Chaffee County Wildfire Risk Assessment

December, 2019
CFRI — 1913

COLORADO FOREST RESTORATION INSTITUTE

FOREST AND RANGELAND STEWARDSHIP
COLORADO STATE UNIVERSITY

Colorado Forest Restoration Institute

The Colorado Forest Restoration Institute (CFRI) was established in 2005 as an application-oriented, science-based outreach and engagement organization hosted by the Department of Forest and Rangeland Stewardship and the Warner College of Natural Resources at Colorado State University. Along with centers at Northern Arizona University and New Mexico Highlands University, CFRI is one of three Institutes that make up the Southwest Ecological Restoration institutes, which were authorized by Congress through the Southwest Forest Health and Wildfire Prevention Act of 2004. We lead collaborations between researchers, managers, and stakeholders to develop, synthesize, and apply locally-relevant, actionable knowledge to inform forest management strategies and achieve wildfire hazard reduction goals in Colorado and the Interior West. Our work informs forest conditions assessments, management goals and objectives, monitoring plans, and adaptive management processes. We help reduce uncertainties and conflicts between managers and stakeholders, streamline planning processes, and enhance the effectiveness of forest management strategies to restore and enhance the resilience of forest ecosystems to wildfires. We complement and supplement the capacities of forest land managers to draw upon and apply locally-relevant scientific information to enhance the credibility of forest management plans. We are trusted to be rigorous and objective in integrating currently-available scientific information into forest management decision-making. We do this through collaborative partnerships involving researchers, forest land managers, interested and affected stakeholders, and communities.

The Colorado Forest Restoration Institute at Colorado State University receives financial support through the Cooperative and International Programs of the U.S. Forest Service, Department of Agriculture, under the Southwest Forest Health and Wildfire Prevention Act.

Colorado State University
Colorado Forest Restoration Institute
Department of Forest & Rangeland Stewardship
Mail Delivery 1472
Colorado State University
Fort Collins, Colorado 80523
(970) 491-4685
cfri.colostate.edu

Publication date: December, 2019
Cover photo credit: Bob Nichols, USDA (CC BY-SA 2.0)

Author: Gannon, Benjamin, Colorado Forest Restoration Institute, *benjamin.gannon@colostate.edu.*

This work supported the creation of the Chaffee County Wildfire Protection plan: https://centralcoloradoconservancy.org/land/wp-content/uploads/Chaffee-Next-Gen-CWPP-Full-Report.pdf

Please use the following citation when referring to this paper:

Gannon, Benjamin (2019). Chaffe County Wildfire Risk Assessment. Colorado Forest Restoration Institute. CFRI-1913.

Table of Contents

Purpose and Scope

The purpose of this wildfire risk assessment is to inform a revision of the Chaffee 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 locally relevant risk assessment for Chaffee 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. 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).

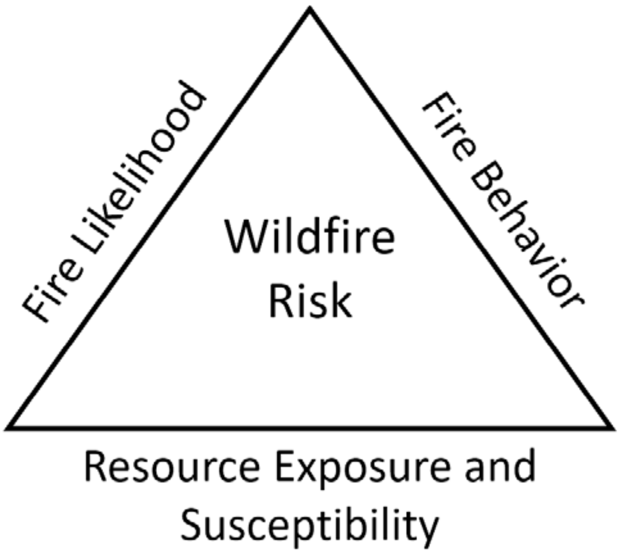


Figure 1: Wildfire risk triangle adapted from Scott et al. (2013).

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 their potential exposure to wildfire by intensity level, and to describe how HVRAs will respond to fire of varying intensity, so wildfire exposure can be translated to effects. 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 Chaffee County Risk Assessment.

Risk Assessment Framework

The Chaffee 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 with an empirical model of burn probability by vegetation type. 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 multiple cNVC measures 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 Chaffee County.

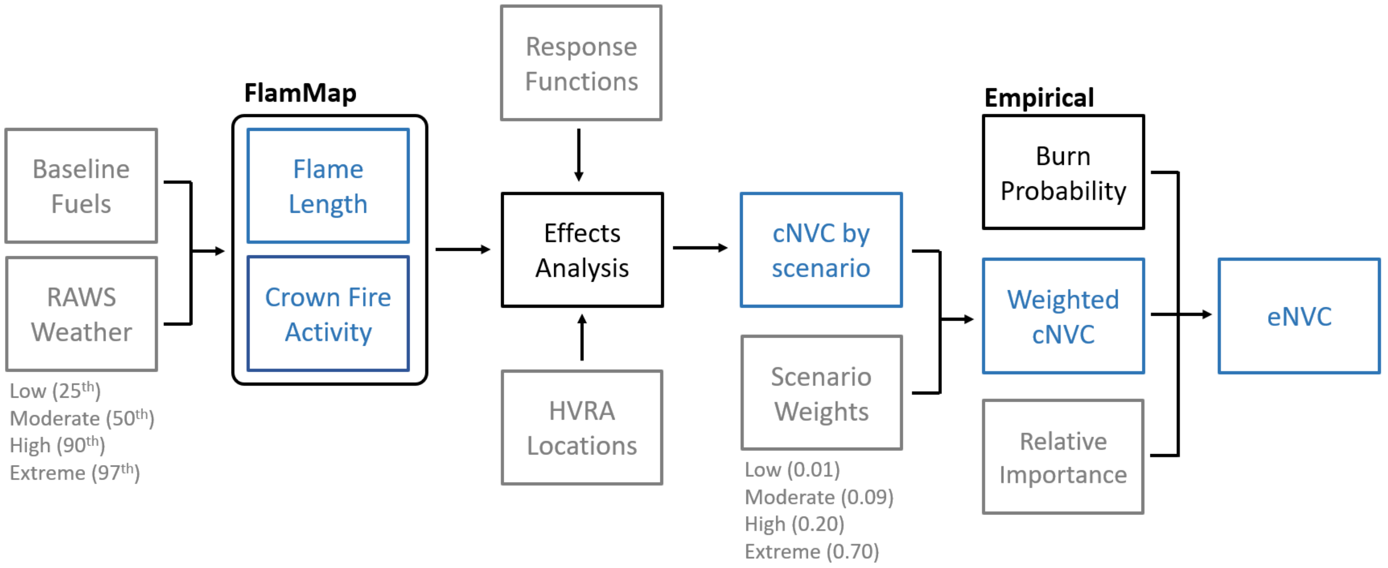


Figure 2: The Chaffee County Risk Assessment is based on the analysis framework from the Colorado Wildfire Risk Assessment (Technosylva 2018).

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 attributes from LANDFIRE (2014) and surface fire behavior fuel attributes from CO-WRA (Technosylva 2018). Canopy fuels were updated to reflect recent fuel treatments. Slope steepness, slope aspect, and elevation came from LANDFIRE (2014). Fire weather scenarios were developed from historical Remote Automated Weather Station (RAWS) data from the six stations within 20 miles of Chaffee County (Jones Hill, Lodgepole Plats, Needle Creek, Red Deer, Salida Mini-RAWS, 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 4.1 (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). Station statistics were aggregated to scenarios with weighted averaging based on the length of record at each station in years. 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 simulation products.

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

		Fuel Moisture %						
Scenario	**Percentile**	**1-hr**	**10-hr**	**100-hr**	**1000-hr**	**Herbaceous**	**Woody**	**Wind Speed 1-min (mph @ 20 ft)**
Low	25	8	11	15	17	82	110	9
Moderate	50	6	7	12	15	43	75	11
High	90	3	4	7	10	5	64	17
Extreme	97	2	3	6	9	3	64	21

Burn Probability Modeling

The original plan for the assessment was to use the CO-WRA burn probability product to represent wildfire likelihood, which is described in Technosylva (2018) and mapped in Appendix II – Burn probability. Based on feedback from both the Community Wildfire Protection Plan Working Group and community at large, we decided to use an empirical estimate of burn probability by vegetation type based on historical fire observations in Chaffee County as further described in Appendix II – Burn probability. 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 CO-WRA. The Community Wildfire Protection Plan Working Group favored this product because it matched their experiences and expectations of fire occurrence in Chaffee County. The data sources, methods, and limitations of this approach are described in Appendix II – Burn probability.

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, wildland-urban interface, wildlife, and recreation concerns in Chaffee 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	Polyline	400	100
Infrastructure	Aircraft Landing Facilities	Point	200	5
	Communication Facilities	Point	200	35
	Electric Power Transmission Lines	Polyline	200	35
	Emergency Service Stations	Point	200	15
	Schools	Point	200	10
Wildland Urban Interface	Low density WUI	Raster	0	47
	High density WUI	Raster	0	53
Water	Critical Water Supplies	Raster	0	65
	Surface diversions	Raster	0	3
	Ground diversions	Raster	0	2
	CSU Pipelines	Polyline	200	10
	CSU Buildings	Point	200	20
Wildlife	Bighorn Sheep Winter Range	Polygon	0	5
	Black Bear Fall Concentration	Polygon	0	10
	Elk Migration Corridors	Polygon	0	5
	Elk Winter Range	Polygon	0	10
	Aquatic Habitat	Raster	0	50
	Mule Deer Migration Corridors	Polygon	0	5
	Mule Deer Winter Range	Polygon	0	10
	Lynx	Polygon	0	5
Recreation	Tourism Businesses	Point	400	10
	Monarch Ski Area	Polygon	0	10
	USFS Recreation Opportunities	Point	400	20
	Trails	Polyline	100	25
	Arkansas Headwaters Recreation Area	Polygon	100	27
	Brown's Canyon National Monument	Polygon	0	3
	Dispersed camping	Polygon	0	5

A workshop was held on June 19, 2019 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 watershed related HVRAs were quantified with a separate process described in Appendix III – Watershed related Conditional Net Value Change (cNVC). Methods to delineate the wildland urban interface and density classes are described in Appendix II – Spatial data processing.

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

		FIL1	FIL2	FIL3	FIL4	FIL5	FIL6
Category	**HVRA**	**0-2 ft**	**2-4 ft**	**4-6 ft**	**6-8 ft**	**8-12 ft**	**> 12 ft**
Life Safety	Evacuation routes	-20	-40	-80	-100	-100	-100
Infrastructure	Aircraft Landing Facilities	0	0	-10	-50	-80	-90
	Communication Facilities	0	0	0	-30	-100	-100
	Electric Power Transmission Lines	0	0	0	-30	-40	-40
	Emergency Service Stations	-10	-30	-60	-80	-100	-100
	Schools	-10	-30	-60	-80	-100	-100
Wildland Urban Interface	Low density WUI	-20	-40	-80	-100	-100	-100
	High density WUI	-40	-80	-100	-100	-100	-100
Water	Critical Water Supplies	NA	NA	NA	NA	NA	NA
	Surface diversions	NA	NA	NA	NA	NA	NA
	Ground diversions	NA	NA	NA	NA	NA	NA
	CSU Pipelines	0	-20	-50	-80	-100	-100
	CSU Buildings	-10	-20	-40	-100	-100	-100
Wildlife	Bighorn Sheep Winter Range	40	20	10	-10	-60	-80
	Black Bear Fall Concentration	40	20	10	-10	-60	-80
	Elk Migration Corridors	40	20	10	-10	-60	-80
	Elk Winter Range	40	20	10	-10	-60	-80
	Aquatic Habitat	NA	NA	NA	NA	NA	NA
	Mule Deer Migration Corridors	40	20	10	-10	-60	-80
	Mule Deer Winter Range	40	20	10	-10	-60	-80
	Lynx	0	-10	-20	-40	-80	-100
Recreation	Tourism Businesses	-10	-20	-40	-80	-100	-100
	Monarch Ski Area	0	-10	-10	-20	-50	-70
	USFS Recreation Opportunities	10	-10	-10	-20	-50	-70
	Trails	10	0	-10	-30	-40	-50
	Arkansas Headwaters Recreation Area	10	-10	-10	-30	-50	-70
	Brown's Canyon National Monument	40	20	10	-10	-10	-10
	Dispersed camping	10	0	-10	-30	-40	-50

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 2). These were assigned by resource experts through small group discussions and full group critique. The relative importance of HVRA categories to Chaffee County was informed by the Envision Chaffee County Community Wildfire Survey, which identified human life safety is the top concern followed by critical infrastructure, water, wildland urban interface, wildlife habitat, and recreation. Local stakeholders assigned relative importance weights based on the survey and small group discussion. 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	24.7
Infrastructure	100	20.6
Water	90	18.6
Wildland Urban Interface	80	16.5
Wildlife	50	10.3
Recreation	45	9.3

Results

The composite wildfire risk map shown in Figure 3 combines the category-level risk maps based on their relative importance to Chaffee 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 low- to mid-elevation forests and woodlands where there is a convergence of HVRAs, hazardous fuel conditions, and high burn probability (Figure 11; Figure 12). Although burn probability is highest in the mid- to high-elevation forests (Appendix II – Burn probability), more risk is associated with pinyon-juniper woodlands because of the high concentration of fire sensitive

HVRAs mapped in the foothills and valley bottoms. There are concentrated areas of high wildfire risk in higher elevation forests where they overlap life safety, infrastructure, and WUI HVRAs. 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), 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.

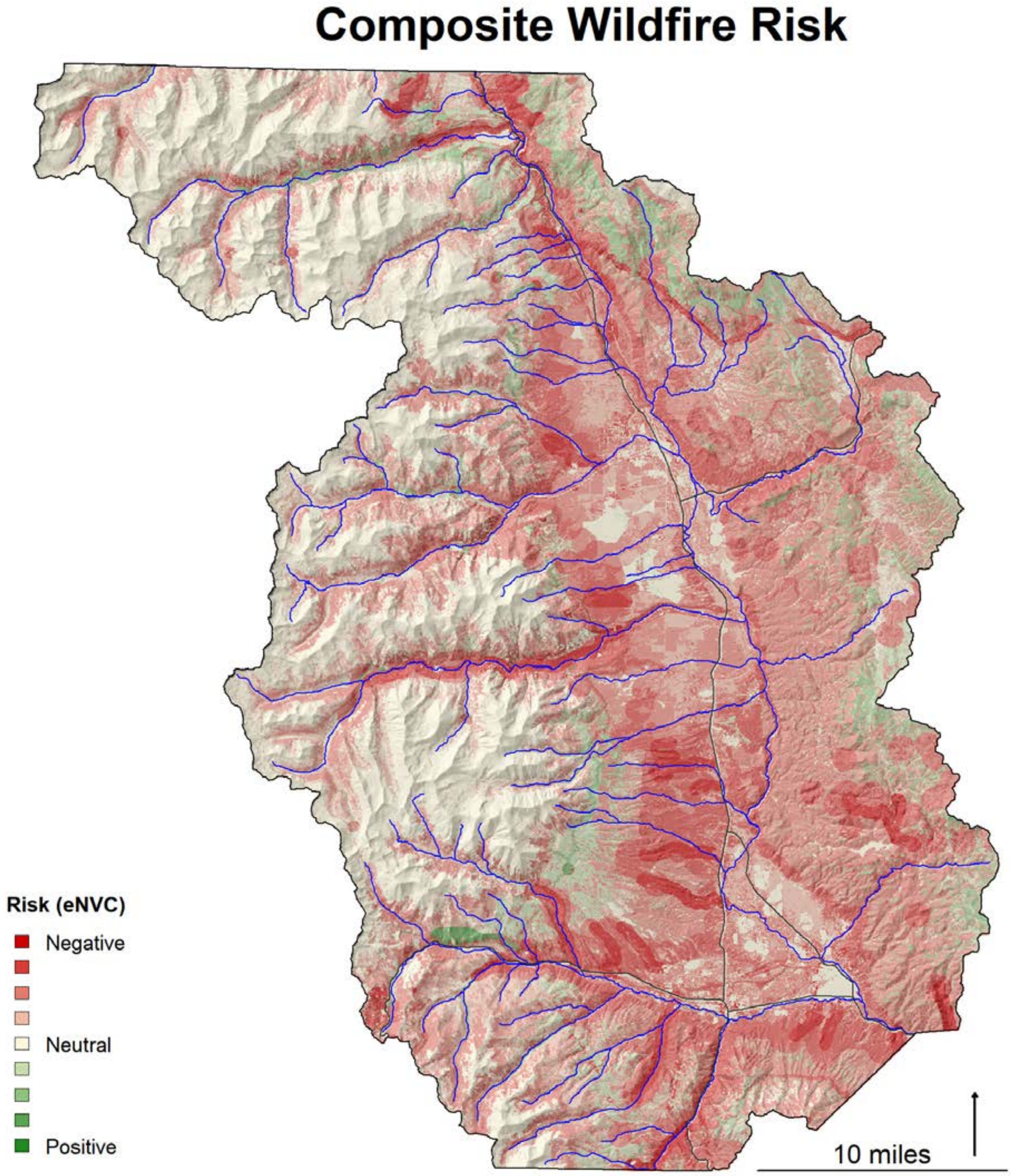


Figure 3: Composite wildfire risk map for Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

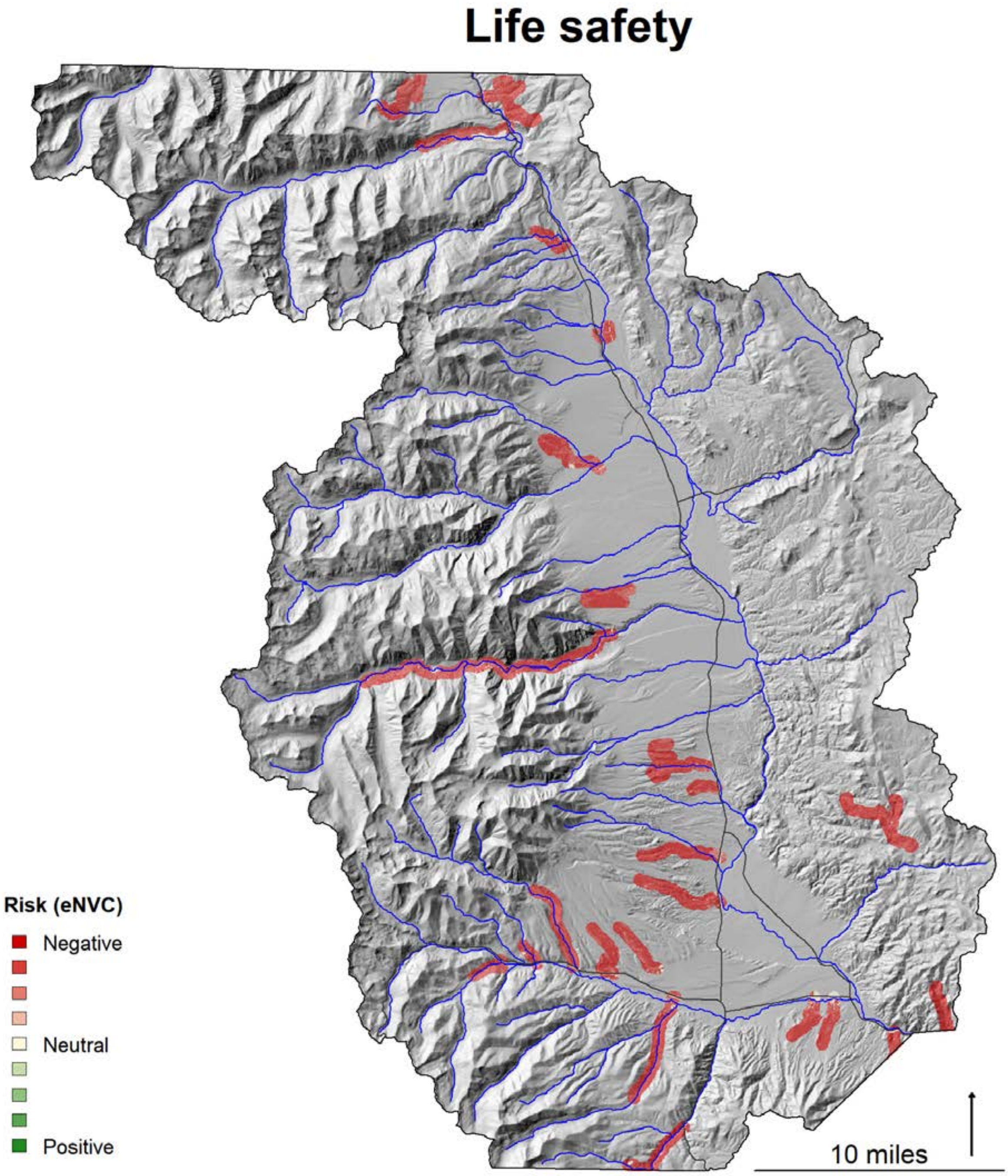


Figure 4: Wildfire risk to life safety in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

