Statewide Landcover and Trees Study

Methodology Overview v1.0

Queensland Government

Prepared by: Remote Sensing Centre, Department of Environment and Science

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List of acronyms

CNN	Convolutional Neural Network
CRF	Conditional Random Fields
DES	Department of Environment and Science
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
QLUMP	Queensland Land Use Mapping Program
RSC	Remote Sensing Centre
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 which 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 reported by SLATS.

Geometric correction

Also referred to as geo-referencing, is the process 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 so as 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 which 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 reported by SLATS but remain in the woody extent.

Partial clearing (minor)

A human-induced clearing event which 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 reported by SLATS 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

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 going forward.

Woody vegetation

Assemblages of woody plants. This includes stands of native vegetation, regrowth following clearing, plantations of native and exotic species, and woody weeds.

Contents

1 Introduction

1.1 Background

1.1.1 History

The Statewide Landcover and Trees Study (SLATS) is a scientific monitoring program and initiative of the Queensland Government in support of the *Vegetation Management Act 1999 (the VMA)* and a range of environment, natural resource and disaster management policy requirements and application. This includes protection and management of the Great Barrier Reef (GBR), State of the Environment reporting, the Regional Ecosystem mapping framework, biodiversity conservation including offsets, fire management and planning, and natural capital and environmental accounting initiatives. SLATS is undertaken by the Remote Sensing Centre (RSC) in the Department of Environment and Science (DES) in partnership with the Queensland Herbarium and the Joint Remote Sensing Research Program (JRSRP). The program works closely with the Department of Resources which administer the VMA and which also has a range of land management responsibilities.

Since the 1990's and until recently, SLATS has monitored woody vegetation loss due to land clearing, applying a methodology which uses Landsat satellite imagery and a combination of automated image classification, desktop analysis and field methods (Queensland Department of Environment and Science, 2018). The program has always, and continues to, maintain a commitment to continuous improvement and scientific development, taking advantage of new computing, data science, satellite, and field technologies as they become available. The program's scientific and technological developments has also facilitated development of other state-wide land cover change monitoring programs undertaken by RSC and the JRSRP, including for ground cover monitoring and fire scar mapping.

1.1.2 The Enhanced SLATS program

In recent years, SLATS has been undertaking a significant program of scientific enhancement and revision aimed at providing a more comprehensive monitoring and reporting framework for the state. The range of enhancements are leveraging and adapting previous developments for SLATS and developing new science to:

- develop a new and robust methodology to produce a detailed map of Queensland's woody vegetation extent, as a baseline for ongoing monitoring and reporting;
- transition monitoring and reporting of woody vegetation clearing from medium spatial resolution Landsat to higher-resolution Sentinel-2 satellite imagery, incorporating the woody vegetation extent;
- develop new approaches for monitoring and mapping woody vegetation regrowth, age (since last disturbance) and density using the extensive Landsat archive and Sentinel-2 satellite imagery;
- develop a vegetation condition assessment and mapping framework called Spatial BioCondition, to map and monitor the 'BioCondition' of Queensland's terrestrial ecosystems (N.B. – this component is led by the Queensland Herbarium); and,
- develop a web-based reporting framework for effective reporting and data delivery.

The intention is for these, and any future enhancements, to significantly increase SLATS' usefulness and value by providing and reporting, an expanded suite of data products, and associated information at spatial and temporal scales suitable for local, regional and state-wide land and biodiversity management applications.

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 (i.e. baselining) 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 of SLATS 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.

SLATS is complemented by other land cover change monitoring programs such as the ground cover and fire scar mapping programs, and the Early Detection System; a regular, targeted, monitoring and proactive compliance tool which also supports the VMA.

SLATS supports policy development and evaluation and compliance for the VMA. It also provides data and information to support a range of existing and emerging Queensland Government initiatives including:

- supporting riparian vegetation extent target reporting and water quality modelling requirements for the Great Barrier Reef Water Quality Protection Plan and Regional Report Cards;
- natural disaster management, planning and response, particularly bushfires;
- informing and supporting investment programs and policy in rapidly emerging growth markets for carbon farming and biodiversity offsets and sustainable agriculture;
- supporting the Government's drought and climate change adaptation programs;
- informing biodiversity conservation including providing data to support updates to Regional Ecosystem mapping and Koala habitat monitoring, mapping and assessment;
- informing the development of new environmental accounts and State of the Environment reporting; and,
- supporting NRM Regional Groups as part of the Natural Resource Investment Plan.

1.3 Changes to SLATS' methodology

1.3.1 Comparing historical and current SLATS reporting and data

It is important to note that the program of enhancement and revision represents a significant departure from the previous Landsat-based methodology and results derived from the revised program will therefore not be comparable with those previously reported by SLATS. In effect, the program has been completely revised, re-baselining vegetation extent monitoring for Queensland, changing the way clearing is mapped, expanding the regions for which clearing is mapped, adding regrowth (i.e. gains) into the monitoring framework, and removing reporting of clearing rates. The program is deliberately taking a forward-looking perspective to establish a monitoring framework that meets a much broader spectrum of end user requirements than the previous methodology supported, and that also makes best use of contemporary technologies.

1.3.2 Timing of the change to SLATS methodology

The timing of the changes in methodology aligns with amendments to the VMA in 2018. While there are some potential limitations of changing SLATS' methods in terms of evaluating the effectiveness of the VMA amendments (i.e. comparing clearing rates before and after the amendments), the baselining of the new program with the amendments means that the current policy framework for the VMA can be more comprehensively assessed with the expanded suite of information. This is also complemented by regular revisions to the Regional Ecosystem mapping, the Early Detection System, and the addition of the Spatial BioCondition mapping.

Notwithstanding the above, a separate scientific study was undertaken by SLATS to develop a methodology that could be used to provide clearing estimates that are more comparable with previous SLATS reporting, should they be required. An overview of the methods developed for this study are provided in the Appendix (Section 7), for information.

The scientific enhancements to SLATS and resulting change in methodology has also been necessitated by several factors. This includes new satellite imagery missions, significant advances in computing science in terms of both computing systems and data analysis, stakeholder expectations, and methodological improvement. More generally, the program's revision has also been driven by the broadening scope of requirements and a range of emerging land management and environmental accounting initiatives that require more comprehensive data and information.

1.3.2.1 Changing technologies

In recent years there has been an emergence of a number of higher spatial-resolution, and in some cases higher temporal-resolution, satellite imagery programs, in addition to the continuation of the Landsat mission. Most notable, and of greatest importance for SLATS is the European Commission's Copernicus Programme which includes the Sentinel-2 satellite mission. Sentinel-2has a long-term mission strategy, and its data capture and provision are assured under agreements between Australian partners and the European Commission and European Space Agency – the Australasian Regional Copernicus Data Hub, of which DES is a partner. The two-satellite-constellation acquires imagery with a 5-day return interval and at spatial resolutions up to 10m. In addition, it has very similar technical specifications to Landsat, meaning a number of SLATS image pre-processing and classification algorithms could be relatively easily transitioned to these sensors, while deriving the additional benefits of the higher spatial and temporal resolution. Further to this, the Queensland Government has also invested in other satellite imagery technologies such as Earth-i (DMC-3) and Planet. These technologies presented additional opportunities to develop new information and data products as part of the SLATS methodology. For example, the woody extent baseline was based on a classification applied to the ~80cm spatial resolution Earth-i (DMC-3) data. While some components of SLATS have transitioned to Sentinel-2 (e.g. the clearing mapping), it is important to note that the United States Geological Survey's Landsat satellite imagery still forms a significant part of SLATS methodology, particularly in the woody regrowth and age (since disturbance) estimation methods which make use of the long time series of Landsat imagery. The extensive and long-term archive of Landsat data and the continued mission of high quality, systematic satellite imagery supports development of time-series approaches and provides redundancy and complementarity to the Sentinel-2 data for SLATS.

