

CONTEMPORARY WILDFIRE HAZARD ACROSS CALIFORNIA

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June 30, 2021

Last updated: July 13, 2021



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1 EXECUTIVE SUMMARY

In July 2019, the Pacific Southwest Region of the U.S. Forest Service contracted with Pyrologix to conduct a spatial wildfire hazard assessment across all land ownerships across the state of California. The project consisted of three parts: fuelscape calibration, wildfire hazard assessment, and summary of wildfire risk to California communities.

In early March 2020, just days before nationwide shutdowns due to Covid-19, Pyrologix led two in-person fuel calibration workshops hosted by the Region and attended by a wide array of local, state, and federal specialists in the fields of fuel characterization, fire ecology, and fire behavior modeling. By mid-summer 2020 Pyrologix produced a 2020 fuelscape. A report describing the methods used to produce the fuelscape is available for download here¹.

In the summer and fall of 2020, Pyrologix used spatial datasets of historical weather and fire occurrence to parameterize and calibrate a comprehensive USFS fire modeling system called FSim to estimate annual burn probability across California. FSim also produced an “event set” that was later used to estimate transmission of fire damage to homes—from the origin locations of simulated wildfires to where their damage occurred. During this time, 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 used several of the assessment results, in conjunction with a housing-unit density dataset (called HUDen²), to summarize wildfire risk to homes across California. Risk to homes was summarized for counties, county divisions, ZIP codes, and Census Populated Places and presented in a separate report entitled “Wildfire Risk to California Communities”³.

This report documents the wildfire hazard simulation portion of the project and represents the best available science across a range of disciplines. 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.

The results produced in this analysis provide a snapshot of wildfire hazard conditions before the 2020 fire season. Following the historic 2020 fire season in California, an update to these results is needed and is already underway. Additionally, a separate expanded effort to assess wildfire risk to homes, critical infrastructure, and surface drinking water is also underway.

¹ CAL Fuelscape report: http://pyrologix.com/wp-content/uploads/2021/06/CAL_FuelscapeReport.pdf

² HuDEN was produced for the Wildfire Risk to Communities project (wildfirerisk.org) and is available for download here: <https://www.fs.usda.gov/rds/archive/catalog/RDS-2020-0060>

³ <http://pyrologix.com/reports/Wildfire-Risk-to-California-Communities.pdf>

1.1 PURPOSE OF THE ASSESSMENT

The purpose of the California State Quantitative Wildfire Hazard Assessment report is to provide foundational information about wildfire hazard across the geographic area. Such information supports wildfire response, regional fuel management planning decisions, and revisions to land and resource management plans. The California State analysis considers:

- likelihood of a fire burning
- the intensity of a fire if one should occur.

To manage wildfire in California, it is essential that accurate 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.

1.2 QUANTITATIVE RISK MODELING FRAMEWORK

The basis for a quantitative framework for assessing wildfire risk to highly valued resources and assets (HVRAs) has been established for many years (Finney, 2005; Scott, 2006). The framework has been implemented across a range of scales, from an individual county (Ager, 2017), a portion of a national forest (Thompson et al., 2013a), individual states (Buckley et al., 2014), to the entire continental United States (Calkin et al., 2010). In this framework, wildfire risk is a function of two main factors: 1) wildfire hazard and 2) HVRA vulnerability (Figure 1).

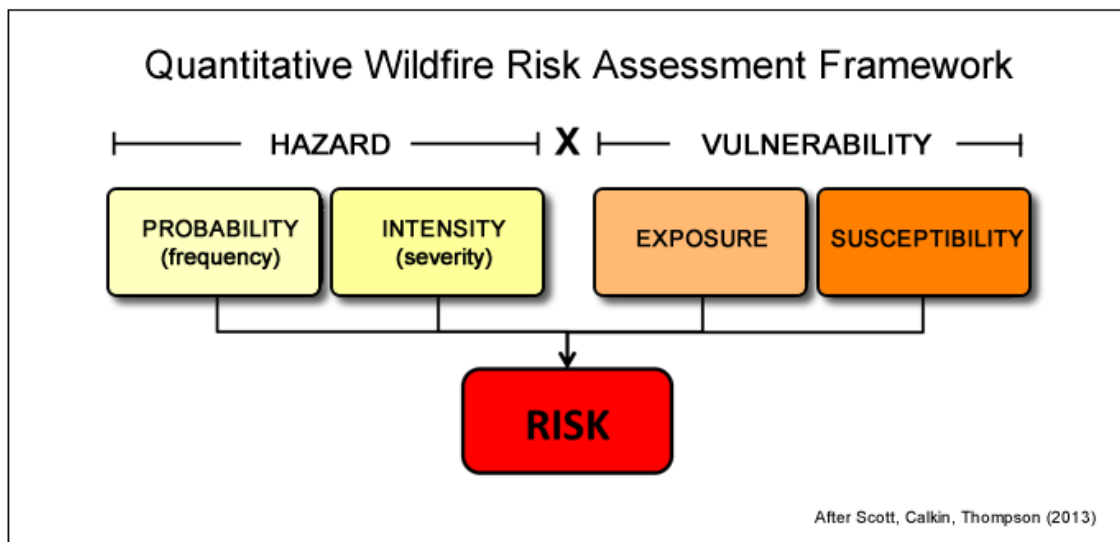


Figure 1. The components of a Quantitative Wildfire Risk Assessment Framework.

Wildfire hazard is a physical situation with the potential for causing damage to vulnerable resources or assets. Quantitatively, wildfire hazard is measured by two main factors: 1) burn probability (or likelihood of burning), and 2) fire intensity (measured as flame length, fireline intensity, or other similar measures).

HVRA vulnerability is also composed of two factors: 1) exposure and 2) susceptibility. Exposure is the placement (or coincidental location) of an HVRA in a hazardous environment—for example, building a home within a flammable landscape. Some HVRA, like wildlife habitat or vegetation types, are not movable; they are not "placed" in hazardous locations. Still, their exposure to wildfire is the wildfire hazard where the habitat exists. Finally, the susceptibility of an HVRA to wildfire is how easily it is damaged by wildfire of different types and intensities. Some assets are fire-hardened and can withstand very intense fires without damage, whereas others are easily damaged by even low-intensity fire.

This report will describe the data and methods used in developing estimates of wildfire probability and intensity for the California State analysis area.

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" (>247.1 acres). 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 California project area were run with 10,000 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 how a simulated wildfire might influence 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 result of wildfire likelihood.

In addition to estimates of wildfire likelihood, FSim produces measurements of predicted wildfire intensities. There are however inherent challenges of estimating intensity with a stochastic simulator. Estimates of wildfire intensity were instead developed using a custom Pyrologix utility

called WildEST (Scott, 2020). WildEST is a deterministic wildfire modeling tool that integrates variable weather input variables and weights them based on how they will likely be realized on the landscape. WildEST is 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

Project boundaries for the California State wildfire hazard assessment were developed to not introduce artificial seamlines during simulation modeling. The developed project boundaries that were used in the FSim modeling are described below in sections 2.2.1- 2.2.3 and can be seen in Figure 2.

2.2.1 ANALYSIS AREA

The Analysis Area is the area for which valid burn probability results are produced. The Analysis Area for the California project was defined as the California state boundary with a 10-kilometer buffer of adjacent lands within the United States.

2.2.2 FIRE OCCURRENCE AREAS

To ensure valid BP results in the Analysis Area and prevent edge effects, it is necessary to allow FSim to start fires outside of the Analysis Area 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 Analysis Area including a 30-km buffer beyond the U.S. border and into Mexico. The buffer provides

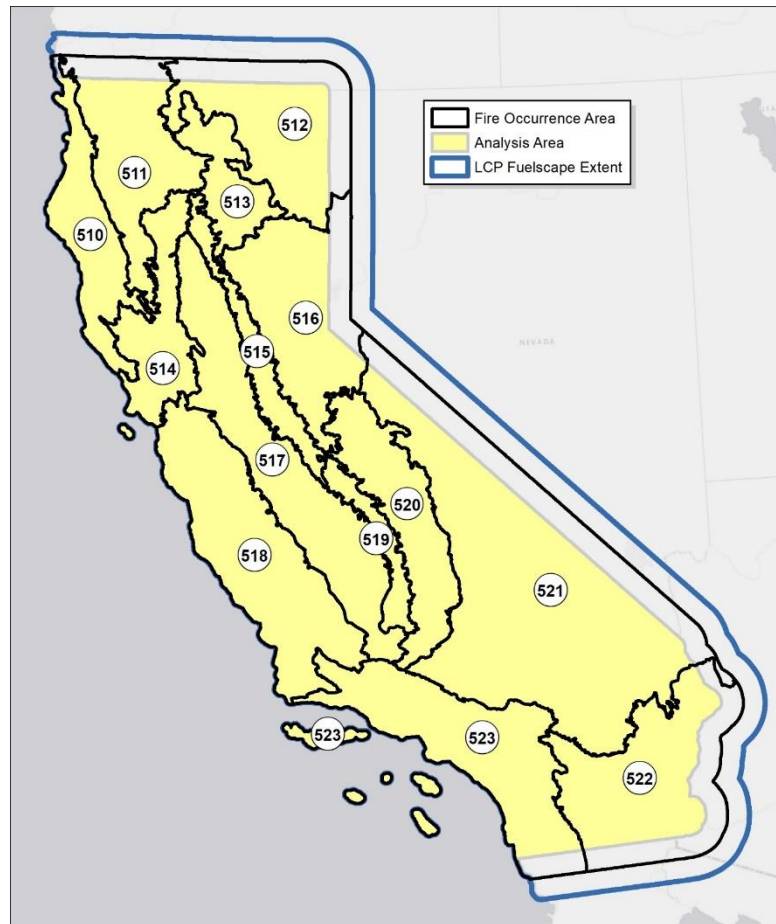


Figure 2 Overview of landscape zones for California State FSim project.

sufficient area to ensure all fires that could reach the Analysis Area are simulated. The Fire Occurrence Area covers roughly 124.1 million acres and is characterized by diverse topographic and vegetation conditions. We divided the overall fire occurrence area into fourteen 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 wildfire occurrence.

These boundaries were generated using a variety of inputs including larger fire occurrence boundaries developed for national-level work (Short, 2020), aggregated level IV EPA Ecoregions, and local fire staff input. For consistency with other FSim projects, we numbered these FOAs 510 through 523.

2.2.3 FUELSCAPE EXTENT

The available fuelscape extent was determined 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 and potentially introduce errors in the calibration process. A map of the Analysis Area, FOA boundaries, and fuelscape extent are presented in Figure 2.

2.3 ANALYSIS METHODS AND INPUT DATA

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 of wildfire across the landscape. Figure 3 below provides a graphical description of the various FSim inputs that are further discussed in Sections 2.3.1 - 2.3.4.

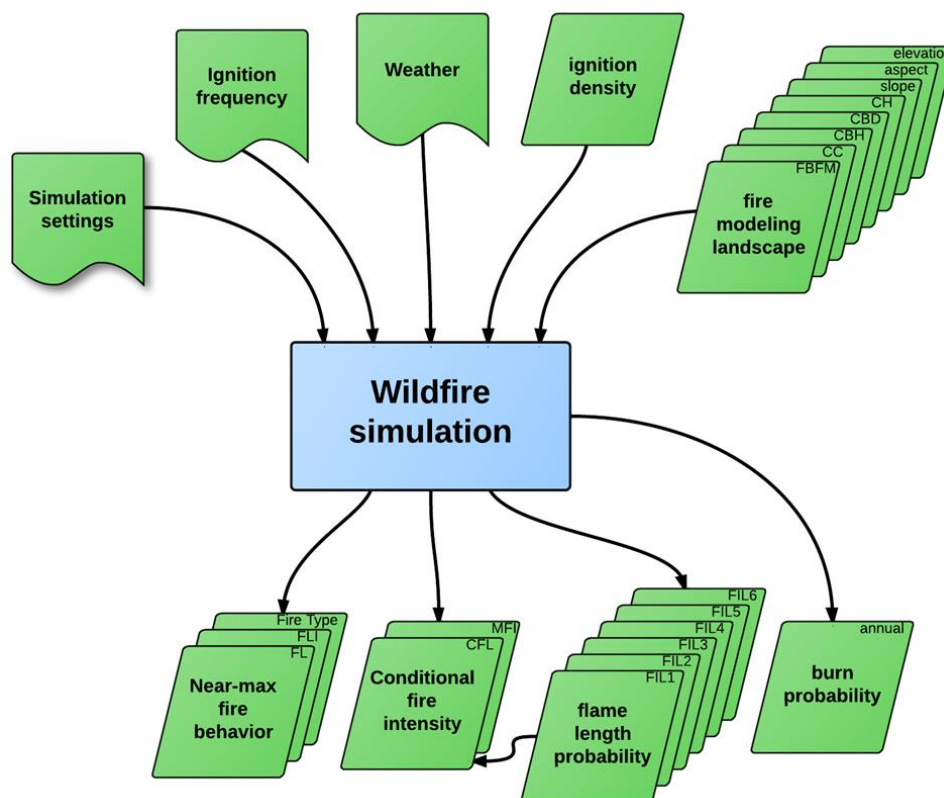


Figure 3. Diagram showing the primary elements used to derive burn probability

2.3.1 FUELSCAPE

The Pacific Southwest Region of the USDA Forest Service contracted Pyrologix to complete an assessment of wildfire hazard across all land ownerships in the state of California. 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 use in this statewide 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 4. The fuelscape datasets can be combined into a single landscape (LCP) file and 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, calibrated based on expert opinion at two fuel calibration workshops, and updated to represent the most recent fuel disturbances through the end of 2019. Further details about the methods and base data used to generate the calibrated California all lands fuelscape are available in the fuelscape report¹.



