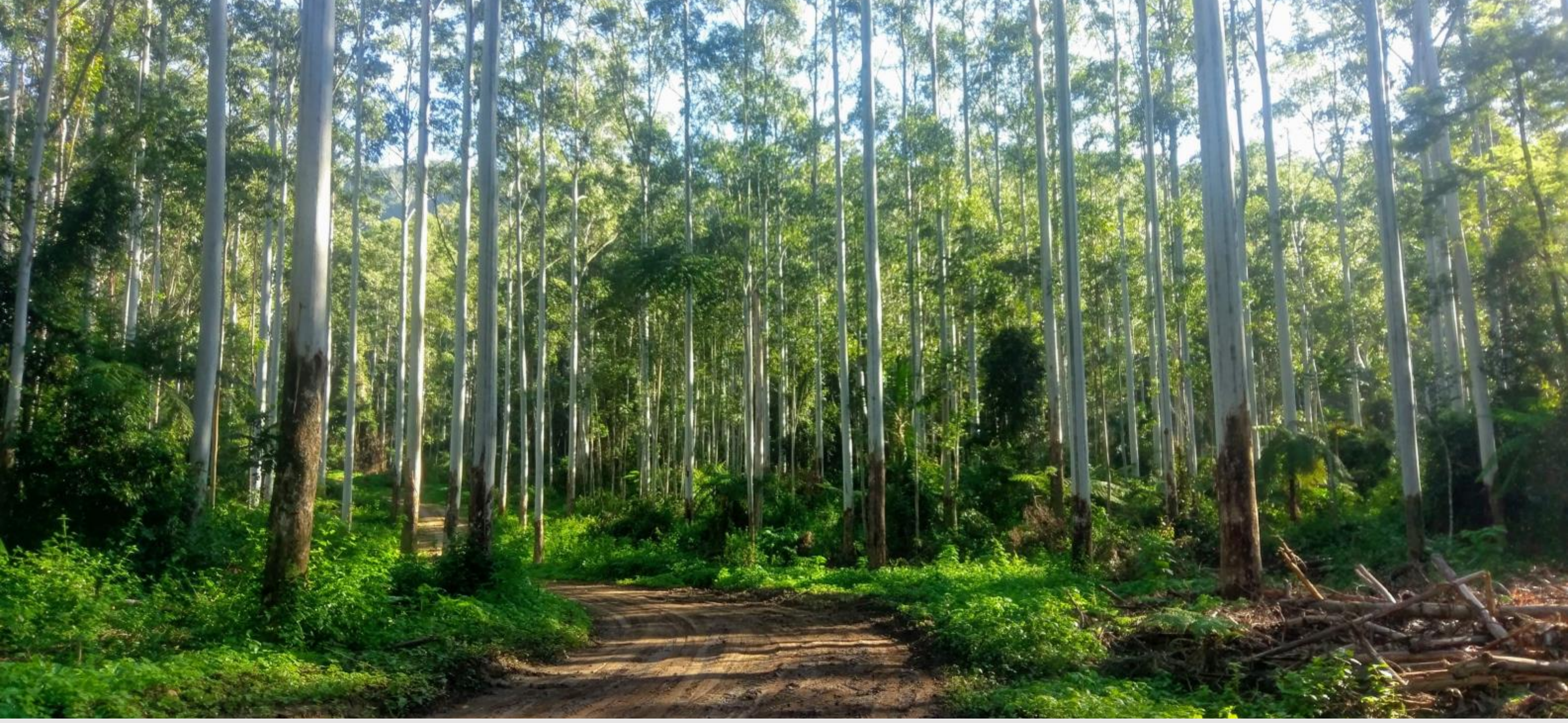

Remote sensing of NSW private native forests

Options and feasibility

October 2023

Disclaimer:

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1. Executive Summary

The Natural Resources Commission (NRC) engaged The Mullion Group to deliver a remote sensing feasibility study in relation to the Private Native Forestry Monitoring, Evaluation and Reporting framework (PNF MER), as specified in the PNF Codes of Practice (the codes). The study objectives are to:

- assess the capability of remote sensing technologies to monitor PNF code conditions and/or biophysical outcomes (noting that not all PNF code conditions or outcomes may be suitable to monitor remotely)
- consider the feasibility of each remote sensing technology, including cost effectiveness, frequency of return sampling, usefulness of data generated, and whole-of-life-cycle considerations such as data storage, processing and analysis
- propose indicators to monitor PNF code conditions and/or biophysical outcomes under the PNF codes
- analyse readily available remote sensing data to demonstrate what the data can explain in terms of outcomes and/or conditions.

This report addresses the first two objectives and sets the scene for final two, which will be addressed in two further reports.

Remote sensing is used widely throughout the world in the context of forest monitoring and can support the PNF MER in considering whether the long-term outcomes listed in the PNF Codes are being maintained. The report is broadly structured around the first four long-term outcomes in the PNF codes:

- maintain forest health and regeneration at site and bioregional scales
- maintain the productive capacity of the private native forest estate at site and bioregional scales
- maintain the persistence of native species at site and bioregional scales
- maintain water quality and soil health at site and bioregional scales.

Cross-references to various PNF code conditions (or clauses) are made, however, remote sensing can only partially inform against many of the conditions, and in some has limited or no utility.

This report begins with a brief introduction to remote sensing and list some common sensors and platforms used in forest monitoring. The concept of spatial scale is introduced, as it is extremely important in ecosystem monitoring and often poorly understood. The outcome statements above refer to site and bioregional scales, which from a remote sensing perspective, require different technologies and approaches. Previous studies suggest that moderate resolution optical satellites like Landsat and Sentinel-2 are unable to accurately characterise impacts from low intensity harvesting and subsequent recovery. In contrast, airborne lidar can be used to measure some post-harvest structural metrics directly (e.g., canopy height and cover), from which important ecological indicators such as canopy fragmentation can be derived.

The report then briefly discusses current programs and products available in NSW, including satellite derived forest cover products, the State-wide Landcover and Tree Study (SLATS) and Biodiversity Indicator Program (BIP). The report then moves into the core sections based on the long-term outcomes: Forest Health, Productive Capacity, Native Species and Water and Soil Health.

Forest health means different things to different people. It may include factors relating to stand structure, composition, processes, function, productivity and resilience. It is also important to note that forest disturbance is natural and, in some respects, essential to a healthy ecosystem. Here, our focus is primarily on the dominant structure of forests (i.e., the trees) and ecosystem health overall. Importantly, from a remote sensing perspective, it is the presentation of symptoms or impacts that we can remotely sense. Attributing disturbance to its cause or correctly diagnosing health from symptoms requires additional information and often expert knowledge.

With respect to maintaining the productive capacity of private native forests, at a bioregion scale, the impacts from current harvesting practices in private native forests are likely negligible. Recent research by Hislop *et al.* (2023b) found that only 0.37% of native forests with current PNF plans in northeast NSW were impacted by harvesting in a one-year period (2020-2021). The area with current PNF plans is around 455,000 ha in the northern code region, or 12% of the private estate. With that in mind, this section focuses more on the site and plot scale, and what can be achieved using lidar technologies.

The PNF codes place a great deal of importance on the persistence of native species and restrict harvesting where threatened species are deemed to be present. In practice, the onus is on the landholder and/or harvesting contractor to follow these prescriptions. Remote sensing-based products can help inform appropriate management, especially at bioregional scales. However, it should be noted that vegetation type and/or habitat maps are modelled products and often have large uncertainties. At present, canopy growth stage and composition can be more accurately mapped through manual 3D (stereo) Aerial Photographic Interpretation, although AI modelling techniques are rapidly advancing and producing improved accuracies. Remote sensing methods that detect presence, and sometimes, abundance of fauna species are based on field samples (e.g., acoustic recorders, thermal sensors on UAVs, human observations), from which we can make broader statistical inferences from.

Remote sensing has limited application in directly monitoring water and soil health in forests. Of most relevance to this outcome, as well as the protection of drainage features condition, are the high-resolution digital terrain models (DTMs) available from airborne lidar. These products can be used to accurately map drainage features and creeks, and potentially study soil erosion. A DTM in conjunction with a canopy height model and/or other optical imagery can be used to study riparian vegetation, from which we can infer the health of the waterway. In addition, slope and aspect layers can be derived from the DTM. Harvesting must not occur on slopes greater than 30 degrees, as soil erosion is more likely on steep slopes. Overseas, high resolution satellite imagery has been shown to have some utility in monitoring large scale landslides.

There are four main dollar costs in relation to remote sensing data: acquisition costs, computer processing costs, data storage and human expertise costs. Acquisition costs for satellite imagery varies from free (e.g., Landsat, Sentinel) to reasonably expensive (e.g., Worldview, Pleiades). Airborne lidar and high-resolution imagery costs tend to be even higher. Computer processing costs can be substantial even for the 'free' imagery, depending on analysis methods. While it is more-or-less free and straightforward to download a single Sentinel-2 scene, it is simply not practical to download 100s or 1000s of scenes to process in time series. Ideally, this processing would take place on high-performance computing facilities that already contain the satellite archive (e.g., NSW Science Data Compute (SDC), Digital Earth Australia (DEA) or Google Earth Engine (GEE)).

Human expertise costs for analysing remote sensing data and drawing accurate conclusions from it are substantial. It remains largely a specialist area, requiring computer programming skills, statistical knowledge and domain expertise (e.g., forest dynamics). In some ways, the ever-increasing availability and capabilities of remote sensing makes is more challenging to derive valuable insights from it. Because of this, there are now numerous private companies which promise to provide 'value added' maps and data. This now includes Planet Labs, for example, which has developed from a satellite data acquisition company into a higher value product supplier. Finally, it is worth noting that financial costs also need to be considered in relation to the broader environmental and social/political costs.

2. Introduction

Private native forestry (PNF) is the sustainable management of native forests on private property in line with the objects of Part 5B of the *Local Land Services Act 2013* (LLS Act). Private native forests represent the largest single component of NSW's native forest estate, accounting for 37 percent of the ~20 million hectares of native forests in NSW. PNF is a key resource for the NSW forestry industry and an important land management option for landholders.

PNF codes of practice (PNF codes / the codes) set out the rules (or conditions) for forestry on private land. The codes cover four regions of NSW: Northern NSW, Southern NSW, River Red Gum forests, and Cypress and Western Hardwood Forests.[1] There are around 500,000 hectares[2] of approved PNF plans distributed across 7.4 million hectares of private native forest in NSW. A landholder must have an approved PNF plan prior to undertaking commercial forestry operations on private land. Properties with an approved PNF plan occur in a mosaic of different land uses and tenures, in various forest types, and each property owner would have different management objectives and forest use and management approaches for their property.

In May 2022, the NSW Government released revised PNF codes following advice from the Natural Resources Commission (Commission) into finalising the codes.[3] The codes support long-term outcomes and establish monitoring, assessment, and adaptive management requirements. The NSW Forest Monitoring Steering Committee (the Committee), independently chaired by the Commission, is tasked with monitoring obligations, including to propose and oversee a PNF Monitoring, Evaluation and Reporting (MER) framework.

The Forest Monitoring Steering Committee has established a cross-agency technical review team to provide input into the development of the PNF MER framework.

Noting that landholder participation in PNF monitoring and research is voluntary, the technical review team are currently considering how remote sensing approaches can be used to facilitate broadscale monitoring of private native forests and reduce user participation bias. To support this, a remote sensing feasibility study is being conducted to better understand the various technologies and the feasibility of these to monitor PNF code conditions and/or outcomes, including cost effectiveness and the usefulness of the data generated.

The new PNF codes support six long-term outcomes, four of which require ongoing monitoring where remote sensing may be applicable. These include:

- maintain forest health and regeneration at site and bioregional scales
- maintain the productive capacity of the private native forest estate at site and bioregional scales
- maintain the persistence of native species at site and bioregional scales
- maintain water quality and soil health at site and bioregional scales.

This report is the first stage in the remote sensing feasibility study and assesses various remote sensing technologies and approaches and their capabilities with respect to monitoring forests at the site and bioregional scales in support of the PNF MER framework. It is the first of three reports in a series, with the second report to focus on identifying potential remote sensing indicators for forest monitoring and the third to put these indicators into practice by providing worked examples and analysis of existing and available datasets.

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1 Local Land Services (n.d.) *Private Native Forestry Codes of Practice*.
2 Local Land Services (n.d.) *Monitoring, evaluation and reporting*.
3 Natural Resources Commission (2022) *Advice on finalising Draft Private Native Forestry Codes of Practice*.

3. Remote sensing background

Remote sensing refers to the process of acquiring information about an object or area by measuring reflected and emitted radiation at a distance. Remote sensing is often associated with data acquired by aircraft or satellite. However, it can also be used for on-site observation using, for example, terrestrial laser scanners or handheld cameras. Indeed, our eyes remotely sense any object we look at. Remote sensing is often thought about only in terms of collecting data, however the data is only the first step in the value chain, which must then be processed into products and information, which in turn provide knowledge and insights to drive actions and policy direction (Figure 1). There is no point in collecting the data if it is not going to be used to derive insights and convert these into policy or management actions.

