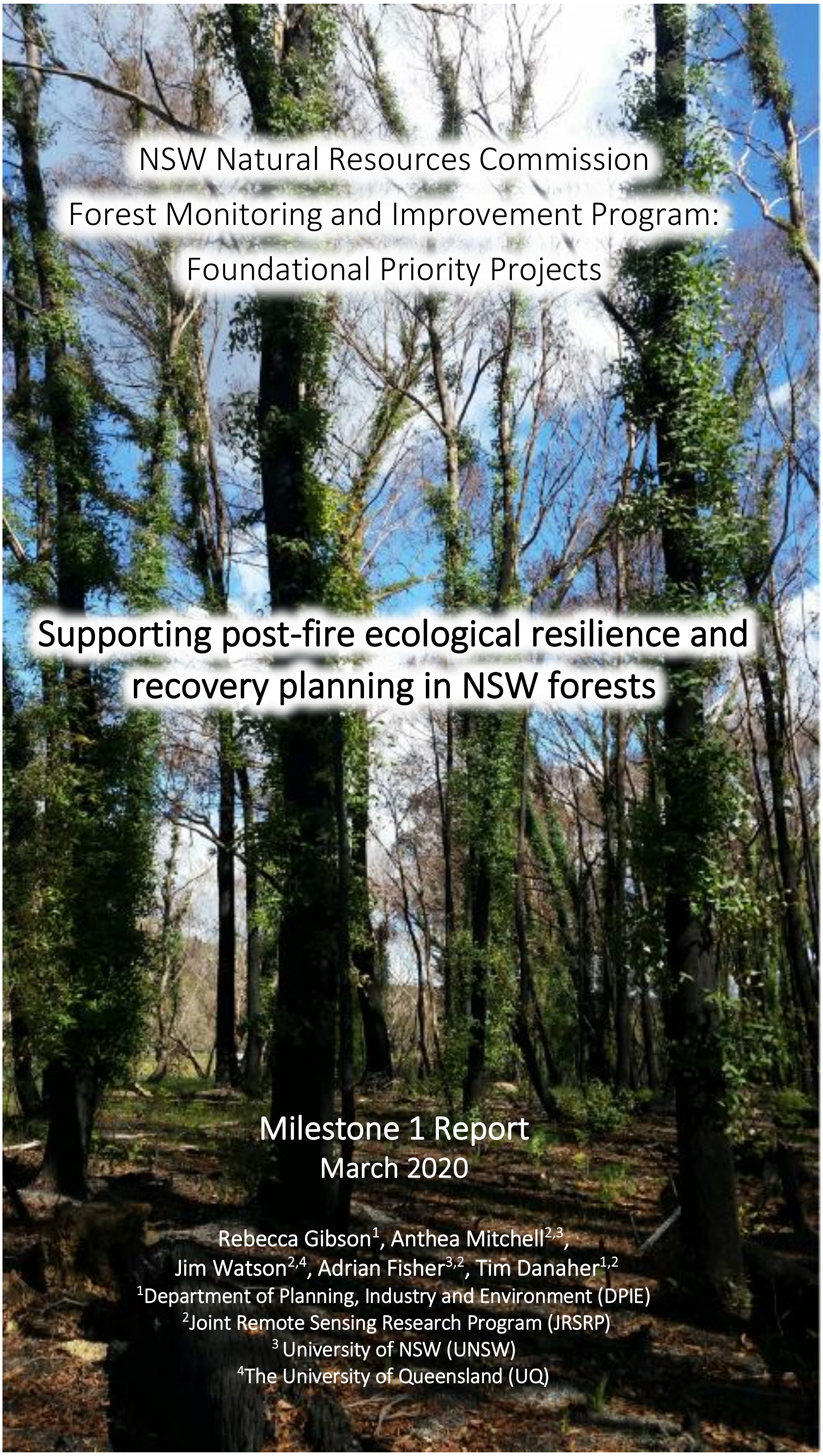

NSW Natural Resources Commission
Forest Monitoring and Improvement Program:
Foundational Priority Projects

Supporting post-fire ecological resilience and recovery planning in NSW forests

Milestone 1 Report
March 2020

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Citation:

Gibson, R.K, Mitchell, A., Watson, Fisher, A., J., Danaher, T. (2020) Supporting post-fire ecological resilience and recovery planning in NSW forests, Milestone 1 Progress Report, Natural Resources Commission Forest Monitoring and Improvements Program, https://www.nrc.nsw.gov.au/fmip

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1. Project aims

The project 'Supporting post-fire ecological resilience and recovery planning in NSW forests' is funded by the NSW Natural Resources Commission Forest Monitoring and Improvement Program's[1] Foundational Priority Projects scheme. The focus of the project is to develop new remote sensing tools for forest managers to undertake risk assessments and subsequently plan and report on post-fire ecological recovery. The project aims to deliver a remote sensing method that measures the proportion of vegetative regrowth since a forest fire event relative to the unburnt or pre-fire state, at regular post-fire intervals. It will deliver this method by undertaking a literature review of existing remote sensing post-fire recovery techniques, model development and testing, and validation fieldwork. The post-fire recovery techniques have the potential to be integrated with the NSW fire extent and severity mapping project, currently in beta testing phase prior to full operationalisation with project partners, the NSW Rural Fire Service. This report presents the project initiation document with literature review (Appendix 1) and research plan, including fieldwork plan.

2. Literature review

Ecological resilience is the capacity of a system to return to its initial state after a perturbation (Holling, 1973, Leps et al., 1982). Post-fire recovery is a successional process towards the pre-fire community structure and function, or to an alternative stable state (Turner et al., 2016). Measuring and monitoring fire severity (Keeley, 2009) and subsequent post-fire vegetation regrowth are essential for understanding the effects of wildfires across the landscape and the ecological resilience of forests. The relationship between fire severity and post-fire recovery rates has long been a focus for ecology and global carbon cycle studies (Turner and Romme, 1999, Liu, 2016) and is becoming a more pressing issue, as the frequency and severity of fire disturbance are expected to continue to increasing due to warmer and drier global climate conditions (Meng et al., 2018, Abatzoglou and Williams, 2016). In the last 10-15 years, remote sensing approaches have been increasingly explored as a tool to examine and understand post-fire recovery, following advances in satellite and airborne sensors, data accessibility, computing storage and processing technology. The literature review of traditional approaches, current best-practice and emerging opportunities in remote sensing of post-fire recovery is provided in Appendix 1.

As discussed in the literature review, a key limitation of remote sensing approaches to monitoring post-fire recovery is the difficulty in separating canopy and understory responses. Mixed signals, noise and saturation limits are common problems for optical reflectance and radar techniques. As such, we propose exploring innovative indices and timeseries statistics, based largely on sub-pixel unmixing models that are calibrated to high quality field data. While many factors are known to influence post-fire recovery rates, such as fire severity, vegetation type, climate and topography, an observational monitoring approach will need to be appropriate for application at the landscape scale across diverse conditions and vegetation types. Calibration of timeseries approaches against known unburnt local sites is likely to be useful as phenology offsets to reduce noise in response signals, without requiring thresholds to be set. Independent quantitative and qualitative field validation methods, sampling a range of vegetation types across fire severity classes (including unburnt reference sites) will provide robust assessment of the performance of candidate approaches.

[1] https://www.nrc.nsw.gov.au/forest-monitoring

Woody vegetation change monitoring is a core part of the remote sensing work within DPIE. While not necessarily specific or limited to fire related change, we have a breadth of experience and existing products and techniques that are well tested. Many products and current research projects are likely to be complimentary, or directly applicable, to post-fire recovery monitoring.

3. Complimentary Projects

The Joint Remote Sensing Research Program[2] (JRSRP) is a collaborative venture between Government and University partners, including the Remote Sensing Centre in the Department of Environment and Science (QLD Government), the Remote Sensing Research Centre in the School of Earth and Environmental Sciences at the University of Queensland, Remote Sensing & Regulatory Mapping at DPIE (NSW Government) and the School of Biological, Earth & Environmental Sciences at the University of New South Wales. There are existing JRSRP projects that have or are developing methods that can be evaluated for application in this post-fire recovery project.

Three projects are aimed at developing methods to map the area of increasing woody vegetation to complement the annual reporting of vegetation clearing provided by SLATS (State-wide Land and Tree Study[3]). One is based on optical imagery (SPOT 5) and uses a vegetation clearing index in reverse. Another project has acquired state-wide ALOS 2 radar imagery for 2009 and 2016 and maps showing change in vegetation basal area are being developed. A third project is using Landsat fractional cover imagery and time series techniques to map long term change in woody vegetation.

