



Northern Colorado Fireshed Wildfire Risk Assessment

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Purpose and Scope

The Northern Colorado Fireweed Collaborative (NCFC) is a large landscape collaborative covering approximately 4 million acres in the Northern Colorado Front Range, roughly from Interstate 70 west of Denver to the Wyoming border. It includes over 50 organizations representing diverse interests, including federal and state land management agencies, watershed coalitions, utilities, local governments, conservation districts, non-profits, and science partners. The NCFC operates as a platform for these entities to coordinate forest management activities and enhance landscape resilience to wildfire by collaboratively identifying, building support for, and implementing projects in strategic priority areas.

This Quantitative Wildfire Risk Assessment (QWRA) was initiated when the Arapaho-Roosevelt (AR) National Forest and NCFC stakeholders requested spatially consistent and up-to-date data on wildfire risk to assist with fuels project planning, fire response, and community outreach. While the Colorado Forest Restoration Institute (CFRI) and United States Forest Service (USFS) comprised the technical team that led the modeling, a diverse group of stakeholders have been involved from inception and through each stage of the iterative QWRA development process.

While the quantitative modeling is informed by science, this is ultimately a values-driven process whereby wildfire risk metrics represent local values. Stakeholders identified the need for and helped with the initial framing of the assessment, identified the highly valued resources and assets (HVRAs) of concern, provided feedback to modify and improve the fire intensity and burn probability modeling, and helped determine the response functions

and relative importance weights necessary for the model to accurately represent local concerns. Additionally, stakeholders helped guide the direction of intermediate and final QWRA outputs so they would be usable for cross-boundary wildfire risk management planning, focus area identification, grant development, and monitoring.

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 weighs the potential consequences of an event by its probability of occurrence. This risk assessment process is an appropriate framework for wildfire because wildfire has considerable spatial and temporal variability in occurrence and intensity over the multi-decade planning periods typically used in land and resource management (Scott et al., 2013). 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, as represented by the three legs of the wildfire risk triangle (Figure 1; Scott et al., 2013). At its core, a wildfire risk assessment is a science-informed and values-driven process.

Wildfire risk assessments require extensive data and modeling to characterize the three legs of the risk triangle (Scott et al., 2013). Spatial fire modeling 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 the expected Net Value Change (eNVC) of each HVRA (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 (i.e., HVRA response functions). 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 QWRA.

Risk Assessment Framework

This QWRA applied the assessment framework from the Colorado Wildfire Risk Assessment (CO-WRA; Technosylva 2018) to locally informed fire simulation products, HVRA spatial data, response functions, and relative importance weights (Figure 2). Fire behavior metrics, including flame lengths and crown fire activity were modeled in FlamMap

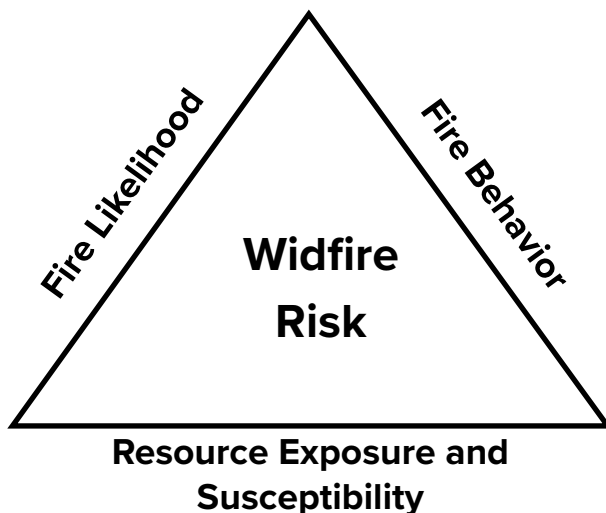


Figure 1: Wildfire risk triangle adapted from Scott et al. (2013).

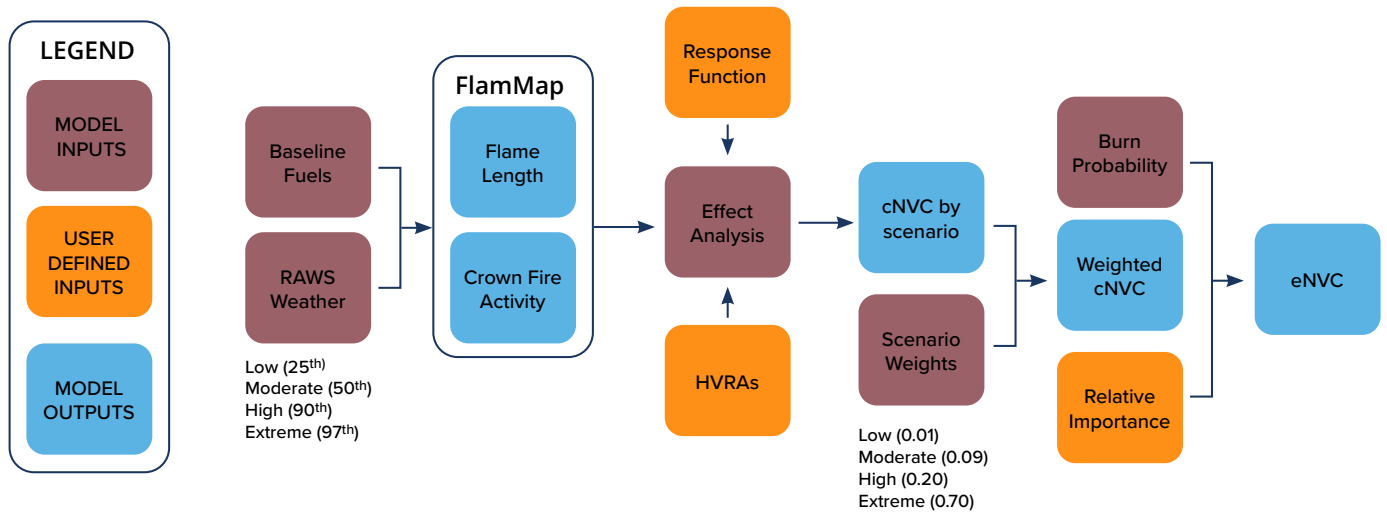


Figure 2: This QWRA is based on the analysis framework from the Colorado Wildfire Risk Assessment (Technosylva 2018).

5 (Finney et al., 2015) for low, moderate, high, and extreme fire weather scenarios. Burn probability was quantified in the Large Fire Simulator (FSim) (Finney et al., 2011). Fire behavior outputs were combined with local data on HVRA locations and stakeholder-informed response functions to calculate conditional Net Value Change (cNVC) for each HVRA and fire weather scenario. cNVC quantifies the change in value conditional on fire occurrence (i.e., if a fire were to burn). This approach assumes all areas of the landscape have an equal chance of burning. The 4 cNVC scenarios for each HVRA were combined with a weighted averaging that favored the high and extreme weather scenarios (Technosylva 2018). Lastly, the cNVC measures for each HVRA were combined with burn probability and relative importance weights to compute a composite eNVC (“risk”) map. The eNVC map accounts for the fact that the likelihood of encountering wildfire varies over space.

Stakeholder Engagement

While the risk assessment is a technical approach to assessing wildfire risk, it is also dependent on user-defined values (Figure 2) and can serve as a useful vehicle for collaboration, cross-boundary planning, and communicating stakeholder concerns. This QWRA was actively discussed in over 20 collaborative meetings with stakeholders during the 16-month development period between June 2021 and September 2022. Prior to conducting the QWRA, stakeholders developed a list of existing watershed and community scale evaluations that partners had been using to prioritize work across portions of the Fireshed. The kickoff meeting introduced the QWRA process, described how it could be used as part of the NCFC’s landscape strategy, and explained how stakeholders could get involved. Initial meetings contributed to project framing and HVRA identification, while subsequent meetings were focused on specific components of the QWRA (i.e., gathering to discuss spatial

data, developing HVRA response functions, assigning relative importance, etc.). General progress updates and next steps were provided to the full NCFC membership regularly at quarterly meetings with presentations and notes shared widely via newsletter and in Box. Several smaller meetings were organized with local stakeholders at the county or ranger district scales to delve into deeper discussions about local needs and next steps. The most engaging meetings involved stakeholders directly using QWRA outputs to support focused localized planning efforts, NEPA planning, and collaboration on joint funding proposals. In these meetings, stakeholders leveraged the QWRA outputs (digital and hard-copy) to support cross-boundary and interagency treatment planning (Figure 3).



Figure 3: Photo of St Vrain Forest Health Partnership collaborative planning meeting with representatives from the US Forest Service, Boulder County and local municipalities and fire districts. Photo: Mike Caggiano

Analysis Extent

The overall project extent included the Arapaho-Roosevelt National Forest, Rocky Mountain National Park, and a 10 km buffer (Figure 4). The final extent encompassed by this buffer included land managed by a variety of federal

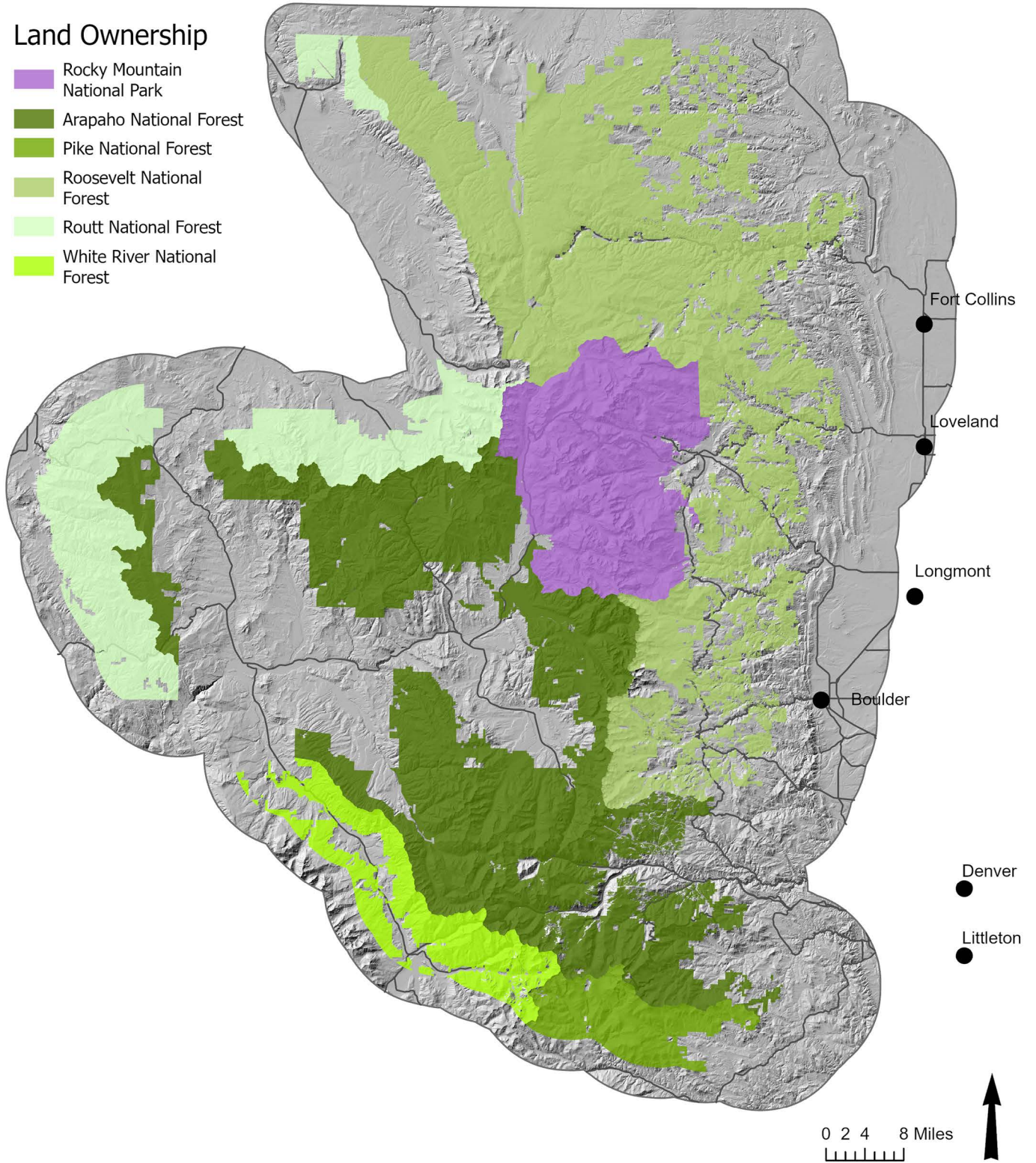


Figure 4: Analysis extent for the NCFC wildfire risk assessment relative to National Forest and National Park boundaries.

agencies, state agencies, local governments, and private citizens. Since much of our HVRA data was derived at the state level, the northern project extent was clipped to the Colorado state boundary to ensure spatially consistent data across the full project. Refer to the “Further limitations” section in Appendix II for additional discussion of modeling extent and limitations.

Fire Behavior Modeling

Two fire behavior metrics - flame length and crown fire activity - were modeled for low, moderate, high, and extreme fire weather scenarios (Table 1) using the FlamMap 5 spatial fire modeling system (Finney et al., 2015). Flame length is frequently used in wildfire risk assessments as an index of fireline intensity (rate of energy release from the fire front) because it is easily interpreted by non-fire resource specialists. Flame length and fireline intensity are strongly correlated (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 (see Appendix III – Watershed Related cNVC). FlamMap requires several inputs including surface and canopy fuels, topography, and weather. Fuels were described with a combination of canopy and surface fuel attributes from LANDFIRE (2020) with some modifications.

The first adjustment was targeted at increasing the intensity of fire behavior in lodgepole pine forests to match recent fire behavior observations (Moriarty et al., 2019). This was accomplished by reducing the canopy base height by 30% and changing any low load (TL1) or moderate load (TL3) conifer litter fuel models to high load conifer litter (TL5; Burgan 2005). Lodgepole pine forests that sustained greater than 25% mountain pine beetle mortality based on Bode et al., (2018) were changed to low load slash blowdown fuel models (SB1) based on conversations with fire managers regarding surface fuels in these areas. Canopy and surface fuels were also updated to reflect recent fuel treatments based on CFRI’s interagency fuel treatment 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 (2020). Fire weather scenarios were developed from historical (2000-2019) Remote Automated Weather Station (RAWS) data from eight stations distributed across the analysis area (Red Feather, Redstone, Estes Park, Sugarloaf, Harbison Meadow, Dumont, Pickle Creek, Corral Creek). Percent fuel moisture was computed for each category of dead and live fuels during a fire season defined as April 01 to October 31 using FireFamilyPlus 5 (Bradshaw and McCormick 2000). The 10-minute average RAWS wind speeds were converted to 1-minute average wind speeds for modeling (Crosby and Chandler 1966). In FlamMap, wind direction was assumed to be upslope to represent a consistent worst-case scenario across aspects. The Scott and Reinhardt (2001) method was used for predicting crown fire activity. The flame length and crown fire activity predictions are available in Appendix I - Fire Behavior Products.

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 grass fuel 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 northern Colorado. The data sources, methods, and limitations of all burn probability approaches are described in Appendix II – Burn Probability 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	8.5	9.8	16.3	100	130	5.3
Moderate	50	5	6.5	12.4	80	110	7.5
High	90	2.3	3.9	8.1	50	80	11.5
Extreme	97	2	3.1	6.6	30	60	14.2

Exposure and Effects Assessment

Local NCFC stakeholders convened to identify the HVRA and underlying spatial data that represented their interests and concerns. This included HVRA related to critical infrastructure, water supply, buildings, wildlife, vegetation, and recreation concerns within the analysis extent (Table 2). Spatial data were assembled in a geodatabase and re-projected to a common coordinate system for analysis.

A Fireshed-wide workshop was held on February 2, 2022 during which over 50 local resource experts broke into smaller groups to define HVRA response to fire by intensity level (i.e., response functions) (Table 3). 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. In other words, stakeholders decided how a particular resource would likely be positively or negatively affected by fire of a given intensity. For example, fire-adapted ponderosa pine forests may be positively affected at low intensities but negatively affected at higher intensities. In contrast, buildings may be negatively affected at all intensities. After the HVRA workshop, we summarized the results and emailed meeting participants and several key specialists to address discrepancies and improve agreement. Final response functions are detailed in Table 3.

