CONTEMPORARY WILDFIRE HAZARD ACROSS COLORADO

PREPARED FOR:
Rocky Mountain Region
United States Forest Service

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1 EXECUTIVE SUMMARY

In February 2019, the Rocky Mountain Region of the U.S. Forest Service contracted with Pyrologix to conduct a spatial wildfire risk assessment for all land ownerships in the state of Colorado. This all-lands effort consisted of calibrating and updating the fuelscape, conducting wildfire hazard modeling, characterizing the response of multiple Highly Valued Resources and Assets (HVRA) to wildfire, and completing wildfire risk calculations.

We leveraged LANDFIRE 2016 Remap 2.0.0 (LF Remap) data to generate a current-condition fuelscape for this effort – updated for recent disturbances and calibrated to reflect the fire behavior potential observed in recent wildfire events. LF Remap was released in the spring of 2019 with significant improvements over previous versions of LANDFIRE, including the use of new satellite imagery and continuous vegetation cover and height classifications[1]. The COAL fuelscape was first produced for use in the 2020 fire season and wildfire hazard modeling using this fuelscape had begun. However, the unprecedented wildfire season of 2020 had a significant impact on the fuelscape used to represent the "current conditions." In light of this, Pyrologix generated a new fuelscape to incorporate the fuel changes from the 2020 wildfires and bring the fuelscape forward to a "2021 capable" timeframe. A report describing the methods used to produce the fuelscape is available for download[2].

The COAL wildfire risk assessment project consisted of three parts: fuelscape update, wildfire hazard assessment, and wildfire risk assessment. Using the updated fuelscape, Pyrologix re-ran simulated wildfires using the spatial datasets of historical weather and fire occurrence to parameterize and calibrate the comprehensive USFS fire modeling system called FSim. The product generated from this modeling is an estimate of annual burn probability across Colorado. FSim also produced an "event set," used to estimate transmission of fire damage or risk to exposed populations and Highly Valued Resources and Assets (HVRA). Transmission analysis ties wildfire risk or damage where it occurs to the origin of simulated wildfires. Pyrologix also applied a comprehensive simulation of potential wildfire behavior characteristics based on FlamMap, another US Forest Service fire modeling system.

These simulations of wildfire hazard (likelihood and intensity) were used to calculate indices of integrated hazard, including Risk to Potential Structures, Suppression Difficulty Index, and Wildfire Hazard Potential. Pyrologix calculated measures of wildfire risk using the flame-length probabilities and mapped HVRA data across the State. The results of these analyses are presented in a separate report titled "Wildfire Risk for All Lands in Colorado."[3]

Finally, in a related effort, Pyrologix used custom weather and fuelscape inputs to explore wildfire risk under select combinations of wind speed and Energy Release Component (ERC), and in a hypothetically treated scenario. This work produced ten additional sets of wildfire intensity and

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[1] Additional information can be found at http://www.landfire.gov/.
[2] COAL Fuelscape report: http://pyrologix.com/reports/COAL_FuelscapeReport.pdf
[3] COAL Wildfire Risk report: http://pyrologix.com/reports/COAL_WildfireRiskReport.pdf

conditional wildfire risk results. These products were used to explore various fire and fuels management scenarios and are presented in an Appendix to the wildfire risk report.

1.1 PURPOSE OF HAZARD MODELING

The purpose of the Colorado All-Lands Wildfire Risk Assessment (COAL) is to provide foundational information about wildfire hazard and risk across all land ownerships within the state of Colorado. The foundation of any wildfire assessment is the wildfire hazard data used to characterize fire behavior on the landscape. To manage wildfire in Colorado, it is essential that accurate and high-resolution wildfire hazard data, to the greatest degree possible, is available to drive fire management strategies. These hazard outputs can be used to inform the planning, prioritization, and implementation of prevention and mitigation activities such as prescribed fire and mechanical fuel treatments. In addition, the hazard data can be used to support fire operations and aid in decision-making for the allocation and positioning of firefighting resources.

In the quantitative framework for assessing wildfire risk to highly valued resources and assets (Scott et al. 2013) wildfire hazard is defined as a physical situation with the potential for causing damage to vulnerable resources or assets. Wildfire hazard is measured by two main factors in this risk assessment framework: 1) burn probability (or likelihood of burning), and 2) fire intensity (measured as flame length, fireline intensity, or other similar measures).

2 WILDFIRE LIKELIHOOD

2.1 OVERVIEW OF METHODS

2.1.1 FSIM

The FSim large-fire simulator was used to quantify wildfire likelihood across the Analysis Area at a pixel size of 120 meters. FSim is a comprehensive fire occurrence, growth, behavior, and suppression simulation system that uses locally relevant fuel, weather, topography, and historical fire occurrence information to make a spatially resolved estimate of the contemporary likelihood and intensity of wildfire across the landscape (Finney et al. 2011).

FSim focuses on the relatively small fraction of wildfires that escape initial attack and become "large" (>100 hectares). Since the occurrence of large fires is relatively rare, FSim generates many thousands of years of simulations to capture a sample size large enough to generate burn probabilities for the entire landscape. An FSim iteration spans one entire year. All Fire Occurrence Areas (FOAs) within the COAL project area were run with either 50,000 or 100,000 iterations.

There is no temporal component to FSim beyond a single wildfire season consisting of up to 365 days. FSim performs independent (and varying) iterations of one year, defined by the fuel, weather, topography, and wildfire occurrence inputs provided. FSim does not account for a simulated wildfire's potential influence on the likelihood or intensity of future wildfires (even within the same simulation year). Each year represents an independent realization of how fires might burn given the current fuelscape and historical weather conditions. FSim integrates all simulated iterations into a probabilistic representation of wildfire likelihood.

In addition to estimates of wildfire likelihood, FSim produces measurements of predicted wildfire intensities. Due to the inherent challenges of estimating intensity with a stochastic simulator, estimates of fire intensity were instead developed using a custom Pyrologix utility called WildEST (Scott 2020). WildEST is a deterministic wildfire modeling tool that integrates spatially continuous weather input variables, weighted based on how they will likely be realized on the landscape. This makes the deterministic intensity values developed with WildEST more robust than the stochastic intensity values developed with FSim. This is especially true in low wildfire occurrence areas where predicted intensity values from FSim are reliant on a very small sample size of potential weather variables. The WildEST methodology is further described in section 3.

2.2 LANDSCAPE ZONES

The project boundaries used in the COAL wildfire hazard assessment are described below in sections 2.2.1 - 2.2.3 and are shown in Figure 1. Project boundaries were developed to avoid introducing artificial data artifacts (seamlines) during FSim modeling.

2.2.1 ANALYSIS AREA

The Analysis Area (AA) is the area for which valid burn probability results are produced. The Analysis Area for the Colorado All Lands project was defined as a 10-kilometer buffer on the state boundary (Figure 1).

2.2.2 FIRE OCCURRENCE AREAS

To ensure valid Burn Probability (BP) results in the AA and prevent artificial reduction in BP near the AA boundary edge, it is necessary to allow FSim to start fires outside of the AA and burn into it. This larger area where simulated fires are started is called the Fire Occurrence Area (FOA). We established the FOA extent as a 30-km buffer on the AA. The buffer provides sufficient area to ensure all fires that could reach the AA are simulated. The Fire Occurrence Area covers roughly 88.6 million acres and is characterized by diverse topographic and vegetation conditions. We divided the overall FOA extent into ten individual FOAs to model this large area where historical fire occurrence and fire weather are highly variable. Individual FOA boundaries were developed to group geographic areas that experience similar patterns of wildfire occurrence. These boundaries were generated using a variety of inputs including large-fire occurrence boundaries developed for national-level work (Short et al. 2020), aggregated level IV EPA Ecoregions, and local fire staff input. For consistency with other FSim projects, we numbered these FOAs 801 through 810.

2.2.3 FUELSCAPE EXTENT

The available fuelscape extent was delineated by adding a 30-km buffer to the FOA extent. This buffer allows fires starting within the FOA to grow unhindered by the edge of the fuelscape, which would otherwise truncate fire growth and affect the simulated fire-size distribution, potentially introducing errors in the calibration process. A map of the AA, FOA boundaries and fuelscape extent are presented in Figure 1.

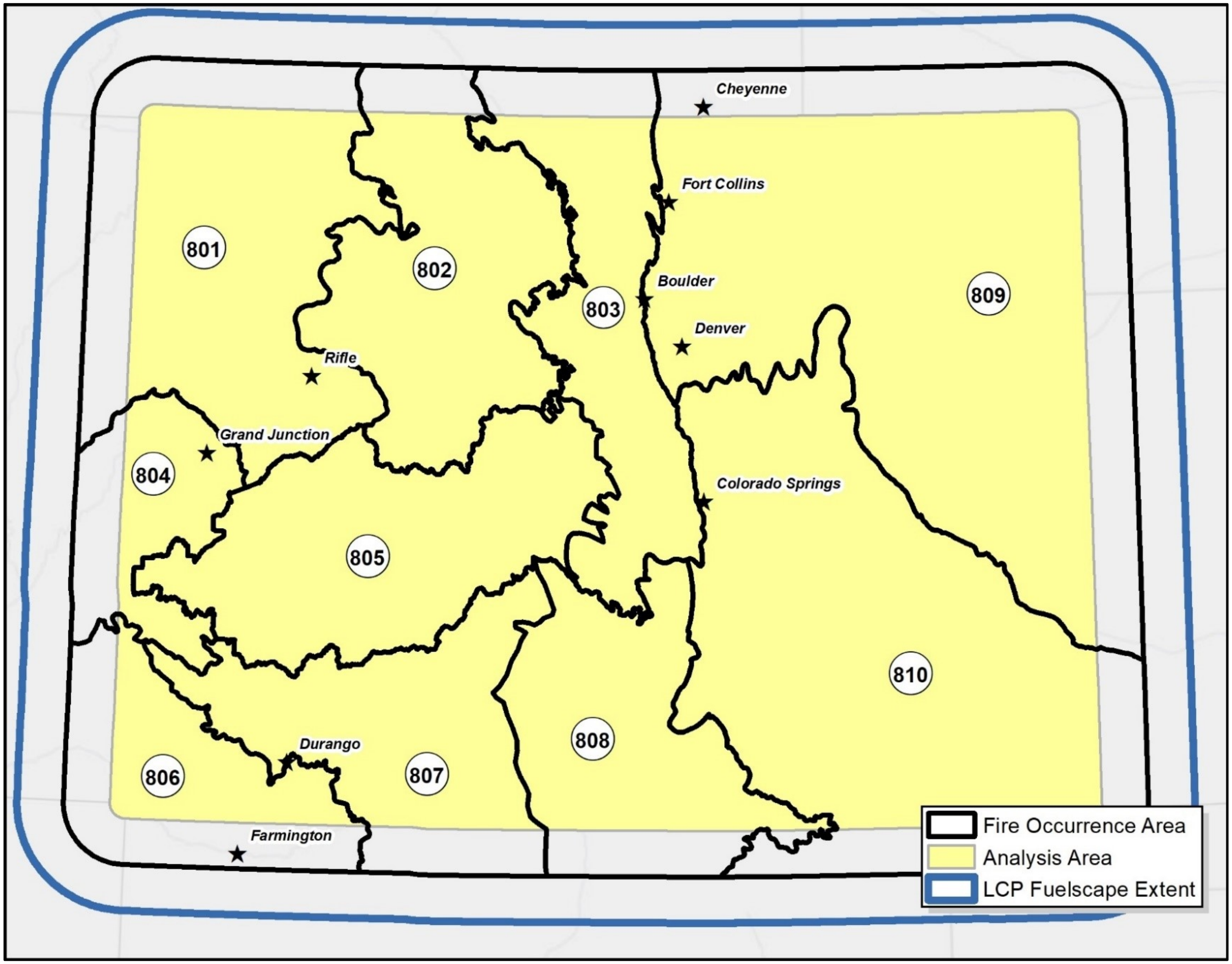

Figure 1. Overview of landscape zones for the COAL FSim project.

2.3 ANALYSIS METHODS AND INPUT DATA

The FSim large-fire simulation system requires inputs characterizing the landscape, historical weather, and information about historical fires. Figure 2 below provides a graphical depiction of the various FSim inputs discussed further in sections 2.3.1 - 2.3.3

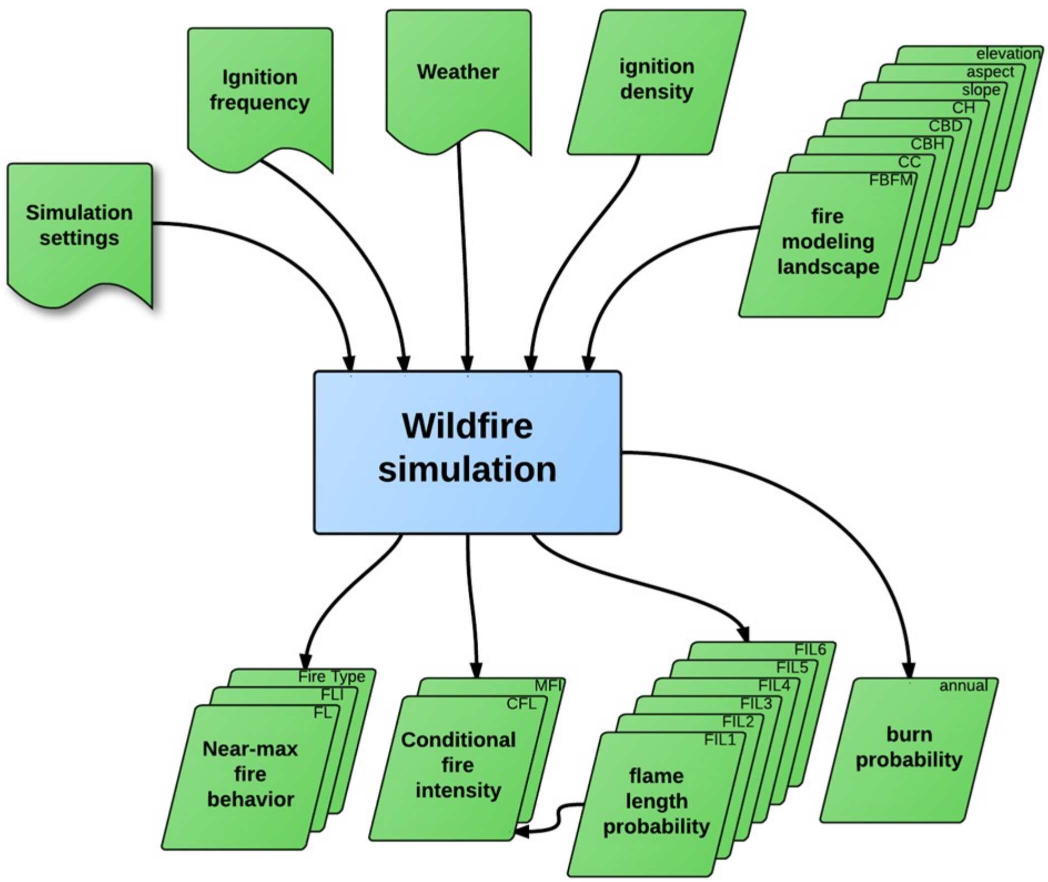

Figure 2. Diagram showing the primary elements used to derive burn probability

2.3.1 FUELSCAPE

The foundation of any wildfire hazard assessment is a current-condition fuelscape updated for recent disturbances and calibrated to reflect the fire behavior potential realized in recent historical wildfire events. LANDFIRE 2016 Remap 2.0.0 (LF Remap) data was leveraged to generate a calibrated fuelscape for this state-wide assessment.

The fuelscape consists of geospatial datasets representing surface fuel model (FM40), canopy cover (CC), canopy height (CH), canopy bulk density (CBD), canopy base height (CBH), and topography characteristics (slope, aspect, elevation). The FM40 dataset can be seen in Figure 3 in groups of similar fuel types. The fuelscape datasets were combined into a single landscape (LCP) file that was used as a fuelscape input in fire modeling programs.

The LANDFIRE 2016 Remap 2.0.0 base data was edited to remove mapping zone seamlines. The base data was also calibrated based on expert opinion at a fuel calibration workshop where local experts met to verify the accuracy of the fuelscape. Finally, the data was updated to represent the most recent fuel disturbances through the end of 2020. Further details about the methods and base data used to generate the calibrated COAL fuelscape are available in the fuelscape report[4]. A map of fuel model groups across the COAL fuelscape can be seen in Figure 3.

