Forest cover trends from time series Landsat data for the Australian continent

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Abstract

In perennial and natural vegetation systems, monitoring changes in vegetation over time is of fundamental interest for identifying and quantifying impacts of management and natural processes. Subtle changes in vegetation cover can be identified by calculating the trends of a vegetation density index over time. In this paper, we apply such an index-trends approach, which has been developed and applied to time series Landsat imagery in rangeland and woodland environments, to continental-scale monitoring of disturbances within forested regions of Australia. This paper describes the operational methods used for the generation of National Forest Trend (NFT) information, which is a time-series summary providing visual indication of within-forest vegetation changes (disturbance and recovery) over time at 25m resolution. This result is based on a national archive of calibrated Landsat TM/ETM+ data from 1989 to 2006 produced for Australia’s National Carbon Accounting System (NCAS). The NCAS was designed in 1999 initially to provide consistent fine-scale classifications for monitoring forest cover extent and changes (i.e. land use change) over the Australian continent using time series Landsat imagery. NFT information identifies more subtle changes within forested areas and provides a capacity to identify processes affecting forests which are of primary interest to ecologists and land managers.
The NFT product relies on the identification of an appropriate Landsat-based vegetation cover index (defined as a linear combination of spectral image bands) that is sensitive to changes in forest density. The time series of index values at a location, derived from calibrated imagery, represents a consistent surrogate to track density changes. To produce the trends summary information, statistical summaries of the index response over time (such as slope and quadratic curvature) are calculated. These calculated index responses of woody vegetation cover are then displayed as maps where the different colours indicate the approximate timing, direction (decline or increase), magnitude and spatial extent of the changes in vegetation cover. These trend images provide a self-contained and easily interpretable summary of vegetation change at scales that are relevant for natural resource management (NRM) and environmental reporting.

**Keywords**
Vegetation density index, forest monitoring, remote sensing, Landsat time series, natural resource management, data visualisation.

1 **Introduction**

Forest vegetation, whether natural, managed for production, or managed for conservation purposes, may be affected by active management or a range of natural processes. Management actions include thinning, selective harvesting and preventative burning. Unmanaged processes include climatic variation (drought), wild fire and recovery, diseases, pests and weeds.

Knowledge of where and when changes in forest vegetation have occurred is fundamental to assessing management impacts and to the identification of processes affecting vegetation. Such information may also be required for regulatory purposes; in Australia, for example, the public has expectations that the condition of the forest estate will be maintained and state agencies are charged with this responsibility. The role of forests as a store of greenhouse gas (GHG) is now universally recognised, and the importance of GHG accounting relating to forest management and degradation is increasing through mechanisms such as REDD (Reducing Emissions from Deforestation and Forest Degradation, www.un-redd.org).

In Australia, land use and forestry represent an important proportion of the country’s GHG accounts. Australia’s National Carbon Accounting System – Land Cover Change Program (NCAS-LCCP) was developed by the Australian Government in recognition of this, and in response to the conditions of the Kyoto Protocol. The NCAS-LCCP framework offers the capability for fine-scale continental mapping and monitoring of land cover using Landsat satellite images.
imagery. This program currently uses over 7000 Landsat MSS, TM and ETM+ images at a resolution of 25m for twenty epochs from 1972 to 2011, making it one of the largest and most intensive land cover monitoring programs of its kind in the world (Furby, 2002; Furby et al., 2008). The NCAS-LCCP has been implemented and used operationally by Australia’s Department of Climate Change and Energy Efficiency (DCCEE) since the early 2000s for carbon accounting purposes at continental scale. Current operational procedures adhere to strict processing guidelines, with the outputs from each processing stage checked in a rigorous quality assurance process. The NCAS archive of satellite imagery and products is now updated on an annual basis, and is the object of a continuous review process with respect to new data sources, technological developments and computational efficiency. The National Forest Trend (NFT) information product described in this paper is based on this national time-series of calibrated Landsat TM/ETM+ imagery assembled and processed within the NCAS program.

The NCAS initially focused on reporting requirements under the UNFCCC (United Nations Framework Convention on Climate Change) and the Kyoto Protocol. Under these agreements, GHG accounting of forest land-use change (LULUCF, permanent forest loss and reforestation) (Brack et al., 2006) was required. The NCAS-LCCP was thus designed to produce consistent time series of forest/non-forest classifications. A forest definition of at least 20% canopy cover with potential to reach over 2 metres in height is used (Australian Government, Department of Climate Change, 2009). Subsequently, the NCAS-LCCP project has developed, or is currently developing, other products based on its archive of Landsat data (Furby et al., 2008; Caccetta et al., 2010). These include methods for the mapping of plantation types (hardwood/softwood), integration of multi-sensor data (from alternative optical sensors or synthetic aperture radar), as well as the extension of the forest mapping procedures to sparse woody vegetation (5 to 20% canopy cover) (Furby et al., 2007).

