CSIRO PUBLISHING

International Journal of Wildland Fire
https://doi.org/10.1071/WF17137

Research Note

Evaluating the Mid-Infrared Bi-spectral Index for improved assessment of low-severity fire effects in a conifer forest

T. Ryan McCarley[A,C], *Alistair M. S. Smith*[A], *Crystal A. Kolden*[A] and *Jason Kreitler*[B]

[A]University of Idaho, Department of Forest, Rangeland, and Fire Sciences, Moscow, ID, 83843, USA.
[B]US Geological Survey, Western Geographic Science Center, Boise, ID, 83706, USA.
[C]Corresponding author. Email: tmccarley@uidaho.edu

Abstract. Remote sensing products provide a vital understanding of wildfire effects across a landscape, but detection and delineation of low- and mixed-severity fire remain difficult. Although data provided by the Monitoring Trends in Burn Severity (MTBS) project are frequently used to assess severity in the United States, alternative indices can offer improvement in the measurement of low-severity fire effects and would be beneficial for future product development and adoption. This research note evaluated one such alternative, the Mid-Infrared Bi-Spectral Index (MIRBI), which was developed in savannah ecosystems to isolate spectral changes caused by burning and reduce noise from other factors. MIRBI, differenced MIRBI (dMIRBI) and burn severity indices used by MTBS were assessed for spectral optimality at distinguishing severity and the ability to differentiate between unburned and burned canopy in a conifer forest. The MIRBI indices were better at isolating changes caused by burning and demonstrated higher spectral separability, particularly at low severity. These findings suggest that MIRBI indices can provide an enhanced alternative or complement to current MTBS products in high-canopy-cover forests for applications such as discernment of fire perimeters and unburned islands, as well as identification of low-severity fire effects.

Additional keywords: Eastern Cascades, MTBS, LiDAR, wildfire.

Received 30 August 2017, accepted 17 April 2018, published online 23 May 2018

Introduction

As the number of large, destructive, so-called 'megafires' increases in the US (Stephens *et al.* 2014; Bowman *et al.* 2017), it is critical to ensure that national data products utilised for science, policy and decision-making are of the highest accuracy and most appropriate for wildfire management needs. Remote sensing is an important tool for understanding the effects of wildfires at landscape scales (Lentile *et al.* 2006). However, the accurate characterisation of low- to moderate-severity fires in high-canopy-cover forests can pose a significant challenge to spectral remote sensing, given these fires produce the greatest change in the understorey rather than at the top of the canopy where changes in reflectance can be more readily observed (Hudak *et al.* 2007; Wulder *et al.* 2009; Kolden *et al.* 2012; McCarley *et al.* 2017*b*). Furthermore, low-severity fires can exhibit a wide variation of fire effects within an area of interest, covering the gamut from small patches of complete combustion to unburned patches (Smith *et al.* 2005; Kolden *et al.* 2012). Numerous spectral indices have been evaluated to predict severity (Lentile *et al.* 2006); the most notable include the Normalised Burn Ratio (NBR), delta NBR (dNBR) and relativised dNBR (RdNBR) (López-García and Caselles 1991; Key and Benson 2006; Miller and Thode 2007). These indices owe a significant part of their popularity to the Monitoring Trends in Burn Severity project (MTBS; www.mtbs.gov, accessed 27 April 2018), which provides an archive of dNBR and RdNBR data for the conterminous United States since 1984 (Eidenshink *et al.* 2007). Although widely used, MTBS products are not without limitations (Kolden *et al.* 2015; Sparks *et al.* 2015), and other indices have outperformed the NBR variants in certain regions (e.g. Hudak *et al.* 2007; Sparks *et al.* 2016; McCarley *et al.* 2017*b*). Furthermore, Roy *et al.* (2006) demonstrated that NBR was not an optimal spectral index based on foundation remote sensing theory, because it is not insensitive to environmental factors such as soil colour and atmospheric effects (Verstraete and Pinty 1996); the former was confirmed and further demonstrated by Smith *et al.* (2010).