2.3.1.1 CUSTOM FUEL MODELS

During the Fuelscape calibration, workshop participants highlighted concerns regarding the under-representation of wildfire in agricultural areas (wheat fields) mapped as non-burnable, urban fuels mapped non-burnable, and the over-representation of wildfire in high elevation, subalpine vegetation. The COAL fuelscape utilizes custom fuel models to represent the potential for wildfire spread in these areas.

Wheatfields were identified as the agricultural fuel of the greatest concern. As a result, the workshop participants requested a customization to portray the potential for wildfire spread into areas that were previously mapped as non-burnable. Pyrologix created a custom fuel model identical to the GR2 but labeled it separately as AG2/242 to allow for further customization.

The burnable-urban custom fuel models were spatially identified using the LANDFIRE EVTs designated as low and moderate-intensity developed: burnable developed areas are represented with 251/BU1, identical to TL9; and burnable roads are represented with 252/BU2, identical to TL3.

High-elevation, subalpine vegetation was identified as having a shortened fire season due to cooler temperatures and delayed snowmelt. Pyrologix created 3 custom fuel models represented with 175/TU5 fuel model; identical to 165/TU5, 111/GR1 fuel model; identical to 101/GR1, and 111/GR1 & 112/GR2 fuel models; identical to 101/GR1 & 102/GR2.

The addition of the custom fuel models allows for the transmission of wildfire in simulation across these areas. To prevent overestimating the likelihood of wildfire in custom fuel models, fuel moisture inputs were modified to allow for wildfire only under 97th percentile ERC conditions for burnable agriculture and urban and under 90th and 97th percentile conditions for the short season fuel models.

[4] COAL Fuelscape report: http://pyrologix.com/reports/COAL_FuelscapeReport.pdf

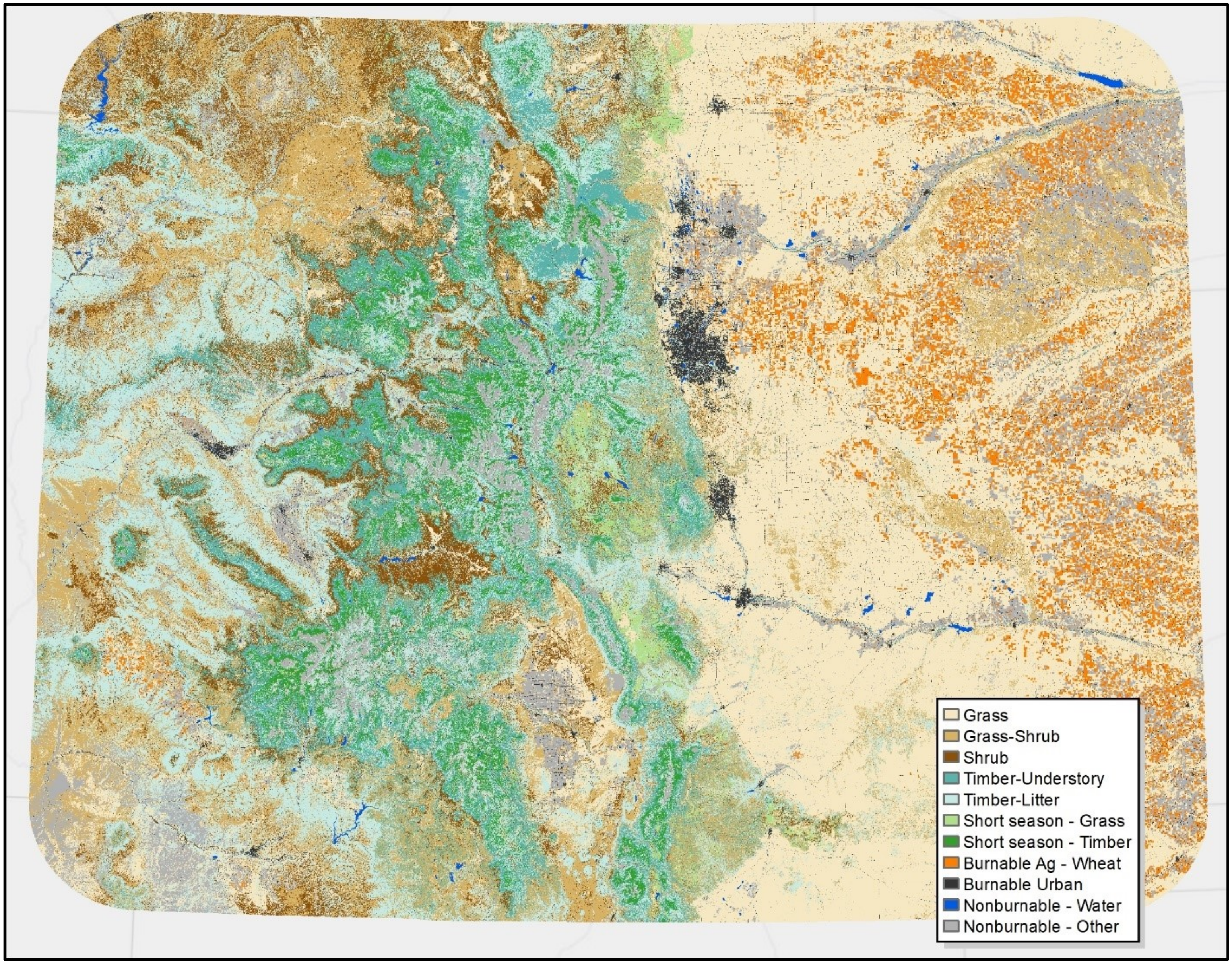

Figure 3. Map of fuel model groups across the COAL fuelscape extent.

2.3.2 HISTORICAL WILDFIRE OCCURRENCE

The Fire Occurrence Database (FOD) which spans 26 years from 1992-2017 was used to quantify historical large-fire occurrence (Short 2021). The FOD data was used to develop model inputs (the fire-day distribution file [FDist] and ignition density grid [IDG]) as well as model calibration targets. Table 1 provides a summary of the annual number of large fires per million acres, mean large-fire size, and annual area burned by large fires per million acres for each FOA (Figure 1). To calculate historical calibration targets in FSim, we defined a large fire as greater than 100 hectares (247.1 ac).

Table 1. Historical large-fire occurrence, 1992-2017, in the COAL FSim project FOAs.

FOA	Mean annual number of large fires	FOA area (M ac)	Mean annual number of large fires per M ac	Mean large-fire size (ac)	Mean annual large-fire area burned (ac)	FOA-mean burn probability
801	8.73	10.17	0.86	2,370	20,690	0.00203
802	1.73	7.24	0.24	3,427	5,931	0.00082
803	2.77	6.09	0.45	5,426	15,027	0.00247
804	2.19	3.14	0.70	1,769	3,878	0.00123
805	1.62	7.48	0.22	1,956	3,159	0.00042
806	1.58	4.68	0.34	2,170	3,422	0.00073
807	1.38	6.21	0.22	7,162	9,916	0.00160
808	1.77	6.09	0.29	4,421	7,822	0.00128
809	3.46	20.75	0.17	2,953	10,223	0.00049
810	6.31	16.79	0.38	2,671	16,848	0.00100

Historical wildfire occurrence varied substantially by FOA (Table 1). FOA 801 experienced the highest annual average of 0.86 large wildfires per million acres, while FOA 809 experienced the lowest annual average of 0.17 large wildfires per million acres. FOA 807 had the largest mean large-fire size of 7,162 acres while FOA 804 had the smallest mean large-fire size with 1,769 acres.

2.3.2.1 IGNITION DENSITY GRID

FSim uses a geospatial layer called the Ignition Density Grid (IDG) to represent the relative large-fire ignition density. FSim stochastically places wildfires according to the IDG, thereby accounting for the spatial variability in historical wildfire occurrence. The entire landscape is saturated with wildfire over the 50,000 - 100,000 simulated iterations, but more ignitions are simulated in areas that have previously experienced large-fire development.

The Ignition Density Grid (IDG) was generated using a mixed-methods approach; averaging the grids resulting from the ArcGIS Kernel Density tool and Point Density tool using 120-m cell size and 75-km search radius. All fires equal to or larger than 100 hectares (247.1 ac) reported in the FOD were used as inputs to the IDG. A map of the IDG input can be seen in Figure 4. The IDG was divided up for each FOA by setting to zero all areas outside of the fire occurrence boundary of that FOA. This allows for a natural blending of results across adjacent FOA boundaries by allowing fires to start only within a single FOA but burn onto adjacent FOAs. Additionally, all custom fuel model pixels and small burnable areas less than 500 acres within other non-burnable or urban areas were masked out of the IDG layer. The IDG enables FSim to produce a spatial pattern of large-fire occurrence consistent with what was observed historically.

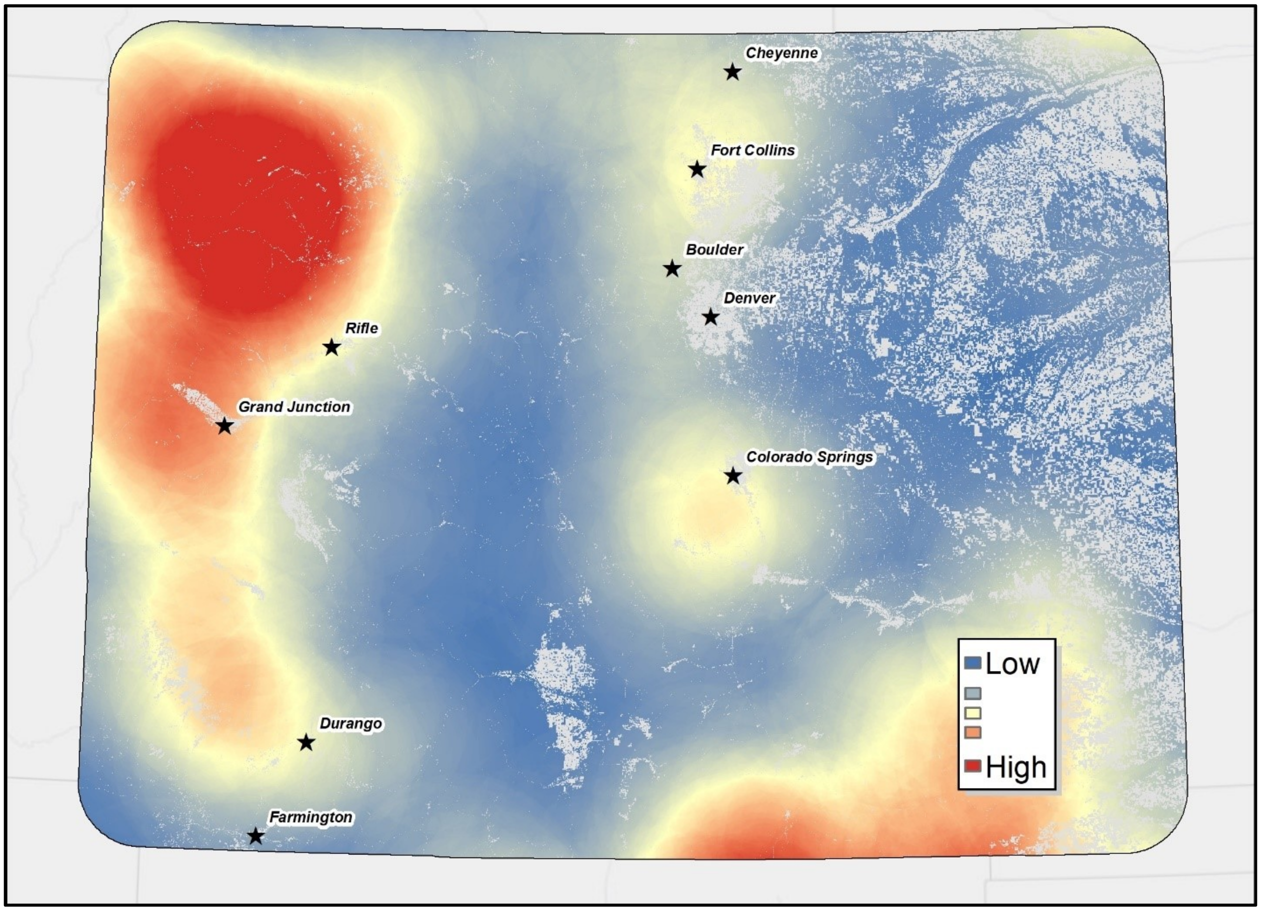

Figure 4. Ignition Density Grid for the COAL Fire Occurrence Area.

2.3.2.2 TRENDS IN WILDFIRE OCCURRENCE

Calibration targets for the FSim model were developed using the USFS Fire Occurrence Database (FOD; 1992-2017). Wildfire occurrence within the COAL analysis area was observed to be non-stationary and therefore not accurately represented by the 26-year FOD mean.

To more accurately account for the observed trends in wildfire occurrence across the analysis area, the ten Fire Occurrence Areas were first grouped into five larger calibration groups of similar historical wildfire occurrence. These five calibration groups can be seen in Figure 5.

These five historical analysis groups were used to limit variability in occurrence so that the overall historical trends could be analyzed. A linear model was fit to wildfire size and frequency with time as the dependent variable for each of the five historical analysis groups (Figure 6). Rather than “hindcasting” to the midpoint of the Fire Occurrence Database, we extrapolated the statistical trend to the year 2020. The extrapolated 2020 trendline varied greatly by FOA group from an estimated decrease of 10% to an increase of 279% in annual acres burned as compared to the FOD mean (1992-2017). The ultimate root cause of the observed trends is not fully understood at this time and is actively being studied and debated in the scientific literature.

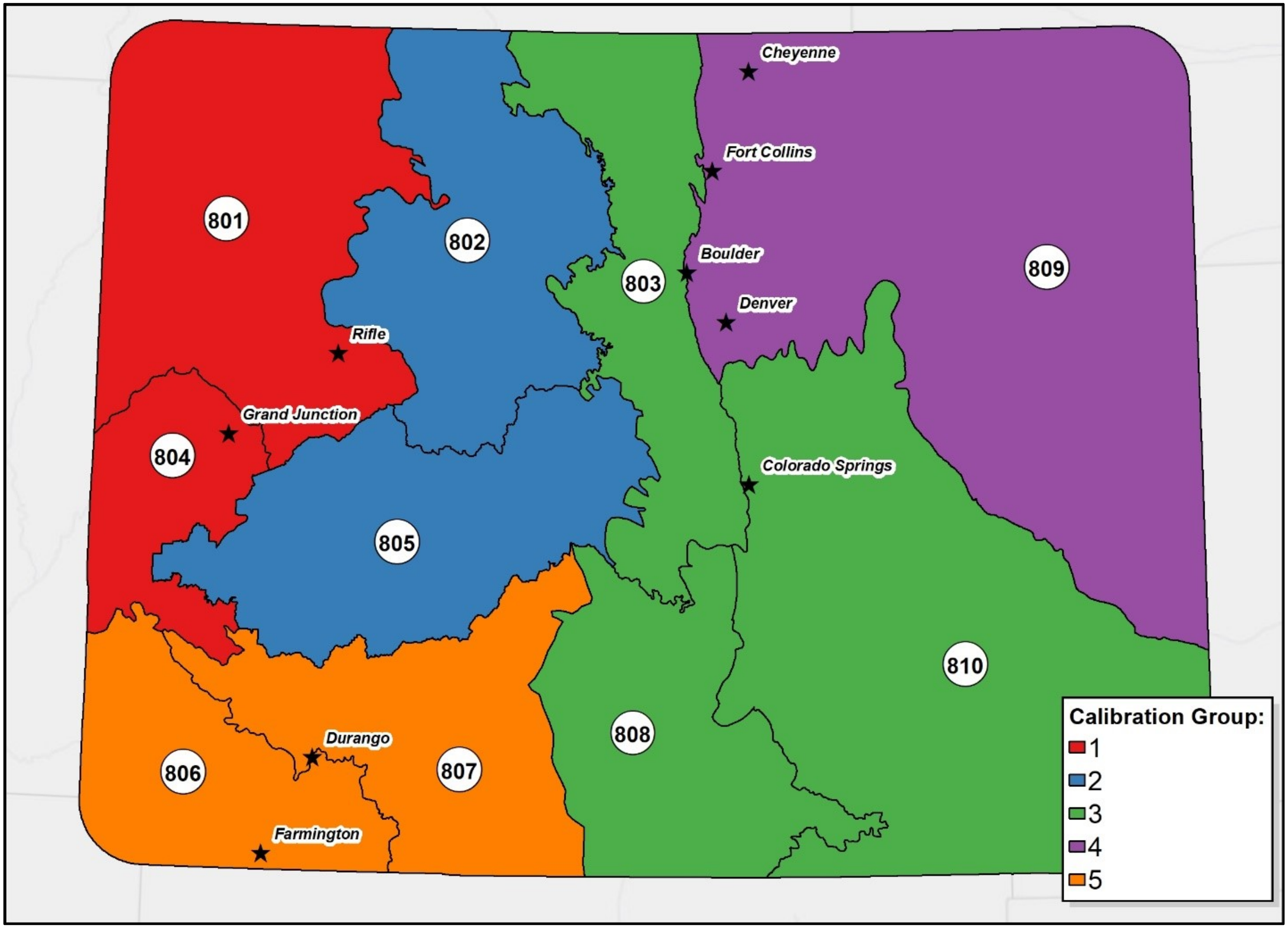

Figure 5. Map of FOA calibration groups used to develop FOA level calibration targets.

