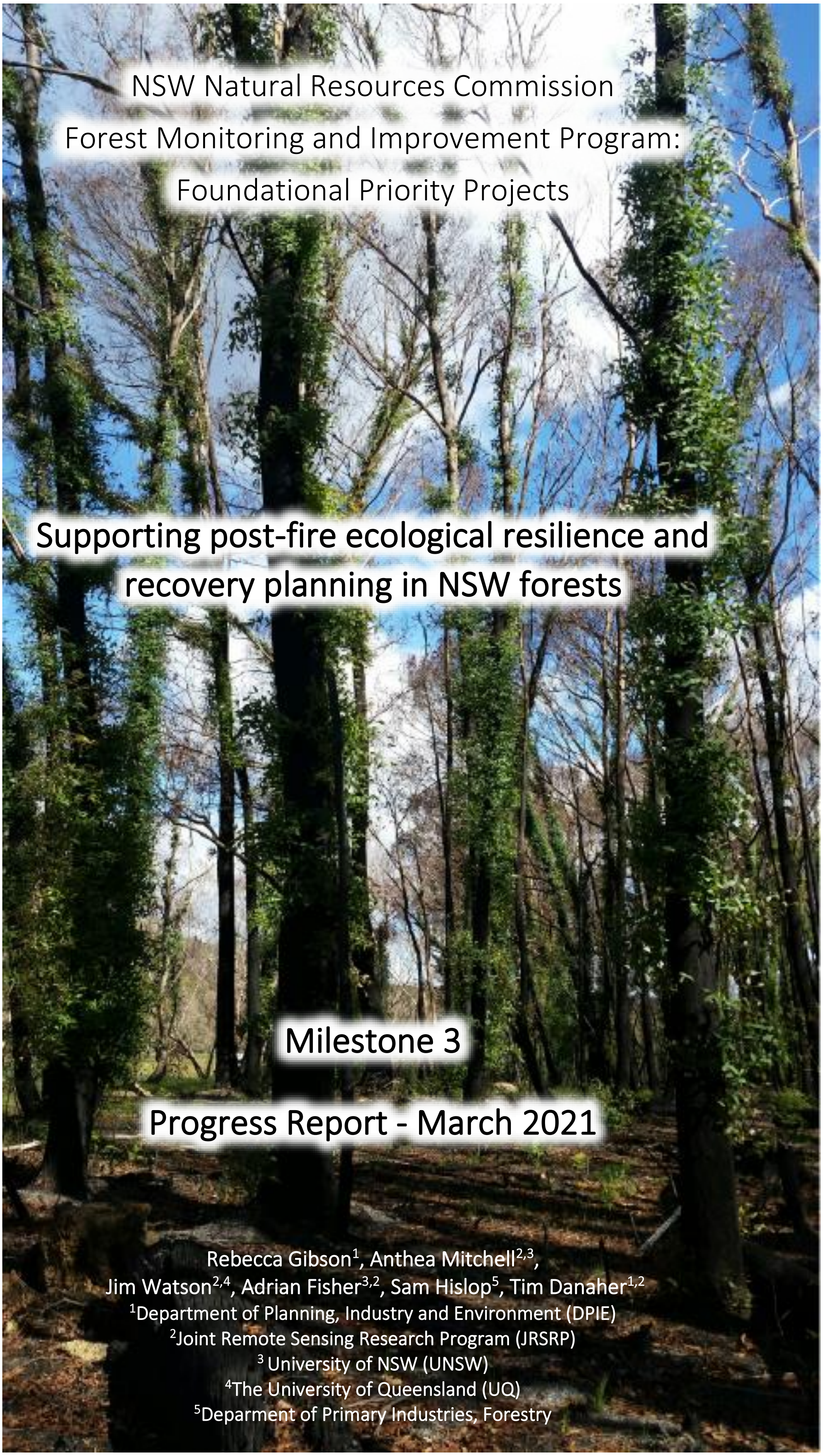

NSW Natural Resources Commission
Forest Monitoring and Improvement Program:
Foundational Priority Projects

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

## Milestone 3

## Progress Report - March 2021

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# Contents

# 1. Summary of Progress

### *Monitoring and predicting post-fire vegetative recovery.*

At the request of the NRC to support Coastal IFOA management inquiries, in February 2021 we delivered preliminary products covering the 2019/20 NSW fire ground including 1-year post-fire spectral recovery and predicted years to recovery. We also provided a comprehensive statistical summary of the distribution of area (ha) and proportions of boundary units across the spectral recovery classes and predicted years to recovery for numerous management zones. The preliminary spectral recovery product likely overestimated the absolute recovery values, due to the extreme preceding drought conditions coupled with drought-breaking rains from the end of the fire season. Nonetheless, the preliminary products served as an adequate relative comparison of values, particularly for within a local area. We continue exploration of spectral indices and a robust method for defining the pre-fire state for the spectral recovery products and building the volume of training data for the predicted years to recovery.

### *Historical fire severity derived products*

We completed a proof-of-concept case study of historical fire severity and derived products for the Blue Mountains region to support recovery planning and inform the development of fire reporting metrics potential indicators of ecological resilience. Data products and statistical analyses of patch-based metrics were delivered to NPWS senior management in March 2021. The results demonstrate the application of patch-based metrics for understanding landscape patterns in unburnt patch configuration following a single fire, as well as long unburnt refugia. The study highlights the need to interpret the results with a lens of appropriate ecological context, as connectivity between patches depends on the species or ecological function of interest. Understanding a composite index, such as patch-based metrics, as representing ecological 'health' or 'resilience' needs to be used in conjunction with more specific measures based on known fire responses. Further integration of this research into our broader post-fire recovery monitoring research will aim to provide quantitative evidence and further understanding of the effect of unburnt canopy patchiness on ecological resilience.

### *Radar method exploration*

One of the aims of our project is to evaluate the potential use of radar in post-fire recovery monitoring. As a first step, we are assessing the effectiveness of Sentinel 1 (C-band) for mapping fire extent and severity, given the extensive training and validation dataset we have developed through the FESM project. This will provide good insight into the potential capability of Sentinel 1 for mapping fire effects, including post-fire recovery. We have used intensity differencing of pre- and post-fire Sentinel-1 data to test its performance using a random forest machine learning framework. This provides independent testing on quantified known measures of immediate post-fire effects on vegetation. Preliminary results indicate the capacity of Sentinel 1 to detect burnt forest with different fire severity levels is highly variable. C-band sensitivity to burn severity may be limited to areas with significant canopy structural change, most notably in high-extreme fire severity classes. We continue to process and analyse data covering more case study fires and evaluate the options for use of radar in a post-fire recovery monitoring workflow.

