CANADIAN JOURNAL OF REMOTE SENSING
2020, VOL. 46, NO. 1, 100–111
https://doi.org/10.1080/07038992.2020.1735931

An Improved Approach for Selecting and Validating Burn Severity Indices in Forested Landscapes

Une approche améliorée pour sélectionner et valider les indices de gravité des feux dans des milieux forestiers

Michael R. Gallagher[a], Nicholas S. Skowronski[b], Richard G. Lathrop[c], Timothy McWilliams[d], and Edwin J. Green[c]

[a]Northern Research Station, USDA Forest Service, New Lisbon, NJ, USA; [b]Northern Research Station, USDA Forest Service, Morgantown, WV, USA; [c]Department of Ecology, Evolution and Natural Resources, Rutgers University, New Brunswick, NJ, USA; [d]Davis College of Agriculture, West Virginia University, Morgantown, WV, USA

ABSTRACT

Burn severity maps based on remotely sensed reflectance data provide a useful way for land managers and researchers to represent and compare spatial variation in fire effects among wildfires and prescribed fires. A need exists for an objective and rigorous selection approach that ensures the best possible spatial predictions of burn severity. The aim of this study was to present and test a methodology for selecting the optimal burn severity index from a suite of calculation and validation options that can be used to produce data for more rigorously comparing ecological effects of fire that occur in contrasting phenologies. In our study, we cross-validated remote sensing data with field data and we tested the predictive ability of 12 cross-validated index calibrations that were generated using common statistical approaches, to predict field-measured burn severity indices collected at burned and unburned areas in New Jersey Pinelands National Reserve. We demonstrate the utility of our approach, provide convincing evidence for the use of CBI as a field-based index over WCBI, and provide a cross-validated method for calculating burn severity in this vegetation type that can be used by managers and researchers.

RÉSUMÉ

Les cartes de gravité des feux basées sur des données de réflectance spectrales fournissent aux gestionnaires et aux chercheurs un moyen utile de représenter et de comparer la variation spatiale des effets des incendies de forêts naturels ou des feux dirigés. Cependant, les multiples méthodes disponibles pour calculer et valider les indices peuvent entraîner des incohérences entre les types de végétation. Le besoin demeure pour une méthode de sélection objective et rigoureuse qui assure les meilleures prévisions cartographiques possibles. Cette étude présente et teste une méthodologie pour sélectionner l'indice de gravité des feux optimale parmi une série d'options de calcul et de validation. Nous avons testé la capacité prédictive de douze indices au moyen d'une validation croisée, indices de télédétection et indices de terrain, générés à l'aide d'approches statistiques couramment utilisées dans la littérature et ce afin de prédire des indices de gravité des feux évaluées sur le terrain pour des zones brûlées et non brûlées du New Jersey Pinelands National Reserve. Nous démontrons l'utilité d'une telle approche, fournissons des preuves convaincantes de l'utilisation du CBI en tant qu'indice sur le terrain par rapport au WCBI, et proposons une méthode de validation croisée pour calculer la gravité des feux dans ce type de végétation qui peut être utilisé par les gestionnaires et les chercheurs.

ARTICLE HISTORY
Received 22 November 2019
Accepted 24 February 2020

Introduction

Burn severity indices are used to quantify the magnitude of ecological change across landscapes that are impacted by fire to estimate spatially explicit fire effects (Kolden et al. 2015; Keeley 2009). Burn severity index maps are most commonly derived from spectral reflectance data (Key and Benson 2006; Garcia and Caselles 1991), which is advantageous to managers in

CONTACT Michael R. Gallagher michael.r.gallagher@usda.gov

need of rapid analyses of fire effects. Field-observed burn severity indices, generated from visually observed fire effects, present an alternative often used for evaluating the accuracy of burn severity index maps created via remote sensing (De Santis and Chuvieco 2009; Picotte and Robertson 2011). Multiple methods exist for calculating burn severity maps from remotely sensed reflectance data, and each results in similar, but unique, indices that vary in accuracy, even with the same input data (Parks et al. 2015; Soverel et al. 2010).

Remotely sensed burn severity indices are typically derived from near infrared (NIR, 700 – 1400 nm) and short-wave infrared (SWIR, 1400 – 2500 nm) wavelengths, as they are theoretically the most receptive to changes in soil and vegetation reflectance incurred by fire (Garcia and Caselles 1991; Key and Benson 1999). The most basic of these indices is the Normalized Burn Ratio (NBR), which is used as a precursor for calculating other NIR and SWIR based burn severity indices (Parks et al. 2014; Soverel et al. 2010). While NBR is an attractive option for its relative simplicity compared to other burn severity indices; being a single date index gives it the inherent disadvantage of only capturing a state of conditions rather than a departure from initial conditions. This limitation can make fire effects indistinguishable from other disturbance effects on vegetation in resultant maps. Differencing pre- and post-fire NBR provides a different index called the differenced Normalized Burn Ratio (dNBR), which resolves the single-date problem (Key and Benson 2006). Relative Differenced Normalized Burn Ratio (RdNBR) and the relative burn ratio (RBR) are also calculated using pre- and post-fire NBR, and are normalized to pre-burn reflectance to account for variation in pre-fire vegetation density (Parks et al. 2014; Miller and Thode 2007).

Field-observed burn severity indices are inherently tedious and dangerous to collect in the post-fire environment and do not provide the wall-to-wall estimates that remote sensing can; but are useful when only relatively few spatially explicit data points are required, such as for calibrating and cross-validating remote sensing indices. The Composite Burn Index (CBI) and the Weighted Composite Burn Index (WCBI) are simple to obtain and the most common field-observed indices found in the literature (Key and Benson 2006; Cansler and McKenzie 2012). These indices are generated using a standardized formula to rank and summarize effects on biotic indicators in different forest strata, such as exposure of soil and scorch height, which are then summarized as a weighted average. WCBI differs from CBI in that the influences of specific forest strata are additionally weighted by their percent cover (Cansler and McKenzie 2012; Soverel et al. 2010). However, the fact that percent cover is often visually estimated post-fire may introduce bias into calculations that is difficult to quantify.

Seasonally variant trends in forest reflectance can be a critical factor to consider when remote sensing burn severity in regions where fire can burn under contrasting phenological conditions, such as in forests of the Eastern US where prescribed fires and wildfires take place during both leaf-on and leaf-off conditions. Under these circumstances, baseline reflectances differ because of the lack of foliage. Similarly, dormant season fires tend to be less damaging to vegetation because soil conditions are cooler and damper, and buffer heating from the fire, leaves of deciduous plants have naturally senesced and are absent from being damaged, and roots have already stored carbohydrates for new growth when the growing season begins. Similarly, intra-annual variation in live plant moisture content has been shown to follow seasonal patterns, relating to variation in flammability and susceptibility to injury (Thomas et al. 2014; Jolly and Johnson 2018). Likewise, the degree of damage or mortality among woody plants from dormant season fire may be difficult to observe in the field before spring leaf-out. Comparing effects to vegetation reflectance between the contrasting baseline reflectances of dormant and growing seasons is methodologically inconsistent and similarly problematic. This presents an important consideration for choosing a methodology to consistently compare burn severities in temperate forest types where fire impacts deciduous species under both dormant and growing season conditions (Gallagher 2017).

