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The utility of Random Forests for wildfire severity mapping

L. Collins[a,b,c,*], P. Griffioen[b,d], G. Newell[b], A. Mellor[e,f]

[a] Department of Ecology, Environment & Evolution, La Trobe University, Bundoora, Victoria 3086, Australia
[b] Arthur Rylah Institute for Environmental Research, Department of Environment, Land, Water and Planning, PO Box 137, Heidelberg, Victoria 3084, Australia
[c] Research Centre for Future Landscapes, La Trobe University, Bundoora, Victoria 3086, Australia
[d] Ecoinformatics Pty Ltd. 20 Alexander Street, Montmorency, Victoria 3094, Australia
[e] Forest, Fire and Regions, Department of Environment, Land, Water and Planning, 8 Nicholson Street, Melbourne, Victoria 3000, Australia
[f] Department of Geospatial Science, RMIT University, Melbourne, Victoria, 3001, Australia

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ABSTRACT

Reliable fire severity mapping is a vital resource for fire scientists and land management agencies globally. Satellite derived pre- and post-fire differenced severity indices (ΔFSI), such as the differenced Normalised Burn Ratio (ΔNBR), are widely used to map the severity of large wildfires. Fire severity classification is commonly undertaken through the identification of severity class thresholds in ΔFSI. However, several shortcomings have been identified with severity classifications using ΔFSI, including poor delineation of low fire severity classes, and unsatisfactory performance when ΔFSI classification thresholds are applied to new landscapes. Our study assesses the performance of the Random Forest classifier (RF) for improving the accuracy of satellite based wildfire severity mapping across heterogeneous landscapes using Landsat imagery. We collected point based fire severity training data (n = 10,855) from sixteen large wildfires occurring across south-eastern Australia between 2006 and 2016. The predictive accuracy of fire severity classification using ΔNBR and the RF incorporating numerous spectral indices, was assessed using bootstrapping and cross validation. Image acquisition and index calculation for each fire was undertaken in Google Earth Engine (GEE). Results of the bootstrapping validation show that the RF classifier had very high classification accuracy (> 95%) for unburnt (UB), crown scorch (CS) and crown consumption (CC) severity classes, and high classification accuracy (> 74%) for low severity classes (crown unburnt, CU; partial crown scorch, PCS). The RF classification outperformed the ΔNBR classification for all severity classes, increasing classification accuracy by between 6%–21%. Cross validation using independent fires produced similar median classification accuracy as the bootstrapping validation, though the RF classification of CU was substantially reduced to ~55%. ΔNBR, ΔNDWI and ΔNDVI were the three most important variables in the RF model. The Landsat satellite platform used to derive the indices had little effect on classification accuracy. Maps produced using the RF classifier in GEE had similar spatial patterns in fire severity classes as maps produced using time-consuming hand digitisation of aerial images. GEE was found to be a highly efficient platform for image acquisition, processing and production of severity maps. Our study shows that fire severity mapping using RF classifiers provides a robust method for broad scale mapping of fire severity across heterogeneous landscapes. Furthermore, the GEE-based classification framework supports the operational application of this approach in a land management agency context for the rapid production of fire severity maps.

1. Introduction

Fire is one of the dominant disturbances across terrestrial ecosystems globally (Bowman et al., 2009). Fire severity is defined as the loss of above- and below-ground organic matter and is correlated with fire intensity within plant communities with similar vegetation structure (Hammill and Bradstock, 2006; Keeley, 2009). Fire severity is an important component of the fire regime, as it influences the post-fire response of plant and animal communities (Bennett et al., 2016; Smucker et al., 2005), alters erosion and water quality (Doerr et al., 2006; Nolan et al., 2015) and influences the likelihood of fire suppression by firefighting crews (Bradstock et al., 2010). Accurate fire severity mapping provides crucial information for policy makers, land managers and researchers (Eidenshink et al., 2007), as well as staff involved in incident control (e.g. post-fire impact assessments). In particular, fire severity mapping can facilitate: (i) burnt area emergency

* Corresponding author.
E-mail address: lcollins241181@gmail.com (L. Collins).

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response (Keeley, 2009), (ii) assessment of decadal trends in fire regimes (Eidenshink et al., 2007), (iii) assessments of the effectiveness of fire management strategies (Price and Bradstock, 2012; Thompson et al., 2007), (iv) improved understanding of fire behaviour (Collins et al., 2014; Holden et al., 2009), and (v) insight into fire regime effects on biota and ecosystem processes (Bennett et al., 2016; Knox and Clarke, 2012; Smith et al., 2016). Broad scale fire severity mapping predominantly uses data from satellite imagery and aerial photography (Keeley, 2009; Kolden et al., 2015; McCarthy et al., 2017), although systematic and reliable mapping of severity is not a common process in many countries (Kolden et al., 2015).

Fire severity mapping using satellite imagery has largely relied on the pre- and post- fire differencing of a spectral index (SI) to derive a single differenced fire severity index (ΔFSI) (Eidenshink et al., 2007; Hammill and Bradstock, 2006; Veraverbeke et al., 2010). The rationale behind this approach is that pre- and post-fire differences in the SI will reflect the degree of environmental change due to fire, and hence fire severity. ΔFSI may be used as a continuous measure of fire severity (e.g. Collins et al., 2007), though often ΔFSI are classified into environmentally meaningful fire severity classes (e.g. Hammill and Bradstock, 2006). The preferred SI used to derive the ΔFSI will vary depending on the ecosystem characteristics or features of interest (e.g. foliage, soil). ΔFSI derived from SI sensitive to foliage health and cover, such as the differenced Normalised Burn Ratio (ΔNBR) (Boer et al., 2008), tend to show a good correlation with field derived measures of fire severity (Hammill and Bradstock, 2006; Parker et al., 2015; Veraverbeke et al., 2010). Consequently, ΔNBR is a widely utilised index for fire severity mapping (Lentile et al., 2006), and is favoured by many fire management agencies (e.g. Kolden et al., 2015). Despite its widespread use, ΔNBR has been shown to be sub-optimal for describing fire severity in some instances (Roy et al., 2006).