### *TLS field data capture and processing*

The Terrestrial Laser Scanner (TLS) field data campaign has continued to expand with additional permanent monitoring sites established. Some delays in the planned schedule have occurred due to extensive rainfall and localised flooding restricting fieldwork through late summer and early autumn. We now expect this may result in a reduced number of site revisits within the timeframe of this project. We continue to make progress on the workflow for processing and analysing the TLS data.

## 2. *Monitoring and predicting post-fire spectral recovery*

### Observational post-fire spectral recovery

A key component of our research is to develop a method that estimates the proportion of vegetative regrowth relative to the unburnt or pre-fire state, with the view to possible integration with the DPIE-RFS semi-automated fire extent and severity mapping system (FESM). Our research has explored candidate indices and methods of defining the pre-fire state, but testing is on-going, particularly for quantitative performance assessment against high precision TLS field data. At the request of the NRC in early 2021, a preliminary spectral recovery product was rapidly generated for 1-yr post-fire across the 2019/20 fire ground in NSW.

*Method*

Based on current literature of the performance of spectral indices from optical sensors for estimating post-fire recovery, indices that incorporate short-wave infrared (SWIR) bands are more successful due to sensitivity to forest structure, moisture, shadowing, and vegetation density. The Normalised Burn Ratio (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 than many other spectral vegetation indices, particularly over longer recovery timeframes. The preliminary 1-yr post-fire NBR spectral recovery product is based on the proportion of the post-fire NBR, relative to the pre-fire NBR.

A prototype scripted workflow for processing the spectral recovery product was written to align the post-fire spectral recovery mapping with the FESM severity mapping system. Spectral recovery maps were produced on a fire-by-fire basis for all fires mapped by FESM in the 2019/20 fire (fires >10ha). The NBR recovery percentage was then reclassified into pixel values from 0 to 10 (see Figure 1). The NBR spectral recovery maps for individual fires were mosaicked into a state-wide product and masked for burnt area as defined by the FESMv3 2019/20 state-wide mosaic (Dec 2020). A comprehensive analysis of summary statistics of area and proportions in each spectral recovery class for numerous land management units and landscape regions was also provided, to assist with local and regional comparisons and support land management decisions.

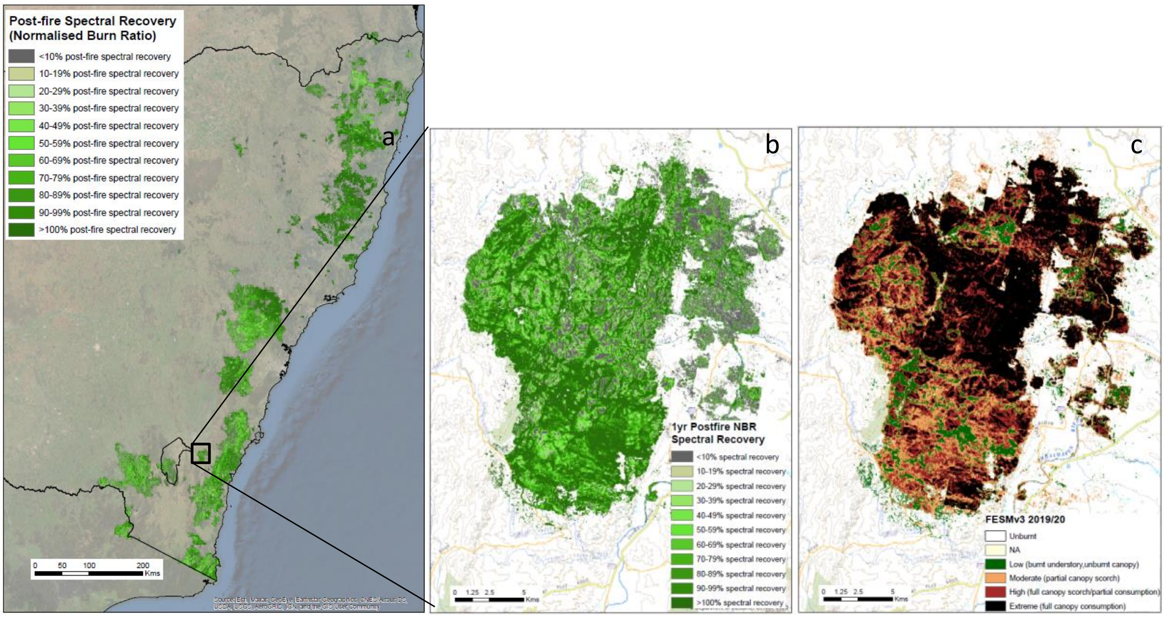



Figure 1 a) 1yr post-fire NBR spectral recovery for the NSW 2019/20 fire ground b) a closer view subset of the 1yr post-fire NBR spectral recovery and c) FESMv3 severity map for the original 2019/20 fire.

*Interpretations and Further Research*
Spectral indices are unitless values that do not directly measure quantitative biophysical properties. This is one of the major limitations of optical sensors in estimating structural effects of fire. Indices measuring the relative sub-pixel fractions of bare, photosynthetic, non-photosynthetic cover, that are calibrated with an extensive network of high-quality field data, may provide a useful 2-dimensional remote sensing surrogate to estimate the quantity of organic matter consumed by fire and subsequent recovery. We will continue to develop and test spectral recovery models with fractional cover indices.

Long standing drought conditions preceded the 2019/20 fire season, resulting in unprecedented widespread fuel dryness. The year following the 2019/20 fires has seen widespread drought-breaking rains with *La Nina* conditions. Disentangling spectral recovery from fire as distinct from the mixed signals of pre-fire vegetation dryness and post-fire vegetation wetness is a significant challenge for remote sensing of post-fire fire recovery. The preliminary 1-year post-fire NBR spectral recovery product does not sample the pre-fire state from a representative long-term baseline condition in which to estimate the recovered condition against. Therefore, the absolute values of spectral recovery in the preliminary product are likely to be an over-estimate and will be most useful for relative comparisons across the state.

## Modelling predicted recovery rate

Information about spectral recovery from past fires can be harnessed to 'predict' future recovery durations, based on knowledge about vegetation type, location, fire severity, etc. Initial exploratory analysis of spectral recovery following past fires in NSW indicate substantial differences across bioregions. This analysis is based on human interpreted reference samples (~1000 randomly assigned 1-hectare patches). A preliminary predicted recovery product was generated at the request of the NRC across the 2019/20 fire ground in NSW (Figure 2). This will help to identify vulnerable areas where management interventions may be most beneficial. A comprehensive analysis of summary statistics of area and proportions in each spectral recovery class for numerous land management units and landscape regions was also provided, to assist with local and regional comparisons and support land management decisions. We continue to build the volume of training data for the predicted years to recovery and further testing aims to improve model accuracy.

