Department of Planning and Environment

Native vegetation regulatory map method statement

Appendices

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List of abbreviations

Abbreviation	Meaning
ACLUMP	Australian Collaborative Land Use and Management Program
ADS	Airborne digital sensor
ALUM	Australian Land Use Management
AOI	Area of interest
API	Aerial photograph interpretation
AUC	Area under the curve
BDI	Blue deficient index
BRDF	Bi-directional reflectance distribution function
CEEC	Critically endangered ecological community
DCDB	Digital Cadastre Database
DCS	Department of Customer Services
DPE	Department of Planning and Environment
DSM	Digital surface model
DTDB	Digital Topographic Database
EDI	Excess difference index
EGI	Excess green index
ERI	Excess red index
ESA	European Space Agency
ETM+	Enhanced thematic mapper
FPC	Foliage projective cover
GCP	Ground control points
HAP	Historic aerial photography
HRG	High resolution geometric
IRS	Image and Remote Sensing
JRSRP	Joint Remote Sensing Research Project
LDAWI	Linear discriminant analysis water index
LiDAR	Light detection and ranging
LLS	Local Land Service
LMDB	Land Management Database
LPI	Land and Property Information
MSI	Multi-spectral instrument
MSS	Multi-spectral scanner
NCI	National Computational Infrastructure
NDI	Normalised difference index
NIR	Near infrared

Abbreviation	Meaning
NVAT	Native Vegetation Assessment Tool
NVNS	Native Vegetation Notification System
NVR Map	Native vegetation regulatory map
OLI	Operational land imager
PADACS	PVP Agreements and Customer Service
PAMS	PVP Administration and Management System
PPC	Plant projective cover
PVP	Property vegetation plans
RGB	Red – green – blue
RMS	Root mean square
RMSE	Root mean square error
ROC	Receiver-operator characteristic
SCD	Seasonal cover disturbance
SDC	Scientific–Data–Compute
SRTM	Shuttle Radar Topography Mission
SVR	Support vector regression
SWIR	Shortwave infrared
TM	Thematic mapper
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VPD	Vapour pressure deficit

	Units of measure
cm	centimetre
ha	hectare
kg	kilogram
km	kilometre
km^2	square kilometre
m	metre
μm	micrometre
nm	nanometre
nm	nanometre
pp/yr	percentage points per year

Appendix A: Foundational spatial datasets

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 metre (m) resolution, had 4 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 infrared (NIR), 2 shortwave infrared (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, including 15 m panchromatic bands and higher resolution thermal bands, and the OLI 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 Department of Planning and Environment (DPE) Scientific-Data-Compute (SDC) 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 SDC, 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 & 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 & 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

Foliage projective cover (FPC) 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 m 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 (root mean square error [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 DPE 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. Groundcover 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 groundcover 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 & 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 hectare (ha) field sites, the vertically projected fraction of bare ground, green vegetation and non-green vegetation were measured for the groundcover, mid-storey (<2 m) and overstorey (>2 m) 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.

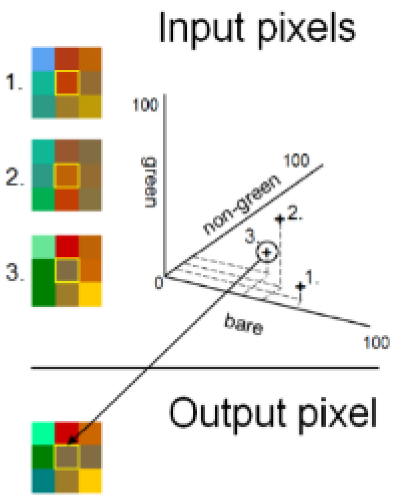
Seasonal Landsat fractional cover

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).

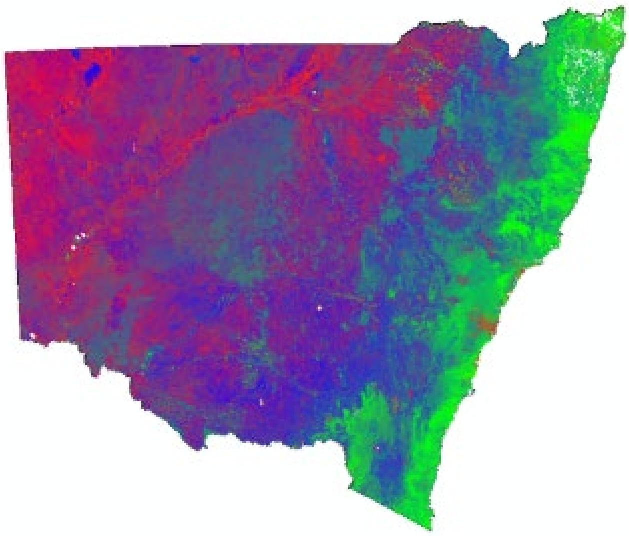
Seasonal fractional cover is generated by selecting pixels from the individual fractional cover product that are most representative of the range of measurements taken by the Landsat satellite throughout the season. We divided the seasons into summer (December–February), autumn (March–May), winter (June–August) and spring (September–November). 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 2013–14, bare ground = red, green vegetation = green, non-green vegetation = blue.

Figure 1 Selection of the 'medoid' pixel and a seasonal fractional cover image for New South Wales

SPOT 5 satellite images

SPOT 5 acquisition

The department 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 2 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 Office of Environment and Heritage (now Department of Planning and Environment) for 2014 and 2015. They were able to ortho-rectify the multispectral imagery with a pixels root mean square (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 multispectral 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 x 7 high-resolution pixel window (35 m x 35 m in this case), separately for each band. Using the local relationship, an estimate of the multispectral 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 Sections 6 and 7 of the *Native Vegetation Regulatory Map Method Statement* ('method statement') 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). A total 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 x 3 Landsat pixels, which is 90 m x 90 m. A regular 1 kilometre (km) x 1 km sample grid was used. We retained those points that were on a slope of less than 5% as determined from the SRTM 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 x 5 pixel window (150 m x 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 D.

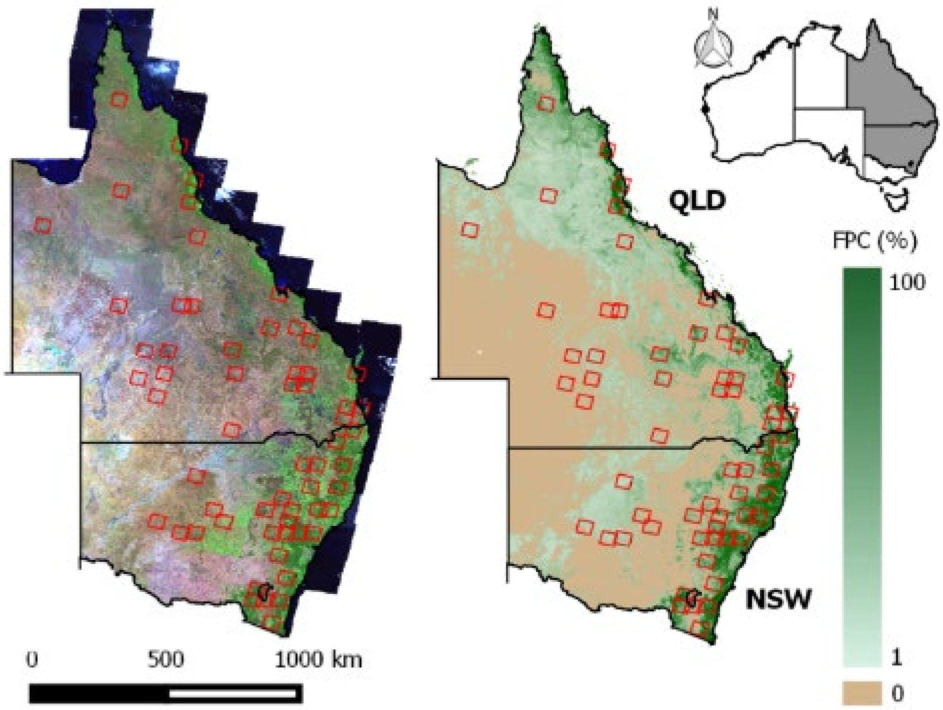


Figure 2 The locations of the SPOT 5 HRG images used to calibrate a model relating the SPOT surface reflectance to Landsat-derived FPC (right image)

SPOT 5 water mask

A linear discriminant analysis water index (LDAWI) (Fisher & Danaher 2013) was developed to enable the mapping of waterbodies using SPOT 5 satellite imagery. A threshold is applied to the index to create a map of waterbodies, 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 4 image bands, and is better at separating water and non-water pixels than the 2 commonly used variations of the normalised difference water index, which each use only 2 image bands. Compared across 2400 validation pixels, from 6 images spanning 4 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 department archive.

Sentinel-2 satellite images

Sentinel-2 acquisition

Sentinel-2 was first launched in June 2015 (Sentinel-2A) with the objective of land monitoring such as vegetation, soil and coastal change. The mission is composed of 2 twin polar orbiting satellites, with Sentinel-2B launched in March 2017. The Sentinel-2 mission was developed by the European Space Agency (ESA) as part of the Copernicus Programme. The mission is designed to give a high revisit frequency of 5 days at the equator. Two additional satellites are planned to be launched in 2021 (Sentinel-2C and Sentinel-2D). The Sentinel-2 satellites each carry a single multispectral instrument (MSI). The MSI imager uses a push-broom capture method. The Sentinel-2 sensors capture data in 13 bands in the visible, near infrared (NIR), and shortwave infrared (SWIR) spectrum. The data are packaged into images according to the spatial resolution of the bands:

- 10 m – bands 2, 3, 4 and 8
- 20 m – bands 5, 6, 7, 8a, 11 and 12
- 60 m – bands 1, 9 and 10.

Sentinel reflectance 10 m

Sentinel-2 10 m reflectance product contains spectral bands 2, 3 and 4 and band 8. These bands represent blue, green, red and NIR wavelengths, respectively. The 20 m SWIR bands can be pan-sharpened to the higher resolution 10 m bands.

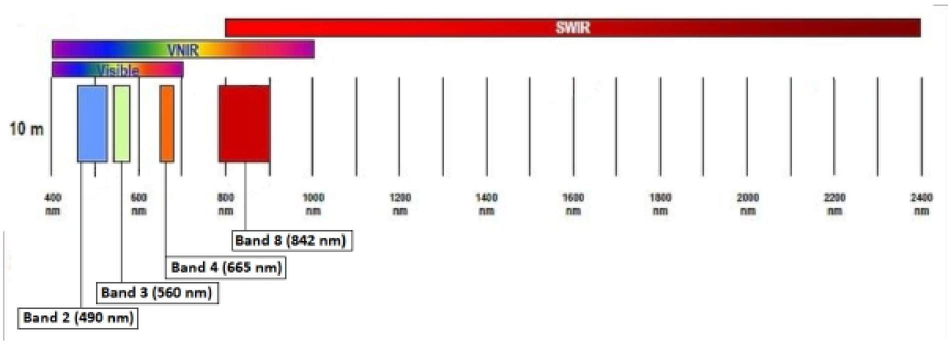


Figure 3 Sentinel-2 10 m spatial resolution bands – B2 (490 nanometres [nm]), B3 (560 nm), B4 (665 nm), B8 (842 nm)

Sentinel reflectance 20 m

Sentinel-2 20 m reflectance product contains spectral bands 5, 6, 7, 8a, 11 and 12. The bands 5 to 7 represent red-edge wavelengths. The band 8a provides NIR spectral information across a narrower range than the 10 m NIR band 8, for more precise measurements. Bands 11 and 12 represent SWIR1 and SWIR2.

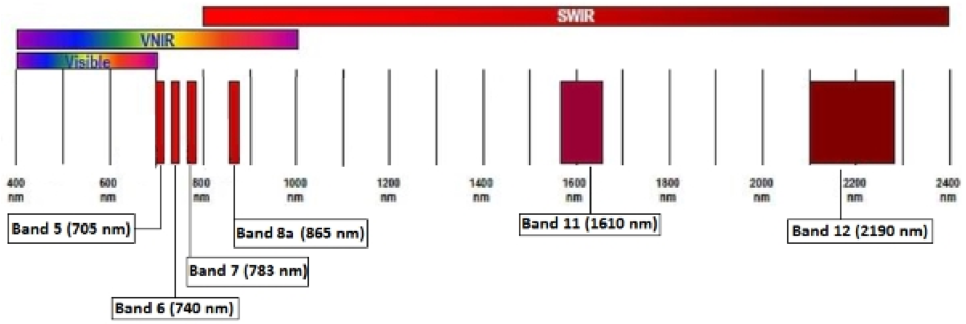


Figure 4 Sentinel-2 20 m spatial resolution bands – B5 (705 nm), B6 (740 nm), B7 (783 nm), B8a (865 nm), B11 (1610 nm) and B12 (2190 nm)

Sentinel reflectance 60 m

Sentinel-2 60 m reflectance product contains band 1, in the violet wavelength, useful for aerosol detection. Bands 9 and 10 are narrow SWIR bands, useful for detecting atmospheric water vapour and clouds. These bands are rarely used in remote sensing of vegetation directly.

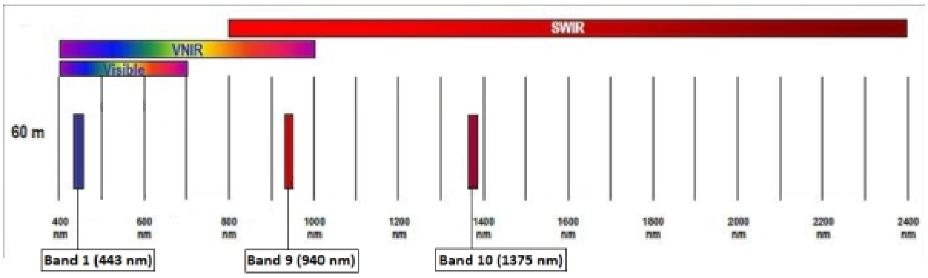


Figure 5 Sentinel-2 60 m spatial resolution bands – B1 (443 nm), B9 (940 nm) and B10 (1375 nm)

Sentinel 2 image pre-processing

The department obtains level 1C products from the National Computing Infrastructure (NCI) Hub. These are 100 km x 100 km tiles and represent at-sensor (top of atmosphere) reflectance. Coefficients are supplied so data can be converted to at-sensor radiance. ESA created these tiles by clipping the data captured on a single orbital path (the paths have a 290 km swath). In many cases the tile contains areas of null data where it overlaps the edge of an orbital path-image (see Figure 6). The department processes and stores all Sentinel-2 image data on the SDC.

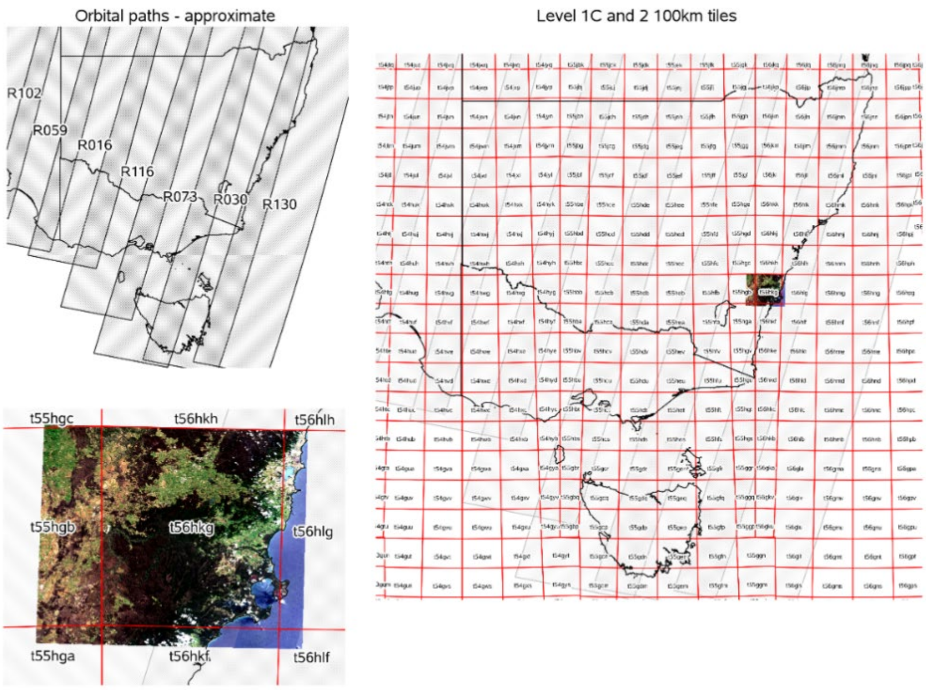


Figure 6 Sentinel-2 paths and tiles

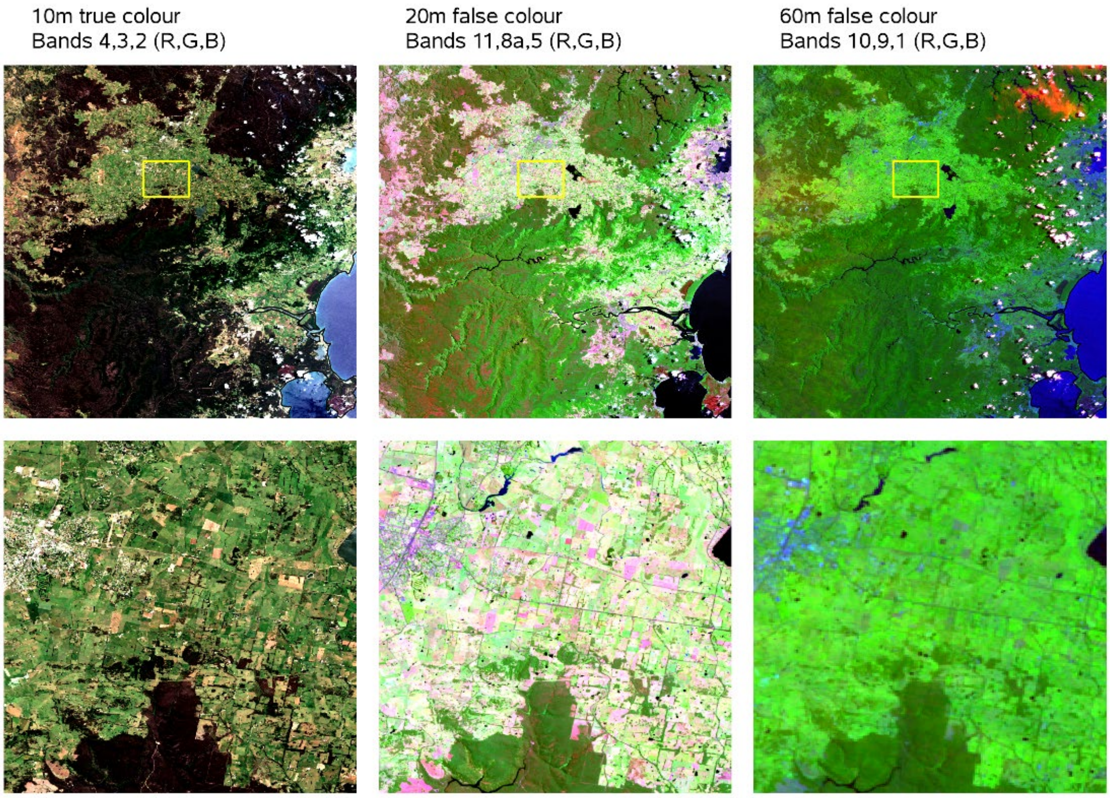


Figure 7 Examples of Sentinel-2 10 m, 20 m and 60 m products at two different locations

The three panels in the top row represent a heavily forested area with a water body in the south-east. The three panels in the bottom row represent a highly modified area dominated by cropping, agriculture and infrastructure.

Planet satellite imagery

Background

Planet™ was founded in 2010 with the first 'Dove' satellite launched in 2013. Planet operates the PlanetScope and SkySat Earth-imaging constellations. Planet also acquired the RapidEye constellation in 2015, providing an archive back to 2009. RapidEye constellation was retired in March 2020. RapidEye satellites have left an archive of 5 m resolution data.

The PlanetScope Dove are about the size of a shoebox and weigh approximately 5 kilograms (kg), smaller than traditional satellites. Doves are launched into space in large batches, in what are called 'flocks'. The oldest Doves that are still imaging Earth were launched in December 2015. There are approximately 180 Dove satellites now in orbit. The Dove satellites image at approximately 3 m resolution.

The SkySat constellation is comprised of 15 satellites. SkySat can be tasked to image any point on Earth in high resolution (0.72 m) and at twice-daily frequency. Skysat 1 was launched in 2013.

Planet imagery products

Two primary Planet products were available for use in the creation and refinement of the native vegetation map:

1. Planet NSW 2017 Mosaic (25 August 2017)
2. Planet NSW monthly base mosaics.

The Planet NSW 2017 Mosaic was created for the department from the Planet imagery archive as close to 25 August 2017 as possible. This layer is a seamless red–green–blue (RGB) composite of Planet images and is in .tiff format tiles compressed to .ecw for viewing purposes. This standalone image layer was commissioned by the department to support the native vegetation reforms.

The NSW monthly base mosaics are a compilation of best available RGB reflectance imagery captured throughout a given month. Planet makes these products available to the department through a web map tile service as .png files which can be incorporated directly into mapping software. This is a subscription-based service provided under contract to the department.

Digital aerial imagery

Department of Customer Services aerial imagery program

Department of Customer Services (DCS) currently provides spatial imagery, captured using state-owned sensors, to NSW Government agencies as shown in Figure 8.

The current aerial image capture programs by DCS include: the standard 50 centimetre (cm) resolution, a 10 cm resolution program covering town areas and emergency response coverage, for example, flood mapping. DCS' standard capture program covers all of New South Wales, as shown in Figure 8. The capture program began in 2007 with updates completed approximately every 5 years or as needed.

