



Prior wildfires influence burn severity of subsequent large fires

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2016-0185.R2
Manuscript Type:	Article
Date Submitted by the Author:	08-Aug-2016
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Keyword:	fire weather, reburn, repeated wildfires, self-regulation, sequential autoregression



1 **Prior wildfires influence burn severity of subsequent large fires**

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19 **Abstract**

20 With longer and more severe fire seasons predicted, incidence and extent of fires is
21 expected to increase in western North America. As more area is burned, past wildfires may
22 influence the spread and burn severity of subsequent fires, with implications for ecosystem
23 resilience and fire management. We examined how previous burn severity, topography,
24 vegetation, and weather influenced burn severity on four wildfires, two in Idaho, one in
25 Washington, and one in British Columbia. These were large fire events, together burning
26 330,000 ha and cost \$165 million USD in fire suppression expenditures. Collectively, these
27 four study fires reburned over 50,000 ha previously burned between 1984 and 2006. We used
28 sequential autoregression to analyze how past fires, topography, vegetation, and weather
29 influenced burn severity. We found that areas burned in the last three decades, at any
30 severity, had significantly lower severity in the subsequent fire. Final models included
31 maximum temperature, vegetation cover type, slope, and elevation as common predictors.
32 Across all study fires and burning conditions within them, burn severity was reduced in
33 previously burned areas, suggesting that burned landscapes mitigate subsequent fire effects
34 even with the extreme fire weather under which these fires burned.

35 **Key words:** fire weather; reburn; repeated wildfires; sequential autoregression; self-
36 regulation

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39 Introduction

40 As a self-regulating process, the pattern of previous fires may limit the progression and burn
41 severity of subsequent wildfires for some time due to limited burnable fuels and changes in
42 forest structure (Agee 1999; Peterson 2002; Parks et al. 2014, 2015; Coop et al. 2016). Over
43 the past century, the legacy of past land use changes and fire exclusion have influenced forest
44 landscapes over much of the western United States (Hessburg et al. 2015). After nearly a
45 century of fire exclusion, many dry forests of the western United States have altered stand
46 structures and landscape patterns that can contribute to larger and more severe wildfire
47 events (Hessburg et al. 2015; Parks et al. 2015). With the onset of warmer, drier summers
48 and warm springs, the number and size of wildfires is increasing in the western US and other
49 fire-prone ecosystems throughout the world (Littell et al. 2009; Jolly et al. 2015). Burn
50 severity, defined as the magnitude of ecological effects of fires (Prichard and Kennedy
51 2014), has been less studied than area burned. With the growing number of large wildfires
52 and costly wildfire seasons, a better understanding of fire on fire interactions and their
53 implications for ecological effects is needed to inform science and management of fires.

54 Previous researchers have found that burn severity of wildfires was influenced by the
55 burn severity of prior fire. To date, many of these studies were in large wilderness areas in
56 which wildfires have had limited fire suppression and were managed and monitored (e.g.
57 Collins et al. 2009; van Wagtendonk et al. 2012; Parks et al. 2014). In studies of past fire
58 interactions in the Sierra Nevada Range, Collins et al. (2009) and van Wagtendonk et al.
59 (2012) found that areas previously burned with low to moderate severity within the past 30-
60 years tended to burn at similar severity in a subsequent fire. However, if an area had
61 previously burned in a high severity fire, a high proportion of the area burned at high severity
62 in a subsequent fire. They attributed this to the fire-induced shift in vegetation from forests to
63 highly flammable shrublands rather than simply a function of post-fire fuel accumulation

64 (van Wagtendonk et al. 2012). Similarly, Holden et al. (2010) found that in wildfires 3 to 14
65 years prior there was a threshold for burn severity above which burn severity is likely to
66 increase in the subsequent fire. Based on inferences from satellite imagery combined with
67 field data, low severity fires often resulted in subsequent low severity fires, but high severity
68 fires resulted in subsequent high severity fires (Holden et al. 2010; Parks et al. 2014a). In this
69 study we focus on non-wilderness areas. Fires outside of wilderness areas are often in drier
70 forest types (Haire et al. 2013), tend to have the highest fire suppression costs, and these
71 areas have high public interest and use.

72 Topography, vegetation, and fire weather influence burn severity of wildfires
73 (Schoennagel et al. 2004; Lentile et al. 2007; Prichard and Kennedy 2014; Birch et al. 2015),
74 but whether these variables supersede or compound the influence of prior fires is not well
75 understood. Previous studies have reported mixed findings on the relative importance of top-
76 down drivers of fire, such as maximum temperature, relative humidity, and wind speeds, and
77 bottom-up drivers, such as vegetation and topography. Bessie and Johnson (1995) and
78 Gedalof et al. (2005) demonstrated that extreme weather conditions can override bottom-up
79 factors, resulting in larger wildfires regardless of fuels and forest types. In contrast, Birch et
80 al. (2015) found that bottom-up factors, including vegetation and site potential, influenced
81 burn severity more than climate and weather. Though multiple researchers have examined
82 bottom-up versus top-down drivers of burn severity, few have analyzed the influence of these
83 factors in previously burned areas over multiple large fires. Some research has found that
84 wildfires burning under very hot, dry, and windy conditions are more likely to overcome fuel
85 breaks even those created by previous wildfires (Pollet and Omi 2002). To better understand
86 the capacity of burn mosaics to be self-regulating, we must understand when and why past
87 wildfires alter subsequent burn severity and when environmental factors or day of burning
88 conditions override the legacy effects of prior fires.

89 Here we focus on the legacy of previous wildfires by examining the drivers of burn
90 severity within reburned areas in non-wilderness forests of the interior northwestern US. We
91 studied the Tripod Complex Fire (central Washington, USA), the East Zone Complex
92 (central Idaho, USA), Cascade Complex Fires (central Idaho, USA), and Kootenay Fire
93 (central British Columbia, Canada); each of which were unusually large, severe, and
94 expensive relative to those of the prior century, and each burned through areas burned by
95 numerous past fires. We used sequential autoregression (SAR) analysis to evaluate the
96 influence of past wildfires, weather and topography on burn severity. SAR has been used in
97 recent studies of burn severity to take advantage of the inherent spatial autocorrelation in
98 burn severity datasets (Wimberly et al. 2009, Prichard and Kennedy 2013). The effectiveness
99 of fuels treatments, including prescribed fires, have been previously studied on two of these
100 wildfires (Hudak et al. 2011; Prichard and Kennedy 2014), but neither included previous
101 wildfires that may have also modified burn severity. Our study was guided by two key
102 questions: (1) How was burn severity of subsequent wildfires influenced by previous
103 wildfires? and (2) What role does weather, vegetation and topographic conditions have on
104 burn severity? These questions are critical for forecasting the implications for future
105 resilience and vulnerability, as well as understanding how post-fire fuel conditions will
106 influence subsequent burn severity and when and where the legacy of these past burns can be
107 used in wildfire management to achieve vegetation management or restoration goals.
108 Additionally, we address how weather, topography, vegetation, and past wildfires to
109 influence subsequent burn severity and how relationships differ between the four events.

110 **Methods**

111 *Study areas*

112 We focused our study on four recent, large wildfires in Idaho, Washington, and British
113 Columbia (Figure 1). These wildfires were chosen due to their large size, high fire

114 suppression costs, and large areas of interactions with previous wildfires. Combined, these
115 four fire complexes burned a total of 330,000 ha and cost over \$165.5 million USD in fire
116 suppression (Filmon 2003; Hudak et al. 2011; Prichard and Kennedy 2015). Our four study
117 fires occurred in years of widespread fires across their respective regions (Filmon 2003;
118 Hudak et al. 2011). In three of the four cases these wildfires were complexes started from
119 multiple ignitions that burned into one another and were managed as a single fire.

