MOODY'S

Moody's Required Model Information

This document represents required model information for rate filing included in partial fulfillment of the catastrophe model certification process. This document includes the model overview and information related to the disclosures specified in the Wildfire Catastrophe Model Checklist including model output and other material reviewed as part of the PRID process.

Model Overview

The model submitted for use in rate filing in California and reviewed under the PRID process is the Moody's RMS U.S. Wildfire HD Model Version 2.0.2. It is delivered on the Risk Modeler application, version 2.45.0, a cloud-based software application on the Moody's Intelligent Risk Platform. The vintage of the USPS Postal Code data used in the development of the wildfire model is December 2023. The model architecture is designed so that application enhancements do not affect the model output and consequently the model version number.

Model Versioning and Change Classification

Upgrades and revisions to RMS Models are done whenever new data, research, or technology become available that result in non-trivial improvements in loss modeling methodology. If a change to one or more components of the model are made, a new model version number is used to designate the updated release.

The versioning scheme includes three parts: [MajorRevision].[MinorRevision].[PatchRevision].

Updates or noteworthy changes increment either [MajorRevision] and/or [MinorRevision] depending on the extent of the update. Both levels correspond with change in loss that would be considered significant to the users.

Updates that are minor and are less than a 'significant loss threshold' result in a change to the [PatchRevision] portion of the model version. [PatchRevisions] replace the current version on the platform.

Moody's issues models that increment the [MajorRevision].[MinorRevision] parameters as a new side-by-side model version on the platform.

Change management is a critical part of using Moody's RMS models. As an example of our commitment, in the case of the USWF model update from Version 1.1.3 to Version 2.0.0, Moody's issued a comprehensive 'Understanding Change in Results' document to support clients in interpreting differences in loss outputs. To further ease change management, both model versions are concurrently supported on Risk Modeler, allowing users to compare results.

Corporate Organizational Structure

The modeling organization responsible for the Moody's RMS U.S. Wildfire Model is Moody's Analytics, which is a subsidiary of Moody's Corporation established in 2007 to focus on non-rating activities, separate from Moody's Ratings.

This structure reflects Moody's acquisition of Risk Management Solutions, Inc. (RMS) in 2021. RMS was a catastrophe modeling firm originally founded in 1989 that became a leading provider of catastrophe models globally. Following its acquisition, RMS catastrophe risk models were rebranded as Moody's RMS, integrating modeling capabilities into Moody's broader analytics and risk management ecosystem.

The Moody's RMS U.S. Wildfire Model was developed in-house by personnel employed by Moody's.

Background

Historically, the (re)insurance industry quantified wildfire risk across California and United States using deterministic tools that related wildfire risk to the presence of fuels and/or historical wildfire loss experience. While these tools provide value, they do not adequately address major catastrophe events that impact beyond the wildland-urban interface into areas of dense exposure like the 2017 Tubbs Fire in Northern California. In recent years, wildfires in California also highlighted the far-ranging impacts of embers and their potential to ignite urban conflagrations, which have been largely understated in underwriting practices to date.

The unprecedented severity of wildfires over the last decade highlighted the need to better understand and quantify the growing risk to various stakeholders. In this context, catastrophe risk models allow for a comprehensive probabilistic assessment of wildfire risk, examining key property and community level attributes to determine potential losses, and also provide a robust mechanism to quantify the impacts of wildfire mitigation measures.

This document provides an overview of the Moody's RMS U.S. Wildfire HD Model built using the latest geospatial, and climatological data to simulate hazards from direct flame, radiant heat hazard, ember accumulations, potential urban conflagrations, and damageable smoke across 100,000 years of synthetic wildfire events.

Application of the Model in Regulatory Processes

Catastrophe models have several broad uses in insurance business including:

Ratemaking

Catastrophe models use a stochastic event set or synthetic catalog representing millions of simulated events to create analytics that can be used by the insurance industry. Typically, the Average annual loss (AAL) metric from the model output is used as one factor to inform potential pricing of insurance policies. AAL for any specific property is calculated by summing the expected loss across all simulated events in the stochastic catalog impacting that specific location. Modeled AAL can be used as a component of the insurance base rate. This is often referred to as the technical rate in by-peril rating methodologies.

Solvency

The modeled stochastic event set can be sorted in such a way as to create an exceedance probability (EP) curve. This curve provides the probability of surpassing any loss level, expressing this probability in the form of a return period. Return periods are calculated by sorting the annual maximum event losses and yearly total losses to create occurrence and aggregate EPs, respectively. These curves are often used to estimate key return period losses, such as 1-in-100 or 1-in-250 to help with solvency, rating agency evaluation, and reinsurance purchasing decisions.

Mitigation Impact Evaluation

The ability of the model to reflect loss variation for individual building characteristics including structural mitigation can be used to develop rating methodologies that include factors related to mitigation. Catastrophe model analyses can be the basis of these relativity studies to inform the mitigation credits to be provided to consumers as part of their insurance policies.

Accessing the Models through Moody's Intelligent Risk Platform

The Risk Modeler™ application, accessible on Moody's Intelligent Risk Platform™, serves as the gateway to the U.S. Wildfire HD Model. Utilizing cloud computing technology, users can input their exposure data, select analysis settings, and receive detailed loss metrics.

Summary of Professional Credentials of Moody's Wildfire Modeling Team

The development of Moody's RMS Wildfire Model is backed by a multidisciplinary team of experts with deep academic credentials and decades of experience across various scientific disciplines including civil & structural engineering, meteorology, climate hazards, environmental science, statistics, atmospheric science, actuarial science, and computer science.

Around twenty personnel with an average tenure of 10+ years in natural hazards modeling, including 11 with Ph.D. degrees, were involved in the hazard and statistical aspects of the model development. Around sixteen staff members with an average tenure of 13+ years in performance evaluation of structures, damage and uncertainty quantification, including 9 with Ph.D. degrees, worked on the vulnerability and actuarial aspects of the model. Around twenty-five developers with an average experience of 18+ years in software development worked on the computer and information science aspects of the model. Furthermore, scores of additional staff members with extensive experience in serving the needs of insurance and reinsurance markets supported the model development on aspects related to requirements gathering, model and application testing, quality control, documentation, client training, etc.

Model Description

The basic components of a catastrophe model include: stochastic event set, hazard, exposure, vulnerability, and financial loss modules**.** First, the model determines the likelihood of different types of wildfire events across the modeled domain. Then for each simulated wildfire event, characterized by an ignition location, fire spread, and burn area, the model resolves individual hazard phenomena, namely, direct flame or heat, ember, and smoke hazard footprints in the affected areas.

These hazard footprints with their associated data such as simulated year and date, heat and ember indices including the impact of urban conflagration components, ignition location, stochastic weather over the course of the fire, fire spread parameters within the footprint, etc., can be used to determine the risk to any exposure set, usually provided through insurance company portfolios. The model is calibrated to generate results that are similar to historically observed patterns of hazard, damage, and loss in wildfire events.

A catastrophic wildfire event would typically be a large fire spread across hundreds and often thousands of acres. Weather and vegetative fuels are both critical to such an event occurring. Most significant catastrophic wildfires require hazardous fuels (e.g. chaparral or forest fuels) and extreme weather conditions (high winds and dry weather). However, catastrophic losses in wildfires do not require fuels or weather that enable the largest burn areas. While large losses are more likely in the same environments as those in which large fires take place, proximity of the fire to the wildland-urban interface and physical interaction of the fire front and embers with the built environment drive large loss potential in wildfire events. For instance, urban conflagration affects denser exposures than that expected from a fire solely within wildland.

Topography can amplify wildfire hazards and subsequent losses, as fires moving uphill or down slope can accelerate, with higher flames and more embers. Exposure composition can be important in catastrophic losses, as physical building characteristics and community layouts can dictate scale and ease of structure fires as well as potential fire-fighting efforts in the event of a wildfire. Beyond allowing individual fires to spread more aggressively, extreme weather conditions can allow multiple fires to trigger around the same time, leading to larger overall burnt area and higher overall damage.

The vulnerability component in the model then quantifies the physical impact of each of the wildfire hazard phenomenon on the exposure at risk in each simulated event. Vulnerability functions or damage curves are characterized by a damage ratio as a function of hazard intensity that vary by building characteristics and any associated mitigation measures.

Lastly, the financial module applies the damage ratio in each event to insurance contract terms to evaluate potential losses to property exposures and aggregates them from individual locations all the way to portfolio-level output. Direct financial losses include the cost to repair and/or replace a structure including the potential increase in cost of materials and labor due to demand surge following a major catastrophe. The model also includes the ability to estimate contents losses as well as losses to time-element coverage such as loss of rental income, additional living expenses, and business interruption.