Techniques have also been developed to map areas of undisturbed vegetation for the Native Vegetation Regulatory map produced by DPIE Science Division, using time series analysis of Landsat fractional cover imagery. An index of disturbance was developed based on the seasonal variation in fractional cover compared to reference undisturbed sites.

4. Research plan

Supporting post-fire ecological resilience and recovery planning in NSW forests is a research and development project aimed at developing remote sensing tools to support forest managers in post-fire recovery management and planning. The specific toolset delivered will depend on outcomes of the research. The proposed workflow is separated into several stages of activity, some of which can be undertaken concurrently. We have identified several primary tasks:

1. Site selection and data acquisition

2. Map burnt area extent

3. Investigate methods of tracking post-fire vegetation recovery

4. Investigate methods of assessing post-fire forest structural change

5. Risk/vulnerability modelling

6. Field validation

7. Reporting and delivery

Task details are given in the following sections.

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[2] https://www.jrsrp.org.au/

[3] https://www.environment.nsw.gov.au/research/AncillaryVegetationProductsDataInventory.htm

Task 1: Site selection and remote sensing data acquisition

Site selection decisions are based on the availability of overlapping pre- and post-fire radar data (Sentinel 1, ALOS2 PALSAR), optical reflectance (Sentinel 2, Landsat) and LiDAR data. Sentinel 1 is available state-wide. Although ALOS2 is not guaranteed over some sites, our request is currently being processed. The acquisition of data will be balanced with decisions on time since last fire, obtaining a diversity of veg types (grassland, heath, forest) for algorithm testing, as well as site accessibility pending park closures, travel time and costs. Final site selection TBC as these issues are resolved.

The following selection of candidate case study fires have been identified as suitable locations for field data collection but may be subject to change with access or other restrictions. These candidates are not the only fires in NSW from the 2019/20 wildfire season with these configurations of available data sets.

Given the scale and severity of the current 2019-2020 wildfire season, many national parks remain closed across NSW. Site access may be difficult or unsafe in some cases. Furthermore, the acquisition of remote sensing data which is currently proposed but not confirmed (e.g. LiDAR and ALOS-2 PALSAR-2), may require case study sites to be revised to take full advantage of those opportunities. Approximately 5 case study fires will be selected from the proposed field sites (Figure 1, Table 1). At least 3 site revisits will be conducted within the timeframe of this project, at 6 monthly intervals. Therefore, the first field site visit for each case study site will occur by June 2020.

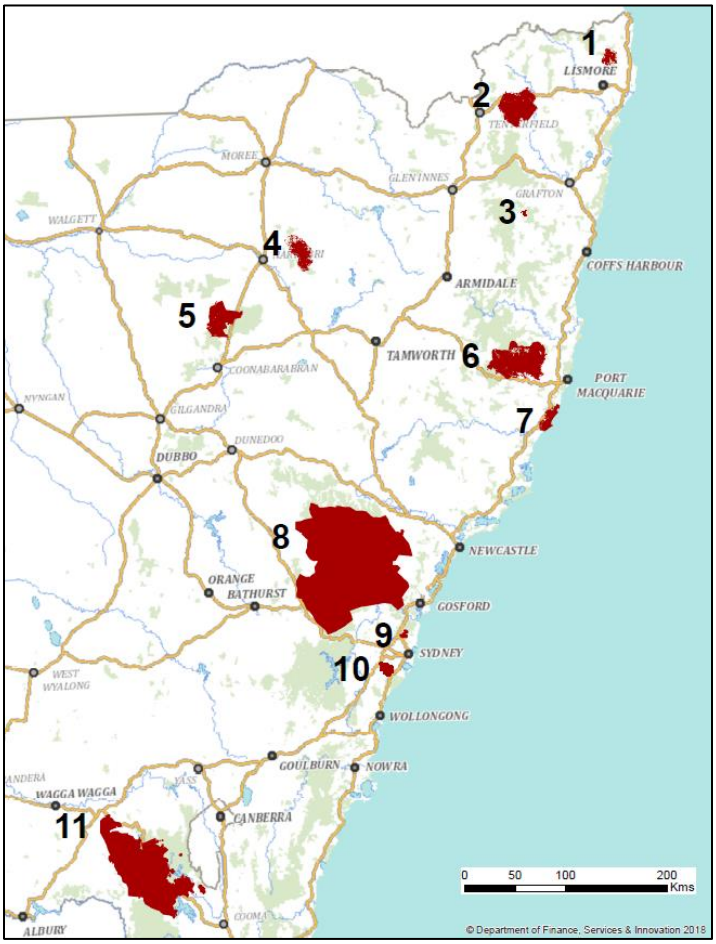

Figure 1 The location of candidate case study fires in NSW: 1. Mt Nardi, 2. Long Gully, Drake 3.Frenchmans West LMZ, 4. Kaputar, 5. Dipper Rd, 6. Stockyard Flat, 7. Bills Crossing, Crowdy, 8. Gospers Mountain, 9. North Turramurra East HR, 10. Moorebank Rd, Holsworthy, 11. Dunns Rd.

Table 1 Candidate case study fires for field data collection

Fire No.	ICON incident	Fire Start Date	Fire End Date	Time Since Fire	Vegetation Formations*	Existing data	Site notes
1	MT Nardi Np, continuation 2, Lismore #19110854943	08/11/19	17/11/2019	4 months	Rainforest, dry sclerophyll and riparian forests	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016 (post-fire likely but tbc), post-fire FESM field assessments.	Good site access and local ranger support. Low cost for travel and accommodation, as site located <1hr for 3 project staff.
2	Long Gully Rd, Drake #19092249539	05/09/2019	27/10/2019	4.5 months	Dry and wet sclerophyll forests, rainforests, tall heath hanging swamps	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016, post-fire FESM severity field assessments. High resolution post-fire ADS photography.	Good site access and local ranger support. Disturbance history includes logging (state forests).
3	Frenchmans West LMZ #18061702948	19/06/2018	26/06/2018	1 year + 9 months	Dry sclerophyll forests	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016 (post-fire likely but tbc), Pre- and post-fire fractional cover field sites.	Remote but good accommodation in Mt Hyland Nature Reserve. HR was patchily low severity/unburnt.
4	Kaputar Fire #19101751804	17/10/2019	4/12/2019	3.5 months	Dry and wet sclerophyll forests, riparian, shrublands	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016 (post-fire likely but tbc).	Although fairly remote, Kaputar is near the Pilliga, so fieldtrips could capture data from both sites.
5	Dipper Road #18011987851	17/01/2018	02/02/2018	2 years + 1 month	Dry sclerophyll and semi-arid shrublands	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016. Basal area data collected in 2018 (now burnt).	Recent and long-term local fire history, useful for historic change analysis.
6	Stockyard Flat – amalgamated #19102753274	27/10/2019	11/11/2019	4 months	Rainforest, wet and dry sclerophyll forests, nonwoody wetlands, dry heath and shrublands.	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016.	Good site access due to research station facilities. Ross Peacock's long-term field observations and local knowledge of fire history.
7	Bills Crossing Crowdy #19102653077	26/10/2019	26/12/2019	2.5 months	Dry sclerophyll forest, nonwoody wetlands, mangroves.	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016 (post-fire likely but tbc).	Easy site access. Low height coastal vegetation would be good for testing sensitivity of methods
8	Gospers Mountain #19102652934	26/10/2019	10/02/2020	1 month	Rainforest, wet and dry sclerophyll forests, heathlands.	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016. Basal area data collected in 2018 (now burnt).	Site accessible for Sydney-based project staff, though rugged and remote terrain in part, other areas with sealed road access.
9	North Turramurra East HR, Ku-ring-gai #18052500945	25/05/2018	30/05/2018	1 year + 10 months	Dry sclerophyll forest, dry heath, Casuarina-dominated stands	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016. Pre- and post-fire fractional cover field sites. Post-fire multispectral drone imagery.	Site easily accessible for Sydney-based project staff, for low travel and accommodation costs.

