

1984–2010 trends in fire burn severity and area for the conterminous US

Joshua J. Picotte^{A,C}, Birgit Peterson^A, Gretchen Meier^A
and Stephen M. Howard^B

^AASRC Federal InuTeq, LLC, Contractor to the United States Geological Survey (USGS), Earth Resources Observation and Science (EROS) Center, 47914 252nd Street, Sioux Falls, SD 57198, USA.¹

^BUnited States Geological Survey (USGS), Earth Resources Observation and Science (EROS) Center, 47914 252nd Street, Sioux Falls, SD 57198, USA.

^CCorresponding author. Email: jpicotte@usgs.gov

Abstract. Burn severity products created by the Monitoring Trends in Burn Severity (MTBS) project were used to analyse historical trends in burn severity. Using a severity metric calculated by modelling the cumulative distribution of differenced Normalized Burn Ratio (dNBR) and Relativized dNBR (RdNBR) data, we examined burn area and burn severity of 4893 historical fires (1984–2010) distributed across the conterminous US (CONUS) and mapped by MTBS. Yearly mean burn severity values (weighted by area), maximum burn severity metric values, mean area of burn, maximum burn area and total burn area were evaluated within 27 US National Vegetation Classification macrogroups. Time series assessments of burned area and severity were performed using Mann–Kendall tests. Burned area and severity varied by vegetation classification, but most vegetation groups showed no detectable change during the 1984–2010 period. Of the 27 analysed vegetation groups, trend analysis revealed burned area increased in eight, and burn severity has increased in seven. This study suggests that burned area and severity, as measured by the severity metric based on dNBR or RdNBR, have not changed substantially for most vegetation groups evaluated within CONUS.

Additional keywords: differenced Normalized Burn Ratio, LANDFIRE Environmental Site Potential, Landsat, MTBS, Relativized differenced Normalized Burn Ratio, sigmoid distribution, wildfire.

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Introduction

Some research has shown increasing wildfire frequency and burned area in many regions within the conterminous US (CONUS) over the past 30 years, likely because of climate and related changes in fuels (Morton *et al.* 2013; Dennison *et al.* 2014) and management practices (e.g. fire exclusion) (Keane *et al.* 2002). It is less clear whether the burn severity of these fires has increased concurrently. Burn severity is defined by the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink *et al.* 2007) and in the present paper as fire-related visible change in biomass and soils that can be remotely sensed.

Using Landsat imagery, MTBS maps the burn severity of all reported fires (i.e. State and Federal fire records) greater than 404 ha in the western CONUS and 202 ha in the eastern CONUS. Within the 1984–2010 timeframe, MTBS assessed burn severity using Normalized Burn Ratio (NBR) products derived from pre-fire and post-fire Landsat Thematic Mapper (TM) and enhanced TM Plus (ETM+) satellite imagery. NBR is calculated by differencing satellite near-infrared (0.77–0.90- μm) and mid-infrared (2.09–2.35- μm) bands, dividing that result by their

sum, and multiplying the value by 1000. Differenced NBR (dNBR) products are created by subtracting post-fire from pre-fire NBR values to yield continuous values between –2000 and 2000. Higher dNBR values relate to the higher amounts of vegetation damage and soil exposure (Key and Benson 2006). Relativized dNBR (RdNBR) is calculated by adjusting the dNBR value by the pre-fire NBR value to account for the amount of pre-fire vegetation cover and greenness (Miller and Thode 2007). MTBS analysts then visually estimate unburned, low, moderate and high burn severity breakpoints to classify the continuous dNBR image. However, classified burn severity images cannot be used to estimate the total burn severity because they are imprecise: burn severity class proportions are only a reflection of the analyst's skill in assessing burn severity (Lutz *et al.* 2011).

Lutz *et al.* (2011) developed the severity metric (*SM*) to consistently characterise the overall burn severity as a function of the distribution of burn severity over the entire burned area. The *SM* is a unitless number ranging from 0 to 1 and is calculated from cumulative probability distribution of the continuous

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dNBR or RdNBR pixel values from within the fire perimeter, and provides a single-value summary of burn severity for the entire burn. *SM* is highly correlated with the mean dNBR or RdNBR for fires with unimodal distributions and is a good approximation of burn severity (Cansler and McKenzie 2014). Quantification of burn severity change is achieved by comparing *SM* values through time using nonlinear methods.