Although useful for general monitoring of permanent land use changes, the NCAS-LCCP was not designed to track more subtle changes in vegetation density within forested areas. This motivated the development of the NFT approach, which aims to locate and highlight changes within forest lands that are more subtle than permanent clearing or reforestation. Canopy cover represents a continuous and dynamic variable, and changes may occur over time within the forest class as a result of active management practices and natural processes. The NFT method described here has been developed in order to summarise these variations through time within the forest cover class. This information specifically highlights disturbances in vegetation cover that may not result in a land use change event in the time-series forest extent classifications. Understanding of such changes in forest cover at relevant scales is important for natural resources condition assessment and land management. Of particular interest are processes related to forest thinning (as a result of selective logging, low intensity fires, drought or disease) as well as
thickening (e.g., recovery from disturbances). At present, the NFT is not used in carbon accounting, but provides detailed evidence of dynamics at national scale which are relevant to evolving accounting rules.

In the past, assessments of trends and changes in vegetation cover have traditionally relied on the comparison of data-derived attributes (e.g., reflectance or vegetation index) between pairs of images acquired at two different dates (Coppin et al., 2004). He et al. (2011), for instance, mapped forest disturbances in the United States through a comparison of a disturbance index computed from Landsat data at 500m resolution acquired in 1990 and 2000. Studies were also conducted using an approach based on multiple two-date comparisons to summarise vegetation cover trends over time (Cohen et al., 2002; Jin and Sader, 2005). Ruelland et al. (2010) investigated the vegetation cover dynamics in a large catchment in Mali, Africa, by assessing changes in multi-class land cover classification maps for three dates between 1967 and 2007. Shimabukuro et al. (1999) illustrated how displays of RGB composite images containing the Landsat-derived shade fraction images for three different years can be used to analyse changes in the forest cover (and thus detect deforestation events) in Rondônia State in the Brazilian Amazon. Further, the PRODES project (Amazon Deforestation Monitoring Project, www.obt.inpe.br/prodes), carried out operationally by Brazil’s National Institute for Space Research (INPE) since 1988, provides an annual mapping of forest clear cuts over the Brazilian Amazon. This is achieved by detecting (abrupt) changes in vegetation cover using Landsat-based fraction images derived from a linear spectral mixing model (Shimabukuro et al., 1998; Arai et al., 2011) and temporal change detection methods (Morton et al., 2005). The closely related project DETER (Deforestation Detection in Real Time Project, http://www.obt.inpe.br/deter) further aims to achieve near real-time deforestation monitoring through the use of MODIS data (Anderson et al., 2005).

To fully exploit the information provided by multiple remote sensing images, methods have been developed that simultaneously account for the data at all available dates along the time series, with most of the proposed algorithms addressing the detection of either abrupt change events (e.g. forest fire or harvesting) or gradual changes (linear trend, e.g., disease or insect damage) occurring during the monitoring period. For instance, Hais et al. (2009) investigated the temporal response of various spectral indices (normalised difference moisture index, NDMI, and Tasselled Cap) to forest clear-cuts and insect damage using a time series of thirteen Landsat scenes in Central Europe from 1985 to 2007. In studies by Jacquin et al. (2010), vegetation cover degradation was quantified in Madagascar savanna ecosystems based on NDVI (normalised difference vegetation index) profiles calculated from MODIS images between 2000 and 2007 (250m resolution); positive/negative linear trends over this period were identified through a decomposition of the time series into trend, seasonal and remainder components. A linear trends
analysis was also used by Röder et al. (2008) to characterise the spatiotemporal patterns of vegetation cover development in Northern Greece using a time series of fifteen Landsat images covering the years 1984–2000; here, vegetation fraction images obtained by spectral unmixing were selected as the target indicator, and spatial patterns were displayed by mapping the magnitude (and direction) of the linear regression’s gain coefficient to discrete low/medium/high classes.

More sophisticated methods for trend analysis can also be found in the current literature. For instance, a method based on decision-tree classification of spectral index trajectories was proposed by Goodwin et al. (2008) for the detection of insect infestations in British Columbia, Canada, using six Landsat scenes acquired during the time period from 1992 to 2006. Viedma et al. (1997) provided an analysis of the rates of ecosystem recovery after fires through nonlinear regression of NDVI values following fire events in time-series Landsat data; this approach was applied in a 900km² test area located on the Mediterranean coast of Spain, using nine Landsat images from 1984 to 1994. Lawrence and Ripple (1999) investigated the dynamics of reforestation in the Mount St. Helens area, Washington, U.S.A., following the 1980 eruption by means of polynomial curve fitting of estimated green vegetation percentage derived from a time series of eight Landsat images between 1984 and 1994. Another method for assessing temporal trends in vegetation cover was provided by Kennedy et al. (2007), whose approach is to search for idealised signatures in the temporal trajectory of spectral values according to a simple least-squares measure of goodness of fit, allowing for simultaneous estimates of discontinuous and continuous phenomena (disturbance date, intensity and post-disturbance recovery); this approach was applied for the detection of changes in land cover in Oregon, U.S.A., using nineteen dates of Landsat imagery between 1984 and 2004. Other works in this area (Kennedy et al., 2010) made use of temporal segmentation of spectral index trajectories (e.g., NDVI, Tasselled Cap Wetness, Normalised Burn Ratio) in a yearly time series of Landsat scenes acquired in North-Western U.S.A. between 1985 and 2007; this approach provides a powerful method to capture both abrupt disturbance events and more subtle long-term processes for discrete pixels or forested plots, albeit at the expense of a complex optimisation process of the many algorithm parameters.

