WILDFIRE RISK AND TREATMENT PRIORITIZATION

FOR THE LOWER NORTH-SOUTH VEGETATION MANAGEMENT PLANNING AREA

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COLORADO FOREST
RESTORATION INSTITUTE
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Photo Credit: Payne Gulch prescribed fire by James Pilsmaker.

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Document Development Statement
This report documents both the methods and spatial planning products that summarize wildfire risk and forest management treatment prioritization within the Lower North-South Vegetation Management planning area. The planning area is part of an upcoming National Environmental Protect Act (NEPA) project on the South Platte Ranger District of the Pike National Forest. The development of spatial planning tools included in this report used the CFRI Risk Assessment and Decision Support (RADS) collaborative planning process. Dozens of stakeholders informed the collaboratively developed model. The goal of this report is to provide US Forest Service Staff with the necessary information to use, update, and share the spatial planning products created by the RADS model.

Acknowledgements
The authors would like to thank CFRI staff Allison Rhea and Jackie Edinger for support and discussion around continuing to advance the RADS modeling process, Anthony Martin for making the maps for this report, and Jarod Dunn for brainstorming how RADS planning tools appropriately fit into the NEPA planning process. Thanks to dozens of participants from various organizations on the South Platte NEPA Interdisciplinary Team for contributing to the development of the RADS model and providing feedback to ensure the highest quality of spatial planning tools. In particular, thank you to the core planning team: Jennifer DeWoody, Rob Addington, James Gerleman, Brian Banks, and Samuel Wallace. Editing by Hannah Brown and document layout and publication by Angela Hollingsworth. This project was funded by the Colorado Forest Restoration Institute through the Southwest Forest Health and Wildfire Prevention Act.

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Introduction

The South Platte Ranger District of the Pike National Forest (located in the central Front Range of Colorado) has a long history of collaborative forest management and restoration. Following the 2020 wildfire season, the district began the process of developing a new landscape-scale project under the formal planning process outlined by the National Environmental Protection Act (NEPA). This project is currently called the Lower North-South Vegetation Management Project (here after the Project). United States Forest Service (USFS) staff created the South Platte NEPA interdisciplinary team to inform the pre-NEPA planning process. The team quickly recognized that the Project needed a plan to strategically locate and prioritize forest management efforts to effectively use forest management funding so it would have the greatest impact on mitigating wildfire risk and promoting forest health.

The Project used the Colorado Forest Restoration Institute's Risk Assessment Decision Support (RADS) tool to inform management planning (Gannon et al. 2019). RADS expands on the risk assessment and planning framework developed by Scott et al. (2013), and follows a similar collaborative process to identify Highly Valued Resources and Assets (HVRAs), evaluate HVRA wildfire risk, and prioritize areas where forest management will have the biggest impact on reducing exceptional wildfire risk for the lowest cost. While the goal is to create spatial planning tools (e.g. maps and GIS layers) that facilitate on-the-ground decisions, the RADS modeling process also strengthens collaboration among partners by integrating a rigorous and science-based modeling approach with a stakeholder-driven social process to inform the RADS model inputs. The RADS model has been used for many landscape-scale planning efforts, including the Chaffee County Community Wildfire Protection Plan (Envision Chafee County, 2020), the Jefferson County Open Space Forest Health Plan (Jefferson County Open Space, 2022), and the Northern Colorado Fireshed Collaborative Spatial Strategy.

The risk assessment model incorporates local spatial data on HVRAs, expertise on HRVA response to wildfire and forest management activities, and relative importance values to create a science-informed, locally-relevant risk assessment for the Project's planning area. Leveraging the risk assessment, the prioritization model identified cost-effective opportunities for management at the project scale using available spatial data on management constraints, including feasibility and cost, to identify where forest management has the largest relative benefit to protect and enhance HVRAs compared to the cost of those management actions (Figure 1).

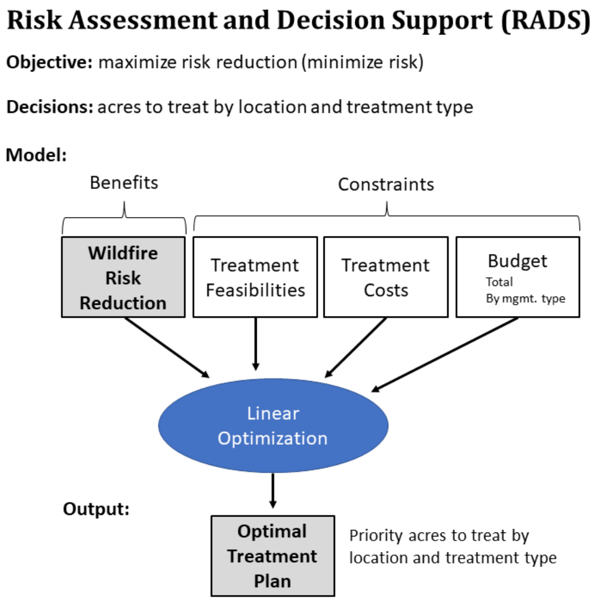


Figure 1. Conceptual diagram of the Risk Assessment and Decision Support (RADS) fuel treatment optimization model. Fuel treatment benefits and constraints are summarized for the feasible treatment area in each treatment unit. Modeling outputs can then demonstrate where treatments will maximize risk reduction for the available budget.

Collaborative Modeling Effort

The RADS modeling effort for the Project was informed by more than 40 individuals from numerous organizations. Most participants were from the U.S. Forest Service (USFS) or the Colorado Forest Restoration Institute (CFRI), with the remainder representing stakeholder organizations such as state and local public land agencies, water providers, research institutions, industry associations, and conservation non-profits. Individuals were involved in the modeling effort at various levels depending on their area of expertise and their organization's involvement in the planning area.

This team provided feedback on initial model inputs (e.g., modeled fire behavior) and selection of highly valued resources and assets (HVRAs). Most collaboration took place during three meetings focused on refining HVRA details used by the model to evaluate wildfire risk across the planning area. For each HVRA, participants discussed and agreed upon the relative importance weight, spatial extent, and wildfire response function. Each meeting tackled specific categories of values and participants were invited to attend meetings based on their area of expertise. A large, in-person workshop addressed all final HVRA categories included in the RADS model: life safety, infrastructure, wildland-urban interface, water, recreation, natural resource use, and vegetation cover. Another meeting focused solely on wildlife values. There was a third meeting focused on cultural resources but, due to data sensitivity, this HVRA category was not included in the model. Cultural resources were an important factor when evaluating impact in the NEPA planning process and were considered in other sections of the overall NEPA analysis. Each meeting began with an overview of the RADS model and a more focused discussion on the role of HVRAs in forest management. Participants then discussed the individual HVRAs and collaboratively decided on relative importance values and wildfire response functions for each. The group came to a consensus on most values but when they did not, sub-groups were formed to further investigate questions or gather additional data needed for decision-making.

The discussion about the lodgepole pine vegetation cover HVRA illustrates how the group made decisions about likely wildfire impacts during these meetings. Lodgepole pine was given a moderate relative importance score because wildfires in this forest type would be of high severity, but high severity fire is not out of the historic range of variability for this forest type. Any disturbance in lodgepole pine forests would open areas for aspen expansion, which the group saw as beneficial. When considering wildfire response functions, the group made note of lodgepole pine stands in the planning area, as they considerably impact fire dynamics. Most stands within the planning area are of mixed age rather than the even-aged or two-aged stands common in other lodgepole pine forests in this region. The group decided that the cumulative impact from fires with flame lengths less than 2 feet would be neutral. Fires with flame lengths between 2 and 8 feet would have a net benefit because they would increase the age diversity of lodgepole pine by removing small patches of trees and creating open areas for seedlings to establish without causing "scorched earth" conditions. When flames are higher than 8 feet, the fires would be destructive but still within the historic range of variability for lodgepole pine forests. The negative wildfire response at higher flame lengths is caused by the length of time needed for vegetation to regrow following these intense fires. The lodgepole pine conversation was a typical decision-making process; similar discussions informed relative importance and wildfire response for all other HVRAs.

Following each of these collaborative meetings, a smaller group of mostly USFS and CFRI staff met regularly and refined the model to the final version presented here. Updates to the model were shared with the larger collaborative group for feedback. Numerous modifications to model inputs, logic, and outputs were made to best represent the knowledge gleaned from collaborative meetings. The model incrementally became more aligned with the South Platte Ranger District's needs and values, expert advice, stakeholder opinion, and scientific research.

Wildfire Risk Assessment Framework

The Wildfire Risk Assessment followed the framework described in Scott et al. (2013), A Wildfire Risk Assessment Framework for Land and Resource Management. This framework has been widely used in other prioritization efforts in Colorado and across the Western US, including the Colorado Wildfire Risk Assessment (CO-WRA) (Technosylva 2018). First, CFRI and USFS gathered relevant data within the local landscape and context to inform fire simulation products, HVRA spatial data and response functions, and relative importance weights within the risk assessment framework (Figure 2).

Fire behavior metrics, including flame lengths and crown fire activity were modeled in FlamMap 5 (Finney et al. 2015) for low, moderate, high, and extreme fire weather scenarios. We considered several burn probability options, but ultimately local fire specialists and the

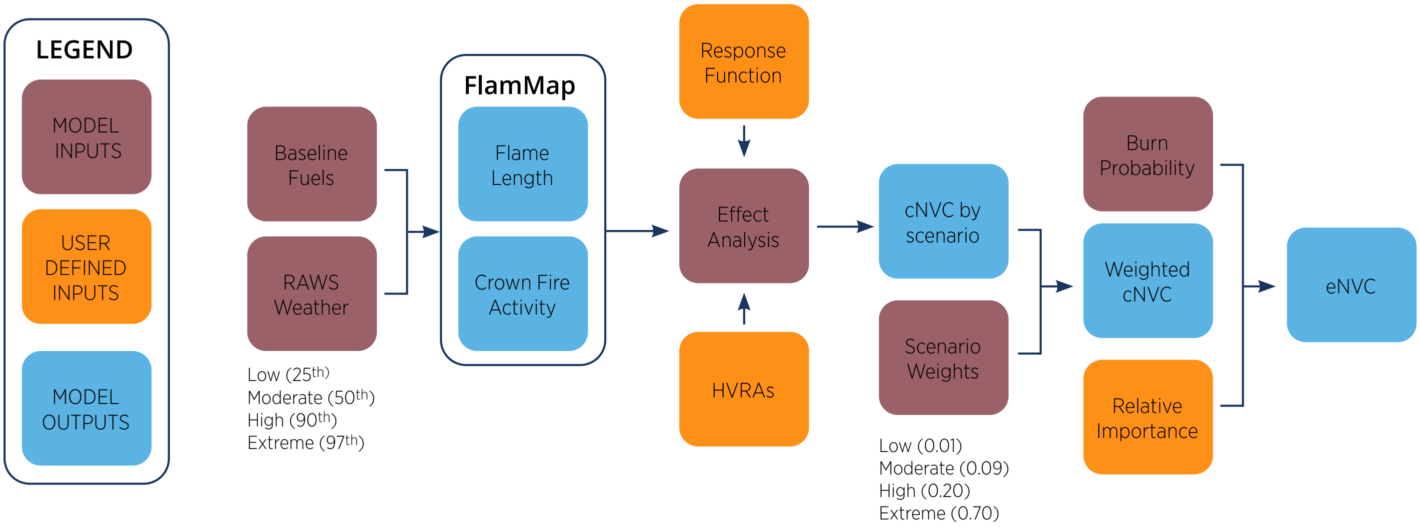


Figure 2. Wildfire Risk Assessment framework (cNVC: conditional net value change; eNVC: expected net value change).

technical team decided to use a locally calibrated burn probability product from the large fire simulator (FSim, Finney et al., 2011). FSim uses a Monte Carlo simulation approach to represent 1,000s-10,000s years of fire activity by linking models for fire weather, ignitions, growth, and suppression. This spatial estimate of burn probability predicts more fire activity in mid to high-elevation forests and less fire activity in the low-elevation woodland and non-forest vegetation types compared to existing products such as CO-WRA (Technoslyva 2018) and National FSim (Short et al. 2020). This matched local experiences and expectations of fire occurrence in the project boundary. See Appendix B (Wildfire Hazard Modeling) for a more detailed description of methods.

Fire behavior outputs were then combined with data on HVRA extent and science-informed responses of HVRAs to wildfire to calculate the conditional Net Value Change (cNVC) for each HVRA and fire weather scenario. The multiple cNVC measures for each HVRA were combined with a weighted averaging that favored the high and extreme fire behavior weather scenarios (Technosylva 2018). Lastly, the cNVC measures for each HVRA were combined with burn probability and relative importance weights to compute a composite expected Net Value Change (eNVC; “risk”) map.

The terms conditional and expected net value change (cNVC and eNVC), wildfire risk, and risk reduction are used. These metrics are unitless and are relative measures of whole actuarial risk that combine and index fire intensity (flame length and crown fire activity), numbers associated with wildfire and treatment response for each HVRA, and the probability of fire occurrence (eNVC only). Wildfire risk is synonymous with cNVC and eNVC, and risk reduction is the difference between eNVC before and after simulated treatments.

HVRAs and relative importance weights

In order to model risk across the landscape, USFS and stakeholders identified data sources representing geospatial HVRAs to include in the assessment and prioritized the importance of HVRAs relative to each other. An optional buffer distance was added to some HVRAs to define a greater zone of influence to represent the area for which an HVRA was expected to influence management actions beyond the spatially mapped extent. Then, relative importance weights were defined at two levels. Each HVRA was placed under a category, and each category was assigned a relative importance value used to weigh the contribution of each HVRA category to the composite risk map (Table 1). For each HVRA, a relative importance weight was assigned to reflect its proportional contribution to an HVRA category (Table 2). HVRA selection and assignment of relative importance was conducted by resource experts through small group discussions and full group critique.

Table 1. Relative importance weights used for combining HVRA categories into a composite risk map.

Category	**Relative Importance**
Life Safety	100
Water	90
WUI	85
Infrastructure	70
Recreation	45
Natural Resource Use	45
Vegetation Cover	45
Wildlife	45

Exposure and effects assessment

Using a science-informed process, resource experts provided input on each HVRA’s response to fire intensity level (Table 2). Relative HVRA response was quantified on a scale from -100 for total loss to +100 for complete restoration to account for both negative and beneficial potential effects of fire. The RADS model used these inputs to generate cNVC raster outputs for each HVRA by applying the response function to the predicted fire behavior within each HVRA’s extent. Each fire weather scenario was assessed separately, and then scenarios were combined into a single cNVC raster for each HVRA using a weighted average (Figure 3). We used the same scenario weighting scheme as CO-WRA (Technosylva 2018), which reflects that the most area was expected to burn under high and extreme fire weather scenarios (Table 3), consistent with recent wildfire activity in Colorado (Haas et al. 2015; Graham et al. 2003). Methods to delineate the wildland-urban-interface-adjacent private property response are described in Appendix B. The response of the water supply risk HVRA was quantified with a separate process described in Appendix C.

Table 3. Probabilities for weighting cNVC calculated for each fire weather scenario.

Scenario	Percentile	Probability
Low	25th	0.01
Moderate	50th	0.09
High	90th	0.20
Extreme	97th	0.70

Table 2. HVRAs included in the risk assessment by category. The buffer distance used to define an influence zone for wildfire around the HVRA, the HVRA relative importance (%) to the category, and the relative wildfire response functions by intensity level are specified. All inputs were defined through a collaborative process using stakeholder input informed by expert opinion and data resources.