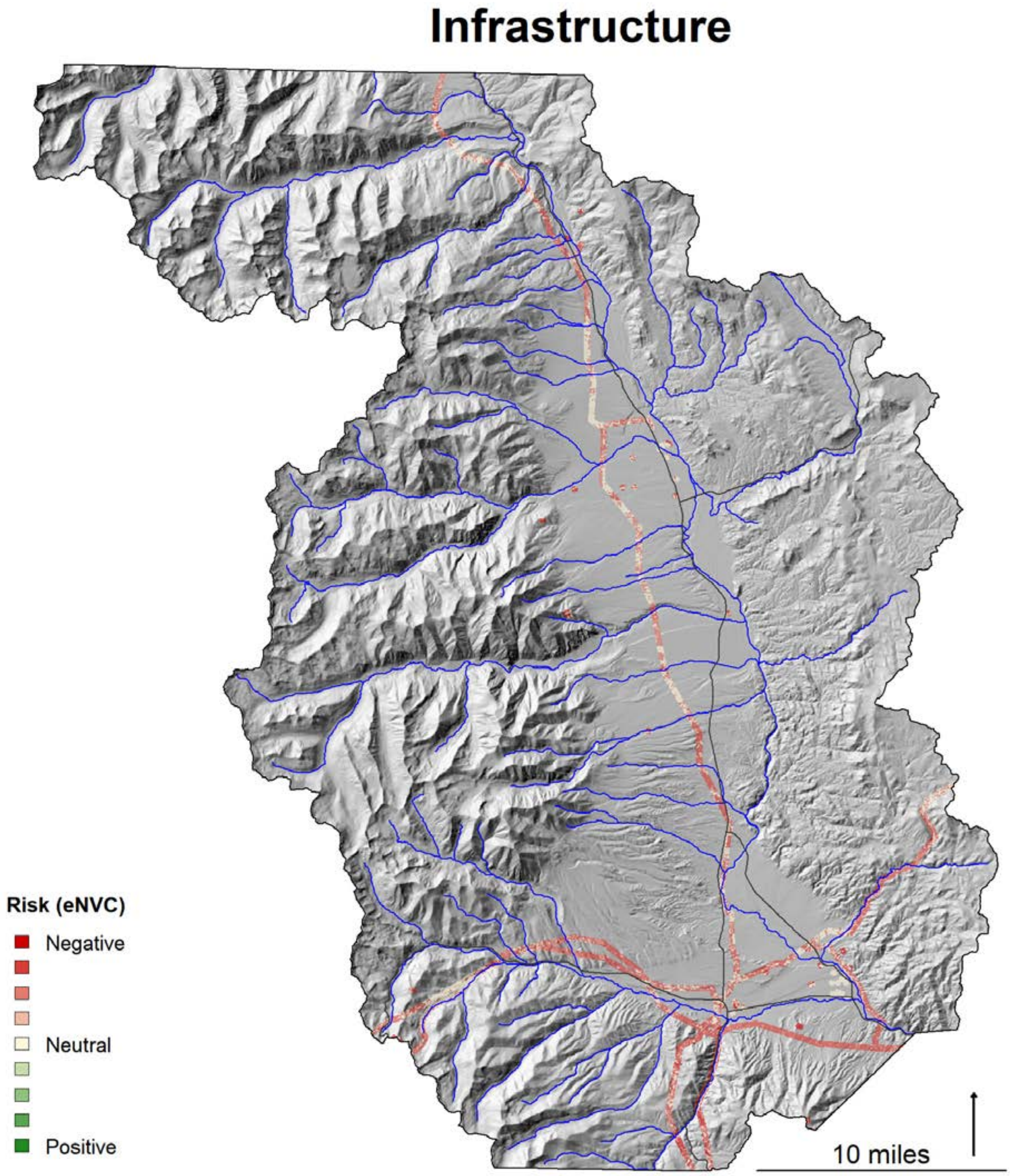


Figure 5: Wildfire risk to infrastructure in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

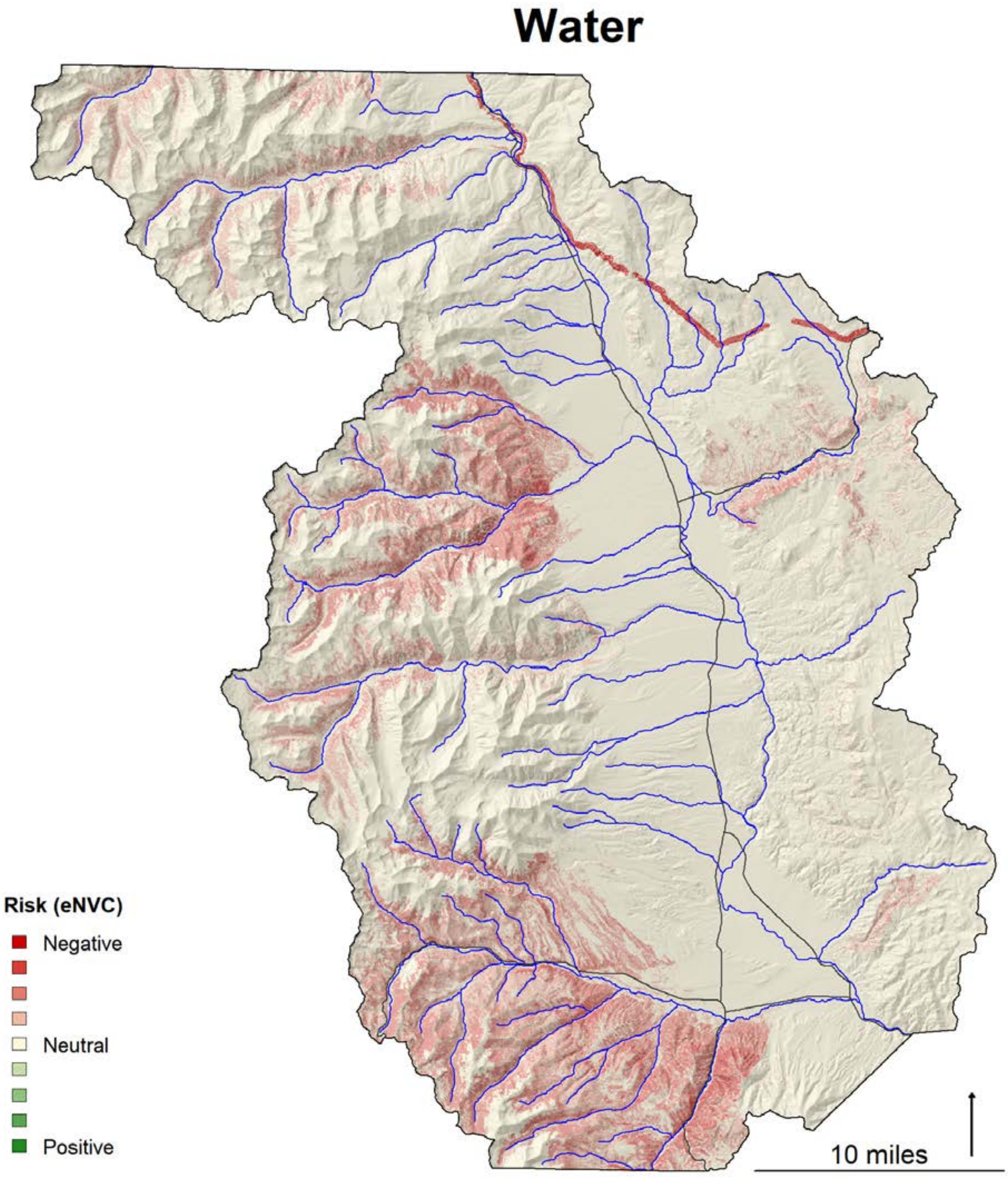


Figure 6: Wildfire risk to water in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

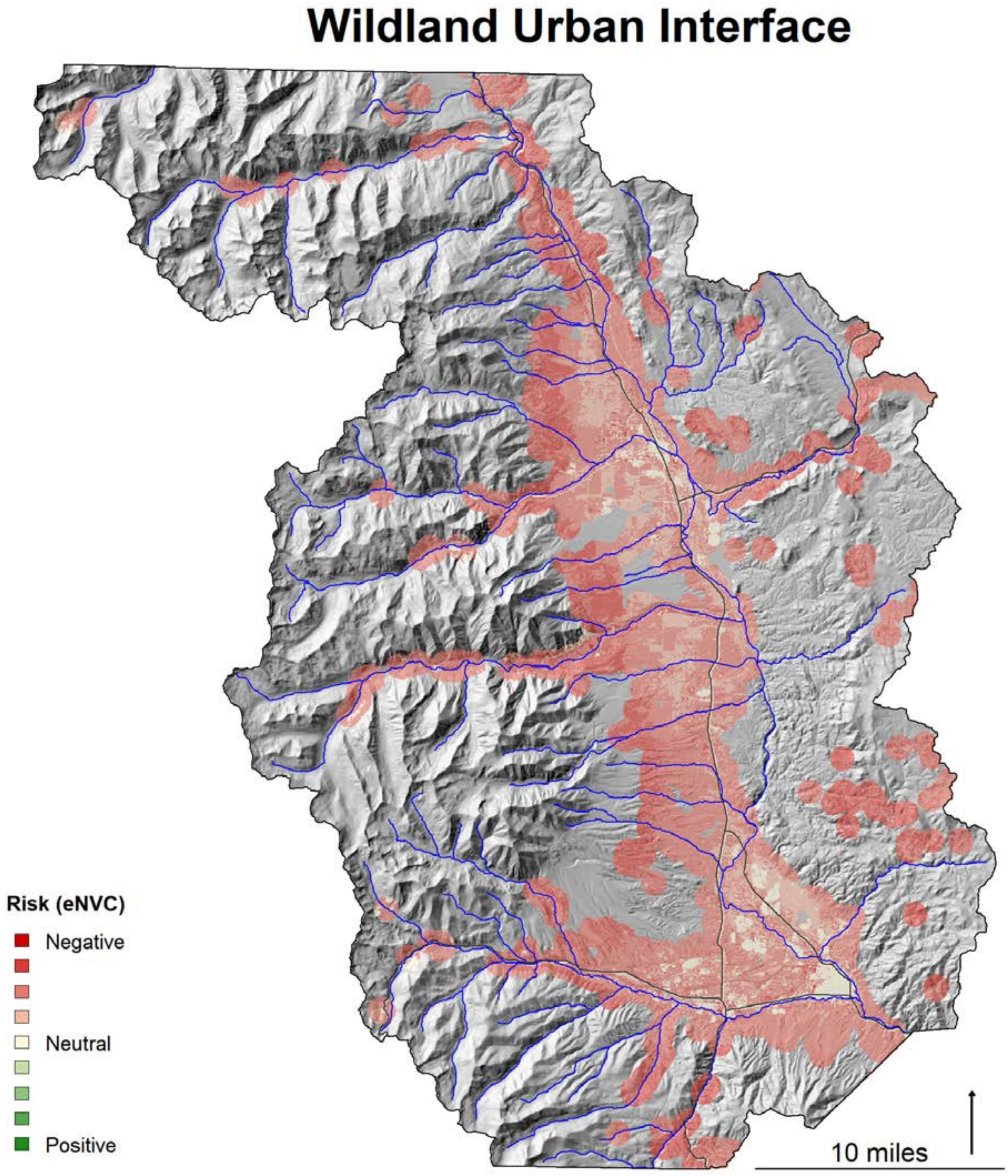


Figure 7: Wildfire risk to Wildland Urban Interface (WUI) in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire. The WUI is where people live, work, shop, and go to school. WUI risk therefore represents the potential for wildfire to harm numerous human assets and to disrupt human lives. For more information on WUI mapping see Appendix II – Spatial data processing.

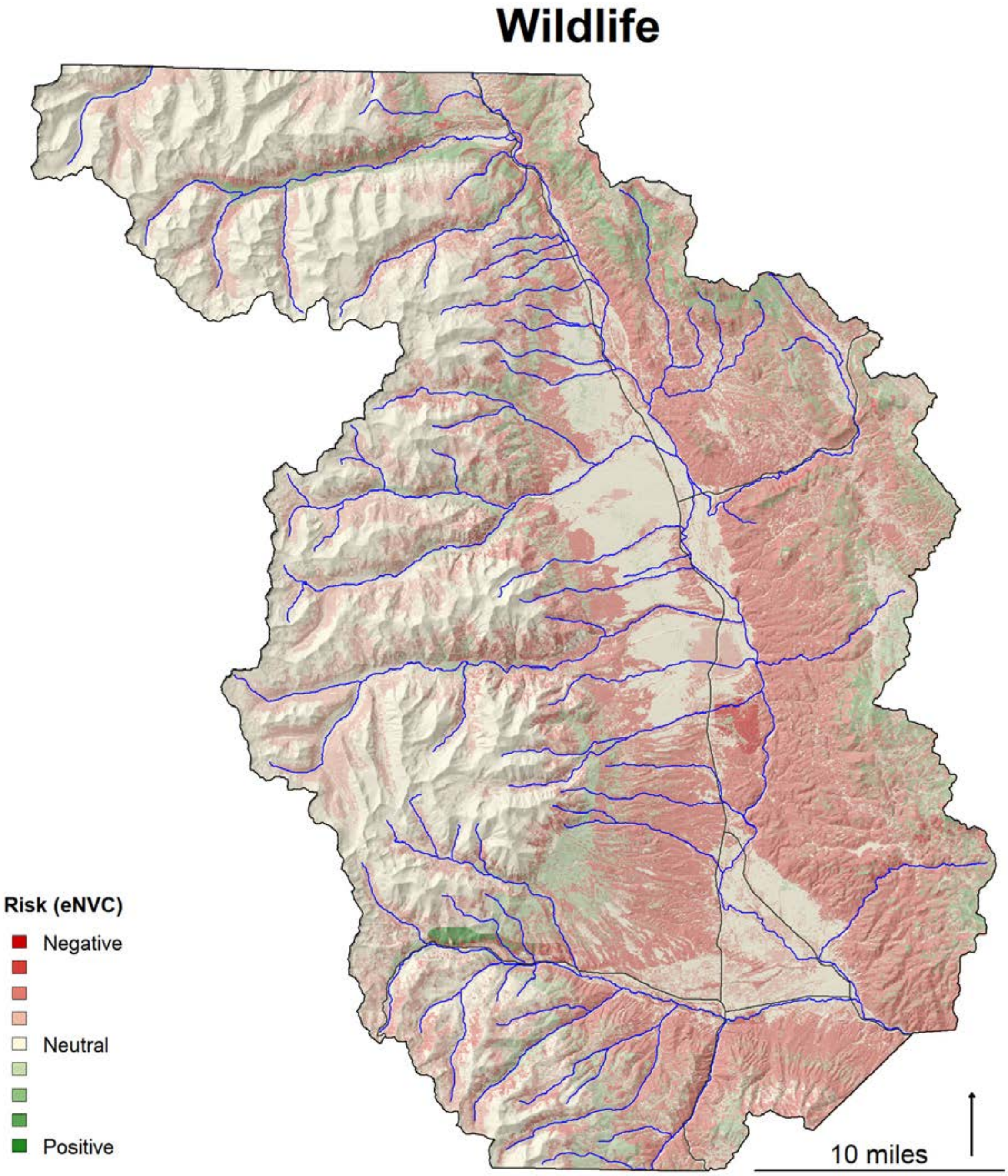


Figure 8: Wildfire risk to wildlife in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

Recreation

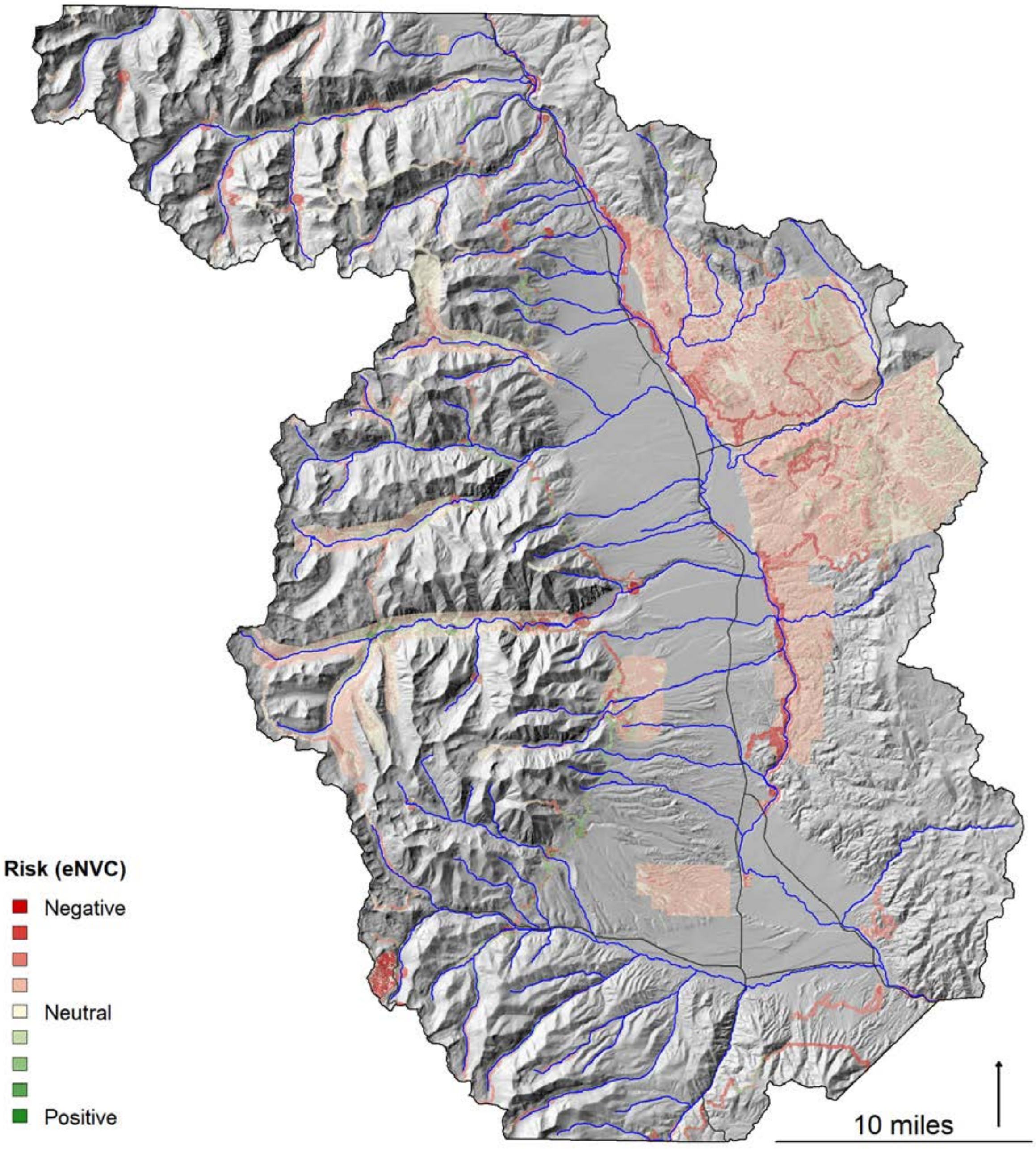


Figure 9: Wildfire risk to recreation in Chaffee County. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

