FROM FORESTS TO FAUCETS PARTNERSHIP

WILDFIRE RISK ASSESSMENT

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COLORADO FOREST RESTORATION INSTITUTE
COLORADO STATE UNIVERSITY

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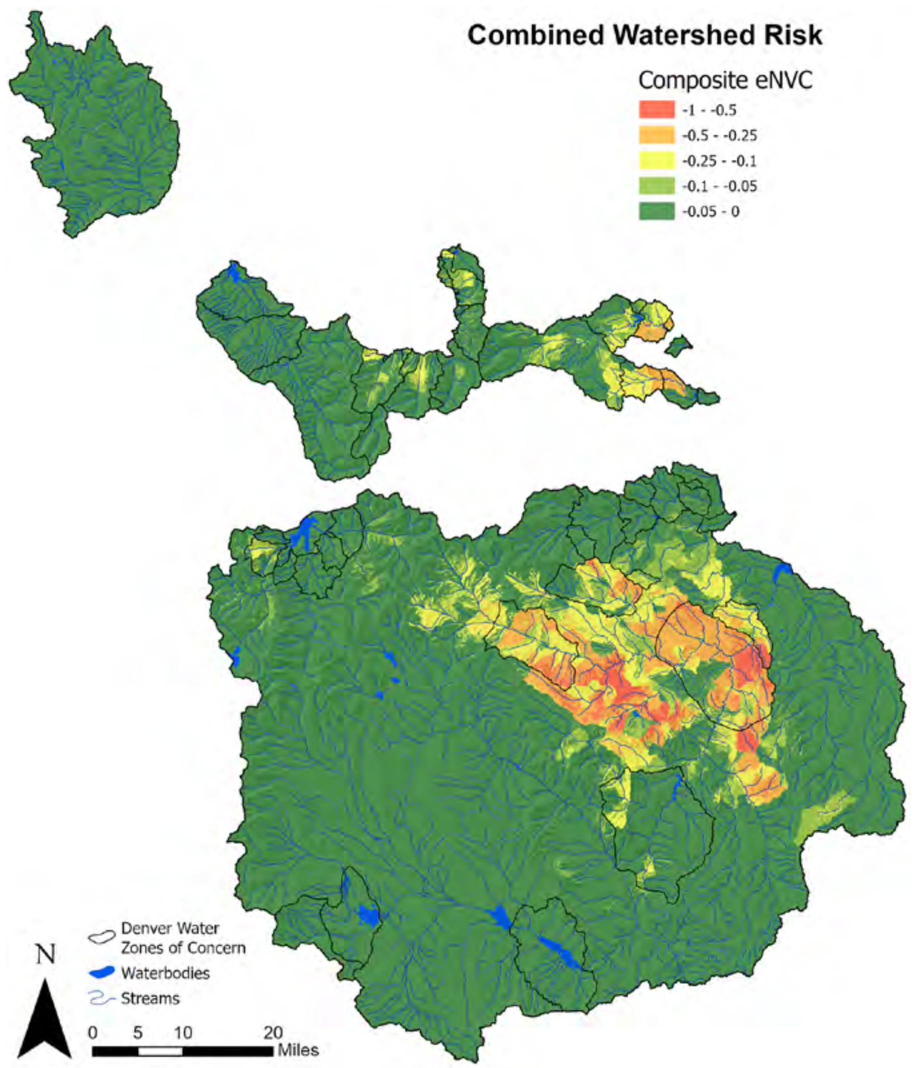
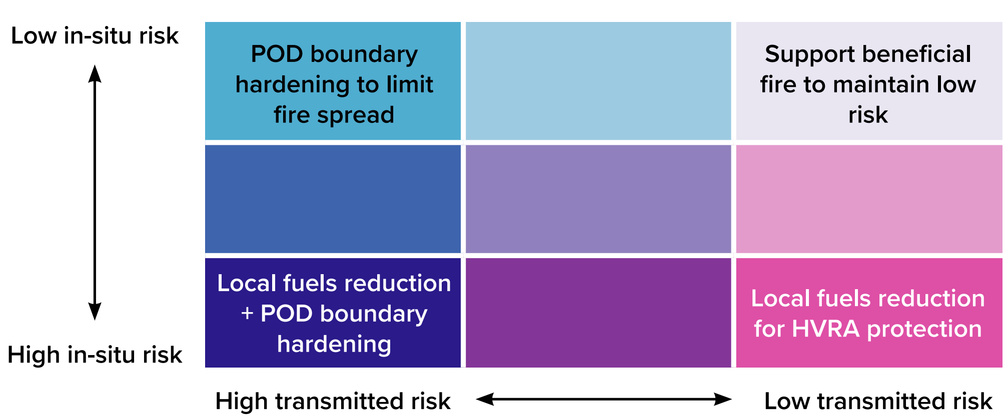
1. Executive Summary

- In 2010 Denver Water formed the From Forests to Faucets Partnership (F2F) to **proactively address watershed related wildfire risks with land and fire management agencies**. Denver Water only owns 2% of the land within the collection system and has no authority for fire management, making collaboration essential to achieve drinking water protection goals. The shared objectives of improving forest resilience and reducing risk of severe wildfire impacts to drinking water support collective action between F2F partners: Denver Water, the USDA Forest Service, the Colorado State Forest Service, the Natural Resources Conservation Service, and the Colorado Forest Restoration Institute.
- In this assessment, "risk" represents the likely impact of post-fire erosion, debris flows, and sediment delivery to drinking water reservoirs, diversions, and pipelines and is weighted by the relative importance of Denver Water's infrastructure (e.g., 1 m^3 of sediment will be more costly to Denver Water if it enters Strontia Springs reservoir than Platte Canyon Reservoir). **Wildfire risk to drinking water is concentrated in the montane zone of the Upper South Platte watershed** where fire-sensitive water infrastructure intersects hazardous fuel conditions and high burn probability.



Composite wildfire risk (measured as expected net value change) based on post-fire erosion, debris flows, and sediment delivery to weighted water infrastructure. Note eNVC incorporates burn probability.

- There are two primary strategies for reducing wildfire risk to drinking water - 1) **reduce fire intensity on hillslopes contributing to or upstream of critical water infrastructure** to address in-situ risk and 2) **limit fire spread into fire-sensitive watersheds** to address transmitted risk. This analysis identified priority actions to support both strategies.

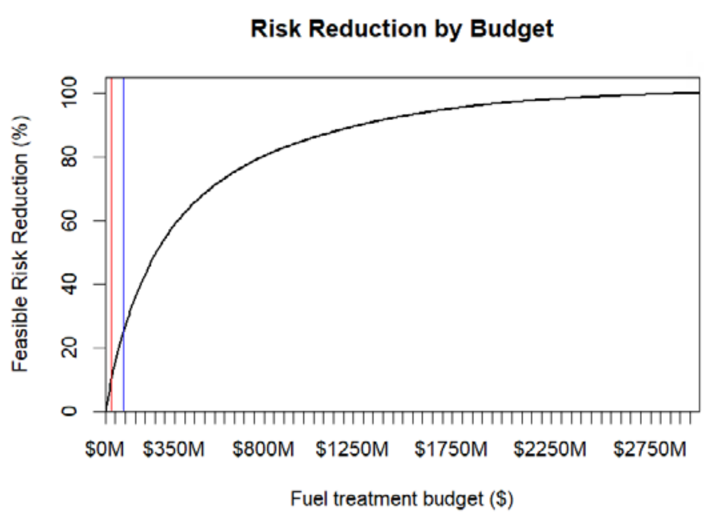


- **Prescribed fire was the most cost-effective vegetation management action** because it reduces both surface and canopy fuels at a relatively low cost. Prescribed fire accounted for 75-100% of the priority acres identified for vegetation management and can serve as a proxy for low to moderate intensity wildfire. Thin only treatments that do not reduce surface fuels are the least effective vegetation management action, but are more effective than the no action alternative.

Summary of treatment type allocation across four prioritization scenarios. Thin is mechanical thin only, RxFire is prescribed fire, Mast is mastication, and Patch is patch cut. In the uncapped scenarios, there were no proportional budget restrictions so prescribed fire, the most cost-effective treatment option, was maximized. In the budget cap scenario, prescribed fire was limited to 75% and patch cuts were limited to 15% of the total budget.

Budget	Thin (acres)	RxFire (acres)	Thin + RxFire (acres)	Mast (acres)	Patch (acres)	Total Priority Acres
$30M uncapped	-	17,558	-	-	-	17,558
$90M uncapped	-	48,535	-	-	1,827	50,362
$30M + budget cap	-	10,465	1,258	-	1,867	13,589
$90M + budget cap	-	31,115	2,536	2,133	5,556	41,340

- This analysis identified the **most cost-effective locations where vegetation management can reduce in-situ risk by moderating fire intensity on hillslopes contributing to or upstream of critical water infrastructure**. The current budgets of $30 million (red line) and $90 million (blue line) address 10% and 25% of feasible risk reduction, respectively. This term “feasible risk reduction” is the ratio between the risk reduction achieved by priority vegetation management and the risk reduction achieved if all feasible areas of the landscape were treated. The treatment plans on the steep, left side of the curve represent the greatest return on investment whereas on the flatter right side of the plot there is limited risk reduction with additional investment. To achieve 99% of feasible risk reduction, the Partnership would have to invest $3 billion in vegetation management.
- **Localized fuels reduction projects can’t eliminate all wildfire risk to drinking water**. With a $90 million investment in vegetation management, the Partnership could reduce <5% of total wildfire risk to drinking water which represents potential risk reductions from vegetation management relative to baseline untreated risk summed across the whole landscape. These total risk reduction estimates are conservative because they only account for local fire behavior and effects (i.e. in-situ risk), but do not account for potential impacts of a treatment on fire spread or probability (i.e. transmitted risk). Even if the Partnership could increase their investment to $3 billion, maximum total risk reduction is only 15%. The remaining 85% of wildfire risk to drinking water cannot be addressed by localized fuels reduction. Fortunately, there are other actions (e.g. floodplain enhancement, sediment reduction structures, and aerial mulching) that can directly reduce post-fire sedimentation risks, but are not modeled in this assessment.



Risk reduction curve across a variety of simulated budgets. The vertical red and blue lines denote the $30M and $90M budgets, respectively. This curve was developed for the uncapped treatment scenario.

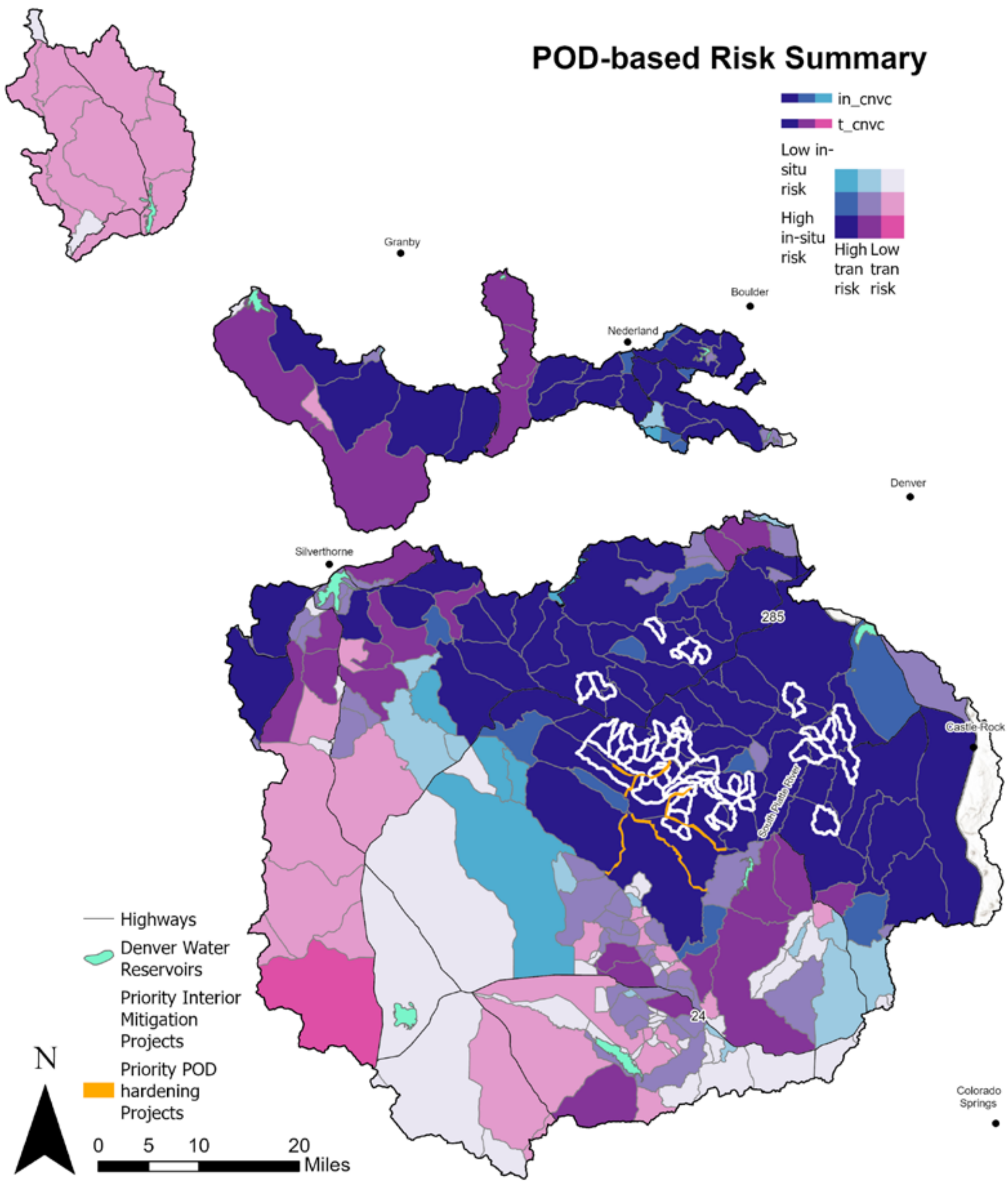
Total and feasible risk reduction estimates for a range of potential budgets. These risk reduction metrics only account for local fire behavior and effects (i.e. in-situ risk), but do not account for potential impacts of a treatment on fire spread or probability (i.e. transmitted risk).

Budget ($)	Total Risk Reduction (%)	Feasible Risk Reduction (%)
30,000,000	1.5	10
90,000,000	3.8	25
3,000,000,000	15.3	99
7,348,500,000	15.5	100

- **Most of the priority acres are located on United States Forest Service land** so inter-agency collaboration is critical. The F2F partnership will strategically target vegetation management in the highest-risk area upstream of the Strontia Springs Reservoir in the Upper South Platte watershed, but will continue partnering with agencies implementing proactive vegetation management throughout Denver Water's collection system.
- **To further reduce wildfire risk, limit fire spread into fire-sensitive watersheds** by aligning vegetation management with strategic fire operations. More specifically, hardening pre-identified potential operational delineation (POD) lines can improve the ease and safety of directly fighting fire, measured as suppression difficulty index. Our analysis identified several priority POD boundaries (orange outlines) where fuels reduction could significantly reduce SDI and limit West to East fire spread into the fire-sensitive PODs in the Upper South Platte watershed. While the proposed treatments fall outside of Denver Water's "zones of concern" they have the potential to build wildfire resilience within their collection system. Actions aimed at reducing fire ignitions (e.g. fire patrols and recreation planning) can also minimize fire spread into high-risk PODs.

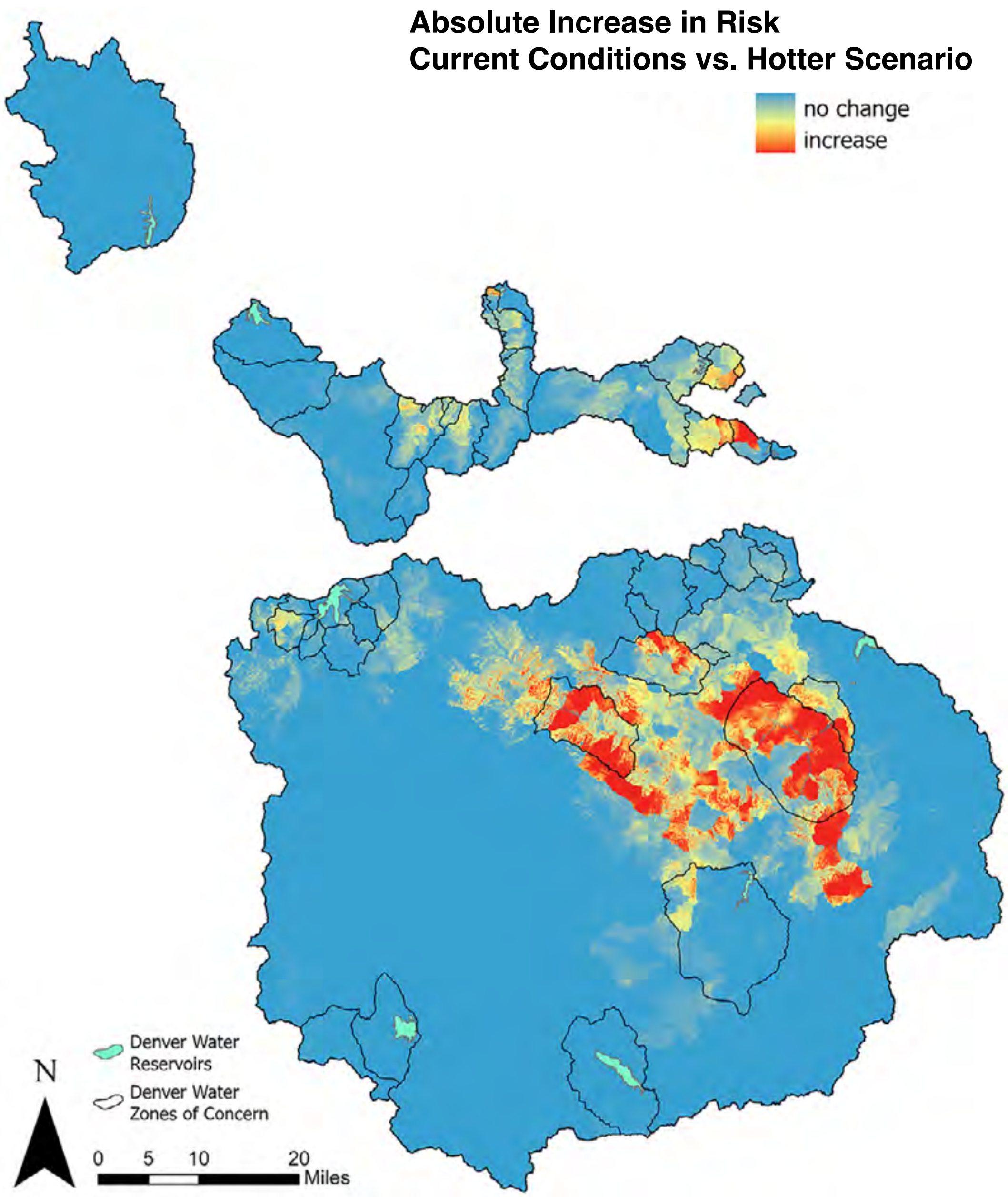
Land ownership distribution for the priority treatments identified in the uncapped $90M scenario.

Ownership	Total Acres	% of Priority Acres
USFS	39,308	78
Private	7,741	15
Other (CPW, County, NGO)	3,312	7



In-situ risk (in_cnvc) and transmitted risk (t_cnvc) matrix summarized by potential operational delineation (POD). Priority management actions for reducing in-situ risk are outlines in white and those prioritized for reducing transmitted risk are outlined in orange. For visualization purposes, the color gradient is based on quantile breaks which equally distributes observations across class intervals.

- Climate warming may disproportionately increase extreme fire behavior and burn probability in sub-alpine forest types dominated by lodgepole pine, Englemann spruce, and subalpine fir, which is already being observed in the Rocky Mountain Region. **However, the greatest warming-driven increases in risk to water supplies are in the montane zone** (ponderosa pine and Douglas-fir), where hazardous fuel conditions and high burn probability intersect with critical water infrastructure that is particularly sensitive to post-fire impacts.



Absolute increase in wildfire risk to drinking water (eNVC) under the hotter scenario compared to current conditions.

2. Purpose and Scope

The Denver Water collection system covers 2.5 million acres in order to provide water for 1.5 million people in the Denver metro area. About half of the collection system is forested and Denver Water only owns about 2% of that land. This compels Denver Water to collaborate with other land management agencies to ensure land management supports their needs for clean source water delivery to utility infrastructure. Denver has determined that wildfire and subsequent sediment delivery to water infrastructure is the greatest threat to Denver's raw water supply. Wildfire is a natural process that can benefit long-term watershed protection and forest resilience. However, watershed impacts following large, severe wildfires in critical watersheds can be costly for water utilities. Denver Water spent $27.7 million on water quality treatment, sediment and debris removal, and remediation to the collection system following the 1996 Buffalo Creek and 2002 Hayman wildfires and is still investing in post-fire recovery. After these detrimental fires, the From Forests To Faucets (F2F) partnership was established between Denver Water, the United States Forest Service, the Colorado State Forest Service, the Natural Resources Conservation Service, and the Colorado Forest Restoration Institute. The goal of the partnership is to improve forest resilience and reduce the risk of severe wildfire impacts on watershed function, particularly in areas connected with critical water infrastructure. Ultimately, collaborative forest restoration and wildfire mitigation amplifies the benefits of watershed protection projects. Since its inception 2010, this partnership has committed $96 million to forest management actions on 120,000 acres in and around the Denver Water zones of concern. As a part of this $96 million commitment, the F2F partnership plans to invest $30 million in forest management activities to reduce wildfire risk to water supplies over the next five years.

A retro-active return on investment analysis of the F2F partnership (2011-2019) found that improving spatial prioritization of fuels reduction would increase economic benefits of wildfire mitigation (Jones et al., 2021). For Denver Water to effectively collaborate with other landowners in their collection area, staff need to clearly articulate wildfire risks to water supply and specific priorities. Thus, Denver Water and the F2F partners initiated this quantitative wildfire risk assessment (QWRA) and fuels reduction prioritization to guide F2F project planning and collectively invest in forest resilience, wildfire risk reduction, and source water protection. The Colorado Forest Restoration Institute (CFRI) leveraged their Risk Assessment and Decision Support (RADS) framework, which integrates collaborative feedback with technical modeling, to support developing priorities with the full F2F partnership. The purpose of this report is to document partner input and technical modeling for the RADS processes to inform future F2F planning and investments.

3. Methods

3.1 Risk Assessment and Decision Support (RADS) Framework

The Risk Assessment and Decision Support (RADS) framework is a collaborative process that 1) quantifies wildfire risk to a community's highly valued resources and assets (HVRAs) and 2) prioritizes vegetation management actions to maximize risk reduction per dollar spent.

Risk Assessment

Risk is a term widely used in economics, engineering, and emergency management to describe the expected impact of an event with uncertain occurrence and magnitude. Risk weighs the potential consequences of an event by its probability of occurrence. Risk assessment is an appropriate framework for wildfire because wildfire has considerable spatial and temporal variability in occurrence and intensity over the multi-decade planning periods typically used in land and resource management. A wildfire risk assessment quantifies and maps expected impact of fire (net value change) for a suite of HVRAs by combining spatial information on fire likelihood, fire intensity, and resource exposure and effects, as represented by the three legs of the wildfire risk triangle (Figure 1; Scott et al., 2013).

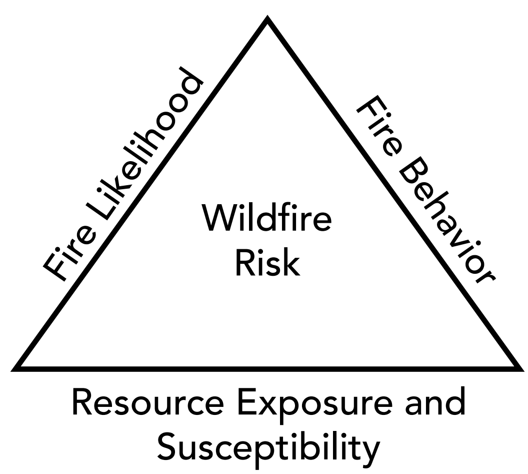


Figure 1: Wildfire risk triangle adapted from Scott et al., (2013).

Wildfire risk assessment requires locally informed fire simulation products, HVRA spatial data, susceptibility of those HVRAs to fire, and relative importance weights (Figure 2). Spatial fire modeling is used to estimate how wildfire likelihood and intensity vary across large landscapes based on fuels, topography, historical ignition patterns, and climate. The intent of this modeling is not to

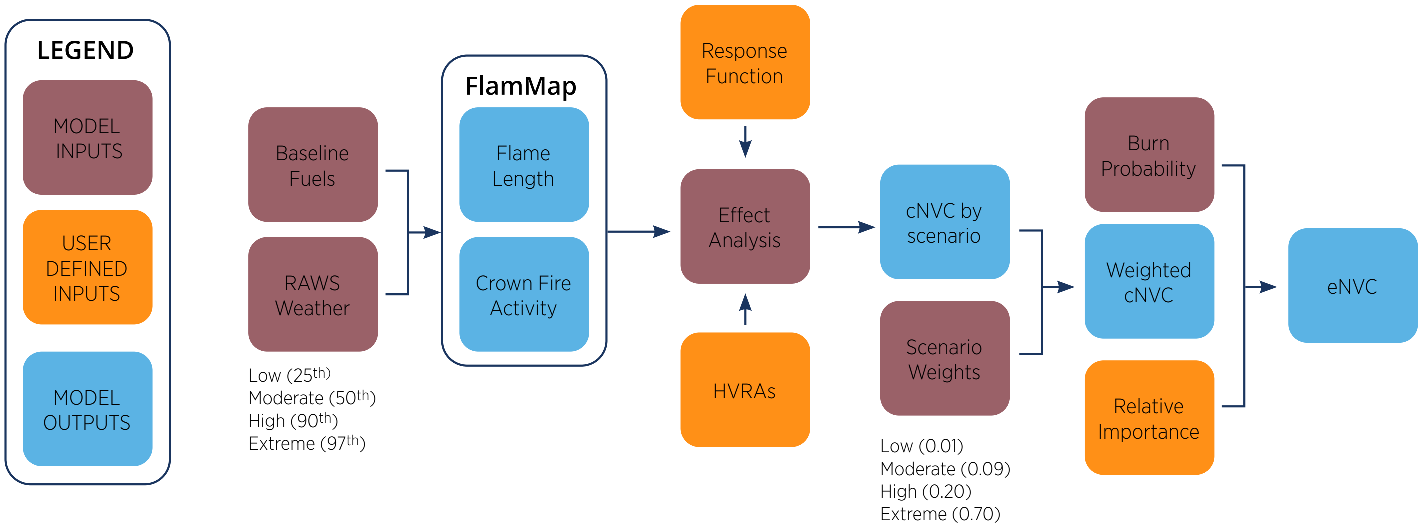


Figure 2: This Quantitative Wildfire Risk Assessment is based on the RMRS-GTR-315 framework (Scott et al., 2013). HVRAs = highly valued resources and assets, cNVC = conditional net value change, and eNVC = expected net value change.

describe the behavior of a specific future wildfire event, but rather the trends in fire occurrence and intensity over many potential future fire seasons. Fire behavior metrics, including flame length and crown fire activity were modeled in FlamMap 6 (Finney et al., 2023) for low, moderate, high, and extreme fire weather scenarios. Fire likelihood was quantified in the Large Fire Simulator (FSim) (Finney et al., 2011). Wildfire consequences are captured with an effects analysis where fire behavior outputs are combined with local data on HVRA locations and susceptibility to wildfire to calculate conditional Net Value Change (cNVC) for each HVRA and fire weather scenario. cNVC represents the change in value conditional on fire occurrence (i.e., if a fire were to burn), which assumes all areas of the landscape have an equal chance of burning. The 4 fire weather scenarios were combined with a weighted averaging that favored the high and extreme weather scenarios (Technosylva, 2018). Lastly, the cNVC measures for each HVRA were combined with burn probability to compute composite eNVC. Thus, the eNVC map represents wildfire risk by accounting for the likelihood of encountering wildfire.

Decision Support

RADS also includes a decision support module that prioritizes the type and location of vegetation management actions to reduce wildfire risk, while also considering feasibility and cost constraints to maximize return on investment (Figure 3). RADS uses a generalized form of the linear programming optimization model described in Gannon et al. (2019) to determine the most cost-effective means of reducing wildfire risk given the specified constraints. National Hydrography Dataset Plus (NHDPlus) catchments were used as the analysis units. Each catchment was attributed with feasible area and the average risk reduction and cost for each vegetation management action. Linear optimization was then used to prioritize vegetation management locations and types into an optimal treatment plan (see Appendix IV – Linear Optimization Model Formulation).

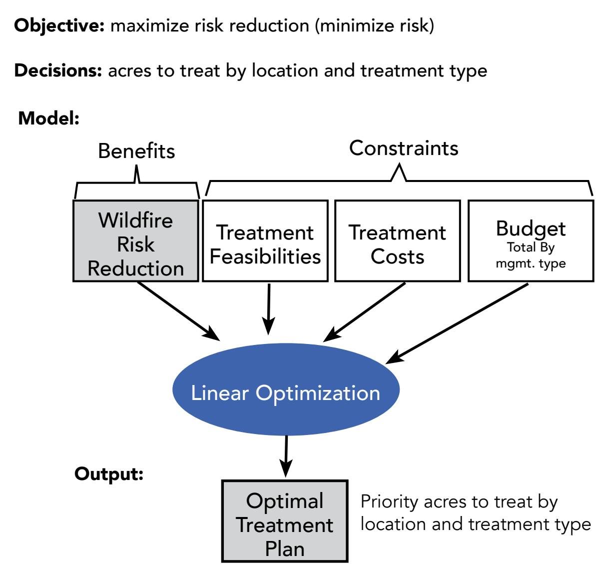


Figure 3: Conceptual framework for fuels reduction module.

3.2 Stakeholder Engagement

The overall project extent encompassed all watersheds within Denver Water's water collection system. This includes the 2% of land owned by Denver Water, as well as all land managed by a variety of federal agencies, state agencies, local governments, non-profits, private citizens, and others (Figure 4). While the risk assessment is a technical approach to quantifying wildfire risk, it is also dependent on integrating user-defined values to inform risk and prioritized risk reduction activities (Figure 2). The process of integrating risk science with agency direction and social values can serve as a useful vehicle for collaboration, cross boundary planning, and communicating stakeholder concerns. Leadership from the F2F partnership charter members, including Denver Water, USFS, CSFS, NRCS, and CFRI, contributed input during bimonthly meetings focused on this assessment as well as numerous emails and phone calls between January 2023 and June 2024. Leadership also served as conduits sharing information with their organization field office staff throughout the process. A smaller core group of Denver Water and CFRI staff met monthly to review preliminary results in more detail and make key decisions to move the analysis along. Feedback from a broader constellation of collaborative partners was incorporated from recently completed risk assessments on the Arapaho Roosevelt National Forest (Rhea et al., 2022), Pike National Forest (Mueller et al., 2023), and Jefferson County Open Space (Jefferson County Open Space 2022) to inform the fire behavior and vegetation management simulations and ensure other key inputs were locally appropriate. The F2F leadership team used targeted engagement with field office staff and partners to ensure other aspects of the modeling such as forest management cost and feasibility were locally appropriate for the F2F analysis goals.

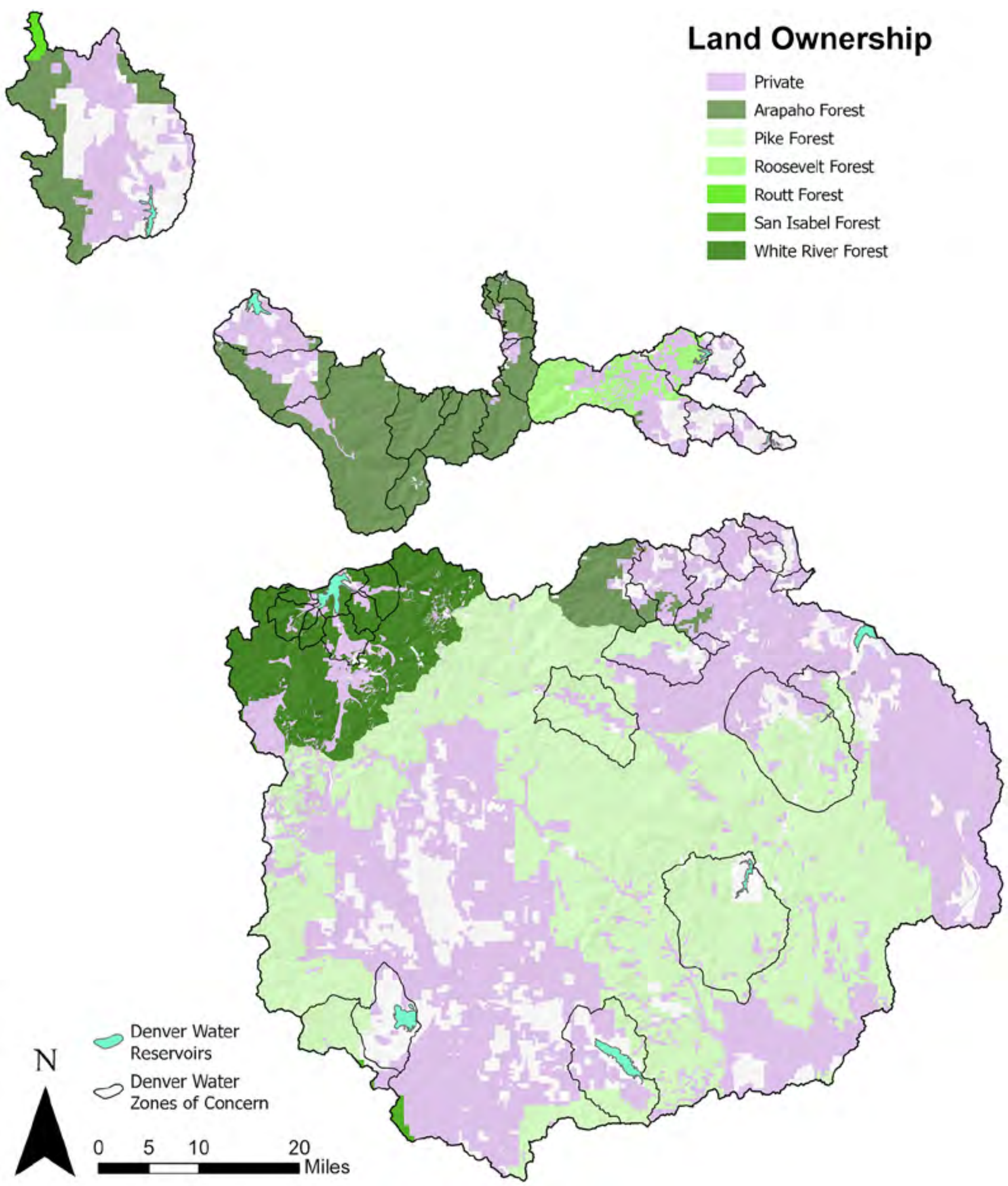


Figure 4: RADS analysis extent relative to Denver Water zones of concern and the primary landowners, the United States Forest Service (greens) and private lands (purple).

3.3 Wildfire Modeling

FlamMap was used to characterize potential fire behavior (Finney, 2023) and FSim was used to estimate pixel-wise annualized burn probability (Finney et al., 2011) within the Denver Water source area. 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 source area. This data was sourced from the LANDFIRE 2020 Remap (LANDFIRE 2020) and underwent some adjustments prior to fire modeling. These included adjustments to the fuel conditions based on forest management activity and wildfires that occurred since the LANDFIRE product was developed in 2020. Additional changes were made to ensure the intensity of fire behavior in lodgepole pine forests matched recent fire behavior observations (Moriarty et al., 2019). This was accomplished by reducing the canopy base height by 30% and changing any low load (TL1) or moderate load (TL3) conifer litter fuel models to high load conifer litter (TL5; Scott and Burgan, 2005) in lodgepole pine dominated forests.