120 The 2006 Tripod Complex on the Okanogan-Wenatchee NF in Washington was, at
121 the time, the largest (70,894 ha) fire event in Washington State and cost \$82 million USD in
122 fire suppression costs (Prichard and Kennedy 2014). Over 65% of the area burned at
123 moderate to high burn severity with stand replacement. The wildfires in this complex ignited
124 from lightning in high elevation forests of lodgepole pine (*Pinus contorta*) and Engelmann
125 spruce (*Picea engelmannii*). The wildfires then spread into surrounding mixed-conifer forests
126 of Douglas-fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*) and western larch
127 (*Larix occidentalis*). As the Tripod Complex spread northeast with prevailing winds, it
128 burned portions of three 2003 burns, three 2001 burns, and burned a small portion of one
129 1994 burn (Figure 2a).

130 The 2003 Kootenay Fire Complex (Kootenay National Park, British Columbia) was
131 one of the largest fire events to have occurred in the Canadian Rockies in park history,
132 burning 17,400 ha and costing \$10.3 million USD for fire suppression. Over 75% of the area
133 burned at moderate to high severity. Pre-fire fuel complexes were comprised of mature
134 mixed-conifer forests of lodgepole pine, Engelmann spruce, and subalpine fir (*Abies*
135 *lasiocarpa*). This wildfire was mostly stand replacing and burned into a wildfire from 2001
136 (Figure 2b). This fire occurred within a Canadian national park, but full suppression of all
137 wildfires was the standard operating procedure before 2004, thus this fire and those points of
138 interaction were similar to the national forest study areas within the US (Day et al. 1990).

139 In 2007, the East Zone and Cascade Complex fires each burned over 128,000 ha on
140 the Boise and Payette National Forests in Idaho (Hudak et al. 2011) and cost \$32.5 and \$40.7
141 million USD respectively in fire suppression. The East Zone and Cascade Complexes burned
142 with mixed burn severity, with 21 to 30% of each wildfire classified as high severity
143 (Stevens-Rumann and Morgan *in press*). These two complexes burned through a wide range
144 of forest types and elevations from subalpine forests and meadows at high elevation to lower
145 tree line dominated by ponderosa pine woodlands. These two wildfires interacted with 31
146 previous wildfires that burned between 1984 and 2006 (Figure 2c). Although the 2007
147 Cascade and East Zone Complexes shared borders, we analyzed these fires separately given
148 their large size and the computational resources required to analyze these large landscapes.

149 *Datasets*

150 We used data from multiple sources to examine drivers of burn severity (Table 1).
151 We assessed the impact of previous wildfires by evaluating burn severity using a continuous
152 Relative Differenced Normalized Burn Ratio (RdNBR; Miller et al. 2009) for the three US
153 fires which was obtained from the Monitoring Trends in Burn Severity (MTBS) project
154 (Eidenshink et al. 2007). We chose RdNBR over other metrics of burn severity because it is
155 generally a reliable predictor of field-validated burn severity (Miller et al. 2009; Prichard and
156 Kennedy 2014) and is especially suitable for heterogeneous vegetation (Parks et al. 2015).
157 Additionally, field-based composite burn index (CBI) values on the Tripod Complex Fire
158 were highly correlated with RdNBR ($R^2 = 0.71$; Prichard and Kennedy 2014). For the
159 Kootenay Fire, we used Differenced Normalized Burn Ratio (dNBR) which was post-
160 processed by Kootenay National Park. Due to the largely homogenous cover type on this fire
161 dNBR was considered to be an appropriate proxy (Miller and Thode 2007).

162 We used the MTBS data for the prior fires for three potential predictor variables.
163 First, we converted continuous RdNBR and dNBR values for past fires into categorical

164 variables of “unchanged/unburned”, “low”, “moderate”, and “high” using metric specific
165 thresholds established by Miller and Thode (2007) to apply consistent classifications between
166 study areas. For our analysis, categorical variables were required to have a base contrast for
167 regression comparisons, thus we used unburned/unchanged as the base contrast. Second, time
168 since fire was assigned for each pixel that experienced 2 or more fires since 1984. For pixels
169 not previously burned we assigned “100” as time since previous fire. We categorized these as
170 “100” years since fire because burn severity data inferred from Landsat satellite imagery is
171 only available after 1984 and most of these forests are known to be dominated by 80-120
172 year old trees (Schellhaas et al. 2001). For pixels that were reburned more than once (i.e.,
173 burned in three or more wildfires between 1984 and 2007), the most recent fire year was used
174 to calculate time since previous fire. This did not occur on the Kootenay Fire and occurred on
175 two percent of the reburned area of the Tripod Fire. On the Cascade Complex Fire this
176 occurred on three percent of reburned pixels and on the East Zone Complex Fires on four
177 percent. Third, to understand possible edge effects, such as fire suppression and changes in
178 fire behavior along a fires perimeter, we used a distance-to-edge metric calculated as the
179 distance of each pixel to the nearest burn perimeter. Although fire management actions
180 during wildfires likely altered fire extent and burn severity, we did not account for them
181 directly as the records of management actions were incomplete.

182 We were able to partially evaluate RdNBR accuracy in reburned areas by examining
183 relationships between field-based Composite Burn Index values and RdNBR values in reburn
184 areas of the 2006 Tripod Complex fires. Field validation plots were established in prescribed
185 burn areas that reburned in the Tripod Complex, and most were classified as low burn
186 severity areas as a result of the treatment effect (Prichard and Kennedy 2014). On these sites,
187 producer’s accuracy was around 40%, however 95% of the misclassification occurred when
188 RdNBR values were close to the burn severity cut-off between unchanged and low or low

189 and moderate severity established by Miller and Thode (2007). Field validation did not differ
190 from that inferred from satellite imagery by more than one category (e.g., low severity
191 classification when field validation was moderate severity).

192 To examine the impact of weather on the day of burning, we acquired fire progression
193 interval layers from the Okanogan-Wenatchee, Boise, and Payette National Forests, and from
194 Kootenay National Park. These progression layers allow us to narrow the time frame within
195 which each pixel burned to a 10-96 hour window depending on the frequency progression
196 intervals were sampled from infrared imagery. We then assigned weather characteristics
197 during each progression interval based on the date each pixel burned. We assigned maximum
198 and average wind taken at 6.1 m above ground, maximum and average air temperature, and
199 minimum relative humidity (RH). These data were acquired from nearby Remote Area
200 Weather Stations (RAWS): the First Butte station for the Tripod, the Tea Pot Idaho station
201 for the Cascade and East Zone (Western Regional Climate Center, <http://www.raws.dri.edu/>,
202 last accessed January 13, 2015), and Vermillion Weather Station (courtesy of Parks Canada,
203 Kootenay National Park). All stations were within 5 km of the nearest burned edge. From the
204 Vermillion weather station, we could only acquire daily mean temperatures, relative
205 humidity, and average wind speed; therefore maximum and minimum values were not
206 available and excluded from the analysis.

207 Vegetation and fuels information was derived from LANDFIRE products (30m
208 resolution; Ryan and Opperman 2013). We used 2001 data to reflect the best data for
209 conditions prior to the three study wildfires. We acquired crown bulk density (CBD), fire
210 regime group (FRG) and canopy cover (CC). We also converted the 40 existing vegetation
211 type (EVT) to seven “cover type” categories, to group similar vegetation types. These cover
212 types were “lodgepole pine”, “ponderosa pine”, “subalpine forest”, “riparian”, “dry-mesic
213 mixed-conifer”, “Douglas-fir/western hemlock”, “grassland/shrubland”. Grasslands and

214 shrublands comprised a relatively small portion of the total study area landscapes with 8% on
215 the Tripod, 15% on the East Zone, and 18% on the Cascade thus we grouped all grasslands
216 and shrublands together for the analysis, even though conditions of these various grassland
217 and shrubland covertypes are known to be highly variable: from subalpine grasslands to low
218 elevation shrublands and grasslands. We used “dry mesic mixed-conifer” as the base contrast
219 for burn severity comparison. Vegetation type and stand origin maps are available from
220 Kootenay National Park, but due to the fairly uniform vegetation types and stand structures
221 we did not include vegetation characteristics for this model.

