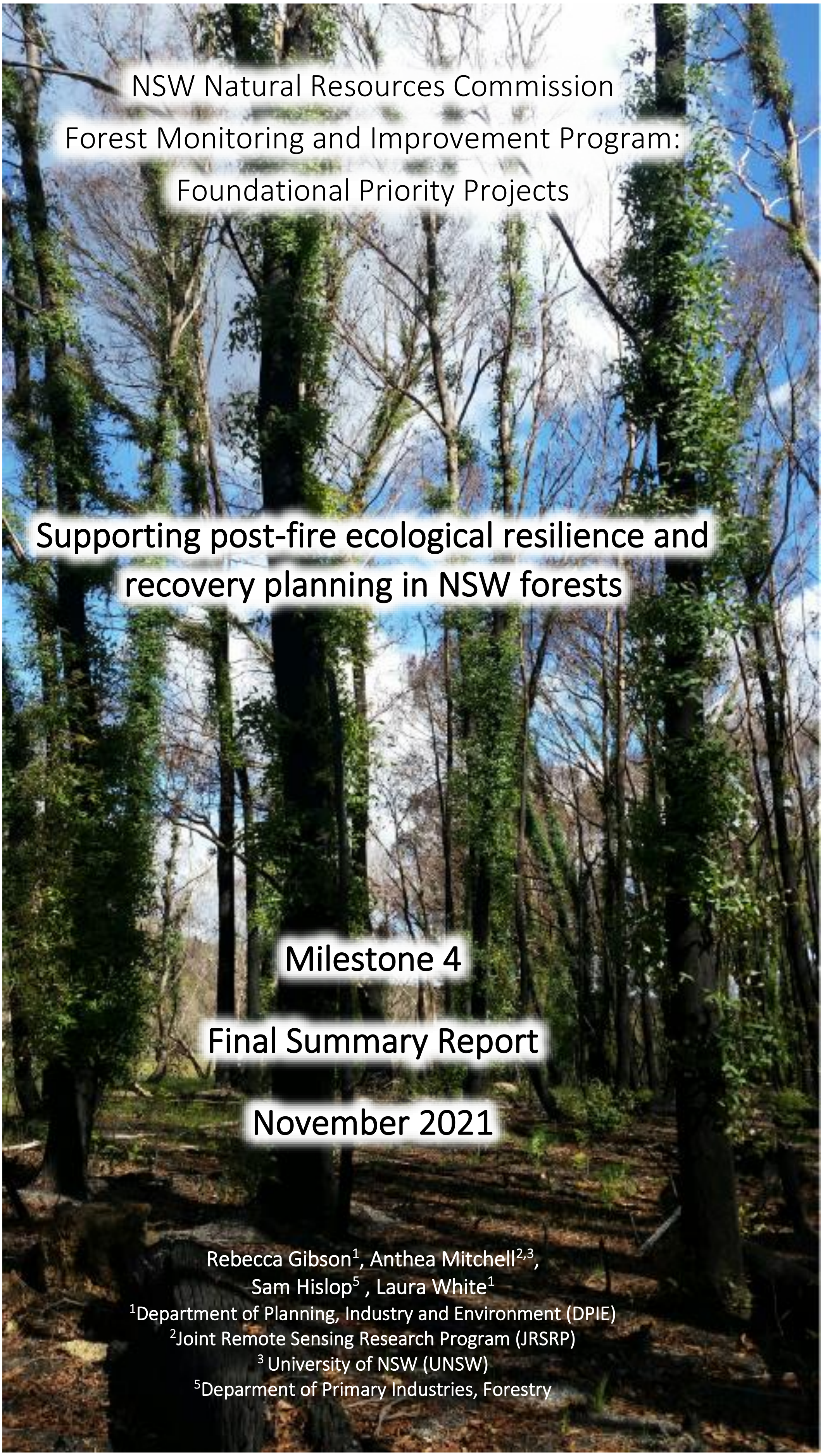

NSW Natural Resources Commission
Forest Monitoring and Improvement Program:
Foundational Priority Projects

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

Milestone 4

Final Summary Report

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Project Aims

The project '*Supporting post-fire ecological resilience and recovery planning in NSW forests*' was funded by the Natural Resources Commission Forest Monitoring and Improvement Program's Foundational Priority Projects scheme. The focus of the project was to develop new remote sensing tools to support forest managers to undertake risk assessments and subsequently plan and report on post-fire ecological recovery. One of the major project aims was to develop a remote sensing method of monitoring post-fire spectral recovery, to estimate vegetative regrowth since a forest fire event for assessment at regular post-fire intervals. We have developed an innovative approach to post-fire spectral recovery monitoring through undertaking literature reviews, model development and testing, and field validation. The post-fire spectral recovery monitoring methodology was designed for integration with the NSW fire extent and severity mapping program. Our research has also focused on complementary lines of research including predictive modelling of years to recovery, historical fire severity and landscape pattern analysis, and testing radar capabilities. This report presents the Final Project Summary Report.

Summary of Outcomes

1. Method for monitoring post-fire spectral recovery

Our research has explored a suite of candidate indices, including derivatives of the normalised burn ratio (NBR), fractional cover indices, and tasselled cap transformation indices. We also extensively explored different approaches including robust definitions of the pre-fire state and the use of unburnt reference offsets.