Category	**HVRA**	**Buffer (m)**	**Relative Importance**	**Wildfire Response – Flame Length (feet)**					
				0-2	**2-4**	**4-6**	**6-8**	**8-12**	**> 12**
Life Safety	Evacuation Routes (roads) - High Priority	100	50	0	-20	-60	-100	-100	-100
	Evacuation Routes (roads) - Medium Priority	100	30	0	-20	-60	-100	-100	-100
	Evacuation Routes (roads) - Low Priority	100	5	0	-20	-60	-100	-100	-100
	Emergency Access Roads	100	15	0	-20	-60	-100	-100	-100
Wildland Urban Interface (WUI)	Structure Loss	0	100	NA	NA	NA	NA	NA	NA
Water	Water Supply Risk	0	100	NA	NA	NA	NA	NA	NA
Infrastructure	Electrical Transmission Lines	100	60	0	-60	-100	-100	-100	-100
	Communication Infrastructure	100	35	-15	-30	-60	-100	-100	-100
	Weather Infrastructure	50	5	-30	-60	-80	-100	-100	-100
Recreation	Recreation Facilities	100	30	-10	-30	-100	-100	-100	-100
	Recreation Site	200	20	-10	-20	-100	-100	-100	-100
	Trails	6	10	10	-10	-80	-80	-80	-80
	Trail Infrastructure (built infrastructure)	25	10	0	-40	-100	-100	-100	-100
	Campgrounds	100	20	0	-40	-100	-100	-100	-100
	Dispersed Campsites	25	10	0	-10	-80	-80	-80	-80
Natural Resource Use	Grazing Infrastructure	50	5	20	-50	-100	-100	-100	-100
	Christmas Tree Cutting Areas	0	40	-30	-60	-100	-100	-100	-100
	Timber Supply Layers	0	55	20	-20	-70	-100	-100	-100
Vegetation Cover	Subalpine (Spruce/Fir)	0	10	0	10	20	10	-60	-90
	Lodgepole Pine	0	15	0	10	20	30	-60	-90
	Aspen	0	20	0	20	50	50	0	0
	Mixed-Conifer	0	20	70	50	50	10	-40	-90
	Ponderosa Pine	0	25	100	100	60	-10	-50	-90
	Shrubland	0	15	20	-10	-50	-80	-90	-100
	Riparian	0	5	10	-5	-30	-50	-100	-100
Wildlife	Bighorn Sheep	0	15	20	40	80	100	100	90
	Elk	0	10	70	70	80	100	60	40
	Mule Deer	0	10	70	70	80	100	90	80
	Black bear	0	5	10	20	40	50	30	20
	Preble's Jumping mouse	0	10	70	40	0	-50	-70	-100
	Pawnee Montane Skipper	0	30	100	100	60	0	-50	-90

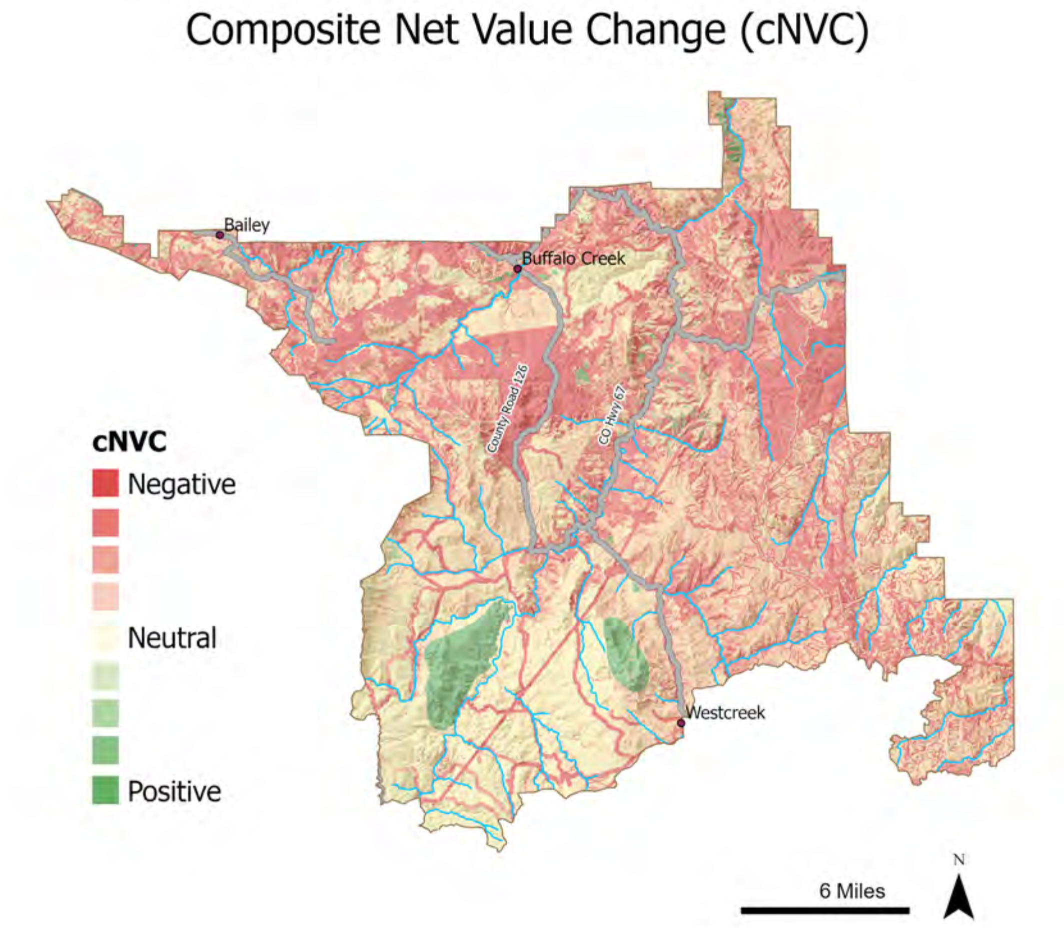


Figure 3. Composite conditional net value change (cNVC) wildfire risk map. Negative cNVC means high risk of negative impacts. Positive cNVC means there is an expected benefit from wildfire.

Wildfire risk within the planning area

Composite wildfire risk maps were generated for the project area (Figure 4, Figures 4a-4h). See Appendix A for an alternative visualization of wildfire risk and benefit based on percentile risk. The more negative the eNVC, the greater the risk to HVRAs from wildfire, while a positive eNVC means there was an expected benefit from wildfire. Within the Project planning area, the greatest risk to multiple HVRAs is concentrated to the north and east. The high potential for fire spread into population centers within the wildland-urban interface along these boundaries is driving higher risk in these areas (Figure 4h). In the same areas, recreation use (Figure 4d) along the Front Range and timber supply areas (Figure 4c) are also increasing risk.

Expected positive benefits from wildfire were concentrated within the southwestern portion of the Project. This area is located in mainly shrubland and grassland vegetation types, which are neutral or generally benefit from exposure to wildfire (Figure 4e). Populations of bighorn sheep, which can benefit from fire-restored habitats, are also located in this area (Figure 4g).

Management units

Prioritization was assessed at three different management unit scales: 1) USGS Watershed Boundary Dataset Hydraulic Unit Code 12 (HUC 12) Watershed catchments, 2) Potential Delineation Units (PODs), 3) USFS Vegetation-based units.

Treatment types

This prioritization considered three treatment types: 1) thin only, 2) prescribed fire only, and 3) thin + prescribed fire; prescribed fire is broadcast burning, not burning of slash piles. For the Wildfire Risk Assessment prioritization, treatments were simulated by altering the baseline fuels data from LANDFIRE (2016) and the Colorado Wildfire Risk Assessment (Technosylva 2018) surface and canopy fuel attributes in accordance with the mean effect sizes for hazardous fuels reduction and forest restoration projects in the western U.S. (Ziegler et al. 2017; Fulé et al. 2012; Stephens et al. 2009; Stephens and Moghaddas 2005). Treatment effects on canopy attributes were applied as proportional adjustments to the pre-treatment data, and treatment effects on surface fuels were represented by changing the fire behavior fuel model (Scott & Burgan 2005; see Appendix B).

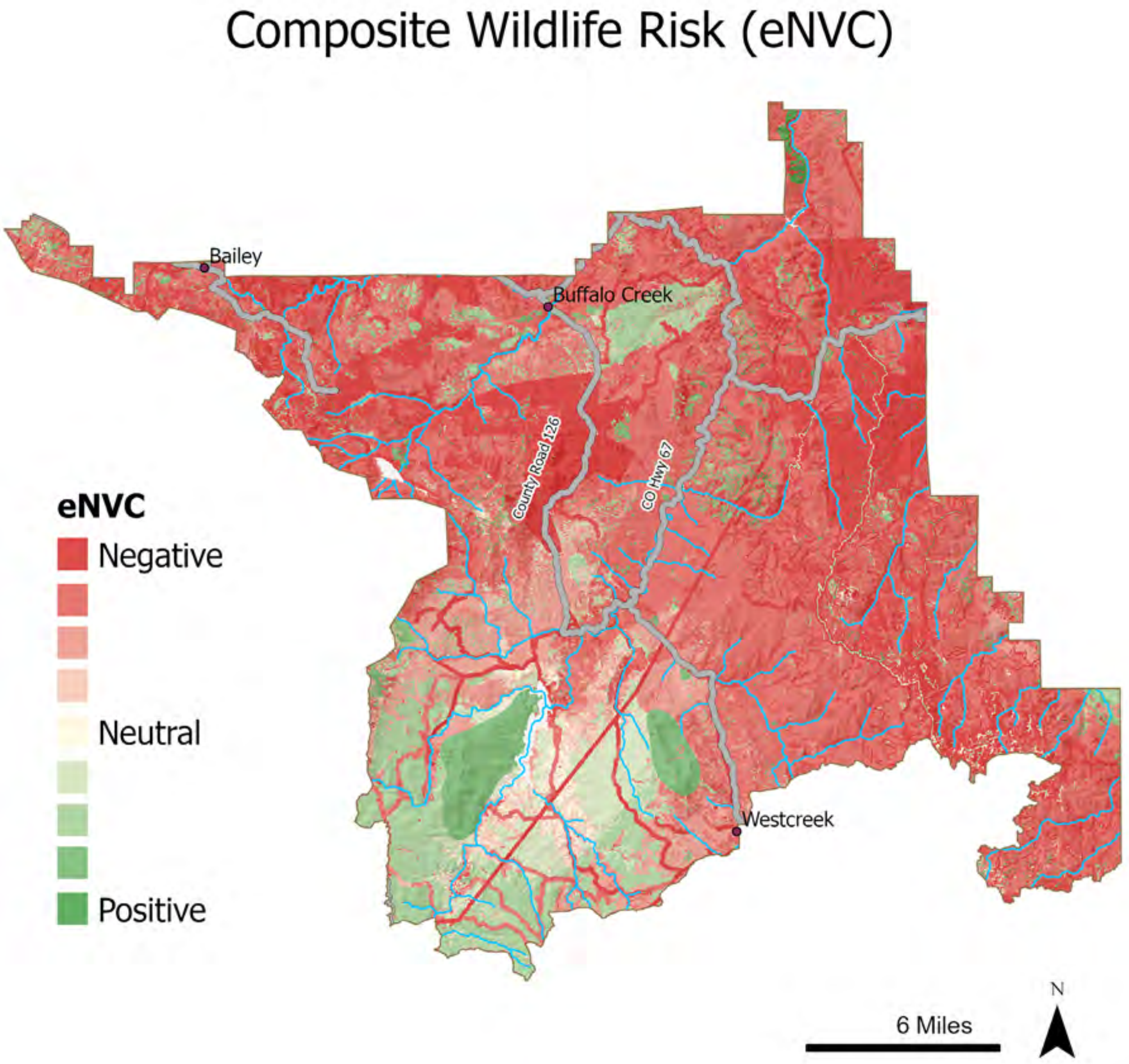


Figure 4. Composite wildfire risk map. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from wildfire.

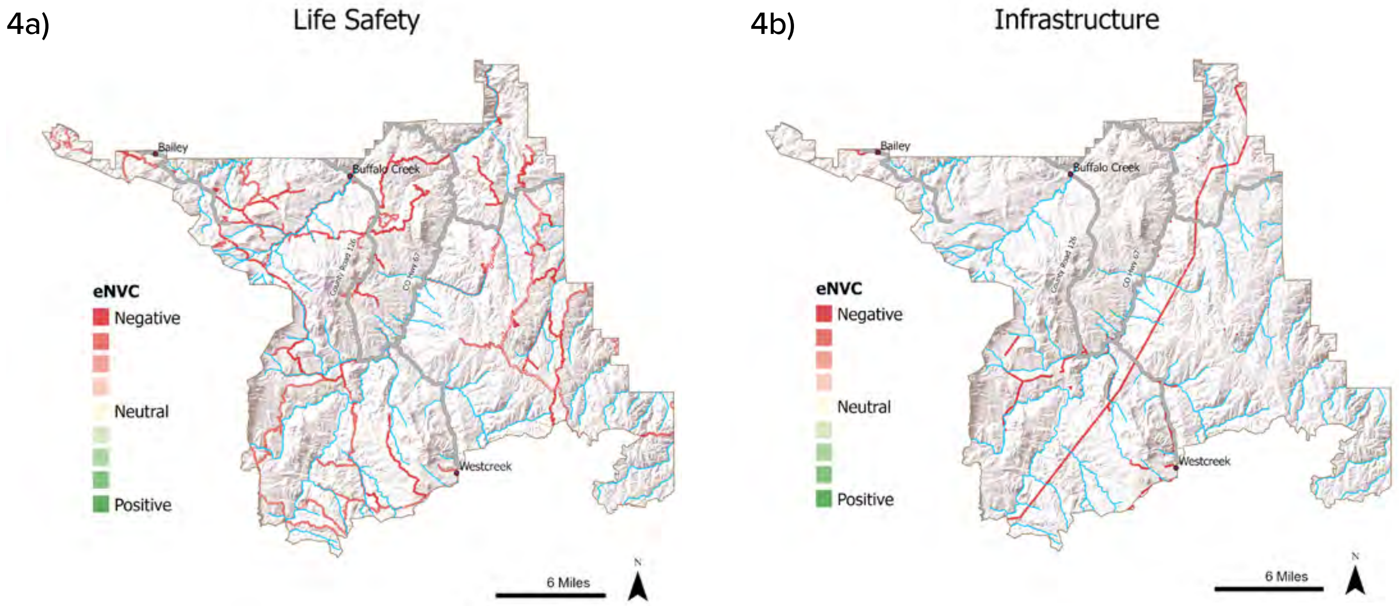
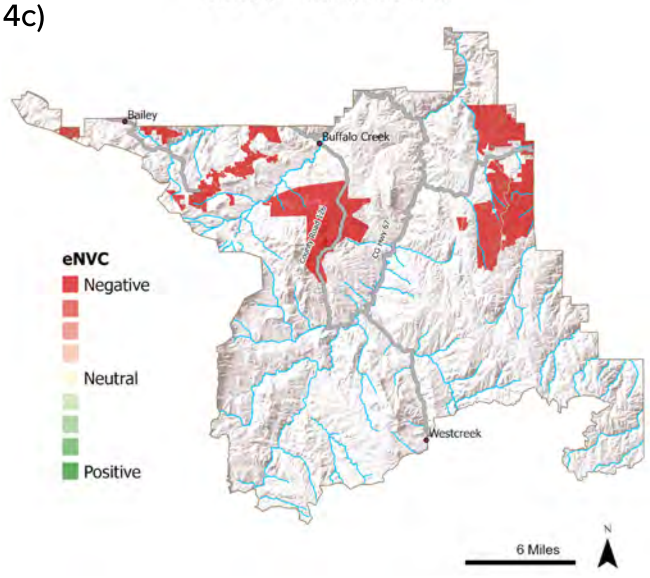
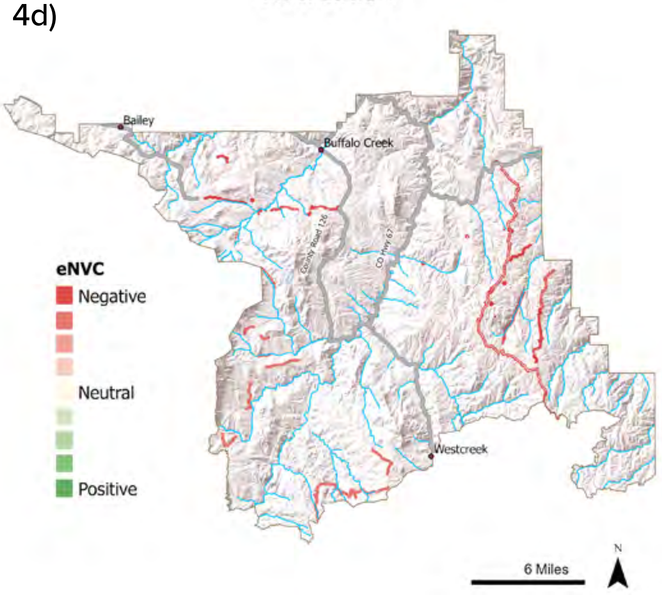


Figure 4a-h. Composite wildfire risk map for each HVRA category. More maps on next page.