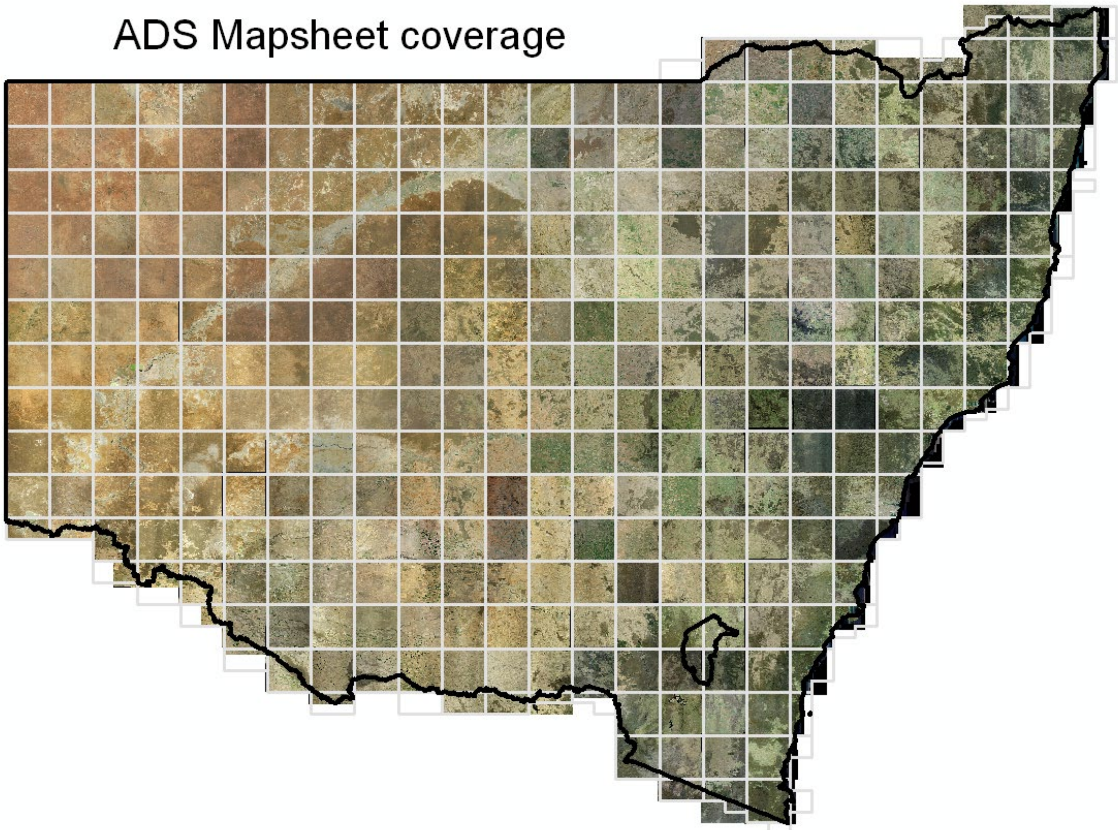


Figure 8 Department of Customer Services' NSW aerial image capture, shown as individual 1:100,000 tiles

Digital aerial imagery products

The digital aerial imagery was captured with a Leica airborne digital sensor (ADS) digital scanner (Sandau et al. 2000). This is a linear push-broom scanner that captures imagery in blue (0.428–0.492 micrometre [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 developed by Leica Geosystems. 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.

Scanned aerial photography – circa 1990

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.

Wet film photographs were captured across New South Wales 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 9.

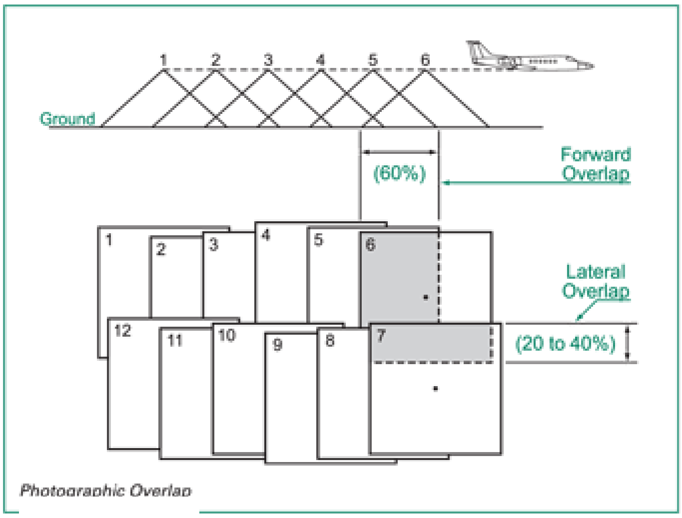


Figure 9 Photographic overlap

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 New South Wales under a memorandum of understanding between Land and Property Information (LPI) and the department. All aerial photographs have been scanned by DCS officers and the memorandum authorises the department to acquire digital film scans from DCS on a regular basis. Imagery sourced from DCS 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 (NVR 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 10 highlights the closeness in time of historical aerial photo coverage to the 1990 date.

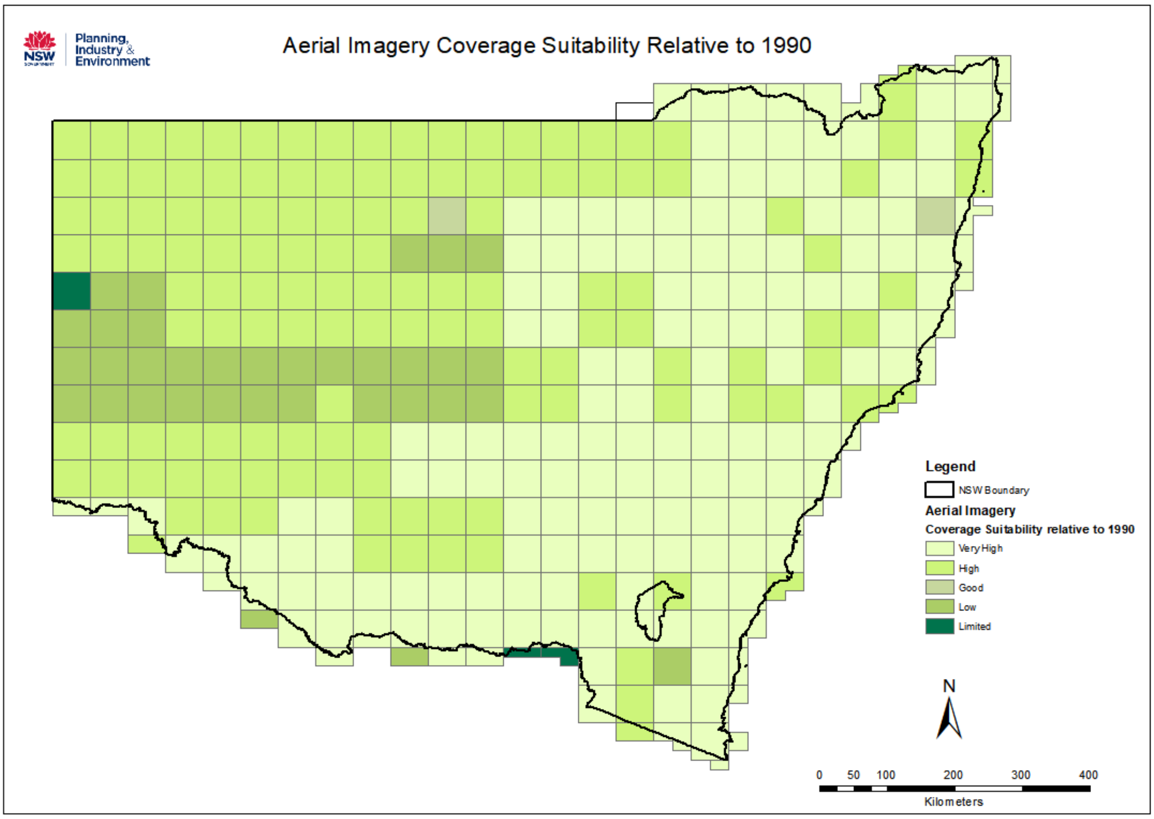


Figure 10 Aerial imagery coverage suitability relative to 1990

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 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.

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 B: Key datasets, sources and associated map products

Section numbers refer to report sections in the *Native Vegetation Regulatory Map Method Statement*.

Dataset	Source	Map product or layer
Landsat imagery archive: circa 1990–2013	United States Geological Survey	Seasonal cover disturbance image products – see Section 5 Detectable clearing events – Section 6.4
Sentinel-2 imagery archive 2015: August 2017	Copernicus Hub	Detectable clearing events – Section 6.4 Visual check of woody extent – Section 6 Map reviews – Section 9
SPOT 5 Imagery archive: 2008–2017	DPE corporate data	Land use – Section 4 NSW Landuse 2003 – Section 4.3 Detectable clearing events – Section 6.4
ADS40/80 imagery: 2007–2017	DPE corporate data Captured by NSW Land and Property Information	Land use – Section 4 Detectable clearing events – Section 6.4
Planet mosaic 2017: ~ 25 August	DPE corporate	Land use – Section 4
Planet monthly web map tile service mosaics	Planet imagery subscription	Land use – Section 4
Historic aerial photos: circa 1990	Image and Remote Sensing (IRS) facility	Land use – Section 4 Reviewing and updating the map – Section 9.4
Landsat foliage projective cover (FPC)	DPE corporate data Created using Landsat imagery archive	Establishing the baseline woody vegetation extent layer – Section 6.3
Landsat fractional cover Seasonal Landsat fractional cover	DPE corporate data Created using Landsat imagery archive	Establishing the baseline woody vegetation extent layer – Section 6.3
Seasonal cover disturbance image products	DPE corporate data	Land use – Section 4 Seasonal cover disturbance image – Section 5

Dataset	Source	Map product or layer
	Created using Landsat fractional cover products	
SPOT 5 FPC	DPE corporate data Created using SPOT 5 imagery archive	Establishing the baseline woody vegetation extent layer – Section 6.3
NSW Digital Cadastral Database	NSW Spatial Services	Exclusions – Section 3
NSW Landuse 2007: 1999–2012	Australian Collaborative Land Use and Management Program (ACLUMP)	Land use – Section 4 Forming the final map product – Section 8
NSW Landuse 2013	ACLUMP	Land use — Section 4 Forming the final map product – Section 8
NSW Landuse 2017	ACLUMP	Land use – Section 4 Forming the final map product – Section 8
2011 woody extent map	DPE corporate data	Establishing the baseline woody vegetation extent layer – Section 6.3
2017 woody extent map	DPE corporate data	Establishing the baseline woody vegetation extent layer – Section 6.3 Detectable clearing events – Section 6.4 Forming the final map product – Section 8
All eras woody vegetation loss	DPE corporate data Created using Statewide Landcover and Trees Study (SLATS) mapping program	Detectable clearing events – Section 6.4 Forming the final map product – Section 8
Vegetation trend map	DPE corporate data Created using Landsat imagery archive	Revising the SLATS maps – Section 6.4.3
Overriding datasets	Refer Appendix F	Overriding map layers – Section 7 Forming the final map product – Section 8
Excluded areas	NSW Digital Cadastral Database DPE corporate data	Exclusion – Section 3 Forming the final map product – Section 8

Appendix C: Supplementary detail for Section 4 (land use)

This appendix provides examples of land use interpretation and more detailed information regarding the accuracy assessment for land use mapping. The land use mapping method uses a range of imagery products in a multiple lines of evidence approach to ensure the best available data is used in creating linework and deciding the correct attribution. How each of these imagery products is used is outlined in the table below.

Rank	Evidence	Use	Accuracy/resolution
1	ADS ~ 2010–2015	Linework, identify (ID) disturbance	50 cm resolution Highest spatial accuracy
1	PlanetAug2017	ID disturbance	5 m resolution
1	SPOT 2016	ID disturbance	5 m resolution
1	SPOT 2013 to 2005	ID disturbance	5 m resolution
1	HAP 1990	ID disturbance circa 1990	Low resolution and spatial accuracy, but adequate to identify disturbance for coding polygon
2	Seasonal cover disturbance imagery products	Used to indicate disturbance that may not have been detected in imagery above. If disturbance is identified a wider range of imagery dates will be reviewed. SCDI response is also considered in the context of topological effects (using contours and interpretation of the landscape from the imagery) as disturbance signatures would often arise from pasture flushes associated with being near water (gullies and along watercourses) or on tops of ridges, where the soils are shallower and more frequented by animals e.g. sheep camps	25 m resolution, Images\Index span designated time period
2	Sentinel-2 2015–2017	Used for additional investigation of SCDI disturbance	10 m resolution, monthly mosaics
2	Landsat imagery archive	Used for additional investigation of SCDI disturbance	30 m resolution, monthly time slices across entire period
3	Field points	> For use in categorising tertiary level and validating SCDImage Products	Single time point, limited distribution

HAP = historic aerial photography.

Appendix C-1: Analyst interpretation rules for land use classes

The table below reflects how analysts apply Australian Land Use Management (ALUM) 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	Excluded	These are sourced from the national parks estate for NSW. Areas are reserved under the NP&W Act 1974. These include national parks, nature reserves, regional parks, state conservation areas, aboriginal areas, historic sites and karst conservation reserves.	Features will be sourced from the datasets identified in Sections 7 & 9 of the method statement. Attempts will be made to ensure these datasets are in accordance with the spatial accuracy of the map.	

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 government 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

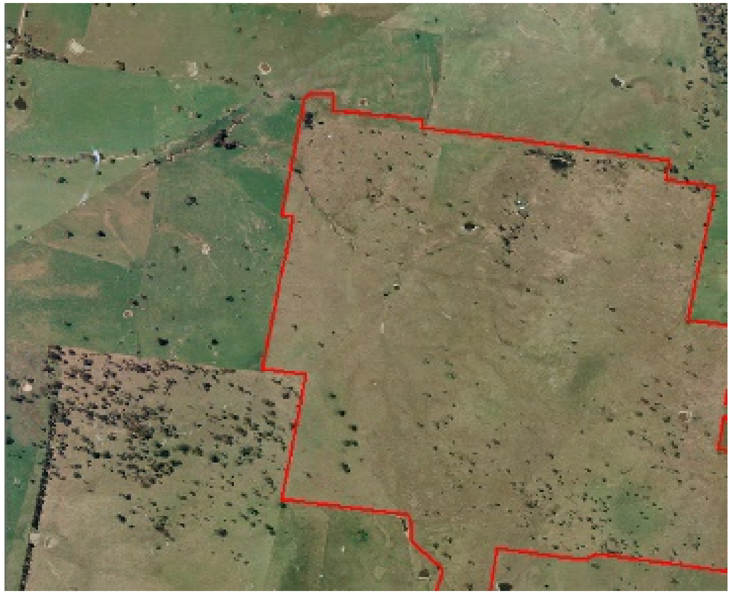
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Salinity treatment site

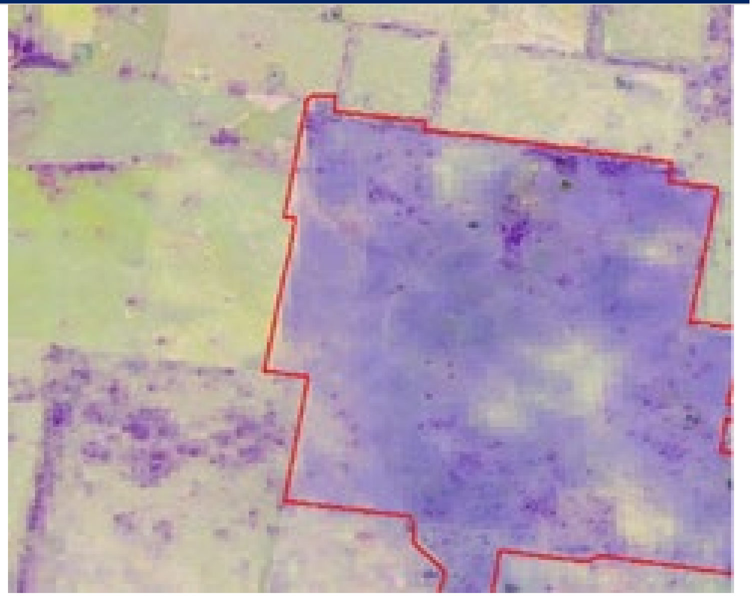
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Biodiversity corridors – habitat

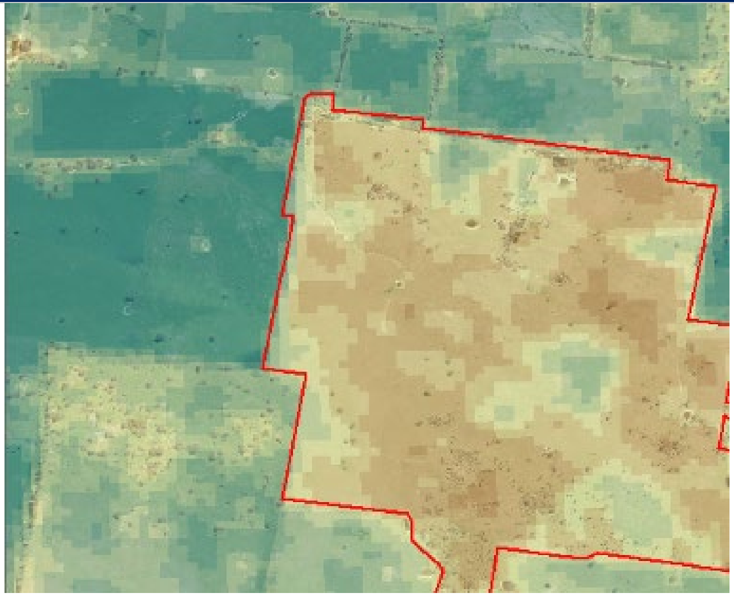
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	1.3.0 Conservation and natural environments – other minimal use	2	May include travelling stock routes and Defence lands, natural forested areas, not subject development or agricultural production.	May include travelling stock routes based on existing land use and fieldwork information. Defence lands based on existing land use and access to Commonwealth holdings (spatial) information.	 Commonwealth Defence lands

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Travelling stock route

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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 disturbance between 1990 and 2017 in the seasonal cover disturbance imagery (SCDI).	Areas that show no visual indication of cultivation activity in available satellite and aerial imagery. Areas also demonstrate low disturbance in the SCDI products (Section 5).	 1992 Aerial photograph

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 SCDImage version 2

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 SCDIndex (version 3)

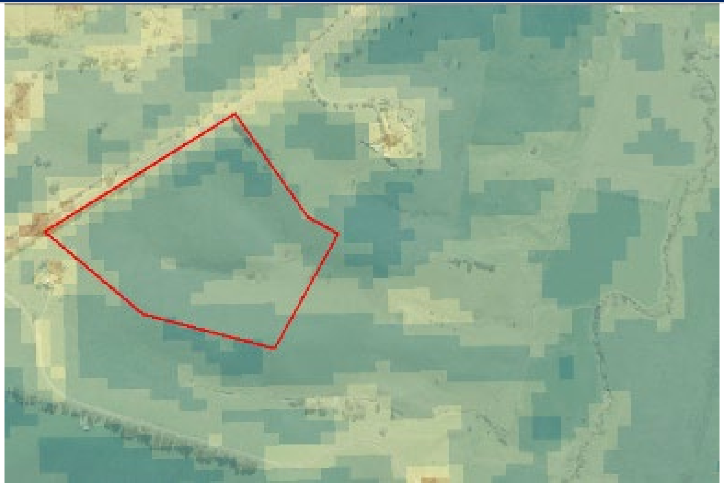
Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 ADS imagery Paddock example: No evidence of agricultural disturbance (land use), low disturbance based on SCDImage in both version 2 and version (indexed product). Surrounding paddocks 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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Hardwood plantation

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 Pine plantation

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 high disturbance in the seasonal cover disturbance imagery. It is likely that the areas have been subject to agricultural activity/disturbance between 1990 and 2017 without the presence of land use patterns or indicators in contemporary satellite or aerial imagery.	 ADS imagery  SCDImage version 2

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 SCDIndex (version 3)  ADS imagery

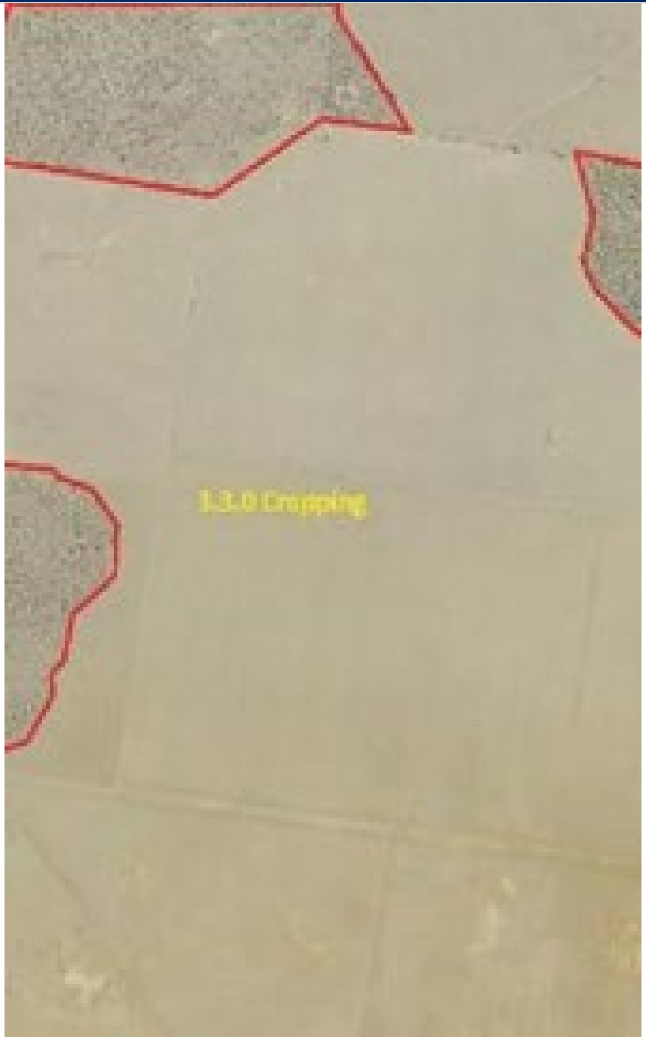
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					Paddock example: Insufficient evidence in aerial/satellite imagery to determine level of agricultural disturbance. Both SCDI products indicate that the paddock has been subject to agricultural modification, when compared to groundcover present in the road reserve on the western boundary of the paddock.
	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 1