In contrast, the Mid-Infrared Bi-spectral Index (MIRBI) was specifically developed as a spectrally optimal index, although it has primarily been used to distinguish burned and unburned pixels in savannah and rangeland ecosystems (Trigg and Flasse 2001; Smith *et al.* 2007; Sparks *et al.* 2015). McCarley *et al.* (2017*b*) found a pre–post-fire differenced version of MIRBI (dMIRBI) outperformed all other spectral indices when predicting relative change in canopy cover due to fire. These preliminary findings suggested that MIRBI could be a useful

Table 1. Common spectral indices used to assess severity and area burned

Abbreviations: MIRBI, Mid-Infrared Bi-spectral Index; dMIRBI, differenced MIRBI; NBR, Normalised Burn Ratio; dNBR, delta NBR; RdNBR, relativised dNBR; ρ is at-surface reflectance for one of the given Landsat bands: near-infrared (NIR), shortwave infrared 1 (SWIR1), or shortwave infrared 2 (SWIR2). The offset is the mean index value for homogeneous unchanged areas that accounts for differences in phenology and moisture between pre- and post-fire images

Burn severity or burned area index	Reference(s)
$\mathrm{MIRBI} = 10\rho_{\mathrm{SWIR1}} - 9.8\rho_{\mathrm{SWIR2}} + 2.0$	Trigg and Flasse (2001), Smith *et al.* (2007)
$\mathrm{dMIRBI} = (\mathrm{MIRBI}_{\mathrm{prefire}} - \mathrm{MIRBI}_{\mathrm{postfire}}) - \mathrm{MIRBI}_{\mathrm{offset}}$	McCarley *et al.* (2017*b*)
$\mathrm{NBR} = ((\rho_{\mathrm{NIR}} - \rho_{\mathrm{SWIR2}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{SWIR2}})) \times 1000$	Key and Benson (2006)
$\mathrm{dNBR} = (\mathrm{NBR}_{\mathrm{prefire}} - \mathrm{NBR}_{\mathrm{postfire}}) - \mathrm{dNBR}_{\mathrm{offset}}$	Key and Benson (2006)
$\mathrm{RdNBR} = \mathrm{dNBR}/(\lvert\mathrm{NBR}_{\mathrm{pre}}\rvert/1000)^{0.5}$	Miller and Thode (2007)

index for distinguishing different levels of fire severity in forested ecosystems. However, a quantitative analysis of the spectral optimality and separability of levels of severity has not yet been performed.

The goal of the present research note was to evaluate MIRBI against more common NBR-based indices in terms of (1) spectral optimality for distinguishing severity, and (2) the ability to distinguish unburned and burned canopy in a conifer forest. Spectral optimality was tested by plotting indices in bi-spectral space and visually assessing how index values responded between unburned and burned samples. A spectral separability analysis was conducted between different levels of severity and unburned pixels in order to determine how well indices distinguished the effects of burning. We utilised a fairly novel bi-temporal light detection and ranging (LiDAR) dataset and Landsat spectral reflectance scenes to conduct these analyses.

Materials and methods

Pre-processing data

This study was conducted on the Pole Creek Fire, which ignited on 9 September 2012 in the Deschutes National Forest along the Eastern Cascades Mountains of central Oregon. This fire was unique in that pre- and post-fire LiDAR data were available to objectively measure changes in canopy cover. The MIRBI, dMIRBI, NBR, dNBR and RdNBR were calculated from pre-fire Landsat Thematic Mapper Plus (TM+) and post-fire Landsat Operational Land Imager (OLI) scenes acquired on 23 July 2011 and 10 June 2013 respectively. These scenes were chosen to minimise cloud cover, snow and differences in phenology and sun-angle, and were transformed to top-of-atmosphere reflectance following standard methods (Chander and Markham 2003) and atmospherically corrected to at-surface-reflectance using the Cos(t) model (Mahiny and Turner 2007) and Dark Object Subtraction (Chavez 1996). Small portions of the study area were omitted where snow or open-water bodies interfered with change-detection analysis. Spectral indices were calculated based on the literature (Table 1).