Fire No.	ICON incident	Fire Start Date	Fire End Date	Time Since Fire	Vegetation Formations*	Existing data	Site notes
10	Moorebank Ave, Holsworthy #18041496605	14/04/2018	30/04/2018	1 year + 11 months	Dry and wet sclerophyll and riparian forests, swamp forests	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016. High resolution post-fire ADS photography. Pre- and post-fire fractional cover field sites.	Defence training area. Site access is difficult due to UXOs but not impossible.
11	Dunns Rd #19122867024	28/12/2019	15/02/2020	1 month	Dry and wet sclerophyll forest, riparian, grassy open woodlands, tall heath.	Sentinel 1, Landsat and Sentinel 2 reflectance and fractional cover, ALOS-2 2016 (post-fire likely but tbc). Disturbance history includes logging (state forests). TERN supersite with long term forest structure records and ground/airborne LiDAR.	Although fairly remote, the far southern tablelands of NSW will be important for comparisons with other climatic regions. Extensive FCNSW plot data on forest structure.

* Based on site observations and mapping (OEH 2017, The NSW State Vegetation Type Map: Methodology for a Regional Scale Map of NSW Plant Community Types. NSW Office of Environment and Heritage, Sydney, Australia).

Time-series of pre- and post-fire remote sensing data will be acquired for each site. This will involve the following:

- Shuttle Radar Topography Mission (SRTM) digital elevation (30 m) data acquisition and preparation. These data will be used to orthorectify remote sensing datasets. A state-wide mosaic is available on DPIE SDC.
- Landsat: download all available standardised surface reflectance products from DPIE SDC
- Sentinel-2: download all available standardised surface reflectance products from DPIE SDC
- Sentinel-1: download all available IWS data from DPIE SDC or SARA (https://copernicus.nci.org.au/sara.client/#/explore?collection=S1).
- ALOS-2 PALSAR-2: acquire pre- and post-fire fine beam (FB) dual polarization[4] (HH+HV) through the Japanese Aerospace Exploration Agency (JAXA) Kyoto & Carbon (K&C) program. A joint request has also been submitted to JAXA for FB coverage over a few hotspot sites and Scansar (100 m resolution) data over the east coast.
- Rainfall data from proximal rain gauges will be collated to assist in identifying suitable dates for acquisition of radar images. Surface moisture affects the backscatter response and ideally only 'dry' images should be used, or those captured at least 5 days after rainfall. Point or gridded climate data will be sourced from SILO (https://www.longpaddock.qld.gov.au/silo/point-data/) or BOM.
- LiDAR data acquisition and preparation (subject to acquisition by Government agencies). This is an optional project task and will be excluded if LiDAR is not available. Alternative options for similar validation data include Terrestrial Laser Scanners (TLS) and unmanned aerial vehicles (UAV).
- Evaluate co-registration accuracy of optical, radar and LiDAR datasets.
- Additional existing datasets may be useful in targeting forested regions, including NSW state-wide foliage projective cover (FPC) and woody extent mapping[5].

Depending on the availability of resources that could potentially be borrowed from research partners, additional data could be collected to provide valuable alternative sources of quantitative measurements of vegetation cover and structure. For example, TLS and UAVs may be available with in-house expertise to capture and analyse the data. These data types provide high density point clouds to generate high resolution 3D images of forest structure and biomass.

To properly assess timeseries approaches, a large number of image-based reference sites will be selected where there have been older historic fires (e.g. 5-20 years since fire). This is a space for time substitution method, in order to build coverage of the full range recovery trajectories (see Figure 2), rather than solely monitoring field reference sites through recovery from immediately post-fire. A selection of image-based references sites will be accessed during fieldtrips to the selected case study sites of recent fires for collection of field validation data.

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[4] Polarization – orientation of the electric vector in an electromagnetic wave, either horizontal or vertical, in radar imaging systems. Remote sensing radars are designed to transmit either vertically polarized or horizontally polarized radiation. This means the electric field of the wave is in a vertical plane or a horizontal plane. Likewise, the radar can receive either vertically or horizontally polarized radiation, or sometimes both. So the polarization of a radar image can be HH for horizontal transmit, horizontal receive, VV for vertical transmit, vertical receive, HV for horizontal transmit, vertical receive and v.v (https://earth.esa.int/handbooks/asar/CNTR5-5.html#eph.asar.gloss.geo:POLARISATION).

[5] https://www.environment.nsw.gov.au/research/AncillaryVegetationProductsDataInventory.htm

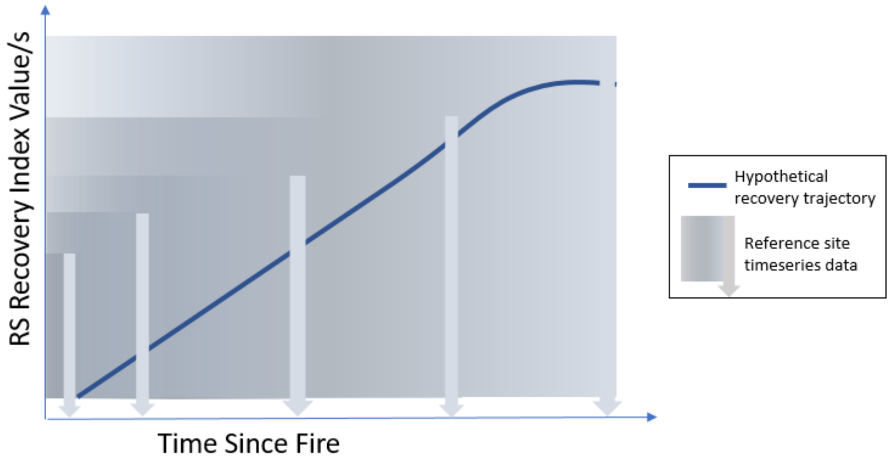

Figure 2 Conceptual model of building observational coverage of full post-fire recovery trajectories through many image-based reference sites across a wide range of time since fire samples, in order to assess the candidate remote sensing (RS) recovery index values.

Task 2: Map fire extent and severity

The spatial extent of burnt area at each site will be mapped as follows:

- Fire severity maps are available for most of east coast NSW for the current season and can be generated for specific sites using pre- and post-fire Sentinel-2 imagery as needed. The severity of fires that occurred prior to the launch of Sentinel 2 (<2015) can also be mapped with the FESM algorithm modified for application to Landsat imagery.
- Fire extent generated from a simple merging of FESM fire severity classes to reveal the total burnt area extent.
- An optional task is to investigate the use of radar data with the existing FESM method to map fire extent and severity. As pointed out in the literature review, there have been some successful studies using L-band SAR to map burn severity. Further research is needed to determine the sensitivity of different radar wavelengths and polarizations to burn severity. Optical (Sentinel-2) and C- and L-band radar data (Sentinel-1 and ALOS-2 PALSAR-2 respectively) will be combined in a machine learning framework to investigate the potential improvements in mapping accuracy.
- If ALOS-2 Scansar data is available, the burnt area of a large part of the east coast will be mapped at 100 m spatial resolution.

Task 3: Tracking post-fire change in vegetation cover over time

Both optical and radar time-series approaches will be investigated to determine viable methods of post-fire vegetation recovery monitoring.

Optical approaches will:

- Capture the temporal trends and variability of recovery based on spectral indices and fractional cover products using established regression and point-to-point fitting techniques. The development of timeseries algorithms will compare commonly used indices such as the NBR (Hislop et al., 2018), as well as innovation with less commonly used radar and fractional cover indices, some of which we will develop as novel indices for testing.
- Assess the application of calibration data, or phenological offsets, from unburnt reference or control pixels that are continuously monitored alongside the fire affected area (Lhermitte et al., 2010). This approach may help to reduce noise common in spectral timeseries approaches

by providing phenological and seasonal corrections for interpreting long-term regrowth of vegetation communities (Song, 2003). An equivalent phenological offset of unburnt training data is incorporated into the automated processing workflow of the FESM system of mapping fire extent and severity in NSW (Gibson et al., 2020).
- Two further techniques under active development in the JRSRP, led by Dr Jim Watson, will be assessed for inclusion in an operational decision support toolset. The first method has proven useful for comparing seasonal vegetation cover trajectories from different time periods (i.e., temporal comparisons of the same location), and the second offers a way of differencing trajectories from different locations (i.e., spatial comparison and characterization).