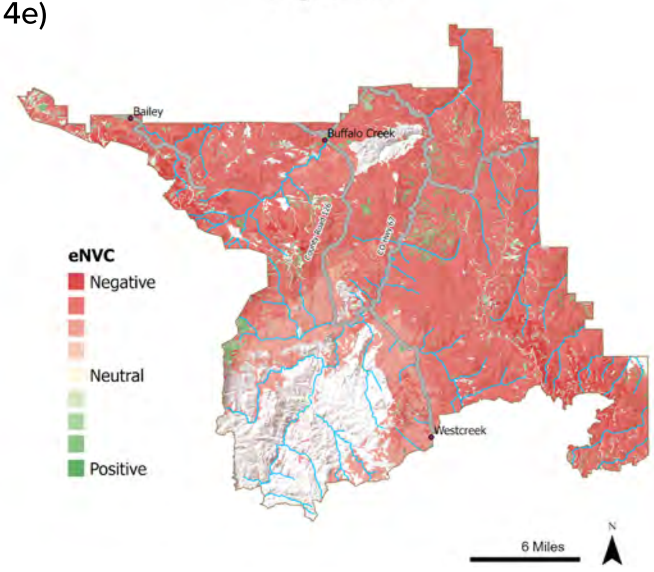
4c) Natural Resource Use



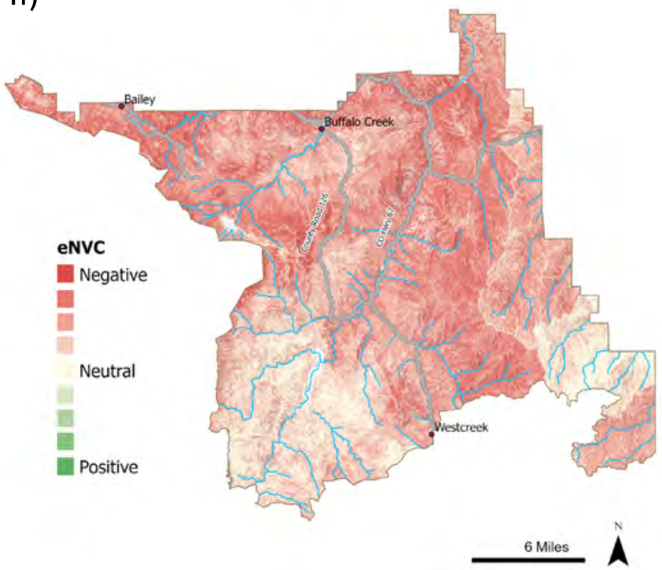
4d) Recreation



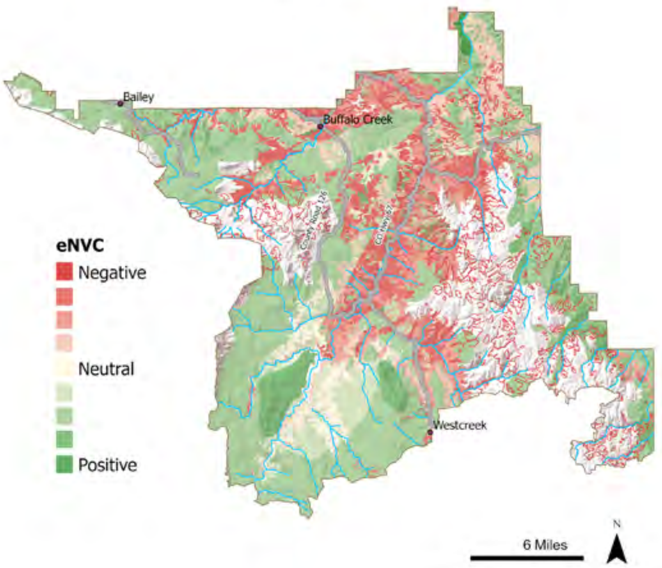
4e) Vegetation



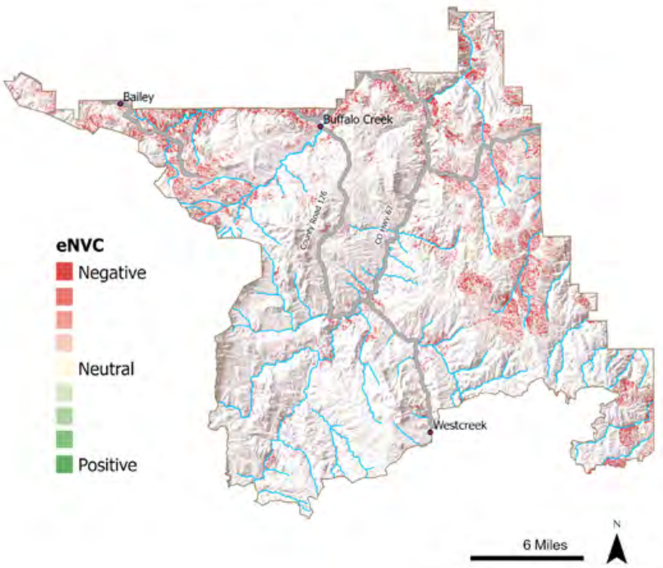
4f) Water



4g) Wildlife



4h) Wildlife Urban Interface



Treatment feasibility

Hard constraints were captured in binary rasters representing whether each pixel was feasible (1) or infeasible (0) for each of the target treatment types. Treatment feasibility does not consider economic constraints, and was meant to capture only the possibility for treatment. Operational constraints such as steep slopes and the practicality of treatment were instead captured with variable treatment costs described in the Treatment Cost section.

Making slopes above 40% or 60% unfeasible was considered; however, only 1,174 acres within the Project area boundary were on slopes above 40% and only 4 acres were on slopes above 60%. This is less than 1% of the Project area, so these areas remain feasible for treatment as this constraint is better captured within treatment costs.

Feasible locations for the thin-only treatment were defined by the following constraints:

- Forest presence (LANDFIRE canopy cover ≥ 10%)
- No treatment in wilderness
- No treatment in upper tier roadless

Feasible locations for the thin + prescribed fire treatment were assumed to be the same as the thin-only treatment. Given these constraints, 182,577 acres or 70% of Project were considered feasible for the thin-only or thin + prescribed fire treatment (Figure 5).

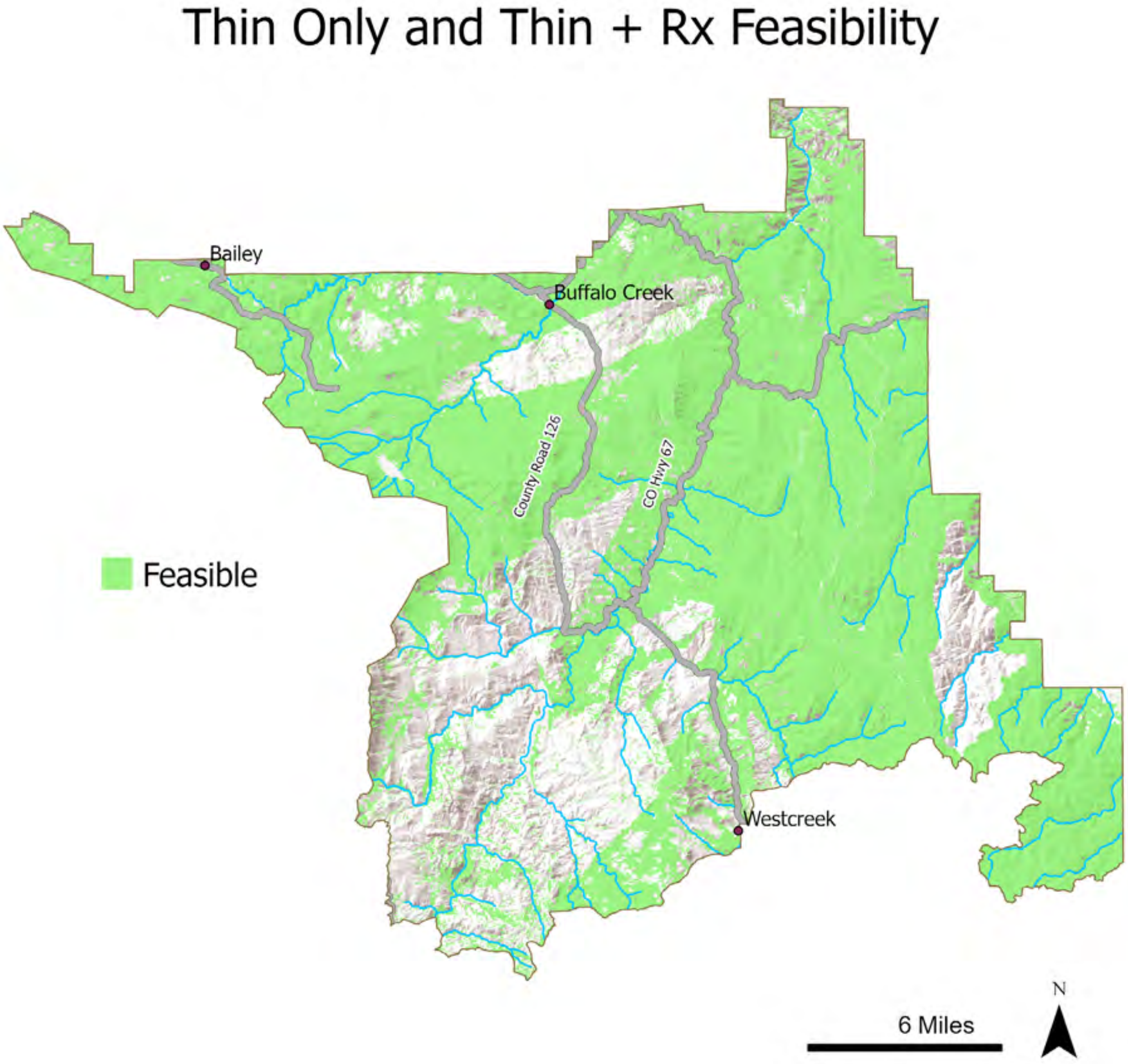


Figure 5. Feasible locations for the thin-only and thin + prescribed fire treatments.

Feasible locations for the prescribed fire-only treatment were limited to “frequent” fire forest, shrubland, and grassland types that can be burned with prescribed fire as a first entry treatment —no high elevation forest types (lodgepole or spruce-fir), developed areas, or non-burnable vegetation types were included.

To capture that it was unrealistic to drastically increase prescribed fire use in the short term, an additional constraint was created to limit spending on prescribed fire to 25% of the total budget. Given these constraints, 215,867 acres or 83% of the Project area were considered feasible for the prescribed fire-only treatments (Figure 6).

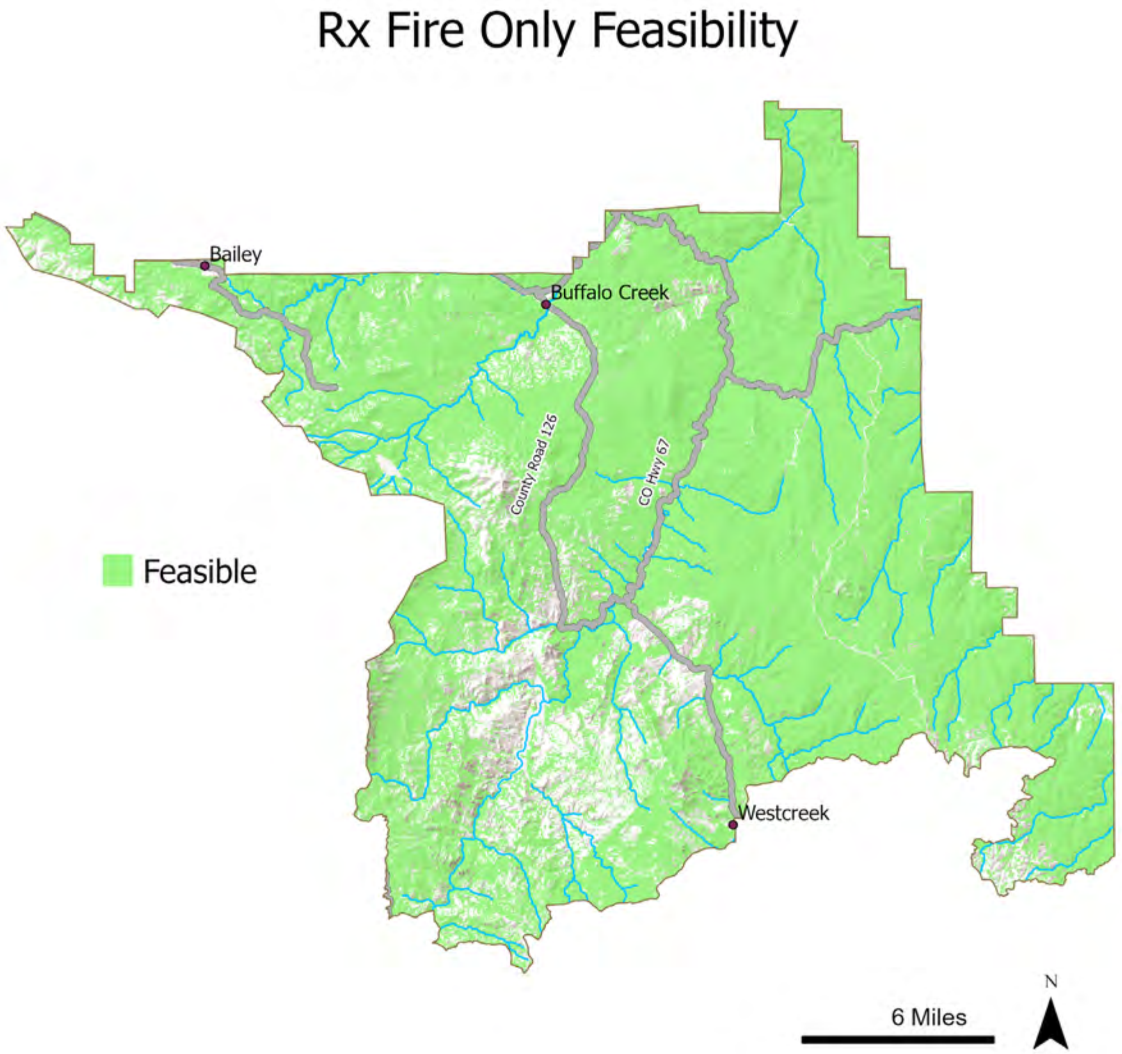


Figure 6. Feasible locations for prescribed fire-only treatment.

Given all management constraints, approximately 226,613 acres or 87% of project area were feasible for thin-only and/or prescribed fire treatments.

Treatment cost

Treatment costs were based primarily on expert opinion because current treatment cost models either do not consider landscape-scale variation (Calkin & Gebert 2006), or require detailed data on stand conditions that is not available for most landscapes (Fight et al. 2006).

Per-acre cost for the thin-only treatment was approximated by adapting a model developed in northern Colorado (Gannon et al. 2019) for use in the Project planning area. Cost was considered a function of base treatment cost under ideal conditions ($2,500/ac), with adjustments for distance from roads and slope steepness. Cost increased with distance from roads > 800 m, and with slope > 40%. Total thinning cost was limited to a maximum of $10,000/ac if the combined costs of road distance and slope adjustments exceeded $10,000/ac. The thin-only treatment costs are shown in Figure 7.

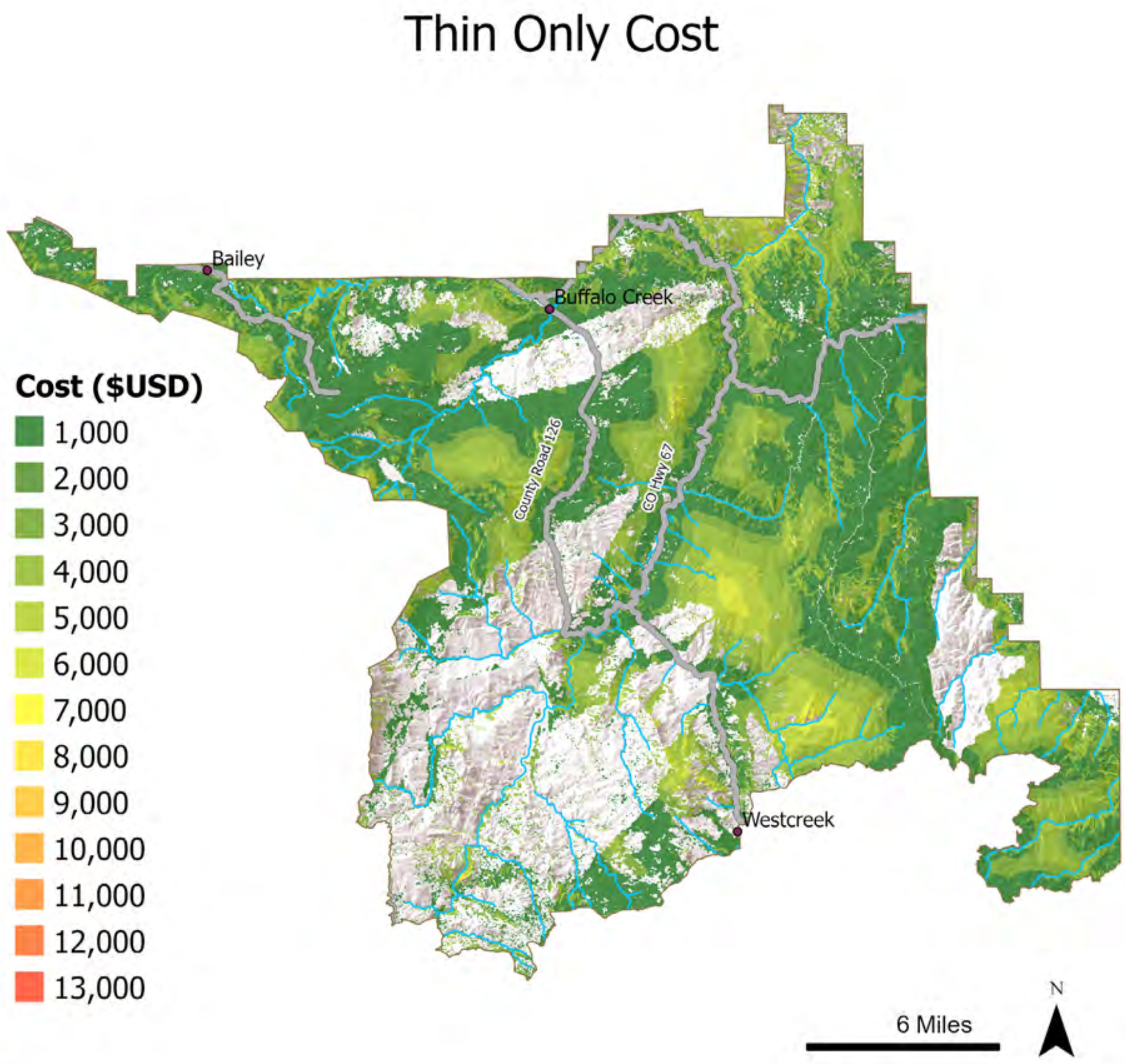


Figure 7. Thin-only treatment costs estimated using distance from roads and slope steepness.

Per-acre cost for the prescribed fire-only treatment was assumed constant depending on the distance from WUI. While prescribed fire costs do vary widely, the causes of this variation are highly site and condition specific and therefore difficult to quantify with coarse spatial data. Prescribed fire costs are difficult to characterize in part because preparation costs are not consistently recorded. We assumed a flat rate of $1,000/ac when > 250m from mapped WUI to cover both the preparation and day-of costs. Within 250 m of mapped WUI, we assumed an increase in costs of $3,000/ac due to extra planning and increased safety measures around homes and structures. The prescribed fire-only treatment costs are shown in Figure 8.

Per-acre cost for the thin + prescribed fire treatment was assumed to be the sum of the thin-only and prescribed fire treatment costs. The thin + prescribed fire treatment costs are shown in Figure 9.