In February 2021, the NRC requested a preliminary recovery product for an assessment of 1-year recovery following the 2019/20 fires in NSW. We delivered a product based on the post-fire NBR value, as a proportion relative to the pre-fire NBR value. This product had a major caveat that it did not sample the pre-fire state from a representative long-term baseline condition. Long standing drought conditions preceded the 2019/20 fire season, resulting in unprecedented widespread fuel dryness which would have likely reduced the pre-fire baseline spectral values, compared to a longer-term average. Therefore, the absolute values of spectral recovery in the preliminary product were likely to be an over-estimate, but it was suitable for relative comparisons across the state. A manuscript documenting this early assessment method is currently under peer review (submitted to IJWF June 2021). As part of the preliminary product, we also delivered a suite of summary statistics in each spectral recovery class for regions of interest and management units, to suit the purposes of the NRC. The tools to generate these summary statistics have been refined throughout this project.

Our research continued, focussing on overcoming known limitations of metrics of recovery that are expressed relative to a pre-fire baseline. Post-fire spectral recovery represented as a proportion of a pre-fire baseline does not necessarily indicate vegetative response following a fire event. For example, where no change occurs between the immediate post-fire and subsequent post-fire spectral index values, methods that use a pre-fire baseline would represents this post-fire value as some proportion of the pre-fire baseline (e.g. 50%). In contrast, methods that examine recovery relative to the disturbance impact would represents this scenario as having had no post-fire spectral recovery since the fire event (i.e. 0%). Furthermore, defining a representative pre-fire baseline is a significant challenge for broad scale remote sensing monitoring approaches. Our attempt to overcome these challenges has focused on an innovative new approach, quantifying stability in the post-fire environment. An example of the classified spatial map (Table 1, Figure 1) and the timeseries plot across severity classes (Figure 2 and Figure 3) for the Bell Range (‘93/94) fire are presented below.

A manuscript on the post-fire stability index is currently under peer review with an international peer-review journal.

Table 1 Standardised classification of the NBR2 Post-fire Stability Index

Pixel value	Label	Values range
13	extreme increase	> 500
12	very large increase	400 to 500
11	large increase	300 to 400
10	moderate increase	200 to 300
9	small increase	100 to 200
8	very small increase	50 to 100
7	stable range	-50 to 50
6	very small decrease	-50 to -100
5	small decrease	-100 to -200
4	moderate decrease	-200 to -300
3	large decrease	-300 to -400
2	very large decrease	-400 to -500
1	extreme decrease	< -500

Figure 1 Classified images of the NBR2 post-fire stability index for the Bell Range ('93/94) fire, for the immediate post-fire image (0yrs) to 8 years post-fire.

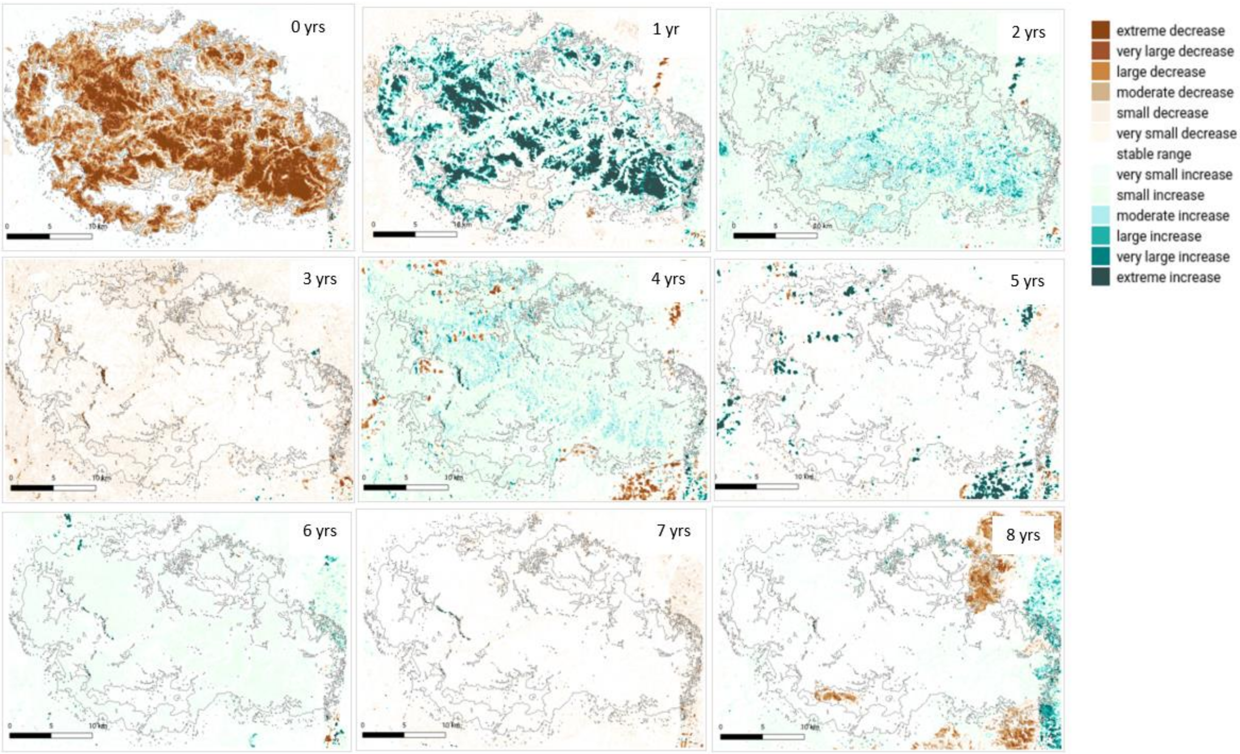


Figure 2 Timeseries plots for the NBR2 post-fire stability index method, for the Bell Range ('93/94) fire from 5 years pre-fire to 8 years post-fire.

