Native vegetation regulatory map: method statement appendices

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Landsat satellite imagery

Landsat acquisition

The first Landsat imagery over Australia was acquired in 1972 using Landsat 1 and a multispectral scanner (MSS) instrument. MSS images were 80 m resolution, had four spectral bands only and lacked the contrast of the later 30 m resolution sensors. The acquisition of MSS imagery using Landsat 1–5 satellites continued until the 1990s. MSS imagery was suitable for mapping vegetation only at broad scales due to its spectral and spatial resolution.

Higher resolution Landsat 5 Thematic Mapper (TM) images were first acquired over Australia in 1986 and regular acquisition commenced in late 1987. The TM images have 7 spectral bands: blue, green, red, near infra-red (NIR), two shortwave infra-red (SWIR) and a thermal band. The spatial resolution of Landsat TM was 30 m for all bands except the thermal band, which was 120 m. The more recent Landsat 7 Enhanced Thematic Mapper (ETM+) and Landsat 8 Operational Land Imager (OLI) instruments have additional enhancements. These include: 15 m panchromatic bands, higher resolution thermal bands and the OLI, which also has additional multispectral bands. These more modern instruments provide images with greater contrast than TM images.

Although the Landsat 7 and 8 instruments have enhancements, they are designed to maintain continuity with Landsat 5 TM bands. Therefore, it is possible to use the time series of Landsat TM, ETM+ and OLI imagery from the late 1980s until today to monitor change in land cover. As Landsat is acquired on a regular basis, there are generally images available every 16 days over that period, although many will be cloudy.

The entire Landsat 5, 7 and 8 image archive has been downloaded from the United States Geological Survey (USGS) and stored on the OEH image and remote sensing (IRS) computing facility. Newly acquired Landsat images are downloaded within a week of acquisition. The USGS supplies Landsat images as a rectified and terrain corrected level 1T product, so downstream products can be created automatically. When new images are loaded on IRS, an automated processing system generates a series of pre-processed image reflectance and derived biophysical products.

Landsat image pre-processing

The 30 m pixel ortho-rectified Landsat images were processed to standardised surface reflectance with a standard nadir view angle and incidence angle of 45° (Flood et al. 2013). This corrected for variations due to atmospheric conditions and the bi-directional reflectance distribution function (BRDF), which also accounted for topographic variations using a 30 m digital surface model (DSM) derived from the 1 second Shuttle Radar Topography Mission (SRTM) data (Farr et al. 2007; Gallant and Read 2009). The BRDF corrections use a model that has been fitted to a set of training data from a range of land surfaces. Pixels that were shaded by steep topographic features present at the scale of the DSM were also masked by assuming parallel rays of light and using a ray-tracing method (Robertson 1989).

Masking of clouds is done using two methods. Cloud, cloud shadow and snow masks based on the Fmask automatic cloud mask algorithm (Zhu and Woodcock 2012) are available for all Landsat images. Manually edited cloud and shadow masks are available for those Landsat images used in annual or biennial monitoring of woody vegetation change.

Water index and water mask

The water index is developed by detecting water and non-water signatures from Landsat satellite imagery for a single date. The water mask is derived from the water index, based on research of an optimal threshold of water discrimination (Danaher & Collett 2006). The water count is represented as a binary count of water presence/absence for each 30 m Landsat pixel. This is the primary product used to develop the water count and water prevalence products, which are based on the Landsat time series (1 Jan 1988 to 31 Dec 2012).

Water count

The water count product is calculated, per pixel, as the sum of the number of observations with water present across the Landsat time series expressed as a fraction of the total number of possible observations in the 25-year period (1 Jan 1988 to 31 Dec 2012). The product has two bands, where band 1 is the number of times water was present across the time series and band 2 is the count of unobscured (i.e. non-null) input pixels, or number of total observations for that pixel. Cloud, cloud-shadow, steep slopes and topographic shadow can affect the ability to count water presence.

Water prevalence

The water prevalence image is extracted from the water count product and classified by proportions of observations with water present. This provides a measure of the relative persistence of water in the landscape (e.g. from always present to rarely and never present). There are 12 classes representing the percentage of times a pixel has had water present out of the total number of observations for that pixel (i.e. Band 1/Band 2 of the water count product). Water prevalence mapping provides information that assists the identification of wetland areas in the landscape.

Landsat foliage projective cover (FPC)

Foliage projective cover is a metric of vegetation cover used in many Australian vegetation classification frameworks. Models relating field measurements of FPC to Landsat imagery have been developed and applied to produce FPC images. The overstorey FPC measurement used in this mapping is defined as the vertically projected percentage cover of photosynthetic foliage from tree and shrub life forms greater than 2 metres high.

Several parametric and machine learning models for prediction of FPC based on site FPC, basal area measurements and Landsat imagery were developed and evaluated (Armston et al. 2009). The results showed all the parametric and machine learning models had similar prediction errors (RMSE < 10%), but the machine learning models had less bias than the parametric models at greater than ~60% overstorey FPC. All models showed greater than 10% bias in plant communities with high herbaceous or understorey FPC.

The FPC model has been applied to every image in the OEH Landsat archive and they have been used with time series techniques to map vegetation extent and long-term FPC of woody vegetation (Danaher et al. 2011).

Landsat fractional cover

The majority of New South Wales is covered by non-woody vegetation so we need a product that enables the monitoring of change in these areas where ground and shrub cover dominates. Ground cover is variable in location and time, changing in response to climate, grazing intensity, cropping cycles and vegetation and fire management. The fractional cover product provides a metric for monitoring change in ground cover in terms of the proportions of green and non-green vegetation cover and bare cover. The Landsat fractional cover product was initially developed using data from Queensland and New South Wales sites

(Scarth, Roeder, and Schmidt 2010) and has been more recently enhanced using site data from other areas in Australia (Guerschman et al. 2015).

The fractions are calculated using a remote sensing mixture model that relates the pixels' reflectance values to known cover values. The model was calibrated using cover values obtained from more than 1000 field sites across all major vegetation groups within Australia. At each of these 1-ha field sites the vertically-projected fraction of bare ground, green vegetation and non-green vegetation were measured for the ground cover, midstorey (<2 metres) and overstorey (>2 metres) layers.

A linear spectral unmixing model was used to relate the field data to the spectral reflectance of the nine Landsat TM/ETM+/OLI pixels (3 x 3 grid) centred on each field site, from the closest image date (Guerschman et al. 2015). The model predicts the fraction of bare ground, green vegetation and non-green vegetation and gives a model fitting error. This gives a fractional cover product for every date a Landsat image is captured.

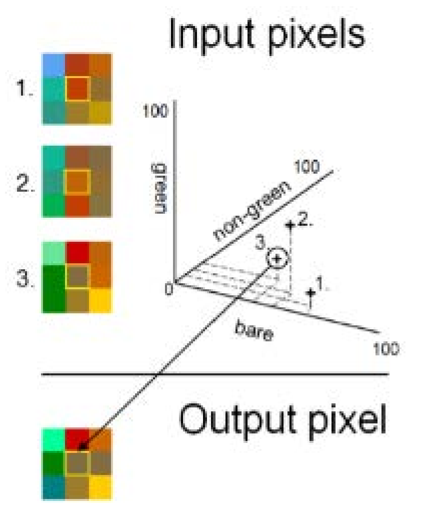
Seasonal Landsat fractional cover

Landsat images are acquired on a 16-day repeat cycle. However, in many parts of New South Wales it takes much longer to collect cloud-free images. The areas of cloud and shadow in each image could be masked out but that is a very time-consuming process. Availability of cloud-free data would vary significantly with location and potentially bias analysis of the time series of images. Instead, a method of creating seasonal composite images was developed (Flood 2013).

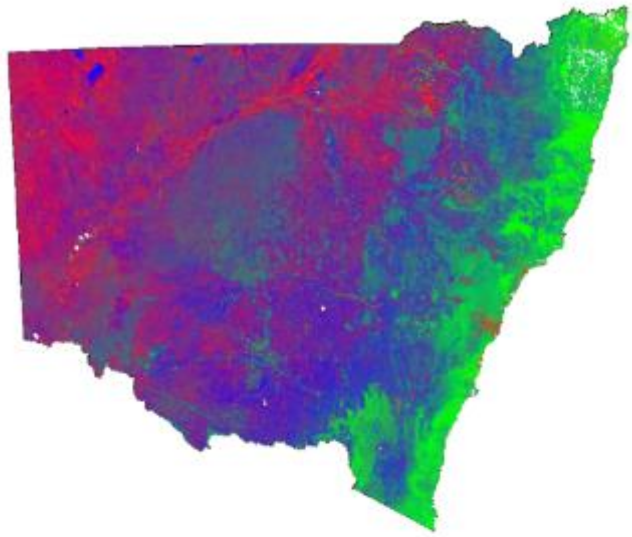
Seasonal fractional cover is generated by selecting pixels from the individual fractional cover product that are most representative of the range of measurements taken by the Landsat satellite throughout the season. We divided the seasons into summer (Dec–Feb), autumn (March–May), winter (June–August) and spring (Sept–Nov). In most cases the seasonal composite approach provides cloud-free images for each season.

The representative pixel is determined by calculating the distance to all other pixels, in feature space, using the sum of squared differences. The pixel that is closest to the centre of the data cloud is chosen as the output pixel. This is referred to as the medoid (Flood 2013). Figure 1 illustrates the selection of the medoid pixel and shows an example seasonal fractional cover mosaic for New South Wales.

Use of the medoid prevents the selection of outliers that may occur when cloud or cloud shadow go undetected. For a representative pixel to be generated at least three unmasked pixels from the time-series of imagery within the season must be available.



The output pixel selected is the one closest to the centre of the data cloud.



Seasonal fractional cover, summer 2013/2014, bare ground = red, green vegetation = green, non-green vegetation = blue.

Figure 1. Selection of the medoid pixel and a seasonal fractional cover image for NSW.

SPOT 5 satellite images

SPOT 5 acquisition

OEH has purchased annual statewide coverages of 10 m resolution SPOT 5 High Resolution Geometric (HRG) imagery, spanning the period 2008 to 2015. SPOT images have four multispectral bands covering green, red, NIR and SWIR wavelengths. The SWIR band images are supplied as 10 m resolution but based on a 20 m resolution sensor. Separate panchromatic images are acquired at the same time. The panchromatic images were acquired using two offset 5 m resolution sensors and supplied as 2.5 m resolution images. Each annual coverage contains around 340 SPOT 5 HRG images.

SPOT 5 image pre-processing

SPOT images are acquired from Airbus Defence and Space as level 1a images, then ortho-rectified to align them with the Universal Transverse Mercator (UTM) map grid. The ortho-rectification was done by contractors for the years 2008–2013 and by OEH for 2014 and 2015. They were able to ortho-rectify the multispectral imagery with a pixels RMS error of better than 0.25 pixels, thereby ensuring sub-pixel registration (Peters 2007).

The ortho-rectified images were processed to standardised surface reflectance images (Flood et al. 2013) with a standard nadir view angle and incidence angle to correct for variations due to atmospheric conditions and the bi-directional reflectance distribution function (BRDF). This correction also accounts for topographic variations using a 30 m digital surface model (DSM). Pixels that were shaded by steep topographic features present at the scale of the DSM were also masked by assuming parallel rays of light and using a ray-tracing method (Robertson 1989). Pixels contaminated by cloud and cloud-shadow were masked using a semi-automated method, which identifies possible cloud and shadow objects and finds those that match, based on the size of each object and the distance between them, followed by manual editing to remove errors (Fisher 2014).

The surface reflectance imagery was sharpened to 5 m pixel size using the panchromatic band. The panchromatic imagery was degraded (by averaging) from its nominal 2.5 m pixel size to 5 m, as this was assessed to be the level at which it was accurately co-registered to the multispectral imagery. This 5 m panchromatic imagery was used to sharpen the multi-spectral surface reflectance imagery, using a simple in-house method designed to preserve the radiometric integrity of the reflectance values. This method uses a Theil-Sen estimator (Sen 1968) on a local window to predict the higher resolution value from the lower resolution and the panchromatic value. It's a robust regression technique used to fit linear relationships by estimating the slope between two sets of points as the median of the slopes between all pairs of points. We used it to fit relationships on a local, per-pixel basis using all the pixels in a 7 by 7 high-resolution pixel window (35 m by 35 m in this case), separately for each band. Using the local relationship, an estimate of the multi-spectral band can be computed from the panchromatic band at the higher resolution.

These 5 m resolution SPOT surface reflectance images were used in the woody vegetation extent and change products referred to in Chapters 6 and 7, and are being used to map recent changes in land use.

SPOT 5 FPC

A product similar to the Landsat FPC images was developed using the SPOT 5 surface reflectance imagery. Since the SPOT 5 imagery has different spectral bands and spatial resolution from those of Landsat, a new FPC model was developed. Ideally we would relate field observations of FPC to the SPOT 5 imagery to calibrate a model, as was done for Landsat data in eastern Australia (Armston et al. 2009). As there was insufficient field data, collected near-coincident with the image acquisitions to calibrate a model directly, we used a cross calibration approach using the existing Landsat FPC products. This method is being prepared for publication so a short description of the method is included below.

To develop a SPOT FPC model we related the surface-reflectance of the 10 m SPOT 5 HRG imagery to the Landsat-derived overstorey FPC (Armston et al. 2009; Danaher et al. 2011). 2485 data points were collected from 60 images (Figure 2). These images were acquired across New South Wales and Queensland to capture a large range of vegetation communities, land types and FPC amounts. We sampled pixels from degraded SPOT and Landsat FPC images. They were degraded to an area equivalent to 3 by 3 Landsat pixels, which is 90 m by 90 m. A regular 1 km by 1 km sample grid was used. We retained those points that were on a slope of less than 5% as determined from the Shuttle Radar Topography Mission DEM, were woody as determined by the Landsat FPC layer, and within an area of homogenous cover. The homogenous criterion was that the coefficient of variation of the Landsat FPC in a 5 by 5 pixel window (150 m by 150 m) was less than 0.05. Degrading the images and choosing pixels on homogeneous sites reduces the influence of small errors between the SPOT and Landsat FPC images on the model. We used a multiple linear regression model to relate the SPOT reflectance to Landsat FPC. The model included terms for each SPOT band and interactions between them. The adjusted r^2 of the model fit was 0.88. While the model was developed using the 10 m SPOT imagery, it has been applied at 5 m resolution on the assumption that a continuous FPC model would scale. The model included terms for each SPOT band λ_i, and interactions between them:

$$F = \beta_0 + \sum_{i=1}^{4} \beta_i f(\lambda_i) + \sum_{i=1}^{3} \sum_{j=i+1}^{4} \beta_{3+i+j} f(\lambda_i) f(\lambda_j)$$

where F is FPC, β are the coefficients, and the function, f, used to remove skewness in the distribution

$$f(x) = log_e(100x + 1)$$

Validation of the FPC values is described Appendix 4.

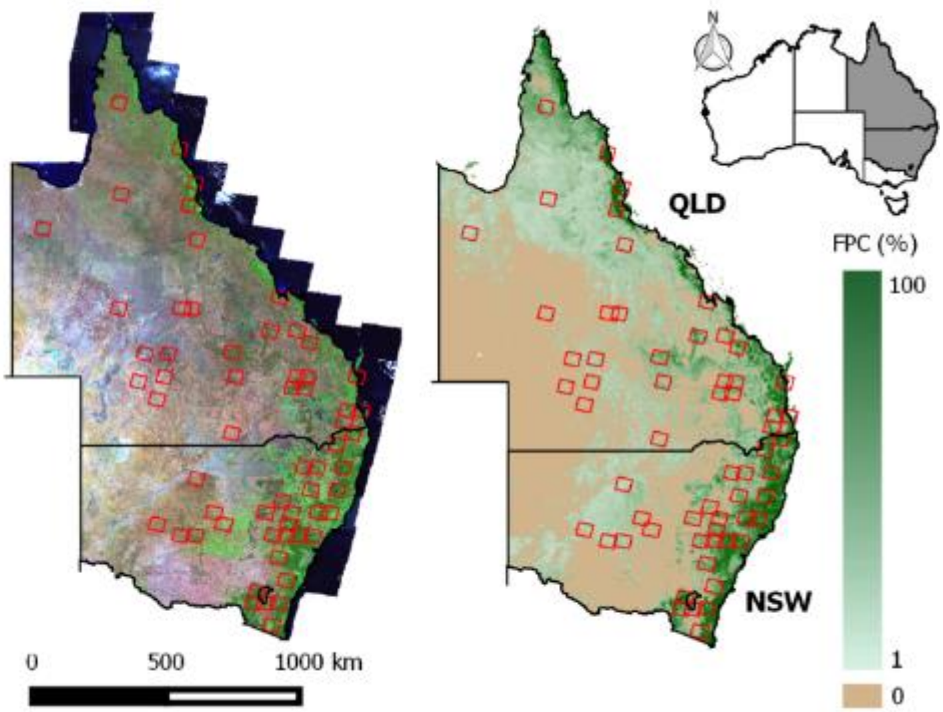


Figure 2. The locations of the SPOT 5 HRG images used to calibrate a model relating the SPOT surface reflectance to Landsat-derived FPC (right image).

SPOT 5 water mask

A linear discriminant analysis water index (LDAWI) (Fisher and Danaher 2013) was developed to enable the mapping of water bodies using SPOT 5 satellite imagery. A threshold is applied to the index to create a map of water bodies, which is used to mask out areas of water when mapping vegetation extent and change.

The water index was created using training data from New South Wales and the multivariate statistical method of linear discriminant analysis classification. The index uses all four image bands, and is better at separating water and non-water pixels than the two commonly used variations of the normalised difference water index, which each use only two image bands. Compared across 2400 validation pixels, from six images spanning four years, the LDAWI attained an overall accuracy of 98%, a producer's accuracy for water of 100%, and a user's accuracy for water of 97%.

These water index images have been processed for every SPOT 5 image in the OEH archive.

Digital aerial imagery

LPI aerial imagery program

Land and property information (LPI) currently provides spatial imagery, captured using State-owned sensors, to NSW State Government agencies[1].

The current aerial image capture programs by LPI include: the standard 50 cm resolution, a 10 cm resolution program covering town areas and emergency response coverage e.g. flood mapping. LPI's standard capture program covers Central and Eastern New South Wales as well as selected areas throughout the Western Division, as shown in Figure 3. The capture program began in 2007 and will be repeated every five years.

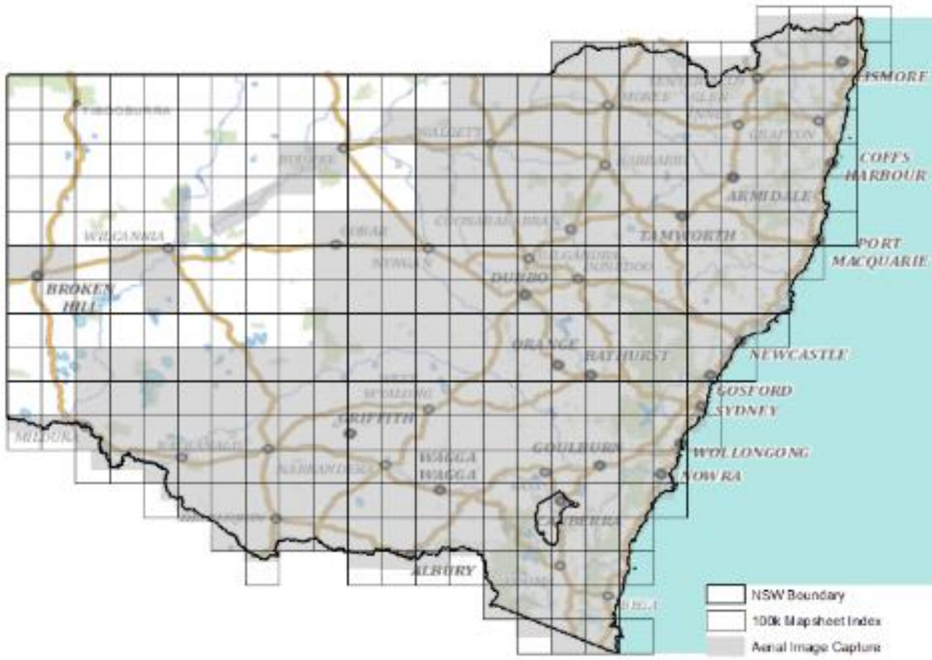


Figure 3. LPI aerial image capture

Aerial imagery products

The imagery was captured with a Leica ADS digital scanner (Sandau et al. 2000). This is a linear push-broom scanner that captures imagery in blue (0.428–0.492 µm), green (0.533–0.587 µm), red (0.608–0.662 µm), near infrared (NIR) (0.833–0.887 µm) and panchromatic bands at 12 bit quantisation, providing very high contrast images. The ADS sensor captures images looking forward, downwards and backwards from the aircraft, which provides stereo imagery.

The image capture, processing and delivery are consistent with well-accepted digital image processing techniques (Leica Geosystems, 2009; 2010). Imagery is captured, aero-triangulated, ortho-rectified and joined into strips that are then mosaicked.

The products are provided as Level 1 data suitable for a digital stereoscopic workstation, and Level 2 products including colour balanced mosaic images.

The mosaics provided through the standard program cover 1:100,000 map sheet areas.

[1] http://www.lpi.nsw.gov.au/mapping_and_imagery/imagery_programs

Scanned aerial photography – circa 1990

Scanned aerial photography introduction and specifications

One of the best ways to gain insight into the characteristics of an area of land and undertake a resource inventory is to use Aerial Photograph Interpretation (API). Aerial photographs are the main source of information about the conditions of the land in terms of native vegetation status circa 1990.

Imagery across New South Wales was captured on a 1:100,000 map sheet basis, each map sheet is known as a 'mission', with multiple flight runs per mission. The time taken to complete a map sheet varied generally from a week to a month, occasionally longer if complications arose such as poor flying conditions or if maintenance was required to the aircraft.

The images were captured with a Wild RC10 camera, which was in operation between 1968 and 1993. Each image was taken with a 60% overlap east–west and a 20–40% north–south, as can be seen in Figure 4.

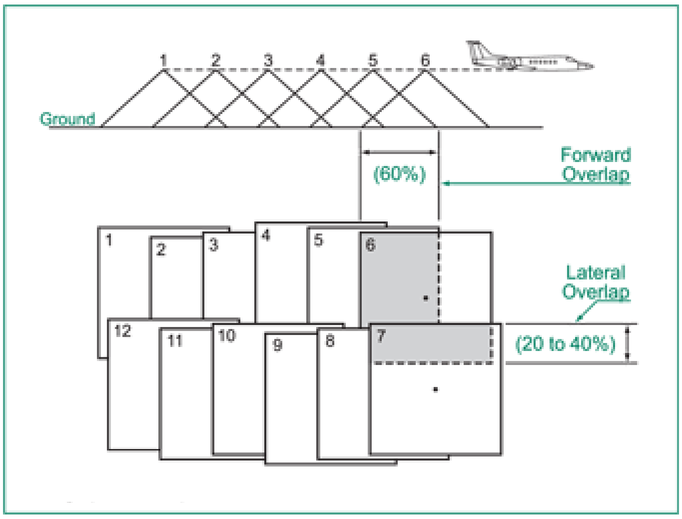


Figure 4. Photographic overlap

The scale of the photography captured varied between coastal and western regions. Generally coastal areas were flown at 4000–4500 m above sea level at a scale of 1:25,000. Western regions were flown at 7500–8000 m above sea level at a scale of 1:50,000. Focal length ranges between 151.45 and 153.10.

Scanned aerial photography acquisition

The aerial photography used to assist in identifying vegetation clearing since circa 1990 was sourced from NSW Land and Property Information (LPI) under a memorandum of understanding between LPI and Office of Environment and Heritage (OEH). All aerial photographs have been scanned by LPI Officers and the memorandum authorises OEH to acquire digital film scans from LPI on a regular basis. Imagery sourced from LPI has been scanned at 1200 dpi from the film diapositive with a specialised air-photo scanner.

Scanned aerial photography coverage

Although New South Wales is covered by historic aerial imagery, some of these images date back to 1962. To be relevant to the Native Vegetation Regulatory Map, images had to have been taken circa 1990, ideally no further than 5 years either side of this date. Coverage of

New South Wales by aerial imagery between the years 1985 and 1995 was reasonably comprehensive, but not complete. Figure 5 highlights the historical aerial photo coverage for 1990.

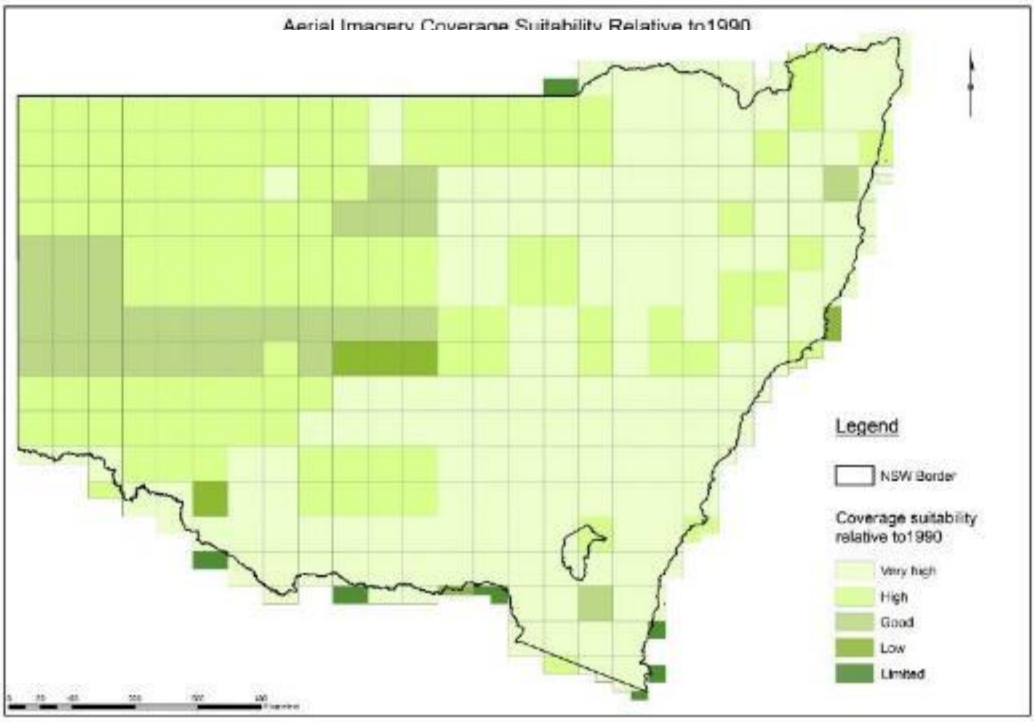


Figure 5. Aerial imagery coverage suitability relative to 1990

Ortho-rectification process

After aerial photographs have been scanned and acquired they are ortho-rectified to align them to a map grid and to remove relief displacement. The location of features in these ortho-rectified images can then be accurately related to a position of the earth's surface. Ortho-rectification of photos is done in blocks of photos corresponding to 1:100,000 map sheets. Due to the 60% overlap between each image, only every second image needed to be ortho-rectified. This still allowed for approximately 20–30% overlap between images used to create the mosaic.

