

ESCAPE PROBABILITY: AN ALTERNATIVE RISK METRIC TO SUPPORT AND
EVALUATE WILDERNESS FIRE MANAGEMENT DECISIONS

By

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Escape probability: an alternative risk metric to support and evaluate wilderness fire management decisions

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Inside many U.S. federally designated wilderness areas, fire suppression is the dominant management strategy largely due to the risk that fires pose to resources adjacent to the wilderness boundary. Opportunities to exploit the fuel treatment and risk-mitigation benefits of allowing wilderness fires to burn are foregone when ignitions are suppressed. Existing risk-based metrics (e.g. burn probability) produced from wildfire simulation models were not designed to inform management of wilderness fires. They focus on the management of fuels, or on suppression resource allocation, not managing ignitions through monitoring strategies for resource benefits. The purpose of this research was to develop a risk-based decision support metric to support wilderness fire management. The metric, escape probability, was developed using the Bob Marshall Wilderness Complex, Montana, USA, (BMWC) as the case study landscape, and applied to evaluate previous management decisions to suppress ignitions within the BMWC. The outputs from two wildfire simulation models, FARSITE (Finney, 1998) and FSim (Finney et al., 2011), were used to map escape probability for two different landscape scenarios in 2007: (1) an 'observed' landscape reflecting fuel conditions as a result of actual wildfire management strategies; and (2) a 'treated' landscape that reflects hypothetical fuels and vegetation assuming suppressed ignitions in 2007 had been allowed to burn. First, wildfire spread and behavior for suppressed ignitions in 2007 were retrospectively simulated using FARSITE. Hypothetical fuels layers were created for each retrospectively simulated fire by modifying the observed pre-fire fuels conditions within the simulated perimeter based on modeled burn severity. The observed and hypothetical fuels layers were then used as inputs in FSim, a large wildfire modeling system commonly used in quantitative wildfire risk analyses. Differences in the likelihood of future wilderness fire escape between the observed and treated landscape scenarios were examined for both inside the simulated area burned by the suppressed ignitions (i.e. the treated area) and the area within several kilometers of the simulated wildfire perimeters (i.e. the off-site effects). Results suggest that larger treated areas arising from ignitions closer to the wilderness boundary had the greatest effect on reducing the likelihood of wilderness fire escape within the treated area. The relationship between ignition location, fire size, and reduction in escape probability outside the treated area was variable. Fire and fuels managers can use escape probability information during strategic decision-making and pre-season planning to allow natural fires to burn absent of suppression, as well as to evaluate the effectiveness of different risk-mitigation strategies based on how the strategies affect future opportunities to allow natural ignitions to burn.

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1. Preface

The research performed in this thesis was part of a larger, collaborative project between The University of Montana and the Aldo Leopold Wilderness Research Institute of the United States Department of Agriculture's Rocky Mountain Research Station. The goal of the project was to retrospectively evaluate alternative wilderness wildfire management strategies based on a wide array of outcomes, including changes in wildfire management costs, potential fire behavior, and landscape fire risk. Three wilderness areas in the western United States were identified as case study landscapes: the Gila-Aldo Leopold Wilderness Complex in New Mexico, the Selway-Bitterroot Wilderness Area in Idaho and Montana, and the Bob Marshall Wilderness Complex in northwestern Montana. Retrospective fire spread and behavior analyses were conducted in all three study areas for all suppressed ignitions during 2007 and 2008. This thesis contains additional, original research performed in the Bob Marshall Wilderness Complex for the 2007 wildfire season, which focused on evaluating management decisions to suppress or not suppress wilderness ignitions based on changes in the future likelihood that unsuppressed wilderness ignitions will escape the wilderness boundary. The methodology contained in this thesis is transferable to the remaining case study areas and the 2008 season, however this thesis only pertains to the Bob Marshall Wilderness Complex and the 2007 wildfire season.

1. Introduction

Efficient forest management in the western United States continues to be hindered by the inability to effectively manage and restore wildfire in fire-prone landscapes. When natural ignitions are successfully suppressed, not only are there negative ecological consequences (e.g., Keane et al., 2002), but opportunities to create fuel breaks that might assist future incident management are foregone (Salazar and Gonzalez-Caban, 1987; Miller and Davis, 2009). This issue is of particular concern in wilderness because continued fire suppression runs counter to the intent of preserving wilderness' natural characteristics and minimizing human intervention on wilderness character. However, exploiting wilderness wildfire as a management tool to reduce future wildfire risk and restore natural fire regimes has been challenging to implement (Parsons and Landres, 1998).

Suppression is the dominant management strategy in most wilderness areas, primarily because of resources outside the wilderness that are at risk if a fire escapes the wilderness boundary. Even if managers have a fire management plan that theoretically gives them the flexibility to allow natural fire spread to occur, this flexibility is constrained by potential consequences of fire crossing into areas where fire is not tolerated (Doane et al., 2006). The potential for damaging outcomes from an escaped wilderness fire is exacerbated by the interacting effects of historic fire exclusion that has increased fuels and fire hazard, increased housing development in close proximity to wilderness areas (Radeloff et al. 2010), and shifting climate patterns that have lengthened and intensified fire seasons (Westerling et al., 2006). Collectively, these factors have contributed to a feedback loop where fuels accumulate, fire risk increases, and

suppression strategies are favored (Arno and Brown, 1991). Furthermore, socio-political pressure to reduce wildfire suppression expenditures has encouraged the use of prompt suppression strategies, because initial attack – if successful – can be an inexpensive, short term solution (Gebert and Black, 2012).

Decision-making in wildfire and fuels management has embraced a quantitative risk-assessment framework, predicated on the principles of actuarial sciences (Fire Executive Council, 2009), whereby wildfire risk is formulated by integrating the likelihood, intensity, and positive and negative effects of wildfire on market and non-market resources, and is calculated in terms of ‘net value change’ (Finney, 2005). Recent advancement in the science and technology of wildfire risk assessment has enabled fire and fuels managers to make risk-informed decisions through the use of geospatial decision support tools (Ager et al., 2011; Calkin et al., 2011b; Finney et al., 2011b; Noonan-Wright et al., 2011). These tools are intended to support suppression resource allocation, prioritize and evaluate the effectiveness of fuels treatments at reducing wildfire risk, monitor trends in wildfire risk through space and time, and document transparent decision-making during incident management (Thompson et al., 2011; Scott et al., 2013; Ager et al., 2013).

Applications of wildfire risk analysis currently frame the fuels and fire management problem in terms of minimizing or mitigating risk, and define goals and success in terms of reducing risk or avoiding loss to valued resources (Calkin et al., 2010; Chung et al., in press). For example, from a risk perspective, the goal for fuels management is to alter the abundance and continuity of surface and canopy fuels in order to reduce the future likelihood and intensity of wildfires (Finney et al., 2007; Ager et al.,

2010), and also to aid in suppression effectiveness (Calkin et al., 2014) . The goal for fire management is to employ strategies that minimize the exposure of valued resources (e.g. private structures, recreation sites, public and private infrastructure, and municipal watersheds) from the adverse effects of wildfire, while also reducing wildland firefighter exposure during suppression efforts. These objectives implicitly create a disconnect between the management of fuels and the management of ignitions, when in fact decisions made in each of these management environments transmits risk to the other, thus changing the context for management decisions in the other environment. From a fuels management standpoint, Reinhardt et al., 2008, p 198, succinctly point out that “fuel treatments should strive to create conditions where fire can occur without the need for suppression”. The need to integrate the management of fuels with the management of ignitions in wildfire risk analysis is a pressing issue given the goals of reducing wildfire suppression costs and restoring wildland fire while simultaneously reducing hazardous fuels at the landscape scale (Miller and Ager, 2012).

Compared to conventional fuels management (i.e. mechanical thinning and management-ignited prescribed fire), wildland fire may not only have the greatest effect on reducing the size and intensity of future wildfires, but is arguably the most appropriate fuels management tool in wilderness and other remote landscapes (Miller, 2003). Findings from recent simulation and observational studies in large wilderness areas have supported the theory that landscapes with relatively intact fire regimes can become self-regulating over time, in that both the size and severity of future fires may be moderated by previous fires (Teske et al., 2012; Haire et al., 2013; Parks et al., in press). Collectively, these findings suggest that wildfires may serve as an effective ‘fuel

treatment' to manage wildfire risk. However, allowing wildfires to burn requires managers and the public to assume some level of exposure to the potential consequences of wildfire. Wildfire risk analysis tools will need to be applied differently than they have in the past in order to support and inform decisions that maximize the opportunities to treat fuels using natural fire.

The purpose of this paper is to quantify the benefits of allowing wilderness fires to burn in terms of changes in future manager decision-space using the quantitative wildfire risk assessment framework. While the benefits of wilderness fires have been quantified using metrics such as changes in future fire likelihood, size, and severity, ultimately it is the flexibility to choose to not aggressively suppress future ignitions that can lead to the restoration of fire as a natural disturbance process and decreased future wildfire risk. This paper addresses the lack of spatially-explicit, risk-based tools available to wilderness fire managers to inform and support decisions to allow natural ignitions to burn by: (a) demonstrating an alternative application of existing wildfire risk analysis tools to support wilderness fire management decisions with a new metric, escape probability; and (b) providing preliminary quantitative evidence about how a fire's attributes (i.e. area burned and proximity to the wilderness boundary) contribute to its effectiveness as a risk-mitigation tool. Such information could inform pre-season planning by identifying areas on the landscape where the threat of wildfire escaping the wilderness is relatively low or high, and by monitoring spatial trends in the likelihood of wilderness fire escape over time.

A description of the study area for this case study is presented in Section 2, followed by a description of the case study methods in Section 3. Sections 4 and 5

present results and the discussion, respectively, and the paper concludes in Section 6 by offering suggestions for future research.

2. Study area

The Bob Marshall Wilderness Complex (BMWC) is located in western Montana, and comprises the Bob Marshall, Great Bear, and Scapegoat Wilderness Areas, which together encompass over 625,000 hectares, as shown in Figure 1. The BMWC is nested inside the larger ‘Crown of the Continent’ ecosystem, a relatively unaltered mountain landscape that serves as the regional headwaters. Elevation ranges from 900 meters along river valley bottoms to 2,800 meters atop mountain peaks. The terrain was extensively shaped during previous glacial periods, evidenced by the extensive topographic relief and deep river valleys. The Continental Divide bisects the BMWC into distinct west-east climatic zones. The western half is characterized as modified maritime, while the eastern half experiences strong continental winds and greater interannual temperature variability (Selkowitz et al., 2002; Keane et al., 1994). Forest composition transitions from mixed-conifer stands to subalpine fir and whitebark pine along an elevational gradient. Relict ponderosa pine/bunchgrass prairie plant communities can be found along gravelly river terraces (Keane et al., 2006). Alpine meadows and rocky outcroppings are commonly found above treeline at higher elevations (Teske et al., 2012).