The U.S. Wildfire HD Model includes ground-up and temporal simulations of building-level losses for each insured coverage and sub-peril, and includes:

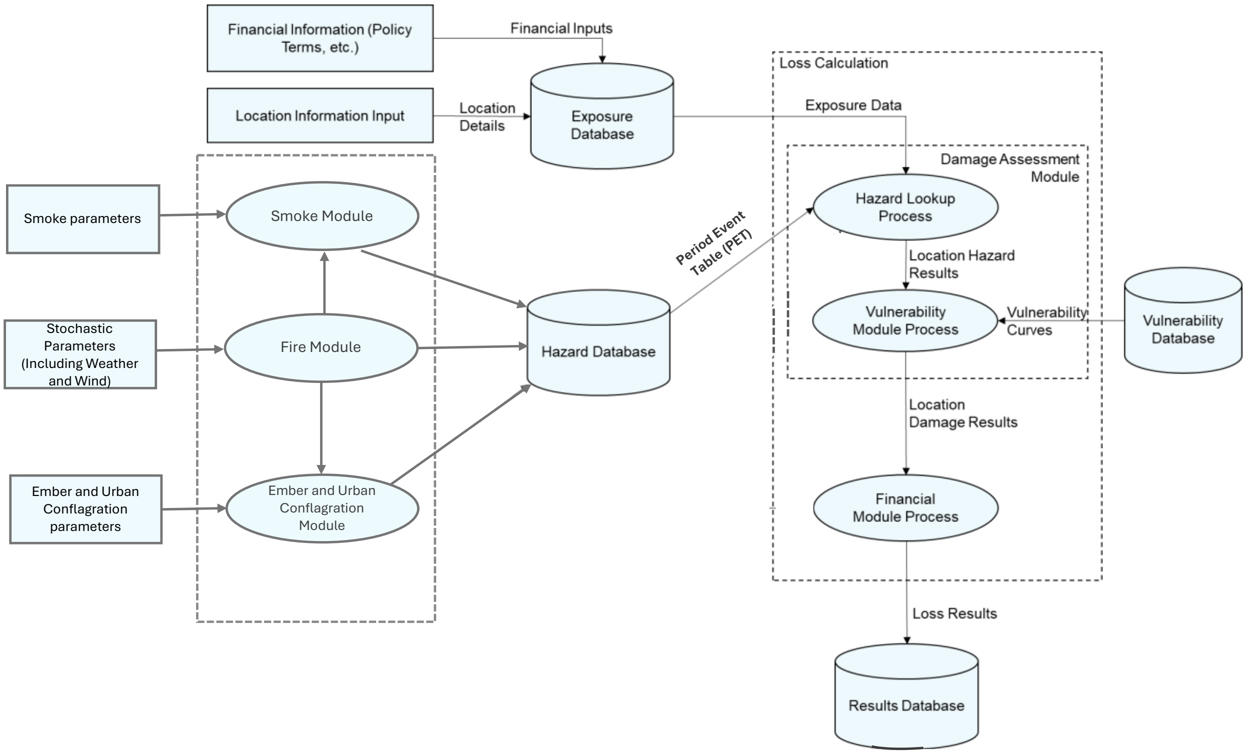
- Simulation-based framework that enables millions of realizations of wildfire scenarios across thousands of simulated years
- Probabilistic approach to model ignition and spread of wildfires, in addition to their associated ember, urban conflagration, and smoke footprints

- High-resolution geospatial data to resolve the high-gradient nature of the peril due to topography, fuel (vegetation), and fire weather parameters
- Multi-parameter vulnerability distributions to reflect the behavior of wildfire claims in a realistic manner and providing enhanced risk differentiation
- Flexible financial model to handle diverse temporal (hours clause) and spatial (distance clause) policy terms

Moody's derived the methodologies used in developing the wildfire model components in collaboration with researchers and experts in historical fire incident datasets, fire occurrence, fire spread, and damage mitigation modeling including those at the U.S. Department of Agriculture, Forest Service (USDA/USFS), CalFire, Insurance Institute for Business and Home Safety (IBHS), etc. The model includes a comprehensive range of stochastic wildfire events over a wide geographic extent at high resolution. The wildfire vulnerability module supports a comprehensive range of risk classes, calibrated using extensive insurance policy and claims data.

Figure 1 illustrates interactions among the major components of the Moody's wildfire catastrophe model.

Figure 1. Moody's Wildfire Catastrophe model components



The model estimates losses from wildfires caused by primary and secondary hazards including those caused by fire (direct flames or radiant heat), ember accumulation, urban conflagration, and smoke. The user has the capability to select losses from fire only, fire only including urban conflagration impacts, or combined impacts of fire and smoke.

Model Geocoding

Geocoding is the process of translating user-supplied address information into geographic location information that can be used by the model. It involves address standardization interpreting formats such as "N." as North, etc., address matching input address elements with valid reference data in internal geographic database at different geocoding resolutions such as street level, postcode, etc., geographic interpolation along street elements, if necessary, for precise location placement corresponding to the geocoding resolution, and ancillary data retrieval to supplement information not supplied by the user, such as county code etc.

Based on user input and after geocoding, the model can analyze exposures and provide loss outputs at the resolutions shown in Table 1.

Table 1. Geocoding resolutions

Name	Description
Coordinate	User-specified latitude/longitude coordinate pairs used directly in modeling process. Only ancillary data retrieval is applied to location supplied with coordinate level geocoding data. This is the most granular resolution for loss estimation in the model.
Building	Geocodes to the center of the building footprint.
Parcel	Geocodes to the center of parcel boundaries for street-address match.
Street Address	The geocoder matches street segment resolution reference data that contains address ranges and side of street parity, including interpolation along and offset from street centerline.
Point of Interest	Geocodes to the center of the business, building, or other feature that matches user-entered name.
Block Face	The geocoder matches street segment resolution reference data that contains address ranges but not side of street parity. Includes interpolation along street centerline.
Street Name	The geocoder matches street name only, either because the address number is invalid or missing. Uses a centroid for the street (length) factoring coarser address input (such as postcode).
Postal Code	The geocoder only has enough information to place the location within a specific postal code (e.g., U.S. ZIP Code). The model samples the location to grid cells across the postal code to determine losses in individual stochastic events. Input at this coarse resolution can have notable influence on the uncertainty in model loss output for a high-gradient peril like wildfire.

Model Geospatial Databases

Various geospatial datasets form the foundation to the hazard and vulnerability components of the model. Geospatial data is sourced from various authoritative providers such as USGS, LANDFIRE, USDA U.S. Forest Service, U.S. Postal Service, U.S. Census, etc., and is verified internally before integration into the model. ZIP Code databases are refreshed regularly and align with USPS publications, while centroids are recalculated based on population or wildfire relevance. The model was developed with USPS ZIP code data from December 2023. Eco-regions and Fire Weather Zones are updated in response to changes in land use, vegetation, or fire history, with updates synchronized across model components through version control and regression testing to maintain consistency and model integrity.

Table 2 below lists the geospatial databases used in the model currently under review.

Table 2. Model Geospatial Databases

Geospatial database	Source
Historical Fire Ignitions	Spatial Wildfire Occurrence Data for the United States, Forest Service Research Data Archives; National Interagency Fire Center (NIFC) Occurrence Sixth Edition
Historical Fire Footprints	U.S. Interagency Program Monitoring Trends in Burn Severity (MTBS- 1984-present) Wildland Fire Decision Support System (WFDSS), U.S. Geological Survey, retired (1984-2017) Geospatial Multi-Agency Coordination for Wildland Fire Support (GEOMAC-2000-2018) NIFC (2000-present) CalFire historical fire footprints (FRAP)
Landscape Data	LANDFIRE Data set LF2.3.0 (late 2023), U.S. Department of Agriculture Forest Service and U.S. Department of the Interior
Weather Data	NOAA North American Regional Reanalysis (NARR) and historical meteorological data from the North American Land Data Assimilation System (NLDAS-2)
Surface and Forest Fuel Models	Internal datasets derived from LANDFIRE
Transmission Lines	Federal Emergency Management Agency HIFLD (2023)
Pyromes / Fire Weather Zones	USDA-Forest Service using ecoregions Short (2022)
ZIP Code Data	United States Postal Service (USPS)

Mapping of Pyromes, Fuel and Landscape data, and Weather data

For the continental U.S., Moody's aggregated the 128 Pyromes provided by USDA Forest Service (Short, 2020) into 98 fire weather zones to differentiate regional fire behavior based on size, fire frequency, similarity in vegetative fuels, topography, and climate across adjacent zones (see Figure 2).