The ortho-rectification process is based on either a fully automated software approach developed by the Joint Remote Sensing Research Project (JRSRP) or the Autosync™ software by Intergraph. The JRSRP software was developed to significantly reduce the time to ortho-rectify photos by using image correlation matching at a number of image resolutions based on hundreds of control points. Where the automated process was not able to match sufficient points and failed, the Autosync software was used. This is a more manual process requiring the operator to visually place at least some of the control points. Generally 6–10 ground control points (GCP) were applied to both the air photo and the corresponding reference image. GCPs were placed strategically around the image. RMSE error was 5 m or less.

Both ortho-rectification methods use a direct linear transformation model and use elevation data to remove height displacement from the images. Elevation data was obtained from LPI as a Digital Surface Model (DSM) based on ADS digital imagery with a resolution of 10 m or better. Where an ADS DSM was unavailable, the 1 second Shuttle Radar Topographic Mission (SRTM) DEM was used with a resolution of 30 m. For the reference image the most recent ADS aerial imagery was used, having a resolution of 0.50 m.

Quality assessments were undertaken on each image following ortho-rectification. Distortion of 1–5 m at the very edge of the images was common, and most likely due to the wider view angle at these points. However, due to the image overlap of approximately 30% distortions had minimal impact on the resultant mosaic.

Due to the significant level of processing time involved to ortho-rectify aerial photos, priority areas were assigned strategically. They were chosen based on clearing history, areas subject to development pressure and where other imagery sources were less extensive.

Mosaic process

To create the map sheet mosaics of the circa 1990 aerial photography, MosaicPro™ by Intergraph was used. Weighted seamlines and colour corrections were used to ensure that colour balancing was consistent across the image mosaic. In some cases variation in colour balancing was not corrected due to variations in sun and view angle across the mosaic. There may be greater discrepancy in colour balance within a mosaic when frames were taken on different dates, or when the surface was highly reflective and affected by flaring (e.g. water).

Seamlines were captured in shapefile format, which provides a reference to each individual aerial photo used in the mosaic.

Appendix 2: Data sets, sources and associated map layers

Data set	Source	Map product or layer
Landsat imagery archive Circa 1990–2013	United States Geological Survey	• Seasonal cover disturbance image Chapter 5 • Detectable clearing events Chapter 6.4
SPOT 5 Imagery archive 2008–2013	OEH Corporate data	• Land use Chapter 4 • NSW 2003 land use Chapter 4.3 • Detectable clearing events Chapter 6.4
ADS40/80 imagery 2007–2013	OEH Corporate data Captured by NSW Land and Property Information	• Land use Chapter 4 • Detectable clearing events Chapter 6.4
Historic aerial photos Circa 1990	Image and Remote Sensing (IRS) facility	• Reviewing and updating the map Chapter 9.4
Landsat foliage projective cover (FPC)	OEH corporate data Created using Landsat imagery archive	• Establishing the baseline woody vegetation extent layer Chapter 6.3
Landsat fractional cover Seasonal Landsat fractional cover	OEH Corporate data Created using Landsat imagery archive	• Establishing the baseline woody vegetation extent layer Chapter 6.3
Seasonal cover disturbance image	OEH Corporate data Created using Landsat fractional cover products	• Land use Chapter 4 • Seasonal cover disturbance image Chapter 5
Spot 5 FPC	OEH corporate data Created using SPOT 5 imagery archive	• Establishing the baseline woody vegetation extent layer Chapter 6.3
NSW digital cadastral database	NSW Spatial Services	• Exclusions Chapter 3
Land use NSW 2003 (1999–2012)	Australian Collaborative Land Use and Management Program	• Land use Chapter 4 • Forming the final map product Chapter 8
2011 woody extent map	OEH corporate data	• Establishing the baseline woody vegetation extent layer Chapter 6.3 •
2013 woody extent map	OEH corporate data	• Establishing the baseline woody vegetation extent layer Chapter 6.3 • Detectable clearing events Chapter 6.4 • Forming the final map product Chapter 8
All eras woody vegetation loss	OEH corporate data	• Detectable clearing events Chapter 6.4 • Forming the final map product Chapter 8

Data set	Source	Map product or layer
	Created using SLATS mapping program	
Vegetation trend map	OEH corporate data Created using Landsat imagery archive	• Revising the SLATS maps Chapter 6.4.3
Overriding datasets	Refer Appendix 6	• Overriding map layers Chapter 7 • Forming the final map product Chapter 8
Excluded areas	NSW Digital Cadastral Database OEH corporate data	• Exclusion Chapter 3 • Forming the final map product Chapter 8

Appendix 3: Supplementary detail for chapter 4 (land use)

This appendix provides examples of land use interpretation and more detailed information regarding the accuracy assessment for land use mapping.

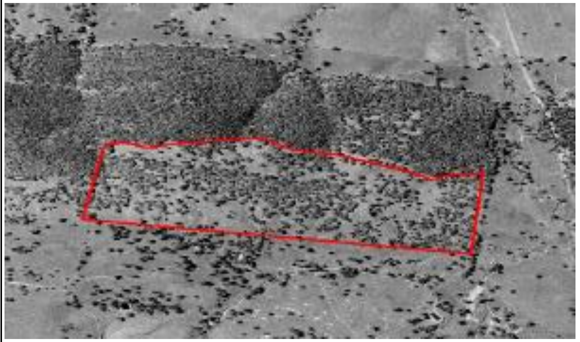
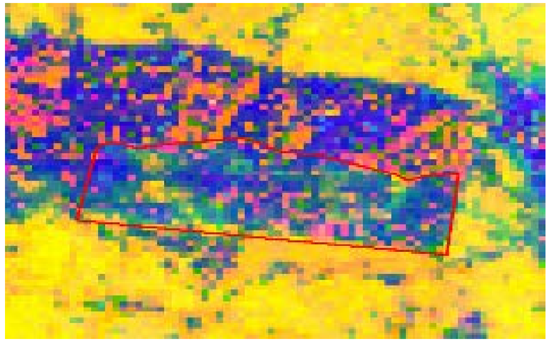
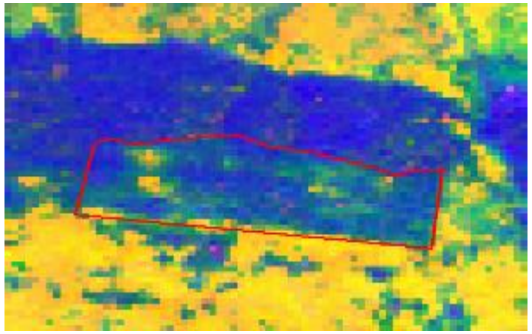
Appendix 3A: Analyst interpretation rules for land use classes

The table below reflects how analysts apply land use classes for a set of frequently encountered land use scenarios across New South Wales. Note that this table is not intended to be comprehensive, and does not constitute an exhaustive list of analyst interpretation rules for all land use classes.

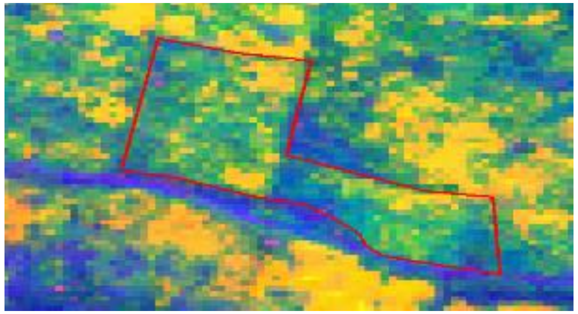
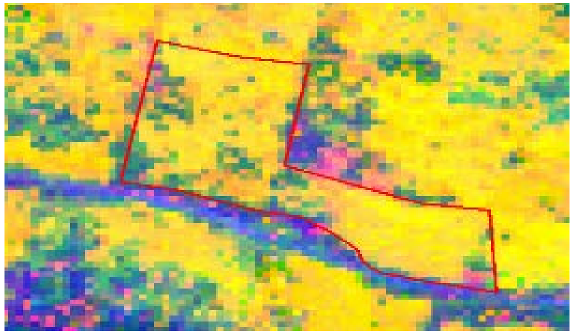
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
1 Conservation and natural environments	1.1.0 Nature conservation	2	Includes conserved areas, remediation orders (OEH and court ordered), Property Vegetation Plans, offsets, bio-banking offsets, conservation agreements and Commonwealth conservation agreements. These are identified in the source attributed to the type in the land use layer.	Features will be sourced from the data sets identified in Chapters 7 & 9 of the method statement. Attempts will be made to ensure these data sets are in accordance with the spatial accuracy of the map.	 Bio-banking example  Bio-banking example  Property agreement exam

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	1.2.0 Managed resource protection	2	On ground environmental works including riparian and land degradation works, and biodiversity corridors. These are mapped category 2 because many of these works have been funded through Commonwealth and State funding sources.	Generally involves fencing and the exclusion of stock – a change in land use. They may include earth works and/or engineering structures for remediation of land degradation. Plantings generally include a mix of overstorey and mid species, often endemic to the region. Biodiversity plantings often link or incorporate existing stands of remnant vegetation, creating corridors of habitat refuges.	 Gully erosion works  Salinity treatment site  Biodiversity corridors – Habitat

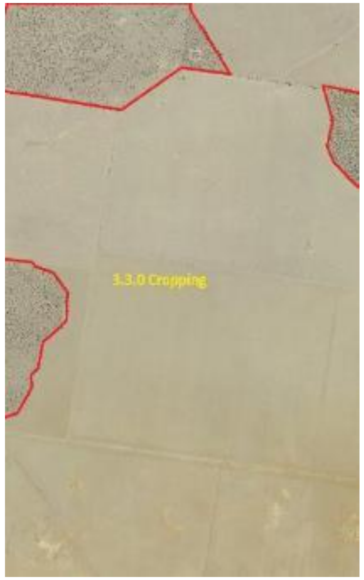
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	1.3.0 Conservation and natural environment s – other minimal use	2	May include travelling stock routes and Defence lands – natural areas, not subject development.	May include travelling stock routes based on existing land use and field work information. Defence lands based on existing land use and access to Commonwealth holdings (spatial) information.	 Commonwealth Defence Lands  Travelling stock route  Travelling stock route

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
2 Production from relatively natural environments	2.1.0 Grazing of native vegetation	2	Areas that show no evidence of agricultural disturbance based on land use patterns and low variability between 1990 and 2013 in the seasonal cover disturbance image	Areas that show no visual indication of cultivation activity in available satellite and aerial imagery. Areas also demonstrate low variability in fractional cover 1990–2013, represented by the blue colour in the seasonal cover disturbance image (Chapter 5).	  1991 Aerial photograph 1987–2013 SCDI   2009–2013 SCDI ADS imagery 2014 Paddock example: No evidence of agricultural disturbance (land use), low disturbance based on seasonal cover disturbance image (SCDI) in both short- and long-time series products. Paddock(s) to the west of example paddock demonstrate the signature of agricultural disturbance in SCDI products, delineating the boundary between ALUM 2.1.0 – grazing of native vegetation to 3.2.0 – grazing of modified pastures, used by staff in the land use mapping process.

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples		
3 Production from dryland agriculture and plantations	3.1.0 Plantation forestry	1	Plantation timber for production harvest.	Plantations generally have linear patterns of evenly spaced planted trees with uniform tonal and growth patterns in height and size. Native vegetation is retained in filter strips along drainage lines, riparian zones and hilltops. Generally found in areas adjacent to, or surrounded by native forests. New plantations are generally established in areas previously cleared for agriculture.	 Pine plantation example	 Hardwood plantation example	 Pine plantation example

Primary ALUM class	**Secondary ALUM class**	**Map category**	**Notes and rules applied**	**Land use description**	**Visual examples**
	3.2.0 Grazing of modified pastures	1	Areas where clearing and disturbance has occurred, but cultivation or sown pastures are not evident.	3.2.0 Grazing of modified pastures will be used for areas demonstrating variability in the seasonal cover disturbance image. It is likely that the areas have been subject to agricultural activity/disturbance between 1990 and 2013 without the presence of land use patterns or indicators in contemporary satellite or aerial imagery.	 ADS imagery 2009  2009–2013 SCDI  1987–2013 SCDI  ADS imagery 2014 Paddock example: Insufficient evidence in aerial/satellite imagery to determine level of agricultural disturbance. SCDI products indicates that the paddock has been subject to agricultural modification, when compared to ground cover present in the road reserve on the western boundary of the paddock.

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	3.2.5 Sown pastures	1	Areas where sown pastures are grown predominantly for stock grazing are mapped as sown grasses 3.2.5. This includes valley flats, alluvial river banks associated with intensive animal production such as dairies, or geographical areas where there is limited or no broad-acre cropping present.	Sown pastures demonstrate linear tracking similar to cropping activity, from the mechanical sowing/ spreading of seed. Some areas identified as sown pastures and cropping are intermixed as part of a cropping rotation 3.3.0. However both are mapped as category 1. 3.2.5 may contain sown pastures that are irrigated, but there is insufficient evidence in the imagery to suggest the presence of irrigation equipment or associated infrastructure.	 Sown pastures example  Sown pastures example  Sown pastures example

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	3.3.0 Cropping	1	Areas/paddocks subject to regular/routine cultivation activity for the purposes of food or stock fodder production. Areas identified as cropping in the map appear to have been subject to cultivation activity in the last 5 or so years, based on high resolution aerial and satellite imagery captured during this period.	Cropping is often evident in satellite and aerial imagery through linear tracking. This often forms the 'headland' or envelope pattern in paddocks, where traditional cropping techniques are used. Precision agriculture (GPS guidance) 'controlled traffic' has resulted in long linear evenly spaced runs with 180-degree turns at the ends of a paddock. Both practices, 'headland pattern' and 'controlled', result in soil compaction from the weight of machinery, which is quite often evident in aerial imagery many years after a paddock has been cropped, where grasses are now present.	 Cropping example 1  Cropping example 2  Cropping example 3 Cropping example 1 illustrates the two types of cropping practices. The paddock on the left of the yellow line shows patterns consistent with GPS 'controlled traffic' and the paddock on the right shows the 'headland pattern'. The 3 cropping examples illustrate the different types of patterns of cropping cycles, subject to the date of imagery and seasonal conditions. Example 1 shows crop stubble present recently after harvest, example 2 shows crop actively growing, and example 3 shows an area of cropping activity that may not have a crop present in the season the image was captured.

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	3.4.0 Perennial horticulture	1	To be mapped to the enterprise level, including the area of operation and associated infrastructure, such as sheds, silos, access tracks, onsite effluent management, dams and onsite farmhouse or accommodation if present. Includes irrigated perennial horticulture.	Perennial horticulture demonstrates linear and evenly spaced rows of planting of tree crops, shrubs or vines. Based on the deciduous nature of the tree or vine crop, foliage may appear abundant in imagery over the spring/summer period and bare in the autumn/winter period. Plantings may have permanent netting structures or temporary netting structures to prevent birds and other animals eating fruits.	 Olive plantation example  Citrus plantation example  Coffee plantation example

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	3.5.0 Seasonal horticulture	1	To be mapped to the enterprise level, including the area of operation and associated infrastructure, such as sheds, silos, access tracks, onsite effluent management, dams and onsite farmhouse or accommodation if present. Includes irrigated seasonal horticulture.	Characterised by exposed soil with linear features associated with growing mounds and furrows used for irrigation and drainage. Growing mounds in some instances may be covered with plastic to protect crop from soil moisture and diseases. In imagery the linear bands of crop foliage may illustrate a uniform growth form and tonal pattern. Bands of differentiating tonal patterns may be the result of varying species grown, for example lettuce species, or the mixed nature of operation where different crops are grown within the same plot.	 Seasonal horticulture – vegetables  Seasonal horticulture – vegetables

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
				Temporary greenhouses used to propagate seedlings or grow seasonal vegetables out of season to be incorporated into 3.5.0. Permanent structures – greenhouses and glass houses to be mapped as 5.1.0.	 Seasonal horticulture – turf farm

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	3.6.0 Land in transition	1	Areas that have been subject to agricultural production, but appear to be in a state of abandonment at the time of mapping. These areas have no apparent intended or change in land use at the time of mapping.	For the purpose of the land use mapping process any perennial horticultural operation that has more than 50% of the plantation removed, or appears to have been left in an abandoned state, will be mapped as 3.6.0. Abandoned seasonal horticultural operation or intensive animal production operation will also be mapped as 3.6.0. These areas have no apparent or intended change in land use at the time of mapping.	 Abandoned poultry operation  Abandoned perennial horticulture  Abandoned seasonal horticulture

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
4 Production from irrigated agriculture and plantations	4.2.0 Grazing irrigated modified pastures	1	Similar to 3.2.5 above, however have associated irrigation infrastructure and likely to be associated with 5.2.0, intensive animal husbandry operations, such as dairy operations and cattle feedlots.	Some areas may be identified as 4.3.0 – irrigated cropping – where there is insufficient evidence in aerial/satellite imagery to suggest an associated link to intensive animal husbandry.	 Centre pivot irrigated pastures  Centre pivot & linear paddock irrigation  Sprinkler irrigated pastures

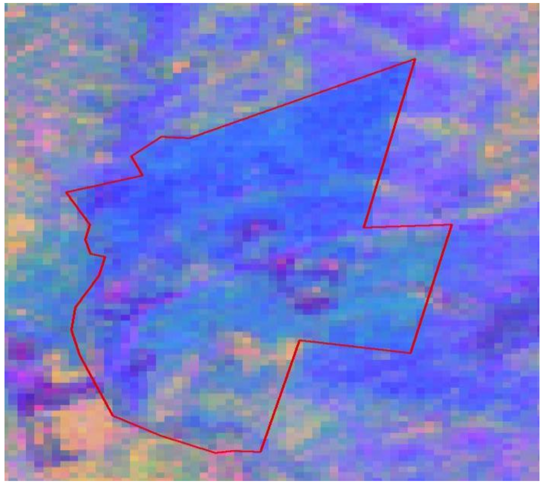
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	4.3.0 Irrigated cropping	1	Areas/paddocks subject to regular/routine cultivation activity for the purposes of food or stock fodder production. Areas identified as cropping in the map appear to have been subject to cultivation activity in the last 5 or so years, based on high resolution aerial and satellite imagery captured during this period. These areas demonstrate associated infrastructure and/or layout.	As per 3.3.0 description above. Irrigation developments will be mapped to the area of the enterprise for the purpose of the map. Irrigated cropping will be identified by land layout (contour, bay banks, irrigation dams and centre pivots), and water-supply channels.	 Irrigation enterprise example  Irrigation district example  Irrigation enterprise example

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
5 Intensive uses	5.1.0 Intensive horticulture	1	To be mapped to the enterprise level, including the area of operation and associated infrastructure, such as sheds, silos, access tracks, onsite effluent management, dams and onsite farmhouse or accommodation if present.	Shade houses and commercial/wholesale nurseries – both mapped to area of the enterprise. Nurseries generally have areas covered by shade houses in areas without cover. Linear bays generally present with blocks of single species present (checkerboard appearance in aerial imagery). Glasshouses are generally linear shed-like structures comprising metal and glass material.	 Commercial nursery operation  Intensive horticulture enterprise  Intensive horticulture enterprise

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.2.0 Intensive animal husbandry	1	Mapped to the extent of the area of operation present at 2013.	Includes dairies and yards, cattle and sheep feedlots, poultry sheds and yards, piggeries, aquaculture, horse studs and agistment properties with infrastructure present and commercial stock and saleyards.	 Beef feedlot enterprise  Piggery enterprise  Poultry enterprise

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.3.0 Manufacturing and industrial	1	Mapped to the extent or area of operation present at 2013. Subject to applicability of the map based on LEP zonings.	Highly modified areas with major infrastructure. Includes factories, foundries, workshops, commercial agricultural business and primary produce processing plants. Examples include abattoirs, wine processing plants, cotton gins, grain storage/silos and agricultural fertilisers.	 Abattoir example  Cotton processing gin  Wine processing plant

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.4.0 Residential and farm infrastructure	1	Mapped to the extent of farm infrastructure including house, associated machinery sheds, and stockyards. Remote communities will be mapped to the extent of development where applicable. Applies to tertiary classes 5.4.1, 5.4.2, 5.4.4 and 5.4.5.	Features to be mapped where greater than 2 ha in size.	 Farm infrastructure – homestead & sheds  Remote Community  Farm infrastructure – Ag production

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.4.3 Rural residential without agriculture	2	Used to define rural residential developments that are predominantly woody cover, where clearing is associated with infrastructure (fence lines, buildings and driveways). It is also used for rural residential where low disturbance is demonstrated in the SCDI (1987-2013) and there is no visual pattern in aerial and satellite imagery to suggest that clearing for agriculture has occurred. This is consistent with the BCA mapping method applied to larger agricultural properties in NSW.	Features to be mapped where greater than 2 ha in size.	  Rural residential – bush blocks  Rural residential – low disturbance based on SCDI time sequence 1987–2013

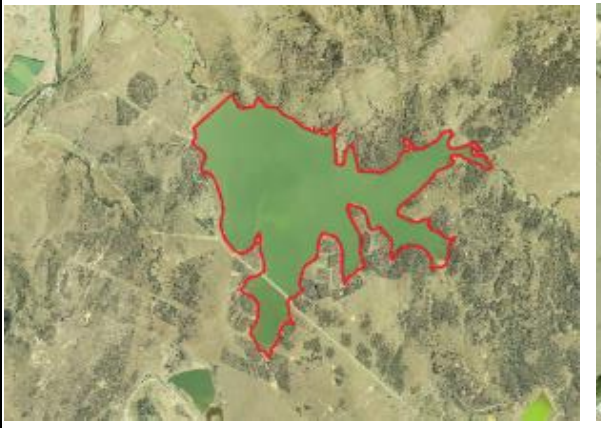
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples		
	5.5.0 Services	*1 & 2	Areas will be subject to assessment based on land use patterns and seasonal cover disturbance images to determine whether area(s) are or have been subject to agricultural disturbance or ongoing modification.	Includes parks, golf courses and research facilities. Example of category 1 areas – sports ovals and golf fairways. Example of category 2 pockets of undisturbed native vegetation present in parklands and golf courses.	 Public recreation – modified disturbance	 Public recreation – mixed	 Public recreation – mixed levels of

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.6.0 Utilities	1	Subject to applicability of the map based on LEP zonings. Power generation, gas and water extraction.	Mapped where the feature/surface expression is greater than 2ha in size.	 Electrical substation  Gas processing/transmission site  Electrical substation
	5.7.0 Transport and communication	*1 & 2	Subject to applicability of the map based on LEP zonings. Roads and rail corridors to be mapped as category 2. Airports and ports will be category 1 and surrounding land will be subject to the seasonal cover disturbance	Regional airports /aerodromes land may be leased for cultivation, where others may retain native grasslands due to low disturbance. Loading facilities both water and rail may be subject to intense	 Regional airport.  Grain storage facility

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
			image to determine whether the area has been subject to a level of disturbance to define whether category 1 or 2 is assigned.	modification in the area of operation, however may have areas of land that have experienced low disturbance over time. Category 2 areas in these areas will be greater than 2ha in size to be mapped.	 Regional aerodrome
	5.8.0 Mining and quarrying	*1 & 2	Mapping the surface expression of the mining/quarrying operations. This includes tailings, stockpiles and processing and/or associated infrastructure.	Areas within the mineral title lease will be subject to land use and seasonal cover disturbance image.	 Open cut mine  Large-scale quarry operation  Quarry operation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	5.9.0 Waste treatment and disposal	*1 & 2	Sewage and water treatment plants and landfill sites – mapped to the surface expression of operation.	Areas within holding, outside of areas of operation, subject to seasonal cover disturbance image to determine level of disturbance. If greater than 2ha and low disturbance – area will be mapped as category 2.	 Water/Sewage treatment facility  Waste management facility  Waste management facility

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
6 Water	6.1.0 Lake	2*	Mapped to the extent of feature.	Areas subject to cropping or other forms of cultivation will be assigned the appropriate secondary ALUM class in ALUM primary classes 3 or 4 (if irrigated). Areas subject to cultivation will be mapped as category 1.	 Inland lake – non production  Inland lake – non production  Inland lake – production

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	6.2.0 Reservoir/Dam	1	Associated with on farm storage of water. Will be mapped if greater than 2Ha in size.	Source of this information will be the land and property information hydro area for farm dams and off river irrigation dams. Additional features will be identified by the SLATS SPOT water product.	 Reservoir example  Large-scale farm dam  Irrigation dam – off river storage

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	6.3.0 River	2	To be mapped as part of the vulnerable lands – protected lands process.	20 m from bed or bank. Used in land use mapping process.	
	6.4.0 Channel/aqueduct	1	To be mapped where the feature is greater than 50 m in width and is not part of on-farm irrigation enterprise.	The channels are associated with large irrigation schemes used to transfer water from river bank to irrigation properties. Often cross and/or run adjacent to roads and travelling stock reserves. Aqueducts are associated with the transfer of water from one water storage to another. Usually for domestic water supply.	 Irrigation supply channel  Aqueduct – domestic water supply  Salt interception scheme

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	6.5.0 Marsh/Wetland	2*	Mapped to the extent of feature.	If area(s) is subject to cropping or other forms of cultivation it will be assigned the appropriate secondary ALUM class in ALUM primary classes 3 or 4 (if irrigated). Areas subject to cultivation will be mapped as category 1.	  Provisional examples – for OEH (internal) discussion.
	6.6.0 Estuary/Coastal Waters	2*	Mapped to the extent of feature applicable to the map.	Areas subject to production applicable to the map will be mapped as category 1.	

Appendix 3B: Land use accuracy assessment method and results

Accuracy assessment

An accuracy assessment was carried out to assess consistency in the mapping process. It tested for consistency between land use mappers, in the accuracy of individual land use classes, and the overall accuracy of the NVR Categories.

The map sheets that were chosen provided a cross-section of land use mappers and regional areas. (See Figure 6.)

