# USFS Region 5 Southern California Quantitative Wildfire Risk Assessment: Methods and Results


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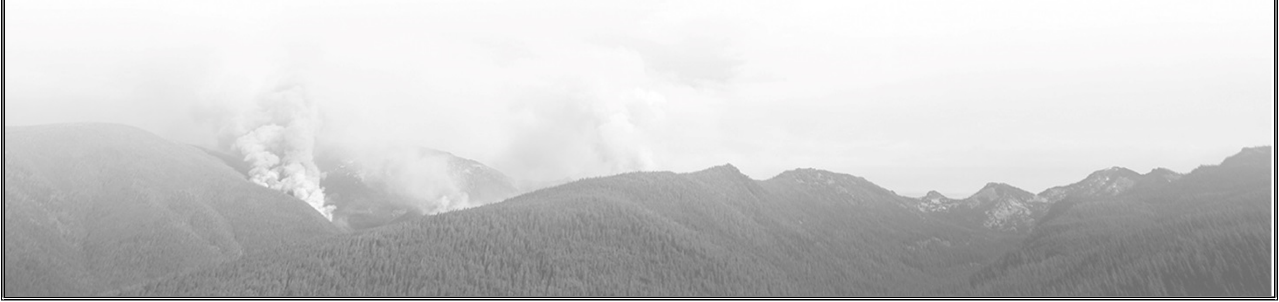

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# 1 Overview of SCRA

## 1.1 Purpose of the Assessment

The purpose of the USFS Region 5 Southern California Wildfire Risk Assessment (SCRA) is to provide foundational information about wildfire hazard and risk to highly valued resources and assets across the geographic area. Such information supports wildfires, regional fuel management planning decisions, and revisions to land and resource management plans. A wildfire risk assessment is a quantitative analysis of the assets and resources across a specific landscape and how they are potentially impacted by wildfire. The SCRA analysis considers several different components, each resolved spatially across the region, including:

- likelihood of a fire burning,
- the intensity of a fire if one should occur,
- the exposure of assets and resources based on their locations, and
- the susceptibility of those assets and resources to wildfire.

Assets are human-made features, such as commercial structures, critical facilities, housing, etc., that have a specific importance or value. Resources are natural features, such as wildlife habitat, federally threatened and endangered plant or animal species, etc. These also have a specific importance or value. Generally, the term “values at risk” has previously been used to describe both assets and resources. For SCRA, the term Highly Valued Resources and Assets (HVRA) is used to describe what has previously been labeled values at risk. There are two reasons for this change in terminology. First, resources and assets are not themselves “values” in any way that term is conventionally defined—they *have* value (importance). Second, while resources and assets may be exposed to wildfire, they are not necessarily “at risk”—that is the purpose of the assessment.

To manage wildfire in Southern California, it is essential that accurate wildfire risk data, to the greatest degree possible, is available to drive fire management strategies. These risk 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 risk data can be used to support fire operations in response to wildfire incidents by identifying those assets and resources most susceptible to fire. This can aid in decision making for prioritizing and positioning of firefighting resources.

## 1.2 Landscape Zones

### 1.2.1 *Analysis Area*

The Analysis Area (AA) is the area for which valid burn probability (BP) results are produced. The AA for the SCRA project was initially defined as an area that encompassed the southern coastal California national forests, three neighboring national monuments, and one national game refuge. All subsequent project boundaries (discussed below) were built from this initial extent. The SCRA analysis includes 5 Administrative Forests: Angeles, Cleveland, Los Padres, San Bernardino, and Sequoia National Forest.

### 1.2.2 *Fire Occurrence Areas*

To ensure valid BP results in the AA and prevent edge effects, 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 that all fires that could reach the AA are simulated. The Fire Occurrence Area covers roughly 27 million acres characterized by diverse topographic and vegetation conditions. To more accurately model this large area where historical fire occurrence and fire weather are highly variable, we divided the overall fire occurrence area into 10 FOAs. Individual FOA boundaries were generated using a variety of inputs including: larger fire occurrence boundaries developed for national-level work (National FSim Pyrome boundaries), aggregated level IV EPA Ecoregions, and USFS fire staff input. For consistency with other FSim projects, we numbered these FOAs 35 through 44.

### 1.2.3 *Fuelscape Extent*

The available fuelscape extent was determined by adding an additional 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 AA, FOA boundaries, and fuelscape extent are presented in Figure 1.

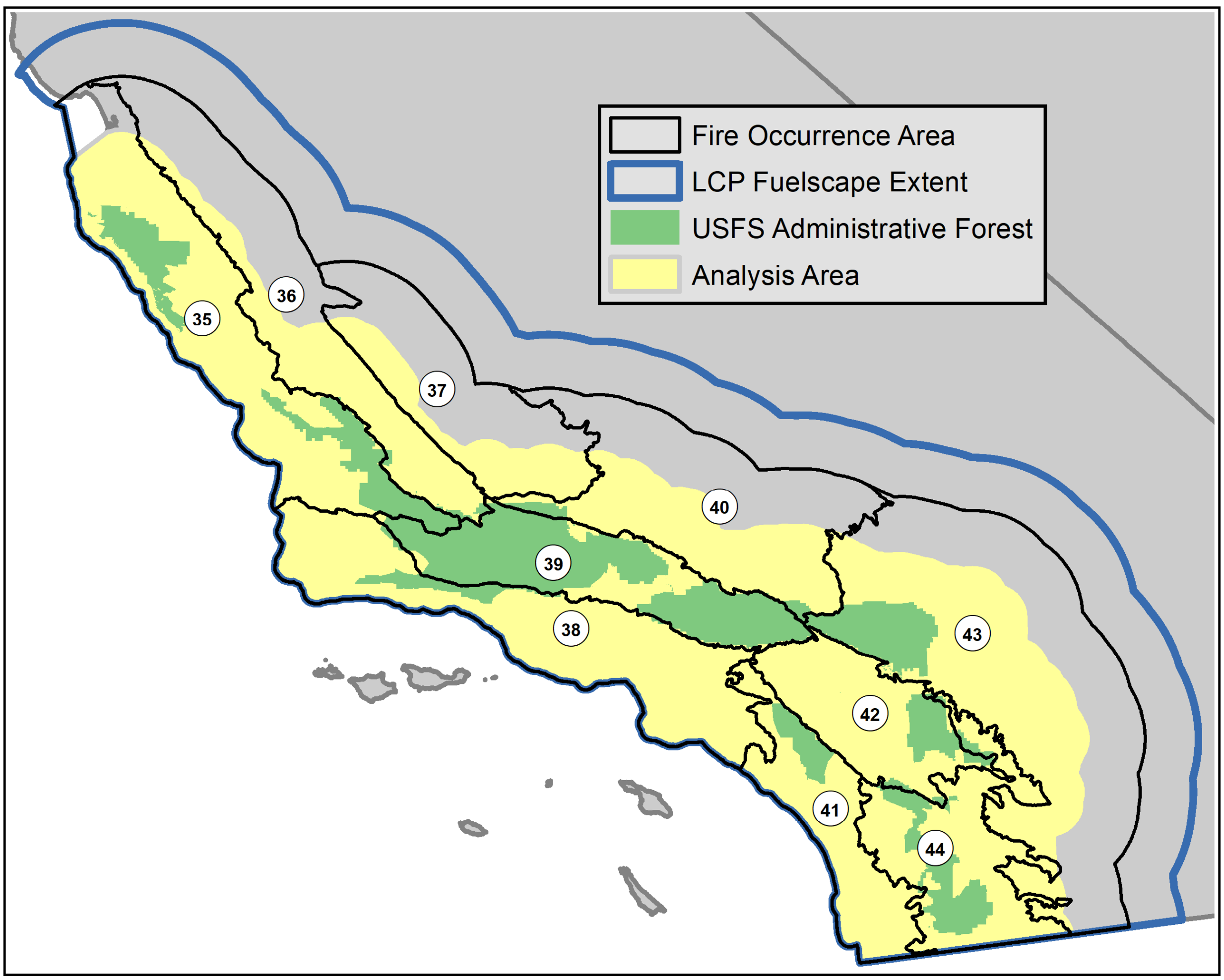


**Figure 1. Overview of landscape zones for SCRA FSim project. USFS administrative forests are shown in green, and the Analysis Area (AA) is shown in yellow. The project produces valid BP results within this AA. To ensure valid BP in the AA, we started fires in the ten numbered fire occurrence areas (FOAs), outlined in black. To prevent fires from reaching the edge of the fuelscape, a buffered fuelscape extent was used, which is represented by the blue outline.**

## 1.3 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 variety of scales, from the continental United States (Calkin *et al.*, 2010), to individual states (Buckley *et al.*, 2014), to a portion of a national forest (Thompson *et al.*, 2013b), to an individual county. In this framework, wildfire risk is a function of two main factors: 1) wildfire hazard and 2) HVRA vulnerability (Figure 2).

**Wildfire hazard** is a physical situation with 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 measure). For this analysis, we used the large fire simulator (FSim) to quantify wildfire potential across the landscape at a pixel size of 180 m (approximately 8 acres per pixel).

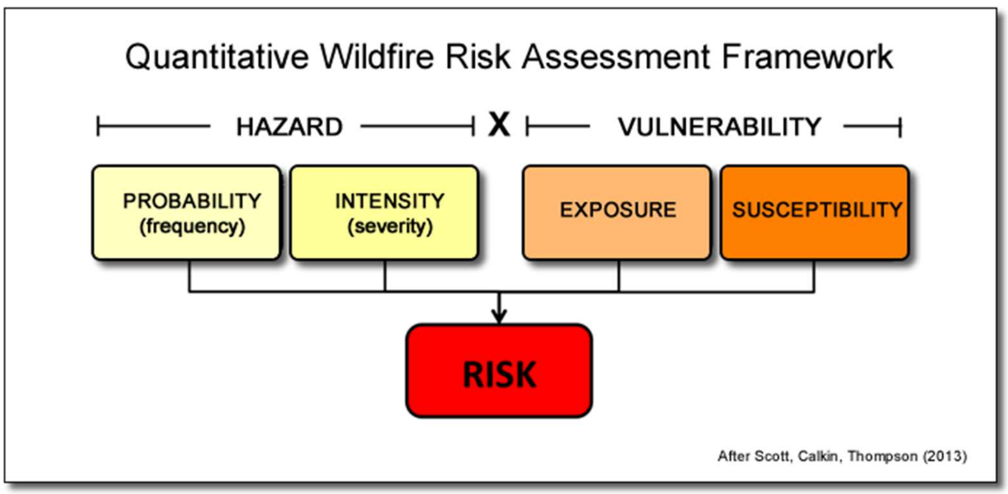


**Figure 2. The components of the Quantitative Wildfire Risk Assessment Framework used for SCRA.**

**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 HVRAs, like critical wildlife habitat or endangered plants, 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.

# 2 Analysis Methods and Input Data

The FSim large-fire simulator was used to quantify wildfire hazard across the AA at a pixel size of 180 m. 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).

## 2.1 Fuelscape

The fuelscape consists of geospatial data layers representing surface fuel model, canopy base height, canopy bulk density, canopy cover, canopy height and topography characteristics (slope, aspect, elevation). We generated the SCRA fuelscape using the LANDFIRE Total Fuel Change Toolbar (LFTFCT). LFTFCT allows users to input existing vegetation and disturbance data, define fuel rulesets, and generate fuel grids. See the LFTFCT Users Guide for more information (Smail *et al.*, 2011). The resulting LFTFCT output fuel grids can then be combined into a single landscape (LCP) file and used as a fuelscape input in various fire modeling programs. Additional information can be found in the LF data modification guide (Helmbrecht and Blankenship, 2016).

Our LFTFCT vegetation and disturbance inputs were derived from LANDFIRE 2014b 30-m raster data. Both the surface and canopy inputs were updated to reflect fuel disturbances occurring between 2015 and 2017. Wildfire fuel disturbances were incorporated using three difference sources: Monitoring Trends in Burn Severity (MTBS) data, Rapid Assessment of Vegetation Condition after Wildfire (RAVG) data, and GeoSpatial Multi-Agency Coordination (GeoMAC) perimeter data. We gathered severity data as available from MTBS, then RAVG, and where severity data was unavailable we relied on final perimeters from GeoMAC. We crosswalked MTBS and RAVG severity to the appropriate disturbance code (112, 122, or 132) corresponding with fire disturbances of low, moderate, or high severity, occurring in the past one to five years. GeoMAC perimeters were assigned a severity disturbance code of 132. We also incorporated non-wildfire fuel disturbances using the Forest Service Activity Tracking System (FACTS) data provided by the USFS regional office staff. Finally, a fuelscape calibration workshop involving resource staff input was held February 12-13, 2018 in San Diego, CA to refine the LFTFCT fuel rulesets for this project. The resulting fuelscape generated by LFTFCT is shown by fuel model group in Figure 3.

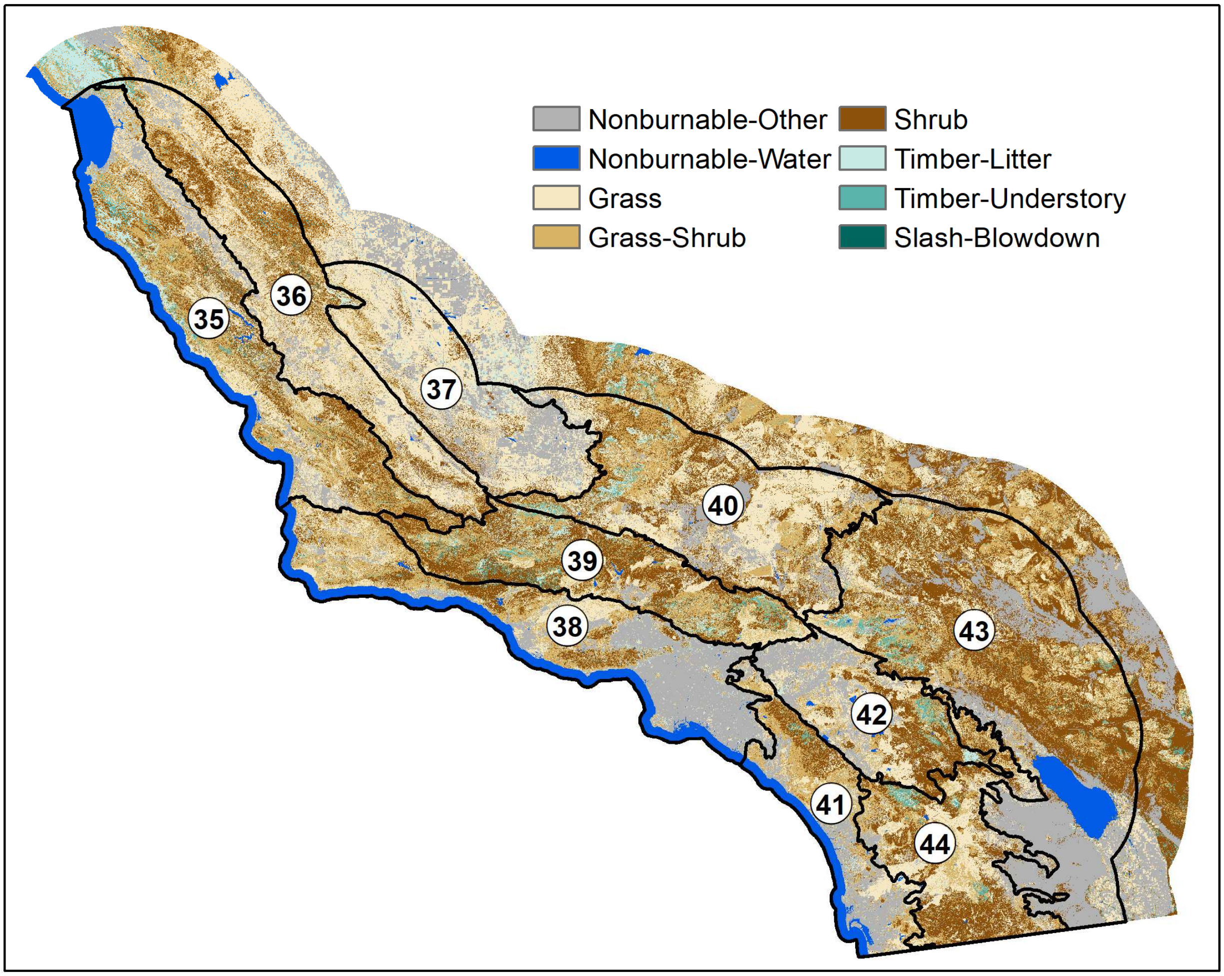


**Figure 3. Map of fuel model groups across the SCRA analysis area.**

## 2.2 Historical Wildfire Occurrence

Historical wildfire occurrence data were used to develop model inputs (the fire-day distribution file [FDist] and ignition density grid [IDG]) as well as for model calibration. For historical, large-fire occurrence we used the Short (2017) Fire Occurrence Database (FOD), which spans the 24-year period 1992-2015. Table 1 summarizes the annual number of large fires per million acres, along with mean large-fire size, and annual area burned by large fires per million acres. For this analysis, we defined a large fire as one greater than 247.1 acres (100 hectares).

**Table 1. Historical large-fire occurrence, 1992-2015, in the SCRA 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 |
|---|---|---|---|---|---|---|
| 35 | 2.9 | 3.53 | 0.814 | 10,824 | 31,118 | 0.0088 |
| 36 | 2.9 | 2.75 | 1.045 | 2,177 | 6,257 | 0.0023 |
| 37 | 3.3 | 2.15 | 1.512 | 2,575 | 8,369 | 0.0039 |
| 38 | 1.8 | 3.00 | 0.611 | 15,423 | 28,275 | 0.0094 |
| 39 | 4.8 | 2.05 | 2.358 | 7,685 | 37,143 | 0.0181 |
| 40 | 3.0 | 3.09 | 0.976 | 2,059 | 6,093 | 0.0020 |
| 41 | 3.0 | 1.47 | 2.041 | 3,543 | 10,630 | 0.0072 |
| 42 | 7.5 | 1.53 | 4.929 | 2,791 | 21,051 | 0.0138 |
| 43 | 3.5 | 5.69 | 0.622 | 5,465 | 19,355 | 0.0034 |
| 44 | 5.1 | 1.97 | 2.602 | 8,111 | 41,570 | 0.0211 |

Historical wildfire occurrence varied widely by FOA (Table 1), with FOA 42 experiencing the highest annual average of 4.93 large wildfires per million acres. FOA 38 had the least frequent rate of occurrence with an annual average of 0.61 large wildfires per million acres. 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 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 2-km 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. The IDG was divided up for each FOA by setting to zero all area 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. The IDG enables FSim to produce a spatial pattern of large-fire occurrence consistent with what was observed historically. Figure 4 shows the ignition density grid for the fire occurrence area.