Significant advances in computing technologies are also enabling SLATS to process and derive additional information from these large data sets in operational frameworks and timeframes that were not previously possible. This has been facilitated by technological advances, and investment by government, in high performance computing and significant developments in open-source software and data science technologies.

1.3.2.2 Changing end user requirements and applications

As mentioned in Section 1.2, the range of applications for SLATS data are broad, and continue to expand and change as existing land management and biodiversity conservation programs evolve, policy changes, and new initiatives emerge. There is also a much greater understanding and appreciation for earth observation information and spatial data in government and the wider industry and community sectors as it becomes more prevalent and commonplace, and as capability to understand and work with the information increases. For SLATS specifically, there has also been some commentary from some key stakeholders that the program was limited, only documenting change in one direction by not accounting for regrowth. In addition, the proliferation of very high spatial resolution satellite and airborne imagery in a range of publicly accessible portals and applications, has added to the public perception that seeing 'more detail' means improved mapping. While this is true to some extent, and SLATS are most definitely capitalising on this benefit, there are other considerations such as temporal and spectral resolution, computing resources and expertise to derive benefit, and the limitation of resources.

The revised program aims to address data gaps or limitations of the previous SLATS methodology to address stakeholder concerns and provide a comprehensive reporting framework supported by information and data products that meet a range of requirements. A detailed, large-scale, woody extent map has never been attempted for Queensland, nor have estimates of age and monitoring of regrowth been undertaken for the state[1]. The aim is to provide a suite of repeatable, comparable outcomes, accounting for change due to both clearing and regrowth while providing the ability to adapt as methods are developed or refined, or there are new information requirements.

1.3.2.3 Methodological improvement

The availability of higher spatial (and temporal) resolution satellite imagery and computing technologies has provided opportunities to improve methods and reporting for SLATS. For example, the detailed woody extent data set has been incorporated into the clearing (and regrowth) mapping components to increase efficiency and consistency. One previous limitation of the clearing mapping was that a SLATS scientist needed to first decide whether an area was woody (or not), which can be difficult to apply consistently in medium resolution satellite imagery, particularly in sparser vegetation communities. The woody extent data, which is based on very high-resolution satellite imagery and rigorous mapping specifications and procedures, eliminates that requirement, improving efficiency and consistency in the clearing data.

The transition to the higher spatial resolution Sentinel-2, combined with the detailed woody extent data also means that the full extent of clearing events within an ecosystem can be better discriminated and delineated. This has four key benefits:

i. the potential for missed clearing or misclassification of clearing or (regrowth) is reduced (compared to previous methods);
ii. lower density open woodlands and shrublands can be included in the analysis ensuring a more comprehensive representation of change for the full range of woody ecosystems in Queensland;
iii. the full extent of a clearing event can be better represented, as opposed to just the pixels of woody vegetation that have changed (as was the case with the Landsat methodology) – this is particularly important in sparser woody vegetation ecosystems; and,
iv. the dependence on other higher resolution satellite imagery to assist decision-making is reduced, thus saving costs, increasing efficiency and consistency in the mapping, and potentially facilitating the use of those other imagery sources for independent accuracy assessment.

Further improvements associated with the transition to Sentinel-2 include:

- improved annual, cloud-free scene selection due to the higher frequency of overpasses with the Sentinel-2 satellites and smaller scene area, resulting in closer-to-annual monitoring periods and eliminating the

[1] Older, high value regrowth has been mapped as part of the Regional Ecosystem mapping framework in support of the VMA

requirement for clearing rate calculations (refer to Appendix A in Queensland Department of Environment and Science, 2018 and Section 4.2.1.5);
- the potential to investigate new and improved approaches for clearing detection and regrowth monitoring using computer vision and/or time-series;
- complementing the EDS, which is also based on Sentinel-2, and therefore ensuring method improvements in either program have potential for incorporation into the respective workflows; and,
- incorporating other land cover information from RSC/JRSRP programs which are also based on Sentinel-2 into SLATS. For example, RSC and the JRSRP are also working on the operational implementation of a Sentinel-2 fire scar mapping program that is expected to inform SLATS mapping and may be directly incorporated into image masking (prior to the clearing analysis) and possibly the land cover change reporting in the future, as is done in NSW (e.g. NSW Department of Planning, Industry & Environment, 2020).

1.3.3 Independent Peer Review

To ensure that the science and outcomes of the enhanced SLATS program are defensible, relevant, effective, and sustainable, the Queensland Government commissioned a peer review of the enhanced program by a panel of independent experts in the fields of remote sensing, ecology, and natural resource management.

In its key findings, the panel concluded that:

- the scope of enhancements is appropriate, fit-for-purpose, defensible and consistent with best practice when compared with similar national and international programs.
- the enhanced program is effective and will have impact with its range of key stakeholders.
- risks to the programs continuity have been carefully considered and minimised.

The expert panel's detailed response included recommendations which focused on: strengthening conceptual and workflow integration; supporting coordination with other existing monitoring programs; stakeholder communication; and, regular reviews to ensure ongoing scientific robustness.

1.4 Purpose of this document

The purpose of this document is to provide an overview of the current SLATS methodology—the methodology developed and implemented for the enhanced SLATS program that relates to woody vegetation monitoring and reporting (hereafter referred to as "SLATS"). The Spatial BioCondition methodology is the subject of a separate document.

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 *Vegetation Management Act 1999*; which defines vegetation as essentially woody native trees or plants, except for mangroves which are protected under other legislation. SLATS monitoring also includes non-native woody vegetation change (refer to Section 2.1.2.1 for details regarding this).

The present scope of SLATS is to map the current extent of woody vegetation in Queensland and monitor and map changes to that extent due to human-induced land clearing and natural or human-induced regrowth. This is limited primarily by what can be reliably identified and mapped in Sentinel-2 satellite imagery, but also informed by other data sources, including very high-resolution satellite imagery.

SLATS also includes additional data and information about the type of clearing activity and its purpose and estimates of the density and age of the vegetation that currently exists, is being cleared, or is regrowing.

The 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 smaller 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 present scope of SLATS excludes a number of land cover, land cover change, and ecological attributes from the monitoring and reporting. This is due to a range of factors including the objectives for SLATS, the limitations of current scientific research to identify and map some attributes accurately, or because other programs in government are already mapping or documenting the attributes. SLATS may address some of these where appropriate in the future, and the program also maintains close ties with other state and commonwealth government programs to minimise duplication and ensure complementarity and information sharing.

Current exclusions from SLATS 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

SLATS do not currently monitor extent, density or change in non-woody vegetation communities. This may be considered in future as part of a greater integration of SLATS with other land cover programs in RSC, particularly the Queensland Ground Cover Monitoring Program.

2.1.2.3 Vegetation height

Vegetation height is not considered in SLATS, as it is not presently possible to reliably estimate height from optical satellite imagery such as Sentinel-2 or Landsat. This may be improved in the future through JRSRP research into the use of radar, LiDAR and potentially combinations of these with optical imagery.

2.1.2.4 Vegetation composition

This information is available in the Queensland Herbarium’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 presently monitored. This is an area of ongoing research in RSC/JRSRP. The FPC product developed for the new program is presently only intended to provide contextual attribution of the vegetation, to assist understanding the types of ecosystems which are being cleared or regrown. While larger increases in FPC over time for a particular location may indeed reflect real densification processes on the ground, insufficient research and validation of this product has been undertaken to reliably use it for tracking change in density as these changes are often quite subtle and within the confidence intervals (i.e. error) of the FPC product.

2.1.2.6 Fire

Fire-affected areas are presently mapped separate to SLATS by RSC/JRSRP in the Queensland Fire Scar Mapping Program. Where SLATS can identify human-induced clearing associated with a fire 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. The 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, 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).

