Evaluation of spectral indices for assessing fire severity in Victorian temperate forests, Australia

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ABSTRACT

There is a lack of comparative analyses of multiple spectral indices in Victorian temperate forests that vary in structure and wildfire response traits. To close this gap, we have evaluated 10 remotely sensed indices across eight areas affected by wildfires in 1998, 2006, 2007, and 2009, which comprise 13 forest types. The analysis was carried out at forest type level and as a function of the regeneration strategies (seeders, basal and epicormic reporters) and structure (tree height and canopy cover). Index performance was evaluated by (i) examining index response across four fire severity levels, (ii) the separability index, and (iii) the optimality values analysis. Initial results demonstrated that there hasn't been a consistency of the best index capacity but there a consistently worse index among forest groups and in overall none of the thermal indices performed better than non-thermal for fire severity estimation within our study.

Keywords

Fire severity; spectral indices; obligate seeder; resprouter; temperate forests

INTRODUCTION

Wildfire is considered an important disturbance agent with a long history of shaping landscape patterns and ecosystem processes, relating to both vegetation distributions and physical structures (Bond and Keeley, 2005; Bowman et al., 2009). Extreme wildfires have significant biophysical and ecological impacts on ecosystems at both global and landscape scales (Veraverbeke et al., 2012). It has been demonstrated that increased wildfire occurrence is associated with climate change (Bowman et al., 2017). Extreme wildfires can affects climate cycle at global scale (Barbosa et al., 1999) while at landscape level, it has been identified as the most influencing factor which removes vegetation layer partially or completely (Veraverbeke, Gitas, Katagis, Polychronaki, Somers and Goossens, 2012) and affects vegetation structure and patterns (Collins et al., 2007; Fairman et al., 2016). Eucalypts, the dominated species groups of *Eucalyptus*, *Corymbia*, *Angophora* occupies 75% of Australian forest areas which have evolved with wildfires (Sullivan et al., 2012; Tng et al., 2012). Especially in

the South-Eastern Australian (SEA), the total forest areas burned by wildfires in Victoria state in the period 1952-2014 was around 8.6 million hectares with half of that area was obtained for the period 2003-2014 (Fairman, Nitschke and Bennett, 2016). The assessment of ecological effects of wildfires provides information (van Wagtendonk et al., 2004) supporting the selection of suitable post-fire treatments at specific sites (Patterson and Yool, 1998), informs vegetation recovery monitoring and planning (Jakubauskas et al., 1990) and provide appropriate baselines for future landscape management (Brewer et al., 2005). Thus, assessing the impact of wildfire on the environment and its distribution throughout burned areas is considered a key tool for quantifying fires' impact on forest ecosystems.

Spectral indices have been extensively tested in boreal forests, temperate conifer and deciduous forests, and Mediterranean forests for fire severity estimation from remote sensing data which utilized both active and passive sensors (Tanase et al., 2015; Trigg and Flasse, 2001; Pereira et al., 1999; Veraverbeke et al., 2010; Harris et al., 2011; Chu and Guo, 2014; Chuvieco et al., 2002; Lee et al., 2008). Such studied were three principal techniques including, spectral un-mixing, simulation techniques, and spectral indices. The latter have been widely used as the most popular approach to provide information on fire severity due to its computational and conceptual simplicity (Veraverbeke, Verstraeten, Lhermitte and Goossens, 2010). A number of remotely sensed indices have been utilized for quantifying fire severity (Patterson and Yool, 1998; White et al., 1996; Chuvieco et al., 2008; Miller and Thode, 2007), often by combining information from visible, near-infrared, and mid-infrared portions of the electromagnetic spectrum. These bands are sensitive to variations in soil colour (visible and mid-infrared), soil composition (mid-infrared), and moisture and chlorophyll (near infrared), land and vegetation properties significantly affected by fire (Miller and Thode, 2007). Spectral indices derived from optical remote sensing data have been widely used for fire-severity classification in forests from local to global scales. variation of spectral indices with plant fire response traits or post fire regeneration remains under-examined, and there remains scope to examine the utility of thermal bands in discriminating among fire severity levels in a range of ecosystems (Holden et al., 2005; Smith et al., 2007; Veraverbeke et al., 2011).