Figure 4. Map of fuel model groups across the California State LCP extent.

2.3.2 HISTORICAL WILDFIRE OCCURRENCE

The Fire Occurrence Database (FOD) that spans the 26 years from 1992-2017 was used to quantify historical large-fire occurrence (Short, 2017). Historical wildfire occurrence data were used to develop model inputs (the fire-day distribution file [FDist] and ignition density grid [IDG]) as well as model calibration targets. Table 1 summarizes 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. For this analysis, we defined a large fire as one greater than 247.1 acres (100 hectares).

Table 1. Historical large-fire occurrence, 1992-2017, in the California 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
510	2.96	5.39	0.55	3,513	10,403	0.0019
511	9.58	7.78	1.23	11,249	107,731	0.0138
512	7.08	9.25	0.76	5,971	42,253	0.0046
513	2.12	3.43	0.62	4,214	8,915	0.0026
514	5.58	4.91	1.14	5,432	30,296	0.0062
515	6.62	2.88	2.30	3,548	23,472	0.0082
516	12.31	9.32	1.32	5,827	71,713	0.0077
517	10.04	10.97	0.92	1,173	11,776	0.0011
519	13.50	11.51	1.17	5,263	71,056	0.0062
520	5.54	1.87	2.96	1,536	8,507	0.0045
521	9.77	6.57	1.49	4,321	42,208	0.0064
522	7.35	27.64	0.27	2,769	20,338	0.0007
523	3.27	11.45	0.32	1,419	4,640	0.0005

Historical wildfire occurrence varied substantially by FOA (Table 1), with FOA 519 experiencing the highest annual average of 2.96 large wildfires per million acres. FOA 521 had the least frequent rate of occurrence with an annual average of 0.27 large wildfires per million acres. FOA 511 has the largest mean large-fire size of 11,249 acres while FOA 517 had the smallest with 1,173 acres.

2.3.2.1 IGNITION DENSITY GRID

To account for the spatial variability in historical wildfire occurrence across the landscape, FSim uses a geospatial layer representing the relative, large-fire ignition density. FSim stochastically places wildfires according to this density grid during simulation. The entire landscape is saturated with wildfire over the 10,000 simulated iterations, but more ignitions are simulated in areas that have previously allowed for large-fire development.

The Ignition Density Grid (IDG) was generated using a mixed-methods approach by averaging the two grids resulting from the Kernel Density tool and the Point Density tool within ArcGIS for a 120-m cell size and 75-km search radius. All fires equal to or larger than 247.1 acres (100 ha) reported in the FOD were used as inputs to the IDG. A map of the developed IDG input can be seen in Figure 5. 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 burnable urban 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.

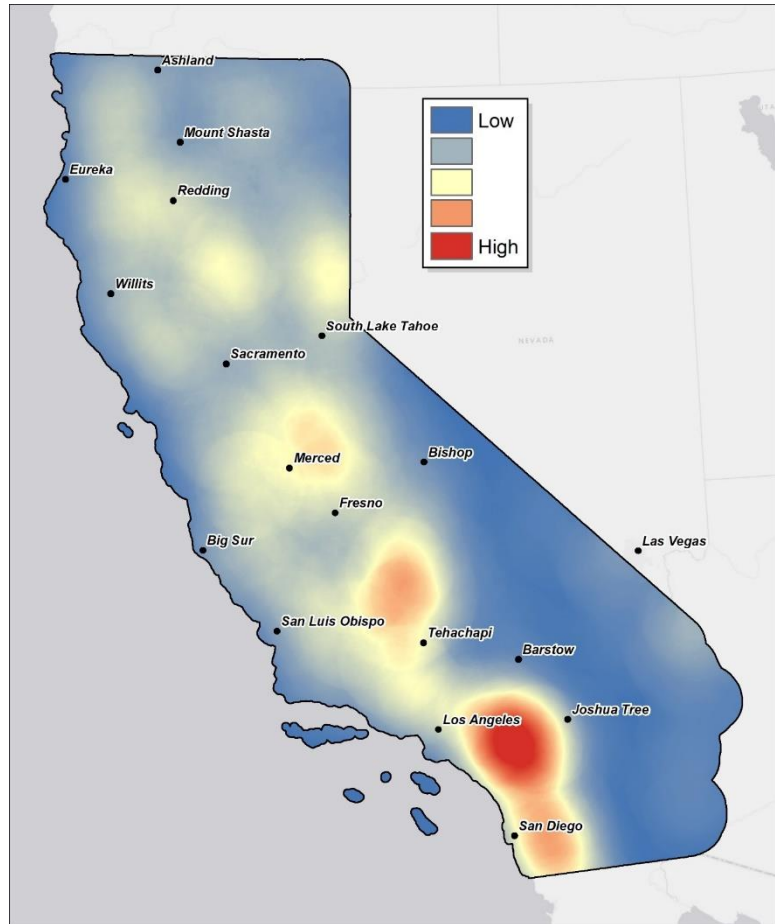


Figure 5. Shows the Ignition Density Grid for the California State Fire Occurrence Area.

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 California State 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 upwards trend in wildfire occurrence across California, the fourteen 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 6.

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 7 - Figure 9). The grey line in each graph represents an estimate of the total area burned per year. Rather than “hindcasting” to the midpoint of the Fire Occurrence Database, we extrapolated the statistical trend to the year 2020, for which we expected roughly twice the annual area burned compared to the center of the reference period. 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.

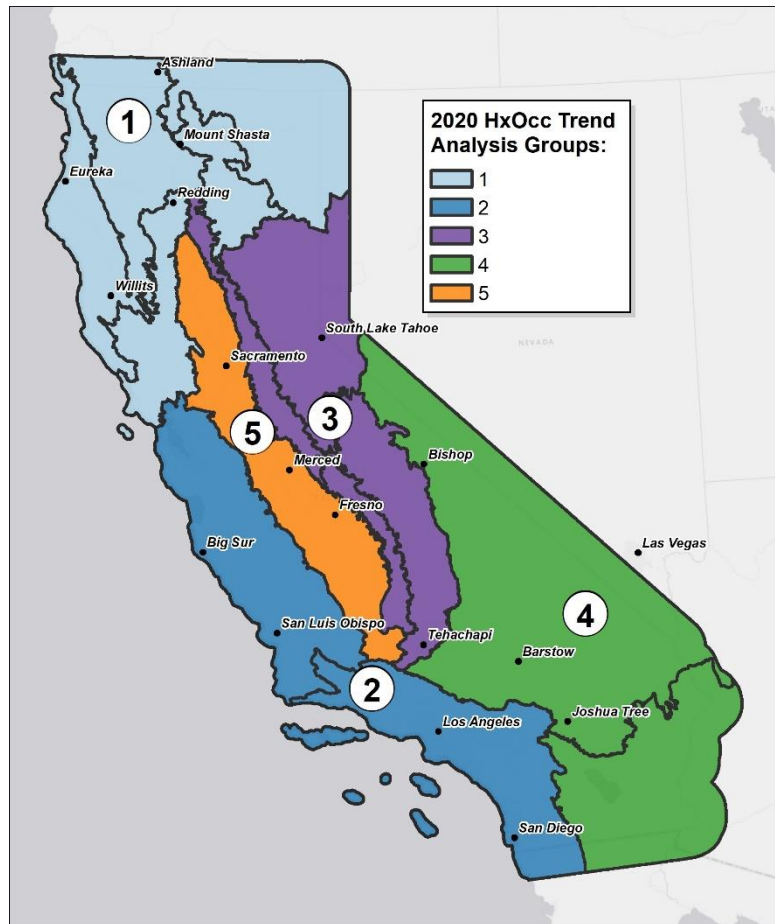


Figure 6. Historical Analysis Groups used in 2020 Trend Analysis.

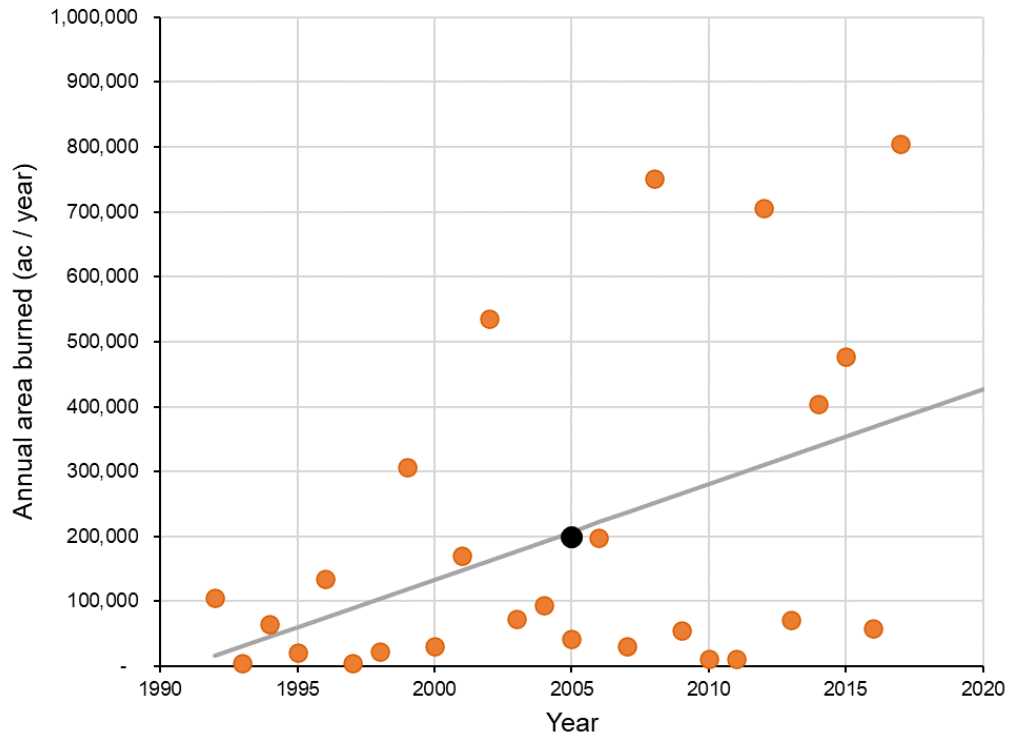


Figure 7. Historical Wildfire Occurrence (1992 - 2017) in analysis Group 1.

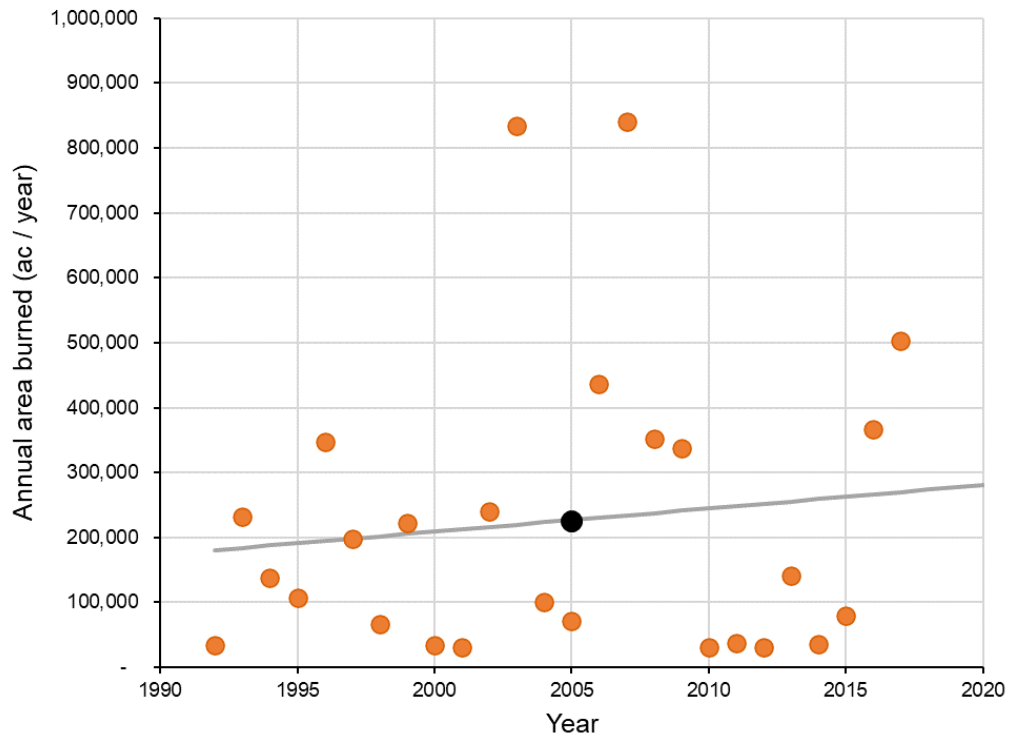


Figure 8. Historical Wildfire Occurrence (1992 - 2017) in analysis Group 2.