Radar approaches will:

- Determine the sensitivity of a radar time-series approach in detecting post-fire regrowth for different fire severity classes and in different vegetation types (e.g., grasslands, heath, different forests). Intensity differencing of monthly time-series Sentinel-1 data should reveal canopy level change as shorter (C-band) wavelengths interact with small foliage components. Annual differencing of longer wavelength (L-band) ALOS-2 PALSAR-2 data may assist in characterising different growth or degradation stages, given the sensitivity to woody structures and biomass. Both intensity and coherence change detection approaches will be investigated. Texture metrics using Sentinel-1 data may provide additional information. The analysis will be undertaken in collaboration with Dr Hsing-Chung Chang, Macquarie University.
- The integration of radar (L-band intensity) and optical (Landsat derived fractional cover) data may also be investigated for tracking post-fire vegetation response.
- Determine the time intervals for which meaningful change can be detected. This will involve tracking post-fire recovery and evaluating the time taken for the signal to return to former levels (i.e., unburnt/undisturbed forest). Recovery rates are typically much longer, of the order of several years or 1-2 decades (e.g., Fernandez-Carrillo *et al*., 2019; Bartels *et al.,* 2016), and so beyond the project timeframe, however, the lessons learned will be used to set up a possible future monitoring framework.

Task 4: Post-fire forest structural metrics and change monitoring

In order to assess possible post-fire forest structural change, the following activities are proposed:

- Determine the viability of detecting post-fire change in basal area (BA) using L-band radar. Historic and more recent (2009 and 2016 respectively) estimates of BA and BA change are available for NSW. These were generated via regression analysis of ALOS PALSAR and ALOS-2 PALSAR-2 HV backscatter and field measurements of BA. An R^2 of 0.7 was obtained between HV backscatter and BA, and the modelled relationship had a cross validated RMSE of 4.83 m^2 ha^{-1} (11.9 %) and small positive bias of 0.02 m^2 ha^{-1} (Mitchell, A., unpublished data). The existing BA model will be applied to post-fire imagery from the current season (pending availability of ALOS-2 data) to assess change in BA from the 2016 baseline. The consistency or otherwise of change in BA with fire severity classes and for different vegetation types will be investigated. How the approach might feed into an operational monitoring framework will be evaluated.
- LiDAR captured over field sites, complemented by field survey, to separate impacts of fire severity on canopy and understory. This is an optional task, subject to acquisition, availability and suitability of LiDAR.
- Post-fire vegetation recovery might involve a change in understorey structural composition. Field methods may have to be explored here given the limitations of optical (sees the canopy

from above and not understorey; limitations of unmixing algorithms) and radar (structural difference needed to separate vegetation types; new growth invisible at L-band) sensors.

Task 5: Risk/vulnerability modelling

A predictive modelling approach will be explored with the aim of assessing post-fire vulnerability to recovery. This would support prioritisation of areas for post-fire recovery management actions:

- Predictive modelling of recovery trajectories will be explored with collaborative partner, Dr Sam Hislop of DPI Forestry, as a potential complementary decision support tool for forest managers in post-fire recovery planning. A predicted recovery trajectory could be applied to a target fire, based on modelled trajectories of previous fires with matched preceding environmental conditions, land use and disturbance histories.

Task 6: Field validation

This study will collect field validation data to assess the performance and sensitivity of various remote sensing approaches being tested and developed. We have several established field protocols used to quantify structural cover and biomass and relate the measurements to satellite data including the star transect method, basal area sweeps and qualitative observations. Several case study fires will be selected for multiple site revisits across the next 18 months (Figure 1, Table 1).

At each case study fire, multiple site locations will be sampled, stratified by fire severity class and including adjacent unburnt reference sites. At each site location, measurements of fractional cover, basal area, regrowth density and qualitative descriptions (including species identification) will be undertaken.

Fractional Cover - Star Transect Method

The star transect method for fractional cover field measurement (Muir et al., 2011) will be one of the standard field measurements undertaken at each field site. Star transects are set up using 3 x 100m line transects, intersecting at the mid-point distributed at 60 degrees intervals in standard orientation (transect 1 = north to south, transect 2 = north-east to south-west, and transect 3 = south-east to north-west). A permanent steel stake will be placed at the centre point to allow for site re-visits. At each metre along the transects, fractional cover measurements are taken in the over-storey using a densitometer (periscope with cross-hairs attached to a staff), mid-storey by intersection with the staff at <2m, and ground strata using a down-facing laser pointer attached to the staff.

A minimum of 2 star transects in unburnt, low and high severity will be undertaken at each site. Unburnt reference sites will not be remeasured in revisit trips. Where possible, 2 different vegetation types will be sampled for each fire. With 5 sites, this provides 50 transects at each time period. Additional transects will be

Basal area sweeps

At each star transect site, basal area will be measured using an optical wedge prism at 7 points including the centre and mid-point of each transect arm. Both live, dead and burnt trees are counted in a full 360° sweep at each point. The BA measurements are averaged to provide site level estimates of BA. Basal area is not expected to change significantly across the project timeframes and so are unlikely to be repeated on subsequent revisits.

Tree measurements

The belt transect method (Grant et al., 2004) will be used to collect a count of woody saplings/regrowth along each of the 3 line transects at each star transect site. Species will be recorded when known, or samples taken back for identification. is not expected to change significantly across the project timeframes and so are unlikely to be repeated on subsequent site revisits. However, this method is adaptable and can be repeated if necessary, depending on rates of change being observed.

Qualitative observations

Sites will be described according to their topography, vegetation structure, soil and erosion characteristics. Where regrowth is observed, the species will be recorded if known, or samples taken back for identification.

At each star transect site, at 7 points including the centre and mid-point of each transect arm, observations and photographs of fire effects on vegetation strata will be taken (see Appendix 2). Photographs of tree canopies will provide reference of foliage damage/loss for different fire severity classes (and possible estimates of canopy cover) and assist in interpreting remote sensing imagery.

Task 7: Reporting and delivery

The science team will align with the NRC on any requirements around reporting on the project. Minimally, we will provide:

- 2 progress reports (October 2020, March 2021)
- A final report (November 2021)
- Face-to-face or phone meetings as requested
- Presentation of results at national conferences, as appropriate.

The final report will outline a proposed monitoring framework, including remote sensing and field data requirements and methods, for assessing post-fire recovery and resilience. Data products, if required, will be delivered electronically via the DPIE SDC or on external storage.

In collaboration with the NRC, it is anticipated that the results of the study will be jointly published in scientific journals and or national/international conferences.

Appendix 1 – Literature Review

Ecological resilience is the capacity of a system to return to its initial state after a perturbation (Holling, 1973, Leps et al., 1982). Post-fire recovery is a successional process towards the pre-fire community structure and function, or to an alternative stable state (Turner et al., 2016). Measuring and monitoring fire severity and subsequent post-fire vegetation regrowth are essential for understanding the effects of wildfires across the landscape and the ecological resilience of forests. The relationship between fire severity and post-fire recovery rates has long been a focus for ecology and global carbon cycle studies (Turner and Romme, 1999, Liu, 2016, Gordon et al., 2017) and is becoming a more pressing issue, as the frequency and severity of fire disturbance are expected to continue to increasing due to warmer and drier global climate conditions (Meng et al., 2018, Abatzoglou and Williams, 2016). In the last 10-15 years, remote sensing approaches have been increasingly explored as a tool to examine and understand post-fire recovery, following advances in satellite and airborne sensors, data accessibility, computing storage and processing technology.

Vegetation community structural responses

Re-establishment of a forest after disturbance from fire can take many years, and during this time several important structural, functional and compositional properties recover at different rates. Understory (e.g., shrub, herbaceous, and woody) vegetation can recover quickly after the fire, however this vegetation has different functional and structural properties compared to the pre-fire canopy. For example, there are large differences between understory and canopy vegetation in lifeform, productivity and capacity for carbon and water storage (Swanson et al. 2011). Separating post-fire forest canopy recovery from understory recovery has broad implications for forest management (Castro et al. 2011; Kotliar et al. 2002), understanding fire effects on the terrestrial water cycle (Mayor et al. 2007), and for simulating the global carbon cycle in Earth System Models (Fisher et al. 2017).

Separating canopy and understory cover/biomass is a significant challenge for remote sensing approaches. In particular, optical sensors can have an obstructed view of the reflectance signals from sub-canopy. Passive sensor-based approaches typically relate post-fire forest recovery rates to the change in reflectance values of the upper-most vegetation layer during the post-fire period, without attempting to separate canopy from sub-canopy components (White et al., 1996, Lhermitte et al., 2010, Hislop et al., 2018). This is often assumed to represent the tree canopy but may involve a mixture of reflectance signal from canopy and sub-canopy components, depending on the canopy openness. In remote sensing studies that have examined post-fire structural responses, active sensors such as LiDAR or radar are normally required to quantify sub-canopy biomass (Gordon et al., 2017). While understory recovery rates have significant short-term influences on fuel dynamics, biomass, hazard and flammability, canopy level recovery to pre-fire conditions is slower and is generally assumed to be a proxy for whole of vegetation community level recovery. Aligning definitions of recovery with definitions of fire severity as the extent of canopy loss or change, supports integrated analyses of fire severity and post-fire recovery (Meng et al., 2018).

