(U 338-E)

Southern California Edison Company

SCE 2026 RAMP Wildfire Power Law White Paper

Rosemead CA
November 3, 2025

SCE 2026 RAMP Wildfire Power Law White Paper

Table Of Contents

SCE 2026 RAMP Wildfire Power Law White Paper

I.

Executive Summary

D.24-05-064 (Risk OIR Phase III Decision) identifies the use of power law distributions capped at *historical* values as a best practice when the utility is estimating tail risk values.[1] While SCE intends to use a power law distribution to establish baseline wildfire risk, as required, this paper presents a method of truncation that is designed to appropriately reflect a broader range of potential future outcomes, including tail risk events which may not be fully reflected by historical wildfire events.

Recent events in California, including the January 2025 wildfires, highlight that relying solely on historical wildfire data may not fully capture the range and severity of the potential tail risk events. If utilities deviate from the referenced methodology, then they are required to develop a white paper for parties to review and comment prior to their RAMP submission.

In this paper, we also describe the limitations of traditional wildfire risk modeling approaches, including both deterministic and stochastic methods. In order to address these limitations, SCE introduces a new scaled hybrid wildfire risk model, called **Wildfire Integrated Model (WIM)**. This new model integrates SCE's existing Technosylva-based FireSight 8 deterministic simulations with stochastic ignition data provided by Moody's RMS U.S. Wildfire HD Model, version 2.0 (RMS 2.0) using well-established spatial aggregation techniques. The WIM is designed to preserve the granularity required for planning, prioritizing, and scoping mitigations, while also capturing tail risk events to an appropriate and reasonable degree, recognizing that historical wildfire data may not fully capture the range of possible future outcomes.

---

[1] It is necessary to truncate a power law distribution when applying the Risk Distribution Framework (RDF) because power laws have infinite or undefined moments (like expected value) unless bounded, making it impossible to compute meaningful expected values, percentiles, or tail risk metrics without imposing an upper limit. Truncation helps ensure that the statistical measures used to evaluate cost-effectiveness and risk tolerance, such as expected loss, Value-at-Risk (VaR), or Conditional Value-at-Risk (CvaR) are mathematically well-defined and are interpretable from a practical standpoint.

II.

Background

Decision 24-05-064 (Risk OIR Phase III Decision) in the Risk-Based Decision-Making Framework for Electric and Gas Utilities Proceeding (Risk OIR R.20-07-013) established the use of a truncated power law distribution model as a best practice for modeling wildfire tail risk.[2] The Commission stated that "a truncated power law ensures the best fit of data to the statistical models and will best enable the Commission to ensure that utility wildfire modeling appropriately reflects considerable wildfire tail risks but does not over-estimate these risks."[3] It further noted that "utility use of truncated power law distribution, by conducting multiple tests of truncation values to determine goodness of fit to existing data, will improve modeling of wildfire tail risk and help ensure that risk estimation is capped at a level reflecting *historical* data."[4]

As SCE stated in opening comments[5] in the Risk OIR Phase III rulemaking on this topic (January 2024), and as illustrated by the January 2025 Southern California wildfires, capping risk metrics based on historical events may not fully capture the probabilities and/or consequences of future events. This is especially true in complex systems such wildfires, which may be exacerbated in the future due to climate change. In his book *Antifragile: Things that gain from disorder*, Nassim Taleb (2012)[6] refers to this tendency to underestimate the likelihood of extreme events simply because they have not occurred in the historical record as the "Lucretius Problem." The Lucretius Problem is the cognitive bias to think that the worst events of the past, like a flood, earthquake, or wildfire, are the worst possible that could ever occur. Taleb argues

---

2 Decision 24-05-064, Conclusion of Law 21 ("The Commission should identify a power law distribution model as a best practice for wildfire tail risk modeling with regard to the optional modeling of tail risk, in addition to expected value, in Row 24 of the RDF.*")*.

3 Decision 24-05-064, Finding of Fact 18.

4 Decision 24-05-064, Finding of Fact 19 (emphasis added).

5 R.20-07-013, January 10, 2024. SCE Opening Comments on ALJ Fogel's Ruling Entering Workshop #6 Material into the Record and Setting Comment Schedule, p. 4

6 Taleb, N. N. (2012). Antifragile: Things that gain from disorder. Random House.

that such reliance on historical experience can limit preparedness for rare but high-consequence events.

The Commission provided utilities the flexibility to propose a different methodology for estimating wildfire tail risk; but if a utility chooses to do so, it must submit a white paper to for review and comment at least 45 days prior to its pre-RAMP workshop.[7] SCE respectfully submits this white paper to fulfill this requirement.

[7] Decision 24-05-064, Conclusion of Law 23 ("If an IOU elects to use a method other than truncated power law to model wildfire tail risk pursuant to Row 24, in addition to presenting the required expected value, the Commission should require the IOU to provide to SPD and serve to the service list of R.20-07-013 a White Paper submission justifying its approach, and related workpapers, no later than 45 days before the IOU's first pre-RAMP workshop and to also attach the White Paper and related work papers to their RAMP filing, clearly indicating any modifications to the previously served White Paper.").

III.

Power Law Distributions

A "power law" distribution describes a statistical relationship between frequency of variables and their associated impacts, such that the frequency of an event is inversely proportional to its magnitude. In practical terms, this means that in systems governed by power laws (e.g., earthquakes, wildfires, city sizes, etc.), even though the majority of the occurrences of these types of event are relatively minor, the total impacts are often dominated by a small number of extreme outlier events. This consistent scaling behavior means that if the frequencies of events were rank ordered by their impact (from highest to lowest), then the impact of the next event diminishes at a predictable rate. This is referred to as "scale invariance" or "scalability" and is a defining feature of power law phenomena. It is also commonly associated with concepts such as the "Pareto Principle" (Pareto, 1935)[8] and the "Principle of Least Effort" (Zipf, 1949).[9] Newman (2005)[10] describes the mathematical relationship of these types of phenomena as follows:

$$P(x) \sim x^{-\alpha}$$

Where:

- "P" is the probability (or frequency) of an event
- "x" is the size of an event
- "α"is the relationship between the probability (or frequency) of an event and the size (or impact) of an event.

In the equation above, the "alpha" variable – also known as the scaling exponent, or tail index - describes the rate at which the probability (or frequency) of an event decreases as its size (or impact) increases. When describing power law relationships, the alpha variable is typically a negative value, given the inverse relationship between these variables. The alpha variable also

[8] Pareto, V. (1935). The Pareto Law. *The Review of Economics and Statistics*, 17(2), 114–123. https://www.jstor.org/stable/1928092.

[9] Zipf, G. K. (1949). *Human behavior and the principle of least effort: An introduction to human ecology*. Addison-Wesley Press.

[10] Newman, M. E. J. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary Physics*, 46(5), 323–351. https://doi.org/10.1080/00107510500052444.

provides valuable information regarding the overall shape and strength of the distribution and the relationship between these variables. A *smaller* alpha value indicates a *heavier* tail, meaning that high-magnitude events occur more frequently relative to the rest of the distribution.
Conversely, a *larger* alpha suggests a *thinner* tail, meaning that extreme impacts are exceedingly rare. These distinctions are central to understanding the behavior of complex systems governed by power laws, such as wildfires.

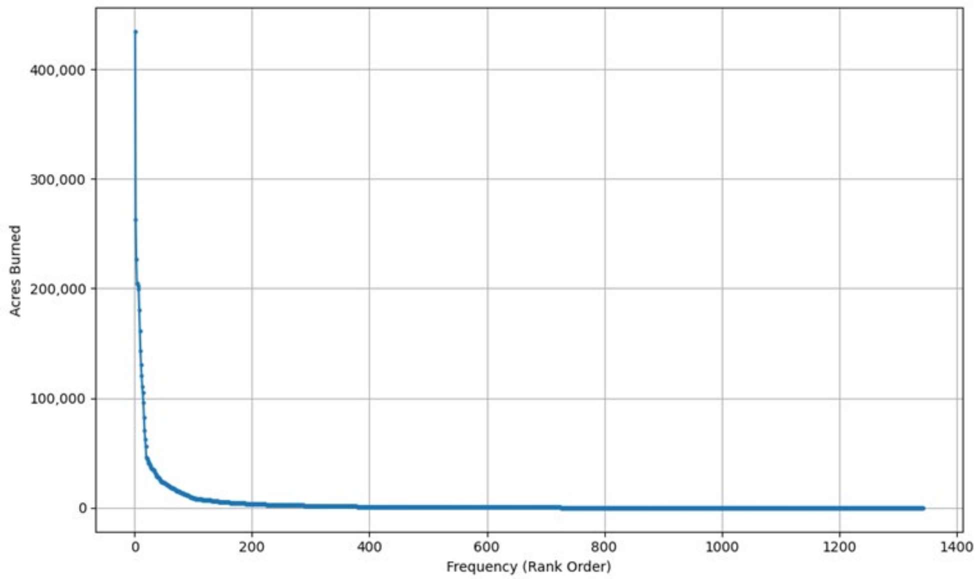
- An alpha (α) of 1 indicates a very heavy-tailed distribution, where large events are relatively frequent. It does not imply a perfect inverse correlation between frequency and size, but rather that the probability of large events decreases slowly with size.
- A smaller alpha (e.g., $\alpha \approx 1.5$ to 2.5) suggests that large wildfire events are more common and distributed throughout the dataset. This reflects a heavier tail, meaning extreme events are not rare outliers but part of the expected distribution.
- A larger alpha (e.g., $\alpha > 3$) implies that high-impact events are increasingly rare, and the distribution has a lighter tail.

This means the probability of very large events drops off more sharply, and the distribution may have finite variance and mean. In Figure III-1, SCE presents such a plot, showing the rank ordered frequency of wildfire events[11] within its service territory (horizontal axis) relative to their impact, in this case the number of acres burned per event (vertical axis). The resulting curve describes their relationship, which is that the majority of wildfire events have a small impact, and only a relatively few events account for the majority of the total impacts. While this pattern is consistent with the heavy-tailed power law wildfire size distributions, it does not provide enough information to readily determine the strength of that relationship as described by Newman.

---

[11] Regardless of ignition source.

Figure III-1
Relationship between the Frequency and Magnitude of Wildfire Events in SCE's Service Territory to Acres Burned for Each Event (1993-2023)[12]



The most practical method for evaluating or determining the strength of this relationship is to re-plot the data using a logarithmic scale. Plotting data on a logarithmic scale, where each interval corresponds to a multiple of a consistent factor – mostly commonly 10x, makes it easier to visually analyze the *relative* change in the frequency of events and their associated impacts. It also prevents the distortion demonstrated in Figure III-1, where a few outlier values can skew shape of the overall distribution. When plotted on a log-log scale, a true power law relationship will appear as a generally straight line, with its slope corresponding to its scaling exponent (alpha).

The formula for transforming a linear relationship between ranked ordered frequency (or probability) and the size (or impact) to a log-log relationship is as follows:

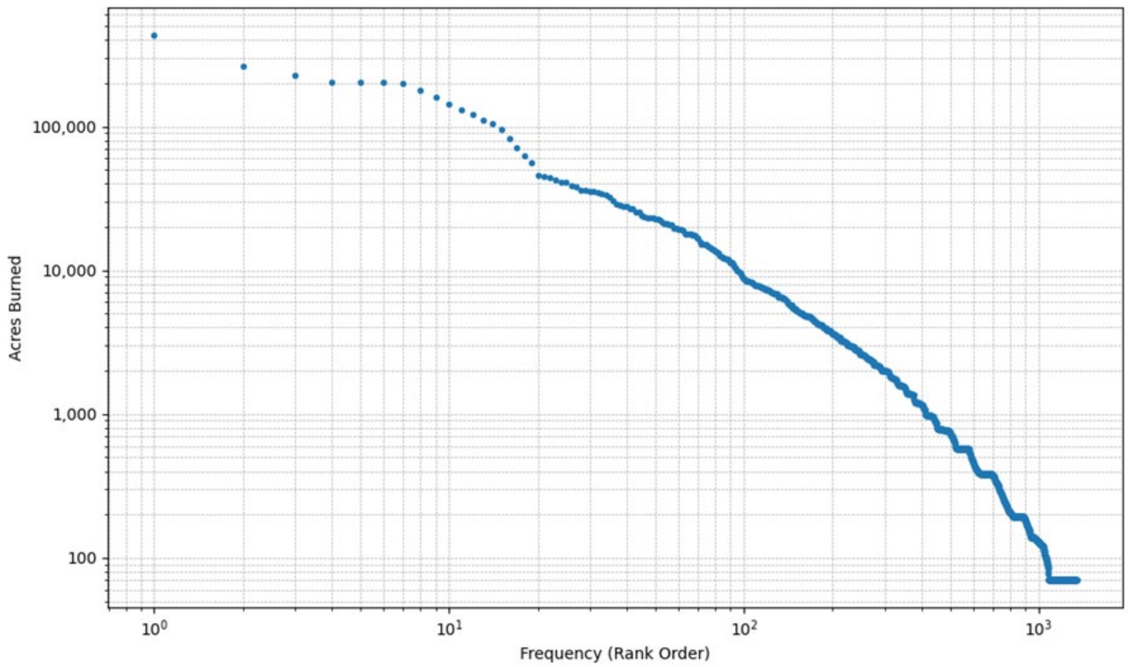
$$logP\ (x) = \alpha \log x + log\ C$$

Where:

- The slope of the line = "$-\alpha$"
- The intercept is at "$log\ C$"

[12] Sonoma Technology. (1993-2023). Firelytics: Wildland Fire Data Dashboard.

Figure III-2
Relationship between the Rank Order Frequency and Magnitude of Acres Burned for Historical Wildfires in SCE's service Territory (1993-2023) plotted using a Log-Log Scale.[13]



The straight-line pattern observed in Figure III-2 provides strong visual evidence that the frequency of wildfires in SCE's service territory, in relation to their size, do generally follow a power law pattern. In fact, this alpha variable, which in this case is ~ 1.75,[14] indicates that while extreme wildfire events are relatively uncommon, they are not as rare as one might intuitively expect. In this example, the distribution has been capped based on historically observed events.

---

[13] Sonoma Technology. (1993-2023). Firelytics: Wildland Fire Data Dashboard.
[14] This alpha was derived from the equation described on pg. 6.

By determining an appropriate truncation point, such as historical events, in this case, it allows one to readily estimate an expected value (weighted average across all possible outcomes), as well as a tail value (some percentage of the maximum value), based on that system-wide metric historical maxima.[15]

[15] RDF Phase IV Decision describes "Consequence (or Impact) as "The effect of the occurrence of a Risk Event. Consequences affect Attributes of a Cost-Benefit Approach and can be represented in the natural units of the Attribute and monetized. Consequence is represented as a probability distribution, from which an expected value or tail risk value can be calculated. The probability distribution of the CoRE is the probability distribution of the sum of the monetized Attributes."

IV.

The Use of Power Law Relationships in Wildfire Risk Modeling

There is a significant amount of academic literature that has explored the use of power law distributions to describe the relationship between wildfire size and associated risk. Strauss et al. (1989)[16] was among the first to suggest that wildfire size distributions exhibit power-law-like behavior. Their hypothesis was later supported by Malamud et al. (1998)[17] as well as Ricotta (1999),[18] both of which described this relationship as a form of "self-organized criticality." Self-Organized Criticality (SOC) describes the phenomena in which complex systems (such as wildfire risk events) naturally evolve into a state where small disturbances can trigger disproportionately large outcomes (e.g., extreme events). Reed and McKelvey (2002)[19] advanced this framework by comparing wildfire risk events using both Power Law models and traditional Gaussian approaches, to determine which of these statistical methods could be used to predict these types of outlier events. Subsequent studies by Brown et al. (2002)[20] and Ricotta (2003)[21] confirmed that power law behavior is a fundamental characteristic of wildfire dynamics.[22] Building on this foundation, Moritz et al. (2005),[23] Malamud et al. (2005)[24], and Holmes et al.

---

[16] Strauss, D., Bednar, L. & Mees, R. Do one percent of the forest fires cause ninety-nine percent of the damage? *Forest Science*. 35, 319–328.

[17] Malamud, B. D., Morein, G., & Turcotte, D. L. (1998). Forest fires: an example of self-organized critical behavior. *Science*, 281(5384), 1840–1842.