Fire Behavior

In this application, FlamMap 6 (Finney et al., 2023) was set up to generate "worst-case" estimates of potential fire behavior under a range of weather scenarios by assuming upslope wind direction and head fire spread. There are two aspects of fire behavior that are relevant to this modeling: flame length (FL) and crown fire activity (CFA). FL is frequently used in wildfire risk assessments as an index of fireline intensity (rate of energy release from the fire front) because it is easily interpreted by non-fire resource specialists and FL and fireline intensity are strongly correlated (Byram, 1959). CFA was used as a proxy for soil burn severity as described in Gannon et al., (2019) to model post-fire watershed impacts (see Section 3.5 Watershed Modeling). CFA simply represents the type of fire expected on a given pixel and is divided into surface fire, passive crown fire, or active crown fire. Surface fires spread only on the surface and do not involve significant ignition of raised canopy fuels. A passive crown fire may involve significant amounts of canopy consumption; however, the canopy fire is not considered self-sustaining and therefore significant energy from the surface fire is needed to sustain tree crown combustion. Active crown fire is the most extreme type of fire behavior and entails continuous horizontal spread of fire from tree crown to tree crown and is often associated with complete or near complete consumption of all available canopy fuel.

FlamMap fire behavior modeling was conducted under a range of weather scenarios that represent the 25th, 50th, 90th, and 97th percentile conditions (Table 1). These percentiles were calculated from observations between 2000 and 2020 to better represent current climate conditions. Given the large spatial scale across which fire behavior was modeled, fire weather percentile conditions were calculated for 7 Remote Automated Weather Station (RAWS) stations distributed across the modeling domain (Figure 5 – Gunsight, Harbison Meadow, Pickle Gulch, Soda Creek, Corral Creek, Cheesman, and Jones Hill). Each station was assigned a buffer distance from 30 to 80 km within which its' weather observations were used to model fire behavior. These overlapping zones allowed each station to have a local influence while being averaged with nearby weather observations. Percent fuel moisture was computed for each category of dead and live fuels during a fire season defined as April 01 to October 31 using FireFamilyPlus 5 (Bradshaw and McCormick, 2000). The 10-minute average RAWS wind speeds were converted to 1-minute average wind speeds for modeling (Crosby and Chandler, 1966). In FlamMap, wind direction was assumed to be upslope to represent a consistent worst-case scenario across aspects. The Scott and Reinhardt (2001) method was used for predicting crown fire activity.

Figure 5: RAWS locations used for fire modeling with Denver Water source area in red. Dotted circles represent the spatial extent at which each station influenced fire behavior modeling.

Table 1: Four weather scenarios were selected for our fire modeling which reflect the 25th, 50th, 90th, and 97th percentiles of fuel moisture, wind speed, etc. based on historic observations. These scenarios were weighted based on the assumption that most area burns under extreme weather conditions.

				FUEL MOISTURE %						
Weather Station	Scenario	Percentile	Weight	1-hr	10-hr	100-hr	1000-hr	Herb.	Woody	Wind Speed 1-min (mph @ 20 ft)
Harison Meadow	Low	25th	0.01	9.1	10.7	17.2	21	96	121	4
	Moderate	50th	0.09	5.6	7.4	14.6	17.6	40	78	7
	High	90th	0.2	3	4.7	10.5	13.7	30	70	12
	Extreme	97th	0.7	2.2	3.8	8.9	11.8	30	70	15
Gunsight	Low	25th	0.01	7.9	9	13.5	15.4	56	92	6
	Moderate	50th	0.09	4.8	6	10.1	12.6	35	63	10
	High	90th	0.2	2.3	3.3	5.9	8.4	30	60	20
	Extreme	97th	0.7	0.7	1.4	3.6	6.1	30	60	24
Soda Creek	Low	25th	0.01	8.8	10.1	15.8	18.8	62	102	5
	Moderate	50th	0.09	5.1	6.7	12.3	15.7	35	70	7
	High	90th	0.2	2.8	4	7.6	11.2	30	70	10
	Extreme	97th	0.7	2	3.2	6.4	9.9	30	70	12
Corral Creek	Low	25th	0.01	8.9	9.9	14.6	17.3	52	97.1	6
	Moderate	50th	0.09	5.5	6.8	11.6	14.8	30	70	9
	High	90th	0.2	2.7	3.9	7.5	11	30	70	14
	Extreme	97th	0.7	1.7	3	6.2	9.5	30	70	17
Pickle Gulch	Low	25th	0.01	10.5	11.1	15.1	18.6	49	93	5
	Moderate	50th	0.09	5.9	7.2	11.4	15.1	30	70	7
	High	90th	0.2	2.9	4	7.1	10.7	30	70	11
	Extreme	97th	0.7	2	3.1	5.8	9.5	30	70	14
Jones Hill	Low	25th	0.01	7.6	8.8	13.6	15.9	48	79	4
	Moderate	50th	0.09	4.9	6	10.2	13	30	60	7
	High	90th	0.2	2.3	3.3	6.3	9.3	30	60	14
	Extreme	97th	0.7	1.6	2.5	5.1	7.9	30	60	17
Cheesman	Low	25th	0.01	6.6	7.7	12.4	13.9	51	90	6
	Moderate	50th	0.09	4.1	5.3	9.4	11.7	30	63	9
	High	90th	0.2	1.7	2.8	5.7	8.4	30	60	18
	Extreme	97th	0.7	1.1	2.1	4.6	7.4	30	60	22

FlamMap outputs for each station were mosaiced together to generate continuous fire behavior rasters across the entire analysis area (Appendix I – Fire Behavior Results). For the wildfire risk modeling, weighted composite products were created to represent the average expected fire behavior at each pixel. This weighting puts much greater emphasis on the outputs for the 90th and 97th percentile weather conditions as most area burned in wildfire occurs in these more extreme conditions (Table 1).

Burn Probability

In contrast to the worst-case approach that we used in FlamMap, FSim was used to generate an estimate of the pixel-wise annualized burn probability by simulating 15,000 years of fire ignition and spread to estimate the annual probability that a given pixel will burn. Burn probability is calculated as the number of times a given pixel burned divided by the total number of simulated ignitions. A burn probability value of 1 means a fire is certain and a value of 0 means a fire is impossible. To accomplish this, FSim combines modules for fire weather, ignitions, growth, and suppression through a stochastic Monte-Carlo simulation approach where fires are ignited and grown independently of one another on a static fuelscape. This simulation accounts for the effects of topography and prevailing wind directions on the rate and direction of fire spread. This captures effects such as lower probabilities of fire on the lee side of large waterbodies, alpine ridgelines, burn scars, 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 significantly alter the landscape fuel condition in the future, updated FSim runs are required to accurately represent the spatial burn probability.

FSim model runs can only accept weather inputs from a single weather station and due to the computational demands of the simulation, the decision was made to split the modeling domain into two zones which were each assigned one representative weather station – Gunsight for the Northwestern domain and Cheesman for the Southeastern domain (Figure 6). The FSim simulations from both domains were conducted at 270 m resolution for 15,000 years of modeled fire activity. Current climate simulation parameters were calibrated such that simulation results matched the observed annual number of fires, mean fire size, and fire size distribution between 2000 and 2020 within a 40 km buffer of the Denver Water source area.

The final annual burn probability (BP) raster produced by FSim underwent some post-processing to account for scale differences between the simulations (270 m) and the final analysis resolution (30 m). First, outputs from the two domains were mosaiced together before setting all pixels with a BP of zero to the 5th percentile BP within the analysis area (Appendix II - Burn Probability Results). This was done to prevent pixels containing wildland fuels from having zero wildfire risk, but still ensuring a relatively low BP. Next, three passes with a 3 x 3 moving window were used to smooth all BP values. The raster was then resampled to 30 m using bilinear interpolation. Finally, all 30 m pixels that were coded as non-burnable based on the 30 m fuelscape developed for the fire behavior modeling were set to have a BP of zero.

3.4 Wildfire Hazard and Risk

Hazard is a physical situation with the potential to cause damage to highly valued resources and assets (HVRAs) (Scott et al., 2013). Hazard is generally represented as conditional net value change (cNVC) which is the change in value conditional on fire occurrence (i.e., if a fire were to burn). Because this approach assumes all areas of the landscape have an equal chance of burning, this metric will highlight the areas on the landscape with concentrations of fire sensitive resources and assets without regard to the modeled probability that they will encounter wildfire.

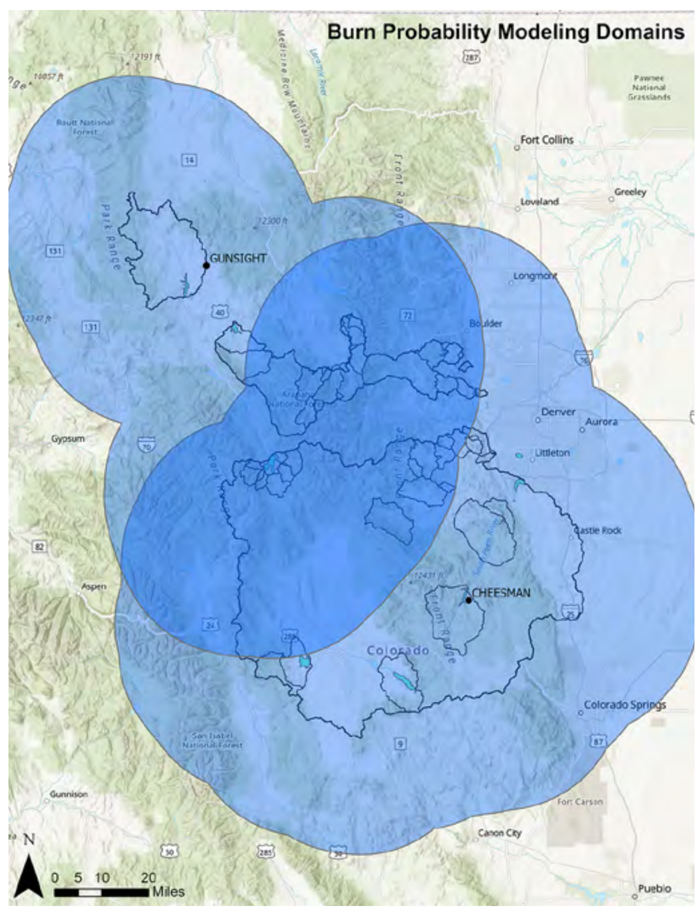


Figure 6: East and west FSim modeling domains in blue with the two representative RAWS stations. Denver Water's zones of concern delineated within the Denver Water source area.

cNVC is particularly relevant during active wildfire incidents where burn probability is no longer determined by historical occurrence trends, but rather the likely spread path of an ongoing wildfire.

Alternatively, wildfire risk accounts for the likelihood that resources and assets encounter wildfire (Scott et al., 2013). Risk is generally represented by expected net value change (eNVC) which weighs the potential consequences of an event by its probability of occurrence. Thus, this metric represents the likely impact of wildfire. Risk is particularly beneficial when planning vegetation management because it will help identify locations that are likely to encounter wildfire. In short, wildfire hazard x burn probability = wildfire risk.

Traditional QWRAs define HVRA susceptibility to fire by intensity level using response functions ranging from -100 for total loss to +100 for radical gain (Scott et al., 2013). In other words, stakeholders decided whether a particular resource would be positively or negatively affected by fire of a given intensity and the relative magnitude of that impact. However, the F2F partnership identified the indirect fire effect of sediment delivery to critical water infrastructure as their primary concern. Thus, we included reservoirs, diversions, and conveyance infrastructure as HVRAs and then characterized post-fire erosion and debris flow risk to each piece of water infrastructure (Table 2).

We included three watershed models which were weighted relative to the estimated cost of sediment removal into one composite wildfire risk metric (Table 2). These relative importance scores were based on the maximum cost estimates of sediment delivery to reservoirs and diversions compared to conveyance infrastructure. Based on internal valuations completed by Denver Water in 2019, the maximum estimated impact cost of sediment delivery to aboveground pipelines would be \$20/m^3 for removing debris with heavy machinery. That is much less costly to Denver Water than sediment delivery to diversions and reservoirs where the max estimated impact costs is \$150 per m^3 based on historical dredging (\$130/m^3) and degraded water quality costs (\$20/m^3) (Jones et al., 2021). Regardless of whether dredging is the direct response to sedimentation, it is reasonable to assume that lost storage has a cost. It is generally less expensive to remove post-fire sediment and debris from diversions compared to reservoirs, but that is already reflected in the infrastructure relative importance scores within each watershed model (see section 2.5 Watershed Modeling). We used the maximum cost ratio of 150:20 (reservoirs and diversions compared to conveyance infrastructure) as our relative importance scores for weighted averaging of the 3 risk layers (Table 2).

Table 2: Three post-fire watershed hazards were included in the risk assessment. This table outlines the relative importance of each which is based on maximum cost estimates to remove sediment and debris from each type of water infrastructure.

Watershed Model	Cost (USD/m^3)	Relative Importance
Hillslope erosion and sediment delivery to reservoirs and diversions	\$150 max for dredging and water treatment	47
Debris flows and sediment delivery to reservoirs and diversions	\$150 max for dredging and water treatment	47
Debris flows and sediment delivery to conveyance infrastructure	\$20 max for heavy machinery	6

3.5 Watershed Modeling

Wildfire risk to water supplies was assessed with watershed models that estimated potential post-fire erosion, debris flows, and sediment transport to water infrastructure (e.g., diversions, reservoirs, & conveyance infrastructure).

The potential mass of post-fire sediment delivered to reservoirs and diversions was modeled with linked hillslope erosion and sediment transport models following the methods in Gannon et al. (2019) and outlined in Figure 7. Post-fire increases in hillslope erosion were predicted with a Geographic Information System-based implementation (Theobald et al., 2010) of the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997). RUSLE is an empirical model of annual gross erosion based on the product of factors representing rainfall erosivity (R), soil erodibility (K), vegetative cover (C), length and slope (LS), and support practices (P). Baseline soil erodibility was described using attributes of the top 15 cm of the soil horizon from SSURGO and as needed from STATSGO to fill missing data (NRCS Soil Survey Staff 2016). Baseline vegetative cover was assigned according to previous reports of cover factor values by vegetation type from the literature as described in Gannon et al. (2019). The combined length and slope factor was calculated using ArcGIS Pro 3.2.2 for terrain analysis of a 30 m digital elevation model per Winchell et al. (2008) with modifications to restrict hillslope lengths to 300 m and LS factor values to 72.15 as suggested in Renard et al. (1997). Fire effects on vegetation cover and soil erodibility (Table 3) were quantified by burn severity using locally relevant empirical observations from Larsen and MacDonald (2007). Soil burn severity was predicted by mapping crown fire activity (Scott and Reinhardt, 2001) categories

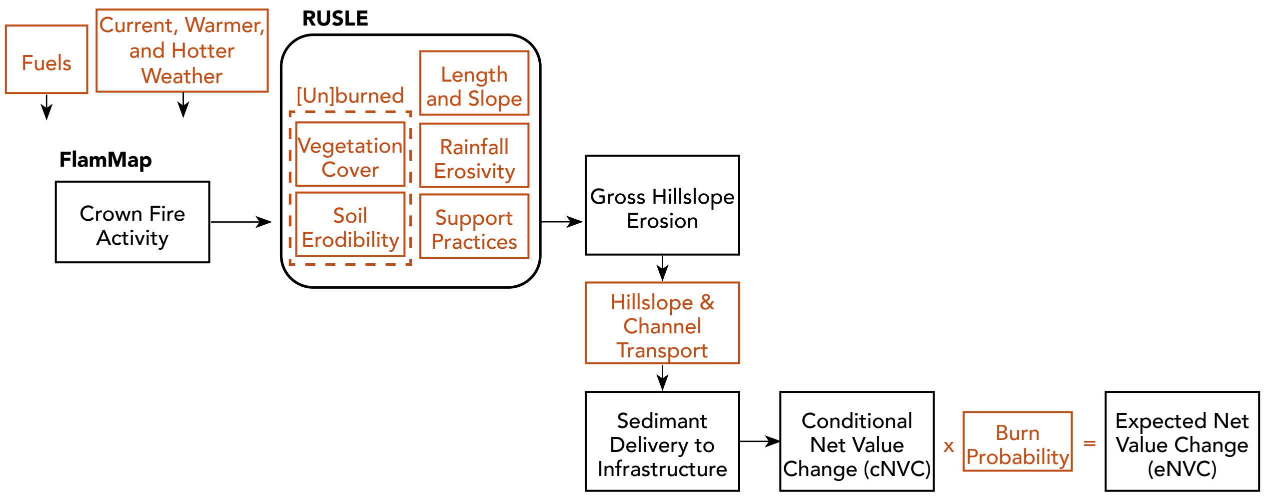


Figure 7: Summary of RUSLE erosion and sediment transport workflow where orange boxes represent model inputs and black boxes represent model outputs.

$A_{y1} = R \times LS \times (C_b \times K_b - C \times K)$ (Equation 1)

Table 3: The C factor is adjusted for forests by assigning the mean post-fire C from Larsen and MacDonald (2007). Proportional adjustments in C are applied to other vegetation types. The K factor is incrementally raised to a two factor increase at high severity.

Burn severity	C factor remap for forests	C factor proportional adjustment for non-forest	K factor proportional adjustment
Low	0.01	1.20	1.50
Moderate	0.05	1.50	1.75
High	0.20	2.00	2.00

of surface fire, passive crown fire, and active crown fire to low, moderate, and high severity respectively. The increase in first year post-fire erosion was estimated by differencing baseline (no subscript) and burned (b subscript) erosion estimates (Equation 1).

The proportion of gross hillslope erosion that is subsequently transported downstream to water infrastructure was then estimated from empirical models of hillslope and channel sediment delivery. First, hillslope sediment delivery ratios (hSDR) were assigned based on distance from a hillslope pixel to the nearest stream (Wagenbrenner and Robichaud, 2014). Generally, hillslopes that are farther from a stream will deliver a smaller proportion of total hillslope erosion because there are more opportunities for sediment retention on longer flowpaths. The maximum hSDR was 0.54 for areas near streams, the minimum was 0.02 for locations further from streams, and channel pixels were assigned a hSDR of one. Channel sediment delivery ratios (cSDR) were then integrated to represent downstream transport to water infrastructure (Frickel et al., 1975). At the time scale of years, some sediment should be stored in floodplains or channels, thus most channels will have cSDR < 1.

Observations of the South Platte Watershed after the Buffalo Creek Fire suggest sediment transport increases in efficiency with slope and discharge (Moody and Martin, 2001). To approximate this effect, we assigned cSDR per 10 km of channel length based on channel gradient and stream order. We also accounted for sediment storage in lakes and reservoirs as a function of waterbody surface area from NHDPlus to reflect that trapping efficiency generally increases with waterbody size.

Finally, sediment delivery was weighted by infrastructure relative importance to capture the differential sediment impacts of each infrastructure component (e.g., 1 m^3 of sediment will be more costly to Denver Water if it enters Strontia Springs reservoir than Platte Canyon Reservoir). In 2019, Denver Water staff from multiple departments collaboratively rated the relative importance of sediment impacts to their infrastructure on a scale from 0 to 100 representing no impact to highest impact in three categories: water treatment, operations (including storage, conveyance, hydropower), and stewardship (ecological and social functions). The three category relative importance values were then averaged into a composite importance value for each piece of infrastructure for a return on investment assessment (Jones et al., 2021). In 2023, Denver Water staff made two revisions to the original relative importance values. First, staff decided that it was more representative of their risk to only average the values directly related to Denver Water's ability to deliver and treat water. Therefore, the treatment and operations values were averaged to determine the composite importance value. Secondly, they added Fraser valley diversions to the infrastructure rankings to represent potential consequences of sediment entering downstream conveyance infrastructure. Ultimately, feedback from multiple departments within Denver Water reached consensus that Strontia Springs Reservoir was rated most important (RI=1) above all other infrastructure. The watershed risk outputs represent the risk of post fire sediment delivery to drinking water drinking water infrastructure weighted by relative importance.

This workflow supports pixel-level estimates of the sediment generated in each hillslope pixel that is delivered to downstream weighted water supply infrastructure (Figure 8). 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 (cNVC). cNVC was then multiplied by burn probability to estimate eNVC.

We modeled debris flow risk separately for 1) reservoirs and diversions and 2) conveyance infrastructure with distinct relative importance weights. Regardless, debris flow risk was quantified with an empirical model of post-fire debris flow probability and volume from the U.S. Geological Survey (USGS) (Cannon et al., 2010). This consists of a multiple logistic regression model to predict debris flow probability and a regression model to predict debris flow

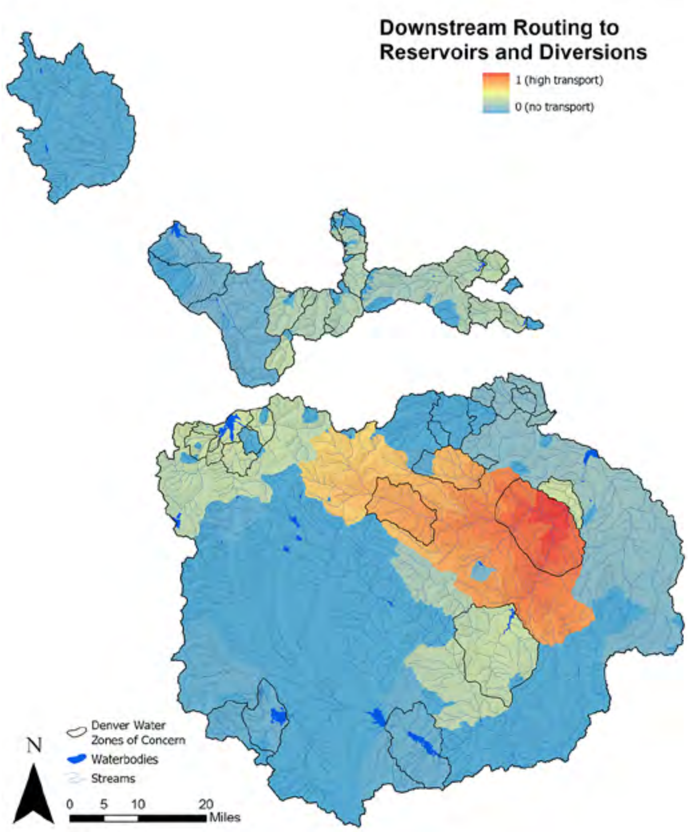


Figure 8: Weighted downstream routing raster to reservoirs and diversions. This accounts for hillslope and channel transport efficiencies as well as infrastructure relative importance.

volume at the catchment-scale, unlike pixel-level erosion estimates from RUSLE. The probability model is described in equations 2 and 3 with variable definitions in Table 4. The volume model is described in equation 4 with variable definitions in Table 4. The full workflow is depicted in Figure 9.

$$x = -0.7+0.03(\%SG30)-1.6(R)+0.06(\%AB)+0.07(I)+0.2(\%C)-0.4(LL) \quad \text{(Equation 2)}$$

$$P = e^x/(1+e^x) \quad \text{(Equation 3)}$$

$$\ln(V)=7.2+0.6(\ln(SG30))+0.7(AB)^{0.5}+0.2(T)^{0.5}+0.3 \quad \text{(Equation 4)}$$

Table 4: Variable definitions, sources, and processing methods for the USGS debris flow model.

Variable	Definition	Source and processing
%SG30	Percent of catchment ≥ 30% slope	Calculated from 30-m digital elevation model
R	Ruggedness, calculated as change in catchment elevation (m) divided by the square root of the catchment area (m^2)	Calculated from 30-m digital elevation model
%AB	Percent of catchment burned at moderate or high severity	From FlamMap modeling in this study
I	Average storm intensity (mm h-1)	From NOAA frequency duration atlas (Perica et al. 2013)
%C	Percent clay content	From top 15 cm of soil from SSURGO and/or STATSGO (NRCS Soil Survey Staff 2016)
LL	Liquid limit	From top 15 cm of soil from SSURGO and/or STATSGO (NRCS Soil Survey Staff 2016)
SG30	Area (km^2) of catchment ≥ 30% slope	Calculated from 30-m digital elevation model
AB	Area (km^2) of catchment burned at moderate or high severity	From FlamMap modeling in this study
T	Total storm rainfall (mm)	Same as intensity from NOAA frequency duration atlas (Perica et al. 2013) for the median one-hour storm duration

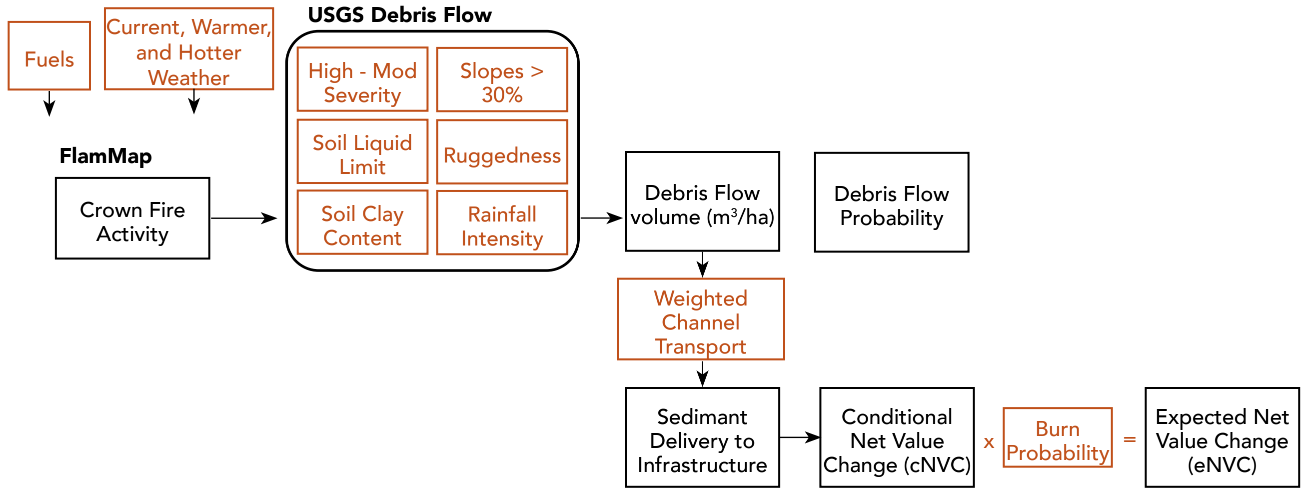


Figure 9: Summary of USGS debris flow model integration within RADS where inputs are orange and outputs are black.

To represent debris flows and sediment delivery to reservoirs and diversions, we applied the USGS debris flow model at the NHD catchment scale given the computational constraints of this model. Expected debris flow volumes were then routed down the flowline network using the same methods described in the erosion modeling section with modification of channel sediment delivery ratios to reflect that debris flow constituents larger than gravel will not transport efficiently through the low order streams in these watersheds. This downstream weighting accounts for the relative importance of each reservoir and diversion (Figure 8).

In several parts of the collection system, water is conveyed through open canals or shallow pipelines that are susceptible to blockage or damage from debris flows originating from upstream catchments. Denver Water staff identified vulnerable conveyance infrastructure in the Upper Fraser Watershed and a limited area of the South Boulder Creek Watershed. It is assumed that the primary response to these events would be mobilizing heavy machinery to remove the debris volume which would be much less expensive than if debris was delivered to a reservoir or diversion point where the likely response would be dredging or increased water treatment costs. Given the smaller geographic scope, we were able to conduct more nuanced modeling to characterize debris flows and sediment delivery to conveyance infrastructure (Figure 10). First, appropriate catchments were delineated to represent potential debris flow initiation zones using the hydrology toolset in ArcGIS Pro 3.2.2. Catchments between 5 acres (2 ha) and 494 ac (2 km^2) in size that directly contribute to the conveyance system were identified. No channel transport is modeled for these catchments. For catchments that do not directly contribute to the conveyance infrastructure, debris was routed down the flowline network using the same methods described in the erosion modeling section with modification of channel sediment delivery ratios to reflect that debris flow constituents larger than gravel will not transport efficiently through the low order streams in these watersheds.

Debris flow outputs should be interpreted cautiously because we calculate the debris flow volume (m^3) conditional on burning as the product of debris flow

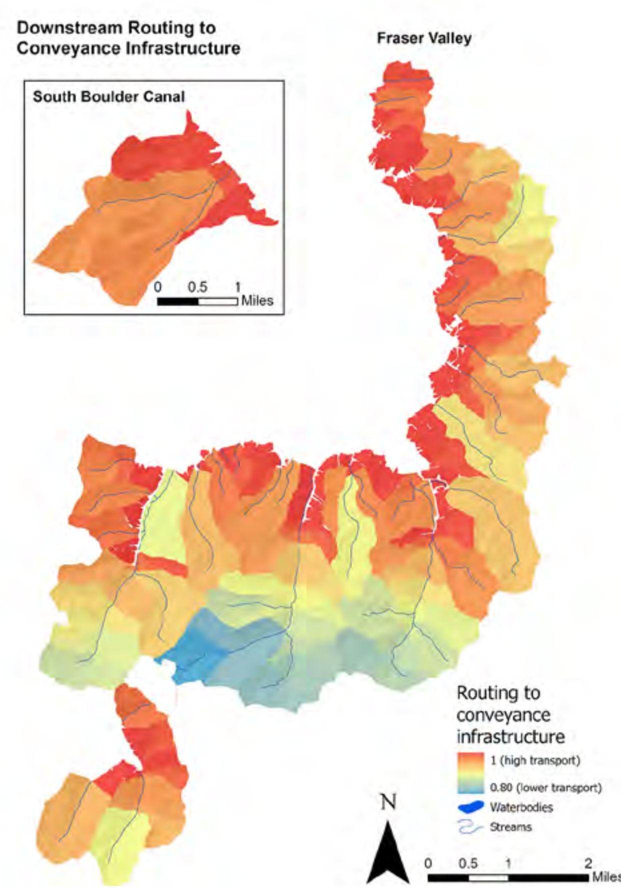


Figure 10: Weighted downstream routing for sediment transport to conveyance infrastructure in Fraser Valley and South Boulder Creek. This accounts for hillslope and channel transport efficiencies as well as infrastructure relative importance.

probability (Equation 3) and potential debris flow volume (Equation 4). In reality, debris flows will either occur or not and their volumes would be best predicted by Equation 4 alone. Additionally, these debris flow volumes were calibrated from field observations in Southern California. Post-fire studies in Colorado have observed 4.4-times lower debris flow volumes than those observed in Southern California (Rengers et al., 2023). These modeled estimates are still useful for relative comparisons in a risk assessment.

3.6 In-Situ and Transmitted Risk

Potential operational delineations (PODs) represent the safest and most effective control lines that could be used to engage with fire. These can be natural (ridges, fuel type transitions, etc.) or human-made (roads, fuel breaks, etc.) features. PODs are dynamic control features that can be created or altered through management actions, natural disturbance, or even shifts in human perceptions. The integration of quantitative wildfire risk assessments and PODs can inform mitigation and fire response strategies in relation to the susceptibility and importance of values on the landscape.

There are two dominant forms of risk that can be summarized for each POD based on quantitative wildfire risk assessments. These calculations sum cNVC to quantify the net impacts of tens of thousands of "known" fires that were simulated in FSim burn probability modeling. The first is **in-situ risk** which represents local wildfire risk to HVRAs within a POD. That is calculated by identifying all FSim perimeters that initiated in a given POD and then summing cNVC for the portion of each perimeter within that POD. If there are fire-sensitive HVRAs within a POD that intersect with high burn probability and fire intensity, in-situ risk will be high. The second type is **transmitted risk** which represents wildfire risk to HVRAs should fire cross a POD line into a neighboring POD. This is calculated by summing cNVC in all simulated fire perimeters and assigning total cNVC to the POD of ignition. This highlights areas with high potential for fire spread into a nearby fire-sensitive PODs and can be thought of as "sources" of risk. Here is another way of distinguishing the two risk types: in-situ risk = if a fire were to start in a POD, what effect would it have on that POD vs. transmitted risk = if a fire were to start in a POD, what effect would it have on neighboring PODS.

Management actions should vary based on the types of risk present in a POD and the specific HVRA you are trying to protect (Table 5). For instance, PODs with low in-situ risk and low transmitted risk might be opportunities to support beneficial fire to maintain that low risk. PODs with low-in situ risk, but high transmitted risk might require POD boundary hardening to allow for beneficial fire within the POD, while limiting the transmission of undesirable fire into nearby fire-sensitive PODs. Alternatively, PODs with high in-situ risk and low transmitted risk are better suited for localized fuels reduction projects in the POD interior for HVRA protection. Finally, PODs with both high in-situ and transmitted risk may require management actions to address both types of risk – POD boundary hardening to limit fire spread and local fuels reduction for HVRA protection. There are alternative management actions that could reduce in-situ risk (e.g. floodplain enhancement, sediment reduction structures, and aerial mulching) or transmitted risk (e.g. reducing human ignitions, fire patrols, and recreation planning), but this report is focused on vegetation management activities. More specifically, this analysis identifies priority fuels reduction projects to 1) reduce fire intensity on hillslope contributing to or upstream of critical water infrastructure to address in-situ risk and 2) limit the spread of undesirable fire into fire-sensitive watersheds to address transmitted risk.

3.7 Prioritization of Vegetation Management in POD Interiors

We first prioritized vegetation management in POD interiors to reduce in-situ risk and protect local critical water infrastructure. We considered five vegetation

Table 5: Bivariate risk matrix that addresses the specific type of risk (in-situ vs. transmitted risk) with an appropriate management action.

	High transmitted risk	↔	Low transmitted risk
Low in-situ risk	POD boundary hardening to limit fire spread		Support beneficial fire to maintain low risk
↕			
High in-situ risk	Local fuels reduction + POD boundary hardening		Local fuels reduction for HVRA protection

management actions: 1) thin only, 2) prescribed fire only, 3) thin followed by prescribed fire, 4) mastication, and 5) patch cut. Vegetation management is simulated by changing baseline surface and canopy fuel attributes (LANDFIRE, 2020) by the mean effect sizes for hazardous fuels reduction and forest restoration projects in the western U.S. (Stephens and Moghaddas 2005; Stephens et al., 2009; Fulé et al., 2012; Ziegler et al., 2017; Ritter et al., 2023). Proportional adjustments are applied to the baseline canopy fuels data to capture the effects of vegetation management on canopy attributes (Table 6).

The effects of vegetation management on surface fuels were incorporated by changing the fire behavior fuel model (Table 7, Scott and Burgan, 2005). For this assessment, it was assumed that the thin only treatment would not alter the fire behavior fuel model, prescribed fire would shift the fire behavior fuel model to the least intense model in the same category and climate type, and thinning followed

Table 6: Vegetation management is simulated with proportional adjustments to baseline, pre-treatment canopy attributes using the below mean effect sizes from fuels reduction and forest restoration projects in the western US. We assumed patch cuts would lead to complete canopy removal forcing all canopy metrics to zero.

Parameter	Thin	RxFire	Thin + RxFire	Mastication	Patch Cut
Canopy Base Height	1.3	1.09	1.3	1.1	0
Canopy Height	1.3	1.13	1.3	1.1	0
Canopy Cover	0.6	0.95	0.6	0.75	0
Canopy Bulk Density	0.6	0.92	0.6	0.8	0

Table 7: The categorical fire behavior fuel model adjustments by vegetation management action. Changes from baseline FBFM's are highlighted with red text.

Fuel Model	Baseline	Thin	RxFire	Masti-cation	PatchCut
NB1	91	91	91	91	91
NB2	92	92	92	92	92
NB3	93	93	93	93	93
NB4	94	94	94	94	94
NB5	95	95	95	95	95
NB6	96	96	96	96	96
NB7	97	97	97	97	97
NB8	98	98	98	98	98
NB9	99	99	99	99	99
GR1	101	101	101	201	101
GR2	102	102	101	201	102
GR3	103	103	103	201	103
GR4	104	104	101	201	104
GR5	105	105	103	201	105
GR6	106	106	103	201	106
GR7	107	107	101	201	107
GR8	108	108	103	201	108
GR9	109	109	103	201	109
GS1	121	121	121	201	121
GS2	122	122	121	201	121
GS3	123	123	123	201	121
GS4	124	124	123	201	121
SH1	141	141	141	202	121
SH2	142	142	141	202	121
SH3	143	143	143	202	121

Fuel Model	Baseline	Thin	RxFire	Masti-cation	PatchCut
SH4	144	144	143	202	121
SH5	145	145	141	202	121
SH6	146	146	143	202	121
SH7	147	147	141	202	121
SH8	148	148	143	202	121
SH9	149	149	143	202	121
TU1	161	161	161	202	121
TU2	162	162	162	202	121
TU3	163	163	162	202	121
TU4	164	164	161	202	121
TU5	165	165	161	202	121
TL1	181	181	181	201	121
TL2	182	182	182	201	121
TL3	183	183	181	201	121
TL4	184	184	181	201	121
TL5	185	185	181	201	121
TL6	186	186	182	201	121
TL7	187	187	181	201	121
TL8	188	188	181	201	121
TL9	189	189	182	201	121
SB1	201	201	201	201	121
SB2	202	202	201	201	121
SB3	203	203	201	201	121
SB4	204	204	201	201	121

by prescribed fire would achieve the same effects as prescribed fire only. Mastication was assumed to push shrub and timber understory fuel models to fuel model 202 (slash blowdown 2) whereas grass, grass shrub, timber litter, and slash blowdown were all forced to fuel model 201 (slash blowdown 1) post-mastication. This reflects how mastication of fuel models with a significant understory shrub component is likely to result in more masticated fuel on the ground. It was assumed that patch cut would be followed by surface management actions that reduced woody biomass accumulation such as piling and burning or removal of the majority of woody material, and thus changes all fuel types to a grass shrub model, with the exception of grass fuel model remaining grass. Decisions about forest management practices were informed by other recent collaboratively developed local risk assessments (Rhea et al., 2022, Mueller et al., 2023, Jefferson County Open Space 2022), as well as additional F2F leadership team communication with their forestry field office staff to update current conditions.