2.1.2.7 Land use and land use change

This is mapped by the Queensland Land Use Mapping Program, a program also undertaken by RSC/JRSRP. SLATS do include some information related to land use, the ’landcover replacement class’ (see Section 3.3.5.2) but this is only meant to be indicative of the land use for which a clearing activity has been undertaken.

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 it is possible to identify and map, but these changes are not presently 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).

2.1.3 Key definitions

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

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 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

The estimated age of a stand of woody vegetation 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

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 >0.5ha). Refer to Section 3.5 for details.

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).

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 framework is based on a conceptual model of initially establishing a detailed baseline account of the woody vegetation extent, age 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 and density are also updated annually to inform reporting. Section 3 provides details about the methods and workflows which support the framework.

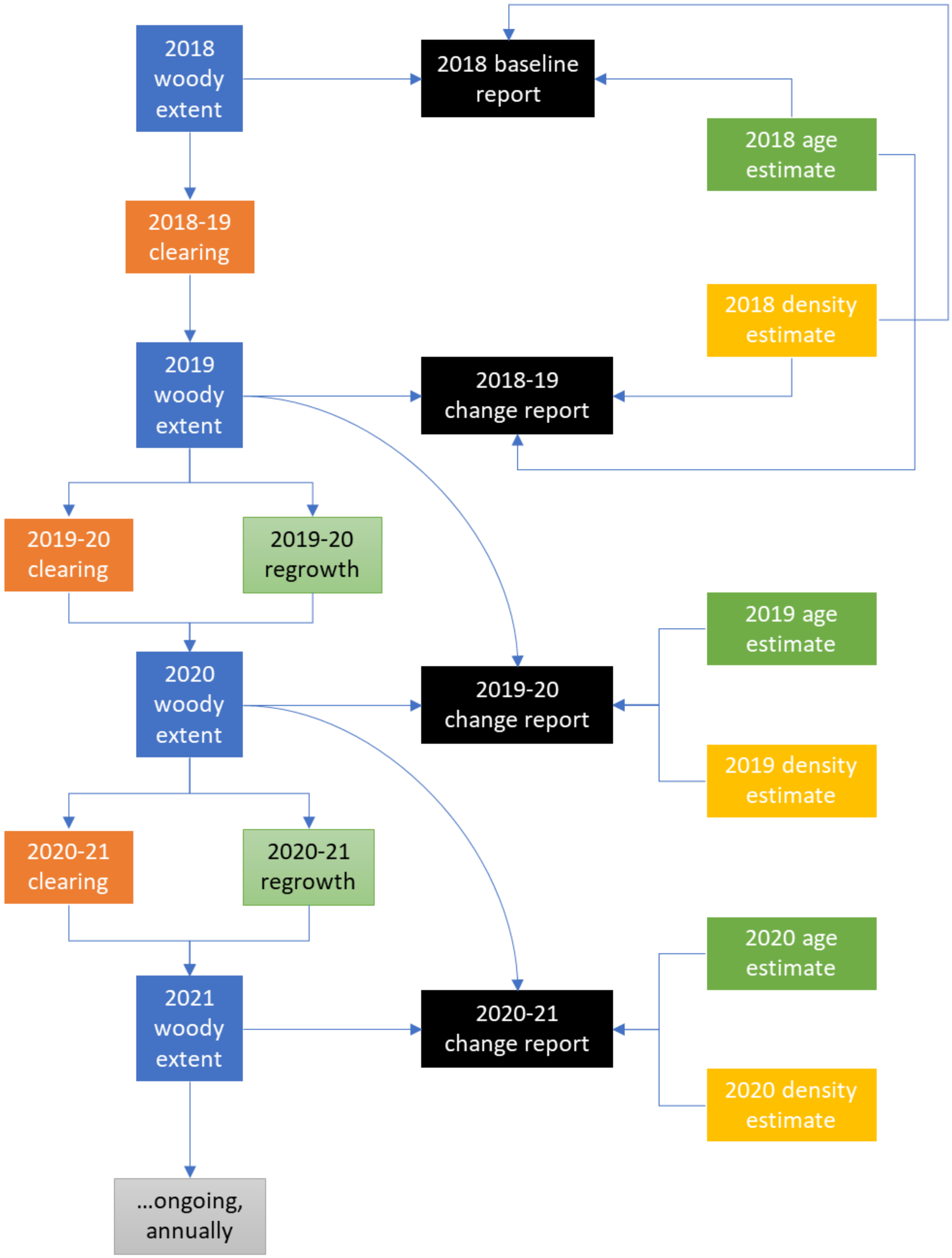

Figure 1 Schematic diagram of the ongoing SLATS monitoring, accounting, and reporting framework

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 by SLATS are subject to quality control systems and standard operating procedures used by DES's RSC for image and field data processing, storage and management. The systems and processes used by SLATS 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 for SLATS is undertaken on the high-performance computing (HPC) facility at the Ecosciences Precinct, Brisbane, supported by systems administrators. The HPC incorporates multi-node Linux cluster, a mass storage on-line disk and near-line tape silo which houses the image archive and downstream products and is connected to the high-speed national science network portal (AARNet) enabling efficient downloading of large data sets.

Image metadata, field and other spatial data sets are stored in RSC's PostgreSQL spatial data base, 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).

Processing is largely done using open-source software with much of the code written using a Python base and open-source or in-house developed libraries. All code written for SLATS is maintained in Git version control repositories, hosted by Gitlab. SLATS is moving towards adoption of containerised processing which allows improved reproducibility and governance of SLATS' processing systems, increased flexibility in research environments and sharing with collaborators, and increased portability in the future as hybrid HPC-cloud or cloud-native solutions are adopted.

3.1.2 Satellite imagery and imagery pre-processing

The primary satellite data used in the various components of the current SLATS program include imagery from: Landsat TM, ETM+ and OLI, Sentinel-2A and -2B, 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 by SLATS as the primary image data for ongoing annual monitoring and reporting of woody vegetation clearing (Section 3.3),regrowth (Section 3.5), and woody density (Section3.6). 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). SLATS has therefore undertaken 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) 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 and current cloud mask performance is variable for Sentinel-2 imagery.

RSC has complete holdings of Sentinel-2A and -2B imagery acquired over Queensland from late 2015 and ongoing. From 2017 onwards this represents a 5-day return interval.

3.1.2.2 Landsat Imagery

The long time series of Landsat imagery (1988-ongoing) is used by SLATS as the primary image data to derive temporal woody vegetation age 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).

Landsat satellite imagery from Landsat-7 and -8 (combined represents an 8-day return interval over all areas of Queensland) is routinely downloaded from the USGS website (earthexplorer.usgs.gov), and processed to surface reflectance as described in Flood (2013a). All 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. Cloud and cloud shadow masks are computed using the *Fmask* methods of Zhu and Woodcock (2012).

RSC holds the complete archive of historic USGS Landsat imagery from Landsat-5 TM, -7 ETM+ and -8 OLI acquired over Queensland during the period 1988 to now.

3.1.2.3 Seasonal Surface Reflectance Composites

SLATS uses time series of seasonal composites of fractional cover (Scarth, 2008) for woody vegetation age 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 creation of the woody extent (Section 3.2).

The data were purchased as 3-band visible (blue, green, red) imagery, pan-sharpened from a nominal resolution of 3.2 m 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 RSC systems, the imagery was resampled, using cubic convolution resampling, into Albers Equal Area projection, sampled to a pixel size of 1m. 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

SLATS uses a range of ancillary data to inform the 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 Libray and the Queensland Government's Queensland Globe.
- Complementary remote sensing products, for example DES'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

RSC hosts a national field data base which incorporates a comprehensive collection of vegetation measurements collected across Queensland and nationally over a 20+ year period, encompassing much of the time 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 the remote sensing products that SLATS uses and produces. Field data including measurements, observations and extensive photos are stored in RSC's PostgreSQL spatial data base.

