Lake County Wildfire Risk Assessment

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CSU Land Acknowledgment: Colorado State University acknowledges, with respect, that the land we are on today is the traditional and ancestral homelands of the Arapaho, Cheyenne, and Ute Nations and peoples. This was also a site of trade, gathering, and healing for numerous other Native tribes. We recognize the Indigenous peoples as original stewards of this land and all the relatives within it. As these words of acknowledgment are spoken and heard, the ties Nations have to their traditional homelands are renewed and reaffirmed. CSU is founded as a land-grant institution, and we accept that our mission must encompass access to education and inclusion. And, significantly, that our founding came at a dire cost to Native Nations and peoples whose land this University was built upon. This acknowledgment is the education and inclusion we must practice in recognizing our institutional history, responsibility, and commitment.

Document Development: This technical report was developed using the collaborative Risk Assessment and Decision Support (RADS) framework developed by CFRI based on the Scott et al (2013) risk assessment process. Our aim was to help apply the latest science within local decision-making context to empower science-informed, actionable knowledge. We received critical input from the Lake County Forest Health Council as well as a smaller team of technical experts and local leadership composed of staff from Lake County government including a County Commissioner, Office of Emergency Management, and Fire Chief, US Forest Service Leadville District Ranger, the Friends of Twin Lakes President, Envision Chaffee County co-lead, and Smoyer and Associates facilitation. The tech and leads team met bi-weekly throughout the year-long planning process to incorporate feedback from the larger Forest Health Council and provide input on key decisions. This report documents the collaborative decision-making process, technical details, and final products of the Lake County Wildfire Risk Assessment to inform the Lake County Community Wildfire Protection Plan.

Acknowledgements: First, we would like to extend sincere thanks to Benjamin Gannon and Brett Wolk for technical model development and creating the template of the collaborative RADS process. Allie Rhea and Scott Ritter conducted the technical modeling and wrote the technical report. Brett Wolk and Stephanie Mueller mentored both Allie and Scott in the analysis methods, were critical participants throughout the stakeholder engagement process, and provided helpful edits to both technical reports. Jackie Edinger supported the data collection, modeling, and community meeting. Document editing and layout by Angela Hollingsworth. We thank Kim Smoyer and Cindy Williams for expert facilitation which kept the process fun and productive, and the Lake County Forest Health Council for thoughtful engagement in input.

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Purpose and Scope

The purpose of this wildfire risk assessment is to inform a revision of the Lake County Community Wildfire Protection Plan (CWPP). The major focus of the risk assessment is incorporating local spatial data on highly valued resources and assets (HVRAs), expertise on HRVA response to wildfire, and relative importance values to create a science informed, locally relevant risk assessment for Lake County.

Methods

Risk is a term widely used in economics, engineering, and emergency management to describe the expected impact of an event with uncertain occurrence and magnitude. Risk is an expected measure because it 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 typical multi-decade planning periods used in land and resource management. A wildfire risk assessment quantifies and maps expected net value change for a suite of HVRAs by combining spatial information on fire likelihood, fire intensity, and resource exposure and effects, which form the three legs of the wildfire risk triangle (Figure 1; Scott et al. 2013).

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

Wildfire risk assessment requires extensive data and modeling to characterize the three legs of the risk triangle. Spatial wildfire simulation is used to estimate how wildfire likelihood and intensity vary across large landscapes based on fuels, topography, ignition sources, and climate. The intent of this modeling is not to describe the behavior of a specific future wildfire, but rather the trends in fire occurrence and intensity over many potential future fire seasons. Wildfire consequences are captured with exposure and effects analyses that relate wildfire likelihood and intensity to HVRA expected Net Value Change (eNVC; Finney 2005). This requires consulting with local resource experts to map HVRAs, so a Geographic Information System (GIS) can be used to quantify how HVRAs will respond to fire of varying intensity. Finally, local input on the relative importance of HVRAs to community well-being are applied as weights to quantify and map a composite risk measure. The following sections describe the mechanics of the Lake County Risk Assessment.

Risk Assessment Framework

The Lake County Risk Assessment applied the assessment framework from the Colorado Wildfire Risk Assessment (CO-WRA; Technosylva 2018) to locally informed fire simulation products, HVRA spatial data and response functions, and relative importance weights (Figure 2). Fire behavior metrics, including flame lengths and crown fire activity were modeled in FlamMap 5 (Finney et al. 2015) for low, moderate, high, and extreme fire weather scenarios. Fire likelihood was quantified in FSim (Finney et al. 2011). Fire behavior outputs were combined with local data on HVRA extent and stakeholder-informed response functions to calculate conditional Net Value Change (cNVC) for each HVRA and fire weather scenario. The 4 cNVC scenarios for each HVRA were combined with a weighted averaging that favored the high and extreme scenarios (Technosylva 2018). Lastly, the cNVC measures for each HVRA were combined with burn probability and relative importance weights to compute a composite eNVC ("risk") map for Lake County.

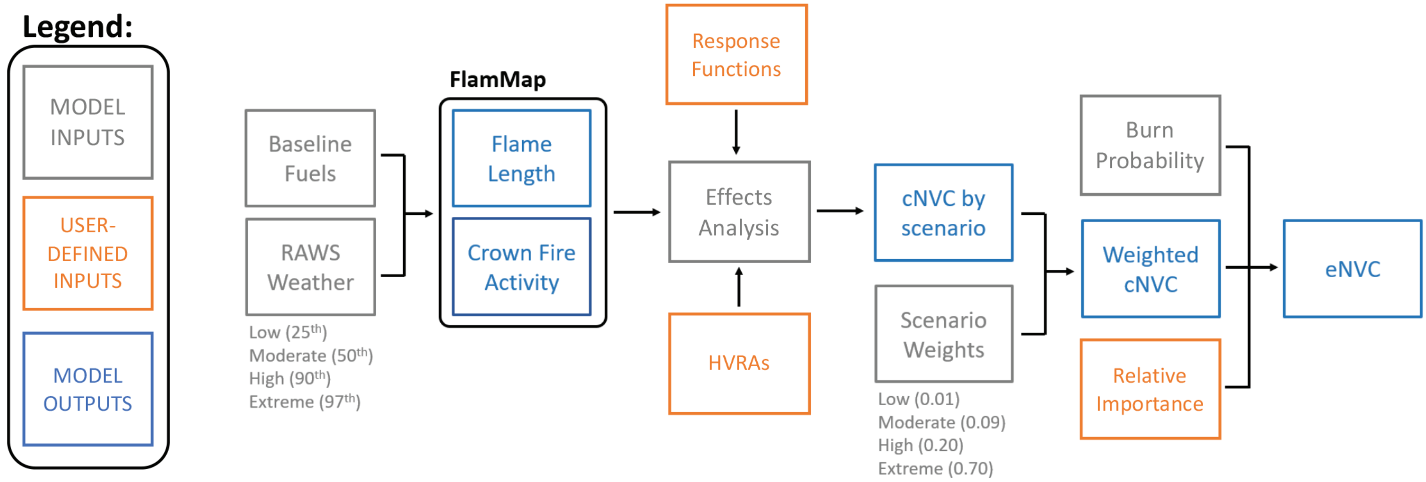

Figure 2: The Lake County Risk Assessment is based on the analysis framework from the Colorado Wildfire Risk Assessment (Technosylva 2018).

Fire Behavior Modeling

Two fire behavior metrics - flame length and crown fire activity - were modeled for low, moderate, high, and extreme fire weather scenarios using the FlamMap 5 spatial fire modeling system (Finney et al. 2015). Flame length is frequently used in wildfire risk assessment as an index of fireline intensity (rate of energy release from the fire front) because it is easily interpreted by non-fire resource specialists. Flame length and fireline intensity are directly related (Byram 1959). Crown fire activity was used as a proxy for soil burn severity as described in Gannon et al. (2019) to model post-fire watershed impacts. FlamMap requires fuels, topography, and weather information. Fuels were described with a combination of canopy and surface fuel attributes from LANDFIRE (2016). Canopy fuels were updated to reflect recent fuel treatments based on CFRI's inter-agency treatments database (Mueller and Caggiano, 2022) and verification with local professionals to ensure recent treatments were captured. Slope steepness, slope aspect, and elevation came from LANDFIRE (2016). Fire weather scenarios were developed from historical (2000-2019) Remote Automated Weather Station (RAWS) data from six stations near Lake County (Jones Hill, Lodgepole Plats, Red Deer, Soda Creek, and Taylor Park). Percent fuel moisture was computed for each category of dead and live fuels during a fire season defined as April 01 to October 31 using FireFamilyPlus 5 (Bradshaw and McCormick 2000). The 10-minute average RAWS wind speeds were converted to 1-minute average wind speeds for modeling (Crosby and Chandler 1966). The fire weather scenarios are described in Table 1. In FlamMap, wind direction was assumed to be upslope to represent a consistent worst-case scenario across aspects. The Scott and Reinhardt (2001) method was used for predicting crown fire activity. The flame length and crown fire activity predictions are available in Appendix I - Fire Behavior Products.

Table 1: Fire weather scenarios used for the risk assessment.

Fuel Moisture (%)							
Scenario	Percentile	1-hr	10-hr	100-hr	Herbaceous	Woody	Wind Speed 1-min (mph @ 20 ft)
Low	25	8	9	15	62	98	9
Moderate	50	5	6	11	32	70	11
High	90	2	3	7	3	64	16
Extreme	97	2	3	6	2	64	19

Burn Probability Modeling

We considered several burn probability options, but ultimately local fire specialists and the technical team decided to use a locally calibrated burn probability product from the large fire simulator (FSim, Finney et al., 2011). FSim uses a Monte Carlo simulation approach to represent 1,000s-10,000s years of fire activity by linking models for fire weather, ignitions, growth, and suppression. This spatial estimate of burn probability predicts more fire activity in mid- to high-elevation forests and less fire activity in the low-elevation woodland and non-forest vegetation types compared to existing products such as CO-WRA (Technoslyva 2018) and National FSim (Short et al. 2016). This matched local experiences and expectations of fire occurrence in Lake County. The data sources, methods, and limitations of all burn probability approaches are described in Appendix II – Burn Probability Products.

Exposure and Effects Assessment

Local stakeholders including land, fire, water, and wildlife managers identified data sources to represent HVRAs related to human life safety, critical infrastructure, water supply, buildings, wildlife, and recreation concerns in Lake County (Table 2). Spatial data were assembled in a geodatabase and re-projected to a common coordinate system for analysis.

Table 2: HVRAs included in the risk assessment by category. The spatial data type, buffer distance used to define an influence zone for wildfire around the HVRA, and the HVRA relative importance (%) to the category are specified.

Category	HVRA	Type	Influence zone (m)	Rel. Imp. (%)
Life safety	Evacuation Routes	Polygon	400	75
	Major Highways	Polyline	200	25
Water	Ditches	Polyline	200	10
	Water conveyance	Polyline	200	10
	Water Treatment Facilities	Point	200	30
	Critical Water Supplies	Raster	0	40
	Mine Tailings	Raster	0	10
Infrastructure	Communications Structures	Point	200	35
	Electrical Transmission Lines	Polyline	100	25
	Emergency Service Stations	Raster	50	15
	Substations	Point	200	25
Wildlife	Elk Habitat	Polygon	0	15
	Bighorn Sheep Winter Range	Polygon	0	15
	Mule Deer Habitat	Polygon	0	15
	Lynx Habitat	Polygon	0	15
	Tier 1 Critical Habitat	Polygon	50	20
	Aquatic Habitat	Raster	0	10
	Wetlands	Polygon	200	10
Buildings	Structures	Polygon	100	90
	Historic Structures	Raster	10	10
Recreation	Ski Cooper	Polygon	200	30
	Trails	Polyline	200	25
	Camping	Point	200	25
	Dispersed Camping	Raster	200	10
	Recreation Assets	Point	200	10

A workshop was held on July 7, 2021 to collect input from local resource experts on HVRA response to fire by intensity level (Table 3). Relative HVRA response was quantified on a scale from -100 for total loss to +100 for radical gain to allow both negative and beneficial effects of fire. The response of water related HVRAs (i.e., critical water supplies, mine tailings, and aquatic habitat) were quantified with a separate process described in Appendix III – Water Related Conditional Net Value Change (cNVC).

Table 3: Relative response functions ranging from -100 to +100 were defined through a collaborative process using stakeholder input. HVRAs with NA were quantified using post-fire watershed modeling described in Appendix III – Water related Conditional Net Value Change (cNVC).

Category	HVRA	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	Evacuation Routes	-20	-40	-80	-100	-100	-100
	Major Highways	-10	-30	-60	-80	-100	-100
Water	Ditches	0	-20	-50	-80	-100	-100
	Water conveyance	0	-20	-50	-80	-100	-100
	Water Treatment Facilities	-10	-20	-40	-100	-100	-100
	Critical Water Supplies	NA	NA	NA	NA	NA	NA
	Mine Tailings	NA	NA	NA	NA	NA	NA
Infrastructure	Communications Structures	-10	-10	-20	-30	-100	-100
	Electrical Transmission Lines	-10	-10	-20	-30	-40	-40
	Emergency Service Stations	-10	-30	-60	-80	-100	-100
	Substations	-10	-10	-20	-30	-40	-40
Wildlife	Elk Habitat	40	20	10	-10	-60	-80
	Bighorn Sheep Winter Range	40	20	10	-10	-60	-80
	Mule Deer Habitat	40	20	10	-10	-60	-80
	Lynx Habitat	0	-10	-20	-40	-80	-100
	Tier 1 Critical Habitat	-10	-20	-40	-60	-80	-100
	Aquatic Habitat	NA	NA	NA	NA	NA	NA
	Wetlands	40	20	10	-10	-60	-80
Buildings	Structures	-20	-40	-80	-100	-100	-100
	Historic Structures	-10	-30	-60	-80	-100	-100
Recreation	Ski Cooper	0	-10	-10	-20	-75	-100
	Trails	10	0	-10	-30	-40	-50
	Camping	10	0	-10	-30	-40	-50
	Dispersed Camping	10	0	-10	-30	-40	-50
	Recreation Assets	10	-10	-10	-20	-50	-70

cNVC rasters were developed for each HVRA by applying the response function to the predicted fire behavior within each HVRA's extent. This was done first by fire weather scenario and then scenarios were combined into a single cNVC raster per HVRA with weighted averaging (Figure 2). We used the same scenario weighting scheme as CO-WRA (Technosylva 2018), which reflects that the most area is expected to burn under high and extreme fire weather scenarios (Table 4), consistent with recent wildfire activity in Colorado (Graham et al. 2003; Haas et al. 2015).

Table 4: Probabilities for weighting cNVC calculated for each fire weather scenario.

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

Relative Importance Weights

Relative importance weights were defined at two levels. For each HVRA, a relative importance weight was assigned to reflect its proportional contribution to an HVRA category (Table 5). These were assigned by resource experts through small group discussions and full group critique. The relative importance of HVRA categories to Lake County was informed by the Lake County Community Wildfire & Recreation Survey, which identified human life safety is the top concern followed by critical infrastructure, water, wildlife habitat, buildings, and recreation. Category relative importance weights were assigned based on an interpolated ranking from the community survey. These relative importance weights were then used to weight the contribution of each HVRA category to the composite risk map.

Table 5: Relative importance weights used for combining HVRA categories into a composite risk map.

Category	Rel. Imp.	Share of total (%)
Life safety	120	24.2
Infrastructure	103	20.8
Water	89	17.9
Wildlife	79	15.9
Buildings	65	13.1
Recreation	40	8.1

Results

The composite wildfire risk map shown in Figure 3 combines the category-level risk maps based on their relative importance to Lake County. Risk by HVRA category is mapped in Figures 4, 5, 6, 7, 8, and 9 and composite conditional Net Value Change is mapped in Figure 10.

Wildfire risk is predominantly concentrated in the mid- to high elevations (9,500-11,000 ft) where there is a convergence of HVRAs, hazardous fuel conditions, and high burn probability (Figure 10). Although burn probability and wildfire risk are highest in the Spruce-Fir and Lodgepole Pine forests (Figure 12; 26), significant risk is associated with lower-elevation sagebrush steppe and mixed conifer forest because of the high concentration of fire sensitive HVRAs mapped in the foothills and valley bottoms (Figure 12). It should be noted that some areas of the landscape are expected to benefit from wildfire (Figure 3) due to low predicted flame lengths that may enhance wildlife and recreation HVRAs (Figure 8; Figure 9).