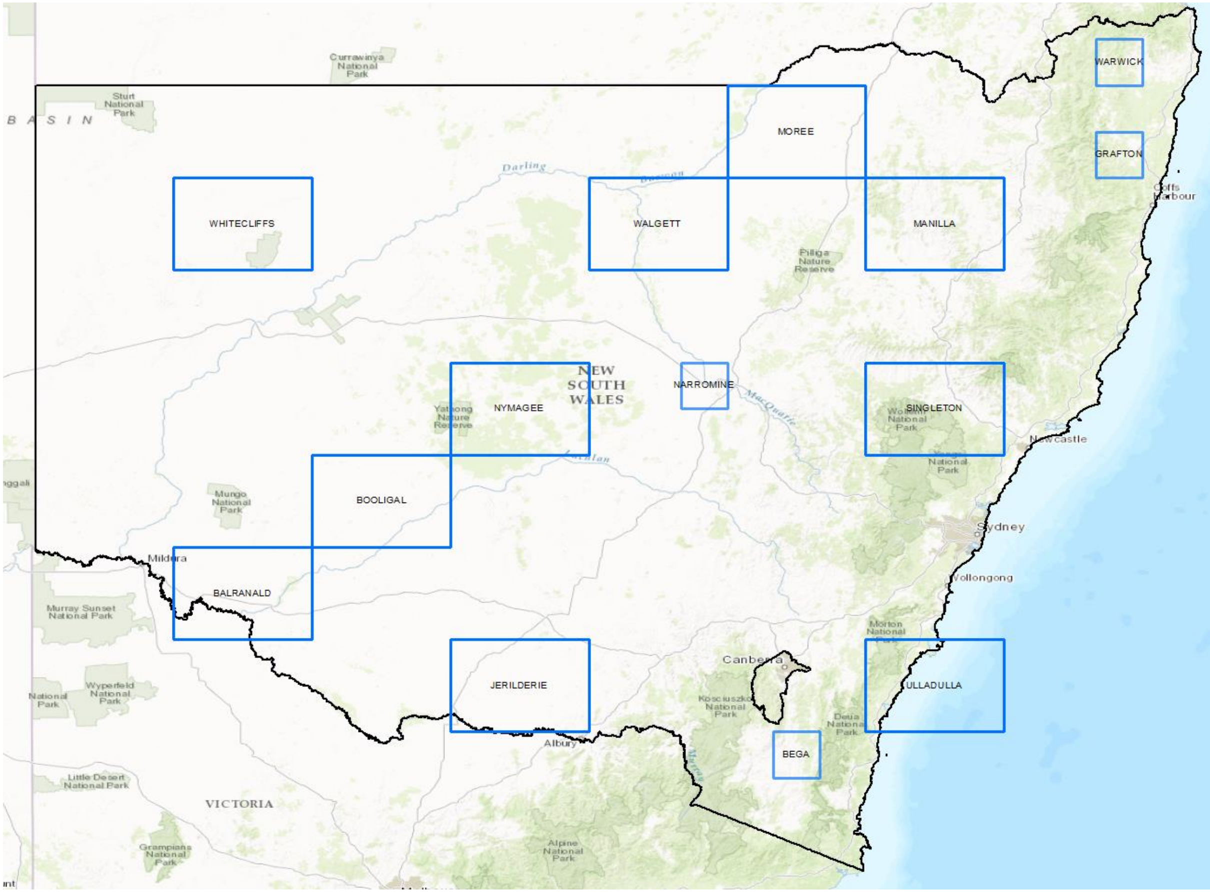


Figure 6. Map sheets covered by accuracy assessment as of December 2016.

Spatial and thematic accuracy is assessed in one process, which means the line work and the thematic accuracy are being assessed together. The statistical method uses a 'frequentist approach' to sampling using 'bootstrapping' to calculate the results (Champagne et al. 2014).

Points are allocated by random stratified sampling using land use classes as the strata. The total area of and number of polygons for each secondary land use class determines the number of points. The larger a land use class is in area and/or the more polygons it has, the more sampling points per map sheet it will have. The classes that are an exception to this rule are the following Australian Land Use Management (ALUM) classes, since they are the most significant land use categories in New South Wales in terms of area and management for native vegetation legislation.

- 2.1.0 – Grazing native vegetation (category 2) – minimum 30 points
- 3.2.0 – Grazing modified pastures (category 1) – minimum 15 points
- 3.3.0 – Cropping (category 1) – minimum 15 points

The assessor then gives each point an ALUM category, using the same information provided to the land use mapper, i.e. a range of SPOT imagery dates, SCDI and ADS40 imagery.

To assess the agreement between the land use mapper and the independent assessor an error matrix is calculated. This identifies the level of agreement between the map category and the identified reference points.

User's accuracy means the field or on-ground location is the point of reference. So, if you were standing in a crop field and you looked at the map, what is the chance of the map showing that it's a crop field.

Producer's accuracy means the land use map is the point of reference. So, if you went to a crop field based on the map, what is the chance of cropping actually being the land use at that location.

The error matrices are calculated by weighting the point observations by the area of the land classes used in the sampling. This removes sampling bias resulting from the different distribution of land classes across the state (Stehman 2014). Overall, producer's and user's accuracy for each class are calculated from the error matrix using standard formula, and 95% confidence intervals are estimated using bootstrapping, where the error distribution is calculated using percentiles from 1000 error matrices resampled with replacement from the overall matrix (Champagne et al. 2014; Gallaun et al. 2015).

Limitations

The points are not field validated. This is due to the tight time constraints of the program and the time required to gain access to private land to assess each of the 200 plus points, per map sheet, generated by the accuracy assessment. In addition to this, the mapping of land use for the NVR mapping was based on the entire 1990–2013 period and an assessment based on recent site observations may not reflect the land use history. If the assessor identified points where the land use could not be confidently interpreted from the desktop, advice was sought from senior mappers or regional experts.

Even if the mapper and the accuracy assessor agree they could both potentially be wrong. However, the following reasons both minimise this concern and ensure high quality mapping:

- Land use mapping is subject to multiple levels of quality assurance before it reaches the accuracy assessment stage – Senior Mapper and peer input during the mapping process, a Peer Review stage, a Regional Operations Review stage.
- The accuracy assessor must also be a land use expert. If an assessor is uncertain about any interpretation decisions they refer to Senior Land Use Mappers or regional experts.
- The use of detailed land use mapping guidelines maintains consistency and standards between mappers.

Accuracy assessment results

The results for the accuracy assessment are presented in Figure 7. The minimum threshold for 'acceptable' overall accuracy is 90% and this was achieved for all map sheets. The figures for the producer's and user's accuracy across the NVR map categories were less than 90% in eight cases. In all these cases the confidence interval range was high, indicating uncertainty in the accuracy statistic for those map sheets. In six of the cases the upper confidence interval was still above 90% and the user's and producer's accuracy was greater than 80%. Those six maps sheets were in areas where the distinction between category 1 and category 2 land was less obvious.

The two other cases had user's or producer's accuracy of less than 80%. They were the Ulladulla 250k (79%) and White Cliffs 250k (25%) maps sheets. These map sheets were thoroughly investigated by the accuracy assessor in consultation with the land use mapper and a senior expert to establish the cause of the low values. The low values resulted from a combination of reference points being distributed across ALUM classes not NVR categories, and the variation in mapped area of the two NVR categories. Specifically:

- The Ulladulla map sheet only just fell below the 90% confidence interval threshold (89%). This map sheet has only 10% of the area mapped as category 1 and this is spread across a large number of land use classes.
- The White Cliffs map sheet has <1% of category 1 land. A number of these category 1 areas are farm dams that were less than 2 ha and therefore the assessor rolled them into the surrounding ALUM class, predominantly grazing native vegetation category 2.

MAPSHEET	Overall Landuse accuracy (%)	*95% confidence interval*	Producer's accuracy (%)		*Producer's 95% confidence interval*		User's Accuracy (%)		*User's 95% confidence interval*	
			Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2
Balranald 250K	**98.33**	95.521-99.846	95.10	99.28	86.157-100.000	98.426-99.974	97.50	98.57	94.455-99.907	95.714-100.000
Bonalbo 100K	**92.60**	87.655-96.721	86.32	95.25	75.334-96.136	91.582-98.876	88.42	94.30	79.180-97.366	88.726-98.515
Booligal 250K	**99.52**	98.929-99.950	99.98	99.49	99.972-99.991	98.874-99.948	92.12	100.00	82.497-99.196	99.998-99.999
Cooma 100K	**95.00**	91.2-98.0	93.20	95.40	80.7-99.7	92.4-98.4	81.20	98.50	68.6-93.7	95.7-99.9
Grafton 100K	**94.70**	93.129-96.004	100.00	96.72	100.000-100.000	94.954-98.237	82.46	100.00	72.532-90.726	100.000-100.000
Jerilderie 250K	**94.58**	92.207-97.123	95.55	92.20	93.262-97.698	84.210-98.509	98.02	83.65	95.556-99.649	74.881-91.641
Narromine 100K	**95.20**	91.3-98.4	94.80	96.70	90.3-98.9	90.2-99.9	99.10	83.40	97.3-100.0	66.9-96.7
Nymagee 250K	**96.20**	93.5-98.1	96.10	96.30	88.9-100.0	94.2-98.1	89.90	98.60	84.1-94.9	95.8-100.0
Manilla 250K	**93.13**	89.470-96.753	92.35	93.75	85.795-98.017	90.343-97.167	91.65	94.28	87.012-96.293	88.572-98.572
Moree 250K	**94.27**	90.992-97.295	95.57	92.25	91.767-98.926	86.532-97.305	95.07	93.01	90.802-98.378	86.193-98.365
Singleton 250K	**93.94**	89.983-97.679	88.15	97.57	80.371-97.201	95.981-98.995	95.80	92.91	92.892-98.284	87.219-98.484
Ulladulla 250K	**90.80**	85.191-95.508	93.56	89.82	82.771-100.000	84.660-94.354	79.49	97.07	67.688-89.189	91.454-100.000
Walgett 250K	**97.93**	97.118-98.663	100.00	97.08	100.000-100.000	95.983-98.095	93.34	100.00	90.742-95.705	100.000-100.000
White Cliffs 250K	**99.89**	99.853-99.928	100.00	99.89	100.000-100.000	99.853-99.928	29.48	100.00	7.325-54.768	100.000-100.000
Average	**95.43**		**95.05**	**95.84**			**86.68**	**95.31**		

Figure 7. Accuracy assessment summary table as of December 2016.

Appendix 4: Development and interpretation of the seasonal cover disturbance image (SCDI)

Development of the seasonal cover disturbance image

The seasonal cover disturbance image (SCDI) combines information from images spanning seasons from summer 1988 to autumn 2013. Landsat fractional cover images (Scarth et al., 2010) were produced using a seasonal composite method (Flood, 2013) and analysed to provide seasonal fractional cover composite images covering the 1988–2013 period.

The pattern of change in seasonal cover for different land use types was analysed by plotting the time series of green and non-green vegetation cover fractions for selected sites. These sites were based on existing surveys and more recent site observation information (Murphy, Leys, and Biesaga 2006; Strong et al. 2016). Figure 8 shows a plot of the cover predictions based on fractional cover images for one cultivation site. The plots for 185 sites of different land use have been summarised as a conceptual diagram in Figure 9.

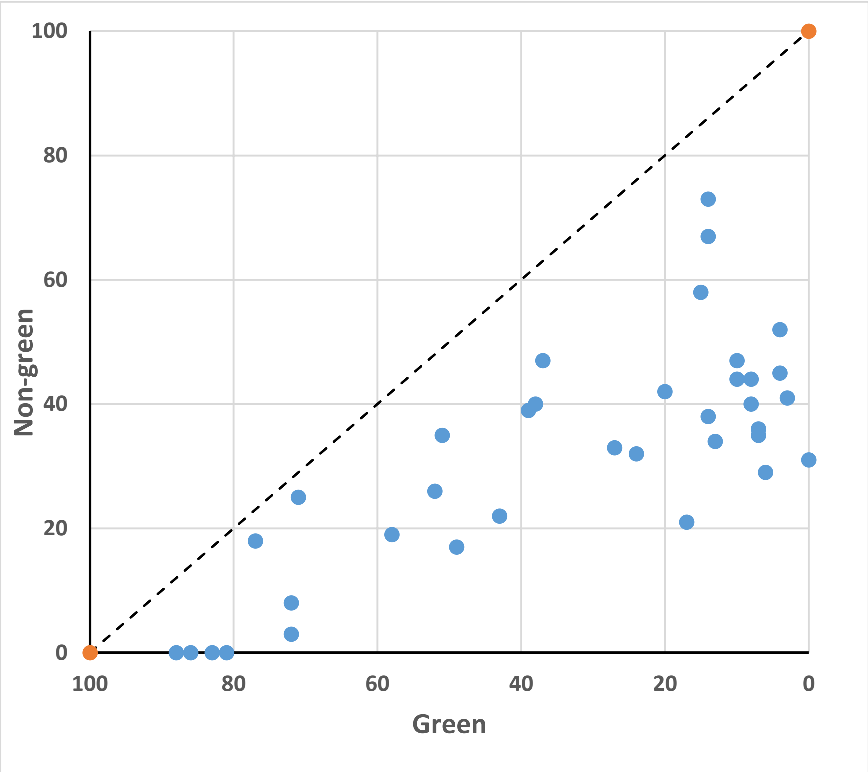


Figure 8. Plot of cover prediction for one cultivation site based on 1988–2013 seasonal fractional cover images

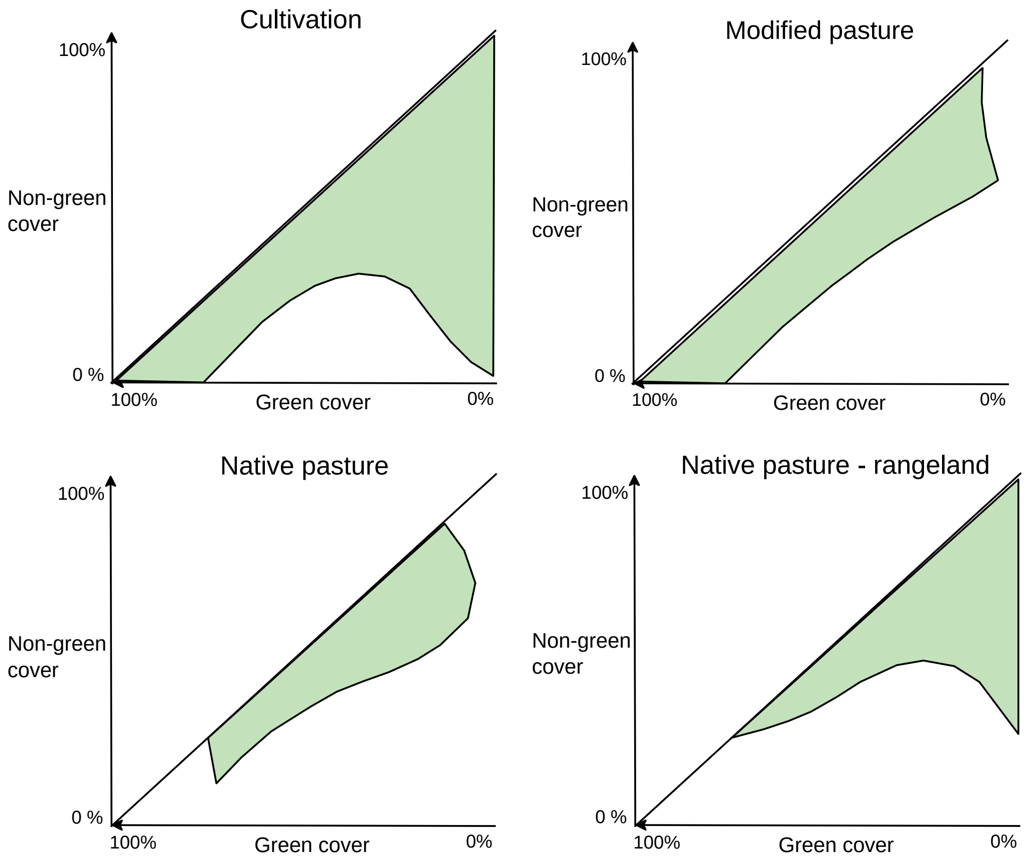


Figure 9. Conceptual plots of time series cover observations for four land use types

A method for summarising this information based on polar coordinates was developed and applied to the time series fractional cover data. For each seasonal cover observation (e.g. each point in Figure 8) an angle from the y axis and distance from the origin were calculated. Using the time series of angle and distance measurements, statistics including the mean, median, minimum, maximum, range and standard deviation were calculated. Figure 10 shows this concept for minimum and maximum distance, and maximum angle. The minimum and maximum distances used were based on the time series percentile values, with the 5% and 95% distance values representing the minimum and maximum. By using the percentile values the effect of anomalies such as cloud and other noise in the satellite data and fire scars were minimised. The range statistic, defined as maximum–minimum, was also based on the percentile minimum and maximum values. Images based on these time series statistics were produced and evaluated for mapping historic land use patterns.

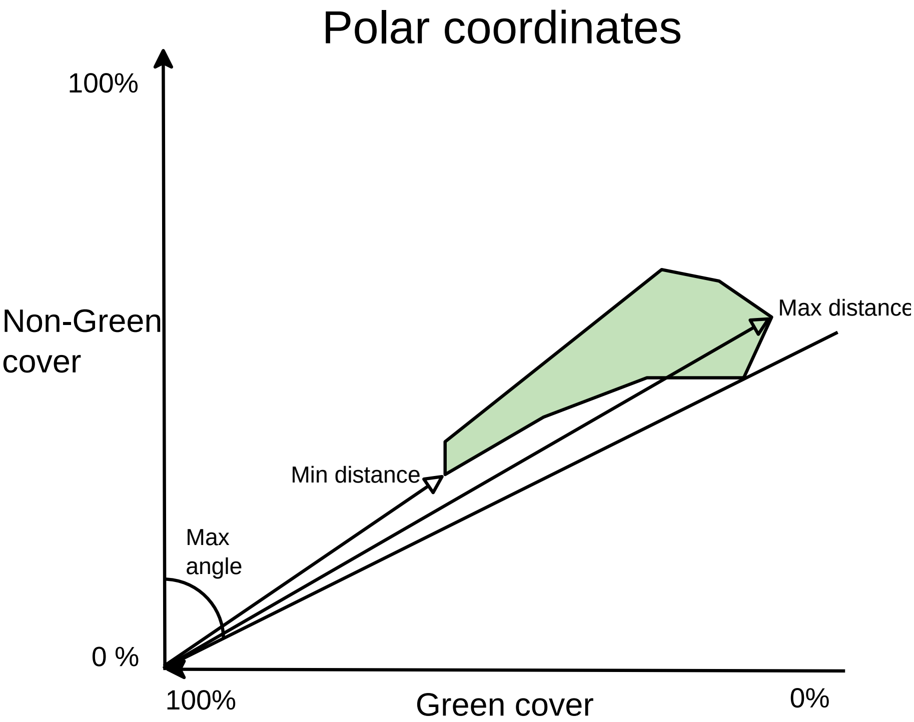


Figure 10. Time series summary for green and non-green vegetation cover polar transformed measurements

The seasonal cover statistics images were evaluated by comparison with:

- existing mapped land use
- high resolution digital aerial imagery
- historical scanned aerial photographs.

The most useful information for improving the interpretation of historic land use was contained in the maximum angle, minimum distance and range in distance images. These three images were combined in a colour composite image with the maximum angle, range and minimum distance shown as red, green and blue respectively (Figure 11).

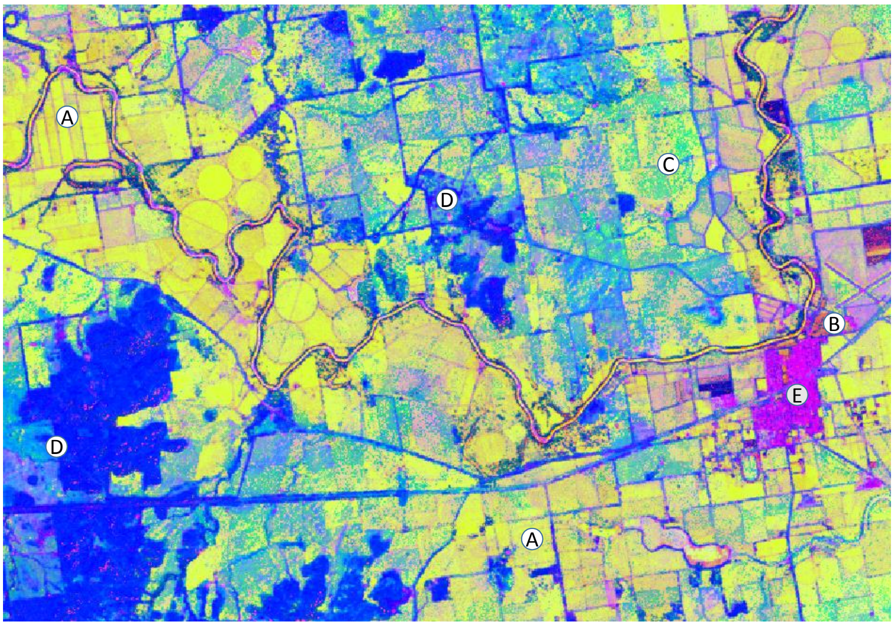


Figure 11. Colour composite image with the maximum angle, range and minimum distance shown as red, green and blue respectively.

Interpretation of the seasonal cover disturbance image

A guide has been developed to assist with the interpretation of the SCDI. As the colours in a composite are dependent on the contrast stretch applied to the image, a set of standard values was developed. The values in Table 1 were applied to images using a linear contrast enhancement.

Table 1. Standard linear contract enhancement values for SCDI images

Band	Display colour	Minimum	Maximum
Maximum angle	Red	58	98
Range in distance	Green	16	100
Minimum distance	Blue	0	60

The following guide to interpretation of colours in the SCDI, is based on images with the contrast enhancement in Table 1 applied. Example areas are shown in Figure 11.

Yellow (A) – is usually crop or improved pasture. The yellow colour is due to a large maximum angle (red), large range in distance (green) and low minimum distance (blue).

Orange/red (B) – is usually crop, improved pasture or woody vegetation in areas that have more water available due to rainfall or soil type. The red colour is due to similar reasons to the yellow above but with a lower range in distance (green).

Yellow/green (C) – is sometimes crop but not always, and additional aerial imagery is required to interpret it. It is similar to the yellow pattern but typically has a lower maximum angle (red), making the colour more green.

Dark blue (D) – is usually native pasture or woody vegetation or a combination of both. It has a lower maximum angle (red), lower range in distance (green) and higher minimum distance (blue), which results in the dark blue colour.

Light blue – is often native pasture or woody but can also be cultivation. It has a higher range in distance (green) and lower minimum distance (blue), which results in the lighter colour blue.

Pink and purple (E) – is often associated with urban, industrial and rangeland areas. They have a large maximum angle (red), relatively low range in distance (green) and mid-range minimum distance (blue), which results in the purple or pink colours.

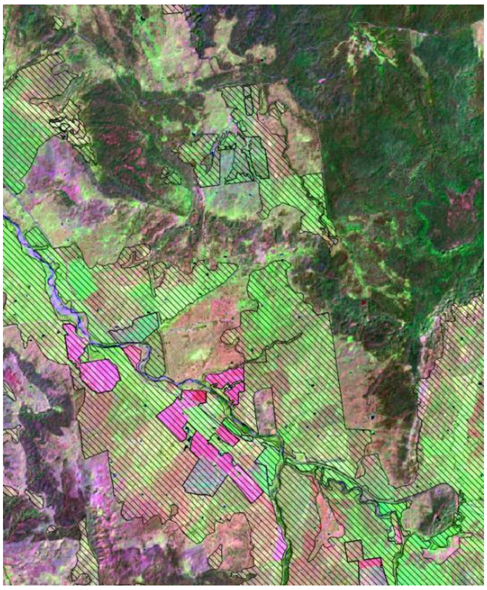
Where further local enhancement of images using a different contrast enhancement is needed the interpretation of the SCDI is done in a relative sense. In these cases the mappers look for patterns in the SCDI where the land use can be interpreted using aerial imagery, then they extrapolate these patterns to other areas in the SCDI image.

Image classification approach

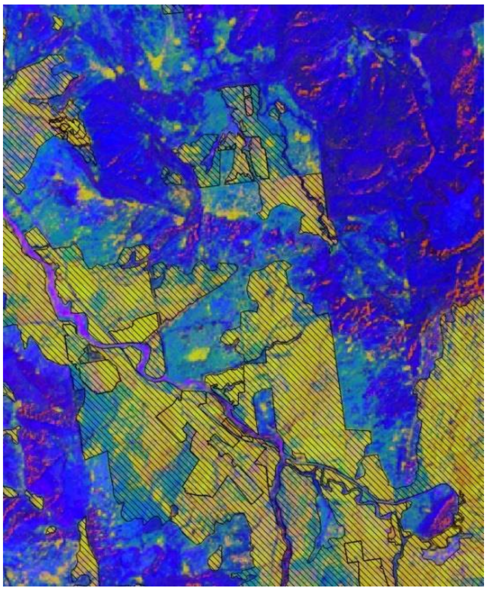
An image classification approach was developed to assist interpretation of the SCDI images for areas where the SCDI was used more regularly in the interpretation of land use. This involved using an unsupervised classification method known as Isodata (Ball and Hall 1965) to create clusters of like areas within the SCDI images. Each image was initially classified into one of 60 image classes. The classes were then grouped to create a single class representing modified pastures or cultivated areas. This grouping was based on local interpretation of the SCDI guided by ADS and SPOT imagery and using recent field observations collected to validate the land use mapping. The classification approach helps to maintain consistent interpretation of the seasonal cover disturbance image when mapping land use and increases the efficiency of the mapping.

The SCDI classification approach is illustrated in Figure 12. It shows an ADS aerial image (a), a 2013 SPOT 5 image (b), 1987–2013 SCDI image (c), and the result of the SCDI classification (d). The areas highlighted in orange in Figure 12 (d) are the areas classified as modified pasture or cultivated. The mapped land use polygons for modified pasture and cultivated areas are overlaid on each of these figures. There is general agreement between the SCDI classification and the mapped land use boundaries. All interpretation of land use was based on a multiple lines of evidence approach and where land use patterns are clearly visible in the higher resolution aerial imagery it was used in preference to the SCDI. The land use mapping interpretation is described in more detail in Chapter 4 of the methods document.

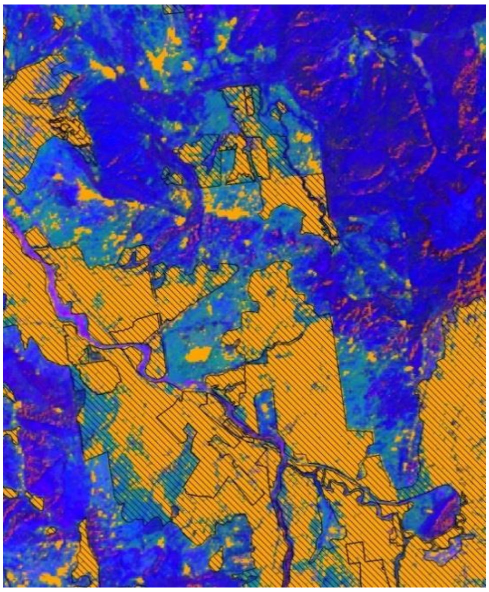
(a)



(b)



(c)



(d)

Figure 12. (a) ADS natural colour composite image; (b) SPOT 5 colour composite image for 2013 with SWIR, NIR and green bands displayed as red, green, blue; (c) SCDI based on 1987–2013 Landsat images; (d) SCDI classification image. The hatched polygons overlaid in black are from the land use map described in Chapter 4.

Appendix 5: Supplementary detail for chapter 6 (identifying and mapping woody vegetation change)

This Appendix provides details of the following four products referred to in Chapter 6 that were used when mapping woody vegetation extent and detectable clearing events:

- woody vegetation extent from SPOT imagery
- detecting tree cover in ADS imagery
- woody vegetation change index
- vegetation trends map.