The objectives of this study were to (1) develop a rigorous selection process to identify the most highly correlated pair of remote sensing and field-based burn severity indices, and (2) to test its use in a new ecosystem with phenologically consistent mapping data. This study is based on the remotely sensed and field-observed burn severity data collected from 23 prescribed fires, 5 wildfires, and 5 unburned forests dominated by an overstory of pitch pine (*Pinus rigida* Mill.) in the New Jersey Pinelands National Reserve. We cross validated remote sensing data with field data using multiple common approaches and statistically compared results to evaluate the most accurate remote sensing and field index pair. We then identify strengths and potential improvements for field indices of burn severity and describe the strengths and

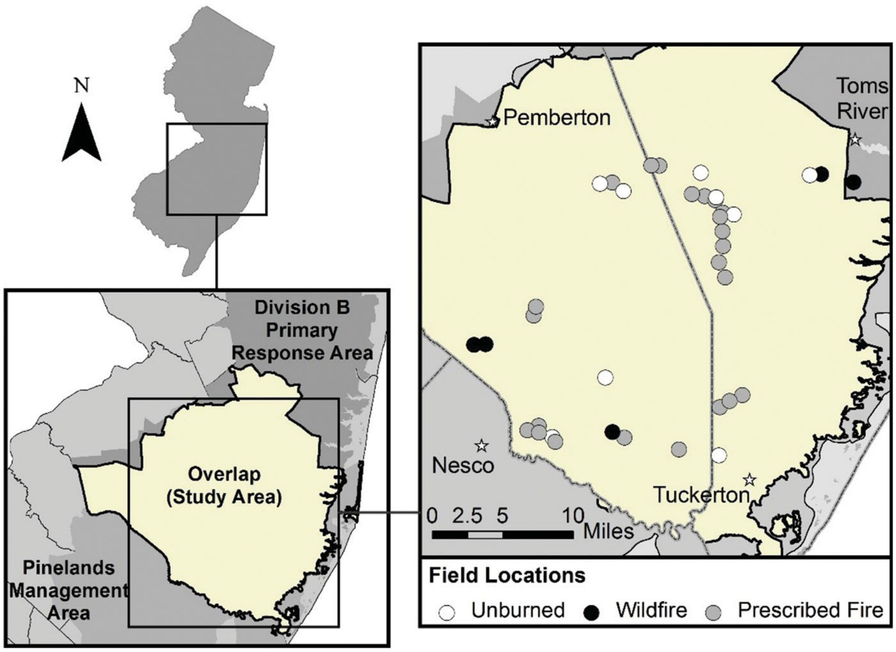

Figure 1. Map of the study area and field locations within the overlap zone of the New Jersey Forest Fire Service Division B primary response area and New Jersey Pinelands Management Area.

weaknesses of the approach offered in this study for use in future fire effects monitoring and research efforts.

Materials and methods

Site description

The study area falls within the New Jersey Forest Fire Service's Division B primary response area, which encompasses 254,033 ha mainly within the Pinelands National Reserve (PNR) in Burlington and Ocean Counties (Figure 1). More than 60% of PNR is comprised of upland forests (Forman 1998; Lathrop and Kaplan 2004), with fire being most frequent in pitch pine-dominated areas. It should be noted that pitch pine is highly adapted to fire and maintains the ability to resprout from epicormic buds along its root collar, trunk, and branches, and recover, after partial or complete crown consumption from fire (Ledig and Little 1998). Pitch pine-dominated stands have understories composed of ericaceous shrubs and shrub oaks, such as lowbush blueberry (*Vaccinium palladum* Aiton and *angustifolium* Aiton), black huckleberry (*Gaylussacia baccata* (Wangenh.) K. Koch.), scrub oak (*Q. ilicifolia*), black jack oak (*Q. marilandica*), and inkberry holly (*Ilex glabra* (L.) A. Gray), and represent a relatively similar mix of species as is found in other oak-dominated and mixedwoods stands of the PNR and other coastal plain pine-dominated forests of the Mid-Atlantic and Northeastern US. As a whole, the PNR is an area of complex wildland urban interface that experiences a higher frequency of wildfires than anywhere else in the region, with multiple large wildfires per decade that exceed 400 ha each in both the dormant season and growing season (Forman and Boerner 1981; La Puma 2012). Dormant-season prescribed fire, on state and federal land, has accounted for twice as much land burned as wildfire on this landscape over at least the past decade (Gallagher 2017). However, legislation signed into law in 2018 has enabled prescribed burning on privately owned land and expanded the burn window into the growing season, which may impact the overall balance of fire size and seasonality on this landscape (Prescribed Burn Act of New Jersey 2018).

Data collection and processing

This study used a sample of 33 pitch pine-dominated stands in the PNR. Between 2012 and 2015, 23 of these stands were treated with mixed intensity dormant season (leaf-off) prescribed fire, 5 were burned in mixed intensity growing season (leaf-on) wildfires, and 5 remained unburned as part of a larger effort to understand the variability in effectiveness of prescribed burning for fuel reduction (Skowronski et al. 2017). Prescribed fires ranged from 2 – 162 ha in size and wildfires ranged from 11 – 277 ha in size. Shapefile data for burn units was collected as part of a separate project and is publicly available and was

Table 1. Prescribed fire, wildfire, and unburned plot information.

Unit	Burn date	Fire size (ha)	Field plots (*n*)
Prescribed fires (Leaf-off)			
AT&T Line	3/3/2013	29	3
Dan's Bridge	3/5/2013	118	3
Experiment 1	3/5/2013	7	12
Fish and Wildlife	3/10/2013	103	1
Cedar Bridge	3/15/2013	162	3
Dead Pheasant	3/15/2013	55	1
Burnt Schoolhouse	3/6/2014	5	1
Experiment 2	3/11/2014	5	12
Bulltown Road	3/14/2014	132	3
Tylertown	3/14/2014	76	3
3 Foot Road	3/15/2014	78	3
Carranza Skit	3/15/2014	53	3
East Sandy Ridge	3/15/2014	56	3
Lacey	3/15/2014	89	3
Rattler Road North	3/15/2014	65	3
Rattler Road South	3/15/2014	76	1
Snuffy's Turnpike	3/16/2014	62	1
Whiting East	3/16/2014	14	3
Whiting Middle	3/16/2014	43	3
Whiting West	3/16/2014	67	3
Burn Experiment	3/23/2014	2	3
Bloody Ridge Road	3/24/2014	58	3
Bodine Field	3/24/2014	39	3
Wildfires (Leaf-on)			
Crossroads Fire	4/24/2014	81	3
Continental Fire	4/24/2014	128	3
Springers Brook Fire	4/25/2014	104	3
Bodine Field Fire	7/7/2014	11	3
Atsion Fire	5/7/2015	277	8
Not burned			
Brendan T. Byrne SF	2005		1
Butterworth Road North	2003		3
Butterworth Road South	2003		3
Jenkins	2011		3
Nugentown	1983		3

acquired from the USDA Forest Service data archive (Skowronski et al. 2017), with the exception of one wildfire, the Atsion Fire, which was acquired with permission from New Jersey Forest Fire Service. Fire behavior and fuel consumption analyses have been previously published for the Experiment 1 (Mueller et al. 2014, El Houssami et al. 2016), Experiment 2 (Mueller et al. 2017, 2018; Filkov et al. 2017), and Cedar Bridge (Clark et al. 2018) prescribed fires used in this study. Across all units, plots measuring 30 m in diameter were established before prescribed fires and immediately following wildfires. Plot center locations were recorded using a Trimble GeoExplorer 6000 GPS paired with a Tornado receiver (Trimble Inc., Sunnyvale, CA, USA), which produced point data estimated to be within 3 m of the actual positions after differential correction, thus facilitating accurate spatial correlation with remotely sensed reflectance data. A total of 77 plots were located in prescribed fires, 20 in wildfires, and 13 in unburned areas (Table 1). Shapefile data for plot locations is publicly available as US Forest Service archived data (Gallagher et al. 2017).