The present paper describes the methodology used to derive change indicators for operational monitoring purposes at a continental scale, allowing for a clear overview of the temporal dynamics in forest vegetation cover over geographical areas at various scales. The indicators are statistical summaries of the temporal responses of a consistent spectral index, calculated for each pixel from a time series of imagery. This work uses a subset of the NCAS archive of Landsat TM/ETM+ data in Australia from 1989 to 2006, with the data in each epoch covering a total of thirty-seven 1:1,000,000 map sheets (see Figure 1) at 25m pixel size. To the best of our knowledge, no operational system presently exists that provides information about
vegetation cover trends in a consistent manner over long data time-series (15+ years) and over such a large geographical area (7.7 million km$^2$) at 25m resolution. This index-trends approach to monitoring cover changes has been comprehensively tested over an extended period in various regions of the Australian continent. First developed and applied in Australia’s rangeland systems (Wallace et al., 1994; Karfs et al., 2000; Karfs and Trueman, 2005), this approach was applied within regional programs in woodland and forested areas to provide information on vegetation change for conservation purposes (Wallace et al., 2006), and also implemented operationally for Western Australia’s south-west region as part of the Land Monitor project (Caccetta et al., 2000) (www.landmonitor.wa.gov.au). These local studies have established the relevance of this kind of trends information for ecology land management applications in Australia, while the NFT product implements this approach at 25m resolution for the entire continent’s forest areas.

**Figure 1**: 1:1,000,000 map sheet boundaries used as the processing regions in the NCAS Land Cover Change Program.

In the following, Section 2 first provides a brief review of the basic processing steps carried out as part of the NCAS-LCCP framework, including procedures related to data pre-processing and derivation of the forest extent information; the vegetation trends methodology applied to these data is subsequently described. Section 3 presents typical examples of the resulting trends images by means of several case studies. A general summary and discussion of the results concludes this paper in Section 4.
2 Materials and methods

In the following we describe the generation of trend information within forested areas. This approach relies on the definition of an appropriate Landsat-based vegetation cover index (defined as a linear combination of spectral image bands) that is sensitive to changes in forest density, and which represents a consistent surrogate to track density changes. Information regarding the temporal trends of the vegetation cover index is subsequently provided by calculating statistical summaries of the index response over time (such as slope and quadratic curvature). These calculated index responses of woody vegetation cover are then displayed as maps where the different colours indicate the approximate timing, direction (decline or increase), magnitude and spatial extent of the changes in vegetation cover. This approach is applied across the Australian continent in areas presenting forest cover, which are identified using existing forest presence/absence products from the NCAS-LCCP.

This approach makes use of two primary sources of existing data: 1) a time-series of Landsat data which is geometrically and radiometrically consistent, and 2) a time-series of national forest presence/absence classifications (here referred to as NFPA) derived from the images. These data have been previously compiled over continental Australia in the frame of DCCEE’s NCAS monitoring system (Furby et al., 2008) using detailed operational specifications, as described by Furby (2002). For the purpose of this paper, we here comment on the features of these data that are of interest in generating the NFT information.

2.1 Landsat data and derived forest classification archive

The Landsat archive compiled by the NCAS-LCCP consists of twenty continental coverages existing as 1:1,000,000 map-sheet mosaics of geometrically aligned and radiometrically calibrated data (Furby et al., 2008) (Figure 1). Only Landsat TM/ETM+ data is used for the NFT, corresponding to an archive of ten coverages between the years 1989 to 2006.