Appendix 5A: Creating and validating the 2011 woody extent map

Introduction

This section provides an overview of the method used to create and assess the accuracy of the 2011 woody extent map. Full details are available in a peer-reviewed scientific journal article (Fisher et al. 2016). This section explains how the 2011 woody extent map was created and validated for accuracy.

The 2011 woody extent map classifies and maps both woody extent and foliage projective cover (see further information in Appendix 1) as ‘woody vegetation’.

As described in section 6.3, the July 2013 woody baseline layer was then created from the 2011 woody extent map.

Process

The process used both automated and manual processing steps (Figure 13). There were four key steps in creating the map, which are described in further detail below:

1. computing the probability of a pixel containing woody vegetation (‘woody probability layer’)
2. mapping woody vegetation by manually thresholding and editing the woody probability layer
3. estimating the FPC for the woody vegetation pixels
4. assessing the accuracy of the map.

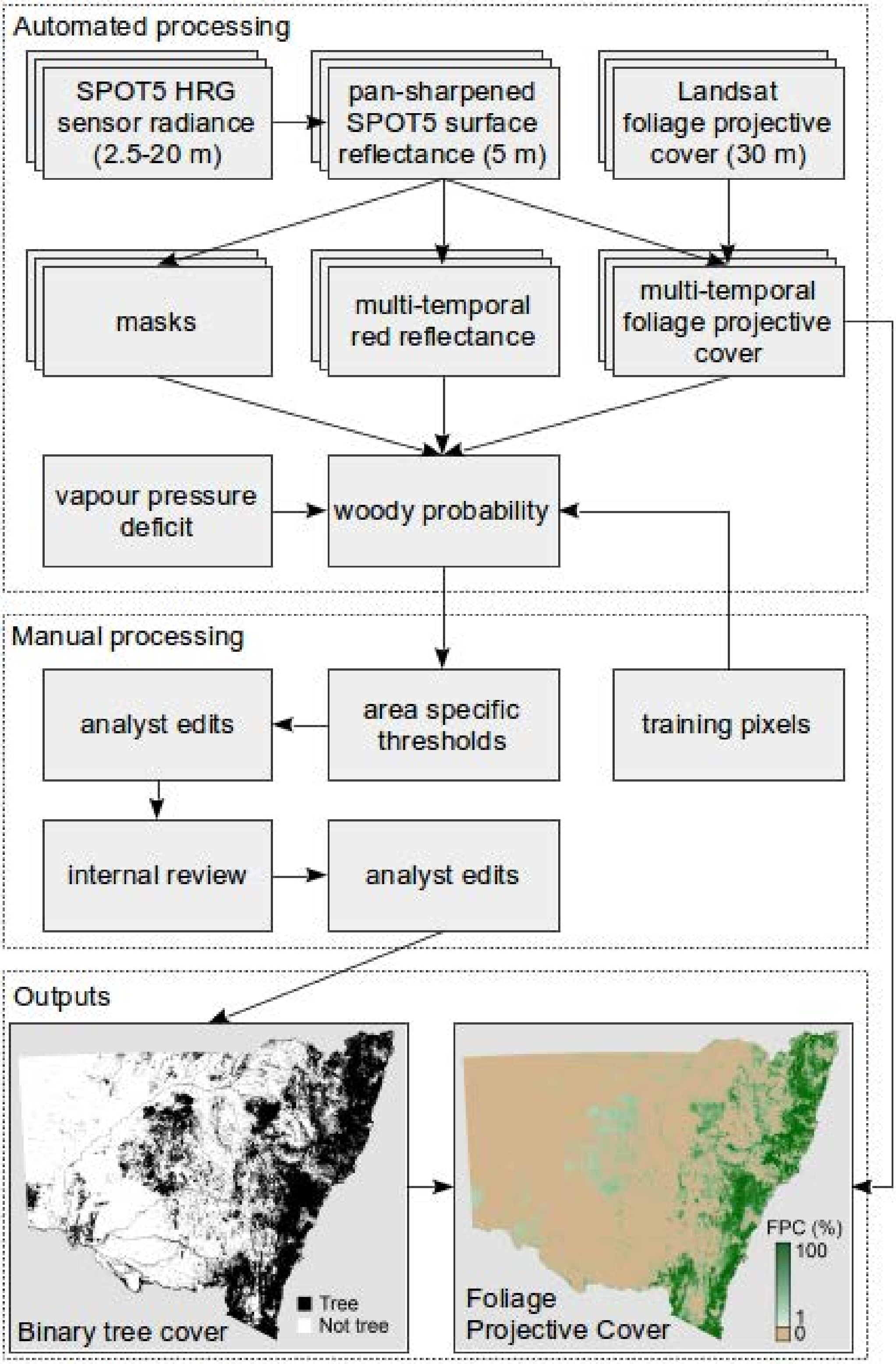


Figure 13. Method for producing the OEH 2011 woody vegetation extent map

Step 1 – computing the woody probability layer

The woody probability layer shows the likelihood of a pixel containing woody vegetation, for every 5 m pixel in the state. It was created by applying a binomial logistic regression model to a time series of SPOT 5 satellite images. The model was trained on image-interpreted points of woody vegetation presence or absence.

The satellite imagery data used was a time series of one complete statewide coverage of SPOT 5 for each year from 2008 to 2011, with a total of 1256 images. Each image was rectified, processed to surface reflectance as modelled with the sensor pointed at nadir and the sun at 45 degrees above the horizon (Appendix 1), and the foliage projective cover ('FPC') model applied (Appendix 1).

The model was trained using 25,930 observations of woody vegetation presence or absence across the state, capturing the variation in vegetation community types (Figure 14C). A stratified random sampling technique was used to locate the points. Analysts visually assessed high-resolution images – ADS (0.5 m pixels) or pan-sharpened SPOT 5 imagery (2.5 m pixels), where no ADS data were available – and classified each point as woody or not.

The model's explanatory variables were:

- smoothed red reflectance, at the mid-point of the time series
- smoothed FPC, at the mid-point of the time series
- variation in FPC over time
- vapour pressure deficit (VPD).

The red reflectance and FPC were used because they are related to the bright non-woody (soil and grass) and green woody features in the landscape respectively (Moffiet, Armston, and Mengersen 2010). In addition, FPC is a direct measure of woody vegetation (Specht and Specht 1999). The variation in FPC was used because woody vegetation tends to have a low variation in FPC over time relative to grass. VPD was used because it is related to the vegetation foliage characteristics and varies spatially. Smaller, needle-like, foliage tends to be found in areas with high VPD and larger, broad-leaf, foliage tends to be found in areas with low VPD. The VPD data were obtained from a gridded data set, interpolated from a network of weather stations (Jeffrey et al. 2001).

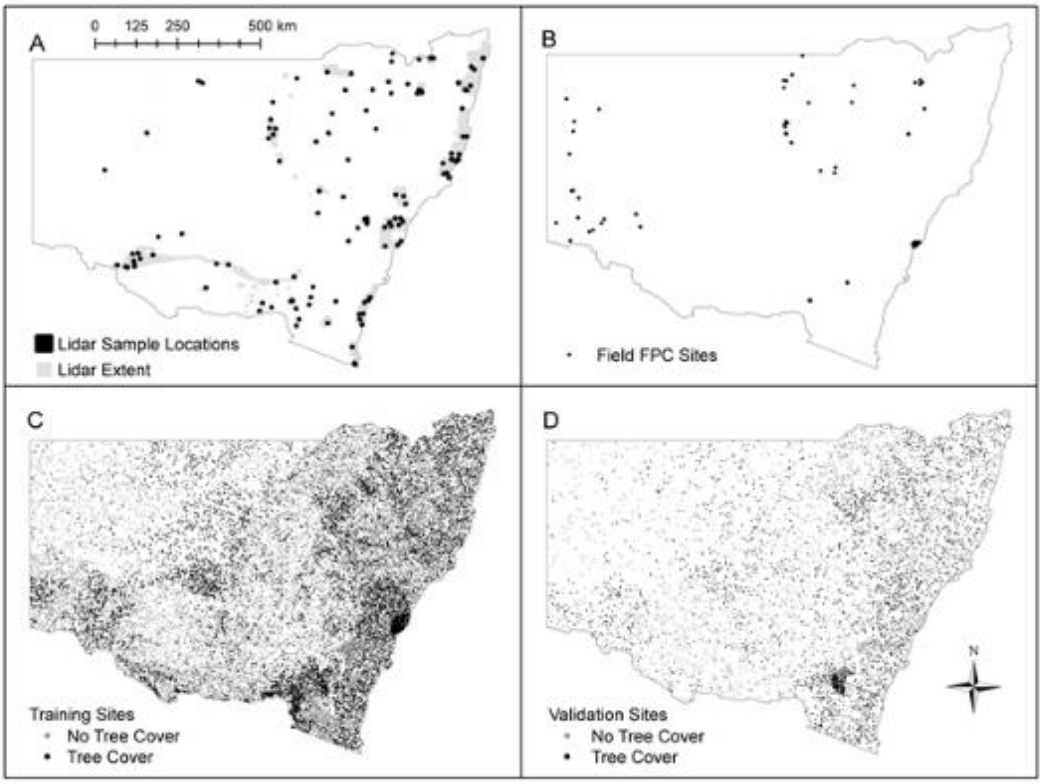


Figure 14. Reference data used in the training and validation of the woody extent and FPC map. A – Lidar data used for validation of the woody extent, B – field data used in the validation of the FPC estimates, C and D – locations of woody (tree cover) presence or absence used in training the probability model (C) and validating the woody extent model (D).

Step 2 – mapping woody vegetation

The woody probability layer was used as the baseline for classifying the pixels as woody or not. The surface was split into 305 tiles of approximately 55 km by 57 km each across the state of New South Wales (Figure 15). They aligned closely with the ground-area sampled by the SPOT images. A probability threshold was manually selected for each tile in order to separate the woody from the non-woody pixels. This was done interactively by visually referencing 2.5 m pan-sharpened SPOT 5 imagery. A pixel was considered woody if the entire pixel covered a patch of visually discernible foliage in the reference image.

Further refinements were made. Firstly by identifying more effective sub-tile thresholds for specific areas and secondly by manually removing woody commission errors or digitising in woody areas. The manual digitising of woody areas was only performed across patches of contiguous forest.

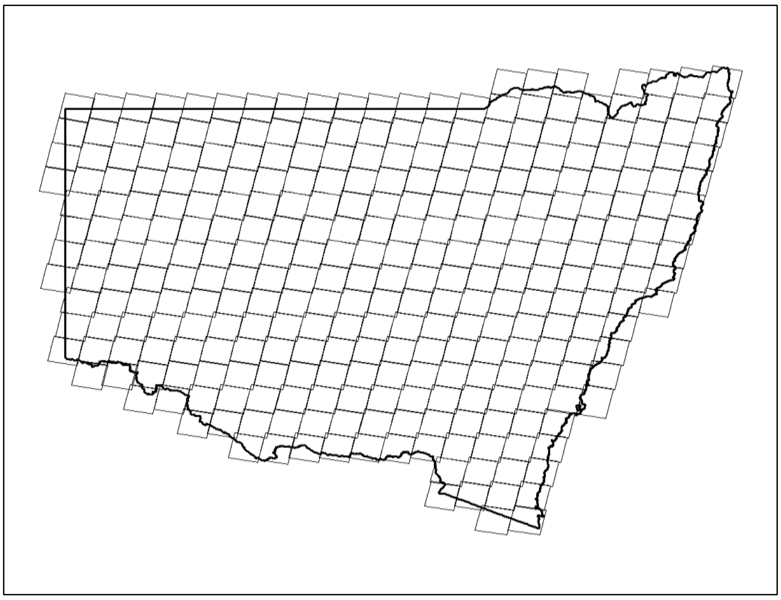


Figure 15. The three hundred and five tiles used when editing the woody extent maps.

Step 3 – estimating the FPC for woody vegetation pixels

The FPC was estimated for each pixel classified as woody. A straight line was fitted to the FPC time series, for each pixel, using robust regression to exclude outliers. The fitted value at the midpoint of each time series was used as the final FPC value.

Step 4 – assessing the accuracy of the map

Validation was performed for the woody extent and FPC layers separately.

The woody extent maps were validated against two independently derived data sets of woody and non-woody vegetation. The first comparison used fine-detailed maps of woody vegetation extent from airborne Lidar surveys (detailed below), and gave an estimate of the overall map accuracy of 88%. The second comparison used an additional 6670 image-interpreted points of woody vegetation presence or absence, collected in the same manner as the training data described previously. This gave an estimate of the overall accuracy as 88%. Table 2 gives the statewide accuracy statistics. Statistics by vegetation formation are available in the journal article (Fisher et al. 2016).

Table 2. Producer's and user's accuracy statistics (%), for the SPOT woody extent maps before manual edits (woody probability with threshold) and after manual edits (edited woody extent).

Sample	Number of points Total	Woody probability with threshold			Edited woody extent		
		Overall	Producer's	User's	Overall	Producer's	User's
Lidar reference	13884067	86	75	82	88	74	89
Visual interpretation	6648	87	75	85	88	73	90

The modelled FPC was compared to field measurements of woody FPC from 75 sites across New South Wales measured between 2009 and 2015 (Figure 14B). A good relationship was found (Figure 16). The field measurements of woody FPC are described in detail below.

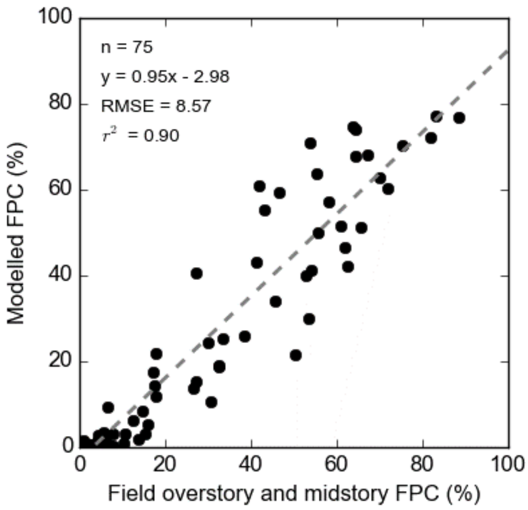


Figure 16. Relationship between SPOT-modelled woody FPC and the combined mid and overstorey field measurements of FPC.

Airborne Lidar estimates of woody extent

Lidar (Light Detection and Ranging) is a technology that can be used to accurately map the location of trees and their structural properties from aircraft (Armston et al. 2009). Pulses of coherent light are emitted from the Lidar instrument towards the ground. These reflect off objects on the ground and are returned to the sensor on the aircraft. The location of each object is obtained from the direction the light pulse was emitted and the time taken for it to return. The intensity of the returned light provides information on the target and whether the pulse reflected off the ground, a tree canopy, or other.

Figure 14A shows the many discrete return Lidar surveys that have been acquired over New South Wales for government use, covering 46,382 km^2 or 6% of the state. A subset of these was carefully selected, across the 17 vegetation formation classes across New South Wales (Keith 2004) within each of the 11 NSW Local Land Service regions (LLS), to minimise bias in the accuracy assessment analysis. The sample of Lidar data covered an area of about 347 km^2, equivalent to more than 13.8 million pixels at 5 m resolution.

When processing, the Lidar returns were spatially sorted into bins aligned with the 5 m SPOT 5 HRG pixels (Bunting et al. 2013). The height of each return above the ground was determined and plant projective cover (PPC) was calculated as the proportion of first returns from canopy higher than 0.5 m within a pixel area (Armston et al. 2009). Lidar woody vegetation extent was defined as pixels where PPC > 0. However bins where PPC > 0 and all returns were < 2 m above the ground were considered understorey and classified as non-woody.

Field estimates of woody FPC

Figure 14B shows the field sites at which FPC was measured. At each site, the star transect method (Muir et al. 2011) was used to record 300 vertical sighting tube observations of the overstorey (woody vegetation >2 m height), midstorey (woody vegetation ≤2 m height) and understorey (herbaceous plants < 2 m height), from a circular area with a radius of 50 m. Overstorey FPC (*FPC*$_o$) was calculated according to the following equation (Armston et al. 2009):

$$FPC_o = \frac{P_{o,g}}{\left(1 - P_{o,b}\right)}$$

where $P_{o,g}$ was the proportion of overstorey green foliage observations and $P_{o,b}$ was the proportion of overstorey branch observations, which are likely to occlude foliage from the observer. As the satellite-derived FPC model would likely be sensitive to both overstorey and midstorey foliage, the combined FPC of the overstorey and midstorey (FPC_{o+m}) was used as the measure of woody FPC. It was calculated as:

$$FPC_{o+m} = \frac{P_{o,g}}{\left(1 - P_{o,b}\right)} + P_{m,g}\left(1 - P_{o,g} - P_{o,b}\right)$$

where $P_{m,g}$ was the proportion of mid-story green foliage observations.

Appendix 5B: Detecting woody vegetation using ADS aerial images

Introduction

The 2013 woody extent map does not detect all of the trees in the landscape. This section contains the technical details on how trees were detected with the ADS images. The output is an image covering each map sheet and with 5 m pixels represents the percentage of woody cover at the same 5 m pixel size as the 2013 woody extent map. These images were used when refining the Native Vegetation Regulatory Map (Chapter 8 and Appendix 7).

Process

The process of creating a map took place in two parts for each ADS image mosaic on the 1:100,000 topographic map sheet. Firstly, each 0.5 m pixel in an ADS image was classified as either woody or not. Secondly, this was degraded to create a map of the percentage of tree cover with 5 m pixels aligned to the SPOT 5-derived woody extent map (Appendix 5A).

Detecting trees

The ADS sensor measures the amount of light reflected from three parts of the light spectrum: blue, green, red and near infrared. Trees were detected in the ADS images by applying a threshold to the green band in the image. Values below the threshold are potentially trees. The green band was used after careful assessment of a number of classifiers (see below for details).

The threshold was determined automatically for each ADS mosaic map sheet using the 2011 SPOT 5 woody extent map. The threshold was determined so that the same percentage of trees is mapped as is present in the 2011 woody extent map. Pixels that corresponded to large water bodies, as determined from the SPOT water index, were ignored.

A single threshold for the whole mosaic does not allow for spatial variations in tree and non-tree characteristics. Therfore, thresholds were determined for 2 x 2-km tiles and applied where they were lower than the whole-mosaic threshold. Further, the tile thresholds were smoothed using a 15 x 15 tile-moving window to eliminate tile edge-effects. Commission errors (falsely detected trees) were caused by some water, shrubs, soil and crop pixels.

Creating the 5-metre tree cover map

Each 0.5 m binary tree map was resampled to a 5 m tree percentage map. Firstly, the 0.5 m binary classification was converted into a percentage, where tree pixels were 100 and non-tree pixels were zero. Secondly, the tree percentage of each 5 m pixel was calculated as the average of the 0.5 m pixels within it. The SPOT 5 woody probability model (Appendix 5A) was also used to identify potential tree commission errors created by shadows, soils and dark green crops. 5 m tree pixels that had a woody probability of zero were flagged.

Map accuracies

The method was applied to the archived ADS topographic map sheet mosaics, producing 0.5 m binary tree maps and 5 m tree percentage maps. Six of the mosaics were selected from across the state to be assessed (yellow in Figure 17). Reference data consisting of 300 pixels were gathered for each 5 m tree percentage map using a stratified random sampling approach, where 100 pixels were randomly selected from the following classes: non-tree, tree (defined as tree percentage > 0%). The ADS imagery was then used to visually determine the true class of each 5 m reference pixel. The overall classification accuracy across all of the 5 m tree percentage maps was 93% (Table 3).

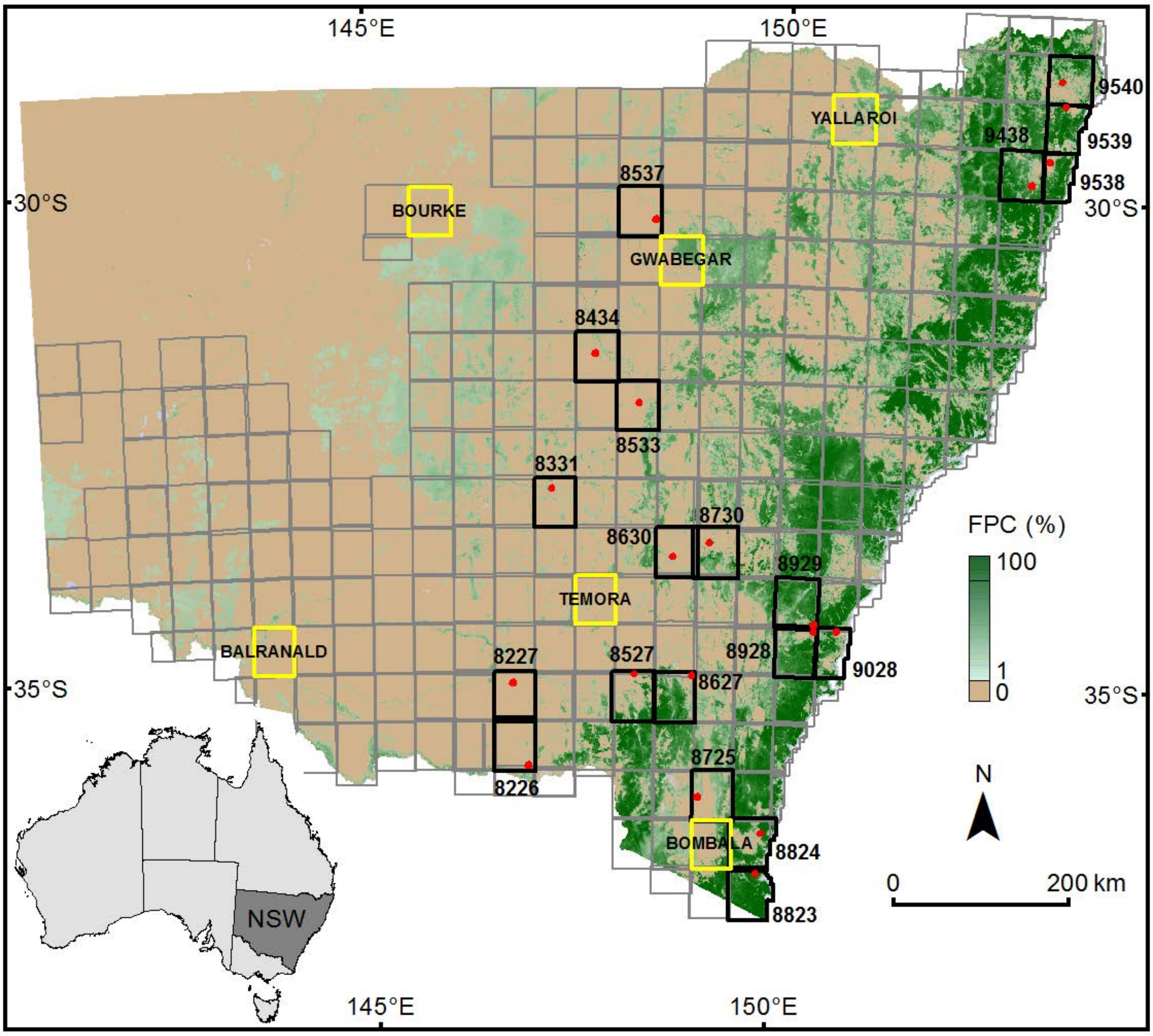


Figure 17. Locations used to train and validate the tree mapping across New South Wales, Australia. Training aerial image mosaics (black), labelled by their map sheet number, were selected from the archive (grey). From each of these 20 images 2 km x 2 km subsets (red) were selected, for which tree maps were derived from airborne Lidar data. Named aerial mosaics used in the validation are also shown (yellow). The background is a map of the 2011 woody extent.

Table 3. Error matrices calculated from all 1800 validation pixels across the six map sheets. All values are percentages.

ADS 5 m tree map					
Overall accuracy = 93		Reference			
		Not tree	Tree	Total	User's Accuracy
Classification	Not tree	62.7	2.3	65.0	96
	Tree	4.9	30.1	35.0	86
	Total	67.6	32.4	100.0	
	Producer's accuracy	93	93		

Determining a classifier

A threshold was applied to the green band, below which the pixels were likely to be trees. This classifier was chosen after testing a number of classifiers. This section briefly outlines the results of those tests.

Training data consisted of 20 samples of ADS imagery selected from across the agricultural landscapes of New South Wales (Figure 17). Each was a 2 x 2-km square that coincided within 12 months of an airborne Lidar survey. The Lidar data was extracted from the archive of regional surveys (Appendix 5A), which were used to create an independently derived set of tree maps at 0.5 m resolution for comparison to the classifiers. Tree canopy height models were generated from the highest first return in each pixel above the ground. Pixels were classified as trees if the canopy height was at least 2 m.

The training data were used to test the red, green and blue (rgb) bands and combinations of them, to determine their effectiveness in classifying the ADS imagery. Near infrared bands were not used because not all images in the archive contain a near infrared band. The indexes tested were: NDI, EGI, ERI, EDI and BDI. They combine the three RGB bands to accentuate the differences between vegetation and non-vegetation and are defined as:

$$NDI = \frac{g - r}{g + r}$$ Normalised difference index

$$EGI = 2g_c - r_c - b_c$$ Excess green index

$$ERI = 1.4r_c - b_c$$ Excess red index

$$EDI = EGI - ERI$$ Excess difference index

$$BDI = 2b_c - g_c - r_c$$ Blue deficient index

where b_c, g_c and r_c are the chromatic coordinates, or the proportion of each band within each pixel. Brightness (B), calculated as the mean of the RGB values, was also considered because trees are usually dark across all RGB bands. The variance of each band calculated using a 3 x 3 moving window was also tested. An example of how the indexes perform on a typical area of trees is given in Figure 18.