CBI and WCBI data were gathered immediately post-fire at each burn severity assessment plot following the CBI field sheet developed by Key and Benson (2006) and WCBI adaptation from Cansler and McKenzie (2012). This worked well to characterize the largely coniferous canopy conditions and changes to the substrate layer across all phenologies; but proved difficult for characterizing damage and mortality to the dense layers of deciduous shrubs and mid-story species immediately following dormant season fires during the leaf-off conditions of the that season. We therefore revisited our plots at the end of the growing season, approximately when spectral data was collected (described later in this section), to confirm damages and mortality in these layers that are more obvious during the growing season.

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scenes were acquired for the growing season immediately preceding and following the fires. Imagery was constrained to Julian dates 176 through 288, or the period of full leaf expansion during the growing season for this region (Clark et al. 2012). Raw ETM + scenes were downloaded as Level 1 data products from the USGS and converted from digital numbers (DN) to radiance and from radiance to top of atmosphere reflectance values to normalize for natural variation in solar angle and the distance between the sun and the Earth (Chander et al. 2009).

Additional relative radiometric correction was performed to synchronize spectral scaling between scenes, and thus adjust for inconsistencies in top of atmosphere reflectance observations made on different dates that can arise from variation in atmospheric conditions. While numerous approaches can be used to correct for different sources of variation in observed reflectance of different types of surfaces, we corrected our imagery using a simple approach intended for forest environments, described by Isaacson et al. (2012). This approach involves normalizing reflectance of multi-temporal images with coniferous forest areas with largely invariant interannual reflectances in a clear baseline image. We performed this normalization using mature stands of Atlantic White Cedar (*Chameacyparis thyoides*), a densely foliated evergreen which are scattered throughout the region and are unlikely to be impacted by disturbances or pests that would confound reflectance between scenes, in a single Landsat 5 Thematic Mapper (TM) scene from August 28, 2010 that was collected on clear day and clouds cloud-free day.

Due to a systematic ETM + sensor error and high frequencies of clouds in imagery, we used

Table 2. Landsat TM and ETM + scenes used to create mosaics.

Year	Date	Path	Row	Image ID
2010	28-Aug	14	32	lt50140322010240
2012	2-Jul	13	32	le70130322012183
	20-Sep	13	32	le70130322012263
	3-Aug	13	32	le70130322012215
2013	25-Jun	14	32	le70140322013176
	5-Aug	13	32	le70130322013217
	6-Sep	13	32	le70130322013249
	15-Oct	14	32	le70140322013288
2014	28-Jun	14	32	le70140322014179
	7-Jul	13	32	le70130322014188
	30-Jul	14	33	le70140332014211
	8-Aug	13	32	le70130322014220
	15-Aug	14	32	le70140322014227
2015	24-Jun	13	32	le70130322015175
	17-Jul	14	32	le70140322015198
	26-Jul	13	32	le70130322015207
	18-Aug	14	32	le70140322015230

multitemporal data to fill gaps and create mosaics that covered our study plots. Our study was conducted following the decommissioning of the TM and partially prior to the commissioning of Landsat 8 Operational Land Imager (OLI) and required us to use ETM + data during the Scan Line Corrector-off period (SLC-off) in which scenes exhibited lines of missing data (for more information on this error see Preliminary Assessment of the Value of Landsat-7 ETM + Data Following Scan Line Corrector Malfunction by Andrefouet et al. (2003)). First, clouds and cloud shadows were manually masked and removed from each scene. Multiple overlapping scenes were mosaicked for single growing seasons, using the most error-free scene with the latest date as the primary scene, and rectifying gaps caused by clouds and the systematic Landsat ETM + Scan Line Corrector-off errors with other scene's based on their completeness (Table 2). No topographic correction was required because the study area is topographically simple.

NBR, *dNBR*, *RdNBR*, and *RBR* were calculated for $2012-2015$ using the mosaicked scenes and the following calculations:

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \tag{1}$$

$$dNBR = NBR_{prefire} - NBR_{postfire} \tag{2}$$

$$RdNBR = \frac{dNBR}{\sqrt{ABS\left(\frac{NBR_{prefire}}{1000}\right)}} \tag{3}$$

$$RBR = \frac{dNBR}{NBR_{prefire} + 1.001} \tag{4}$$

We checked for potentially confounding effects of using multi-temporal data in mosaics by comparing pre- and post-fire NBR in stands adjacent to each burn unit and found that post-burn reflectance was within 3% of pre-burn reflectance on average and deemed acceptable for the purposes of this study. Using the GPS points from each burn severity field plot, values were extracted from the burn severity rasters by averaging a 3×3 window of pixels. This approach or other spatial averaging approaches are a standard way of accounting for spatial error in the remotely sensed datasets (Cansler and McKenzie 2012; Miller and Thode 2007). Burn severity maps for each burn, in terms of RdNBR, can be seen in the Appendix of this manuscript.

Evaluation of remote sensing data with field data

A series of models were developed to examine the accuracy of the selected remotely sensed indices for predicting CBI and WCBI indices in the New Jersey Pinelands. These models varied in terms of remote sensing index and field-based index pairing, as well as equation form. Indices used are listed in previous sections of this manuscript, and the most commonly used equation forms were determined from the literature as polynomial, exponential, and sigmoidal, and can produce widely differing results but have yet to be compared in a single environment (Chen et al. 2011; Warner et al. 2017; Wimberly and Reilly 2007; Picotte and Robertson 2011). These equations are given as:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + e \tag{5}$$

$$y = \beta_0 + \beta_1\left(1 - e^{-\beta_2 x}\right) + e \tag{6}$$

$$y = \frac{\beta_0}{1 + e^{-(\beta_1(x-\beta_2))}} + e \tag{7}$$

where y = field burn severity index, x = remotely sensed burn severity index, e = random error, and the β' s are model coefficients estimated from the data through model fitting.