Table 8: Vegetation management feasibility and cost constraints integrated in the prioritization.

Vegetation Management	Feasibility	Cost
Thin	No wilderness or upper tier roadless, >10% canopy cover	\$2,800/acre base cost + linear increase with slopes > 40% and distances from road > 800 m up to max of \$10,000/acre
Prescribed Fire	No lodgepole or spruce-fir	*Surface fire during 25th % fire weather*: \$900/ acre > 250 m from structure, \$1800 when <250 m from a structure *Crown fire during 25th % fire weather*: \$2000/ acre > 250 m from structure, \$4000 when <250 m from a structure
Thin followed by Prescribed Fire	No wilderness or upper tier roadless, >10% canopy cover, no lodgepole or spruce-fir	Mechanical thin only \$ + RxFire only \$ (\$3,700 – \$10,000)
Patch Cut	No wilderness or upper tier roadless, canopy cover > 10%, only lodgepole and spruce-fir	\$2,800/acre base cost + linear increase with slopes > 40% and distances from road > 800 m up to max of \$10,000/acre
Mastication	No wilderness or upper tier roadless, >10% canopy cover	\$2000/acre + linear increase with slopes > 40%, linear increase with Crown Bulk Density above 50th percentile, and distances from road > 800 m up to max of \$10,000/acre

After adjusting canopy and surface fuels for each vegetation management scenario, wildfire behavior and watershed models were re-run for the full analysis extent following the same framework laid out in Figure 2. Both cNVC and eNVC were calculated for the baseline, thin, RxFire, thin + RxFire, mastication, and patch cut scenarios. The difference between baseline eNVC and treated eNVC represents the potential risk reduction of a given vegetation management action.

Operational constraints of vegetation management were captured by including feasibility and cost criteria in the planning process (Table 8). Hard constraints (e.g. wilderness, roadless, or forest type) are captured in binary rasters representing the feasibility of vegetation management (i.e., each pixel is feasible (1) or infeasible (0)). Risk reduction estimates are restricted to areas where a given vegetation management action is feasible. Economic constraints are instead captured with variable vegetation management costs. These cost estimates are then integrated into the return on investment calculations used to maximize risk reduction per dollar spent (Table 8).

Feasibility and cost criteria were informed through past risk assessments (e.g. Rhea et al., 2022, Mueller et al., 2023, Jefferson County Open Space 2022), extensive conversation with the F2F leadership team, and input on management practices from field foresters throughout the F2F planning area across federal and non-federal land management agencies. Vegetation management was generally restricted to forested lands (>10% canopy cover) that fall outside of wilderness and upper tier roadless areas. The one exception was prescribed fire which could be applied to grass and shrubland ecosystems and, in some cases, is allowed in wilderness and upper tier roadless areas. First and second-entry prescribed fire were excluded from lodgepole, spruce, and subalpine fir-dominated forests because it is generally ecologically incompatible with those forest ecosystems and is not commonly implemented by managers. Conversely, patch cuts were restricted to lodgepole, spruce, and subalpine fir-dominated forests to represent current management practices that mimic stand replacing disturbances. While fire behavior and forest processes are dynamic in all forest environments, these feasibility criteria generally align with dominant ecological processes and commonly applied management practices in these vegetation types. Base cost estimates were informed by fuels managers in local field offices of USFS, NRCS and local conservation districts, CSFS, and CFRI staff expertise. Cost often increased with slopes >40% and distances from road > 800 m to capture the operational constraints of managing vegetation on steep acres with poor access, but vegetation management was not categorically excluded in these areas. Prescribed fire costs varied with predicted fire type and distance from structures. We used 25th percentile fire behavior which is most similar to weather conditions when prescribed fires are currently implemented. The assumption here is that first-entry prescribed fires should be relatively inexpensive to implement when they are expected to burn as low severity surface fires. Forests that are likely to burn as crown fire, even under 25th percentile weather, will likely require additional treatment (i.e. pre-RxFire thinning or enhancement of control features) or more complex planning, so costs were assumed to roughly double in those areas. Additionally, we assume planning and implementation costs of prescribed fire to double when near (<250 m) existing structures. Finally, mastication costs included a linear increase with crown bulk density, which is closely related to tree basal area, to account for potential cost increases from slower operations and/or hauling residual fuels off site when anticipated residual fuel depths exceed 2-3 inches. Maps of vegetation management feasibility, cost, and cost effectiveness are included in Appendix III – Vegetation Management Assumptions.

A linear optimization (see Appendix IV – Linear Optimization Model Formulation) prioritizes the locations and types of vegetation management where risk reduction, measured by change in eNVC, is maximized relative to costs under any target budget level. Areas selected at lower budget levels are more cost effective to achieve desired outcomes than those selected at higher budget levels. The F2F partnership selected budget levels of $30 million and $90 million to achieve the most cost-effective (bang for the buck) reduction of wildfire risk. The $30M budget was based on estimated F2F partnership funding of $6M per year over the next 5 years, as committed through a June 2022 Memorandum of Understanding. The $90M was seen as an aspirational budget for F2F implementation over longer time periods, or if funding and implementation were to increase with additional federal and state wildfire funding programs. Evaluation of the cost-benefit curve can help inform tradeoffs of continued investments in forest management compared with other potential risk reduction activities.

Proportional budget caps can also be included in the prioritization to constrain the proportion of the total budget allocated to a given vegetation management action. We ran two fuels reduction prioritizations, one where no vegetation management actions were capped at a maximum budget proportion ("uncapped") and one where we applied a 80% budget cap on RxFire and 15% budget cap on patch cuts ("capped"). The uncapped scenario maximizes model return on investment. The large areas prioritized for RxFire also identify opportunities with high potential to leverage beneficial wildfire burning under similar prescribed fire conditions in specific areas of the watershed. The capped scenario was intended to reflect agency hesitation and current capacity constraints for implementing prescribed fire over large areas within these watersheds, particularly on non-federal lands. Results from both uncapped and capped scenarios are presented in section 4.2.

3.8 Prioritization of Vegetation Management Along POD Boundaries

Aligning vegetation management with strategic fire management operations will yield additional opportunities to increase return on investment and improve system resilience to wildfire. We used the suppression difficulty index (SDI) to prioritize vegetation management along POD boundaries to limit risk transmission to nearby critical water infrastructure. SDI quantitatively ranks the relative difficulty of performing fire control work and is based on potential fire behavior, the difficulty of the terrain (i.e. slope), the difficulty of access (i.e. roads, trails, and vegetation), and predicted rates of line construction (i.e. fuel type and access) (Rodríguez y Silva et al., 2020). Lower SDI values represent increased efficiency and safety of suppression operations based on current landscape conditions. SDI can also be used to prioritize pre-fire vegetation management projects that reduce the difficulty of future suppression actions. To do so, we calculated SDI for current fuels and for the five vegetation management actions outlined in section 3.7. The difference between baseline SDI and treated SDI represents the potential of a vegetation management action to reduce suppression difficulty (i.e. make it easier and safer to directly fight fire) and will be referred to as ΔSDI. We leveraged ΔSDI data for a thin followed by prescribed fire treatment under 90th percentile fire weather to prioritize key opportunities for POD line hardening in strategic locations that limit fire transmission to nearby fire-sensitive PODs.

Table 9: Fire weather for the "warmer" scenario which reflect the 25th, 50th, 90th, and 97th percentiles of fuel moisture, wind speed, etc. These scenarios were weighted based on the assumption that most area burns under extreme weather conditions.

				FUEL MOISTURE %						
Weather Station	Scenario	Percentile	Weight	1-hr	10-hr	100-hr	1000-hr	Herb.	Woody	Wind Speed 1-min (mph @ 20 ft)
Harison Meadow	Low	25th	0.01	8.6	10.1	16.2	19.6	91.8	115.9	4
	Moderate	50th	0.09	5.2	6.8	13.4	16.3	35.6	73.6	7
	High	90th	0.2	2.7	4.1	9.3	12.3	25.1	65.1	12
	Extreme	97th	0.7	1.8	3.2	7.6	10.4	25.1	65.1	15
Gunsight	Low	25th	0.01	7.4	8.4	12.6	14.3	50.8	87.2	6
	Moderate	50th	0.09	4.4	5.4	9.2	11.4	30	58.6	10
	High	90th	0.2	2	2.7	4.9	7.2	25	55	20
	Extreme	97th	0.7	0.3	0.8	2	3.7	25	55	24
Soda Creek	Low	25th	0.01	8.1	9.2	14.4	16.8	56.7	96.8	5
	Moderate	50th	0.09	4.5	5.9	10.8	13.8	29.6	64.6	7
	High	90th	0.2	2.2	3.2	6.2	9.3	24.6	64.6	10
	Extreme	97th	0.7	1.5	2.4	4.9	8	24.6	64.6	12
Corral Creek	Low	25th	0.01	8.1	9	13.3	15.4	44.9	90.1	6
	Moderate	50th	0.09	4.8	5.9	10.1	12.9	23	63	9
	High	90th	0.2	2.1	3	6	9	23	63	14
	Extreme	97th	0.7	1.5	2.1	4.8	7.4	23	63	17
Pickle Gulch	Low	25th	0.01	9.9	10.5	14.1	17.2	43.2	87.5	5
	Moderate	50th	0.09	5.4	6.6	10.5	13.8	24.6	64.6	7
	High	90th	0.2	2.5	3.4	6.1	9.5	24.6	64.6	11
	Extreme	97th	0.7	1.6	2.5	4.8	8.1	24.6	64.6	14
Jones Hill	Low	25th	0.01	6.9	7.9	12.1	13.9	45	75.3	4
	Moderate	50th	0.09	4.2	5.1	8.7	11.1	26.2	56.2	7
	High	90th	0.2	1.7	2.4	4.7	7.2	26.2	56.2	14
	Extreme	97th	0.7	1.1	1.6	3.6	5.6	26.2	56.2	17
Cheesman	Low	25th	0.01	6	7	11.1	12.3	46.5	85.6	6
	Moderate	50th	0.09	3.6	4.6	8.2	10.1	25.4	58.7	9
	High	90th	0.2	1.3	2.1	4.5	6.7	25.4	55.4	18
	Extreme	97th	0.7	0.8	1.4	3.3	5.5	25.4	55.4	22

Table 10: Fire weather for the "hotter" scenario which reflect the 25th, 50th, 90th, and 97th percentiles of fuel moisture, wind speed, etc. These scenarios were weighted based on the assumption that most area burns under extreme weather conditions.

				FUEL MOISTURE %						
Weather Station	Scenario	Percentile	Weight	1-hr	10-hr	100-hr	1000-hr	Herb.	Woody	Wind Speed 1-min (mph @ 20 ft)
Harison Meadow	Low	25th	0.01	8.1	9.5	15	18	77.9	101.9	4
	Moderate	50th	0.09	4.7	6.2	12.2	14.7	21.6	59.6	7
	High	90th	0.2	2.2	3.5	7.9	10.6	11.1	51.2	12
	Extreme	97th	0.7	1.5	2.6	6.2	8.6	11.1	51.2	15
Gunsight	Low	25th	0.01	7.1	8.1	12	13.5	46.7	83.1	6
	Moderate	50th	0.09	4.1	5.1	8.6	10.7	25.9	54.5	10
	High	90th	0.2	1.7	2.4	4.3	6.3	20.9	50.9	20
	Extreme	97th	0.7	0.1	0.5	1.2	2.4	20.9	50.9	24
Soda Creek	Low	25th	0.01	7.7	8.8	13.6	15.8	52.8	92.9	5
	Moderate	50th	0.09	4.2	5.4	10	12.7	25.7	60.7	7
	High	90th	0.2	1.9	2.7	5.3	8.1	20.7	60.7	10
	Extreme	97th	0.7	1.2	1.9	4.1	6.6	20.7	60.7	12
Corral Creek	Low	25th	0.01	7.5	8.4	12.3	14.2	41.2	86.4	6
	Moderate	50th	0.09	4.3	5.3	9	11.5	19.3	59.3	9
	High	90th	0.2	1.7	2.4	4.9	7.4	19.3	59.3	14
	Extreme	97th	0.7	0.9	1.5	3.5	5.6	19.3	59.3	17
Pickle Gulch	Low	25th	0.01	9.5	10.1	13.4	16.3	42.7	86.99	5
	Moderate	50th	0.09	5.1	6.2	9.8	12.9	24.1	64.1	7
	High	90th	0.2	2.2	3	5.4	8.5	24.1	64.1	11
	Extreme	97th	0.7	1.3	2.1	4.1	7.1	24.1	64.1	14
Jones Hill	Low	25th	0.01	6.8	7.9	12	13.8	42.7	73.1	4
	Moderate	50th	0.09	4.1	5.1	8.7	11	23.9	53.9	7
	High	90th	0.2	1.6	2.4	4.6	7	23.9	53.9	14
	Extreme	97th	0.7	1	1.6	3.5	5.5	23.9	53.9	17
Cheesman	Low	25th	0.01	5.6	6.6	10.4	11.4	41.9	81	6
	Moderate	50th	0.09	3.2	4.2	7.4	9.2	20.8	54.1	9
	High	90th	0.2	1	1.7	3.7	5.6	20.8	54.1	18
	Extreme	97th	0.7	0.6	1	2.3	4.1	20.8	54.1	22

3.9 Climate Warming Simulations

To assess the impacts of a warming climate on future wildfire risk, we also integrated two warming simulations that represent the impact of global warming on fuel moisture. The selected simulations represent plausible future conditions in the decades to come and are not tied to a specific timescale.

Lynker consulting group worked with the Denver Water climate team to identify a set of climate change models that represent two scenarios of warming. Lynker utilized the climate change modeling completed as part of the Colorado River Water Availability Study Phase II (CRWAS-II) to select model output that was representative of a "warmer" and "hotter" climate. For each of these scenarios, mean monthly temperature change factors were pulled from a subset of climate change models from the CRWAS-II archive and applied to historic RAWS temperature data to estimate climate-adjusted temperature, which was then used to calculate climate-adjusted standardized precipitation-evapotranspiration index (SPEI) (Begueria and Viente-Serrano, 2017). A station-specific linear regression was developed between SPEI and fuel moisture using historic data and then climate-adjusted SPEI was used to project fuel moisture for the two warming scenarios (Table 9-Table 10). Projections were then integrated into the risk assessment with the only change being fuel moisture inputs to wildfire models. Climate-adjusted fire behavior and burn probability were then input into the watershed models.

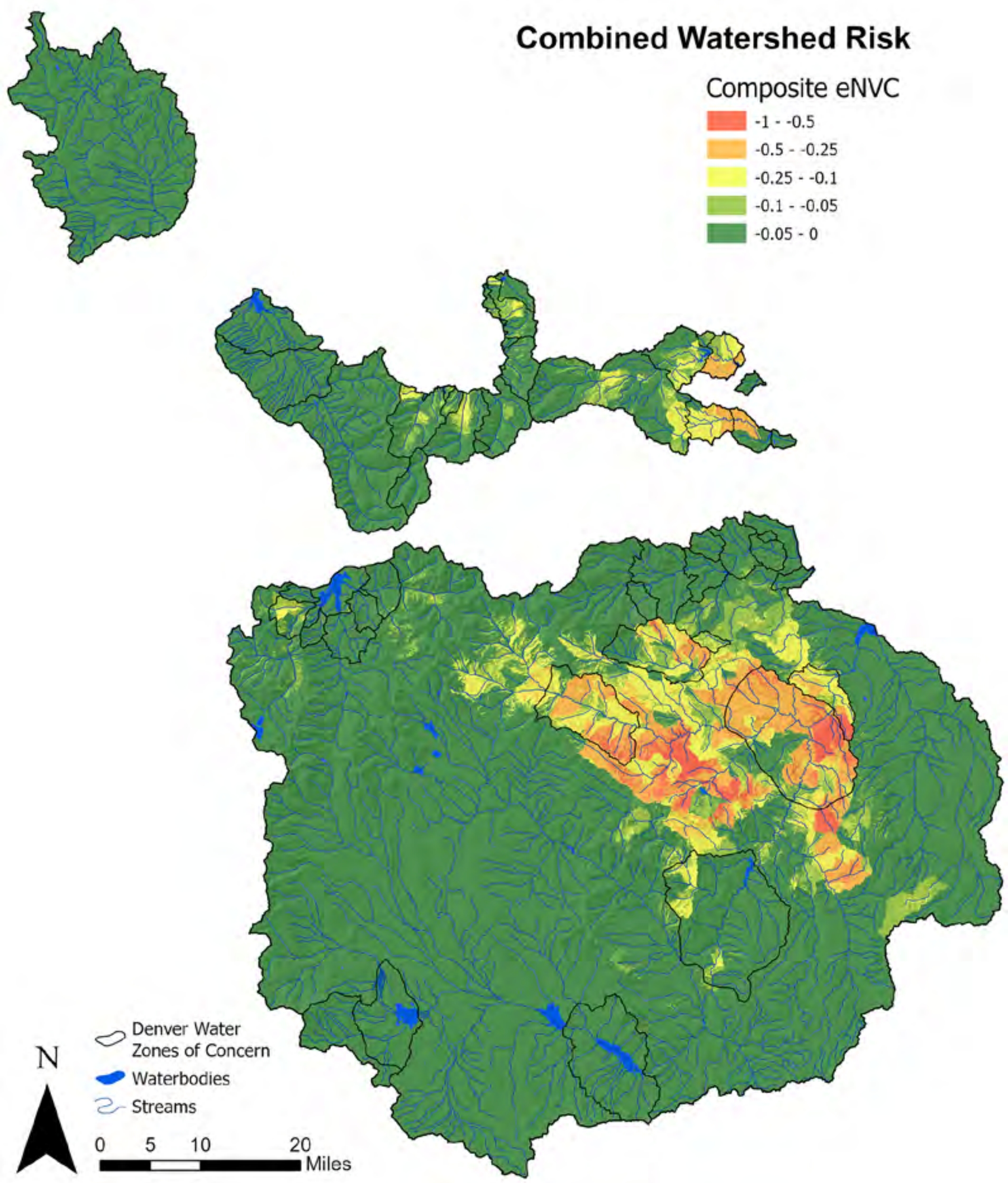


Figure 11: Composite watershed risk (expected net value change) based on post-fire erosion, debris flows, and sediment delivery to weighted water infrastructure. This eNVC metric includes burn probability and water infrastructure relative importance weights.

This is a relatively new and simple approach for integrating warming into wildfire risk assessments, so it is important to clearly understand the limitations of this approach. These simulations only account for climate-driven increases in temperature. Increasing temperatures were translated to reduced fuel moisture based on historic linear relations with SPEI. This assumes that SPEI and fuel moisture have a linear relationship and that the historic linear regression still holds when extrapolated into the future. Furthermore, we did not simulate climate-driven changes in wind, precipitation, or other variables given the uncertainty in projecting these changes in Colorado. There is generally an expectation that rainfall intensity will increase with climate change, but the frequency, timing, and spatial distribution remains poorly understood and thus was not incorporated into our modeling.

4. Results

4.1 Current Wildfire Risk

Composite wildfire risk, measured as expected net value change, represents the expected impacts of post-fire hillslope erosion, debris flows, and sediment transport while also considering the relative importance of water infrastructure. Risk is a unitless metric that ranges from 0 (neutral effect of fire on a resource) to −100 (100% loss of a resource). This assessment does not capture the potential positive impacts of wildfire on drinking water because risk is directly rescaled from post-fire sediment yields, which is defined as a negative consequence. However, the Partnership acknowledges that fire is a critical component of healthy watersheds. The composite risk map (Figure 11) is derived from three watershed risk models (Figure 12-14) that are weighted together based on the maximum estimated costs of removing sediment from water infrastructure (Table 2). These risk products account for spatially variable burn probability (see Appendix II – Burn Probability Results) and are generally the preferred dataset for fuels reduction planning scenarios since the benefit of vegetation management is conditional on the probability of the treatment encountering wildfire.

Wildfire risk (eNVC) is greatest in the lower to mid-elevations of Denver Water's collection system (Figure 15) in ponderosa pine and mixed conifer forests (Figure 16) where high burn probability (see Appendix II – Burn Probability Results) intersects susceptible critical water infrastructure. More specifically, risk is generally concentrated in areas of the Upper South Platte watershed that have not experienced fire in roughly the past 30 years. The Strontia, Bailey, and High Line Canal zones of concern were associated with the greatest wildfire risk to drinking water, on average (Figure 17). This is driven by hazardous fuel conditions (see Appendix I – Fire Behavior

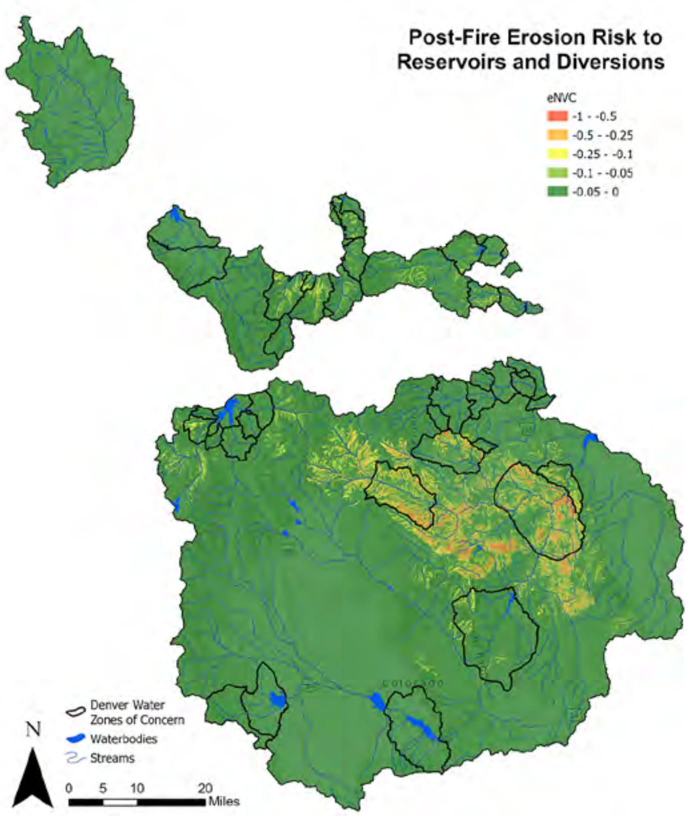


Figure 12: Post-fire erosion risk to reservoirs and diversions. This eNVC metric includes burn probability and water infrastructure relative importance weights.

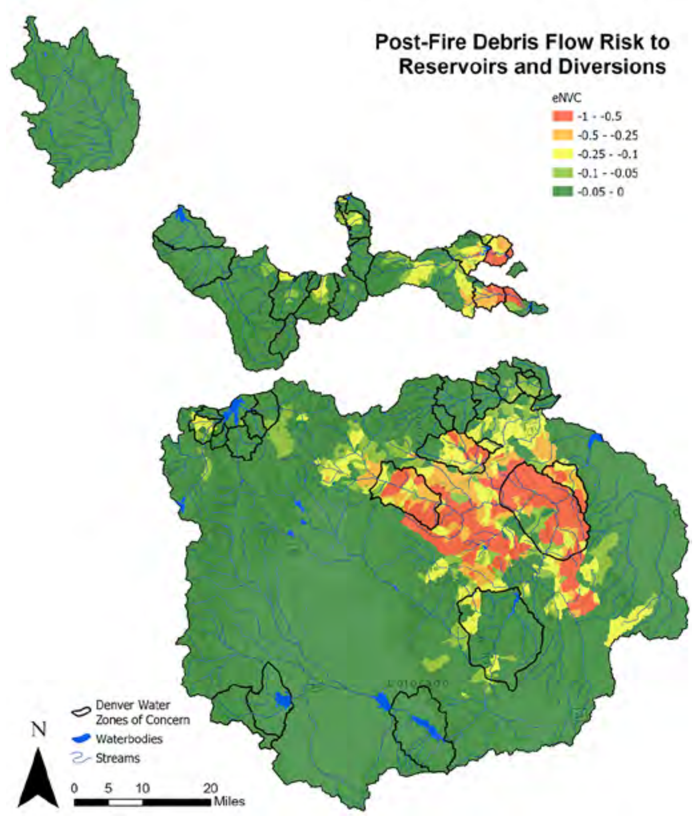


Figure 13: Post-fire debris flow risk to reservoirs and diversions. This eNVC metric includes burn probability and water infrastructure relative importance weights.

Results), high burn probability (see Appendix II – Burn Probability Results), and high connectivity with critical water infrastructure (Figure 8). It is important to note that significant risk remains in other areas of the water collection system and outside of the current "zones of concern" in areas that are highly connected to critical water infrastructure. For example, the headwaters of Buffalo Creek, just west of the Buffalo Creek burn perimeter, contains very high wildfire risk to drinking water (Figure 11) because of hazardous fuel conditions and strong connectivity with the Strontia Springs reservoir (Figure 8). Additionally, the North Fork of the South Platte, between the Bailey and Strontia zones of concern, is also associated with high risk of post-fire sediment delivery to Strontia Springs Reservoir (Figure 8). This implies that risk zones may be larger than previously thought for some water supplies. In contrast, the Turkey Creek and Evergreen zones of concern are in watersheds that, currently, Denver Water can only use in very limited quantities of water. Thus, they do not pose as great of a risk to Denver's critical water infrastructure at this time. Finally, the Cheesman zone of concern does not contain much risk because there has been minimal post-fire tree regeneration within the 2002 Hayman fire perimeter, which covers much of that contributing area. Fire intensity is modeled to be low (Figures 34-41), and even if a fire were to burn in Cheesman's contributing area, any post-fire sediment that was mobilized would be deposited in Cheesman reservoir which is large and relatively insensitive to storage loss, restricting sediment from being transported to more susceptible downstream infrastructure like Strontia Springs reservoir. Outside of the South Platte watershed, the Ralston and South Boulder zones of concern had the highest risk (Figure 17) which was primarily driven by post-fire debris flow risk to Ralston reservoir (Figure 13) and the South Boulder Canal diversion (Figure 14).

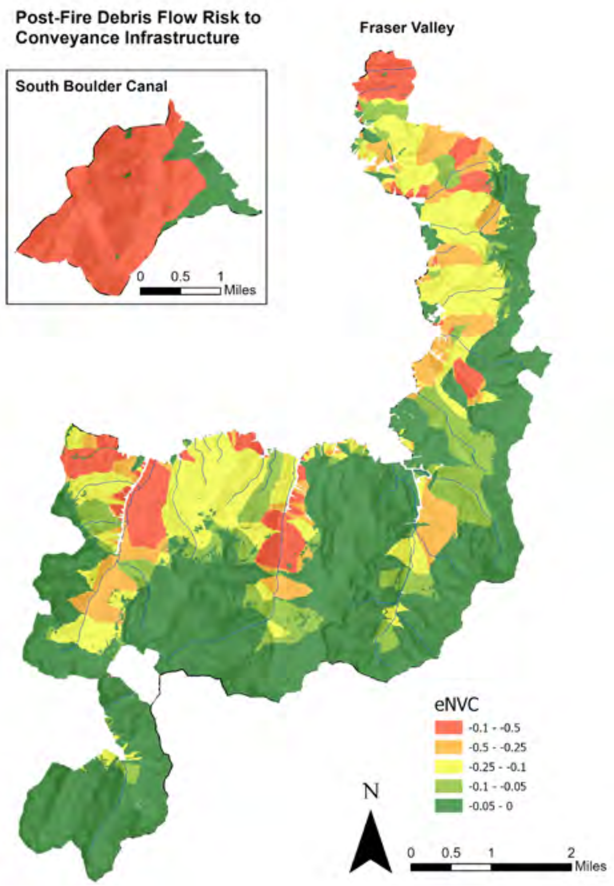


Figure 14: Post-fire debris flow risk to water conveyance infrastructure. This eNVC metric includes burn probability and water infrastructure relative importance weights.

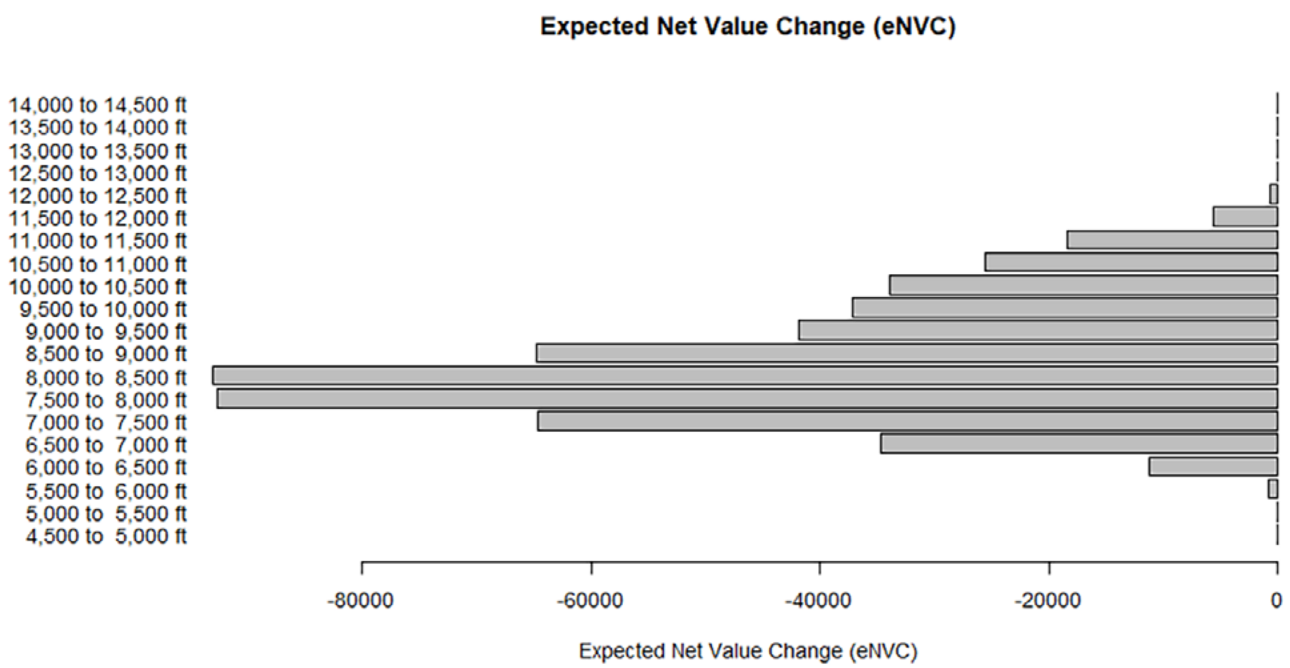


Figure 15: Risk of post-fire sediment impacts to critical water infrastructure (expected Net Value Change) by elevation.

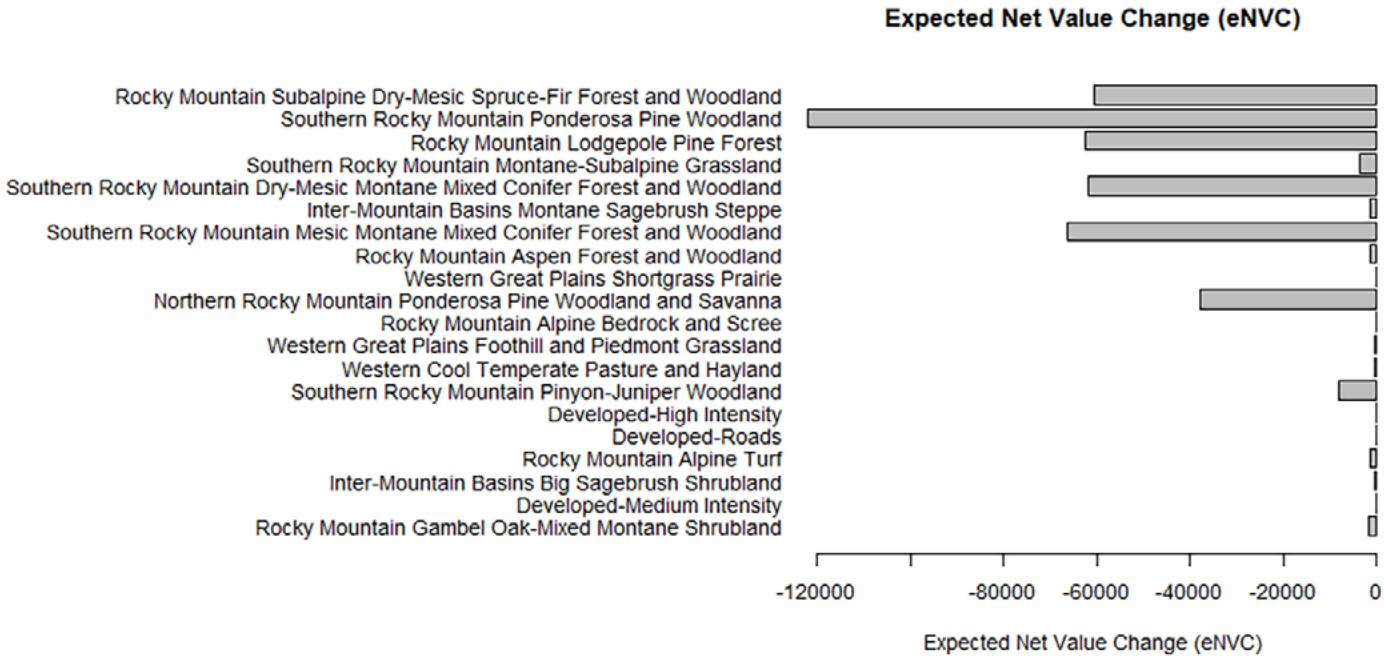


Figure 16: Risk of post-fire sediment impacts to critical water infrastructure (expected Net Value Change) by existing vegetation type from LANDFIRE (2020).

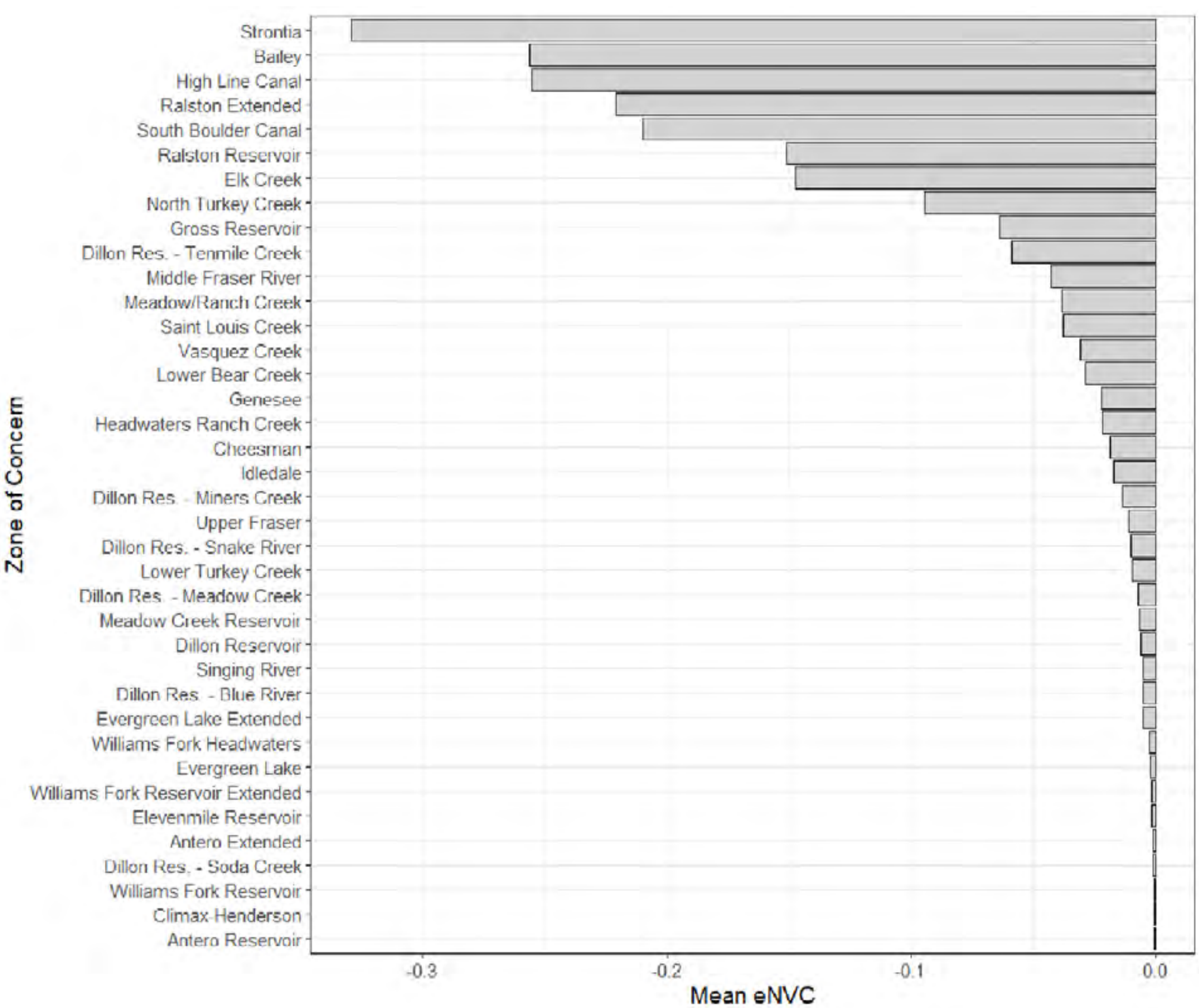


Figure 17: Mean risk of post-fire sediment impacts to critical water infrastructure (expected Net Value Change) within each of Denver Water's zones of concern.

