Comparison of Six Fire Severity Classification Methods Using Montana and Washington Wildland Fires

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Abstract—*Fire severity classifications are used in the post-fire environment to describe fire effects, such as soil alteration or fuel consumption, on the forest floor. Most of the developed classifications are limited because they address very specific fire effects or post-burn characteristics in the burned environment. However, because fire effects vary so much among soil, hydrology, vegetation, chemistry, particulate, and spatial distribution, it is important to realize that the impressions of burn severity are governed by the method used to classify the fire effects. The objective of this study was to determine (1) how severity classes derived from each tested method compared with the Composite Burn Index, which is a standard field assessment for fire severity that is commonly used in the United States; and (2) how well the fire severity classes obtained from six different classification methods agreed with each other.*

Comparisons of fire severity classes were made on 289 field plots from 15 fires across Montana and Washington. Severity classes were made for two types of field classifications, including (1) a fire severity matrix (Ryan and Noste 1985), and (2) soil post-fire indices (Jain and others 2012); three remote sensing methods, including (1) the Monitoring Trends in Burn Severity (MTBS) classification (Eidenshink and others 2007), (2) a modification of the relativized differenced normalized burn ratio (RdNBR) classification for plots in the northwestern United States, and (3) the Burned Area Emergency Rehabilitation (BAER/BARC) classification; and a modeling approach created by Keane and others (2010) called FIREHARM. The severity classes derived from these six methods were compared to on-site field assessments of fire severity using the Composite Burn Index (CBI). The two field classifications corresponded best with CBI (Kendal tau b > 0.61, ASE = 0.4). Remote sensing classification classes corresponded to CBI classes only half of the time (Kendal tau b = 0.53, ASE = 0.04). The modeling approach had low to negative correlations with all other methods and the average correspondence among all the classification types was 38%.

Keywords: *Composite Burn Index, dNBR, FIREHARM, fire severity matrix, RdNBR, soil post-fire indices*

Introduction

Fire and burn severity classifications are used by land managers to describe, summarize, and communicate the physical and chemical effects of burning after prescribed burning or wildland fire. These summary classifications are often very specific to certain attributes of the ecosystem and, in general, describe only a restricted portion of the fire effects that occur due to burning. Severity designations derived from these classifications are used by managers to specify ecological damage after wildfire or plan management activities for ecological and economic recovery of the burned area. Management activities may include restoration of vegetation in general (Lentile and others 2007) or rare and endangered species in particular (Dudley and others 2012), plans for mitigating food and habitat loss for specific wildlife species (Hanson and Odion 2014), recovery of the soil or hydrologic features (Cerda and Robichaud 2009; Erickson and White 2008; Kinoshita and Hogue 2011), post-fire vegetation response (Epting and Verbyla 2005), logging activities to remove dead tree boles (Fraver and others 2011), or assessment of future fire danger after initial fuels have burned (Holden and others 2010). They may also inform perceptions on timelines for economic recovery or the future of a burned area for tourism and recreation. In this paper, the term fire severity is used to denote the magnitude of fire-caused damage to vegetation and fuels and general descriptions of fire impacts, such as fire effects on soil (Simard 1991). Burn severity is reserved for classifications created in remote sensing applications because the term has a long history of use in the remote sensing field (Dillon and others 2011; Lentile and others 2006; Lentile and others 2007). Using either fire or burn severity classifications, the response to, or and planning for, burns classed as "high severity" may be very different than for burns classed as "low severity" so it is important to choose a classification that accurately assesses and summarizes the physical or chemical effects of a fire.

Today, individual fire severity classifications exist for field observations, simulation modeling, and remotely sensed fire effects but each classification system has its limitations. Most are generally stand-alone entities. Most are not designed specifically to match field observations of severity at the plot or site scales; nor are they necessarily designed to evaluate the

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same types of fire effects. Many are tailored to meet the needs of a specific application, such as classifying changes in soil characteristics, vegetation, or fuel consumption. They are not designed to provide a detailed description of the range of multiple fire effects that occur with fire. Specific fire effects on soils have been characterized in descriptions and classifications by DeBano (1991), Jain and others (2009), and (Parsons and others 2010). Fuel characterizations of fire severity include descriptions and classifications by Cushon and others (2003), Lutes and others (2009), Ottmar and others (2007), and Sikkink and Keane (2012). Classes of vegetation damage from first- and second-order fire effects have been described by Lutes and others (2006), Thompson and Spies (2009), Perez and Moreno (1998), and Brown and others (2000). Fire severity classifications have been created for post-fire vegetation response (Agee 1981; Hessburg and others 2007; Keane and others 2004; Russell-Smith and Edwards 2006) and for prediction of post-fire response (Brown and Smith 2000; Keane and others 1990; Lutes and others 2009; Sikkink and Keane 2012). Alternately, classes of burn severity are also created using the difference between pre- and post-fire satellite images (Key 2006; Key and Benson 2006; Miller and Thode 2007). Red and infrared signals capture differences between pre- and post-fire scenes to calculate the normalized difference burn ratio (NDVI). NDVI integrates changes in greenness (i.e., loss of vegetation or increase in soil exposure) and a post-burn charcoal signal (i.e., increased post-fire infrared signal) to describe the degree of post-fire change on large spatial scales. The data used to create each of these fire and burn severity classifications reduce complex interactions of fire, fuels, biota, and the biophysical environment into three general categories of low, medium, and high.

The objectives of this study were to (1) determine how well the classes from each classification method agreed with the burn characteristics assessed at each field site where a common, standard measure of fire severity in the United States was used; and (2) explore how well the classes derived from the various classifications agreed with each other. By exploring how a diverse set of classifications with different origins and scales compared in their assessments of fire severity, the problems encountered when using each method can be highlighted and improvements can be made to the entire fire severity classification process.