3.2 Woody extent mapping

3.2.1 Overview

A woody extent data set was required to inform operational mapping components (particularly the clearing) and to form the baseline and effectively establish the ledger for the woody vegetation change accounting framework of SLATS, particularly the clearing mapping. The data set would also serve as a useful stand-alone data product for a range of other applications where detailed woody extent mapping is required, addressing a data gap for the government.

A dataset 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 by a team of scientists to produce a detailed map of woody vegetation extent for Queensland.

The 2017 woody extent was subsequently manually revised and updated using SLATS clearing data for the 2017-2018 reporting period and once available, the 2018 Earth-i image mosaic. This is more fully described in Section 4.1.1. The resulting 2018 woody vegetation map provides the baseline for SLATS' ongoing monitoring, accounting and reporting.

3.2.2 Mapping specifications

The scale of the woody extent data set is 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 were represented, but also to enable SLATS scientists to define extent boundaries consistently and accurately. Delineating woody vegetation extent boundaries below this threshold can be ambiguous. Recognizing that in optical imagery it is very challenging to estimate height, 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 is important to note that the imagery was not originally purchased for use in this work, but was used here opportunistically, as it was the most detailed recent satellite imagery available for the whole of Queensland. It was also at a spatial resolution, allowing a higher level of detail, particularly in regions of sparse, open vegetation, than is routinely feasible with moderate resolution satellite imagery from Sentinel-2 and Landsat.

3.2.4 Automated classification

CNNs are a subset of machine learning algorithms which 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 needs to be 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 are 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 must be larger than the objects and textures to be detected. In this case, it needed to allow sampling 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 covers, 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 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.

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 1 m.

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 means that in any model run, subsets which were held out were independent of the model. This gives 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 form part of a larger area/ecosystem (or stand) of classified woody areas, 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 needs of existing datasets/programs, and expert knowledge. These decisions were based on considerations for the SLATS and Spatial BioCondition programs, and other vegetation monitoring applications, as well as ecological characteristics of the vegetation. No distinction was made between native and non-native vegetation – woody vegetation such as woody weeds and horticultural crops are 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 edits to a master dataset. Each scientist undertaking the editing was assigned a unique connection file to access the dataset. Tiles comprised of a 25x25km systematic grid were used to sub-divide and manage the dataset, and to track mapping progress.

Each scientist was allocated an area to assess (subset by Queensland's bioregion) 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, also building landscape knowledge to apply in other operational components of SLATS.

SLATS scientists visually checked mapping polygons 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 (QLUMP 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 increase discussion between staff and achieve greater consistency between mappers in implementing decision rules. Scientists checked the editing of colleagues and provided feedback as comments in a point-based dataset. Areas of disagreement or confusion were discussed across the wider team and decisions documented. This process was successful in fostering a collaborative approach within the team and resulted in increased accuracy and consistency between editors.

Separate to the initial peer review, a QA process was conducted by senior staff members throughout the entire editing phase. Maintaining consistency across a large team of editors was critical in ensuring a high-quality dataset. The QA process allowed senior staff 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-represented with regards 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 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 cloud-affected areas 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 a consistency in the map currency. All re-modelled areas were then subject to the same editing and review process described 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 SLATS 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 Final processing and filtering

Upon completion of the editing process for the 2017 data set, and subsequent updating of the mapping to 2018 and 2019 using the SLATS clearing data for the 2017-18 and 2018-19 reporting periods respectively (refer to Section 4.1.1 for details relating to these updates), a series of cleaning and filtering processes were applied to the dataset. These processes were programmed in ArcGIS and iterated over the mapping, which was segmented for processing efficiency and manageability. The processing was designed to remove artefacts and minor error associated with the editing and updating processes. A final filter was applied to remove any features below the minimum mapping area of 0.5ha.

3.2.6 Data products

The woody extent mapping and updating has produced one single vector data set, with attributes stored in a geodatabase that enable production of woody extent for a given year, or data about woody vegetation extent change between years, as well as a range of queries across multiple years and regions. Initially, SLATS will release a woody extent for 2018 (the baseline year) and for 2019, the year which incorporates the first change monitoring period for the new methodology. The 2017 data set will be released at a later date as a stand-alone product.

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. In terms of the revised program's framework, it is also a fundamental component of the woody vegetation account, documenting the woody extent loss and adding to the non-woody areas which are monitored for regrowth in further reporting 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 reporting period, SLATS has mapped the location and extent of woody vegetation clearing across the state of Queensland using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) imagery. 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. For this and other reasons previously mentioned in Section 1.3.2, SLATS has transitioned 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 from 2018 onwards.

The historic 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 models 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 general, the Landsat two-date method still applies to Sentinel-2 imagery, however there has been some necessary adaptation and modification of both the clearing index (detailed in Section 3.3.4) and the subsequent manual refinement approach (detailed in Section 3.3.5) necessitated by differences between Landsat and Sentinel-2 data (resolution, radiometrics and length of time series) and particularly 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 clearing mapping is undertaken (on-screen) at a scale of approximately 1:20,000, The minimum clearing size delineated is 0.25ha. As noted in Section 2.1.1 the 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 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 uses 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 are 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 current period. 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 15th August giving preference to minimal cloud cover, smoke, haze and greenness. Dry season imagery (July-Sept) tends to show the greatest contrast between woody vegetation and grass. Reasons for nominating the August 15 date are outlined in Section 4.2.1.5.

Approximately 60 of the 245 Sentinel-2 tiles are a composite of two dates (usually only a couple of days apart) due to the satellite flight path schedule. All official SLATS dates are stored in a database for use by 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 reporting 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 reporting period is used to identify any non-woody pixels in the clearing probability classes. For the 2018-19 reporting period, this is the 2018 baseline woody extent. 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, these areas are still very much a focus of the mapping, however, at least in the early stages of the new program, an additional set of classes are used to identify potential clearing outside of the woody extent to ensure areas missed by the woody extent are still mapped if clearing has occurred. 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 reporting 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 the concept of 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 woody area (crown and inter-crown gap pixels) impacted by the clearing event. This area is referred throughout this document as a “clearing footprint”. This is more representative of the total area impacted by the clearing event and 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*. This provides an indication only of the land cover/land use purpose for which the vegetation was cleared or modified. The landcover replacement classes are described in Table 4. The 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

Additional attribution discriminates the type of clearing activity in terms of how much destruction or modification of the vegetation has occurred for any clearing event. 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 reporting period such that partially cleared areas remain in the woody extent and are therefore considered in future reporting periods for further clearing activity and areas where the vegetation is completely removed or destroyed are subtracted from the woody extent and reported as a loss in the accounting framework (and will then be monitored for future regrowth).

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. >10% crown cover) to non-woody (i.e. <10% crown cover). Full clearing will result in removal from the woody vegetation extent dataset.
ii. Partial clearing (major) refers to clearing areas where more than 50% of the patch area has been removed and >10%crown cover vegetation remaining.
iii. Partial clearing (minor) is used where < 50% of the clearing patch has been removed.

The three classes are all reported as clearing activity but distinguished in ongoing SLATS annual reports of clearing areas.