Our hypothesis was that temperate forests in the Victorian temperate forest ecosystems, Australia, characterized by diverse wildfire response traits, may show different spectral responses making fire severity estimation from optical Landsat data difficult. Additionally, whether one spectral index can be used to quantify wildfire severity for whole types of forest ecosystems was a controversial debate over last decades (Veraverbeke, Verstraeten, Lhermitte and Goossens, 2010). Therefore, we compared the performance of ten spectral indices, to assess fire severity across 13 forest ecosystems varying in tree height, canopy cover, and post-fire regeneration strategies. We utilized Landsat 5 TM imagery due to the high spatial resolution (30 m) and the long-term archives available. High spatial resolution over heterogeneous forested landscapes such as those in Victorian temperate forest ecosystems, Australia ensures homogeneity of vegetation conditions within the relatively small pixels. The study addressed two research questions:

1. Do resprouter and obligate seeder require different optical spectral indices for wildfire severity estimation?
2. Which spectral index is the best for fire severity estimation in resprouter and obligate seeder forest ecosystems?

MATERIALS AND METHODS

Study area

This study was conducted in the Victorian temperate forest ecosystems, Australia which are characterized with infrequent wildfires regime since early 1900s (Peel et al., 2007). The total forest area burnt in Victoria from 2006 to 2011 accounts for 6% of Australian total burnt areas (ABARES, 2017). The climate across the study area is temperate with warm summer where the temperature is above 10 degrees Celsius but less than 22 degrees Celsius and lack of dry season (no dry summer or dry winter) (Peel, Finlayson and McMahon, 2007). The annual mean temperature across the Victoria state range from wound 12.6ºC in the South East region to 14.7ºC in the North and North West regions of the state (Timbal et al., 2016). According to the Intergovernmental Panel on Climate Change (IPCC), the climate change for the SEA was projected increasing from 0.4 to 1.2ºC in the mean annual temperature by the 2020s and ranging from 1 to 4.6ºC by the 2080s however the changes in annual precipitation were predicted to decrease by 1% to 41% in the same periods (Murphy and Timbal, 2008). The rainfall in Victoria is characterized as higher on the South of the Great Dividing Range (divides Victoria by East – West direction) compared to the North (Lacey and Grayson, 1998) and the SEA region has experienced a trend on below average to lowest rainfall on rainfall record during 1900–2006 (Murphy and Timbal, 2008). Regarding to bushfires, South-eastern Australia has been considered to have highest risks for wildfires during spring, summer and autumn (Hennessey et al., 2005). The temperate forest ecosystems in the SEA dominated by

three mature species of 'resprouters' (species survive fire and resprout); 'obligate seeders' (species die from wildfires and rely on seed to regenerate) (Fairman, Nitschke and Bennett, 2016), and 'mixed traits' (species which are able to resprout and to germinate seeds after fire) (Kasel et al., 2017). Bush fire historical data showed a total area of 4.3 million ha of eucalypt forests were burned by wildfires during 2003-2014 in Victoria State of the SEA which almost equal to the total burned forest area of the last 50 years in 1952-2002 (4.4 million ha) (Fairman, Nitschke and Bennett, 2016).

Reference datasets

Reference data included 3,826 plots with associated fire severity estimates. The reference dataset was derived by (i) field assessment and (ii) aerial photo interpretation of severity levels. 502 field plots (FP) were obtained from the Department of Environment and Primary Industries (DEPI), Victoria. The field plots were collected within two months after the Black Saturday fire in 2009 and contain information on four fire severity classes: unburnt, low, moderate, and high (Tanase, Kennedy and Aponte, 2015). The classification of fire severity levels was defined by the Department of Sustainability and Environment (DSE), Victoria as Unburnt: no crown scorch severity with less than 1% of eucalypt and non-eucalypt crowns are scorched; Low severity: light crown scorch with 1 - 35% of eucalypt crowns are scorched; Moderate severity: moderate crown scorch with 30-65% of eucalypt crowns are scorched; High severity: crown burn with 70-100% of eucalypt crowns are burnt (Department of Environment, 2017).