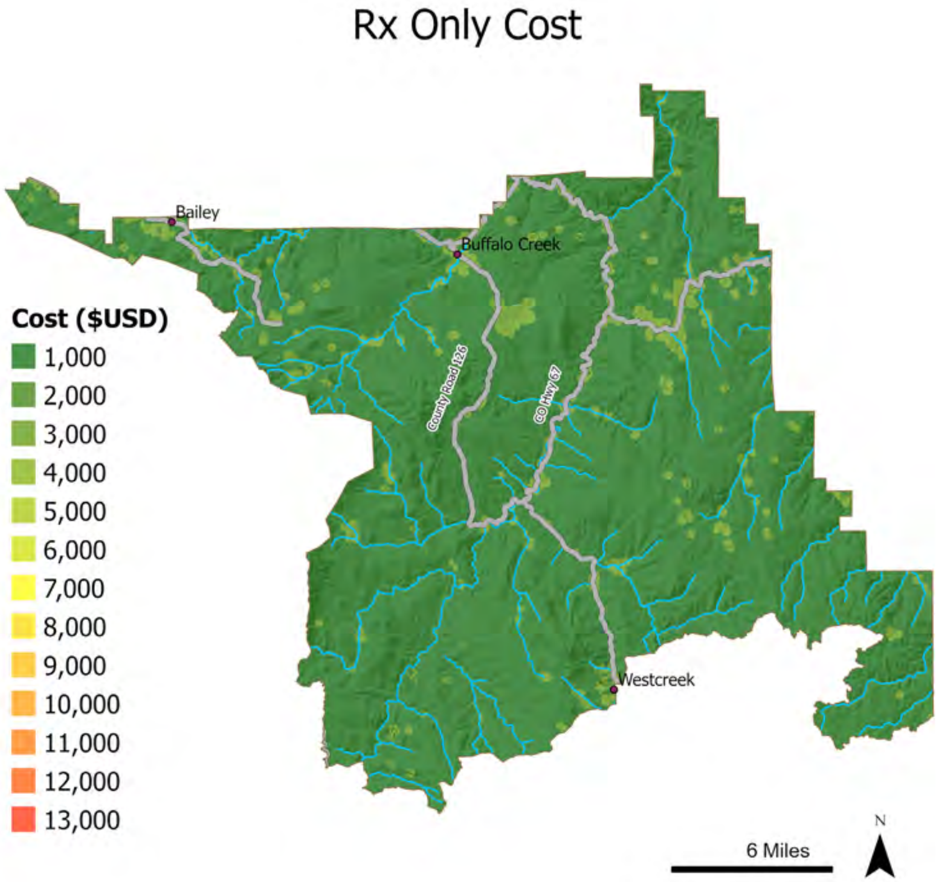


Figure 8. Prescribed fire-only treatment costs for estimated as a constant value based on distance to WUI.

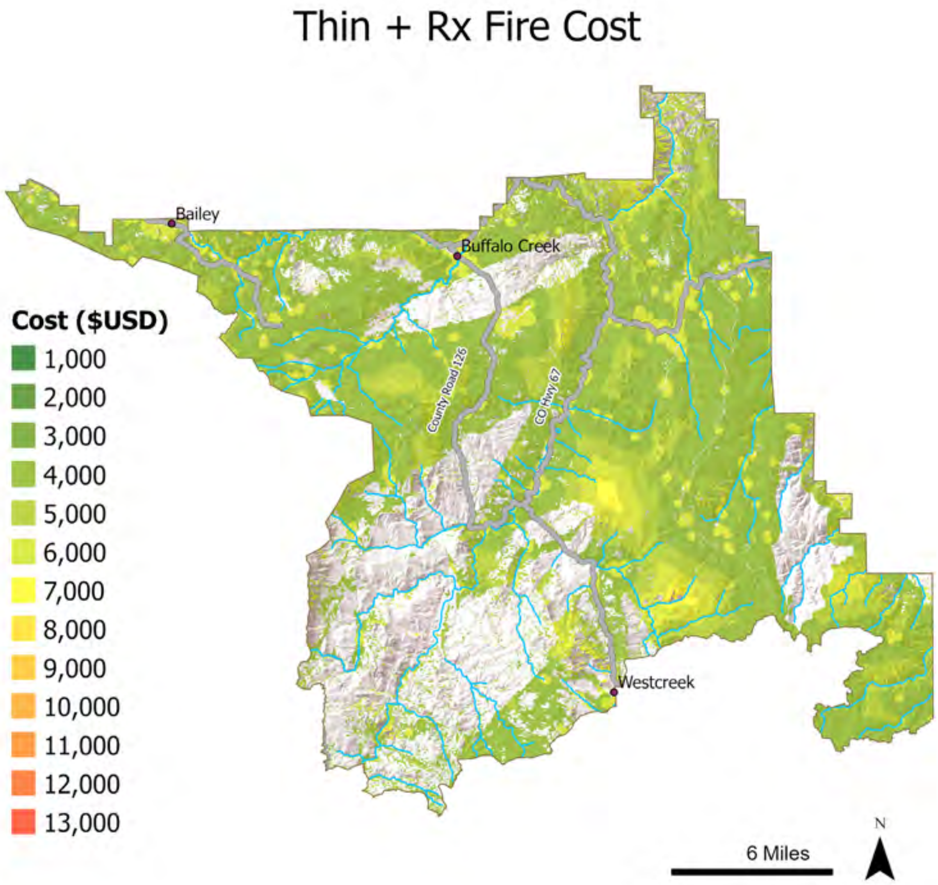


Figure 9. Thin + prescribed fire treatment costs for estimated as the sum of the thin-only and prescribed fire costs.

Risk reduction

The risk reduction benefit of treatment was assessed on a per-pixel basis as the difference between current risk and simulated post-treatment risk using the Wildfire Risk Assessment. Fuel treatments affect fire behavior (flame lengths, crown fire activity) as modeled with FlamMap 5 (Finney et al. 2015), but not burn probability. This approach was consistent with the primary objectives of fuel treatments (Reinhardt et al. 2008), but it could underestimate fuel treatment benefits where they are expected to reduce area burned (Thompson et al. 2013). Risk reduction estimates are mapped for each treatment type in Figure 10 through Figure 12.

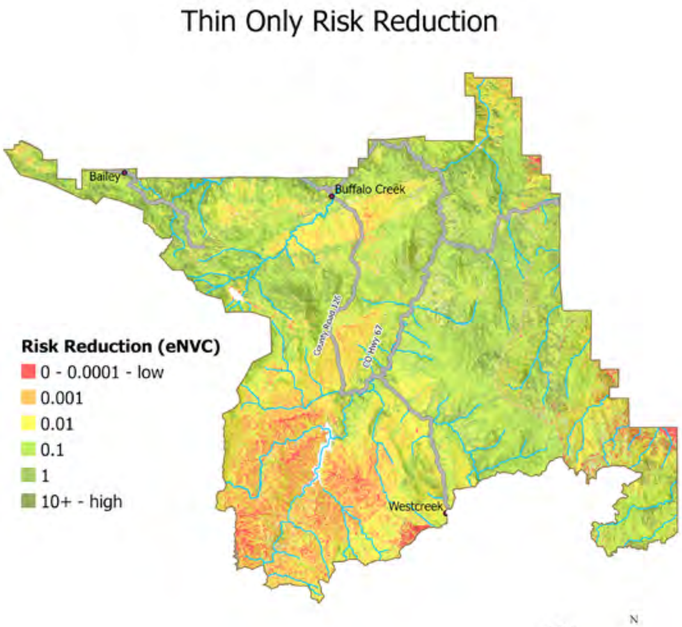


Figure 10. Estimated risk reduction for the thin-only treatment.

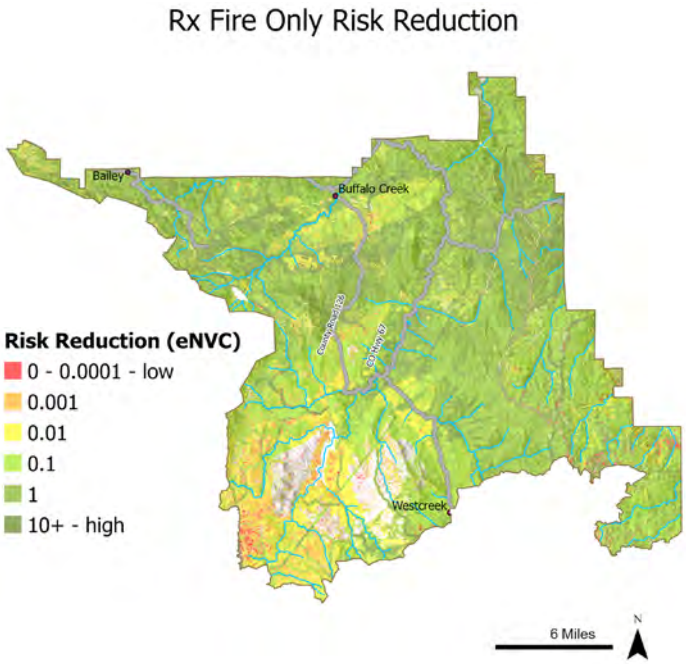


Figure 11. Estimated risk reduction for the prescribed fire-only treatment.

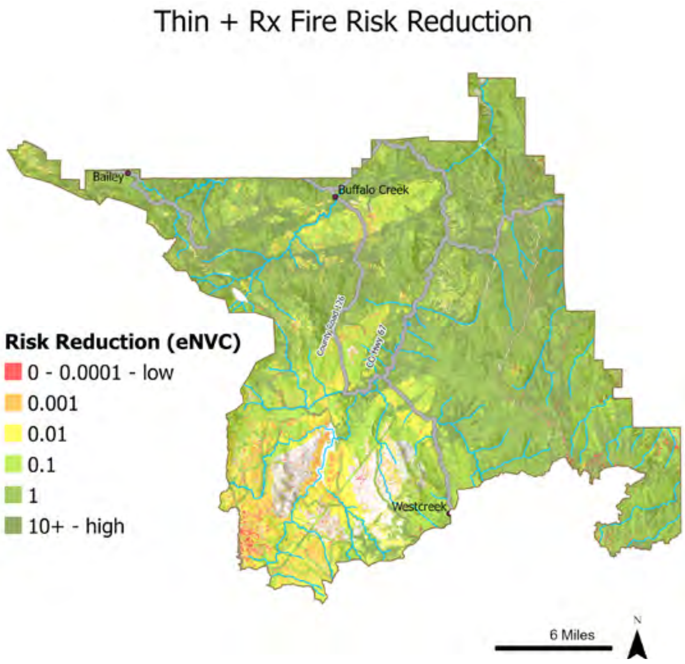


Figure 12. Estimated risk reduction for the thin + prescribed fire treatment.

For all treatments, the greatest risk (eNVC) reduction was spread throughout the northern and eastern half of the project area where the majority of the risk was initially indicated. The prescribed fire-only treatment reduced risk over a greater area than the thin-only treatment. The thin + prescribed fire treatment showed the greatest risk reduction per pixel since it was essentially two treatments, each incrementally decreasing risk.

Fuel treatment prioritization

After assessing wildfire risk, the RADS model prioritized fuel treatment type and location considering the constraints on treatment feasibility and cost. RADS uses a generalized form of the linear programming optimization model described in Gannon et al. (2019) to select treatment locations and types that maximize risk reduction for a given budget.

Spatial scales provide an important organizational framework for forest management, because actions at one scale influence outcomes at other scales. Priorities can change when looking across scales (Addington et al. 2018); therefore, spatial management units were defined at three different scales for more comprehensive decision-making within the Project boundary. The model resulted in four treatment plan options that represent the most cost-effective means to reduce wildfire risk at different scales given the specified feasibility and budget constraints (Table 4).

Table 4. Management unit and priority budget range and increments of the four resulting prioritization plans.

Management Unit	Budget Range (in millions)
HUC 12 Catchment	$100-$600 in $100 increments
POD	$100-$600 in $100 increments
Vegetation Units	$100-$600 in $100 increments
Vegetation Units	$5-$25 in $5 increments

The RADS model identified the optimal treatment locations and types for a wide range of budget levels from $5M to $600M. Areas selected at a lower budget level were more cost effective than those selected at higher budget levels. Cost effectiveness (Figures 13-15) in the RADS model balanced risk reduction with treatment cost (risk reduction/treatment cost), and often selected the more expensive thin + prescribed fire treatment because there was substantial benefit to treating both canopy and surface fuels.

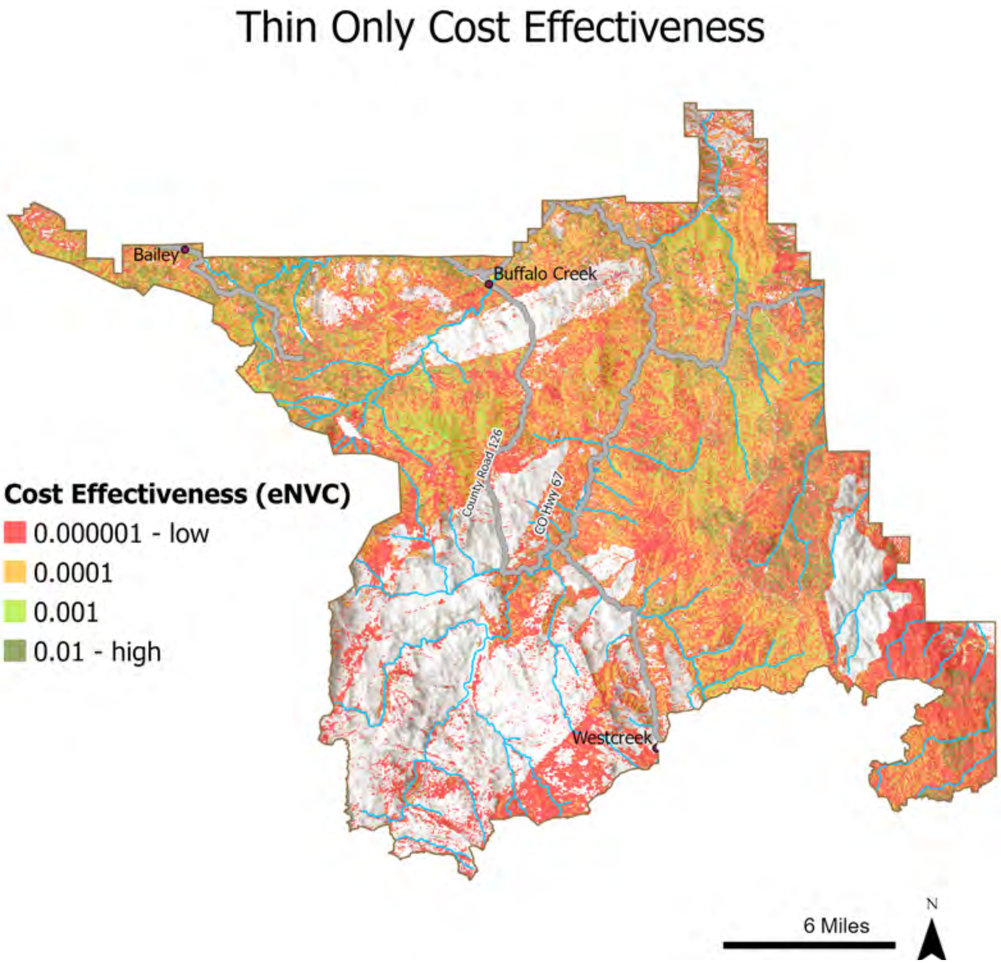


Figure 13. Cost effectiveness for the thin-only treatment.

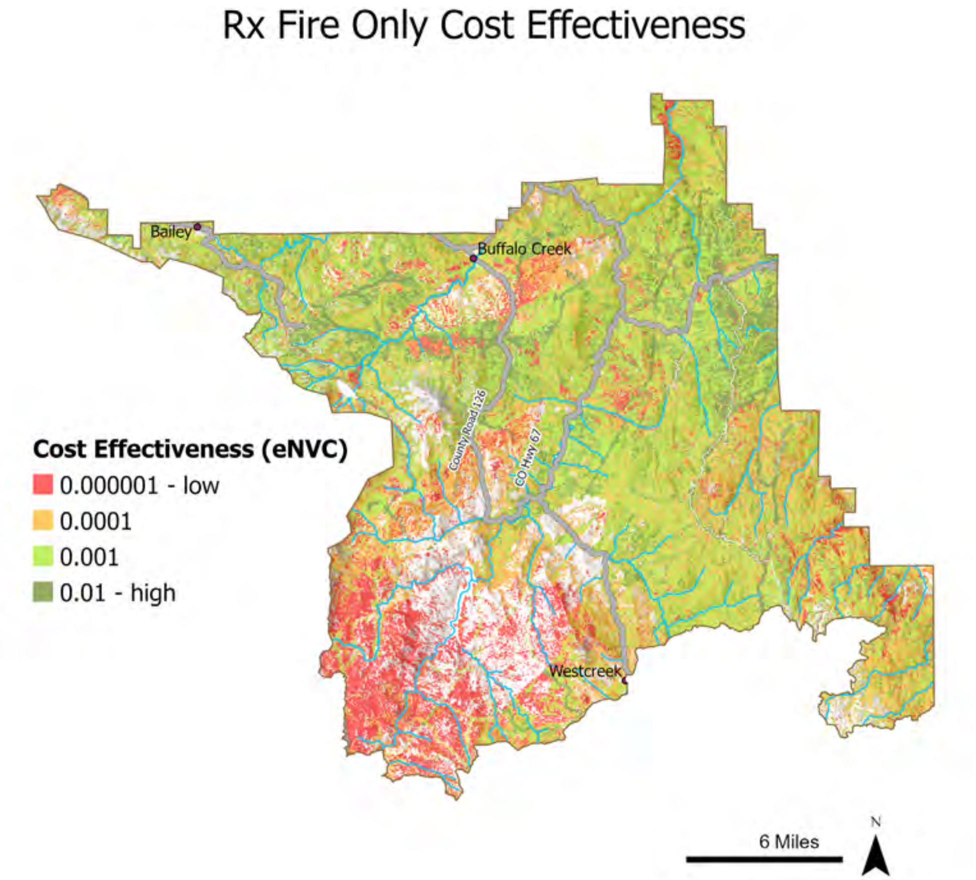


Figure 14. Cost effectiveness for the prescribed fire-only treatment.