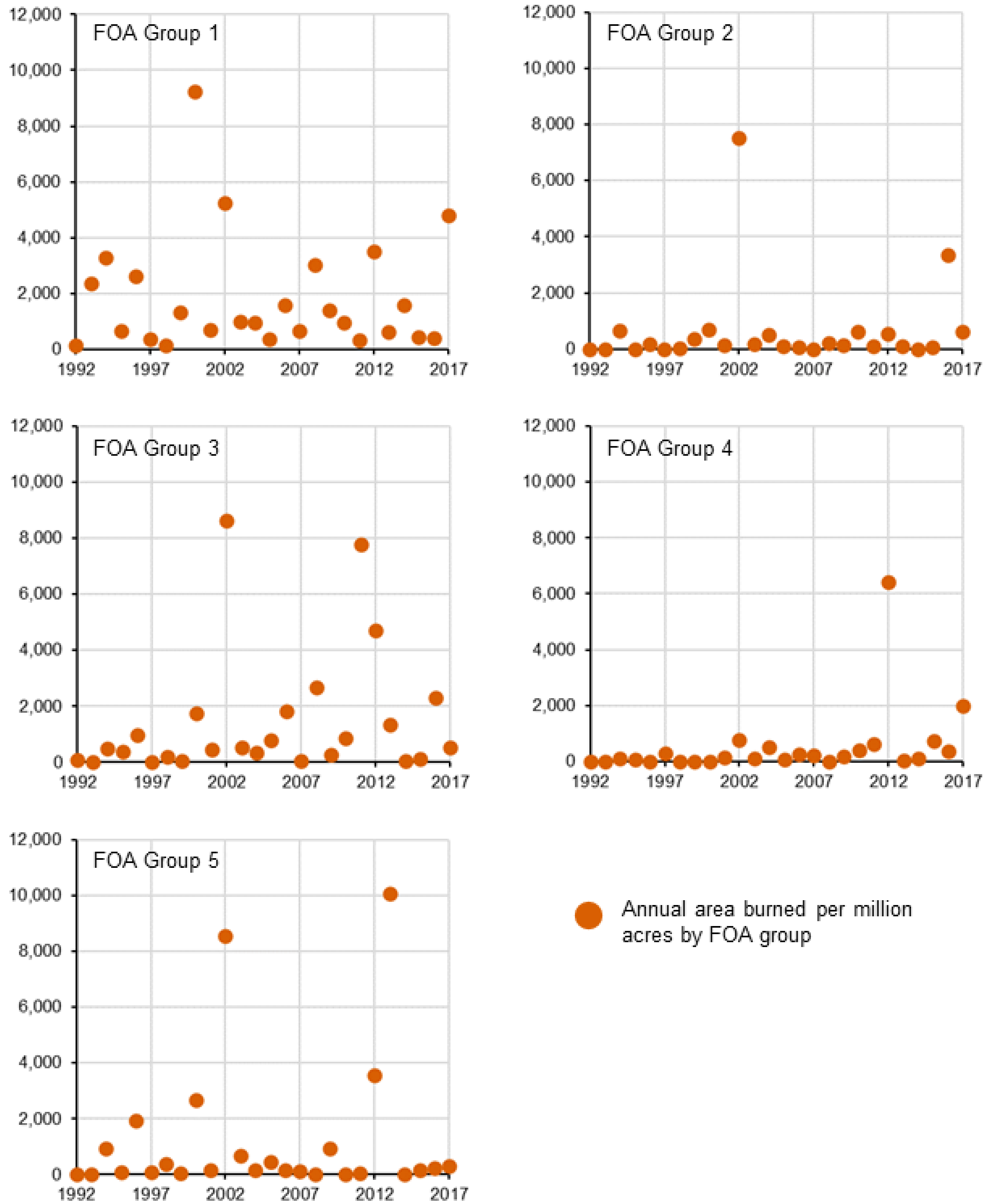

Figure 6. Historical Wildfire Occurrence (1992 – 2017) trends by FOA calibration groups.

The difference in the mean number and size of wildfires per FOA group as compared to the Fire Occurrence Database mean (1992-2017) is represented in Table 2. The FSim model was calibrated to the 2020 FOD trend to prevent "hindcasting" to the midpoint of the Fire Occurrence Database and to generate the most accurate estimate possible of wildfire likelihood.

Table 2. Adjustments to calibration targets to account for trends in wildfire occurrence.

2020 Historical Occurrence Analysis Groups	Description of Group	Δ Mean Large-Fire Size	Δ Mean annual number of large fires per million acres	Δ Acres Burned / YR
1	Northwest	1.40	0.64	0.90
2	West – Central	0.99	1.42	1.41
3	Central – Southeast	1.40	1.24	1.73
4	Northeast	1.13	2.46	2.79
5	Southwest	1.74	0.88	1.52

2.3.3 HISTORICAL WEATHER

FSim requires three weather-related inputs: monthly distribution of wind speed and direction, live and dead fuel moisture content by year-round percentile of the Energy Release Component (ERC) variable of the National Fire Danger Rating System (NFDRS 2002) for fuel model G (ERC-G) class, and seasonal trend (daily) in the mean and standard deviation of ERC-G. We used two data sources for these weather inputs. For the wind speed and direction distributions, we used the hourly (1200 to 2000 hours), 10-minute average values (2 mi/h calm wind), recorded at selected Remote Automatic Weather Stations (RAWS). Stations with relatively long and consistent records and moderate wind activity were preferentially selected to produce the most stable FSim results.

Energy Release Component (ERC) values were extracted from Dr. Matt Jolly's historical, gridded ERC rasters for the period 1992-2017. This nationally available dataset provides values that are not influenced by periods of RAWS inactivity outside of the fire season. The RAWS stations selected for winds and ERC sample sites for each FOA are shown in Figure 7 and Table 3 and discussed further in the following sections.

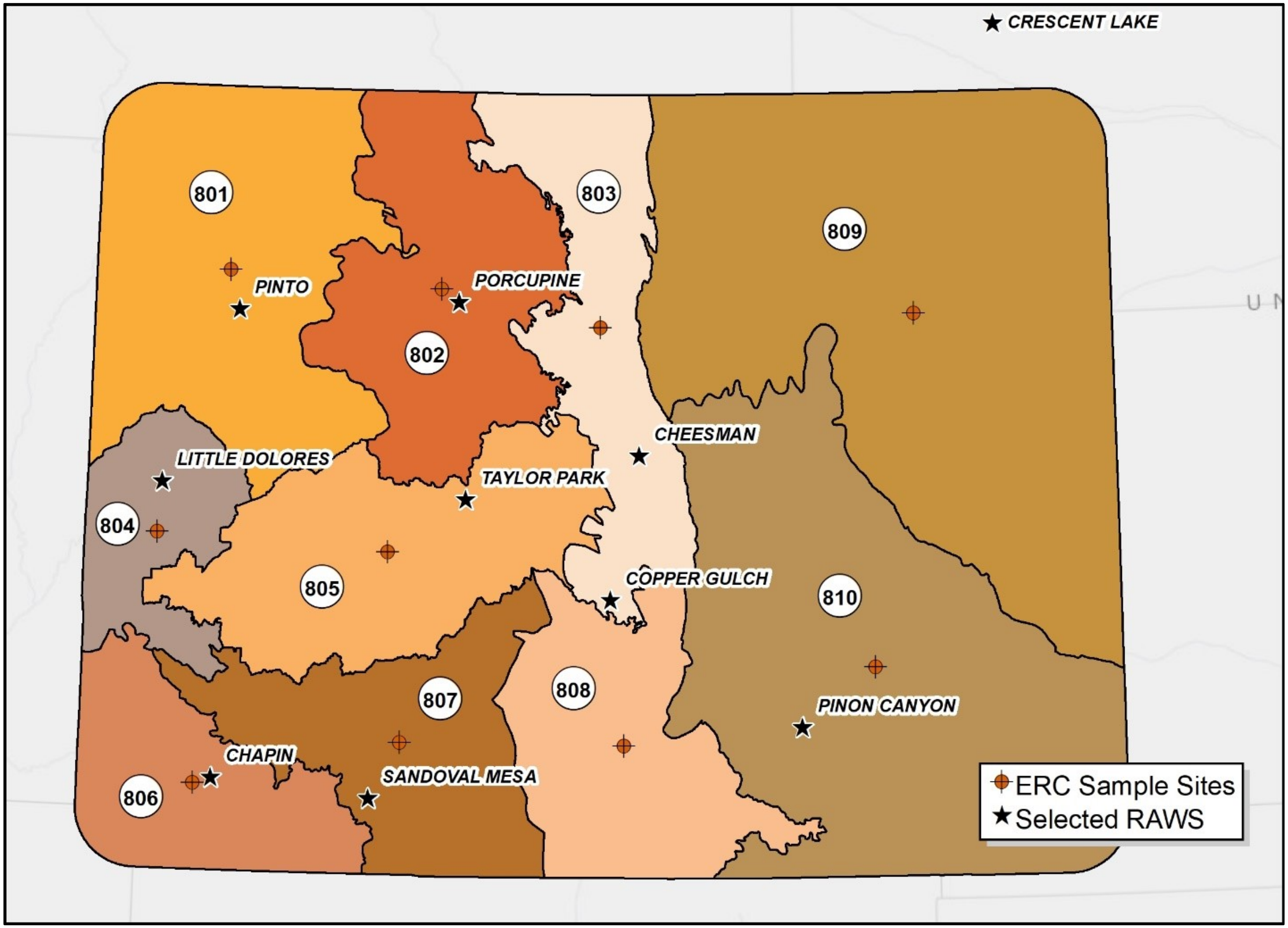

Figure 7. Map of the RAWS and ERC sample points that were used for the COAL FSim project. Selected RAWS data were used to generate hourly sustained wind speed and direction distributions.

Table 3. List of selected RAWS by Fire Occurrence Area.

FOA	Station ID	Station Name
801	051402	Pinto
802	050406	Porcupine Creek
803	053102	Cheesman
804	052410	Little Delores
805	052812	Taylor Park
806	055704	Chapin
807	055902	SanDoval
808	053904	Copper Gulch
809	252101	Crescent Lake
810	056202	Pinion Canyon

2.3.3.1 FIRE-DAY DISTRIBUTION FILE (FDIST)

Fire-day Distribution files are used by FSim to generate stochastic fire ignitions based on the historical relationship between large fires and ERC. The FDist files were generated using an R script that summarizes historical ERC and wildfire occurrence data, performs logistic regression, and then outputs the results in the required FDist format.

The FDist file provides FSim with logistic regression coefficients that predict the likelihood of a large fire occurrence as a function of ERC and tabulates the distribution of large fires by large-fire day. A large-fire day is a day when at least one large fire occurred historically. The logistic regression coefficients together describe large-fire day likelihood *P(LFD)* at a given ERC(G) as follows:

$$P(LFD) = \frac{1}{1 + e^{-B_a * - B_b * ERC(G)}}$$

Coefficient *a* describes the likelihood of a large fire at the lowest ERCs, and coefficient *b* determines the relative difference in the likelihood of a large fire at lower versus higher ERC values.

2.3.3.2 FIRE RISK FILE (FRISK)

Fire risk files were generated for each RAWS using FireFamilyPlus version 4.1 and updated to incorporate simulated ERC percentiles. These files summarize the historical ERC stream for the FOA, along with wind speed and direction data for the selected RAWS. The final selection of RAWS stations represents suggestions by local fire personnel with knowledge of nearby stations and their ability to represent general wind patterns within a FOA.

2.3.3.3 FUEL MOISTURE FILE (FMS)

Modeled fire behavior is robust to minor changes in dead fuel moisture, so a standardized set of stylized FMS input files (representing the 80th, 90th, and 97th percentile conditions) for 1-,10-, 100-hour, live herbaceous, and live woody fuels was developed (Table 4).

Table 4. Fuel Moisture values used in wildfire simulation for the 80th/90th/97th percentile ERCs

Fuel Model Group	1-hr	10-hr	100-hr	Live-Herb	Live-Woody
Grass / Shrub	4 / 3 / 2	5 / 4 / 3	6 / 5 / 4	90 / 65 / 45	110 / 100 / 90
Timber / Slash	6 / 5 / 4	7 / 6 / 5	8 / 7 / 6	90 / 65 / 45	110 / 100 / 90
Short Season	45 / 3 / 2	45 / 4 / 3	45 / 5 / 4	150 / 65 / 45	150 / 100 / 90
Burnable Ag (Wheat)	45 / 45 / 4	45 / 45 / 5	45 / 45 / 6	150 / 150 / 45	150 / 150 / 90
Burnable Urban	45 / 45 / 4	45 / 45 / 5	45 / 45 / 6	150 / 150 / 45	150 / 150 / 90

2.3.3.4 ENERGY RELEASE COMPONENT FILE (ERC)

We sampled historical ERC-G values from a spatial dataset derived from North American Regional Reanalysis (NARR) 4-km ERC-G dataset (Jolly 2014). Historical ERC-G grid values are available for the years 1979-2017 and historical fire occurrence data is available for 1992-2018. We used the overlapping years of 1992-2017 to develop a logistic regression of the probability of a large-fire day based on ERC-G utilizing a fire size of 10 acres.

Historical ERCs were sampled at an advantageous location within each FOA. Those locations are found on relatively flat ground with little or no canopy cover in the general area within the FOA where large fires have historically occurred. These historical ERC values were used in conjunction with the FOD to generate FSim's FDist input file, but not to generate the FRisk file. ERC percentile information in the FRisk file was generated from the simulated ERC stream, described below. This approach ensures consistency between the simulated and historical ERCs.

For simulated ERCs in FSim, we used a feature of FSim that allows the user to supply a stream of ERC values for each FOA. Isaac Grenfell, a statistician at the Missoula Fire Sciences Lab, has generated 1,000 years of daily ERC values (365,000 ERC values) sampled from Jolly's historical ERCs. The simulated ERC values Grenfell produces are "coordinated" in that a given year and day for one FOA corresponds to the same year and day in all other FOAs—their values only differ due to their location on the landscape. This coordination permits the analysis of fire-year information across all FOAs.

2.4 WILDFIRE SIMULATION

The FSim large-fire simulator was used to quantify wildfire hazard across the landscape at a pixel size of 120 m (3.5 acres per pixel). Due to the highly varied nature of weather and fire occurrence across the large landscape, we ran FSim for each of the ten FOAs independently and then compiled the runs into a single data product. For each FOA, we parameterized and calibrated FSim based on the location of historical fire ignitions within the FOA, which is consistent with how the historical record is compiled. We then used FSim to start fires only within each FOA but allowed those fires to spread outside of the FOA. This, too, is consistent with how the historical record is compiled.

2.4.1 MODEL CALIBRATION

FSim simulations for each FOA were calibrated to a 2020 trend analysis of historical large fire occurrence including mean historical large-fire size, and mean annual area burned per million acres. Calibration targets were adjusted from the mean values over the historical record based on methods outlined in section 2.3.2.2. Additionally, care was taken to match simulated wildfire size distributions to the historical record and allow for the occurrence of simulated fires larger than any observed historically. While only large-fire sizes (>247.1 acres) were considered in calibration, numerous small fires were also simulated. However, the impact of small fires on landscape-level burn probability is negligible.

To calibrate each FOA, we started with baseline inputs and a starting rate-of-spread adjustment (ADJ) factor file informed by experience on previous projects. All runs were completed at 120-m resolution. Each FOA was calibrated separately, and final simulations were run with either 50,000 or 100,000 iterations. The final model input files and settings can be seen in Table 5. The ten FOAs were then integrated into an overall result for the analysis area.