Figure 2. USDA Pyromes (left) and Fire Weather Zones used in the Moody's Wildfire model (right)

The model uses LANDFIRE data to determine local fire behavior characteristics according to the well-accepted Anderson 13 Fire Fuel Behavior model. LANDFIRE layers consisted of 30m data for Anderson fuel, canopy cover, canopy height, canopy base height, canopy bulk density, slope, and aspect from the most recent dataset available at the time of development (LF2.3.0, December 2022).

Moody's processed weather data from NLDAS-2 data to generate historical and stochastic weather for the wildfire simulations. The primary source of weather data used for wildfire model simulations is the NLDAS dataset (Xia et al., 2012), which included hourly temperature, precipitation, specific humidity, solar radiation, and U- and V- winds at 1/8th degree weather cell resolution. This was supplemented by the monthly ENSO index using the ONI index values available from NOAA. The fire weather content used in the model is daily ERC-G, Fuel Moisture (computed using Nelson and GSI methodologies), wind speed and wind direction.

The computed fire weather index, ERC-G, informed by historical fuel moistures, captures the volatility of the historical record. The variability embedded within the historical period of data was used with the principal component analysis (PCA) statistical approach to represent variability in the temporal and spatial domains. The simulated ERC-G distributions were compared against historical distributions for each fire weather zone to determine their validity and appropriateness.

Wildfire Hazards

The model simulates the lifecycle of a wildfire - from weather conditions that influence the risk of ignition and fire spread, through to its final containment. It leverages widely accepted methods in the fire behavior modeling community and observational data from reliable sources as described in the following sections:.

Landscape Parameters

The primary building blocks in wildfire modeling are the underlying fuel and landscape characteristics. The model used the U.S. Federal LANDFIRE data layers as the primary source for information of vegetative fuels, canopy characteristics, and topography elements. The LANDFIRE data layers, available at 30m resolution for the entire modeled domain, also incorporate in its fuel layers the impacts of large-scale vegetation management efforts (till 2024) to mitigate wildfire risk. Moody's resampled these landscape parameters to 50m, the native hazard resolution in the model, to obtain site hazard characteristics that determine location-specific hazard in each event such as Distance to Vegetation, Fuel type, and Slope.

Given the extent of the fire spread process, Moody's further aggregated these landscape layers to 250m to generate fire footprints for all simulated wildfire events. In the fire spread process, the model also accounts for relative proportion of vegetative and urban cells within each 250m grid cell in the Wildland-Urban Interface to represent the impacts of fire suppression since burnable areas in the vicinity of urban developments have lower fire risk compared to wildland, all else being equal, due to fire-fighting efforts to protect exposures from an oncoming wildfire.

Prior to using landscape parameters for wildfire hazard generation, Moody's cleaned and processed the LANDFIRE data layers and made specific modifications to the fuel layer. Firstly, we updated the fuel type in select areas, making accommodation for fuels and canopy values assigned to areas within recent burn scars, based on discussions with LANDFIRE fire behavior specialists. These changes also informed subsequent revisions to LANDFIRE data layers released to public at a later date. In addition, we treated small urban parks across the entire domain as non-burnable for the purposes of modeling catastrophic wildfires. These changes result in more realistic fire behavior as well as consistent fire spread characteristics, and yield more accurate fire frequency.

Historical Fire Data

Moody's used historical fire data from the database created by Karen Short (Short, 2022), including the National Interagency Fire Occurrence Sixth Edition (1992-2020). In addition, the model also leveraged other historical fire databases such as MTBS data (1984-2023), GeoMAC data (2000-2018), and updates from NIFC (2000-2022) to assess historical burn probability. Moody's reviewed the data for consistency across different sources, and modifications were done to the extent of removing erroneous or duplicate records and counting historical footprints only once in case of multiple versions across different sources. The model considered ignitions and burn area for historical wildfires that were larger than 100 acres for model development, calibration, and validation.

Fuel Loading and Fire Spread Parameters

The Moody's wildfire model is developed based on methods described in FlamMap (USDA Forest Service) and the U.S. National Fire Danger Rating System, NFDRS (Cohen et al., 1985). The model uses the same fire spread parameters including fuel loading based on fuel types, canopy characteristics, and topography inputs from LANDFIRE data layers.

The model uses fixed fire behavior to simulate fire spread of both stochastic fires and historical fires under current conditions. However, we used LANDFIRE datasets of contemporaneous vintages to simulate fire spread and reconstruct historical fire footprints used for model loss validation. It is important to note that while the model includes hazard footprints for historical wildfires, they do not affect the stochastic rates used for rate making in California.

Historical Weather Variables

The model used hourly gridded weather at 1/8th degree resolution from NLDAS-2 for historical weather data described by weather variables such as wind speed (U and V), precipitation, temperature, specific humidity, and solar radiation. For local windspeed corrections, particularly for historical footprint generation, we also leveraged weather data from local and RAWS weather stations.

As part of fire weather simulations, we computed relative humidity from hourly gridded weather data as the ratio of vapor pressure over saturation vapor pressure using standard weather equations and the August-Roche-Magnus formula for saturation vapor pressure and Dalton's Law for vapor pressure.

To estimate fuel moistures, we used the Nelson (2007) method for dead fuel moistures and Growing Season Index (NFDRS, 2016) for live fuel moisture. Daily values are obtained from hourly dead fuel moistures by taking smoothed low values reflecting typical fire spread conditions over the course of a day.

Following the FlamMap (2006) approach, ERC-G values computed from the fuel moistures are used as input into the fire behavior model used in the NFDRS.

Climate Change Impacts and Current Climate

Several recent studies highlighted the changing patterns in temperature and fire weather due to climate change and their correlation with increasing frequency and severity of wildfires in California (Abatzoglou, J. T., et al, 2016, Jones, et al, 2024, Jain, et al, 2024). We adjusted the historical fire weather data, detrending the ERC-G parameter, which is a key indicator of the fuel dryness used in the model. As part of this process, we detrended the underlying weather data, temperature, precipitation, and humidity, from NLDAS-2 dataset (1980-2022, 1/8th degree resolution: Xia et al, 2012) using local correlation to global surface temperature anomalies. This approach results in adjusted historical weather that is representative of the current period (2025), while preserving the variability.

At the scale of California, the overall impact of the detrending approach to reflect current climate is an increase in the ERC-G parameter. However, the magnitude and direction of ERC-G differences between the historical and current climate sets vary spatially across the state. In the model, higher ERC-G leads to more fires (higher ignition rate) and more active fire spread (larger fires, with more intense flame lengths), enabling the model to match the observed fire frequency and severity in California more closely and reflect present day wildfire risk more accurately.

Stochastic Fire Weather Simulation

Fire weather index is a comprehensive term used to represent the 'dryness' of environment based on fuel moisture content, which itself depends on basic meteorological factors such as temperature, precipitation, and relative humidity. The model uses Energy Release Component for representative NFDRS fuel type G, ERC-G, to characterize the fire weather index since it correlates with the risk of ignitions and fire spreading. ERC-G is computed from fuel moistures using standard fire spread modeling practices (Cohen et al. 1985).

Moody's used the Principal Component Analysis (PCA) approach and the detrended historical ERC-G to simulate stochastic daily ERC-G with the ENSO weather index (Oceanic Nino Index) as an additional model component. The model used observed ENSO index in history (1900-2021) to map the index to each of the simulated 100,000 years, enabling adequate representation of the annual and seasonal variability observed in history in the stochastic fire weather simulations. Based on the simulated ERC-G and ENSO indices, stochastic wind speeds are sampled from historically observed wind speeds, mapping each stochastic year and month to a historical year and month. Stochastic wind speeds therefore capture the full range and seasonality of wind speeds observed in history (1981-2024).

Since gridded weather tends to smooth extreme values, the model incorporated a frequency-based approach for bias correction and to simulate severe weather conditions, including katabatic winds that are typically observed in California and known popularly as Santa Ana winds, Sundowner winds, or Diablo winds. If severe weather conditions are triggered during a simulated event based on a significant fraction of the Pyrome experiencing dry and windy weather, gridded weather in susceptible weather cells is modified to reflect effects of local gusts or katabatic winds.

The model simulates thousands of current year realizations with simulated daily wind speeds, directions, and fire weather index (ERC-G) values developed based on detrended historical distributions.

Moody's compared distributions of simulated ERC-G values against detrended historical ERC-G values in each fire weather zone to ensure that the simulated weather appropriately captures extreme fire events that drive losses in catastrophic wildfires.

Stochastic Fire Ignitions

A majority of wildfires in the U.S. including in California are caused by humans and therefore occur more frequently near population centers (Syphard et al., 2007, Balch et al., 2017, Coogan et al., 2020). Weather, represented by windspeed and dryness, is also a critical driver for ignitions to develop into significant fire sizes, once they are started (Urbieta et al., 2015). While historical ignition locations and causes form a reasonable basis to calibrate modeled ignition probabilities, they do not represent all locations and conditions where wildfires may ignite (Karen Short et al., 2015).

