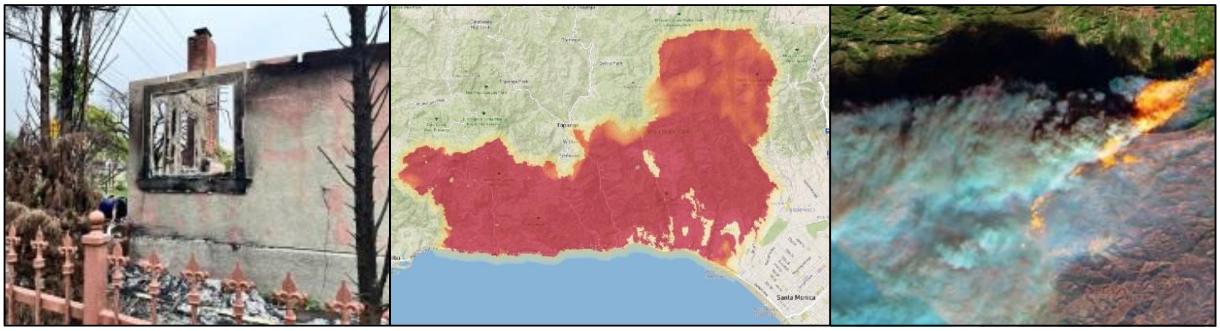
KCC US Wildfire Reference Model

Version 3.0

Required Model Information

Disclosures



Submitted in compliance with the January 2025
Wildfire Catastrophe Model Checklist

JULY 2025

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Introduction

This document contains a subset of responses to the wildfire catastrophe model checklist that are proposed for required model information for this model. The subset was selected based upon relevance for the purpose of required model information and avoiding duplication, where possible. Responses for some disclosures may contain information that addresses other disclosures not directly cited in this document. Numbering of the disclosures has been retained to be consistent with the Wildfire Catastrophe Model Checklist January 1, 2025 Issue (Updated February 19, 2025).

General Disclosures

G-1: Scope of the Wildfire Catastrophe Model and Its Implementation

1. ***Specify the wildfire catastrophe model version identification and, if relevant, the third-party vendor that produced the model. If the wildfire catastrophe model is implemented on more than one platform, specify each platform identifying the primary platform and the distinguishing aspects of each platform. Specify whether there is a more recent version of this model available from the vendor and, if so, why this more recent version is not being used.***

   The KCC US Wildfire Reference Model is Version 3.0 on the RiskInsight® platform Versions 4.14.0 and 4.15.1. This is the most recent version of the model.

2. ***Provide a comprehensive summary of the wildfire catastrophe model, including without limitation the wildfire behavior model (also known as wildfire hazard model) and any other aggregate or actuarial model that uses the results from the wildfire hazard model. This summary should include a technical description of the wildfire catastrophe model and all of its modules, submodules, and each major component (including their spatiotemporal resolution) used to project loss costs and probable maximum loss levels for damage to insured residential and habitational property from wildfire events causing damage in California. Describe the theoretical basis of the wildfire catastrophe model and include a thorough description of the methodology and input data used for the model and its modules, particularly on components of the wildfire hazard model such as, (without limitation as applicable), fire and wind interactions, ignition locations, climate/meteorological and terrain inputs and parameters, and the wildfire fuel mode (e.g. fuel type and fuel moisture); the vulnerability components; and the insured loss components used in the wildfire catastrophe model. The description should be complete and must not reference unpublished work. Additionally, with each version of the model, description of comprehensive validation and verification studies conducted according to the American Institute of Aeronautics and Astronautics (AIAA G-077-1998 Guide for the Verification and Validation of Computational Fluid Dynamics Simulations) and/or other comparable modeling industry standards on model components must be included.***

   The KCC US Wildfire Reference Model captures the propagation of wildfires and wildfire smoke with high-resolution data sources and advanced simulation techniques. The model covers the entire contiguous US and accounts for the risk in both high-frequency wildfire areas like California and low-frequency areas such as the Northeast.

   Wildfires require a dynamic modeling approach that can capture the high-resolution factors determining the direction and rate of fire spread. Unlike hurricanes and earthquakes, where modeled parameters follow relatively predictable relationships throughout the lifecycle of an event, wildfires are highly responsive to small changes in the environment. This introduces high spatial and temporal sensitivity, where a slight change in winds or topography can affect the resulting intensity footprint, which is captured by the KCC model.

As a fire progresses, small variations in available fuels can significantly exacerbate or impede burning. The KCC US Wildfire Reference Model incorporates high-resolution fuel data for the entire contiguous US to accurately represent fire propagation.

The atmospheric environment also quickly changes with surface-level moisture and winds, which greatly affect the intensity of wildfires. The moisture content of both the atmospheric environment and fuels influences the ease with which fires can ignite. More moisture results in a less conducive environment for wildfire formation and propagation. Likewise, high winds encourage and give direction to wildfires, increasing their intensity and causing them to spread faster.

Similar to fuel types, moisture and climatological winds vary by location. Even within the same region, one area may be more prone to humidity and high winds than another due to differences in climatology and topography. As a result, region-level data do not provide the fine resolution necessary to capture the small-scale features of wildfires. In the KCC model, atmospheric conditions are captured at high resolution for every location in the US to accurately model fire progression.

In addition to individual events responding strongly to small-scale environmental conditions, large-scale changes to the atmospheric environment and forest management can increase or decrease wildfire activity. Wildfires are expected to increase in severity as the climate warms, and forest management practices—which are dependent on available resources and local policies—can impact future wildfire seasons. Exposure in the wildland urban interface (WUI) is also continually expanding, increasing the potential for large loss-producing wildfires.

To accurately model wildfires and capture all of these effects, KCC scientists developed an innovative physical modeling approach that leverages high-resolution data and advanced scientific methodologies. The KCC methodology incorporates both historical data and the expected impacts of a warming climate.

The KCC wildfire model is a multi-peril model (MPM), and estimated losses can be viewed by sub-peril—fire and smoke—or in aggregate. Each model component is independently developed utilizing the most current scientific literature and high-resolution data sources.

The KCC US Wildfire Reference Model has four primary components that interoperate on the RiskInsight® open loss modeling platform:

- Event Catalog Module
- Intensity Module
- Vulnerability Module
- Financial Module

Event Catalog Module

The KCC US Wildfire Reference Model includes a Historical Event Catalog and a Stochastic Event Catalog. The Historical Event Catalog includes 62 benchmark wildfire events from 1991 to January 2025 that caused notable impacts across the contiguous US, 39 of which occurred in California.

The Stochastic Event Catalog includes over one million potential future events. The frequency and intensity of events are determined through a combination of analyses on historical wildfire data, fuels, topography, climatology, and the vapor pressure deficit (VPD). These analyses enable the model to account for past events while applying present day conditions to determine the potential extent and severity of future wildfire impacts.

To ensure complete and consistent spatial coverage of the wildfire hazard, ignitions occur on evenly spaced grid points. Every ignition site and fire size combination within the KCC US Wildfire Reference Model has an associated rate corresponding to the likelihood of occurrence. Rates vary spatially within Fire Regions based on consideration of historical fire occurrences, the location of infrastructure such as transmission lines, and VPD. Ignition rates are zero in some areas, such as irrigated agricultural areas, urban areas, and barren land.

The impacts of climate change to date on fire frequency and severity are accounted for in the KCC Stochastic Event Catalog. KCC's advanced, scientific approach for integrating the effects of climate change into the KCC Wildfire Model incorporates observed trends in VPD and the robust, non-linear relationship between VPD and area burned (e.g., Turco et al., 2022; Williams et al., 2019). KCC scientists determine the historical trends in VPD for every Fire Region and use those trends to compute climate-conditioned frequencies, guided by the established VPD-area burned relationship.

Intensity Footprint Module

The Intensity Footprint Module creates the intensity footprints for each event. Fire and smoke can impact a structure independently or in combination. As such, two separate intensity footprints—fire and smoke—are developed for each event, representing the likelihood of each sub-peril at every location.

Fire intensity is determined by a number of factors, including fuel type and characteristics, moisture, winds, and topography. KCC scientists construct the surface fuel database by analyzing the most recent 30-meter resolution surface fuel classification from the LANDFIRE program—a collaboration between the US Forest Service and the Department of the Interior, with fuel categorization based on the Scott and Burgan 40 fuel model (Scott 2005). KCC scientists apply several enhancements to account for disturbances and the expansion of developed areas that have occurred since the construction of the most recent LANDFIRE data.

Fuel changes can happen via disturbances, such as mechanical removal of fuels, insects, disease, or fire. Thousands of succession rules are applied to the vegetation in the disturbed areas to represent the post-disturbance response in surface fuels. The most recent LANDFIRE surface fuel dataset includes disturbances through the year 2023. For more recent fire disturbances, KCC scientists update the LANDFIRE surface fuel data by replacing the fuels within disturbed areas with the fuel types that are associated with the successional rules developed by LANDFIRE. The KCC fuel dataset includes all disturbances through the January 2025 Palisades and Eaton fires. In addition to fuel disturbances, expansion of developed areas into the wildland changes fire behavior. KCC scientists and engineers supplement the LANDFIRE data with an analysis of building density intended to capture more recently built developments.

To identify the wind patterns that are most likely to cause rapidly spreading fires at every location, KCC scientists analyze the wind data from the High-Resolution Rapid Refresh (HRRR) Model initialization analysis for conditions that are warm and dry enough to support wildfires. A Machine Learning (ML) method is employed to identify and classify high wind patterns (e.g., Dowell et al., 2022; James et al., 2022) that vary both spatially and in time.

Based on these factors, the model generates the intensity footprints by simulating the fire spread and flame length (Roose et al., 2008; Scott, 2020), while also incorporating information about fire suppression efforts.

Wildfires can impact non-wildland areas through ember transport which can cause secondary fires (spot fires) and ignite structures (branding) far from the fire front. Winds during a fire determine the distance and direction that an ember will travel. Strong winds are expected to carry an ember farther before it loses its heat. Vegetation type impacts the effectiveness of branding. For example, larger flame lengths typical of forested regions lead to enhanced transport of embers with a denser and longer-lived live ember fraction field. This is represented in the wildfire footprints by a branding zone that extends further from the fire front in forested regions. KCC scientists represent the live ember fraction field as an ellipse around locations on the active fire front (Finney, 2004; Zigner et al., 2020).

Building-to-building burning is how wildfires can spread in urban areas. Because the fuels typical of wildfires are no longer present in these areas, KCC scientists determine fire intensities within the built environment that account for the different modes of fire spread in urban areas: ember ignition, direct flame impingement, and radiation (Purnomo et al., 2024). To capture these effects, the footprint intensities at locations experiencing building-to-building burning depend on the branding intensity as a measure of the ember density, the wind speed, and the building spacing.

As wildfires burn, they emit a smoke plume that rises and spreads. As the plume expands, it diffuses and becomes less dense. The wind can transport smoke far outside the bounds of the fire, causing damage as the smoke travels back down to the surface.

The smoke intensities are modeled via a physics-based dispersion model. To generate smoke intensity footprints, KCC scientists utilize relevant parameters from the creation of fire intensity footprints: the fire perimeter and the wind conditions. The maximum smoke intensity over the duration of the event for every location is then incorporated into the smoke intensity footprint.

Vulnerability Module

The Vulnerability Module incorporates thousands of vulnerability functions reflecting differences in construction, occupancy, age of structure, and other property-specific characteristics. For each combination of building characteristics, damages are estimated separately for building, appurtenant structures, contents, and time element coverages. Several sources of information are utilized for the development and validation of the vulnerability functions including published literature, results of post-event damage surveys, analytical and experimental research, and detailed claims data.

Fire and smoke affect structures differently. Fire damage typically causes extreme damage over a small area, while smoke causes low levels of damage across a large area. When smoke infiltrates a house through vents, openings, and HVAC, interior elements can become damaged. Small smoke and soot particles infiltrate pores and cracks in wood, walls, and fabrics. Each sub-peril has an independently-derived set of vulnerability functions representing its unique impacts. The mean damage ratios (MDRs) provided by the Vulnerability Module capture potential damage given different intensity levels and property characteristics.

Development of the base building vulnerability functions follow a probabilistic framework. Under a given wildfire footprint intensity, a building can be in one of many different damage states. For example, the CAL FIRE damage inspection (DINS) data classifies buildings to be in one of No Damage, Affected, Minor, Major, and Destroyed (DINS 2024). For an area of many buildings affected by the same wildfire intensity, the result is a distribution of these damage states. For high intensities, this distribution is skewed towards the higher damage states, and vice versa for lower intensities. KCC engineers establish the proportion of buildings in each damage state at every intensity from which building fragility functions are established (Gernay et al. 2016). This methodology is consistent with the state-of-the-science in the field of structural engineering for vulnerability development. The results are validated using DINS data and high-resolution insurer claims data.

Varying damage states have different repair costs. Minor damage results in repair costs that are on average a small proportion of the total value, whereas, for major damage or severe damage, the repair costs are high and can even amount to be 100% of the building value. For each wildfire intensity, the MDR is calculated as the repair cost divided by building value.

Once the base vulnerability functions are developed, relativities between other building characteristics, such as the number of stories, year-built, and occupancy, for the various construction types are established using scientific literature (Cohen 2000; Cohen 2004; Manzello et al. 2012; Hakes et al. 2017; Quarles 2017; Hedayati et al. 2018, Hedayati et al. 2019; Nguyen and Kaye 2021; Nazare et al. 2021; IBHS 2021; Barforoush and Du Preez 2022; Hedayati et al. 2022; Lopes et al. 2023; Quarles et al. 2023; Hedayati et al. 2023), building code requirements (California Building Code, International Wildland Urban Interface Code, International Fire Code), observations from post-disaster surveys reports (Maranghides and Mell 2011; IBHS 2020; Uribe 2021; Knapp et al. 2021; Fischer et al. 2022; Lee et al. 2024), results from KCC post-event surveys—including the 2025 Palisades and Eaton Fires—and engineering judgment. The base vulnerability functions are then disaggregated into distinct combinations of all primary building characteristics. KCC engineers thoroughly inspect each vulnerability function during development process to ensure consistency and logical relativities. Moreover, the process of vulnerability function development and the vulnerability functions themselves have been peer reviewed internally and externally by experts in structural engineering.

In addition to the primary building characteristics, the KCC Vulnerability Module incorporates secondary characteristics, mitigation measures, and community-level mitigation programs. The KCC model incorporates 18 property-level secondary characteristics, each with a set of pre-defined options that can be chosen to appropriately modify the base vulnerability functions. Risk also varies based on community-level mitigation programs. These programs are the Firewise USA program and the Fire Risk Reduction Community List (FRRCL). Properties in Firewise and FRRCL communities are considered to be less vulnerable than other locations.

The vulnerability functions are validated with billions of dollars of high-resolution insurer claims and loss data. The majority of the insurer claims data are available at the location level resolution and have been provided separately for each sub-peril.

Financial Module

The full range of damage levels around the mean (the secondary uncertainty) is considered for each MDR with non-parametric distributions in the Financial Module. RiskInsight represents secondary uncertainty distributions as discrete bins, where each bin corresponds to the probability of experiencing a specific damage level and every distribution includes a non-zero probability mass at 0 and at 100 percent loss. Secondary uncertainty is always considered in the loss calculations.

There are 100,000 secondary uncertainty distributions for MDRs ranging from .00001 to 1. KCC scientists developed a complex iterative process to create these distributions so that the following mathematical constraints are met:

- The probabilities add up to 1
- The MDRs are maintained
- The probability mass at 0 falls as the MDR increases
- The probability mass at 1 rises as the MDR increases

The figure below illustrates the implementation of secondary uncertainty in the model.

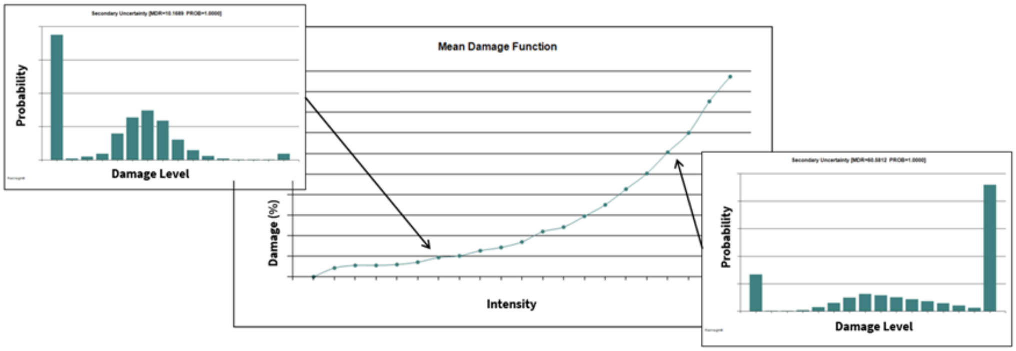

Figure 1 - Secondary uncertainty for different MDRs

The Financial Module calculates losses at the location level and for individual coverages separately. Location-level losses can be aggregated to different levels of resolution, such as five-digit ZIP codes or counties. These losses serve as the basis for loss cost and probable maximum loss estimates.

The KCC model provides all traditional risk metrics calculated from the robust Stochastic Event Catalog. Exceedance probability (EP) curves, average annual losses (AALs), tail value at risk (TVaR), probable maximum losses (PMLs), and other metrics are accessible and viewable with RiskInsight's built-in charting and mapping tools.

3. Provide a flowchart that illustrates interactions among the major wildfire catastrophe model components.

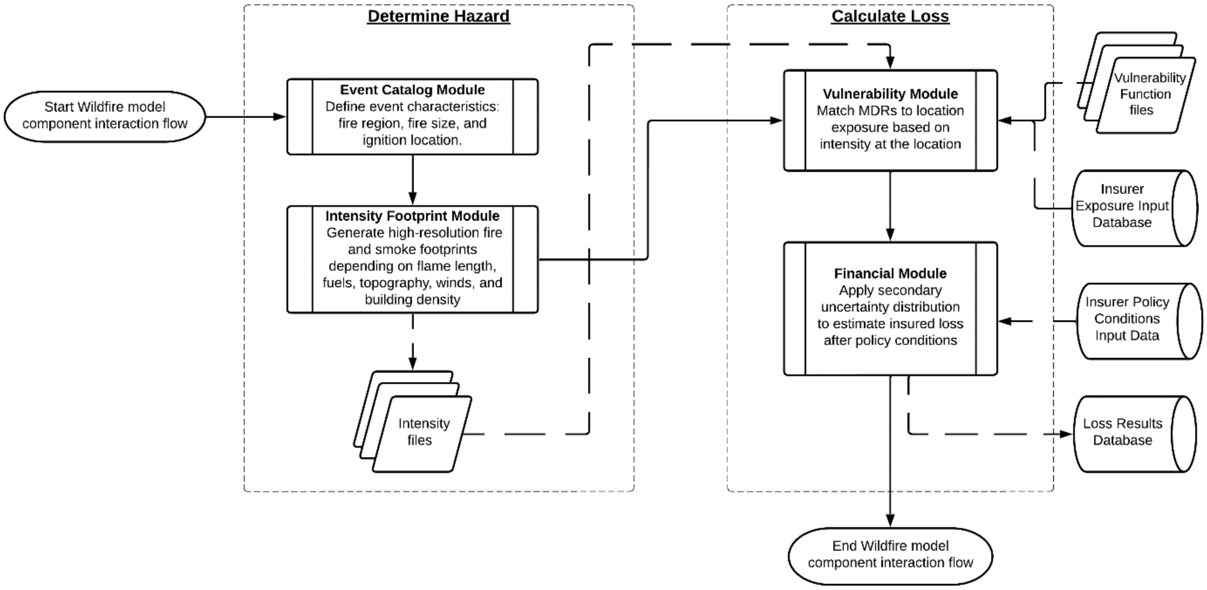

Figure 2 - Flowchart of major model components of the KCC US Wildfire Reference Model

6. Provide a comprehensive list of complete references pertinent to the wildfire catastrophe model by guideline grouping using professional citation standards.

Hazard

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G-2: Qualifications of Modeling Organization Personnel and Consultants Engaged in Development of the Wildfire Catastrophe Model

1. Modeling Organization Background

A. Describe the ownership structure of the modeling organization engaged in the development of the wildfire catastrophe model. Describe affiliations with other companies and entities and the nature of the relationship, if any. Indicate if the modeling organization has changed its name and explain the circumstances.

KCC is a privately held firm with no external affiliations and has not changed its name.

B. ***If the wildfire catastrophe model is developed by an entity other than the modeling organization, describe its organizational structure and indicate how proprietary rights and control over the wildfire catastrophe model and its components are exercised. If more than one entity is involved in the development of the model, describe all involved.***

KCC developed the KCC US Wildfire Reference Model without an external entity and holds all proprietary rights and control over the model.

D. ***Describe any services other than wildfire modeling provided by the modeling organization.***

KCC professionals are globally recognized experts in catastrophe risk assessment and management with extensive experience in all types of natural perils, including wildfires, severe convective storms, tropical cyclones, extratropical cyclones, floods, and earthquakes. KCC provides consulting services and licenses software to the insurance industry.

The KCC suite of models currently includes US wildfire, hurricane, storm surge, inland flood, severe convective storm (SCS), earthquake, and winter storm; Canada earthquake; Japan typhoon and earthquake; Australia earthquake and tropical cyclone; New Zealand earthquake; Mexico earthquake; South America earthquake; Central America earthquake; European windstorm; and Caribbean hurricane and earthquake. KCC clients can access these models on a service basis or by licensing the models as part of the RiskInsight® loss modeling platform. KCC models are licensed on an ongoing basis by top 10 US Property and Casualty (P&C) insurers, super regionals, Florida domestic insurers, and global insurers, reinsurers, and insurance linked securities (ILS) funds.

Along with developing and licensing advanced models, KCC consultants conduct comprehensive reviews of the models and modeling processes for the world’s largest (re)insurers and US primary insurers. Other consulting services include M&A due diligence, peer company analyses, and executive briefings.

E. ***Indicate if the modeling organization has ever been involved directly in litigation or challenged by a governmental authority where the credibility of one of its wildfire catastrophe model versions for projection of wildfire loss costs or wildfire probable maximum loss levels was disputed. Describe the nature of each case and its conclusion.***

KCC has not been involved in litigation or challenged by a government authority regarding loss cost or probable maximum loss projections for a US wildfire model.

2. *Professional Credentials*

A. ***Provide in a tabular format (a) the highest degree obtained (discipline and university), (b) employment or consultant status and tenure in years, and (c) relevant experience, publications, and responsibilities of individuals currently involved in the acceptability process or in any of the following aspects of the wildfire catastrophe model:***

- ***i. Hazard***
- ***ii. Statistics***
- ***iii. Vulnerability***
- ***iv. Actuarial Science***
- ***v. Computer/Information Science***

KCC professionals possess a wide range of skills and expertise in fields including atmospheric science, engineering, computer science, statistics, and data science honed through experience and education. All model developers hold PhDs in their fields. At each stage of model development, these experts evaluate and test the model for accuracy and reliability using accepted methodologies and rigorous standards appropriate to their respective disciplines.

Each section of this submission has been developed and validated by experts in their respective fields, as follows:

General

The KCC US Wildfire Reference Model and this submission have been thoroughly reviewed by catastrophe modeling experts and pioneers in the industry. The team has extensive experience in weather, climate, and catastrophe modeling, pricing, and risk management. KCC experts have conducted comprehensive reviews of catastrophe models and catastrophe modeling processes for regional, national, and global insurers. These reviews have entailed detailed model evaluations, peer review studies, and M&A due diligence.

KCC regularly engages with regulators, rating agencies, and legislators to advance awareness of catastrophe risk and to ensure that KCC's models meet all regulatory standards.

Hazard

The hazard portion of the KCC US Wildfire Reference Model has been developed by a team of PhD scientists with many years of experience in weather, climate, and catastrophe modeling. Wildfire modeling research performed by KCC scientists has resulted in many publications in high impact factor journals.

KCC scientists conducted doctoral and post-doctoral research on numerical weather and climate models, model development of numerical weather prediction systems and analytical frameworks on the dynamics of the atmosphere, as well as field-based research.

KCC scientists have published research on aerosol dispersal and the effects of wildfires and land use change on carbon cycle feedbacks and global climate forcing. The published research investigates the interactions among aerosols and the large-scale motion of the atmosphere, including the dust radiative impacts on tropical waves, the subsequent impact of tropical waves on large dust transport, and the ozone impacts on the vertically propagating waves in the stratosphere.

KCC experts participated in the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports (ARs) as contributing and lead authors and collaborated with scientists around the world on the Fire Modeling Intercomparison Project (FireMIP).

Statistics

KCC data science experts possess extensive research experience in Bayesian statistics, regression modeling, mixed effects modeling, time series modeling, multivariate models, and data analytics. Published research includes novel Bayesian statistical methods for various data settings with applications to financial costs of climate events, which was supported by the National Science Foundation.

KCC scientists have utilized various statistical analyses, including principal component analysis, empirical orthogonal functions, and regression analysis. These analyses provide detailed insight into the spatial and temporal behavior of several atmospheric phenomena, including dust-coupled tropical waves, the Madden-Julian Oscillation, and vertically propagating Rossby and Kelvin waves.

In recent projects, the team has developed several innovative approaches to address complex climate-related challenges, including specialized statistical techniques for modeling meteorological components such as maximum sustained wind speed, radius of maximum winds, and the frequency of catastrophic events, with an emphasis on incorporating the projected impacts of climate change; and deep learning algorithms designed to accurately detect mesoscale convective systems (MCS), such as squall lines, bow echoes, and derechos, to track changes in their intensity and structure over time.

Vulnerability

The KCC vulnerability team includes experts with many years of experience in engineering analysis and catastrophe modeling.

KCC engineers possess a range of experience, including structural engineering, structure analysis, aerodynamic simulations, probabilistic analysis, statistical analysis, reliability assessment, and wind tunnel experiments. Members of the team also have experience in laboratory testing of large-scale structures, structural analysis and design, and numerical modeling of structures. KCC engineers also possess experience in the construction industry in both designing and constructing commercial and multi-family residential buildings. Their fieldwork includes post-event surveys for major events, including the Palisades, Eaton, and Lahaina wildfires.

The vulnerability components of the KCC US Wildfire Reference Model were peer reviewed by an external consultant with over 10 years of experience in structural engineering roles, with extensive experience in structural fire analysis and design of fire-resistant structural assemblies. The consultant participated in the Camp Fire Reconnaissance as a member of the NSF team, and is member of the ASCE Technical Committee on Fire Protection of Structures and the Society of Fire Protection Engineers.

Actuarial

KCC risk analysts and data analysts have extensive experience in working with insurer exposure data and catastrophe loss analytics. They are experts on various loss modeling platforms and have used the KCC software platform, RiskInsight® to perform loss analyses for major insurers, to conduct detailed claims analyses, and to provide insurers with estimates of claims and losses as catastrophe events are unfolding in real time. KCC analysts are also responsible for designing automated processes to aid in model and exposure validation and for form creation and validation for this submission. The team is led by senior leaders with decades of experience in the insurance and catastrophe modeling industry.

Additionally, the financial and actuarial components of the model were peer-reviewed by an external expert with over 20 years of experience in the insurance and catastrophe modeling industries, with extensive experience in risk management, reinsurance, catastrophe modeling, and reserving and is an Associate of the Casualty Actuarial Society. This expert previously led the risk management and ceded reinsurance teams for catastrophe-exposed primary insurers. In these roles, she conducted model reviews, led the companies' exposure management processes, developed profitability models, and helped develop both reinsurance structures and reinsurance placements.

Computational Information

The KCC Software Development team is led by an expert in the field with over 40 years of experience in software design and development who architected and designed the RiskInsight® loss modeling platform. The team includes software developers, software engineers, DevOps engineers, and software product managers who work extensively on the RiskInsight platform on which the KCC US Wildfire Reference Model is run.

The Software Development team is responsible for all aspects of the RiskInsight platform, including the development of model building and management tools, KCC's advanced financial module and loss analysis engine, API suite, interactive dashboards, and spatial mapping framework. The KCC team has implemented a robust software development lifecycle process with detailed CI/CD pipelines, and support for on premise or cloud native deployments of the KCC models. Additionally, the software development team maintains detailed documentation for all phases of the SDLC including requirements specifications, data schemas, testing plans, and user guides.

Members of the Software Development team came to KCC with a range of experience and backgrounds, including deep experience in the .NET ecosystem, SQL databases, modern frontend UI, and performant computational engines. Software developers also have graduate research experience leveraging advanced statistical techniques to identify correlations in data and developed software to convert raw data into an appropriate input for computer simulations and have studied distributed systems, computer organization, parallel programming, and algorithm design and analysis.

3. Independent Peer Review

A. Provide reviewer names, qualifications, affiliation, and dates of external independent peer reviews that have been performed on the following components as currently functioning in the wildfire catastrophe model:

i. Hazard

ii. Statistics

iii. Vulnerability

The Vulnerability Module was reviewed by Dr. Kevin Mueller, PhD, PE, PSP in 2025

iv. Actuarial Science

The Actuarial Science component was peer reviewed by Melinda Vasecka, ACAS, in 2025

v. Computer/Information Science

B. Provide documentation of independent peer reviews directly relevant to the modeling organization responses to the current guidelines, disclosures, and forms for wildfire catastrophe models. Identify any unresolved or outstanding issues as a result of these reviews.

There are no unresolved or outstanding issues. The peer review letters written by Dr. Mueller and Ms. Vasecka have been provided separately.

C. Describe the nature of any on-going or functional relationship the modeling organization has with any of the persons performing the independent peer reviews.

KCC has no ongoing or functional relationship to Dr. Mueller or Ms. Vasecka other than as peer reviewers.

G-3: Location / Geospatial Information for Data Inputs

1. Provide a description of the geographic information system (GIS) software and tools used for geocoding.

RiskInsight® calls out to a standalone web service—developed internally by KCC and called the Geocoder—to perform geocoding. The Geocoder relies on two third-party services—Smarty and MapBox. Smarty provides both address standardization and geocoding services. MapBox provides geocoding services.

2. ***List the current geospatial databases used by the wildfire catastrophe model and the model components to which they relate. Provide the effective (official United States Postal Service) dates corresponding to the ZIP Code databases, if applicable.***

   KCC uses USPS ZIP Code data that is post-processed by a third-party vendor Claritas. KCC's current iteration of ZIP Code database is from January 2024.

   The KCC ZIP Code database used in the model is developed from the proprietary Claritas data set and supplemented with data obtained from the Census, as further explained in G-3 #6. KCC has a documented procedure for accessing recent updates to USPS ZIP Codes and verifying that all valid Postal Codes from the USPS exist in the KCC ZIP Code database. Each time the KCC ZIP Code database is updated, SMEs verify that dependent components remain consistent with any changes to the ZIP Code database.

   KCC uses four geospatial databases to create the Insured Exposure Location dataset: ZIP Code boundaries generated by Claritas, ZIP Code population-weighted centroids acquired from Claritas, the FEMA USA Structures database, and the TIGER/Line Shapefiles of the US Census Blocks. Each of these products are compiled using the recent release of the USPS ZIP Code data. The effective date of KCC's ZIP Code databases is January 2024.

3. ***Describe in detail how invalid geospatial locations (including ZIP Codes if applicable) are handled.***

   During the geocoding process, if an address—including its ZIP Code—is found to be invalid, the record is rejected and the user is notified. Users have the option to correct the data and then re-enter it into the exposure database, such as by directly setting the latitude and longitude or entering a valid ZIP Code. Validation is performed against user-provided latitude longitude pairs. Invalid pairs are rejected and the user is notified.