Model selection was achieved through a two-step process in which the best model to predict each form of the dependent variable (e.g. CBI and WCBI) was established using a k-fold cross validation, and then those models were reevaluated to determine that which was most suitable. Across all burns, field observations indicated that the range of low to high severity was represented but overall was skewed toward the lower end of the range of severity. We thus ensured that the training data and test data in each of the k-fold iteration always represented the entire range of the data by ordering data by field index value and then dividing the entire dataset into 5 quantiles. 80% of data from each quantile were randomly chosen as training data, while the remaining 20% of data were reserved for testing. In this way, the dataset was

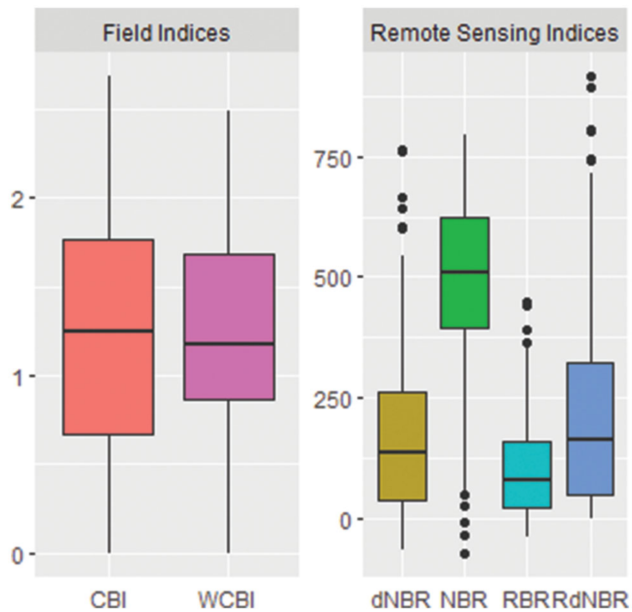

Figure 2. Boxplots summarizing observations of burn severity across all plots using 3 field indices and four remote sensing indices.

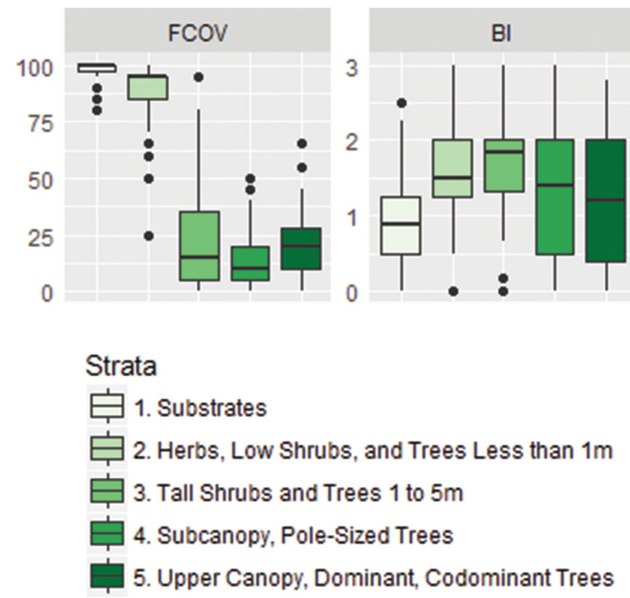

Figure 3. Box plots of observed pre-fire percent cover (FCOV) and post-fire Burn Index (BI) data by forest strata.

randomly resorted at each k-fold iteration into new combinations of training and testing data, while providing balance of burn severity in the training and testing data. Model results were ranked using sum of squared errors (SSE) as a primary criterion and Akaike's Information Criterion (AIC) as a tie breaker when SSE values were equal. We then compared CBI and WCBI by rerunning the highest-ranking model for each using the full dataset (e.g., not split into test and training data) to produce new coefficient estimates for each model, which were then compared.

Results

Field observed CBI values ranged from 0 to 2.68, representing 89% of the possible range of the index (CBI ranges 0–3), while observed WCBI ranged from 0 to 2.49, representing only 83% of the possible range of burn severity (WCBI ranges 0–3). Although mean CBI and WCBI values were similar, the range and variance of WCBI was substantially lower (Figure 2). Percent cover (i.e. FCOV), used to weight the influence of each strata in the calculation of WCBI, tended to approach 100% in the lowest two forest stratum and had very low variability. FCOV was substantially lower and more variable in the upper 3 strata that represent the midstory and overstory, muting the effects in the canopy which can be substantially different and more visible in reflectance data (Figure 3).

On average, models using NBR had a lower AIC and SSE than the bi-temporal remote sensing indices when predicting either CBI or WCBI, regardless of the model form (Tables 3 and 4). Similarly, models using the polynomial equation form produced lower SSE values on average in both CBI and WCBI model groups compared to exponential or sigmoidal equation forms. Models with sigmoidal equations performed poorly in comparison despite their prevalence in previous work.

Table 3. Akaike's Information Criterion (AIC) and sum of squared error (SSE) for candidate models of CBI and WCBI.

Dependent variable	Eqn. form	Independent variable	SSE	AIC
CBI	Pol	NBR	4.4	87.6
		dNBR	4.1	82.6
		rdNBR	4.1	82.4
		RBR	4.2	82.4
	Exp	NBR	4.4	87.5
		dNBR	4.9	100.9
		RdNBR	5.0	100.9
		RBR	4.9	99.3
	Sig	NBR	4.2	80.9
		dNBR	4.2	81.8
		RdNBR	4.4	82.0
		RBR	4.3	82.0
WCBI	Pol	NBR	3.9	77.0
		dNBR	4.0	79.7
		RdNBR	4.1	79.3
		RBR	4.0	79.5
	Exp	NBR	3.9	76.8
		dNBR	4.8	95.3
		RdNBR	4.8	95.3
		RBR	4.7	94.1
	Sig	NBR	4.1	80.3
		dNBR	4.2	79.8
		RdNBR	4.3	80.3
		RBR	4.1	80.0

AIC and SSE values represent averages across all models from the cross validation segment of each fold.

Table 4. Maximum likelihood estimates and two standard errors (2 SE) for coefficients of models predictive of field indices of burn severity from remotely sensed indices of burn severity.

Predicted index (field)	Eqn. form	Predictor index (remote sensing)	β_0	2 SE	β_1	2 SE	β_2	2 SE
CBI	Pol	NBR	1.242	0.005	−5.619	0.034	−1.152	0.017
		dNBR	1.245	0.005	5.584	0.031	−1.648	0.02
		rdNBR	1.24	0.006	5.536	0.03	−1.67	0.02
		RBR	1.24	0.005	5.583	0.031	−1.568	0.02
	Exp	NBR	2.486	0.004	1	0.043	0.002	2.57E-05
		dNBR	0.625	0.004	−161.448	1.667	2.07E-05	1.69E-07
		rdNBR	0.607	0.005	−115.223	2.157	2.48E-05	2.89E-07
		rbr	0.62	0.004	−185.639	1.978	3.03E-05	2.56E-07
	Sig	NBR	2.182	0.007	0.011	0.001	1.42E + 02	1.02E + 01
		dNBR	2.358	0.007	0.01	9.59E-05	148.17	0.96
		rbr	2.34	0.007	0.016	0	88.39	0.59
		rdNBR	2.329	0.007	0.008	8.62E-05	179.40	1.18
WCBI	Pol	NBR	1.234	0.005	−4.734	0.03	−1.165	0.019
		dNBR	1.232	0.004	4.624	0.027	−1.528	0.021
		rdNBR	1.229	0.005	4.62	0.028	−1.523	0.021
		RBR	1.229	0.005	4.638	0.027	−1.439	0.02
	Exp	NBR	2.215	0.003	0.552	0.054	2.00E-03	2.99E-05
		dNBR	0.72	0.004	−145.908	1.734	1.91E-05	1.92E-07
		rdNBR	0.702	0.004	−111.658	2.507	2.18E-05	3.18E-07
		rbr	0.713	0.005	−167.233	1.857	2.80E-05	2.44E-07
	Sig	NBR	2.17	0.006	0.11	0.001	143.49	10.48
		rbr	2.166	0.006	0.014	1.53E-04	73.82	0.52
		dNBR	2.161	0.006	0.009	9.51E-05	120.75	0.83
		rdNBR	2.147	0.007	0.007	5.91E-05	150.25	1.06

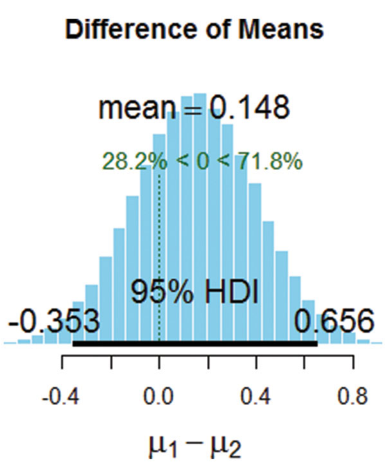

Figure 4. Significance testing for differences between AIC values of the CBI-polynomial-dNBR model and the CBI-polynomial-RdNBR model.