Table 4 Codes used for the SLATS clearing mapping attribution, including *landcover replacement class* and partial and full clearing attributes

	Code	Description	Examples	Reported as Clearing	Remain as Woody Vegetation
Human induced clearing activity	40	Possible clearing	For review	No	Yes
	41	**Full** clearing where the woody vegetation has been converted from woody (i.e. greater than 10% crown cover) to non-woody (i.e. less than 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** where >=50% area of vegetation removed within patch and >10% crown cover remaining	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 remaining	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 >10% crown cover remaining	Disturbance including removal of understorey	Yes	Yes
	42	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	Clearing to *settlement*	Clearing for housing estates, shops, hospitals etc.	Yes	No
	48	Clearing to *mine*	Mining activities including expansion of open cut mining, CSG pads, coal exploration areas and large quarries	Yes	No
	51	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	Clearing to timber plantation	Clearing within State forests or exotic and native plantations. Reported as *forestry* landcover replacement class.	Yes	No
	58	Missed clearing	Missed clearing from previous monitoring period.	-	No
	59	Missed clearing prior to woody extent	Missed clearing prior to woody/incorrect woody extent. Used for adjustments to woody extent in transaction report.	-	No

	80	Intermediate code designating strip clearing. These are re-evaluated during post-processing and assigned either 41, 71 or 75)	Strip clearing and fodder harvesting but only in the Mulga lands	Yes	Depends on final attribution as either 41, 71 or 75. Refer to those codes for details.
Non-human induced change	12	Fire	Active or recent fire scars	No	Yes
	16	Drying	Vegetation is drier than in previous year	No	Yes
	52	Flood damage	Change due to flooding event	No	**Yes
	54	Landslip damage	Change due to a landslip	No	**No
	56	Cyclone damage	Change due to cyclone	No	**Yes
	57	Natural tree death	Tree dieback where it can be identified and verified	No	**Yes

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

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. Considerable time (8- 10months) is spent by a team of remote sensing scientists to complete this stage for the whole state. 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.

The manual mapping stage is conducted in two passes: initial editing of 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, as well as historical clearing data and any ancillary imagery used to aid interpretation. Editing/quality review is undertaken directly on the change classification raster. The woody vegetation clearing index (Section 3.3.4) provides a good starting point for the change classification helping to focus the manual mapping effort to those areas where clearing is most likely to have occurred.

After each mapping pass, the edited change classification 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 RSC 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 the *ERDAS IMAGINE 2018* software package which includes a suite of tools for viewing and enhancing imagery. The software allows editors to recode pixels in the change classification, enabling direct recoding of the change areas using the codes given in Table 4, Section 3.3.5.2.

The first pass involves a scientist reviewing the change classification layer and associated Sentinel-2 imagery and identifying and recoding pixels in accordance with the codes in Table 4 and the Sentinel-2 mapping guidelines to map the full extent of the clearing event (i.e. the clearing footprint). 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 enable the clearing footprint to be fully mapped. In this case, pixels mapped as 'no change' must also be recoded and included in the clearing event. Some additional research was undertaken to try and further optimise these thresholds but was unable to yield any marked improvement. It should be noted that during the first pass, the scientists make their assessment guided primarily by the Sentinel-2 imagery with minimal reference to ancillary data to maintain consistency in scale and interpretation for the program.

The second pass of the manual editing is undertaken by a senior DES remote sensing scientist to provide an independent check. It effectively replicates the first pass with some areas recoded or areas which have been re-coded in the first pass 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 change raster to the HPC image 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.

3.3.5.4 Post-processing the clearing mapping

The clearing mapping for the individual Sentinel-2 tiles are mosaiced into a single state-wide data set. An additional manual assessment and refinement exercise is undertaken to edge match the mapping in overlapping regions between adjacent images to ensure a seamless data set for the state. The raster mosaic is polygonised and integrated into the woody extent geodatabase, enabling updating of the woody extent for the reporting period, while maintaining the full set of clearing data and attributes (see Section 4.1.1). Finally, the vector data: updated woody extent and clearing 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.

3.3.6 Data products

The final SLATS state-wide clearing data set is archived in raster form, for use in the reporting framework, and vector form, for publication.

3.4 Woody vegetation age (since last disturbance) estimation

3.4.1 Overview

The goal is to estimate the age of woody vegetation that was woody as of the 2018 baseline year to enable tracking of vegetation age over time, and 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

To do this, a method which combines Landsat time series, the high-resolution woody extent, and a sequential classifier to estimate the likelihood of woody cover over a 31-year period has been developed. This research has resulted in new approach to modelling land cover over long periods using a sampling framework that requires minimal temporal coverage.

For a given Landsat pixel, the modelling approach generates a time series of woody probabilities. A simple set of heuristic rules are then used to detect patterns in the woody probability sequence that might characterise a typical woody regrowth response curve and track that regrowth event over time. Regrowth detection 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. The disturbance may be due to a clearing event or other disturbance such as fire, flood, drought-related tree death etc.

3.4.2 Data

Thirty-one years (1988 to 2019) of seasonal Landsat fractional cover components at 30m spatial resolution were used (Scarth *et al*., 2008). The fractional cover data consisted 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 components for every 12-month period (e.g., Sept. to Sept. and covering five seasons, spring to spring inclusive).

The 2017 woody extent data set for the nominal 2016/2017 period was used as sample strata to generate woody/non-woody training sequences for a Conditional Random Field (CRF) classifier (described below in Section 3.4.3.1). The 2017 woody extent data were resampled from 10m to 30m spatial resolution to align spatially with the Landsat time series.

The historical SLATS Landsat clearing data (1988-2018) was an additional input informing age since disturbance.

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 existing 2017 woody extent was used to generate random stratified samples over space, resulting in thousands of samples that intersected the manually scrutinised woody extent dataset. In practice, further stratified samples with additional land cover edge stratum (e.g. woody cover 90 m from a non-woody pixel) were included that ensured 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 were sequences of fractional cover over 31 years, but the training sample pool described above intersected a single period (2016/2017). Therefore, the samples were augmented to match the Landsat sequence length to train a CRF classifier. To do this, a subset of samples was first 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, regular grids of 150km x 150km across the state were used, with each grid representing an independent mapping zone. After woody/non-woody samples around a particular grid were collected, thousands of 31-year sequences were generated, where each sequence consisted of samples within the mapping zone. It is important to note that each sample's class label in each sequence was always *woody* or *not woody* during 2016/2017, and the associated Landsat data were always seasonal fractions from September 2016 to September 2017. 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 dataset 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 31 years of fractional cover sequences [$(bare, green, non\text{-}green)_{1988}, \ldots, (bare, green, non\text{-}green)_{2019}$], with corresponding woody/non-woody class label sequences (e.g., [$woody_{1988}, \ldots, non\text{-}woody_{2019}$]). These data were used to train CRF models for each 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 [$(p(w), p(nw))_{1988}, \ldots, (p(w), p(nw))_{2019}$], 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 estimates

The age of woody vegetation since last disturbance was estimated using the woody probability time series introduced above, followed by spatial and temporal cross-checks against the baseline woody extent and the SLATS clearing record. The timing and age of the most recent regrowth period was estimated over 1988-2019 using a heuristic approach.

Four thresholds guided this work: a minimum and maximum probability, a minimum proportional change between consecutive years, and a minimum number of consecutive years required for regrowth consideration. As a starting point, we only considered candidate regrowth pixels if the probability at a particular time iteration started below the baseline minimum probability threshold (i.e. high confidence of a sample not being woody at the start of a regrowth period). After identifying a candidate regrowth pixel for a start year, the change in probabilities was then tracked over time until the proportional change in probabilities between consecutive years fell below the minimum proportional change threshold or the probabilities exceeded the maximum probability threshold. If the latter condition was satisfied first, the end of the regrowth period was the year when the proportional change fell below the minimum proportional change threshold, or the iteration reached the end of the time series. If at any point in time, the probability fell below the baseline minimum probability threshold a new iteration was triggered, and the incremental age reset to 0. Finally, regrowth periods that exceeded the minimum number of consecutive years were documented as regrowth.

This approach was used to assign an age to woody pixels in the 2018 woody extent. The SLATS historic Landsat clearing data set (30m; 1988-2018) was used to constrain the age estimates, so that the woody age since disturbance could not be greater than the age since last clearing recorded by SLATS. Where regrowth was not detected but clearing was recorded, the age was simply adjusted to the time since clearing. Where regrowth was detected, the age was recorded as the time since the start of the most recent regrowth period. Where no regrowth or clearing was detected, we assume that woody vegetation in the baseline was persistent since the beginning of the time series (i.e. at least 31 years of age), providing an additional condition was met: that the minimum probability over time exceeded a threshold value of 0.5, otherwise the age was unable to be determined and attributed as *indeterminant*. It is expected that further refinement of the model and heuristic approach will improve the ability to estimate age in these areas.