[18] Ricotta, C., Avena, G., & Marchetti, M. (1999). The flaming sandpile: Self-organized criticality and wildfires. *Ecological Modelling*, 119(1), 73–77.

[19] Reed, W. J., & McKelvey, K. S. (2002). Power-law behaviour and parametric models for the size distribution of forest fires. *Ecological Modelling*, 150(3), 239–254.

[20] Brown, J. H., Gupta, V. K., Li, B.-L., Milne, B. T., Restrepo, C., & West, G. B. (2002). The fractal nature of nature: power laws, ecological complexity, and biodiversity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 357(1421), 619–626.

[21] Ricotta, C. (2003). Fractal size distributions of wildfires in hierarchical landscapes: Natura facit saltus? *Comments on Theoretical Biology*, 8(1), 93–101.

[22] More specifically, patterns of wildfire frequency and size follow a Pareto distribution. Pareto distributions are a specific type of power law distribution in which there is an established minimum threshold value.

[23] Moritz, M. A., Morais, M. E., Summerell, L. A., Carlson, J. M., & Doyle, J. (2005). Wildfires, complexity, and highly optimized tolerance. *Proceedings of the National Academy of Sciences*, 102(50), 17912–17917.

[24] Malamud, B. D., Millington, J. D. A., & Perry, G. L. W. (2005). Characterizing wildfire regimes in the United States. *Proceedings of the National Academy of Sciences*, 102(13), 4694–4699.

(2008)[25] applied these principles to wildfire management, advocating for the use of power law models to capture macro-level patterns in fire size while balancing analytical rigor with practical utility.

However, the academic literature indicates that although power-law relationships offer useful insights into macro-level wildfire patterns, their applicability to risk assessment at finer spatial scales (e.g., regional or local) is limited, particularly in areas with sparse data. In fact, Falk et al. (2007)[26] demonstrated that the dynamic interactions between the built environment, topography, vegetation, and localized weather patterns exert significantly more influence on fire behavior at a smaller spatial scales. This nuance may not be fully represented in macro-level view of wildfire risk (e.g., as depicted in Figures 1 and 2).

Similarly, McKenzie et al. (2011)[27] argued that to support a robust risk assessment, any study of wildfire risk events should be scaled to reflect localized heterogeneity in fuels, ignition sources, and meteorological conditions Ricotta (2014).[28] Keeley and Syphard (2015, 2016)[29] supported this assessment, noting that a small subset of ignition sources - particularly those near densely populated areas - can materially influence overall wildfire risk, beyond what macro-level patterns alone suggest. Most recently, Lin and Newberry (2023)[30] similarly cautioned that reliance solely on generalized power law models may obscure localized patterns. Taken together, these findings collectively underscore the importance of integrating spatial granularity into wildfire risk modeling frameworks to help ensure that mitigation strategies remain responsive to the specific characteristics of the landscape.

---

[25] Holmes, E. P., Peng, R., & Woods, I. (2008). Statistical analysis of large wildfires. *Environmetrics*, 14(6), 583–602.

[26] Falk, D. A., Miller, C., McKenzie, D., & Black, A. E. (2007). Cross-scale analysis of fire regimes. *Ecosystems*, 10(5), 809–823.

[27] McKenzie, D., Miller, C., & Falk, D. A. (2011). The landscape ecology of fire. Springer.

[28] Ricotta, C., & Di Vito, S. (2014). Scaling properties of forest fire sizes in Italy. Ecological Modelling, 286, 1–5.

[29] Syphard AD, Keeley JE (2015) Location, timing and extent of wildfire vary by cause of ignition. *International Journal of Wildland Fire* 24, 37–47. doi:10.1071/WF14024; Syphard AD, Keeley JE (2016) Historical reconstructions of California wildfires vary by data source. *International Journal of Wildland Fire* 25, 1221–1227. doi:10.1071/WF16050.

[30] Lin, Q., & Newberry, M. (2023). Seeing through noise in power laws.

The U.S. Forest Service (USFS) has similarly noted the necessity of analyzing wildfire risk at a more regionalized spatial scale, to better reflect the diverse national forests it manages. Instead of relying upon a single system-wide model describing these power-law relationships across all national forests, their efforts have focused on understanding the patterns of wildfire risk specific to homogenous sub-regions. In 2020, Short et al.[31] introduced a methodology using k-means clustering[32] to subdivide the contiguous United States into geographically distinct regions characterized by relatively homogeneous wildfire activity, referred to as "pyromes." These data used to construct these pyromes were derived from a comprehensive database of historical wildfires (Short et al., 2015).[33] This database includes, in addition to ignition point location, associated behavioral characteristic associated with those wildfires, including final fire size, seasonality, ignition sources, and other relevant metrics. To enhance the precision of these resulting classifications, once initially defined, these pyromes were further refined using additional spatial datasets, including predominant fuel type, canopy cover, terrain, slope, as well as other environmental factors.

The final result is a map of over 128 pyromes ranging in size from approximately 1.8 million to 46 million acres (Figure IV-3, Map 1 depicts pyromes in Southern California). These pyromes, in turn, provide a foundation for calibrating several of USFS's deterministic and stochastic wildfire models. These models, most notably FSim,[34] use the statistical properties of each pyrome to generate pyrome-specific wildfire hazard profiles, including power-law

[31] Short, K. C., Grenfell, I. C., Riley, K. L., & Vogler, K. C. (2020). Pyromes of the conterminous United States [Data set]. *U.S. Forest Service Research Data Archive*. https://doi.org/10.2737/RDS-2020-0020 1.

[32] K-means clustering is an algorithm that groups similar, unlabeled data points into a predetermined number of clusters (K) by iteratively assigning data points to the nearest cluster center (centroid) and then updating the centroids to be the mean of their assigned points. See MacQueen, J. B. (1967). Some Methods for classification and Analysis of Multivariate Observations. Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability. Vol. 1. University of California Press. pp. 281–297.

[33] Short, Karen C. 2015. Spatial wildfire occurrence data for the United States, 1992-2013 [FPA_FOD_20150323]. Fort Collins, CO: *Forest Service Research Data Archive*. https://doi.org/10.2737/RDS-2013-0009.3.

[34] U.S. Forest Service. (2025, April 9). *FSim–Wildfire Risk Simulation*. Missoula Fire Sciences Laboratory. https://research.fs.usda.gov/firelab/products/dataandtools/fsim-wildfire-risk-simulation.

distributions comparing the rank order frequency of wildfire ignitions to their impacts (e.g., wildfire size). Notably, however, the distributions of wildfire sizes within each pyrome are not artificially capped or truncated based on historical extremes; instead, they are used to shape probabilistic forecasts[35] that reflect the unique fire dynamics of each region.

The FSim model, for instance, utilizes the scaling factors (e.g., α) as well as other descriptive statistics to shape, or scale, the power-law distributions within each pyrome to estimate the burn probability of a given spatial unit (i.e., pixel), based on landscape conditions. At this point, it is important to note that FSim is a wildfire *hazard* model rather than wildfire *risk* model, as defined by the RDF.[36] Wildfire *hazard* models are used to estimate the likelihood and intensity of wildfire[37] occurrence based on environmental conditions (like vegetation, topography, and weather), whereas wildfire *risk* models are an additional factor in how wildfire hazard could potentially impact assets, people, and infrastructure. Wildfire hazard metrics are particularly valuable for the U.S. Forest Service in that they help to identify areas that are susceptible to wildfire ignition and spread. However, the fact that they contain no attribution of the potential consequences of wildfire events makes them less-than-ideal when a utility is assessing risk.

Another limiting factor of these regional wildfire hazard models is that because they are optimized for identifying macro-level trends, they often lack the spatial granularity required for site-specific mitigation assessment and prioritization. Additionally, there are wildfires that burn

[35] These probabilistic forecasts generally do not extend beyond known historical maxima.

[36] While the RDF does not provide a definition of hazard, the CPUC recognizes that "hazards" are distinctly different than "risks" and in the Climate Adaptation Phase II Decision (D2.4-08-005) it established a working group to harmonize on key terms. In that working group, parties have aligned on the term [Climate] Hazard, which is defined as "The potential occurrence of a natural or human- induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources." In the Risk OIR Phase IV Decision D25-08-032 Appendix A, Risk-Based Decision-Making Framework, "Risk" is defined as "The potential for the occurrence of an event that would be desirable to avoid, expressed in terms of a combination of various Outcomes of an adverse event and their associated Probabilities. Risk is the product of LoRE and CoRE and represented as a probability distribution, from which an expected value or tail risk value can be calculated."

[37] Wildfire intensity is the amount of energy a fire releases over a given area and time, often measured in terms of flame length, rate of spread, or energy release.

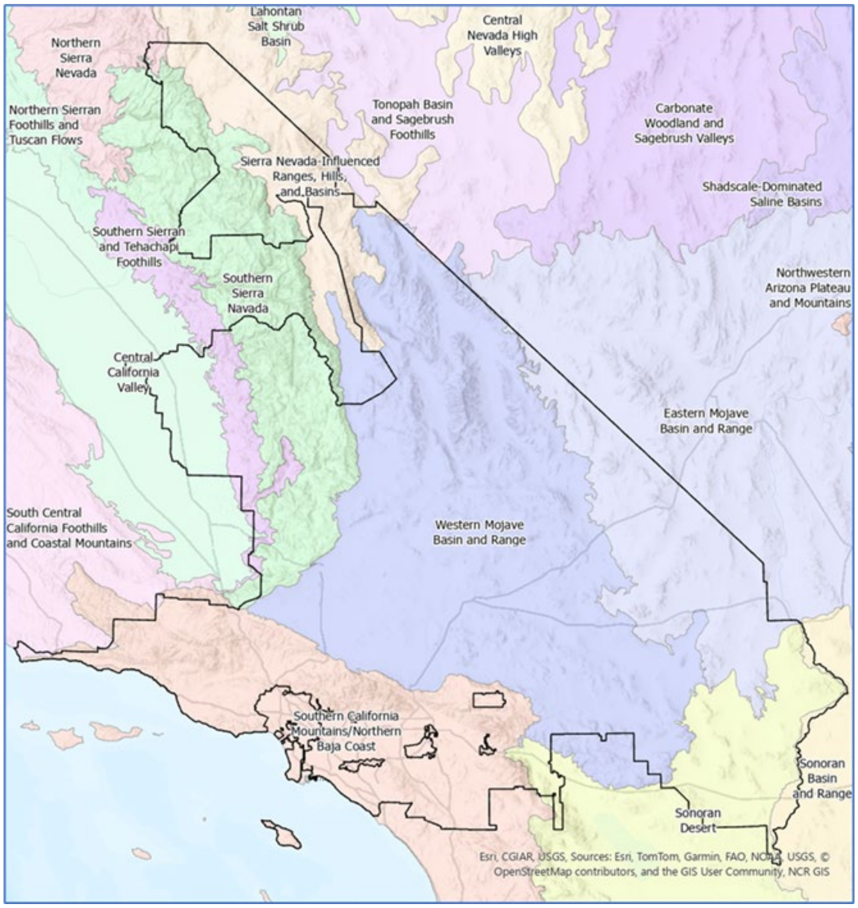
uncontrolled over hundreds of thousands or even a million acres in remote timberland, which do not threaten human populations. Such wildfires arguably have significantly less deleterious societal impacts than much smaller wildfires that become urban conflagrations.

Despite these limitations, USFS ignition databases such as the Fire Program Analysis Fire-Occurrence Database (FPA FOD; Short, 2021)[38] are widely used as inputs into wildfire catastrophe models used by the insurance industry, including Moody's RMS U.S. Wildfire HD Models version 2.0 (RMS 2.0).[39] Catastrophe models, like the RMS 2.0 model, use the shaping functions from these USFS studies, as well as other inputs such as an Industry Exposure Database (IED) to shape their stochastic simulations from which they associate additional variables to capture finer-scale wildfire dynamics as well as the potential consequences of individual ignition events. These catastrophe models do not strictly limit potential consequences to historical values. Instead, they incorporate pyrome-specific distributions from the U.S. Forest Service to simulate a wide range of possible outcomes across tens of thousands of stochastic iterations. This approach offers a more comprehensive representation of both the expected annual losses for a given region and the associated tail risks.

38 Short, Karen C. 2021. Spatial wildfire occurrence data for the United States, 1992-2018 [FPA_FOD_20210617]. 5th Edition. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.5.

39 Moody's (RMS). Climate Change Modeling and Cat Models. (2023). *NSF Academy: Insurance and Climate Risk Workshop* (p. 48). Northeast Regional Climate Center, Cornell University. https://www.nrcc.cornell.edu/workshops/insurance/nsf_academy.pdf.

Figure IV-3
Map 1: U.S. Forest Service Pyromes in Southern California (Short et al. 2020)



A. SCE Fire Climate Zones (FCZ)

SCE has also leveraged the USFS pyrome concept to disaggregate its service territory into discrete areas subject to similar levels of wildfire hazard, which it refers to as Fire Climate Zones (FCZs). These FCZs were constructed by correlating historical wildfire events with environmental variables generally associated with fire behavior, such as live and dead fuel moisture, wind conditions (including sustained winds and gusts), as well as other relevant factors. SCE uses these FCZs to support Public Safety Power Shutoff (PSPS) decision-making, including de-energization thresholds. More recently, SCE has also these FCZs to inform Fire Weather Day (FWD) selection for its Technosylva-based FireSight 8 deterministic wildfire risk model (SCE 2025).[40] Please refer to Appendix A for a description of each of these FCZs. Figure IV-4, Map 2 depicts Southern California Edison, Fire Climate Zones.

While these FCZs reflect wildfire *hazard* rather than a full measure of wildfire *risk*, they nonetheless provide a useful framework to illustrate the concepts discussed in the previous section – notably how the distribution of wildfire risk can vary at the regional level.
To demonstrate this concept, SCE examined how the relationship between rank order frequency of wildfire ignitions and their associated impacts (e.g., wildfire acres burned) differed between FCZs. Keeley and Syphard (2018)[41] identified two dominant fire regimes in California: one primarily driven by fuel accumulation and the other by wind dynamics. Their research demonstrated that wildfire behavior, seasonality, and impacts differ markedly across regions, with some areas experiencing hybrid regimes influenced by both factors. Fuel-driven wildfires are more common in the northern and mountainous regions of the state, typically ignited by lightning during the summer and fueled by accumulated biomass. In contrast, wind-driven wildfires are prevalent in southern and coastal areas, often occurring during fall and winter months under the influence of strong seasonal foehn winds[42] (e.g., Santa Anas, Sundowners) and burn through grass, shrub, and chaparral fuels near the wildland-urban interface (WUI). These regional variations should show up in both the power law relationship between these two factors, as well as the scaling metric, otherwise known as the alpha variable.

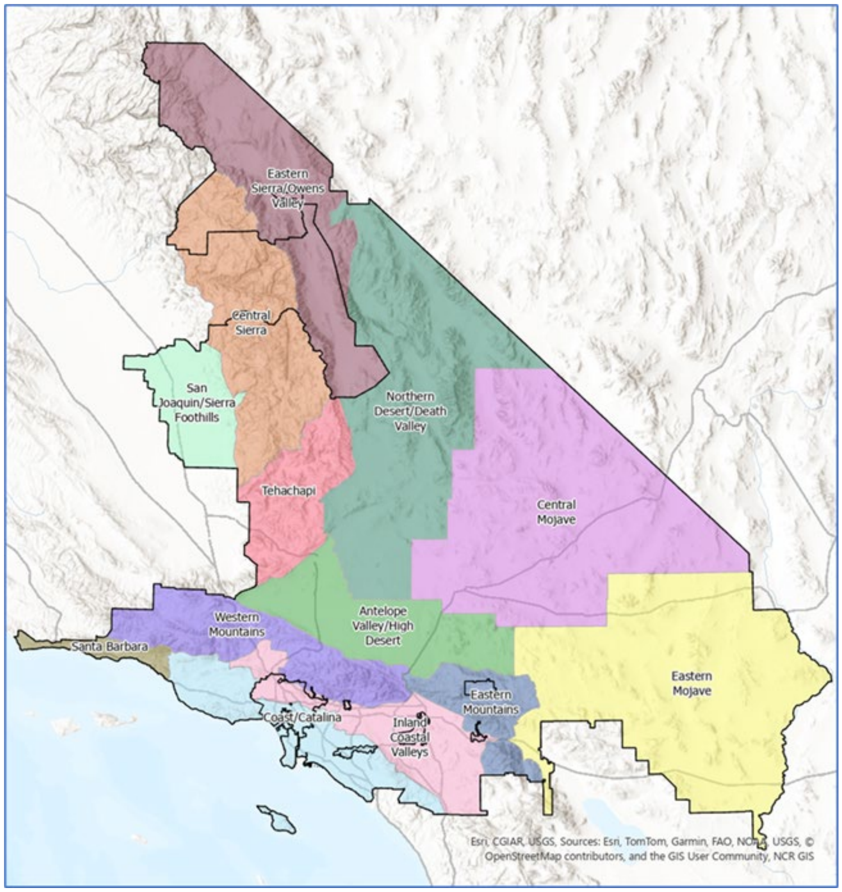
---

40 SCE Wildfire Mitigation Plan 2026-2028, Sec. 4.

41 Keeley, J. E., & Syphard, A. D. (2018). Twenty-first century California, USA, wildfires: Fuel-dominated vs. wind-dominated fires. *Fire Ecology*, 14(1), 1–15. https://doi.org/10.1186/s42408-019-0041-0.