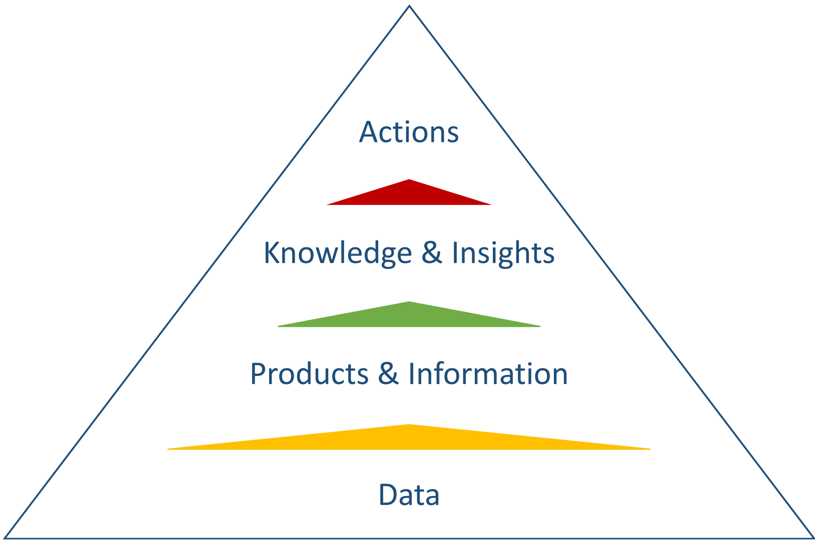

Figure 1. Remote sensing value chain pyramid

There are two main categories of sensors – passive and active. Passive sensors rely on the light provided by the sun to measure reflected energy, or alternatively, the emitted energy (i.e., heat) of an object. Passive sensors include cameras operating in the visible spectrum and multi-spectral instruments which typically collect information in the visible, near infrared and (sometimes) thermal infrared portions of the electromagnetic spectrum. In contrast, active sensors transmit energy directly and measure the returning signal. Active sensors include radar, sonar and lidar.

Remote sensing is used extensively for monitoring forests, due largely to the fact that forests extend across large areas and practical limitations restrict in-situ observations. Table 1 outlines sensors and platforms commonly used for monitoring forests.

Table 1. Common remote sensing systems used in forest monitoring

Sensor / platform	Area covered	Type	Spectral resolution	Spatial resolution	Revisit frequency
MODIS	Global	Multispectral, Thermal	36 bands	250m – 1km	Daily
Landsat 8/9	Global	Multispectral, Thermal	11 bands	30m	8 days
Sentinel 2	Global	Multispectral	13 bands	10-60m	5 days
Sentinel 1	Global	Radar	C-band	10m	12 days

ALOS 2	Global	Radar	L-band	1-100m	14 days
PlanetScope	Global	Multispectral	8 bands	~3m	Daily
Skysat	Global / district	Multispectral	5 bands	50cm	Daily (tasked)
Worldview 3	Global / district	Multispectral, panchromatic	8 bands	31cm – 3.7m	Daily (tasked)
Pleiades Neo 2	Global / district	Multispectral, panchromatic	6 bands	30cm – 1.2 m	Daily (tasked)
Aircraft	District	High resolution RGB/NIR	3-4 bands	10cm	As required
Airborne laser scanning	District	Lidar	NIR	10-50 points m^{-2}	As required
Terrestrial laser scanning	Plot	Lidar	NIR	> 1000 points m^{-2}	As required
Mobile laser scanning	Plot	Lidar	NIR	> 1000 points m^{-2}	As required
GEDI	Global	Lidar (samples)	NIR	~25m footprint	Onboard ISS

Earth observation satellites

There are two main categories of Earth observation satellites – geostationary and polar orbiting. Geostationary satellites always ‘see’ the same part of the Earth. To achieve this, they must be placed in an orbit approximately 36,000km from Earth, so that their orbital period matches the Earth’s rotation. Most communications and weather satellites (e.g., Himawari 8, used by the Bureau of Meteorology) are geostationary. In contrast, polar orbiting satellites orbit the Earth around the poles. Typically, these satellites are between 400-800km from Earth, make a complete orbit in around 90-100 minutes and are designed to be sun-synchronous, meaning that they pass the equator at the same local time with each orbit.

Generally, there is a trade-off between spatial and temporal resolutions, meaning that the higher the spatial resolution, the lower (less frequent) the temporal resolution. To counter this trade-off, companies like Planet operate constellations of satellites (currently ~200)[4], which together can provide daily coverage at higher spatial resolution (~3m). The first PlanetScope ‘dove’ satellites (about the size of a shoebox) were launched in 2016.

In addition to ‘always-on’ satellites, which constantly collect wall-to-wall imagery at known frequencies, there are a number of ‘tasking’ satellites, which can be tasked to collect high resolution imagery over a particular area. Planet SkySat satellites are one example. Together there are 21 SkySat satellites, which offer 4 band imagery at 50cm spatial resolution. Customers can request imagery over a particular area and the next time a SkySat satellite is in the vicinity it can be pointed to a particular area. The NSW government (through DPE) currently has a subscription with Planet,

[4] https://www.planet.com/products/

which allows view access to the PlanetScope archive along with the ability to request SkySat imagery over smaller areas.

Spatial scales

The term spatial resolution is typically used to refer to the pixel size in an image. However, it can be more accurately described in terms of the ability to resolve an object. Putting aside these particulars, it is perhaps more useful to think about spatial scales more generally, which could include resolution, coverage and the object or phenomenon in question. There may be an inclination to regard high resolution imagery as better than low resolution. However, in the case of forest monitoring, this may not be true. With high resolution imagery, the focus shifts to individual trees rather than the forest as a whole. Figure 1 shows an area of native timber harvesting (high intensity) at different spatial scales, including Landsat (30m), Sentinel-2 (10m), Planet (~3m) and Google Earth (airborne ~25cm).

Figure 2. Example of native forest harvesting at different spatial resolutions

Temporal scales

Geostationary weather satellites like Himawari-8 provide updated images across Australia every 10 minutes. However, the spatial resolution is 1-2km for most bands (with the exception of the red band, which is 500m). The Moderate Resolution Imaging Spectroradiometer (MODIS) sensors onboard the Aqua and Terra satellites are examples of polar orbiting satellites that provide global coverage near daily at spatial resolution of 250-1000m. Landsat-8 on the other hand, provides images with much higher spatial resolution (30m) but with a revisit frequency of 16 days. Note that through much of the Landsat program, there have been two satellites in operation, with complementary orbiting patterns, enabling a revisit time of 8 days. Similarly, there are two Sentinel-2 satellites, which together offer a revisit period of 5 days. Landsat data is readily available for Australia from 1988 onwards and Sentinel-2 from 2015 onwards.

Cloud cover and image compositing

In it important to recognise that the temporal resolutions mentioned above do not guarantee a clear image free from cloud. The optical sensors on satellites like Landsat and Sentinel-2 cannot penetrate cloud. Therefore, in some regions of the world, you may wait months for a clear image. However, many images may be only partially obscured by cloud, meaning that the clear parts can still contain valuable information. Recognising this, researchers have developed automated algorithms for, firstly, masking clouds and cloud shadows (e.g., Zhu *et al.* 2015) and secondly, creating new composite images from a collection of images from the same time period (e.g., from the same month or season) (White *et al.* 2014). An alternative option for overcoming cloud issues is to use satellite radar, which has the ability to penetrate clouds. Radar sensors are showing promise in areas of persistent cloud-cover such as the tropics (e.g., Aquino *et al.* 2022).

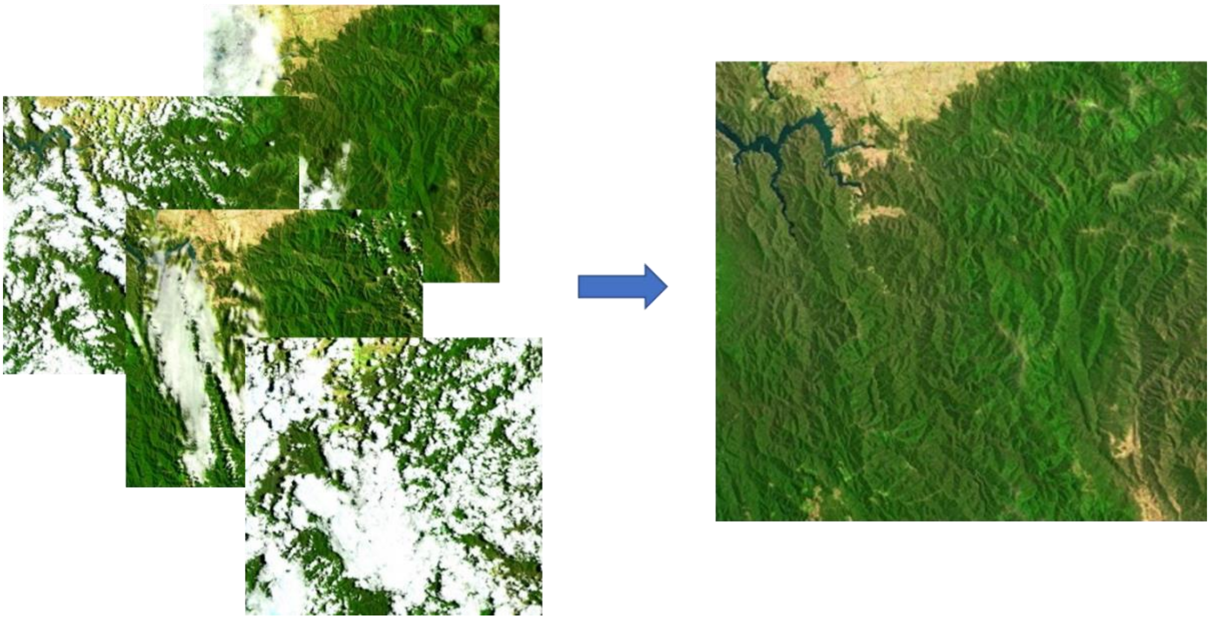

Figure 3. A visual representation of how pixel-based image compositing results in a cloud-free composite image

Measured versus modelled data

The distinction between measured and modelled values in remote sensing is at times unclear. It could be argued that most data we use is modelled. For example, the satellite imagery has already been through several processing steps to convert it from the values recorded at the sensor into meaningful reflectance values, which are typically meant to represent the reflectance of an object on the Earth's surface. Likewise, lidar-derived measures such as canopy height are modelled based on the location of the sensor and an approximation of the ground surface in a defined three-dimensional space. Indeed, even a common field measurement like tree diameter at breast height (DBH) is an approximation which assumes that a tree stem is a circle at the point of measurement.

For practical purposes, however, it is worth treating some data, like satellite imagery, lidar metrics and field data, as measured values which we accept as an approximation of the truth. It is then possible to create spatial models, using parametric equations or machine learning, to derive other variables of interest. A typical model will take the form y = f(x), where y is a singular response (or dependent) variable that we wish to model (e.g., above-ground biomass) and x is a collection of measured variables (referred to as covariate, predictor, explanatory or independent variables). The process is then to either mathematically compute a formula describing the relationship between y and the x variables or train a (supervised) machine learning model to do it. Both approaches require training (or reference) samples that we accept as being the truth. In the example of above-ground biomass, the reference data is typically computed from field plots.

Design-based sampling

Traditional forest inventories are based on a network of randomly selected field plots based on a statistically defendable design-based sample. These samples can be used to compute estimates of certain attributes for the entire forest estate. In an enhanced forest inventory, remote sensing data is used to compliment the field data to provide spatially explicit results and/or stratify the landscape to guide the plot selection process and increase the precision of estimates (White *et al.* 2013, Melville *et al.* 2015). Even without field plots, we can borrow from the principles of sampling, particularly the key elements of randomness and estimation, in a remote sensing only approach. That is, remote sensing data does not need to be wall-to-wall. We can use a selection of samples to make inferences about the whole estate, an approach used by Hislop *et al* (2021) to estimate historical large-scale disturbance impacts across eastern NSW forests.

4. Current products and programs in NSW

There are a number of current products and programs in NSW that may be relevant to the PNF MER framework. It is recommended that the PNF MER framework adopt existing products where possible, particularly for bioregional scale monitoring. However, it is unlikely that many of these products, particularly those derived from moderate resolution satellite imagery, will be directly applicable to the monitoring of the low intensity selective harvesting undertaken in PNF.

This section briefly outlines some of the current forest monitoring products and programs currently in place in NSW and Australia, including forest cover products, the State-wide Landcover and Tree Study (SLATS) and the Biodiversity Indicator Program (BIP). A more comprehensive overview for is provided in Appendix A of this report.

Table 2. Overview of current remote sensing products and programs that may assist the PNF MER framework (further details are provided in Appendix A).

Product/program	Description
National Forests and Sparse Woody Vegetation Data	National annual forest cover product, modelled from Landsat data at (~25m) resolution. Three class product with forest (>20% canopy cover), sparse woody (5-20% cover) and non-forest. Currently covers years 1988-2021.
State-wide Landcover and Tree Study (SLATS)	Maps and attributes the location of woody clearing. Based on Landsat data in early years, then SPOT (5m) and now Sentinel-2 (10m).
Foliage Projective Cover (FPC)	FPC of 11-12% is considered the equivalent to a canopy cover (CC) of 20%. Produced by DPE and used in various other products.
Fractional Cover	Separates pixels into sub-fractions of soil, vegetation and woody components. Available from various places, including TERN, DEA and through DPE.
Biodiversity Indicator Program (BIP)	In response to the NSW Biodiversity Conservation Act 2016, DPE established the Biodiversity Indicator Program (BIP) to assess the status of biodiversity in NSW. The BIP required development of a suite of indicators to measure different aspects of biodiversity and ecological integrity across the landscape.
State Vegetation Type Mapping (SVTM)	This program provides current maps of the three levels of vegetation classification hierarchy: Plant Community Type, Vegetation Class and Vegetation Formation.
Spatial Services low resolution lidar	Low resolution lidar (2-4 points m^{-2}), collected between 2010 and 2019, primarily for to derive accurate elevation models.
State-wide Digital Elevation Model (DEM)	Derived from lidar and photogrammetry with 5m resolution. Available from the NSW Spatial Collaboration Portal.
Local Land Services high resolution lidar transects	Collected over a sample of 253 PNF properties in 2020 and 2021.

