What is the color when black is burned? Quantifying (re)burn severity using field and satellite indices

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Abstract

Background

Trends of accelerating area burned in many regions worldwide are leading to increases in the amount of area experiencing short-interval reburns (i.e., fires occurring two or more times in the same place within 1–3 decades). Field and satellite indices of burn severity are well tested in forests experiencing a single recent fire, but the reliability of these indices in short-interval reburns is poorly understood. We tested how a commonly used field index (the Composite Burn Index, CBI) and satellite index (the Relative differenced Normalized Burn Ratio, RdNBR) compared to eight individual field measures of burn severity in reburns vs. areas burned in a single recent fire. We also tested if relationships in reburns depended on whether the first fire was stand replacing (fire that is lethal to most dominant trees).

Results

The correspondence between both CBI and RdNBR with individual burn severity measures differed in reburns compared to single fires for some metrics of burn severity. Divergence in the relationship between both CBI and RdNBR vs field measures was greatest when reburns occurred following a preceding stand-replacing fire, and measures were more comparable to single fires when the first fire was non-stand replacing (i.e., lower severity). When reburns occurred where a preceding fire was stand-replacing, CBI and RdNBR underestimated burn severity in the 2nd fire for tree-canopy metrics (e.g., canopy cover loss, tree mortality), as post-fire forests in early developmental stages are vulnerable to greater severity in a second fire. Conversely, when reburns followed a preceding fire that was not stand replacing, both CBI and RdNBR overestimated surface burn severity, as past low severity fires leave behind live fire resistant trees and can stimulate resprouting understory vegetation. Finally, neither CBI nor RdNBR were able to accurately detect the amount of deep wood charring that has emerged as an important product in reburns – particularly where both fires are stand-replacing.

Conclusion

Our findings inform interpretability of commonly used indices of burn severity in reburns, which is becoming an increasingly common application as fire activity increases.

Introduction

Increasing area burned in forested regions around the world is leading to many areas burning more than once in short-interval reburns (areas that have experienced two fires within 1–3 decades, Prichard et al. 2017). Reburns are expected in any fire-prone region, though their consequences can differ based on ecological context. For example, in forests adapted to historically frequent fire, short-interval reburns can represent a return to historical fire-return intervals and foster resilience to fire (Larson et al. 2013). In
contrast, in forests with historically longer fire-return intervals, short-interval reburns can produce novel extreme levels of burn severity and catalyze ecological shifts (Donato et al. 2009, Turner et al. 2019). Building an understanding of how to quantify burn severity in reburns and accurately tracking trends in such metrics is important for characterizing how fire regimes are changing.

Reliable and widely used indices exist to measure burn severity in the field, with satellites, and linking field- and satellite data. The Composite Burn Index, or CBI, is a unitless semi-quantitative ocular estimation of burn severity across five forest strata developed to validate remote sensing measures based on the normalized burn ratio (NBR) which is sensitive to fire-caused vegetation changes (Key and Benson 2006). CBI is useful in that it is a relatively quick (requiring less than one hour per plot) field protocol which corresponds well with field measures based on plant injury, fuel consumption, and tree mortality (Miller et al. 2009). Individual field measures such as fire-killed basal area and char height have also been established as metrics of burn severity (Harvey et al. 2014), and CBI generally corresponds well with many independently measured metrics (Saberi et al. 2022). Plot-level measures of burn severity, such as CBI, have been used to calibrate satellite-derived burn severity indices—allowing for the wall-to-wall mapping of burn severity across broad spatial extents. For example, RdNBR (relative differenced normalized burn ratio, Miller and Thode, 2007) is one of the most commonly used indices (Lentile et al. 2006) and provides an index of burn severity by calculating the ratio of the difference between the near infrared and shortwave infrared bands from pre-and post-fire Landsat imagery. Despite the widespread use of these field and satellite indices to measure burn severity in both single burns and reburns (e.g., Parks et al. 2014a, Harvey et al. 2016a), how well they perform in short-interval reburns has not been widely tested.