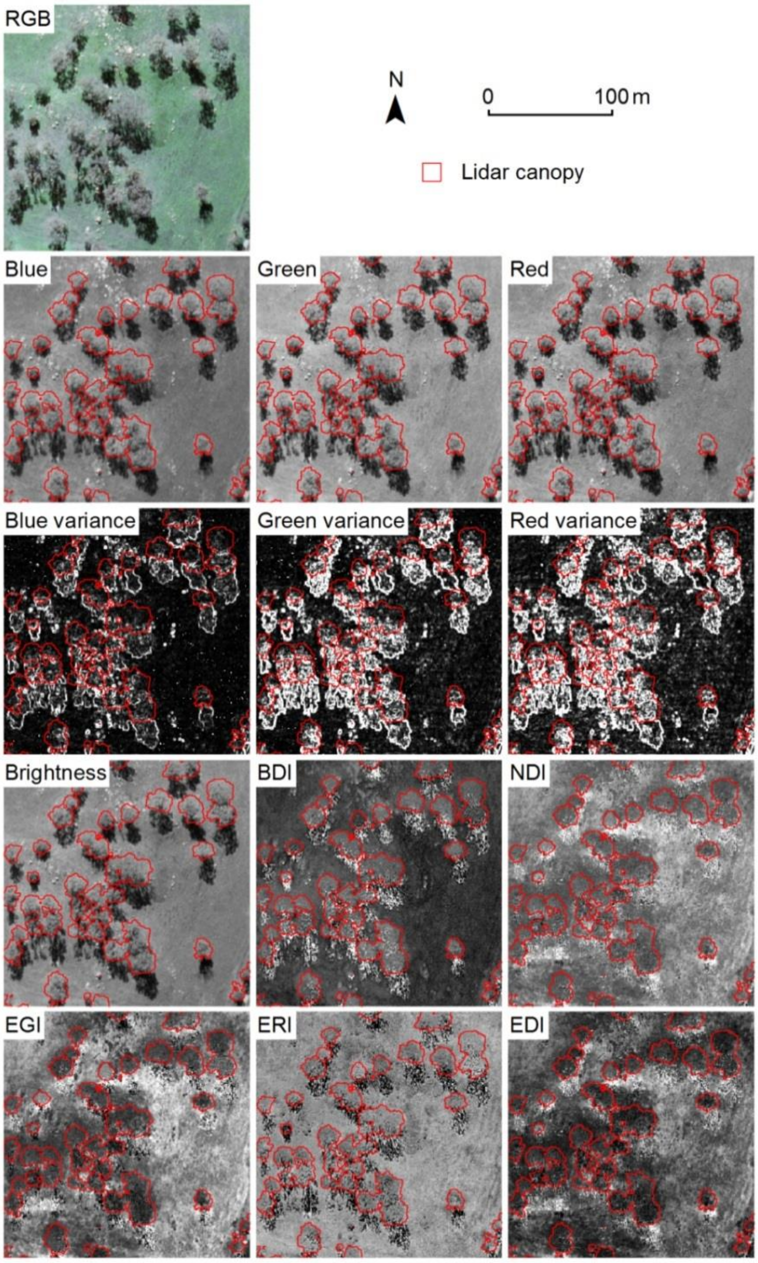


Figure 18. Examples of the indexes tested for classifying trees using simple thresholds on high-resolution imagery. They show; red, green and blue bands including the variance of the bands calculated within a 3 x 3 window, brightness, the normalised difference index (NDI), the excess green index (EGI), the excess red index (ERI); the excess difference index (EDI) and the blue deficient index (BDI).

The performance of the indexes in classifying tree pixels was compared across the 20 training images using receiver-operator characteristic (ROC) curves and area under the curve (AUC); a high AUC is indicative of a good classifier. Of the 20 training images, the green band had the largest AUC in 8 images (Figure 19) and the largest mean AUC across the 20 images, and usually had ROC curves with large AUC values (Figure 19). The blue band also had the largest AUC in 8 images, while brightness also had a large mean AUC, as did the blue and red bands. Of the other indexes, EDI performed the best with the largest AUC in 2 images, though in general the band combinations and band variance did not perform well (Figure 19).

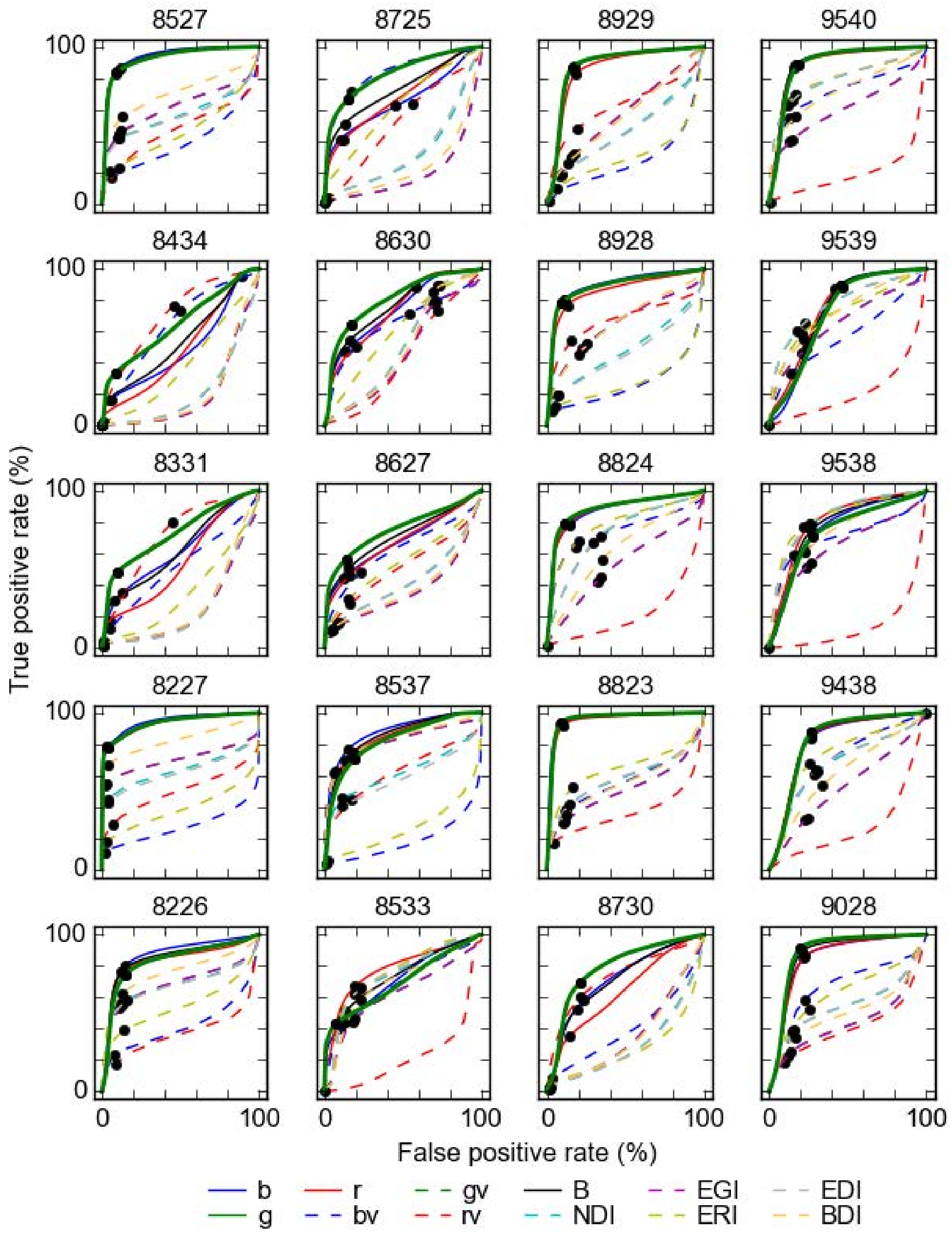


Figure 19. The accuracy of classifying tree and non-tree pixels using different bands and indexes for a range of thresholds, using receiver-operator characteristic (ROC) curves. The circles represent the position of the optimum thresholds that minimised the total error determined by the true and false positive rates. The 20 plots are labelled by their map sheet number (Figure 17). The indexes tested were the blue (b), green (g) and red (r) bands; the variance of these bands calculated within a 3 x 3 window (bv, gv, rv); brightness (B); the normalised difference index (NDI); the excess green index (EGI); the excess red index (ERI); the excess difference index (EDI); and the blue deficient index (BDI).

Appendix 5C: Process to detect woody vegetation loss in the SLATS program – change index model

Introduction

This section describes the SPOT 5 and Landsat change index models and their limitations. These models were used to detect woody vegetation loss as part of the SLATS mapping program. The models created change index images, which were automatically thresholded at a number of levels to produce a change likelihood image that OEH analysts interpreted, alongside satellite imagery, to map woody vegetation clearing.

The change index

In simple terms, the change index uses a ‘before’ and an ‘after’ image (Figure 20). The index performs well in the following circumstances:

- there is a clear difference in the spectral signatures of corresponding pixels between the two images dates
- this difference matches a typical vegetation loss signature.

In Figure 20, areas detected as being cleared were well vegetated in the before image and the pixels appear relatively dark in tone. In the after image the pixels corresponding to cleared areas appear relatively lighter in tone. That is due to the loss of green foliage and branches, which are dark and create shadows, and also due to the exposure of the relatively brighter soil. The ‘change index’ image shows these areas as light shades of grey to white. The change likelihood image is created from the grey levels in the index image and are coloured as grey through to red, with red having the highest likelihood of change.

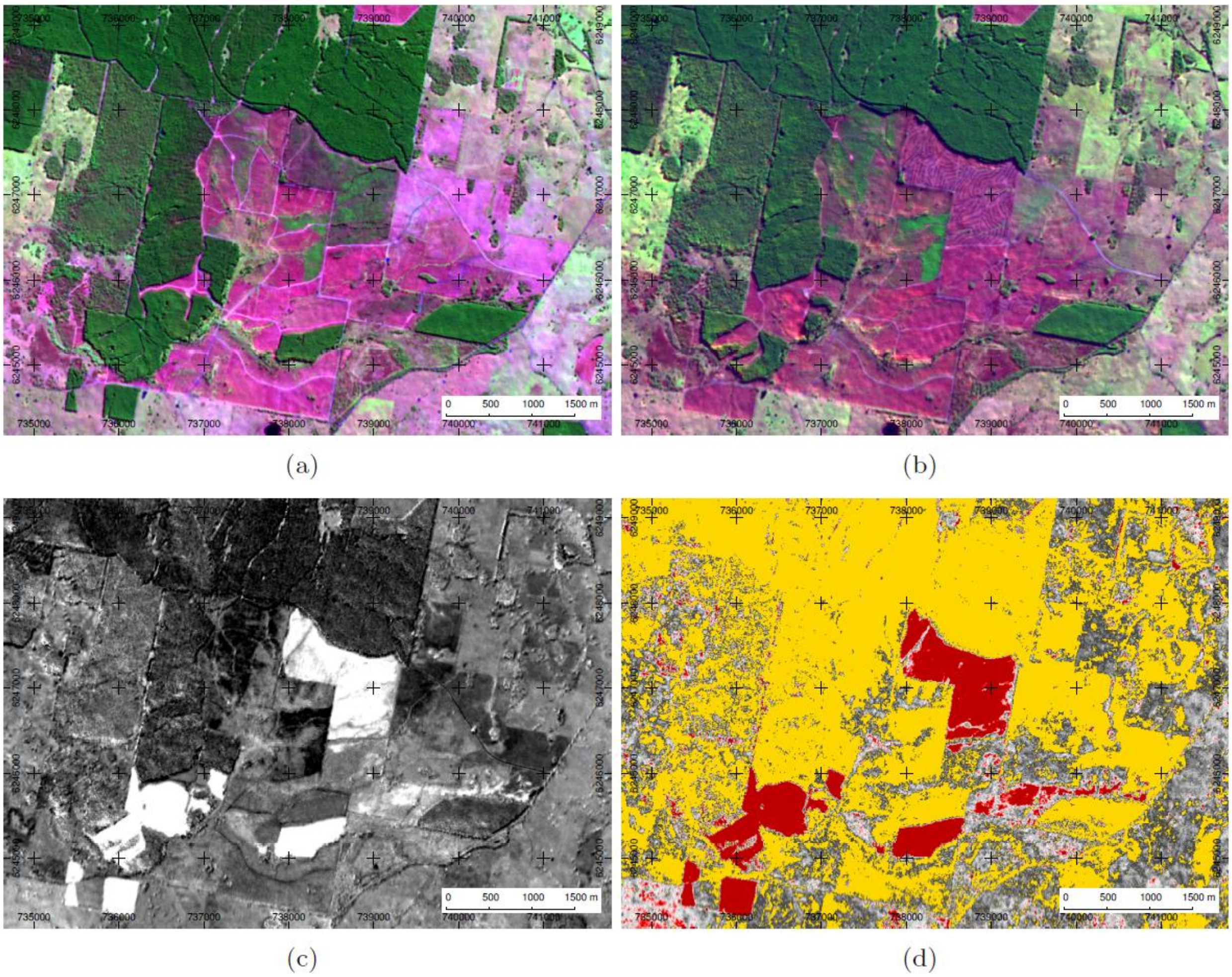


Figure 20. Example of the change index (c) and likelihood (d) images created from two SPOT 5 images, before (a) and after (b) clearing has occurred. The white areas in the change index are likely clearing. They were thresholded at various levels to create the change-likelihood image, where red areas are most likely clearing, grey levels from dark grey to white are progressively less likely clearing, and yellow areas are not clearing.

The change likelihood image is not a confirmation that change has occurred. In practice, OEH analysts interpret the change likelihood images (Figure 20d). Most effort is focused on the high likelihood areas, but analysts are also able to scan satellite images in the locations identified as lowest likelihood, to identify any evidence of change. Where the analyst confirms that woody vegetation loss has occurred they assign a pixel value to the area that corresponds to the reason for the change. The reason is one of: agriculture, infrastructure, forestry, fire or other natural processes (e.g. landslips).

The index performs best when the images were captured during dry periods. This maximises the number of cases where woody loss results in an increase in pixel brightness and is therefore identifiable. However, sometimes these conditions are not met, including when clouds were captured in the images or the images were acquired during relatively wet periods. In these circumstances, woody vegetation loss can go undetected or be falsely detected. To overcome this risk, OEH reviewed the SLATS maps using information on green vegetation trends (Appendix 5D).

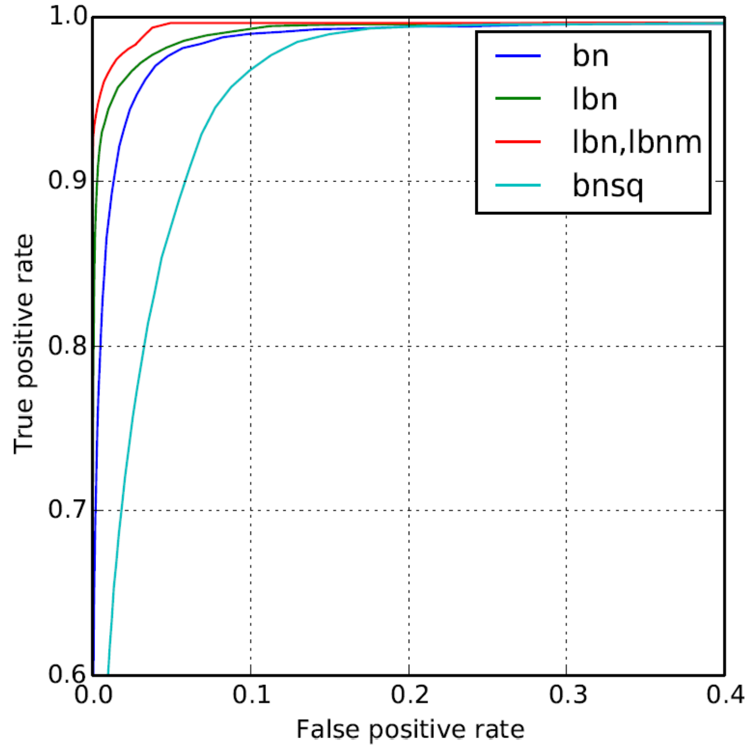
The change indexes for Landsat and SPOT use multiple linear regression models (Scarth, Gillingham, and Muir 2008). The predictor variables in the models were:

- for the SPOT model: the reflectance values from all bands at both dates

- for the Landsat model: the reflectance values from the green, red, shortwave infrared and mid infrared bands at both dates; differences in the FPC values at both dates; and the difference in the FPC value at the second (later) date from the long-term trend in FPC.

Accuracy of the change index models

In developing the change indexes a number of predictor variables, and combinations of them, were tested. The best performing indexes were those with the largest area under the curve (AUC) using receiver-operator characteristic (ROC) curves (Figure 21). These were used as the indexes to create the change index images used in the SLATS program. The reference data used was taken from SLATS maps that analysts had edited, so the accuracies of the reference data was assumed to be high.



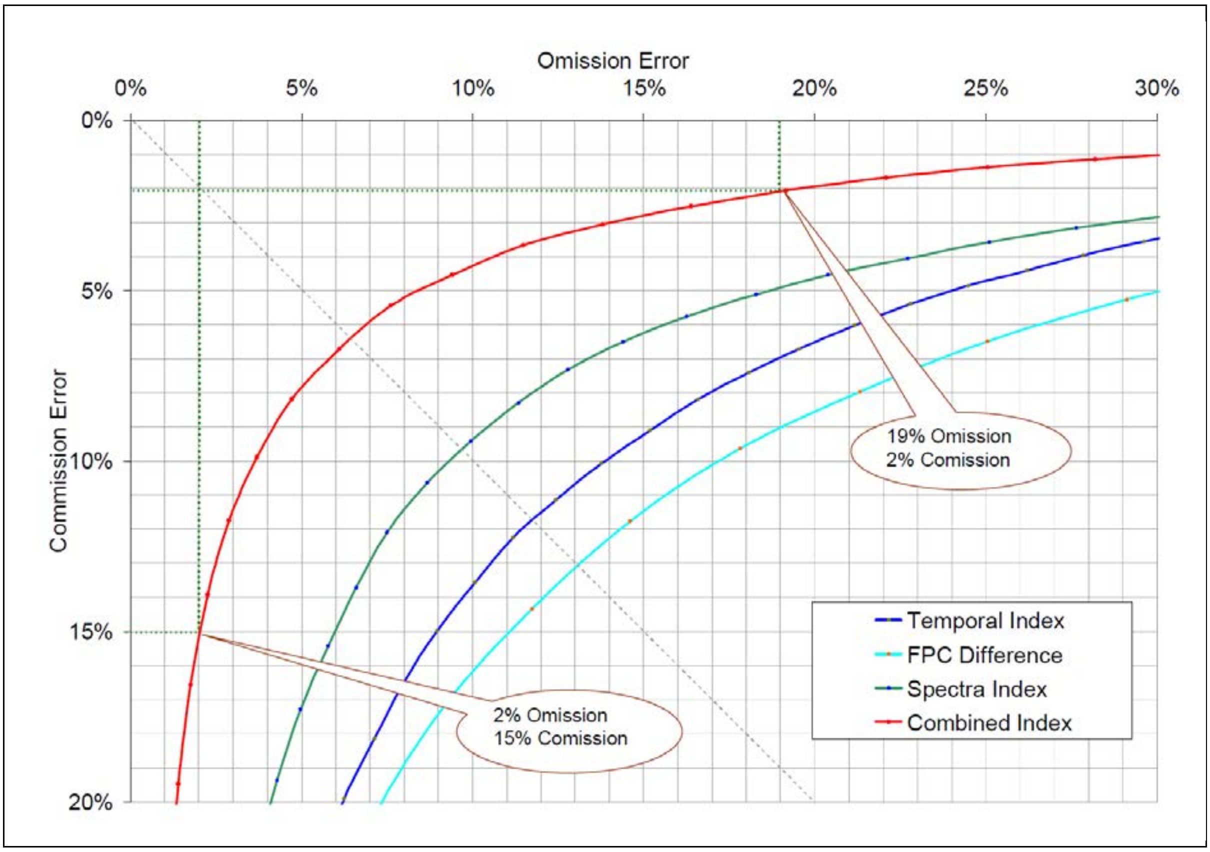


Figure 21. The receiver-operator characteristic curves of the change indexes used in the SLATS program (red curves) for SPOT (top) and Landsat (bottom). The bottom image was take from (Scarth, Gillingham, and Muir 2008).

The goal of the SLATS program is to map all clearing events. Achieving a high accuracy of the change index is important to make the mapping process efficient, but there is a trade-off between high accuracy and detecting all change events. The bottom part of Figure 21 illustrates this and how the likelihood images were interpreted. The dark red pixels in the change likelihood image (a high change index value) are very likely to be change. But if a threshold was only applied at a high index value then many change events would not be mapped because a threshold like this corresponds to high omission errors. So lower thresholds must be used, but this comes at the expense of including many pixels that did not change (light grey pixels in the change likelihood image). Analysts focus on the red areas, but also assess the light grey areas, to ensure that the vast majority of clearing is mapped. Therefore, the checking and editing phase is critical to achieve both low omission and commission errors in the final clearing map.

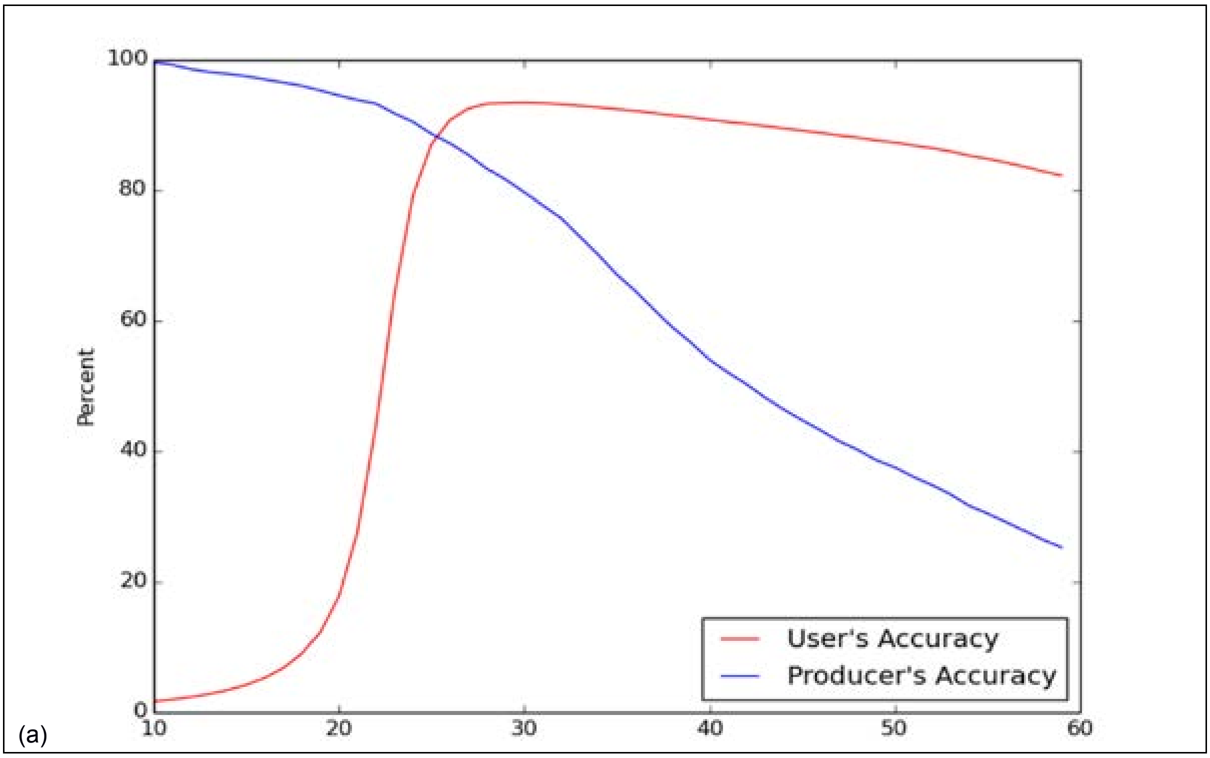
The accuracies of the change indexes are assessed at different threshold levels (Figure 22), to identify two accuracy components:

1. User's accuracy: the percentage of pixels that the model classifies as woody vegetation loss that were verified as correct (i.e. cleared).
2. Producer's accuracy: the percentage of areas that constituted woody vegetation loss and which were accurately classified by OEH (regardless of how they were classified in the change index).

Figure 22 shows that the SPOT index is able to produce both high user and producer accuracies at the same time. The Landsat index cannot do this – but neither is perfect, which explains the need for analysts to interpret the images.

For example, Figure 22(a) shows that at an index value of 30, the SPOT user's accuracy of 93% occurs when the producer's accuracy is 80%. This means that should there be no further editing by analysts, 93% of the pixels at a threshold of 30 would be woody vegetation loss, and OEH would capture 80% of all loss that has occurred. Or alternatively, 7% of the pixels mapped as woody vegetation loss would be incorrect and 20% of pixels where loss occurred would go undetected.

As another example, Figure 22(b) shows that at an index value of 39 the peak in user's accuracy for Landsat is 11.7% (i.e. 88.3% of predicted loss would be incorrect). This result is supported by the visual checks by OEH analysts who have found that very few of the pixels detected by the Landsat change index are woody vegetation loss. At the same peak (code 39), the producer's accuracy is less than 50% – that is, more than half of the pixels of woody vegetation loss would go undetected. That is why pixels with a code down to 34 are checked because they have a producer's accuracy near 100%, that is, most of the woody vegetation loss events are detected events. But with the trade-off that the user's accuracy is very low, that is, most pixels with this value are not woody vegetation loss, which is why analysts screen these pixels.



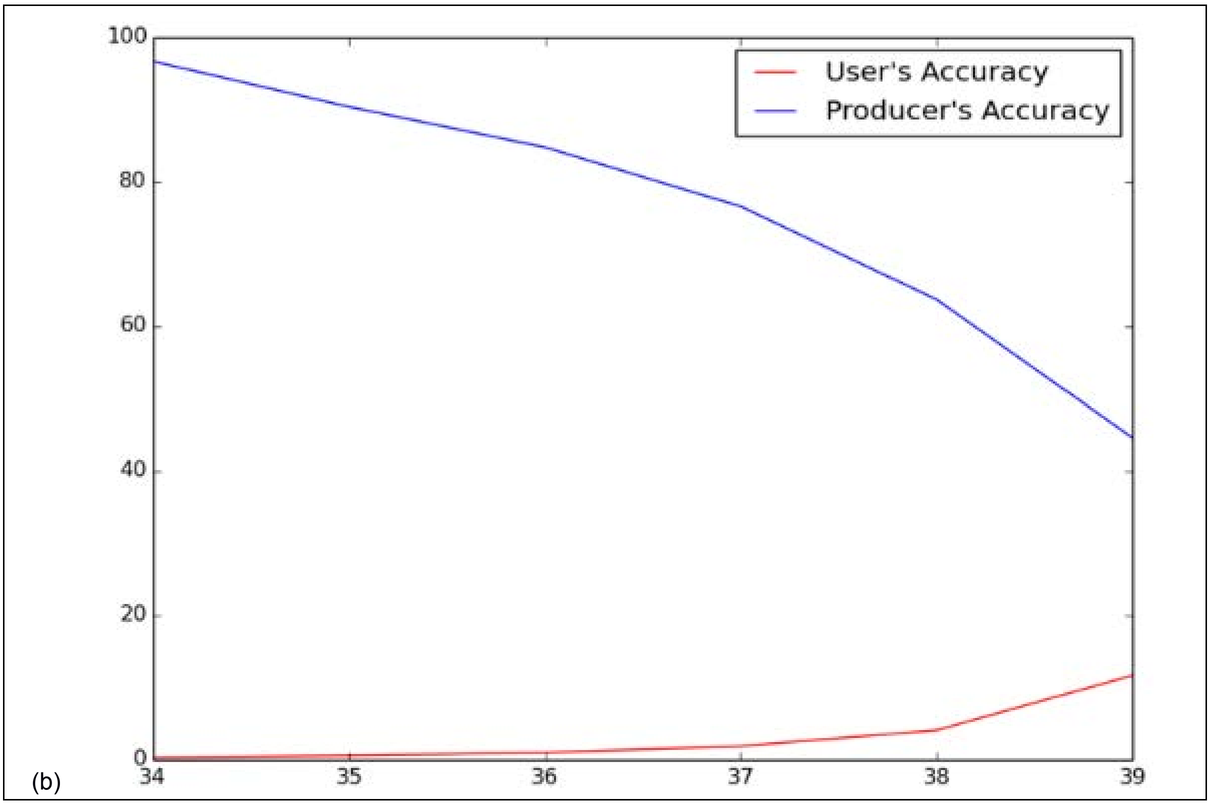


Figure 22. Estimates of the user's and producer's accuracies for the SPOT (a) and Landsat (b) change indexes at different index values (x-axis).

