WILDFIRE RISK ASSESSMENT AND TREATMENT PRIORITIZATION

FOR THE GUNNISON COUNTY COMMUNITY WILDFIRE PROTECTION PLAN

AUTHORS: Jackie Edinger, Jarod Dunn, Alex Heeren, Allison Rhea, Scott Ritter, and Brett Wolk

COLORADO FOREST RESTORATION INSTITUTE
COLORADO STATE UNIVERSITY

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Document Development Statement: Gunnison County is in the process of developing a new Community Wildfire Protection Plan (CWPP) to identify how wildfire will impact their community and develop clear steps they can take to be more wildfire-ready. CFRI's Risk Assessment and Decision Support (RADS) process was used to develop the collaborative planning process and spatial planning tools documented in this report. Dozens of partners informed the collaboratively developed model. The resulting CWPP will provide a common operating picture that organizations and community members in Gunnison County can follow to prepare for, respond to, and recover from wildfire. This report documents both the methods and spatial planning products that quantify wildfire risk and prioritize forest management activities within the CWPP analysis extent.

Jackie Edinger, Alex Heeren, Allison Rhea, and Scott Ritter conducted the modeling. Jarod Dunn, Jackie Edinger, and Brett Wolk coordinated stakeholder engagement. Jackie Edinger, Jarod Dunn, Alex Heeren, Allison Rhea, Scott Ritter, and Brett Wolk wrote and reviewed the technical report. Brett Wolk secured funding and provided project administration.

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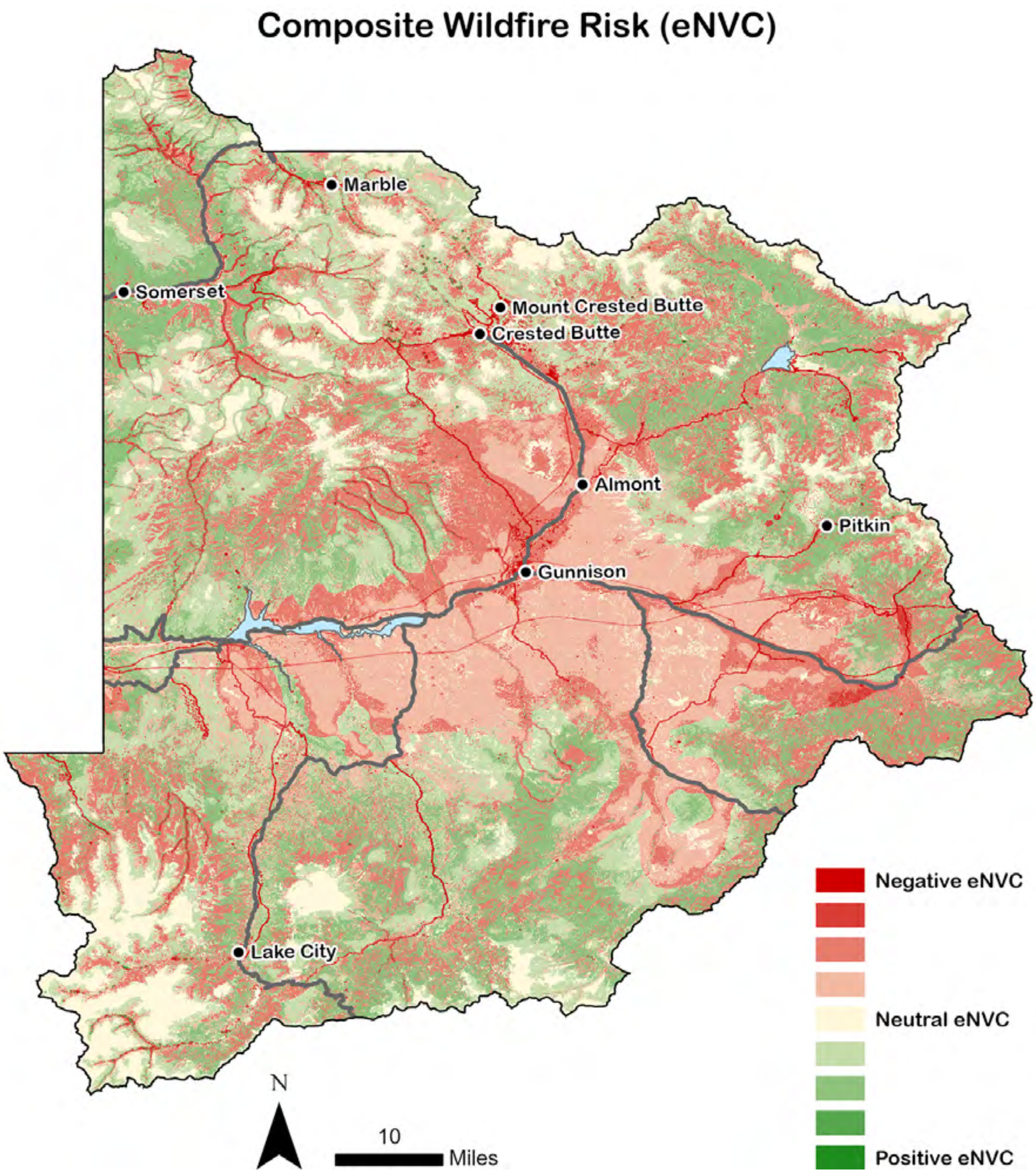
1. Executive Summary

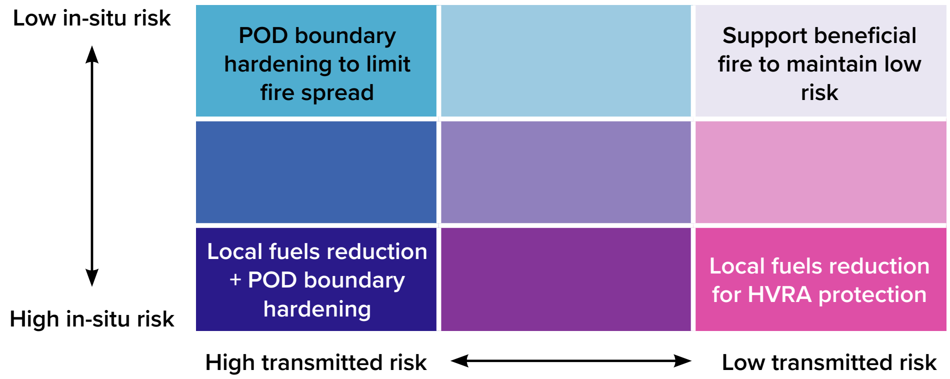
- The upcoming Gunnison County Community Wildfire Protection Plan (CWPP) will provide a common operating picture for organizations and community members in Gunnison County to mitigate against, prepare for, respond to, and recover from wildfire. The Colorado Forest Restoration Institute (CFRI) at Colorado State University led local partners through the Risk Assessment and Decision Support (RADS) framework to collaboratively understand and quantify wildfire risk to the community's highly valued resources and assets (HVRAs), prioritize vegetation management activities to maximize risk reduction per dollar spent, and align vegetation management with fire response strategies to create an integrated approach to living with fire.

- Wildfire risk describes wildfire interactions with 34 locally identified HVRAs on a spectrum from negative to beneficial fire effects. The wildfire risk assessment results show the greatest risk concentrated around the towns of Gunnison and Crested Butte where there is a high density of infrastructure and primary evacuation routes, with many areas showing expected net benefit from wildfire interspersed with localized risk.



Composite wildfire risk map. Negative expected net value change (eNVC) represents high risk where negative wildfire impacts are expected (red). Positive eNVC means there is an expected benefit from wildfire (green).

- This analysis considered two strategies for reducing wildfire risk to HVRAs: 1) reduce fire intensity near sensitive values (i.e., in-situ risk), and 2) limit undesirable fire spread across the landscape into sensitive areas (i.e., transmitted risk). These management activities are described within the potential operational delineations (PODs) framework, a spatial fire management network that represents the safest and most effective control lines to engage with during fire response.



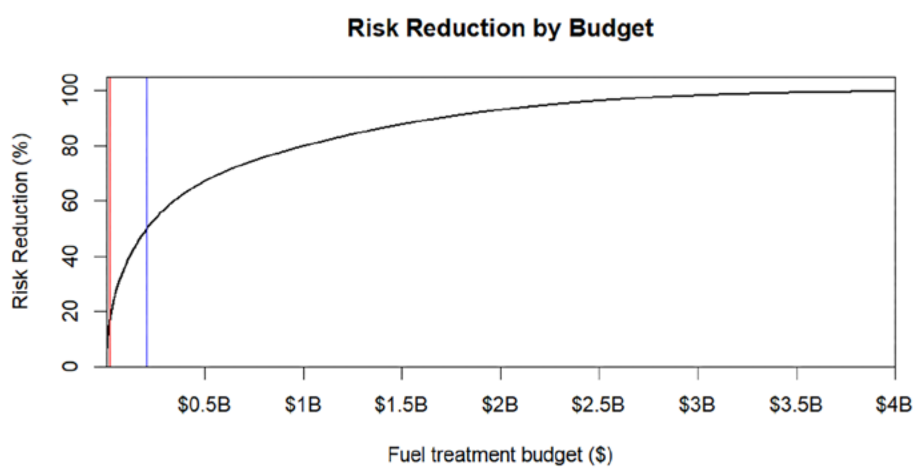
Bivariate risk matrix that addresses the specific type of risk (in-situ vs. transmitted risk) with an appropriate management activity in relation to Potential Operations Delineations (PODs) and highly valued resources and assets (HVRAs). In-situ risk = if a fire were to start in a POD, what effect would it have on that POD. Transmitted risk = if a fire were to start in a POD, what effect would it have on neighboring PODs.

- Prescribed fire was the most cost-effective vegetation management activity because it reduces both canopy and surface fuels at a relatively low cost. While mechanical thinning alone was the least cost-effective vegetation management activity, targeted mechanical thinning can enhance prescribed fire applications and fire response opportunities within PODs.

Summary of treatment type allocation across four budget scenarios. Total priority acres are the sum of all treatment types.

Budget	Mechanical Thin (acres)	Low Severity Prescribed Fire (acres)	High Severity Prescribed Fire (acres)	Mechanical Thin + Prescribed Fire (acres)	Mastication (acres)	Patch Cut (acres)	Total Priority Acres
$15 million	-	3,084	3,484	-	189	2,303	9,060
$50 million	-	13,965	11,238	210	1,334	4,751	31,498
$100 million	-	26,276	20,433	210	3,577	13,320	63,817
$200 million	402	67,216	36,024	782	8,996	16,395	129,815

- This analysis identified the most cost-effective locations where vegetation management can mitigate in-situ risk by reducing fire intensity around fire-sensitive HVRAs. The majority of vegetation management activities that are most cost-effective at reducing community wildfire risk involve prescribed fire on U.S. Forest Service land, so they are a key partner to collaborate with to help the county better live with fire.

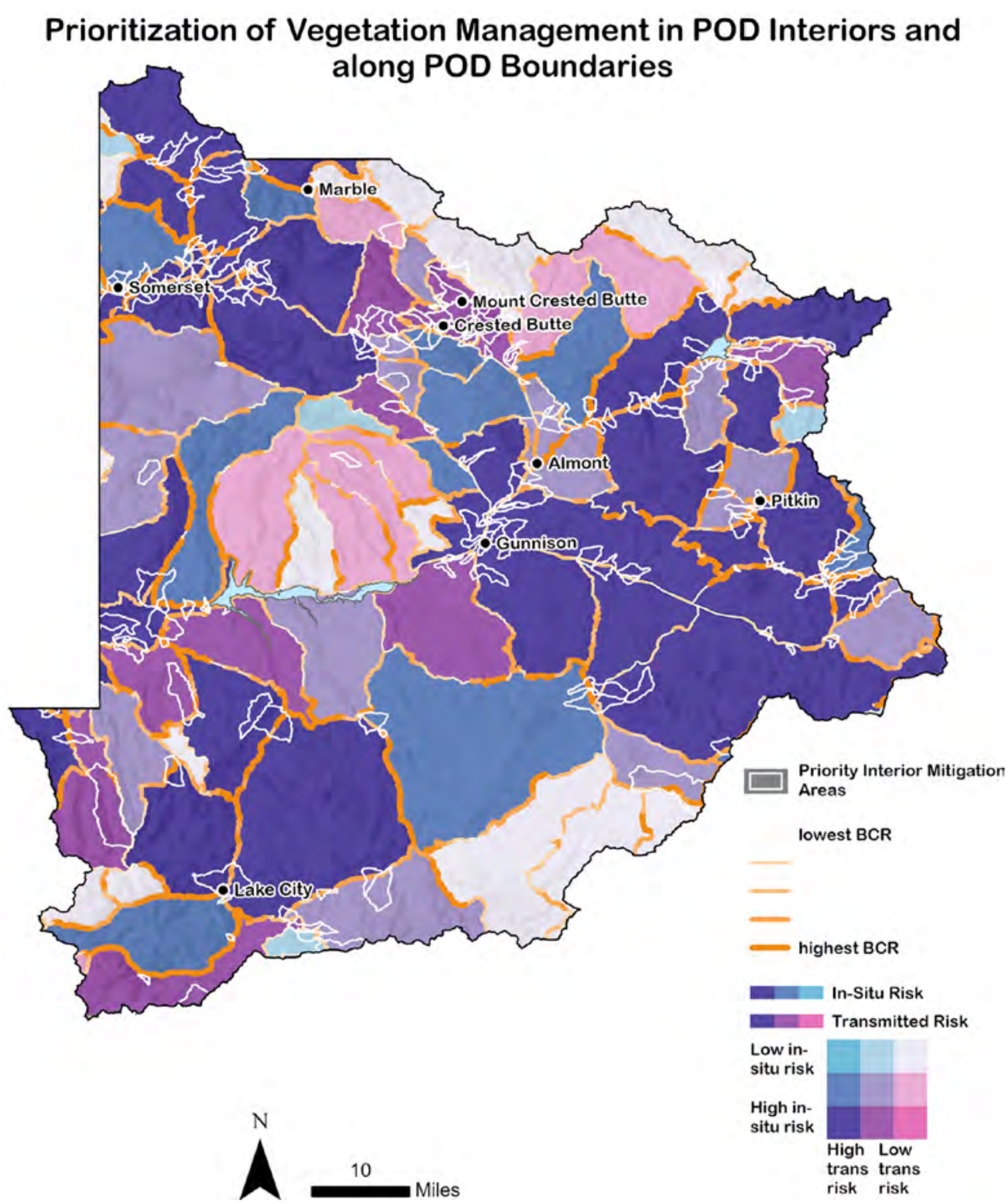


Feasible risk reduction curve across a variety of simulated budgets. The steeper the curve, the more risk is reduced per dollar spent (i.e., greater "bang for the buck"). A $15 million budget (red line) could reduce feasible risk by 16%, and other simulated budgets up to $200 million (blue line) could reduce feasible risk by 49%. To achieve 99% of feasible risk reduction, CWPP partners would have to invest $3.3 billion in vegetation management.

- Vegetation management along POD boundaries was also evaluated for its potential to support fire response, whether strategically restricting fire movement into fire-sensitive PODs or supporting opportunities for beneficial fire. When seeking to address transmitted risk, consider prioritizing POD lines that (1) offer large potential reductions in suppression difficulty index (SDI), (2) intersect with high transmitted risk PODs, and (3) form long, contiguous segments to enhance fire containment.
- This analysis uses PODs as the foundation for operationalizing The National Cohesive Wildland Fire Management Strategy, which helps communities to live with fire. POD interior and boundary prioritizations help guide vegetation management for resilient landscapes and safe and effective wildfire response. In areas where vegetation management is infeasible or inefficient, alternative risk reduction actions are necessary, especially to promote fire adapted communities.

Summary land ownerships within priority polygons identified in the $200 million scenario.

Ownership	Total Acres	% of Polygon Treatment Units
U.S. Forest Service (USFS)	157,697	90
Bureau of Land Management (BLM)	11,464	7
Local/State/Private	4,792	3



Priority POD interior management activities (white outlines) combined with benefit-cost ratio (BCR=ΔSDI/USD) of POD boundary treatments (orange color gradient). The dark purple PODs have the greatest in-situ and transmitted risk, while the light purple PODs (top right of matrix) are in a condition to receive beneficial fire.

2. Purpose and Scope

After the 2020 wildfire season, concern about the health and resiliency of the Upper Gunnison River Watershed ecosystems prompted an informal collaborative group to form the Upper Gunnison Shared Stewardship Council (UGSSC). The group includes local government, the Colorado State Forest Service (CSFS), the U.S. Forest Service (USFS), other federal agencies, fire protection districts, water and electric utilities, wildlife experts, non-profit groups, and community members. The Colorado Forest Restoration Institute (CFRI) at Colorado State University provided support using the Risk Assessment and Decision Support (RADS) framework (Gannon et al., 2019; see also Dunn & Wolk, 2023) to quantify wildfire risk and develop management priorities with the UGSSC. This technical report documents the application of the RADS framework to inform the updated Gunnison County Community Wildfire Protection Plan (CWPP) by quantifying wildfire risk and helping to develop management priorities with the UGSSC.

The RADS model has been used in other prioritization efforts in Colorado, including the Chaffee County CWPP (Envision Chaffee County, 2020), the Lake County CWPP (Lake County, 2022), the Pike National Forest's Wildfire Risk and Treatment Prioritization (Mueller et al., 2023), and the Forests to Faucets Partnership's Wildfire Risk Assessment (Rhea et al., 2024).

Risk Assessment and Decision Support (RADS) Approach to Spatial Planning

RADS builds on the quantitative wildfire risk assessment process of identifying highly valued resources and assets (HVRAs) and quantifying wildfire risk to those HVRAs (Scott et al., 2013). The risk assessment portion of RADS incorporates locally-reviewed and adapted spatial data on HVRAs, science-informed expertise on HVRA response to wildfire and forest management activities, and collaboratively-developed relative importance rankings of HVRAs to quantify wildfire risk within the UGSSC's planning area. CFRI's decision support goes a step further to help prioritize areas where forest vegetation management (e.g., forest thinning, prescribed fire, patch cutting, mastication) will have the biggest impact on reducing wildfire risk for the lowest cost (i.e., where the return on investment is greatest). This entails gathering and inputting local data on the costs and constraints of vegetation management activities, combined with their impacts on fire behavior to alter wildfire risk. While one goal of the RADS modeling process is to create spatial planning tools (e.g., maps and GIS layers) that help inform on-the-ground decisions, the social process of shared learning how fire interacts with local values also strengthens collaboration among partners.

CFRI's spatial planning process also incorporates Potential Operational Delineations (PODs) as a guiding principle to inform fire-adapted communities. PODs define fire management and planning units bounded by potential control features (e.g., ridges, roads, burned areas, treatment boundaries) that could be leveraged for fire containment during a wildfire or prescribed fire (USFS, 2022). PODs are also building blocks for developing a landscape strategy for living with wildfire, and a spatial tool for decision-making that can be used for strategic vegetation management and more (Caggiano & Beveridge, 2022). When combined, RADS and PODs communicate where the values the community cares about (HVRAs) are situated in relation to the operational aspects of wildfire management to inform how fire interacts with a community and their likely ability to manage fire across the landscape. Risk assessment outputs summarize the susceptibility of values at risk within each POD, while the decision support outputs provide the most efficient vegetation management activities within the PODs.

Our spatial planning process helps to identify actions to take before, during, and after a wildfire occurs. RADS and PODs together create a shared understanding of values at risk, tactical fire operations, and management options that advance a strategy for preparing for and managing fire on the landscape consistent with the National Cohesive Wildland Fire Strategy: 1) Resilient landscapes, 2) Fire Adapted Communities, and 3) Safe and Effective Fire Response (Wildland Fire Leadership Council, 2023). Crucially RADS not only identifies where vegetation management will effectively reduce risk, but also identifies where there is risk on the landscape that cannot be addressed with vegetation management. This helps target areas to do other activities that reduce risk to HVRAs such as home hardening, increasing campfire patrols to reduce human ignitions, and updating building codes.

3. Methods

3.1 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 activities to maximize risk reduction per dollar invested.

Risk Assessment

Risk is a widely used term 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 the 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).

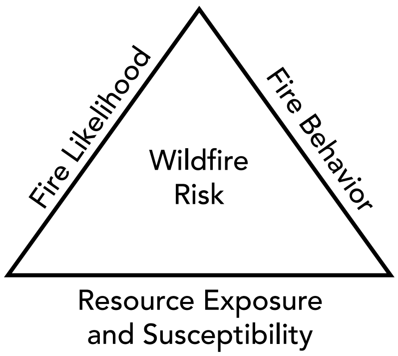


Figure 1. Wildfire risk triangle adapted from Scott et al., (2013).

The RADS wildfire risk assessment requires locally informed fire simulation products, spatial data on HVRAs, susceptibility of those HVRAs to fire, and HVRA 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 describe the behavior of a specific future wildfire event, but rather the trends in fire occurrence and intensity over many potential future fire seasons. Details for the fire modeling conducted for this risk assessment are provided in section 3.3.

Decision Support

RADS also includes a decision support module that prioritizes the type and location of forest vegetation management activities 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 along with the average risk reduction and cost for each vegetation management activity. Linear optimization was then used to prioritize vegetation management locations and types into optimal treatment plans by budget (see Appendix E – Linear Optimization Model Formulation).

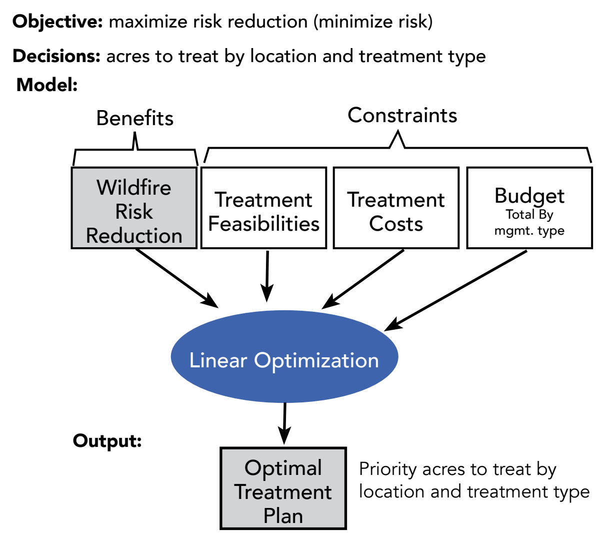


Figure 3. Conceptual diagram of the Risk Assessment and Decision Support (RADS) treatment optimization model. Fuel treatment benefits and constraints are summarized for the feasible area in each treatment unit. Modeling outputs demonstrate where vegetation management will maximize risk reduction for the available budget.

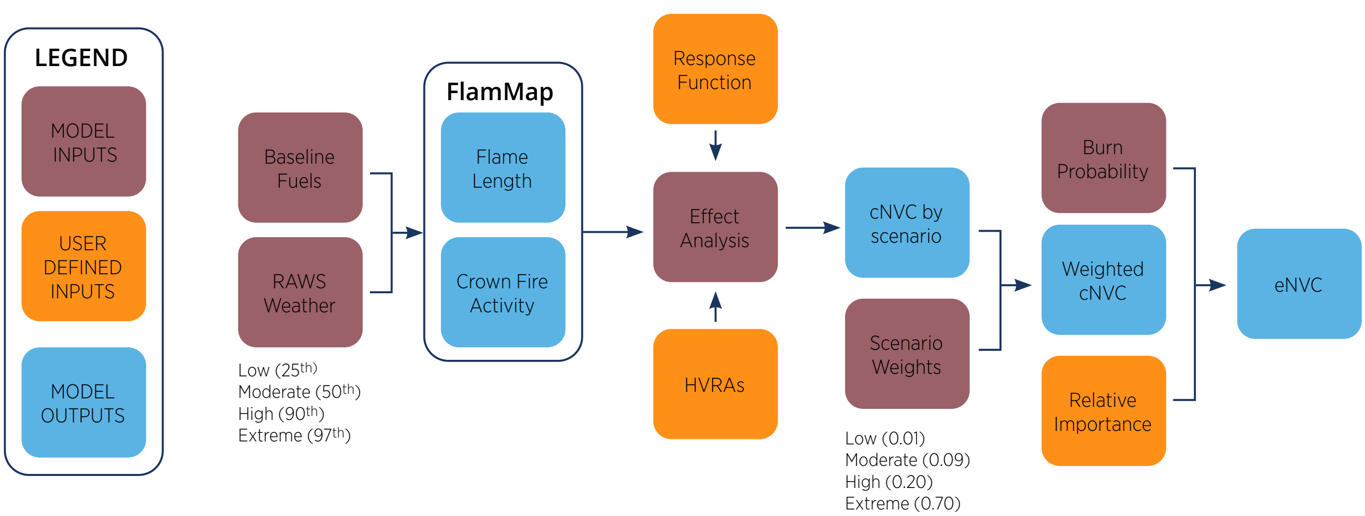


Figure 2. This Quantitative Wildfire Risk Assessment is based on the RMRS-GTR-315 framework (Scott et al., 2013). HVRAs = highly valued resources and assets, cNVC = conditional net value change, and eNVC = expected net value change.

3.2 Collaborative Modeling Effort

The analysis extent for this risk assessment encompassed all of Gunnison County and extended south into Hinsdale and Saguache counties to include the entire Upper Gunnison River Basin. The southern extent follows the Continental Divide and aligns with wildfire initial attack and emergency response jurisdiction for Gunnison County. The area includes land managed by the U.S. Forest Service (USFS), Bureau of Land Management (BLM), National Park Service, the Ute Mountain Ute Tribe, 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 also depends on user-defined values to inform risk and prioritize risk reduction activities (Figure 2). The process of integrating risk science with agency direction and social values important to the local community is crucial for making the plan meaningful to the community. When plans are co-developed between academic researchers and place-based partners, they are more likely to serve as a useful vehicle for collaboration, cross-boundary planning, and communicating interested and affected parties' concerns (Brown et al., 2024). CFRI's RADS model and planning framework supports this integration. CRFI began presenting RADS to the UGSSC in 2021, and kept intermittent contact with the group between 2021–2023 to discuss with UGSSC leadership the possibility of using RADS to inform the planned update for the Gunnison County CWPP. The UGSSC initiated a formal planning and collaboration process in Fall 2023 through bimonthly meetings to prepare for developing RADS by hiring a facilitator, developing a project timeline, and identifying key individuals to serve on the CWPP

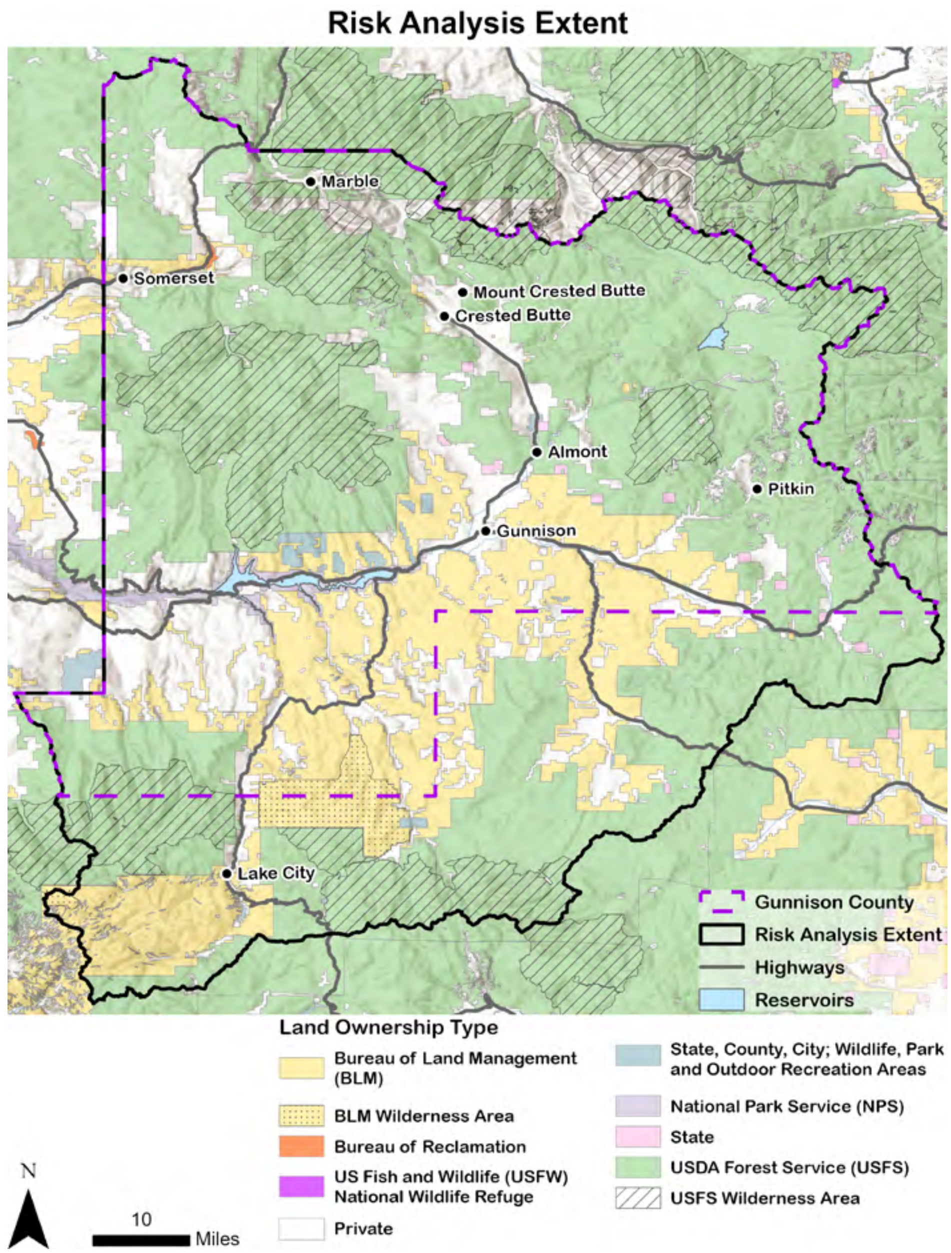


Figure 4. RADS analysis extent relative to various land ownerships, county lines, major highways, and reservoirs.

Leads team. The Leads team met more frequently--initially monthly and then progressing to twice monthly towards the end of the CWPP process--to have more in-depth conversations on preliminary results to help move the RADS process along. The Leads team included representatives from Gunnison County Emergency Management (GCEM), West Region Wildfire Council, USFS, BLM, JEO Consulting Group, and CFRI. Leads team members communicated with field office staff and partners to ensure other aspects of the modeling were locally appropriate and aligned with UGSSC goals.

Multiple parties engaged in planning and communication activities to support the CWPP development. In February 2024, GCEM met with local fire and fuels managers to identify and update the Potential Operational Delineations (PODs) network across all land ownerships within the analysis extent. Between February 2024 and February 2025, CFRI conducted numerous subgroup and topic-specific meetings and communicated with individuals via email and phone to gather broad input and feedback to ensure the modeling was informed by locally relevant data. Subgroup meetings included discussions of HVRA categories, fire behavior modeling, fire impacts to water resources, and costs and constraints of management activities. In September 2024, the UGSSC held two public map walks, one in Gunnison and one in Crested Butte, to provide updates on the CWPP's progress and get public feedback on draft RADS products.

Identifying Highly Valued Resources and Assets (HVRAs)

A core element of producing a RADS model that is locally relevant and creates a common operating picture for the community is partners working collaboratively to identify HVRAs according to each specific community. RADS is most effective when only "highly valued" resources and assets are included; too many HVRAs would dilute the importance of any one resource or asset, while too few would result in an incomplete assessment of risk. For this reason, groups must reach consensus about HVRAs to model risk across the landscape. The UGSSC identified all potential HVRAs ranging from roads and buildings to cultural sites and viewscapes. CFRI staff led UGSSC participants through an exercise to identify an initial list of HVRAs. This involved a presentation and discussion of what HVRAs are, then in-person and virtual participants wrote their ideas on sticky notes and were asked to group them together in logical categories (i.e., water supply and infrastructure, wildlife habitat, etc.). In the following months and several subsequent meetings, many HVRAs were eventually eliminated or lumped together because they were too similar to each other, were not high enough of a priority, or consistent spatial data was not available. Other suggested HVRAs that at first seemed similar were split into distinct HVRAs because they respond to wildfire differently (e.g., high-density vs. low-density buildings). In subsequent meetings, members of the Leads team identified experts in each HVRA category and invited them to participate in virtual HVRA workshops focused on (1) Life Safety, Infrastructure, and Buildings, (2) Water, (3) Recreation, and (4) Wildlife and Vegetation. Each meeting began with an overview of the RADS model. Participants then reviewed spatial data for each HVRA, evaluated how each HVRA responds to wildfire, and determined the relative importance of the HVRA within its category. Some groups met multiple times, and one of the UGSSC's regular bimonthly meetings was held as a larger workshop-style session to gather feedback from the entire UGSSC on all proposed HVRAs.