The response of water-related HVRA (i.e., critical water supplies and designated waters) were quantified with a separate process described in Appendix III - Water Related cNVC. This is because water resources are susceptible to the indirect, rather than direct, impacts of wildfire. Thus, we modeled the impacts of post-fire erosion and sediment transport to characterize water-related net value change.

cNVC rasters were developed for each HVRA by applying the response function to the modeled fire behavior within each HVRA's extent. This was done first by fire weather scenario, and then the

Table 2: HVRA 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. (%)
Infrastructure	Monitoring stations	Point	200	10
	Roads	Polyline	200	35
	Electrical Substations and Transmission Lines	Raster	100	20
	Mines	Point	100	5
	Historic Structures	Raster	100	10
	Communications	Point	200	20
Recreation	Trails	Polyline	200	20
	Trailheads	Point	200	20
	Camping	Point	200	20
	Recreation Assets	Point	200	20
	Ski Resorts	Polygon	200	20
WUI	Buildings	Point	100	100
Wildlife	Preble's Jumping Mouse Habitat	Polygon	200	28
	Lynx Habitat	Polygon	0	32
	Greenback Cutthroat Trout Habitat	Polygon	200	40
Water	Critical Water Supply	Raster	0	70
	Designated Waters	Raster	0	30
Vegetation	Old Growth Forest	Polygon	200	15
	Grassland	Raster	0	4
	Sagebrush	Raster	0	4
	Pinyon-Juniper	Raster	0	3
	Spruce Fir	Raster	0	5
	Mixed Shrubland	Raster	0	5
	Aspen-Mixed Conifer	Raster	0	11
	Aspen	Raster	0	11
	Riparian	Raster	0	11
	Ponderosa Pine	Raster	0	11
	Mixed Conifer	Raster	0	11
	Lodgepole Pine	Raster	0	9

Table 3: Response functions ranging from -100 to +100 were defined through a collaborative process using stakeholder input. HVRAs with NA were quantified using supplemental modeling described in Appendix III – Water related 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
Infrastructure	Monitoring Stations	-10	-20	-40	-100	-100	-100
	Roads	0	0	-10	-40	-60	-80
	Electrical Stations	0	0	-20	-30	-100	-100
	Mines	0	0	-20	-60	-60	-80
	Historic Structures	-30	-30	-60	-80	-100	-100
	Communications	0	0	-20	-30	-100	-100
Recreation	Trails	20	10	-10	-30	-60	-80
	Trailheads	20	0	-10	-30	-40	-50
	Camping	10	0	-10	-30	-50	-60
	Recreation Assets	10	-10	-10	-20	-50	-70
	Ski Resorts	10	10	0	-20	-50	-70
WUI	Buildings	-10	-40	-80	-100	-100	-100
Wildlife	Preble's Jumping Mouse Habitat	20	10	0	-20	-40	-60
	Lynx Habitat	0	-10	-20	-40	-80	-100
	Greenback Cutthroat Trout Habitat	50	30	10	-30	-60	-100
Water	Critical Water Supply	NA	NA	NA	NA	NA	NA
	Designated Waters	NA	NA	NA	NA	NA	NA
Vegetation	Old Growth Forest	30	30	0	-30	-60	-80
	Grassland	60	60	60	60	60	60
	Sagebrush	20	20	-60	-60	-60	-80
	Pinyon-Juniper	40	40	0	-20	-40	-60
	Spruce Fir	0	0	0	30	30	30
	Mixed Shrubland	60	60	60	60	60	60
	Aspen-Mixed Conifer	60	60	60	30	30	30
	Aspen	50	50	50	30	30	30
	Riparian	40	50	30	10	-10	-50
	Ponderosa Pine	60	100	60	20	-40	-60
	Mixed Conifer	30	40	50	50	20	-20
	Lodgepole Pine	30	30	40	50	30	10

Table 4: Four weather scenarios were selected for our fire modeling which reflect the 25th, 50th, 90th, and 97th percentiles of fuel moisture, wind speed, etc. These scenarios were weighted based on the assumption that most area burns under extreme weather conditions.

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

4 weather scenarios were combined into a single cNVC raster per HVRA using weighted averaging (Table 4). 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, consistent with recent wildfire activity in Colorado (Graham et al., 2003; Haas et al., 2015).

Relative Importance Weights

Relative importance weights were defined at two levels - for each HVRA (Table 2) and each category (Table 5). For each HVRA, a relative importance weight was assigned to reflect that HVRA's proportional contribution to an HVRA category (Table 2). Then each category was assigned a relative importance value used to weight the contribution of each HVRA category to the composite risk map (Table 5). Due to the overall extent of the NCFC, number of participants, and ongoing COVID-19 concerns, we assessed relative importance using an online survey. This survey included many of the same land managers and decision makers who were involved with the HVRA identification, though we invited participation from the full membership of the NCFC via email. We provided individuals a two-week window to provide input based on the priorities of the organization they represented. These values were then assessed by the technical team through subsequent small group discussions and internal critique. This process identified water as the top

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

Category	Rel. Imp.	Share of total (%)
Water	100	24
WUI	80	19
Infrastructure	70	17
Recreation	65	16
Wildlife	50	12
Vegetation	50	12

concern, followed by WUI, infrastructure, recreation, wildlife habitat, and vegetation. Relative importance weights were evaluated to ensure individual resources (such as roads, communications structures, electrical lines, etc.) were not dominating the assessment, and were then used to weight the contribution of each HVRA category (e.g., Infrastructure) to the composite risk map.

Results

Composite wildfire risk represents total eNVC by combining the category-level risk maps based on their relative importance to the NCFC. The total eNVC map (Figure 5) and the eNVC maps split by HVRA category (Figures 6-11) all show the modeled wildfire risk after accounting for spatially variable burn probability. 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 12) which represents the risk to all HVRA categories without regard of burn probability. Thus, cNVC represents wildfire risk if we assume everywhere on the landscape has an equal chance of burning.

The spatial distribution of composite cNVC is not too dissimilar from the composite risk map (eNVC) because both account for the overlap between hazardous fuel conditions and HVRA categories. However, cNVC removes the impact of spatially variable burn probability and therefore highlights the areas on the landscape with concentrations of fire sensitive HVRA categories without regard to the modeled probability that they will actually encounter wildfire. As mean burn probability is greater on the Front Range, cNVC shows a more equal risk profile East to West than eNVC. One application where cNVC is particularly relevant is during active wildfire incidents where burn probability is no longer determined by historical occurrence trends, vegetation patterns, and prevailing wind directions, but rather the likely spread path of an actual ongoing wildfire.

Wildfire risk, measured as eNVC, is predominantly concentrated in lower elevations (7,500-8,500 ft) (Figure 13), particularly in ponderosa pine forests (Figure 14) where there is a convergence of fire sensitive HVRA categories (Figures 6-11), hazardous fuel conditions (Figure 24), and high burn probability (Figure 30). There is also high risk associated with spruce-fir and lodgepole pine forests (Figure 14), where the expected annual area burned is high (Figure 29). It should be noted that some areas of the landscape are expected to benefit from wildfire (Figure 5); in these areas low predicted flame lengths may enhance vegetation and recreation HVRA categories (Figures 10-11).

Geospatial Database

Table 6: Hierarchical structure of data and data sources for each highly valued resource and asset (HVRA). A short description of each dataset and a URL for download can be found in the Box geodatabase file titled "HVRA_metadata.xlsx".

	Category	HVRA	Data Source
Composite	Infrastructure	Communications	Homeland Infrastructure Foundation-Level Data
		Electrical	Homeland Infrastructure Foundation-Level Data
		Historic structures	National Park Service
		Mines	Colorado Division of Reclamation, Mining, and Safety
		Monitoring stations	Natural Resource Conservation Service, US Geological Survey, and Western Regional Climate Center
		Roads	Colorado Department of Transportation and US Forest Service
	Recreation	Camping	Bureau of Land Management, US Forest Service, and Rocky Mountain National Park
		Recreation assets	Bureau of Land Management and US Forest Service
		Ski areas	US Forest Service
		Trailheads	Colorado Trail Explorer
		Trails	Colorado Trail Explorer
	Vegetation	Aspen	LANDFIRE
		Aspen mixed conifer	LANDFIRE
		Grassland	LANDFIRE
		Lodgepole	LANDFIRE
		Mixed conifer	LANDFIRE
		Mixed shrubland	LANDFIRE
		Old growth forest	Arapaho-Roosevelt National Forest
		Pinyon juniper	LANDFIRE
		Ponderosa pine	LANDFIRE
		Riparian	LANDFIRE
		Sagebrush	LANDFIRE
		Spruce fir	LANDFIRE
	Water	Critical water supply	Colorado Department of Public Health and Environment & local water utilities
		Designated waters	Colorado Parks and Wildlife and US Forest Service
	Wildlife	Greenback cutthroat trout	Arapaho-Roosevelt National Forest
		Lynx	Colorado Parks and Wildlife
		Preble's jumping mouse	US Fish and Wildlife
	WUI	Buildings	Microsoft Bing

All geospatial data is available in a shared [Box database](#) and an [ArcGIS Online map](#). The geodatabase includes all highly valued resource and asset inputs, fire modeling layers, and intermediate and final composite risk outputs. These outputs are summarized at various scales (Table 6), and are intended for use in project planning, grant applications, NEPA planning, integration with PODs, etc. The geodatabase is structured as follows:

HVRA shapefiles (i.e., vector data)

1. Infrastructure
2. Recreation
3. Vegetation
4. Water
5. Wildlife
6. WUI

HVRA rasters (i.e., rasterized vector data that includes influence zone buffers)

1. Infrastructure
2. Recreation
3. Vegetation
4. Water
5. Wildlife
6. WUI

Fire modeling

1. Burn probability
2. Fire behavior

Conditional NVC (cNVC)

1. By category
 - a. Infrastructure
 - b. Recreation
 - c. Vegetation
 - d. Water
 - e. Wildlife
 - f. WUI
2. By HVRA
3. Composite

Expected NVC (eNVC)

1. By category
 - a. Infrastructure
 - b. Recreation
 - c. Vegetation
 - d. Water
 - e. Wildlife
 - f. WUI
2. By HVRA
3. Composite

HVRA GIS data came from various public data sources which are documented in Table 6 and the BOX geodatabase file titled “HVRA_metadata.xlsx”. The folder titled “HVRA_shapefiles.gdb” houses all vector GIS data (i.e., points, polygons, and polylines). These data were then buffered with user-defined zones of influence (Table 2) and rasterized. Resulting raster data can be found in the “HVRA_rasters” folder.

Fire behavior and burn probability maps and rasters are stored in the “Fire_modeling” folder. Flame length was modeled for 4 weather scenarios and files are labeled by percentile (Table 4). We included rasters as .tif files and attached suggested symbology in .lyrx files. While the .lyrx files will only work with ArcGIS Pro, the suggested symbology is documented in the “raster_symbology” text file in the “symbology” folder and can be manually applied to the .tif files.

Conditional net value change is the product of flame length and HVRA-specific response functions over a range of wildfire intensity classes. In short, it represents the likely impact of fire to HVRAs if a fire were to burn in a given pixel. We include .pdf maps, .tif rasters, and .lyrx rasters with suggested symbology at the HVRA level, at the category level, and as a composite of all categories. Again, the suggested symbology is captured in the .lyrx files for ArcGIS Pro users and documented in the “raster_symbology” text file.

Expected net value change is the product of burn probability and conditional net value change so this product represents the likely impact of fire to HVRAs considering the likelihood of fire occurring in any given pixel. Again, we include .pdf maps, .tif rasters, and .lyrx rasters with suggested symbology at the category level and as a composite of all categories.

Baseline Composite Wildfire Risk

Expected Net Value Change

- Negative
- Neutral
- Positive

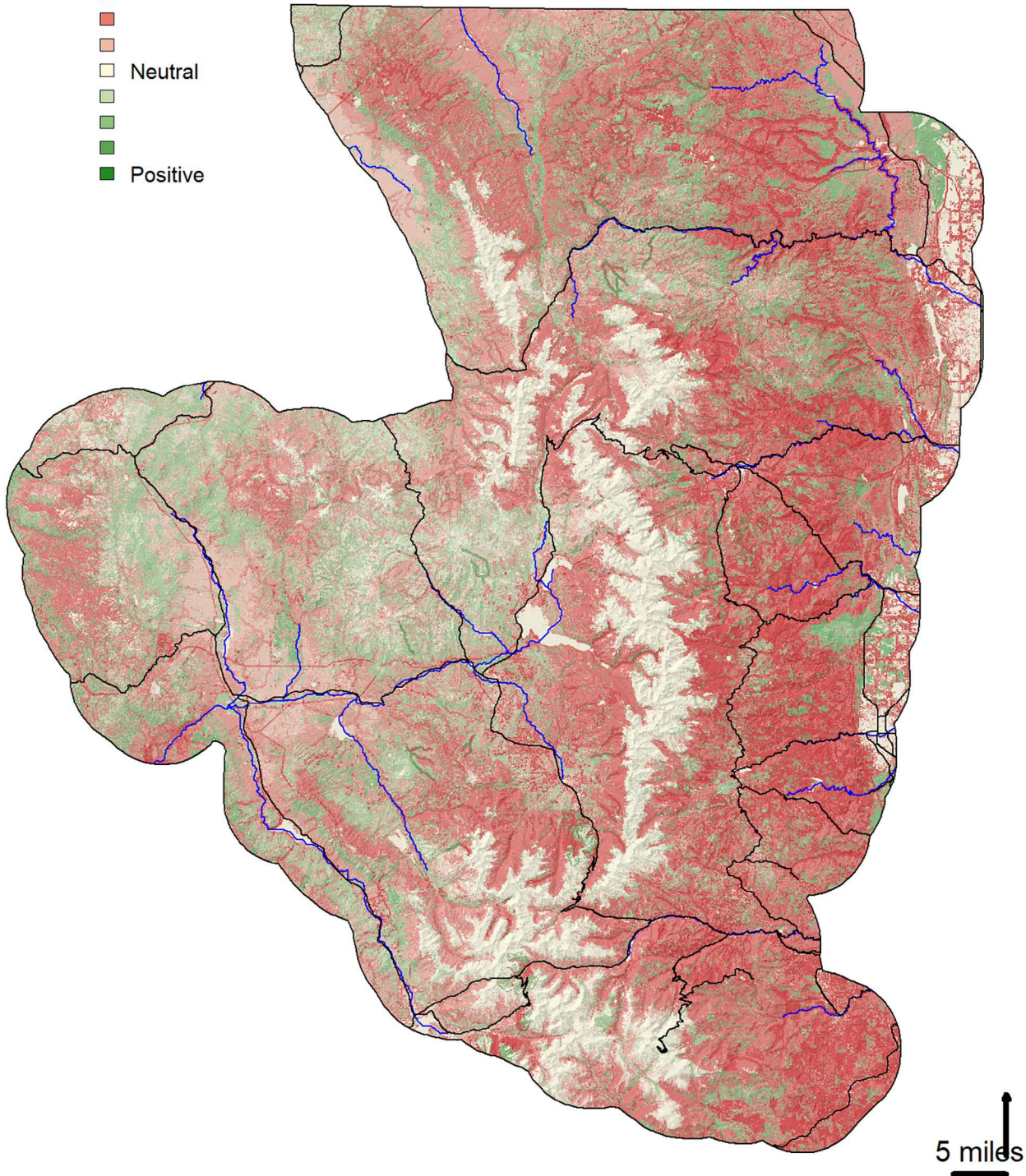


Figure 5: Composite wildfire risk map for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire. eNVC measures account for both the HVRA susceptibility and probability of wildfire.

INFRASTRUCTURE

Expected Net Value Change

- Negative
- Neutral
- Positive

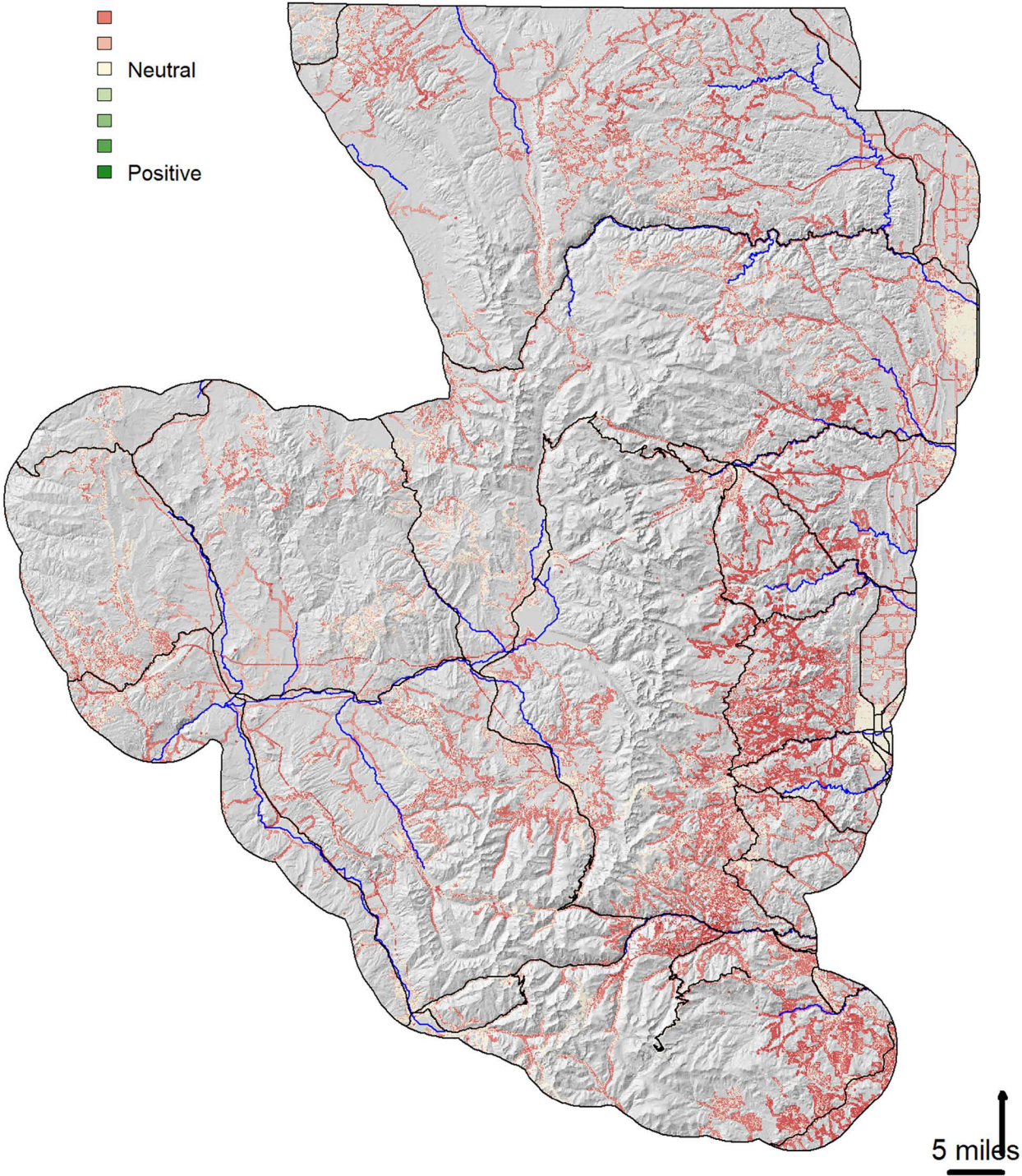


Figure 6: Wildfire risk to infrastructure for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