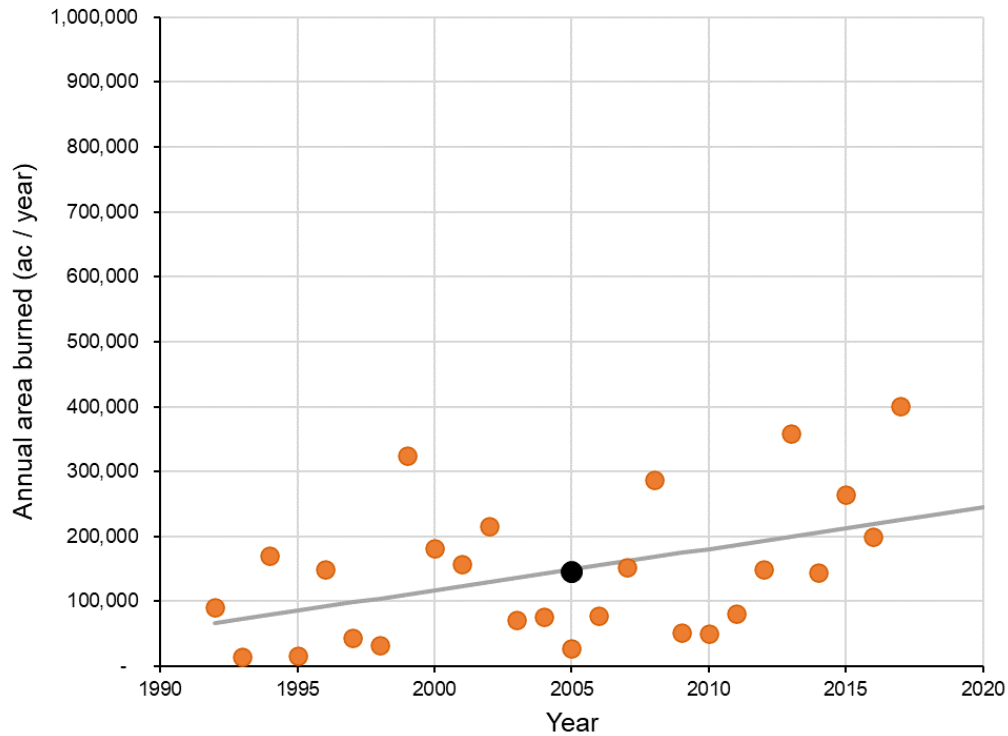


Figure 9. Historical Wildfire Occurrence (1992 – 2017) in analysis Group 3

The difference in the mean number and size of wildfires per FOA as compared to the Fire Occurrence Database mean (1992-2017) is represented in Table 2. There was no trend found in the historical occurrence groups 4 and 5. There was, however, a strong upward trend in total overall occurrence in groups 1, 2, and 3 as seen in Figure 7 - Figure 9. Calibrating to the 2020 FOD trend resulted in an increase of 1.68-2.14X in the area burned in Groups 1-3. 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	North Coast, Klamath Mountains, and Modoc	2.02	1.35	2.14
2	South Coast and Transverse Ranges	2.47	0.55	1.25
3	Sierra Nevada	1.65	0.98	1.68
4	Mojave Desert	1.00	1.00	1.00
5	Central Valley	1.00	1.00	1.00

2.3.3 HISTORICAL WEATHER

Weather information was sampled from the California 2-km gridded hourly weather data product generated by the Desert Research Institute using the Weather Research and Forecasting weather model (version 3.5.1; Skamarock et al. 2008). From the original gridded raster data set, 168 sample points were extracted and assigned to individual Sub-FOAs. 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.

For the wind speed and direction distributions, we used the hourly (1200 to 2000 hours), 10-minute average values (2 mph calm wind) from each weather sample point. The values from an individual sample point were averaged equally for mean wind speed and direction with all extracted sample points within a FOA. This method prevented seamlines between Sub-FOAs while also allowing for additional spatial resolution of weather data not before implemented in the FSim model. Additionally, ERCs values were extracted from a representative sample point within a Fire Occurrence Area and used for each Sub-FOA within that FOA. The Wind and ERC sample points are shown in Figure 10, and the FSim inputs developed from the gridded base data are discussed further in the following sections (2.3.3.1 - 2.3.3.4).

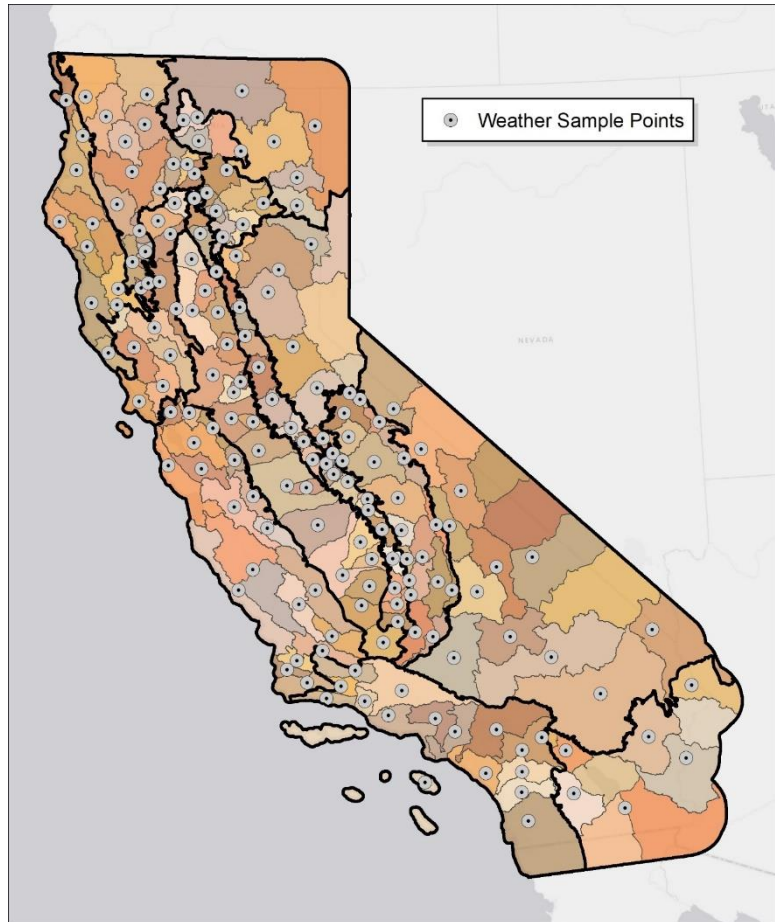


Figure 10. Sample points from the 2-km gridded hourly WRF dataset generated by DRI.

2.3.3.1 FIRE-DAY DISTRIBUTION FILE (FDIST)

Fire-day Distribution files are used by FSim to generate stochastic fire ignitions as a function of ERC. The FDist files were generated using an R script that summarizes historical ERC and wildfire occurrence data, performs logistic regression, and then formats the results into the required FDist format.

The FDist file provides FSim with logistic regression coefficients that predict the likelihood of a large fire occurrence based on the historical relationship between large fires and 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 extracted sample point using FireFamilyPlus version 4.1 and updated to incorporate extracted ERC percentiles (as described in section 2.3.3.4). These files summarize the historical ERC stream for the FOA, along with wind speed and direction data.

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 3).

Table 3. 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	5 / 4 / 3	6 / 5 / 4	7 / 6 / 5	90 / 65 / 45	110 / 100 / 90
Timber / Slash	7 / 6 / 5	8 / 7 / 6	9 / 8 / 7	90 / 65 / 45	110 / 100 / 90
Burnable Urban	45 / 45 / 6	45 / 45 / 7	45 / 45 / 8	120 / 120 / 65	110 / 100 / 100

Fuel moistures in the custom Burnable Urban (FM 251 & 252) fuel models were set above the moisture of extinction for the 80th and 90th percentile ERC bins. This was done to only allow a simulated wildfire to burn within these fuel groups under the most extreme weather conditions (97th percentile). This method maintains the potential for high modeled fire intensity while not vastly over-predicting burn probability.

2.3.3.4 ENERGY RELEASE COMPONENT FILE (ERC)

We sampled historical ERC-G values from the California 2-km gridded hourly weather data product generated by the Desert Research Institute using the Weather Research and Forecasting weather model (version 3.5.1; Skamarock et al. 2008). These values were used to generate a FRISK file. A 1,000 iteration FSim run was then simulated with each FRISK file to generate a sample of 365,000 days of ERCs for each FOA. The generated ERC stream was used in each Sub-FOA within a FOA to provide a “coordinated” ERC stream across the Fire Occurrence Area. The simulated ERC values

are “coordinated” so a given year and day for one Sub-FOA corresponds to the same year and day in all SubFOAs within a given FOA. It should be noted that this method does not allow for the coordination of ERCs between Fire Occurrence Areas.

2.3.4 SUPPRESSION MODELING

FSim contains a suppression or containment module that simulates the likelihood that, on any given day of a simulation, the modeled wildfire will be contained and therefore no longer grow on subsequent days. The suppression module also includes a perimeter trimming algorithm that simulates progressive containment of a fire perimeter over time. The suppression module, therefore, shortens the duration of a wildfire and keeps the overall size smaller for a given duration. To represent suppression efforts more accurately across the state, the trimming algorithm or suppression factor (SF) was adjusted spatially by Direct Protection Area (DPA). Each Sub-FOA was assigned a SF based on a weighted average of the relative coverage of various DPAs where: Federal-USFS received a SF of 3.0, Federal-Other (BLM, NPS, USFW, etc.) 2.0, Local 1.5, and State 2.0. The FSim model was ultimately

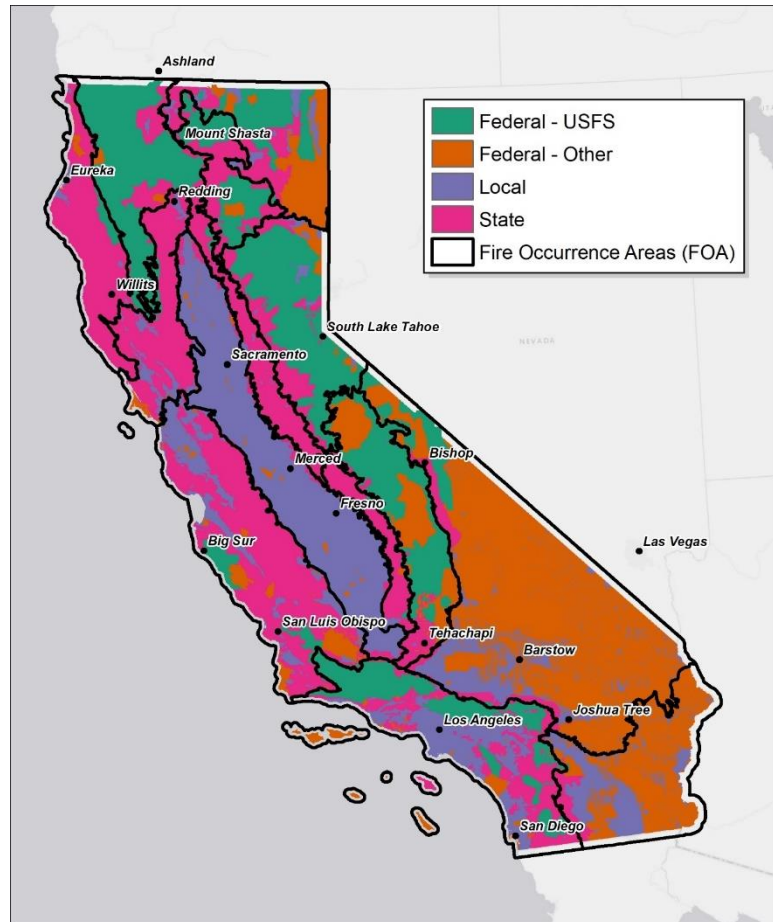


Figure 11. Map of Direct Protection Area (DPA) for the California State analysis area.

calibrated to the number and size (adjusted to account for the 2020 trend analysis) of wildfires within the historical occurrence record. However, accounting for the spatial variability in SF by DPA improves the accuracy of modeled wildfire perimeters as well as the distribution of burn probability with a Fire Occurrence Area. A map of Direct Protection Areas within California can be seen in Figure 11.