Given the uncertainties associated with predicting future wildfire activity (see Appendix II – Burn Probability Products), we also report a composite measure of conditional Net Value Change (cNVC; Figure 10), which does not factor in burn probability. The spatial distribution of composite cNVC is not too dissimilar from the composite risk map because both maps account for the overlap between hazardous fuel conditions and HVRAs. Accounting for burn probability shifts risk away from the lower elevation woodlands and non-forest vegetation to the mid- to high-elevation forests.

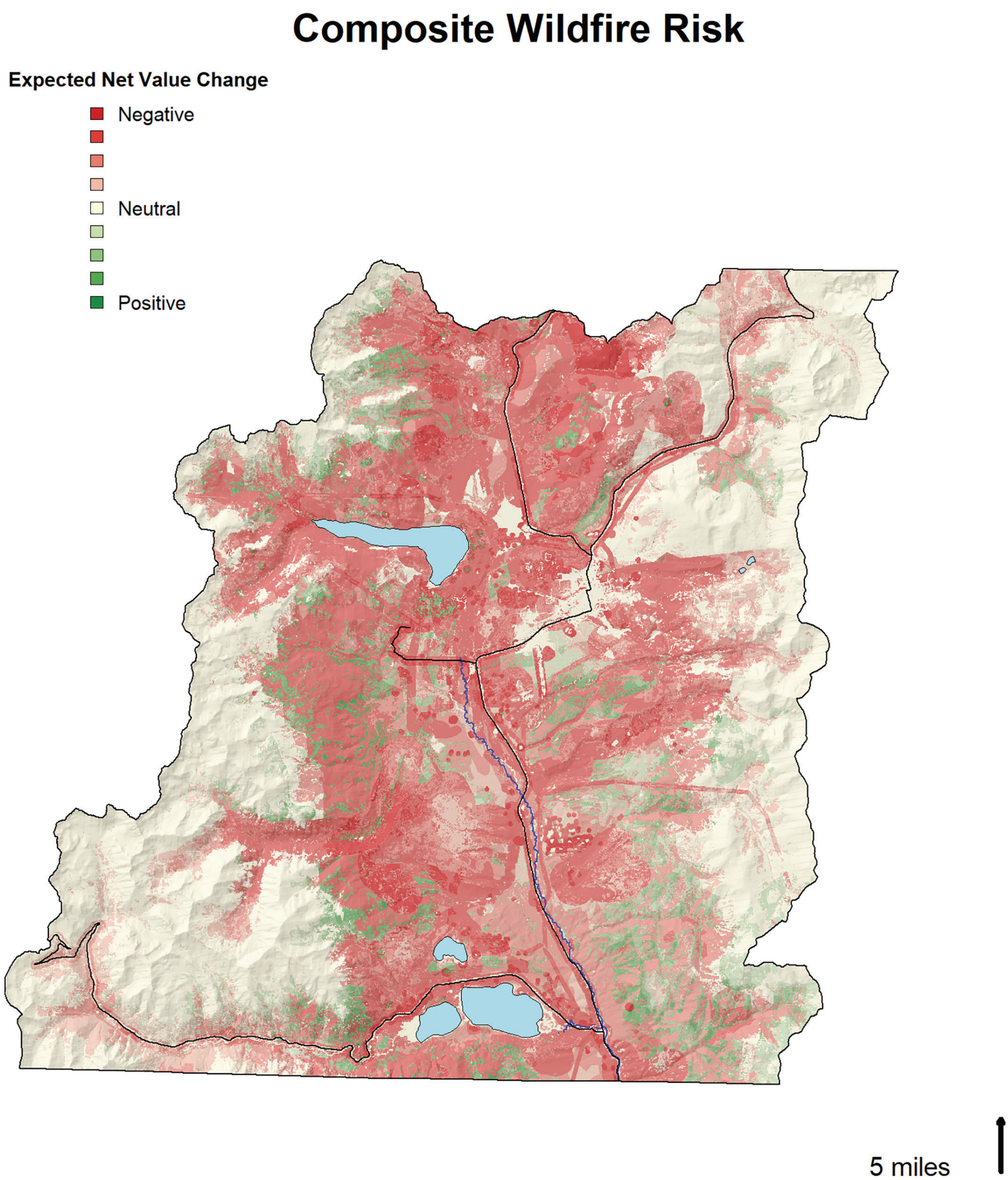

Figure 3: Composite wildfire risk map for Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire. eNVC measures account for both the effect and probability of wildfire.

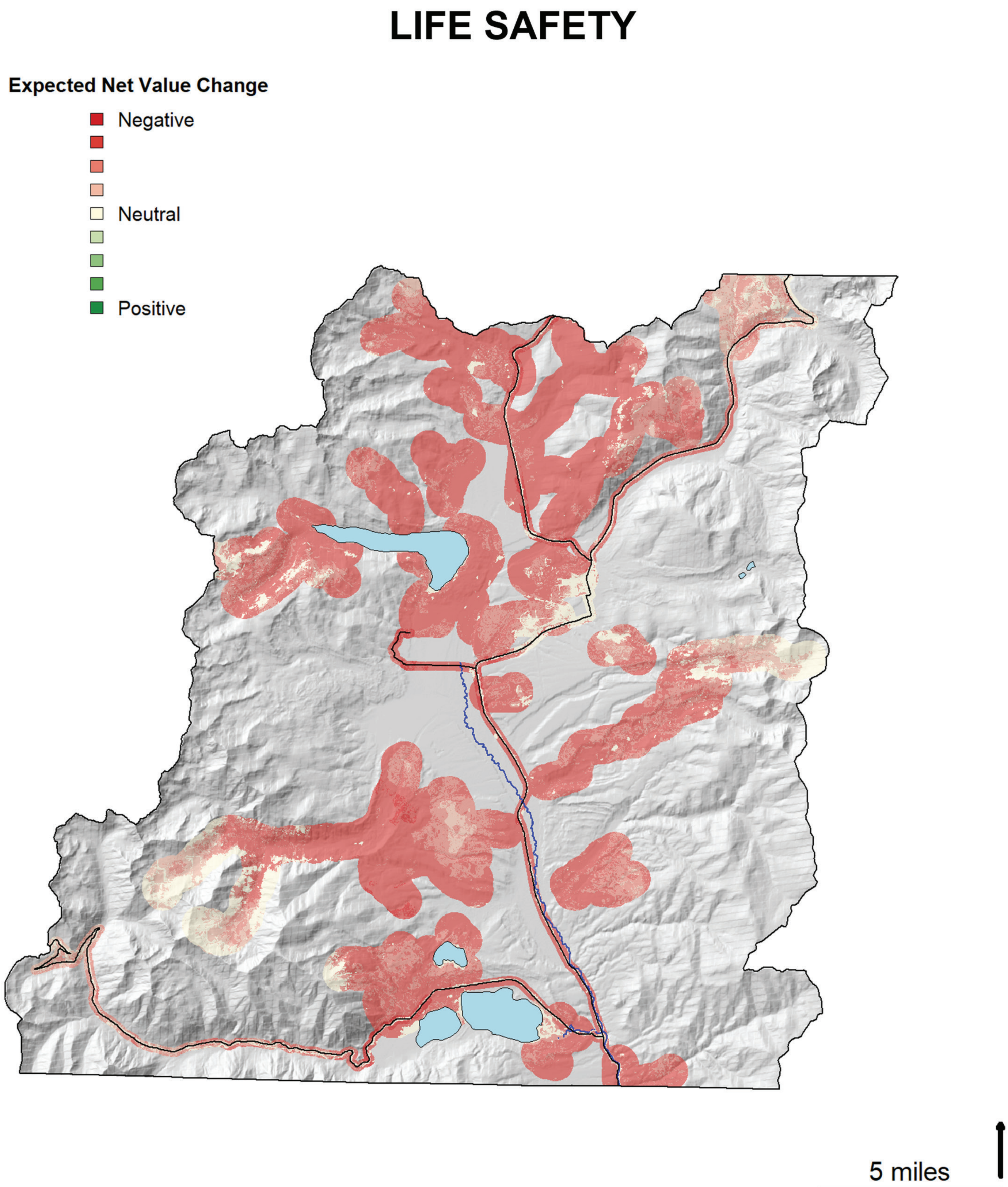

Figure 4: Wildfire risk to life safety in Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

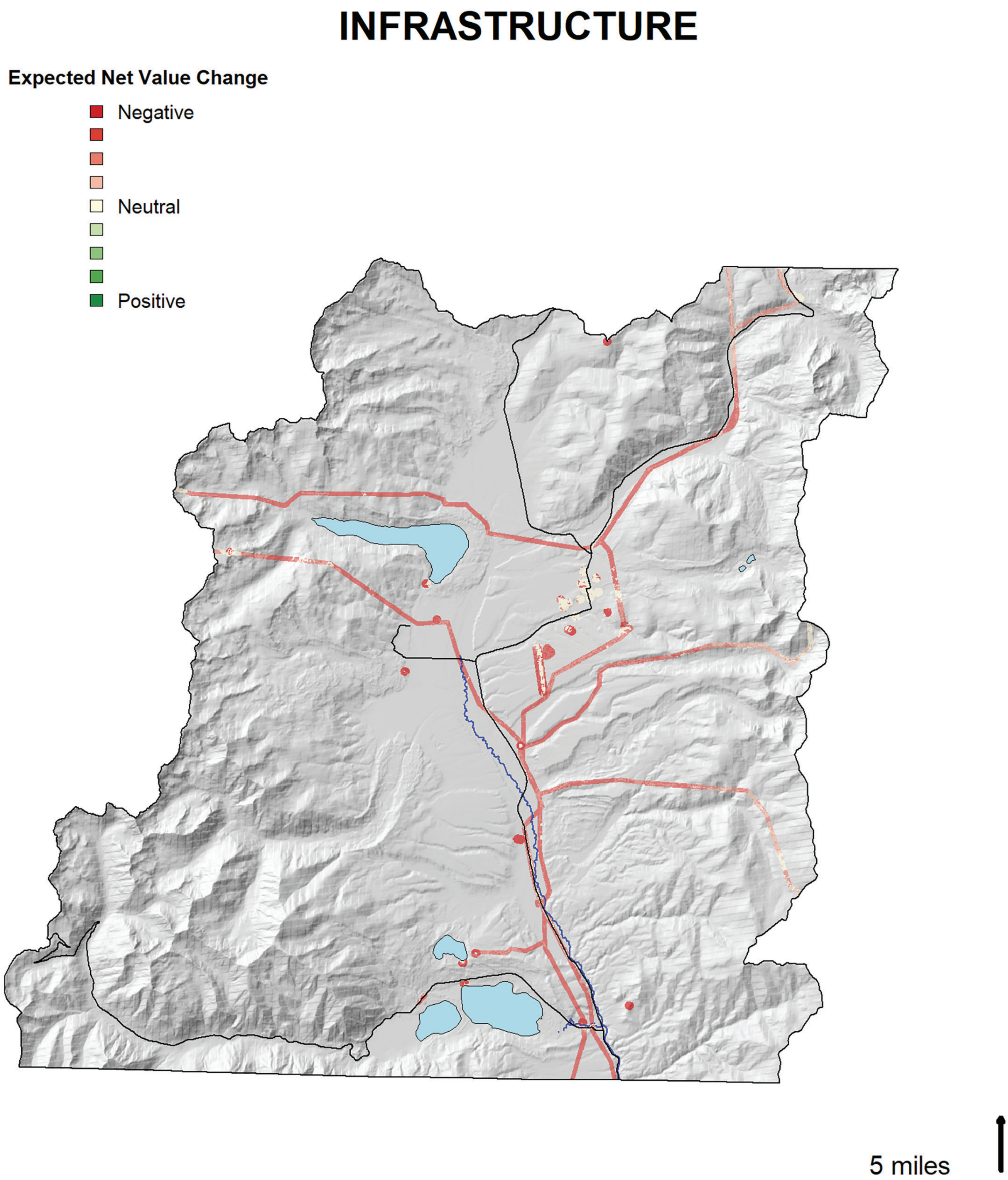

Figure 5: Wildfire risk to infrastructure in Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

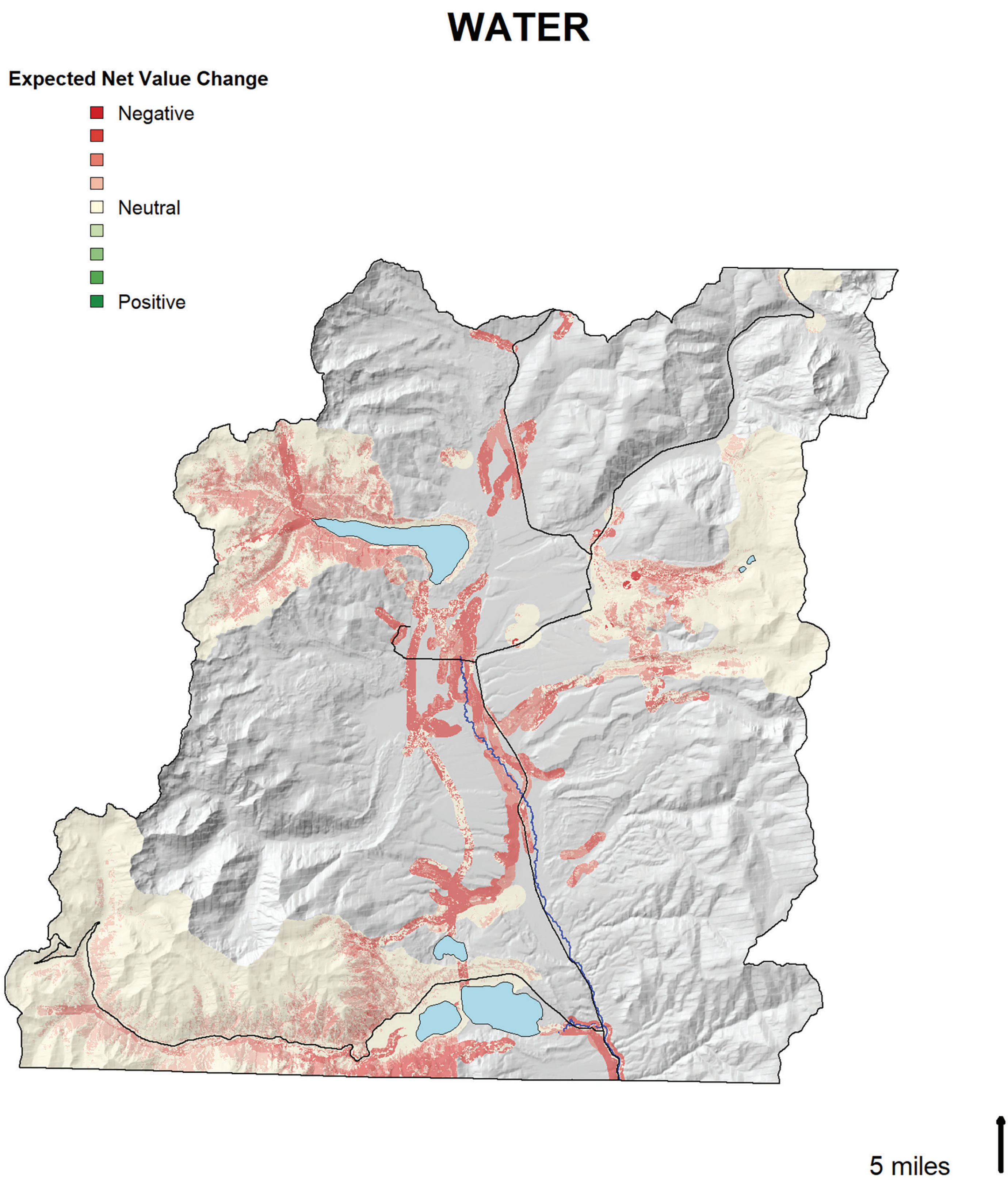

Figure 6: Wildfire risk to water in Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