Given the uncertainties associated with predicting future wildfire activity, we also report a composite measure of conditional Net Value Change (cNVC; Figure 18) which represents hazard without the modeled probability of encountering wildfire. These cNVC analyses assume everywhere on the landscape has an equal chance of burning and are particularly relevant during active wildfire incidents to inform values at risk in the likely spread path of an ongoing wildfire. The spatial distribution of composite hazard (cNVC) is similar to the composite risk map (eNVC) because both account for the overlap between hazardous fuel conditions and weighted importance of critical water infrastructure.

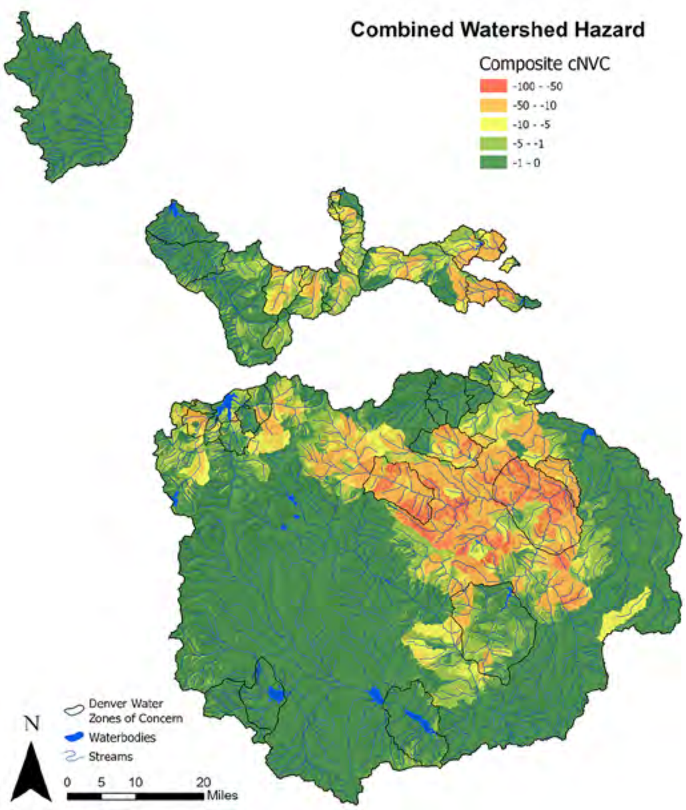


Figure 18: Composite watershed hazard (conditional net value change) based on post-fire erosion, debris flows, and sediment delivery to weighted water infrastructure. Note this product does not incorporate burn probability.

The risk assessment clearly demonstrates that wildfire risk to water supplies is highly variable across the collection system due to the differences in forest condition, post-fire hazards, and connectivity to critical water infrastructure (Figure 11). The second goal of RADS was to identify where wildfire risk to drinking water can be reduced by forest management actions. In order to do that, we considered where risk could most effectively be reduced directly (e.g. in-situ risk), as well as indirectly (e.g. transmitted risk) through aligning forest management to support fire management operations. This analysis was possible because POD networks were already completed for this entire analysis extent in previous workshops lead by the Pike San Isabel, Arapaho Roosevelt, and White River National Forests. In-situ and transmitted risk could be calculated for each POD to inform the prioritization of vegetation management (Figure 19). Refer to section 3.6 for risk type definitions and calculations. Light purple PODs (upper right of Table 5) are associated with low in-situ and transmitted risk and may be good locations to support beneficial fire. Dark purple to pink PODS (bottom row of Table 5) are associated with high in-situ risk which can be addressed with vegetation management in POD interiors to reduce local risk to HVRAs. Dark purple to blue PODs (left column of Table 5) are associated with high transmitted risk and therefore might benefit from POD boundary hardening to limit risk transmission to nearby fire-sensitive PODs. The following sections outline priority vegetation management opportunities in both POD interiors and boundaries to reduce in-situ and transmitted risk, respectively.

Table 11: Summary of treatment type allocation across four prioritization scenarios. Thin is mechanical thin only, RxFire is prescribed fire, Mast is mastication, and Patch is patch cut. In the uncapped scenarios, there were no proportional budget restrictions so prescribed fire, the most cost-effective treatment option, was maximized. In the budget cap scenario, prescribed fire was limited to 80% and patch cuts were limited to 15% of the total budget.

Budget	Thin (acres)	RxFire (acres)	Thin + RxFire (acres)	Mast (acres)	Patch (acres)	Total Priority Acres	Total RR (%)	Feas RR (%)
$30M uncapped	-	17,558	-	-	-	17,558	1.5	12
$90M uncapped	-	48,535	-	-	1,827	50,362	3.84	30
$30M + budget cap	-	10,465	1,258	-	1,867	13,589	1.26	10
$90M + budget cap	-	31,115	2,536	2,133	5,556	41,340	3.38	27

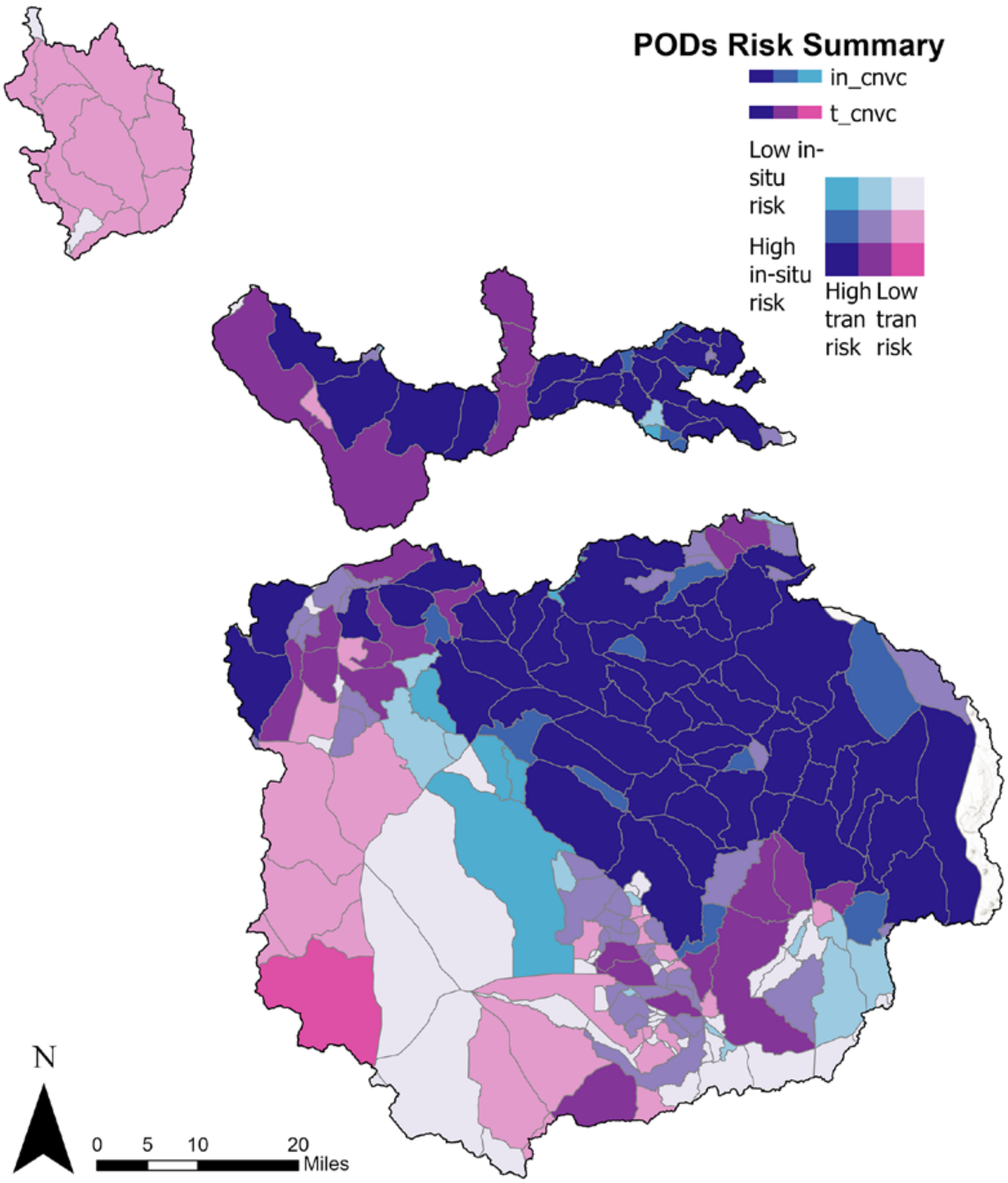


Figure 19: In-situ risk (in_cnvc) and transmitted risk (t_cnvc) matrix summarized by potential operational delineation (POD). For visualization purposes, the color gradient is based on quantile breaks which equally distributes observations across class intervals.

4.2 Prioritization of Vegetation Management in POD Interiors

To reduce in-situ risk, vegetation management was prioritized within POD interiors where they would yield the greatest risk reduction per dollar spent (i.e. "bang for the buck") (Figure 20). Maximizing by bang for the buck means that priority forest management actions can sometimes be costly to implement, but only if modeling predicted they would be more effective at reducing risk and a better investment than less expensive, but less effective forest management actions. Vegetation management priorities generally targeted dense forests on steep slopes (e.g. where potential for post-fire erosion and debris flows is generally the greatest) near high value water infrastructure to minimize post-fire sediment impacts. Furthermore, vegetation management was prioritized in catchments whose drainage paths to the water supply are not interrupted by waterbodies or other barriers to sediment transport that may already mitigate post-fire impacts to the target water supply.

We evaluated 4 scenarios to prioritize the locations and types of vegetation management that maximize risk reduction per dollar spent (Table 11). We first considered two budget levels – a $30M budget based on estimated F2F partnership funding over the next 5 years and a $90M aspirational budget for implementation over longer time periods or if funding and implementation were to increase with policy changes. Areas selected at lower budget levels are more cost effective and a higher priority than those selected at higher budget levels. We also used proportional budget caps to constrain the proportion of the total budget allocated to a given vegetation management action since there was a wide range in benefit-cost ratios (Figures 58-62). This resulted in uncapped and capped prioritization scenarios to consider for future planning efforts. The four treatment scenarios identified 13,589-50,362 priority acres for vegetation management, primarily in the montane zone of the upper South Platte watershed (Figure 21).

In the uncapped scenario, prescribed fire was the preferred vegetation management action across all budget levels because it reduces both surface and canopy fuels at a relatively low cost (Figure 22). Prescribed fire was assigned to 96-100% of priority acres in the uncapped scenarios (Table 11) which highlights an opportunity for increased use of this fuels reduction tool. The prescribed fire modeling assumptions approximate where wildfire burning under similarly moderate weather conditions and in specific areas of the watershed can benefit source water protection.

However, agency hesitation and capacity constraints may prohibit the implementation of prescribed fire over large areas within these watersheds, particularly on non-federal lands. Given this reality, we also included a capped scenario where prescribed fire was limited to 80% and patch cut to 15% of total budget allocation. This scenario demonstrates the "next best" vegetation management action if prescribed fire or beneficial wildfire cannot be applied to ≥96% of priority acres due to operational or social constraints (Figure 22). In general, mastication was the next best vegetation management action in ponderosa pine and mixed conifer forests and patch cut was the next best in lodgepole, spruce, and fir forests.

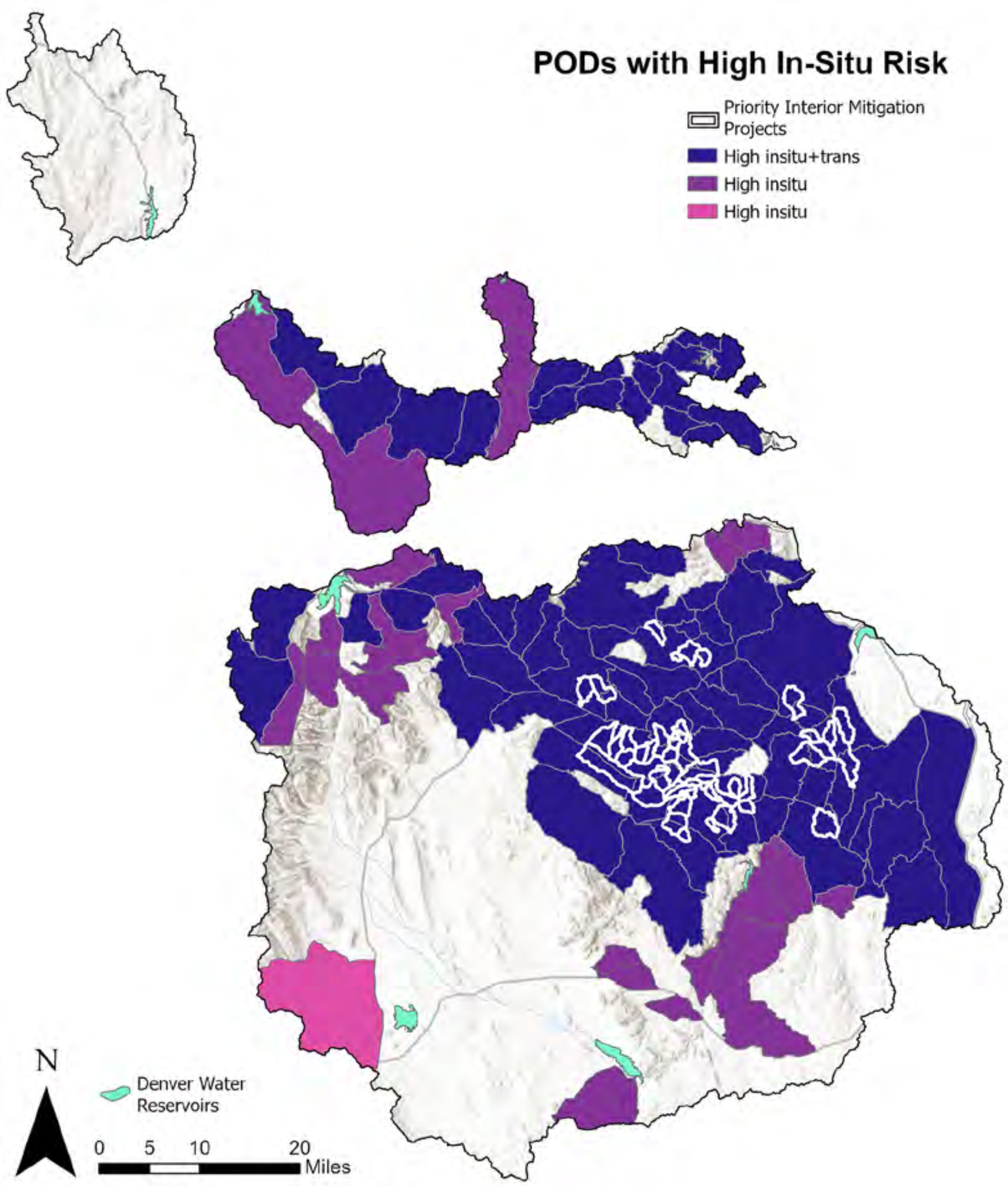


Figure 20: Vegetation management priorities within POD interiors (white outlines) relative to PODs with high in-situ risk (dark blue - purple). These treatment priorities come from the uncapped $90 million treatment scenario.

Thin only treatments were never selected, aligning with science research that surface fuel management is key to moderating wildfire risk (Davis et al., 2024).

Based on the $90M uncapped scenario, priority treatment units overlapped a variety of land ownerships. 39,308 acres, which represents 78% of the priority POD interior treatments, were located on United States Forest Service land. Another 7,741 acres or 15% of the priority treatments were located on private lands. The remaining 3,312 or 7% of priority treatments were located on Colorado Parks and Wildlife, County, or non-governmental land. Inter-agency collaboration will be necessary to meet risk reduction goals.

The linear optimization model was also run across the full range of possible treatment budgets to estimate the maximum potential of vegetation management to reduce risk (Figure 23). Monitoring and evaluation of this cost-benefit curve can help inform the value of continued investments in forest management compared with other potential risk reduction activities. Treatment plans on the left side of the plot where the curve is steep represent the greatest bang for the buck. As the curve flattens to the right, there is limited return on additional investment. The $30M and $90M treatment plans address 8-25% of feasible risk (Table 11), which is the ratio between the risk reduction achieved by the selected vegetation management and the risk reduction achieved if all feasible areas of the landscape were treated. Ultimately, this represents the proportion of wildfire risk that can be mitigated by fuels reduction considering the feasibility, cost, and effects of vegetation management. To achieve 99% of feasible risk reduction, the partnership would have to invest $3 billion to treat roughly 900,000 acres (Figure 23). If the Partnership were to treat all 2.49 million feasible acres, it would cost an additional $4.95 billion ($7.95 billion total) and only increase feasible risk reduction by 1%.

With a $90 million investment in vegetation management, the Partnership could reduce <5% of total wildfire risk to drinking water (Table 11), which represents potential risk reductions from vegetation management relative to baseline risk summed across the whole landscape. Even if the Partnership could increase their investment to $3 billion, maximum total risk reduction is only 15%. The remaining 85% of wildfire risk to drinking water cannot be addressed by localized fuels reduction. Total risk reductions values are generally quite small because 1) the entire landscape cannot be treated given feasibility and budget constraints, 2) vegetation management is not 100% effective at reducing wildfire risk to water supplies, and 3) these estimates only account for the impact of a treatment on local fire behavior and effects, not impacts on fire

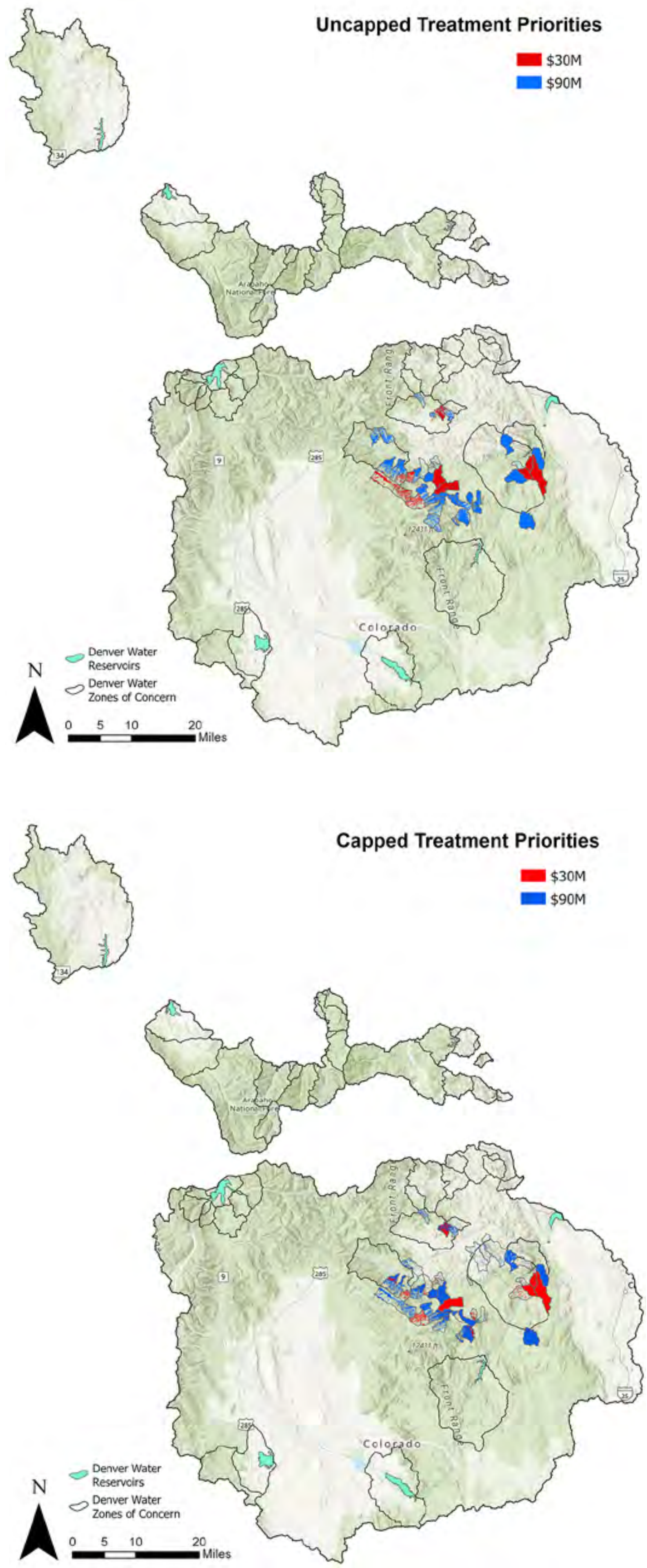
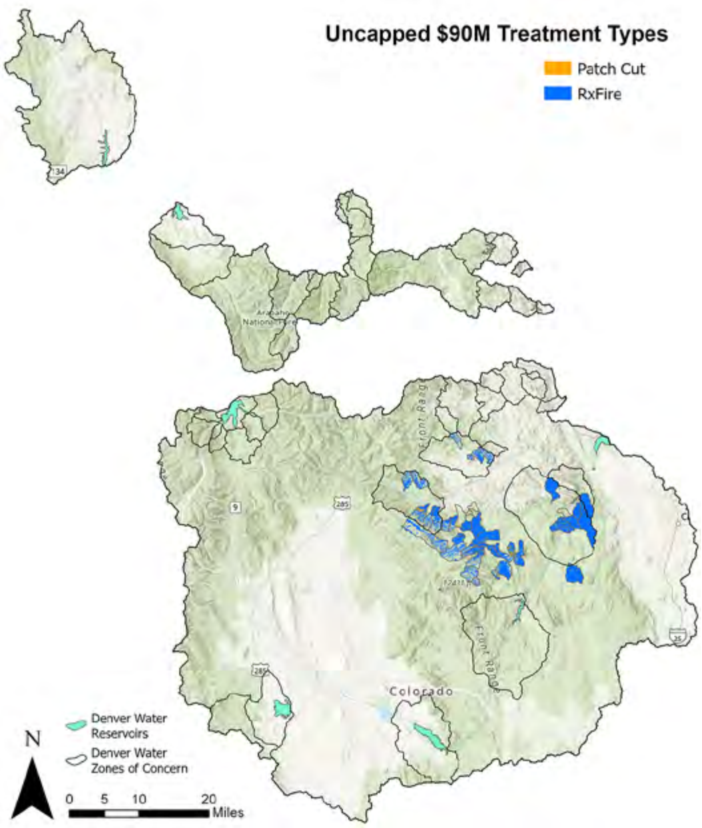


Figure 21: Vegetation management priorities for $30M (red) and $90M (red + blue) budgets. No vegetation management actions were capped by budget proportion in the "uncapped" scenario on the upper map. RxFire was capped at 80% and Patch cut at 15% of total budget allocation in the "capped" scenario on the lower map.



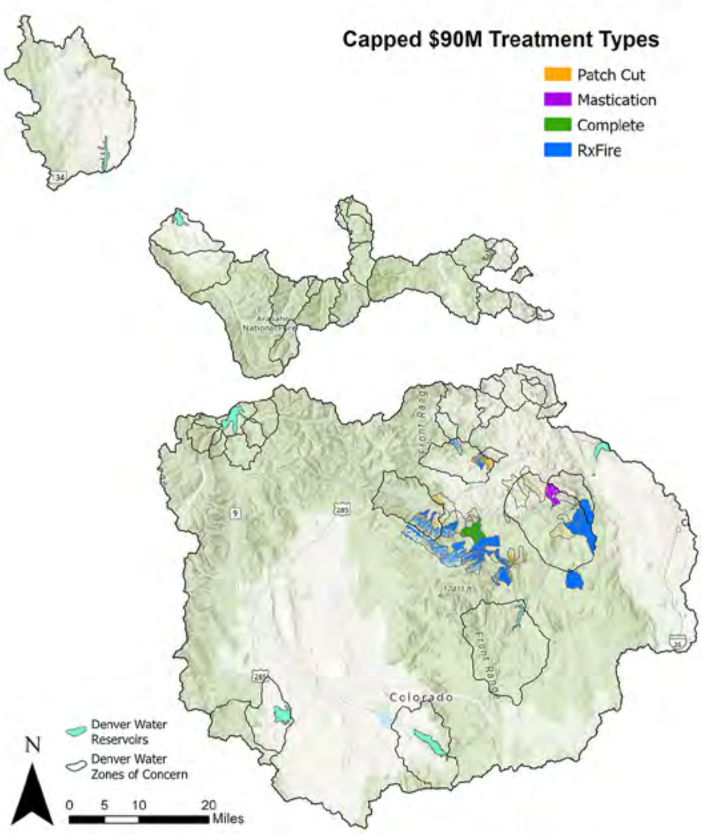


Figure 22: Optimal type of vegetation management for the $90M budget. No vegetation management actions were capped by budget proportion in the "uncapped" scenario on the upper map. RxFire was capped at 80% and Patch cut at 15% of total budget allocation in the "capped" scenario on the lower map.

spread or probability. However, this does reflect the reality that localized fuels reduction projects cannot eliminate all wildfire risk to drinking water. Managers will have to deploy diverse management actions to further reduce in situ risk (e.g. floodplain enhancement, sediment reduction structures, and aerial mulching) and transmitted risk (e.g. POD boundary hardening, fire patrols, and recreation planning).

There are also some factors that are unique to this study that limit risk reduction. For example, this risk assessment defines all fire impacts as negative because they are based on post-fire sediment delivery to water infrastructure which, by definition, is a negative effect. Thus, this QWRA doesn't capture the potentially positive impacts of wildfire on source water protection and constrains risk reduction estimates relative to other similar analyses (Rhea et al., 2022, Mueller et al., 2023, Jefferson County Open Space 2022). Secondly, the watershed modeling in this assessment is based on crown fire activity (unburned, surface fire, passive crown fire, or active crown fire) rather than flame length outputs that are used in most QWRAs to define response functions. In order to achieve risk reduction, forest management actions have to change crown fire activity (i.e. passive crown fire to surface fire) which is much harder than incrementally reducing flame length (i.e. 12 ft to 10 ft flame length), again limiting risk reduction potential relative to other analyses (Rhea et al., 2022, Mueller et al., 2023, Jefferson County Open Space 2022). Finally, the larger budget of $90 million treats less than 2% of the 2.5 million acre landscape based on our cost estimates. Running RADS over a smaller, more targeted spatial extent would generally result in larger risk reduction estimates for a given budget simply because you could treat more risk within the landscape being analyzed.

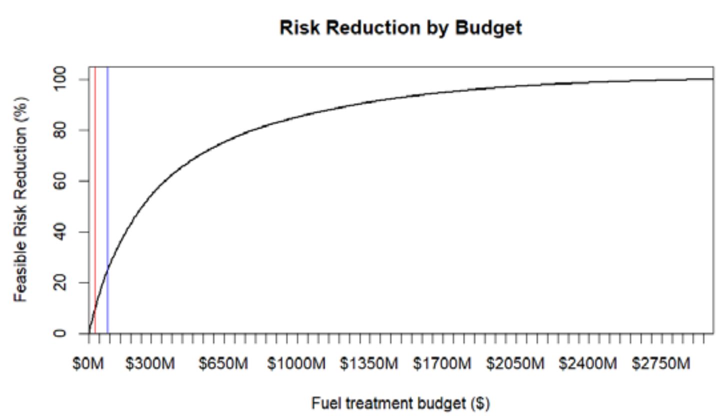


Figure 23: Risk reduction curve across a variety of simulated budgets. The vertical red line denotes the $30M budget while the blue line denotes the $90M budget. The farther left on the curve or the steeper the curve, the more risk is reduced per dollar spent and the greater your "bang for the buck". This curve was developed for the uncapped treatment scenario.

4.3 Prioritization of Vegetation Management Along POD Boundaries

We also prioritized POD boundary hardening treatments to limit fire spread into fire sensitive watersheds and reduce transmitted risk. This assessment identified POD lines where 1) fuels reduction can reduce the difficulty of fire suppression and 2) in strategic locations that reduce fire spread into fire-sensitive PODs. We first calculated change in fire Suppression Difficulty Index (ΔSDI) for a thinning followed by prescribed fire scenario in 300-m buffers around every POD line (Figure 24). Lower ΔSDI values (light yellows) could be driven by 1) low baseline SDI (i.e. grassy, flat terrain) or 2) a limited treatment effect on suppression difficulty. Higher ΔSDI values (dark greens) indicate that pre-fire fuels reduction can have a greater impact on future fire suppression and thus should be prioritized. We then compared ignition density, fire spread, and risk maps to identify strategic locations to prevent fire spread to fire-sensitive PODs. For example, the Early Gulch and Topaz PODs have a significant number of fire ignitions when summed at the POD level (Figure 25) and potential for eastward spread into the Upper South Platte watershed, where critical water infrastructure is susceptible to post-fire sedimentation. The POD boundaries outlined in orange represent strategic locations where fuels reduction could reasonably reduce fire suppression difficulty. While the proposed treatments fall outside of Denver Water's zones of concern, they have the potential to build wildfire resilience within their collection system.

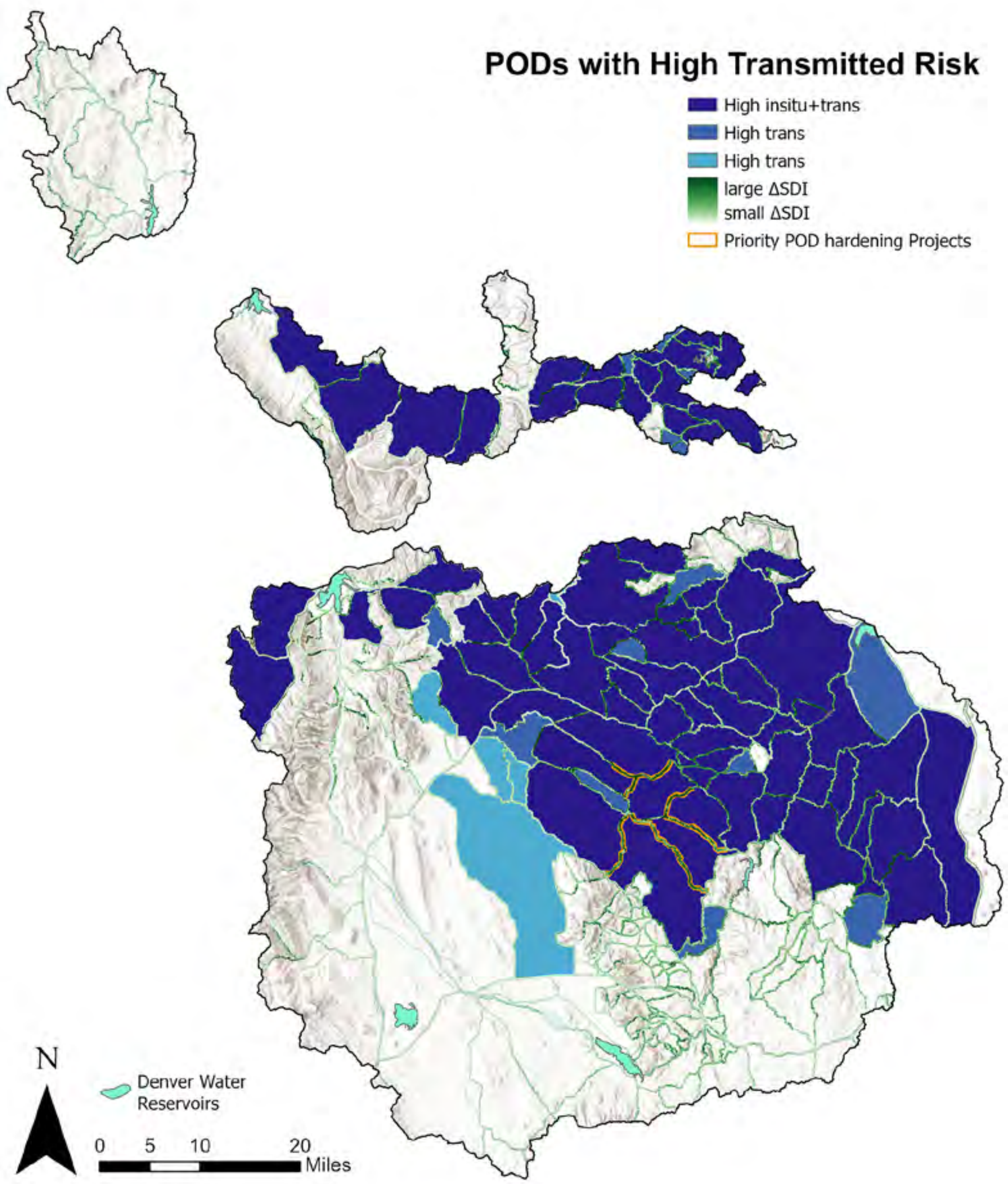


Figure 24: Change in suppression difficulty index (ΔSDI, yellow-green) which was used to prioritize POD boundary treatments along PODs with high transmission risk (dark to light blue).

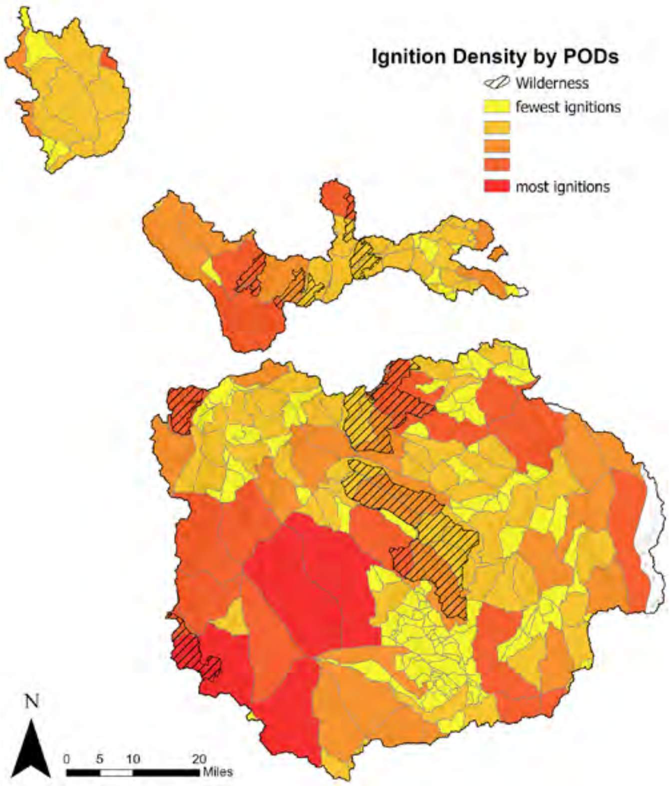


Figure 25: Total number of fire ignitions from tens of thousands of FSim burn probability simulations summed by POD.