2.4 WILDFIRE SIMULATION

The FSim large-fire simulator was used to quantify wildfire hazard across the landscape at a pixel size of 120m (4 acres per pixel). 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).

Due to the highly varied nature of weather and fire occurrence across the large landscape, we ran FSim for each of the fourteen FOAs independently and then compiled the fourteen 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 upward 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 10,000 iterations. The fourteen FOAs were then integrated into an overall result for the analysis area.

2.4.2 INTEGRATING FOAS

We used the natural-weighting method of integrating adjacent FOAs that we developed on an earlier project (Thompson et al., 2013b). With this method, well within the boundary of a FOA (roughly 30 km from any boundary), the results are influenced only by that FOA. Near the border with another FOA, the results will be influenced by that adjacent FOA. The weighting of each FOA is in proportion to its contribution to the overall burn probability at each pixel.

2.5 WILDFIRE MODELING RESULTS

The FSim model produces estimates of burn probability as well as measures of fire intensity including flame length exceedance probability, conditional flame length, 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. FSim generated 120-m resolution estimates of burn probability. These results were further downscaled to 30-m resolution using a methodology described in section 2.5.1 and presented in Figure 12.

2.5.1 UPSAMPLING FSIM RESULTS

FSim's stochastic simulation approach can be computationally intensive and therefore, time constraining on large landscapes. A challenge, therefore, 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 120-m FSim 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, the lowest BP value resulting from our FSim simulations) 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).

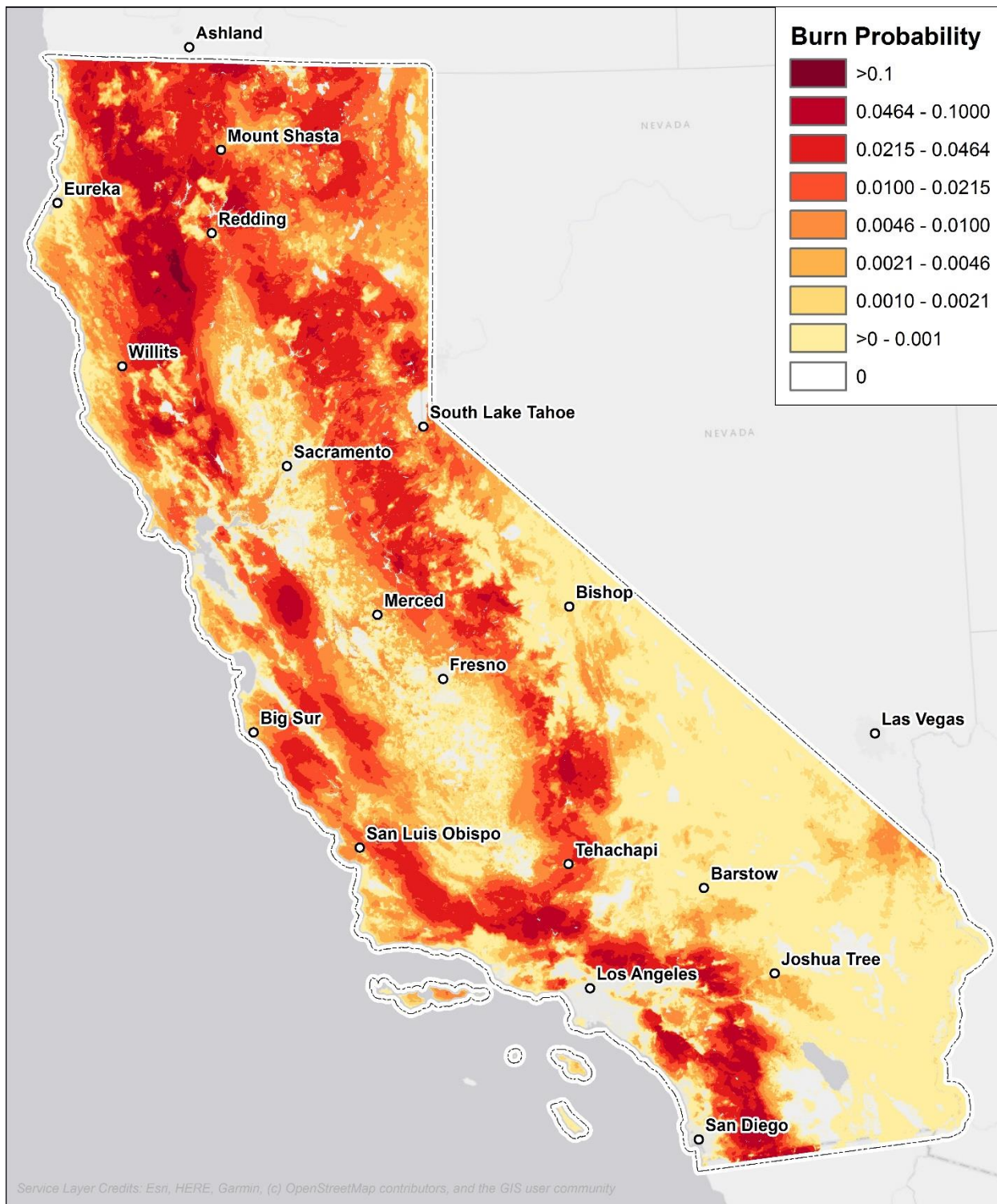


Figure 12. Map of integrated FSim burn probability results for the California study area at 30-m resolution.

3 WILDFIRE BEHAVIOR CHARACTERISTICS

3.1 OVERVIEW OF METHODS

To estimate wildfire characteristics across California 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, wind direction, 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 this weather type probability (WTP) weighting process in WildEST to produce headfire 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 - 3.3.2.

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 run for the main FSim fire occurrence modeling. For national-scale projects the resolution is 270 m; for CAL the resolution was 120 m. Even though fuelscape information is available from LANDFIRE at 30-m resolution,

FSim cannot use that resolution due to excessive run time. In contrast, WildEST can run on large landscapes at 30-m resolution.

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 FIL, 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 different FLPs for the same pixel.

WildEST is deterministic, so it does not suffer from a Monte Carlo simulator's sample-size problem. And WildEST can be used to generate both headfire 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. FSim has limited support for applying terrain-adapted winds using WindNinja.

WildEST uses gridded historical weather data at a spatial resolution of 2 km for CAL (coarser for areas outside of California). 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 topology⁴ on fire intensity. For example, the land on the lee side of a large nonburnable feature (such as a lake, for

⁴ Fire spread topology is the network of possible fire spread pathways given the fire environment.

example) is less likely than other land to experience a headfire, because a headfire cannot spread across the lake; instead, a fire must flank past 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, 2-km gridded, hourly weather data produced by the Desert Research Institute using the Weather Research and Forecasting (WRF) weather model (version 3.5.1; Skamarock et al. 2008), covering the period 2003-2018, to generate 30-m resolution Weather-Type Probability (WTP) rasters seamlessly covering the state. For each hour in the 2003-2018 timeframe, we first calculated an area burned index (ABI) as follows:

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

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 MPH, and burn minutes is defined from a lookup table (Table 4) as a function of wind speed and daily Energy Release Component percentiles.

Table 4. Burn minutes table for calculating area burned index (ABI).

Wind Speed Bin (MPH)	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 hourly ABI values were then summed across the timeframe within specific weather scenarios, which are defined by wind speed, wind direction, and moisture condition bins.

There are nine wind speed bins:

0-3, 3-8, 8-13, 13-18, 18-23, 23-28, 28-33, 33-38, and \geq 38 MPH

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, 292.5-337.5⁰

And there are three 1-hr timelag moisture content bins:

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

The combination of wind speed, wind direction, and moisture content classes results in a total of 216 unique weather scenarios. Note that if fine dead fuel moisture content was above 12% or the ERC value was below 40, then the ABI values for those conditions were not included in the sums.

The total ABI was calculated for each weather scenario and normalized by the total ABI for all weather scenarios for a given 2-km pixel. These percentages were smoothed and upsampled to 30-m resolution using a 1-km radius circular window and snapped to the fuel model raster. The percentage rasters were renormalized once more after upsampling to 30 m to ensure the sum of WTPs across all weather types summed to one in each 30-m pixel.

The WTPs differ from the simple temporal relative frequency (TRF) of each weather type. That is because a weather type is weighted not only by how often it occurs in the weather record (TRF) but also by the relative area burned for that weather type (ABI). The TRFs are inherently incorporated into the WTP rasters by taking the sum of ABI. A given weather type will be weighted higher for higher wind speed, higher ERC, and higher SPI. These WTP rasters are used with subsequent FlamMap fire modeling as weighting factors on fire characteristics.

3.2 FLAME FRONT CHARACTERISTICS

The WildEST flame front characteristics include headfire rate of spread and headfire flame length, as well as conditional probabilities for fire type, operational control, and headfire 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 (seam lines) in the fuelscape and in the WTPs. As a result, the headfire 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 14). 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 15). 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%). 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 5):

1. Non-fuel
2. Surface fire
3. Underburn⁵
4. Low-grade passive crown fire
5. Mid-grade passive crown fire
6. High-grade passive crown fire
7. Active crown fire

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 nonburnable).

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 overall rate of spread and intensity.

⁵ The term underburn is used rather than surface fire to distinguish from the situation where there is no forest canopy present.

Table 5. 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 16.

3.2.4 PROBABILITY OF OPERATIONAL CONTROL

Operational-control probability rasters indicate the probability that the headfire 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 headfire 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 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 17.

3.2.5 HEADFIRE FLAME-LENGTH PROBABILITIES (OPS FLPS)

Headfire flame-length probabilities incorporate only the headfire spread direction and are therefore recommended for use in operational settings (Ops FLPs); they characterize more conservative estimates of hazard by 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. Headfire flame-length probabilities are shown in Figure 18.

3.2.6 “FIRE-EFFECTS” FLAME-LENGTH PROBABILITIES

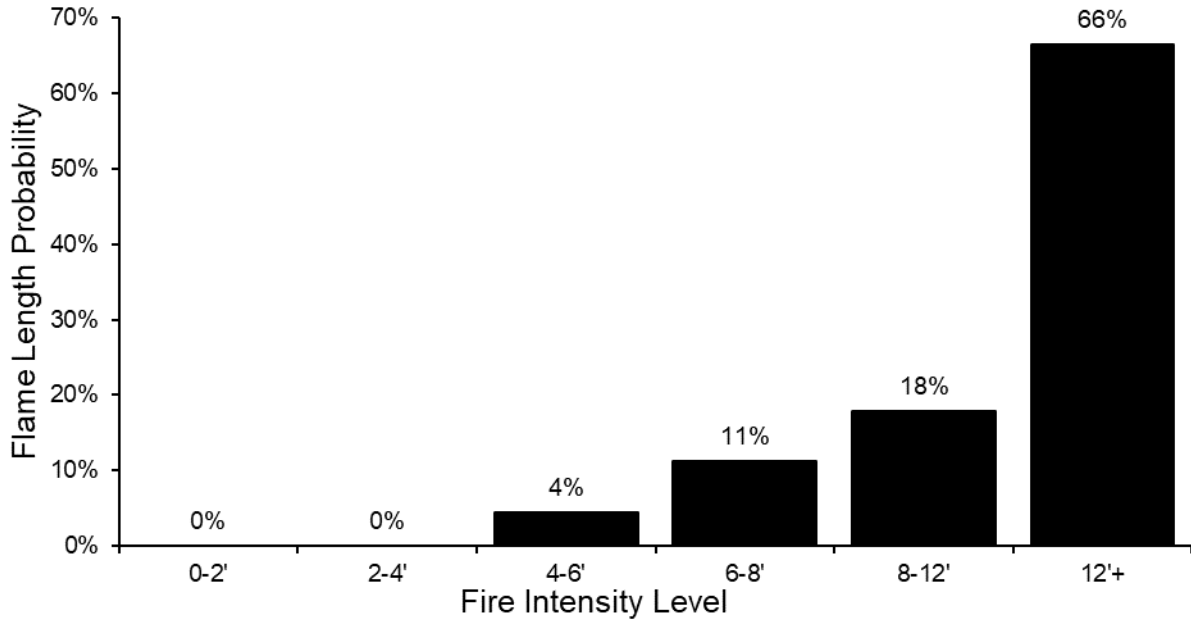
All the WildEST results described thus far above apply to the head of a fire, but a free-burning wildfire spreads in all directions and therefore exhibits a range of flanking and backing behavior in addition to heading behavior. Flanking and backing fires exhibit a lower spread rate and intensity than 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 headfire spread and intensity, so we apply adjustments to headfire 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 13, 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/m³. For that fuel complex (and for the climatology of that location), we estimate that headfire flame length will exceed 12 feet 66% 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% of the time and will be lower than four feet 5% 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 and others 2013). These fire-effects FLPs are a close analog to FSim’s FLPs and are used for the same purpose.

Like the headfire 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 19.