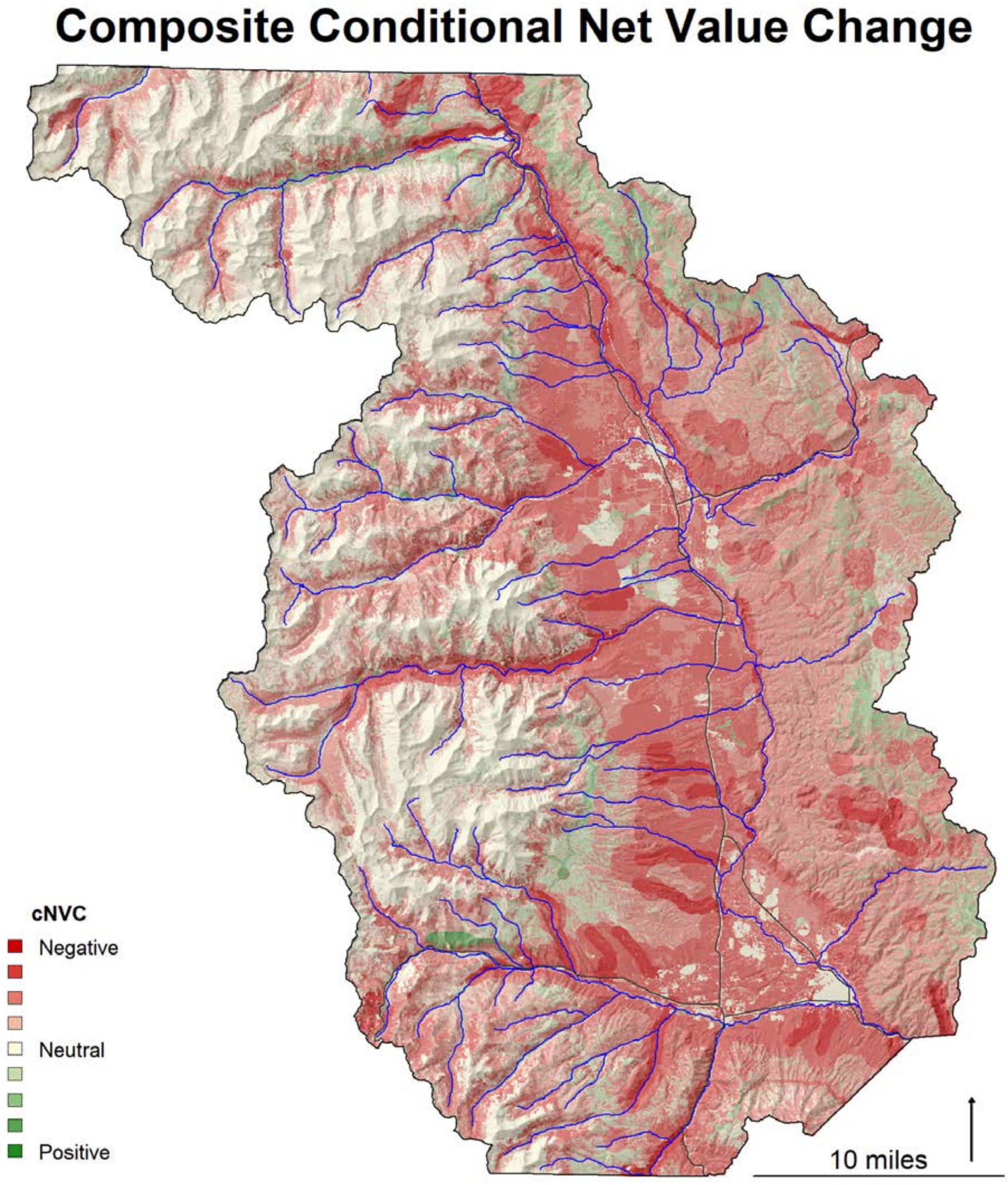


Figure 10: Composite conditional Net Value Change (cNVC) map for Chaffee County. Negative cNVC means net losses. Positive cNVC means net benefits.

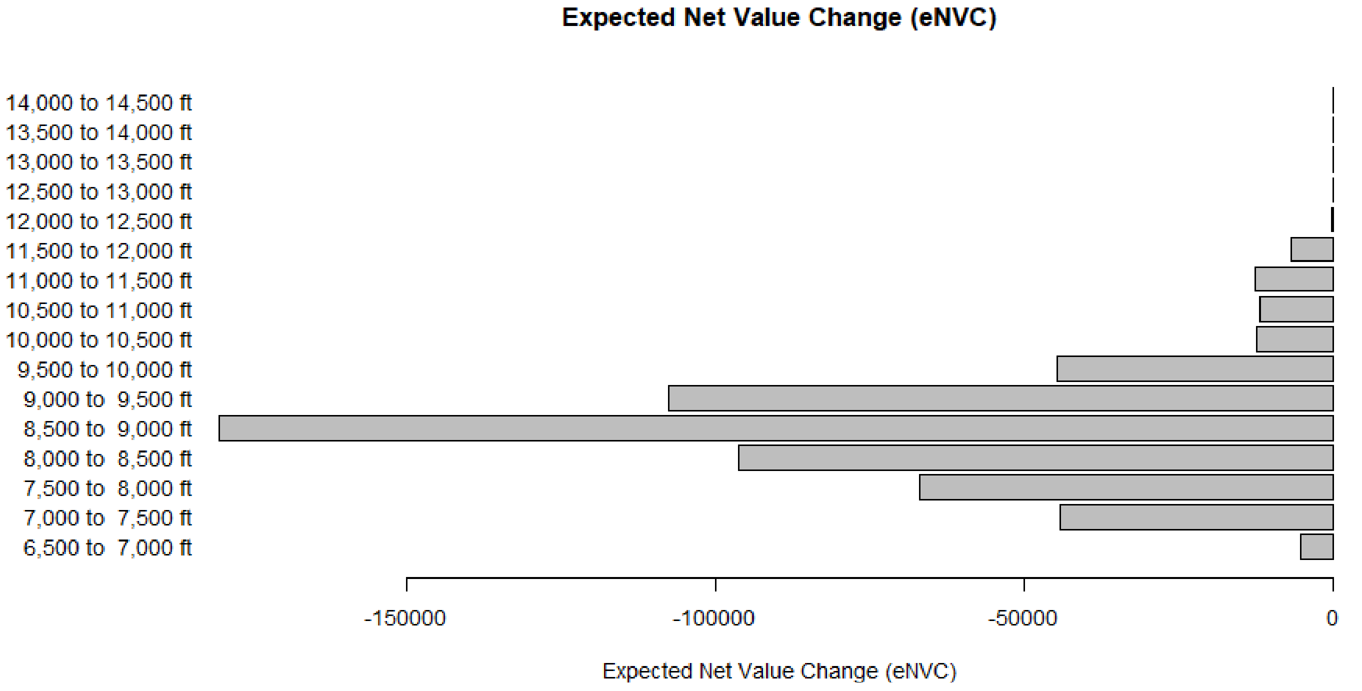


Figure 11: Risk (expected Net Value Change) distribution across elevation bins.

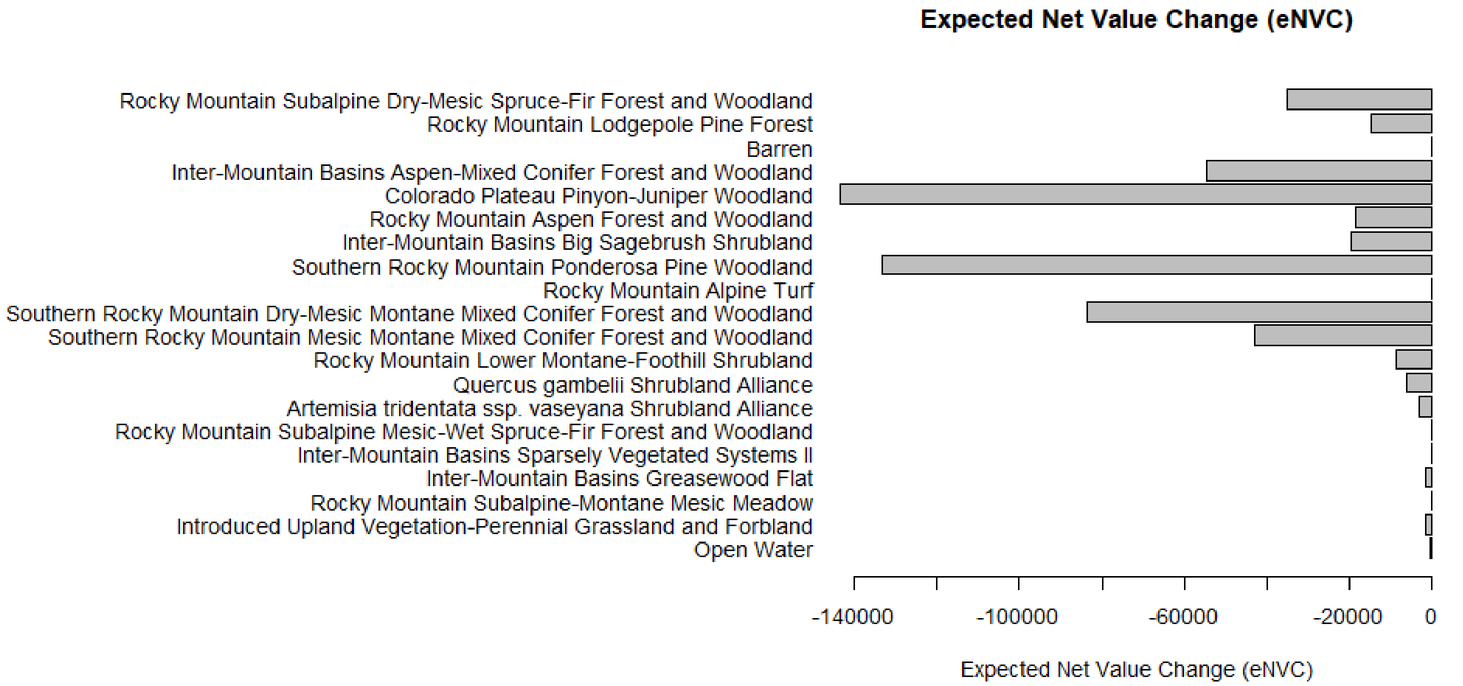


Figure 12: Risk (expected Net Value Change) by existing vegetation type from LANDFIRE (2014).

References

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

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

Caggiano MD, Tinkham WT, Hoffman C, Cheng AS, Hawbaker TJ (2016) High resolution mapping of development in the wildland-urban interface using object based image extraction. *Heliyon* **2**, e00174. doi:10.1016/j.heliyon.2016.e00174

Coe JA, Kean JW, McCoy SW, Staley DM, Wasklewicz TA (2010) Chalk Creek Valley: Colorado's natural debris-flow laboratory. *In* Through the Generations: Geologic and Anthropogenic Field Excursions in the Rocky Mountains from Modern to Ancient: Geological Society of America Field Guide 18. LA Morgan, SL Quane eds. p 95–117, doi:10.1130/2010.0018(05).

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

Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management* **211**, 97-108. doi:10.1016/j.foreco.2005.02.010

Finney MA, Brittain S, Seli RC, McHugh CW, Gangi L (2015) FlamMap: fire mapping and analysis system (version 5.0) [Software]. Available from http://www.firelab.org/document/flammap-software

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

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

GeoMAC (2019) Fire history perimeters 2000-2019. Geospatial Multi-Agency Coordination. Available online: https://www.geomac.gov/

Graham RT (2003) Hayman Fire case study. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-114. (Ogden, UT, USA)

Haas JR, Calkin DE, Thompson MP (2015) Wildfire risk transmission in the Colorado Front Range, USA. *Risk Analysis* **35(2)**, 226–240. doi:10.1111/risa.12270

LANDFIRE (2014) Fuel, topography, existing vegetation type, and fuel disturbance layers, LANDFIRE 1.4.0., U.S. Geological Survey. Available from http://landfire.cr.usgs.gov/viewer/

Larsen IJ, MacDonald LH (2007) Predicting post-fire sediment yields at the hillslope scale: testing RUSLE and disturbed WEPP. *Water Resources Research* **43**, W11412. doi:10.1029/2006WR005560

Maranghides A, McNamara D, Vihnanek R, Restaino J, Leland C (2015) A case study of a community affected by the Waldo Fire – event timeline and defensive actions. National Institute of Technology (NIST) Technical Note 1910. doi:10.6028/NIST.TN.1910

Microsoft (2018) United States Building Footprints Data. Available from https://github.com/Microsoft/USBuildingFootprints

Miller C, Ager AA (2013) A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire* **22**, 1-14. doi:10.1071/WF11114

MTBS (2019) Burned area boundaries 1984-2017. Monitoring Trends in Burn Severity Project, USDA Forest Service and US Geological Survey. Available online: https://data.fs.usda.gov/geodata/edw/datasets.php

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

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

Page WG, Alexander ME, Jenkins MJ (2013) Wildfire's resistance to control in mountain pine beetle-attacked lodgepole pine forests. *The Forestry Chronicle* **89(6)**, 783-794.

Parisien M-A, Snetsinger S, Greenberg JA, Nelson CR, Schoennagel T, Dobrowski SZ, Moritz MA (2012) Spatial variability in wildfire probability across the western United States. *International Journal of Wildland Fire* **21**, 313-327. doi:10.1071/WF11044

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

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

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

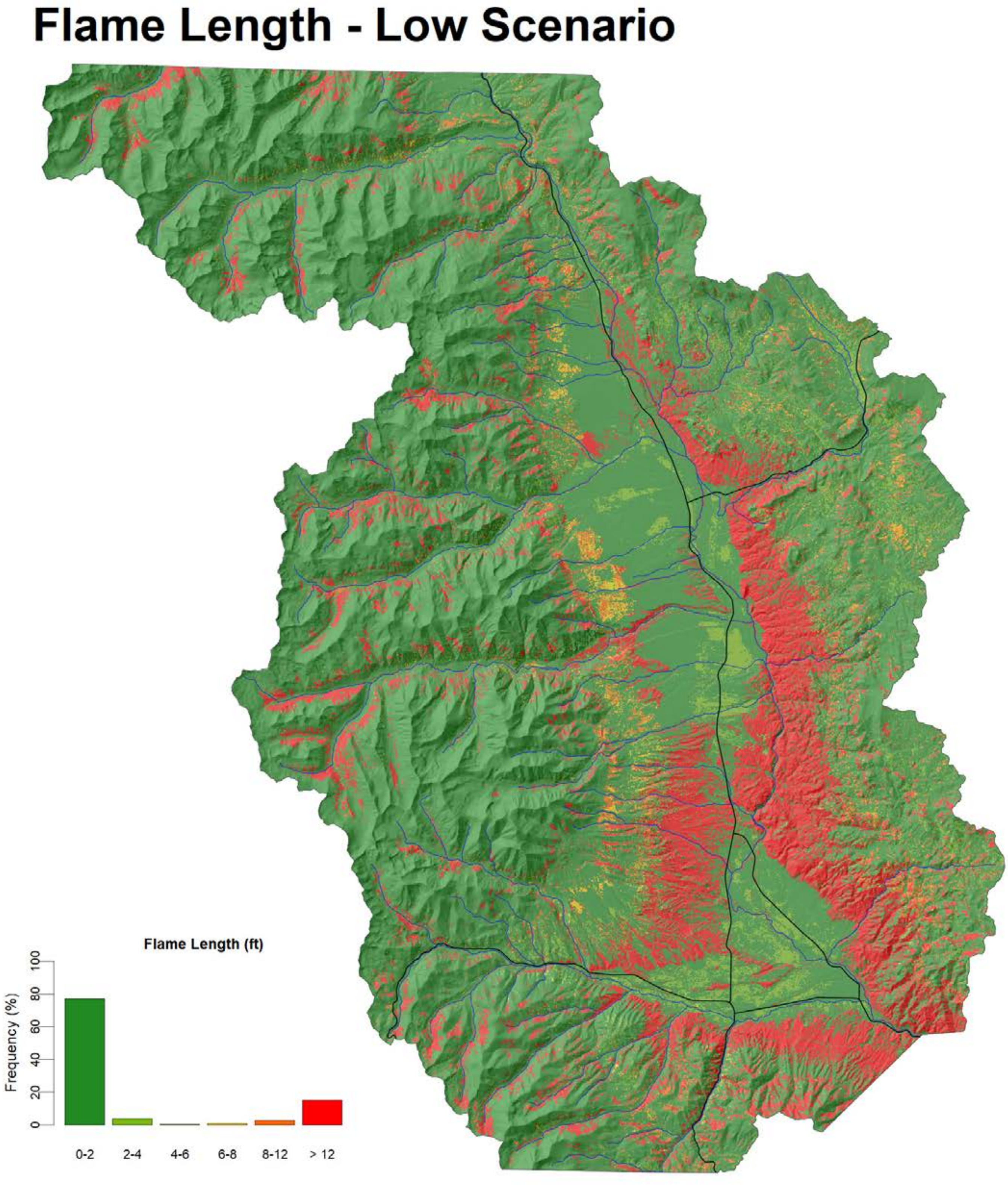
Short KC, Finney MA, Scott JH, Gilbertson-Day JW, Grenfell IC (2016) Spatial dataset of probabilistic wildfire risk components for the conterminous United States. USDA Forest Service Research Data Archive. doi:10.2737/RDS-2016-0034. (Fort Collins, CO)

Short KC (2017) Spatial wildfire occurrence data for the United States, 1992-2015 [FPA_FOD_20170508]. 4th Edition. USDA Forest Service Research Data Archive. doi:10.2737/RDS-2013-0009.4 (Fort Collins, CO)