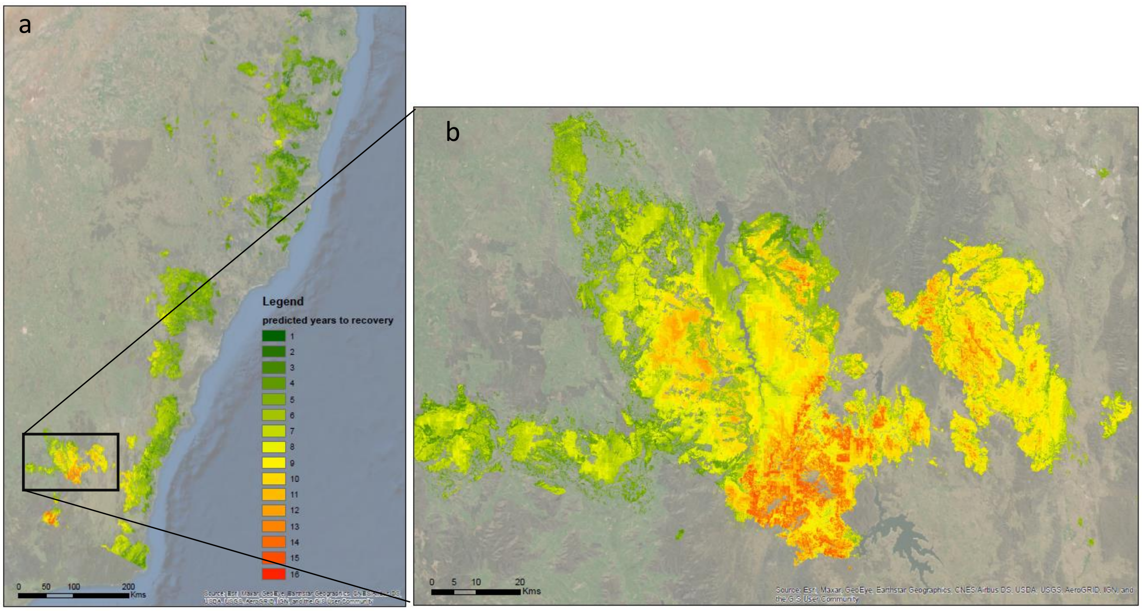



Figure 2 Predictive model of the number of years to spectral recovery for a) the NSW 2019/20 fire ground and b) the southern rangelands.

## 3. Historical severity and derived products

### *Background*

We have recently been involved in a package of work at the request of the NPWS Deputy Secretary and senior management for a rapid assessment of the effects of fire on reserves within the Blue Mountains area, with a view to informing appropriate indicators used to measure 'ecological health'. Although this case study was not in the original scope of work for this research project, the objectives closely align so the time investment was considered mutually beneficial and complementary. Directly working with senior land managers to craft fit-for-purpose tools derived from remote sensing of fire is a major benefit to the outcomes of our project.

Existing indicators of effects of fire focus on fire frequency, time since last fire and inter-fire interval as a measure of whether the fire regime is appropriate for the ecosystem. The measurement of other variables such as severity and patchiness may provide improved understanding of the impacts and response of flora, fauna and ecosystems to fire. Unburnt patches within a fire extent may act as refugia, facilitating survival and persistence of species. However, patchiness and edge effects may have contrasting values depending on the ecological context.

There is uncertainty about the appropriate scale at which unburnt mosaics should be maintained, and this will vary between ecosystems. Furthermore, it is unlikely that the unburnt patch configuration resulting from a single fire event will provide robust information about ecological resilience. However, long unburnt refugia over 10, 20 and 30 years may provide more significant insights.

### *Method*

#### *Fire severity derived products - unburnt refugia*

The first major component of this case study was to map historical severity for the Blue Mountains study area. The previously completed work in adapting the sentinel 2 FESM algorithm for application on Landsat imagery was the prerequisite that allowed the Blue Mountains archive from 1989 to 2020 to be mapped. Fire year mosaics were produced by compositing the individual severity maps in each fire year. A binary reclassification of the FESM severity classes was made to represent burnt canopy and unburnt canopy. Using the burnt canopy fire year mosaics, time since canopy fire and canopy fire frequency products were subsequently generated.

To provide greater ecological context of unburnt refugia (unburnt canopy in 2019/20 and unburnt canopy for >30yrs), vegetation structural formation mapping (Keith formations) were used to divide the landscape. Differences between vegetation types impacts fire behaviour, plant responses to fire and habitat and resources available for animals. The 3 most common vegetation types in the Blue Mountains were used to subset the unburnt canopy mapping: dry sclerophyll, wet sclerophyll and heathlands. These images were used for the patch-based landscape pattern analysis.

FRAGSTATS metrics selected for this case study included class area, patch density, Euclidean nearest neighbour distance (mean, standard deviation, and coefficient of variation), and cohesion. Unburnt canopy products (2019/20 and >30yrs) by vegetation types were used as the input images, and were clipped by 3 landscape sampling plot sizes; 500m radius, 5km radius and the whole Blue Mountains study area. The open-source standalone software FRAGSTATS v4.2.1 was used to build a fragstats categorical model (.fca), a class descriptors file (.fcd) and a fragstats batch import script (.fbt). This model set up was then executed for each veg type-landscape scale and temporal scale (unburnt canopy 2019/20 vs unburnt canopy >30yrs) combination.

## *Results*

### *Landscape pattern analysis of patch metrics*

There was high variation in all patch metrics between vegetation type, spatial (sample plot site) and temporal (2019/20 vs >30yrs) scales. In some cases, this is reflective of the relative abundance of the vegetation types in the landscape, with dry sclerophyll dominating the area and heathlands representing a small proportion. Patch density (n/100ha) was higher for the smaller sampling units, for all vegetation types and temporal scales. Spatial scales of investigation may impose limitations on some metrics by establishing the lower and upper limits of resolution for the analysis of landscape pattern composition and configuration. Thus, caution is advised in comparing values calculated for metrics among images with different resolutions.

### *Interpretation and further work*

The results so far demonstrate the application of fragmentation statistics for understanding landscape patterns in unburnt patch configuration following a single fire, as well as long unburnt refugia across several decades of fire impacts. Connectivity between patches depends on the species or ecological function of interest. Patches that are considered connected from the perspective of bird dispersal might not be so for lizards, seed dispersal or fire spread. While unburnt patches within a fire extent may act as refugia, facilitating survival and persistence of species, patch metrics may represent contrasting values depending on the ecological context. For example, high patch density may increase habitat suitability for some animal species, for example, it may increase their ability to use and/or recolonise burnt areas. In contrast, high patch density can increase edge effects such as predation rates, depending on the species and ecosystems. Understanding a composite index, such as patch-based metrics, as representing ecological ‘health’ or ‘resilience’ needs to be used in conjunction with more specific measures based on known fire responses. Further integration of this research into our broader post-fire recovery monitoring research will aim to provide quantitative evidence and further understanding of the effect of unburnt canopy patchiness on ecological resilience.