Once identified, HVRAs were ranked based on their relative importance to the community. Relative importance weights were defined at two levels: 1) relative importance between categories (Table 1), and 2) individual HVRA relative importance within categories (Table 2). Life safety was ranked as the most important category whereas recreation, the lowest ranked category, was valued as roughly a third as important at life safety. Relative importance rankings were assigned to each HVRA to reflect its proportional contribution to its category (Table 2). For example, ski areas were the most highly valued HVRA within the recreation category, followed by camping and built recreation infrastructure, and finally trails. An optional buffer distance was added to some HVRAs to represent the area for which an HVRA was expected to influence management actions beyond the spatially mapped extent. Resource experts and representatives of participating land management agencies discussed HVRA spatial extent, buffer distance, and relative importance via email and at additional meetings focused on specific HVRA categories. The iterative nature of the meetings helped the group move toward consensus on what is valued in the landscape, how those values respond to wildfire, and tradeoffs between the HVRAs.

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

Category	Relative Importance
Life Safety	100
Infrastructure	73
Recreation	31
Buildings	63
Water	79
Wildlife	54
Vegetation	48

Table 2. HVRAs included in the risk assessment by category. HVRA relative importance (%) within each category and wildfire response functions by fire intensity level (FIL) are specified. All inputs were defined through a collaborative process using UGSSC input informed by expert opinion and data resources. See full HVRA worksheet for detailed justifications.

Category	HVRA	Relative Importance of HVRA	WILDFIRE RESPONSE FIL1 (0-2 ft)	FIL2 (2-4 ft)	FIL3 (4-6 ft)	FIL4 (6-8 ft)	FIL5 (8-12 ft)	FIL6 (>12 ft)
LIFE SAFETY	Primary Evacuation Routes	100	-20	-40	-80	-100	-100	-100
INFRASTRUCTURE	Electrical Transmission Lines	25	-10	-10	-20	-30	-100	-100
	Substations/energy distribution stations	10	-10	-10	-20	-30	-100	-100
	Communication Infrastructure	15	-10	-10	-20	-30	-100	-100
	Monitoring (non-water) Infrastructure	5	-30	-60	-80	-100	-100	-100
	Emergency Service Stations	20	-40	-80	-100	-100	-100	-100
	Water Infrastructure	25	-10	-20	-40	-100	-100	-100
BUILDINGS	Low density buildings	40	-20	-40	-80	-100	-100	-100
	High density buildings	60	-40	-80	-100	-100	-100	-100
WATER	Surface Drinking Water	98	NA	NA	NA	NA	NA	NA
	Mines	2	NA	NA	NA	NA	NA	NA
RECREATION	Camping	20	10	0	-10	-30	-40	-50
	Built Recreation Infrastructure	20	20	0	-10	-30	-40	-50
	Trails	10	0	-5	-10	-15	-20	-25
	Ski Areas	50	0	-10	-10	-20	-75	-100
WILDLIFE	Bighorn Sheep - Overall Range	6	20	40	80	100	100	90
	Elk - Winter Range	6	70	70	80	100	60	40
	Lynx - Potential Habitat	15	0	-10	-20	-40	-80	-100
	Mule Deer - Winter Range	6	70	70	80	100	90	80
	Sage Grouse - Overall Range	40	-20	-30	-50	-80	-100	-100
	Cutthroat Trout - HUC 12 Presence	15	15	0	-30	-40	-60	-85
	Moose - Winter Range	6	70	70	80	80	50	30
	Pronghorn Antelope - Overall Range	6	20	40	80	100	100	90
VEGETATION	Agriculture	10	0	-10	-10	-10	-10	-10
	Aspen	13	25	30	35	40	45	50
	High Elevation Meadows	8	30	30	30	30	30	30
	Lodgepole Pine	12	30	30	30	50	50	50
	Mixed Conifer	3	30	30	40	50	20	-20
	Pinyon-Juniper	2	25	40	0	0	0	-60
	Ponderosa Pine	3	60	100	60	20	-40	-60
	Riparian	18	30	60	20	-20	-40	-60
	Sagebrush	14	20	20	-60	-60	-60	-80
	Shrubland	5	30	30	30	30	30	30
	Spruce Fir	12	25	40	0	-40	-40	-60

The response functions and relative importance rankings of HVRAs reflect the best available science balanced with local expertise. The life safety category which represents primary evacuation routes was unanimously ranked as the most important category among UGSSC participants. Life safety, buildings, and infrastructure HVRA response functions were largely based on the response functions of previous risk assessments, such as the Lake County CWPP (Lake County, 2022) and the Pike National Forest's Wildfire Risk and Treatment Prioritization (Mueller et al., 2023), with some modifications to reflect local input. For example, most electrical transmission lines are supported with wooden poles and more susceptible to damage at greater flame lengths. Because most buildings in Gunnison County are considered low-density (< 1.5 buildings per acre), low density housing was given a higher relative importance compared to previous risk assessments. The group was concerned about the potential for post-fire erosion and mobilization of metals from mine tailings to negatively impact drinking water after fire so those secondary impacts are captured by watershed models detailed in Appendix C – Water Modeling rather than with response functions. Ski resorts were the most important recreation HVRA because of their high replacement costs compared to trail networks which maintain value even if burned at low flame lengths. Colorado Parks and Wildlife recommended initial wildlife response functions. Many participants expressed the need for Gunnison sage grouse habitat to be ranked higher than other species. The group also decided to eliminate species with limited spatial data available (e.g., the Uncompahgre butterfly). Lastly, all vegetation response functions were initially based on the Colorado All-Lands Risk Assessment (COAL, Napoli et al., 2022). Aspen, lodgepole pine, and spruce-fir were the most abundant forest types in the county so they were given higher relative importance rankings than the less abundant ponderosa pine and pinyon-juniper ecosystems. For a full list of justifications for all HVRAs, see the full HVRA worksheet developed by the UGSSC Leads team and participants.

3.3 Wildfire Modeling

The RADS process incorporates both fire behavior and burn probability to model wildfire risk to HVRAs.

Fire Behavior

In this application, FlamMap 6 (Finney et al., 2023) was used to simulate potential fire behavior under a range of weather scenarios. In summary, these model runs represent "worst-case" estimates of potential fire behavior 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 (i.e., 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 the impacts of post-fire erosion and sediment delivery to drinking water reservoirs and diversions (see Appendix C – Water Modeling). CFA represents the type of fire expected on a given 30-meter pixel: surface fire, passive crown fire, or active crown fire. Surface fires spread only on the surface and do not involve significant ignition of fuels in tree canopies. A passive crown fire may involve significant amounts of canopy consumption; however, the canopy fire is not considered self-sustaining, and significant energy from the surface fire is needed to sustain tree crown combustion. Active crown fire is the most extreme type of fire behavior, 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 was run on a "fuelscape" that represents the spatial distribution of the fire behavior fuel model (Scott & Burgan, 2005), canopy base height, canopy height, canopy bulk density, slope, elevation, and aspect across the entire source area. These data were sourced from the LANDFIRE 2022 Remap (LANDFIRE, 2022) and adjusted prior to fire modeling; we reduced the canopy base height by 30% and changed any low load (TL1) or moderate load (TL3) conifer litter fuel models to high load conifer litter (TL5; Scott & Burgan, 2005) in lodgepole pine dominated forests to ensure modeled intensity of fire behavior in lodgepole pine forests matched recent fire behavior observations (Moriarty et al., 2019).

FlamMap fire behavior modeling was conducted under a range of weather scenarios that represent the 25th, 50th, 75th, 90th, 97th, and 100th percentile conditions (Table 3). These percentiles were calculated from historic observations between 2000 and 2023 to represent current mean climate conditions. Given the large spatial scale across which fire behavior was modeled, fire weather percentile conditions were calculated from two Remote Automated Weather Station (RAWS) stations in the modeling domain – Taylor Park and Huntsman Mesa (Table 3). Percent fuel moisture was computed for each category of dead and live fuels during a fire season (defined as April 1-October 31) using FireFamilyPlus 5 (Bradshaw & McCormick, 2000). The 10-minute average RAWS wind speeds were converted to 1-minute average wind speeds for modeling (Crosby & Chandler, 1966). In FlamMap, wind direction was assumed to be upslope to represent a consistent worst-case scenario across aspects.

Table 3. Fire weather inputs to FlamMap fire behavior modeling. Fuel moisture and wind speed values represent the mean from Taylor Park and Huntsman Mesa RAWS stations. These weather scenarios are weighted to favor the more extreme fire weather when most fires burn.

			FUEL MOISTURE (%)						
Scenario	Percentile	Weight	1-hr	10-hr	100-hr	1000-hr	Herb.	Woody	Wind Speed 1-min (mph @ 20 ft)
Low	25th	0.01	21	17	15	15	100	130	8
Moderate	50th	0.09	12	13	13	14	80	110	9
High	90th	0.2	7.5	9.5	10.5	11.5	50	80	12.5
Extreme	97th	0.7	5.8	7.5	8.5	10.5	30	60	17

The Scott and Reinhardt (2001) method was used for predicting crown fire activity.

FlamMap outputs for each station were mosaiced together to generate continuous fire behavior rasters across the entire analysis area (Appendix B – Wildfire Behavior and Probability Modeling). For the wildfire risk modeling, weighted composite products were created to represent the average expected fire behavior at each pixel. We used the same scenario weighting scheme as CO-WRA (Technosylva, 2018), which puts much greater emphasis on the outputs for the 90th and 97th percentile weather conditions than the 25th and 50th percentile because most area is expected to burn under high and extreme fire weather scenarios (Table 3), consistent with recent wildfire activity in Colorado (Graham et al., 2003; Haas et al., 2015). The 75th and 100th percentile scenarios are not considered in the composite risk products, but can be accessed in the geodatabase (See section 4.5).

Burn Probability

In this assessment, annual burn probability was based on FSim outputs from the Colorado All-Lands Risk Assessment (COAL, Napoli et al., 2022). FSim models thousands of potential fire events given historical weather and ignitions, forest density, and topography to estimate the annual probability that a given pixel will burn. Each simulated fire is ignited and grown independently of one another on a static fuelscape. 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.

3.4 Wildfire Hazard and Risk

Hazard is a physical situation with the potential to cause damage to 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 for the modeled probability that they will encounter wildfire. 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.

Risk weighs the potential consequences of a fire by its probability of occurrence (Scott et al., 2013). Risk is generally represented by expected net value change (eNVC) which represents the likely impact of wildfire. eNVC is particularly beneficial when planning vegetation management because it will help identify locations that are likely to encounter wildfire in the future.

Both wildfire hazard (cNVC) and risk (eNVC) are unitless, relative metrics that represent impacts of fire to HVRAs within a risk assessment extent, but cannot be used for comparisons between risk assessments. Risk will always be a smaller value than hazard because it is multiplied by burn probability, which is always less than one (i.e., wildfire hazard x burn probability = wildfire risk).

HVRA susceptibility to fire is defined by fire intensity level using **response functions** ranging from -100 for total loss to +100 for radical gain (Scott et al., 2013). UGSSC partners and resource experts decided whether a particular resource would be positively or negatively affected by fire of a given intensity and the relative magnitude of that impact by assigning each HVRA a response function between -100 and +100 (Table 2).

The flame length within each pixel is converted to cNVC according to that HVRA's response function. For example, if a primary evacuation route was expected to have 0-2 foot flame lengths, cNVC would be −20 (Table 2). cNVC was calculated for each fire weather scenario separately, and then scenarios were combined into a single cNVC raster per HVRA with weighted averaging ("Weighted cNVC" in Figure 2). These weights are summarized in Table 3. Instead of using response functions, wildfire risk to drinking water was quantified with a separate process described in Appendix C – Water Modeling. Methods to separate high- and low-density buildings into distinct HVRAs are described in Appendix A – Spatial Data Processing.

3.5 In-Situ and Transmitted Risk

Potential Operational Delineations (PODs) represent the safest and most effective control lines 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 perception. 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 (USDA Forest Service Rocky Mountain Research Station, 2022).

We summarize two types of risk for each POD based on quantitative wildfire risk assessments. These calculations sum cNVC to quantify the net impacts of tens of thousands of fires simulated in FSim burn probability modeling. The first type is **in-situ risk**, which answers the question "if a fire were to start in a POD, what effect would it have on that POD?" In-situ risk represents local wildfire risk to HVRAs within a POD and is calculated by identifying all simulated fire 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 answers the question "if a fire were to start in a POD, what effect would it have on neighboring PODs?". This represents wildfire risk transmission to HVRAs should fire cross a POD line into a neighboring POD. Transmitted risk 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 nearby fire-sensitive PODs and can be thought of as "sources" of risk.

Management activities should vary based on the types of risk present in a POD and the specific HVRA the community is trying to protect (Table 4). For instance, PODs with low in-situ risk and low transmitted risk suggest opportunities to support beneficial fire to maintain that low risk. PODs with low in-situ risk but high transmitted risk represent areas where POD boundaries could be hardened to limit the transmission of undesirable fire into nearby fire-sensitive PODs, while supporting the application of beneficial fire within the POD. Alternatively, PODs with high in-situ risk and low transmitted risk may benefit most from targeted fuel reduction treatments near the specific fire-sensitive HVRAs within the POD. Finally, PODs with both high in-situ and transmitted risk may require management activities to address both types of risk: POD boundary hardening to limit fire spread, and local fuels reduction for HVRA protection. There are alternative management activities that should also be considered to potentially reduce in-situ risk (e.g., reducing structural ignitability, creating defensible space, floodplain enhancement, etc.) or transmitted risk (e.g., reducing human ignitions, campfire patrols, increased fire response capacity). However, this analysis focused on prioritizing vegetation management activities. More specifically, this analysis identifies priority fuels reduction projects to 1) reduce wildfire risk around HVRAs to address in-situ risk and 2) limit the spread of undesirable fire into fire-sensitive PODs to address transmitted risk.

Table 4. Bivariate risk matrix that addresses the specific type of risk (in-situ vs. transmitted risk) with an appropriate management activity in relation to Potential Operations Delineations (PODs) and highly valued resources and assets (HVRAs).

	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

3.6 Prioritization of Vegetation Management in Potential Operational Delineation (POD) Interiors

Six vegetation management activities were analyzed to compare in-situ risk reduction within POD interiors: 1) mechanical thin only, 2) low-severity prescribed fire, 3) high-severity prescribed fire, 4) mechanical thin followed by prescribed fire, 5) mastication, and 6) patch cut. Prescribed fire refers to broadcast application of fire across an area, not burning of slash piles. Because prescribed fire is applied differently to align with the ecology of various forest types, its effects were modeled separately as low or high severity. Vegetation management is simulated by making changes to existing canopy and surface fuel attributes (LANDFIRE, 2022). Proportional adjustments are applied to the baseline canopy fuels data based on mean effect sizes for hazardous fuels reduction on canopy attributes in the western U.S. (Fulé et al., 2012; Ritter et al., 2013; Stephens & Moghaddas, 2005; Stephens et al., 2009; Ziegler et al., 2017) (Table 5). While forest management techniques can be implemented to achieve a variety of tree densities, modeled canopy adjustments were largest for patch cuts, followed by high-severity prescribed fire, mechanical thinning, mastication, and low-severity prescribed fire, in descending order.

The effects of vegetation management on surface fuels were modeled by changing the fire behavior fuel model (FBFM) (Table 6, Scott & Burgan, 2005). A fuel model characterizes the surface fuel type and loading for fire behavior modeling. For this assessment, we assumed:

- The mechanical thin-only treatment would not alter surface fuels.
- Both high- and low-severity prescribed fire would shift the fire behavior fuel model to the least intense fuel model in the same category and climate type.
- Mechanical thinning followed by prescribed fire would achieve the same surface fuel effects as prescribed fire only.
- Mastication in fuelscapes with a significant understory shrub component is likely to result in more fuel on the ground. To account for this treatment effect, we shifted understory shrub-heavy fuel models to various slash blowdown fuel models (SB1, SB2).
- Patch cut treatments would manage logging slash through pile burns or removal and therefore the post-treatment fuel model would be modified to either a grass or grass-shrub model.

After adjusting canopy and surface fuels for each vegetation management scenario, wildfire behavior models were re-run for the full analysis extent and both cNVC and eNVC were calculated for the baseline (i.e., existing) and for all six vegetation management scenarios following the same framework laid out in Figure 2. The difference between baseline eNVC and treated eNVC represents the potential risk reduction of a given vegetation management activity.

Treatment Feasibility and Cost

Feasibility and cost constraints were considered for each vegetation management activity used in the prioritization based on past risk assessments (e.g., Mueller et al., 2023; Rhea et al., 2022; Rhea et al., 2024), extensive conversation with the UGSSC Leads team, and focus groups with foresters and land managers. These treatment cost and feasibility constraints are used when calculating risk reduction per dollar spent (Figure 3). Treatment constraints are described in Table 7 and mapped in Appendix D – Vegetation Management Assumptions.

Hard feasibility constraints are captured in binary rasters (i.e., each pixel is feasible (1) or infeasible (0)). Risk reduction is only calculated in areas where a given vegetation management activity is feasible. Vegetation management was generally restricted to forested lands (> 10% canopy cover) that fall outside of USFS wilderness and upper tier roadless areas. While fire behavior and forest processes are dynamic in all forest environments, feasibility criteria generally align with dominant ecological processes and commonly applied management practices in these vegetation types (Hood et al., 2021). For example, patch cuts were restricted to aspen, lodgepole, spruce, and subalpine fir-dominated forests to represent

Table 5. 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. Mech Thin is mechanical thinning and RxFire is prescribed fire. To understand the size of these treatment effects, look for the difference between 1 and the adjustment made. For example, Mech Thin canopy base height would increase by 30% (1 + 0.3), while Mech Thin canopy cover would decrease by 40% (1 - 0.4).

Treatment	Mech Thin	Low Severity Rx Fire	High Severity Rx Fire	Mech Thin + Rx Fire	Mastication	Patch Cut
Canopy Base Height	1.3	1.1	1.5	1.3	1.2	0
Canopy Height	1.3	1.1	1.5	1.3	1.2	0
Canopy Cover	0.6	0.85	0.2	0.6	0.7	0
Canopy Bulk Density	0.6	0.85	0.2	0.6	0.6	0

Table 6. The categorical fire behavior fuel model (FBFM) by vegetation management activity. Changes from baseline FBFMs are highlighted in red text. Fuel models are grouped by fire-carrying fuel type. NB is nonburnable, GR is grass, GS is grass-shrub, SH is shrub, TU is timber-understory, TL is timber litter, and SB is slash-blowdown (Scott & Burgan, 2005). Higher numbers represent increased loading of a given fuel type.

Fuel Model	Baseline	Mechanical Thin	Low Severity Prescribed Fire	High Severity Prescribed Fire	Mechanical Thin + Prescribed Fire	Mastication	Patch Cut
NB1	91	91	91	91	91	91	91
NB2	92	92	92	92	92	92	92
NB3	93	93	93	93	93	93	93
NB4	94	94	94	94	94	94	94
NB5	95	95	95	95	95	95	95
NB6	96	96	96	96	96	96	96
NB7	97	97	97	97	97	97	97
NB8	98	98	98	98	98	98	98
NB9	99	99	99	99	99	99	99
GR1	101	101	101	101	101	201	101
GR2	102	102	101	101	101	201	102
GR3	103	103	103	103	103	201	103
GR4	104	104	101	101	101	201	104
GR5	105	105	103	103	103	201	105
GR6	106	106	103	103	103	201	106
GR7	107	107	101	101	101	201	107
GR8	108	108	103	103	103	201	108
GR9	109	109	103	103	103	201	109
GS1	121	121	121	121	121	201	121
GS2	122	122	121	121	121	201	121
GS3	123	123	123	123	123	201	121
GS4	124	124	123	123	123	201	121
SH1	141	141	141	141	141	202	121
SH2	142	142	141	141	141	202	121
SH3	143	143	143	143	143	202	121
SH4	144	144	143	143	143	202	121
SH5	145	145	141	141	141	202	121
SH6	146	146	143	143	143	202	121
SH7	147	147	141	141	141	202	121
SH8	148	148	143	143	143	202	121
SH9	149	149	143	143	143	202	121
TU1	161	161	161	161	161	202	121
TU2	162	162	162	162	162	202	121
TU3	163	163	162	162	162	202	121
TU4	164	164	161	161	161	202	121
TU5	165	165	161	161	161	202	121
TL1	181	181	181	181	181	201	121
TL2	182	182	182	182	182	201	121
TL3	183	183	181	181	181	201	121
TL4	184	184	181	181	181	201	121
TL5	185	185	181	181	181	201	121
TL6	186	186	182	182	182	201	121
TL7	187	187	181	181	181	201	121
TL8	188	188	181	181	181	201	121
TL9	189	189	182	182	182	201	121
SB1	201	201	201	201	201	201	121
SB2	202	202	201	201	201	201	121
SB3	203	203	201	201	201	201	121
SB4	204	204	201	201	201	201	121

current management practices that mimic stand-replacing disturbance. Because foresters in Gunnison County indicated their intention to use two prescribed fire intensities, we incorporated both low- and high-severity prescribed fire management activities to align with forest ecology: 1) low-severity prescribed fire in ponderosa pine and mixed conifer frequent-fire forests that clears out the understory while retaining a majority of the overstory; and 2) high-severity prescribed fire in lodgepole pine and spruce-fir forest types to remove large, dead fuels and mimic the stand-replacing fires these ecosystems are more adapted to. Both prescribed fire types significantly reduce surface fuel loading (Table 6), but high-severity prescribed fire results in larger canopy fuel changes than low-severity prescribed fire (Table 5).

The cost of management activities increases as they become more labor- and resource-intensive, (i.e., a variable cost). Using a variable cost approach allows more land to be considered for treatment instead of identified as non-feasible acres due to operational constraints. For example, instead of prohibiting thinning operations on steep slopes with poor access, such treatments were considered feasible and given a higher cost per acre. In other words, rather than eliminating a potentially expensive treatment, the optimization model considers all possible treatment combinations and evaluates if the risk reduction from more expensive treatments is worth the higher cost. Base cost estimates were informed by fuels managers in local field offices of the USFS, CSFS, and BLM, as well as CFRI staff expertise. Treatment cost generally increased when

Table 7. Vegetation management feasibility and cost constraints used in the prioritization. Additional feasibility details can be found in Appendix D - Vegetation Management Assumptions.

Treatment	Feasibility	Cost
Mechanical Thin	No wilderness or upper tier roadless, > 10% canopy cover	$3,000/acre base cost + linear increase with slopes > 30% and distances from road > 800 m up to max of $10,000/acre
Low-Severity Prescribed Fire	Ponderosa pine, mixed conifer, Douglas-fir, pinyon-juniper, aspen, and other vegetation types	**Lower Complexity Fire** (i.e., when fire activity is modeled as surface fire during 25th % fire weather): $900/acre > 250 m from structure, $1,800/acre < 250 m from a structure **Higher Complexity Fire with Additional Prep** (i.e., when fire activity is modeled as crown fire during 25th % fire weather): $2,000/acre > 250 m from structure, $4,000/acre < 250 m from a structure
High-Severity Prescribed Fire	Lodgepole pine and spruce-fir forest types only	**Lower Complexity Fire** (i.e., when fire activity is modeled as surface fire during 25th % fire weather): $900/acre > 250 m from structure, $1,800/acre < 250 m from a structure **Higher Complexity Fire with Additional Prep** (i.e., when fire activity is modeled as crown fire during 25th % fire weather): $2,000/acre > 250 m from structure, $4,000/acre < 250 m from a structure
Mechanical Thin followed by Prescribed Fire	No wilderness or upper tier roadless, > 10% canopy cover	Mechanical thin only cost + low severity prescribed fire cost ($3,900 – $10,000) up to max of $10,000/acre
Mastication	No wilderness or upper tier roadless, > 10% canopy cover	$2,000/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
Patch Cut	No wilderness or upper tier roadless, > 10% canopy cover; lodgepole, spruce-fir, and aspen forest types only	$1,200/acre base cost + linear increase with slopes > 40% and distances from road > 800 m up to max of $10,000/acre

slopes exceed 30-40% and distance from a road exceeds 800 m. Mastication costs also included a linear increase with crown bulk density, which represents the size and density of trees in an area, to account for slower operations, costs of hauling some residual fuels off site, and to limit mastication applications where anticipated high residual mulch depths would reduce treatment effectiveness. Both high- and low-severity prescribed fire-only treatment costs increased in more complex burning situations. Fire behavior modeled under 25th percentile weather, which is the most similar to weather conditions when prescribed fires are currently implemented, was used to modify cost. The assumption here is that first-entry prescribed fires should be relatively low complexity and less costly to implement when they are expected to burn as low-severity surface fires. Costs were assumed to roughly double in areas that carry crown fire, even under 25th percentile weather conditions, to account for the additional work needed to implement prescribed fire. Higher complexity fires near homes or in stands that carry crown fire will likely require additional prep work (e.g., reducing tree density, managing ladder fuels, enhancing fire containment features, etc.), more complex implementation (e.g., use of backing fires, modified ignition spacing, larger burn area, etc.), or additional community engagement, coordination, and communication.

Fuel Treatment Prioritization

After assessing wildfire risk, the RADS model prioritizes fuel treatment type and location considering the locally-derived constraints on treatment feasibility and cost and the effects of each treatment on modifying fire behavior. RADS uses a generalized form of the linear programming optimization model described in Gannon et al., (2019) to select treatment locations and types that maximize risk reduction for a given budget. Formulas used in this treatment optimization are included in Appendix E – Linear Optimization Model Formulation. In short, the optimization calculates mean risk reduction achieved per dollar spent on each treatment type within the feasible area of each unit managed (i.e., NHDPlus catchment). The model then selects the treatment types and locations for the greatest risk reduction per dollar spent.

The RADS model identified the optimal treatment locations and vegetation management activity types to reduce up to 100% of in-situ wildfire risk that is feasible to address through forest management. This helped inform decisions among the CWPP planning group to target a range of budget levels and risk reduction goals. The CWPP Leads team focused on planning for budgets ranging from $15 million to $200 million that could achieve up to 50% of feasible risk reduction. Areas selected for management activities at lower budget levels are more cost-effective than those selected at higher budget levels. This fuel treatment prioritization focuses on wildfire risk that can be mitigated by vegetation management; however, vegetation management alone cannot remove all the risk to resources and assets. The returns for reducing additional risk with higher budgets decrease as the treatment plan starts to include lower-priority areas where benefits are low and/or treatment costs are high. Our prioritization process identifies the most cost-effective acres as the highest priority, informing where the treatment plan can gain the biggest "bang for the buck" by implementing vegetation management. Evaluation of the cost-benefit curve can help inform tradeoffs of continued investments in forest management focused on reducing in-situ wildfire risk compared with other potential risk reduction activities.

3.7 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 and community resilience to wildfire (Caggiano & Beveridge 2022; Thompson et al., 2017). Section 3.6 describes how calculated risk reduction per dollar spent was used to prioritize POD interior treatments. Here we applied the same concepts, but used different metrics to prioritize vegetation management along POD boundaries. POD boundaries represent pre-identified locations on the landscape where fire could potentially be more effectively engaged. In this case, instead of risk reduction we quantify the change in **suppression difficulty index (SDI)** per dollar spent to prioritize POD boundary treatments that limit risk transmission to fire-sensitive HVRAs in neighboring PODs. SDI quantitatively ranks the relative difficulty of performing fire control work 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) (Rodriguez y Silva et al., 2020). Lower SDI values represent increased efficiency and safety of suppression operations based on current landscape conditions.

Forest management practices that remove woody fuels and reduce the likelihood of fire transitioning from the surface to the forest canopy decrease fire intensity. We assume that reducing fire intensity enhances firefighter access and containment opportunities to ameliorate suppression operations; however, we can only measure the effects of reduced fire intensity on the suppression difficulty index, which provides a relative indicator of ease and safety. To quantify these impacts, fire behavior simulations were used to calculate baseline SDI, reflecting the existing fuelscape as represented by 2022 LANDFIRE data under 90th percentile weather conditions. SDI following mechanical thinning was calculated from modified surface fuels and canopy characteristics through theoretical fuel reduction methods described in Tables 6 and 7. The difference between baseline SDI and mechanical thinning SDI represents the potential of thinning to reduce suppression difficulty index (i.e., make it easier and safer to directly fight fire) and will be referred to as **ΔSDI**.

To identify where POD boundary hardening could most improve the suppression difficulty index, we calculated ΔSDI along all POD lines buffered to 300 meters. We also considered the relatively lower cost of roadside thinning projects by reducing the base mechanical thinning costs used to assess in-situ risk from $3,000 per acre to $1,000 per acre. This adjustment was based on locally-informed suggestions that similar roadside thinning projects in the area typically cost $800–$3,000 per acre. However, not all POD lines follow road networks, so we maintained a linear cost increase with slopes > 30% and distances from road > 800 m. Again, our model does not prohibit POD boundary work from taking place in steep terrain with poor access, but we do account for and consider the resulting increased expenses. We then calculated the reduction in suppression difficulty index and divided that by treatment cost to quantify the benefit-cost ratio (BCR=ΔSDI/USD) of thinning treatments individually for each 2-km POD segment. While we do not identify specific priority treatment units, we present a map of cost-effectiveness that is meant to aid in sequencing POD boundary hardening treatments. Managers can use the map to identify cost-effective POD segments that can be combined to create greater connectivity of containment features.

POD boundary treatments could reduce fire transmission to nearby fire-sensitive PODs and strengthen control lines to improve fire response. Pre-treated POD boundaries may require little to no additional work during a wildfire, making them valuable for indirect or direct attack during active wildfire incidents. They may also facilitate safer introduction of prescribed fire within a POD and provide fire managers with more flexibility in deciding whether to suppress or manage a fire where it might offer ecological benefits. See Figure 5 for an illustrated example of a roadside fuel break treatment that could help in reducing SDI (Thompson, 2023).

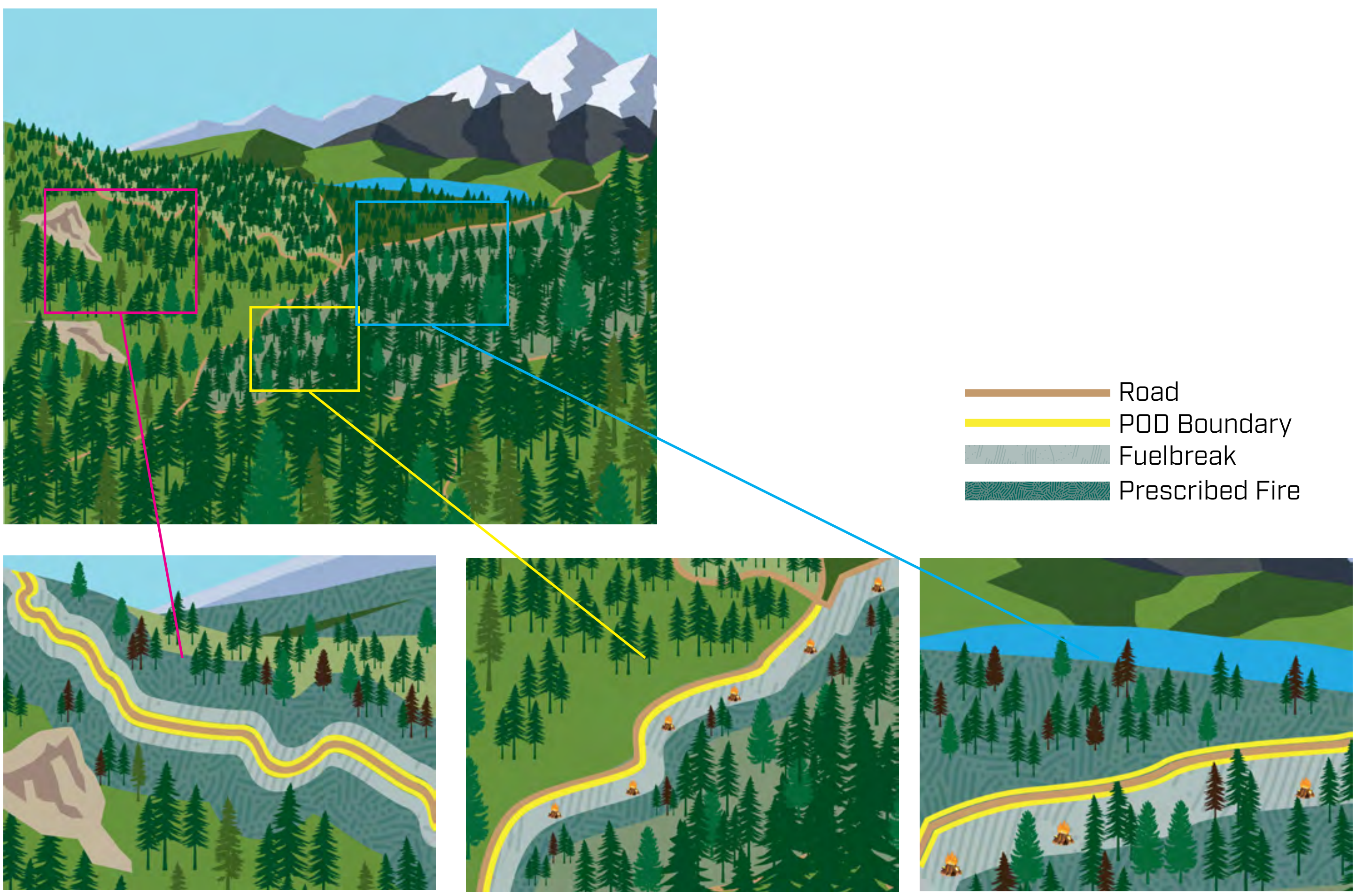


Figure 5. Stylized illustration of a coordinated system of landscape fuels management activities— a strategy—that builds fuel breaks along POD boundaries to expand proactive application of fire and reduce wildfire risk. Figure by Angela Hollingsworth, Colorado Forest Restoration Institute (Thompson, 2023).