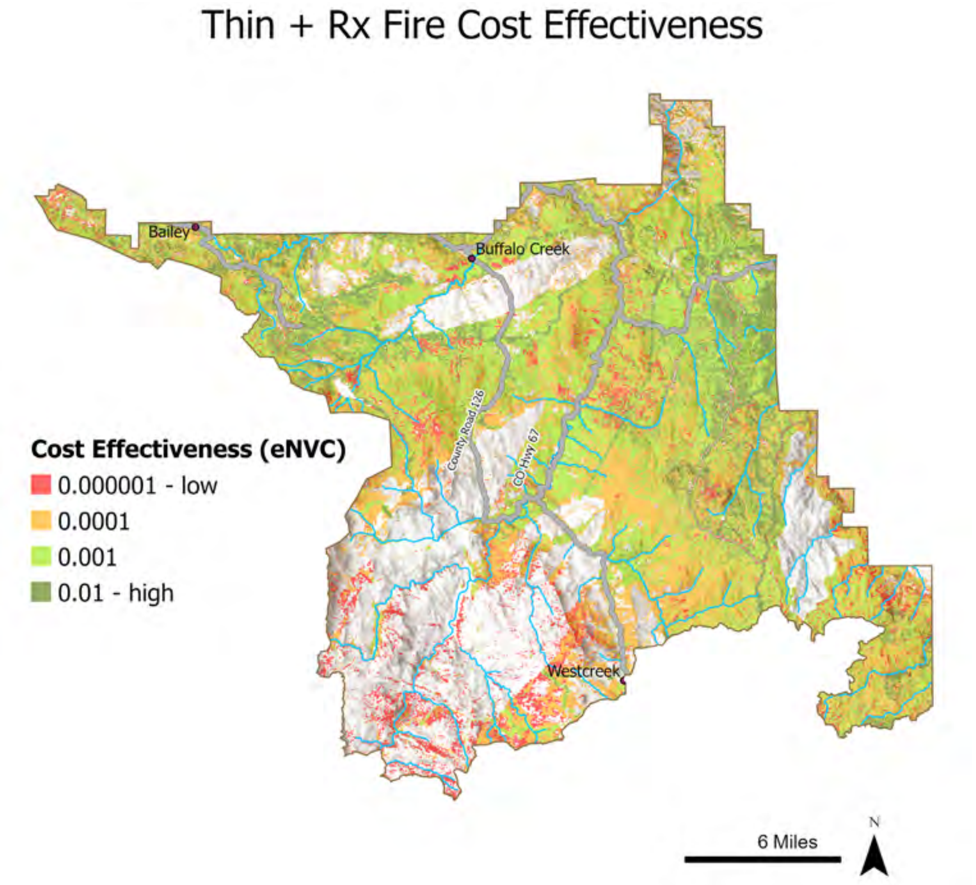


Figure 15. Cost effectiveness for the thin + prescribed fire treatment.

Wildfire risk priorities and risk reduction by budget

Forest management seeks to reduce risks to acceptable levels. These fuel treatment prioritization plans focus on risk reduction that can be mitigated by forest management; however, forest management alone cannot reduce all of the risk to resources and assets. Treatment acres and locations were prioritized by maximizing risk reduction relative to treatment costs. The returns for reducing additional risk with higher budgets decrease as the treatment plan starts to include lower priority acres where benefits are low and/or treatment costs are high. This prioritization process highlights the most cost-effective acres as the highest priority, informing where the treatment plan can gain the biggest 'bang for the buck' by implementing forest management.

HUC 12 Catchment

The HUC 12 Catchment wildfire risk prioritization map prioritized 171,465 feasible acres within the Project boundary for the $600M budget (Figure 16a). There were 41,209 feasible acres identified as first priority within 10 catchments (Table 5). Higher priority catchments were located along the north and eastern boundaries of the Project planning area and generally decreased in priority moving south and west.

Table 5. Feasible acres by priority for each prioritization plan.

Management Unit	Priority 1	Priority 2	Priority 3	Priority 4	Priority 5	Priority 6
	Acres	Acres	Acres	Acres	Acres	Acres
HUC 12 Catchment	41,209	40,243	42,544	13,685	16,434	17,349
POD	40,433	42,205	40,726	40	21,201	8,080
Vegetation Units ($600M)	40,952	42,155	41,722	41,578	21,983	10,300
Vegetation Units ($25M)	2,094	2,098	2,117	2,110	2,171	

An avoided risk analysis showed that treating the highest priority acres would reduce approximately 40% of the risk that can be mitigated by forest management with a budget of approximately $100 million (3% of total risk; Figure 16b). Increasing the budget to $600 million to treat all the priority acres would reduce risk by an additional 59%, for a total of 99% risk that can be mitigated by forest management reduced (8% of total risk). Thin + prescribed fire was identified as the most cost-effective treatment across the possible range of budgets to achieve the greatest amount of wildfire risk reduction (Figure 16b).

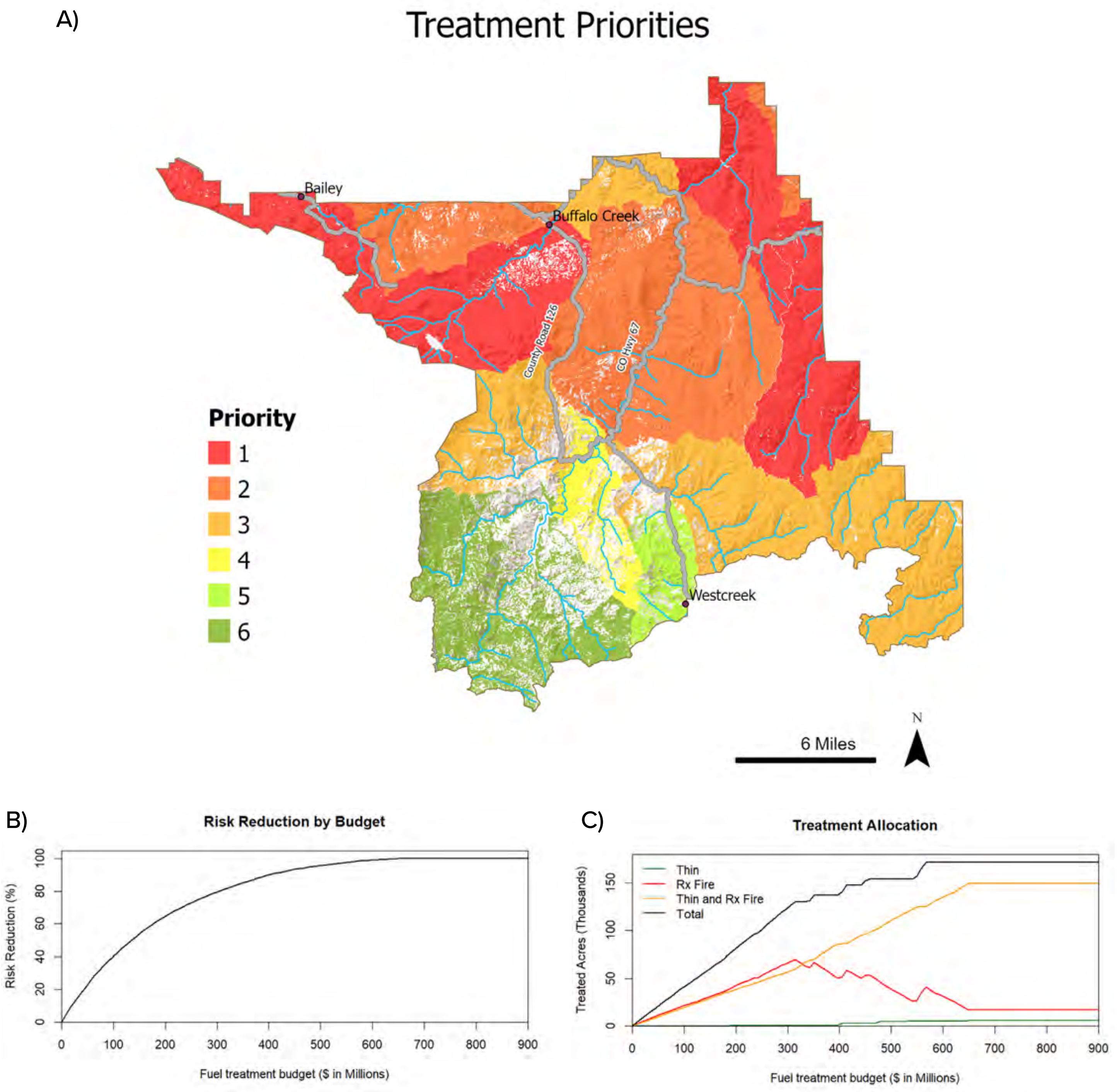


Figure 16. Wildfire risk fuel treatment prioritization of HUC 12 Catchments. Treatment priorities correspond to fuel treatment budgets from $100M to $600M, incrementally increasing by $100M. The top panel shows cumulative wildfire risk reduction achieved as budgets increase to support more forest treatment. Risk reduction is presented as the percent of total risk reduction that can be mitigated by forest management if every feasible acre is treated. Idealized treatment type allocations are tracked across the possible range of budgets in the lower panels for wildfire risk.

PODs

The PODs wildfire risk prioritization map prioritized 152,685 feasible acres within the Project boundary for the $600M budget (Figure 17a). There were 40,433 feasible acres identified as first priority within 10 units (Table 5). Higher-priority PODs were located along the northwest and eastern boundaries of the Project planning area, and priority decreased moving south and west.

An avoided risk analysis showed that treating the highest priority acres would reduce approximately 42% of the risk that can be mitigated by forest management with a budget of approximately $100 million (3% of total risk; Figure 17b).

Increasing the budget to $600 million to treat all of the priority acres would reduce risk by another 68% and treat all of the feasible risk that can be mitigated by forest management (8% of total risk). Thin + prescribed fire was identified as the most cost-effective treatment across the possible range of budgets to achieve the greatest amount of wildfire risk reduction (Figure 17b).

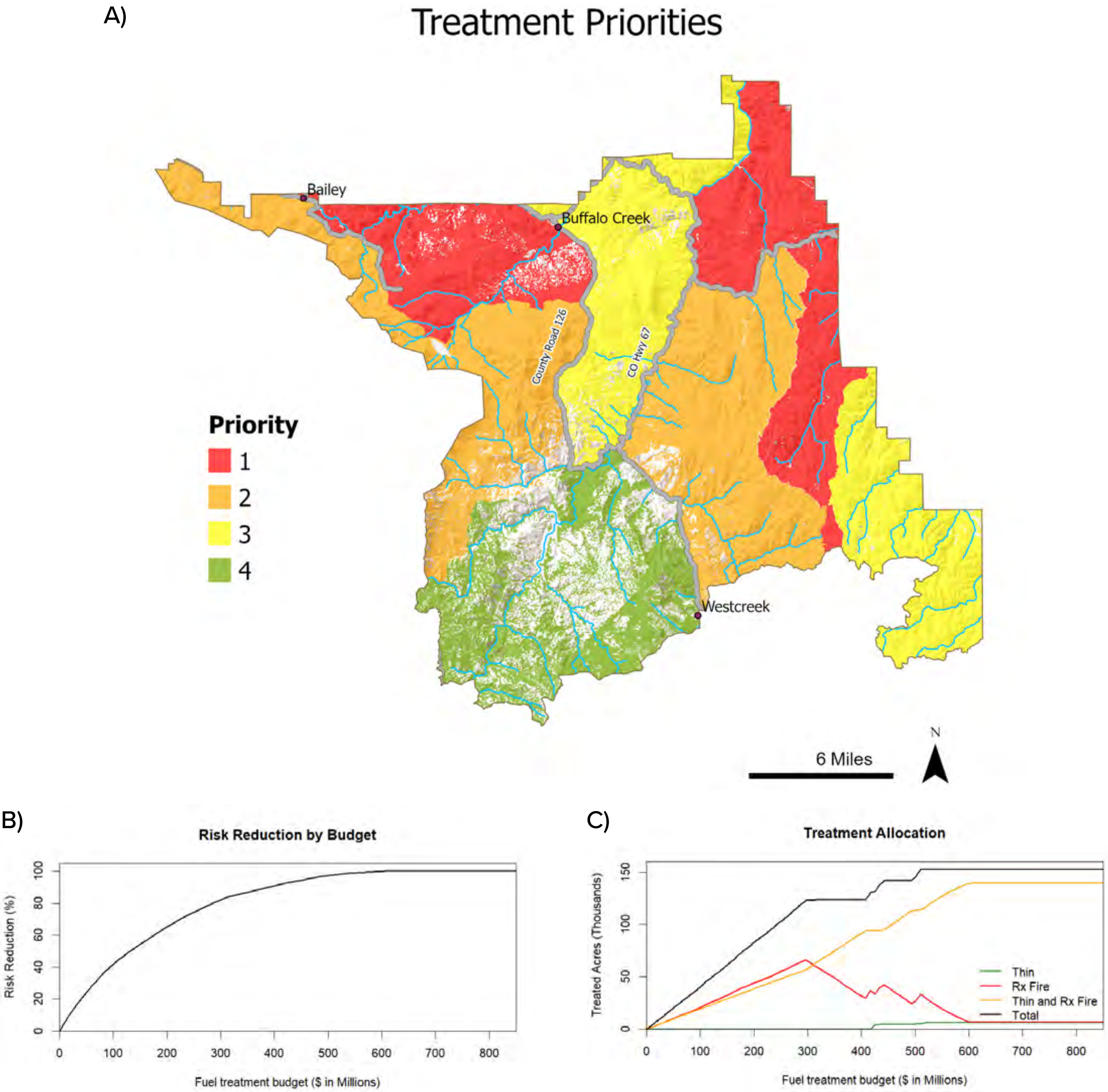


Figure 17. Wildfire risk fuel treatment prioritization of POD. Treatment priorities correspond to fuel treatment budgets from $100M to $600M, incrementally increasing by $100M. The top panels show cumulative wildfire risk reduction achieved as budgets increase to support more forest treatment. Risk reduction is presented as the percent of total risk reduction that can be mitigated by forest management if every feasible acre is treated. Idealized treatment type allocations are tracked across the possible range of budgets in the lower panels for wildfire risk.

Vegetation Units

The Vegetation Units wildfire risk prioritization map prioritized 198,690 feasible acres within the Project boundary and the $600M budget (Figure 18a). There were 40,952 feasible acres identified as first priority within 40 units (Figure 18b). Higher-priority units were located along the northwest and eastern boundaries of the Project planning area.

Medium-priority units were located in the central area of the Project planning area, and the lowest-priority units were generally located in the southern half of the Project planning area.

An avoided risk analysis showed that treating the highest priority acres would reduce approximately 38% of the risk that can be mitigated by forest management with a budget of approximately $100 million (6% of total risk; Figure 18b). Increasing the budget to $600 million to treat all the priority acres would reduce risk by another 58% for a total of 97% risk reduction that can be mitigated by forest management (16% of total risk). Prescribed fire-only and the thin + prescribed fire treatments were identified as the most cost-effective across the possible range of budgets to achieve the greatest amount of wildfire risk reduction (Figure 18b). Notably, after spending approximately $400M, prescribed fire alone was decreasingly effective at reducing wildfire risk.