Table 5. Summary of final-run inputs for each FOA.

Final run	Number of Iterations	ADJ file	Trimming factor	FRisk	FDist file	LCP file
801r12	50,000	Foa801v4.adj	2.0	Foa801v3.FRISK	Foa801v4.fdist	FOA_801_120v5.lcp
802r12	100,000	Foa802v6.adj	2.0	Foa802v3.FRISK	Foa802v4.fdist	FOA_802_120v5.lcp
803r12	100,000	Foa803v6.adj	2.0	Foa803v5.FRISK	Foa803v3.fdist	FOA_803_120v5.lcp
804r12	100,000	Foa804v4.adj	2.0	Foa804v3.FRISK	Foa804v4.fdist	FOA_804_120v5.lcp
805r12	100,000	Foa805v4.adj	2.0	Foa805v3.FRISK	Foa805v4.fdist	FOA_805_120v5.lcp
806r12	100,000	Foa806v4.adj	2.0	Foa806v3.FRISK	Foa806v4.fdist	FOA_806_120v5.lcp
807r12	100,000	Foa807v6.adj	2.0	Foa807v5.FRISK	Foa807v4.fdist	FOA_807_120v5.lcp
808r12	100,000	Foa808v5.adj	2.0	Foa808v5.FRISK	Foa808v4.fdist	FOA_808_120v5.lcp
809r12	50,000	Foa809v6.adj	2.0	Foa809v3.FRISK	Foa809v5.fdist	FOA_809_120v5.lcp
810r12	50,000	Foa810v6.adj	2.0	Foa810v3.FRISK	Foa810v4.fdist	FOA_810_120v5.lcp

2.5 WILDFIRE MODELING RESULTS

The FSim model produces estimates of burn probability as well as measures of fire intensity including flame length probabilities and mean fireline intensity. While FSim does generate measures of wildfire intensity, the WildEST-derived intensity estimates (described below in section 3) are more reliable than those generated stochastically within FSim. The WildEST intensity values were used in all developed effects analyses. The FSim model generated 120-m resolution estimates of burn probability. These results were further downscaled to 30-m resolution to match the WildEST intensity resolution using a methodology described in section 2.5.1 and presented in Figure 8.

2.5.1 UPSAMPLING FSIM RESULTS

FSim's stochastic simulation approach can be computationally intensive and time constraining on large landscapes. A challenge is to determine a resolution sufficiently fine to retain detail in fuel and terrain features yet produce calibrated results in a reasonable timeframe. Moreover, HVRA are often mapped at the same resolution as the final BP produced by FSim. To enable greater resolution on HVRA mapping, we chose to upsample the FSim burn probability (BP) rasters to 30 m.

The FSim fire modeling included custom burnable-urban fuel models. Without accounting for any potential burnability in developed areas, simulated wildfires would stop at the edge of burnable fuel. To address this issue, we allow fires to spread through burnable-urban pixels, which produces simulated fire perimeters that can continue spreading through developed areas. However, because of the many unknowns and challenges in modeling the potential for home-to-home spread in landscape-scale fire modeling, we ultimately minimize the influence of burn probability values associated with burnable-urban pixels and instead prefer to smooth probabilities from adjacent wildlands within a specified distance as described below.

We upsampled the FSim BP raster using a multi-step process. First, we used the ESRI ArcGIS Focal Statistics tool to perform two rectangular, low-pass filters at the 120-m resolution, calculating the mean value of burnable pixels only (including burn probability values on burnable-urban pixels), within a 3-pixel by 3-pixel moving window. These steps allowed us to "backfill" burnable pixels at 30 m that were coincident with non-burnable fuel at 120 m. We subsequently resampled the resulting 120-m BP raster to 30 m using bilinear resampling. If, after running two low-pass filters, burnable pixels had BP values of zero, we set a threshold value of 1-in-10,000 (0.001) to avoid assigning zero probability values on burnable pixels with some burning potential.

We then smoothed burn probability values from nearby burnable fuel onto adjacent non-burnable pixels to capture the low likelihood, but high consequence event of an urban conflagration. Before running the smoothing steps, we masked the 30-m resampled raster to burnable pixels only, removing BP values from burnable-urban pixels. Additionally, we removed BP values from small, burnable islands less than 500 ha. The purpose of removing burnable urban, non-burnable fuel, and small burnable islands is to prevent smoothing from these pixels, and in particular, to prevent golf courses and urban parks from spreading wildfires to nearby homes.

The resulting resampled raster was then smoothed again using the ESRI ArcGIS Focal Statistics tool to perform three low-pass filters at a 300 m resolution, allowing for spread from burnable pixels to nearby non-burnable pixels. Each focal smoothing operation incrementally reduces burn probability by including zero values on non-burnable pixels (other than water and ice) in the focal mean calculation. This reduces burn probability on non-burnable fuel relative to the burnable fuel nearby. The 900 m smoothing distance is consistent with work by Caggiano et al. (2020) showing that all home losses to wildfire from 2000 to 2018 were within 850 m of wildland vegetation. By removing the modeled BP on burnable-urban pixels, and in its place smoothing burn probability onto those pixels, we reduce wildfire likelihood and control the distance those values are spread. If small burnable islands were not populated through BP smoothing, they were assigned a threshold value of 1-in-100,000 (0.00001).

To prevent overestimating the potential for wheat fields to burn, we handled the spread of wildfire into burnable agriculture in the same manner as described above for the burnable urban fuel model.

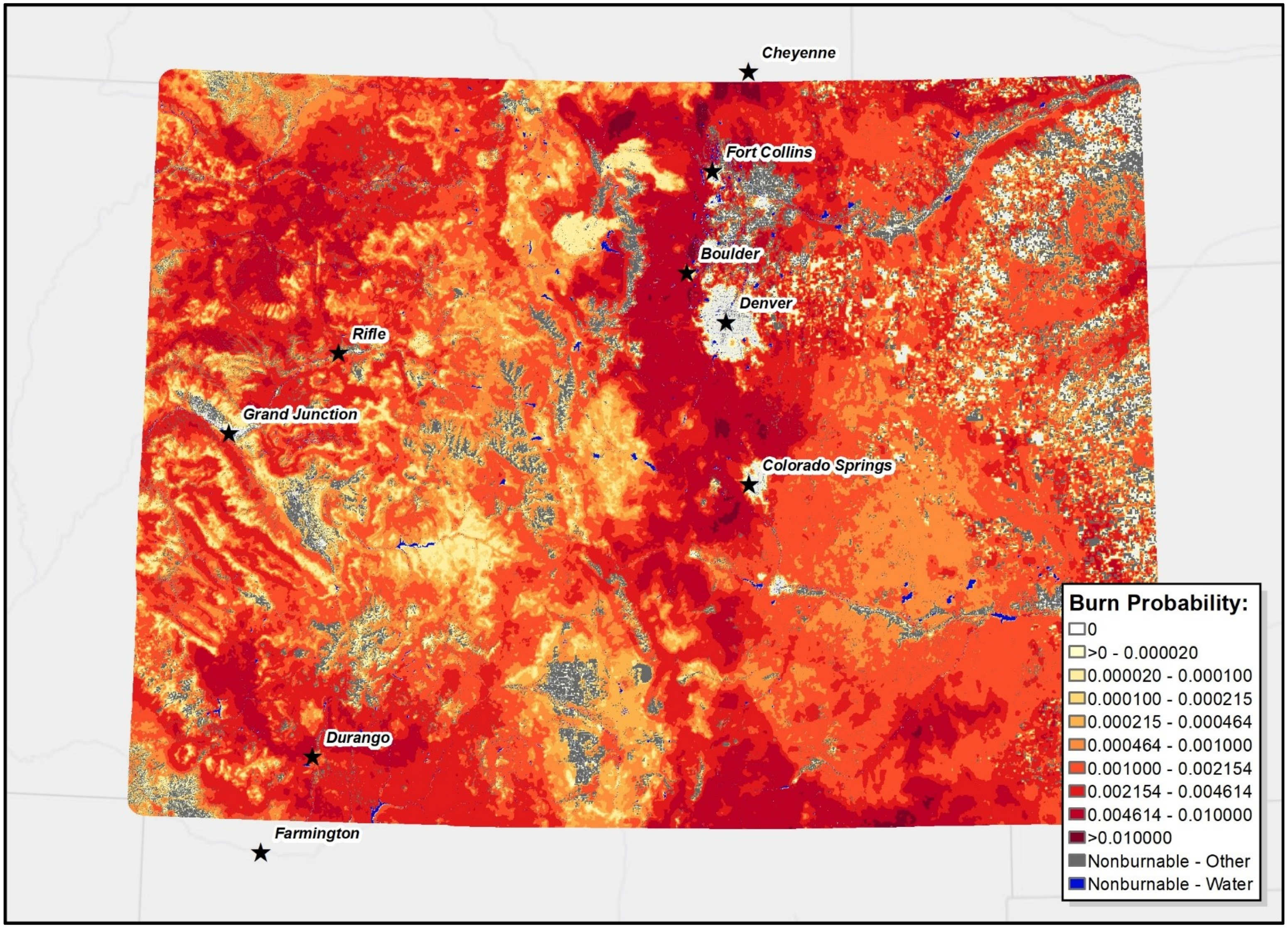

Figure 8. Map of integrated FSim burn probability results for the COAL study area at 30-m resolution.

3 WILDFIRE BEHAVIOR CHARACTERISTICS

3.1 OVERVIEW OF METHODS

To estimate wildfire characteristics across the state of Colorado we used a scripted geospatial modeling process called WildEST (for Wildfire Exposure Simulation Tool). WildEST uses the command-line version of FlamMap to perform 216 basic deterministic simulations of fire behavior characteristics for a range of weather types (combinations of wind speed and fuel moisture content). Additionally, we integrate the dead fuel moisture conditioning feature of FlamMap, so dead fuel moisture content is sensitive to canopy cover and topography (slope, aspect, and elevation). We also use pre-calculated Wind Ninja grids representing terrain-adapted wind speed and direction. These grids were generated at 120-m resolution then upsampled to 30-m resolution before use in FlamMap.

Rather than weighting the 216 results solely according to the temporal relative frequencies (TRFs) of the weather types, the WildEST process integrates results by weighting them according to their weather type probabilities (WTP), which gives higher weight to high-spread conditions into the calculations. The process of developing the WTP rasters is described in Section 3.1.2 below.

The majority of WildEST results apply to the head of the fire. However, for use in fire-effects calculations, WildEST also generates Flame-Length Probability rasters (FLPs) that incorporate non-heading spread directions (Scott 2020), for which fire intensity is considerably lower than at the head of the fire. These "fire-effects FLPs" or “NVC FLPs" are analogous to FLP rasters produced by FSim.

We use the weather type probability (WTP) weighting process in WildEST to produce head-fire characteristics rasters (e.g., mean flame length), fire-type probability rasters, ember characteristics rasters, and non-heading characteristics rasters (for use in an effects analysis). Together, these rasters are useful for mapping the fire behavior that characterizes each pixel on the landscape. Each output is described in the respective following sections 3.2.1 - 3.2.6.

3.1.1 FSIM VERSUS WILDEST

Our use of command-line FlamMap in WildEST for this landscape-scale hazard assessment is a departure from what has been standard practice for USFS wildfire risk assessments that use FSim. Typically, such hazard assessments have used FSim for both the wildfire likelihood (burn probability) and wildfire intensity (flame-length probability) components of the assessment. Pyrologix developed the WildEST process to address a few shortcomings present when using FSim for fire intensity results.

3.1.1.1 SPATIAL RESOLUTION

The spatial resolution (grid cell size) is limited to the resolution used for the main FSim fire occurrence modeling. For national-scale projects the resolution is 270 m; for COAL the resolution was 120 m. Even though fuelscape information is available from LANDFIRE at a 30-m resolution, FSim cannot use that resolution due to excessive run time. In contrast, WildEST does not contain this limitation and can produce results at 30-m resolution on large landscapes.

3.1.1.2 MODEL TYPE

FSim is a Monte Carlo simulator, so the fire intensity results it can produce are limited to 1) the mean fireline intensity of simulated fires that burned each grid cell, and 2) the conditional probability that flame length will be in each of six flame-length classes, called Fire Intensity Levels (FILs). In FSim, flame length always accounts for the effect of relative spread direction (heading, flanking, backing). Because the flame-length probabilities (FLPs) are determined by tallying the relative fraction of times a grid cell burned in each Fire Intensity Level[5], they suffer from a problem of low sample size, especially in places where BP is low. For example, where BP is 1-in-500 (0.002), a pixel would burn 20 times over 10,000 iterations. The flame length of those 20 fires is tallied into six flame-length bins. That is a small sample size to provide a stable estimate of the true flame-length probabilities. Running FSim a second time could generate vastly different FLPs for the same pixel.

WildEST is deterministic, so it does not suffer from a Monte Carlo simulator's sample-size problem. Additionally, WildEST can be used to generate both head-fire and non-heading fire intensity results.

3.1.1.3 FIRE CHARACTERISTICS PRODUCED

FSim produces only two measures of fire intensity for each simulation: mean fireline intensity (MFI) and flame-length probability (FLP) for six Fire Intensity Levels.

In contrast, we use WildEST to generate a wide array of fire characteristics, including the rate of spread, heat per unit area, type of fire, crown fraction burned, and maximum ember travel distance. These additional fire characteristics allow the calculation of additional measures of wildfire hazard, including ember production and ember load, and Suppression Difficulty Index.

3.1.1.4 SPATIAL PRECISION OF WEATHER DATA

FSim is limited to using just one stream of weather for a large area (millions of acres). FSim does not support dead fuel moisture conditioning, which accounts for the effects of elevation, canopy cover, slope steepness, and aspect on dead fuel moisture content. Additionally, FSim has limited support for applying terrain-adapted winds using WindNinja.

WildEST uses gridded historical weather data at a spatial resolution of 4 km for COAL. We use both fuel moisture conditioning and WindNinja at 30-m resolution to produce continuously variable fire characteristics results free of seamlines due to weather inputs.

3.1.1.5 TOPOLOGY EFFECTS

One advantage of FSim is that it inherently accounts for any effects of fire spread topology[6] on fire intensity. For example, the land on the lee side of a large non-burnable feature (such as a lake) is less

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[5] The Fire Intensity Levels (FILs) reported by FSim are: 0-2 ft, 2-4 ft, 4-6 ft, 6-8 ft, 8-12 ft, and >12 ft for FILs 1-6, respectively.

[6] Fire spread topology is the network of possible fire spread pathways given the fire environment.

likely than other parts of the landscape to experience a head-fire, because a heading fire cannot spread across the lake; instead, a fire must flank past or around this location, resulting in lower fire intensity. This topology effect is pronounced for short-duration fires or when there is a single fire-carrying wind direction. If fire can be carried across the landscape in multiple directions, the topology effect is smaller.

WildEST cannot address such topological effects. Each location is evaluated using only the fuel, weather, and topography at the location, with no consideration for adjacent nonburnable features that could potentially reduce intensity by reducing the potential for heading spread.

3.1.2 WEATHER TYPE PROBABILITY RASTERS

We used a bias-corrected, 4-km gridded daily weather dataset derived from gridMET historical weather (Abatzoglou 2013) for the 20-year period 2000-2019 to derive weather type probabilities used to weight the fire characteristics in the WildEST process.

The gridMET dataset provides daily wind speed grids but contains bias on annual timescales relative to other national products with finer spatial resolutions. We corrected this bias using the National Renewable Energy Laboratory (NREL) annual average wind speed dataset (Draxl et al. 2015) by deriving a daily correction factor from the overlapping time periods of the two datasets (2007-2013).

Weather type probabilities (WTPs) are a function of the area burned index (ABI), calculated for each day in the 2000-2019 timeframe as follows:

$$ABI = SPI * WS^2 * BurnMinutes * LFP$$

where SPI is the Schroeder Probability of Ignition (Schroeder 1969), a function of temperature and fine fuel moisture content, WS is the open wind speed in mi/h, burn minutes is defined from a lookup table (Table 6) as a function of wind speed and daily ERC percentiles, and LFP is the large fire probability as a function of daily ERC.

Table 6. Burn minutes table for calculating area burned index (ABI).