The NCAS specifications for image acquisition were targeted towards the dry season, representing imagery with as little short-lived seasonal or ephemeral cover as possible and providing the best discrimination between forest and non-forest cover (Wallace and Furby, 1994; Wallace et al., 2006). The Landsat data were thus acquired as close as possible to June–August for northern Australia and January–March for southern Australia, corresponding to the dry season in these regions. Landsat data from outside these optimal date windows were occasionally used where imagery from the targeted dry season was unsuitable due to cloud cover, large-scale natural events (wildfires, floods, smoke, etc.) and noise (e.g., sensor deficiencies). These specific criteria
were developed for the NFPA products. For the purpose of NFT (as described below), phenological variations have the potential to affect the results, and hence seasonal variations should be minimised. As Australian forests are (almost without exception) non-deciduous, phenological variation of understorey is the major consideration. The convergence zone of the north and south regions (date selection) occurs north of the Tropic of Capricorn. For most of the continent, this area is either desert or dry savanna, where there is very little forest and dry conditions are likely throughout the year. To complete the national coverages, all Landsat images were processed using the following steps:

1. orthorectification to a common spatial reference, using earth-orbital model and cross-correlation feature matching technique (Caccetta et al., 2007)
2. top-of-atmosphere reflectance calibration (sun angle and distance correction) for each image band (Vermote et al., 1997)
3. correction of scene-to-scene differences using bi-directional reflectance distribution functions (BRDF, see (Danaher et al., 2001)) for each image band (Wu et al., 2001)
4. calibration to a common spectral reference (“like values”) using invariant targets (Furby and Campbell, 2001)
5. where required (in areas with significant terrain variations), correction for viewing geometry effects resulting from differential terrain illumination (Wu et al., 2004)
6. removal of “corrupted” data such as regions affected by smoke, clouds or sensor deficiencies
7. mosaicking of the individual Landsat scenes into 1:1,000,000 map sheets.

Key aspects of each of these processing stages are discussed in more detail by Furby, Caccetta, et al. (2008) and Caccetta et al. (2007), and full operational details are provided by Furby (2002). After each step, the results were independently assessed against documented accuracy and consistency standards through a quality assurance process: images and products processed by operators were submitted and independently checked before being accepted for the NCAS archive (Furby, 2002).

Figure 2 (right) shows an example of a typical NFPA map from the NCAS-LCCP, obtained for a 30km×30km region at the northern edge of the Perth metropolitan area in Western Australia. Forest cover in the region is predominantly native banksia woodland and pine plantations. In the forest extent map on the right of the figure, areas identified as forest are shown in dark green while non-forest regions are white.
2.2 Spectral index for forest cover trends

The NFT aims to provide information regarding changes in forest cover in the form of visual presentations of statistical summaries of the temporal trends in vegetation density. The development of the NFT from the image time-series therefore relies on the existence of a suitable spectral index that is sensitive to vegetation density changes across a range of different vegetation types. There is a considerable history and literature on the derivation of Landsat-based cover indices in a range of environments, including indices that are widely applicable across vegetation types, see, e.g., (Pickup et al., 1993; Danaher et al., 2004; Wallace et al., 2006). Typical approaches to the definition of such indices are usually based on regression or discriminant analyses using ground sites where the vegetation parameter of interest has been measured or estimated. An important task in the derivation of the NFT was the evaluation and comparison of different results based on local versus global indices.

An approach to apply local zone-based indices was first considered to generate the NFT. As part of the NCAS forest mapping program, (linear) directed discriminant analyses (Campbell and Atchley, 1981) were applied in each of approximately 140 stratification zones covering the Australian continent in order to identify spectral indices providing the best separation between the woody vegetation and other (non-woody) cover types. This approach provides locally optimal results for classification across the many different bio-geographical areas within the continent. These local discriminant functions (linear indices), which also typically provide an ordination
from woody to non-woody, were considered as candidate indices from which trends could be calculated for each zone. In practice, a significant drawback of applying zone-specific indices for trend calculation was that it led to numerical discontinuities in the calculated trends at the stratification zone boundaries. The use of local indices thus did not allow for a seamless comparison of trends over areas larger than the stratification zones, and this zone-based approach was ultimately discarded in the NFT context in favour of a more generally applicable index.

The main objective of the NFT is to identify and represent different patterns of change in woody density. A common density index providing a consistent representation of change across zones is desirable, even if not locally optimal; such an index was selected for the whole continent for consistency. A number of different candidate indices were tested and compared quantitatively through discriminant analyses providing measures of discrimination between training sites of varying density (Furby, 2002). Visual comparison of trend images using different indices was also carried out. As a result, the NFT was based on the simple woodiness index $I_w$ defined as the combination of the following Landsat TM bands:

$$I_w = 512 - (TM\_band\_3 + TM\_band\_5).$$

(1)

The linear combination $TM\_band\_3 + TM\_band\_5$ represents one of the most common indices indentified in different stratification zones to derive the NFPA classifications. The sum of the two bands represents a “brightness index” that is negatively correlated with vegetation density; by inverting its sign, the selected index $I_w$ becomes positively correlated with vegetation density. The offset value of 512 is arbitrary and is added for convenience so that values of $I_w$ are positive when used in conjunction with 8-bit Landsat data. In other studies, this index has proved to be effective in tracking woodland changes in pastoral zones (Curry et al., 2008), and has been shown to be correlated both with leaf area index and vegetation cover estimates in forest plantations and native banksia woodlands (Boniecka, 2002). This spectral index is also used operationally for perennial vegetation monitoring as part of the Land Monitor project in Western Australia (Caccetta et al., 2000).