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Sown pastures example 2

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Sown pastures example 3

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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Cropping example 3

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					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 three 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

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 Citrus plantation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Coffee plantation

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. Temporary greenhouses used to propagate seedlings or grow seasonal	 Seasonal horticulture – vegetables

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
				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 – vegetables

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Centre pivot & linear paddock irrigation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Irrigation district

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Irrigation enterprise

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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Intensive horticulture enterprise

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Intensive horticulture enterprise

Primary ALUM class	Secondary ALUM class	Map categor y	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

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 Piggery enterprise

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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 2017. 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

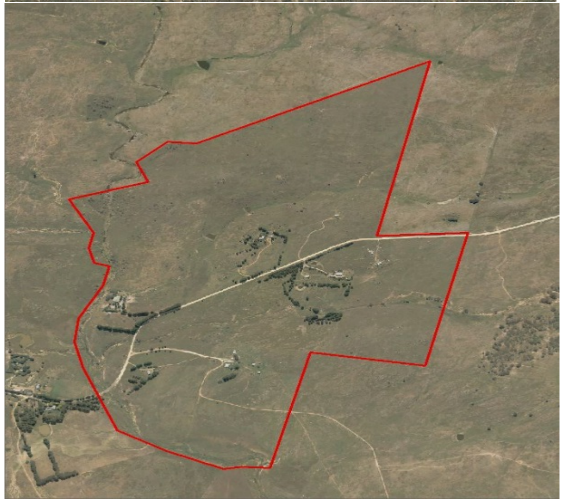
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Cotton processing gin

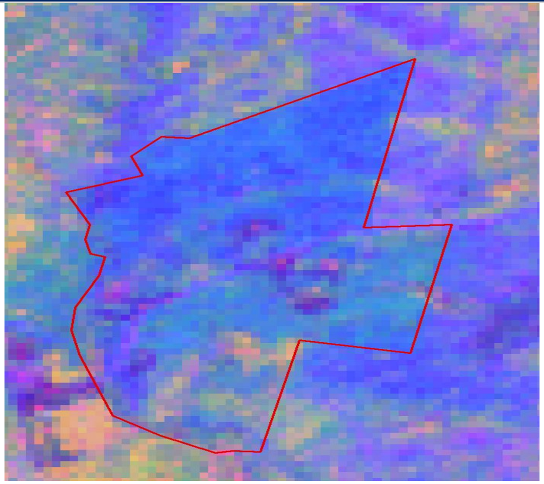
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Wine processing plant

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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Remote community

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 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 NVR mapping method applied to larger agricultural	Features to be mapped where greater than 2 ha in size.	  Rural residential – bush blocks

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
			properties in NSW.		 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 areas 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 areas – undisturbed native vegetation present in parklands and golf courses.	 Public recreation – modified

Public recreation – mixed

Primary ALUM class	Secondary ALUM class	Map categor y	Notes and rules applied	Land use description	Visual examples
					 Public recreation – mixed levels of disturbance

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 2 ha in size.	 Electrical substation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Gas processing/transmission site

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Electrical substation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	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 image to determine whether the area has been subject to a level of disturbance to define whether category 1 or 2 is assigned.	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 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 airport Grain storage facility

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Regional aerodrome

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	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

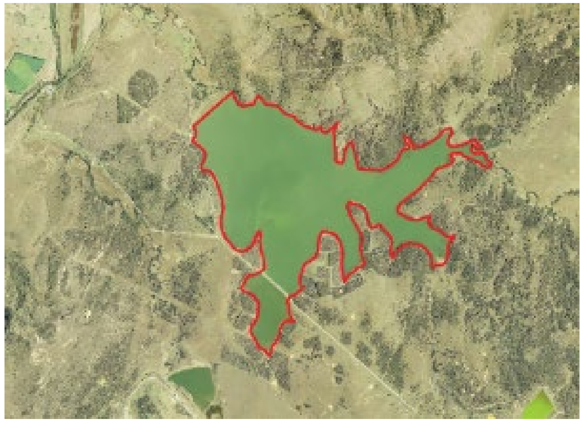
Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Large-scale quarry operation

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Quarry operation

Primary ALUM class	Secondary ALUM class	Map categor y	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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Waste management facility
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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 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 2 ha 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  Large-scale farm dam

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Irrigation dam – off-river storage
	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.	

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
	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

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Salt interception scheme

6.5.0 Marsh/Wetland	2	Mapped to the extent of feature.	If areas 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.	

Primary ALUM class	Secondary ALUM class	Map category	Notes and rules applied	Land use description	Visual examples
					 Marsh/Wetland- conservation
	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 C-2: NSW Landuse 2013 accuracy assessment method and results

Accuracy assessment

An accuracy assessment was carried out on the NSW Landuse 2013 map layer to assess the mapping method. It tested for consistency between land use mappers, in the accuracy of individual land use classes, and the overall accuracy of the native vegetation regulatory map (NVR Map) categories.

The map sheets selected ensured an analysis of mappers' skill against the known variation of land use across the State (see Figure 11). The same staff and method with updated imagery and ancillary layers were used to build the NSW Landuse 2017 map from the 2013 baseline.

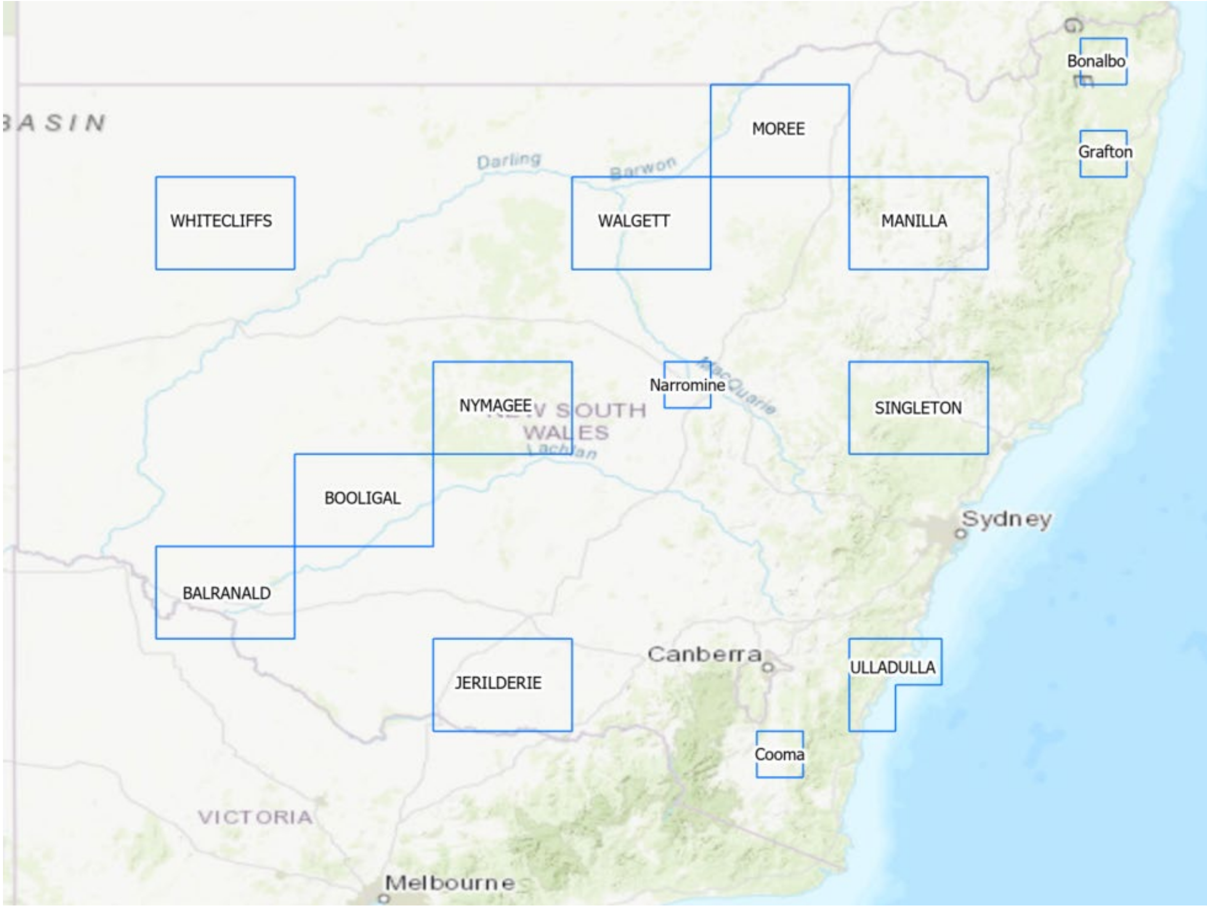


Figure 11 Map sheets covered by accuracy assessment as of December 2016

The spatial accuracy (i.e. the accuracy of the line work) and thematic accuracy were assessed in one process. The statistical method uses a 'frequentist approach' to sampling using 'bootstrapping' to calculate the results (Champagne et al. 2014).

Points are allocated by random stratification within each land use class. The more dominant a land use class, the more sampling points per map sheet it will have. The exception to the rule, as they are the most significant in terms of area and management for native vegetation in New South Wales, include the following Australian Land Use Management (ALUM) classes:

- 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 applies the map method to each point to determine the ALUM category, and an error matrix is generated to assess the agreement between the land use mapper and the independent assessor, by comparing the map categorisation for all reference points across all map sheets.

The assessor's accuracy (or producer's accuracy) refers to the likelihood that a reference point matches what a mapper has categorised it as, and the opposite is true for the mapper's accuracy (or user's accuracy).

The error matrices are calculated by weighting the point observations against the area of the land classes used in the sampling, thereby removing the sampling bias resulting from differences in land class distribution across the State (Stehman 2014). The overall accuracy for each class is calculated from the error matrix using a standard formula. The 95% confidence intervals are estimated using bootstrapping, where the error distribution is computed using percentiles from a thousand error matrices resampled with replacement from the overall matrix (Champagne et al. 2014; Gallaun et al. 2015).

Limitations

Due to the program's tight time constraints, the points were not field validated. Also, a one-off observation in 2016 may not accurately reflect the history of land use within the 1990 to 2013 window the NVR Map represents.

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 shown in Table 1 below. All map sheets achieved the 90% minimum threshold for overall NVR category accuracy. The accuracy was less than 90% in 8 sheets when the assessors' and mappers' accuracy figures were considered. However, the confidence interval range was high, indicating uncertainty in the accuracy statistic. In 6 cases, the overall upper confidence interval was still above 90%, and the individual user's greater than 80%. It was found that the distinction between NVR category land was less obvious in these sheets.

The two other cases with an individual user's accuracy of less than 80% were the Ulladulla 250,000 (79%) and White Cliffs 250,000 (29%) maps sheets. These maps 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 the reference points being distributed across ALUM classes not NVR categories, and the variation in mapped area of the 2 NVR categories. Specifically:

- The Ulladulla map sheet had only 10% mapped as category 1 and was represented by a broad range of land use classes which were harder to classify (e.g. plantation native forestry) against a native backdrop.
- The White Cliffs sheet has <1% mapped as category 1 land. A number of these category 1 areas are farm dams that were applied to the map using an ancillary layer. However, as the dams were less than 2 hectares, the assessor rolled them into the surrounding ALUM class, predominantly grazing native vegetation category 2.

Table 1 Accuracy assessment summary table as of December 2016

Map sheet	Overall NVR	95% CI	Producer's		Assessor's 95% CI		User's accuracy		Mappers' 95% CI	
			Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2
Balranald 250K	98.33	95.52–99.85	95.10	99.28	86.16–100.00	98.43–99.97	97.50	98.57	94.46–99.91	95.71–100.00
Bonalbo 100K	92.60	87.66–96.72	86.32	95.25	75.33–96.14	91.58–98.88	88.42	94.30	79.18–97.37	88.73–98.52
Booligal 250K	99.52	98.93–99.95	99.98	99.49	99.97–99.99	98.87–99.95	92.12	100.00	82.50–99.20	100.00–100.00
Cooma 100K	95.00	91.20–98.00	93.20	95.40	80.70–99.70	92.40–98.40	81.20	98.50	68.60–93.70	95.70–99.90
Grafton 100K	94.70	93.13–96.00	100.00	96.72	100.00–100.00	94.95–98.24	82.46	100.00	72.53–90.73	100.00–100.00
Jerilderie 250K	94.58	92.21–97.12	95.55	92.20	93.26–97.70	84.21–98.51	98.02	83.65	95.56–99.65	74.88–91.64
Narromine 100K	95.20	91.30–98.40	94.80	96.70	90.30–98.90	90.20–99.90	99.10	83.40	97.30–100.00	66.90–96.70
Nymagee 250K	96.20	93.50–98.10	96.10	96.30	88.90–100.00	94.20–98.10	89.90	98.60	84.10–94.90	95.80–100.00
Manilla 250K	93.13	89.47–96.75	92.35	93.75	85.80–98.02	90.34–97.17	91.65	94.28	87.01–96.29	88.57–98.57
Moree 250K	94.27	90.99–97.30	95.57	92.25	91.77–98.93	86.53–97.31	95.07	93.01	90.80–98.38	86.19–98.37
Singleton 250K	93.94	89.98–97.68	88.15	97.57	80.37–97.20	95.98–99.00	95.80	92.91	92.89–98.28	87.22–98.48
Ulladulla 250K	90.80	85.19–95.51	93.56	89.82	82.77–100.00	84.66–94.35	79.49	97.07	67.69–89.19	91.45–100.00
Walgett 250K	97.93	97.12–98.66	100.00	97.08	100.00–100.00	95.98–98.10	93.34	100.00	90.74–95.71	100.00–100.00
White Cliffs 250K	99.89	99.85–99.93	100.00	99.89	100.00–100.00	99.85–99.93	29.48	100.00	7.33–54.77	100.00–100.00

Map sheet	Overall NVR	95% CI	Producer's		Assessor's 95% CI		User's accuracy		Mappers' 95% CI	
			Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2	Cat 1	Cat 2
Average	95.44		95.05	95.84			86.68	95.31		

Notes:

CI = confidence interval

K = thousand scale, e.g. 250K is 1:250,000

Cat 1 = category 1 – exempt land

Cat 2 = category 2 – regulated land

Appendix D: Development and interpretation of the seasonal cover disturbance image and index

Development of the seasonal cover disturbance image – version 1

The seasonal cover disturbance image (SCDImage) combines information from images spanning seasons from summer 1988 to winter 2017. 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 1988–2017 period. The seasonal fractional cover images were used to develop metrics that characterised the variation in green and non-green vegetation. Statistical transformations were used to summarise the information in the 30-year time series into a small number of images that could be interpreted visually or used in an image classification method.

For the original SCDImage.v1, the fractional cover data was converted to polar coordinates in the green and non-green cover space and time-series statistics were calculated based on the polar angle and distance measurements (Powell et al. 2019). Using the time series of angle and distance measurements, statistics including the mean, median, minimum, maximum, range and standard deviation were calculated. 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. 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.

Development of the seasonal cover disturbance image – version 2

Feedback from the early rounds of mapping suggested the SCDImage.v1 would sometimes miss or over-estimate cover disturbance in some areas. A second version of the SCDImage was created after reviewing an increased number of time-series statistics to help reduce areas of confusion.

For the SCDImage.v2 product, an increased number of time-series statistics were calculated and evaluated, without use of the polar transformation used in SCDImage.v1. Percentile minimum (5%) and maximum (95%), measures of variance and skewness of the distribution were included as possible model inputs aimed at either quantifying the range of variation in fractional cover space. The median and mean were included to assist as statewide standardisation measure, for example, as a comparative measure of potential cover. These statistics were calculated based on total cover, green cover and green proportion, where green proportion equals the green fraction of total cover. The green proportion calculation provides similar information to the original polar transformation in the SCDImage.v1.

The difference in fractional cover between consecutive time-series seasonal cover observations was also calculated and used to provide a measure of how rapidly cover is changing. These difference images require 2 consecutive cover observations so a single missing time-series cover observation can cause the loss of 2 cover difference observations. Hence, the cover difference images are based on less samples than the cover observations. The same set of time-series statistics calculated using the cover observations we also calculated using the cover difference measurements for total cover, green cover and green proportion.

The time-series statistic layers were evaluated against existing mapped land use, high-resolution digital aerial imagery and roadside survey observations. The level of background noise in the statistical layers was also a consideration in their evaluation.

The following time-series statistics were considered as the most related to mapped areas of modification and disturbance:

- mean
- median
- coefficient of variation (for cover time series only)
- standard deviation (for cover difference time series only)
- 5th percentile
- 95th percentile
- 5th–95th percentile range.

The most informative three of these layers were selected for the SCDImage.v2 which is formed by displaying the three time-series statistical layers listed in Table 2 as a colour composite image with a linear contrast enhancement applied to the image. These 3 layers were chosen as they were assessed as containing the most relevant information for mapping non-woody disturbance and modification. All the statistics listed above were considered in the SCDIndex model.

Table 2 Standard time-series layers for SCDImage.v2

Time series statistic layer	Display colour
Green proportion 95th percentile	Red
Green proportion 5th to 95th percentile range	Green
Total cover 5th percentile	Blue

This version, the SCDImage.v2, was used for most of the NVR Map and was also used to check NVR mapping that used the SCDImage.v1 product.

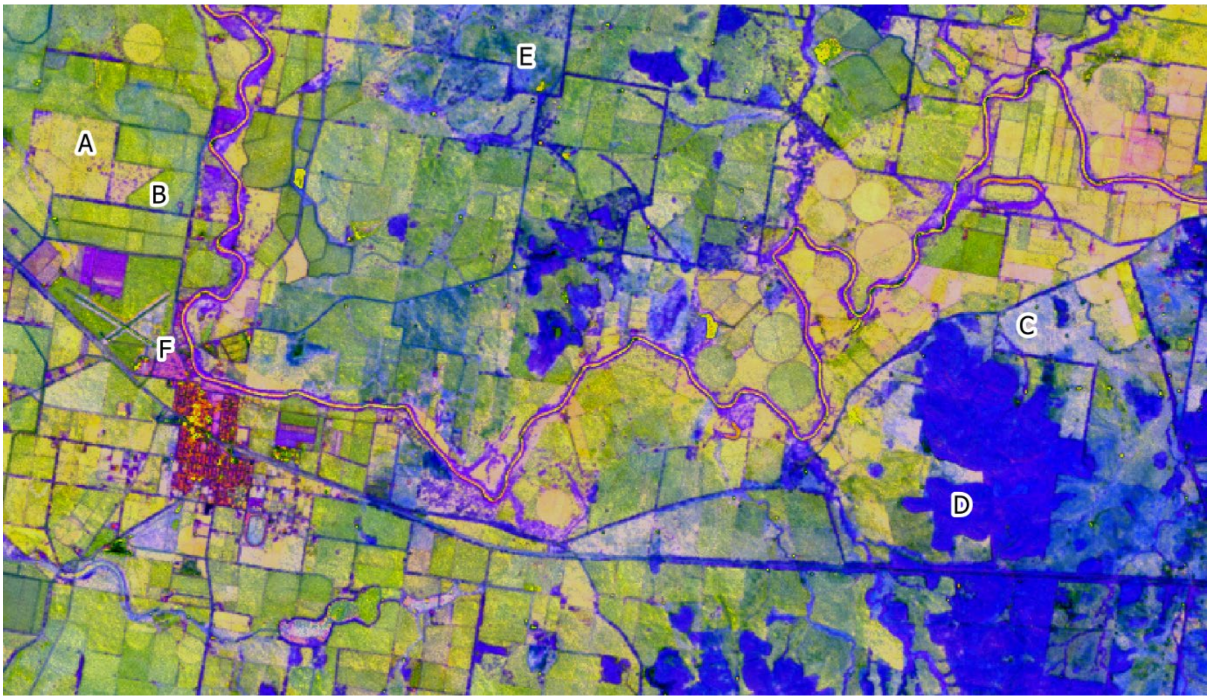


Figure 12 Colour composite image with the 95th percentile green proportion, 5th – 95th green proportion range and total cover 5th percentile shown as red, green and blue respectively. Alpha labels are explained in the text.

Interpretation of the seasonal cover disturbance image – version 2

The following guide has been developed to assist with interpretation of colours in the SCDImage.v2 product. Example areas are shown in Figure 12.

- Yellow (A) – is usually crop or improved pasture regularly managed throughout the time series.
- Yellow/Green (B) – is also usually associated with cropping and modified pastures.
- Blue/Yellow (C) – tends to indicate old cropping land that was regularly used early in the time series but has been left to naturalise.
- Dark blue/Purple (D) – is usually woody vegetation that is persistent throughout the seasons over the time series.
- Light blue (E) – is often native pasture or woody vegetation, but can also be paddocks with an older history of cultivation.
- Pink (F) – tends to represent the outliers within a landscape such as urban and industrial areas, golf courses and parks. It can also occur in areas frequented by snow covering and plantation forestry production. The land use for these areas is usually easy to identify from high-resolution imagery.

As the colours in the SCDImage are dependent on the local contrast stretch applied to the image, interpretation of the SCDImage should also be done in a relative sense. The mappers look for patterns in the SCDImage where the land use can be interpreted using aerial imagery, then they extrapolate these patterns to other areas in the SCDImage.

Development of the seasonal cover disturbance index

The SCDIndex was developed later in the mapping program after developing a set of training data based on high-resolution satellite imagery, time-series sites based on visual interpretation of Landsat imagery covering 1987–2017, and roadside survey observations. The index was developed using this training data and many of the image statistic layers evaluated for the SCDImage. It is an extension of the SCDImage concept, but the model approach allows for inclusion of more time-series information than just the 3 layers in the SCDImage.

The level of disturbance or modification is predicted and assigned an index value in the zero to one range which can be displayed as a number of disturbance classes or as a continuous tone image. This approach makes the interpretation of disturbance and modification less subjective than with the SCDImage. However, the SCDIndex was still used in a multiple lines of evidence approach with other data sources.