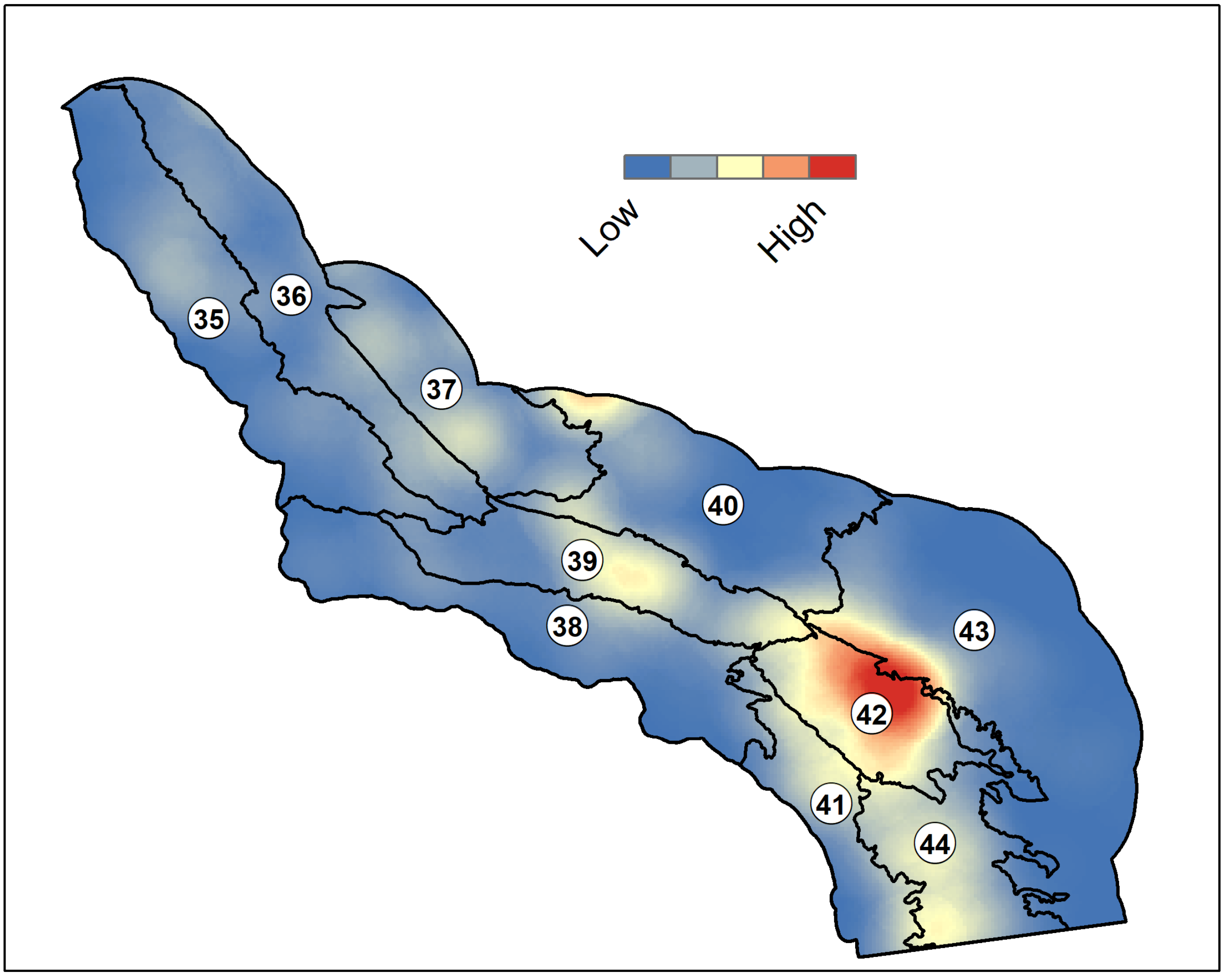


**Figure 4. Ignition density grid used in FSim simulations.**

## 2.3 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 recorded at selected Remote Automatic Weather Stations (RAWS). Station selection was informed by experiential knowledge provided by regional fire and fuels personnel. Stations with relatively long and consistent records and moderate wind activity were preferentially selected to produce the most reasonable and stable FSim results.

Rather than rely on ERC values produced from RAWS data which may be influenced by periods of station inactivity outside of the fire season, we extracted ERC values from Dr. Matt Jolly's historical, gridded ERC rasters for the period 1992-2012 (Jolly, 2014). The RAWS stations selected for winds and ERC sample sites for each FOA are shown in Figure 5, and discussed further in the following sections.

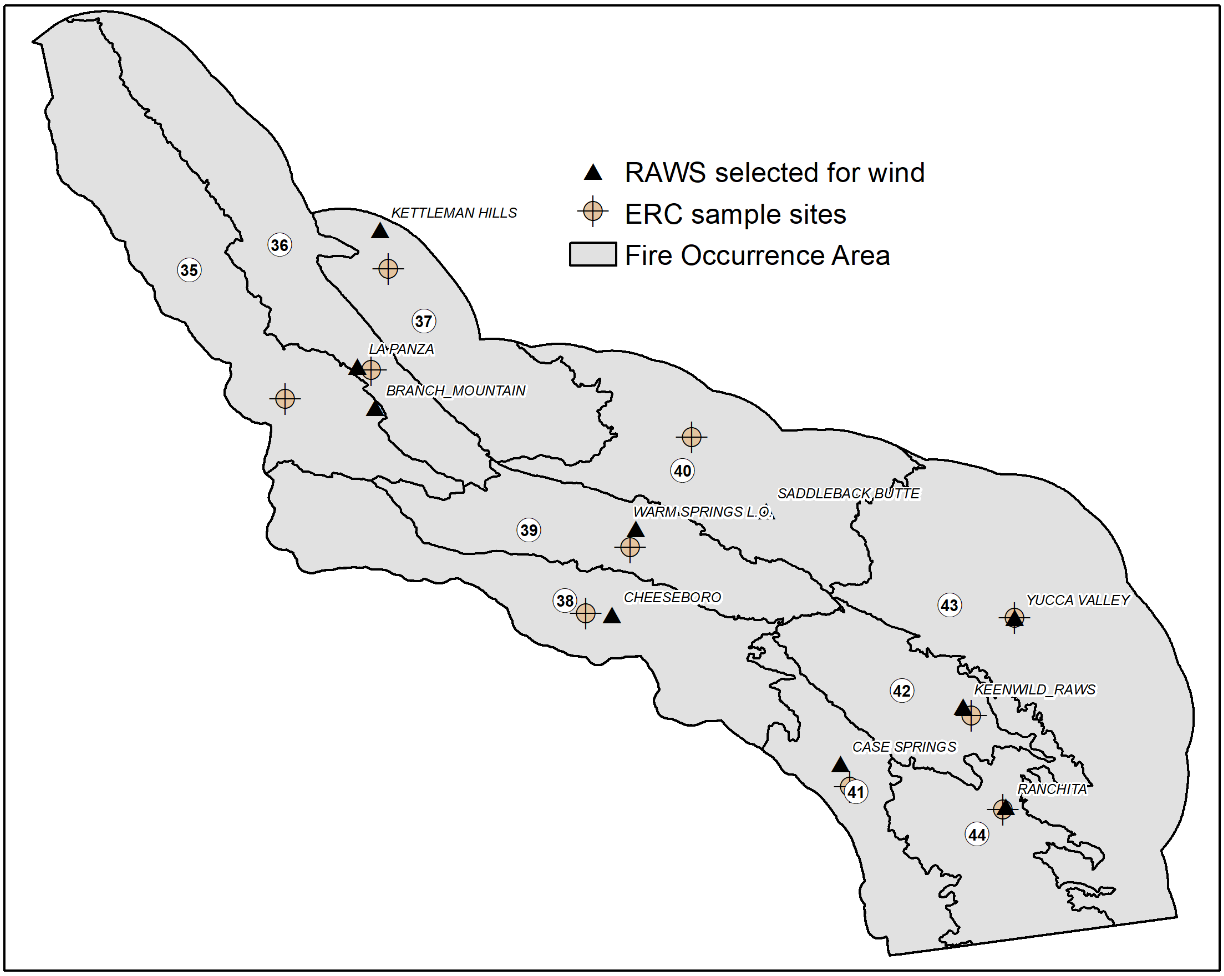


**Figure 5. RAWS stations and ERC sample sites used for the SCRA FSim project. RAWS data were used for hourly sustained wind speed.**

## 2.3.1 *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 likelihood of a large fire at lower versus higher ERC values.

### 2.3.2 *Fire Risk File (Frisk)*

Fire risk files were generated for each RAWS using FireFamilyPlus (FFPlus) and updated to incorporate simulated ERC percentiles (as described in section 2.3.4). 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 regional fire personnel with knowledge of nearby stations and their ability to represent general wind patterns within a FOA. Some of the recommended stations did not produce wind speeds high enough, on average, to produce historically observed fire behavior. Therefore, in FOAs 35 and 42 we adjusted wind speeds to meet our historical calibration targets, while maintaining the wind directions recommended by local experts.

### 2.3.3 *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.

### 2.3.4 *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 1979-2012 and historical fire occurrence data is available for 1992-2015. We used the overlapping years of 1992-2012 to develop a logistic regression of probability of a large-fire day in relation to ERC-G.

Historical ERCs were sampled at an advantageous location within each FOA. Those locations are found on relative 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 new feature of FSim that allows the user to supply a stream of ERC values for each FOA. Isaac Grenfell, statistician at the Missoula Fire Sciences Lab, has generated 1,000 years of daily ERC values (365,000 ERC values) on the same 4-km grid as 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 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 180 m (8 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). Figure 6 diagrams the many components needed as inputs to FSim.

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 10 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.

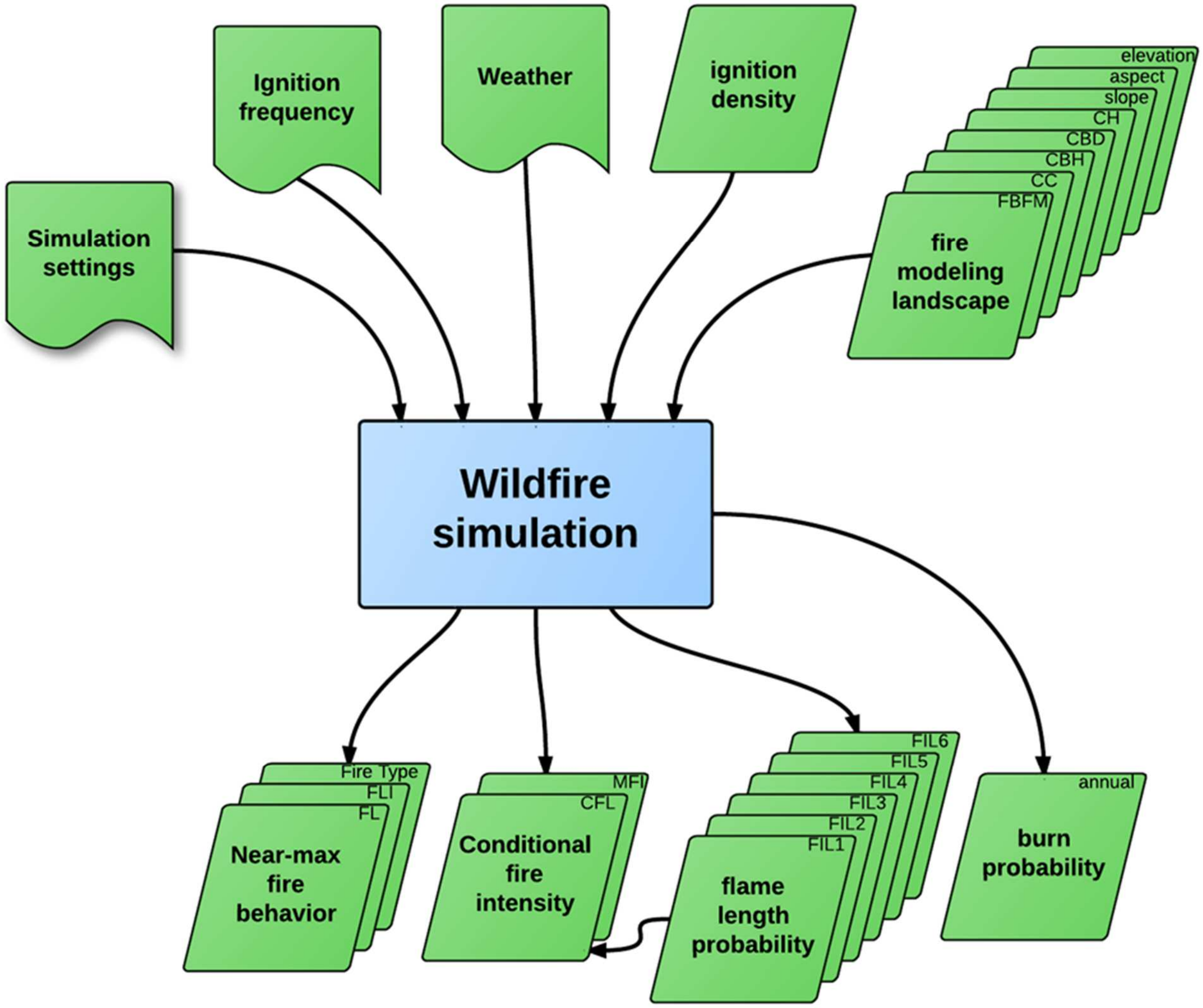


**Figure 6. Diagram showing the primary elements used to derive Burn Probability.**

### 2.4.1 *Model Calibration*

FSim simulations for each FOA were calibrated to historical measures of large fire occurrence including: mean historical large-fire size, mean annual burn probability, mean annual number of large fires per million acres, and mean annual area burned per million acres. From these measures, two calculations are particularly useful for comparing against and adjusting FSim results: 1) mean large fire size, and 2) number of large fires per million acres.

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. The final model inputs can be seen below in Table 2. All runs were completed at 180-m resolution. Each FOA was calibrated separately to well within the 70% confidence interval and final simulations were run with 100,000 iterations. The ten FOAs were then integrated into an overall result for the analysis area.

**Table 2. Summary of final-run inputs for each FOA.**

| Final run | Number of Iterations | ADJ file | Trimming factor | Frisk | FDist file | LCP file |
|---|---|---|---|---|---|---|
| 35r7 | 100,000 | foa35_v5 | 2.0 | foa35v1 | foa35v2 | FOA_35_1_180 |
| 36r6 | 100,000 | foa36_v4 | 2.0 | foa36v1 | Foa36v3 | FOA_36_1_180 |
| 37r7 | 100,000 | foa37_v2 | 2.0 | foa37v1 | foa37v2 | FOA_37_1_180 |
| 38r10 | 100,000 | foa38_v5 | 2.0 | foa38v1 | foa38v2 | FOA_38_1_180 |
| 39r10 | 100,000 | foa39_v6 | 2.0 | foa39v1 | foa39v3 | FOA_39_1_180 |
| 40r9 | 100,000 | foa40_v3 | 2.0 | foa40v2 | foa40v4 | FOA_40_1_180 |
| 41r7 | 100,000 | foa41_v3 | 2.0 | foa41v1 | foa41v3 | FOA_41_1_180 |
| 42r6 | 100,000 | foa42_v3 | 2.0 | foa42v1 | foa42v3 | FOA_42_1_180 |
| 43r6 | 100,000 | foa43_v3 | 2.0 | foa43v1 | foa43v2 | FOA_43_1_180 |
| 44r7 | 100,000 | foa44_v4 | 2.0 | foa44v1 | foa44v2 | FOA_44_1_180 |

### 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.*, 2013a). 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 (BP) at each pixel.

### 2.4.3 *Modeling Near-Max Potential Wildfire Behavior*

The FSim model develops estimates of burn probability and how wildfire intensities will most likely be realized on the landscape given a range of historical weather conditions. In addition to this data, some planning efforts can help be informed by estimates of near-maximum potential wildfire behavior that can be estimated using the NEXUS model (Scott, 1999). Near-maximum potential behavior was modeled on $97^{TH}$ percentile fuel moisture conditions and a 20-mph upslope sustained 20 ft. windspeed (calibrated with the WindNinja model).

# 3 HVRA Characterization

Highly Valued Resources and Assets (HVRA) are the resources and assets on the landscape most likely to be protected from or enhanced by wildfire and those considered in a Land and Resource Management Plans, Fire Management Plans, or in spatial fire planning in the Wildland Fire Decision Support System (WFDSS). The key criterion is that they must be of high value to warrant inclusion in this type of assessment, both for the sake of keeping the assessment regional in focus and to avoid valuing everything to the point nothing is truly highly valued. There are three primary components to HVRA characterization: HVRAs must be identified and their spatial extent mapped, their response to fire (positive, negative, or neutral) must be characterized, and their relative importance with respect to each other must be determined.

## 3.1 HVRA Identification

This analysis focuses solely on risk to human communities and the housing units associated with each community. We restricted housing unit and community boundary spatial data to the FOA extent defined in Section 1.2 and summarized results within this portion of the community boundary.

## 3.2 Response Functions

Each HVRA selected for the assessment must also have an associated response to fire, whether it is positive or negative. We used a response function for housing-unit loss based on the potential for home destruction even at low intensity levels as supported by Cohen and Stratton (2008) and consistent with home losses at lower flame lengths observed in recent California wildfire events.

The flame length values corresponding to the fire intensity levels reported by FSim are shown in Table 3. The response functions (RFs) used in the risk results are shown in Table 3.The table shows positive values, however, the value refers to a negative percent of loss or damage to structures or housing-units.