In this paper, we compare the *SM* values for 1984–2010 fires assessed by MTBS to determine whether burn severity and burned area have changed for 27 vegetation groups within CONUS.

Methods

Fire perimeter, dNBR, RdNBR and classified burn severity images were obtained from MTBS (<http://www.mtbs.gov>, accessed 1 January 2016) for CONUS. The MTBS project maps prescribed fires and wildfires, but we assessed only wildfires. For consistency in vegetation during the time period, fires were grouped by LANDFIRE 2010 Environmental Site Potential (ESP) climate-constrained vegetation types (see Rollins 2009; for a full description of ESP). ESP types were further grouped into US National Vegetation Classification (NVC) macrogroups (hereafter: ‘vegetation groups’) to regionally subdivide the vegetation within CONUS into smaller, ecologically meaningful

units. A summary of the ESP types and related NVC vegetation groups is provided in Table S1 and Fig. S1 in the supplementary material (available online). The dominant NVC vegetation group, i.e. largest area, was determined for each fire. We excluded all herbaceous vegetation-dominated fires from analysis because other studies have found it difficult to assess burn severity in grasslands, which are usually totally consumed when burned (Roy *et al.* 2006; Stambaugh *et al.* 2015). We also excluded vegetation groups that had a sample size of less than 30 fires. In all, 27 NVC vegetation groups were examined (Table 1).

We sampled a maximum of 1100 pixels per fire, yielding ~7 000 000 pixels. Pixels were chosen based on the percentage of pixels in the unburned, low, moderate and high burn severity classes within the burned perimeter, and then stochastically selecting the same percentage of coincident pixels from the dNBR and RdNBR images to provide a sample with a distribution representative of all pixels within the burned boundary.

The distribution of dNBR and RdNBR pixels for each fire was examined using the diptest (Hartigan and Hartigan 1985; Hartigan 1985; Mächler 2004) to determine if the distribution of the data was multimodal. Multimodal fires (diptest: $P \leq 0.05$) were dropped (Table 1) because their cumulative distribution residuals violated the assumption of normality (Lutz *et al.* 2011). From the total of 10 137 fires assessed by MTBS, 4893 fires

Table 1. Vegetation groupings examined in this study

Area sample size (*n*), sample size of fires (*n*) examined by differenced Normalized Burn Ratio (dNBR) and relativised dNBR (RdNBR), total area (ha) of all included fires (Area), area of return (Overlap) and percentage of dominant vegetation type per vegetation grouping (% Veg) examined in this study that are not composed solely of grassland and have at least 30 samples

Vegetation group	Area <i>n</i>	dNBR <i>n</i>	RdNBR <i>n</i>	Area (ha)	Overlap (ha)	% Veg
California chaparral	122	120	114	740 113	257 502	62%
California coastal scrub	117	115	113	311 033	201 269	62%
California forest and woodland	232	228	219	683 803	208 394	74%
Central Midwest oak forest	190	185	185	254 272	92 576	76%
East Cascades oak–ponderosa pine forest and woodland	165	159	155	516 503	51 846	72%
East Gulf coastal plain northern loess bluff forest	134	124	123	103 826	59 079	63%
Great Basin and Intermountain tall sagebrush shrubland and steppe	1189	1133	1152	4 867 008	2 663 129	77%
Great Basin saltbush scrub	148	147	147	817 386	415 888	52%
Great Plains sand grassland and shrubland	54	52	52	307 387	5782	67%
Intermountain singleleaf pinyon–Utah juniper–Western juniper woodland	540	503	508	1 895 365	640 298	61%
Laurentian and Acadian northern hardwood–conifer mesic forest	43	41	41	169 867	49 916	59%
Longleaf pine woodland	72	65	64	54 251	30 548	55%
Madrean lowland evergreen woodland	114	112	108	301 964	89 363	56%
Mojave–Sonoran semi-desert scrub	248	235	237	932 302	260 725	71%
North American Atlantic and Gulf coast salt marsh	59	59	59	77 382	139 428	93%
North American boreal flooded	36	36	36	155 260	230 040	62%
Northern Rocky Mountain foothill conifer wooded steppe	383	374	367	1 455 491	170 740	68%
Pond-cypress basin swamp	102	94	90	98 202	32 458	68%
Rocky Mountain subalpine–high montane conifer forest	148	119	110	894 083	123 752	78%
Sonora–Mojave mixed salt desert scrub	51	51	51	96 011	38 742	68%
Southern coastal plain evergreen hardwood and conifer swamp	79	70	72	68 842	24 327	53%
Southern Rocky Mountain lower montane forest	180	177	173	601 256	126 511	78%
Southern Rocky Mountain two-needle pinyon–one-seed juniper woodland	232	214	215	437 388	67 174	61%
Vancouverian lowland and montane forest	41	37	35	76 912	12 931	83%
Vancouverian subalpine forest	38	38	38	43 635	6326	54%
Warm and cool desert alkali-saline wetland	88	85	86	242 445	163 111	37%
Warm interior chaparral	88	81	80	176 081	38 796	59%
Total or mean	4893	4654	4630	16 378 068	6 200 650	66%