Wind Speed Bin (mi/h)	ERC < 80th percentile	ERC 80-90th percentile	ERC 90-97th percentile	ERC >= 97th percentile
0-3	30	30	30	30
3-8	30	30	60	120
8-13	30	60	120	180
13-18	60	120	180	240
18-23	120	180	240	300
23-28	180	240	300	450
28-33	240	300	450	600
33-38	300	450	600	600
>= 38	450	600	600	600

The large fire probability (LFP) is a prediction from logistic regressions derived from observed large fires within the fire occurrence database ([FOD] Short 2021) and their corresponding ERC's. A 150-km moving window was used to select fire observations, creating a logistic regression for each 4-km pixel. We also accounted for the amount of burnable area in the 150-km window by dividing the probability by the fraction of burnable area to prevent bias due to coastlines and other areas with less burnable land. We defined 216 unique weather scenarios based on wind speed, wind direction, and moisture content. The weather parameters associated with each ABI value were binned according to the reported weather conditions for a given day.

There are nine wind speed bins:

0-3, 3-8, 8-13, 13-18, 18-23, 23-28, 28-33, 33-38, and >= 38 mi/h

There are eight wind direction bins:

337.5-22.5, 22.5-67.5, 67.5-112.5, 112.5-157.5, 157.5-202.5, 202.5-247.5, 247.5-292.5, 292.5-337.5^0

And there are three 1-hr time-lag moisture content bins:

<4, 4-6, and 6-12%

The ABI values were then summed within a weather-scenario bin and normalized by the total ABI for all weather scenarios for a given 4-km pixel – thereby collapsing the daily ABI values across 20 years into 216 weather-type probability (WTP) rasters as fractions of the total ABI. These fractions were smoothed and upsampled to 30-m resolution using a 3x3 weighted sum at 4km, with bilinear resampling to snap to the 30-m fuel model raster. The percentage rasters were renormalized once more after upsampling to 30 m to ensure the WTPs summed to one across all weather types in each 30-m pixel. Note that if fine dead fuel moisture content was above 12 percent, then the ABI values for those conditions were not included in the sums.

The WTPs integrate the potential relative area burned for that weather type (ABI) and the relative frequency of weather scenarios by summing the daily ABI values each time a weather scenario occurred in the observation record. A weather type with higher wind speed, higher ERC values, and higher SPI will receive a weighting according to the larger ABI value, but weather types with lower ABI values occurring at high enough frequencies may ultimately receive a larger weighting. These WTP rasters are used to weight FlamMap fire model outputs that then produce integrated fire characteristic values across the different weather scenarios.

3.1.2.1 MODELING CUSTOM WEATHER SCENARIOS

Section 3.1.2 above described the development of the weather probabilities utilized for all of the hazard products described within this report as well as the risk analysis calculations detailed in the Wildfire Risk Report[7]. Additionally, we produced a separate set of analyses based on unique weighting schemes that can be viewed in the appendix of the Wildfire Risk Report.

[7] http://pyrologix.com/reports/COAL_WildfireRiskReport.pdf

3.2 FLAME FRONT CHARACTERISTICS

The WildEST flame front characteristics include head-fire rate of spread and head-fire flame length, as well as conditional probabilities for fire type, operational control, and head-fire flame length. These characteristics are described below in sections 3.2.1 - 3.2.5. WildEST also produces "fire-effects" flame-length probabilities, which are calculated in a way that incorporates non-heading spread directions (section 3.2.6). Great care was taken to eliminate artificial data artifacts (seamlines) in the fuelscape and the WTPs. As a result, the head-fire characteristics rasters are also free of such artifacts.

3.2.1 RATE OF SPREAD (ROS)

Rate of spread (ROS) is the weighted-average rate of spread in meters per minute for a given pixel in the fuelscape, including any contribution of crown fire spread rate under a given weather type (Figure 10). Weighted ROS is calculated as the sum-product of 216 ROS rasters and their corresponding WTPs.

3.2.2 FLAME LENGTH (FL)

Flame length is the weighted-average flame length in feet for a given pixel in the fuelscape, including any contribution of crown fire under a given weather type (Figure 11). Weighted FL is calculated as the sum-product of 216 FL rasters and their corresponding WTPs.

3.2.3 FIRE-TYPE PROBABILITY (FTP)

Fire-type probability rasters indicate the conditional probability that a given pixel will experience a certain type of fire. At a given pixel, the sum of fire-type probabilities equals 1 (100 percent). The FTPs indicate the range of fire types that can be produced by the fire environment and their relative prevalence.

We define seven fire types (Table 7):

1. Non-fuel
2. Surface fire
3. Underburn[8]
4. Low-grade passive crown fire
5. Mid-grade passive crown fire
6. High-grade passive crown fire
7. Active crown fire

[8] The term underburn is used rather than surface fire to distinguish from the situation where there is no forest canopy present.

The non-fuel "fire type" is assigned to pixels that do not have burnable fuel in the fuelscape and therefore do not experience any type of fire. The possible raster values for non-fuel probability are either 0 (burnable fuel is present) or 1 (the pixel is non-burnable).

Similarly, the surface fire type is assigned to pixels with burnable fuel but without forest canopy present. In these cases, surface fire is the only possibility. We distinguish this type from an underburn because the latter indicates that crowning was possible, but not achieved. The raster value for this fire-type probability is 1 if the pixel is burnable but does not have a canopy or 0 for all other cases.

The remaining five fire types require a pixel to have 1) a burnable surface fuel model and 2) a tree canopy present, representing the possibility of a crown fire under some conditions. Raster probability values range from 0 to 1. Crown fire types are commonly classified as either passive or active. But passive crown fire represents a large range of crowning behavior from a single tree torching up to nearly continuous large-group torching. We, therefore, divided passive crown fire into three sub-classes based on the crown fraction burned (CFB) estimated for the fire environment. Crown fraction burned represents the fraction of the canopy fuel contributing to the overall rate of spread and intensity.

Table 7. The WildEST Type of Fire classification.

Type of fire	Burnable land cover?	Forest canopy present?	Crown Fraction Burned (%)
Non-fuel	No		-
Surface	Yes	No	-
Underburn	Yes	Yes	0
Low-grade passive	Yes	Yes	0<CFB<25
Mid-grade passive	Yes	Yes	25<CFB<60
High-grade passive	Yes	Yes	60<CFB<90
Active	Yes	Yes	90<CFB

The fire-type rasters are additive for a given pixel, with the sum of all seven fire-type rasters for a given pixel equaling 1. The seven fire-type probabilities are shown in Figure 12.

3.2.4 PROBABILITY OF OPERATIONAL CONTROL

Operational-control probability rasters indicate the probability that the head-fire flame length in each pixel will exceed a defined threshold for a certain type of operational control. The three levels of control are manual control, mechanical control, and extreme fire behavior. We estimate these probabilities by summing the WTP values for all weather types for which head-fire FL exceeds the threshold value.

Manual control is generally considered to have a threshold of 4 feet during wildfire operations. Therefore, the probability of exceeding manual control raster displays the likelihood of exceeding 4-foot heading flame lengths.

Similarly, mechanical control is generally considered to have a threshold of 8 feet, and the probability raster displays the likelihood of exceeding 8-foot heading flame lengths. Extreme fire behavior utilizes the general threshold of 11-foot flame lengths.

This information could be used as a supplement to the Suppression Difficulty Index when planning wildfire suppression operations for a given area of the landscape. The operational control probabilities are shown in Figure 13.

3.2.5 HEAD FIRE FLAME-LENGTH PROBABILITIES (OPS FLPS)

Head-fire flame-length probabilities incorporate only the head-fire spread direction and are therefore recommended for use in operational settings (Ops FLPs); they characterize more conservative estimates of hazard by including heading-only intensities and spread rates and not those associated with flanking and backing spread directions. These Ops FLPs are consistent with the exceedance probabilities for operation control described in the previous section. Head-fire flame-length probabilities are shown in Figure 14.

3.2.6 "FIRE-EFFECTS" FLAME-LENGTH PROBABILITIES

All the WildEST results described thus far apply to the head of a fire, but a free-burning wildfire spreads in all directions and therefore exhibits a range of flanking and backing behavior in addition to heading behavior. Flanking and backing fires exhibit a lower spread rate and intensity than at the head of a fire (Catchpole et al. 1982; Catchpole et al. 1992) FSim and other stochastic wildfire simulators inherently capture non-heading fire spread and intensity. The deterministic approach we use in WildEST inherently captures only head-fire spread and intensity, so we apply adjustments to head-fire intensity based on the geometry of an assumed fire spread ellipse (Scott 2020).

The FLP differences between heading and non-heading FLPs are illustrated in Figure 9, which is an example fuel complex consisting of surface fire behavior fuel model TU5, with a canopy base height of 0.3 m and a canopy bulk density of 0.11 kg/m^3. For that fuel complex (and for the climatology of that location), we estimate that head-fire flame length will exceed 12 feet 66 percent of the time the pixel burns, and never produce flame lengths less than 4 feet. After accounting for flanking and backing behavior, we estimate flame length will exceed 12 feet only 42 percent of the time and will be lower than four feet 5 percent of the time.

The WildEST non-heading characteristics include non-heading flame-length probabilities, which we call "fire-effects" FLPs because they are designed for use in an Effects Analysis in a landscape wildfire risk assessment as described in USFS GTR-315 (Scott et al. 2013). These fire-effects FLPs are a close analog to FSim's FLPs and are used for the same purpose.

Like the head-fire FLPs described above, we produce non-heading FLPs for the same six standard flame-length classes (also called Fire Intensity Levels). Fire-effects flame-length probabilities are shown in Figure 15.

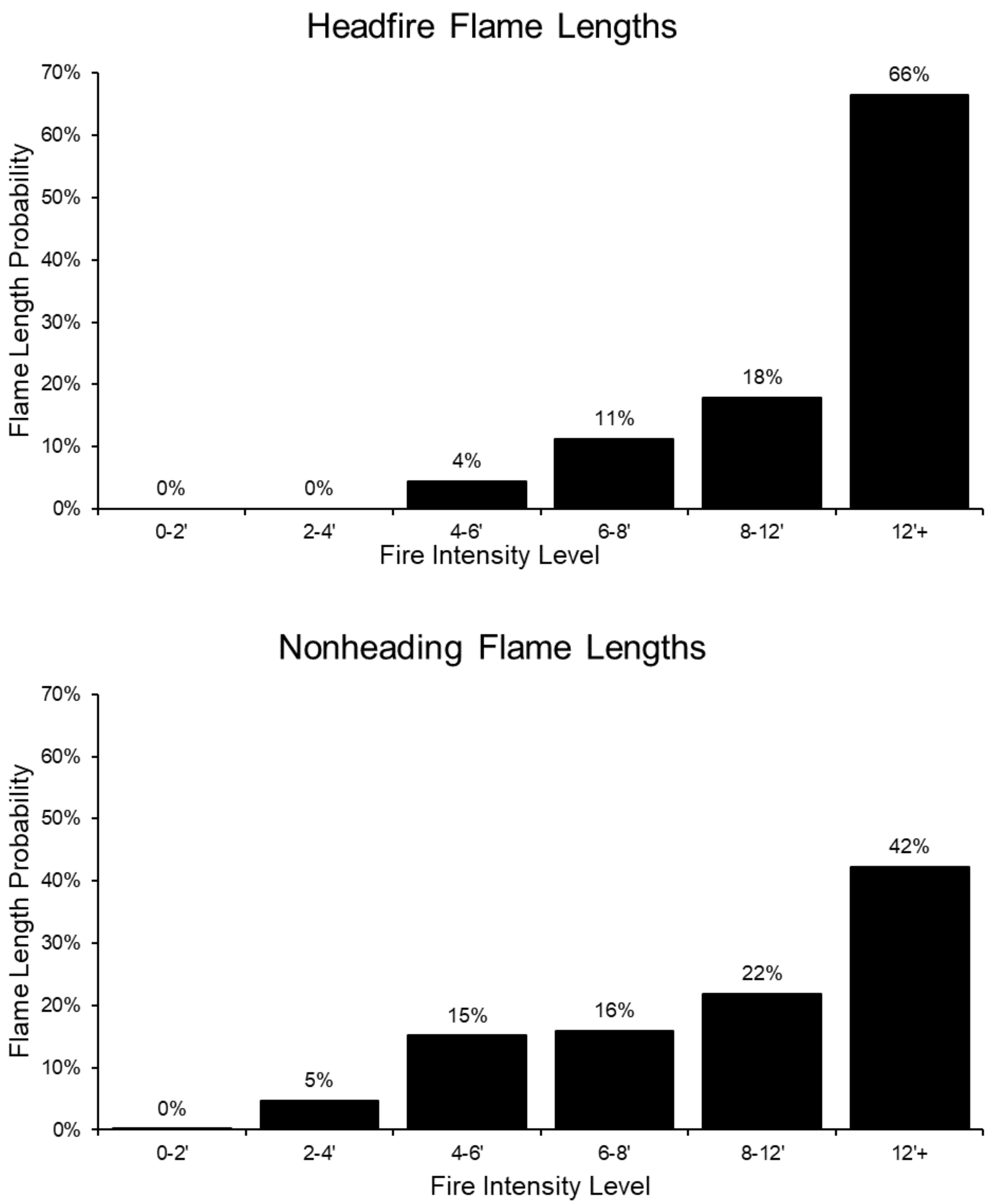

Figure 9. Head-fire flame-length probabilities (top) and non-heading (or "fire effects") flame-length probabilities (bottom).

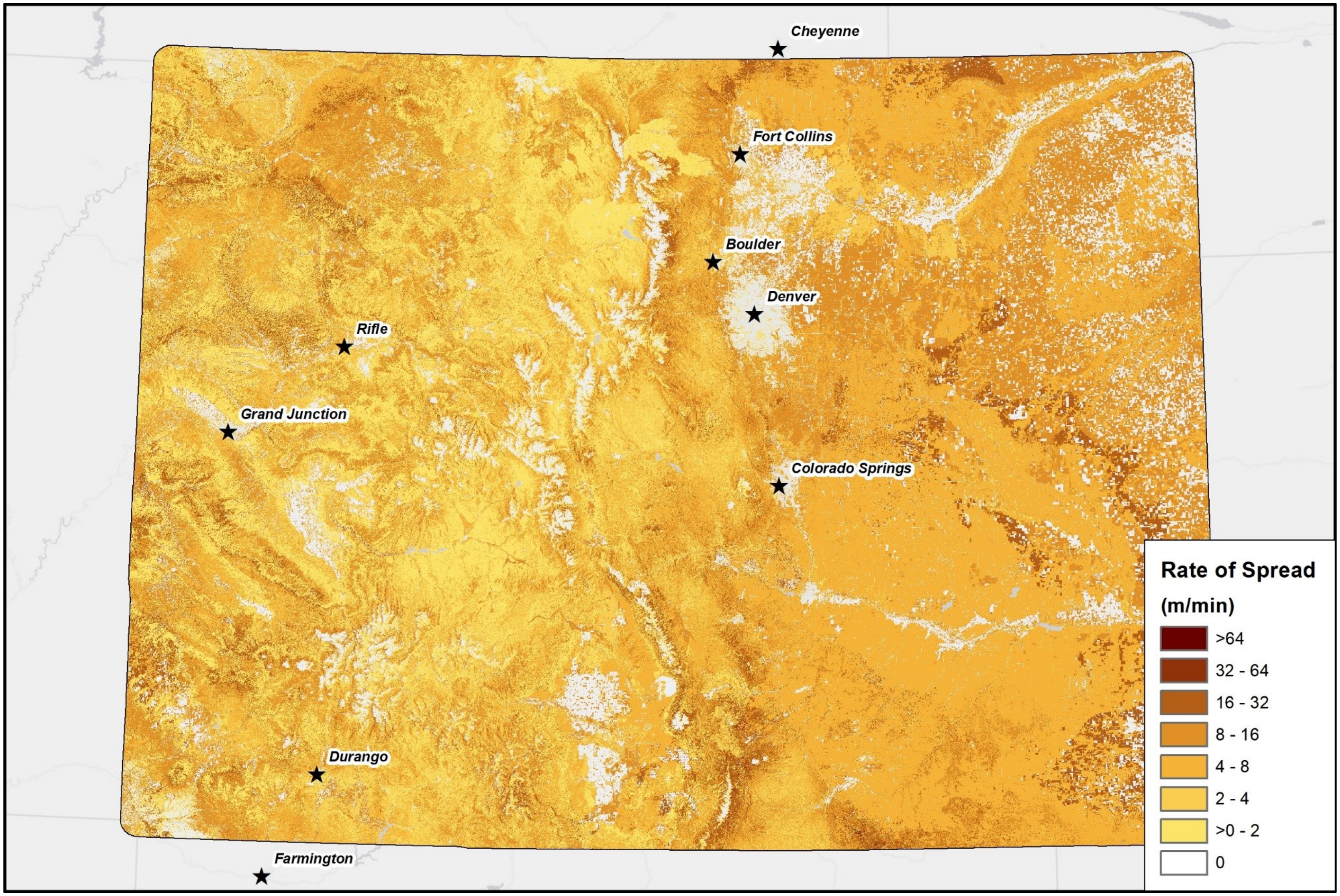

Figure 10. Map of WildEST 30-m Rate of Spread (m/min) for the COAL analysis area.