State forests high resolution lidar	Collected at various times over the past decade. Latest captures collected in 2022/23.
High resolution imagery	High resolution aerial imagery (12-50cm) is available at various time steps and areas (often captured with airborne lidar). This is usually red, green, blue (RGB) but sometimes includes near-infrared (NIR).

5. PNF code outcomes and conditions where remote sensing may be applicable

Remote sensing may have limited application in monitoring many of the code conditions directly, particularly without coincident field data. However, there are a number of conditions that can be at least partially monitored using a range of different remote sensing approaches, which may help inform the PNF MER framework. These conditions are summarised in Table 3 and addressed more comprehensively in the following sections.

Table 3. Summary table of PNF code outcomes and conditions and related satellite and airborne remote sensing approaches

Outcome	Approaches	Useful for	Other comments
Maintain forest health and regeneration at site and bioregional scales	At a bioregional scale: Moderate resolution satellite times series	Good for large scale disturbances. Limited utility for low intensity disturbances such as PNF. May help inform on whether there is a divergence from 'baseline' disturbance regimes	Used extensively in monitoring wildfire impacts and associated forest recovery. Also useful for monitoring other large-scale disturbances (e.g. drought, pests & disease)
	At a site scale: airborne lidar (airborne laser scanning - ALS)	Can be used to model structural complexity of a stand, landscape heterogeneity, connectivity and gaps	These measures are only one component of forest health and different in different forest systems. Spatial scale has a large influence on results
	High-resolution imagery	Can potentially be used to look at tree health and regrowth	Needs expert interpretation
Maintain productive capacity at site and bioregional scales	At a site scale: Canopy height models (CHMs) from ALS	Can provide an accurate measure of area harvested	Need pre and post CHMs for this method
	ALS derived models	Can provide ball-park estimates of basal area and volume	Needs training data (e.g., field data and/or property records)
Maintain persistence of native species at site and bioregional scales	At a bioregional scale: habitat modelling with satellite imagery	Large scale models	Probably of limited use to the PNF MER. Large uncertainties

Outcome	Approaches	Useful for	Other comments
	At a site scale: ALS	As above, can be used to model structural complexity of a stand, landscape heterogeneity, connectivity and gaps	Hard to define what measures are best. Different fauna species prefer different forest structure
	High-resolution imagery and/or ALS	Can be used to look at whether exclusion zones are maintained, including potentially information on tree species	Requires human interpretation
Maintain water quality and soil health at site and bioregional scales	At a bioregional scale: satellite time series	Large scale mass movements of soil can potentially be monitored with satellite remote sensing	Soil movements due to PNF unlikely to be large
	At a site scale: ALS derived Digital Terrain Models (DTMs)	Can be used for determining drainage features and roads/tracks. Also useful for soil erosion modelling	May need pre- and post-harvest data
Specific conditions			
Silvicultural method / area harvested	ALS derived CHMs	Can highlight areas harvested	Need pre- and post-harvest lidar for accuracy
Canopy gaps and adjacency limits	ALS derived CHMs	Canopy gaps can be derived from CHMs by defining simple height thresholds (e.g., > 2m)	Forests often contain many gaps naturally. This is also influenced by spatial scale.
Basal area / volume	ALS spatial models	Spatial models	Models require calibration (i.e., field data). May not be accurate.
Regeneration	ALS time series	Tracking structural recovery over time	Regeneration as specified in the codes cannot to be accurately monitored without on-ground assessment. ALS time-series costly.

Outcome	Approaches	Useful for	Other comments
Exclusions maintained	ALS and/or high-resolution imagery (either satellite or airborne)	Exclusion zones can potentially be defined with ALS DTMs and monitored using either ALS CHMs or high-res imagery.	May require significant human interpretation
Retention of habitat trees	Interpretation of ALS and/or high-res imagery for tree species ID and crown size	Can be used in fauna distribution modelling	Requires expert human interpretation
Construction and maintenance of forest infrastructure	ALS derived DTMs	DTMs can be used to identify roading, snig tracks and road cross banks	Requires pre- and post-harvest lidar to determine changes
Pests and weeds	High-res imagery	Determining broad categories of vegetation	Under the PNF codes, remote sensing may be of limited use. Expert interpreters may be able to classify high impact weeds (e.g., lantana) from high-res imagery
Fire management	Satellite time series	Large scale fire impacts and recovery	Remote sensing has limited applicability to fire management as specified in the codes (i.e., low intensity prescribed fire). Much more applicability in general fire management.

From the perspective of the long-term outcomes, at both site and bioregional scales, remote sensing perhaps has greater applicability than directly monitoring individual conditions. It is through that lens that we present the information in the following sections. Figure 4 below indicates the four long-term outcomes and lists some of the code conditions where remote sensing is relevant. Noting that some conditions are applicable across different outcomes, the colours indicate which section of report the conditions are discussed in.

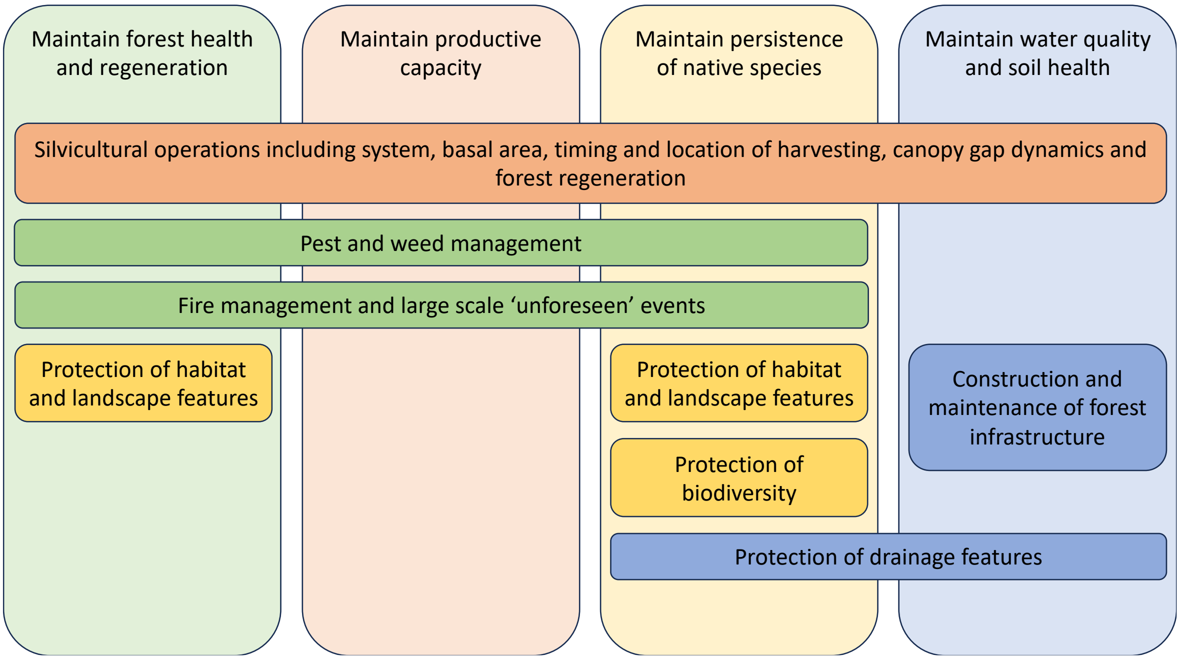

Figure 4. The four long-term outcomes from the PNF codes, cross-referenced with a selection of code conditions. The colours indicate which section of the report the various conditions are discussed in.

6. Forest health

Section summary

This section explores the application of remote sensing in its ability to detect and monitor canopy disturbance, particularly at bioregional scales. This includes:

- Fire severity and recovery
- Large scale drought impacts
- Pests and diseases

The information presented here is most relevant to section 4.3(5) of the PNF codes, where 'unforeseen' events which have the potential to cause environmental damage at the bioregion scale may lead to a review of harvesting practices by the Minister. The remote sensing of fire discussed here has little use for condition 7 (Fire Management), which is focussed on low severity prescribed burning.

Much of this section focuses on forest ecosystem health as a whole, of which large scale disturbances and satellite remote sensing play a greater role. PNF operations perhaps have little influence on forest health at this scale, but it is important that local scale forest/tree health is considered in the context of overall ecosystem health. More detail on site scale forest health measures such as stand complexity and local landscape heterogeny is provided in Section 8, after the technical details of lidar are discussed in Section 7.

Remote sensing technologies discussed in this chapter include:

Technology	Scale	Acquisition cost	Expertise needed
Landsat time series	Regional	Free	High
Sentinel-2 time series	Regional	Free	High
PlanetScope 'Dove' satellites	Regional / Property	~Free (NSW Govt has a licence)	High
Worldview-3/ Pleaides-Neo	Property	High	Very high
RPAS (UAVs) high-res imagery and lidar	Sub-property / plot	Medium	Very high

Introduction

Forest health can include ecological, economic, and sociocultural factors, including stand structure, composition, processes, function, productivity and resilience. The term 'forest condition' may also be used to describe forest health. In this discussion, we focus of the dominant structure of forests (i.e., the trees) using a synoptic view of the canopy.

Damaging agents which impact on tree/stand health include both physical disturbances from climatic processes including fire, drought and storms and biological agents such as insect pests and diseases. In some respects, forest disturbance is a natural and essential part of a healthy forest system, helping to maintain biodiversity and cycle nutrients and carbon. It can adversely affect forests when the frequency or severity is outside of 'natural' ranges (e.g., two fires in quick succession).

Remotely sensed data can quantify both forest stand and tree damage symptoms in terms of structure and physiological status and offer an alternative to traditional field-based approaches for assessing and monitoring forest health (Torres *et al.* 2021).

The success of detecting and monitoring the health of native forests is governed by the ability to relate the temporal, spatial and spectral characteristics of canopy (or tree crown) damage symptoms with remotely sensed data sensitive to the damage symptoms. For this to occur, knowledge of the progression of damage symptoms both spatially and temporarily is required. Past studies on assessing the health of forests have relied on the detection of foliar symptoms from a synoptic perspective and the expression of these symptoms in spectral signals that can be distinguished from healthy vegetation. Many studies have been published that compare the capabilities of optical remote sensing systems for assessing and monitoring the health of native forests affected by insect pests and fungal diseases. A number of recent reviews summarise these approaches (e.g., Rullen-Silva *et al.* 2013, Hall *et al.* 2016; Lausch *et al*. 2017, Torres *et al.* 2021). Fewer studies claim success in detecting 'early signals' of loss of tree vigour in native forests and have commonly relied on time series analysis of satellite imagery (e.g., Rogers *et al.* 2018). The remote detection of changes in tree structure that relate to poor health (e.g., crown dieback) is advancing, especially with the use of lidar and the application of deep learning computer vision algorithms (discussed below, in Estranda *et al.* (2023)).

Spectral vegetation indices

Spectral vegetation indices are generated by combining spectral reflectance values from two or more wavelengths (or wavebands) to provide a single value that relates to the vegetation feature of interest. The popularity of vegetation indices (VI) derived from broadband multispectral imagery, such as the Normalized Difference Vegetation Index (NDVI) is due, in part, to their ease of use, robustness and transferability. NDVI is derived from the red and near-Infrared bands and produces values that relate to green biomass and photosynthetic capacity of vegetation. However, NDVI is also sensitive to atmosphere and background soil effects as well as 'saturating' at high biomass values and hence is not always the preferred VI for monitoring the health of dense canopy native forests (Huang *et al*. 2021).

While simple, single date VIs such as the NDVI can successfully detect crown death (e.g., Meddens *et al*. 2011), the on-going deployment of satellite optical sensors with increasing number of broad spectral bands, has resulted in dozens of other vegetation indices being developed. Many of these alternative VIs are showing abilities in discriminating between categories of crown damage severity (e.g., Woodward *et al*. 2018, Dalponte *et al*. 2022). An important recent addition has been the red edge waveband (approximately at 680-750 nm), which is included in the Sentinel-2, Pleaides-Neo and WorldView-3 satellite sensors. This wavelength region is important for assessing vegetation health because of the red edge data responsiveness to changes in foliar chlorophyll content (Eitel *et al*. 2011, Abdull *et al* 2018). Eitel *et al.* 2011 reported that the Normalized Difference Red-Edge Index (NDRE) obtained from the RapidEye satellite was able to detect tree stress almost two weeks earlier than the NDVI. Adbollahnejad *et al.* (2021) also advocated the benefit of the coastal blue and red edge bands available in WorldView-2 imagery for the early detection of European spruce bark beetle (*Ips typographus* L.) attacks.

High resolution satellites

In addition to increased spectral resolution, an increasing number of satellites now offer higher spatial resolution compared to the moderate resolution, open-source sensors such as Landsat (30 m pixels). For example, Sentinel-2 satellites provide open-source imagery with 13 bands, with most bands at 10 m or 20 m spatial resolution and has been shown to be more effective at detecting early canopy damage symptoms than Landsat-8 (e.g., Abdullah *et al.* 2018). In 2014, the commercial satellite WorldView-3 (DigitalGlobe) was launched. This satellite provides 8 band multispectral imagery at very high spatial resolution (VHR) providing 1.24 m multispectral pixels. The higher spatial, spectral and temporal resolutions of Sentinel-2 and other recent commercial satellites such as WorldView-3 offer greater dexterity and a higher likelihood of obtaining cloud-free imagery for application in broad-scale forest disturbance and canopy health monitoring mapping.

In a parallel development, a series of commercial micro-satellite constellations have recently been launched. For example, the PlanetScope constellation of micro-satellites (‘doves’) provide both high spatial (~3 m for multispectral bands) and high temporal resolution (daily). However, while this imagery tends to be less expensive imagery from the larger satellite sensors that have a similar high spatial resolution (e.g., WorldView 3 (1.24 m) & Pleiades (1.2 m)) the much smaller satellites tend not to have the radiometric and spatial consistency that larger satellites can provide, which makes automated time series analysis challenging.

