of the co-registration of the images.

Ideally, all images would be calibrated to standard reflectance units. However, when comparing images to detect change, it is sufficient to convert the raw digital counts to be consistent with a chosen reference image. A three-step approach has been implemented: (i) correction to scaled top-of-atmosphere reflectance; (ii) correction for surface reflectance properties by application of bi-directional reflectance distribution function (BRDF) kernels (Danaher et al, 2001); and (iii) calibration to 'like values' using invariant targets (Furby and Campbell, 2001).

Terrain illumination effects can result in different signals from the same cover on bright and dark sides of hills. This is particularly problematic for time series imagery where terrain effects vary with acquisition dates. The details of the terrain illumination correction used can be found in (Wu et al., 2004). It is based on the C-correction (Teillet et al., 1982) and incorporates a ray tracing algorithm for identifying true shadow. A high-resolution digital elevation model (DEM) is required to achieve adequate removal of terrain effects.

2.3 Thresholding

Thresholding is the name given to the process of creating a forest cover probability image classification for each individual image (singe-epoch). The steps are:

1. Stratification of the data into 'zones', where land cover types within a zone have similar spectral properties.
2. Creation of a 'base' forest cover probability image by:
    - locating training samples of all the major forest and non-forest cover types;
    - investigating the spectral separability of the training samples to identify indices (linear combinations of image bands) which can adequately separate forest and non-forest cover; and
    - identifying thresholds to allocate pixels to forest, non-forest or uncertain cover classes and hence calculate a probability of forest cover for each pixel.
3. Masking of the calibrated data to remove 'corrupted' data, which include dropouts, data affected by fire, smoke and cloud.
4. Creation of forest cover probability images for the other epochs by using a matching process to automatically estimate appropriate thresholds for the new images for the given indices for each stratification zone.

The first two steps are performed only during the initial implementation of the processing. As subsequent epochs are added to the existing sequence (annual updates) only steps 3 and 4 are performed.

Canonical variate analyses (Campbell and Atchley, 1981) and directed contrasts between forest and non-forest areas (McKay and Campbell, 1982) are used to derive indices that best separate such areas. This targeted approach allows indices with the best possible discrimination to be derived locally for each stratification zone, rather than applying common indices over the whole country. The indices are smoothed (Campbell and Furby, 1994) to make them more robust over the range of cover types and image dates for each stratification zone. These analyses also provide an objective measure of the number of indices required for adequate discrimination. Typically two or three indices are required. The first is a 'woodiness' index that discriminates between forest and most other cover types. The remaining indices tend to 'mask' specific cover types not adequately separated by the first index. Generally, there is a continuum of index values between forest and non-forest cover. Thresholds are used to partition the image into regions that can confidently be labelled as forest and non-forest with a region of uncertainty in-between. The thresholds determine the probability assigned to each pixel.

Manually setting the thresholds to partition the each image into certain forest, certain non-forest and uncertain for every stratification zone is one of the most labour intensive steps in the forest cover monitoring process. A method to automatically derive thresholds for a new image by matching to a base image for which thresholds have already been set was developed (Caccetta and Bryant, 2002). The matching finds thresholds that minimise the difference between the base probability image and the probability image for the new epoch. The automation reduces the processing time (and hence costs) and increases the temporal consistency of the products obtained

2.4 Multi-temporal classification

The multi-temporal analysis resolves the uncertainty and more accurately detects genuine change by combining the information from multiple dates; i.e. sequences of probabilities of forest cover. Regions of forest cover either remain forest, perhaps with variations in the density, or are deforested. Regions of non-forest cover remain non-forest or are replanted to forest cover. Each of these circumstances has a clear temporal signature. A signature that varies very rapidly between forest and non-forest cover or shows forest cover only for a single epoch is a very unlikely long-term trend for genuine forest cover. Temporal rules are used to weight against such areas being labelled as forest cover in any time slice. This strategy significantly reduces the amount of false change detected when comparing any two epochs. Similarly, the temporal rules use the whole temporal sequence of probabilities to infer the cover type of uncertain or masked areas.