4. ***Describe the data, methods, and process used in the wildfire catastrophe model to convert among street addresses, geocode locations (latitude-longitude), and eco-regions or relevant wildfire spatial areas designated by the modeling organization, as well as conversion to ZIP Codes if applicable.***

   When a new address is imported into the exposure database, it is first checked to see if the geocode is already in the database. If not, the address goes through the USPS standardization process where it is sub-divided into its individual components, which are then standardized one at a time (e.g., "California" standardizes to "CA," as would an error like "Californ,"). If the address passes the standardization process, a geocode is requested from KCC's geocoder. The geocoder then converts the input address into a latitude-longitude pairing at the highest possible resolution (ideally street address, but, for example, if an exact match to the street number cannot be found, a centroid interpolated along the street segment containing that address may be returned). If the geocoder is not able to provide a geocode that is based on the full physical address, the address is assigned a population-weighted ZIP Code centroid geocode.

5. ***List and provide a brief description of each wildfire catastrophe model eco-regions and relevant wildfire spatial-based database, including any ZIP Code-based database, if applicable, and centroids.***

   The KCC US Wildfire Reference Model leverages the following databases:

   ZIP Code Boundaries

   KCC obtains ZIP Code boundary data from Claritas, which uses the USPS ZIP Code database to construct polygons for postal ZIP Codes based on carrier route boundaries. These boundaries are used for the creation of thematic maps for aggregation of factors like insured value and loss in RiskInsight. This feature affords users the ability to perform visual inspection at a variety of scales, including the ZIP Code-level.

   ZIP Code Centroids

KCC's centroids are based on data from Claritas' "ZIPCENT24" dataset. ZIP code centroids are validated against US Census Data and FEMA USA Structures database. The centroids are population-based (weighted), rather than geometric, and a documented automated verification process is employed to ensure points are within the polygon boundaries, are not over water, and represent the population centroid. A visual inspection is performed by KCC to confirm the centroids are satisfactory prior to inclusion in the model. The geocoded centroids are used to estimate losses when address-level geocoding is not available.

Fire Risk Reduction Community List (FRRCL)

The Fire Risk Reduction Community List (FRRCL) is a list of local agencies (e.g., city, county, fire district) that meet best practices for local fire planning developed and maintained by The California State Board of Forestry and Fire Protection. There are 11 cities, 7 counties, and 32 districts that met the FRRCL eligibility criteria on the 2024 FRRCL. Using the 2024 FRRCL, KCC engineers collected the latest shapefiles for each community at city, county, and district levels to determine the total coverage area. If the FRRCL information is not provided in the exposure data, the RiskInsight GeoEnhancer assigns a FRRCL designation to the locations based on their latitude and longitude and the boundaries of the FRRCL local agencies.

The KCC FRRCL database is used in the model to assign a FRRCL designation to the locations based on their latitude and longitude. The KCC FRRCL database is used in the model to assign a FRRCL designation to the locations based on their latitude and longitude. KCC engineers developed this database based on the California State Board of Forestry and Fire Protection (the Board) list of FRRCL communities—which is scheduled to be updated every two years—and the boundary files from FRRCL local agencies. The KCC FRRCL database is updated every two years as the new list of communities becomes available.

Fire Regions

Because the likelihood of wildfires varies by region across the US, KCC scientists defined Fire Regions that account for the factors influencing wildfire risk, including climate and ecosystem characteristics. The Fire Region shapes and boundaries are derived through analyses of historical wildfire activity, climatological factors, vegetation regimes, and ecosystem boundary data. The KCC process for defining Fire Regions is consistent with published methods for delineating the boundaries of fire regimes, also known as pyromes.

6. ***Describe the process for updating wildfire catastrophe model eco-region and relevant wildfire spatial- based databases, including ZIP Code-based databases if applicable.***

KCC reviews annual updates to ZIP Code data from a third-party vendor Claritas. This process includes comprehensive quality control measures. ZIP boundaries and centroids are subject to automated testing to verify that no points fall in a waterbody or outside a ZIP boundary. The procedure for reviewing and updating ZIP Code data is as follows:

1. Acquire updated ZIP code data from the provider on an annual basis.
2. Confirm the updated data schema is correct and supported by KCC.
3. Confirm that all valid Postal Codes from the most recent download from the USPS are included.
4. Confirm the data values are valid. Any corrupt geometries or centroids identified are recorded.
5. After the data are validated, comparisons to previous vintage data and to other known datasets, including the US Census Block population data, is performed in a GIS application to isolate differences.

6. Any provider centroids that fall over water or are significantly displaced from independently prepared population weighted centroids are identified and recommended changes to provider centroids are proposed.
7. Approved changes are deployed for use in the exposure databases.

KCC reviews the most recent FRRCL, which is updated by The California State Board of Forestry and Fire Protection every two years. Each update may include additions or removals of eligible communities. KCC then collects the latest shapefiles corresponding to these communities at city, county, and district levels to ensure accurate geospatial representation of the most recent FRRCL.

KCC reviews the recent scientific literature related to pyromes and ecological data in the US, as well as surface fuel and canopy fuel dataset updates, to inform any necessary refinements to the KCC Fire Regions database. Relevant data and research sources include Short (2020), Cattau et al. (2022), the LANDFIRE program surface fuel and canopy fuel datasets, the MTBS historical fire data, and the Environmental Protection Agency (EPA) eco-regions. All available data are reviewed and assessed by KCC scientists to make determinations about updates to the Fire Regions, which are then reviewed and approved by KCC subject matter experts.

G-4: Independence of Wildfire Catastrophe Model Components

1. ***Describe the process used to ensure that the primary components of the wildfire catastrophe model (hazard, vulnerability, and actuarial components) operate independently and do not compensate, calibrate, or adjust for any bias or deficiencies arising from any other component.***

As a part of the model development process, each component is independently validated to ensure that no components are biased. These validations are completed using external data with as many different perspectives as feasible to ensure the consistency and validity of validation results. If a component does not pass a validation test, the component is re-evaluated by KCC scientists, engineers, and/or other modeling experts to ensure the correctness and accuracy of the component.

Additionally, components are analyzed during the model development process to ensure that a logical relationship to risk is held throughout the entire model. These analyses include visual inspection of event footprints against location-level loss costs to verify that higher wildfire risk areas with larger flame lengths and less effective fire suppression exhibit higher losses and examining losses by building type or secondary modifier to ensure the appropriate building types consistently sustain losses appropriate to their expected vulnerability.

The KCC US Wildfire Reference Model is theoretically sound and has no compensation for potential bias within any component of the model.

Hazard Disclosures

H-1: Base Wildfire Set

1. ***Specify the historical wildfire dataset(s) release date and the time-period used to develop and implement fire occurrence frequency and behavior characteristics, such as fire intensity, fire severity, and fire perimeters, into the wildfire hazard model.***

    The KCC US Wildfire Reference Model Base Wildfire Set is comprised of historical fire perimeter and fire severity data from historical events sourced from the Monitoring Trends in Burn Severity (MTBS) database (Eidenshink et al., 2007; Picotte et al., 2020). The dataset covers events from 1984 to 2023 and was most recently updated on October 31, 2024.

    The MTBS fire perimeters and burn severity data are derived from the Normalized Burn Ratio (NBR) as calculated from LandSat at 30-m resolution. This dataset has been leveraged in numerous studies of California wildfires (e.g., Abatzoglou and Williams, 2016; Williams et al., 2019; Williams et al., 2022; Turco et al., 2023).

2. ***If the modeling organization has made any modifications to the historical wildfire dataset(s) or to the Base Wildfire Set related to fire occurrence frequency and behavior characteristics, provide justification for such modifications.***

    Annual wildfire frequencies in the KCC US Wildfire Reference Model are based on the Base Wildfire Set with an adjustment for trends in wildfire activity in California due to climate change. The fire frequency and area burned data in the Base Wildfire Set have been conditioned to ensure that the KCC modeled fire frequencies align with the present day climate and lead to an accurate view of current wildfire risk in a manner consistent with the current scientific consensus (e.g., Abatzoglou et al., 2021; Abatzoglou and Williams, 2016; Turco et al., 2022; Williams et al., 2019).

3. ***Include a flowchart illustrating how changes in the historical wildfire dataset(s) and Base Wildfire Set(s) database are used in the calculation of wildfire distribution, including with respect to both fire occurrence frequency and area burned.***

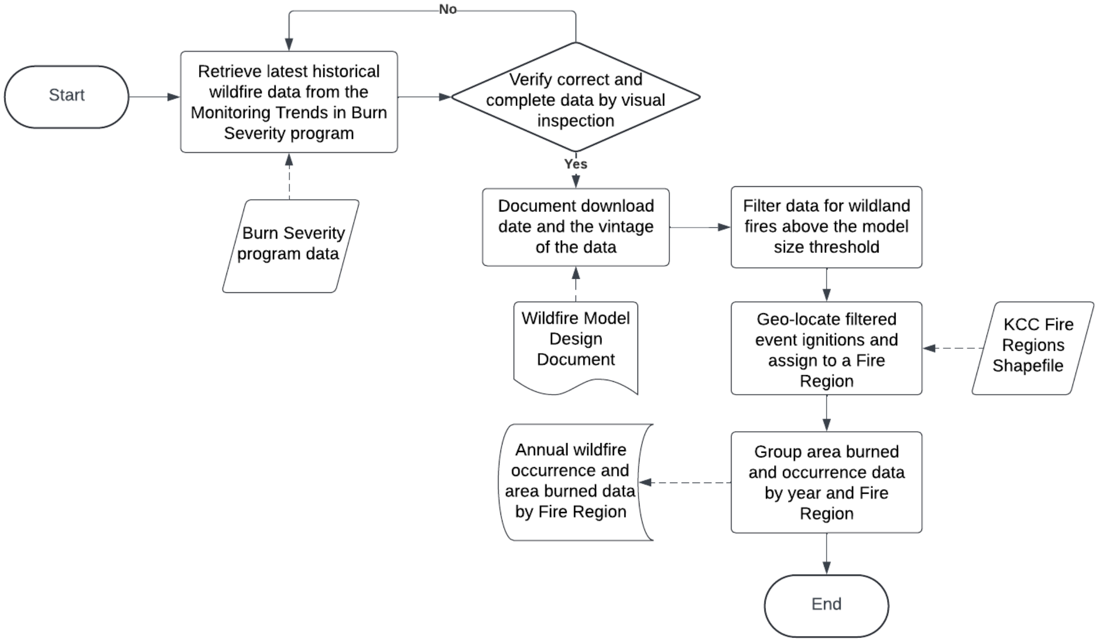


Figure 3 - Flowchart illustrating the process of updating the model fire occurrence and area burned data based on the historical wildfire datasets

4. ***If the wildfire hazard model and/or any associated sub-models incorporate systematic modification of the historical data leading to differences from the historical wildfire dataset(s), describe how this is incorporated and provide comparisons to the Base Wildfire Set and modeled wildfire events (stochastic event set), including fire occurrence frequency and area burned.***

The historical fire occurrence frequency and area burned data are trended to account for climate change for the purpose of determining model fire frequencies and sizes that are consistent with the current climate. The annual area burned within each KCC Fire Region is trended in accordance with environmental changes in that region, as measured by observed historical trends in the vapor pressure deficit (VPD). The magnitude of the adjustment depends on the VPD trend in each region, which is computed using high resolution observations, time since the fires occurred, and whether the region is forested or non-forested. The trended historical area burned data are utilized to calculate the model fire occurrence frequency and area burned for each region.

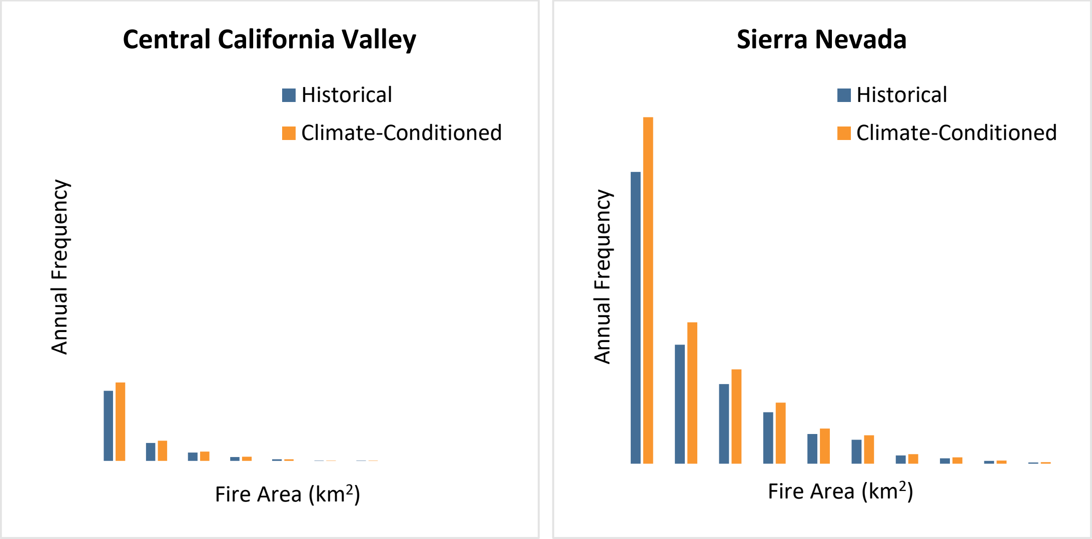


Figure 4 - Frequency-size distribution illustrating climate-conditioning of the historical catalog through 2024 for two example fire regions in California

5. ***If the modeling organization has accounted for climate change in either developing stochastic events set(s) based on the historical record or modifying other components in the wildfire hazard model development, (i) specify additional data, databases, and modifications used and (ii) justify their use and explain their impact in modeling California fire occurrence frequency and behavior characteristics in view of the peer-reviewed scientific literature and in relation to the model's assumptions and sensitivity to spatiotemporal resolutions.***

The KCC US Wildfire Reference Model accounts for the impacts of warming global temperatures on wildfire frequency and size following the current scientific consensus on climate change and wildfires (e.g., Seneviratne et al., 2021). As temperatures rise, key changes occur that increase the water holding capacity of air and decrease the available moisture in the environment—especially in wildfire-prone areas.

The VPD—measured in hectopascals (hPa)—is an atmospheric variable that describes the capacity of an air mass to hold moisture beyond what is available. A high VPD is correlated with warmer temperatures, lower precipitation, and—most important for wildfire—drier fuels. Recent studies have shown that the VPD more accurately predicts the total area burned per year for wildfires in the US than temperature or precipitation alone (e.g., Williams et al., 2019; Abatzoglou et al., 2021). Trends in VPD are calculated with gridded VPD data from the Parameter-elevation Regressions on Independent Slope Model (PRISM) repository, which is a high-resolution, observations-based dataset of atmospheric variables covering the US. PRISM temperature and humidity data are available monthly, allowing KCC scientists to isolate the fire season for trend analyses. Since trends in VPD vary geographically, analyses are conducted separately for each KCC Fire Region.

The Fire Region vegetation data are additionally utilized to determine the robust, non-linear relationship between VPD and area burned. The analyses show that forested regions respond more quickly to VPD changes than non-forested regions. As a result, the degree of climate conditioning is largest for the forested areas of California, including the Northern California Mountains and Sierras.

The KCC modeled fire frequencies are determined based on the climate-conditioned historical wildfire data. This process ensures that the KCC modeled fire frequencies align with the present-day climate and lead to an accurate view of current wildfire risk.

6. ***If the modeling organization has accounted for changes in fuels or other input variables to account for changes not related to climate change in the wildfire hazard model development, such as the impact of fuel treatments, (i) specify additional data, databases, and modifications used and (ii) justify their use and explain their impact in modeling California fire occurrence frequency and behavior characteristics in view of the peer- reviewed scientific literature and in relation to the model's assumptions and sensitivity to spatiotemporal resolutions.***

   The LANDFIRE surface fuel database is applied to simulate fire spread in the KCC US Wildfire Reference Model. Fuel changes can happen via disturbances, such as mechanical removal of fuels, insects, disease, or fire. The most recent LANDFIRE surface fuel dataset includes disturbances through the year 2023. For more recent fire disturbances, KCC scientists update the LANDFIRE surface fuel data by replacing the fuels within disturbed areas with the fuel types that are associated with the successional rules developed by LANDFIRE. The KCC fuel dataset includes all disturbances through January 2025, including the Palisades and Eaton fires.

   In addition to fuel disturbances, expansion of developed areas into the wildland changes fire behavior. While urban areas can be affected by fires through branding and building-to-building burning, the fire spread in urban environments behaves differently compared to wildlands.

   The latest urban land cover type data from LANDFIRE are incorporated into the KCC surface fuel data. In order to capture more recently built developments, KCC scientists and engineers supplement the LANDFIRE urban land cover data with the following analyses of building density.

   KCC scientists and engineers compile databases of building locations and building footprint areas from several sources, including the National Structure Inventory, USA Structures from FEMA, and the Microsoft Building Footprint data. Building location data are then converted to building density at a high-resolution. By comparing building density to the urban area classification in the surface fuels, followed by analyses of satellite data, KCC scientists identify new housing developments in areas that were previously considered wildland. The KCC surface fuel database is then updated to reflect the recent building developments.

H-2: Wildfire Hazard Model Inputs, Parameters, and Characteristics

1. ***Identify the wildfire inputs and parameters related to physical conditions referenced in the corresponding guideline that are used in the wildfire hazard model to simulate the range of possible ignitions and fire spread, and provide justification, including with respect to: the dataset basis for fitted distribution; the methods used, including to represent spatial parameters and temporal parameters if applicable; any smoothing techniques employed; and citations to relevant peer- reviewed scientific literature as applicable.***

   The wildfire input parameters for the fire spread simulator determine the ignition location and the area to which the fire spreads.

   To ensure that there are no gaps in the spatial coverage and no under or over-representation of the hazard at any location, ignition sites are appropriately spaced across the US. While potential ignition sites are placed on a high-resolution grid for consistent spatial coverage, the rate of occurrence varies by ignition point.

   The spacing of ignition sites is determined by the radius of an idealized fire. For each area burned value, the radius is determined by simulating fire development without topography or wind influencing fire spread. The idealized radius of each fire size is then analyzed to determine the grid on which ignition sites are placed. The spacing ensures that the modeled impacts for every location in a region are commensurate with local factors, such as topography, winds, and available fuels.

Every ignition site and fire size combination within the KCC US Wildfire Reference Model has an associated rate corresponding to the likelihood of occurrence. Rates vary spatially within Fire Regions based on consideration of historical fire occurrences and VPD. The ignition rates are also influenced by power infrastructure—i.e., fires are more likely to start near transmission lines in the wildland.

Ignition rates are zero in some areas, such as irrigated agricultural areas, urban areas, and barren land.

Simulated wildfire spread proceeds from each ignition location. Wildfire spread is a complex process driven by small-scale variations in vegetation type and density, topography, firebreaks (whether naturally occurring or manmade), moisture, and wind speed. Capturing these variations requires high-resolution datasets and a model that is capable of simulating fires at a high resolution over a large area. KCC scientists developed a dynamic, time-stepping model that explicitly simulates the propagation of wildland fire at 30-meter resolution. Along with fire spread through the vegetated and WUI regions, the model captures fire potential in urban areas through the processes of branding and building-to-building burning.

The fire intensity footprints incorporate a number of factors that influence the spread of wildfires, including:

- Fuel type and characteristics
- Moisture
- Topography
- Winds

Based on these factors, the model generates the intensity footprints by simulating the following methods in which fires spread or are prevented from spreading:

- Wildland fire spread
- Spotting and branding
- Building-to-building burning
- Fire suppression

The intensities within the footprint depend on the intensity of the fire (flame length), winds, and building density to different degrees depending on the mode of fire spread. The three modes of fire spread are direct flame, radiant heat, and ember transport.

All methods for simulating wildfire spread with these inputs and characteristics are based on information documented in the scientific and technical literature.

2. ***Describe the method, reason, and supporting material for selecting wildfire parameters, including with respect to urban conflagration (such as building materials) to represent combustion, fire spread, and abatement in urban areas.***

Building-to-building burning occurs in the model footprints outside of the wildland where embers are being transported into developed areas. All modes of building-to-building fire spread depend on structure spacing. KCC scientists determine the spacing of structures with the high-resolution building density dataset. When the structure spacing is low, less than 10 m, the fire can spread by any of the three modes (ember transport, direct flame contact, and radiant heat) and building-to-building burning is more likely to occur. As the spacing increases, fire spread between buildings is less likely but can still occur by ember transport.

In addition to the structure spacing, determined from the building density, the likelihood of building-to-building burning and the intensity of the fire depends on the wind speed and the density of embers being transported into the built environment.

High ember density occurs close to the fire front and increases the likelihood of building-to-building burning. Under high wind conditions, fire spread between buildings can occur more quickly by ember transport. To capture all of these effects, the footprint intensities at locations experiencing building-to-building burning depend on the branding intensity as a measure of the ember density, the wind speed, and the building density.

The method of modeling of fire spread within the building-to-building burning zone is supported by recent scientific work (e.g., Purnomo et al., 2024) and by KCC scientists analyses of recent urban conflagration fires including Tubbs (2017), Marshall (2021), and Lahaina (2023).

Under certain conditions, fire intensities can be reduced through fire suppression activities. During a wildfire, population proxies such as building clustering are often implicit in the strategies that fire agencies implement to prioritize resource allocation (Stasiewics and Paveglio, 2022). KCC scientists calculate the resources available for suppression for each location, which depends on the behavior of the fire in the adjacent wildland (i.e., the winds and flame lengths), and the local distribution of the structures. The behavior of the fire is directly output from the physical fire spread. To determine distributions of structures, KCC scientists calculate an average building count on a high resolution grid. The number of buildings per square kilometer then informs the amount of effort required to protect the properties. Low building clustering decreases the likelihood that the fire will be contained due to the difficulty of maintaining fire containment lines to protect isolated or widely-spaced buildings.

3. ***Identify whether wildfire parameters are modeled as random variables, functions, or fixed values for the stochastic events set. Provide rationale for the choice of parameter representations.***

The intensity footprints are simulated with a physics-based model that requires physical variables as inputs to determine the fire spread behavior. Certain variables like fuel type and topography are fixed in time but vary spatially, whereas other variables including winds vary in space and time; outputs like flame length are determined with functions.

The event catalog utilizes functions of the historical data to partly determine the rates of a potential ignition at a location. Functions are also fit to the historical data to inform the annual and seasonal fire activity in the Stochastic Event Catalog. The selection of events for the year loss table is random but depends on the event rates and ensures there is no overlap in fire occurrences each year.

4. ***Describe if and how any wildfire parameters are treated differently in the Base Wildfire Set and stochastic events set(s) and provide rationale.***

The same fire spread model is applied for events in both the Base Wildfire Set and Stochastic Event Catalog. In the Base Wildfire Set, fire perimeters are pre-determined. In the Stochastic Event Catalog, the ignition and final burned area are input for each event and the model fire spread proceeds following those criteria.

5. ***Describe the spatiotemporal treatment of fire intensity, flame length, crown fires, ember deposition and any other relevant fire behavior parameters (which alternatively can be disclosed in conjunction with the treatment of fuel loads and weather in H-4 and H-5 below).***

Intensity footprints from the model depend on flame-lengths from surface and crown fires, branding by ember transport, urban conflagration, and suppression. At each pixel in the wildland, the flame lengths are calculated and mapped to specific intensities. The relationship between the modeled intensity and flame lengths follows the Roose (2008) FIL6 scale. Intensities may then be adjusted depending on other processes, such as suppression and non-wildland spread, which depend on flame length and other physical and environmental information relevant to the location.

6. ***Describe whether and how fuel moisture content is calculated from the weather inputs. Provide specific equations or methods and how these data are used in the fire model (e.g., does the model account for dynamic fuel moisture driven by changing weather conditions?).***

   Fuel moisture is calculated from a climatological perspective for the model using soil moisture as a proxy variable as in previous studies (e.g., Rabin et al., 2018; Kloster et al., 2010; Li et al., 2013). This parameter varies spatially across California. The determination of the climatological values for the moisture content follows Huug van den Dool et al. (2003).

7. ***Describe the representation and treatment of ignition sources (natural and human), including utility sources, consistent with current state-of-the-science and empirically determined probabilistic spatial distributions. Describe, if incorporated, modifications to ignition risk because of mitigation and resiliency efforts, such as due to utility and other infrastructure mitigation efforts. Describe any adjustments to ignition risk depending on weather (e.g., as it affects power infrastructure ignition risk).***

   Wildfire ignitions can be either natural (i.e., lightning strikes) or human-caused. While natural ignitions are randomly distributed spatially, human-caused ignitions are more common near populated areas and infrastructure like roads and utilities. In the KCC model, to ensure that there are no gaps in the spatial coverage and no under or over-representation of the hazard at any location, ignition sites are appropriately spaced across the US.

   The probability of ignition is determined by the frequency distribution for a given fire region, which is climate conditioned. Spatial variations in ignition frequencies within a region are determined by factors that include the climatological VPD. The localized VPD is known to influence multiple stages of fire growth, including ignition probability (Sedano and Randerson 2014; Alizadeh et al. 2024). Spatial variations in rates depend on the relative VPD within the region, which is represented by the average summertime VPD. In addition to VPD, rates in California increase if ignition locations are in proximity of a power line/ignition framework.

   Fire footprint simulation in the KCC US Wildfire Reference Model begins at an ignition point and spreads outward based on a physical fire behavior model. The KCC model fire spread methodology in wildland areas follows the Rothermel Fire Behavior Model and applies the characteristics of fuels defined by the fuel classification. Parameters defined by the fuel classifications are utilized to calculate the heat required for ignition, the likely propagation given the slope and wind conditions, and the reaction intensity (or heat release) of the fire.

   Heat required for fire spread is introduced to fuels through radiative and convective energy. Radiative energy refers to the heat that is released from the fire itself and transferred to nearby fuels. Convective heat refers to heat transferred by the warming air around a fire. Both exist ahead of a fire front and contribute to drying fuels and reducing moisture content in the environment. Because all moisture must be evaporated from fuels prior to their ignition, pre-dehydration of fuels and the environment can considerably increase fire spread.

   The energy required to ignite different fuels is determined through a mathematical expression that includes the moisture of the fuel and the known temperature of ignition.

   The total energy released from a fire is the result of combustion, a chemical reaction in which organic matter and oxygen burn to produce heat and gaseous byproducts. The amount of energy released by this process is captured by the reaction intensity, which determines the total amount of energy released from the fire front. When combined with the propagating flux ratio—which accounts for the fraction of the total reaction intensity that is transferred to adjacent fuel particles—the total amount of energy transferred can be determined.

The total energy released depends on a number of fuel characteristics, including fineness, fuel load, and moisture, which are described by the fuel model.

The rate of fire spread is modeled by accounting for all these factors. At every time step, the amount of heat being released by each gridded point is calculated, and neighboring cells are ignited depending on the amount of energy required for an ignition.

From the rate of spread, the flame length is calculated for every location ignited. The flame length is a measurable indicator of fire intensity and is defined as the distance between the flame tip and the midpoint of the flame depth at the flame base. The flame length also depends on the reaction intensity and the residence time, which is a function of the vegetation type. Therefore, the flame length will increase with higher wind speeds, as the rate of spread goes up, and will be highest for the most intensely burning surface fuels.

8. ***Describe and justify the incorporation of the effects of fuel treatments, prescribed burning, and other wildfire-related landscape and fuels management, whether in the model or underlying fuels layers.***

   Fuels are treated by incorporating the latest disturbance data available. Based on the disturbance type and severity of the disturbance, fuels are treated by updating the fuel type on a pixel basis in a manner consistent with succession rules for recent disturbances. This includes disturbances that have yet to be incorporated into the LANDFIRE 2023 Fuel dataset (i.e., LANDFIRE 2024 Preliminary Disturbance (PDist), which incorporates all disturbances from November 2023, through October, 2024, and more recent wildfire disturbance data from the MTBS including the Palisades and Eaton fires).

9. ***Describe the historical wildfire dataset(s) used as the basis for the Base Wildfire Set, including resolution. Discuss the appropriateness of the wildfire stochastic events set with reference to the historical wildfire dataset(s).***

   The KCC US Wildfire Reference Model Base Wildfire Set is comprised of historical fire perimeter and fire severity data from historical events sourced from the MTBS database (Eidenshink et al., 2007; Picotte et al., 2020), which covers events from 1984 to 2023. The MTBS fire perimeters and burn severity data are derived from the NBR as calculated from LandSat at 30-m resolution. This dataset has been leveraged in numerous studies of California wildfires (e.g., Abatzoglou and Williams, 2016; Williams et al., 2019; Williams et al., 2022; Turco et al., 2023).

   The frequency and size of the events in the stochastic catalog are determined from the statistics of the historical events from the MTBS dataset within each KCC Fire Region. Adjustments to the fire frequencies are applied to account for the impacts of climate change and spatial variability in ignition sources and humidity, but the stochastic events have their basis in the historical record. Comparisons of historical fire frequency and size from the MTBS dataset to that of the stochastic catalog show good agreement with consideration of the noise in the historical data that results from the relatively shorter period of record.

10. ***If the Base Wildfire Set is partitioned or modified, describe how the wildfire parameters are affected.***

    The Base Wildfire Set is not partitioned. The annual area burned by the fires in the Base Wildfire Set is modified for the purpose of determining the climate change-adjusted fire frequencies in the Stochastic Event Catalog. After applying the climate change modification, the trended historical area burned data are utilized to calculate the model fire occurrence frequency and area burned for each region. For California regions, the climate change adjustment increases the frequency of fires in the model.

11. ***Describe any evolution over time of the functional representation of wildfire parameters during an individual wildfire life cycle, such as fire-weather interactions and fuel moisture modifications.***

    Fire spread model inputs, including surface fuels, fuel moisture, topography, and building density, are spatially variable but considered fixed in time for an individual event. For events that are driven by high winds, a shift from the high wind pattern to the moderate wind pattern can occur during fire spread when the fire has already burned for a sufficient time under the high winds. This shift mainly applies to the larger size fires in the catalog that may burn for weeks, as is common historically.

H-3: Wildfire Probability Distributions

1. ***Provide a complete list of the assumptions used in creating the wildfire stochastic events sets or other datasets based on the Base Wildfire Set.***

    The Stochastic Event Catalog is comprised of over 1,000,000 potential future events in California designed to ensure complete and consistent spatial coverage of the wildfire hazard across the state. The catalog includes wildfires of varying severity that are assigned a rate based on the fire characteristics and environmental factors at each location.

    Because the likelihood of wildfires varies by region across the US, KCC scientists defined Fire Regions that account for many factors influencing wildfire risk, including geology, soils, vegetation, climate, land use, wildlife, and hydrology. These Fire Regions incorporate data from Environmental Protection Agency (EPA) ecoregions along with historical fire databases and the surface fuel dataset.

    For each KCC Fire Region, wildfire frequencies are determined, which are based, in part, on the historical data from the MTBS dataset. Wildfire activity has a robust relationship between fire severity—measured by size—and fire frequency. Less severe, or smaller, wildfires occur more frequently than severe, large wildfires, following a power law relationship that has been observed across the globe and recreated in modeling simulations (e.g., Hantson et al., 2015; Haas et al., 2022). The power law coefficients for each Fire Region are fit using the historical data from the MTBS dataset.

    To accurately capture wildfire severity across the US, ten fire sizes are included in the Stochastic Event Catalog, ranging from 10,000 acres (40 km^2) to 2,000,000 acres (8,300 km^2). To ensure that there are no gaps in the spatial coverage and no under- or over-representation of the hazard at any location, ignition sites are appropriately spaced across the US. The spacing of ignition sites is determined by the radius of an idealized fire. For each area burned value, the radius is determined by simulating fire development without topography or wind influencing fire spread. The idealized radius of each fire size is then analyzed to determine the grid on which ignition sites are placed.