The manual interpretation of aerial imagery acquired by piloted aircraft has long been used for mapping forest health. Airborne digital multispectral imagery has also been used in models to detect and classify canopy damage symptoms (Windrim *et al.* 2020). Recently, Remotely Piloted Aircraft Systems (RPAS) (also referred to as UAVs or drones) have also been evaluated for small-scale forest health assessment (Ecke *et al.* 2022). Both aircraft and RPAS operate at much lower altitudes than satellites and so can provide even higher spatial resolution (< 10 cm). This permits tree level detection and segmentation used in the health classification of individual tree crowns. This approach reduces spectral noise from non-tree crown elements such as understorey vegetation and novel deep learning algorithms are rapidly advancing producing continued improvement in tree crown health classification (Zhao *et al.* 2023). Importantly, sampled very high spatial Imagery acquired by RPAS and aircraft is now often used as a source of reference (training/calibration/validation) data required for scaling up modelled parameters based on regional scale satellite imagery (e.g., Abdollahnejad *et al.* 2021).

Time series analysis of satellite imagery for detection of forest disturbance

Change detection based on multi-temporal satellite images is now a common approach to monitoring forest disturbances from numerous damaging agents including fire, pest insects and pathogens (e.g., Senf *et al*. 2015). Several optical satellite sensors acquire consistent and repeatable measurements over large areas at regular time intervals, enabling cost-effective spatially explicit monitoring of forests. A time series of a suitable spectral index can then be analysed through time at a pixel level (Figure 5). Numerous time series change detection algorithms have been proposed (Zhu 2017) that permit time series analysis revealing spectral trajectories that quantify impact metrics such as disturbance magnitude and recovery length. These metrics can then be incorporated into spatial models classifying the disturbance. Hislop *et al*. (2019), for example, used Landsat NBR data to map disturbance magnitude and recovery length across large areas of forests burnt between 2002 and 2009 in Victoria. Spectral recovery is somewhat limited in its ability to represent functional, structural or compositional recovery of complex forests but White *et al.* (2019) demonstrate that it can act as a reasonable surrogate. Hislop *et al*. (2018, 2019) defined spectral recovery in terms of the number of years to recover to the full pre-disturbance value of the spectral index.

This type of analysis is well suited to large areas and abrupt disturbances such as wildfire and high intensity timber harvesting (e.g., White *et al*. 2022) however, subtle changes in the forest canopy such as gradual stress from drought, can be more challenging. Recently, however, the use of dense time series data (e.g., monthly) has been successfully applied to detect multiple types of forest disturbances in eucalypt forests including slow decline based on the shape of the spectral trajectories (Hislop *et al*. 2023). Vogelmann *et al*. (2016) concluded that one of the biggest challenges for studying gradual change was the lack of appropriate data for validating results. Importantly auxiliary information from multiple sources such as forest fire mapping and health monitoring programs can used to help interpret the spectral trends (Hislop *et al.* 2021).

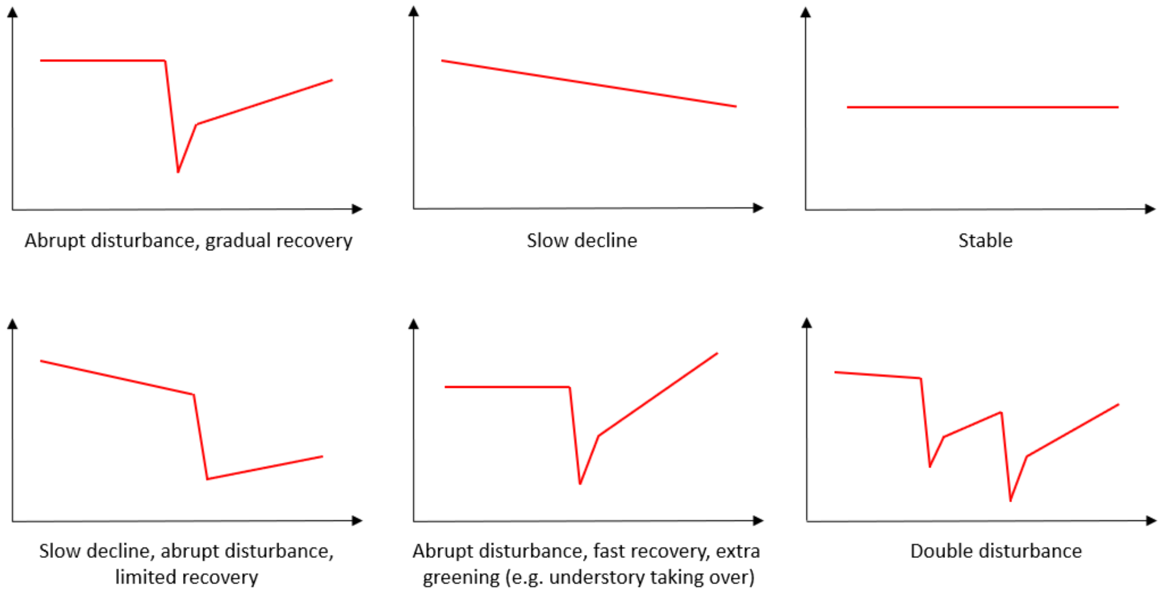

Figure 5. Indicative pixel trajectories of a spectral index sensitive to canopy disturbance

Fire disturbance

Fire is the principal disturbance agent in NSW native forests. The recent increased frequency and severity of wildfires and drought is likely due to climate change, a pattern which is being observed globally (Nolan *et al.* 2022). In the PNF codes, the section on fire management refers to the use of prescribed fire for fuel reduction or other environmental objectives, essentially stating that fires should be low intensity. This is one component of fire management and one where remote sensing, particularly via satellite, has limited application. Remote sensing is used extensively in fire management more broadly, including for pre-fire assessments of fuel loads and moisture, active remote sensing during fires and assessing post-fire impacts. Here we principally focus on post-fire impacts.

Accurate estimates of the extent and severity of fire impacts is essential for post-fire forest management. Traditional methods of wildfire mapping such as ground surveys or Aerial Photographic Interpretation (API) are time-consuming and have limitations in terms of costs and repeatability. Satellite data, however, can deliver rapid information to map changes to fire and drought impacted forest canopies in a precise, prompt, and affordable way (Hislop *et al.* 2023a).

Common spectral indices used to detect and monitor fire severity are typically based on the Normalized Burn Ratio (NBR) which uses the Near Infrared (NIR) and Shortwave Infrared (SWIR) wavelengths. NBR is sensitive to forest moisture and structure while NDVI is more sensitive to vegetation 'greenness' (Hislop *et al.* 2018). The classification of fire severity classes using single spectral indices such as dNBR (differenced NBR) or RdNBR (dNBR normalized with the square root of a pre-fire NBR to account for variability in vegetation composition) have become standard methodology for mapping fire severity. Consistency in the mapping of fire severity classes can be improved through the application of machine learning modelling techniques, such as the random forest (RF) classifier. Collins *et al*. (2018), for example, improved fire severity mapping accuracies through using RF. They also highlighted the importance of the training dataset, including number of points, sample balance and the geographic source of sample data were all important considerations for the use of satellite imagery and RF classification when mapping fire severity.

The inclusion of other forms of spectral information may also improve fire severity mapping accuracy. For example, Gibson *et al.* (2020) introduced estimates of fractional cover derived from spectral un-mixing into RF modelling, in addition to common NBR indices. Spectral un-mixing estimates the relative sub-pixel fractions of photosynthetic and non-photosynthetic vegetation as well as bare soil, using a calibrated relationship with high quality, quantitative field data (Guerschman *et al.* 2015).

The most accurate RF model from Gibson *et al.* (2020) included both Sentinel-2 based NBR reflectance indices and fractional cover indices. Highest mapping accuracies occurred for mapping unburnt and high severity wildfire in landscapes with moderate canopy density and low topographic ruggedness. Higher rates of misclassification occurred for the low and moderate fire severity classes and in areas of dense canopy cover and rugged topography. This in part, is due to the limitations of optical sensors in viewing the burnt understorey of low severity classes under conditions of high canopy cover and high topographic complexity.

The results from Gibson *et al.* 2020 have contributed to the current methodology applied by NSW DPE to produce annual fire extent and severity mapping (FESM), based on temporal Sentinel-2 temporal imagery and machine learning. The FESM has five classes of fire severity (Table 1). The product is produced at 10 m pixel resolution and modelled from Sentinel-2 imagery following the robust method presented in Gibson *et al.* (2020). The FESM machine learning models are trained on fire severity class samples from approximately half a million training data points, interpreted from high resolution post-fire aerial photography.

Table 4. Description of the five fire severity classes presented in the FESM products

Severity class	Description
Unburnt	Unburnt surface with green canopy
Low	Burnt surface with unburnt canopy
Moderate	Partial canopy scorch
High	Full canopy scorch (± partial canopy consumption)
Extreme	Full canopy consumption

NSW DPE has recently produced a report that summarises the FESM analyses for the 2021-2022 fire year, two years after the devastating Black Summer of 2019-2020. It is planned that future annual reports will be issued routinely in August each year. This is accompanied by the FESM spatial data being made available on the DPE’s Sharing and Enabling Environmental Data (SEED) portal.

Gibson *et al.* (2022) recently published a methodology using satellite imagery that can assess and monitor post-fire recovery using a post-fire stability index. Higher values in the post-fire stability index were shown to be associated with higher levels of field-based measures of FPC and canopy cover. This methodology closely compliments the DPE FESM program and may become operational in the near future (R. Gibson *pers. comms.*).

Drought disturbance

Water stress directly limits gaseous exchanges, reduces transpiration and arrests photosynthesis in foliage and if not reversed results in leaf wilting and mortality. The 2018-2019 drought across eastern NSW was one of the worst on record and a key driver behind the unprecedented 2019-2020 fire season. While the impacts of these fires received widespread attention, there were also considerable impacts from the drought itself, including widespread canopy collapse from tree mortality and stand dieback.

Several studies have demonstrated the capability of temporal, broad band satellite imagery to detect severe drought in forests. Byer & Jin (2017) used MODIS multispectral time-series imagery and derived a trend series of normalised spectral indices (z scores). They then used Random Forest algorithms, trained with forest aerial detection surveys data, to detect tree mortality based on the remote sensing metrics and topographical variables. In a similar study, Caccamo *et al.* (2011) evaluated the capability of MODIS time series of eight indices created from 2000 to 2009 to monitor drought in forests within the Sydney Basin bioregion. The results were then compared to spatially and temporally coincident values of the Standardized Precipitation Index. Their results identified that the Normalized Difference Water Index was a reliable indicator of drought. This VI is sensitive to change in leaf water content of leaves and in fact uses the same NIR and SWIR wavebands as used in the NBR, effectively detecting leaf necrosis. The early detection of tree water stress is possible and can be achieved through the use of narrow waveband indices (i.e., hyperspectral imagery) or through using thermal infrared imaging (Le *et al.* 2023).

Recently, Hislop *et al*. (2023a) presented a novel method using dense Sentinel-2 time series imagery to map eucalypt canopy damage due to both drought and fire across a large area. To areas identified as forest they applied a mask related to local fire history. Sentinel-2 monthly time series were then accessed and NBR values calculated with the aim of highlighting areas of forest where the NBR index was significantly below a pre-disturbance ‘stable’ period. Because forest types vary across the region, they naturally have different spectral and temporal signatures. Therefore, different disturbance threshold values were used for each bioregion. To objectively define appropriate threshold values, a previously collected human interpreted reference dataset was used (Hislop *et al.* 2021). The dataset consists of 500 randomly selected 1 ha plots in the forested areas of each bioregion (5,000 in total), which were visually interpreted using Landsat data and available ancillary information to establish disturbance history from 1988 to 2020. The study of Hislop *et al*. (2023a) resulted in the production of maps and associated statistics of forests disturbed by drought, fire and both drought and fire and demonstrates the potential of Sentinel-2 data for monitoring the dynamic nature of native forests in NSW.

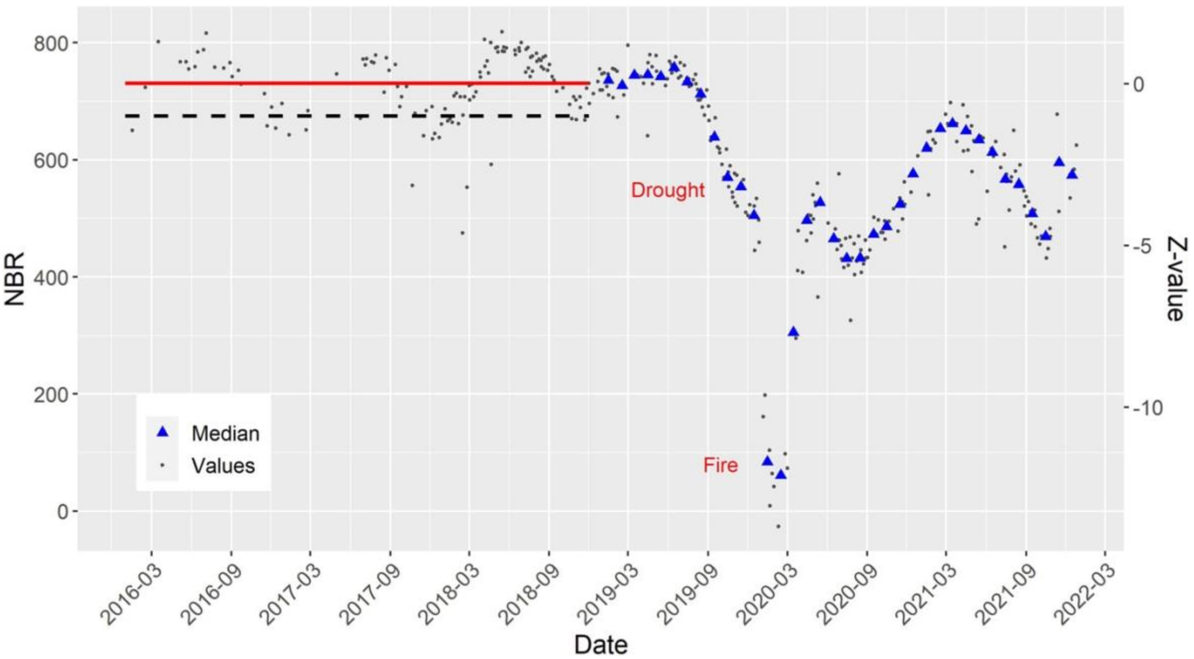

Figure 6. Example of an individual Sentinel-2 pixel through time. NBR values are shown in grey and the monthly median values for 2019 onward in blue. The horizontal lines are the mean and standard deviation for the stable period (2016–2018), used to calculate the z-values (secondary y-axis). From Hislop *et al.* (2023a).