This index product was not available for the development of the 2013 mapping included in the initial NVR Map but was used when the map was revised using 2017 imagery.

Training site data

The development of a training site dataset was a significant task as the length of the time period when disturbance could occur often required time-consuming historic interpretation. High-resolution imagery and roadside surveys were used to identify disturbed areas that were visible at the time of the image acquisition or fieldwork. However, areas that appear as undisturbed may have had some historic disturbance in the past but have recovered to an undisturbed state, so a time-series check was required.

A Landsat time-series point method was developed to interpret the areas where disturbance could not be identified in the SPOT or other high-resolution imagery, and field observations were either inconclusive or unavailable. An automated image selection and retrieval process was established to recall the complete Landsat time series for specified small sample areas and provide them as GeoTif images with a consistent contrast enhancement applied. These sample areas were generally approximately 6 km x 6 km in size. The time series of images were then viewed using a slide show viewer and selected images of interest also viewed in ArcMap or QGIS where they were compared to other high-resolution image layers.

Generally, a number of sites were assessed in each time-series sample area. By focusing on the ‘point’ in relation to the surrounding land cover the assessor quickly scrolls through every scene sequentially for the 30-year time period. This process allows for differentiation between natural seasonal changes seen in native or less disturbed areas, to more frequent or abrupt variations represented by modified landscapes. Once the time-series images at a site had been scanned a number of times, one of the disturbance classes in Table 3 was assigned. Noting that even if a site was obviously disturbed once back in 1995, for example, it was still identified as disturbed. Some sites were difficult to interpret, possibly due to a combination of soil and vegetation type, landform and rainfall frequency. These sites were assigned value of 3. The majority of the time-series based sites were subsequently field checked to assist in determining disturbance likelihood noting the current groundcover species assemblage and land use activity.

Table 3 Disturbance classes used for training site data

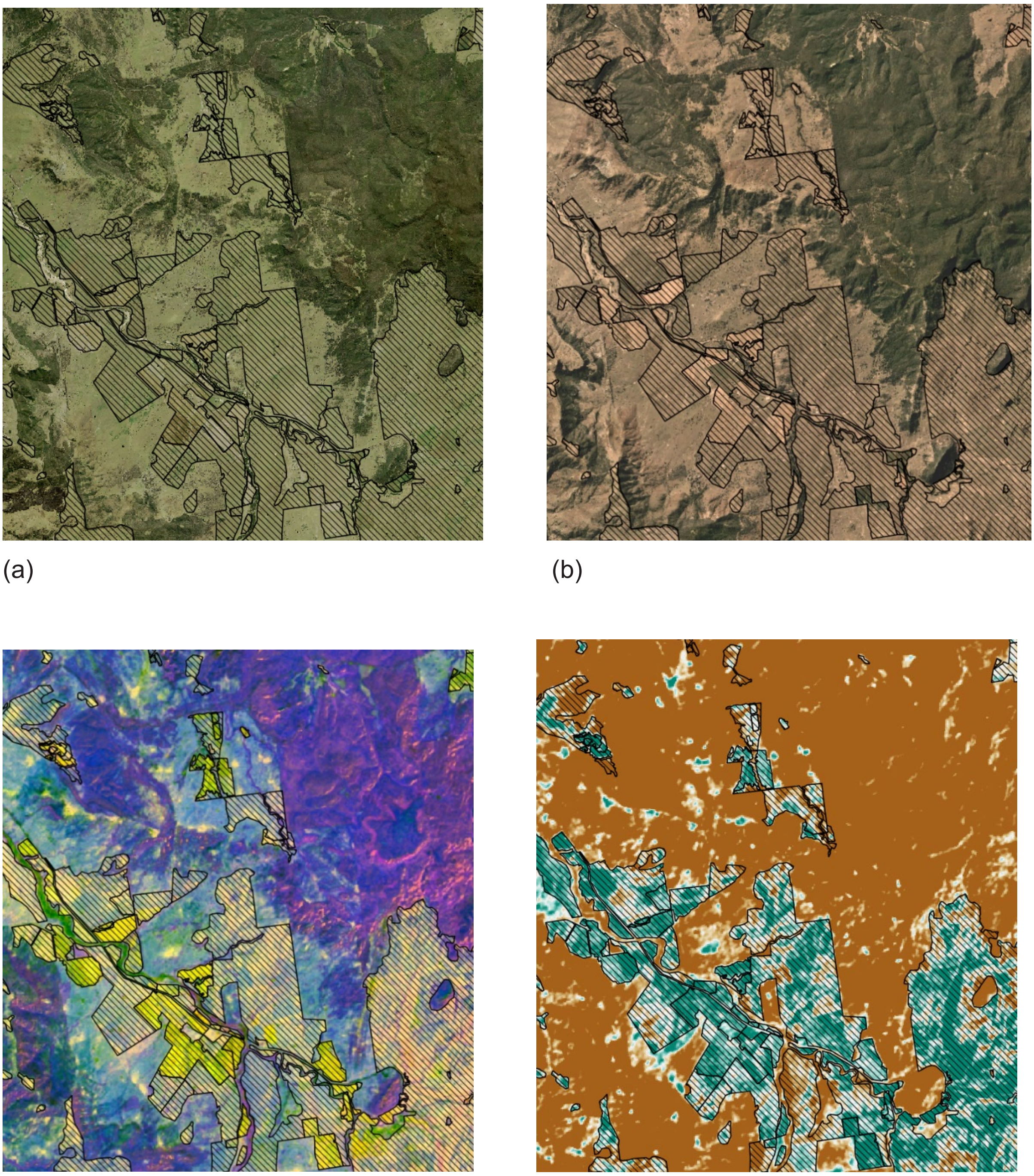
Disturbance class	Description
1	High certainty undisturbed
2	Likely undisturbed
3	Uncertain
4	Likely disturbed
5	High certainty disturbed

The training site selection was initially based on sampling a range of land cover types across a range of geographic areas to establish the feasibility of the model. These sites were based on recent high-resolution imagery, the time-series assessment method and some field surveys. The network of sites was expanded progressively to target more regions, additional land cover types and regions where the model predictions seemed incorrect. As new sites were collected the model was re-evaluated and more sites were measured in an iterative approach. Over 800 sites were established. The iterative approach was appropriate, as the model was evaluated against imagery sources covering the entire State not just against the training data used. In effect, data available for validation was more than four orders of magnitude more than used to fit the model.

The cost of collecting training sites resulted in a relatively low proportion of training data, and initial work indicated that the fractional cover statistics were not linearly separable across these sites. Consequently, a support vector regression (SVR) approach was used to implement the SCDIndex, as this method can handle higher-order data relationships without being susceptible to false ‘local optima’ solutions (Smola & Schölkopf 2004). After being fitted with the standardised training data, the SVR model was used to produce a continuous index for every available Landsat fractional cover time series in New South Wales. We used a threefold cross validation grid search to find the optimal parameters.

The SCDIndex product is illustrated in Figure 13. It shows an ADS aerial image (a), a 2017 Planet image (b), 1987–2017 SCDImage.v2 (c), and SCDIndex image (d). The mapped land use polygons for modified pasture and cultivated areas are overlaid on each of these figures. The SCDIndex image is represented by a colour ramp ranging from brown for low disturbance to aqua for high disturbance. The white areas represent the middle of the disturbance range.

There is general agreement between the SCDImage.v2 and SCDIndex images 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 SCDImage or SCDIndex. The land use mapping interpretation is described in more detail in Section 4 of the method statement.



(a) (b) (c) (d)

Figure 13 (a) ADS natural colour composite image for 2012; (b) Planet colour composite image for 2017; (c) SCDImage.v2 based on 1987–2017 Landsat images; (d) SCDIndex image based on 1987–2017 Landsat images.

The hatched polygons overlaid in black are land use data indicating either cultivated areas or modified pasture.

Development of a seasonal cover disturbance difference index

To augment the SCDIndex disturbance information, a seasonal cover disturbance difference index (SCD Difference Index) was developed to directly measure changes between two specific time periods, without requiring training site data. The motivations for this product were: (i) the need to assess whether changes have occurred more recently (i.e. since 2013) where there is insufficient data to use the SCDIndex approach, and (ii) to allow the team to compare scenario-specific time periods of interest.

For a given area and 2 time periods (t_0 and t_1), the SCD Difference Index is a spatially representable continuous index that summarises key statistical differences between the Landsat fractional cover values of dates t_0 and t_1. For a given Landsat pixel, the time series of total cover (green + non-green) and green proportion (green / total cover) are calculated for t_0 and t_1. The k-sample Anderson-Darling test (Scholz & Stephens 1987) is separately applied to (total cover (t_0), total cover (t_1)), and (green_proportion (t_0), green_proportion (t_1)), and then the absolute values of these 2 results are summed to create the SCD Difference Index value for that pixel. An example of the SCD Difference Index is shown in Figure 14.

The reason the k-sample Anderson-Darling test was chosen is that it tests for similarity between the different total cover and green proportion populations without needing to know the distribution function that describes these populations. This makes it generally applicable across most areas. One disadvantage is the difference rasters are not directly comparable with difference rasters derived from other time periods, so the value of this product is as a further additional line of evidence when mapping recent non-woody change.

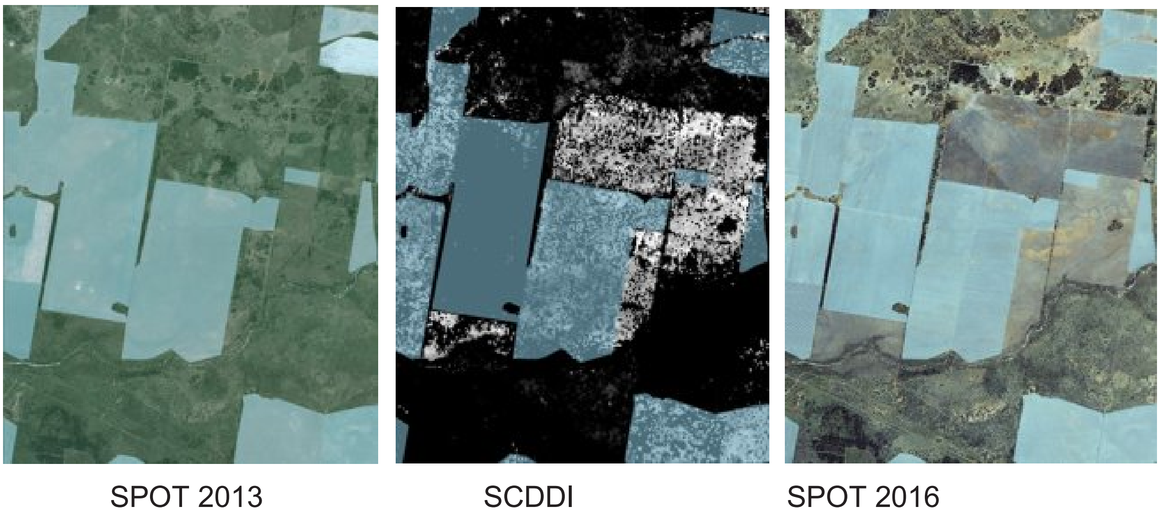


Figure 14 Seasonal cover disturbance difference index (SCD Difference Index) for the period 2013–2016 showing recent disturbance as white, with SPOT images shown for comparison

Appendix E: Supplementary detail for Section 6 (identifying and mapping woody vegetation change)

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

- woody vegetation extent from SPOT imagery (see E-1)
- detecting tree cover in ADS imagery (see E-2)
- woody vegetation change index (see E-3)
- vegetation trends map (see E-4).

Appendix E-1: 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 of the method statement, the August 2017 woody baseline layer was then created from the 2011 woody extent map.

Process

The process used both automated and manual processing steps (Figure 15). There were 4 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 foliage projective cover (FPC) for the woody vegetation pixels
4. assessing the accuracy of the map.

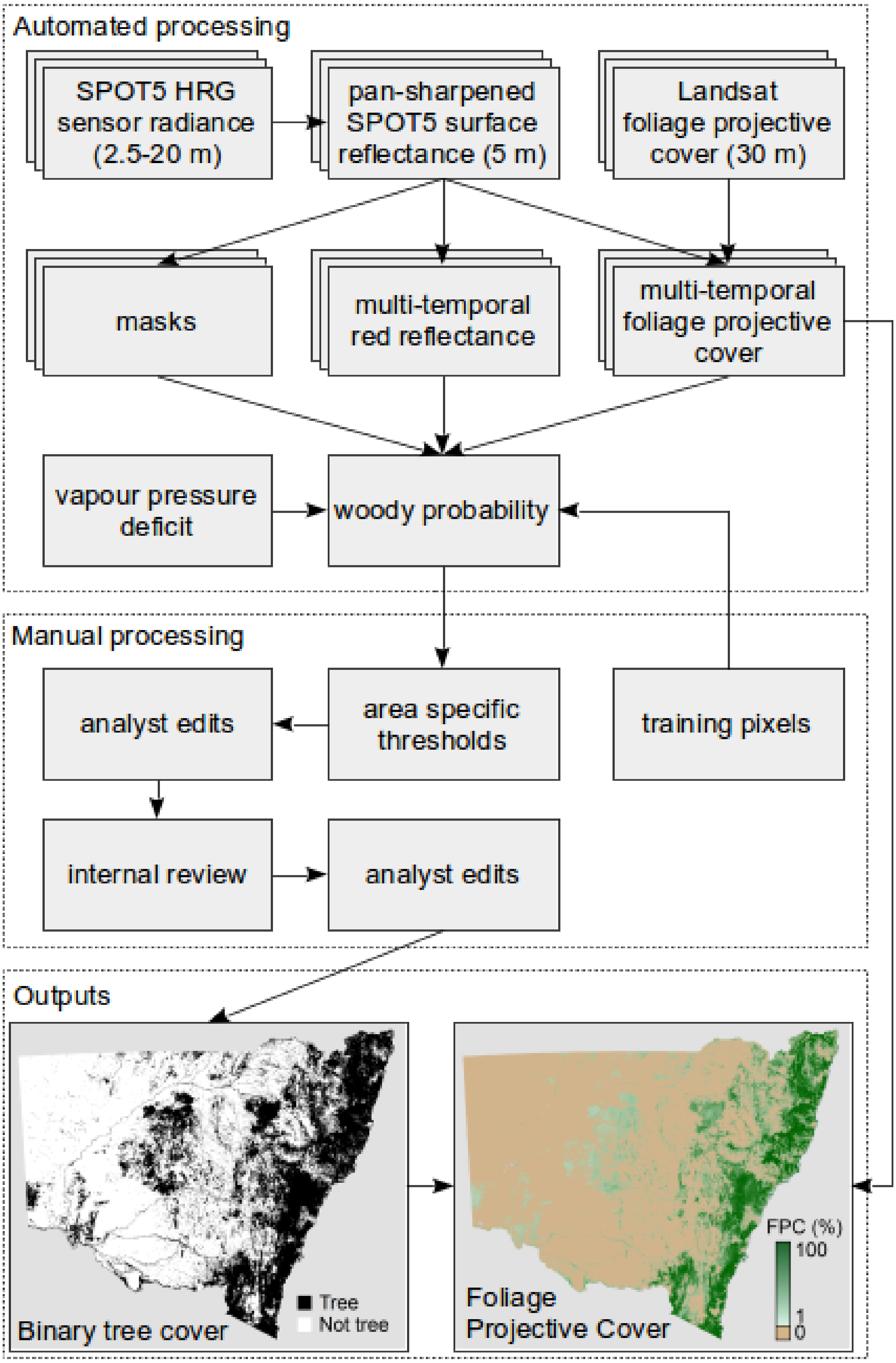


Figure 15 Method for producing the DPE 2011 woody vegetation extent map

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 A), and the foliage projective cover (FPC) model applied (Appendix A).

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 16C). 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 & Mengersen 2010). In addition, FPC is a direct measure of woody vegetation (Specht & 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 dataset, interpolated from a network of weather stations (Jeffrey et al. 2001).

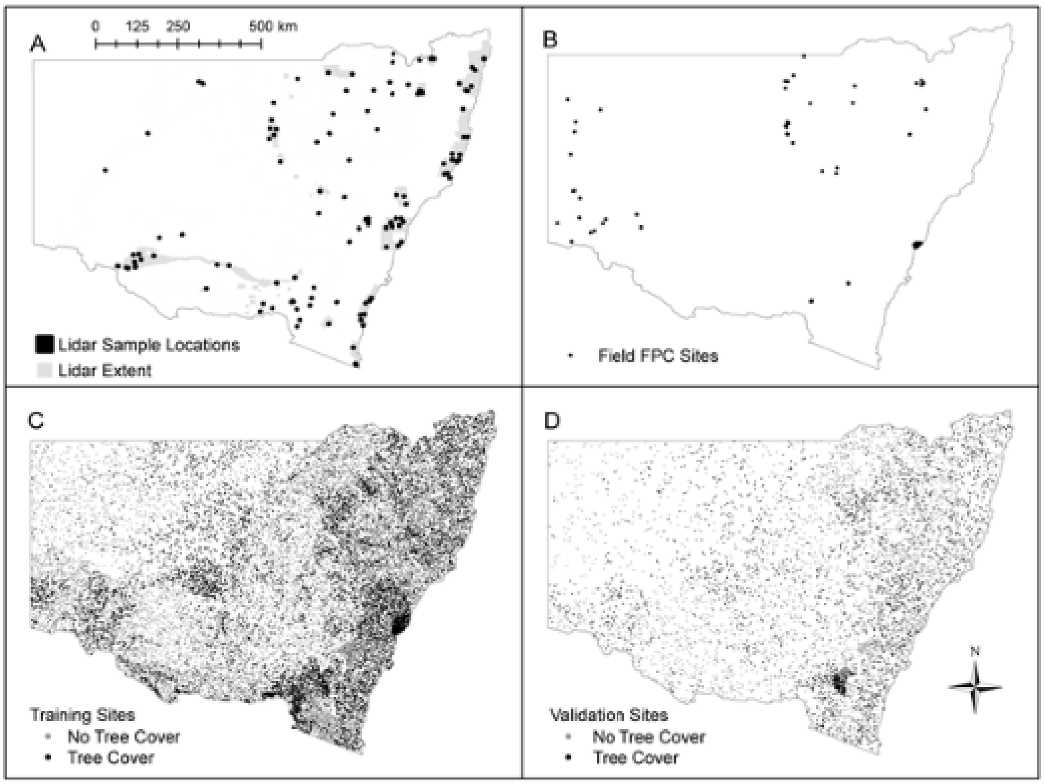


Figure 16 Reference data used in the training and validation of the woody extent and FPC map

A – light detection and ranging (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 x 57 km across New South Wales (Figure 17). 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.

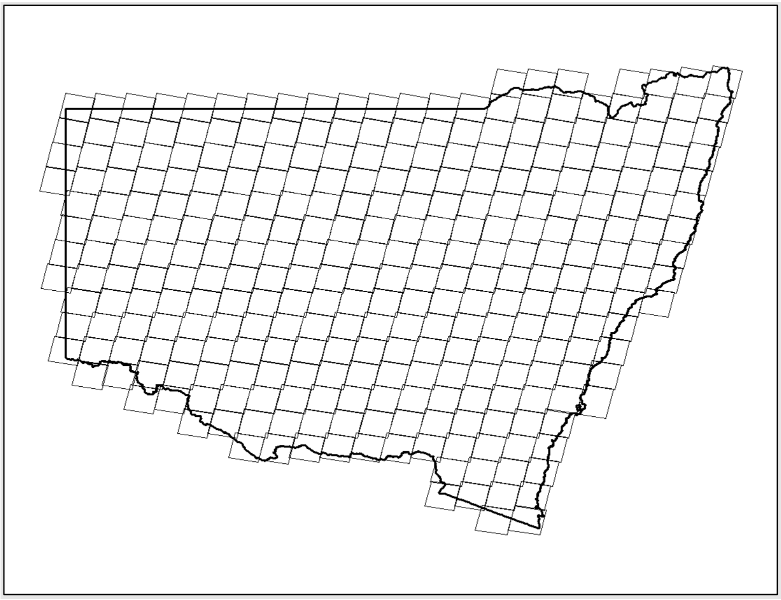


Figure 17 The 305 tiles used when editing the woody extent maps

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 mid-point 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 2 independently derived datasets of woody and non-woody vegetation. The first comparison used fine-detailed maps of woody vegetation extent from airborne light detection and ranging (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 4 gives the statewide accuracy statistics. Statistics by vegetation formation are available in Fisher et al. (2016).

Table 4 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	Woody probability with threshold (%)			Edited woody extent (%)		
		Overall	**Producer's**	**User's**	**Overall**	**Producer's**	**User's**
LiDAR reference	13,884,067	86	75	82	88	74	89
Visual interpretation	6,648	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 16B). A good relationship was found (Figure 18). The field measurements of woody FPC are described in detail below.

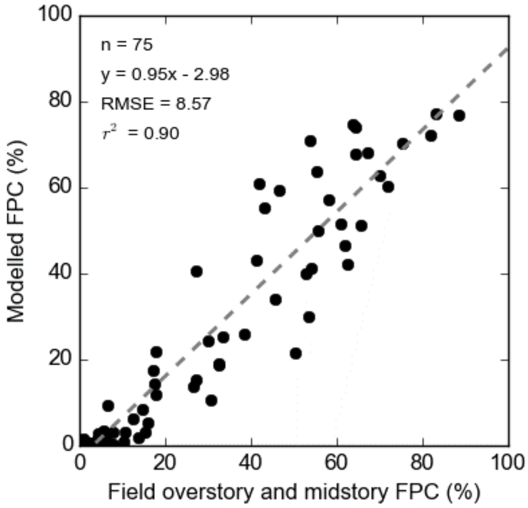


Figure 18 Relationship between SPOT-modelled woody FPC and the combined mid-storey and overstorey field measurements of FPC

Airborne LiDAR estimates of woody extent

LiDAR 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 16A 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 16B 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), mid-storey (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 mid-storey foliage, the combined FPC of the overstorey and mid-storey (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 E-2: Detecting woody vegetation using ADS aerial images

Introduction

The August 2017 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 with 5 m pixels representing the percentage of woody cover at the same 5 m pixel size as the August 2017 woody extent map. These images were used when refining the NVR Map (see Section 8 of the method statement and Appendix G).