222 Topographic and landscape indices were evaluated, including potential incoming
223 solar radiation summarized over one calendar year period (Fu and Rich 1999), elevation (m),
224 slope (degrees; ESRI 2011), and steady state topographic wetness index (TWI). TWI was
225 derived using Evans’ (2003) script. Three topographic position indices including topographic
226 position index (TPI), ridge/ridge-like position, and valley/valley-like position, were
227 calculated within a 100-m neighborhood of each pixel using methods developed by Weiss
228 (2001). The basic TPI calculation compares the elevation of each cell in a DEM to the mean
229 elevation within the nearest-neighborhood of each pixel. Ridgetop or ridge-like positions are
230 defined as positive TPI values (0-2.0), representing locations that are higher than the average
231 of their surroundings, and valley or valley-like positions defined as negative TPI values (-2 to
232 0).

233 *Data Analysis*

234 We used Sequential Autoregression (SAR) analysis (Wimberly et al. 2009) to
235 evaluate how previous burn severity, topography, vegetation, and weather, influenced burn
236 severity. Our response variable was burn severity on each of our four study fires represented
237 by continuous RdNBR or dNBR values. Candidate predictor variables included: weather
238 variables, burn severity classification of past wildfire events (e.g., unchanged/unburned, low,

239 moderate, and high), time since previous fire, topographic variables, vegetation types, and
240 fuel characteristics (Table 1). We examined colinearity between possible predictor variables
241 with simple pairwise correlations and excluded correlated variables ($r > 0.85$; Nash and
242 Bradford 2001) from the same model. The SAR models were constructed in R programming
243 language (R Development Core Team 2011) and methods were published by Wimberly et al.
244 (2009) and Prichard and Kennedy (2014). We compared individual variable models using
245 Akaike's Information Criterion (AIC; Akaike 1974), and selected the final multivariate
246 models based on lowest AIC values. We tested multiple models and removed variables when
247 the AIC value was not reduced by more than 50 (Supplementary Table 1).

248 Prichard and Kennedy (2014) demonstrated that using a 30m nearest neighborhood
249 distance minimized both AIC and Moran's I, and we confirmed with Moran's I that our final
250 models did not have autocorrelation of the residuals at this neighborhood distance. Although
251 SAR analyses define the SAR neighborhood weighted matrix by subsampling to reduce
252 computational resources and time (Kissling and Carl 2008), we assigned point data
253 information to each 30-m pixel across the entirety of each of our four study fires, including
254 areas previously unburned. In the Cascade and East Zone Complex, a spatially continuous
255 dataset was impossible due to a failure of the Landsat 7 EMT+ scan line correction
256 mechanism (known as SLC off condition; Howard and Lacasse 2004; Supplementary Figure
257 1). In these two wildfires, we used all available points, skipping the 150-m scan line areas
258 and treating pixels surrounding the scan lines as true neighbors. To address the possibility
259 that missing data skewed results of our SAR analysis, we performed a test of bias by
260 examining the distribution of cover type and topographic variables within these scan lines
261 versus areas with RdNBR data. Our examination of pixels within and outside the scan lines
262 showed that the distribution of canopy cover, elevation, slope, solar radiation and
263 topographic wetness index were nearly identical for both the Cascade and East Zone

264 Complex fires (Figure 3), and therefore that there was no bias due to scan line errors.

265 In addition to examining these fires as continuous study sites, across all cover types
266 we did two additional SAR analyses within each study fire to determine how past fires
267 influenced burn severity within different forest types, we refer to these as “cover type
268 models”. To extract data for these analyses we grouped our previous cover types into “low
269 elevation forest type” (Douglas-fir/hemlock, ponderosa pine, dry-mesic mixed-conifer) and a
270 “high elevation forest type” (lodgepole pine, subalpine fir), and ran the SAR analysis on only
271 points that fell within each of these broad forest type classifications. Only two factors were
272 considered in this model: time since previous fire and past burn severity.

273 **Results**

274 Final SAR models of burn severity, based on lowest AIC values, varied between
275 study areas, but past burn severity was a strong predictor on all sites. The Tripod, Cascade
276 and East Zone SAR models included distance to edge, valley bottom, maximum temperature,
277 and cover type (Table 2 and 3). In addition to these common five variables, the final model
278 for Tripod included canopy cover, elevation, and slope. The East Zone final model also
279 included elevation, TWI, and maximum wind gusts on day of burning and the Cascade final
280 model included slope, time since fire, maximum wind gusts on day of burning, and canopy
281 cover. The Kootenay fire did not have vegetation variables; the final model included distance
282 to edge, hill, elevation, average temperature and past burn severity. Many other predictor
283 variables were significant predictors of RdNBR or dNBR but were not included in the final
284 models, based on lowest AIC values.

285 *Past wildfires*

286 Past burn severity had a negative relationship on subsequent burn severity on all four
287 study fires. Compared to areas unburned/unchanged in previous fires, previously burned
288 pixels had reduced burn severity (Table 3, Figure 4). Areas that burned at high severity in the

289 Tripod and Kootenay fires contributed to the largest reduction in burn severity in the
290 subsequent fire, while low burn severity areas had the smallest reduction or did not differ
291 significantly from previously unburned/unchanged points. Conversely, on the East Zone and
292 Cascade fires, areas that previously burned at low severity had the largest reduction in reburn
293 severity compared to unburned areas.

294 Slightly different results were observed in the cover type models. The relationship to
295 past burn severity was maintained within both low elevation and high elevation forest types
296 on the Tripod, but the estimates on East Zone and Cascade fires varied from the full models.
297 On the East Zone, high elevation forest types had the largest decreases in burn severity on
298 sites previously burned at high severity, while low elevation forest types experienced the
299 lowest burn severity after previously experiencing a low severity fire. On the Cascade fire the
300 pattern was the same in both forest types: the lowest burn severity was observed after
301 previously experiencing a low severity fire, while areas that experienced a high severity fire
302 had significantly higher burn severity than unburned areas. (Table 4)

303 Distance to edge was a significant predictor and had a positive relationship on burn
304 severity, reflecting that regardless of whether sites were previously burned, interior regions
305 of these large fires had higher burn severity than the perimeters. This applied to all four fires
306 we studied.

307 Time since past fire had mixed effects in the various models. On the Cascade fire
308 burn severity was lower the longer time since fire, and though significant it was not included
309 in the East Zone or Cascade models due to only small decreases in the best model AIC
310 values. However, in the cover type models when forest types were analyzed individually,
311 time since past fire proved to have a positive relationship on all three study areas (Table 4).

312 *Fire weather, vegetation, and topography*

313 Of the weather variables analyzed, the most important predictors of burn severity

314 were maximum temperature and minimum RH on the Tripod, average temperature and
315 average RH on the Kootenay, and maximum temperature and maximum wind speed on the
316 East Zone and Cascade fires. Because temperature and relative humidity were highly and
317 inversely correlated, only maximum temperature, the stronger of the two predictors based on
318 lower AIC values, was included in the final model for the Tripod. Maximum temperature and
319 maximum wind speed were included in the final model for the East Zone and Cascade. Burn
320 severity was positively correlated with maximum temperature, but the relationship to
321 maximum wind gust was mixed on the different study areas. On the East Zone Complex
322 higher burn severity was correlated with higher maximum wind speeds, but a negative
323 correlation was observed with burn severity on the Cascade Complex.