In addition to analysis of freely available MODIS, Landsat & Sentinel 2 satellite time series data, some higher resolution commercial satellite products and aerial imagery have also been evaluated to detect drought-induced dieback at much finer spatial resolution. Fitzgerald *et al.* (2023) integrated temporal PlanetScope imagery (3m pixels) and hyperspectral airborne imagery to investigate drought-induced dieback of a red stringybark population in South Australia.

Bell Miner Associated Dieback

A notable health issue that occurs in NSW native forests is Bell Miner Associated Dieback (BMAD), which has been listed as a key threatening process. High densities of bell miners are associated with decreased avian abundance and diversity and a subsequent increase in insect (psyllids) related foliage damage in susceptible eucalypt crowns. This dieback syndrome affects both the physiological status of tree crowns and stand structure and often co-occurs with the presence of a dense shrubby understorey with a sparse eucalypt canopy (Stone *et al.* 2008). Haywood & Stone (2011) developed a modelling framework that used multi-sourced spatial datasets that included spectral data (SPOT-5), structural data (ALS), and topographical data (aspect and topographic wetness index), to produce maps predicting the presence of BMAD. The training data was obtained using a stratified random sampling methodology with the allocation of 30 plots to four spectral strata. Six models were evaluated and concluded that the random forest ensemble classifier was the most accurate model (AUC=0.97).

Efforts to map BMAD over large scales with moderate resolution satellite imagery have largely been unsuccessful. This is because of difficulties in separating understory from canopy reflectance in optical imagery combined with the relatively small areas impacted by BMAD, proportionally speaking. An alternative approach for mapping health related symptoms, including BMAD, is through the use of aerial surveys. In Australia, aerial surveys are regularly used to map plantation forest health, with annual programs running since the mid-1990s in some jurisdictions (Carnegie *et al.* 2018). Between 2015 and 2017, aerial surveys targeting BMAD were undertaken across approximately 1 Mha of native forest in northern NSW. The forest health expert mapped BMAD impacted areas totalling 43,000 ha (4%) (A. Carnegie, *pers comms*).

7. Productive capacity

Section summary

This section focusses principally on the remote sensing of forest structure, including components such as tree heights, basal area and aboveground biomass. Lidar is the most relevant remote sensing technology in this regard, which can be collected from terrestrial, airborne and spaceborne systems.

Monitoring of forest structure from lidar can help ensure that the silvicultural operations outlined in condition 5 of the Codes are appropriate in supporting the productive capacity of private native forests in NSW. The approaches here are not able to measure basal area and regeneration directly, as outlined in the codes, as these techniques require direct field measurements.

Remote sensing technologies discussed in this chapter include:

Technology	Scale	Acquisition cost	Expertise needed
Airborne laser scanning (ALS)	Property / regional	High	High
Terrestrial laser scanning (TLS)	Plot	Medium (if equipment already owned)	Very high
Mobile laser scanning (MLS)	Plot	Medium (if equipment already owned)	Very high
GEDI	Regional (samples)	Free	Very high

Successful sustainable management of native forests requires information on both forest composition and structural diversity, where structural diversity explains the arrangement and distribution of the structure of vegetation elements. Forest structure can be quantified in myriad ways, including the prediction of individual components (e.g., tree diameters and heights, basal area, aboveground biomass) or through stand-level measurements of vegetation strata and stand succession. Assessment of stand structure contributes directly to estimates of timber volume, carbon storage and habitat suitability and can therefore provide information on both forest health and productive capacity.

Airborne Laser Scanning (ALS)

Lidar (Light Detection and Ranging) datasets provide a means to evaluate the 3D structure of forests with reduced effort and costs compared to ground-based measurements. While tree level measurements such as tree height, stem diameter and tree density can be reliably obtained by field crew, estimates of plot level structural attributes such as understorey density and cover, are often inaccurate, imprecise, and time-consuming. There are now numerous lidar derived metrics that can accurately estimate both stand-level (e.g., Carrasco *et al.* 2019) and tree-level (e.g., Karna *et al.* 2019) attributes.

Many lidar derived metrics are based on the vertical distribution of points in a defined horizontal area (Figure 7). The metric p95, for example, which is often used to indicate canopy top height, is the height at which 95% of the points are below. Common lidar metrics based on the vertical distribution of points include top height (e.g., p95), average height, measures of variance (e.g., standard deviation) and canopy cover, which is typically equal to the number of 1st returns above a certain height (2 m) divided by all 1st returns.

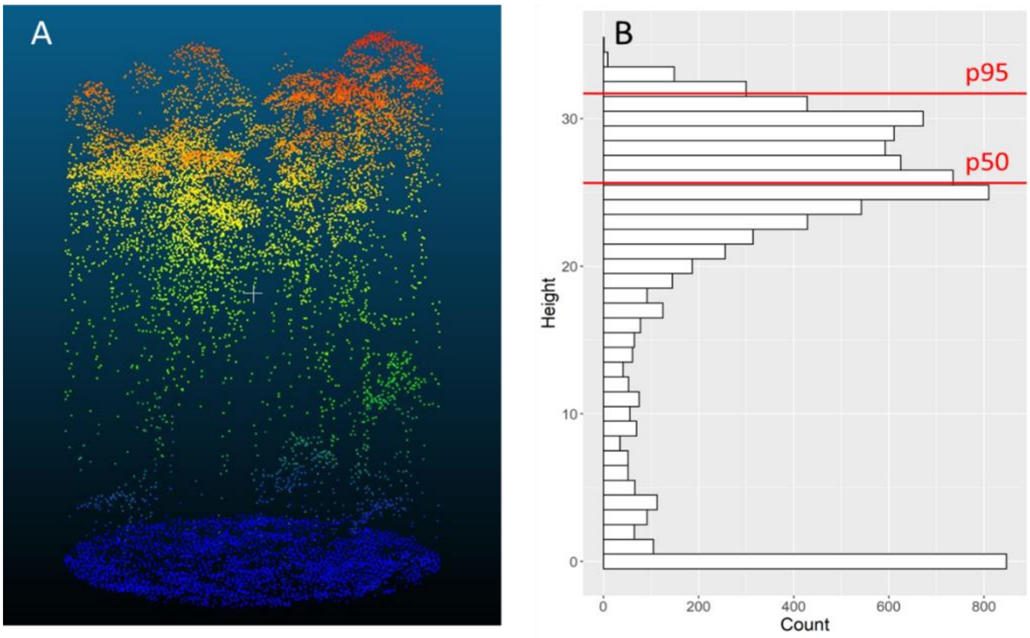

Figure 7. Example of a lidar point cloud over a plot (A) and the resulting distribution of height values (B), with the 50th and 95th percentiles shown in red.

Lidar data acquired by aircraft (Airborne Laser Scanning, ALS) can cover forests at the regional-level and provide information related to the structural conditions presented by the dominant canopy and larger trees. By placing a regular grid of (e.g., 30 x 30 m) across the ALS extent, we can calculate the different lidar metrics for every grid cell to create maps across the landscape (Figure 8), which can in turn be used in machine learning models. ALS data is frequently now used operationally for plot imputation to create wall-to-wall estimates of inventory metrics such as basal area and above ground biomass (e.g., White *et al*. 2013, Dash *et al.* 2015).

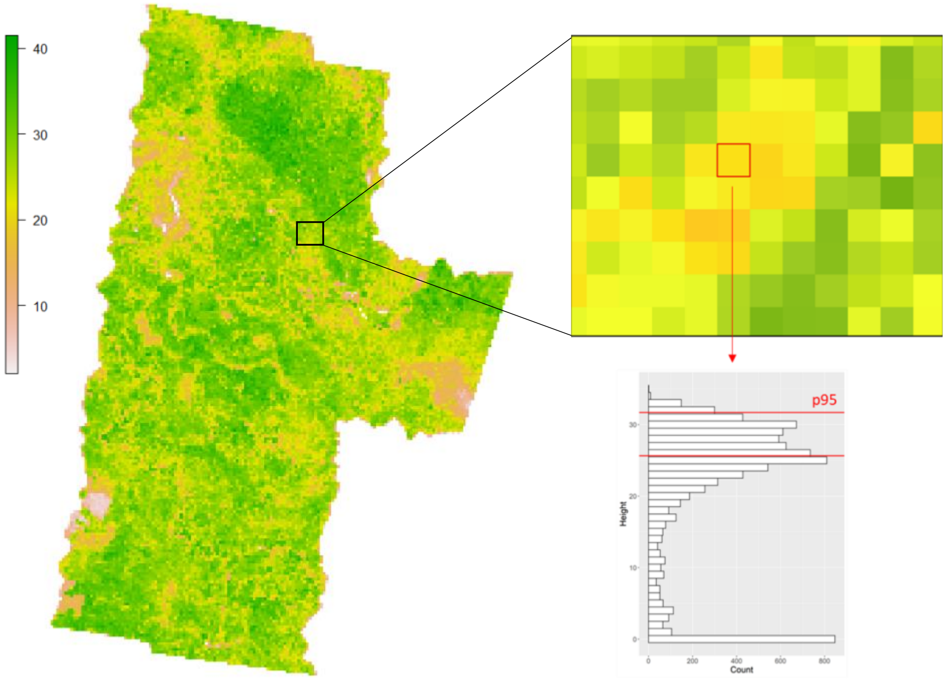

Figure 8. Example of a lidar metric (p95) calculated from the height distribution of points in each grid cell (pixel) across a lidar extent.

The structural metrics that can be derived from ALS can be categorized into four main categories: cover, height, horizontal variability and vertical variability (Bakx *et al.* 2019). ALS may not be able to fully capture the vertical distribution of all foliage in complex, multilayered and dense forests due to the attenuation of the laser pulses. However, vertical profiling using ALS data has been successfully demonstrated in some native eucalypt forests. For example, Wilkes *et al.* (2016) used ALS data and successfully identified the vertical strata in several forest types in Victoria. Jiang (2020) was also able to extract height percentiles and the density of points within height classes to provide canopy profile models for a comparison of eucalypt forest structure in the Central Highlands of Victoria. The density of points was assumed to represent foliage density in different height strata and used to examine the connectivity between vertical layers. Thus, in addition to predicting traditional inventory metrics, ALS-derived vegetation metrics are now being applied to quantify a broader suite of forest stand assessments such as habitat suitability (e.g., Ciuti *et al*. 2018, Bakx *et al.* 2019, Carrasco *et al*. 2019) along with above ground biomass estimates (e.g., Kim *et al*. 2016).

One of the most useful ecological applications of ALS is the direct acquisition of vertical foliage distribution and associated foliar densities, which provide detailed information of both the forest canopy, subcanopy elements and individual trees. The leaf area density (LAD) metric estimates total leaf area per unit volume and requires the sampled space to be divided into volumetric pixels (referred to as voxels) (Carrasco *et al*. 2019). Voxel-based metrics are based on summarizing the lidar points that fall within each voxel and are directly influenced by the chosen voxel dimensions. Voxel-based metrics have used to predict forest inventory attributes and canopy attributes such as leaf area index (Pearse *et al.* 2019). For example, LAD estimates are related to leaf area index and gap fraction (Carrasco *et al.* 2019) and can be derived using programs such as the R package lidR (Roussel *et al*. 2018).

In addition to the calculation of ALS metrics that describe forest height, height variability and cover, Jarron *et al.* (2020) also included more complex lidar metrics related to stand structural complexity into a regression model that classified sub-canopy components. Included for consideration in their modelling were the vertical complexity index (VCI) (van Ewijk *et al.* 2011) and the vertical rumple index. The rumble index is a canopy complexity metric calculated by dividing the 3D surface area by the 2D surface (Roussel *et al.* 2020).

Lidar metrics characterising the distribution and density of vegetation within forest stands have also been used to classify forest successional stages (van Ewijk *et al.* 2011). Falkowski *et al.* (2009), for example, applied Random Forest modelling to classify forest successional stages in the inland northwest USA, based upon 34 lidar height metrics. Their optimal model had an overall accuracy of 90%.

ALS data is advocated as means for estimating forest Above Ground Biomass (AGB) when combined with field samples. For example, Chan *et al.* (2021) successfully estimated AGB over Hong Kong using ALS derived plot metrics, allometric equations and a sample of field-measured structured variables through applying a simple regression modelling methodology. In a study covering even larger areas in the eastern USA, Deo *et al*. (2021) efficiently estimated forest AGB developed a statistical modelling framework that integrated forest inventory plot data with spatial predictors from Landsat time-series imagery and ALS strip samples.