4.4 Warming Impacts on Wildfire Risk

The "warmer" and "hotter" climate warming scenarios allowed us to simulate the effect of increasing temperatures on fuel moisture, and subsequently wildfire risk to water infrastructure. Extreme fire behavior was relatively insensitive to warming (Figures 26, 29, and 30) because it is simulated under 97th percentile weather conditions when fuels are already incredibly dry across all vegetation types, flame lengths are large, and fire behavior is not particularly sensitive to changes in fuel moisture from warming temperatures. Extreme fire behavior was the least sensitive to warming in grass and shrub-dominated ecosystems (Figure 26). Lodgepole and Spruce Fir had the greatest absolute and percent increase in flame lengths under the 97th percentile fire weather scenario. While extreme fire behavior may increase the most in higher elevation forest types, this had little effect on the location of post-fire watershed risk because Denver Water's fire-sensitive critical water infrastructure is concentrated in the montane zone.

Across all forested ecosystems, mean annual burn probability increased by 19% (0.001) and 47% (0.002) with the "warmer" and "hotter" scenarios, respectively (Figures 27, 31, and 32). Burn probability is more sensitive to warming than fire behavior because FSim simulations capture fire spread under a range of more moderate weather conditions. These warming scenarios also reduced energy release component (ERC) enough during the shoulder seasons to lengthen the fire season, particularly into the early Spring. The drier weather conditions result in more extreme fire danger days where spread rates are high and fire suppression is ineffective, which allowed more fires to escape simulated suppression activities and grow to a large size. This analysis extent captures the transition between warmer, drier forest types that burn most frequently and the cooler, wetter forest types that burn least frequently (Schoennagel et al., 2004; Sherriff and Veblen 2007). Thus, burn probability is generally higher in the eastern slope of the Front Range compared to the high mountains of Park, Summit, and Grand Counties. The eastern slope of the Front Range has experienced substantial wildfire activity in recent decades, so the predicted burn probability is generally high except where recent fires have reduced fuels (e.g. Hayman and Buffalo Creek fires) (Figure 45). In contrast, fire occurrence in high elevation forests of the region is generally thought to be limited by the cooler and wetter climate and shorter fire season (Schoennagel et al., 2004). However, Rocky Mountain subalpine forests are now burning more than at any point in the past 2,000 years (Higuera et al., 2021). Changes in climate, forest conditions (i.e., insect mortality), and increased human land use patterns have combined to make large, intense fires much more frequent, especially in Colorado's high elevation forests where wildfires used to be rare events (Figure 31). The custom FSim outputs used in this assessment show greater burn probability in high elevation forests than past national-scale FSim products (Short et al., 2020). Based on our warming simulations, Ponderosa Pine and mixed conifer forests experienced the largest absolute increases in burn probability whereas Spruce-Fir and Lodgepole Pine forests had the largest percent increases in burn probability with the "hotter" scenario (Figure 27).

Both net value change metrics (cNVC and eNVC) include infrastructure relative importance weights, so hazard and risk are consistently concentrated in the Upper South Platte watershed upstream of Strontia Springs Reservoir, a critical component of Denver Water's drinking water collection system that is susceptible to fire effects. Even though sub-alpine forests are increasingly likely to burn and experience post-fire erosion and debris flows, sediment generated in that zone will either be transported to less sensitive water infrastructure or there is more potential for hillslope or in-stream sediment deposition and storage on long flowpaths to critical infrastructure in the montane zone. Infrastructure relative importance weights are consistent across warming scenarios and can dilute differential effects of warming on fire behavior and likelihood by forest type. Hazard, measured as cNVC, is relatively insensitive to warming because it is only influenced by changes in fire behavior, which is minimally increased in the warming scenarios (Figure 28). In contrast, wildfire risk to critical water infrastructure, measured as eNVC, is more sensitive to warming because it is influenced by changes in fire behavior and burn probability (Figure 33). The greatest climate-driven increases in risk were concentrated in ponderosa pine and mixed conifer forests

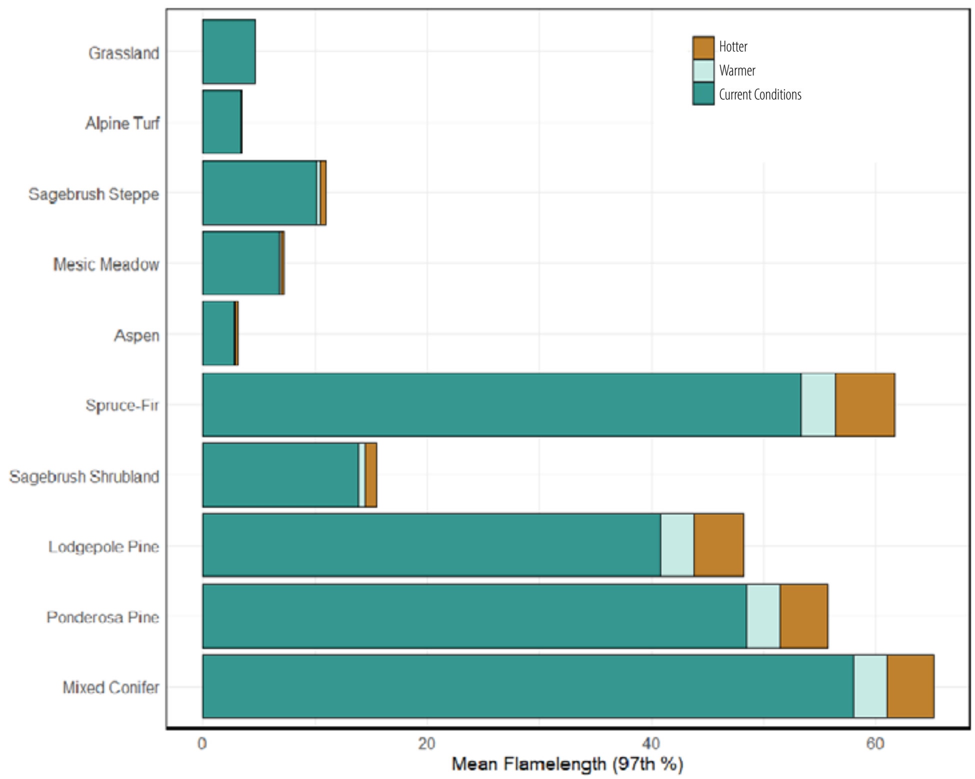


Figure 26: Mean flame length under the 97th percentile weather scenario (i.e. extreme fire behavior) by vegetation type (Landfire 2020) cumulative across all three climate scenarios.

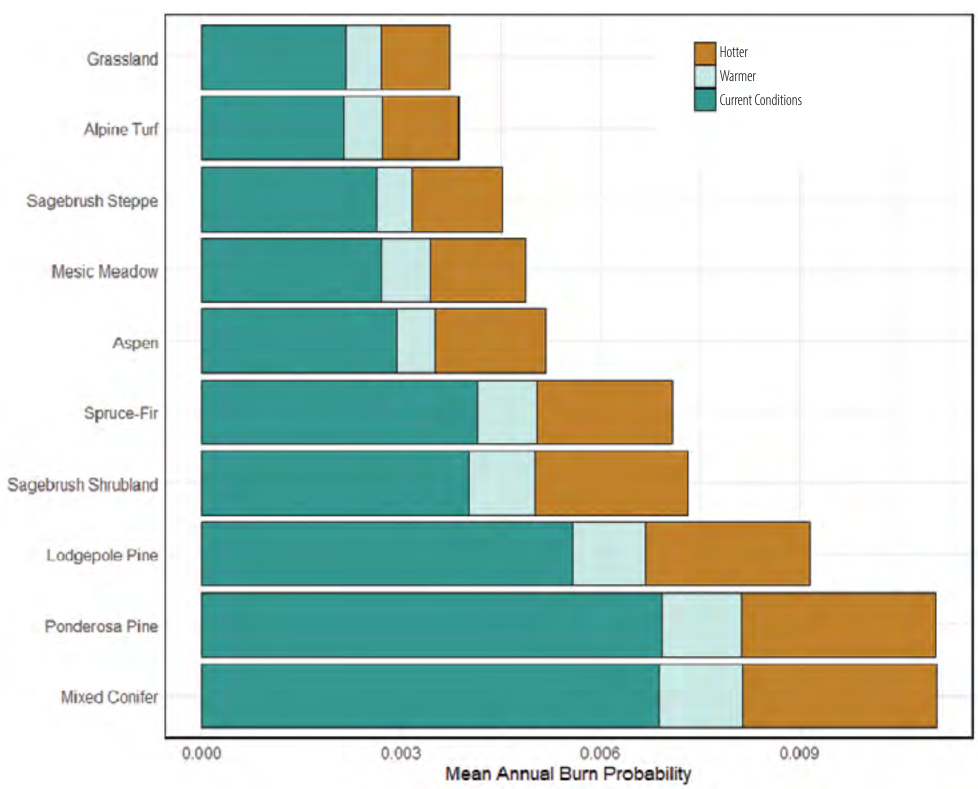


Figure 27: Mean annual burn probability by vegetation type (Landfire 2020) showing cumulative probability across all three climate scenarios.

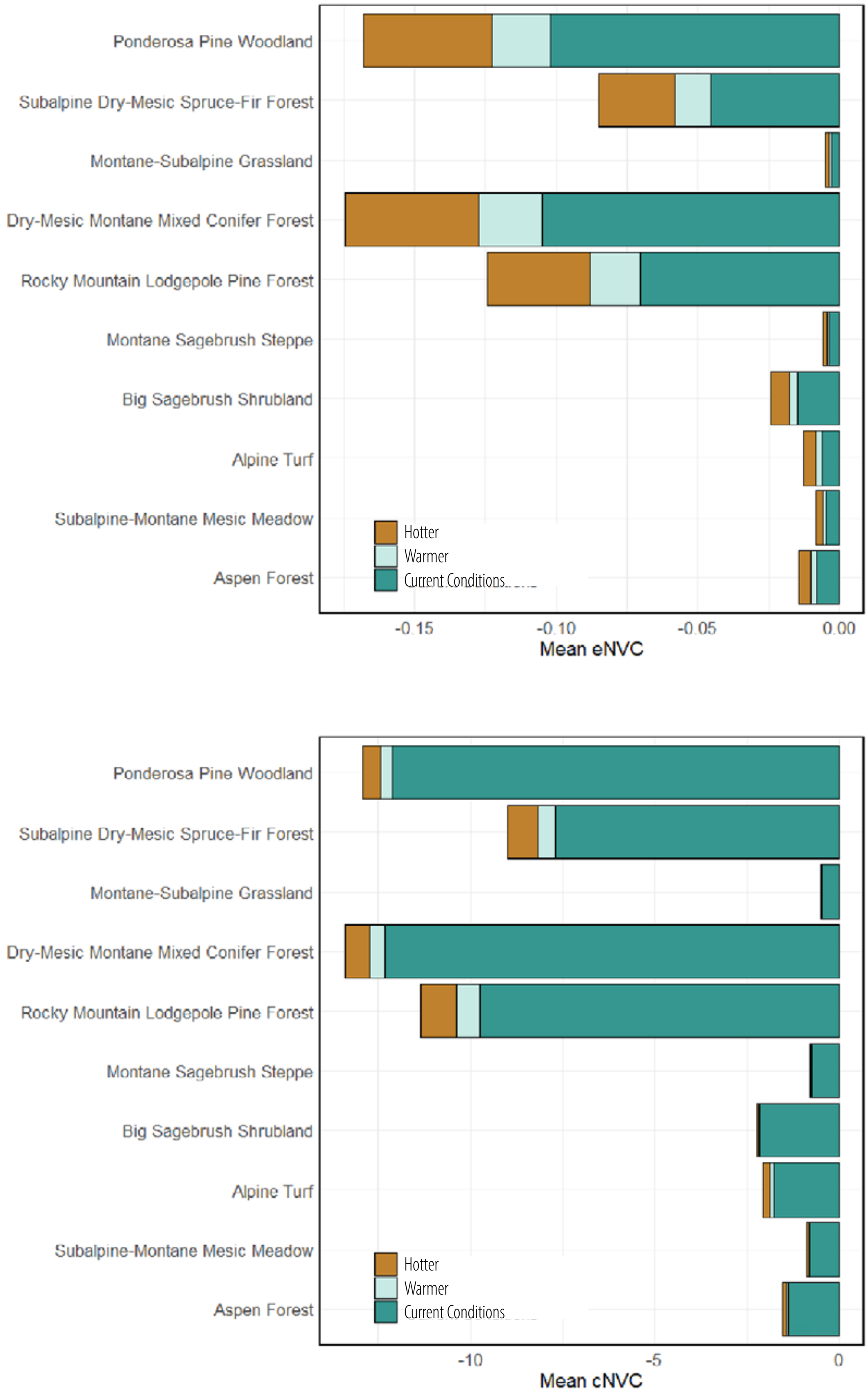


Figure 28: Average wildfire hazard (cNVC, upper) and risk (eNVC, lower) by vegetation type and cumulative across the three climate scenarios. Both net value change metrics account for infrastructure relative importance but only eNVC accounts for burn probability.

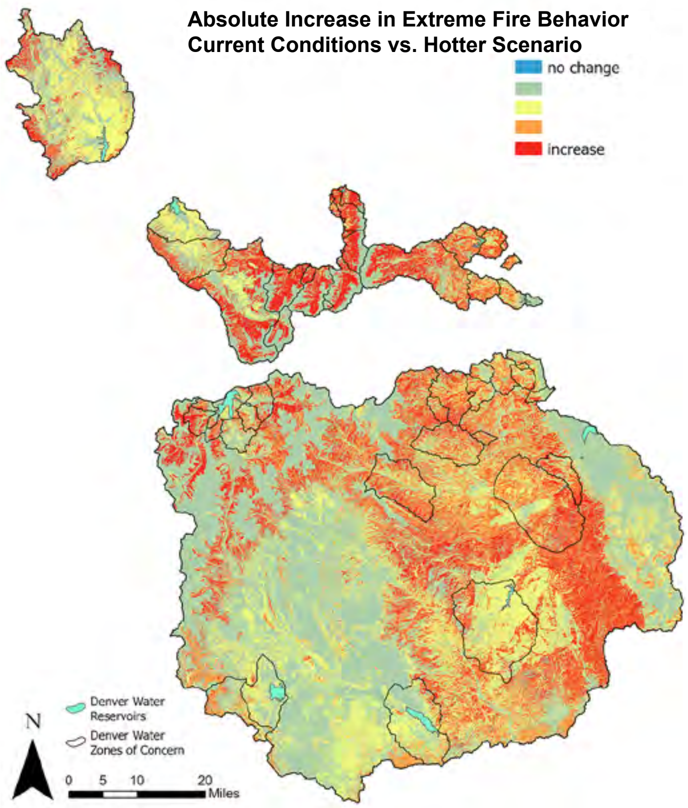


Figure 29: Absolute increase in flame length (ft) during the 97th percentile fire weather (extreme fire behavior) under the "hotter" scenario.

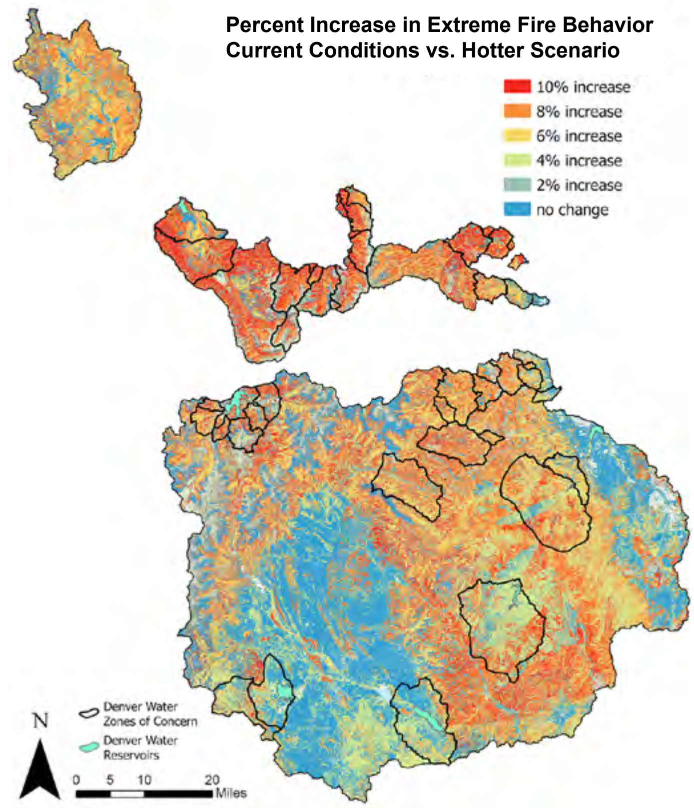


Figure 30: Percent increase in flame length (ft) during the 97th percentile fire weather (extreme fire behavior) under the "hotter" scenario relative to current conditions.

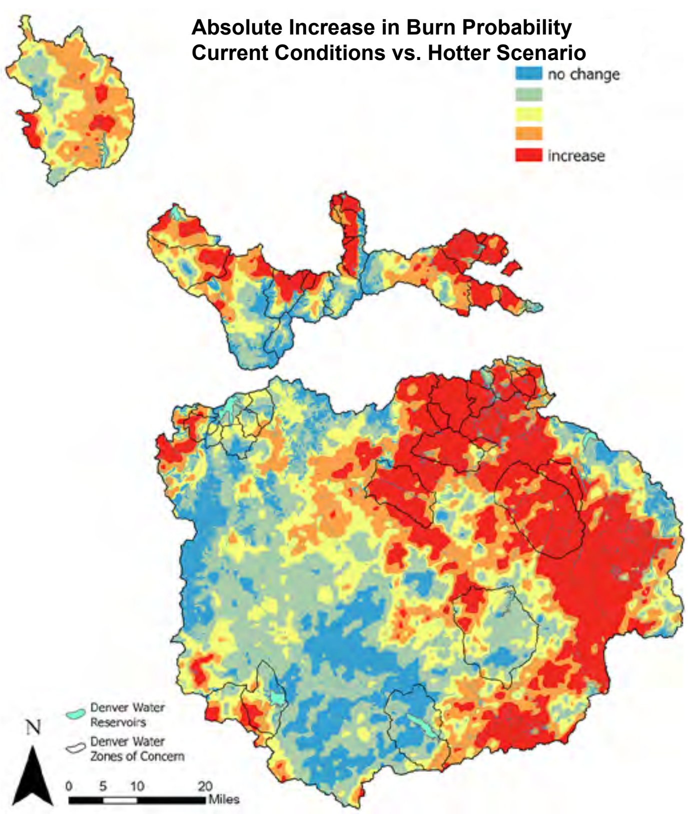


Figure 31: Absolute increase in burn probability under the "hotter" scenario.

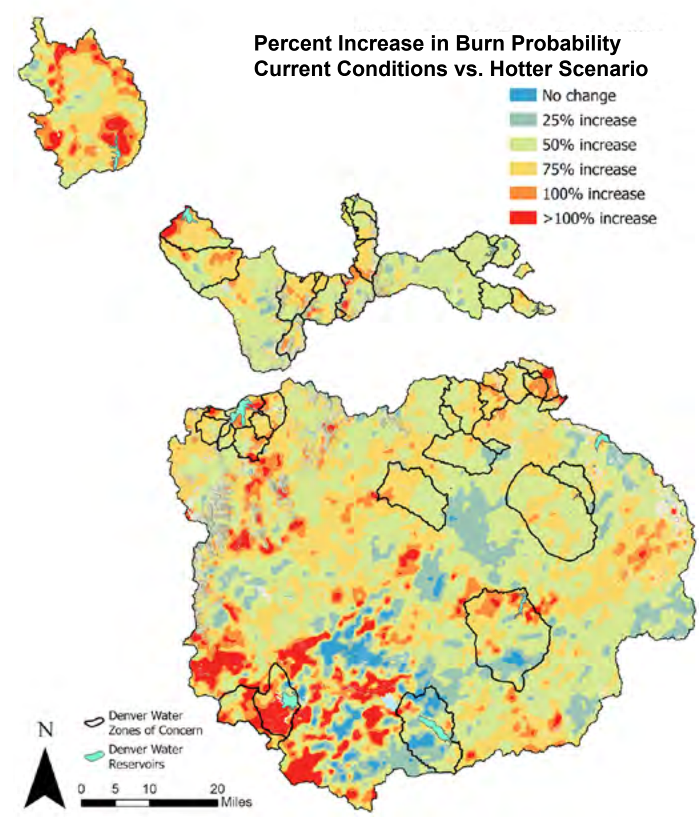


Figure 32: Percent increase in burn probability under the "hotter" scenario relative to current conditions.

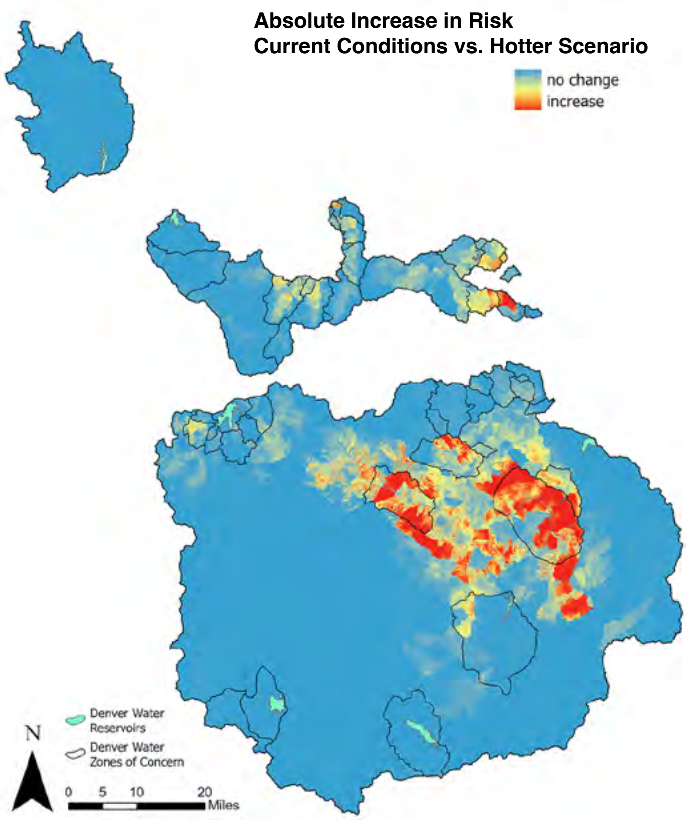


Figure 33: Absolute increase in wildfire risk to drinking water (eNVC) under the hotter scenario.

in the Upper South Platte watershed where the highest value water infrastructure intersects with the highest burn probabilities (Figure 33). There are also some notable increases in risk in the Ralston, South Boulder Canal, and Fraser Valley contributing areas (Figure 33). While climate warming may disproportionately increase extreme fire behavior and burn probability in sub-alpine forest types, Ponderosa Pine and Douglas Fir are associated with the greatest warming-driven increases in risk because of those forest types surround the most important water infrastructure in this collection system.

4.5 Geospatial Database

All geospatial data is available in a shared BOX database and an ArcGIS online map. The geodatabase includes reference layers, wildfire modeling outputs, hazard and risk outputs, as well as the uncapped and capped vegetation management plans. These data products are intended for use in landscape-scale project selection, grant applications, and integration with PODs, but should be paired with field surveys for project-level planning. The geodatabase is structured as follows:

Fire behavior and burn probability rasters are stored in the "Fire_modeling" folder. Flame length was modeled for 4 weather percentiles (25th, 50th, 90th, and 97th) and is labeled "FL_percentile". Crown fire activity is similarly labeled "CFA_percentile". Burn probability is labeled "BP". We included rasters as .tif files and attached suggested symbology in .lyrx files.

Conditional net value change is the product of flame length and HVRA-specific net value change over a range of fire behavior. In short, it represents the likely impact of fire to water supplies if a fire were to burn in a given pixel. We include .tif rasters and .lyrx rasters with suggested symbology for composite wildfire hazard.

Expected net value change is the product of burn probability and conditional net value change so this product represents the likely impact of fire to water supplies considering the likelihood of fire occurring in any given pixel. Again, we include .tif rasters and .lyrx rasters with suggested symbology for each watershed model and as a composite using relative importance weights.

The management constraints folder includes cost, feasibility, and cost effectiveness rasters for each vegetation management action. The treatment plans folder contains the vegetation management priorities and types for both the capped and uncapped prioritization. Finally, the general layers folder contains helpful spatial overlays like zones of concern, PODs, major highways and streams, land ownership, forest type, etc.

5. References

Beguería S, Vicente-Serrano SM (2017) SPEI: Calculation of the Standardized Precipitation-Evapotranspiration Index. R package version 1.7. Retrieved from https://cran.r-project.org/package=SPEI.

Bradshaw L, McCormick E (2000) FireFamily Plus user's guide, version 2.0. USDA Forest Service, Rocky Mountain Research Station, General Technical Report. RMRS-GTR-67WWW.

Byram GM (1959) Combustion of forest fuels. In Forest fire: control and use. Ed. KP Davis. McGraw-Hill. p 61-89. (New York, NY).

Cannon SH, Gartner JE, Rupert MG, Michael JA, Rea AH, Parrett C (2010) Predicting the probability and volume of post-wildfire debris flows in the intermountain western United States. GSA Bulletin. 122(1-2): 127-144. https://doi-org.ezproxy2.library.colostate.edu/10.1130/B26459.1.

Crosby JS, Chandler CC (1966) Get the most from your windspeed observation. Fire Control Notes. 27, 12–13.

Davis KT, Peeler J, Fargione J, Haugo RD, Metlen KL, Robles MD, and Woolley T (2024) Tamm review: A meta-analysis of tinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. Forest Ecology and Management. 561: 121885.

Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC (2011) A simulation of probabilistic wildfire risk components for the continental United States. Stochastic Environmental Research and Risk Assessment. 25: 973-1000.

Finney MA, Brittain S, Seli RC, McHugh CW, and Gangi L (2023) FlamMap: Fire Mapping and Analysis System (Version 6) [Software]. Available from https://www.firelab.org/project/flammap.

Frickel DG, Shown LM, Patton PC (1975) An evaluation of hillslope and channel erosion related to oil-shale development in the Piceance basin, north-western Colorado. Colorado Department of Natural Resources, Colorado Water Resources Circular 30. (Denver, CO, USA)

Fulé PZ, Crouse JE, Roccaforte JP, Kailes EL (2012) Do thinning and/or burning treatments in western USA ponderosa or Jeffery pine-dominated forests help restore natural fire behavior? Forest Ecology and Management. 269. https://doi.org/10.1016/j.foreco.2011.12.025.

Gannon BM, Wei Y, MacDonald LH, Kampf SK, Jones KW, Cannon JB, Wolk BH, Cheng AS, Addington RN, Thompson MP (2019) Prioritizing fuels reduction for water supply protection. International Journal of Wildland Fire. 28(1), 785-803. doi:10.1071/WF18182.

Higuera PE, Shuman BN, Wolf KD (2021) Rocky Mountain subalpine forests now burning more than any time in recent millennia. Proceedings of the National Academy of Sciences. 118(25).

Jefferson County Open Space (2022). Jefferson County Open Space Forest Health Plan. Jefferson County Open Space, Golden, Colorado. Available at https://www.jeffco.us/DocumentCenter/View/33433/JCOS-Forest-Health-Plan-?bidId=.

Jones KW, Chamberlain JL, Gannon B, and Wolk B (2021). A Cost-Benefit Analysis of Denver's Forests to Faucets Program, 2011-2019. CFRI-2102. https://cfri.colostate.edu/wp-content/uploads/sites/22/2021/02/Jones-et-al-F2F-ROI-Final.pdf

LANDFIRE (2020) Fuel, topography, existing vegetation type, and fuel disturbance layers, LANDFIRE 2.2.0., U.S. Geological Survey. Available from http://landfire.cr.usgs.gov/viewer/.

Larsen IJ, MacDonald LH (2007) Predicting post-fire sediment yields at the hillslope scale: testing RUSLE and disturbed WEPP. Water Resources Research. 43. doi:10.1029/2006WR005560.

Moody JA, Martin DA (2001) Initial hydrologic and geomorphic response following a wildfire in the Colorado Front Range. Earth Surface Processes and Landforms. 26, 1049–1070. doi:10.1002/esp.253.

Moriarty K, Cheng AS, Hoffman CM, Cottrell SP, Alexander ME (2019) Firefighter observations of "surprising" fire behavior in mountain pine beetle-attacked lodgepole pine forests. Fire. 2(34). doi:10.3390/fire2020034.

Mueller SE, Slack AW, Ritter SM, Hunter TM (2023) Wildfire Risk and Treatment Prioritization for the Lower North-South Vegetation Management Planning Area. Colorado Forest Restoration Institute. CFRI-2314. https://cfri.colostate.edu/wp-content/uploads/sites/22/2023/11/WRTP_LowerNS_VegPlanMngt_CFRI2314.pdf

NRCS Soil Survey Staff (2016) Web soil survey. USDA Natural Resources Conservation Service. Available at https://websoilsurvey.nrcs.usda.gov/.

Perica S, Martin D, Pavlovic S, Roy I, St. Laurent M, Trypaluk C, Unruh D, Yekta M, Bonnin G (2013) NOAA Atlas 14, Vol. 8 Version 2, precipitation frequency atlas of the United States, Midwestern States. (NOAA, National Weather Service: Silver Spring, MD, USA).

Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC (1997) Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agricultural Research Service Agricultural Handbook no. 703. (Washington, DC, USA).

Rengers FK, Bower S, Knapp A, Kean JW, vonLembke DW, Thomas MA, Kostelnik J, Barnhart KR, Bethel M, Gartner JE, Hille M, Staley DM, Anderson J, Roberts EK, DeLong SB, Lane B, Ridgway P, and Murphy BP (2023) Evaluating Post-Wildfire Debris Flow Rainfall Thresholds and Volume Models at the 2020 Grizzly Creek Fire in Glenwood Canyon, Colorado, USA. EGUsphere. https://doi.org/10.5194/egusphere-2023-2063, 2023.

Rhea A, Ritter S, Caggiano M, Huayhuaca C, and Edinger J, (2022) Northern Colorado Fireshed Wildfire Risk Assessment. Colorado Forest Restoration Institute. CFRI-2221. https://cfri.colostate.edu/wp-content/uploads/sites/22/2022/10/Rhea_et_al_2022_NorthernColoradoFireshedWildfireRiskAssessment_CFRI_2221.pdf

Ritter S, Morici K, and Stevens-Rumann C (2023) Efficacy of prescribed fire as a fuel reduction treatment in the Colorado Front Range. Canadian Journal of Forest Research. 53(6).

Rodríguez y Silva F, O'Connor CD, Thompson MP, Martínez JMM, and Calkin DE (2020) Modelling suppression difficulty: current and future applications. International Journal of Wildland Fire. 29(8). https://doi.org/10.1071/WF19042.

Schoennagel T, Veblen TT, Romme WH (2004) The interaction of fire, fuels, and climate across Rocky Mountain Forests. BioScience. 54(7). https://doi.org/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

Scott JH, Burgan RE (2005) Standard fire behavior fuel models: A comprehensive set for use with Rothermel's surface fire spread model. USDA Forest Service, Rocky Mountain Research Station, General Technical Report. RMRS-GTR-153.

Scott JH, Reinhardt ED (2001) Assessing crown fire potential by linking models of surface and crown fire behavior. USDA Forest Service, Rocky Mountain Research Station, General Technical Research Paper. RMRS-RP-29.

Scott JH, Thompson MP, Calkin DE (2013) A wildfire risk assessment framework for land and resource management. USDA Forest Service, Rocky Mountain Research Station, General Technical Report. RMRS-GTR-315.

Sherriff RL, Veblen TT (2007) A spatially-explicit reconstruction of historical fire occurrence in the Ponderosa Pine zone of the Colorado Front Range. Ecosystems. 10.

Short KC, Finney MA, Vogler KC, Scott JH, Gilbertson-Day JW and Grenfell IC (2020) Spatial datasets of probabilistic wildfire risk components for the United States (270m).

Stephens SL, Moghaddas JJ (2005) Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed coniFer forest. Forest Ecology and Management. 215(1-3). https://doi.org/10.1016/j.foreco.2005.03.070.

Stephens SL, Moghaddas JJ, Hartsough BR, Moghaddas EEY, Clinton NE (2009) Fuel treatment effects on stand-level carbon pools, treatment-related emissions, and fire risk in a Sierra Nevada mixed-conifer forest. Canadian Journal of Forest Research. 39(8). https://doi.org/10.1139/X09-081.

Technosylva (2018) 2017 Colorado Wildfire Risk Assessment Update. Report to the Colorado State Forest Service.

Theobald DM, Merritt DM, Norman JB (2010) Assessment of threats to riparian ecosystems in the western US. Report to the Western Environmental Threats Assessment Center, Prineville, OR by the USDA Stream Systems Technology Center and Colorado State University.

Wagenbrenner JW, Robichaud PR (2014) Post-fire bedload sediment delivery across spatial scales in the interior western United States. Earth Surface Processes and Landforms. 39, 865–876. doi:10.1002/esp.3488.

Winchell MF, Jackson SH, Wadley AM, Srinivasan R (2008) Extension and validation of a geographic information system-based method for calculating the Revised Universal Soil Loss Equation length-slope factor for erosion risk assessments in large watersheds. Journal of Soil and Water Conservation. 63, 105–111.

Ziegler JP, Hoffman C, Battaglia M, Mell W (2017) Spatially explicit measurements of forest structure and fire behavior following restoration treatments in dry forests. Forest Ecology and Management. 386, 1-12. https://doi.org/10.1016/j.foreco.2016.12.002.

Appendix I – Fire Behavior Results

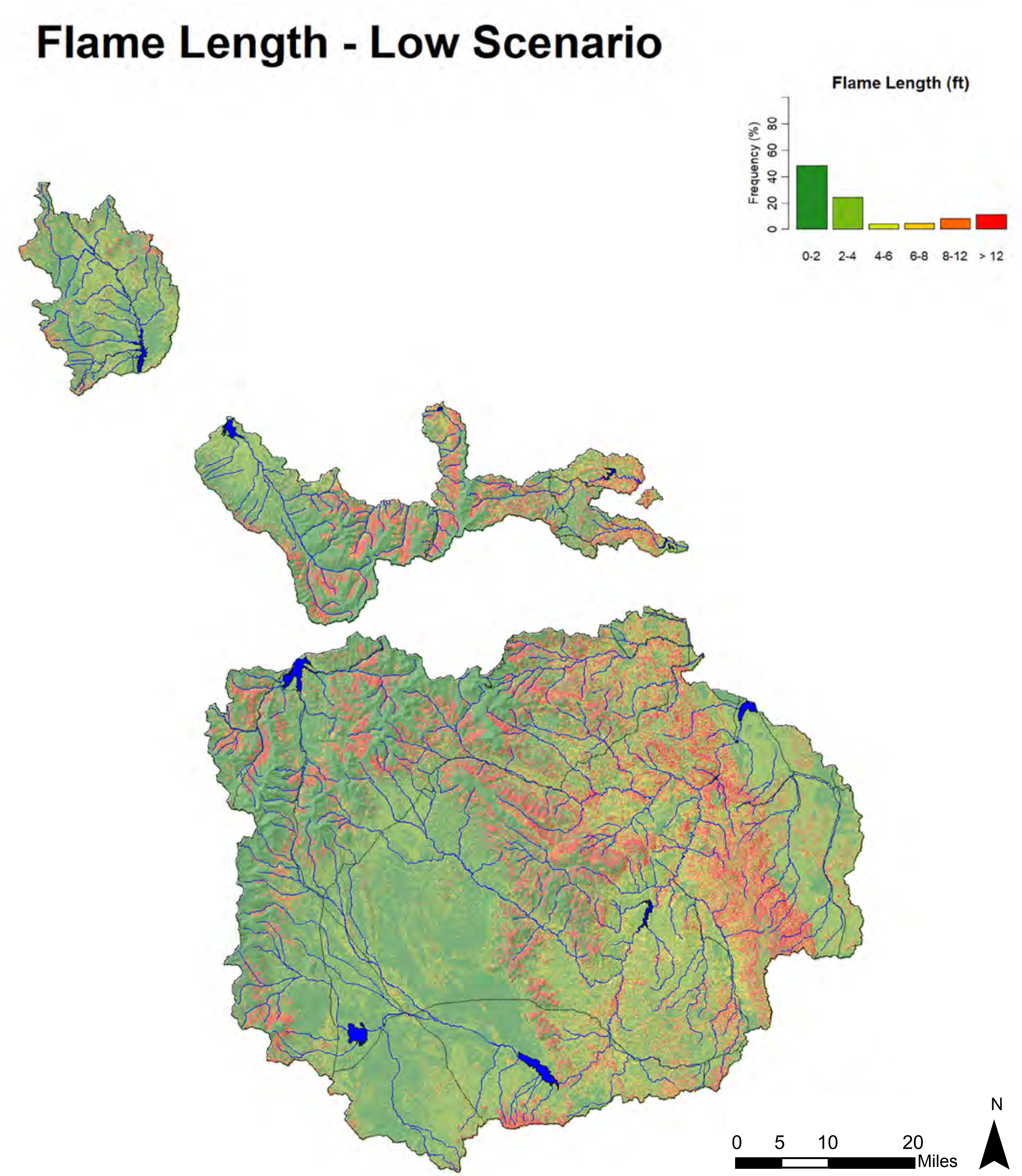


Figure 34: Modeled flame length (ft) for the low fire weather scenario (25th percentile).