    The spacing ensures that the modeled impacts for every location in a region are commensurate with local factors, such as topography, winds, and available fuels. While potential ignition sites are placed on a high resolution grid for consistent spatial coverage, the rate of occurrence varies by ignition point.

    Adjustments to the fire rates at each ignition location are applied to account for the impacts of climate change and spatial variability in ignition sources and humidity. In addition, ignition rates are zero in some areas, such as irrigated agricultural areas and urban areas, where dry surface fuels are not sufficient to support the ignition of a conflagration.

3. ***Provide a map and the criteria used by the modeling organization to delineate appropriate wildfire eco-regions/wildfire-specific spatial areas for the State of California.***

    Because the likelihood of wildfires varies by region across the US, KCC scientists defined Fire Regions that account for the factors influencing wildfire risk, including climate and ecosystem characteristics. The Fire Region shapes and boundaries are derived through analyses of historical wildfire activity, climatological factors, vegetation regimes, and ecosystem boundary data. The KCC process for defining Fire Regions is similar to published methods for delineating the boundaries of fire regimes, also known as pyromes (e.g., Short, 2020; Cattau et al., 2022).

There are ten Fire Regions for California, but five of the regions comprise most of the area within the state: the California Foothills, California Mountains, Sierras, Central Valley, and Southern California.

Fire activity does not often change smoothly from one region to another. For example, the Sierra Nevada region in eastern California is characterized by high elevation forests with widespread timber litter fuels. Wildfires are frequent in this Fire Region and can reach large sizes during the dry summers that are typical of the area's seasonal climatology. While climate conditions are similar for the neighboring region of the Central Valley, the region sits at sea level and is comprised of agriculture, grasses, and small shrubs. Therefore, the Central Valley has much lower fire activity given the significant vegetation differences compared to the Sierras.

Figure 5 - Map of the KCC Fire Regions in California

4. ***Provide a brief rationale for the probability distributions used for all wildfire input parameters and characteristics, including to develop frequency distributions as a function of location and temporal variability and, if specifically modeled, inclusive of wildfires that spread across state lines including through urban conflagration. Demonstrate the quality of fit.***

Fire Occurrence Frequencies

Fire occurrence frequency for fires of different sizes is modeled with a power law function with coefficients fit by Fire Region to the historical event data from the MTBS dataset. A power law function has been used in many studies to represent the relationship between fire frequency and fire area burned in nature and in models (i.e., Malamud et al., 2005; Hantson et al., 2015; Cattau et al., 2022). The following plots compare historical fire occurrence frequencies to the modeled frequencies across two Fire

Regions: Sierra Nevada and Central California Valley. The agreement between the modeled and historical data is justified both graphically and through the Pearson's chi-squared test described in Disclosure S-1 #7.

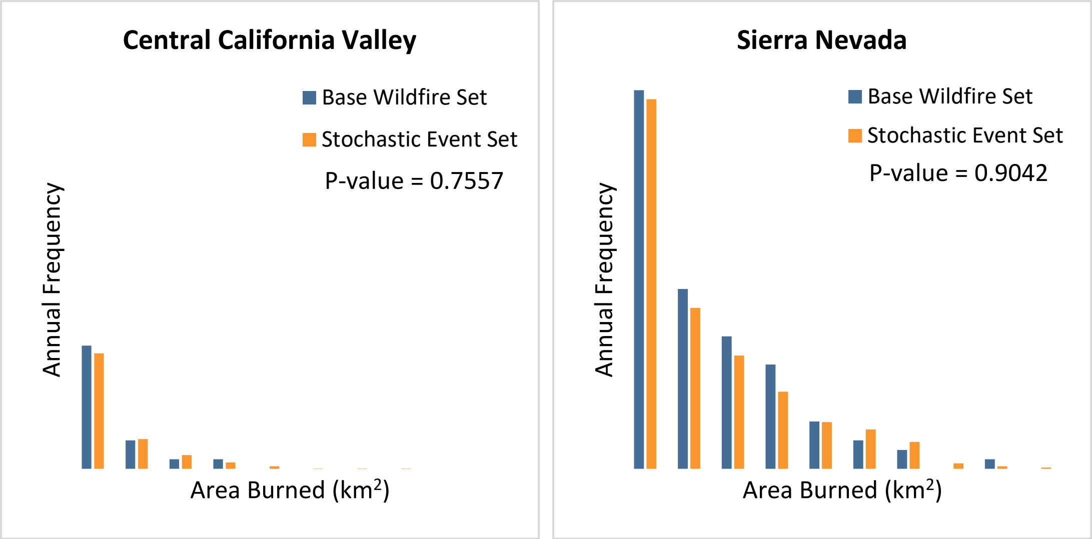


Figure 6 - Comparison of fire occurrence frequencies between the Base Wildfire Set and the Stochastic Event Set across the Central California Valley and Sierra Nevada

Fire Events per Year

The number of events per year is sampled using a smoothed kernel density empirical distribution, which is fit to historical wildfire data. The distribution is chosen due to its flexibility in modeling California's wildfire frequency pattern with the incorporation of climate change. The choice of the distribution is further validated through a goodness-of-fit test, described in Disclosure S-1 #7.

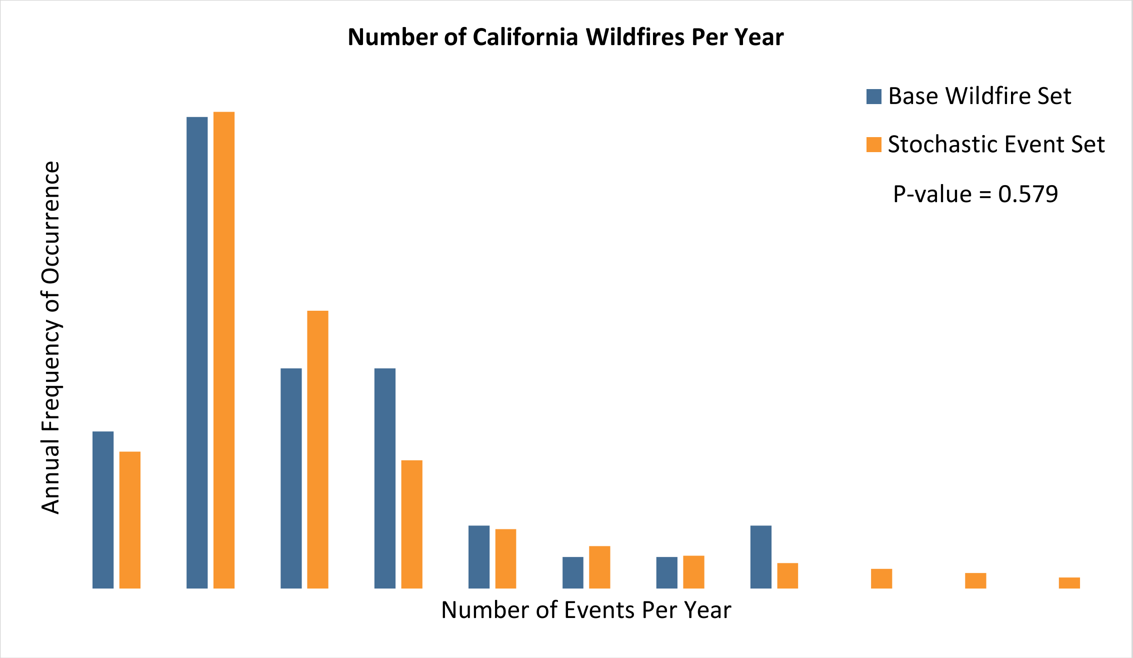


Figure 7 - Comparison of California fire events per year between the Base Wildfire Set and the Stochastic Event Set

6. ***Provide one or more graphics that compares the distribution of modeled wildfire occurrence frequency and burned area with the Base Wildfire Set, including with respect to seasonality.***

In the following plots, the frequency of wildfires of different sizes from the Base Wildfire Set is compared to the frequencies in the stochastic event set, and the seasonal cycle of wildfires for California is shown for the historical data and the stochastic event set.

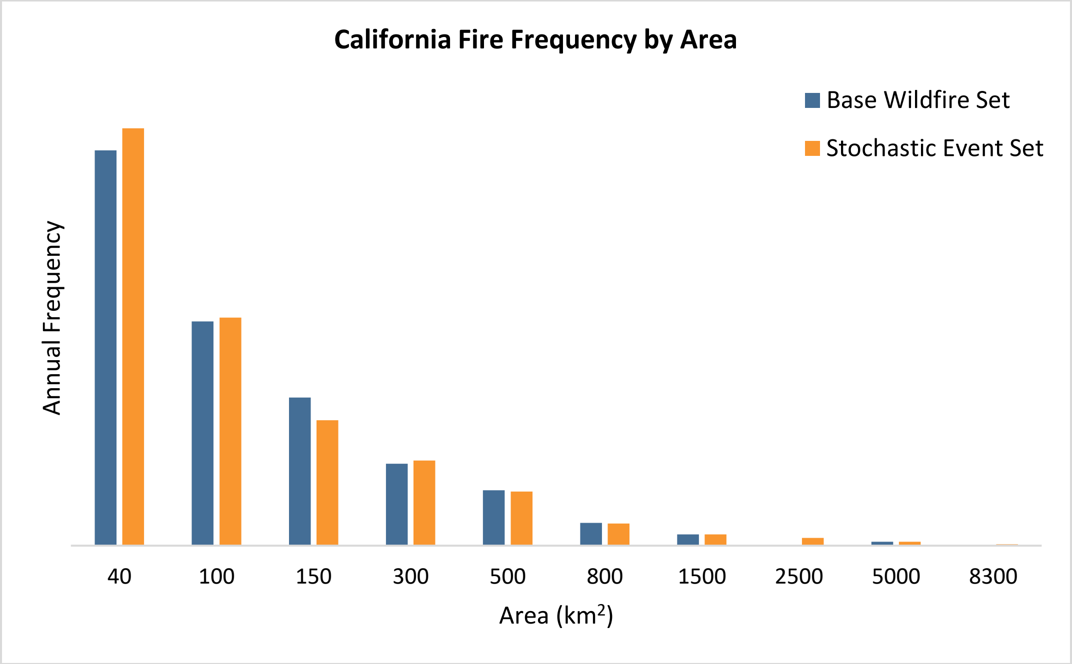


Figure 8 - Frequency of fires of different sizes in the Base Wildfire Set and the Stochastic Event Set for California

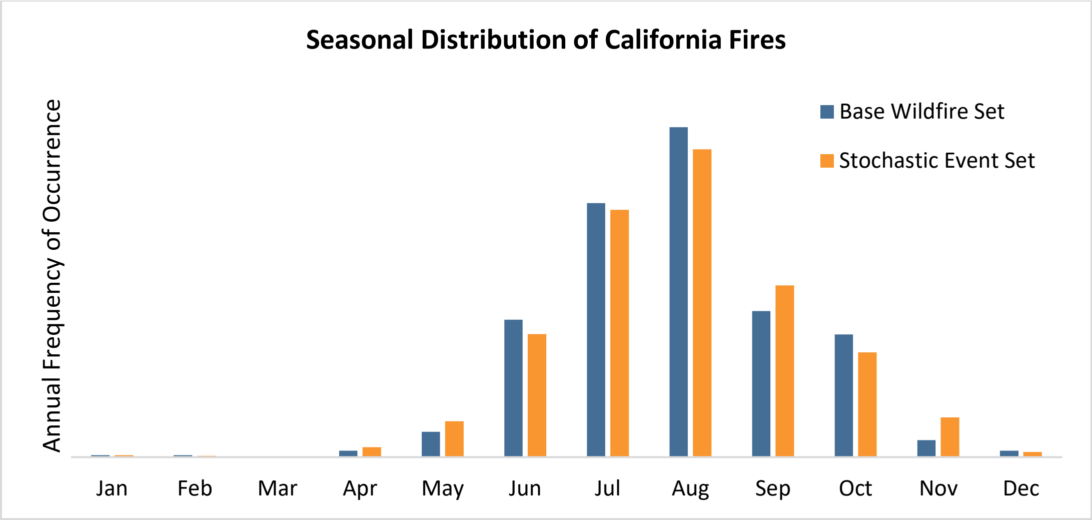


Figure 9 - Seasonal distribution of California wildfires from the Base Wildfire Set and the Stochastic Event Set

H-4: Wildfire Fuel Model

1. ***Describe the source and specific spatial fuel map(s) used for the full range of simulated fire-weather conditions. If they change dynamically, describe the methods for this change and show examples. If spatial fuel maps were modified, detail and justify every modification and provide a copy of the modified spatial fuel map(s).***

KCC scientists construct the surface fuel database by analyzing the 30-meter resolution surface fuel classification from the LANDFIRE program—a collaboration between the US Forest Service and the Department of the Interior. The version of the spatial fuel data is the LANDFIRE 2023 Update (LF 2023) with the following products utilized in the KCC fire spread model: Scott and Burgan Fire Behavior Fuel Model, the Forest Canopy Bulk Density, the Forest Canopy Base Height, and the Forest Canopy Cover. These spatial fuel maps are considered static in the KCC fire spread model to ensure representation of current fuels.

Fuel changes can happen via disturbances, such as mechanical removal of fuels, insects, disease, or fire. The most recent LANDFIRE surface fuel dataset includes disturbances through the year 2023. For more recent fire disturbances, KCC scientists update the LANDFIRE surface fuel data by replacing the fuels within disturbed areas with the fuel types that are associated with the successional rules developed by LANDFIRE. The KCC fuel dataset includes all disturbances through January 2025, including the Palisades and Eaton fires.

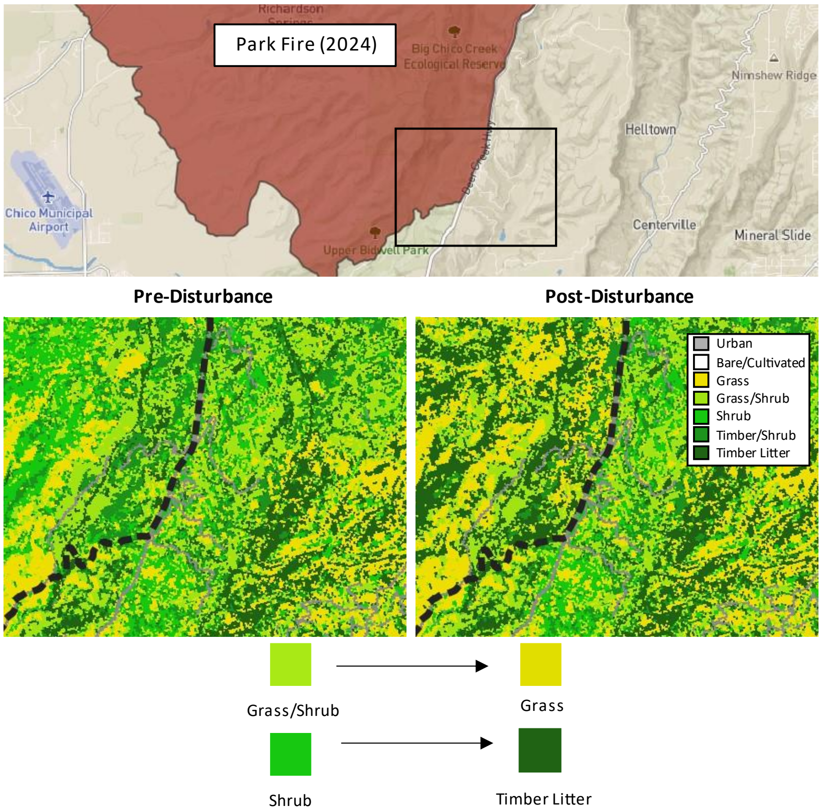


Figure 10 - Example of fuel changes within the perimeter of the Park Fire (west of the dashed line). The disturbed area changed from grass/shrub and shrub (light greens and greens) to grass and timber litter (yellows and dark greens).

In addition to fuel disturbances, expansion of developed areas into the wildland changes fire behavior. While urban areas can be affected by fires through branding and building-to-building burning, the fire spread in urban environments behaves differently compared to wildlands.

The latest urban land cover type data from LANDFIRE are incorporated into the KCC surface fuel data, which KCC scientists and engineers then supplement with an analysis of building density intended to capture more recently built developments.

KCC scientists and engineers compile databases of building locations and building footprint areas from several sources, including the National Structure Inventory, USA Structures from FEMA, and the Microsoft Building Footprint data. Building location data are then converted to building density at a high-resolution. By comparing building density to the urban area classification in the surface fuels, followed by analyses of satellite data, KCC scientists identify new housing developments in areas that were previously considered wildland. These building developments are then added to the KCC surface fuels.

2. ***Describe dataset(s), methodology, resolution and update frequency used to account for variation of fuel loading in the wildfire hazard model where applicable, including with respect to fuel treatments and any other forest management actions, as well as past fire occurrence frequency. Document and justify any difference in the methodology for treating historical and stochastic events sets.***

   Variations in fuel loading are accounted for by incorporating updates to the spatial fuel maps from LANDFIRE into the KCC fire spread model. Fuels are treated by incorporating the latest disturbance data available. Based on the disturbance type and severity of the disturbance, fuels are treated by changing the fuel type of each pixel that is based on the changes to fuel types by applying succession rules for recent disturbances. This includes disturbances that have yet to be incorporated into the LANDFIRE 2023 Fuel dataset (i.e., LANDFIRE 2024 Preliminary Disturbance (PDist), which incorporates all disturbances from November 2023, through October, 2024, and more recent wildfire disturbance data from the MTBS including the Palisades and Eaton fires). Historical and stochastic events are treated the same in this respect.

3. ***If wildland-urban interface (WUI) fuels, urban fuels, or both are accounted for in the model, describe how they are parameterized and included.***

   Vegetated locations in the WUI and within otherwise urban areas are explicitly represented as surface fuels in the LANDFIRE database at 30-m resolution. For non-vegetated urban locations, building-to-building burning is captured through the application of building spacing data instead of urban fuels.

4. ***Identify all non-meteorological variables (including topography, slope, and fuels) that affect fire intensity estimation or wildfire rate of spread.***

   The following non-meteorological variables affect fire intensity and spread in the KCC fire spread model:

   - Topographical slope
   - Topographical aspect
   - Surface fuel characteristics
   - Canopy fuel characteristics
   - Fuel breaks
   - Firefighter access

   The rate of fire spread depends on the slope of the terrain in the direction the fire is spreading, requiring data on both the steepness of the elevation change and the aspect of the slope at the location of the fire front. In the absence of winds, fires spread fastest uphill because fires generate heat that increases the buoyancy of air, causing flames to rise. Consequently, flames emit more thermal energy on the uphill side of a mountain. The impact of topography depends on the relative change in elevation across some distance, i.e., the slope. KCC scientists utilize the terrain slope and aspect information from the LANDFIRE program and validate these datasets against the slope and aspect data calculated from the USGS 3DEP Elevation Program digital elevation model (DEM).

In order to determine the flammability of different fuels and to simulate fire spread, KCC scientists classify surface fuels according to the Scott and Burgan fire behavior fuel model (Scott, 2015). This fuel model includes 40 fuel classifications distinguishing fuels by their load and associated climate conditions. The surface fuel type determines how easily the fuel will ignite, how fast the fire will spread, and the intensity of the fire.

Canopy fuels include live branches and leaves as well as debris caught in tree branches. Fires that spread to the canopy can generate high flame lengths because of the dense canopy fuel and the fast spread rates that are characteristic of such fires. To classify canopy fuels, KCC scientists determine the canopy cover, the canopy bulk density, and the base height of a canopy.

Firebreaks are gaps in fuel continuity that can slow or stop fire spread in the crossing direction. The gaps can be naturally occurring (i.e., rivers) or human-caused (i.e., roads, mechanical clearing of vegetation). Firebreaks are incorporated into the KCC fire spread model through the high-resolution and up-to-date surface fuel dataset as described in Disclosure H-4 #1.

Firefighter access and resources to suppress fire spread depend on road networks, the character of the vegetation, and the local distribution of the structures. Fire suppression efforts are more effective in areas where road networks make an active fire more accessible to firefighters and equipment. The effectiveness of suppression is also impacted by vegetation type. For example, forested areas that are composed of timber litter, dense shrubs, or blowdown trees have higher fuel loads than non-forested areas, which are composed of fine grasses and sparsely populated shrubs, and as a result often burn with higher intensity and with larger flame lengths. Fire suppression is more challenging under these conditions.

In contrast, regions dominated by grasses and shrubs support fires with smaller flame lengths that are easier to suppress. These effects are captured in the model by reducing the effectiveness of firefighting and fire suppression in direct relation to the fire flame length.

Populated areas with a high number of clustered buildings tend to benefit most from suppression efforts due to the priorities of local and federal fire management agencies. The level of fire suppression applied to the intensity footprint is also impacted by the density and clustering of buildings.

KCC scientists determine the average building density at each pixel (30 m^2) contained in the intensity footprint. The number of buildings per square kilometer then informs the amount of effort required to protect the properties. Low building clustering decreases the likelihood that the fire will be contained due to the difficulty of maintaining fire containment lines to protect a larger number of buildings.

5. ***Provide the collection and publication dates of the land use and land cover data used in the wildfire hazard model and justify their timeliness for California.***

The LF 2023 spatial fuel datasets utilized by the KCC fire spread model were published in October 2023. This version of the LANDFIRE datasets is the most recent available and represents the surface fuels as they are today in California with only minor differences due to very recent vegetation disturbance. Areas affected by these very recent disturbances are accounted for with updates to the dataset as described in Disclosure H-4 #1.

6. ***Describe the methodology used to convert land use and land cover information into a spatial distribution of fuel loading in California if used to generate the fuel layers.***

   Surface fuel data from the LANDFIRE program are applied directly to calculate the model fire spread, eliminating the need for conversion from land use and land cover information.

7. ***Describe any variations in the treatment of weather and ignition in relation to fuel and fuel moisture in the wildfire hazard model for stochastic versus historical events and justify this variation.***

   Simulations of historical wildfire events begin at the recorded ignition point, whereas the ignition locations for stochastic events are determined based on the evenly spaced ignition grids. Surface fuel datasets are treated the same for historical and stochastic events, both use the LF 2023 updated datasets. Additional aspects of the fire spread, including fuel moisture, are treated the same way for historical and stochastic events.

H-5: Weather inputs

1. ***Describe and cite the source(s) of all the weather data used. Include all the variables that are used, their spatial and temporal attributes, and, as applicable, methodology related to create means, variability, and extremes for individual meteorological variables.***

   Weather data applied in the KCC US Wildfire Reference Model include winds and temperature, which impact fire spread, and VPD, which is part of the event rate calculation.

   Actual wind and temperature data are obtained from the HRRR Model. The variables include the 10-meter horizontal wind and the 2-meter air and dewpoint temperatures. The HRRR model is a real-time atmospheric model from NOAA that has a spatial resolution of three kilometers and a temporal resolution of three hours, accounting for complex wind patterns over topographical terrains (Dowell et al., 2022; James et al., 2022).

   Winds that drive fire spread from the model are filtered to include the times that the conditions are conducive for fire spread. The filtering process computes a fire metric that depends on the anomalies in temperature and dewpoint temperature at the ignition location to remove winds that occur with widespread precipitation or outside of the typical fire season.

   At every ignition location, typical wind conditions are computed from the remaining, fire-conducive wind data and a Machine Learning (ML) method—K-means clustering—is utilized to identify and classify high wind patterns. The K-means clustering algorithm has been used to identify synoptic to local-scale wind patterns driven by a variety of meteorological processes, including winter-time winds (Gorgun and Mentes 2024; Fang et al., 2021), coastal sea-breezes (Di Bernardino et al., 2022) and typhoons (Wang et al., 2024).

   The clustering algorithm searches the time series of wind data at each location and finds groups, or clusters, of extreme wind events that are typical for that location. The quality of each cluster is measured with a silhouette score—a score based on each cluster's compactness and separation from neighboring clusters. A cluster of wind data is considered a typical high wind event for the location if it has a large silhouette score.

   Each cluster represents the direction of high winds at a single location: the ignition point. A composite analysis is applied to the HRRR wind fields to build the spatial pattern of winds that occur across the surrounding area when winds are extreme at the ignition point. Wind data for the same dates and times contained in each cluster are combined for all surrounding locations. The result is a spatially variable wind field that is consistent with the larger extreme wind pattern. In certain areas, the clustering analysis can result in multiple high wind patterns associated with a single ignition location. An example of two wind patterns classified by the ML method is shown below, which identifies variations of downsloping winds near Santa Barbara, CA.

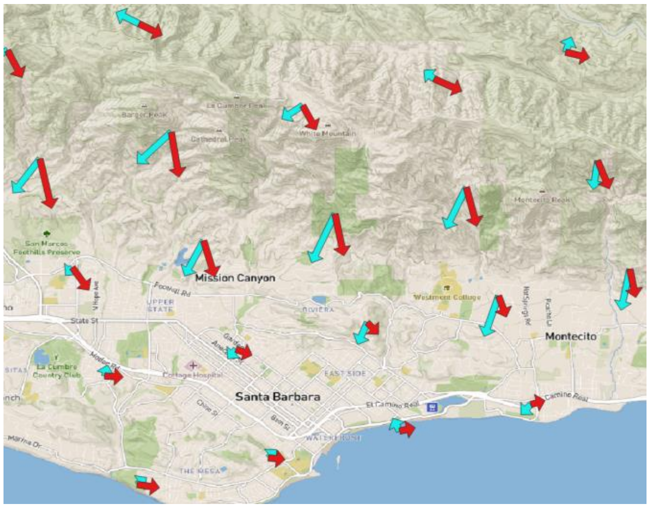


Figure 11 - Arrows depicting two complex wind patterns near Santa Barbara, CA, associated with downsloping winds. The wind patterns depict a directional change in the downsloping winds, which are southwestward (blue) and southeastward (red), as well as directional differences near the coast and on the plateau of the Santa Ynez Mountains.

In addition to the wind data, humidity data are incorporated into the wildfire model. KCC scientists calculate the 30-year average VPD during peak wildfire season across the entire US on a high-resolution grid. This dataset is extracted from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) developed by Oregon State University and supported by the USDA Risk Management Agency.

Using the climatological VPD, the annual occurrence rate for each fire ignition site is estimated based on the severity distributions developed for the Fire Region. Ignitions in low VPD areas have a relatively lower rate of wildfires compared to ignitions in high VPD areas. The differences for the rates of fires within a region are shown for a portion of Northern California below.

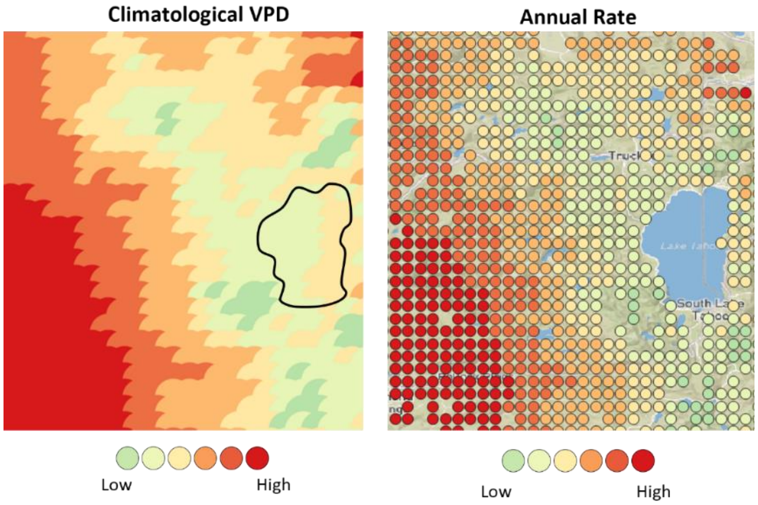


Figure 12 - Relative rates by ignition point (right) for fires in the Sierras of Northern California, near Lake Tahoe (black outline). The rates by ignition point are partially based on the climatological local VPD (left).

2. ***Provide a rationale for how the selected weather inputs reflect localized weather specific to fire hazards for the timespan being simulated.***

   To identify the wind patterns that are most likely to cause rapidly spreading fires at every location, KCC scientists analyze the wind data for conditions that are conducive to wildfires. The filtering process removes winds that occur with widespread precipitation or outside of the typical fire season for each location.

   The VPD climatological data are limited to the California wildfire season to be most representative of the atmospheric moisture during the time of year when most fires occur.

3. ***Provide a rationale for how the selected weather inputs account for sufficient variability in extreme fire weather conditions commensurate with modern climatology.***

   In the KCC US Wildfire Reference Model, wind patterns are generated for both average and extreme wind conditions at every ignition location. Extreme wind patterns are identified by performing the K-Means clustering on the highest wind speeds reported in the entire dataset. The highest winds are selected by quantile to ensure that the analysis includes extreme wind data specific to each ignition location.

4. ***Describe any methodology used to process the weather data (e.g., bias correction, downscaling efforts). Provide justification and citations to existing literature where relevant.***

   To identify the wind patterns that are most likely to cause rapidly spreading fires at every location, KCC scientists analyze the wind data for conditions that are warm and dry enough to support wildfires. Fire-conducive conditions are determined from a metric that represents the temperature, VPD, and season of the year, and is applied in filtering of the wind data. The filtering process removes winds that occur with widespread precipitation or outside of the typical fire season for each location.

   Typical wind conditions are computed from the remaining, fire-conducive wind data for every ignition location and a Machine Learning (ML) method—K-means clustering—is employed to identify and classify high wind patterns, following a similar method as Di Bernardino et al. (2022). K-means clustering has been applied in several recent studies of surface winds and other atmospheric variables (i.e. Yesilbudak et al., 2016; Gorgun and Mentes, 2024; Wang et al., 2024). The clustering algorithm searches the time series of wind data at each location and finds groups, or clusters, of extreme wind events that are typical for that location. The quality of each cluster is measured with a silhouette score—a score based on each cluster's compactness and separation from neighboring clusters. A cluster of wind data is considered a typical high wind event for the location if it has a large silhouette score.

Each cluster represents the direction of high winds at a single location: the ignition point. A composite analysis is applied to the HRRR wind fields to build the spatial pattern of winds that occur across the surrounding area when winds are extreme at the ignition point. Wind data for the same dates and times contained in each cluster are combined for all surrounding locations. The result is a spatially variable wind field that is consistent with the local meteorology. In certain areas, the clustering analysis can result in multiple high wind patterns associated with a single ignition location.

5. ***Detail how air moisture and fuel moisture content is calculated from weather inputs. Provide specific equations or methods of how this is accomplished.***

Fuel moisture is strongly correlated with soil moisture (Qi et al., 2012; Krueger et al., 2022). Therefore, a soil moisture variable is used to represent fuel moisture in the fire behavior and spread model, based on a recent climatology of soil moisture from the Climate Prediction Center to ensure that the relative spatial variability in this parameter is consistent with present day conditions. The ratio of fuel moisture to dry weight is determined as a proxy of the average fire season soil moisture, similar to previous studies (e.g., Rabin et al., 2018; Kloster et al., 2010; Li et al., 2013).

6. ***Demonstrate the consistency of the weather inputs with observed data, including for extreme fire weather conditions. Comparisons of the weather inputs should at least be shown for wind speed and relative humidity. Describe and justify the appropriateness of the weather inputs taken from weather databases used in the weather validation to represent annual and seasonal variations as well as to appropriately capture extreme fire events that drive losses.***

Fire spread rate and direction are largely determined by winds. Strong winds lead to higher rates of spread and can cause wildfires to cross natural and manmade fire breaks such as rivers and roads. High wind events are particularly important for fire impacts because they can lead to wildfires that spread rapidly and are difficult to suppress. The direction and speed of high wind events vary significantly by location. Even within the same region, one area may be more prone to stronger winds than another due to differences in climatology and topography.