Severity levels for the remaining plots were derived from aerial photo interpretation (API) of high resolution airborne optical images. Aerial photo interpretation of fire impacts is carried out by the Department of Environment, Land, Water & Planning (DELWP) (Department of Environment, 2017) for selected fires occurring after 1998 on primarily public lands and provided in a vector format. From the 23 fires with severity information forming the DELWP dataset, only 06 major wildfires (total burned area for each fire over 5,000 ha) were selected for the analysis. Further, only fires with the same severity classification as the field dataset were kept as for old fires a different classification scheme of severity levels was used. As a result, 3,324 API plots were generated as centroids of polygons pertaining to the selected fires. The 3,826 reference plots were intersected with the forest types (locally know as Ecological Vegetation Division -EVD) map to add information on forest type at plot level.

Regarding to remote sensing data, sixteen original Landsat TM scenes were obtained from the U.S. Geological Survey (USGS) Earth Explorer ((USGS), 2017) for the eight fires analyzed (pre- and post-fire images). The pre-fire and post-fire images, acquired during the wildfire season (October to April), were selected to minimize the effects of forest phenology and atmospheric conditions differences at the time of acquisition. The result is Universal Transverse Mercator (UTM) Landsat products in Geotiff format for Band 3-5 and band 7 at 30m spatial resolution and for Thermal band with the format at 120m spatial resolution, which was resampled at 30m. The images were masked for clouds and shadows using the Fmask algorithm ((USGS), 2017) which has a proved accuracy of 96.4% (Zhu and Woodcock, 2012). The masked Landsat 5 TM images were atmospherically corrected using Atmospheric Correction for rugged terrain (ACTOR 3) in ERDAS IMAGINE 2014 software.

Methods

Forest type classification

Using DELWP fire history dataset (Department of Environment, 2017) 13 forest types (locally known as Ecological vegetation divisions – EVD) of south eastern Victoria most affected by wildfires in terms of annual burnt area over the past three decades were selected for the analysis. These forest types account for 86.41% of Victorian forests and 59.95% of the wildfire burned area in Victoria in 1927-2017. The 13 forest types were characterized as a function of structure (e.g., canopy height and canopy cover, etc) (Specht and Australia, 1972), and post-fire regeneration strategy of the dominant tree species (i.e., seeders -S, resprouters -R, and mixed seeders and resprouters -RS). As a result, the 13 forest types were classified into six major categories: open forest resprouter (OF-R); closed forest resprouter (CF-R); woodland resprouter (WR); low woodland resprouter (LW-R); open forest mixed traits (OF-RS) and closed-forest obligate seeder (CF-S).

Spectral indexes

The performance of 10 widely used spectral indices including the dNDVI, dNBR, dNDWI, dNBRT, dNDVIT, dVI6T, dMSAVI, dBAI, dMIRBI and dCSI was analyzed. These indices are computed using a combination of Landsat spectral bands 3, 4, 5, 6 and 7. The indices were selected based on their sensitivities to changes in forest ecosystems status and their capacities for fire severity assessment as demonstrated by previous studies over

diverse biomes and forest types (van Wagtendonk, Root and Key, 2004; Veraverbeke, Verstraeten, Lhermitte and Goossens, 2010; Harris, Veraverbeke and Hook, 2011; Chu and Guo, 2014; Smith, Drake, Wooster, Hudak, Holden and Gibbons, 2007; Allen and Sorbel, 2008; Epting et al., 2005; De Santis and Chuvieco, 2007; Tanase et al., 2011; Duffy et al., 2007; Hoy et al., 2008; Soverel et al., 2010; Escuin et al., 2008; French et al., 2008; Hall et al., 2008).