Greenness indices, including the normalised difference vegetation index (NDVI), were considered and tested but were not selected for the NFT. Apart from limited areas of high rainfall, the perennial vegetation in most Australian forests and woodlands does not possess a strong “green” component. Greenness indices such as NDVI are strongly influenced by the ephemeral cover (understorey), and thus do not usually provide a reliable indicator for perennial vegetation change in Australian vegetation (Bastin et al., 1995; Wallace et al., 2006). As a further example, the alternative index:

$$I_w' = TM\_band\_2 + TM\_band\_3 + TM\_band\_5 - 2 \times TM\_band\_4$$

(2)
was also considered and compared with $I_w$. In the NCAS forest classification analyses, this index was identified as being effective for forest/non-forest discrimination in a number of stratification zones. Through visual inspection, it was however found to be less appropriate for the purpose of generating trends across multiple strata as this specific band combination responds to both the canopy density and ephemeral vegetation greenness, ultimately leading to ambiguity in the interpretability of the trends.

It is important to note that the concept of cover or density index has a particular meaning in the NFT context presented in this work. Changes in the index $I_w$ provide a consistently-interpretable surrogate for changes in vegetation density, for the purpose of tracking and comparing relative changes over time. In other words, changes in the index value over time are indicative of changes in the vegetation density at the considered location. This index therefore provides a quantitative estimate of change in density or cover; it does not provide an absolute estimate of the cover, which would require calibration to measured field data for specific vegetation types and regions. Trials on the derivation of national vegetation density from NCAS images are reported by Chia et al. (2006).

The curves in Figure 3 show the temporal responses of the mean value of index $I_w$ obtained for the four areas identified in Figure 2 (left). The timing and magnitude of the changes in the density index are clearly identifiable in this plot. Here, the index values can be seen to increase for site A, decline after 1998 for site B, and remain stable for site C, while site D shows a period of significant decrease followed by an increase in its index response.

**Figure 3:** examples of temporal responses for index $I_w$. The curve labels correspond to the four areas identified in Figure 2 (over which the index values are averaged); the curves’ respective colours correspond to the colour of the selected geographical areas in the resulting NFT maps (see Section 2.5 and Figure 5 further below).
2.3 NFT computation as statistical summaries of index change over time

At its core, the NFT relies on a consistent method to summarise change information from responses of the woodiness index over time, and to subsequently display this information in a meaningful and concise manner. A temporal plot of the index value as shown in Figure 3 represents one of the simplest ways to track and compare changes over time; this approach however can only be applied to the particular geographical areas for which such plots are generated. On the other hand, statistical summaries (as described in this section) can be used to generate images that summarise the temporal changes over large geographical areas.

A first step in the NFT computation is to choose the time period (image sequence) of interest. A six-band image of statistical summaries is then calculated from the temporal sequence of index values \( I_w \) for each pixel, using established regression techniques. The linear and quadratic components are estimated by fitting orthogonal polynomials, providing independent estimates of linear and quadratic coefficients (Draper and Smith, 1981, Section 5.6). The six summary variables, which are computed from the temporal sequence of index data for each pixel in the chosen time period, are as follows:

1. mean value of index \( I_w \) over time
2. linear coefficient (slope), i.e., estimated linear rate of change of \( I_w \) per year
3. quadratic coefficient (curvature)
4. standard deviation from mean
5. residual mean squared error from fitted linear model
6. residual mean squared error from fitted quadratic model.

The range of these calculated trend parameters depends on the chosen index \( I_w \) as well as changes in the environment. In the NFT, the results are scaled to fit within a suitable range (8 or 16 bit) for subsequent display purposes. The calculated values summarise the temporal changes and variability for each pixel. For example, average long term changes will be summarised by the linear coefficient; if the response is close to a straight line, curvature and residual values will be low. In Figure 3, the trajectory of the stable site C has little variation and will have a linear coefficient (slope) close to zero, while the linear coefficients for the recovering site A and the declining site B will be positive and negative, respectively. Site D is far from stable but has little overall slope, and its disturbance and recovery will be evidenced by a positive quadratic coefficient. These calculated values may be displayed in a variety of ways to highlight different aspects of the temporal response; the standard display used in the NFT is described in Section 2.5 below.
2.4 Operational considerations

2.4.1 Selection of time interval

In summarising temporal trends, an important question arises with regards to the length of the time interval used for the summaries. The interpretability of simple shape parameters, such as slope and curvature, will depend on the length of time over which the trend is calculated. Over longer time periods, several events may influence the trend (e.g., two subsequent bush fires), resulting in a complex response that is not easily summarised by the slope and curvature measures (Kennedy et al., 2010). Trend parameters computed for shorter time periods are easier to interpret but will also be more strongly influenced by the exact timing of the beginning and end of the interval, thus potentially emphasising particular changes. For regional NRM applications, selection of a particular period (or from a curve fitting perspective: defining break points) guided by knowledge of climate and management history may be desirable. However, since the timing of events varies spatially, this approach has the complication of making a visual comparison of trends from adjacent pixels (or areas) more challenging.