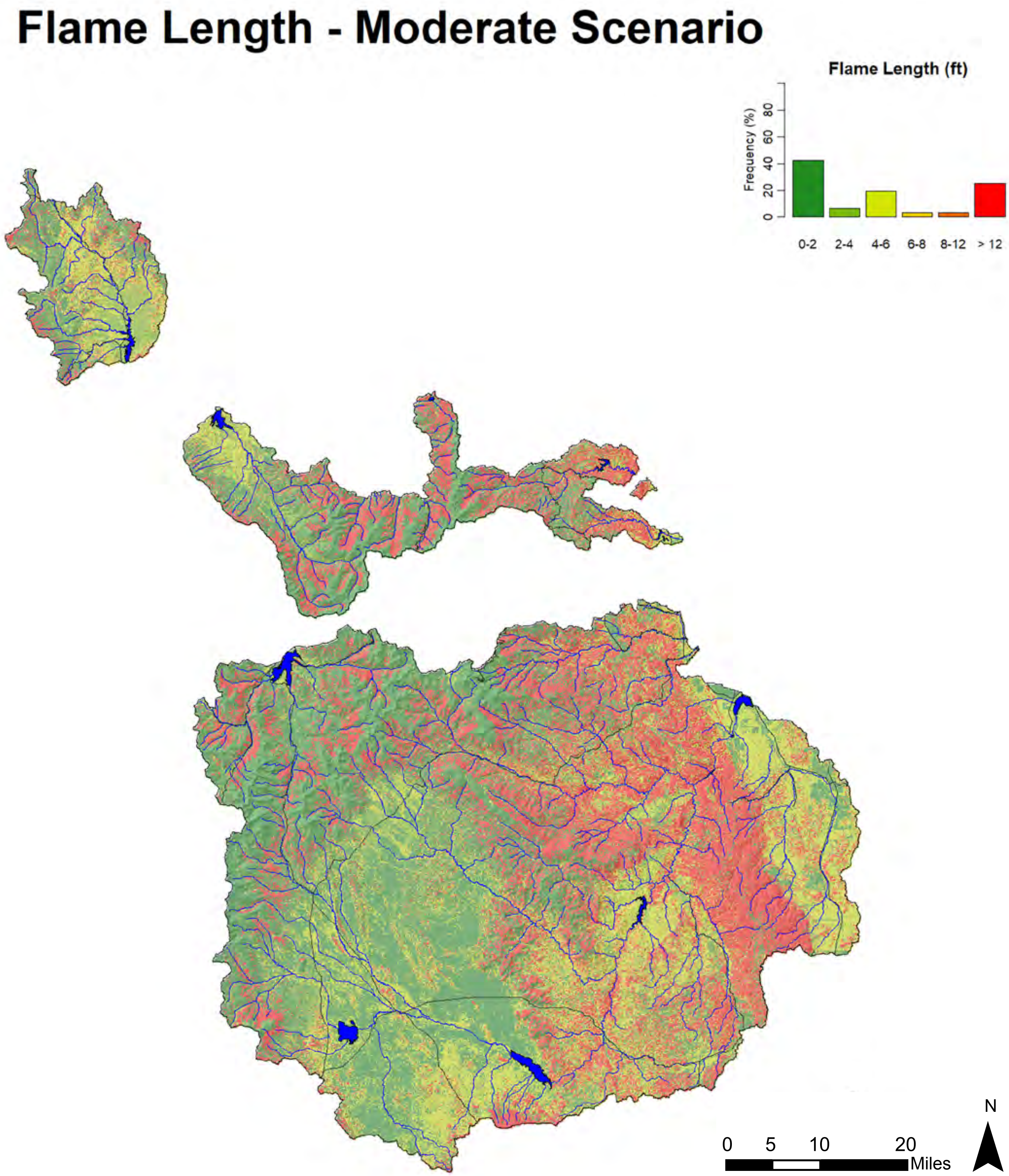


Figure 35: Modeled flame length (ft) for the moderate fire weather scenario (50th percentile).

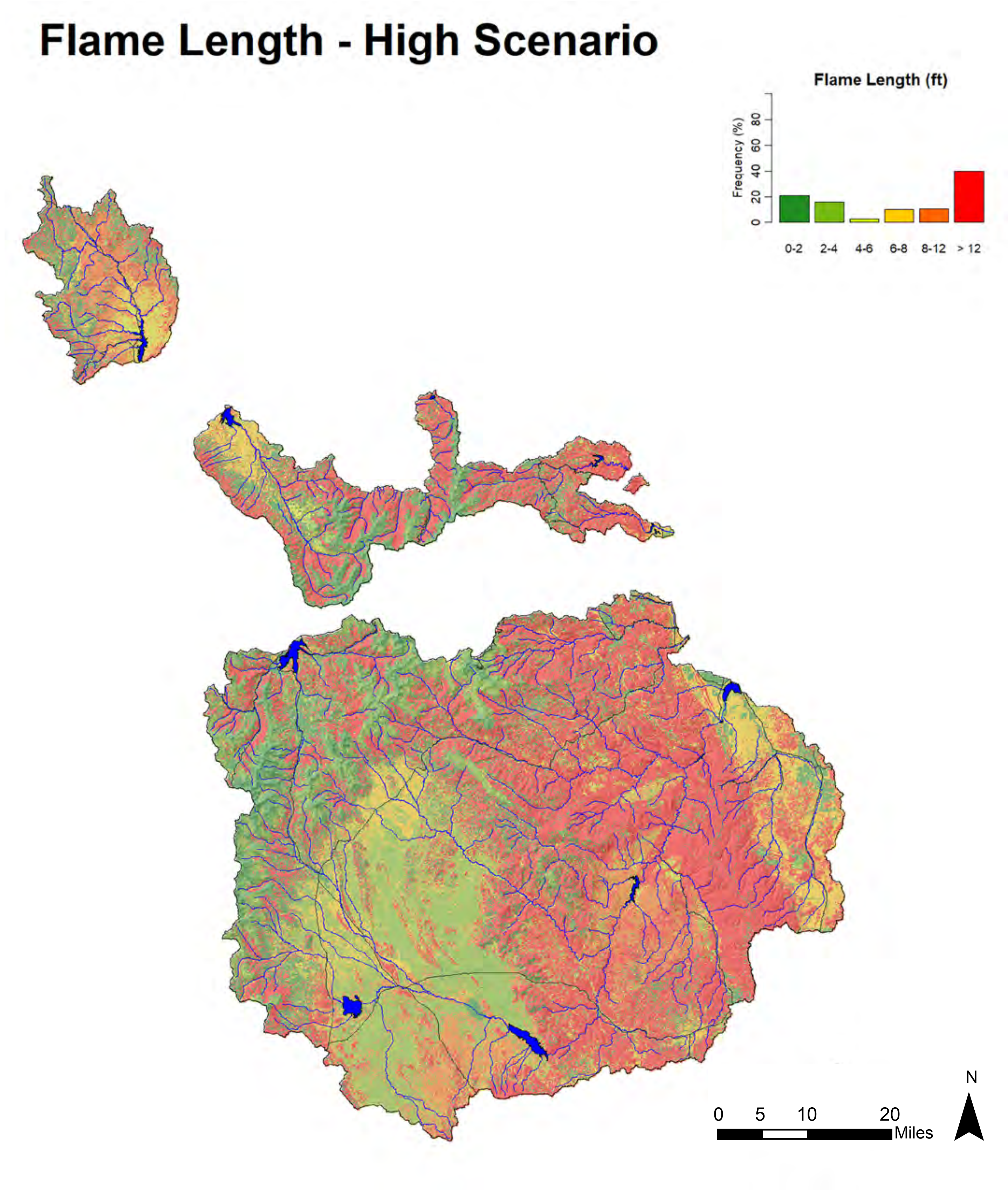


Figure 36: Modeled flame length (ft) for the high fire weather scenario (90th percentile).

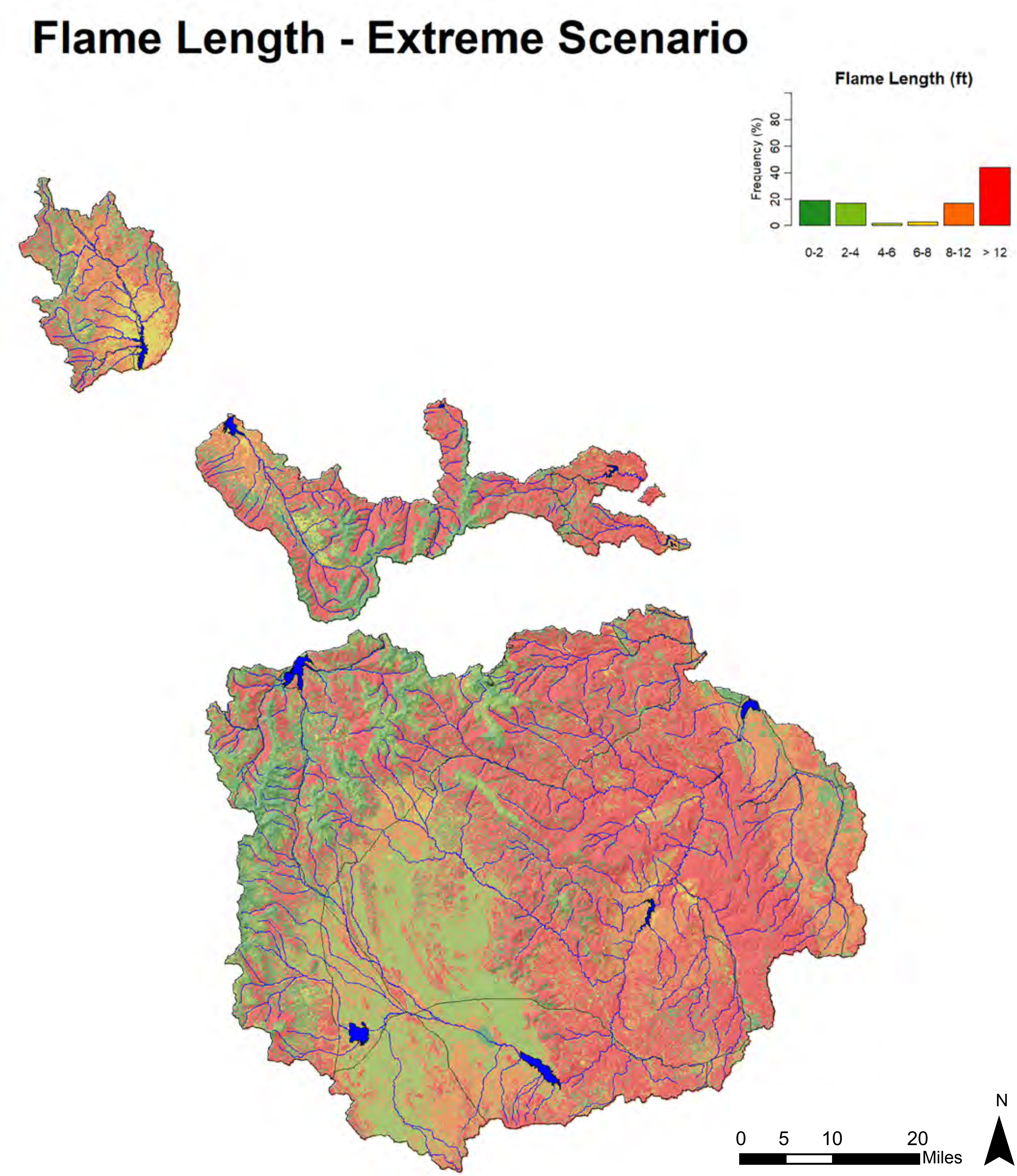


Figure 37: Modeled flame length (ft) for the extreme fire weather scenario (97th percentile).

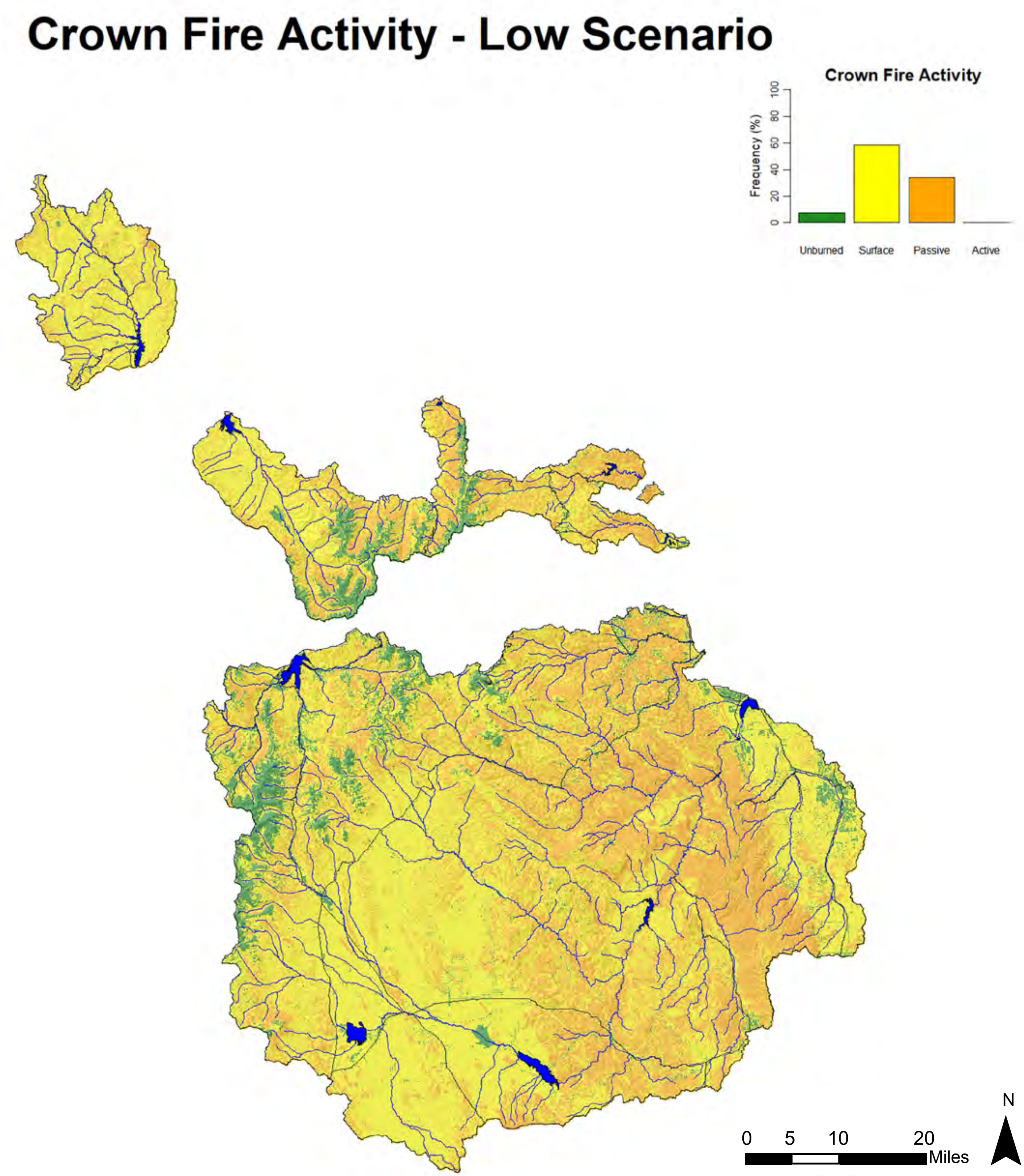


Figure 38: Modeled crown fire activity for the low fire weather scenario (25th percentile).

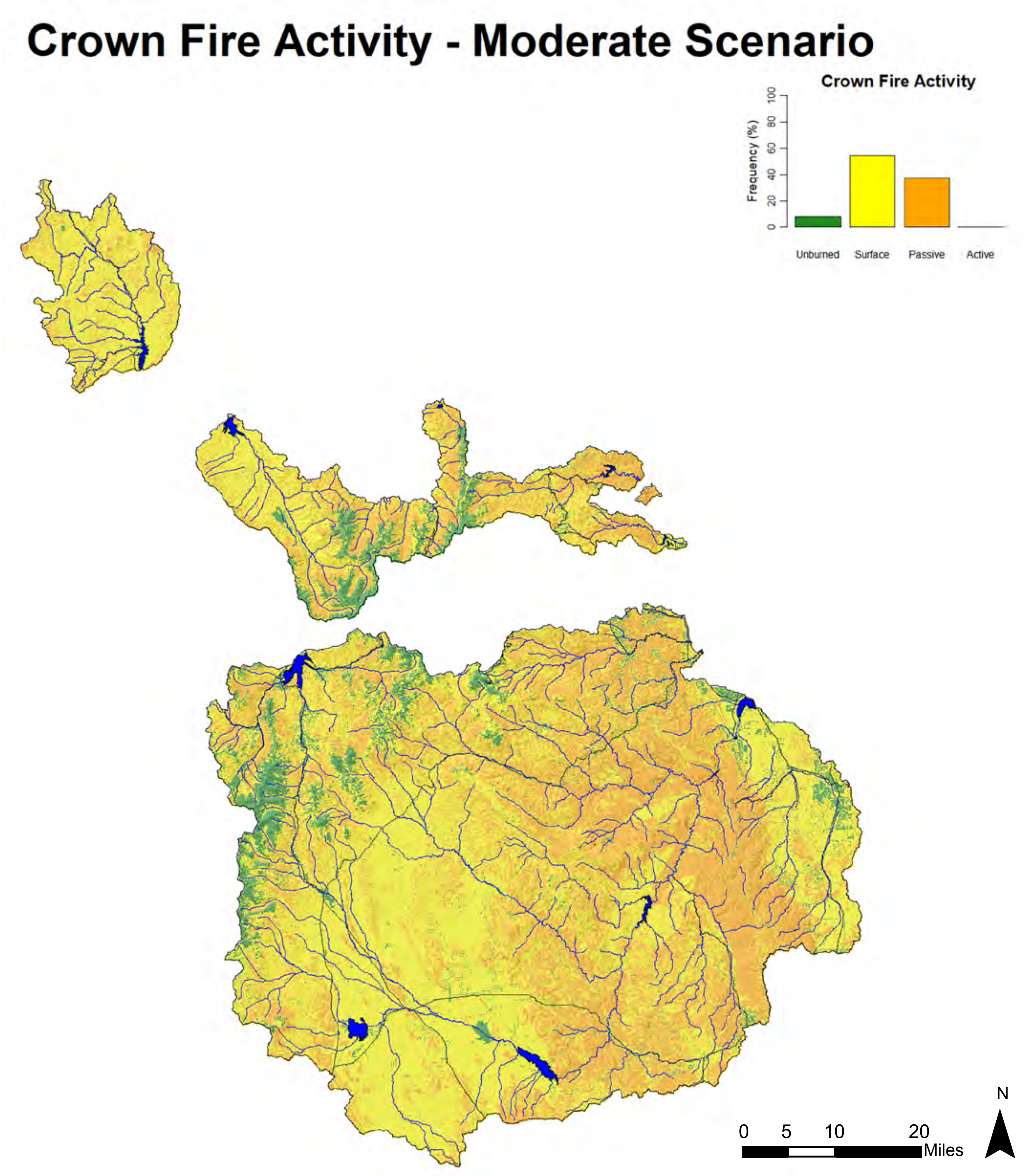


Figure 39: Modeled crown fire activity for the moderate fire weather scenario (50th percentile).

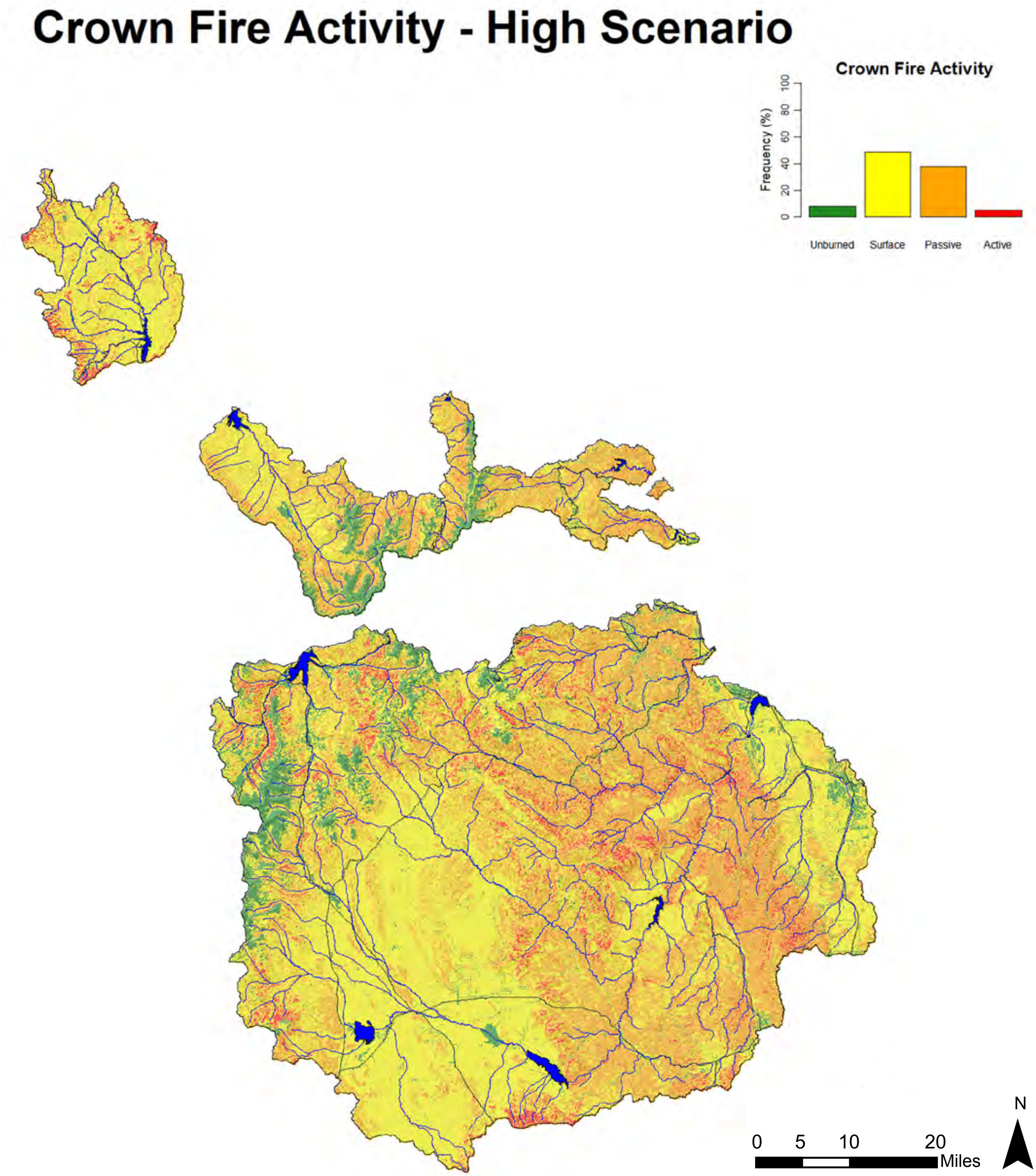


Figure 40: Modeled crown fire activity for the high fire weather scenario (90th percentile).

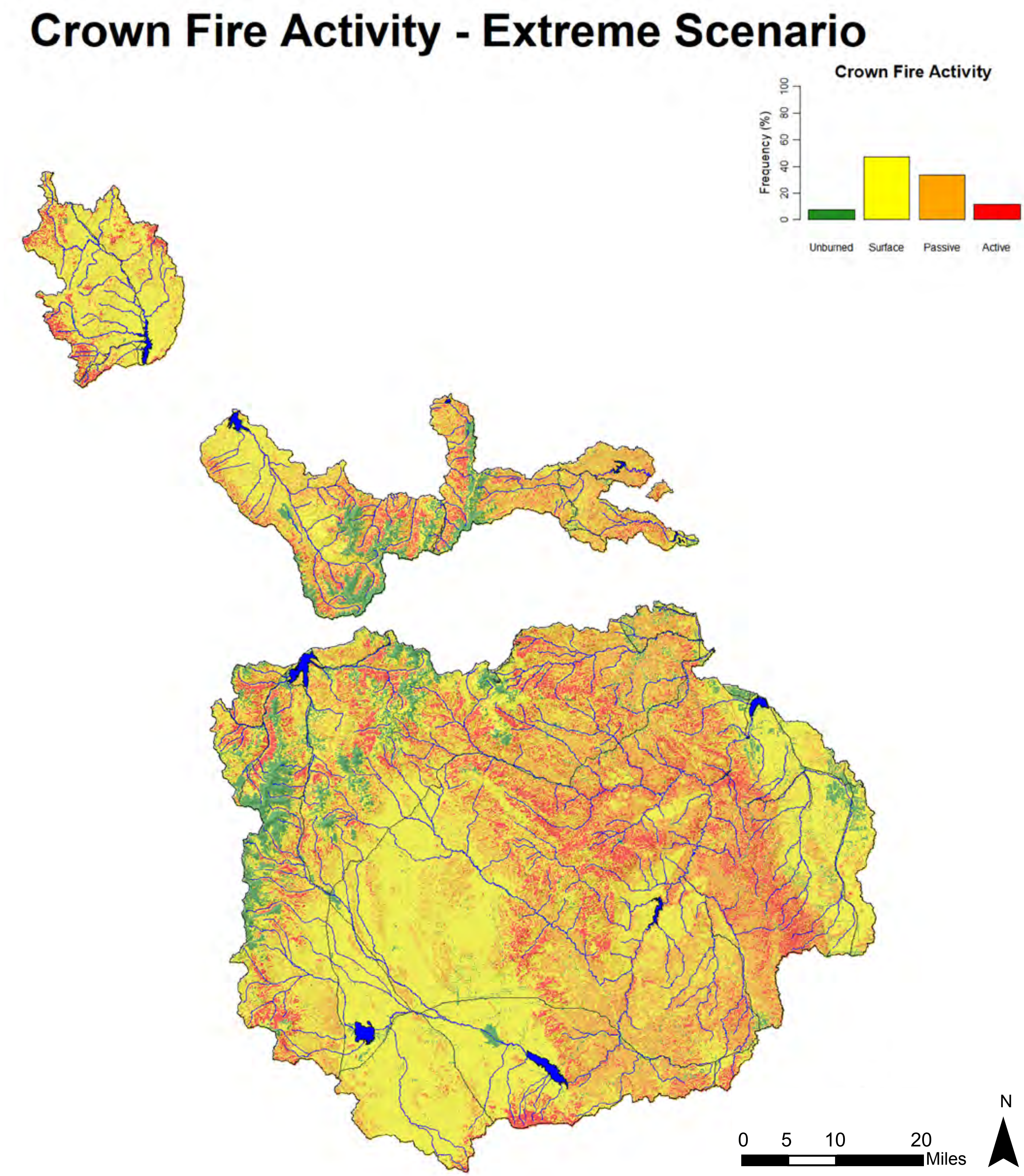


Figure 41: Modeled crown fire activity for the extreme fire weather scenario (97th percentile).

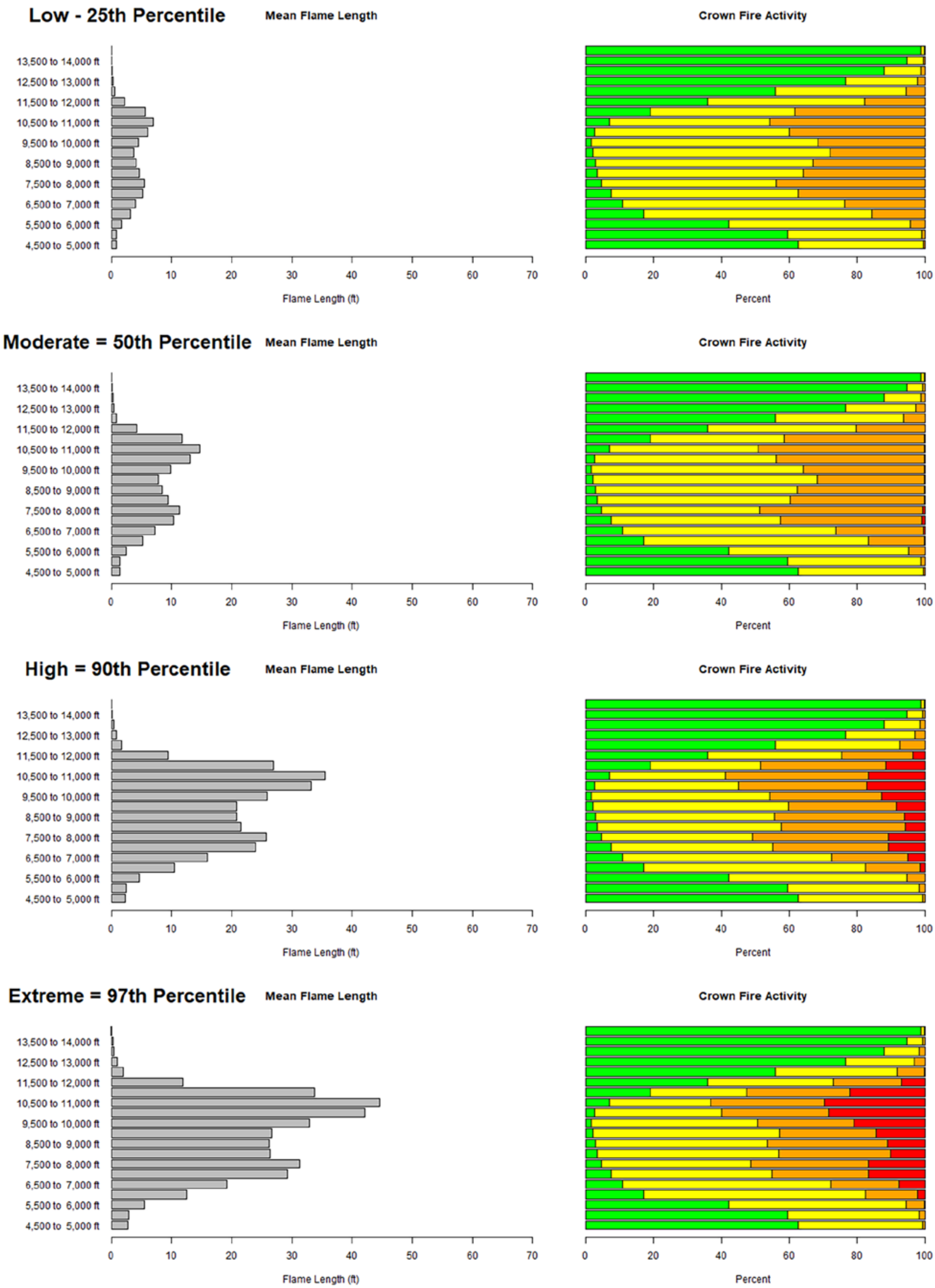


Figure 42: Summary of fire behavior by elevation. The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

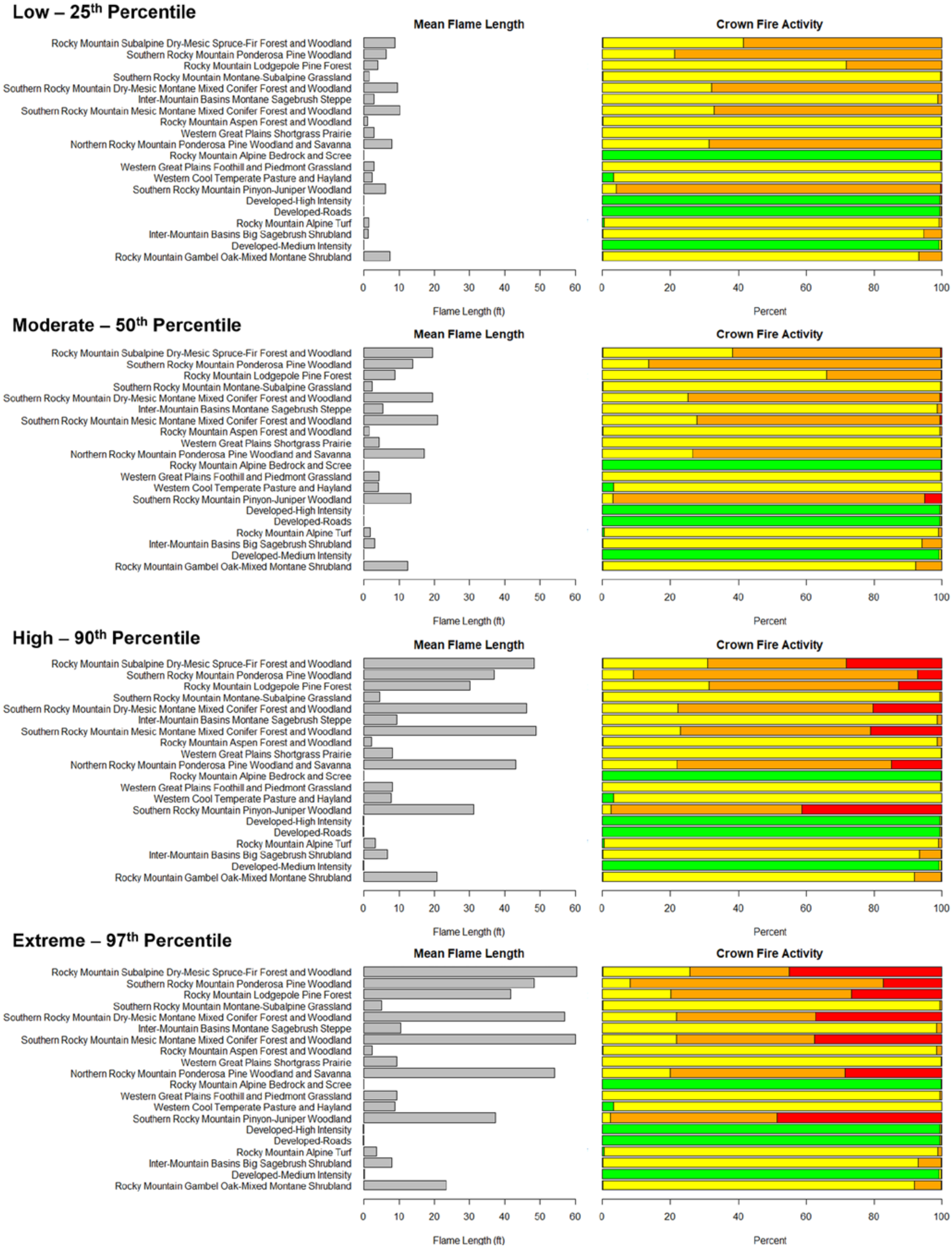


Figure 43: Summary of fire behavior by existing vegetation type from LANDFIRE (2020). The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

Appendix II – Burn Probability Results

Burn probability is calculated as the number of times a given pixel burned divided by the total number of simulated ignitions. A burn probability value of 1 means a fire is certain and a value of 0 means a fire is impossible. Maximum simulated burn probability was 0.014 in this assessment (Figure 45).