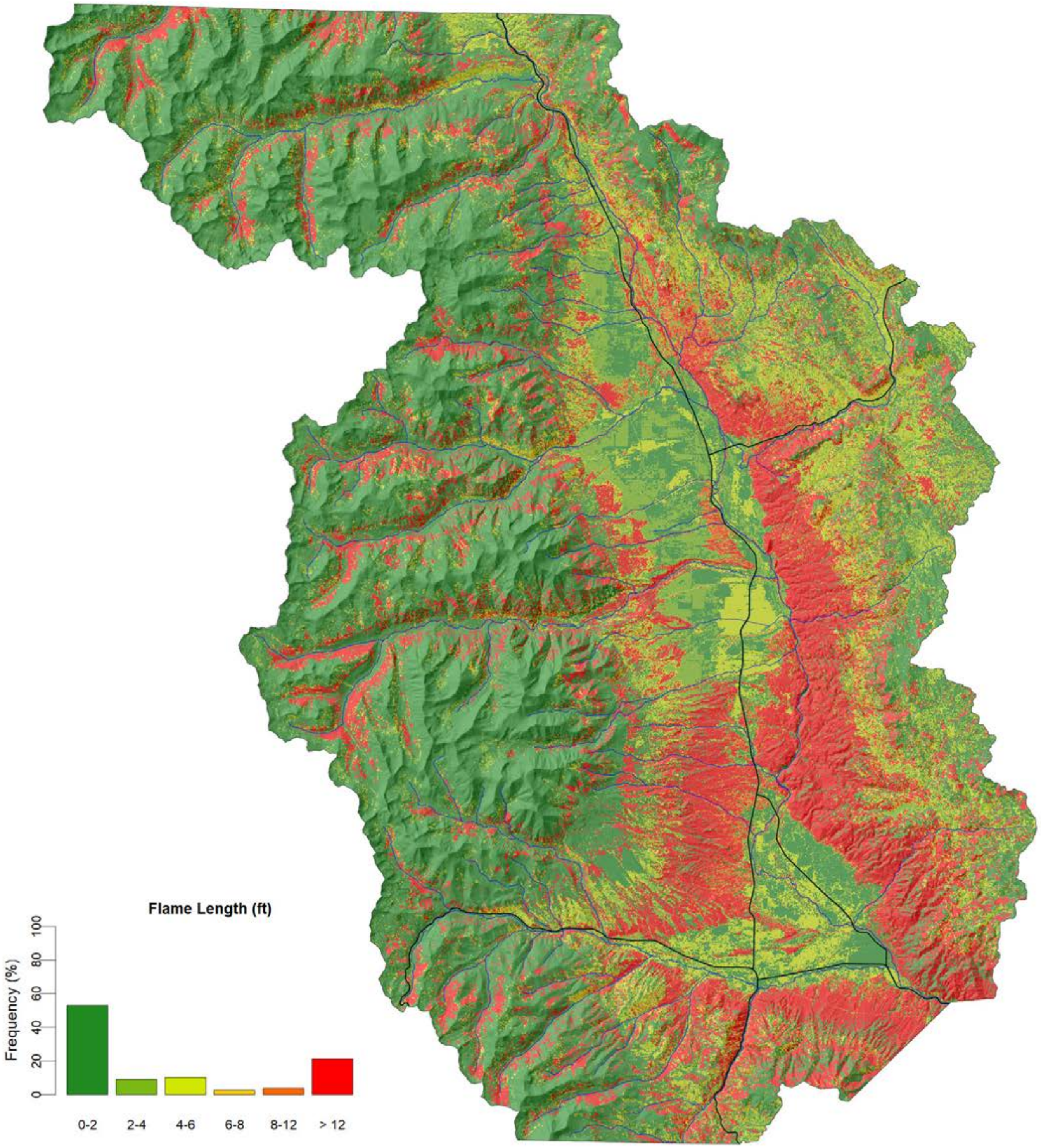
Technosylva (2018) 2017 Colorado Wildfire Risk Assessment Update. Report to the Colorado State Forest Service. (La Jolla, CA, USA)

Wagenbrenner JW, Robichaud PR (2014) Post-fire bedload sediment delivery across spatial scales in the interior western United States. *Earth Surface Processes and Landforms* **39**, 865–876. doi:10.1002/esp.348