remained for analysis. The exclusions resulted in sample data not being available for every vegetation group for every year.

The dNBR pixel values between -200 and 1200 accounted for 99% of the range of the calculated dNBR values for each vegetation group except California coastal scrub and North American boreal flooded (98%). A sigmoidal curve function was fitted to the cumulative dNBR distribution using Eqn 1, where a is the steepness of the curve and b is the midpoint x value:

$$y = \frac{1.0}{1.0 + e^{-a(x-b)}} \quad (1)$$

SM was calculated by subtracting the area under the curve from 1 (Lutz *et al.* 2011):

$$SM = 1 - \sum_{i=-200}^{1200} \frac{\text{Proportion of pixels} \leq i}{1401} \quad (2)$$

The entire range of data assessed ($i + 1$) was equal to 1401 (Eqn 2) for dNBR. Higher SM values indicate higher overall burn severity.

We compared the dNBR and RdNBR SM estimates in all analyses using the Wilcoxon signed rank sum paired test to determine if they were significantly different from one another ($P < 0.001$). Values between -600 and 2000 were found to account for 99% of the calculated RdNBR data values in all vegetation groups except California coastal scrub (97%), North American Atlantic and Gulf Coast Marsh (98%) and North American boreal forest (97%).

Burn severity has been shown to be correlated with fire size (Lutz *et al.* 2009; Miller and Safford 2012; Cansler and McKenzie 2014). To reduce bias in evaluating mean severity per year and reassess whether burn severity has increased over the 1984–2010 time frame, an area-weighted mean SM value (\overline{SM}_A , Eqn 3) was calculated using the following formula (A , area in hectares):

$$\overline{SM}_A = \frac{\sum SM(A)}{\sum A} \quad (3)$$

Unitless \overline{SM}_A values range from 0 to 1. The yearly maximum SM value was found to assess whether extreme fire events are increasing in severity. Yearly \overline{SM}_A and maximum SM (SM_{\max}) values were then assessed through time using Mann–Kendall tests (Mann 1945; Kendall 1975). Slope trends were calculated using the Theil–Sen estimator (Theil 1950; Sen 1968). We assumed a P value < 0.05 is indicative of the significance for the Mann–Kendall tests (slope not equal to zero). Slope values indicate the trend’s relative rate of change. Using Mann–Kendall tests has the potential to cause Type II errors (Yue *et al.* 2002) when assessing trends for shorter time series and result in errors due to temporal autocorrelation (von Storch 1999). Additionally, there were years when no \overline{SM}_A or SM_{\max} data were available. To address these problems and identify whether a trend existed over the 27 years of the time series, we performed a bootstrap resampling procedure where the data were randomly resampled 10 000 times to determine whether their Theil–Sen slopes were significantly different from zero using the same methodology as Dennison *et al.* (2014). The trend assessment methodologies (including bootstrapping procedures) were also applied to assess mean and maximum fire area to determine whether changes in fire size were evident through time in the vegetation groups.