Moody's used a General Additive Model (GAM) approach for simulating wildfire ignitions. We calibrated the ignition parameters using historical datasets of fire ignitions from USDA Forest Service (Short, 2020) and historical fire weather conditions. The ignition component of the model simulates wildfire ignitions on a daily basis based on simulated daily fire weather index and simulated daily windspeeds as function of distance to populated areas, considering the geographic location and long-term weather conditions.

The model also leverages available information on historical cause of wildfires to attribute a fraction of simulated ignitions to utility networks in each fire weather zone (California Public Utility Commission, R.08-11-005) based on simulated fire weather parameters, seasonality, and distance to power lines. In recent years, utility companies have been investing resources to harden their network to mitigate wildfire risk (Macomber et al., 2024). The model considers the impact of existing network hardening measures (vegetation management, covered conductors, PSPS, fast relay, undergrounding, etc.) under current climate conditions by removing a fraction of simulated ignitions based on publicly available information and learnings from collaborative research with utility companies across California and other states. The attributions and mitigation impacts are made regionally as function of simulated fire weather based on spatial distribution of transmission and distribution lines in the state of California and current mitigation practices (California Office of Energy Infrastructure Safety, 2023-2025).

Stochastic Hazard Footprint Simulation

For every simulated ignition, the model includes a footprint for heat hazard reflecting the rate of spread and energy release component parameters as well as an ember footprint representing the accumulated ember load from burned vegetation, considering the impacts of urban conflagration.

The hazard model uses a wide range of inputs and methods to simulate ignitions, fire spread, ember, smoke, and urban conflagration. The model uses relevant inputs such as historical ignitions, fire perimeters, historical weather, and landscape data to reconstruct historical wildfire footprints to confirm its ability to adequately represent major wildfires observed in California and for model loss validation exercises. While the model used the same approach to generate historical and stochastic fire, ember, and smoke footprints, the reconstruction of historical fires was done using contemporaneous fuel layers of appropriate vintage instead of the current day fuels. It is important to note that while the model includes hazard footprints for historical wildfires, they do not affect the stochastic rates used for rate making in California.

The model uses well-accepted parameters by the U.S. Department of Agriculture Forest Service and U.S. Environmental Protection Agency to simulate hazard footprints and their intensities (radiant heat and flames, embers, and smoke). The modeled heat footprints are derived based on Energy Release Component, Flame length, Rate of spread, and canopy characteristics of fire footprints. The ember footprint is derived from ember accumulation component of fire spread, the smoke footprint from the amount of burned vegetation as described in subsequent sections in this document. The U.S. Wildfire HD Model contains over 160 million stochastic events, each with a heat, ember, and a smoke footprint, of which over 13 million events impact exposures in California.

Fire Spread Model

For each simulated ignition, the model estimates fire progression using simulated fire weather, affected fuel types, their fire behaviors, and landscape characteristics. These interactions are calculated using well-known techniques and fire spread algorithms described in models such as FlamMap (Finney, 2006) and FSim (Finney, 2011a) developed by USDA Forest Service, leading to a wide range of simulated fire footprint shapes and sizes to adequately reflect observed wildfires in history.

The fire spread model inputs include LANDFIRE Fuel and topographic data (version LF.2.3.0; December 2023), fuel parameters such as fuel loading, surface to volume ratio, moisture of extinction, canopy parameters including cover fraction, base height, canopy height, canopy bulk density, topography parameters such as slope and aspect, as well as simulated daily ERC-G, daily fuel moistures, daily wind speed, daily wind direction, and simulated ignition locations.

Within the model, fire spread is simulated under the conditions of each day and 1/8th degree weather cell, with fires able to grow over multiple days or weather cells. The fire spread model computes parameters at 250m resolution for rate of spread, dominant fire direction, Energy Release Component (ERC) for the specific burned fuel, flame length, and maximum spotting distance using NFDRS equations.

Furthermore, the model considers temporal and spatial variations in fuel moisture, wind speed and direction, as well as variations in topography to accurately simulate wildfire spread under different conditions such as surface fires, canopy fires, and torching fires. For instance, as ERC-G, windspeeds, wind directions are simulated daily, the resulting parameters that determine fire progression including rate of spread, fuel moistures, etc., can also vary daily and reflect the time-varying aspect of input parameters during the life of a wildfire event.

The model also considers spotting of fires to represent jumps across roadways, water bodies, etc., as well as the impacts of fire suppression, which is complex and depends on many factors including fire characteristics, terrain, urban proximity, fire management practices, and extreme weather conditions.

The fire spread model was run on non-detrended historical weather, historical fuels (LANDFIRE LF2.3.0), and historical ignitions to calibrate the spread parameters vis a vis fire size distributions in each Pyrome. This was done with the same underlying fuel and weather components (including fuel moistures) as the stochastic fires, albeit with different ignition and weather inputs.

The model also accounts for fire suppression impacts at various length scales including at a regional (Pyrome) level based on fire spread parameter calibration, local level (at the Wildland-Urban Interface), including suppression impacts that increase over the duration of the fire. Suppression impacts also vary by event, representing the uncertainty in potential firefighting efforts as observed in historical wildfires. In addition to the explicit consideration in the fire spread model, the model allows local scale fire suppression impacts at individual community and property levels to be represented via exposure inputs using secondary attributes (active or passive suppression) and site-specific mechanical treatment of fuel or distance to vegetation inputs.

The model simulates wildfires at continental scale, i.e., the fire spread model does not stop at state, county, or Pyrome boundaries. While the majority of wildfires affecting exposures in California originate in the state, fires starting in neighboring states can also spread into California and such infrequent scenarios are also represented in modeled stochastic simulations.

The output from the fire spread model, specifically rate of spread and ERC are then used to obtain location-specific hazard intensity as a composite heat index (adjusted flame length) based on additional model-default or user-specified inputs for fuel, slope, and distance to vegetation as described in later sections in the document. The resulting hazard intensity informs the heat vulnerability functions to estimate damage from radiant heat and direct flame threat.

Ember & Urban Conflagration Simulation

During a wildfire, multiple hazards influence the likelihood of structure ignition and subsequent damage and destruction. In addition to direct contact with flames or when exposed to radiative heat or hot gases from nearby burning vegetation, buildings can ignite and burn from ember showers as a wildfire progresses (Manzello S. L., 2014). The model explicitly characterizes ember transport and accumulation corresponding to each simulated wildfire depending on simulated fire weather, fuel type, wind speed, and other geophysical attributes such as topography, and the amount of fuel burned considering uncertainty in wind direction. Spotting and ember transport behavior were based on equations used in FlamMap (Finney, 2006) for the fire spread and ember accumulation components, and on the Albini approach (Albini, 1979) for the maximum distance.

Moreover, in dense urban areas near the wildland, the model also captures building-to-building fire spread under high wind speeds to represent the urban conflagration phenomenon observed in events such as the 2017 Tubbs fire (Coffey park) and more recently in the 2025 Palisades (Pacific Palisades) and 2025 Eaton (Altadena) fires leveraging well-accepted methods that represent similar behavior in urban fires following earthquakes (Mortgat, et al, 2004, Lee et al. 2008; Sizheng and Davidson 2013; Hamada 1951, 1975). While conflagrations following earthquakes and wildfires have similarities, the underlying processes driving the extent, severity, and containment of the conflagration differ due to the causes and characteristics of wildfire compared to fires triggered by ground shaking. The urban conflagration model uses several parameters to simulate the likelihood and severity of urban conflagration including the accumulated ember load, building density and street width, and simulated fire weather conditions on a daily basis. It also considers uncertainties in windspeeds, wind direction, as well as firefighting capacity to determine if and how far the conflagration can propagate into an urban area. Moody's calibrated the parameters of the urban conflagration model using detailed fire footprints, damage and exposure data, as well as based on observations from post-event field reconnaissance data for some of the historical wildfires that witnessed this phenomenon.

The impact of the urban conflagration is represented within the ember footprint with a significant increase in ember load in areas affected by the simulated conflagration that yields damage ratios representing near total destruction. The output from the ember model is then used to inform the intensity used in the ember-specific vulnerability functions.