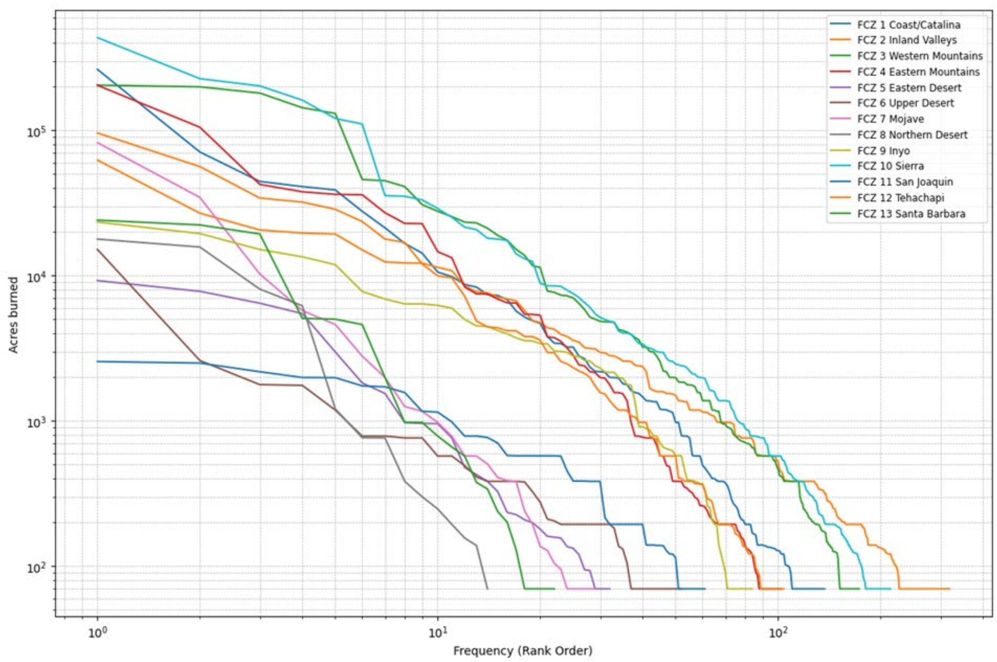
42 Foehn, or Katabatic winds, are warm dry winds originating from the leeward side of any mountain range that expand rapidly through mountain passes.

Figure IV-4
Map 2: Southern California Edison (SCE) Fire Climate Zones (FCZ)



The result of this analysis confirms that there is significant variability across FCZs in both power law relationships (e.g., alpha variables) and the underlying descriptive statics (e.g., number of ignition events, maximum observed historical wildfire sizes). Figure IV-5 below demonstrate this variability in both absolute shape – for example, some plots exhibit a steeper slope – and in the truncation points based on the historically observed wildfire sizes in each individual FCZ (see Appendix B for individual FCZ level log-log plots). This highlights the importance of exercising caution when calibrating granular wildfire risk models with system-wide power law relationships, as such system-wide distributions may over-represent wildfire hazards in some regions and under-represent them in others, particularly for areas with such a diverse fire ecosystem. Put simply, relying on the average across all distributions may not fully reflect the characteristics of any individual distribution. In *The Flaw of Averages: Why we underestimate risk in the face of uncertainty*, Sam Savage explains how relying on these types of average values in decision-making can obscure variability and uncertainty, potentially leading to less accurate assessments (Savage 2009).[43]

Figure IV-5
Relationship between the Rank Order Frequency and Magnitude of Acres Burned for Historical Wildfires in each Fire Climate Zone (FCZ) in SCE's Service Territory (1993-2023) plotted using a Log-Log Scale.[44]



The concerns with that approach are also apparent based on examining the descriptive statistics underlying these distributions (see Table IV-1). For instance, the count of historical wildfire ignition events (i.e., frequency) in FCZ 8 - Northern Desert is 14 events, while the count in FCZ 2 – Inland Valleys is 319 ignition events, a ~23x difference. Similarly, the mean wildfire size in FCZ 11 – San Joaquin is only 557 acres, while the mean wildfire size in FCZ 4 – Eastern Mountains is 8,255 acres, a ~15x difference. The difference is more pronounced at the tail of

[43] Savage, S. L. (2009). The flaw of averages: Why we underestimate risk in the face of uncertainty. Wiley.

[44] Sonoma Technology. (1993-2023). Firelytics: Wildland Fire Data Dashboard.

these distributions. The maximum observed historical wildfire size in FCZ 5 – Eastern Desert is 9,236 acres, while the maximum observed historical wildfire size in FCZ 10 – Sierra is over 430,000 acres, a ~47x difference.

Finally, it is important to note that the strength of the power-law relationship, as represented by the alpha (or scaling factor), differs across each of these regions. For example, the alpha for FCZ 11 -San Joaquin is ~1.15, indicating a heavy-tailed distribution where relatively few large wildfires dominate the overall impact. In contrast, FCZ 8 - Northern Desert) exhibits a higher alpha of ~ 2.31, suggesting that large wildfires occur more frequently relative to the rest of the distribution. These findings underscore the need to account for regional variability as well as the presence of other localized drivers, even when employing power law frameworks to understand natural phenomena, such as wildfire. It also underscores the importance of examining not just *absolute* metrics, such as acres burned, but also the underlying distributional characteristics, such as the strength of power law relationships (e.g., the alpha variable), to more accurately assess and compare wildfire hazard across regions.

Table IV-1
Descriptive Statistics of Acres Burned for Historical Wildfires in each Fire Climate Zone (FCZ) in SCE's Service Territory (1993-2023)[45]

Fire Climate Zone	Count	Mean (Acres)	Max (Acres)	Alpha (α)
FCZ 1 Coast/Catalina	137	5,081	262,736	1.94
FCZ 2 Inland Valleys	319	1,381	62,369	1.51
FCZ 3 Western Mountains	173	8,225	204,683	1.96
FCZ 4 Eastern Mountains	102	6,643	204,228	2.07
FCZ 5 Eastern Desert	32	1,342	9,236	1.71
FCZ 6 Upper Desert	52	656	15,139	1.27
FCZ 7 Mojave	29	5,190	82,259	2.26
FCZ 8 Northern Desert	14	3,718	17,836	2.31
FCZ 9 Inyo	84	2,602	23,357	1.62
FCZ 10 Sierra	214	8,335	434,617	1.97
FCZ 11 San Joaquin	61	557	2,561	1.15
FCZ 12 Tehachapi	104	4,122	95,875	1.90
FCZ 13 Santa Barbara	22	4,001	24,090	2.30

[45] Sonoma Technology. (1993-2023). Firelytics: Wildland Fire Data Dashboard.

B. Factors (Other than Wildfire Size) more Associated with Catastrophic Wildfire Risk

While these power law relationships of wildfire acres burned are useful for understanding the associated regional patterns of wildfire hazards, wildfire acres burned alone do not fully account for wildfire risk. In fact, there is significant supporting literature that Extreme Wildfire Events (EWEs) are not solely defined by wildfire sizes or their intensity (Tedim et al.,2019),[46] and that one should consider additional dimensions, many of which may not necessarily correlate at the local level to wildfire size. Instead, the literature characterizes these EWEs as those which overwhelm existing wildfire management systems and/or produce disproportionate environmental and social impacts. Such factors are all highly dependent on the local context. Recent events such as the Eaton (2025) and Palisades (2025) wildfires illustrate this point. Despite the relatively modest number of acres burned in both the Eaton (2025) and Palisade (2025) fires,[47] their proximity to densely populated areas resulted in the destruction of thousands of homes and significant loss of life. These wildfires serve as a stark reminder that decades of urban expansion into the WUI, historical approaches to land and fire management,[48] lack of sufficient home hardening,[49] as well as accelerating climate change have fundamentally altered wildfire behavior. In fact, many believe that future events are likely to far exceed historical precedents (Westerling and Bryant, 2008).[50]

---

[46] Tedim, F., Leone, V., Coughlan, M., Bouillon, C., Xanthopoulos, G., Royé, D., Correia, F. J. M., & Ferreira, C. (2019). Extreme wildfire events: The definition. In Extreme Wildfire Events and Disasters: Root Causes and New Management Strategies (pp. 3-29). Elsevier. https://doi.org/10.1016/B978-0-12-815721-3.00001-1.

[47] Estimated final fire sizes for: Eaton – 14,021 acres burned; Palisades 23,448.

[48] Some have posited that overly aggressive forest fire suppression has led to a phenomena known as the "fire suppression paradox," in which rapid response to wildfire events interferes with the natural and necessary ecological role of wildfires, leading to a building of fuel, which, once ignited tend to be more severe and harder to suppress. For additional information, see: Kreider, M. R., Higuera, P. E., Parks, S. A., Rice, W. L., White, N., & Larson, A. J. (2024). Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation. Nature Communications, 15, Article 46702. https://doi.org/10.1038/s41467-024-46702-0

[49] See U.S. Fire Administration. (2022). Wildland Urban Interface: A look at issues and resolutions. U.S. Department of Homeland Security. https://www.usfa.fema.gov/downloads/pdf/publications/wui-issues-resolutions-report.pdf

[50] Westerling, A. L., & Bryant, B. P. (2008). Climate change and wildfire in California. *Climatic Change, 87*(Suppl 1), 231–249. https://doi.org/10.1007/s10584-007-9363-z.

Indeed, there is ample evidence that structure loss, and by extension, loss of life, are more strongly associated with micro-scale exposure and vulnerability factors rather than wildfire size alone. One of the first studies to explore these factors (Cohen 1998)[51] demonstrated that the proximity of structures to vegetation (wildland), as well as the radiant heat from the wildfire itself are more correlative to structure impacts than overall fire perimeter. A joint study by RMS, NAIC, and IBHS (2020)[52] echoed these findings, and further demonstrated that building materials, defensible space, and exposure within the wildland-urban interface (WUI) are more predictive of insured losses than wildfire size. More recent analyses by Troy et al. (2022)[53] and Johnson et al. (2023),[54] both of which used CalFire Damage Inspection (DINs) data from the 2018 Camp Fire, to further validate that building construction type and proximity to the WUI are key determinants of structure loss. Additionally, Zhou and Cova (2022)[55] highlighted the role of ember-driven ignitions and conflagration risk, finding that even low levels of ember exposure significantly increased the probability of structure loss during the 2017 Tubbs Fire. Follow-on

---

[51] Cohen, J. D. (1998). Modeling potential structure ignitions from flame radiation exposure. USDA Forest Service. https://www.fs.usda.gov/rm/pubs_other/rmrs_1998_cohen_j001.pdf.

[52] Risk Management Solutions (RMS), National Association of Insurance Commissioners (NAIC), & Insurance Institute for Business and Home Safety (IBHS). (2020). Application of wildfire mitigation to insured property exposure. National Association of Insurance Commissioners. https://content.naic.org/sites/default/files/cipr_report_wildfire_mitigation.pdf.

[53] Troy, A., Alvarado, E., & Dether, D. (2022). Structure survival in the 2018 Camp Fire: The role of building characteristics and defensible space. International Journal of Wildland Fire, 31(10), 933-944. https://www.publish.csiro.au/WF/pdf/WF21176.

[54] Johnson, B. A., Thompson, M. P., & Wei, Y. (2023). Exploring and testing wildfire risk decision-making in the face of deep uncertainty. Natural Hazards and Earth System Sciences, 23(4), 789-808. https://doi.org/10.5194/nhess-23-789-2023.

[55] Zhou, Y., & Cova, T. J. (2022). Community-level risk assessment of structure vulnerability to WUI fire conditions in the 2017 Tubbs Fire. Academia.edu. https://www.academia.edu/105155091/Community_level_risk_assessment_of_structure_vulnerability_to_WUI_fire_conditions_in_the_2017_Tubbs_Fire.

studies by Weber et al. (2021),[56] Wei et al. (2023),[57] and Conlisk et al. (2024)[58] identified additional factors, such as road density (i.e., egress), suppression difficulty, response time, wind conditions, terrain, and community preparedness, as more correlated with structural impacts than wildfire size alone. The growing body of academic literature supports continued development of utility wildfire risk models that, rather than relying solely on correlations from truncated historical patterns, towards those that incorporate granular environmental factors to better characterize the potential impact of future extreme wildfire events.

SCE also performed its own empirical analysis of the correlative factors associated with wildfire risk in Southern California. Using the California Office of Energy Infrastructure Safety (OEIS) definition of "catastrophic" wildfires: those involving 5,000 or more acres burned, 500 or more structures impacted, or at least one fatality,[59] SCE performed two analyses. To help ensure a robust sample size, the dataset includes both utility-involved and non-utility-involved wildfire events (see Appendix C for a complete list). This approach allows for a more comprehensive assessment of wildfire risk by incorporating a broader spectrum of event types and impact profiles. In the first analysis, SCE used a pairwise comparison to evaluate the relative strength of wildfire size as a predictor of structure and population impacts, assuming that system-wide relationships are reliable proxies (see Figure IV-6). In the second analysis, SCE used a correlation matrix to determine which other factors may be more correlated to structure loss based on individual FCZs (see Table IV-2).

The resulting pairwise analysis (see Figure IV-6) indicates a weak, yet somewhat positive correlation between wildfire size to both structure population impacts. However, while this may

---

56 Buechi, H., Weber, P., Heard, S., Cameron, D., & Plantinga, A. J. (2021). Long-term trends in wildfire damages in California. International Journal of Wildland Fire, 30(10), 757–762. https://doi.org/10.1071/WF21024 1.