The LiDAR data were acquired in October 2009 and October 2013 by Watershed Sciences Inc. (Corvallis, OR, USA) with a Leica ALS50 sensor (Leica Geosystems, St Gallen, Switzerland) at 900 m above ground level, a 28° field of view, and at least 50% side-lap, at a density of 8 pulses m^{-2}. The data were normalised for height, binned to match the Landsat pixels, and clipped to above 0.15 m to ensure measurement of vegetation. Pre- and post-fire canopy cover was derived from the number of LiDAR returns in a voxel higher than 1.8 m, the threshold for understorey used by Brown *et al.* (1982). Percentage relative change in canopy cover (RdCC) was calculated as the difference between pre- and post-fire canopy cover divided by pre-fire canopy cover times 100. Further details of the LiDAR processing are described in McCarley *et al.* (2017*b*), and the data are available publicly through the Forest Service Research Data Archive (McCarley *et al.* 2018).

Analysis

Following the procedures of Trigg and Flasse (2001) and Roy *et al.* (2006), Landsat OLI bands that comprise MIRBI (shortwave infrared (SWIR) 1 (1.55–1.75 μm) and SWIR 2 (2.08–2.35 μm)) and NBR (near infrared (NIR; 0.76–0.90 μm) and SWIR 2) were plotted in bi-spectral space and overlaid with isolines representing the index values. Using LiDAR-estimated relative change in canopy cover to define fire effects, three severity stratifications were classified: unburned areas, areas in the lowest 10th percentile of relative canopy change, and areas in the highest 10th percentile of relative canopy cover change. One hundred randomly sampled points were collected from each stratification, allowing visual assessment of optimality, where changes between the three stratifications perpendicular to the isolines should be due to increasing severity and changes parallel to the isolines should be due to perturbing factors (Roy *et al.* 2006).

Spectral separability was assessed for MIRBI, dMIRBI, NBR, dNBR and RdNBR using pixels outside the fire perimeter and relative change in canopy cover binned to 10th percentile increments to ensure comparable severity classes. For this analysis, all non-masked pixels within the LiDAR acquisition area were used. Following similar studies (Kaufman and Remer 1994; Pereira 1999; Smith *et al.* 2007), separability values were calculated between unburned pixels and each severity class for all the spectral indices using Eqn 1:

$$\mathrm{M} = (\mu_{\mathrm{u}} - \mu_{\mathrm{b}})/(\sigma_{\mathrm{u}x} + \sigma_{\mathrm{b}x}) \quad (1)$$

where M is the separability statistic, μ_{u} and $\sigma_{\mathrm{u}x}$ are the mean and standard deviation of the unburned pixels, and μ_{b} and $\sigma_{\mathrm{b}x}$ are the mean and standard deviation for burned pixels of severity group x. The M-statistic can be calculated for individual bands or

