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Prior wildfires influence burn severity of subsequent large fires

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Manuscripts

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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Introduction

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

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

518

519   **Acknowledgements**

528

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665

1 **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

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	P	Estimate	SE	P	Estimate	SE	P	Estimate	SE	P
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	-	-	-

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*
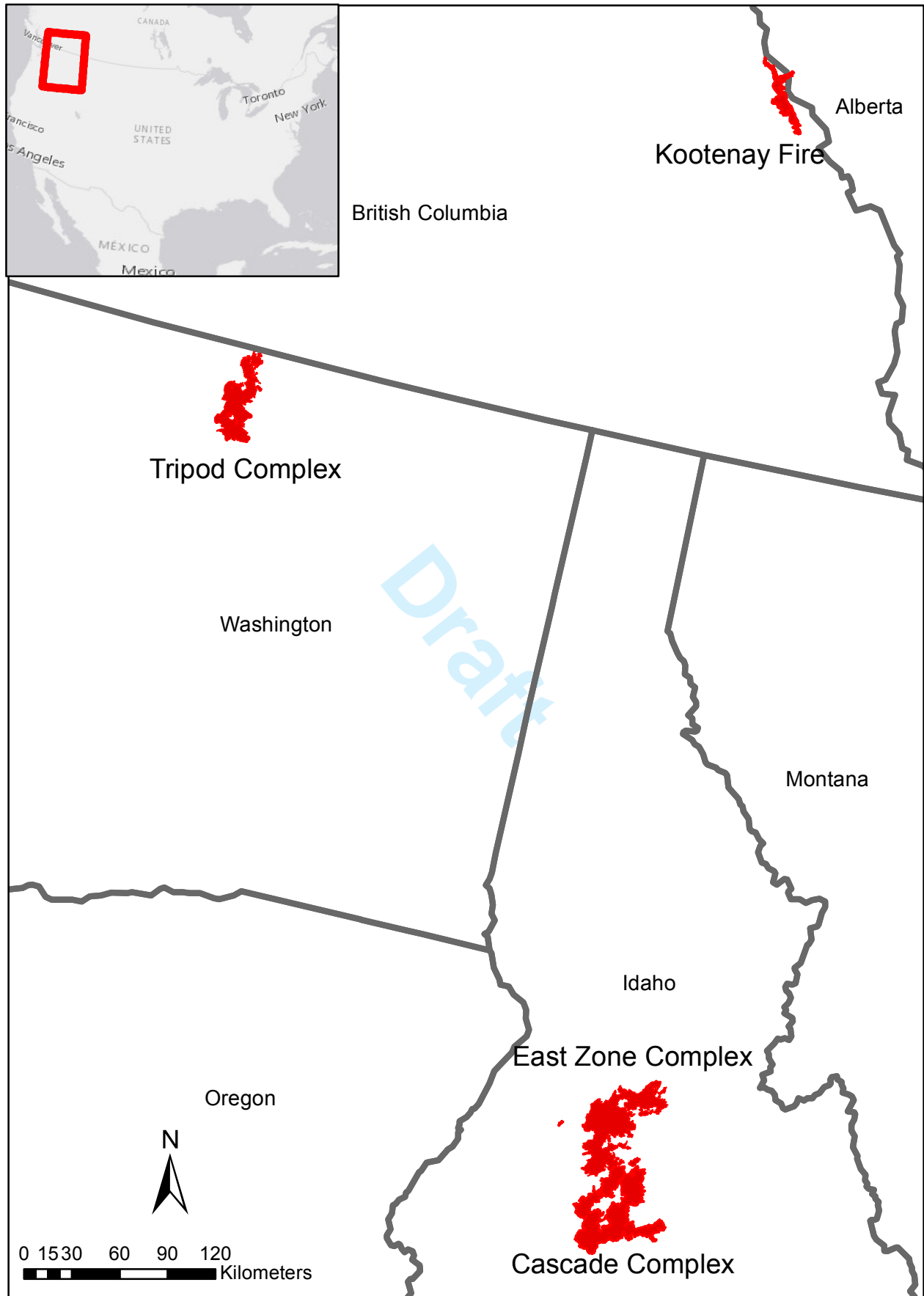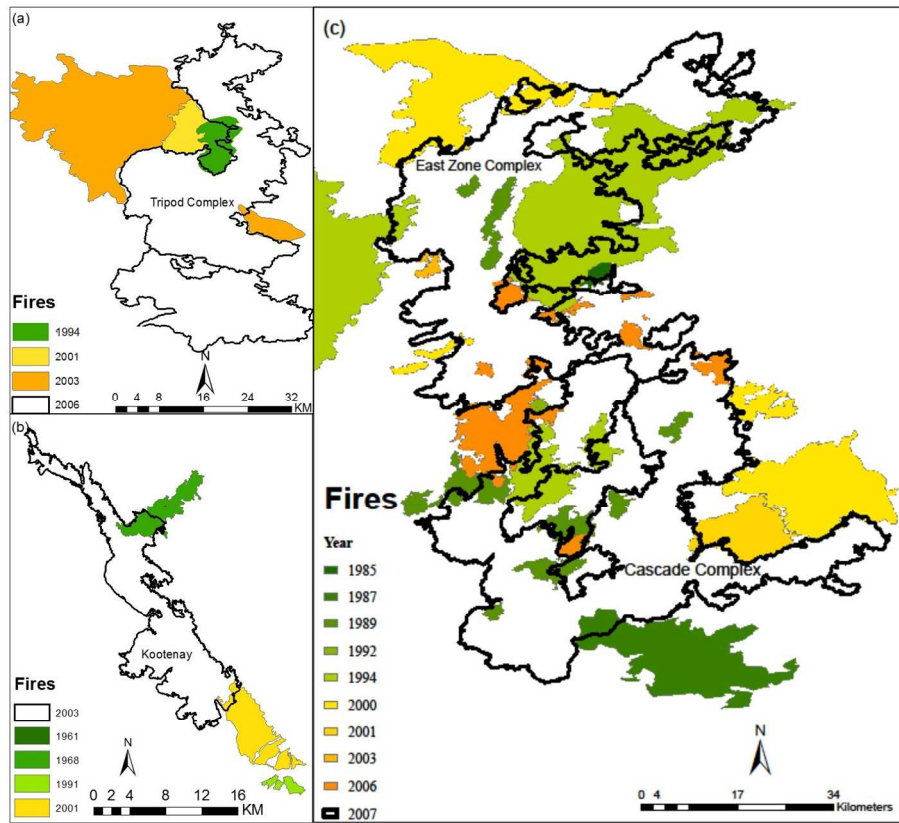
Figure 2. (a) Tripod Complex, (b) Kootenay Fire, (c) East Zone Complex and Cascade Complex with perimeters of previous wildfire. Older past fires are indicated with greens, while more recent fires are indicated in orange and yellows.
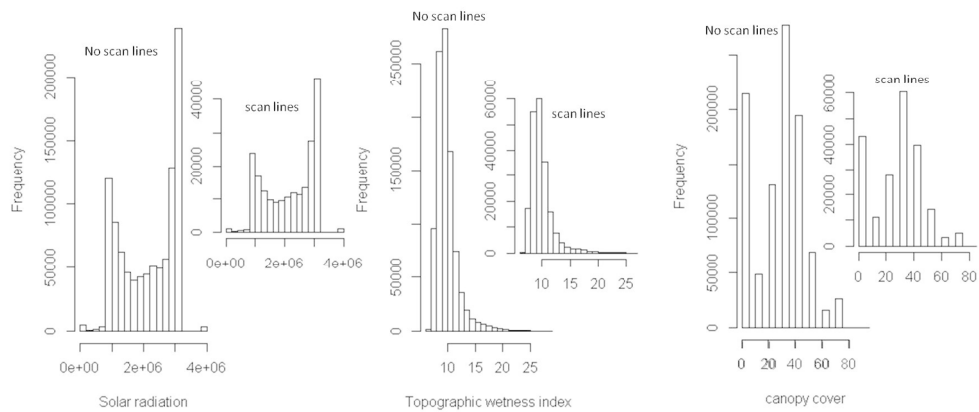
287x274mm (150 x 150 DPI)