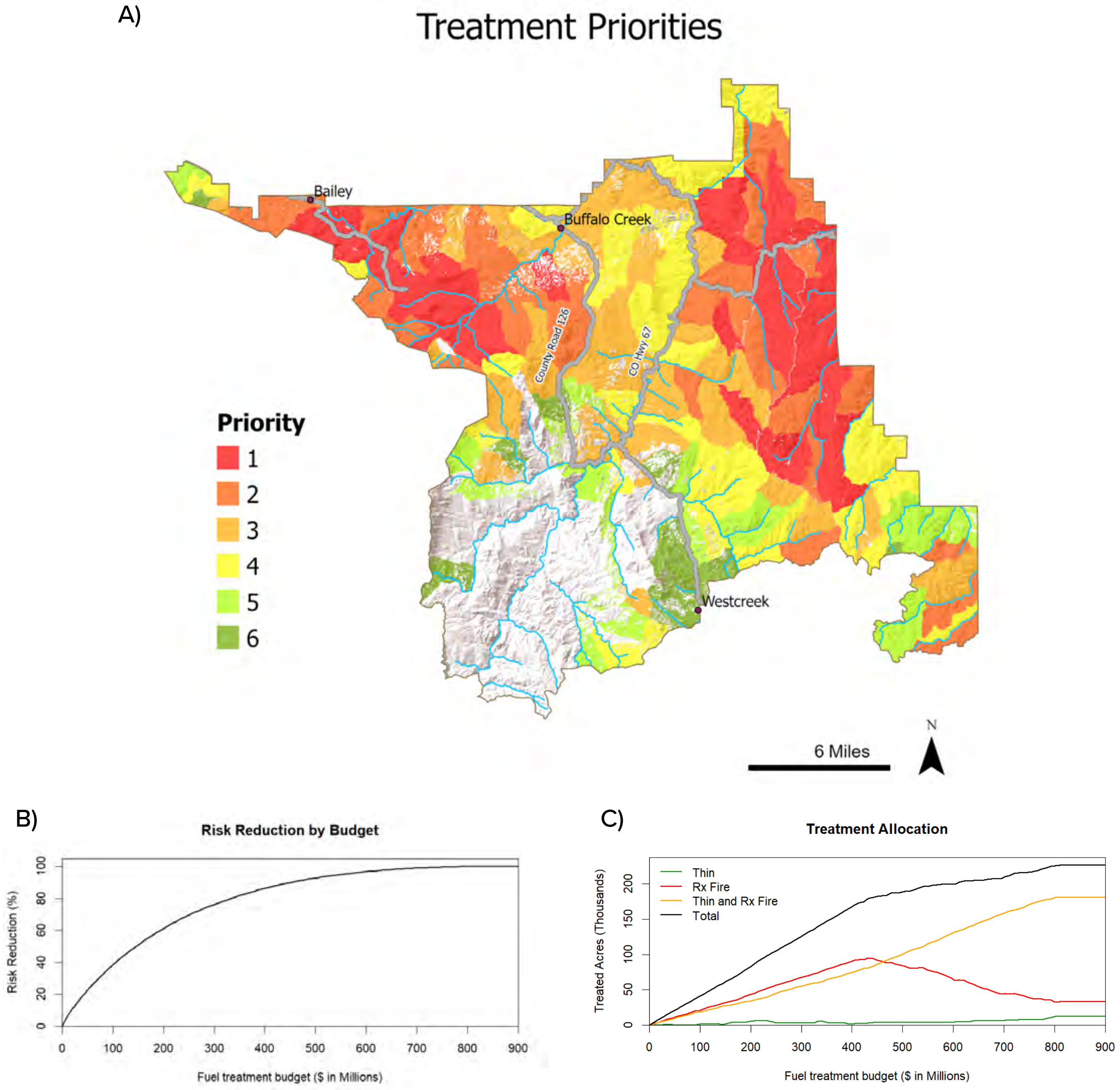


Figure 18. Wildfire risk fuel treatment prioritization of Vegetation Units. Treatment priorities correspond to fuel treatment budgets from $100M to $600M, incrementally increasing by $100M. The top panels show cumulative wildfire risk reduction achieved as budgets increase to support more forest treatment. Risk reduction is presented as the percent of total risk reduction that can be mitigated by forest management if every feasible acre is treated. Idealized treatment type allocations are tracked across the possible range of budgets in the lower panels for wildfire risk.

The Vegetation Units wildfire risk prioritization map prioritized 10,590 feasible acres within the Project boundary for the $25M budget (Figure 19a). There were 2,094 feasible acres identified as first priority within 2 catchments (Figure 19b). The highest-priority units were located towards the northeast border of the Project planning area; though, all units but one second priority unit were located along the eastern border of the Project planning area under this small budget scenario.

An avoided risk analysis showed that treating the highest priority acres would reduce risk by approximately 3% of the risk that can be mitigated by forest management with a budget of approximately $5 million (1% of total risk; Figure 19b). Prescribed fire only and the thin + prescribed fire treatments were identified as the most cost-effective across the possible range of budgets to achieve the greatest amount of wildfire risk reduction (Figure 18b).

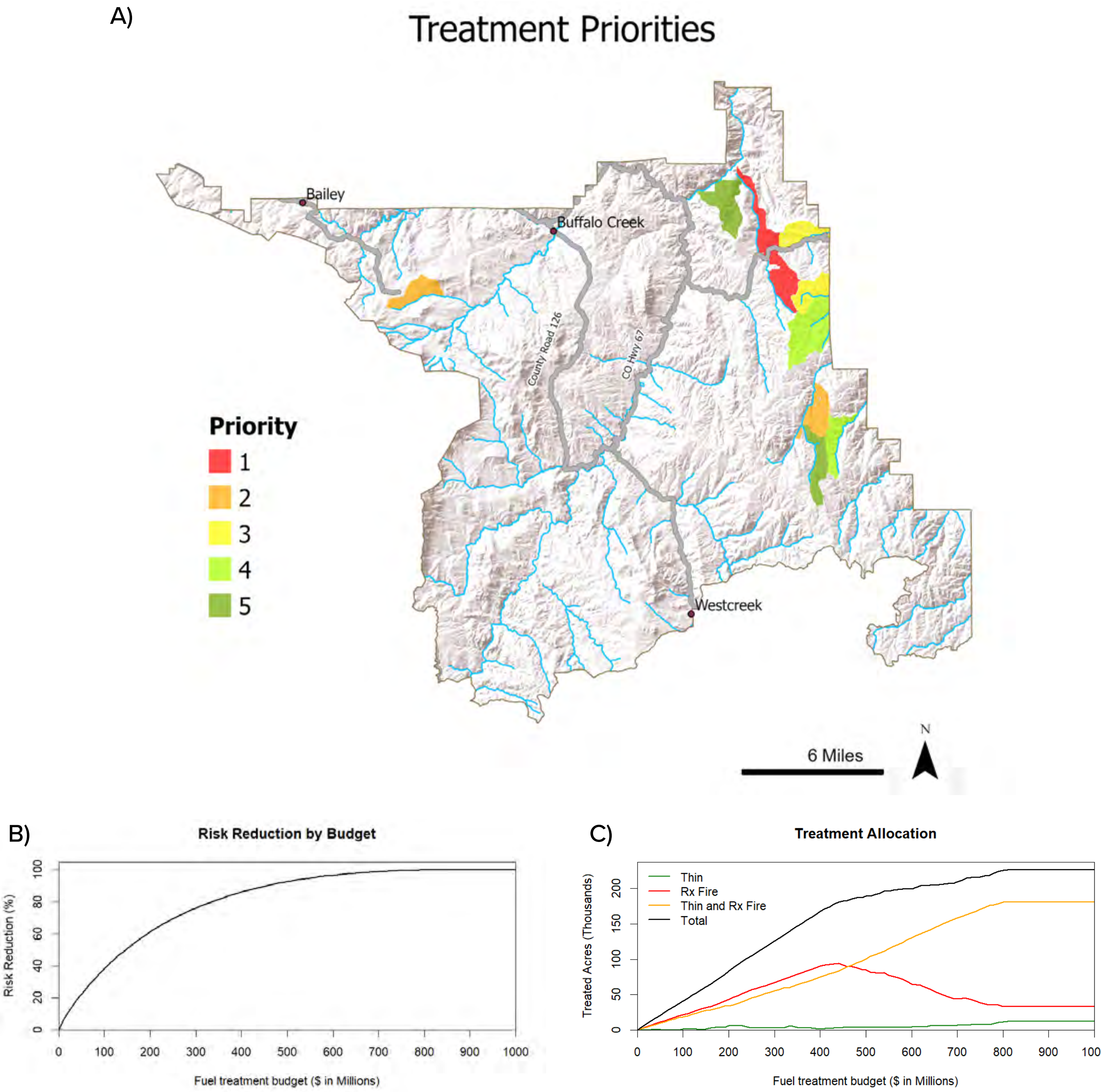


Figure 19. Wildfire risk fuel treatment prioritization of Vegetation Units. Treatment priorities correspond to fuel treatment budgets from $5M to $25M, incrementally increasing by $5M. The top panels show cumulative wildfire risk reduction achieved as budgets increase to support more forest treatment. Risk reduction is presented as the percent of total risk reduction that can be mitigated by forest management if every feasible acre is treated. Idealized treatment type allocations are tracked across the possible range of budgets in the lower panels for wildfire risk.

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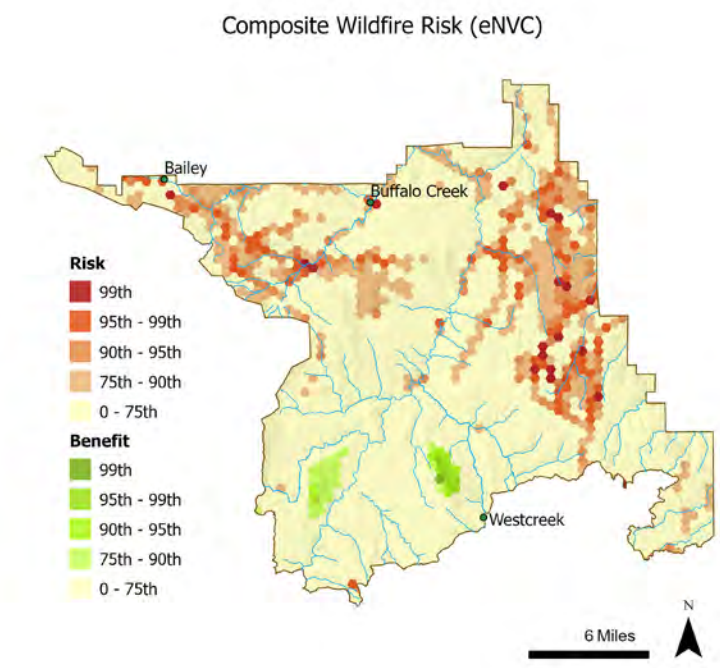
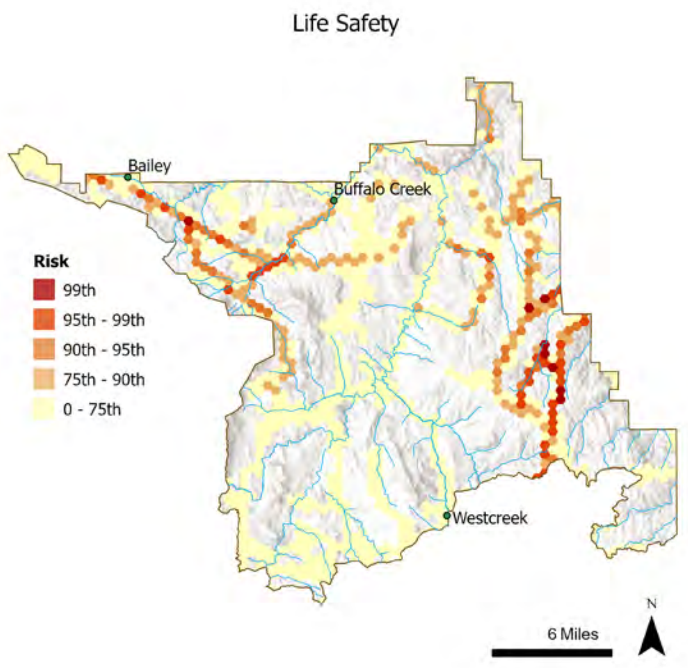
APPENDIX A: Wildfire Risk - Expected Net Value Change (eNVC) Percentile Figures

Expected net value change (eNVC) or wildfire risk percentile maps were created by summarizing total risk (eNVC) within 125-acre hexagonal units and calculating the 75th, 90th, 95th, and 99th percentile values of wildfire risk and wildfire benefit. The purpose of these figures is to act as a visual aid and highlight areas of the landscape at relative higher risk or higher benefit from wildfire for the composite wildfire risk and each HVRA category wildfire risk map.



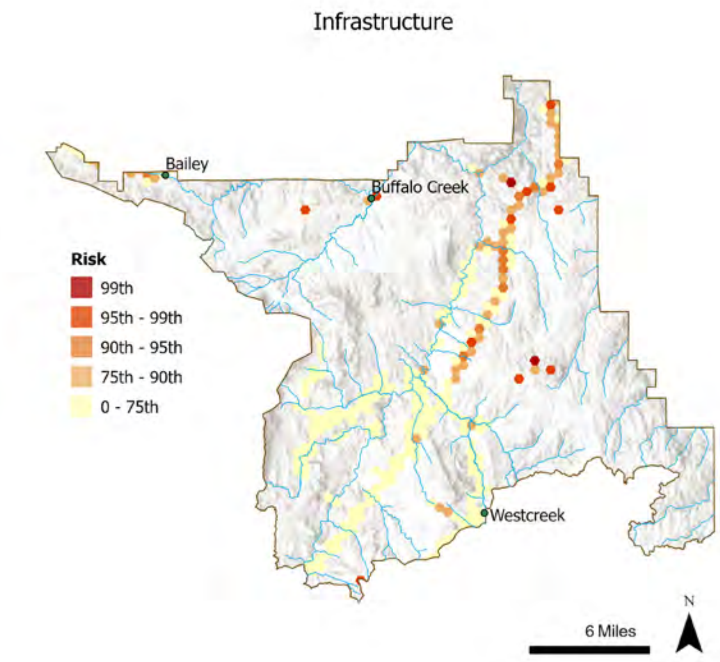
Composite Wildfire Risk (eNVC)

Figure A1. Composite wildfire risk percentile map.



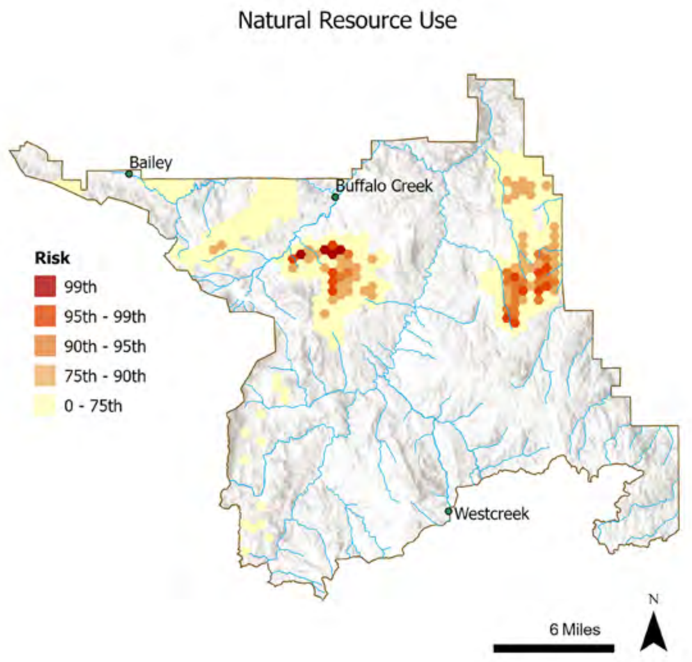
Life Safety

Figure A2. Wildfire risk to life/safety percentile map.



Infrastructure

Figure A3. Wildfire risk to infrastructure percentile map.



Natural Resource Use

Figure A4. Wildfire risk to natural resource use percentile map.

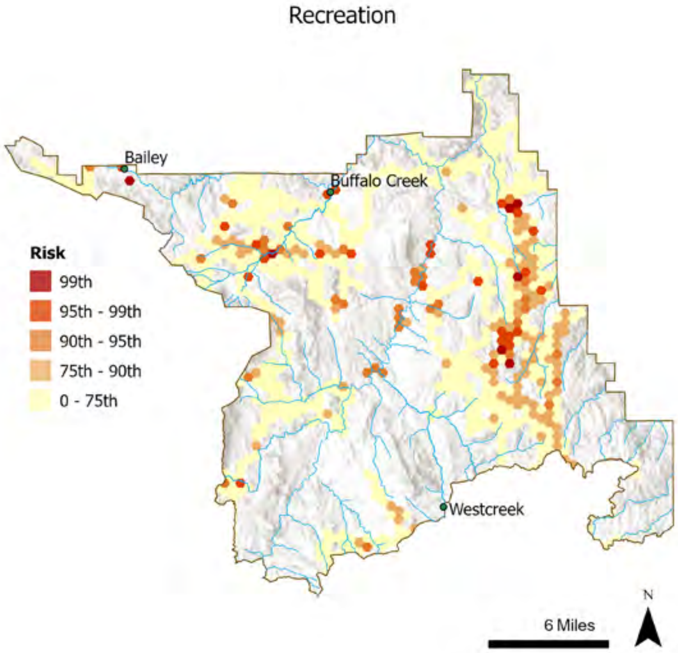


Figure A5. Wildfire risk to recreation percentile map.

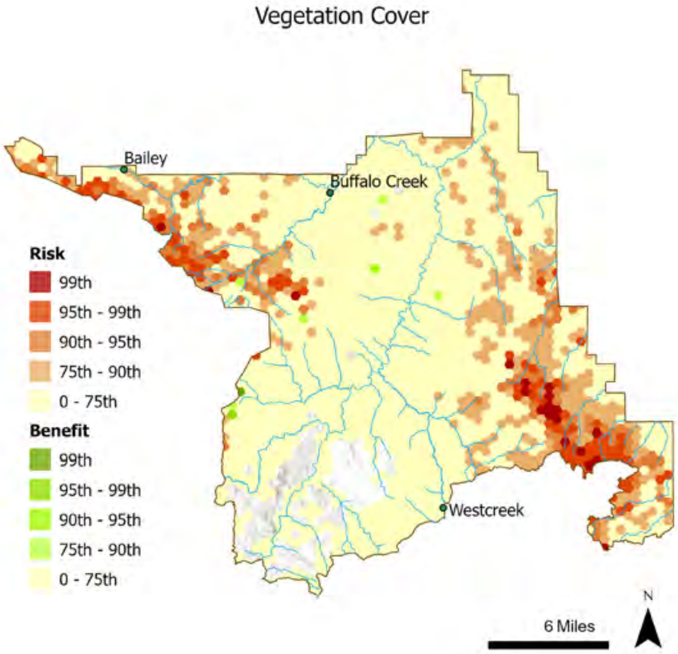


Figure A6. Wildfire risk to vegetation cover percentile map.

