Statewide Landcover and Trees Study

Methodology Overview – Version 1.3

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Department of Environment, Tourism, Science and Innovation

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List of acronyms

CNN	Convolutional Neural Network
CRF	Conditional Random Fields
DETSI	Department of Environment, Tourism, Science and Innovation
DMC-3	Disaster Monitoring Constellation-3
EDS	Early (Clearing) Detection System
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus
FPC	Foliage Projective Cover
GBR	Great Barrier Reef
JRSRP	Joint Remote Sensing Research Program
MCCV	Monte Carlo Cross Validation
NDVI	Normalised Difference Vegetation Index
NSW	New South Wales
NVIS	National Vegetation Information System
OLI	Operational Land Imager
SLATS	Statewide Landcover and Trees Study
TM	Thematic Mapper
USGS	United States Geological Survey
VMA	*Vegetation Management Act 1999*

Glossary

Albers equal-area projection

A conic map projection which preserves the area of features. This projection is suitable for use when calculating the area of features.

Clearing activity

Human activity which results in the full or partial removal or destruction of woody vegetation from an area.

Foliage projective cover (FPC)

FPC is defined as the fraction of ground covered by the vertical projection of photosynthetic foliage of all strata (Specht, 1983). FPC is a metric that is used in remote sensing (i.e. satellite-based monitoring) as a direct estimate of the foliage (or leaves) on vegetation when viewed (vertically or near-vertically) from above, as is the perspective of the satellite. Herein, FPC refers to the foliage of woody plants only and is expressed as a percentage where: 0% FPC implies there is no woody plant foliage cover; and 100% FPC implies total or complete woody plant foliage cover.

Full clearing

A human-induced clearing event that results in the complete removal or destruction of woody vegetation, converting an area from woody to non-woody (i.e. less than 10% woody crown cover remains). These are areas that were mapped as woody in the woody extent map, but the clearing activity has sufficiently removed or destroyed enough woody vegetation to render the location non-woody, thus removing them from the woody extent map. These areas are included as one of the categories of clearing activity in SLATS reporting.

Geometric correction

Also referred to as geo-referencing, this process is used to accurately register satellite images to a ground coordinate system.

Image composite

An image composite refers to the multi-temporal compositing of image scenes. In the SLATS process, image composites are primarily used to address incomplete coverage of a Sentinel-2 tile on any one date due to the satellite orbital path, or to replace cloudy areas from one date with clear data from another date to maximise the useable data per scene.

Image mosaic

An image mosaic, as referred to in the SLATS process, is produced by combining multiple individual image scenes to produce a single seamless mosaic for the state of Queensland.

Partial clearing (major)

A human-induced clearing event that results in the partial but significant removal or destruction of woody vegetation. These are areas where greater than 50% of the woody vegetation has been affected by clearing but the area remains woody (i.e. greater than 10% crown cover remains). These areas are included as one of the categories of clearing activity in SLATS reporting but remain in the woody extent.

Partial clearing (minor)

A human-induced clearing event that results in partial, minor removal or destruction of woody vegetation. These are areas where the woody vegetation has been modified but less than 50% of the area has been affected by clearing, and it remains woody (i.e. greater than 10% crown cover remains). These areas are included as one of the categories of clearing activity in SLATS reporting but remain in the woody extent.

Radiometric standardisation

Refers to the process of correcting satellite imagery for atmospheric effects, seasonal differences in reflectance due to sun-sensor-ground geometry, and sensor characteristics. This standardisation or correction is particularly important for image mosaicking and comparing images over multiple time periods.

Woody plants

A plant that produces wood as its primary structural tissue. Woody plants may be trees, shrubs or lianas and are usually perennial.

Woody baseline

The 2018 map of woody vegetation extent (greater than 10% crown cover and minimum patch size of 0.5ha), which forms the basis for SLATS woody vegetation monitoring, accounting, and reporting.

Woody vegetation

Assemblages of woody plants. This includes stands of native vegetation, regrowth following clearing, plantations of native and exotic species, and woody weeds. In SLATS mapping, it refers to assemblages of woody plants that are greater than 10% crown cover and a minimum patch size of 0.5ha.

Contents

1 Introduction

1.1 Background

The Statewide Landcover and Trees Study (SLATS) is a scientific monitoring program undertaken by the Department of Environment, Tourism, Science and Innovation (DETSI) in partnership with the Joint Remote Sensing Research Program (JRSRP) and the Queensland Herbarium and Biodiversity Sciences. The program works closely with the Department of Natural Resources and Mines, Manufacturing and Regional and Rural Development (DNRMMRRD) which administers the *Vegetation Management Act 1999* (VMA).

SLATS uses satellite imagery and field data to monitor and report changes in woody vegetation extent in Queensland and provide information about other woody vegetation attributes such as foliage density and age.

Data, reporting and other information from SLATS supports the VMA and a range of environment, natural resource and disaster management policy requirements and applications. This includes protection and management of the Great Barrier Reef (GBR), State of the Environment reporting, the Regional Ecosystem mapping framework, biodiversity conservation, fire management and planning, and natural capital and environmental accounting initiatives.

1.2 Objectives of SLATS

The primary objective of SLATS is to monitor, map and account for changes in the extent of woody vegetation across the state of Queensland on an annual basis. This includes documenting the current extent and monitoring and mapping changes to that extent due to human-induced land clearing and natural or human-induced regrowth.

A secondary objective is to provide additional data and information about the type of clearing activity and its purpose, and about the density and age of the vegetation that currently exists, is being cleared, or is regrowing. Where possible, SLATS will also map losses or disturbances to woody vegetation through natural causes such as cyclone damage or fire.

SLATS is complemented by other land cover change monitoring for ground cover and fire scars, and the Early Detection System—a regular, targeted, monitoring and proactive compliance tool which also supports the VMA.

1.3 Historical changes to SLATS methodology

SLATS monitoring and reporting methodology, up to and including the 2017-18 report, was primarily based on Landsat satellite imagery, and focussed on woody vegetation clearing mapping. From 2018-19 onwards, SLATS has used a completely revised methodology that is primarily based on Sentinel-2 satellite imagery. This methodology incorporates additional monitoring and mapping components, including a woody vegetation extent, and woody vegetation regrowth.

Due to the revision of the SLATS methodology, including the transition from Landsat to Sentinel-2 satellite imagery, SLATS reporting and data from 2018-19 is not directly comparable with reporting and data up to, and including, the 2017-18 SLATS report. However, as part of SLATS revisions a separate scientific study was undertaken to provide clearing estimates that were more comparable with previous SLATS reporting. An overview of the methods developed for that study are provided in the Appendix (Section 6).

1.4 Purpose of this document

The purpose of this document is to provide an overview of the current SLATS methodology which is based primarily on Sentinel-2 satellite imagery.

1.5 Independent peer review

The current SLATS methodology was the subject of a comprehensive independent peer review in 2021. The review was led by CSIRO and included experts in remote sensing, ecology, and natural resource management.

The review considered the science underpinning the program and its effectiveness in supporting environment and natural resource information requirements. It found that the methods are appropriate and consistent with best practice scientific reporting, and that the program will have ongoing impact for environment and natural resource management in Queensland. The review made several recommendations for further (or future) improvements, and these are being addressed where appropriate, and as time and resources permit.

2 The SLATS monitoring and reporting framework

2.1 Scope and key definitions

2.1.1 In scope

In general, SLATS monitors woody vegetation in line with the definition of vegetation in the VMA, which defines vegetation as woody native trees or plants, except for mangroves which are protected under other legislation. Due to the difficulty of discriminating native and non-native woody vegetation in the landscape using satellite imagery, non-native woody vegetation change is also included in SLATS monitoring and reporting (refer to Section 2.1.2.1 for details regarding this).

The scope of SLATS is to maintain a map of the current extent of woody vegetation in Queensland by monitoring and mapping annual changes to that extent due to human-induced land clearing and natural or human-induced regrowth. This is limited by what can be reliably identified and mapped using Sentinel-2 satellite imagery, but also informed by other data sources, including Landsat time-series, very high-resolution satellite imagery, and field verification.

SLATS also aims to determine the type of clearing activity and its purpose and to estimate the density of the vegetation that currently exists, is being cleared, or is regrowing. Time-series methods are also used to estimate the time since the woody vegetation was last disturbed and, where possible to detect, the time since it had started to regrow following a disturbance event.

An initial baseline woody extent aimed to capture all woody vegetation as at (nominally) August 2018 that has a crown cover of 10% and above (approximately 5-6% FPC) and a minimum patch size of 0.5ha. This includes woody vegetation in very sparse, sparse, mid-dense and dense classes (Table 1). Thereafter, all monitoring and mapping of changes to the woody extent (i.e. due to clearing and regrowth) are mapped for the same crown cover criteria but using a minimum patch size of 0.25ha.

Table 1: Overview of structural (vegetation density) formations for woody vegetation as used in SLATS reporting. Adapted from Scarth *et al.*, 2019.

Foliage Projective Cover (FPC) or Crown Cover (CC)			
Very Sparse/Isolated <10% FPC 0.25-20% CC	Sparse 10-30% FPC 20-50% CC	Mid-dense 30-70% FPC 50-80% CC	Dense 70-100% FPC >80% CC
tall open woodland open woodland low open woodland tall open shrubland low open shrubland	tall woodland woodland low woodland tall shrubland low shrubland	tall open forest open forest low open forest open scrub open heath	tall closed forest closed forest low closed forest closed scrub closed heath

2.1.2 Out of scope

The current scope of SLATS monitoring and reporting excludes some land cover, land cover change, and ecological attributes. This is due to a range of factors including the objectives for SLATS, the limitations of current scientific research to identify and accurately map some attributes state-wide, or because other programs in government are already mapping or documenting the attributes. Some of these may be addressed, where appropriate, in the future. Close ties with other states and the commonwealth government are maintained to minimise duplication and ensure complementarity and information sharing.

Out of scope attributes are briefly outlined in the following subsections.

2.1.2.1 Distinguishing native woody vegetation from non-native woody vegetation

SLATS mostly monitors native woody vegetation change but due to the difficulty of separating native and non-native woody vegetation using satellite imagery, especially woody weed species such as Prickly acacia (*Valchellia nilotica*), Parkinsonia (*Parkinsonia aculeata*) and Lantana (*Lantana camara*), reporting for some regions or localised areas will likely include some non-native woody vegetation change.

2.1.2.2 Non-woody vegetation change monitoring

The extent, density or change in non-woody vegetation communities is not currently monitored. Refer to Ground Cover Monitoring for further information regarding how non-woody vegetation is monitored. Further information about non-woody regional ecosystems (e.g. grasslands) can be found in the Regional Ecosystem framework.

2.1.2.3 Vegetation height

Vegetation height is not currently considered as part of the definition of woody vegetation nor is it considered as part of the mapping methodology. The 2022-23 SLATS report introduces information about the height of vegetation for areas affected by clearing activity (refer to Section 4.2.1.3).

2.1.2.4 Vegetation composition

This information is available in the Queensland Herbarium and Biodiversity Science's Regional Ecosystem mapping for Queensland.

2.1.2.5 Vegetation densification (i.e. thickening)

Vegetation densification, sometimes also referred to as thickening, is not currently monitored. This is an area of ongoing research. The current FPC product is intended to provide contextual attribution of the vegetation density to assist understanding of the structural attributes of the ecosystems which are being cleared or regrown. While larger increases in the FPC product over time for a particular location may reflect real densification processes on the ground, insufficient research and validation has been undertaken to reliably use it for tracking change in density as these changes are often quite subtle. It is worth noting that the process of encroachment—the colonisation of a previously non-woody area by woody vegetation—will be monitored as a change in woody vegetation extent as part of the regrowth monitoring, where the change can be reliably identified and mapped following SLATS mapping specifications.

2.1.2.6 Fire

Fire-affected areas are mapped separately to SLATS. Refer to Fire Scar Mapping for further information. Where SLATS can identify that fire was used as part of a human-induced clearing event, this is mapped. However, fire-affected areas are generally assumed to be temporary, non-anthropogenic changes in woody vegetation, even if the ignition source was human induced. It is important to note that some estimates of vegetation age may be affected by historical fire events; regrowth age estimates may be influenced by fire and other natural disturbances which impact the canopy significantly, even if temporarily. If a fire or other natural disturbance such as cyclone damage, flood etc. causes the modelled woody probabilities to fall below a given threshold and this causes a break point, regrowth tracking is reset, and age would be determined from the 'next' period of regrowth/recovery detected after that point in time (depending on the other heuristic conditions—refer to Section 3.4.3 for further details).

2.1.2.7 Land use and land use change

Land use mapping it undertaken separately to SLATS. Refer to Land Use Mapping for further information. SLATS includes some information related to land use—the *landcover replacement class* (see Section 3.3.5.2)—but this is only intended to be indicative of the land use for which a clearing activity has been undertaken, or where regrowth is occurring.

2.1.2.8 Other natural or non-human-induced change

SLATS attributes natural or non-human-induced changes as part of the clearing mapping process where they are possible to identify and map but these changes are not included in any reporting. This includes change due to natural disaster impacts (e.g. cyclones, floods, droughts) and other natural tree death (e.g. senescence, dieback).

2.1.2.9 Carbon sequestration or greenhouse gas emissions monitoring and reporting

SLATS does not provide estimates for greenhouse gas emissions inventory purposes. The SLATS methodology and planned improvements such as age, height, and cover estimates are intended to help inform carbon sequestration and greenhouse gas emissions reporting, where appropriate.

2.1.3 Key definitions

The following are key definitions as they apply in the context of the SLATS monitoring, reporting, and accounting framework. The definitions are based on what can be reliably identified and mapped consistently over large areas using (mostly) satellite imagery. For other terms and definitions used in this document, refer to the glossary.

2.1.3.1 Woody vegetation

Assemblages of woody plants with greater than 10% crown cover. These may be trees, shrubs, or lianas, and are usually perennial. An assemblage may include uncleared native vegetation, regrowth following a previous clearing event (or events), plantations of native and/or exotic species, and woody weeds.

2.1.3.2 Woody vegetation clearing activity

The anthropogenic (i.e. human-induced) removal or destruction of woody vegetation. This may be 'full clearing' (i.e. a conversion from woody to non-woody), or 'partial clearing' (i.e. there has been some clearing activity for a given location, but it is not sufficient to render the area non-woody). Refer to Section 3.3 for details.