WATER

Expected Net Value Change

- Negative
- Negative
- Negative
- Neutral
- Neutral
- Positive
- Positive

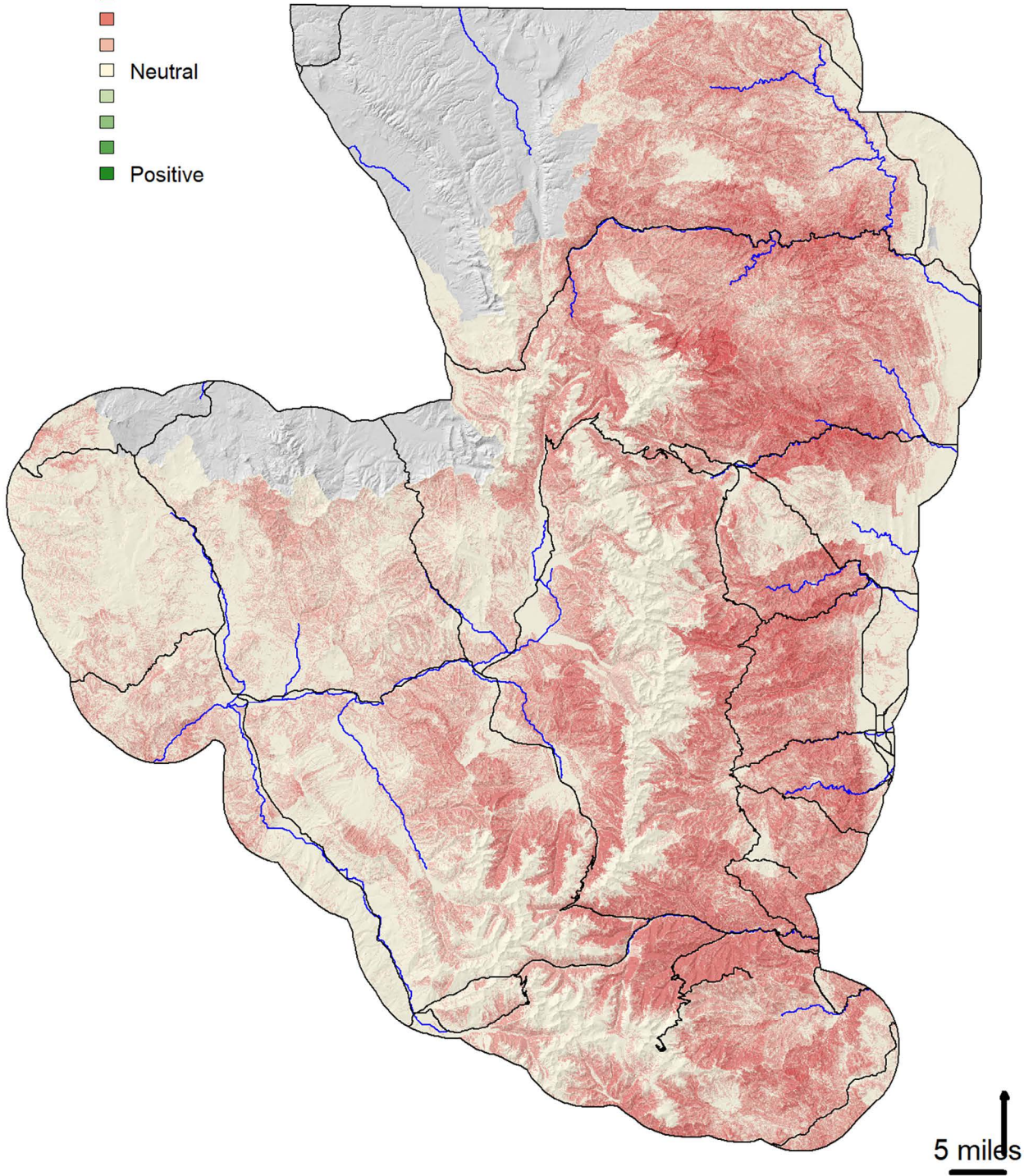


Figure 7: Wildfire risk to water for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

WUI

Expected Net Value Change

- Negative
- Negative
- Negative
- Neutral
- Neutral
- Positive
- Positive

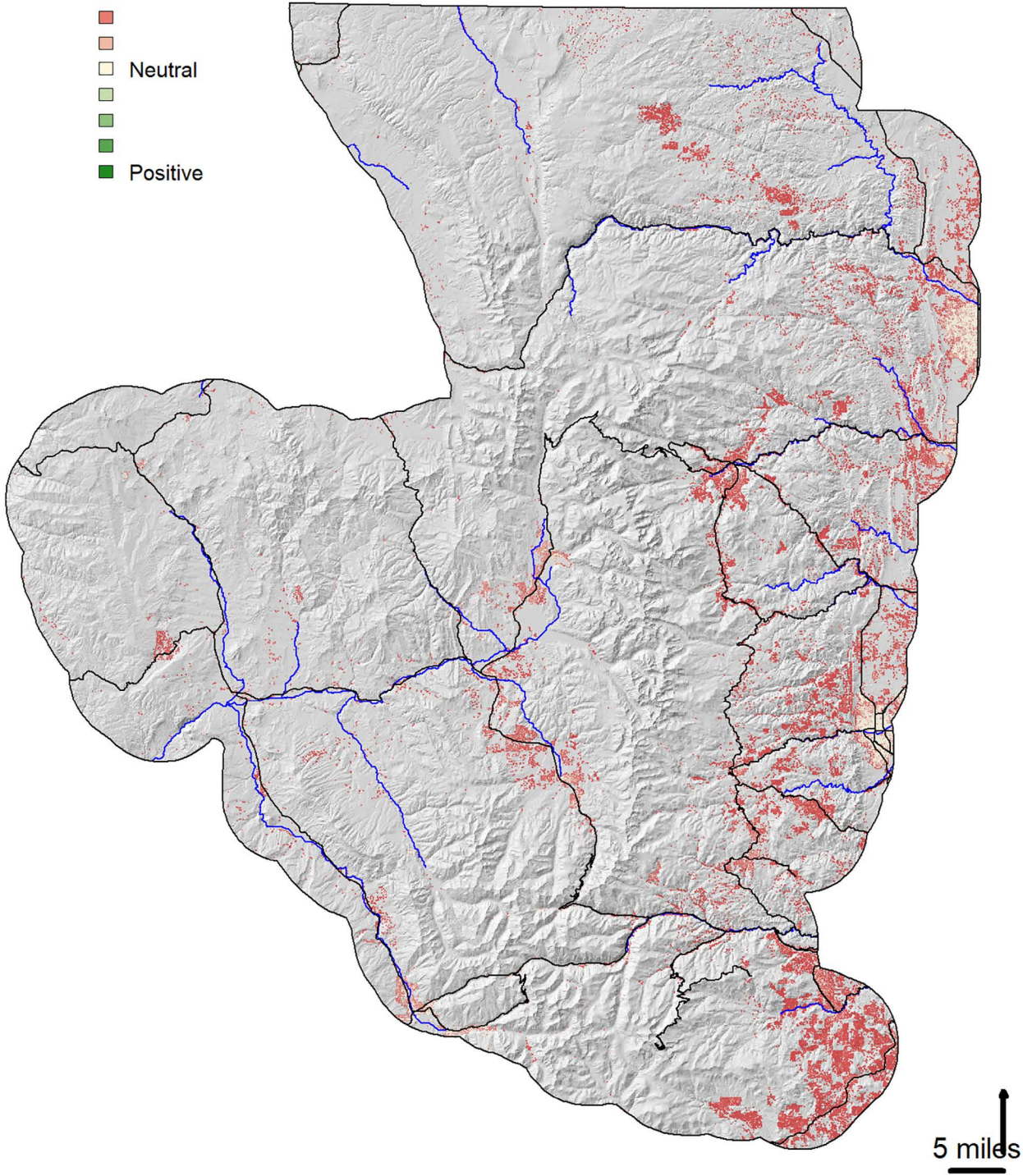


Figure 8: Wildfire risk to buildings for the analysis extent. This includes both individual structures from [Microsoft](#) as well as historic structures from the National Park Service. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

WILDLIFE

Expected Net Value Change

- Negative
- Neutral
- Positive

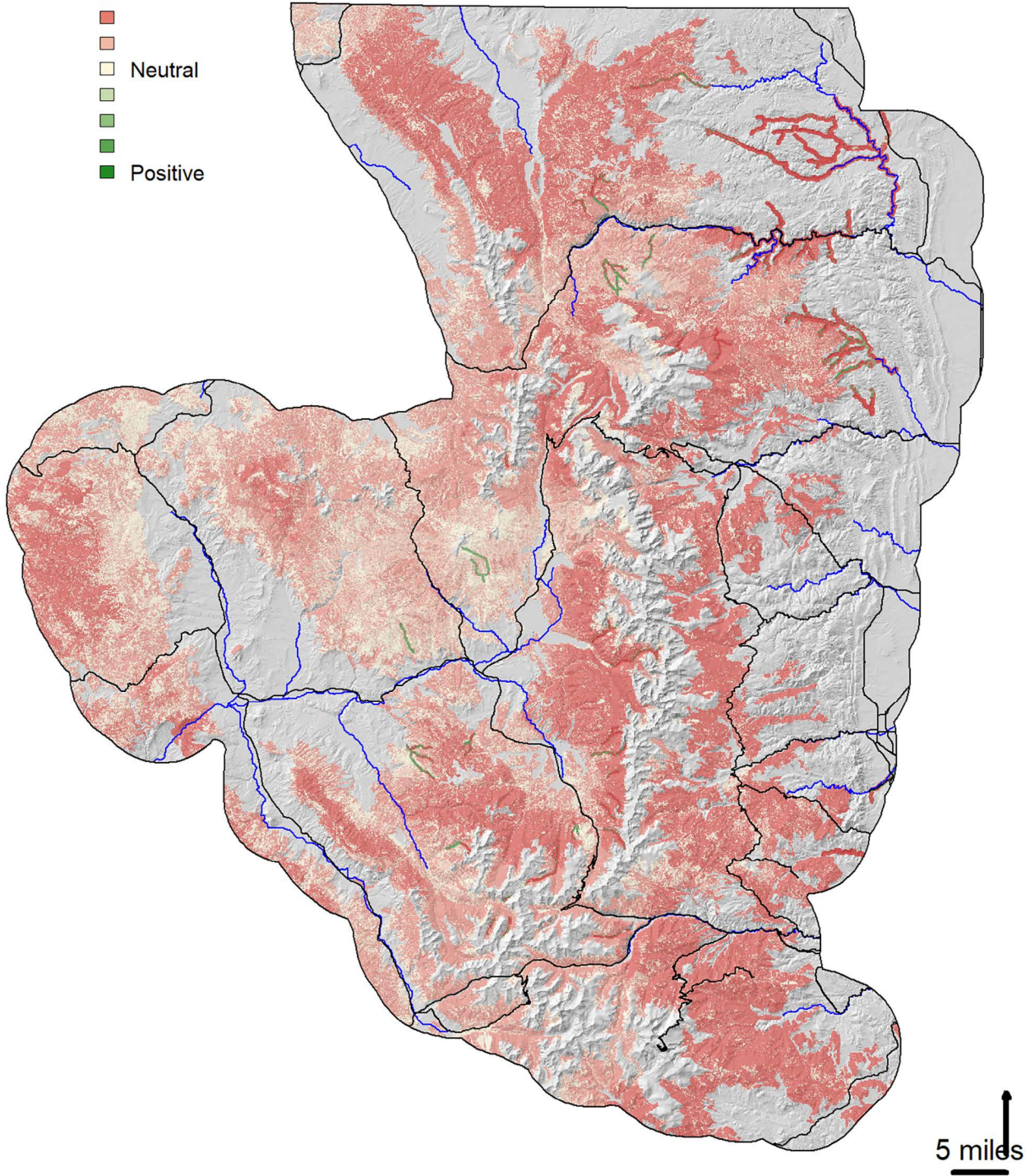


Figure 9: Wildfire risk to wildlife for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

RECREATION

Expected Net Value Change

- Negative
- Neutral
- Positive
- Positive
- Positive

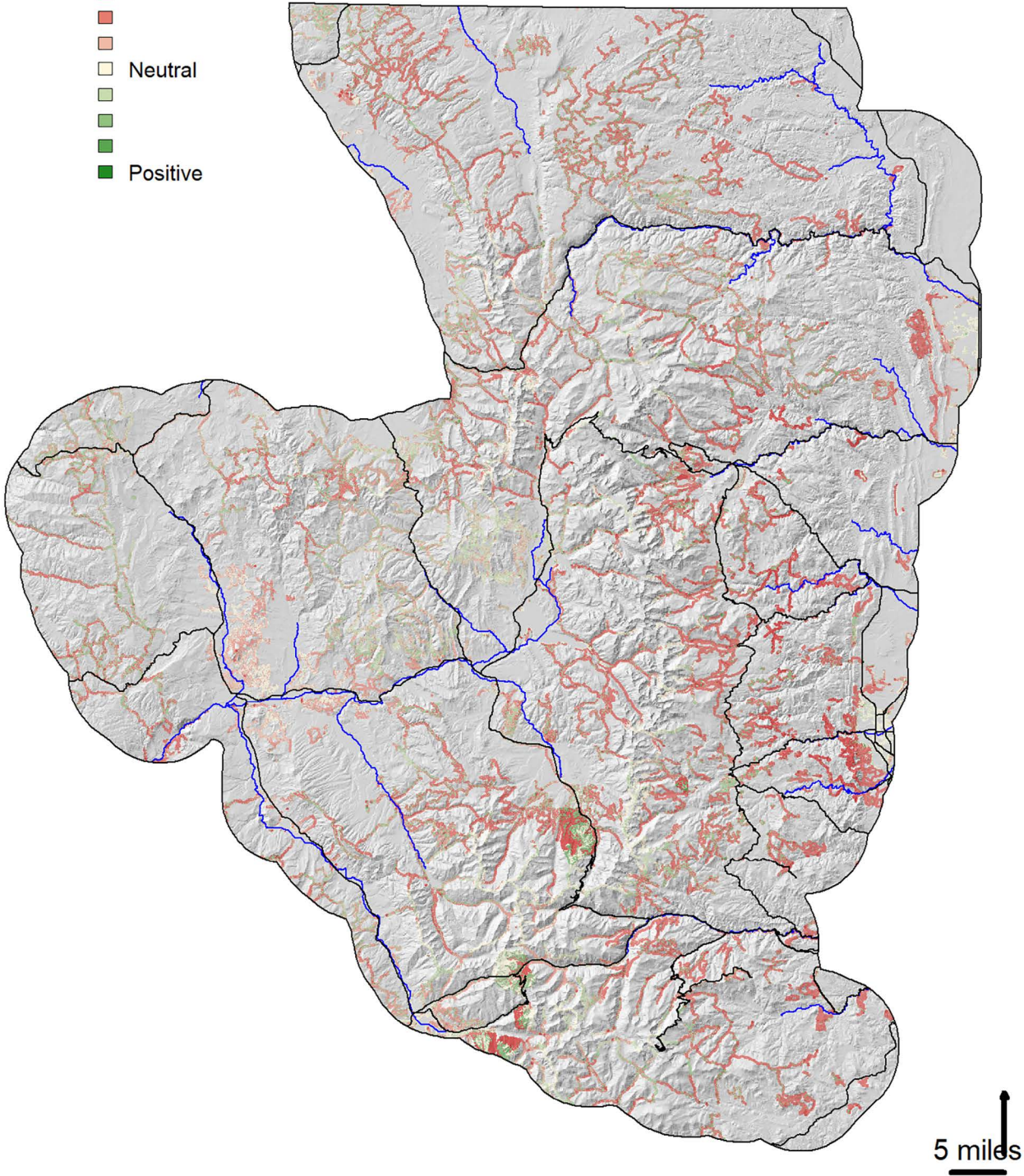


Figure 10: Wildfire risk to recreation for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

VEGETATION

Expected Net Value Change

- Negative
- Neutral
- Positive

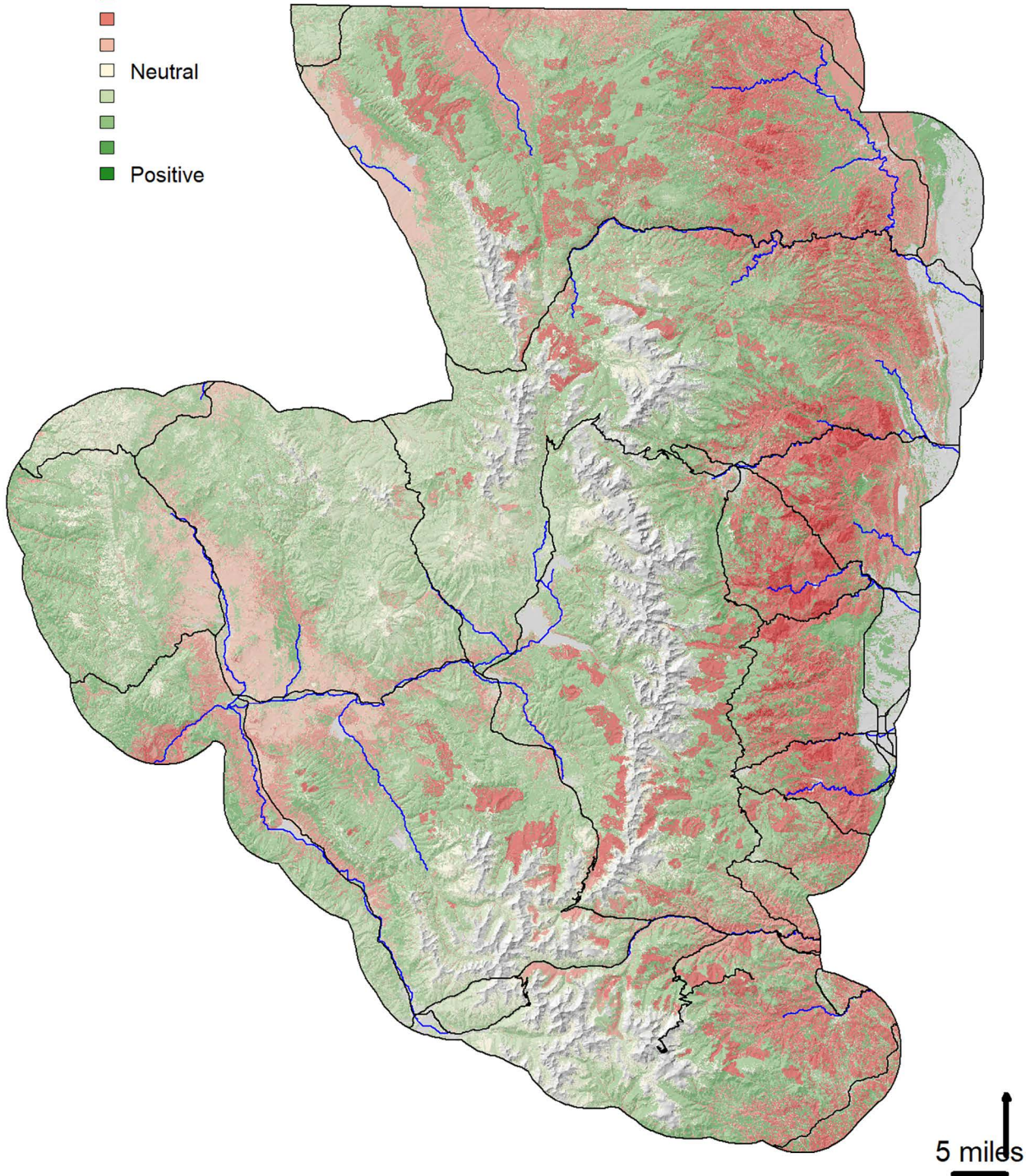


Figure 11: Wildfire risk to vegetation for the analysis extent. Negative eNVC means high risk. Positive eNVC means there is an expected benefit from fire.