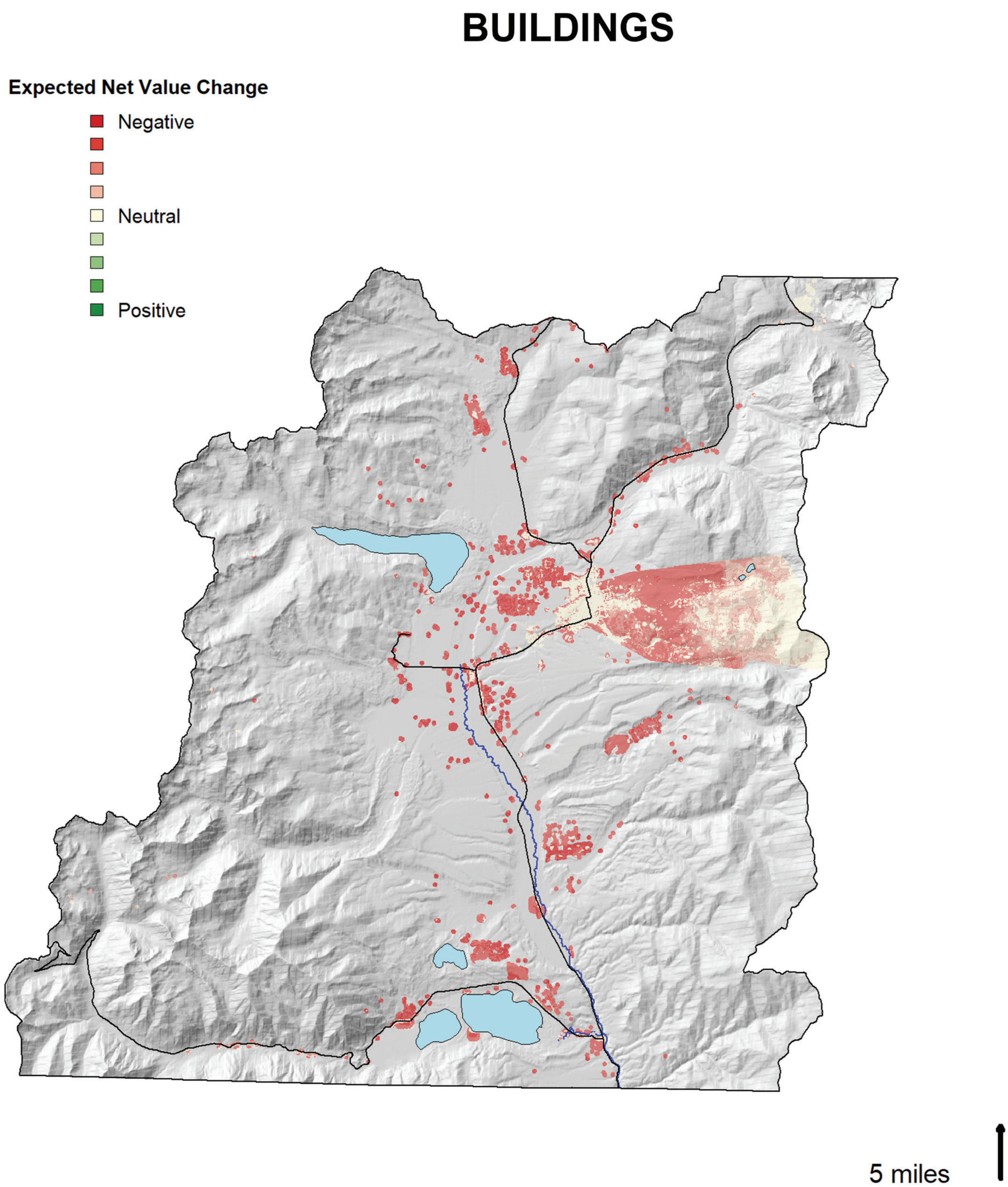

Figure 7: Wildfire risk to buildings in Lake County. This includes both individual structures from Microsoft as well as historic structures from the National Park Service. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

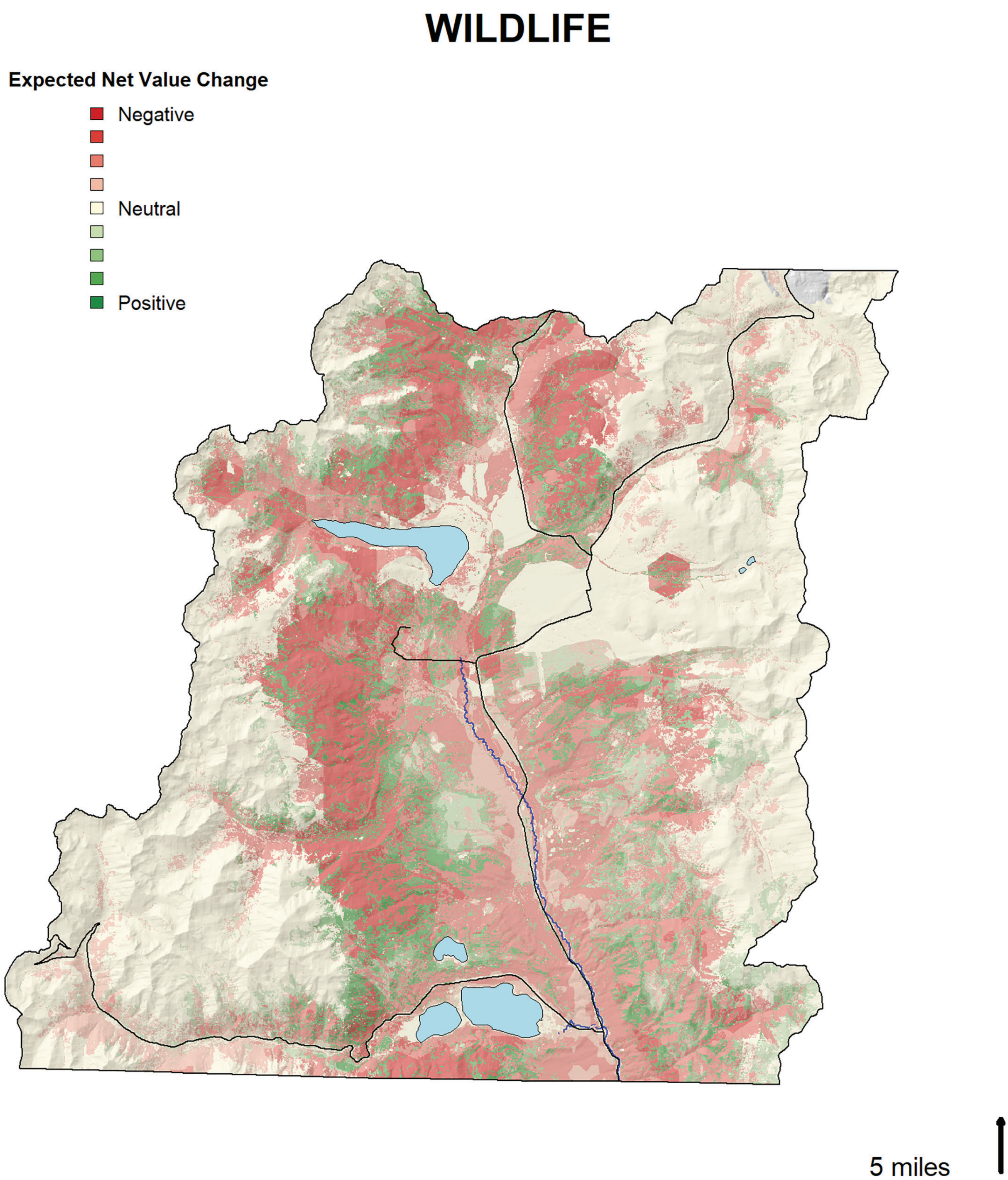

Figure 8: Wildfire risk to wildlife in Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

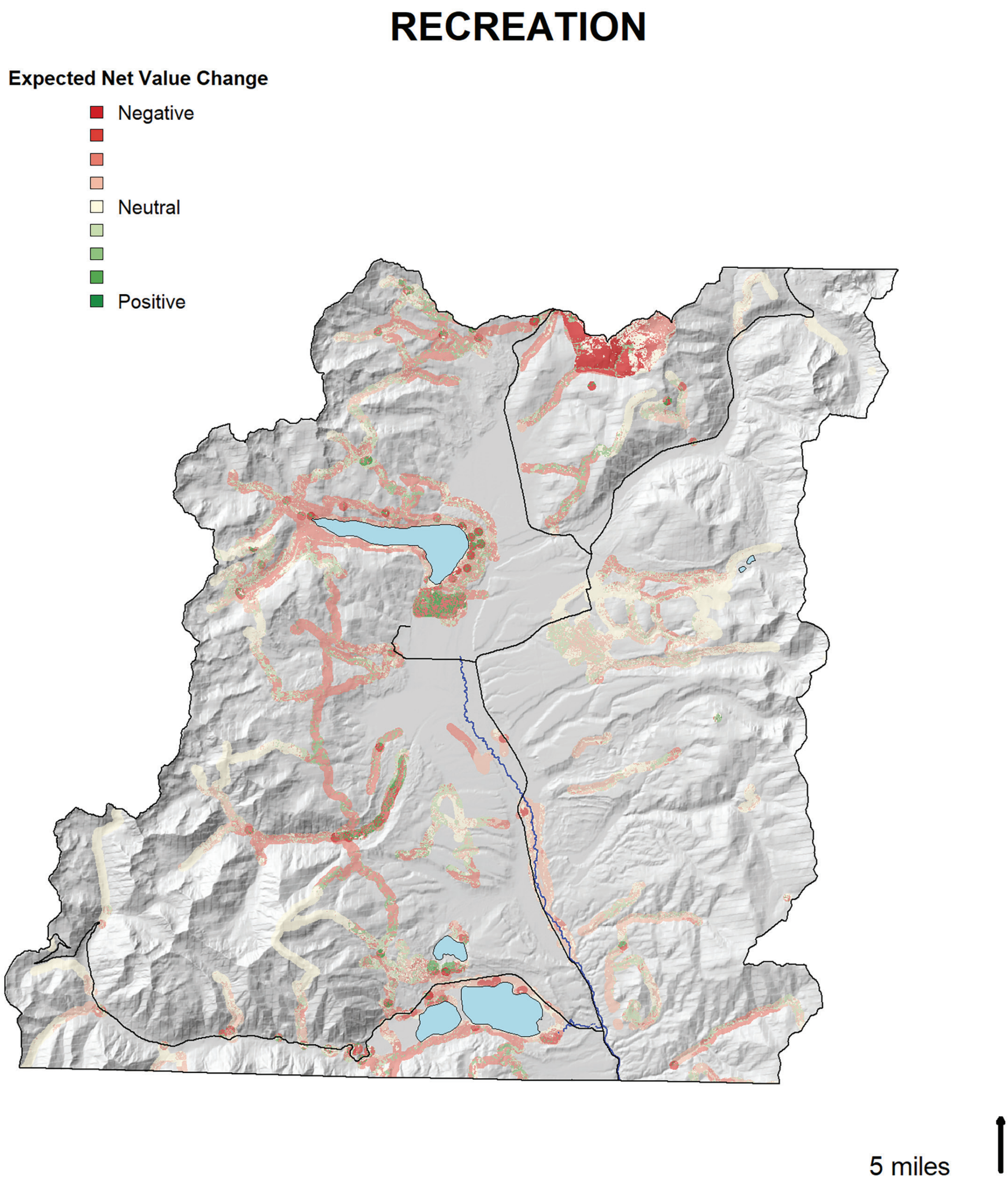

Figure 9: Wildfire risk to recreation in Lake County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

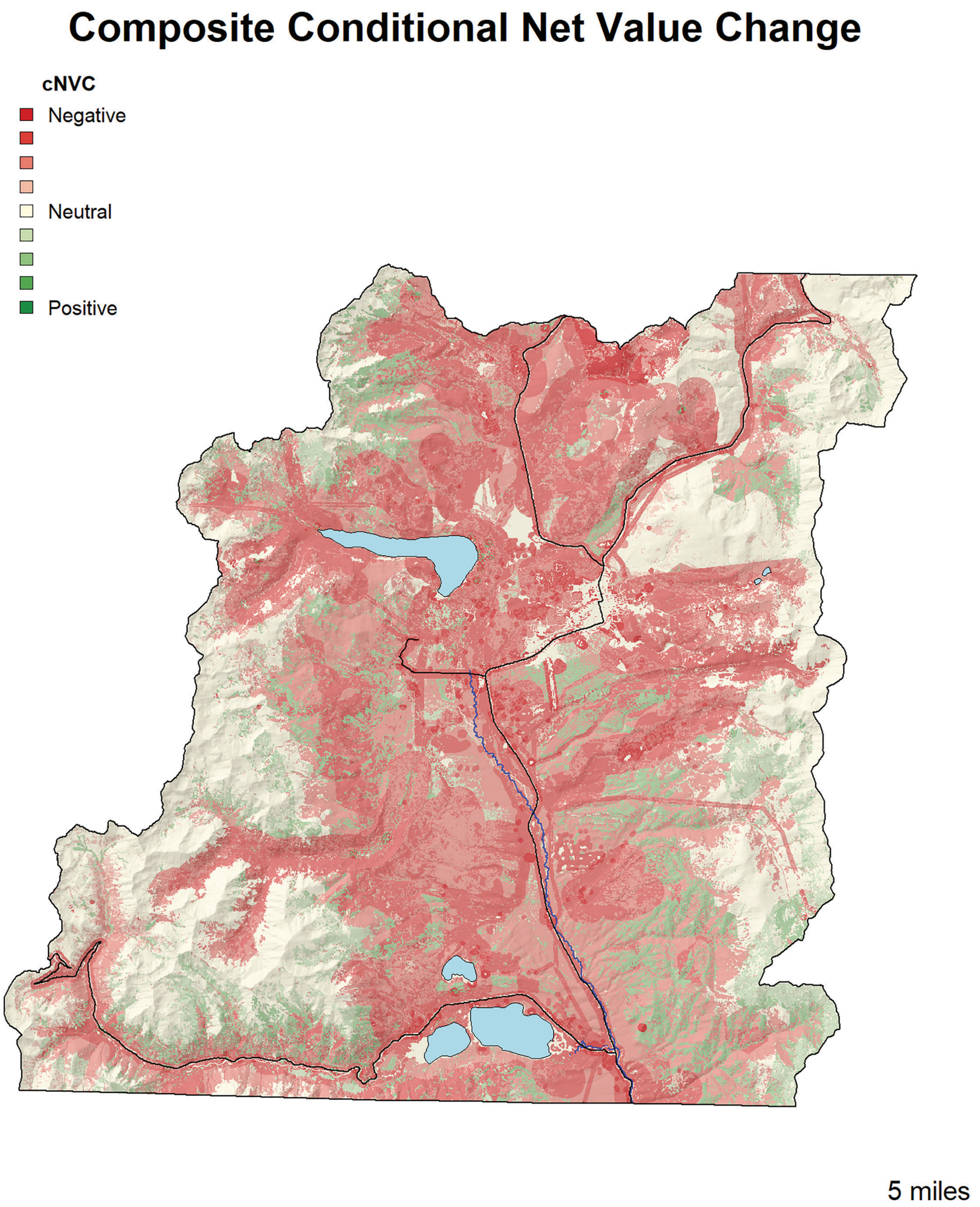

Figure 10: Composite conditional Net Value Change (cNVC) map for Lake County. Negative cNVC means net losses. Positive cNVC means net benefits. This product does not account for burn probability.

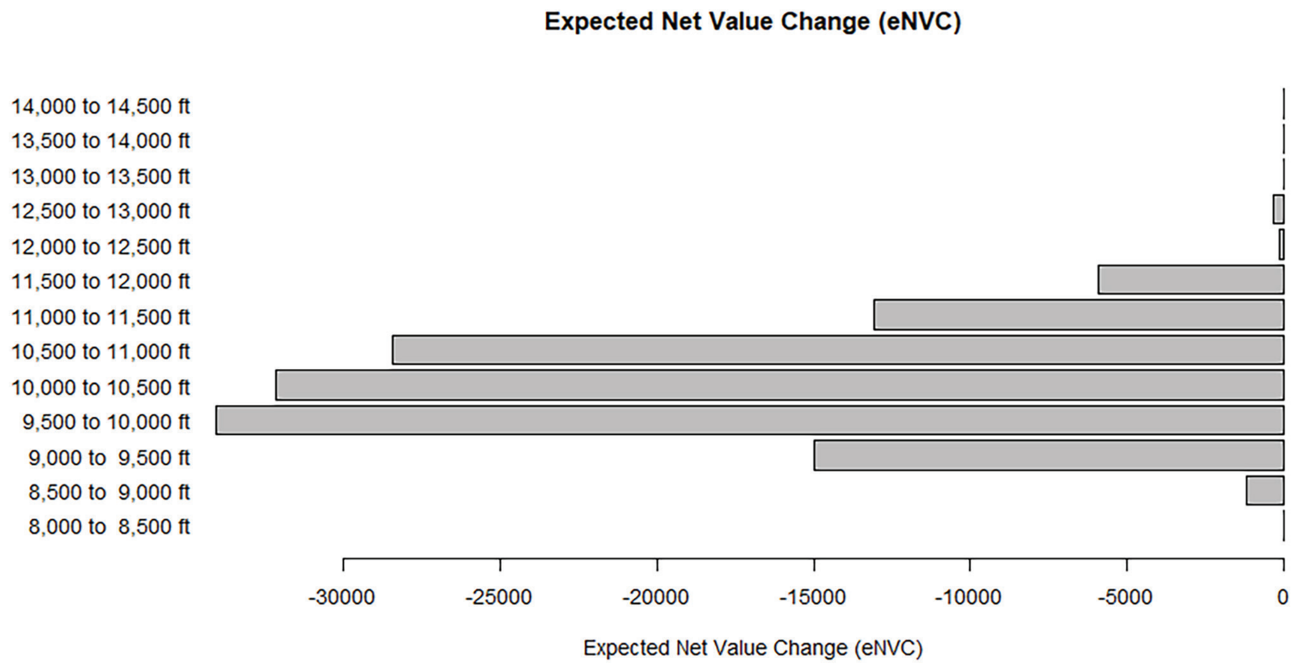

Figure 11: Risk (expected Net Value Change) distribution across elevation bins.