The higher accuracy of the SPOT change index compared to the Landsat index is largely due to the higher spatial resolution of the images. The comparison in Figure 23 shows that small areas of woody clearing, like single paddock trees, are detected better using the SPOT data than Landsat.

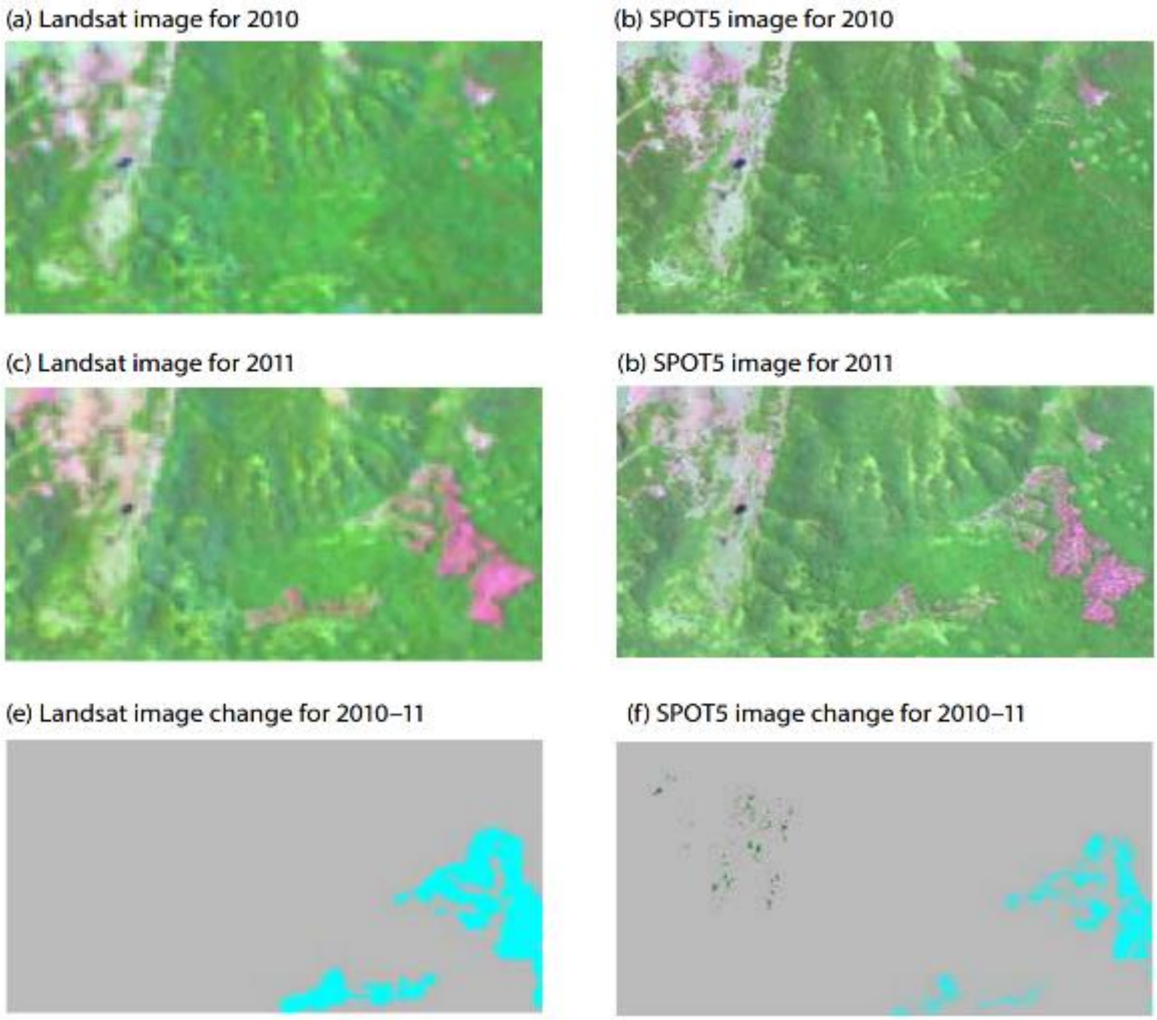


Figure 23. Comparison of SPOT 5 and Landsat 5 woody vegetation change showing the effects of the difference in resolution. SPOT 5 detects clearing of scattered trees that were missed by Landsat 5, as shown by the dark green areas in images (e) and (f). Both are able to detect large areas of clearing, as shown by the blue areas in images (e) and (f). However, the area estimated by Landsat 5 (52 ha) is larger than the SPOT 5 estimate (25 ha), because it was unable to detect the many gaps in the clearing.

Change eras from the SLATS mapping program

Table 4 shows the years in which woody vegetation loss maps were produced by the SLATS program and the source of the image date used.

Table 4. Satellite images (from Landsat and SPOT satellite programs) used to map woody vegetation loss across change eras.

^Mapping was done for both Landsat and SPOT5 data. +The 2013–2014 era is currently being mapped. *The nominal pixel size of Landsat imagery is 30 m, but for some eras this data has been resampled to 25 m. Likewise the nominal resolution of SPOT 5 HRG data is 10 m, but it has been sharpened using the panchromatic band to 5 m for all change eras except 2008–2009.

Change era	**Satellite sensor**	**Image pixel size***
1988–1990	Landsat 5 TM	25 m
1990–1992	Landsat 5 TM	25 m
1992–1994	Landsat 5 TM	25 m
1994–1996	Landsat 5 TM	25 m
1996–1998	Landsat 5 TM	25 m
1998–2000	Landsat 5 TM, Landsat 7 ETM+	25 m
2002–2004	Landsat 5 TM, Landsat 7 ETM+	25 m
2004–2006	Landsat 5 TM, Landsat 7 ETM+	25 m
2006–2007	Landsat 5 TM	25 m
2007–2008	Landsat 5 TM	25 m
2008–2009[^]	Landsat 5 TM	25 m
2009–2010[^]	Landsat 5 TM	30 m
2010–2011[^]	Landsat 5 TM	30 m
2008–2009[^]	SPOT 5 HRG	10 m
2009–2010[^]	SPOT 5 HRG	5 m
2010–2011[^]	SPOT 5 HRG	5 m
2011–2012	SPOT 5 HRG	5 m
2012–2013	SPOT 5 HRG	5 m
2013–2014[+]	SPOT 5 HRG	5 m

Appendix 5D: Process used to create the woody vegetation trend map

Introduction

The process used to detect woody vegetation loss (Appendix 5C) uses two input images and specific weather and climatic conditions (e.g. dry ground and cloud-free) for the change index to perform at its best. Woody vegetation loss can go undetected or be falsely detected when these conditions aren't met. This section outlines the woody vegetation trend map that was used to refine the woody vegetation loss (SLATS) maps. Chapter 6 describes how it was used in the mapping process.

OEH synthesised 25 years of Landsat 5 TM and Landsat 7 ETM+ (about 30,000 images) to produce a map of vegetation trends (increasing or decreasing) for New South Wales from December 1987 to February 2013 (Figure 24).

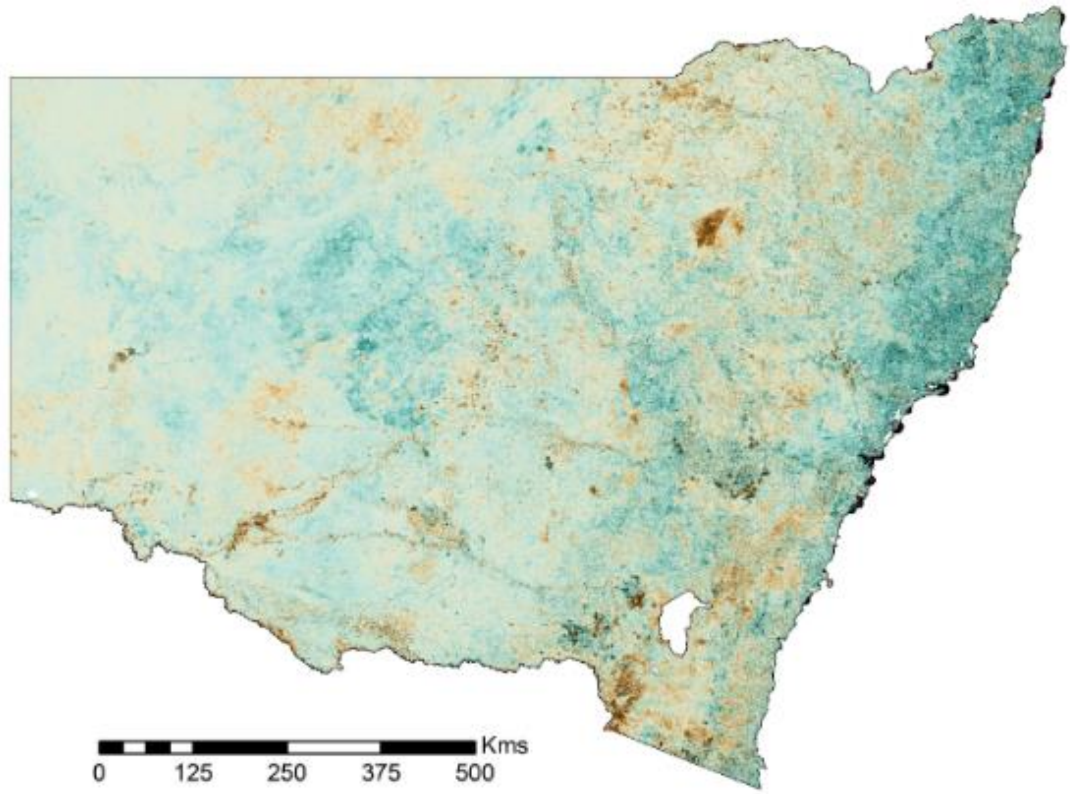


Figure 24. The vegetation trend map for New South Wales. An increasing trend is shown as green and a decreasing trend as brown. The darker the colour the greater the trend.

Method

The method involves firstly calculating the persistent-green vegetation-cover fraction every quarter in the time series, and then estimating the linear trend from the quarterly estimates. The persistent-green vegetation-cover fraction is the proportion of vegetation within a pixel that does not completely senesce within a year. It primarily consists of foliage on woody vegetation, though there are some exceptions. Some inland grasses, such as spinifex (*Triodia* sp) for example, can remain green all year round. Improved pastures and some higher rainfall coastal areas may also have a herbaceous component that stays green year round.

The green cover fraction from the Landsat seasonal fractional cover images (Appendix 1) was the input data. A minimum-value smoothing approach was used to model the persistent-green cover. Figure 25 shows, for a single pixel, the seasonal time series of green vegetation cover (the points), the smoothed persistent-green cover (green line) and the linear trend fit to the smoothed line (black line). It was the slope of this trend line that was mapped (Figure 24).

The green, smoothed line was calculated by fitting a smoothing spline $f(t)$ to minimise

$$\sum_{i=1}^{n}\{w_i(y_i - f(t_i))\}^2 + \lambda\int_a^b \{f''(t)\}^2 dt$$

Where y_i is the green fraction of the ith observation occurring at time t_i, λ is a fixed smoothing parameter, w_i is a weight and $a \le t_1 \le \cdots \le t_n \le b$. $y_i - f(t_i)$ is the residual difference between the green cover fraction and the smoothed line. The estimation of the smoothed persistent green line consisted of multiple smooth spline fits, starting initially with $w_i = 1$ for $i = 1, \ldots, n$. At each iteration, observations lying above the smooth spline were given zero weight, and observations below the line were weighted proportional to the size of the residual. A simple outlier filter was also applied so that at each step, observations with residuals greater than 3 standard deviations from the residual mean are given zero weight. Observations greater than 2 standard deviations but less than 3 are also given less weight.

The trend (black line in Figure 25) was calculated by fitting a straight line to the persistent green line. It is the slope of this trend line that was mapped (Figure 24). The units of the slope are percentage points per year (pp/yr). The minimum/maximum slope recorded in the map was ±1.0 pp/yr. Trends larger than this were clamped to ±1.0. So very large changes over the time period were evident as large positive or negative trends in the map, which may be related to woody clearing events (as described in Chapter 6).

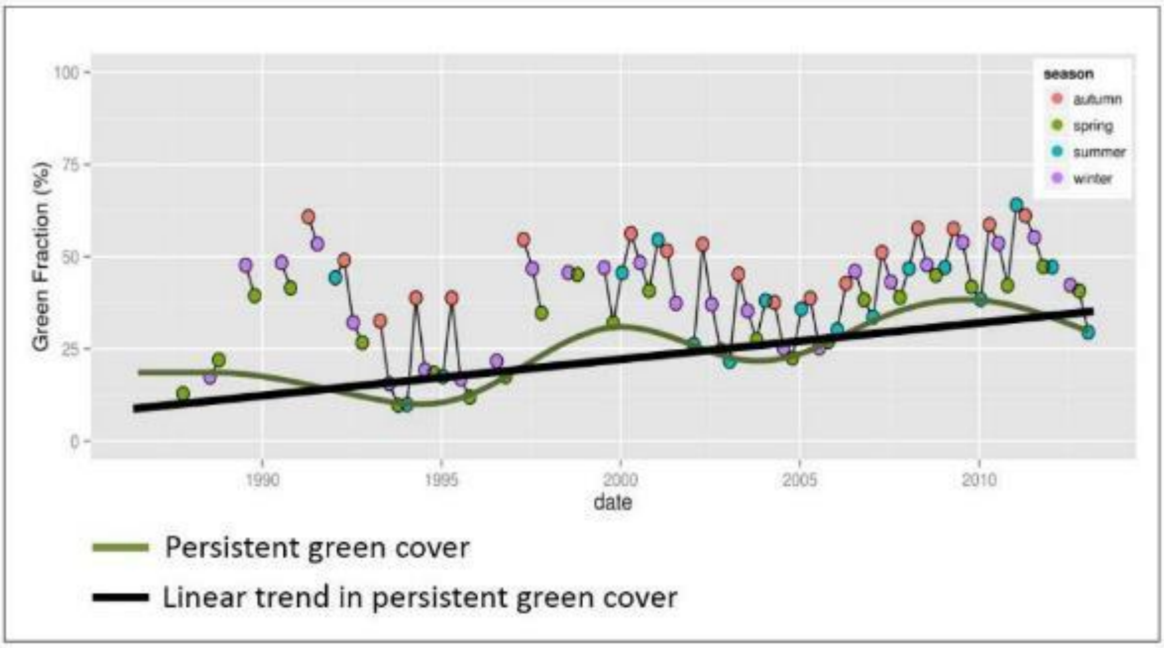


Figure 25. A time series of the seasonal green vegetation cover fraction for a single pixel (coloured dots). A smooth line (the green line), which represents the persistent-green vegetation component, is fit to the minimum of the time series. A straight line (the black line) is then fit to the smooth line; the slope of this line is the green vegetation trend.

Accuracy of the quarterly persistent-green cover values

The quarterly persistent-green cover values were compared to field-measured persistent green cover values collected in the same period (Figure 26(a)). The star transect method (Muir et al. 2011) was used to collect field observations as described in Appendix 5A and the field-measured persistent-green cover fraction calculated as for the FPC from the overstorey and midstorey components also described in Appendix 5A:

$$FPC_{o+m} = \frac{P_{o,g}}{(1 - P_{o,b})} + P_{m,g}(1 - P_{o,g} - P_{o,b})$$

The comparison of field estimates of persistent green with field estimates of overstorey green also shows that there is a strong relationship between these metrics. In other words, most of the persistent green observed in the field comes from overstorey components, and persistent green is thus broadly representative of woody vegetation cover. Figure 26(b) shows this relationship. By definition, persistent green is always at least as high as overstorey green, but in some cases the difference can be considerable. Locations in which the difference between persistent green and overstorey green are greater than 12.5 percentage points are indicated with hollow circles. These are sites where the midstorey contributes significantly to the green signal observed by the sensor. Inspection of these sites reveals the contribution is most commonly from the presence of *Xanthorrhoea* sp, *Carissa ovata*, heathland and woody regrowth after tree clearing.

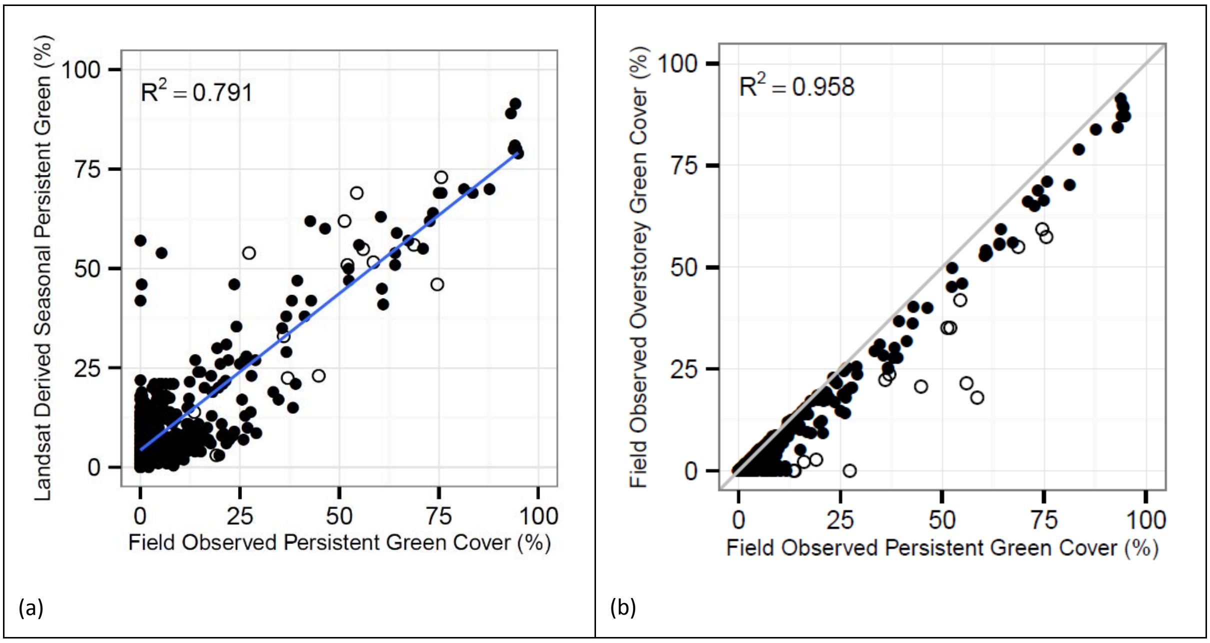


Figure 26. Relationship between Landsat-derived persistent green and field observed persistent-green cover (a). In most locations, persistent green comes predominantly from overstorey plants (b) The open circles represent those sites in which the mid- and understorey contributes significantly to persistent green, defined as a difference greater than 12.5 percentage points.

Appendix 6: Data sets used for prescribed area layers[2]

The prescribed area layers listed below are incorporated into the NVR maps based on the precedence value in the table. In locations where the prescribed areas overlap, it is the one with the highest precedence value that will be visible in the map.

Precedence	Category	Description	LLS Act Section	LLS Regulation Section	Custodian	Comments
5	Category 1	Re-categorised by agency head to Category 1	60K (3)		OEH	
5	Category 1	Approved by native vegetation panel	60ZE (3) 60K (3)		OEH	
5	Category 1	Biodiversity certified	60H (3)		OEH	
1	Category 1	Land cleared of native vegetation as at 1 January 1990, unless unlawfully cleared after 1 Jan 1990	60H (1)(a) 60H (4)(b)			
1	Category 1	PVP clearing, both broadscale and paddock trees (legally cleared since 1990)	60H (1)(b)		OEH	See PVP note below
1	Category 1	Low conservation value grasslands not unlawfully cleared	60H (2)(a) 60H (4)(c)			
1	Category 1	Land containing only low conservation value groundcover	60 H (2)(c)	109(1)		
1	Category 1	Identified regrowth / continuing use in a PVP	60H (2)(b)		OEH	See PVP note below
1	Category 1	Regrowth date change in a PVP	60H (2)(b)		OEH	See PVP note below

[2] Note that this table will need to be updated with finalised legislative provisions once the Bill is finalised.

Precedence	Category	Description	LLS Act Section	LLS Regulation Section	Custodian	Comments
1	Category 1	PVP offset - LGA RAMA cleared area	60H (1)(b)		OEH	See PVP note below
1	Category 1	Increased infrastructure width - PVP	60H (1)(b)		OEH	See PVP note below
1	Category 1	Paddock tree code of practice cleared area	60H (1)(b)		OEH	See PVP note below
2	Category 2	Land not cleared of native vegetation as at 1 January 1990	60I (1)(a)			
2	Category 2	Unlawful clearing prosecutions – conviction or finding of guilt	60I (1)(b)	115	OEH	See Prosecution note below
2	Category 2	Unlawful clearing – civil court order to remedy or restrain contravention	60I (1)(b)	115		
2	Category 2	Grown or preserved with public funds (LLS database)	60I (2)(a)		LLS	Spatial data and attribute accuracy inconsistent
2	Category 2	Preserved with public funds – Green Army 20 million trees	60I (2)(a)		DOEE	Spatial data from the Biodiversity Conservation Grants for projects from March 2009 until July 2017.
2	Category 2	Preserved with public funds – Saving Our Species funded sites	60I (2)(a)		OEH	
2	Category 2	Grasslands that are not low conservation value	60I (2)(e)			
2	Category 2	Previously subject to remedial direction	60I (2)(f)			If current, then sensitive.
2	Category 2	Groundcover that is not low conservation value	60I (2)(n)	109(2)		
2	Category 2	Travelling Stock Reserve unless in Western Division	60I (2)(n)	113(1)(l)	Spatial Services	Central and eastern divisions only

Precedence	Category	Description	LLS Act Section	LLS Regulation Section	Custodian	Comments
2	Category 2	Low conservation value grasslands beneath canopy/dropline Cat 2 woody veg	60I (2)(n)	113(1)(g)		
2	Category 2	Re-categorised by agency head to Category 2	60K (3)		OEH	
3	Category 2 Vulnerable	Vulnerable land – protected riparian	60I (2)(b) 60F (2)(c)		OEH	Generated by OEH from existing riparian data sets. Riparian data set has a positional accuracy <100 m.
3	Category 2 Vulnerable	Vulnerable land – special category	60I (2)(b) 60F (2)(c)		OEH	Data set digitised from scanned rectified topo maps (scale ranging from 1:25,000, to 1:100,000)
3	Category 2 Vulnerable	Vulnerable land – steep or highly erodible land	60I (2)(b) 60F (2)(c)		OEH	Generated by OEH. Combines State Protected Land steep or highly erodible data set and lands > or equal to 18 degrees (3:1, 33%) The central and eastern part of NSW positional accuracy is 12.5 m or better where aligned with ADS DEM.
4	Category 2 Sensitive	Sepp 26 – littoral rainforest	60I (2)(i)	108(2)(b)	DPE	
4	Category 2 Sensitive	Sepp 14 – coastal wetlands	60I (2)(i)	108(2)(b)	DPE	
4	Category 2 Sensitive	Ramsar wetland	60I (2)(k)	108(2)(b)	DOEE/ OEH	Spatial data may be misaligned by up to 150 m.

Precedence	Category	Description	LLS Act Section	LLS Regulation Section	Custodian	Comments
4	Category 2 Sensitive	Critically endangered ecological community (CEEC)	60I (2)(m)	108(2)(b)	OEH	Mapping may be an overestimate of the CEEC in some places due to the broad nature of the composite data sets.
4	Category 2 Sensitive	Critically endangered plants	60I (2)(l)	108(2)(b) 112	OEH	
4	Category 2 Sensitive	Biodiversity stewardship agreements including biobanking agreements	60I (2)(c)	cl. 13(1) Savings & Transitional Regulation	OEH	Subject to cadastral errors and may be indicative only.
4	Category 2 Sensitive	Conservation agreements under BC Act or NPW Act	60I (2)(c) 60I (2)(n)	113 (1)(b)	OEH	Subject to cadastral errors, generated from 1:25,000 topographic maps
4	Category 2 Sensitive	Wildlife refuge agreements under Part 5 BC Act	60I (2)(c)			
4	Category 2 Sensitive	NCT trust agreement	60I (2)(n)	113 (1)(e)	Nature Conservation Trust	Subject to cadastral errors
4	Category 2 Sensitive	Subject to set aside requirement in accordance with land management (native vegetation) code	60I (2)(d)	108 (2)(b)		
4	Category 2 Sensitive	Registered property agreements	60I (2)(n)	113 (1)(d)	OEH	Subject to cadastral errors
4	Category 2 Sensitive	Core Koala Habitat	60I (2)(j)	108(2)(b)	DPE	Gazetted KPoM
4	Category 2 Sensitive	Southern Mallee conservation agreements	60I (2)(n)	113(1)(h)	OEH	Subject to cadastral errors
4	Category 2 Sensitive	PVP Offset	60I (2)(h)	108(2)(a)	OEH	See PVP note below

Precedence	Category	Description	LLS Act Section	LLS Regulation Section	Custodian	Comments
4	Category 2 Sensitive	Self-assessable code Ministerial order set aside	60I (2)(h)	108(2)(a)	OEH	See PVP note below
4	Category 2 Sensitive	Current Conservation PVP	60G (3)(c)	108 (2)(e)	OEH	See PVP note below
4	Category 2 Sensitive	Current Incentive PVP	60G (3)(c)	108 (2)(e)	OEH	See PVP note below
4	Category 2 Sensitive	Current remedial direction	60G (20(c) 60I (2)(f)	108(2)(a)	OEH	Reverts to category 2 when agreement expires
4	Category 2 Sensitive	Biodiversity certified conservation measure	60I (2)(g)	108 (2)(b)	OEH	Captured by Council as per standard technical requirements of LEP Maps, therefore may be subject to cadastral error
4	Category 2 Sensitive	Approved private native forest	60G (3)(c)	108(2)(d)	EPA	May be entire property mapped not just area subject to Private Native Forestry Agreement. Reverts to category 2 when finalised.
4	Category 2 Sensitive	High conservation value grasslands/groundcover	60G (3)(c)	108(2)(f)	OEH	
4	Category 2 Sensitive	Recommended by EAH for declaration as AOBV	60G (3)(c)	108(2)(g)	OEH	
4	Category 2 Sensitive	Set aside for nature conservation/native veg offset as DC condition	60I (2)(n)	113(1)(i)		
4	Category 2 Sensitive	Private native forestry – rainforest	60I (2)(n)	113(1)(k)	EPA	
4	Category 2 Sensitive	Private native forestry – old growth	60I (2)(n)	113(1)(j)	EPA	
4	Category 2 Sensitive	Plantation required retained vegetation	60I (2)(n)	113(1)(f)	DPI	

PVP note

PVP information has been captured from a variety of databases. PVP data used above has been extracted from the PAMS, PADACS and LMDB databases, along with notifications captured by the NVNS system. Each of the databases is described in more detail below:

PAMS (PVP Administration and Management System) – Data collected using ArcView 3.3 from December 2005 to May 2008. Data digitised by CMA staff in the process of developing property vegetation plans (PVPs). Underlying imagery was predominantly SPOT 5.