Results

Fire time series analyses

Seven of the 27 vegetation groups exhibited a significant increasing trend in either SM_{\max} or \overline{SM}_A during the 1984–2010 time period as determined by both the Mann–Kendall and bootstrapped Mann–Kendall tests (Table 2 and Fig. 1). Decreasing burn severity through time was not evident in any of the vegetation groups. Different trends were identified depending on whether the dNBR or RdNBR assessment was used. dNBR-assessed severity exhibited changes in \overline{SM}_A ($n = 3$) and SM_{\max} ($n = 4$), whereas RdNBR ($n = 3$) only exhibited

Table 2. Vegetation groups that showed a statistical increase in the severity metric (SM) through time derived from differenced Normalized Burn Ratio (dNBR) and relativised dNBR (RdNBR)

Mann–Kendall time series assessment of the significant changes (Sen’s slope; slope in severity metric per year) by yearly mean (weighted by area) or maximum (Max) dNBR and RdNBR Severity Metric (SM) values during the 1984–2010 time period, stratified by Vegetation Group. Refer to Table 1 for the sample size per assessment type (i.e. dNBR n and RdNBR n). P values from 10 000-iteration blocked bootstrapping procedure were also calculated where significance is indicated by one asterisk ($0.01 > P \leq 0.05$), two asterisks ($0.001 > P \leq 0.01$) and three asterisks ($P \leq 0.001$)

Vegetation group	Assessment type	SM type	Slope	P value
California chaparral	dNBR	Max	0.006	0.010**
California chaparral	dNBR	Mean	0.005	0.041*
Central Midwest oak forest	dNBR	Max	0.009	0.036*
Central Midwest oak forest	RdNBR	Max	0.012	0.025*
Madrean lowland evergreen woodland	RdNBR	Max	0.005	0.024*
Rocky Mountain subalpine–high montane conifer forest	dNBR	Max	0.009	0.038*
Southern Rocky Mountain lower montane forest	dNBR	Max	0.007	0.005**
Southern Rocky Mountain lower montane forest	RdNBR	Max	0.013	0.001***
Warm and cool desert alkali-saline wetland	dNBR	Mean	0.002	0.048*
Warm interior chaparral	dNBR	Mean	0.005	0.018*