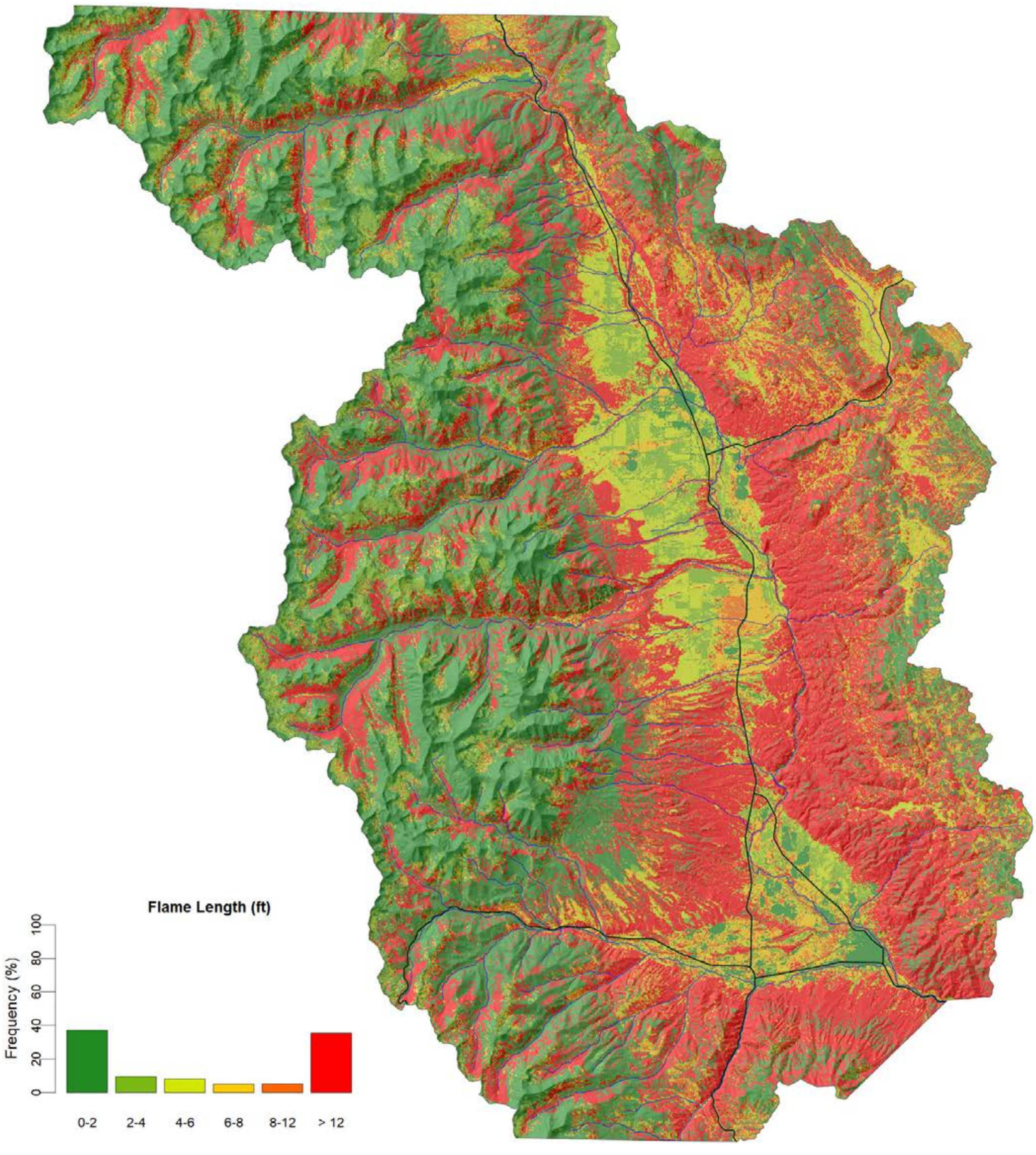
Appendix I - Fire simulation products



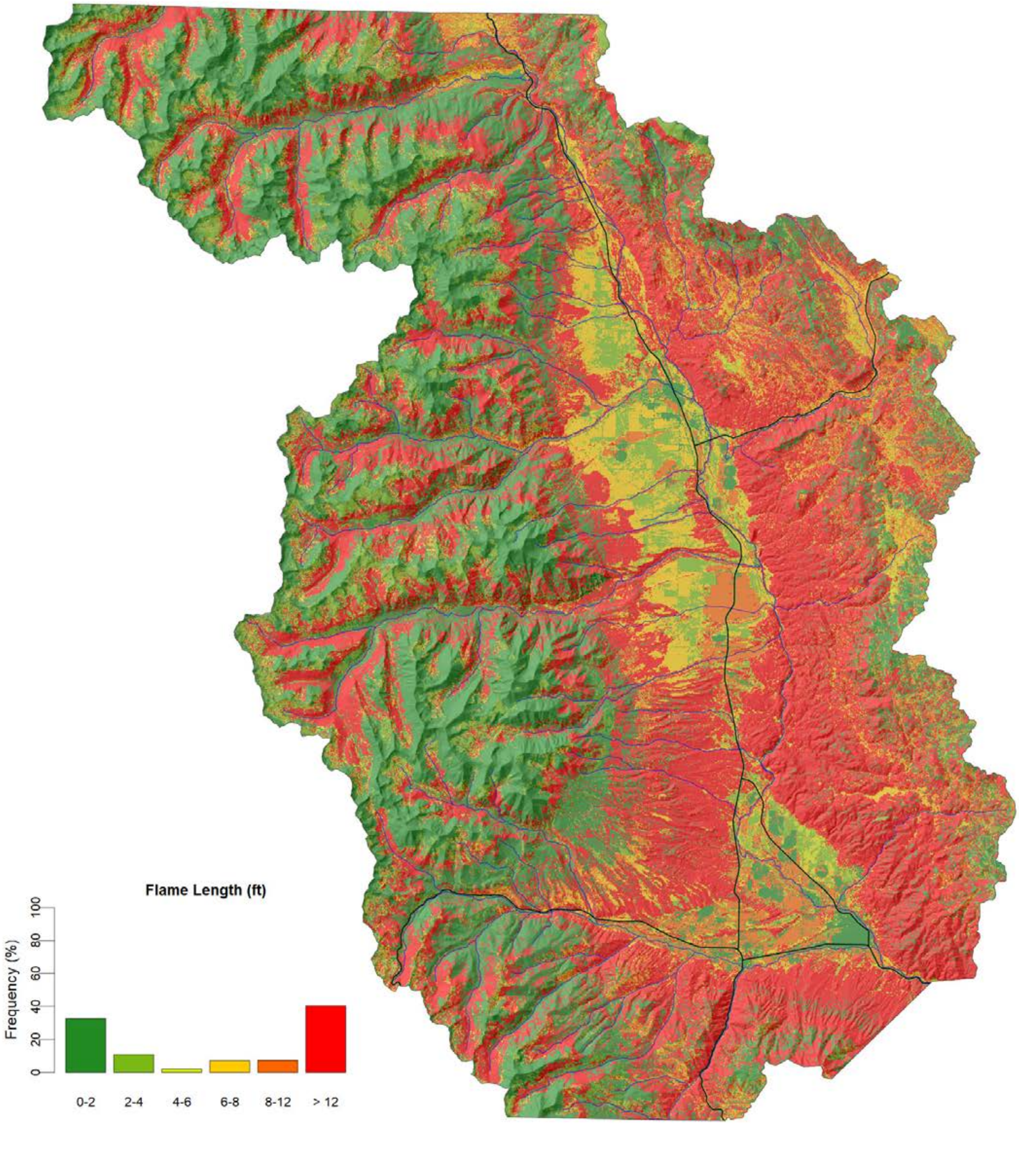
Flame Length - Moderate Scenario



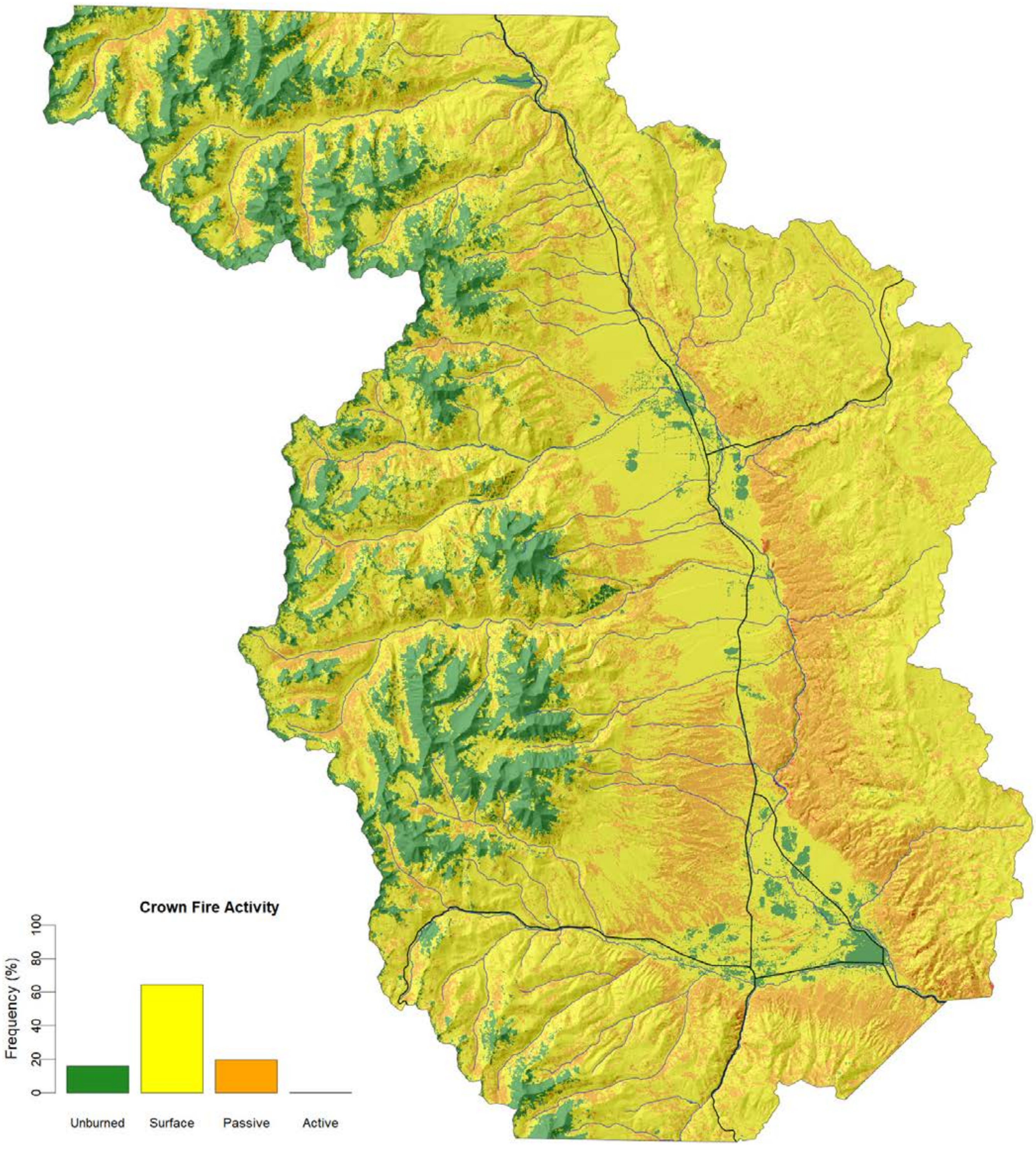
Flame Length - High Scenario



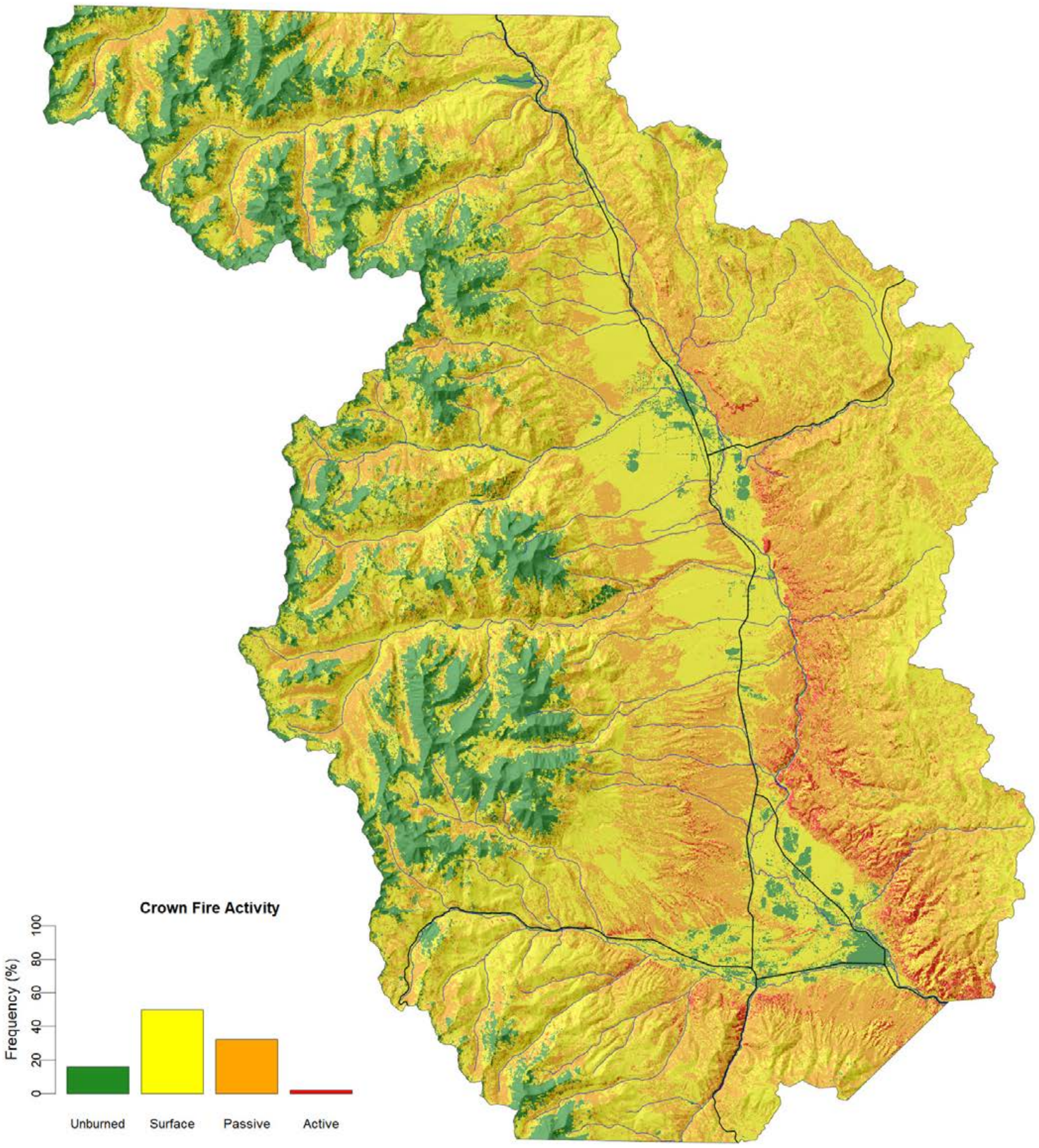
Flame Length - Extreme Scenario



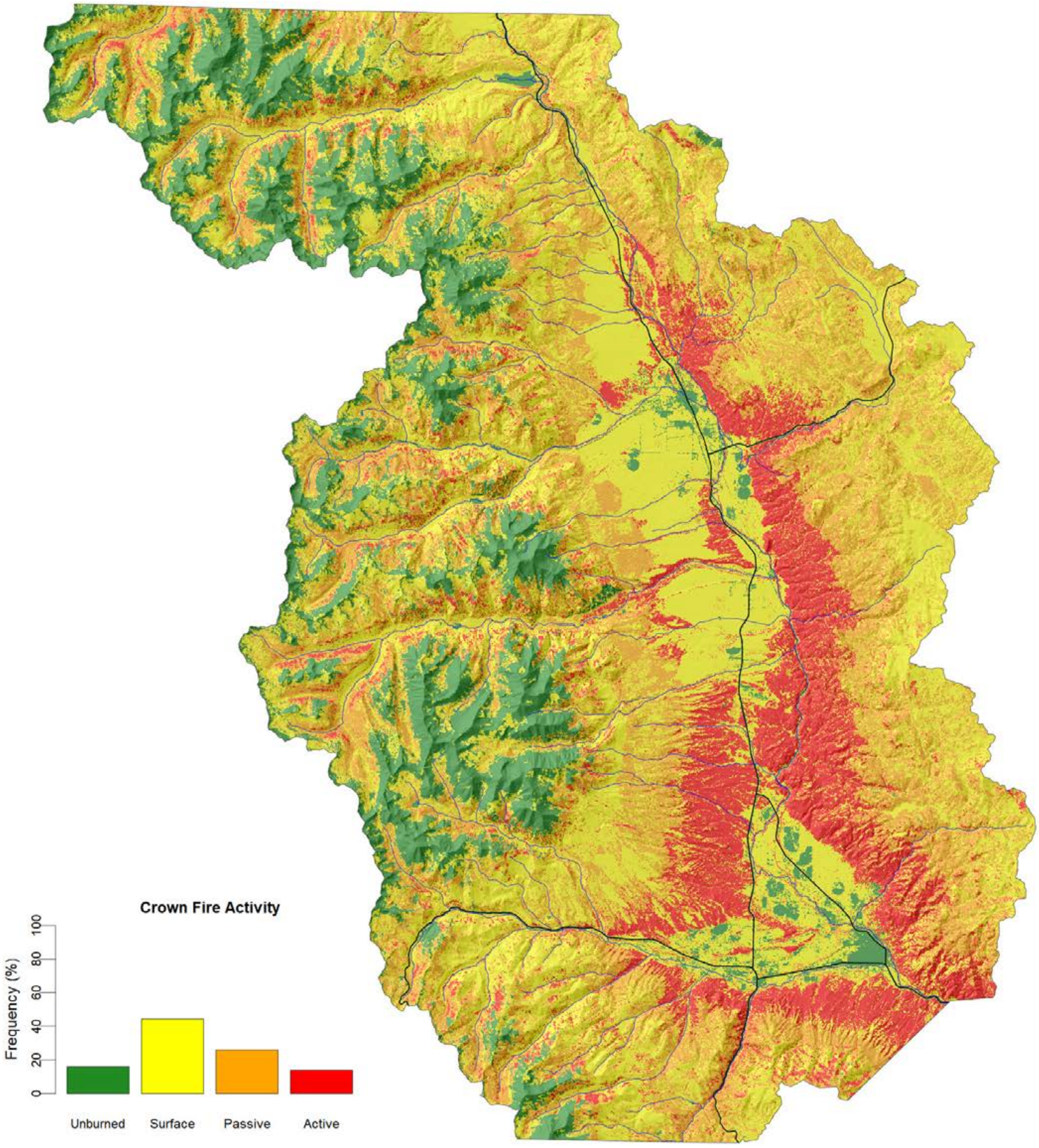
Crown Fire Activity - Low Scenario



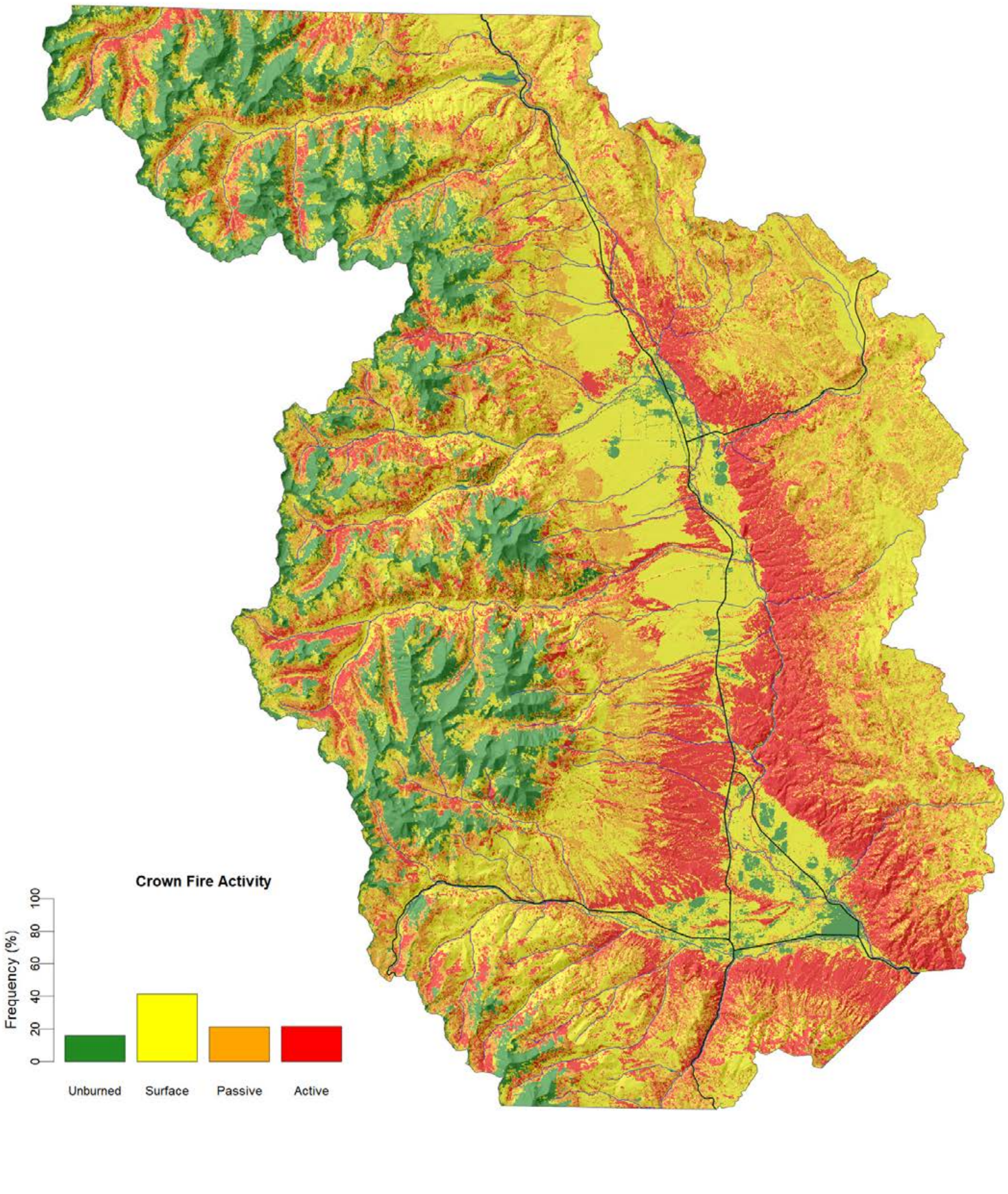
Crown Fire Activity - Moderate Scenario



Crown Fire Activity - High Scenario



Crown Fire Activity - Extreme Scenario



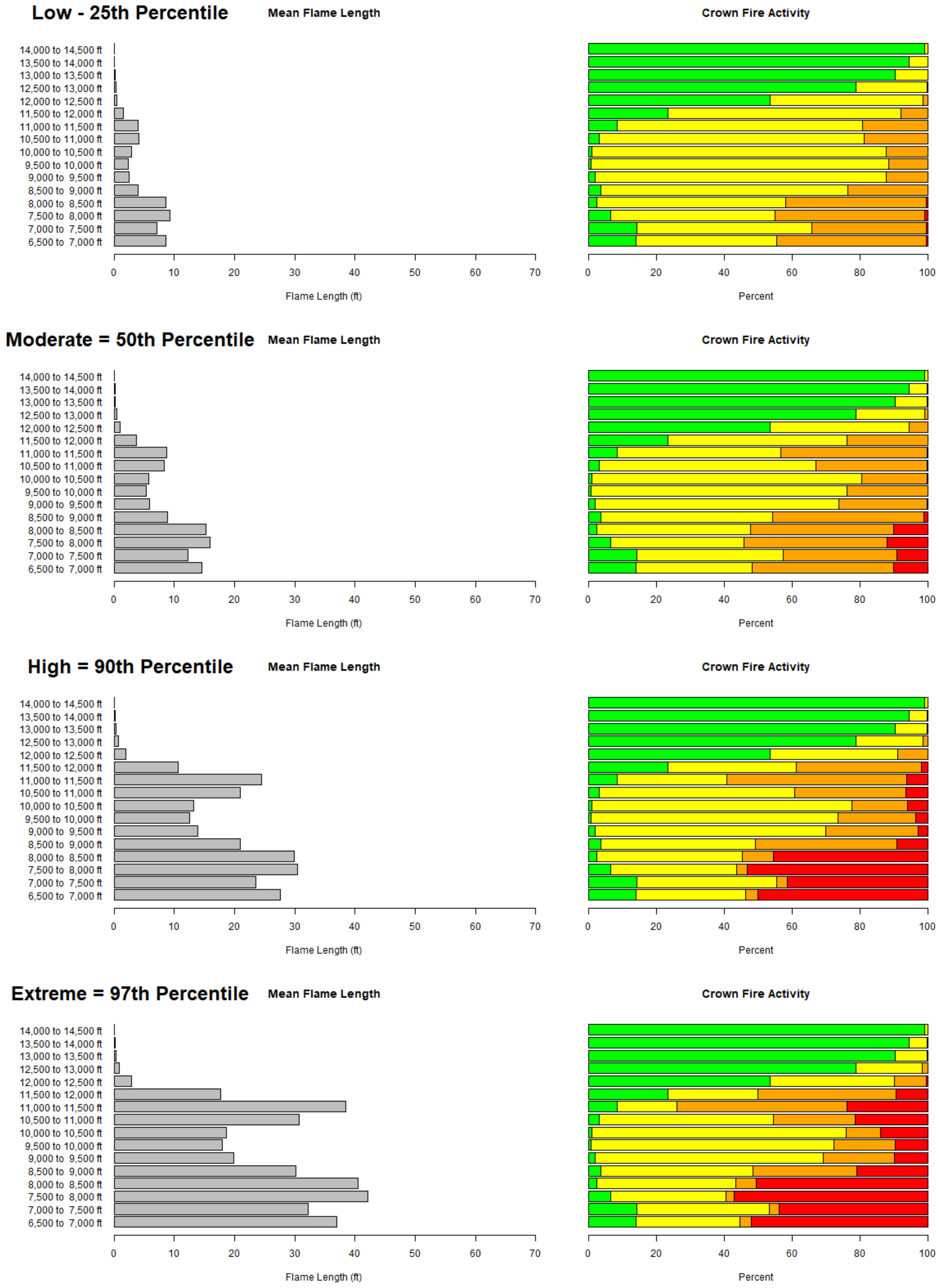


Figure 13: Summary of fire behavior by elevation. The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

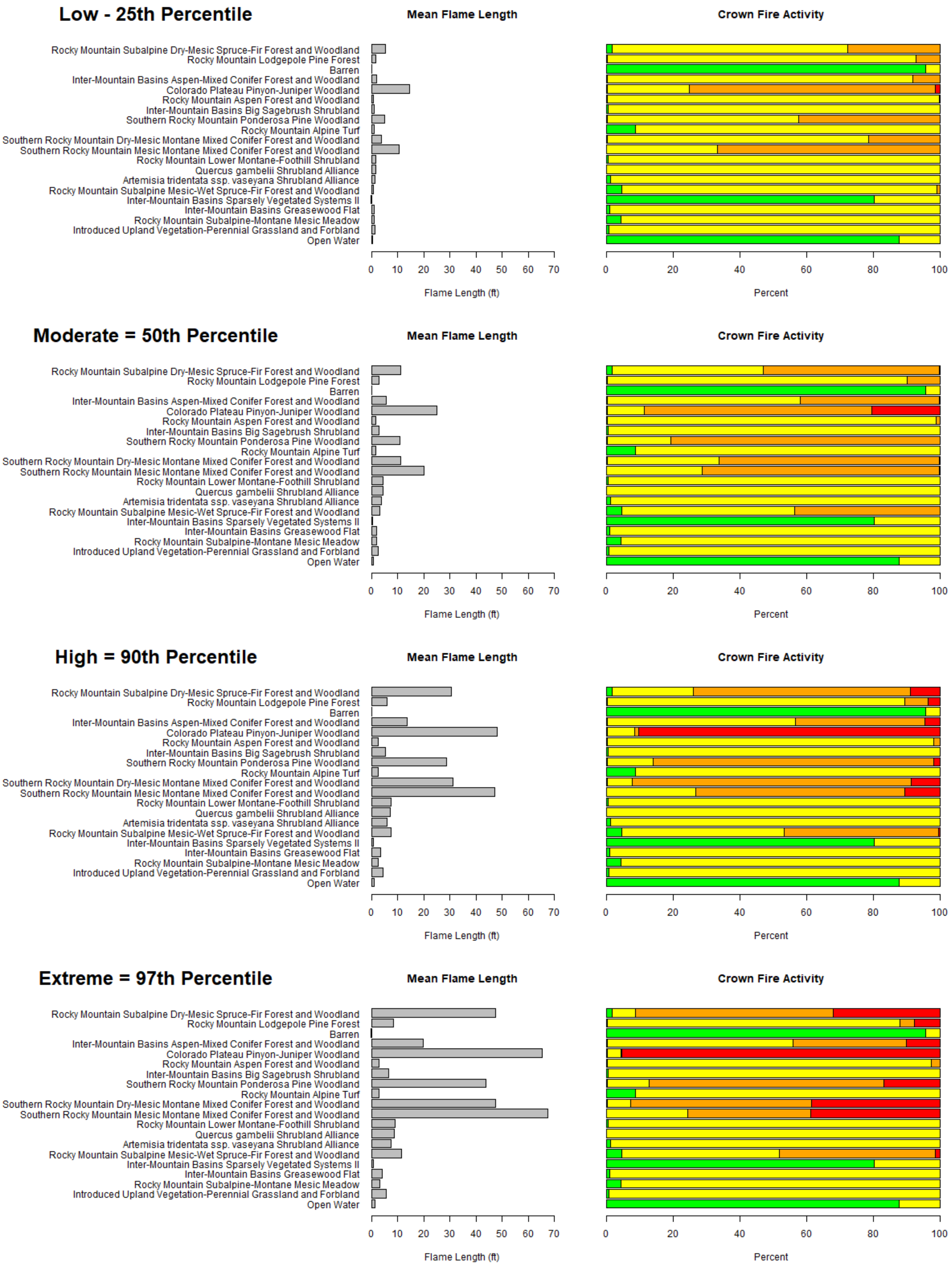


Figure 14: Summary of fire behavior by existing vegetation type from LANDFIRE (2014). The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

Appendix II – Burn probability

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.

Critique of existing products

The burn probability product originally chosen for this assessment came from the Colorado Wildfire Risk Assessment (CO-WRA) completed by Technosylva for the Colorado State Forest Service. Their methods involved a hybrid approach where:

1) fires were simulated from ignition points generated in a regular grid under high and extreme fire weather then processed to calculate burn probability as the number of times each pixel burned over the number of simulations; and

2) the resulting burn probability estimates were weighted based on a smoothed surface of historical ignition density (Technosylva 2018).

The results of this analysis are shown in Figure 15Figure 1. CO-WRA predicts much higher burn probability in the woodland, shrub, and grass vegetation types that dominate the low foothills and valley bottoms because these vegetation types are assigned fuel models with fast rates of spread. This simulation approach captures the shadowing effects of topography and barriers (rivers and highways) that oppose fire spread in the dominant wind directions (west and southwest). The National Large Fire Simulator (FSim) burn probability from Short *et al.* (2016) predicts similar burn probability patterns across vegetation types. The National FSim burn probability was deemed unsuitable for the assessment because the Arkansas Valley has a stark seamline through it from falling on the boundary between two fire modeling pyromes.

Both the Community Wildfire Protection Plan Working Group and members of the public expressed concern that the CO-WRA burn probability did not match their observations of recent fires or their expectations about fire occurrence across the County. CO-WRA predicts most fire activity will occur in low elevation pinyon pine and sagebrush vegetation (Figure 16; Figure 17), which conflicts with managers experience that large fires predominantly burn in mid- to high-elevation forests. A possible explanation for this discrepancy is that neither CO-WRA or National FSim account for initial attack success. 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.

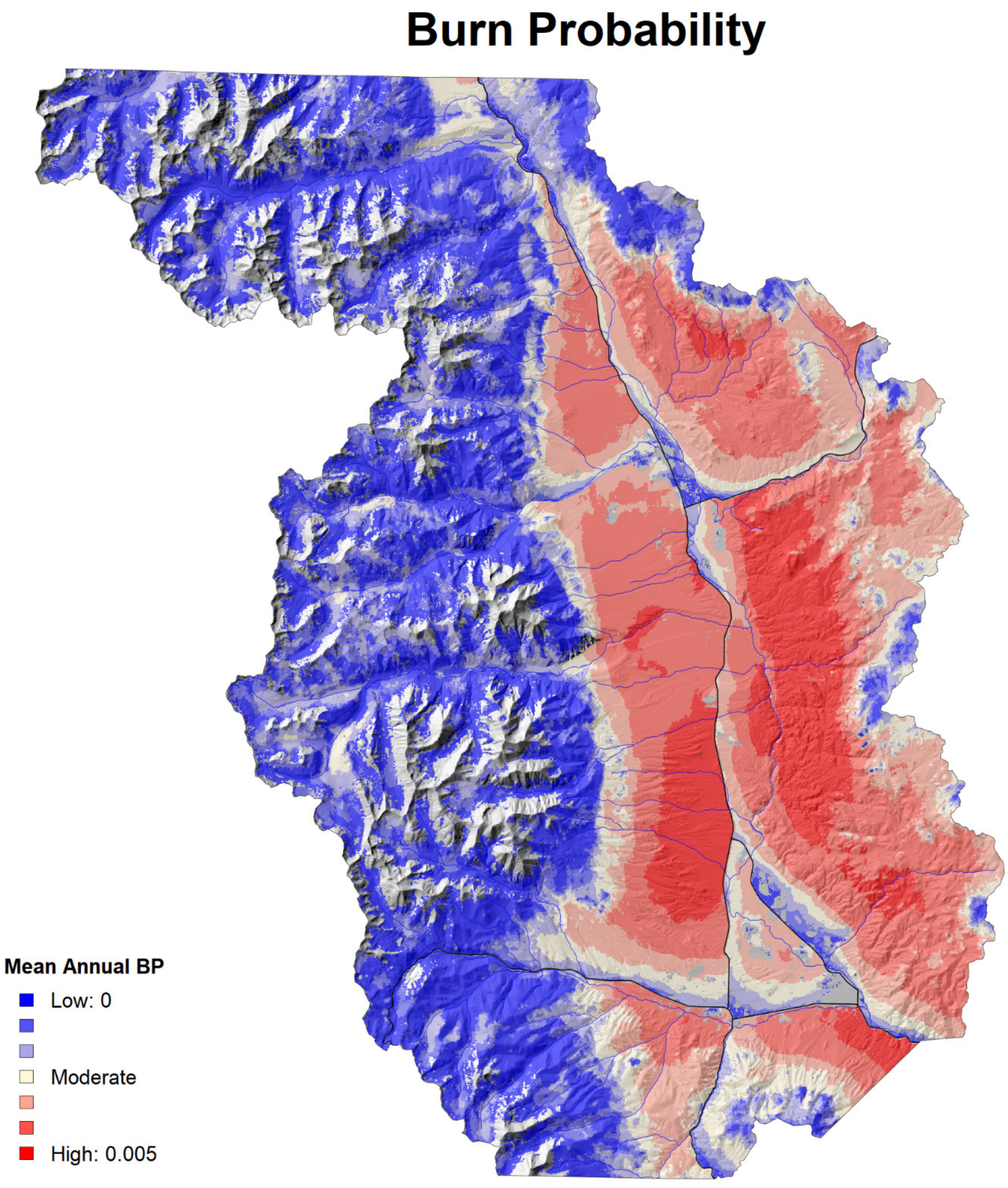


Figure 15: Burn probability from CO-WRA (Technosylva 2018). Note that values are binned into geometric intervals to enhance contrast.