Composite Conditional Net Value Change

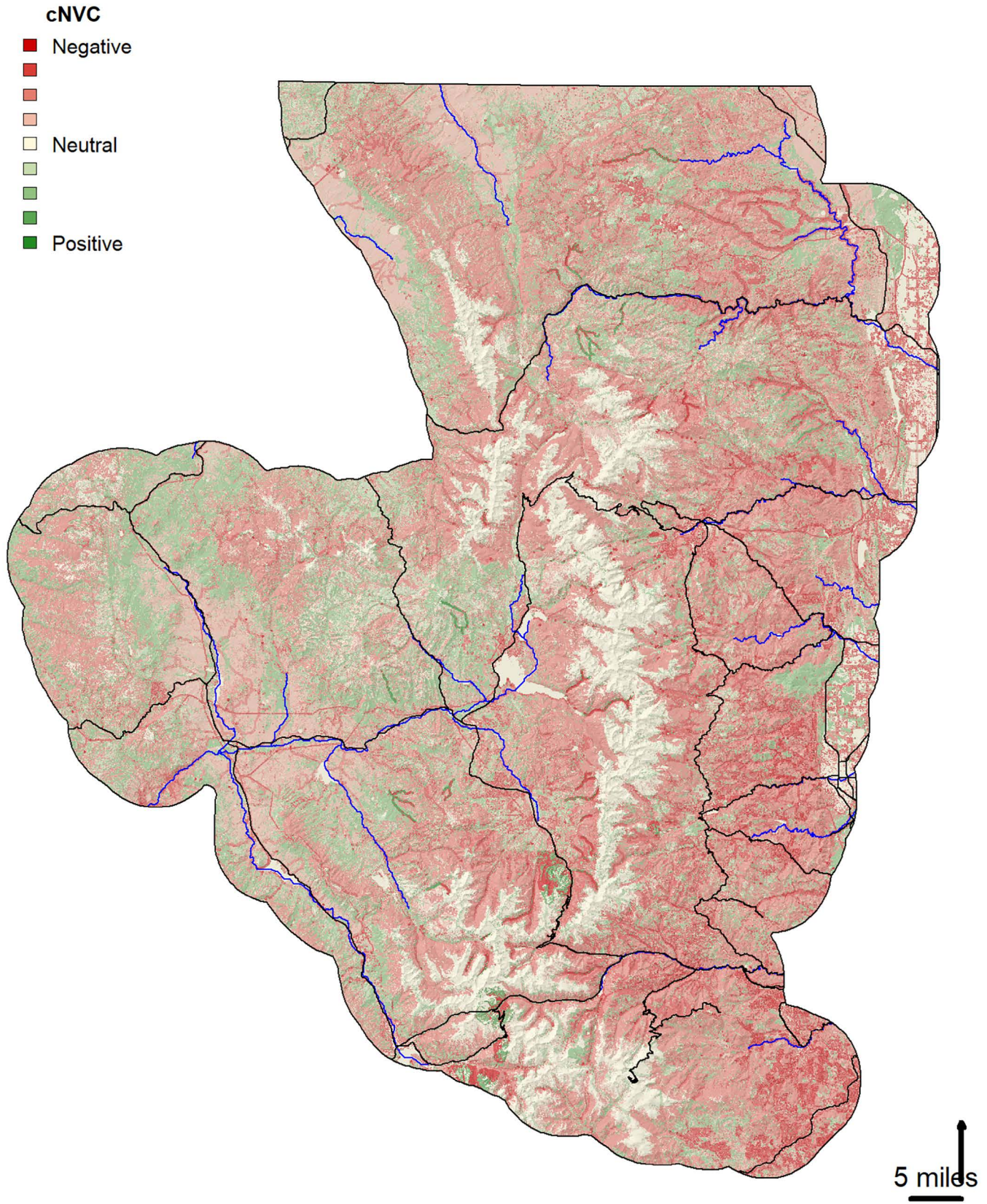


Figure 12: Composite conditional net value change (cNVC) map for the analysis extent. Negative cNVC means net losses. Positive cNVC means net benefits. This product does not account for burn probability.

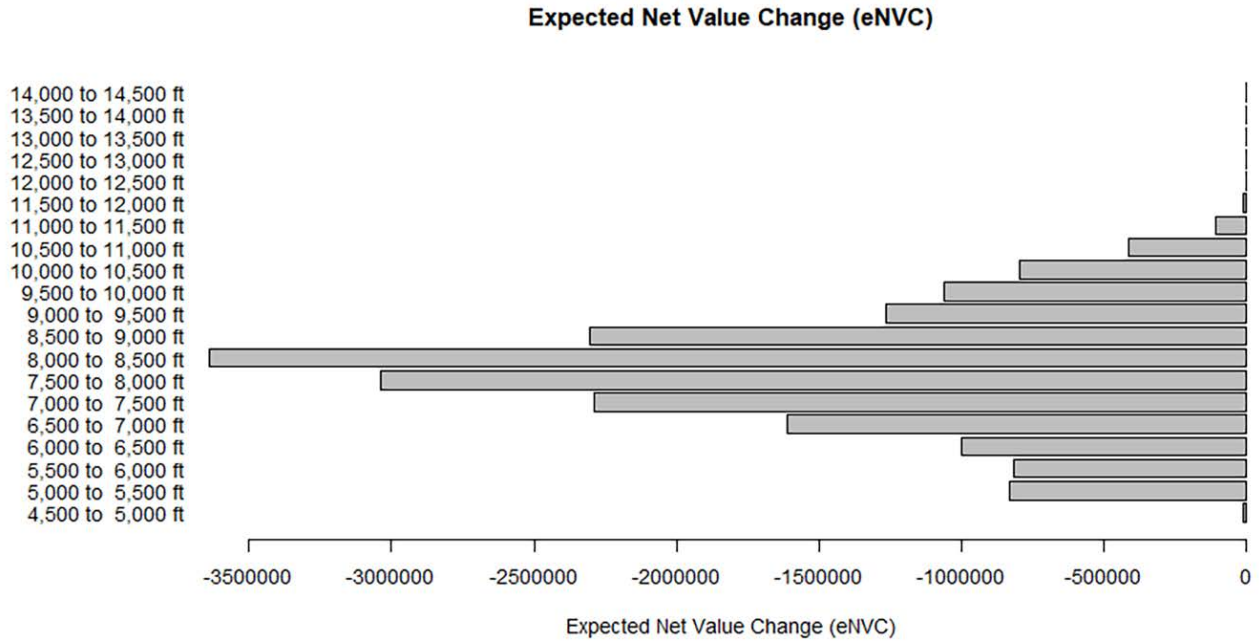


Figure 13: Risk (expected Net Value Change) distribution across elevation bins.

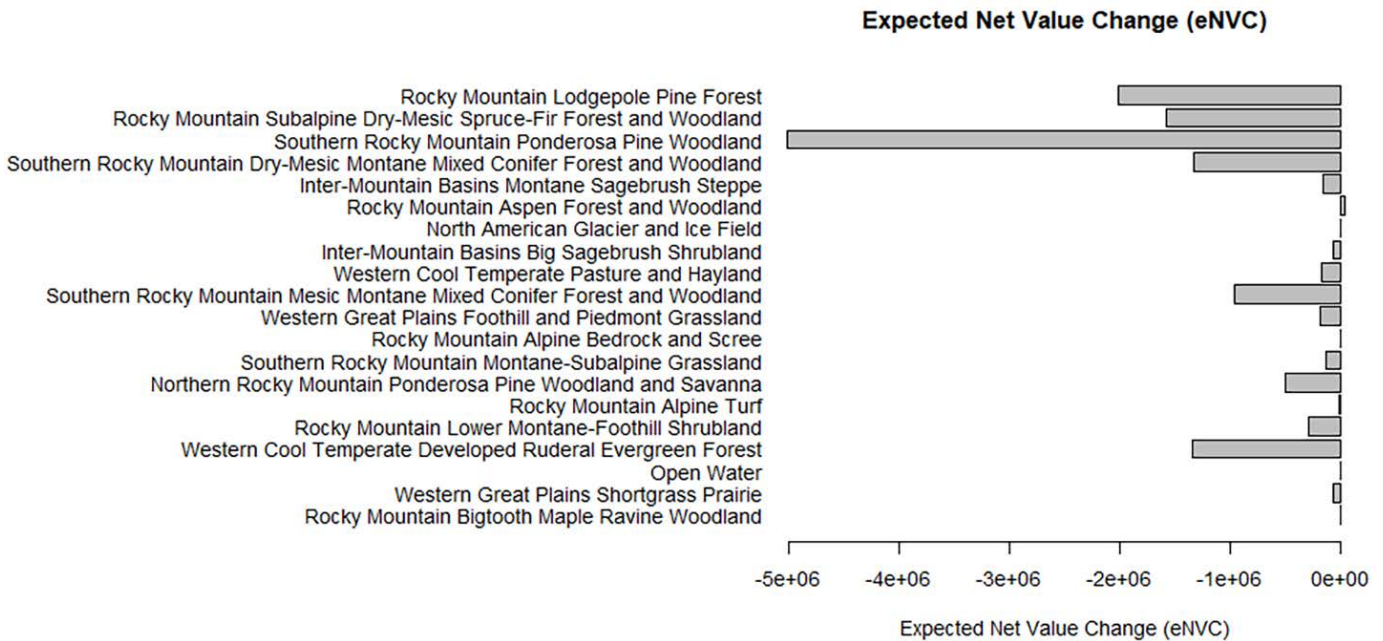


Figure 14: Risk (expected Net Value Change) by existing vegetation type from LANDFIRE (2020).

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Appendix I - Fire Behavior Products

Flame Length - Low Scenario

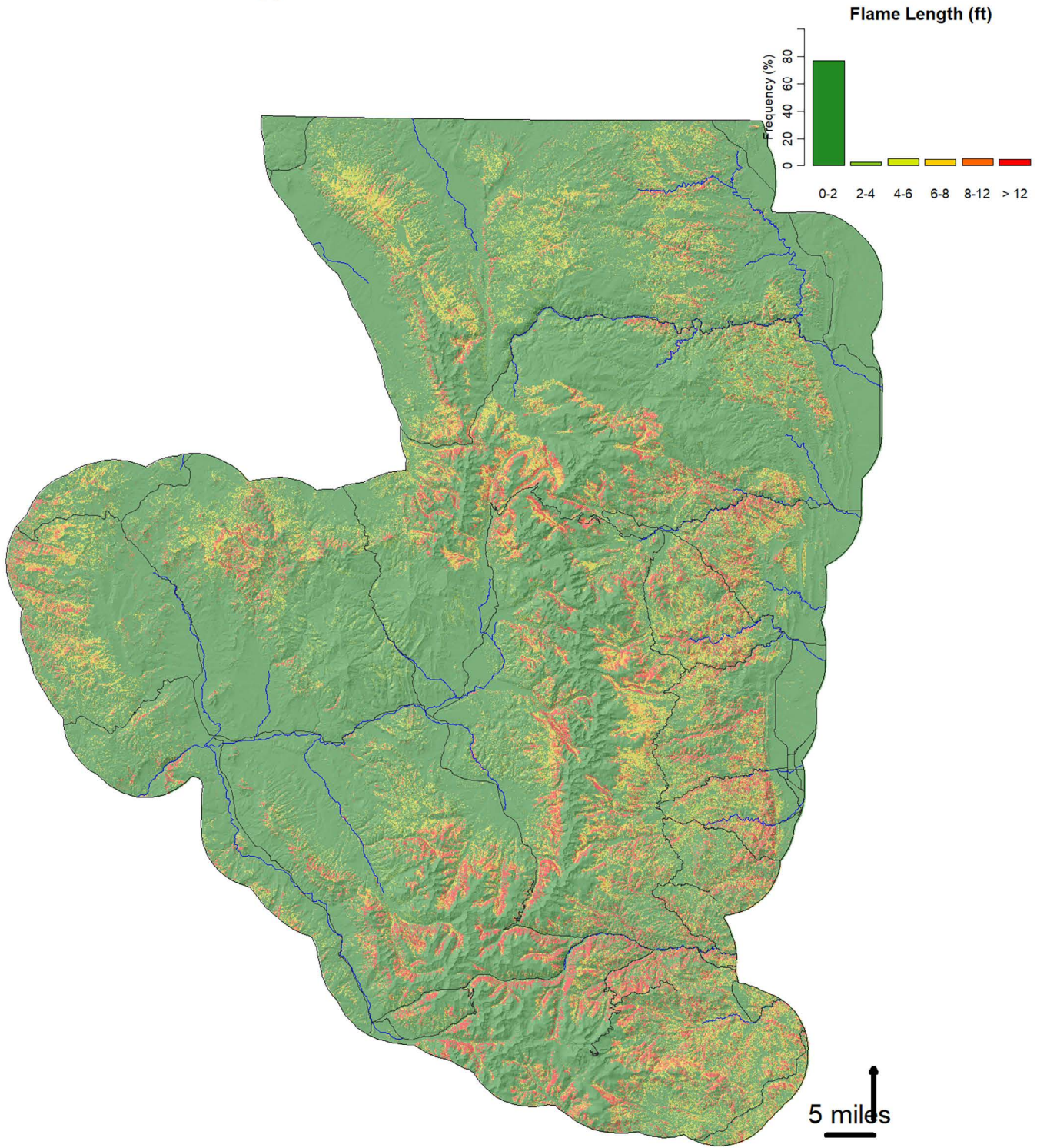


Figure 15: Modeled flame length (ft) for the low fire weather scenario.

Flame Length - Moderate Scenario

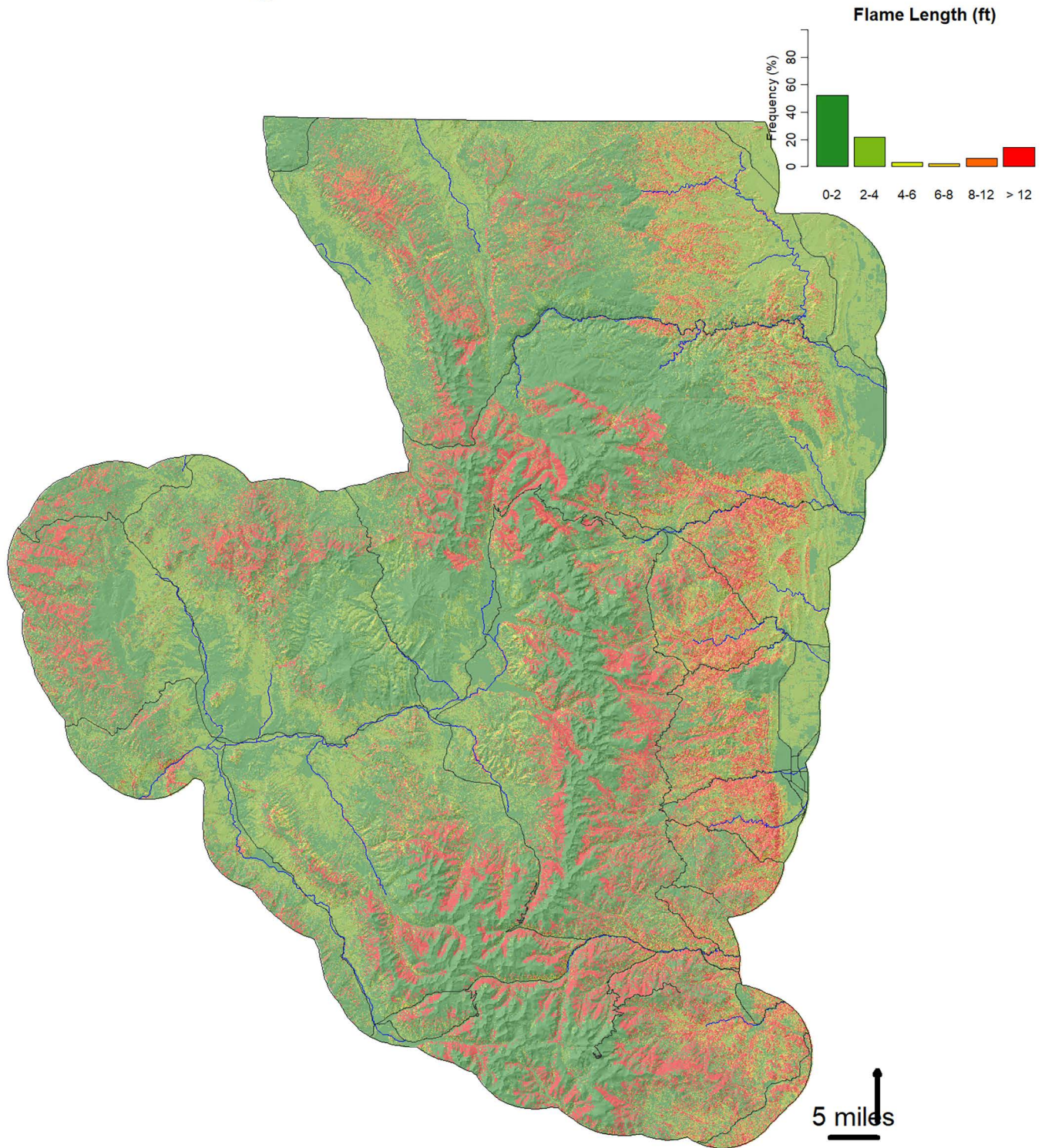


Figure 16: Modeled flame length (ft) for the moderate fire weather scenario.