A short-interval reburn may affect how these indices record burn severity in several ways. First, the severity (the magnitude of fire impacts on vegetation, Keeley 2009) of the first fire can affect forest structure in ways that lead to different post-fire vegetation that a second fire encounters. For example, a first fire that is non-stand replacing (i.e., burns at low severity) is unlikely to drastically alter forest structure, leaving behind biological legacies such as live thick-barked, fire resistant trees if they were present pre-fire. This is particularly likely in low-severity and frequent-fire regimes dominated by trees with adaptations to survive low-intensity fires, and understory vegetation that can either resprout or regenerate from seed (Agee 1996). Conversely, a first fire that is stand-replacing (high severity) produces greater effects on stand structure and leaves fewer post-fire live biological legacies. This outcome is more likely to occur in high-severity fire regimes dominated by trees with fewer adaptations to survive fire, but instead possessing adaptations such as aerial seedbanks or wind-dispersed seed (Agee 1996). As such forests are in an early-seral stage following one fire, this can lead to reburns where the 2nd fire encounters young fire-sensitive tree seedlings and saplings with tree crowns close to the forest floor. In such cases, burn severity in the 2nd fire can be so extreme that most above-ground live and downed woody material is consumed (e.g., Turner et al. 2019, Fig. 1, bottom right panel). Thus, it is possible that burn severity indices well-calibrated to single-fires may relate differently to burn severity in reburns depending on the severity of—and structural legacies left behind by—the first fire.
In this study, we address these gaps by asking the following research questions. First, how does the relationship between eight independent field measures of burn severity and CBI (Q1) and RdNBR (Q2) vary between single fires and areas that have experienced short-interval reburns? Further, in each question, we tested whether the relationship depended on if the first fire in a reburn was stand-replacing. We expect the relationships between individual field measures of burn severity and both CBI and RdNBR to differ depending on the severity of the previous burn and the magnitude of initial fire-caused changes to forest structure (i.e., what biological legacies remain after one fire). For RdNBR, we expected differences to depend on the ability of the top-down perspective of the satellite to capture spectral signatures from different forest strata or different stand densities. Finally, we were interested in testing how well either CBI or RdNBR captured indices of extreme burn severity (e.g., deep charring and combustion of woody material) that has been observed in recent short-interval fires (Turner et al. 2019).

**Methods**

**Study Area**

The study area spans forested areas of the northwestern USA from the westside of the Cascade Mountains to the US Northern Rockies, across five states in the Western United States (ID, MT, OR, WA, WY). Sampled forests were conifer dominated, containing thick-barked, fire-resistant trees at lower elevations including Douglas-fir and ponderosa pine, as well as thin-barked trees that recruit post-fire such as lodgepole pine at higher elevations (Agee 1996). The study area spans a wide elevation, moisture, and forest type gradient, and was purposefully chosen to include reburn areas with both short- and long-interval reburns (Table A1, see Saberi et al. 2022 for details).

**Data collection**

One-year post-fire burn severity field data were collected from within 14 fires across nine Nationals Forests and two National Parks in the Interior Pacific Northwest (Table A1) during the summers of 2017 and 2018. Seven of these fire perimeters were characterized as reburns, meaning that they had experienced more than one fire within the past 30 years as recorded in the Landsat satellite fire record (Table A1). Measures of burn severity used in this study included CBI and eight individual field measures, in addition to RdNBR.

**Field Sampling**

Field site selection and methods are explained in detail in Saberi et al. (2022), and briefly described here. In each plot, we measured CBI and eight individual and independently quantified metrics of burn severity: change in live canopy cover, an index of needle retention, tree mortality (by basal area and number of trees), tree charring (height and circumference of tree bole), deep charring on the tree bole, and surface char on the forest floor (Table A2). Prior to field sampling, fire perimeters were identified as containing reburns by analyzing where past MTBS fires (dating back to 1984, the start date for MTBS-mapped fires) overlapped with the selected fire perimeters in ArcGIS 10.6.1, and sampling occurred within the reburn
perimeters. In the field, trees were assessed to determine if they were live pre-fire (i.e., survived the previous fire if the plot was a reburn) or dead pre-fire (i.e., had been killed in the fire preceding the reburn), and each reburned plot was recorded as having an initial fire that was either stand-replacing or non-stand replacing. Field plot assignment by this category was cross-referenced for reburn plots with RdNBR maps of the first fire used to confirm the severity of the first fire.