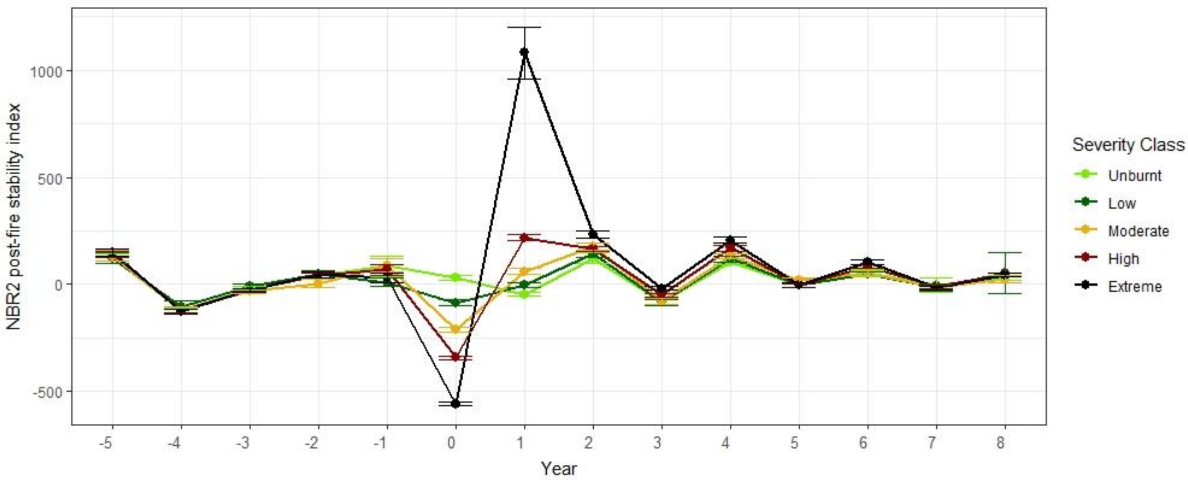
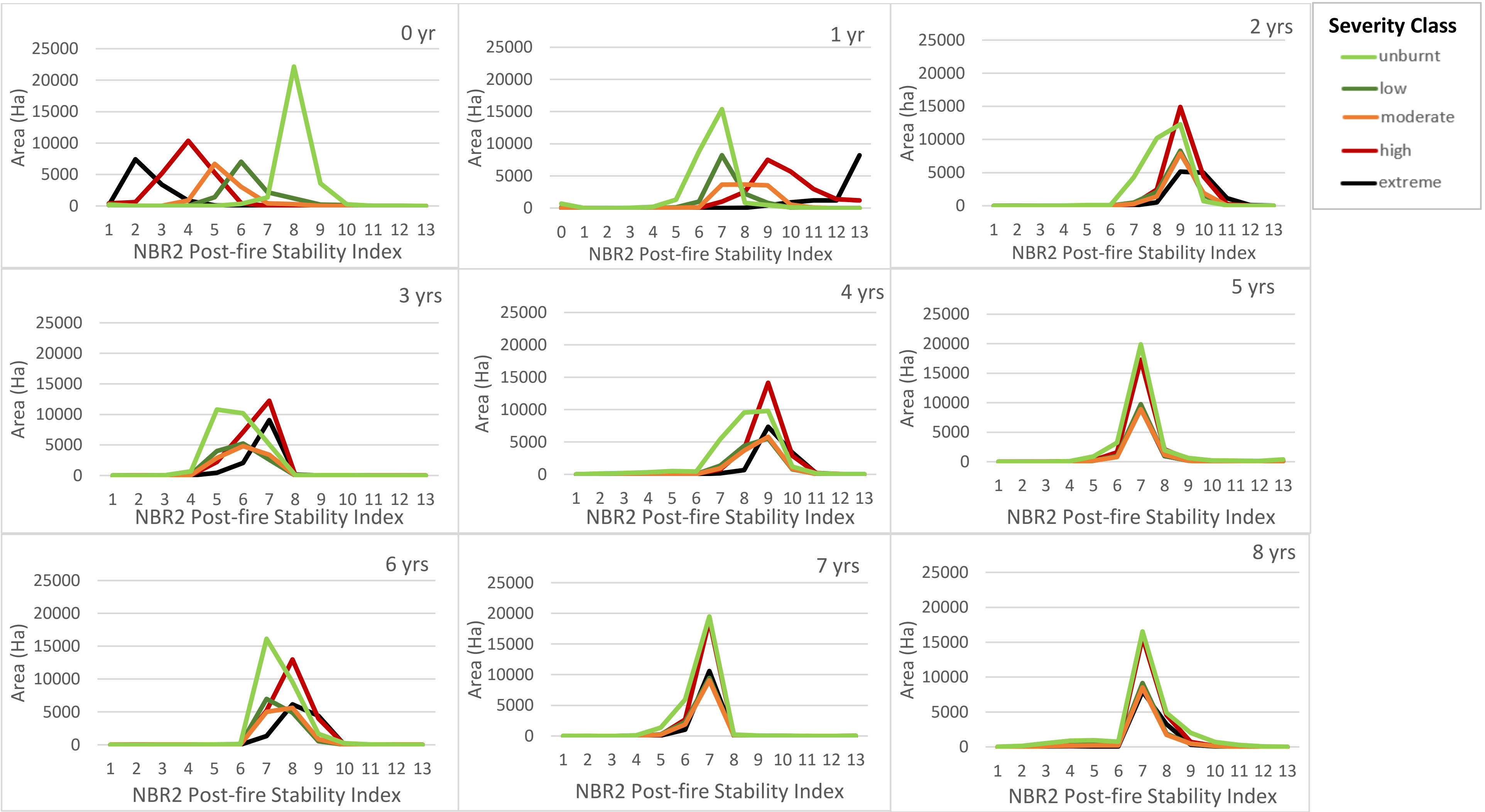


Figure 3 Plots showing the area in hectares by severity class across the NBR2 post-fire stability index classes, for the Bell Range ('93/94) fire, for the immediate post-fire image (0yrs) to 8 years post-fire.