At the time of the creation of the NFT, the NCAS-LCCP archive of Landsat TM/ETM+ imagery included the following ten epochs: 1989, 1991, 1992, 1995, 1998, 2000, 2002, 2004, 2005 and 2006. Based on the above considerations, the NFT was produced for two different time periods: one interval including the full time series from 1989 to 2006 (10 dates), and a shorter time interval spanning the period from 2000 to 2006 (5 dates).

2.4.2 Missing data and non-forest masking

Cloud-affected areas and corrupted data in the Landsat time series were replaced with ‘null’ values and treated as missing data. Also, within the map-sheet mosaics, some of the images that are adequate for NFPA classification are not suitable for calculating the forest cover trends due to unusual phenological cover responses (greening of understorey) resulting from out-of-season date selection or unusual seasonal conditions. These Landsat scenes were also replaced with null values. In the NFT, trends summaries were not calculated for any pixel containing three or more nulls in the time series.

As the density trends are here related to forest cover changes, non-forest areas are identified using the existing NFPA data. A ‘never-forest’ mask was created from these layers to mask out any pixel where woody cover is absent in all epochs in the time series. Separate masks were generated for both the 1989–2006 and the 2000–2006 time series.
2.5 Vegetation trends maps

In order to achieve easily interpretable results, standard visual displays are produced from the statistical summaries. It must be noted that numerous ways of presenting the six-band trend summaries are possible, and that no single image display can capture all of the information represented in the temporal responses or the associated statistical parameters (linear slope, curvature, variation, etc.). The standard display described in the following has been found to be easy to interpret while providing useful information for a variety of purposes.

The linear coefficient (slope) typically provides the most widely relevant and interpretable information on average change over time, essentially indicating whether a pixel is stable (slope near zero), declining (negative slope) or increasing (positive slope); examples from Figure 3 are described in Section 2.3 above. For standard display purposes, a linear decrease in the index (indicating decline of cover) is shown in shades of red, while a linear increase of the index (increase in cover) is displayed with shades of blue. The larger the slope, the brighter the colour appears. Green is used to display the positive quadratic curvature component, which indicates a decline followed by a recovery in vegetation density over the time period. Consequently, mixed colours are an indication of different temporal response shapes as follows: shades of yellow (linear decrease with positive quadratic component) indicate overall loss of density with a major decline early in the period, while shades of cyan (linear increase with positive quadratic component) indicate a phase of significant recovery late in the period. Regions that remain black have a slope near zero and are essentially stable over the period. Finally, white (or off-white) is used for areas that have never had any forest cover during the time interval for which the trend is calculated (never-forest mask).

3 Results

3.1 Continental-scale forest cover trends

The NFT images were generated as standard NCAS 1:1,000,000 map sheets at 25m pixel resolution. Figure 4 presents the NFT results for the 1989–2006 and 2000–2006 time series. The various (large-scale) trends in vegetation cover across continental Australia are clearly visible in these images.
Figure 4: Australia-wide NFT for the 1989–2006 time series (left) and the 2000–2006 time series (right); in this display, the ‘never-forest’ mask is shown in off-white (pale yellow). In the 1989–2006 NFT, the missing tile in the centre-right of the image is due to a lack of data in earlier years for this map sheet.

Figure 5 shows the 1989–2006 and 2000–2006 NFT maps for the area shown in Figure 2. Here, both images reveal spatially-explicit information which clearly highlights the varying dynamics of vegetation change across the area over the two considered time periods. Active processes here include fire, forestry and urban expansion; the NFT products provide a visual summary of the impacts of these processes over the two periods. The attribution of causes of the change in different areas is made using local knowledge. As indicated in Figure 3, area A experiences a significant increase of vegetation cover during the 1989–2006 period (here due to recovery of native woodland after fire) and consequently appears as solid blue in the corresponding NFT map (Figure 5, left). As the vegetation density gain for this region mostly occurs between 1989 and 2000, the corresponding area in the 2000–2006 NFT map (Figure 5, right) appears as stable/black. Having mostly lost vegetation cover between 2000 and 2006, area B appears in red in both NFT maps. Site C, with no significant changes in vegetation density throughout the 1989–2006 time period, appears stable in both maps. In area D, a fire event in 1998 created a temporal index response corresponding to a vegetation decline followed by a relatively quick period of recovery (see Figure 3): this region therefore appears with shades of green in the 1989–2006 NFT. As the fire event occurred prior to 2000, the 2000–2006 NFT map for site D indicates a period of (mild) post-fire recovery, with corresponding shades of blue.
NFT colour legend (with respect to the selected time interval)
- : decline in vegetation cover
- : increase in vegetation cover
- : decline followed by recovery
- : major early decline with some late recovery
- : some early decline with major late recovery