Several different meteorological factors can drive high wind events that are conducive to fire spread. Downsloping wind events are perhaps the most well-known given their drying and warming nature. Downsloping winds are driven by a gradient in surface pressure oriented perpendicular to steep, downward sloping topography.

There are several types of downsloping winds. For example, in Northern California, Diablo winds are typically set up by the passage of an upper-level trough that builds a high-pressure system over the north Great Basin and turns the jet stream south, which further supports strong northeasterly winds. Meanwhile, Santa Ana and Sundowner winds impact Southern California with easterly to northerly winds that are driven by intense nighttime radiative cooling.

KCC scientists capture all of these high wind patterns by applying machine learning methods to high-resolution surface wind data. Actual wind speeds and directions are obtained from the HRRR Model. The HRRR model is a real-time atmospheric model from the National Oceanic and Atmospheric Administration (NOAA) that has a spatial resolution of three kilometers and a temporal resolution of three hours, so it accounts for complex wind patterns over topographical terrains.

Comparisons of the model event wind speeds to observed winds from the Remote Automatic Weather Stations (RAWS) network demonstrate that the speed and direction of high wind events are captured by the model for locations in California, including those that experience downslope winds, and those locations for which high winds are driven by other atmospheric processes. In this validation, KCC wildfire model winds representing average conditions and extreme conditions, derived from the HRRR model data, are compared to the distribution of winds observed at sites across California. Extreme wind speeds are expected to be in the top 2% of the observed distribution and the average wind speeds are expected to be comparable to the observed mean.

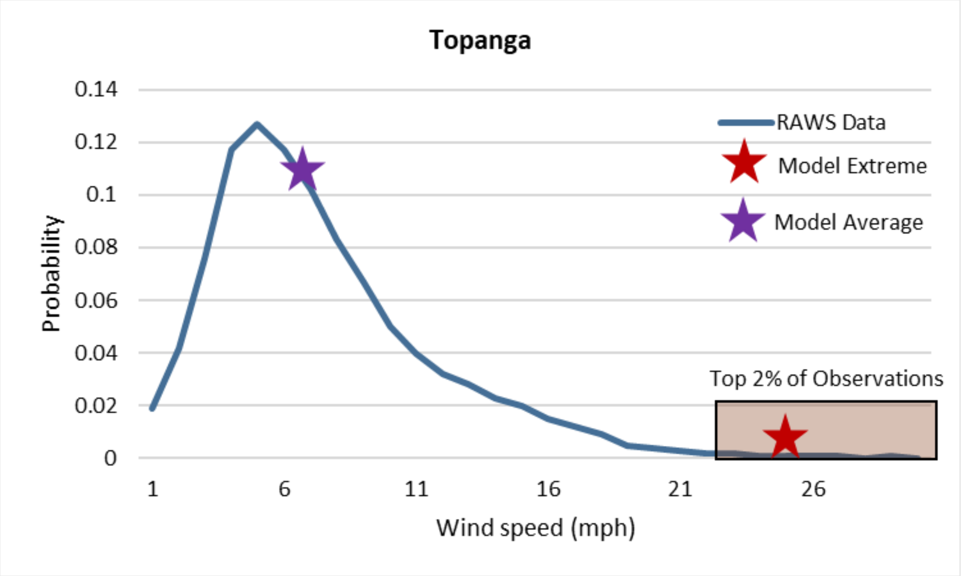


Figure 13 - Comparisons of model extreme and average wind speeds to observed winds from the Remote Automatic Weather Stations (RAWS) network. The model average is consistent with the average of the observed winds which are both higher than the peak in the probability curve due to the right-skewed nature of the observed wind speed distribution at Topanga and at stations across California.

The impact of humidity on wildfire spread in the KCC US Wildfire Model is represented by variations in fuel moisture, which is determined by the ratio of soil moisture to dry weight for the average fire season. Soil moisture climatology data are from the Climate Prediction Center’s gridded, monthly soil moisture product, which is utilized for studies of wildfires in the western US and other regions (e.g., Chikamoto et al., 2023; Kim et al., 2020). The soil moisture climatology data are validated with measurements of soil moisture at sites across California as reported by the Soil Climate Analysis Network.

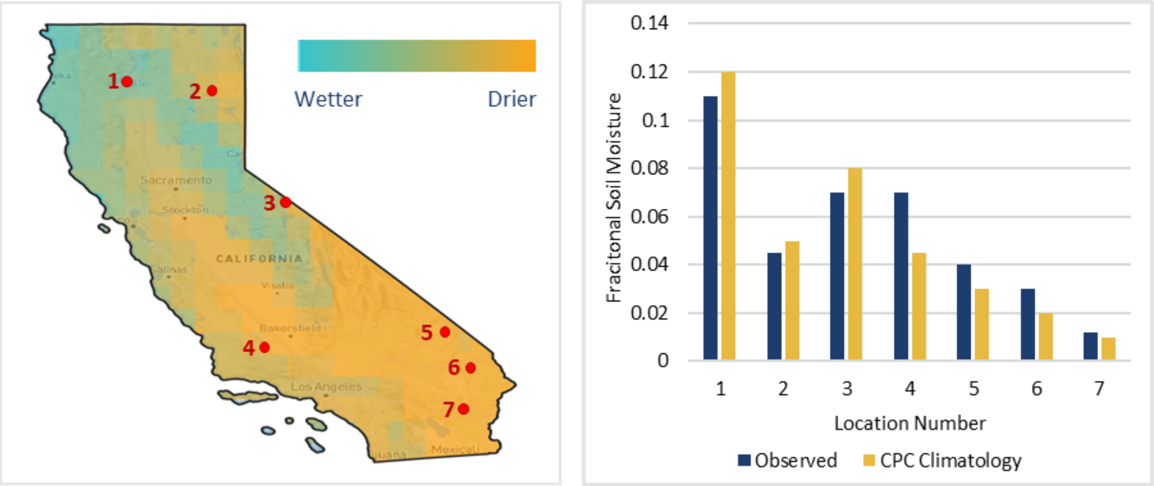


Figure 14 - Comparison of the soil moisture climatology data for California to measurements of soil moisture at several sites across the state

H-6: Present Day Climate Change Adjustments

1. ***Describe the approach used to account for ongoing changes in climate in adjusting weather inputs to present day conditions. Specify any ancillary datasets (e.g., climate models) used to account for such changes and any statistical processing used.***

The KCC US Wildfire Reference Model accounts for the impacts of warming global temperatures on wildfire frequency and size following the current scientific consensus on climate change and wildfires (e.g., Seneviratne et al., 2021). As temperatures rise, key changes occur that increase the water holding capacity of air and decrease the available moisture in the environment—especially in wildfire-prone areas.

The VPD—measured in hectopascals (hPa)—is an atmospheric variable that describes the capacity of an air mass to hold moisture beyond what is available. A high VPD is correlated with warmer temperatures, lower precipitation, and—most important for wildfire—drier fuels. Recent studies have shown that the VPD more accurately predicts the total area burned per year for wildfires in the US than temperature or precipitation alone (e.g., Williams et al., 2019; Abatzoglou et al., 2021).

To assess the relationship between VPD and wildfire activity, correlation analyses were performed using historical data on summer VPD and summer wildfire burned area in both forested and non-forested regions of California. In forested areas (north coast and Sierra Nevada), the Spearman correlation coefficient was 0.709, indicating a strong monotonic relationship between VPD and burned area. This aligns with findings from the KCC US Wildfire Reference Model, which highlights a nonlinear dependence of wildfire activity on VPD in forested ecosystems, where higher VPD drives increased flammability and fire spread. The correlation was statistically significant ($p\text{-value} < 0.05$), confirming that the observed relationship is robust. In non-forested regions (south coast and central valley), the Spearman correlation coefficient was 0.346, reflecting a weaker monotonic relationship.

The nonlinear influence of VPD is less pronounced in these areas, due to differences in vegetation structure—grasslands and shrublands respond to moisture stress more rapidly than forests, leading to earlier fuel desiccation and a decoupling of fire activity from peak VPD later in the season. Additionally, factors such as ignition patterns and wind-driven fire spread (as captured in the KCC framework) play a more dominant role in these ecosystems.

Trends in VPD are calculated with gridded VPD data from the Parameter-elevation Regressions on Independent Slope Model (PRISM) repository, which is a high-resolution, observations-based dataset of atmospheric variables covering the US. PRISM temperature and humidity data are available monthly, allowing KCC scientists to isolate the fire season for trend analyses.

Since trends in VPD vary geographically, analyses are conducted separately for each KCC Fire Region. The annual area burned is climate conditioned based on how the VPD is changing in the Fire Region, how long ago the fire occurred, and the dominant vegetation type in the region. This process ensures that the KCC modeled fire frequencies align with the present-day climate and lead to an accurate view of current wildfire risk.

While there is scientific consensus on climate change impacts on VPD, there is no such consensus for climate change impacts on extreme wind events. Studies of climate change trends in extreme wind events, such as the frequency and seasonality of dry downsloping winds, have been inconclusive (cf. Miller and Schlegel, 2006 with Guzman-Morales and Gershunov, 2019). Therefore, utilization of existing data can capture the majority of wind regimes responsible for potentially driving many of the damaging wildfires in the current climate.

The climate change conditioning of the KCC US Wildfire Reference Model is quantified through the VPD variable and applied in the model catalog as a change in the frequency and area burned of the model fires. Fuel moisture is strongly correlated with soil moisture (Qi et al., 2012; Krueger et al., 2022). Therefore, a soil moisture variable is used to represent fuel moisture in the fire behavior and spread model, based on a recent climatology of soil moisture from the Climate Prediction Center to ensure that the relative spatial variability in this parameter is consistent with present day conditions.

2. ***Specify which variables were adjusted in cases where only a subset was changed and provide justification.***

The entire dataset of historical wildfires was included without subsets in the climate change conditioning analyses.

H-7: Wildfire Hazard Model Validation

1. ***Please provide a schematic or diagram that represents the overall architecture of the wildfire hazard model, including all components (inputs, parameters including other sub-models/model components, and outputs).***

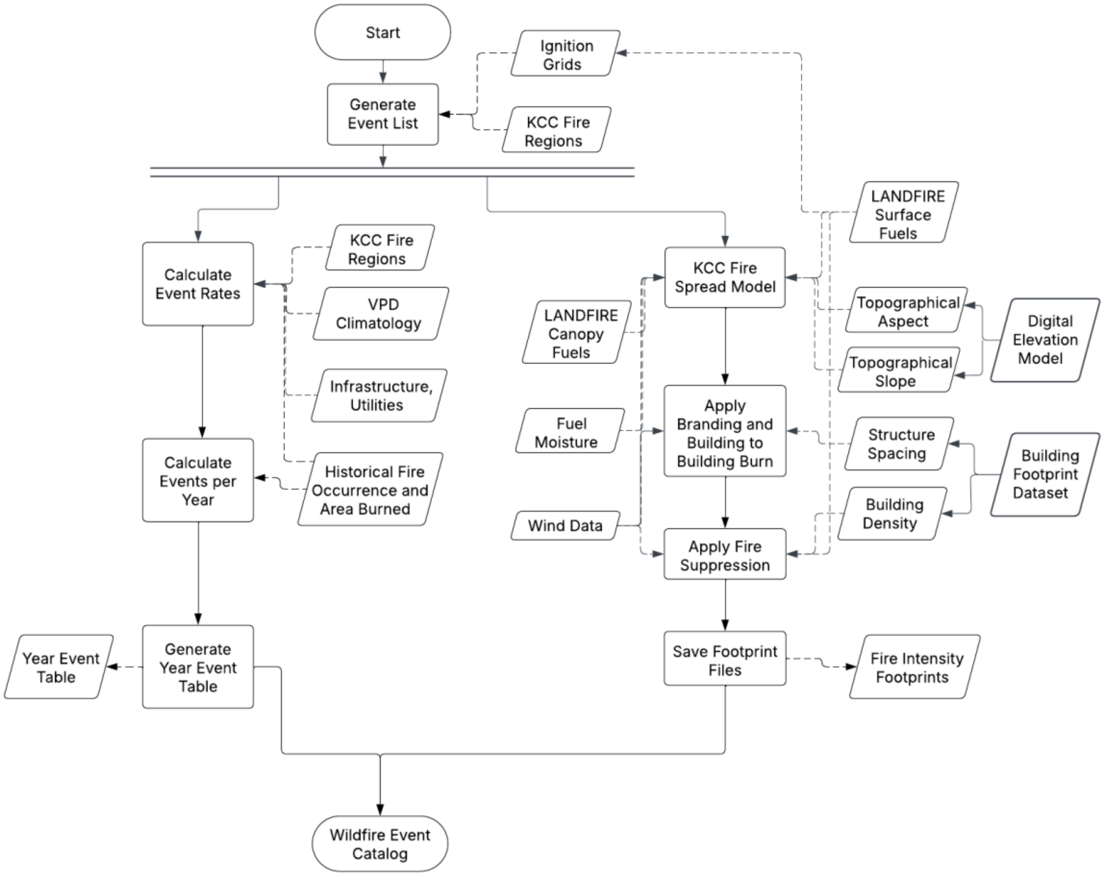


Figure 15 - Flowchart representing the process of generating the hazard component of the KCC US Wildfire Reference Model

2. ***For each sub-model or model component, specify the sub-model or model component; how it is modified and validated, including, but not limited to, by comparing trends or with past fires; and cite papers and sources. Provide a justification for any specific sub-model or model component that is not validated.***

All components of the KCC US Wildfire Reference Model have been validated against historical data, including for full datasets and for individual events where appropriate. Validation of the frequency and severity of California wildfires in the KCC Wildfire Stochastic Catalog is demonstrated in the comparisons to the Base Wildfire Set in Form H-1 and Form H-2.

To validate the fire intensity footprints, KCC scientists leverage three types of data:

1. Remote sensing imagery (from space-based or aircraft platforms)
2. Site surveys
3. Damage information

The fire spread component of the KCC US Wildfire Reference Model is validated with comparisons to historical wildfires. The comparisons include data from LANDSAT imagery and the fire severity data for historical fire perimeters from the MTBS. These data are especially important for validating the fire intensity calculation in the fire spread model and the effectiveness of fire suppression within the perimeter.

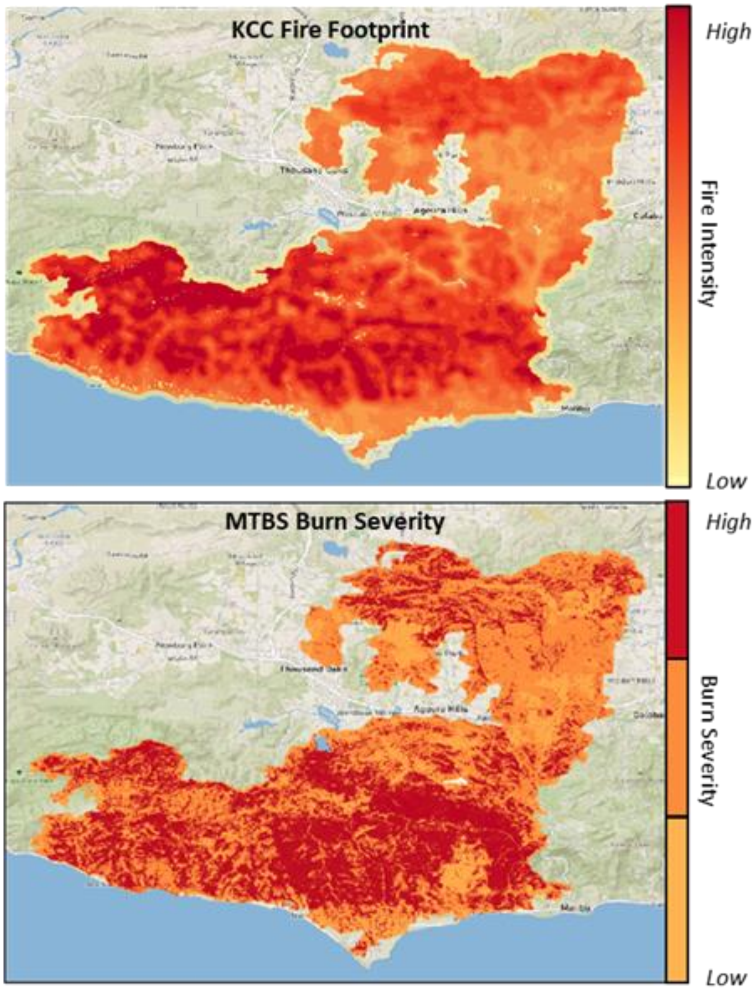


Figure 16 - KCC fire footprint (top) compared to the MTBS burn severity map (bottom) from the Woolsey Fire (2018)

The climate change trending of the historical wildfire set is validated by comparison to the results of recent research (e.g., Williams et al., (2019); Abatzoglou et al., 2021). The study found that increases in fire season VPD lead to a non-linear increasing response in area burned and that the magnitude of the relationship was highest for forested regions. The KCC analyses of VPD and area burned data for California replicate the Williams et al. (2019) results and then extend the analysis to include more recent years.

Validation of the hazard component of the model—the Event Catalog and Intensity Footprint modules combined— is demonstrated by comparisons of KCC high-resolution loss cost maps created on a high-resolution grid to other external sources of hazard information, such as the CAL FIRE Fire Hazard Severity Zones.

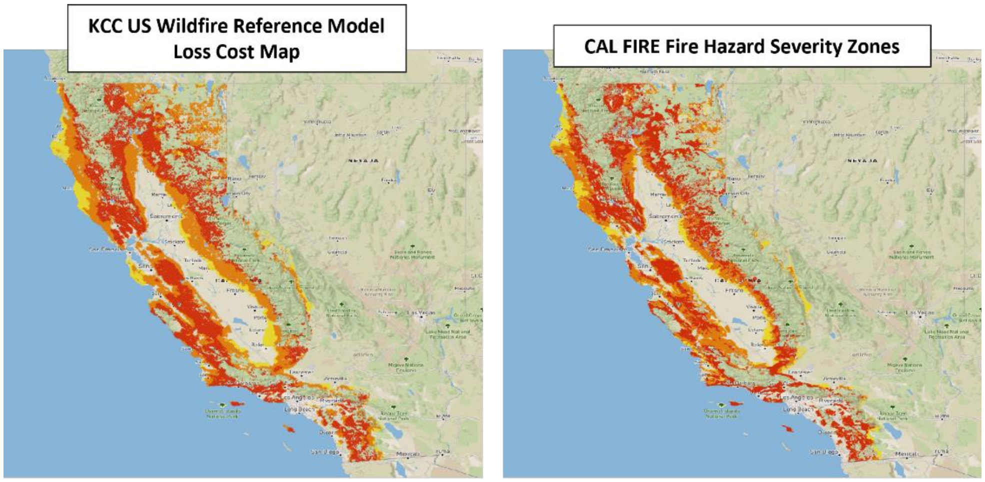


Figure 17 - KCC California Wildfire loss cost map (left) compared to the CAL FIRE Fire Hazard Severity Zones map (right). Note: Fire Hazard Severity Zones are not input to the model and are only used as validation.

Statistical Disclosures

S-1: Modeled Results and Goodness-of-Fit

1. ***Identify the framework that governs the spatiotemporal statistical modeling approach used for the wildfire loss estimates and the overall model outputs including the inference and diagnostic methods, and reasoning for computation of posteriors.***

   The spatial component of the model is derived from historical wildfire regions and location-specific environmental factors, including climate change impacts, ensuring comprehensive hazard coverage. Wildfire ignitions are simulated on a spatially unbiased grid, with the KCC Stochastic Event Catalog comprising over 100,000 stochastically-generated ignition location and weather pattern combinations across California. Each ignition location and weather pattern is assigned a location-specific event rate based on fire behavior and environmental conditions, capturing regional variability in risk.

   The temporal component is represented in the Year Loss Table (YLT), where a 100,000-year catalog simulates long-term wildfire risk. The number of events per year is sampled using an empirical distribution, developed from a discrete kernel density smoother fitted to historical wildfire data and validated through goodness-of-fit tests. The Event Loss Table (ELT) combines mean event losses with event rates, while the YLT incorporates uncertainty by sampling from the ELT. Within the YLT framework, the model guarantees that sampled events do not repeat in the same year and that each location experiences at most one burn event per simulated year.

   Posterior computations quantify uncertainty and refine model outputs, supported by robust inference from historical data, environmental factors, and stochastic simulation. Diagnostic methods—including historical loss validation and sensitivity analysis—ensure the reliability and accuracy of the model.

4. ***Provide the dates and location of wildfire loss of the insurance and wildfire claims data used for validation and verification of the wildfire actuarial and financial model.***

Event	Location	Date
Sand	Los Angeles County	July 22 – August 3, 2016
Atlas	Napa and Solano Counties	October 8 – October 28, 2017
Nuns	Sonoma County	October 8 – October 31, 2017
Tubbs	Sonoma and Napa Counties	October 8 – October 31, 2017
Mendocino Lake Complex	Mendocino County	October 22 – December 1, 2017
Thomas	Ventura and Santa Barbara Counties	December 4, 2017 – January 12, 2018
Creek (2017)	Los Angeles County	December 5, 2017 – January 9, 2018
Lilac	San Diego County	December 7 – December 16, 2017
Carr	Shasta and Trinity Counties	July 23 – August 30, 2018
Ranch	Mendocino, Lake, Colusa, and Glenn Counties	July 27 – September 18, 2018
River	Mendocino, Lake, Colusa, and Glenn Counties	July 27 – September 18, 2018
Camp	Butte County	November 8 – November 25, 2018
Woolsey	Ventura and Los Angeles Counties	November 8 – November 21, 2018
Creek	Los Angeles County	December 5, 2017 – January 9, 2018
Saddleridge	Los Angeles County	October 10 – October 31, 2019
Kincade	Sonoma County	October 23 – November 6, 2019
CZU Lightning Complex	San Mateo and Santa Cruz Counties	August 16 – September 22, 2020
SCU Lightning Complex	Santa Clara, Alameda, Contra Costa, San Joaquin, Merced, and Stanislaus Counties	August 16 – October 1, 2020
LNU Lightning Complex	Lake, Napa, Sonoma, Solano, and Yolo Counties	August 17 – October 2, 2020
North Complex	Plumas and Butte Counties	August 17 – December 3, 2020
Carmel	Monterey County	August 18 – September 4 2020
Creek	Fresno and Medera Counties	September 4 – December 24, 2020
Bobcat	Los Angeles County	September 6 – November 27, 2020
Glass	Napa and Sonoma Counties	September 17 – October 20, 2020

Caldor	Butte, Plumas, Shasta, Tehama, and Lassen Counties	July 13 – October 25, 2021
Dixie	El Dorado, Amador, and Alpine Counties	August 14 – October 21, 2021
Park	Butte and Tehama Counties	July 24 – September 26, 2024
Mountain	Ventura County	November 6 – November 27, 2024
Palisades	Los Angeles County	January 7 – January 31, 2025
Eaton	Los Angeles County	January 7 – January 31, 2025

Table 1 – Dates and locations of wildfire claims data used for validation of the actuarial and financial model in California

5. ***Provide an assessment of uncertainty in wildfire probable maximum loss levels and wildfire loss costs for wildfire output ranges at the appropriate spatiotemporal scales using confidence intervals or other scientific characterizations of uncertainty.***

   The uncertainty in wildfire probable maximum loss levels was characterized using confidence intervals. To calculate the uncertainty intervals for an event, the expected value and variance in loss experienced at each location (as defined by the location's secondary uncertainty distribution) within the event footprint is aggregated to determine the event's expected loss and variance. The 10% (lower bound) and 90% (upper bound) wildfire loss levels are estimated from each event's expected loss and variance using properties of sums of random variables and Chebyshev's theorem.

7. ***Provide graphical comparisons of modeled and historical data and goodness-of-fit tests for the wildfire hazard model, the vulnerability model(s), the actuarial/financial model(s), and the overall wildfire catastrophe model (Examples to include are fire occurrence frequencies, area burned, and physical damages.) The following items may be included:***
    - ***For final model outputs: Difference between individual incurred historical losses and modeled losses at different spatial and temporal aggregation levels.***
    - ***For fire models, if variables and outputs exist in the modeling pipeline, the following may be used, for example:***
        - ***Difference between observed and modeled area burned at different spatial and temporal scales.***
        - ***Difference between observed and modeled number of habitational structures damaged (found in the burnt area) at different spatial scales.***
        - ***Difference between reported and modeled fire arrival times at different spatial scales.***

Fire Occurrence Frequencies

The wildfires in the United States exhibit robust frequency-area power-law behavior. This is supported by empirical evidence and theoretical studies, including the work of Malamud et al. (2005), which demonstrate that wildfire regimes consistently adhere to this scaling relationship. The following plots compare historical fire occurrence frequencies to those modeled by the power-law function for two California ecoregions: Central California Valley and Sierra Nevada. Both graphical analyses and Pearson's chi-squared tests confirm strong agreement between the observed and modeled data. For the Sierra Nevada, the test results (χ^2= 1.575, degree of freedom = 5, p-value = 0.904) suggest an excellent fit. The Central California Valley similarly shows high consistency (χ^2= 0.097, degree of freedom = 1, p-value = 0.756). These findings reinforce the applicability of power-law scaling in characterizing wildfire distributions across these regions.

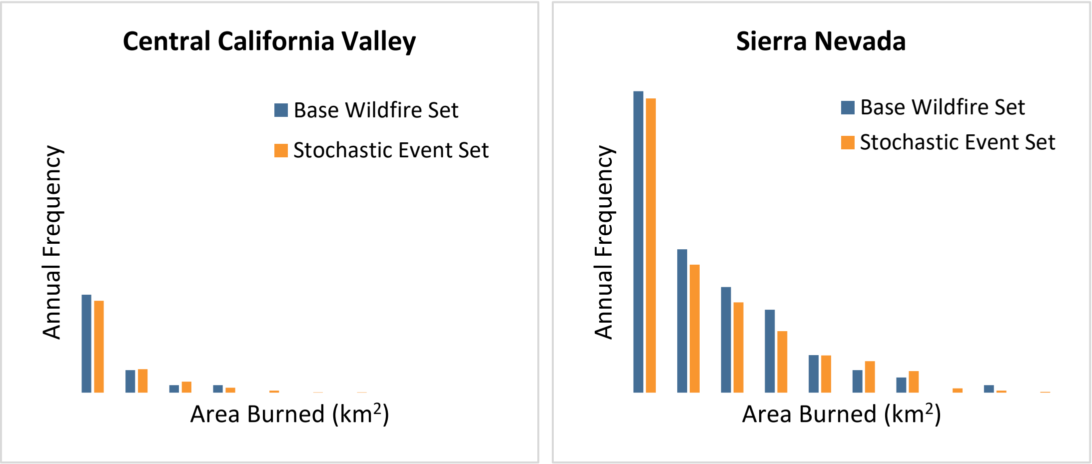


Figure 18 - Comparison of fire occurrence frequencies between the Base Wildfire Set and the Stochastic Event Set across the Central California Valley and Sierra Nevada

Fire Events per Year

The number of wildfires per year in the YLT is modeled using an empirical distribution developed through discrete kernel density estimation (with a triangle kernel). This approach provides greater flexibility in capturing California's wildfire frequency patterns with the incorporation of climate change. The following plot compares historical wildfire events per year to the modeled figures in California. The modeled distribution aligns well with historical data, as evidenced both visually and through Pearson's chi-squared test (χ^2= 2.873, degree of freedom = 4, p-value = 0. 579), indicating a strong goodness of fit. Notably, the model's longer tail, representing more years with higher fire counts, reflects the increasing influence of climate change on wildfire frequency. Despite this incorporation of climate-driven extremes, the statistical fit remains robust, further validating the chosen distribution.

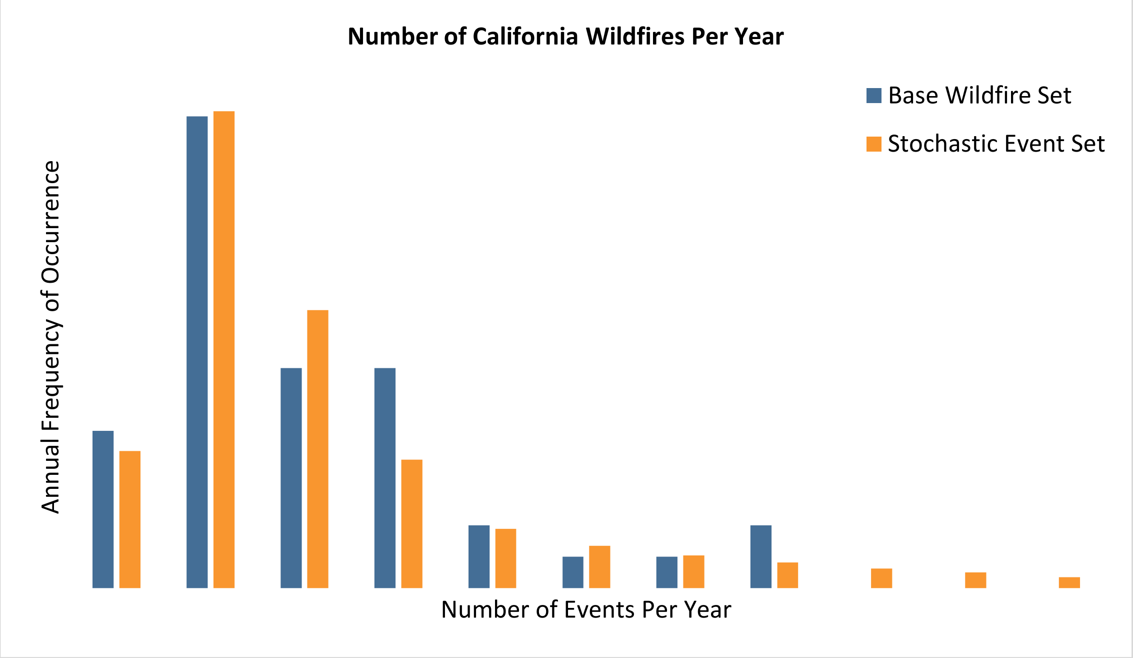


Figure 19 - Comparison of California fire events per year between the Base Wildfire Set and the Stochastic Event Set

Seasonal Distribution of Fire Occurrences

The seasonal distribution of wildfire occurrences is modeled using an empirical distribution function derived through discrete kernel density estimation (with a triangle kernel). This non-parametric approach captures the temporal patterns of historical fire events in California while providing greater flexibility than conventional parametric distributions. The model's performance is evaluated both visually and statistically. Graphical comparison shows strong agreement between the kernel density estimate and observed seasonal fire patterns. This alignment is further supported by Pearson's chi-squared test (χ^2= 12.627, degree of freedom = 7, p-value = 0. 082), indicating the model provides a good fit to the historical data while effectively representing the characteristic seasonal variability of wildfire occurrences in California.