2.1.3.3 Woody vegetation age since disturbance

The estimated time since the woody vegetation was last significantly disturbed, or where possible to detect, the time since it started to grow or regrow following a disturbance. Estimates are based on time series modelling of woody vegetation and SLATS change history within the period 1988 to present. Refer to Section 3.4 for details.

2.1.3.4 Woody vegetation regrowth (or regrowth)

Woody vegetation that has regrown due to natural or human-induced processes and is determined to be sufficiently woody to be added to the woody extent data set (i.e. meets the criteria of having 10% crown cover and stand area of >0.25ha). Refer to Section 3.5 for details. As noted in Section 2.1.2.5, regrowth can include areas where encroachment has occurred.

2.1.3.5 Woody vegetation density

The estimated density of woody vegetation's foliage cover based on a data product that estimates FPC and is derived from Sentinel-2 satellite imagery, calibrated by field estimates of FPC (refer to Section 3.6 for details). It is important to note that FPC is different to crown cover in that it considers only the area covered by foliage within a crown, whereas crown cover is the entire area of the crown. Crown cover is much more straightforward to visualise and map in manual mapping approaches. FPC considers the gap fraction in the canopy when viewed from above and requires field-based calibration data which estimates the gap fraction, and hence, foliage cover.

2.2 Overview of the SLATS monitoring, accounting, and reporting framework

Figure 1 is a schematic diagram of the key components and timeline which forms the basis of the SLATS monitoring, accounting, and reporting framework. The current framework is based on a conceptual model of establishing a detailed baseline account of the woody vegetation extent, age since disturbance and density for the state (as of 2018), and then monitoring and accounting changes to that extent due to clearing and regrowth, reporting annually. Estimates of woody vegetation age since disturbance and density are also updated annually to inform reporting. Section 3 provides details about the methods and workflows which support the framework.

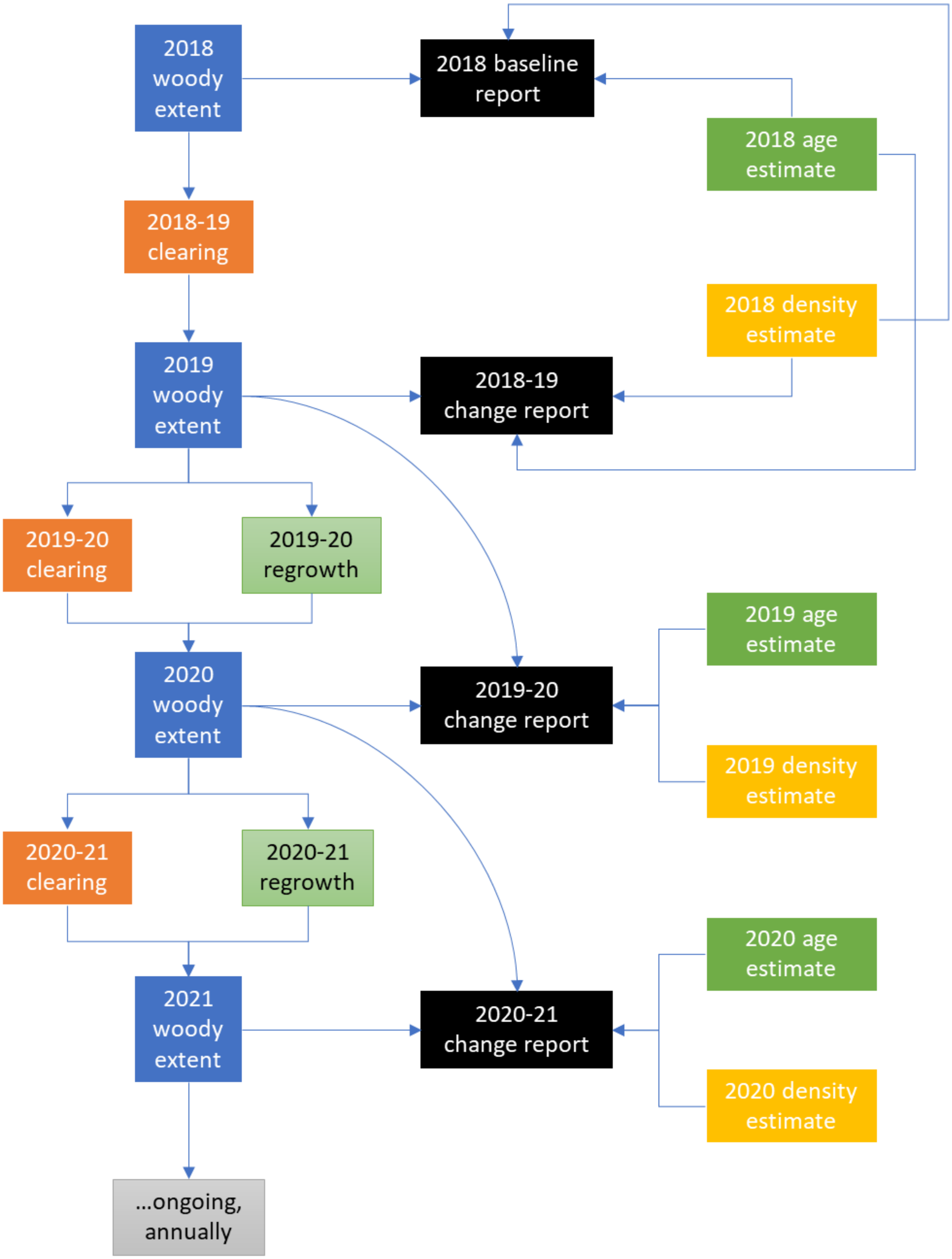

Figure 1 Schematic example of the SLATS monitoring, accounting, and reporting framework

3 Methods

3.1 Systems and data

SLATS is supported by an extensive computing infrastructure and comprehensive archive of data. Data and programs (i.e. algorithms or code) used and produced are subject to quality control systems and standard operating procedures for image and field data processing, storage, and management. The systems and processes used are fully documented in a WIKI-based system and include peer-reviewed processes. All image processing follows internationally accepted and/or published standards. Data sourced from external parties are not incorporated into the workflow without appropriate metadata, including lineage statements.

3.1.1 Systems

All data processing is undertaken on the high-performance computing (HPC) facility at the Ecosciences Precinct, Brisbane. The HPC incorporates a multi-node Linux cluster, a mass storage on-line disk and near-line tape silo which houses the image archive and downstream products. The HPC is connected to the high-speed national science network portal (AARNet) enabling efficient downloading of large data sets, particularly Sentinel-2 data from the Copernicus Australasia Regional Data Hub.

Much of the data processing for SLATS is now done "inside" *containers* that are run on the HPC cluster using Singularity software. A container is an executable application that packages all the system tools and libraries, code, dependencies, and configuration associated with a given application, allowing portable and reproducible workflows. Singularity containers are single immutable files, designed to run securely on multi-use HPC clusters, while allowing for future cloud-based computing.

The SLATS codebase is written in Python, using open-source or in-house developed libraries. All code written for SLATS is maintained in Git version control repositories, hosted by Gitlab. The code is deployed as an installable python package (although currently only available inhouse) and installed in a container. SLATS uses the Gitlab Continuous Integration and Delivery (CI/CD) pipelines to automatically test, build, and deploy our code packages upon any updates to the code-base and dependencies. Changes to the code also trigger rebuilding, testing and deployment of an updated container. Both packages and containers are versioned to maintain complete separation between development and production and ensure reproducible workflows.

Image metadata, field and other spatial data sets are stored in a PostgreSQL spatial database, which is integrated with the image archive and processing systems to enable efficient querying of /access to SLATS data sets. Imagery and other data sets are governed by a naming convention which is systematic, structured, and descriptive, and supports automated processing (Flood and Danaher, 2013).

3.1.2 Satellite imagery and imagery pre-processing

The primary satellite data used includes imagery from: Sentinel-2 missions; Landsat TM, ETM+ and OLI; and DMC-3 TripleSat (Earth-i).

3.1.2.1 Sentinel-2 imagery

Sentinel-2 MSI imagery (10m/20m) from ESA's Copernicus program is used as the primary image data for ongoing annual monitoring and reporting of woody vegetation clearing (Section 3.3), regrowth (Section 3.5), and density (Section 3.6). It is also used together with Earth-i and other very high-resolution data to inform woody extent refinement (Section 3.2).

Level 1C Sentinel-2 image products are routinely downloaded from the Australasian Regional Copernicus Data Hub (http://www.copernicus.gov.au/) and then processed to surface reflectance as described in Flood (2013a). The imagery is geometrically corrected by ESA. Currently, ESA's geometric correction process is fully operational with geolocation accuracy reported to be within one 10m pixel. However, in the early part of the time series (2016-2019) ESA's quality tracking shows variable performance with long-term average location accuracy closer to 11m at 95% confidence (exceeding one 10m pixel; ESA, 2019). DETSI therefore undertook an additional geometric co-registration step of end-date image to start-date image for a small number of image pairs used in SLATS clearing detection. This was required to reduce misregistration effects in the clearing index. For processing of indices developed for Landsat such as FPC, fractional cover and the SLATS clearing index, the Sentinel-2 20m (Landsat-analogous) short-wave infrared (SWIR) bands are resampled to 10m using cubic convolution. Processing of these indices is described in the relevant sections. Cloud and cloud shadow masks are computed using the methods of Zhu *et al*., (2015). Cloud and shadow masks are no longer used in the production of the SLATS clearing index as cloud-free image selection is almost always possible for Sentinel-2 imagery given the temporal frequency. DETSI has complete holdings of Sentinel-2A and -2B imagery acquired over Queensland from late 2015 and ongoing. From 2017 onwards this represents a five-day return interval.

3.1.2.2 Landsat imagery

The long time series of Landsat imagery (1988-ongoing) is used as the primary image data to derive temporal woody vegetation age since disturbance estimates (Section 3.4). It is also used extensively as an ancillary data set to provide historical context in SLATS change detection (Section 3.3) and woody extent refinement (Section 3.2), and to augment the shorter Sentinel-2 time series in regrowth detection (Section 3.5).

DETSI acquires Collection-2 Landsat-8 and -9 satellite imagery from the USGS, combined this represents an eight-day return interval over all areas of Queensland. The Landsat imagery is accessed via a nightly automatic process that queries all new imagery using the USGS Machine-to-Machine (M2M) API tool (https://m2m.cr.usgs.gov/) and then downloads the data from their Amazon Web Services (AWS) object storage service (S3). Prior to this, Collection-1 Landsat data was downloaded directly from the USGS Earth Explorer site. DETSI ceased downloads of Landsat-7 on 30 November 2021 as Landsat-9 data came fully online. Landsat-7 has the SLC-off issue and was considered redundant given availability of Landsat-8 and -9 in addition to Sentinel-2A and 2B data. Landsat imagery is geometrically corrected by the USGS. Analyses by the USGS suggest that the locational error is below a single pixel (Storey *et al*., 2014). SLATS uses the USGS geometric correction without modification. All Landsat data are processed to surface reflectance as described in Flood (2013a). Cloud and cloud shadow masks are computed using the *Fmask* methods of Zhu and Woodcock (2012).

DETSI holds the complete archive of historic USGS Landsat imagery from Landsat-5 TM, -7 ETM+ (up to 30 November 2021), -8 OLI, and -9 OLI-2 acquired over Queensland during the period 1988 to present.

3.1.2.3 Seasonal fractional cover composites

Time series of seasonal composites of fractional cover (Scarth, 2008) are used for woody vegetation age since disturbance estimates (Section 3.4) and regrowth detection (Section 3.5).

Three-monthly seasonal fractional cover composites are produced for Queensland for both Landsat (30m) and Sentinel-2 (10m) processing streams using the medoid method described in Flood (2013b). Prior to compositing, topographic shadow, cloud and cloud shadow masks are applied.

3.1.2.4 Earth-i DMC-3 Imagery

High-resolution (~80cm) satellite image mosaics of Queensland were purchased by the Queensland Government for the years 2016, 2017 and 2018. The 2017 and 2018 mosaics were the primary image data used in the development of the woody extent (Section 3.2).

The data were purchased as three-band visible (blue, green, red) imagery, pan-sharpened from a nominal resolution of 3.2m to 80cm pixel size. The imagery was captured as many small tiles over a range of months, extending between April and November in each year, by the Disaster Management Constellation (DMC) program's three DMC-3 TripleSat satellites. For each year, the imagery was pan-sharpened, colour-balanced and mosaicked by Earth-i, and finally supplied as 32 large mosaic tiles covering the whole of Queensland, with some overlap between tiles. Once on the DETSI systems, the imagery was resampled into Albers Equal Area projection and a pixel size of 1m using cubic convolution resampling. The DMC satellites are pointable, allowing for view angles up to 30 degrees off-nadir to avoid cloud contamination. This allowed for largely cloud-free image mosaics, however some small cloud and poor image quality effects, due in part to larger view angles, are evident in all the mosaics.

3.1.2.5 Ancillary data

A range of ancillary data are used to inform the SLATS operational mapping components. These data include:

- high resolution satellite imagery and aerial photography available through online image services such as Planet (QSat), Google Earth, One Atlas Living Library, ESRI World Imagery, and the Queensland Government's Queensland Globe
- complementary remote sensing products, for example DETSI's Sentinel-2 fire scar data, and the Northern Australia Fire Information's fire hotspots and fire scar maps (https://www.firenorth.org.au/nafi3/)
- airborne lidar and terrestrial laser scanner data
- regional ecosystem mapping.

3.1.3 Field data

DETSI hosts a national field database which incorporates a comprehensive collection of vegetation measurements collected across Queensland and nationally over a 20+ year period, encompassing much of the time that Landsat and Sentinel-2 satellites have been operating. Field data such as the star transect collection of vegetation cover measurements (Muir, 2011) are used to calibrate and validate remote sensing products. Field data including quantitative measurements, qualitative observations and extensive photos are stored in DETSI's PostgreSQL spatial database.