Methods

This study compared burn severity classes obtained using the Composite Burn Index (CBI) and six current classification methods of very different types (Table 1). CBI integrates two methodologies to describe changes due to burning, which include calibration and validation of 30-meter Landsat data (e.g., the Normalized Burn Ratio) with on-site change and relative change in the vegetation and soil characteristics from the pre-burn conditions that are detected in the field sampling (Key and Benson 2006). CBI is semi-quantitative and summarizes fire effects that have occurred in five different strata on each site, as well as changes in soil characteristics, into a single fire severity number. Changes in vegetation are assessed from the ground substrate to upper tree canopy making the site assessment with CBI more complete than many other classification systems. Each site is also analyzed individually for changes from the pre-burn condition for each CBI assessment, so the resulting burn severity values can normally be compared across different landscapes (Key and Benson 2006). The six classification methods included (1) a fire severity matrix designed by Ryan and Noste (1985), (2) the soil post-fire indices designed by Jain and others (2012); (3) a simulation model that used weather and tree canopy information specific to each fire location to predict fire effects at each site (Keane and others 2010); and remote sensing classification systems from the (4) Monitoring Trends in Burn Severity (MTBS) web site (Eidenshink and others 2007), (5) RdNBR classes developed by the University of Washington (Cansler 2011; Kopper 2012; Prichard and others 2010), and (6) classes from the Burned Area Emergency Rehabilitation (BAER/BARC) program (www.fs.fed.us/eng/rsac/baer/barc.html). Classification methods 1 and 2 are normally assessed in the field and utilize changes in substrate and tree canopy as primary characteristics for the severity assessment. Classification 3 is a predictive, pre-fire technology tuned to local vegetation, fuels, moistures, or historical fire regime. Classification methods 4, 5, and 6 are remote sensing techniques that classify amount of change between a pre- and post-fire environment.

Reference Data

The reference or "ground truth" used in the classification comparisons was field data from Composite Burn Index (CBI) assessments (Key and Benson 1999; Key and Benson 2006). CBI field data was collected at 289 plot locations from within 15 fires across Montana and Washington, USA (Fig. 1). The CBI plots were established within fire perimeters that differed in burn year, burn season, acres burned, ignition cause, and dominant vegetation (Table 2). All CBI assessments were done one year post-burn at each site using the form designated by Key and Benson (2006). Locations of all plots were logged with personal GPS units (accuracy +/- 15 m). CBI work was conducted with a crew of two to four employees; Montana sites were measured by Forest Service personnel and Washington sites were measured by professors and students from the University of Washington.

Although CBI may not be a perfect candidate for ground truth, the completeness of CBI fire data, its known relationship to remote sensing classifications (Miller and others 2009; Miller and Thode 2007), and its wide-spread use in the United States made it the most comprehensive, on-site evaluation of burn severity available to use as "ground truth" for this study. Many studies have found correlations between CBI and burn severity measurements derived from satellite imagery (French and others 2008). Other research has revealed relationships between image-based metrics and specific measurable fire effects (Hudak and others 2007; Karau and Keane 2010; Keeley and others 2008; Miller and others 2009). In many of these studies, CBI was the metric used to evaluate comparisons of burn severity classes with fire effects on the ground. GeoCBI,

Table 1—Summary of characteristics and source information for the six severity classification methods.

Classification Name	Classification Type	Reference Abbreviation	Number of Classes	Classification Purpose	Main Variables Used to Create Classification	Citation
1 Fire Severity Matrix	Field	FSM	5 broad (20 sub)	Describe fire effects using a fire severity matrix with semi-quantitative variables	Depth of Char, Flame Length	Ryan and Noste, 1985
2 Soil Post-Fire Indices	Field	SPFI	5 broad (12 sub)	Create a consistent index that describes post-fire environment and ecosystem recovery	Organic matter consumed, mineral soil color	Jain et al, 2012
3 FIREHARM Model	Simulation	FIREHARM	4	Create maps of fire hazard and risk across multiple spatial scales (burn severity is one output of FIREHARM)	Weather inputs, fuel moisture, fuel characteristics, tree layers, soil depth and texture, leaf area index	Keane and others, 2010
4 Monitoring Trends in Burn Severity (MTBS) differenced Normalized Burn Ratio	Remote Sensing	dNBR	4	Consistently map burn severity and fire perimeters for the United States	Pre-burn and post-burn satellite imagery (reflectance bands)	www.mtbs.gov
5 Relativized differenced normalized burn ratio (RdNBR) Cansler adjustment	Remote Sensing	RdNBR	4	Utilizes regression analysis adjustment to customize MTBS RdNBR for northwest U.S. forests	Pre-burn and post-burn satellite imagery (reflectance bands)	Cansler, 2011; Cansler and McKenzie, 2012; Miller and Thode, 2007
6 Burned Area Emergency Rehabilitation (BAER)	Remote Sensing	BAER/BARC	4	Evaluate burned area within 7 days of burn for threats to life, property, or natural resources due to post-fire flooding and erosion	Vegetation consumed, soil characteristics, geologic characteristics, tree layers, hydrology	http://www.fs.fed.us/eng/rsac/baer/barc.html