2. Method for predicting years to recovery

Information about forest recovery from past fires can be harnessed to 'predict' future recovery durations, based on knowledge about vegetation type, location, fire severity, etc. After initial exploratory analysis of spectral recovery following past fires in NSW indicated substantial differences across bioregions, a model was developed to predict spectral recovery across forests burned in the NSW 2019-20 fires. A preliminary predicted recovery product was provided to the NRC earlier this year (2021), based on approximately 1000 reference samples.

The model training data was based on a forest disturbance reference dataset, collected as part of a separate body of work (Hislop et al., 2022). Briefly, this reference dataset contains 5000 1-hectare circular plots, randomly sampled from forested areas in each of 10 bioregions covering eastern NSW (500 in each bioregion). Each plot was systematically interpreted via a desktop exercise to attribute the disturbance history across the last 3 decades, using Landsat satellite imagery and a range of ancillary data. For each disturbance attributed, the spectral recovery duration was estimated by visually interpreting seasonal NBR time-series trajectories and noting the year when the spectral recovery returns to its pre-disturbance level.

Further work has been undertaken in the last six months to gather additional training data for the recovery model. The training dataset now contains 1932 samples. The response variable for the model was the spectral recovery duration in years. A range of predictor variables were selected to capture variation in the landscape and fire behaviour, including a range of NBR values (e.g. pre-fire, post-fire and dNBR), a range of climate variables (e.g. mean annual temperate, annual precipitation etc), and a range of topographic variables (e.g. elevation, aspect, GEDI height). A Random Forests regression model was developed in R, using the default parameters, and subsequently used to predict spectral recovery length across the 2019-20 fire extent.

The model was assessed using the internal Random Forests out-of-bag estimation. The variance in recovery duration explained by the model was 58.95%. The model indicated that the dNBR (fire severity) was the most important predictor, although even after removing both dNBR and the NBR post-fire, the model still performs reasonably well (~50% variance explained). These results suggest that forest recovery is strongly influenced by location and forest type and can, to some extent, be predicted immediately post-fire. The results indicate a level of consistency in the resilience of native eucalypt forests in southeast Australia. However, multiple fires in quick succession may hinder this resilience.

An example of the predicted recovery over the 2019-20 fire extent is shown in Figure 4. Except for the NBR directly post-fire and the dNBR (as a proxy for fire severity), the other predictor layers are largely static. The climate variables, for example, are based on averages, not post-fire conditions. This means that the model can be applied to new fires soon after the fire event, to gain initial insights into expected recovery. Incorporating multiple disturbances (e.g. two fires in quick succession) may further improve the model.

A manuscript documenting this research is currently under preparation for submission to an international journal.

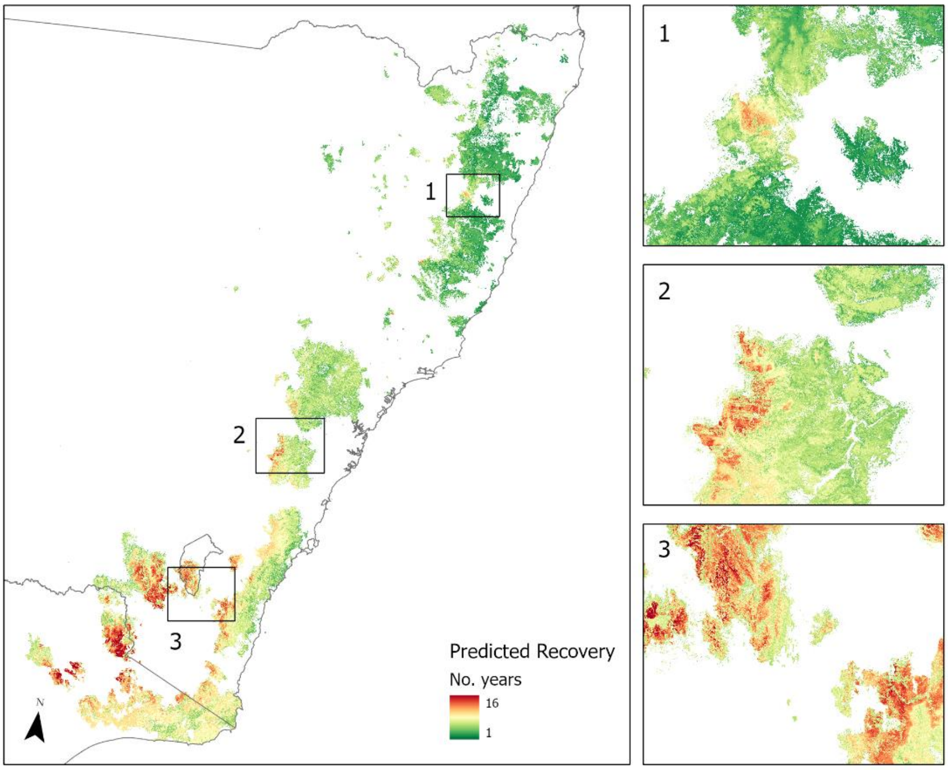


Figure 4 Predicted spectral recovery duration across the 2019-20 fire extent, with inset maps of selected regions

3. Field validation

Field data for 1yr post-fire vegetative response

During 2021, we leveraged our collaborative networks to access high quality field data captured across 88 sites burnt in the 2019/20 fires for 1yr post-fire vegetation surveys in the Blue Mountains and Alpine regions. This was not in the original scope of this project but was sought to help overcome the extensive Covid-19 restrictions and prolonged heavy rainfall that limited our planned TLS field surveys. This field data has been utilised to great effect and represents a significant gain for this project. We greatly appreciate the contributions of Dr Rachael Nolan (Western Sydney University) and Dr Josh Dorrough (DPIE EES).