When ranking models based primarily on SSE and secondarily on AIC, two candidate models (e.g. CBI/dNBR/polynomial and CBI/RdNBR/polynomial) tied as highest rank with the same SSE and nearly the same AIC across all iterations of the k-fold process (Table 3). We attempted to break this tie by conducting a difference of means test, which is a Bayesian analog to the *t*-test, using the BEST package in R (Kruschke 2013). However, the resulting highest density interval for the posterior probability of the difference means contained 0, indicating that the models were not statistically different and the tie was sustained (Figure 4). Therefore, both models were considered in the final evaluation along with the highest ranking WCBI model to be re-run with full dataset as a final evaluation step. Coefficients of determination for the observed vs. predicted values were 0.74 for both CBI models and 0.68 for the WCBI model, indicating that both CBI models performed better than the WCBI model (Figure 5). Figure 6 provides examples of representative prescribed fire and wildfire RdNBR maps created using the final approach.

Discussion

We present a framework for rigorously selecting methods and demonstrate its potential by using it to evaluate the optimal combination of spectral index, field index, and predictive model form for predicting burn severity in the pitch pine-dominated forests of the New Jersey Pinelands. Our study indicates that monitoring and comparing ecological effects of fires across broad spatial extents and differing phenological conditions can be simplified using spectral burn severity indices, yet the accuracy of evaluations and comparisons made within and between studies made using these indices hinges on consistent use of rigorously selected methods for generating predictions. Our results offer a justifiable approach to comparing and selecting indices that is statistically robust to uneven distributions of burn severity values and fires that occur under differing phenological conditions, and avoids pseudoreplication that is present in some other studies from pooling plots within burn units at the landscape level (Allen and Sorbel 2008; Kasischke et al. 2008). Our results demonstrate how fire effects

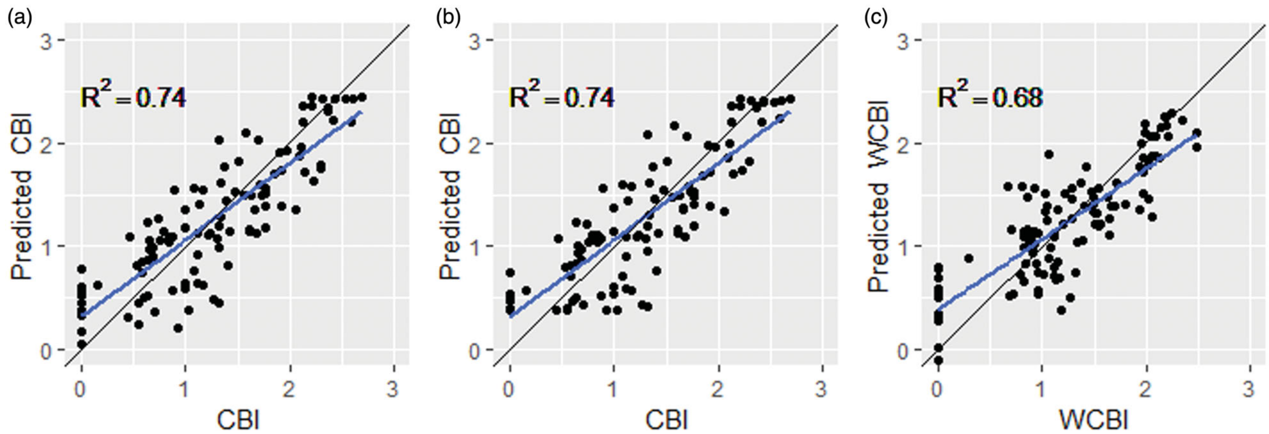

Figure 5. Linear regression plots of actual CBI field observations vs. predicted CBI observations from (a) dNBR-polynomial model (b) RdNBR-polynomial model, and (c) plot of WCBI field observations predicted from NBR-exponential model.

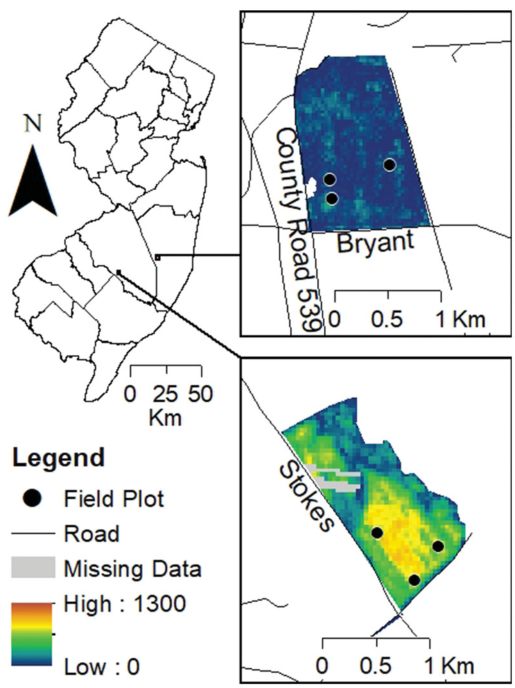

Figure 6. RdNBR burn severity maps and field plot locations for the Cedar Bridge prescribed fire and the Springer's Brook Fire, which are representative of prescribed fire and wildfires in the study area. Note that field plot sizes appear larger than their true size to facilitate viewing (see methods for actual size descriptions).

in dense understory strata had a dominating influence on WCBI, reducing its sensitivity to the full scope of fire effects throughout the vertical forest profile. We also found that dNBR and RdNBR performed better than NBR or RBR for burn severity monitoring in the New Jersey Pinelands, although it should be noted that most models performed fairly well. In our study, dNBR and RdNBR were found to predict CBI equally well when using a polynomial model, and future users could justify use of either index. This finding supports the results of the only other previously published study on burn severity in the New Jersey Pinelands, which found that CBI was correlated with dNBR data generated using the spectral data from WV-3, and highlights the potential for future monitoring and research in this environment with burn severity (Warner et al. 2017).