There are some limitations to the age since disturbance estimation. It is assumed that the SLATS clearing data always records a transition from woody to non-woody, however, the Landsat clearing record does contain partial clearing. Additionally, the newly established woody extent baseline contains sparse and/or young woody vegetation that may not have been detectable by Landsat – either by the CRF modelling approach or by SLATS in previous reporting periods and was therefore not able to be monitored at that scale. Missing data in the CRF fractional cover model inputs due to 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, triggering the restart of a new regrowth tracking iteration.

3.4.4 Data products and outputs

Thirty-one years (1988-2019) of woody probabilities across the state at Landsat 30m spatial resolution have been produced. The data values indicate the probability (range of 0 to 1) that a pixel is predominantly woody.

The regrowth event raster captures the start and end year of the most recent detected regrowth event.

The woody age since disturbance raster contains the age in years since the last significant disturbance of the 2018 baseline woody extent. This is used in the reporting framework to further inform breakdowns of clearing and woody vegetation in Queensland. The woody age since disturbance estimates do not account for multiple clearing events – only reflecting the time since the most recent clearing event.

3.5 Woody vegetation regrowth mapping

3.5.1 Overview

The aim is to monitor regrowth annually using Sentinel-2 imagery as part of the SLATS annual analysis of woody vegetation change, commencing with the 2019-20 reporting period. In the first Sentinel-2-based reporting period, 2018-19, it is assumed that existing regrowth has already been 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 mapping will be included in the 2019-20 reporting period, and annual reporting thereafter.

The woody vegetation regrowth mapping approach is similar to that used for the clearing mapping in that a two-stage approach is used. Firstly, the automatic detection of candidate regrowth areas for consideration is undertaken using a similar CRF modelling approach as used for long term Landsat-based age attribution (Section 3.4) but applied to a shorter, rolling Sentinel-2 time series. This is then followed by a manual assessment and mapping process to determine if a candidate regrowth area is sufficiently woody to be counted as regrowth and added back to the woody account.

Where it can be mapped using the methods described below, regrowth will be delineated and added into the woody extent, effectively a 'gain' in the context of the accounting framework.

3.5.2 Methods

Following the work described in Section 3.4, the likelihood of woody cover over time was estimated. However, the regrowth monitoring framework was different from the long-term age attribution in two key ways: (i) a shorter, 10-year time series of Sentinel-2 imagery supplemented with up-sampled Landsat imagery was used instead of 30+ year Landsat sequence; and, (ii) the timing and rate of regrowth was modelled by fitting functional shapes and parsimoniously selecting the best fit over the time period.

3.5.2.1 Short-term woody probabilities

Sequential-based CRF woody probability estimates over ten years were utilised for this modelling approach. The timeframe chosen was designed to shorten the prediction sequence compared to the 31-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 was 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 was resampled from 30m spatial resolution to 10m spatial resolution to align the Landsat and 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 were only interested in the final year of the 10-year period (described in Section 3.5.2.2) and only used the 10-year Landsat/Sentinel-2 sequence to help stabilise woody/non-woody transition estimates. The same 'temporal augmentation' approach was used to sample and fit a CRF model, using 10-year sequences instead of 31-year sequences.

As an example of how this would work in a monitoring framework, assume the monitoring year in question is 2020. Therefore, a 10-year time series would consist of resampled Landsat data from 2010 to June 2015. The remaining five years of the time series (i.e. 2015-2020) would consist of Sentinel-2 imagery only. For a given pixel, the woody likelihood from 2010-2020 (i.e. 10 annual probabilities) is estimated. These woody/non-woody probabilities would be used in the regrowth models (described below) to estimate the presence (or not) of regrowth in 2020. This process would be repeated 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 estimates), which would allow for a sub-annual monitoring framework.

3.5.2.2 Regrowth estimates

For the long-term age attribution, a heuristic approach is used to estimate the start and end of a regrowth period. However, a different, functional approach was used in this monitoring framework. More specifically, starting with a 10-year sequence of woody probabilities (described above), four shapes of linear, gaussian, logistic, and hyperbolic functional form were optimised by fitting time (X) vs. woody probabilities (y). The fit with the lowest Akaike information criterion (AIC) score was chosen. Then, using the fit with the lowest AIC the regrowth age and rate are calculated using derivatives of the curve (particular to each functional shape).

3.5.2.3 Regrowth mapping

The operational mapping of regrowth for SLATS is yet to be finalised and is being incorporated in the 2019-20monitoring period for the first time, which is only just commencing at the time of writing. It is expected that the mapping approach will take the regrowth estimates described in Section 3.5.2.2 above and implement them in a manual mapping and verification process that resembles the clearing mapping process described in Section 3.3.5. It is also expected that a set of mapping specifications and decision rules will be developed iteratively as the mapping method is refined but will generally follow the specification required for the woody extent (i.e. minimum crown cover of 10% and minimum patch/stand size of 0.5ha).

3.5.3 Data products and outputs

For the end year of a monitoring period, the woody probability, the age of regrowth (years), and the rate of current regrowth are produced. The regrowth mapping will be integrated with the woody extent data set.

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 many Australian vegetation classification frameworks. In the current program, SLATS uses the FPC metric derived from Sentinel-2 imagery to provide broad 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, RSC has produced FPC using a model applied to Landsat, calibrated by field observations (Armston, 2009, Kitchen, 2010). 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.

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) due to a range of factors.

3.6.2 Data

The updated FPC model was developed based on:

- Two-year (8 season) time series of Landsat seasonal surface reflectance composites (using 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.
- The national data set of historic 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 in excess of 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 seasonal surface reflectance composites, radiometrically adjusted to match Landsat using relationships described in Flood (2017). As an example, a 2016-2018 FPC estimation was produced to accompany the baseline 2018 woody extent.

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 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 $NDVI_{min}$ is the second lowest value of NDVI for the 2-year period of seasonal surface reflectance and c_0, c_1, c_2 are the model coefficients. 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.

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

3.6.3.2 FPC Prediction

The FPC model is applied to a 2-year (8 season) time series of Sentinel-2 seasonal surface reflectance composites to produce an FPC image. Finally, the woody extent data set (3.4) 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.

3.6.4 Data products and outputs

To constrain the FPC image to areas of known, mapped woody vegetation, the woody extent data set 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.

The final product is a state-wide Sentinel-2 Foliage Projective Cover for the 2-year period. This product will be released as a stand-alone SLATS data product as it is in high demand for 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

As previously mentioned, the woody extent is intended to form the foundation for the woody vegetation (annual) change accounting framework. As the woody extent data set is a 2017 map, and the baseline year for the revised mapping program is 2018, the first step was to update the 2017 map to 2018. Then, as per the accounting framework, once the clearing mapping for 2018-19 was completed, a 2019 update could be produced.

4.1.1.1 2018 Update

The previously released 2017-18 SLATS Landsat clearing data set was used to inform an update to the woody extent to a 2018 baseline. Differences in mapping 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 datasets. The SLATS 2017-18 clearing data set was produced using Landsat imagery, at a period prior to the incorporation of the woody extent dataset into the SLATS clearing mapping process. As such, the resolution is coarser than the woody extent product, and the data set was created using the Landsat pixel-based mapping approach rather than the current clearing footprint approach (refer to Sections 1.3.2.1 and 3.3.5.1). The definition of “woody” also varied slightly between the two datasets. The minimum woody density for inclusion in the 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. Further, 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 significant modification, but enough woody material remains to be retained in the woody extent dataset.