Vegetation types at field survey sites included four dry sclerophyll forest types (Western Slopes Dry Sclerophyll, Sydney Hinterland Dry Sclerophyll, South-east Dry Sclerophyll, Southern Tableland Dry Sclerophyll Forests) and one wet sclerophyll forest type (Southern Tableland Wet Sclerophyll). For field survey sites in the Blue Mountains and South Coast regions, 15 plots were established in each forest type, while in the Alpine region, 28 plots had been established prior to the 2019/20 fire for a different purpose and were opportunistically re-sampled for post-fire responses, giving a total of 88 plots. The balance of field plots across severity classes was limited as low and extreme fire severity were rarely located within the same forest type. Furthermore, given the extensive burned area of the 2019-20 fire season, locating unburnt forest in some cases was difficult.

At all field plots, vegetation classification aligning with Keith (2004), and fire severity classification aligning with Gibson et al (2020) were assessed. For sampling undertaken within the Blue Mountains and South Coast regions, plot design followed Jenkins et al. (2016) with two 45 m transects; along a north-south axis and an east-west axis. For sampling undertaken within the Alpine region, plot design was a variable width 20m belt transect. At each plot, percentages were recorded of tree basal area with topkill (this includes dead stems and stems with basal resprouting only), and tree basal area that were dead (this includes dead stems only). Calculation excluded stems that had fallen post-fire or 'stags' that were dead before the fire. Some of the unburnt plots had topkill or dead trees, but these were only included if the topkill (or death) looked recent, i.e. where we could identify the species or genus. These measures were recombined to produce 3 vegetative response categories labelled as 1. no resprouting, 2. basal only resprouting, and 3. canopy cover (+/- resprouting). At all field survey sites excluding the Alpine Complex, foliage projective cover (FPC), which takes account of gaps within the crown perimeters (Macfarlane et al., 2007), was calculated from upward looking site photos, following Fuentes et al. (2008).

The central point of each plot was buffered to 45m radius and pixel values were extracted from the 1-year post-fire stability index product. Generalised linear models were used to assess whether (1) field measures (FPC, no resprouting, basal resprouting and canopy cover +/- resprouting) were correlated with fire severity classes (unburnt, low, moderate, high and extreme) and (2) field-based on field measures of post-fire response could be predicted by the candidate indices of post-fire recovery and fire severity. All statistical analyses and plots were undertaken in R (v4.1.1).

The analysis of this field validation data is included in the manuscript on the post-fire stability index, which is currently in review with an international peer-review journal.

Terrestrial Laser Scanner (TLS) monitoring

Following extensive rainfall and localised flooding restricting fieldwork through late summer and early autumn in 2021, the Covid-19 restrictions in NSW throughout winter and spring 2021 saw significant delays to our planned TLS field data campaign. This has resulted in a reduced number of site revisits that were planned within the timeframe of this project.

In lieu of fieldwork, we spent time on developing the technical processing workflow and field protocols to allow for high precision repeat site surveys. Through leveraging our JRSRP research partnerships with Dr Nick Goodwin and Dr Robert Denham, we now have an automated workflow process that generates a standard suite of products. We have processed and undertaken preliminary analyses on the TLS site data collected to date. However, the site revisit data that we were unable to capture is expected to be where powerful insights can be gained from the TLS data regarding post-fire recovery. Our TLS monitoring campaign is expected to continue into 2022 and beyond, with regularly site revisits across an expanded network, to support ongoing validation of our post-fire recovery monitoring method.

4. Historical fire severity and landscape pattern analysis

Directly working with senior land managers in NPWS to craft fit-for-purpose tools derived from remote sensing of fire has been a major benefit to the outcomes of our project. The proof-of-concept case study of historical fire severity (from 1989 to 2021) for the Blue Mountains region to support recovery planning and reporting was accepted, with a further set of 8 priority regions requested for mapping. 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. We also delivered a suite of summary statistical breakdowns of area and proportions in each class for regions of interest and management units, to suit the purposes of NPWS. We have completed 3 stages of work to deliver 30yrs of historical severity mapping and timeseries derived products for 8 priority regions in NSW. Stage 4 priority regions are to be confirmed, as well as refinements of previously delivered regions to handle missing data and incorporate end user feedback, before datasets will be made publicly available. The FESM processing of historical fires has greatly supported other aspects of this project, such as integration with the post-fire spectral recovery monitoring method and for post-processing of patch metrics.

Exploration of patch-metrics used the open-source standalone software FRAGSTATS v4.2.1 to calculate metrics selected for the Blue Mountains case study including class area, patch density, Euclidean nearest neighbour distance (mean, standard deviation, and coefficient of variation), and cohesion. This preliminary work demonstrated difficulties with interpretation the multiple metrics at varying scales. 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.

Our further research into appropriate patch-based metrics has focused on a more robust yet simplified metric of landscape fire spatial patterns, the high-severity decay coefficient (Collins et al., 2017). The method for generating this patch metric has been automated and programmed for potential integration with the FESM operational system. Examples of the high-severity decay curves against distance to edge (**Figure *5***) and the corresponding spatial representation of each decay coefficient (**Figure *6***) are provided for a set of fires from the 2019/20 season. The method allows for comparative assessment between fires, for example, Mt. Nardi had 1.3% of high severity patch area that was greater than 50m from patch edges, South Kos fire had 11.2% of high severity patch area that was greater than 50m from patch edges and Currowan fire had 36.7% of high severity patch area that was greater than 50m from patch edges, and 8.5% that was greater than 150m from patch edges (**Figure *5***).