Smoke hazard Simulation

For each simulated wildfire, in addition to the fire and ember footprints, the model also includes a damaging smoke footprint developed based on latest models used in the wildfire community for smoke emission, transport, and deposition and U.S. Environmental Protection Agency's guidelines on hazardous smoke impacts in terms of concentrations of fine particulate matter known as PM2.5 (U.S. EPA, 2016). The model estimates smoke hazard based on simulating the amount of smoke particulate matter emitted using USDA Forest Service's Fuel and Fire Tools (FERA 2014), the distance of smoke particulate dispersion using USDA Forest Service's VSMOKE model (Lavdas, 1996), considering local uncertainties in wind direction and moisture conditions to account for the turbulent nature of wildfire conditions aiding smoke spread, and the concentration of deposited particulates.

The VSMOKE model, commonly used to assess air quality impacts on public health and visibility for prescribed burns, uses a Gaussian plume dispersion approach to estimate hourly downwind ground-level PM2.5 concentrations based on input emission profiles and wind information. In this approach, the extent of damaging smoke depends on the type of fuel burning, the time of the year, and fire size that drives the amount of smoke particulates emitted during the wildfire as well as weather conditions that determine the dispersion and deposition of potential smoke particulates.

Site Hazard Data

Research has shown that local site conditions in the immediate vicinity of a structure critically affect the chances of structure ignition during a wildfire from the combined effect of radiant heat, flames, and embers. In particular, the effect of heat footprints is highly dependent on these local conditions at a site.

The Moody's RMS wildfire model contains model-default values at 50m resolution for each of the site hazard parameters affecting wildfire hazard, namely, fuel type, slope, and distance to vegetation. Users can override these default values for each location with site-specific inputs, if available. This is the primary mechanism to capture risk mitigation associated with maintaining a defensible space as specified in many building code ordinances.

Fuel Type— If there are changes in fuel landscape due to urbanization of land, clearing a defensible space, or recently experienced wildfire, users can override the model-default fuel type to a value more representative of the current state of vegetation to reflect the changed (lowered) risk profile. The model supports over 10 different fuel type classifications.

Slope— High slopes can aid in preheating the structure before the arrival of a fire front and also pose challenges for fire-fighting. While the model-default reflects the average terrain across a 50-m cell, slope at the site of individual buildings can vary due to presence of hills or road cutbacks, which can alleviate some of the risk. Users can override model-default value with location-specific input of slope (in percentage).

Distance to Vegetation—The presence of defensible space around a structure can be captured in the model using this parameter. The model-default values represent an average across a 50-m cell. Users can override this value with site-specific distance to vegetation input (in feet or meters). This input parameter can significantly impact the hazard index for both heat and ember hazards and resulting modeled losses.

Mechanical Treatment— To account for future wildfire risk modification programs, the model allows users to specify risk reduction potential due to mechanical thinning of trees and other fuel modification based on severity, extent, and time since treatment. This input impacts (reduces) both the heat and ember risk at individual property level and can be used to reflect impacts of location (property or community-specific) fire prevention measures.

During run time, for each affected location in each simulated wildfire event, the model combines the hazard intensities from the fire (and ember) footprints at 250m resolution with the model-default 50m values or user-specified location values for site hazard to obtain the Composite Heat Index parameter (and Ember accumulation load parameter). The Composite Heat Index is an adjustment to the flame length estimated using the rate of spread and ERC parameters from the fire footprints to account for site-specific differences in defensible space in terms of distance to vegetation (e.g. the same flame length farther away from a structure is less likely to result in structure ignition and subsequent damage), fuel type (e.g. likelihood of fire suppression activity and residence time, or the time a structure is exposed to the flaming front, is different in grass fires compared to forest fires), and slope of terrain (steeper slopes can increase pre-heating time). Studies done by Moody's using claims data from 30+ major catastrophic wildfires revealed that in areas with vegetative fuels, observed damage intensity is better correlated to the Composite Heat Index than flame length alone.

Vulnerability

The U.S. Wildfire HD Model expresses damage to properties through vulnerability functions, also known as vulnerability curves or damage curves. Wildfire vulnerability functions consider the bespoke nature of modeled hazard and are developed to work consistently with the modeled hazard in terms of intensity and resolution. Modeled damage functions reflect the combined effect of probability of ignition to a structure when faced with radiant heat, flames, and embers, as well as the conditional damage once a structure is ignited.

The model includes separate vulnerability functions for each hazard (i.e., direct flame and radiant heat, embers, and smoke). The model combines damage ratios for radiant heat and flames based on the composite heat index and for accumulated ember load to output the fire risk for every location. For analyses that include fire and smoke, the model combines damage from both sub-perils to determine the overall damage for each individual coverage (structure, contents, and time-element).

Primary Characteristics

In the U.S. Wildfire HD Models, damage curves for heat, embers, and smoke represent the average vulnerability of a class of buildings for a specific combination of primary characteristics representing 40 occupancy types, 12 construction classes, 3 year-built bands, 5 number of story bands, and 3 floor area ranges. In all, the model supports over 750 combinations of primary attributes representing a comprehensive range of building classes with 70 unique curves the represent the vulnerability of residential structures including for single-family, multi-family dwelling and manufactured homes (see Table 3).

Each supported combination has separate damage functions for building and contents coverages.

Table 3. Moody's Primary building classification options

Construction Class
Unknown
Wood Frame
Masonry
Unreinforced Masonry
Reinforced Masonry
Reinforced Concrete
Reinforced Concrete with Concrete Roof Deck
Reinforced Concrete with Wood frame in upper floors
Tilt-up
Reinforced Concrete with Wood or Metal Roof
Steel
Light Metal
Personal Autos
Auto Dealerships

Number of Stories
Unknown
1
2–3
≥ 4

Year Band
Unknown
Pre 1996
1996–2008
2009 or later

Floor Area	
Single-Family	Commercial
1–5,000 ft^2	1–5,000 ft^2
> 5,000 ft^2	5,000ft^2–25,000 ft^2
	> 25,000 ft^2

Occupancy
Unknown
Residential - Single Family
Residential - Multiple Family
Residential - Multi-Family Condo Association
Residential - Multi-Family Condo Unit Owner
Commercial - Temporary Lodging
Commercial - Retail Stores and Entertainment
Commercial - Offices and Professional Services
Commercial - Parking
Commercial - Agriculture
Commercial - Religion
Commercial - Education
Commercial - General Commercial
Commercial - Gasoline Service Stations
Commercial - Restaurants
Industrial - General Industrial
Industrial - Highly Combustible
Industrial - Non-Combustible

Moody's collected over $1 billion in location-specific claims loss data from insurance companies for the purposes of developing and calibrating structure, contents, and time-element vulnerability functions associated with fire and smoke hazards across 22 historical wildfires in the U.S. The detailed claims and associated exposure data provided by insurers contained building characteristics as well as property (coverage) values and policy terms. Moody's performed extensive quality checks to process and use the claims data to derive insights that informed the vulnerability functions.

In addition, Moody's also used detailed damage information for more than 60,000 buildings (see Table 4), out of a total of 330,000 affected buildings within the fire perimeters of 32 historical wildfires across the U.S. While much of this damage data is available from the CalFire DINS dataset, others were obtained from other publicly available sources.

Table 4.: List of historical U.S. wildfires used to develop and calibrate modeled heat and ember hazard indices and vulnerability functions

Fire	Date	Country-State
Cedar Fire	October/November 2003	U.S. – California
Witch Fire	October/November 2007	U.S. – California
Black Forest Fire	June 2013	U.S. – Colorado
Valley Fire	September 2015	U.S. – California
Butte Fire	September 2015	U.S. – California
Chimney Tops 2 Fire	November/December 2016	U.S. – Tennessee
Wine County Fires	October 2017	U.S. – California
Thomas Fire	December 2017/January 2018	U.S. – California
Camp Fire	November 2018	U.S. – California
Woolsey Fire	November 2018	U.S. – California
Carr Fire	July/August 2018	U.S. – California
Kincade Fire	October/November 2019	U.S. – California
LNU Lightning Fires Complex	August - October 2020	U.S. – California
CZU Lightning Fires Complex	August/September 2020	U.S. – California
SCU Lightning Fires Complex	August - October 2020	U.S. – California
North Fires Complex (NCU)	August - December 2020	U.S. – California
Creek Fire	September - December 2020	U.S. – California
Glass Fire	September/October 2020	U.S. – California
August Fires Complex	August - November 2020	U.S. – California
BEU Fires Complex	August/September 2020	U.S. – California
Bobcat Fire	September - November 2020	U.S. – California
Bond Fire	December 2020	U.S. – California
Silverado Fire	October/November 2020	U.S. – California
Slater Fire	September - November 2020	U.S. – California
SQF Fires Complex	August 2020/January 2021	U.S. – California
Zogg Fire	September/October 2020	U.S. – California
Almeda Fires Drive	September 2020	U.S. – Oregon
Marshall Fire	December 2021/January 2022	U.S. – Colorado
Caldor Fire	August - October 2021	U.S. – California

Fire	Date	Country-State
Dixie Fire	July - October 2021	U.S. – California
Lahaina Fire	August/September 2023	U.S. – Hawaii
Kula Fire	August/September 2023	U.S. – Hawaii

Moody's validated the modeled vulnerability and hazard using insurance company portfolios and corresponding observed historical losses for the following events shown in Table 5 .