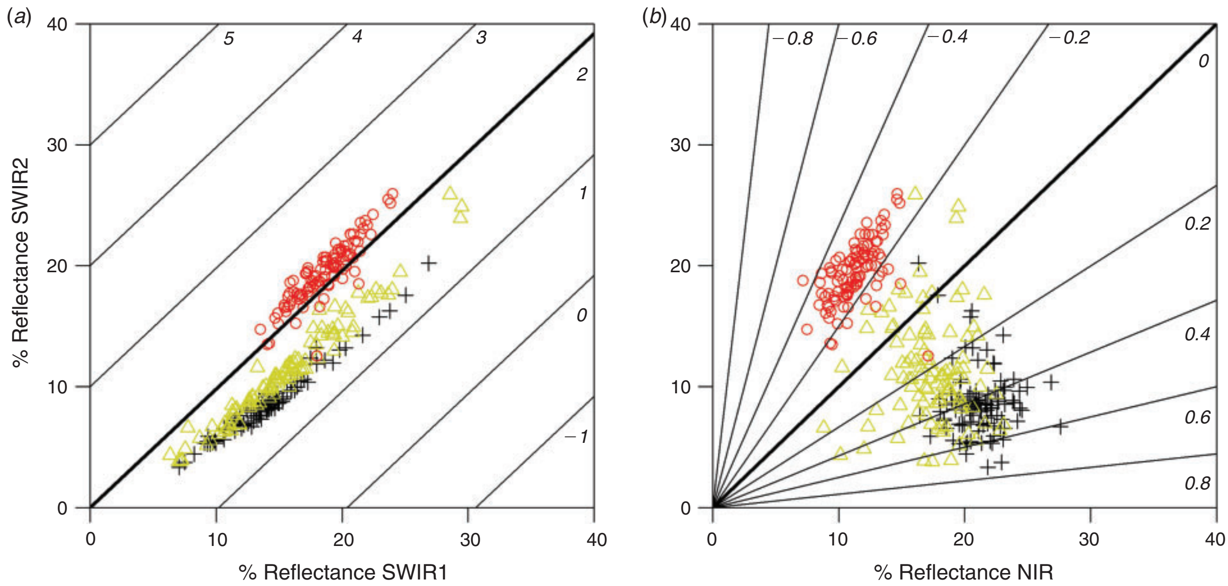

Fig. 1. Percentage reflectance in the Landsat bands (shortwave infrared 1 (SWIR1), shortwave infrared 2 (SWIR2), and near-infrared (NIR)) used to calculate (*a*) the Mid-Infrared Bi-spectral Index (MIRBI); and (*b*) the Normalised Burn Ratio (NBR) for randomly sampled points in unburned areas outside the Pole Creek fire perimeter (black crosses) and areas classified in the bottom 10th (yellow triangles) and top 10th (red circles) percentiles of relative canopy cover change.

Relative change in canopy cover (Percentiles)	MIRBI	dMIRBI	NBR	dNBR	RdNBR	Relative change in canopy cover (% change)
0–10th	0.82	0.75	0.31	0.5	0.39	0–3%
10–20th	0.89	0.76	0.29	0.55	0.42	3–6%
20–30th	0.95	0.76	0.32	0.65	0.49	6–11%
30–40th	0.97	0.74	0.46	0.82	0.58	11–17%
40–50th	1	0.8	0.77	0.99	0.71	17–25%
50–60th	1.16	1	1.17	1.16	0.8	25–35%
60–70th	1.46	1.39	1.59	1.33	0.9	35–46%
70–80th	1.91	1.95	1.98	1.54	1.01	46–58%
80–90th	2.44	2.59	2.29	1.68	0.95	58–68%
90–100th	2.94	3.13	2.5	1.52	0.88	68–100%

Fig. 2. Spectral separability between unburned pixels and burn severity (relative change in canopy cover) binned by 10th percentiles of the severity distribution. Values >1 are considered separable, values between 0.75 and 1 are moderately separable, and values <0.75 are not separable.

values of spectral indices. Comparisons with M-statistic values >1 are considered separable, values between 0.75 and 1 are moderately separable, and M-statistic values <0.75 are not separable. The ideal index would be separable (i.e. M-statistic >1) at all levels of severity, and the separability between unburned and burned pixels should increase with increasing severity to distinguish among increasing levels of canopy-based fire effects.