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.
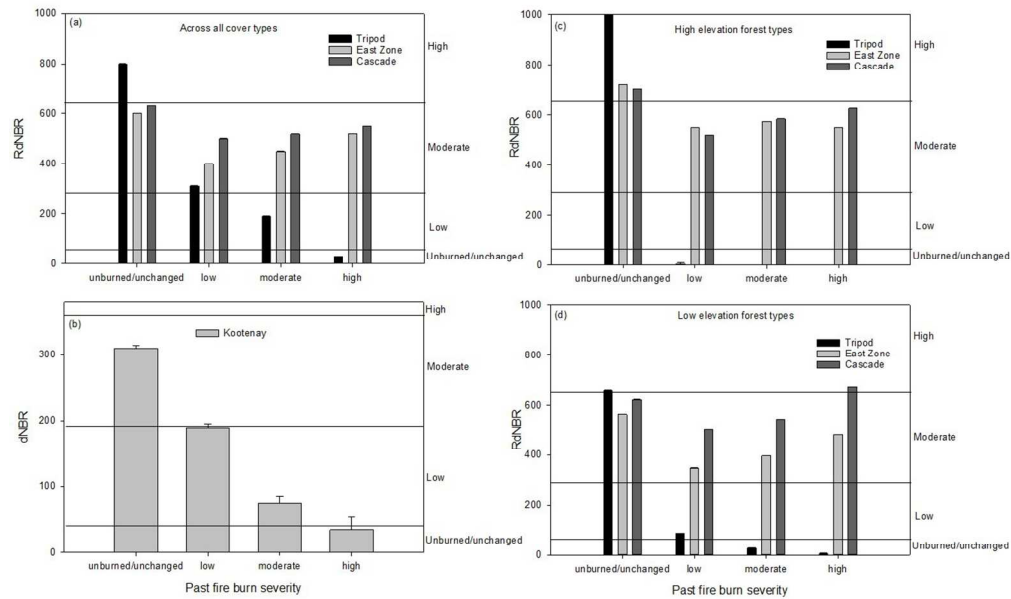
304x139mm (150 x 150 DPI)

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.
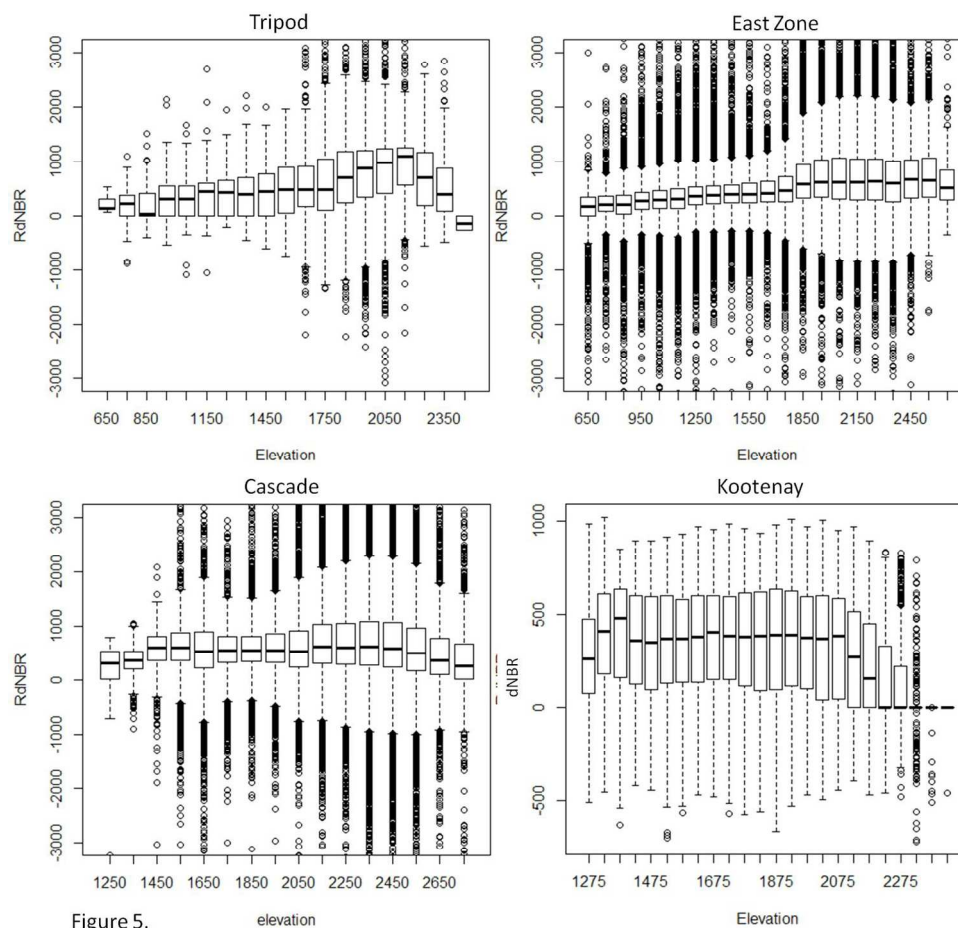
225x150mm (150 x 150 DPI)