Spectral indices sensitivity to fire severity classes

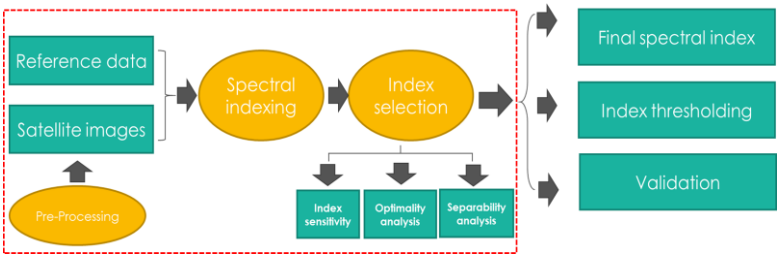


Figure 1. Conceptual framework for the evaluation of spectral indices for assessing fire severity in Victorian temperate forests, Australia

Three lines of evidence were used to analyze spectral indices sensitivity to fire severity levels: (i) the analysis of variance (ANOVA) and pairwise comparisons, (ii) the separability index (M) and (iii) the optimality values (O). First, ANOVA followed up by pairwise Tukey Simultaneous tests for differences of means were carried out to evaluate the capacity of each temporal difference (pre- to post-fire spectral indices) in discriminating the four fire severity levels. Second, the separability index (Equation (1)) was used to estimate the effectiveness of spectral indices to discriminate between areas burned with different severity levels (Schepers et al., 2014). The higher the separability index M, the better the discrimination between classes. To evaluate the overall index sensitivity, we calculated the average value M for each index (AVG M index) as in Equation (2).

$$M_n = \frac{|\mu b - \mu u|}{\delta b + \delta u} \tag{1}$$

where μb and μu are the mean values of the considered spectral band for the analyzed classes, δb and δu are the corresponding standard deviations, and n takes the values 1, 2, and 3 when analyzing separability between Unburnt to Low, Low to Moderate, and Moderate to High classes.

$$\text{AVG } M_{index} = 0.1 * M_1 + 0.3 * M_2 + 0.6 * M_3 \tag{2}$$

where the weights (0.1, 0.3 and 0.6) were assigned considering the importance of fire severity classes for Forest and Fire Management in Victoria, Australia.

Last, the optimality index was used to evaluate which index is more sensitive to post-fire reflectance changes according to (Roy et al., 2006), (Escuin, Navarro and Fernández, 2008), and (Veraverbeke, Verstraeten, Lhermitte and Goossens, 2010) (Veraverbeke et al., 2010). After fire, pixel reflectance values are displaced from unburned (U) to burned (B) as shown in Figure 2. O resembles the position of an optimally sensed burned pixel. The selected index is sensitive to the displacement |UO| and insensitive to the displacement |OB| with index optimality being computed as in Equation (3) (Roy, Boschetti and Trigg, 2006):

$$\text{Optimality} = 1 - \frac{|OB|}{|UB|} \tag{3}$$

Three optimality values are computed for each index, one between each severity class: Unburnt to Low, Low to Moderate, and Moderate to High classes. As for the M analysis, an overall optimality value is computed for each index as a weighted average of the three values (Equation 4).

$$\text{AVG Optimality} = 0.1*O1 + 0.3*O2 + 0.6*O3 \tag{4}$$

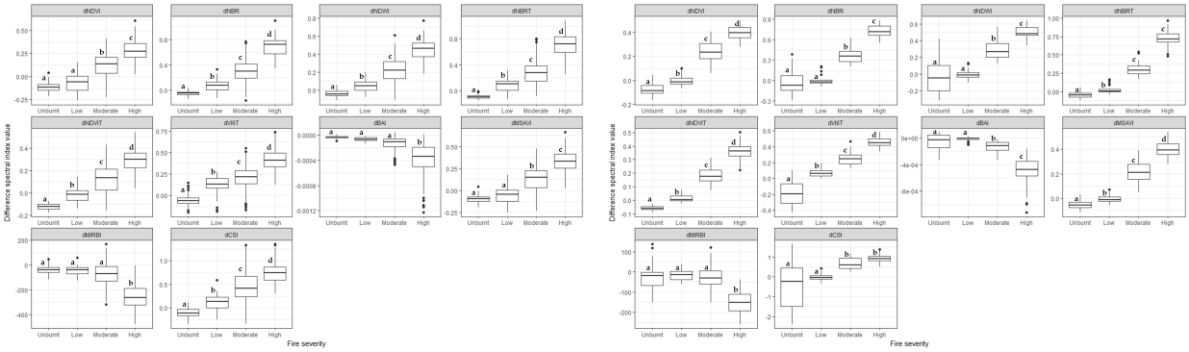
where O1, O2, O3 are optimality median values for low; moderate; and high severity.