## 4. Sensitivity of Sentinel 1 radar to immediate post-fire effects on vegetation

### *Background*

One of the aims of our project is to evaluate the potential use of C-band radar in post-fire recovery monitoring. As a first step, we are assessing the effectiveness of Sentinel 1 (C-band) for mapping fire extent and severity, given the extensive training and validation dataset we have developed through the FESM project. This will provide good insight into the potential capability of Sentinel 1 for mapping fire effects, including post-fire recovery. We aim to also test radar-based post-fire recovery methods against the quantitative field validation data we are currently capturing (See section 6. TLS field data capture and processing).

We've used intensity differencing of pre- and post-fire Sentinel 1 data to test its performance using a random forest machine learning framework (i.e. the method used by FESM severity mapping). This will provide independent testing on quantified known measures of immediate post-fire effects on vegetation. Through comparisons of independent and combined optical and radar models, we set out to answer the following:

- What is the sensitivity of C-band radar to fire severity
- Which metrics assist in discriminating fire severity
- How does a combined optical-radar model perform compared to optical-only and radar-only models
- How do trained and predictive models perform

### *Method*

#### *Pre- and post-fire intensity differencing*

Sentinel 1 and Sentinel 2 pre- and post-fire image stacks were prepared for 8 study sites (including Sri Ivan, White cedars, Wollemi, Holsworthy, Sir Bertram RNP, Tathra, Mt Canobolas and Pilliga) where historic fire events were observed (2017-2018). Sentinel 1 data were orthorectified and radiometrically calibrated to gamma0 using ESA's SNAP v7.0 software. Pre- and post-fire images were differenced and clipped to the extent of each site. Dr Michael Chang (Macquarie University) assisted in the analysis.

#### *Independent and combined fire severity models*

Using a cross-validation framework with independent training and validation data, we have systematically compared multiple indices derived from optical, radar and secondary texture indices across different pixel window sizes (Table 1). We also compared the integration of radar and optical data in combined models. Training data for unburnt and burnt areas (5 severity classes) were identified on ADS imagery. Site trained models (referred to as 'trained' from hereafter) are compared against 'predictive' models (using data from all other case study fires).

Table 1 Matrix of variables used in the comparison of models. The base index, texture statistic and pixel window size were combined to produce the input indices.

| Sensor type | Base index | Texture statistic | Pixel window size |
|---|---|---|---|
| reflectance | dNBR | Mean | 5 |
| reflectance | RdNBR | Variance | 7 |
| reflectance | SWIR dNBR2 | Contrast | 11 |
| reflectance | SWIR RdNBR2 | $2^{nd}$ moment | |
| fractional cover | Total cover | Homogeneity | |
| fractional cover | Bare cover | Dissimilarity | |
| radar | Radar - VV | Correlation | |
| radar | Radar - VH | | |

Balanced accuracy statistics were generated, as well as overall accuracy and Kappa values, which determines the statistical agreement between the model and the validation data and allows comparative performance between models. For each model and the predictive model including all input indices, we calculated the mean decrease in Gini (Gini impurity criterion), which measures the similarity of a given element with respect to the rest of the classes and is used to find the best split selection at each node of the random forest decision tree. The mean decrease in Gini was ordered from highest to lowest, to rank the input indices according to variable importance.

*Results*

Here we present a subset of the preliminary results, to visually demonstrate the comparative mapping for the Wollemi and Sir Bertram RNP fires.

*Wollemi*

Wollemi is composed of mostly medium open eucalypt forest and was affected by a fire event between 28/1 - 15/2 2018. The darkest areas in the pre- minus post-fire images mostly fall in areas of layover/shadow where the backscatter is considered unreliable (Figure 3a. and Figure 4a). Brighter areas are where the post-fire backscatter is lower than the pre-fire backscatter and are likely burnt. The purple tones in the RGB colour composite represent areas where the VV backscatter has increased post-fire, suggesting more severe burning in these areas.

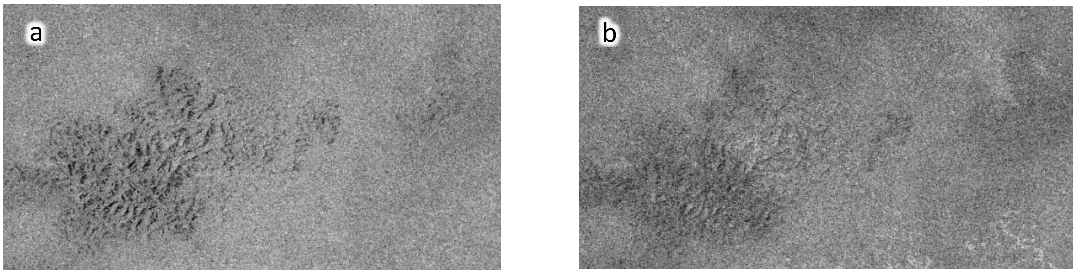



Figure 3 a) VV pre- minus post-fire difference and b) VH pre- minus post- fire difference

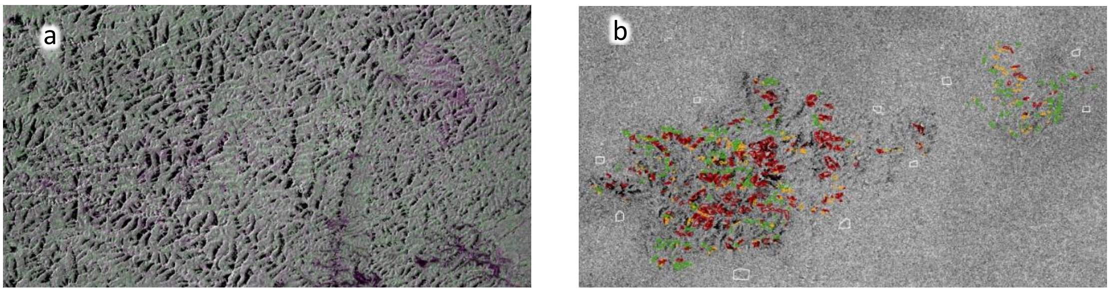



Figure 4 a) Post-fire VV:VH:VV RGB colour composite with layover/shadow mask overlain (black). The layover/shadow mask shows areas of unreliable backscatter in steep terrain, and b) VV pre- minus post-fire difference with fire severity training polygons overlain

There is high variability in the co-polarized VV and cross-polarized VH backscatter response in both burnt and unburnt forests at Wollemi. VV backscatter increases with increasing fire severity. The mean pre- minus post-fire VV difference shows negative values for moderate-high severity classes (Figure 5), and the majority of ROIs in classes 3 - 5 show negative mean VV difference. Likely there are some areas with enough canopy consumption that the radar signal is interacting with exposed trunks or the ground surface, thereby increasing the VV backscatter.