The ability of NSW government agencies to secure ALS data has recently improved through the purchase of a hybrid LiDAR/spectral sensor (Leica City Mapper 2S) by the Service NSW Environmental Spatial Programs. In addition, the NSW Rural Fire Service is evaluating the purchase of an airborne Geiger-mode LiDAR sensor which has the capacity to cover larger areas more cost effectively than traditional ALS.

Canopy height models (CHMs)

As well as the metrics discussed above, ALS can be used to derive Canopy Height Models. CHMs are two-dimensional representations of the height of the forest canopy (Figure 9). There are numerous algorithms for computing a CHM. Typically, they are based on subtracting the difference between the first returns (top of canopy) and the last returns (ground surface). Khosravipour *et al.* (2014) introduced a 'pit-free' algorithm to create a more realistic (smooth) surface of the canopy. In recent work, Hislop *et al.* (2023b) used a CHM differencing technique, from lidar samples collected in 2020 and 2021, to estimate the amount of timber harvesting in private native forests in northern NSW in a one-year period. The authors estimated that only 0.37% of forest with active PNF plans was harvested during this period.

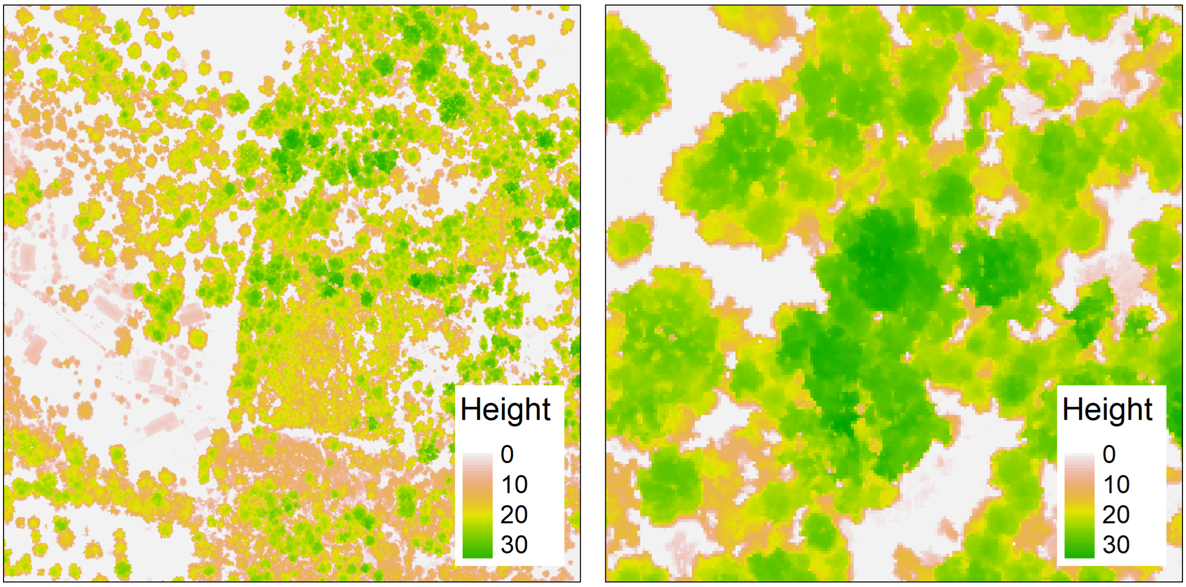

Figure 9. Example of a 1 m CHM derived from airborne lidar. The second image is a 'zoomed in' area of the first.

CHMs are also useful for exploring local canopy gap dynamics, which are important drivers in forest functional processes. Silva *et al.* (2019) created an R package ForestGapR to automate gap detection and compute gap statistics from CHMs. The work of Hislop *et al*. (2023b) could be extended to explore gap dynamics from the multi-date lidar available over some PNF properties.

RPAS mounted lidar

Remotely Piloted Aircraft Systems (RPAS), also referred to as Unmanned Aerial Vehicles (UAVs), or more commonly 'drones', are increasing in popularity, including in forest contexts. RPAS-mounted lidar technology is advancing rapidly, providing data of very high resolution (e.g., DJI Zenmuse L1). In terms of point densities, the data from these instruments falls somewhere between ALS and terrestrial lidar. At present, most RPAS Lidar platforms are flown above the canopy and hence need to contend with the occlusions presented by closed canopy conditions. This restricts accuracies obtained for stem measurements such as diameter (Neuville *et al.* 2021). More recently, RPAS-lidar systems are being developed and trialled for below-canopy forest surveys (e.g., Hyyppä *et al*. 2020a & b). However, these systems need collision avoidance capabilities and are thus still a nascent area of development.

Hyyppä *et al.* (2020a) compared four types of laser scanning platforms, a backpack and hand-held Mobile Laser Scanning (MLS) system, an under-canopy RPAS and an above-canopy RPAS, for measuring tree level structural attributes. They concluded that the two ground-based mobile scanning methods and the under-canopy UAV laser scanning system enabled the estimation of DBH, stem curve and stem volume with a sufficient accuracy for operational applications in forests with low- to medium-levels of understorey vegetation. These results, however, were not achieved by the above-canopy RPAS.

Terrestrial lidar instruments

ALS sensors are positioned above the canopy and hence have limited capacity to directly measure tree stem parameters such as DBH, whereas Terrestrial (TLS) and Mobile Laser Scanning (MLS) sensors are positioned below the canopy with a 'bottom up' perspective. While survey grade TLS sensors can provide very accurate point cloud data, occlusion effects require a plot to be scanned from multiple locations which can be time-consuming. MLS systems, on the other hand, add the aspect of movement along a track (trajectory) and can reduce tree level inaccuracies created by occlusion by incorporating many views during data collection as well as increasing the areas scanned. A significant advantage of MLS technology is the removal of the need for accurate Global Navigation Satellite System (GNSS) signals, which can be disrupted by forest canopy, through the adoption of Simultaneous Location and Mapping (SLAM) technology (Gollob *et al.* 2020). One disadvantage of point cloud data acquired by MLS scanners is the non-uniformity of the pulse density, however, point clouds can be normalised by using voxels.

In a boreal forest in Finland, Hyyppa *et al.* (2020a) compared the accuracies of hand-held, backpack and under-canopy UAV MLS instruments in terms of their ability to estimate DBH and stem volume and concluded that all three methods provided plot-level volume estimates similar or even slightly better than manual measurements. In Australia and New Zealand, the MLS Emesent Hovermap has recently received considerable attention as an alternative approach to manual field collection (i.e., as a plot- and tree-level sampling tool). See details in Stone & Hislop (2022) and here[5].

Several open-source packages are now available that apply individual tree segmentation algorithms using dense point cloud data acquired by TLS or MLS instruments, including the Forest Structure Complexity Tool (FSCT; Krisanski *et al.* 2021)[6] and TLS2trees (Wilkes, *et al.* 2022)[7]. Adapting and improving these packages specifically for NSW native forests would significantly improve both the accuracy and efficiency of ground-based data collection compared to current manual methods.

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[5] https://interpine.nz/adding-the-emesent-hovermap-slam-lidar-solution-to-our-services/

[6] Forest Structure Complexity Tool (FSCT) available at https://github.com/SKrisanski/FSCT

[7] TLS2trees: a scalable tree segmentation pipeline for TLS data available at https://github.com/philwiles/TLS2trees

In a recent study (R. Jiang in Stone & Hislop 2022), developed a method aimed at improving the accuracy of tree height estimates obtained in the FSCT based on tree-level-PAD profiles (similar to LAD estimates but for the entire plant structure not just the foliage) and was able to classify trees as either occurring in the canopy, sub canopy or as dead trees (stags) or those that had a significant dieback crown (dead top). This new workflow involved building separate tree-level PAD profiles for three categories (1) foliage only, (2) stem only and (3) foliage + stem. Based on changes of PAD by height it was possible to identify height breaks that distinguished between upper and lower leaf density strata. Importantly, the application of this approach using dense ALS data could potentially improve the detection of dead and dying trees at both the site and landscape scale.

In addition, current research is being undertaken to incorporate tree segmented MLS point clouds into a Virtual Reality environment for visual and on-screen measurements (D. Herries, Interpine Innovation NZ; M. Bryson, University of Sydney; W. Chinthamit, University of Tasmania, *pers comm*.). Preliminary analysis of Hovermap derived point cloud data collected in dense native eucalypt forest resulted in the successful detection of tree stems and estimation of DBH. It is hoped that this research will progress the accuracy and the operational adoption of MLS instruments such as the Emesent Hovermap for inventory assessment of PNF monitoring plots.

Satellite derived forest height estimates

The vegetation maps provided in the TERN AusCover databases include vegetation height which have been produced by integrating satellite data obtained from ALOS-1 PALSAR (radar), Landsat (spectral) and ICESat/GLAS (Lidar) (Scarth *et al.* 2023). While the resultant vegetation height accuracies are comparable with ALS derived heights, especially over dense canopies, the horizontal accuracy of this data is not suitable for fine scales. The more recent Global Ecosystem Dynamics Investigation (GEDI) lidar instrument on the International Space station has better horizontal accuracy (+/- 9 m). GEDI has been collecting lidar samples (~25 m footprint) since 2019 (it is currently off-line but should return in 2024). GEDI data was used by Pourrahmati *et al.* (2023) to generate canopy height models over forests in Germany. They reported that the GEDI canopy height over conifer forests was slightly more accurate (RMSE = 6.61m) than that over broadleaf forests (RMSE = 8.30m). Healey *et al.* (2020) also demonstrated the value of integrating samples of lidar data (obtained from GEDI) with wall-to-wall coverage of Landsat imagery. They demonstrated that Landsat-based maps of structural variables such as height and biomass can substantially benefited from calibration with GEDI data through minimizing signal saturation commonly associated with passive optical sensors.

In Australia, Huettermann *et al.* (2023) recently published research which used the GEDI simulator to simulate GEDI data from ALS from pre-fire and the real GEDI data post-fire to study vegetation response in a range of GEDI metrics.

Photogrammetric approaches

Forest canopy heights can also be derived from high-overlap digital camera imagery. Tree heights can be estimated using stereo aerial images within a specialised hardware/software system designed for manual Aerial Photographic Interpretation (API) or via software based on the Structure from Motion methodology (e.g., Agisoft Metashape), which is commonly applied to imagery acquired by RPAs. Canopy Height Models are obtained by subtracting a Digital Terrain Model (bare earth elevation) from a Digital Surface Model (elevation of the top of a surface including vegetation and all other objects). This approach is now commonly applied to high spatial resolution RGB imagery acquired by RPAS, enabling both tree crown detection and height estimation. Srivastava *et al.* (2022), for example, used RPAS-derived RGB images acquired over native forest in southeast Queensland to derive a CHM which was successfully processed to estimate tree heights of individual trees. The authors do acknowledge however, that their approach would be more challenging in dense forests with overlapping tree crowns.

8. Persistence of Native species

Section summary

The persistence of native species (both flora and fauna) is essential if native timber harvesting is to continue. The codes dedicate many pages to the protection of the environment, including conditions on the protection of significant landscape features, habitat and biodiversity. Many of the conditions are focused at the tree-level (e.g., habitat trees, hollow bearing trees), features that are unable to be mapped with any confidence using remote sensing, particularly from above the canopy.

At a site scale, measures of structural complexity, landscape heterogeneity and canopy/understory connectiveness may support the persistence of native species, along with maintaining exclusion zones around drainage features and other important landscape features. These metrics can be best captured with lidar, the technical details of which are discussed in Section 7.

Remote sensing technologies discussed in this section include:

Technology	Scale	Acquisition cost	Expertise needed
Sentinel-2	Property / regional	Free	High
WorldView-3	Property	High	Very high
Aerial imagery	Property / plot	High	Very high
Lidar	Property	High	High
RPAS thermal imagery	Sub-property	Medium (if equipment already owned)	Very high
Acoustic arrays	Property	High	Very high

The PNF codes provide detailed requirements under Condition 8. Protection of the environment. A literal interpretation of these conditions at the site scale cannot be achieved with confidence using remote sensing approaches in many cases. However, we offer a brief assessment of some of the features mentioned in the code here in Table 5. Note that in some cases, features may be able to be mapped through manual stereo API approaches.

Table 5. Landscape/site and tree features mentioned in the PNF codes and the relevance of remote sensing for monitoring these features.

Landscape/site feature	Remote sensing relevance
Threatened ecological communities	Relies on existing data. High-res remote sensing can assist in determining whether exclusion zones are maintained.
Threatened populations	As above

Areas of outstanding biodiversity value, rainforest, old-growth forest	As above
Wetlands, heathlands	Can use existing products, which are typically derived from satellite remote sensing
Rocky outcrops	Medium to high resolution remote sensing products can show rocky outcrops with high confidence
Cliffs, caves, tunnels or disused mineshafts	Lidar (i.e., a DTM) may be able to highlight these features under the tree canopy
Steep slopes	Slope can be calculated accurately from a lidar DTM. At larger scales, there are existing DTM/DEMs available (e.g., NSW government DEM or global products such as the Shuttle Radar Topography Mission (SRTM)
Aboriginal object or place	If object/place is known and accurately mapped, high-resolution lidar or imagery could be used to look at exclusion zones
Heritage items	See above
Mass movement / erosion	Pre- and post-harvest lidar derived DTMs could be compared to assess soil movements. There are also spectral indices such as the Barren Soil Index (BSI) that have been proposed to monitor larger landslides from satellite imagery.
Tree features	
Hollow bearing tree	Unable to use remote sensing to directly map with confidence at this point in time. Success has been achieved using modelling approaches to model 'probability' of tree hollows across a region.
Dead standing tree	Could potentially be automated with high-resolution lidar (see Section 7. Terrestrial lidar instruments) or high-resolution RGB and advanced machine learning.
Feed tree	Would need expert interpretation of high-resolution imagery to accurately determine tree species
Recruitment tree	Needs field assessment, open to some interpretation
Roost, nest or food resource trees	Needs expert field assessment

Site scale forest structure

Structural measures such as complexity (Krisanski *et al.* 2021), landscape heterogeneity (Liccari *et al.* 2022) and canopy/understory connectivity (Keeley *et al*. 2021) are considered to be important indicators of both forest health and the protection of native fauna species. At a site scale, ALS (as discussed in Section 7) is the most useful remote sensing technology for determining forest structure. Canopy connectivity and gaps can be defined using CHMs (Silva *et al.* 2019) or by splitting the point-clouds into layers and/or using voxelization techniques and plant area density profiles (see Section 7). Complexity (or understory) richness can be inferred from lidar metrics calculated from the vertical height profile (e.g., standard deviation) or by using advanced techniques to determine canopy strata (Wilkes *et al.* 2016). Note that forests full of weeds such as lantana may present as being structurally more diverse, so these complexity metrics cannot be considered a complete solution. In addition, the importance of spatial scale with these measures cannot be over-stated: different scales will represent the landscape differently.