Headfire Flame Lengths



Nonheading Flame Lengths

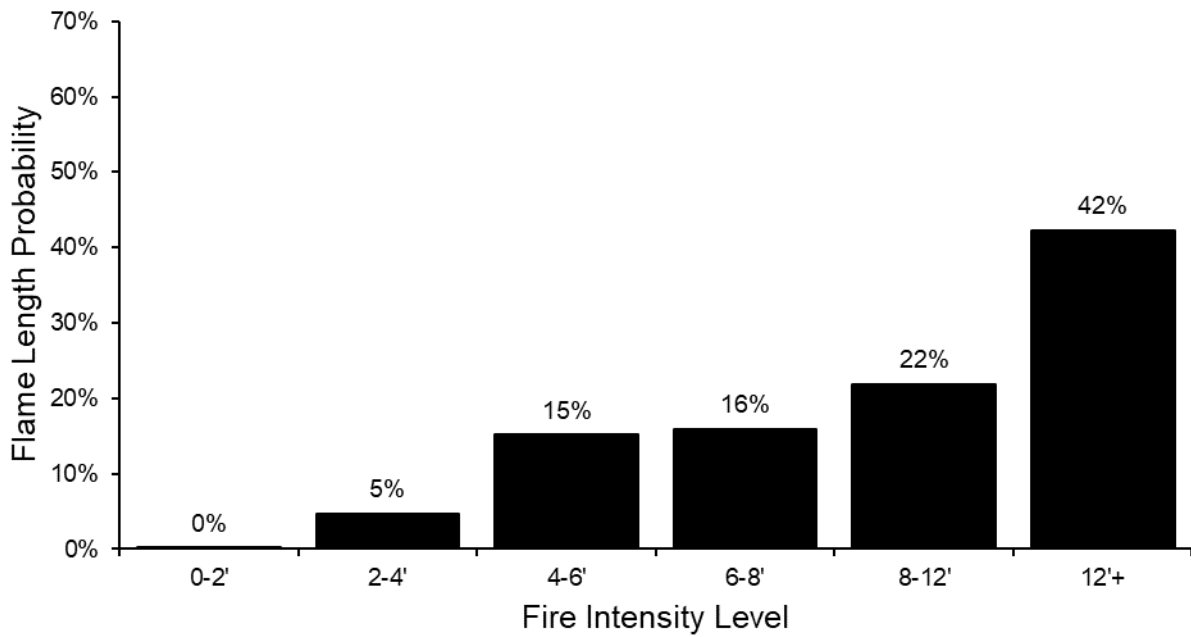


Figure 13. Headfire flame-length probabilities (top) and non-heading (or “fire effects”) flame-length probabilities (bottom).

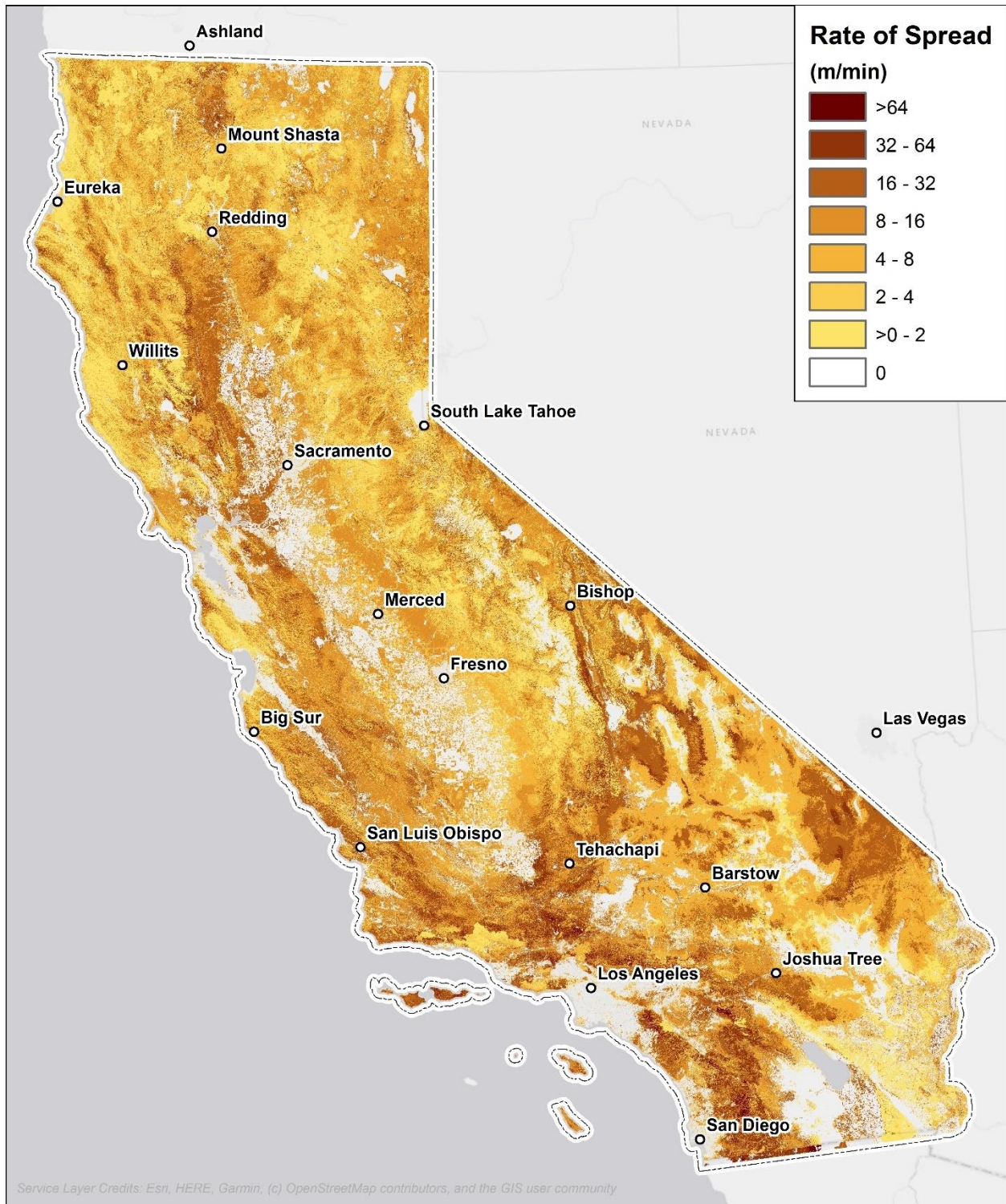


Figure 14. Map of WildEST 30-m Rate of Spread (m/min) for the CAL analysis area.

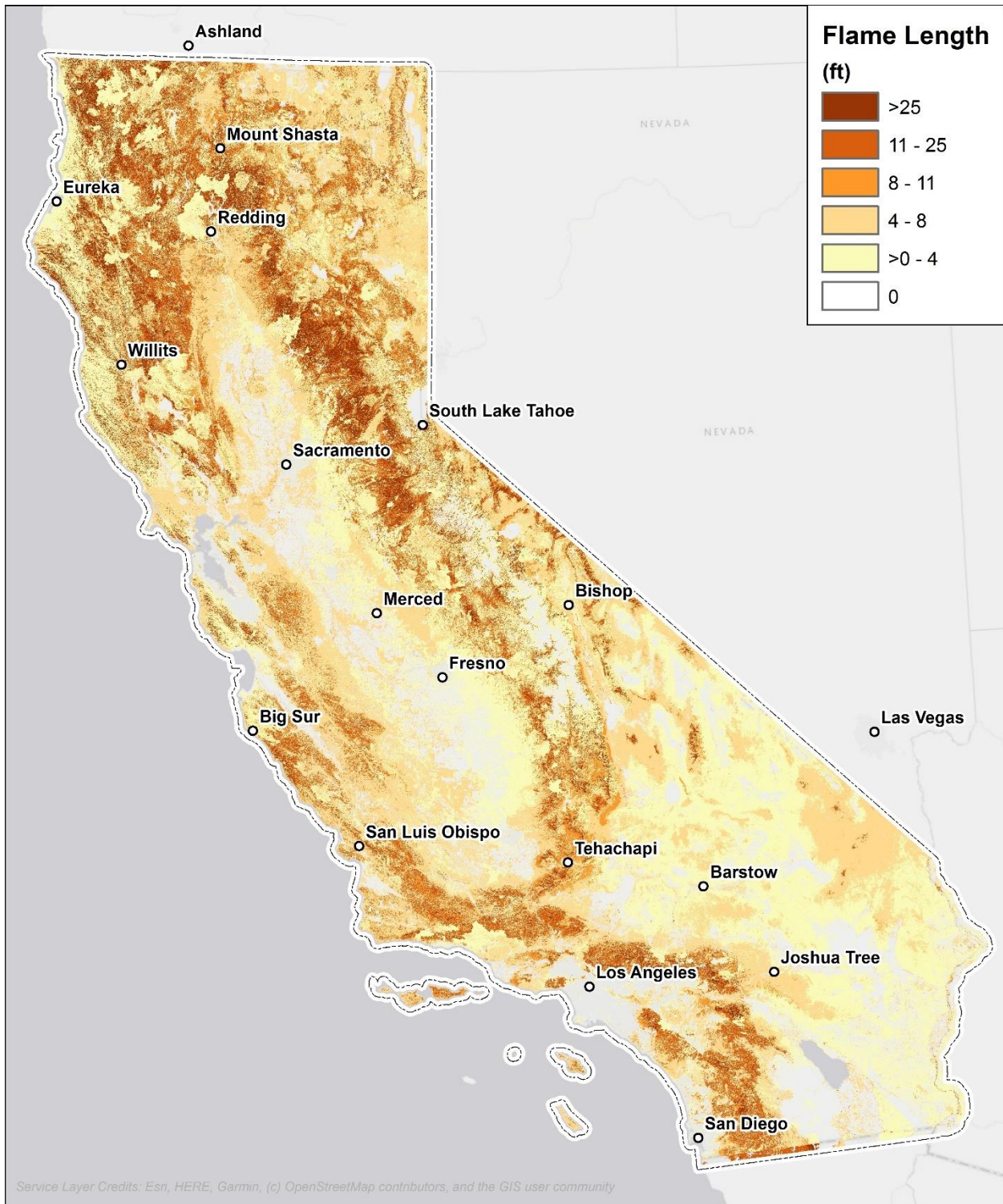


Figure 15. Map of WildEST 30-m Mean Flame Length (ft) for the CAL analysis area.

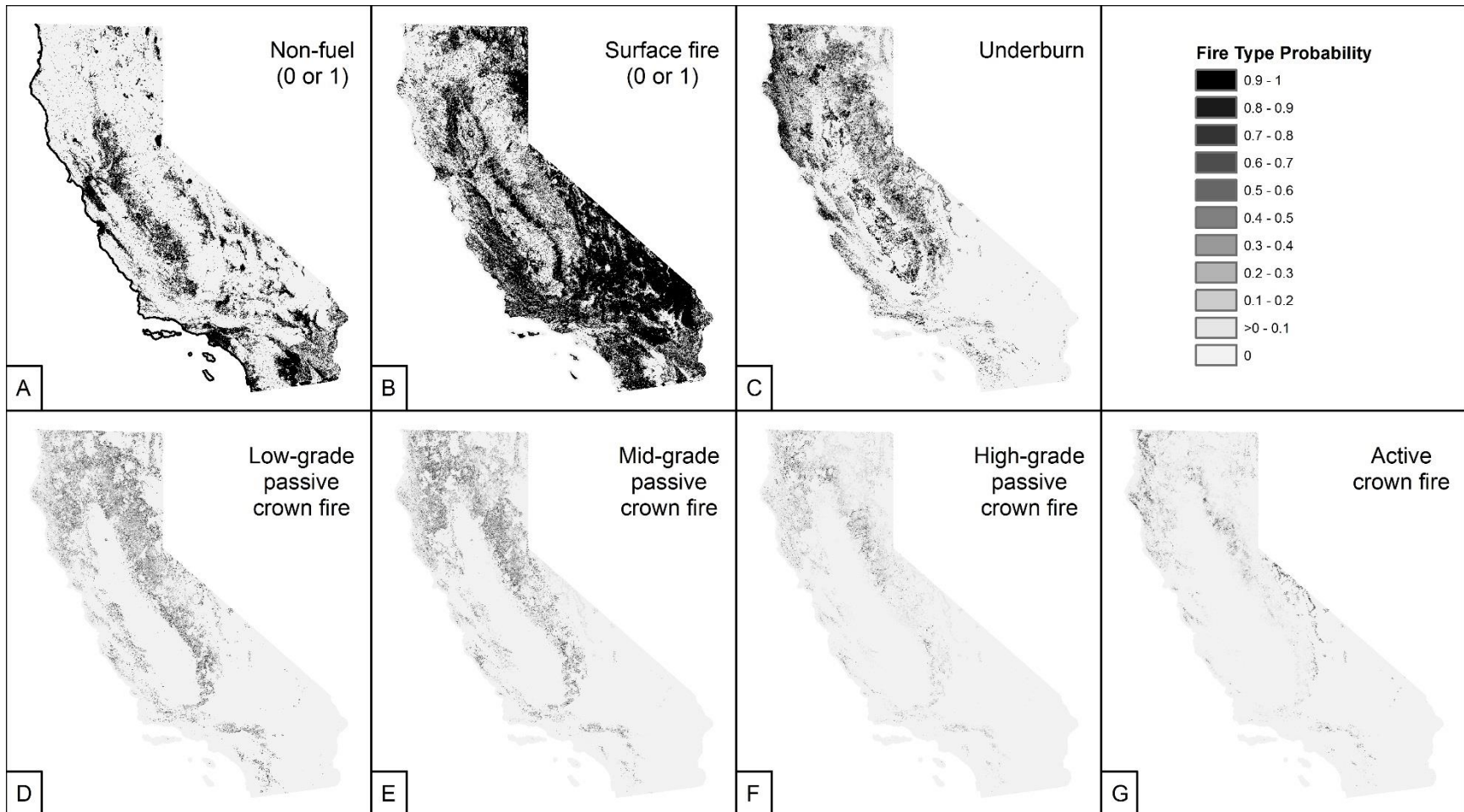


Figure 16. Map of WildEST 30-m Fire Type Probabilities for the CAL analysis area. These include (A) non-fuel, (B) surface, (C) underburn, (D) low-grade passive crown fire, (E) mid-grade passive crown fire, (F) high-grade passive crown fire, and (G) active crown fire. Probabilities range in value from 0 to 1, with (A) and (B) being binary rasters of only values 0 and 1.