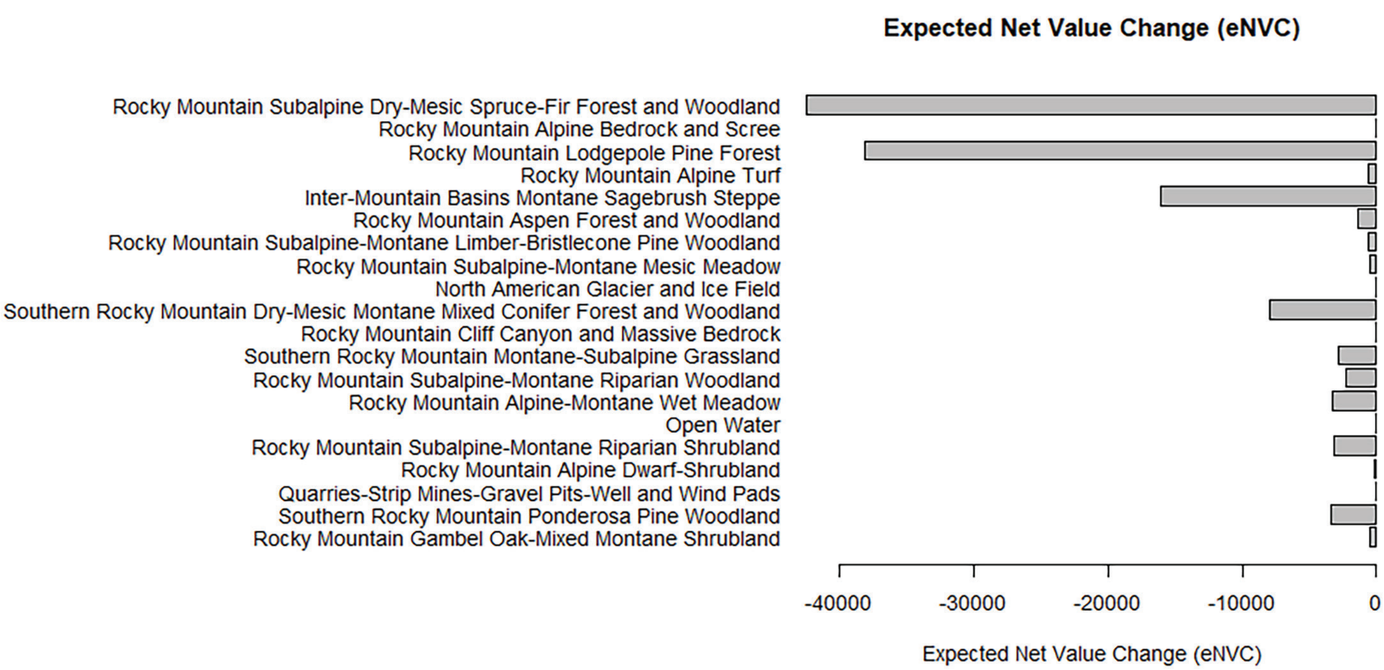

Figure 12: Risk (expected Net Value Change) by existing vegetation type from LANDFIRE (2016).

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Appendix I - Fire Behavior Products

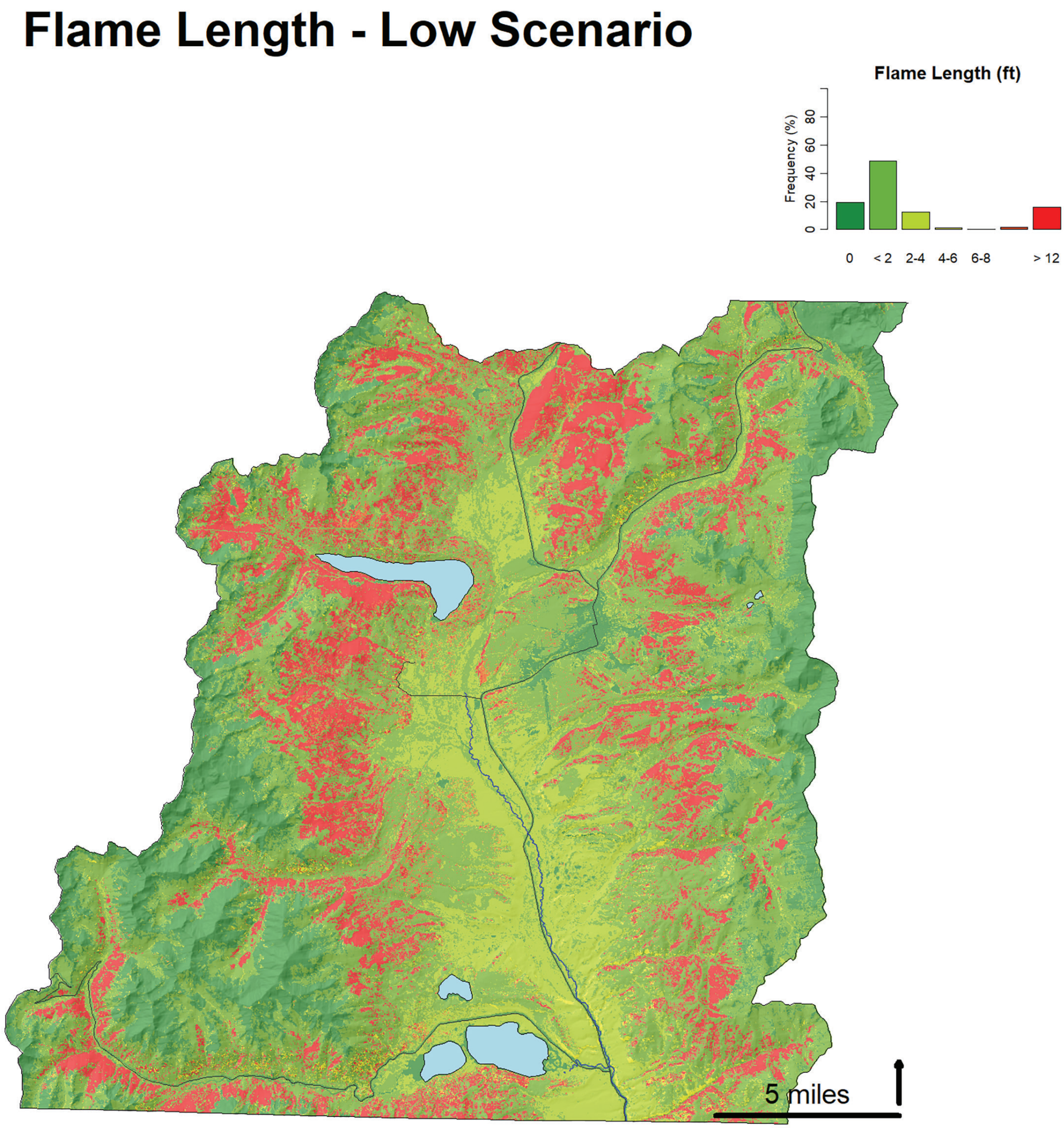

Figure 13: Modeled flame length (ft) for the low fire weather scenario.

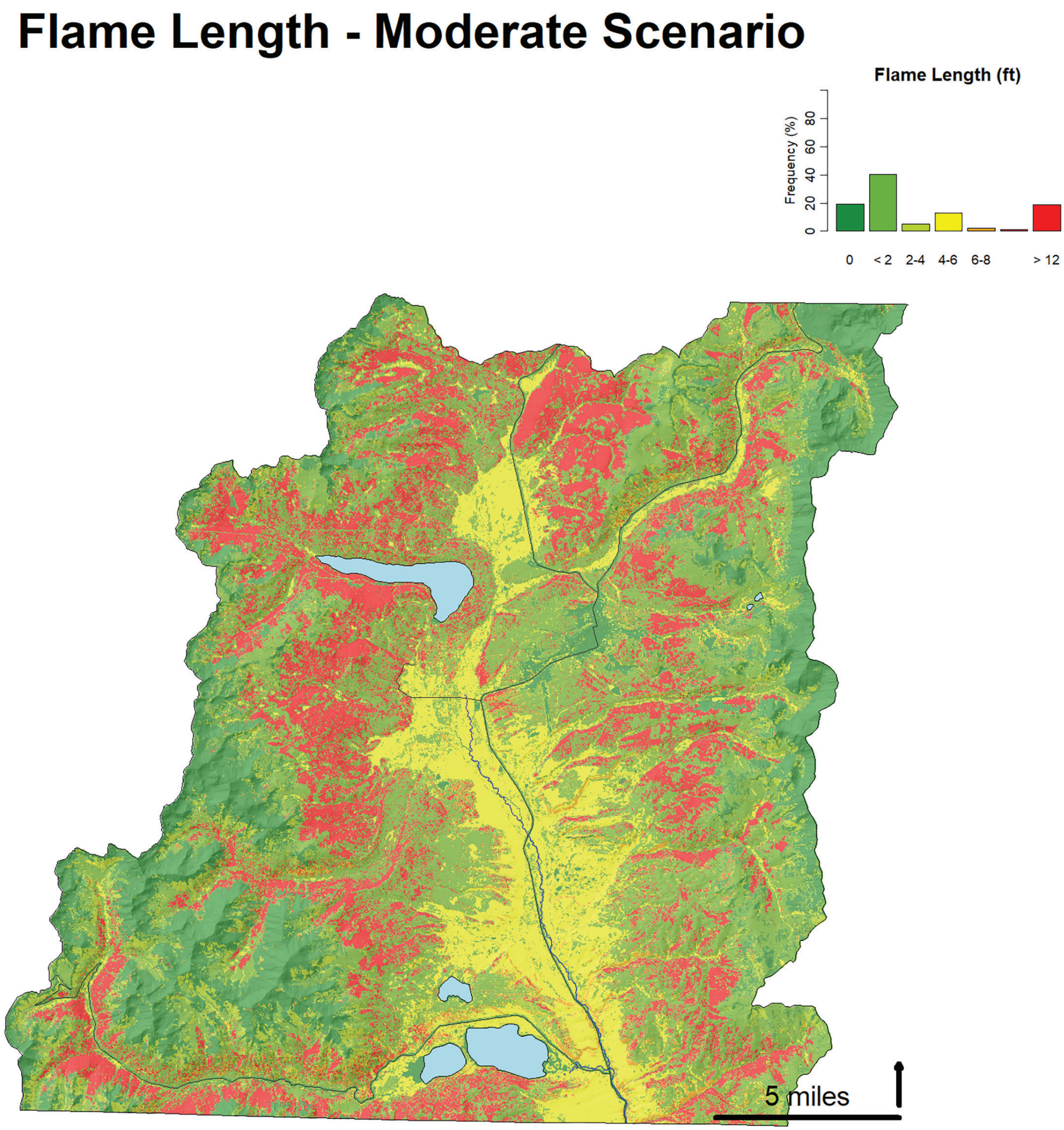

Figure 14: Modeled flame length (ft) for the moderate fire weather scenario.

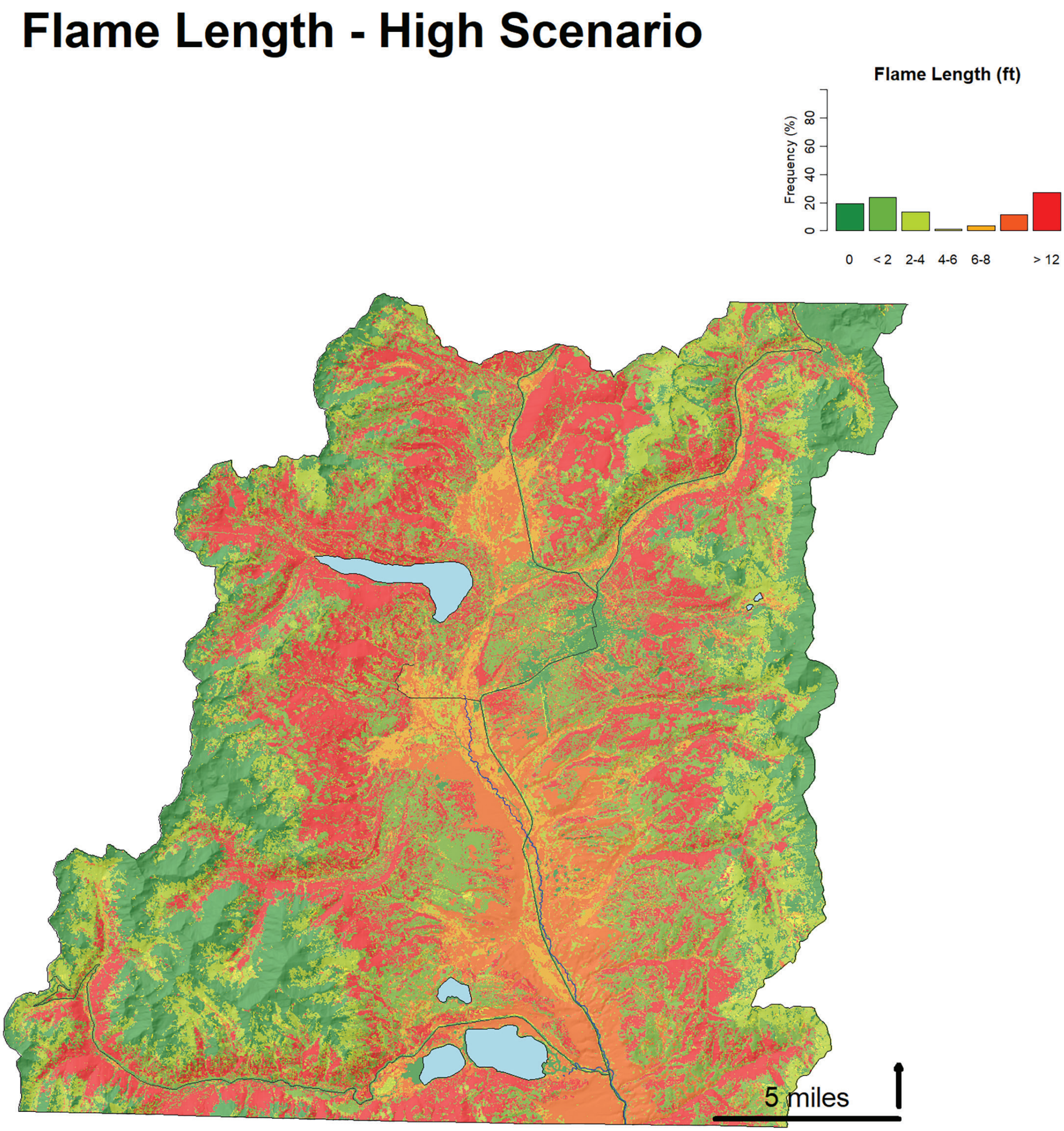

Figure 15: Modeled flame length (ft) for the high fire weather scenario.