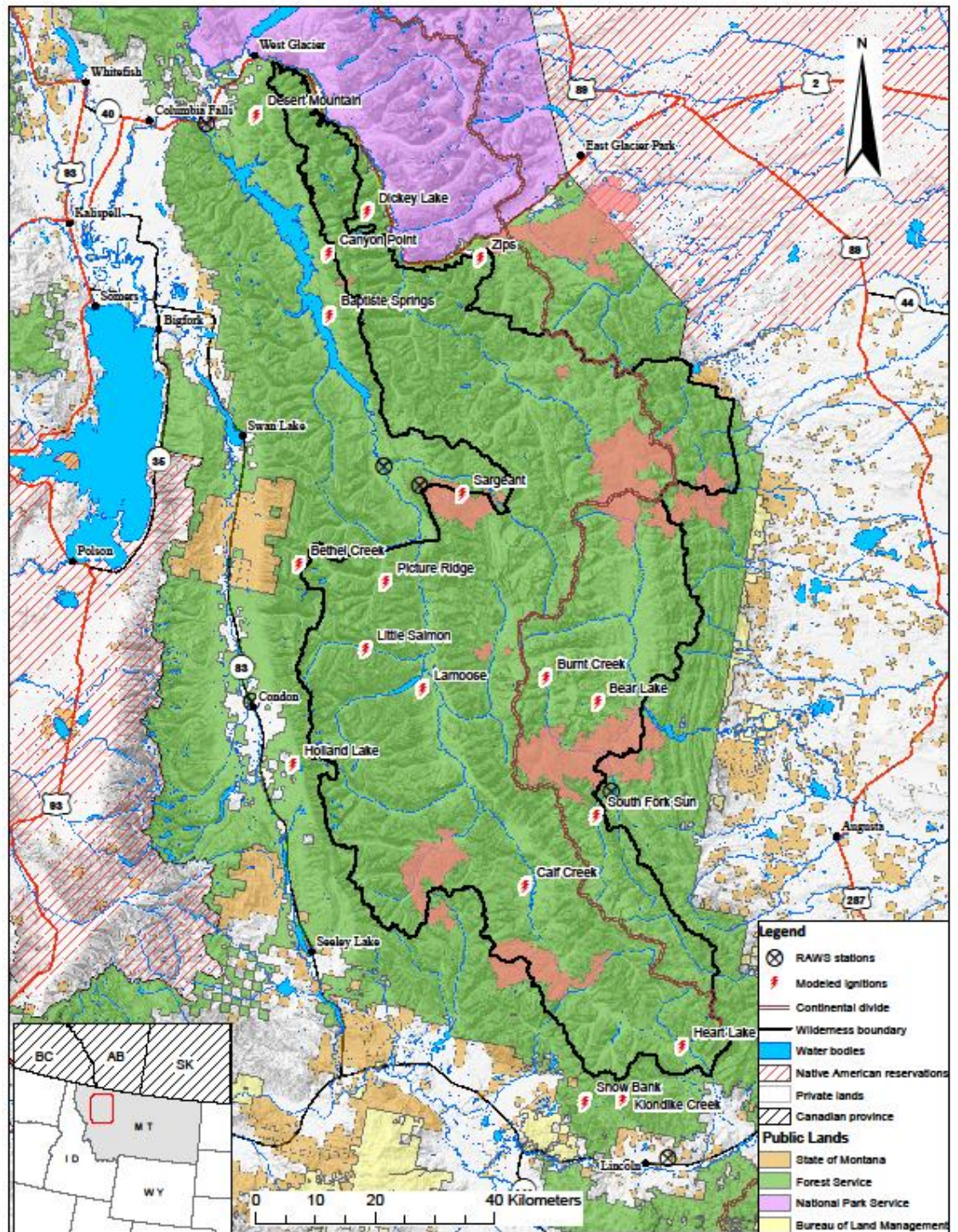


Figure 1. Study area with different land ownership designations, perimeters of large wildfires that occurred in 2007 (red polygons), and the suppressed ignition locations used in the case study analysis.

The size and intensity of historic wildfires in the BMWC were highly variable prior to the onset of 20th century fire suppression policies. Similar to other mid-elevation forested areas in the region, fire regimes varied from high-frequency/low-severity in dry, lower elevation sites to low-frequency/high-severity in higher elevation sites (Arno, 1980). However, the majority of historic fires in the BMWC were characterized as mixed-severity, defined as fires that exhibit highly variable effects (i.e. mortality, biomass consumption) in both space and time depending on vegetation, topography, and burning conditions (Arno et al., 2000). Contemporary fire regimes in the northern Rockies appear to be less departed from historical fire regimes compared to other forested ecosystems because of two reasons: 1) the relatively short time frame since the advent of fire suppression policies has had little effect in forested ecosystems with long fire return intervals; and 2) suppression tactics have had little effect on the size and severity of large fires, further limiting the consequences of fire suppression in the northern Rockies on contemporary fire regimes (Keane et al., 2008).

The fire management plan for the BMWC permits wildfires to burn in nearly all of the three wilderness areas, with the exception of two small exclusion zones along the eastern boundary (USDA, 2007). According to the National Wildfire Coordinating Group, between 1985 and 2011 approximately 25% of the fires in the greater BMWC were not suppressed and allowed to burn for resource benefits, which altogether burned over 325,000 hectares (<https://famtest.nwcg.gov/fam-web>). Anecdotal information suggests that natural ignitions are suppressed for myriad reasons, including health effects related to smoke management, potential loss of outfitter camps within the wilderness,

sedimentation of agricultural reservoirs, and threats to private inholdings located near the edge of the wilderness boundary.

3. Case study methods

The year chosen for this case study, 2007, was a very active fire season in the BMWC with several large fires, and a year in which the USDA Forest Service and other federal agencies were aggressively implementing the strategy of appropriate management response (AMR) to wildland fires in the northern Rockies. The AMR strategy encouraged consideration of the full spectrum of wildfire management strategies, whether the objective was protecting valued resources or managing fire for its benefits (Lessons Learned Center, 2007). During the 2007 fire season, 25 ignitions were successfully suppressed during initial attack, while 56,901 hectares burned in the BMWC. This case study explored the potential effects that 18¹ of these suppressed ignitions might have had on mitigating future fire risk (in terms of reducing the likelihood that future fires escape the wilderness) if they had been allowed to burn (Figure 1).

There is no firmly established approach to retrospectively evaluate the future wildfire management benefits that may have been derived had ignitions that were historically suppressed been allowed to burn (Davis et al., 2010). Figure 2 displays the parallel procedure that was adopted in this study to create comparative landscape scenarios for the post-2007 wildfire season. First, the observed scenario represented the actual fuels and vegetation at the end of the 2007 season. Second, a set of alternative landscape scenarios were simulated to represent the effects on fuels and vegetation that would have resulted if the suppressed ignitions from 2007 had been allowed to burn. These effects on fuels can be thought of as treatments, and the 18 fires that would have created them are referred to as “treatment fires” throughout the paper. One treatment

¹ The remaining seven suppressed ignitions were excluded from the analysis to avoid interacting effects between fires whose simulated perimeters substantially overlapped due to ignition locations in close proximity to one another.

scenario represented the collective effects of all 18 treatment fires (i.e. cumulative-treatment scenario); alternative scenarios were also created to represent the effects of each individual treatment fire (i.e. individual treatment scenarios). Analyzing each simulated fire individually was necessary to ensure that differences in the likelihood of wilderness fire escape between the observed and treatment scenarios were not confounded by the effects of nearby fires. Observed and alternative scenarios were used as inputs to conduct an exposure analysis and compute and compare the probability of escape.

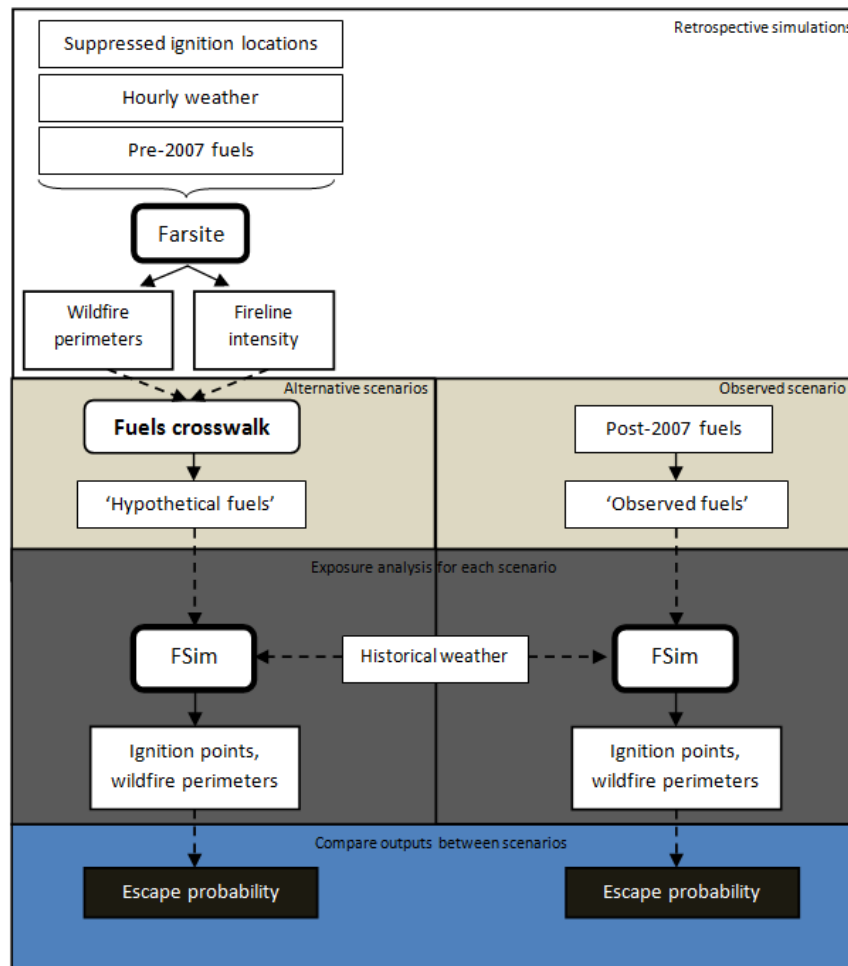


Figure 2. Parallel procedures used to develop observed and alternative landscape scenarios for input to the exposure analysis to compare escape probabilities. Solid black arrows represent the flow of outputs from a process, while the dashed arrows represent the flow of inputs into a process.

3.1. Observed landscape scenario

For the observed landscape scenario, the fuel conditions at the end of the 2007 season were described using LANDFIRE 2008 data (hereafter “LF-2008”), a consistent, comprehensive, and seamless data source at 30 meter spatial resolution (Rollins, 2009). LF-2008 is an updated version of LANDFIRE National (hereafter “LF-national”), which is the original LANDFIRE release. LF-2008 accounts for changes in fuel conditions due to wildfires that occurred between 1999 and 2008.

LF-2008 reflected conditions resulting from large disturbances that may have occurred through the end of the 2008 season, but since there were no large disturbances in 2008 in the study area, these data adequately represented conditions at the end of the 2007 season. The following LF-2008 spatial datasets representing surface and canopy fuel conditions were used as the ‘observed fuels’ in the observed landscape scenario, and subsequently used the exposure analysis (Figure 2): fire behavior fuel model (FBFM) (Scott and Burgan, 2005), canopy cover (CC), canopy bulk density (CBD), canopy height (CH), and crown base height (CBH) .

3.2. Treatment scenarios

Three major steps were required for creating the treatment scenarios: 1) modifying the LF-2008 data to reflect fuels and vegetation that would have existed prior to the 2007 season; 2) retrospectively simulating wildfire spread and behavior for the 18 treatment fires during 2007; and 3) altering fuels and vegetation to reflect the effects of those 18 fires.

LF-2008 reflected fuel conditions at the end of the 2007 wildfire season; a season that included several large wildfires in the BMWC. Because fuels layers that were representative of the conditions immediately before the 2007 fire season were needed for the retrospective simulations, LF-2008 was modified by “backfilling” areas that burned in 2007 with LF-national. LF-2008 data were used for all areas except those that burned in 2007. Raw LF-national data could not be used to backfill the burned areas because several inaccuracies were found with the dataset and revised in subsequent updates. The research community revealed that stand height values were underestimated, and canopy cover values were overestimated (Nelson et al., 2013).

To determine the relationship between LF-national and LF-2008, we took a random sample of 33,000 pixels that were not recently burned according to the LF-2008 disturbance layer. For continuous variables (i.e. canopy bulk density, canopy base height), a simple linear regression was fit with LF-2008 values as the response variable and LF-national as the sole predictor. The coefficient for LF-national was then used as a multiplier in order to update LF-national for pixels inside the fire perimeters of actual fires from 2007. For categorical variables (i.e. canopy cover, canopy height, fuel model), LF-national was updated based on the sample mode from LF-2008.

To retrospectively simulate where the 18 treatment fires would have burned, the newly created pre-2007 fuels layers were used as input to the fire growth modeling system FARSITE. FARSITE incorporates standard fire behavior models of surface fire spread (Rothermel, 1972; Albini, 1976), crown fire spread (Rothermel, 1991; Van Wagner, 1977; Van Wagner, 1993), fuel moisture dynamics (Nelson, 2001), spotting (Albini, 1979) and fire acceleration (Forestry Canada Fire Danger Group, 1992) to

simulate two-dimensional wildfire spread through complex terrain (Finney, 1998). The coordinates for the 18 suppressed ignitions and the weather data from 2007 were obtained from the National Fire and Aviation Management Web Applications (FAMWEB) data warehouse (<https://famtest.nwcg.gov/fam-web>). Hourly weather streams were created using data from nearby Remote Automated Weather Stations (RAWS) obtained through FAMWEB. Table 1 shows which weather station was paired with each ignition. Active burning periods were restricted to hours when observed relative humidity was less than 30% in an effort to only simulate fire growth during weather conditions conducive for fire spread. Simulations occurred in one-hour time steps, which effectively assumes that factors controlling fire spread are held constant during the time step. Season-ending events were defined as greater than 19 mm of precipitation over a three day period after September 22.