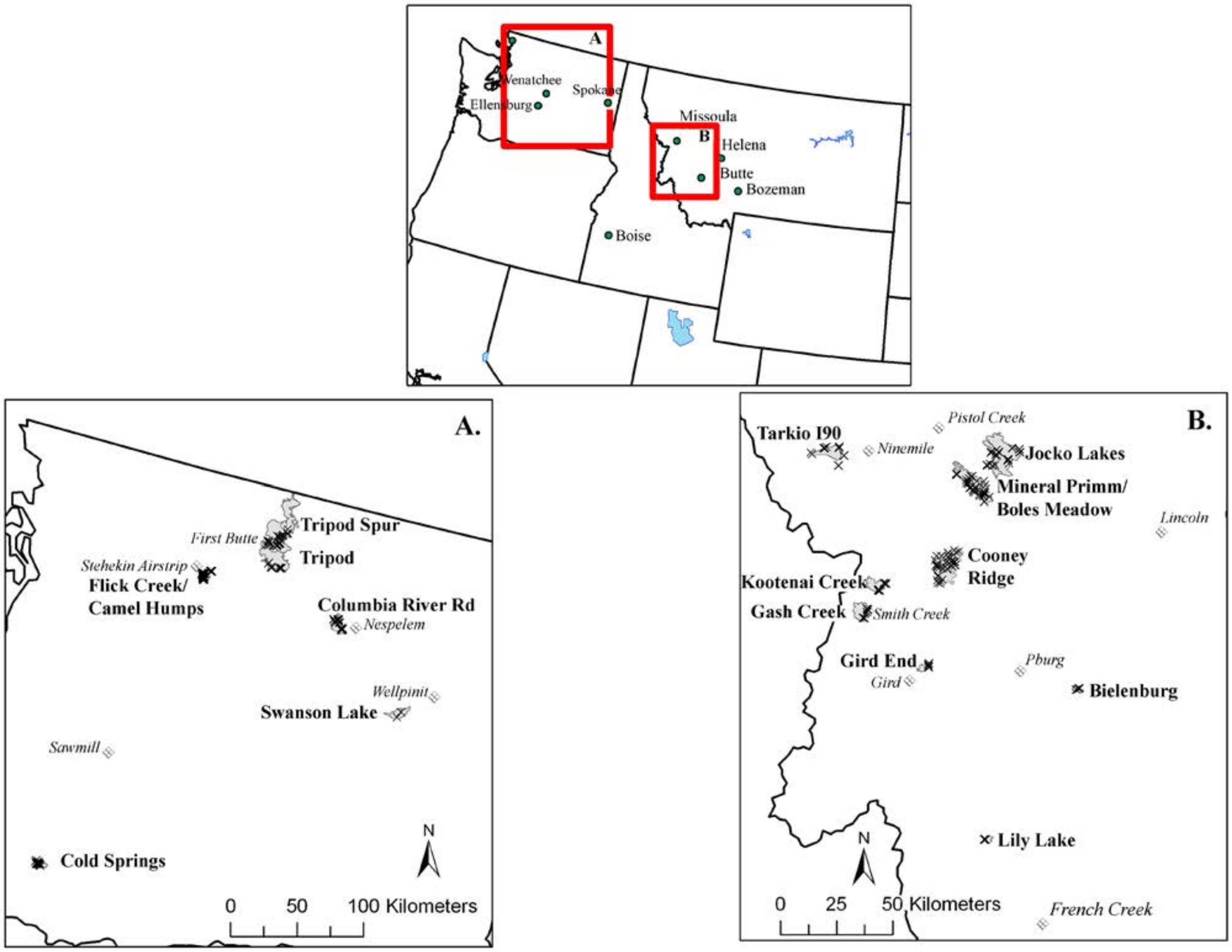

Figure 1—Fire locations in Montana and Washington, USA, used in the comparisons for this study. Weather stations are shown as diamonds near the sites.

which was developed by De Santis and Chuvieco (2009) to improve the correlations between CBI and satellite imagery, was not utilized in this study because neither the fraction of cover nor the leaf area index for each vegetation strata were collected with the field data. Therefore, GeoCBI values could not be computed.

Within the CBI field forms, fire effects were evaluated for five vegetation strata that ranged from substrate at the ground to the upper canopy of big trees. The characteristics used to gauge fire severity in the CBI stratum are defined in Table 3. Within each stratum, a fire severity index was assigned a value from zero to three based on (1) percentage of change due directly to burning or (2) on actual measurements of fire effects (e.g., char height). The values ranged from unburned (CBI = 0) to high fire severity (CBI = 3). Key and Benson (2006) assigned the breakpoints between the low, medium, and high severity values based on their field experience, desire to balance the factors and criteria to not over or under estimate fire effects, and correlation work with remote sensing values. CBI totals were summed and averaged by strata and by site to provide a single number representing an ordinal classification of fire effects at each site. The sites for this study ranged from very lightly burned (CBI<1.0) to severely burned (CBI = 3.0) (Fig. 2).

Fire Severity Classifications

Classifications created from post-fire field assessments of fire effects included Ryan and Noste's (1985) fire severity matrix (FSM) and Jain and others's (2012) soil post-fire indices (SPFI). The FSM classification used flame-length height and depth of char (i.e., unburned to deep) as critical factors in differentiating classes (Ryan and Noste 1985). Because the FSM used forest floor conditions, especially duff consumption and soil alteration, to determine the depth of char, two characteristics from the CBI form, Substrate A: Duff consumed and Substrate A: Soil Rock Cover Color, were used in tandem to determine a CBI value for depth of char (Table 3). Char height from the big trees (Substrate E) was used to determine flame-length (Table 3). If no big trees were present on the plot, char height was assessed using Substrate D: Intermediate trees. The Ryan and Noste (1985) classes could be grouped into four general classes from the CBI assessments, which corresponded to "unburned," "low," "moderate," and "high" fire severity as shown on Table 4.