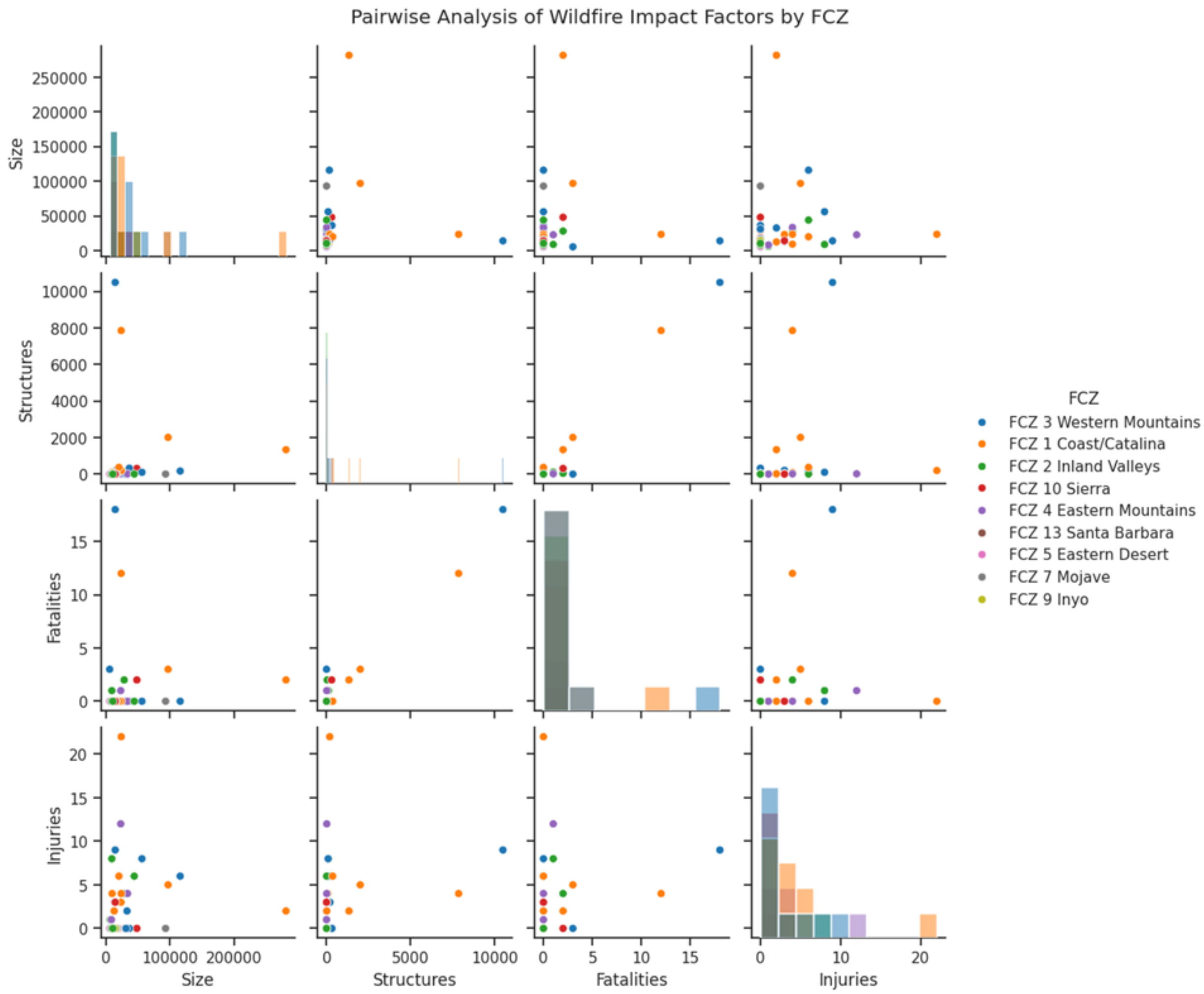
57 Wei, Y., Gannon, B., Young, J., Belval, E., Thompson, M., O'Connor, C., & Calkin, D. (2023). Estimating WUI exposure probability to a nearby wildfire. Fire Ecology, 19, Article 30. https://doi.org/10.1186/s42408-023-00191-6.

58 Conlisk, E., Syphard, A. D., & Keeley, J. E. (2024). Evidence of increasing wildfire damage with decreasing property price in Southern California fires. PLOS ONE, 19(1), e0289999.

59 There data prior to 2016 is incomplete for structure and/or population loss. We limited the scope of this analysis to wildfires meeting the OEIS definition of "catastrophic" wildfire from 2016-2025.

suggest some causal correlation between the two factors, the relationship is not very consistent. There are several notable, almost perfectly uncorrelated outliers, that demonstrate that wildfires in which a relatively modest number of acres are burned still resulted in significant structural and population losses. The histograms along the top left to bottom right diagonal in Figure IV-6 depict the distribution of each individual variable, including their range, central tendency, skewness, as well as any outliers in the correlation. The remaining scatter plots represent the relationship between each pair of variables, with each point representing a single paired observation. A distribution of points trending from the lower left to the upper right indicates a positive correlation between variables, while a distribution of points from the lower right to the upper left are indicative of a negative correlation. It is notable in this analysis that wildfire size alone is not a reliable predictor of impact severity. Overall, the scatter plots show weak trends and high variability, while the histograms reveal skewed distributions and outliers, indicating that extreme events heavily influence observed impacts.

Figure IV-6
Pairwise Analysis of Structure and Population Impacts in Relation to Wildfire Size System-wide in Southern California Edison (SCEs) Service Territory (2016-2025) based on the OEIS Definition of Catastrophic Wildfires



In the second analysis, SCE used a correlation matrix to further assess these relationships for individual Fire Climate Zones (FCZs). This correlation matrix enabled SCE to determine the relative strength of the relationship between multiple variables. Each value in these matrices is a correlation coefficient, ranging from –1 to +1. A coefficient closer to +1 indicates a strong positive relationship between two variables on each axis, while values near –1 reflect a strong negative correlation between those variables. Whereas correlation values near zero suggest little to no relationship between the variables. This visual framework allows one to readily discern meaningful correlations between variables, as well as determine whether or not those same correlations hold true across regions.[60]

Table IV-2
Correlation Matrix of Structure and Population Impacts in Relation to Wildfire Size System-wide in Southern California Edison Service Territory (2016-2025) based on the OEIS Definition of Catastrophic Wildfires.

	Fire Size vs Structures	Fire Size vs Fatalities	Fire Size vs Injuries	Structures vs Fatalities	Structures vs Injuries	Fatalities vs Injuries
FCZ 1 Coast/Catalina	0.09	0.09	-0.11	0.99	-0.04	-0.07
FCZ 2 Inland Valleys	-0.08	0.24	0.51	0.62	0.78	0.50
FCZ 3 Western Mountains	-0.19	-0.25	0.43	0.98	0.61	0.56
FCZ 4 Eastern Mountains	0.78	0.30	0.56	0.57	0.8	0.94
FCZ 5 Eastern Desert	*	*	*	*	*	*
FCZ 6 Upper Desert	*	*	*	*	*	*
FCZ 7 Mojave	*	*	*	*	*	*
FCZ 8 Northern Desert	*	*	*	*	*	*
FCZ 9 Inyo	*	*	*	*	*	*
FCZ 10 Sierra	0.86	0.86	-0.22	1	-0.20	-0.20
FCZ 11 San Joaquin	*	*	*	*	*	*
FCZ 12 Tehachapi	*	*	*	*	*	*
FCZ 13 Santa Barbara	*	*	*	*	*	*

The resulting analysis provides several important insights with respect to the relationship between wildfire size, structure impacts, as well as fatalities and serious injuries. The most obvious insight is that most of the structure and population impacts are generally concentrated in only a few regions within SCE's service territory, primarily along the Wildland Urban Interface (WUI) (see Figure IV-7, Map 3), and that there is simply not enough historical data from which to develop meaningful correlations for other regions. Additionally, even amongst the FCZs in which there is adequate data from which to draw a correlation, in only two of those regions, FCZ 4 – Eastern Mountains and FCZ 10 – Sierras, is there a positive correlation between wildfire size

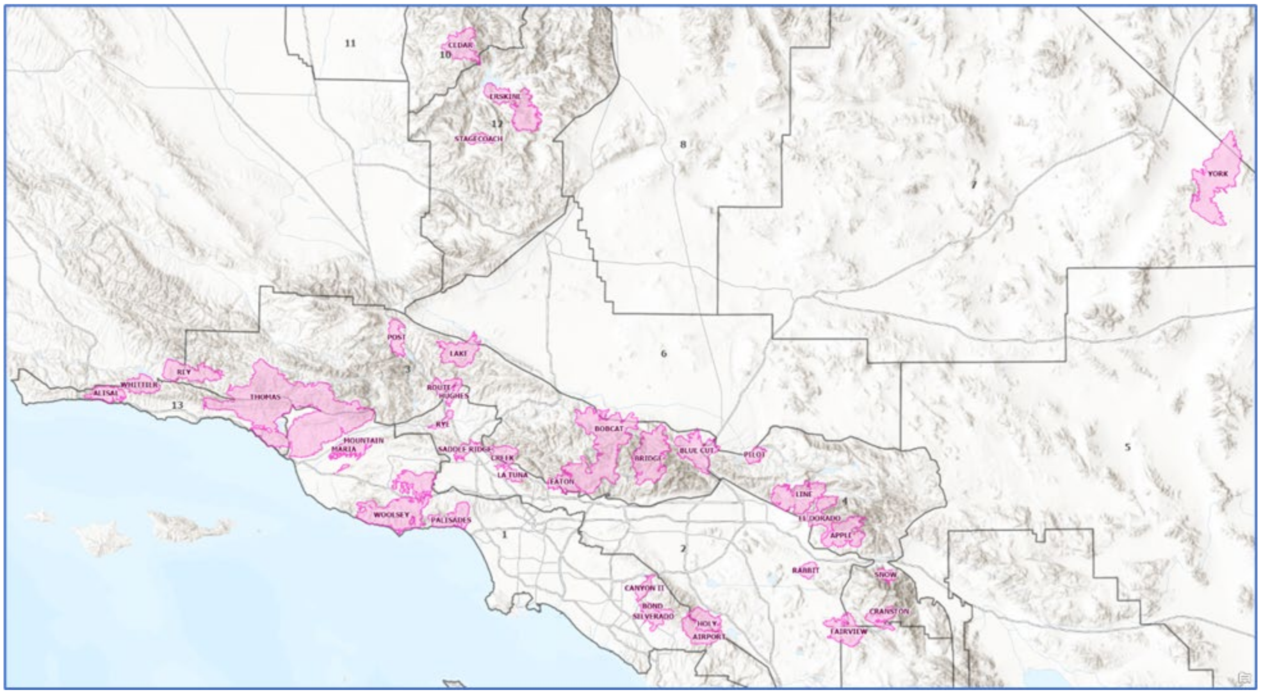
[60] The cell shading- from light blue to dark blue – is indicative of the strength of the correlative relationship between variables.

and structure impacts. Finally, the correlation analysis suggests a strong correlation across nearly all FCZs between structure impacts and both fatalities and serious injuries.[61] These findings reinforce the importance of regionalized analysis and also highlight the need to account for other correlative factors that may simply not be present within the historical wildfire record alone.

Further examination of the correlation matrix analysis reveals several additional important patterns. First, the strength and direction of relationships vary widely across Fire Climate Zones (FCZs), underscoring the regional nature of wildfire impacts. For example, FCZ 4 (Eastern Mountains) and FCZ 10 (Sierra) exhibit strong positive correlations between wildfire size and structure losses, while other zones show weak or even negative correlations, indicating that fire size alone is not a consistent predictor of damage. Second, structural losses are strongly correlated with fatalities and injuries across nearly all zones with sufficient data, suggesting that the extent of structural damage is a reliable indicator of human impact severity. Third, while some regions, such as FCZ 2 (Inland Valleys), show moderate correlations between fire size and injuries, most zones demonstrate little to no relationship, reinforcing the influence of other factors like WUI proximity and preparedness. Finally, large gaps in historical data for several FCZs limit system-wide conclusions and highlight the need for improved data collection and modeling to better understand wildfire risk in underrepresented areas.

[61] An exception is observed in FCZ 1 where wildfire events appear to result in more fatalities than reported serious injuries, suggesting a unique vulnerability profile.

Figure IV-7
Map 3: Map of SCE Fire Climate Zones in Proximity to Wildland Urban Interface (WUI) overlaid with Major Wildfires (2016-2023)



With this in mind, SCE explored several additional variables, namely the WUI density, the proximity of structures to ignition sources, as well as potential delays in dispatching suppression resources to determine to what extent these other factor may serve as better predictors of wildfire risk. To do so, SCE replicated data from Johnson et al. (2023),[62] who focused on analyzing the determinant factors of structures loss to wildfires. The results of this correlation matrix confirm this hypothesis (See Table IV-3). In addition to confirming earlier observations that wildfire size alone is a relatively weak predictor of structure loss, particularly in Southern California, a correlation of just 0.22, it also highlights that there are several other factors that are more strongly correlated to structure loss, and, by extension, population impacts.[63] These include proximity to the ignition source (0.69), WUI density (0.81), as well as

62 Johnson, B. R., Ager, A. A., Evers, C. R., Hulse, D. W., Nielsen-Pincus, M., Sheehan, T. J., & Bolte, J. P. (2023). Exploring and testing wildfire risk decision-making in the face of deep uncertainty. Fire, 6(7), 276. https://doi.org/10.3390/fire6070276.

63 See earlier footnote.

structure density (0.77). We also note that suppression delay (0.62) also shows a meaningful positive correlation, reinforcing the importance of timely response in mitigating losses. These findings confirm research by Macdonald (2023)[64] that these factors are more closely associated with the loss of people and property than acreage burned.[65]

Table IV-3
Correlation Matrix of Structure Loss in Relation to Other Drivers of Wildfire Risk (recreated from factors cited by Johnson et. al 2023)

	WUI Density	Ignition proximity	Suppression Delay	Structure Density	Wildfire Size	Structure Loss
WUI Density	1	0.65	0.58	0.72	0.21	0.81
Ignition proximity	0.65	1	0.49	0.6	0.18	0.69
Suppression Delay	0.58	0.49	1	0.55	0.25	0.63
Structure Density	0.72	0.6	0.55	1	0.29	0.77
Wildfire Size	0.21	0.18	0.25	0.29	1	0.22
Structure Loss	0.81	0.69	0.63	0.77	0.22	1

C. Key Findings

- Power-Law Distributions – While wildfire size across SCE's service territory generally follows a power law distribution, the strength of that relationship, as represented by the alpha parameter, varies significantly across individual regions (e.g., Fire Climate Zones (FCZs)) within SCE's service territory. Utilities can benefit from developing appropriately granular distributions to better characterize wildfire risk and help reduce uncertainty associated with the use of macro-level (e.g. system-wide) distributions.

---

64 MacDonald, G., Wall, T., Enquist, C. A. F., et al. (2023). Drivers of California's changing wildfires: A state-of-the-knowledge synthesis. International Journal of Wildland Fire. https://doi.org/10.1071/WF22155.

65 The cell shading- from light blue to dark blue – is indicative of the strength of the correlative relationship between variables.

- Historical Distributions – The Commission should reconsider the Finding of Fact stating that the use of a truncated power-law distribution based on various goodness of fit tests of **historical** patterns of wildfire risk. Historical truncation points may not fully capture tend to future tail risk, as such events are often underrepresented in traditional models. These findings are particularly relevant, given that they directly influence long-term wildfire mitigation strategies.
- Acres Burned is an Insufficient Proxy for Wildfire Risk – Wildfire size alone (e.g. acres burned) is a weak predictor of losses to people and property in Southern California. Events like the Eaton (2025) and Palisades (2025) fires underscore that even relatively modestly sized wildfires can result in catastrophic outcomes when in proximity to populated areas.
- Other Factors are More Correlative to Wildfire Risk than Acres Burned – Location-specific risk factors, such as proximity to ignition source, exposure within the WUI, structure density, and suppression delay, are significantly stronger predictors of structure and population impacts. Correlation analyses confirm that these variables are more closely associated with structure loss and population impacts than wildfire size alone and should be incorporated in utility risk models.

V.

SCE's Alternative Modeling Approach – Wildfire Integrated Model (WIM)

In the following section, SCE presents an alternative wildfire modeling approach designed to develop more granular distributions of wildfire risk that aligns with Commission guidance to use power law distributions, while also addressing the key findings noted in the previous sections.

A. SCE's Wildfire Integrated Model (WIM):

- Is not limited by the historical record of wildfire risk events in which there may be an insufficient record; nor deterministic simulation times (e.g., 8 or 24 hours), both of which likely under-represent future tail risk events.
- Maintains the asset-level spatial granularity of SCE's existing operational risk model, which is critical to comply with Risk OIR Phase IV guidance to represent risk at the Risk Reduction Unit (RRU).[66]
- Addresses Risk OIR Phase IV guidance to represent wildfire consequences as a probability distribution, from which expected value and tail risk values can be calculated.[67]
- Integrates stochastic ignition data sets, which account for correlative factors that are more closely associated with tail risk events, and are widely used by the insurance industry, including the California Department of Insurance.[68]
- Uses well-known spatial aggregation and mathematical scaling (Taleb 2022) techniques to ensure the distribution of potential consequences of simulated wildfire events are adequately represented at the most granular level practical.

---

[66] D.25-08-032, RDF Phase IV Appendix A "Risk Reporting Unit"

[67] D.25-08-032, RDF Phase IV Appendix A "Consequence"

[68] Reinsurance News. (2025, September 22). Moody's latest wildfire model completes California Department of Insurance review. https://www.reinsurancene.ws/moodys-latest-wildfire-model-completes-california-department-of-insurance-review/.