Table 1. RAWS used in retrospective simulations for each suppressed ignition.

=====	
Fire Name	RAWS

Dickey Lake	Hungry Horse RS
Desert Mountain	Hungry Horse RS
Sargeant	Spotted Bear RS
Holland Lake	Condon
Picture Ridge	Spotted Bear RS
Canyon Point	Hungry Horse RS
Lamoose	Spotted Bear RS
Zips	Hungry Horse RS
Bear Lake	Benchmark
Calf Creek	Spotted Bear RS
Burnt Creek	Benchmark
Little Salmon	Spotted Bear RS
Southfork Sun	Benchmark
Snow Bank	Lincoln
Klondike Creek	Lincoln
Bethel Creek	Condon
Baptiste Springs	Spotted Bear RS
Heart Lake	Lincoln

The final step of creating the treatment scenarios was to update fuel layers to reflect the post-fire conditions of the 18 treatment fires. Because LF-2008 reflected changes in LF-national due to fire, it was possible to detect consistent patterns between pre- and post-fire fuel conditions that were dependent upon burn severity as quantified by the Monitoring Trends in Burn Severity (MTBS) project (Eidenshink et al. 2007). LF-2008 was updated within the 18 simulated footprints using these observed patterns (pers. comm., Sean Parks, February 10, 2014). LF-2008 within the 18 simulated footprints were updated using the modeled fireline intensity outputs from FARSITE, information on observed burn severity from MTBS data, and information on how LANDFIRE data is updated using MTBS data. For fires that actually did burn within the study area in 2007, MTBS data suggest that very low severity comprised 23% of the area burned, low severity comprised 20%, moderate severity 23%, and high severity 34%. These proportions were used to classify the fireline intensity output from FARSITE into burn severity classes: the lowest 23% predicted fireline intensity from FARSITE was classified as ‘very low’ severity, the next lowest 20% of fireline intensity values as ‘low’ severity, the next 23% as moderate severity, and the remaining 34% as high severity. The end result was a crosswalk between pre-fire and post-fire fuel characteristics that was applied to all simulated burned areas. Table 2 reports an example of the crosswalk for fuel model TU5, described as having a high load conifer litter with shrub understory fuelbed. Figure 3 displays the adjustments made to the observed FBFM that resulted in the FBFM used in the alternative scenarios. See Appendix for further details regarding the fireline intensity crosswalks.

Table 2. An example of the crosswalk between pre- and post-fire fuel characteristics for the TU5 FBFM.

Pre- fire FBFM	Predicted Burn severity	Post-fire FBFM	Post-fire CC (%)	Post-fire CBD (kg/m ³)	Post-fire CBH (m)	Post-fire CH (m)
TU5	Very low	TL3 ¹	35	0.08	4	17.5
TU5	Low	TL3 ¹	35	0.08	4	17.5
TU5	Moderate	TL1 ²	35	0.06	28	17.5
TU5	High	GR1 ³	0	0	0	0

Notes: 1. Moderate load conifer litter

2. Light to moderate load, fuels 1 to 2 inches deep

3. Grass is short, patchy, and possibly heavily grazed

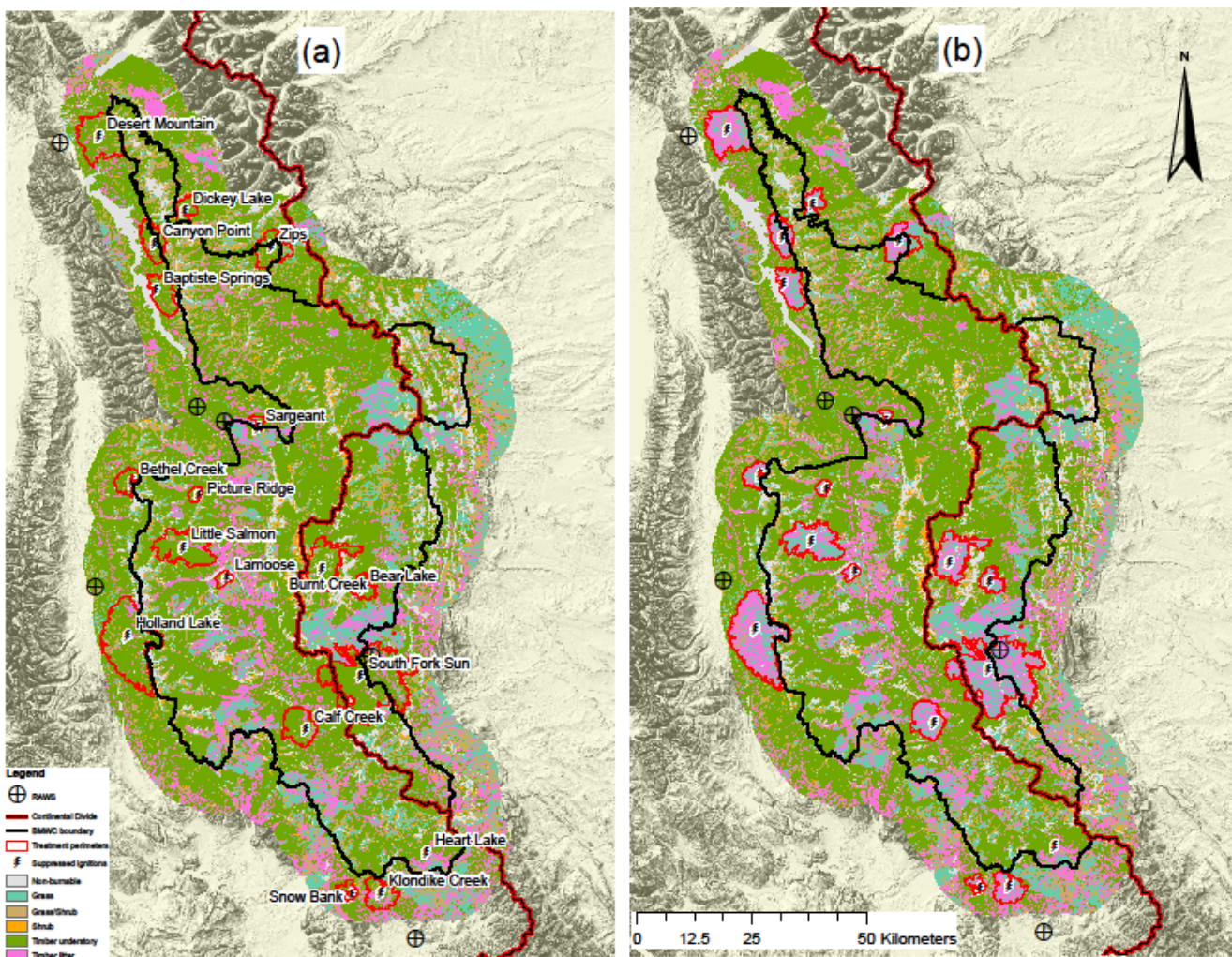


Figure 3. Maps showing FBFM used in the exposure analysis for the (a) observed and (b) treated landscape scenario (i.e. after retrospective fire behavior simulations of suppressed ignitions).

3.3. Exposure analyses for observed and alternative landscape scenarios

For the exposure analysis, FSim, a large wildfire occurrence and growth simulation system (Finney et al., 2011a), was used to simulate unsuppressed, individual wildfire spread for 25,000 artificial fire seasons for the observed and alternative landscape scenarios. FSim uses the annual and interannual statistical variability in historic weather and ignition probability grids to generate maps of burn probability. While spatially-explicit ignition probability grids can be incorporated into FSim, random ignition locations were used in this analysis. Historic weather data was obtained from the Spotted Bear Lookout RAWS Station, which is located in the northwest portion of the study area and contains data from 1980 – 2009. Simulations were performed at a 270 meter resolution rather than at the native spatial resolution of the input data (30 m) because of the computational demands associated with finer scale data. The random ignition locations and simulated weather in FSim were identical for all the landscape scenarios, thereby allowing differences in escape probability between scenarios to be attributed to the different fuels conditions resulting from the treatment fires². In initial simulations, it was found that FSim produced much smaller and fewer fires than observed historically (1980-2009), and that the highest simulated burn probabilities were observed in recently burned areas and in high elevations. Consequently, FSim inputs were incrementally adjusted to calibrate the model until the number of fires per year, annual area burned, and median fire size were within 5% of the observed values. For example, the rate of spread for grass fuel types was reduced to 10% of the original values in effort to reduce burn probability in recently burned areas, and default fuel moisture values were

² Even if ignition locations and weather streams are held constant between separate simulations, small differences in FSim outputs can be noticed because of the stochasticity of simulated spot fires.

adjusted to modify simulated fire growth and ultimately shift the fire size distribution so that more, larger fires were simulated (pers. comm., Sean Parks).

3.4. Mapping the conditional probability of an escaped ignition

Ignitions simulated in FSim that started within the BMWC and whose simulated perimeters subsequently breached the wilderness boundary were identified. An ignition's simulated fire perimeter needed only to be outside the BMWC an infinitesimal amount to be classified as escaped; no minimum threshold was set for the amount of simulated area burned outside of the wilderness to qualify as an escape. Escape probability (EP) was calculated for each pixel within the wilderness as the proportion of ignitions simulated in FSim that had been identified as escapes occurring within a circular moving window centered on that pixel. The area of the window was 1256 ha, which corresponds to a radius equal to 2 km, and was slightly larger than the mean fire size simulated in FSim (918 ha). The window size was chosen in an effort to conservatively estimate EP at each point on the landscape. Because of the lack of precedent for choosing an appropriate window size to smooth the ignitions, a relatively large window size that deemphasized the relative importance of each individual ignition was deemed appropriate.

EP grids were generated for the observed and treated landscape scenarios. Contour lines were fit through EP values at specified thresholds: 0.01, 0.025, 0.05, 0.10, 0.25, and 0.50. The area contained within each of the EP intervals was then computed and compared between the scenarios.

3.5 Evaluating the effectiveness of treatment fires on escape probability

Individual treatment fires were evaluated based on their ability to ameliorate escape probability within and surrounding the simulated treated area. Average EP within each treatment fire perimeter was calculated for the observed and individual treatment scenarios. Scatterplots of average change in escape probability versus distance to the wilderness boundary were made to explore the effect that distance to the wilderness had on reducing EP. The effect within each treatment fire's perimeter was also summarized by examining the area occupied by each of the seven EP classes and comparing the individual treatment scenarios to the observed scenario.

Effects of each of the 18 treatment fires were also examined by summarizing changes in EP within the immediate area surrounding each treatment fire perimeter. Simulated treatment fire perimeters were incrementally buffered by 250 meters out to 5 km, and average difference in EP between the observed and alternative scenarios were calculated inside each non-overlapping buffered ring. An example of this procedure is shown in Figure 4. The equation used to calculate the 95% confidence intervals for the mean difference in EP ($\bar{x}_1 - \bar{x}_2$) is:

$$(\bar{x}_1 - \bar{x}_2) \pm t_{df} * \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

Where t_{df} is the critical value from the t distribution corresponding to a 0.05 error level, and the degrees of freedom, df , equals:

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{1}{n_1 - 1} \left(\frac{s_1^2}{n_1}\right)^2 + \frac{1}{n_2 - 1} \left(\frac{s_2^2}{n_2}\right)^2}$$

where s_1^2 and n_1 is the sample standard deviation and sample size (i.e. number of pixels) from the observed landscape scenario, respectively, and s_2^2 and n_2 are the sample standard deviation and sample size from the treated landscape scenario, respectively. The difference in mean EP is statistically insignificant when the 95% confidence interval contains the value of zero.