The soil post-fire index (SPFI) used the abundance of surface organic matter and mineral soil color to differentiate five fire severity classes from zero to four (Jain and others 2012). Each of the five broad classes was divided into subclasses

Table 2—Characteristics of the tested wildfires fires from Montana and Washington.

Fire Name	State	Total CBI field plots	Acres burned	Fire Year	Start Date[A]	Cause[B]	Date 100% Contained	Dominant Vegetation
Bielenburg	MT	6	1,480	2009	7/12/2009	L	10/23/2009	Interior Douglas Fir
Cooney Ridge	MT	26	25,740	2003	8/8/2003	L	12/31/2003	Interior Douglas Fir
Gash Creek	MT	5	9,880	2006	7/24/2006	U	12/8/2006	Englemann Spruce-Subalpine Fir
Gird End	MT	9	3,270	2009	9/9/2009	L	10/26/2009	Lodgepole Pine-Englemann Spruce
Jocko Lakes	MT	13	35,560	2007	8/31/2007	L	12/4/2007	Interior Douglas Fir
Kootenai Creek	MT	14	8,410	2009	7/12/2009	L	11/31/09	Interior Douglas Fir
Lily Lake	MT	9	2,020	2009	8/13/2009	L	10/16/2009	Lodgepole Pine-Interior Douglas Fir
Mineral Primm	MT	25	20,890	2003	8/6/2003	L	12/31//03	Interior Douglas Fir
MP Boles Meadow	MT	3	4,290	2003	8/8/2003	L	8/23/2003	Interior Douglas Fir
Tarkio I90	MT	9	10,950	2005	8/4/2005	U	8/17/2005	Interior Douglas Fir/Interior Ponderosa Pine
Camel Humps	WA	28	130	2008	7/23/2008	L	8/1/2006	Englemann Spruce-Subalpine Fir - Whitebark Pine
Cold Springs	WA	28	7,729	2008	7/12/2008	L	8/1/2008	Interior Douglas Fir/Grand Fir
Flick Creek	WA	100	7,050	2006	7/26/2006	H	10/19/2006	Interior Douglas Fir
Tripod	WA	14	59,710	2006	7/24/2006	U	11/9/2006	Interior Douglas Fir
Tripod Spur	WA	29	115,120	2006	7/3/2006	L	11/9/2006	Interior Douglas Fir/Ponderosa Pine/Engleman Spruce- Subalpine Fir

[A] Based on National Incident Management Coordination Center (NIMCC) incident management situation reports
[B] Cause: L = Lightening; U = Undetermined; H = Human

Table 3—Composite Burn Index (CBI) characteristics used in this study and their corresponding fire severity values (from Key and Benson 2006).

Strata Rating Factors	Fire Severity Scale						
	No Effect	Low		Moderate		High	
	0.0	**0.5**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**
A. Substrates							
Litter/Light fuel consumed	Unchanged	—	50% litter	—	100 % litter	80% light fuel	98%
Duff	Unchanged	—	Light Char	—	50% loss deep char	—	Consumed
Medium Fuel, 3-8 in.	Unchanged	—	20% Consumed	—	40% Consumed	—	>60% loss, deep char
Heavy Fuel, > 8 in.	Unchanged	—	10% Loss	—	25% loss, deep char	—	>40% loss, deep char
Soil and Rock Cover/Color	Unchanged	—	10% Change	—	40% Change	—	>80% change
B. Herbs, low shrubs and trees less than 3 feet (1 meter)							
% Foliage altered (black-brown)	Unchanged	—	30%	—	80%	95%	100% + branch loss
Frequency % living	100%	—	90%	—	50%	<20%	None
C. Tall Shrubs and trees 3 to 16 ft (1 to 5 meters)							
Frequency % living	100%	—	90%	—	30%	<15%	<1%
D. Intermediate Trees (Subcanopy, pole-sized trees)							
% Canopy mortality	None	—	15%	—	60%	80%	100%
Char height (meters)	None	—	1.5 m (5 ft)	—	2.8 m (9.24 ft)	—	>5m (16 ft)
E. Big trees (Upper canopy, dominant, codominant trees)							
% Canopy mortality	None	—	10%	—	50%	70%	100%
Char height (meters)	None	—	1.8 m (6 ft)	—	4 m (13 ft)	—	>7m (23 ft)
Pre-fire Conditions:							
% pre-fire cover: Litter = Duff = Soil/Rock =							
Pre-fire depth (inches): Litter = Duff = Fuel Bed =							