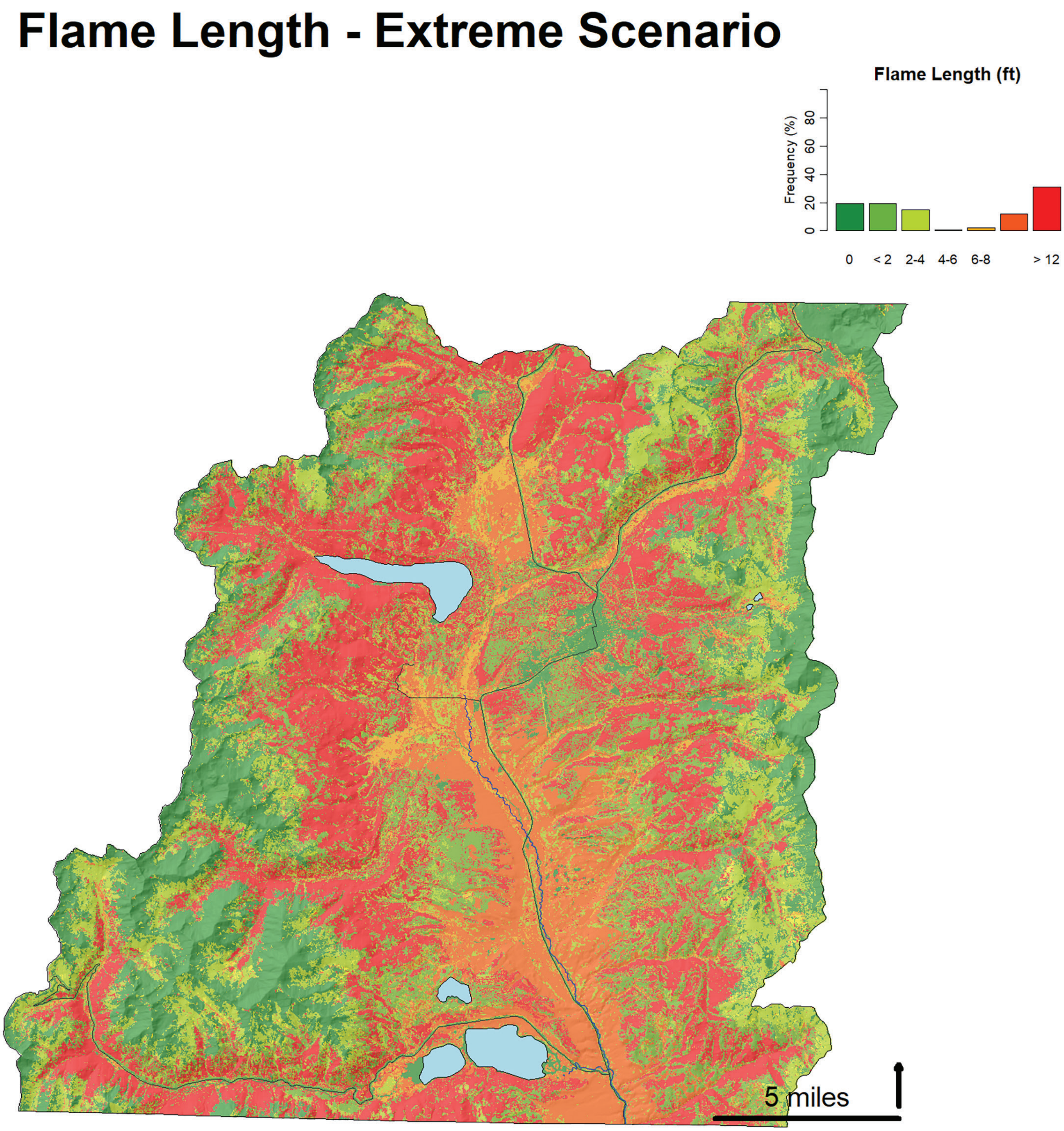

Figure 16: Modeled flame length (ft) for the extreme fire weather scenario.

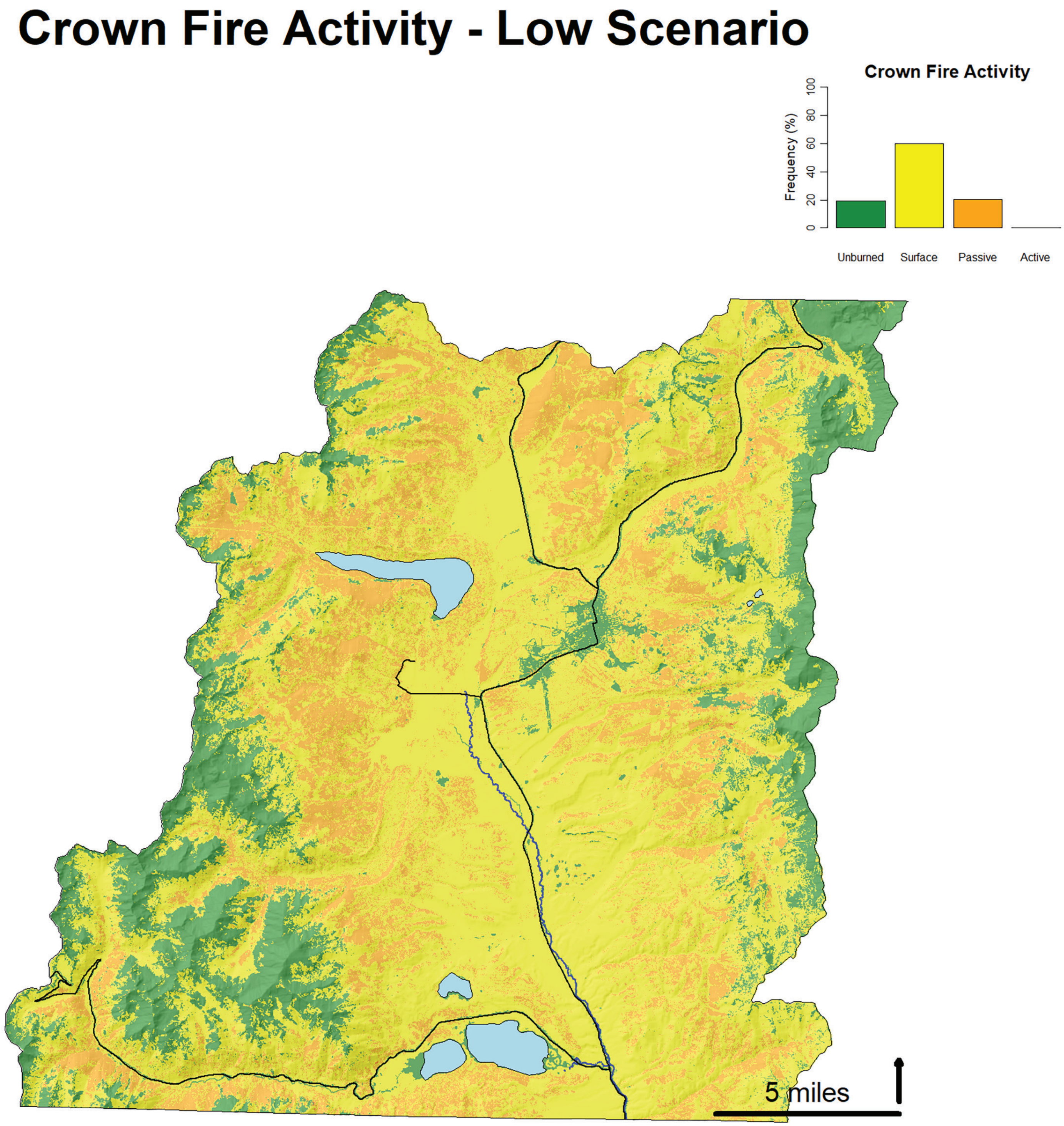

Figure 17: Modeled crown fire activity for the low fire weather scenario.

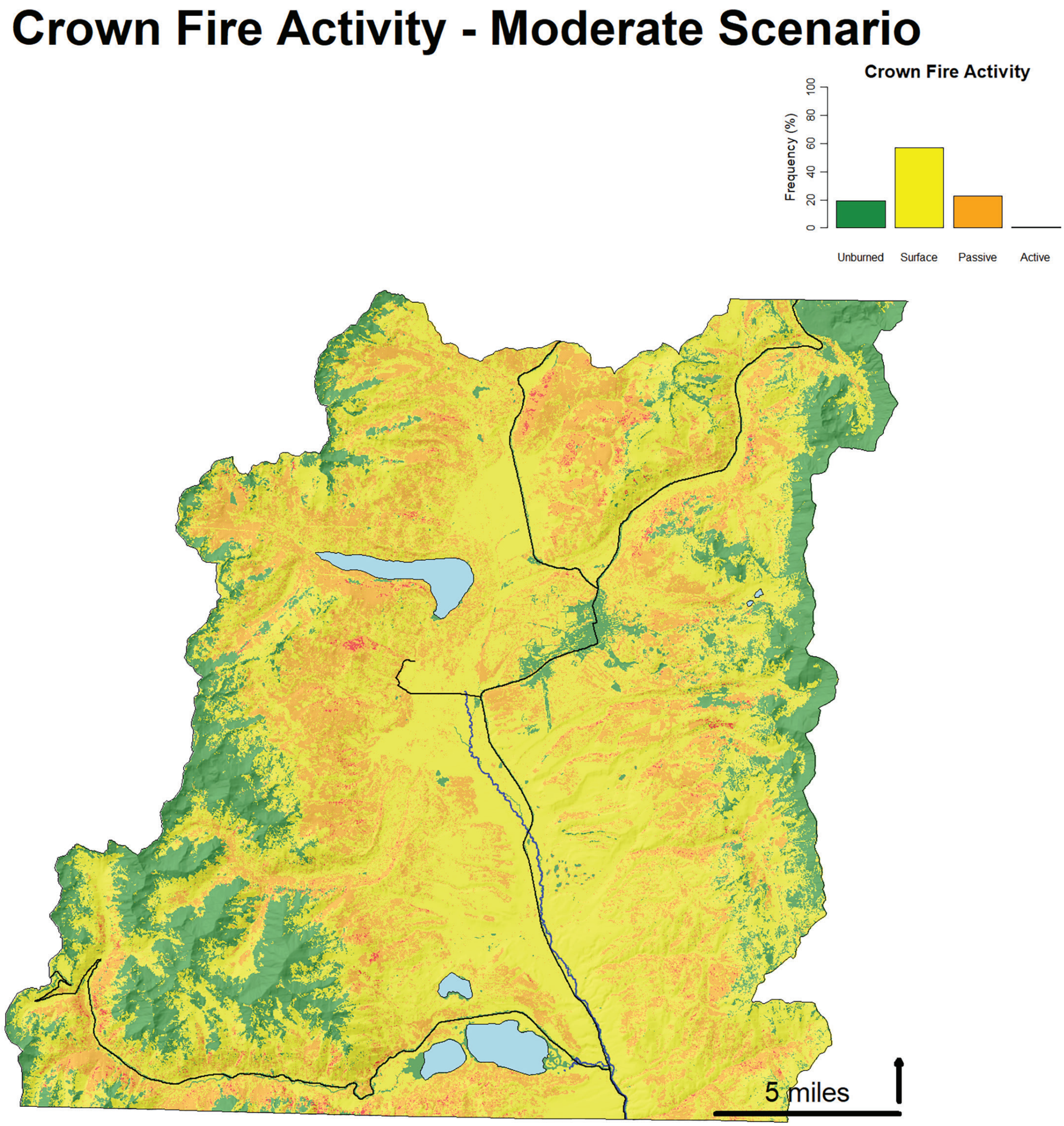

Figure 18: Modeled crown fire activity for the moderate fire weather scenario.

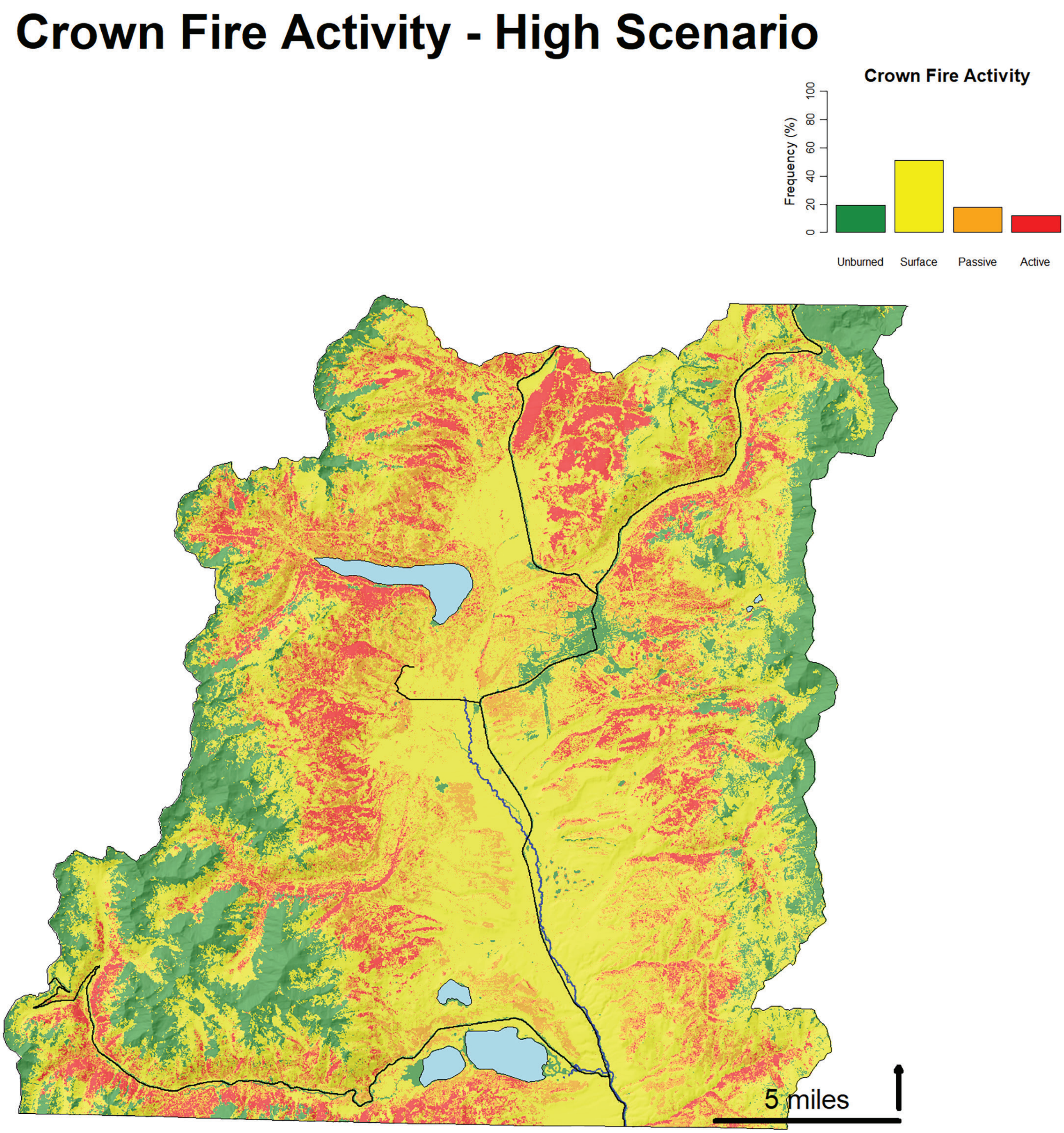

Figure 19: Modeled crown fire activity for the high fire weather scenario.