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 E-1).

Detecting trees

The ADS sensor measures the amount of light reflected from 4 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 waterbodies, 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. Therefore, thresholds were determined for 2 km 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 m 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 E-1) was also used to identify potential tree commission errors created by shadows, soils and dark green crops. Any 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 use for validation (see tiles with yellow outline in Figure 19; the capture dates of the images are given in Table 5). 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 6).

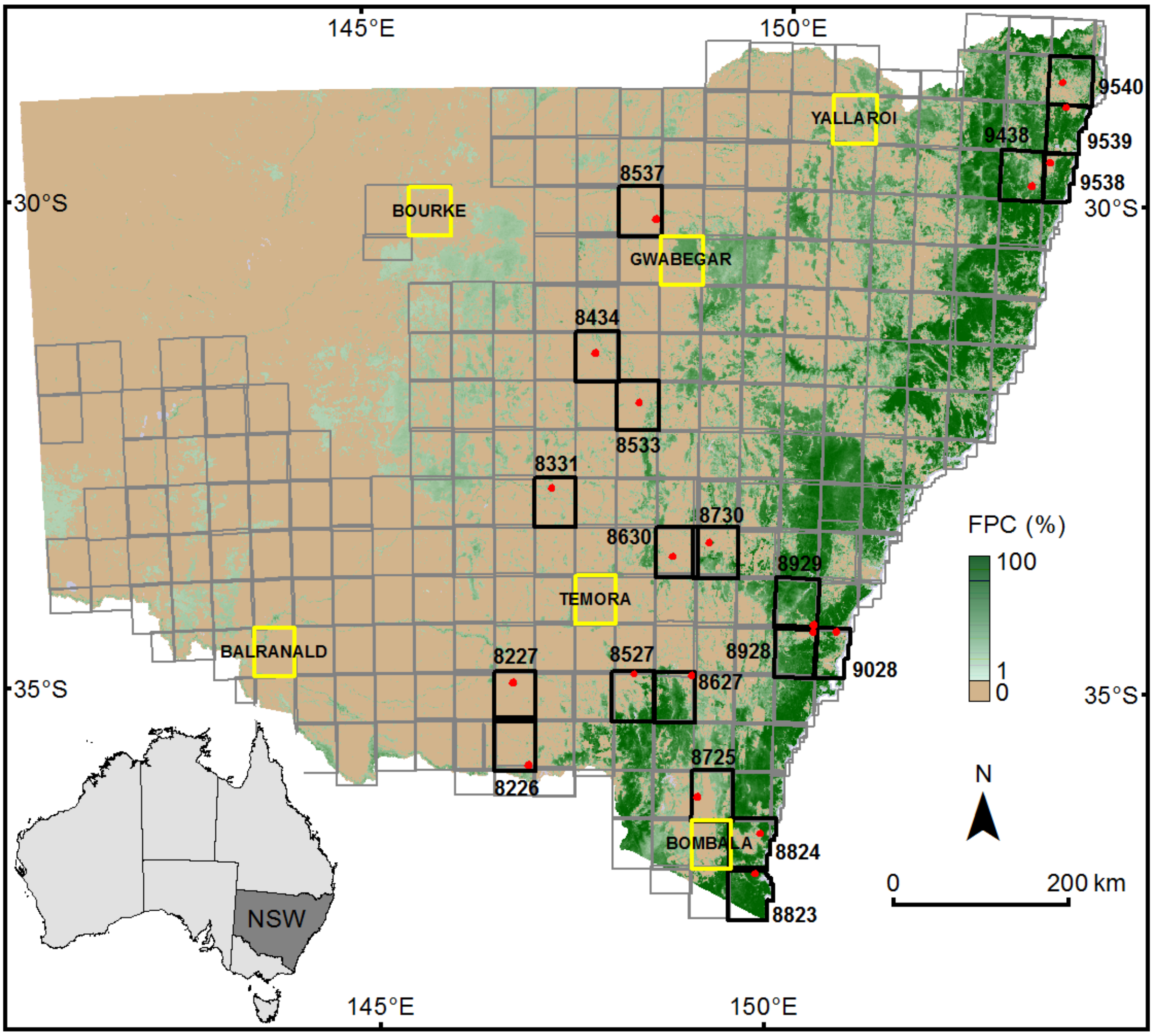


Figure 19 Locations used to train and validate the tree mapping across New South Wales

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 5 The date (in YYYYMMDD format) of the ADS imagery used for each 100,000 topographic map sheet in training and validating the ADS tree detection model

The dates are nominal: for each map sheet, the data is a mosaic of imagery captured on multiple flight-lines flown over several, usually consecutive, days. The date shown is the earliest date.

Map sheet	Date	Purpose
7628	20120105	Validation
8037	20150731	Validation
8226	20140222	Training
8227	20141218	Training
8331	20130914	Training
8429	20070918	Validation
8434	20130827	Training
8527	20140201	Validation
8533	20151006	Validation
8537	20130905	Validation
8627	20131025	Validation
8630	20140507	Validation
8636	20100629	Training
8724	20110224	Training
8725	20110307	Validation
8730	20140713	Validation
8823	20140110	Validation
8824	20140113	Validation
8928	20131219	Validation
8929	20131012	Validation
9028	20140111	Validation
9039	20110815	Training
9438	20101016	Validation
9538	20100612	Validation
9539	20090925	Validation
9540	20090916	Validation

Table 6 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	96
	Tree	4.9	30.1	35	86
	Total	67.6	32.4	100	
	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 19). Each was a 2 km 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 E-1), 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 3 RGB bands to accentuate the differences between vegetation and non-vegetation and are defined as:

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

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

Excess red index $ERI = 1.4r_c - b_c$

Excess difference index $EDI = EGI - ERI$

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

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 20.

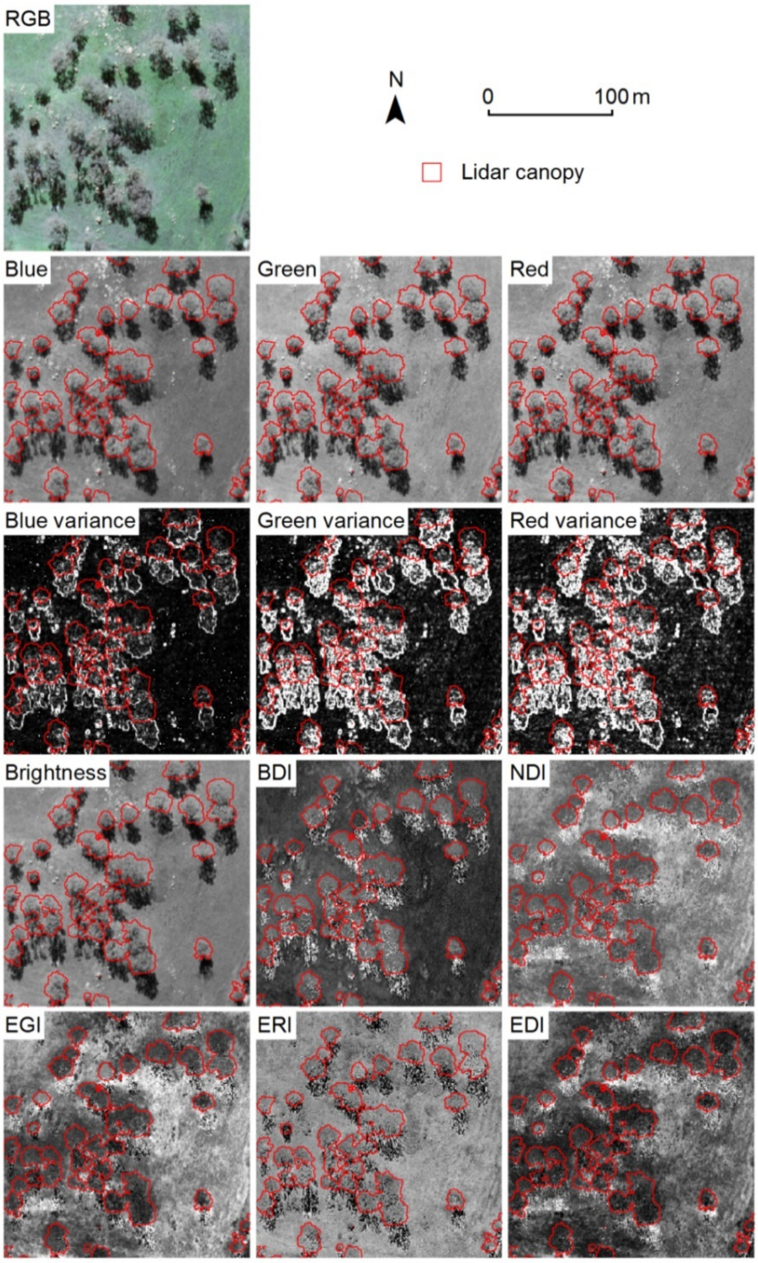


Figure 20 Examples of the indexes tested for classifying trees using simple thresholds on high-resolution imagery

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 eight images (Figure 21) and the largest mean AUC across the 20 images, and usually had ROC curves with large AUC values (Figure 21). The blue band also had the largest AUC in eight 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 two images, though in general the band combinations and band variance did not perform well (Figure 21).

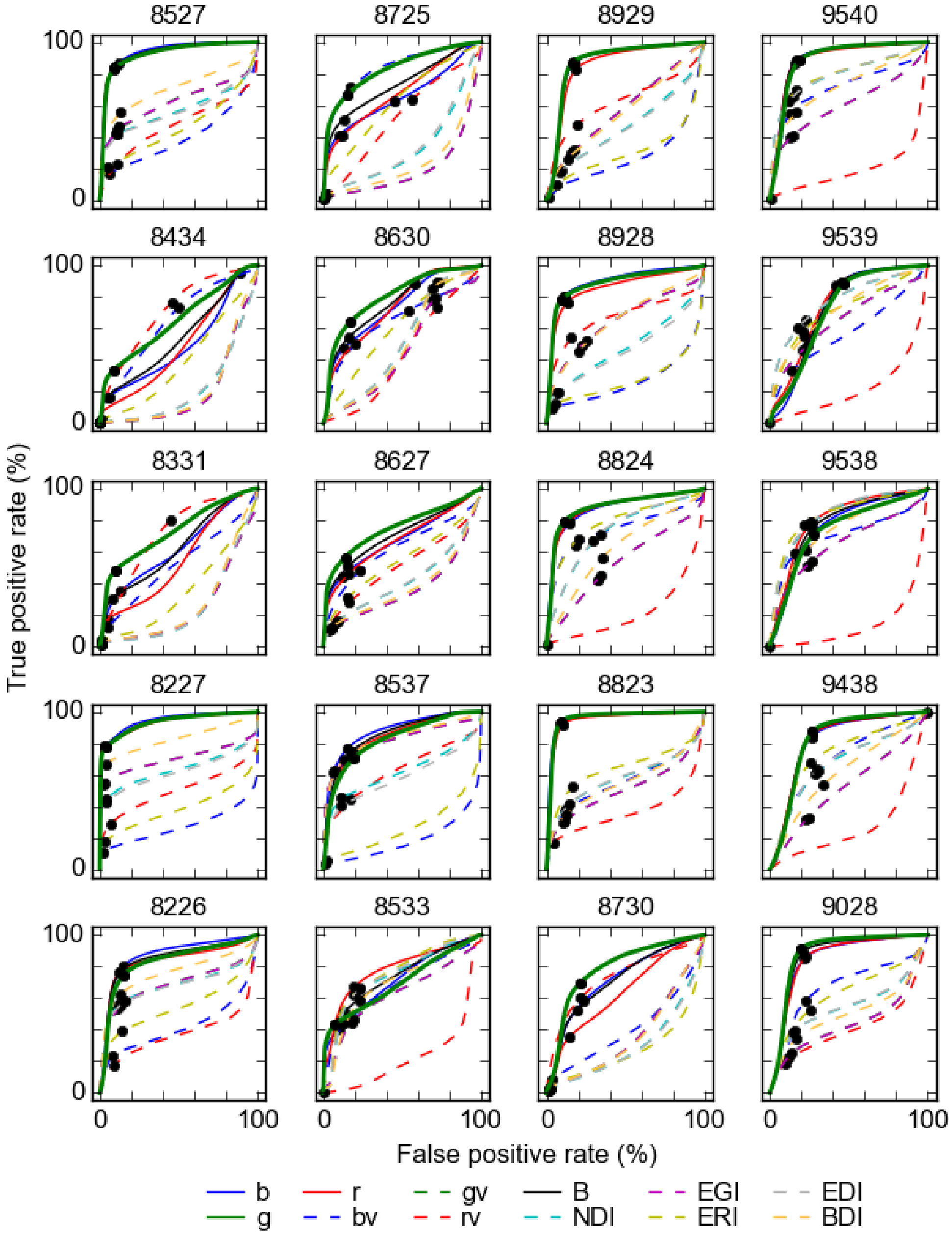


Figure 21 The accuracy of classifying tree and non-tree pixels using different bands and indexes for a range of thresholds, using receiver-operator characteristic (ROC) curves

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 (see Figure 19). 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 E-3: 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 department analysts interpreted, alongside satellite imagery, to map woody vegetation clearing. Note that the SPOT index was also used with the corresponding bands on the Sentinel-2 images.

The change index

In simple terms, the change index uses a ‘before’ and an ‘after’ image (Figure 22). The index performs well in the following circumstances:

- when there is a clear difference in the spectral signatures of corresponding pixels between the 2 images dates
- when this difference matches a typical vegetation loss signature.

In Figure 22, 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.

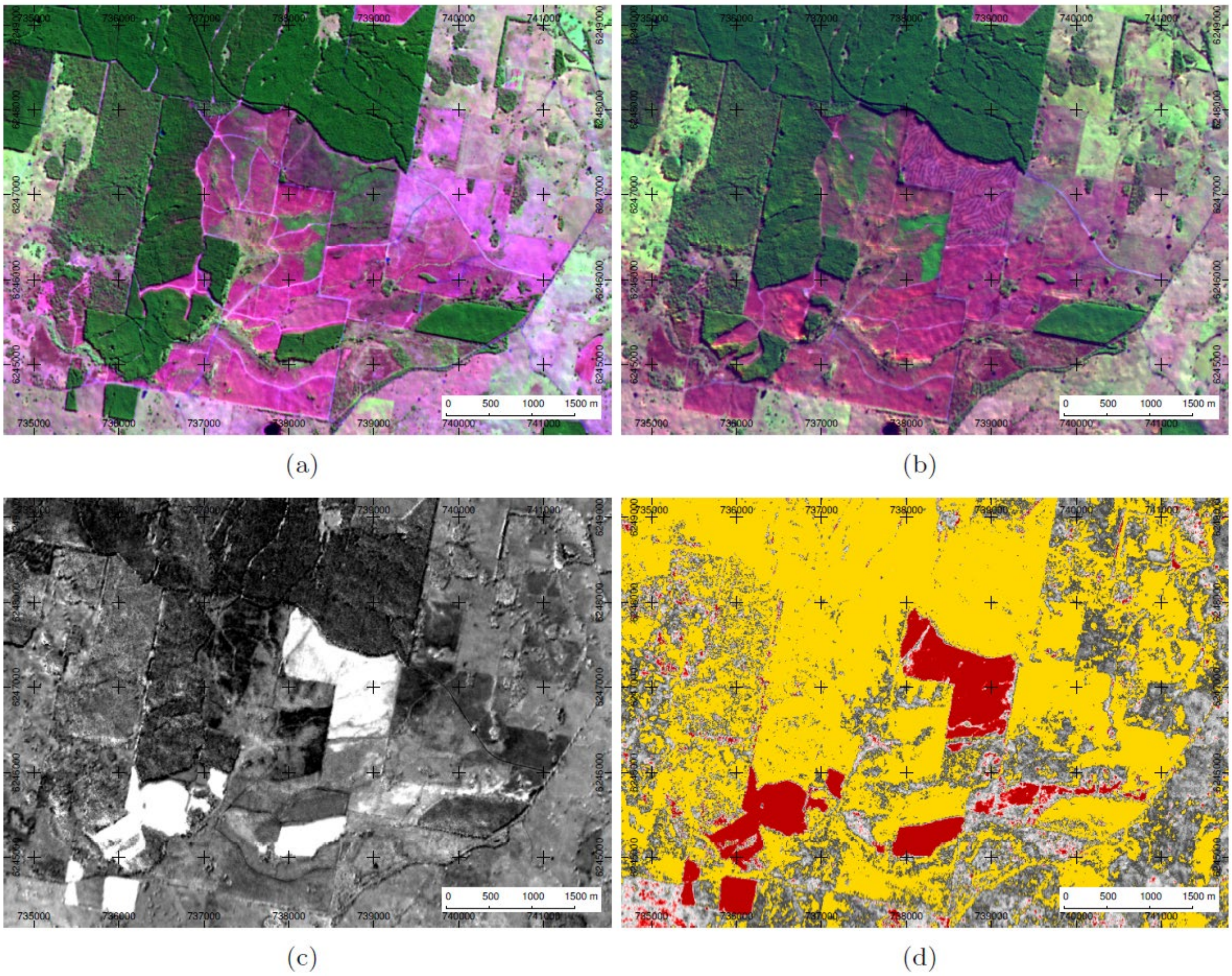


Figure 22 Example of the change index (c) and change likelihood (d) images created from two SPOT 5 images, before (a) and after (b) clearing has occurred

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, department analysts interpret the change likelihood images (Figure 22d). 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, namely either 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, the department reviewed the SLATS maps using information on green vegetation trends (Appendix E-4).

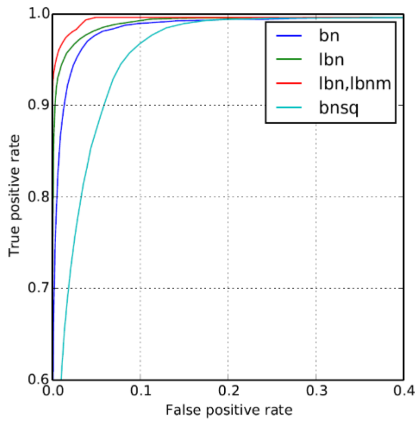
The change indexes for Landsat and SPOT use multiple linear regression models (Scarth, Gillingham & Muir 2008). The predictor variables in the models were:

- for the SPOT model (also used with Sentinel-2) – 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 23). 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.

(a)



(b)

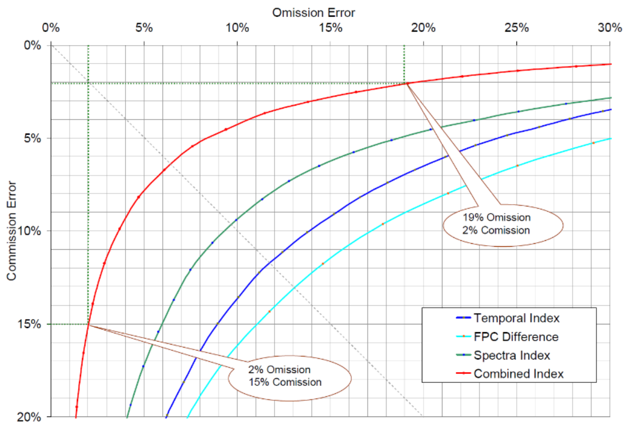


Figure 23 The receiver-operator characteristic (ROC) curves of the change indexes used in the SLATS program (red curves) for SPOT (a) and Landsat (b)

Source: The Landsat (b) image was taken from (Scarth, Gillingham & 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. Chart (b) in Figure 23 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 24), 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 the department (regardless of how they were classified in the change index).

Figure 24 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 24(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 the department 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 24(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 department 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.

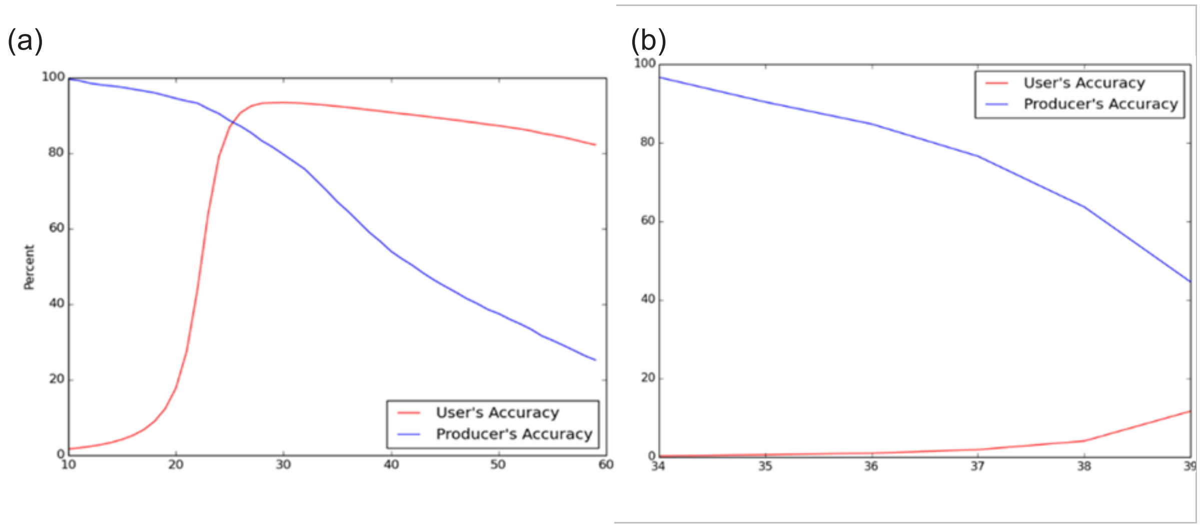


Figure 24 Estimates of the user’s and producer’s accuracies for the SPOT (a) and Landsat (b) change indexes at different index values (x-axis)

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 25 shows that small areas of woody clearing, like single paddock trees, are detected better using the SPOT data than Landsat.