A comprehensive manual checking and editing approach was used to modify the data for the SLATS 2017-18 reporting period to allow for easier integration. SLATS scientists checked each significant (> 2 hectares) clearing event using the relevant Sentinel-2 imagery for the clearing date. A Sentinel-2 based clearing index was also used to identify missed clearing not included in the 2017-18 Landsat clearing data set. Manual editing was applied to include missed clearing from the 2017-18 reporting period, and to fully delineate the whole clearing footprint in line with the current approach for clearing mapping. 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. Following post-processing (refer to Section 4.1.1.3) the result was a 2018 woody extent map for the state.

4.1.1.2 2019 Update

The mapping for the SLATS 2018-19 reporting period integrated more seamlessly with the woody extent dataset as the Sentinel-2 based clearing mapping approaches are more specifically designed for integration with the woody extent with more closely matching 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 has resulted in some complex clearing patterns and hence some difficulty determining full clearing (updated to non-woody in the woody extent) or partial clearing (remaining woody in the woody extent). Where cleared strips could be defined and they met the woody extent criteria for linear features of 20m minimum width, they were manually delineated and coded as full or partial (major) clearing (code accordingly (codes 41 and 71 respectively, Table 4). Following post-processing (refer to Section 4.1.1.3) the result was a 2019 update to the woody extent map for the state.

4.1.1.3 Post-processing to produce a single woody extent data set, with annual change attributes

A series of Arcpy batch scripts was used to process the revised 2017-18 clearing data set (Section 4.1.1.1) and clip it into the woody extent dataset, attributing full clearing as non-woody in a separate dedicated 2018 attribute field. Similarly, the 2018-19 clearing data set was incorporated into the woody extent (Section 4.1.1.2) and attributed in a 2019 field as either woody or non-woody depending on the clearing mapping attribution code (Table 4). All remaining 2017 (uncleared) woody extent polygons were replicated into the 2018 and 2019 attribute fields. The result is a single dataset containing multiple epochs with a separate field for each woody extent year. From this, a 2018 and a 2019 woody extent data set has been produced.

4.1.1.4 Future updates

It is expected that the 2020 update using the 2019-20 clearing data set will be even more straightforward as the clearing mapping approach is now more fully developed. The program is also finalising the development of an automated method for more refined mapping in complex woody vegetation clearing patterns associated with fodder harvesting and strip clearing specifically.

In subsequent reporting periods, as clearing and regrowth mapping is finalised, annual updating of the woody extent will continue. For the foreseeable future this will continue to be a post-hoc data integration exercise. The longer-term vision for SLATS is a fully integrated editing framework such that all editing is done directly on a master woody extent layer. Change attribution would be managed through the attribute table supporting it and adding new polygons or splitting existing polygons. This has been scoped to some extent, but it was decided that this approach requires even more significant modification of some mapping methods and was considered to be too much of a departure from previous methods to be feasibly developed and implemented in the required timeframe.

It is acknowledged that the maintenance of the woody extent is not 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. SLATS will continue to develop mechanisms for tracking, modifying and reporting these errors with the intention of distinguishing additions and subtractions due to error/mapping refinement in any ongoing reporting of the woody extent, and woody extent change.

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 will be released as web-based reports. Spatial data sets and data summaries as annual reports will be available via the SLATS data products web page, with supporting data downloadable from the reporting pages.

This will enable 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 revised reporting series commences with a 2018 baseline woody vegetation extent report, a 2018-19 clearing report, and then from 2019-20 onwards, annual reporting of clearing and regrowth.

4.2.1.1 The SLATS cross-tabulation and regional data summaries

The area of change in Queensland is summarised in a very large 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 (LGAs),
- Natural Resource Management (NRM) 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 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 git 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 future SLATS reporting, which will annually monitor and account for woody vegetation extent and change in Queensland. The revised and enhanced SLATS methodology now monitors and report changes in woody vegetation extent against this baseline. The report also includes information relating to woody vegetation density and age estimates.

4.2.1.3 The annual SLATS report

The annual SLATS report will summarise, and report changes due to gains (regrowth) and losses (clearing) in woody vegetation across Queensland for the nominal period from August to the following August. The first of these reports, for the 2018-19 monitoring period, only includes changes due to woody vegetation clearing activity—regrowth reporting is not included. It is assumed that existing regrowth in 2018-19has been mapped and characterised in the 2018 woody vegetation extent baseline (Sections 3.5 and 4.2.1.2).

Annual SLATS reports will provide the key findings and a range of graphical and tabulated clearing activity summarised by:

- type of clearing activity: full, partial (major) and partial (minor) clearing
- Landcover replacement class
- broad categories of age and density of woody vegetation affected by clearing activity
- vegetation management status including Regulated Vegetation Management (RVM) Map category and vegetation management class
- breakdowns by bioregion with other regional summaries available via open data
- a transaction summary of woody vegetation change over the period.

It is important to note that clearing in remnant and non-remnant areas, as mapped by the regional ecosystems, is not reported. This is because clearing in areas with remnant vegetation does not always result in a conversion to non-remnant vegetation.

4.2.1.4 Data Products

Data products produced by the program are prepared and 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 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, basically all of 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, the revised program will no longer report annualised rates, rather reporting the actual areal change figures. This generally makes reporting simpler and perhaps most importantly, simplifies the reporting and communication for a general audience.

5 The ongoing SLATS program

As discussed in Section 4.1.1.4, the annual updating of the woody extent and reporting of changes to that extent as clearing and regrowth are mapped, will continue. Woody vegetation age will also continue to be tracked and estimated for any new regrowth added, and density estimates using the FPC will be updated on a rolling two-year basis in line with its methodology. Thus, the foundations of the accounting framework which have been established as part of the major program of enhancements to SLATS will be maintained, following the same specifications to ensure comparability into the future.

SLATS maintains a focus on using best available research and remote sensing and computing science to continue to improve the program and the information it provides. Potential areas for research and development include:

- Fully integrating the manual workflows for clearing and regrowth mapping with the woody extent data set to improve mapping efficiency and consistency and make for seamless integration of these three key components of the accounting framework.
- Investigating improved clearing detection algorithms. Research is already being undertaken in the JRSRP to better estimate woody vegetation in Sentinel-2 using the CNN architectures with a view to develop improved Sentinel-2 based extent products and change detection. There is also significant potential in the CRF methods developed for the regrowth and age estimation to detect clearing, particularly given the success of the temporal augmentation approach for training the model.
- Undertaking quantitative accuracy assessment of the program outputs when new, independent sources of imagery become available that are of sufficient spatial resolution to identify clearing and regrowth with a high degree of confidence.

- Incorporating fire scar mapping into SLATS for masking and reporting.
- Investigating active and passive sensing for improving calibration and validation of program components and for deriving woody vegetation structural attributes to augment the age and density estimation. The JRSRP has significant expertise, well-developed workflows and collaborative partnerships for the use of L-Band radar (ALOS), ground-, air-, and space-borne LiDAR, and optical remote sensing, including the combination of these to derive vegetation structural attributes.
- Further revision of the FPC as new models of fractional cover become available and field data and LiDAR data archives are expanded.
- Further refinement of the Conditional Random Fields woody likelihood modelling and associated regrowth age heuristics.

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7 Appendices

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

7.1.1 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 reporting period. In addition to increasing the spatial resolution from 30m to 10m by changing the satellite base imagery to Sentinel-2, the program 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 reporting periods is particularly problematic as it becomes difficult to assess the impact of legislative changes. A series of amendments to the VMA were passed in 2018 to reintroduce a number of the laws which were repealed by the previous government, and to repeal some laws which were contributing to increased clearing. The intention of the amendments was primarily to reduce clearing rates in regulated vegetation. However, the effect of the amendments would not be directly measurable because the estimates of clearing based on the revised SLATS methodology are not directly comparable with previously reported clearing rates. 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.

7.1.2 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).

7.1.2.1 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.