Results

Randomly sampled MIRBI and NBR values were plotted in bi-spectral space for unburned pixels and pixels in the top 10th and bottom 10th percentiles of severity (Fig. 1). The three stratifications for MIRBI bands fell into lines parallel with continuous MIRBI index values, suggesting that environmental factors (i.e. soil colour) caused spectral displacement along isolines. Meanwhile, displacement caused by burning was largely perpendicular to isolines, although there was some confusion between the unburned and low severity (bottom 10th percentile of severity) where reflectance in SWIR 1 (1.55–1.75 µm) and SWIR 2 (2.08–2.35 µm) was low. For NBR, the top 10th percentile and bottom 10th percentile of severity were well differentiated, with the higher-severity pixels tending to fall into a line parallel with NBR isolines. However, compared with MIRBI, greater confusion was observed for lower severity and unburned, which varied perpendicular to NBR isolines, suggesting environmental factors were affecting spectral change in the same direction as changes caused by burning.

Spectral separability was assessed for MIRBI, dMIRBI, NBR, dNBR and RdNBR between unburned pixels in the LiDAR acquisition area and relative change in canopy cover (RdCC) within the fire perimeter binned to 10th percentile increments (Fig. 2). Using a threshold of 1, no index was separable at severities below the 40th percentile (17% RdCC), although MIRBI and dMIRBI were nearly always moderately separable (M-statistic >0.75). The MIRBI index was best at distinguishing burned and unburned, being separable above the 40th percentile, whereas dMIRBI, NBR and dNBR were all separable above the 50th percentile (25% RdCC). RdNBR was