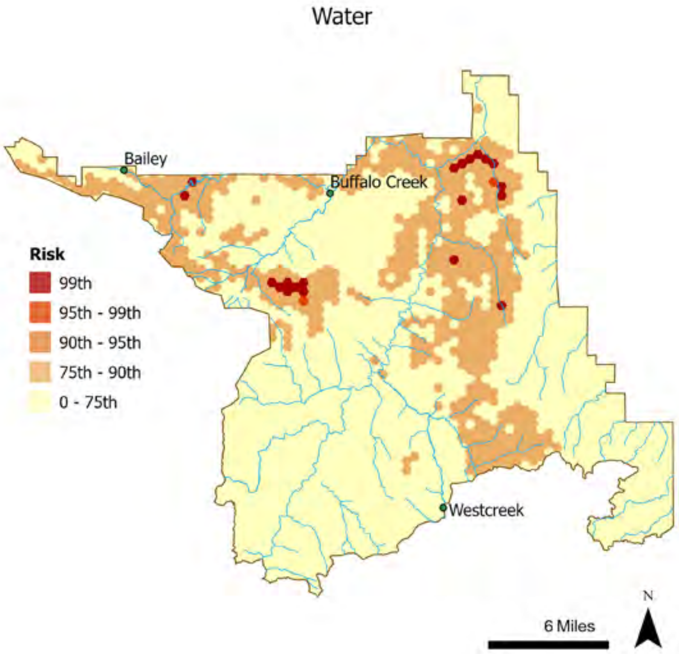


Figure A7. Wildfire risk to water resources percentile map.

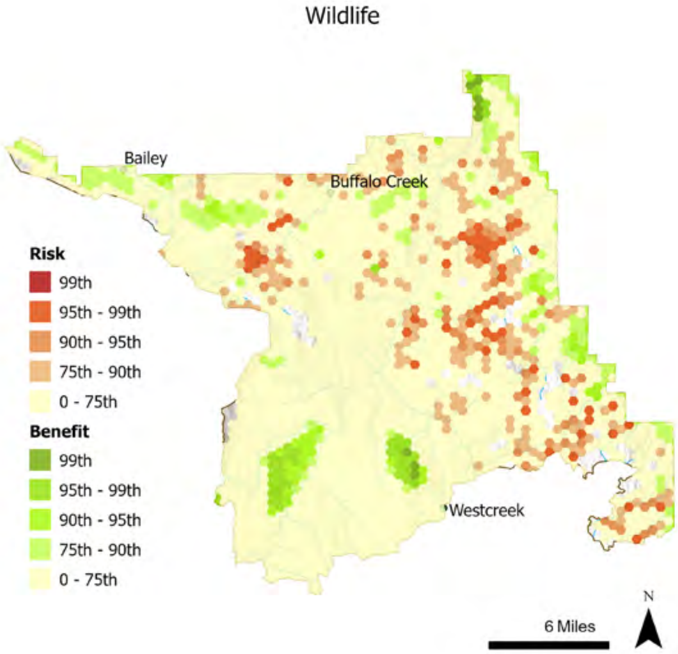


Figure A8. Wildfire risk to wildlife percentile map

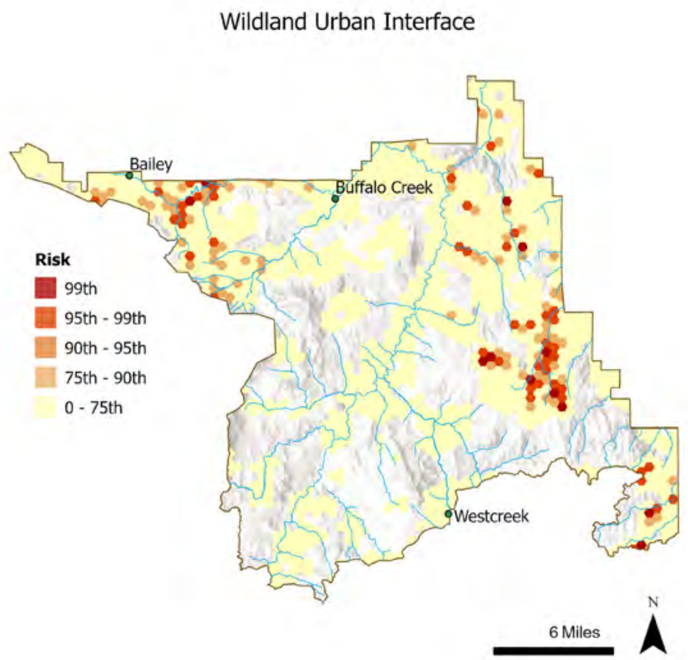


Figure A9. Wildfire risk to wildland urban interface (WUI) percentile map.

APPENDIX B: Wildfire Behavior and Probability Modeling

To characterize wildfire behavior and activity within the South Platte NEPA planning area the FlamMap 6.1 (Finney 2006) and FSim (Finney et al. 2011) fire models were used. FlamMap was used to characterize potential fire behavior and FSim was used to estimate pixel-wise annualized burn probability. Both FlamMap and FSim were run on an identical "fuelscape" that represents the spatial distribution of the fire behavior fuel model (Scott and Burgan 2005), canopy base height, canopy height, canopy bulk density, slope, elevation, and aspect across the entire analysis area. This data was sourced from the LandFire 2016 Remap (LF; https://landfire.gov/) and underwent some adjustments to account for landscape fuel changes that have occurred since 2016.

Potential fire behavior was characterized based on the FlamMap flame length prediction for each 30 m pixel within the landscape under 25th, 50th, 90th and 97th percentile weather conditions (Figure B2 – B5). This flame length prediction can be seen as the "worst case" for a given weather scenario as the model output assumes wind and fire spread are aligned in the upslope direction. Therefore, the model does not account for topographic factors or prevailing wind directions that may result in certain pixels being more likely to sustain flanking or backing fire during an actual wildfire event. Though such factors are not included in the fire behavior modeling they are well captured in the estimated burn probability as predicted by FSim (Figure B1). Crown fire activity was modeled using the Scott and Reinhardt (2001) method (Figure B6-B9).

FSim works by simulating 1,000s to 10,000s of years of weather, fire ignitions, fire spread, and fire suppression to estimate the annual probability a given pixel will burn. To accomplish this, FSim combines modules for weather, fire ignitions, fire growth, and fire suppression through a Monte-Carlo simulation approach where fires are ignited and grown independently of one another on a static fuelscape. In doing so it accounts for topology and prevailing wind directions on the rate and directions of fire spread capturing effects such as lower probabilities of fire on the lee side of large waterbodies, alpine ridgelines, fire footprints, etc. As fires burn independently on a static fuelscape, fires are not self-regulating, and the simulation results are valid only for the current landscape condition. As large fires and other management actions alter the landscape fuel condition in the future, updated FSim runs would be required to accurately represent the spatial burn probability. The FSim simulations were conducted at 90m resolution and simulation parameters were calibrated such that the simulation results matched the observed annual number of fires, mean fire size, and fire size distribution between 2000 and 2020 within a 30 km buffer of the analysis area.

Landscape Fuel Adjustments

The first step in our wildfire simulation process was to develop a continuous fuelscape layer by modifying the LandFire 2016 Remap data (LF) to account for changes to the fuelscape between 2016 and 2021. Modifications were made to the LF fuelscape to account for changes due to recent fuel treatments and prescribed and unplanned wildfires within the analysis area (Table B1 and B2). Further modifications were made to increase the surface fuels to TL5 and reduce the canopy base height by 30% in Lodgepole pine forest types to ensure better alignment between modeled fire behavior and observations from recent wildfire events.

Table B1. Modifications to the surface fuel model based on fuel treatment type or wildfire severity category.

Initial FBFM40	Initial Code	Manage	Rx Fire	Rearrange	Low Sev. WF	Mod. Sev. WF	High Sev. WF
GR1	101	101	101	201	101	101	101
GR2	102	102	101	201	101	101	101
GR3	103	103	101	201	101	101	101
GR4	104	104	101	201	101	101	101
GR5	105	105	101	201	101	101	101
GR6	106	106	101	201	101	101	101
GR7	107	107	101	201	101	101	101
GR8	108	108	101	201	101	101	101
GR9	109	109	101	201	101	101	101
GS1	121	121	121	201	121	121	101
GS2	122	122	121	201	121	121	101
GS3	123	123	121	201	121	121	101
GS4	124	124	121	201	121	121	101
SH1	141	141	141	201	141	141	101
SH2	142	142	141	201	141	141	101
SH3	143	143	141	201	141	141	101
SH4	144	144	141	201	141	141	101
SH5	145	145	141	201	141	141	101
SH6	146	146	141	201	141	141	101
SH7	147	147	141	201	141	141	101
SH8	148	148	141	201	141	141	101
SH9	149	149	141	201	141	141	101
TU1	161	161	161	201	161	161	101
TU2	162	162	161	201	161	161	101
TU3	163	163	161	201	161	161	101
TU4	164	164	161	201	161	161	101
TU5	165	165	161	201	161	161	101
TL1	181	181	181	201	181	181	101
TL2	182	182	181	201	181	181	101
TL3	183	183	181	201	181	181	101
TL4	184	184	181	201	181	181	101
TL5	185	185	181	201	181	181	101
TL6	186	186	181	201	181	181	101
TL7	187	187	181	201	181	181	101
TL8	188	188	181	201	181	181	101
TL9	189	189	181	201	181	181	101
SB1	201	201	201	201	201	201	101
SB2	202	201	201	201	201	201	101
SB3	203	201	201	201	201	201	101
SB4	204	201	201	201	201	201	101

Table B2. Modifications to the canopy fuel parameters based on fuel treatment type or wildfire severity category.

Treatment	Canopy Bulk Density Adjustment Factor	Canopy Base Height Adjustment Factor	Canopy Cover Adjustment Factor	Canopy Height Adjustment Factor
Thin	0.6	1.2	0.7	1.2
RxFire	0.92	1.09	0.95	1.13
Complete	0.5	1.2	0.75	1.2
Low Sev WF	0.85	1.1	0.85	1.1
Mod Sev WF	0.45	1.25	0.45	1.25
High Sev WF	0.1	1.5	0.1	1.5

FlamMap Percentile Weather Scenarios

To develop the weather scenarios for the FlamMap fire behavior simulations, daily weather data between 2000 and 2020 was acquired from the Cheeseman RAWS station. This station was selected for its long period of record and as it is the driest, more exposed station in the planning area therefore making our modeling more conservative and representing the worst-case scenario. From this daily record, the 25th, 50th, 90th and 97th percentile ERC values and the associated fuel moistures and wind conditions were identified (Table A3). Simulations were then completed using each of the four percentile weather scenarios.

Table B3. Weather scenarios based on all data since 2000 from the Cheeseman RAWS.

Scenario	20-ft Wind Speed (MPH)	1 hr Moisture (%)	10 hr Moisture (%)	100 hr Moisture (%)	1000 hr Moisture (%)	Live Herbacious Moisture (%)	Live Woody Moisture (%)
25th Percentile	5.25	35	35	23	29	90	120
50th Percentile	7.5	10	11	17	21	60	90
90th Percentile	11.5	4	5	10	13	30	60
97th Percentile	14.2	2	4	8	11	30	60

FSim Fire Weather

Consistent with the approaches of other large scale FSim modeling efforts (Short et al. 2020) a single representative weather station (Cheesman RAWS) was used to generate simulated weather across the analysis area based on all daily weather observations since 2000. Fire Family Plus (Bradshaw et al. 2000) was used to build a fire risk (FRISK) file from these data that summarizes annual percentile weather scenarios and builds tables representing the distributions of wind speed and direction during each month. FSim then uses this FRISK file to generate thousands of years of potential weather and randomly pulls daily wind speeds and directions from the observed historical monthly distributions. In this way FSim uses seasonal weather scenarios that align with the interannual variability and seasonal trends within the historical record and account for seasonality in the prevailing wind direction and speed.

FSim Ignition Density

FSim ignition locations are selected by randomly selecting an x-y coordinate for each potential fire. This random selection is influenced by inputting an ignition probability raster that defines the relative chance of any location on the landscape of being selected. This allows the locations of fire ignitions in FSim to match the observed spatial variability of human and natural ignitions across the analysis area. This raster was generated identifying the ignition locations of all fires >20 acres in the historical fire record (Short 2021) and the Kernel density tool in ArcGIS Pro 2.8 was then used to convert the point ignition data into a continuous raster surface.

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Supplemental Figures

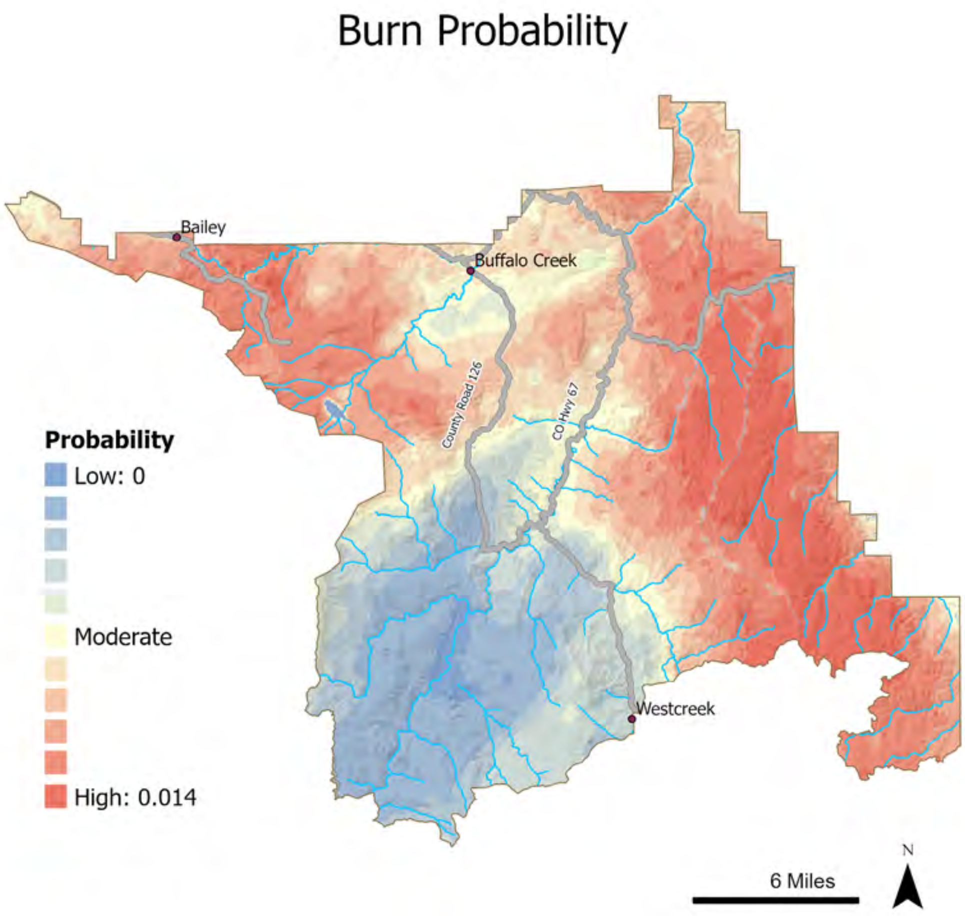

Figure B1. Burn probability.

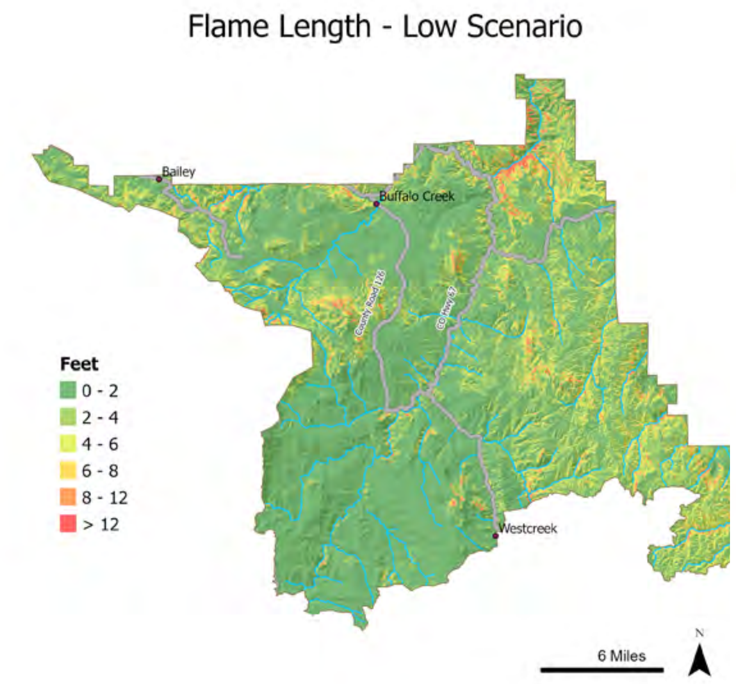

Figure B2. Flame length (ft) modeled with FlamMap 5 for the low weather scenario.

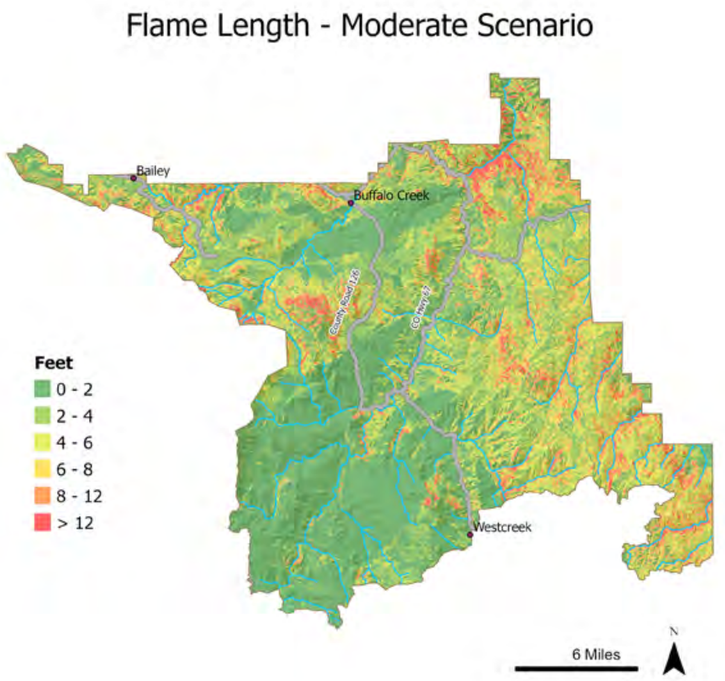

Figure B3. Flame length (ft) modeled with FlamMap 5 for the moderate weather scenario.