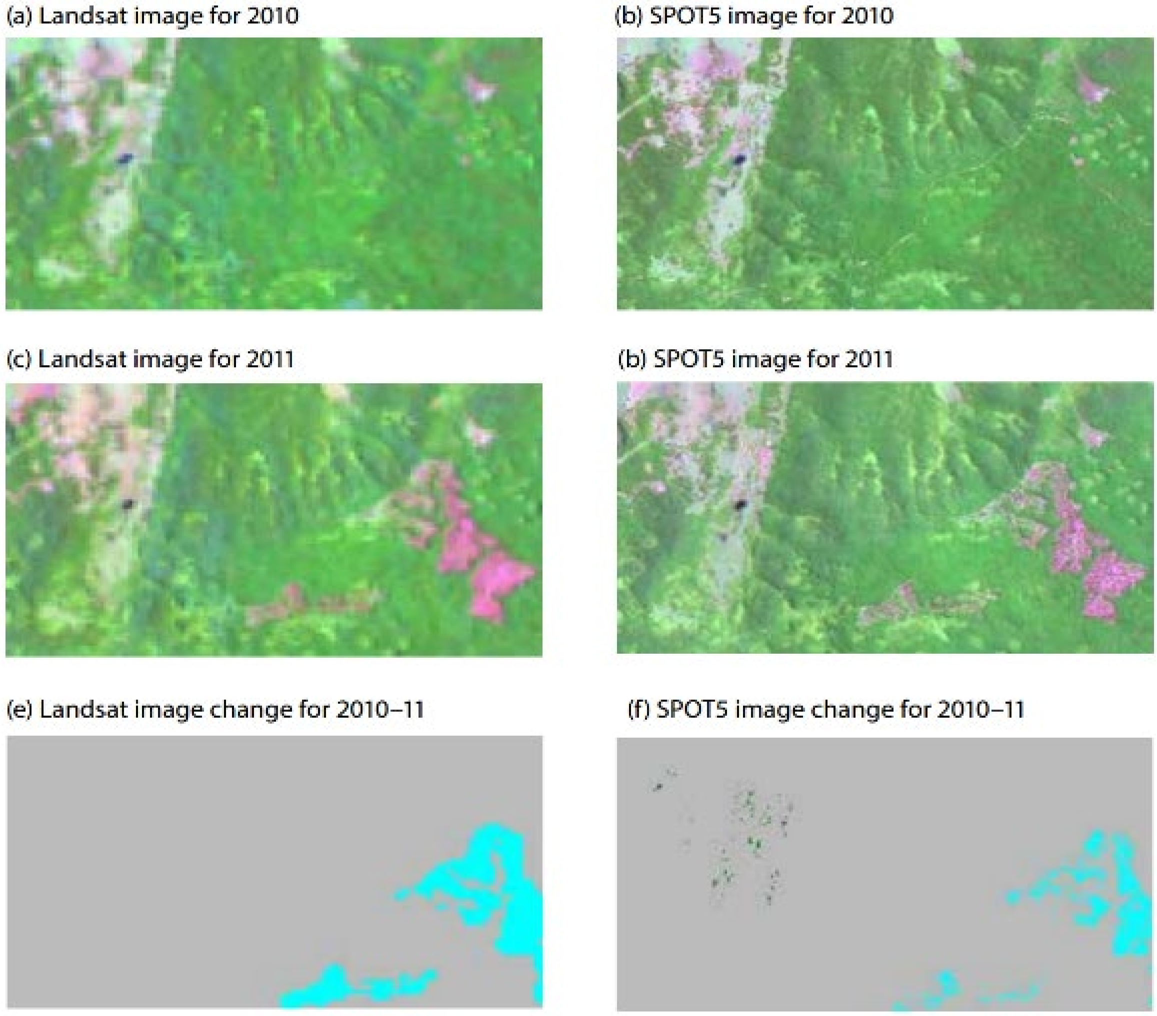


Figure 25 Comparison of SPOT 5 and Landsat 5 woody vegetation change showing the effects of the difference in resolution

SPOT 5 detects clearing of scattered trees, as shown by the dark green areas in image (f), that were missed by Landsat 5 (no dark green areas in image (e)). 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 7 shows the years in which woody vegetation loss maps were produced by the SLATS program, and the source of the image date used.

Table 7 Satellite images (from Landsat, SPOT and Sentinel-2 satellite programs) used to map woody vegetation loss across change eras

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
2014–2015	SPOT 5 HRG	5 m
2015–2016[+]	SPOT5 HRG and Sentinel-2	5 m
2016–2017[+]	SPOT5 HRG and Sentinel-2	5 m
2017–August 2017[$]	Sentinel-2	10 m

* 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.

^ Mapping for both Landsat and SPOT 5 data was included in the NVR Map.

Landsat data not included in NVR Map as it was superseded by the SPOT 5 data.

+ The 2015–2016 and 2016–2017 maps were created by running the change index model using images captured two years apart (a SPOT 5 image in 2015 and a Sentinel-2 image in circa January 2017), with analysts interpreting the era in which change occurred using a circa January 2016 Sentinel-2 image.

$ The final change period was sub-annual, from circa January 2017 to circa August 2017 to coincide with the commencement of the LLS Act.

Appendix E-4: Process used to create the woody vegetation trend map

Introduction

The process used to detect woody vegetation loss (Appendix E-3) uses 2 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. Section 6 of the method statement describes how it was used in the mapping process.

The department 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 26).

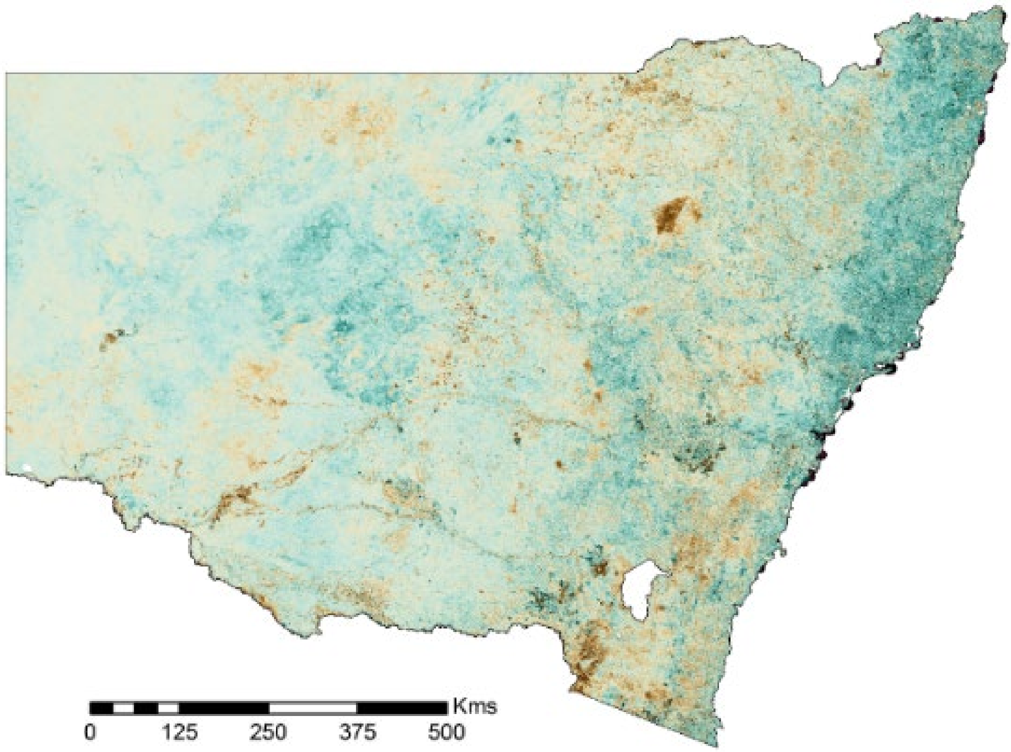


Figure 26 The vegetation trend map for New South Wales 1987–2013

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.), 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 A) was the input data. A minimum-value smoothing approach was used to model the persistent green cover. Figure 27 shows, for a single pixel, the seasonal time series of green vegetation cover (the coloured 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.

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

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

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 $i = 1, \dots, n$. 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 27) was calculated by fitting a straight line to the persistent green line. It is the slope of this trend line that was mapped (Figure 26). 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 Section 6 of the method statement).

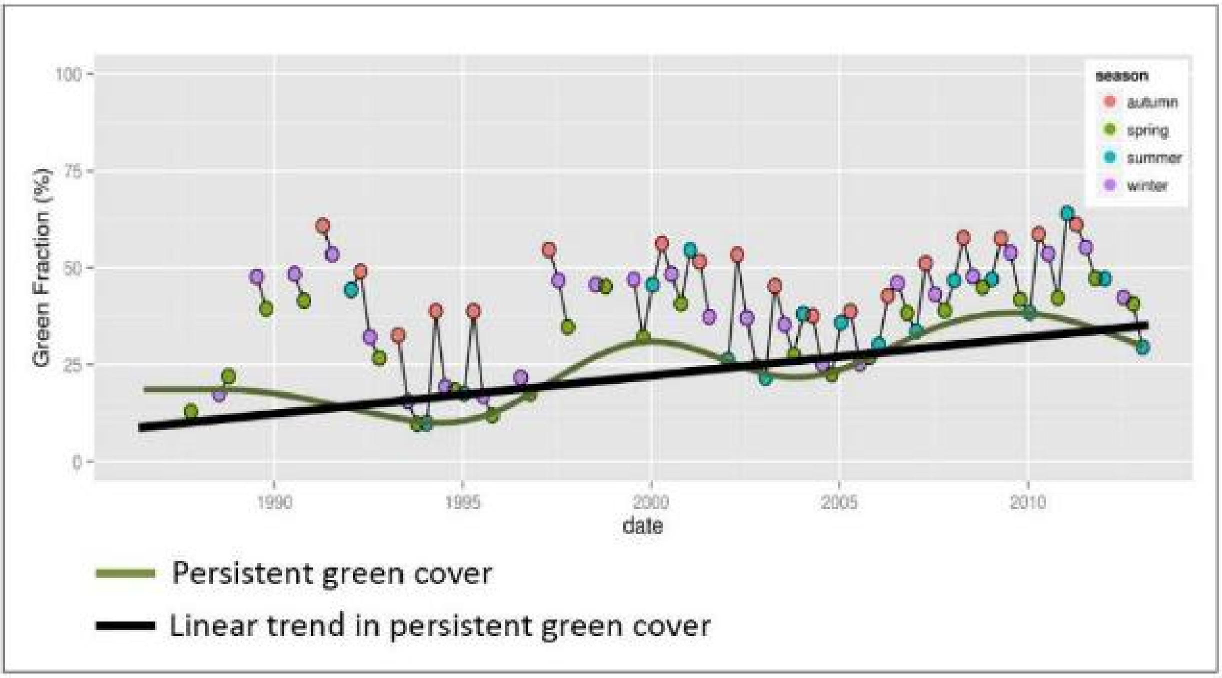


Figure 27 A time series of the seasonal green vegetation cover fraction for a single pixel (coloured dots)

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 28(a)). The star transect method (Muir et al. 2011) was used to collect field observations as described in Appendix E-1 and the field-measured persistent green cover fraction calculated as for the FPC from the overstorey and mid-storey components also described in Appendix E-1:

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

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 28(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 mid-storey contributes significantly to the green signal observed by the sensor. Inspection of these sites reveals the contribution is most commonly from the presence of grass trees (*Xanthorrhoea* spp.), currant bush (*Carissa ovata*), heathland and woody regrowth after tree clearing.

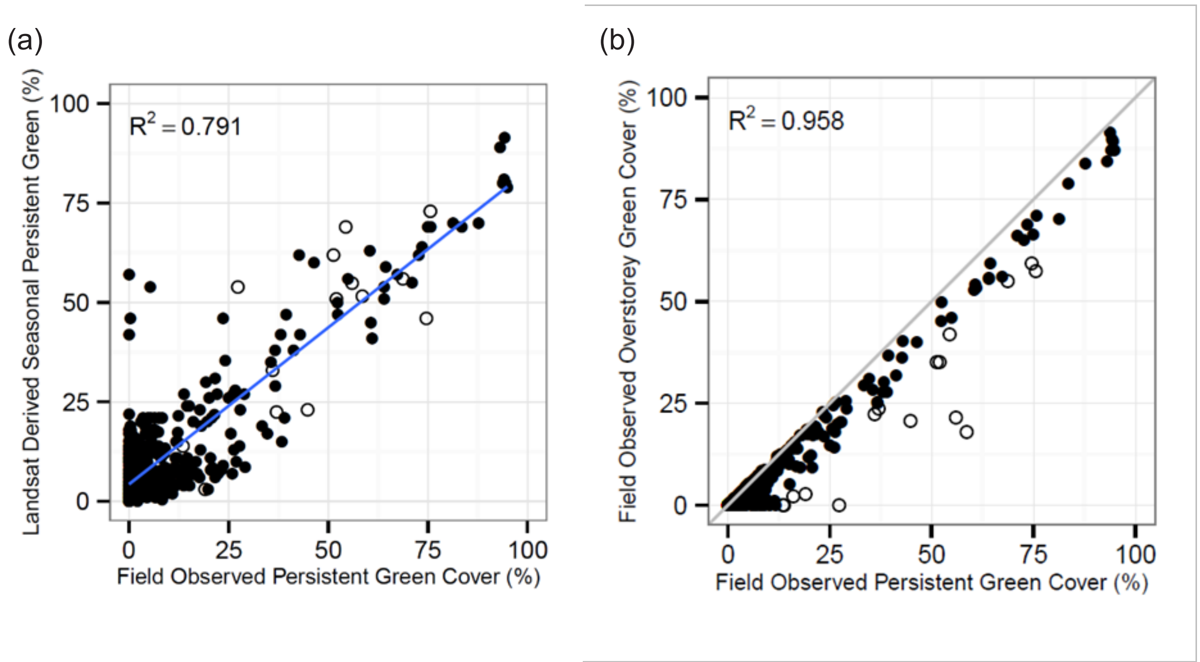


Figure 28 Relationship between Landsat-derived persistent green and field-observed persistent green cover (a)

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

Appendix F: Datasets used for prescribed area layers

The prescribed area layers listed below are incorporated into the NVR maps based on the build order in the table. In locations where the prescribed areas overlap, it is the one with the highest build order value that will be represented in the map. These layers are applied to the map after the initial NVR Map category assignment in which the NSW Landuse, detectable clearing events and woody vegetation extent layers are combined.

Notes:

This table is correct at the time of publication. Any amendments to the legislative package may modify this table.

^ Biodiversity Conservation (Savings and Transitional) Regulation 2017.

DAWE = Commonwealth Department of Agriculture, Water and the Environment (previously Department of Energy and Environment).

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
50	Category 1	Biodiversity certified	60H(3)		DPE	
40	Category 2–sensitive	Ramsar wetland	60I(2)(k)	108(2)(b)	DAWE/DPE	Spatial data may be misaligned by up to 150 m
40	Category 2–sensitive	Critically endangered ecological community (CEEC)	60I(2)(m)	108(2)(b)	DPE	Mapping may be an overestimate of the CEEC in some places due to the broad nature of the composite datasets
40	Category 2–sensitive	Critically endangered plants	60I(2)(l)	108(2)(b); 112	DPE	
40	Category 2–sensitive	Biodiversity stewardship agreements including biobanking agreements	60I(2)(c)	cl. 13(1) Savings & Transitional Regulation ^	DPE	Subject to cadastral errors and may be indicative only

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
40	Category 2–sensitive	Conservation agreements under Biodiversity Conservation Act (BC Act) or National Parks and Wildlife Act (NPW Act)	60I(2)(c); 60I(2)(n)	113(1)(b)	DPE	Subject to cadastral errors, generated from 1:25,000 topographic maps
40	Category 2–sensitive	Wildlife refuge agreements under Part 5 BC Act	60I(2)(c)			
40	Category 2–sensitive	Nature Conservation Trust (NCT) agreement	60I(2)(n)	113(1)(e)	NCT	Subject to cadastral errors
40	Category 2–sensitive	Subject to set aside requirement in accordance with land management (native vegetation) code	60I(2)(d)	108(2)(b)		
40	Category 2–sensitive	Registered property agreements	60I(2)(n)	113(1)(d)	DPE	Subject to cadastral errors
40	Category 2–sensitive	Core koala habitat	60I(2)(j)	108(2)(b)	DPE	Gazetted koala plan of management (KPoM)
40	Category 2–sensitive	Southern Mallee conservation agreements	60I(2)(n)	113(1)(h)	DPE	Subject to cadastral errors
40	Category 2–sensitive	Property vegetation plan (PVP) offset	60I(2)(h)	108(2)(b)	DPE	See F-1 PVP notes below
40	Category 2–sensitive	Self-assessable code, Ministerial order or set aside	60I(2)(h)	113(1)(i)	DPE	See F-1 PVP notes below
40	Category 2–sensitive	Current Conservation PVP	60G(3)(c)	108(2)(e)	DPE	See F-1 PVP notes below
40	Category 2–sensitive	Current Incentive PVP	60G(3)(c)	108(2)(e)	DPE	See F-1 PVP notes below
40	Category 2–sensitive	Current remedial direction	60I(2)(f)	108(2)(a)	DPE	Reverts to category 2 when agreement expires

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
40	Category 2–sensitive	Biodiversity certified conservation measure	60I(2)(g)	108(2)(b)	DPE	Captured by Council as per standard technical requirements of local environment plan (LEP) maps, therefore may be subject to cadastral error
40	Category 2–sensitive	High conservation value grasslands/groundcover	60G(3)(c)	108(2)(f)	DPE	
40	Category 2–sensitive	Recommended by Environment Agency Head for declaration as Area of Biodiversity Value (AOBV)	60G(3)(c)	108(2)(g)	DPE	
40	Category 2–sensitive	Set aside for nature conservation/native veg offset as development consent condition	60I(2)(n)	113(1)(i)		
40	Category 2–sensitive	Private native forestry – rainforest	60I(2)(n)	113(1)(k)	EPA	
40	Category 2–sensitive	Private native forestry – old growth	60I(2)(n)	113(1)(j)	EPA	
40	Category 2–sensitive	Plantation required retained vegetation	60I(2)(n)	113(1)(f)	DPI	
40	Category 2–sensitive	Coastal Management SEPP – coastal wetlands – core area	60I(2)(i)		DPE	Replaces SEPP 14
40	Category 2–sensitive	Coastal Management SEPP – littoral rainforest – core area	60I(2)(i)		DPE	Replaces SEPP 26
40	Category 2–sensitive	Set aside area established under the Local Land Services Act (LLS Act)	60I(2)(c); 60I(2)(n)	113(b); 113(d); 108(2)(a)	LLS	

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
40	Category 2–sensitive	Enforceable undertaking under LLS Act	60I(2)(b); 60I(2)(f)	108(2)(a)	LLS	
40	Category 2–sensitive	Plantation retained drainage buffer	60I(2)(n)	113(1)(f)	DPI	
30	Category 2–vulnerable	Vulnerable land – protected riparian	60I(2)(b); 60F(2)(c)		DPE	Generated by Environmental Agency Head from existing riparian datasets. Riparian dataset has a positional accuracy <100 m. See F-2 Vulnerable lands note below.
30	Category 2–vulnerable	Vulnerable land – special category	60I(2)(b); 60F(2)(c)		DPE	Dataset digitised from scanned rectified topo maps (scale ranging from 1:25,000, to 1:100,000)
30	Category 2–vulnerable	Vulnerable land – steep or highly erodible land	60I(2)(b); 60F(2)(c)		DPE	Lands ≥18 degrees as defined by the SME DEM slope data. F-2 Vulnerable lands note below.
20	Category 2	Unlawful clearing prosecutions – conviction or finding of guilt	60I(1)(b)	115	DPE	See F-3 Prosecution note below
20	Category 2	Unlawful clearing – civil court order to remedy or restrain contravention	60I(1)(b)	115		
20	Category 2	Grown or preserved with public funds (LLS database)	60I(2)(a)		LLS	Spatial data and attribute accuracy inconsistent
20	Category 2	Preserved with public funds – Green Army 20 million trees	60I(2)(a)		DAWE	Spatial data from the Biodiversity Conservation Grants for projects from March 2009 until July 2017

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
20	Category 2	Preserved with public funds – *Saving Our Species* funded sites	60I(2)(a)		DPE	
20	Category 2	Grasslands that are not low conservation value	60I(2)(e)			
20	Category 2	Previously subject to remedial direction	60I(2)(f)			If current, then sensitive
20	Category 2	Groundcover that is not low conservation value	60I(2)(n)	109(2)		
20	Category 2	Travelling stock reserve unless in Western Division	60I(2)(n)	113(1)(l)	Spatial Services	Central and eastern divisions only
20	Category 2	Low conservation value grasslands beneath canopy or drip line of Cat 2 woody veg	60I(2)(n)	113(1)(g)		
20	Category 2	Coastal Management SEPP – coastal wetlands – buffer	60I(2)(i)	108(5)	DPE	Replaces SEPP 14
20	Category 2	Coastal Management SEPP – littoral rainforest – buffer	60I(2)(i)	108(5)	DPE	Replaces SEPP 26
20	Category 2	Private native forestry – live	60I(2)(n)	113(1)(a); 108(2)(c)	LLS	
20	Category 2	Private native forestry – finalised	60I(2)(n)	113(1)(a); 108(2)(c)	LLS	
10	Category 1	PVP clearing, both broadscale and paddock trees (legally cleared since 1990)	60H(1)(b)		DPE	See F-1 PVP notes; broadscale and paddock trees below
10	Category 1	Identified regrowth / continuing use in a PVP	60H(1)(a)		DPE	See F-1 PVP notes; identified regrowth below
10	Category 1	Regrowth date change in a PVP	60H(2)(b)		DPE	See F-1 PVP notes; regrowth date change below

Build order	Category	Description	LLS Act section	LLS Regulation clause	Custodian	Comments
10	Category 1	PVP offset – local government area routine agricultural management activity (RAMA) cleared area	60H(1)(b)		DPE	See F-1 PVP notes below
10	Category 1	Increased infrastructure width – PVP	60H(1)(b)		DPE	See F-1 PVP notes below
10	Category 1	Paddock tree code of practice cleared area	60H(1)(b)		DPE	See F-1 PVP notes; paddock tree code of practice below
10	Category 1	Clearing authorised under other legislation	60O(a)(b)			
5	Category 1	Low conservation value grasslands not unlawfully cleared	60H(2)(a) 60H(4)(c)			
5	Category 1	Land containing only low conservation value groundcover	60H(2)(c)	109(1)		

Appendix F-1: PVP notes

Property vegetation plan (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 Native Vegetation Notification System (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 former Catchment Management Authority (CMA) staff in the process of developing 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 Local Land Service (LLS) staff in the process of developing 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 PVPs.
- **NVNS** (Native Vegetation Notification System) – Data collected using online web mapping tool developed by the department 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 Native Vegetation Regulations 2013. In all applications, underlying imagery was predominantly SPOT 5. The NSW Digital Cadastral Database (DCDB) formed the basis of property boundary identification, which in some cases influenced the position of polygons being drawn in the relevant agreement.