Tree species mapping

NSW DPE continues to update its State Vegetation Type Mapping (SVTM). This program provides current maps of the three levels of vegetation classification hierarchy: Plant Community Type, Vegetation Class and Vegetation Formation[8].

Another approach to mapping the composition of forests is focused on classifying the composition of forest cover (i.e., the assemblages of mature trees) into principal forest types (Baur 1965). Based on the Baur's description of forest types, aerial photo interpretation (API) has been used to map these tree assemblages across some NSW forests. A subsequent process was then used to classify the forest types into groupings called Yield Association Groups (YAGs). YAGs are defined by the tree canopy species mix, elevation above sea level, site wetness and canopy height of mature trees (A. Kathuria, Biometrician, NSW DPI, *pers comm*.). A report on the YAG classification across all forest tenures for the NSW north coast was made available on-line by NSW DPI in 2018[9]. This approach is currently being replicated for the NSW south coast.

A key parameter for koala habitat information is the presence and density of their preferred tree species. This has been addressed, in part, through the predictive modelling of koala tree species. Tree species records for this modelling were extracted from the NSW BioNet Vegetation Information System[10].

Traditionally, the mapping of forest composition has been undertaken at the stand scale using stereo aerial photography and manual API. Skilled API operators can accurately map forest types, especially when presented with unclear boundaries. Unfortunately, at present in NSW, both stereo aerial photography and ALS data is not supported by a systematic acquisition program. Recently, however, the application of satellite data for mapping tree species over regional forests has been successfully demonstrated overseas. Melnky *et al.* (2023), for example, successfully developed classifiers of forest species using Sentinel-2 images in north-western Ukraine. Ferreira (2019) used high resolution imagery acquired by WorldView-3 and applied an individual tree crown-based approach to large, distinct tree crowns in a tropical forest in south-eastern Brazil. In Germany, Shi, Wang, *et al*. (2018) used lidar metrics for mapping tree species and Shi, Skidmore, *et al.* (2018) explored the added benefits of including hyperspectral data. However, in these studies the forest canopies tend to be taxonomically diverse with relatively discrete tree crowns. Closed-canopy, coastal sclerophyll forests in eastern NSW are dominated by eucalypt species, with the species within subgenus groupings being taxonomically and structurally very similar. Under these circumstances the mapping of eucalypt tree species is possible but requires very high spectral and spatial resolution data; for example, narrow band, hyperspectral imagery and ALS. Both of these options are often considered too expensive for operational deployment (e.g., Lucas *et al*. 2008, Youngentob *et al.* 2011).

[8] https://www.environment.nsw.gov.au/topics/animals-and-plants/biodiversity/nsw-bionet/state-vegetation-type-map

[9] https://www.dpi.nsw.gov.au/__data/assets/pdf_file/0004/849199/YAG-classification-guide-and-mapping-accuracy-report.pdf

[10] https://www.environment.nsw.gov.au/topics/animals-and-plants/biodiversity/nsw-bionet

Fauna monitoring

In Australia, two remote sensing approaches have been developed for surveying fauna, principally as result of the interest in koalas. These include (1) the use of RPAS-derived thermal imagery and (2) ground-based acoustic sensors. Corcoran *et al*. (2019) have developed an automated approach that processes thermal imagery for the object detection of koalas in eucalypt canopies using deep learning algorithms trained on annotated images of known koala and non-koala heat signatures. The application of RPAS thermal imagery was supported by Howell *et al.* (2022) who demonstrated that this approach was cost-effective compared to on-ground surveys using spotlighting. One of the issues of this approach, however, relates to current Civil Aviation Safety Authority visual 'line-of-sight' (VLOS) requirements for operating RPAS which can be challenging in forests. Recently, however, this requirement has been modified with CASA now able to authorise Beyond VLOS approvals for specific applications.

Passive acoustic field instruments can remotely record the presence of vocalising species, including the nocturnal bellowing of male koalas during their mating season in Spring (Law *et al*. 2022). Importantly the recordings can be scanned by acoustic software and analysed automatically through application of species-specific recognizers. False positives can be checked manually through visualizing the audio spectrograms and listening to recordings. Law *et al*. (2022) deployed acoustic recorders to record male koalas in sites stratified according to timber harvesting history. They concluded that their approach was a highly effective method for assessing koala occupancy. The authors did not find that timber harvesting reduced koala density in NSW north-coast forests. Currently both NSW DPE and CSIRO have koala monitoring programs that involve comparing both these two surveying methodologies.

9. Water quality and soil health

Section summary

Current soil and water monitoring in NSW forests is limited. Accurate monitoring generally requires on-ground sampling. Currently, soil databases such as the NSW Soil and Land Information (SALIS) hold very limited soil health data from native forests. A major factor contributing to loss of soil health and stability is erosion. From a remote sensing perspective, particularly with respect to monitoring the localised impacts of sediment and protecting drainage features, accurate Digital Terrain Models (DTMs) derived from lidar perhaps offer the most use. Stream networks and drainage features can be readily extracted from DTMs, which can be buffered to define exclusion zones. Multi-date lidar can highlight areas of change, including possible soil erosion, along with whether exclusion zones around drainage features are maintained. DTMs could also be used to map and monitor forestry related infrastructure (in particular, roads and tracks).

Remote sensing technologies discussed in this section include:

Technology	Scale	Acquisition cost	Expertise needed
Lidar derived DTMs	Property / regional	High (for new acquisitions)	High
High-res imagery	Property	High	Medium
Single-photon / geiger-mode lidar	Property / regional	High	Very high

Accurate monitoring of soil and water health requires field samples, which can then be used in conjunction with spatial information on climate, topography etc. to create modelled wall-to-wall products, such as those in the Australian Soil and Landscape Grid[11]. Note that these large area products are largely just correlations between sparse soil samples and a range of covariates including topography, climate, vegetation etc. Even at a local scale, soil components can vary greatly. At present, available soil data in NSW forests is extremely limited (Moyce *et al.* 2021).

Two comprehensive reviews on monitoring water quality and quantity have been published by the NSW NRC (Alluvium 2021; Guo *et al.* 2022) and are available on their publication website[12]. Notwithstanding the two current water monitoring programs (i.e., the WaterNSW continuous water monitoring network and the program managed by FCNSW), both reports acknowledge the existence of gaps in spatial and temporal water monitoring data across native forests in NSW. The methods applied for obtaining data for the priority water quality and quantity indicators require on-ground sampling. Automatic digital sensors and logging devices can also be utilised, but subsequent laboratory analysis is also often required and hence these water monitoring programs are expensive to maintain. Similarly, the monitoring of soil health requires the collection and analysis of soil profile samples. Soil survey methodologies are time consuming, require expertise and are hence expensive. These data can then be used in conjunction with spatial information such as climate grids and gamma-ray radiometric data (Cook *et al.* 1996) to generate soil condition maps. The resultant maps tend to at a relatively low spatial resolution, (e.g., 90 m grid size).

[11] https://esoil.io/TERNLandscapes/Public/Pages/SLGA/
[12] https://www.nrc.nsw.gov.au/publications

Remote sensing technology can also be used to detect and monitor soil erosion processes at both local and regional scales (Casagli *et al.* 2023). There are a range of spectral indices that have been proposed for detecting landslides (e.g., the Barren Soil Index (BSI) using Sentinel-2 imagery[13]). The use of very high-resolution optical satellite imagery in combination with LiDAR data has also been successfully applied to monitor mass soil movement. Recently, hillside erosion rates for the RFA regions in NSW were modelled using satellite spectral and LiDAR derived products (Moyce *et al.* 2021). Sediment delivery hazard mapping has also been achieved within a GIS workflow incorporating ALS derived products, local climatic variables and field assessments (Alluvium 2022). At a local scale, if not covered by forest canopy, overlap airborne imagery can be used to identify local erosion processes such as channel initiation points and fans (Nyman 2023).

In addition, high-resolution aerial or satellite imagery can potentially be used to monitor whether exclusion zones are maintained, particularly when these zones are already defined. Exclusion zones around waterways are considered important for maintaining water quality, by preventing erosion.

Digital Terrain Models (DTMs)

Lidar sensor technology is continuously advancing with increasing point density and accuracy (discussed earlier in Section 7), resulting in improved resolution and spatial accuracies to produce fine-scale Digital Terrain Models (DTMs; also called Digital Elevation Models (DEMs)). These three-dimensional spatial models of the Earth's surface are fundamental for deriving topographic parameters and for the modelling used in terrain hydrology studies, including mapping stream morphology and stream banks, as well as detailed road mapping. Protection of drainage features is a key code condition – high resolution DTMs are the best technology for mapping these. In the absence of high-resolution products, lower resolution elevation products such as the global Shuttle Radar Topography Mission (SRTM) product can be used (30 m). However, NSW has comprehensive elevation data available state-wide at 5 m resolution which would be more suitable where high-resolution lidar is not available[14].

DTMs can be used in soil erosion modelling, particularly if there are multiple time-steps available. High resolution DTMs can also provide information on forestry infrastructure (in particular, roads and tracks), the maintenance of which is important for reducing flow-on impacts (e.g., erosion entering waterways). DTMs can also be used for watershed analysis (i.e., determining the flows of water across an area). Forests tend to act as catchment areas for water supply, so there is often an economic incentive to understand water flows and maintain water quality. Disturbance events such as wildfire are often seen as detrimental to water supply due to flow on effects.

At local sites, another source of high-density lidar data can be obtained from MLS systems and RPAS platforms (discussed earlier in Section 7), including under-canopy RPAS scanning systems (e.g., Hyyppa *et al.* 2020 a & b). These very high-resolution datasets are suitable for monitoring minor changes in channels, drill networks and stream crossings, and can be used to evaluate localised impacts of sediment and runoff delivery. At a landscape scale, the recent advent of airborne Geiger-mode and Single-photon lidar systems may provide a more cost-effective solution to repeat ALS surveys and could be applied to detect changes in topographical features. Single-photon and Geiger-mode lidar provides denser point clouds while flying faster and operating at higher altitudes compared to traditional linear ALS sensors. A study by Yu *et al.* (2020) comparing single-photon and multi-photon (conventional) ALS captured over a boreal forest in southern Finland concluded that both systems produced ground surface (e.g., DEMs) and forest canopy characteristics to a similar accuracy. Currently the NSW Rural Fire service is evaluating the purchase of an airborne Geiger mode lidar system.

[13] https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/landslide_detection_rapid_mapping/
[14] https://portal.spatial.nsw.gov.au/portal/apps/sites/#/homepage

10. Conclusions and findings

This report has assessed a range of remote sensing technologies and products in their ability to monitor forests in the context of the current PNF codes of practice and the related PNF MER framework. The main findings are as follows:

- Many of the code conditions can only be partially monitored using remote sensing only approaches.
- Remote sensing has a greater role in terms of bioregional scale monitoring, which is an appropriate scale for satellites such as Landsat and Sentinel to be used.
- Site scale monitoring needs airborne lidar and high-resolution imagery at a minimum. Ideally, coincident terrestrial lidar and other field measurements would complement this.
- The PNF MER should make use of existing products and programs where possible, noting that these may not be suitable for site scale monitoring.
- Any assessment of remote sensing costs needs to consider costs (and benefits) at all levels of the value chain, including processing and expertise costs.

The next report in this series is to focus on potential remote sensing indicators that can assist with PNF monitoring.

Appendix A – Details of existing products and programs

Satellite Forest Cover

Forests in Australia are defined as an area that is dominated by trees, usually with a single stem and a mature stand height exceeding 2 metres and with existing or potential crown cover of overstorey strata of about equal to or greater than 20 percent. Hence, forest crown cover is a popular structural descriptor for reporting on the status of forests (e.g., Australia's State of Forests report). The reported metrics are area estimates of forest cover, which is often used as a proxy for forest extent. Remote sensing technologies are essential for achieving these estimates.

Forest extent is commonly captured as either Crown Projective Cover (CPC, or crown/canopy cover, CC) or Foliage Projective Cover (FPC). CPC is the proportion of ground area covered by the vertical projection of tree crowns and treats the entire tree crown as an opaque projection. FPC relates to the proportion of ground area covered by the vertical projection of foliage of tree crowns and is a measure of foliar density. Scarth *et al.* (2008) developed an empirical relationship between FPC and CC. Typically, a CPC of 20% is comparable with an FPC of 11 to 12%, dependent on region and forest type. In NSW, overstorey FPC was initially predicted using Landsat satellite imagery (30m), followed by a series of higher spatial resolution SPOT 5 datasets (5m) and now has been adapted to use Sentinel-2 imagery (10m). The FPC metric is the foundational estimate used in both the Queensland and NSW Statewide Landcover and Tree Study (SLATS) programs.