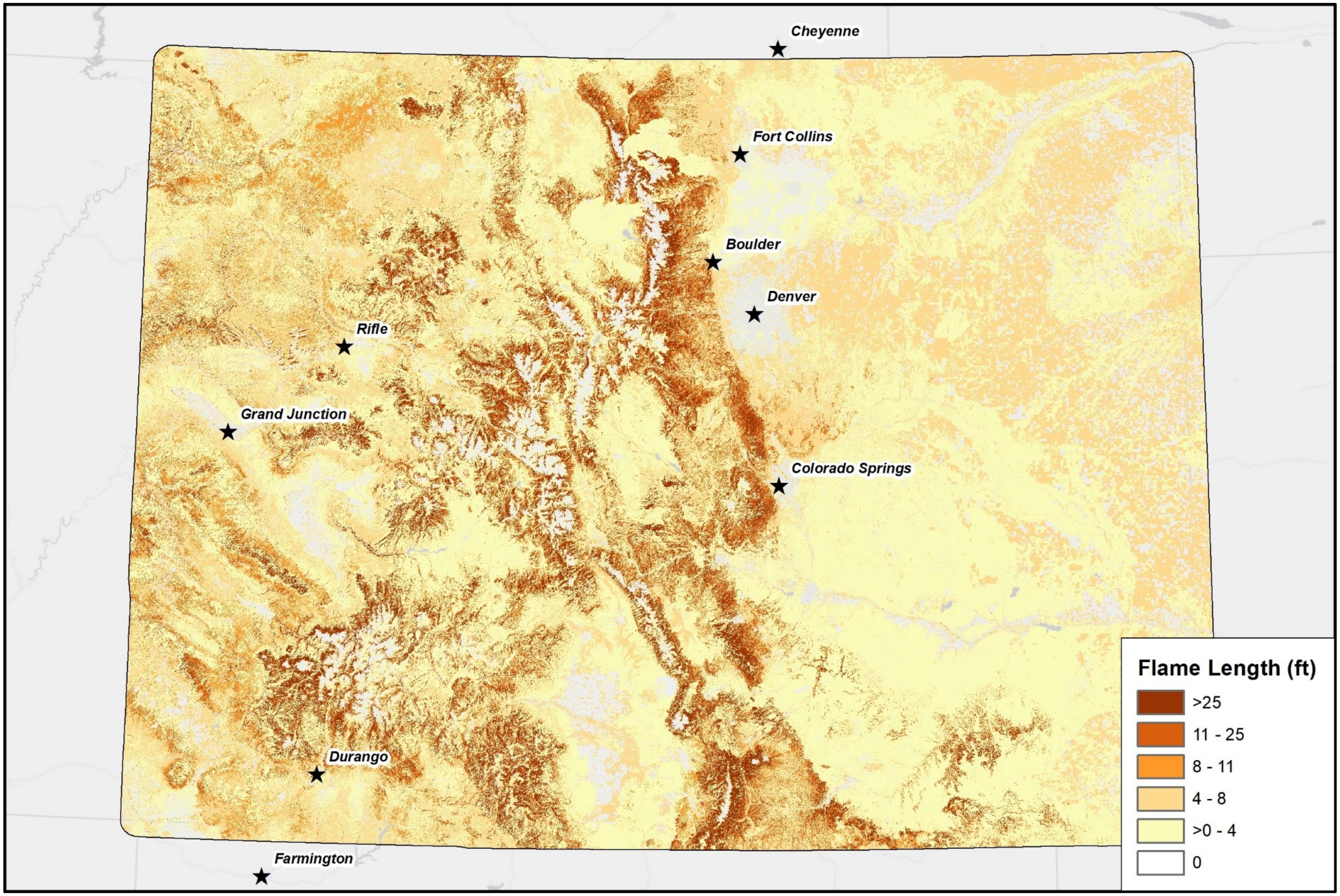

Figure 11. Map of WildEST 30-m Mean Flame Length (ft) for the COAL analysis area.

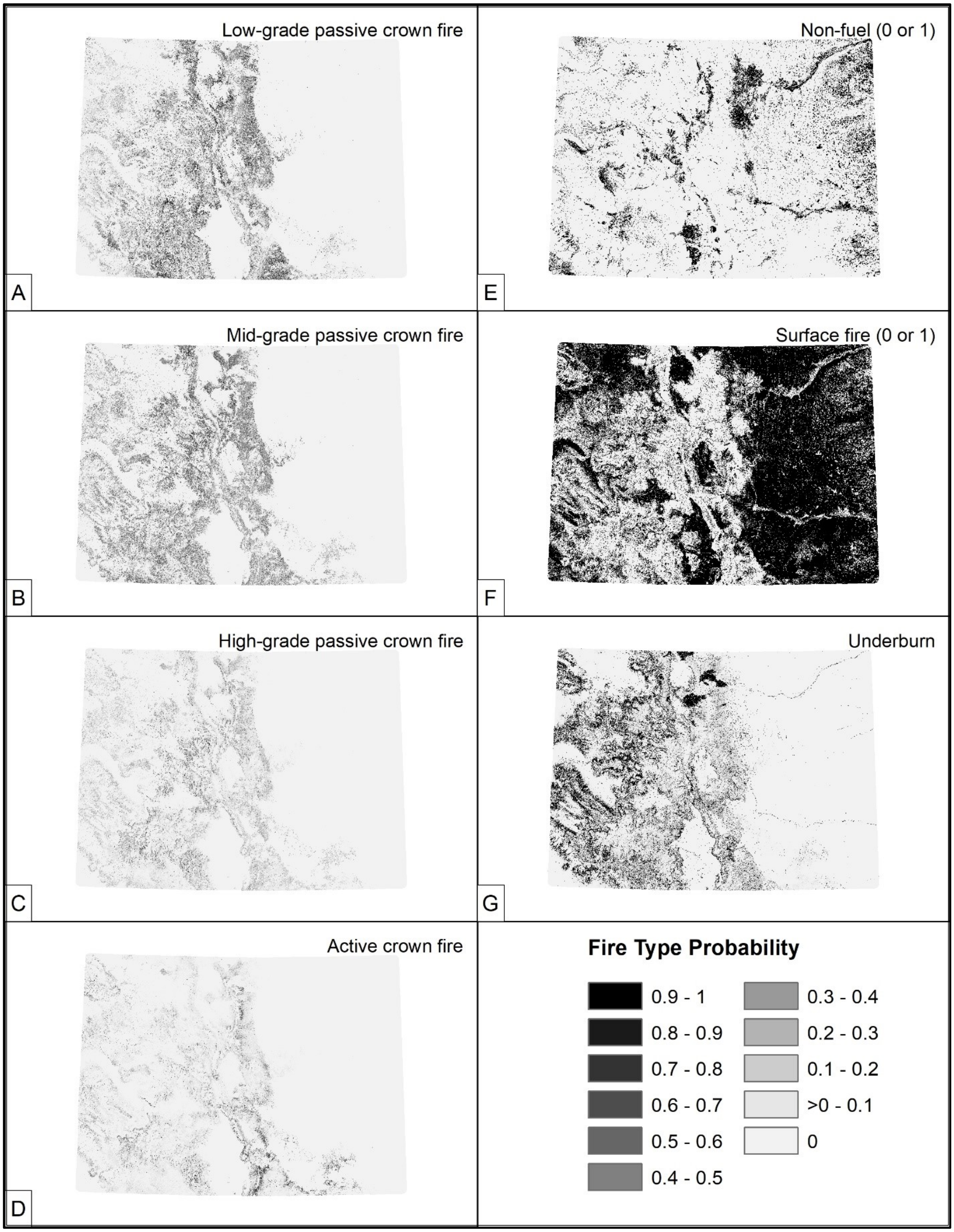

Figure 12. Map of WildEST 30-m Fire Type Probabilities for the COAL analysis area. These include (A) low-grade passive crown fire, (B) mid-grade passive crown fire, (C) high-grade passive crown fire, (D) active crown fire, (E) non-fuel, (F) surface fire, and (G) underburn. Probabilities range in value from 0 to 1, with (E) and (F) being binary rasters of only values 0 and 1.

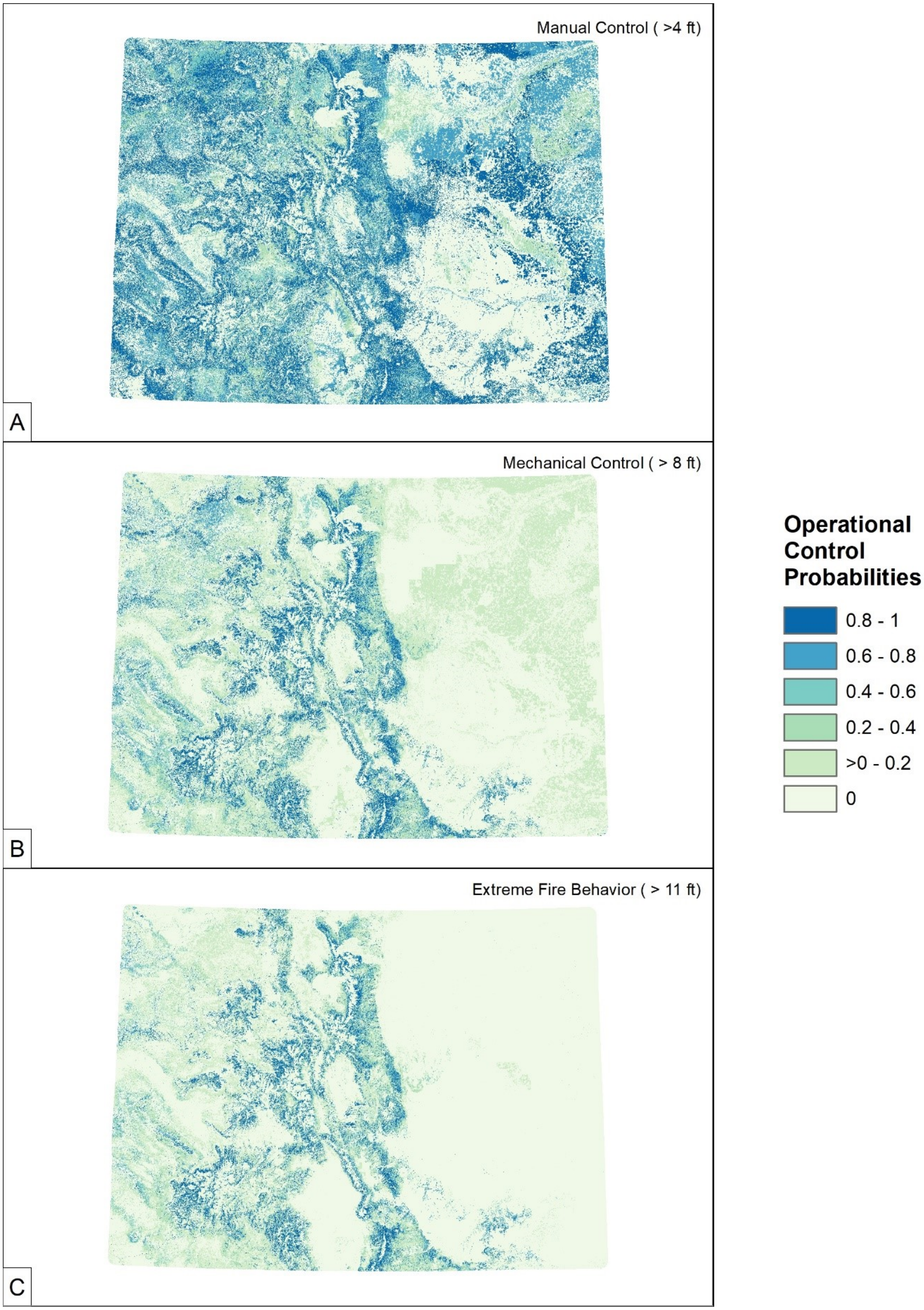

Figure 13. Map of WildEST 30-m Operation Control Probabilities for the COAL analysis area.

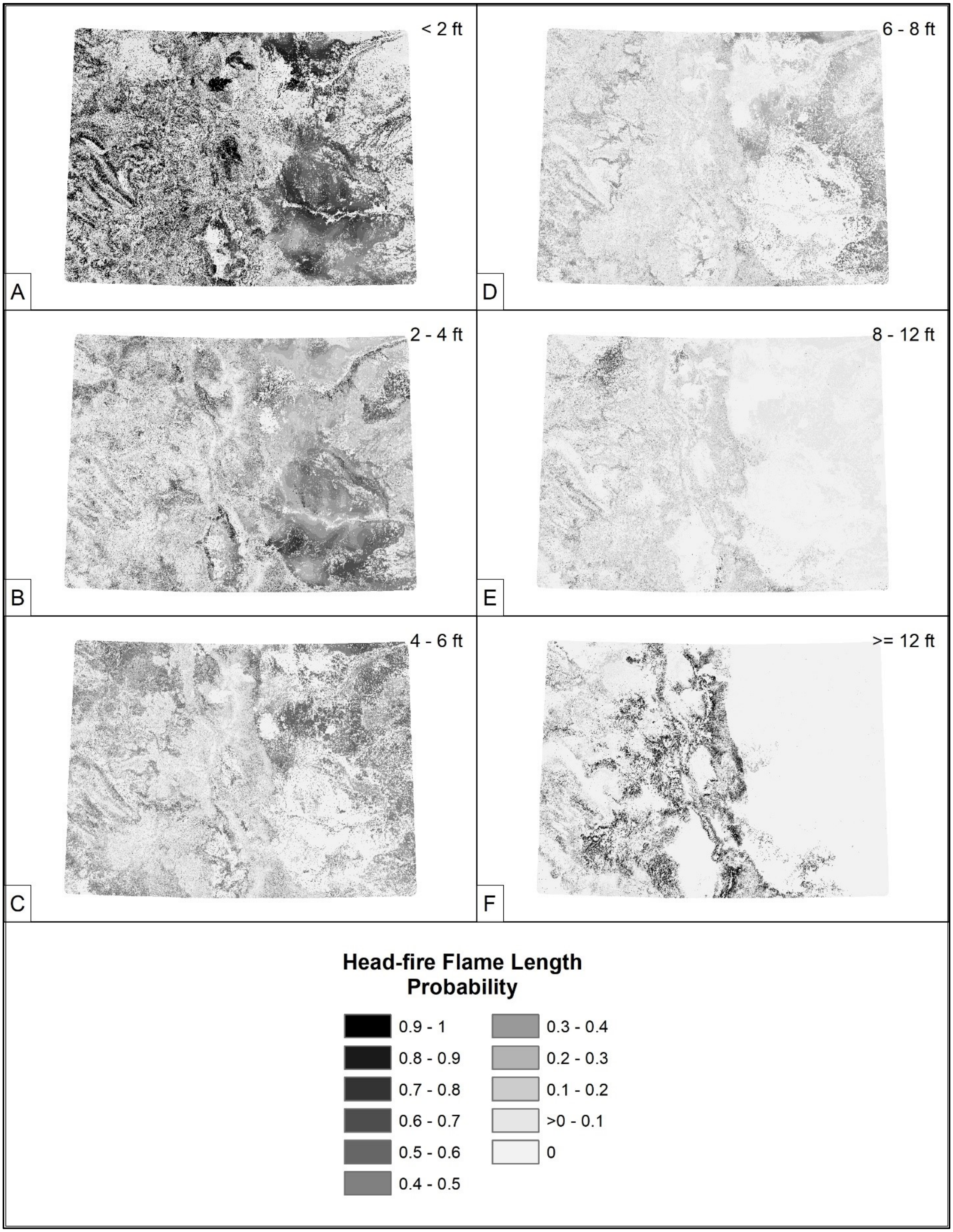

Figure 14. Map of WildEST 30-m heading FLPs for the COAL analysis area. Panels A-F shows the FLP for the heading flame-length bin specified. The sum of panels A-F for any given pixel equals one.