PVP clearing, both broadscale and paddock trees (legally cleared since 1990) – Land will only change categories once clearing authorised under the PVP has been completed.

Identified regrowth / continuing use in a PVP – Some PVPs that identify regrowth or the continuation of existing farming activities, may only declare certain strata of vegetation as regrowth. This means that remaining vegetation may be remnant vegetation and thus required to be categorised as category 2 – regulated land.

Regrowth date change in a PVP – Some PVPs that identify regrowth and reset the regrowth date may only declare certain strata of vegetation as regrowth. This means that remaining vegetation may be remnant vegetation and thus required to be categorised as category 2 – regulated land.

Paddock tree code of practice cleared area – Land will only change categories once clearing authorised under the paddock tree code notification has been completed.

Appendix F-2: Vulnerable lands note

Vulnerable lands comprise three individual components: protected riparian, steep lands and special category lands. Special category lands have been carried over from existing mapping, while the riparian and steep lands layer have the potential to be refined with inclusion of more recent or higher resolution imagery.

Protected riparian

NSW Spatial Services maintain and produce topographic maps for New South Wales. The various hydrological features that appear on topographic maps such as streams, lakes and pools have been digitised and stored in a geographic database called the Digital

Topographic Database (DTDB). The DTDB stores geographic features, classes or layers as either points, lines or polygons which represent the different topographic features, such as stream centrelines, waterbodies, contour lines and infrastructure for New South Wales.

Originally stream features were mapped using stereoscopic imagery interpretation from 1:25,000 or 1:50,000 scale aerial photographs. Since 2007, new digital aerial imagery (ADS) has been used to progressively update some of the topographic streams data, however, this is not yet fully comprehensive across the State.

Hydro-features in the DTDB are tagged or attributed with various standard descriptors such as a 'name', 'natural or man-made channels', 'perennial/non-perennial' etc.

NVR Map – Riparian refinement process

The department selected relevant components of the Hydroline and HydroArea feature classes from the DTDB and applied a buffer with watercourses receiving 22.5 m (assumes an average 5 m wide stream) and waterbodies 20 m buffers respectively. This buffer distance has been used in previous legislation.

For the NVR Map application, only topographic streams identified as 'natural' and that had an assigned 'name' were used. Other manual edits have been completed to remove riparian features where the land use has eliminated the natural stream features since the topographic map was created. For example, where a raised irrigation dam occurs through an intermittent waterway.

Supplementary information identifying prescribed streams status (section 26D of the now repealed *Water Act 1912*) was integrated into the protected riparian layer to facilitate the consideration of continuing protection over these areas.

The topographic maps are updated infrequently and may not reflect the current situation or they may not have used the most up-to-date imagery.

The aerial imagery used by the original topographic mappers to identify the stream features in some parts of the State may be of a lower resolution than currently available.

The main potential sources of inaccuracies for the vulnerable riparian land dataset are:

- displacement in the source topographic hydrological feature data
- generalisation or displacement due to original scale and technique of topographic mapping
- natural movement of streams over time
- incorrect assignment of names to minor stream segments
- old or isolated flow channels and flood runners mapped as waterbodies
- recent stream channel modification due to land use.

If any inconsistencies are found as part of a map review or annual update, these areas receive individual desktop assessment looking at current high-resolution digital imagery, time-series analysis and updated streamline information based off up-to-date digital elevation model data. All recommended changes are peer reviewed and go through an approval process before integration into the NVR Map.

Steep lands

The revised steep lands data layer has been created from the DCS surface model enhancement 5 m elevation data.

Data was captured between 2012 and 2018 from photogrammetric (ADS) and LiDAR point cloud-based sources.

Data issues relating to combining differing data of varying resolutions, file types, naming, coordinate systems, incorrect zone designation and height datum were cleansed and then assembled into 100,000 mosaics with smoothing applied.

Slope was generated by using the Horn method (Horn 1981) with a 3 x 3 nearest neighbourhood algorithm. Areas identified as steep land, being 18 degrees or greater, were reclassified to produce a Stage 1 Steep layer.

Stage 2 involved fill and elimination of small features less than or equal to 1000 m^2 to provide a layer at the NVR Map scale.

Data checks have been completed on the initial DCS surface model and derived steep land products. This involved some reprocessing of areas where issues were identified and substitution with SRTM-derived data where no other reliable data was available.

Onsite inspections have verified the accuracy of the slope product on selected sites.

Areas subject to map review prior to the steep lands update have followed the same processing method that has now been adopted by the new version of steep lands. An assessment of review of recommendations and final approval were performed prior to integration into the map.

Appendix F-3: Prosecution note

In the majority of cases the boundary has been spatially captured based on the area that the department 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 activities (RAMAs). The area captured for cases prior to 2014 have predominantly been based on land parcel information of lot/DP. For those cases since 2014 the area defined represents the vegetation modified or removed. These areas will include areas cleared under RAMAs. The area captured represents the area to be remediated and has been captured from a number of sources.

Appendix G: Further details on map formation

This appendix provides further details related to the map formation process described in Section 8 of the method statement. Each land use class is given a map formation rule, which determines how the NSW Landuse, woody vegetation, and woody clearing layers are combined to determine the initial map category (Appendix G-1). The maps are then further refined by analysts as outlined in Appendix G-2.

Appendix G-1: Map formation rules for each land use class

Table 8 sets out the map formation rules for the initial map category assignments. The map categories within a rule can vary depending on the presence (or absence) of woody vegetation and/or detectable clearing events. These rules are scripted and applied automatically.

Table 8 The map formation rules for the initial map category assignments

Map formation rule	Woody in the woody vegetation extent map	Clearing detected	Map category
1	Not considered	Not considered	1
2	No	Not considered	1
2	Yes	No	2
2	Yes	Yes	1
3	No	Not considered	1
3	Yes	Not considered	2
4	Not considered	Not considered	2
5	Not considered	Yes	1
5	Not considered	No	2

Table 9 shows the map formation rule assigned to each land use class which was used to determine map category using the land use, woody extent and detectable clearing layers (see Section 8 of the method statement). 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). Section 4 of the method statement lists all ALUM classes.

Table 9 The map formation rule assigned to each land use class, to determine the map category assignment using the land use, woody extent, and detectable clearing layers

ALUM class	Description	Map formation rule	ALUM class	Description	Map formation 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	5	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 G-2: Checking and refining the map

Introduction

There are known limitations to the 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 E-1). Limitations of SLATS clearing data were largely due the 30 m Landsat pixel (Appendix E-3), which can result in larger areas being mapped as cleared than were actually cleared on the ground. As a result, some of the initial map category assignments are incorrect, so analysts checked and refined the maps.

The ADS tree cover maps (Appendix E-2) 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, where every pixel (with a size of 5 m) 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 and clearing data. Table 10 summarises where the woody cover 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, in regular thresholds of increasing cover, 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 10). The final column shows the pixel codes and colours in the refinements image the analyst examined.

Table 10 The conditions under which a re-assignment of the map category could occur based on information from the land use, woody extent, ADS tree cover and detectable clearing layers

Map formation rule	Woody in the woody extent map	Woody in the ADS tree cover map	Clearing detected	Potential re-assignment 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 NVR Map that could be improved by reviewing the refinements image, and satellite (SPOT and Sentinel-2) and aerial (ADS) images. All decisions are based on the Sentinel-2 imagery closest to the date of 25 August 2017. The ADS and SPOT 5 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, four frames of view are concurrently set-up as shown in Figure 29. 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 satellite 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.

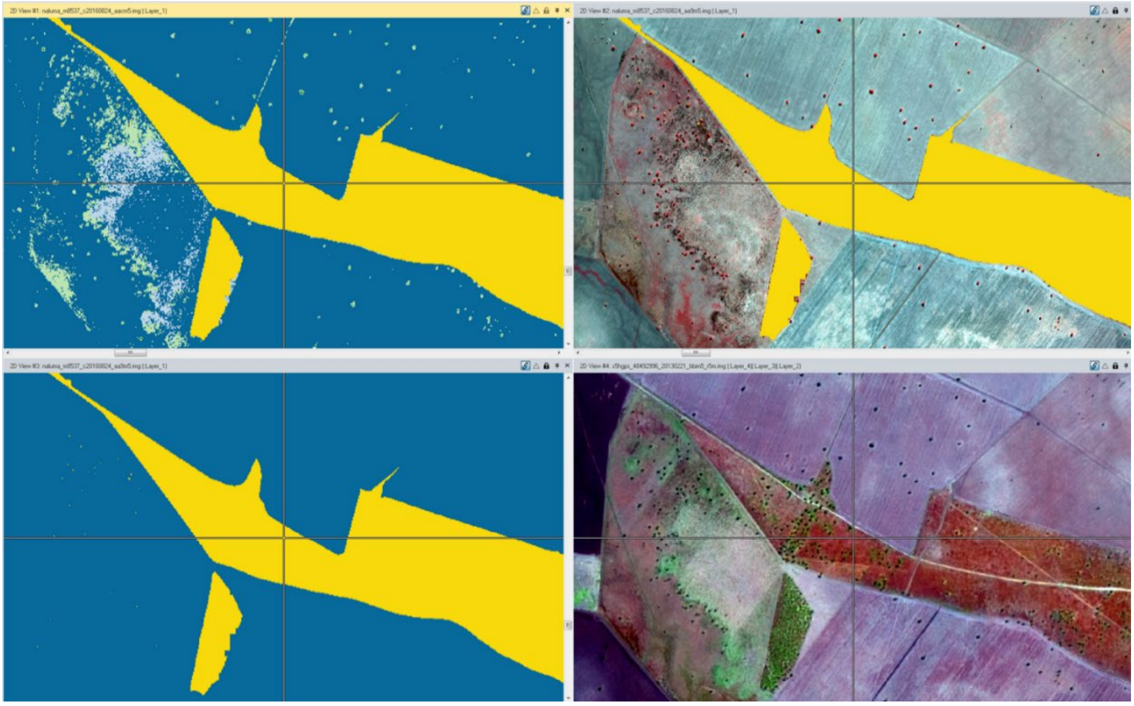


Figure 29 Refinements process set-up in ERDAS Imagine: Refinements image (top left), draft NVR Map (bottom left), ADS image with draft NVR Map category 2 overlay (top right), satellite images (bottom right).

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 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 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 11 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 10) 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, 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 11.

Historic aerial photography circa 1990 mosaics

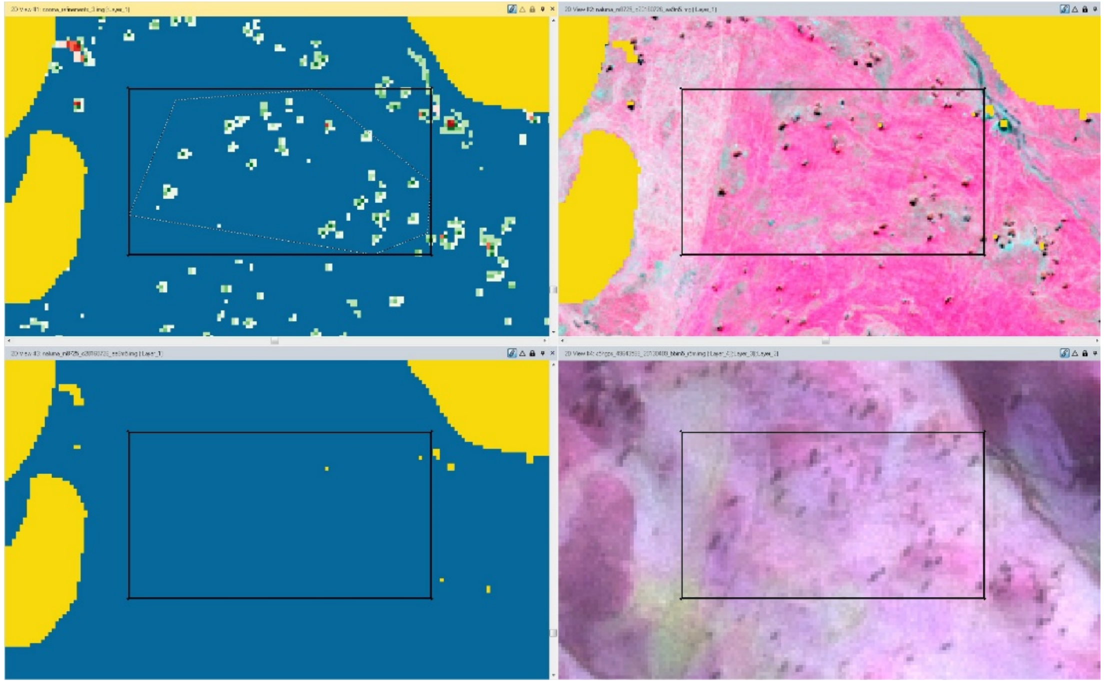
Historic aerial photography (HAP) circa 1990 mosaics provide direct evidence of the presence or absence of woody vegetation at that time. The HAP mosaics are used because they remove any subjectivity when estimating the size of woody vegetation visible in the satellite imagery (circa 2017) that could possibly represent regrowth since 1990.

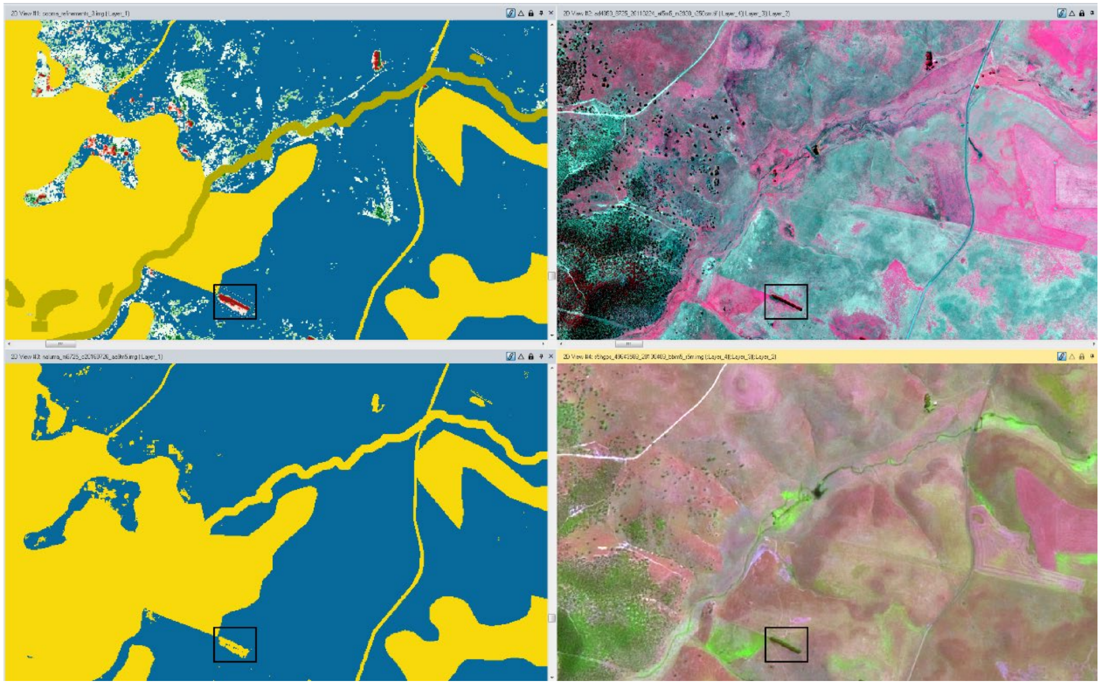
Where available, HAP mosaics are used in the refinements process to support decisions about the addition and removal of woody vegetation from SPOT woody extent, based on presence or absence circa 1990. HAP mosaics were loaded into ERDAS Imagine, in view #3 (bottom left) instead of the draft NVR Map.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

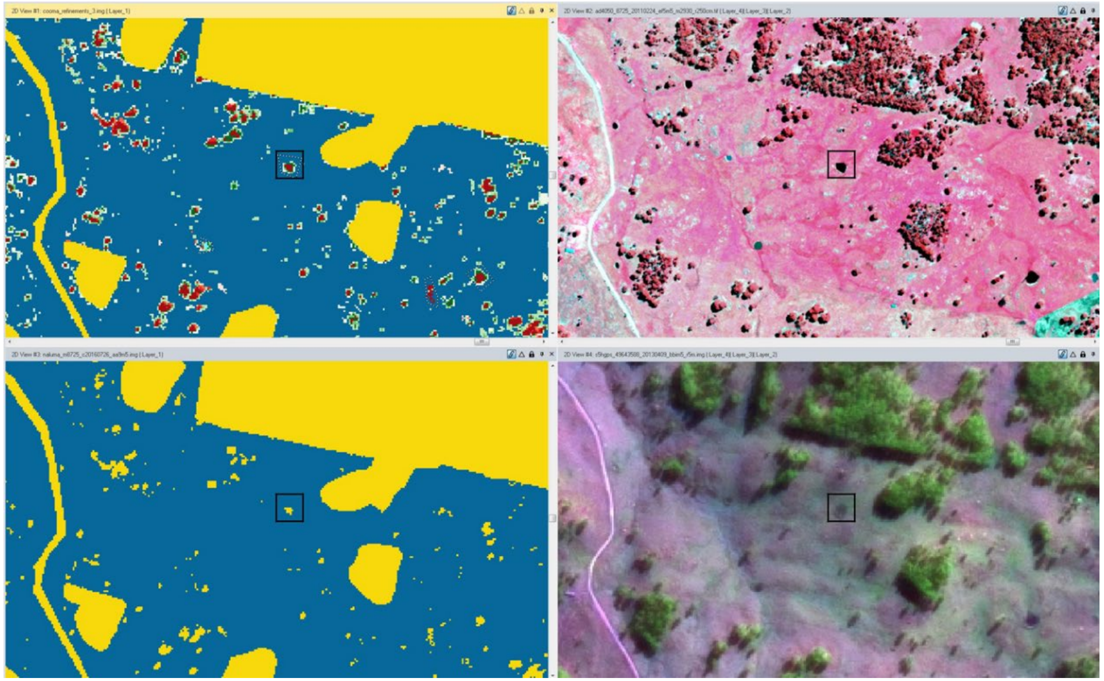
Refinement decisions supported by HAP data apply to all the same conditions of potential re-assignment of the NVR Map categories as the standard refinements process (see Table 10). Refinements made using HAP mosaics used the codes 61 for removal from SPOT woody extent (pixel values 30–39) and 62 for 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.

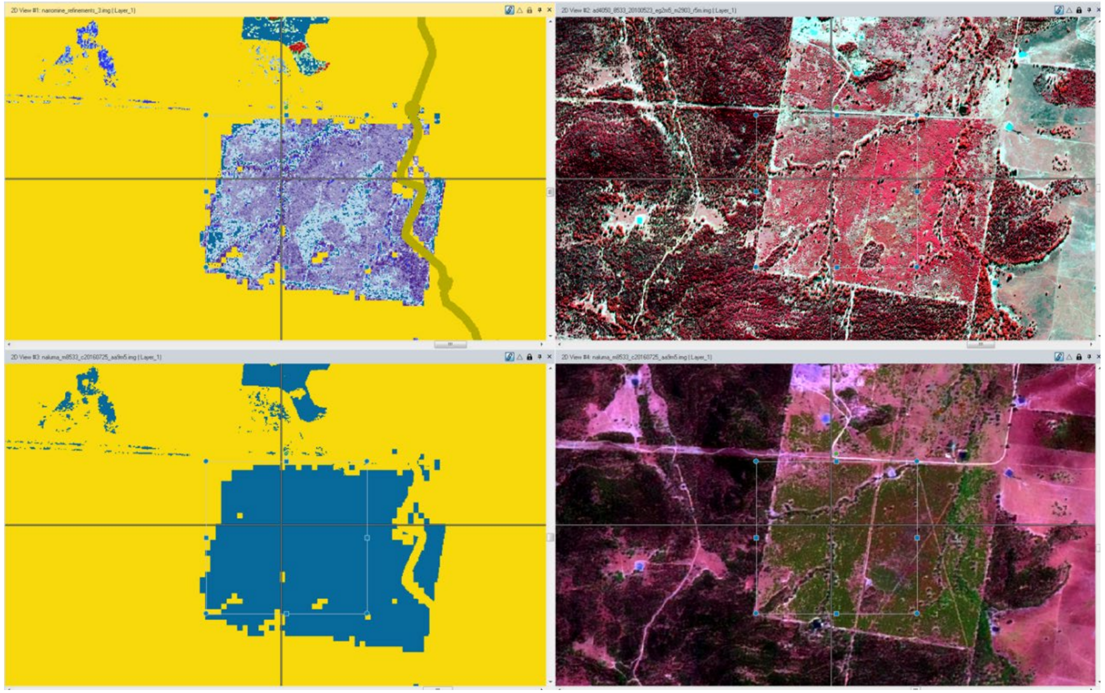
It is anticipated the use of HAP mosaics will continue during further refinements of updates to the NVR Map. Examples of refinement decisions supported by HAP mosaics are included below in Table 11.