324 Of the LANDFIRE variables, vegetation canopy cover and cover type were the most
325 important predictors of burn severity (Table 3). Forest canopy bulk density was also a
326 significant predictor. However, because of the high correlation between canopy cover and
327 canopy bulk density, only canopy cover was included in the final models. Valley bottom,
328 ridge top, and TPI metrics were significant predictors of burn severity. Valley bottom, which
329 was inversely correlated to ridge top, was included in final model for the Tripod, East Zone,
330 and Cascade study areas because it was a better predictor. Valley bottom was inversely
331 related to burn severity; valley bottoms burned less severely than ridges and steep slopes. TPI
332 was highly correlated with both of these metrics and was therefore excluded in the final
333 model on these three fires. On the Kootenay Fire, TPI was significant and the best predictor
334 but was excluded from the final model because it only minimally reduced the model AIC
335 value.

336 Elevation was a significant predictor of burn severity on the Tripod, East Zone, and
337 Kootenay fires. Burn severity was positively correlated with elevation on these three fires,
338 with increasing burn severity at higher elevations up to 2150 m on the Tripod, 2450 m on the

339 Cascade, 2550 m on the East Zone, and 2075m on the Kootenay. Above these elevations,
340 burn severity decreased across the highest elevations of each fire area (Figure 5).

341 As slope and TWI were highly correlated, and slope was a slightly stronger predictor
342 than TWI for the Tripod and Cascade (Table 3). Slope was positively related to burn severity
343 on the Tripod and negatively related to burn severity in the Cascade and Kootenay. For East
344 Zone, TWI was the stronger predictor and was inversely related to burn severity.

345 **Discussion**

346 Within each study area, top-down drivers such as weather (high temperatures, high
347 windspeeds and low relative humidity) influenced fire effects as did bottom-up factors
348 including topography, vegetation type and past wildfire effects (Parisien et al. 2011; Birch et
349 al. 2015). Over the coming decades, the ecological footprint of heterogeneous burn severity
350 patterns will contribute to the mosaic of vegetation response and will likely influence future
351 landscape dynamics.

352 *Evidence of self-regulation in past burns*

353 The drivers of burn severity were remarkably similar across these four large and
354 different landscapes, each with different land uses and fire history legacy. As these large fires
355 burned across diverse topography and vegetation, burn severity generally was reduced by
356 previous wildfires (Figure 4). Surface fuels and tree density, critical to fire behavior, were
357 likely reduced on these previously burned areas (Stevens-Rumann and Morgan *in press*).
358 Lower fuel connectivity may have led to associated reductions in subsequent fire behavior
359 and effects (Alexander and Cruz 2012). While the reduction in fuel may be beneficial from a
360 fire suppression stand point, these changes in fuel may indicate large changes in vegetation
361 type (e.g. Stevens-Rumann and Morgan *in press*; Harvey et al. 2016)

362 Although lower burn severity was observed in previously burned areas on all four
363 study sites, the impact of prior burn severity varied by study site (Figure 4a and b). The

364 results from Tripod and Kootenay directly contrasts with recent studies in which low to
365 moderate previous burn severity resulted in a reduction in subsequent burn severity but high
366 severity fires were often followed by high severity fires (Collins et al. 2009; Holden et al.
367 2010; Parks et al. 2014a; Harvey et al. 2016). Differences may be explained by slow
368 vegetation response in the Tripod and Kootenay compared to other study locations, such as
369 Yosemite National Park, where flammable shrub fields can regenerate rapidly following high
370 burn severity fire (Collins et al. 2009; van Wagendonk et al. 2012). Another potential reason
371 for this difference may be that our study areas are outside of wilderness and experienced
372 different fire suppression actions and prior land uses. Fire suppression on the edge of the past
373 fires, including containment lines and burnout operations, may have effectively reduced fire
374 spread and/or decreasing subsequent burn severity, especially within older wildfires. We
375 could not account for this except with our distance to edge metric due to the lack of
376 geospatial data of fire suppression activities.

377 In forested cover types, burn severity increased as the time since fire increased on all
378 study fires, and this relationship was generally strongest in dry forest types (Table 4), as was
379 reported by others (Holden et al. 2010; Haire et al. 2013; Parks et al. 2014). In these
380 ecosystems with shorter fire return intervals, previously burned areas only act as barriers or
381 mitigate burn severity for short periods of time due to rapid accumulations of grasses, other
382 herbs, shrubs and fine wood (e.g. Peterson 2002; Parks et al. 2015).

383 Patches of stand-replacing fire or areas maintained by frequent surface fires create
384 fuel heterogeneity that may reduce subsequent fire spread or burn severity (Hessburg et al.
385 2015). The marked decrease in burn severity across most previously burned areas supports
386 this concept. In both high elevation, moist forests and low elevation, dry forests on the East
387 Zone, Tripod, and Kootenay Fires, high burn severity in an initial fire resulted in lower burn
388 severity in subsequent fires, with the exception of forested cover types on the Cascade.

389 Although other variables were also important to our predictive models of burn severity, large
390 decreases in burn severity associated with previous severity indicates that these altered
391 landscapes are less likely to burn severely again within the first two decades following a fire
392 (Hudak et al. 2010; Prichard and Kennedy 2014; Harvey et al. 2016).

393 The capacity of past burn mosaics to self-regulate is not well understood given the
394 deficit of fire in many dry forest landscapes over the past century (Hessburg et al. 2007;
395 Marlon et al. 2012). Fire on fire interactions are still relatively uncommon across dry forest
396 landscapes but will become more prevalent in the coming decades as wildfires continue with
397 warmer, drier summers predicted for much of the western United States (Littell et al. 2009;
398 Cansler and McKenzie 2014). The amount of area reburned in our study landscapes was
399 small (roughly 3% of the total fire area), but proportion of areas reburned will likely increase
400 with climate change. Fire activity has already dramatically increased in the past decade, with
401 3.7 million ha burned nationally in 2015, 45% more than the previous 10-year average
402 (<http://www.nifc.gov>).

403 Because previous wildfires mitigated burn severity under extreme conditions, we
404 expect past wildfires to be particularly effective at shaping landscapes when subsequent fires
405 burn under less extreme fire weather (Pollet and Omi 2002). Past wildfires can alter burn
406 severity and even fire spread, acting as temporary fuel breaks (Teske et al. 2012; Haire et al.
407 2013; Parks et al. 2014, 2015), and a single fire may be sufficient to initiate self-regulation.
408 However, large stand-replacing wildfires also may result in a large, homogenous area of
409 similar fuels that, in the absence of subsequent finer-scale disturbances, could predispose
410 landscapes to subsequently large fire events that further homogenize landscapes (Peterson
411 2002). Smaller fires, in particular, may be critical to creating landscape patterns that would
412 be less conducive to burning in subsequent large, stand-replacing events (Hessburg et al.
413 2015) and prevent large vegetation type conversions (Harvey et al. 2016; Stevens-Rumann

414 and Morgan *in press*). Currently, a common fire management strategy is to suppress all
415 wildfires. However, fires that burn under mild or average weather conditions may provide
416 critical heterogeneity in vegetation cover and structure that mitigates area burned and
417 patterns of burn severity in subsequent wildfires (Hessburg et al. 2015, Kemp et al. 2015).

418 *Fire weather*

419 In general, higher temperatures, lower relative humidity and in some cases stronger
420 winds were related to higher burn severity (Table 3). Our results suggest that on more
421 extreme weather days, fires burn more severely, fueled by reduced thresholds to burning and
422 the influence of wind on fire spread and intensity (Birch et al. 2015; Cansler and McKenzie
423 2014). The weather variables, broadly summarized from nearby weather stations, in the final
424 models suggests that nearby weather stations may be a decent proxy for finer-scale, fire-
425 weather relationships (Prichard and Kennedy 2014). However, we found some inconsistent
426 relationships: on the East Zone fire burn severity increased with higher winds, while the
427 opposite relationship was observed on the Cascade. Fine-scale variability in weather patterns
428 were undetectable using coarse-scale data and may be the reason for this inconsistent
429 relationship (Taylor et al. 2004). Although progression maps allowed us to relate burn
430 severity at a pixel to the weather at the general time of burning, progression intervals varied
431 from < 24 hours to four days of burning, and the weather conditions at the time a given pixel
432 burned could be poorly represented by summarized weather over the progression interval.