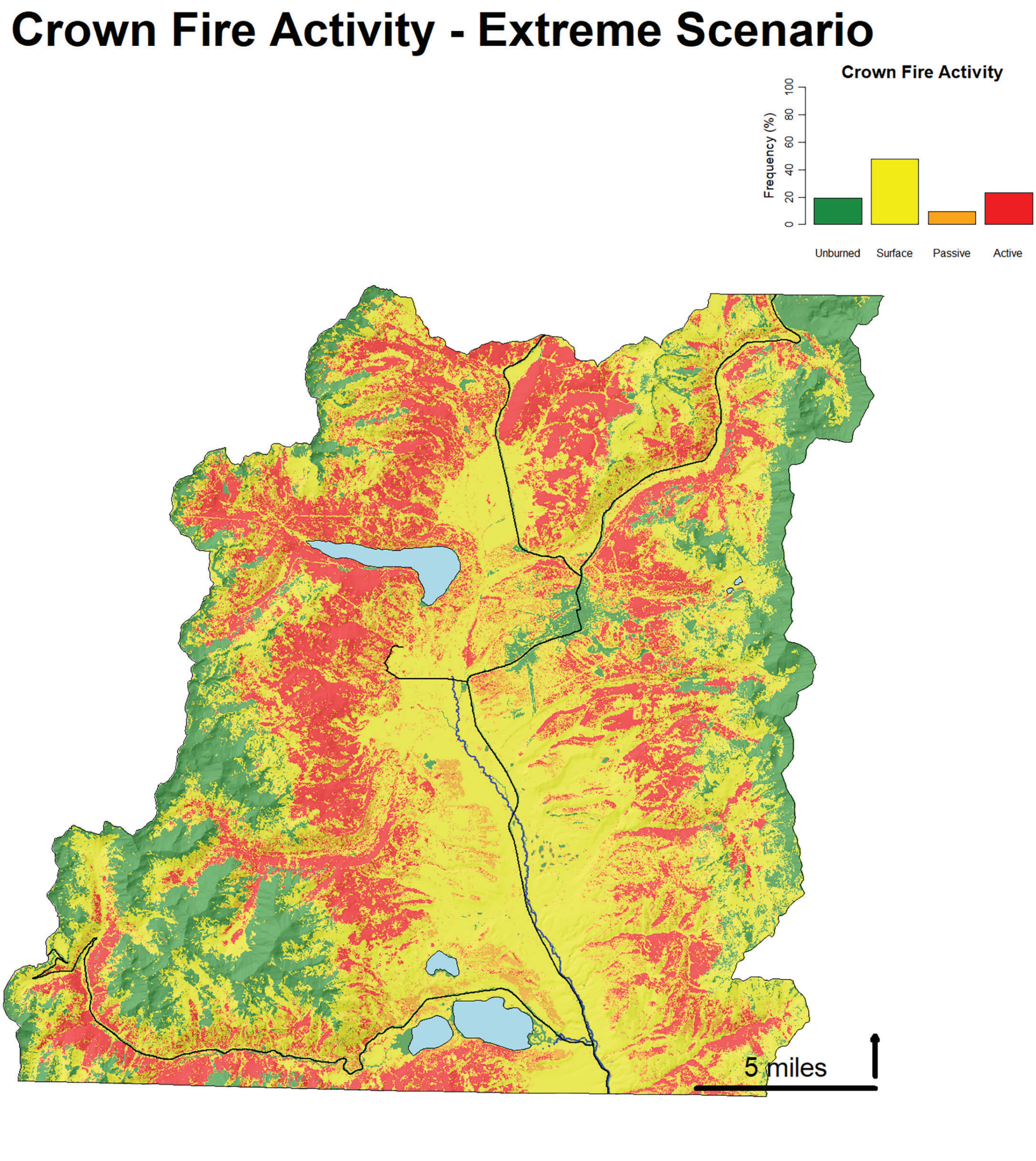

Figure 20: Modeled crown fire activity for the extreme fire weather scenario.

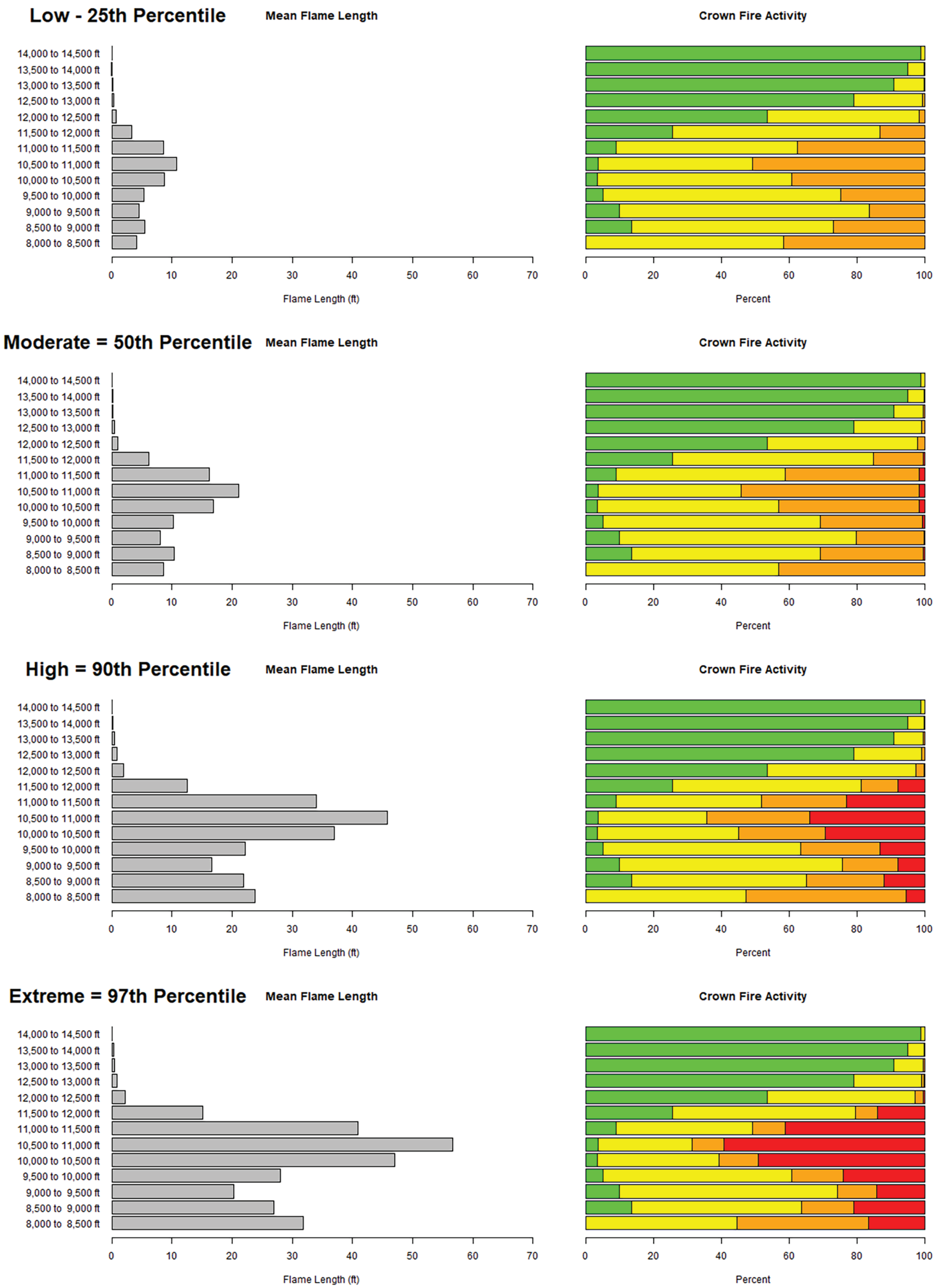

Figure 21: Summary of fire behavior by elevation. The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

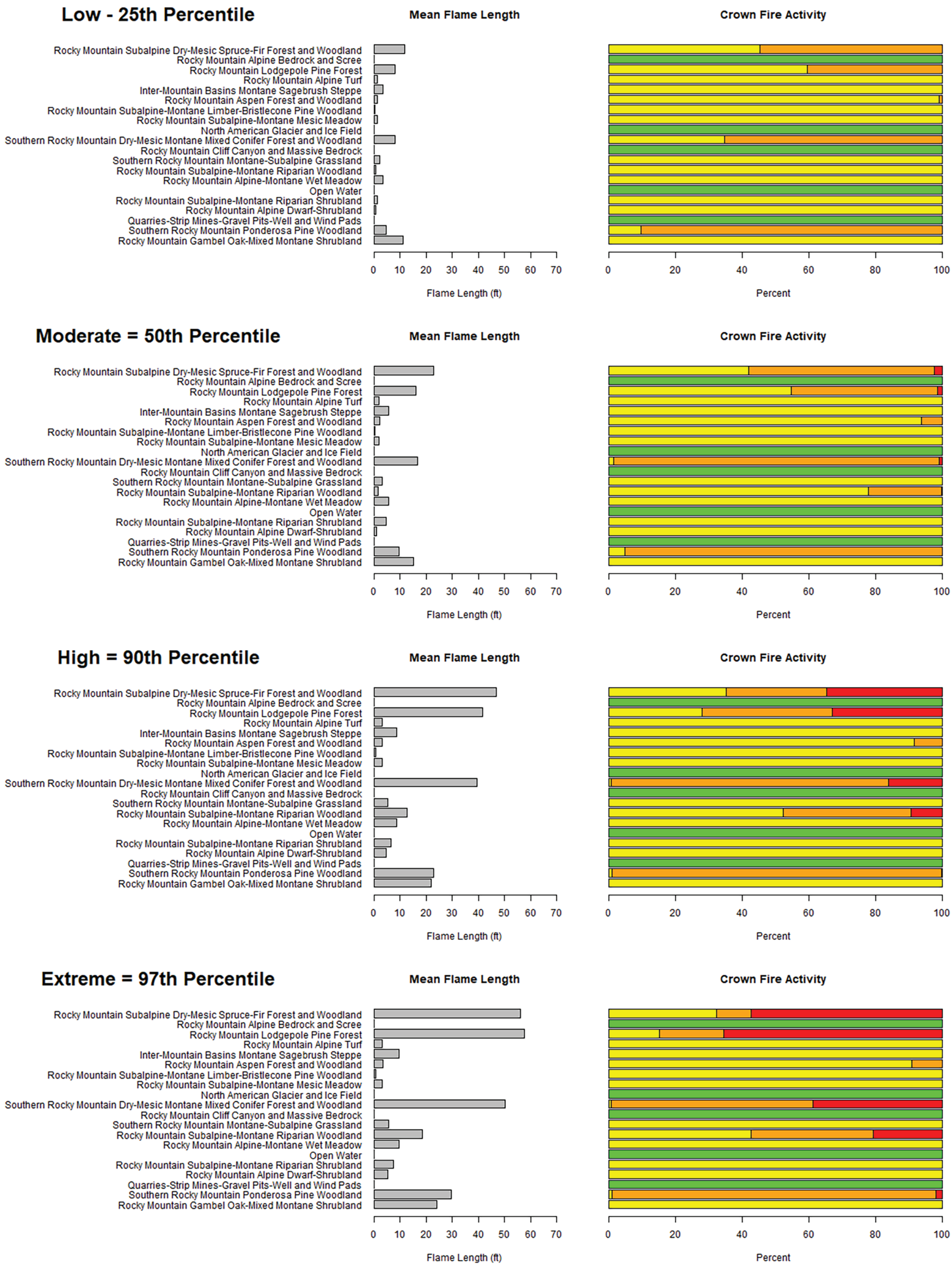

Figure 22: Summary of fire behavior by existing vegetation type from LANDFIRE (2016). The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

Appendix II – Burn Probability Products

Burn probability is a spatially explicit estimate of fire likelihood often derived from simulation modeling of fire spread, which can incorporate information on fire ignition sources, fire weather, fuels, topography, and barriers to fire spread (Finney 2005; Miller and Ager 2013; Scott et al. 2013). The precise methods for burn probability modeling vary by project objectives, model function, and model data requirements. We considered several burn probability products – two of which were publicly-available and two of which were produced by CFRI. The pros and cons of each approach are outlined below (Table 6).

Table 6: Summary of pros and cons associated with each potential burn probability product

Burn Probability Product	Pros	Cons
CO-WRA (Technosylva 2018)	>2M simulated fires in CO that capture spatial barriers to fire spread	Assumes uniform ignition density and under-estimates fire suppression in grass fuel types
National FSim (Short et al. 2016)	Accounts for spatially variable ignition density and barriers to fire spread	Predicted very low burn probabilities throughout Lake County
Empirical probability by vegetation type (CFRI)	State-wide area burned (2000-2020) in each vegetation type	Probability is the same across each vegetation type and assumes future fires will follow a similar distribution as historic
Local FSim (CFRI)	Accounts for spatially variable ignition density and barriers to fire spread & projects current trends 5 years into the future	Assumes historical observations of fire activity and weather are valid for forecasting

Critique of existing products

Local stakeholders expressed concern that these existing burn probability products did not match their observations of recent fires or their expectations about future fire occurrence across the County. The Colorado Wildfire Risk Assessment (CO-WRA, Technosylva 2018) predicts most fire activity will occur in woodland, shrub, and grass vegetation types that dominate the low foothills and valley bottoms, which conflicts with managers experience that large fires predominantly burn in mid- to high-elevation forests. The national-scale Large Fire Simulator (FSim) burn probability product from Short et al. (2016) predicts low burn probability across all vegetation types. A possible explanation for this discrepancy is that CO-WRA and the National FSim product predict low spread rates in higher elevation forests and the CO-WRA approach does not account for fire suppression. Fire managers expressed that wildfire detection, accessibility, and resistance to control factors including fuel type and topography are the primary drivers of area burned. Fire managers expect greater potential for large fires in the timber fuel types, especially in spruce-fir forests affected by recent insect outbreaks, because of low accessibility and high resistance to control. In contrast, fires are quickly detected, accessed, and suppressed in the woodland, shrub, and grass vegetation types of the foothills and valley bottoms. While the risk of large wildfires in Lake County has historically been quite low, Rocky Mountain subalpine forests are now burning more than at any point in the past 2,000 years (Higuera et al. 2021). Changes in climate, forest conditions (i.e., insect mortality), and increased human land use patterns have combined to make large, intense fires much more frequent, especially in Colorado's high elevation forests where wildfires used to be rare events. Given the aligning trends in both climate and fire management strategies, we explored alternative fire modeling products that reflect increased fire activity in higher elevations.

Empirical burn probability alternative

We developed an empirical estimate of burn probability based on historical observations of area burned by vegetation type within that state of Colorado between 2000 and 2020. The analysis was completed across the state of Colorado due to a low number of fires in the area around Lake County within the time period selected for analysis. By looking at only fires that occurred since 2000, we were also able to capture the observed effects of a warming climate on fire activity in high elevation forests (Higuera et al. 2021). Vegetation type, based on the Southwest Regional Gap analysis (Lowry et al. 2007), was chosen as the foundation for burn probability because of the obvious connection to fuel conditions and its association with elevation and topography which influence accessibility and resistance to control.

We assembled fire history records from Monitoring Trends in Burn Severity (MTBS 2019) and the National Interagency Fire Center (NIFC 2021). NFIC fire perimeters were dissolved by fire name and year to represent the final fire perimeters. The two datasets were then merged and manually critiqued to select the best representation of fires captured in multiple datasets and to remove any obvious duplicate records.

Vegetation type was characterized using the Southwest Regional Gap product (Lowry et al. 2007). A GIS was used to calculate the area burned by vegetation type for each fire. The records were then summarized to calculate the total area burned by vegetation type within the analysis area. Burn probability was then calculated for each vegetation type as the observed area burned divided by the total area of the vegetation type divided by the period of the fire history record (2000-2020). The resulting probabilities were then mapped to vegetation types using a GIS. Two modifications were made for logical consistency: 1) any areas mapped as non-burnable by LANDFIRE (2014) were reassigned zero burn probability, and 2) any areas mapped as burnable by LANDFIRE but without a history of fire were assigned the lower 5th percentile of non-zero burn probabilities. The historical records suggest that fire activity is more prevalent at in mid- to high-elevation forests and far less prevalent in pinyon pine woodlands than predicted by CO-WRA.

However, there are several limitations associated with this empirical approach.

1. **Space for time substitution.** We expanded the geographic extent of our analysis to increase the fire observation size, which can introduce error if biophysical conditions and fire management differ outside Lake County.
2. **Imperfect fire history and vegetation data.** The spatial precision of the fire occurrence data is imperfect. Inaccuracies in the Southwest Regional Gap vegetation type or poor match between current vegetation and vegetation at the time of fire occurrence may contribute to errors in the analysis.
3. **No accounting of factors other than vegetation.** Burn probability can also vary across large landscapes due to spatial variation in ignition sources, climate, topography, barriers to fire spread, and fire management.
4. **No accounting of past fire effects on future burn probability.** Past fire occurrence can modify future fire spread, especially in recently burned areas. However, this is probably of minor concern given that only ~0.25% of the analysis extent burned in the last 27 years.

Although there are limitations with this simple empirical approach, it is consistent with west-wide models of burn probability that account for additional factors. For example, Parisien et al. (2012) found that burn probability increases with measures of remoteness and topographic roughness, which are interpreted as proxies for fire suppression influence. They also found fire activity peaked at intermediate levels of gross primary productivity, which are associated with forested vegetation, and increase unimodally with the proportional coverage of burnable fuels, which decreases near agricultural and urban land uses. In fact, their maps show much lower burn probability in the grass and shrub dominated valleys of Colorado compared to forests, which agrees with our empirical estimates but conflicts with both CO-WRAP and National FSim models of burn probability. The trend of most area burning in mid- to high-elevation forests (i.e., Spruce-Fir and Lodgepole-pine) around Lake County is also consistent with changing perceptions of firefighter risk and appropriate suppression strategies in beetle impacted forests (Page et al. 2013; Moriarty et al. 2019). The shift towards indirect fire containment versus direct attack in forest with abundant snags and jack strawed logs implies that we may see more area burning in lodgepole pine and spruce-fir forests than we did in the past.