Due to climate change and the increased use of prescribed fire, fires burn across a broader range of seasonal variation in forest plant phenology. One example of this is the difference in reflectance between dormant and growing season conditions of deciduous and mixed composition forests of the eastern US. Traditional approaches that use spectral burn severity indices have approached image acquisition based on a window of time that is relatively close to the calendar date of an individual fire, which is very useful for guiding time-sensitive, post-fire environmental interventions, such as to mitigate post-fire erosion, but may be less informative for use in monitoring and comparing effects of many fires that occur under different phenological conditions. This is because certain critically informative fire effects are most easily evaluated as impacts to foliage or foliar responses (i.e. mortality of deciduous plants, responses of fire adapted conifers) and are exceedingly difficult to evaluate for dormant season fires before foliage has had the opportunity to regenerate. For this reason, field and spectral-based evaluations of dormant season burn severity may have limited accuracy when conducted in the dormant season alone, because key impacts to vegetation can be difficult to evaluate especially for low to moderate severity fires. Our results suggest that using growing season reflectance data can be a robust way for comparing burn severity for fires that occur in dormant and growing season conditions (i.e. leaf-off and leaf-on). Once burn severity indices are calibrated for a vegetation type using this approach, annual landscape-scale evaluations of prescribed fire and wildfire effects could be efficiently predicted with minimal spectral data requirements. We feel this approach could be especially useful in other Eastern regions where prescribed fires and wildfires occur in both the dormant and growing seasons. Similarly, the average fire size in many areas of the Eastern US can be smaller than those which are monitored automatically and freely available as Monitoring Trends in Burn Severity products (https://www.mtbs.gov/), which also uses spectral data relative to fire date rather than phenology.

Statistically sound selection and validation of remotely sensed burn severity indices can be complicated given the variable distributions of burn severity between fires and variable forest types within and among burns that need to be accounted for. Some previous studies have pooled point data replicates from independent burns (e.g., numerous points within individual burns) to conduct a single regression analysis (Allen and Sorbel 2008; Kasischke et al. 2008); however, this represents pseudoreplication and ignores uneven sampling and burn severity distributions between fires. Future studies can easily avoid such problems by employing the k-fold leave one out process that we have presented and solve for unevenness in point and burn severity distributions with the ordering step we have suggested. We also suggest using measures of model fit other than the coefficient of determination when using non-linear regression to compare burn severity datasets, when it is no longer bounded by 0 and 1 and thus difficult to interpret. Our results demonstrate SSE or AIC as a superior alternative to compare non-linear relationships, as they provide more clarity and consistency regardless of regression form. These methods can increase statistical rigor and comparability of future burn severity research and better leverage the richness of datasets collected across numerous fires.

Our results contrast with findings from fires in California conifer forests that RdNBR provides significantly better predictions of CBI than dNBR (Miller and Thode 2007) and with findings from a study of 18 fires in conifer forests across the Western US that suggested that RBR produced significantly better predictions than RdNBR (Parks et al. 2014). It should be noted that these studies did not investigate the full suite of burn severity indices or the influence that selected equation forms may have had on their resultant predictions, which can influence predictions as shown in our results. Their results may also differ because of major differences in vegetation type, vegetation structure, and substrate qualities that can influence reflectance (Stoner and Baumgardner 1981; Eriksson et al. 2006; Wang and Li 2013). Another key difference between studies is that those in the west were mostly growing season fires, while those in this study were primarily dormant season fires, which may influence drivers of first-order fire effects (e.g. leaf scorch vs. girdling or fine root damage) and impacts vertical distributions of fire effects that influence burn severity. Our results are in agreement with those of the only other burn severity study that has been conducted in New Jersey Pinelands (Warner, Skowronski, and Gallagher). In that study, a comparison between bi-temporal WorldView-3 NIR and SWIR data and field observed CBI demonstrated the potential for conducting burn severity studies on dormant season prescribed fire in the New Jersey Pinelands. While it is difficult to directly compare our statistics to those of that study due to methodological differences, our study appears to have found similarly robust relationships between spectral and CBI data, which is notable due to the greater spatial, spectral, and temporal precision of the previous study.

Our study found that WCBI had reduced sensitivity to fire effects, compared to CBI, due to the influence of vertical vegetation structure patterns on FCOV. This was interesting given the lower SSE and AIC of WCBI in most cases; however it was substantially underpredicted by remote sensing data, especially at high severities. In the New Jersey Pinelands, a dense cover of detritus and understory vegetation layers skew WCBI to primarily reflect effects in those layers, somewhat to the exclusion of effects in the canopy. This is problematic because both low and high intensity fires can have a large impact on substrates and understory vegetation, but increasing severity will produce a broader range of effects in the canopy. A more suitable metric than FCOV for scaling the influence of strata might be actual leaf area index (LAI), because it would account for the amount of vegetation, which does not necessarily co-vary with percent cover when LAI is vertically distributed. Vertical distributions of vegetation often vary from stand to stand throughout the PNR (Skowronski et al. 2011, 2014, 2007) and in other forest landscapes (Lacki et al. 2017; McCarley et al. 2017; Hoff et al. 2019) due to prior forest management and disturbances that redistribute leaf area and forest structure. Vertical LAI and forest structure is difficult to assess across broad spatial extents using physical sampling methods, especially within tall forest canopies; however, new approaches that use terrestrial laser scanners offer a new potential to rapidly accomplish this with high precision (Rouzbeh Kargar et al. 2019; Zhu et al. 2018; Rowell et al. 2020).

Our results and those of Warner et al. (2017) highlight the potential for spectral burn severity indices to be used in pine pitch barren forest types for future fire effects monitoring and fire ecology research efforts. As the largest population of this globally-rare, fire-dependent, forest type, such monitoring and research efforts in the New Jersey Pinelands can be critically important for guiding the restoration and maintenance of other smaller pitch pine barrens landscapes which are either too small or receive too little fire to conduct landscape scale work necessary for understanding certain ecological mechanisms of fire. Future landscape-scale investigations of weather conditions and ignition patterns that drive fire behavior and resultant fire effects are a logical next step and would provide useful findings that would aid in the refinement of numerical models that predict fire behavior and prescribed fire prescriptions for specific outcomes.

Certain shortcomings of our study can be avoided in future studies. First, we needed to use a series of preprocessing steps to conduct our analysis due to the limitations of the data sources that were available when we began our study; however, current and expected data products now come pre-processed as ground reflectance data. Presently, Landsat ground reflectance products for Landsat TM and ETM + are freely available (https://glovis.usgs.gov/), are much simpler to directly use without pre-processing, and may provide a slight improvement in results, compared to the radiometrically corrected top of atmosphere reflectance in this study (Young et al. 2017). Likewise, Landsat 8 and future Landsat 9 data will provide new gap-free data that was not available during the time period of the study, reducing the need to mosaic as many scenes. Likewise, WorldView-3 is a privately owned platform that can provide higher spectral and spatial resolution NIR and SWIR data for burn severity studies than Landsat products, although it must be tasked to collect specific imagery (Warner et al. 2017; McKenna et al. 2018).

Conclusions

Our study aimed to test a methodology for selecting the optimal burn severity index from a suite of calculation and validation options in the Pinelands National Reserve. We present a new approach that is statistically rigorous and is flexible for incorporating data from fires with uneven distributions of severity or which have occurred under differing baseline reflectances. We found that dNBR and RdNBR were more correlated with field data than NBR or RBR, which agrees with previous research in this environment, but conflicts with findings in some western conifer forest types. We also compared CBI and WCBI as field methods for evaluating burn severity and identified fundamental problems with using WCBI in this environment, due to patterning in vertical distributions of forest material. Our method for selecting optimal burn severity indices can be repeated in other systems using similar or different input indices if desired. Finally, the results of this study support the use of burn severity indices as a monitoring and research tool for examining ecological fire effects across rare pitch pine barrens landscapes. However, those indices are less suitable for rapid post-fire burn severity assessments that do not need to be compared to other fires and are intended to guide short-term post-fire efforts to mitigate further environmental damage.