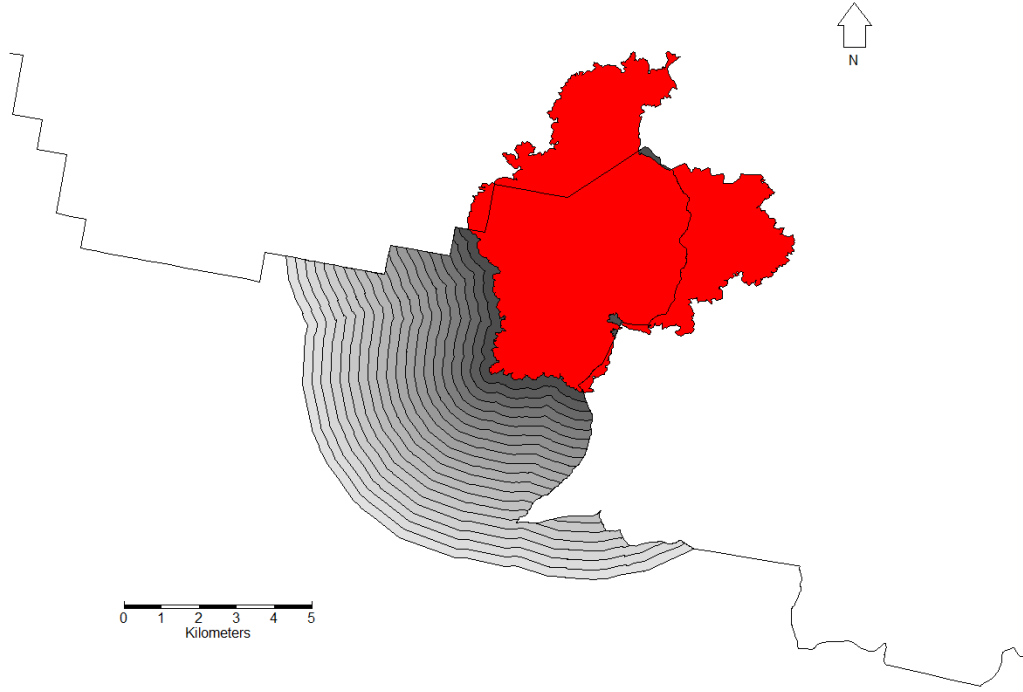


Figure 4. Example of the incremental buffering procedure for the Zips treatment fire. Buffered rings shown in gray scale. The footprint of the treatment fire is shown in red. The black line around the outside of the image is the BMWC boundary.

4. Results

Results for the cumulative treatment scenario are presented in section 4.1, followed by results for the individual treatment scenarios in section 4.2.

4.1 Cumulative treatment scenario

Figure 5 illustrates considerable spatial variation in EP in the observed and cumulative treatment scenarios, with the highest EP values along the edge of the wilderness boundary and the lowest values generally found deep within the interior of the BMWC. In both scenarios, the largest contiguous areas of low EP (i.e., area within the 1% EP contour) are found in the central and southern portion of the BMWC. The most noticeable expansion of the 1% EP contour is found near the South Fork Sun and Calf Creek treatment fires. The 1% EP contour extends along the wilderness boundary for about 10 km along the western edge in both scenarios. There were five simulated wildfires that started outside the wilderness and did not burn inside the BMWC and therefore had no effect on EP. In total, the treatment fires burned 95,355 ha inside the BMWC, or 15.26% of the total area.

Area of EP less than 1% is 20,329 hectares larger in the cumulative-treatment scenario compared to the observed scenario, as shown in Figure 6. The total study area within the 1% EP class increased by 3% in the cumulative treatment scenario. For each of the remaining EP classes, the area within each class is reduced in the treated scenario. While these reductions appear small and indicate that the treatment fires had little impact at shifting the EP distribution across the entire BMWC, it is important to remember that

these results represent possible changes in EP following only a single year of allowing natural ignitions to burn.

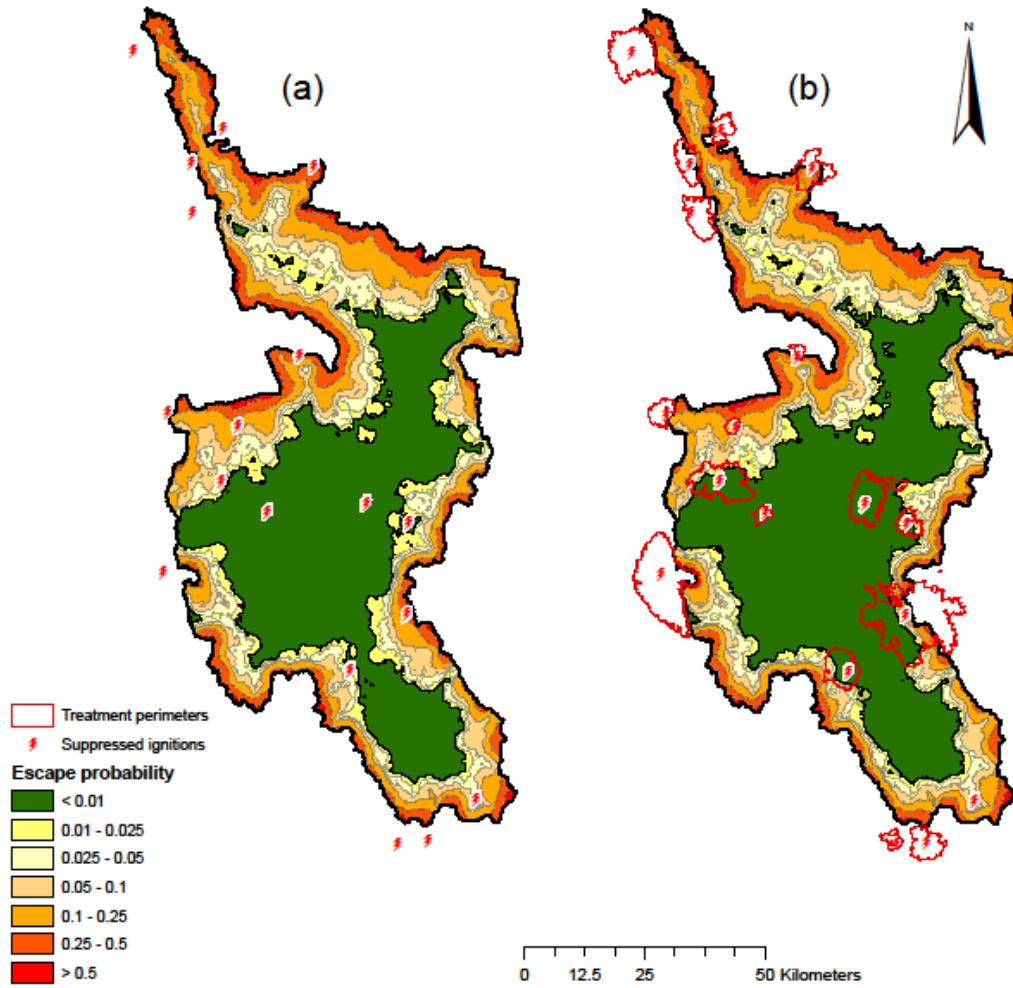


Figure 5. Escape probability for the (a) observed and (b) treated landscape scenarios that reflects the cumulative effects of the 18 treatment fires. The ignition locations of treatment fires are labeled in (a) and the treatment fire perimeters are shown in (b) as red polygons.

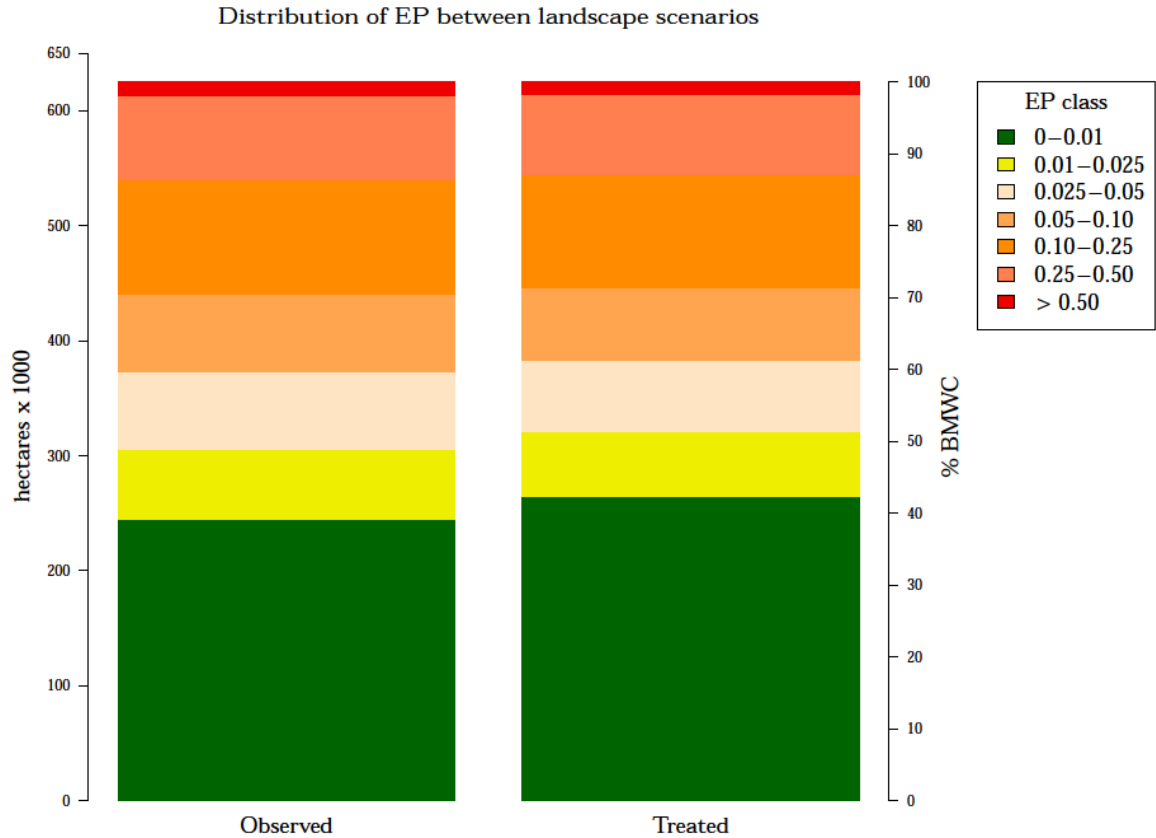


Figure 6. Stacked bar charts showing the area within each escape probability class for the observed and treated landscape scenarios.

4.2 Individual treatment scenarios

Individual alternative scenarios were evaluated for 13 of the 18 treatment fires. The remaining five treatment fires were excluded either because they were entirely outside the wilderness boundary and did not affect EP (i.e. the Snow Bank, Klondike Creek, Bethel Creek, and Baptiste Springs ignitions), or did not grow larger than a single pixel (i.e. Heart Lake). Figure 7 shows how the change in average EP (observed minus treated) for pixels within the perimeter of each of the 13 treatment fires decreases with distance from the treatment fire's ignition point to the BMWC boundary.