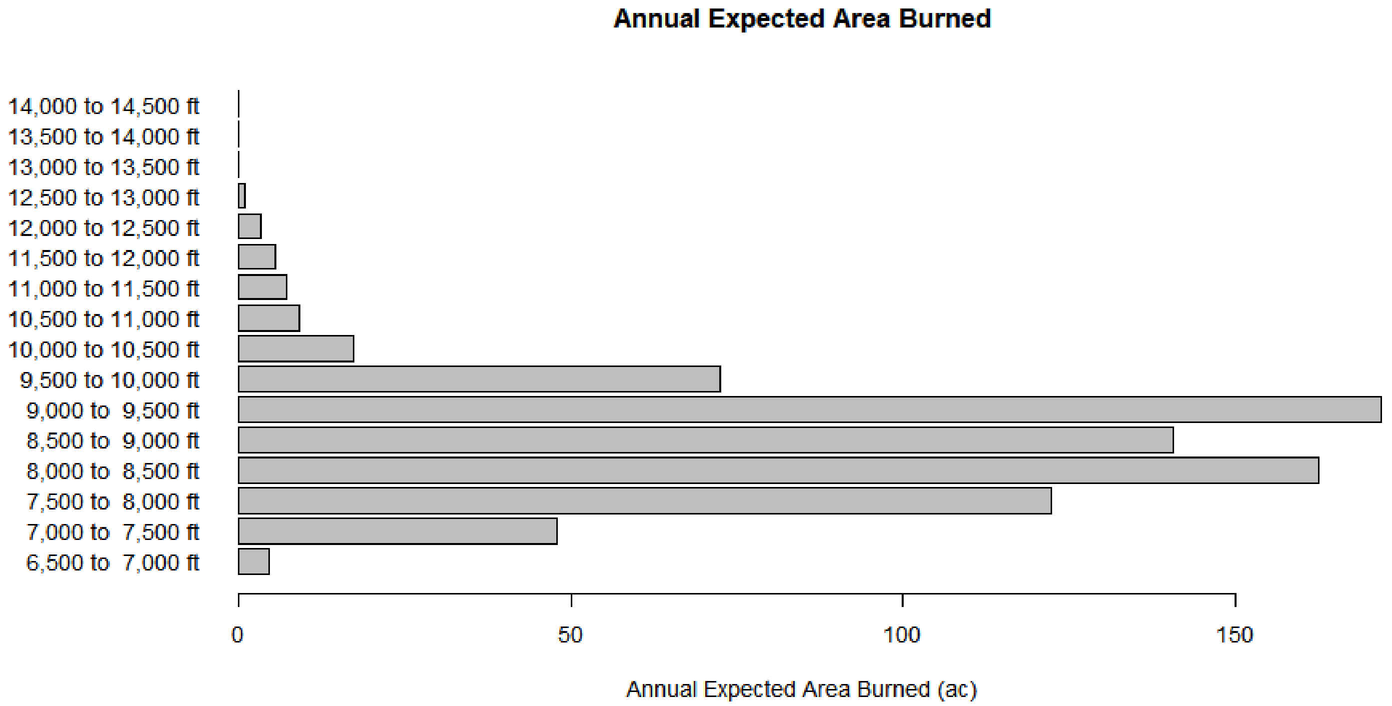


Figure 16: Expected area burned by elevation from the CO-WRA burn probability.

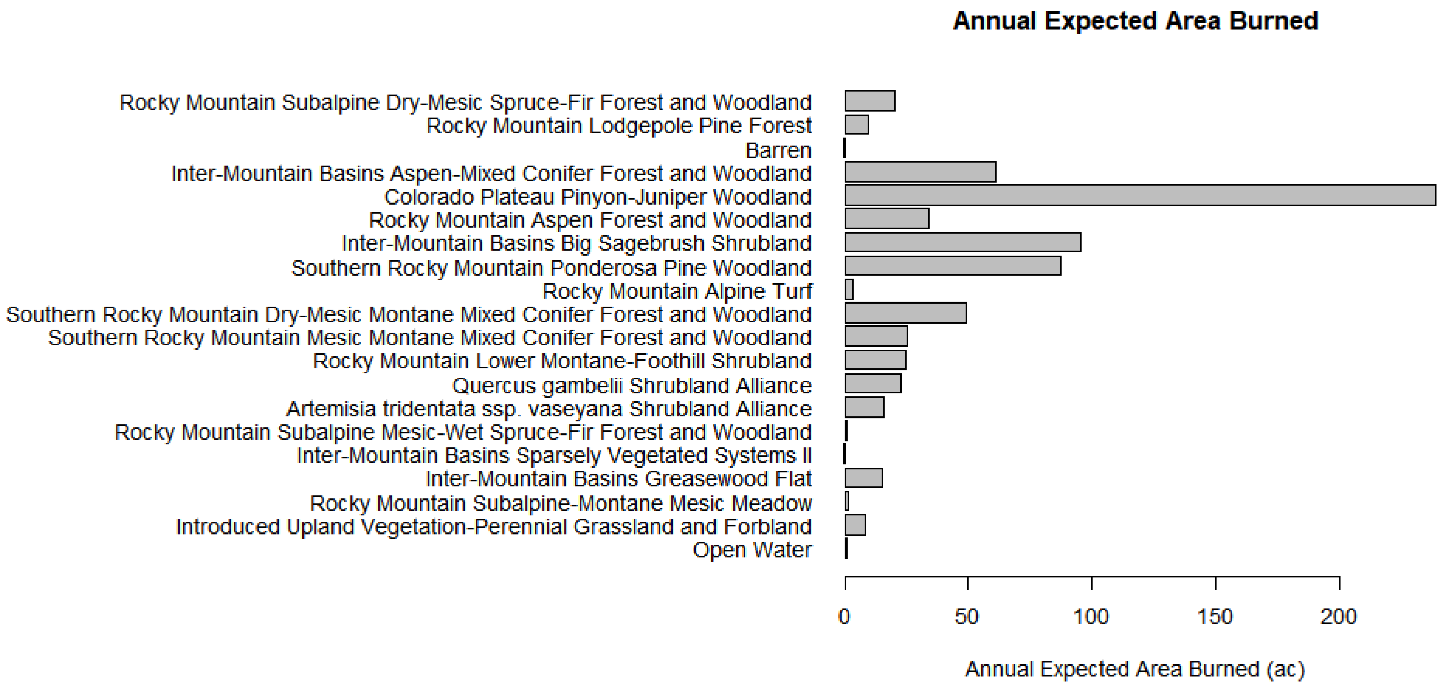


Figure 17: Expected area burned by LANDFIRE existing vegetation type from the CO-WRA burn probability.

Empirical burn probability alternative

We developed an empirical estimate of burn probability based on historical observations of area burned by vegetation type within an analysis area defined by a 20-mile buffer around Chaffee County. The 20-mile buffer was chosen as a reasonable compromise between increasing the number of fire observations and ensuring biophysical conditions and fire management within the analysis area are representative of Chaffee County. Vegetation type 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), the Geospatial Multi-Agency Coordination (GeoMAC; 2019), and the Fire Occurrence Database (FOD; Short *et al.* 2017). The dataset characteristics are described in Table 6.

Table 6: Fire history sources used in the analysis.

Source	Format	Fire types	Time span (years)
MTBS	Final perimeter polygons	Large fires (> 1,000 ac)	1984-2017
GeoMAC	Daily perimeter polygons	Fires of significant concern (generally large fires)	2000-2019
FOD	Point	All available fire location data from multiple agencies	1992-2015

To make use of these three fire history datasets, we first standardized attributes and converted FOD points into polygons based on reported fire size assuming a circular fire shape. Most large fires are captured by MTBS and GeoMAC, so the assumption of circular shape has little influence on estimates of area burned by vegetation. The FOD point data were also dissolved by fire name and year to reduce the influence of duplicate reports. GeoMAC daily fire perimeters were dissolved by fire name and year to represent the final fire perimeters. The three 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. The final fire history record included 954 fires, 16 of which came from GeoMAC and 938 of which came from the FOD (Figure 18). These fires collectively burned 50,524 acres of the 3,276,751 acre analysis extent. No MTBS fires were included in the analysis because all were documented with higher precision by GeoMAC.

Vegetation type was characterized with Existing Vegetation Type (EVT) from LANDFIRE (2014). 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 (1992-2019). 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 5^{th} percentile of non-zero burn probabilities. The empirical burn probability results are shown in Figure 19. 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-WRAP (Figure 20; Figure 21).

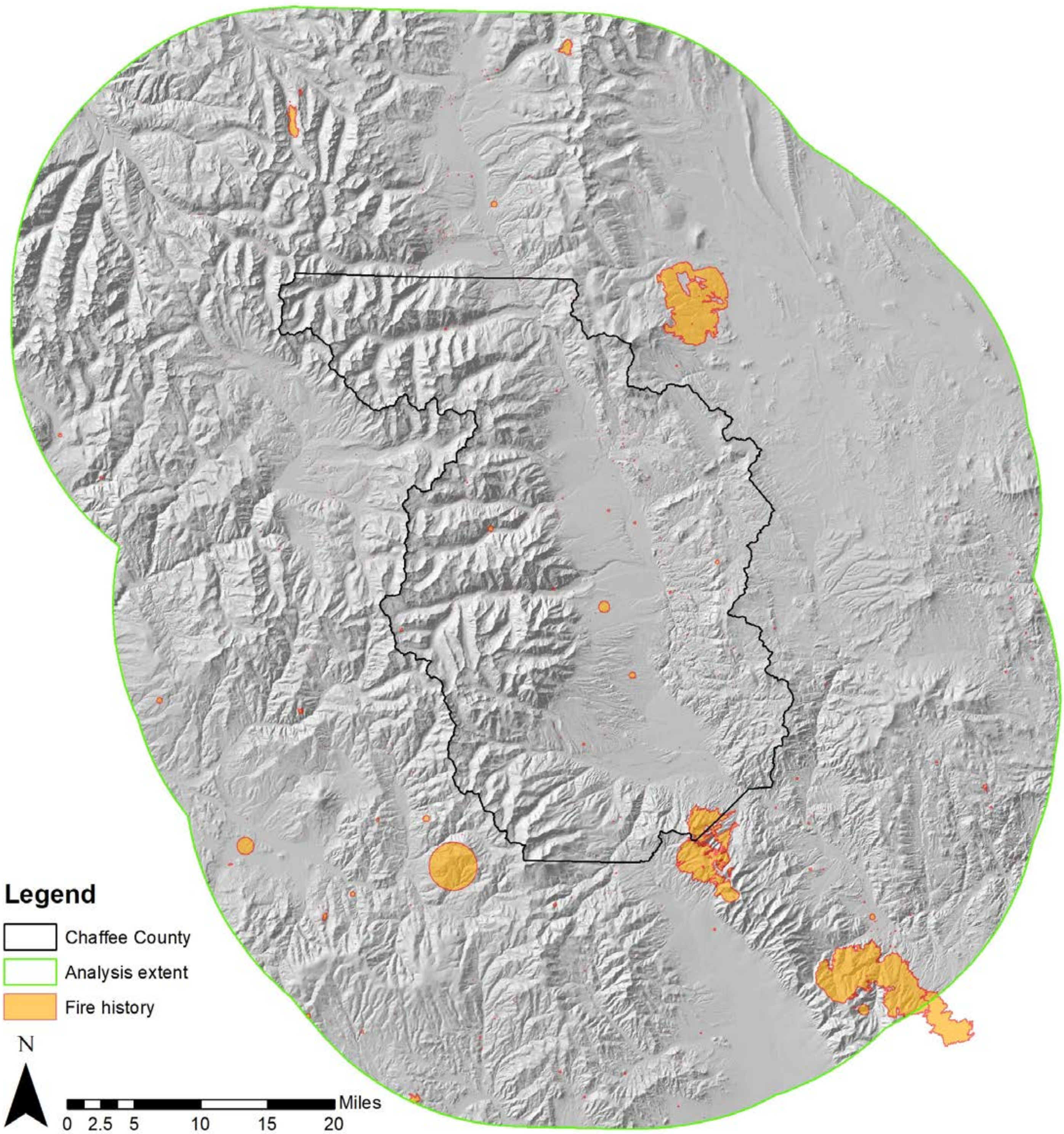


Figure 18: Fires used in the empirical burn probability analysis.

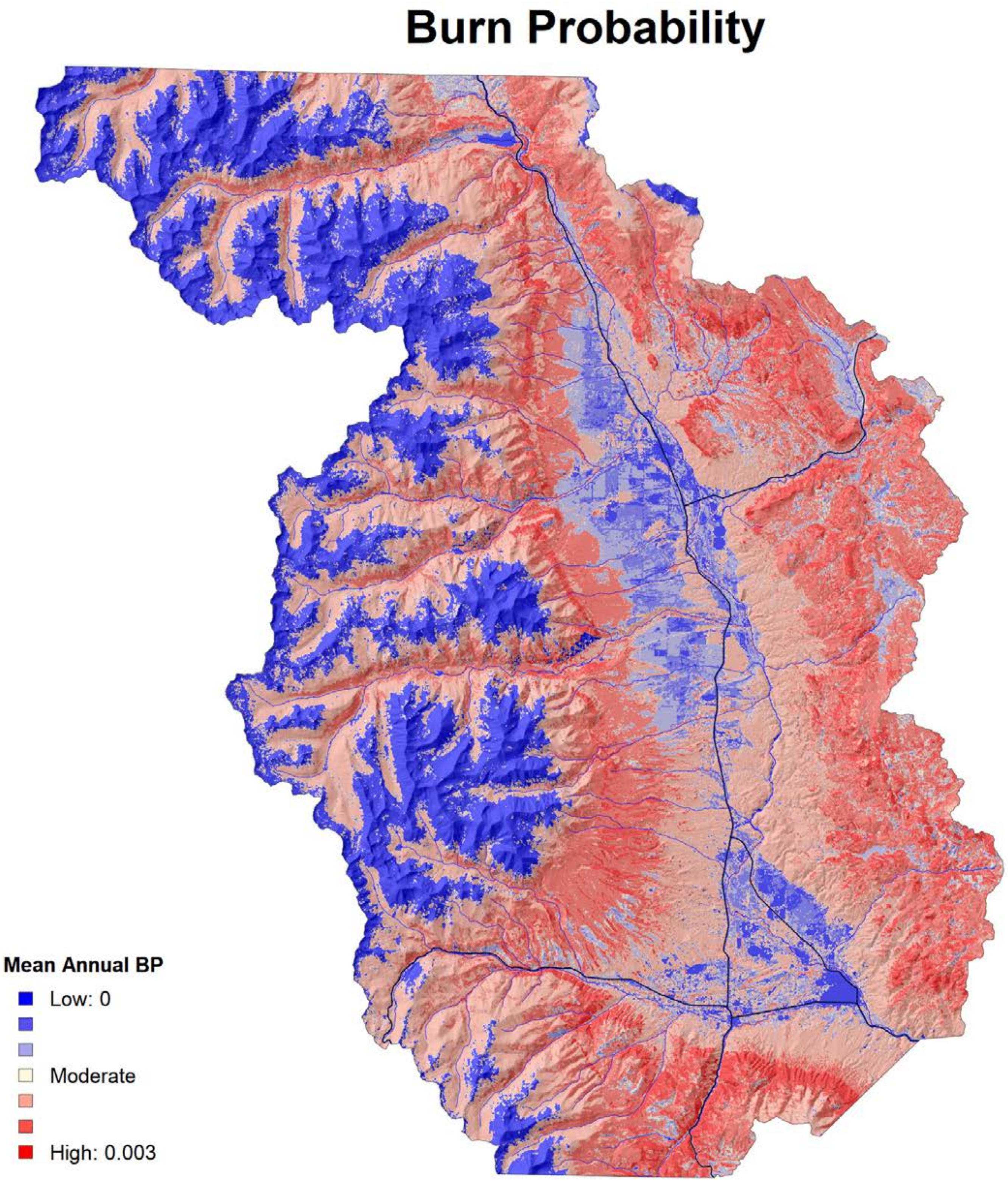


Figure 19: Empirical burn probability by vegetation type used for the Chaffee County Risk Assessment.