Integration of this research into our broader post-fire recovery monitoring research has aimed to provide further understanding of the effect of fire severity patchiness on ecological resilience. A manuscript documenting this research is currently being prepared for submission to an international peer-review journal.

Figure 5 High-severity decay curves for a set of wildfires from the 2019-20 fire season.

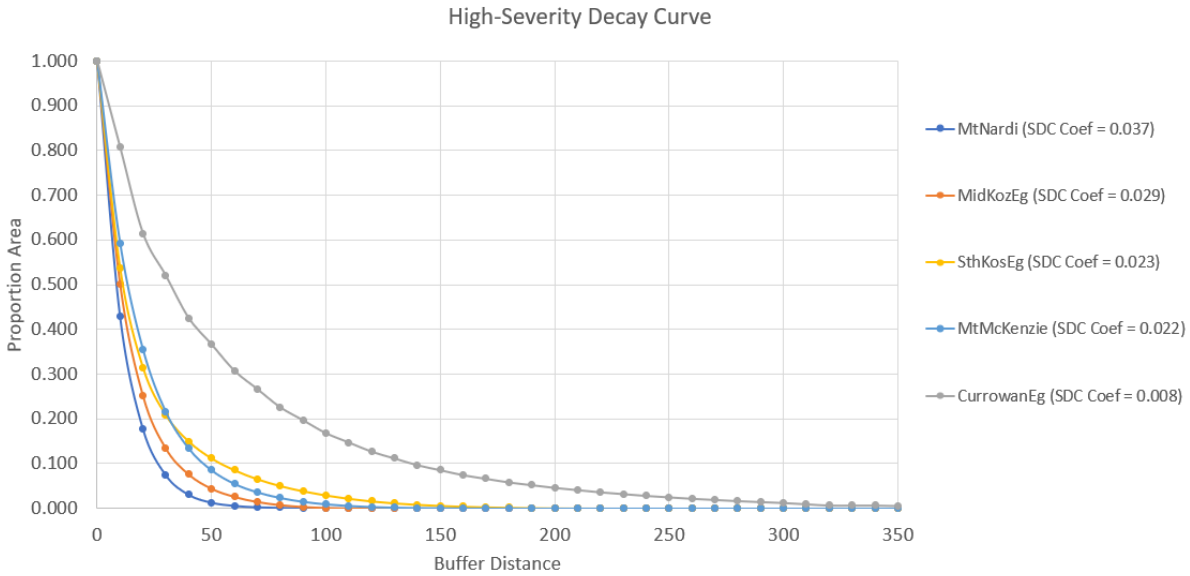
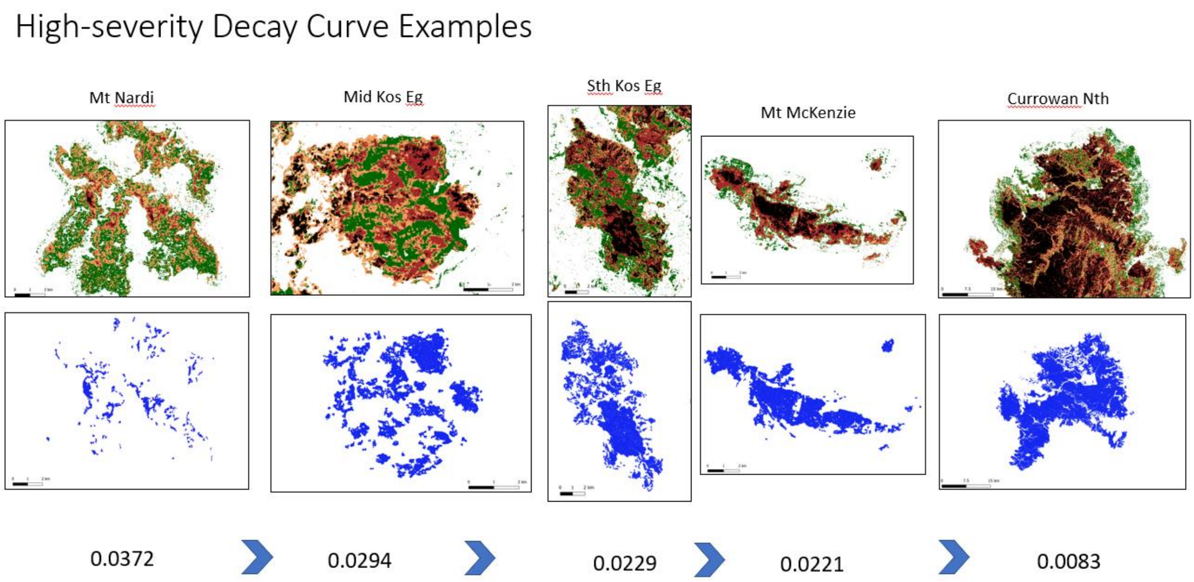


Figure 6 Fire severity maps and the high + extreme severity (blue) that the high-severity decay coefficient is generated from for a set of wildfires from the 2019-20 fire season. Decay coefficient is the value underneath the maps for each case, in decending order from left to right.



5. Radar method exploration

Sensitivity of Sentinel 1 to immediate post-fire effects on vegetation

One of the aims of our project was to evaluate the potential use of radar in post-fire recovery monitoring. Active sensors such as radar have greater potential to add information on the third dimension of biophysical structure compared to the more traditional two-dimensional optical remotely sensed data. Sentinel-1 C-band radar is a short wavelength (~5.6 cm) with limited penetration of dense vegetation canopies. Penetration depth depends on vegetation type and growth stage and is typically greater at longer wavelengths. However, Sentinel 1 is freely available data with state-wide coverage at relatively high frequency site re-capture.