4. Results

4.1 Wildfire Risk

Composite wildfire risk, measured as expected net value change (eNVC), represents the likely impacts of wildfire to all 34 weighted highly valued resources and assets (HVRAs). More negative eNVC represents greater risk from wildfire whereas positive eNVC represents expected benefit from wildfire. Within the CWPP planning area, the greatest wildfire risk is concentrated around the towns of Gunnison and Crested Butte where there is a high density of infrastructure and primary evacuation routes (Figure 6).

Wildfire risk is highly variable across the analysis extent due to differences in fire behavior and burn probability, a wide variety of vegetation types, and wildlife species of concern that have starkly contrasting responses to wildfire. The major drivers of risk in the analysis extent include areas with high building density (Figure 7d), major highways (Figure 7a), drinking water (Figure 7e), powerlines (Figure 7b), Crested Butte Ski Resort (Figure 7c), and cutthroat trout habitat (Figure 7f). After roads, the land cover types with the highest risk are subalpine spruce-fir forests and sagebrush (Figure 8). For a map of vegetation types, see Figure 9.

Many HVRAs have positive response functions, indicating that wildfire would improve or enhance their ecosystem function or otherwise benefit the resource. Ponderosa pine, mixed conifer, and lodgepole pine forest types are generally expected to benefit from wildfire (Figure 7g). These tree species have evolved to benefit from or even depend on fire for their survival (Fulé et al., 2009). Populations of bighorn sheep, elk, and mule deer, which rely on mixed landscapes of dense forest interspersed with open forest canopy that typically follow wildfire, often overlap with these vegetation types (Figure 7f). These HVRAs drive wildfire benefit in areas where they have little overlap with other values that are at high risk of negative wildfire impacts.

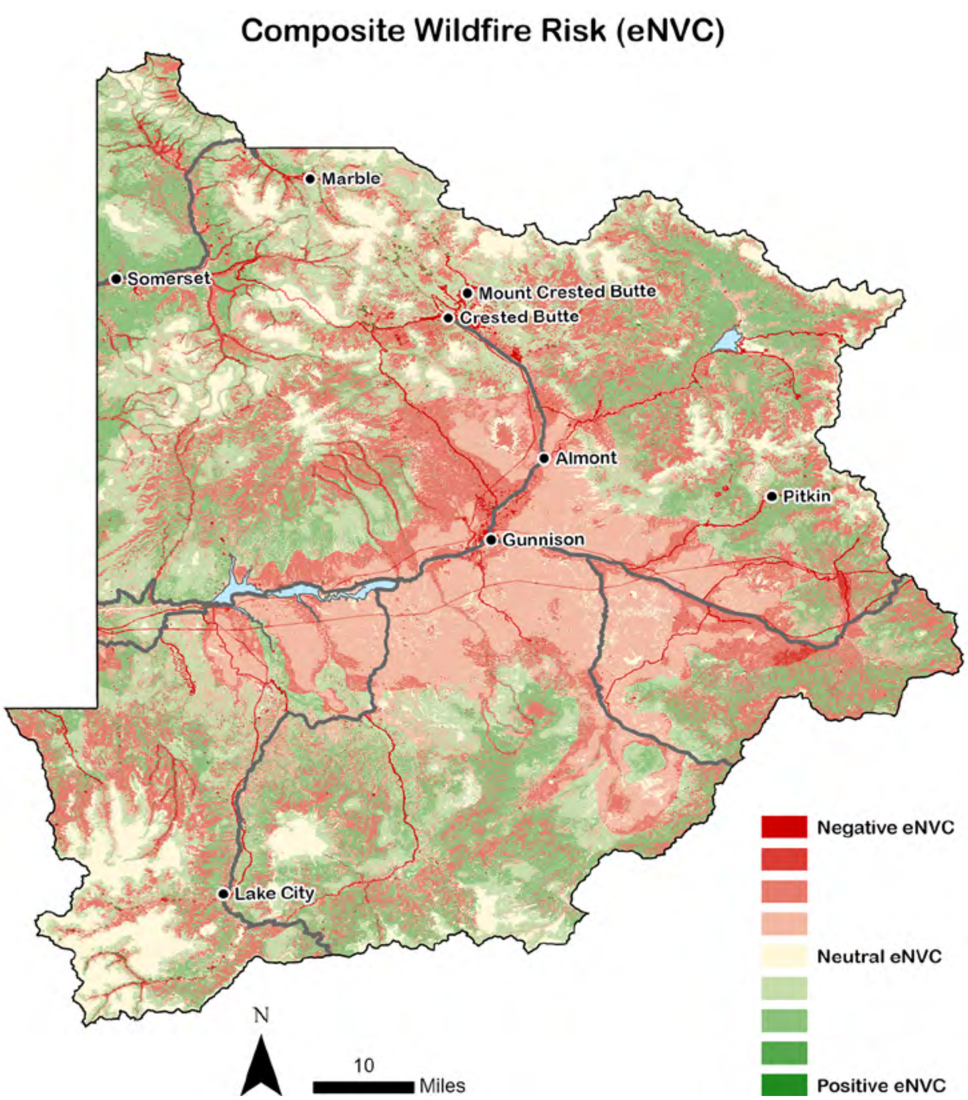


Figure 6. Composite wildfire risk map. Negative eNVC represents high risk where negative wildfire impacts are expected (red). Positive eNVC means there is an expected benefit from wildfire (green).

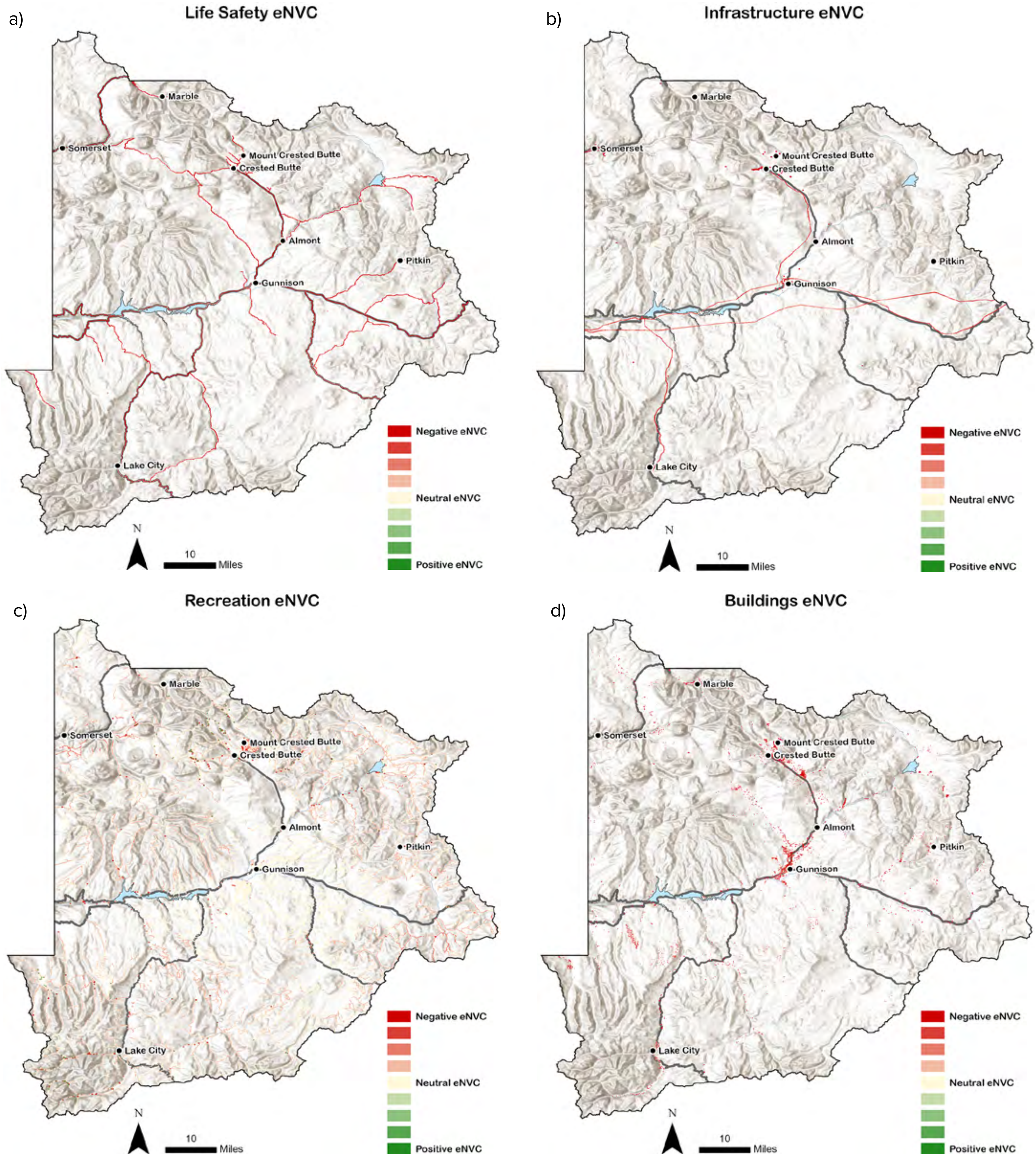
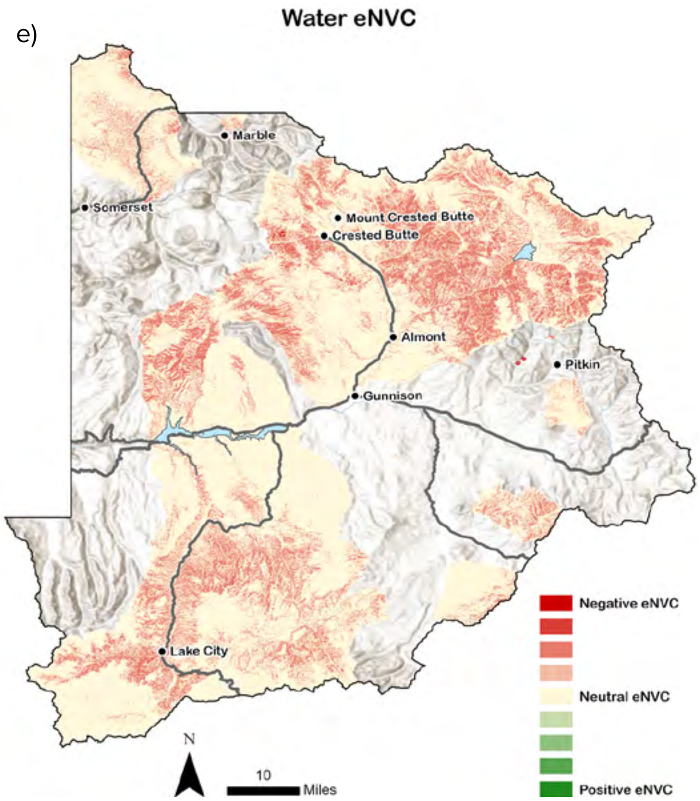
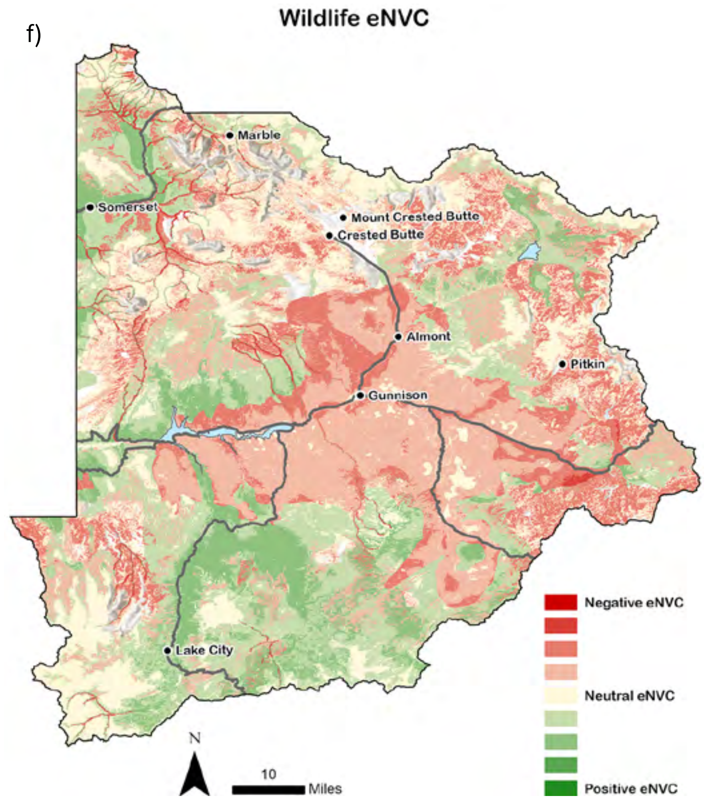


Figure 7a-g. Composite wildfire risk map for each HVRA category. Maps continue on next page.





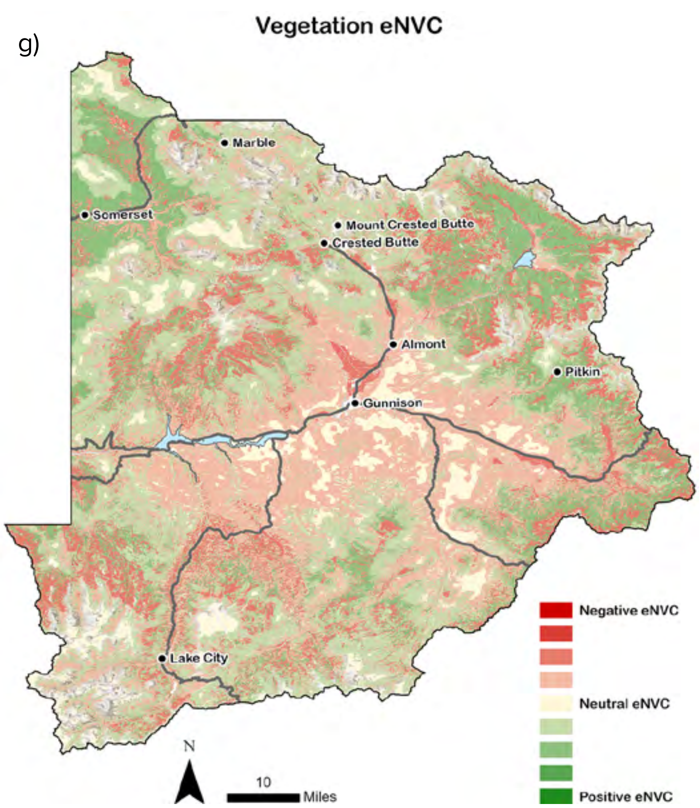


Figure 7a-g. Composite wildfire risk map for each HVRA category.

Much of the wildfire risk throughout the central Gunnison valley is driven by sagebrush vegetation (Figure 7g) and sage grouse habitat (Figure 7f). This is caused by a combination of high relative importance and negative response functions. While the sagebrush ecosystem and wildlife within it is highly fire-adapted, invasive grasses and the societal impacts of potentially losing critical sage grouse habitat resulted in overall negative wildfire impacts in this area. Sage grouse habitat was given the highest relative importance ranking out of all wildlife species ranges and it is expected to respond negatively to wildfire at any flame length (Table 2). Scientists at Colorado Parks and Wildlife and the United States Geological Survey emphasized that sage grouse habitat is some of the most intact wildlife habitat in the county and vegetation management was unlikely to change wildfire impacts or improve its suitability for the species (K. Griffin, personal communication, September 30, 2024; C. Aldridge, personal communication, October 15, 2024).

Given the uncertainties associated with predicting future wildfire activity, we also report a composite measure of conditional net value change (cNVC; Figure 10) which represents hazard without the modeled probability of encountering wildfire. These cNVC analyses assume every pixel on the landscape has an equal chance of burning and are particularly relevant during active wildfire incidents to inform fire managers of the values at risk in the likely spread path of an ongoing wildfire. The spatial distribution of composite hazard (cNVC) is similar to that of the composite risk map (eNVC) because both account for the overlap between hazardous fuel conditions and the susceptibility of HVRAs to fire.

We also calculated in-situ and transmitted risk by POD to align forest and fire operations when prioritizing vegetation management (Figure 11). Refer to section 3.5 for risk type definitions and calculations. Dark purple to pink PODs (bottom row of Table 4) are PODs with high in-situ risk where vegetation management in POD interiors can reduce risk near HVRAs. Dark purple to blue PODs (left column of Table 4) are PODs with high transmitted risk; these might benefit from POD boundary hardening to limit

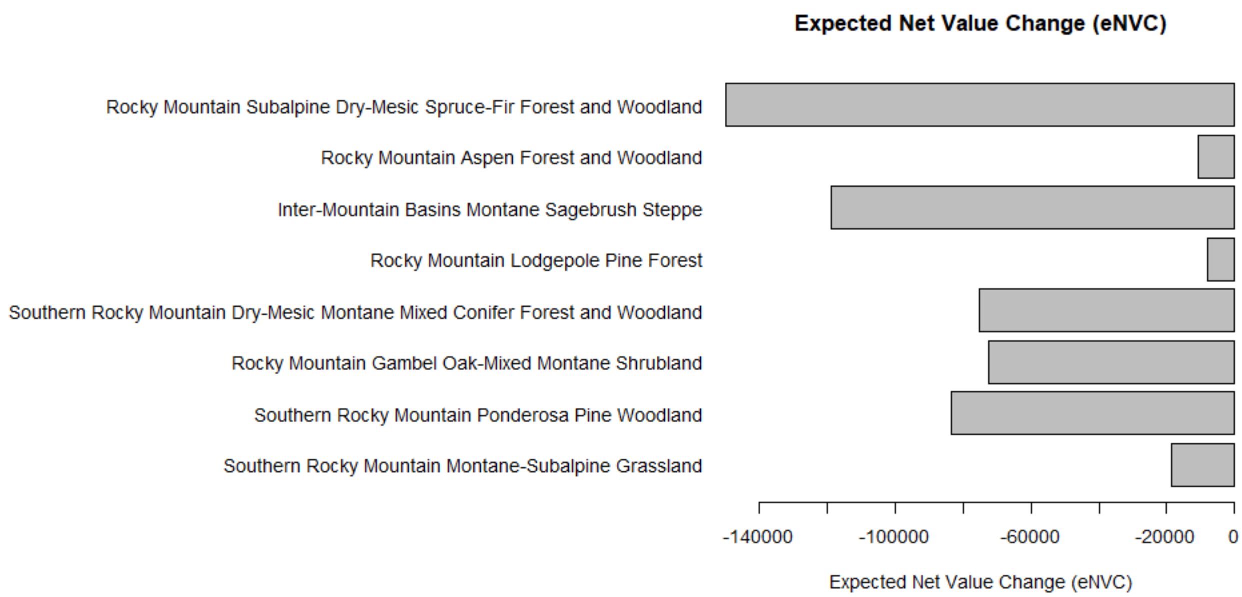


Figure 8. Risk (expected net value change) by existing vegetation type (LANDFIRE, 2023) in order of most to least abundant vegetation type.

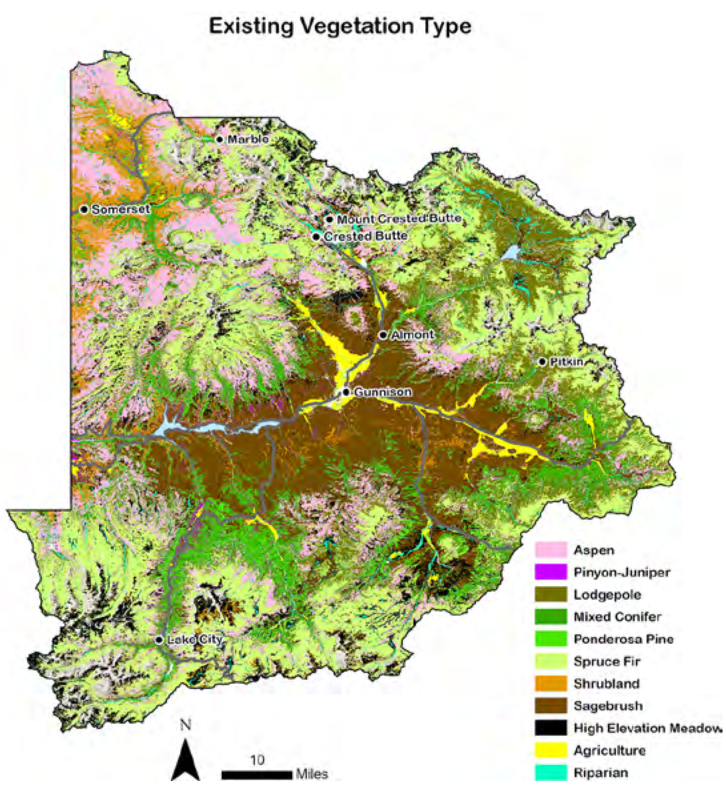


Figure 9. Existing vegetation type from LANDFIRE (2020).

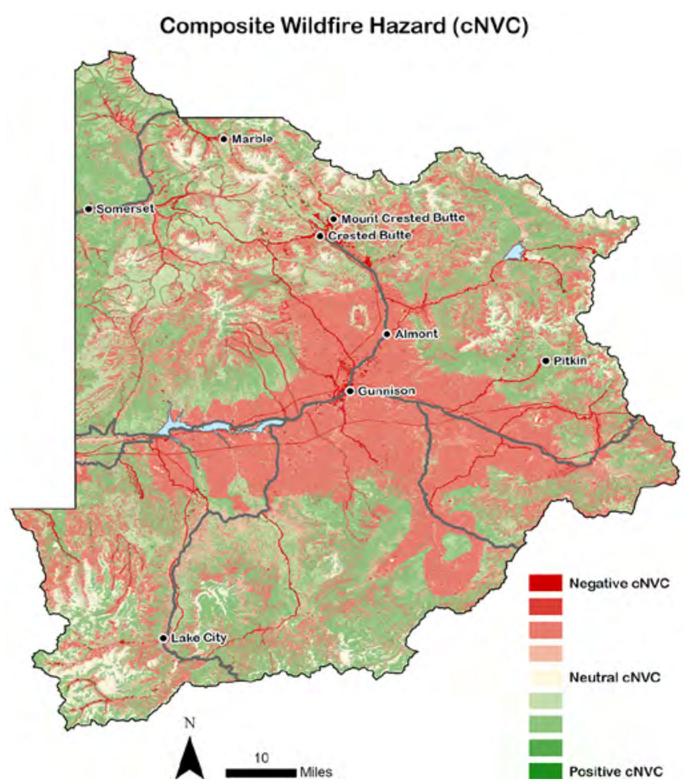


Figure 10. Composite wildfire hazard (conditional net value change, or cNVC). Negative cNVC means negative impacts. Positive cNVC means there is an expected benefit from wildfire. Note this product does not incorporate burn probability.

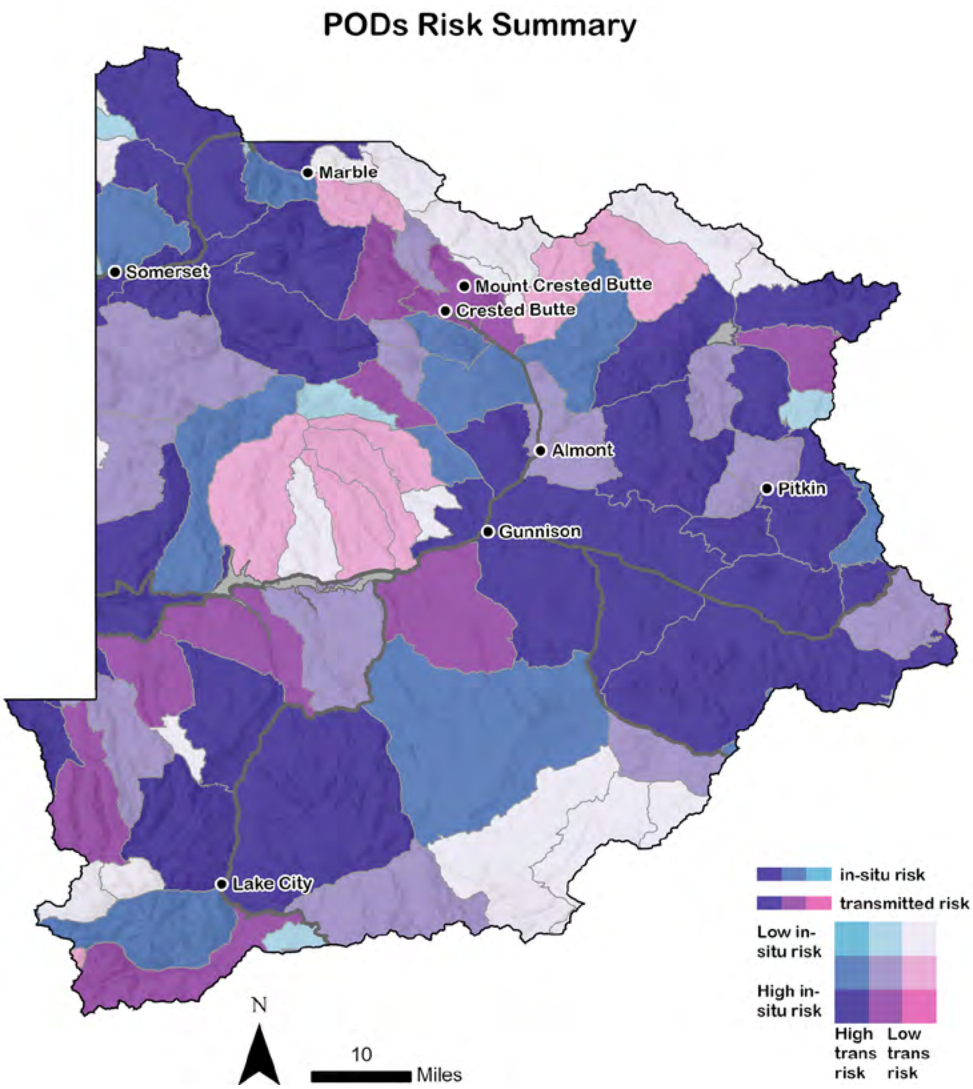


Figure 11. In-situ risk and transmitted risk matrix summarized by Potential Operational Delineation (POD). The dark purple PODs have the greatest in-situ and transmitted risk, while the light purple PODs (top right of matrix) are in a condition to receive beneficial fire.

the spread of undesirable fire into nearby fire-sensitive PODs. The lightest color blue and pink PODs are most suitable for beneficial use of fire. The following sections outline priority vegetation management opportunities in both POD interiors and boundaries to reduce in-situ and transmitted risk, respectively.

4.2 Prioritization of Vegetation Management in POD Interiors

To reduce in-situ risk, vegetation management was prioritized within POD interiors where activities would yield the greatest risk reduction per dollar spent (i.e., "bang for the buck"). Often in this assessment, priority areas for projects tend to be located in dense forests close to roads, where potential for risk reduction is high, and costs are low due to relatively easy access. However, maximizing bang for the buck means that the model may sometimes select vegetation management activities that are costly to implement but are more effective at reducing risk than less expensive and less effective alternatives.

The collaborative group considered four budget scenarios for prioritizing the locations and types of vegetation management that maximize risk reduction per dollar spent (Figure 12). Areas selected at lower budget levels are more cost effective (i.e., more benefits at a lower cost) and therefore a higher priority than those selected at higher budget levels. The four budget scenarios identify between 9,060 and 129,815 priority acres for vegetation management (Table 8). Maps of cost effectiveness for all six vegetation management types are in Appendix D – Vegetation Management Assumptions.

Risk Reduction

Feasible risk reduction measures how much risk would be lowered by vegetation management in priority areas compared to the maximum possible risk reduction if all treatable areas were managed. The linear optimization model estimates the maximum potential of vegetation management to reduce risk across a range of possible budgets (Figure 13). Treatment plans on the left side of the plot where the curve is the steepest represent the greatest bang for the buck. Treating the highest priority acres (i.e., the first $15 million) would reduce approximately 15.8% of feasible risk that can be mitigated by vegetation management (Table 9; Figure 13). Increasing the budget to $200 million would reduce feasible risk by an additional 34%, for a total of 50% of risk that can be mitigated by vegetation management. As budget size continues to increase, the slope of the risk reduction curve decreases, representing less risk reduction achieved for every dollar spent. In other words, as the curve flattens to the right, there is limited return on additional investment in vegetation management.

The cost-benefit curve can be used to communicate the limitations of vegetation management and the need for other risk reduction strategies. To achieve 99% of feasible risk reduction, $3.3 billion would need to be invested to

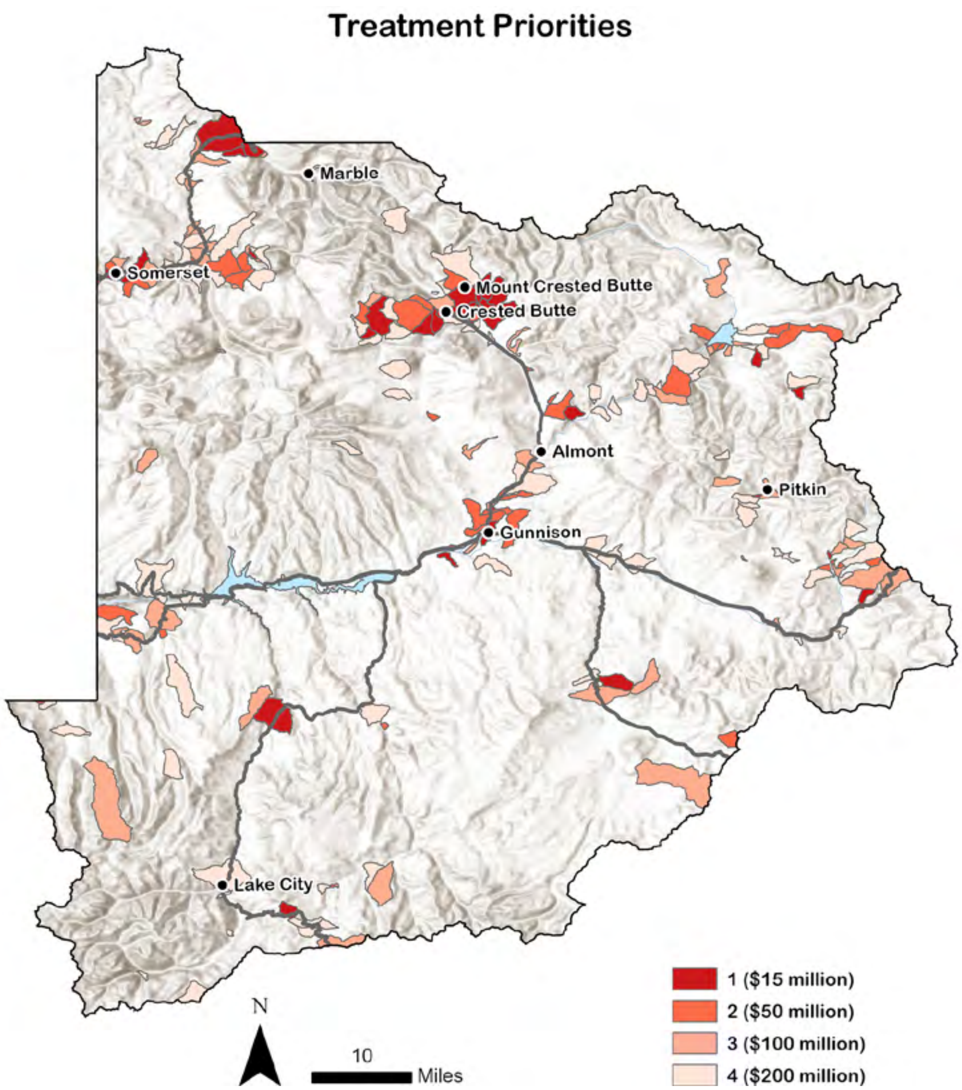


Figure 12. Vegetation management priorities within POD interiors. Each polygon represents a NHDPlus catchment which was used as the management unit. Treatment priorities correspond to fuel treatment budgets of $15 million to $200 million.