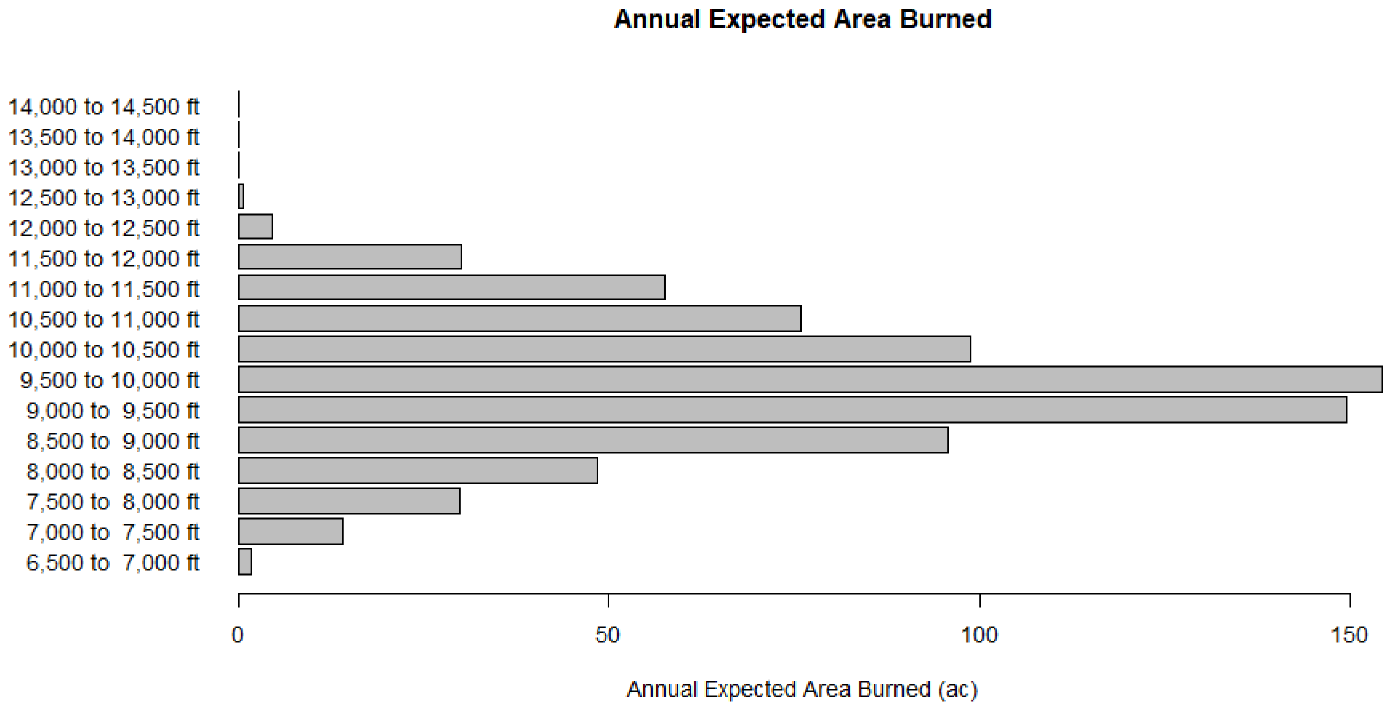


Figure 20: Expected area burned by elevation from the empirical burn probability estimates.

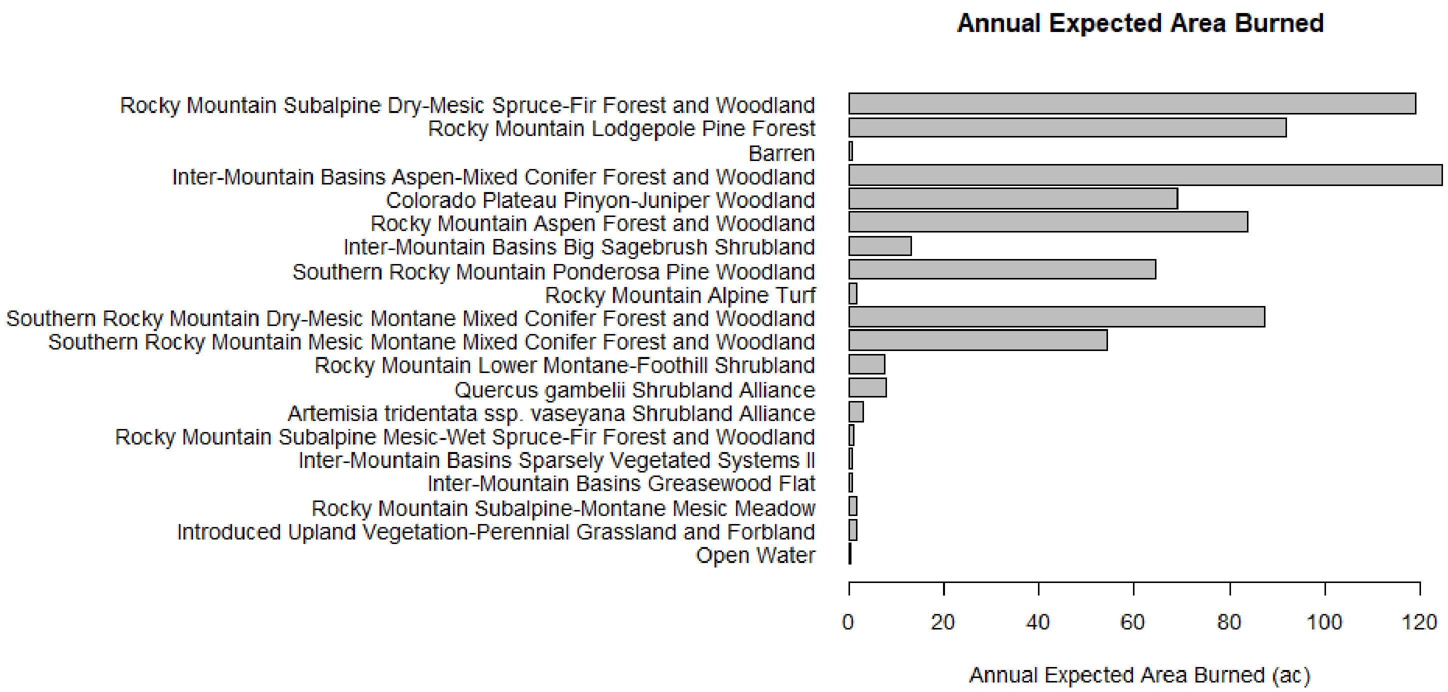


Figure 21: Expected area burned by LANDFIRE existing vegetation type from the CO-WRA burn probability.

Community Wildfire Protection Plan Working Group input

Forest and fire managers in the Community Wildfire Protection Plan Working Group expressed opinions that the empirical burn probability was a more accurate representation of fire likelihood than the CO-WRAP product and voted unanimously at the November 1st, 2019 meeting to use the empirical burn probability. The Colorado Forest Restoration Institute team made it clear that using historical estimates of burn probability by vegetation type has several limitations including:

1. **Small sample size.** Just three fires account for 75% of the observed are burned and just five fires account for 90% of the area burned (Table 7).
2. **Space for time substitution.** We made a space for time substitution to increase the fire observation size, which can introduce error if biophysical conditions and fire management differ outside Chaffee County.
3. **Imperfect fire history and vegetation data.** The spatial precision of the fire occurrence data is imperfect and use of the FOD required the assumption of circular fires. Inaccuracies in the existing vegetation type from LANDFIRE (2014) or poor match between current vegetation and vegetation at the time of fire occurrence may contribute to errors in the analysis.
4. **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.
5. **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 1.5% 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 around Chaffee 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.

Table 7: Characteristics of fires that burned more than 100 acres in the analysis extent.

Name	Year	Source	Acres burned	Cum. Percent	Most abundant vegetation type	Second most abundant vegetation type
Hayden Pass	2016	GeoMAC	16,274	32.2	Southern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	Colorado Plateau Pinyon-Juniper Woodland
Weston Pass	2018	GeoMAC	13,035	58.0	Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	Southern Rocky Mountain Ponderosa Pine Woodland
Decker	2019	GeoMAC	8,900	75.6	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	Rocky Mountain Aspen Forest and Woodland
Mustang Creek	2000	FOD	6,495	88.5	Rocky Mountain Lodgepole Pine Forest	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland
Ox Cart	2013	GeoMAC	1,153	90.8	Barren	Southern Rocky Mountain Montane-Subalpine Grassland
Doyleville	2012	FOD	801	92.3	Rocky Mountain Lower Montane-Foothill Shrubland	Western Cool Temperate Pasture and Hayland
Granite lake	2019	GeoMAC	722	93.8	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	Barren
Treasure	2012	GeoMAC	415	94.6	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	Southern Rocky Mountain Montane-Subalpine Grassland
Unnamed	2010	FOD	344	95.3	Colorado Plateau Pinyon-Juniper Woodland	Inter-Mountain Basins Big Sagebrush Shrubland
Duckett	2011	GeoMAC	327	95.9	Southern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest and Woodland	Inter-Mountain Basins Semi-Desert Grassland
Big Cottonwood	2007	FOD	295	96.5	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	Rocky Mountain Lodgepole Pine Forest
Trickle Mountain	2013	GeoMAC	205	96.9	Southern Rocky Mountain Montane-Subalpine Grassland	Southern Rocky Mountain Ponderosa Pine Woodland
Unnamed	1992	FOD	112	97.1	Rocky Mountain Lodgepole Pine Forest	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland
Buck Park #2 WFU	2005	FOD	110	97.4	Colorado Plateau Pinyon-Juniper Woodland	Inter-Mountain Basins Big Sagebrush Shrubland

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, 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.

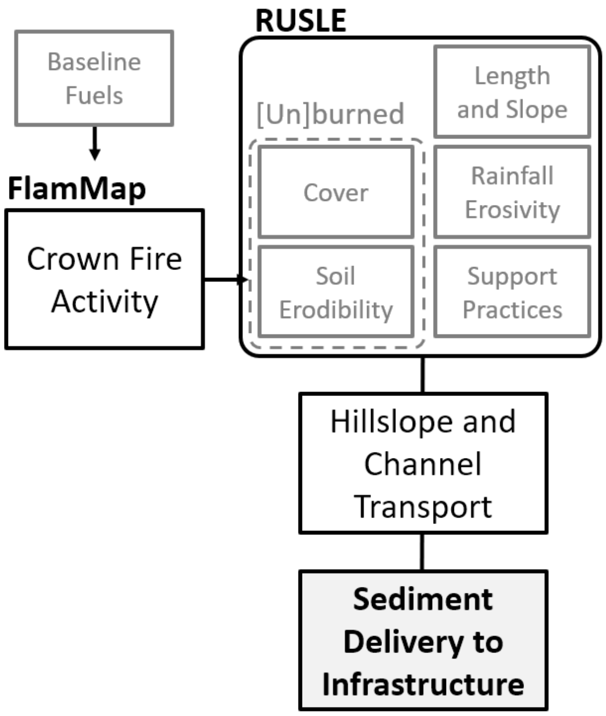


Figure 22: Workflow used to quantify potential post-fire sediment delivery to water infrastructure from each pixel of the landscape.

This framework was applied with slight modifications to quantify the conditional net value change of critical water supplies, surface diversions, ground diversions, 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). Local critique of the erosion outputs revealed that an area of erosion concern around the Chalk Cliffs was not represented in the soils data. We increased soil erodibility by a factor of five to account for the extreme erosion hazard in the zeolite alteration zone (Coe *et al.* 2010).

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. 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 23.

Table 8: Relative importance of critical water supplies as defined by local stakeholders.

Name	Rel. Imp.
Buena Vista Diversion	1
Salida Diversion	1
Cottonwood Lake	0.4
O'Haver Lake	0.4
North Fork Reservoir	0.2
Pasquale Springs	0.12
Boss Lake Reservoir	0.12
Rainbow Lake	0.12
Alpine Lake	0.12
Clear Creek Reservoir	0.12
Moltz Reservoir	0.12
Twin Lakes	0.12

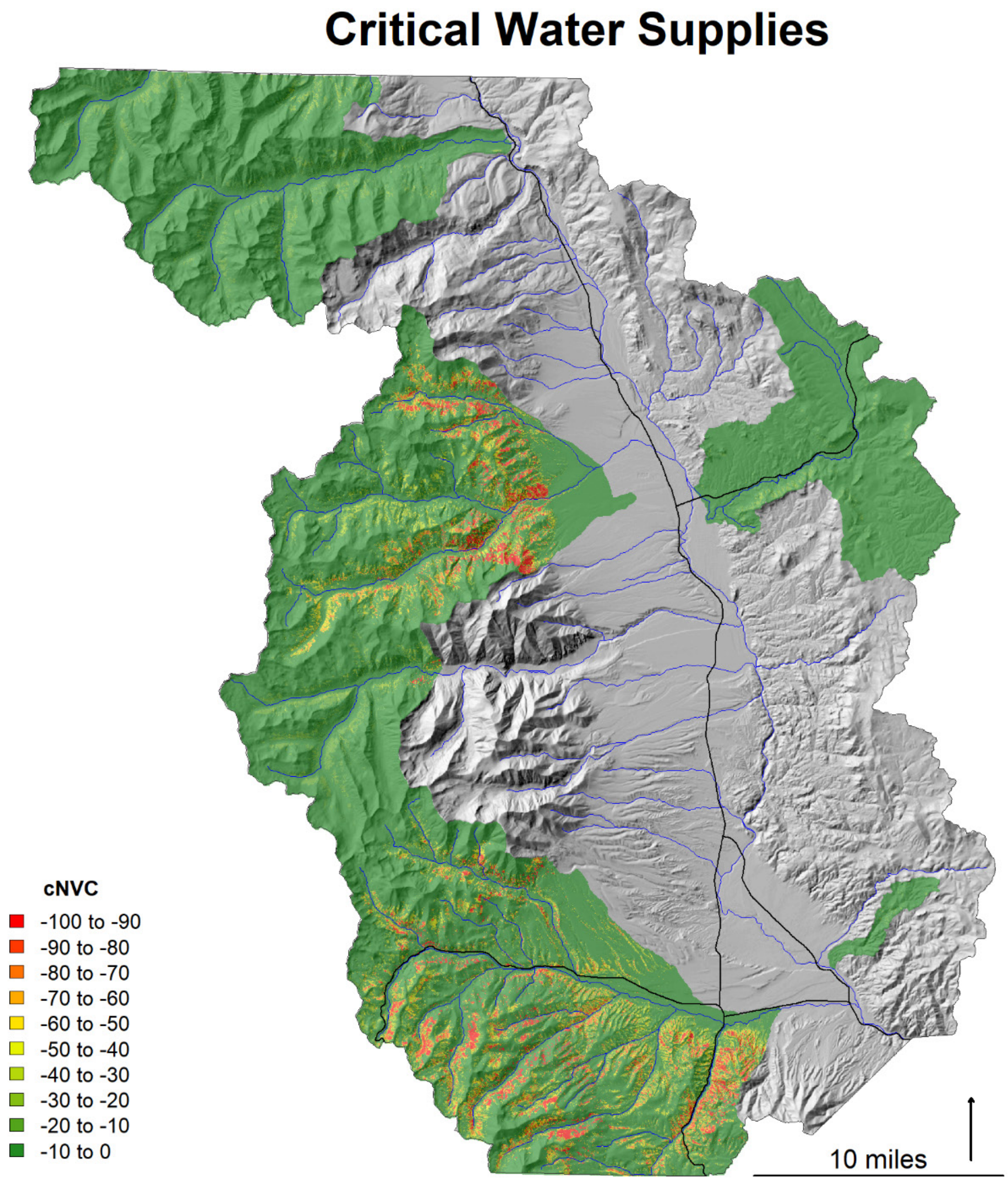


Figure 23: Critical water supplies conditional Net Value Change.

Surface Diversions

It was acknowledged that many small surface diversions exist for drinking and agricultural water. To capture these, we summed the total decreed diversion rate (in cfs) for ditches and pipelines in the Colorado Division of Water Resources (CODWR) structures database for each catchment. This measure was then normalized to a scale from 0 to 1 by dividing by the maximum catchment-level diversion rate (in cfs) and applied as weights to the sediment delivery predictions. It was assumed these structures have similar sensitivity as the critical water supplies. 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 24.

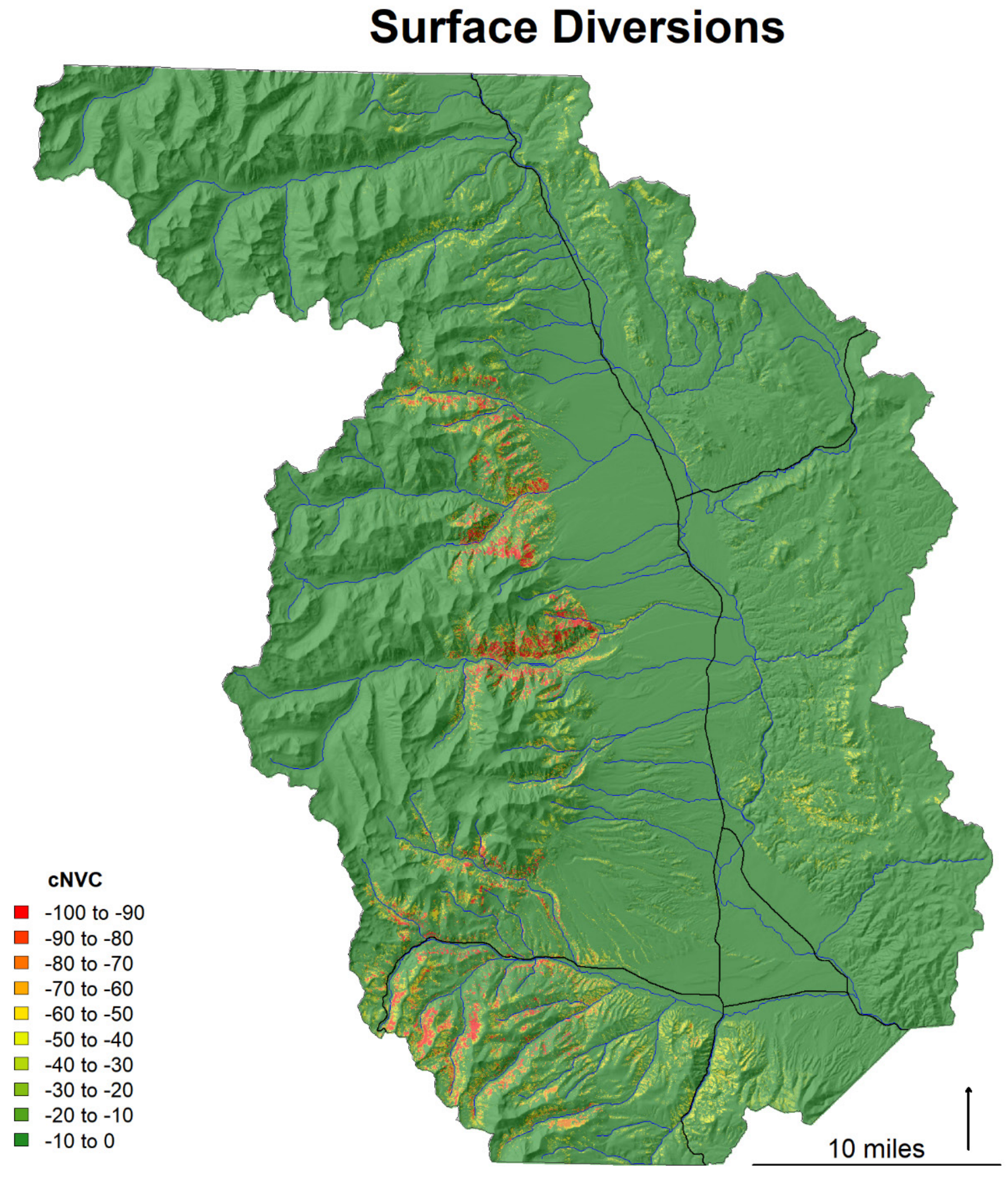


Figure 24: Surface diversions conditional Net Value Change.

Ground Diversions

Stakeholders noted that ground water sources are often impacted by local erosion and sediment deposition. Therefore, impacts to ground water sources including wells (and well groups), seeps, and springs were assumed to be proportional to the local hillslope erosion rate. Ground water use was quantified using the total decreed diversion rate (in cfs) for ground water sources in the Colorado Division of Water Resources (CODWR) structures database within a 400 m circular radius around each pixel. This measure was then normalized to a scale from 0 to 1 by dividing by the maximum pixel-level diversion rate (in cfs) and applied as weights to the hillslope erosion predictions. Given that we don't expect the actual ground water sources to be impacted by fire, just the surface equipment, we linearly rescaled the hillslope erosion predictions so that 0 to 50 Mg ha^{-1} corresponds to 0 to -50 percent value change. The final cNVC is mapped in Figure 25.