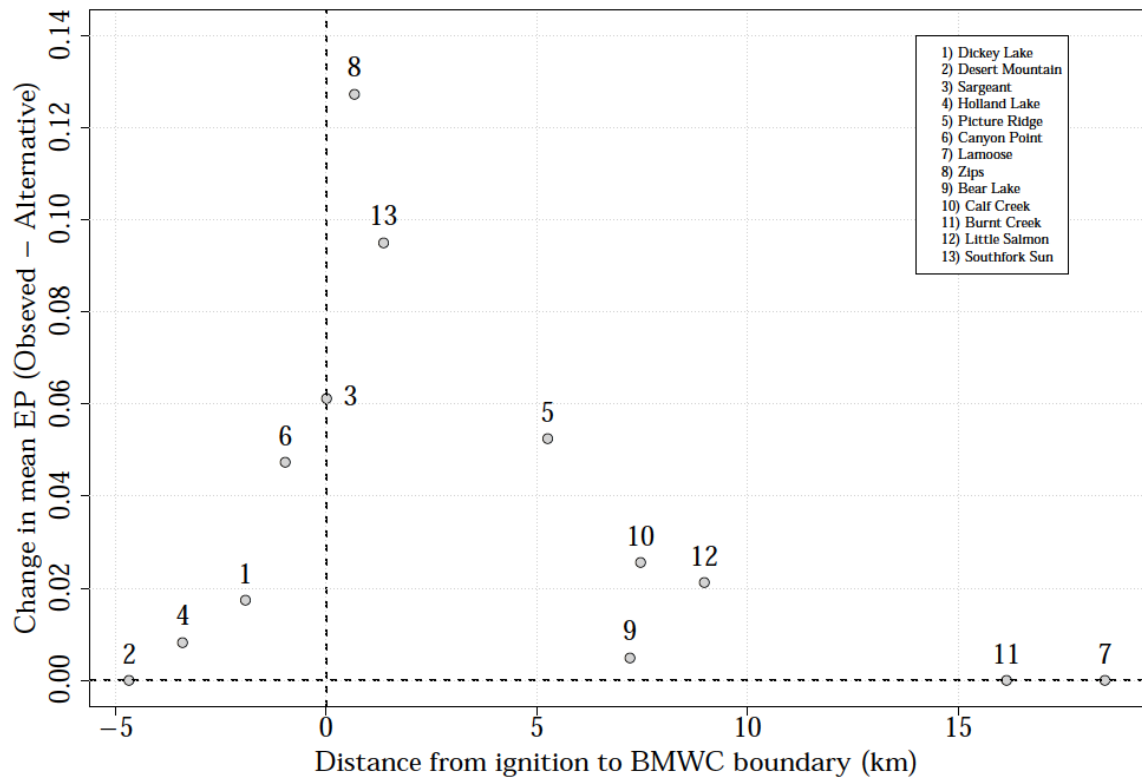


Figure 7. Change in average escape probability within the treatment fire perimeters plotted against the distance from the treatment fire’s ignition point to the BMWC boundary. Negative distances indicate ignition locations outside the BMWC boundary. Treatment fires are numbered in ascending order of simulated area burned within the BMWC.

The effect within each treatment fire’s perimeter was also summarized by examining the area occupied by each of the seven EP classes and comparing the individual treatment scenario to the observed scenario. Change in the area within each EP class within each of the 13 treatment fire perimeters that burned at least partially in the BMWC is reported in Figure 8. Positive values mean the area comprising a given EP class increased in the individual treatment scenario relative to the observed scenario, while negative values represent reductions in area in the individual treatment scenario. Summing the positive and negative value changes within each treatment fire equals zero, since gains in one EP class must be offset by losses in another. The treatment fires are ordered along the x-axis

by area burned inside the BMWC boundary and size of each treatment fire is provided in parentheses.

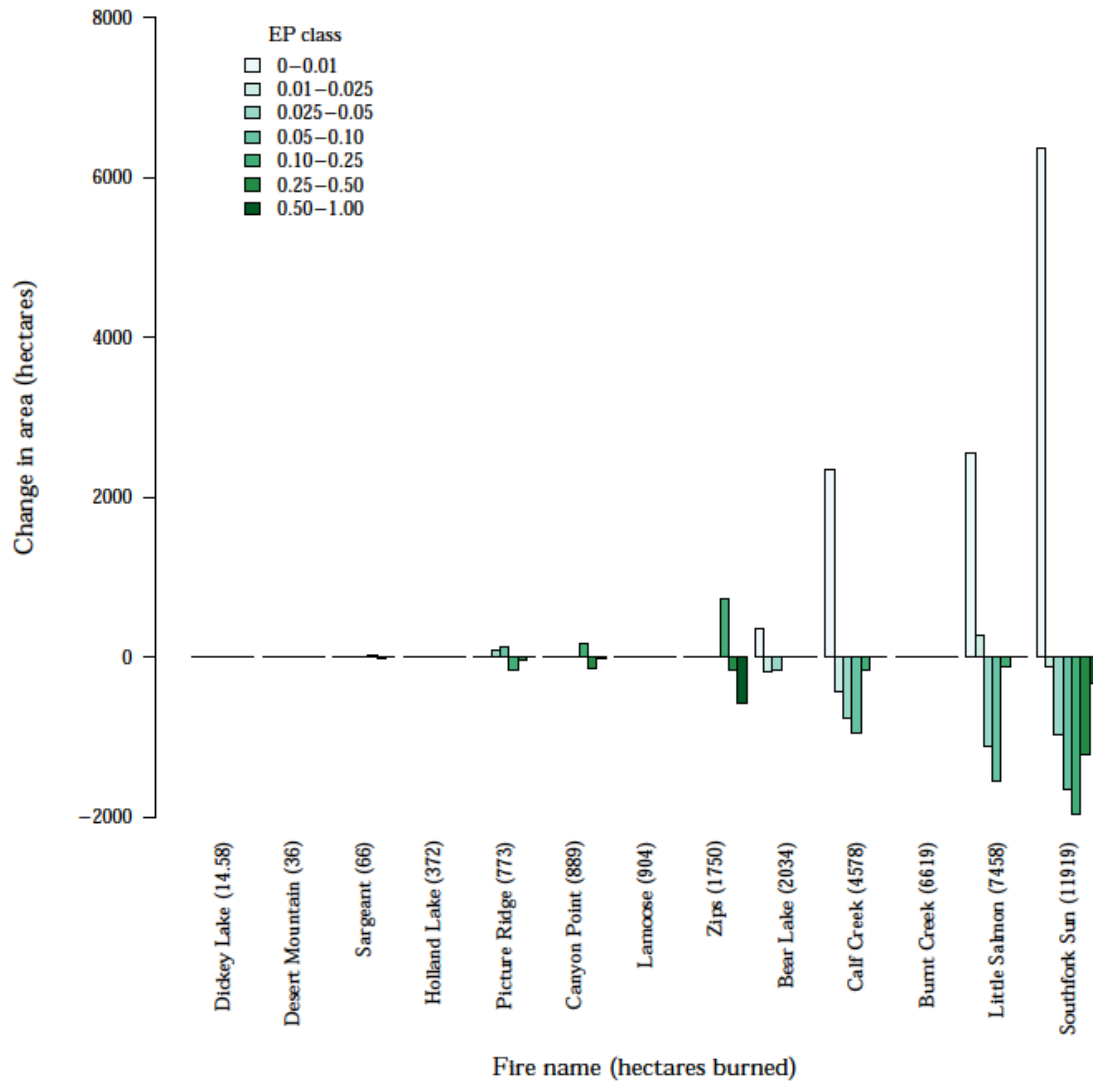


Figure 8. Change in area for each escape probability class within treated areas between the observed and individual treatment scenarios.

In general, the larger treatment fires showed more of a difference between the individual treatment and observed landscape scenarios, with the most dramatic differences being within the 0.01 EP class. The only fires to create additional area within

the 0.01 EP class were four of the five largest treatment fires. Of the 13 treatment fires that burned at least partially inside the BMWC, five (including four less than 1000 ha) showed no difference in EP between the individual treatment and observed landscape scenarios. Interestingly, this group included the third largest simulated fire, Burnt Creek. The Sargeant, Picture Ridge, Canyon Point, and Zips treatment fires had small effects on EP within their respective perimeters. The Zips treatment fire had the largest effect on reducing the area containing EP values greater than 0.50.

Differences in mean EP between the individual treatment and observed landscape scenarios extend outside the treatment fire perimeters, but there is considerable variation both within and among treatment fires. Figure 9 plots difference in average EP within the buffered rings against the buffered distance for each individual alternative landscape scenario. Treatment fires are presented in order of increasing size from left to right and top to bottom. The shaded region represents the 95% confidence interval for the mean difference in EP between the observed and alternative scenarios calculated within each 250 m buffered ring. Mean difference in EP decreases with buffer distance, and in some cases differences extended out to 4 km. However, the 95% confidence intervals are wide, and differences become statistically insignificant beyond about 1 km for all treatment fires (i.e. when the 95% confidence intervals overlap with y-values equal to zero). Some small treatment fires (e.g. Canyon Point, Picture Ridge, and Sargeant) show mean differences in EP for pixels that extend at least 2 km outside the treatment fire perimeters. However, these differences are only statistically significant at the 0.05 level out to roughly 500 meters.

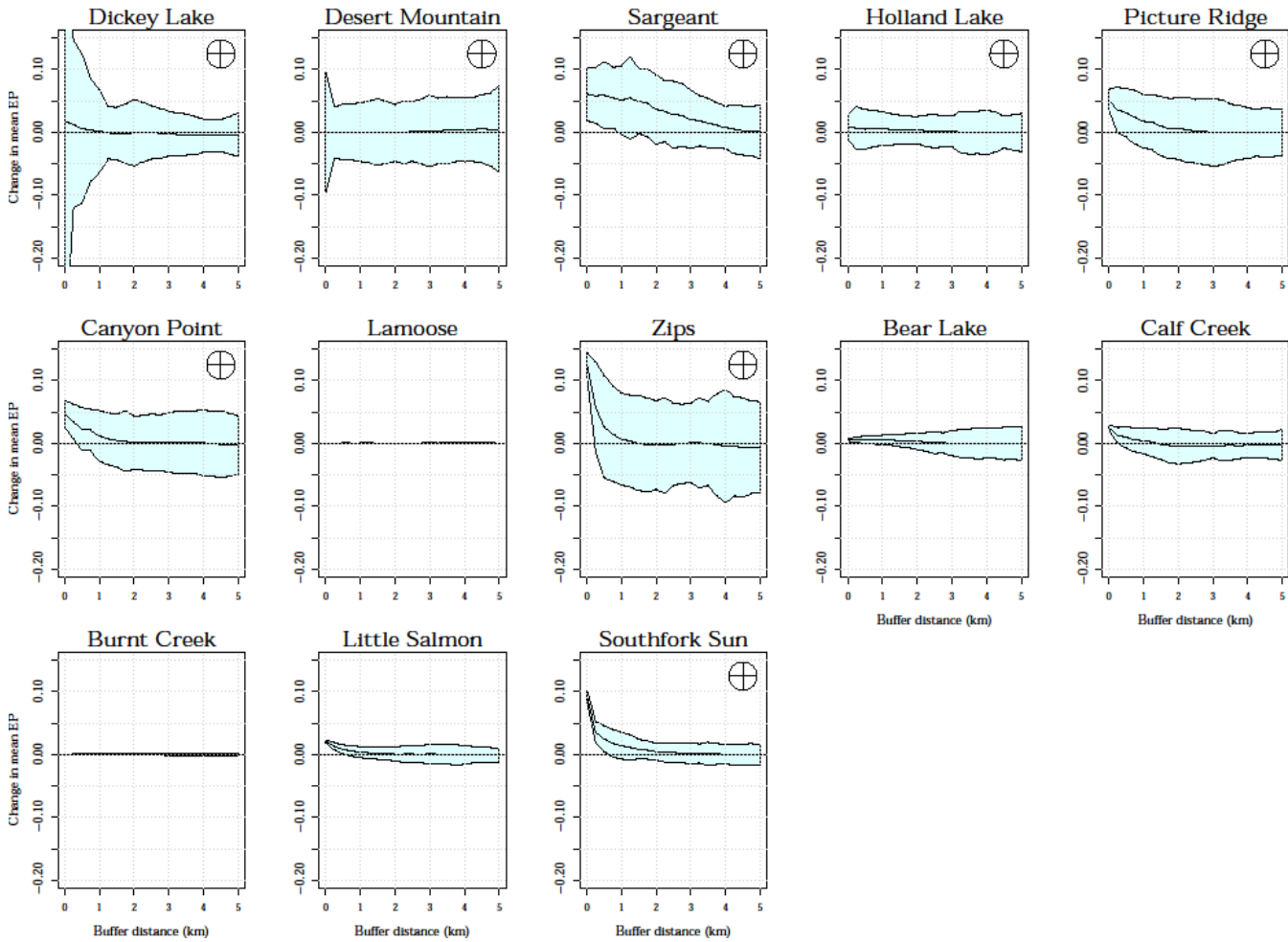


Figure 9. Change in average escape probability as a function of distance to simulated treatment perimeter for each individual treatment scenario. Blue shaded areas represent 95% confidence intervals for the difference in mean escape probability. Ignition points for treatment fires identified with a bull's eye were located within 5 km of the wilderness boundary.

The Calf Creek and Little Salmon treatment fires were only marginally effective at reducing EP outside their perimeters, although each was responsible for creating additional area containing EP values below 1% within the treated area (Figure 7). The Zips and South Fork Sun treatment fires had the largest effect on reducing EP within a close distance to their perimeters. No changes in escape probabilities were observed outside of the treated area for the Lamoose and Burnt Creek fires. Little to no change in EP outside of the treated areas was observed for the Dickey Lake, Desert Mountain, Holland Lake, and Bear Lake treatment fires. EP was highly variable at close distances

from the treatment fire perimeter for the Dickey Lake and Desert Mountain treatment fires.