Flame Length - High Scenario

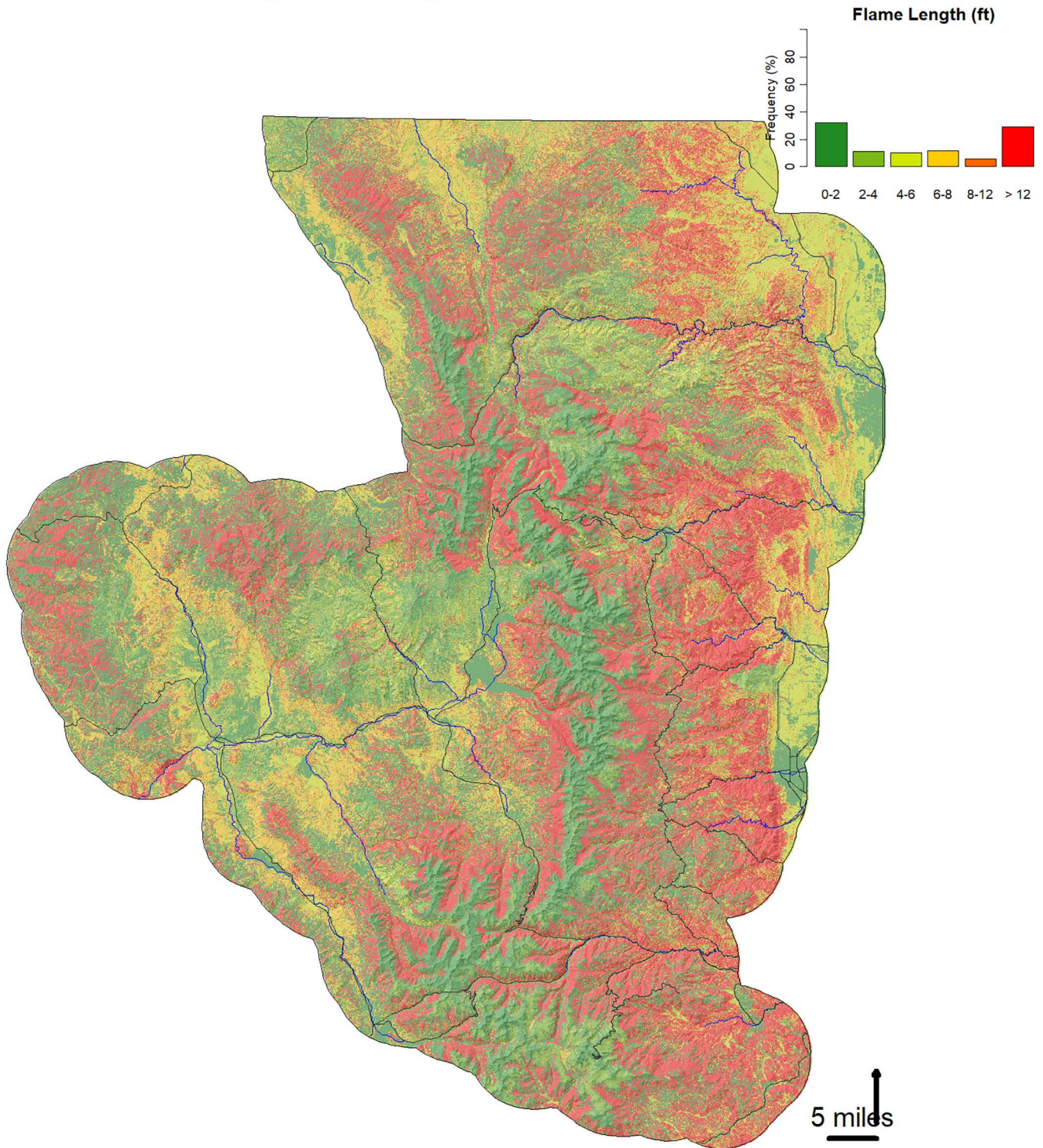


Figure 17: Modeled flame length (ft) for the high fire weather scenario.

Flame Length - Extreme Scenario

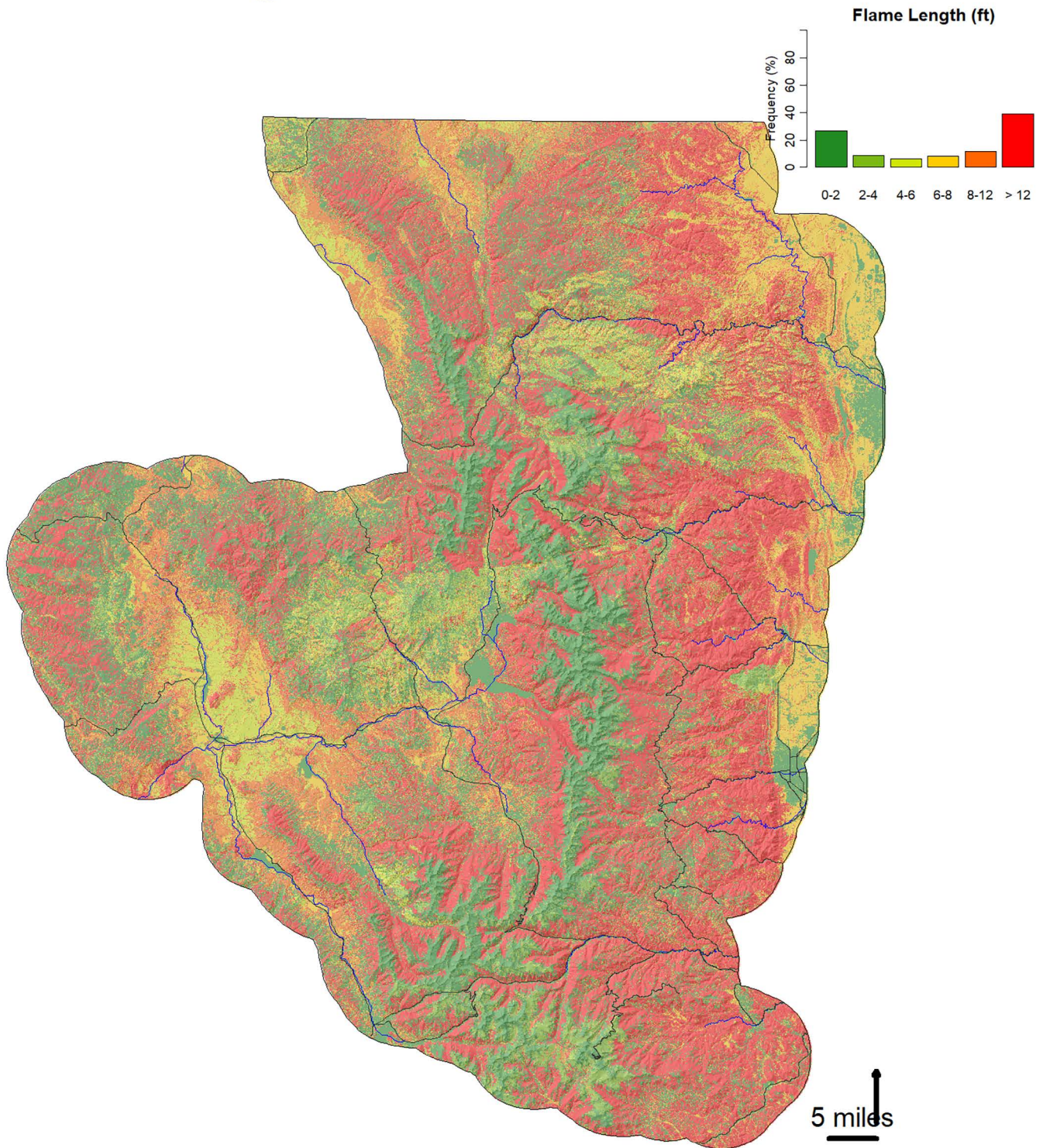


Figure 18: Modeled flame length (ft) for the extreme fire weather scenario.

Crown Fire Activity - Low Scenario

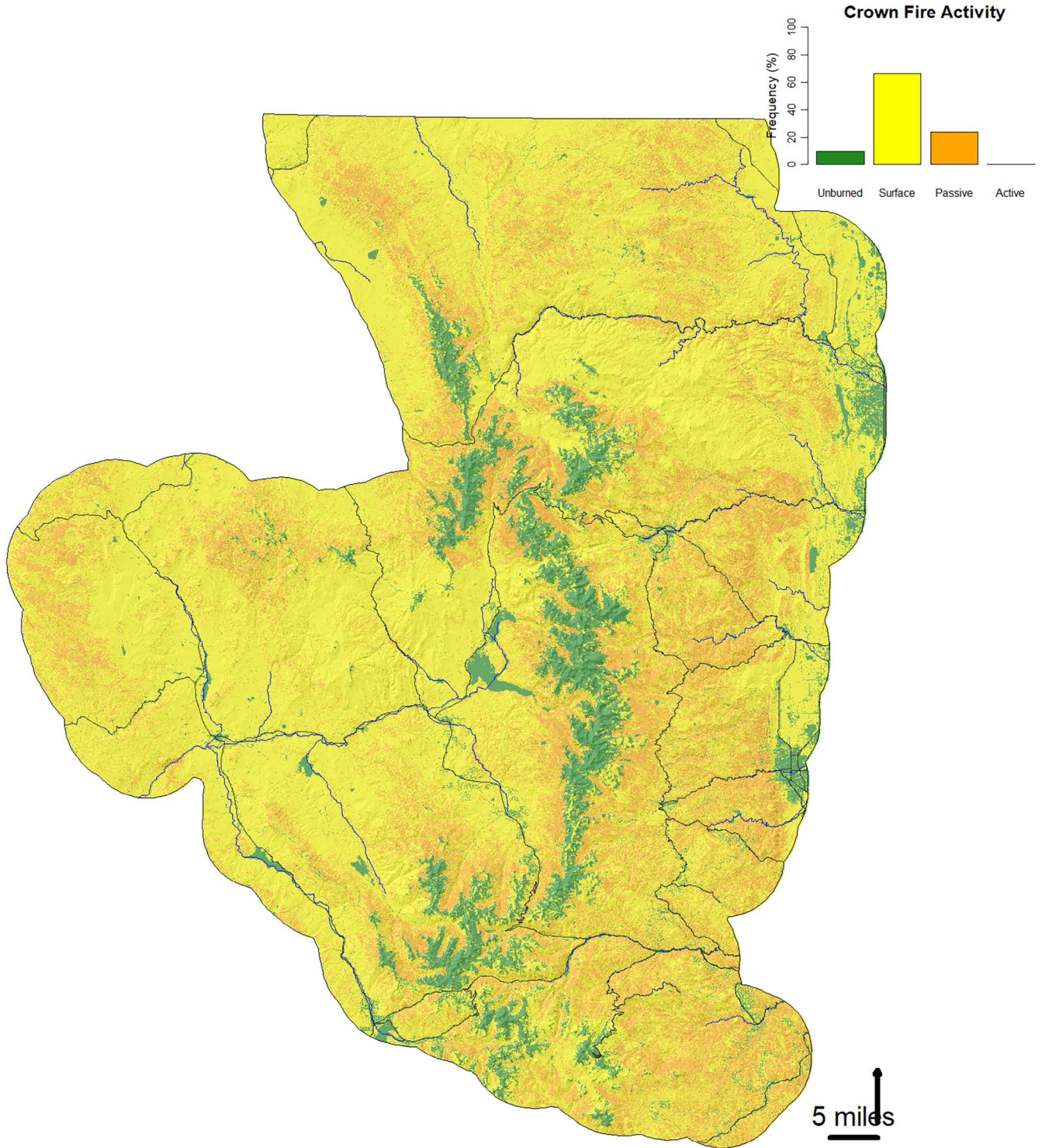


Figure 19: Modeled crown fire activity for the low fire weather scenario.

Crown Fire Activity - Moderate Scenario

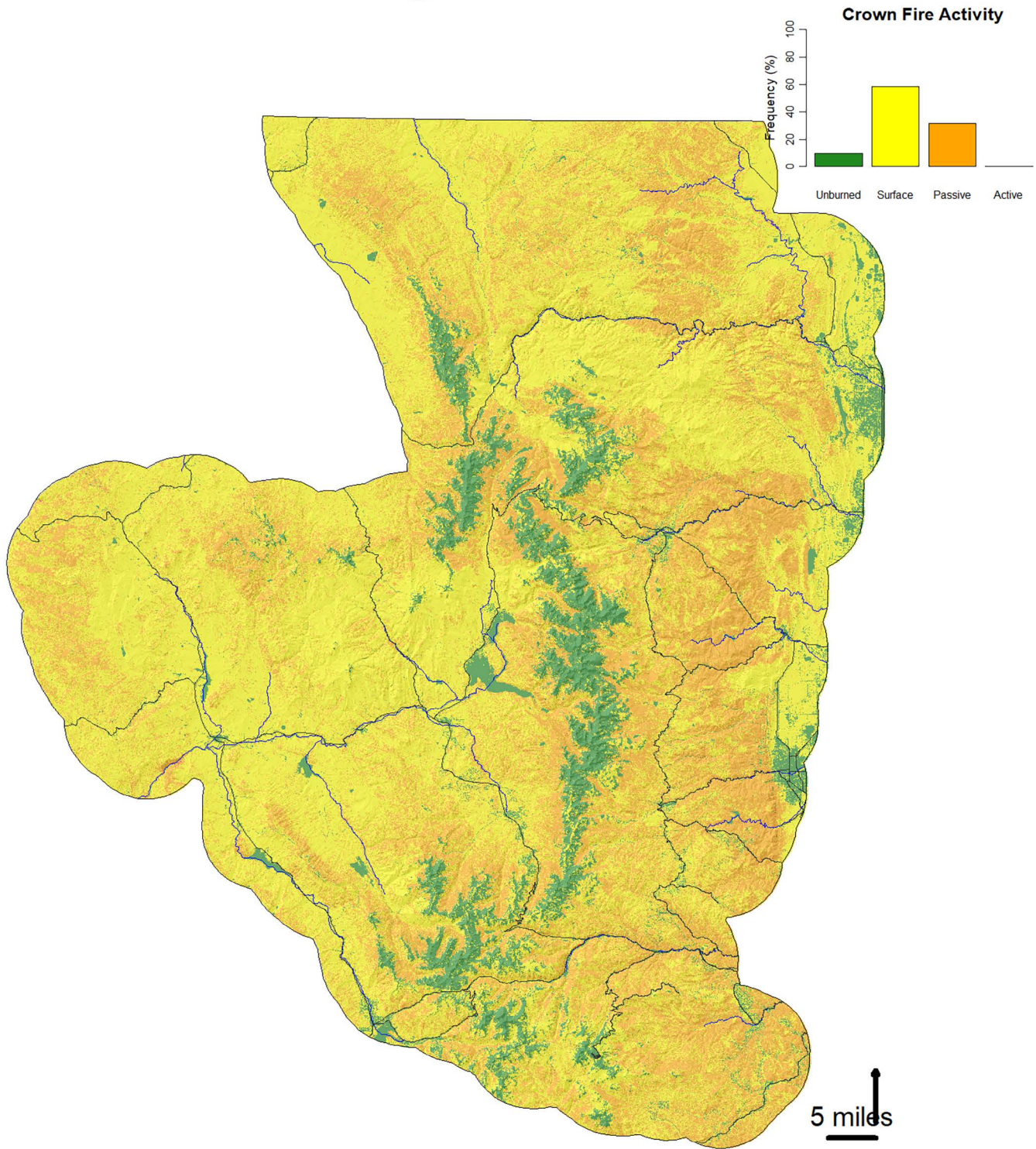


Figure 20: Modeled crown fire activity for the moderate fire weather scenario.