VH backscatter decreases with increasing fire severity. The mean pre- minus post-fire VH difference shows positive values for all severity classes (Figure 5). The post-fire VH backscatter is lower, particularly in high-extreme severity classes, as there are less scatterers in the canopy.

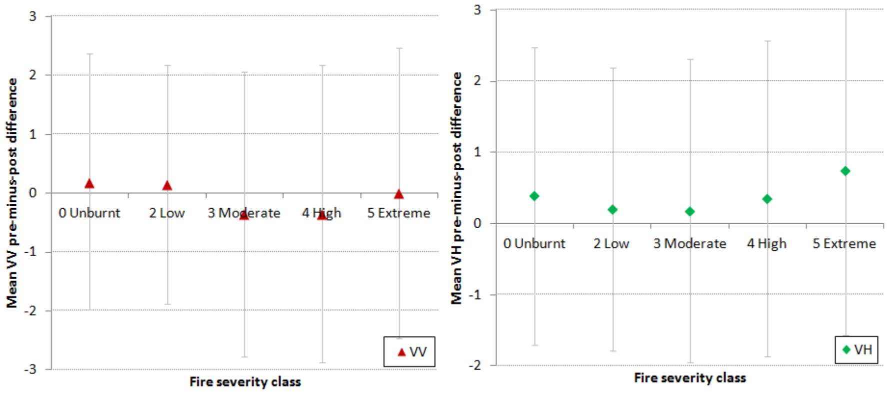



Figure 5 Scatter plots of mean pre- minus post-fire for VV (red triangle) and VH (green diamond) intensity difference for ROIs in unburnt and fire severity classes 2 - 5 at Wollemi. Standard deviations shown in grey bars.

Trained random forest (RF) models (i.e. includes severity training data for the target fire) outperform predictive models (i.e. excludes severity training data for the target fire, and predicts using all other fires in the training dataset; Figure 4). The radar-only trained RF model exhibits the most sensitivity to the high severity class where the most structural change in the canopy is observed.

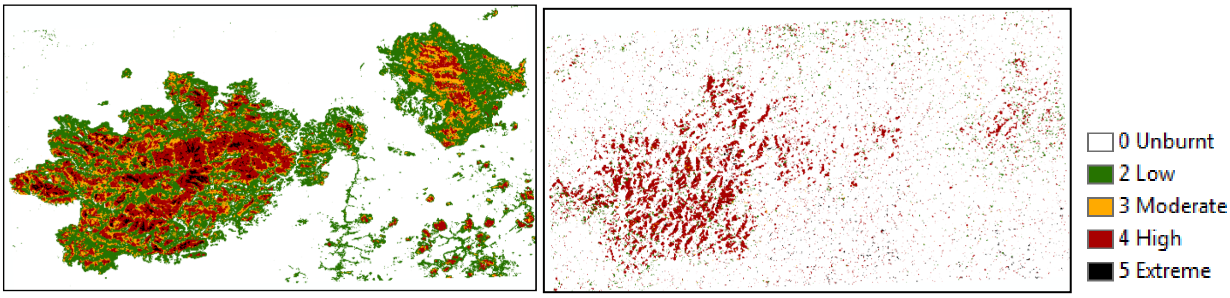



Figure 6 a) Optical-only trained RF model result and b) Radar-only trained RF model result

<u>Sir Bertram RNP</u>

The site in the Royal NP comprises mostly medium eucalypt woodland, scrub, heath and patches of rainforest. The area was affected by a fire event between 20/1 – 25/1 2018. Brighter areas in the pre- minus post-fire VH image have lower post-fire backscatter and were burnt (Figure 7). Darker areas in the pre- minus post-fire VV image are where the VV backscatter has increased post-fire. These areas were more severely burnt and appear in purple tones in the RGB colour composite.

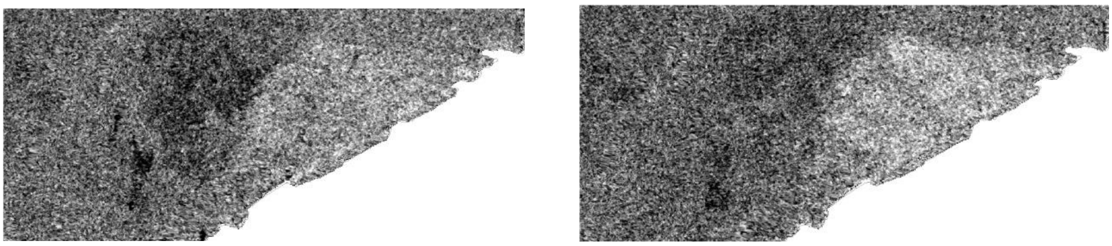


*Figure 7 a) VV pre- minus post-fire difference and b) VH pre- minus post- fire difference*

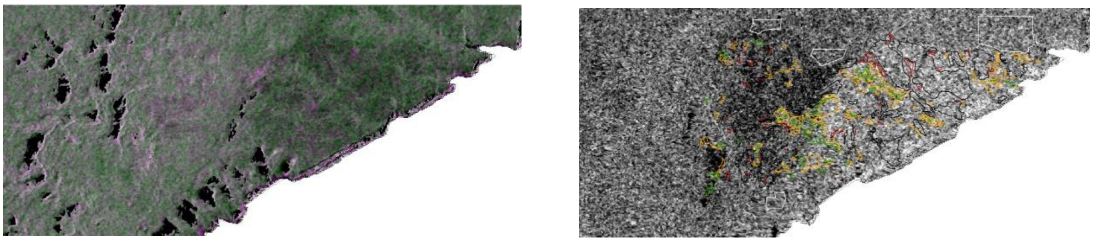


Figure 8 a) Post-fire VV:VH:VV RGB colour composite with layover/shadow mask overlain (black) and b) VV pre- minus post-fire difference with fire severity training polygons overlain

The mean pre- minus post-fire VV difference shows negative values for unburnt-low and extreme classes, and in Figure 8, the majority of ROIs in these classes show negative mean VV pre- minus post-fire difference. Many of the ROIs in inland heath and tall scrub were extremely burnt and an increase in VV backscatter was observed in these areas indicative of greater surface scattering. The mean pre- minus post-fire VH difference shows positive values for high-extreme severity classes (Figure 9). ROIs in centrally located forest patches exhibited lower post-fire VH backscatter. On the coast, a decrease in VH backscatter was observed in heath while the response at VV was mixed. ROIs in these areas corresponded with extreme fire severity.