Of the 13 treatment fire ignitions, eight were located within 5 km of the BMWC boundary. Interestingly, seven of these treatment fires exhibited the greatest variability in mean difference in EP. The only treatment fire located within 5 km of the BMWC boundary that did not exhibit substantial variability in mean difference in EP was the Southfork Sun.

5. Discussion

The results of this case study demonstrate a risk-based methodology used to generate escape probabilities, an alternative metric that can be used to identify where on a landscape using fire as a wildfire risk mitigation tool may be feasible, and how proximity to wilderness boundary and size of treated area contribute to a fire's effectiveness at reducing escape probability.

This section begins by summarizing the effects of ignition location and treatment fire size on changes in EP within the treated area in sections 5.1 and 5.2, respectively. Offsite treatment effects are then discussed in section 5.3. Section 5.4 is devoted to a discussion of the similarities and differences between burn probability and escape probability, with particular attention given to existing decision-support tools used to inform and evaluate fire and fuels decision-making. Section 5.5 provides a brief overview of recent wildfire exposure analyses related to this case study. Section 5.6 then provides a description of the major limitations of the research, and section 5.7 outlines the management implications of this research. The section concludes by offering suggestions for future research in section 5.8.

5.1 Effects of proximity of ignition location to the wilderness boundary on EP within individual treatment perimeters

The location of the retrospectively simulated wildfires was an important determinant of changes in EP between observed and treated scenarios (Figure 7). Ignitions located in close proximity to the wilderness boundary had larger effects on reducing future EP within the treated area, compared to ignitions located in the interior of

the wilderness. This is due, in part, to EP in the interior of the wilderness being low in the observed landscape scenario, thus limiting the potential beneficial treatment effect of fires located relatively further away from the wilderness boundary.

EP in the observed landscape scenario tended to decrease with distance from the wilderness boundary (Figure 5), and this was more dramatic in the southern portion of the BMWC compared to the northern portion. This may be a reflection of recent (i.e 1984 – 2007) fire activity in the southern portion of the BMWC, in that potential rates of fire spread are lower in recently burned areas, reducing the likelihood that fires will reach the wilderness boundary. Conversely, fire information from the MTBS dataset reveal that few fires have burned in the northern part of the BMWC during this time frame, which may explain why relatively higher EP values extend further into the northern interior of the BMWC. The fuel models populated in recently burned areas may have low spread rates, thus recently burned areas are still an effective barrier to simulated fire spread. It may also be less likely that simulated fires in FSim starting in the interior of the southern portion of wilderness will reach the boundary, because they must spread over longer distances compared to the northern portion due to the geometry of the BMWC.

5.2 Effects of simulated fire size on EP within individual treatment perimeters

The four smallest treatment fires had little to no effect on the area within each EP class inside their respective simulated perimeters (Figure 8). This is likely driven by the fact that the window size was relatively large compared to the treatment fire size, as well as that the coarse spatial resolution used in the exposure analysis may not adequately capture fine-scale changes in EP for smaller treatment fires. Larger treatment fires

caused the more dramatic shifts in the EP distribution, however, the effect of the size of treated area on reductions in EP was highly dependent on the ignition's location.

Relatively large treatment fires in the core area of the wilderness and within or proximate to areas with low EP (e.g. Burnt Creek) had little to no effect on EP within their perimeter.

The area within the treated perimeters containing EP values less than 1% increased in four of the five largest individual treatment fires. For three of these four fires (Little Salmon, Calf Creek, and Bear Creek) their ignition location near the edge of the 1% EP contour in the observed landscape scenario could explain why such increases were observed. The Southfork Sun treatment fire was also effective at creating additional area of EP values less than 1%, even though the ignition was not located near EP values less than 0.01 in the observed landscape scenario. It appears that the Southfork Sun treatment fire burned sufficiently large to create area within its perimeter containing EP values less than 0.01. Indeed, the Southfork Sun treatment fire burned up to the 0.01 contour of the observed landscape scenario.

5.3 Off-site effects of individual treatment fires on EP

The location of the suppressed ignitions with respect to the wilderness boundary and the size of treated area interact in such a way that predicting off-site treatment effects is difficult. Both small and large treatment fires affected EP outside their respective treated areas. While the Sargeant, Picture Ridge, and Canyon Point treatment fires did not grow to more than 900 hectares, and while each of these fires had little effect on EP within their perimeters, each reduced mean EP values at least 2 km outside their perimeters.

That is, it appears that simulated ignitions located relatively far away from these treatment fires tended to escape the wilderness less frequently in the treated scenario.

It is plausible that the orientation of the treatment fire perimeters with respect to the main direction of fire spread (i.e. angle along the major axis of a spreading fire), may explain a portion of why such large offsite effects were observed for the relatively small treatment fires. It is not possible to confirm this because although simulated wind speed and direction in FSim are drawn from a joint distribution of historic observations, those distributions do not apply uniformly across the landscape because the integrated wind flow model, WindNinja (Forthofer et al., 2009), adjusts those speeds and directions based on terrain. In areas with dramatic topographic relief, such as the BMWC, the influence of terrain on wind speed, direction, and ultimately simulated fire spread, can be significant and difficult to disentangle from other biophysical drivers of fire spread (Parisien et al., 2011).

It is not surprising to see small off-site effects for the treatment fires located further away from the wilderness boundary because much of the buffered EP values in both the observed and alternative scenarios are less than 0.01. Fine-scale reductions in EP outside the treated area may be masked when averaging the change in EP throughout each buffered ring, and this effect may be most pronounced in areas with little variability in EP (i.e. areas further away from the wilderness boundary).

The greatest variability in off-site treatment effects was observed for treatment fires that ignited within 5 km of the wilderness boundary. However, the Southfork Sun treatment fire, which also ignited within 5 km of the wilderness boundary, exhibited relatively little variation in mean reduction in EP outside the simulated fire perimeter.

This may be a result of the fact that, for treatment fires located close to the wilderness boundary, the non-overlapping buffers were cut off in some directions because they extended outside of the wilderness boundary. Fewer grid cells were then sampled in each non-overlapping buffer, possibly leading to an artificially high estimate of the variability. The second explanation for this phenomenon is that pixels proximate to the edge of the wilderness boundary exhibited high variation in EP in the observed landscape scenario (Figure 5). It is noticeable that EP values are most elastic near the edge of the wilderness boundary; small changes in distance from the pixel to the wilderness boundary results in a large change in EP. As such, it is expected that mean differences in EP would also exhibit a high degree of variability. The Southfork Sun treatment fire was an outlier in that it burned near the wilderness boundary, yet exhibited relatively low variability around mean difference in EP. This may be because the large area burned by the fire meant that the non-overlapping buffers were proportionally large and sampled a greater number of pixels. Also, this treatment fire's perimeter extended into areas containing 0.01 EP values, so the non-overlapping buffers sampled areas with relatively little variability in EP.

5.4 Relating escape probability to burn probability to support and evaluate fire and fuels management decisions

As demonstrated in this case study analysis, the EP approach can serve as a platform to begin investigating how the opportunities to not aggressively suppress wildfires expand or contract with decisions to suppress or not suppress natural ignitions, and should be viewed as a complement to the existing suite of wildfire risk tools, specifically

those involving the use of burn probability models. Burn probability models characterize the propensity of a given location on the landscape to experience wildfire, and arose out of the need to synthesize the highly stochastic nature of wildfire occurrence and spread in both space and time (Miller, 2003b). Burn probability models do not currently incorporate forest and vegetation succession through time, unlike integrated landscape fire simulation models that can account for interactions between disturbances, climatic variability, and succession on landscape structure and ecosystem processes (e.g. Keane et al., 2011). Rather, their strengths lie in their ability to accurately model the dynamics of ignitions, fuels, weather, and fire spread at large spatial scales to provide a realistic depiction of fire likelihood for a given landscape condition. Such information can inform strategic fire and fuels management decisions at large spatial extents (Miller et al., 2008). The versatility of burn probability modeling is evident in their recent applications that address highly diverse and wide-ranging fire and fuels management issues: designing and evaluating the location of mechanical fuel treatments to protect wildlife habitat, the Wildland Urban Interface (WUI) and stand structure (Ager et al., 2010); statistical investigations into the role of biophysical, anthropogenic, and climatic factors on fire likelihood from regional to global scales (Parisien and Moritz, 2009; Krawchuck et al., 2009; Parks et al., 2011; Parisien et al., 2011; Parks et al., 2012); quantitative risk assessments to support the Cohesive Wildfire Management Strategy (Calkin et al., 2011a); and informing suppression resource allocation and management decision-making during ongoing incidents (Calkin et al., 2011b).

Despite their widespread application within the wildfire science and management community, burn probability models have yet to be used to their fullest extent to support

initial decisions to allow natural ignitions to burn. In both wilderness and non-wilderness areas, an overwhelming management focus on avoiding losses of human and natural assets to wildfire constrain opportunities for managers to exploit the risk-mitigation benefits by allowing natural fire to burn, and may even perpetuate highly risk-averse management decisions that can lead to inefficient outcomes. From a risk management perspective, the central tenant of studies involving the use of burn probability models is to evaluate hazardous fuel removal treatments whose objectives are to mitigate future wildfire risk to highly valued resources and assets. There are three main reasons why this framework is potentially insufficient to address the issues facing management of wilderness fires: 1) reducing wildfire risk inside the wilderness is not necessarily the main objective in wilderness fire management because fires inside the wilderness are ecologically desirable ; 2) many of the resources at risk of fire lie outside the wilderness boundary; and 3) traditional means of reducing fire risk (i.e. prescribed fire and mechanical thinning) are not widely used in wilderness areas because of legal and social constraints that restrict anthropogenic manipulation of the landscape. Recent research and decades of qualitative observations have shown that previous wildfires can moderate the spread and severity of future wildfires in wilderness landscapes, effectively serving as both a risk-mitigation tool and a necessary disturbance process to promote resilient forest ecosystems (Teske et al., 2012; Parks et al., 2012; Holden et al, 2010; Larson et al., 2013). However, spatially-explicit tools that inform managers of opportunities and constraints to allow fires to burn, and which are consistent with the principles of risk analysis, are lacking.

As we further understand the fuel treatment benefits derived from wildfires, the need for risk-based decision-support tools that more clearly support decisions to allow wildfires to burn absent of suppression becomes even greater. Currently, wildfire managers have access to outputs from FSPro (Finney et al., 2011b), a real-time burn probability model through the Wildland Fire Decision Support System (WFDSS, Noonan-Wright et al., 2011). FSPro creates thousands of artificial weather scenarios based on an autoregressive analysis of observed ERC values, and then simulates fire spread from either an ignition point or current fire perimeter using these synthetic values. This produces a burn probability map that quantifies the likelihood that the fire or ignition reaches a given point on the landscape over a finite time-span, typically 10-14 days. Maps of highly valued resources and assets can be overlaid with FSPro outputs to characterize wildfire exposure and inform suppression resource allocation to areas where there exists a significant potential for negative impacts due to fire (Calkin et al., 2011b).

Information regarding the likelihood of fire reaching any point on the landscape can guide implementation of a suppression strategy. Current wildfire management policy states that fires can be managed under multiple objectives, where some portions of a fire are actively suppressed while others are passively monitored. FSPro provides vital information that managers can use to efficiently distribute suppression resources during incident management. However, for at least two reasons it seems unlikely that this decision-support tool alone can be used to support and evaluate initial decisions to allow wilderness fires to burn. First, wilderness managers are concerned with the risks associated with early season ignitions that potentially become large, season-long events, generally much longer than 10-14 days. The likelihood that large fires will impact

resources outside the wilderness increases as fires burn for long time periods. Oftentimes large, long-duration fires become extinguished by favorable weather or season-ending weather events, rather than from effective suppression (Finney et al., 2009). Therefore, wilderness managers may benefit from information regarding the likelihood that an ignition will reach an undesired location throughout the remainder of the fire season, not just within the forthcoming two weeks.