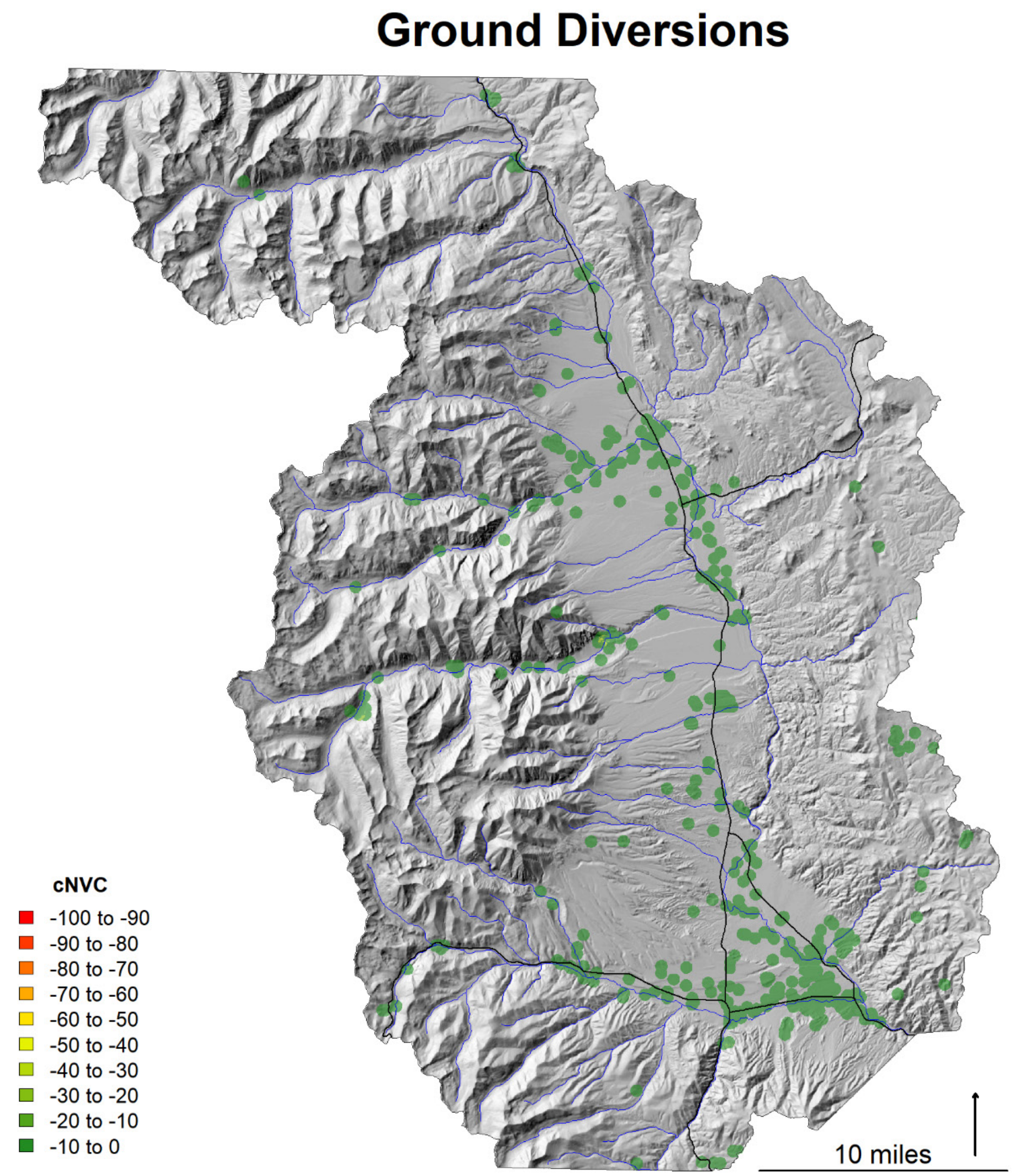


Figure 25: Ground diversions conditional Net Value Change.

Aquatic Habitat

The first draft of the risk assessment included the Gold Medal reaches of the Arkansas River with a quarter mile buffer around it to represent critical aquatic habitat. Feedback from stakeholders, especially Colorado Parks and Wildlife, suggested it was important to expand this to represent the importance of tributaries. To capture this, we predicted post-fire sediment delivery to the Gold Medal reaches of the Arkansas River. The pixel-level estimates of sediment delivery to Arkansas River were linearly rescaled so that 0 to 50 Mg ha^{-1} corresponds to 0 to -80 percent value change. The final cNVC is mapped in Figure 26.

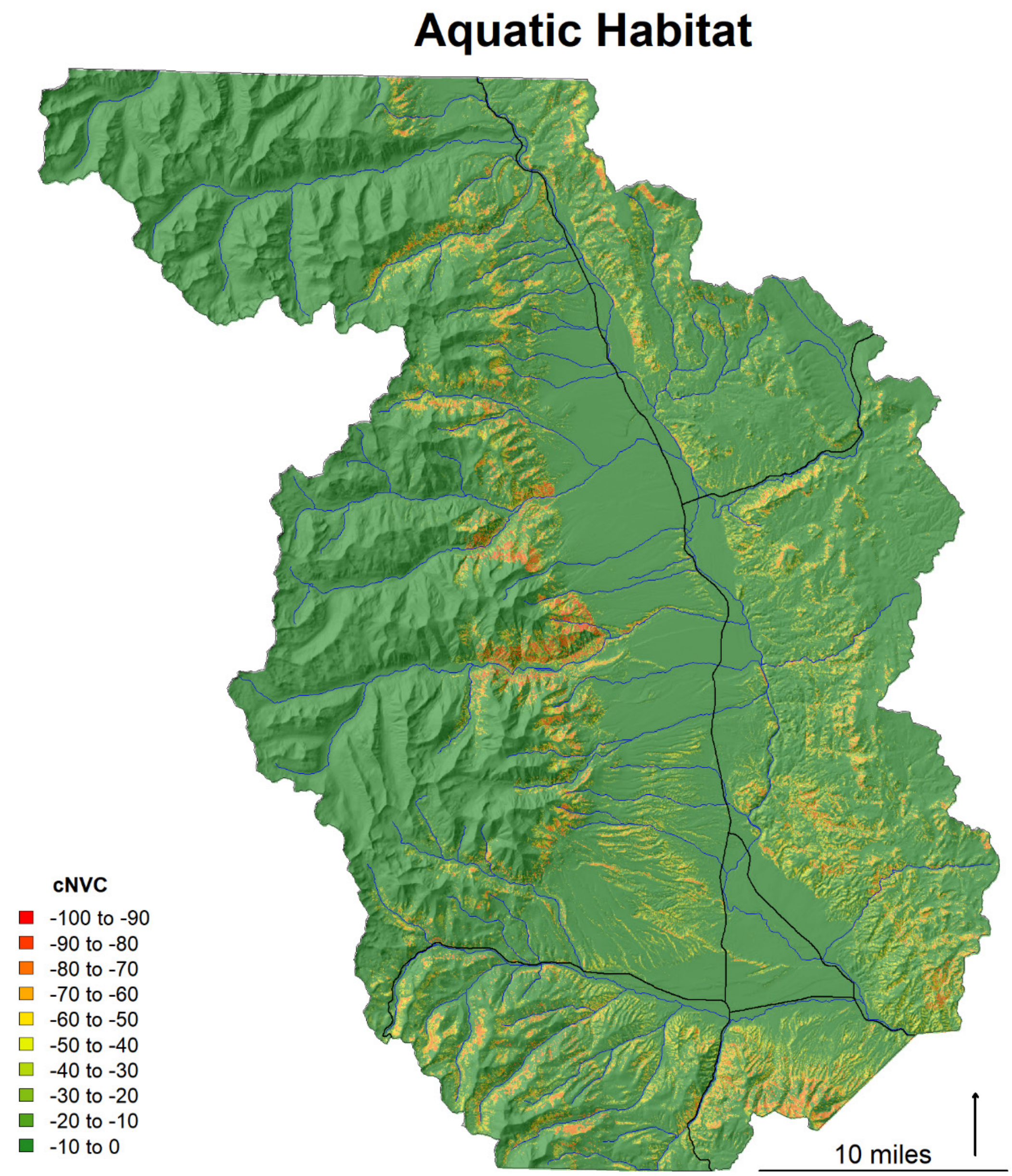


Figure 26: Aquatic habitat conditional Net Value Change.

Appendix IV – Spatial data processing

Wildland Urban Interface

Wildland urban interface (WUI) was defined from two datasets that mapped structures using object based remote sensing image extraction methods (Caggiano *et al.* 2016; Microsoft 2018). These methods produce either point or polygon vector data representing individual structure centroids or footprints with high, but not perfect accuracy. We used the building point locations from Caggiano *et al.* (2016) as our base data for the analysis because of the known high overall accuracy (95%) of the building extraction process and its low omission (5%) and commission (3%) rates. The Microsoft (2018) building footprints were converted into points representing building centroids to supplement the primary data source.

Structure omission errors can lead to underestimating WUI extent, whereas structure commission errors can lead to overestimating WUI extent. We minimized the effect of these errors using two steps:

1) We manually reviewed the two data sources to remove false positives (structures that do not exist) to reduce the effect of commission errors.

2) We then merged the two data sources for the buffer analysis used to define WUI extent to reduce the effect of omission errors in each dataset.

Manual review of false positives

The manual review process focused primarily on WUI structures at the fringe because they have the strongest influence on WUI area. That is, a false positive does little to change WUI extent when located near a true positive, but it has a large effect on WUI extent when mapped far from the closest true positive. We first reviewed the Caggiano *et al.* (2016) data using recent reference imagery from multiple sources, parcel ownership information, road data, and topographic maps. Any mapped structures that could not be confirmed with imagery were deleted, as were structures associated with mining or communication infrastructure. Object based image extraction methods do not have the ability to discern if structures are permanent dwellings. The most common non-permanent dwelling structures captured in these datasets included large recreational vehicles, campground and trailhead outhouses, agricultural and ranching outbuildings, and historical homestead and mining structures. These methods also mistakenly mapped certain rock and vegetation features as structures. When non-dwelling structures could be identified from imagery, they were deleted. We then focused our quality control of the Microsoft (2018) data on points that fell outside a 200 m buffer around the cleaned Caggiano *et al.* (2016) data. The reasoning is that false positives within 200 m of mapped structures have little effect on WUI extent. The same deletion criteria were applied. The manual review process reduced the structures mapped in Chaffee County from 10,266 to 10,251 for the Caggiano *et al.* (2016) dataset and from 14,114 to 13,980 for the Microsoft (2018) dataset. Additional false positives were removed from adjacent counties. The final structures used to define WUI extent are mapped in Figure 27.

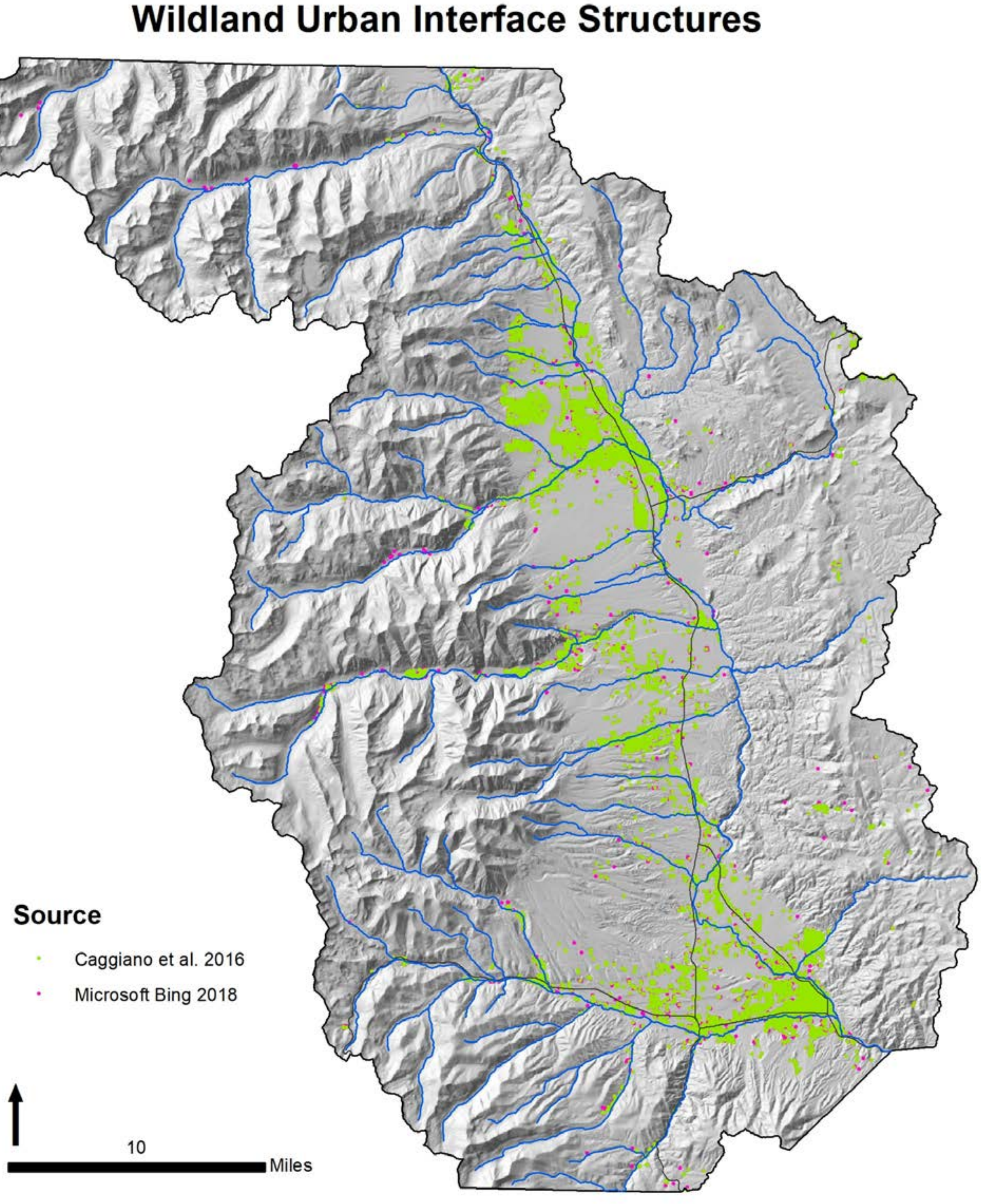


Figure 27: Structures included in the analysis to define wildland urban interface used in the risk assessment.

WUI definition from the merged dataset

WUI extent was then defined as any area within a 0.5-mile radius buffer around structures mapped in either dataset. The 0.5-mile radius buffer was chosen to be consistent with the 2009 risk assessment. WUI extent defined from the merged dataset differed by only 5-10% from WUI defined from either of the individual datasets.

WUI density

WUI was partitioned into low (< 1.5 structures/acre) and high density (≥ 1.5 structures/acre) classes based on local input that greater loss is expected in high density areas similar to observations from the Waldo Canyon Fire in Colorado Springs (Maranghides *et al.* 2015). High density was defined as areas with ≥ 1.5 structures/acre in either the Caggiano *et al.* (2016) or Microsoft (2018) datasets. Structure density was calculated at 30 m resolution using the *point density* tool in ArcGIS 10.3 with a 50 m circular neighborhood size. The high density WUI class was assigned a higher loss response function to reflect greater potential for structure-to-structure ignition. Relative importance weights were assigned based on relative frequency of structures within the low and high WUI density classes. Of the 24,231 WUI structures mapped in both datasets, 47% fall in the low density WUI zone and 53% fall in the high density zone. The final WUI extent is mapped by density class in Figure 28.

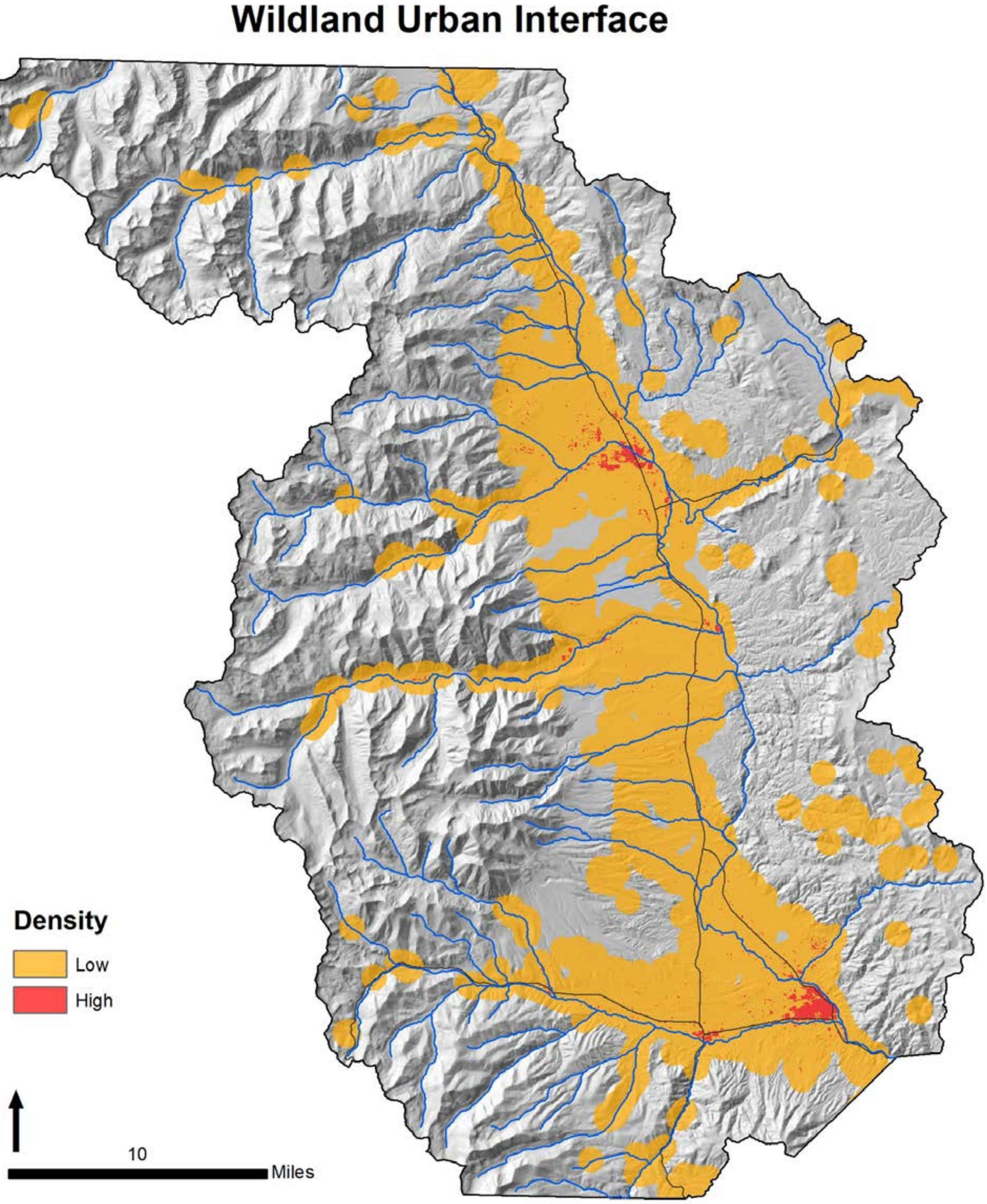


Figure 28: Wildland urban interface extent by density class used in the risk assessment.