Recovery trajectories

Post-fire recovery is generally best understood in the context of timeseries analyses, examining factors influencing recovery trajectories. Post-fire recovery is a second-order effect of fire. The interaction of first-order fire effects (fire extent and severity) with environmental variables, such as rainfall and climate conditions, influence the post-fire recovery trajectory over time. Post-fire recovery trajectories generally measure the rate of change, by some chosen metric, from immediately after a fire until an end point whereby the rate of change is indistinguishable from adjacent or reference areas that did not burn. This may occur across many decades after a fire (Song, 2003, Fernandez-Manso et al., 2016). Plant establishment and growth rates are generally higher under favourable post-fire climatic conditions, such as higher precipitation and moisture availability (Harvey et al., 2016). However, the rate of recovery after fire will depend on many factors such as ecosystem productivity, local and regional weather patterns, the timing and severity of fire and vegetation type.

Post-fire forest recovery trajectories are closely connected to fire severity, with higher severity typically associated with longer rates of recovery, although this can vary by vegetation type (Hislop et al., 2019b). Fernandez-Manso *et al* (2016) observed that vegetation cover affected by low severity fire recovered to its original state after 7 years; moderate severity recovered after 13 years; and high severity fire was estimated to recover after 20 years. In some communities, high severity burns may deplete soil stored seed bank or destroy vegetative resprouting organs (Wright and Fensham, 2016). By contrast, in other communities, high severity fires may promote greater rates of regrowth (Gordon et al., 2017).

Post-fire vegetation recovery trajectories may also vary between species within a community and between conspecific individuals (Bellingham and Sparrow, 2000). A homogenous area of extreme fire severity (i.e. 100% post-fire loss of above ground biomass) may display heterogeneous patterns in rates of vegetative resprouting in one vegetation community, while another community may display a more even and rapid rate of resprouting or regrowth. For example, the recovery trajectory of a closed forest with a mix of resprouter and obligate-seeder plant functional types may be more heterogenous than an open grassland ecosystem. Such variation in recovery from fire can create difficulty in applying and interpreting metrics of post-fire recovery between different communities. This highlights the importance of local knowledge on interpreting remote sensing post-fire recovery products for applications in forest management decisions.

As fire frequency and severity are expected to intensify with warmer and drier climates, there is likely to be compounding influences on forest community resilience. For example, altered seed bank dynamics and reduced growth rates as site conditions change under intensified fire regimes and declining moisture availability may slow forest recovery or change successional trajectories (Liu and Yang, 2014, Johnstone et al., 2009). Wardell-Johnson *et al* (2017) found stand height and biomass had not recovered to pre-1937 levels by 2015. Canopy height remained 5.06 m (11%) less and biomass 25% less, 78 years after the fire. The combination of intense fire and a warmer, drier climate appeared to have prevented recovery of forest height and structure. Timeseries approaches could be useful in detecting whether post-fire recovery is unlikely to reach pre-fire conditions by assessing the annual rate of change. Quantifying the differences between a stable state and the pre-fire conditions will be an important metric in measuring ecological resilience in forests facing significant impacts due to changing fire regimes and climate. Observational monitoring of post-fire recovery is needed as a fundamental baseline dataset, in order to make inferences about the factors affecting recovery rates and priorities for possible management intervention to support rehabilitation and resilience (Gitas et al., 2012).

Recovery trajectories derived from timeseries datasets are an improvement over simple two-date change detection models because they capture the temporal variability that occurs after fires, including inter- and intra-annual trends. The primary challenge when using multitemporal imagery to monitor forest regrowth is to identify the relevant features of a time series while dismissing noise introduced by ephemeral changes in illumination, phenology, atmospheric condition and geometric registration (Kennedy et al., 2010, Song, 2003). Temporal segmentation strategies with both regression-based and point-to-point fitting of spectral indices as a function of time, allow the representation of both slowly evolving processes, such as regrowth, and abrupt events, such as forest harvest. A common approach is to use control parameters and threshold-based filtering to reduce false positive detections (Kennedy et al., 2010).

Passive Sensors

Remote sensing methods of monitoring post-fire recovery typically track individual pixel values over time using various spectral indices. Many studies have examined timeseries of vegetation indices in post-fire recovery analyses, inclugin as the normalised differenced vegetation index (NDVI; Malak and Pausas, 2006, Hope et al., 2007), the normalized burn ratio (NBR) (Lentile et al., 2007 (Hudak et al., 2007), the char fraction (Smith et al., 2007), Tasselled-cap transformations and others. Indices such as NDVI, which captures chlorophyll concentration or canopy 'greenness', are generally considered relatively poor at assessing post-fire recovery, because grasses and other non-woody vegetation that colonise a site after fire rapidly return the NDVI signal to its pre-fire state, typically in 3–5 years post-fire (Pickell et al., 2016, Hislop et al., 2018). By contrast, indices that incorporate short-wave infrared (SWIR) bands are more successfully used in post-fire recovery analyses, as these indices are sensitive to forest structure, moisture, shadowing, and vegetation density (Schroeder et al., 2011, Liu, 2016). The NBR index is a ratio of the near infra-red (NIR) to SWIR band and has been demonstrated to have greater sensitivity to finer changes in vegetation cover after disturbance over much longer (8–10 years) recovery timeframes (Hislop et al., 2018). The use of multiple post-fire recovery reflectance indices in a machine learning framework has recently been demonstrated to out-perform any single algorithm alone (Hislop et al., 2019a). This is consistent with other recent findings for different remote sensing-based landscape change modelling applications (Gibson et al., 2020, Mathan and Krishnaveni, 2020).(Guershman et al., 2015, Scarth et al., 2010)

The Landsat satellite program has one of the longest continuous captures, with an archive of data consistently captured since 1988, and ongoing into the foreseeable future. The Landsat-based Detection of Trends in Disturbance and Recovery (Landtrendr), based on the Landsat SWIR band, has been widely tested for recovery monitoring applications (Kennedy et al., 2010). Examples of results… It requires a recovery curve pattern assumed a priori (Kennedy et al. 2007; Kennedy et al. 2010), which may be a limitation for applying the model at a landscape scale without local knowledge.

Spectral indices are unitless values that do not directly measure any biophysical property. Indices measuring the relative cover of photosynthetic, non-photosynthetic material and bare ground may provide a more useful 2-dimensional remote sensing surrogate to estimate the quantity of organic matter consumed by fire and recovering than traditional reflectance-based estimates (e.g. NBR). Furthermore, spectral indices that assign a single value to a pixel do not capture this subpixel variability. Sub-pixel unmixing, or fractional cover analyses can decompose the remote sensing signal in order to determine a pixel's composition of the relative fractions of photosynthetic, non-photosynthetic and bare cover (Scarth et al., 2010, Guershman et al., 2015). Although not widely applied in post-fire recovery monitoring approaches, spectral unmixing has been used for multitemporal cover change mapping (Okin, 2007).

Ground truthing based on limited sample sets is always suggested for calibration and validation purposes of any remote sensing earth observation method (Gitas et al., 2012). Calibration data, or phenological offsets, from unburnt reference or control pixels that are continuous monitored alongside the fire affected area (Lhermitte et al., 2010). This approach may help to reduce noise common in spectral timeseries approaches by providing phenological and seasonal corrections for interpreting long-term regrowth of vegetation communities (Song, 2003). An equivalent phenological offset of unburnt training data is incorporated into the automated processing workflow of the FESM system of mapping fire extent and severity in NSW (Gibson et al., 2020).

Active Sensors

Recent and advanced remote sensing technology includes active sensor systems, such as Light Detection and Ranging (LiDAR) and Synthetic aperture radars (SAR). These provide an opportunity to more accurately determine fire effects on the landscape compared to other reflectance-based methods. An advantage of active sensors is that the data is not obstructed by cloud cover or influenced by solar angle effects, as for most passive sensors. Active remote sensing data are more sensitive to forest biomass and structural properties compared to passive instrument data.

Synthetic Aperture Radar

Data acquired SAR may provide a complementary source of information on the impacts of wildfire. Unlike optical sensors, radar can penetrate cloud, haze and smoke, and is sensitive to forest structure and biomass. Longer wavelengths (e.g., L-band, ~24 cm) penetrate the vegetation canopy and interact with large woody structures and the ground surface. Shorter C-band wavelengths (~5.6 cm) are sensitive to the canopy volume. Methods based on SAR have been developed for burned area and fire severity mapping and post-fire recovery in a range of forest types and biomes.