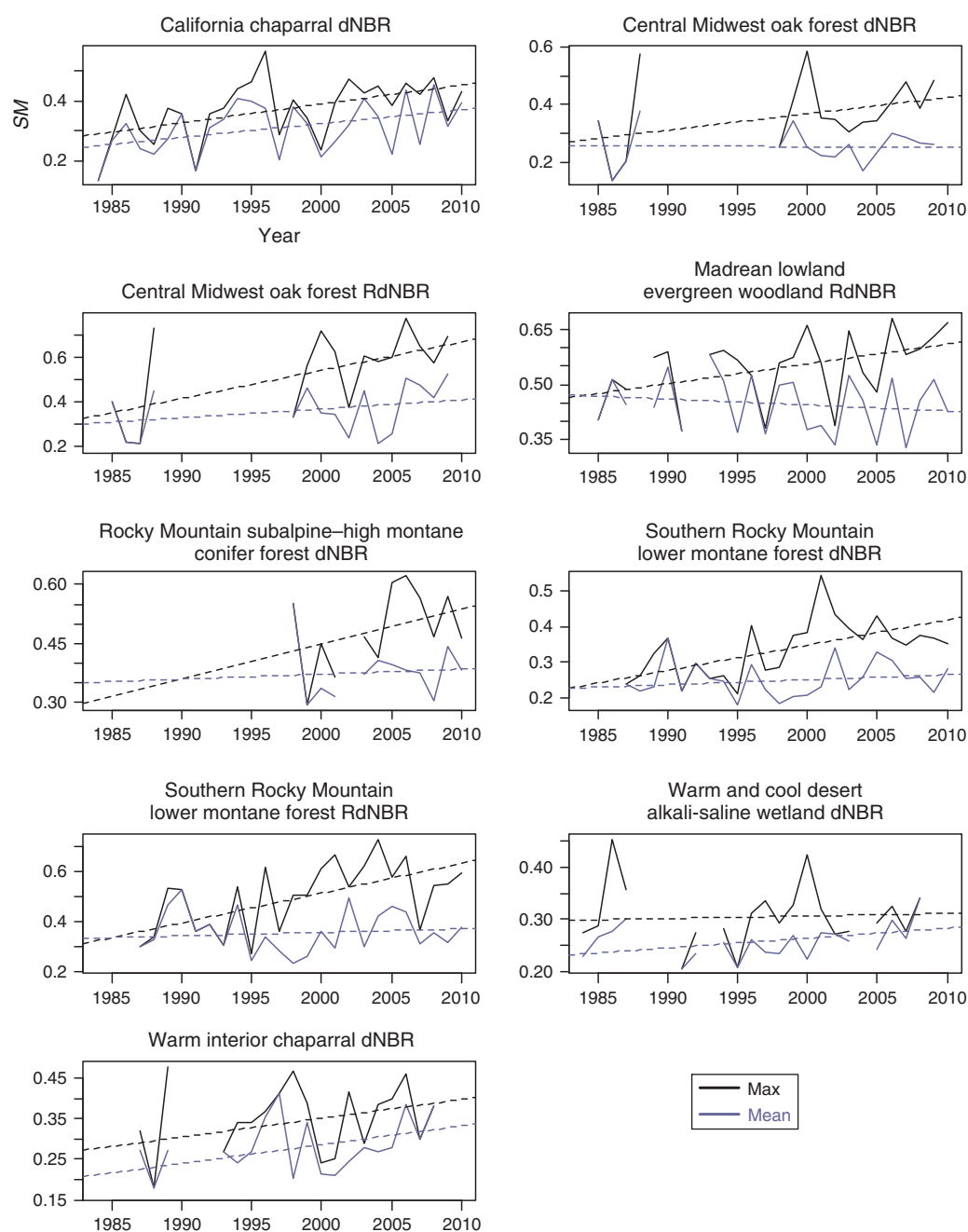


Fig. 1. Time series of area-weighted mean (Mean; dark grey line) or maximum (Max; black line) dNBR or RdNBR severity metric (SM) value for each vegetation group that exhibited a significant trend in SM over time. Trend lines per Mean or Max SM time series are included (dashed lines). dNBR, differenced Normalized Burn Ratio; RdNBR, relativized dNBR.

trends in SM_{\max} . In only two vegetation groups did both dNBR and RdNBR show the same trend in SM_{\max} .

Large wildfires significantly increased in area for only 8 of the 27 vegetation groups (Fig. 2). Mean, maximum and total area significantly increased through time for five, five and six groups, respectively (Table 3). All significant trends in area, except maximum area for Madrean lowland evergreen woodland, were also significant when assessed by bootstrapped Mann–Kendall tests.

Discussion

Our results indicate that burn severity, as estimated by SM , is not increasing within most of the vegetation groups assessed. Increased mean burn severity was evident in only 3 of 27 vegetation groups; however, where burn severity is increasing, yearly extreme fire events appear to be getting more severe. Our results also indicated that fire size is not increasing in most of the vegetation groups assessed. However, in areas where burn