The approach of fire severity classification using a single ΔFSI has a number of limitations that restrict the application of the method across space and time. First, ΔFSI values are not comparable across structurally distinct vegetation classes (e.g. forest and shrubland; Hammill and Bradstock, 2006; Miller et al., 2009; Parker et al., 2015). This is because vegetation structure influences SI values (Boer et al., 2008), hence the maximum value of a ΔFSI will be determined by pre-fire vegetation state (Brewer et al., 2005; Miller et al., 2009; Roy et al., 2006). Consequently, accurate severity classification with a single ΔFSI will require adjustments to the thresholds for each vegetation type examined (Brewer et al., 2005; Hammill and Bradstock, 2006), which reduces the broad scale usefulness of the approach. Second, low fire severity classes, or classes that are a composite of fire severity effects (e.g. partial crown scorch), can be difficult to distinguish with a single ΔFSI (Hammill and Bradstock, 2006; Miller et al., 2009). This partially reflects limitations in the type of change that a single SI can detect and difficulties in distinguishing pixels with mixed cover types (Miller et al., 2009). Fire alters a range of ecosystem properties, including foliage cover, health and moisture content and the amount of bare soil and charcoal; each which influence spectral reflectance (White et al., 1996). Classification methods using empirical models that can incorporate information from multiple ΔFSI sensitive to a range of environmental conditions as well as SIs related to pre-fire vegetation conditions may facilitate improved fire severity classification (e.g. Brewer et al., 2005). Physical based models, such as Radiative Transfer Models that simulate spectral signatures at the leaf and canopy scale, have also been successfully used to predict burn severity (e.g. Composite Burn Index) from satellite imagery (e.g. De Santis et al., 2009), and may outperform ΔFSI such as ΔNBR (De Santis et al., 2010).

Machine learning (ML), defined as the application of statistical techniques and algorithms for identifying patterns in data and making predictions from those patterns, are now commonly applied in remote sensing classification (Graves et al., 2016; Heydari and Mountrakis, 2018; Rogan et al., 2008). ML techniques perform better than simple classifiers in dealing with complex interactions between scene complexity, scale and aggregation and have improved discrimination of classes in heterogeneous landscapes (typical in remote sensing) with low inter-class separability and high intra-class variability (Ghimire et al., 2012). Random Forest (RF) (Breiman, 2001) is a popular machine learning technique, commonly applied in remote sensing (Belgiu and Drăguţ, 2016). Frequently cited advantages of RF classifiers over other machine learning techniques include its excellent classification results and processing speed (Belgiu and Drăguţ, 2016; Du et al., 2015), its ability to handle noise and outliers in complex measurement space (Mellor et al., 2015; Rodriguez-Galiano et al., 2012), and characterize complex variable interactions (Cutler et al., 2007). The RF classifier is well suited to addressing fire mapping problems (e.g. Meddens et al., 2016; Ramo and Chuvieco, 2017), as it can consider multiple environmental variables simultaneously (Hultquist et al., 2014; Meddens et al., 2016), and has been found to be better suited for fire severity mapping than other ML classifiers (Hultquist et al., 2014). Despite the commonly cited advantages of ML classifiers like RF, they have rarely been utilised for fire severity classification (Barrett et al., 2011; Hultquist et al., 2014; Meddens et al., 2016).

Studies assessing the utility of ML classification techniques for fire severity mapping have been limited by the size and extent of training and validation data, and have not performed cross validation using fires that were not included in training data (e.g. Brewer et al., 2005; Hultquist et al., 2014; Meddens et al., 2016). Consequently, the true utility of ML classifiers, such as RF, as a tool to reliably produce fire severity mapping across heterogeneous landscapes has not been assessed. The aim of our study was to:

(i) assess the performance of RF for classifying fire severity using several indices derived from moderate resolution (30 m) Landsat imagery;
(ii) compare the RF classification to a single index classification using ΔNBR, both within and outside the set of training fires;
(iii) assess the relative importance of different indices in improving fire severity classification; and
(iv) examine how additional sampling effort from new fires can improve RF classification accuracy of these fires.

2. Methods

2.1. Study area

The study included sixteen large wildfires, ranging from 1800 to > 120,000 ha in extent, that occurred between 2006 and 2016 in Victoria, Australia (Fig. 1). The wildfires used in this study were selected based on the availability of (i) high resolution (≤ 35 cm) visible and infrared aerial photography captured shortly after the fire ignition date (i.e. within ~2–3 months) and (ii) Landsat imagery to produce pre- and post-fire cloud free mosaics. Fire severity was spatially heterogeneous within the wildfire perimeters, covering the range of fire severity classes distinguishable with aerial photography (Table 1, SM1). The fires occurred in a range of vegetation communities including heathlands (i.e. shrub dominated communities), open forests and woodlands, tall forests and pine plantations. Grass and sedge dominated communities were excluded from the study, as were arid and semi-arid woody vegetation communities.

2.2. Fire severity data

Fire severity data used in this study for classifier training and validation was derived using aerial photo interpretation and digitisation. High resolution visible and infrared aerial photography has been effectively used to distinguish fire severity classes (Table 1) in Australian forests, woodlands and shrublands, with high correlations being observed between photo and field based measures of fire severity (Hammill and Bradstock, 2006; McCarthy et al., 2017). Five fire