Second, FSPro was designed to assist real-time incident decision-making and is not applicable to landscape-scale evaluation of fire and fuels management. There are two important limitations to using FSPro in order to evaluate the effectiveness of fuel treatments: 1) changes in fire spread from all ignitions across a landscape that could potentially interact with the treated area would be neglected; and 2) the simulated weather streams used in FSPro are based on real-time forecasted conditions. FSPro simulates fire spread from a single ignition or fire perimeter, so in order to understand treatment fire effects on future fire spread across a large landscape, one would need to apply FSPro multiple times using different ignition locations or fire perimeters each time. This is likely to be time-intensive and is not what FSPro was designed for. Also, the simulated weather streams used in FSPro do not capture the full range of conditions under which future fires can burn, only those which are forecast in the near future. A more complete understanding of fuel treatment effectiveness would entail simulating fire spread under a more complete range of possible burning conditions, not just those which are predicted to occur in the near future.

Escape probabilities in this case study were derived from the same simulation model used to estimate burn probability (FSim). As such, maps of escape probability and burn

probability share some of the same strengths and weaknesses, yet have important differences in their interpretation and application to strategic fire and fuels management. The main similarity between the two metrics is that both are spatially-explicit and probabilistic, with relatively straight-forward interpretations. The main difference between maps of burn probability and escape probability is that the latter more closely links how fire is transmitted across the landscape back to an ignition location, while burn probability encapsulates how fire spread from ignitions distributed across the landscape affect the likelihood that any location of the landscape will burn. Thus, it is difficult to ascertain how likely it is that a particular ignition will pose risks to human and natural assets using burn probability information alone. Attempts have been made to intergrate burn probability maps with fire size information to characterize fire source-sink relationships (i.e. where fires generally start and stop on the landscape) (Ager et al. 2012). In a case study presented in Ager et al. (2012), outputs from the burn probability model RANDIG (Finney, 2006) were used to map a source-sink ratio as the logged ratio of fire size to burn probability for each pixel in the study area. Appropriate interpretation of such a metric is less clear than both burn probability and escape probability, and it is difficult to determine how best to apply such a metric to inform and evaluate manager decision-making.

5.5 Comparison to published fire exposure analyses

Similar studies to the case study presented here have used FSim outputs to characterize wildfire exposure. Thompson et al. (2013) delineated the ‘fire-shed’ for a rare butterfly in the state of Colorado by buffering the concave hull of all simulated

ignitions that intersected designated critical habitat polygons. Scott et al. (2012) tabulated the proportion of unsuppressed simulated ignitions that reached Wildland Urban Interface (WUI) defense zones surrounding the mountain community of Jackson, Wyoming, and used this approach to evaluate a hypothetical management policy where a fraction of ignitions in each month were not suppressed. Each of these approaches, however, lacked one of the fundamental components in wildfire risk analysis. The framework to delineate fire sheds outlined in Thompson et al. (2013) is inherently spatial, but by using a fixed buffer distance around their ‘problem’ ignitions, it ignored the probabilistic aspect of wildfire behavior and occurrence within the delineated fire shed. That is, the likelihood of an ignition reaching the critical habitat is going to vary within the fire shed, with ignitions located closer and/or in areas with high fuel connectivity likely posing a greater risk to the resource compared to ignitions further away or adjacent to natural barriers of fire spread. Conversely, Scott et al. (2012) summarized their results in terms of the likelihood of ignitions reaching a specific point on the landscape. However, their results were presented aspatially, making it challenging to know where on the landscape fires with low or high likelihoods of reaching the WUI zones occur. The approach used to characterize wilderness wildfire exposure developed in this case study closely adheres to the core principles of wildfire risk analysis in that it is both a spatially-explicit and probabilistic metric, and relates to the extensive research into mapping burn probabilities for strategic fire and fuels management planning (Miller et al., 2008; Finney et al., 2007; Ager et al., 2010).

5.6 Limitations of modeling assumptions and analytical methods

There are five important limitations that affect interpretation and extrapolation of the results from this case study:

- 1) data are likely spatially autocorrelated, perhaps leading to a biased estimate of mean and variance;
- 2) arbitrary window size used to smooth the point data;
- 3) coarse spatial resolution and no spatially explicit ignition probability grid was used in FSim;
- 4) assumptions regarding post-fire fuels conditions; and
- 5) results were not stratified by season.

This case study did not correct for spatial dependencies, but future analyses of EP should consider that observations are correlated across space and that the assumption of independence across observations, necessary when using classical parameter estimators of the sample mean and variance, is violated, leading to biased estimates (Legendre and Fortin, 1989). This can be resolved through the use of spatial statistical techniques that explicitly account for spatial heterogeneity. Investigations of the top-down (e.g. climate) versus bottom-up (e.g. ignitions, fuels, topography) environmental drivers of burn probability have used variograms to define the threshold distance between grid cells at which observations are no longer correlated, then drawn samples of the data (i.e. grid cells) across the landscape that were no closer in space than this threshold distance (Parks et al., 2013; Krawchuk et al., 2009; Parisien et al., 2011). The theoretical variogram is a function characterizing the strength of spatial dependencies of spatial random field or

stochastic process, defined as the variance of the difference between values at two locations across realizations of the field (Cressie, 1993). Theoretically, samples drawn using this approach are no longer correlated across space, suggesting that classical parameter estimators can then provide an unbiased estimate of the sample mean and variance.

There is little statistical or ecological justification for the size of the window used to smooth the simulated point data into pixel-based probability estimates. Because the density of simulated ignition points averaged 0.55 per 270 m grid cell, simply calculating the proportion of escaped ignitions on a cell-by-cell basis would have resulted in unrealistic spatial patterns of EP and high variability within each grid cell. However, simulating a sufficient number of ignitions to reasonably estimate the likelihood of escaped ignitions without using a moving window approach is prohibited by the computational demands of FSim. The rationale behind the 2 km radius of the moving window was 1) to obtain a larger sample of ignition points for each grid cell to ensure relatively robust escape probability estimates could be obtained, and 2) because it is possible that within a small geographic extent there were inconsistencies in which ignitions were identified as “escaped” due to differences in simulated fire growth. That is, holding other factors constant (e.g. timing of ignition, simulated weather), it is possible that slight variations in topography could result in different patterns of fire spread, and ultimately escape probability, from simulated ignitions within close proximity to each other. In areas with steep environmental gradients such as the BMWC, calibrating a wildfire occurrence and growth simulation model such as FSim in order to obtain reasonable estimates of fire likelihood (or escape likelihood) is challenging and

requires scrutiny of input data and diligent calibration of model parameters (Parisien et al., 2013).

Rather than assigning a value equal to the proportion of escaped ignitions using a subjectively chosen fixed window size, as was performed in this study, an alternative approach where the simulated ignition points that escaped are considered a type of spatial point process data could be implemented. A spatial point pattern is a set of locations in n -dimensional space at which events have been recorded, such as the diameter of a tree in a forest or the location of a lightning strike (Diggle, 2003). Non-parametric kernel density estimators are a type of probability density function commonly used when modeling spatial point process data. This approach can be used to estimate the intensity of the events across a study region (Diggle, 1985). Kernel density estimators require a bandwidth parameter that defines how far away in space to search for other events when estimating the intensity at any given location. In that sense, the bandwidth parameter in the kernel density estimator can be interpreted similar to the radius of the moving window used in this case study. In practice, an optimal bandwidth size that minimizes the Mean Squared Error can be solved for using cross-validation approaches (Berman and Diggle, 1989). This partially resolves the need to make strict assumptions regarding the spatial extent of a given ignition points' influence by providing a statistical foundation for choosing a window size.

Because FSim was ran for each individual treatment fire, it was necessary to scale up the input data from 90 m to 270 m in order to reduce the processing time needed for each simulation. Each simulation took five hours to complete using the scaled 270 m input data, while preliminary simulations performed at 90 m resolutions took roughly five

days. The likely consequences of using a 270 m resolution are that less fine scale patterns in EP are captured, along with slightly less confidence in identifying escaped ignitions, because simulated fire perimeters in FSim become more distorted as the spatial resolution (i.e. cell size) increases.

Because wildfire ignitions are influenced by both anthropogenic and environmental factors, the choice to use random ignitions in this analysis requires justification. FSim supports spatially-explicit ignition grids, in which portions of the landscape receive a weight proportional to the relative likelihood that an ignition will occur there. Typically, logistic regression or a machine learning algorithm (e.g. Random Forests, Classification and Regression Trees) is used along with spatial covariates to model the likelihood of an ignition occurring at each pixel across a landscape. At relatively small spatial scales, research shows that the use of spatially-explicit ignition density grids in wildfire simulation models can produce markedly different spatial patterns of burn probability relative to random ignitions (Lowery, 2012). However, at large spatial scales, research in the northern Rockies and the boreal forests of Canada has shown the effect of ignition patterns (i.e. random versus clustered) on simulated burn probability is less important compared to fuel arrangement and topography (Parisien et al., 2011). Given that the BMWC is large at over 625,000 ha, it is possible that the effect of using random simulated ignition points on EP is negligible.

It was assumed that the proportion of each burn severity class inside the retrospectively simulated fire perimeters would have been equal to the proportion of burn severity classes that was observed across the entire BMWC in 2007. This assumption is important because the assignment of different burn severity classes to each pixel

determined how the fuels layers were adjusted to reflect post-fire effects. Determining the influence of assigning different post-fire fuel models on EP is outside the scope of this thesis. A sensitivity analysis where different fuel models are populated within the simulated treatment fire perimeters could test the robustness of results found in this case study to the assumed post-fire fuel model. To avoid issues related to the sensitivity of changes in EP due to fuel models that were assigned within the simulated burned area, future work investigating the role of wildfire as a risk-mitigation tool could simply use an observed LANDFIRE dataset and a subsequent update, such as LF-2008 and LANDFIRE 2010. However, this option was not relevant in this case study since this analysis focused on quantifying the potential consequences of actions not taken.

Results represent the likelihood of escaped ignitions across an entire fire season and were not stratified by the timing of the ignition within a given season. It is likely that EP values vary according to when and under what conditions an ignition starts (Scott et al., 2012), and such considerations may be significant. From a manager's perspective, quantitative metrics that characterize how the risk of unsuppressed wilderness fires reaching the wilderness boundary fluctuates throughout a fire season could inform initial attack decision-making. However, because of the additional parameterization requirements to accurately model the seasonal distribution of ignitions in FSim, while simultaneously ensuring that annual parameters (i.e. number of fires, mean area burned) were within a 5% tolerance of observed values, the choice was made to analyze simulation outputs at the temporal resolution of an individual fire season.

5.7 Management implications

Our simulation results suggest that, in some cases, allowing wildfires to burn may decrease the future likelihood of unsuppressed ignitions escaping the BMWC boundary. Results from the cumulative-treatment scenario provide a starting point for how fire and fuels managers might use such information in future strategic planning. For illustrative purposes, the 1% EP threshold has been selected as an acceptable level of risk for society to bear. Our results suggest that allowing ignitions to burn that start within and near the edge of the 1% EP contour can increase the future area within the 1% EP contour with relatively little risk of fire escape. The collective effects from the 13 treatment fires revealed that the area containing EP values less than 0.01 increased by 3.25% of the total area within the BMWC. Given that this analysis only evaluated management decisions in a single year, there is a strong possibility for substantial decreases in landscape fire risk over the long term through the use of fire, although there may be an upper ecological threshold to the annual area burned, beyond which forest structure begins to depart from desired future conditions (Miller, 2007). Managers will need to tradeoff the initial risk of allowing an ignition to burn and the long-term benefits that may accrue from such management decisions. Allowing ignitions to burn that start within, but near the edge, of the 1% EP contour is challenging for a wilderness fire manager, yet may prove to be highly effective at expanding their future options when faced with an unplanned ignition.

Our results complement findings from a recent simulation study that demonstrated the possibility for substantial wildfire suppression cost savings over long-term time horizons from allowing more wildfires to burn, which disrupts future wildfire spread and reduces future fire sizes (Houtman et al., 2013). Similarly, reductions in EP in this case study

were caused by the fuel breaks created by the retrospectively simulated wildfires that mitigated future simulated wildfire spread. Since in this analysis the ignition locations and simulated weather conditions were held constant between all of the observed and treatment landscape scenarios, changes in EP can be attributed to the post-fire fuel conditions due to the treatment fires.