PADACS (PVP Agreements and Customer Service) – Data collected using ArcGis Engine Runtime 9.x application embedded within NVAT (Native Vegetation Assessment Tool) from May 2008 to September 2015. Data digitised by CMA and LLS staff in the process of developing property vegetation plans (PVPs). Underlying imagery was predominantly SPOT 5.

LMDB (Land Management Database) – Data collected using ArcGis 10.2 application embedded from September 2015 to present. Data digitised by LLS staff in the process of developing property vegetation plans (PVPs).

NVNS (Native Vegetation Notification System) – Data collected using online web mapping tool developed by OEH and used by landholders and LLS staff to digitise clearing and set aside areas under codes of practice as part of notification requirements of the NV Regulations 2013. In all applications, underlying imagery was predominantly SPOT 5. The NSW DCDB formed the basis of property boundary identification, which in some cases influenced the position of polygons being drawn in the relevant agreement.

Prosecution note.

In the majority of cases the boundary has been spatially captured based on the area that OEH alleged was illegally cleared. In those instances where this was not possible the area has been based on land parcel information of lot/dp. These areas may not reflect the final areas agreed in court and may include areas cleared under Routine Agricultural Management Activties. The area captured for cases prior to 2014 have predominantly been based on land parcel information of lot/dp. For those cases post 2014 the area defined represents the vegetation modified or removed (area of offence is ok if you want to use this). These areas will include areas cleared under Routine Agricultural Management Activties. The area captured represents the area to be remediated and has been captured from a number of sources

Appendix 7: Further details on map formation

This appendix provides further details related to the map formation process described in Chapter 8.

Appendix 7A: map formation rules for each land use class

Table 5. The map formation rule assigned to each land use class, to determine the map category assignment using the land use, 2013 woody extent, and detectable clearing layers (Chapter 8). The tertiary ALUM classes (those where the class code does not end with zero) are shown only if their map rule differs from its secondary class (class code ends with zero). Chapter 4 lists all ALUM classes.

ALUM class	Description	Mapping rule	ALUM class	Description	Mapping rule
1.1.0	Nature conservation	4	5.3.0	Manufacturing and industrial	2
1.2.0	Managed resource protection	4	5.4.0	Residential and farm infrastructure	2
1.3.0	Other minimal use	4	5.5.0	Services	2
2.1.0	Grazing native vegetation	5	5.6.0	Utilities	2
2.2.0	Production forestry	4	5.7.0	Transport and communication	4
3.1.0	Plantation forestry	1	5.8.0	Mining	2
3.2.0	Grazing modified pastures	2	5.9.0	Waste treatment and disposal	2
3.3.0	Cropping	3	6.1.0	Lake	4
3.4.0	Perennial horticulture	1	6.1.2	Lake – production	1
3.5.0	Seasonal horticulture	1	6.1.3	Lake – intensive use	1
3.6.0	Land in transition	1	6.2.0	Reservoir/dam	2
4.1.0	Irrigated plantation forestry	1	6.3.0	River	4
4.2.0	Grazing irrigated modified pastures	3	6.4.0	Channel/aqueduct	2
4.3.0	Irrigated cropping	3	6.5.0	Marsh/wetland	4
4.4.0	Irrigated perennial horticulture	1	6.5.2	Marsh/wetland – production	2
4.5.0	Irrigated seasonal horticulture	1	6.5.3	Marsh/wetland – intensive use	2
4.6.0	Land in transition	1	6.6.0	Estuary/coastal waters	4
5.1.0	Intensive horticulture	1	6.6.2	Estuary/coastal waters - production	2
5.2.0	Intensive animal husbandry	2	6.6.3	Estuary/coastal waters – intensive use	2

Appendix 7B: checking and refining the map

Introduction

There are known limitations to the 2013 woody extent and detectable woody-clearing layers. There were mapping errors in the woody extent map with trees either not mapped or falsely mapped (Appendix 5A). Limitations of SLATS clearing data were largely due the 30 m Landsat pixel (Appendix 5C), which can result in larger areas being mapped than were actually cleared on the ground. As a result the initial map category assignments might be incorrect so analysts checked and refined the maps.

The ADS tree cover maps (Appendix 5B), or woody probability images (appendix 5A) where no ADS images were available (far north-west New South Wales), are the basis for refining the maps. They are used to create a 'refinements' image (see below), which analysts examine through a systematic review of every 1:100,000 topographic map sheet.

The refinements image

A refinements image is created for each 1:100,000 map sheet, whereby every pixel has a value of either 1 or 2 (corresponding to category 1 or 2) or a potential woody refinement code. The refinement codes are derived from a combination of the mapping rules with woody cover (or probability) and clearing data. Table 6 summarises where the woody cover (or probability) layers are applied and whether the pixel would be a candidate for potential woody vegetation addition (change to category 2) or removal (change to category 1). Each category is given a unique colour. Each category is subdivided by ADS tree cover (or woody probability), in regular thresholds of increasing cover (or probability), to assist the analysts to determine the extent of pixels to edit in the refinements image. Each subdivision is assigned a different pixel code and a different shade of the category's colour (Table 6).

Table 6. The conditions under which a reassignment of the map category could occur based on information from the land use, 2013 woody extent, ADS tree cover and detectable clearing layers. The final column shows the pixel codes and colours in the refinements image the analyst examined.

Map formation rule	Woody in the 2013 map	Woody in the ADS tree cover (or SPOT woody probability) map	Clearing detected	Potential reassignment to category	Refinements image codes
2 or 3	No	Yes	No	2	11–14 (green)
2, 3 or 5	No	Yes	Yes	2	15–19 (blue)
2 or 5	Yes	Yes or No	Yes	2	20–24 (purple)
2 or 3	Yes	Yes or No	No	1	30–34 (red)
3	Yes	Yes or No	Yes	1	35–39 (orange)

Refinements process and guidelines

In the refinements process, the analysts' task is to identify areas of the Native Vegetation Regulatory (NVR) Map that could be improved by reviewing the refinements image, the SPOT images and the ADS image (where available). All decisions are based on the SPOT imagery closest to the date of July 2013. The ADS imagery is used only to assist with identifying features, because of its higher resolution. Using the ERDAS Imagine software, for a given 1:100,000 map sheet, 4 frames of view are concurrently setup as shown in Figure 27. The refinements image is in the top left, the draft NVR map in the bottom left, the ADS image in the top right and the SPOT images in the bottom right. The draft NVR map is overlaid on either the ADS or SPOT images with category 1 made fully transparent (displaying category 2). The NVR map overlay may be flickered on and off as an interpretation aid for rapid assessment of refinement decisions.

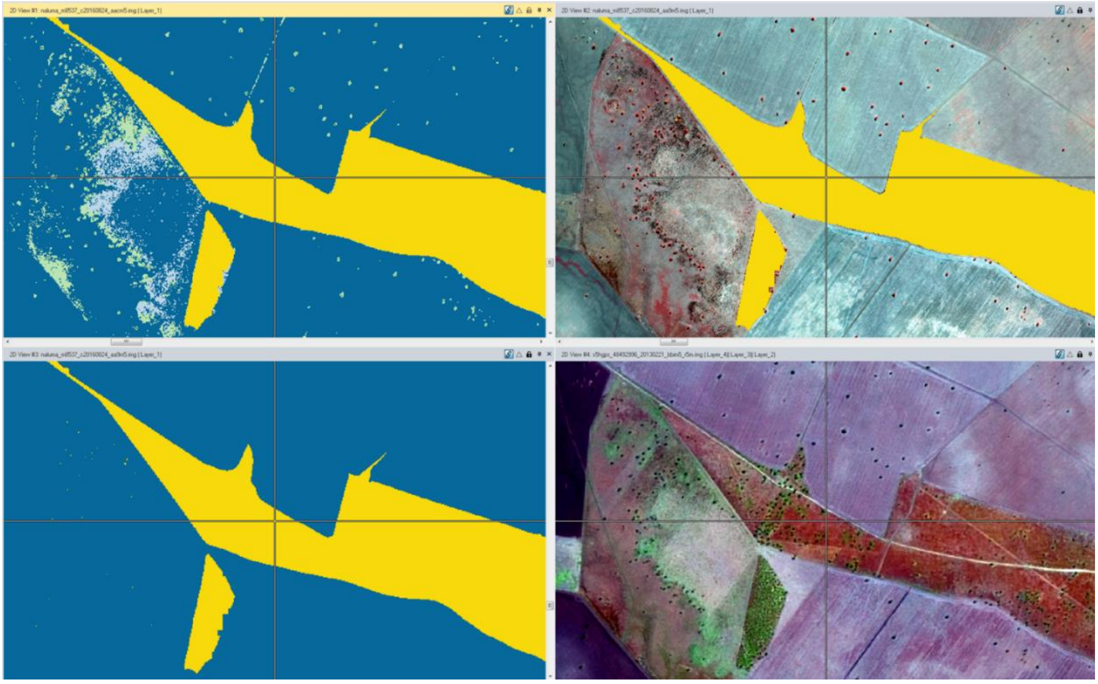


Figure 27 Refinements process set up in ERDAS Imagine: Refinements image (top left), draft NVR map (bottom left), ADS image with draft NVR map category 2 overlay (top right), SPOT images (bottom right).

The viewer frames are linked and set to 1:10,000 scale and the analyst systematically examines each scene, in a regular stepwise pattern, identifying areas of refinements. Decisions are made regarding areas of woody vegetation that need to be added to category 2 (due to 2013 woody extent omission errors or over-representation of clearing from Landsat), or areas of category 2 that need to be changed to category 1 (due to 2013 woody extent commission errors or land use mapping errors). Areas requiring refinement are selected using an area of interest (AOI) polygon. The pixel values in the refinements image representing the required change are selected in the recode tool, with a new value entered as either 42 (change to category 2) or 41 (change to category 1). The new values are then applied to the pixels in the refinements image within the AOI.

Rare cases of land use mapping refinements are handled in the same manner, with pixel values of 1 (category 1) in the refinements image recoded to 52 (change to category 2, distinguished from woody vegetation additions) or pixel values of 2 (category 2) recoded to 51 (change to category 1).

Table 7 contains the range of refinement decisions that were encountered and used by the analysts as a mapping guide. It shows the situation, the rationale behind the decisions and the action taken to edit the refinements image.

Removal of exotics from SPOT woody extent

Large linear plantings of exotic species, such as along fence lines or property boundaries, were inconsistently captured in either category 1 or category 2 by the SPOT and ADS modelling of woody vegetation extent. There were also some instances of land use mapping that incorrectly identified exotic plantings as native vegetation. Large linear plantings of exotic species were removed from category 2 during the refinements process, where time permitted. The process for removing these plantings occurred as a separate task by a small team of spatial analysts, to ensure accuracy and consistency in the interpretation of exotic species in SPOT and ADS imagery.

Where exotic plantings were identified as captured in category 2 by SPOT woody extent, the analyst selected the appropriate pixel values in the range of 30–34 (see Table 6) and recoded to 71. Where exotic plantings were identified as captured in category 2 because of land use mapping (i.e. incorrectly identified as native trees), the analyst selected the relevant area and recoded pixel values of 2 to 73. All other aspects of the standard refinement process were followed.

Several regions across New South Wales were identified as having particularly numerous examples of exotic plantings along fence lines and property boundaries. The New England Tablelands and Canberra and surrounding areas were targeted in the process of removing exotics from SPOT woody extent, as much as time permitted.

It is anticipated this process will continue during further refinements of updates to the NVR map. Examples of exotic plantings that were removed from SPOT woody extent are included below in Table 7.

Historic aerial photography circa 1990 mosaics

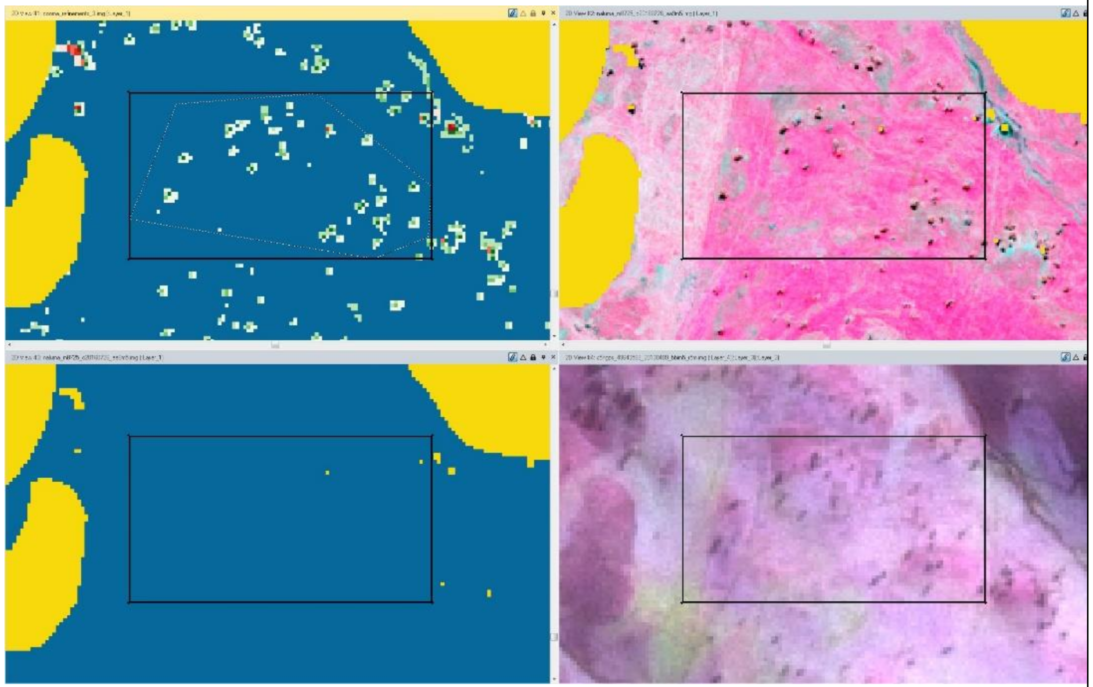
Historic aerial photography (HAP) circa 1990 mosaics provide direct evidence of the presence or absence of woody vegetation at that time. The HAP mosaics are needed because they remove any subjectivity when estimating the size of woody vegetation visible in SPOT imagery (c 2013) that could possibly represent regrowth since 1990.

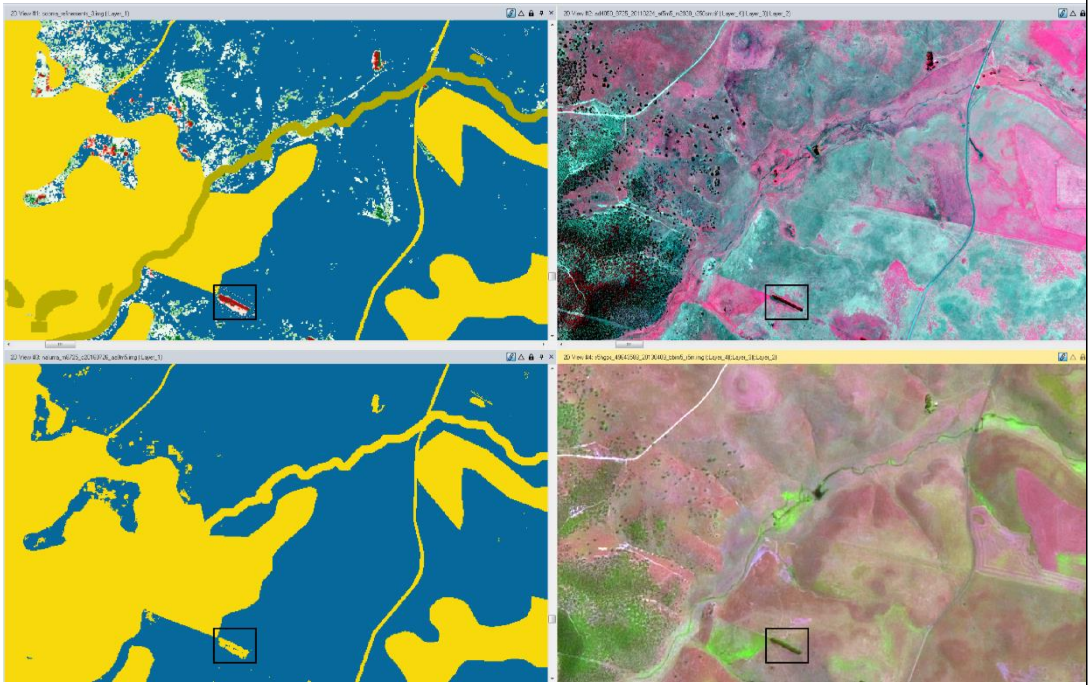
Where available, HAP mosaics are used in the refinements process, to support decisions about the addition and removal of woody vegetation from SPOT woody extent, based on presence or absence c 1990. HAP mosaics were loaded into ERDAS Imagine, in view #3 (bottom left) instead of the aa9. All other aspects of the standard refinement procedure are followed.

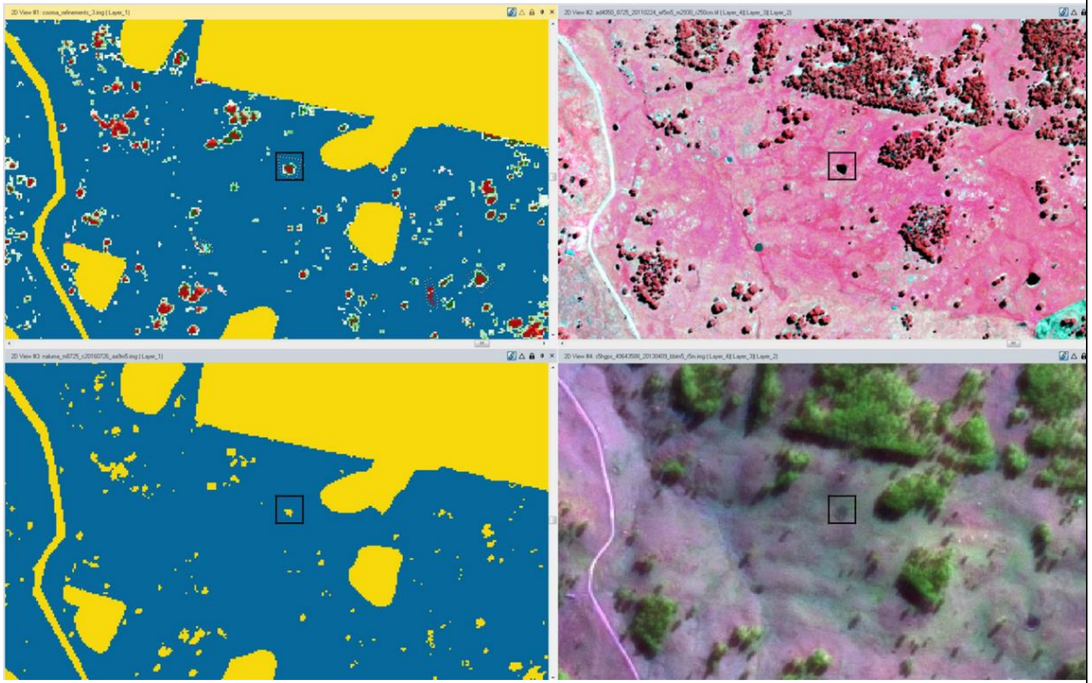
Refinement decisions supported by HAP data apply to all the same conditions of potential re-assignment of the NVR map categories as the standard refinements process (see Table 6). Refinements made using HAP mosaics used the codes 61 for removal from SPOT woody extent (pixel values 30–39) and 62 for additions to SPOT woody extent (pixel values 11–24). Where land use mapping required a change due to HAP-supported decision, the codes 81 (change to category 1) and 82 (change to category 2) are used.

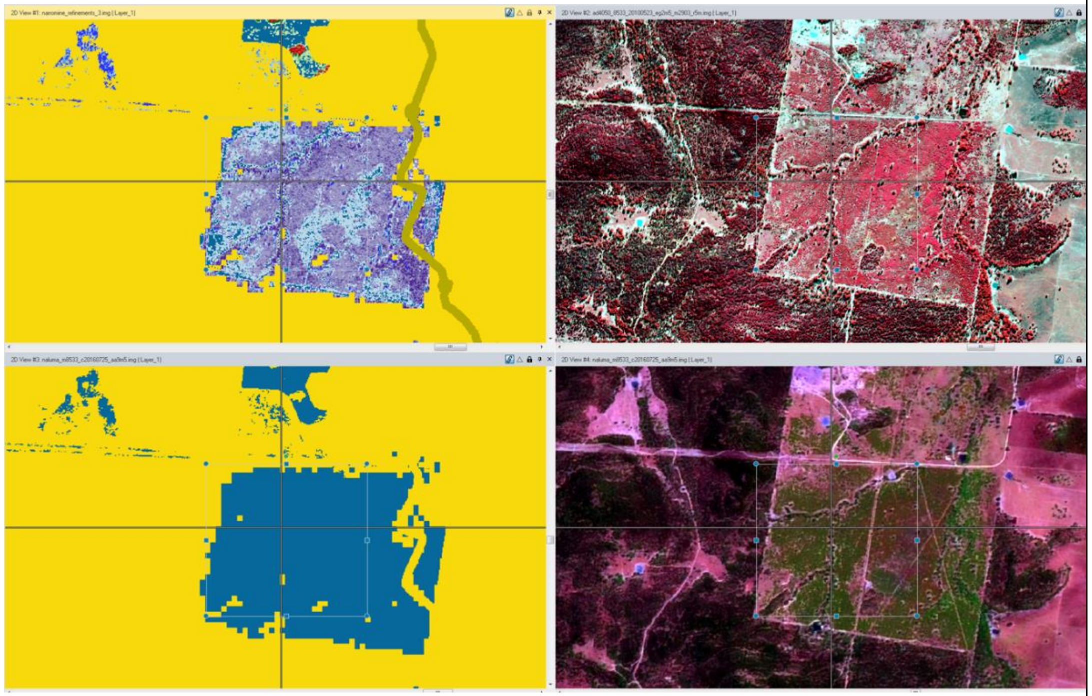
It is anticipated the use of HAP mosaics will continue during further refinements of updates to the NVR map. Examples of refinement decisions supported by HAP mosaics are included below in Table 7.

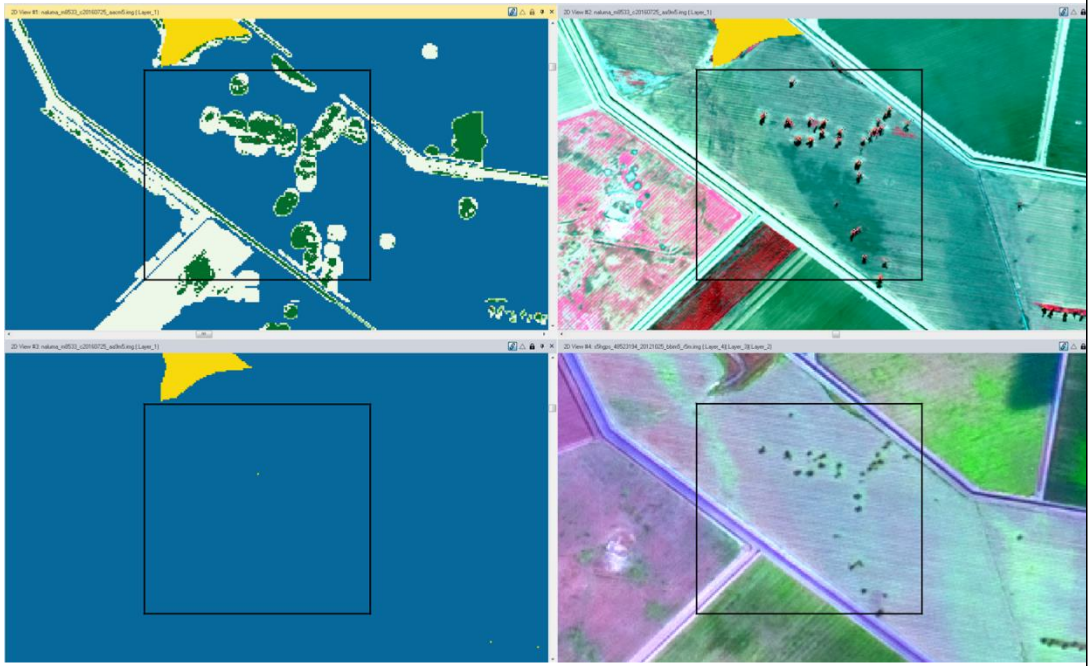
Table 7. The mapping guidelines used by analysts when deciding if map categories needed to be changed.