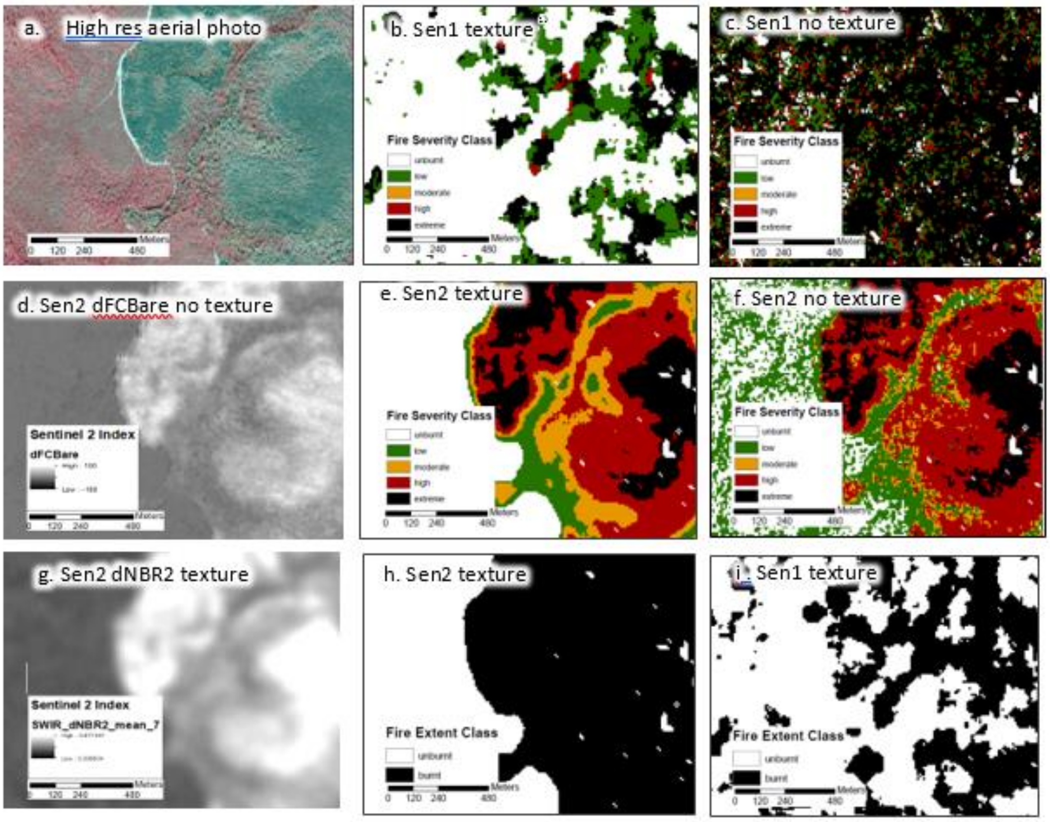
As a first step in examining radar capabilities for fire mapping, we systematically compared Sentinel 1 against Sentinel 2 for mapping fire extent and severity, given the extensive training and validation dataset we have developed through the FESM project. We used the same random forest supervised classification framework as described in Gibson et al. (2020). Separate models were generated for Sentinel 1 and Sentinel 2, with and without image texture indices, for fire severity (unburnt, low, moderate, high, and extreme) and fire extent (burnt, unburnt).

The results indicate the capability of C-band SAR in detecting burnt area and characterising fire severity is linked to a sensitivity to structural change. C-band sensitivity is limited to areas with significant canopy structural change, i.e., partial or complete canopy consumption, as occurs in high-extreme fire severity. The removal of small foliage elements in the canopy directly influences C-band backscatter, with changes in volume and multi-path volume scattering. Cross-polarized (VH) backscatter shows increasing sensitivity to burn severity. With significant loss of canopy volume, there is potential for the signal to interact with the exposed ground surface, resulting in elevated co-polarized (VV) backscatter. In the absence of structural change, i.e., forest areas with lower - burn severity, these areas are difficult to separate from unburnt forest. This contrasts with optical data where strong spectral sensitivity is found across fire severity classes.

The addition of texture indices was found to increase the classification accuracy of fire severity and extent on account of their sensitivity to textural variation in burnt and unburnt areas. Mapping accuracy using Sentinel 1 was highly variable however and linked to site environmental variables. Steeper terrain and rapid saturation of the C-band signal in dense, high biomass forest increases the difficulty in detecting the burnt area. A manuscript documenting the outcomes of this research is currently in review with an international peer-review journal.

It was not possible to secure longer wavelength L-band radar data during the project. The longer wavelength is expected to have increased sensitivity to burn severity and may assist in monitoring post-fire recovery in fast-growing species such as eucalypts. There may be future opportunity to investigate the sensitivity of L-band radar to fire severity.

Figure 7 Visual examples of results for a sample of cross-validation models of the Holsworthy fire; a. high resolution post-fire aerial photography in near-infrared false colour display, b. Sentinel 1 fire severity model including texture indices, c. Sentinel 1 fire severity model excluding texture indices, d. Sentinel 2 change in Bare cover fraction (dFCBare) input index, e. Sentinel 2 fire severity model including texture indices, f. Sentinel 2 fire severity model excluding texture indices, g. Sentinel 2 dNBR2 input index for texture index (mean, kernel=7), h. Sentinel 2 fire extent model including texture indices, i. Sentinel 1 fire extent model including texture indices.