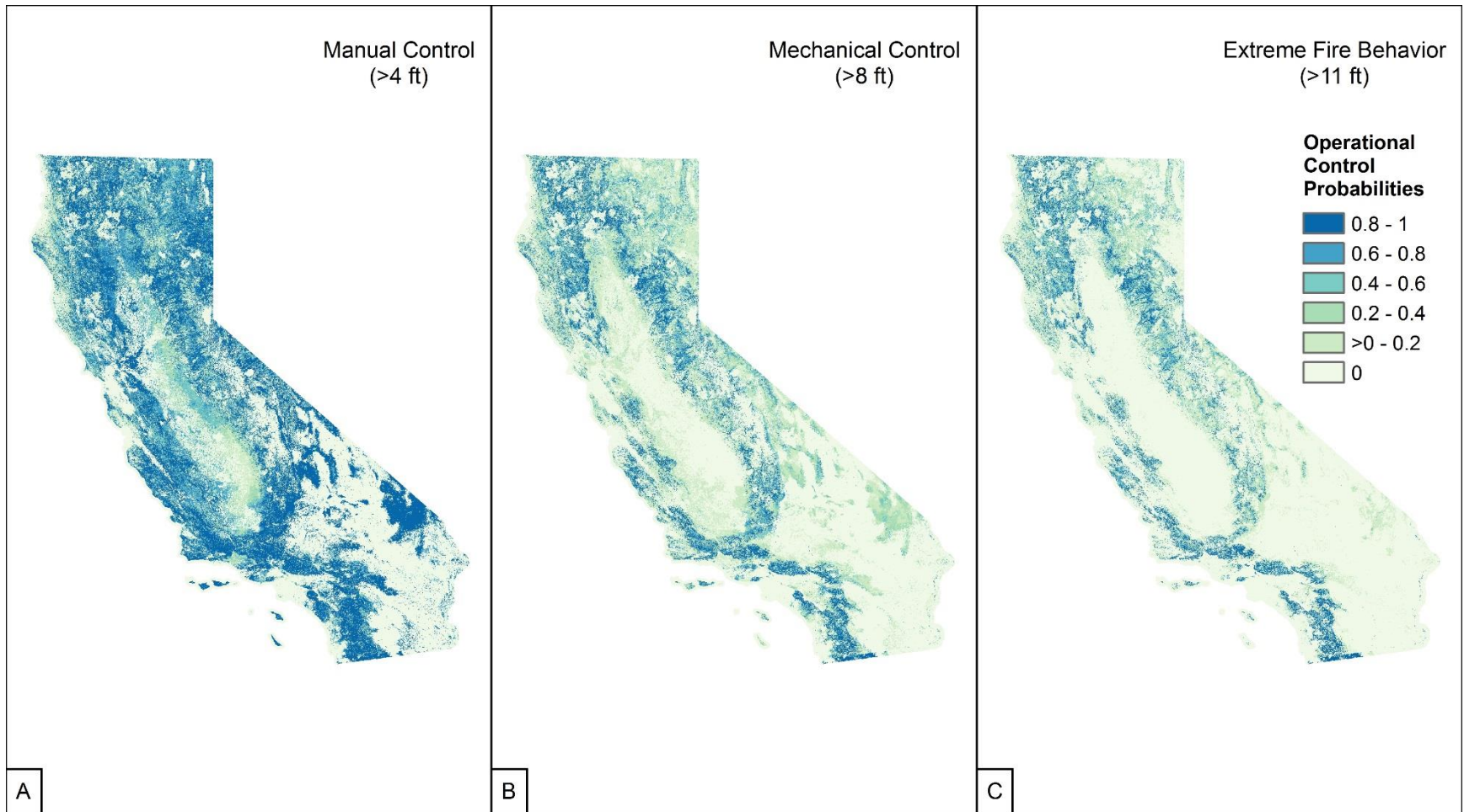


Figure 17. Map of WildEST 30-m Operation Control Probabilities for the CAL analysis area.

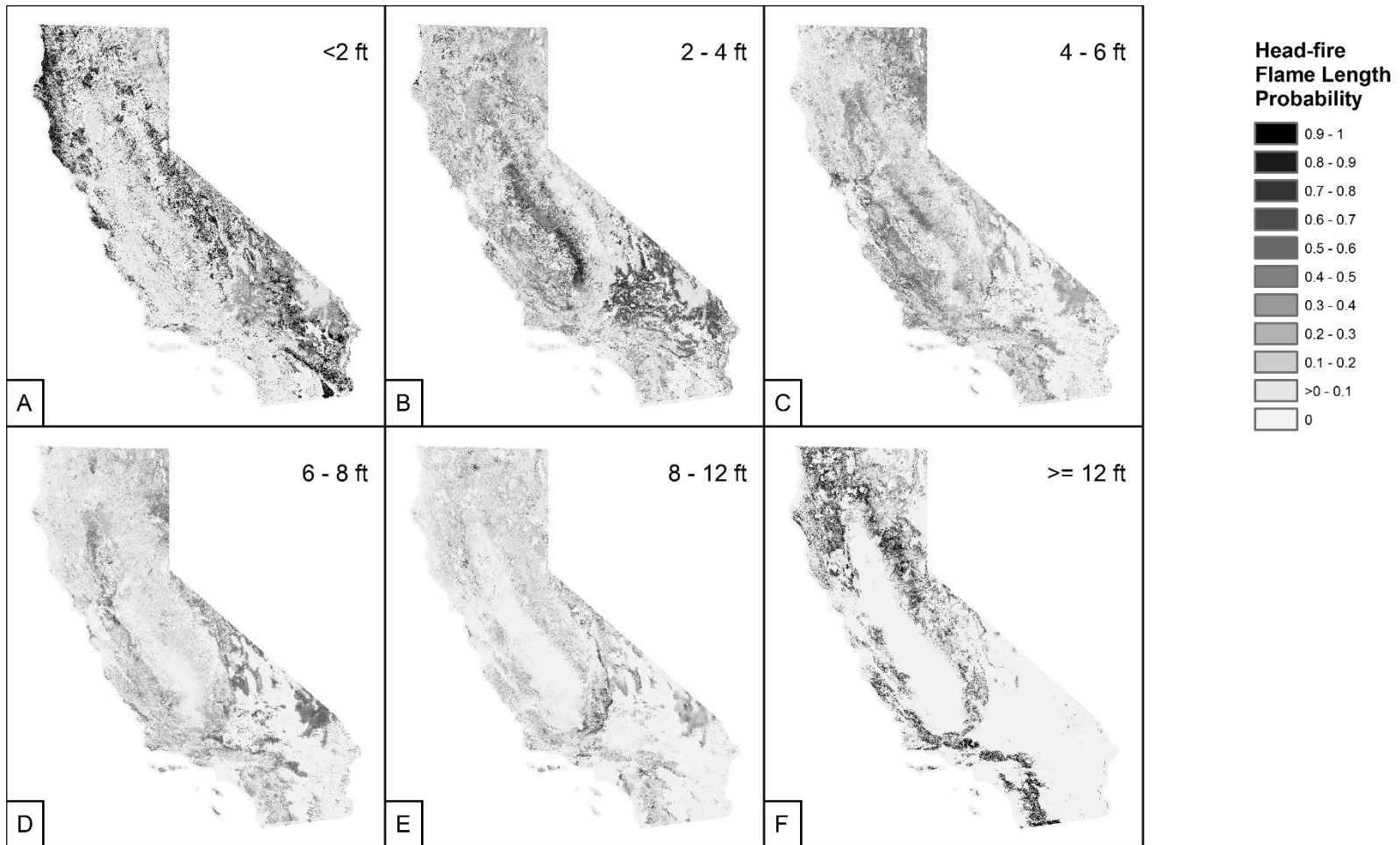


Figure 18. Map of WildEST 30-m heading FLPs for the CAL analysis area. Panels A-F show the FLP for the heading flame-length bin specified. The sum of A-F for any given pixel equals 1.

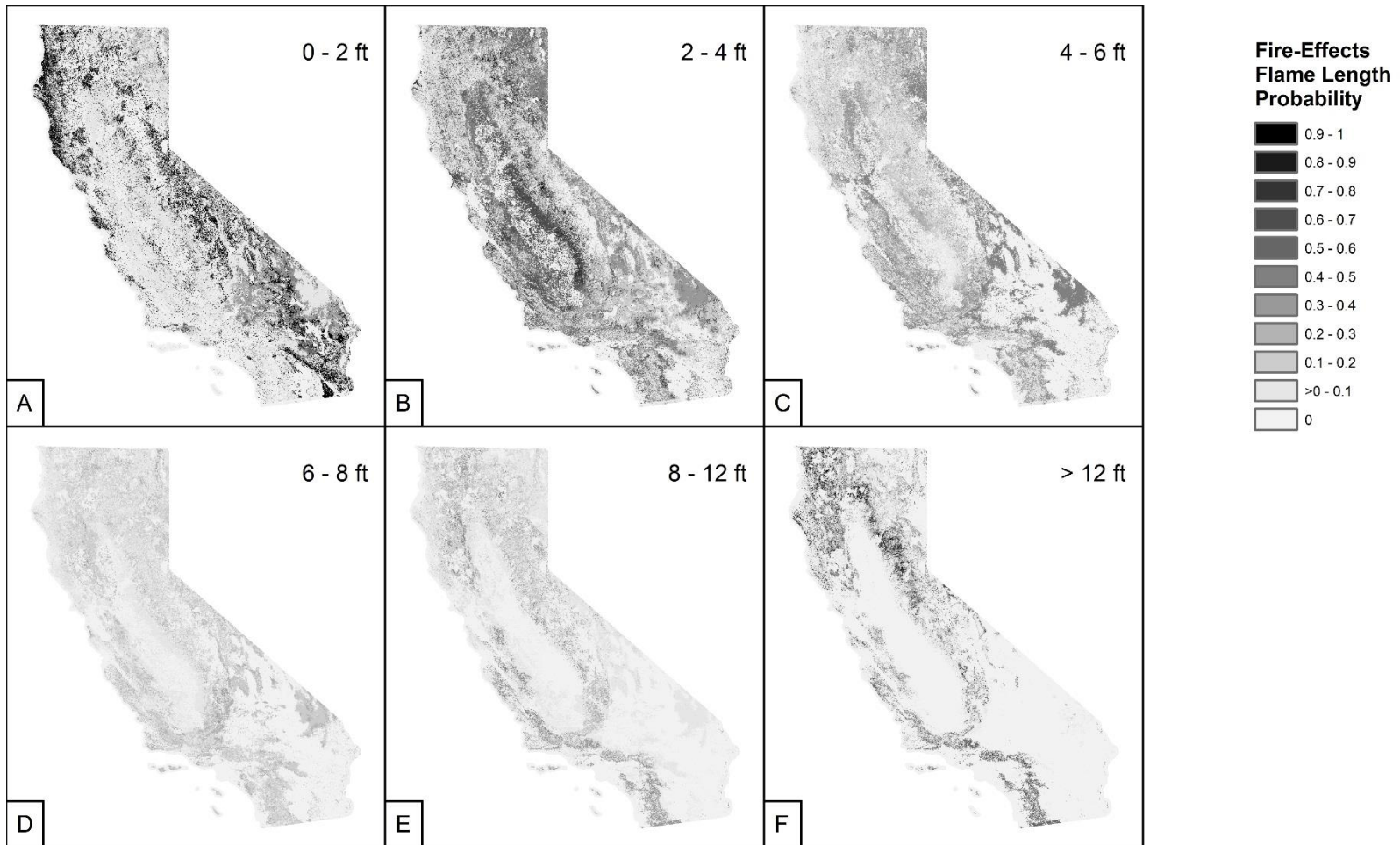


Figure 19. Map of WildEST 30-m fire-effects FLPs for the CAL analysis area. A-F show the FLP for the fire-effects flame-length bin specified. The sum of A-F for any given pixel equals 1.