Acknowledgments

The authors thank Steven Holmes, Jim Dusha, Shawn Judy, Scott Knaurer, John Earlin, Ashley House, Brian Corvinus, and Tom Gerber of the New Jersey Forest Fire Service for their invaluable support in the field. We thank also Kevin Hiers and Alexis Everland of Tall Timbers Research Station, Kenneth L. Clark of the US Forest Service Northern Research Station, and Anne-Marie Litak for their thoughtful suggestions that improved this paper.

Funding

This research was funded in part by Joint Fire Sciences [grant number 12-1-03-11] and by the United States Department of Defense, Strategic Environmental Research and Development Program contract 16 RC02-016.

References

Allen, J.L., and Sorbel, B. 2008. "Assessing the differenced Normalized Burn Ratio's ability to map burn severity in the boreal forest and tundra ecosystems of Alaska's national parks." *International Journal of Wildland Fire*, Vol. 17(No. 4): 463–475.

Andrefouet, S., Bindschadler, R., Brown de Colstoun, E., Choate, M., Chomentowski, W., Christopherson, J., Doorn, B., et al. 2003. *Preliminary Assessment of the Value of Landsat-7 ETM + Data Following Scan Line Corrector Malfunction*. Sioux Falls, SD, USA: US Geological Survey, EROS Data Center.

Cansler, C.A., and McKenzie, D. 2012. "How robust are burn severity indices when applied in a new region? Evaluation of alternate field-based and remote-sensing methods." *Remote Sensing*, Vol. 4(No. 2): 456–483.

Chander, G., Markham, B.L., and Helder, D.L. 2009. "Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors." *Remote Sensing of Environment*, Vol. 113(No. 5): 893–903.

Chen, X., Vogelmann, J.E., Rollins, M., Ohlen, D., Key, C.H., Yang, L., Huang, C., and Shi, H. 2011. "Detecting post-fire burn severity and vegetation recovery using multitemporal remote sensing spectral indices and field-collected composite burn index data in a ponderosa pine forest." *International Journal of Remote Sensing*, Vol. 32(No. 23): 7905–7927.

Clark, K., Renninger, H., Skowronski, N., Gallagher, M., and Schäfer, K. 2018. "Decadal-scale reduction in forest net ecosystem production following insect defoliation contrasts with short-term impacts of prescribed fires." *Forests*, Vol. 9(No. 3): 145.

Clark, K.L., Skowronski, N., Gallagher, M., Renninger, H., and Schäfer, K. 2012. "Effects of invasive insects and fire on forest energy exchange and evapotranspiration in the New Jersey pinelands." *Agricultural and Forest Meteorology*, Vol. 166–167: 50–61.

De Santis, A., and Chuvieco, E. 2009. "GeoCBI: A modified version of the Composite Burn Index for the initial assessment of the short-term burn severity from remotely sensed data." *Remote Sensing of Environment*, Vol. 113(No. 3): 554–562.

El Houssami, M., Mueller, E., Filkov, A., Thomas, J.C., Skowronski, N., Gallagher, M.R., Clark, K., Kremens, R., and Simeoni, A. 2016. "Experimental procedures characterising firebrand generation in wildland fires." *Fire Technology*, Vol. 52(No. 3): 731–751.

Eriksson, H.M., Eklundh, L., Kuusk, A., and Nilson, T. 2006. "Impact of understory vegetation on forest canopy reflectance and remotely sensed LAI estimates." *Remote Sensing of Environment*, Vol. 103(No. 4): 408–418.

Filkov, A., Prohanov, S., Mueller, E., Kasymov, D., Martynov, P., El Houssami, M., Thomas, J., Skowronski, N., Butler, B., and Gallagher, M. 2017. "Investigation of firebrand production during prescribed fires conducted in a pine forest." *Proceedings of the Combustion Institute*, Vol. 36(No. 2): 3263–3270.

Forman, R.T.T. 1998. *Pine Barrens: Ecosystems and Landscape*. New Brunswick, NJ: Rutgers University Press.

Forman, R.T.T., and Boerner, R.E. 1981. "Fire frequency and the pine barrens of New Jersey." *Bulletin of the Torrey Botanical Club*, Vol. 108(No. 1): 34–50.

Gallagher, M.R. 2017. *Monitoring fire effects in the New Jersey Pine Barrens with burn severity indices*. Ph.D. Thesis. New Brunswick, NJ: Rutgers University.

Gallagher, M.R., Clark, K.L., Thomas, J.C., Mell, W.E., Hadden, R.M., Mueller, E.V., Kremens, R.L., et al. 2017. *New Jersey Fuel Treatment Effects: Pre- and Post-Burn Biometric Data*. Fort Collins, CO: Forest Service Research Data Archive.

Garcia, M.J.L., and Caselles, V. 1991. "Mapping burns and natural reforestation using Thematic Mapper data." *Geocarto International*, Vol. 6(No. 1): 31–37.

Hoff, V., Rowell, E., Teske, C., Queen, L., and Wallace, T. 2019. "Assessing the relationship between forest structure and fire severity on the North Rim of the Grand Canyon." *Fire*, Vol. 2(No. 1): 10.

Isaacson, B.N., Serbin, S.P., and Townsend, P.A. 2012. "Detection of relative differences in phenology of forest species using Landsat and MODIS." *Landscape Ecology*, Vol. 27(No. 4): 529–543.

Jolly, W., and Johnson, D. 2018. "Pyro-ecophysiology: shifting the paradigm of live wildland fuel research." *Fire*, Vol. 1(No. 1): 8.

Kasischke, E.S., Turetsky, M.R., Ottmar, R.D., French, N.H.F., Hoy, E.E., and Kane, E.S. 2008. "Evaluation of the composite burn index for assessing fire severity in Alaskan black spruce forests." *International Journal of Wildland Fire*, Vol. 17(No. 4): 515–526.

Keeley, J.E. 2009. "Fire intensity, fire severity and burn severity: a brief review and suggested usage." *International Journal of Wildland Fire*, Vol. 18(No. 1): 116–126.

Key, C.H., and Benson, N.C. 1999. *The Normalized Burn Ratio (NBR): A Landsat TM Radiometric Measure of Burn Severity*. Bozeman, MT: United States Geological Survey, Northern Rocky Mountain Science Center.

Key, C.H., and Benson, N.C. 2006. *Landscape Assessment (LA)*. FIREMON: Fire Effects Monitoring and Inventory System. Gen. Tech. Rep. RMRS-GTR-164-CD. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Kolden, C.A., Smith, A.M.S., and Abatzoglou, J.T. 2015. "Limitations and utilisation of monitoring trends in Burn Severity products for assessing wildfire severity in the USA." *International Journal of Wildland Fire*, Vol. 24(No. 7): 1023–1028.

Kruschke, J.K. 2013. "Bayesian estimation supersedes the t test." *Journal of Experimental Psychology: General*, Vol. 142(No. 2): 573–603.

La Puma, I.P. 2012. *Fire in the Pines: A landscape Perspective of Human-Induced Ecological Change in the Pinelands of New Jersey*. New Brunswick: Rutgers University, Graduate School.