Table 8. Summary of treatment type allocation across four budget scenarios. Total priority acres are the sum of all treatment types.

Budget	Mechanical Thin (acres)	Low Severity Prescribed Fire (acres)	High Severity Prescribed Fire (acres)	Mechanical Thin + Prescribed Fire (acres)	Mastication (acres)	Patch Cut (acres)	Total Priority Acres
$15 million	-	3,084	3,484	-	189	2,303	9,060
$50 million	-	13,965	11,238	210	1,334	4,751	31,498
$100 million	-	26,276	20,433	210	3,577	13,320	63,817
$200 million	402	67,216	36,024	782	8,996	16,395	129,815

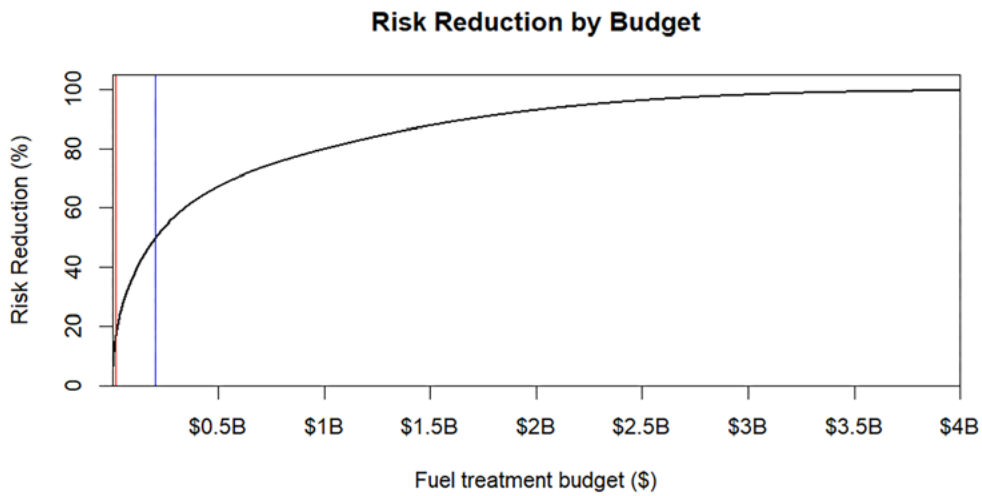


Figure 13. Feasible risk reduction curve across a variety of simulated budgets. The vertical red line denotes the $15 million budget and the blue line denotes the $200 million budget. The steeper the curve, the more risk is reduced per dollar spent and "bang for the buck" is greater.

Table 9. Summary of risk reduction across a large range of hypothetical budget scenarios. The total number of acres feasible for treatment in the project extent is 1,903,939. The total size of the analysis extent is 2,901,682 acres.

Budget	Total Priority Acres	Proportion of Feasible Acres Treated (%)	Proportion of Total Acres Treated (%)	Feasible Risk Reduction (%)	Total Risk Reduction (%)
$15 million	9,060	0.48	0.31	15.8	1.52
$50 million	31,498	1.65	1.09	27.6	2.65
$100 million	63,817	3.35	2.20	37.1	3.57
$200 million	129,815	6.82	4.47	49.5	4.76
$1 billion	632,757	33.2	21.81	79.9	7.69
$5.1 billion	1,903,939	100	65.62	100	9.62

treat roughly 1.8 million acres (Figure 13). Treating all 1.9 million feasible acres would cost an additional $1.8 billion ($5.1 billion total), and only reduce feasible risk by an additional 1%. The cost-benefit curve helps Gunnison County to evaluate tradeoffs and restrict investing in forest management that has limited impact. This allows them to efficiently allocate resources in the highest priority areas and enhance the community's ability to better live with fire.

However, even if every feasible acre were treated by one of the six treatment types, some risk would remain in the treated areas, and there would still be a substantial amount of risk left on the landscape in untreatable areas. To account for this, we also calculate **total risk reduction** which measures how much risk could be reduced by vegetation management compared to the total baseline untreated risk across the entire area analyzed. 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).

When interpreting total risk reduction estimates, it is helpful to consider the proportion of the landscape that is being treated under a given budget scenario (Table 9). The first priority $15 million budget treats less than 1% of the landscape but reduces feasible risk by 16%. The subsequent $50 million, $100 million, and $200 million budgets treat 1%, 2.2%, and 4.5% of the landscape and reduce feasible risk by 28%, 37%, and 49%, respectively. These higher priority, lower budgets disproportionately reduce risk relative to the treated acreage. Much larger hypothetical budgets of $1 billion and $5.1 billion would require implementing forest management actions across much larger areas to make a sizable difference in feasible risk reduction. The reduction of vegetation management cost-effectiveness at higher budgets helps partners weigh tradeoffs of where and how much vegetation management they want to implement compared with other potential actions in order to achieve goals in the CWPP.

Choosing Treatment Types

Prescribed fire was the most cost-effective vegetation management activity across all budget levels (Table 8), because prescribed fire effectively reduces fuels for a relatively low cost compared to the other treatment types. When summed across low severity, high severity, and mechanical thinning + prescribed fire treatment types, prescribed fire is the suggested treatment type for 70-80% of priority acres (Table 8; Figure 14; Figure 15). The prescribed fire treatment assumptions include costs for some additional planning and preparation that can be done in advance to prepare the landscape and communities for increased burning. This analysis provides a planning benchmark and communication tool to build capacity and social support over time for increased use of prescribed fire as a management tool. While wildfire burning under extreme weather conditions may have negative impacts, the prescribed fire priority areas are a resource for managers to show them where planned and unplanned fire can be leveraged under moderate weather conditions to efficiently reduce risk across the county.

High-severity prescribed fire is the dominant suggested treatment type in spruce-fir and lodgepole pine forests. Low-severity prescribed fire is commonly selected by

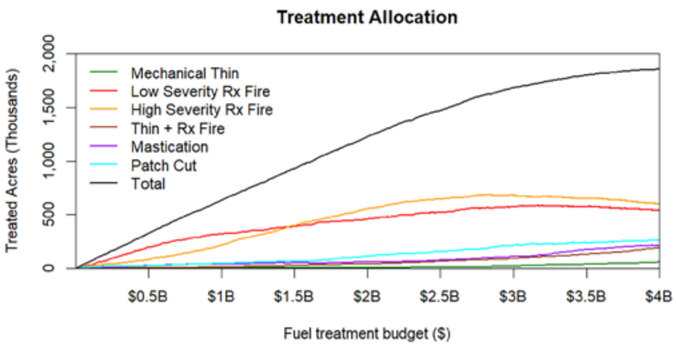


Figure 14. Treatment type allocations across ranges of budgets for vegetation management.

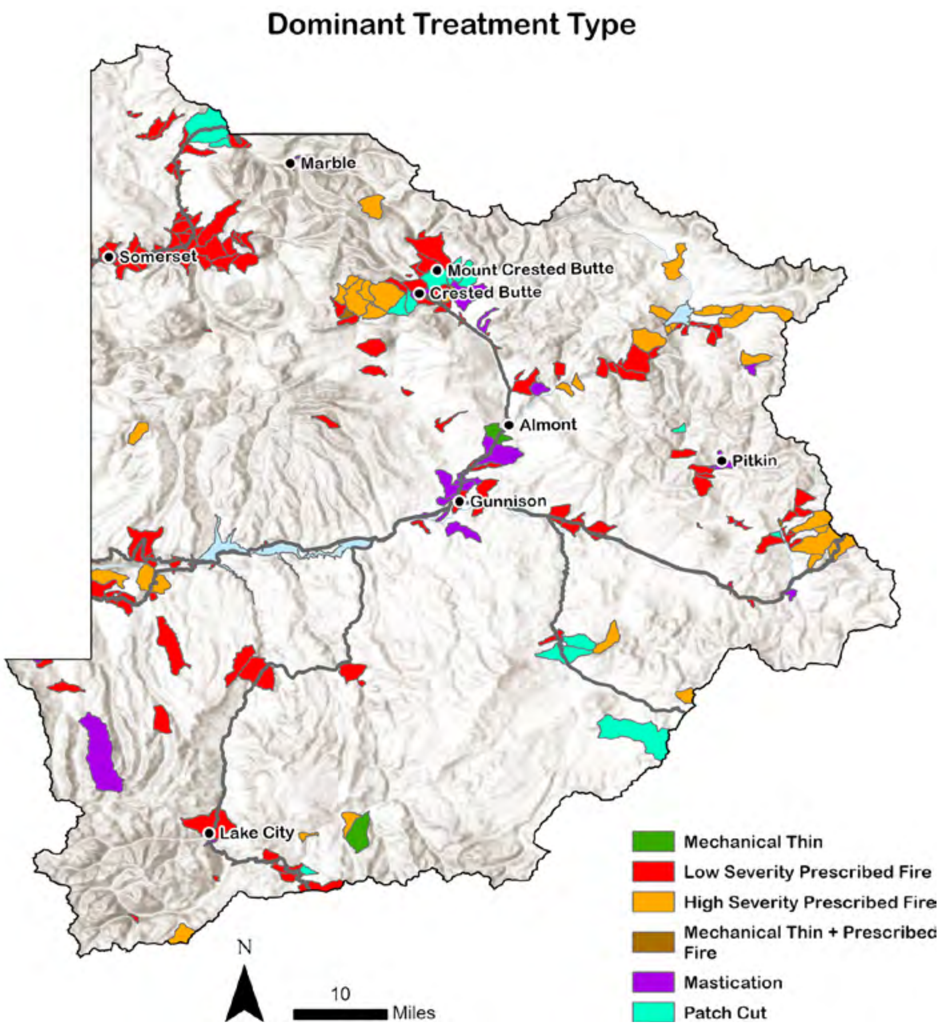


Figure 15. The most cost-effective treatment type for each priority treatment polygon in the $200 million budget. Multiple treatments could be recommended for each unit, but only one dominant treatment type is shown within a NHDPlus catchment polygon (i.e., the treatment unit) for visualization purposes. Not all area within these polygons is considered feasible for the identified treatment. For example, high-severity prescribed fire is only feasible in lodgepole pine and spruce-fir forests, not in other vegetation types. Vegetation management is generally restricted to forested landscapes (i.e., > 10% canopy cover or specific forest types in feasibility constraints) to support the protection of highly functional riparian zones within the priority treatment polygons. See Appendix D – Vegetation Management Assumptions for maps of feasibility by treatment type.

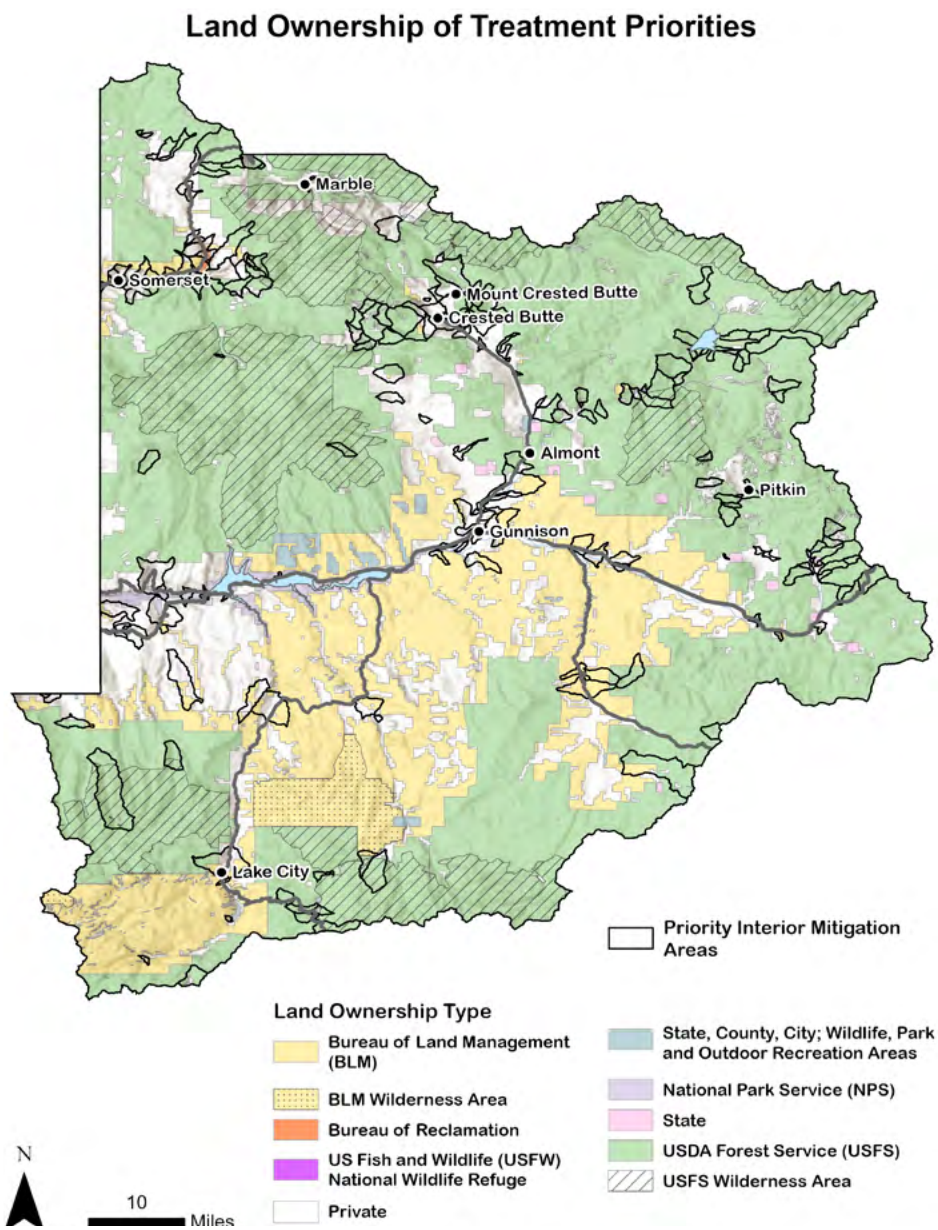


Figure 16. Priority POD interior vegetation management activities relative to land ownership types.

the model in mixed conifer, ponderosa pine, aspen, and pinyon-juniper forests. Patch cut is the next most cost-effective treatment type, most common in spruce-fir and lodgepole pine. Mechanical thin was rarely selected by the model (< 1% of priority treatments, Table 8, Figure 15). Our model assumes mechanical thinning treatments have no effect on surface fuels (Table 6), so thinning risk reduction estimates are relatively low. This aligns with research that surface fuel management is key to moderating wildfire risk (Davis et al., 2024). However, mechanical thinning or other preparation may be necessary to adjust fuel loads before some priority areas can be safely or effectively burned. These assumptions are included in the prescribed fire cost and feasibility constraints. The analysis suggests mechanical thinning of forests will yield the greatest benefit when aligned closely with facilitating prescribed fire applications and enhancing fire response opportunities within the PODs network.

Priority treatment units overlap a variety of land ownerships (Figure 16). 157,697 acres, representing 90% of the priority POD interior treatments, were located on USFS land. Another 11,464 acres or 7% of the priority treatments were located on BLM land. The remaining 4,792 acres or 3% of priority treatment units were located on local, state, or private land. Most priority acres for wildfire risk reduction are on USFS land, so they are a key partner in collaborating with other land agencies and individuals in Gunnison County to pool and share resources.

4.3 Prioritization of Vegetation Management Along POD Boundaries

The goal of many fuel reduction treatments is to moderate future fire behavior, which in turn should make fire response operations safer and more effective. We evaluated how vegetation management along POD boundaries could reduce transmitted risk (see section 3.7 for methods). We calculated a second benefit-cost ratio (BCR) to describe the reduction in suppression difficulty index per dollar spent (USD) for a mechanical thinning scenario along buffered POD segments. Figure 17 illustrates the BCR of POD boundary treatments (shown in orange) alongside areas of high transmitted risk (gray PODs). Lower BCR values (thinner, light orange lines) indicate that mechanical thinning is expensive relative to the suppression difficulty reduction achieved. This can be attributed to a combination of factors such as already low suppression difficulty index under current conditions (e.g., in grasslands or flat terrain), minimal impact of thinning on suppression difficulty index, or high costs of thinning. Conversely, higher BCR values (thicker, dark orange lines) show that each dollar spent is more efficient and effective at reducing suppression difficulty, making mechanical thinning more cost-effective in these areas.

When management objectives include mitigating transmitted risk, the analysis offers opportunities to indirectly reduce wildfire risk to HVRAs by prioritizing POD lines that (1) offer a high benefit-cost ratio (ΔSDI/USD), (2) intersect with high transmitted risk PODs, and (3) form long, contiguous segments to enhance opportunities for fire containment. Focusing on PODs with high BCR ensures the efficient allocation of limited resources. Targeting treatments around PODs with high transmitted risk could provide opportunities to prevent fire from spreading into fire-sensitive areas. Additionally, contiguous treated areas along POD lines could offer more

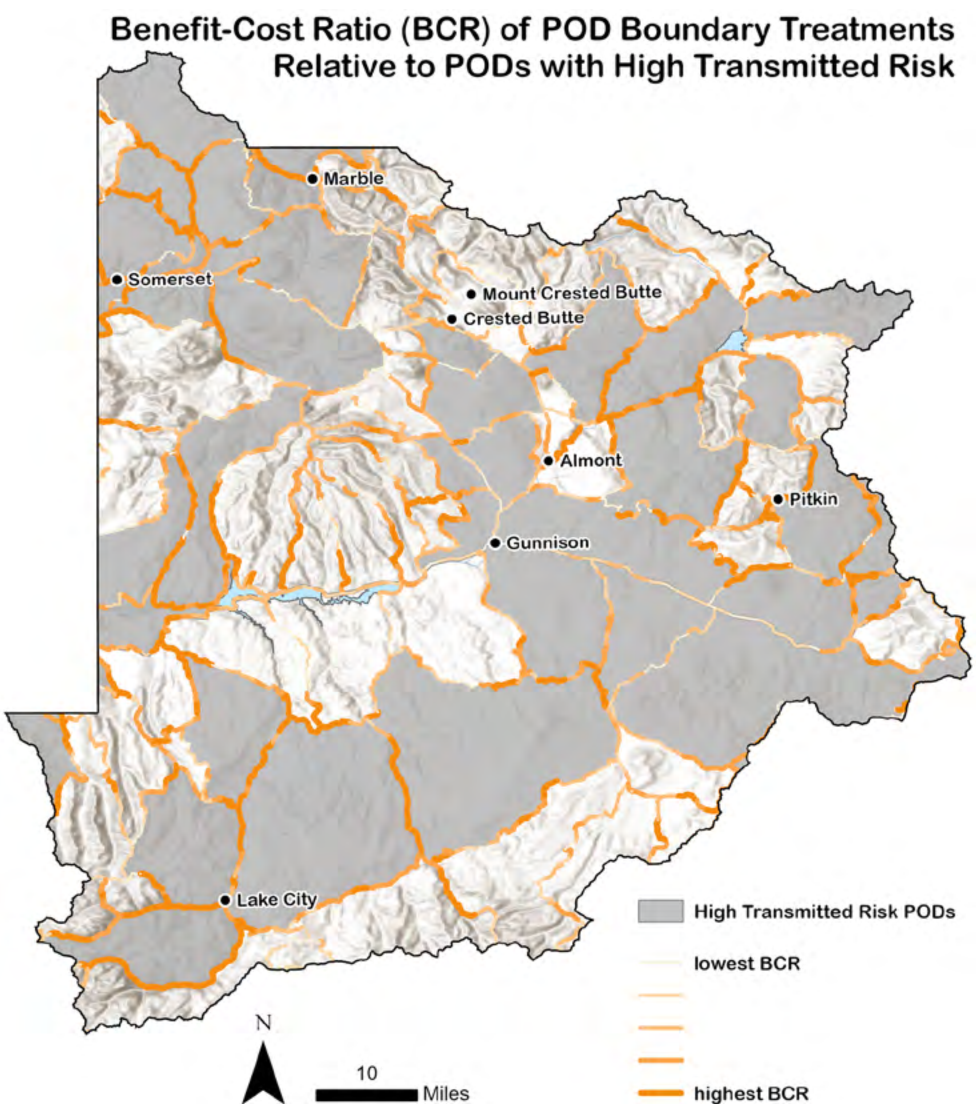


Figure 17. Prioritization of POD boundary treatments relative to PODs with high transmitted risk (gray). This benefit-cost ratio (BCR) is calculated as reduction in suppression difficulty index (ΔSDI) per dollar spent for a mechanical thinning scenario and is depicted in the orange color ramp, with darkest orange for the highest BCR treatments and light orange for the lowest BCR treatments.

fire response options, and are often more cost-efficient than short, disconnected treatments would be.

POD boundary work offers potential benefits for improving operational fire response, safely and effectively leveraging fire for risk reduction, and enhancing beneficial wildfire impacts. While operational outcomes depend on active fire behavior, landscape conditions, and available fire response resources, pre-season POD boundary preparation could improve fire response effectiveness by increasing firefighter access and rate of fire line construction. Treated POD boundaries may help firefighters limit fire transmission into adjacent fire-sensitive PODs or reduce the need for extensive on-the-ground preparation during an active fire, allowing resources to be allocated to other priority areas and potentially lowering overall fire response demands. In addition to supporting suppression efforts, treated POD boundaries could create more opportunities to accommodate beneficial fire through prescribed burns and managed wildfire rather than defaulting to full suppression strategies. POD boundary treatments can be developed to strategically reduce transmitted risk and efficiently minimize exposure of community values to negative wildfire impacts. Strategically designed POD boundary treatments may enhance firefighter safety, provides opportunities to reduce risk safely using wildfire as a management tool, and can support ecological fire objectives. Creating more efficient and effective fire response opportunities provides a foundation for future fire management, enhancing both operational effectiveness and long-term landscape resilience.

This POD boundary analysis should be viewed as a decision support tool that guides prioritization efforts, but does not identify a prescriptive set of priorities. These results are most powerful when paired with local knowledge of fire behavior, fire spread direction, ignition density, and on-the-ground conditions. For example, the area around Lake City includes several high-transmitted-risk PODs that contain high BCR POD boundary segments where high-impact treatments could be implemented. However, this analysis does not currently account for likely fire spread direction. Incorporating local knowledge of fire movement can help refine priorities and determine where to most effectively locate POD boundary work (i.e., whether to target the north, east, south, or west side of a POD) to limit the spread of fire into sensitive areas. It may also be beneficial to consider where treatments are already in place.

While this analysis identifies where reducing SDI is most effective, future research is needed to provide clearer, data-driven insights into fire movement across POD boundaries. Potential advancements include incorporating the direction of simulated fire spread, summing the number of fires that transmit from the POD of origin, and identifying where fires most frequently cross POD boundaries. This would offer a more comprehensive understanding of fire transmission risk and improve prioritizing management activities for POD boundary hardening.

4.4 Bringing it All Together

The National Cohesive Wildland Fire Management Strategy, also known as the Cohesive Strategy (Figure 18, [Wildland Fire Management Strategy, 2023]) prepares communities to mitigate, receive, respond to, and recover from wildfires. Gunnison County managers can use the RADS results to guide the operationalization of the Cohesive Strategy. Figure 19 shows POD line BCRs relative to the interior POD treatment priorities identified in [section 4.2], with different risk gradients for risk transmission and in-situ risk. In this technical report we have outlined strategies to address wildfire risk along these different gradients (e.g., risk can be addressed in PODs with both high in-situ risk and high transmitted risk with a combination of fuel reduction around values at risk and POD boundary hardening).

While Figure 19 does not identify locations of individual projects, it communicates Gunnison County's landscape plan to live with wildfire by prioritizing activities that are consistent with the three pillars of the Cohesive Strategy. First is safe, effective, risk-based fire response.

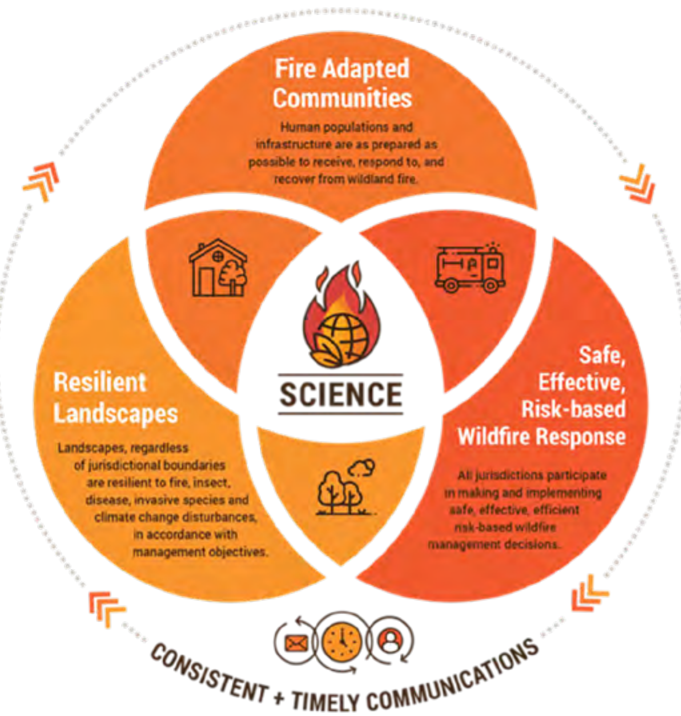


Figure 18. The three components of the National Cohesive Wildland Fire Management Strategy (2023).

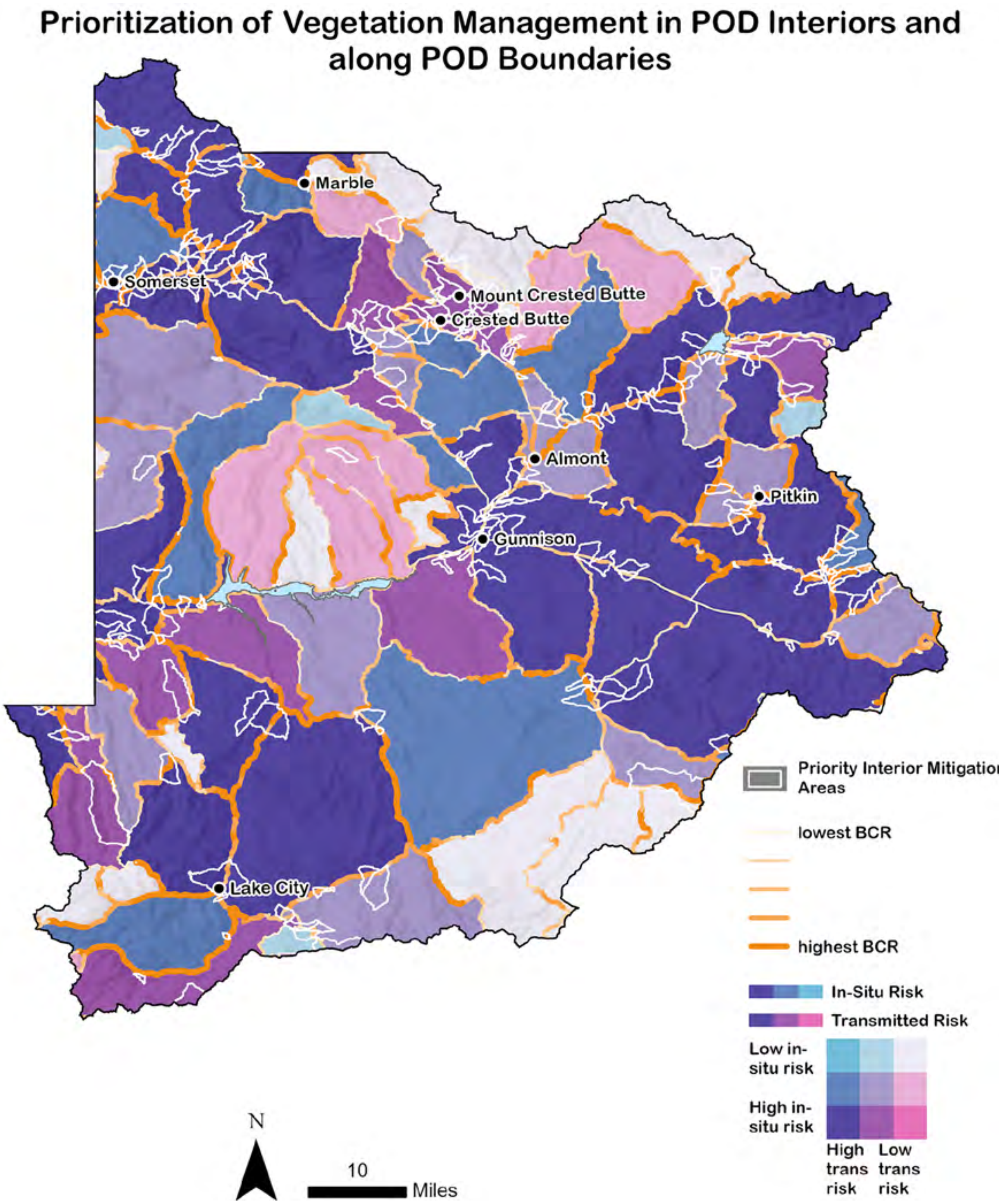


Figure 19. Priority POD interior management activities (white outlines) combined with benefit-cost ratio (BCR=ΔSDI/USD) of POD boundary treatments (orange color gradient) relative to POD summaries of in-situ and transmitted risk.

POD boundary hardening could be strategically applied to reduce SDI and improve the safety of wildfire responders (section 4.3). Second, interior POD vegetation management supports planning for resilient landscapes (section 4.2). The third component of the Cohesive Strategy is fire adapted communities. While the RADS process helps to identify areas suitable for vegetation management to reduce risk, it also highlights where such treatments are infeasible or inefficient, and efforts could be better focused on preparing human populations and infrastructure to receive fire. In these areas, other risk-reduction measures are needed, such as updating building codes to reduce structure flammability, assisting residents in creating defensible space around their homes, or creating redundancy in drinking water supplies. In summary, the POD interior and POD boundary prioritizations help guide vegetation management for resilient landscapes and effective response while also identifying where alternative actions are necessary to reduce additional risk to promote fire adapted communities.

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, and prioritizations of vegetation management activities. 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:

1) HVRA_shapefiles.gdb (i.e., vector data)
2) HVRA rasters
3) Fire modeling
4) Conditional net value change (cNVC)
5) Expected net value change (eNVC)
6) Management constraints
7) Treatment priorities
8) General layers

GIS data corresponding to the HVRAs listed in Table 2 and in a Box spreadsheet are saved in folders 1 and 2. The folder titled "HVRA_shapefiles.gdb" houses all vector GIS data (i.e., points, polygons, and polylines). These data were then buffered and rasterized. Resulting raster data can be found in the "HVRA_rasters" folder. Vegetation HVRA rasters derived from LANDFIRE Existing Vegetation Type are also saved in this folder. The data source of each HVRA is documented in the file "HVRA_metadata.xlsx".

Fire behavior and burn probability rasters are stored in the "Fire_modeling" folder. Flame length and crown fire activity were modeled for six weather percentiles (25th, 50th, 75th, 90th, 97th, and 100th). We included rasters as .tif files and attached suggested symbology in .lyrx files.

Conditional net value change is the modeled response of each HVRA to fire at various flame lengths. In short, it represents the likely impact of fire to HVRAs if a fire were to burn in a given pixel. We include .tif rasters and .lyrx rasters with suggested symbology for each individual HVRA, each HVRA category, and composite wildfire hazard. We also include a folder containing a cNVC raster for each HVRA (34) for each weather scenario (6), for a total of 204 individual .tif rasters.

Expected net value change is the product of burn probability and conditional net value change, and represents the expected impact of fire to HVRAs considering the likelihood of fire actually occurring in any given pixel. Again, we include .tif rasters and .lyrx rasters with suggested symbology for each individual HVRA, each HVRA category, and the composite eNVC using relative importance weights.

The management constraints folder includes cost, feasibility, and benefit-cost ratio (BCR) rasters for each vegetation management activity. These are applicable only to interior POD treatment prioritizations (section 4.2).

The treatment priorities folder contains the vegetation management priorities for both POD interiors and POD boundaries.

Finally, the general layers folder contains helpful spatial overlays including PODs, major highways and streams, land ownership, vegetation types, and more.

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Appendix A: Spatial Data Processing

Building density was derived from Microsoft Bing (2020) and Federal Emergency Management Agency (FEMA, 2022) datasets. Microsoft Bing, our primary data source, uses AI-driven object-based remote sensing to extract building footprints from high-resolution aerial imagery. While highly accurate, occasional errors can arise due to factors such as image resolution, shadowing, dense urban environments, and the model's tendency to regularize building shapes. In more rural areas, the model may misclassify natural features like rock outcroppings as structures due to their geometric similarity to buildings in aerial imagery.