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 given the fire environment there, given that a fire occurs. 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 20, 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 20, 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 20, 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 20, D).

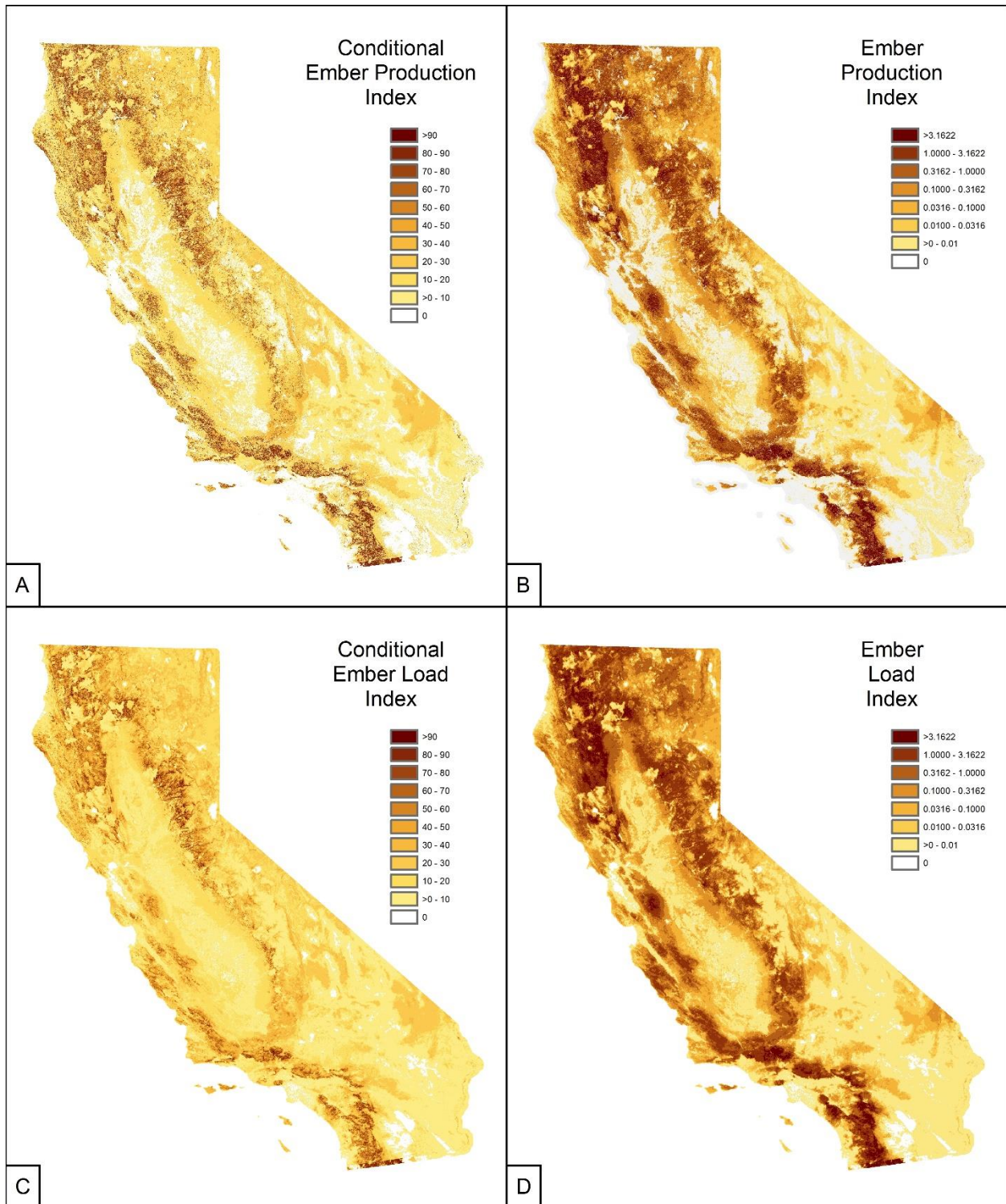


Figure 20. Map of WildEST 30-m ember indices for the CAL analysis area. These include (A) conditional Ember Production Index, (B) Ember Production Index, (C) conditional Ember Load Index, and (D) Ember Load Index. Probabilities range in value from 0 to 1.

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 6. 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 21 and Figure 22 show cRPS and RPS, respectively.

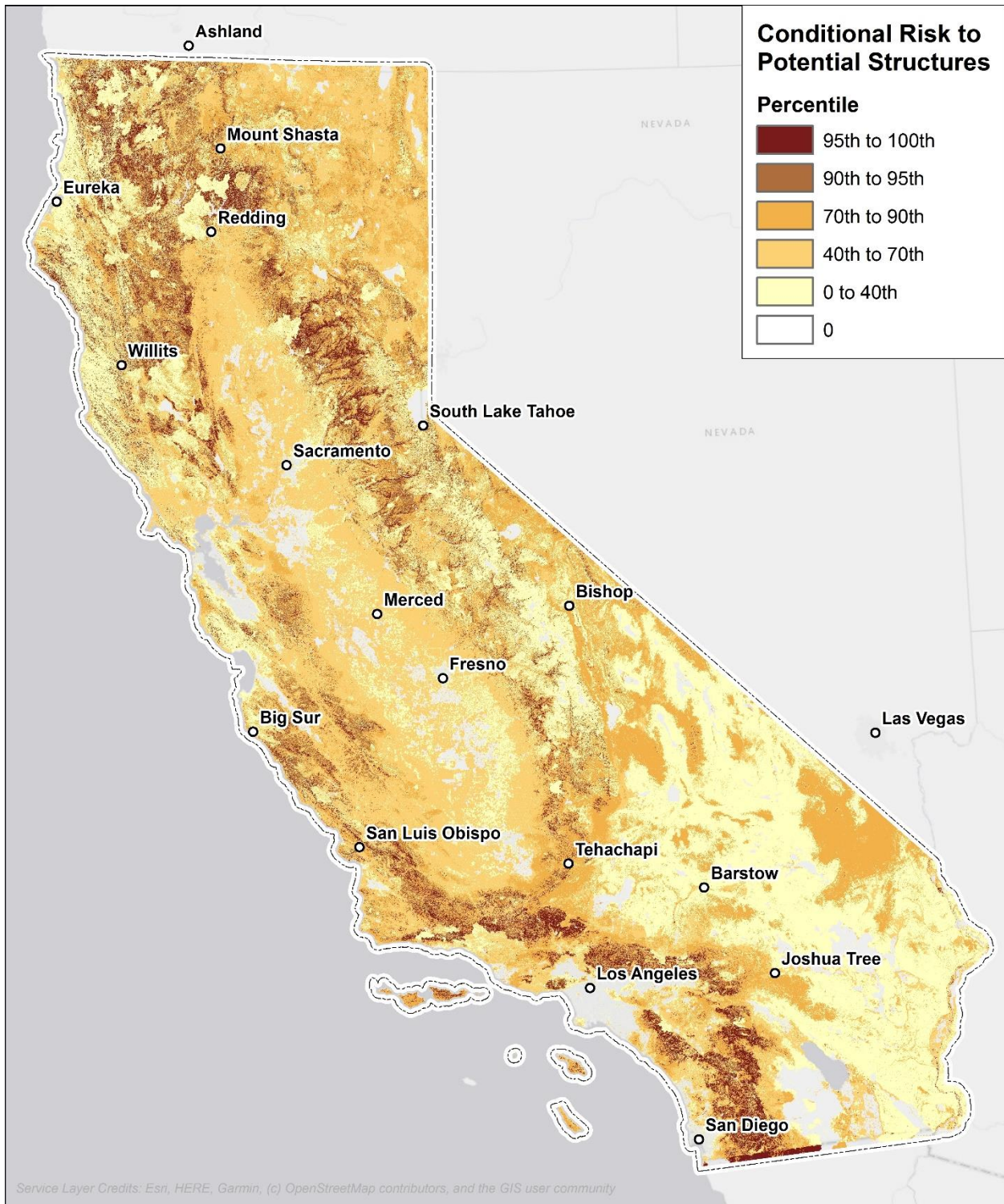


Figure 21. Map of 30-m conditional Risk to Potential Structures for the CAL analysis area.

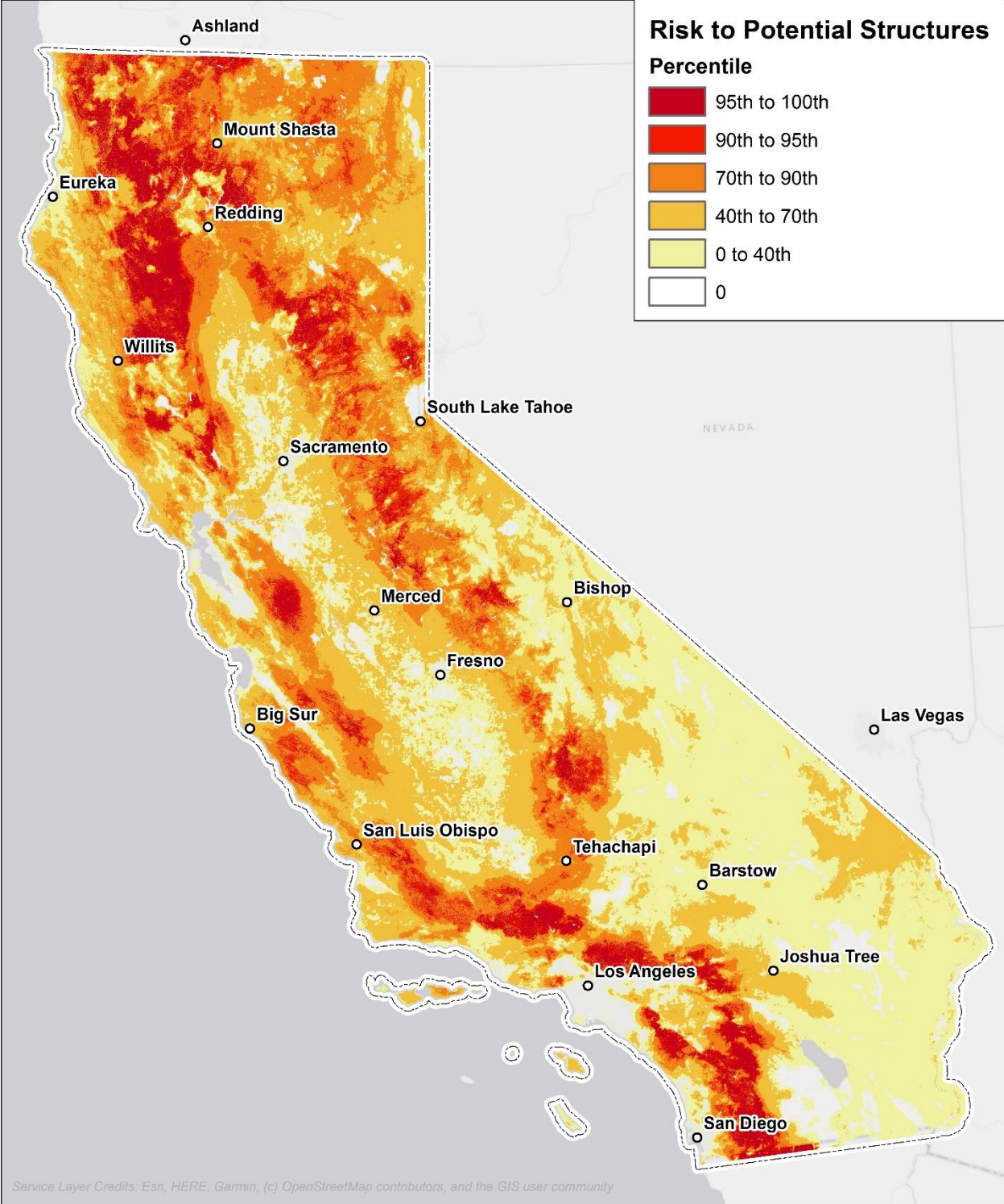


Figure 22. Map of 30-m Risk to Potential Structures for the CAL analysis area.

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.

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 CAL vegetation inputs (derived from LANDFIRE 2016), 30-m CAL fuel model outputs, 30-m CAL burn probability results, and 30-m CAL fire-effects flame-length probabilities from the WildEST wildfire behavior results. WHP is shown in Figure 23.