Over the course of the last several years, parties who have participated in the CPUC Risk OIR proceeding, as well as the OEIS Risk Management Working Group (RMWG), have noted the relative strengths and limitations of both deterministic and probabilistic wildfire risk models. In fact, the California Wildfire Advisory Safety Board (WASB), in its recent recommendations to OEIS, noted that "Effective decision making and oversight both require a better understanding of the distribution of risk, especially "tail risk" of the most extreme events" (WASB, 2025, pg. 25).[69] As such, they cite a study by Heinrich et al. (2022), which recommends using a multi-model approach to reduce the uncertainty associated with relying on a single model.[70]

SCE appreciates the attention given to this matter by our regulators, our partner utilities, as well as with various wildfire model vendors on this topic. To that end, after consulting relevant academic literature regarding potential approaches to this challenges, and exploring multiple potential paths forward (Tonini, 2022,[71] Singh et al. 2024,[72] Schwerdtner et al., 2024,[73] Singh, 2025,[74] Young et al., 2025[75]), SCE has modified its approach to wildfire risk modeling in a manner that is responsive to stakeholder recommendations.

---

[69] Wildfire Advisory Safety Board. (2025, June 4). Recommendations to the Office of Energy Infrastructure Safety. Office of Energy Infrastructure Safety. https://energysafety.ca.gov/news/2025/06/04/wsab-adopts-annual-recommendations-for-energy-safety-wildfire-mitigation-plan-requirements/.

[70] Heinrich, Torsten, Juan Sabuco, and J. Doyne Farmer, "A simulation of the insurance industry: the problem of risk model homogeneity," Journal of Economic Interaction and Coordination 17, 2022: 535–576, https://doi.org/10.1007/s11403-021-00319-4.

[71] Tonini, M., Pereira, M. G., & Fiorucci, P. (2022). Performance and Efficiency of Machine Learning Based Approaches for Wildfire Susceptibility Mapping. Environmental Sciences Proceedings, 17(1), 38. https://doi.org/10.3390/environsciproc2022017038.

[72] Singh, R., Chen, Y., & Martinez, J. (2024). Hybrid modeling approaches for wildfire risk prediction: Integrating physics-based and machine learning models. Environmental Modelling & Software, 167, 105456.

[73] Schwerdtner, P., Law, F., Wang, Q., Gazen, C., Chen, Y.-F., Ihme, M., & Peherstorfer, B. (2024). Uncertainty quantification in coupled wildfire–atmosphere simulations at scale. PNAS Nexus, 3(12), pgae554. https://doi.org/10.1093/pnasnexus/pgae554.

[74] Singh, H., Ang, L.-M., Paudyal, D., Acuna, M., Srivastava, P. K., & Srivastava, S. K. (2025). A comprehensive review of empirical and dynamic wildfire simulators and machine learning techniques used for the prediction of wildfire in Australia. Technology, Knowledge and Learning, 30, 935–968. https://doi.org/10.1007/s10758-025-09839-5.

[75] Young, T. M., Liang, J., & Smith, A. R. (2025). Wildfire risk modeling in a changing climate: Integrating fuel dynamics and suppression uncertainty. Environmental Modelling & Software. https://doi.org/10.1016/j.envsoft.2025.105678.

SCE's new **Wildfire Integrated Model (WIM)** can be described as a scaled hybrid wildfire risk model. It combines the precision and granularity of SCE's existing Technosylva-based Wildfire Analyst, FireSight 8[76] ("FireSight 8") deterministic wildfire risk model with the probabilistic depth of Moody's RMS U.S. Wildfire HD Models 2.0's [77] ("RMS 2.0") stochastic ignition dataset. The resulting WIM architecture enables the derivation of full distributions at each individual asset for both expected and tail risk values for each natural unit consequence (e.g., acres burned, structures damaged, and structures destroyed). In turn, these asset-based distributions can be aggregated to derive system-wide distributions for each of these natural unit consequences.

SCE notes that it has intentionally designed an aggregation approach so that new versions from these existing vendors, as well as other vendors SCE may wish to explore, can be readily integrated.

In the following sections, SCE discusses the relative strengths and limitations of each of these types of models and provides a high-level description of how this new scaled hybrid model builds upon these strengths, while addressing each of their limitations.

B. Technosylva's Wildfire Analyst, SCE FireSight 8

Since 2018, SCE has employed several generations of Technosylva's physics-based deterministic wildfire risk planning model – Wildfire Analyst (FireSight 8)[78] – to guide the prioritization and deployment of its physical and operational wildfire mitigations. Deterministic and probabilistic wildfire risk models differ fundamentally in how they represent uncertainty and

---

[76] SCE's current version of Technosylva's Wildfire Analysis is known as FireSight 8. SCE has performed two model runs using the FireSight 8 model: one based on historical ("present day") conditions, and an additional model run based on future climate conditions (e.g., SSP 3.7 ensemble, year 2050) in compliance with Risk OIR Phase III Guidance for SCE's Climate Pilot. SCE will provide additional information regarding this "FireSight 8 (Climate)" scenario in a future Climate Pilot White paper.

[77] Moody's RMS Wildfire HD 2.0 https://www.moodys.com/web/en/us/capabilities/catastrophe-modeling/wildfire.html.

[78] As indicated above, the most recent SCE-calibrated version of Technosylva's Wildfire Analyst is known as FireSight 8.

variability in wildfire behavior across spatial and temporal scales (Singh 2025).[79] Deterministic models, such as FireSight 8 rely upon pre-determined fixed inputs (e.g., historical or forecast weather, vegetation, topography, and infrastructure) to simulate scenario-specific outcomes. These types of models are particularly effective at leveraging high-resolution environmental data to simulate fire ignition, spread, and impact under these defined conditions. In such, they are extremely useful in understanding how small perturbations in wind and weather conditions (e.g., Fire Weather Days (FWD)) can impact the resulting consequences of wildfire events. Collectively, these scenario specific outcomes can be used to derive quasi-probabilistic consequence curves, as SCE presented in its most recent 2026-2028 Wildfire Mitigation Plan.[80]

Because they follow a rule-based structure without incorporating randomness, the scenario-based outputs of deterministic model are relatively simple to interpret and communicate. These tools integrate high-resolution weather, fuel, and topographic data to simulate fire behavior under defined conditions, and critically, they can attribute the consequences of simulated ignition events back to specific ignition sources (see Figure V-8). This capability makes them particularly well-suited for a range of infrastructure-focused applications where precision, granularity, and ease of understanding are key. In addition to FireSight, SCE also uses FireSim as well as FireRisk to support a range of other operational activities. The use of FireSim allows SCE to perform "what if" scenarios using data from active wildfire events to inform its response. Similarly, SCE leverages FireRisk, which uses weather forecasts to inform operational decision-making when fire weather conditions are imminent (e.g., Public Safety Power Shutoff decision-making).

---

79 Singh, H., Ang, L.-M., Paudyal, D., Acuna, M., Srivastava, P. K., & Srivastava, S. K. (2025). A comprehensive review of empirical and dynamic wildfire simulators and machine learning techniques used for the prediction of wildfire in Australia. Technology, Knowledge and Learning, 30, 935–968. https://doi.org/10.1007/s10758-025-09839-5.

80 See 5.2.2.2.2.2 Updated Fire Weather Day Methodology, ppg. 82 – 89, specifically Figures 5-33 and 5-34 on pg. 89.

It's important to note that while there are several other open-source deterministic wildfire risk modeling tools (e.g., FARSITE,[81] BehavePlus,[82] ELMFIRE,[83] and FlamMap[84]), these tools often require extensive manual input, configuration, and calibration. Additionally, these open-source tools lack the ability to attribute simulated wildfire consequences back to individual utility assets, limiting their usefulness for asset-specific risk mitigation. Instead, SCE has chosen to continue to utilize Technosylva's deterministic tools for these reasons. Further, they are widely used by dozens of other utilities and fire agencies to convert fire behavior modelling into effective strategies for mitigating, as well as responding to, wildfire events.

The advantages of deterministic wildfire risk models also highlight their most notable limitations. Because these deterministic models rely on fine-scale environmental inputs (e.g., weather and wind data, fuel types, fuel moisture levels, ignition point spacing, etc.) the accuracy of the resulting simulations is directly tied to the precision and reliability of these inputs. Any errors, biases, or outdated data inputs can significantly distort predicted fire behavior, particularly as wildfire simulations are extended beyond a certain point in duration (e.g., such as after the first burning period, typically 8 hours, or even 24 hours).[85]

Given the volume of input data and the computing power required to run these simulations while correcting for systemic biases through the simulation period, deterministic wildfire simulations runs are often truncated to short time frames (USFS 2021).[86] The drawback of this approach is that this artificial truncation limits their ability to capture the full range of

---

81 Finney, M. A. (1998). FARSITE: Fire Area Simulator—model development and evaluation. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

82 Andrews, P. L. (2007). BehavePlus fire modeling system: Version 4.0 user's guide. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

83 Lautenberger, C. (2025). ELMFIRE: Eulerian Level Set Model of FIRE spread [Computer software]. from https://elmfire.io.

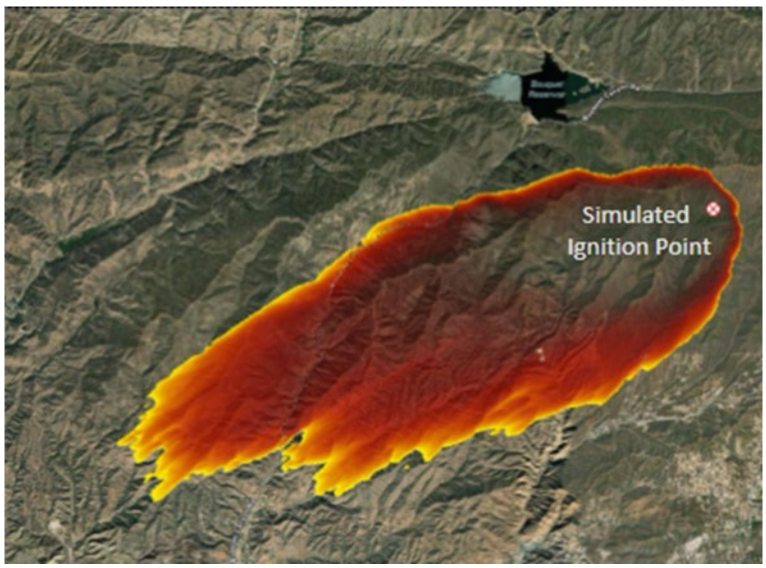
84 Finney, M. A., & Andrews, P. L. (2006). FlamMap: Fire mapping and analysis system. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. Retrieved from https://www.fs.usda.gov.

85 SCE used the FireSight 8 24-hour simulation data for this scaled hybrid model, rather than its FireSight 8 8-hour simulation data, in its previous models, given that the distributions from the 24-hour model were more readily scalable based on higher-level hexagon-based distributions.

86 U.S. Forest Service. (2021). Deep learning for high-resolution wildfire modeling. Missoula Fire Sciences Laboratory. from https://research.fs.usda.gov/firelab/projects/deeplearning.

possible outcomes, particularly those rare, but high-impact events, which occur under dynamic conditions. While these types of models have sufficient precision and granularity for utilities to assess and tailor mitigations based on an understanding of localized risk, these limitations highlight the importance of supplementing deterministic models, such as FireSight 8, with probabilistic approaches that can better represent a full range of potential uncertainty in associated outcomes.

Figure V-8
Example FireSight 8 Deterministic Ignition Simulation



C. Moody's RMS U.S. Wildfire HD Models, version 2.0 ("RMS 2.0") Ignition Data Set

Unlike deterministic models, which rely on fixed inputs, probabilistic (or stochastic) wildfire ignition data sets, such as Moody's RMS Wildfire HD 2.0 Ignition Data Set (RMS 2.0)[87] are comprised of tens of thousands of simulated years (i.e., stochastic years). The resulting stochastic ignition simulations incorporate uncertainty and variability by applying statistical distributions to develop randomized combinations of inputs. The RMS 2.0 ignition data set contains 16.5 million wildfire ignition simulations across the United States and Canada, each comprised of different combinations of weather and wind conditions, fuel moisture, as well as

[87] See additional information regarding the RMS U.S. Wildfire HD Model at https://www.moodys.com/web/en/us/capabilities/catastrophe-modeling/wildfire.html.

ignition modifiers designed to simulate suppression ineffectiveness/delays, ember and smoke damage to structures beyond the fire perimeter, structure-to-structure conflagration, as well as other factors more often associated with tail risk events (RMS 2019).[88] These resulting simulated consequences are then calibrated through the RMS Industry Exposure Database (IED),[89] which itself is derived from known insured losses for similar types of ignition events. This approach allows probabilistic models, such the RMS stochastic ignition data set, to capture the full range of fire outcomes. This includes rare, high-impact tail-risk events, which are often beyond historically observed conditions but are well within the realm of possibility.

By simulating variability and interdependence across both environmental and human-influenced factors, unconstrained by simulation times, data sets such as these are particularly effective at identifying generalized trends at both macro (e.g., system-wide), as well as meso (e.g., regional) spatial scales. Their ability to quantify uncertainty and assess exposure at these scales makes them particularly valuable for strategic planning, insurance risk modeling, and policy development, where the focus is on long-term trends and risk distributions are more important. As such, these models are widely favored by the insurance industry, academic researchers, and policy makers, who need to prioritize an understanding of systemic risk over the precision required for operational decision-making (e.g., granular, micro-level).

Despite their strengths, stochastic wildfire risk models present several challenges when attempting to use them to inform utility risk mitigation decisions. First and foremost, these models often lack the spatial granularity needed to attribute risk back to individual ignition sources, such as individual assets. This limitation is particularly significant for utilities that require asset-level insights to inform targeted mitigation strategies. The reason for this limitation

---

88 Risk Management Solutions, Inc. (2019). U.S. Wildfire HD Model datasheet. https://forms2.rms.com/rs/729-DJX-565/images/rms-us-wildfire-hd-model-datasheet.pdf.

89 The RMS Industry Exposure Database (IED) is a high-resolution dataset that aggregates information on insurable assets—such as buildings and properties—used to estimate industry-wide losses from catastrophic events and support risk modeling and insurance analytics. Moody's RMS - Define exposures.\ - RMS Intelligent Risk Platform website. Retrieved from https://developer.rms.com/risk-modeler/docs/define-exposures

is that the computational demands required to run stochastic models, as mentioned earlier, require thousands of simulated fire-years across varied permutations of environmental and infrastructure variables. In other words, these types of models require an immense amount of processing power (Thompson et al. 2019).[90]

To manage the vast amount of computing power required, stochastic modelers often reduce the granularity and quality of their inputs. For example, instead of using high resolution Scott and Burgan 40 LANDFIRE fuel models[91] which are generally used in deterministic models, many stochastic models make do with coarser resolution Anderson 13 LANDFIRE fuel models.[92] While this improves computational efficiency, the selection of less refined model inputs, particularly at smaller spatial scales, also tends to obscure localized environmental conditions, particularly those that influence fire behavior near utility assets. This challenge is especially pronounced in densely populated WUI, where a significant number of individual utility assets may be present, and where small variations in structure spacing, vegetation, and defensible space can significantly alter fire outcomes (Naik 2025). Finally, because these models do not attribute any of these resulting fire outcomes to individual, discrete ignition sources, it has limited their usefulness in asset-specific mitigation planning and prioritization.

D. Methodology used to Create the Wildfire Integrated Model (WIM)

Given the limitations inherent to both types of approaches, SCE has developed a scaled hybrid wildfire risk modeling approach designed to bridge the precision and granularity of deterministic models, with the capability to understand a full range of probabilistic outcomes to better capture rare, but potentially catastrophic tail risk events.

---

[90] Thompson, M. P., Calkin, D. E., Finney, M. A., Gebert, K. M., & Hand, M. S. (2019). Risk management and analytics in wildfire response. Current Forestry Reports, 5(3), 226–239. https://doi.org/10.1007/s40725-019-00101-.

[91] Scott, J. H., & Burgan, R. E. (2005). Standard fire behavior fuel models: A comprehensive set for use with Rothermel's surface fire spread model (General Technical Report RMRS-GTR-153). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. https://www.fs.usda.gov/rm/pubs/rmrs_gtr153.pdf.

[92] Anderson, H. E. (1982). Aids to determining fuel models for estimating fire behavior (General Technical Report INT-122). U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.

In the following sections, SCE describes at a high level the methodology used to create its new **Wildfire Integrated Model (WIM)** with particular emphasis on the architecture employed. SCE notes that it designed this scaled hybrid architecture in such a way so that new model versions from its current vendors, as well as other vendors OEIS may wish for SCE to explore, can be readily integrated. SCE is open to providing additional information regarding the individual components of each model to relevant stakeholders based on the terms, conditions, and confidentiality agreements we have with each individual entity at the time of our 2026 RAMP filing.