Crown Fire Activity - High Scenario

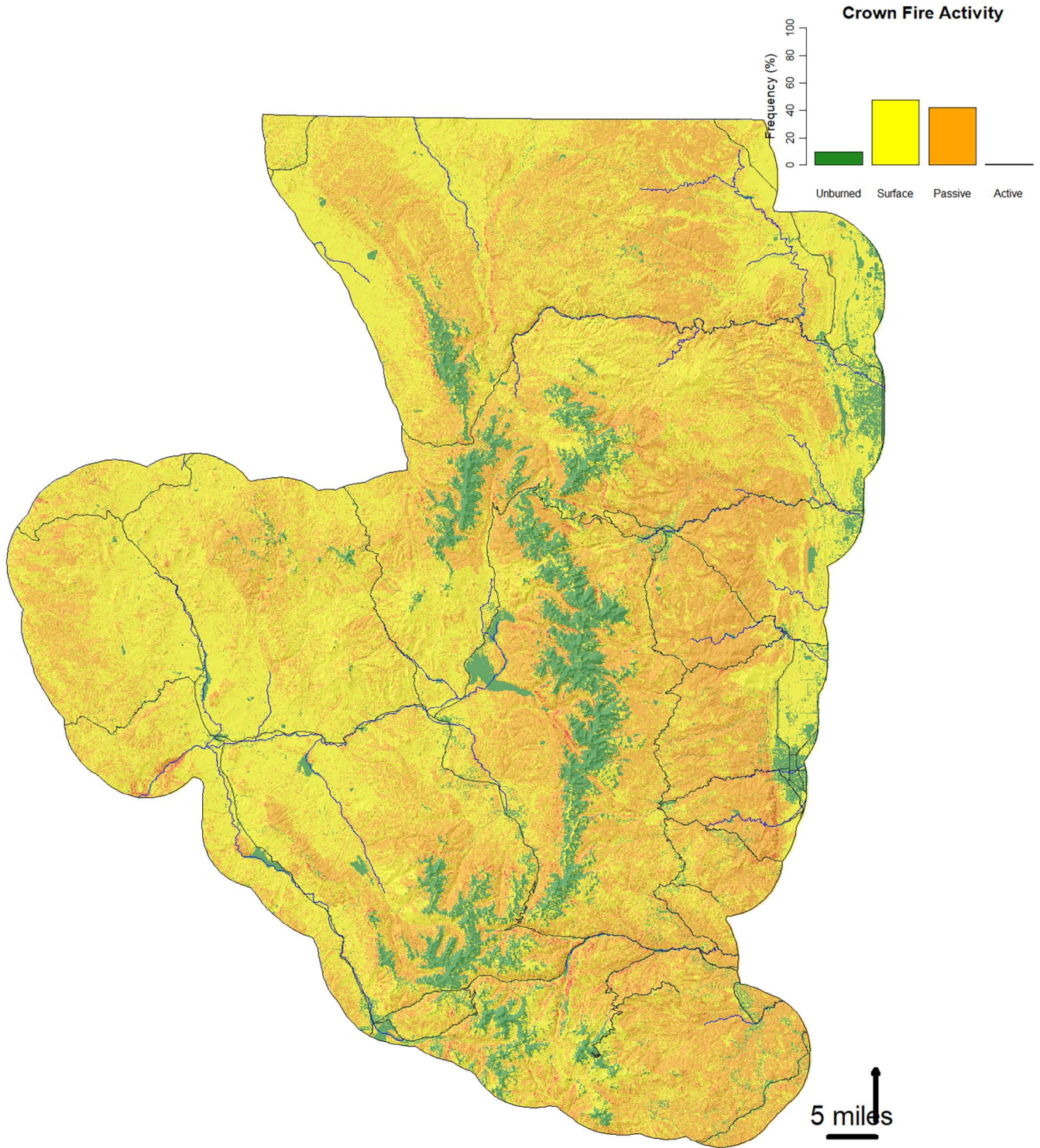


Figure 21: Modeled crown fire activity for the high fire weather scenario.

Crown Fire Activity - Extreme Scenario

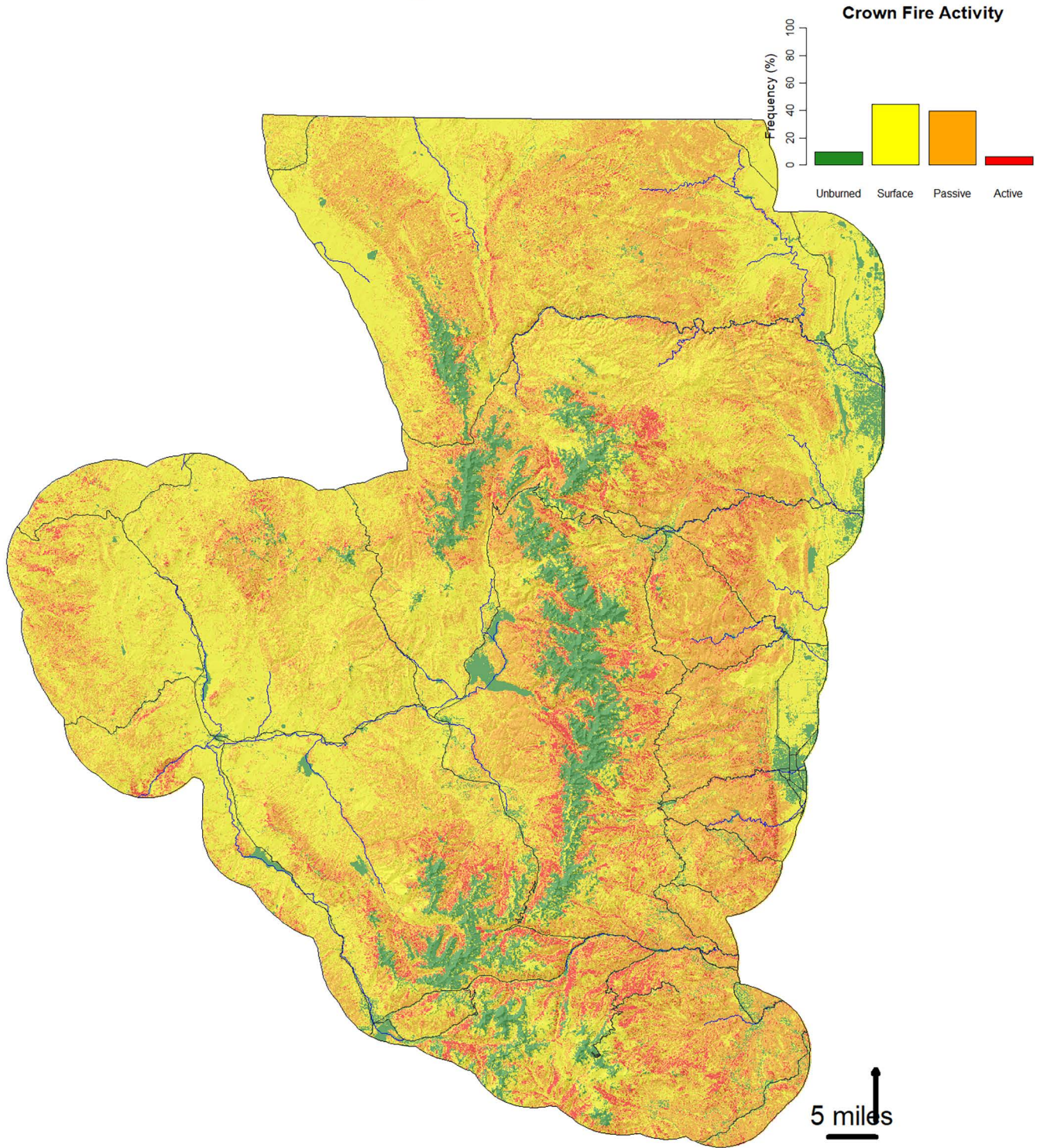


Figure 22: Modeled crown fire activity for the extreme fire weather scenario.

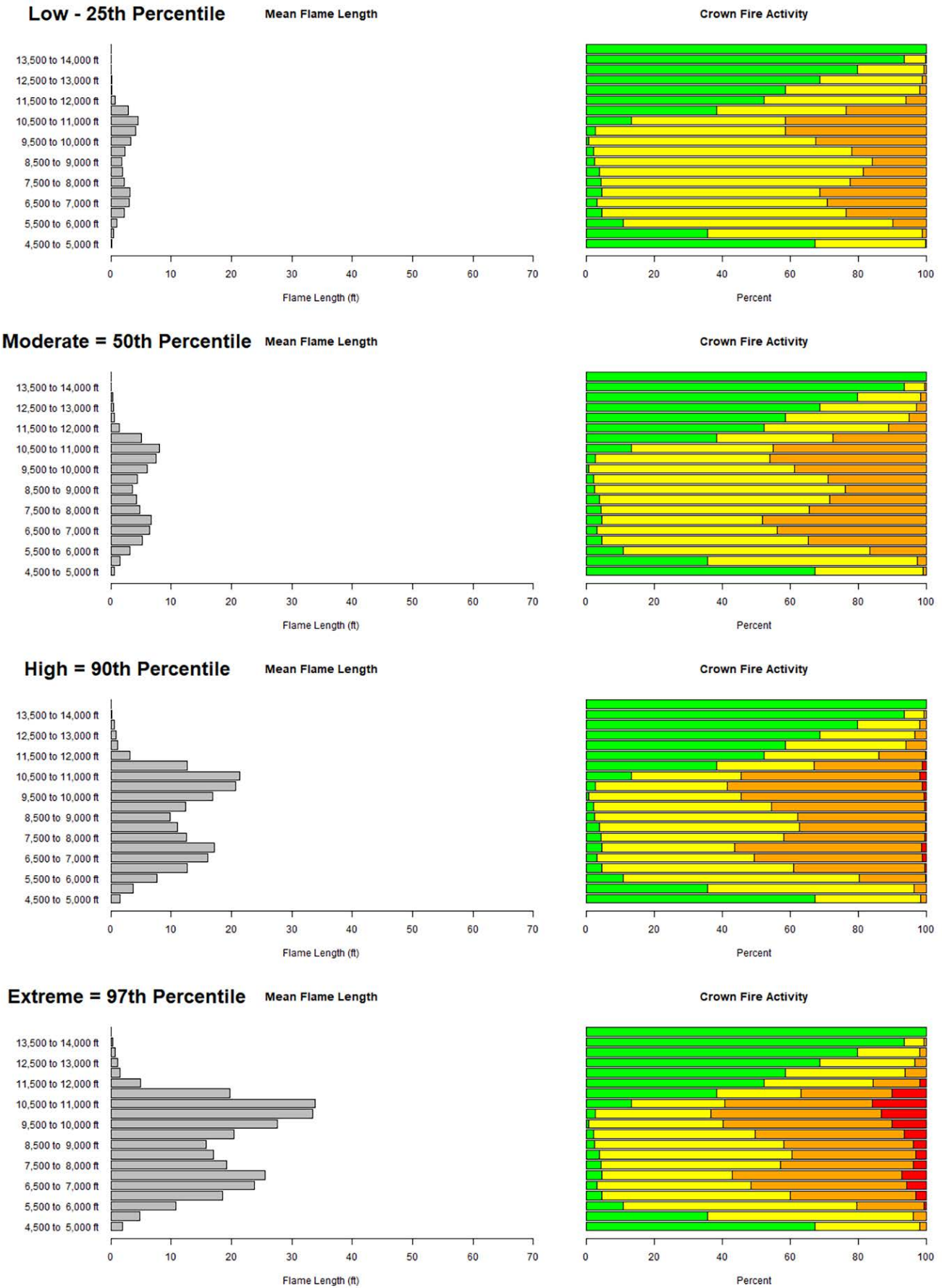
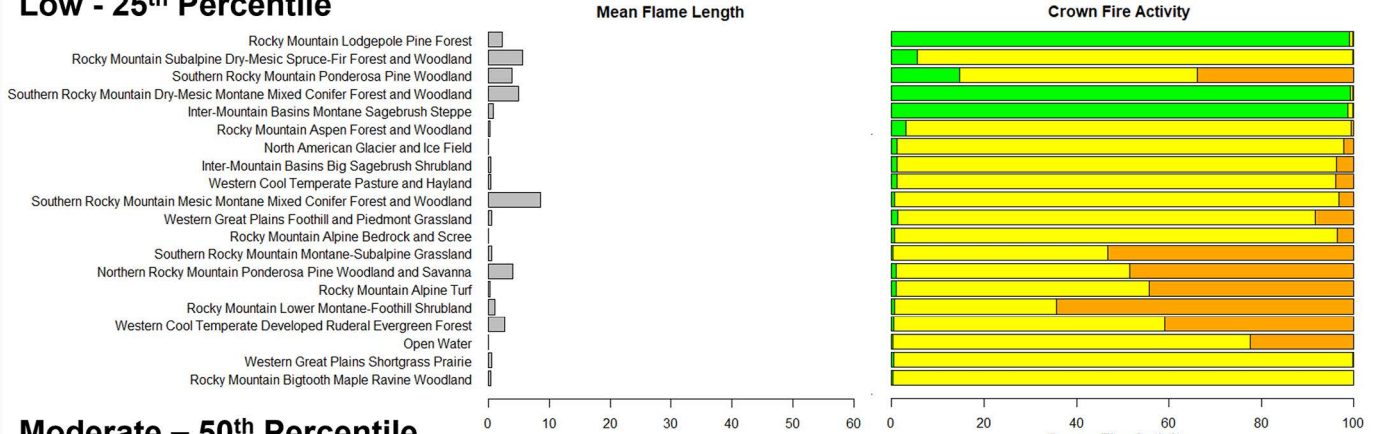
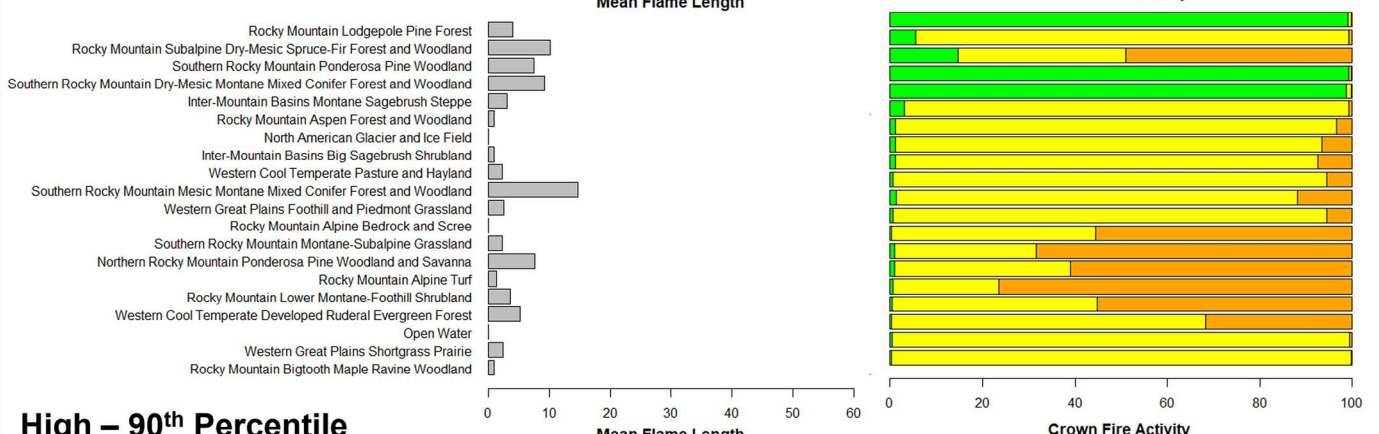


Figure 23: Summary of fire behavior by elevation. The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

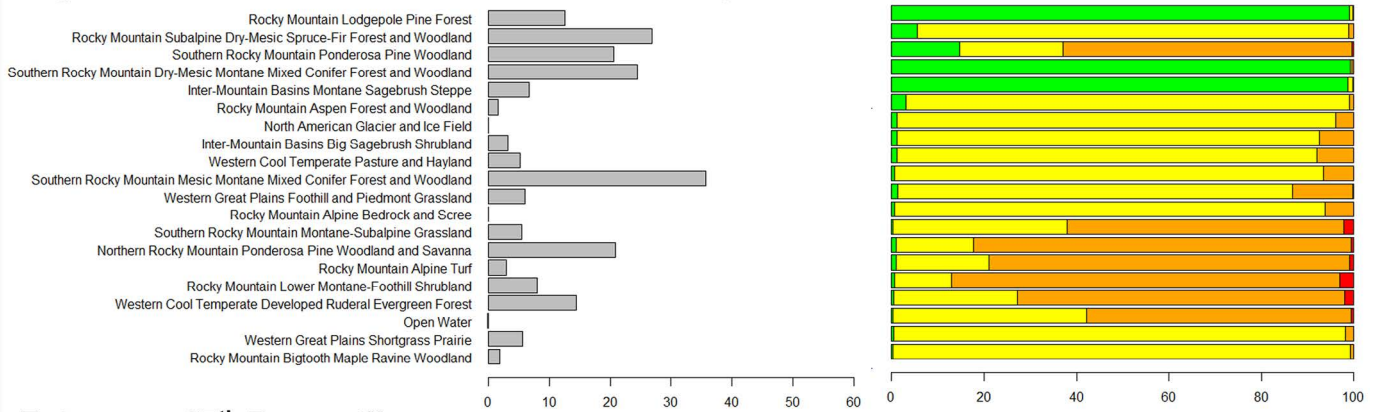
Low - 25th Percentile



Moderate - 50th Percentile



High - 90th Percentile



Extreme - 97th Percentile

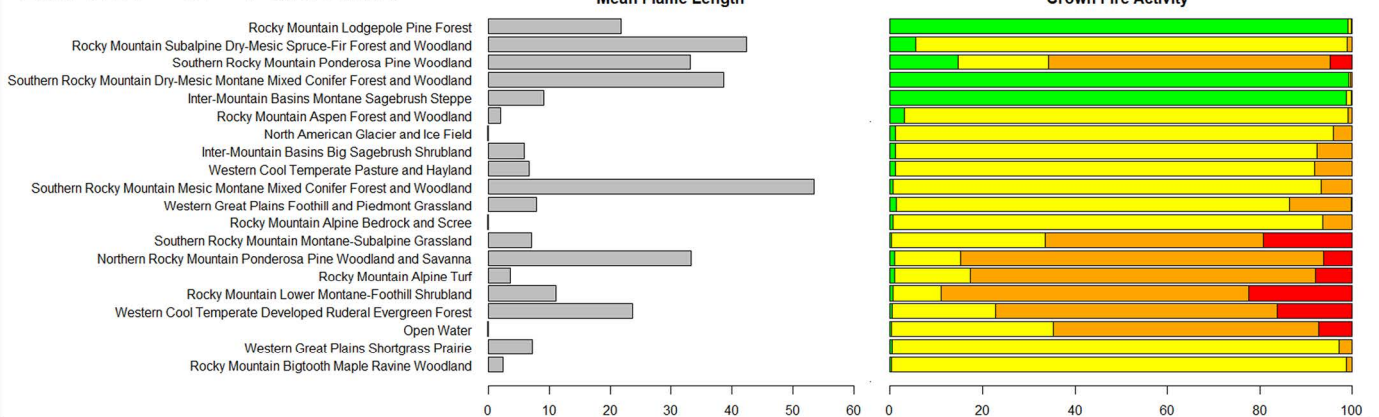


Figure 24: Summary of fire behavior by existing vegetation type from LANDFIRE (2020). The stacked barplot color scheme is green = unburned, yellow = surface fire, orange = passive crown fire, and red = active crown fire.