Bayesian networks (conditional probability networks) which are parameterised as conditional Gaussian distributions are used to perform the multi-temporal classification. They provide a framework that allows for the assessment and propagation of uncertainty during the classification of multiple sources of data of varying quality or accuracy. The scheme for combining data is based upon techniques presented in Lauritzen and Spiegelhalter (1988) and Lauritzen (1992).

The network can be represented as a graph, where the nodes of the graph represent random variables and the edges of the graph represent (conditional) independence assumptions between the variables. An example of a network for mapping and monitoring forest extent is shown in figure 1 (for a different example applied to dryland salinity, see Furby et al, 2008). The circles and rectangles represent the nodes of the graph. The rectangles represent variables that are observed, in this case the estimated forest cover probability image from the thresholding of each single-date image. The probability is used, rather than a hard class label, to reflect the relative certainty of the classification. The circles represent variables that are not directly observed, in this case the true forest extent map at each date. Values for these variables can be inferred from the other variables.

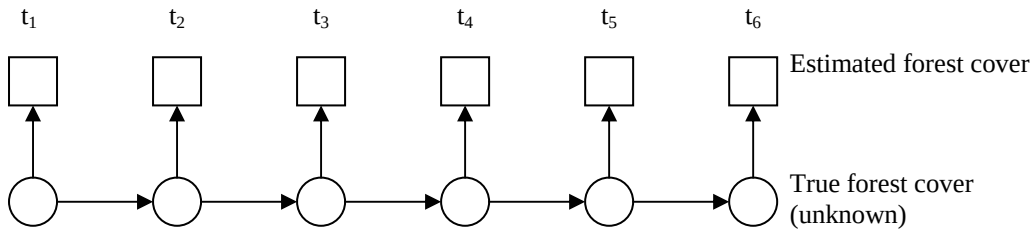

Figure 1: An example of a simplified (six-epoch) conditional probability network for forest extent mapping and monitoring.

The graph edges or 'arrows' represent relationships between the variables. Observing a particular value for a variable provides some information about all the other variables to which it is connected. The rules, or the relationships between the variables, are expressed in terms of conditional probability tables. Error rates tables link the estimated forest extent map to the true forest extent at each date (vertical arrows in figure 1). The error rates tables describe the accuracy (uncertainty) of the single-epoch maps. The relative level of confidence varies with image quality. For a typical image with good discrimination of forest and non-forest cover the probability that an area is correctly labelled is assumed to be 0.95. Decreasing vales, 0.90, 0.80 and 0.70, are used for a small, moderate or severe loss of discrimination. Temporal rules link the true forest extent maps through time (horizontal arrows in figure 1). The probability of change depends on the time interval between the successive maps. It was found that for a time interval between images of one year a probability of change of 0.05 (probability of constant cover of 0.95) produced acceptable results in all regions. This probability was then modified for the time interval between images according to the formula Probability (constant cover) = 0.95^{td}= 1 – Probability (change); where td = t_1-t_2 is the number of years between successive epochs.

Change layers (clearing and regrowth) are calculated from the refined forest cover probability images by subtraction. These become the inputs into the carbon modelling process together with climate, vegetation and soil type and land use practice data.

2.5 Manual Attribution

The products from the land cover change mapping provide the location, spatial extent and time of forest to non-forest transitions (and the reverse) that are input into the carbon modelling process. However, the Revised 1996 Intergovernmental Panel on Climate Change (IPCC) Guidelines require that only carbon stock change that is associated with directly human induced land use change be included in the national account. The land cover change products are attributed so that the areas where the cover change is not a land use change or where the change was not directly human-induced are excluded. Masks of the areas affected by fire are created as part of the thresholding processing. A tenure mask is used to exclude tenures that do not reflect a land use change (e.g. state forestry and national parks). However, further masks are created manually to exclude areas of land cover change attributable to factors such as dieback, salinisation, drought and seasonal flushing where there is no clear land use change after the deforestation or regrowth event.