Sensitivity of Sentinel 1 to longer-term post-fire vegetation recovery

As part of our evaluation of the potential use of C-band radar in longer-term post-fire recovery monitoring, we aimed to test time-series methods over several historic and contemporary fire events. Monthly time-series of Sentinel 1 were processed for multiple sites, diverse in vegetation cover, topography and burn severity. Time-series profiles of co- and cross-polarized backscatter were extracted to analyse trends for 1 year pre-fire and up to 3 years post-fire. Backscatter signatures were analysed to investigate the relationship between fire impact and short-term tree survival and longer-term recovery. Recovery indices were generated that represent fire impact and recovery from post-fire and pre-fire baselines.

The time-series trends show us the immediate impact of the fire on C-band VV and VH backscatter and how the signal recovers thereafter. Recovery is a gradual process and the increase in post-fire VH backscatter is indicative of active canopy-level recovery. The change in VV backscatter is relative to burn severity and whether the ground surface is exposed to the radar signal. After 3 years, the backscatter may not have recovered to pre-fire levels, but shows an upward trend.

Tree survival can be assessed through the VH backscatter variation 1 year post-fire, and tree recovery as the amount of VH backscatter recovered several years on compared to post-fire and pre-fire (baseline) values. The post-fire statistics typically show a positive change in VH backscatter, indicative of active recovery and formation of new canopy elements. Recovery in the first year is highly variable and dependent on vegetation type and biomass levels pre-fire. Decreases in VH backscatter may be associated with post-fire tree crown death and less active canopy growth. Despite ongoing recovery, a negative relationship between fire impact and pre-fire backscatter means that vegetation density and biomass have not yet recovered to former levels. Difference images were generated that provide visual representation of these effects. C-band radar shows strong potential for tracking post-fire processes and recovery. Further advances are to be made by integrating with longer wavelength radar data and validating with field observations.

At the time of writing this Final Summary Report, a grant proposal was in preparation. If successful, this will allow us to continue the research on multi-platform integration for post-fire recovery monitoring.

Next Steps

The research we've completed as part of the '*Supporting post-fire ecological resilience and recovery planning in NSW forests*' project has provided strong progress towards a remote sensing approach to monitoring post-fire spectral recovery, as well as complementary tools to support forest managers to undertake risk assessments and subsequently plan and report on post-fire ecological recovery. The following section summarises the key tasks and further research we will be focusing on, provided adequate resourcing is secured.

Post-fire spectral recovery monitoring

- Ongoing development and programming efficiencies to translate the research into an operational workflow
- Incorporating end user feedback to further develop tools to support interpretations, summary metrics and reporting
- Future version updates may be expected with ongoing field validation and application in wider range of ecosystems
- The classification scheme of the product may be varied following end user feedback
- Decisions will be required on how routine and widely applied the post-fire recovery monitoring will be. This will largely depend on resourcing and end user requirements.

Predicted years to recovery

- Further research on the relationships between the modelled predicted years to recovery and the observational monitoring of post-fire spectral recovery may help to refine the methods of each product. Ongoing collaboration on this work is planned, commensurate with current resourcing and priorities.

Landscape severity pattern analyses

- Integration of high severity patch analyses into with post-fire recovery monitoring aims to provide further understanding of the effect of fire severity patchiness on ecological resilience.
- A comprehensive landscape ecology study is being undertaken from a remote sensing and spatial science perspective, with resources currently available
- Ongoing research is likely to also require high quality field data for validation, which is currently not planned or resourced.

Integrated Radar/Optics Research

- Capabilities of optical and radar have been assessed independently in this study to gauge usefulness and further understand relative sensitivities for mapping fire extent, severity and recovery. The combined use and potential integration in an operational monitoring framework warrants further investigation.
- A grant proposal is currently in preparation. If successful, this will allow us to continue the research on multi-platform integration for post-fire recovery monitoring.

References

Collins, B. M., Stevens, J. T., Miller, J. D., Stephens, S. L., Brown, P. M., & North, M. P. (2017). Alternative characterization of forest fire regimes: incorporating spatial patterns. *Landscape Ecology*, *32*, 1543-1552. https://doi.org/DOI:10.1007/s10980-017-0528-5

Fuentes, S., Palmer, A. R., Taylor, D., Zeppel, M., Whitely, R., & Eamus, D. (2008). An automated procedure for estimating the leaf area index (LAI) of woodland ecosystems using digital imagery, MATLAB programming and its application to an examination of the relationship between remotely sensed and field measurements of LAI. *Functional Plant Biology*, *35*, 1070-1079.

Gibson, R., Danaher, T., Hehir, W., & 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). https://doi.org/doi.org/10.1016/j.rse.2020.111702

Hislop, S., Haywood, A., Alaibakhsh, M., Nguyen, T., Soto-Berelov, M., Jones, S., & Stone, C. (2022). A reference data framework for the application of satellite time series to monitor forest disturbance. *International Journal of Applied Earth Observation*, *in press*.

Jenkins, M. E., Bell, T. L., Poon, L. F., Aponte, C., & Adams, M. A. (2016). Production of pyrogenic carbon during planned fires in forests of East Gippsland, Victoria. *Forest Ecology and Management*, *373*, 9-16.

Keith, D. A. (2004). *Ocean shores to desert dunes: The native vegetation of NSW and the ACT*. Department of Environment and Conservation, NSW.

Macfarlane, C., Arndt, S. K., Livesley, S. J., Edgar, A. C., White, D. A., Adams, M. A., & Eamus, D. (2007). Estimation of leaf area index in eucalypt forest with verticle foliage, using cover and fullframe fisheye photography. *Forest Ecology and Management*, *242*, 756-763. https://doi.org/doi:10.1016/j.foreco.2007.02.021