Figure 5: NFT image corresponding to the area depicted in Figure 2 (30km×30km region north of Perth, Western Australia) for the 1989–2006 time series (left) and the 2000–2006 time series (right). The never-forest masks are shown here in white. Boxes indicate the four areas of interest shown in Figure 2.

NFT displays as shown in Figure 5 represent a self-contained and easily interpretable result. They provide visual information regarding the direction and timing of the vegetation cover change (display colour), the magnitude of the change (colour brightness), as well as the spatial extent of change. Plots of index time traces from particular areas, as shown in Figure 3, can be used to further quantify and compare changes for particular areas as a complement to this spatial picture of vegetation density change.

3.2 Example case studies

The standard NFT colour maps are produced as a result of quantitative processing and provide evidence of stability or change in forest cover over time. Without further information, they do not provide information on causes, ecological impacts, or the GHG implications of such changes. In this section, example case studies are presented where local knowledge of land management practices is used to illustrate the information provided by the maps. These studies serve to demonstrate the use of the NFT in various regions of the Australian continent for the detection and communication of processes affecting forest vegetation.
3.2.1 Wildfire

Figure 6 shows a region of native bush at the edge of the cleared agricultural land near the town of Hyden in the south-west of Western Australia. The bushland in this region has been heavily affected by fire: a fire-impacted area is obvious in the north-east of the 2006 Landsat image (Figure 6, left). Controlled burns are not usually applied in this region to reduce fuel loads, and wildfires are only controlled when they threaten cleared agricultural land or infrastructure. The cover loss tends to be significant and the recovery can take many years. Areas which were burnt early or before the beginning of the time series appear in blue (showing recovery), while fires in the middle of the sequence appear in green (showing both disturbance and post-fire recovery). Fires towards the end of the sequence appear in red showing overall cover loss in the period. The standard NFT product indicates the approximate timing and direction of changes; approximate dates of fires impacting particular areas can be confirmed by examining the individual Landsat images or index trace plots.

![Figure 6](image)

**Figure 6: 2006 Landsat image (left, bands 5,4,3 in RGB) and 1989–2006 NFT image display (right) for a 110km×110km region of predominantly native forest near Hyden in Western Australia. Never-forest areas (here long-cleared farmland or sparse vegetation) are masked in white in the NFT image.**
3.2.2 Forest plantations and logging

Figure 7 shows a region of forest operations in state forest in eastern Victoria. The NFT image (right) illustrates the areas and approximate timing of forest logging and recovery. The management strategy is to log in small coupes (selective or clear fell); regrowth appears rapidly within one or two years. The stands that appear in dark blue have been increasing in density since the early part of the time series and show a predominantly linear growth pattern. The stands that were harvested around the middle of the time series and replanted appear in green, while red areas here identify more recent harvesting. The colours in such stands are bright since the cover changes are relatively extreme (harvest and fast regrowth).

<table>
<thead>
<tr>
<th>NFT colour legend</th>
</tr>
</thead>
<tbody>
<tr>
<td>: decline in vegetation cover</td>
</tr>
<tr>
<td>: increase in vegetation cover</td>
</tr>
<tr>
<td>: some early decline with major late recovery</td>
</tr>
</tbody>
</table>

**Figure 7:** 2006 Landsat image (left, bands 5,4,3 in RGB) and 1989–2006 NFT image display (right) for a 20km×20km region of state forest in eastern Victoria.

3.2.3 Mining, rehabilitation and controlled burning

Figure 8 shows a 20km×20km area south-east of Perth in Western Australia. In this region, the native vegetation is eucalypt forest with varying understorey species, and active processes include areas of open-cut bauxite mining: new mining operations appear in bright red in the top of the NFT image, and older rehabilitated areas appear in blue (top-left). Again, the NFT provides evidence of the changes in different areas; causal factors are provided from local knowledge. Recent clearing in the centre-south of the area also displays as bright red. Regions
with less vivid colours can also be identified in the NFT image (e.g., dark red area to the right of the cleared patch). These colours indicate density changes from rotational controlled burning (low-intensity understorey fires used to reduce fuel loads), whose impact on the forest density is less pronounced compared to mining or logging operations. Here again, the colour variations provide an indication of the timing and intensity of the impact and subsequent recovery.

Figure 8: 2006 Landsat image (left, bands 5,4,3 in RGB) and 1989–2006 NFT image display (right) for a 20km×20km region south-east of the Perth metropolitan area in Western Australia.