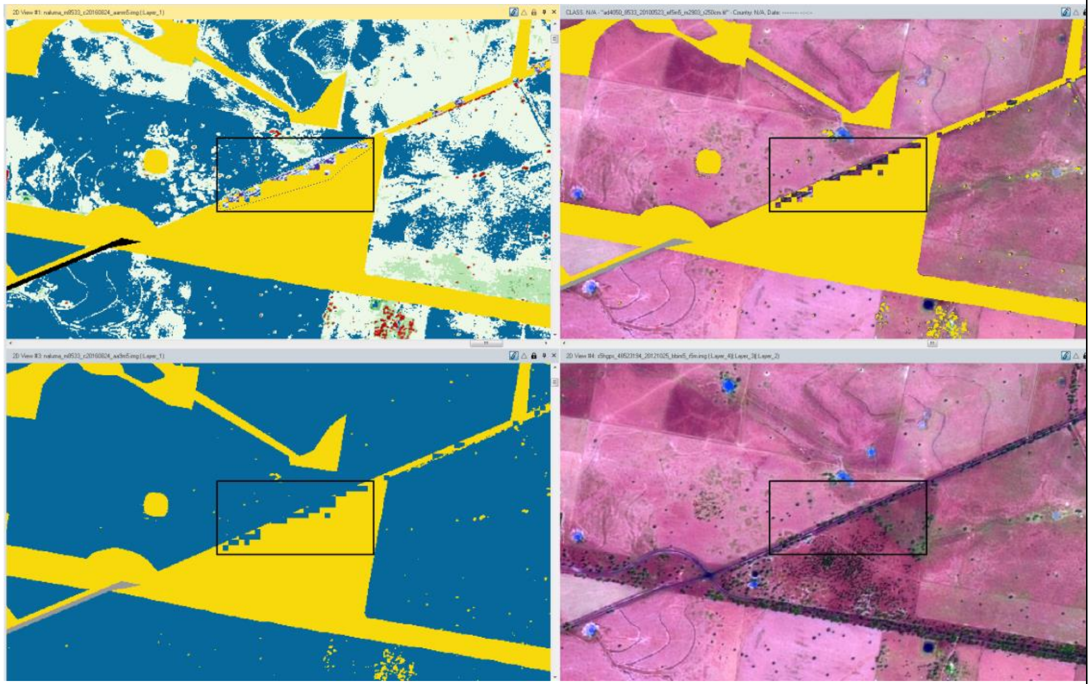
Situation	Refinement decision and pixel recoding	Visual example
Scattered paddock trees present in SPOT imagery (bottom right) but not captured in category 2 in the initial NVR map (bottom left).	Potential refinement codes (top left) are green (11:14) indicating a potential addition and no clearing data in the lineage. This example represents a 2013 woody extent omission error. Decision: add the woody vegetation to category 2 Action: pixel values of 14 and 13 recoded to 42	

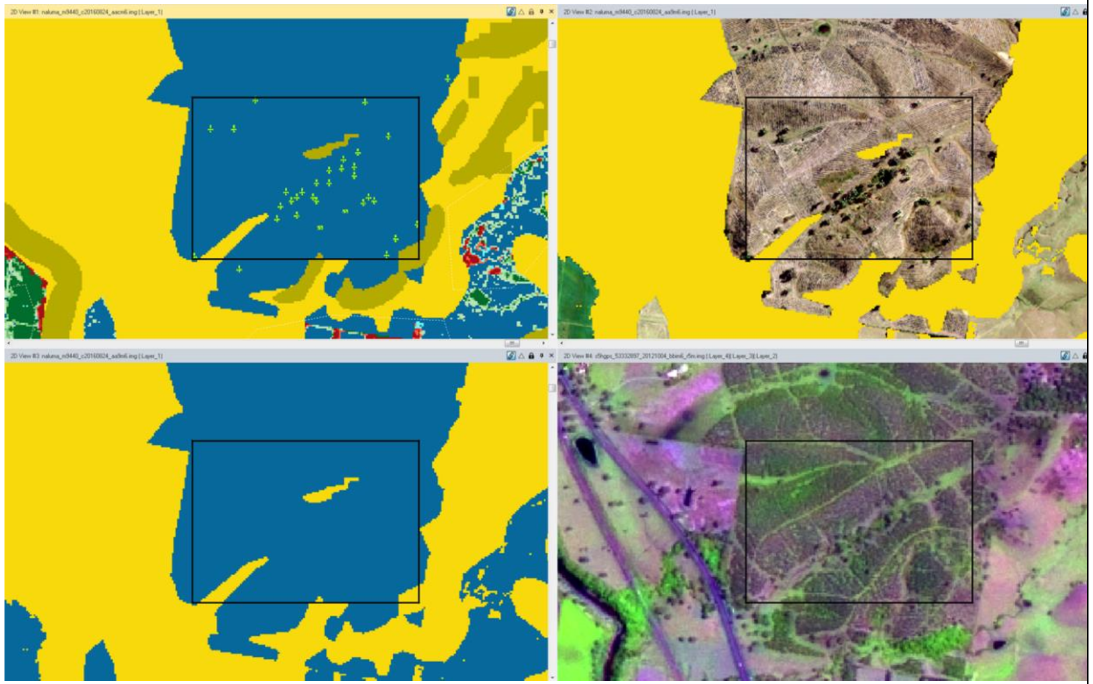
Situation	Refinement decision and pixel recoding	Visual example
An area of category 2 in the initial map over-represents the true extent of the woody vegetation present in the SPOT imagery.	Potential refinement codes are pink/red (30:34) indicating a potential removal and no clearing data in the lineage. This example represents a 2013 woody extent commission error. Decision: remove the area of non-woody vegetation from category 2 to category 1 Action: pixel values of 30 recoded to 41	

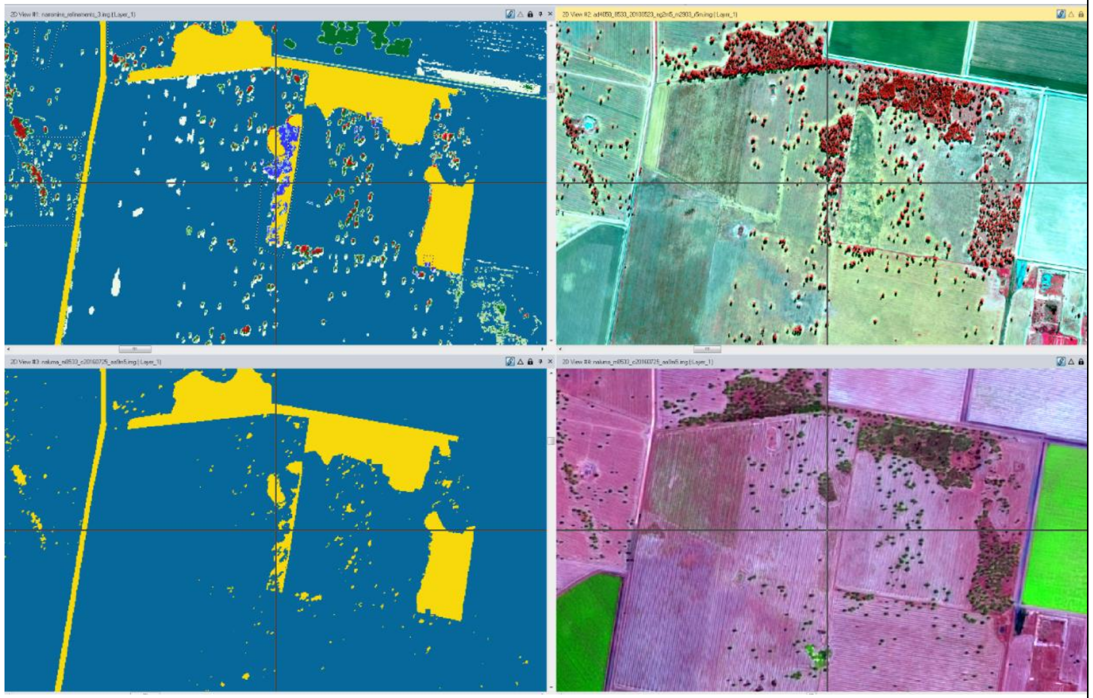
Situation	Refinement decision and pixel recoding	Visual example
Non-woody vegetation (a dam) is captured as category 2 due to an error in the 2013 woody extent data.	Potential refinement codes are red (34) indicating the area is a candidate for potential removal from category 2. The area was identified as woody in SPOT woody extent and as having a high probability of being woody in ADS woody probability. Dark water bodies and shadows are sources of commission errors in the ADS tree cover data, due to the persistent, dark reflectance signature that is similar to that of woody vegetation. This highlights the importance of an analyst's interpretation from the ADS and SPOT imagery to determine refinement decisions (i.e. rather than automating the application of tree cover data). Decision: Remove the area of the dam from category 2 to category 1 Action: pixel values of 34 recoded to 41	

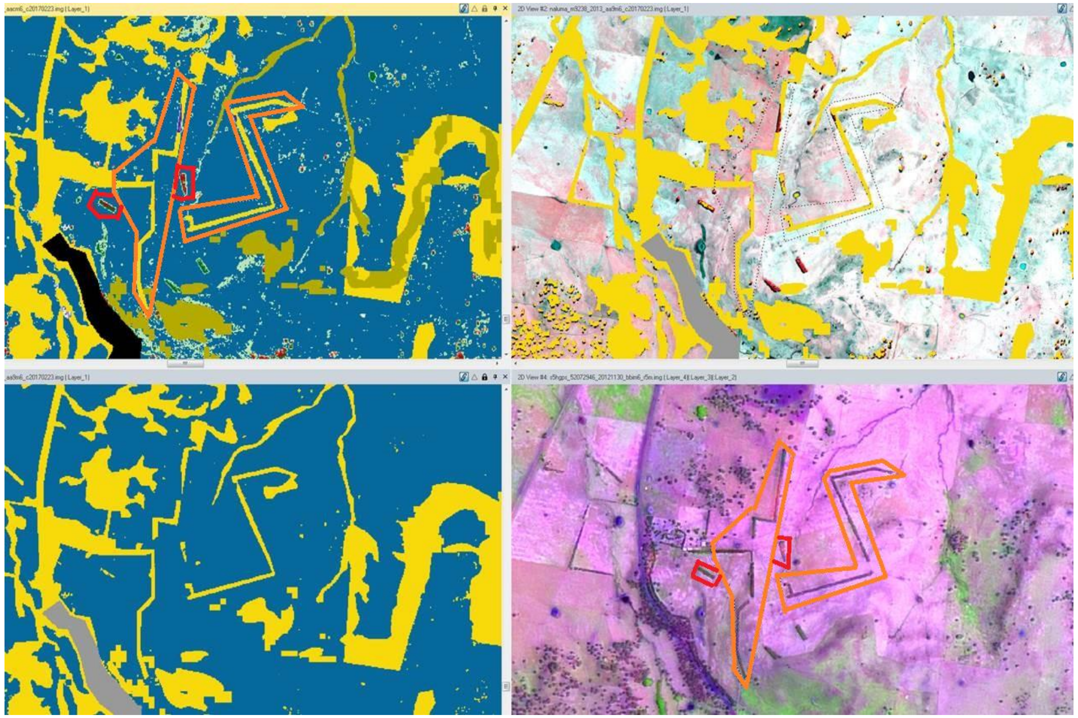
Situation	Refinement decision and pixel recoding	Visual example
Small areas of uncleared woody vegetation, within a larger area of clearing, are not appropriately captured as category 2.	Potential refinement codes are purple (20:24) indicating the area is a candidate for potential addition to category 2 and has SLATS clearing data in the lineage. Decisions about adding woody to category 2 were carefully considered when there is SLATS clearing data in the lineage of the refinements codes (i.e. blues and purples), due to uncertainty about what could possibly be regrowth from an early clearing event that may now be indistinguishable from the surrounding vegetation. A clear difference in growth stage (i.e. age of vegetation) was required as evidence to support adding woody vegetation to category 2 that was likely never cleared within a larger slab of cleared area, captured in Landsat SLATS eras. Strong delineation between tree cover codes often reflect such differences in growth stage, as seen in this example. The landscape context was used to support these decisions, matching the size and structure of surrounding vegetation that has not been cleared. Decision: add areas of vegetation to category 2 that are clearly older growth stages and were probably never cleared Action: pixel values of 24 recoded to 42	

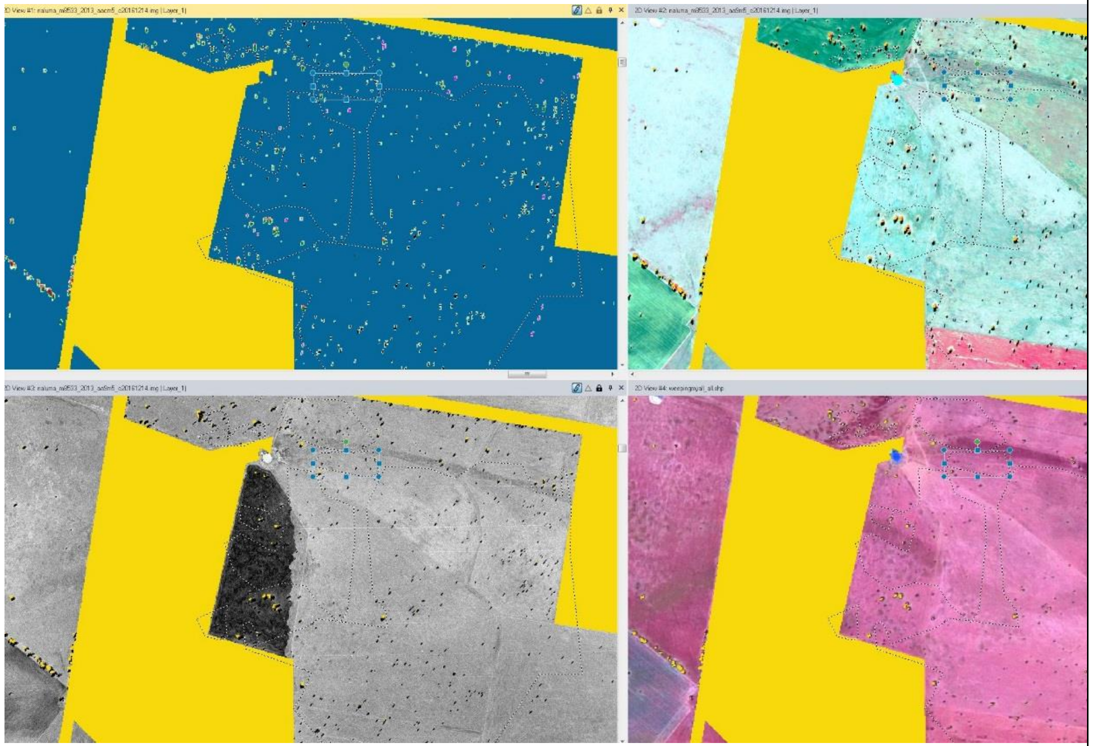
Situation	Refinement decision and pixel recoding	Visual example
Scattered paddock trees present in SPOT imagery but not captured in category 2 in the initial NVR map.	Potential refinement codes are green (11:14) indicating a potential addition and no clearing data in the lineage. However, the codes in the refinements image of the highest probability (14) vastly over-represent the true extent of woody vegetation that needs to be mapped. This is probably due to the area being persistently wet with dark reflectance, similar to the reflectance signature of woody vegetation. Smaller areas within the green refinements codes were selected using the point AOI tool within view #4 (bottom right, SPOT image), applying a region grow standard of 6 pixels, to represent the canopy of the mature trees. With linked AOIs across views, the refinements image can be easily recoded. Decision: add woody vegetation to category 2 Action: pixel values of 14 within the point AOI regions recoded to 42	

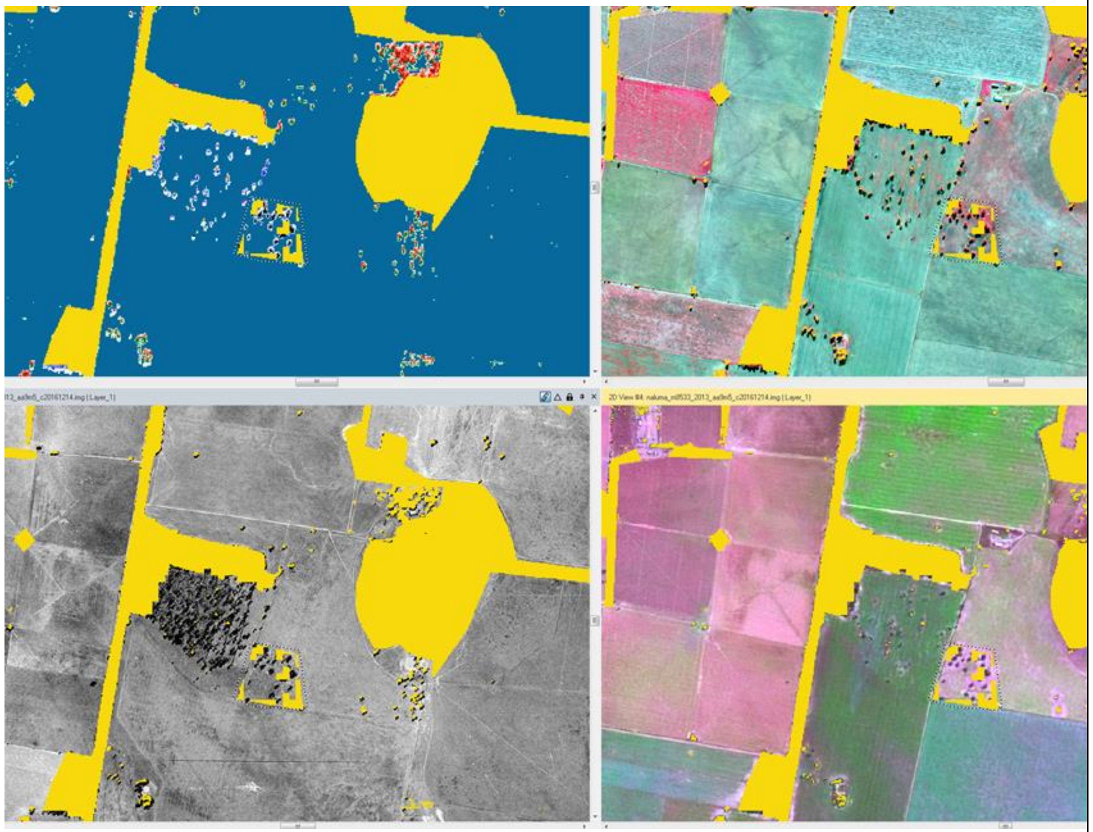
Situation	Refinement decision and pixel recoding	Visual example
ADS imagery was not available for this map sheet (far west NSW), so SPOT woody probability data was used instead of ADS tree cover. The Landsat SLATS clearing data over-represents an area of clearing along a roadside.	Potential refinement codes are purple (20:24) indicating a potential addition and clearing data in the lineage. In the same manner as ADS tree cover, SPOT woody probability data differentiates the denser, more mature canopies that were probably not cleared. Parts of the edge of the Landsat SLATS pixels need to be added to category 2. Decision: add to category 2 the areas of woody vegetation that are clearly older growth stages and were probably never cleared Action: pixel values of 24 recoded to 42	

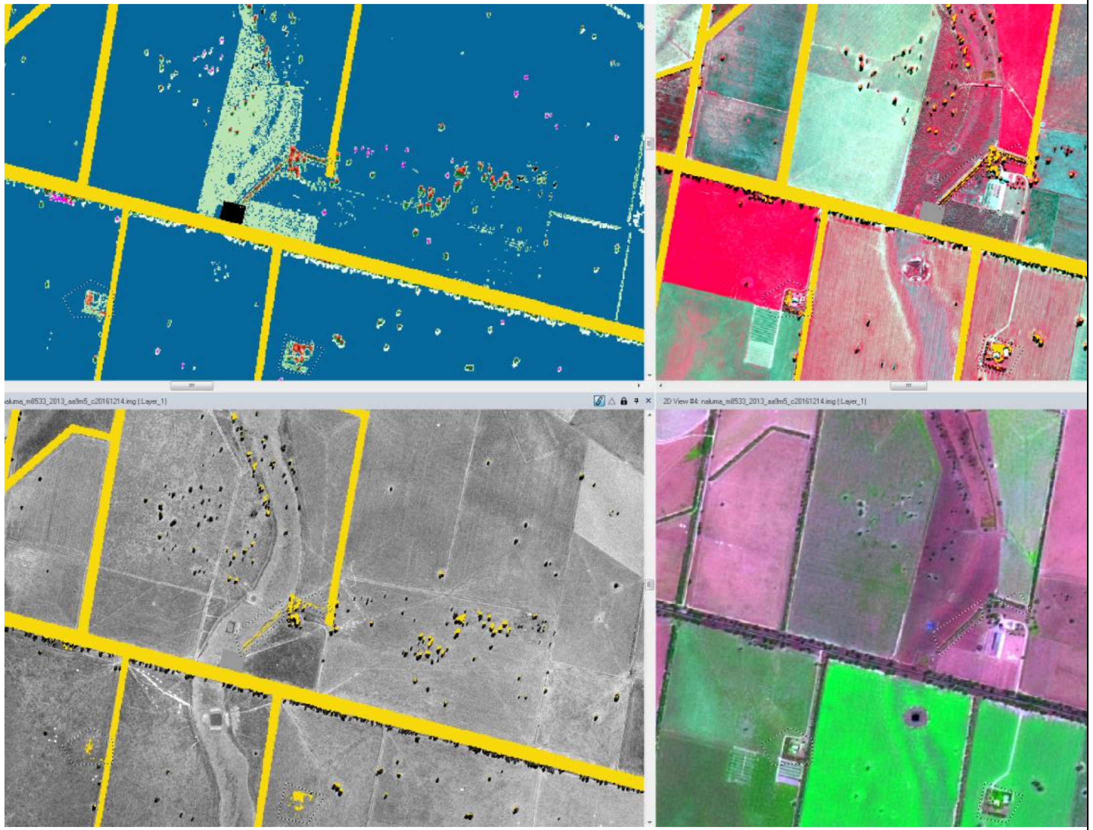
Situation	Refinement decision and pixel recoding	Visual example
Land use areas subject to NVR mapping rule 1 (always category 1) include perennial horticulture. However, occasionally large native trees may be present within the mapped land use boundary.	No refinement codes are available within the area of mapped perennial horticulture. However, large trees present in the SPOT and ADS imagery have probably never been cleared and should be captured as category 2. With approval from a senior team leader, the analysts selected the mature trees with the point AOI tool within view #3 or 4, applying a region grow standard of 6 pixels. The refinements image can then be edited within the point AOIs. Decision: add remnant woody vegetation to category 2 Action: On approval, recode pixel values of 1 (within point AOIs) to 52	

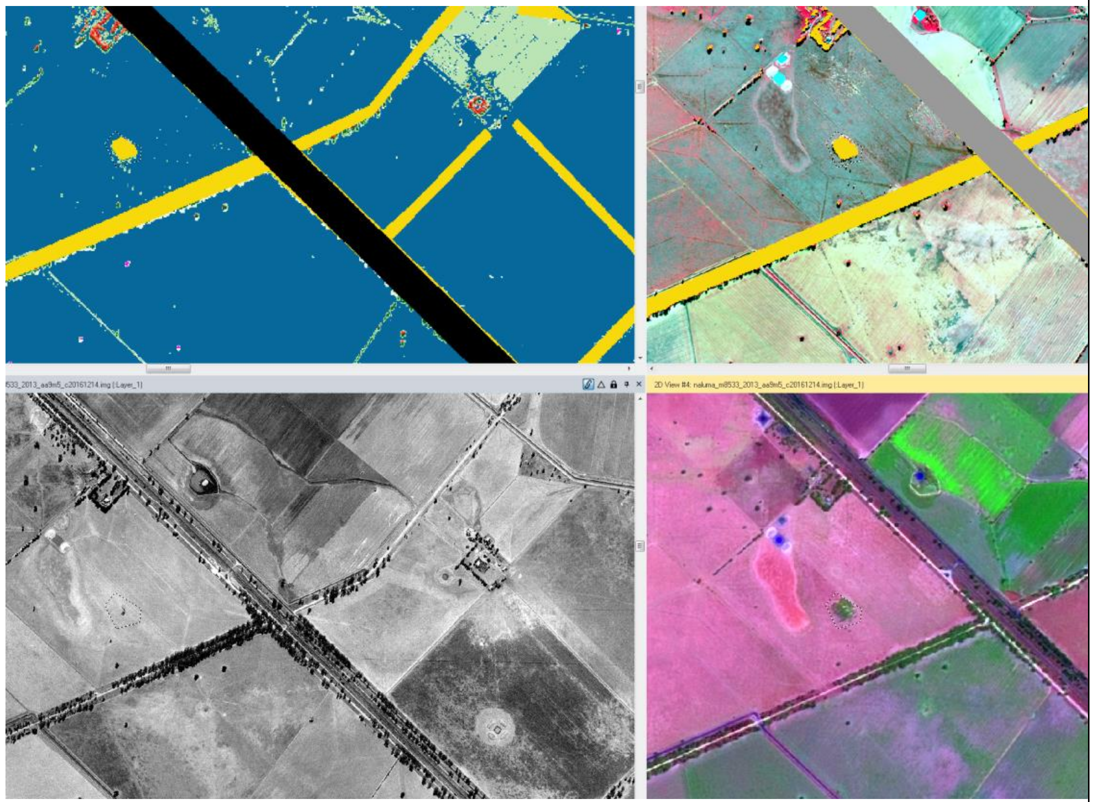
Situation	Refinement decision and pixel recoding	Visual example
An area of category 2 that is not present as woody vegetation in the SPOT imagery and the land use pattern indicates the area should be category 1, consistent with surrounding landscape.	This is a rare occurrence of a land use mapping error. Comparison of the ADS and SPOT imagery indicates the area had been recently cleared of vegetation (between the ADS imagery date and the SPOT imagery date) and subsequently cropped. Using the SPOT imagery for the decision, and with approval from a senior team leader, the area of category 2 needs to be changed to category 1. Decision: Edit land use mapping to change area of category 2 to category 1 Action: On approval, recode pixel values of 2 to 51	

Situation	Refinement decision and pixel recoding	Visual example
Large linear plantings of exotic species are inconsistently captured in category 2 via SPOT woody extent and incorrectly captured as category 2 via land use mapping.	As part of the separate process undertaken by one analyst, the exotic plantings in this scene were identified in SPOT and ADS imagery. The interpretation cues included large, densely planted trees with a thick homogenous canopy of a dark green colour typical of introduced conifers. Decision: Potential refinement codes within the red polygons (top left) are red (30:34) indicating potential removal from category 2. Action: Pixels within the red polygons of values 30–34 were selected and recoded to 71 to remove from SPOT woody extent. Decision: Land use mapping within the orange polygons (top left) incorrectly captures exotic plantings as category 2 Action: Pixels within the orange polygons of value 2 were recoded to 73 to remove from category 2 via change to the land use mapping.	

Situation	Refinement decision and pixel recoding	Visual example
Scattered paddock trees present in SPOT imagery (bottom right) and the 1990 HAP mosaic (bottom left) but not captured in category 2 in the initial NVR map (overlaid in views 2,3 and 4 with category 1 made 100% opaque).	Potential refinement codes (top left) are green (11:14) indicating a potential addition and no clearing data in the lineage. This example represents a 2013 woody extent omission error. The HAP mosaic confirms the presence of the woody vegetation c 1990. Decision: add the woody vegetation to category 2 Action: pixel values of 14 and 13 were recoded to 62	

Situation	Refinement decision and pixel recoding	Visual example
Small areas of uncleared woody vegetation, within a larger area of clearing, are not appropriately captured as category 2.	Potential refinement codes are purple (20:24) indicating the area is a candidate for potential addition to category 2 and has SLATS clearing data in the lineage. The HAP mosaic confirms the presence of the woody vegetation c 1990, suggesting the trees were most likely never cleared between 1990 and 2013 and should be captured in category 2. Decision: add areas of vegetation to category 2 that were probably never cleared Action: pixel values of 23 and 24 were recoded to 62	

Situation	Refinement decision and pixel recoding	Visual example
A small linear strip of vegetation along a roadside is captured in category 2 via SPOT woody extent. However, the area contained no vegetation c 1990.	Potential refinement codes are pink/red (30:34) indicating a potential removal and no clearing data in the lineage. The area contains no woody vegetation c 1990. Given the surrounding land use mapping delineates the wider area as category 1, these pixels should not be captured as category 2. Decision: remove the area of non-woody vegetation from category 2 to category 1 Action: pixel values of 30 recoded to 61	

Situation	Refinement decision and pixel recoding	Visual example
An area of category 2 that is not present as woody vegetation in the c 1990 HAP mosaic and the land use pattern indicates the area should be category 1, consistent with surrounding landscape.	This is a rare occurrence of a land use mapping change based on c 1990 HAP data. With approval from a senior team leader, the area of category 2 needs to be changed to category 1. Decision: Edit land use mapping to change area of category 2 to category 1 Action: On approval, recode pixel values of 2 to 81	

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