**Table 3. Flame length values corresponding to Fire Intensity Levels used in assigning response functions.**

| Fire Intensity Level (FIL) | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Flame Length Range (feet) | 0-2 | 2-4 | 4-6 | 6-8 | 8-12 | 12+ |
| Housing-unit response function | 25 | 40 | 55 | 70 | 85 | 100 |

## 3.3 HVRA Characterization Results

### 3.3.1 *Housing unit data*

The LandScan CONUS Night-Time Population database provides national population estimates within a 3 arc-second grid. We calculated mean population density at 30 m within a 300-m radius and converted to housing-unit density by estimating 2.53 reside in each house Figure 7. We then converted housing-unit density to housing-unit counts for risk summaries.

For this assessment, housing units were considered *directly* exposed to wildfire if they were located on burnable land cover[1]. Housing units were considered *indirectly* exposed to wildfire if they were located on nonburnable land cover (other than open water or ice) but within 1.5 km of contiguous, burnable land cover at least 500 ha in size. Only directly or indirectly exposed housing units are summarized in this report. Nonexposed housing units (those within an urban core, for example) are not included.

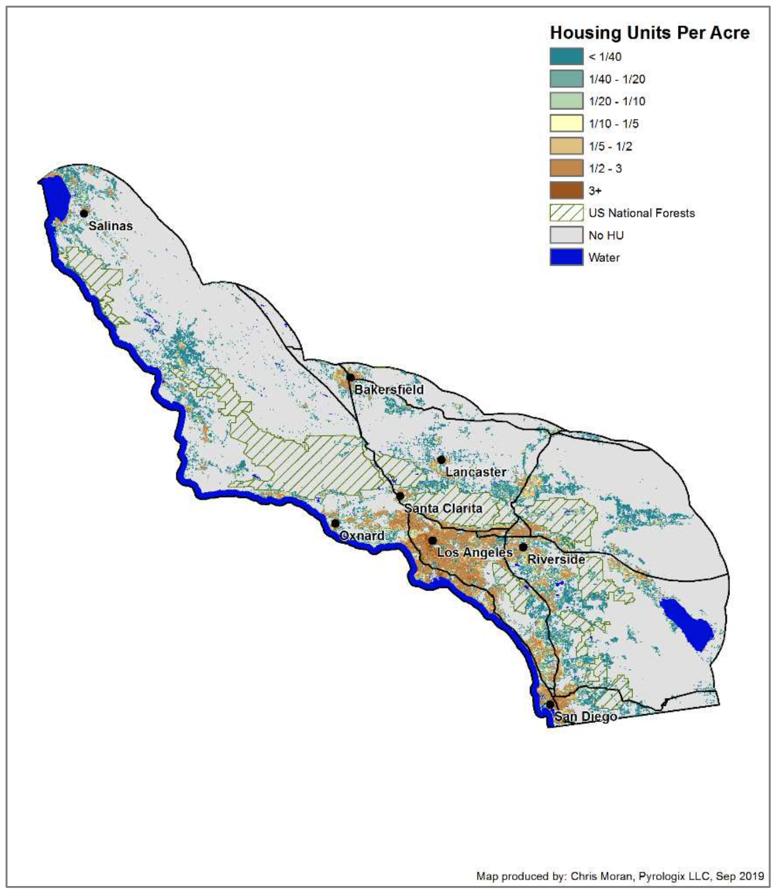


**Figure 7. Mean number of housing units per acre on the SCRA landscape.**

[1]Burnable and nonburnable land cover is characterized by the LANDFIRE 2014b FBFM40 data layer (www.landfire.org) updated as discussed in Section 2.1. Burnable land cover includes land covered by grasses, forbs, shrubs, tree litter, understory trees, or logging slash. Nonburnable land cover includes urban areas, irrigated agricultural land, permanent snow or ice, bare ground, and open water.

## 3.3.2 *Human communities*

We defined a human community as the housing units within a community core as defined by the Populated Place Areas dataset produced by the United States Census Bureau plus the population within a 45-minute drive of the boundary of the community core (Ager *et al.*, 2018). Summing the housing-unit count values for all locations in a named community provides an estimate of the total number of housing units in the community.

# 3.4 Effects Analysis Methods

An effects analysis quantifies wildfire risk as the expected value of net response (Finney, 2005; Scott *et al.*, 2013b) also known as expected net value change (eNVC). This approach has been applied at a national scale (Calkin *et al.*, 2010), in regional and sub-regional assessments (Thompson *et al.*, 2015; Thompson *et al.*, 2016) and several forest-level assessments of wildfire risk (Scott and Helmbrecht, 2010; Scott *et al.*, 2013a). Effects analysis relies on input from resource specialists to produce a tabular response function for each HVRA occurring in the analysis area. A response function is a tabulation of the relative change in value of an HVRA if it were to burn in each of six flame-length classes. A positive value in a response function indicates a benefit, or increase in value; a negative value indicates a loss, or decrease in value. Response function values ranged from -100 (greatest possible loss of resource value) to +100 (greatest possible increase in value).

## 3.4.1 *Effects Analysis Calculations*

Integrating HVRAs with differing units of measure (for example, habitat vs. homes) requires relative importance (RI) values for each HVRA/sub-HVRA. Because this analysis uses only one HVRA (human communities), no overall relative importance value is needed. However, because the number of housing units per pixel varies spatially, we leverage that value as the sub-HVRA weighting, or relative importance per pixel (RIPP) for human communities.

The RF and RIPP values were combined with estimates of the flame-length probability (FLP) in each of the six flame-length classes to estimate conditional NVC (cNVC) as the sum-product of flame-length probability (FLP) and response function value (RF) over all the six flame-length classes, with a weighting factor adjustment for the relative importance per unit area of the HVRA, as follows:

$$cNVC_j = \sum_{i}^{n} FLP_i * RF_{ij} * RIPP_j$$

where i refers to flame length class (n = 6), j refers to each HVRA, and RIPP is the weighting factor based on the relative importance and relative extent[2] (number of pixels) of each HVRA. The cNVC calculation shown above places each pixel on a common scale (relative importance), allowing them to be summed across all HVRA (when more than one) to produce the total cNVC at a given pixel:

$$cNVC = \sum_{j}^{m} cNVC_j$$

[2] When calculating cNVC for multiple HVRA with varying extents on the landscape, the relative extent and number of pixels of each HVRA must be considered when determining the RIPP.

where cNVC is calculated for each pixel in the analysis area. Finally, eNVC for each pixel is calculated as the product of cNVC and annual BP:

$$eNVC = cNVC * BP$$

### 3.4.2 *Downscaling FSim Results for Effects Analysis*

FSim's stochastic simulation approach can be computationally intensive and therefore time constraining on large landscapes. The challenge is to determine a sufficiently fine resolution that retains detail in fuel and terrain features while producing calibrated results in a reasonable timeframe. We chose to downscale the original, 180-m FSim results to 30 m, consistent with the 30 m HVRA mapping. We refer to the following downscaling approach as 'upsampling'.

An additional issue is overcome during the upsampling process. LANDFIRE fuel maps classify most developed urban areas as nonburnable fuel types which stop simulated fires at urban boundaries. Recent CA fires have demonstrated that urban areas can support fire spread similar to those burning in wildland areas. Until fire models can simulate such behavior, spatial techniques can 'ooze' burn probability (BP) into adjacent nonburnable urban areas to mimic the effects of urban wildfire spread. The oozing process can be significantly influenced by isolated islands of burnable fuels (e.g. urban parks). These 'islands' of BP were identified, removed prior to oozing, and then placed back in the data layer after oozing.

To upsample the 180-m FSIM BP to 30 m, burnable fuel models at the 30-m resolution that were considered nonburnable at the 180-m resolution must be attributed appropriate BP values. This was accomplished by running two low-pass filters over the nonzero BP values at 180 m. The result was resampled to 30 m using cubic convolution allowing zero BP cells to become nonzero. All nonburnable fuel types were forced to zero BP. After resampling, the BP was oozed into adjacent nonburnable fuel types with three iterative, 500-m focal means from contiguous patches at least 500 ha. The total distance BP can be spread into nonburnable areas is 1.5 km (approximately 2 km in the diagonal direction). This oozing could occur in bare ground, agricultural, and urban fuel models but not water or snow/ice fuel models. The oozed BP values rapidly diminish with distance from source BP but still show nonzero BP to highlight the potential for rare urban conflagration events.

## 3.5 Risk Transmission Analysis Methods

The potential for fires occurring in different parts of the landscape to expose housing units is a function of spatial variation in fire occurrence and fire growth potential (which is simulated by FSim), in conjunction with spatial variation in housing-unit count. To evaluate this potential, we summed the number of housing units within each simulated fire perimeter, then attributed the start location of each fire with that number. In order to capture the indirectly exposed housing-units in a manner consistent with the upsampling methodology used in the Effects Analysis, we generated an exposure mask (Figure 8) using the same iterative smoothing approach described in Section 3.4.2. Housing units located on burnable fuel received an exposure mask value of one and all indirectly exposed housing units received a fractional exposure value less than one, based on the distance from the burnable fuel serving as a source of exposure. We adjust housing units exposed by multiplying the number of housing units by the exposure mask value in each pixel.

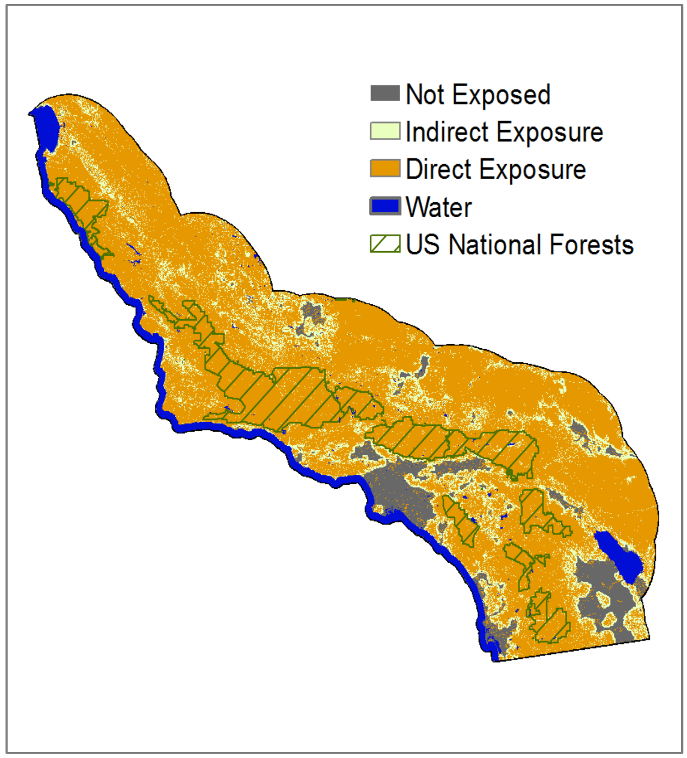


**Figure 8. Exposure mask identifying portions of the landscape directly exposed to wildfire (i.e. in burnable fuel) versus those indirectly exposed to wildfire (i.e. within 1.5 km of contiguous burnable fuel >500 ha).**

# 4 Analysis Results

## 4.1 Model Calibration to Historical Occurrence

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 10 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. All FOAs were calibrated to well within the 70% confidence interval for average wildfire size and frequency. Additionally, we calibrated each FOA to accurately mimic the distribution of wildfire sizes in the historical record to allow for future fireshed, WUI housing risk, or other types of analyis that utilize the perimiter event set.

## 4.2 FSim Results

FSim burn probability, flame length exceedance probability, and conditional flame length model results are presented for the SCRA analysis area in sections 4.2.1, 4.2.2, and 4.2.3, respectively. Additionally, all FSim results are presented in the Deliverables folder and are described in further detail in section 6. FSim produced wildfire hazard results for each FOA, including burn probability and conditional flame length probability. From the base FSim outputs, flame length exceedance probabilities were calculated for each FOA. The ten FOAs were combined using the calculations described above to produce integrated maps of wildfire hazard for the entire analysis area.