Belenguer-Plomer *et al.* (2017) mapped burned area extent in Orinoco Basin, Colombia, using a region-growing approach applied to a 4-image time-series of Sentinel-1 VH polarization normalized difference temporal index (NDTI) images. Variability in backscatter around the mean was used to refine the detection of burnt objects and false positives (e.g., water). Omission and commission errors of 18.67 and 28.62% were obtained. Verheggen *et al.*(2016) demonstrated the benefits of integrating Sentinel-1 and Sentinel-2 data for burnt area mapping in Congo basin, with each sensor compensating for the limitations of the other (e.g., cloud in S2 and sensitivity to surface moisture in S1).

Mathieu *et al.* (2019) examined pre- and post-fire dual polarized (VV, VH) signatures in Sentinel-1A data acquired over savannah woodland in Kruger National Park, South Africa. Low intensity surface fires are common in this environment, with most impacts felt on the grass layer and little damage to trees. A systematic backscatter decrease was observed from pre- to post-fire conditions, with mean backscatter decreases of 1.61 dB and 0.99 dB for VH and VV polarizations respectively. Burning of the grass layer leads to a decrease in C-band backscatter as this frequency is sensitive to small sized scatterers. VH polarization was more sensitive to surface fire effects, due largely to changes in grass volume scattering. VV polarization showed slightly higher sensitivity to fire impacts with increasing woody cover.

There have been a few successful studies investigating the sensitivity of radar backscatter at different frequencies to burn severity levels. Tanase *et al.* (2010a) observed an increase in co-polarized backscatter with burn severity at X- and C-bands and a decrease at L-band in Mediterranean pine forest in Spain. There was a decrease in the cross-polarization response with burn severity at all frequencies. The loss of leaves and branches results in a reduction of backscatter from the canopy and potential to increase soil exposure. In Tanase *et al.* (2010b), L-band interferometric coherence showed high sensitivity to burn severity, and potential to discriminate intermediate burn severities. Full polarimetric L-band data also facilitated the differentiation of fire severity classes (Tanase et al., 2014). The influence of incidence angle was stronger at C-band, and longer wavelengths were deemed more appropriate for burn severity estimation.

While most SAR-based studies have concentrated on the impacts of wildfire, a few studies have assessed the outcomes of prescribed burning. Fernandez-Carrillo *et al.* (2019) modelled three fire severity classes using standardized and normalized radar burn ratio (RBR) and normalized difference backscatter intensity (NDBI) derived from ALOS-2 data over eucalypt forests in Western Australia. The overall impact of the prescribed burn was estimated with relatively high accuracy (79 %) when using cross-polarized (HV) backscatter acquired under dry conditions. The RBR decreased with fire severity, while a linear increase in NDBI with fire severity was observed. Post-fire recovery was assessed by analysing the backscatter a year after the burn event. The sensitivity of L-band HV to changes in the density of canopy scattering elements may lend itself to tree survival and recovery monitoring and evaluating the success of prescribed burns.

SAR also provides an opportunity to monitor post-fire regrowth and successional stage (Chu and Guo, 2014). L-band sensitivity to forest structural parameters allows for differentiation of forest growth and degradation stage (e.g. Lucas et al., 2014, Joshi et al., 2015). Soil moisture effects are limiting however, and must be addressed in order to avoid misclassification of regrowth stage (Chu and Guo, 2014). Tanase *et al.* (2011) identified 5 phases of regrowth in Mediterranean forest (Spain) and 4 regrowth phases in boreal forest (Alaska) using ALOS PALSAR data. L-band was superior to C and X-bands in detecting recently burnt forests. X-band was the least sensitive to forest regrowth.

LiDAR

Discrete-return airborne LiDAR collected at high spatial resolution has been used to accurately measure forest height, canopy-cover and other metrics of the vertical distribution of vegetation, and modelled with field data to predict basal area, volume, biomass, foliage projective cover and leaf area index (Kane et al., 2013, McCarley et al., 2017, Lefsky et al., 2002, Gordon et al., 2017, Fisher et al., 2020). The application of LiDAR in estimating post-fire recovery is limited by the sparse coverage of pre-fire data and the expense of acquiring new post-fire data.

Multi-temporal LiDAR has been applied in studies of ecosystem change (Hudak et al., 2012, Skowronski et al., 2014), though relatively few studies have used multi-temporal LiDAR to spatially match pre- and post-fire LiDAR to quantify fire effects. Changes in lidar instrument/survey acquisition parameters and processing methods between lidar data sets captured at different times will also influence the changes observed in lidar derived vegetation structure metrics due to fire severity and recovery (Fisher et al., 2020, Disney et al., 2010, Næsset, 2009, Korpela et al., 2012). Due to these difficulties, and the cost of repeated lidar acquisitions, it may be more appropriate to view lidar data as a method of accurately measuring post-fire forest structure, for independent validation of the satellite-based methods. This is dependent on where and when NSW Government agencies acquires lidar data during the timeframes of the project.

Integration of passive and active approaches

Multi-sensor approaches to vegetation recovery monitoring are increasingly being explored, especially as compute power and processing limitations are reduced with advancing technology. The combined use of optical and radar sensor data may help overcome the limitations of each sensor (e.g., optical data is affected by cloud and radar is sensitive to surface moisture and topography). Both types of sensors offer a unique view of the forest, with optical sensors responding to the vegetation condition and radar responding to forest structure and biomass.

Numerous studies report the limitation of optical reflectance techniques in quantifying post-fire recovery in measures comparable to field-based estimates of forest recovery. This has been largely attributed to the lack of discrimination between canopy and understory recovery (Castro et al. 2011; Fisher et al. 2017), and the contamination effect on reflectance signals of the early post-fire flush in understory growth of seedlings and herbaceous plants as well as epicormic shoots (Meng et al., 2018). Understory vegetation (e.g., shrub, herbaceous, and woody) can recover quickly after a fire event. However, the structure and function of understory vegetation is different compared to the pre-fire canopy, in terms of lifeform, productivity and capacity for carbon and water storage (Swanson et al. 2011).

Operational monitoring of vegetation recovery

Access to suitable data (optical/radar and spatial/temporal coverage) is a critical component of an operational monitoring program. Optical (multispectral) reflectance imagery is freely available at medium resolution (10 – 30 m). Sentinel-2 (post 2016) data is available at 10 m resolution and on a 5-day repeat cycle. Landsat is widely available, and the extensive archives allow for longer term vegetation studies.

With the recent exception of Sentinel-1, data from most satellite radars are available commercially. Limited data is available for research purposes through space agency PI programs. Sentinel-1 data is freely available through the European Space Agency (ESA). Data acquired in interferometric wide (IW) swath mode are available for global land areas at high spatial (20 m) and temporal (12 days) resolution. The shorter wavelength C-band data (~5.6 cm) largely interact with the small vegetation components present in the canopy volume. Longer wavelength radars, e.g., those operating at L-band (~24 cm), such as the ALOS-2 PALSAR-2 are better suited to quantifying forest structure and biomass. With recent changes to JAXAs observation scenario, ALOS-2 fine beam data (~10 m) will only be acquired once yearly however, with coarser resolution (100 m) Scansar data acquired more frequently over land areas. ALOS-2 data is currently available commercially. Archive ALOS PALSAR (2007-2011) is freely available and well suited to change analysis. Continuity of L-band SAR data is at least assured with the scheduled launch of ALOS-4.

A new generation of instruments designed to improve our estimates of canopy biomass and structure provide new and exciting opportunities for vegetation recovery monitoring. ESA are planning to launch a P-band BIOMASS mission in 2021, specifically targeted at quantifying global forest carbon and flux. This will become the first P-band (~68 cm) satellite SAR in operation. The data will provide more accurate estimates of above ground biomass in tropical, temperate and boreal regions, and inform on forest disturbance and recovery. BIOMASS data are unlikely to be available during this project, however, their use in future monitoring of forest recovery should be explored.

NASA have deployed the Global Ecosystem Dynamics Investigation (GEDI) LiDAR on the International Space Station (ISS). GEDI provides full waveform lidar measurements for detailed 3D reconstruction of the forest. Information on surface topography, canopy height and cover metrics and vertical structure metrics can be extracted from GEDI waveforms. The data are considered useful for studies on forest biomass, disturbance and recovery, carbon sequestration and biodiversity. GEDI is designed to collect data between 51.6° N latitude and 51.6° S latitude. Within this area, GEDI gathers data from approximately four percent of the earth's surface, including both tropical and temperate forests. While not global in coverage, GEDI could provide useful calibration data of other remote sensing products.