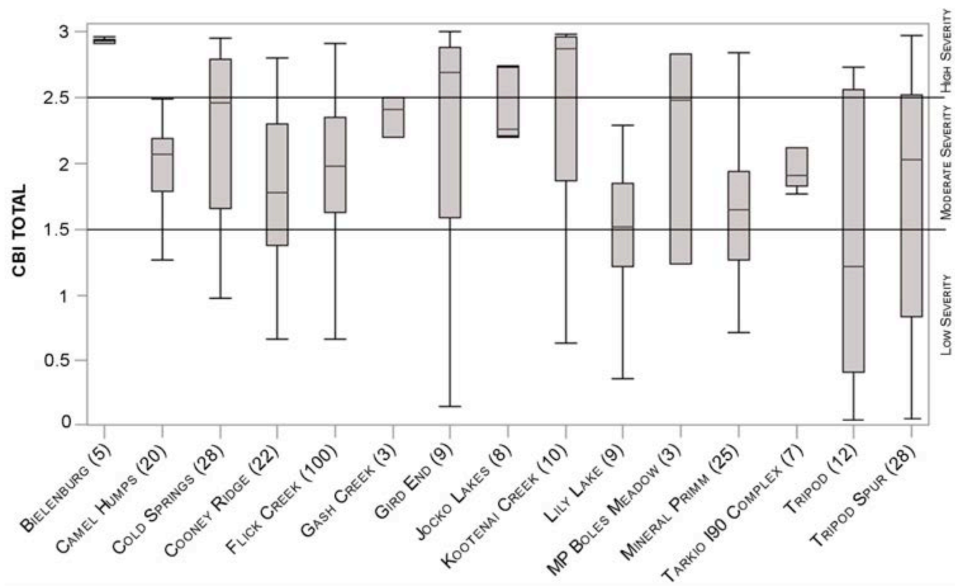

Figure 2—Distribution of Composite Burn Index (CBI) values used in the six-method comparison. CBI breakpoints for low, moderate, and high severity from Lutes and others 2006 are shown on right. Total number of field CBI plots is shown for each fire in parentheses beside the fire name. Boxes show the 25th, 50th, and 75th percentiles; whiskers show the maximum and minimum values. All CBI plots were collected one year post-burn from areas within mixed-conifer forests.

Table 4. Ryan and Noste (1985) classification linked to the CBI characteristics and values that would correspond to each class. The CBI equivalents are taken from the CBI data form (Lutes and others 2006). Ryan and Noste (1985) flame length classes are linked to big tree char height (far right). Ryan and Noste (1985) depth of char classes are linked to CBI substrate A and soil effects as in the lower table. Cell shading designates classes used in this study: white = unburned, light gray = low severity; medium gray = moderate severity; dark gray = high severity.

Flame Length Class	Char Height (m) Equivalent to Flame Length classes					CBI Equivalent (Big Trees Char Height)
5	>35.6 m	5-U	5-L	5-M	5-D	NA
4	19.50-35.59 m	4-U	4-L	4-M	4-D	NA
3	7.0-19.49 m	3-U	3-L	3-M	3-D	3
2	2.0-6.99 m	2-U	2-L	2-M	2-D	2
1	0-1.99 m	1-U	1-L	1-M	1-D	1
		Unburned	**Light**	**Moderate**	**Deep**	
		Depth of Char Class				

CBI Equivalents to Depth of Char Class (above)

	Unburned	Light	Moderate	Deep
Substrate A	0-0.49	0.5-1.49	0.5-1.49	1.5-3.0
Soil and Rock Color/Cover		0-1	>1	

based on the percentage organic matter consumed. The SPFI criteria were converted to CBI equivalents by matching two characteristics from the CBI form. These included (1) Substrate A: Soil Rock Cover Color and (2) Substrate A: Frequency of living material after fire (Table 3). The two CBI characteristics were matched to the soil indices as shown as in Table 5. Where the author's requirements did not exactly match percentages within the CBI data, the percentages with the least difference between the author's and the CBI form were chosen. The five categories for this comparison were designated as shown in Table 5.

The fire severity classifications derived from simulation modeling were based on output from the Fire Hazard and Risk Model (FIREHARM) (Keane and others 2010) and the First Order Fire Effects Model (FOFEM) (Keane and others 1995). The FIREHARM model required inputs of biomass values, weather conditions, and fuel moistures from each fire location for the time of the burn. Weather conditions for the period of the fire were obtained from the Western Regional Climate Center. Information on the fires was obtained from situation reports produced by the National Fire and Aviation Management (National Interagency Fire Center 2012). Fuel moistures were obtained by inputting weather conditions from the nearest weather stations for the period of the fire into Fire Family Plus (FFP) (https://www.frames.gov/rcs/7000/7026.org and http://www.firemodels.org/index.

Table 5. Jain and others (2012) soil indices used to classify post-fire severity based on soil color and organic matter present. Equivalent CBI values based on soil alteration (shown at right of table) and frequency of living material (shown below table) were assigned to the nearest percentage or soil characteristic that would fit the CBI data form. Cell shading designates classes used in this study: na = not applicable; white = unburned, light gray = low severity; medium gray = moderate severity; dark gray = high severity.

Soil Alteration						**CBI Equivalent (Substrate A: Soil Alteration)**	**CBI Burn Severity Class Substrate**
Orange charred soil	NA	NA	2.4	3.4	4.4	3.00	High
Grey-white charred soil	NA	NA	2.3	3.3	4.3	2.01 to ≤ 3.0	High
Black charred soil	NA	NA	2.2	3.2	4.2	1.01 to ≤ 2.0	Moderate
Unburned mineral soil	0.0	1.0	2.1	3.1	4.1	≤ 1.0	Unburned-Low
	100	≥85	>85 to ≤40	<40	0%		
	Surface Organic Matter Present (%)						
CBI Equivalent (Frequency of living material)	0 to ≤ 0.5	0.51 to ≤ 1.25	1.26 to ≤ 2.25	2.26 to < 3.0	3.0		

php/firefamilyplus-software/firefamilplus-downloads). The fuels, fuel moistures, and soil moistures (if available) were incorporated into a FIREHARM model run. The results assigned a predicted fire severity value to each pixel within the fire perimeters for each run. FIREHARM results for severity were one (low), two (medium), and three (high), which were considered to correspond to low, medium, and high CBI fire severities, respectively.