**Remote Sensing Indices**

We used RdNBR as the satellite burn severity index to compare to field measures. We conducted an analysis comparing the relationships between CBI, and dNBR, RdNBR, and RBR, which suggested differences among indices in their correspondence to CBI were minimal to non-detectable (Figures A1, Tables A3, A4, also shown in Harvey et al. 2019). Fire perimeters were obtained from the USFS Geospatial Technology Applications Center (GTAC). We calculated RdNBR in Google Earth Engine using two methods as follows: 1) the mean composite method detailed in Parks et al. (2018) and 2) using single pre- and post- fire imagery as established by MTBS.

For the single image method, pre-fire, and post-fire imagery for each of the 14 fires was obtained from the Landsat 8 Surface Reflectance Tier 1 Datasets from the Google Earth Engine satellite imagery catalog, at 30-m pixel resolution (Table A5). Dates for pre-fire and post-fire LANDSAT imagery were selected by finding the date of the highest NDVI value in the year prior to each fire. This was to account for the time of peak ‘greenness’ in each fire area. Date of maximum NDVI was calculated in GEE using the MODIS 250 m NDVI product. Pre- and post-re Landsat imagery was selected from the GEE catalog by only considering images within three weeks of the anniversary date and with no cloud cover. We accounted for potential phenological differences between pre and post-fire imagery by producing the dNBR offset value for each fire (Key and Benson 2006). The dNBR offset is useful when comparing burn severity among multiple fires, as the baseline spectral signature for green vegetation is set per fire. We determined the dNBR offset by calculating the mean dNBR value across all pixels located in a 180-m buffer around each fire perimeter (Parks et al. 2018), which quantifies dNBR differences among unburned pixels. The dNBR offset was subtracted from the original dNBR rasters, and the dNBR with the offset was used in calculation of RdNBR and RBR. Once DNBR, RdNBR, and RBR were calculated, raster values corresponding to each individual plot point were extracted using the extract function in the ‘raster’ package in R (version 3.4.3) via bilinear interpolation. We present results in this paper using the mean composite method (Parks et al. 2018) in this paper as this method has become commonly adopted; we detected no qualitative difference in burn severity metrics between the mean composite method and the single pre-and post-fire image method (Appendix B).

**Data Analysis**

To test the correspondence of each field measure with CBI (Q1) or RdNBR (Q2) in reburns, we created zero-one inflated beta (ZOIB) (Ospina and Ferarri 2012) regression models with the quantitative field measure as the response variable and CBI or RdNBR as the predictor variable. We fit general additive models, specifying zero/one beta inflated distributions to allow for 0 and 1 as values for the response
variable using the ‘gamlss’ package in R version 3.4.3 (see Saberi et al. 2022 for model details). For both model types, reburn levels were incorporated into the model structure. There were three levels of reburn, each indicating the severity of the previous burn and were codified as follows: no reburn, non-stand replacing, and stand replacing. We used a strength of evidence approach by evaluating p-values at different levels (strong at p < 0.01 level, moderate at < .05, suggestive at < .10, Muff et al. 2022) for each factor level and interaction term would indicate if the intercept and/or slope for the model differs depending on the severity of the first burn. We adopted this approach to mitigate the exclusion of potentially meaningful ecological relationships in inherently noisy observational field data (Ramsey and Schafer 2012). We also developed models without the reburn interaction term and present those models for use regionally calibrated models of burn severity more generally (Appendix C). Originally, 315 plots were sampled in the field, but analysis was limited to 313 plots since issues with overlap of pre and post fire Landsat imagery did not allow for indices to be calculated for two plots. The dataset was then further constrained to 297 plots when we reduced the data to only include 95% of the range of RdNBR values because extreme values can result from mathematical difficulties in the denominator of RdNBR (Parks et al. 2014b).