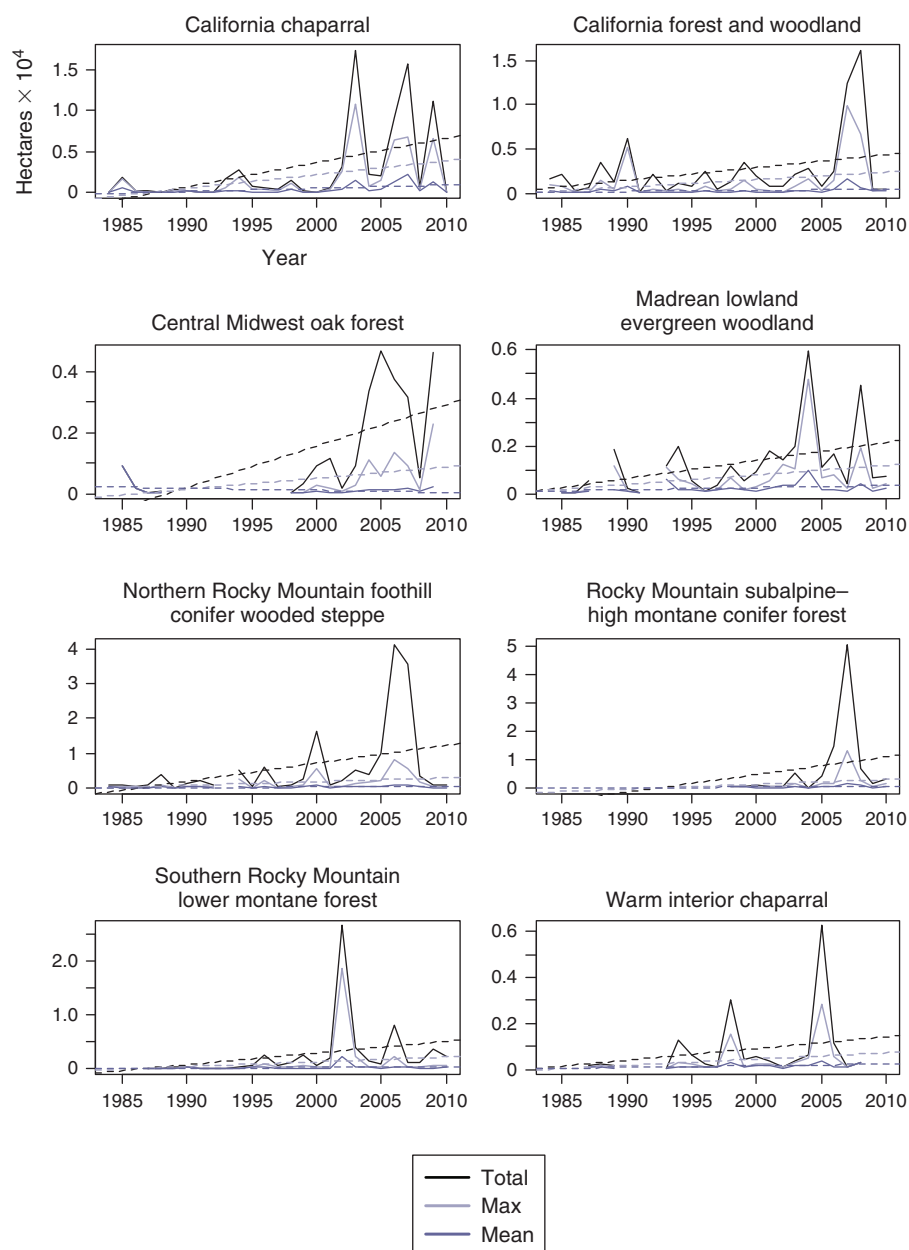


Fig. 2. Time series of total (black line), maximum (Max; light grey line) and mean (Mean; dark grey line) area (hectares $\times 10^4$) for each significant vegetation group that exhibited a significant trend in area over time. Trend lines per Total, Mean or Max area time series are included (dashed lines).

severity increased, fires got larger, with pronounced increases from 2000 onward, and burn severity became more variable during the study period (Figs 1 and 2).

Variation in fire size and burn severity

Other studies have shown increasing fire size within US regions (Finco *et al.* 2012; Dennison *et al.* 2014; Zhao *et al.* 2015). Observed trends in total area were similar between our study and the study of Dennison *et al.* (2014) within warm interior chaparrals and the Madrean lowland evergreen woodlands of Arizona–New Mexico Mountains and for large fires within

warm deserts (warm interior chaparral) and Mediterranean California (California chaparral). We did not find trends in total area or large fires related to vegetation groups in the Southern Plains or trends in large fires in the Arizona–New Mexico Mountains as did Dennison *et al.* (2014), who also did not find significant burned area trends in the Rocky Mountains, whereas we did (Fig. 2). We also found similarities in trends between the finding of Zhao *et al.* (2015) of increasing fire size in the northern Rocky Mountains, although their results were not significant. Differences between the studies' results may be attributable to how fires were assigned to vegetation groups and the associated

Table 3. Vegetation groups that showed a significant increase in fire area through time

Mann–Kendall time series assessment of the changes (Sen's slope; slope in mean area and maximum area per year) in yearly mean or maximum area values during the 1984–2010 time period, stratified by Vegetation Group. Refer to Table 1 for the sample size (Area n) for each vegetation group. P values from 10 000-iteration blocked bootstrapping procedure were also calculated where significance is indicated by * ($0.01 > P \leq 0.05$) and ** ($0.001 > P \leq 0.01$)