### 4.2.1 *Burn Probability*

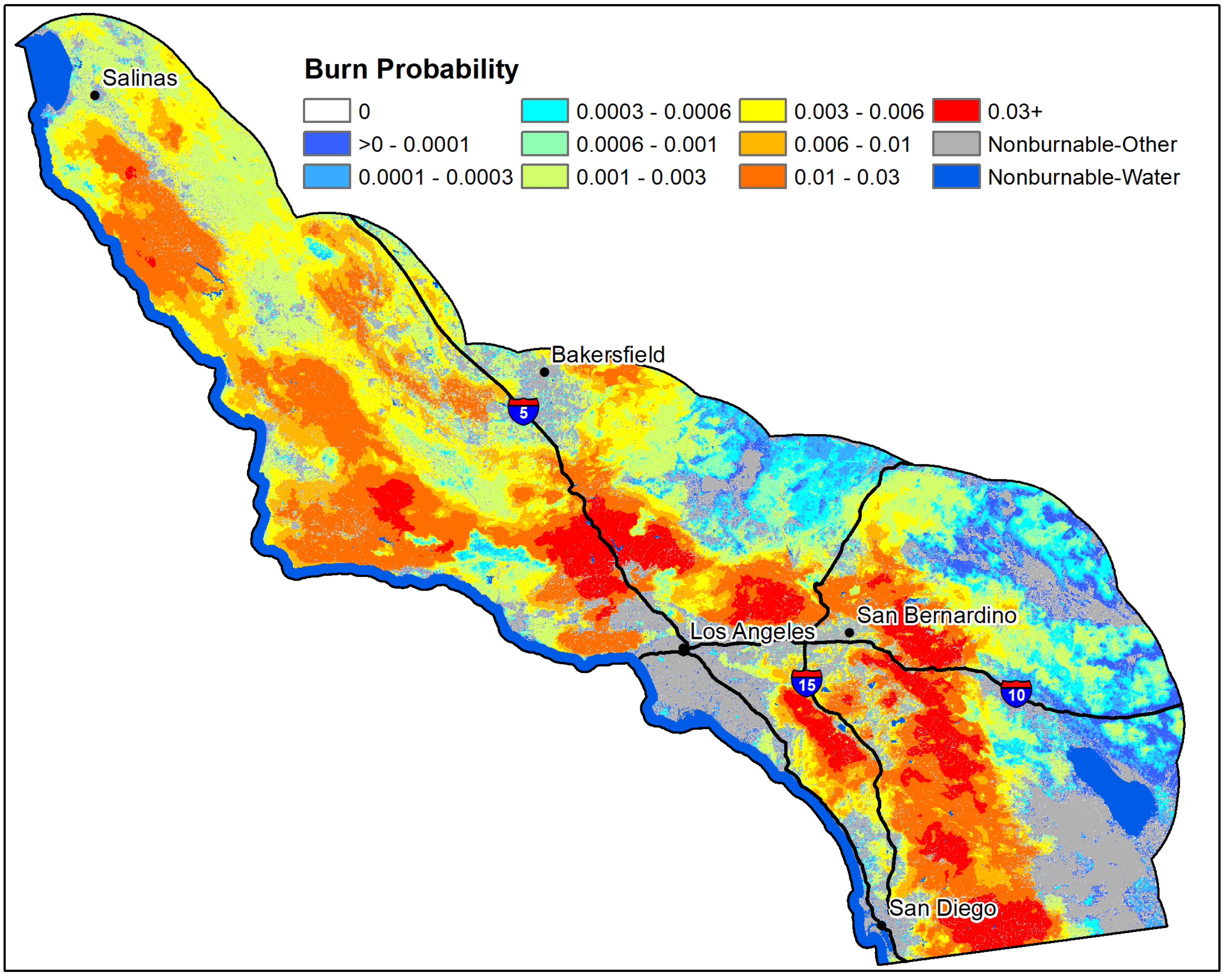


**Figure 9. Map of integrated FSim burn probability results for the SCRA study area.**

## 4.2.2 *Flame Length Exceedance Probability*

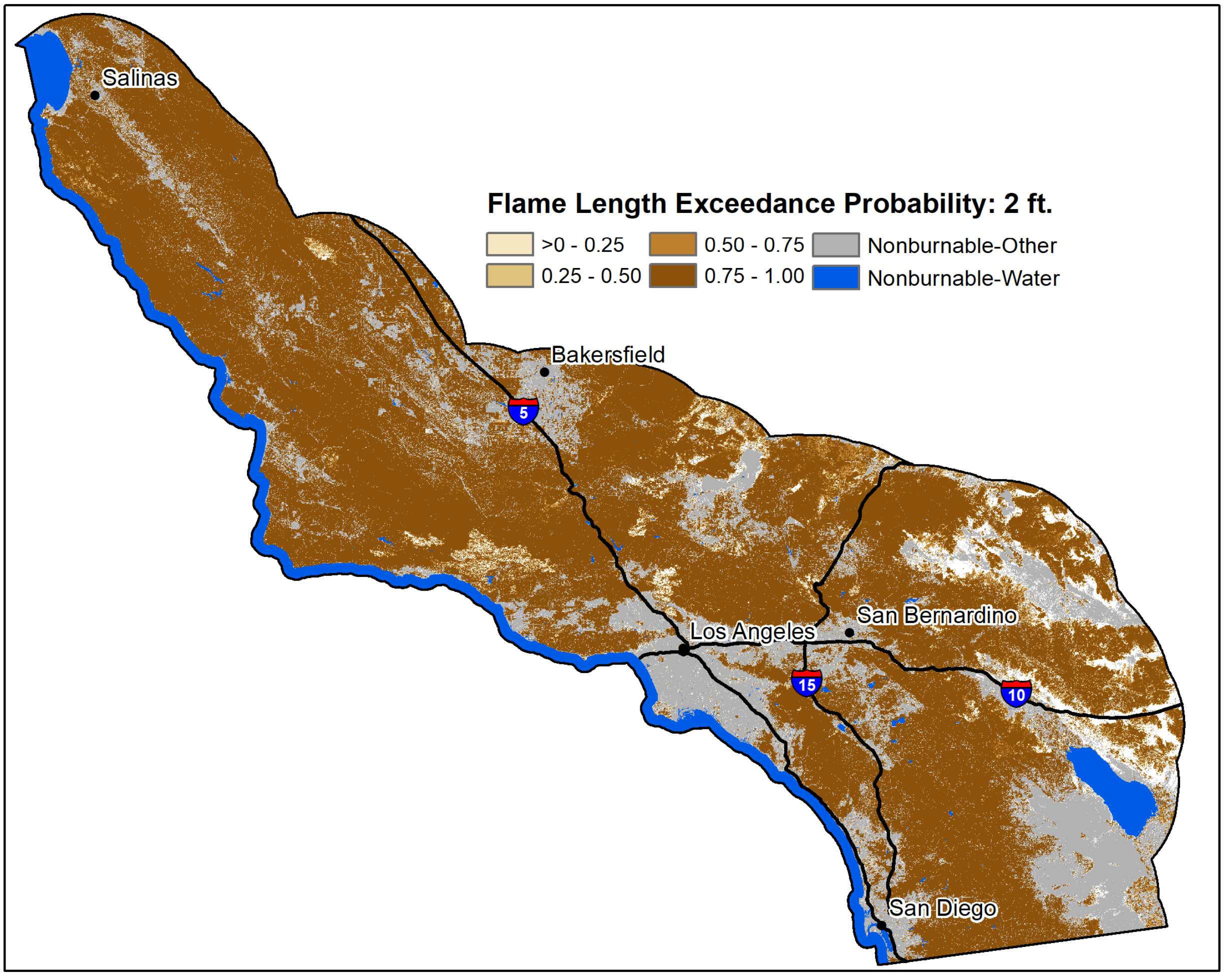


**Figure 10. Map of FSim flame length exceedance probability: 2-ft. results for the SCRA study area.**

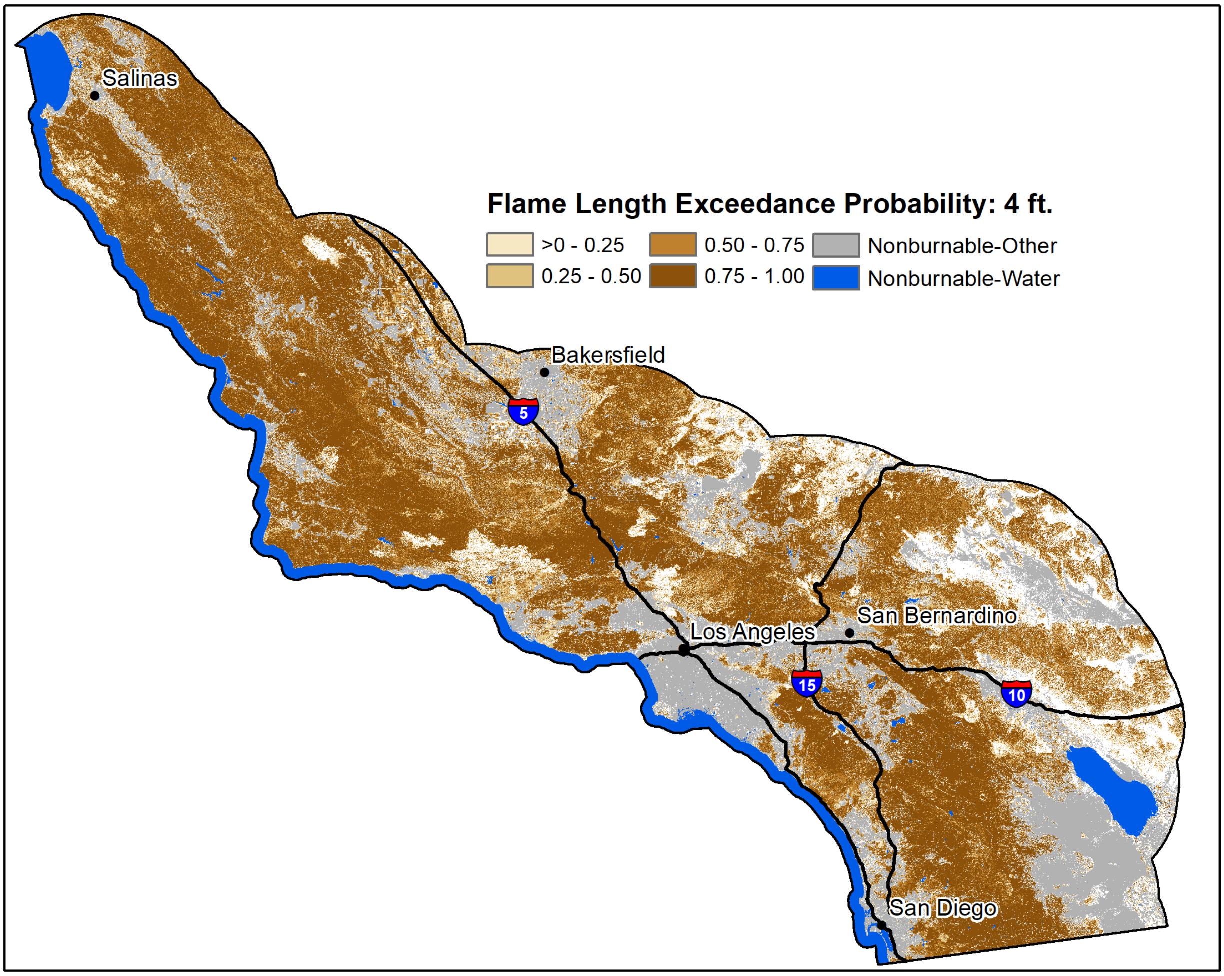


**Figure 11. Map of FSim flame length exceedance probability: 4-ft. results for the SCRA study area.**

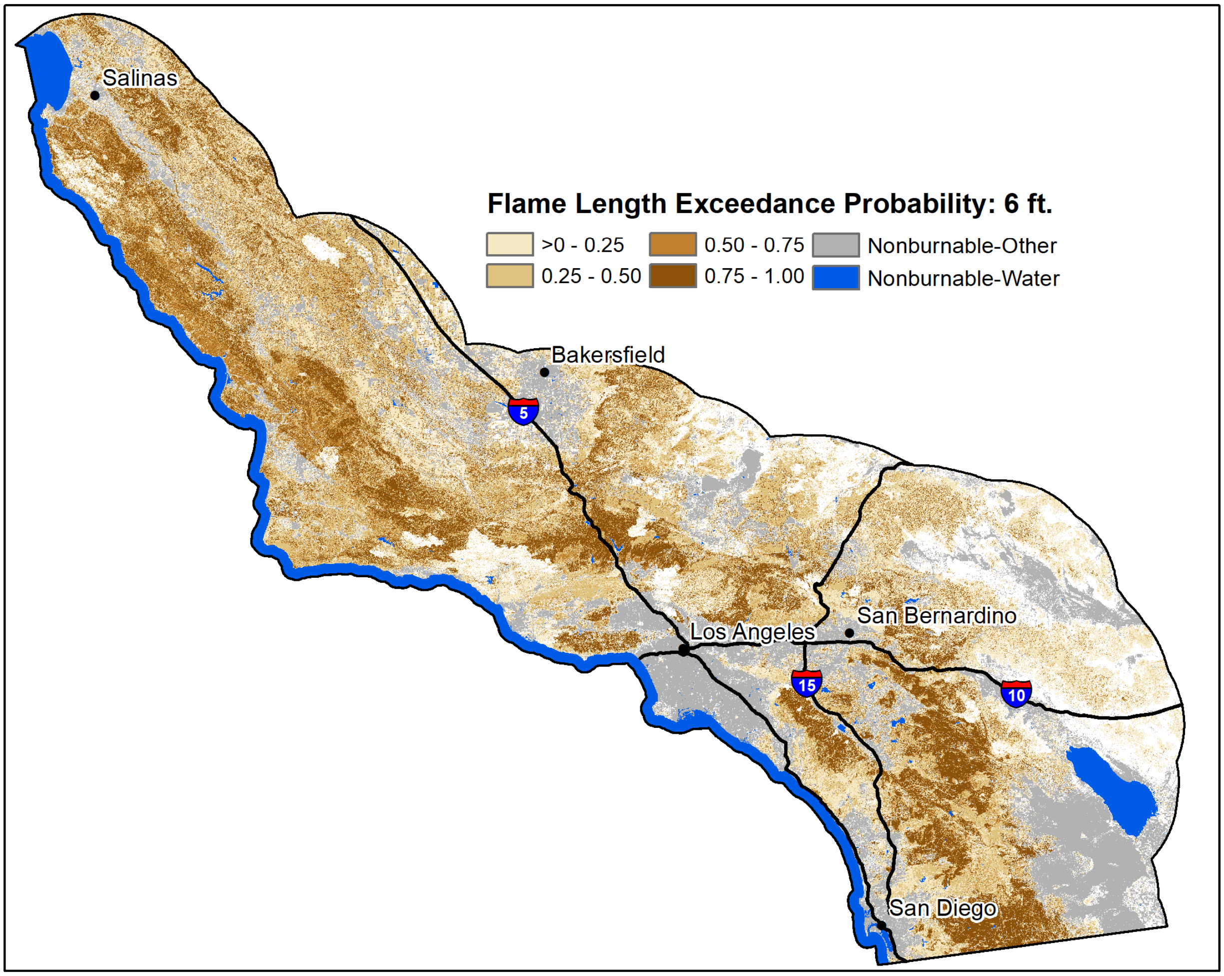


**Figure 12. Map of FSim flame length exceedance probability: 6-ft. results for the SCRA study area.**

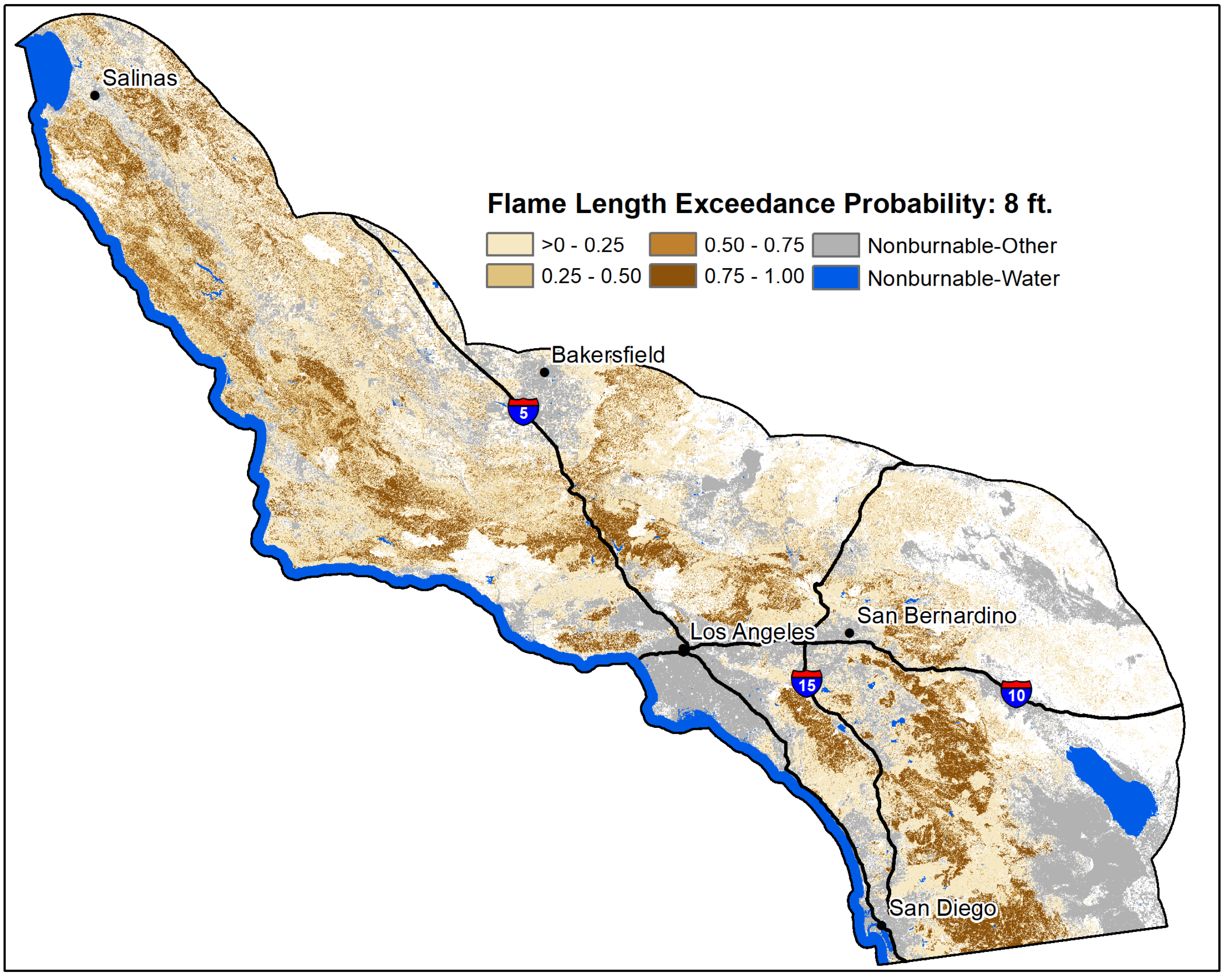


**Figure 13. Map of FSim flame length exceedance probability: 8-ft. results for the SCRA study area**

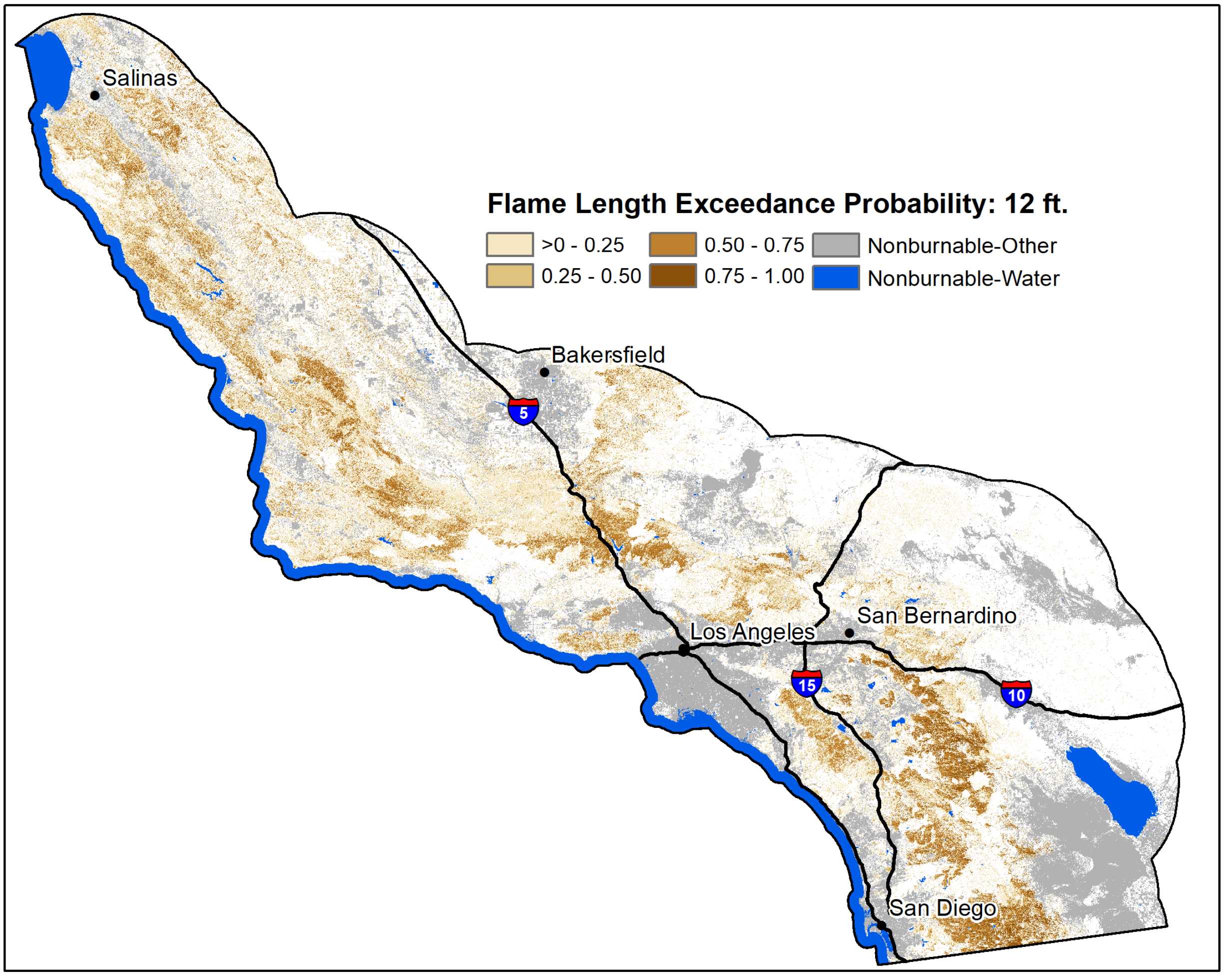


**Figure 14. Map of FSim flame length exceedance probability: 12-ft. results for the SCRA study area**

### 4.2.3 *Conditional Flame Length*

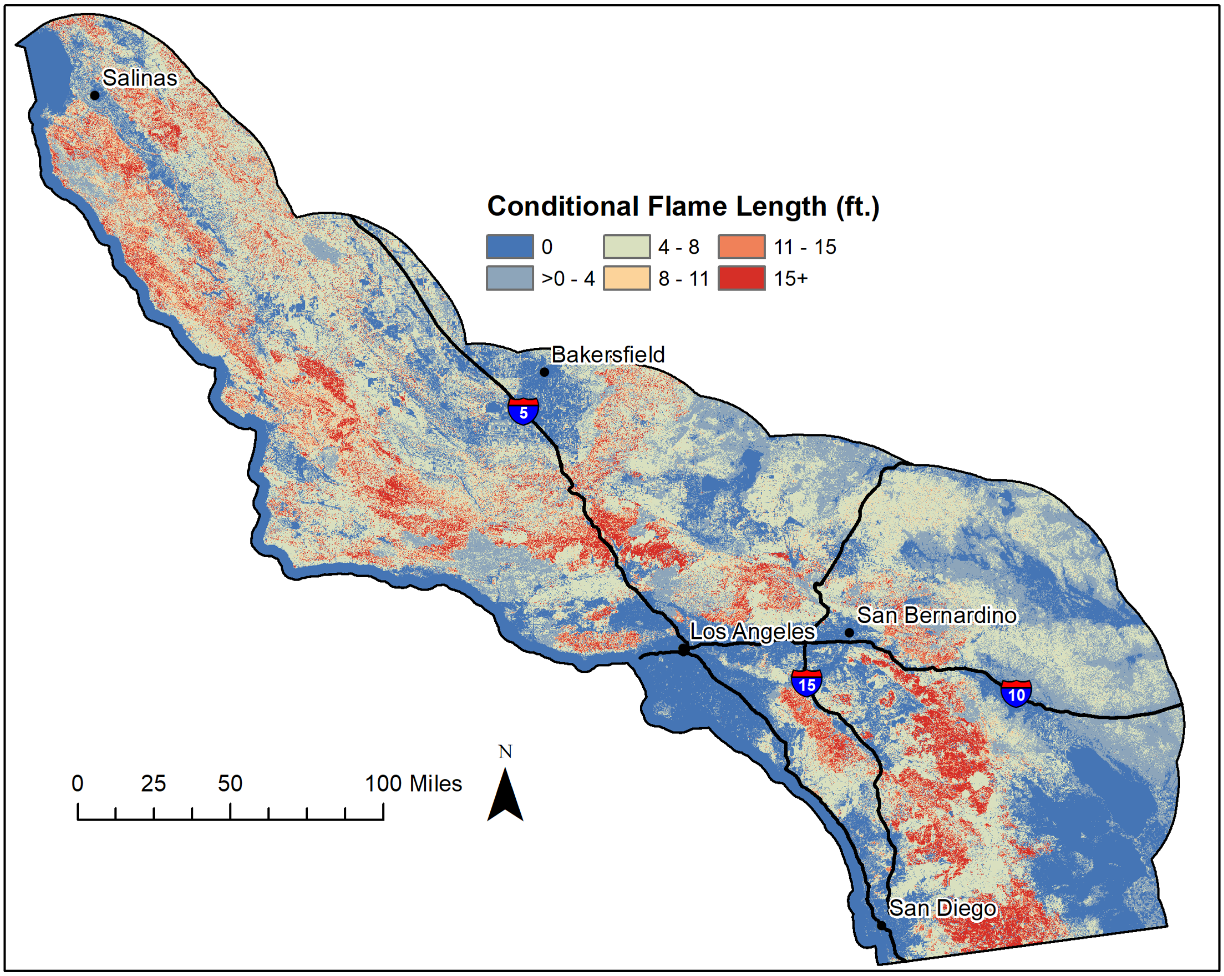


**Figure 15. Map of integrated FSim conditional flame length results for the SCRA study area.**

## 4.3 Near-Max Wildfire Behavior: NEXUS Results

NEXUS near-maximum wildfire behavior outputs are presented for the SCRA analysis area in sections 4.3.1 - 4.3.8. Additionally, all NEXUS results are presented in the Deliverables folder and are described in further detail in section 6.2. NEXUS-produced wildfire hazard results include: expanded fire type, crown fraction burned, Torching Index, Crowning Index, potential flame length, fireline intensity, heat per unit area, and rate of spread.