3.2 Woody extent mapping

3.2.1 Overview

A woody extent data set was developed to inform clearing and regrowth mapping and to form the baseline for the woody vegetation change accounting framework of SLATS. The baseline woody extent data set and subsequent annual updates also serve as useful stand-alone data products for a range of other applications where detailed woody extent mapping is required. To develop the woody extent baseline, a data set showing the presence/absence of woody vegetation was derived from a Convolutional Neural Network (CNN) classification and the 2017 high resolution (re-sampled) Earth-i (1m) satellite imagery (Flood *et al*., 2019). This initial output then underwent extensive manual refinement to produce a detailed map of woody vegetation extent for Queensland. The 2017 woody extent was subsequently manually revised and updated, informed by SLATS clearing data for the 2017-2018 monitoring period, and once available, the 2018 Earth-i image mosaic (refer Section 4.1.1.1). The resulting 2018 woody vegetation extent map established the baseline for ongoing monitoring, accounting, and reporting.

At the end of each annual SLATS monitoring period the woody extent is updated using the clearing and regrowth mapping for that period (refer Section 4.1.1).

3.2.2 Mapping specifications

The scale of the baseline woody extent data set was intended to capture features visible at a nominal map scale of 1:10,000: stands of woody vegetation greater than 0.5ha with a crown cover greater than 10% are represented. A minimum width of 20m was applied to linear features. The 10% crown cover was chosen to ensure sparser vegetation in the rangelands of Queensland was represented, and to enable extent boundaries to be defined consistently and accurately; delineating woody vegetation extent boundaries below this threshold can be ambiguous. Recognising that it is very challenging to estimate height in optical imagery, there is currently no height specification.

3.2.3 Data

The 2017, 1m resolution Earth-I DMC-3 mosaic (Section 3.1.2.4) was used as the primary data source in the CNN woody classification and subsequent interpretation and manual refinement of the woody extent map.

It has a spatial resolution that allows a higher level of detail than is routinely feasible with moderate resolution satellite imagery from Sentinel-2 and Landsat. This is particularly important for mapping regions of sparse, open vegetation.

3.2.4 Automated classification

Convolutional Neural Networks (CNN) are a subset of machine learning algorithms that exploit patterns, texture, and shapes in images, and have been shown to outperform traditional classifiers. In particular, the U-net CNN (Ronneberger, 2015) was chosen as it is less reliant on extensive training data than other CNN approaches and results in a per-pixel classification of the original data. The U-net is structured around stepwise filtering and degrading of imagery to different resolutions and then upscaling back to original resolution, allowing detection of structures and textures at different scales.

3.2.4.1 Training data

The U-net model was trained on many small patches of the source data, in this case the Earth-i imagery, each with a corresponding label image in which all pixels were labelled with the correct class: in this case, woody or non-woody. A patch size of 128 x 128 pixels was used. The patch size had to be larger than the objects and textures to be detected. In this case, it needed to allow the sampling of whole groups of trees in sometimes sparse canopies, rather than single tree crowns.

As there was not an appropriate high-resolution woody/non-woody data set available, the required labels were derived from a set of 1km x 1km Earth-i image subsets, regularly sampled from a grid across each of the 32 mosaic tiles. After eliminating subsets with cloud or poor image quality and augmenting with targeted sampling in regions of under-represented, highly diverse land cover types, a set of 827 image subsets were used to develop the set of woody/non-woody labels. A simple threshold-based classification of the Earth-i green band coupled with a binary closing filter was used to produce an initial woody/non-woody classification for each image subset. These were then manually refined to produce the set of correct woody/non-woody labels. The required training patches of 128 x 128 pixel were then extracted from each image-label pair in an overlapping grid and used in the model.

In the development of the woody extent map training data, an operator interpretation of woody vegetation as captured in high resolution imagery was required. It is worth noting that in (very) high resolution imagery, a single tree crown can be captured by many pixels, conceptually different from representations of woody vegetation in moderate resolution satellite images from Sentinel-2 and Landsat, where a single pixel can be larger than a single tree crown.

No attempt was made to map individual tree crowns, but rather contiguous regions of woody vegetation cover which include tree/large shrub crowns, shadows, and the gaps between crowns, at a wide range of densities, broadly consistent with existing coarser scale mapping of regional ecosystems (Flood, *et al.,* 2019). These textures are the primary visual indicators of woody cover, at a range of densities. Biophysical quantities such as height were implicit in the human operator's view of the imagery, but are not always easily quantifiable from optical imagery, even with a pixel size of 1m.

3.2.4.2 Model performance

The model's ability to predict woody/non-woody pixels was assessed as approximately 90% accurate using Monte Carlo Cross Validation (MCCV), and with consistent performance across most of Queensland (no spatial bias). The MCCV involved 50 repetitions of the model fit, where in each iteration 70% of the training data subsets were used to fit the model and 30% withheld for validation. This meant that in any model run, subsets which were held out were independent of the model. This gave a robust measure of accuracy from a number of accuracy assessments, each one conducted on an independent data set.

3.2.4.3 Woody classification

All training data were used to produce the final model, and the model then used to produce a 2017 woody classification for Queensland from the 1m resolution Earth-i mosaic tiles.

3.2.4.4 Downscaling for manual refinement

The 1m resolution classification was downscaled to 10m to better match the intended mapping scale, suitable for integration with Sentinel-2-based monitoring and to facilitate practical manual editing. In the downscaling, a 10m pixel was labelled as woody if >= 10% of intersecting 1m pixels were labelled woody. A 10m binary closing filter was applied to connect small fragments that formed part of a larger area/ecosystem (or stand) of classified woody areas, and also to reduce the detail to manageable levels for editing, and to counter the errors associated with inconsistent mapping of individual crowns and the effects of crown shading and illumination in the 1m data. As a final step, small clumps of woody vegetation and gaps (non-woody clumps) were filtered to implement the minimum mapping unit of 0.5ha.

3.2.5 Manual editing and refinement

3.2.5.1 Decision rules

Features were categorised as either woody or non-woody based on a set of decision rules informed by visual inspection of the data, the requirements of existing data sets/programs, and expert knowledge. These decisions were based on considerations for SLATS and Spatial BioCondition and other vegetation monitoring applications, as well as the ecological characteristics of the vegetation. No distinction was made between native and non-native vegetation—woody vegetation such as woody weeds and horticultural crops is included as woody in the final classification.

3.2.5.2 Manual editing

The data set was manually refined using a vector-editing approach in ArcGIS Pro software. A PostgreSQL distributed geodatabase was utilised to version data and enable reconciliation of edited data to a master data set. Each scientist undertaking the editing was assigned a unique connection file to access the data set. Tiles comprised of a 25 x 25km systematic grid were used to sub-divide and manage the data set and to track mapping progress.

Each scientist was allocated an area to assess (subset by Queensland's bioregions) allowing for defined regions for editing so that specific experience and knowledge was developed of the features and vegetation types for the respective bioregion. Each scientist worked across a number of different bioregions over the course of the project. . Mapping polygons were visually checked against available satellite imagery (Earth-i 2017, Sentinel-2) at an on-screen scale of ~1:10,000. Misclassification or spatial (i.e. boundary) errors were edited using the suite of editing tools within the software package. These errors were generally caused by misclassification in the U-net modelling and could be due to factors attributable to the imagery (i.e. cloud, geometric/radiometric distortion, quality of imagery/colour balancing), or low accuracy in the modelling prediction. Where there was ambiguity in the classification of a feature, ancillary data was utilised to aid interpretation. Generally, ancillary data was limited to regional ecosystem data (Queensland Herbarium 2019), land use data (Queensland Department of Environment and Science, 2019), and previous SLATS clearing data. Expert opinion from senior botanists at the Queensland Herbarium was sought for specific areas of uncertainty or for specific vegetation types.

3.2.5.3 Mapping peer review and quality assurance (QA)

An in-house peer review process was established for the initial few months of the project to encourage discussion and achieve greater consistency between the scientists in implementing decision rules. Scientists checked the editing of colleagues and provided feedback as comments in a point-based data set. Areas of disagreement or confusion were discussed across the wider team and decisions documented.

Additional to the initial peer review, a QA process was conducted by senior scientists throughout the entire editing phase to ensure accuracy and consistency. The QA process allowed senior scientists to review all mapping with the goal of identifying and editing any obvious errors and providing feedback to editors in a timely manner. The process involved a systematic visual inspection of the edited outputs, similar to the original editing workflow but with a focus on final corrections and identification of woody vegetation, under- or over-representation of woody areas, with specific regard to the mapping specifications.

3.2.5.4 Refinement through re-modelling

Certain features (i.e. urban, sparse vegetation, regrowth, mangroves) were not consistently predicted in the original CNN modelling resulting in excessive manual editing. Urban areas were particularly poorly classified and significantly over-estimated woody vegetation presence, likely due to shadowing effects and spectral/textural confusion from buildings and other infrastructure interspersed with woody vegetation, and also likely due to under-representation of urban areas in the training data set. Additionally, the generalised filtering processes used to degrade from 1m to 10m for manual refinement did not always adequately represent highly detailed land use/cover types as urban. For these areas, an iterative modelling approach was trialled using the U-net architecture (as described in Section 3.2.4) to create a more accurate baseline for further checking/editing. The trial was conducted using data from edited mapping in the Cairns urban region where the overestimated woody vegetation in urban areas had been removed by manual editing. This was then used to re-train a U-net model and predict woody vegetation in urban areas in Southeast Queensland. On visual inspection, outputs from the remodelled predictions in urban areas were more accurate and required significantly less manual editing. Based on this result, further urban regions across Queensland were re-modelled and used as the new baseline for further editing.

Re-modelling was also expanded to other areas where the original model predictions of woody vegetation were determined to be poor or inconsistent following visual inspection. These areas included: low woody regrowth in the Brigalow Belt; sparse patchy vegetation in the Mulga Lands; and mangroves and wetlands in Cape York and the Gulf Plains. Once available, the Earth-i 2018 imagery allowed for further remodelling for areas that were cloud-affected in the 2017 baseline. Training data for these re-modelling exercises was derived from the edited woody extent mapping within the same region as the area being re-modelled. Care was taken to ensure no vegetation change had occurred to ensure consistency in the map currency. All re-modelled areas were then subject to the same editing and review process described in Sections 3.2.5.2 and 3.2.5.3.

3.2.5.5 Field work

An extensive field program was undertaken to provide SLATS scientists with the opportunity to calibrate their desktop image interpretation with on-ground observations. Largely qualitative observation, the field work facilitated a greater understanding of the vegetation types within and between bioregions, improving consistency within the team in applying decision rules at the desktop. Field work also allowed for checking and refinement of the mapping. Areas of uncertainty or ambiguity in the mapping were accessed by vehicle where possible and observations of vegetation type, age, and condition were recorded, and field photographs were captured at the location if required. Further observations were captured opportunistically at points-of-interest *en route*. At the conclusion of each field trip, observations and photographs were compiled into a central database and used to further refine the mapping, where required.

3.2.5.6 Updating from 2017 to 2018 baseline

On completion of the 2017 woody extent map, it was subsequently updated to create the 2018 woody extent baseline using the SLATS clearing data for the 2017-18 monitoring period (detailed in Section 4.1.1.1) and filtered to maintain the 0.5ha minimum mapping specification (refer Section 4.1.1.4).

3.2.5.7 Successive annual updates

The woody extent is updated annually at the end of each SLATS monitoring period using the completed clearing (from 2018-19 onwards) and regrowth (from 2019-20 onwards) mapping for that period. The procedures for successive updating of the woody extent are detailed in Section 4.1.1.

3.2.6 Data products

The woody extent baseline and subsequent annual updates (refer to Section 4.1.1) are stored in one single vector data set, with attributes stored in a geodatabase that enable production of a woody extent for a given year, or data about woody vegetation extent change between years. The woody extent for 2018 (the baseline year) and subsequent woody extent updates for each annual monitoring period are published as open data.

3.3 Woody vegetation clearing mapping

3.3.1 Overview

Historically, and ongoing, a state-wide clearing data set is required to inform policy evaluation for the VMA, as well as to service a range of land management and biodiversity conservation requirements across government. It is also a fundamental component of the woody vegetation account, documenting the woody extent loss, and cleared areas are also monitored for regrowth in subsequent monitoring periods. Woody vegetation clearing is defined as the removal or destruction of woody vegetation by human-induced (i.e. anthropogenic) means.

For over twenty years, and up until the 2017-18 monitoring period, the location and extent of woody vegetation clearing across the state of Queensland using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) imagery has been mapped. The ability to detect woody vegetation change due to clearing, particularly in Queensland's sparser woodlands, is ultimately limited by the 30m spatial resolution of the Landsat imagery. The previous Landsat-based clearing mapping method detected woody vegetation change between two dry season Landsat images approximately twelve months apart. The mapping process involved two stages: (i) the automated generation of a woody vegetation clearing index that characterises reflectance differences between the two image dates and highlights possible clearing of woody vegetation as a probability measure (Scarth *et al.*,2008); and (ii) extensive visual interpretation, manual refinement and quality assurance checking of the possible clearing detections to produce a final, high quality, clearing data set.

In the current methodology SLATS has transitioned from the Landsat approach to use Sentinel-2 satellite imagery at a spatial resolution of 10m to improve the detection and mapping of woody vegetation clearing.

In general, the Landsat two-date method still applies to the Sentinel-2 based approach for clearing mapping. However, there has been some necessary adaptation and modification of both the clearing index (detailed in Section 3.3.4) and the manual refinement approach (detailed in Section 3.3.5). This has been necessitated by sensor and capture differences between Landsat and Sentinel-2 data (resolution, radiometric characteristics, and length of time series), and particularly due to the explicit incorporation of the woody vegetation extent data in the mapping process.

3.3.2 Mapping specifications

The Landsat woody vegetation clearing index has been adapted to apply to Sentinel-2 10m data and the manual refinement and quality checking is all undertaken at a scale suited to Sentinel-2's 10m spatial resolution.

The minimum clearing size delineated is 0.25ha. As noted in Section 2.1.1 the 2018 baseline woody extent aimed to capture all woody vegetation as at (nominally) August 2018 that has a crown cover of 10% and above (approximately 5-6% FPC) and a minimum patch size of 0.5ha. This includes woody vegetation in very sparse, sparse, mid-dense and dense classes (Table 1). Thereafter, all monitoring and mapping of changes to the woody extent (i.e. due to clearing and regrowth) are mapped for the same crown cover criteria but using a smaller minimum patch size of 0.25ha.

These specifications are a compromise between requirements for the maintenance and updating of the woody extent data, deriving the benefits of the higher spatial resolution of Sentinel-2 data, and providing clearing data at a suitable level of detail to address a range of user requirements while maintaining consistency and efficiency for the annual program.