3. Plantation Type Mapping Methodology

In areas where new forest growth has been identified, the carbon modelling can be improved by using growth models specific to the new forest type (hardwood or softwood plantation, environmental planting or native regrowth). However, existing data for forest / plantation class is of variable quality, is inconsistent within and between states, is irregularly updated and is often at inappropriate spatial scales for integrating with the forest cover mapping. That is, nationally consistent forest type classifications were not available at an appropriate spatial and temporal scale for use in the carbon modelling.

Chia et al (2006b) showed that hardwood and softwood plantations could be discriminated from each other and from native cover using Landsat TM and ETM+ image data. Environmental plantings (of native species) and native regrowth are not separable. There was significantly less discrimination between these classes when considering Landsat MSS data. Using the Landsat TM / ETM+ imagery in the NCAS-LCCP time series, plantation type maps are created for post-1990 Kyoto compliant regrowth (areas of trees planted on non-forest land in 1990) as follows:

1. Composite (average) the image data for all regions of forest from the present back to the most recent ‘regrowth’ event.
2. Identify training samples of softwood, hardwood and native regrowth using ground-truth information from existing mapping where available.
3. Use canonical variate analysis to investigate the spectral separability of the training sites and form spectral classes (similar image spectral response) for a classification.
4. Apply a neighbourhood-modified maximum likelihood classifier (Campbell and Wallace, 1989) to derive plantation type labels.
5. Mask out areas that are not Kyoto-compliant regrowth.
6. Manual attribution where contextual information is used to exclude or relabel regrowth classes that cannot be separated spectrally.

This product is updated annually (steps 1, 4, 5 and 6) along with the forest extent and change mapping.

The initial compositing step was adopted in the initial processing based on effort considerations. In theory a single date classifier trained to recognise all the likely forest types could be applied to each Landsat TM / ETM+ image in the time series to produce a temporal sequence of forest type labels. In practice this is not feasible due to limitations in calibration accuracy, and variability due to mismatches in acquisition dates and seasonal differences. The effect is most observable in classes that have low spectral separation (of the order of a few digital counts). The alternative is to optimise the classifier for each image date. This also allows new plantation types to be accommodated. Temporal models can be used to increase the accuracy of the time series classification as a whole. However, the approach is operator intensive and time consuming (a rough estimate, of the order of twenty person years was made for the plantation regions of the Australian continent assuming nine epochs in the time series).

Although there is less discrimination using Landsat MSS data, in many cases mature softwoods are spectrally separable from other forest types. Softwood is the predominant plantation type in Australia prior to 1990. This observation allowed the development of a pre-1990 plantation inventory product that identifies softwood plantations (Furby et al, 2008). The steps in the processing are:

1. Select training sites that represent softwood plantations, native forest and bare land;

2. Perform canonical variate analyses to assess the spectral separability of training sites and aggregate into spectral classes;
3. Perform a maximum likelihood classification so that each pixel is assigned a probability of belonging to each spectral class;
4. Apply a conditional probability network combining all single-epoch classifications, incorporating both spatial and temporal sequencing rules to identify softwood/native classes.
5. Insert into the NCAS-LCCP forest extent layers.
6. Manual attribution where contextual information is used to exclude or relabel classes that cannot be separated spectrally.

4. Forest Density Mapping

Changes in forest density may also contribute significantly to the carbon budget, and are of major significance in natural resource management. Landsat data has frequently been used for the estimation of biophysical parameters, such as cover or crown density. Regression analyses of image and ground data have commonly been applied. A Landsat-derived estimate of perennial vegetation density for the entire continent using a recently developed regression tree technique known as *random forests* is being developed (Chia et al, 2006a). Random forests is a tree ensemble technique. It is a powerful non-parametric technique that has numerous advantages such as the ability to handle very large data sets and large numbers of variables, it does not over fit and it is computationally efficient (Breiman, 2001).