We evaluated model fit for all models using the area under receiver operating characteristic curves (AUC) for a sequence of proportion thresholds for the continuous field measure of burn severity (0.05, 0.275, 0.5, 0.725, and 0.95). This approach allowed us to assess model fit across the burn severity gradient. AUC values were calculated by dichotomizing the field response proportions into zeroes and ones if they were above or below the given threshold values. As an AUC value below 0.5 indicates poor model fit/capacity to distinguish presence or absence, (Pearce and Ferrier 2000), we did not display values below this level.

Results

The relationship between CBI and independent field measures of burn severity in reburns was variable when compared to relationships in single fires, and divergence among models was generally greatest when the first fire was stand-replacing. When the first fire was stand-replacing, CBI in the 2nd fire underestimated canopy cover change, needle loss, basal area (BA) killed by fire, and char height when compared to single burns (Fig. 2A, C, E, K). When the 1st fire was not stand-replacing, the only difference between reburns and single burns was for surface char, where CBI overestimated surface char compared to single burns (Fig. 20). CBI did not correspond to deep charring on woody material (deep char) in reburns, regardless of the severity of the first fire (Fig. 2M, Table A6, A7). Model fit ranged from AUC 0.82 for deep char to AUC of 0.99 for tree mortality by basal area, tree mortality by number of trees, and bole scorch (Fig. 2F, H, L, Table A6, A7).

The relationship between RdNBR and field measures of burn severity was mostly similar between single burns and reburns when the 1st fire was non-stand-replacing and diverged more when reburns followed preceding stand-replacing fires (Fig. 3). When the first fire was stand-replacing, RdNBR in the 2nd fire underestimated canopy cover loss, needle loss, BA killed by fire, and trees killed by fire, compared to single burns (Fig. 3C, E, G). When the 1st fire was not stand-replacing, the only difference was for surface
char, where RdNBR overestimated surface char compared to single burns (Fig. 3Q, Table A8,9). The RdNBR-based models had a high predictive ability for canopy measures, with the model for canopy cover, needle loss, killed basal area and killed trees having an average AUC of 0.93, 0.95, 0.97 and 0.97, respectively across all burn severity thresholds (Fig. 3D, F, H, J, and Table A8, A9). Similar to CBI, the relationship between RdNBR and deep char in reburns was not significant (Fig. 3O, Table A9).

**Discussion**

By testing the relationship between widely used field and satellite indices of burn severity in short-interval fires, our study highlights several key insights for understanding fire effects in reburned landscapes. First, the meaning of CBI and RdNBR relative to their calibrated values in single fires differs in reburns, but differences depend on the severity of the preceding fire. When short-interval fires occur where preceding fires were stand-replacing, both indices underestimate metrics of tree canopy burn severity, likely because reburned forests are in an early-seral stage that is more sensitive to fire. In contrast, when short-interval fires occur following preceding fires that were not stand-replacing (i.e., low severity), both indices performed consistently well, with one exception being an overestimation of surface burn severity. This outcome is likely because preceding low-severity fires do not strongly alter forest structure but do stimulate understory vegetation response. Second, neither CBI nor RdNBR corresponded to deep charring of woody material in short-interval reburns, which has become common as reburns occur. This suggests that both indices may be missing an ecological emergent dimension of changing fire regimes that can be explored in future work. Collectively, these findings suggest that burn severity metrics calibrated for single fires provide valuable information in reburns but may underestimate or overestimate burn severity depending on the severity of preceding fires.

**Under-or over-estimation of burn severity in reburns depends on severity of preceding fire**

The underestimation of burn severity in reburns by CBI and RdNBR when the preceding fire was stand-replacing are likely due to several factors related to the stage of forest recovery from the past fire. Burn severity metrics that were most underestimated in these cases were all related to tree canopy effects: canopy cover, tree mortality, needle and branch retention, and char height. This underestimation is likely due to the magnitude of initial fire-caused change to forest structure by stand-replacing fires, as well as the corresponding fire adaptations to stand-replacing regimes. First, stand replacing fires are a hard reset, where any potential fire resisting traits such as thick bark and high tree crowns are lost temporarily as young post-fire forests recover through succession. For species that can develop such fire adaptive traits, it may require some time before trees are again able to resist fire, and recovery times vary based on abundance of sprouting species in the ecosystem (Hood et al. 2018, Stevens et al. 2020). Severe fires regularly occur in forests where trees have adaptations to reproduce following fire (rather than survive fire), such as via canopy seedbanks with species like lodgepole pine (Tinker et al. 1994). In early seral stages characterized by young, small, and high-density lodgepole pine trees (Turner et al. 2016), the tree
canopy strata is much more vulnerable to fire than an older stand with larger and sparser trees (Kashian et al. 2005) that have a better chance of surviving fire.