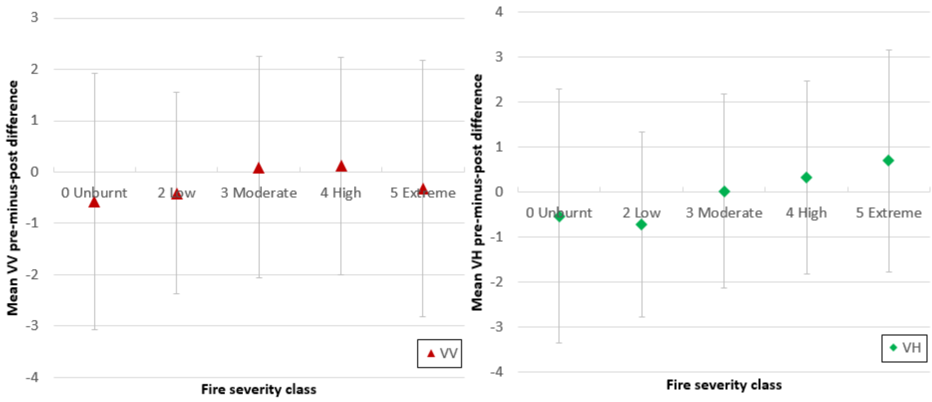



Figure 9 Scatter plots of mean pre- minus post-fire VV (red triangle) and VH (green diamond) intensity difference for ROIs in unburnt and fire severity classes 2 - 5 at RNP. Standard deviations shown in grey bars.

Trained RF models typically outperformed the predictive models for mapping fire severity. The predictive models appeared to over-predict the high severity class. Trained radar-only and optical-only RF models are comparable for the extreme severity class, however the moderate severity class is better predicted in the optical-only model.

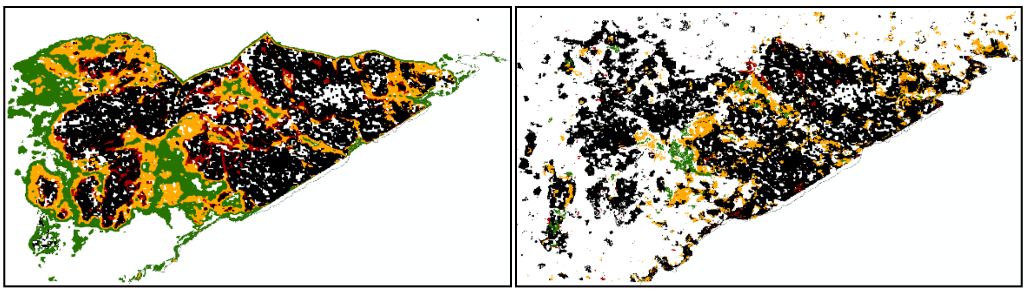


Figure 10 a) Optical-only trained RF model result and b) Radar-only trained RF model result

## Initial findings and further work

From the 2 out of 8 sites that have been processed, the following observations are made:

- High variability in VV and VH backscattering is observed in unburnt and burnt forests on account of radar speckle and the range of fire severity classes encountered.
- The capacity of C-band SAR to detect burnt forest with different fire severity levels is highly variable. C-band sensitivity to burn severity may be limited to areas with significant canopy structural change, i.e., where leaves and branches are partially or wholly consumed, most notably in high-extreme severity classes. Changes in canopy structure directly influence the C-band signal, with changes in volume and multi-path volume scattering mechanisms.
- VH backscatter shows increasing sensitivity to fire severity. A decrease in post-fire VH backscatter is observed in high-extreme severity classes, indicative of the loss of scatterers in the canopy.
- With the loss of canopy volume in burnt forest, there is potential for the radar signal to interact with the ground surface, resulting in elevated VV backscatter.
- Trained RF models have high overall capacity for predicting fire severity at that site, however, perform poorly outside the target area.

The remaining 6 sites will be processed and analysed.

## 5. Sensitivity of Sentinel 1 radar to longer-term post-fire vegetation recovery

### *Background*

Part of our ongoing research is assessing the application of Sentinel 1 for post-fire recovery mapping. We aim to evaluate the sensitivity of a radar time-series approach in detecting post-fire recovery for different fire severity classes and vegetation cover types.

Active sensors such as synthetic aperture radar (SAR) are more sensitive to forest biomass and structural properties compared to passive instrument data. SAR data are also not obstructed by cloud cover or influenced by solar angle. However, the present major limitation for the application for post-fire recovery monitoring of SAR data is the spatial coverage and historical data availability to assess accuracy. Topography and rainfall can also strongly influence the radar backscattering response and so understanding the local environmental context is important when interpreting SAR imagery.

### *Method*

Monthly time-series of Sentinel-1 data were processed for 8 sites to investigate post-fire recovery response. The sites represent areas affected by contemporary (2019/20) and historic fire events (2017/18):

- 2-year monthly time-series (2019-2020) of Sentinel-1 were processed for Busbys and Mt Nardi, Shark ck, Bees Nest, Kingsgate and Clouds Creek, Bills crossing and Kaputar.
- 4-year monthly time-series (2017-2020) were processed for the Pilliga, Mt Canobolas and Putty rd.

Sentinel 1 data were co-registered, orthorectified and radiometrically calibrated to gamma0 (db) using ESA SNAP v8.0. Batch processing was implemented on DPIE's high performance computing system (SDC). The mean and standard deviation of the backscatter was extracted for regions of interest (ROIs) identified on ADS and/or FESM mapped severity classes.

### *Results*

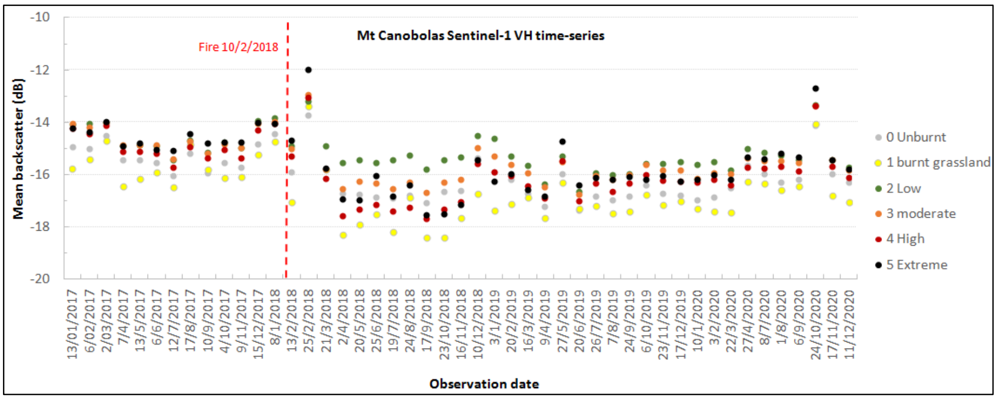
Initial findings from the time-series analysis of C-band backscatter and mapped fire severity classes for Mt Canobolas and Kaputar are presented here.