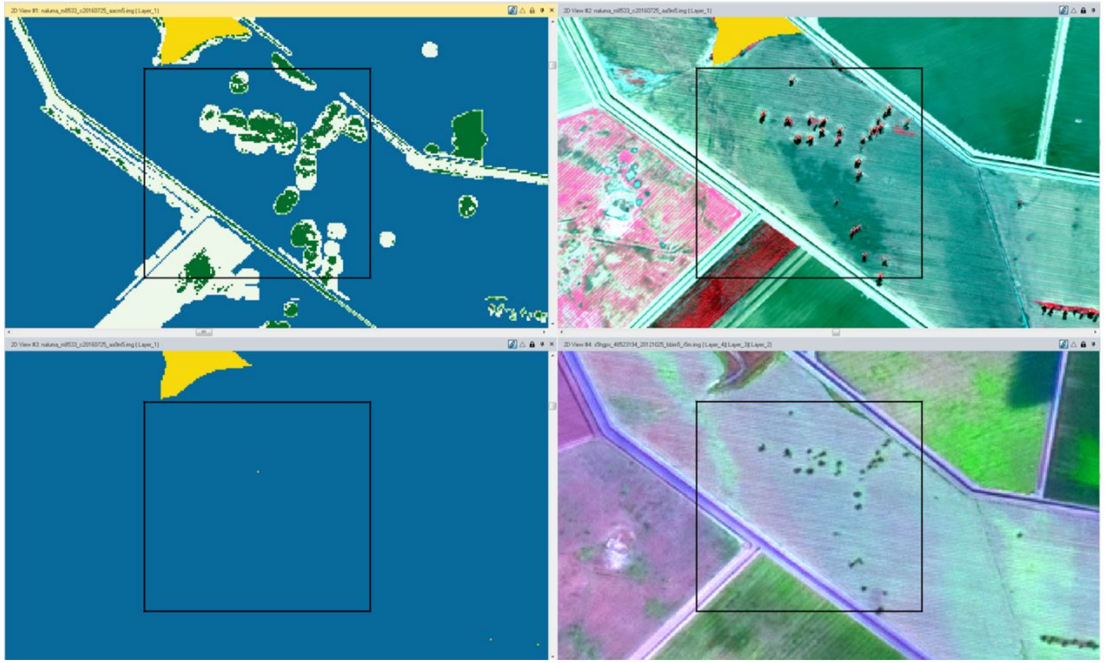
Table 11 The mapping guidelines used by analysts when deciding if map categories needed to be changed

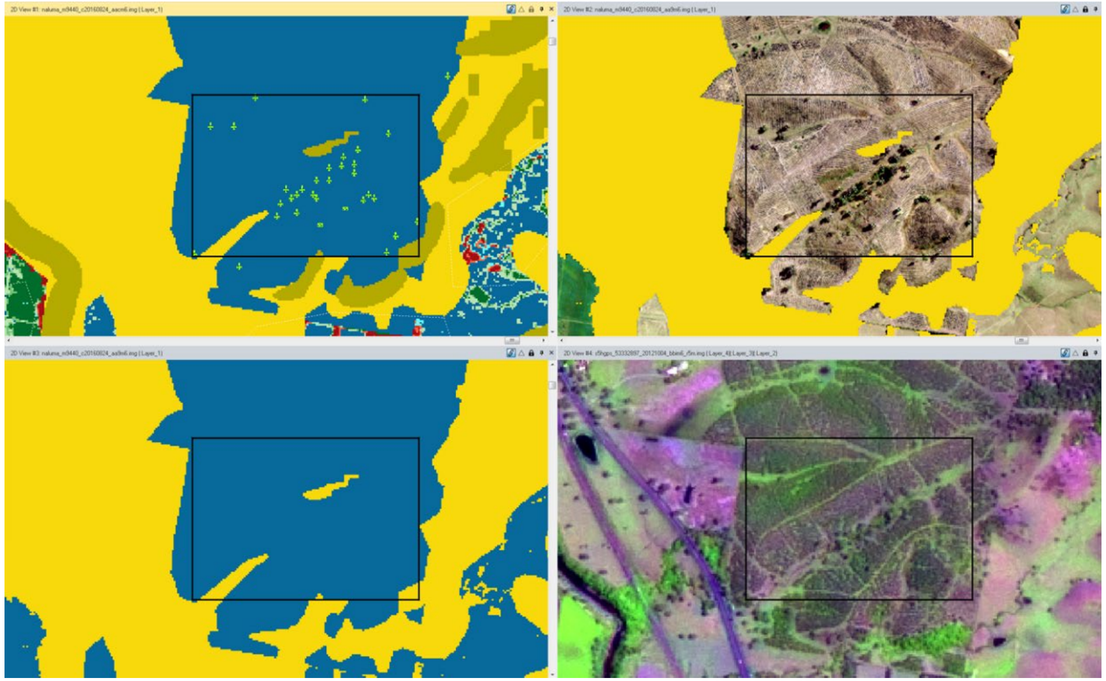
Situation	Refinement decision and pixel recoding	Visual example
Scattered paddock trees present in satellite imagery (bottom right) but not captured in category 2 in the initial NVR Map (bottom left).	Potential refinement codes (top left) are green (11:14) indicating a potential addition and no clearing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

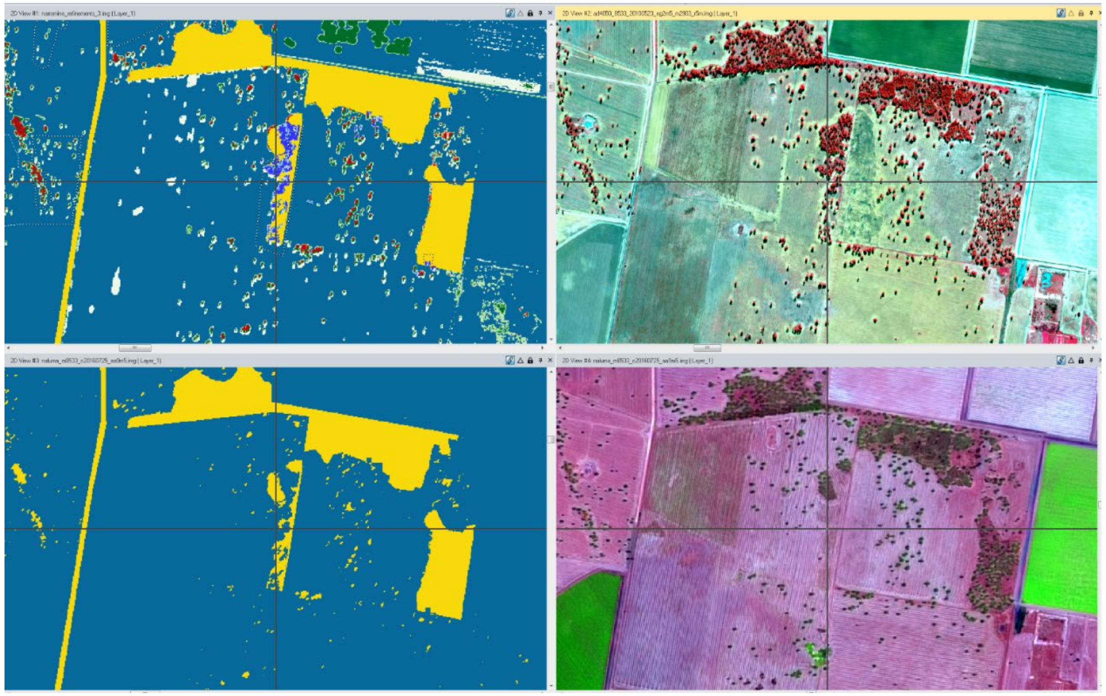
Situation	Refinement decision and pixel recoding	Visual example
An area of category 2 in the initial map over-represents the true extent of the woody vegetation present in the satellite imagery.	Potential refinement codes are pink/red (30:34) indicating a potential removal and no clearing data in the lineage. This example represents a 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	

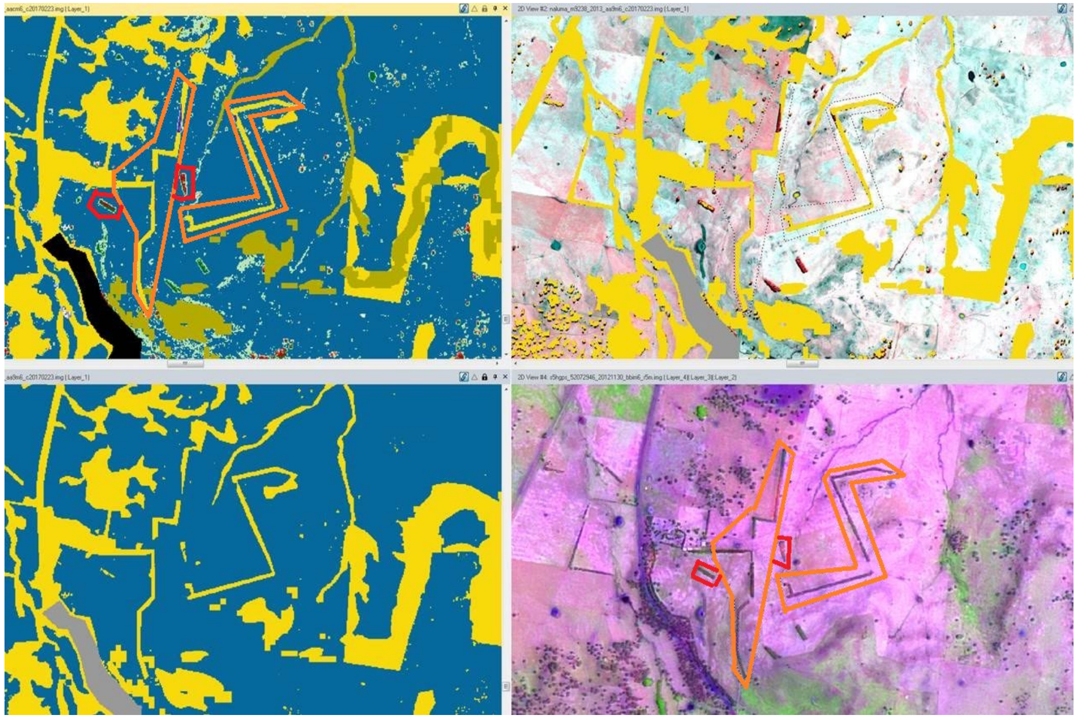
Situation	Refinement decision and pixel recoding	Visual example
Non-woody vegetation (a dam) is captured as category 2 due to an error in the woody extent data.	Potential refinement codes are red (34) indicating the area is a candidate for potential removal from category 2. The area was identified as woody in SPOT woody extent and as having high cover in ADS tree cover. Dark waterbodies 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 satellite 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	

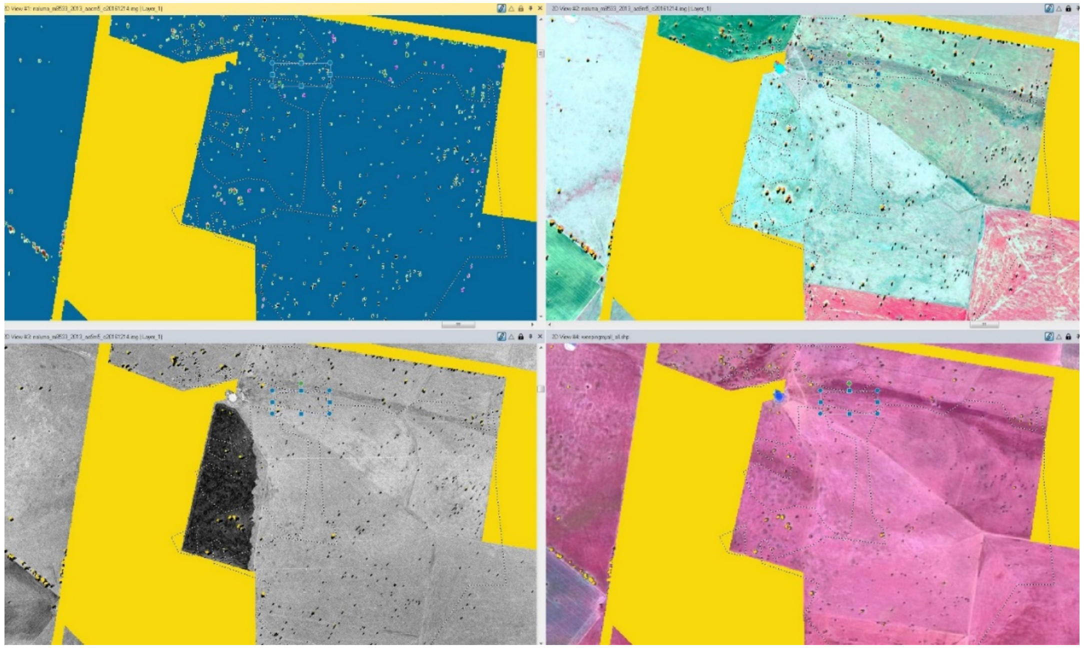
Situation	Refinement decision and pixel recoding	Visual example
Small areas of uncleared woody vegetation, within a larger area of clearing, are not appropriately captured as category 2.	Potential refinement codes are purple (20:24) indicating the area is a candidate for potential addition to category 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	

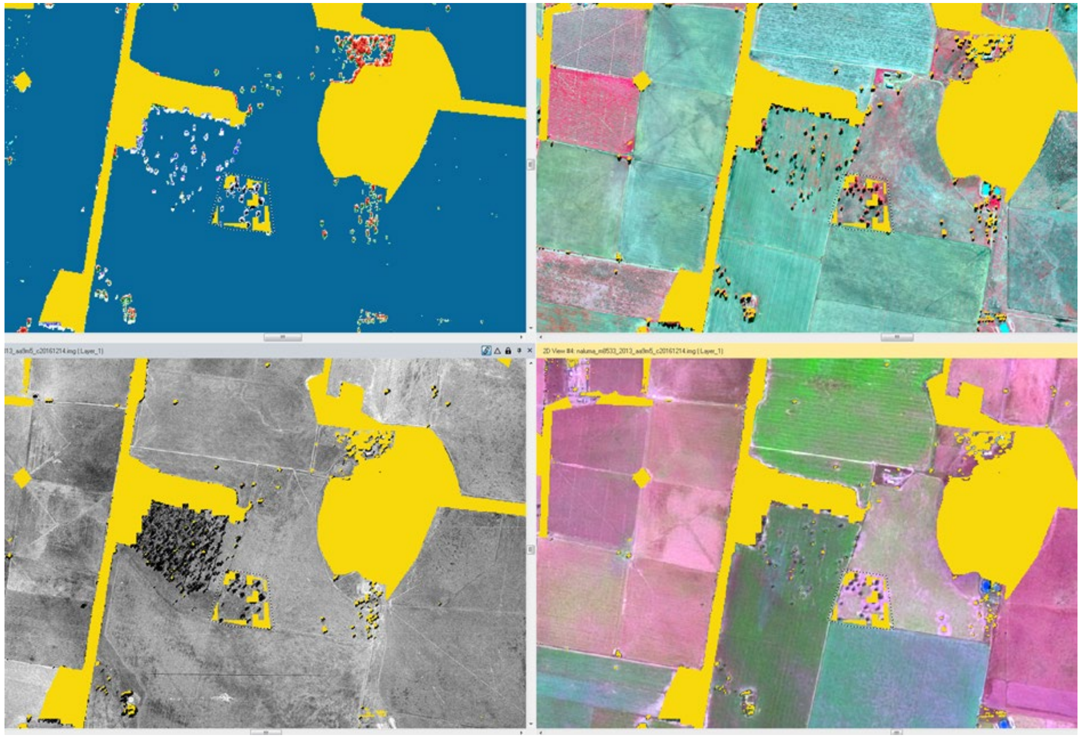
Situation	Refinement decision and pixel recoding	Visual example
Scattered paddock trees present in satellite imagery but not captured in category 2 in the initial NVR Map.	Potential refinement codes are green (11:14) indicating a potential addition and no clearing data in the lineage. However, the codes in the refinements image (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, satellite 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	

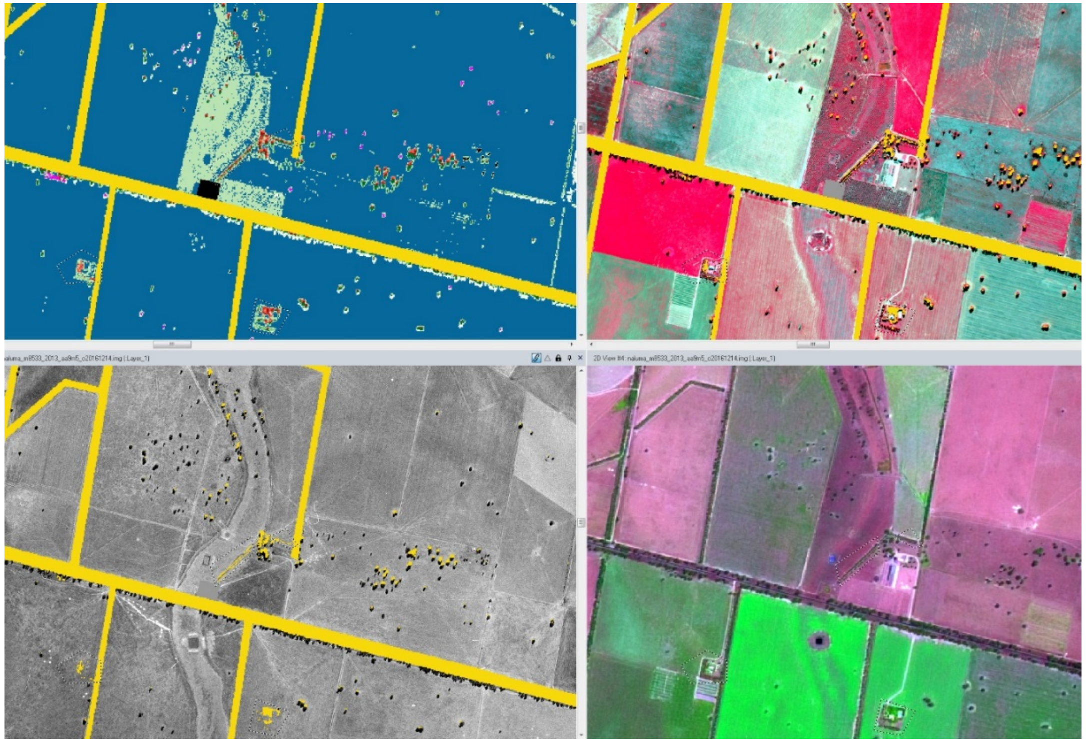
Situation	Refinement decision and pixel recoding	Visual example
Land use areas subject to NVR mapping rule 1 (always category 1) include perennial horticulture. However, occasionally large native trees may be present within the mapped land use boundary.	No refinement codes are available within the area of mapped perennial horticulture. However, large trees present in the 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	

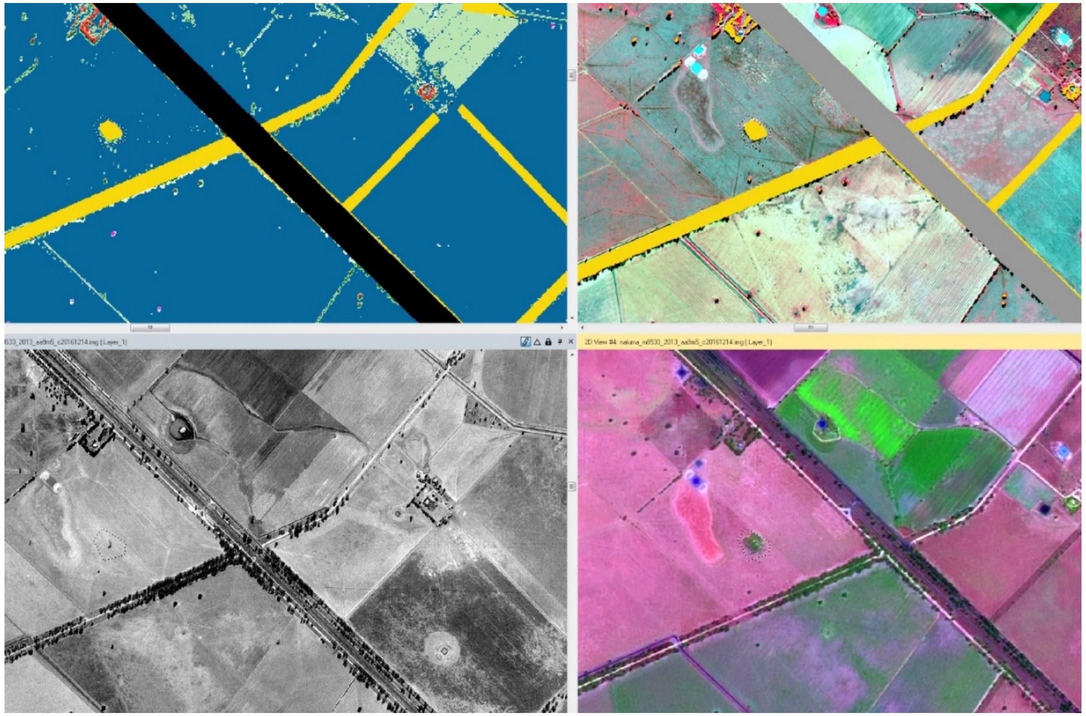
Situation	Refinement decision and pixel recoding	Visual example
An area of category 2 that is not present as woody vegetation in the satellite imagery and the land use pattern indicates the area should be category 1, consistent with surrounding landscape.	This is a rare occurrence of a land use mapping error. Comparison of the ADS and satellite imagery indicates the area had been recently cleared of vegetation (between the ADS imagery date and the satellite imagery date) and subsequently cropped. Using the satellite 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 the 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 satellite 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 woody extent omission error. The HAP mosaic confirms the presence of the woody vegetation circa 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 circa 1990, suggesting the trees were most likely never cleared between 1990 and 2017 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 circa 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 circa 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 circa 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 circa 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	

More information

- Spatial Services

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