Table 5. Wildfire events where insurance companies provided portfolios and claims for model development

Wildfire Event	Year	States Affected
Sayre Fire	2008	California
Marek, Sesnon Fire	2008	California
Tea Fire	2008	California
Bastrop Fire	2011	Texas
Waldo Fire	2012	Colorado
Oklahoma Fire	2012	Oklahoma
Black Forest Fire	2013	Colorado
Witch Fire	2007	California
Sayre Fire	2008	California
Butte Fire	2015	California
Valley Fire	2015	California
Witch Fire	2007	California

In addition to claims and damage information, Moody's developed an analytical framework to capture adequate risk differentiation in the model that considered various factors influencing structure performance when exposed to different ignition sources including radiant heat, flames, and embers. For instance, type of roof covering, percentage and type of openings (e.g., single-pane or double-pane windows), and likelihood of active fire suppression are some of the factors explicitly considered in the analytical framework to differentiate vulnerability across various occupancy types and construction classes. Research by the Insurance Institute for Business and Home Safety (IBHS) on ember threat to various roofing and structural elements and interactions with the Californian Department of Forestry and Fire Protection (CALFIRE) also informed the analytical model used to develop structure and contents vulnerability differentiation.

For every building vulnerability function, there is a separately derived content vulnerability function. Therefore, the number of contents functions is the same as that listed earlier for building. In general, contents damage occurs once fire breaches the building envelope during a wildfire and increases rapidly with increase in hazard intensity. Moody's derived contents vulnerability functions considering building damage thresholds representing envelope breach, susceptibility of different types of contents to fire and smoke, and salvage potential.

Different vulnerability relationships are used for personal residential, commercial residential, mobile/manufactured homes, condo unit owners, apartment renter unit locations and also commercial and industrial properties for contents coverage similar to building.

The model uses structure damage functions to estimate damage to appurtenant structures (Coverage B) given similarities in building characteristics as well as observed damage. In addition, the model allows users to specify appropriate secondary modifiers to reflect additional damage to appurtenant structures such as fences, screen enclosures, etc.

In addition, building and contents vulnerability, the model assesses building downtime and subsequent time element losses (i.e., additional living expenses and business interruption) by considering the loss of function and restoration time of the property, referred to as facility downtime. The model correlates loss of function and repair/restoration times in each event for each analyzed location as a function of damage state of the affected property determined by the structure damage ratio. The model includes separate time-element and structure damage relationships for all occupancy classes supported. However, since the underlying structure damage varies by other primary attributes, time-element vulnerability also varies for each combination of supported building class attributes.

In addition to direct time-element losses, the model also includes distinct time-element functions due to evacuation and/or infrastructure damage such as power lines and other utilities, referred to as infrastructure downtime. The impacts of infrastructure damage and evacuation on prolonging time for rebuilding or restoring loss of function in wildfire events can be significant within and in the vicinity of burn scar.

For each location in each simulated wildfire event, the model computes both facility downtime and infrastructure downtime and then uses the larger of two estimates as the time-element vulnerability to compute losses for business interruption and additional living expenses.

When one or more primary attributes (occupancy type, construction class, number of stories, year of construction, floor area) are not specified by the user, the model applies, by default, region-specific building inventory weights to develop a composite weighted-average function. For instance, for a specified occupancy type (e.g., single-family dwelling or commercial residential), the loss cost for an unknown residential construction type is computed using a composite vulnerability function that is a weighted average of the vulnerability functions corresponding to unique combinations of height, year built, and construction class for the specified occupancy type.

The California inventory distributions implemented in the Moody's RMS model are specified by ZIP Code and are based on an extensive industry database compiled using authoritative third-party data sources and in-house research on property exposure data, and analysis of aerial and satellite imagery.

Mitigation Measures

A critical aspect of modeling wildfire losses accurately is to recognize the possibility of structures surviving wildfires and adopting mitigation measures increases the chances of survival. Recent research on building performance shows that the factors most critical to the survivability of a structure in wildfires include site-specific parameters that impact hazard intensity such as defensible space, slope, etc., as well as building attributes such as roofing, siding, and decking. With heightened awareness of wildfire risk after recent catastrophe events and new research on roof materials, fire retardant gels, and suppression tactics, wildfire-resistant mitigation practices are now more commonplace.

In the model, the vulnerability of any individual building relative to others in that group depends on site-specific inputs that can significantly alter (lower) the ignition probability as well as conditional damage to the structure when ignited. The model enables capturing mitigation attributes— their value, presence or lack of, and type—and the variation in expected performance through exposure data inputs for secondary modifiers and site hazard.

In the wildfire model, when both occupancy type and construction class characteristics are input, users can avail several modifiers and options for each modifier. If either of them is not specified, the model ignores secondary modifier inputs. When secondary modifiers are specified along with the required primary characteristics, the base (unmodified) vulnerability curves corresponding to the combination of primary characteristic inputs are adjusted based on the selected options. The adjustment is a scalar that can decrease or increase the base vulnerability curves depending on the option selected, sub-peril (heat, ember, and smoke), and hazard intensity. While mitigation measures reduce the damage potential (lower vulnerability), specific modifier options (such as presence of combustible decking, etc.,) can also increase the damage potential.

A review of structure performance in past wildfires indicates that the highest chances of survival are observed when home hardening focused on system-level mitigation. As such, the model provides substantial credit for risk reduction programs like “IBHS Wildfire Prepared Home” classification, which requires multiple mitigation measures including defensible space to be implemented. However, the model also provides nominal to notable credits for individual mitigation measures as well. The impact of a specific mitigation measure on modeled loss costs varies by geographic location, which determines the potential hazard intensity at the site, and selected primary characteristics, which determines the base vulnerability. In general, key mitigation measures that can have notable impacts in terms of modeled risk reduction for residential buildings in California include Distance to Vegetation or Defensible space (up to 80%), Community Preparedness (up to 20%), Fire resistant windows (up to 10%), Class A roof covering (up to 10%), etc.

The default setting for each of the modifiers is "unknown". So, if no modifier options are chosen, the base (average or typical) vulnerability curve corresponding to the input primary characteristics is used in the model.

Users may change one or more mitigation factors from the unknown state based on specific attributes for the modeled structure. The model combines the impacts of individual mitigation factors with a multiplicative methodology to reflect the total effect of different attributes, which may yield an ultimate increase or decrease to the modeled loss.

Several secondary modifiers are commonly collected on homeowners’ policies and others such as slope setback and roof vents are commonly recorded during physical inspection of the property. Table 6 lists the secondary modifiers supported in the model.

Table 6. Secondary Modifiers available in the Moody's RMS U.S. Wildfire HD Model

Secondary Modifier	Description	Number of Options	Selected List of Available Options
Roof System Covering	Users can specify either a roof cover material type from which the model infers a typical flammability class, or a fire rating class	15	• Unknown • Concrete/clay tiles • Wood shakes • Normal shingle • Concrete roof • Class A Fire Rating • Class B Fire Rating • Class C Fire Rating
Roof Shape	Roof shape affects a building's susceptibility to flames and radiant heat.	9	• Unknown • Flat roof with parapets • Flat roof without parapets • Hip roof with slope less than or equal to 6:12 (26.5 degrees) • Hip roof with slope greater than 6:12 • (26.5 degrees) • Gable roof with slope less than or equal to 6:12 (26.5 degrees) • Gable roof with slope greater than 6:12 (26.5 degrees) • Braced gable roof with slope less than or equal to 6:12 (26.5 degrees) • Braced gable roof with slope greater than 6:12 (26.5 degrees)
Roof Age or Condition	Specify age of roof.	5	• Unknown • 0–5 years • 6–10 years • 11 years or more • Obvious signs of deterioration and distress
Roof Vents	Roof vents allow embers and smoke to infiltrate the structure causing ignitions and, smoke damage.	6	• Unknown • None • Wildfire Resistant Vents • Partially Resistant Vents
Ember Accumulators	Ember accumulators are areas on the building's roof and envelope that allow wind-borne embers to pile up and ignite other combustible objects.	4	• Unknown • None to few • Abundant
Suppression	Captures likelihood of active (private fire-fighting) or passive (sprinklers) local suppression at the property.	4	• Unknown • Active Suppression • Passive Suppression • None
Sprinkler Presence	Dedicated exterior sprinkler systems intended for wildfire applications and/or interior sprinklers.	3	• Unknown • Present • Absent
Construction Quality	Rated property-hardening measures such as IBHS Wildfire Prepared programs etc can reduce the risk significantly.	4	• Obvious signs of deterioration or distress • Certified design & construction • IBHS WF Prepared Home • IBHS WF Prepared Home Plus
Slope Setback	Properties located on a slope are at	3	• Unknown