The remote sensing data for classifying burn severity using the differenced normalized burn ratio (dNBR) was obtained from the Monitoring Trends in Burn Severity (MTBS) web site (http://mtbs.gov). This data was based on assessments of vegetation change, charcoal signal, soil characteristics, and other biological changes after fire. It consists of four classes: unburned, low, medium, and high. Normally, MTBS recommends using continuous dNBR rasters instead of the class thresholds in fine-scale studies like the small burned areas examined in this study so that better results may be obtained in the classification process. For this study, a geospatial information system (GIS) layer containing both continuous raster values and the class values for dNBR was downloaded for each of the 15 fires to compare the values at each site. The class values were ultimately used for comparisons because they seemed more comparable to the distinct classes of the other burn severity methods, but it could be argued that the fine-scale comparison to CBI should not be expected to perform well using these class values. Fire severity class and continuous values were extracted for dNBR at each CBI plot location using Geospatial Data Extraction Library (GDAL) software (Open Source Geospatial Foundation 2011). The pixel values were derived from cells within a 5 x 5 grid cell area (each cell was 30m x 30m) at each CBI field location to provide average classed values for fire severity using dNBR. The 5x5 grid provided variation for the burn severity that could not be obtained from a single grid cell. The unburned, low, medium, and high severity classes resulting from dNBR pixel extractions were considered to correspond to CBI unburned (<0.49), low (0.5-1.49), moderate (1.5-2.49), and high (≥2.5), respectively.

Classified RdNBR data were also obtained from MTBS. Some research has shown that RdNBR is better for classifying vegetation change across large landscapes than dNBR because it removes bias from the amount of pre-fire vegetation and provides a relative rather than absolute measure of the changes in vegetation between pre- and post-fire imagery (Miller and Thode 2007). It has also been shown to be more regionally consistent in its relationship to field-measured burn severity (Zhu and others 2006; Miller and Thode, 2007). However, others have found that RdNBR is either not superior to dNBR (Cansler and McKenzie 2012; Soverel 2010) or other indices work better than RdNBR for severity classifications (Parks and others 2014; Sparks and others 2014). Because of its relative nature, RdNBR could conceivably produce different classification values for each CBI sample site within the 15 fires. For this study, we further adjusted the relative RdNBR values using breakpoints suggested by Cansler (2011), which were shown to improve RdNBR measures for forested areas in the Northwest and more closely match field CBI values taken from northwestern forests. The Cansler (2011) modification uses cutoffs of 106, 218, and 456 for remotely sensed class thresholds for dNBR; and cutoffs of 189, 372, and 703 for low, low-moderate, and moderate-high remotely sensed class thresholds for RdNBR (Cansler and McKenzie 2012). As with the dNBR, GIS layers for RdNBR were downloaded from MTBS, pixel values extracted from 5x5 grid cell units for each CBI site, and the RdNBR, CBI, and other classification techniques were compared. The RdNBR classes corresponded to CBI values as stated above for dNBR.

The Burned Area Emergency Recovery (BAER) Program produces recovery plans using burned area recovery classifications (BARC) that show changes in burned area reflectance due to loss of vegetation and charring of soil. GIS layers for BAER were produced by the USDA Forest Service Remote Sensing Application Center and downloaded for this study from the MTBS website (www.mtbs.gov). BARC layers are produced only for fires requested by BAER teams, not for all fires that are processed via MTBS. When BARC classifications are produced, however, they have the same range of correlation values as the RdNBR and dNBR when the layers are available, so they are no better or worse than the dNBR or RdNBR data from which they are created. However, they have a different purpose and focus than other remote sensing products, which can be reflected in their classification process. They were included in this study because BARC data are used for very specific purposes in recovery plans and they can classify burn severity differently because of their particular focus on erosion and soil heating. The extraction procedures, classifications, and relationships to CBI were the same as with the dNBR and RdNBR data.

Data Analyses

A contingency table was created from the table analysis procedure using table analysis with the SAS statistical program (SAS Institute Inc. 2008). The table shows the total number of CBI plots that matched on four severity classes – unburned, low, moderate, and high – and how differences varied between each of the method pairs. Because each method had varying amounts of missing data due to lack of some characteristics in the field data, percentages of agreement were calculated based on the number of plots available for each comparison not on the total number of CBI plots available to the study. A non-parametric ordered class statistic, the Kendal Tau statistic (K) (Canover 1999), was used to show the strength of the relationship between pairs of ordered classes and the direction of correlation. Kendal Tau b = +1 represented paired classes that increased in value together (i.e., a perfect positive correlation); Kendal Tau b = -1 represented an increase of one class with a corresponding decrease with its paired class (i.e., a perfect negative correlation). The Jonckheere-Terpstra (J) test (Canover 1999) was the non-parametric test used to investigate whether there were significant differences in the correlation in the medians of ordered classes. Differences were considered statistically significant if $p<0.05$.

Results

Comparisons of the CBI field assessments with results from each of the classification methods showed that the SPFI had the highest significant positive correlation with CBI classes (K = 0.75) but this index also had the smallest number of plots that could be assigned soil index values (Table 6). The other field classification that was developed by Ryan and Noste (1985), the FSM, also correlated reasonably well, and positively, with CBI at K = 0.66. The dNBR and RdNBR remote sensing classifications had lower correlations with CBI at approximately 50%, and BARC classes did not correlate with CBI well at all (K = 0.18). All of the classifications compared to CBI were significant in direction and strength using the J test.

The comparison of classification results with each other resulted in a wide range of correlation strengths and directions. The strongest correlations were between the two remote sensing classifications. The dNBR correlated with RdNBR strongly and positively at K = 0.76. The two field classifications, the FSM and the SPFI, also correlated well with each other (K = 0.70). SPFI also correlated moderately well with classes from remote sensing methods, including the dNBR (K = 0.43) and RdNBR (K = 0.57); but no correlations could be computed between SPFI and FIREHARM or BARC because so few plots could be assigned the soil index values. The simulation modeling method (FIREHARM) correlated weakly with all other methods (Table 6) and ranged from 0.01 with dNBR to 0.29 with FSI. The correlations of FIREHARM with RdNBR and BARC were both slightly negative, but only significant for BARC (J = 0.001). The least correlation overall occurred with BARC, which had weak correlations with all classification types except the RdNBR Cansler classification (K = 0.44). In combination, all classification methods varied considerably in their correlation strength and direction and the average percentage of agreement between any two methods was 38% for all pairs (Table 6).