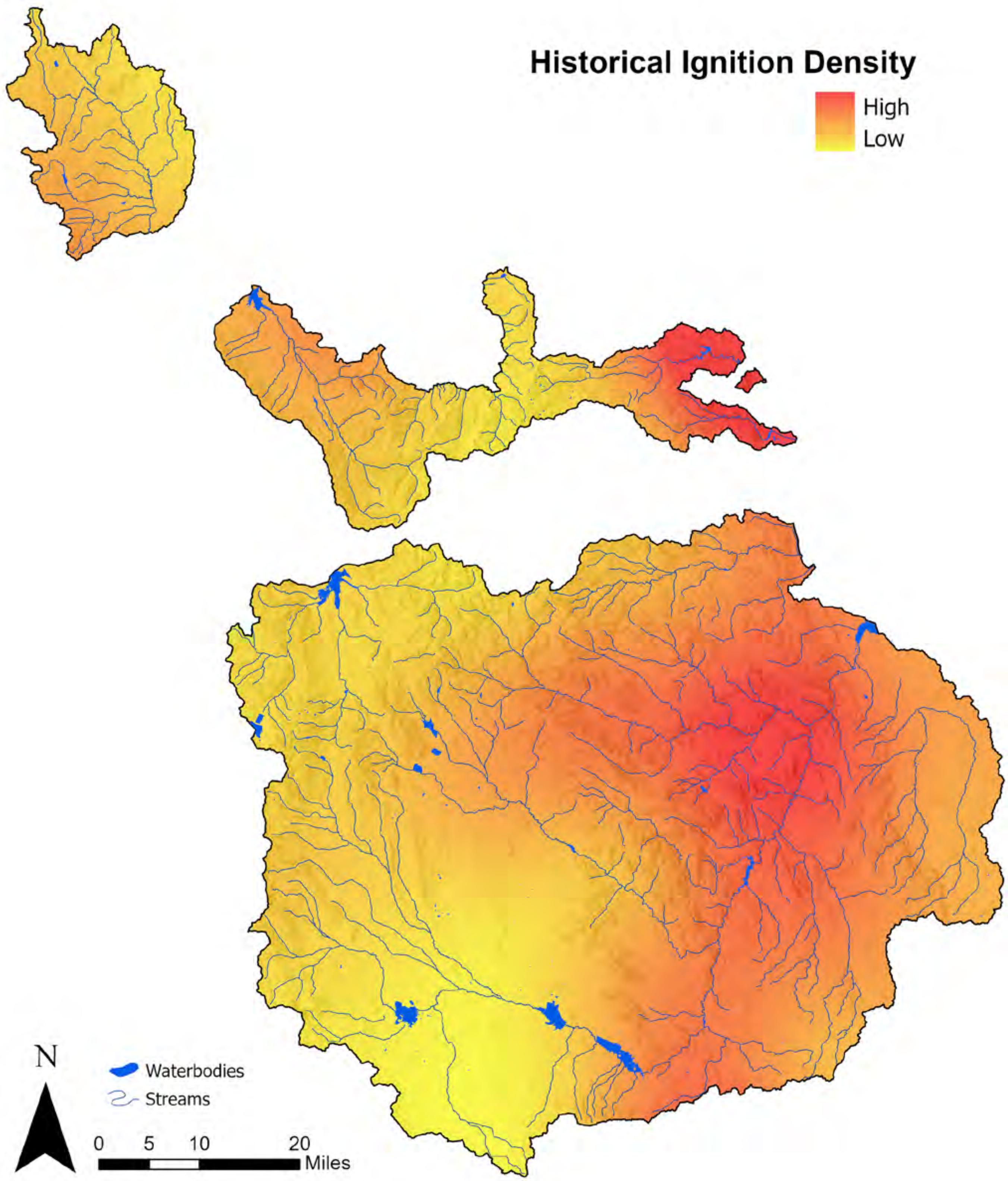


Figure 44: Historical fire ignition density in the QWRA analysis extent.

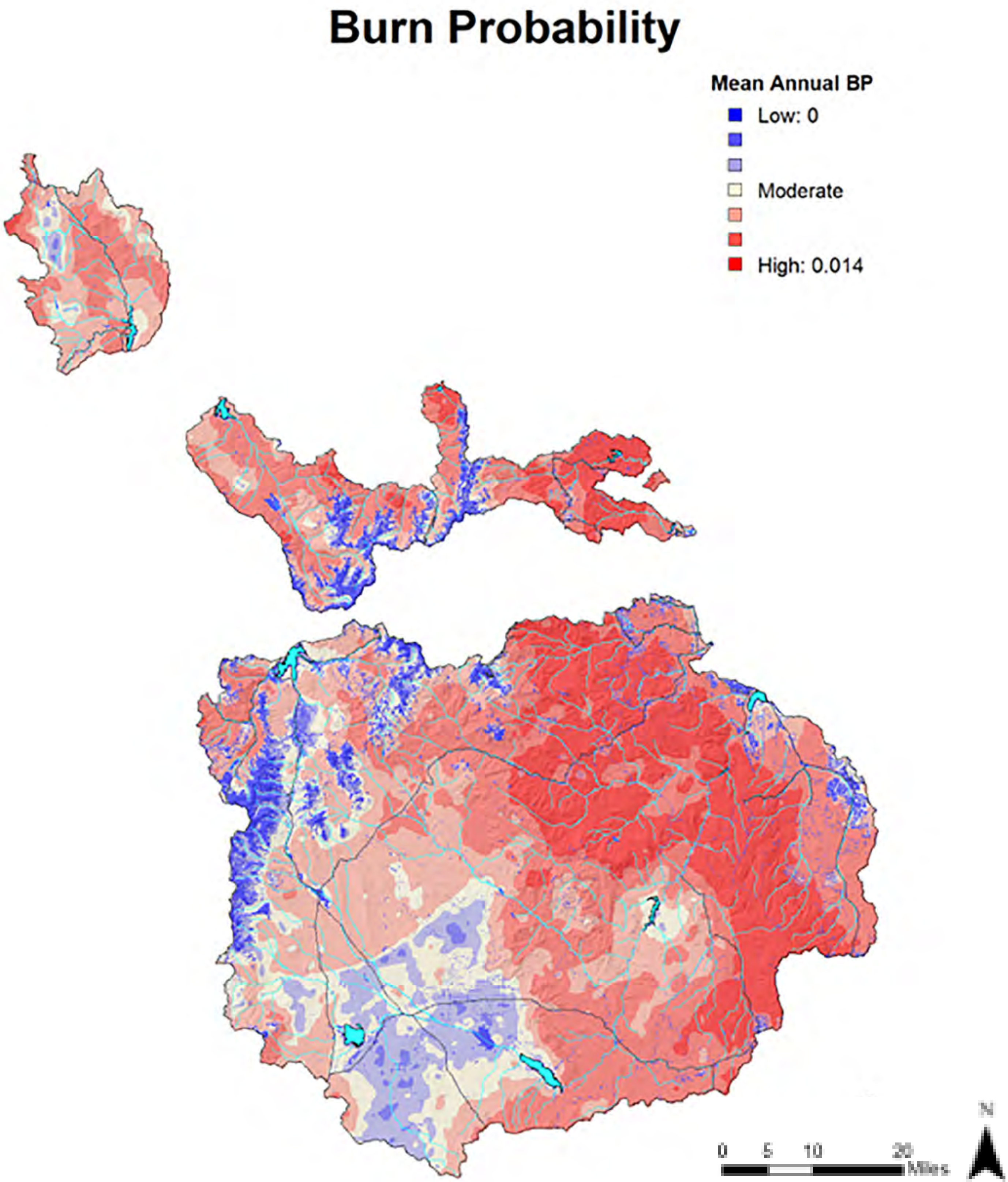


Figure 45: The FSim burn probability product used for the QWRA analysis.

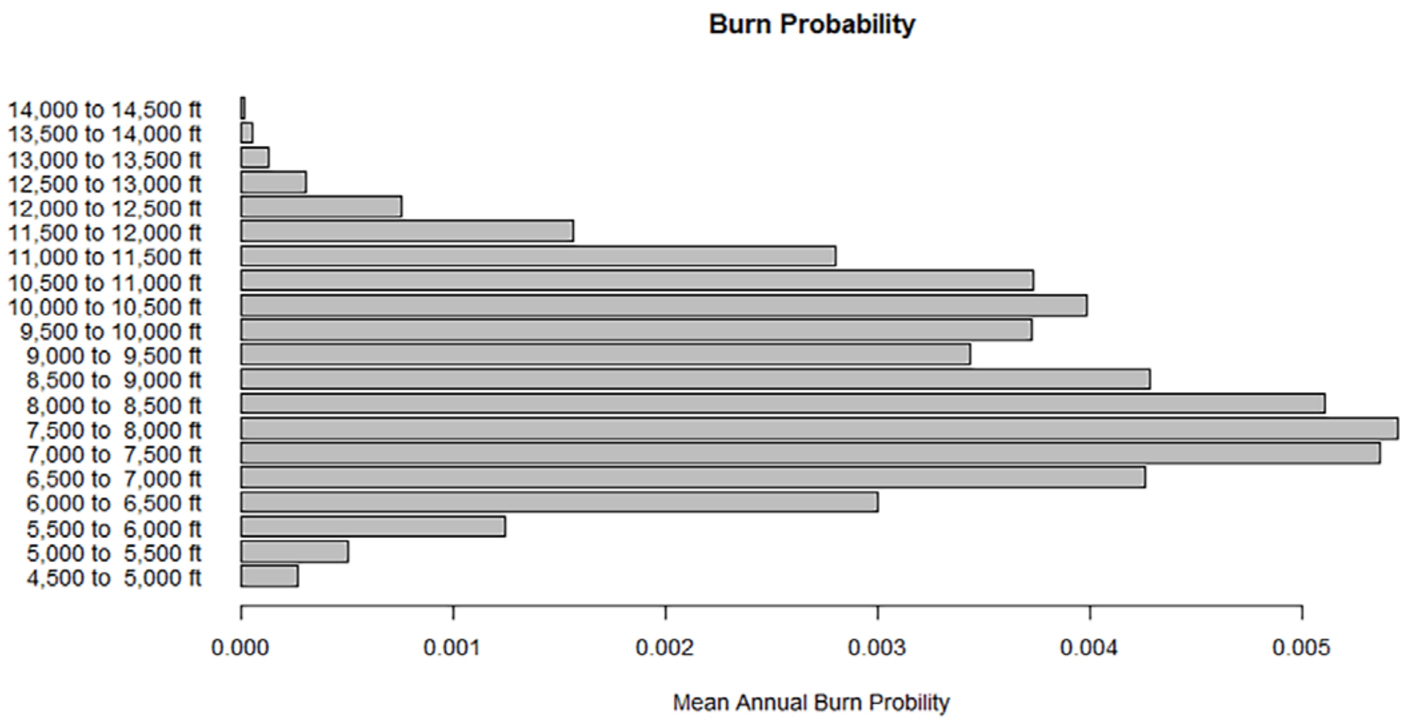


Figure 46: Expected area burned by elevation based on local FSim burn probability.

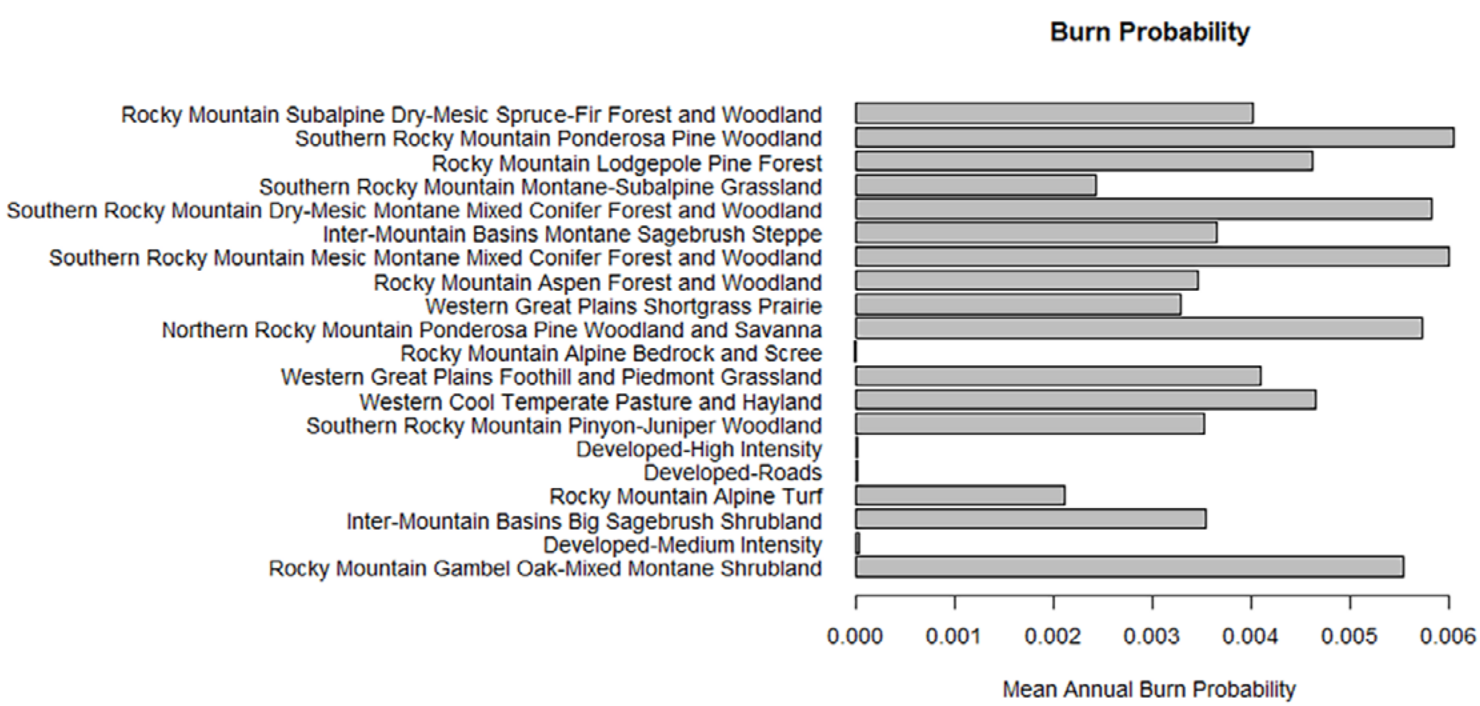


Figure 47: Expected area burned by LANDFIRE existing vegetation type based on local FSim burn probability.

Appendix III – Vegetation Management Assumptions

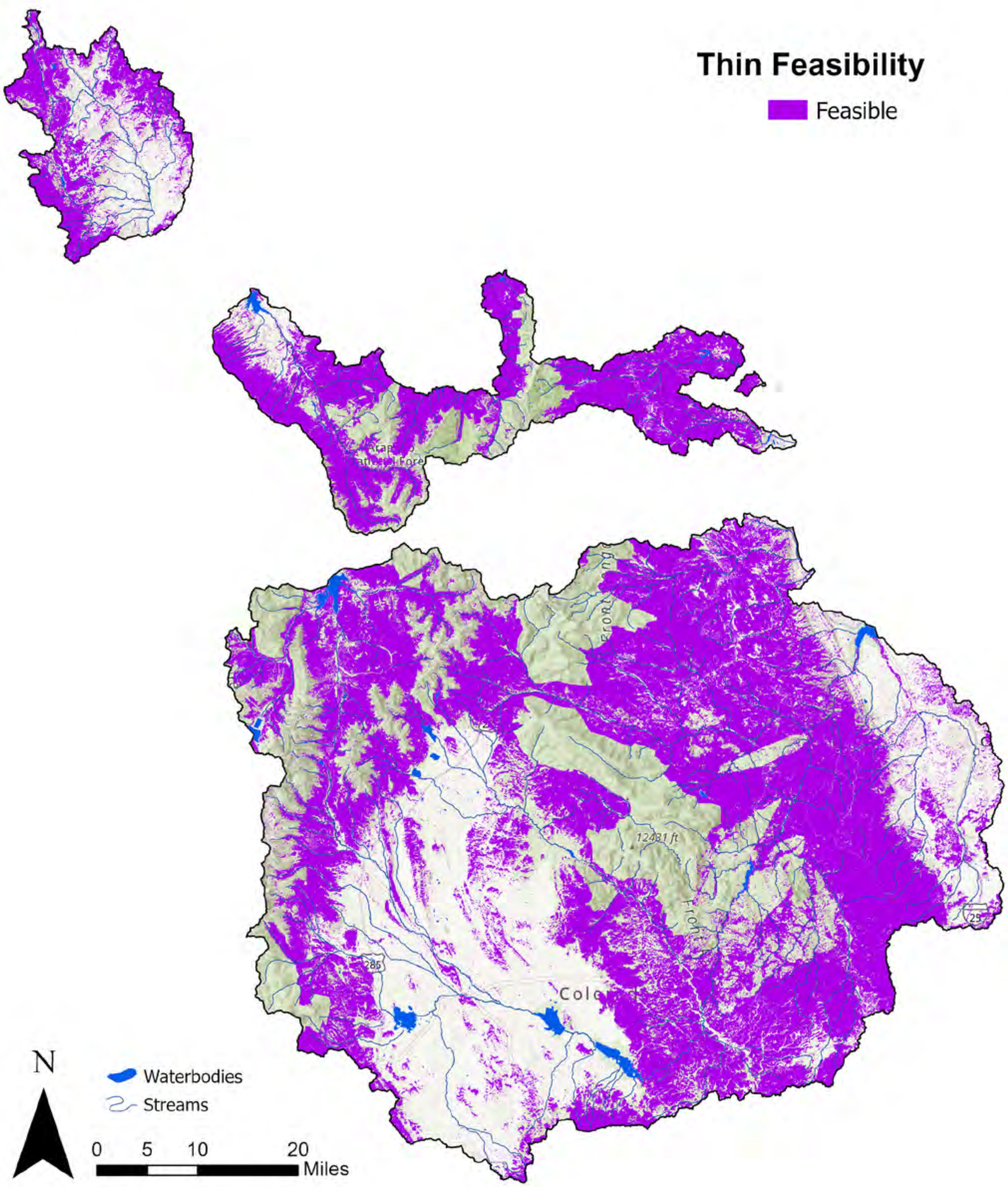


Figure 48: Feasibility of thin only treatment.

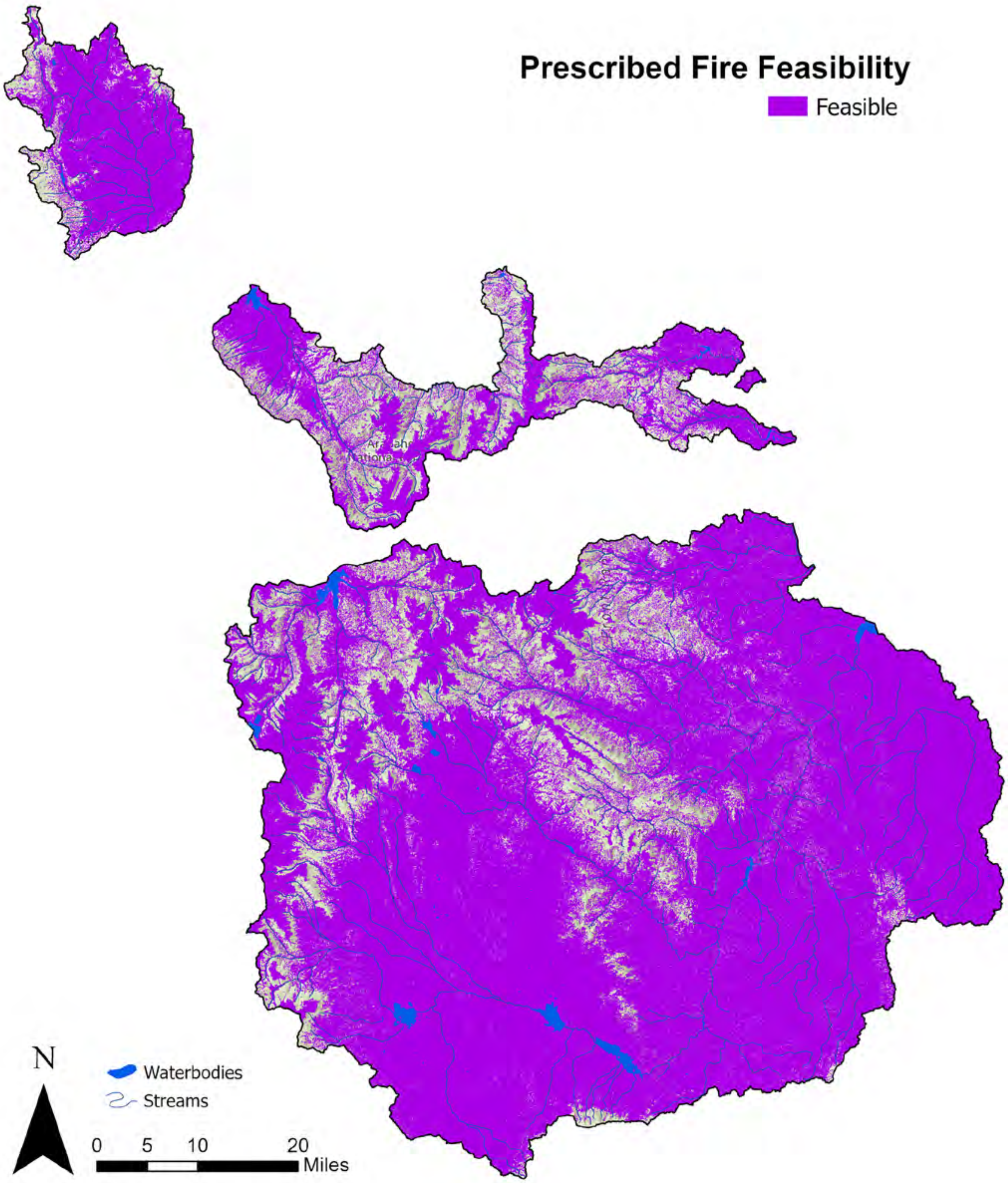


Figure 49: Feasibility of prescribed fire only treatment.

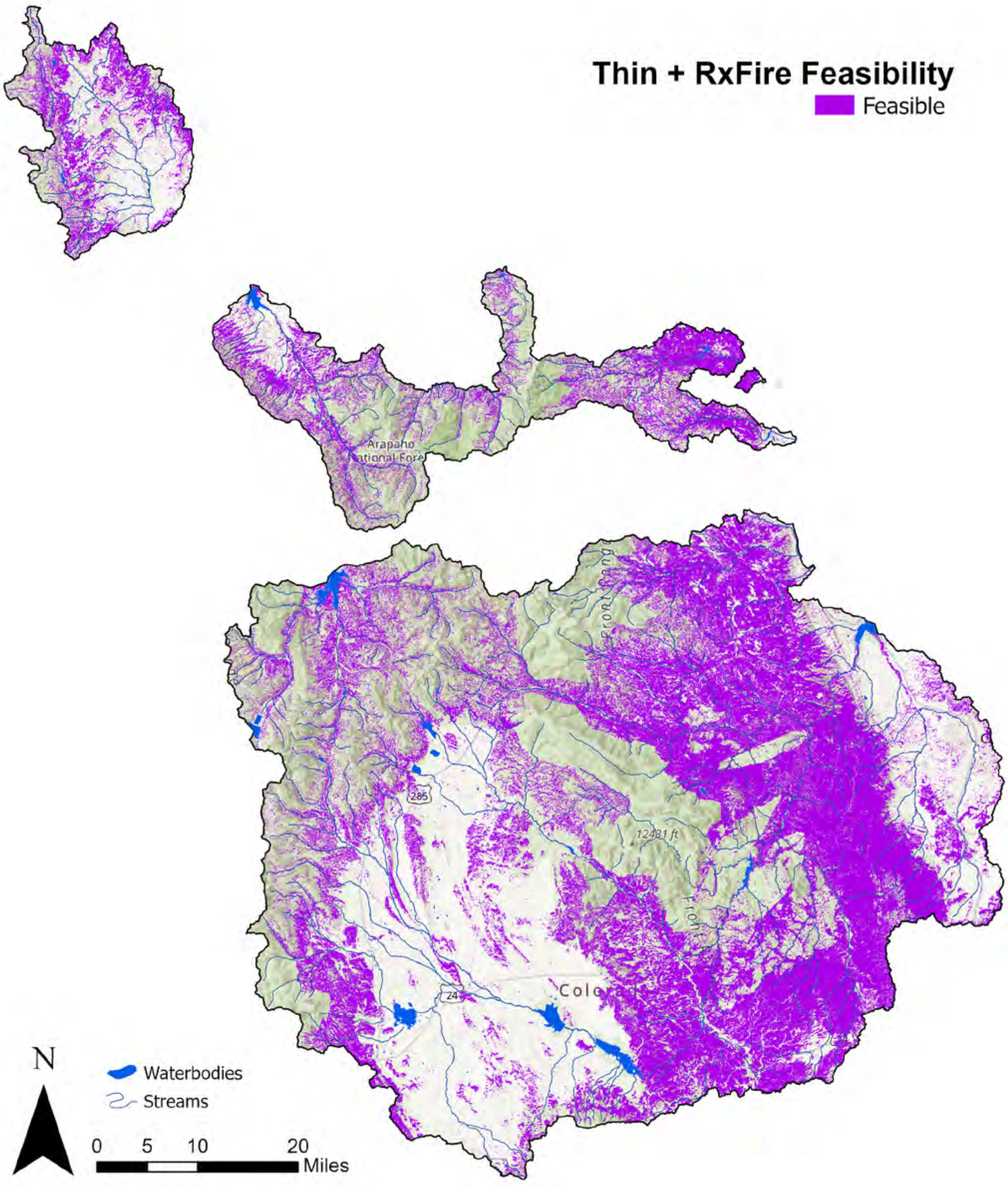


Figure 50: Feasibility of thin followed by prescribed fire treatment.

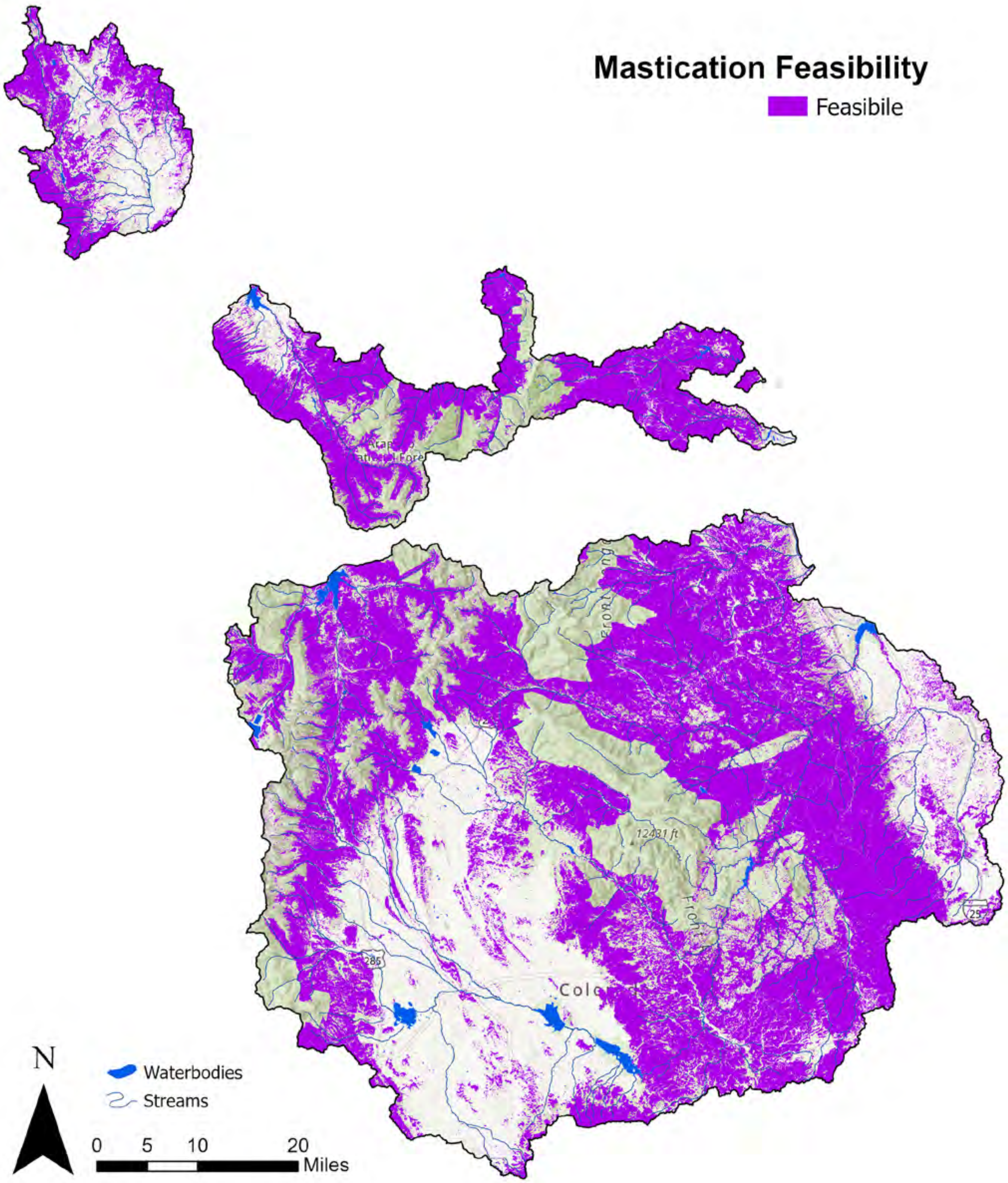


Figure 51: Feasibility of mastication treatment.

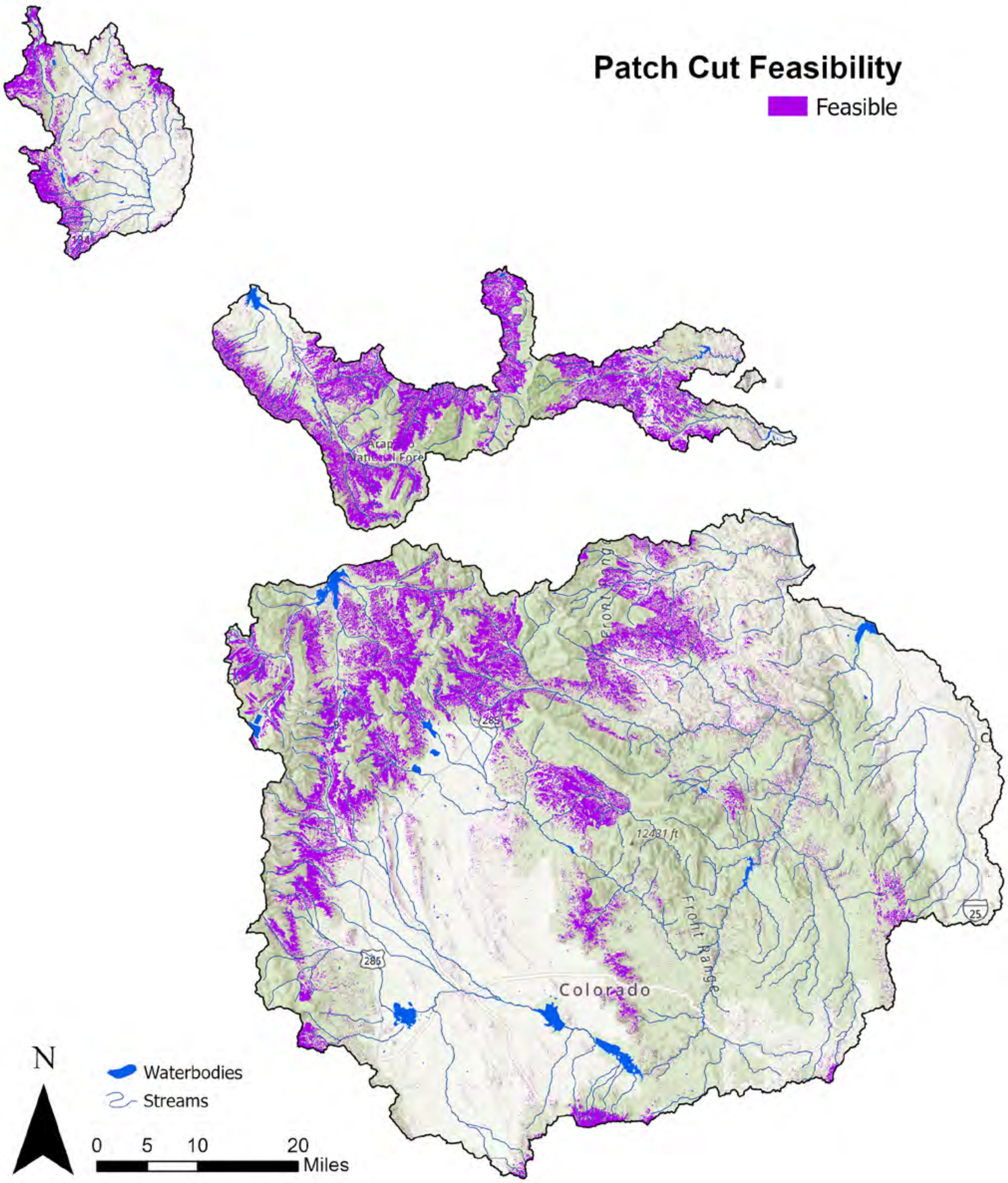


Figure 52: Feasibility of patch cut treatment.

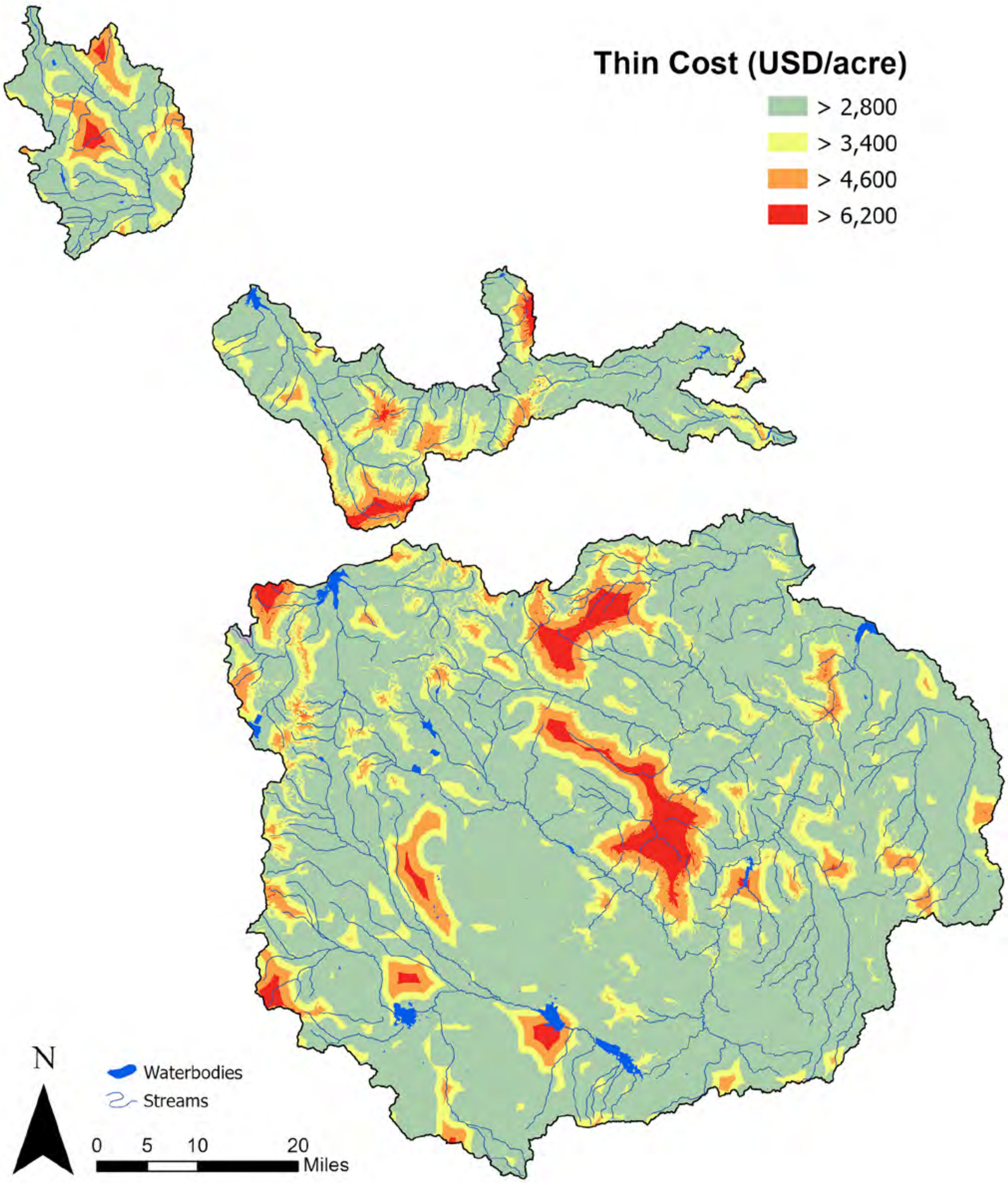


Figure 53: Cost (USD/acre) of thin only treatment.