To create a more complete and reliable structure dataset, FEMA's USA Structures dataset was used as a secondary data source to supplement areas where the Bing dataset may have omitted buildings. FEMA's dataset, derived from high-resolution aerial imagery and LiDAR data, provides a nationwide inventory of structures larger than 450 square feet. It is used to support disaster response, wildfire risk assessments, and mitigation planning. By integrating imagery with elevation data, the FEMA dataset enhances accuracy, particularly in urban areas. While highly precise, limitations include potential misclassification of natural landforms in remote regions and challenges in detecting small or temporary structures.

Using these combined datasets, we generated a building density dataset to quantify the distribution of structures across the study area. Building density was calculated as the number of structures per unit area, providing a spatial representation of development.

1) *We minimized the effects of commission errors that would over-estimate building density* by using the "Near" tool in ArcGIS Pro to calculate the distance from each building polygon to the nearest road. Building polygons located more than 1,500 meters from a road were removed, as structures at such distances are uncommon. To establish a reasonable threshold, we cross-referenced aerial imagery in Google Earth, ensuring that the selected cutoff effectively differentiated true structures from erroneous classifications. This approach significantly reduced false positives, particularly in remote and alpine regions, where rock outcroppings were frequently misidentified as buildings.
2) *We minimized the effects of omission errors that would under-estimate building density* by identifying all FEMA structures that did not intersect with Bing building footprints and converting them to centroid points. Any points within 20 meters of a Bing centroid were assumed to correspond to the same building and were removed to prevent duplication. Additionally, FEMA building points located more than 500 meters from a road were excluded, using a more conservative threshold than the Bing dataset to reduce the likelihood of incorporating extraneous structures. To further refine the dataset, only buildings classified under Residential, Commercial, Education, Assembly, Industrial, or Agriculture were retained, while "Unclassified" structures were removed. Buildings with a listed property address were prioritized for inclusion.

After converting both datasets from polygons to points, they were merged into a single dataset, resulting in a total of 23,069 building points—20,933 from Bing and 2,136 from FEMA. To ensure consistency with other vector data used in RADS, we included buildings within a 10-kilometer buffer beyond the risk analysis extent. As a result, the total building count reflects structures both within the project area and in the surrounding buffer zone, slightly exceeding the number of buildings located strictly within the study extent.

To account for buildings constructed after the datasets were published, additional building points were manually digitized using high-resolution basemap imagery. This process involved visually identifying structures that were absent from the Bing and FEMA datasets and delineating their locations to ensure a more current and comprehensive representation of the built environment. Approximately 100 buildings were added in downtown Gunnison, improving the dataset's accuracy for recent development. This manual verification and digitization step helped address temporal limitations of the source data and reduce potential underestimation of building density.

Building Density

Buildings were partitioned into low (< 1.5 structures/acre) and high density (≥ 1.5 structures/acre) classes based on the assumption that greater loss is expected in high density areas, as in observations from the Waldo Canyon Fire in Colorado Springs (Maranghides et al., 2015). The same cutoff was also used in the Chaffee County Wildfire Risk Assessment (Gannon et al., 2019). Structure density was calculated at 30-meter resolution using the point density tool in ArcGIS Pro with a 50-meter circular neighborhood size. The high-density building class was assigned a more negative, or higher loss, response function to reflect greater potential for structure-to-structure ignition.

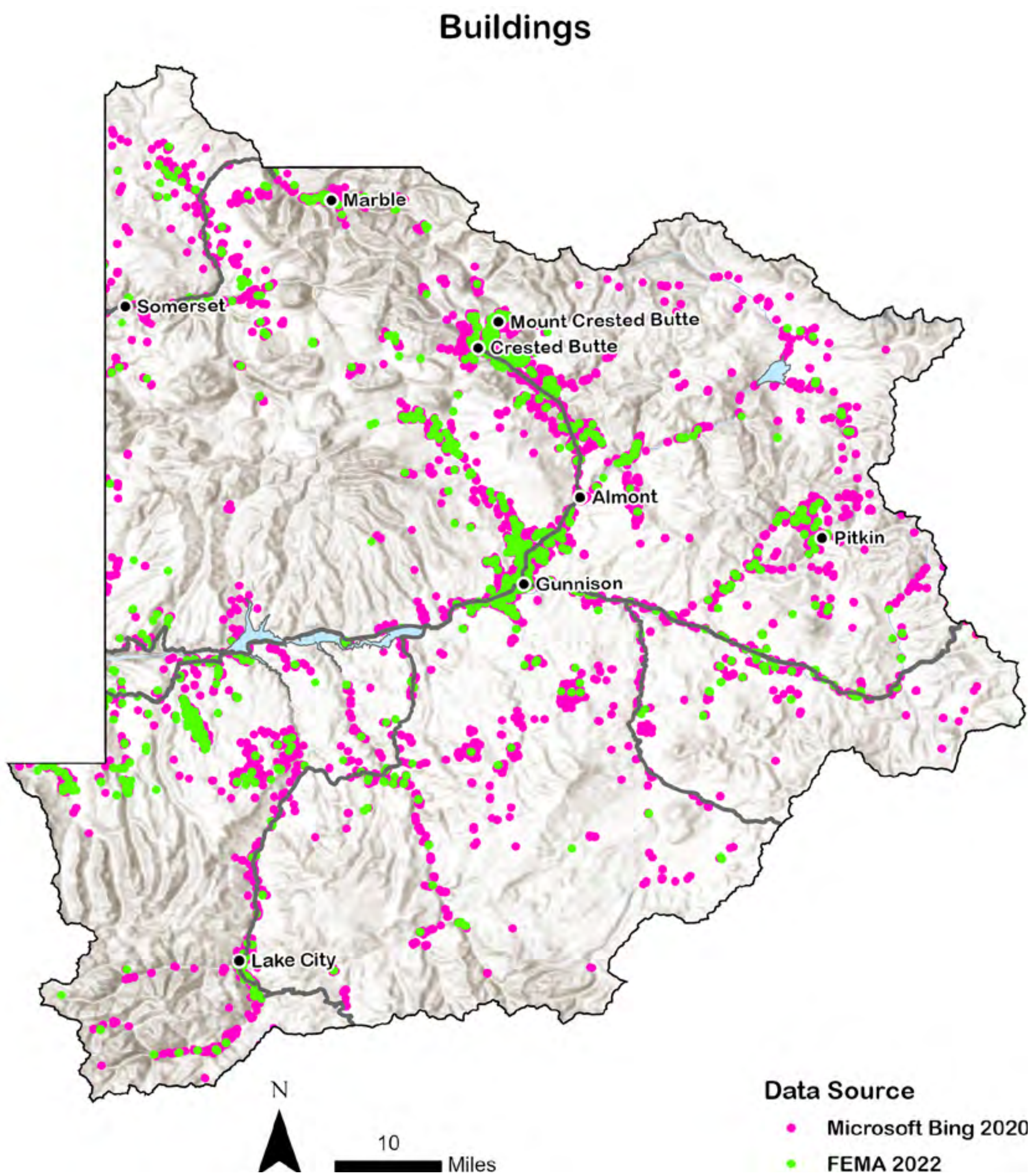

Figure A1. Building points included in the analysis. These points were converted to building density rasters which became the HVRA spatial extent used in the risk assessment.

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Appendix B: Wildfire Behavior and Probability Modeling

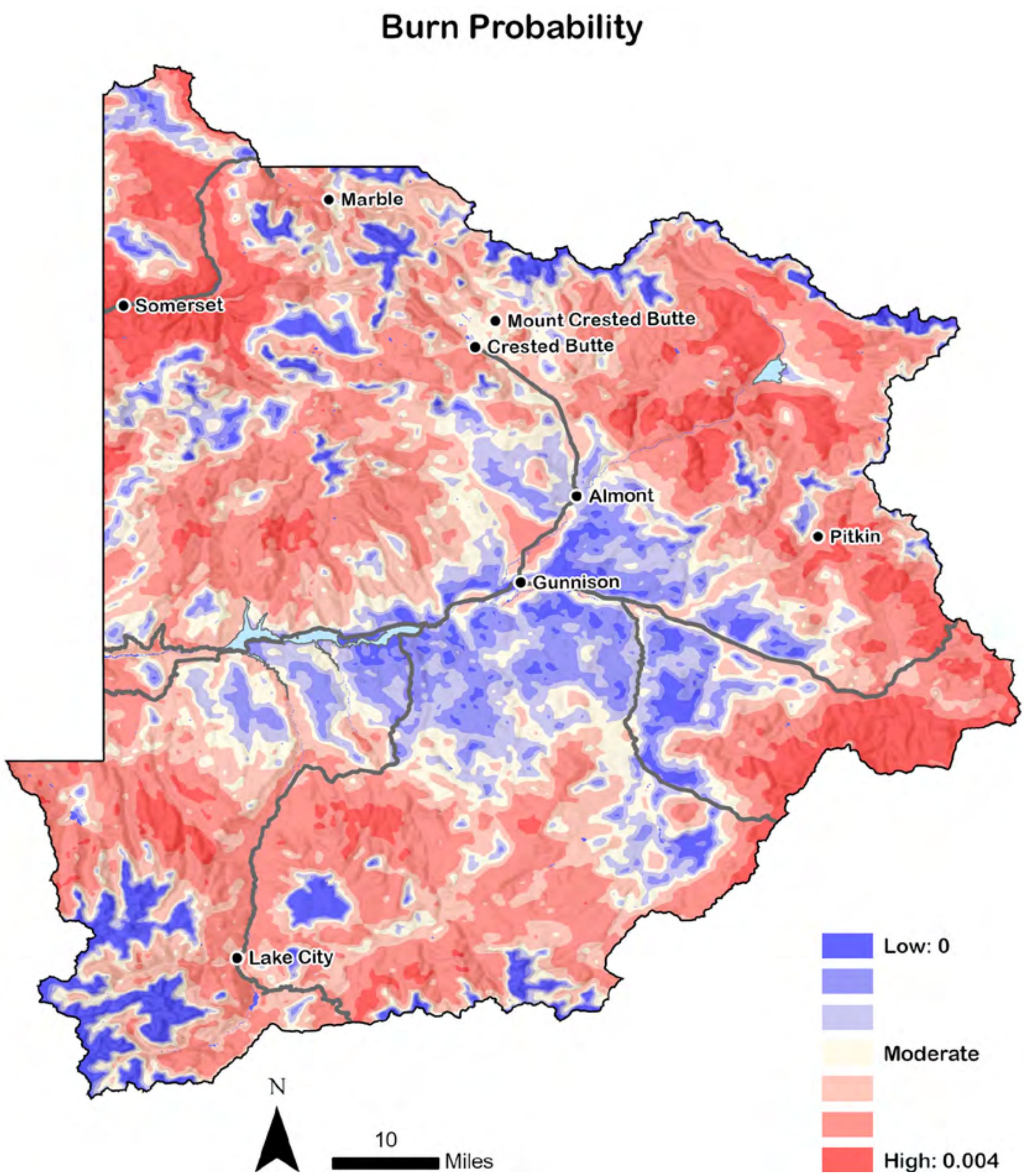

Figure B1. The burn probability product used for the risk assessment (Napoli et al., 2022).

Table B1. Fire weather inputs to FlamMap fire behavior modeling. Fuel moisture and wind speed values represent the mean from Taylor Park and Huntsman Mesa RAWS stations. These weather scenarios are weighted to favor the more extreme fire weather when most fires burn.

	FUEL MOISTURE (%)						
Percentile	1-hr	10-hr	100-hr	1000-hr	Herb.	Woody	Wind Speed 1-min (mph @ 20 ft)
25th	21	17	15	15	100	130	8
50th	12	13	13	14	80	110	9
75th	9	11	12	13	70	90	10.5
90th	7.5	9.5	10.5	11.5	50	80	12.5
97th	5.8	7.5	8.5	10.5	30	60	17
100th	5.8	7.5	8.5	10.5	30	60	33

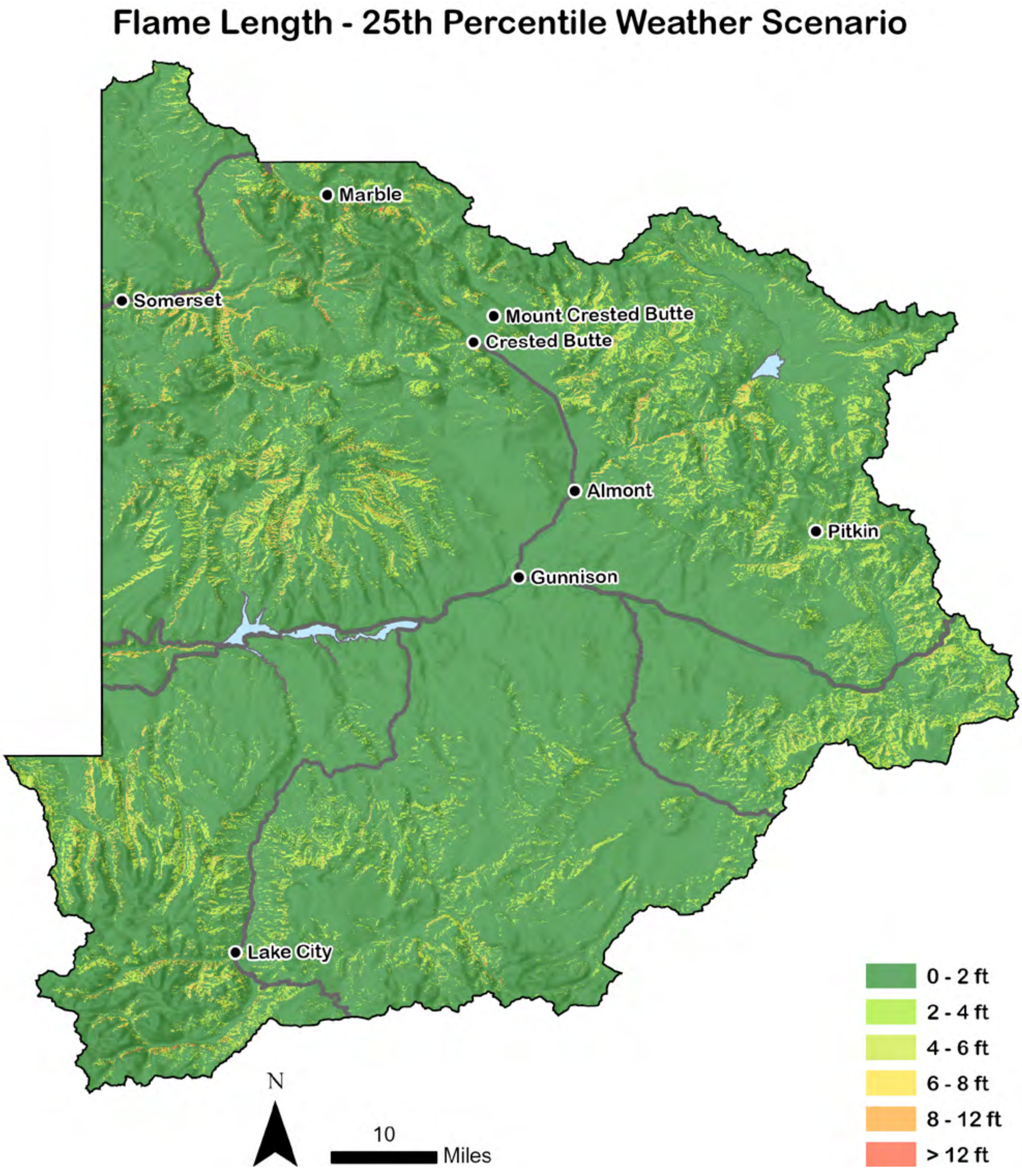

Figure B2. Modeled flame length (ft) for the 25th percentile (low) weather scenario.

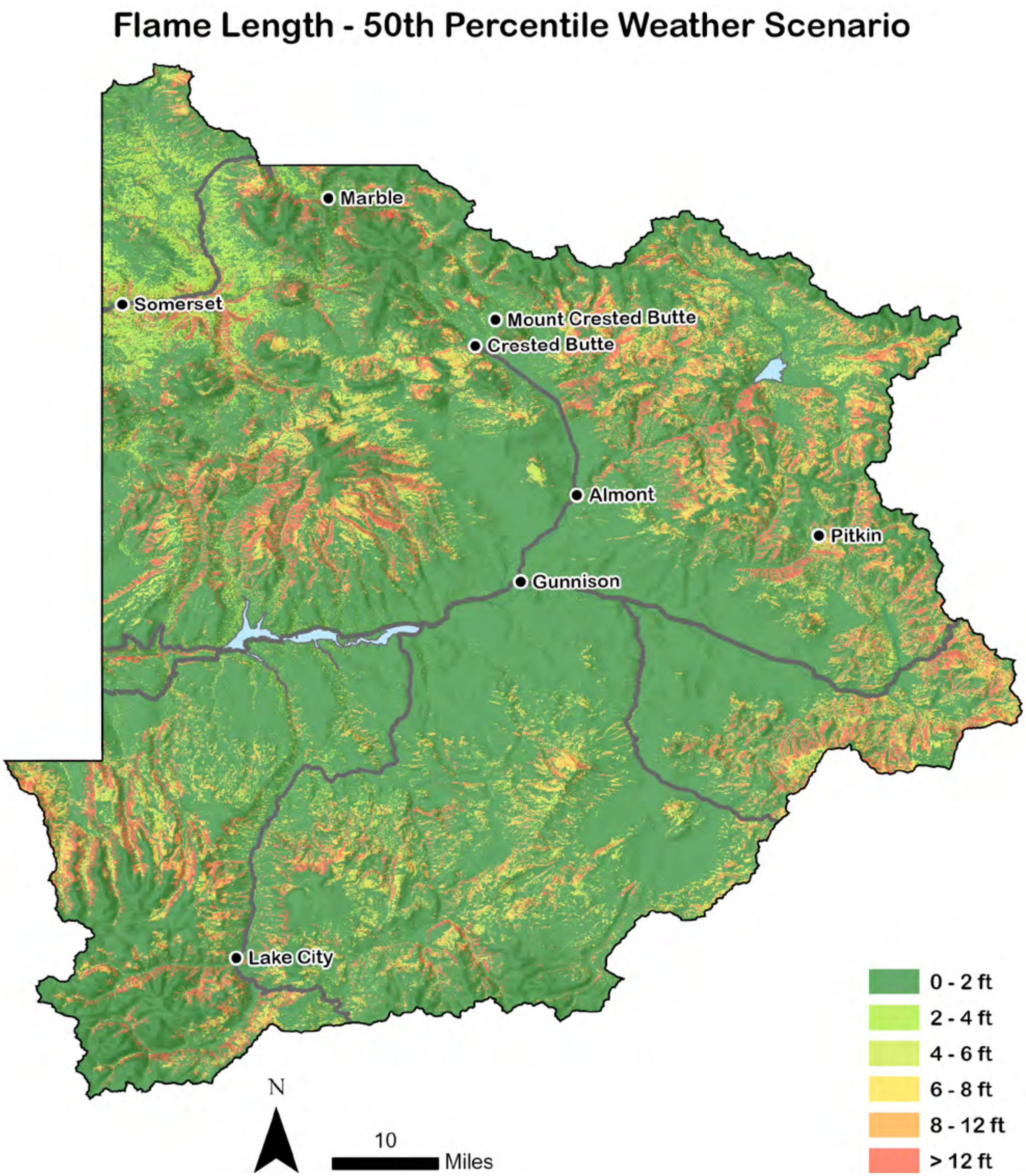

Figure B3. Modeled flame length (ft) for the 50th percentile (moderate) weather scenario.

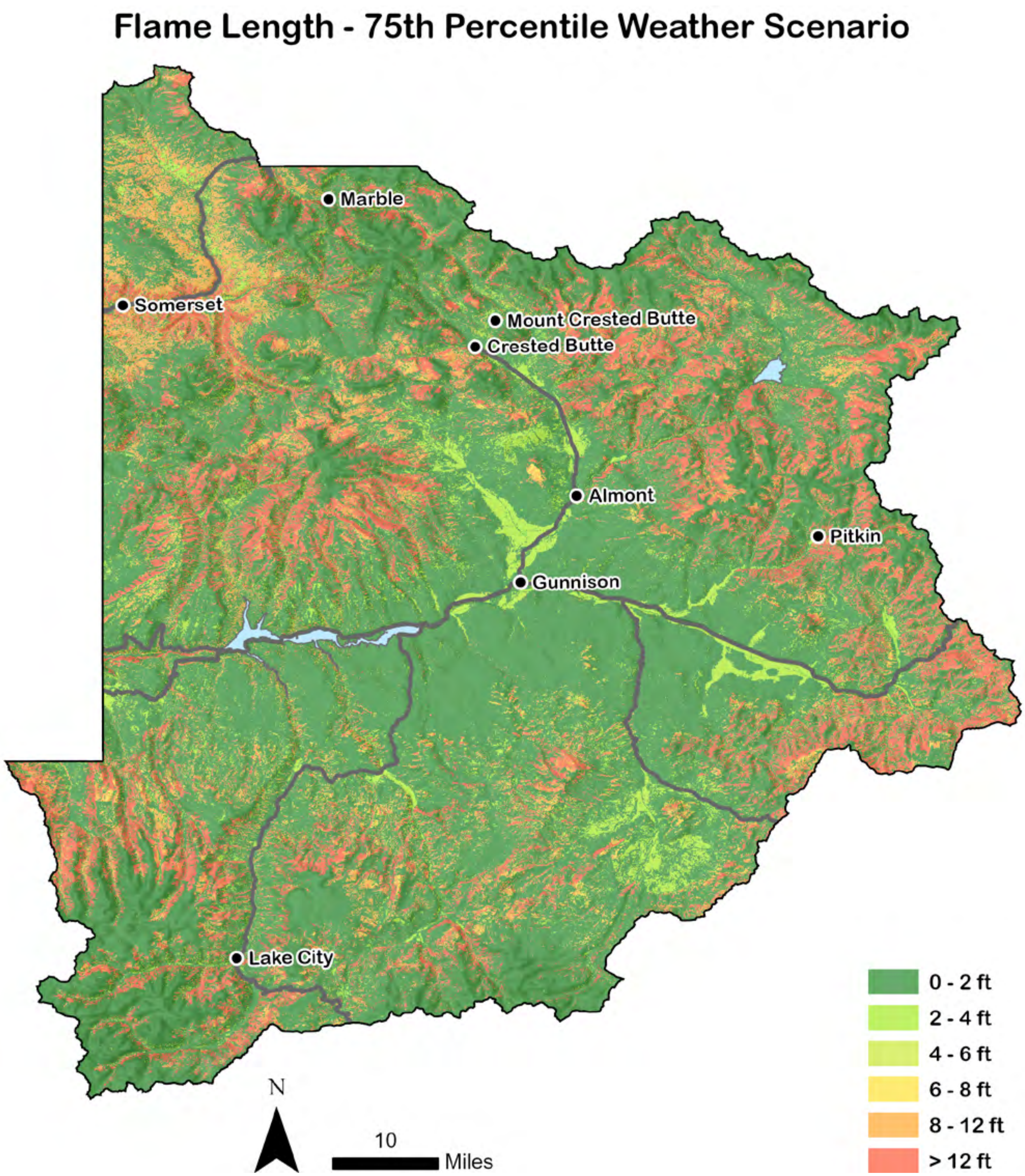

Figure B4. Modeled flame length (ft) for the 75th percentile weather scenario. This was not used to generate risk assessment outputs but may have utility for prescribed or wildfire planning.

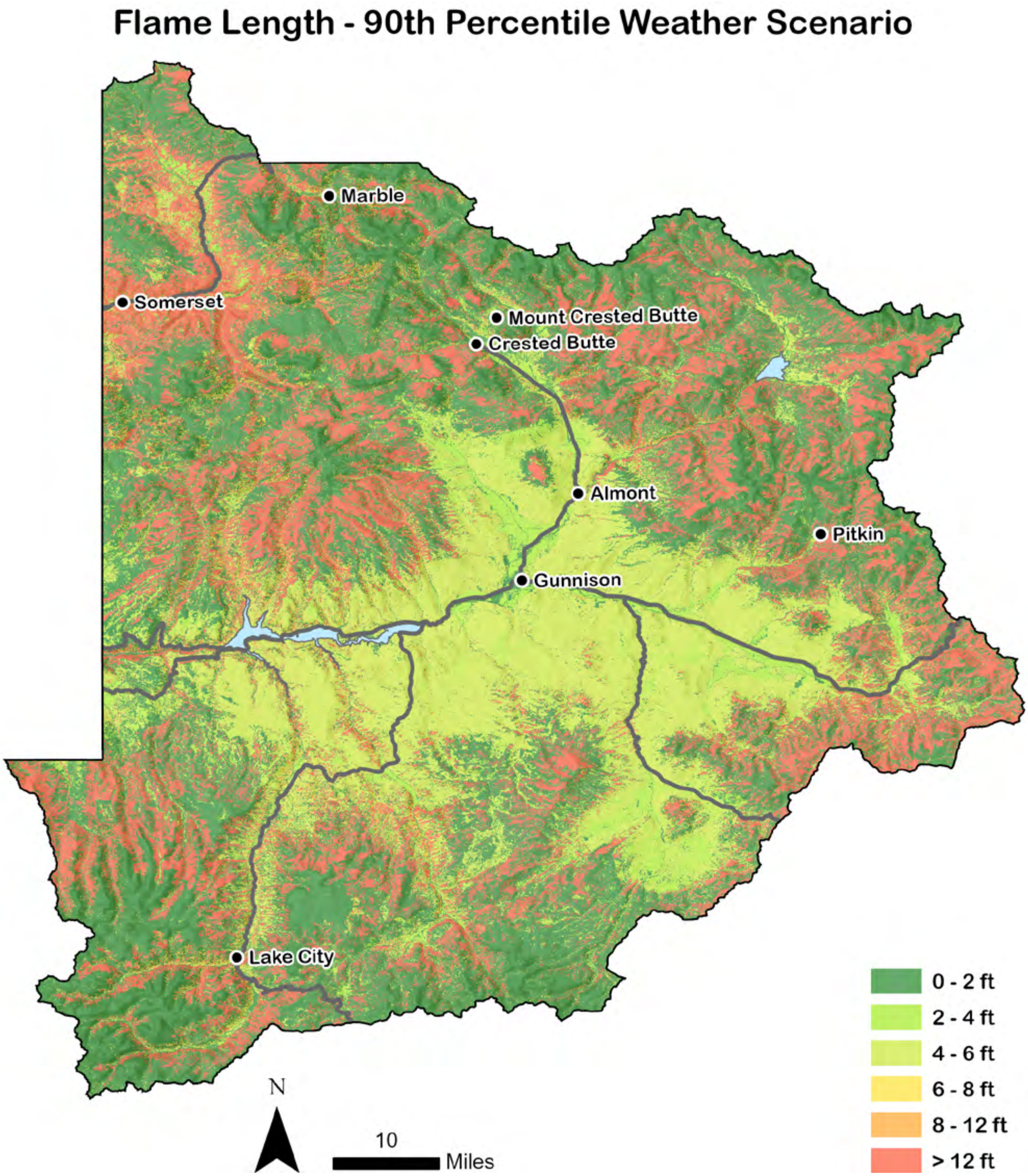

Figure B5. Modeled flame length (ft) for the 90th percentile (high) weather scenario.

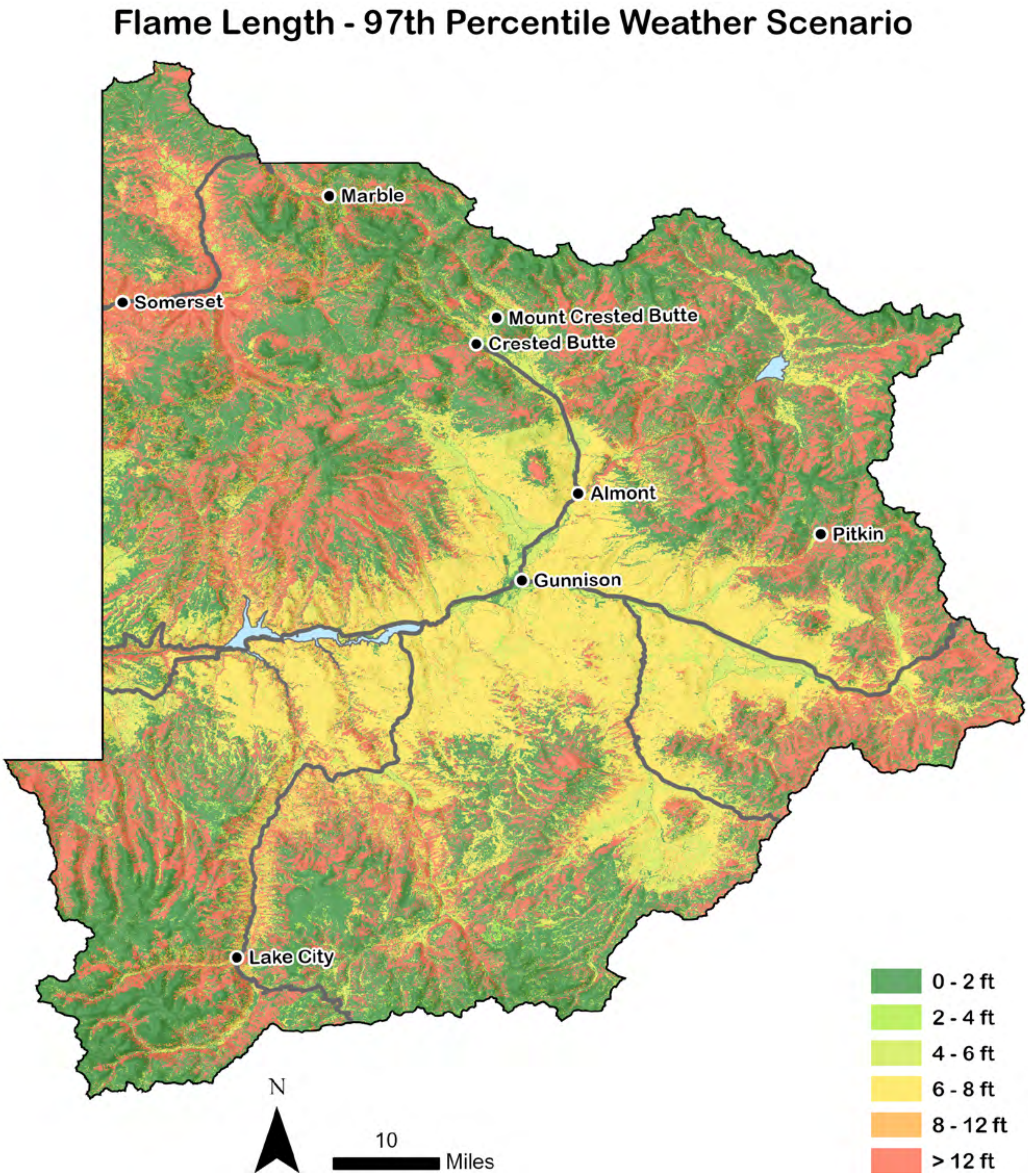

Figure B6. Modeled flame length (ft) for the 97th percentile (extreme) weather scenario.