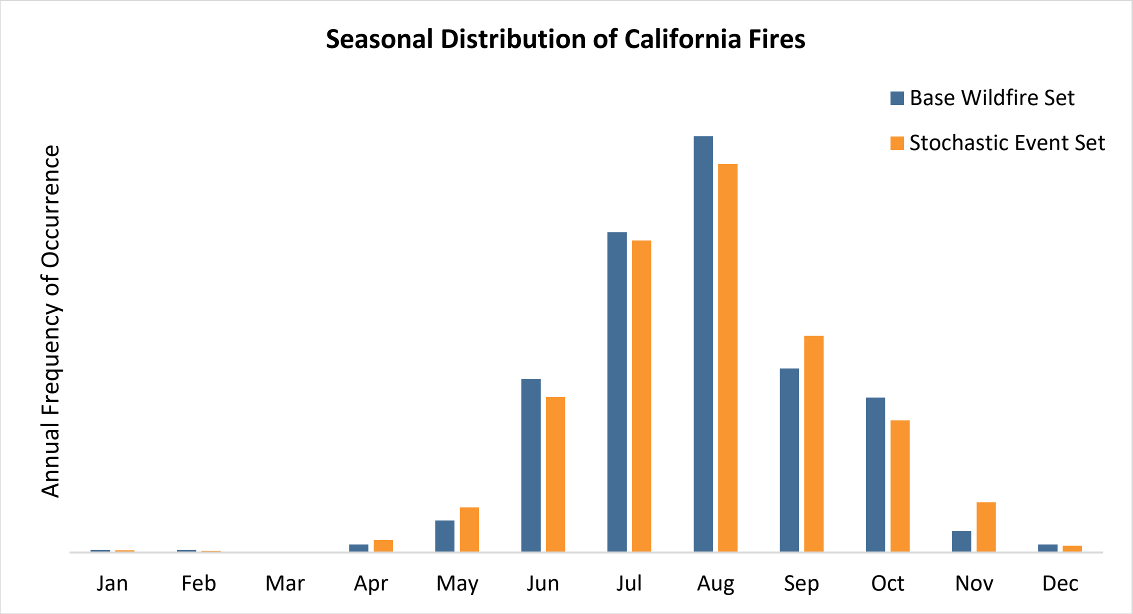


Figure 20 - Seasonal distribution of California wildfires from the Base Wildfire Set and the Stochastic Event Set

S-2: Sensitivity Analysis for Wildfire Catastrophe Model Output

1. ***Identify the most sensitive aspect of the wildfire hazard model, the vulnerability model(s), the actuarial/financial model(s), and the overall wildfire catastrophe model and the basis for making this determination.***

Each component of the KCC Wildfire Reference Model, i.e., hazard, vulnerability, and financial, has been rigorously analyzed to identify the most impactful factors for modeled wildfire losses. KCC scientists and engineers conducted detailed sensitivity analyses tailored to each model component, applying appropriate statistical methods to quantify the relative impact of key parameters.

Hazard

The most sensitive aspect of the KCC wildfire hazard model is wind speed, based on findings from a detailed sensitivity analysis conducted by KCC scientists. The sensitivity analysis follows the methodology detailed by Iman et al. (2002) for assessing the sensitivity of model losses to changes in parameter values. This analysis used standardized regression coefficients to quantify how variations in specific input parameters influence modeled loss. By standardizing the inputs, this method allows for a direct comparison of the relative influence of different variables on the output loss, thus providing a robust basis for identifying sensitivity.

Wildfires require a dynamic modeling approach that can capture the high-resolution factors determining the direction and rate of fire spread. Unlike hurricanes and earthquakes, where modeled parameters follow relatively predictable relationships throughout the lifecycle of an event, wildfires are highly responsive to small changes in the environment. This introduces high spatial and temporal sensitivity, where a slight change in winds or topography can affect the resulting intensity footprint, which is captured by the KCC wildfire hazard model.

The variables tested include the 10-m wind speed, slope angle, and soil moisture. The direction of the winds and topography, i.e., the slope bearing and wind direction, were fixed for the analysis. The range of the variables used to conduct the sensitivity analysis are shown below in Table 2. The wind speeds ranges were chosen to represent realistic sustained wind speeds that range from calm conditions to winds observed for downsloping wind events (Abatzoglou et al. 2013). The slope angle includes both uphill (negative angle) and downhill (positive angle) impacts on the fire spread; the selected 30-degree maximum angle assumption is consistent with the steepest slopes that support fire spread in California. For soil moisture, which serves as a proxy for fuel moisture in the fire spread model, the ranges correspond to the 5th and 95th percentile of the summertime climatological soil moisture in the Western US, which it taken from the Climate Prediction Center.

Variable	Range
10-m Wind Speed	0 to 35 mph
Slope Angle	-30° to 30°
Fractional Soil Moisture	0.02 to 0.15

Table 2 - Full range of input hazard parameters in the sensitivity analysis

The analyses were conducted by simulating fire footprints with four homogenous fuel categories according to LANDFIRE 2023. The fuel categories include short grass, shrub, timber understory and timber. Specifically, they are: 102 - Low-load, dry climate grass with limited fine, dead fuel; 122 - Moderate-load, dry climate grass-shrub with 1–3 ft shrubs and high spread rate; 142 - Moderate-load dry climate shrub with woody litter, low spread and flame length; 165 - Very high-load, dry climate timber-shrub with heavy forest litter and shrub understory. These fuel types were chosen because they are representative fuels that are classified in California. Because the fire footprints are impacting structures, fuel categories that are classified as urban, or some other non-burnable pixel according to Landfire 2023, were unchanged.

To isolate the impact of the input variables, all fire footprints were generated at a fixed ignition location and simulated to reach a fixed fire size. The area chosen is in the San Gabriel mountains in Southern California, where a fixed ignition was positioned 5 miles into the wildland, and the fire was simulated to grow to a size of ~25,000 acres. The slope bearing was directed northeast because it roughly aligns with the existing bearing for the San Gabriel mountains, while the wind direction was directed southwest, which is consistent with the direction of down sloping winds that affect the region. An example footprint, along with the test area, is shown in Figure 21.

Figure 21 - Test area and example fire footprint for the sensitivity/uncertainty analysis

Across all fuel types, wind speed consistently showed the highest standardized regression coefficient (in absolute value), indicating it had the greatest influence on modeled loss. This finding is consistent with the physical dynamics of fire behavior, as higher wind speeds directly drive fire spread and intensity, particularly in more open or grass-dominated fuel environments. Slope angle ranked second in sensitivity, still playing a significant role, especially in hilly or mountainous terrain where it can accelerate upslope fire movement. These results are summarized in Figure 22, which illustrates the relative importance of each input parameter across different fuel types.

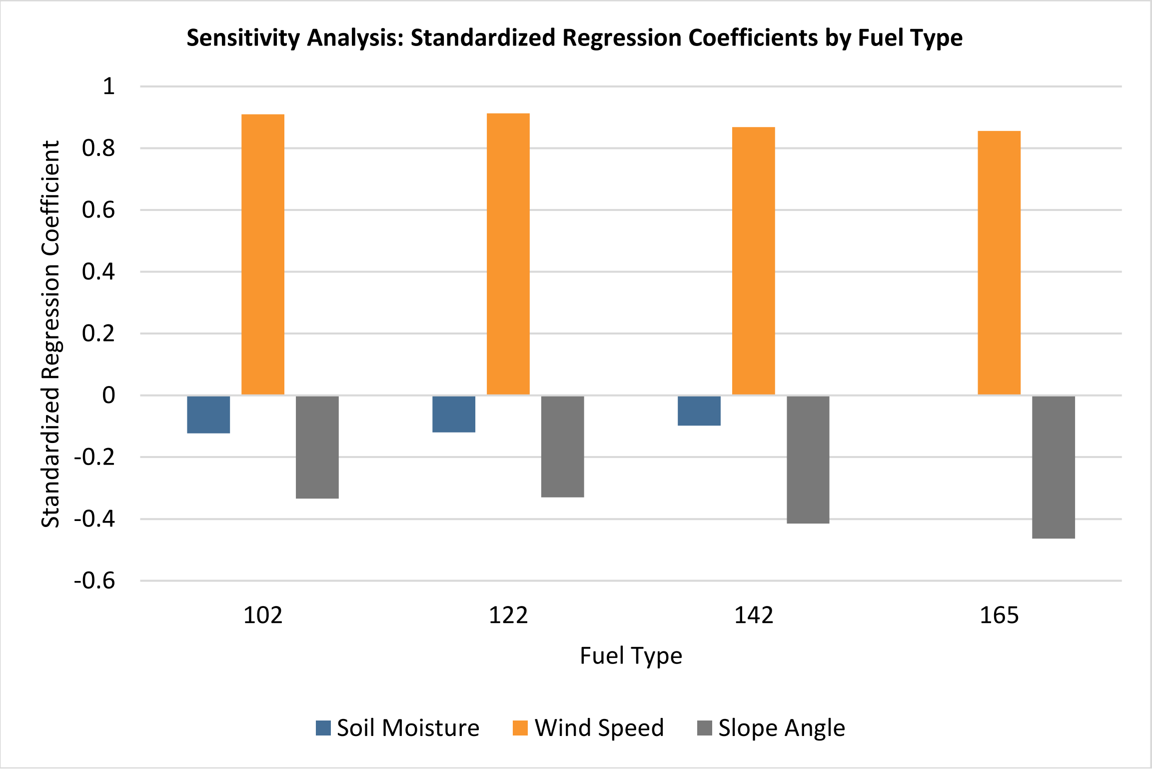


Figure 22 - Standardized regression coefficients of hazard input parameters by fuel type.

Vulnerability

The most sensitive primary building characteristic of the KCC wildfire vulnerability module is year-built, based on findings from a detailed sensitivity analysis conducted by KCC engineers. This analysis evaluated the variation in MDRs between the least and most vulnerable options given other input parameters constant. Four primary building characteristics (i.e., construction, occupancy, number of stories, and year-built) were assessed.

Financial

The most sensitive aspect of the KCC financial module is the secondary uncertainty sampling. Unlike the hazard and vulnerability components, the financial module does not rely on multiple variables, making traditional sensitivity methods, such as the Iman et al. (2002) methodology used for testing the hazard components, unsuitable for sensitivity analysis. However, KCC experts performed rigorous statistical tests to confirm that sampling errors are negligible within the model.

As detailed in Disclosure S-4 #1, KCC uses a stratified sampling method to estimate wildfire losses, generating 1,000 samples per event to balance computational efficiency and statistical accuracy. Tests varying the sample size from 10 to 3,000 confirmed that 1,000 samples yield negligible error at the location level.

3. ***Identify the aspect or parameter of the wildfire catastrophe model with the greatest contribution to the outputs under full range of model runs and the basis for making this determination, as well as other input variables that impact the magnitude of the output when varied simultaneously. Describe the degree to which these sensitivities affect output results and provide illustrative examples.***

   As described in Disclosure S-2 #1, wind speed in the wildfire hazard model has the greatest contribution to the output losses under full range of model runs. This conclusion is based on the standardized regression coefficient, which quantifies the relative influence of input variables on modeled losses. Wind speeds provide faster fire spread and more extreme fire behavior, which in very strong wind conditions occurs irrespective of fuel category. Based on the setup of the analysis, the winds allow the fire to affect a great urban area with higher intensities as the fire expands outward to its target size. Winds also promote a greater extent of impact into the urban areas and reduce the impacts of suppression, consistent with many of the large loss wildfires of the past. No other variables impact the magnitude of the output when the input variables, i.e., soil moisture, wind speed, and slope angle, are varied simultaneously.

4. ***Describe how other aspects of the wildfire catastrophe model may have a significant impact on the sensitivities in output results and the basis for making this determination.***

   From a hazard perspective, other aspects of the wildfire model that have an impact on the sensitivity of the modeled losses would include the impacts of canopy fire spread. In the above sensitivity analysis in Disclosure S-2 #1 and uncertainty analysis in Disclosure S-3 #1, fire spread was restricted to the surface. In a canopy fire, fuel category, as well as canopy characteristics, would play a significant role on losses because canopy fire spreading can extend much farther into urban areas than surface fires. Selecting an analysis location in the mountains of Southern California excluded this impact. This determination was made by studies performed by KCC scientists on both uniform exposure and actual exposure.

S-3: Uncertainty Analysis for Wildfire Catastrophe Model Output

1. ***Identify the major contributors to the uncertainty in wildfire catastrophe model outputs, the basis for making this determination, and the quantification for each of those major contributors. Provide a full discussion of the type and direction (forward propagation, inverse propagation) of the uncertainties and the degree to which they affect output results and illustrate with relevant examples.***

   An uncertainty analysis was conducted by KCC scientists to identify the dominant sources of uncertainty in wildfire loss estimates and to quantify their individual contributions. This uncertainty analysis follows the methodology detailed by Iman et al. (2002) for assessing the uncertainty in model losses when parameter values are varied. The analysis focused on three key hazard parameters: soil moisture, wind speed, and slope angle, and assessed their impact across four representative fuel types, as described in Disclosure S-2 #1. The method involved computing the expected percentage reduction in the variance of loss cost, a measure of how much overall model uncertainty could be reduced if a given input variable were known precisely. Specifically, for each input parameter, the analysis compared the variance of loss when only that parameter was varied (while others were held fixed) to the variance when all parameters were varied. The ratio of these variances provides an estimate of each parameter's relative contribution to total model uncertainty. This approach offers a quantitative basis for prioritizing uncertainty reduction efforts in hazard modeling.

The analysis revealed that wind speed is the dominant contributor to the uncertainty in modeled loss across all fuel types. For each of the four representative fuel types (102, 122, 142, and 165), wind speed consistently emerged as the primary driver of variance in loss estimates. This indicates that reducing uncertainty in wind speed would result in the most significant decrease in the overall variance of modeled wildfire loss. Slope angle was identified as the second-most influential factor, contributing notably to uncertainty—particularly in fuel types with greater topographic variation. These findings are illustrated in Figure 23, which shows the percentage reduction in output variance attributable to each input parameter across the different fuel types.

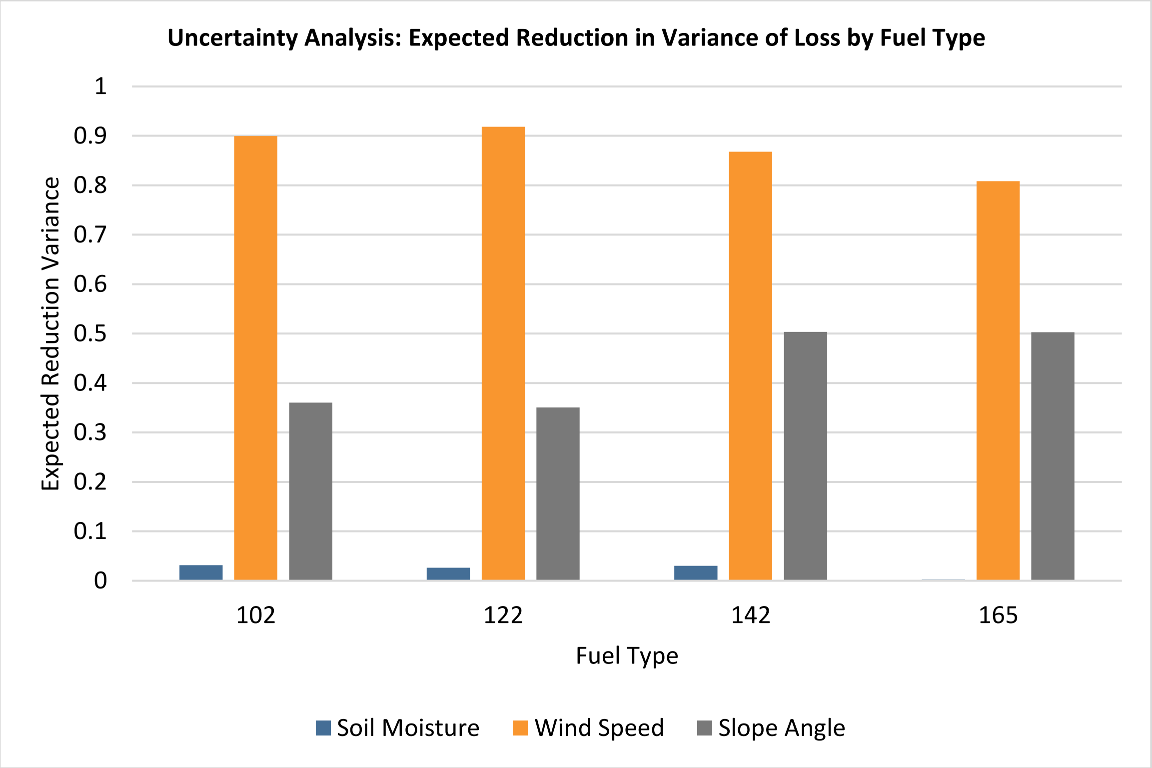


Figure 23 - Expected reduction in variance of loss caused by hazard input parameters by fuel type

2. ***Describe how other aspects of the wildfire catastrophe model or their combined effects may have a significant impact on the uncertainties in modeled loss outputs and loss results and the basis for making this determination. In case of a multicomponent catastrophe model, provide characterization of uncertainty for each component or module (e.g. hazard module, vulnerability module, and the actuarial/financial module), and describe the input and output uncertainties once all components are connected.***

As described in the response to Disclosure S-4 #1, wildfire frequency and severity are determined from the parameter distributions identified in Form S-2 based on power law fits to the Base Wildfire Set in each KCC Fire Region. Catalog events are then assigned to model years based on the annual wildfire frequency empirical distribution, described in Form S-2, that represents the annual wildfire frequency, with some years containing no events and other years containing one or more events. The resulting catalog represents the primary uncertainty in the model, and the relative frequency and severity of wildfires occurring in different California locations.

As explained in the response to G-1 #2, empirical distributions consider the full range of damage levels (the secondary uncertainty) that can occur around the MDR in the vulnerability functions. The secondary uncertainty is always considered in loss calculations for each location and each coverage type.

S-4: Aggregation & Convolution Levels

1. ***Describe and justify the sampling, aggregation plan, and the adopted spatiotemporal resolution used to obtain the average annual wildfire loss costs and wildfire loss output ranges. For example, for a Monte Carlo simulation, indicate steps taken to determine sample size. For an importance sampling design or other sampling scheme, describe the underpinnings of the design and how it achieves the required performance.***

Sampling and Aggregation Plan

The sampling plan is critical for a catastrophe model, as it must ensure complete and consistent spatial coverage while incorporating an appropriate number of events and their characteristics into the stochastic catalog.

The KCC US Wildfire Reference Model uses a sophisticated sampling procedure to create a Stochastic Event Catalog with over one million potential future events in California. Wildfire frequencies and severities in California are determined for 10 Fire Regions, accounting for factors like geology, vegetation, climate, and land use. Historical data, such as the MTBS dataset, informs fire frequency, while fire size distributions are derived from historical perimeters of 7,500 acres or larger, excluding smaller fires that are often quickly suppressed or cause minimal damage.

Wildfire frequency and severity follow parameter distributions that replicate the globally observed power law relationship—smaller, less severe wildfires occur more frequently than larger, catastrophic events. To capture this spectrum, the model includes ten fire sizes, ranging from 10,000 to 2,000,000 acres.

To ensure no gaps or over/under-representation of hazard at any location, ignition sites are strategically placed on a high-resolution grid with spacing determined by the idealized radius of each fire size. This radius is derived from simulated fire growth under uniform conditions (excluding topography and wind bias), ensuring consistent spatial representation. The resulting ten distinct grid resolutions account for varying fire sizes, with ignition rates adjusted by regional likelihoods. Each ignition site and fire size combination is assigned a location-specific rate of occurrence, informed by historical fire patterns, proximity to ignition drivers (e.g., transmission lines), wind severity, and climate-conditioned VPD trends, which modulate fire frequencies to reflect present-day risk.

This methodology ensures that modeled impacts align with local factors (topography, wind, fuel availability) while maintaining statistical robustness. The resulting catalog supports precise loss estimates at both county and location-level resolutions.

KCC scientists and engineers employ a stratified sampling approach to estimate wildfire losses. Stratified sampling is chosen to ensure a representative distribution of loss outcomes across the range of possible damage scenarios. By default, 1,000 samples are generated for each event to balance computational efficiency with the need for robust statistical accuracy. For each property location, the stratified sampling process considers four coverage types: building, appurtenant structures, contents, and time element. Each coverage type has its own vulnerability functions, but the losses for contents, time element, and appurtenant structures are assumed to be fully correlated with building damage. This assumption reflects the physical relationship between building damage and the associated losses to other coverage types.

After generating estimated wildfire losses for each simulated sample, the mean event loss is calculated and combined with the event rate to form the Event Loss Table (ELT). The Year Loss Table (YLT) is then aggregated by sampling from the ELT and incorporating uncertainty into the mean event losses. A

100,000-year catalog is constructed by sampling the number of events per year using an empirical distribution fitted to historical data.

Spatiotemporal Resolution

The model operates at a high spatial resolution, with losses calculated for individual property locations within wildfire event footprints. Spatially, the coverage is derived from historical fire regions and incorporates location-specific environmental factors, including the influence of climate change. Ignition points are placed on a spatially unbiased grid to ensure representative sampling across regions. The KCC Stochastic Event Catalog includes over one million potential future events across California, with event rates estimated by location to reflect regional wildfire likelihoods. Temporally, the model generates a 100,000-year catalog to support long-term risk assessment. The number of events per year and their seasonal patterns are sampled from empirical distributions fitted to historical data, ensuring realistic temporal variability in wildfire occurrence. This granular approach captures local variations in hazard intensity, vulnerability, and exposure while maintaining a robust representation of wildfire risk over time.

S-5: Replication of Known Wildfire Losses

1. ***Describe the nature and results of the analyses performed to validate the wildfire loss projections generated separately for personal and commercial residential property wildfire losses. Include analyses for the 2018, 2020, and 2021 wildfire seasons and sample population that represents the diversity of the observed event types and losses, including representative of the various eco-regions or other relevant wildfire-specific spatial areas, to the extent data are available.***

KCC has been provided with detailed claims data from insurance companies for 45 historical wildfires going back to 2016, 30 of which impacted the state of California. The list of wildfires is shown below, along with the amount of total insured value (TIV) by personal residential, commercial residential, and manufactured homes.

Fire Name	Year
Sand	2016
Tennessee (Chimney Tops 2)	2016
Atlas	2017
Nuns	2017
Tubbs	2017
Mendocino Lake Complex	2017
Thomas	2017
Creek (2017)	2017
Lilac	2017
Spring Creek	2018
Carr	2018

Fire Name	Year
River	2018
Ranch	2018
Camp	2018
Woolsey	2018
Saddleridge	2019
Kincade	2019
LNU Lightning Complex	2020
CZU Lightning	2020
SCU Lightning	2020
Carmel	2020
Creek (2020)	2020
Almeda	2020

Fire Name	Year
North Complex	2020
Babb	2020
Beachie Creek	2020
Holiday Farm	2020
Riverside	2020
Echo Mountain Complex	2020
Glass	2020
Bobcat	2020
Cameron Peak	2020
East Troublesome	2020
Slater	2020
Mussett Bayou	2020

Fire Name	Year
Dixie	2021
Caldor	2021
Marshall	2021
Hermits Peak	2022

Fire Name	Year
Gray	2023
South Fork	2024
Park	2024
Mountain	2024

Fire Name	Year
Palisades	2025
Eaton	2025

Table 3 - Wildfires included in KCC estimated claims and loss validation

Policy Type	Total TIV
Personal Residential	47,105,981,986,858
Commercial Residential	1,005,232,584,053
Manufactured Homes	142,562,092,998

Table 4 - TIV by residential policy types included in the claims and loss validation data

KCC scientists and engineers have conducted rigorous analyses of the provided high-resolution insurer claims data. KCC engineers mapped each individual claim amount to the policy generating that claim so the claims data could be analyzed separately by construction, occupancy, year built, and other property characteristics. Most of the claims were also identified by coverage.

Event	Company	Actual	Modeled
Atlas (2017)	Company A	310,808,982	331,658,801
	Company B	148,576,775	163,398,198
	Company D	96,448,346	138,352,486
	Total	**555,834,103**	**633,409,486**
Nuns (2017)	Company A	194,389,940	232,157,945
	Company C	4,464,231	1,573,488
	Total	**198,854,171**	**233,731,433**
Mendocino Lake Complex (2017)	Company A	60,710,675	67,660,691
	Company D	2,680,826	2,882,219
	Total	**63,391,501**	**70,542,910**
Tubbs (2017)	Company A	1,487,169,875	1,497,559,301
	Company B	588,926,824	578,232,672
	Company C	16,592,844	11,239,852
	Company D	710,449,144	571,259,454
	Total	**2,803,138,686**	**2,658,291,280**

Event	Company	Actual	Modeled
Thomas (2017)	Company B	165,174,966	213,044,758
	Company C	9,148,142	6,163,630
	Company D	75,519,420	116,418,121
	Total	**249,842,528**	**335,626,509**
Creek (2017)	Company D	8,087,967	9,054,253
Carr (2018)	Company B	84,916,706	112,077,377
	Company C	17,838,323	6,982,635
	Company D	114,936,597	146,502,809
	Total	**217,691,626**	**265,562,821**
Camp (2018)	Company A	2,138,479,259	2,226,456,682
	Company B	193,688,085	236,459,114
	Company C	18,562,012	28,215,580
	Company D	962,258,196	948,968,659
	Total	**3,312,987,551**	**3,440,100,035**
Woolsey (2018)	Company A	684,820,710	647,085,920
	Company B	173,340,134	195,006,061
	Company C	38,013,155	49,140,378
	Company D	221,640,033	210,685,029
	Total	**1,117,814,032**	**1,101,917,388**
Kincade (2019)	Company B	50,668,370	53,730,588
	Company C	7,524,496	7,960,134
	Company D	54,199,113	71,244,049
	Total	**112,391,978**	**132,934,770**
CZU Lightning (2020)	Company B	136,403,666	145,551,702
	Company D	31,480,080	36,623,375
	Total	**167,883,746**	**182,175,077**
LNU Lightning Complex (2020)	Company B	111,152,153	138,833,416
	Company D	37,276,921	47,748,179
	Total	**148,429,074**	**186,581,595**
Creek (2020)	Company D	4,029,377	3,999,209
Bobcat (2020)	Company B	12,177,377	18,873,633
	Company D	6,206,608	4,104,378
	Total	**18,383,986**	**22,978,011**
Glass (2020)	Company B	123,758,983	123,352,904

Event	Company	Actual	Modeled
	Company D	270,445,104	203,115,965
	Total	**394,204,087**	**326,468,869**
Dixie (2021)	Company D	18,101,800	24,434,092
Caldor (2021)	Company C	4,538,407	7,059,196
	Company D	7,145,529	2,943,241
	Total	**11,683,936**	**10,002,437**
All Events	**Total**	**9,402,750,149**	**9,637,810,173**

Table 5 - Actual versus modeled fire and smoke losses for historical wildfire events (disguised insurer data)

The Wilcoxon signed-rank test was performed to validate the generated loss outputs of the wildfire catastrophe model against actual claims data. This test is a non-parametric statistical test used to compare two paired samples when the assumption of normality is not met by the data. The test statistic is the signed-rank sum T, which is the sum of the ranks of the absolute differences between the actual and modeled losses, adjusted for the direction (sign) of the differences. The test was conducted at a 95% confidence level, meaning there is a 95% probability that the conclusion drawn from the test is correct, assuming the null hypothesis is true. The significance level (α) was set to 0.05. The p-value obtained from the Wilcoxon Signed-Rank Test on the validation dataset, comprising a selected set of claims data, was 0.2334. Hence, we fail to reject the null hypothesis and conclude that there is no statistically significant difference between the claims and modeled losses based on this validation sample.

The difference between historical and modeled annual average statewide wildfire loss costs is reasonable and expected. Given the relatively short timeframe of the historical record—40 years—it is anticipated that the modeled annual average statewide wildfire loss cost will exceed the historical loss cost. The wildfire model must take into account wildfires that have not yet occurred, but could arise in the future, including events that are more extreme than those recorded in the historical data. Generally, the annual average loss costs from wildfires are dominated by the largest loss-generating events, which typically occur during severe wildfire seasons affecting heavily populated areas. In the historical record, significant wildfires have not always impacted the most densely populated regions of California. The wildfire model must consider the potential for major wildfires with devastating impacts on all areas prone to such events, accounting for climate variations and land management practices that may influence the intensity and spread of future wildfires.

Statistical validation tests were performed to ensure the KCC US Wildfire Reference Model simulated loss estimates align with historical losses. To rigorously test the model’s accuracy, a bootstrapped confidence interval analysis is performed. This involves taking 10,000 random draws of 40-year samples from the 100,000-year stochastic catalog, simulating a historical observation period. For each sample, the difference between average annual historical and modeled loss costs is computed. The resulting distribution of differences is used to construct a 95% confidence interval. Model validation is achieved by confirming that zero fell within this interval, demonstrating no statistically significant bias between modeled and historical loss costs.

Vulnerability Disclosures

V-1: Derivation of Habitational Building Wildfire Vulnerability Functions

Building damage during wildfires occurs as a result of one or more of the following three mechanisms: embers, radiant heat, and direct flame contact. Building vulnerability functions incorporate the relative likelihood of each mechanism at every wildfire intensity level.

Embers are the most frequent cause of building damage during wildfires. When embers land on or near a building, they ignite nearby vegetation and accumulated debris on the roof, ridges, and gutters. Embers can also enter the building through openings and vents and ignite furnishings inside the building or materials in the attic.

At low wildfire intensities, small amounts of ember accumulation on various building components such as roof cover and ridges can cause components to partially burn or melt. Melted window seals, cracked windows, and localized heat damage to wall siding and eaves are some of the common damage modes in low intensity areas.

As the fire intensity increases, the ember density increases as well. At moderate intensities, the higher accumulation of embers leads to more spot fires and consequentially create more fire pathways to building damage. Burning of nearby fuel sources such as dry shrubs, fences, and appurtenant structures result in radiant heat or direct flame contact sufficient to cause exterior and interior building damage. Exterior components like wall sidings and roof covers can have localized combustion that has not spread to other components. Cracked and broken windows and doors, and damage to gutters and soffits are other common damage modes at moderate intensities.

At high intensities, which affect areas that typically fall within the fire perimeter, all three mechanisms of damage are prevalent. These areas are inundated with high ember volume and experience the highest possible radiant heat flux. Fire could penetrate the building or cause extreme damage to exterior components.

The vulnerability of a building to radiant heat depends on the intensity of the fire surrounding it. The radiant heat must be hot enough and the exposure time long enough for combustible building components to ignite or suffer other forms of degradation, such as glass breakage or delamination in windows or warping and melting of wall siding.

Post-event surveys have revealed that building damage due to radiant heat is not as prevalent as damage due to embers. For building damage to ensue, the source of the heat must be close to the building—less than 20 ft away. Direct flame contact results from a burning fuel source (e.g., fence, dry vegetation, appurtenant structure) close to a building.

The component damage modes and building resistance to varying degrees of hazard severity have been demonstrated by academic literature on laboratory experiments of building components subjected to artificially simulated wildfire impacts, including ember showers, radiant heat, and direct flame exposure (Cohen 2000; Cohen 2004; Manzello et al. 2012; Hakes et al. 2017; Quarles 2017; Hedayati et al. 2019, Hedayati et al. 2022; Nguyen and Kaye 2021; Nazare et al. 2021; IBHS 2021; Barforoush and Du Preez 2022; Lopes et al. 2023; Quarles et al. 2023; Hedayati et al. 2023).

Additionally, post-event surveys and data show how these damage modes are manifested in wildfires. Site surveys are conducted to determine the degree of damage to individual structures. KCC engineers and other organizations such as the Insurance Institute for Business & Home Safety (IBHS) conduct site surveys following wildfire events. The surveys involve collecting information to identify the severity of damage to impacted structures, as well as the source fuels associated with the damage.

Development of secondary characteristics also incorporates the relative impact of fire damage mechanisms. The wildfire mitigation measures listed in the following table help to reduce the likelihood of ignition from at least one of these ignition mechanisms.