In contrast to reburns occurring after preceding stand-replacing fire, our findings suggest that interpretations of CBI and RdNBR in reburns that follow preceding low-severity fires are more comparable to their widely used interpretation in single fires. Similar to above, this is also likely because of effects of preceding low severity fires as well as where fire regimes and plant adaptations in line with low-severity fire coincide. A low-severity fire that is not stand-replacing, by definition, leaves behind live legacy trees that survive one fire. Therefore, the live forest structure that the 2nd fire encounters is similar to the forest structure of the 1st fire, suggesting that any index of burn severity should perform similarly in both fires. In addition, low severity fires are more likely to occur in frequent-fire regimes where trees have adaptations to survive fire, and understory vegetation can bounce back quickly post-fire (Stevens et al. 2020) – furthering the likelihood of similar conditions encountered by subsequent fires.

The one exception to indices performing relatively similar to single burns when reburns follow preceding low-severity fires is that CBI and RdNBR both overestimated surface burn severity in reburns. This is likely because non-stand replacing fires are more likely to occur in fire regimes with sparse canopy cover and more vigorous ground cover vegetation, such as in dry forests and woodlands (Harvey et al. 2016b, Reilly et al. 2017). For example, in a ponderosa pine forest or woodland, frequent surface fires lead to widely spaced and fire-resistant trees interspersed with grasses/herbaceous between large canopy gaps (Agee 1996). Plots with high understory vegetation cover pre-fire are likely to have greater capacity for high understory cover vegetation post-fire, although there is high variability in post-fire vegetation response for low severity burns (Lentile et al. 2007). Therefore, such areas are likely to have resprouting vegetation that obscures post-fire surface charring (the measure that was overestimated by CBI and RdNBR in such conditions). As CBI and RdNBR indices are measured one-year post fire, this capacity for post-fire understory vegetation recovery may obscure surface burn severity that remains more exposed post-fire in more closed-canopy forests. This is especially relevant for RdNBR, as spectral indices of surface charring can be less visible from a satellite where vegetative resprouting can obscure the forest floor. Fire can influence phenology dates detected via satellites (Peckham et al. 2008), and in systems with vigorous understory vegetation, post-fire green up can occur relatively soon after fire.

**Challenges with detecting extreme burn severity and deep charring**

Deep charring of woody material—one outcome that is related to extreme levels of burn severity (Turner et al. 2019)—was not related to either CBI or RdNBR. Stand-replacing fires, by definition, produce large numbers of snags and downed logs, and in a second fire, much of this woody material can be consumed and/or remain as fragments coated with deep char (Fig. 1, bottom right panel). The CBI protocol only considers deep char in one out of five forest strata (substrate), and subsequently does not capture deep char that may occur along boles of trees (Saberi et al. 2022). However, this deeply charred material is important, as it alters the structure and function of the postfire landscape (Talucci and Krawchuk 2019,
Donato et al. 2016, Harvey et al. 2014, Campbell et al. 2007) and represents altered post-fire structural legacies that are becoming more common with overlapping disturbances (Harvey et al. 2014; Talucci and Krawchuk 2019). Deep char is more likely to occur when a tree is already dead at the time of fire (e.g., from the previous burn) (Talucci and Krawchuk 2019), so the ability to model deep char from CBI in reburns is an important area of future research. High severity reburns can increase the production of deep char (Donato et al. 2016), which could have implications for ecosystem structure and function. For example, the conversion of snag biomass to deeply charred material alters the fundamental structure of coarse woody debris which in turn influences carbon and nutrient cycling (Talucci and Krawchuk 2019, Harmon 2001). Augmentations to CBI that consider deep char not just on the forest floor but on trees could help to better understand deep char in reburns and any associated changes to ecosystem function.