Lacki, M.J., Dodd, L.E., Skowronski, N.S., Dickinson, M.B., and Rieske L.K. 2017. "Relationships among burn severity, forest canopy structure and bat activity from spring burns in oak–hickory forests." *International Journal of Wildland Fire*, Vol. 26(No. 11): 963–972.

Lathrop, R., and Kaplan, M.B. 2004. *New Jersey Land Use/Land Cover Update: 2000–2001*, p. 35. New Jersey Department of Environmental Protection.

Ledig, F.T., and Little, S. 1998. "Pitch pine (*Pinus rigida* Mill.): ecology, physiology and genetics." In *Pine Barrens Ecosystem and Landscape*, edited by Richard T.T. Forman, 347–372. New Brunswick, NJ: Rutgers University Press.

McCarley, T.R., Kolden, C.A., Vaillant, N.M., Hudak, A.T., Smith, A.M.S., Wing, B.M., Kellogg, B.S., and Kreitler, J. 2017. "Multi-temporal LiDAR and Landsat quantification of fire-induced changes to forest structure." *Remote Sensing of Environment*, Vol. 191: 419–432.

McKenna, P., Phinn, S., and Erskine, P.D. 2018. "Fire severity and vegetation recovery on mine site rehabilitation using WorldView-3 imagery." *Fire*, Vol. 1(No. 2): 22.

Miller, J.D., and Thode, A.E. 2007. "Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR)." *Remote Sensing of Environment*, Vol. 109(No. 1):pp. 66–80.

Mueller, E., Skowronski, N., Simeoni, A., Clark, K., Kremens, R., Mell, W., Gallagher, M., Thomas, J., Filkov, A., El Houssami, M., Hom, J., and Butler, B. 2014. "Fuel treatment effectiveness in reducing fire intensity and spread rate-An experimental overview." In *Proceedings of 4th Fire Behavior and Fuels Conference,* edited by D.D. Wade, and R.L. Fox; M.L. Robinson, comp.; Raleigh, NC, 18–22 February 2013 and St. Petersburg, Russia, 1–4 July 2013. Missoula, MT: International Association of Wildland Fire. pp. 360–362.

Mueller, E.V., Skowronski, N., Thomas, J.C., Clark, K., Gallagher, M.R., Hadden, R.M., Mell, W., and Simeoni, A. 2018. "Local measurements of wildland fire dynamics in a field-scale experiment." *Combustion and Flame*, Vol. 194: 452–463.

Mueller, E.V., Skowronski, N., Clark, K., Gallagher, M., Kremens, R., Thomas, J.C., El Houssami, M., et al. 2017. "Utilization of remote sensing techniques for the quantification of fire behavior in two pine stands." *Fire Safety Journal*, Vol. 91: 845–854.

Parks, S., Dillon, G., and Miller, C. 2014. "A new metric for quantifying burn severity: The relativized burn ratio." *Remote Sensing*, Vol. 6(No. 3): 1827–1844.

Parks, S.A., Holsinger, L.M., Miller, C., and Nelson, C.R. 2015. "Wildland fire as a self-regulating mechanism: The role of previous burns and weather in limiting fire progression." *Ecological Applications*, Vol. 25(No. 6): 1478–1492.

Parks, S.A., Parisien, M.A., Miller, C., and Dobrowski, S.Z. 2014. "Fire activity and severity in the western US vary along proxy gradients representing fuel amount and fuel moisture." *PLoS One.*, Vol. 9(No. 6): e99699.

Picotte, J.J., and Robertson, K.M. 2011. "Validation of remote sensing of burn severity in south-eastern US ecosystems." *International Journal of Wildland Fire*, Vol. 20(No. 3): 453–464.

Rouzbeh Kargar, A., MacKenzie, R., Asner, G.P., and Van Aardt, J. 2019. "A density-based approach for leaf area index assessment in a complex forest environment using a terrestrial laser scanner." *Remote Sensing*, Vol. 11(No. 15): 1791.

Rowell, E., Loudermilk, E.L., Hawley, C., Pokswinski, S., Seielstad, C., Queen, L., O'Brien, J.J., Hudak, A.T., Goodrick, S., and Hiers, J.K. 2020. "Coupling terrestrial laser scanning with 3D fuel biomass sampling for advancing wildland fuels characterization." *Forest Ecology and Management*, Vol. 462: 117945.

Skowronski, N., Clark, K., Nelson, R., Hom, J., and Patterson, M. 2007. "Remotely sensed measurements of forest structure and fuel loads in the Pinelands of New Jersey." *Remote Sensing of Environment*, Vol. 108(No. 2): 123–129.

Skowronski, N.S., Simeoni, A.A., Clark, K.L., Mell, W.E., Hadden, R.M., Gallagher, M.R., Mueller, E.V., et al. 2017. *New Jersey Treatment Effects: Burn Units*. Fort Collins, CO: Forest Service Research Data Archive.

Skowronski, N.S., Clark, K.L., Duveneck, M., and Hom, J. 2011. "Three-dimensional canopy fuel loading predicted using upward and downward sensing LiDAR systems." *Remote Sensing of Environment*, Vol. 115(No. 2): 703–714.

Skowronski, N.S., Clark, K.L., Gallagher, M., Birdsey, R.A., and Hom, J.L. 2014. "Airborne laser scanner-assisted estimation of aboveground biomass change in a temperate oak–pine forest." *Remote Sensing of Environment*, Vol. 151: 166–174.

Soverel, N.O., Perrakis, D.D.B., and Coops, N.C. 2010. "Estimating burn severity from Landsat dNBR and RdNBR indices across western Canada." *Remote Sensing of Environment*, Vol. 114(No. 9): 1896–1909.

Stoner, E.R., and Baumgardner, M.F. 1981. "Characteristic variations in reflectance of surface soils 1." *Soil Science Society of America Journal*, Vol. 45(No. 6): 1161–1165.

Thomas, J.C., Simeoni, A.A., Gallagher, M.R., and Skowronski, N.S. 2014. "An experimental study evaluating the burning dynamics of pitch pine needle beds using the FPA." *Fire Safety Science*, Vol. 11: 1406–1419.

Wang, Q., and Li, P. 2013. "Canopy vertical heterogeneity plays a critical role in reflectance simulation." *Agricultural and Forest Meteorology*, Vol. 169: 111–121.

Warner, T.A., Skowronski, N.S., and Gallagher, M.R. 2017. "High spatial resolution burn severity mapping of the New Jersey Pine Barrens with WorldView-3 near-infrared and shortwave infrared imagery." *International Journal of Remote Sensing*, Vol. 38(No. 2): 598–616.

Wimberly, M., and Reilly, M. 2007. "Assessment of fire severity and species diversity in the southern Appalachians using Landsat TM and ETM + imagery." *Remote Sensing of Environment*, Vol. 108(No. 2): 189–197.

Young, N.E., Anderson, R.S., Chignell, S.M., Vorster, A.G., Lawrence, R., and Evangelista, P.H. 2017. "A survival guide to Landsat preprocessing." *Ecology*, Vol. 98(No. 4): 920–932.

Zhu, X., Skidmore, A.K., Wang, T., Liu, J., Darvishzadeh, R., Shi, Y., Premier, J., and Heurich, M. 2018. "Improving leaf area index (LAI) estimation by correcting for clumping and woody effects using terrestrial laser scanning." *Agricultural and Forest Meteorology*, Vol. 263: 276–286.