The National Forest and Sparse Woody Vegetation Data (NFSW)[15] was developed for the National Carbon Accounting System (NCAS) and is now released annually by the Australian Government Dept. of Climate Change, Energy, the Environment and Water (DCCEEW). The NFSW has been used in previous NRC and PNF research to define forest extent for NSW (e.g., Spatial Vision 2022a & b; M. Alaibakhsh, NSW DPI Forest Science, *pers. comm*.). It is derived from a time series of Landsat imagery (1988–2021) and maps three classes of vegetation at a spatial scale of ~25m: forest cover (> 20%), sparse woody vegetation (5–19% cover) and non-woody vegetation, with a minimum mappable unit of 0.2 ha. The three-class classification includes temporal smoothing using 'conditional probability networks'. Improvements applied to the analytical methodologies, however, have complicated the interpretation of trends in forest cover extent and other higher-resolution datasets are required for validation (Mutendeudzi *et al.* 2013, Soto-Berelov *et al.* 2018).

While the NFSW forest canopy cover product performs well at national/state levels, it is less reliable when applied to local areas. Nevertheless, the nationally consistent product offers a good starting point for many regional applications. Accuracy can be improved through a series of land use and vegetation type exclusion masking. This is achieved by manual editing and intersecting with other spatial datasets such as the NSW State Vegetation Type Map (SVTM), Environmental Planning Instrument EPI land zoning, Land use 2013 and horticultural layers (e.g., avocado, mango and macadamia crops).

This masking approach was also adopted by Spatial Vision (2022a & b) where they initially filtered the NFSW forest cover product using land use layers and the SVTM to identify only true forests. The SVTM (NSW DPE, 2020) is based on a 3-tier classification comprising 'formation', 'class' and 'type'. The 'class' level was used to differentiate forest and non-forest vegetation communities. In addition, Spatial Vision also applied a further 'temporal sequence refinement' methodology using fuzzy logic and probability (Spatial Vision 2022a). They then compared their final 2020/2021 product with a filtered State-wide Landcover and Tree Survey (SLATS) layer. They reported that the two layers were 93.5% correlated.

Numerous studies have demonstrated that satellite optical sensors and airborne cameras with higher spatial resolution than Landsat or Sentinel-2 can accurately map forest canopy cover. Planet,

[15] available at data.gov.au

for example, offers SkySat satellite imagery with very high spatial resolution (0.5 m) or PlanetScope (~3 m), which could potentially replace traditional aircraft camera imagery for local forest extent mapping. However, while the imagery acquired by the small satellite constellations (e.g., PlanetScope) tend to be relatively cheap, they also have poorer geo-referencing performance than the more expensive satellites (e.g., Pleiades). Nevertheless, these higher resolution products can be used as reference data to validate some forest parameters, including forest cover, for the large-area canopy products where sample on-ground assessment is not a viable option (Corona *et al.* 2015).

Lidar Forest Cover

Light Detection and Ranging (lidar) sensors are active systems that can be used to generate high resolution, 3-dimensional structural information including canopy cover estimations. The Global Ecosystem Dynamics Investigation (GEDI) is a spaceborne lidar system on the International Space Station that has been providing high laser-ranging observations of forest 3D forest structure since 2019 at country-wide scales, all-be-it as orbital tracking footprints. GEDI data from these footprints have now been successfully integrated with wall-to-wall optical satellite imagery, such as Landsat, to improve the estimates of forest cover and height (Zhu *et al.* 2023).

At a local/regional scale there are several well-established methodologies for applying airborne laser scanning (ALS) data to derive canopy cover using lidar pulse return classifications (e.g., Karma *et al*. 2020, Taneja *et al.* 2023) and Canopy Height Models (CHMs) (e.g., Ma 2017, Hislop *et al*. 2023b). Karma *et al*. (2020) compared several canopy metrics including canopy cover, derived from multi-temporal ALS, to examine pre- and post-fire stand structure in native forests in the Central Highlands of Victoria. In a recent study, Hislop *et al.* (2023b) examined crown level changes in native eucalypt canopy over a one-year period through a methodology that used the differences in CHMs derived from two datasets of spatially coincident lidar transects.

The acquisition costs associated with ALS data are relatively expensive compared to wall-to-wall satellite imagery. Costs can be reduced if aerial samples are collected in a robust design-based sampling framework to enable estimates of the population (e.g., estimates of canopy cover over the regional area of interest). For example, Matasci *et al.* (2018) used ALS sample 'plots' and multitemporal Landsat composites to model forest cover, height and biomass for the entire boral area of Canada. Luther *et al.* (2019) also applied a hierarchical sampling approach, using ground plots along with lidar covering a sub-area and spatially comprehensive satellite and environmental data, to improve the accuracy of several forest attributes, including forest cover over a broad area.

State-wide Landcover and Tree Study (SLATS)

The main aim of the NSW SLATS program is to map the location and extent of woody vegetation loss each year; it was developed as a vegetation monitoring compliance tool[16]. The program, which began in 2006, has vegetation loss products covering every two years from 1988–2006 and annually from 2006 onwards. Updated woody vegetation extent maps and the SLATS mapping are combined to differentiate areas of woody vegetation cleared by agriculture, infrastructure, forestry or major natural disturbances (e.g., fire).

Initially NSW fractional cover products and resultant woody vegetation loss maps were derived using Landsat imagery, then during the period 2008 to 2015, higher resolution SPOT-5 imagery (5 m) was used, with results for 2015 and 2016 based on analysis of imagery from SPOT-5, SPOT-6 and Sentinel-2 satellite sensors. More recently the SLATS methodology has been updated to use only Sentinel-2 imagery (10 m). The application of the change detection algorithm results in the production of temporal woody vegetation extent maps showing the location, extent and foliage

[16] https://www.environment.nsw.gov.au/topics/animals-and-plants/native-vegetation/landcover-science/statewide-landcover-tree-study.

cover of woody vegetation across all tenures of NSW. Any detection of change is then validated manually by experts before the maps and results are collated for state-wide reporting.

At present, the process identifies loss in the forestry landcover class attributed to timber harvesting activities. However, current research is aimed at enabling the SLATS program to also monitor for increases in forest cover including regrowth, using Sentinel-2 imagery (T. Danaher, Science, Economics & Insights, NSW DPE, *pers. comm.).* The SLATS FPC product is being improved by, in part, using terrestrial Lidar for better calibration and validation of the Sentinel-2 FPC product. A multi-temporal method combining the lidar calibrated Sentinel-2 FPC layers will assist in reducing the omission/commission errors associated with single date FPC images.

To date, the SLATS woody extent product (presence/absence map showing areas having FPC $\geq$11 to 12%) has fewer time-points available for monitoring forest extent than the NFWS product, as well as being derived from different satellite sensors (i.e., Landsat, SPOT and Sentinel-2). However, since 2017, the SLATS program has been using only Sentinel 2 imagery, which provides radiometrically and geometrically consistent data. Current and historical SLATS data is available through the Sharing and Enabling Environmental Data (SEED) portal.

Because the focus of SLATS is clearing, it is not suitable in its current form to pick up selective harvesting, particularly the low intensity types practiced in private forests. However, the program is a good example of a framework (e.g., image acquisition, high performance computing, on-going funding) which could be adapted for broader forest monitoring purposes.

Biodiversity Indicator Program (BIP)

In response to the NSW Biodiversity Conservation Act 2016, DPE has established the Biodiversity Indicator Program (BIP) to assess the status of biodiversity in NSW[17]. The BIP required development of a suite of indicators to measure different aspects of biodiversity and ecological integrity. These indicators have been defined within a hierarchical class structure covering multiple elements of biodiversity and ecological integrity; the methods are provided in a technical report[18]. The first Biodiversity Outlook Report was released in 2020[19]. The BIP habitat condition theme provides indicators which measure the capacity to maintain natural functions and processes that support terrestrial species and ecosystems. To date, only two of these indicators, Ecological Condition and Ecological Carrying Capacity, have received attention for specific adaption to native forests. This was undertaken through the NRC FMIP Forest Extent, Condition & Health project.

Ecological condition (BIP indicator 3.1a) measures the generalised quality of terrestrial habitat, estimating its intactness and naturalness at each location in NSW. Ecological carrying capacity (BIP indicator 3.1c) provides two related perspectives on habitat connectivity: the important role each location plays in maintaining the integrity of its broader habitat network (its link value); and how well connected the habitat is at any location in relation to its surrounding habitat (its spatial context). Both the loss of ecological condition and the fragmentation of native vegetation contribute to the amount of ecological carrying capacity remaining in each reporting unit (e.g., NSW Biodiversity Outlook Report – First assessment, Page 41). Because vegetation fragmentation directly affects ecological carrying capacity, researchers working on the NSW BIP aim to progress forest specific landscape fragmentation modelling and a forest specific indicator for connectivity. Regarding metrics associated with fragmentation, Drielsma *et al.* (2007a & b) found that there was no single measure from the collection of FRAGSTATS metrics (McGarigal *et al.* 2012) that encapsulated the closely related issues around landscape pattern of habitat quality, patch size, inter-

[17] https://www.environment.nsw.gov.au/topics/animals-and-plants/biodiversity/biodiversity-indicator-program.
[18] Measuring Biodiversity and Ecological Integrity in NSW: Method for the Biodiversity Indicator Program https://www.environment.nsw.gov.au/-/media/OEH/Corporate-Site/Documents/Animals-and-plants/Biodiversity/measuring-biodiversity-and-ecological-integrity-in-nsw-method-190132.pdf
[19] https://www.environment.nsw.gov.au/research-and-publications/publications-search/biodiversity-outlook-report

patch distances and patch shape. Moreover, they found that the patch concept was inappropriate to many Australian landscapes, which are better characterised as heterogeneous or variegated.

The provision of trends in vegetation condition and landscape fragmentation will rely on new forest extent and health mapping, vegetation type classifications, and both remotely sensed and field-based monitoring data. Ground-based data (e.g., parameters derived using the NSW Biodiversity Assessment Method (DPIE 2020)) are used to train, calibrate and validate new forest condition models. It should be noted that the framework for baseline reporting of forest condition and fragmentation was developed using spatial raster datasets at 90 m resolution, however, the intent is to downscale the spatial resolution, with particular focus on Sentinel-2 imagery.

A reporting framework has been developed and applied to existing measures of ecological condition and ecological carrying capacity developed for presenting summary results in the Biodiversity Outlook Reports. One outcome of the NRC FMIP Forest Extent, Condition and Health project was an adaption of this Reporting Framework based on forest extent, designed to report on forest condition and landscape fragmentation using a selection of reporting units considered relevant to forest management in eastern NSW across a range of different management scales (J. Love, Science, Economics and Insights, NSW DPE, *pers. comm*.). At present, the forest extent-version of the framework is structured to report on tenure aggregated to State forests, national parks and other (private and crown land), as well as the NSW Regional Forest Agreement (RFA) areas, however, it could be adapted to also include the PNF code regions (J. Love, Science, Economics and Insights, NSW DPE, *pers. comm*.). In addition, this framework is proposed to underpin the BIP dashboard reporting process.

Existing Datasets

The appendices provided with DPE's 2022 Native vegetation regulatory map method statement[20] provides a description of the foundational spatial datasets used in many of DPE's programs, including Landsat, SPOT-5 and Sentinel-2 derived spatial products such as foliage projective cover. It also identifies satellite imagery from higher spatial resolution sensors managed by Planet (i.e., SkySat and PlanetScope). DPE now manages a NSW wide subscription for Planet imagery. This imagery is available on an as needs basis (e.g., monitoring natural disasters and for validation and accuracy assessments). However, due to the less consistent temporal and spatial concurrence of many of these high-resolution spatial datasets it is likely that the open-source Sentinel-2 imagery will continue to provide the large-area, temporal baseline imagery for many of the DPE spatial products.

Very high resolution imagery is provided through the NSW Dept. of Customer Services aerial imagery program, including digital photography and airborne laser scanning data and is accessible from their Spatial Collaboration Portal[21]. Their capture programs occur within a spatial/temporal panel system but can also respond quickly to natural disasters. The Airborne Laser Scanning (ALS) acquisition program now provides accurate elevation products across NSW. Lidar data is continuing to be captured at various densities over specific project extents, such as urban development for flood risk assessment.

Another source of NSW government data is available from the NSW Data Analytics Centre, which manages and maintains Data.NSW[22]. Spatial data for NSW is also available through the Sharing and Enabling Environmental Data (SEED) portal[23]. SEED represents a collaborative effort between government agencies to provide environmental data in a single source. For example, the SLATS woody change layers can be obtained through the SEED portal.

[20] https://www.environment.nsw.gov.au/research-and-publications/publications-search/native-vegetation-regulatory-map-method-statement
[21] https://portal.spatial.nsw.gov.au/portal/apps/sites/#/homepage
[22] https://data.nsw.gov.au/nsw-data-analytics-centre
[23] https://www.seed.nsw.gov.au/

NSW DPE have also developed a high-performance computing facility (Science Data Compute, SDC) which is used for data processing and storage of remote sensed datasets and derived products. The SDC Image and Data Library provides a source of truth for a range of satellite and aerial imagery products.

At a national level, there are several sources of spatial datasets that relate to forests, which can be accessed through the Terrestrial Ecosystem Research Network (TERN) data discovery portal[24]. This includes a national map of vegetation height and cover derived from ALOS-1 PALSAR, Landsat and ICEsat/GLAS (Scarth *et al.* 2019). Finally, Geoscience Australia's Digital Earth Australia (DEA)[25] Open Data Cube is a collaboration with the National Computational Infrastructure (NCI) and provides access to Landsat and Sentinel-2 'Analysis Ready Data' archived imagery. DEA also provides open access to a series of vegetation spatial products, including Landsat-derived products such as Fractional Cover.

[24] https://portal.tern.org.au/

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