Mitigation Measure	**Helps mitigate ignition due to**		
	Direct Flame	**Radiant Heat**	**Embers**
Defensible Space	**Yes**	**Yes**	**Yes**
Non-combustible Roof Cover	**Yes**	No	**Yes**
Ventilation Screens	No	No	**Yes**
Enclosed Eaves and Overhang	No	**Yes**	**Yes**
Non-combustible Wall Siding	**Yes**	**Yes**	No
Strong Glazing Type	**Yes**	**Yes**	**Yes**
Fire Sprinklers	**Yes**	No	**Yes**
Compliant Deck and Attached Structures	**Yes**	**Yes**	**Yes**
Non-combustible Fence	**Yes**	**Yes**	**Yes**
Minimum Distance to Closest Appurtenant Structure	**Yes**	**Yes**	**Yes**
Minimum 6-inch Non-Combustible Vertical Clearance	No	No	**Yes**
Roof Geometry	No	No	**Yes**
Gutters	No	No	**Yes**
Fire-Resistant Shutters	**Yes**	**Yes**	**Yes**
Fire-Resistant Exterior Doors	**Yes**	**Yes**	**Yes**
Fire-Resistant Skylights	No	No	**Yes**
Fire-Resistant Garage Doors	**Yes**	**Yes**	**Yes**
IBHS Wildfire Prepared Home	**Yes**	**Yes**	**Yes**

Table 6 - Summary of the effectiveness of each mitigation measure in preventing damage from the three causes of wildfire damage.

3. Provide a flowchart documenting the process by which the wildfire vulnerability functions for habitational buildings for personal and commercial residential properties are derived and implemented.

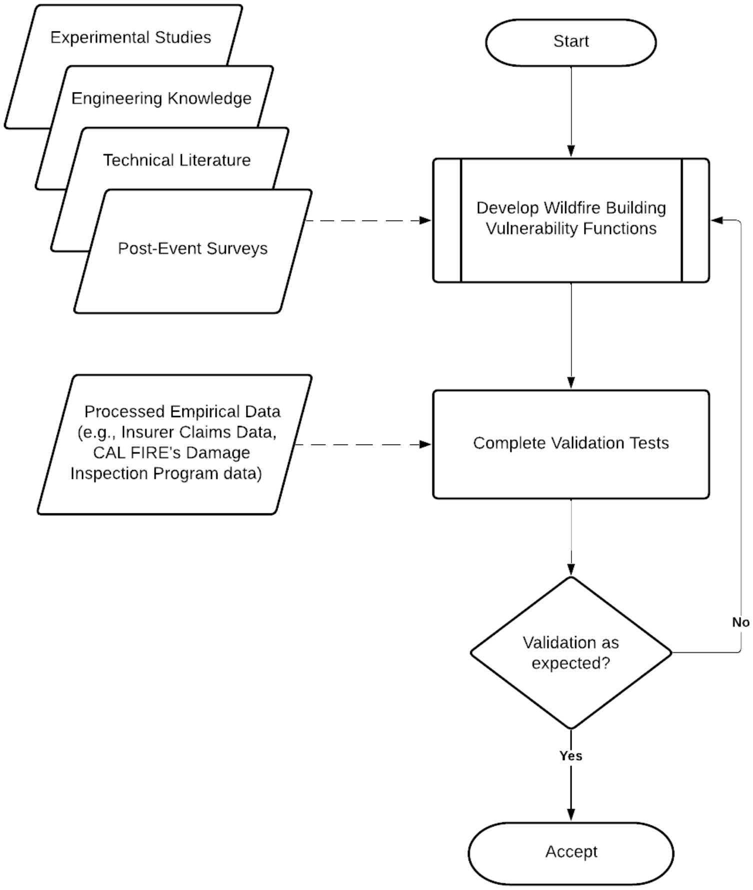


Figure 24 - Flowchart documenting process of wildfire building vulnerability function development.

4. ***Describe the nature, source, and extent of any wildfire claims data used to develop the personal and commercial residential building wildfire vulnerability functions, including, as applicable, summarizing laboratory or field testing and post-event site investigations; provide a brief description of the resulting use of these data in the validation of the wildfire vulnerability functions. Describe in detail the breakdown of data into number of policies, number of insurers, dates of wildfire loss, amount of wildfire loss, number of exposures, and amount of dollar exposure, including treatment of incomplete and missing values; separated into personal residential building structures, commercial residential building structures, and manufactured homes. If the end-user's wildfire claims data can be used in the development of the vulnerability functions or if the end-user can make adjustments to property value or insurance-to-value (ITV) assumptions to the base claims data, identify and justify the range of possible adjustment to the base claims data, including insurance-to-value (ITV) assumptions, assumptions made due to incomplete wildfire claims data, and adjustments for depreciation. Justification for all actual adjustments made for modeling losses for a specific rate filing will need to be submitted with such filing, including a comparison of how those actual adjustments fall within the range of possible adjustments.***

Development of wildfire vulnerability functions is performed in two phases, as shown in Figure 24. The first phase involves the derivation of vulnerability functions based on several sources of information, including scientific literature that pertain to experimental studies, post-event surveys, and other technical literature such as building codes, test standards, and data sheets. The second phase is validation using CAL FIRE DINS and claims data.

CAL FIRE DINS data used for validation consists of damage observation data from 27 historical wildfires in California (Table 7). DINS data classifies the locations surveyed by CAL FIRE into the following damage states: “No Damage”, “Affected”, “Minor”, “Major”, and “Destroyed”. The proportion of buildings in each damage state is used for validating the underlying assumptions of the vulnerability functions.

Event	Number of Observations in DINS
Camp	23,624
Eaton	18,421
Palisades	12,072
Tubbs	6,023
LNU Lightning Complex	5,121
CZU Lightning Complex	4,820
Glass	4,767
Caldor	4,444
Dixie	3,841
Creek	3,467
Valley	2,493
Woolsey	2,007
Carr	1,890
Kincade	1,568
Nuns	1,554

Event	Number of Observations in DINS
Atlas	1,372
Thomas	1,365
Butte	964
Redwood	580
River	534
Slater	449
Ranch	273
Bobcat	228
Lilac	221
Saddleridge	122
Sand	4
Carmel	1

Table 7 - Historical wildfires in the CAL FIRE DINS data used to validate building vulnerability functions.

KCC has established a comprehensive framework for acquiring and analyzing insurer claims data, as illustrated in Figure 25. KCC maintains an external Claims Data Request Letter and internal Claims Processing Guide to facilitate the receival and use of claims data. Additionally, insurers are provided detailed guidance on the required fields and key considerations for providing claims information, including methods for separating wildfire catastrophe losses from attritional claims.

Prior to analysis, claims data are meticulously reviewed for completeness, accuracy, and reasonability. KCC engineers mapped each individual claim amount to the policy generating that claim so the claims data could be analyzed separately by construction, occupancy, year built, and other property characteristics. Most of the claims were also identified by coverage. The contemporaneous exposure data were provided for all policies in force during the dates of each wildfire (not just those with claims), which is required for estimating the MDRs. KCC communicates with individual insurers to confirm interpretation of fields and to share control totals. The modeled and actual losses were compared by building attribute, such as construction type and year built.

KCC has been provided with detailed claims data from 5 insurance companies for 45 historical wildfire events across the US, 30 of which impacted the state of California.

Insurers	Events	Losses ($ billion)
5	45	5.84

Table 8 - Breakdown of claims data used for validation of vulnerability functions

The number of policies and the amount of exposure by policy type is summarized in the following table.

Policy Type	Number of Policies	Exposure ($)
Personal Residential	93,208,427	47,105,981,986,858
Commercial Residential	69,776	1,005,232,584,053
Manufactured Homes	908,070	142,562,092,998

Table 9 - Number of policies and amount of exposure used for detailed claims analyses

The amount of loss data analyzed can be separated by line of business as follows: $5.47 billion for personal residential, $121 million for commercial residential and $247 million for manufactured homes.

KCC professionals maintain ongoing relationships with our client companies, particularly primary insurers who have shared their detailed claims data. Along with conducting independent post-event damage surveys, KCC scientists and engineers accompany our clients' claims adjusters after events to obtain firsthand knowledge on how policy provisions and exclusions and other contractual provisions are applied during the claims adjusting process. To the extent possible, these factors are captured in the KCC US Wildfire Reference Model. With respect to wildfire claims data, wildfires from 2004 to 2025 are used in the model validation process. This means the validation data are relatively current with respect to capturing today's construction practices and characteristics. The following workflow chart shows the KCC process for analyzing client data.

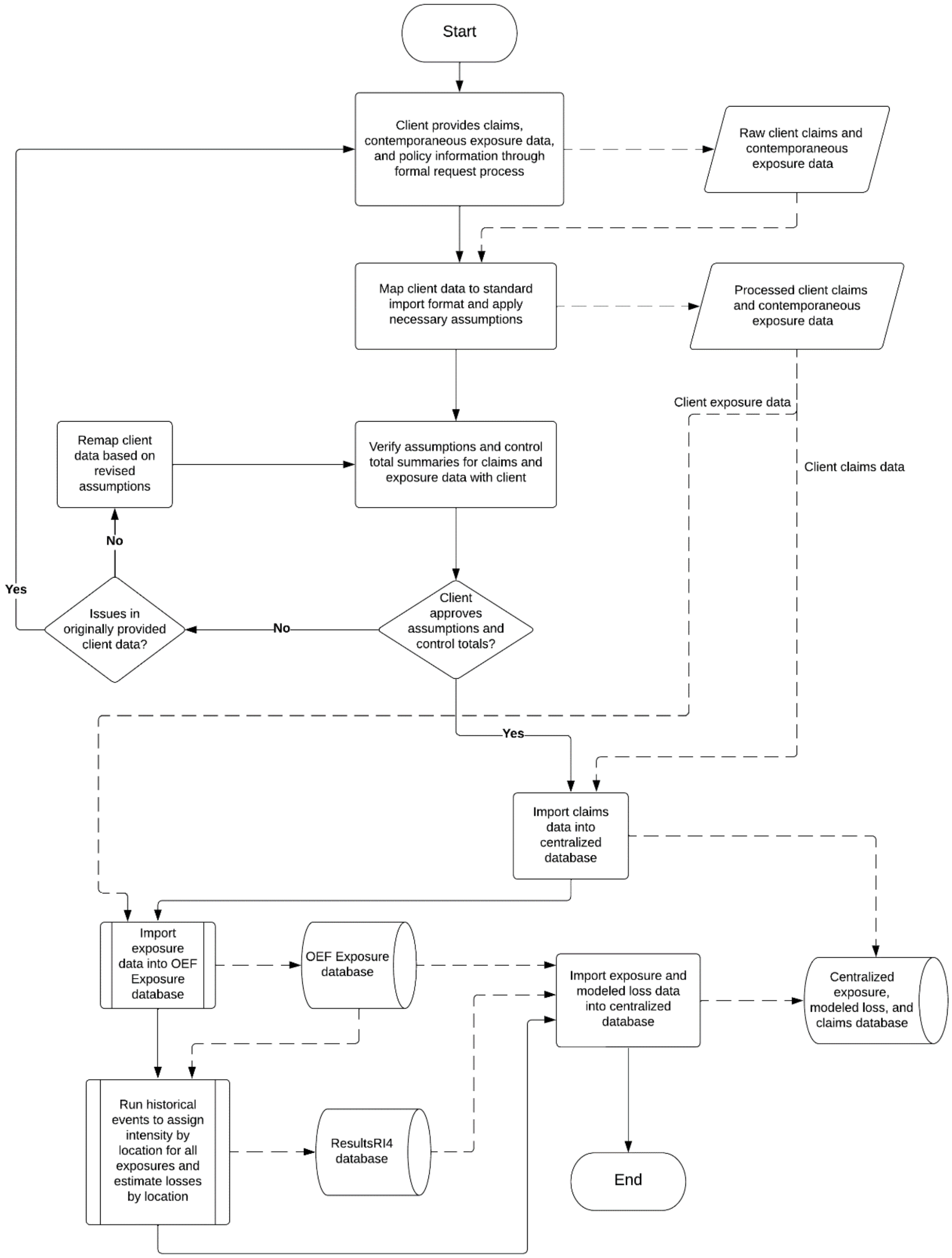


Figure 25 - Workflow diagram for analyzing insurer claims data and preparing the data for model validation

6. Describe the sources, quantification, and treatment of uncertainties associated with the building wildfire vulnerability functions.

The vulnerability functions provide estimates of the mean damage in response to the wildfire intensity experienced at the location. For each building type (combination of construction, occupancy, year built, and height) there are four vulnerability functions representing the MDRs for the building, appurtenant structure, contents, and time element coverages.

The MDRs from the vulnerability functions are expressed as percentages of the coverage replacement values. For each MDR, the RiskInsight® Financial Module considers the full range of damage levels around the mean (the secondary uncertainty) with empirical distributions. Empirical distributions are chosen because actual wildfire losses do not exhibit a simple central behavior, and these distributions better correlate with reality and actual claims experience.

RiskInsight® represents the secondary uncertainty distributions as discrete bins, where each bin corresponds to the probability of experiencing a specific damage level, and every distribution includes a non-zero probability mass at 0 and at 100 percent loss. Secondary uncertainty is always considered in loss calculations.

There are 100,000 secondary uncertainty distributions for MDRs ranging from 0.00001 to 1. KCC scientists developed a complex iterative process to create these distributions so that the following mathematical constraints are met:

- The probabilities add up to 1
- The MDRs are maintained
- The probability mass at 0 falls as the MDR increases
- The probability mass at 1 rises as the MDR increases

The diagram below illustrates the implementation of secondary uncertainty in the KCC US Wildfire Reference Model.

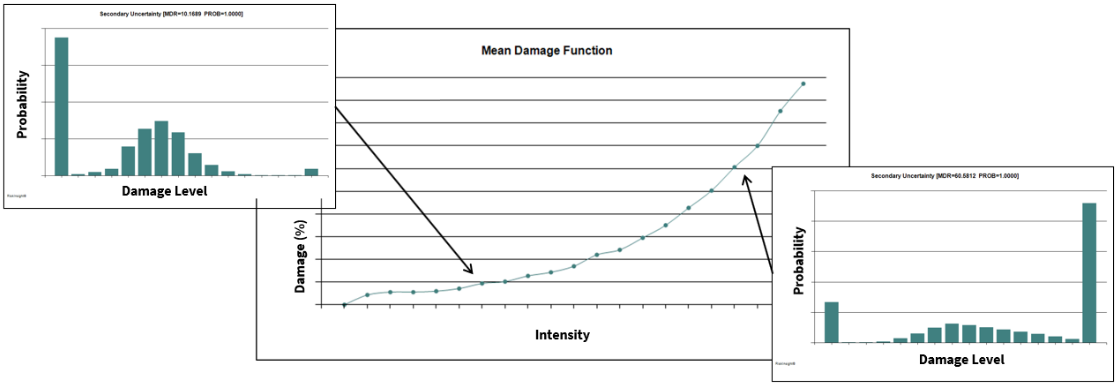


Figure 26 - Varying secondary uncertainty at different MDRs

7. ***Describe the categories of the different building wildfire vulnerability functions for personal and commercial residential buildings. Specifically, for every unique building wildfire vulnerability function, include descriptions and consideration in the development of: the building types, building construction elements (including, as applicable, statewide and county wildfire-related building codes and enforcement) and primary building characteristics; structure separation and density, ecoregions or other justified, relevant delineation of distinctive fire regimes within the state of California; year of construction; and occupancy types. Describe and justify assumptions made based on year of construction alone or together with other factors. Provide the total number of building wildfire vulnerability functions available for use in the catastrophe model for personal and commercial residential classifications.***

There are over 400 total building vulnerability functions in California for personal and commercial residential classifications based on the following primary building characteristics:

- Construction
- Occupancy
- Number of stories
- Year-built

Construction

Primary construction materials influence a structure's potential vulnerability when exposed to wildfire. Manufactured homes and wood frame structures are generally more vulnerable than buildings constructed of concrete and steel. The following table lists the base construction types.

Construction Type	Description
Wood Frame	Buildings where the exterior walls and roof frame are constructed using wood studs. The wall sidings are constructed using wood or other combustible materials, including wood iron-clad, stucco on wood, or plaster on combustible supports. Also includes aluminum or plastic siding over frame.
Masonry	Buildings where the exterior (and some interior) walls are load-bearing and constructed of masonry, non-combustible, or fire resistive materials such as adobe, brick, concrete, gypsum block, hollow concrete block, stone, tile, or other non-combustible materials. No steel reinforcement. The roofs are typically made of wood frame construction.
Reinforced Concrete	Buildings where the beams and columns are constructed of reinforced concrete. Infill walls are typically constructed of masonry. Floors are constructed of concrete slabs, steel, or wooden joists.
Steel	Buildings where the beams and columns are constructed using steel.
Light Metal	Buildings constructed of light gauge steel frames. The walls can be constructed of brick veneer, Exterior Insulation and Finish System (EIFS), plywood, corrugated metal sheets, etc. Roof covering can be corrugated steel or similar to wood frame buildings. Here columns and beams are not rigidly connected and do not act as a frame. Lateral resistance is made by braces.
Unknown	Represented by an exposure-weighted average of the above and does not include manufactured homes.

Construction Type	Description
Manufactured Home	Prefabricated housing units trucked to the site and placed on isolated piers, jack stands, or masonry block foundations. Floors and roofs of mobile homes are usually constructed with plywood and outside surfaces are covered with vinyl or sheet metal.

Table 10 - Construction types in the KCC US Wildfire Reference Model applicable to personal and commercial residential classifications

Occupancy

Occupancy type is also an indicator of building vulnerability. This is mainly due to differences in architectural requirements, construction practices and level of engienering attention. Site built homoes are grouped into either single-family home, multi-family home, or condo unit (owner or condo association).

Number of Stories

The number of stories of a building impacts its vulnerability. Taller buildings are typically constructed to a more stringent set of building code requirements and fire safety mechanisms. They receive more attention to detail than their low-rise counterparts. Taller buildings also tend to use reinforced concrete and steel as construction material compared to wood-frame for shorter buildings. Reinforced concrete and steel are less vulnerable than wood-frame buildings. The KCC US Wildfire Reference Model height classifications are shown in the following table.

Description	Number of Stories
Single Family Home	1-3
Manufactured/Mobile Home	1-3
Multi-Family homes, apartments, and Condominiums	1-3
	4-8
	≥ 9
	Unknown

Table 11 - Height bands for personal and commercial residential classifications

Year Built

California has made several code changes over the years that warrant additional year-built bands in the KCC model. The first unified building standards in California were established in 1978 (effective in 1979) under the California Code of Regulation Title 24. The California Building Code (CBC) focused on auxiliary components such as mechanical, electrical, and fire protection, including fire alarms and sprinkler systems.

Between 1979 and 1996, many editions of the CBC were released. This included the enactment of Public Resources Code (PRC) 4201-4204, which required State Responsibility Areas (SRAs) to be classified into Fire Hazard Safety Zones (FHSZs) and to be assigned ratings reflecting the severity of fire hazard expected in these zones. The goal of the FHSZs was to provide specific designations for the application of mitigation activities, which included defensible space and the use of specific construction materials within the WUI.

A few years later, the enactment of PRC 4291 required homeowners in wildland areas to maintain a 30 ft buffer of defensible space around structures, or to the property line. After the Tunnel Fire in 1991, the Bates Bill (AB 337) was passed, which mandated evaluation of the potential fire hazard in Local Responsibility Areas (LRAs) and the notification of local jurisdictions of areas where Very High Fire Hazard Severity Zones (VHFHSZs) existed.

In 1997, California law was updated to mandate the requirement for Class A fire-resistant roofs in high hazard areas. Assembly Bill 423 simplified enforcement of the new roofing codes by outlawing the use of unrated roofing materials throughout the state.

In 2008, Chapter 7A of the CBC was enacted. Every three years since 2008, Chapter 7A has been reviewed by a committee within the Office of the State Fire Marshal. To meet the requirements of Chapter 7A, buildings must have specific fire-resistant features:

- Roof covers are required to have a Class A roof such as Class A shingles, Tile, or metal
- Gutters, whether metal or vinyl, must include covers to prevent the accumulation of debris
- While enclosed eaves are not mandatory, open eaves must use double the materials for blocking and rafters to enhance fire resistance
- Ventilation openings must be approved by the Office of the State Fire Marshal Building Material Listing Program to ensure they are both flame and ember-resistant
- Exterior walls, doors, windows, and deck walking surface materials must meet at least one of the fire-resistant standards. For example, windows must comply with one of these options: multipaned glazing with at least one tempered pane, glass block units, a fire-resistance rating of at least 20 minutes, or meeting the requirements of Surface Feet per Minute (SFM 12-7A-2) requirements.

The California building regulations are incorporated into the KCC year-built bands, as shown in the following table.

Year-built Band	Year-built Range
YBB1	≤ 1978
YBB2	1979-1996
YBB3	1997-2007
YBB4	≥ 2008
Unknown	

Table 12 - California year built bands in the KCC Wildfire Model

8. ***Describe the process by which local and statewide fire-fighting practices, or other active fire- suppression strategies are considered in the development of vulnerability functions, if applicable. If any of these factors are also considered in the hazard modeling, describe the process by which their effects are apportioned between hazard and vulnerability analysis.***

Fire suppression is predominantly captured in the hazard module of the KCC US Wildfire Reference Model. Within the hazard module, KCC scientists calculate the resources available for suppression and how successful they are likely to be for each location, which depends on access to the fire, the character of the vegetation, and the local distribution of the structures.

Community-level mitigation programs that improve fire suppression strategies are captured in the vulnerability module. These programs are the Firewise USA program and the Fire Risk Reduction Community List (FRRCL).

Firewise USA Program

The Firewise USA program (Firewise) is developed and maintained by the NFPA. NFPA identifies communities with “Firewise sites in Good Standing” for their proactive wildfire preparedness and mitigation efforts. Applicants for Firewise can be any community in the US with a minimum of eight dwelling units and a maximum of 2,500 dwelling units. Applicants may join Firewise on approval of their application, with an annual renewal requirement. There are over 2,000 Firewise communities in the US, including over 1,000 communities in California as of 2024.

To be recognized as a Firewise community, the community must conduct wildfire risk assessments with local fire departments and develop wildfire mitigation planning that aligns with the assessments. The wildfire risk assessments focus on mitigation measures of buildings, vegetation types, housing density, and topography, among other factors. The applicant must also report the implementation of mitigation plans and investments (i.e., time and/or expense) through NFPA Firewise program management portal.

Through strategic planning, education, and implementation of mitigation measures, Firewise communities work to reduce their risk of wildfire losses.

Fire Risk Reduction Community List (FRRCL)

The Fire Risk Reduction Community List (FRRCL) is developed and maintained by The California State Board of Forestry and Fire Protection (the Board). The first iteration began July 1, 2022 and was updated in 2024. FRRCL is a list of local agencies (e.g., city, county, fire district) that meet best practices for local fire planning. The local agencies on the list are eligible to receive priority in fire prevention grant funding applications. There are 11 cities, 7 counties, and 32 districts that met the FRRCL eligibility criteria on 2024 FRRCL.

To be eligible for the FRRCL, a local agency must meet certain criteria developed by the Board. FRRCL eligible criteria are developed to ensure that a local agency qualifying for the list demonstrates both compliance with the Board’s requirements and dedication to fire planning that exceeds state minimum standards.

For example, a city or county must comply with Subdivision Survey Reports by adding secondary egress to communities to improve fire safety. Otherwise, the communities will be re-designated as Very High Hazard Zones where more stringent requirements on wildfire resistance are required. Alternatively, applicants may qualify by developing a plan to address mitigation planning and implementation efforts. There are also qualification criteria associated with adopting building codes and wildfire regulations, coordinating with other wildfire protection programs, vegetation management plans, and equivalent means of local fire planning.

FRRCL is a new program, and the communities on this list have recently established a wildfire mitigation plan verified by the Board. The impact on individual communities will not be immediate. Widespread implementation of these plans will take time and depends on several factors, including local enforcement and available community resources. Over time, the effectiveness of mitigation plan measures is expected to grow, though the rate of impact will likely vary by community. During each update of the KCC Reference Model, these impacts will be reassessed using the most recent evidence obtained from DINS and insurer claims data along with post-event survey observations.

9. ***Describe the relationship between wildfire vulnerability functions for habitational buildings/structures and secondary and appurtenant structures, and their consistency with insurance company wildfire claims data, including description and justification for any assumptions regarding the characteristics and treatment of secondary and appurtenant structures.***

   In the KCC US Wildfire Reference model, the losses for appurtenant structures are calculated separately from other coverages.

Building-to-building fire spread can exacerbate the rate of wildfire spread in urban areas. If an appurtenant structure catches fire within 20 feet of a building, it can transfer heat to the main structure and cause the main structure to ignite. Appurtenant structures in between buildings can act as a bridge and allow fire to more easily spread as it goes from main structure to appurtenant structure, to the next main structure. A nearby appurtenant structure significantly increases the vulnerability of a property because if it ignites, it can cause the main structure to be damaged by direct flame impingement, radiant heat, and/or ignition by embers. Proximity of buildings to combustible appurtenant structures is a secondary characteristic in the KCC Wildfire Model.

The relationship between building and appurtenant structure vulnerability functions used in the KCC Wildfire Reference Model is consistent with insurance claims data.

10. ***Describe the assumptions, data (including both industry and end-user's insurance wildfire claims data), methods, and processes used to develop building wildfire vulnerability functions when:***

    A. residential construction types are unknown.

    B. one or more primary building characteristics are unknown, but one or more wildfire-relevant or secondary characteristics of buildings are known.

    C. one or more wildfire-relevant or secondary characteristics of buildings are unknown.

    D. building input characteristics are conflicting.

    Separate building vulnerability functions have been developed for construction type, year-built, occupancy type, and number of stories. Beside the distinct applicable combinations of those characteristics, vulnerability functions for cases where one or more of these building attributes is unknown/missing were developed by exposure weighted averaging the known vulnerability functions to create composite vulnerability functions to handle cases where one or more attribute is unknown.

    When the primary building characteristics are unknown, but one or more of the secondary characteristics are known, the composite vulnerability function is modified appropriately by the known secondary characteristics.

    When secondary characteristics of buildings are unknown, no modifications are made to the mean damage ratio as returned by the combination of primary characteristics.

    Prior to running a loss analysis, exposure information must be imported into RiskInsight®. During import, RiskInsight® performs validation on all input exposure attributes. The valid data types and input options are detailed in the *RiskInsight® OEF2 Database Schema* user documentation. An initial level of validation ensures that on an individual risk characteristic resolution, such as wall siding type, only valid and non-conflicting information is entered. All exposure locations contained in the input file that do not pass the validation rules due to conflicting input characteristics are reported in the Exposure Import Log, are not imported into RiskInsight®, and are not available for loss analysis.

11. ***Identify the direct flame contact, radiant heat exposure, ember exposure or deposition rate, and relevant residence time (e.g., the duration of direct flame contact, radiant heat exposure, and ember exposure) at which the wildfire model begins to estimate damage; if different wildfire behavior-related factor(s) are used to estimate when damage begins (for example, flame height, fire intensity), or if functions are instead based on statistical analysis of historical loss data, describe and provide justification.***

    The KCC Wildfire Model intensity depends on flame lengths from surface and crown fires, branding by ember transport, urban conflagration, and suppression, as discussed in Disclosure H-2 #5. By design, the lowest value of KCC wildfire intensity correlates to areas where damage starts. The model estimates non-zero damage starting from the lowest intensity.

12. Describe the threshold of damage (e.g. percentage of damage) at or above which the wildfire catastrophe model assumes a total building loss.

The vulnerability functions are computed as the ratio of repair cost to replacement cost and not a ratio of physical damage. Therefore, no assumption is required for a total loss threshold. For example, a repair cost of 70% or 80% of the total value can be realized when physical damage is, say 30%. The figure below shows the proportion of claims that fall in each MDR bin. Each bin has non-zero proportion of the claims indicating that no assumption regarding a threshold is necessary.

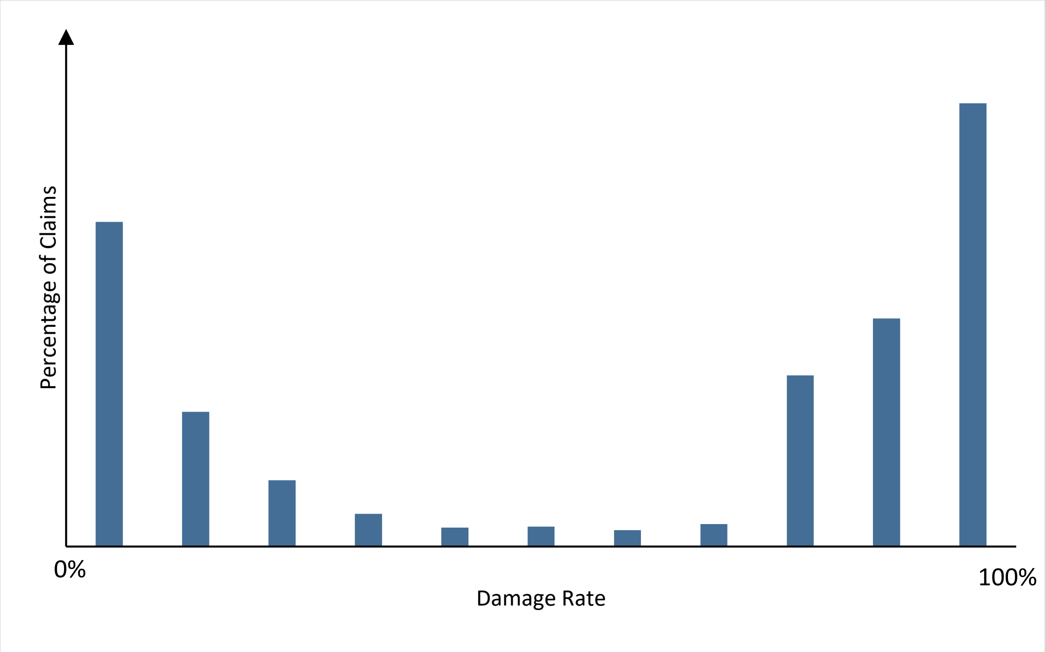


Figure 27 - Percentage of claims that fall into different MDR bins.