Secondary Modifier	Description	Number of Options	Selected List of Available Options
	higher risk of wildfire. Increasing the distance from the structure to the crest of the slope (set back) can reduce the risk.		• Minimal set back • Adequate set back
Wall Cladding Type	The flammability of wall cladding affects structure ignitions. Specify a wall cladding material type from which the model infers a typical flammability class.	13	• Unknown • Brick veneer • Metal sheathing • Wood • EIFS (exterior insulation finishing system) • Impact rated glazing • Stucco • Vinyl siding terminating at least 12” above ground • Wood siding terminating at least 12” above ground and/or with fire retarding treatment
Residential Appurtenant Structures	Residential appurtenant structures refer to fences, carports, and screened enclosures that can readily ignite. The risk is lower if appurtenant structures are generally over 10 feet away from the main building.	16	• Unknown • None • Fences / Carport • Attached screen enclosure / Lanai • Detached screen enclosure / Lanai • Skylights • Roof-mounted mechanically attached PV array • Combustible fence / detached structure adjacent to primary structure • Combustible fence / detached structure at least 10 ft away from primary structure
Commercial Appurtenant Structures	Commercial appurtenant structures refer to large signs and external ornamentation that can easily ignite.	12	• Unknown • Large signs • Extensive ornamentation • None • Roof-mounted mechanically attached PV array • Large signs and roof-mounted ballasted PV array • Combustible signage / structure adjacent to primary structure • Combustible signage / structure at least 10 ft away from primary structure
Patio Deck	Wooden deck patios on the exterior are a common source of structure ignitions from heat and embers during a wildfire.	5	• Unknown • No deck present • Wood decking • Non-combustible decking • Fully enclosed non-combustible decking with no flammable / combustible material storage below
Opening Heat Resistance	Wildfire-resistant openings and double pane glazing can resist radiant heat effects in a wildfire.	7	• Unknown • Single-pane windows and glass door – Wildfire vulnerable skylights • Single-pane windows and glass door – Wildfire resistant skylights • Single-pane windows and glass door – No skylights • Double-paned windows and glass door – Wildfire vulnerable skylights • Double-paned windows and glass door - No skylights • All openings compliant with wildfire resistant code

Secondary Modifier	Description	Number of Options	Selected List of Available Options
Accessibility Condition	Ability of fire fighters to access the area in the vicinity of a structure can significantly affect its chances of survival in a wildfire	5	• Unknown • Community that has implemented wildfire mitigation activities • Typical water supply and in-and-out access for fire-suppression activities
Community Preparedness	Communities with specific wildfire prevention plans have varying levels of regulations and enforcement. Many programs are mostly voluntary, and enforcement can vary dramatically from community to community.	5	• Unknown • None • Level 1 Preparedness - Voluntary • Level 2 Preparedness - Semi mandatory regulations and variable enforcement • Level 3 Preparedness - Mandatory regulations and enforcement with regular inspection

Uncertainty and Sampling

The model represents the uncertainty in damage (partly from uncertainty in modeled hazard intensity as well as uncertainty in structure performance) through a four-parameter Beta or Kumaraswamy distribution. The four parameters include the mean damage ratio, the coefficient of variation, the probability of no loss (representing successful fire suppression activity) and the probability of total loss (representing complete burned down of structures). This approach allows the model to represent the full suite of observed damage in historical wildfires, including partial losses.

For each location in each affected event, the model then samples a damage ratio from the multi-parameter distribution defined based on the vulnerability functions for the input building characteristics. The sampled damage ratio for a specific event and risk, and consequently its AAL or loss cost, is not affected by the presence or absence of other risks.

The uncertainties associated with the damage curves are derived from statistical analyses of historical building loss data for different building classes and coverage types. These statistical analyses indicate that the uncertainty, as measured by the coefficient of variation (CV), is a function of the mean damage ratio (MDR) and reduces with increasing hazard and damage.

Post-Event Loss Amplification

Moody's quantifies demand surge and additional factors that can increase potential repair costs after major wildfires via post-event loss amplification (PLA). The PLA model considers three major components that escalate loss following major catastrophic events

- "Economic" demand surge (EDS), which represents an increase in the costs of building materials and labor as demand exceeds supply. This factor has the biggest overall impact on PLA after major events.
- Claims Inflation (CI), which represents repair cost inflation due to difficulties in fully adjusting claims following a catastrophic event. Given the limited number claims in wildfires compared to other perils, claims inflation has near-zero impact on modeled wildfire losses.
- Super Catastrophe Scenarios, which represents coverage and loss expansion due to a complex collection of factors such as containment failures, evacuation effects, and systemic economic downturns in selected urban areas. This factor typically impacts high return period wildfires striking dense exposures in and around major metropolitan areas. Primary escalation for super catastrophe

events occurs with respect to time-element losses. In California, Super Cat impacts also account for the likelihood and potential impacts of landslides or mudflows shortly after major wildfires as observed in historical events such as the 2017 Thomas fire.

- The PLA model also accounts for scenarios when multiple wildfires may occur in the same region and cumulatively create loss that is sufficient to trigger demand surge, and in extreme cases, urban conflagrations damaging entire communities, including the infrastructure, leading to super catastrophic scenarios with larger impacts on time element losses.
- Additionally, some aspects of Law and Ordinance are also captured in PLA factors in the model to represent scenarios that may trigger regional mandates to speed up or encourage recovery such as contents loss payments without inventory, coverage extension or rollover directives, etc.

Each of these PLA components has a different trigger and a unique loss escalation function that quantifies aspects of loss amplification noted in historical catastrophe events. The model quantifies PLA factors distinctly by coverage (building, contents, and time element) and applies them to all ground up loss estimates on a per-event basis before the application of any financial structures such as deductibles, or limits.

The impact of PLA on event losses can be significant as observed in historical wildfire events. At the individual property level, the impact of PLA on modeled loss costs and probable maximum losses depends on the underlying geographic, hazard, and vulnerability characteristics that determine the risk for that location. At the portfolio level, the impacts of PLA depend on the coverage, value, and geographic distribution of exposures within the portfolio. In general, the expected range of the magnitude of impact of PLA on AAL for the purposes of ratemaking can vary from minor (~1%) to notable (~20%) impacts in some densely populated areas.

Financial Model

The framework of the financial model for wildfire is the same across all perils within the family of HD models. For every wildfire event, the model calculates ground up losses for each exposure at risk at their respective location, for each coverage based on user inputs and default information, if not provided by the user (e.g., number of stories, distance to vegetation, surface fuel, etc.) using site-specific hazard and vulnerability functions. The financial model then applies to the ground up losses, user-input policy terms for the coverage, location, and/or account such as deductibles and limits, to compute gross losses.

To calculate losses, the model translates sampled damage ratio for each stochastic event derived in the vulnerability module into dollar loss by multiplying the coverage-specific damage ratio by the input coverage value. For a given level of hazard, unique samples from the severity distribution can result in different damage ratios, and thus different levels of modeled loss. Since the damage ratio is sampled at location level for each event, the order in which exposures are entered in the financial model does not affect the modeled loss. The loss cost is equal to the expected loss divided by the exposure.

Within each simulated wildfire footprint, the model uses spatial correlation between location loss distributions to account for similarities within a community in wildland, or wildland-urban interface (mitigation, built environment, fire suppression, etc.). The spatial correlation is minor and has no impact on modeled location-level losses including location-level AAL and loss costs. The model then aggregates simulated ground up and gross losses based on location-specific sampled damage ratios to assess losses at portfolio level. The specified spatial correlation does not impact portfolio AAL and has only a minor impact on portfolio EP losses depending on portfolio characteristics.

The Moody's Wildfire HD Model can effectively capture various types of terms, conditions, deductibles, and coverage limits of policy forms. The modeling capabilities include variability in construction (several types of construction classes including mobile/manufactured homes), occupancy types, coverages for building, contents and time element, or A, B, C, and D. Given these variables as input, any combination or policy form as well as their limits and deductibles can be entered in the user interface and modeled for either commercial or personal lines.