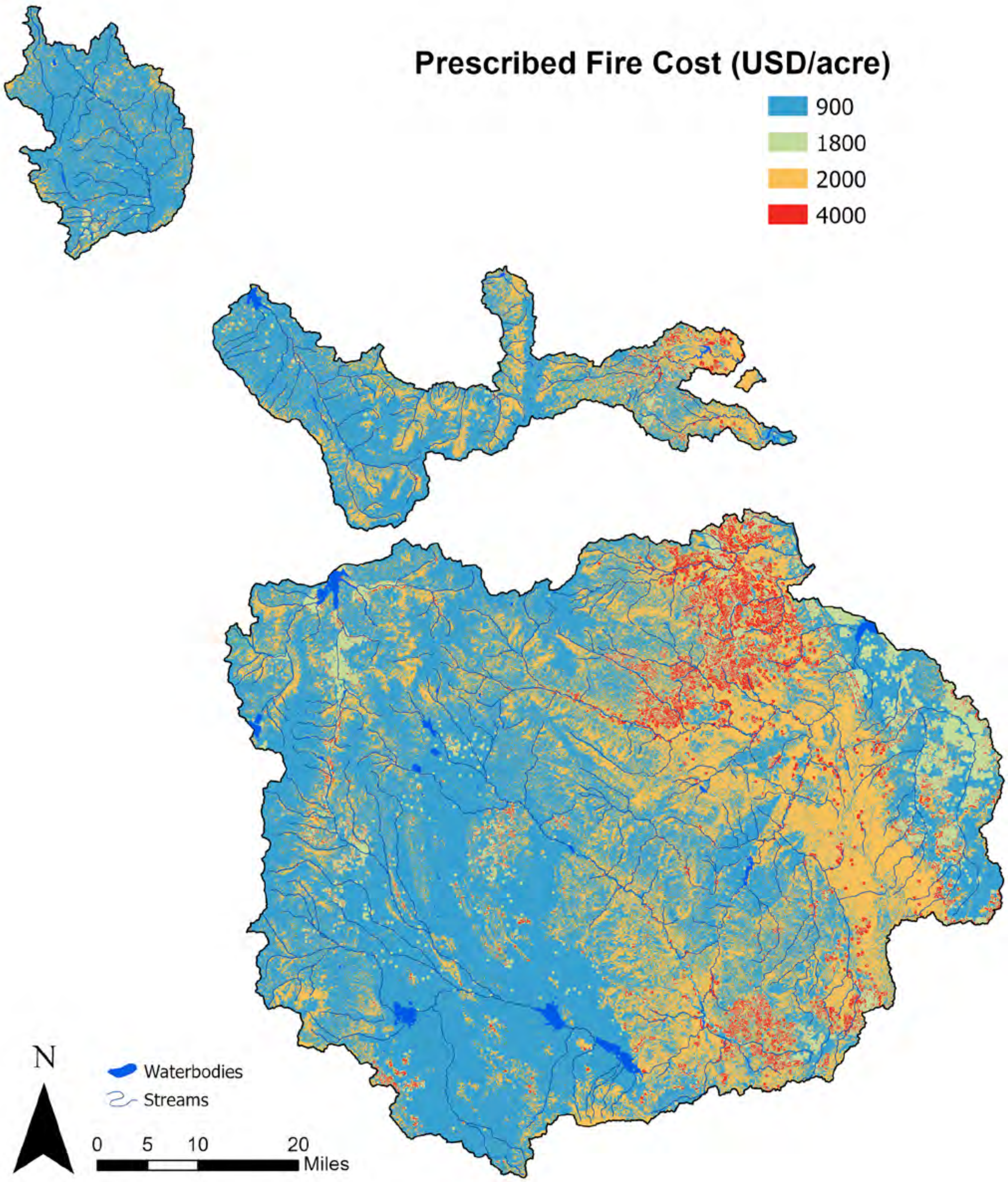


Figure 54: Cost (USD/acre) of prescribed fire only treatment. Note this color scale differs from other treatment cost maps.

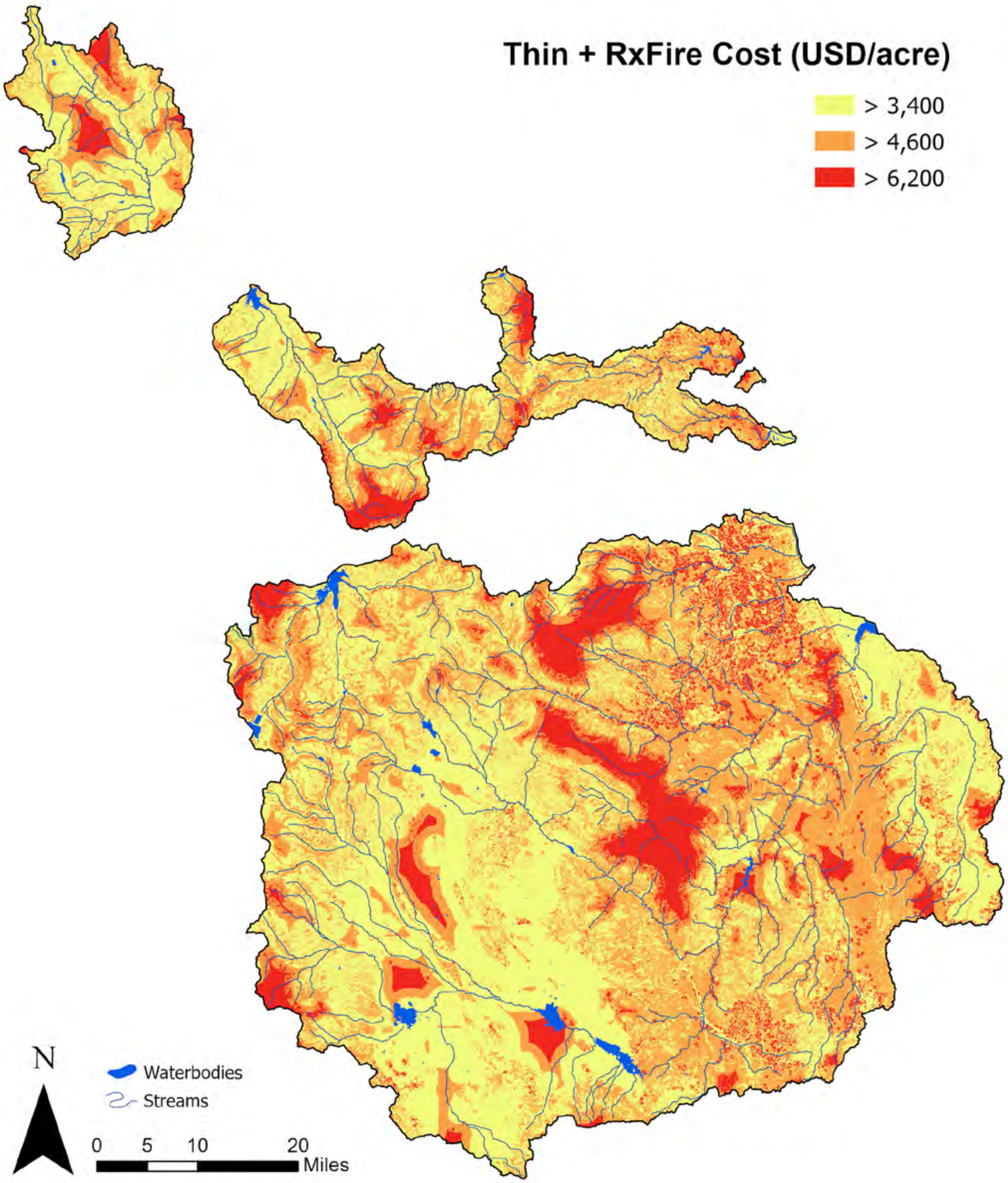


Figure 55: Cost (USD/acre) of thin followed by prescribed fire treatment.

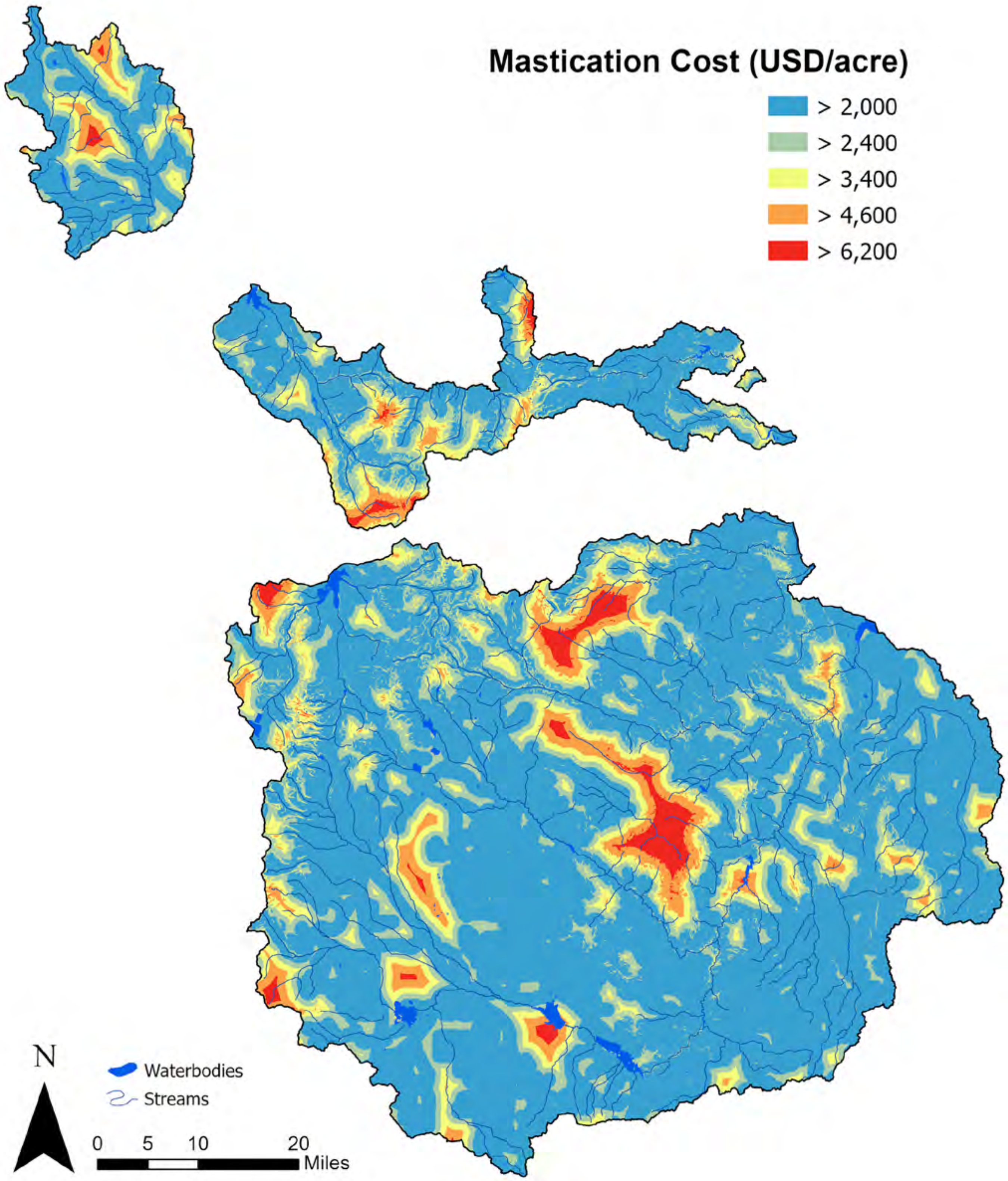


Figure 56: Cost (USD/acre) of mastication treatment.

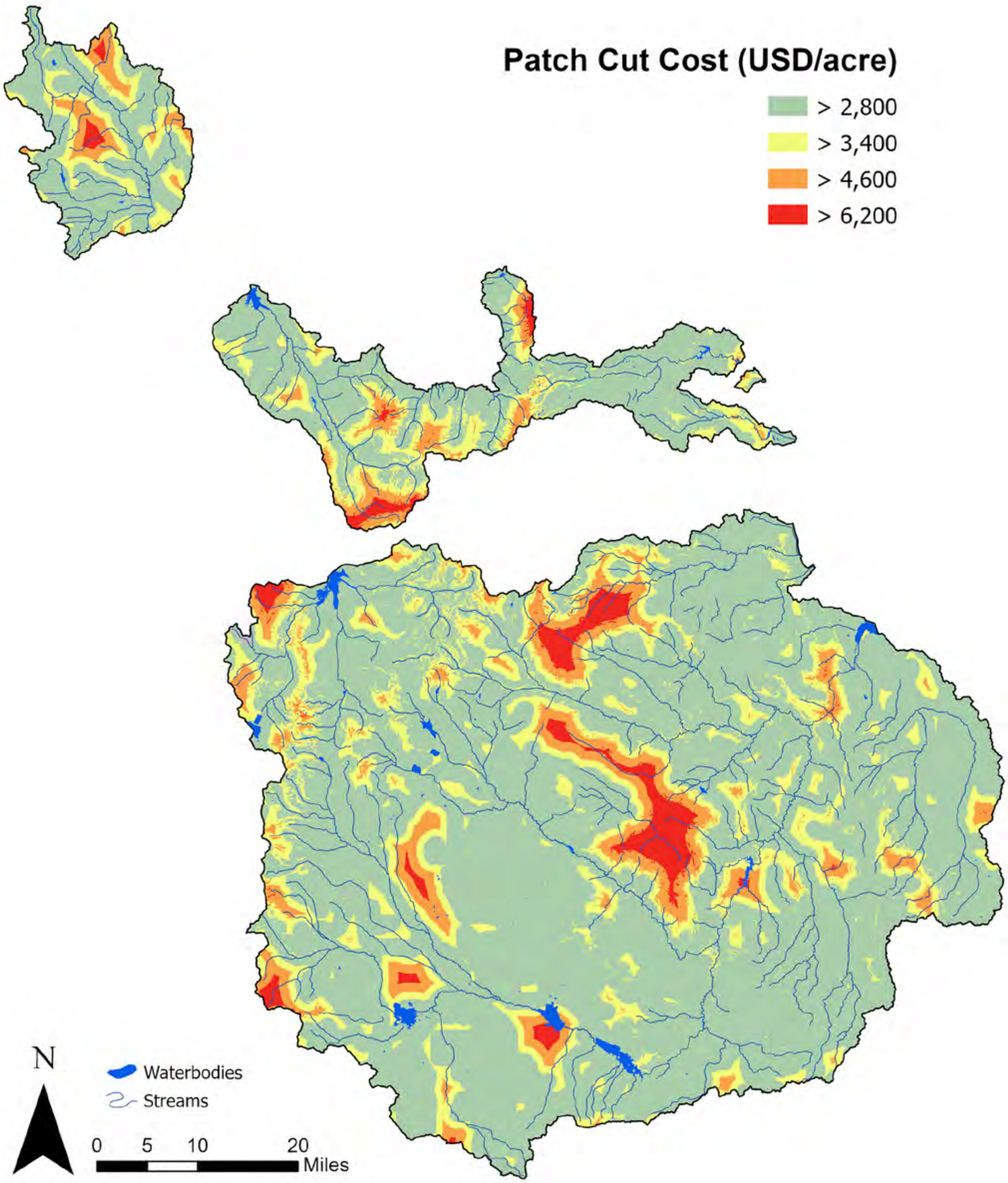


Figure 57 Cost (USD/acre) of patch cut treatment.

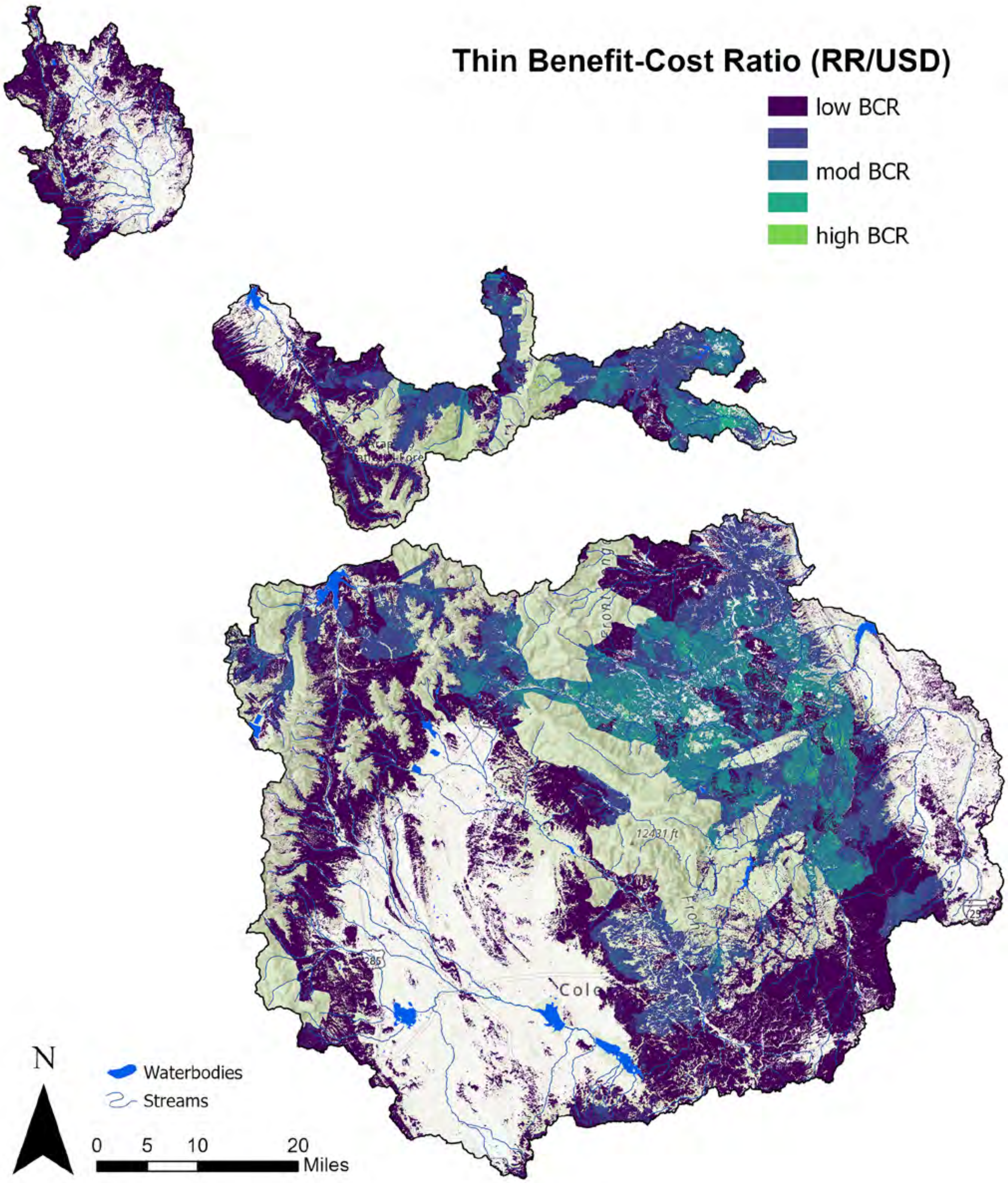


Figure 58: Benefit-cost ratio of the thin only treatment. BCR is measured as risk reduction (baseline eNVC - treated eNVC) per dollar spent within feasible treatment areas.

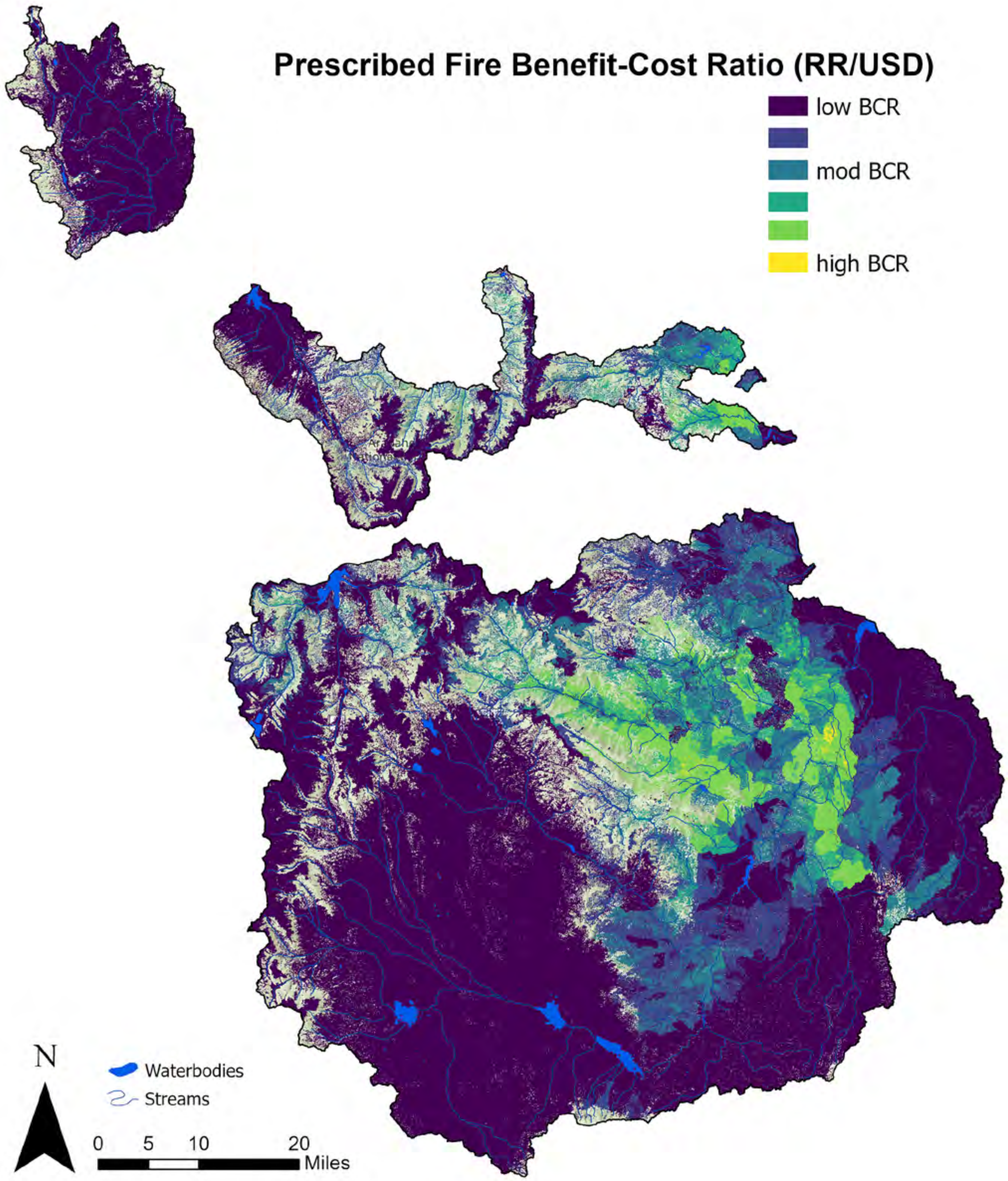


Figure 59: Benefit-cost ratio of the prescribed fire only treatment. BCR is measured as risk reduction (baseline eNVC - treated eNVC) per dollar spent within feasible treatment areas.

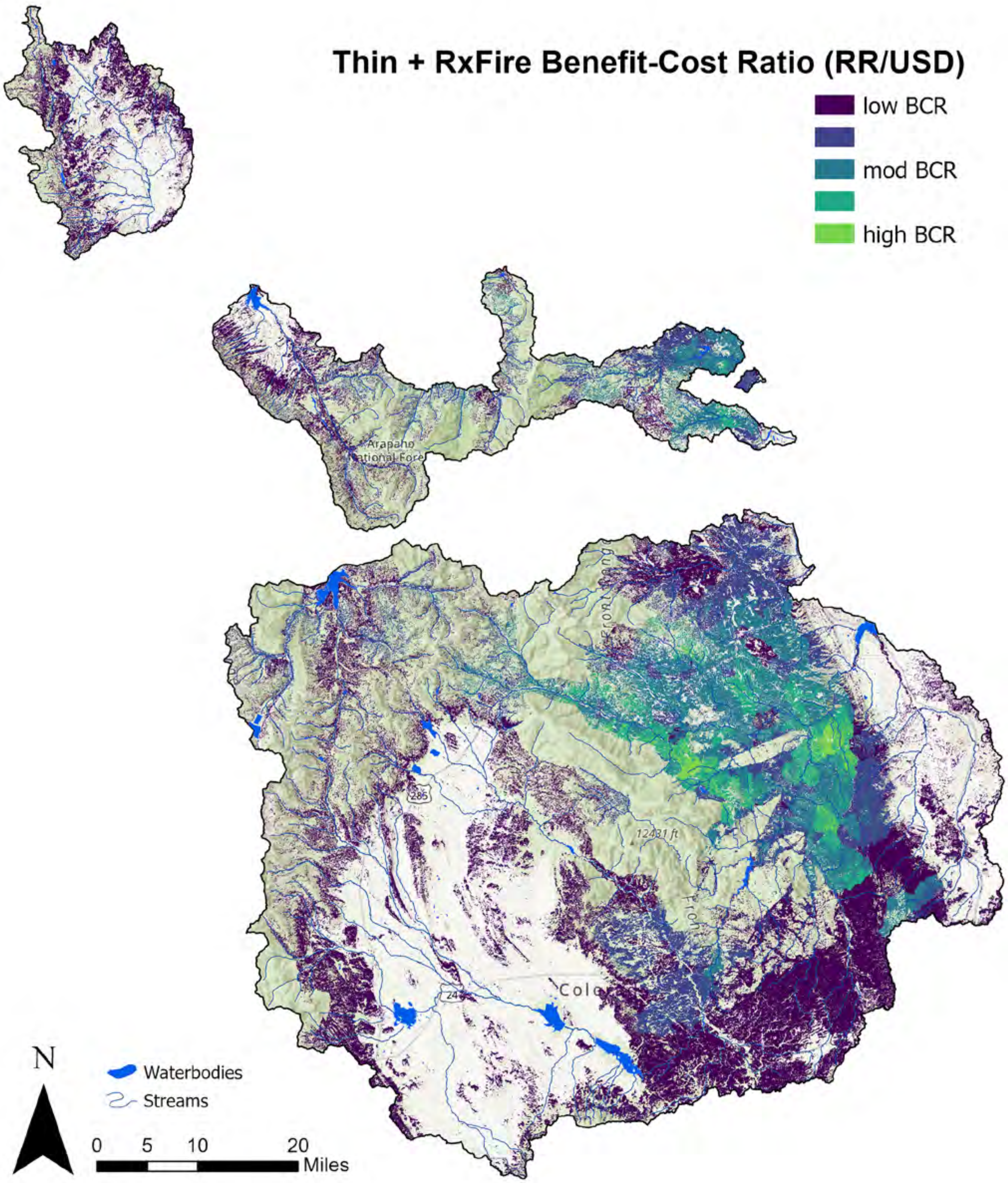


Figure 60: Benefit-cost ratio of the thin followed by prescribed fire treatment. BCR is measured as risk reduction (baseline eNVC - treated eNVC) per dollar spent within feasible treatment areas.

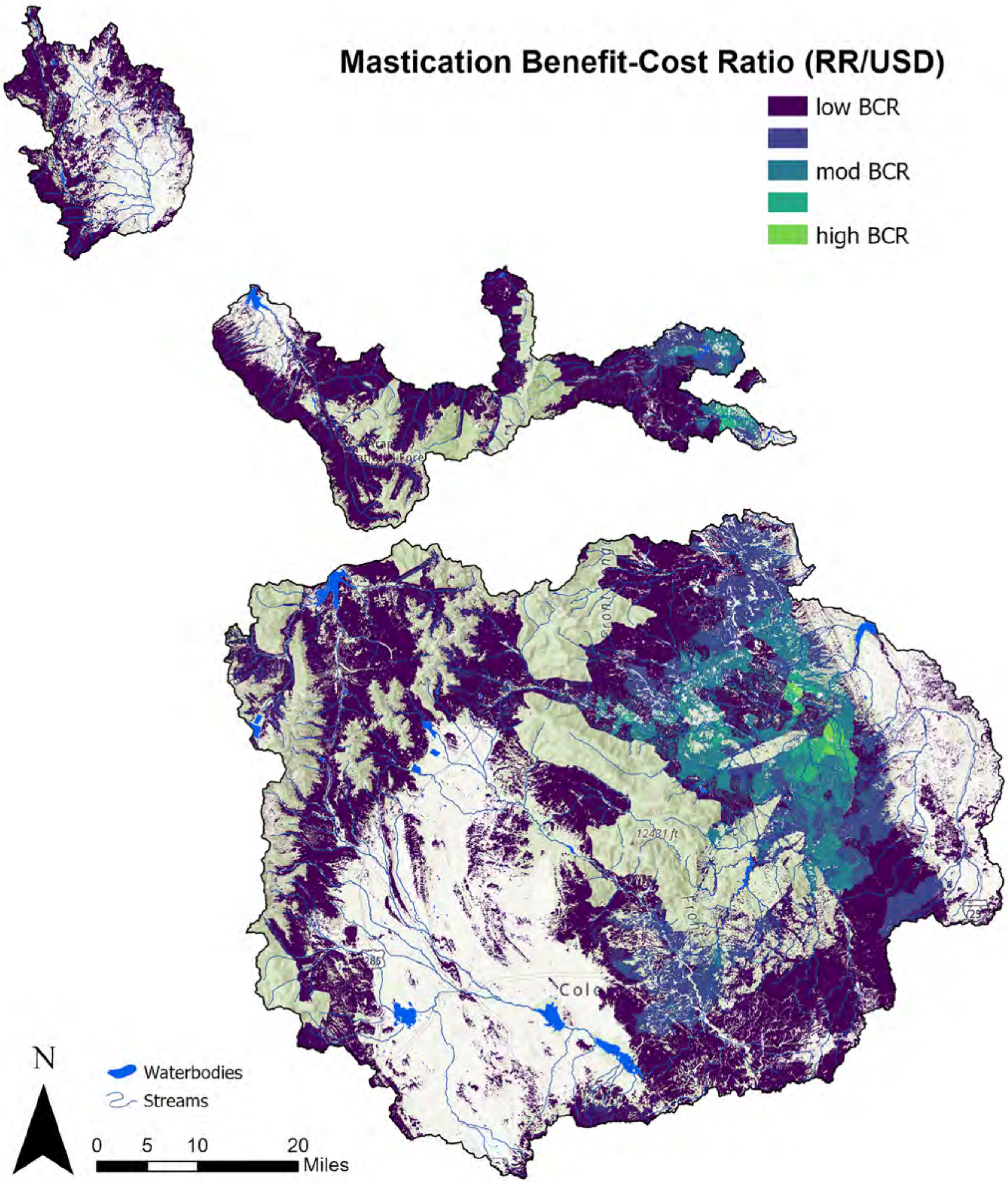


Figure 61: Benefit-cost ratio of the mastication treatment. BCR is measured as risk reduction (baseline eNVC - treated eNVC) per dollar spent within feasible treatment areas.

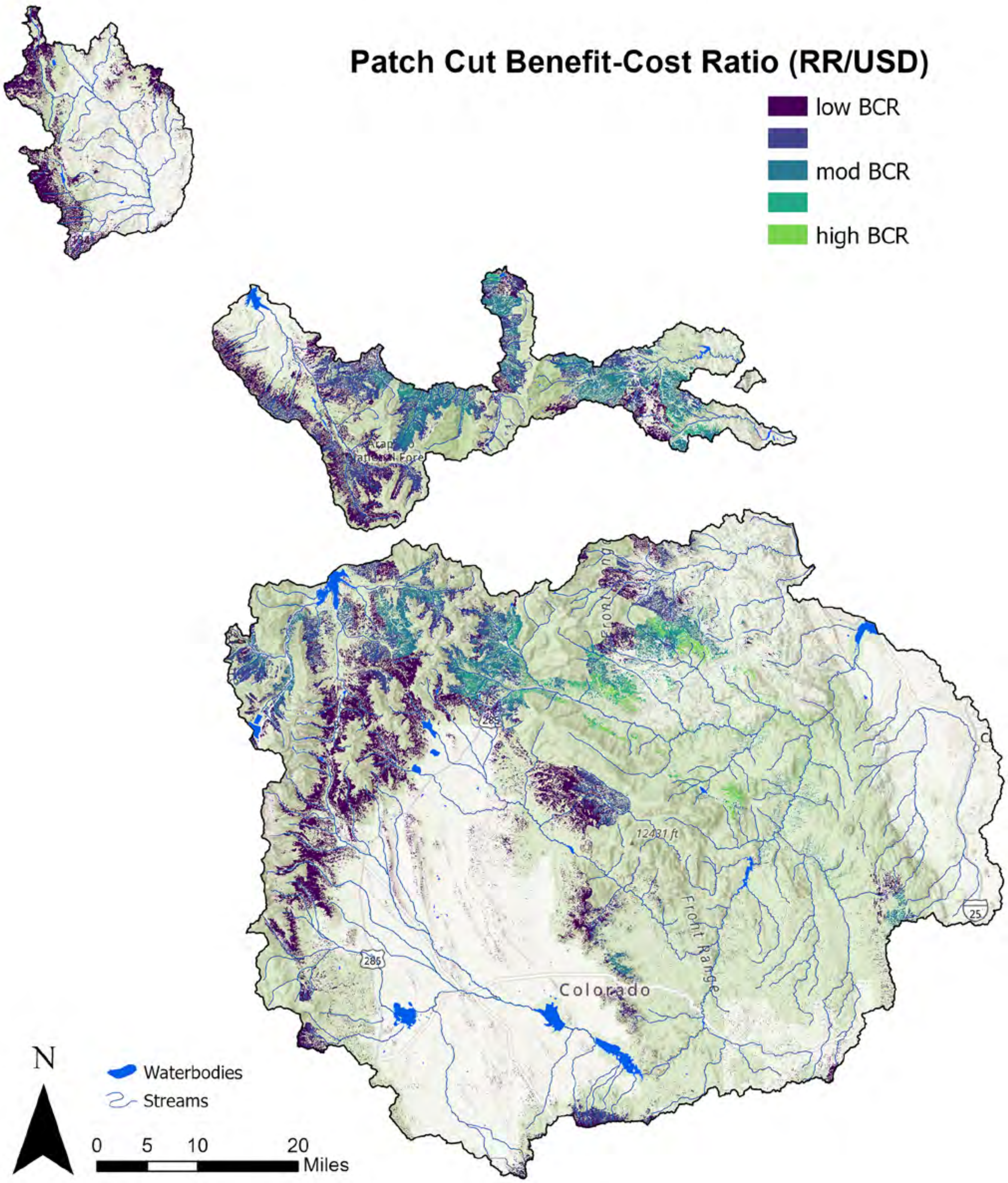


Figure 62: Benefit-cost ratio of the patch cut treatment. BCR is measured as risk reduction (baseline eNVC - treated eNVC) per dollar spent within feasible treatment areas.

Appendix IV – Linear Optimization Model Formulation

Objective function:

$$\max Z = \sum_{i=1}^{N}\sum_{t=1}^{P} RR_{i,t} * x_{i,t}$$

Constraints:

$$x_{i,t} \le F_{i,t} \qquad \forall\, i,t$$

$$\sum_{t=1}^{P} x_{i,t} \le tF_i \qquad \forall\, i$$

$$x_{i,t} \ge 0 \qquad \forall\, i,t$$

$$\sum_{i=1}^{N}\sum_{t=1}^{P} TC_{i,t} * x_{i,t} \le Budget * BP_t \qquad \forall\, i,t$$

$$\sum_{i=1}^{N}\sum_{t=1}^{P} TC_{i,t} * x_{i,t} \le Budget$$ ▒i,t

Subscript notation:

i is used to index treatment units from 1 to N

t is used to index treatment types from 1 to P

Decision variables:

xi,t is the area (ac) of treatment t assigned to treatment unit i

Parameters:

Z is the total risk reduction (unitless)

RRi,t is the risk reduction per acre of treatment t applied to treatment unit i

Fi,t is the feasible area (ac) for treatment t in treatment unit i

tFi is the total feasible area (ac) for any treatment in treatment unit i

TCi,t is the cost ($/ac) of applying treatment t in treatment unit i

Budget is the funding available for fuel treatment ($)

BPt is the maximum budget proportion that can be allocated to treatment type t

Minimum and maximum treatment sizes (ac) are also imposed on the model by pre-processing decision units to eliminate those that fall under the minimum treatment size and by shrinking the feasible acres for those decision units that exceed the maximum treatment size. Treatment types could also be restricted by a proportion of the total budget.