The lack of relationship between deep char and RdNBR in short-interval reburns was likely for different reasons than those for CBI. The ability of spectral remote sensing to distinguish between deeply charred material and woody material that was only killed by fire is currently not well known. Spectroscopy of pine bark and wood shows differences in the unique spectral signatures for woody material that was burned and/or heated for different lengths of time, which relates to different levels of charred wood (Reeves et al. 2008). However, the spectral similarities between charred and deeply charred woody materials have not spurred the development and/or calibration of bands that can distinguish between the two (Reeves et al. 2008). Thus, it is likely that the spectral bands used to calculate NBR cannot distinguish deeply charred material from simply charred dead trees and may be a reason for difficulties in modeling deep char from RdNBR in reburns. Another reason may be the viewing angle of the satellite sensor. Most features land surfaces (such as forests) have three-dimensional characteristics and their reflectance values change with changes in the view angle (Liang et al. 2000). Multi-angular observations may improve reflectance information retrieval (Schlerf and Atzberger 2012). Landsat 8 hardcodes the view zenith angle to “0”, or directly overhead (Vermote et al. 2016), which may explain the difficulty in modeling deep char from RdNBR. Deep char on a tree bole may be facing towards the side instead of the sky, where it could be identified from an overhead satellite. It is possible that the incorporation of different or multiple viewing angles would produce different reflectance values that may be able to detect deep char on tree surface. Using different or multiple viewing angles from the Landsat Collection 1 Angle Coefficient file (https://www.usgs.gov) to develop stronger relationships with deep char could be a future direction of research.

**Conclusion**

As fire activity increases and more areas burn multiple times in short succession, accurate monitoring and assessment of (re)burn severity becomes more important. Overall, our models show that both CBI and RdNBR relate to burn severity similarly for some measures, and divergence for others, between areas that have burned once or twice recent decades. In general, our results suggest that these widely used indices of burn severity may be under-predicting canopy burn severity in reburns where the preceding fire was stand-replacing, and over-predicting surface burn severity in reburns where the preceding fire was non-stand-replacing. Further, neither index corresponded to deep charring of woody material, suggesting
that this important aspect of extreme burn severity that can occur in short-interval reburns is not being captured by burn severity mapping efforts. These findings can help qualitatively inform where burn severity in reburns is being under- or over-estimated and can guide development of better quantitative adjustments to improve burn severity assessments in the future.

**Declarations**

*apply lab standard verbiage upon review/acceptance/etc**

**Ethics approval and consent to participate**

Not applicable

**Consent for publication**

Not applicable

**Availability of data and material**

The datasets generated and/or analysed during the current study are available in the author’s Zenodo repository, [link to be posted upon publication]

**Competing interests**

The authors declare that they have no competing interests.

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**Authors’ contributions**

SJ Saberi collected and analyzed the data and wrote the manuscript. BJ Harvey conceived of the study and was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

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References


**Figures**
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**Figure 1**

Photos of burn severity in plots across differing severities of a previous burn.
Figure 2

Zero/one inflated beta regression models for each of the eight individual burn severity metrics with CBI as the predictor variable. In the first column, the black line shows model prediction values for non-reburns, while the blue line represents non-stand replacing reburns and the red line represents stand replacing reburns. The polygon around each line shows 95% confidence around mean predicted values from bootstrapping. Grey dots are the raw data points from the 313 sampled plots. The second column
contains AUC values for each of the eight regression models across five thresholds of burn severity (which were created as dichotomization thresholds to produce ROC curves). Overall AUC values represent overall average across five thresholds.

Figure 3

Zero/one inflated beta regression models for each of the eight individual burn severity metrics with RdNBR (mean composite method) as the predictor variable. In the first column, the black line shows model prediction values for non-reburs, while the blue line represents non-stand replacing reburns and the red line represents stand replacing reburns. The polygon around each line shows 95% confidence around mean predicted values from bootstrapping. Grey dots are the raw data points from the 313 sampled plots. The second column contains AUC values for each of the eight regression models across five thresholds of burn severity (which were created as dichotomization thresholds to produce ROC curves). Overall AUC values represent overall average across five thresholds.

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