Step 1: Overlay UH3 Hexagon Lattice onto RMS 2.0 Ignition Data Set

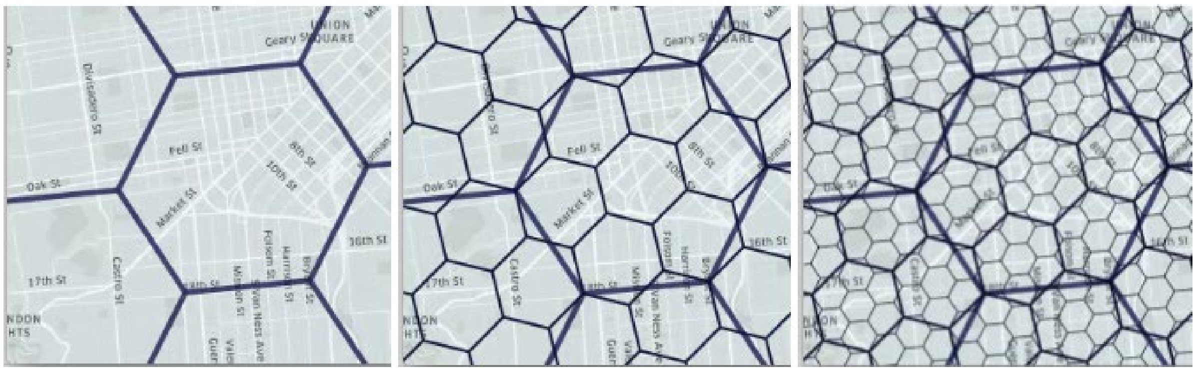
The integration process begins by aligning the FireSight 8 model outputs with the RMS 2.0 stochastic ignition dataset. To perform this step, SCE leveraged the Uber H3 (UH3) Spatial Hierarchical Indexing system (see Figure V-9).[93] Nested hexagonal polygons such as those used in the UH3 system offer uniform adjacency and minimal edge effects,[94] making them ideal for aggregating and disaggregating spatial data. Use of the UH3 hexagonal grid structure enables SCE to leverage an industry standard comprised of a predefined, consistent spatial resolution across diverse terrain. This allows for scalable and precise alignment of wildfire consequence data across various datasets, many of which - such as the case with FireSight 8 and RMS 2.0 - are at different spatial resolutions. This aggregation technique allowed SCE to develop a methodology to consistently extract natural unit consequences (e.g. acres burned, buildings destroyed, and buildings damaged) from both models at sub-regional spatial scales in a statistically robust manner.

---

93 https://www.uber.com/blog/h3/.

94 In spatial statistics, "edge effects" refer to biases or distortions in statistical analysis that occur near the boundaries of a study area, where data may be incomplete or interactions with neighboring regions are not fully captured.

Figure V-9
Uber H43 Hexagons at Varying Levels of Spatial Aggregation



This step involved converting both asset-based FireSight 8 data, as well as RMS 2.0 ignition data into geospatial coordinates, then assigning those individual locations to UH3 hexagons at the appropriate UH3 spatial resolution. The FireSight 8 data were spatially indexed[95] and aggregated at H3 Level 8 (L8) whereas the RMS 2.0 data is spatially indexed at H3 Level 7 (L7).[96] These resolutions were chosen to ensure the lowest level of aggregation while ensuring there was enough stochastic information available to derive the descriptive statistics (e.g., mean, standard deviation, 98 pct., etc.) for each model.

Step 2: Developing Descriptive Statistics from RMS 2.0 Ignition Data

In this step, SCE calculated the descriptive statistics for RMS 2.0 ignition data using the UH3 L7 hexagons across its service territory. This involved transforming the raw stochastic ignition datasets within a given hexagon into descriptive statistics[97] (e.g., mean, standard deviation, 98 pct., etc.), then use these moments to derive a full distribution (see illustrative

---

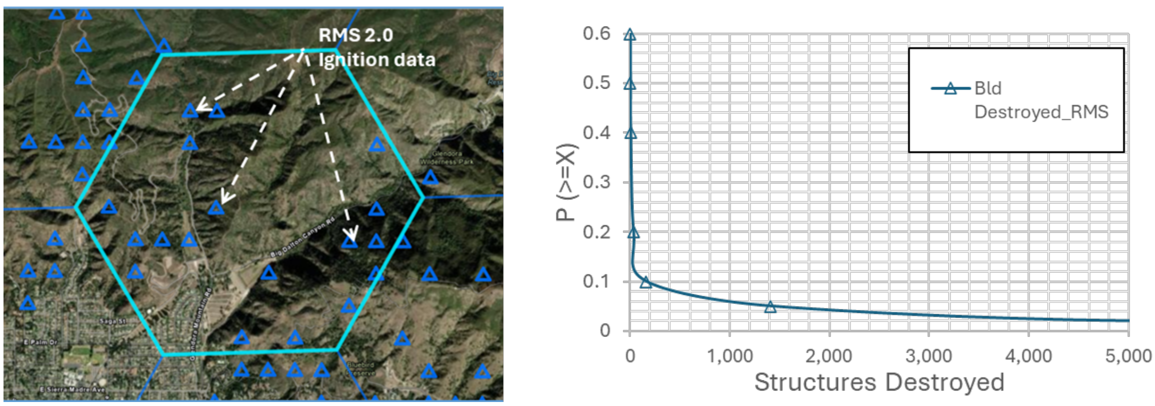
[95] In spatial statistics, spatially indexed refers to data that is organized or tagged based on geographic or spatial coordinates, allowing each observation to be associated with a specific location in space. This indexing enables spatial analysis, such as identifying patterns, relationships, or dependencies across geographic areas.

[96] H3 Level 7 hexagons are 5.161293360 km2, whereas H3 Level 8 hexagons are 0.737327598 km2. H3 Geo. Tables of cell statistics across resolutions. H3 Concepts and Guides. https://h3geo.org/docs/core-library/restable/#average-area-in-km2.

[97] Descriptive statistics refers to the metrics use to describe statistical “moments” within a set of data. These moments include, mean, median, mode, skew, kurtosis, etc.

example in Figure V-10). In this step, the mean of these data were used to characterize the central tendency of the data and percentiles were used to quantify the distribution of values across different thresholds. Additionally, the tail values were used to capture the variability of the tail, while and the maximum value in data set were used to determine an appropriate truncation point (e.g., maxima).

Figure V-10
Illustrative Example of Deriving Descriptive Statistics using RMS 2.0 Ignition Data at the UH3 L7 Hexagon-Level



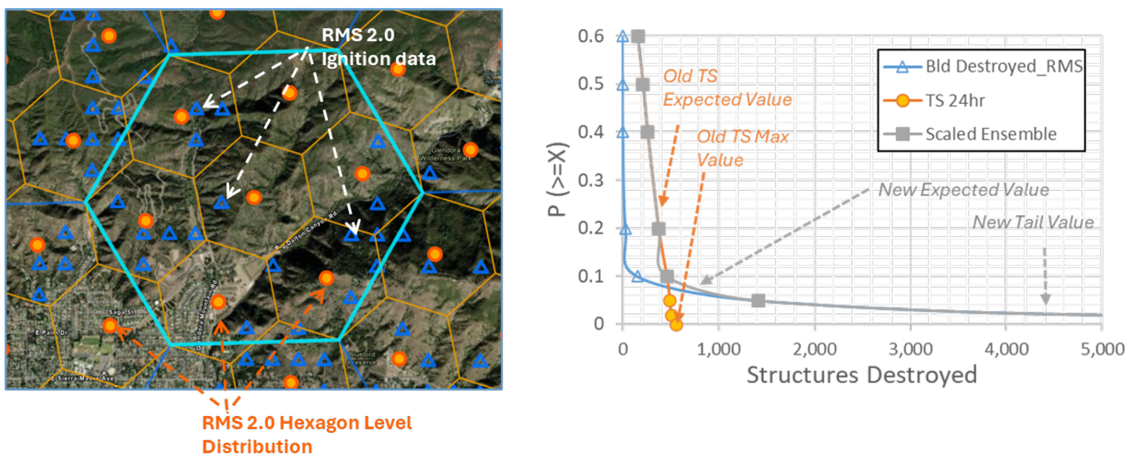
Step 3: Comparing RMS 2.0 Ignition L7 Hexagon-level Descriptive Statistics to FireSight 8 24-hour L8 Hexagon-Level Distributions.

Once descriptive statistics for each natural unit consequence in the RMS 2.0 data set had been derived for each L7 hexagon, the next step in the process was to compare these distributions to the corresponding natural unit consequence distributions from each of the more granular asset-based Firesight 8 24-hour at the underlying L8 hexagon-level (see Figure V-11). This comparison of the descriptive statistics across spatial scales served as the basis for deriving scaling factors, which, in turn, were used to rescale the original FireSight 8 values at individual assets.[98] This ensured that a distribution could be derived from the resulting percentiles of the combined, scaled model, while the distribution of the consequence vales at each asset were

[98] The maxima were set to a minimum value of "1" to prevent inadvertent downscaling in some locations.

appropriately truncated so that those consequences would not be overstated. See Appendix D for an illustrative example of the spatial scaling process.

Figure V-11
Illustrative Example of Scaling Asset-Level FireSight 8 24-hour Distributions based on Hexagon-Level Pareto Descriptive Statistics from RMS 2.0 Ignition Data



In order to perform this scaling process, SCE leveraged concepts by Taleb (2022)[99] who recommended scaling the lower-level distribution (e.g. the FireSight 8, UH3 L8 data) using a nonlinear operator that respects the higher-level distributions (e.g. RMS 2.0, UH3 L7 data). In this way, the overall scaled distribution is representative of localized phenomena, while not exceeding the physical limits of the phenomena being assessed.

The equation for this scaling process, "Z" as recommend by Taleb is as follows:

$$Z = \left(\sum_{i=1}^{n} Y_i^{\alpha} \right)^{1/\alpha}$$

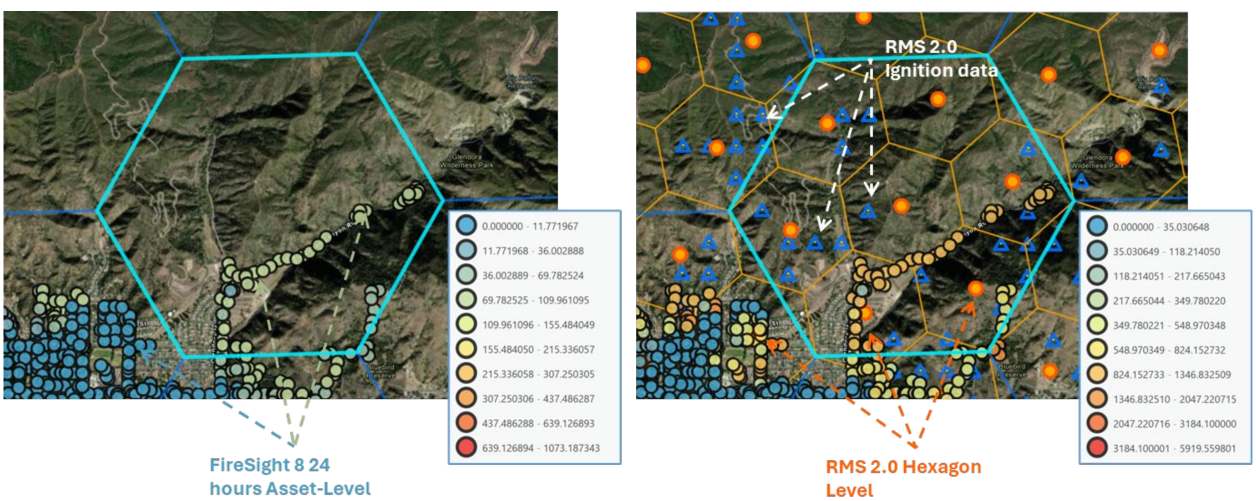
Where:

- "i" are the percentile risk values for hexagon-based distribution.
- "α" is the scaling exponent that controls the sensitivity of the aggregation.
- "n" is the number of observations being aggregated.

[99] Taleb, N. N. (2022). Statistical consequences of fat tails: Real World Preasymptotics, Epistemology, and Applications (2nd rev. ed.). https://doi.org/10.48550/arXiv.2001.10488.

By appending the original FireSight 8 asset-based data with derived "scalars" at each percentile this approach preserves the granular asset-based distribution, while making it more representative of a full distribution of possible outcomes as represented by the higher-level hexagon-based RMS 2.0 stochastic data set (See Figure V-11, gray line). SCE notes that it calculated separate scalars for each level of aggregation, as well as each natural unit consequence (e.g., acres burned, buildings destroyed, and buildings damaged). This process resulted in scaled values for each natural unit consequence at each percentile for individual assets within SCE service territory (see left (scaled) and right (re-scaled) values in Figure V-12). The resulting re-scaled expected and tail values from each of these distributions for natural unit consequence outputs, in turn, were used to derive monetized safety and financial values for the purpose of wildfire risk assessment.[100]

Figure V-12
Illustrative Example of Unscaled Asset-Level FireSight 8 24-hour Distributions vs Scaled Asset-Level FireSight 8 24-hour Distributions



100 Monetized reliability values are derived based of a different level of asset-based aggregation methodology as prescribed in Risk OIR Phase II guidance (e.g. ICE 2.0 values, SPD feedback on 2024 PG&E RAMP).

Step 4: Fit Lower-Level Distributions to a System Level Power Law Distribution

Once the original FireSight 8 asset-based natural consequence values had been re-scaled at the appropriate spatial resolution, the next step involved fitting the distribution of natural unit consequences (acres burned, structures destroyed, structures damages) from the resulting WIM to fit a (see Figure V-13 (acres burned) & Figure V-14 (buildings destroyed)) to a system-level Power Law distribution. In order to accomplish this, SCE applied the methods recommended by Nassim Taleb in Section 3 of *The Statistical Consequences of Fat Tails* (Taleb 2022).[101]
The methodology he recommended involved scaling the distributions from two models into a single distribution by using a cumulative distribution function (CDF). Mathematically, this involved applying a transformation to random variables "x" (natural unit consequence) in each data set so that the corresponding dependent variable "y" (frequency) in the same data set follows a Pareto distribution.

The transformation he recommended is defined as:

$$y = \frac{1}{1 - F(x)}$$

Where:

$F(x)$ is the cumulative distribution function of the original variable "x"

This type of transformation effectively "fattens" the tail of the distribution by amplifying the impact of extreme values. In other words, instead of treating all values in the distribution equally, the transformation equation is used to re-weight certain values so that rare, extreme events become more prominent. Taleb (2022) emphasizes that this approach is necessary to capture the true statistical behavior of systems exposed to extreme risks (e.g. wildfire events), which, at the macro-level exhibit the properties of fat-tailed Pareto-like distributions.

[101] Taleb, N. N. (2022). Statistical consequences of fat tails: Real World Preasymptotics, Epistemology, and Applications (2nd rev. ed.). https://doi.org/10.48550/arXiv.2001.10488.

Figure V-13 and Figure V-14 provide illustrative examples of rank order cumulative distribution functions utilizing the "expected value" at each asset using these new transformed scaled FireSight 8 distributions (i.e., the WIM).[102] As noted in these examples, while the Technosylva-based FireSight 8 model somewhat adequately captures the consequences of catastrophic wildfires at the expected value, the addition scalars using the RMS 2.0 stochastic ignition data set ensures that tail risk events are better represented. It is important to also note, as described earlier in this white paper, that there is not a consistent relationship between wildfire size and structure impacts. For instance, note that the largest historical fires in terms of acres burned (Figure V-13) are not correlated to the same points on the distribution to the historical wildfires with greatest numbers of buildings destroyed (e.g. Eaton 2025).

[102] For illustrative purposes only, SCE also overlaid the natural unit consequences of historical wildfires in SCE's service territory in order to compare the resulting system-level WIM model, as well as each individual model.