Operational post-fire recovery monitoring in Australia is largely conducted at local scales with field-based measurements. Observations by site-based land managers is the primary data that informs post-fire recovery resources and activities. While national and state land management agencies may coordinate post-fire recovery responses, a landscape scale monitoring framework is not operational. While some jurisdictions in Australia may conduct various fire mapping operations, data types and quality are disjunct and generally not complimentary as there is no coordinated cohesive approach. Internationally, one of the most comprehensive fire mapping and monitoring operational systems to aspire to is the European forest fire platform; the SAFER project (www.emergencyresponse.eu), led by INSA (Ingeniería y Servicios Aeroespaciales, Spain) coordinating the activities of Spain, Portugal, France, Italy and Greece. SAFER satellite-derived fire products are automated, or semi-automated and include fire danger forecasting, active fire detection and fire radiative power monitoring, rapid burned area mapping for emergency response operations, and post-fire severity and recovery products. Fire products are provided to end users using a dedicated GeoPortal (www.insageoservices.com).

References

Abatzoglou, J. T. and Williams, A. P. (2016) 'Impact of anthropogenic climate change on wildfire across western US forests', *PNAS,* 113, pp. 11770-11775.

Belenguer-Plomer, M. A., Chuvieco, E. and Tanase, M. A. 'Sentinel-1 based algorithm to detect burned area. '. *Proceedings of the 11th EARSeL Forest Fires SIG Workshop*, Chania, Greece.

Bellingham, P. J. and Sparrow, A. D. (2000) 'Resprouting as a life history strategy in woody plant communities', *Oikos,* 89(2), pp. 409-416.

Chu, T. and Guo, X. (2014) 'R emote sensing techniques in monitoring post-fire effects and patterns of forest recovery in boreal forest regions: a review. ', *Remote Sensing,* 6, pp. 470-520.

Disney, M. I., Kalogirou, V., Lewis, P., Prieto-Blanco, A., Hancock, S. and Pfeifer, M. (2010) 'Simulating the impact of discrete-return lidar systems and survey characteristics over young conifer and broadleaf forests', *Remote Sensing of Environment,* 114, pp. 1546-1560.

Fernandez-Carrillo, A., McCaw, L. and Tanase, M. A. (2019) 'Estimate prescribed fire impacts and post-fire tree survival in eucalyptus forests of Western Australia with L-band SAR data. ', *Remote Sensing of Environment,* 244, pp. 133-144.

Fernandez-Manso, A., Quintano, C. and Roberts, D. A. (2016) 'Burn severity influence on post-fire vegetation cover resilience from Landsat MESMA fraction images time series in Mediterranean forest ecosystems', *Remote Sensing of Environment,* 184, pp. 112-123.

Fisher, A., Armston, J., Goodwin, N. and Scarth, P. (2020) 'Modelling canopy gap probability, foliage projective cover and crown projective cover from airborne lidar metrics in Australian forests and woodlands', *Remote Sensing of Environment,* 237(111520).

Gibson, R., Danaher, T., Hehir, W. and Collins, L. (2020) 'A remote sensing approach to mapping fire severity in south-eastern Australia using sentinel 2 and random forest', *Remote Sensing of Environment,* 240(111702).

Gitas, I., Mitri, G., Veraverbeke, S. and Polychronaki, A. (2012) 'Advances in remote sensing of post-fire vegetation recovery monitoring - a review', in Temilola, F. (ed.) *Remote Sensing of Biomass - Principles and Applications*: IntechOpen.

Gordon, C., Price, O. F. and Tasker, E. M. (2017) 'Mapping and exploring variation in post-fire vegetation recovery following mixed severity wildfire using airborne LiDAR', *Ecological Applications,* 27(5), pp. 1618-1632.

Grant, T. A., Madden, E. M., Murphy, R. K., Smith, K. A. and Nenneman, M. P. (2004) 'Monitoring native prairie vegetation: the belt transect method', *Ecological Restoration,* 22(4), pp. 1543-4079.

Guershman, J. P., Scarth, P. F., McVicar, T. R., Renzullo, L. J., Malthus, T. J., Stewart, J. B., Rickards, J. E. and Trevithick, R. (2015) 'Assessing the effects of site heterogeneity and soil properties when umixing photosynthetic vegetation, non-photosynthetic vegetation and bare soil fractions from Landsat and MODIS data', *Remote Sensing of Environment,* 16, pp. 12-26.

Harvey, B. J., Donato, D. C. and Turner, M. G. (2016) 'High and dry: post-fire tree seedling establishment in subalpine forests decreases with post-fire drought and large stand-replacing burn patches', 25(655-669).

Hislop, S., Jones, S., Soto-Berelov, M., Skidmore, A., Haywood, A. and Nguyen, T. H. (2018) 'Using Landsat spectral indices in time-series to assess wildfire disturbance and recovery', *Remote sensing,* 10(460).

Hislop, S., Jones, S., Soto-Berelov, M., Skidmore, A., Haywood, A. and Nguyen, T. H. (2019a) 'A fusion approach to forest disturbance mapping using time series ensemble techniques', *Remote Sensing of Environment,* 221, pp. 188-197.

Hislop, S., Jones, S., Soto-Berelov, M., Skidmore, A., Haywood, A. and Nguyen, T. H. (2019b) 'High fire disturbance in forests leads to longer recovery, but varies by forest type', *Remote Sensing in Ecology and Conservation,* 5(4), pp. 376-388.

Holling, C. S. (1973) 'Resilience and Stability of Ecological Systems', *Annual Review of Ecology and Systematics,* 4, pp. 1-23.

Hudak, A. T., Morgan, P., Bobbitt, M. J., Smith, A. M. S., Lewis, S. A., Lentile, L. B., Robichaud, P. R., Clark, J. T. and McKinley, R. A. (2007) 'The relationship of multispectral satellite imagery to immediate fire effects', *Fire Ecology Special Issue,* 3(1), pp. 64-90.

Hudak, A. T., Strand, E., Veirling, L. A. and Falkowski, M. J. (2012) 'Quantifying above forest carbon pools and fluxes from repeat LiDAR surveys', *Remote Sensing of Environment,* 123, pp. 25-40.

Johnstone, J. F., Hollingsworth, T. N., Chapin, F. S. and Mack, M. C. (2009) 'Changes in fire regime break the legacy lock on successional trajectories in Alaskan boreal forest', *Global Change Biology,* 16(4), pp. 1281-1295.

Joshi, N., Mitchard, E. T. A., Woo, N., Torres, J., Moll-Rocek, J., Ehammer, A., Collins, M., Jepsen, M. R. and Fensholt, R. (2015) 'Mapping dynamics of deforestation and forest degradation in tropical forests using radar satellite data.', *Environmental Research Letters,* 10(034014).

Kane, V. R., Lutz, J. A., Roberts, S. L., Smith, D. F., McGaughey, R. J., Povak, N. A. and Brooks, M. L. (2013) 'Landscape-scale effects of fire severity on mixed-conifer and red fir forest structure in Yosemite National Park', *Forest Ecology and Management,* 287, pp. 17-31.

Keeley, J. E. (2009) 'Fire intensity, fire severity and burn severity - a brief review and suggested usage', *International Journal of Wildland Fire,* 18, pp. 116-126.

Kennedy, R. E., Yang, Z. and Cohen, W. B. (2010) 'Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - temporal segmentation algorithms', *Remote Sensing of Environment,* 114, pp. 2897-2910.

Korpela, I., Hovi, A. and Morsdorf, F. (2012) 'Understory trees in airborne LiDAR data - selective mapping due to transmission losses and echo-triggering mechanisms', *Remote Sensing of Environment,* 119, pp. 92-104.

Lefsky, M. A., Cohen, W. B., Parker, G. G. and Harding, D. J. (2002) 'Lidar remote sensing for ecosystem studies', *Bioscience,* 52(1), pp. 19-30.

Leps, J., Osbornova-Kosinova, J. and Rejmanek, M. (1982) 'Community stability, complexity and species life history strategies', *Vegetatio,* 50(1), pp. 53-63.

Lhermitte, S., Verbesselt, J., Verstraeten, W. W. and Coppin, P. (2010) 'A pixel based regeneration index using time series similarity and spatial context', *Photogrammetric Engineering and Remote Sensing,* 76(6), pp. 673-682.