3.3.3 Data

3.3.3.1 Sentinel-2 imagery

The current clearing detection methods use Sentinel-2 imagery corrected to surface reflectance (Section 3.1.2.1). There are 245 Sentinel-2 tiles covering the state of Queensland. As in the Landsat monitoring approach, for each tile, a pair of Sentinel-2 surface reflectance images is used to represent the start and end dates of the 12-month monitoring period. The Sentinel-2 end date for the previous monitoring period becomes the start date for the next monitoring period, and so on. At the start of each monitoring period, the set of end date images covering Queensland are manually selected to be as close as possible to a nominal dry season date of 15 August giving preference to minimal cloud cover, smoke, haze, and greenness. Dry season imagery (July-September or late winter to early spring) generally shows the greatest contrast between woody vegetation and grass, where woody vegetation generally persists with some vigour and the grass/herbaceous layer tends to dry and wither, particularly in the rangeland and savanna environments, but also in the more temperate and near-coastal environments. If image dates are selected any later, woody vegetation may also have dried and/or there is some risk of early wet season rains leading to greening up of the landscape, both of which can reduce the contrast between woody and non-woody vegetation, including in areas that may have been cleared in the past year. Reasons for nominating the 15 August date are further outlined in Section 4.2.1.5.

Approximately 60 of the 245 Sentinel-2 tiles in any annual image selection are a composite of two dates to achieve complete coverage of the tile due to the satellite flight path schedule. When compositing is required, image dates are selected to be as close as possible (typically a few days apart), whilst minimising cloud and misregistration effects in the composite. A separate spatial raster is created to record the source date of each pixel in the composite, enabling the start and end dates of the monitoring period to be tracked at the pixel level. All SLATS dates are stored in a database for ease of calling from in-house scripts and general SQL queries.

3.3.3.2 Woody vegetation clearing index training data

The original Landsat woody vegetation clearing index was developed using training data derived from historic finalised SLATS clearing data mapped over numerous monitoring periods covering 2000-01 to 2010-11 (Scarth, Gillingham, and Muir, 2008). The original Landsat model was in part reliant on a long time series component, not applicable to the short Sentinel-2 time series. Nor was a large set of finalised Sentinel-2 clearing data available to train a new model directly on Sentinel-2 imagery.

Leveraging from work undertaken by NSW SLATS to adapt the original Landsat clearing index to SPOT imagery (Flood *et al*. 2020), a new form of the model (Equation 1c in Flood *et al*. 2020) was fitted on the original Landsat historic clearing training data set. The resulting index was then adapted to Sentinel-2 imagery using the radiometric relationships described in Flood (2017) to transform Sentinel-2 reflectance values to Landsat equivalents. This is possible given that the spectral bands are similar to those available from the Landsat sensor (Table 2).

Table 2: Resolution and spectral window for each of the corresponding bands for each sensor

	Sentinel-2 MSI			Landsat 8 OLI		
Generic band name	Pixel resolution (m)	Band number	Spectral wavelength (µm)	Pixel resolution (m)	Band number	Spectral wavelength (µm)
Green	10	3	543-578	30	2	530-590
Red	10	4	650-680	30	3	640-670
Near Infra-Red (NIR)	10	8	785-900	30	4	850-880
Short Wave Infra-Red 1 (SWIR 1)	20	11	1565-1655	30	5	1570-1650
Short Wave Infra-Red 2 (SWIR 2)	20	12	2100-2280	30	7	2110-2290

3.3.4 Automated clearing detection

The modelled woody vegetation clearing index generates values ranging between 0 and 1000 where 0 indicates no clearing and 1000 indicates a very high probability of clearing. In Scarth *et al*. (2008), Receiver-Operator Curve analysis of the Landsat clearing index was used to select six distinct thresholds resulting in a clearing classification based broadly on the likelihood of clearing whilst balancing omission and commission errors. A similar set of thresholds was applied to the Sentinel-2 based woody vegetation clearing index resulting in a set of six classes approximating varying likelihood of clearing from low through to very high. These classes are then used to inform mapping decisions by scientists in the manual refinement stage.

The woody extent for the start year in the monitoring period is used to identify any non-woody pixels in the clearing probability classes. For example, for 2018-19, this is the 2018 baseline woody extent, for 2019-20 it would be the 2019 woody extent, and so on. Ideally, pixels which are non-woody to start with would be eliminated from further scrutiny and the manual editing stage would only need to consider the woody areas for clearing assessment. Generally, the woody areas are still a focus of the mapping, however, at least in the early stages of the current methodology, an additional set of classes is used to identify potential clearing outside of the woody extent t. The woody and non-woody probability clearing classes are labelled with a set of codes listed in Table 3.

The woody vegetation clearing index and change classification rasters are automatically generated for each of the 245 image pairs of start and end dates covering Queensland for the monitoring period.

Table 3: Clearing index thresholds in the change classification layer for woody and non-woody areas delineating classes ranging from low to increasing probability of clearing.

Clearing index threshold	>420	370-420	320-370	270-320	220-270	170-220
Woody change classification codes	39	38	37	36	35	34
Non woody change classification codes	69	68	67	66	65	64

3.3.5 Clearing mapping

3.3.5.1 Mapping clearing using Sentinel-2 vs Landsat

Transitioning the woody vegetation clearing monitoring from medium resolution Landsat imagery with 30m pixels to high resolution Sentinel-2 imagery with 10m pixels involved a significant change in the scale of the monitoring. This in turn necessitated a change in clearing mapping. The medium resolution Landsat data was able to be used as a woody classifier (either modelled via, for example Foliage Projective Cover models, or by manual interpretation) since a single Landsat pixel tended to be larger than an individual shrub or tree crown. Each pixel captures both the crown and inter-crown gap of an area of woody vegetation. As resolution increases, this model starts to break down, since each pixel becomes a progressively purer representation of crown or non-crown (Zhang et. al. 2019). At higher and higher resolutions, a woody area then consists of both woody and non-woody pixels, particularly in ecosystems which are naturally more open. Given the scale change, an unbiased estimate of the area cleared changes from counting woody change pixels, to delineating the pixels which comprise the area or stand of woody vegetation which includes the crown and inter-crown (i.e. gaps between crowns) impacted by the clearing event. This area is referenced throughout this document as a “clearing footprint". This is more representative of the total area impacted by the clearing event and is more independent of the resolution of the sensor.

3.3.5.2 Attribution including 'landcover replacement classes'

During the manual editing stage, each area of woody vegetation clearing is attributed with a *landcover replacement class* (Table 4). This provides an indication only of the land cover/land use purpose for which the vegetation was cleared or modified. Assignment of these classes is primarily based on visual interpretation, with reference to ancillary data sources. In areas where there are many different forms of land use, it can be difficult to interpret the final landcover replacement class and therefore this classification is indicative only. For example, land assigned to the class *pasture* may later be converted to *settlement* or other classes. Landcover replacement classes used in the Sentinel-2 change monitoring have been adapted from the Landsat-based clearing monitoring.

Table 4: SLATS replacement landcover

Replacement land cover	Description
Pasture	Grazing and other general agricultural land management practices—this class includes clearing for pasture, internal property tracks, fence lines or fire breaks.
Crop	Cropping or horticultural purposes.
Forestry	Timber harvesting in state or privately owned native or exotic (e.g. pine) forests or plantations.
Mine	Mining activities (including coal seam gas infrastructure).
Infrastructure	Utilities such as roads, railways, water storage, pipelines, powerlines etc.
Settlement	Urban development.

Additional attribution discriminates the type of clearing activity in terms of how much modification of the vegetation has occurred. This serves two purposes: (i) areas which are partially modified are able to be reported as such, thus providing a more nuanced component to the reporting of the clearing areas – this is particularly relevant for those regions where partial clearing is routinely undertaken under VMA codes or in unregulated areas for routine agricultural land management (e.g. fodder clearing and harvesting in the Mulga Lands); and (ii) it enables updating of the woody extent after each monitoring period such that partially cleared areas remain in the woody extent and are therefore considered in future monitoring.

Three classes are used to represent the degree of modification:

i. ***Full clearing*** refers to clearing areas where the clearing activity has resulted in conversion from woody (i.e. greater than 10% crown cover) to non-woody (i.e. less than 10% crown cover). Full clearing will result in removal from the woody vegetation extent data set.

ii. ***Partial clearing (major)*** refers to clearing areas where greater than 50% of the patch area has been removed and greater than 10% crown cover remains. These areas remain in the woody extent.

iii. ***Partial clearing (minor)*** refers to where less than 50% of the clearing patch has been removed and greater than 10% crown cover remains. These areas remain in the woody extent.

The three classes are all reported as clearing activity but distinguished in SLATS reporting. The full list of pixel attribution codes used during manual mapping of vegetation clearing is detailed in Table 5 together with how each informs the reporting of clearing and woody extent updating.

Table 5: Codes used in mapping and attribution of vegetation clearing, including landcover replacement class, partial and full clearing attribution, and how each code informs reporting and updating of the woody extent.

	Code	Description	Examples	Reported as Clearing	Remain as Woody Vegetation
Human-induced clearing activity	40	Possible clearing	For review	No	Yes
	41	Full clearing to *pasture:* where vegetation has been converted from woody (i.e. >10% crown cover) to non-woody (i.e. <10% crown cover)	All clearing to *pasture*, internal property roads and tracks, fence lines, fire breaks. Single house pads in rural and semi-rural areas, golf courses	Yes	No
	71	Partial clearing major to *pasture: where* >=50% area of vegetation removed within patch and >10% crown cover remains	Clearing to *pasture* and still woody. Poisoning where dead trees left standing.	Yes	Yes
	73	Partial clearing major to *forestry*: where >= 50% area of vegetation removed within patch and >10% crown cover remains	Clearing to *forestry* and still woody. *Forestry* includes timber harvesting on state- or privately-owned lands, where it can be verified.	Yes	Yes

	75	Partial clearing minor*:* where <50% area of vegetation removed and >10% crown cover remains	Disturbance including removal of understorey.	Yes	Yes
	42	Full clearing to *crop*	Within or adjoining existing cropping area where paddock has been ploughed for planting orchard/crops. Clearing of woody orchards (including grape vines) for horticultural purposes.	Yes	No
	46	Full clearing to *settlement*	Clearing for housing estates, shops, hospitals etc.	Yes	No
	48	Full clearing to *mine*	Mining activities including expansion of open cut mining, CSG pads, coal exploration areas and large quarries	Yes	No
	51	Full clearing to *infrastructure*	Dedicated roads, gas pipelines, rail & easements, airport runways and gravel pits beside roads. Dams and aquaculture ponds. Permanent linear features cleared between CSG pads.	Yes	No
	53	Full clearing to *forestry*	Clearing within State forests or exotic and native plantations.	Yes	No
	58	*Adjustment*: adjustment to the woody extent due to missed clearing	Correction for missed clearing in previous monitoring period.	No[†]	No
	59	*Adjustment*: adjustment to woody extent due to previous incorrect mapping	Correction to remove vegetation due to incorrect mapping.	No[†]	No

	80	*Intermediate code*: designates strip clearing. These are re-evaluated during post-processing and assigned either 41, 71 or 75). Refer to Section 3.3.5.4 for details.	Strip clearing and fodder harvesting but only in the Mulga lands.	Yes	Depends on final attribution .
Non-human induced change	54	Non-human induced change. Used to map natural change events that result in semi-permanent or permanent loss/alteration of the woody vegetation. Note: Change due to bushfires is not considered a semi-permanent or permanent loss/alteration.	Landslips, extensive cyclone damage, drought death, dieback, flood damage	No	Depends on extent of damage

***Evaluated and attributed on case-by-case basis*

†Reported as adjustment to woody extent but not included in clearing areas.

3.3.5.3 Manual mapping methods

The manual mapping stage is critically important to production of the final high-quality woody vegetation clearing maps. The need for extensive manual editing is required because naturally occurring events can affect vegetation in ways that appear similar to woody vegetation clearing in the imagery and clearing index. For example, damage by storms, fire and drought can all cause a reduction in canopy health or cover that can influence the woody vegetation clearing index in a similar way to a clearing event. In addition, seasonal effects, atmospheric conditions, and other factors can affect how reflectance from land cover types, especially vegetation, appears from one satellite image date to the next. Image corrections attempt to account for this as best as possible, but effects remain that can mean that image differencing detects changes which are undesirable. Hence, no matter how good an algorithm is, there is still no approach that can provide the level of discrimination and accuracy that a trained scientist can achieve.

The manual mapping stage is conducted in two passes: initial editing to identify and delineate vegetation clearing using the automatically generated clearing classifications, followed by extensive review and quality assessment. For each mapping pass, automated processes (python scripts) recall the required image inputs to the analyst's local working directory. For a given Sentinel-2 tile this includes: the selected Sentinel-2 start and end date imagery, the automatically generated change classification and clearing index, and historical clearing data along with any ancillary data or imagery used to aid interpretation. Editing/quality review is undertaken directly on the woody extent data. Attribute domains are utilised to enable fast and efficient attribution of clearing codes to a specified woody extent polygon where clearing has been detected and helps to minimise attribute errors by the operator. The woody vegetation clearing index (Section 3.3.4) provides a useful starting point for the change classification, helping to focus the manual mapping effort on those areas where clearing is most likely to have occurred. SLATS scientists modify and/or attribute the woody extent polygons depending on the area that is interpreted as being affected by clearing. In some cases, this means the linework for a woody extent polygon needs to be modified and attributed if it is only partly affected by either full or partial clearing. In other cases where the entire polygon is affected, the linework is not modified, only the attributes.

The first pass involves a scientist reviewing the change classification layer and associated Sentinel-2 imagery to identify and map the full extent of a clearing event (clearing footprint) in accordance with the codes in Table 5 and the Sentinel-2 mapping guidelines. Scientists draw upon their own expert landscape knowledge and that of others in the SLATS team to aid decision making. Sometimes the pre-defined probability thresholds on the clearing index do not identify the full clearing footprint. In this case, manual delineation of the vegetation change through image interpretation is required.

The second pass of the manual editing is undertaken by a senior remote sensing scientist to provide an independent check. It involves quality checks to validate clearing has occurred where it has been mapped in the first pass, modify the clearing footprint if required, and check for missed areas of clearing. Discrepancies are highlighted for further review and discussion where required. The mapping team regularly discuss issues, areas of interest and mapping specifications to ensure consistency and continuous improvement. During this second pass, the senior scientist may make judicious use of other high-resolution imagery sources to confirm difficult to interpret areas such as occurs where the vegetation is sparse, or the clearing activity is difficult to distinguish. The scientists make the required updates, and a script is run to save the final data set to the HPC archive.