Appendix II – Burn Probability Products

Burn probability is a spatially explicit estimate of fire likelihood that is often derived from simulation modeling of fire spread. This 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

Local stakeholders expressed concern that existing burn probability products did not match their observations of recent fires or their expectations about future fire occurrence across the analysis extent. 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, but values are particularly low in high elevation forest 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 probability of large wildfires at high elevations 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.

Local FSim Burn Probability Alternative

Based on perceived shortcomings associated with the existing CO-WRA and the National FSim 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 fire 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. This simulation 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 significantly alter the landscape fuel condition in the future, updated FSim runs are required to accurately represent the spatial burn probability.

The FSim simulations for this QWRA were conducted at 270 m resolution for 15,000 years of modeled fire activity and simulation parameters were calibrated such that simulation results matched the observed annual number of fires, mean fire size, and fire size distribution between 2000 and 2020 within a 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 and spreads into the analysis area. This matches with concerns of future fire events similar to the 2020 East Troublesome and Cameron Peak fires, 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 (Red Feather RAWS) was used to generate simulated weather across the analysis area based on all daily weather observations since 2000. The Red Feather 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 Energy Release Component (ERC) streams and randomly pulls daily wind speeds and directions from the observed historical monthly

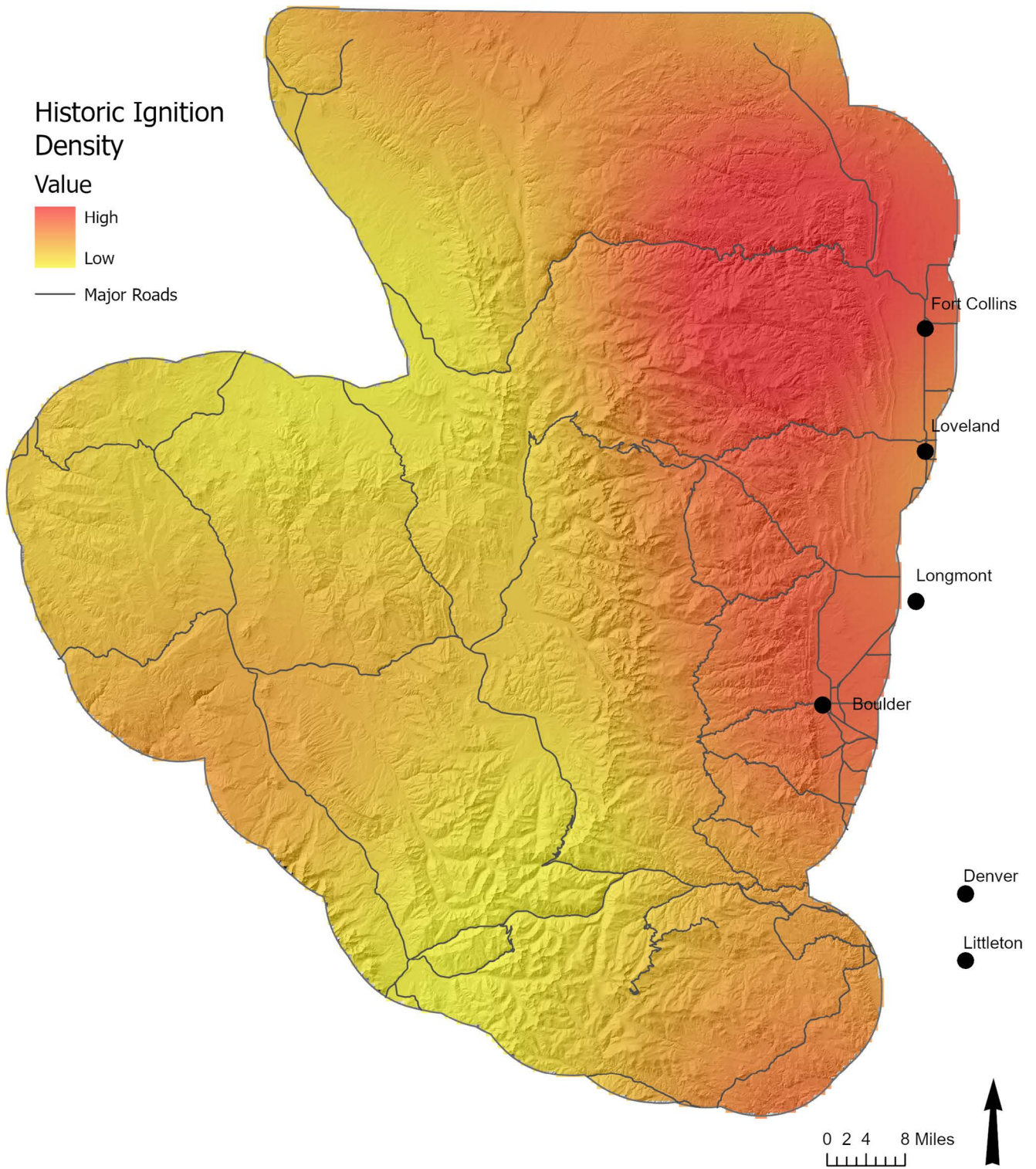


Figure 25: Historical fire ignition density in the QWRA analysis extent.

distributions. In this way, FSim uses seasonal weather scenarios that align with the interannual variability and seasonal trends within the historical record and accounts for seasonality in the prevailing wind direction and speed.

FSim ignition locations are randomly selected for each potential fire based on a historic ignition probability raster that defines the relative chance of any location on the landscape experiencing an ignition. 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 NCFC 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 25).

The final annual burn probability (BP) raster produced by FSim underwent some post-processing to account for scale differences between the simulations (270 m) and the final analysis resolution (30 m) (Figure 26). First, all pixels with a BP of zero were set to the 5th percentile BP within the analysis area. This was done to prevent pixels containing wildland fuels from having zero wildfire risk. Next, a 3 x 3 moving window was used to smooth all BP values. The raster was then resampled to 30 m using bilinear interpolation. Finally, all 30 m pixels that were coded as non-burnable based on the 30 m fuelscape developed for the fire behavior modeling were set to have a BP of zero.

Further Limitations

It is important to note that this analysis was focused around the Arapaho-Roosevelt National Forest and as a result, many highly developed areas in the grasslands to the east of the analysis extent were excluded despite the very real wildfire risk in these areas. There were several reasons for this exclusion. The first was a matter of practicality. In order for this QWRA to be locally relevant, the analysis area needed to end somewhere and very early in the process the decision was made to limit analysis to a 10 km buffer around the perimeter of the Arapaho-Roosevelt National Forest. Other considerations that led to this analysis area were more technical in nature. For one, available fire behavior models are not currently capable of predicting fire spread through dense urban areas and subdivisions where the primary fire-carrying fuels are not wildland vegetation, but rather the homes and structures themselves. Significant wildfire intrusions into densely developed areas are extremely rare and only occur under the most extreme of conditions such as those observed during the 2021 Marshall fire. Techniques to accurately predict the occurrence and impacts of such urban conflagrations are under development, but there is

currently insufficient empirical data or validated models available to characterize the conditions under which such events are expected to occur. Therefore, the risk scores assigned to the highly, developed urban areas that did fall within our modeling extent should be understood as an underestimate of potential risk. This is due to the fact that we could not adequately model the likelihood of low probability, high impact events that lead to urban fire development and structure-to-structure fire spread. A related consideration is that the mitigation actions necessary to reduce the probability and consequences of such events are outside the control of land management agencies. The primary driver of risk in these dense, grassland-adjacent communities is structure ignitability as homes along the community edge become a primary source of firebrands to interior homes setting off a cascade of home ignitions and the potential for mass fire development. Therefore, actions such as enhanced building codes (on both new and existing structures) at the county level are an effective tool for mitigating future urban fire events. Though there is a role for actions such as targeted prescribed fire, mowing, and grazing to reduce grass fuels adjacent to these communities, the impacts of such actions are very short-lived, requiring yearly maintenance, and are ineffective without associated structure hardening. As a primary objective for the QWRA was to support forest management and fuels project planning, it was prudent to focus our modeling efforts on areas where vegetation management actions are likely to yield the greatest benefits and where we were able to accurately model fire behavior. Despite the technical challenges that precluded accurately modeling the spatial risk of fire spread into dense, urban communities, the Marshall fire, and other urban conflagrations nationally, highlight the need for local and state governments to consider enhanced regulations on building materials, fencing and landscaping, and development density to limit the potential for home-to-home fire spread to result in future mass home loss events.

Burn Probability

Mean Annual BP

- Low: 0
- Moderate
- High: 0.032

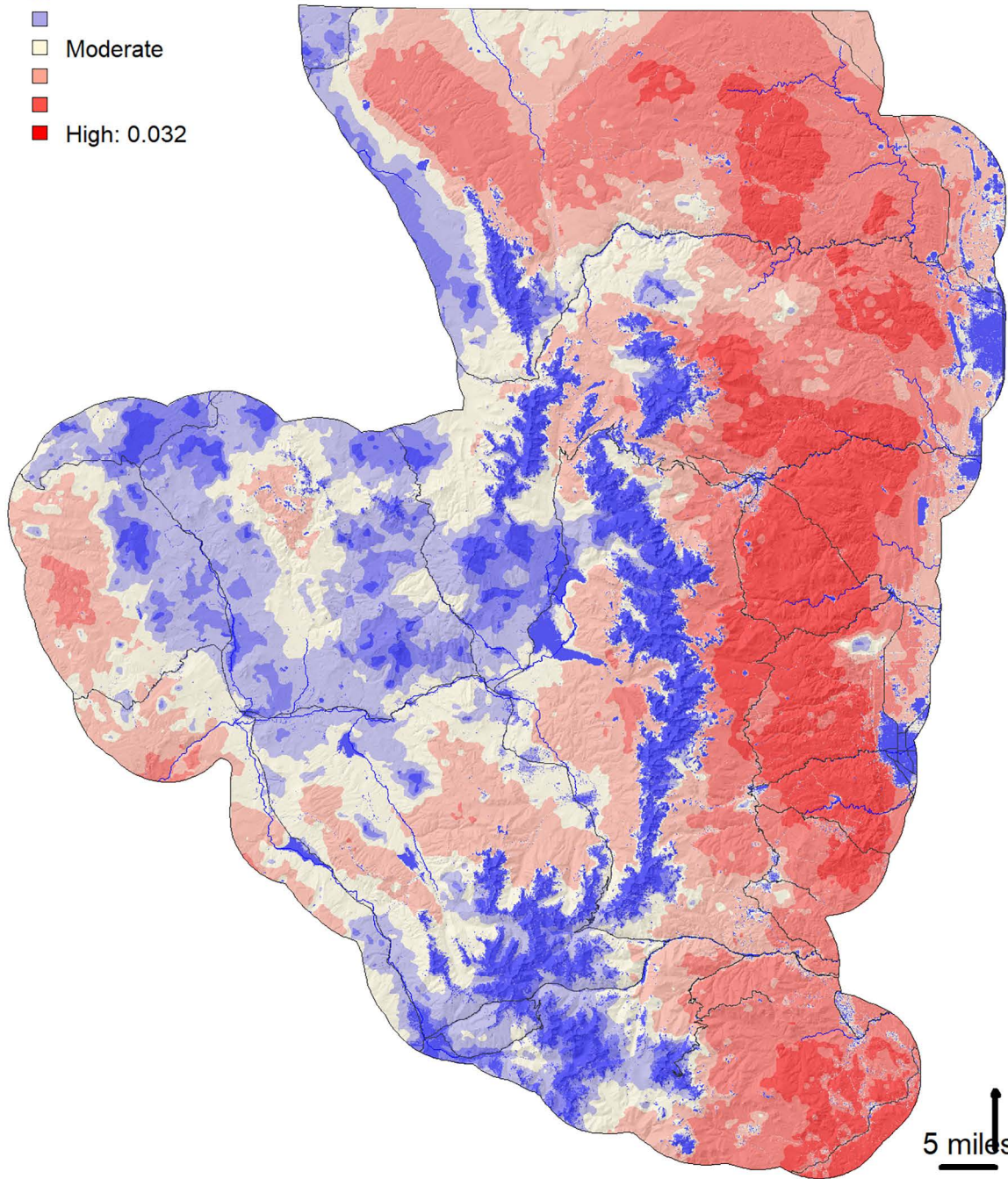


Figure 26: The FSim burn probability product used for the QWRA analysis extent.

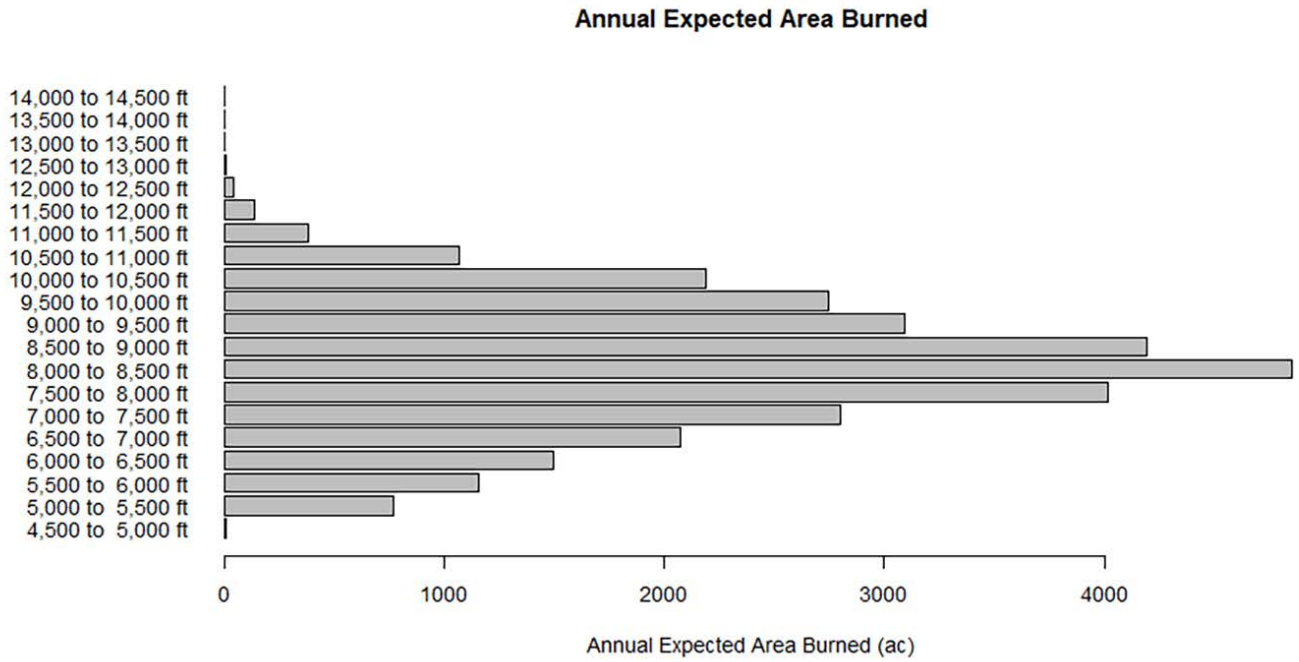


Figure 27: Expected annual area burned (acres) by elevation based on local FSim burn probability.

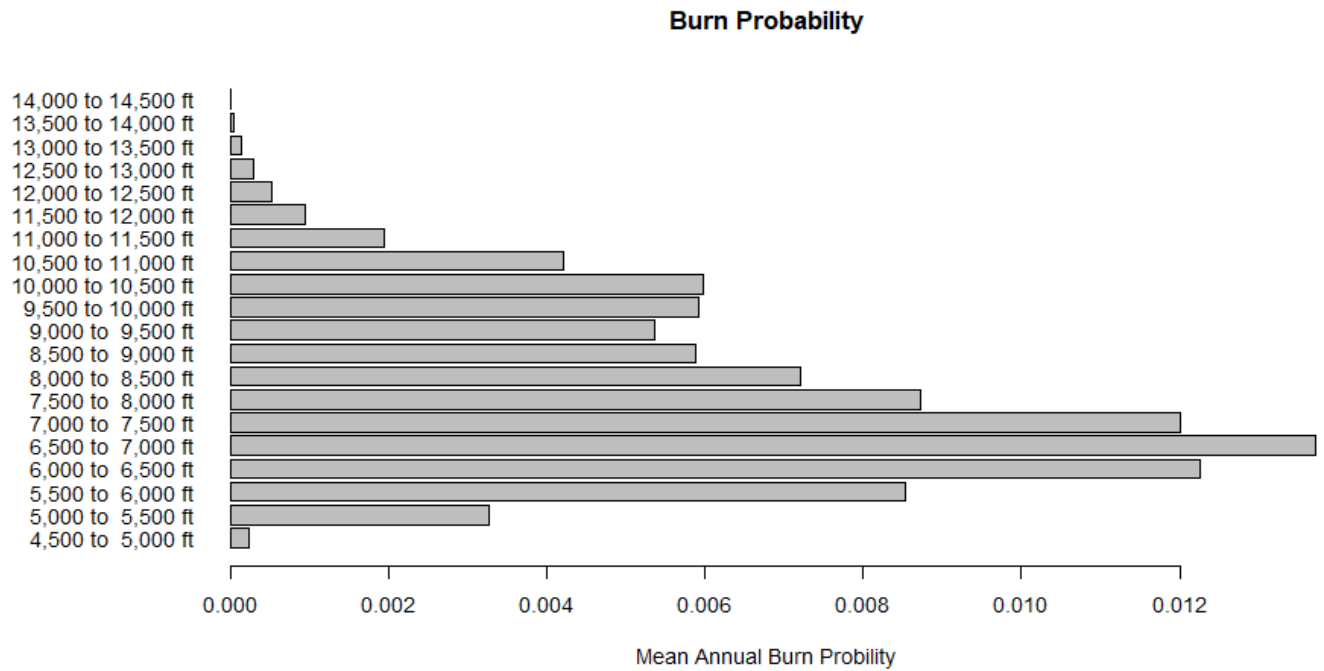


Figure 28: Mean annual burn probability by elevation based on local FSim burn probability.