V-2: Derivation of Building Contents Wildfire Vulnerability Functions: loss and smoke

2. ***Provide a flowchart documenting the process by which the contents wildfire vulnerability functions are derived and implemented.***

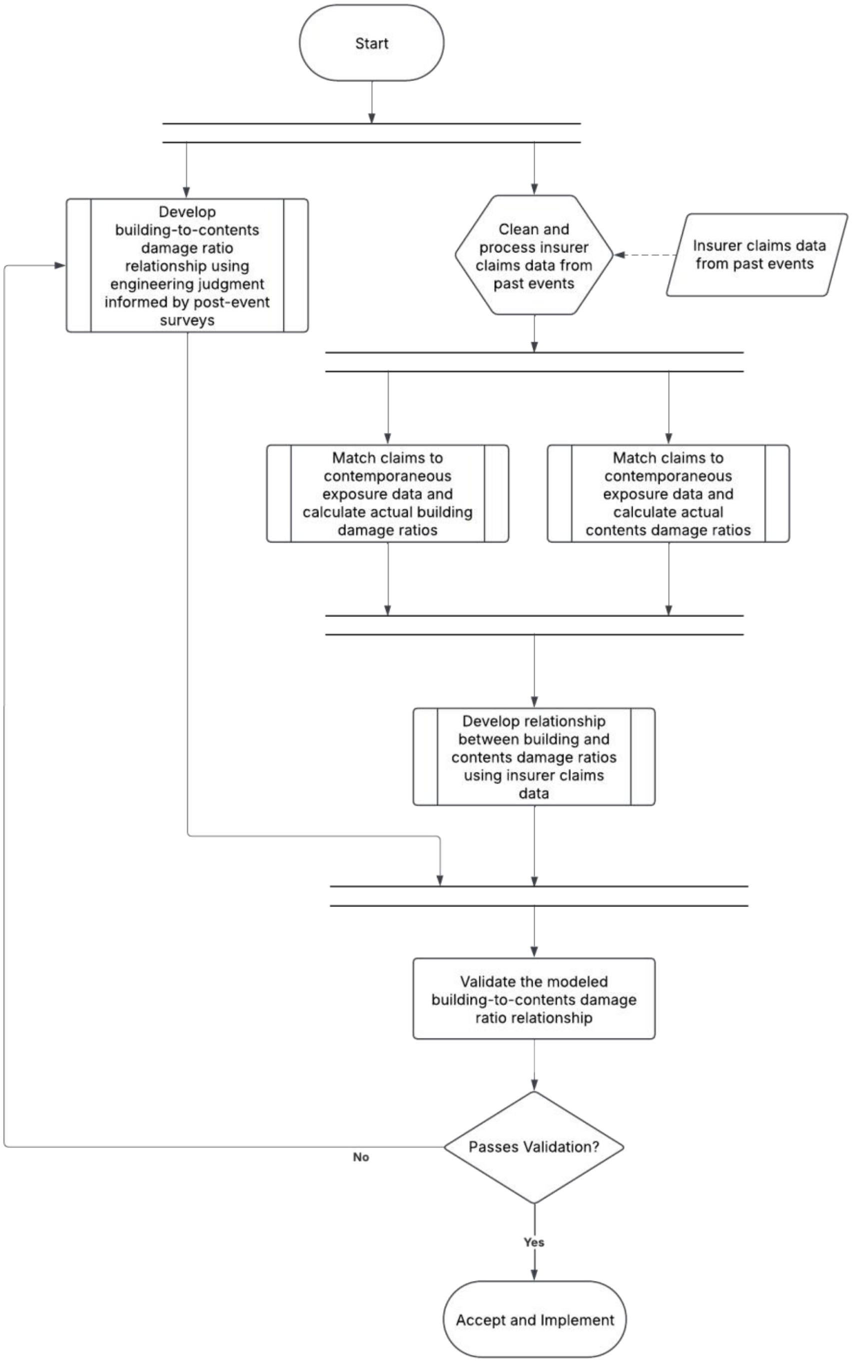


Figure 28 - Flowchart documenting process of wildfire contents vulnerability function development

3. ***Describe the assumptions, data, methods, and processes used to develop and validate the contents wildfire vulnerability functions. Describe and justify assumptions made based on occupancy alone or together with other factors citing scientific literature supporting the chosen methodology and assumptions.***

Fire

The process of developing the contents vulnerability functions for the fire sub-peril is shown in Figure 28. Contents damage depends on the level of damage to the building. As such, the KCC US Wildfire Reference Model uses a building-to-contents relationship to estimate the contents losses and the contents wildfire vulnerability functions correspond to building vulnerability functions—as the building damage increases so does the contents damage.

However, the relationship between building damage and contents damage is not constant. Contents are damaged only after a threshold level of building damage is reached. At low building damage, such as minor roofing and wall siding damage or cracked windows, there is no contents damage because the envelope elements are still intact, and the flames did not reach inside the building.

As the building envelope deteriorates, heat and flames enter the structure and damage exposed contents through broken windows and doors, as well as small crevices in the wall bottom and top plates and roof eaves. In addition, localized combustion of exterior walls leads to smoke damage. At this point, the contents to building damage ratio starts increasing nonlinearly.

Once the building envelope is breached, fire and heat penetrate the roof and wall sheathing, damaging the interior finishes. In addition, the smoke generated by burning building components leads to greater contents damage and higher contents to building damage ratio.

When the fire reaches the electrical wiring chase, duct or space heaters, and other flammable contents and fire convection becomes evident, the contents damage exceeds the building damage.

The building-to-contents relationship function is developed based on engineering judgment informed by academic literature (Barret and Quarles 2024; Laranjeira and Cruz 2014; Stiefel et al. 1990) and post-event surveys, and are further validated using insurer claims data.

Smoke

Development of the contents vulnerability functions for smoke follows a similar method as that for fire where contents damage is correlated with building damage. However, the relationship between contents damage and building damage is different for smoke than fire.

Smoke impacts a much larger area with lower damage severity relative to fire. Low intensities occur near the edge of the smoke footprint, which is farthest away from the area impacted by fire. At low smoke intensities, typical actions required are deodorizing and replacement of few contents. Therefore, at low intensities, the smoke MDR for building and contents are low and smoke MDR is higher than building MDR.

At medium to high intensities, closer to the fire, chemical damage, and soot deposition results in many more contents to be discarded. There is also accompanying building damage on exterior and interior walls, ceilings, and floor. Detoxification, soot-removal, and other chemical treatment can be necessary. Contents MDR would still be higher than the building MDR. More details are provided in the response to Disclosure V-2 #5.

4. ***Provide the total number of contents wildfire vulnerability functions. Describe whether different and multiple contents wildfire vulnerability functions are used for personal residential building structures, commercial residential building structures, and manufactured homes and the basis for such, including without limitation as applicable, unit location for condo owners, multiplexes, and apartment renters and differentiation between various habitational building and unit classes. Describe as well whether building occupancies are accounted within each such content vulnerability functions.***

   There are over 400 contents vulnerability functions. For each combination of distinct building characteristics, a unique building vulnerability function is developed from which the contents vulnerability function is derived. As a result, different contents vulnerability functions correspond to different building characteristics.

5. ***If smoke damage is explicitly modeled, describe the assumptions, data, methods, and processes used to develop and validate the contents smoke-related vulnerability functions and their relationship to the structure and contents wildfire vulnerability functions; if smoke damage is not explicitly modeled, describe the treatment of smoke damage within all of the wildfire vulnerability functions for contents, including with respect to different habitational building and unit classes.***

   Smoke damage is explicitly modeled in the KCC US Wildfire Reference Model. Unlike fire damage, which typically causes extreme damage over a small area, smoke causes low levels of damage across a large area. When smoke infiltrates a house through vents, openings, and HVAC, interior elements can become damaged. Small smoke and soot particles infiltrate pores and cracks in wood, walls, and fabrics (Averett 2024).

   While some contents can be salvaged, mostly in areas affected by low smoke intensities, the porousness of the material greatly impacts the cost and effectiveness of salvage efforts. Wood floors, for example, can absorb smoke particles that are extremely difficult to remove, and upholstered furniture, curtains, and rugs may need to be completely replaced. As a result, contents and some interior finishing materials are most likely to be damaged from smoke exposure.

   Repair costs for smoke damage can vary significantly depending on the type of smoke damage and the corresponding repair strategy – soot and smoke residues can linger on walls, carpeting, and furniture, and cleaning charges can vary depending on the amount of exposed property as well as the time since the smoke impact. The more time that passes, the more difficult the cleaning process becomes and therefore, the higher the costs.

   Toxic odors and stains can also remain close to absorbent surfaces such as upholstered furniture, carpeting and walls. Deodorizing methods such as ozone treatment, thermal fogging, and whole-house purifying treatments are used to eliminate odors by breaking down the odor-causing compounds.

   Smoke vulnerability functions are developed through expert judgment and validated against claims data. Figure 29 shows the various repair actions required at different smoke intensity levels. Locations affected by low smoke intensities result in milder damage modes and fewer impacted rooms and contents. Typical actions required at low intensities are deodorizing and replacement of few contents. Therefore, at low intensities, the smoke MDR for building and contents are low. The prevailing rates for deodorizing can vary between 0.1% to 0.5% of the total building value. For example, if the average replacement value of a house is $600,000, the repair cost can vary from $600 to $3000. However, not every house impacted by the low intensity bands of the footprint would require repair. Historical loss experience has shown that most houses that fall within the low intensity smoke affected areas do not report a loss. Therefore, to derive a portfolio level MDR, the damage rate at a single building level is appropriately scaled down.

   At medium levels of smoke intensity, chemical damage is possible, caused by remnants of microscopic particles sticking to metals, fabrics, and walls. Such damage requires detoxification of surfaces through treatments that break down the chemicals in combination with ozone treatments to remove them from the property. Many contents such as furniture, upholstery, curtains, and carpet may not be salvageable and therefore need replacement due to deposits of visible soot particles. Light soot removal may also be required in isolated areas, followed by further cleaning and painting. The repairs are more expensive and therefore the MDRs for both building and contents are much higher than that at lower intensities. The repair costs for a single location can vary from 0.8% to 2.5% of the building value. These ratios are further scaled to reflect the likelihood of incurring this level of smoke damage.

At high levels of smoke intensity, typically just outside the fire perimeter, much higher damage can be observed. There can be heavy soot deposition both inside and outside the building. Smoke and soot can enter HVAC or electrical ducts and can cause significant cleaning costs. Even building components such as wall siding, roof cover, doors, and windows may need replacement. The repairs will also involve higher costs resulting from more severe levels of toxic odors and chemical deposits. The costs can vary between 3% to 15% of the building value. However, such high costs are only incurred by small proportion of the smoke exposed locations, which is captured by scaling down the building level damage rate to obtain a portfolio level MDR.

The contents MDR at all intensities is set higher than the building MDR because smoke damaged contents are typically replaced whereas smoke damaged building components such as walls, floors and ceilings are treated or repaired.

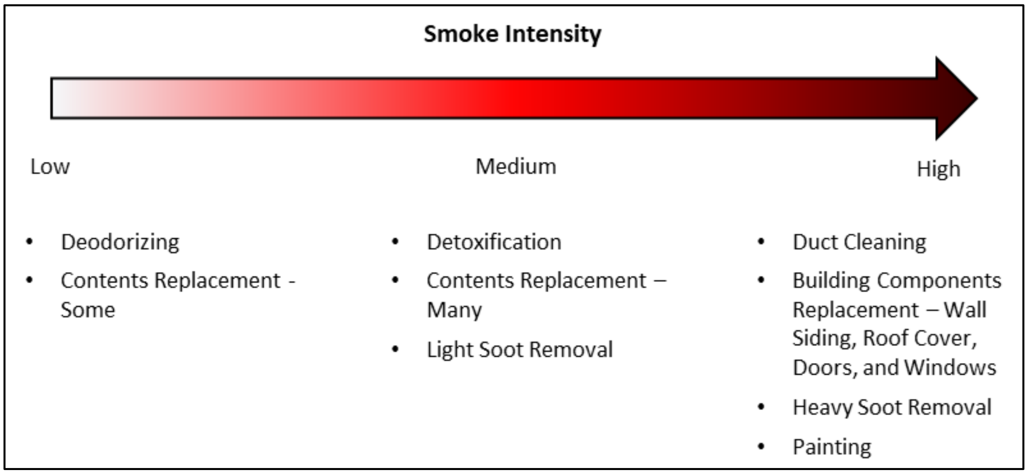


Figure 29 - Types of smoke-related repairs classified by intensity.

Smoke vulnerability functions are validated using insurance claims data.

6. ***Describe the sources, quantification, and treatment of uncertainties associated with the contents' wildfire vulnerability functions.***

The sources, quantification, and treatment of uncertainties associated with contents vulnerability functions are the same as the uncertainty associated with the building vulnerability functions, as outlined in Disclosure V-1 #6. The selection of secondary uncertainty distributions is based on the MDRs from the contents vulnerability functions.

V-3: Derivation of Time Element Wildfire Vulnerability Functions

3. ***Describe and justify the assumptions, data, methods, and processes used to develop and validate the time element wildfire vulnerability functions, including time to repair or replace damaged habitational structures and treatment of relevant spatiotemporal data and selection of resolution, citing scientific literature supporting the chosen methodology and assumptions.***

Losses causing time element claims can be divided into direct losses and indirect losses, which are captured using a building-to-time element relationship. Direct time element losses refer to the time it takes to repair the damaged building to the point where the occupants can return, which is dependent on the building damage ratio. Indirect time element losses are a combination of factors related to the event, including evacuation, loss of access to the building due to infrastructure disruption, and the length of time before repairs can begin. This relationship was developed based on engineering judgment supported by scientific literature (Peloton 2020, Lee et al. 2024, Alexandre et al. 2015), cost analysis, repair analysis, historical data, and post-event site investigations.

The development of the time element vulnerability functions was supported by relevant spatiotemporal data such as building permit data associated with historical wildfire events and average repair time by building component, which are consistent with peer-reviewed scientific literature (Peloton 2020, Lee et al. 2024, Alexandre et al. 2015).

The central assumption used in the derivation of time element vulnerability functions is that time element related losses are proportional to building damage related losses. Hence, building-to-time element relationships are developed and used to derive the time element vulnerability functions from the building vulnerability functions. Losses causing time element claims can be divided into indirect losses and direct losses. Indirect losses arise from factors that extend the recovery timeline, such as infrastructure disruption, mandatory evacuation, and claims processes. Direct losses are associated with the time required to repair or rebuild damaged buildings. The complexity and extent of damage caused by wildfires can cause longer repair times for fire-damaged buildings compared to other natural hazards. The repair process for fire-damaged buildings can take significant time due to multiple factors (Baradaranshoraka 2017). Fire can cause extensive damage to buildings, including the buildings' foundations and supporting structures. Additional restoration efforts may be required in cases of smoke damage, as well as water damage from fire suppression. Both losses are captured in the KCC US Wildfire Reference Model, which uses a building-to-time element relationship to estimate time element losses.

4. ***Describe how time element wildfire vulnerability functions take into consideration the damage to local and regional infrastructure.***

One of the components reliant on engineering judgment is the effect that local and regional infrastructure disruption has on the amount of time between a building being uninhabitable and occupants returning. This effect could be independent of the repair time (for example, a building with no damage but located in an area with infrastructure disruption) or coincide with the repair time (such as if infrastructure disruption delayed repairs to a damaged building). The time element vulnerability functions do not explicitly distinguish between the direct loss (repair time) and indirect loss (e.g., infrastructure disruption, mandatory evacuation, claims processes). However, the effects of indirect loss, including the damage to local and regional infrastructure, are accounted for implicitly in the development of the building-to-time element relationships, which are used to derive the time element vulnerability functions.

5. ***Describe the relationship between the different building classes and time element wildfire vulnerability functions.***

Time element vulnerability functions reflect the time required for a building to be repaired, which is largely dependent on the building's damage state. Therefore, the time element vulnerability functions generally follow the building vulnerability functions so that as the building damage level increases (or decreases) so does the time element loss.

7. ***Describe the sources, quantification, and treatment of uncertainties associated with the time element wildfire vulnerability functions.***

The sources, quantification, and treatment of uncertainties associated with time element vulnerability functions are the same as the uncertainty associated with the building vulnerability functions, as outlined in Disclosure V-1 #6. The selection of secondary uncertainty distributions is based on the MDRs from the time element vulnerability functions.

V-4: Wildfire Mitigation Measures and Buildings' Secondary Characteristics

2. ***Describe the procedures used to calculate the impact of wildfire mitigation measures and secondary characteristics of buildings, including statistical or simulation software, its identification, and current version, and code or scripts if applicable. Describe whether or not such procedures have been modified since the last version previously submitted.***

The effects of wildfire mitigation measures and buildings' secondary characteristics on wildfire vulnerability are captured using modification factors that increase or decrease the building vulnerability functions. The default vulnerability functions are those developed for the distinct combinations of primary building characteristics described in Guideline V-1.

The wildfire mitigation measures and secondary characteristics relevant to building wildfire vulnerability include defensible space, roof covering and assemblies, roof geometry, gutters, ventilation, glazing type, fire-resistant shutters, fire-resistant skylights, fire-resistant exterior doors, fire-resistant garage doors, appurtenant structures, attached structure, wall siding, overhangs, sprinkler types, fences, minimum vertical clearance on wall siding, IBHS Wildfire Prepared Home, and community-level mitigation designations.

The impact of wildfire mitigation measures and secondary characteristics is developed based on engineering judgment supported by empirical data, post-fire assessments, and scientific literature (IBHS, 2021; Hakes et al., 2017; Syphard et al., 2019; Hedayati et al., 2023; Dossi et al., 2022). The development process considers how mitigation measures reduce the likelihood of ignition from at least one of these ignition mechanisms: direct flame exposure, radiant heat, and embers.

The impact of these mitigation measures varies based on wildfire footprint intensity. For example, the presence of sufficient defensible space impacts the vulnerability function at all intensities. Conversely, measures that prevent embers from entering a building (e.g., fire-resistance ventilation) have a more significant impact at lower intensities than at higher intensities. This variation is carefully evaluated to ensure that the effectiveness of each mitigation measure aligns with the best available engineering understanding.

To maintain consistency with engineering principles, the relative ranking of mitigation measures is also considered. Defensible space is recognized as one of the most effective mitigation measures, as it directly reduces exposures to all three ignition mechanisms. Other measures reduce exposure to specific ignition mechanisms—non-combustible vents which are highly effective against embers, and fire-resistant wall siding which helps to mitigate radiant heat and direct flame exposure—but their overall impact is lower compared to defensible space. This ranking process ensures that all mitigation measures are considered appropriately within the model, maintaining logical consistency in their impact on wildfire vulnerability.

This is the first version of the KCC US Wildfire Reference Model submitted for review.

3. ***Describe how different landscaping features (e.g., defensible space) related to wildfire mitigation measures on the property are considered in the development of the wildfire vulnerability functions and how their treatment compares to other factors in the model. Explain which characteristics of landscaping functions are considered. If any of these factors are also considered in the hazard modeling, describe the process by which their effects are apportioned between hazard and vulnerability analysis.***

   Landscaping features (e.g., defensible space) related to wildfire mitigation measures on the property are considered as wildfire mitigation measures in the KCC US Wildfire Reference model, which are captured using modification factors that increase or decrease the building vulnerability functions. Landscaping features are not considered in the development of the wildfire vulnerability functions, which account for the distinct combinations of primary building characteristics described in Guideline V-1. This ensures that landscaping features are separately accounted for without cumulative consideration in those vulnerability functions. None of these landscaping factors are considered in the hazard module.

5. ***Describe how wildfire mitigation measures and secondary characteristics of buildings are implemented in the vulnerability model. Identify any assumptions.***

   In the KCC US Wildfire Reference Model, the impact of wildfire mitigation measures and secondary characteristics on building vulnerability is captured using modification factors. For each secondary characteristic or mitigation measure listed in Form G8, there is a set of options that modify the building vulnerability functions based on user input data. Modification factors vary by wildfire intensity. The relative impacts of different wildfire mitigation measures at the highest wildfire intensity are shown in the following table. Modification factors for community level mitigation measures (Fire Risk Reduction Community List and Firewise designations) are applied after the net impact of property level mitigation is calculated. If there is no input for a certain secondary characteristic (if it is unknown), no modification is applied to the vulnerability function. If there are multiple secondary characteristic inputs, the combined effect is first calculated before modifying the vulnerability function.

Secondary Characteristic	Relative Impact
IBHS Wildfire Prepared Home	Most Impact
Defensible Space	↓
Roof Covering and Assemblies	
Minimum Vertical Clearance	
Wall Siding Type	
Fences	
Ventilation Type	
Decks and Other Attached Structures	
Appurtenant Structures	
Fire-Resistance Shutters	
Fire Risk Reduction Community List (FRRCL) Designation	
Firewise Designation	
Eaves, Overhangs, and Soffits	
Gutters	
Sprinkler Type	
Glazing Type	
Fire-Resistant Garage Doors	
Roof Geometry	
Fire-Resistant Exterior Doors	
Fire-Resistant Skylights	Least Impact

Table 13 - Relative impact of different wildfire mitigation measures at the highest wildfire intensity.

6. ***Describe how the effects of multiple wildfire mitigation measures (different building elements, materials, defensible space, and immediate and surrounding vegetation up to 100 feet) and secondary characteristics of buildings are combined in the model and the process used to ensure that multiple wildfire mitigation measures and secondary characteristics of buildings are correctly combined.***

   The modeling of specific mitigation measures is multivariate and accounts for unique combinations of factors by systematically combining the effects of multiple mitigation measures. The impact of ecoregion differences is already accounted for in the hazard module, and the output of the hazard module (i.e., wildfire footprint intensity) influences the effectiveness of mitigation measures.

   All examples referenced in the Safer from Wildfires framework and CCR 2644.9 (d)(1)(A) and (d)(1)(B) are accounted for in the KCC US Wildfire Reference Model.

   The process of combining the effects of multiple wildfire mitigation measures and secondary characteristics is based on the interaction between secondary characteristics.

   The presence of one mitigation measure can partly reduce the impact of another mitigation measure. For example, if a building is known to have Class A roofing, it receives some credit (say X) in terms of reduced MDR compared to an “Unknown” roof. If that same building has defensible space (say a credit Y), the combined credit would not be a simple addition (X + Y) of their individual credits. It would be a value that is higher than each individual credit, but still lower than X + Y.

   The KCC model utilizes an interaction matrix to implement this relationship. Given the status of any secondary characteristic, the modifiers of all other features are appropriately adjusted by applying the factors provided by this interaction matrix.

   In cases where the secondary characteristics have no interaction, for example ventilation and glazing types, the combined effect is computed by adding the impact that each secondary characteristics has on the vulnerability function. For example, if non-combustible ventilation decreases the vulnerability by 10% and glazing type decreases the vulnerability by 3%, the combined effect would be a decrease of 13% in the vulnerability.

7. ***Describe how building and contents damage are affected by performance of wildfire mitigation measures and secondary characteristics of buildings. Identify any assumptions.***

   Building damage decreases with the implementation of wildfire mitigation measures because the relative vulnerability decreases. Secondary characteristics can increase or decrease the building vulnerability. Contents damage changes in proportion with the building damage as the contents vulnerability functions are developed from the building vulnerability functions.

8. ***Describe how wildfire mitigation measures and secondary characteristics of buildings affect the uncertainty of the vulnerability. Identify any assumptions***

   In the KCC US Wildfire Reference Model, the uncertainty around vulnerability is a function of the level of damage. During loss calculation, the mitigation measures and secondary characteristics will modify the MDRs, hence modifying the secondary uncertainty of the vulnerability. No other assumptions are made with respect to the mitigation measures and secondary characteristics.

Actuarial Disclosures

A-1: Loss Data and End-User Input Data

1. ***Describe the data, methods and assumptions used to calibrate modeled wildfire losses based on historical insurance claims or other post-disaster loss data, including how wildfire catastrophe losses were defined, ascertained, and apportioned from such claims or post-disaster loss data.***

    KCC scientists and engineers have conducted rigorous analyses of high-resolution insurer claims data for 30 California wildfires and available DINS data (DINS 2024) for 27 California wildfires.

    KCC has established a comprehensive framework for acquiring and analyzing insurer claims data. KCC provides insurers detailed guidance on the required fields and key considerations for providing claims information, including methods for separating wildfire catastrophe losses from attritional claims. Prior to analysis, claims data is meticulously reviewed for completeness, accuracy, and reasonability. KCC engineers mapped each individual claim amount to the policy generating that claim so the claims data could be analyzed separately by construction, occupancy, year built, and other property characteristics. Most of the claims were also identified by coverage. The contemporaneous exposure data were provided for all policies in force during the dates of each wildfire (not just those with claims), which is required for estimating the MDRs. The modeled and actual losses were compared by building attribute, such as construction type and year built.

    KCC engineers have implemented a rigorous process for evaluating DINS data, including addressing observed deficiencies in the exposure and methods for translating DINS damage states to estimates of insured losses. Contemporaneous industry exposure data is utilized to estimate the numbers and values of structures impacted by each event, and modeled versus actual comparisons are reviewed during the model validation process.

8. ***Describe actions performed to ensure the validity of the end-user or other input data used for wildfire catastrophe model inputs or for validation/verification.***

    Model input data are provided by the user for each catastrophe loss analysis. RiskInsight® performs validation tests during exposure data import and includes exposure data validation tools within the user interface that assist users in verifying data integrity. All modifications, adjustments, assumptions, inputs and input file identification, and defaults necessary to use the wildfire model are actuarially sound and are included with the wildfire model output report and in the RiskInsight® documentation. Treatment of missing values required to run the wildfire model are actuarially sound and described in the RiskInsight® documentation.

    Validation testing includes confirming that postal codes are in a 5 digit or 5+4 digit format, and that construction and occupancy codes match supported options. When a validation error occurs during exposure data import, the offending input record is flagged and reported to the user in the Exposure Import Log and is not imported into the KCC exposure database. The user has the opportunity to correct the error, and if the augmented record passes all import exposure validation tests, it can then be imported into the exposure database.

    All modifications, adjustments, assumptions, inputs and input file identification, and defaults necessary to use the wildfire model are actuarially sound and are included with the wildfire model output report and in the RiskInsight® documentation. Treatment of missing values required to run the wildfire model are actuarially sound and described in the RiskInsight® documentation.

9. ***Disclose if and how changing the order of the wildfire catastrophe model input exposure data produces different modeled output or results.***

   Changing the order of the KCC US Wildfire Reference Model input exposure data does not produce different wildfire model output or results.

10. ***Disclose if removing or adding policies from the wildfire catastrophe model input file affects the modeled output or results for the remaining policies.***

    Removing or adding policies from the KCC US Wildfire Reference Model input file will not affect the wildfire model output for the remaining policies.

A-2: Wildfire Events Resulting in Modeled Wildfire Losses

1. ***Disclose the definition or parameters/distinctions used to categorize wildfire losses as catastrophic or to segregate wildfire losses from other fire-related losses, including with respect to partial losses.***

   The KCC definition of a wildfire event is a fire that ignites in the wildland and burns to a size of at least 7,500 acres (including all area within the fire perimeter) or caused at least $25 million in estimated insurance industry loss historically. Wildfire losses include loss from structure damage incurred from direct impacts of the fire, and damage from wildfire smoke.

2. ***Describe how damage from wildfire model generated fires is excluded or included in the calculation of wildfire loss costs and wildfire probable maximum loss levels for California, including the treatment of wildfires originating outside California that spread across state lines including through urban conflagration.***

   Losses from all wildfires that meet the KCC wildfire definition are included in loss cost and PML calculations. For wildfires that originate outside of California but ultimately cause loss in California, only losses from California locations are included in California loss cost and PML calculations.

3. ***Identify any and all components of wildfire-related damage (including without limitation fire, smoke, landslide, debris flow, water damage from fire suppression, and tree damage) and describe how each such component is treated in the calculation of wildfire loss costs and wildfire probable maximum loss levels for California.***

   The KCC US Wildfire Reference Model explicitly includes wildfire-related damage from fire and smoke. The wildfire loss costs and probable maximum loss levels for California in this submission include both fire and smoke losses and exclude the impact of any other components of wildfire-related damage such as landslide, debris flow, water damage from fire suppression, and tree damage.

A-3: Wildfire Coverages

1. ***Describe the methods used in the wildfire catastrophe model to calculate wildfire loss costs for habitational building coverage associated with personal and commercial residential properties.***

   When the exposure data are read into the model, each location is assigned a reference vulnerability function code appropriate for the attributes of that property. Personal residential properties are identified by occupancy codes that are different from the commercial residential occupancy codes. The reference vulnerability function code is used to assign the appropriate vulnerability function to the individual location property. The appropriate building vulnerability function is used to estimate the habitational building ground-up loss from each event in the simulated catalog using the wildfire intensity from that event at the property location. The gross losses are calculated by applying secondary uncertainty and the policy terms. Annual wildfire losses are calculated by multiplying losses by their respective event rates and summing them across all events. Annual wildfire loss costs are calculated by dividing the average annual wildfire losses by the appropriate exposure and multiplying by 1,000.

A-4: Modeled Wildfire Loss Cost and Wildfire Probable Maximum Loss Level Considerations

3. ***Describe how the wildfire catastrophe model incorporates demand surge and/or post-loss amplification in the calculation of wildfire loss costs and wildfire probable maximum loss levels and provide ratios of wildfire loss costs and wildfire probable maximum loss with and without demand surge and with/without each other post loss amplification mechanisms. Provide the range of demand surge used.***

In the KCC U.S. Wildfire Reference Model, demand surge is applied to insurer ground-up losses based on the total industry loss for each event. The event-level demand surge factor ranges from 1.0 to 1.2, with higher industry losses expected to generate greater demand surge. While the impact will vary by insurer portfolio, most wildfires result in relatively low industry losses and therefore do not trigger significant demand surge. As a result, the expected impact on insurer loss costs is typically in the low to mid single-digit percentage range.

A-5: Wildfire Policy Conditions

1. ***Describe the methods used in the wildfire catastrophe model to treat deductibles (both flat and percentage), policy limits, and insurance-to-value criteria when projecting wildfire loss costs and wildfire probable maximum loss levels. Discuss data or documentation used to validate the method used by the wildfire catastrophe model.***

The methods used in the development of mathematical distributions to reflect the effects of deductibles and policy limits are actuarially sound.

The model generates mean damage ratios (MDRs), which represent the cost to repair the damage divided by the replacement value of the property. For each MDR, the model considers the secondary uncertainty, which is the full probability distribution of damage levels around the mean, using empirical distributions. The secondary uncertainty distribution is used to apply the effects of deductibles and limits.

$$\text{Expected Insured Loss} = \int_0^1 f_{\overline{D}}(x)\left\{Coins\% * max\left[0, min\left(PL, x * RV - DED\right)\right]\right\}dx$$

where

$f_{\overline{D}}(x)$ = Secondary Uncertainty Distribution

Coins% = Coinsurance Percentage

x = Damage Ratio Variable

RV = Replacement Value

PL = Policy Limit

DED = Deductible

In application, $f_{\overline{D}}(x)$ is discretized and numerical integration is used to estimate the expected insured loss.

Percentage deductibles are converted into flat deductibles by multiplying them by the appropriate coverage amount. Flat deductibles are used directly. The model estimates a mean damage ratio, to which a secondary uncertainty function is applied. The model caps the losses at the policy limits. If desired by the user, insurance-to-value assumptions can be made to the input data prior to the user importing the data into the KCC database. KCC validated the wildfire model by performing detailed analysis on client claims data, including ground-up and gross losses.

2. Describe if and how the wildfire catastrophe model treats policy exclusions and loss settlement provisions.

Policy exclusions are implicitly factored into the model to the extent that they are included in claims data. Loss settlement provisions are not included in the wildfire model loss estimates. The insurer claims data used to validate the model excludes loss adjustment expenses.

3. Describe if and how the wildfire catastrophe model treats hours clauses.

The model includes all losses that occur during the lifetime of each modeled wildfire event and does not apply hours clauses to exclude impacted locations from the wildfire loss costs or probable maximum loss calculations.

A-6: Wildfire Loss Outputs and Logical Relationships to Risk

9. Identify the assumptions used to account for the effects of coinsurance on commercial residential property wildfire loss costs

The KCC US Wildfire Reference Model accounts for the effects of coinsurance by applying a participation percentage to the estimated losses. This data field is provided by the user and represents the percentage of the loss assumed by the insured.

Appendix A: Form G-8

Form G-8: Wildfire Catastrophe Model Settings and Input

Purpose: This form is used to document the model setting options and expected input to the model.

- ***A.*** ***Use the tables below to document the options available to the user of the wildfire catastrophe model, the standard settings of the wildfire catastrophe model expected to be used in the ratemaking context, and the expected input to the model. The table should indicate which features the user must include in the data that is imported, and which are automatically filled in the model if a user does not import them.***

- ***B.*** ***Include annotated examples of a data import log and an analysis log. In the "Import/Analysis log location" column of each table include a letter reference for where the relevant user choice is indicated in the logs.***

- ***C.*** ***Along with this form, submit a recorded video that serves as guidance for the import and analysis log. This video should focus only on the options and features that are anticipated in the context of a rate filing. This video should demonstrate what error flags are possible and how to interpret summary statistics from the data import. For example, how many exposure included mitigation features details, geospatial granularity of imported data, and level of geocoding.***

  A video providing an overview of the use and interpretation for Form G-8 for the KCC US Wildfire Model Version 3.0 has been provided.