### 4.3.1 *Near-Max Wildfire Behavior: Expanded Fire Type*

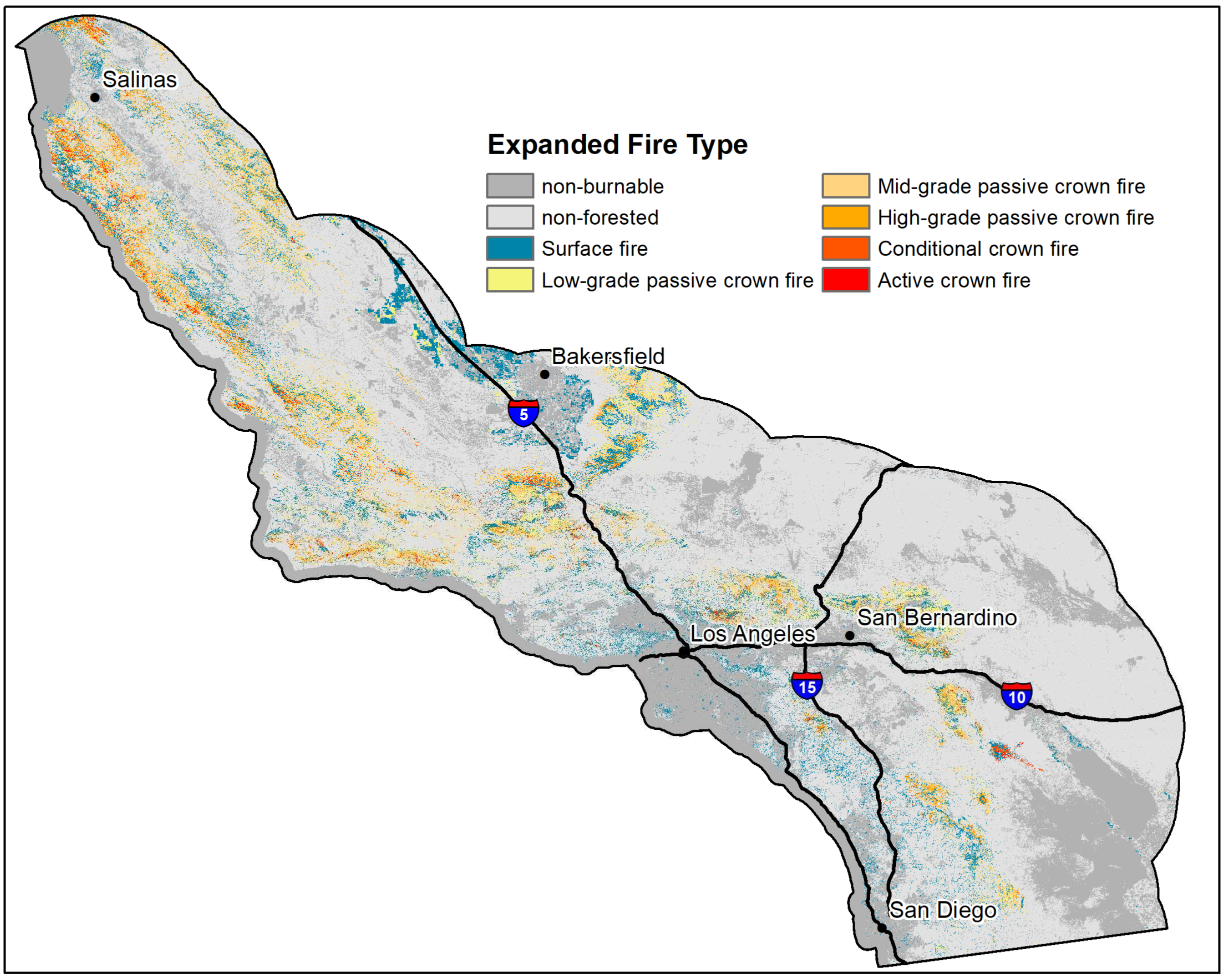


**Figure 16. Map of NEXUS expanded fire type results for the SCRA study area.**

## 4.3.2 *Near-Max Wildfire Behavior: Crown Fraction Burned*

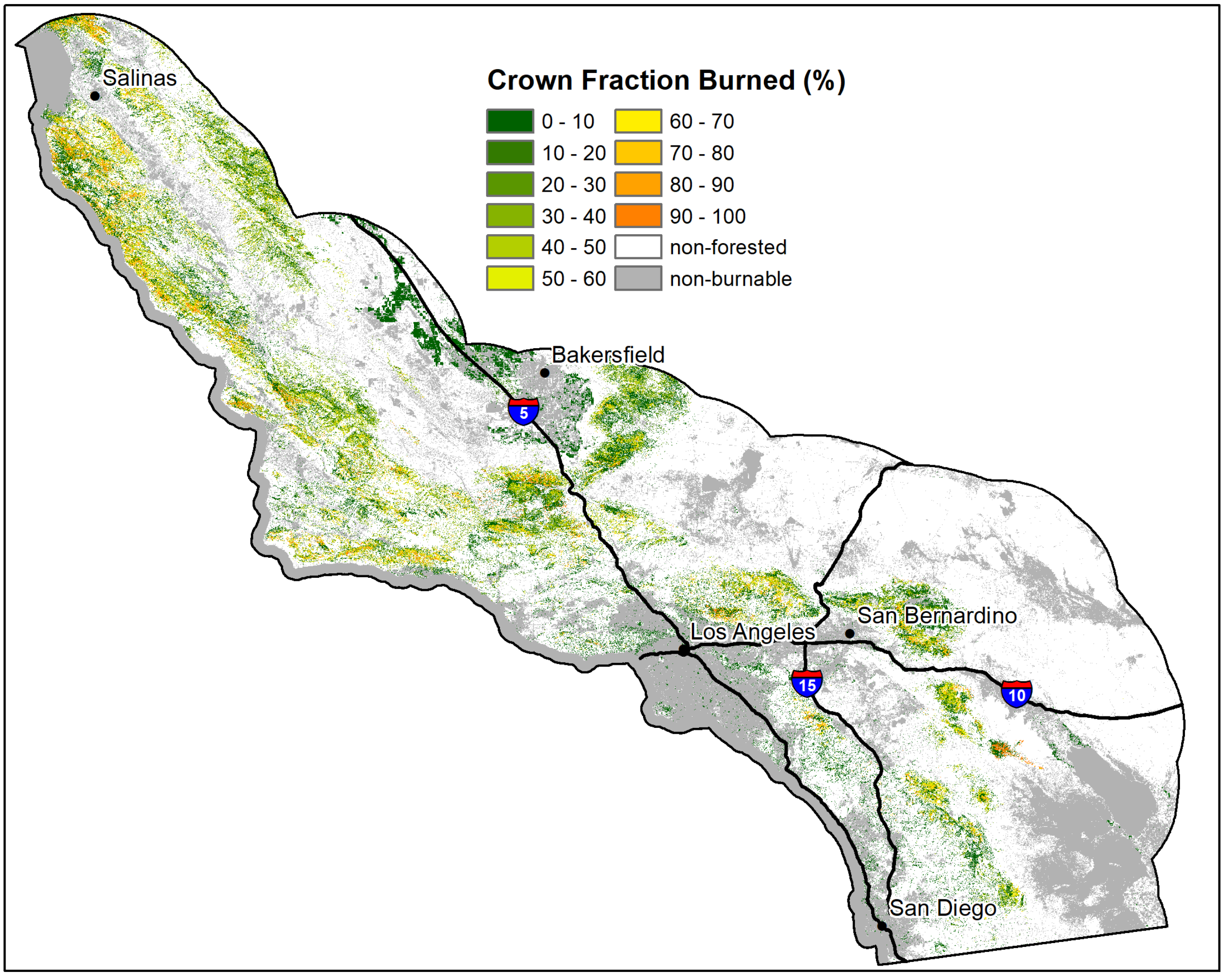


**Figure 17. Map of NEXUS crown fraction burned results for the SCRA study area.**

### 4.3.3 *Near-Max Wildfire Behavior: Torching Index*

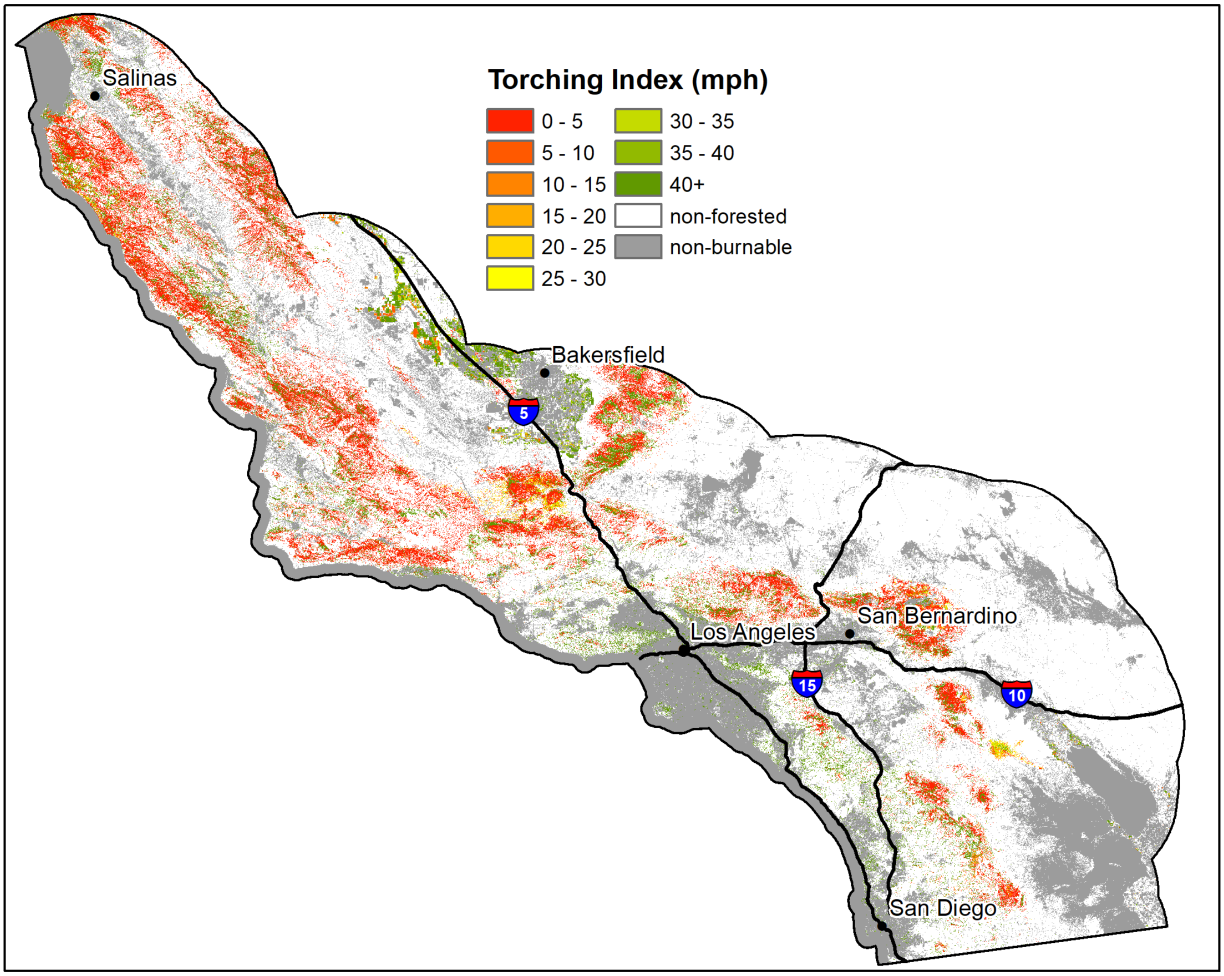


**Figure 18. Map of NEXUS Torching Index results for the SCRA study area.**

## 4.3.4 *Near-Max Wildfire Behavior: Crowning Index*

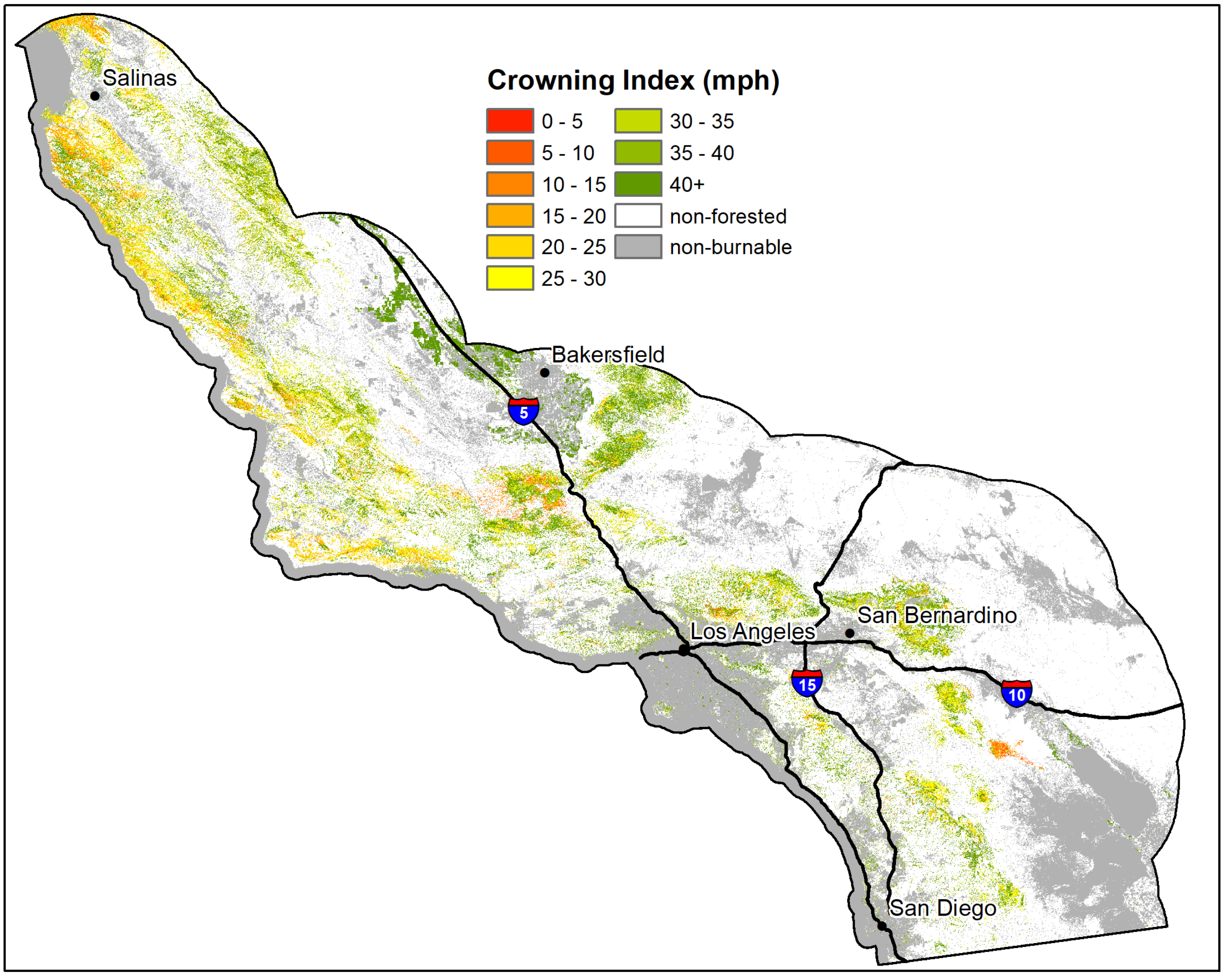


**Figure 19 Map of NEXUS Crowning Index results for the SCRA study area.**

### 4.3.5 *Near-Max Wildfire Behavior: Potential Flame Length*

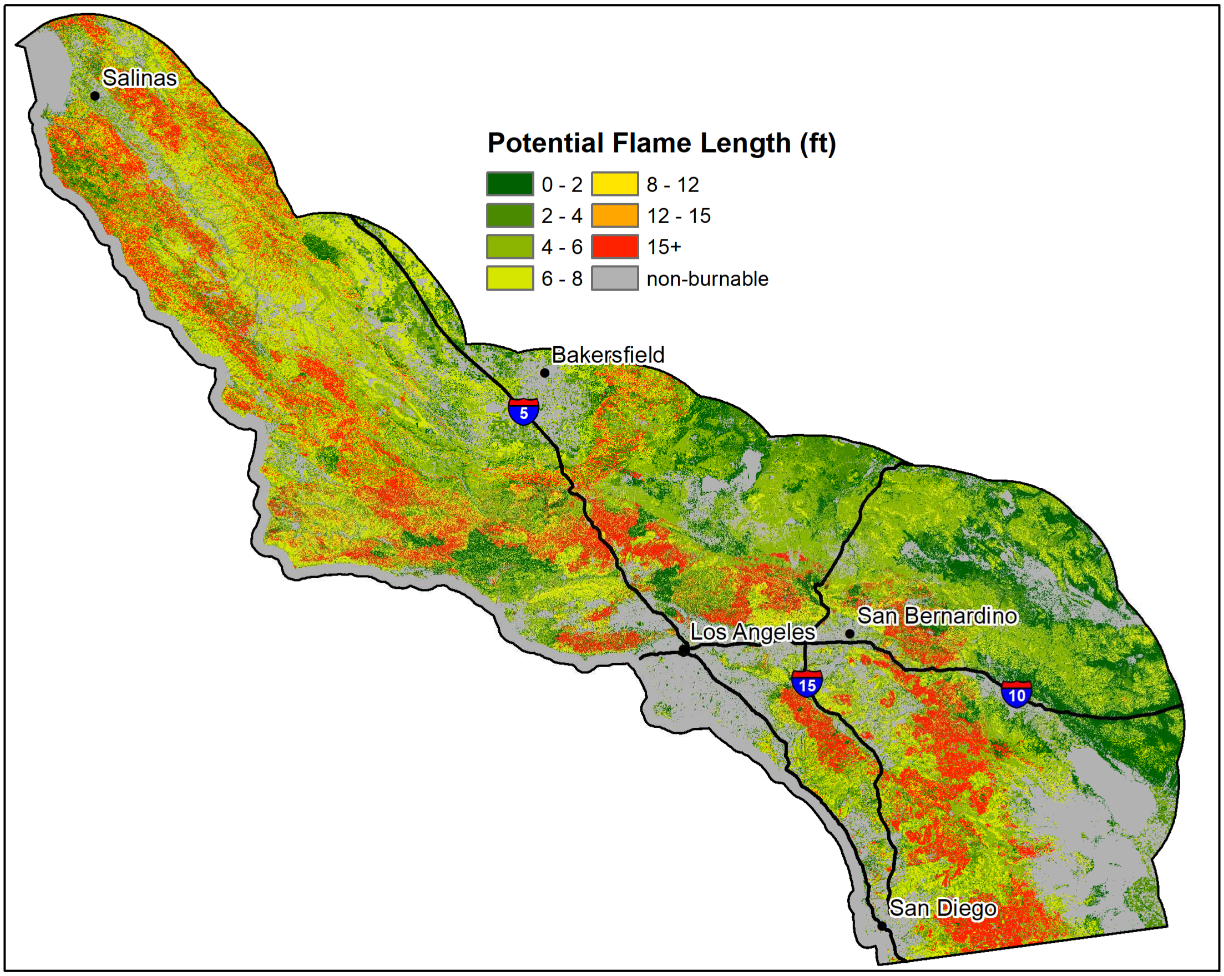


**Figure 20. Map of NEXUS potential flame length results for the SCRA study area.**

## 4.3.6 *Near-Max Wildfire Behavior: Fire Line Intensity*

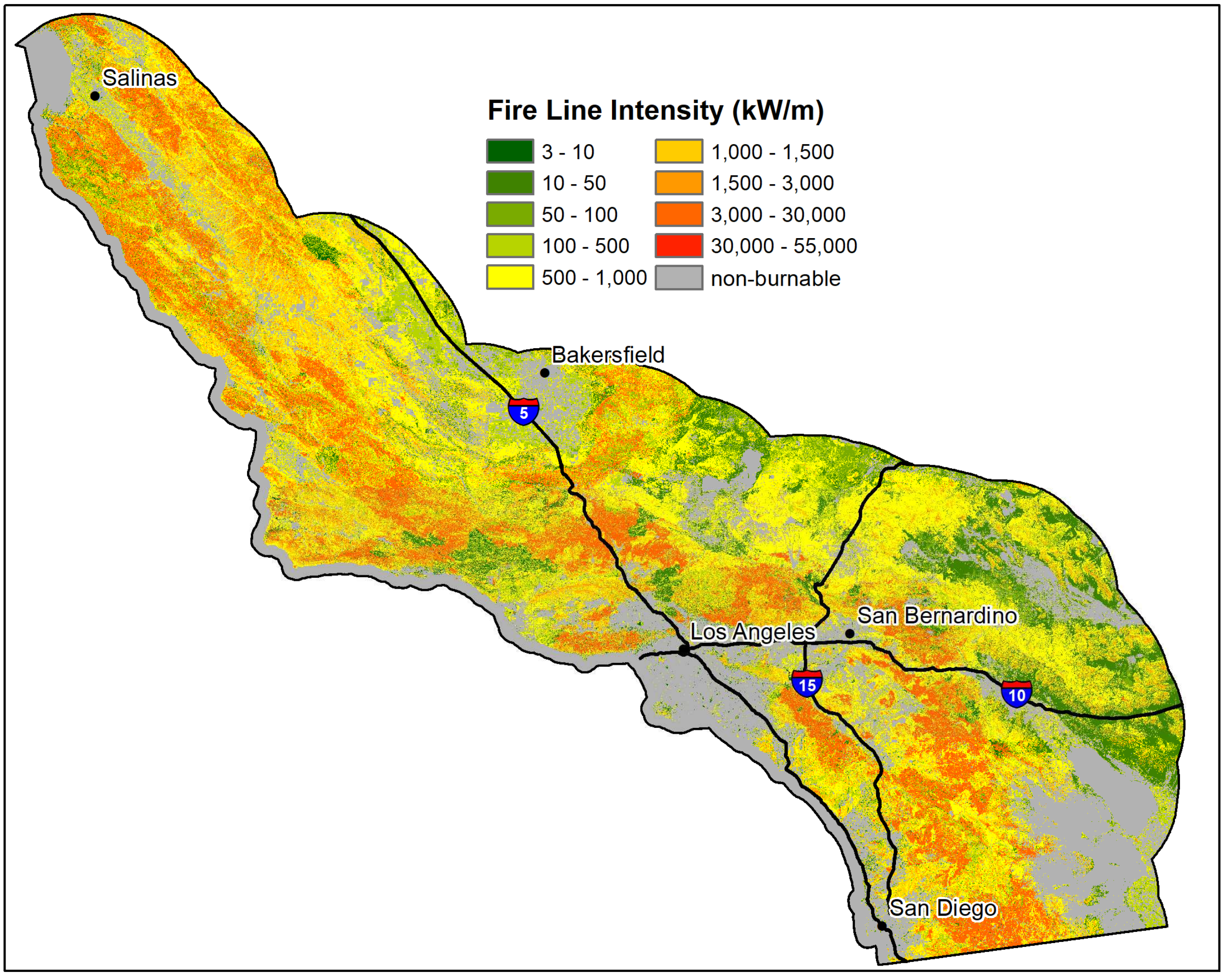


**Figure 21. Map of NEXUS fire line intensity results for the SCRA study area.**

### 4.3.7 *Near-Max Wildfire Behavior: Heat Per Unit Area*

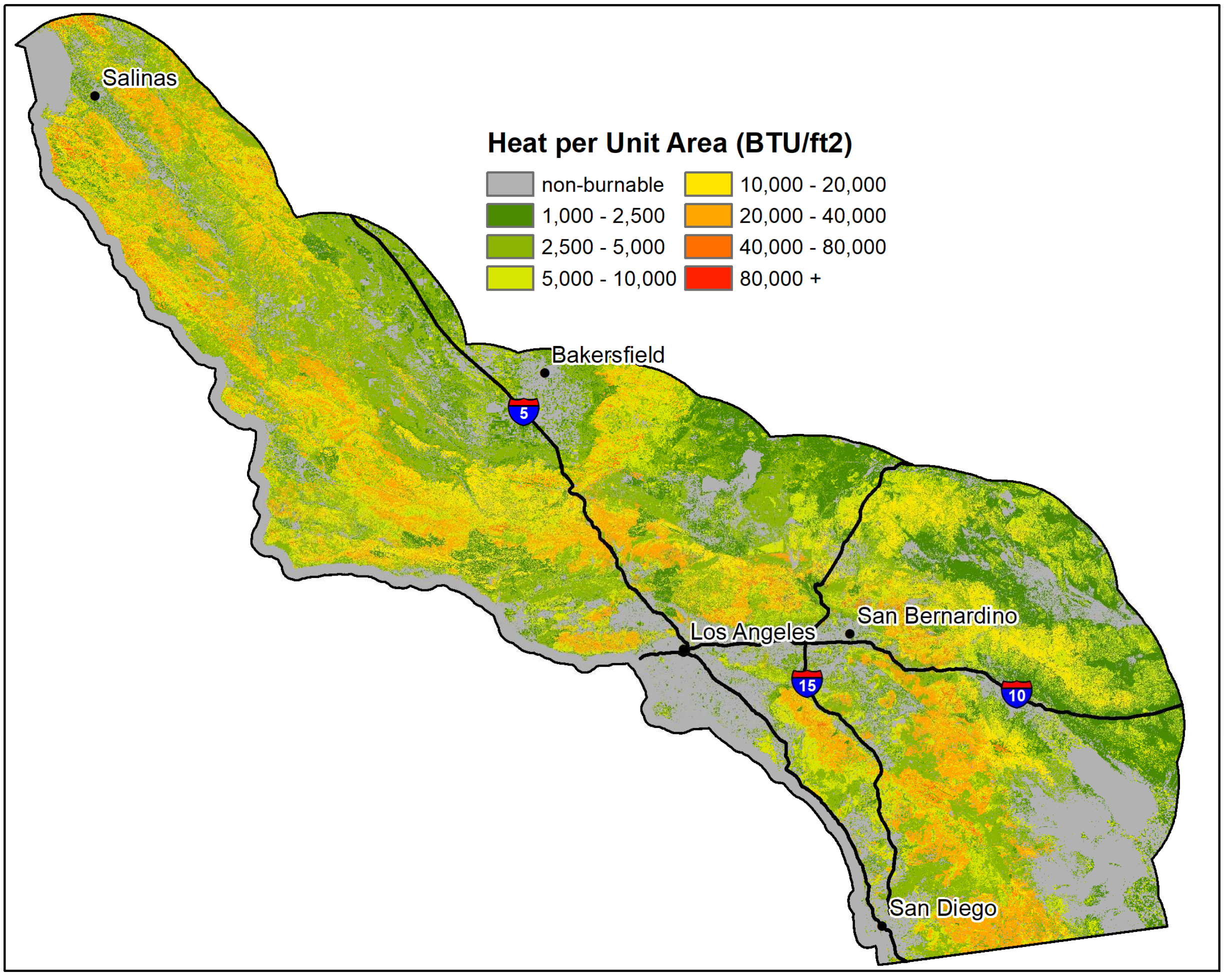