*Mt Canobolas*

The fire event at Mt Canobolas occurred between February 10 - 16, 2018 and mostly affected areas of eucalypt woodland. Some small patches of surrounding softwood plantation and non-forest areas were burnt as well. Visual interpretation of timeseries imagery indicated burnt areas show lower VV and VH backscatter compared to the pre-fire scene. Subsequent increase in brightness in these areas by the end of the time-series is indicative of recovery of the vegetation. Unburnt areas show limited change in brightness.

Lower VH backscatter is observed in burnt forest as there is less vegetative material to interact with in the canopy. A decrease in VH backscatter is observed at Mt Canobolas following the fire event. A gradual increase in VH backscatter is observed thereafter as the canopy recovers. The post-fire VH backscatter decreases as fire severity increases. In more severely burnt forest, there is less opportunity for volume scattering in the canopy and hence lower VH backscatter. Recovery of the VH signal is proportionally greater in the high-extreme severity classes than the low-moderate severity classes (Figure 11). VV backscatter also decreases post-fire but the decrease is of a lesser magnitude than at VH. This suggests that although the canopy was burnt, it was not burnt extensively to the point where the trunks or ground surface were exposed to the radar signal.

C-band VH is sensitive to grass volume and burnt grassland exhibits lower VH and slightly higher VV backscatter compared to its pre-fire state (Figure 11). Unburnt areas exhibit a decrease in VH backscatter and relatively stable VV backscatter. The 2 peaks in VV and VH backscatter observed on 25/2/2018 and 24/10/2020 are likely due to rainfall in the days prior to imaging (Figure 11).



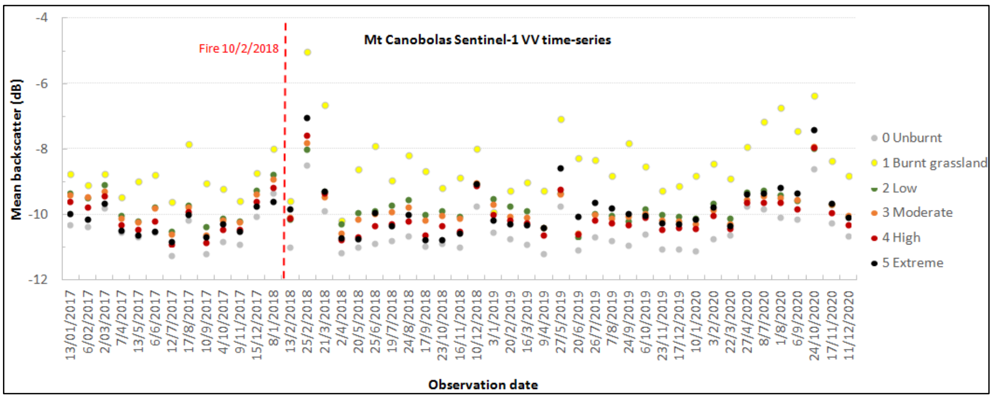




Figure 11. Time-series of mean VH (top) and VV (bottom) backscatter extracted from ROIs and averaged by severity class.

Short-term regrowth is indicated by the amount of backscatter increase in the first year after a fire event, while longer-term recovery is indicated by the difference in backscatter with respect to pre-fire levels. Positive changes in VH backscatter were observed 1 year after the fire event. The magnitude of change was greatest in the high-extreme severity class. It is possible that in more severely burnt areas, new scatterers are being generated at a faster pace than in areas burnt at lower severity. Over the long-term, the magnitude of recovery is greatest in the high-extreme severity classes.

*Kaputar*

The fire in Kaputar occurred between 17/10 - 29/11 2019 and mostly affected areas of eucalypt woodland. Burnt forest exhibits lower VH and mixed VV backscatter compared to the pre-fire image. Some of the burnt areas have recovered as indicated by the increase in brightness at the time-series end. Unburnt forest shows limited change in backscatter over the time period.

A decrease in VH backscatter was observed post-fire in high-extreme fire severity classes (Figure 12). The loss of vegetative material in the canopy means there are less opportunities for volume scattering at VH. The VH backscatter in these classes increased to pre-fire levels by around 6 months. Post-fire VV backscatter did not change significantly, however a gradual increase in VV was observed for all severity classes in the first 6 months post-fire. The backscatter response from unburnt areas was reasonably stable across the timeframe.

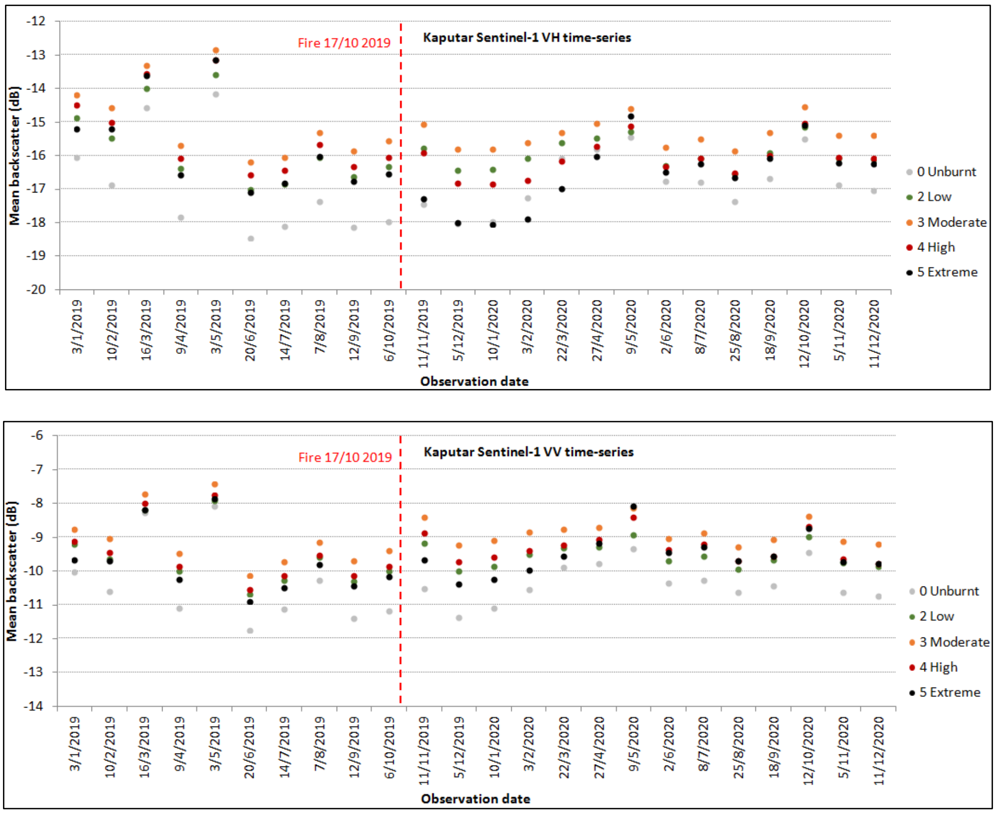



Figure 12. Time-series of mean VH (top) and VV (bottom) backscatter extracted from ROIs and averaged by severity class.