This two-pass process ensures a high level of accuracy and consistency in the final map. Note that some western tiles, where there is historically very little or no clearing activity, are only subject to the first pass. Any areas in these regions that are uncertain during this single pass are discussed with senior scientists to maintain consistency.

After each mapping pass, the edited data is versioned and archived and each editing stage is automatically logged in a spatial database table together with operator name and time stamps. All procedures are documented on the DETSI/JRSRP Wiki.

All manual editing is supported by a set of documented mapping guidelines, which guides scientists in determining the full extent of the clearing footprint. This is a 'living' document, updated as procedures are refined, or decisions clarified. The manual editing work is done using ESRI's ArcGIS Pro software which includes a suite of tools for viewing and enhancing imagery. The software allows editors to edit or modify polygons and to assign attributes using the codes given in Table 5. In any mapping period, change mapping is clipped into a Master version of the woody extent. A new attribution field is added to the data's attribute table (database) which enables vegetation changes in any particular area to be tracked through time without losing changes to linework. Where required to produce a dataset for any particular release date, the attributes are used to merge or dissolve linework to produce a final map reflecting the changes made in the given mapping period (refer to Section 4.1.1.4 for further details).

3.3.5.4 Post-processing strip clearing mapping for the Mulga Lands bioregion (code 80)

Strip clearing and other fodder harvesting methods can result in complex clearing patterns which are difficult to map. This type of clearing activity is particularly prevalent in the Mulga Lands bioregion where fodder harvesting practices are common and some provisions in the VMA allow for this type of clearing to ensure stock can be fed during drought. Clearing patterns in this bioregion can include obvious strips which may exceed the specifications for linear features (i.e. 20m width) or complex criss-crossing patterns or narrow strips which are below the specifications for linear features. The SLATS change algorithm, while accurate at detecting strip clearing events, does not always provide enough detail to accurately delineate these various types of strip clearing without significant additional manual updating. Therefore, to ensure objectivity and repeatability, as well as accurate delineation of strip clearing in the Mulga Lands bioregion, a *post hoc* mapping process was developed.

During the first pass SLATS clearing mapping, strip clearing events that are not well-defined in the clearing index, or are difficult to efficiently map to SLATS specifications, are mapped by delineating the outer boundary of the clearing event and attributing the area as code 80 (an intermediate code). A *post hoc* process then applies an image segmentation model, trained by accurate mapping of woody vegetation in the local region, to provide an improved delineation of the cleared strips. This is then manually reviewed and refined as required to provide an accurate delineation of the clearing. The clearing is then attributed accordingly as either full or partial (major) clearing and coded accordingly (i.e. codes 41 and 71 respectively; Table 5).

3.3.5.5 Post-processing the clearing mapping

In what is effectively a third, and final, mapping stage, a post-processing step is undertaken by senior DETSI remote sensing scientists to moderate the clearing mapping across tiles. This involves some targeted, and some random, selection of tiles and moderating the clearing for accuracy and consistency. It also helps to ensure the tiles from western areas of the state which have only been subject to the first pass of editing, do get some review and consistency checks applied to them. During this step, changes are made as required based on expert opinion.

An additional manual refinement exercise is undertaken to edge match the mapping in overlapping regions between adjacent tiles to ensure a seamless data set for the state.

Prior to integration into the woody extent master database, the clearing polygons are intersected with a forestry vector data set to ensure that clearing events that fall within regions where there are known forestry plantations are correctly attributed as *Clearing to forestry*. The forestry vector is derived from the union of *Agricultural land audit - current forestry plantations – Queensland* (Department of Agriculture and Fisheries) and *Queensland Digital Cadastral Database* (DNRMMRD*)*, where base tenure is *state forest*, *forest reserve* or *timber reserve*. These data sets are downloaded from the Queensland Government Spatial Catalogue for the date closest to the start of the given monitoring period.

The clearing polygons are then integrated into the woody extent geodatabase following the procedures of Section 4.1.1.4, as part of the annual woody extent updating.

3.3.6 Data products

The final state-wide clearing data set is stored in vector form and released as vector for public access via Open Data portals. It is also converted to raster for use in the reporting framework.

3.4 Woody vegetation age since last disturbance estimation

3.4.1 Overview

The initial aim was to estimate the age of woody vegetation in the 2018 baseline year, to then enable tracking of vegetation age over time in successive annual updates to the woody extent (refer Section 4.1.1) to provide environmental and contextual data that makes the woody extent, clearing and regrowth mapping more useful for a range of policy and land management purposes.

This research has resulted in a new approach to modelling land cover over long periods using a sampling framework that requires minimal temporal coverage. The method combines Landsat time series, the high-resolution woody extent, and a sequential classifier to estimate the likelihood of woody cover for each year over the length of the Landsat time series (30+ years).

Due to the limits of the time series-based age estimation, woody vegetation age is defined as:

> *The estimated time since the woody vegetation was last significantly disturbed, or where possible to detect, the time since it started to grow or regrow following a significant disturbance. A disturbance may be due to a clearing event or other disturbance such as fire, flood, drought-related tree death etc.*

For a given Landsat pixel, the sequential classifier generates a 30+ year time series of woody probabilities. Heuristic rules are then used to detect patterns in the woody probability sequence that might characterise a typical persistent woody vegetation growth (or regrowth) response curve and track that behaviour over time. The estimated age from the probability sequence is combined with the SLATS Landsat clearing record to provide a preliminary estimation of age since last disturbance for all woody pixels recorded in the 2018 baseline woody extent and to track the age in subsequent woody extent updates, including assigning age estimates to any new regrowth that is mapped.

3.4.2 Data

A thirty-three-year time series (1988 to 2021) of seasonal Landsat fractional cover components at 30m spatial resolution (Scarth *et al*., 2008) was used to estimate the age since disturbance of all woody pixels in the 2018 baseline woody extent and the 2019 through to 2021 (inclusive) annually updated woody extent rasters. From 2022 onwards, an extended time series of seasonal Landsat fractional cover (adding in all recently processed seasonal fractional cover up until the most recent Spring season) is processed to assign an age estimation to newly mapped regrowth in that monitoring period, and to any pixels where an age was unable to be estimated previously. The fractional cover data consist of bare, green, and non-green sub-pixel components. Seasonal data were generated by calculating the medoid (Flood, 2013) for every three-month period (i.e. calendar season). Thus, there were 15 fractional cover components for every 12-month period (covering five seasons, Spring to Spring inclusive).

The 2019 woody extent data set was used as sample strata to generate woody/non-woody training sequences for a Conditional Random Field classifier (described below in Section 3.4.3.1). The 2019 woody extent data were resampled from 10m to 30m spatial resolution to align spatially with the Landsat time series.

The historical SLATS Landsat (1988-2018) and Sentinel-2 (2018-ongoing) clearing data sets are additional inputs used to constrain the age since disturbance estimates for each monitoring period.

3.4.3 Methods

3.4.3.1 Conditional Random Fields

Conditional Random Fields (CRFs) are a discriminative supervised classifier designed for sequential data (Lafferty *et al.*, 2001). CRFs are commonly used in the field of Natural Language Processing (NLP), which uses machine learning to understand sequential context in human languages. In the NLP field, a sequence might be represented by a sentence, and each word would consist of a set of predictive features. The goal of CRFs is to estimate the likelihood of transitioning between states (i.e. from one word to another). In this work, we used CRFs in a similar manner but applied to remotely sensed data. Therefore, our sequence for an individual pixel was a time series of seasonal fractional cover estimates. The sequence states were 12-month periods and the predictive features for each state consisted of fractional cover components over each 12-month timeframe.

3.4.3.2 Sample framework using temporal augmentation

CRFs are a supervised classifier and, therefore, require example class labels to optimise the state transitions. Collecting repeat training data for these types of temporal sequences over large areas is challenging. Therefore, a sampling method was developed that uses available land cover classifications over any number of time periods to generate sequences of training labels. This method is referred to as 'temporal augmentation'.

With this approach, the 2019 woody extent was used to generate random stratified samples over space, resulting in thousands of samples that intersected the manually scrutinised woody extent data set. In practice, further stratified samples with additional land cover edge stratum (e.g. woody cover 90m from a non-woody pixel) were included to ensure that mixed pixels were represented in the sample pool. This random sample pool provided a starting point for woody/non-woody training examples. Next, training sequences (augmentation) from this static pool were generated.

The Landsat time series used for prediction were sequences of fractional cover data over 33 years, but the training sample pool only included labels from the 2019 woody extent, which coincided with a single year of seasonal medoid fractional cover data (approximated as Spring 2018 - Spring 2019 inclusive). Therefore, the samples were augmented to match the 33-year Landsat sequence length to train a CRF classifier. To do this, a subset of samples was selected within a mapping zone. A mapping zone could theoretically consist of any region, such as an ecological biome or administrative boundary. In this work, a regular grid of 150km x 150km across the state was used, with each grid cell representing an independent mapping zone. After woody/non-woody samples were collected for a particular mapping zone, thousands of 33-year pseudo-sequences were generated, where each pseudo-sequence consisted of samples spatially distributed across the mapping zone. It is important to note that each sample's class label in each sequence was always *woody* or *non-woody* in the 2019 woody extent, and the associated Landsat data was always the set of seasonal cover fractions from the single year approximated by Spring 2018 - Spring 2019 (inclusive). Therefore, these sequences were pseudo sequences because they did not represent real time series. By generating thousands of random permutations, though, this temporal augmentation approach provided a sequential data set for a CRF model to "learn" transitions between different land cover states (e.g., woody to woody, woody to non-woody, and non-woody to woody).

3.4.3.3 Woody probability estimates

The CRF classifier optimises the conditional distribution $p(y|X)$, which is the probability of y (e.g., a sequence of class labels) given a set of predictive features X (e.g., a sequence of predictive features). In this work, X and y were Landsat fractional cover time series and woody/non-woody label sequences, respectively, both taken from the temporal augmentation sample pool described in Section 3.4.3.2. More specifically, the predictive features consisted of 33 years of fractional cover sequences [$(bare, green, non\text{-}green)_{1988}$, …, $(bare, green, non\text{-}green)_{2021}$], with corresponding woody/non-woody class label pseudo-sequences (e.g., [$woody_{1988}$, …, $non\text{-}woody_{2021}$]). These data were used to train CRF models for each 150km X 150km mapping zone. As described above, a CRF estimates the transition likelihood between land cover states. Thus, for an individual pixel the transition likelihoods between sequence states are estimated with the assumption that there is co-dependency between labels. For example, a CRF trained on the woody/non-woody sequential data estimates likelihoods as [$(p(w), p(nw))_{1988}$, ..., $(p(w), p(nw))_{2021}$], where the 1988 estimates might consist of a 0.7 and 0.3 likelihood of the pixel being predominantly woody and non-woody, respectively (i.e. $(p(w)=0.7, p(nw)=0.3)_{1988}$).

3.4.3.4 Woody age since disturbance estimates

The start and end years of the *most recent period of regrowth or persistent woody* were estimated from the 1988-2021 time series of woody probabilities using a heuristic approach. Four thresholds guided this work:

- minimum baseline probability threshold: 0.05
- minimum woody probability: 0.5
- minimum proportional change: 0.01, and
- minimum number of consecutive years: 3.

For each pixel, the woody probabilities were evaluated to determine if the sequence at each time step was:

a) *increasing*, characterised by a proportional change in probabilities exceeding the *minimum proportional change* and the probability exceeding the *baseline probability threshold*, or

b) *woody*, characterised by the probability exceeding the *minimum woody probability threshold*. If the *increasing* or *woody* condition was met, the age was incremented.

If at a given time step, the incremental age exceeded the *minimum number of consecutive years* as *increasing or woody*, then the start and end years of that period were recorded. The start year recorded the time step at which the *increasing or woody* condition was first satisfied. The end year was incremented at each successive time step until either the end of the time series or until neither *woody* nor *increasing* conditions were satisfied, in which case, the incremental age was reset to zero, and the iteration restarted from that time step.

The SLATS historic Landsat (30m; 1988-2018) and Sentinel-2 (10m; 2018+) clearing data sets were used to constrain the modelled age estimates, so that the woody age since disturbance could not be greater than the time since last (full) clearing event recorded by SLATS, as follows:

- Where an historical SLATS clearing event was recorded for a given pixel, the age was estimated as the most recent of the last clearing event, and the estimated start of the last predicted regrowth/woody period.
- Where there were persistently high woody probabilities (exceeding minimum woody probability) over the entire sequence, an age equal to the length of the time series was assigned.

- Where no age could be estimated with any confidence due to an absence of clearing history and no detectable trends in the woody probability sequence, a label of "indeterminant" was assigned.

The SLATS Sentinel-2 partial clearing classes, and previous Landsat "Thinning" classes were excluded from use in age estimation.

Updates to the heuristic rules since the publication of *Statewide Landcover and Trees Study (SLATS) Sentinel-2 – 2018* have resulted in improved tracking of persistent woody vegetation over time, and increased ability to detect young regrowth. This in turn has resulted in fewer woody pixels with an 'indeterminant' age.

From 2022 onwards, the woody age since disturbance is annually updated with some variation from the methods described above:

- For all woody pixels where no clearing or new regrowth has been mapped in the given monitoring period, the woody age since disturbance is incremented by 1 from the previous year.
- Where full clearing was mapped, the woody age is reset to zero.
- Where woody additions were added to the woody extent or the age in the previous year was "indeterminant", the age is estimated using the methods described in this section, applied to an extended time series of seasonal Landsat fractional cover (Section 3.4.3), constrained by all historic Landsat and Sentinel-2 SLATS clearing record up to and including the given monitoring period.

3.4.4 Limitations

Limitations to the woody vegetation age since disturbance estimation:

- The 2018 baseline woody extent contains sparse and/or young woody vegetation that may not have been detectable at the Landsat scale, either in the CRF modelling approach or in previous monitoring periods and was therefore unable to be monitored at that scale.
- Missing data in the fractional cover data that is used as model inputs to the CRF due to factors such as persistent cloud or topographic shadow as well as real but transient disturbance events such as fire or flood may cause woody probabilities to fall to 0, confounding age estimates.
- There may be clearing omissions from the SLATS record due to scale effects or mapping errors that impact the ability to estimate age for a given pixel.
- There may also be clearing events in the Landsat record that did not involve a full transition from woody to non-woody and are therefore still woody in the 2018 baseline woody extent.
- Mismatches in scale and mapping specifications between the historic Landsat clearing data sets and the higher resolution 2018 baseline woody extent can result in artefacts in the age data set. For

example, edge effects or small non-woody features such as roads and buildings which were the result of a past mapped clearing event but are currently included in the 2018 baseline woody extent due to minimum mapping unit specifications.