Local FSim burn probability alternative

Based on perceived shortcomings associated with the existing burn probability products CFRI undertook FSim modeling for the analysis area. FSim estimates pixel-wise annualized burn probability by simulating 1,000s to 10,000s of years of weather, fire ignitions, fire spread, and fire suppression to estimate the annual probability that a given pixel will burn. To accomplish this, FSim combines modules for weather, fire ignitions, fire growth, and fire suppression through a stochastic Monte-Carlo simulation approach where fires are ignited and grown independently of one another on a static fuelscape. In doing so it accounts for the effects of topology and prevailing wind directions on the rate and direction of fire spread. This captures effects such as lower probabilities of fire on the lee side of large waterbodies, alpine ridgelines, burn scars, etc. As fires burn independently on a static fuelscape, fires are not self-regulating, and the simulation results are valid only for the current landscape condition. As large fires and other management actions alter the landscape fuel condition in the future, updated FSim runs are required to accurately represent the spatial burn probability.

The FSim simulations were conducted at 270m resolution for 30,000 years of modeled fire activity and simulation parameters were calibrated such that the simulations results matched the observed annual number of fires, mean fire size, and fire size distribution between 2000 and 2020 within a 50 km buffer of the analysis area. This large buffer distance has two benefits. First, it allows for a greater sample of the historical fire activity within the local area and second, it allows the model to simulate the scenario where an extremely large fire starts well outside the county and spreads into the Lake County analysis area. This matches with concerns of future fire events similar to the East Troublesome and Cameron Peak fires observed in 2020 which both burned through high elevation forest types and spread approximately 50-60 km from their ignition locations.

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

FSim ignition locations are selected by randomly selecting a x-y coordinate for each potential fire that is influenced by an ignition probability raster defining the relative chance of any location on the landscape being selected. This allows the locations of fire ignitions in FSim to match the observed spatial variability of human and natural ignitions across the analysis area. This raster was generated by identifying the ignition locations of all fires >20 acres in the historical fire record (Short 2021) within the 50 km buffer of the Lake County analysis areas. The Kernel density tool in ArcGIS Pro 2.8 was then used to convert the point ignition data into a continuous raster surface (Figure 23).

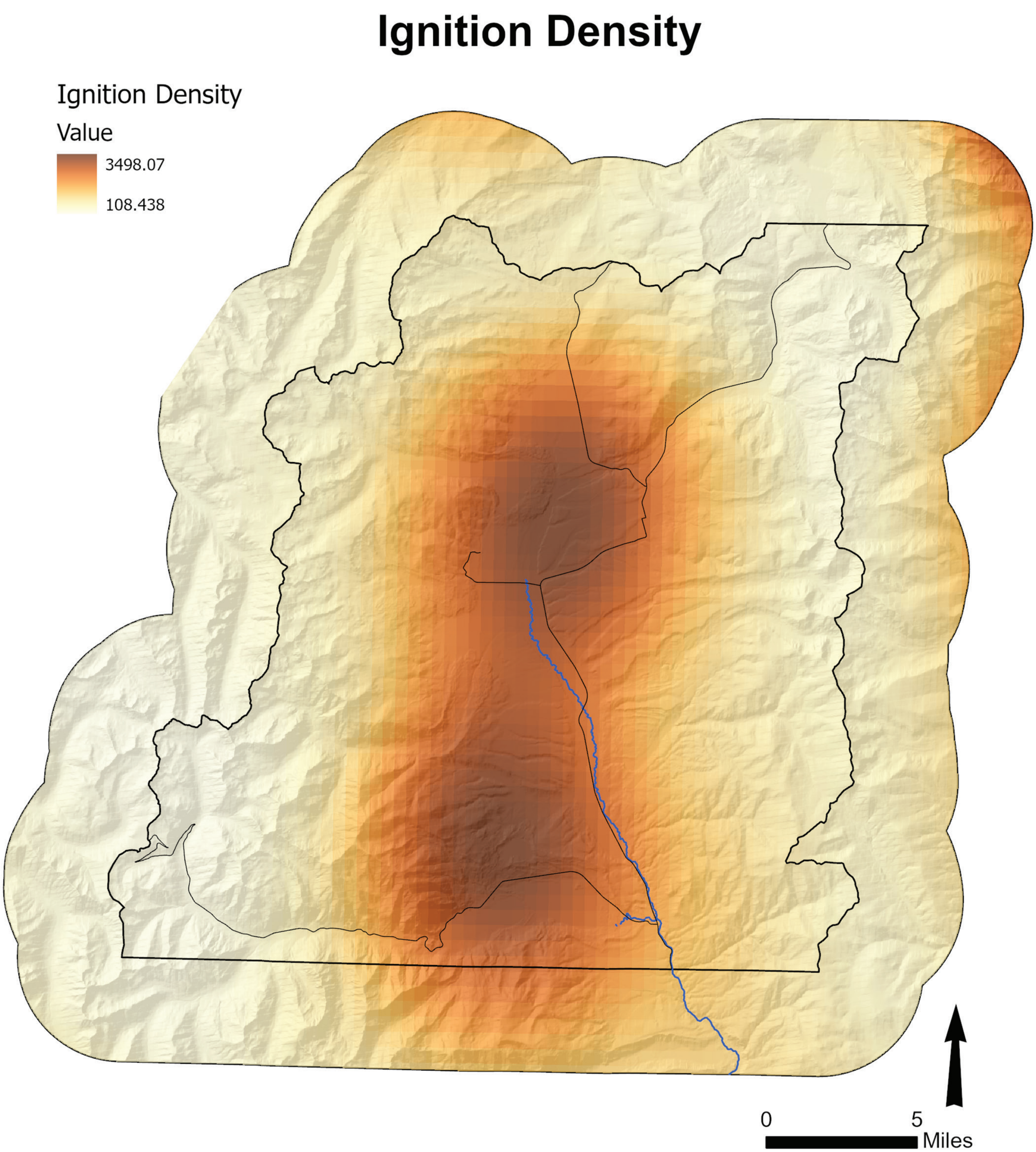

Figure 23: Historical fire ignition density in Lake County.

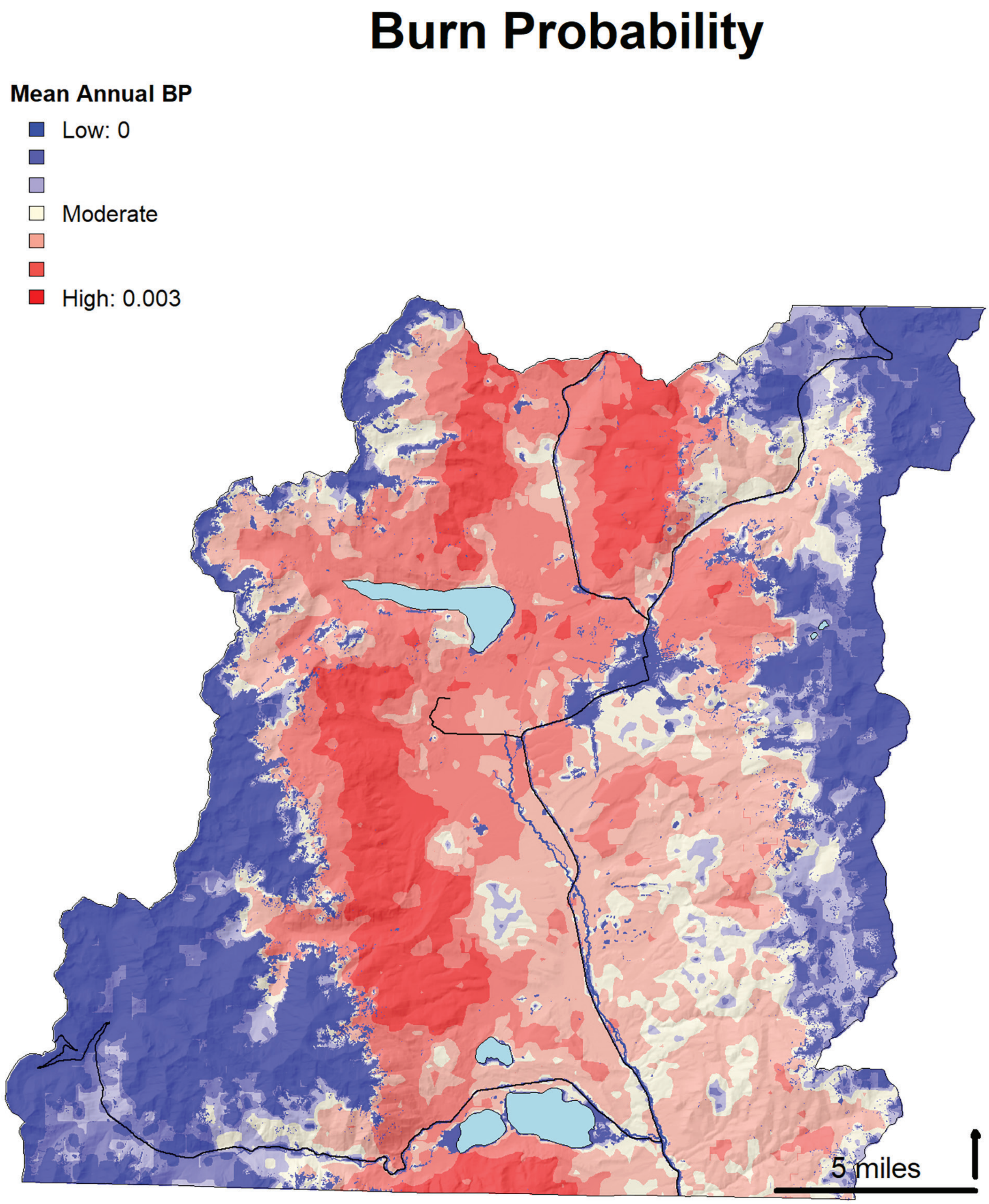

Figure 24: The local FSim burn probability product used for the Lake County Risk Assessment.

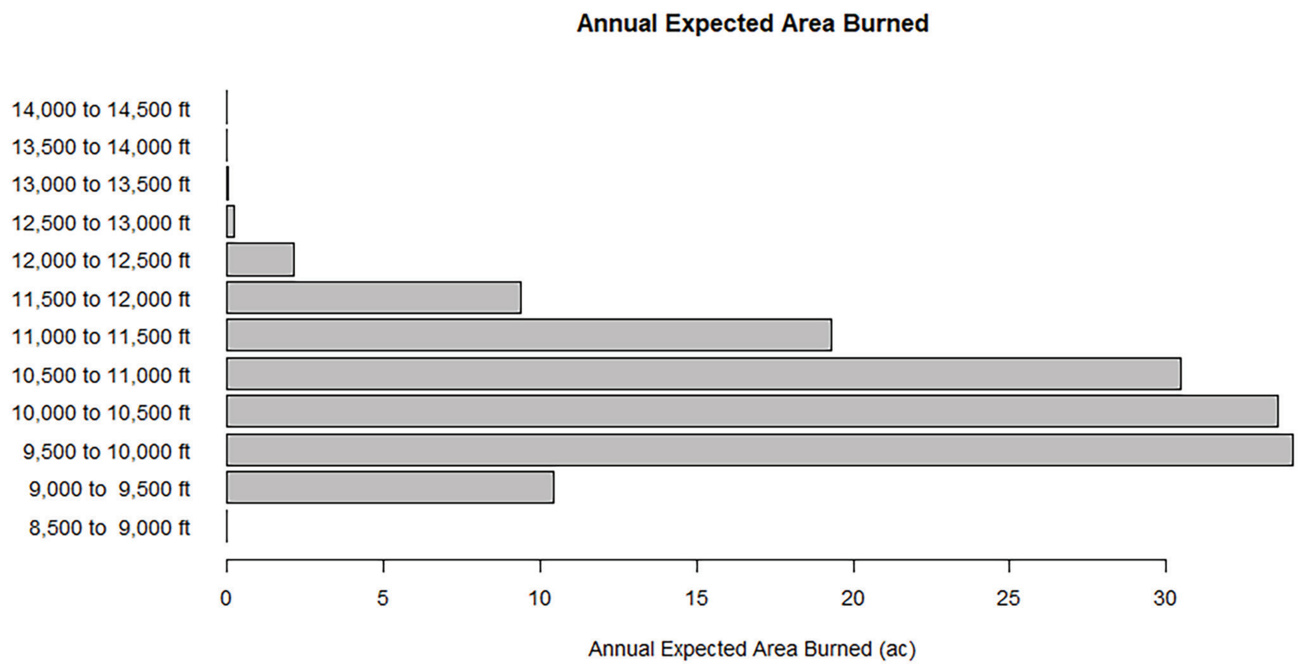

Figure 25: Expected area burned by elevation based on local FSim burn probability.

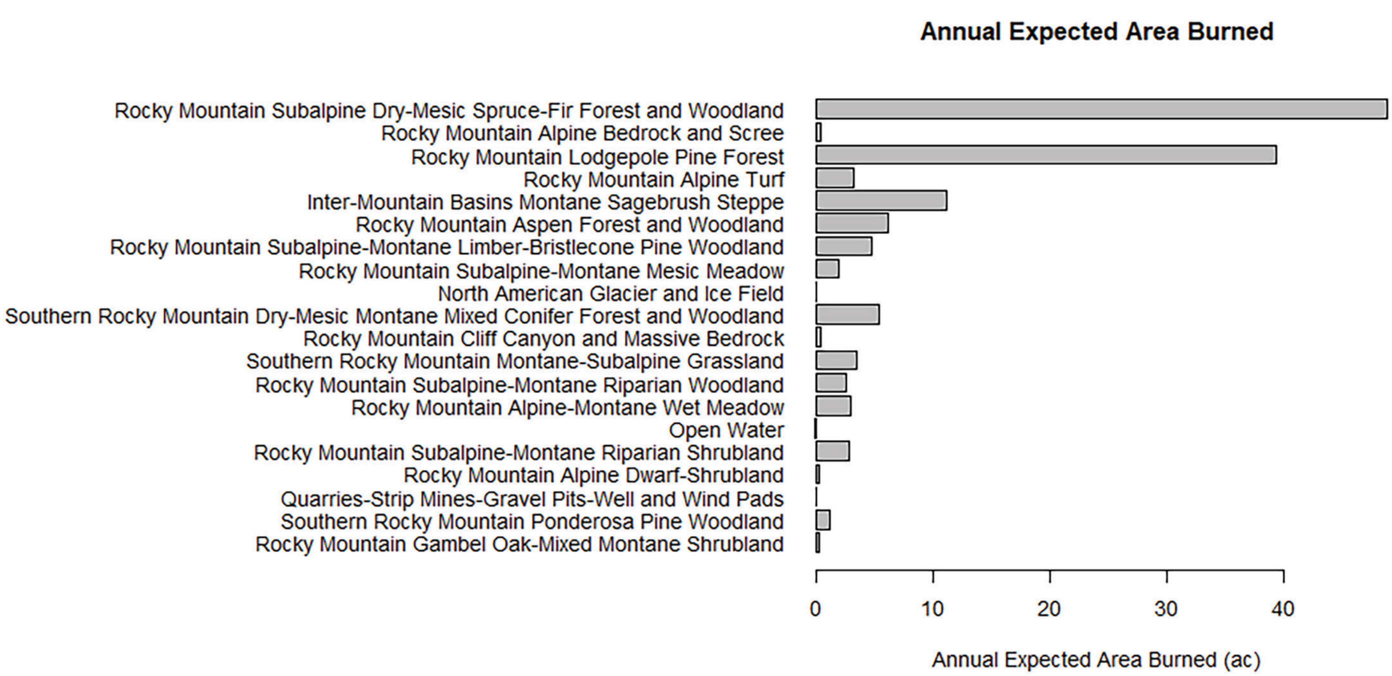

Figure 26: Expected area burned by LANDFIRE existing vegetation type based on local FSim burn probability.