For the FSM, dNBR, and RdNBR classifications, the total percent of classes that did not agree with the CBI assessment was spread relatively evenly among all the other classes so no consistent under- or over-assignments in classification were detected. For the CBI:SPFI pair, most of the classification differences came in the Soil Index Class 4 (44%). For the CBI:FIREHARM pair, the most classification differences were in its moderate and high severity classes. However, because FIREHARM had no unburned (Class 1) assessments for these fires, the value of this trend is limited.

Discussion

Classifications describing fire severity on the landscape have traditionally filled important roles in fire research because they integrate complex interactions and fire effects into more limited systems that are easy to understand. They have enabled managers and researchers to communicate impressions of severity with a common language. They have also acted as springboards for deeper inquiry and research on many different types of fire effects. The drawback of having many different classifications for describing fire severity is that it can be confusing to choose which classification will best describe fire effects on any given burned area or landscape; it also complicates communication. For some locations and purposes, fire effects may be adequately communicated by the simplistic, low-medium-high terminology; for others, a more robust classification may be required to adequately describe a full range of fire effects. Currently, communicating a range of fire effects is cumbersome because it requires determining a burn severity class from a specialized classification that does not necessarily match classifications obtained from other methods. It can also be confusing because the terms fire severity and burn severity have been used interchangeably in the past (Keeley 2009).

Assigning classes to unburned, low, medium, and high categories within this study was difficult for a number of reasons. Each classification method required unique interpretations and/or judgment calls to condense its classification into four standard classes that ranged from unburned to high. For the

Table 6. Contingency table showing statistical comparisons for each fire and burn severity classification method using 5 x 5 analysis grids to evaluate burn severity. Comparisons were based on the number of plots that matched in paired fire or burn severity classifications using unburned and low, medium, and high severity categories. Percentages are based on the number of plots analyzed for the respective methods divided by 289 total plots. CBI = Composite Burn Index used as ground truth; FSM = Ryan and Noste's (1985) Fire Severity Matrix; SPFI = Jain and others (2012) soil post-fire index; FIREHARM = Fire Hazard and Risk Model (Keane and others 2010); dNBR = differenced normalized burn ratio from Monitoring and Trends in Burn Severity; RdNBR (Cansler) = relativized differenced normalized burn ratio using Cansler's (2011) adjustment specifically for vegetation in the Northwest, USA; and BARC/BAER = Burned Area Reflectance Classification. Kendall's tau values are color coded as follows: <0.2 white, 0.2 to 0.4 light gray, and >0.4 dark gray. Group medians tested in the Jonckheere-Terpstra (J) non-parametric test were considered significantly different at <0.05.

Compared method	Field methods		Modelling methods	Remote-sensing methods		
	FSM	**SPFI**	**FIREHARM**	**dNBR**	**RdNBR (Cansler)**	**BARC/BAER**
CBI	**217 (75%)**	**25 (9%)**	**288 (99%)**	**288 (99%)**	**288 (99%)**	**183 (63%)**
missing values	72	264	1	1	1	106
Kendall's tau[a]	0.607	0.752	0.120	0.539	0.527	0.181
J test[b]	<0.0001	<0.0001	0.015	<0.0001	<0.0001	0.003
FSM		**25 (9%)**	**218 (75%)**	**218 (75%)**	**218 (75%)**	**153 (53%)**
missing values		264	71	71	71	136
Kendall's tau[a]		0.704	0.294	0.394	0.342	0.058
J test[b]		<0.0001	<0.0001	<0.0001	<0.0001	0.410
SPFI			**25 (9%)**	**25 (9%)**	**25 (9%)**	**0 (0%)**
missing values			264	264	264	289
Kendall's tau[a]			**	0.433	0.576	**
J test[b]			**	0.017	0.0005	**
FIREHARM				**289 (100%)**	**289 (100%)**	**184 (64%)**
missing values				0	0	105
Kendall's tau[a]				0.012	-0.074	-0.219
J test[b]				0.411	0.087	0.0014
dNBR					**289 (100%)**	**184 (64%)**
missing values					0	105
Kendall's tau[a]					0.761	0.325
J test[b]					<0.0001	<0.0001
RdNBR (Cansler)						**184 (64%)**
missing values						105
Kendall's tau[a]						0.441
J test[b]						<0.0001
Total plots	**218**	**25**	**289**	**289**	**289**	**184**

[a] Kendall's tau test (K) for differences between classes of ordered, categorical data; values $-1 \leq K \leq 1$; -1 = perfect negative correlation, +1 = perfect positive correlation, 0 = no correlation.
[b] Jonckheere-Terpstra non-parametric test for differences in medians between ordered classes. Values are probabilities <1.0.
** Unable to calculate statistics because rows or columns are all zeros.