7.1.2.2 Satellite data

7.1.2.2.1 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 reporting period. For 2019, 21 Landsat scenes that cover the Brigalow Belt Bioregion were selected using the following criteria: (i) scene date should be as close as possible to the Sentinel 2 date for 2018-19; (b) images should be from the dry season to maximize contrast; and (c) scenes with the lowest cloud cover and similar green/dryness between Landsat and Sentinel 2 were preferred. No composites were used.

7.1.2.2.2 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.

7.1.2.2.3 Ancillary data

AIRBUS very high-resolution resolution imagery (https://www.intelligence-airbusds.com/) 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.

7.1.2.2.4 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 wide by 6.5km high, 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.

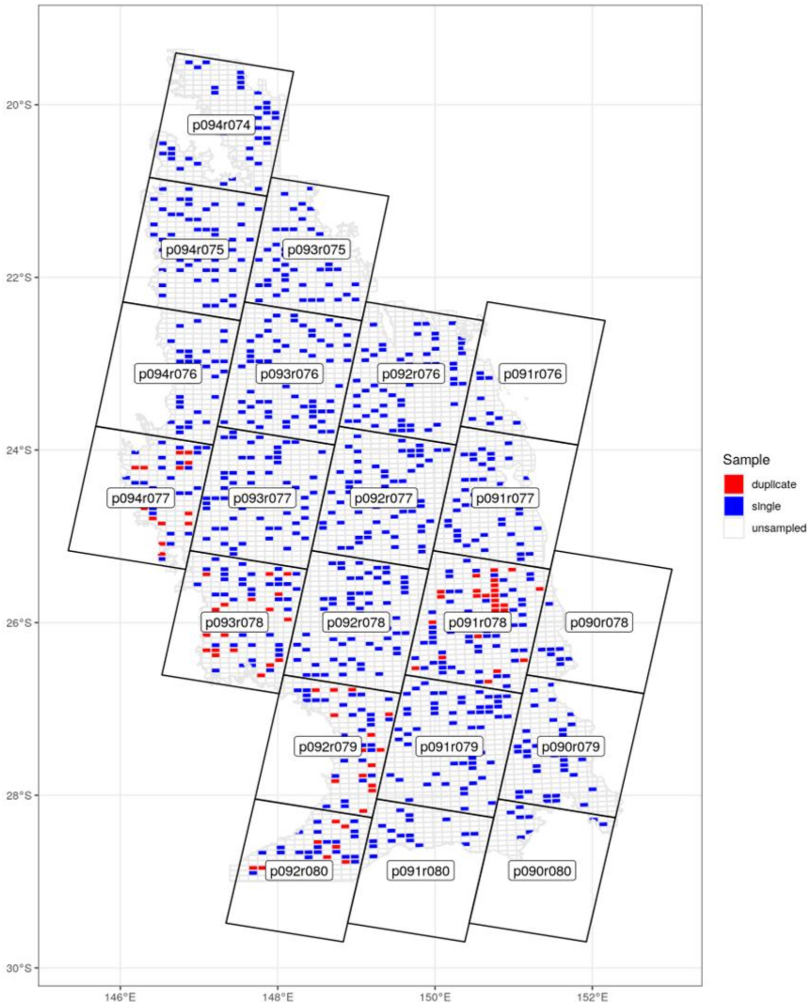


Figure 2 – Sample units for the study

7.1.2.3 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.

7.1.2.4 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 900m2).

7.1.3 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 5). The 95% confidence interval suggests that this is a significant increase from the 2017-18 period

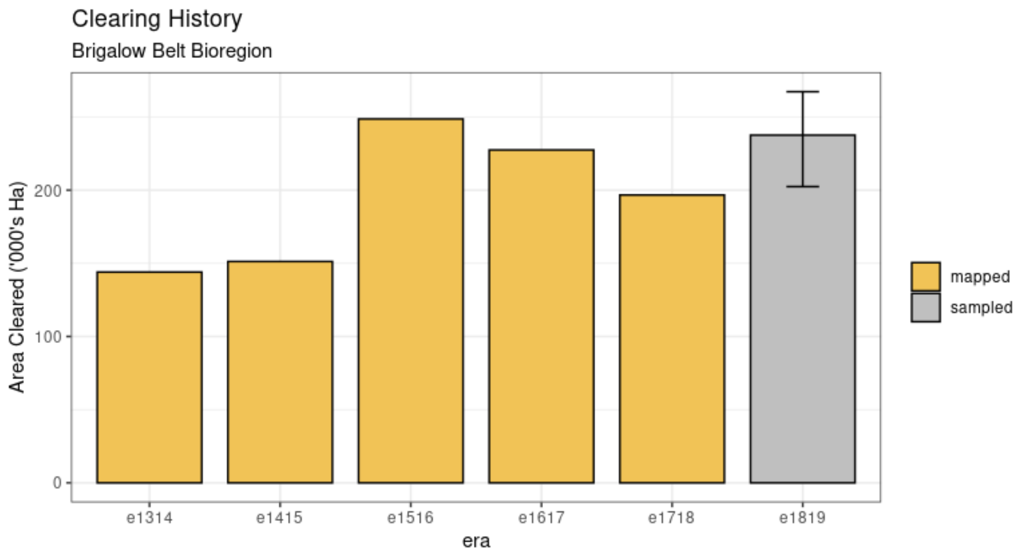
Table 5 Summary of estimated total clearing for the Brigalow Belt bioregion in the 2018-19 period

	Area (1000'sha)			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 the Brigalow Belt was 35,550 hectares in remnant areas and 199,270 hectares in non-remnant areas (Table 6). 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 6 Summary of estimated clearing area for the Brigalow Belt bioregion in the 2018-19 period

	Area (1000'sha)			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%**



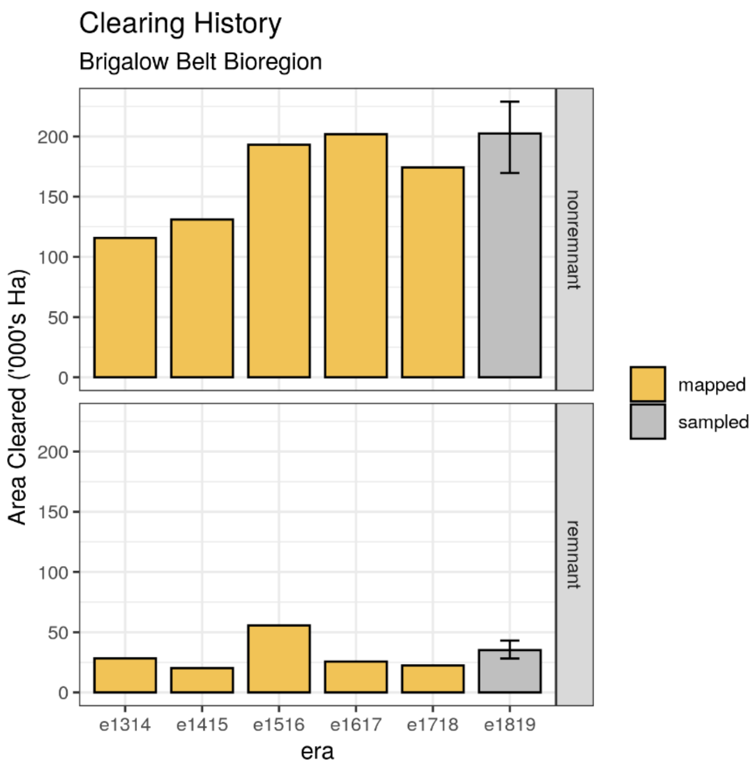


Figure 3 - Clearing areas for Brigalow Belt bioregion from 2013-14 to 2018-19 for all clearing (top) and separated into clearing in remnant and non-remnant areas (bottom). The sampling-based estimates are presented as grey bars, with the 95% confidence interval superimposed.

7.1.4 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 Sentinel2 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 reporting 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 reporting 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 reporting 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.