3.4.5 Data products and outputs

Thirty-three years (1988-2021) of woody probabilities across the state at Landsat 30m spatial resolution have been produced. The data values indicate the likelihood (range of 0 to 1) that a pixel is predominantly woody.

The Queensland mosaic of estimated regrowth periods (1988-2021) captures the start and end year of the most recent detected regrowth or persistent woody period for each pixel over that period at Landsat 30m spatial resolution.

The woody age since disturbance rasters record the estimated age since disturbance (years) of woody pixels for the given year of woody extent at Sentinel-2 10m spatial resolution. Currently this includes 2018, 2019 and 2020 mosaics over Queensland with the intention to produce updates for each annual monitoring period.

3.5 Woody vegetation regrowth mapping

3.5.1 Overview

Regrowth, or new regrowth, is a change (i.e. a gain or addition) to the woody vegetation extent where regrowing vegetation meets the definition of woody vegetation. Therefore, the aim is to detect and map new regrowth using Sentinel-2 imagery.

The woody vegetation regrowth mapping approach involves extensive manual image interpretation and desktop mapping procedures, informed by data from automated time-series modelling. Similar to the clearing mapping, the manual mapping process ensures a comprehensive and accurate assessment of regrowth and includes review and quality assurance checking. An automated spatial prediction of candidate regrowth probabilities derived from a CRF modelling approach is used to guide the manual mapping effort (refer to Section 3.5.2.2). Regrowth mapped through this process is added to the woody extent and is considered a 'gain' in the context of the SLATS accounting framework.

In the first Sentinel-2-based monitoring period, 2018-19, it was assumed that existing regrowth was already mapped and characterised in the 2018 baseline woody vegetation extent. As regrowth generally occurs on time scales greater than one year, mapping and monitoring of new regrowth commenced from the 2019-20 monitoring period and has been included in annual monitoring thereafter. The annual time-step for mapping regrowth will be reviewed after completion of several monitoring periods to determine if it is what is most effective and efficient.

It is acknowledged that regrowth can occur in areas that are already mapped as woody vegetation. As noted in Section 2.1.2.5, this process, referred to as densification, does not result in a change in woody vegetation extent and as such is currently out of current scope. Other similar processes such as encroachment of woody vegetation into native grasslands that result in a change in the woody extent will be mapped where the new regrowth can be reliably detected and mapped following the methods described below.

3.5.2 Methods

3.5.2.1 Manual Mapping Process

The primary method for regrowth mapping is a comprehensive process of manual image interpretation, assessment and mapping for the entire state. This process is currently conducted annually to identify and map new regrowth that is not already captured in the woody extent. Quality assurance checking is conducted to ensure the accuracy and reliability of the mapping. The CRF predicted regrowth candidates (Section 3.5.2.2) are used as an ancillary source of data that can assist in identifying potential regrowth areas. This ensures a comprehensive assessment of regrowth, in line with the level of effort and approach used for the clearing mapping process.

The manual process follows a similar structure to the clearing mapping described in Section 3.3.5.3. Automated processes (Python scripts) are applied to a given Sentinel-2 tile to recall into a local GIS (ArcGIS Pro) instance: the Sentinel-2 imagery; the (CRF) candidate regrowth estimates; the woody extent for editing; and relevant additional ancillary data for that tile. The ancillary data is used to guide and inform the decision-making process and includes historical SLATS clearing data, land use information, and additional high-resolution imagery where available for the tile in a data range that is suitable for the given mapping period.

Identifying new regrowth in satellite imagery is challenging due to regrowth processes generally being a slow and gradual increase in woody vegetation over several years, and because it often occurs in landscapes with highly variable land cover dynamics. To address these effects, a time series of historical Sentinel-2 imagery is employed to establish a recurrent trend in woody vegetation that minimises uncertainty in the reflectance characteristics and patterns associated with new regrowth in the satellite imagery.

As a minimum, regrowth needs to be observable in at least two consecutive years with obvious trees crowns identifiable in the imagery to be considered and mapped as regrowth. This ensures that non-woody ground cover is not incorrectly included in the mapping product and that new growth is only added where there is sufficient certainty that established woody vegetation is present at any given location.

Regrowth that is mapped is classified using the attributes listed in Table 6. As with the clearing mapping, these attributes are intended to provide an indication of the purpose for which the land is used at the location where the regrowth is mapped. Where potential regrowth is identified but has not developed to a suitable stage, or uncertainty remains, the area is flagged for potential regrowth to be reassessed in the following mapping period.

As a final step in the process, quality assessment is conducted to check and validate mapped regrowth thus ensuring consistency and further minimising uncertainty in mapped regrowth. Field work is also undertaken to further validate mapped regrowth and to confirm that the correct classification (Table 6) has been applied. Field observations help improve certainty in regrowth mapping, calibrate the interpretation of woody vegetation in satellite imagery, enable the collection of data to inform future method improvements, and enhance overall landscape knowledge within the SLATS team.

3.5.2.2 Automated Candidate Modelling

To support the manual mapping process, automated detection of candidate regrowth areas is undertaken using a CRF modelling approach similar to that used for Landsat-based age estimation (Section 3.4), but applied to a shorter, rolling Sentinel-2 time series.

Time sequences of woody probabilities are used to predict candidate new regrowth areas. The regrowth monitoring framework differs from the age attribution as follows:

i. a shorter, 10-year time series of Sentinel-2 imagery supplemented with up-sampled Landsat imagery is used instead of 30+ year Landsat sequence; and

ii. regrowth is estimated with a modified set of heuristic rules adapted for the shorter time series and with a focus on young regrowth that is not currently in the woody extent.

3.5.2.3 Short-term woody probabilities

Sequential-based CRF woody probability estimates over ten years are utilised for this modelling approach. The timeframe chosen was designed to shorten the prediction sequence compared to the 33-year age estimates while maintaining sufficient temporal resolution to model temporal co-dependencies between woody/non-woody transitions. Any 10-year sequence ending around 2020 precedes the first Sentinel-2 launch date of 23 June 2015. Therefore, the Sentinel-2 time series is supplemented with Landsat data prior to the beginning of the Sentinel-2 era. Alternatively, the monitoring timeframe could be shortened to less than 10 years to use Sentinel-2 only. However, tests showed that sequences of less than five years were not sufficiently long enough for a CRF model to optimise land cover transitions. The Landsat is resampled from 30m to 10m spatial resolution to align with the Sentinel-2 grids. The practice of up-sampling coarser resolution imagery without ancillary information (e.g., fusion) is typically discouraged. However, in this case the Landsat data helped serve as a run-up period for the CRF model. That is, in practice, we are only interested in the final year of the 10-year period (refer Section 3.5.2.4) and only using the 10-year Landsat/Sentinel-2 sequence to help stabilise woody/non-woody transition estimates. The same 'temporal augmentation' approach is used to sample and fit a CRF model, using 10-year sequences instead of 33-year sequences.

As an example of how this works in the SLATS monitoring framework, for the monitoring period 2019-20, the 10-year time series consisted of resampled Landsat data from 2010 to June 2015. The remaining five years of the time series (i.e. 2015-2020) consisted of Sentinel-2 imagery only. For a given pixel, the sequence of woody likelihood from 2010-2020 (i.e. 10 annual probabilities) was estimated. These woody/non-woody probability sequences were then used in the heuristic model (refer Section 3.5.2.4) to estimate the presence (or not) of potential regrowth in 2020. This process was repeated for the following monitoring year (2021) by shifting the input time series to 2011-2021 and applying the same CRF model. The time series would ultimately consist of Sentinel-2-only during the 2025 monitoring year with a 2015-2025 time series. This approach could also be applied to timesteps of finer temporal granularity (e.g. monthly instead of seasonal input data), which would allow for a sub-annual monitoring framework.

3.5.2.4 Regrowth candidate identification

Candidates for regrowth areas are identified using the rolling ten-year time series of woody probabilities (Section 3.5.2.3), and a heuristic classification similar to that used for woody age since disturbance estimation (Section 3.4) and with a similar but reduced set of thresholds: *minimum woody probability*, *minimum proportional change*, and *nconsec years* (the minimum consecutive number of years of regrowing or woody period). For the 2019-20 monitoring period these thresholds were: 0.5, 0.05, and 3, respectively.

As an initial condition, only pixels which are not already woody at the start of the given monitoring period are considered as potential candidates. For these non-woody pixels, the sequential woody probabilities are assessed to determine if a regrowth response is evident. Unlike in the age estimation, it is only the last period of *nconsec years* up to and including the end year of the monitoring period which is of interest. If the change in probabilities at each time step exceeds the *minimum proportional change* over the last *nconsec years* and the woody probability at the end year exceeds the *minimum woody probability threshold,* then the pixel is identified as an initial candidate.

As an example, for the monitoring period 2019–20, pixels which were non-woody in the 2019 woody extent data set were assessed to determine if they displayed a proportional increase in probabilities greater than 0.05 relative to the previous year, over all three years, 2018 – 2020 (inclusive). Those which met that condition and also had a woody probability exceeding 0.5 at 2020 were potential candidates.

Filtering was applied to the set of candidate regrowth pixels to remove clumps of candidate pixels smaller than 0.5ha. These candidate areas are then used as a guide in the manual mapping process outlined in Section 3.5.2.1.

Table 6: Codes used for the SLATS regrowth mapping attribution.

	Code	Description	Examples
Regrowth Activity	3	Possible regrowth	Vegetation that has been identified as possible regrowth, but there is insufficient evidence to include it in the reporting. Flagged for future monitoring.
	21	Regrowth in *Pasture*	All native and non-native woody vegetation regrowth in *pasture lands.*
	22	Regrowth in *Cropping*	New and regrowing woody crops and horticulture, including fodder crops and tree fruits and nuts.
	23	Regrowth in *Forestry*	Regrowth in timber plantations and state forests. *Forestry* includes timber on state- or privately-owned lands, where it can be verified.
	24	Regrowth in *Mine*	Regrowth in mining areas. i.e., rehabilitation.
	26	Regrowth in *Settlement*	Regrowth in urban residential areas such as gardens and parklands.
	27	Regrowth in *Infrastructure*	Regrowth along rail lines, airports, industrial complexes.
	28	*Adjustment*: incorrect clearing	Incorrect full clearing in the previous mapping period added back into the woody extent. Reported as an adjustment.
	29	*Adjustment*: incorrect non-woody vegetation	Correction to add vegetation due to incorrect mapping in the woody extent. Reported as an adjustment.

3.5.3 Data products and outputs

After finalising, the regrowth together with the clearing data sets are integrated with the woody extent data set to provide an updated woody extent and change attributes (Section 4.1.1).

3.6 Woody vegetation density estimation using foliage projective cover

3.6.1 Overview

Foliage projective cover (FPC) is a metric of vegetation cover used in some Australian vegetation classification frameworks. FPC is defined as the fraction of ground covered by the vertical projection of photosynthetic foliage of all strata (Specht, 1983). An FPC metric derived from Sentinel-2 imagery is used to provide estimates about the range of tree and shrub densities represented in woody vegetation across Queensland, and in the context of the monitoring framework, the vegetation clearing and regrowth mapping.

For some time, DETSI has produced FPC data using a model applied to Landsat, calibrated by field observations (Armston, 2009, Kitchen, 2010). For the current SLATS methodology, an updated model was developed which relates field measurements of FPC to 2-year time series of NDVI computed from Landsat seasonal surface reflectance composites. As with the woody vegetation clearing index (Section 3.3.3.2), there is insufficient field data that coincides with the Sentinel-2 satellite program. The model was therefore fitted on Landsat imagery using a significantly expanded set of field data than was used for the previous Landsat FPC model fitting. The model is then applied to analogous Sentinel-2 seasonal surface reflectance composites to produce an FPC image, using the radiometric relationships established between Sentinel-2 and Landsat in Flood (2017). This is intended to represent the FPC for that 2-year period rather than any single date, hence why SLATS reporting uses the data broadly to provide context in regard to woody vegetation densities in the woody extent, and loss and gain of density classes due to clearing activity and new regrowth, respectively.

The data set is generally expected to provide a reasonable estimate of the range of FPC values for any given stand of woody vegetation, but it is expected there will be over- and under-estimation of absolute FPC values for any specific location (i.e. pixel).

3.6.2 Data

The updated FPC model was developed based on:

i. A two-year (eight-season) time series of Landsat seasonal surface reflectance composites (using the medoid method of Flood, 2013b). Use of the seasonal composites aims to reduce noise and cloud contamination in surface reflectance while still capturing much of the seasonal variation.

ii. The national data set of star-transect field data (Muir et al., 2011) from which measures of FPC can be derived. At the time of the model development, this was more than 4000 individual sites.

In the model, FPC is the combined green fraction of foliage from over- and mid-storey foliage from woody plants (trees and shrubs). While it would be desirable to have a model fitted to Sentinel-2 imagery, little of the available field data has been collected since the launch of Sentinel-2.

To produce a Sentinel-2 FPC product that represents a given period, the model is applied to two-year time series of Sentinel-2 surface reflectance seasonal composites, radiometrically adjusted to match Landsat using relationships described in Flood (2017).

For SLATS monitoring and reporting, the two-year time series for FPC production is selected to best estimate FPC of woody pixels for a given woody extent data set. The start and end seasons are chosen to best approximate the SLATS annual monitoring period (nominally August through to August) and so that *all* seasonal input data precede the nominal date of woody extent (August of given year). This ensures that the maximum NDVI pixel used to estimate FPC for the given woody extent is not influenced by woody vegetation change that occurs in the successive monitoring period. As an example, the published *Statewide Landcover and Trees Study (SLATS) Sentinel-2 – 2018 Foliage Projective Cover (FPC) – Queensland*, estimates FPC for the 2018 woody extent, using season reflectance composites from the two years preceding: Winter 2016 – Autumn 2018 (inclusive).