Figure V-13
System-level Distribution of Wildfire Integrated Model (WIM) Power-law fit (log-log plot) at Expected Value (Acres Burned)

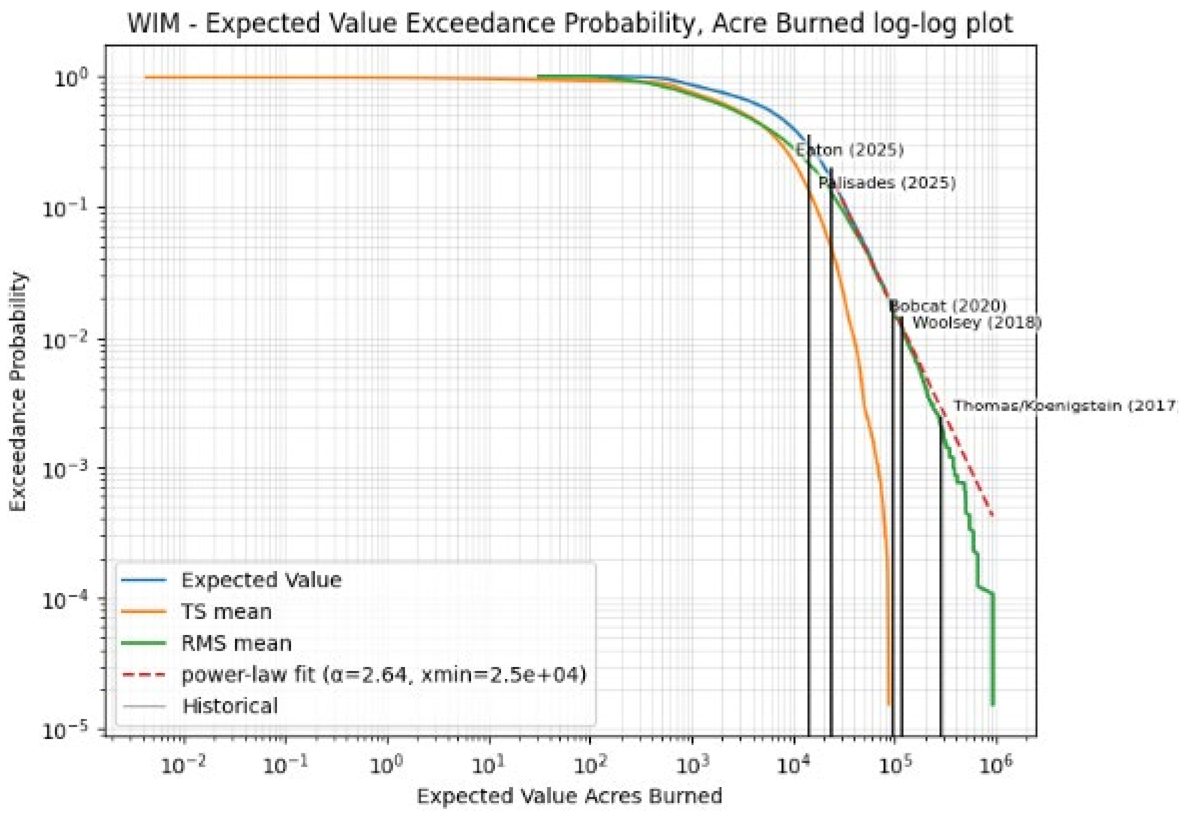
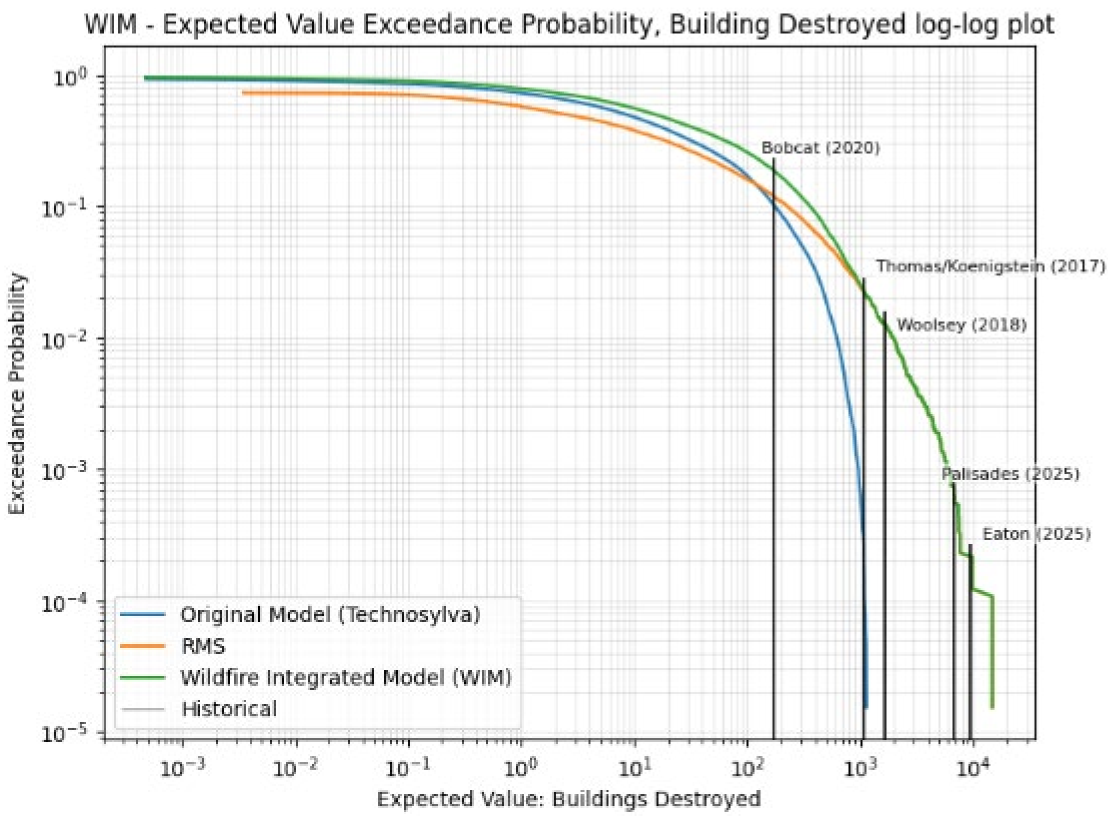


Figure V-14
System-level Distribution of Wildfire Integrated Model (WIM) Power-law fit (log-log plot) at Expected Value (Buildings Destroyed)



Additional Methodological Assumptions

SCE notes that it employed several simplifying assumptions in this new scaled hybrid wildfire modeling approach. First, it assumed that the distribution of risk in each hexagon was well represented by the underlying raw stochastic ignition event data. In doing so, it avoided traditional parameter estimation techniques (e.g., Maximum Likelihood Estimation (MLE)) that are more appropriate for calibrating gaussian (i.e., normal) distributions. Instead, SCE was able to use distribution scaling techniques consistent with Extreme Value Theory (EVT) as recommended by Taleb, as previously discussed. Also, SCE truncating these scaled distributions based on the maximum values present in the RMS 2.0 stochastic ignition data set. This allowed SCE to rely upon a reasonable estimate of tail risk values at relatively granular spatial scales based on the physical limits of the local environment, while not over- or under- representing this risk. This would not have been possible if system-wide calibration techniques were employed.

Finally, in order to ensure there was a statistically robust enough dataset from which to draw these distributions, SCE performed a series of tests to determine the appropriate size of the H3 grids to use. In cases where there was not enough stochastic data at the selected H3 scale from which to derive a distribution, SCE defaulted to using the raw, unfitted RMS 2.0 data to generate statistical anchors (e.g. mean, max, 98 percentile). In these locations, such as FCZ 8 Northern Desert, where wildfires are not prevalent, those statistical anchors were used to scale the asset-level data. While we acknowledge that this approach may increase the uncertainty of estimates in certain locations, we also note that by using those rules it avoided the reliance on unstable moments in the distribution,[103] which may be present simply due to the small sample sizes in those locations.

[103] In statistical distributions, an unstable moment refers to a situation where one or more moments (such as the mean, variance, skewness, or kurtosis) of a distribution are undefined or infinite, often due to heavy tails or discontinuities in the probability density function.

VI.

Conclusions

Based on the guidance in D.24-05-064 (Risk OIR Phase III Decision) which requires that utilities develop a white paper for parties to review and comment prior to their RAMP submission if they deviate from the best practice for the utility estimations of tail risk, SCE submits this white paper for review and comment by parties. In this white paper, SCE describes an alternative approach to derive tail values using a truncated power law distribution that extends beyond historical wildfire events. We discuss the limitations of relying solely on a system-wide approach calibrated to the number of acres burned, as well as the respective strengths and limitations of both deterministic and stochastic modeling approaches.

Finally, to address these limitations, SCE introduces a new scaled hybrid Wildfire Integrated Model (WIM) comprised of its existing FireSight 8 deterministic model with the RMS 2.0 stochastic ignition data. This new model preserves the granularity required for mitigation planning, prioritization and scoping, while also adequately capturing tail risk events, including those which may not be present in the historical record. SCE notes that it also intends to leverage the WIM for its RAMP Climate Pilot, although with a slightly different version of the existing FireSight 8 model using climate-informed data (e.g. FireSight 8 (Climate)) consistent with Commission guidance.

Appendix A

Summary of the Location, Climate, Vegetation, and Pre-dominant Fire Regime in each of SCE's Fire Climate Zones (FCZs)

Appendix A: Summary of the Location, Climate, Vegetation, and Pre-dominant Fire Regime in each of SCE's Fire Climate Zones (FCZs).

Fire Climate Zone 1 – Coast/ Catalina

- Location: Southern California coast from Ventura/Santa Barbara to Orange County.
- Climate: Mild year-round; marine influence; moderate sea breezes.
- Vegetation: Grasses, coastal chaparral, isolated timber.
- Pre-dominant Fire Regime: Infrequent but potentially severe; influenced by Santa Ana winds.

Fire Climate Zone 2 – Inland Valleys

- Location: Santa Clarita, San Fernando, San Gabriel Valleys to Inland Empire.
- Climate: Hot summers (often >100°F), mild winters.
- Vegetation: Grasses, chaparral, isolated timber.
- Pre-dominant Fire Regime: High during dry summers and Santa Ana wind events; rapid fire spread possible.

Fire Climate Zone 3 – Western Mountains

- Location: Angeles and Los Padres National Forests.
- Climate: Variable due to elevation; snow in winter.
- Vegetation: Grassland, chaparral, desert sagebrush.
- Pre-dominant Fire Regime: Summer fuel-driven fires; fall wind-driven fires are hard to suppress.

Fire Climate Zone 4 – Eastern Mountains

- Location: San Bernardino and San Jacinto Mountains.
- Climate: Similar to Zone 3; strong winds in Banning Pass.
- Vegetation: Desert sagebrush, timber, chaparral, grasslands.
- Pre-dominant Fire Regime: Summer fuel-driven fires; fall wind-driven fires.

Fire Climate Zone 5 – Eastern Desert

- Location: East of Banning Pass.
- Climate: Very hot summers (>115°F); low precipitation.
- Vegetation: Sparse desert sagebrush.
- Pre-dominant Fire Regime: Low due to sparse vegetation; fires often along transportation corridors.

Fire Climate Zone 6 – Upper Desert

- Location: High desert plains, Antelope Valley.
- Climate: Hot, dry, and extremely windy.
- Vegetation: Desert sagebrush, grassland, chaparral, timber.

- Pre-dominant Fire Regime: Wind-driven fires; larger fires near foothills.

Fire Climate Zone 7 – Mojave
- Location: Eastern high desert near California-Nevada border.
- Climate: Hot summers; monsoonal thunderstorms.
- Vegetation: Desert sagebrush, grassland, isolated timber.
- Pre-dominant Fire Regime: Summer lightning-induced fires; limited spread due to sparse vegetation.

Fire Climate Zone 8 – Northern Desert
- Location: Death Valley and Panamint Range.
- Climate: Hottest zone; dry with occasional monsoons.
- Vegetation: Sparse sagebrush, scattered timber.
- Pre-dominant Fire Regime: Infrequent due to low vegetation; lightning-induced fires possible.

Fire Climate Zone 9 – Inyo
- Location: Owens Valley between Eastern Sierras and White Mountains.
- Climate: Hot summers in valleys; snowy winters in mountains.
- Vegetation: Sagebrush, mixed timber, grasslands.
- Pre-dominant Fire Regime: Summer/fall wind-driven fires; mostly confined to valleys.

Fire Climate Zone 10 – Sierra
- Location: Sierra and Sequoia National Forests.
- Climate: Milder summers; snowy winters.
- Vegetation: Mostly mixed timber and chaparral.
- Pre-dominant Fire Regime: Summer fuel-driven fires; frequent lightning ignitions.

Fire Climate Zone 11 – San Joaquin
- Location: San Joaquin Valley and Sierra foothills.
- Climate: Hot, dry summers; mild winters.
- Vegetation: Agriculture, grassland, chaparral, mixed timber.
- Pre-dominant Fire Regime: Primarily fuel-driven fires in eastern foothills.

Fire Climate Zone 12 – Tehachapi
- Location: Lake Isabella vicinity and areas south to include the Tehachapi's.
- Climate: Hot and dry summers; relatively mild winters.
- Vegetation: Mostly grassland and oak woodlands interspersed with areas of sagebrush; mixed timber at higher elevations.
- Pre-dominant Fire Regime: Summer fuel-driven fires; but also, wind driven wildfires in the mountain passes.

Fire Climate Zone 13 – Santa Barbara

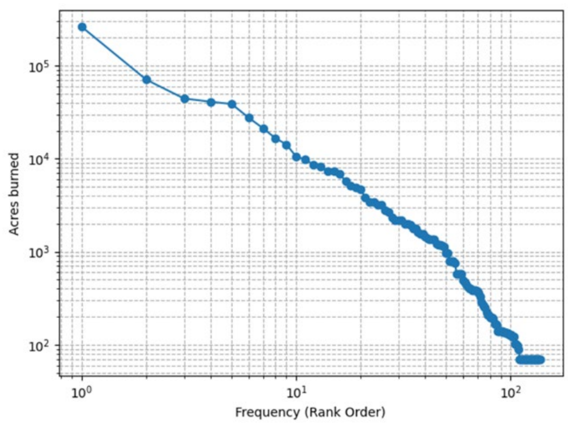
- Location: Coastal strip within Santa Barbara County.
- Climate: Mild year-round; marine influence; moderate sea breezes except for Sundowner winds during the summer months.
- Vegetation: Grasses, coastal chaparral, isolated timber.
- Pre-dominant Fire Regime: Infrequent but potentially severe; influenced by Sundowner winds.