The overall performance of each index was then indicated as the sum of the three scores (one per analysis) per forest type. The overall performance of each index when discriminating the four fire severity levels was summarized by aggregating the three scores into one value for each forest type. Top indices were confirmed for each group of forests based on the average scores. Thus, the highest performing indices were identified for each forest group by averaging the scores of the forest types forming that group.

PRELIMINARY RESULTS

Spectral indices sensitivity to fire severity classes

According to the ANOVA analysis in Figure 2, the dNBR and the dNDWI outperformed all other indices in the OF-R. For the CF-S, the dNDVIT, dVI6T and dMSAVI showed their better capacity in classifying fire severity. The dBAI and the dMIRBI showed the poorest capacity in discriminating all levels of severity for both OF-R and CF-S.

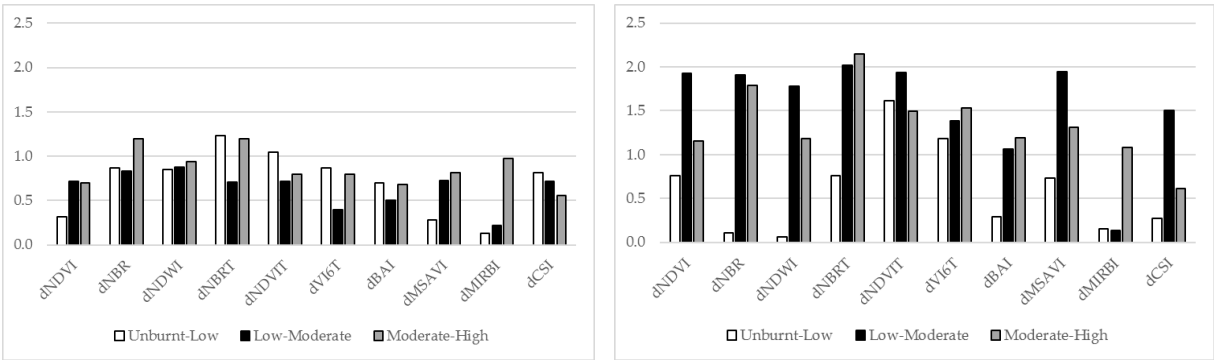


OF-R: Grassy / heathy Dry Forest CF–S: Moist Forest

Figure 2. Boxplots of spectral indices by fire severity classes. An example for ANOVA test results from resprouter (R) and obligate seeder (S) forests. Letters indicate significant differences in Tukey test (p<0.05)

Separability analysis

The separability analysis (M values) results illustrate that the dNBR and dNBRT were the best indices in terms of separability which obtained highest capacity for discriminating fire severity for both the OF-R and CF-S. The worse index was experienced with the dMIRBI for both type of forests.