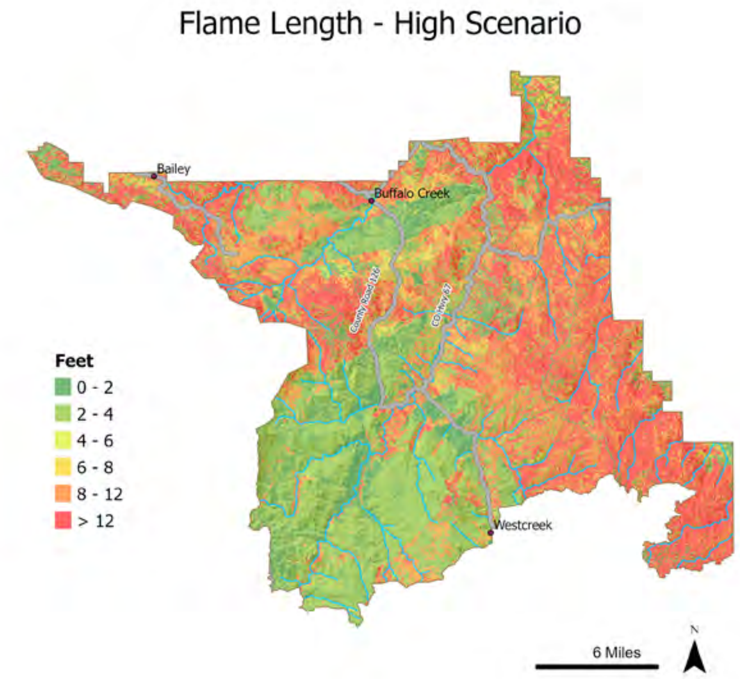

Figure B4. Flame length (ft) modeled with FlamMap 5 for the high weather scenario.

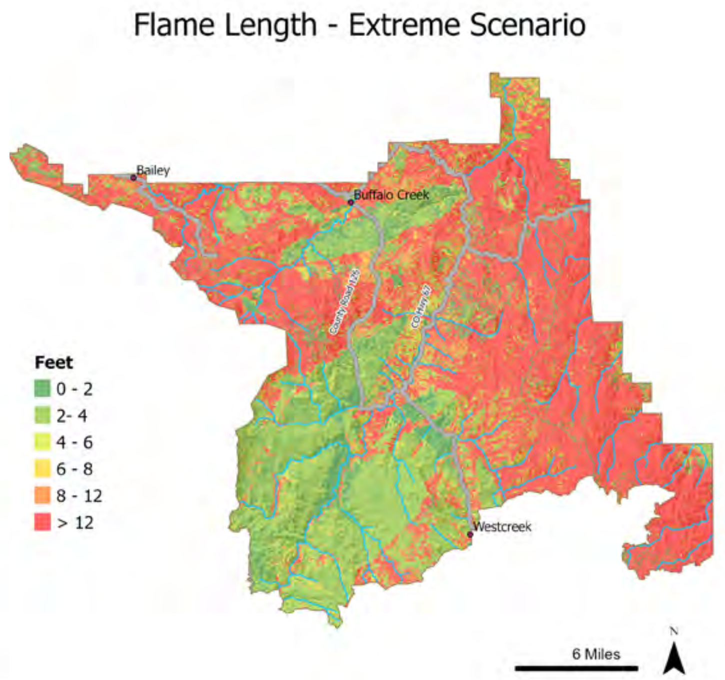

Figure B5. Flame length (ft) modeled with FlamMap 5 for the extreme weather scenario.

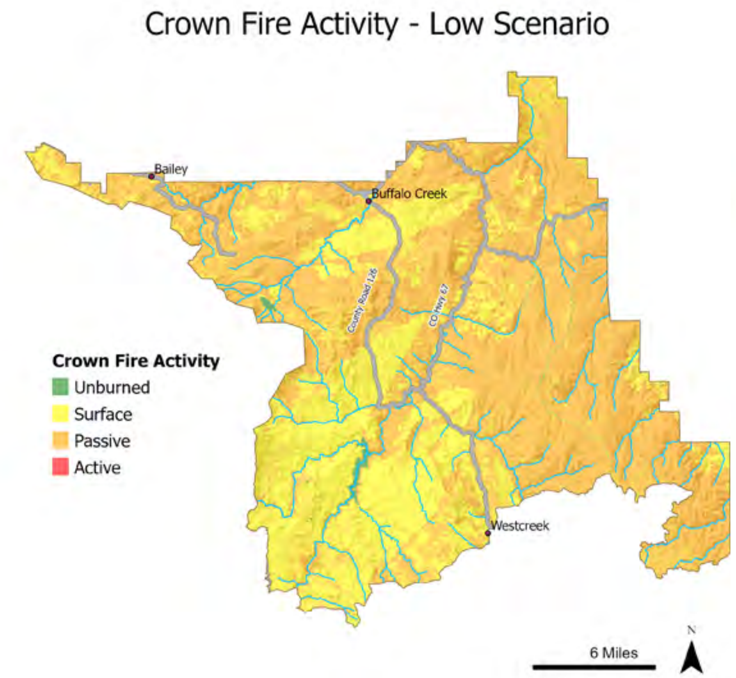

Figure B6. Crown fire activity modeled with FlamMap 5 for the low weather scenario.

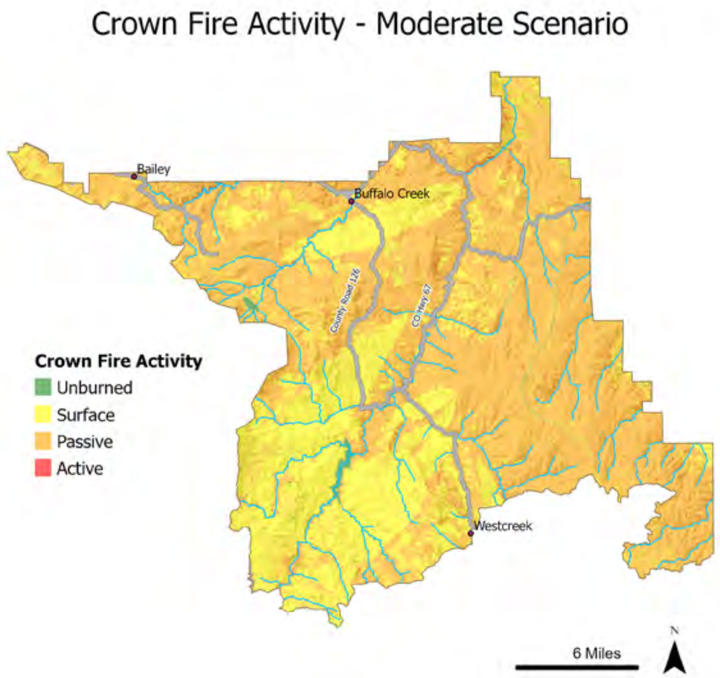

Figure B7. Crown fire activity modeled with FlamMap 5 for the moderate weather scenario.

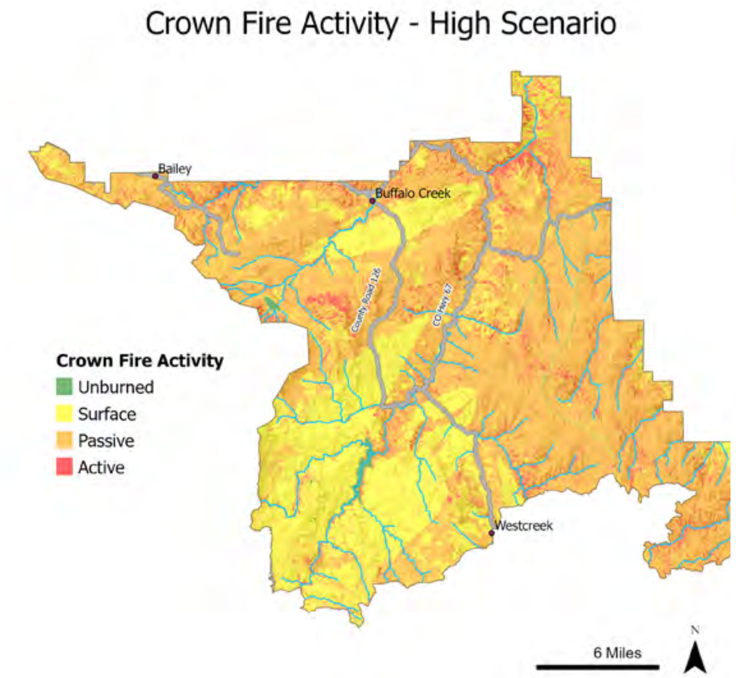

Figure B8. Crown fire activity modeled with FlamMap 5 for the high weather scenario.

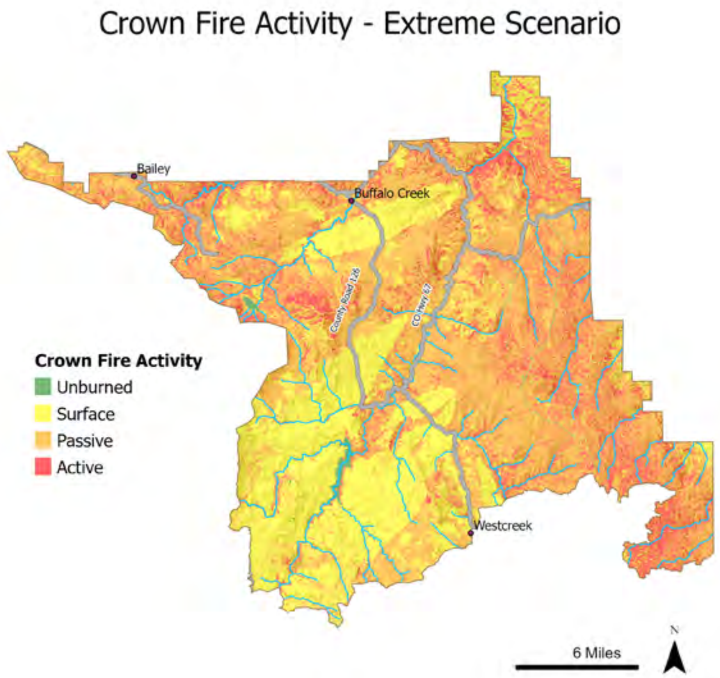

Figure B9. Crown fire activity modeled with FlamMap 5 for the extreme weather scenario.

APPENDIX C: Water Modeling

Wildfire risk to watershed related HVRAs was assessed with supplemental modeling that estimates potential post-fire erosion and sediment transport to water supply diversions, reservoirs, and designated waters following the methods in Gannon et al. (2019). Soil burn severity was predicted by mapping crown fire activity (Scott and Reinhardt 2001) categories of surface fire, passive crown fire, and active crown fire to low, moderate, and high severity respectively. Post-fire erosion was estimated with the Revised Universal Soil Loss Equation (Renard et al., 1997) using empirical observations of post-fire change in cover and soil erodibility by burn severity (Larsen and MacDonald 2007). Sediment transport to water supplies was estimated based on empirical models of hillslope and channel sediment delivery ratio (Wagenbrenner and Robichaud 2014; Frickel et al., 1975). This workflow supports pixel-level estimates of the sediment generated in each pixel that is delivered to downstream values at risk (Figure C1).

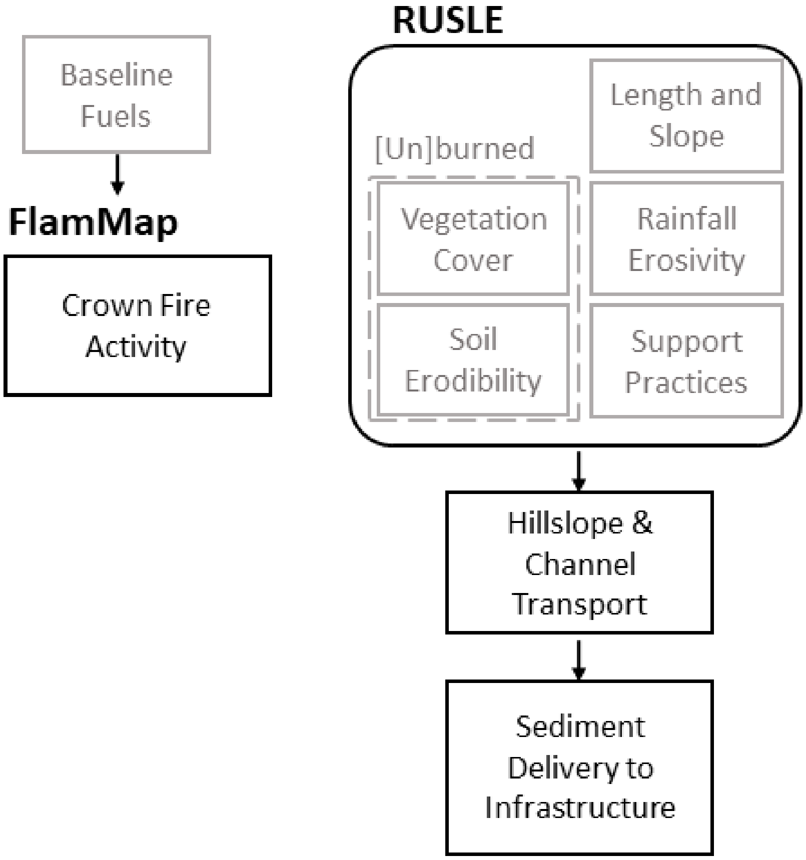

Figure C1: Workflow used to quantify potential post-fire sediment delivery from each pixel of the landscape.

This framework was applied with slight modifications to quantify the conditional net value change of critical water supplies and designated waters. Like the regular cNVC calculations, these metrics were calculated for each fire weather scenario and then combined into a single cNVC raster by a weighted averaging.

Critical Water Supplies

Local water utilities provided locations for water supply infrastructure (i.e., diversions and reservoirs). Infrastructure relative importance was based on operations and treatment constraints that were rescaled between 0 for the least important to 1 for the most important. These ratings were applied as weights to express the importance, or impact, of sediment delivered to each water supply. It was assumed that ≥ 50 Mg ha-1 of sediment delivery to infrastructure in the first post-fire year is a dramatic loss based on the reported sediment yield from hillslope erosion after the 1996 Buffalo Creek Fire (68 Mg ha-1; Moody and Martin 2001). Therefore, the pixel-level estimates of sediment delivery to water infrastructure were linearly rescaled so that 0 to 50 Mg ha-1 of sediment corresponds to 0 to -100 percent value change. The final cNVC is mapped in Figure C2.

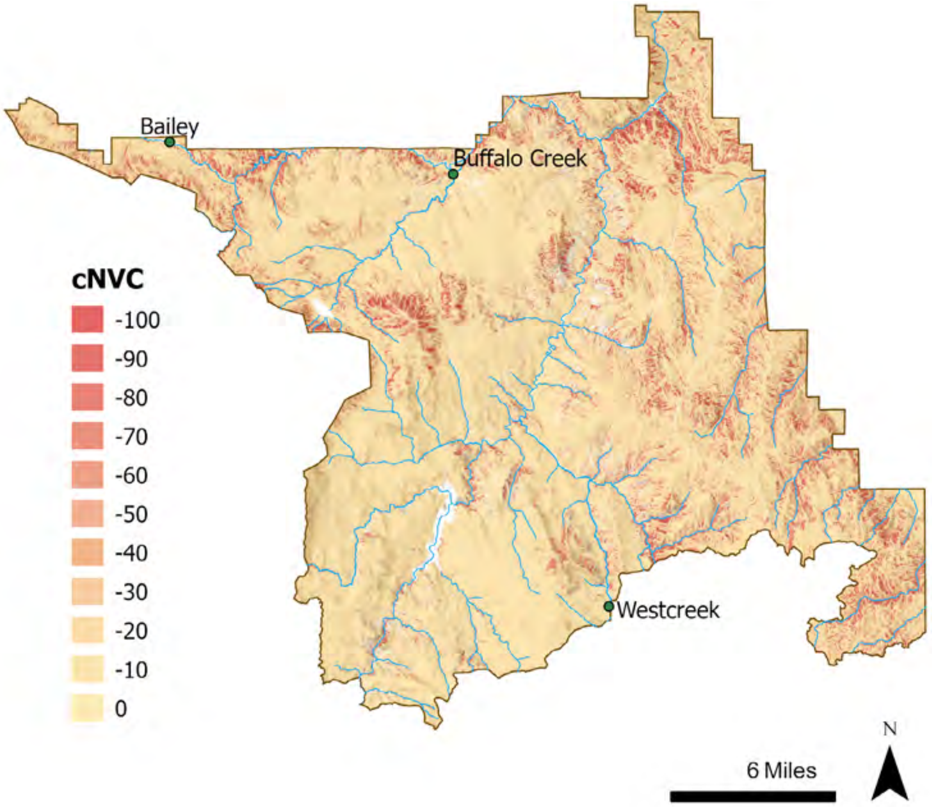

Figure C2: Conditional net value change of water supply risk.

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