Liu, Z. (2016) 'Effects of climate and fire on short-term vegetation recovery in the boreal larch forests of Northeastern China', *Scientific Reports,* 6(37572).

Liu, Z. and Yang, J. (2014) 'Quantifying ecological drivers of ecosystem productivity of the early-successional boreal *Larix gmelinii* forest', *Ecosphere,* 5(7), pp. Article 84.

Lucas, R. M., Clewley, D., Accad, A., Butler, D., Armston, J., Bowen, M., Bunting, P., Carreiras, J., Dwyer, J., Eyre, T., Kelly, A., McAlpine, C., Pollock, S. and Seabrook, L. (2014) 'Mapping forest growth and degradation stage in the Brigalow Belt Bioregion of Australia through integration of ALOS PALSAR and Landsat-derived foliage projective cover data.', *Remote Sensing of Environment,* 155, pp. 42-57.

Mathan, M. and Krishnaveni, M. (2020) 'Monitoring spatio-temporal dynamics of urban and peri-urban land transitions using ensemble of remote sensing spectral indices—a case study of Chennai Metropolitan Area, India', *Environmental monitoring and assessment,* 192(15).

Mathieu, R., Main, R., Roy, D. R., Naidoo, L. and Yang, H. (2019) 'The effect of surface fire in savannah systems in the Kruger National Park (KNP), South Africa, on the backscatter of C-band Sentinel-1 images.', *Fire,* 2(3), pp. 37.

McCarley, T. R., Kolden, C. A., Vaillant, N. M., Hudak, A. T., Smith, A. M. S., Wing, B. M., Kellogg, B. S. and Kreitler, J. (2017) 'Multi-temporal LiDAR and Landsat quantification of fire-induced changes to forest structure', *Remote Sensing of Environment,* 191, pp. 419-432.

Meng, R., Wu, J., Zhao, F., Cook, B. D., Hanavan, R. P. and Serbin, S. P. (2018) 'Measuring short-term post-fire forest recovery across a burn severity gradient in a mixed pine-oak forest using multi-sensor remote sensing techniques', *Remote Sensing of Environment,* 210, pp. 282-296.

Muir, J., Schmidt, M., Tindall, D., Trevithick, R., Scarth, P. and Stewart, J. B. (2011) *Field measurements of fractional ground cover: A technical handbook supporting ground cover monitoring for Australia*, Canberra: Australian Bureau of Agricultural and Resource Economics and Sciences.

Næsset, E. (2009) 'Effects of different sensors, flying altitudes, and pulse repetition frequencies on forest canopy metrics and biophysical stand properties derived from small-footprint airborne laser data.', *Remote Sensing of Environment,* 113, pp. 148-159.

Pickell, P. D., Hermosilla, T., Frazier, R. J., Coops, N. C. and Wulder, M. A. (2016) 'Forest recovery trends derived from Landsat time series for North American boreal forests.', *International Journal of Remote Sensing,* 37, pp. 138–149.

Scarth, P., Roder, A. and Schmidt, M. 'Tracking grazing pressure and climate interaction - The role of Landsat fractional cover in time series analysis'. *Proceedings of the 15th Australasian Remote Sensing and Photogrammetry Conference*, Alice Springs, Australia.

Schroeder, T. A., Wulder, M. A., Healey, S. P. and Moisen, G. G. (2011) 'Mapping wildfire and clearcut harvest disturbances i n boreal forests with Landsat time series data.', *Remote Sensing of Environment,* 115, pp. 1421-1433.

Skowronski, N., Clark, K. L., Gallagher, M. R. and Hom, J. (2014) 'Airborne laser scanner-assisted estimation of aboveground biomass change in a temperate oak–pine forest', *Remote Sensing of Environment,* 151, pp. 166-174.

Song, C. H. (2003) 'Monitoring forest succession with multitemporal Landsat images: Factors of Uncertainty,' *IEEE Transactions on Geoscience and Remote Sensing,,* 41(11), pp. 2557-2567.

Tanase, M., De La Riva, J., Santoro, M., Pérez-Cabello, F. and Kasischke, E. (2011) 'Sensitivity of SAR data to post-fire forest regrowth in Mediterranean and boreal forests. ', *Remote Sensing of Environment,* 115(8), pp. 2075-2085.

Tanase, M. A., Santoro, M., Aponte, C. and De La Riva, J. (2014) 'Polarimetric properties of burned forest areas at C- and L-band.', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 7(1), pp. 267-276.

Tanase, M. A., Santoro, M., De La Riva, J., Pérez-Cabello, F. and Le Toan, T. (2010a) 'Sensitivity of X-, C- and L-band SAR backscatter to burn severity in Mediterranean Pine forests.', *IEEE Transactions on Geoscience and Remote Sensing,* 48(10), pp. 3663-3675.

Tanase, M. A., Santoro, M., Wegmuller, U., de la Riva, J. and Perez-Cabello, F. (2010b) 'Properties of X-, C-, and L-band repeat-pass interferometric SAR coherence in Mediterranean pine forests affected by fires', *Remote Sensing of Environment,* 114, pp. 2182-2194.

Turner, M. G. and Romme, W. H. (1999) 'Pre-fire heterogeneity, fire severity and early post-fire plant establishment in subalpine forests of Yellowstone National Park, Wyoming.', *International Journal of Wildland Fire,* 9, pp. 21-36.

Turner, M. G., Whitby, T. G., Tinker, D. B. and Romme, W. (2016) 'Twenty-four years after the Yellowstone Fires: Are postfire lodgepole pine stands converging in structure and function?', *Ecology,* 97(5), pp. 1260-1273.

Verheggen, A., Eva, H., Ceccherini, G., Achard, F., Gond, V., Gourlet-Fleury, S. and Cerutti, P. O. (2016) 'The potential of Sentinel satellites for burnt area mapping and monitoring in the Congo Basin forests.', *Remote Sensing,* 8, pp. 986.

Wardell-Johnson, G., Crellin, L., Napier, C., Meigs, G., Stevenson, A. and Wong, S. I. (2017) 'Has canopy height and biomass recovered 78 years after an intense fire in south-western Australia's red tingle

(Eucalyptus jacksonii) forests?', *International Journal of Wildland Fire,* 26, pp. 148-155.

White, J. D., Ryan, K. C., Key, C. C. and Running, S. W. (1996) 'Remote sensing of forest fire severity and vegetation recovery', *International Journal of Wildland Fire,* 6(3), pp. 125-136.

Wright, B. R. and Fensham, R. J. (2016) 'Relationships between fire severity and recruitment in arid grassland dominated by the obligate-seeding soft spinifex (Triodia pungens)', *International Journal of Wildland Fire,* 25, pp. 1264-1272.

Appendix 2 – Qualitative field validation forms

Table 1 FESM field validation: a. Fire Severity Class, b. vegetation type, c. foliage projective cover

a. FESM Fire Severity Class:		
Severity class	**Description**	**% foliage fire affected**
0 = Unburnt	Unburnt surface with green canopy	0% canopy and understory burnt
1 = Burnt Grassland	Burnt grassland or open grassy woodland. Unburnt canopy, if present.	100% grassland burnt, 0% canopy burnt (if present)
2 = Low	Burnt understory with unburnt canopy	>10% burnt understory >90% green canopy
3 = Moderate	Partial canopy scorch	20-90% canopy scorch
4 = High	Complete canopy scorch (+/- partial canopy consumption)	>90% canopy scorched, <50% canopy consumed
5 = Extreme	Complete canopy consumption	>50% canopy biomass consumed

b. Vegetation type (select from below):	
Dry Sclerophyll, Wet Sclerophyll, Dry Heath, Wet Heath, Shrublands, Tall Shrublands >2m, Shrubby regrowth, Rock/rocky outcrop, Riparian forest/woodland, Rainforest, Open Grassy Woodland, Grassland:	
c. Foliage Projective Cover estimate (select from below):	
Low cover <30%; moderate cover 30-70%; high cover >70%	

Table 2. Structural Effects of Fire

	Scorch height above ground	**Vegetation Layer**			
		Tree	**Sub-canopy**	**Shrubs**	**Ground (grass etc)**
Height (m)					
% cover of living vegetation					
% cover of vegetation scorched (brown) but not fully consumed by fire					
% cover of vegetation that would have been fully consumed by fire					

*To estimate % cover, imagine vertically projecting each vegetation layer onto the ground and estimate how much of the ground would be covered