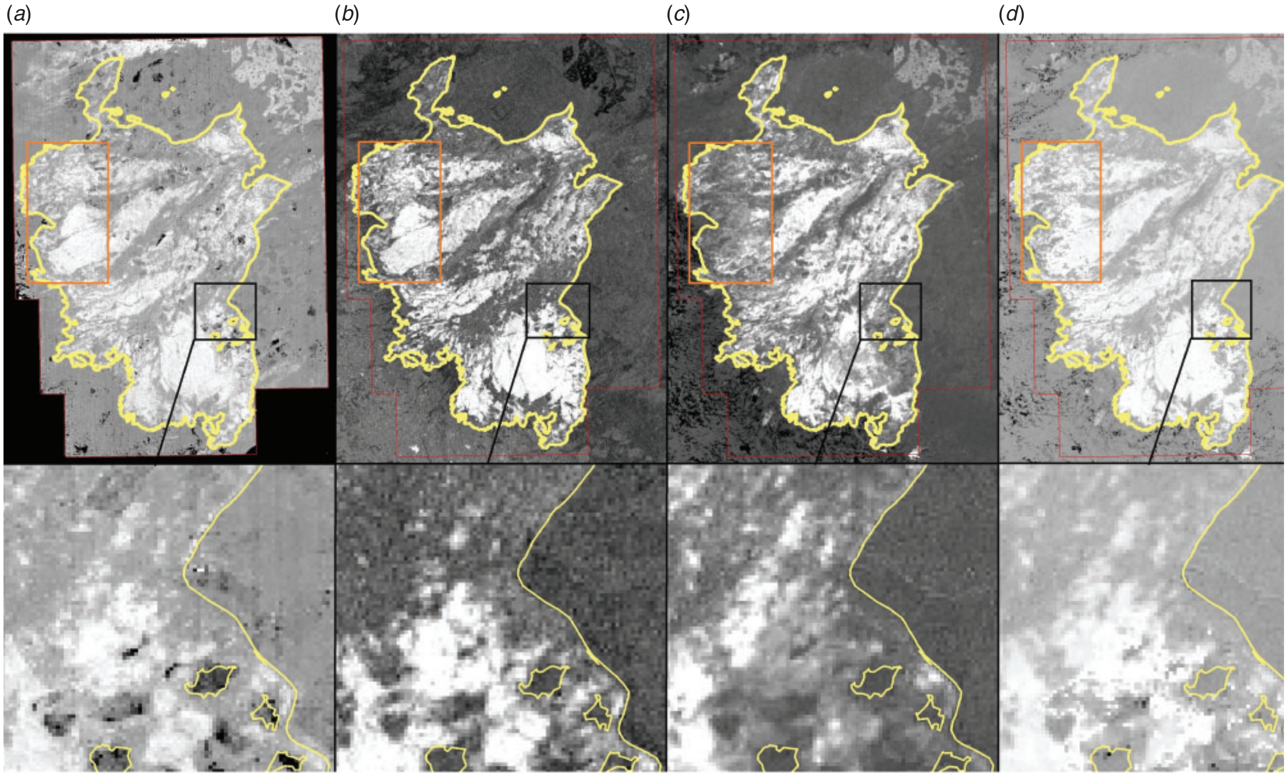

Fig. 3. Spatial comparison of relative change in canopy cover (RdCC) (*a*); differenced Mid-Infrared Bi-spectral Index (dMIRBI) (*b*); delta Normalised Burn Ratio (dNBR) (*c*); and relative dNBR (RdNBR) (*d*). The dMIRBI compares most favourably with RdCC in the inset area (bottom) where unburned islands were present, as well as the north-western portion of the fire (highlighted in orange) where there were substantial pre-fire mountain pine beetle impacts (McCarley *et al.* 2017*a*).

only separable from unburned pixels between the 70th and 80th percentiles (46–58% RdCC). Consistent with distinguishing levels of severity, most indices generally exhibited increased separability as severity increased. However, dNBR and RdNBR separability began to drop at the highest severity levels, whereas MIRBI, dMIRBI and NBR separability increased.

Discussion

Spectral index optimality

An optimal spectral index for measuring fire effects is sensitive to changes caused by burning and insensitive to environmental factors such as soil colour and atmospheric effects (Verstraete and Pinty 1996). In the present study, changes in severity between unburned, lower 10th percentile and upper 10th percentile of relative change in canopy cover yielded increasing MIRBI index values, whereas variation within classes (i.e. environmental factors) was distributed along isolines and thus had minimal effect on index value. This suggests an optimal index.

The spectral displacement caused by burning observed for NBR appeared more optimal than what was described using field measurements in Roy *et al.* (2006), perhaps as a result of the spectral aggregation at the Landsat scale, or differences in NBR performance between conifer and rangeland ecosystems. However, the confusion between unburned and low-severity (lower 10th percentile) pixels and the variation perpendicular to isolines within severity classes were readily apparent. This variation suggests that NBR is a less optimal index, a result that concurs with Roy *et al.* (2006), as environmental factors within a defined class should not affect the index value. In practice, this would result in a wide range of NBR values corresponding to small differences in fire effects, potentially misleading the interpretation of such values. Certain applications, such as the discernment of unburned islands and accurate delineation of fire perimeters, have significant implications for characterising post-fire ecosystem heterogeneity and resilience (Kolden and Weisberg 2007; Kolden *et al.* 2012; Sparks *et al.* 2015; Meddens *et al.* 2016). From what was observed in the present study, the utilisation of an optimal index such as MIRBI may be more suited to these efforts than NBR.

Separability of fire effects

Overall, MIRBI was the best index for distinguishing between burned and unburned pixels across all percentile levels and is consistent with the bi-spectral space plots (Fig. 1). Lower separability that was observed between unburned and low-severity fire effects is consistent with Smith *et al.* (2007), who noted that although MIRBI was developed using a field spectroradiometer (Trigg and Flasse 2001), satellite sensor pixels include a mixture of burned and unburned surfaces that reduce separability. Additionally, issues with discerning low-severity fire effects from satellite imagery in conifer forests are well documented

(Hudak *et al.* 2007; Wulder *et al.* 2009; Kolden *et al.* 2012; McCarley *et al.* 2017*b*), and are likely to have produced additional confusion given the differences between spectral and structural change.