FSM method, assigning a class required determining a flame height for a classification whose upper limits reached 35+ meters from CBI char height, but height was not evaluated higher than 5 m in the field. For the SPFI, the process of assigning fire severity to the CBI plots required using soils literature to determine how a color change from black to red in the substrate should be interpreted from the CBI substrate values. In some cases, assigning classes to appropriate categories was problematic because the CBI form was not filled out completely in the field. Missing values for pre-fire conditions, including litter and duff, made converting the SPFI and the FSM to appropriate fire severity classes especially difficult. For these particular burn severity classification methods, alteration of the substrate due to fire was critical to class assignments and would have been easier to do if the percent pre-fire cover of substrate fuels had been completely filled out on the CBI long form in the field. It can be argued that if a single decision had been made differently when assigning values to fire effects in any of these methods it may have changed the outcome of some of the paired comparisons. No doubt, this is true, but the process of determining which specific factors need to be measured after a burn or which fire effect needs to be highlighted for management action will, in any event, require similar decisions to be made by managers.

One notable result from this study is that remote sensing classification methods do not agree on class designations among themselves more than 75% of the time for the same grid space on the ground or correlate with CBI values more than 53% of the time. One probable reason is that the RdNBR used for this study was altered from traditional RdNBR thresholds to improve its accuracy in forests of the northwestern U.S. Even though both RdNR and dNBR are mapped at 900 m^2 using extensive quality standards, the different methods of processing the satellite data (continuous vs. class thresholds) do give different results for site and point locations especially when "tuned" to a specific landscape. While CBI correlations with remote sensing classes are only marginal in this study, the lack of agreement between remote sensing classifications and the CBI should not be a surprise. A significant amount of literature has demonstrated either poor correlations between CBI and remotely sensed data or correlations that are comparable in scale to those found in this study. Cocke and others (2005) found 75% agreement between dNBR and CBI and Robertson (2006) found 79% agreement compared to the 53% correlations of this study; but poor correlations were found by Clark and Bobbe (2006), Epting and others (2005), and Kasischke and others (2008), among others.

Modeling approaches to classifying burn severity are problematic because models are, by definition, only general representations of what happens in nature. The FIREHARM model correlated best with the FSM but the correlation was not strong (K = 0.29). Both of these classification methods use substrate and tree canopy in some manner to assign fire severity; but FIREHARM had very little variation within the 289 plots tested for this study (i.e., 83% of the CBI plots fell in the Moderate-Severity class), so the odds of agreeing with other methods that classified most burns as moderate were greatly increased (42% of the CBI values in FIREHARM and FSM were moderate severity). In contrast, the classes developed by Sikkink and Keane (2012) also resulted from a modeling approach but their classes could be related to CBI classes more closely because they encompassed soil heating with fire charcteristics and had a larger number of severity categories (Table 7).

Although the classification methods explored in this study utilize very specific fire effects to determine a picture of severity, their usefulness to managers and research is limited by the specificity and lack of flexibility of each classification. Many fire effects are important to the public in addition to vegetation loss and soil charring. For some managers, smoke production and hydrophobicity are just as important for public health and soil recovery. Many fire effects like these are not included in common fire severity classifications and currently have no possibility of being included in them in the future. Improving the classification process to meet the diverse needs of users may require a new approach that integrates field and remote sensing of burn characteristics more completely than in the past. It may involve developing modules within a classification that objectively describe classes of fire effects in soils (changes in color, texture, hydrophobicity, nutrients, etc.), the canopy (char height, canopy color, loss of greenness), hydrology (erosion, leaching, changes in rock color, etc.), fuels (percent biomass reduction, percent substrate change, etc.), the atmosphere (smoke, chemicals, etc.), and the landscape (percent changes in greenness, canopy loss, exposure of soil) (see Morgan and others (in press)). Integrating modules that describe different type of fire severity into a multifaceted classification system could provide a more comprehensive description of fire effects and create a more encompassing tool for classifying local and landscape effects and heterogeneity of fire severity on the landscape. It could also make classification and characterization of fire severity more objective, versatile, standardized, and inclusive in order to better meet research and management needs.

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Table 7—Relationship between the fire effects and fire characteristics used to create nine-classes of burn severity in Sikkink and Keane (2012) and the assignment of Composite Burn Index (CBI) values (Key and Benson 2006). PREDICT classes 4, 5, and 6 correspond to CBI low burn severity (i.e., CBI <1.5); classes 5, 6, 8, and 9 to CBI moderate severity , and classes 1, 7, and 8 to CBI high severity (CBI ≥ 2.5).

Fire Effect/ Fire characteristic	Unit	Matching CBI effect	PREDICT's Severity Classes								
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Soil heating (upper 1 cm)	°C	Substrate A: soil and Rock Cover/color	201	28	41	20	22	20	209	101	20
Soil heating (depth heated to 60°C) [a]	cm	Substrate A: Soil and Rock Cover/color	5	0	0.5	0	0	0	6	3	0
Total consumption kg m^{-2}	kg m^{-2}	Substrate A: Fuels Consumed	38	17	33	55	81	34	66	26	75
% duff and litter [b]	%		88	82	87	93	37	68	30	73	96
% cwd [c]	%		12	18	13	7	63	32	60	27	4
Fire Intensity	KW m^{-2}		115	88	4,374	12,839	125	58	116	72	153
Flame duration	sec		1,140	300	60	60	3,810	1,185	3,180	1,095	1,245
Smoke duration	sec		9,975	7,365	3,795	4,088	29,430	13,890	24,225	10,110	17,040
Total burn time	sec		3,225	1,485	75	60	7,995	4,875	7,995	3,825	3,885
		CBI assignment:	**2.5**	**1.0**	**1.0**	**0.5**	**1.5**	**1.5**	**2.5**	**2.5**	**1.5**

[a] Soil heating depth = 0 is surface heating only
[b] Percent computed on the total median value of biomass for duff and fine fuel component for each class
[c] Percent computed on the median value of total coarse woody debris biomass for each class

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