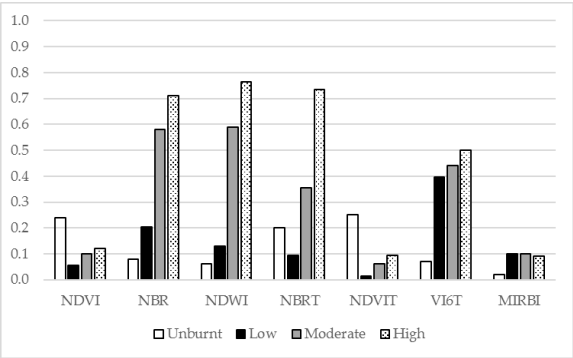


OF-R: Grassy / heathy Dry Forest CF–S: Moist Forest

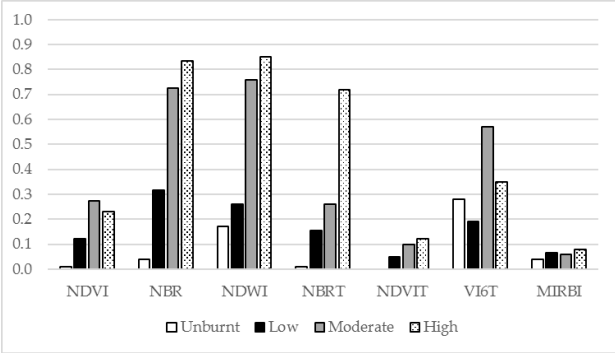
Figure 3. Bar charts of M values 10 difference indices (dVI) between pre- and post-fire spectral indices derived from Landsat satellite images at four different classes: unburnt to low, moderate and high severity) for (R) and (S)

Optimality analysis of spectral indices

The results from Optimality analysis showed that the NBR and NDWI achieved highest median optimality values in both the OF-R and CF-S with their better capacity in term of optimality values for classifying fire severity at moderate and high severity classes. Results from optimality analysis of spectral indices showed that the poorest capacity index was obtained for the MIRBI for both forest types in Figure 4.



OF-R: Grassy / heathy Dry Forest



CF–S: Moist Forest

Figure 4. Bar charts for median values of 10 spectral indices' optimality derived from Landsat satellite images at four different classes: unburnt to low, moderate and high severity) for the resprouter (R), obligate seeder (S). Optimality values for NDVI, BAI and MSAVI are equal; Optimality values for NDWI and CSI are also equal dues to the same input bands for calculating these optimality values.

DISCUSSION

The importance of forest traits and structure classification

This is very important to classify forest ecosystems based on their traits and structure before employing spectral indices derived from remotely sensed data for fire severity estimation with two broad post fire regeneration traits mechanisms of resprouting and seedling because different vegetation types influence differently on fire severity detection (Hammill and Bradstock, 2006) and metrics for fire severity estimation vary with different forest ecosystems (Keeley, 2009). The structural attribute (height and foliage projective cover of overstorey and undestorey strata) and fire response trait of each forest plant communities need to be integrated when accessing fire severity from remote sensing data. An obvious example for that can be seen from the OF-R ecosystems are characterized with mid-dense projective foliage cover (10-30%), in which the dominant trees are resprouting species, so after the wildfires the above ground mortality reflects the mortality of the entire vegetation communities. Therefore, in the immediate stage after the wildfires at high fire severity level, all the plant parts consumed. As a result, fire-induced reflectance increase clearer in the index with longer wavelength Landsat TM band 7 (2.08 to 2.35 µm) (Veraverbeke, Harris and Hook, 2011) for example the dNBR index compared to other indices without band 7 such as index the dNDVI.

One size doesn't fit all: index suitability varies with forest type

The preliminary results from our index sensitivity analysis indicated that index capacity to separate among the four defined severity classes differed among forest types. This is consistent with understanding that the suitability of different spectral indices to map fire severity varies with the characteristics of the dominant vegetation (Hammill and Bradstock, 2006; Keeley, 2009).

A combination of three methods used from this study confirmed that our results from resprouter (R) forests continue to support the dNBR index for fire severity classification which agreed with the results from Alaska studies by Murphy et al. (Murphy et al., 2008), Allen and Sorbel (Allen and Sorbel, 2008), Harris et al. (Harris, Veraverbeke and Hook, 2011) who supported the operational use of the NBR by the Burned Area Emergency Rehabilitation project in chaparral shrublands, study by Escuin Navarro et al. (Escuin, Navarro and Fernández, 2008) which stated that the pre-/post-fire difference indices dNBR and dNDVI are the most suitable ones for carrying out the discrimination between pixels not burned by a fire, and Eldar Kurbanox et al. 2017 who found that dNBR is a robust index for classifying and measuring burn severity over a broad range of forests.