*Further work*

Analysis of monthly time-series of Sentinel 1 data over historic and contemporary fire affected sites is ongoing. Radar indices and proportionate recovery to pre-fire levels will be investigated. The potential application of C-band radar in post-fire recovery monitoring will be evaluated in the process.

## 6. TLS Field Data Capture and Processing

### *Long-term monitoring survey plots*

We have continued setting up permanent TLS post-fire recovery monitoring sites (see *Table 2*). Several more sites have been established at Mt Kaputar and in the Pilliga region. Our proposed sites in the Shark Creek fire in Yuragir NP have been located with site reconnaissance but fieldwork was postponed due to rain. Similarly, fieldwork for the Bees Nest fire in Guy Fawkes River NP had been scheduled a couple of times but was postponed due to a persistently rainy conditions over summer and early autumn. Additional single-visit sites with longer time since fire may also be opportunistically captured during our site re-visit field trips.

Table 2 Permanent TLS post-fire recovery monitoring site location details

<table>
<tr><th>Reference Fire</th><th>Fire year</th><th>Location</th><th>Site Name</th><th>Project Name</th><th>Fire Severity</th></tr>
<tr><td rowspan="4">Liberation Trail</td><td rowspan="4">2019/20</td><td rowspan="4">Clouds Creek SF</td><td>Cloudscreek1</td><td>200923_122611</td><td>unburnt/low</td></tr>
<tr><td>Cloudscreek2</td><td>200923_154324</td><td>high/extreme</td></tr>
<tr><td>Cloudscreek3</td><td>200924_102321</td><td>unburnt/low</td></tr>
<tr><td>Cloudscreek4</td><td>200924_130236</td><td>high/extreme</td></tr>
<tr><td rowspan="2">Mt Kaputar</td><td rowspan="2">2019/20</td><td rowspan="2">Mt Kaputar NP</td><td>Kaputar1</td><td>201103_144650</td><td>unburnt/low</td></tr>
<tr><td>Kaputar2</td><td>201105_091053</td><td>high/extreme</td></tr>
<tr><td rowspan="2">Dipper Rd</td><td rowspan="2">2017/18</td><td rowspan="2">Pilliga</td><td>Pilliga1</td><td>201104_092055</td><td>high/extreme</td></tr>
<tr><td>Pilliga2</td><td>201104_120320</td><td>unburnt/low</td></tr>
<tr><td rowspan="2">Whirlybrook Trail</td><td rowspan="2">2014/15</td><td rowspan="2">Pilliga</td><td>Pilliga3</td><td>201106_112412</td><td>unburnt/low</td></tr>
<tr><td>Pilliga4</td><td>201106_083738</td><td>high/extreme</td></tr>
<tr><td rowspan="2">Redbank Nth</td><td rowspan="2">2012/13</td><td rowspan="2">Pilliga</td><td>Pilliga5</td><td>201109_123446</td><td>high/extreme</td></tr>
<tr><td>Pilliga6</td><td>201110_101247</td><td>unburnt/low</td></tr>
<tr><td rowspan="2">Dipper Rd</td><td rowspan="2">2017/18</td><td rowspan="2">Pilliga</td><td>Pilliga11</td><td>201112_123013</td><td>unburnt/low</td></tr>
<tr><td>Pilliga12</td><td>201113_092733</td><td>high/extreme</td></tr>
<tr><td rowspan="2">Shark Creek</td><td rowspan="2">2019/20</td><td rowspan="2">Yuragir NP</td><td>3</td><td>TBC</td><td>unburnt/low</td></tr>
<tr><td>3</td><td>TBC</td><td>high/extreme</td></tr>
<tr><td rowspan="2">Bees Nest</td><td rowspan="2">2019/20</td><td rowspan="2">Guy Fawkes River NP</td><td>4</td><td>TBC</td><td>unburnt/low</td></tr>
<tr><td>4</td><td>TBC</td><td>high/extreme</td></tr>
</table>

### *Automated data processing workflows*

Significant investment of our time in the past few months has been focused on technical development and training of field protocols to allow for high precision repeat site surveys, as well as data management and automating workflows for file naming conventions, data storage, pre- and post-processing, and analysis. We have leveraged significant in-house expertise through our JRSRP research partner Dr Nick Goodwin, to implement much of the previously scripted workflows developed in QLD (Department of Environment and Science) through the JRSRP (Joint Remote Sensing Research Program). Ongoing development and testing are still taking place to further refine processing efficiencies and data analysis output.

# 7. Next tasks

The following section summarises the key tasks we will be focusing on over the next 8 months, before the final report due in November 2021.

### *Historical Fire Severity and post-fire recovery decision support tools*

- Continue working with NPWS fire managers on application of results from the Blue Mountains Case Study
- Investigate quantitative evidence and further understanding of the effect of unburnt canopy patchiness on ecological resilience.
- Secure resourcing to allow expanding historical fire severity mapping for other case study regions in NSW

### *Optical sensor analysis*

- Further explore candidate spectral and fractional cover indices across a wider range of vegetation, climate and topographic conditions,
- Further investigate rigorous methods for defining the pre-fire state for relative comparison or the post-fire state, and explore application of local unburnt reference sites.
- Validation of indices against quantitative TLS field data

### *Radar sensor analysis*

- Further co-registration and processing of monthly sentinel-1 time-series and exploration of time-series metrics for post-fire recovery
- Continue comparative analysis of radar-only, optical-only and combined approaches

### *TLS field data*

- Continue setting up permanent TLS monitoring sites
- Refine post-processing data analysis scripted workflow
- Conduct preliminary analysis of TLS field data comparisons to satellite-derived relative recovery products.
- Secure resourcing to allow expanding TLS monitoring site network and on-going site revisits

### *Predictive post-fire recovery risk modelling*

- Continue building the reference sample database
- Generate spatial data products of predicted recovery rates over the 2019-2020 fire extent