**Figure 22. Map of NEXUS heat per unit area results for the SCRA study area.**

## 4.3.8 *Near-Max Wildfire Behavior: Rate of Spread*

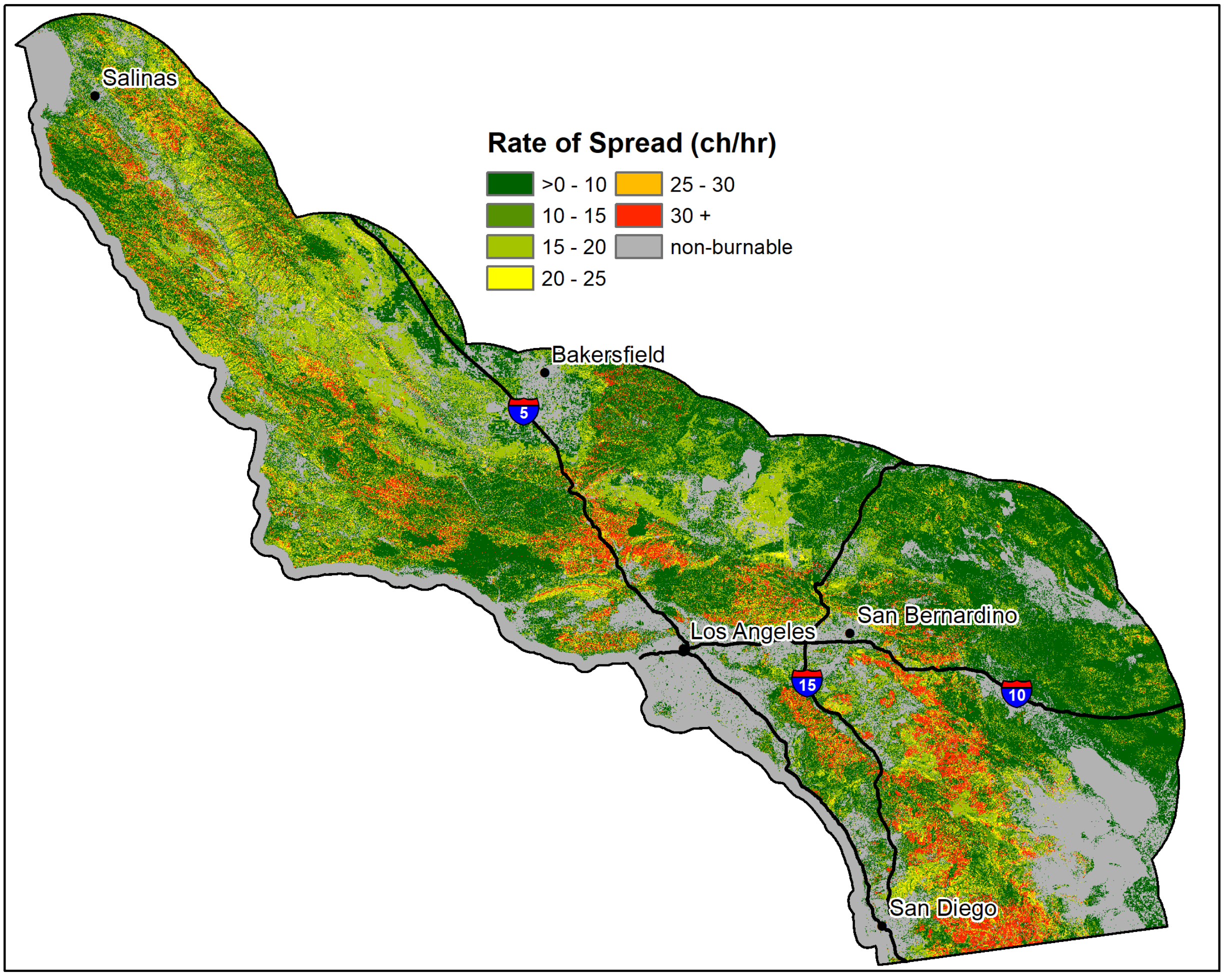


**Figure 23. Map of NEXUS rate of spread results for the SCRA study area.**

## 4.4 Effects Analysis Results

The final results of the wildfire risk calculations described in section 3.4.1 are the spatial grids of cNVC and eNVC, representing both the conditional and expected change in value from wildfire disturbance to housing-units included in the analysis. Results are therefore limited to those pixels that have a housing unit count and a non-zero burn probability. Both cNVC and eNVC characterize a general housing-unit response to fire and the relative importance within the context of the assessment, however eNVC additionally captures the relative likelihood of wildfire disturbance through the inclusion of burn probability. Figure 24 shows cNVC results across the SCRA analysis area, with lower risk to housing units shown in pink and greater risk shown in dark purple. Adjusting cNVC by fire likelihood (i.e., burn probability) focuses the map to the areas with both the greatest wildfire likelihood and the greatest consequence as seen in the eNVC map in Figure 25.