Vegetation group	Mean area		Maximum area		Total area	
	Slope	P value	Slope	P value	Slope	P value
California chaparral	141.900	0.005**	421.000	0.007**	732.841	0.010**
California forest and woodland	52.968	0.037*	118.109	0.243	229.016	0.453
Central Midwest oak forest	43.300	0.093	223.332	0.008**	996.633	0.003**
Madrean lowland evergreen woodland	66.308	0.05*	180.738	0.035	512.918	0.031*
Northern Rocky Mountain foothill conifer wooded steppe	31.527	0.332	405.900	0.094	1422.408	0.015**
Rocky Mountain subalpine–high montane conifer forest	107.795	0.138	850.850	0.023**	2229.500	0.018*
Southern Rocky Mountain lower montane forest	58.444	0.001**	209.816	<0.001**	938.058	<0.001**
Warm interior chaparral	50.244	0.013**	131.689	0.015**	167.529	0.102

variation in the number of fires examined. We utilised finer vegetation groupings to divide the fires into landscape-scale ecological subunits that are relevant to land managers.

Our observed trends in MTBS burn severity differed from previous studies that examined burn severity in the western US (Dillon *et al.* 2011; Miller and Safford 2012). We did not observe an increase in burn severity within Californian forests and woodlands as Miller and Safford (2012) or Mallek *et al.* (2013) found; however, Lutz *et al.* (2011) also did not find a trend. Differences between the studies may be attributed to study scale, i.e. large scale (Sierra Nevada Mountains, CA; Miller and Safford 2012) versus smaller scale (Yosemite National Park, CA; Lutz *et al.* 2011). These differences may also be attributed to local land management. For example, Miller *et al.* (2012) found trends in the Sierra Nevada Mountains (CA) on US Forest Service lands but no trends in National Park Service lands with the same vegetation, presumably because of prescribed fires on Park Service lands. We did find evidence of increasing burn severity in the southern Rocky Mountain lower montane forest, Madrean lowland evergreen woodland, and warm interior chaparral, which aligns with the findings Dillon *et al.* (2011) that burn severity increased in the Southwest. Like Dillon *et al.* (2011), we also found that burn severity had not increased in vegetation groups within the northwestern US. Discrepancies are likely due to the reduction in the number of fires that were examined in the present study. We only examined the MTBS fires that met our criteria, and that was less than half of all MTBS fires.

Both dNBR and RdNBR showed trends in burn severity; however, they did not exhibit the same trends (Table 2). Burn severity trend estimates were only similar for both dNBR and RdNBR in the central Midwest oak forest and southern Rocky Mountain lower montane forest vegetation groups. Variances may be explained by the different suitability of dNBR and RdNBR to estimate burn severity in different vegetation groups. RdNBR has been shown to work well in areas of heterogeneous vegetation (Miller and Thode 2007; Miller *et al.* 2009) and some areas of dense vegetation within the western US (Cansler and McKenzie 2014; Parks *et al.* 2014a), whereas dNBR has been

shown to be more effective in other areas of dense evergreen forests in western Canada (Soverel *et al.* 2010) and the south-eastern US (Picotte and Robertson 2011). The dNBR and RdNBR sensitivity to vegetation heterogeneity and density may also explain the differences in the trend assessments within Madrean lowland evergreen woodland, Rocky Mountain subalpine–high montane conifer forest, and warm and cool desert alkali-saline wetlands. It is concerning that RdNBR did not show similar trends in SM_A and SM_{max} when compared with dNBR estimates in California chaparral. De Santis *et al.* (2010) found RdNBR to be a better estimator of burn severity when compared with ground-estimated burn severity in Californian chaparral. However, Keeley *et al.* (2008) found dNBR to be more correlated with ground-estimated burn severity. These mixed findings suggest that there may be problems in using RdNBR or dNBR to assess burn severity in chaparral and similar vegetation.