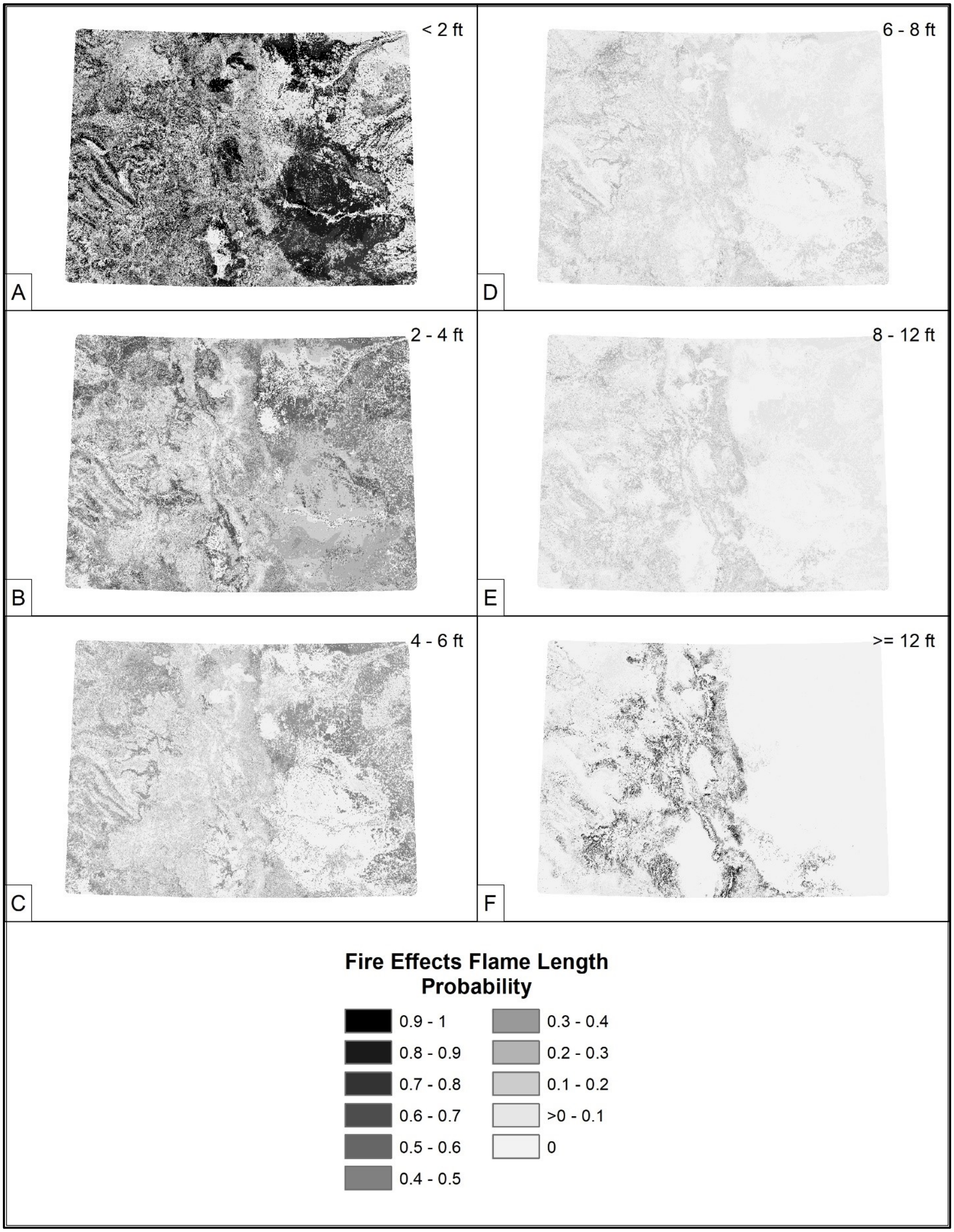

Figure 15. Map of WildEST 30-m fire-effects FLPs for the COAL analysis area. Panels A-F shows the FLP for the fire-effects flame-length bin specified. The sum of panels A-F for any given pixel equals one.

3.3 EMBER CHARACTERISTICS

The WildEST modeling contains a module for producing indices of conditional and expected ember production and load. The Conditional Ember Production Index (cEPI) is an index of the relative number of embers lofted at a given landscape pixel if a fire were to occur. Ember Production Index (EPI) is the expected value of cEPI; it is the expected annual relative number of embers lofted from a given landscape pixel.

The Conditional Ember Load Index (cELI) is a relative index of the relative number of embers that land at a given landscape location, including nonburnable pixels. Finally, Ember Load Index combines the conditional ELI and the likelihood of that ember load occurring. All ember characteristics are based on headfire behavior. These are described below in sections 3.3.1 - 3.3.2.

3.3.1 EMBER PRODUCTION INDEX

The Conditional Ember Production Index (cEPI) represents the relative number of embers produced at a pixel as a function of the fire environment. Being “conditional”, cEPI does not account for variation in burn probability across the landscape (Figure 16, A). The expected ember production index (EPI) is calculated by multiplying cEPI and burn probability (BP):

$$EPI = cEPI * BP$$

Given that EPI does incorporate burn probability, this index can help identify both the likelihood of areas being visited by fire and their potential for producing embers—information that is useful for fuel treatment prioritization to reduce ember production (Figure 16, B).

3.3.2 EMBER LOAD INDEX

The ember load indices represent relative ember load at a pixel. Similar to ember production, ember load is also based on surface and canopy fuel characteristics, climate, and topography at the pixel. Ember load incorporates downwind ember travel.

The conditional Ember Load Index (cELI) does not account for burn probability and can be used to identify where on the landscape hardening buildings to resist ember ignition may be needed (Figure 16, C).

The Ember Load Index (ELI) incorporates burn probability; however, ELI is not simply the multiplication of condition ember load (cELI) and burn probability (BP). Rather, BP is incorporated into calculations of the ember production before the distribution of embers across the landscape to determine ember load. Given that ELI incorporates burn probability, this index can be used to identify where on the landscape hardening buildings may be needed to resist ignition and the priority for doing so according to the likelihood of the area being visited by fire (Figure 16, D).

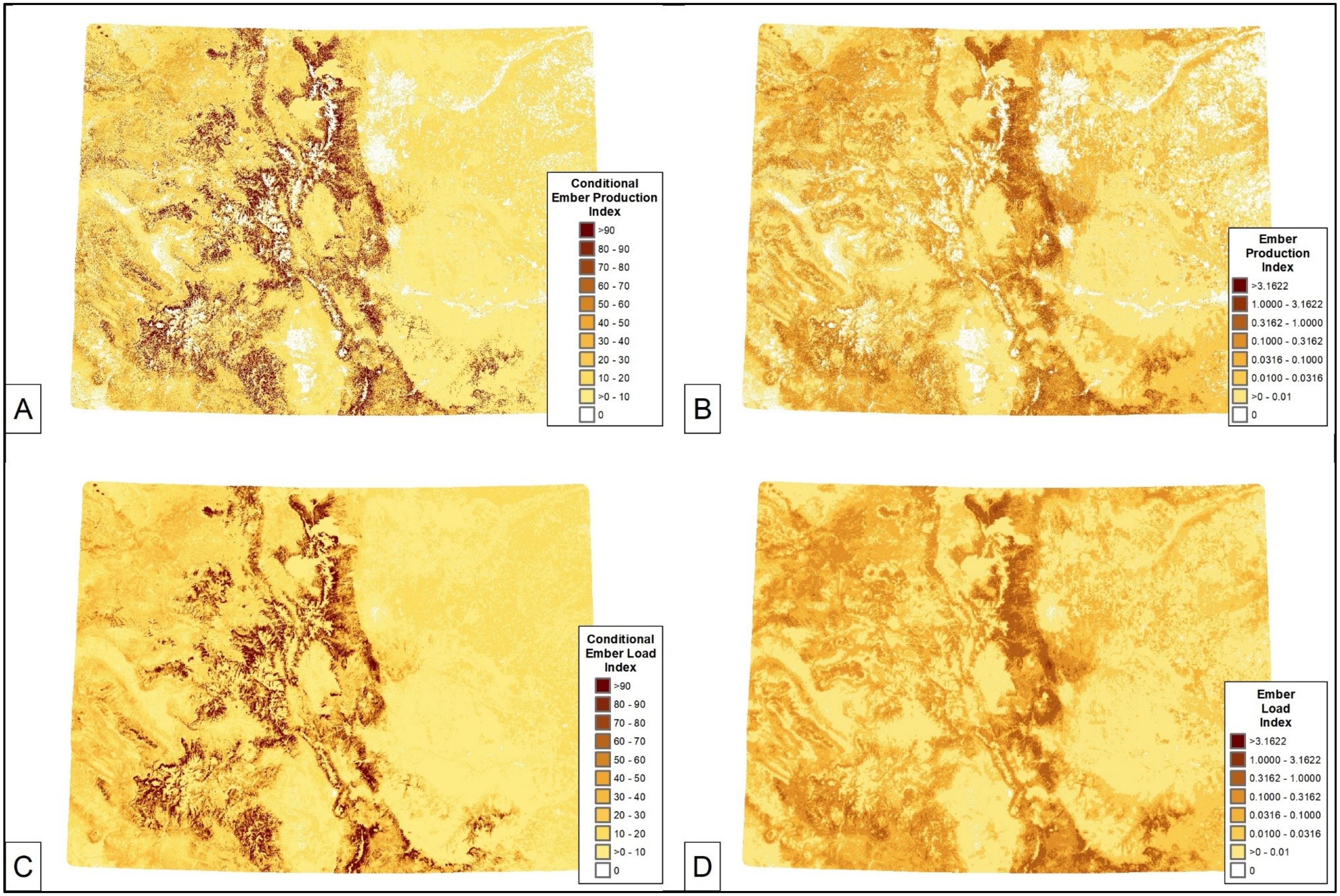

Figure 16. Map of WildEST 30-m ember indices for the COAL analysis area. These include (A) conditional Ember Production Index, (B) Ember Production Index, (C) conditional Ember Load Index, and (D) Ember Load Index.

4 INTEGRATED HAZARD

4.1 RISK TO POTENTIAL STRUCTURES (RPS)

Conditional risk to potential structures (cRPS) dataset represents the potential consequences of fire to a home at a given location if a fire were to occur and if a home were located there. It is a measure that integrates wildfire intensity with generalized consequences to a home on every pixel but does not account for the actual probability of fire occurrence.

The response function characterizing potential consequences to an exposed structure was applied to all burnable fuel types on the landscape regardless of whether an actual structure is present or not. The response function does not consider building materials of structures and is meant as a measure of the relative effect of fire intensity on structure exposure. The RPS response function is provided below:

Table 8. Risk to Potential Structures response function by flame length class.

Fire Intensity Level	Response Function value
0<FL<2	25
2<FL<4	40
4<FL<6	55
6<FL<8	70
8<FL<12	85
12<FL	100

These results were calculated using 30-m "fire-effects" flame-length probabilities from the WildEST wildfire behavior results and then smoothed into nonburnable areas to match the extent of the burn probability raster. A cRPS value of 0 means no damage to a structure, and a value of 100 represents a complete loss.

The expected risk to potential structures (RPS) dataset represents a measure that integrates wildfire likelihood and intensity with generalized consequences to a home on every pixel. For every place on the landscape, it poses the hypothetical question, "What would be the relative risk to a house or other structure if one existed here?" This allows comparison of wildfire risk in places where homes already exist to places where new construction may be proposed. RPS is calculated by multiplying conditional risk to potential structures (cRPS) and burn probability (BP):

$$RPS = cRPS * BP$$

Figure 17 and Figure 18 show cRPS and RPS, respectively.

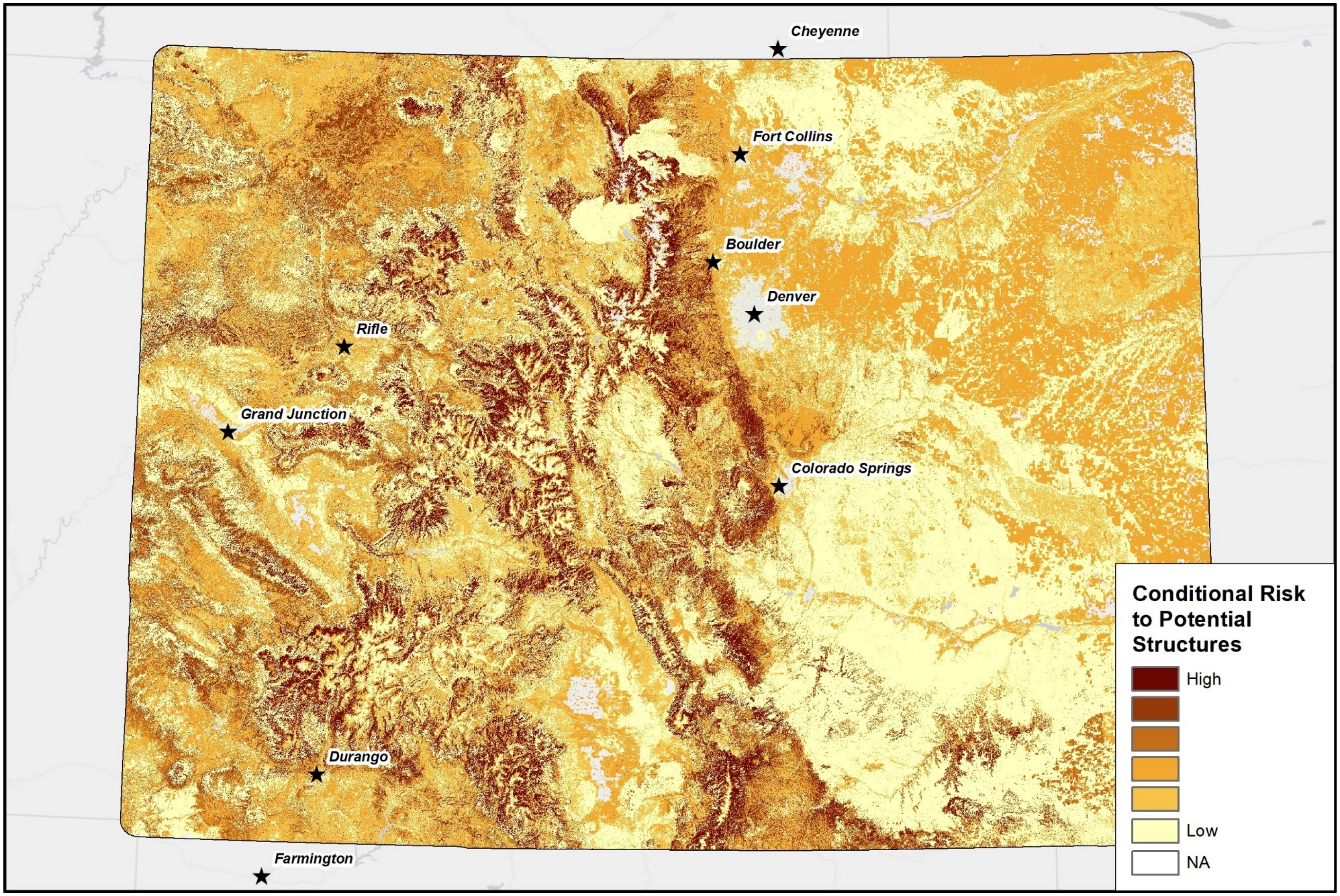

Figure 17. Map of 30-m resolution conditional Risk to Potential Structures for the COAL analysis area.