Appendix III – Watershed Related Conditional Net Value Change (cNVC)

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

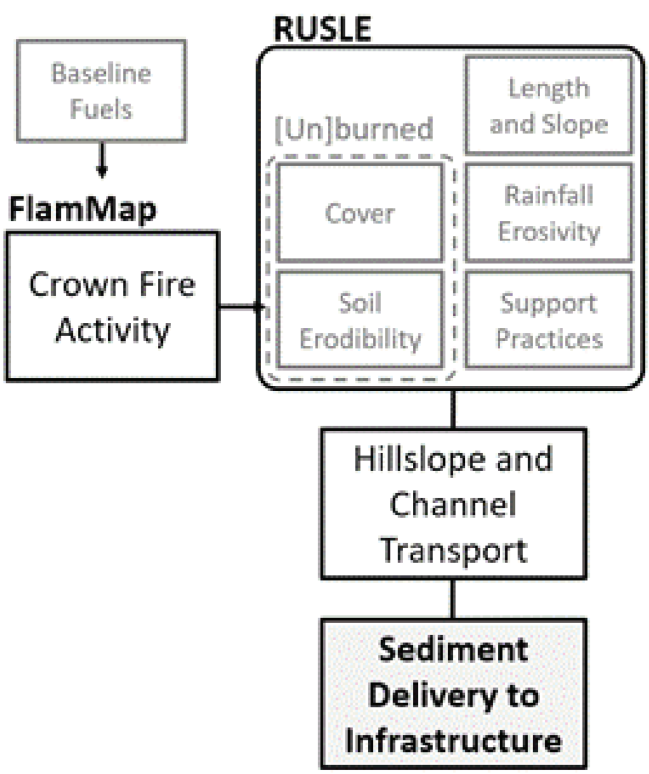

Figure 27: Workflow used to quantify potential post-fire sediment delivery from each pixel of the landscape.

This framework was applied with slight modifications to quantify the conditional net value change of critical water supplies, mine tailings, and aquatic habitat. Like the regular cNVC calculations, these metrics were calculated for each fire weather scenario and then combined into a single cNVC raster by a weighting averaging using their probabilities of occurrence (Table 4).

Critical Water Supplies

For critical water supplies, local stakeholder input was used to rank their relative importance on a scale from 0 for least important to 1 for most important (Table 7). These ratings were applied as weights to express the importance (impact) of sediment delivered to each water supply. It was assumed that ≥ 50 Mg ha-1 of sediment delivery to infrastructure in the first post-fire year is a dramatic loss based on the reported sediment yield from hillslope erosion after the 1996 Buffalo Creek Fire (68 Mg ha-1; Moody and Martin 2001). Therefore, the pixel-level estimates of sediment delivery to water infrastructure were linearly rescaled so that 0 to 50 Mg ha-1 corresponds to 0 to -100 percent value change. The final cNVC is mapped in Figure 28.

Table 7: Relative importance of critical water supplies as defined by local stakeholders

Infrastructure	Rel. Imp.
Twin Reservoir	1
Turquoise Reservoir	1
Big Evans Reservoir	1
Big Evans Intake	0.9
Mountain Lake	0.8
Evans Gulch #2 Reservoir	0.8
Iowa Gulch Intake	0.5
Birdseye Gulch Diversion	0.2

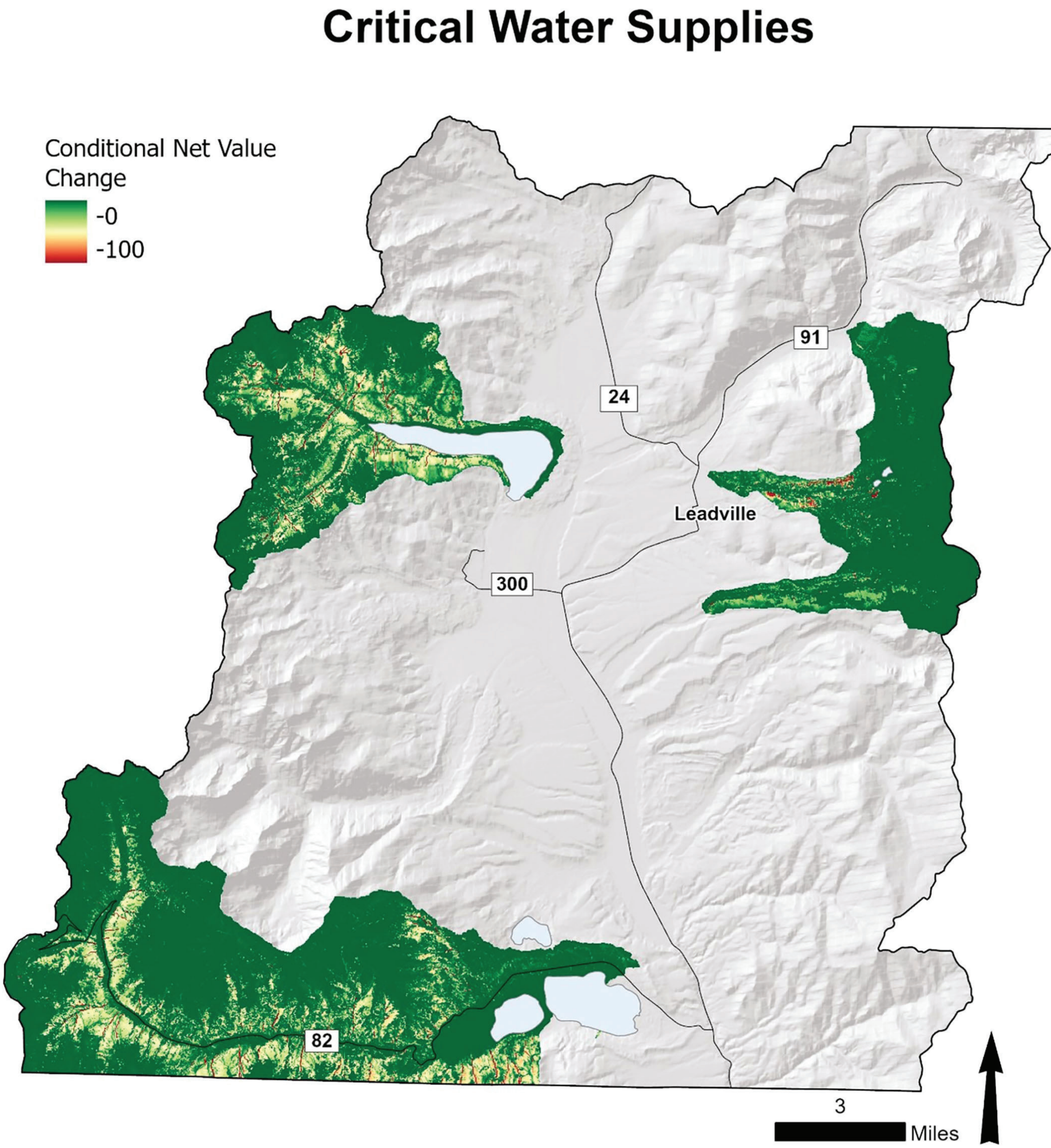

Figure 28: Critical water supplies conditional Net Value Change.

Mine Tailings

Water-focused stakeholders expressed concern for mines contaminating water supply given the long history of mining within Lake County. We originally addressed this concern by integrating all historic, permitted, and active mines within Lake County and applying one discrete response function. However, there were >5,500 mine features that, when buffered, covered much of Lake County. After subsequent discussions, stakeholders and water providers voiced that the primary concern was the potential for remobilization of mine tailings and subsequent delivery to surface waters due to post-fire runoff and erosion. We adjusted our approach to integrate a watershed model, similar to the Chaffee

County groundwater model, that captured potential secondary effects of fire on mine tailings. To start, the mine dataset was filtered to only include mine tailings features (i.e., "mine dump" or "tailings" features in the USGS dataset, n=114). Each tailings point was buffered by 400 m. We then modeled potnetial post-fire increase in sediment delivery to streams within each buffer zone and linearly rescaled to cNVC values between 0 - -100. We felt that rescaling to a maximum of -100 was more appropriate than the -50 value used in the Chaffee county groundwater assessment because this represents the pollution of all downstream water bodies with mine waste that is high in Mg, Zn, Cd, Fe, etc and could threaten human and aquatic health. Risk of remobilization is captured by the gross hillslope erosion magnitude in the surrounding 400 m buffer. Potential for delivery to streams is captured by the hillslope sediment delivery ratio that is used to convert gross hillslope erosion to net sediment delivery to streams. The sediment delivery ratio is equal to 1 near the stream corridor (i.e., all hillslope erosion will be transported to the

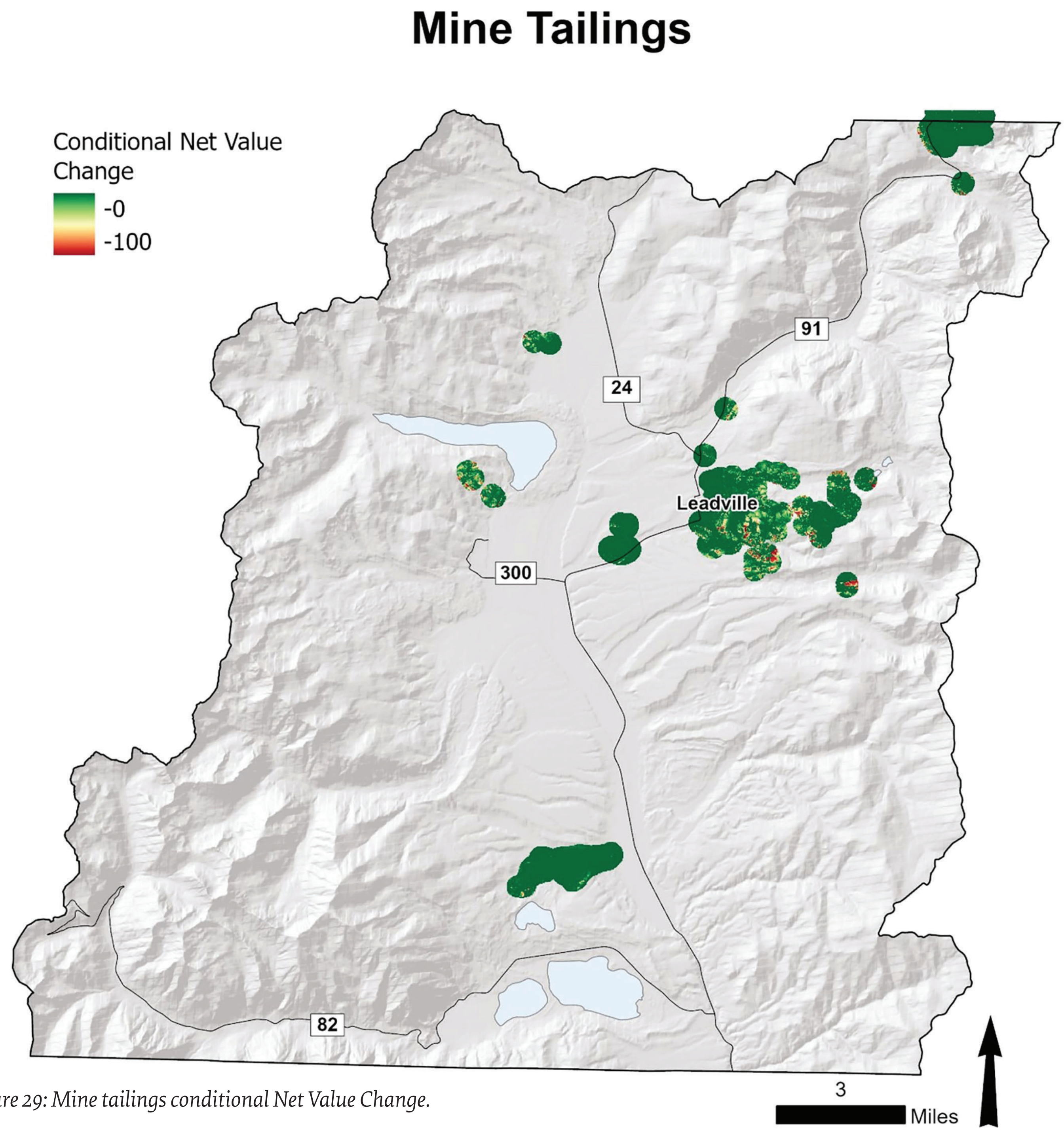

Figure 29: Mine tailings conditional Net Value Change.

stream) and decreases with distance from stream. The final cNVC is mapped in Figure 29.

Aquatic Habitat

To capture the importance of Gold Medal waters and tributaries, we predicted post-fire sediment delivery to the Gold Medal reaches of the Arkansas River. The pixel-level estimates of sediment delivery to the Arkansas River were linearly rescaled so that 0 to 50 Mg ha-1 corresponds to 0 to -100 percent value change. The final cNVC is mapped in Figure 30.

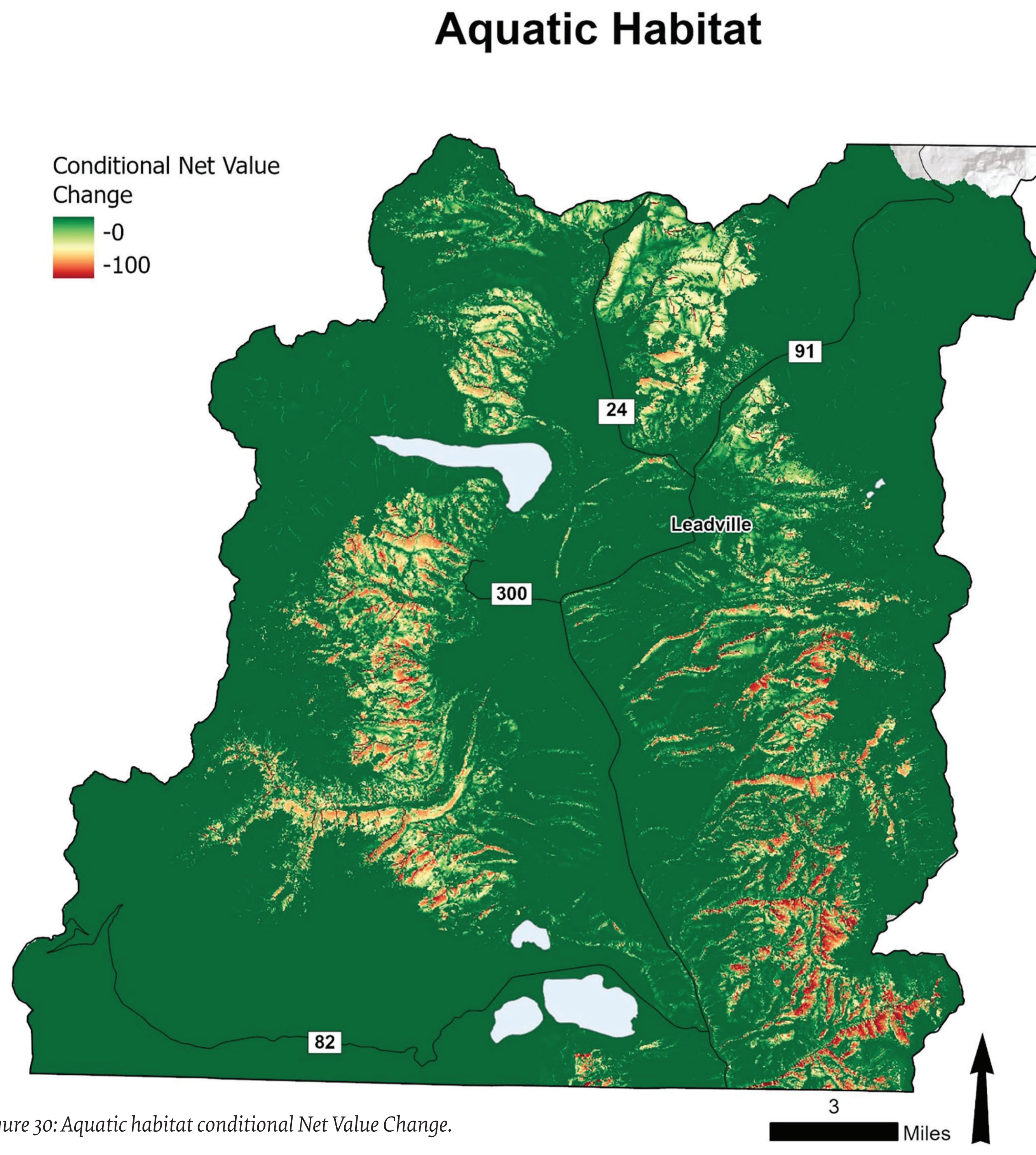

Figure 30: Aquatic habitat conditional Net Value Change.