Wildfire management decision-making is currently supported and documented through the interactive decision-support system WFDSS (Noonan-Wright et al., 2012). Inside WFDSS, incident managers can choose to use the newly created Spatial Fire Management planning tool which allows users to view fire management and strategic objective information through an interactive GIS to support decisionmaking. For fires that ignite within wilderness areas, it is possible that escape probability information could be included to provide wilderness fire managers with quantitative, spatially-explicit information regarding the likelihood that the fire will breach the wilderness boundary and impact resources outside the wilderness.

5.8 Future research

Several research threads could extend the EP approach outlined in this case study. Exploring how the EP zones change throughout a fire season may help identify windows of opportunity to allow wilderness fires to burn when the escape risk is acceptably low. EP has a strong seasonal component to its interpretation that was not fully explored in this thesis, however, previous seasonal analyses of the likelihood of fire reaching specific points on the landscape has demonstrated that the risks between allowing early versus late season ignitions to burn vary (Scott et al., 2012). A spatially-explicit seasonal

analysis of the likelihood of fires spreading outside the wilderness may prove to be especially useful for managers of small wilderness areas where the concerns of fires escaping the wilderness are even more of a constraint to fire use compared to expansive wilderness areas, such as the BMWC.

It may be possible to disentangle the apparent complex interactions between terrain, fuels, ignitions, and weather on EP within and adjacent to treatment areas through the use of a simulation experiment that generates thousands of artificial treatment fires, wherein treatment size, location, shape, and orientation are systematically varied. Similar simulation approaches have been used to isolate the relative importance of different landscape variables on burn probability (e.g. Parisien et al., 2010). Figure 10 shows the EP classes in detail for the observed landscape scenario. The White River flows from north to south, while the South Fork of the Flathead River has its headwaters inside the BMWC and flows north into Hungry Horse Reservoir. Qualitatively it appears that high EP values extend farther into the wilderness near the South Fork of the Flathead River, while low EP values extend closer to the wilderness boundary near the White River. It is possible that the orientation of the drainages with respect to dominant wind direction help to explain such micro-scale variation in the spatial patterns of EP. Results from case studies in California have revealed that fires have preferential orientation patterns that align with the shape and orientation of watersheds (Barros et al., 2013). However, it is very likely that there are other interacting factors that influence the spatial distribution of EP.

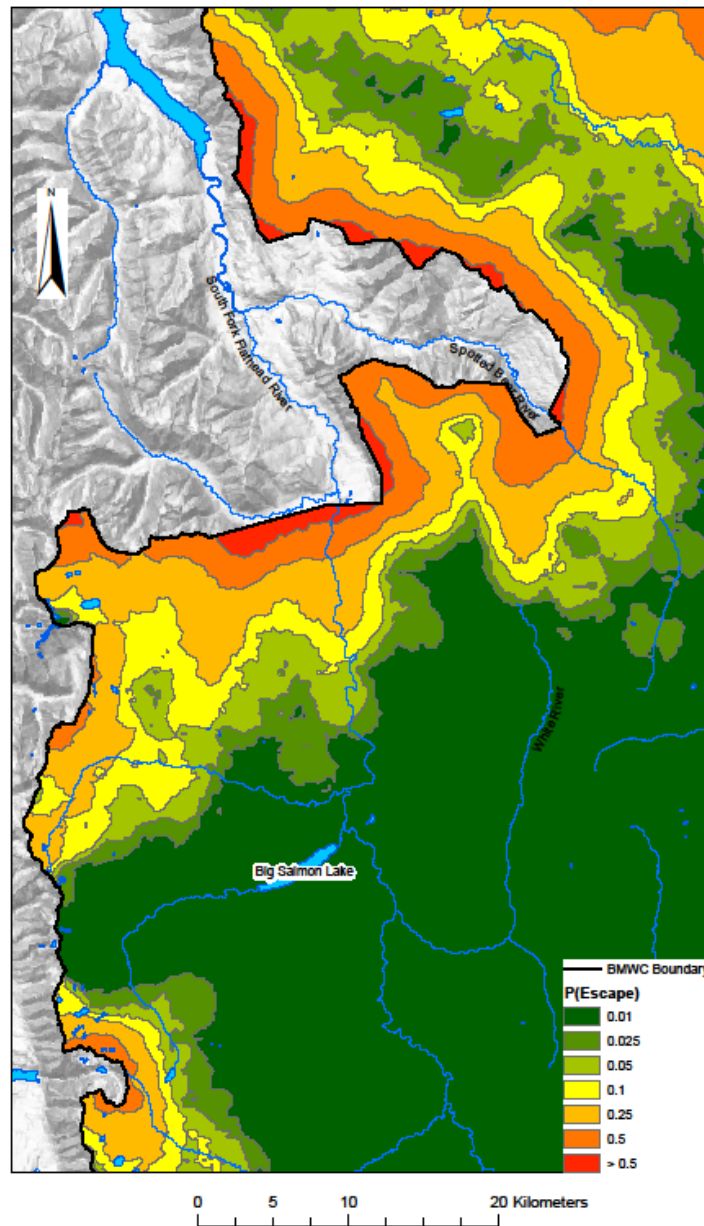


Figure 10. Classified escape probabilities for the observed landscape scenario for a selected portion of the BWC.

Attention to the temporal dynamics of fire risk will be necessary as managers face challenges associated with rapid climate change. Climate change effects could constrain the future decision-space for managers. If the flexibility managers have to allow fires to burn is predicted to shrink in the coming decades due to effects of climate change (e.g.

longer fire seasons, more extreme weather conditions, etc.), allowing natural ignitions to burn today may provide a safeguard to ensure that managers have multiple options to reduce future risk, including through the use of natural fire as a risk-mitigation tool.

The EP approach demonstrated in this case study may provide a useful framework for future work in the optimal placement of mechanical treatments. Rather than thinking of fuels treatments simply as a way to reduce the likelihood and/or intensity of wildfire, the spatio-temporal placement of fuels treatments could be designed in such a way that opportunities for managers to use less aggressive suppression strategies within wilderness are expanded (Reinhardt et al., 2008). This differs from how fuel treatments are typically prioritized which is predicated on a combination of reductions in wildfire likelihood, intensity, and effects on market and non-market resources, and does not consider or support the fuel treatment benefits of wildfire arising from less aggressive suppression strategies (Ager et al., 2013). A revised fuel treatment placement strategy where treatments are scheduled in areas adjacent to the wilderness boundary, where the likelihood of wildfire escaping is relatively high, could provide wilderness managers with additional opportunities to allow natural wilderness fires to burn by decreasing the risk such unsuppressed fires pose to resources outside the wilderness. In non-wilderness areas, consideration over the fuel treatment benefits of fire, along with how such benefits influence future manager decision space, could be incorporated into the design and implementation of traditional fuel treatments in an effort to maximize opportunities for managers to allow natural fire to burn.

6. Conclusion

There is a pressing need within the wildfire management community to integrate the management of fuels with the management of ignitions. In wilderness areas where traditional means of removing hazardous fuels are unavailable, managers' only opportunities to reduce fuels and decrease future wildfire risk is through the use of unplanned ignitions. Allowing natural ignitions to burn is a risky endeavor because of the likelihood that fire will spread to undesired areas on the landscape, such as outside the wilderness where private homes, infrastructure, habitat, and municipal watersheds are at risk of short-term, negative impacts, along with the chance that such fires will become large, difficult to contain and financially expensive to suppress. While there are numerous extant decision support tools available to wildfire managers intended to support efficient, risk-based decision-making, these tools do not provide the necessary information to wilderness managers who are looking to maximize opportunities to allow natural ignitions to burn.

In this case study, the tools of wildfire risk analysis were used develop escape probability, an alternative risk-based metric to support wilderness fire management decisions. The extent to which allowing previously suppressed ignitions to burn might reduce this likelihood in the near future was then explored through a retrospective modeling exercise. Complex interactions among treatment size and proximity to wilderness boundary were apparent. Larger treatment fires were more effective at reducing the likelihood of escaped ignitions from inside the treatment fire perimeter relative to smaller treatment fires. However, large treated areas were not a sufficient condition to reduce future escape probabilities within or near the treated area. The

location of the treatment fire with respect to the wilderness boundary appeared to have a large influence on the future likelihood of wilderness fire escape. Both large and small treatment fires that burned along or near the wilderness boundary reduced EP within their simulated perimeter. Large treatment fires in the interior of the wilderness, where observed EP is typically low, had little effect on EP within the treated area. The effects of proximity to wilderness boundary and size of treated area on off-site reductions in escape probabilities were less clear, although treatment fires that burned near the wilderness boundary were more effective at reducing the future likelihood of escaped ignitions surrounding the treated area.

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Appendix: Crosswalking FARSITE fireline intensity to burn severity

Fireline intensity values as modeled in FARSITE were classified into discrete burn severity classes to provide a platform to then modify the fuel models within the simulated perimeter. Because there is no clear empirical relationship between satellite-derived burn severity and modeled fireline intensity, it was assumed that the proportions in each of the four observed burn severity classes (i.e. very low, low, moderate, high) from 2007 in the Bob Marshall Wilderness Complex would be represented in the modeled fireline intensity aggregated amongst all treatment fires. An empirical cumulative density function was fit using modeled fireline intensity values for all of the treatment fires. Next, the fireline intensity values corresponding to the observed cumulative values were identified. Table A1 shows the proportions of observed burn severity in 2007 in the Bob Marshall Wilderness Complex, along with the associated cumulative value and the identified threshold fireline intensity values. These fireline intensity values were then used as the threshold value to classify fireline intensity into burn severity for each of the individual treatment fires. Because the distribution of modeled fireline intensity varied between the treatment fires, the proportion of crosswalked burn severity also varied between the treatment fires.

Table A1. Proportion of observed burn severity in the BMWC in 2007, their associated cumulative values, and crosswalked fireline intensity thresholds.

Burn severity class	Observed proportion	Observed cumulative	Fireline intensity threshold
Very low	0.23	0.23	1
Low	0.20	0.43	5
Moderate	0.23	0.66	41
High	0.34	1.00	n/a

Figure A1 shows the cumulative distribution of modeled fireline intensity aggregated between all retrospectively simulated fires.

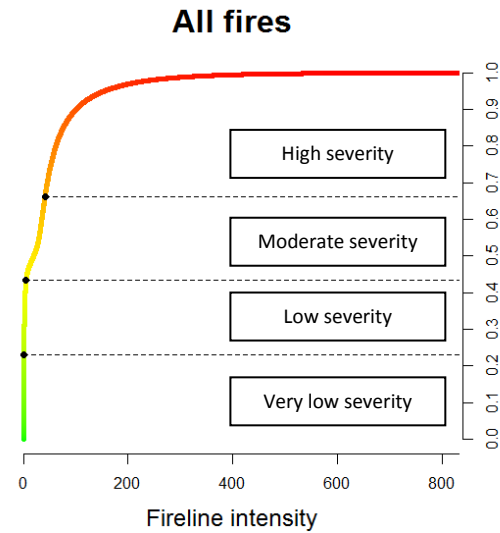


Figure A1. Cumulative distribution of fireline intensity aggregated across all treatment fires, with threshold fireline intensity values identified which were used to classify burn severity for each individual treatment fire.

Table A2. Proportions of classified burn severity for each treatment fire.

Treatment fire	Proportion of very low severity	Proportion of low severity	Proportion of moderate severity	Proportion of high severity
Dickey Lake	0.20	0.21	0.23	0.35
Desert Mountain	0.26	0.21	0.28	0.26
Sargeant	0.19	0.09	0.22	0.49
Holland Lake	0.21	0.22	0.29	0.27
Picture Ridge	0.17	0.08	0.22	0.52
Canyon Point	0.28	0.22	0.22	0.27
Lamoose	0.28	0.20	0.25	0.26
Zips	0.35	0.27	0.21	0.17
Bear Lake	0.17	0.09	0.26	0.47
Calf Creek	0.22	0.15	0.28	0.36
Burnt Creek	0.30	0.22	0.19	0.29
Little Salmon	0.24	0.15	0.17	0.44
Southfork Sun	0.23	0.19	0.19	0.39
Snow Bank	0.18	0.26	0.18	0.39
Klondike Creek	0.24	0.36	0.20	0.20
Bethel Creek	0.19	0.22	0.25	0.34
Baptiste Springs	0.22	0.21	0.24	0.33