4 Discussion

This paper describes the methodology used for the operational production of the NFT products for the Australian continent, and presents examples of the change information they provide. The processing is based on the NCAS-LCCP archive of calibrated Landsat TM/ETM+ and NFPA data for the time period from 1989 to 2006, with trends summaries derived at 25m pixel resolution for all forested areas in Australia. The NFT provides a consistent and spatially-explicit indication of historic vegetation changes in forested areas at continental scale, which has previously been unavailable.

The NFT products rely on two critical elements: 1) a time series of calibrated imagery chosen from ecologically sensible dates, and 2) a spectral index which is sensitive to changes in
vegetation caused by management actions and natural processes across a range of forest types. The case studies above illustrate the resulting NFT products and their interpretation in different contexts. Additional information and knowledge are needed to understand and confirm the causes and ecological impacts of the changes. Studies using index-trend products have been carried out in a range of forest and woodland environments to provide guidance for ground sampling processes, and to quantify and explain particular changes in vegetation cover affecting a region. Existing data such as vegetation type and landform maps are typically used in such studies, but index trends provide the key change information. Examples include identification of areas of vegetation decline from disease or salinity within large conservation areas, and studies of vegetation recovery and succession after fire (Wallace et al., 2006). NFT results in map form have high communication value and are readily interpreted by land managers. These products provide an important tool for natural resource management and conservation, and can be used to detect and guide investigations of the ecological impact of a variety of events affecting the vegetation cover such as wildfires, disease, and forestry logging. There has been a considerable investment in Australia in NRM activities including revegetation and protection of native vegetation. The NFT provides a means to track and compare the temporal responses of these areas with unmanaged vegetation.

Changes in forest density are clearly relevant to GHG fluxes in forest areas. The ability to detect and quantify such changes is important to the evolving concepts for carbon accounting such as REDD. The NFT provides spatially detailed qualitative information on the stability or the timing and direction of changes in forest cover, though attribution of causes of the changes requires additional information. Estimation of associated biomass changes or carbon fluxes would require further modelling or ground estimation for different vegetation and disturbance processes. The NFT and its underlying index data provide the potential to stratify forest areas on the basis of gradual or abrupt changes, and thus may form the basis to calculate area statements for different disturbance levels which is relevant for REDD-style accounting. For example, in areas of active forestry (as shown in the case study in Section 3.2.2), the NFT provides visual indication of stable areas and the timing of forest disturbance; application of thresholds to the underlying index data can provide area statements for logging in each period. Policy direction and considerable measurement and modelling effort would be required to quantify GHG implications of the changes revealed in the NFT products in different forest types. The NFT products could be used to provide guidance to sampling schemes on the basis of change history so as to estimate, model and validate GHG effects of overall forest management, as well as to provide credible means to quantify and communicate overall changes relevant to policy.

The NFT described here was completed in September 2008. As new epochs are added to the existing time series, the results will be updated. With an increasing length of the monitoring
time period, decisions will need to be made on the selection of relevant time intervals, either automatically (e.g., as considered by Kennedy et al. (2010)) or in a supervised fashion based on other data. Further research will be necessary to determine the best strategy for making the results easily accessible and interpretable by natural resource managers. Also, to date, standard errors associated with image calibration and its subsequent impact on the index values have been estimated for a limited number of sites, and should be extended in order to better quantify the significance of changes in other areas (Zhu et al., 2006).

In producing the NFT as a consistent national product, a number of pragmatic decisions were made; these were based on previous experience and comparison of alternatives. It is recognised that a standard trends product cannot be optimal for all problems and scales. For example, policy or management changes or particular climatic events may dictate a particular period of interest for a local area. To enable NFT-type products to be tailored to more local questions, the NCAS-LCCP dataset of Landsat imagery is publicly available, as are the processing standards which allow this time series to be augmented with other dates of imagery. This provides the opportunity to produce and display trends information for specific questions based on the time period and index most appropriate for those areas. The approach can thus be readily applied to natural vegetation in rangeland and desert systems in Australia using the NCAS-LCCP archive.

The NFT product relies on a spectral index providing a consistent surrogate for perennial vegetation cover. As such, phenological variations (in understorey or deciduous forest) which affect the index will also affect the interpretability of the product. The decisions in producing the NFT which minimised these effects were discussed in this paper. In dense closed-canopy forests, spectral indices may saturate and thus may not detect minor changes; given some ground data, the discriminant analysis procedures described in Section 2.2 provide a means to examine this potential limitation. Within these limitations, the approach may be applied widely to perennial vegetation systems, provided that cloud-free data are available, and appropriate dates can be sourced with consideration for phenological responses of the system. The plans to make available free calibrated Landsat time series imagery through USGS will also enable wider application of this approach.

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Bibliography