Appendix B

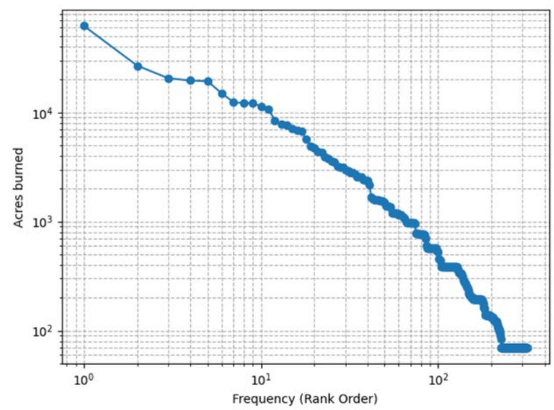
Log-Log Plot of Wildfire Risk (Acres Burned) for SCE Fire Climate Zones (FCZ)

Appendix B: Log-Log Plot of Wildfire Risk (Acres Burned) for SCE Fire Climate Zones (FCZ)

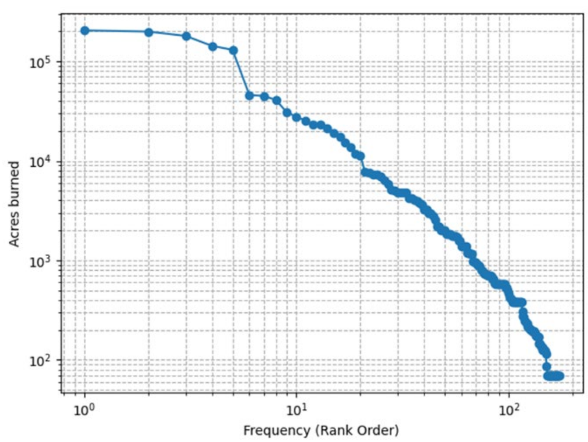
FCZ 1 Coast/Catalina



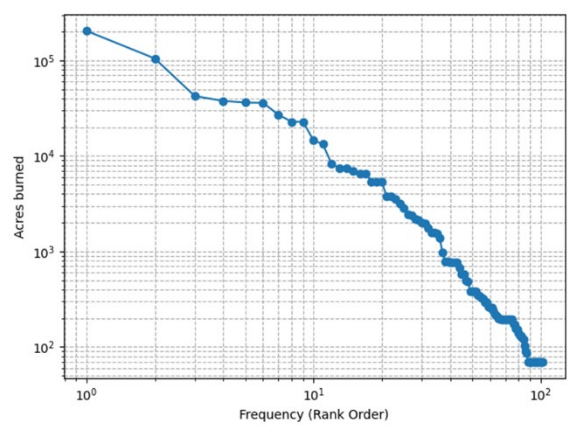
FCZ 2 Inland Valleys



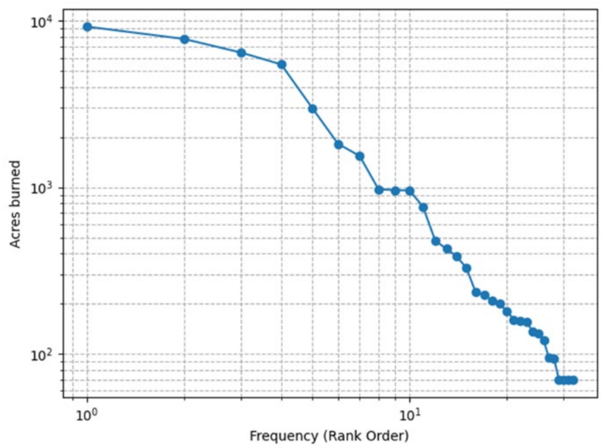
FCZ 3 Western Mountains



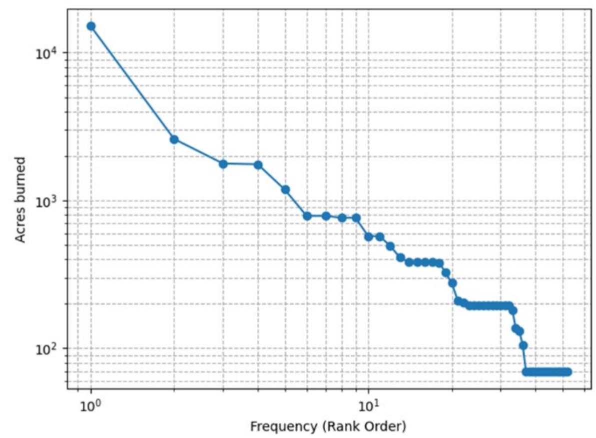
FCZ 4 Eastern Mountains



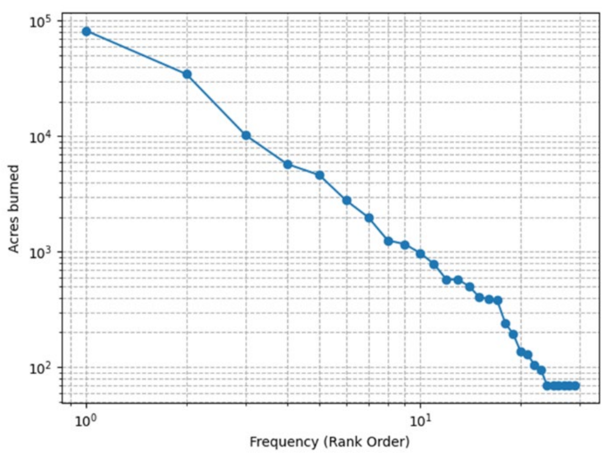
FCZ 5 Eastern Desert



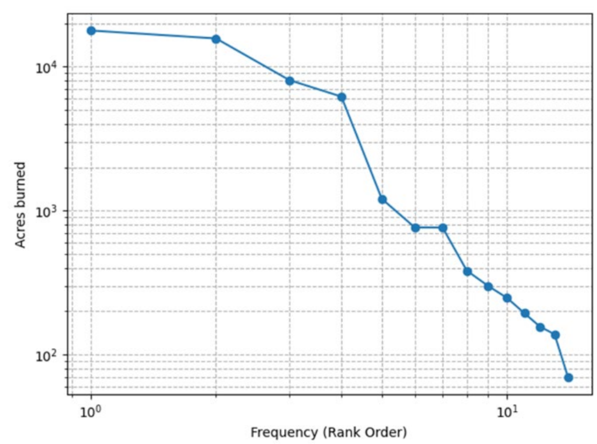
FCZ 6 Upper Desert



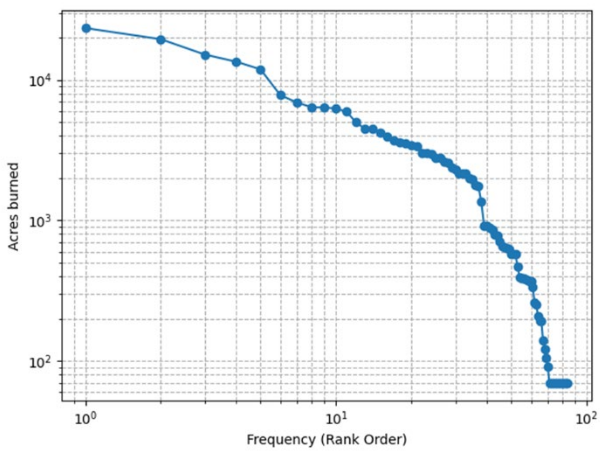
FCZ 7 Mojave



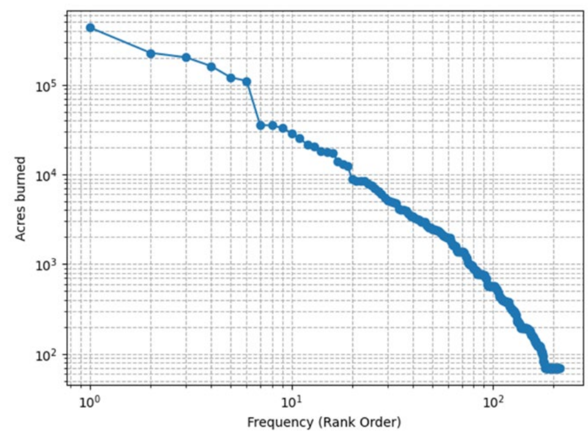
FCZ 8 Northern Desert



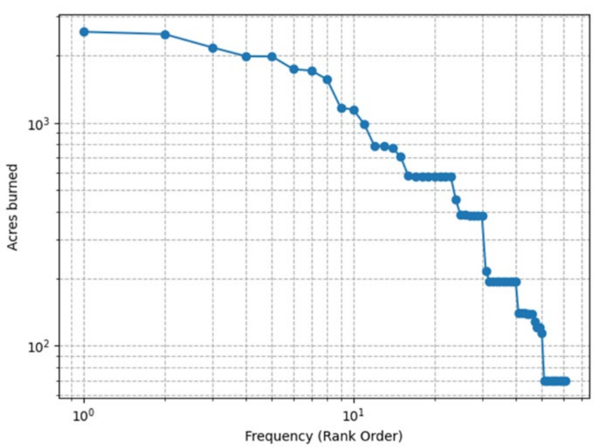
FCZ 9 Inyo



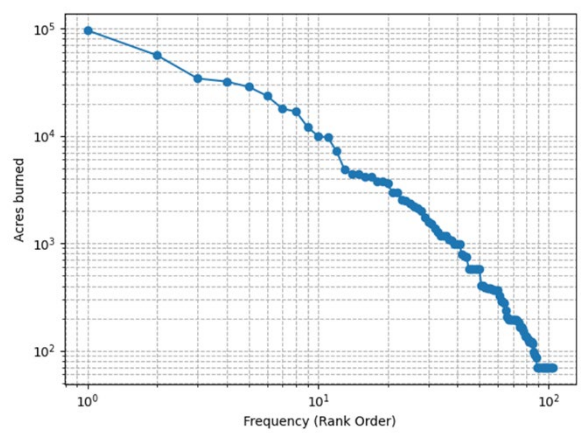
FCZ 10 Sierra



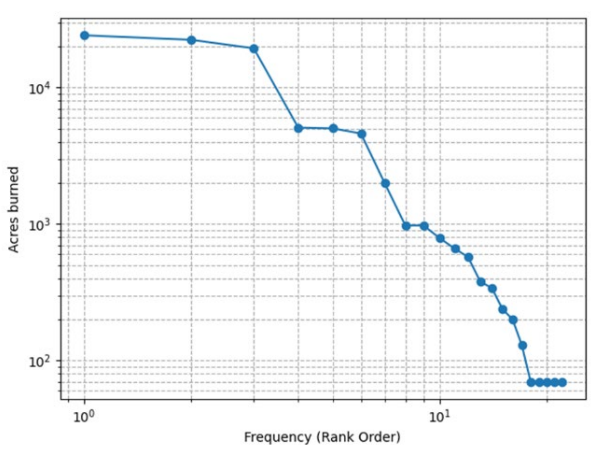
FCZ 11 San Joaquin



FCZ 12 Tehachapi



FCZ 13 Santa Barbara



Appendix C

Catastrophic Wildfires in Southern California Edison Territory (2016-2025) that Meet OEIS Definition

Appendix C: Catastrophic Wildfires in Southern California Edison Territory (2016-2025) that Meet OEIS Definition

(Source: Individual CalFire Incident Pages Supplemented with additional research)

Season	Year	Wildfire Name	FCZ	Wildfire Size	Struct. Dest.	Struct. Dam.	Fatalities	Serious Injuries
Summer	2016	Erskine	FCZ 10 Sierra	48,019	309	0	2	0
Summer	2016	Cedar	FCZ 10 Sierra	29,322	0	0	0	0
Summer	2016	Rey	FCZ 3 Western Mountains	32,606	5	0	0	2
Summer	2016	Blue Cut	FCZ 3 Western Mountains	36,274	321	3	0	0
Summer	2016	San Gabriel Complex	FCZ 3 Western Mountains	5,399	0	0	3	0
Summer	2016	Pilot	FCZ 4 Eastern Mountains	8,110	0	0	0	1
Winter	2017	Thomas/ Koenigstein	FCZ 1 Coast/Catalina	281,893	1063	274	2	2
Fall	2017	Canyon 2	FCZ 1 Coast/Catalina	9,217	25	55	0	4
Summer	2017	Lion	FCZ 10 Sierra	18,900	0	0	0	0
Summer	2017	Whittier	FCZ 13 Santa Barbara	18,430	0	0	0	0
Winter	2017	Rye	FCZ 2 Inland Valleys	6,049	6	3	0	1
Summer	2017	La Tuna	FCZ 2 Inland Valleys	7,194	0	0	0	0
Winter	2017	Creek	FCZ 3 Western Mountains	15,619	123	81	0	3
Winter	2018	Woolsey	FCZ 1 Coast/Catalina	96,949	1,643	364	3	5
Summer	2018	Holy	FCZ 1 Coast/Catalina	23,136	24	0	0	3
Summer	2018	Cranston	FCZ 4 Eastern Mountains	13,139	12	0	0	3
Fall	2019	Maria	FCZ 1 Coast/Catalina	9,999	4	0	0	0
Fall	2019	Saddle Ridge	FCZ 2 Inland Valleys	8,799	25	88	1	8
Fall	2020	Silverado	FCZ 1 Coast/Catalina	12,466	5	11	0	2

Season	Year	Wildfire Name	FCZ	Wildfire Size	Struct. Dest.	Struct. Dam.	Fatalities	Serious Injuries
Winter	2020	Bond	FCZ 1 Coast/Catalina	6,686	0	0	0	0
Summer	2020	Stagecoach	FCZ 10 Sierra	7,760	0	0	0	0
Summer	2020	Bobcat	FCZ 3 Western Mountains	115,997	169	0	0	6
Summer	2020	Lake	FCZ 3 Western Mountains	31,089	0	0	0	0
Summer	2020	Snow	FCZ 4 Eastern Mountains	6,254	0	0	0	0
Summer	2020	El Dorado	FCZ 4 Eastern Mountains	22,744	10	6	1	12
Summer	2020	Apple	FCZ 4 Eastern Mountains	33,424	13	0	0	4
Summer	2021	Walkers	FCZ 10 Sierra	8,777	0	0	0	0
Fall	2021	Alisal	FCZ 13 Santa Barbara	16,970	0	0	0	0
Summer	2022	Fairview	FCZ 2 Inland Valleys	28,098	35	6	2	4
Summer	2022	Route	FCZ 3 Western Mountains	5,208	0	0	0	0
Spring	2022	Lost Lake	FCZ 5 Eastern Desert	5,856	0	0	0	0
Summer	2023	Rabbit	FCZ 2 Inland Valleys	8,355	0	0	0	0
Summer	2023	York	FCZ 7 Mojave	93,078	3	0	0	0
Summer	2024	Airport	FCZ 1 Coast/Catalina	23,526	160	34	0	22
Winter	2024	Mountain	FCZ 1 Coast/Catalina	19,904	243	127	0	6
Summer	2024	Coffee Pot	FCZ 10 Sierra	14,104	0	0	0	3
Summer	2024	Line	FCZ 2 Inland Valleys	43,978	1	4	0	6
Summer	2024	Bridge	FCZ 3 Western Mountains	56,030	81	17	0	8
Summer	2024	Post	FCZ 3 Western Mountains	15,563	0	0	0	0
Summer	2024	Corral	FCZ 9 Inyo	14,168	0	0	0	0

Season	Year	Wildfire Name	FCZ	Wildfire Size	Struct. Dest.	Struct. Dam.	Fatalities	Serious Injuries
Winter	2025	Palisades	FCZ 1 Coast/Catalina	23,448	6,837	1017	12	4
Winter	2025	Hughes	FCZ 2 Inland Valleys	10,425	0	0	0	0
Winter	2025	Eaton	FCZ 3 Western Mountains	14,021	9,414	1,074	18	9

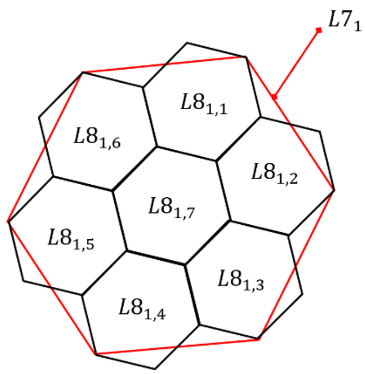
Appendix D

Numerical Examples of Scaling Process

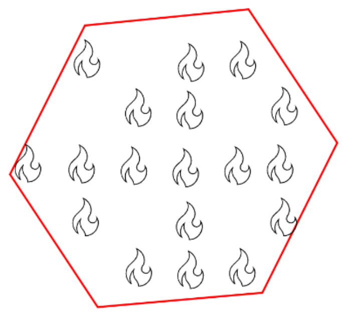
Appendix D: Numerical Examples of Scaling Process

Sample Calculation

H3 Hexagon Parent Child Relationship



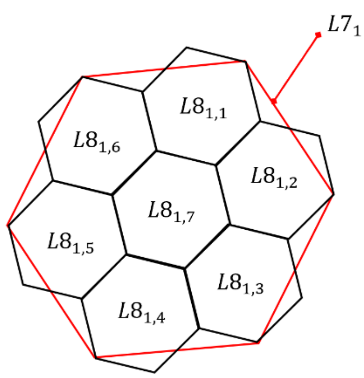
Determine Percentiles for Stochastic Data at H3 L7



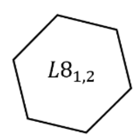
Percentile $L7_1$	Acres Burned
20	788
40	2,795
50	6,224
...	...
98	126,580
100	135,367

*Stochastic models seed ignitions points on a grid, and multiple ignitions could occur in the same location (e.g. ignitions are stacked)

H3 Hexagon Parent Child Relationship



Determine Percentiles for Deterministic Data at H3 L8



Percentile $L8_{1,2}$	Acres Burned
20	2,436
40	2664
50	2851
...	...
98	8,846
100	10,525

Calculate Scalers from $L7_1$ to $L8_{1,2}$

Percentile	Acres Burned $L7_1$	Acres Burned $L8_{1,2}$	Scaler* $L7_1/L8_{1,2}$
20	788	2,436	1
40	2,795	2664	1.05
50	6,224	2851	2.18
...	...	...	...
98	126,580	8,846	14.31
100	135,367	10,525	12.86

$$* \, Scaler, x = \begin{cases} 1 & if\ x < 1 \\ x & if\ x \geq 1 \end{cases}$$