Part A: Model Information

Category	Option	Default Selection	Expected Selection for Rate Filing	User Selection for Rate Filing	Notes	Analysis Report Location
Model	Several – licensed models vary by user	N/A	KCC Wildfire_NAM-US_v3.0			A
Event Catalog	Stochastic, Historical, Live	N/A	STOC included			B
Sub-Perils	Multiple – sub-perils vary by selected model	KCC Wildfire_NAM-US_v3.0 - Fire, KCC Wildfire_NAM-US_v3.0 - Smoke	KCC Wildfire_NAM-US_v3.0 - Fire, KCC Wildfire_NAM-US_v3.0 - Smoke			C
Software Version	Several – licensed software version may vary by user	N/A	RiskInsight® Version 4.14.0 OR RiskInsight® Version 4.15.1		Auto-populated by software. User may not adjust the software version that is installed at their company	D
Database Version	KCC OEF2.0 – KCC OEF2.6	KCC OEF2.6	KCC OEF2.6		Database version is determined at time of exposure creation	E

Table 14 - Model information options available to the user of the wildfire catastrophe model, the standard settings of the wildfire model required to be used in the ratemaking context (Default Selection), and the expected input (Expected Selection for Rate Filing)

Part A: Loss Analysis Information

Category	Option	Default Selection	Expected Selection for Rate Filing	User Selection for Rate Filing	Notes	Analysis Report Location
Loss Resolution	Event Totals Only Losses by Location Losses by Layer Losses by LOB Losses by Country Losses by State Losses by County Losses by ZIP Losses by CRESTA Losses by Country and LOB Losses by State and LOB Losses by County and LOB Losses by ZIP and LOB Losses by CRESTA and LOB	Event Totals Only	Depends on user		Loss resolution does not impact loss cost results for a rate filing. Users will select an option that is most appropriate for their analytical purposes.	F
AAL Resolution - Geography	None Country State ZIP County CRESTA	None	Depends on user		AAL resolution does not impact loss cost results. However, it is expected that the resolution chosen for the model settings will be at an equal or higher resolution than that which is submitted in the rate filing.	F
AAL Resolution - Business	None Account Policy Location	None	Depends on user		AAL resolution does not impact loss cost results. However, it is expected that the resolution chosen for the model settings will be at an equal or higher resolution than that which is submitted in the rate filing.	F

Category	Option	Default Selection	Expected Selection for Rate Filing	User Selection for Rate Filing	Notes	Analysis Report Location
AAL Resolution - by LOB	On	Off	Depends on user		AAL resolution does not impact loss cost results. However, it is expected that the resolution chosen for the model settings will be at an equal or higher resolution than that which is submitted in the rate filing.	F
	Off					
Demand Surge	On	On	Yes			G
	Off					
Secondary Modifiers	On	On	Yes			H
	Off					
Endorsements	On	On	Yes			I
	Off					
Currency	See KCC Documentation	USD	USD			J
Multi-Location Policy Correlation	None	Medium	Medium			K
	Low					
	Medium					
	High					
	Full					
Sub-Peril Leakage	N/A	N/A	N/A			N/A

Table 15 - Loss analysis information options available to the user of the wildfire catastrophe model. Note: User must input “CA” for State, and only CA risks are valid for a CA rate filing. Typically know values are populated for Occupancy Code, Construction Code, Year Built, and Stories, and an unknown value will be assigned if not populated by the user. See Exposure Control Totals section for more details.

Part A: Primary Characteristics

Category	Options	Usage in Rate Filing	Unknown Calculation	Input Method	Import/Analysis Log Location	Notes
Occupancy Code	See Example Output for Primary Characteristics	Typically populated with known values	Distributed based on California building inventory	User input through exposure data	N/A - Information stored in exposure database	See Exposure Control Totals
Construction Code	See Example Output for Primary Characteristics	Typically populated with known values	Distributed based on California building inventory	User input through exposure data	N/A - Information stored in exposure database	
Year Built	Integer value between 0 and current year, inclusive	Typically populated with known values	Distributed based on California building inventory	User input through exposure data	N/A - Information stored in exposure database	
Stories	Integer value between 0 and 999, inclusive	Typically populated with known values	Distributed based on California building inventory	User input through exposure data	N/A - Information stored in exposure database	
State	Any U.S. State	Expected to be "CA"	Distributed based on US building inventory	User input through exposure data	N/A - Information stored in exposure database	

Table 16 - Primary characteristics options available to the user of the wildfire catastrophe model, the standard settings of the wildfire model required to be used in the ratemaking context (default selection), and the expected input (selection for rate filing). User input is only required for State. For Occupancy Code, Construction Code, Year Built, and Stories, an unknown value will be assigned if not populated by the user.

Part A: Secondary Characteristics and Mitigation Features

Mitigation Measure / Secondary Characteristic	Database Field	Options	Description	Usage in Rate Filing
Defensible Space	DefensibleSpaceCode	Unknown No Defensible Space Zone 1 only Zones 1 and 2, no Zone 3 Zones 1, 2, and 3 Zone 2 only Zone 3 only Zones 2 and 3	Defensible space is an area in which vegetation, debris, and other types of fuels have been treated or cleared to slow fire spread.	The choice and prevalence of secondary modifiers differ depending on the exposure
Roof Coverings and Assemblies	RoofCoverFireRatingCode	Unknown Class A rated Not Class A rated	Roof coverings and assemblies have a significant impact on vulnerability because they are the most vulnerable components of the building envelope to branding and embers due to their horizontal orientation and size. Only Class A rated roofs are effective in mitigating wildfire risk (Quarles et al. 2010; Hedayati et al. 2023; Barret and Quarles 2024). Class A rated in the KCC model includes roofs that are rated Class A “stand alone” and “by assembly”.	The choice and prevalence of secondary modifiers differ depending on the exposure
Roof Geometry	RoofGeometryCode	Unknown Flat Gable Hip Complex Stepped Shed Mansard Pyramid Gambrel	Roof geometry affects how and where embers may accumulate during wildfires. Simple roofs with few intersecting planes generally shed embers more effectively. In contrast, more complex geometries can create pockets where embers are more likely to settle.	The choice and prevalence of secondary modifiers differ depending on the exposure

Mitigation Measure / Secondary Characteristic	Database Field	Options	Description	Usage in Rate Filing
Gutters	GutterFireCode	Unknown	Gutters can be vulnerable to ember ignition, particularly when made from combustible materials or lacking non-combustible covers.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Non-combustible gutters		
		Non-combustible gutters with non-combustible covers		
		Combustible gutters		
		No gutters		
Ventilation Type	RoofVentilationCode	Unknown	Embers and hot gases can enter an attic or crawl space through ventilation.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Combustible		
		Non-combustible		
		No Ventilation		
Eaves, Overhangs, and Soffits	OverhangCode	Unknown	Overhangs and other components of exterior walls can trap wind-borne embers, convective heat, and radiant heat.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Combustible		
		Non-combustible		
		No eaves or overhang ventilation		
Wall Siding Type	WallSidingFireCode	Unknown	Siding can ignite if flames or embers enter the cavity behind it or if flames spread vertically, impinging on windows and eaves.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Combustible		
		Fire-resistant		
Glazing Type	GlassTypeCode	Unknown	Glazing, which refers to the glass, plastic, or fiberglass-reinforced translucent material of windows, sliding glass doors, etc., is commonly vulnerable to wildfires.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Fire-resistant		
		Ordinary and combustible		
Fire-Resistant Shutters	FireResistantShutterCode	Unknown	Fire-resistant shutters add protection by shielding openings from direct flame contact, radiant heat, and embers. These shutters are typically made of non-combustible materials and must meet fire-resistance standards.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Yes		
		No		

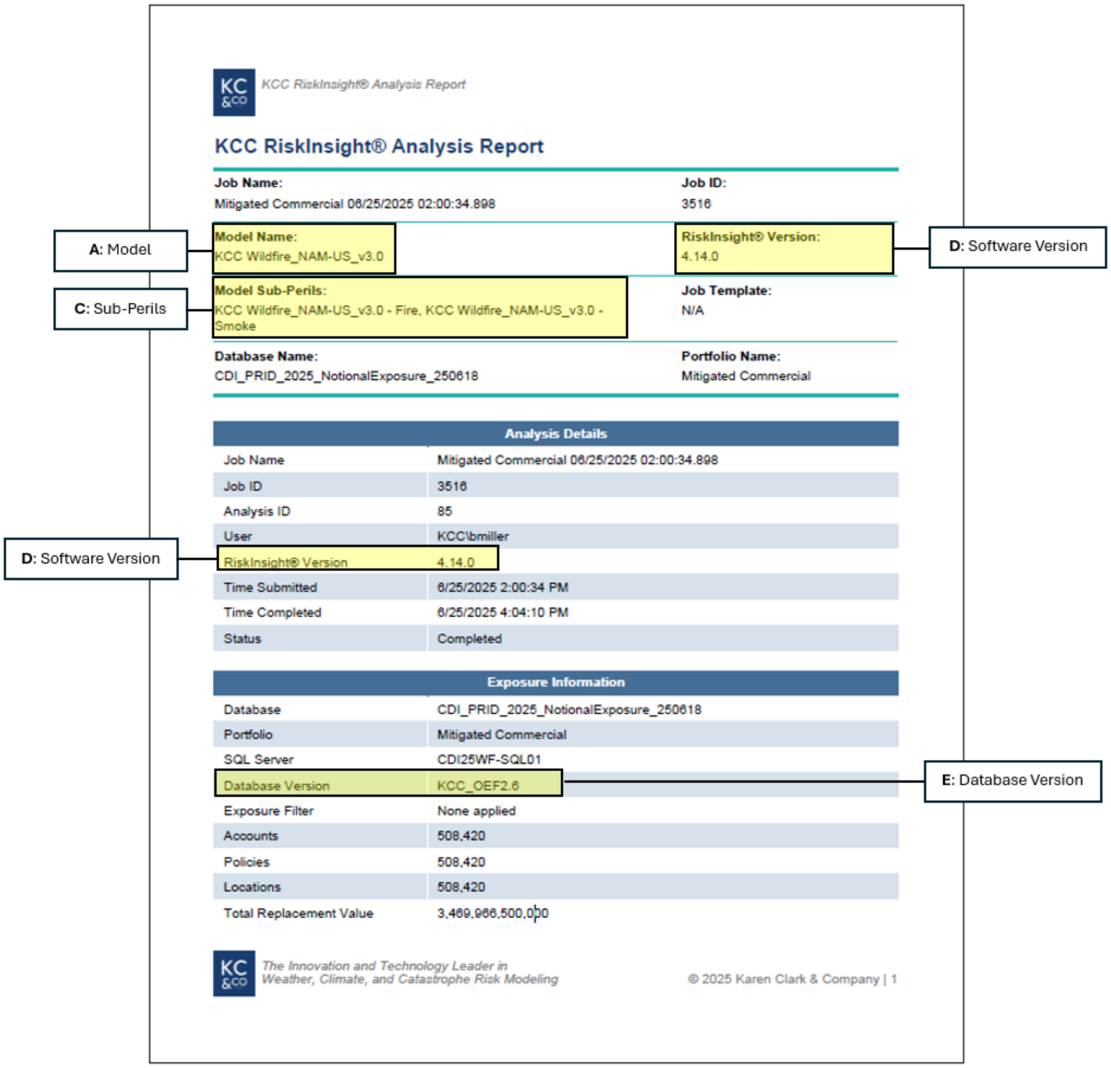
Mitigation Measure / Secondary Characteristic	Database Field	Options	Description	Usage in Rate Filing
Fire-Resistant Skylights	FireResistantSkylightCode	Unknown Yes No	Skylights are vulnerable to direct flames, radiant heat, and embers during wildfires. Fire-resistant skylights are typically made from non-combustible or fire-rated materials.	The choice and prevalence of secondary modifiers differ depending on the exposure
Fire-Resistant Exterior Doors	FireResistantExteriorDoorCode	Unknown Yes No	Exterior doors are vulnerable to direct flames, radiant heat, and embers during wildfires, especially if made from combustible materials. Fire-resistant doors, typically made from non-combustible or fire-rated materials, provide added protection.	The choice and prevalence of secondary modifiers differ depending on the exposure
Fire-Resistant Garage Doors	FireResistantGarageDoorCode	Unknown Yes No	Garage doors are vulnerable to direct flames, radiant heat, and embers during wildfires. Non-combustible or fire-rated materials are required for fire-resistant garage doors.	The choice and prevalence of secondary modifiers differ depending on the exposure
Sprinkler Type	IsFireSprinklerAvailable	Unknown No Sprinkler External Sprinkler Internal Sprinkler Both Internal and External Sprinkler	The presence of internal and external fire sprinklers reduces the likelihood of fire damage to a building.	The choice and prevalence of secondary modifiers differ depending on the exposure
Decks and Other Attached Structures	AttachedStructureFireCode	Unknown Attached Structures without fire resistance Attached Structures with fire resistance No Attached Structures	The presence of decks and other attached structures can also impact the potential losses from wildfires.	The choice and prevalence of secondary modifiers differ depending on the exposure

Mitigation Measure / Secondary Characteristic	Database Field	Options	Description	Usage in Rate Filing
Fences	CombustibleFencingCode	Unknown Non-combustible, vented Non-combustible, solid barrier Combustible fence within five feet Combustible fence outside five feet	The presence of a fence can cause accumulation of firebrands at the base of the fence, which can ignite the debris and consequently ignite the fence.	The choice and prevalence of secondary modifiers differ depending on the exposure
Appurtenant Structures	AppurtenantStructCombustCode	Unknown Combustible appurtenant structures within 10 feet No combustible appurtenant structures within 10 feet No combustible appurtenant structures within 20 feet No combustible appurtenant structures within 30 feet	A nearby appurtenant structure significantly increases the vulnerability of a property because if it ignites, it can cause the main structure to be damaged by direct flame impingement, radiant heat, and/or ignition by firebrands.	The choice and prevalence of secondary modifiers differ depending on the exposure
Minimum Vertical Clearance	CombustibleVertClearanceCode	Unknown At least 6 inches of noncombustible vertical clearance at bottom of exterior surface present No clearance present	Without adequate ground-to-siding clearance, embers can accumulate at the base of a wall and ignite the siding directly.	The choice and prevalence of secondary modifiers differ depending on the exposure
IBHS Wildfire Prepared Home	IBHSWildfirePreparedHomeCode	Unknown Base Plus	IBHS Wildfire Prepared Home is a set of mitigation measures developed to reduce wildfire risk through a combination of strategies. These could include defensible space, Class A roofing, ember-resistant vents, non-combustible materials for sidings, and more	The choice and prevalence of secondary modifiers differ depending on the exposure
Fire Risk Reduction Community List (FRRCL) Designation	FireRiskReductionCommunityCode	No Yes, City or County Yes, Others	The California FRRCL designates local agencies that meet the best practices for local fire planning.	The choice and prevalence of secondary modifiers differ depending on the exposure

Mitigation Measure / Secondary Characteristic	Database Field	Options	Description	Usage in Rate Filing
Firewise Designation	FirewiseCommunityCode	No	National Fire Protection Association (NFPA) identifies communities with “Firewise USA Site in Good Standing” (Firewise) for their proactive wildfire preparedness and mitigation efforts.	The choice and prevalence of secondary modifiers differ depending on the exposure
		Yes		

Table 17 - Secondary characteristics and mitigation features options available to the user of the wildfire catastrophe model. Note: Input is not required for any of these values. A NULL value will be assigned if not populated by the user. All values are input through exposure data and information is stored in the exposure database and not included in the import/analysis log. Unknown or NULL values for all inputs will have no impact on losses. See Exposure Control Totals section for more details.

Part B: Annotated Analysis Log



KCC RiskInsight® Analysis Report

KCC RiskInsight® Analysis Report

Job Name:
Mitigated Commercial 06/25/2025 02:00:34.898

Job ID:
3516

Model Name:
KCC Wildfire_NAM-US_v3.0

RiskInsight® Version:
4.14.0

Model Sub-Perils:
KCC Wildfire_NAM-US_v3.0 - Fire, KCC Wildfire_NAM-US_v3.0 - Smoke

Job Template:
N/A

Database Name:
CDI_PRID_2025_NotionalExposure_250618

Portfolio Name:
Mitigated Commercial

Analysis Details	
Job Name	Mitigated Commercial 06/25/2025 02:00:34.898
Job ID	3516
Analysis ID	85
User	KCC\bmiller
RiskInsight® Version	4.14.0
Time Submitted	6/25/2025 2:00:34 PM
Time Completed	6/25/2025 4:04:10 PM
Status	Completed

Exposure Information	
Database	CDI_PRID_2025_NotionalExposure_250618
Portfolio	Mitigated Commercial
SQL Server	CDI25WF-SQL01
Database Version	KCC_OEF2.6
Exposure Filter	None applied
Accounts	508,420
Policies	508,420
Locations	508,420
Total Replacement Value	3,469,966,500,000

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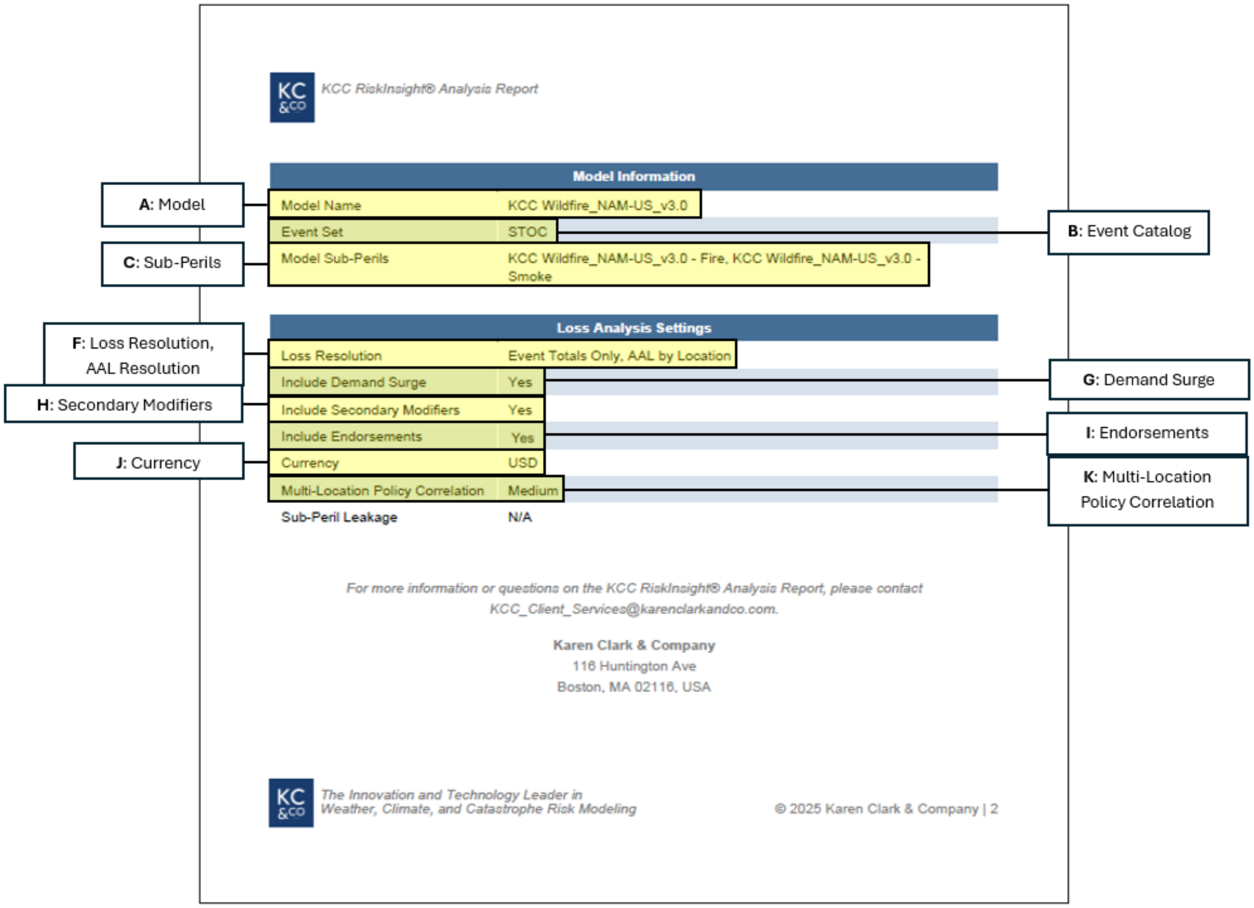

KCC RiskInsight® Analysis Report

Model Information	
Model Name	KCC Wildfire_NAM-US_v3.0
Event Set	STOC
Model Sub-Perils	KCC Wildfire_NAM-US_v3.0 - Fire, KCC Wildfire_NAM-US_v3.0 - Smoke

Loss Analysis Settings	
Loss Resolution	Event Totals Only, AAL by Location
Include Demand Surge	Yes
Include Secondary Modifiers	Yes
Include Endorsements	Yes
Currency	USD
Multi-Location Policy Correlation	Medium
Sub-Peril Leakage	N/A

For more information or questions on the KCC RiskInsight® Analysis Report, please contact KCC_Client_Services@karenclarkandco.com.

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Figure 30 - Annotated analysis log

Supplemental Material: Exposure Control Totals

As a part of a rate filing with the Wildfire model, users of the model should prepare control totals on their exposure data to ensure it is valid for analysis. This is a key component in the modeling process that is typically conducted by the insurer at several different stages, including before the data is imported into the KCC OEF format.

KCC provides insurers with scripts that produce control totals relevant to the Wildfire model. This enables insurers to quickly understand, and report on, the key exposure variables that influence Wildfire model output.

The tables below demonstrate the output of the KCC scripts that insurers use to summarize their Wildfire exposure data.

Example Output for Primary Characteristics

Overall Control Totals			
Database Name	**Portfolio Name**	**Risk Count**	**TIV**
Sample_Database	Sample_Portfolio	508,420	508,420,000,000

Construction				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
Construction Code	KCC	WD10	Wood - Wood Frame	88.89
Construction Code	KCC	UK00	Unknown	4.43
Construction Code	KCC	WD11	Wood - Wood Frame, Masonry Veneer	4.47
Construction Code	KCC	MS00	Masonry	2.22

Occupancy				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
Occupancy Code	ATC	1	SFH	84.38
Occupancy Code	ATC	2	MFH	7.78
Occupancy Code	ATC	43	Multi-Family Dwelling Condominium Unit Owner	7.84

Year Built				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
Year Built Band	N/A	Before 1979	Before 1979	53.34
Year Built Band	N/A	1979 - 1996	1979 - 1996	19.44
Year Built Band	N/A	1997 - 2007	1997 - 2007	15.45

Year Built				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
Year Built Band	N/A	After 2007	After 2007	9.19
Year Built Band	N/A	0	Unknown	2.58

Stories				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
Stories Band	N/A	1	1 Story	52.01
Stories Band	N/A	2	2 Stories	39.89
Stories Band	N/A	0	Unknown	4.98
Stories Band	N/A	3	3 Stories	2.33
Stories Band	N/A	4-6 Stories	4-6 Stories	0.63
Stories Band	N/A	7+ Stories	7+ Stories	0.14

State				
Primary Characteristic	**KCC Schema**	**KCC Code**	**Description**	**Percent of TIV**
State	N/A	CA	California	100.00

Geocoding Summary		
Geocode Source	**Geocode Resolution**	**Percent of TIV**
KCC	Exact address	98.13
KCC	Relaxed address	1.28
KCC	ZIP9 centroid	0.59

Example Output for Secondary Characteristics

Column Name	Enumeration	Value	Percent Of TIV
IBHSWildfirePreparedHomeCode	0	Unknown	54.7
IBHSWildfirePreparedHomeCode	1	Base	25.1
IBHSWildfirePreparedHomeCode	2	Plus	20.2
DefensibleSpaceCode	0	Unknown	13.4
DefensibleSpaceCode	1	No Defensible Space	23.6

Column Name	Enumeration	Value	Percent Of TIV
DefensibleSpaceCode	2	Zone 1 only	10.2
DefensibleSpaceCode	3	Zones 1 and 2	18.3
DefensibleSpaceCode	4	Zones 1, 2, and 3	24.1
DefensibleSpaceCode	5	Zone 2	4.2
DefensibleSpaceCode	6	Zone 3	6.2
DefensibleSpaceCode	7	Zones 2 and 3	0.0
RoofCoverFireRatingCode	0	Unknown	45.1
RoofCoverFireRatingCode	1	Class A	26.7
RoofCoverFireRatingCode	2	Not Class A	28.2
CombustibleVertClearanceCode	0	Unknown	74.1
CombustibleVertClearanceCode	1	Yes	11.7
CombustibleVertClearanceCode	2	No	14.2
WallSidingFireCode	0	Unknown	28.5
WallSidingFireCode	1	Combustible	33.2
WallSidingFireCode	2	Fire-resistant	38.3
CombustibleFencingCode	0	Unknown	16.2
CombustibleFencingCode	1	No fence	21.5
CombustibleFencingCode	2	No combustible fence, vented	17.
CombustibleFencingCode	3	Combustible fence within 5 ft	12.7
CombustibleFencingCode	4	Combustible fence outside 5 ft	28.1
CombustibleFencingCode	5	No combustible fence, solid barrier	4.2
RoofVentilationCode	0	Unknown	12.2
RoofVentilationCode	1	Combustible, Roof	10.5
RoofVentilationCode	2	Combustible, Others	8.8
RoofVentilationCode	3	Combustible, Roof and Others	4.3
RoofVentilationCode	4	Non-combustible, Roof	32.9
RoofVentilationCode	5	Non-combustible, Others	20.2
RoofVentilationCode	6	Non-combustible, Roof and Others	6.8
RoofVentilationCode	7	No Ventilation	4.3
AttachedStructureFireCode	0	Unknown	52.2
AttachedStructureFireCode	1	Attached Structures without fire resistance	28.5

Column Name	Enumeration	Value	Percent Of TIV
AttachedStructureFireCode	2	Attached Structures with fire resistance	8.6
AttachedStructureFireCode	3	No Attached Structures	10.7
CombustibleAppurtStructureCode	0	Unknown	8.2
CombustibleAppurtStructureCode	1	<= 10 ft	13.4
CombustibleAppurtStructureCode	2	> 10 ft	46.4
CombustibleAppurtStructureCode	3	> 20 ft	29.2
CombustibleAppurtStructureCode	4	> 30 ft	2.8
FireResistantShutterCode	0	Unknown	12.2
FireResistantShutterCode	1	Ye	70.2
FireResistantShutterCode	2	No	17.6
OverhangCode	0	Unknown	25.7
OverhangCode	1	Combustible	18.8
OverhangCode	2	Non-combustible	34.1
OverhangCode	3	No overhangs	21.4
GlassTypeCode	0	Unknown	11.2
GlassTypeCode	1	Annealed	24.5
GlassTypeCode	2	Tempered	8.5
GlassTypeCode	3	Heat strengthened	15.9
GlassTypeCode	4	Laminated	20.1
GlassTypeCode	5	Insulating glass units	7.2
GlassTypeCode	6	Non-impact Rated	3.4
GlassTypeCode	7	Impact Rated	2.3
GlassTypeCode	8	Single-Pane	4.2
GlassTypeCode	9	Multi-Pane	2.7
GutterFireCode	0	Unknown	38.1
GutterFireCode	1	Non-combustible gutters	16.2
GutterFireCode	2	Non-combustible gutters with noncombustible cover	35.4
GutterFireCode	3	Combustible gutters	10.3
GutterFireCode	4	No gutters	0.0
FireResistantGarageDoorCode	0	Unknown	45.4
FireResistantGarageDoorCode	1	Yes	31.4

Column Name	Enumeration	Value	Percent Of TIV
FireResistantGarageDoorCode	2	No	23.2
FireResistantExteriorDoorCode	0	Unknown	48.2
FireResistantExteriorDoorCode	1	Yes	28.2
FireResistantExteriorDoorCode	2	No	23.6
IsFireSprinklerAvailableCode	0	Unknown	0.0
IsFireSprinklerAvailableCode	1	No Sprinkler	2.5
IsFireSprinklerAvailableCode	2	Yes, External Sprinkler	7.1
IsFireSprinklerAvailableCode	3	Yes, Internal Sprinkler	14.2
IsFireSprinklerAvailableCode	4	Yes, Both	76.2
FireResistantSkylightCode	0	Unknown	47.3
FireResistantSkylightCode	1	Yes	38.5
FireResistantSkylightCode	2	No	14.2
RoofGeometryCode	0	Unknown	2.3
RoofGeometryCode	1	Flat	24.5
RoofGeometryCode	2	Gable without bracing	15.6
RoofGeometryCode	3	Hip	18.2
RoofGeometryCode	4	Complex	2.7
RoofGeometryCode	5	Stepped	5.2
RoofGeometryCode	6	Shed	8.6
RoofGeometryCode	7	Mansard	14.1
RoofGeometryCode	8	Gable with bracing	6.2
RoofGeometryCode	9	Pyramid	1.2
RoofGeometryCode	10	Gambrel	1.4
FirewiseCommunityCode	0	Unknown	4.7
FirewiseCommunityCode	1	Yes	61.6
FirewiseCommunityCode	2	No	33.7
FireRiskReductionCommunityCode	0	Unknown	5.3
FireRiskReductionCommunityCode	1	Not FRRCL	38.4
FireRiskReductionCommunityCode	2	FRRCL: Non-City/Non-County	22.1
FireRiskReductionCommunityCode	3	FRRCL: City/County	34.2

Appendix B: Acronyms

AAL: Average Annual Loss

API: Application Programming Interface

ASOP: Actuarial Standards of Practice

CBC: California Building Code

CPU: Central Processing Unit

CRESTA: Catastrophe Risk Evaluation and Standardizing Target Accumulations

CZU: San Mateo–Santa Cruz Unit

DEM: Digital elevation model

DEV: KCC Software Development environment

DINS: CAL FIRE Damage Inspection

ELT: Event Loss Table

EP: Exceedance Probability

EPA: Environmental Protection Agency

FHSZ: Fire Hazard Safety Zones

FRRCL: Fire Risk Reduction Community List

HRRR: High-Resolution Rapid Refresh

IBHS: Insurance Institute for Business & Home Safety

ISO: International Organization for Standardization

IT: Information Technology

JSON: JavaScript Object Notation

KPD: KCC Industry Property Database

LNU: Sonoma–Lake–Napa Unit

LOB: Line of Business

LRA: Local Responsibility Areas

MDR: Mean Damage Ratio

MFA: Multifactor Authentication

MH: Manufactured Homes

ML: Machine Learning

MTBS: Monitoring Trends in Burn Severity

NBR: Normalized Burn Ratio

NOAA: National Oceanic and Atmospheric Administration

OEF: Open Exposure Format

Pdist: Preliminary Disturbance

PGP: Pretty Good Privacy

PML: Probable Maximum Losses

PRC: Public Resources Code

PRISM: Parameter-elevation Regressions on Independent Slope Model

QA: Quality Assurance

RAM: Random-access memory

RAWS: Remote Automatic Weather Stations

RDP: Remote Desktop Protocol

SCU: Santa Clara Unit

SFTP: Secure File Transfer Protocol

SMB: Server Message Block

SQL: Structured Query Language

SRA: State Responsibility Areas

TFS: Microsoft Team Foundation Server

TIV: Total Insured Value

TSV: Tab Separated Values

TVaR: Tail Value at Risk

UI: User interface

USDA: United States Department of Agriculture

USGS: United States Geological Survey

VHFHSZ: Very High Fire Hazard Severity Zones

VPD: Vapor Pressure Deficit

VPN: Virtual Private Network

XML: eXtensible Markup Language

YAML: Yet Another Markup Language

YLT: Year Loss Table