3.6.3 Methods

3.6.3.1 Model fitting

The FPC model relates the field measured green fraction of mid- and over-storey foliage cover to the minimum value of NDVI calculated from 2-years of Landsat seasonal surface reflectance composites. NDVI is a standard vegetation index used in remote sensing which is highly correlated with vegetation photosynthesis (Rouse, 1974). Other indices and metrics were tested but yielded equivalent or worse results therefore NDVI was chosen for simplicity and as it is a widely known index of vegetation cover.

The FPC model is sensitive to fluctuations in vegetation greenness, leading to anomalies such as high FPC on irrigated pastures or locations with very green herbaceous or grass understoreys. A given pixel in the output FPC image represents the predicted FPC in the season with the least green/driest vegetation cover over the 2-year period assumed to be that with the least influence of seasonally variable herbaceous vegetation and grasses on the more seasonally stable woody FPC estimates. The two-year period was used partly because it represents a period relative to tree growth but was also constrained due to the limited availability of imagery in the early Sentinel-2 time series. Other time periods were tested but did not improve estimates.

The fitted model is a simple quadratic model with three coefficients:

$$FPC = c_0 + c_1 NDVI_{min} + c_2 NDVI^2_{min}$$

Where:

$c_o = 6.98$

$c_1 = 65.73$

$c_2 = 51.32$

$NDVI_{min}$ is the second lowest value of NDVI for the 2-year period of seasonal surface reflectance

The second lowest value was chosen as cloud contamination due to failure of cloud masking in the seasonal surface reflectance composites may also result in very low values of NDVI. Predicted FPC is clipped to values between 0 and 100.

Model performance was assessed with Monte Carlo Cross Validation (MCCV).

3.6.3.2 FPC prediction

The FPC model is applied to the two-year time series of Sentinel-2 surface reflectance seasonal composites to produce an FPC image. Finally, the woody extent data set (Section 3.2.6) is used to reset FPC values in non-woody regions to zero to eliminate over-estimation of FPC in green pastures, cropping regions and other non-woody landscapes that may be persistently green.

3.6.4 Data products and outputs

The final product is a state-wide Sentinel-2 Foliage Projective Cover estimated for a given woody extent and used in reporting of woody vegetation density. It is also released as a stand-alone data product to support a range of applications, particularly related to carbon, fire and biodiversity programs, and grazing (i.e. pasture biomass) modelling and prediction.

4 Data integration, reporting and accounting

4.1 Data integration

4.1.1 Annual updating of the woody extent

The woody extent (Section 3.2) forms the foundation of the SLATS woody vegetation (annual) change accounting framework (Section 2.2). In each annual monitoring period, the woody extent is updated by integrating the SLATS clearing (from 2018-19 onward), and regrowth mapping (from 2019-20 onward). For a given monitoring period, both the woody extent and change are used in reporting. The updated woody extent is then used to initialise change mapping for the next period of mapping and reporting.

During the initial transition to the Sentinel-2-based monitoring (over 2018-19) when the woody extent data set and enhanced monitoring framework were still under development there were several transitional steps required to integrate the change mapping and woody extent data sets (Sections 4.1.1.1 and 4.1.1.2). Following this transitional period, annual updating routinely involves adding areas of regrowth to, and taking away areas of full clearing, from the woody extent (Section 4.1.1.3). Areas of partial clearing (minor and major partial clearing activity) remain in the woody extent but are attributed for reporting purposes and to inform future monitoring.

The maintenance of the woody extent is not always as straightforward as subtracting the clearing and adding the regrowth each year. It is inevitable that there will be ongoing refinements due to misclassification and error as well as spatial data management operations. Annual updating and maintenance of the woody extent allows for some corrections due to errors in the woody extent, regrowth or clearing mapping in a previous mapping period. Updates due to corrections are integrated similarly to clearing and regrowth but are coded and reported separately to distinguish additions and subtractions due to error/mapping refinement.

4.1.1.1 2018 update

The initial woody extent map (Section 3.2) was derived from 2017 Earth-I imagery. As a 2018 woody extent baseline was required for the revised SLATS framework, the first step was to update the 2017 map to 2018 and establish the baseline.

The previously released 2017-18 SLATS Landsat clearing data set was used to inform the update of the woody extent data set from 2017 to the 2018. Differences in scale, specifications, and definitions between the 2017 woody extent and the 2017-18 Landsat-based clearing data set presented some difficulties for seamless integration of the two data sets. The SLATS 2017-18 clearing data set was produced using Landsat imagery prior to the incorporation of the woody extent data set into the SLATS clearing mapping process. As such, the resolution is generally coarser than the woody extent product. Further, the pixel-based Landsat clearing mapping approach differs from the current Sentinel-2 footprint mapping approach (refer to Section 3.3.5.1). The definition of “woody” also varied between the two data sets. The minimum woody density for inclusion in the current woody extent is ~10% crown cover (~5% FPC) as mapped from Earth-i and Sentinel-2 imagery. The Landsat-based method used a more conservative woody threshold of ~20% crown cover (~10-11% FPC), or that which is detectable in Landsat imagery. Finally, the 2017-18 Landsat-based SLATS clearing data set did not include the partial clearing categories used in the current method (Section 3.3.5.2) which identify clearing activity where there has been modification, but enough woody material remains to be retained in the woody extent data set.

A comprehensive manual checking and editing approach was used to update the SLATS 2017-18 clearing data to align with the scale and definition of the 2017 woody extent to allow for easier integration. Scientists checked each clearing event greater than 2ha using Sentinel-2 imagery for the relevant monitoring end date. A Sentinel-2 based clearing index was also used to identify missed clearing not recorded in the 2017-18 Landsat clearing data set. Manual editing was applied to include missed clearing from the 2017-18 monitoring period, and to fully delineate the whole clearing footprint where clearing had been mapped using the Landsat methods. Each event was also reviewed to determine if full or partial clearing had occurred as per the current approach. Full clearing areas were removed from the woody extent and partial clearing remained in the woody extent map. The updated woody extent was filtered to remove polygons <0.5ha, the minimum mapping unit for the woody extent baseline. The result was a 2018 statewide baseline woody extent map.

4.1.1.2 2019 update

Integration of clearing mapping and woody extent for the first Sentinel-2-based 2018-19 monitoring period was more seamless, as the Sentinel-2 clearing and woody extent data sets are, by design, integrated at the outset of change mapping, and more closely aligned in mapping scale and resolution. As the program was still refining partial and full clearing mapping categories, there was some additional assessment and editing required to further refine these areas as part of the 2019 update. This was particularly the case in areas such as the Mulga Lands bioregion where strip clearing and other fodder harvesting management resulted in some complex clearing patterns and hence some difficulty determining full clearing (which are updated to non-woody in the woody extent) or partial clearing (which remain in the woody extent). Where cleared strips could be defined and met the woody extent criteria for linear features i.e. 20m minimum width), they were manually delineated and coded as full or partial (major) clearing (codes 41 and 71 respectively, Table 5). Following post-processing attribution and filtering (described in Section 4.1.1.4) the result was a 2019 update to the statewide woody extent map.

4.1.1.3 Ongoing annual updates

From 2019-20 onwards, the revised SLATS methodology described herein was more fully established, and updates to the woody extent routinely incorporate annual gains due to regrowth as well as losses due to clearing. For example, the 2020 update involved subtracting the 2019-20 full clearing, adding the 2020 regrowth, attributing woody polygons impacted by partial clearing activity and integrating corrections for incorrect woody extent or previous clearing mapping. The development of an automated method for more refined mapping in complex woody vegetation clearing patterns associated with fodder harvesting and strip clearing specifically (Section 3.3.5.4) has also been finalised and will be applied as required for future monitoring periods.

From the 2021-22 monitoring period and ongoing, SLATS is a fully integrated editing framework such that all editing is done directly on a master woody extent layer. Change attribution is managed through the data set’s attribute table and adding new polygons or splitting existing polygons as required.

4.1.1.4 Post-processing and attribution

A series of Arcpy batch scripts is used to apply cleaning and filtering to remove artefacts associated with the editing and updating procedures. Finally, the updated woody extent and change polygons are filtered to remove slivers and patches which are less than 0.25ha to ensure the ongoing monitoring specification of 0.25ha minimum mapping unit are maintained in the data set.

For a given monitoring period, a new attribute field is added to the master woody extent database to record the updated woody extent attribute for each change polygon. Another is added to record the clearing or regrowth attribution codes (Table 5 and Table 6 respectively) for that monitoring period. For example, upon completion of the 2019-20 change mapping, the clearing and regrowth polygons were incorporated into the master woody extent database by adding a *2020* field, where polygons were recorded as either woody or non-woody depending on the clearing or regrowth attribution codes and a *2019-20 Change* field was added to record the clearing and regrowth attribution codes. Full clearing and regrowth involve a conversion from woody to non-woody and non-woody to woody respectively. Partial clearing involves only an update in the Change field for the relevant period. All remaining unchanged woody extent polygons are replicated into the attribute field corresponding to the updated year. The result is a single data set containing multiple epochs with a separate field for each woody extent year and fields recording the landcover class attributed to the change for each period.

4.2 Reporting

4.2.1 The reporting package

The data products described in the sections above provide the basis for combining SLATS information with other data to monitor and account for woody vegetation extent and change in Queensland on an annual basis. Annual reports are released as web-based reports. The spatial data sets and annual reports are made available via the SLATS data products web page and Open Data, with supporting data also downloadable from the reporting pages.

This ensures full transparency and enables SLATS information and data to be accessible to a range of stakeholders and users in formats that service a range of requirements and analyses.

The SLATS reporting series associated with the current methodology commenced with the 2018 baseline woody vegetation extent and 2018-19 clearing reports, and from 2019-20 onwards, annual reporting of extent, clearing and (new) regrowth.

4.2.1.1 The SLATS cross-tabulation and regional data summaries

The area of change in Queensland is summarised in cross-tabulation using several grouping layers including those listed in Section 4.2.1.3, but also including a wider range of regional and administrative boundaries:

- Local Government Areas
- Natural Resource Management regions
- Catchments

- Biogeographic subregions

This creates a large table, from which flexible summaries can be easily made using simple queries. For example, the area of woody vegetation for 2019 can be calculated by the sum of the area in 2018 less the area mapped as cleared. More complex breakdowns of clearing activity, for example, by Regulated Vegetation Management (RVM) Map category, catchment and clearing type can be summarised.

This change table forms the basis for the web-based reporting and the regional data summaries available as Open Data. It also provides a simple, pre-processed mechanism for arbitrary reporting on request.

The procedure for creating the table is captured in a dedicated Gitlab repository. The workflow makes use of the Snakemake package (Mölder et. Al. 2021) and container processing (Kurtzer, Sochat & Bauer 2017) to ensure repeatability and process governance.

4.2.1.2 The 2018 baseline woody vegetation extent report

The 2018 baseline woody vegetation extent report provides the initial baseline for ongoing SLATS reporting, which annually monitors and accounts for woody vegetation extent and change in Queensland. The revised SLATS methodology described herein monitors and reports change in woody vegetation extent against this baseline. The report also includes information relating to woody vegetation density and age since disturbance estimates.

4.2.1.3 The annual SLATS report

The annual SLATS report summarises, and reports changes due to gains (regrowth) and losses (clearing) in woody vegetation across Queensland for the nominal period from August to the following August. Annual SLATS reports provide the key findings, and a range of graphical and tabulated woody vegetation change activity summarised by:

- regrowth and type of clearing activity: full, partial (major) and partial (minor) clearing
- landcover replacement class
- categories of age and density of woody vegetation
- vegetation management status including RVM Map category and vegetation management class
- bioregions, with other regional summaries available via open data e.g. Local Government Areas, catchments
- a transaction summary of woody vegetation change over the period.

The 2022-23 SLATS report introduces information about the height of vegetation for areas affected by clearing activity. Clearing activity is summarised by vegetation height based on data from the global canopy height data set published by Lang et al. (2023). This is a 10m spatial resolution estimate of canopy height, based on a model relating Sentinel-2 reflectance to vegetation height data from the space-borne LiDAR from the Global Ecosystem Dynamics Investigation (GEDI) mission. A preliminary assessment of these data was undertaken using LiDAR data to assess the model's performance for Queensland. This found that the accuracy was acceptable for the purpose of summarising SLATS clearing activity data by broad height categories.

4.2.1.4 Data products

Data products produced are released as Open Data. This includes the clearing and regrowth data, the woody extent data, the age and density products, and any data associated with reporting and regional summaries.

4.2.1.5 A note on reporting areas vs rates

Historically, SLATS has reported annual rates of clearing mostly due to the difficulty of acquiring two cloud-free dates of Landsat imagery one year apart (Appendix A in Queensland Department of Environment and Science, 2018). For example, the start and end dates selected could be as little as 8 months, or as much as 15-16 months apart, sometimes for adjacent path/rows. Thus, clearing *areas* were adjusted (i.e. annualised) to account for this time lag and to enable comparative annual reporting. The increased temporal resolution of the Sentinel-2 satellites (5-day return interval vs Landsat's 16-day) means that opportunities for obtaining cloud-free imagery much closer to 12 months apart are significantly increased. For example, an analysis of the SLATS-selected cloud-free Sentinel-2 tiles for 2019 showed that if a nominal date of August 15 was chosen, all the Sentinel-2 tiles for the state were within one month of that date. The only tiles which were not within one month were some coastal tiles in the far North of Cape York which have very little landmass and are generally cloud-affected year-round. As such, annualised rates are no longer reported and have been replaced by the actual areal change figures.

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6 Appendix

6.1 Landsat continuity: a sample-based estimation of woody clearing in 2018–19 using SLATS Landsat-based methodology

6.1.1 Introduction

SLATS has been detecting woody vegetation clearing based on Landsat for over 30 years. As detailed in the previous sections of this document, SLATS has undergone significant methodological changes starting from the 2018-19 monitoring period. In addition to increasing the spatial resolution from 30m to 10m by changing the satellite base imagery to Sentinel-2, the study has adopted a more comprehensive approach in which the clearing footprint is mapped as cleared instead of just single pixels of woody change. This treatment of clearing as a landscape phenomenon is supported by the incorporation of the woody vegetation extent product into the mapping process to identify which patches are woody. These methodological changes mean that clearing estimates obtained from this new approach are not comparable to previous clearing estimates based on Landsat.