For most indices tested, separability increased with relative change in canopy cover, demonstrating the ability to distinguish between increasing levels of canopy-based fire effects. On visual comparison of relative change in canopy cover vs the three differenced indices tested (Fig. 3), dMIRBI appears to most accurately match fire effects (specifically, change in canopy cover), especially in areas that are highly heterogeneous in terms of severity. The contrast observed here is consistent with the large difference in separability across levels of severity compared with dNBR and RdNBR (Fig. 2). The dMIRBI also appeared to more accurately represent relative change in canopy cover in areas where pre-fire mountain pine beetle (MPB) outbreak was known to have occurred (McCarley *et al.* 2017*a*). In this respect, dNBR performed poorly, although McCarley *et al.* (2017*b*) observed much better correlation between this index and absolute change in canopy cover. The RdNBR identified relative change in MPB-affected areas, but not as clearly as dMIRBI. Additionally, RdNBR was notable for exhibiting the least sensitivity across fire-induced changes as well as not being separable (M-statistic <1) from unburned pixels for almost all classes. This is consistent with poor relationships that were previously observed for this index in conifer forests (Hudak *et al.* 2007; McCarley *et al.* 2017*b*).

As the present research note evaluated only one fire, it is difficult to draw the conclusion that the patterns observed here would be regionally or nationally consistent. However, this highlights the broader need to understand how spectral indices may perform differently across ecosystems when calibrated to specific biophysical measures of change and provides the framework for more research. The Rapid Assessment of Vegetation Condition after Wildfire (RAVG; https://www.fs.fed.us/postfirevegcondition/, accessed 27 April 2018) is developed using RdNBR, although the equation was derived in California using modelled changes in structure (Miller *et al.* 2009; Miller and Quayle 2015). Results of the current study suggest that RdNBR was not the most appropriate index for measuring relative change in canopy cover for the Pole Creek Fire, raising reasonable doubt about the widespread applicability of national products such as RAVG that rely solely on spectral change.

Conclusions

Recent efforts in the scientific community have pushed for more meaningful measures of fire effects beyond spectral change. One such measure uses multitemporal LiDAR (e.g. Kane *et al.* 2013, McCarley *et al.* 2017*b*) to quantify structural changes from fire. However, the cost and availability of LiDAR are currently prohibitive for widespread application. Another proposed approach is to use the measurement of fire radiative energy as a predictor of changes in net primary productivity (Smith *et al.* 2016, 2017; Sparks *et al.* 2016), but this is restricted to either acquisition during the fire event or modelling. Therefore, MIRBI and dMIRBI, when calibrated to specific fire effects, may still offer a viable moderate-scale, easily acquirable method of predicting fire effects. It is likely that there is no 'one-size-fits-all' burn severity spectral index and that a suite of data will be required to fine-tune for factors such as ecosystem differences and the fire effect of interest for a given study. Equally, defining burn severity and fire effects based on specific biometrics remains critical to reducing ambiguity in the processes measured (Lentile *et al.* 2006; Kolden *et al.* 2015; Smith *et al.* 2016). Future work defining landscape-scale fire effects would benefit from utilising a wide range of techniques, rather than one-dimensional off-the-shelf products such as MTBS, in order to more accurately quantify and understand the post-fire landscape.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

The authors are grateful for valuable feedback from the associate editor and the other internal and external reviewers. This work was partially funded by the US Forest Service (USFS) under Joint Venture Agreement 13-JV-11261900–072, by the National Science Foundation (NSF) under award DMS-1520873, and by the Department of the Interior Northwest Climate Science Center (NW CSC) through Cooperative Agreement G14AP00177 from the US Geological Survey (USGS). Its contents are solely the responsibility of the authors and do not necessarily represent the views of the USFS, NSF or NW CSC. This manuscript is submitted for publication with the understanding that the United States Government is authorised to reproduce and distribute reprints for Governmental purposes. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US Government.

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