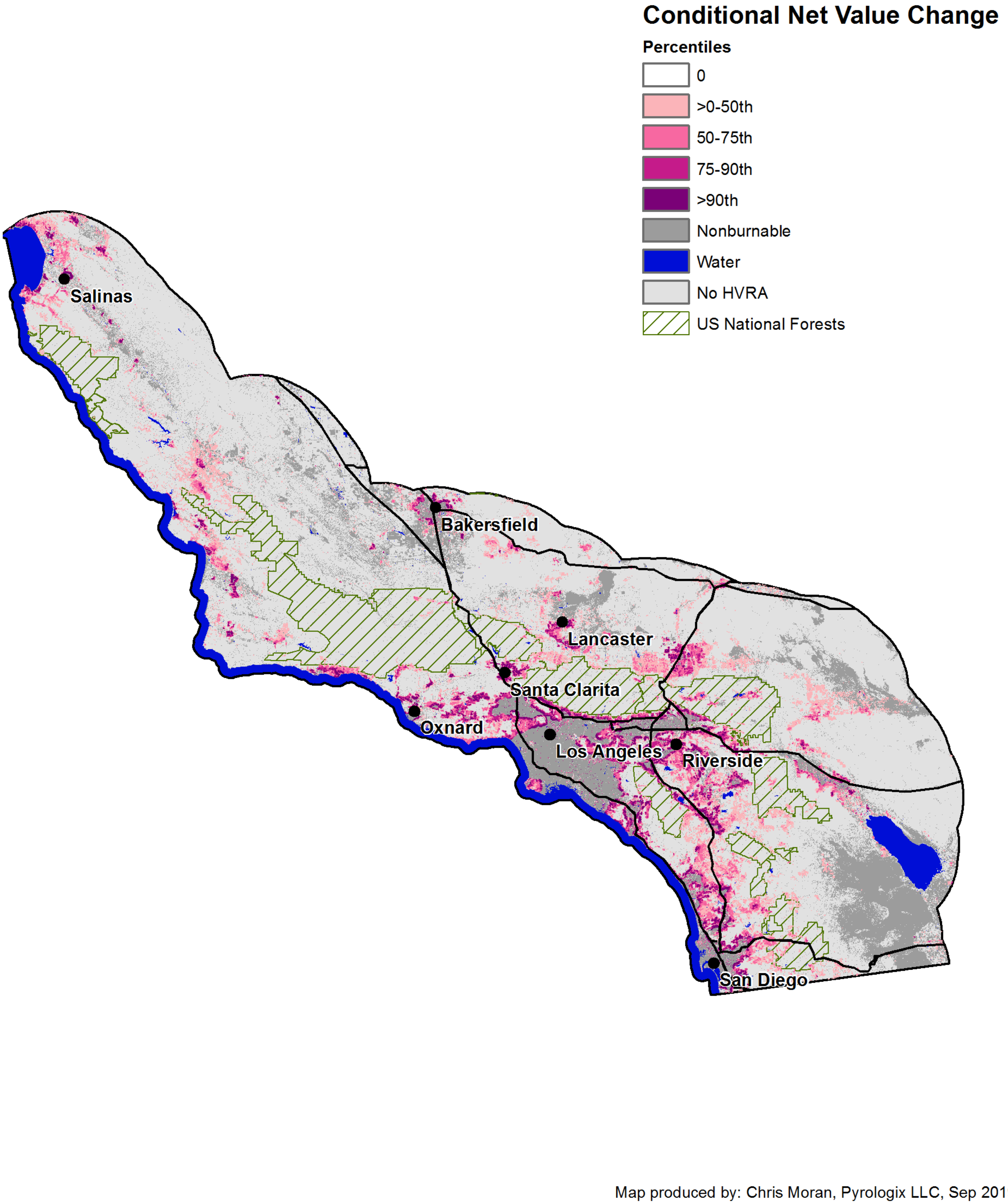


**Figure 24. Conditional Housing-Unit Net Value Change (cNVC) for the SCRA landscape.**

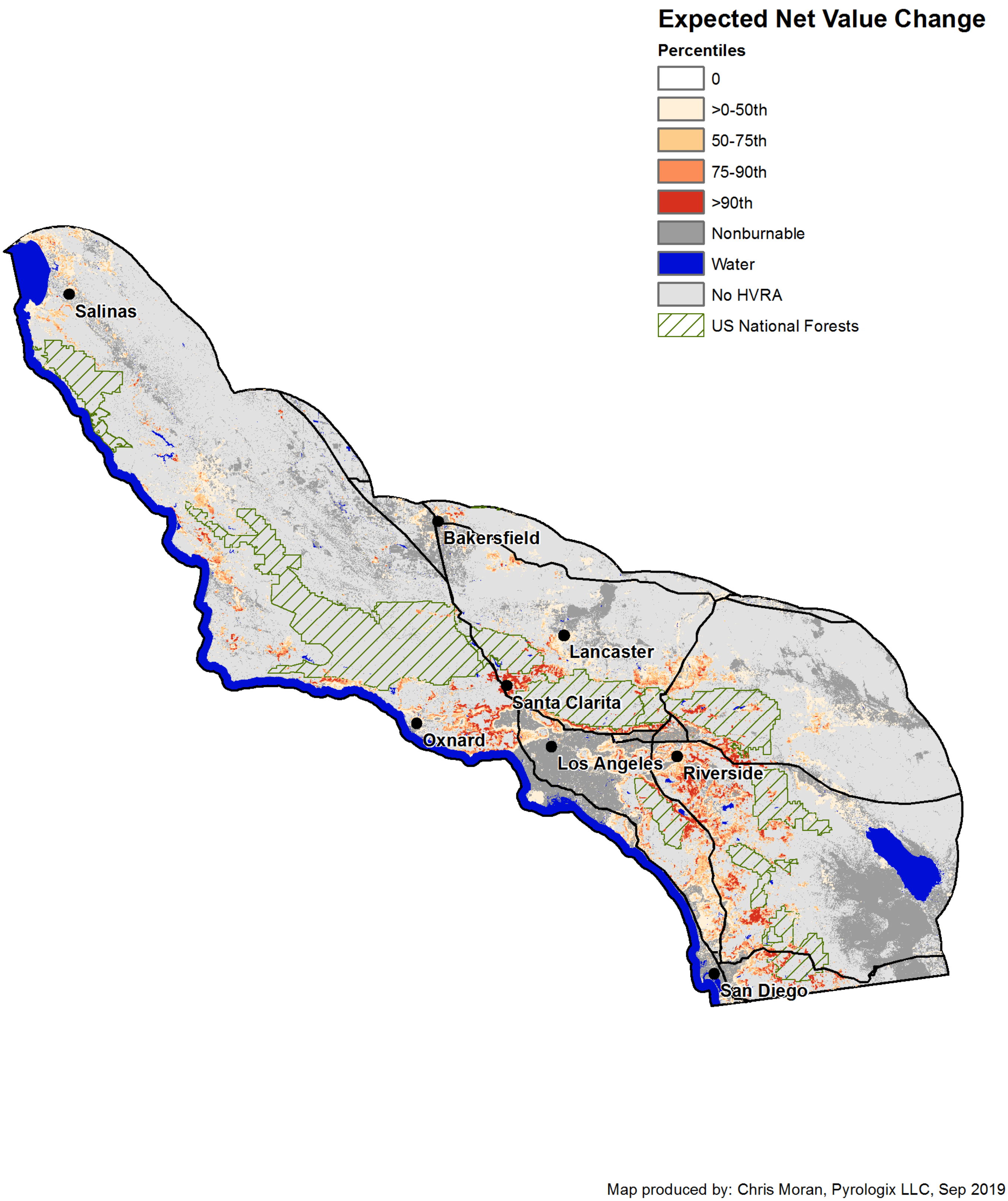


**Figure 25. Expected Housing-Unit Net Value Change (eNVC) for the SCRA landscape.**

## 4.4.1 *Ranking Communities by Housing-Unit Risk*

We first generated raster data representing the expected annual risk to housing units exposed to wildfire (the product of housing-unit count and risk to potential structures [RPS]). We then summed those results within each community; a community with more housing units can therefore have a greater community-wide risk. The resulting sum represents the cumulative annual risk to housing units within a community. The top 50 communities by this measure are listed in Table 4.

A community can be ranked as high-risk due a combination of RPS or high population (housing-units). To illustrate those contributing factors, we plotted RPS against total exposed housing unit count (Figure 26). Both axes are plotted on a common-log scale. The top 50 communities (black dots) fall along a line with those on the bottom right (e.g. Campo) having higher RPS and fewer housing units and those on the upper left (e.g. Los Angeles) having lower RPS but more housing units. The communities with the highest RPS could be further evaluated for wildfire mitigation opportunities to reduce susceptibility and exposure near the homes.

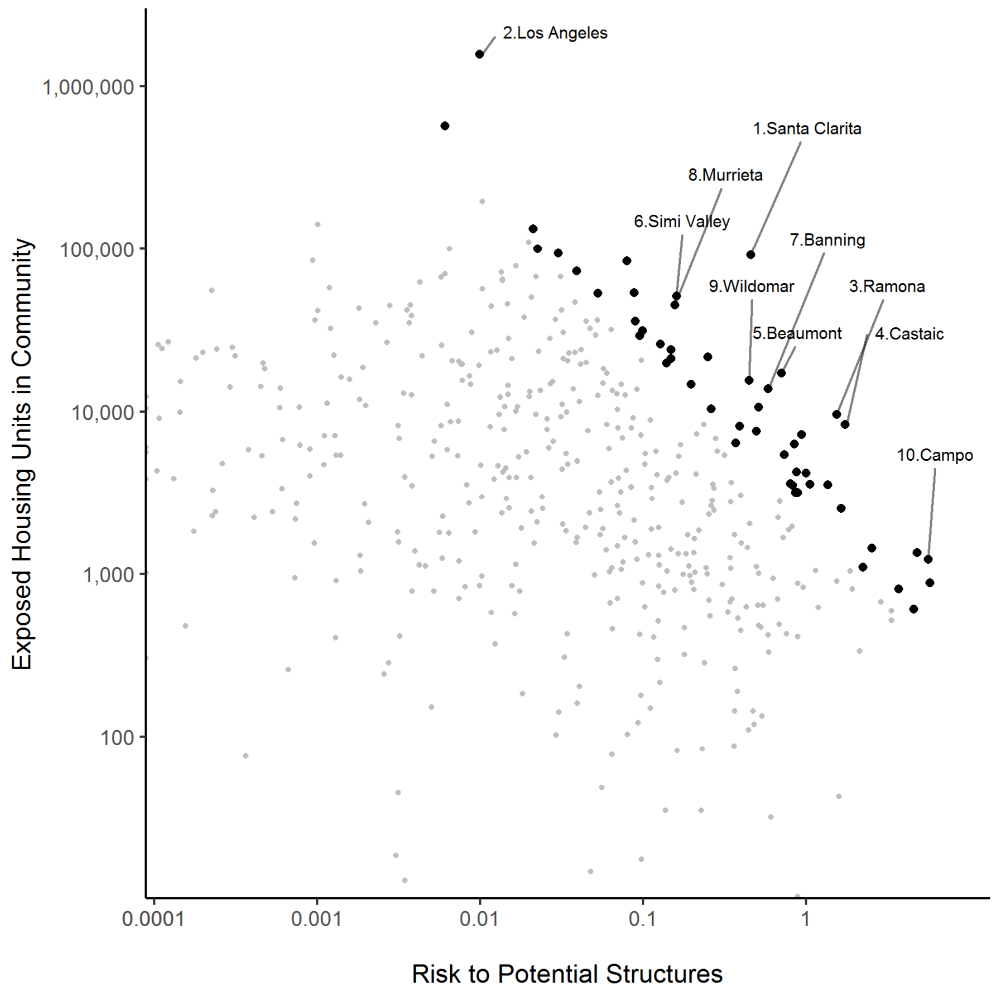


**Figure 26. Risk to potential structures in relation to total exposed housing units for Southern California communities. The top 50 most-exposed communities (by cumulative annual housing-unit exposure) are the bolded. The top ten are labeled with the community name. The small gray dots show the remaining communities within the AA. Communities with less than a 0.0001 RPS (86 communities) are not shown. Axes are shown on a common-log scale (base 10).**

**Table 4. The 50 communities in SCRA with greatest cumulative housing-unit risk from wildfire[3]. The RPS rank indicates the mean (typical) housing-unit risk of housing units within each community.**

| Community Risk Ranking | Community Name | Total Exposed HU | Expected Annual HU Risk | HU-Weighted Mean RPS | RPS Rank |
|---|---|---|---|---|---|
| 1 | Santa Clarita | 92,244 | 42241.67 | 0.46 | 61 |
| 2 | Los Angeles | 1,575,455 | 15653.53 | 0.01 | 328 |
| 3 | Ramona | 9,579 | 14804.38 | 1.55 | 18 |
| 4 | Castaic | 8,283 | 14410.14 | 1.74 | 14 |
| 5 | Beaumont | 17,242 | 12243.41 | 0.71 | 40 |
| 6 | Simi Valley | 51,262 | 8227.77 | 0.16 | 126 |
| 7 | Banning | 13,746 | 8072.20 | 0.59 | 49 |
| 8 | Murrieta | 45,123 | 7073.50 | 0.16 | 129 |
| 9 | Wildomar | 15,466 | 6929.98 | 0.45 | 63 |
| 10 | Campo | 1,229 | 6914.06 | 5.62 | 2 |
| 11 | Valley Center | 7,222 | 6781.80 | 0.94 | 25 |
| 12 | Moreno Valley | 84,513 | 6753.43 | 0.08 | 180 |
| 13 | Agua Dulce | 1,354 | 6512.22 | 4.81 | 3 |
| 14 | Yucaipa | 21,678 | 5431.18 | 0.25 | 98 |
| 15 | Calabasas | 10,591 | 5425.28 | 0.51 | 53 |
| 16 | Alpine | 6,281 | 5338.28 | 0.85 | 32 |
| 17 | Hasley Canyon | 883 | 5106.60 | 5.79 | 1 |
| 18 | Jamul | 3,531 | 4811.49 | 1.36 | 19 |
| 19 | Temecula | 53,714 | 4748.80 | 0.09 | 173 |
| 20 | Lake Arrowhead | 4,183 | 4180.08 | 1.00 | 23 |
| 21 | Acton | 2,517 | 4144.38 | 1.65 | 15 |
| 22 | Lakeland Village | 5,416 | 3989.64 | 0.74 | 38 |
| 23 | Calimesa | 3,573 | 3795.75 | 1.06 | 22 |
| 24 | Mead Valley | 7,563 | 3761.66 | 0.50 | 57 |
| 25 | San Diego Country Estates | 4,260 | 3721.71 | 0.87 | 30 |
| 26 | Anza | 1,435 | 3641.69 | 2.54 | 9 |
| 27 | Lake Elsinore | 23,962 | 3569.53 | 0.15 | 131 |
| 28 | San Diego | 573,436 | 3498.65 | 0.01 | 353 |
| 29 | San Luis Obispo | 25,902 | 3303.88 | 0.13 | 139 |
| 30 | Hemet | 35,878 | 3219.18 | 0.09 | 171 |
| 31 | Stevenson Ranch | 8,146 | 3181.68 | 0.39 | 70 |
| 32 | Fallbrook | 21,083 | 3140.71 | 0.15 | 130 |
| 33 | Perris | 31,341 | 3103.16 | 0.10 | 161 |
| 34 | Val Verde | 807 | 3006.22 | 3.72 | 5 |
| 35 | Crestline | 3,510 | 2914.22 | 0.83 | 33 |
| 36 | Good Hope | 3,595 | 2896.14 | 0.81 | 35 |
| 37 | Moorpark | 14,674 | 2891.16 | 0.20 | 113 |
| 38 | Rancho Cucamonga | 72,928 | 2848.27 | 0.04 | 236 |
| 39 | Fontana | 94,287 | 2842.37 | 0.03 | 258 |
| 40 | Riverside | 133,764 | 2834.30 | 0.02 | 277 |
| 41 | Cherry Valley | 3,169 | 2830.07 | 0.89 | 26 |
| 42 | Thousand Oaks | 53,454 | 2828.81 | 0.05 | 216 |
| 43 | Apple Valley | 29,310 | 2790.28 | 0.10 | 167 |
| 44 | San Jacinto | 19,846 | 2777.02 | 0.14 | 136 |
| 45 | Potrero | 605 | 2770.26 | 4.58 | 4 |
| 46 | Lake Mathews | 3,169 | 2724.18 | 0.86 | 31 |
| 47 | Temescal Valley | 10,355 | 2702.81 | 0.26 | 94 |
| 48 | Descanso | 1,098 | 2460.28 | 2.24 | 10 |
| 49 | Malibu | 6,384 | 2374.56 | 0.37 | 73 |
| 50 | San Bernardino | 100,247 | 2266.41 | 0.02 | 272 |

[3] The full list of communities is provided in the Excel spreadsheet titled “SCRA_Community_ZoneSummaries.xls” in the project deliverables folder.