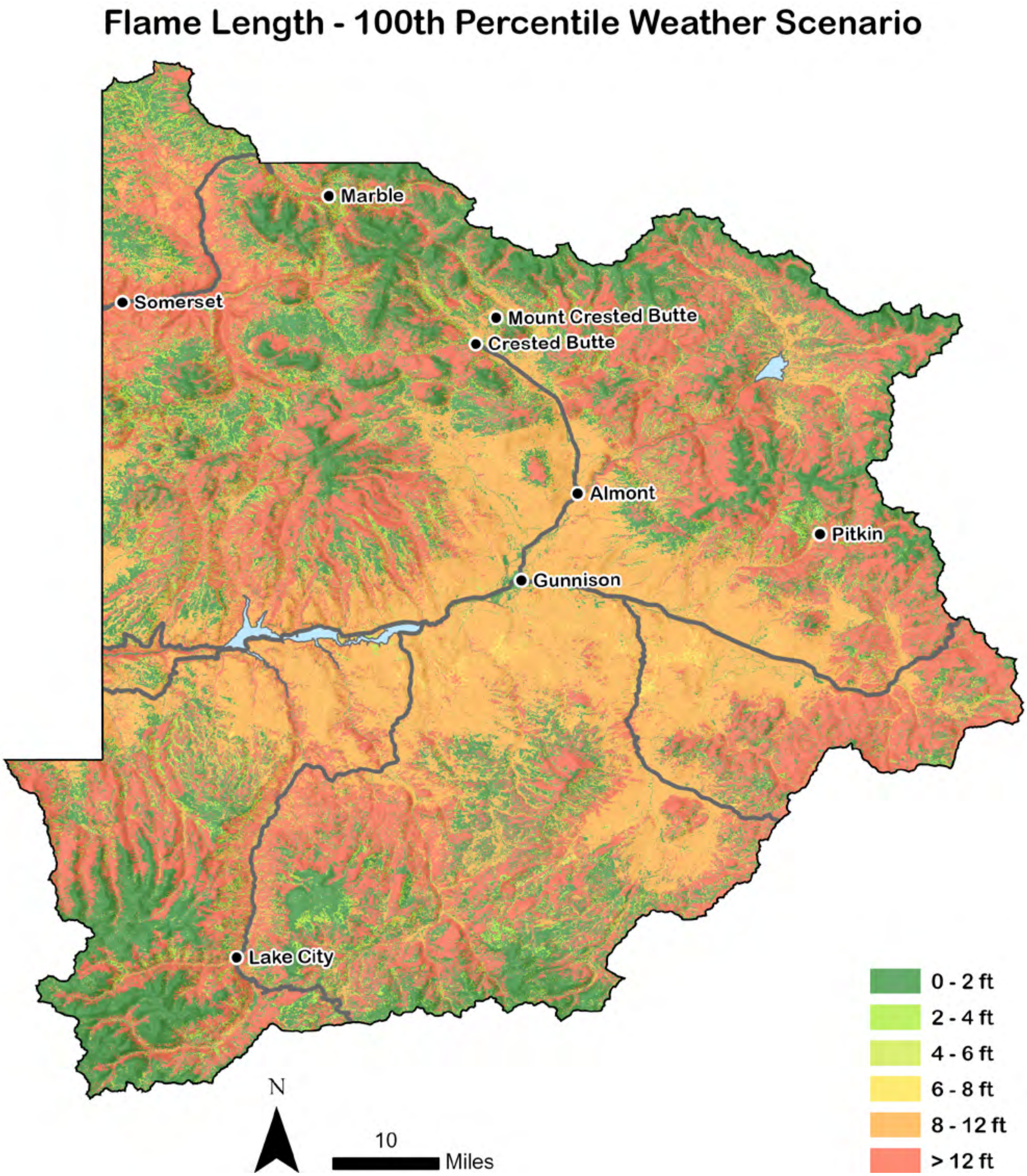

Figure B7. Modeled flame length (ft) for the 100th percentile weather scenario. This was not used to generate risk assessment outputs but may have utility for prescribed or wildfire planning.

Figure B8. Modeled crown fire activity for the 25th percentile (low) weather scenario.

Figure B9. Modeled crown fire activity for the 50th percentile (moderate) weather scenario.

Figure B10. Modeled crown fire activity for the 75th percentile weather scenario. This was not used to generate risk assessment outputs but may have utility for prescribed or wildfire planning.

Figure B11. Modeled crown fire activity for the 90th percentile (high) weather scenario.

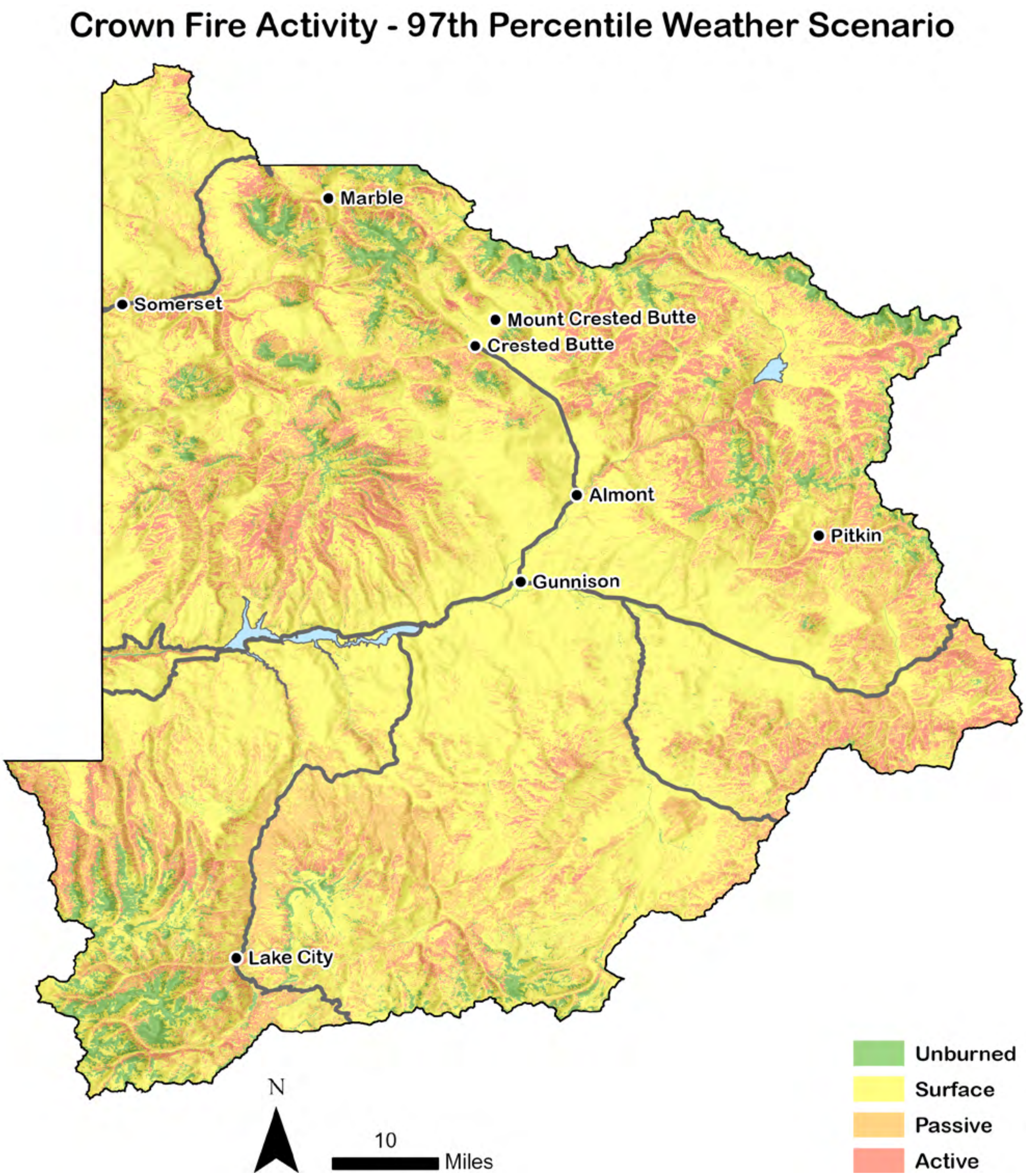

Figure B12. Modeled crown fire activity for the 97th percentile (extreme) weather scenario.

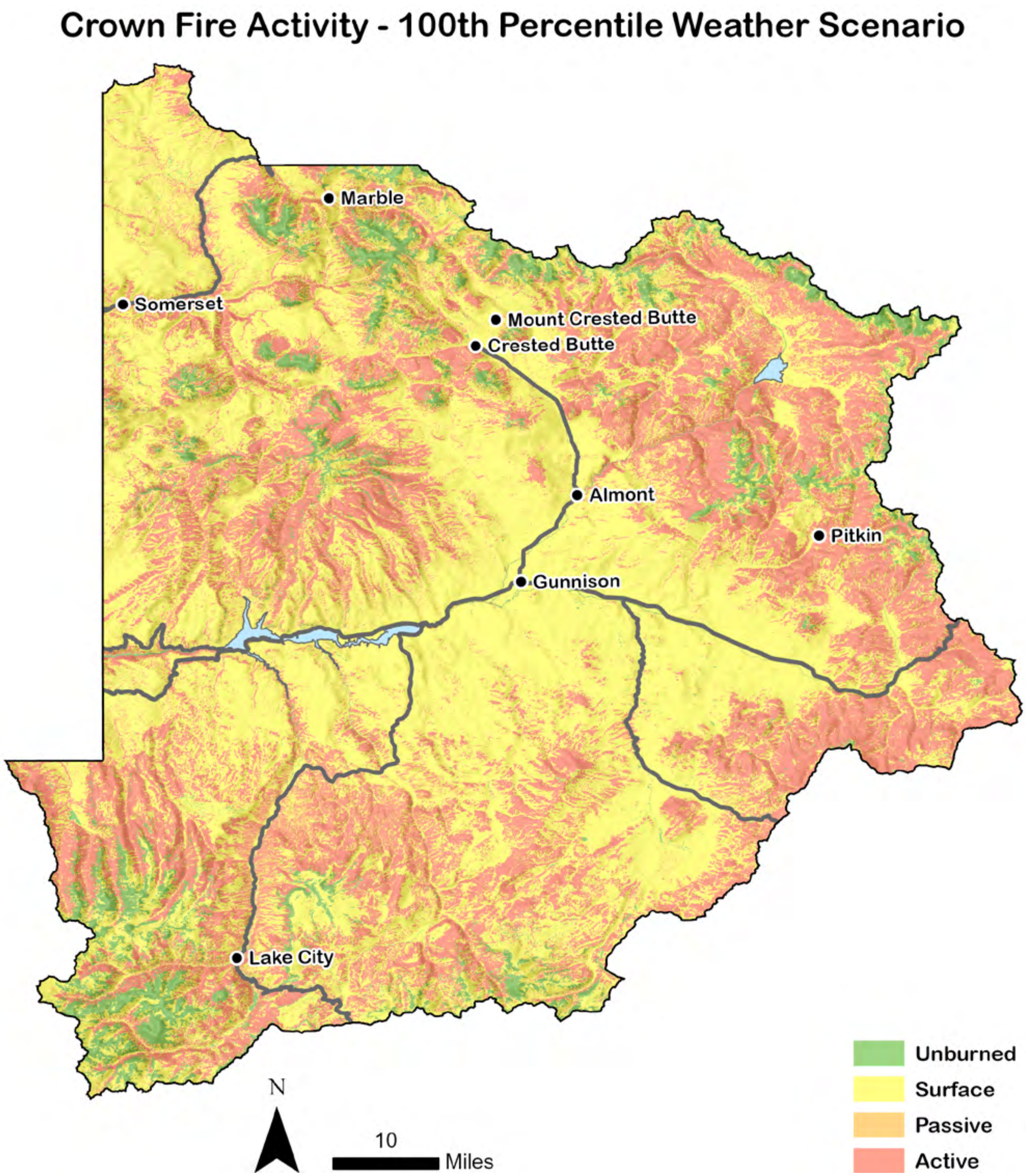

Figure B13. Modeled crown fire activity for the 100th percentile weather scenario. This was not used to generate risk assessment outputs but may have utility for prescribed or wildfire planning.

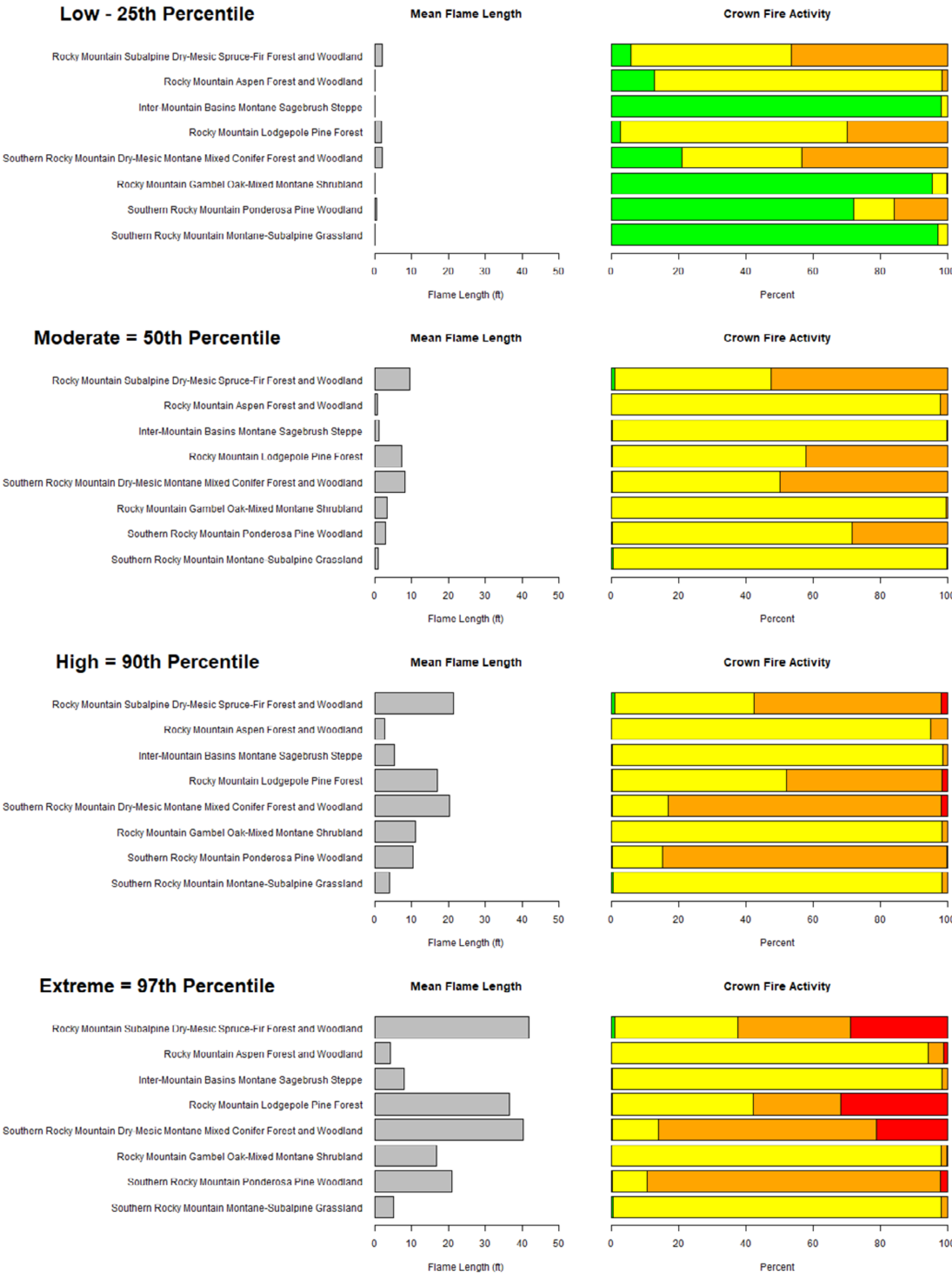

Figure B14. Summary of fire behavior by existing vegetation type from LANDFIRE (2022). The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

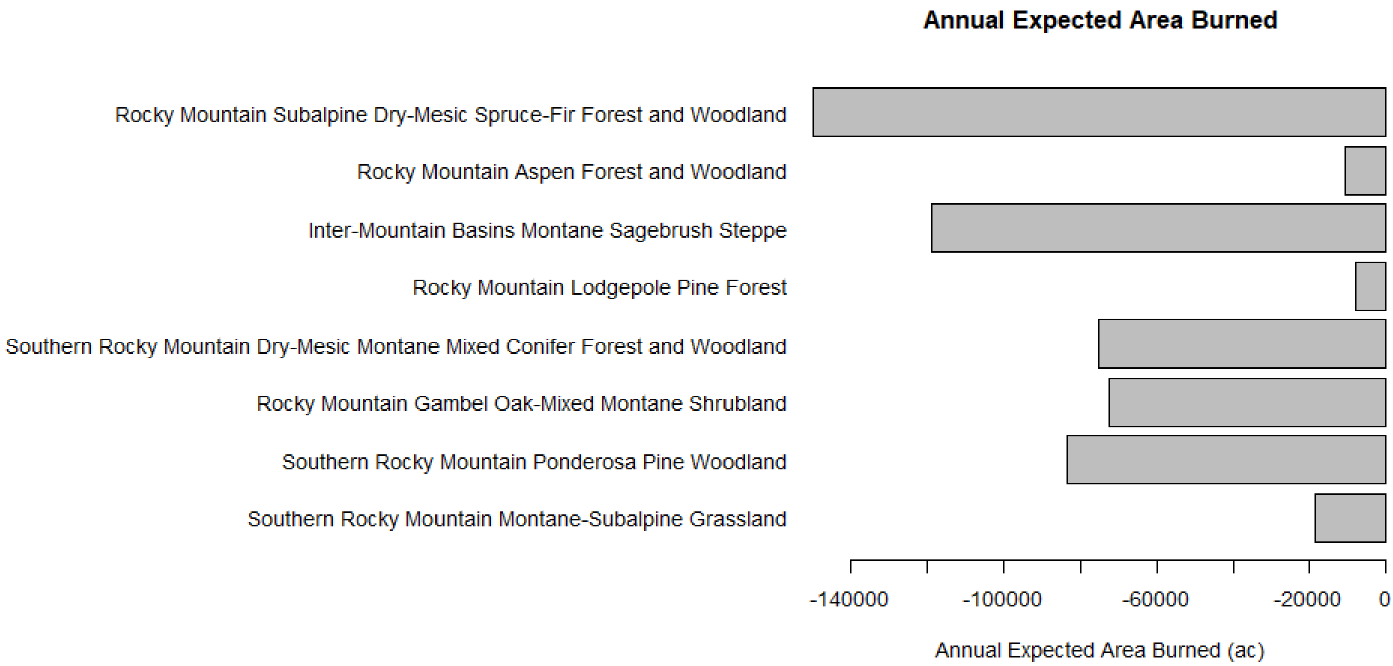

Figure B15. Expected area burned by LANDFIRE (2022) existing vegetation type based on burn probability from (Napoli et al., 2022).

Appendix C: Water Modeling

Wildfire risk to water-related HVRAs was assessed with supplemental modeling that estimates potential post-fire erosion and sediment transport to surface drinking water infrastructure and mines following the methods outlined in Gannon et al., (2019). FlamMap predicts both crown fire activity which is an input for watershed models and flame length which is used to quantify cNVC for all non-water HVRAs based on response functions (section 3.3). Soil burn severity was predicted by reclassifying FlamMap crown fire activity (Scott & Reinhardt, 2001) categories of surface fire, passive crown fire, and active crown fire to correspond to low, moderate, and high severity respectively. Post-fire erosion was estimated with the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997) using empirical observations of post-fire change in cover and soil erodibility by burn severity (Larsen & MacDonald, 2007). We then apply empirical models of hillslope and channel sediment delivery ratio to convert RUSLE hillslope erosion estimates to sediment delivery to water infrastructure (Frickel et al., 1975; Wagenbrenner & Robichaud, 2014). This workflow supports pixel-level estimates of the sediment generated in each pixel that is delivered to downstream values at risk (Figure C1). Sediment yield estimates (i.e., a volume) were then linearly rescaled to cNVC (i.e., a unitless relative metric) following HVRA-specific methods described in subsequent sections so all water and non-water HVRAs could be assessed on the same scale. cNVC was calculated for each fire weather scenario and then combined into a single cNVC raster by a weighted averaging (Table 3). Like all other HVRA categories, cNVC was then multiplied by burn probability to estimate eNVC.

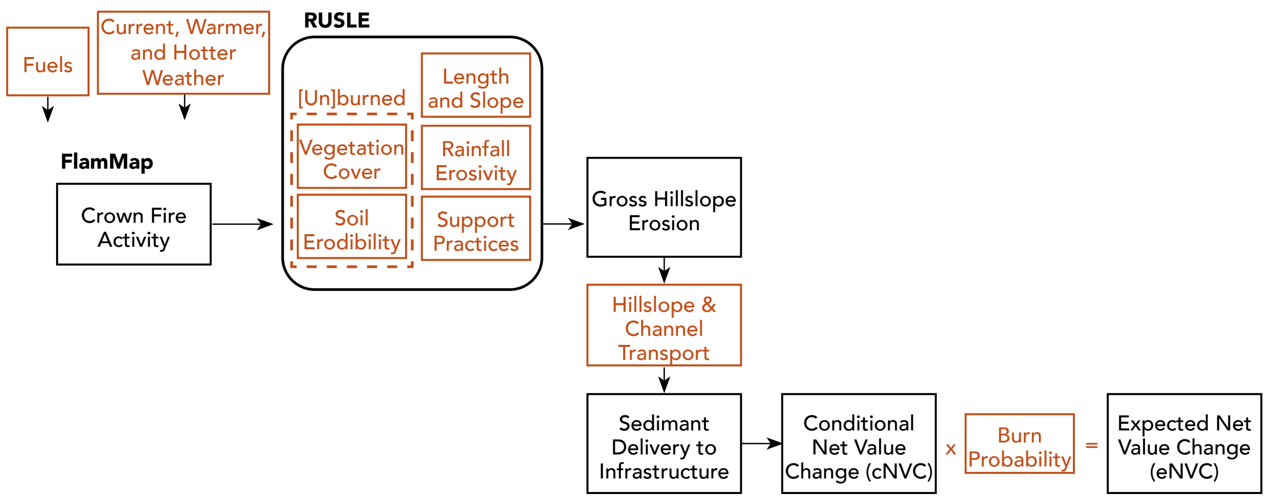

Figure C1: Erosion modeling workflow used to quantify potential post-fire sediment delivery from each pixel on the landscape.

Surface Drinking Water

The surface drinking water HVRA represents the potential impacts of post-fire erosion and sediment delivery to drinking water reservoirs and diversions. The first step to understanding post-fire sedimentation impacts is mapping drinking water reservoirs and diversions throughout the landscape. We derived GIS data from JW Associates' zones of concern (JW Associates Inc., 2023a), which were developed in 2023 for the Upper Gunnison Watershed Wildfire Assessment (JW Associates Inc., 2023b). That reservoir and diversion spatial data was reviewed by the Gunnison water subgroup for completeness and accuracy. During that meeting, the water subgroup agreed on the following relative importance weighting scheme: infrastructure that is actively used for drinking water (1), infrastructure that is not actively used for drinking water, but could be used as augmentation or for in-county releases as needed (0.75), infrastructure that is not used for drinking water, but has major recreational uses (0.50), and infrastructure that is not used for drinking water or major recreational uses (0.25). The list of reservoirs and diversions included in this assessment and their associated relative importance is outlined below (Table C1). The relative importance values are used to down-weight sediment delivery to less critical infrastructure and ensure that a megagram (Mg) of sediment reaching infrastructure with a relative importance of 1 is more impactful than infrastructure with a relative importance of 0.25. Weighted sediment yield estimates were then rescaled to unitless cNVC values. 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 & Martin, 2001). Therefore, the pixel-level estimates of sediment delivery to water infrastructure were linearly rescaled so that 0 to 50 Mg ha-1 of sediment corresponds to 0 to -100 percent value change. The final cNVC is mapped in Figure C2.

Figure C2. Surface drinking water conditional net value change (cNVC).

Table C1. Relative importance (RI) of surface drinking water infrastructure as defined by local participants based on active and potential drinking water and recreational uses.

Infrastructure Name	Relative Importance
Marble diversion	1
Coal Creek	1
Wildcat Creek	1
Lake Grant	1
Meridian Lake Reservoir	1
Mt. Crested Butte Water & Sanitation Diversion	1
Lake Irwin	1
Lake City	1
Gunnison County Dos Rios	1
Taylor Park Reservoir	0.75
Lake San Cristobal	0.75
Long Lake	0.75
Blue Mesa Reservoir	0.5
Paonia Reservoir	0.25
Kenny Moore Reservoir	0.25
Spring Creek Reservoir	0.25
Hot Springs Reservoir	0.25
McDonough Reservoir	0.25
Dome Lakes	0.25
Vouga Reservoir	0.25
Needle Creek Reservoir	0.25
Sonderquist Reservoir	0.25

Remaining drinking water infrastructure, including aboveground pipelines, pump houses, storage tanks, water treatment plants, and wastewater treatment plants, is captured in the Infrastructure HVRA category as a separate water infrastructure HVRA (Table 2). GIS data came from Colorado Division of Public Health and Environment and Safe Drinking Water Information System databases, which were then supplemented with GIS data from local water providers including the Town of Crested Butte, Mt. Crested Butte Water and Sanitation District, Skyland Water District, City of Gunnison, Gunnison County Water and Sanitation District, Lake City Water and Sanitation, and Marble Water Company. The water infrastructure HVRA is meant to capture the direct, negative impacts of physical structures being lost in a fire. Indirect impacts of increased treatment costs associated with higher suspended sediment loads are captured in the surface drinking water HVRA described above.

Mines

The water subgroup also expressed concern for mines contaminating water resources given the long history of mining within Gunnison County. The group's primary concern was the potential for remobilization of mine tailings and subsequent delivery to surface waters due to post-fire runoff and erosion. We followed the same mine tailings procedure developed in the Lake County risk assessment (Rhea & Ritter, 2022). Gross hillslope erosion estimates represent the potential for surface transport around tailings features. Estimates of sediment delivery to streams then account for hillslope transport efficiency. For example, steep slopes near streams will efficiently transport most hillslope erosion to streams, unlike low relief hillslopes far away from streams. To start, the United States Geological Survey (USGS) historic mine dataset was filtered to only include mine tailings features (i.e., "mine dump" or "tailings" features). After local review of this dataset, we also included Standard Mine's superfund site and associated water treatment plant. Each tailings point was buffered by 400 meters. We then modeled potential post-fire increase in sediment delivery to streams within each buffer zone and linearly rescaled to cNVC values between 0 and -100. We felt that rescaling to a maximum of -100 was appropriate because this represents the pollution of all downstream water bodies with mine waste that is high in metals (e.g., Mg, Zn, Cd, Fe, etc) and could threaten human and aquatic health. Mine tailings cNVC is mapped in Figure C2.

Figure C3. Mine tailings conditional net value change (cNVC).

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Appendix D: Vegetation Management Assumptions

Table D1. List of species by existing vegetation type (EVT, LANDFIRE 2022), that are considered feasible for low-severity and high-severity prescribed fire and for patch cut. Pixel values of 1 indicate that the given EVT can receive that treatment (i.e., is feasible), while pixel values of 0 indicate that it is infeasible. Mechanical thin and mastication treatment feasibility was determined by minimum canopy cover thresholds, not EVT. Mechanical thin followed by prescribed fire feasibility is restricted to all vegetation types that are feasible for either low-severity or high-severity prescribed fire. Unlisted EVTs, including developed land, were infeasible for all treatment types.

EVT Value	EVT Name	Low Severity Prescribed Fire	High Severity Prescribed Fire	Patch Cut
7011	Rocky Mountain Aspen Forest and Woodland	1	0	1
7016	Colorado Plateau Pinyon-Juniper Woodland	1	0	0
7049	Rocky Mountain Foothill Limber Pine-Juniper Woodland	1	0	0
7050	Rocky Mountain Lodgepole Pine Forest	0	1	1
7051	Southern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	1	0	0
7052	Southern Rocky Mountain Mesic Montane Mixed Conifer Forest and Woodland	1	0	0
7054	Southern Rocky Mountain Ponderosa Pine Woodland	1	0	0
7055	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	0	1	1
7056	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland	0	1	1
7059	Southern Rocky Mountain Pinyon-Juniper Woodland	1	0	0
7061	Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	1	0	1
7086	Rocky Mountain Lower Montane-Foothill Shrubland	1	0	0
7107	Rocky Mountain Gambel Oak-Mixed Montane Shrubland	1	0	0
7117	Southern Rocky Mountain Ponderosa Pine Savanna	1	0	0
7132	Central Mixedgrass Prairie Grassland	1	0	0
7135	Inter-Mountain Basins Semi-Desert Grassland	1	0	0
7141	Northwestern Great Plains Mixedgrass Prairie	1	0	0
7146	Southern Rocky Mountain Montane-Subalpine Grassland	1	0	0
7147	Western Great Plains Foothill and Piedmont Grassland	1	0	0
7149	Western Great Plains Shortgrass Prairie	1	0	0
7150	Western Great Plains Tallgrass Prairie	1	0	0
7179	Northwestern Great Plains-Black Hills Ponderosa Pine Woodland and Savanna	1	0	0
7193	Recently Logged-Tree Cover	1	0	0
7195	Recently Burned-Herb and Grass Cover	1	0	0
7197	Recently Burned-Tree Cover	1	0	0
7200	Recently Disturbed Other-Tree Cover	1	0	0
7207	Central Mixedgrass Prairie Shrubland	1	0	0
7385	Great Plains Wooded Draw and Ravine Woodland	1	0	0
9019	Rocky Mountain Lower Montane-Foothill Riparian Woodland	1	0	0
9309	Great Basin & Intermountain Introduced Perennial Grassland and Forbland	1	0	0
9816	Northern & Central Plains Ruderal & Planted Grassland	1	0	0
9828	Interior Western North American Temperate Ruderal Grassland	1	0	0

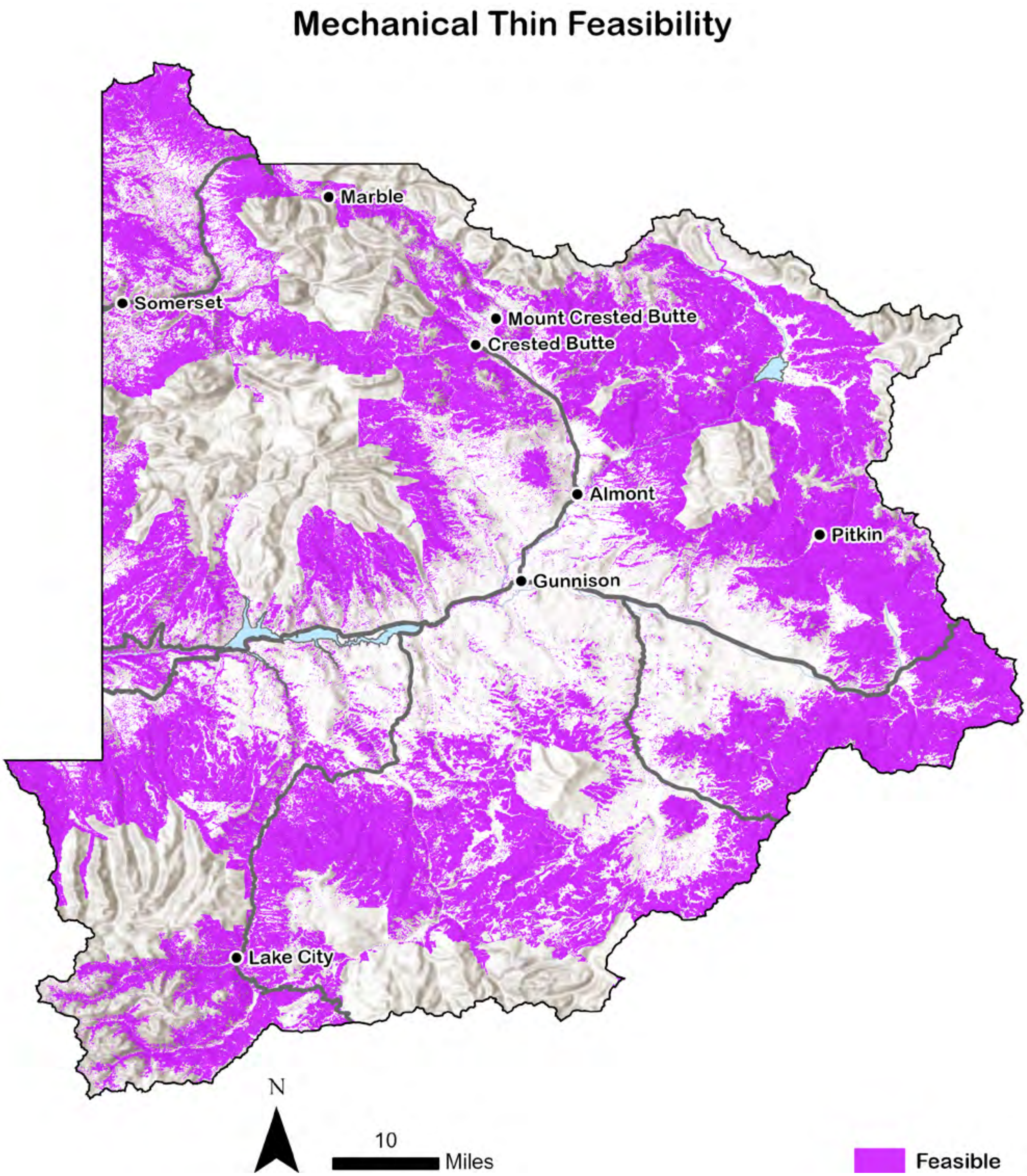

Figure D1. Feasibility of mechanical thin only treatment.