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.
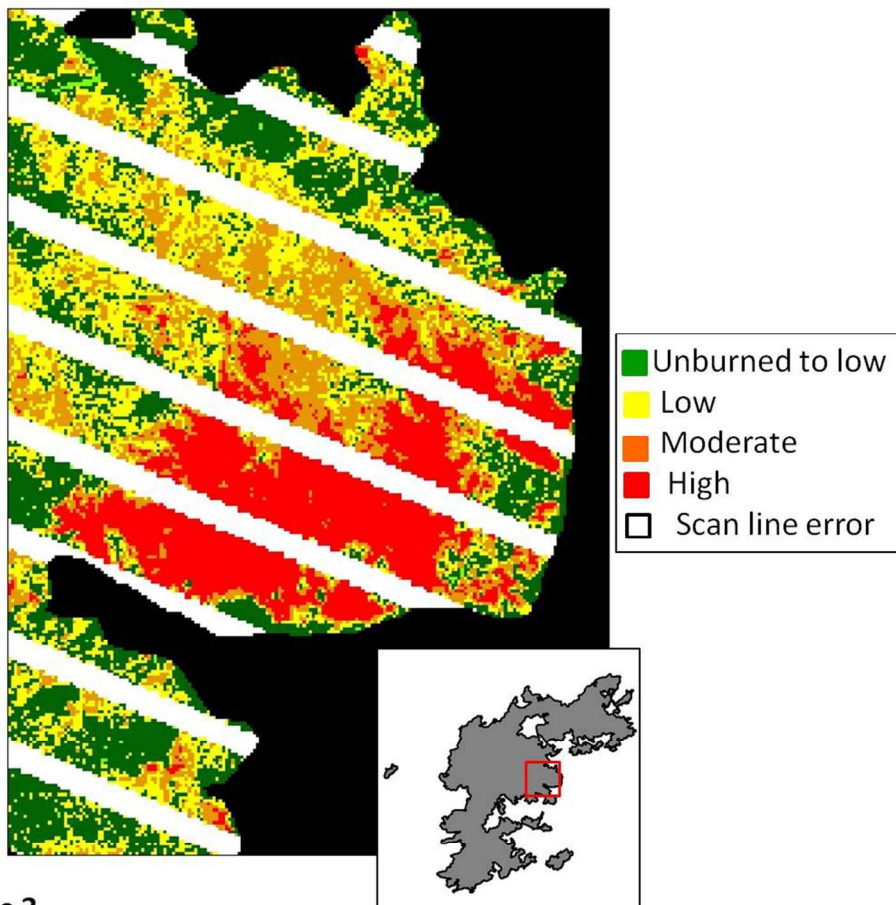
282x277mm (150 x 150 DPI)

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)