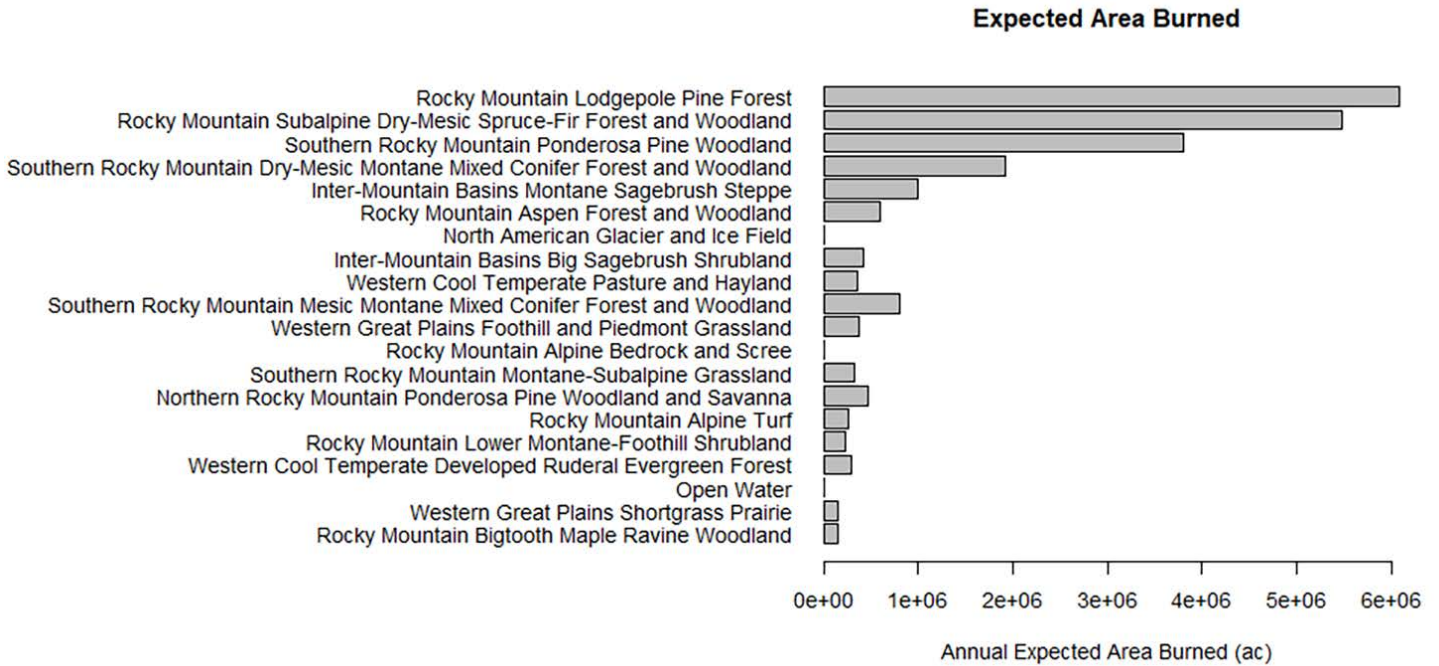


Figure 29: Expected annual area burned (acres) by LANDFIRE existing vegetation type based on local FSim burn probability.

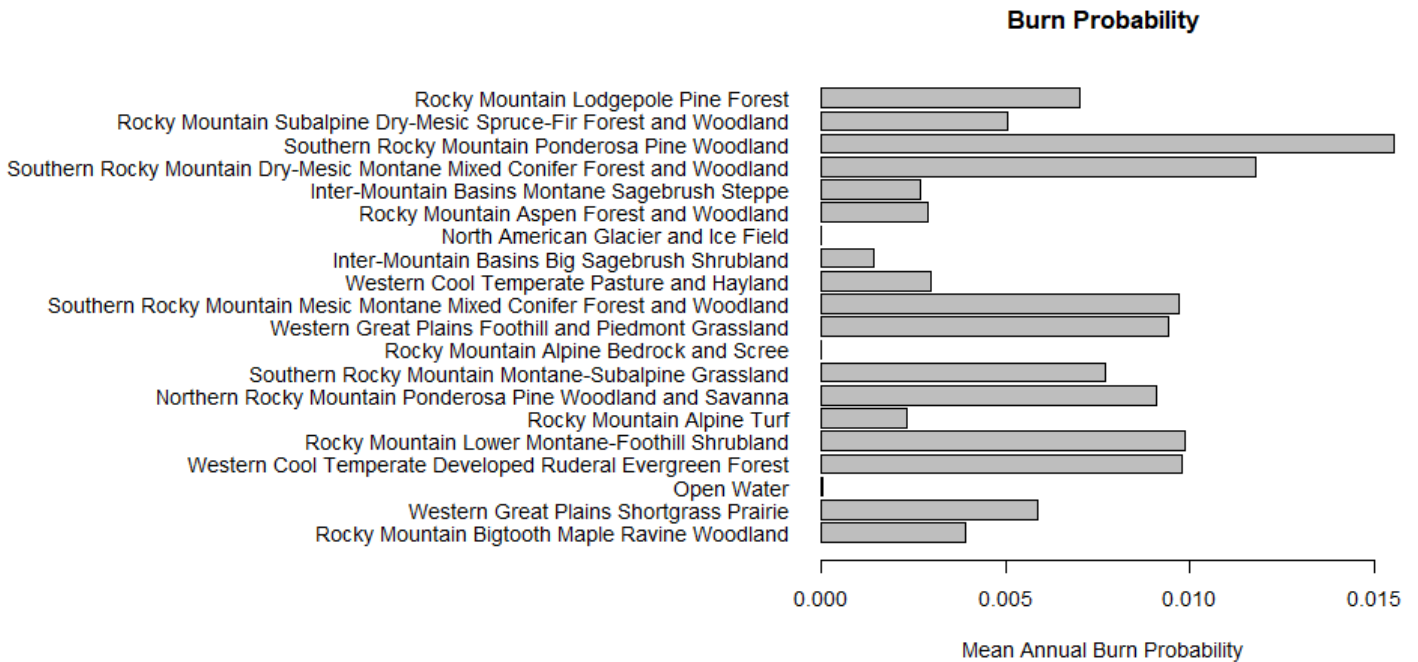


Figure 30: Mean annual burn probability for each LANDFIRE existing vegetation type based on local FSim burn probability.

Appendix III – Watershed Related cNVC

Wildfire risk to watershed related HVRA was assessed with supplemental modeling that estimates potential post-fire erosion and sediment transport to water supply diversions, reservoirs, and designated waters following the methods in Gannon et al., (2019). Soil burn severity was predicted by mapping crown fire activity (Scott and Reinhardt 2001) categories of surface fire, passive crown fire, and active crown fire to low, moderate, and high severity respectively. Post-fire erosion was estimated with the Revised Universal Soil Loss Equation (Renard et al., 1997) using empirical observations of post-fire change in cover and soil erodibility by burn severity (Larsen and MacDonald 2007). Sediment transport to water supplies was estimated based on empirical models of hillslope and channel sediment delivery ratio (Wagenbrenner and Robichaud 2014; Frickel et al., 1975). This workflow supports pixel-level estimates of the sediment generated in each pixel that is delivered to downstream values at risk (Figure 31).

This framework was applied with slight modifications to quantify the conditional net value change of critical water supplies and designated waters. Like the regular cNVC calculations, these metrics were calculated for each fire weather scenario and then combined into a single cNVC raster by a weighted averaging (Table 4).

Critical Water Supplies

Water supply infrastructure (i.e., diversions and reservoirs) were mapped by integrating datasets from the Colorado Division of Public Health & Environment and local water utilities. Infrastructure importance was based on the Forest to Faucet drinking water importance values (Mack et al., 2022) that were rescaled between 0 for the least important to 1 for the most important. This importance value considers the population served, distance from population, and annual streamflow generation at the HUC 12 scale. These ratings were applied as weights to express the importance, or impact, of sediment delivered to each water supply. During a review of the Forest to Faucet ratings with water providers, it was noted that the population served by Colorado-Big Thompson (CBT) water was not accounted for in this rating schema. Therefore, we decided to manually increase the relative importance of all water supply infrastructure above Windy Gap (i.e., source area of CBT water). It was assumed that $\geq 50 \text{ Mg ha}^{-1}$ of sediment delivery to infrastructure in the first post-fire year is a dramatic loss based on the reported sediment yield from hillslope erosion after the 1996 Buffalo Creek Fire (68 Mg ha^{-1} ; Moody and Martin 2001). Therefore, the pixel-level estimates of sediment delivery to water infrastructure were linearly rescaled so that 0 to 50 Mg ha^{-1} of sediment corresponds to 0 to -100 percent value change. The final cNVC is mapped in Figure 32.

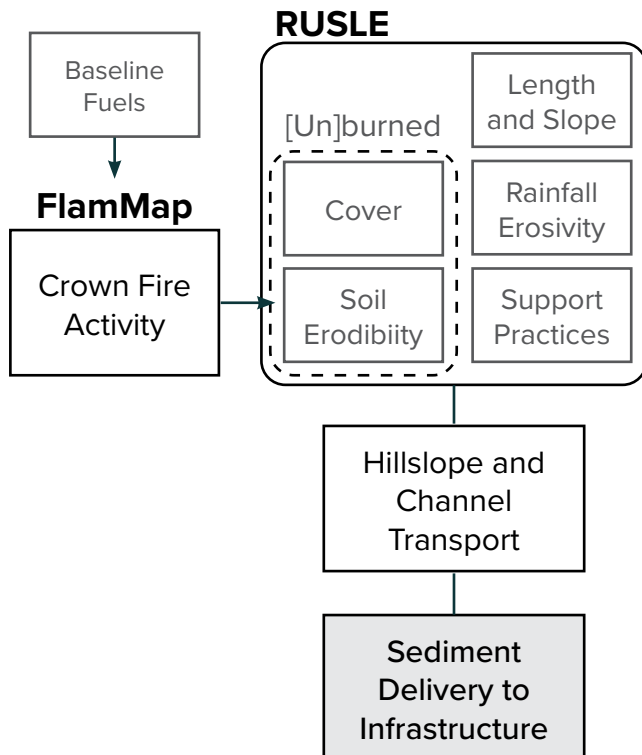


Figure 31: Workflow used to quantify potential post-fire sediment delivery from each pixel of the landscape.

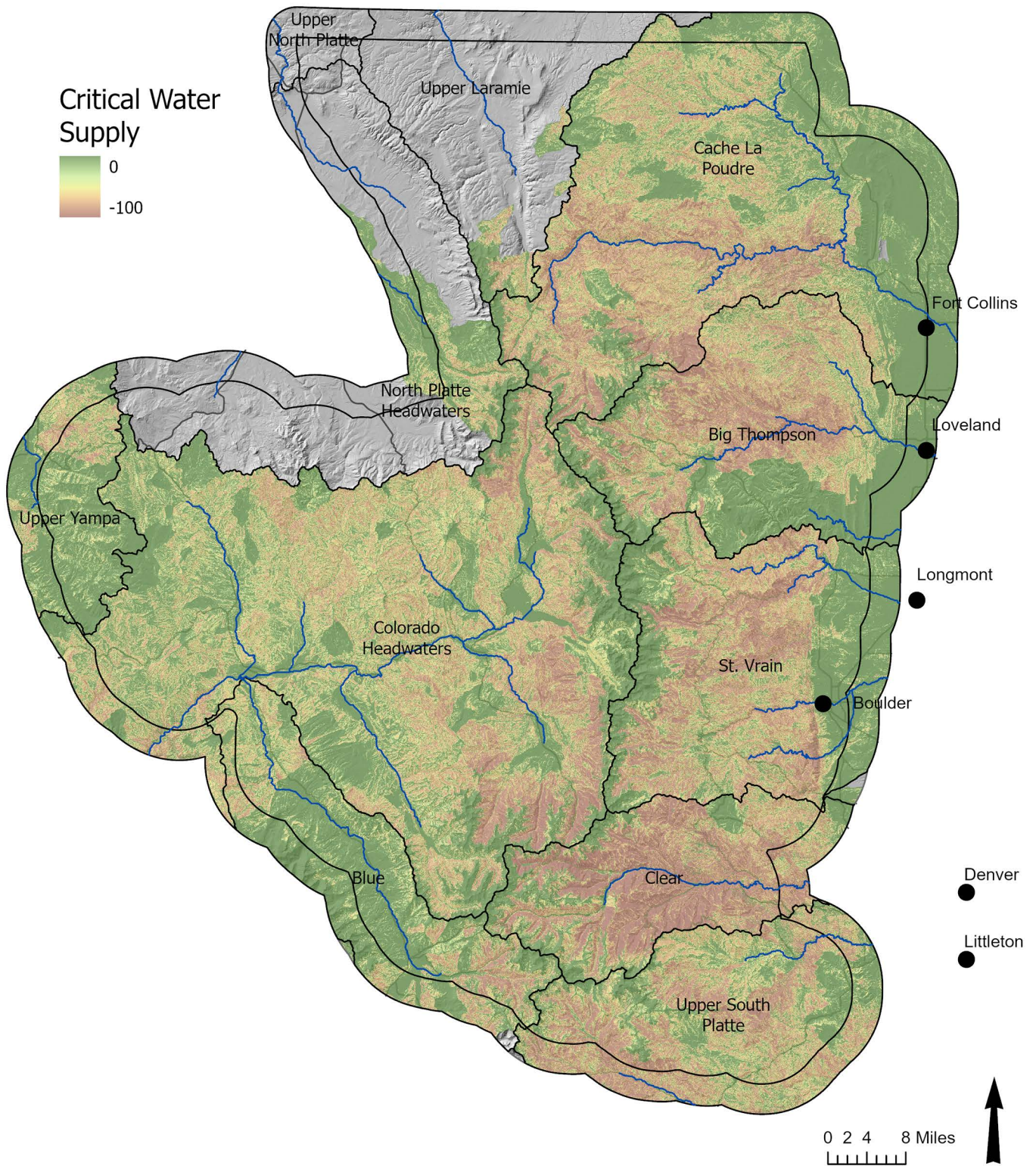


Figure 32: Conditional net value change of critical drinking water supplies.

Designated Waters

To capture the importance of designated waters and associated tributaries, we predicted post-fire sediment delivery to the Gold Medal reaches of the Colorado River and the Wild and Scenic Cache La Poudre River. The pixel-level estimates of sediment delivery to these rivers 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 33.

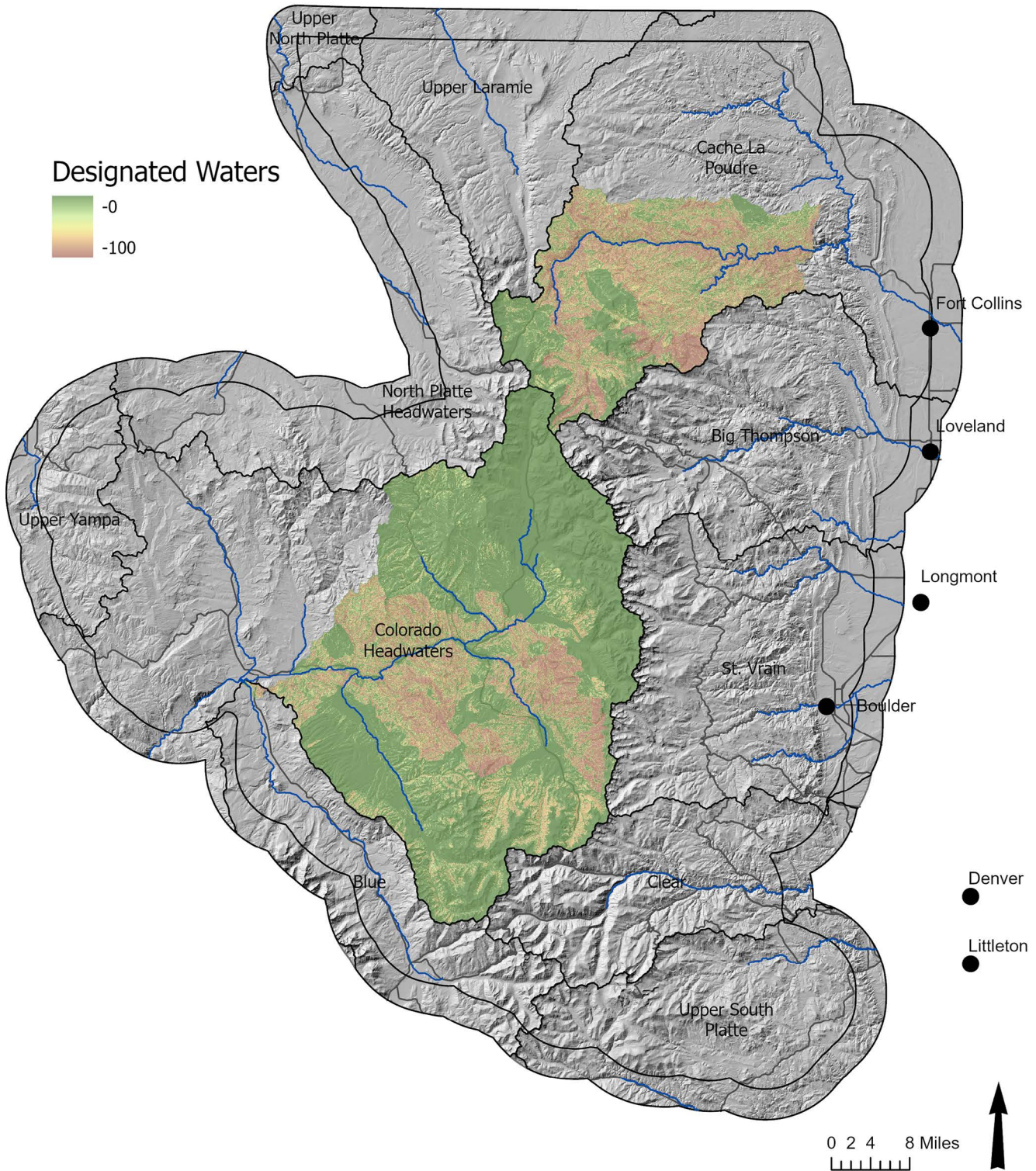


Figure 33: Conditional net value change of designated waters (i.e., Gold Medal reaches of the Colorado River and the Wild and Scenic Cache la Poudre River)