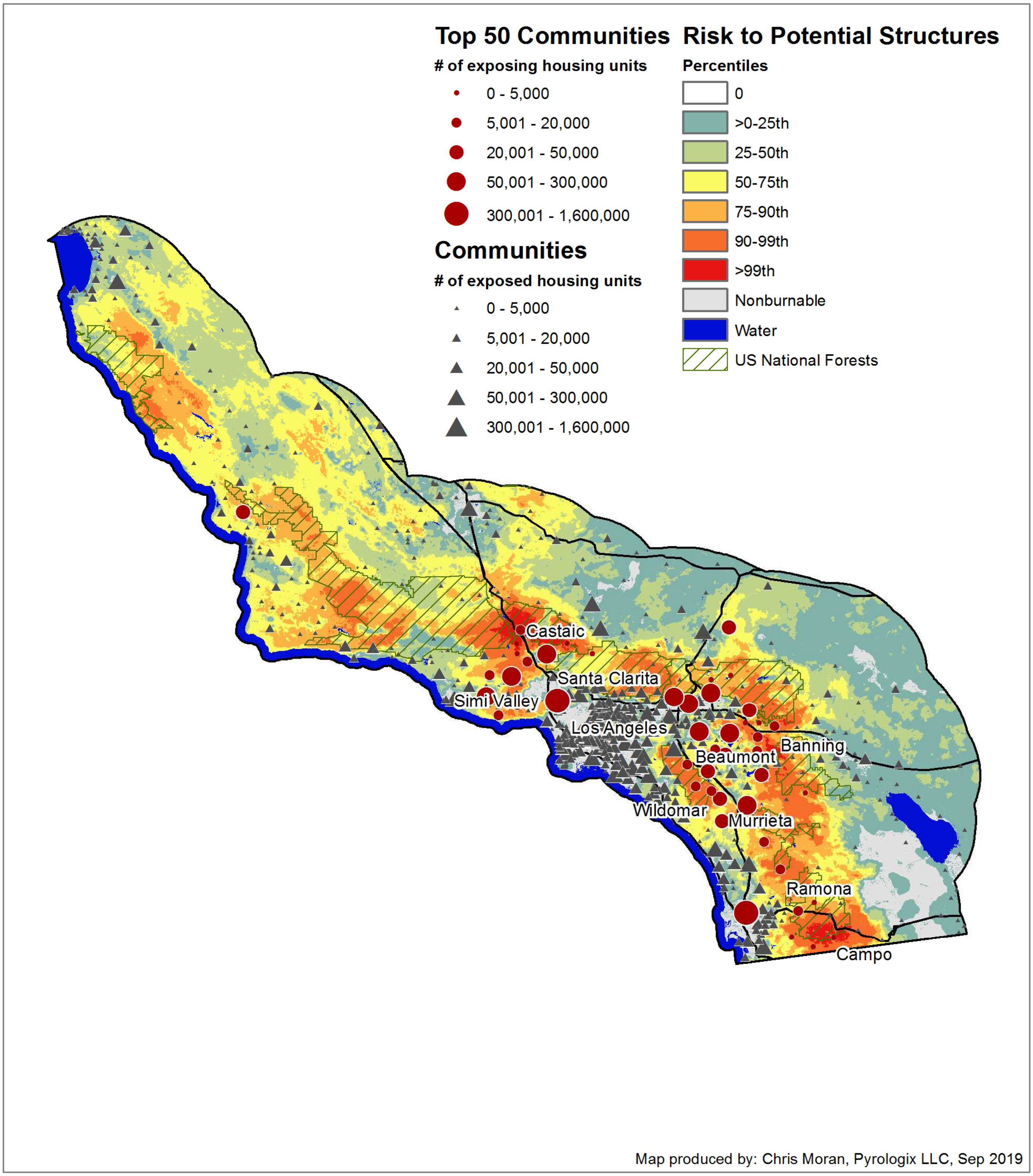


**Figure 27. Annual Risk to Potential Structures and exposed human communities across the SCRA project area. The 50 most-exposed communities are mapped in dark red and all other communities and their associated exposed housing-unit counts are shown in grey triangles. The top-ten most at-risk communities are labeled in the map. The most at-risk communities are located in areas with greatest landscape-level annual wildfire risk to structures risk based on the FSim modeling results.**

### 4.4.2 *Landscape-wide sources of housing-unit exposure*

We assessed the relative potential for different parts of the landscape to produce wildfires that expose housing units by summing the exposure-adjusted number of housing units within each simulated perimeter plus a 1.5-km buffer and tied that value to the ignition location on the landscape. We then created a smoothed surface based on thousands of simulated ignitions in a 10-km moving window that represents the relative annual number of housing units exposed per square kilometer by fires originating across the landscape (Figure 27). Even though a small number of large fires account for the vast majority of wildfire area burned (Strauss and others 1989) it appears that wildfires originating near populated areas are responsible for the vast majority of the housing-unit exposure. The areas of higher exposure-source tend to fall predominantly near where communities exist with relatively few areas occurring within National Forest lands as seen in Figure 27.

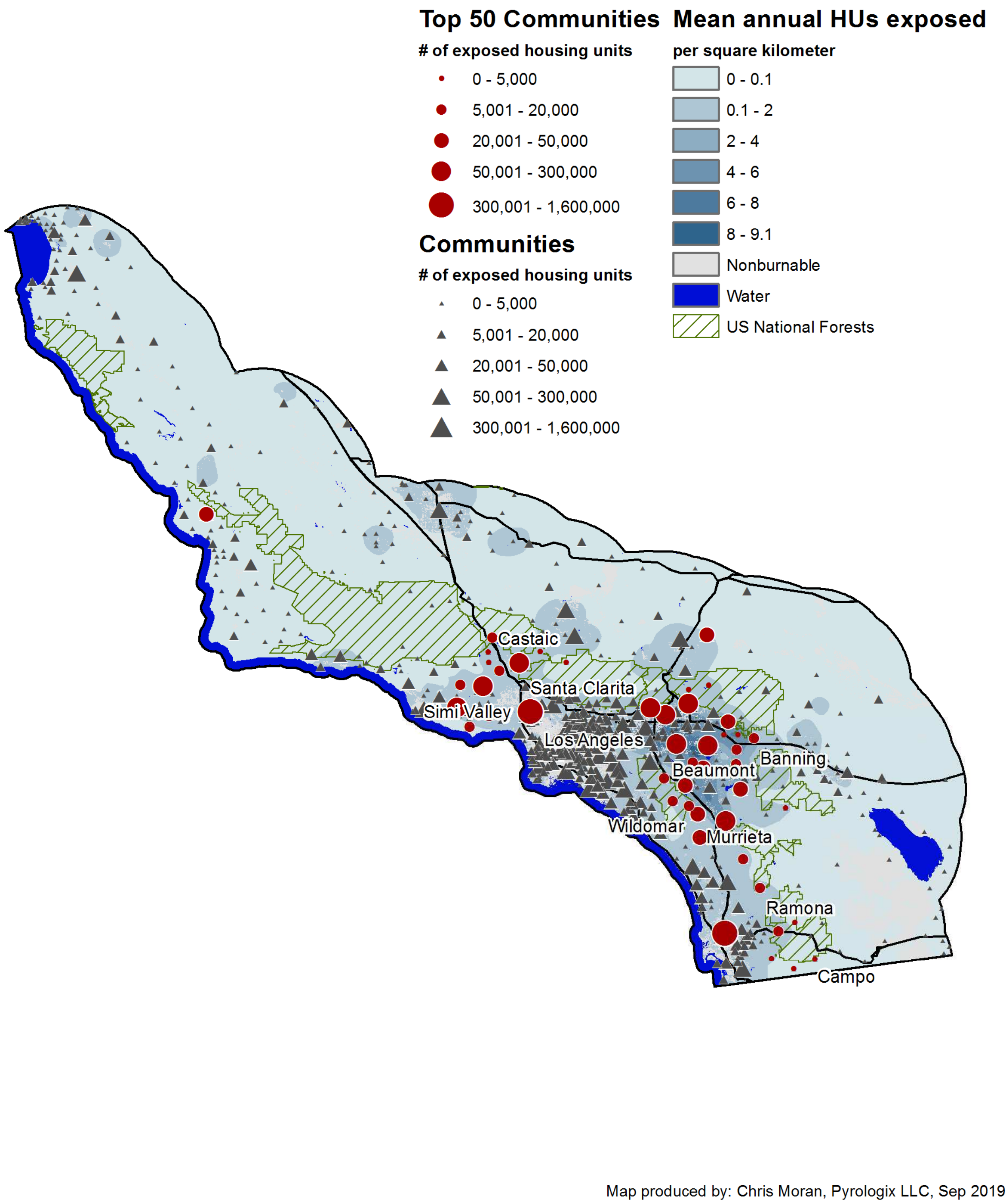


**Figure 28. Annual transmitted housing-unit exposure across the SCRA project area. The 50 most-exposed communities are mapped in dark red and all other communities and their associated exposed housing-unit counts are shown in grey triangles. The top-ten most at-risk communities are labeled in the map. Though the National Forest lands account for some of the transmitted exposure to housing-units, the greatest source of exposure is in the Beaumont area to the east of Los Angeles and outside of National Forest Administrative boundaries.**

# 5 Analysis Summary

The USFS Region 5 Southern California Quantitative Wildfire Risk Analysis provides foundational information about wildfire hazard and risk to highly valued resources and assets across the Region. The results represent 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 local resource planning staff and Fire/Fuels Planners. This analysis can provide great utility in a range of applications including: resource planning, prioritization and implementation of prevention and mitigation activities, and wildfire incident response planning. Lastly, this analysis should be viewed as a living document. While the effort to parameterize and to calibrate model inputs should remain static, the landscape file should be periodically revisited and updated to account for future forest disturbances.

# 6 Data Dictionary

## 6.1 FSim Results

- FSim modeling results are presented in three geodatabases:
  - **SCRA_180m100k.gdb** – FSim Mosaic results for the 10 FOAs and 30 sub-FOAs in the SCRA project area.
  - **SCRA_AllPerims.gdb** – Event set outputs from FSim that includes all simulated wildfire perimeters.
  - **SCRA_AllIgnitions.gdb** – Event set outputs from FSim that include the start location of all simulated wildfire perimeters.

1. **SCRA_180m100k.gdb** – This geodatabase contains 14 rasters representing mosaic results from the FSim simulations in the 10 FOAs within the SCRA project area:
   a. **FLEP_2 –**

      This dataset represents the conditional probability of exceeding a nominal flame-length value (also known as flame-length exceedance probability, or FLEP). There are five FLEP rasters. FLEP_2 is the conditional probability of exceeding a flame length of 2 feet; it is calculated as the sum of iFLP_FIL2 through iFLP_FIL6. FLEP_GT4 is the conditional probability of exceeding a flame length of 4 feet; it is calculated as the sum of iFLP_FIL3 through iFLP_FIL6. FLEP_GT6 is the conditional probability of exceeding a flame length of 6 feet; it is calculated as the sum of iFLP_FIL4 through iFLP_FIL6. FLEP_GT8 is the conditional probability of exceeding a flame length of 8 feet; it is calculated as the sum of iFLP_FIL5 and iFLP_FIL6. There is no raster for FLEP_GT0 because, by definition, for all burnable pixels there is a 100 percent probability that flame length will exceed 0, given that a fire occurs.

   b. **FLEP_4** – see FLEP_2 description above
   c. **FLEP_6** – see FLEP_2 description above
   d. **FLEP_8** – see FLEP_2 description above
   e. **FLEP_12** – see FLEP_2 description above
   f. **iBP –**

      This dataset is a 180-m cell size raster representing annual burn probability across the project area. The individual-FOA BPs were integrated into this overall result for the project area using a natural-weighting method that Pyrologix developed on an earlier project and subsequently published (Thompson and others 2013; "Assessing Watershed-Wildfire Risks on National Forest System Lands in the Rocky Mountain Region of the United States"). With this method, BP values for pixels well within the boundary of a FOA are influenced only by that FOA. Near the border with another FOA the results are influenced by that adjacent FOA. The weighting of each FOA is in proportion to its contribution to the overall BP at each pixel.

   g. **iCFL –**

      This dataset is a 180-m cell size raster representing the mean conditional flame length (given that a fire occurs). It is a measure of the central tendency of flame length (ft.). This raster was calculated as the sum-product of iFLP_FILx and the midpoint flame length of each of the six iFLP_FILs. For iFLP_FIL6, for which there is no midpoint, we used a surrogate flame length of 100 feet (representing torching trees).

   h. **iFLP_FIL1 –**

This dataset is a 180-m cell size raster representing the mean conditional flame length (given that a fire occurs). This is also called the flame-length probability (FLP) and is a measure of the central tendency of flame length. This raster was calculated as the sum-product of the probability at each flame-length class and the midpoint flame length value of each of the six FILs. For FIL6, for which there is no midpoint, we used a surrogate flame length of 100 feet (representing torching trees) in timber fuel models and a flame length of 20 feet in all in grass, grass-shrub and shrub fuel types.

The individual-FOA iFLP_FILx rasters were integrated into this overall result for the project area using a natural-weighting method that Pyrologix developed on an earlier project and subsequently published (Thompson and others 2013; “Assessing Watershed-Wildfire Risks on National Forest System Lands in the Rocky Mountain Region of the United States”). With this method, the iFLP_FILx values for pixels well within the boundary of a FOA are influenced only by that FOA. Near the border with another FOA the results are also influenced by that adjacent FOA. The weighting of each FOA is in proportion to its contribution to the overall BP at each pixel.

i. **iFLP_FIL2** – see iFLP_FIL1 description above
j. **iFLP_FIL3** – see iFLP_FIL1 description above
k. **iFLP_FIL4** – see iFLP_FIL1 description above
l. **iFLP_FIL5** – see iFLP_FIL1 description above
m. **iFLP_FIL6** – see iFLP_FIL1 description above
n. **iMFI –**

This dataset is a 180-m cell size raster representing the mean conditional fireline intensity (kW/m) given that a fire occurs. It is a measure of the central tendency of fireline intensity. The individual-FOA MFI rasters were integrated into this overall result for the project area using a natural-weighting method that Pyrologix developed on an earlier project and subsequently published (Thompson and others 2013; “Assessing Watershed-Wildfire Risks on National Forest System Lands in the Rocky Mountain Region of the United States”). With this method, the iMFI values for pixels well within the boundary of a FOA are influenced only by that FOA. Near the border with another FOA the results are also influenced by that adjacent FOA. The weighting of each FOA is in proportion to its contribution to the overall BP at each pixel.

2. **SCRA_AllPerims.gdb –** This dataset represents the simulated wildfire perimeters within each of the ten Fire Occurrence Areas (FOA) that comprise the SCRA project area. Each ‘_Perims’ feature class includes an attribute table with the following attributes:

a. **FIRE_NUMBE** - the unique fire number for a simulation
b. **THREAD_NUM** - the thread number that simulated the fire (the number of threads is determined by the number of CPUs in the workstation, the number of processing cores per CPU, and whether the cores are hyperthreaded.)
c. **ERC_STARTD** - the ERC(G) value on the start day of the fire
d. **ERC_PERCEN** - the ERC(G) percentile associated with ERC_STARTD. The ERC_PERCEN is a simple lookup from the ERC_STARTD from the "percentiles" section of the .frisk file.
e. **NUM_BURNDA** - the number of days the fire burned during the simulation. This does not include any no-burn days (days below the 80th percentile ERC)
f. **START_DAY** - the Julian day of the fire start
g. **YEAR** - the iteration number (year) for which the fire was simulated
h. **Xcoord/Ycoord** - the coordinates of the fire's ignition point

i. **CONTAIN** - the reason for the cessation of fire growth on the simulated fire
j. **FOA** – the FOA number where the ignition is located
k. **UNQ_ID** – concatenation of FOA number and FIRE_NUMBE
l. **NumIterations** – the number of iterations within a simulation. Individual FOAs were run with 10,000 iterations. When generating additional analytical products from the FSim event set, results must be weighted by iteration number to avoid introducing error
m. **GIS_SizeAc** – the final wildfire size (acres) generated as an ArcGIS calculation based on feature geometry
n. **GIS_SizeHa** – the final wildfire size (hectares) generated as an ArcGIS calculation based on feature geometry
o. **FSim_SizeAc** - is the final wildfire size (acres) generated within FSim based on raster pixel count. Best-practice is to calculate GIS acres for each perimeter instead of relying on SizeAc, especially if subsequent analyses will be based on GIS acres
p. **NumParts** – Number of geometry parts in the simulated wildfire perimeter
q. **ContainsIgn** – True/False value (1,0) that describes if the location of the ignition point is contained within the simulated wildfire perimeter polygon. The ignition may not be included within the simulated perimeter due to how FSIM converts pixel geometry to polygon geometry or as a result of a post processing script that removed small artifacts generated from the FSim trimming suppression algorithm.

3. **SCRA_AllIgnitions.gdb –** This dataset represents the simulated fire start locations within each of the ten Fire Occurrence Areas (FOA) that comprise the SCRA project area. Each '_AllIgnitions' feature class includes an attribute table with the following attributes:

a. **FIRE_NUMBE** - the unique fire number for a simulation
b. **THREAD_NUM** - the thread number that simulated the fire (the number of threads is determined by the number of CPUs in the workstation, the number of processing cores per CPU, and whether the cores are hyperthreaded.)
c. **ERC_STARTD** - the ERC(G) value on the start day of the fire
d. **ERC_PERCEN** - the ERC(G) percentile associated with ERC_STARTD. The ERC_PERCEN is a simple lookup from the ERC_STARTD from the "percentiles" section of the .frisk file.
e. **NUM_BURNDA** - the number of days the fire burned during the simulation. This does not include any no-burn days (days below the 80th percentile ERC)
f. **START_DAY** - the Julian day of the fire start
g. **YEAR** - the iteration number (year) for which the fire was simulated
h. **Xcoord/Ycoord** - the coordinates of the fire's ignition point
i. **CONTAIN** - the reason for the cessation of fire growth on the simulated fire
j. **FOA** – the FOA number where the ignition is located
k. **UNQ_ID** – concatenation of FOA number and FIRE_NUMBE
l. **NumIterations** – the number of iterations within a simulation. Individual FOAs were run with 10,000 iterations. When generating additional analytical products from the FSim event set, results must be weighted by iteration number to avoid introducing error
m. **GIS_SizeAc** – the final wildfire size (acres) generated as an ArcGIS calculation based on feature geometry
n. **GIS_SizeHa** – the final wildfire size (hectares) generated as an ArcGIS calculation based on feature geometry
o. **FSim_SizeAc** - is the final wildfire size (acres) generated within FSim based on raster count. Best-practice is to calculate GIS acres for each perimeter instead of relying on SizeAc, especially if subsequent analyses will be based on GIS acres
p. **NumParts** – Number of geometry parts in the simulated wildfire perimeter

q. **ContainsIgn** – True/False value (1,0) that describes if the location of the ignition point is contained within the simulated wildfire perimeter polygon. The ignition may not be included within the simulated perimeter due to how FSim converts pixel geometry to polygon geometry or as a result of a post processing script that removed small artifacts generated from the FSim trimming suppression algorithm.

## 6.2 NEXUS Results

1. **MaxPotFireBehavior.gdb** – This geodatabase contains one raster named GNexus_97th that contains the following attributes:
    a. **VALUE –** Unique value
    b. **COUNT** – Pixel count
    c. **SCNname** – Unique value used within NEXUS model
    d. **NxFireType** – Fire type (0 = Non-burnable, 1 = Non-forested, 2 = Surface fire, 3 = Low-grade passive fire, 4 = Mid-grade passive crown fire, 5 = High-grade passive crown fire, 6 = Conditional crown fire, 7 = Active crown fire)
    e. **NxTypeLbl** – Fire type (A = Active crown Fire, C = Conditional crown fire, NB = Non-burnable, NF = Non-forested, P1 = Low-grade passive crown fire, P2 = Mid-grade passive crown fire, P3 = High-grade passive crown fire, S = Surface fire
    f. **CRFB –** Crown fraction burned (%)
    g. **TI** - Torching index (mi/hr)
    h. **CI** - Crowning Index (mi/hr)
    i. **FL** - Flame length (ft)
    j. **FLI** - Fire line intensity (kW/m)
    k. **HPUA** - Heat per unit area (BTU/ft2)
    l. **ROS** - Rate of spread (ch/hr)

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