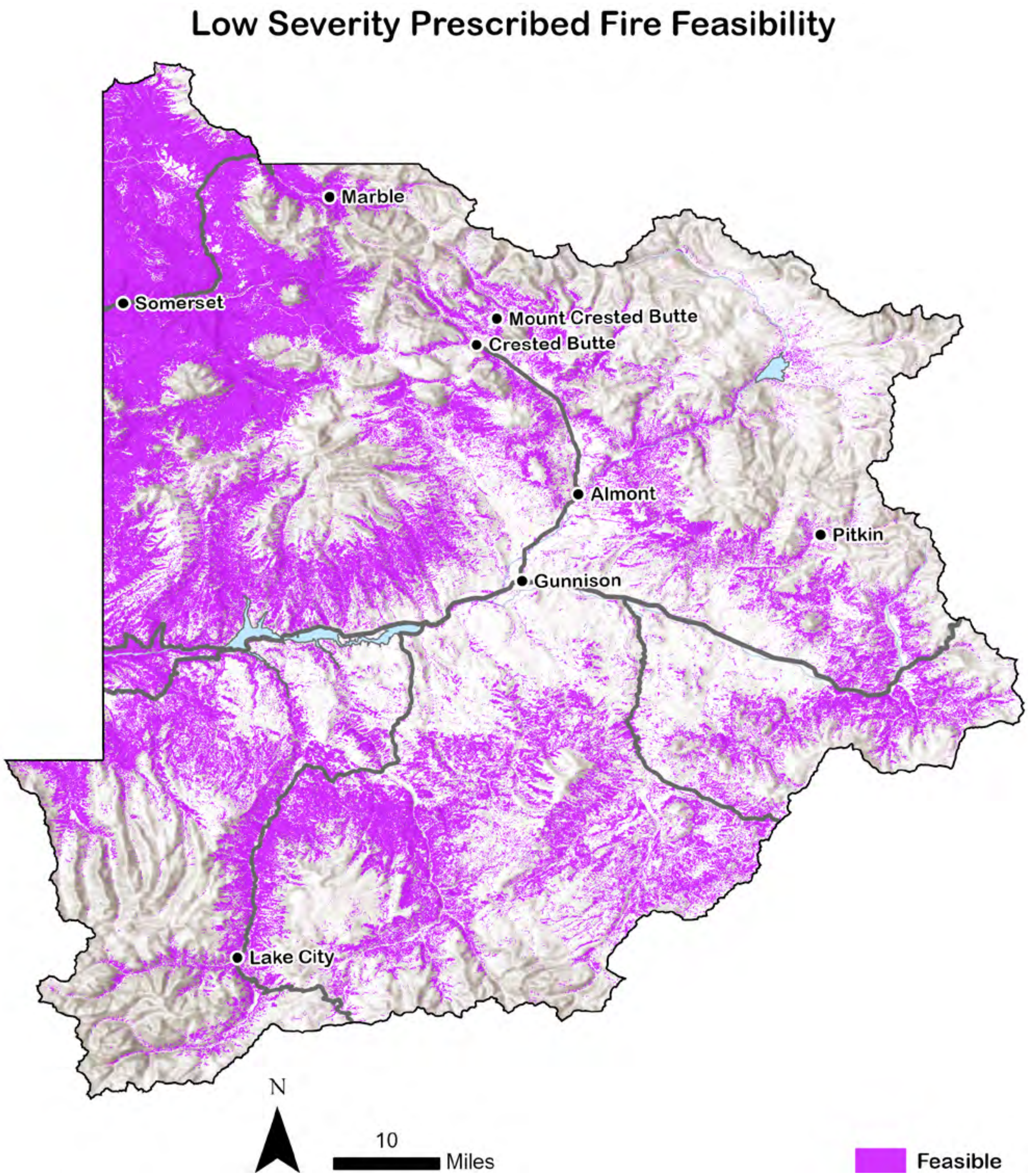

Figure D2. Feasibility of low severity prescribed fire treatment.

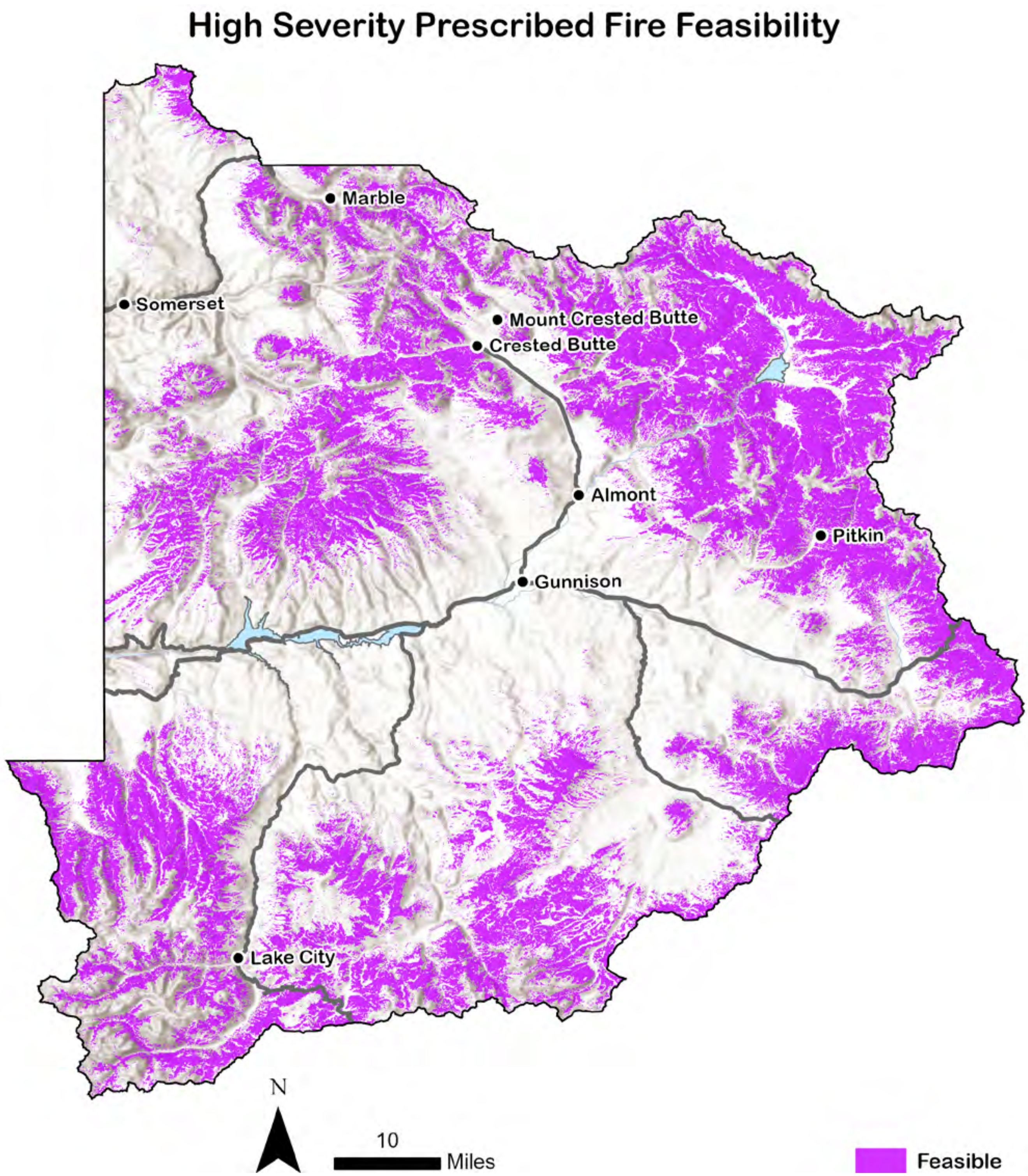

Figure D3. Feasibility of high severity prescribed fire treatment.

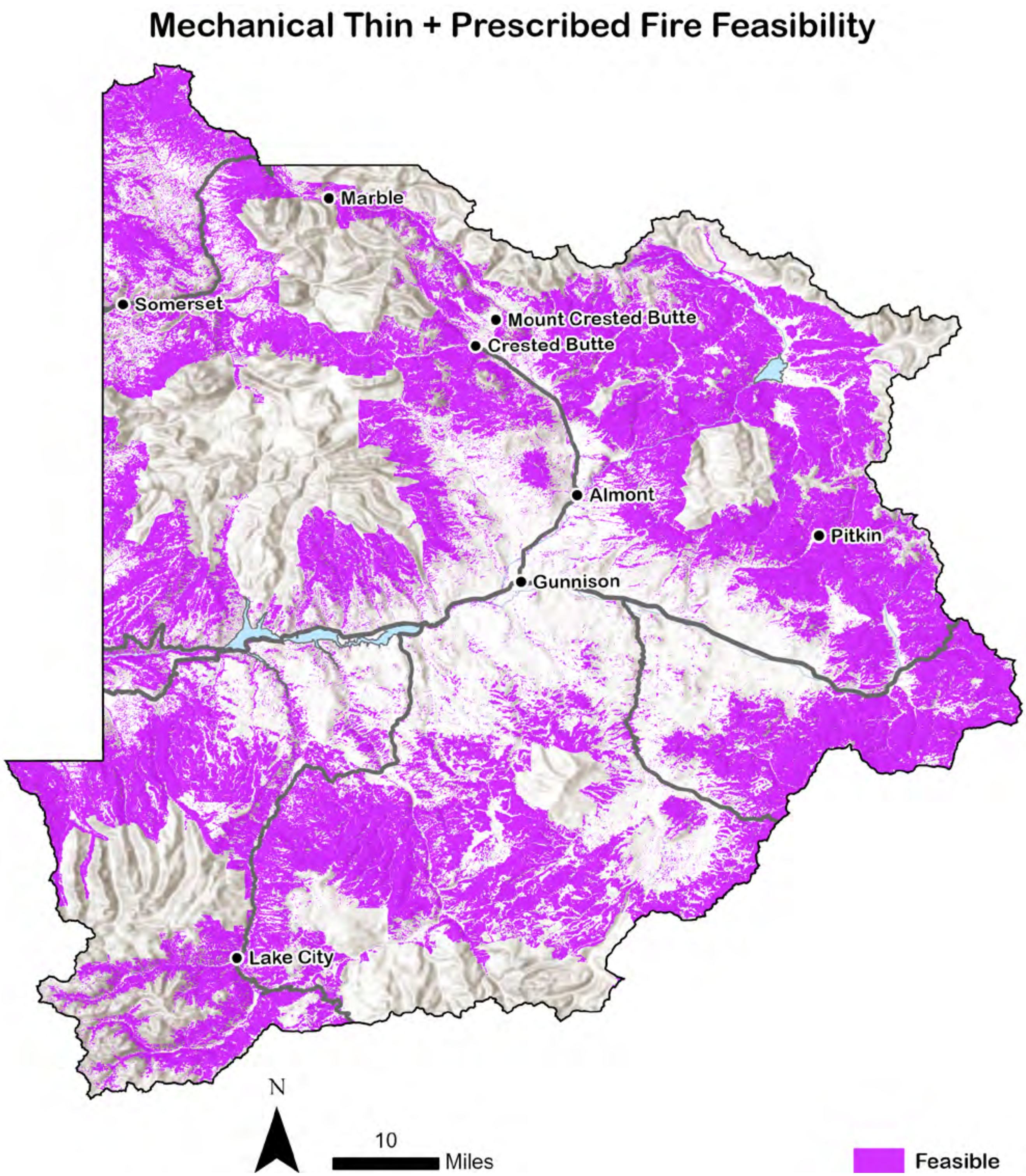

Figure D4. Feasibility of mechanical thin followed by prescribed fire treatment.

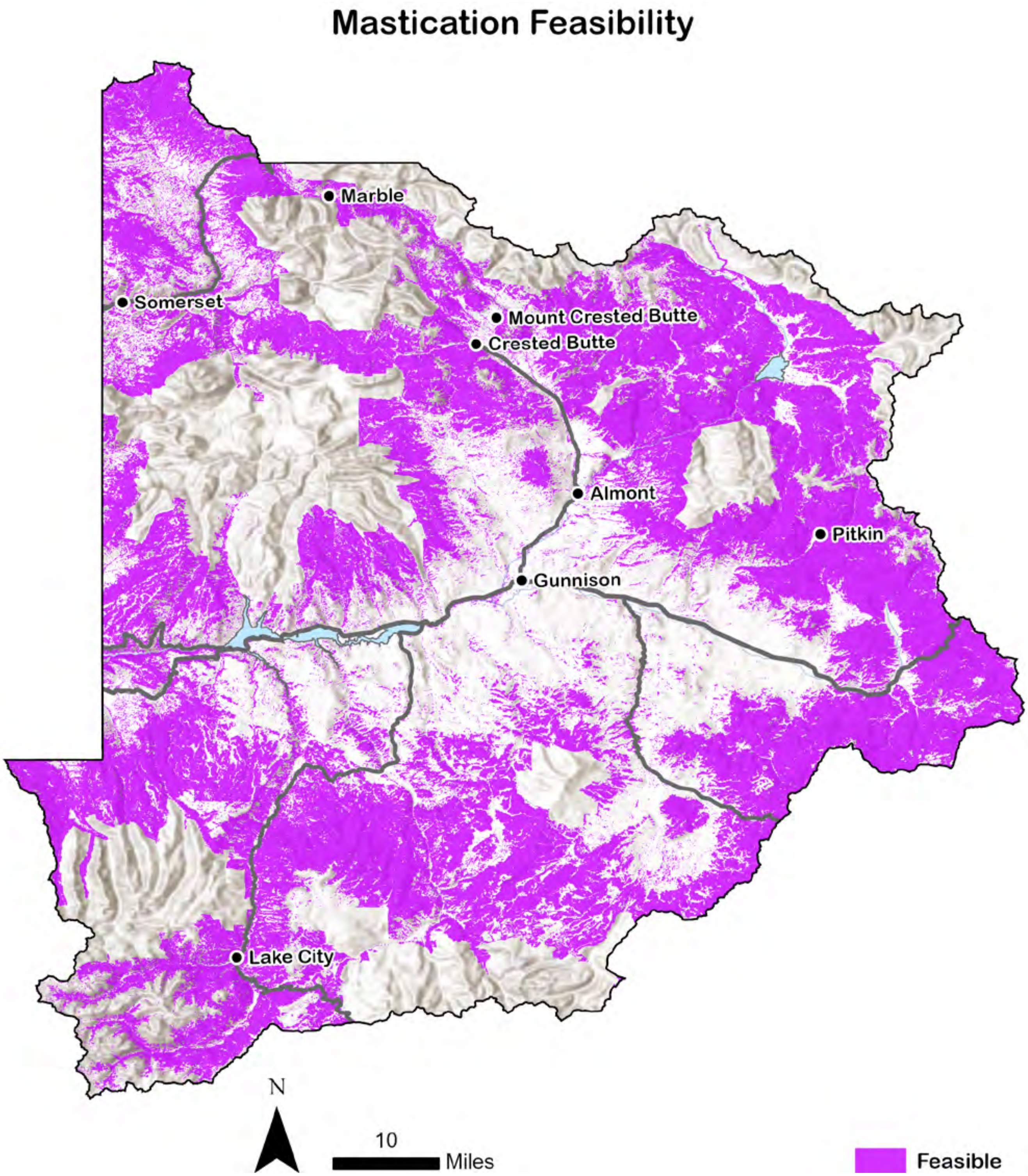

Figure D5. Feasibility of mastication treatment.

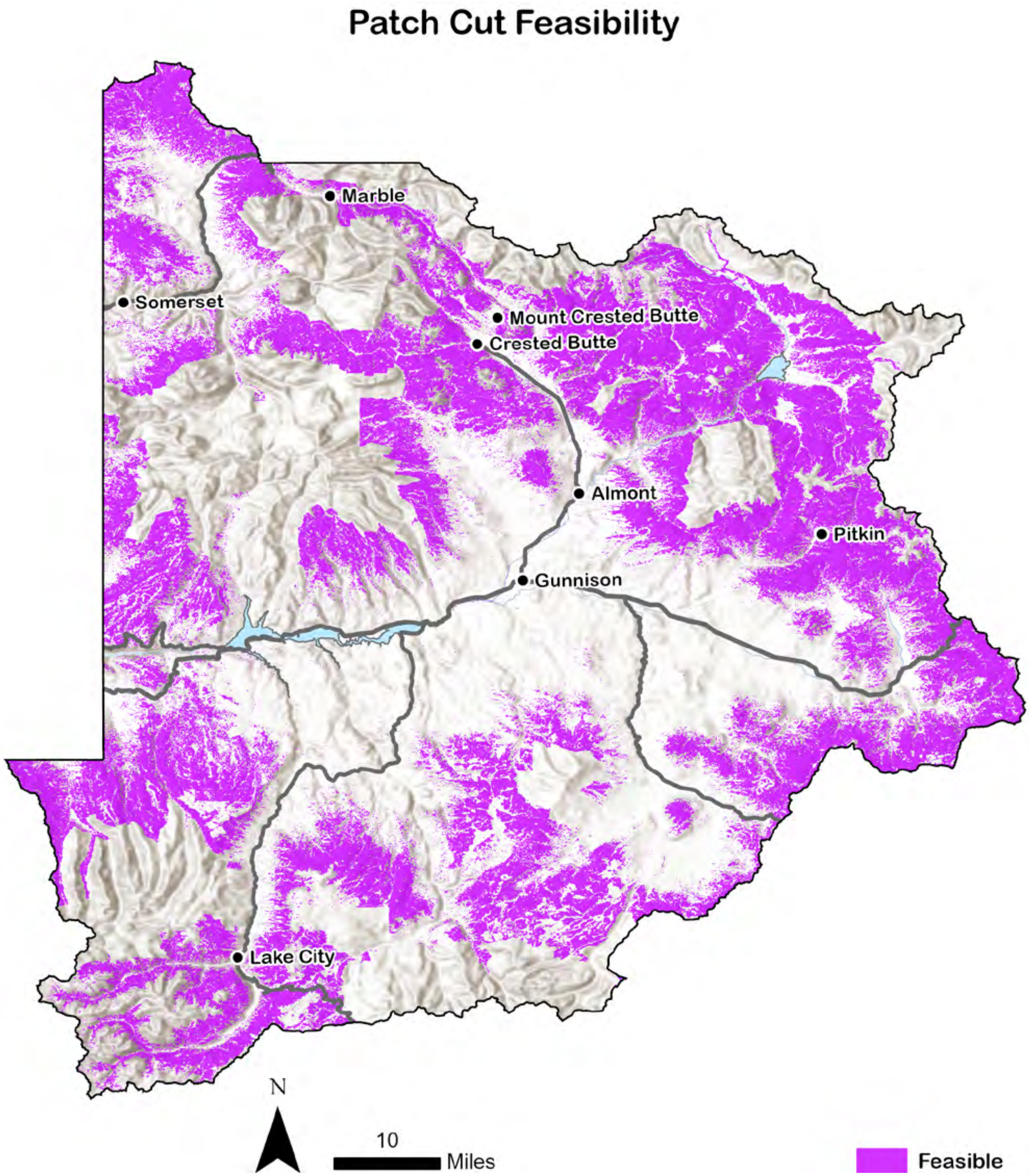

Figure D6. Feasibility of patch cut treatment.

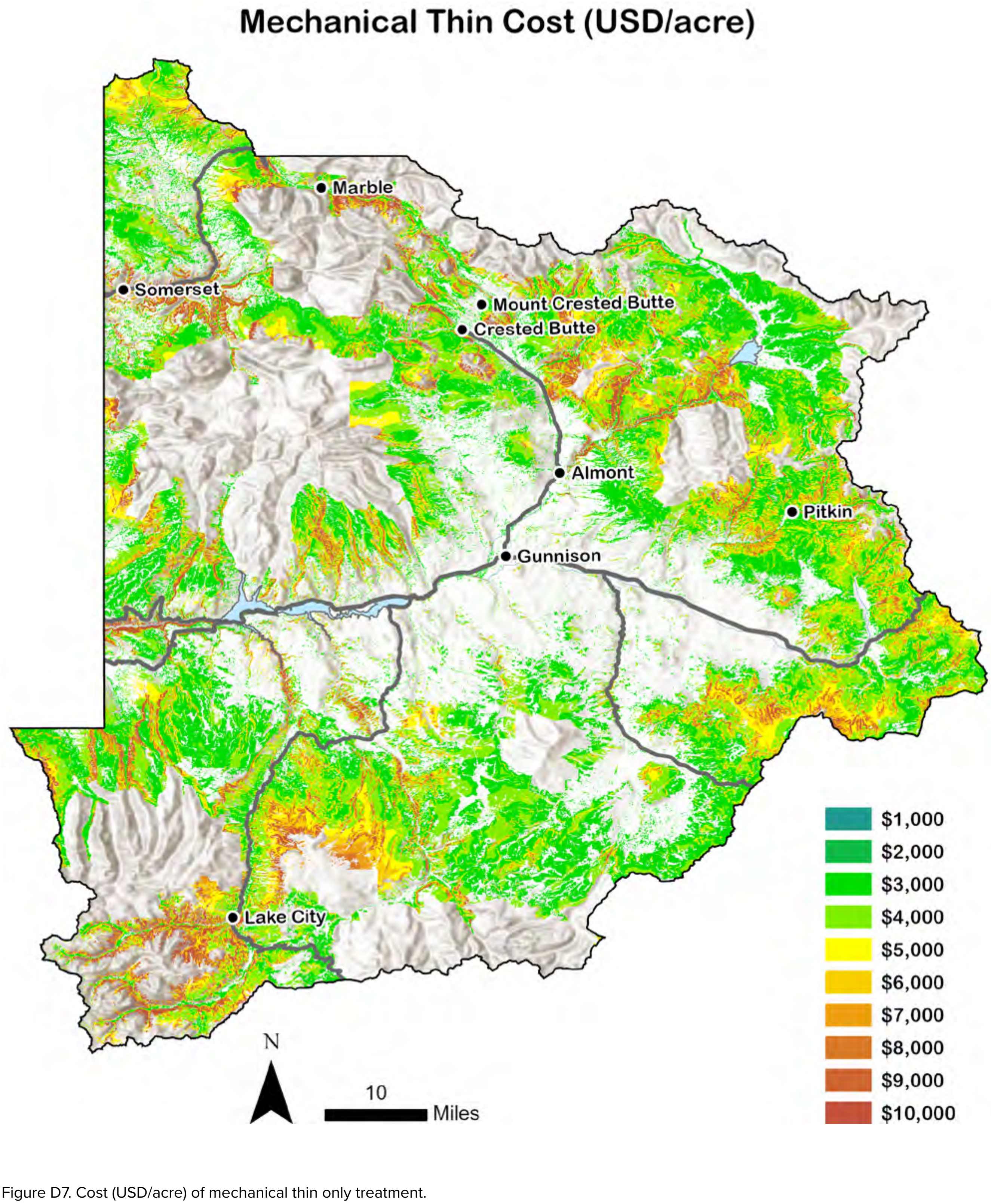

Figure D7. Cost (USD/acre) of mechanical thin only treatment.

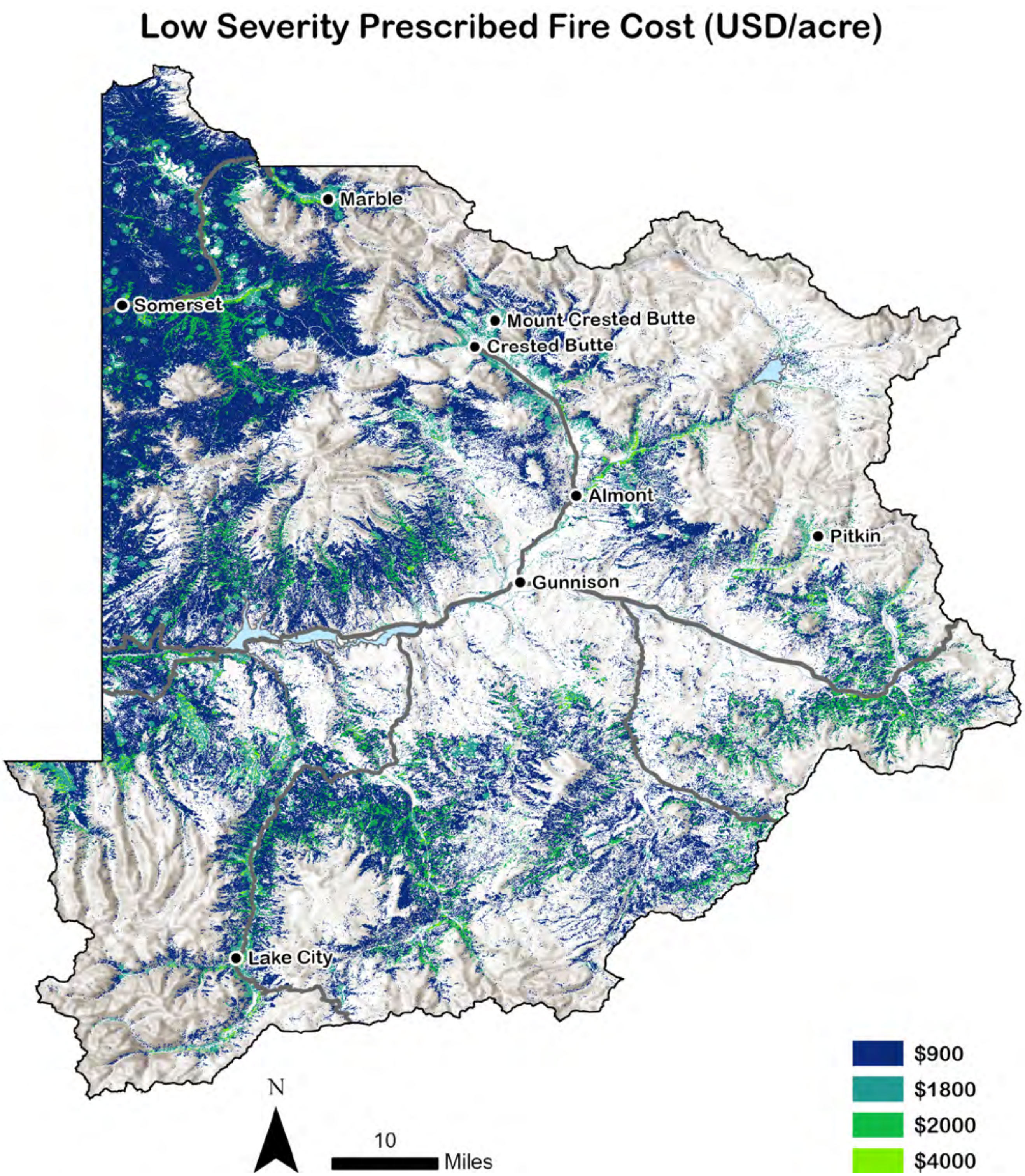

Figure D8. Cost (USD/acre) of low severity prescribed fire treatment.

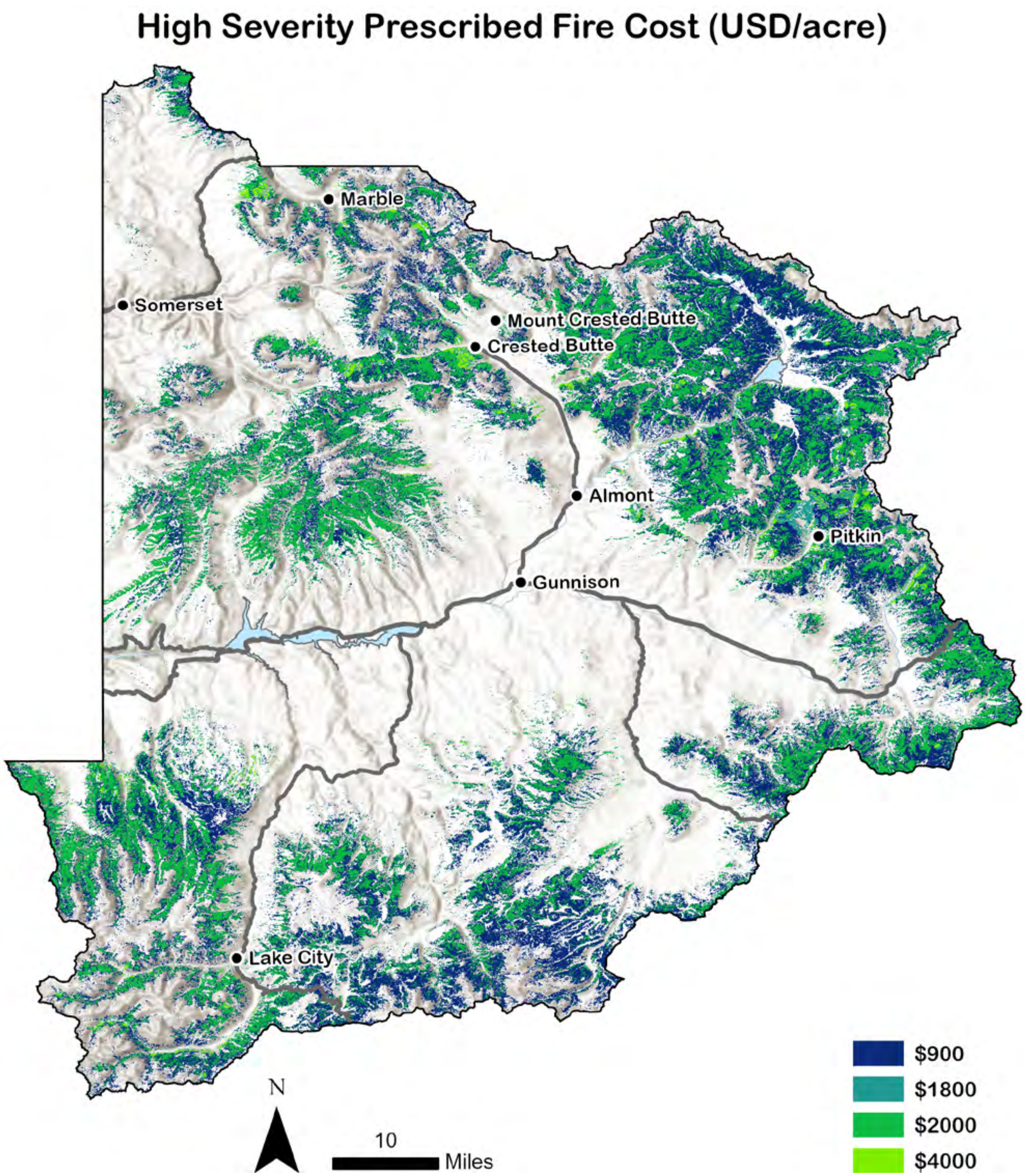

Figure D9. Cost (USD/acre) of high severity prescribed fire treatment.

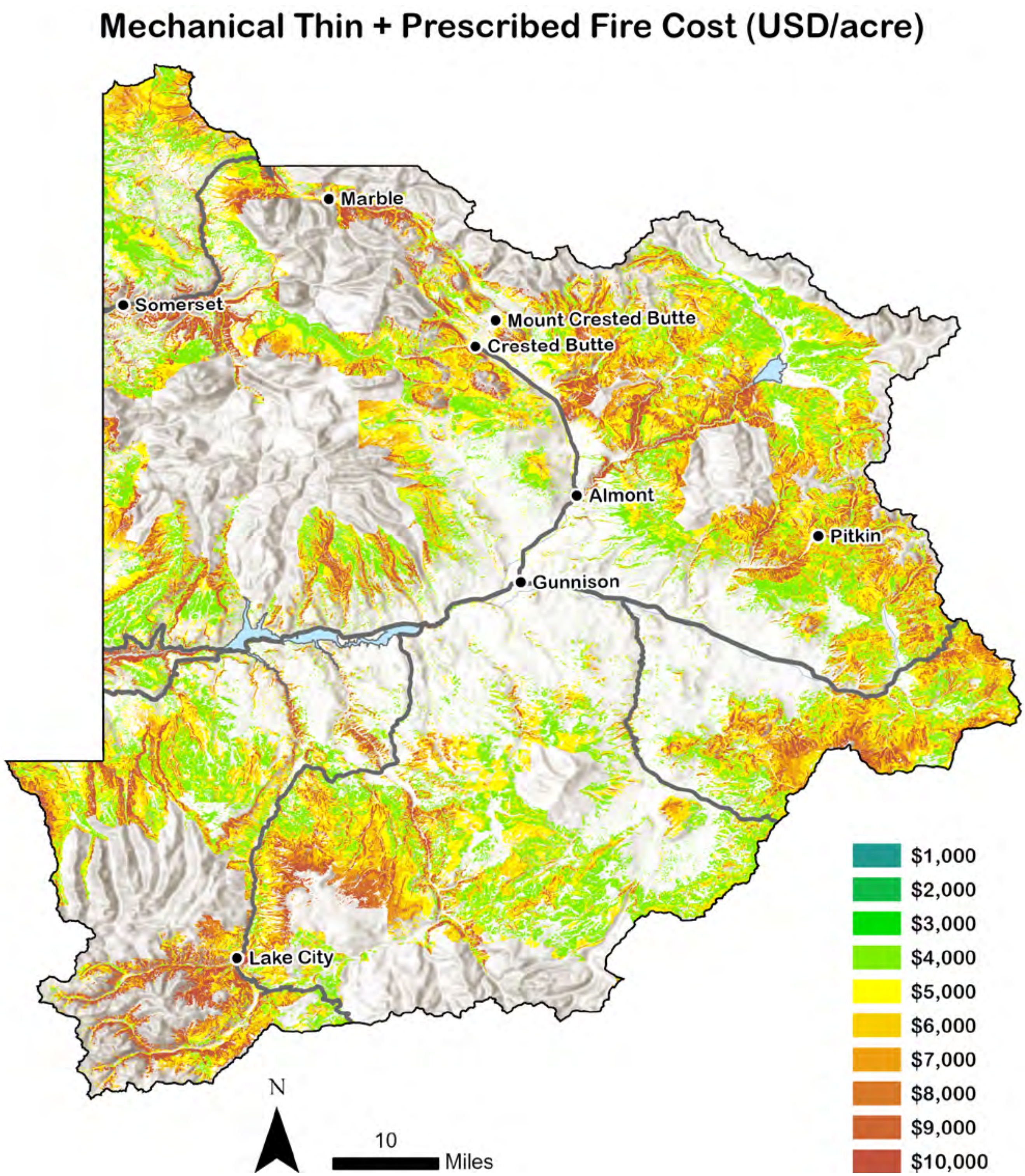

Figure D10. Cost (USD/acre) of mechanical thin followed by prescribed fire treatment.