433 *Vegetation*

434 Denser, closed-canopy forests burned at higher severity than open canopy forests, as
435 would be expected from past studies (Schoennagel et al. 2004). Severity was highest in the
436 high elevation forest types (Table 3 and 4). Multi-layered, conifer forests dominated by thin-
437 barked trees burn with a higher proportion of high severity, stand-replacing fires and are
438 characterized by either mixed or high-severity fire regimes (Bigler et al. 2005; Prichard and

439 Kennedy et al. 2014). In contrast, dry, low elevation forest types (i.e., dry-mesic mixed-
440 conifer, ponderosa pine, Douglas-fir cover types) generally burned at lower burn severity on
441 the Tripod, Cascade, and East Zone fires.

442 Burn severity in grasslands and shrublands was more severe than dry-mesic mixed
443 conifer forests. Given the variation among and within these grouped vegetation types from
444 alpine meadows to low elevation grasslands/shrublands interpretation may be difficult and
445 skew relationships with burn severity. Additionally, burn severity is known to be difficult to
446 infer from satellite imagery one-year post-fire in many of these grass and shrub cover types
447 given the rapid vegetation recovery within one year (van Wagtendonk et al. 2012).

448 *Topography*

449 Across study sites, we found that burn severity was related to topographic variables
450 including slope gradient, elevation and TWI (Table 3). Across all sites, burn severity
451 increased as slope gradient increased, which is corroborated by other studies (e.g. Birch et al.
452 2015). Burn severity decreased as TWI increased, similar to other studies (Holden et al.
453 2009). These relationships may be related to changes in fire behavior across topographical
454 and moisture gradients. As wildfires spread up steep, drier slopes, fire intensity generally
455 increases, transition from surface to crown fire is more possible, and rate of spread and flame
456 lengths increase (Scott and Reinhardt 2001). Airflow in valley bottoms is also sometimes
457 restricted and may be related to generally lower burn severity in valley-like settings (Finney
458 and McAllister 2011).

459 The positive correlation between burn severity and elevation is likely a result of fuel
460 moisture gradients and differences in vegetation types. Low elevation areas of the Cascade,
461 East Zone and Tripod fires were dominated by relatively fire-resistant, thick-barked species
462 such as ponderosa pine and mature Douglas-fir. Conversely, mid- to high elevation areas
463 were dominated by higher density mixed conifer forests dominated by thin-barked species

464 such as lodgepole pine and subalpine fir that are more readily killed by even low intensity
465 fires (Agee 1999). Across forested areas of the western US, as elevation increases so do fire
466 return intervals and the proportion of high burn severity when fires occur (Schoennagel et al
467 2004).

468 The highest elevations in our study areas generally had low burn severities that were
469 comparable to the burn severity of low elevation sites (Figure 5). Subalpine and alpine areas
470 often have higher fuel moisture, lower temperature, higher relative humidity, and less
471 burnable vegetation at or above tree line (Schoennagel et al. 2004). Reduced burn severity at
472 the highest elevations was especially demonstrated in the Kootenay and Tripod study areas.
473 On the Kootenay fire, burn severity declined above approximately 2100 m elevation. On the
474 Tripod Complex, post-burn imagery indicated that subalpine meadows did not burn; the
475 subsequent fires burned around subalpine meadows or only consumed tree islands within
476 them.

477 **Conclusions**

478 Our study provides strong evidence that the landscape patterns created by past
479 wildfires influenced subsequent wildfire burn severity, creating a landscape legacy of burn
480 mosaics. While many factors influence burn severity, previous wildfires reduced burn
481 severity on all four subsequent large fires. Considering the extreme fire weather under which
482 these fires burned, it is important to note that the bottom-up factors of past fires, vegetation,
483 and topography influenced burn severity. Our research supports the consideration of
484 managing wildfires to burn into previously burned landscapes as these may continue to
485 reduce burn severity under most fire weather conditions and allow fire to return to fire-prone
486 landscapes (Hessburg et al. 2015).

487 Because we studied wildfires in non-wilderness areas, the study areas provide some
488 insights into the influence of past wildfires during operational management of on-going,

489 large wildfires. For example, during the 2003 Kootenay Fires, the 1968 Vermillion Fire was
490 effectively used in a burnout operation to halt the eastward spread of Kootenay Complex into
491 old-growth Engelmann spruce and subalpine fir forests of the Bow Valley and Banff
492 National Park (Rick Kubian, Parks Canada, personal communication). Fires in Idaho in
493 recent decades have been extensive, with over 46% of the Boise National Forest burned since
494 1984. In response, some incident management teams are making strategic decisions to take
495 advantage of where previous fires may limit the spread of subsequent fires (Bob Schindelar,
496 Boise National Forest, personal communication). Likewise, even during large fire spread
497 days, the 2006 Tripod Complex fire was corralled by several recent wildfires that occurred
498 from 1994-2003 and even the 1970 Forks fire which was composed of young, regenerating
499 lodgepole pine with sparse surface fuels (Gray and Prichard 2015). Following the 2006
500 Tripod fire, two subsequent wildfires, including the 2014 Carlton Complex and the 2015
501 Okanogan Complex, shared borders with the Tripod perimeter and these were the only parts
502 of the fire complexes that were not actively suppressed. Incident command communicated to
503 the public that there were insufficient fuels to carry active fire spread within the Tripod burn
504 area, and while the wildfires burned to the edge of the Tripod burn area, they did not advance
505 into the recently burned landscapes.

506 Previously burned areas are considered in both active fire management
507 (http://wfdss.usgs.gov/wfdss/WFDSS_Home.shtml last accessed 28 June 28, 2016) and in
508 achieving land management goals. Given the rising cost of fire suppression (Calkin et al.
509 2015), knowing when and where areas are expected to burn less severely can help to reduce
510 the costs of future large wildfire events while assisting land managers in making the fire
511 management decisions consistent with land management plans and restoration priorities
512 (Hessburg et al. 2015). Wildfires, even the large fire events studied here, possess some
513 attributes of self-regulation, and managing for the interaction of these events can contribute

514 to restoring the resilience of fire-prone landscapes. Allowing more wildfires to burn,
515 especially in dry forest types, may not only serve land management by potentially mitigating
516 future burn severity, but also promote more fire resilient landscapes that can withstand the
517 impacts of repeated disturbances that will become ever more present with climate change.
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519 **Acknowledgements**

520 We thank A. Arnold, T. Zalesky, and J. Romain for assistance with field data
521 collection and the Okanogan-Wenatchee, Payette, and Boise National Forests and National
522 Parks Canada personnel, including M. Pillers and S. Kovach, for local information and data
523 layers. We thank B. Salter, K. Konis, and R.Gray for assistance with data acquisition, and C.
524 Hoffman, P. Hessburg, J. Hicke and anonymous reviewers for their helpful reviews. Funding
525 was provided by Joint Fire Science Program (Project # 14-1-02-33 and the USDA Forest
526 Service Rocky Mountain Research Station under agreements RJVA # 14-JV-11261987-047
527 and 12-JV-11221637-136, Modification #1.

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TABLES

2 **Table 1.** Candidate predictor variables for sequential autoregression (SAR) modeling for the
3 four study areas (Tripod, Cascade, East Zone, and Kootenay*).