The inability to compare the 2018-19 clearing results with previous monitoring periods is potentially problematic as it becomes difficult to assess the impact of legislative changes or other policy changes. It also means the data cannot be used in other long-term studies without some consideration for the changes between methodologies. Furthermore, as the new methodology involves a change in the way that the clearing is being mapped, it is not possible to simply model the predicted Landsat-based area using a degradation model. Therefore, there is a need to generate estimates of clearing that are Landsat based and that follows the previous SLATS methodology.

The aim of this work is to present a sample-based estimate of the area cleared based on the SLATS Landsat-based methodology to provide an estimate of clearing in 2018-19 which can be compared with previously reported SLATS clearing rates. In other words, this work looked at what would have been mapped if SLATS had continued a similar mapping process based on Landsat.

6.1.2 Methods

Given time and resource limitations, it was not feasible to run a parallel Landsat/Sentinel-2 change mapping exercise. As an alternative, a sample-based approach in a subset of the state was developed. The established SLATS methodology for the mapping clearing was followed (Queensland Department of Environment and Science, 2018).

6.1.2.1 Study area

The study area was the Brigalow Belt Bioregion. This area was selected because it has historically been an area of relatively high clearing rates, has a range of land uses and ecosystems and includes over half of the Great Barrier Reef catchment area.

6.1.2.2 Satellite data

6.1.2.2.1 Landsat scenes

Landsat scenes from 2018 were compared to selected scenes from 2019. The 2018 scenes were those that had been previously used for the end date of the 2017-18 monitoring period. For 2019, 21 Landsat scenes that cover the Brigalow Belt Bioregion were selected using the following criteria:

- scene date should be as close as possible to the Sentinel 2 date for 2018-19;
- images should be from the dry season to maximize contrast, and
- scenes with the lowest cloud cover and similar green/dryness between Landsat and Sentinel-2 were preferred. No composites were used.

6.1.2.2.2 Clearing classification

The Landsat-based clearing index (Scarth *et al*., 2008) was applied to the pairs of Landsat dates to produce a clearing probability layer which could then be edited by SLATS scientists.

6.1.2.2.3 Ancillary data

AIRBUS very high-resolution resolution imagery (https://www.intelligence-airbusds.com/imagery/oneatlas/data/) and Sentinel 2 were used to guide decisions. Ancillary data is used to assist determinations for woody/non woody vegetation, and if clearing is identified, confirm that the changes are indeed human-induced clearing.

6.1.2.3 Sampling design

A grid that covers the Brigalow Belt Bioregion was produced using geoprocessing tools from ArcPro v2.4.2. The area was divided into 5,189 units (Figure 2). The size of each grid cell was defined based on the mapping scale used in the interpretation (1:37000). Each cell corresponds to 11.5km by 6.5km, which is the size of the window desktop viewer at the scale used by the editing scientist. The grid was overlaid with the 21 Landsat scene footprints, and information on the path/row was assigned to each cell along with a unique identifier. Each grid cell corresponds to one sampling unit.

A series of eligibility criteria were applied to the sampling units to filter those units that were considered impractical to include in the sample. To be included in the sample, units should be completely located within a scene and contain at least 70% of valid pixels (i.e. coastal units with only a small portion of land were removed). In addition, only units that contain at least one probability pixel derived from the clearing index classification were included. This criterion was based on analysis of previous monitoring periods which demonstrate that areas without an initial indication of potential clearing are very rarely identified as being cleared. A simple random sample of 20% of the eligible sampling units per scene was taken. To provide information on operator variability, a second sample of 20% was taken from 5 scenes, half of which had been evaluated in the first round.

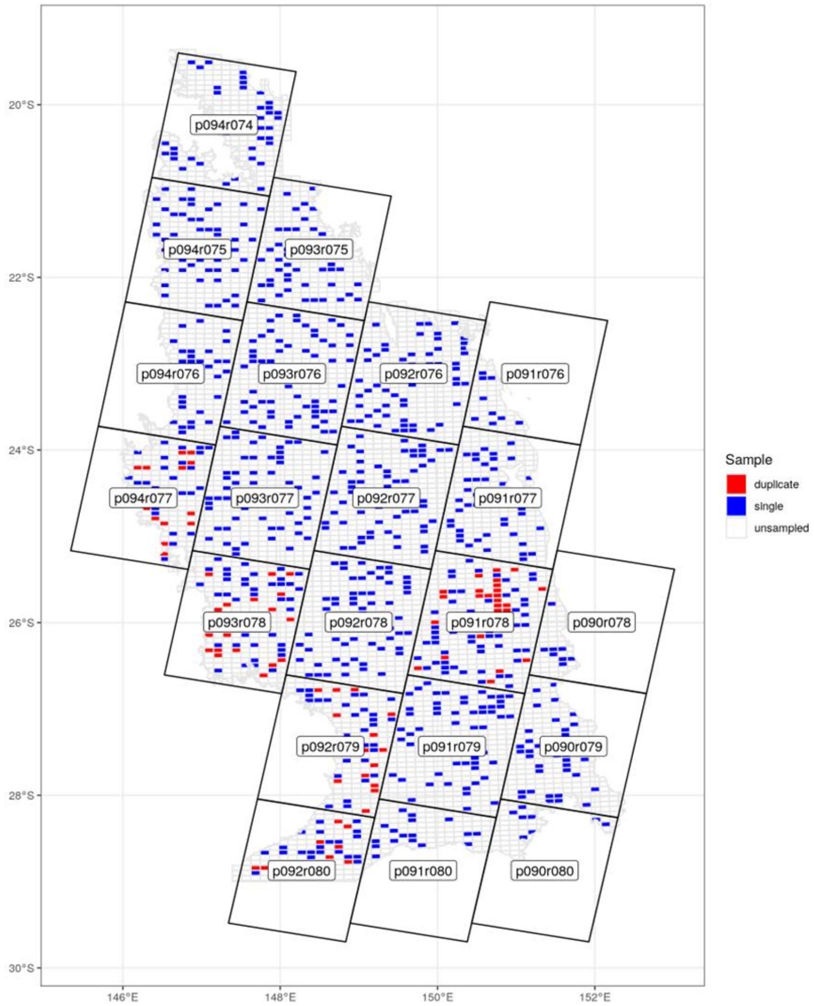

Figure 2. Sample units for the study

6.1.2.4 Image interpretation process

Each unit in the sample was assessed using the same interpretation approach for SLATS as previous monitoring periods. To account for interpretation variability half of the sampling units in five of the scenes were interpreted twice by different scientists. The scientists undertaking the editing did not know if the unit that was being assessed had been previously evaluated or not. As with standard SLATS methodology, each of the sampling units that was edited was checked by a senior scientist to maximize consistency and guarantee the quality of the product.

6.1.2.5 Sample-based estimation of the area cleared

The proportion of cleared pixels from all the valid pixels in each sampling unit was estimated. A cross tabulation between the edited raster and the most recent remnant vegetation map, for each sampled unit was done. Each unit was then summarised as the proportion of pixels marked as cleared relative to the total number of valid pixels (excluding cloud, no data, water etc pixels) in the unit.

The mean proportion of pixels that were cleared in remnant and non-remnant vegetation was estimated. The estimated area cleared was obtained as the product of the mean proportion of cleared pixels by the number of valid pixels within the Brigalow Belt Bioregion for 2017-18. Results were converted from pixels to ha by multiplying by 0.09 (each pixel 900m^2).

6.1.3 Results

The estimated area of total clearing in the Brigalow Belt in 2018-19 was 234,810 hectares, an increase of 38,160 hectares compared to the 2017-18 period (Table 7). The 95% confidence interval suggests that this is a significant increase from the 2017-18 period.

Table 7: Summary of estimated total clearing for the Brigalow Belt bioregion in the 2018-19 period

	Area (1000’s ha)			Change	
Veg Class	**e1718**	**e1819**	**95% CI**	**Delta**	**% Change**
All	196.65	234.81	(202.38, 267.24)	38.16	19%

The estimated clearing area for the 2018-19 monitoring period in the Brigalow Belt was 35,550 hectares in remnant areas and 199,270 hectares in non-remnant areas (Table 8). This represents a 58% and 14% increase, respectively, compared to the previous monitoring period. The 95% confidence interval suggests that this difference is significant for remnant clearing. This estimate is consistent with the previous three monitoring periods (Figure 3).

Table 8: Summary of estimated clearing area for the Brigalow Belt bioregion in the 2018-19 period

	Area (1000's ha)			Change	
Veg Class	e1718	e1819	95% CI	Delta	% Change
Remnant	22.46	35.55	(28.10, 42.99)	13.09	58%
Non-remnant	174.19	199.27	(169.65, 228.89)	25.07	14%

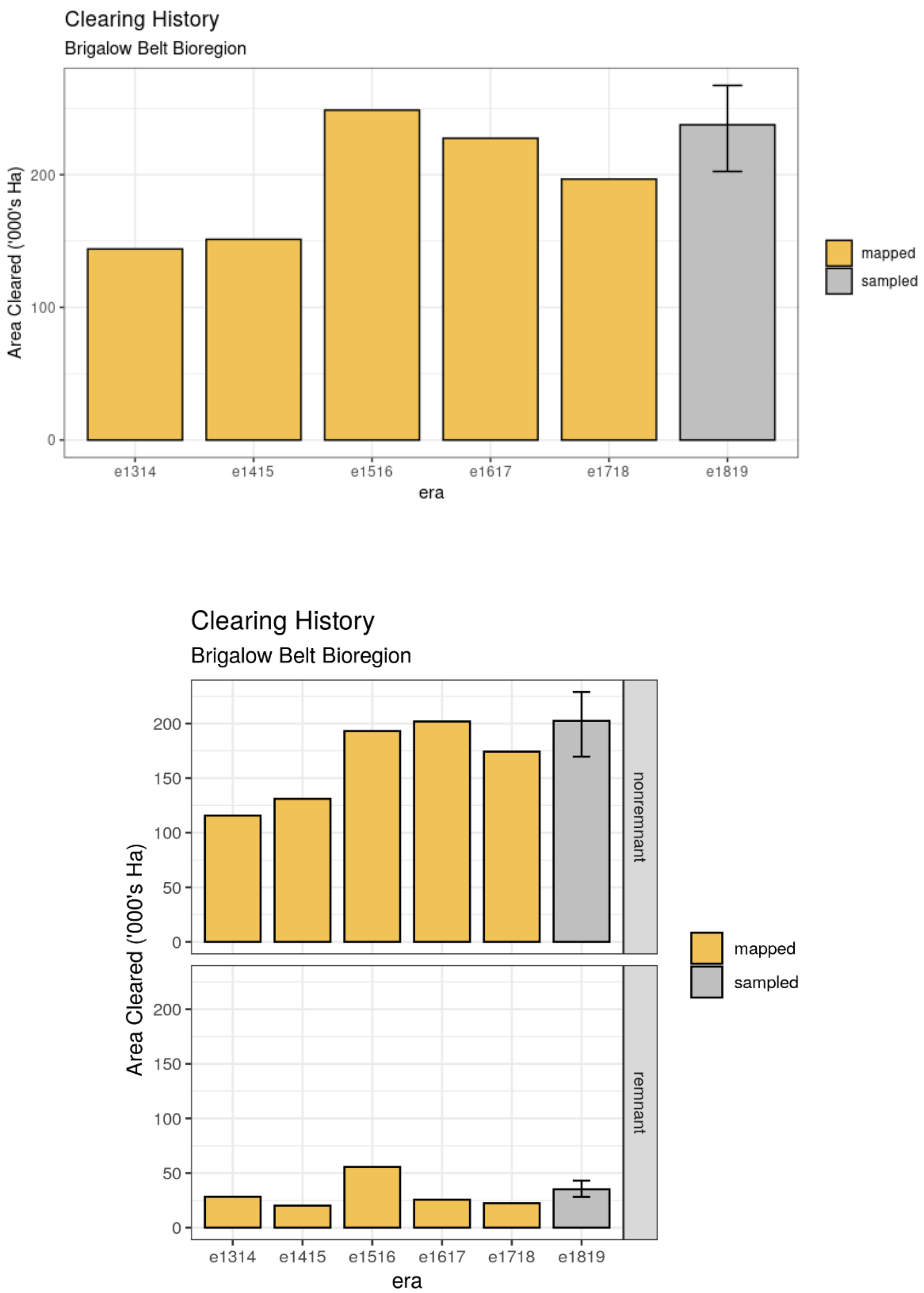

Figure 3. Clearing areas for Brigalow Belt bioregion from 2013-14 to 2018-19 for all clearing (top) and separated into clearing in remnant and non-remnant areas (bottom). The sampling-based estimates are presented as grey bars, with the 95% confidence interval superimposed.

6.1.4 Conclusion

The results of this study estimate that using the SLATS Landsat-based methodology, there was 234,810 hectares of clearing in the Brigalow Belt in 2018-19. This would be an increase of 19% in the area cleared in the Brigalow Belt in 2018-19 compared to the 2017-18 monitoring period which had 196,650 hectares of clearing mapped. The estimates of total clearing are consistent with previous recent monitoring periods. Importantly, there is no evidence that clearing rates have reduced between the 2017-18 and 2018-19 monitoring periods.

There are some difficulties in implementing a sampling approach to faithfully recreate the conditions that would have been in place if the SLATS program had continued with Landsat instead of moving to Sentinel-2 data. Significant user variability, for example, was identified in this exercise, and given the small size of the team available to do the sampling exercise could have introduced some bias. It should be noted though that the results also aligned with observations of senior scientists from their Sentinel-2-based mapping for the 2018-19 monitoring period.

The study demonstrated a method for estimating a clearing area for a given region, based on a stratified sample. Areas estimates were obtained, with confidence intervals. Thus, comparisons could be made with previously reported clearing figures to determine if clearing had significantly increased, decreased, or remained at similar levels as the previous monitoring period(s). The method therefore represents an efficient approach for obtaining clearing estimates if the aim is to provide indicative figures to guide decision-making. The sample-based method is similar to statistical sampling approaches applied in other areas of official reporting, such as is undertaken by the Australian Bureau of Statistics. It is therefore not a new concept in the context of official reporting and could be considered where future comparable estimates of Landsat-based clearing mapping are required. However, it is anticipated that once the Sentinel-2 based program undertakes two or three monitoring periods, this requirement may diminish. That said, the historical context that the SLATS Landsat clearing record provides with respect to environmental and policy change in Queensland is pivotal to understanding the current and future state of Queensland's ecosystems and the policy which is intended to protect them while maintaining sustainable development, particularly for agriculture. The method presented has the potential to continue to contribute to that record.