The overall pattern in the ANOVA results obviously presents there is no single index can perform its capacity for discriminating all fire severity classes for all forest types within this study. Secondly, there has been a consistency of the poorest indices capacity among forest groups within this study. The BAI and MIRBI obtained for the poorest indices among all forest types for classifying all fires severity levels. In an agreement with the ANOVA approach, the separability analysis from this study again that there hasn't been a consistency of the best indices capacity among forest types but there consistently worse indices among forest groups. The optimality analysis results continued to support findings from Escuin Navarro et al. (Escuin et al., 2008) and show the results contrast with those obtained by Roy et al. (Roy et al., 2006), who report very low NBR

optimality values (mean of 0.1) calculated with LANDSAT in the African savannah. This finding also supports results on selecting different spectral indices for fire severity assessment work differently in different forest types and fire response traits from ANOVA test and M analysis.

Our results disagree with research results from Hoy et al. 2008 which founds that "the NBR and its derivatives, as well as the other spectroscopic indices and image transforms derived from satellite imagery, were not suitable for the mapping of fire severity". The NDWI index-based approach, which has not been used before in Australia for fire severity estimation, also perform well along with the NBR approach for not only OF-R but also CF-S. Regarding to the thermal spectral indices, the current study evaluated the dNDVIT, dNBRT, dVI6T however in agreement with previous studies of fire-severity in coniferous forest, broadleaved forest, shrublands and olive groves forest (Veraverbeke, Verstraeten, Lhermitte and Goossens, 2010), chaparral ecosystems (Harris, Veraverbeke and Hook, 2011), temperate rain forests (Marino et al., 2016), in overall none of the thermal indices performed better than the non-thermal in all forest functional groups within our study.

Two of the evaluated indices, BAI and MIRBI, were consistently poor performers across all forest types. BAI has been identified as one of the best indices to map burnt areas (Chuvieco, Martín and Palacios, 2002), but our study suggests it is not suitable for distinguishing fire-severity classes in temperate eucalypt forests. Our results agree with Harris et al. (Harris, Veraverbeke and Hook, 2011) who noted the similarly weak performance of BAI and MIRBI indices in fire severity assessments, but are in contrast to the findings of Lu He and Tong (Lu et al., 2016) for fire-severity assessments in grasslands.

Research perspectives

The information on the best performance spectral indices for fire severity estimation from optical remote sensing data from this study provides a great information for wildfire and forest ecology researchers who are interested in quantifying impacts of wildfires on not only different ecosystems in Victorian temperate forests Australia but also for impact assessment of wildfires on communities and researchers interested in impacts of wildfires on recovery process of these ecosystems. Further research studies need to pay attention on quantifying changes in fire severity patterns over major types of ecological vegetation divisions (EVDs) in Victorian temperate forests, Australia. And modelling works need to be employed to simulate driving factors influencing post fire regeneration and forest recovery in Victorian temperate forests, Australia.

To our knowledge, this study presents one of the most comprehensive analyses of fire severity estimation from remote sensing data in Australia. For South Eastern Australian eucalypt forests, this is the only comparative study that evaluates the most commonly used optical spectral indices for fire severity assessment at landscape level. Our results confirmed that fire severity may be estimated from optical images. The initial findings of the current research study again support the application of Landsat TM satellite images and spectral indexing approaches for fire severity assessment.

Limitation

We are currently working on final index selection for each forest type; threshold determination and validation for the best indices confirmed for each forest type within this study. As a result, this short ("work in progress") academic paper lacks the full details on thresholds and validation of thresholds for the best index for each forest type along with the discussions for these works.

CONCLUSION

In summary, preliminary results from three methods of evaluation showed that there is no single spectral index with high capacity for wild fire severity estimation in all forest types based on their traits in this study. Our preliminary results from ANOVA tests; M analysis and Optimality analysis confirmed that there hasn't been a consistency of the best indices capacity among forest types but there a consistently worse index among forest groups. None of the thermal indices performed better than the non-thermal in all forest functional groups within our study. Our preliminary results continue supporting the application of Landsat TM satellite images and spectral indexing approaches for fire severity assessment.

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