Variable	Definition
Wildfire data	
PastSev-Past burn severity	Categorical RdNBR (unburned/unchanged, low, moderate, high)
Edge-Distance to edge (m)	Distance from study fire perimeter
TSF-Time since previous fire	Number of years since each pixel burned
Fire weather	
MaxTemp-Maximum temperature (°C)	Maximum temperature over progression interval
AvgTemp-Average temperature (°C)	Average temperature over progression interval
MaxGust-Maximum wind speed (kph)	Maximum recorded wind over progression interval
AvgGust-Average wind speed (kph)	Average wind speed over progression interval
MinRH-Minimum RH (%)	Minimum relative humidity over progression interval
Vegetation	
CBD-Canopy bulk density (kg m ³)	Bulk density of available canopy fuel
CovType-Cover Type	Derived from existing vegetation type
CC-Canopy Cover (%)	Canopy cover of vegetation
Topography	
Elev-Elevation (m)	National elevation dataset
Slope (degrees)	Slope gradient
Solar radiation (WH m ⁻²)	Potential incoming solar radiation (no cloud cover)
TWI- Topographic wetness	Topographic Wetness Index
TPI-Topographic position index	Discrete classified TPI raster
Valley	Fuzzy valley bottom or 'valley-like' position
Ridgetop	Fuzzy ridgetop or 'ridge-like' position

4

5

* Due to the fairly uniform vegetation types and stand structures on the Kootenay we did not
6 include vegetation characteristics for this model.

7

Table 2. Final sequential autoregression full models of relative differenced Normalized Burn Ratio (RdNBR) for the Tripod, Cascade, East Zone, and differenced Normalized Burn Ratio (dNBR) for the Kootenay study areas. N is the number of points analyzed.

Model	Predictor variables	N	R ²	AIC
Tripod	CC, CovType, Edge, Elev, MaxTemp, PastSev, Slope, Valley	326,541	0.92	4,884,497
East Zone	CovType, Edge, Elev, MaxGust, MaxTemp, PastSev, TWI, Valley	905,805	0.73	12,705,742
Cascade	CC, CovType, Edge, MaxGust, MaxTemp, PastSev, Slope, TSF, Valley	975,414	0.77	13,736,440
Kootenay	AvgTemp, Edge, Elev, Slope, PastSev	88,272	0.90	1,080,976

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Table 3. Outputs for final SAR model for each variable. Past burn severity (PastSev) was categorized into unburned/unchanged (as the baseline), low, moderate, and high according to thresholds in Miller and Thode (2007). Cover type (CovType) was categorized into dry-mesic mixed conifer (DMC; as the baseline), douglas-fir/hemlock (DFHE), grassland/shrubland (GRASS/SHRUB), lodgepole pine dominated (LP), ponderosa pine dominated (PP), riparian areas (RIP), and subalpine fir dominate (SUBALP). Relationship to burn severity is distinguished by the “estimate,” with the standard error (SE) and p-value (P), indicated for each variable.

Variables	Tripod			East Zone			Cascade			Kootenay		
	Estimate	SE	<i>P</i>	Estimate	SE	<i>P</i>	Estimate	SE	<i>P</i>	Estimate	SE	<i>P</i>
Intercept	-428.00	29.40	<0.0001	-71.43	7.37	<0.0001	704.00	31.60	<0.0001	129.60	36.78	0.0004
Edge	0.13	0.01	<0.0001	0.03	0.01	<0.0001	0.04	0.01	<0.0001	0.18	0.008	<0.0001
Valley	-0.12	0.02	<0.0001	-0.52	0.02	<0.0001	-0.67	0.25	<0.0001	-	-	-
MaxTemp	1.57	0.09	<0.0001	3.42	0.13	<0.0001	7.30	0.20	<0.0001	-	-	-
AvgTemp	-	-	-	-	-	-	-	-	-	8.23	0.79	<0.0001
Past Sev – Low	-16.60	2.12	<0.0001	-16.85	1.29	<0.0001	-284.00	27.50	<0.0001	0.42	7.84	0.96
Past Sev – Moderate	-28.90	2.71	<0.0001	-17.00	1.76	<0.0001	-266.00	27.40	<0.0001	-19.68	8.83	0.03
Past Sev – High	-42.10	3.18	<0.0001	-25.50	2.40	<0.0001	-246.00	27.50	<0.0001	-54.16	13.58	<0.0001
Slope	1.38	0.13	<0.0001	-	-	-	-0.48	0.11	<0.0001	-0.18	0.04	0.03
TWI	-	-	-	-5.15	0.18	<0.0001	-	-	-	-	-	-
CovType DFHE	4.44	8.16	0.59	7.08	1.45	<0.0001	0.34	2.69	0.90	-	-	-
CovType GRASS/SHRUB	3.48	1.42	0.014	13.90	1.74	<0.0001	8.10	2.91	0.005	-	-	-
CovType LP	2.45	0.91	0.0070	7.72	1.86	<0.0001	8.84	2.84	0.002	-	-	-

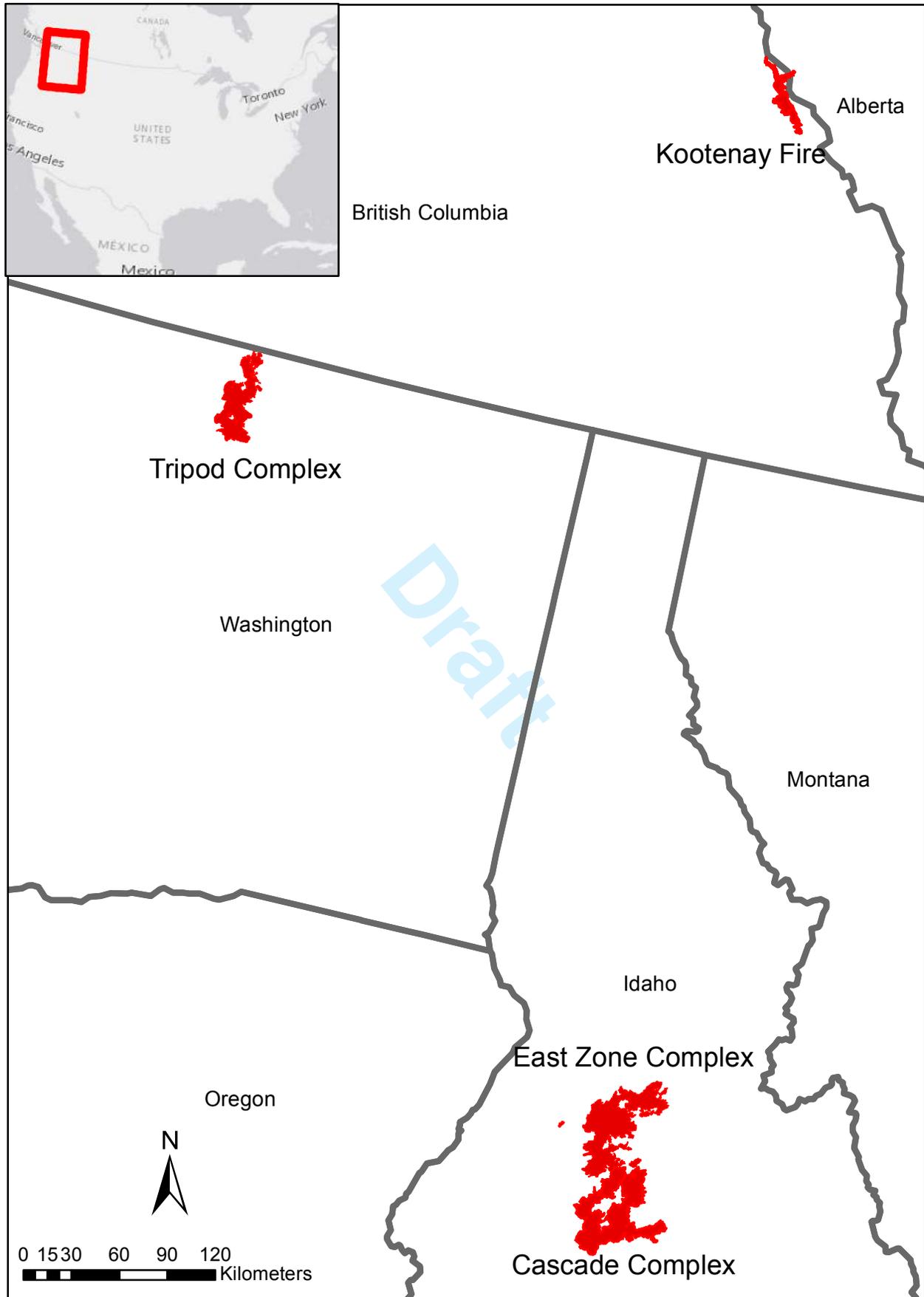
CovType PP	-6.01	2.81	0.033	3.09	2.08	0.13	-2.41	4.40	0.58	-	-	-
CovType RIP	-44.60	3.02	<0.0001	-1.58	2.85	0.58	-8.36	3.53	0.02	-	-	-
CovType SUBALP	2.93	0.89	0.0010	10.20	1.66	<0.0001	10.90	2.79	<0.0001	-	-	-
Elev	0.47	0.02	<0.0001	0.31	0.01	<0.0001	-	-	-	0.094	0.019	<0.0001
CC	0.70	0.03	<0.0001	-	-	-	6.44	0.027	<0.0001	-	-	-
MaxGust	-	-	-	1.26	0.23	<0.0001	-3.55	0.20	<0.0001	-	-	-
TSF	-	-	-	-	-	-	-3.30	0.31	<0.0001	-	-	-