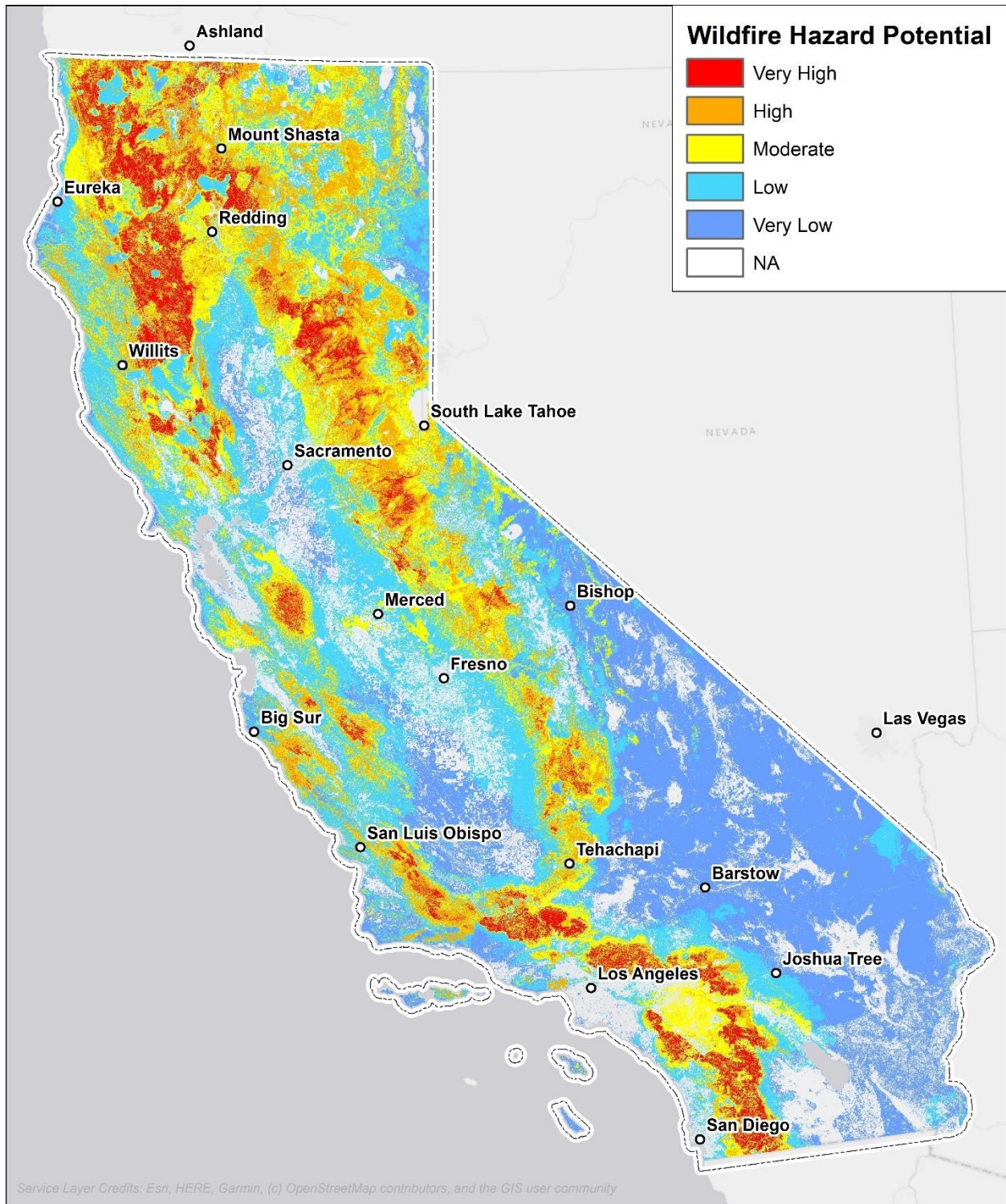


Figure 23. Map of 30-m Wildfire Hazard Potential for CAL analysis area.

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 and others (2016), Rodriguez y Silva and others (2014), and Rodriguez y Silva and others (2020). SDI is shown in Figure 24.

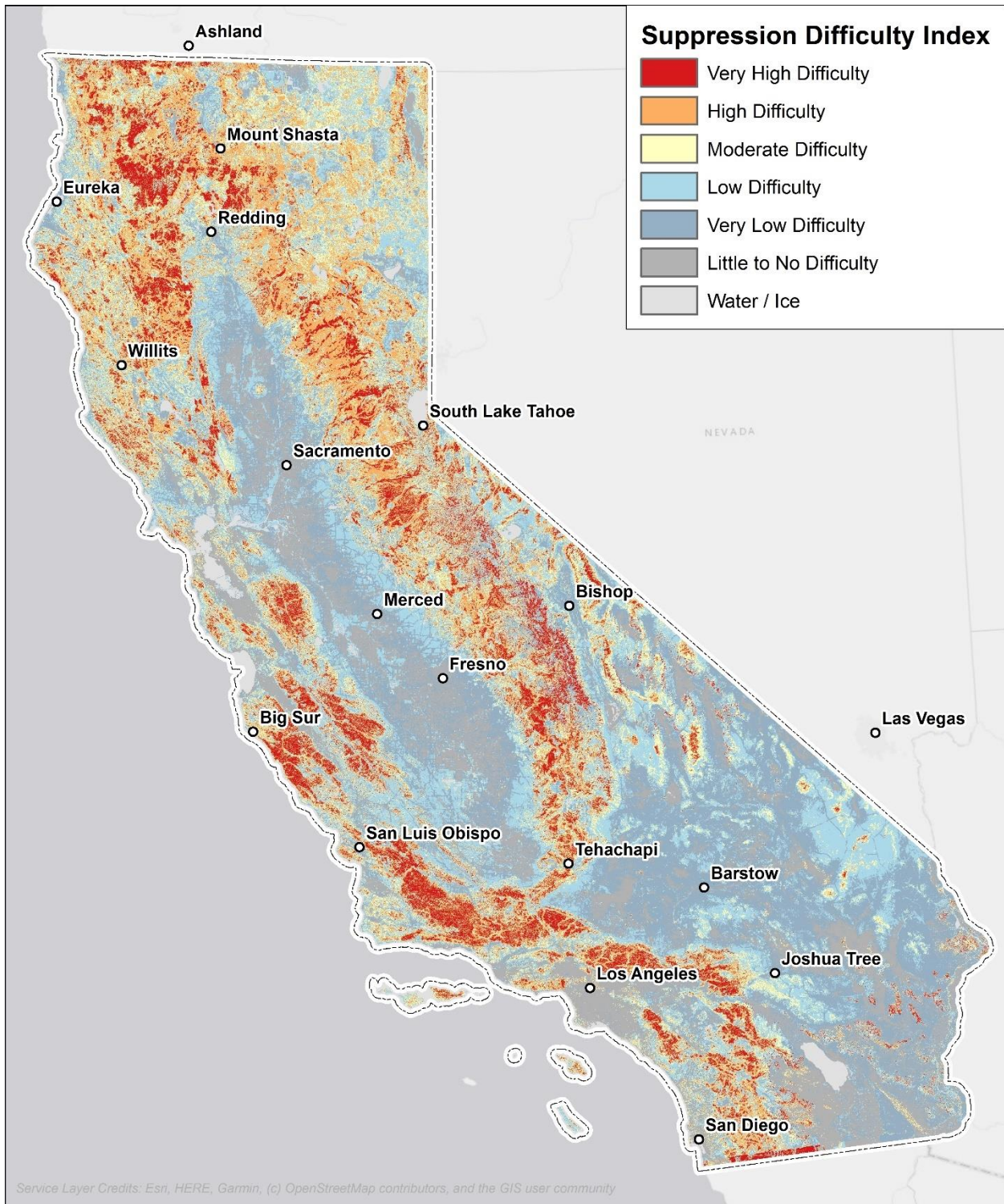


Figure 24. Map of 30-m Suppression Difficulty Index for CAL analysis area.

5 DISCUSSION

The California all-lands wildfire hazard assessment, whose methods and results are described in this report, incorporated data sources and methods not before used for an assessment over an area as large as the state of California.

- 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 incorporated a high-quality gridded historical weather dataset produced by the Desert Research Institute for Cal FIRE. That dataset was used for both FSim and WildEST. This dataset, when processed to produce downscaled 30-m Weather-Type Probability rasters, generated seamlessly variable weather across the state.
- We applied WildEST, a spatial wildfire characteristics simulation process based on FlamMap, at the native 30-m fuelscape resolution. We applied a new ember module to estimate ember production and load across the state as a function of fuel, climate, and topography.
- 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 roughly twice the 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. 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.

The results produced in this analysis provide a snapshot of wildfire hazard conditions before the 2020 fire season. Following the historic 2020 fire season in California, an update to these results is needed and is already underway. Additionally, a separate expanded effort to assess wildfire risk to homes, critical infrastructure, and surface drinking water is also underway.

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7 DATA PRODUCTS

The California Hazard 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 about data product background and development procedures can be found in the metadata of each data product.

Deliverable Folder	Data Product	Description
Wildfire hazard modeling with FSim		
2.1	Annual burn probability raster (30m)	Subfolder 2.1 contains two burn probability (BP) rasters. The first raster is in an ESRI 10.7 geodatabase and is the original 120-m FSim BP output raster. The second raster is the final preferred 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 10.7 layer file for recommended BP symbology.
2.2	Mean fireline intensity raster (30m)	Subfolder 2.2 contains two mean fireline intensity (MFI) rasters. The first raster is in an ESRI 10.7 geodatabase and is the original 120-m FSim MFI output raster. The second raster is an upsampled 30-m MFI raster in standalone TIFF format, however, neither raster is recommended for further applications. The subfolder also contains an ESRI ArcMap 10.7 layer file for internal MFI review.
2.3	Flame-length probability (six FILs; 30m)	Subfolder 2.3 contains 12 flame-length probability (FLP) rasters. Six of the rasters are in an ESRI 10.7 geodatabase and are the original 120-m FSim FLP output rasters. The remaining six rasters are upsampled 30-m FLP rasters in standalone TIFF format, however, neither set of rasters is recommended for further applications. Please see the six fire-effects FLP rasters in Task 3.7 instead. The subfolder also contains six corresponding ESRI ArcMap 10.7 layer files for internal FSim FLP review.
2.4	Event set (minimum 10,000 years)	Subfolder 2.4 contains an ESRI 10.7 geodatabase that contains 28 feature classes: one FSim wildfire ignition event set feature class and one FSim wildfire perimeter event set feature class for each of the 14 CAL FOAs.

Deliverable Folder	Data Product	Description
Fire behavior modeling (plus embers)		
3.1	Weighted rate of spread (wROS)	Subfolder 3.1 contains the 30-m weighted rate of spread raster in TIFF format and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
3.2	Weighted flame length (wFL)	Subfolder 3.2 contains the 30-m weighted flame length raster in TIFF format and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
3.3	Fire-type probability (FTP)	Subfolder 3.3 contains six 30-m fire-effects flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.
3.4	Probability of manual control	Subfolder 3.4 contains the 30-m probability of manual control raster in TIFF format, and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
3.5	Probability of mechanical control	Subfolder 3.5 contains the 30-m probability of mechanical control raster in TIFF format, and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
3.6	Probability of extreme fire behavior	Subfolder 3.6 contains the 30-m probability of extreme fire behavior raster in TIFF format and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
3.7	Fire-effects flame-length probabilities (FLPs)	Subfolder 3.7 contains six 30-m fire-effects flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.
3.8	Head-fire flame-length probabilities (Ops FLPs)	Subfolder 3.8 contains six 30-m head-fire flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.
3.9	Ember Production Index (cEPI/EPI)	Subfolder 3.9 contains two 30-m rasters in TIFF format. The first raster is the conditional Ember Production Index (cEPI). The second raster is the expected Ember Production Index (EPI). The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.
3.10	Ember Load Index (cELI/ELI)	Subfolder 3.10 contains two 30-m rasters in TIFF format. The first raster is the conditional Ember Load Index (cELI). The second raster is the expected Ember Load Index (ELI). The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.

Deliverable Folder	Data Product	Description
Integrated Hazard		
4.1	Risk to Potential Structures raster (cRPS/RPS)	Subfolder 4.1 contains two 30-m rasters in TIFF format. The first raster is conditional Risk to Potential Structures (cRPS). The second raster is the expected Risk to Potential Structures (RPS). The subfolder also contains the corresponding ESRI ArcMap 10.7 layer files for recommended symbology.
4.2	Wildfire Hazard Potential raster (WHP)	Subfolder 4.2 contains the 30-m Wildfire Hazard Potential (WHP) raster in TIFF format and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.
4.3	Suppression Difficulty Index raster (SDI)	Subfolder 4.3 contains the 30-m Suppression Difficulty Index (SDI) raster in TIFF format and the corresponding ESRI ArcMap 10.7 layer file for recommended symbology.

THANK YOU

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