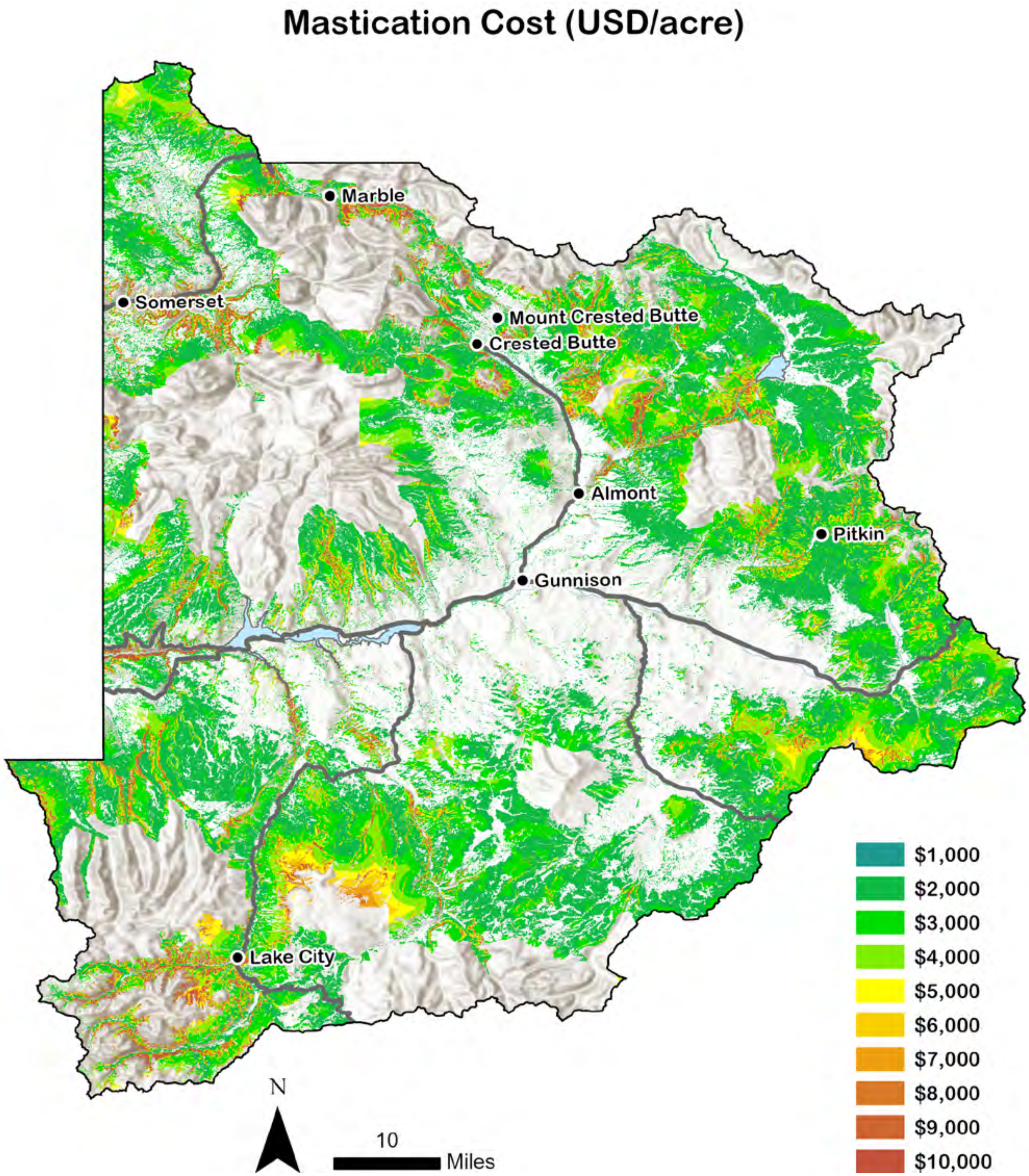

Figure D11. Cost (USD/acre) of mastication treatment.

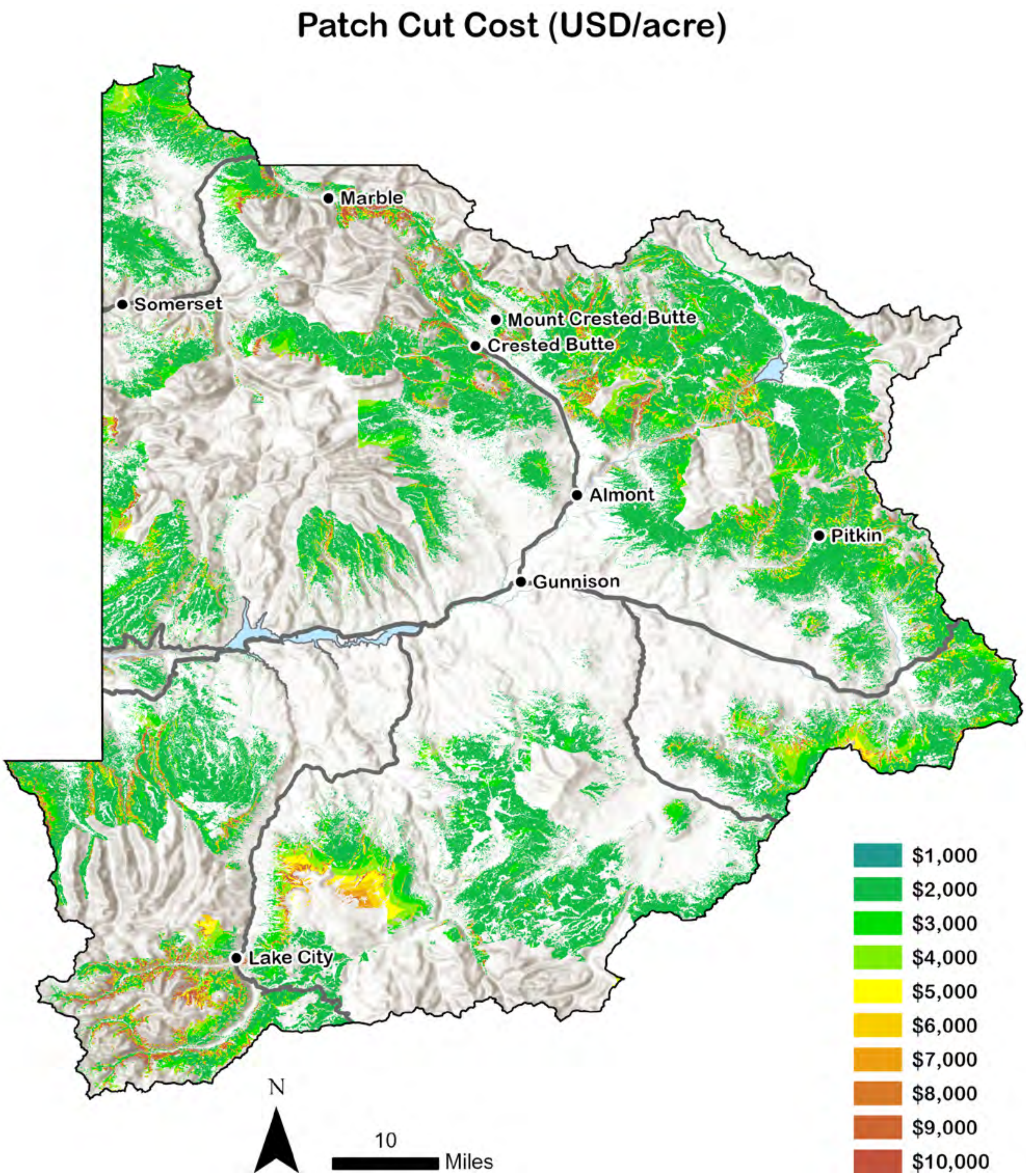

Figure D12. Cost (USD/acre) of patch cut treatment.

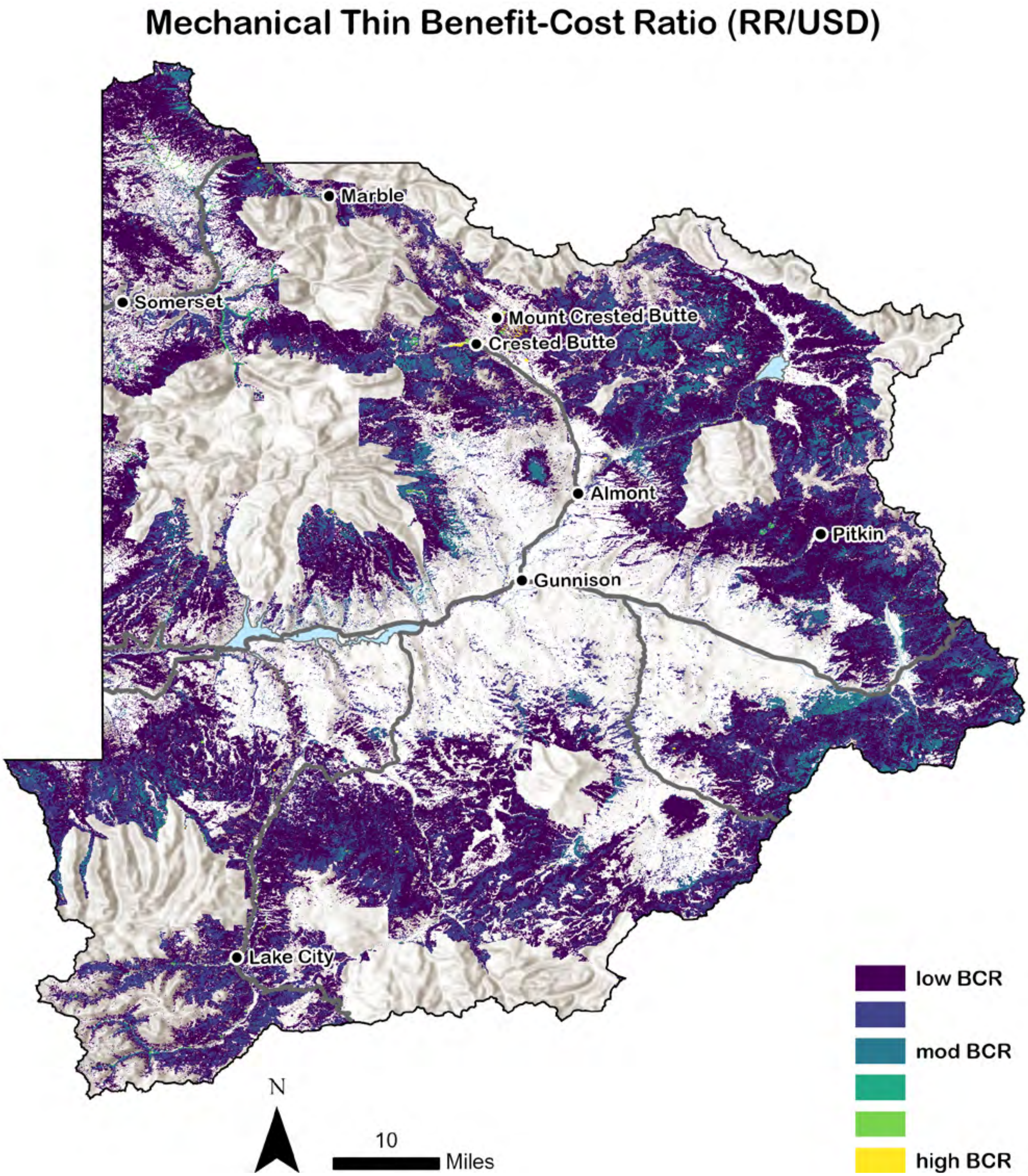

Figure D13. Benefit-cost ratio of the mechanical thin only treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

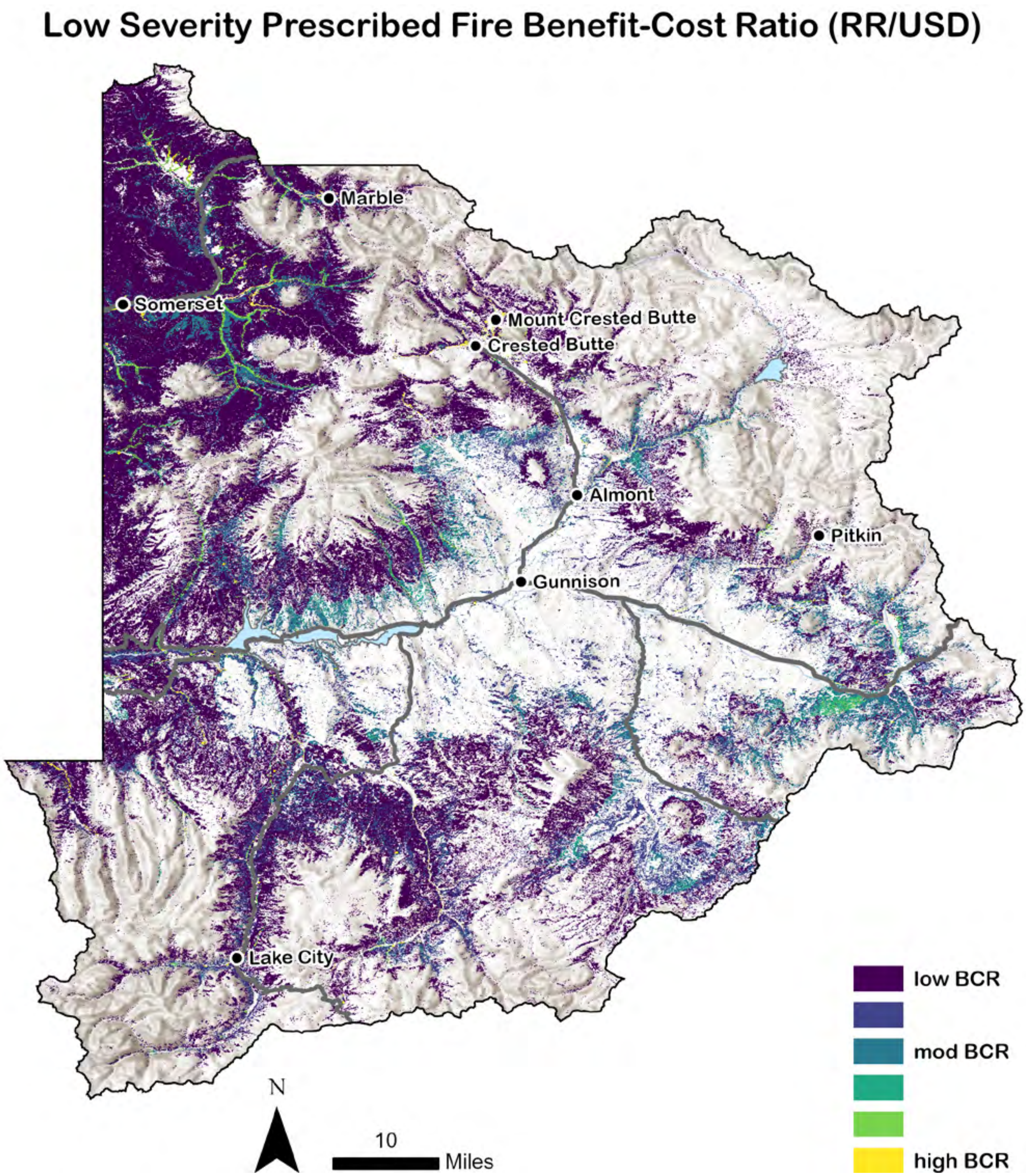

Figure D14. Benefit-cost ratio of the low severity prescribed fire treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

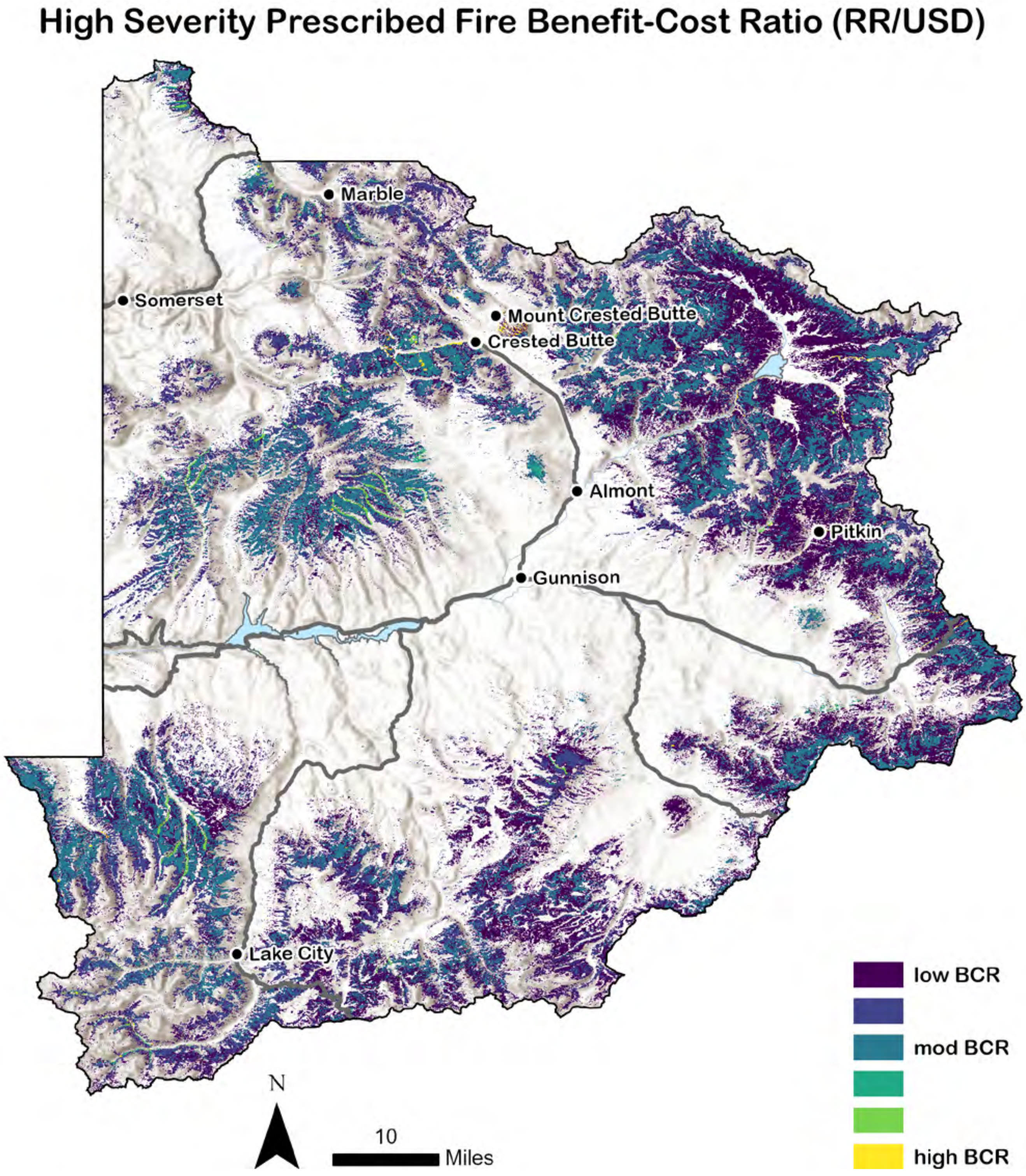

Figure D15. Benefit-cost ratio of the high severity prescribed fire treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

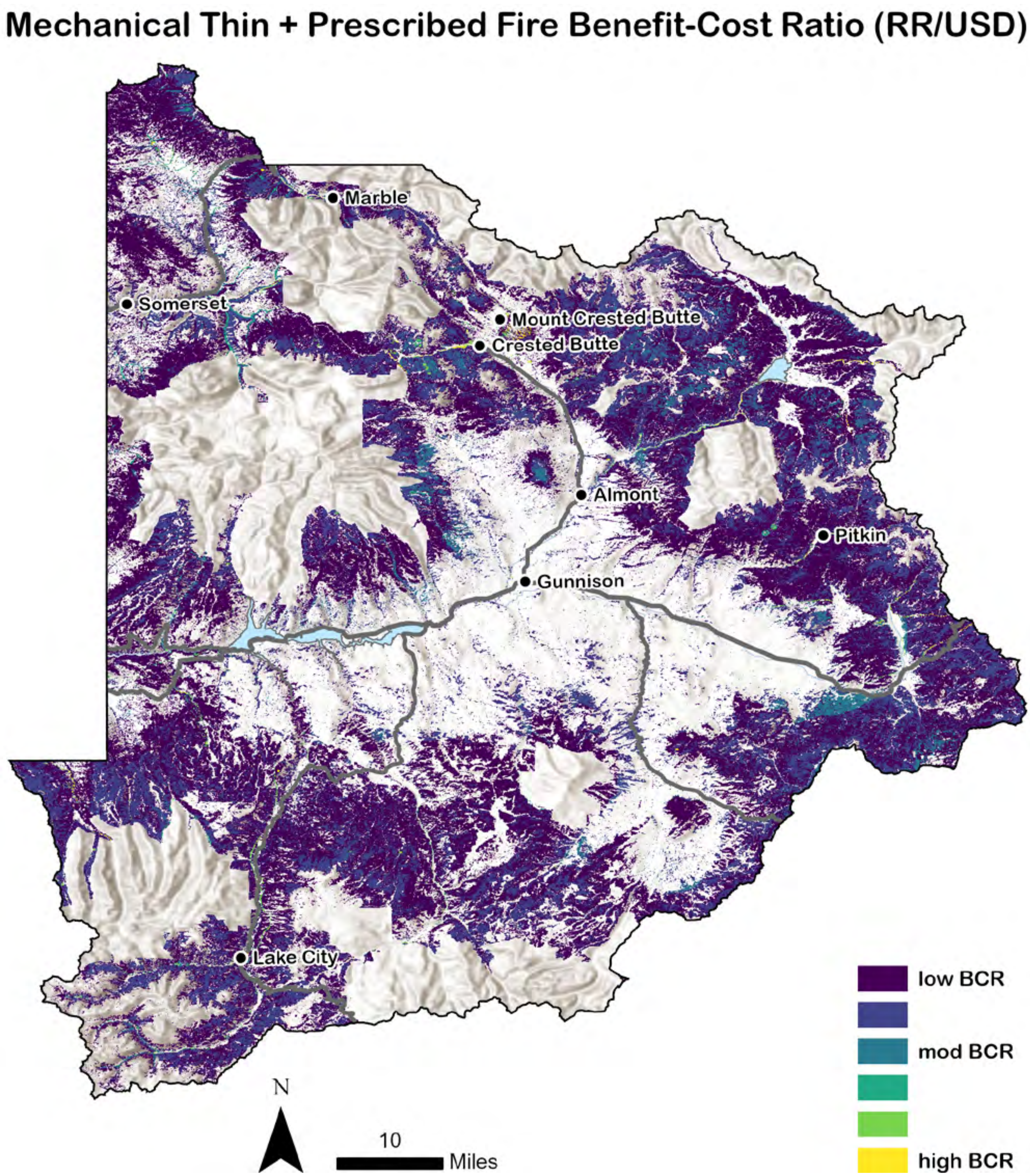

Figure D16. Benefit-cost ratio of the mechanical thin followed by prescribed fire treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

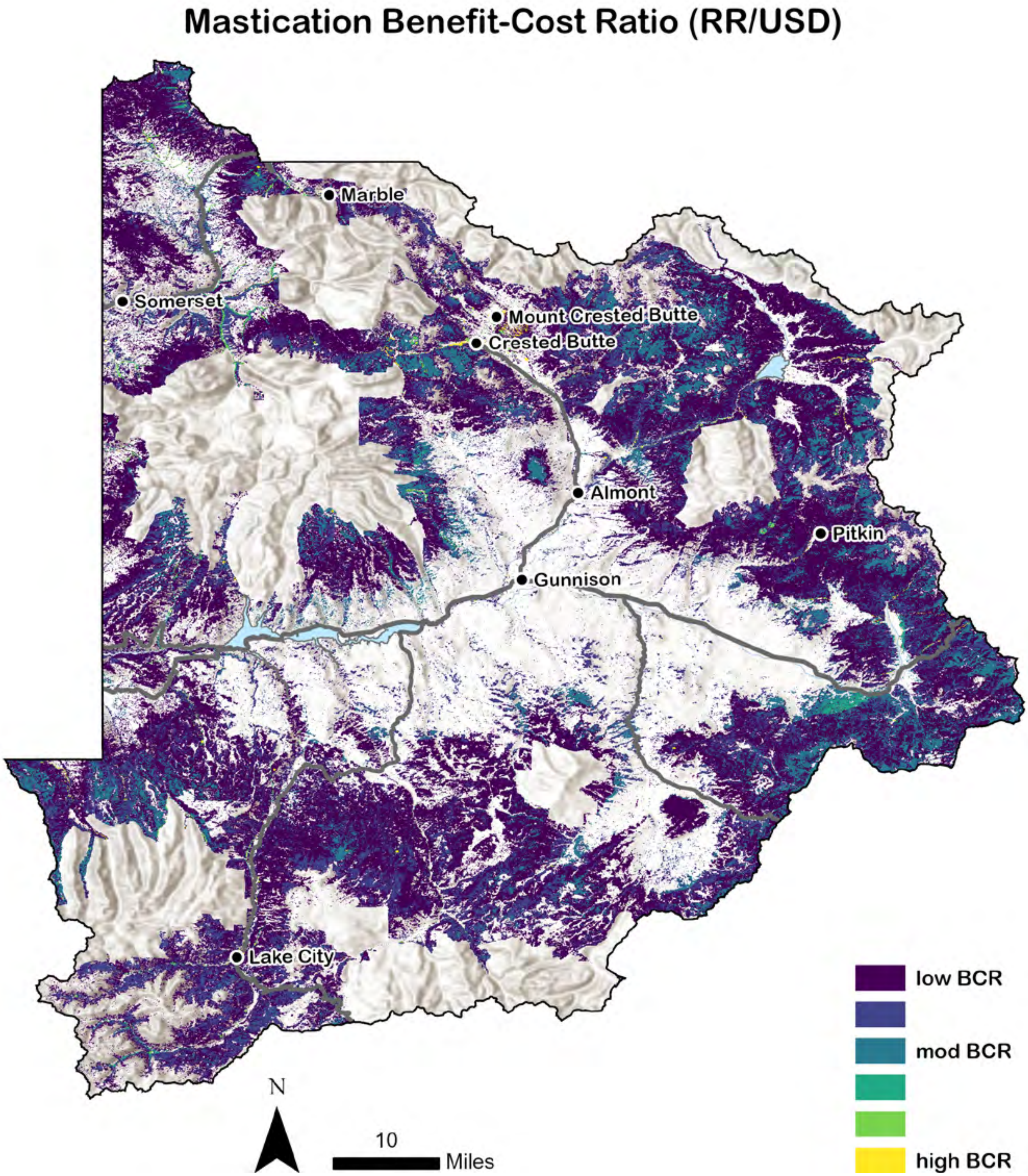

Figure D17. Benefit-cost ratio of the mastication treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

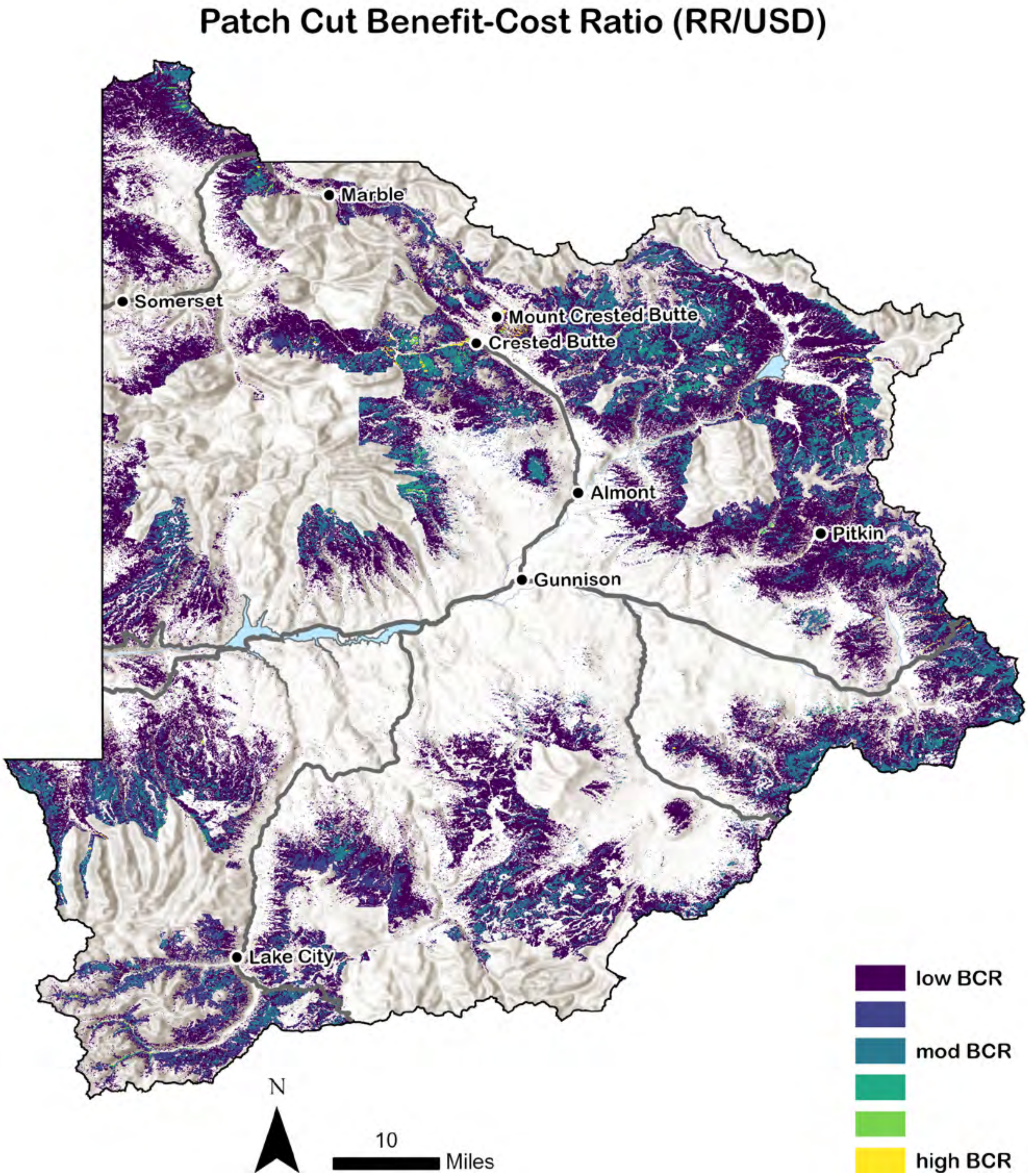

Figure D18. Benefit-cost ratio of the patch cut treatment. BCR is measured as RR, or risk reduction (baseline eNVC - treated eNVC), per dollar spent within feasible treatment areas.

Appendix E: Linear Optimization Model Formulation

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

Constraints:

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

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

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

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

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

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:

$x_{i,t}$ is the area (in acres, or ac) of treatment t assigned to treatment unit i

Parameters:

Z is the total risk reduction (unitless)

$RR_{i,t}$ is the risk reduction per acre of treatment t applied to treatment unit i

$F_{i,t}$ is the feasible area (ac) for treatment t in treatment unit i

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

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

Budget is the funding available for fuel treatment ($)

BP_t 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.