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Table 4. Results of cover type SAR analysis, performed on points identified as a “low elevation forest type” (Douglas-fir/hemlock, ponderosa pine, dry-mesic mixed-conifer) and a “high elevation forest type” (lodgepole pine, subalpine fir). Values are the regression estimate of time since fire and past burn severity (low moderate, high) in comparison to previously unburned/unchanged points. Asterisks indicate significance at $\alpha=0.05$ level.

Area	Elevation (Forest type)	time since fire	Past severity-low	Past severity-moderate	Past severity-high
Cascade	High	0.09*	-15.88*	-1.71	22.01*
	low	0.23*	-29.20*	-14.91*	17.08*
East Zone	high	0.63*	-49.92*	-64.01*	-71.58*
	low	0.41*	-36.30*	-37.07*	-29.61*
Tripod	high	1.30*	-100.08*	-188.58*	-281.46*
	low	5.28*	-378.03*	-465.61*	-520.36*



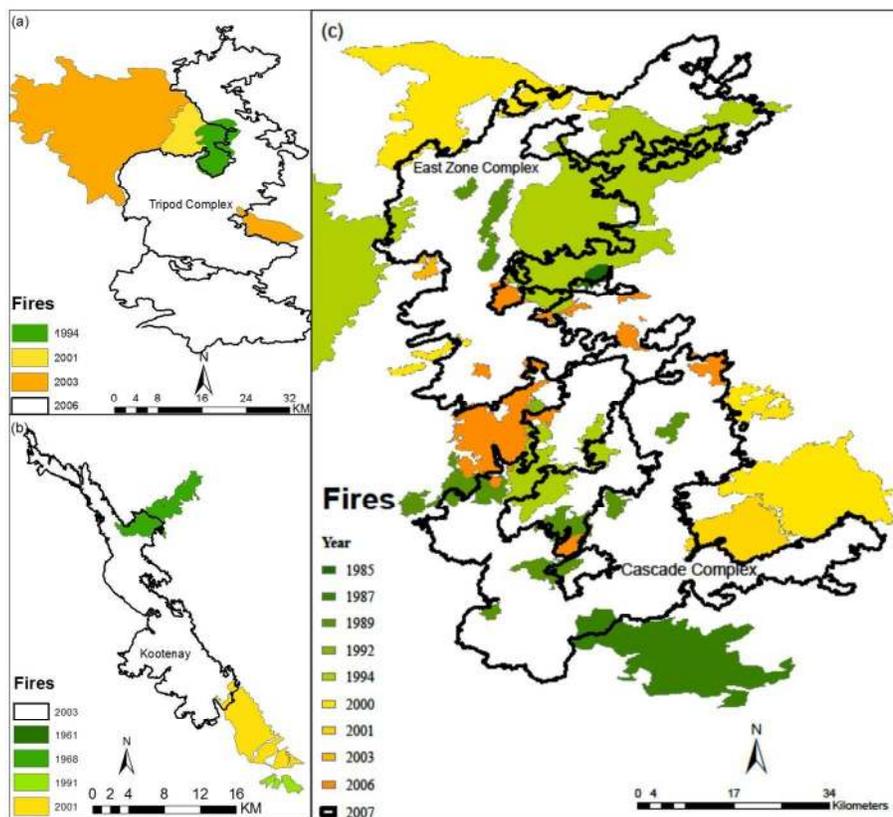


Figure 2. (a) Tripod Complex, (b) Kootenay Fire, (c) East Zone Complex and Cascade Complex with perimeters of previous wildfire. Older past fires are indicated with greens, while more recent fires are indicated in orange and yellows.

287x274mm (150 x 150 DPI)

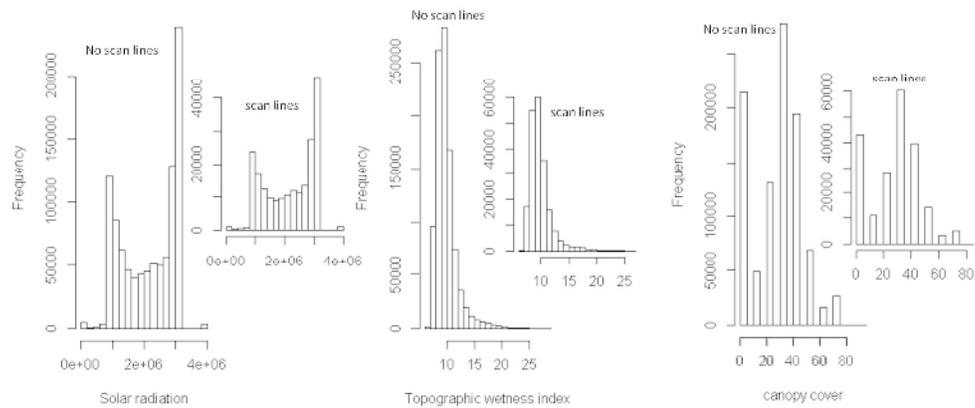


Figure 4.

Figure 3. Distribution of topographic (solar radiation and topographic wetness index) and vegetation (canopy cover) variables using our East Zone dataset which excluded the scan lines compared to a dataset of the pixels within the scan lines which we were unable to use due to lack of burn severity information. Distributions are very similar for both, reducing the possibility of bias with the missing data.