Standard methods were defined to provide density 'ground truth' from the available Ikonos image archive. Nearly 1000 high spatial resolution Ikonos images acquired in 2002/03 across the country were used to select approximately 2000 training sites. Canopy density for each site is estimated by independent experts using a documented protocol. Stratification zones are used as a guide in selecting training sites so that they represent a range of densities in each zone. For each site, a grid is superimposed over each sample areas in the Ikonos images, and absence or presence of trees is counted. The proportion of trees in each grid is then recorded as the density for that site. The initial studies highlighted inconsistencies and gaps in the current training data that are now being addressed. New Ikonos images have been purchased, and new training sites are being selected for resolving uncertainty where present data are sparse and to make the distribution of the training sites across the country more comprehensive. The density estimation for the original training sites is also being reviewed.

5. Sparse Cover monitoring

To meet Australia's current definition of forest, a land cover must have 20% tree crown cover and the potential to reach greater than 2m in height. Increasingly there are requirements to map and monitor current and historical changes in areas of sparse perennial vegetation with canopy cover below this threshold. This need primarily arises from the need to better understand the types of transitions occurring from forest to non-forest, particularly those forests transitioning between forest and sparse, as well as for natural resource management of perennials more generally. In addition, there are requirements for national consistent vegetation cover information for land and water management and modelling (National Water Commission 2006).

Using only the spectral information in the Landsat TM/ETM+ data, sparse perennial vegetation cannot be reliably discriminated from other ground cover types; however by including information from image texture the results can be significantly improved (Caccetta and Furby, 2004 and Furby, Wallace and Caccetta, 2007). Working from fine resolution orthophotos, texture measures at a range of spatial resolutions were derived using an overcomplete wavelet decomposition (Unser, 1995) with Haar basis functions. Canonical variate analysis was applied to quantify over what range of spatial resolutions the texture provided discrimination between sparse woodland and other cover types. The analyses suggested that an instrument with pixel size no better than 10m would be sufficient for the application. Results also suggested that texture at 20m and above (approximately that of Landsat TM/ETM+ data), along with spectral information, would considerably improve mapping of sparse vegetation.

The processing steps are identical to those for the forest cover monitoring, with the addition of the calculation of a smoothed texture image from the first or 'woodiness' index for each stratification zone and

the use of an additional texture index calculated from the smoothed texture image. Texture is calculated at two spatial resolutions using an overcomplete wavelet decomposition (Unser, 1995) with Haar basis functions. it was observed during the processing of multi-date images, that spatial smoothing of the texture estimates was required. To achieve smoothing within cover type units while retaining edges which arise from cover type boundaries, a filter based on the Adaptive CMAP algorithm described by McConnell and Oliver (1996) was applied to each texture resolution. The spectral thresholds are linked to those from the forest cover mapping to ensure consistency and continuity with the existing forest extent and change mapping.

6. Discussion

The ongoing annual forest extent and change and post-1990 Kyoto compliant plantation mapping updates will continue at least throughout the 2008 to 2012 commitment period. Sensor comparison studies have been undertaken (Furby and Wu, 2006 and 2007 and Wu et al, 2006) to assess alternative strategies should Landsat data continuity become an issue. At the time of writing the methodology for the sparse cover monitoring has been established and tested. Sparse cover 'bases' have been created for a little over half the country, ready to outsource the thresholding processing to commercial entities. The initial 2002 forest density map is being updated with improved training data. Methods to map urban extent and change from the Landsat image time series are being developed with pilot studies being undertaken. Prototype trend products based on cover indices are also being developed. A small pilot study of the land cover change methodology has been conducted in China (Wu et al, 2005) and a larger pilot study of the full land cover change and carbon modelling methodology is about to be undertaken.

The Land Cover Change Program has already delivered an archive of consistently processed, multi-temporal satellite imagery and derived land cover products for fifteen national coverages at 25m scale for the 6th largest country (by land area) in the world. The ortho-rectified and calibrated image archive is publicly available as a resource that can be used to help inform a range of natural resource management issues.

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