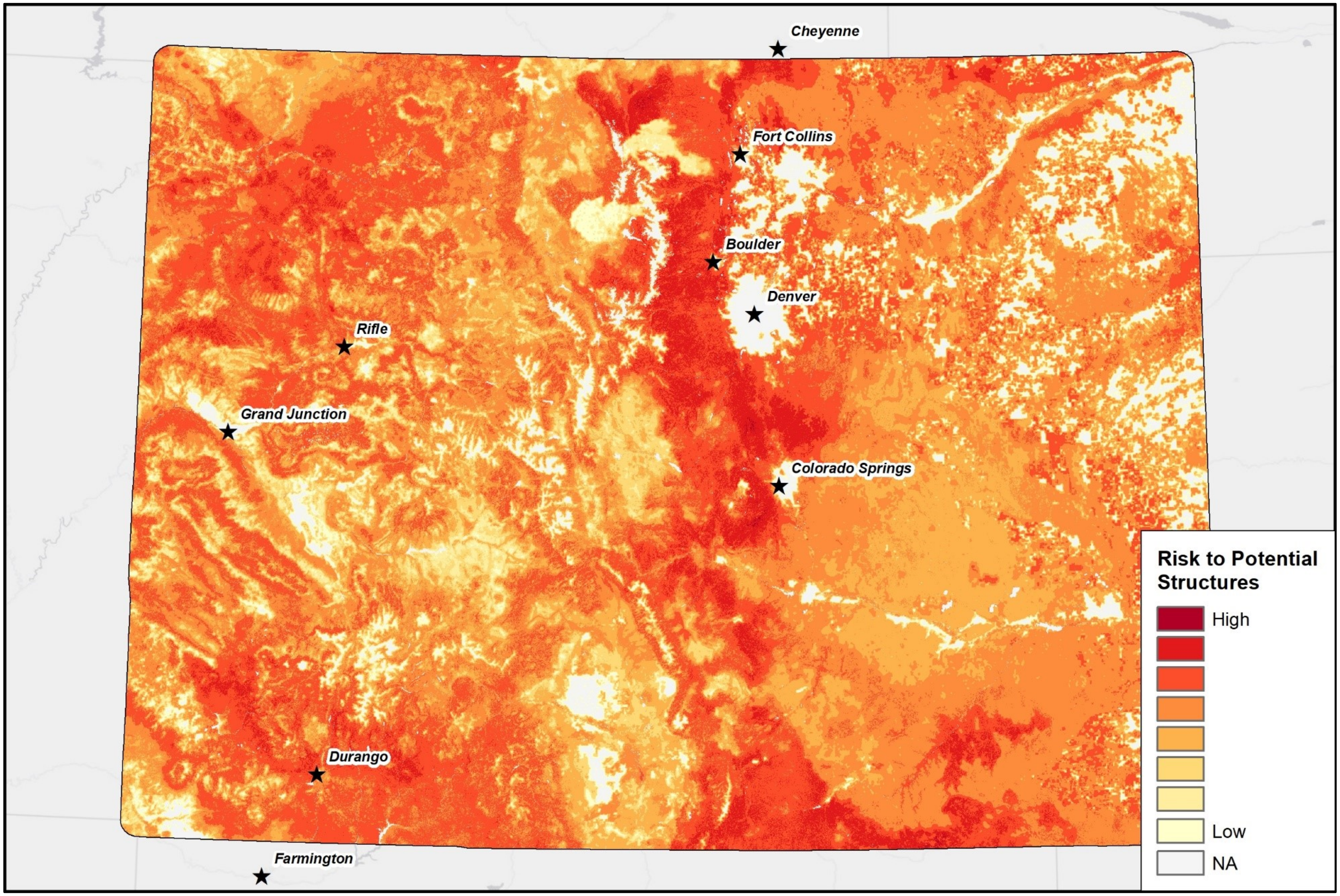

Figure 18. Map of 30-m resolution Risk to Potential Structures for the COAL analysis area.

4.2 WILDFIRE HAZARD POTENTIAL (WHP)

Wildfire Hazard Potential (WHP) is an index that quantifies the relative potential for wildfire that may be difficult to control. WHP can be used as a measure to help prioritize where fuel treatments may be needed to reduce the intensity of future wildfires.

We calculated WHP following the methods established by Dillon et al. (2015) and Dillon (2018). The original methods utilize lower-resolution FSim inputs, while our approach uses higher-resolution inputs including 30-m vegetation inputs (derived from LANDFIRE 2016), 30-m calibrated fuel model outputs, 30-m COAL burn probability results, and 30-m fire-effects flame-length probabilities from the WildEST wildfire behavior results. WHP is shown in Figure 19.

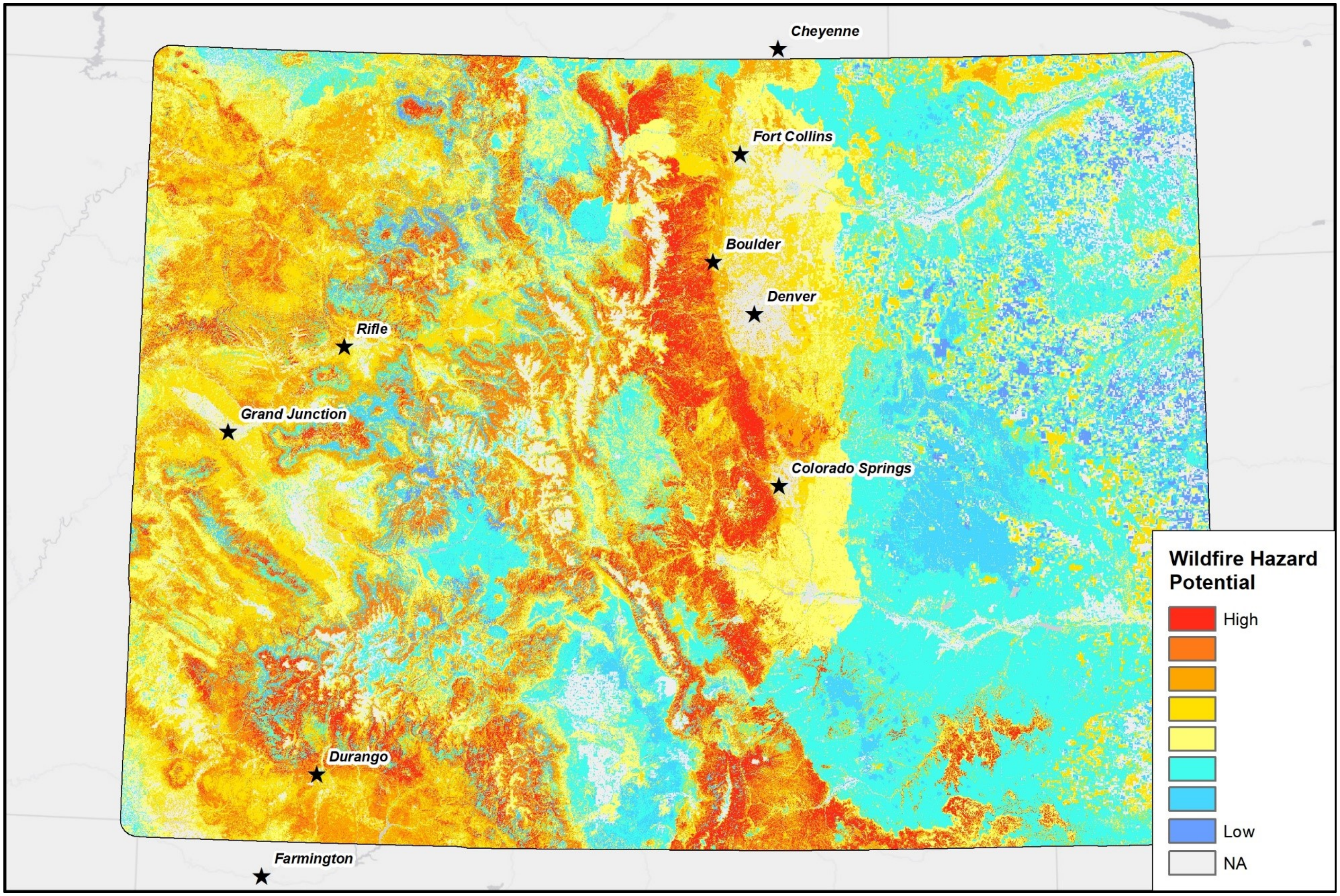

Figure 19. Map of 30-m resolution Wildfire Hazard Potential for COAL analysis area.

4.3 SUPPRESSION DIFFICULTY INDEX (SDI)

This dataset is a raster representing the Suppression Difficulty Index (SDI) across the project area. Wildfire Suppression Difficulty Index is a quantitative rating of the relative difficulty in performing fire control work. SDI factors in topography, fuels, expected fire behavior under severe fire weather conditions, firefighter line production rates in various fuel types, and accessibility (distance from roads/trails) to assess relative suppression difficulty.

We utilized the version of the SDI methods that was adopted for general use in the 2020 fire season. The SDI can be used to help inform strategic and tactical fire management decisions. Fire behavior inputs were modeled in WildEST at 30 m resolution, incorporating both temporal frequencies of weather types and the influence of high-spread conditions as well. Additional information on the SDI is available in O'Connor et al. (2016), Rodriguez y Silva et al. (2014), and Rodriguez y Silva et al. (2020). SDI is shown in Figure 20.

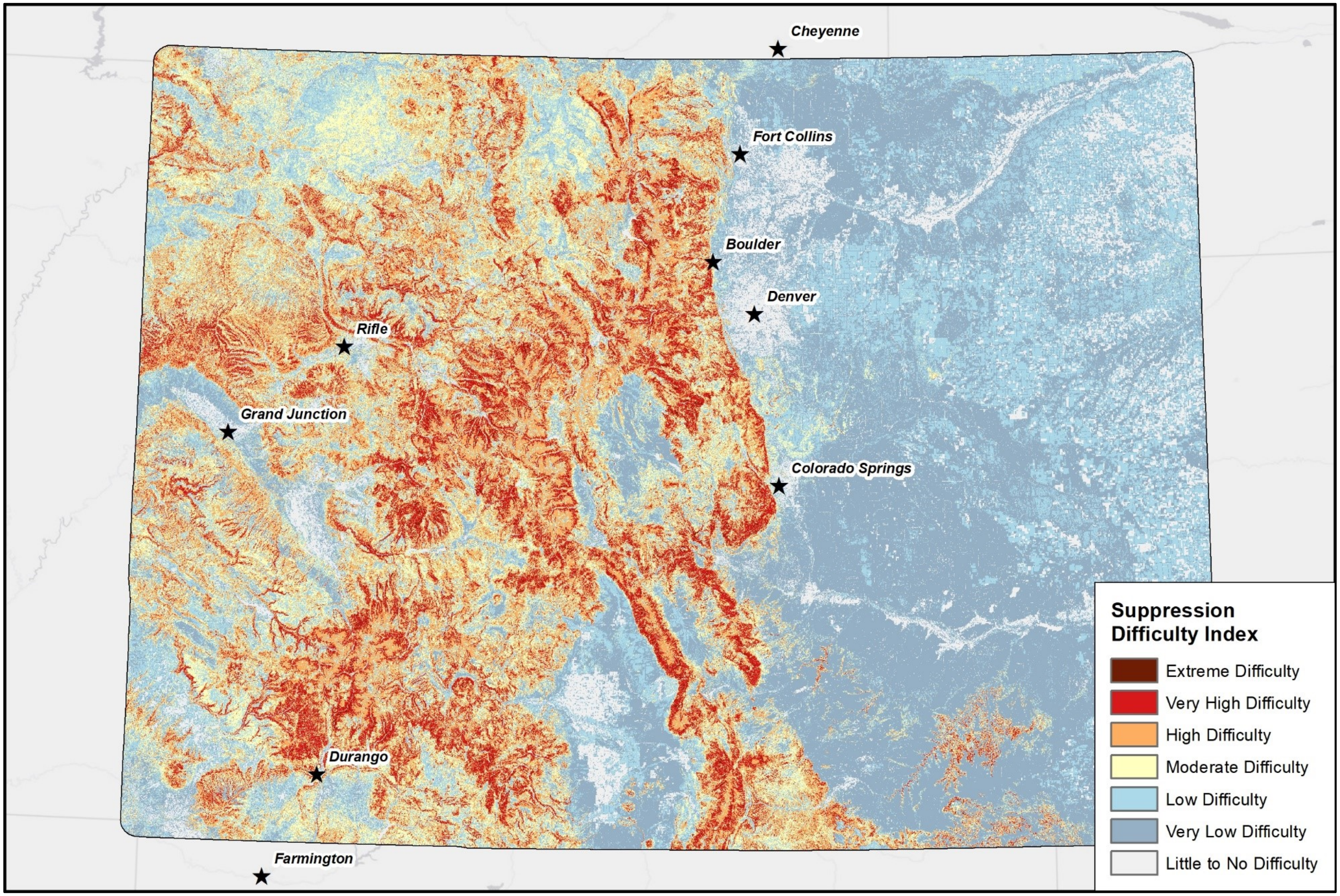

Figure 20. Map of 30-m resolution Suppression Difficulty Index for COAL analysis area.

5 DISCUSSION

The Colorado All-lands Wildfire Hazard Assessment, whose methods and results are described in this report, incorporated data sources and methods not previously used for an assessment of its size. This assessment relied on LANDFIRE's Remap (version 2.0.0) data for vegetation characteristics. The base LANDFIRE fuel mapping rules were critiqued and edited by local, state, and federal specialists. Substantial improvements were made over LANDFIRE's fuel mapping methods, allowing us to make the greatest use of the newly available Remap data.

The assessment relied on gridded, historical, weather data produced by gridMET (Abatzoglou 2013) used in the WildEST fire behavior calculations. This dataset, when processed to produce downscaled 30-m Weather-Type Probability rasters, generated seamlessly variable weather across the COAL analysis extent. We applied WildEST, a spatial wildfire characteristics simulation process based on FlamMap, at the native 30-m fuelscape resolution to provide fine-scale fire behavior results across the analysis area.

Finally, the wildfire likelihood simulation for this assessment was conducted to account for the statistical trends in fire occurrence evident in the historical record. Rather than "hindcasting" to the midpoint of the Fire Occurrence Database, we extrapolated the statistical trend to the year 2020, for which we expected variable annual area burned compared to the center of the reference period.

This report documents the wildfire hazard simulation portion of the project and represents the best available science across a range of disciplines. The results produced in this analysis provide a snapshot of wildfire hazard conditions before the 2021 fire season. While this report was generated by Pyrologix LLC, the overall analysis was developed as a collaborative effort with numerous agencies and partners providing data and feedback.

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7 DATA PRODUCTS

The Colorado All-Lands Wildfire Risk Assessment required the development of a wide range of data products. The section below outlines those datasets, with a brief description, based on provided data deliverables. More detailed descriptions of data product background and development procedures can be found in the metadata of each data product.

Data Product	Description
Annual burn probability raster (30m)	Subfolder 5.1 contains an upsampled, 30-m BP raster in standalone TIFF format and is the raster that should be used in standard applications. The subfolder also contains an ESRI ArcMap 10.3 layer file for recommended BP symbology.
Event set (minimum 10,000 years)	Subfolder 2.3.2 contains two ESRI 10.3 geodatabases that contain 10 feature classes each. The Ignitions geodatabase contains one FSim wildfire ignition event set feature class for each of the 10 COAL FOAs, and the Perims geodatabase contains one FSim wildfire perimeter event set feature class for each of the 10 COAL FOAs.
FSim Inputs	Subfolder 2.3.3.1 contains ten folders; one for each set of inputs used to run FSim for each COAL FOA.

Data Product	Description
Fire Behavior Modeling and Integrated Hazard	
Flame Front Characteristics	Subfolder 7.1 contains the 30-m rasters for: • weighted rate of spread (wROS) • weighted flame length (wFL) • weighted fireline intensity (wFLI) • weighted heat per unit area (wHPA) Each raster is in TIFF format. This subfolder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Fire-type probability (FTP)	Subfolder 7.2 contains six 30-m fire-effects flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for recommended symbology.
Operational Control Probabilities	Subfolder 7.3 contains the 30-m rasters for: • probability of manual control • probability of mechanical control • probability of extreme fire behavior Each raster is in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Fire-effects flame-length probabilities (FLPs)	Subfolder 7.4 contains six 30-m fire-effects flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for recommended symbology.
Head-fire flame-length probabilities (Ops FLPs)	Subfolder 7.5 contains six 30-m head-fire flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for recommended symbology.
Ember Production and Load Indices	Subfolder 7.6 contains the 30-m rasters for: • Conditional Ember Production Index (cEPI) • Ember Production Index (EPI) • Conditional Ember Load Index (cELI) • Ember load Index (ELI) Each raster is in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Integrated Hazard Products	Subfolder 5.3 contains four 30-m rasters in TIFF format: • Conditional Risk to Potential Structures (cRPS). • Expected Risk to Potential Structures (RPS). • Wildfire Hazard Potential (WHP) • Suppression Difficulty Index (SDI) The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for each raster with recommended symbology.

8 CHANGE LOG

The change log documents changes made to this document after the initial submission.

Date	Location of Change	Author	Description of Change
3/16/2022	-	-	Initial submission

THANK YOU

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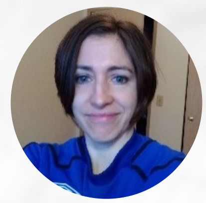

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The Colorado all-lands wildfire risk assessment was conducted by Pyrologix, a wildfire hazard and risk assessment research firm based in Missoula, Montana.

For More Information Please Visit:

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