The small number of discernible burn severity trends in the vegetation groups examined may have also been influenced by the reburning of previously burned areas. On average, 38% of the fire area within the vegetation groups burned at least twice (Overlap, Table 1). Areas recently burned may exhibit lower burn severity because there is less fuel to burn (Parks *et al.* 2014b; Prichard and Kennedy 2014), although some areas previously burned with prescribed fire can reburn with higher severity (Thompson and Spies 2009; Perry *et al.* 2011). Additionally, if an area has been severely burnt in the past, it may have undergone a vegetative change (e.g. reduction in tree density) and cannot burn as severely as its past vegetative state (van Mantgem *et al.* 2011).

Potential MTBS limitations

Using Landsat reflectance imagery to assess burn severity is problematic because it only characterises severity based on its spectral characteristics, which are further influenced by variables such as time since fire and the quality of pre- and post-fire imagery. Both dNBR and RdNBR have variable success when compared with ground-collected burn severity assessments (Miller and Thode 2007; De Santis *et al.* 2010; Cansler and

McKenzie 2012) such as the Composite Burn Index (CBI), and can have <60% agreement in forested ecosystems (Cansler and McKenzie 2012). Agreement between CBI and dNBR or RdNBR was <50% in grasslands (Stambaugh *et al.* 2015) and the use of NBR has been found to be problematic in African savannas (Roy *et al.* 2006). Areas with trees or shrubs with a herbaceous understorey, however, can have >60% agreement with CBI (Picotte and Robertson 2011; Stambaugh *et al.* 2015), which suggests that dNBR and RdNBR may be adequate to assess burn severity in mixed woody and herbaceous areas. Differences in the accuracy of dNBR or RdNBR estimates of burn severity are therefore likely to be vegetation-dependent. Neither dNBR nor RdNBR may represent ecosystem responses post-fire (Keeley *et al.* 2008), which further reduces their usefulness in monitoring post-fire ecosystem response.

In the current study, all initial (i.e. assessment immediately after fire during the same growing season) and extended (i.e. assessment within 1–2 years post-fire during the peak of the growing season) assessments of burn severity were pooled together. This could introduce error due to differences in the amount of time between fire end date and post-fire Landsat scene date. Burn severity estimates can change through time because of the regrowth of vegetation and delayed death of fire-damaged trees (Key 2005; Zhu *et al.* 2006; Picotte and Robertson 2011). This problem is mitigated by the MTBS protocol to map areas of rapid regrowth (southeastern CONUS) with initial assessments and areas of slower regrowth (western CONUS) with extended assessments.

Some fires assessed by MTBS after 2003 were mapped using Landsat 7 ETM+ imagery, which is missing up to 22% of its data owing to the failure of the Scan Line Corrector (SLC) on 31 May 2003. MTBS products that were generated using SLC-off imagery may have significant areas masked out, thereby distorting the true distribution of pixels in each severity class. Furthermore, all imagery is subject to data gaps resulting from clouds, cloud shadows and ephemeral water. All of these data gaps have the potential to skew the *SM* values by changing the cumulative distribution of dNBR and RdNBR pixel values.

These potential problems are compounded by the fact that the Landsat TM and ETM+ historical archive encompasses a short time period. Past fire history, climate and land management practices (i.e. before 1984) have shaped the fire-prone ecosystems within CONUS. Twenty-seven years is a fairly narrow slice of fire history and not necessarily representative of an area's longer-term trends in burn severity. The lack of significant trends found in the 1984 to 2010 data record may be an artefact and not reflect actual trends, which are confounded by different management practices or obscured by interannual variability. Additionally, there are data gaps that could impact the robustness of the trend analysis results. These findings suggest that more detailed regional assessments of trends in severity are needed.

Conclusions

Overall, we found that burned area and burn severity did not change for most vegetation groups. In those few vegetation groups where we were able to find distinct increases in burn severity over time, we did not assess whether these changes

corresponded with on-the-ground changes in burn severity. It is possible that the satellite-based trends do not correspond to actual landscape conditions, although our observed trends in the southern Rockies are similar to a previous study that utilised ground data (Dillon *et al.* 2011). dNBR and RdNBR *SM* values that do not consistently agree suggest that care should be taken when using either metric and the optimal remote sensing method should be used, when known, for a specific vegetation group. This is the first study that has attempted to use satellite-derived datasets to quantitatively determine whether burn severity is changing throughout CONUS, using the reduced MTBS archive. More work will be needed to assess whether *SM* is suitable for all vegetation groups within CONUS.

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