304x139mm (150 x 150 DPI)

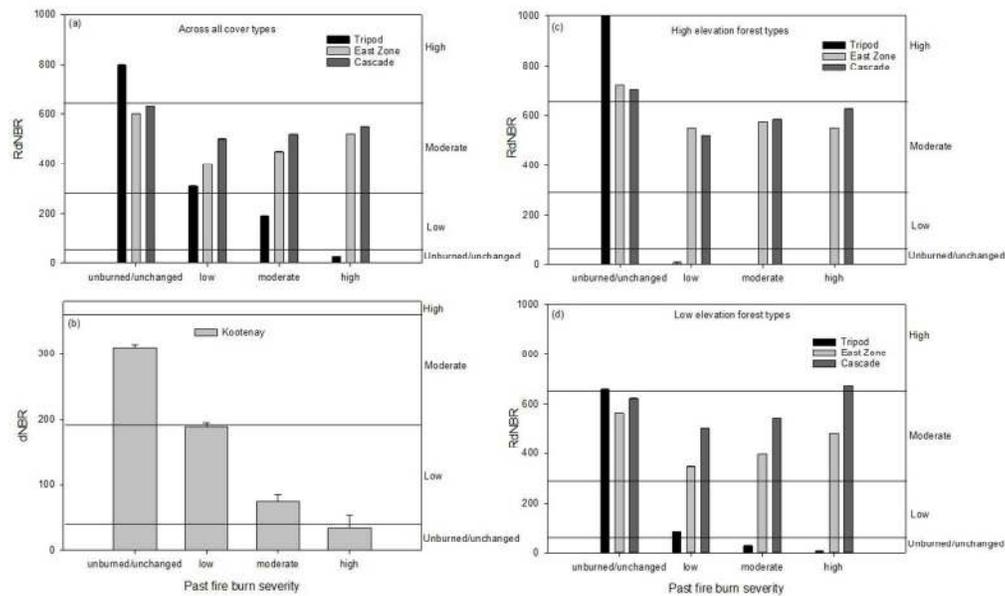


Figure 4.

Figure 4. RdNBR or dNBR response by past fire burn severity on each fire. The left axis is a continuous RdNBR/dNBR metric, while the right axis identifies the burn severity thresholds we used based on Miller and Thode (2007) of unchanged/unburned, low, moderate, and high severity. (a) is the RdNBR response to burn severity on the Tripod (black), East Zone (light gray), and Cascade (dark gray) Fires across all cover types. (b) is the dNBR response to past burn severity on the Kootenay Fire. (c) is the RdNBR response to past burn severity in "high elevation" forest types. (d) is the RdNBR response to past burn severity in "low elevation" forest types.

225x150mm (150 x 150 DPI)

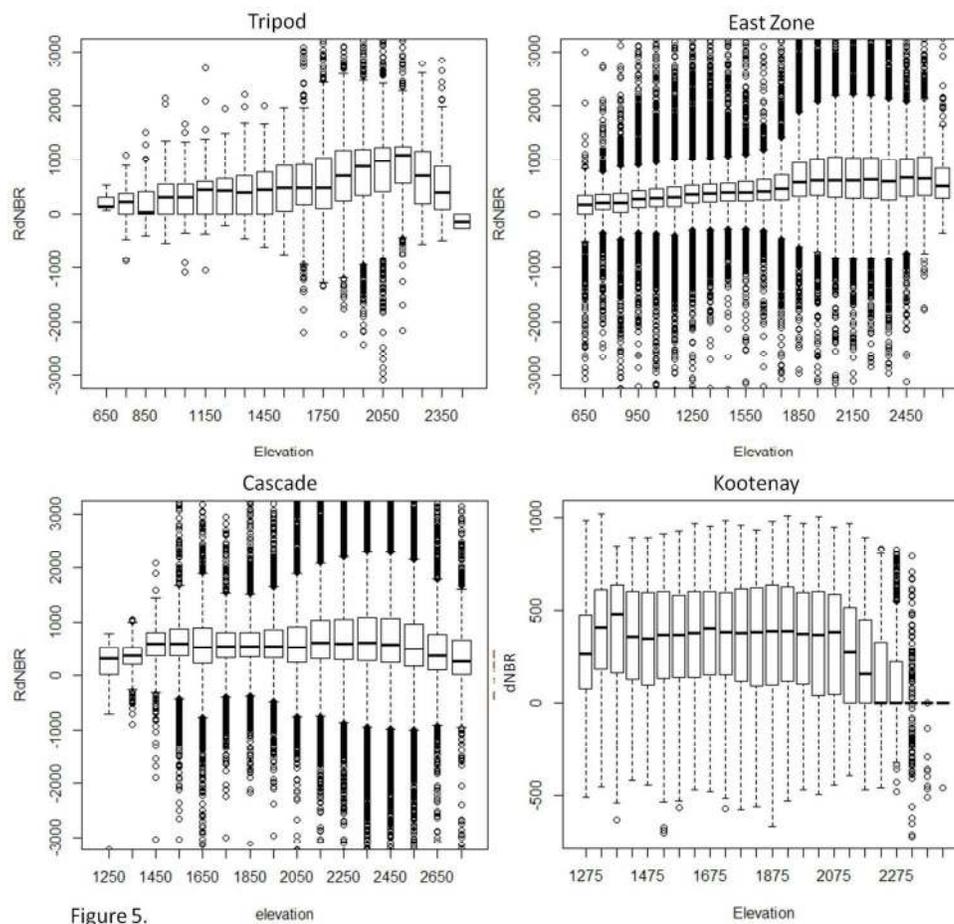


Figure 5.

Figure 5. Box and whisker plots of RdNBR and dNBR response by elevation. Tripod is in the top left, East Zone in the top right, Cascade on the bottom left, and Kootenay in the bottom right.

282x277mm (150 x 150 DPI)

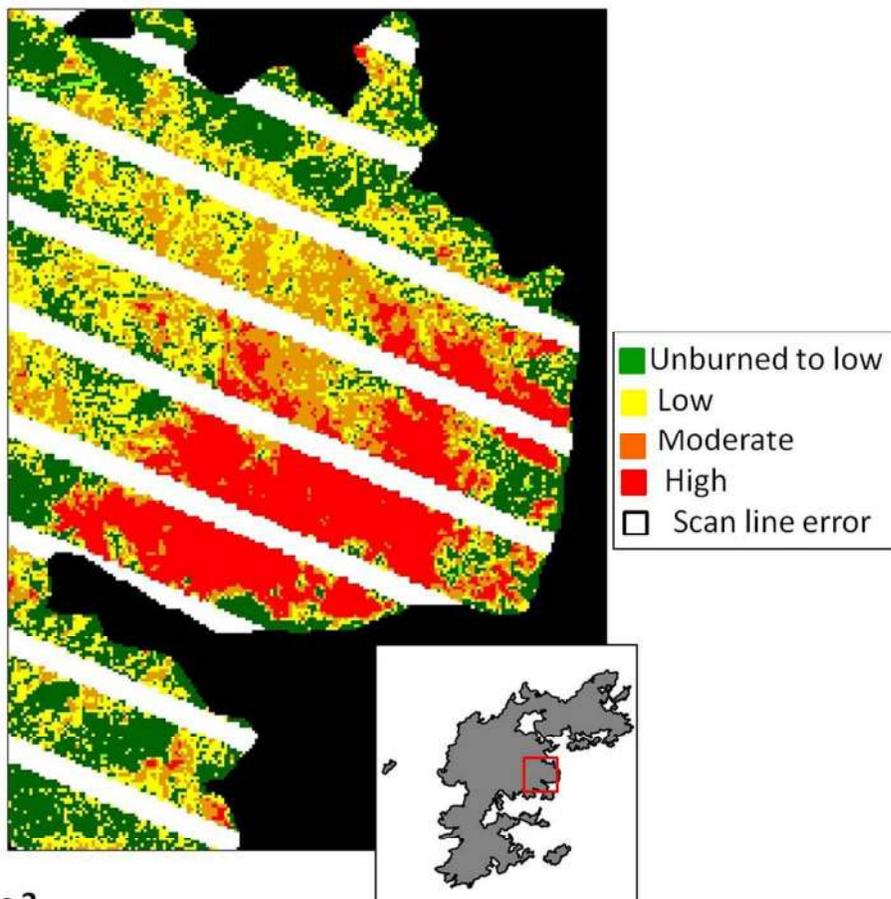


Figure 3.

Supplemental Figure 1: Example of scan line errors in the Landsat satellite data on the East Zone Complex Fire. White lines indicate missing data; lines are 150 m wide.

187x190mm (150 x 150 DPI)