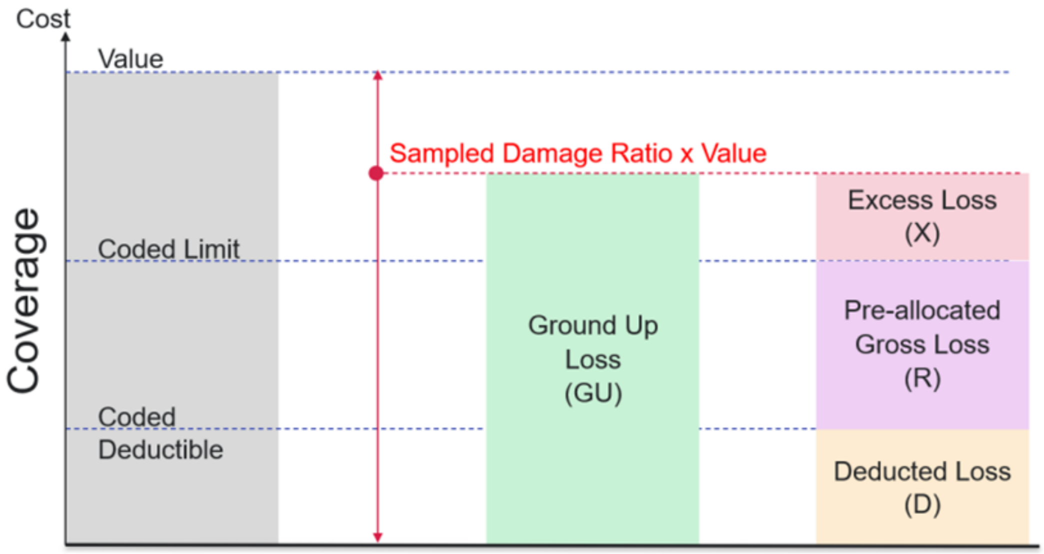
Deductibles can be entered as either a percentage of the insured value or as a straight dollar value. The model computes loss as a percentage of the property values, which are input parameters. The insured amount is assumed to be the same as the input property value unless a specific insured value is input. If the insured amount is lower than the input property value, the insured amount is treated as a limit to the insurer's liability. The model assumes that the property value input is the true property value. Gross losses that a location experiences from a modeled event will be the net of Ground-up loss and the impact of limits and deductibles.

For example, assume an insurer has a policy on its books for a building with an insured value of $100,000 with a $80,000 limit and a $10,000 deductible. Consider a situation where a stochastic wildfire event in the model samples a 100% damage ratio. The ground-up loss in this case would be $100,000 (100%*$100,000). However, the gross loss from this event loss would reflect the $10,000 deductible as well as the fact that the limit of loss for this notional policy is capped and would thus be $80,000. If the same policy has a 10% deductible, the resulting gross losses would be the same since the effective deductible would again be $10,000 ($100,000 * 0.1 = $10,000).

The model allows users to enter limit extensions at location coverage level. These are often included in terms such as Guaranteed Replacement Cost coverage, or Ordinance and Law coverage. In the event of significant damage in an event, such policy provisions enable insurance payouts in excess of the state limit to cover additional costs due to demand surge and/or to bring the (re)building up to the latest building code provisions. For a specific exposure location, when limit extension is input by the user along with corresponding coverage limit, the model applies the extended limit for all events where the location is affected by a simulated wildfire event and the sampled damage ratio exceeds a threshold representing the destruction and rebuilding requirement. Unless limit extensions are applied based on user-specific input in the exposure data, modeled gross losses are constrained (never exceed) the input limit specified by the user.

As shown in Figure 3, In the HD financial model, ground up loss (GU) is compared to the coded terms in order to calculate the losses that are either below the deductible or above the limit. These losses are not borne by the insurer. They are called the deducted loss (D) for the loss below the coded deductible value and excess loss (X) for loss above the limit. The remaining loss, which might be covered by the insurer, is called the recoverable (R). This is also referred to as pre-allocated gross loss because the impact of higher level terms and conditions have not yet been allocated back down the hierarchy (location coverage, location, policy coverage, policy in that order). The impact of these terms can adjust the D and X values and can impact the final (allocated) gross loss amount. The financial model starts by applying this logic at the location coverage level of the financial hierarchy, once the sampled damage ratio per sub-peril or cause of loss is applied to the coverage value, including the impact of post-event loss amplification. Note that deductibles and limits are optional at the location coverage level.

Figure 3. Application of primary terms to loss.



The model assumes that the user input value is the true property value and any assumptions regarding insurance to value must be made by the user prior to running the model. The Moody's wildfire model has separate inputs for values and limits.

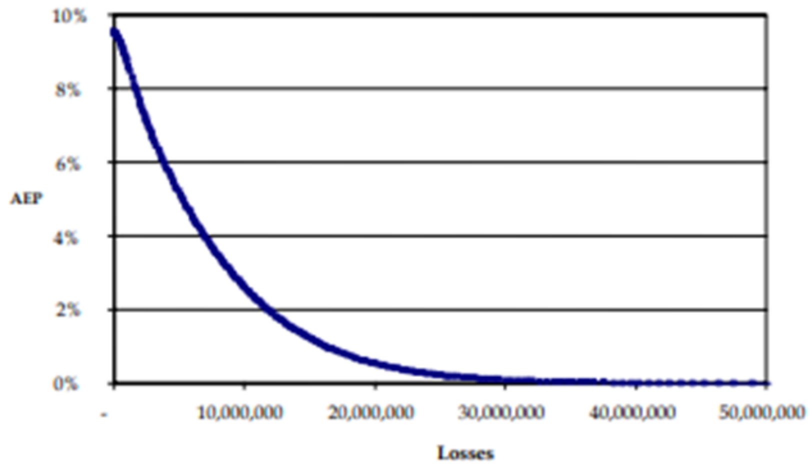
- Changing the order of the model exposure data does not produce a difference in model output or results.
- Each original policy (policies remaining or policies that existed before additions) will have the same AAL after removing or adding policies.

Exceedance Probability

The stochastic event set from the model can be sorted in such a way as to create an exceedance probability (EP) curve (Lee, 1988). This curve provides the probability of surpassing any loss level, expressing this probability in the form of a return period. Return periods are calculated by sorting the occurrence and yearly losses to create occurrence (OEP) and aggregate (AEP) curves, respectively.

For a given portfolio or structure at risk, an EP curve is a graphical representation of the probability, p, that a certain level of loss, $X, will be surpassed. The x-axis measures the loss in dollars, and the y-axis depicts the annual probability that losses will exceed a particular level. Figure 4 below depicts a hypothetical AEP curve which provides, for a specific loss, the likelihood that losses will exceed that given loss level. The term "probable maximum loss" is often referred to as a loss at a specified return period (e.g. 100years or 200years) and represents the loss on the EP curve associated with that return period (e.g. EP loss for an annual rate of 1% or 0.5%, respectively).

Figure 4. Example of aggregate exceedance probability curve



The overall expected loss for the entire set of events is the sum of the expected losses of each of the individual events for a given year. AAL is the average of annual sum of losses for all events in the stochastic set across the simulated number of years (e.g. 100,000 years) for any specific location/building, account, or portfolio. It is graphically represented as the area under the EP curve.

Treatment of Uncertainty

The primary uncertainty in the model is driven by the hazard – the likelihood of a wildfire occurrence, its spatial extent, and intensity of hazards produced. This uncertainty is represented by the different scenarios simulated across 100,000 realizations of the current year (2025). As such, all the weather, landscape, and topographical parameters affecting wildfire occurrence and severity at any location drive the uncertainty in loss costs and probable maximum losses for an exposure location, account, or portfolio.

Further to the primary uncertainty represented via stochastic simulations of different wildfire scenarios, the model also considers secondary uncertainty that is characterized by the multi-parameter damage distribution. As such, all exposure input building characteristics driving the sampled damage ratios, including primary attributes like year built, etc., and secondary attributes like roof vents, decking, etc. can notably influence the uncertainties in modeled loss costs and probably maximum losses as described in earlier sections.

In addition to the modeled uncertainties discussed above, exposure uncertainty in terms of the input coverage values, location address attributes etc. can also have a significant impact on modeled loss output. Moody's provides recommendations and best practices to its insurance clients in terms of appropriate data capture for use in its models and to reduce the impact of exposure uncertainty on model loss outputs.

Convergence and Sampling Error

The Moody's model includes 100,000 years of stochastic ignitions to allow for the loss results to converge given the sampling methodology used in the model.

Moody's tested the convergence on number of years through an iterative procedure by calculating the AAL at different geographic levels (state, county, postal code) with an increasing number of simulated years up to 100,000 years for different levels of hazard to ensure modeled losses are converged and stable. In general, given the nature of wildfire hazard in California in terms of frequency and severity, the model achieved convergence in much fewer number of years. Nevertheless, the model provides a robust event set covering 100,000 years to adequately represent even very low-probability scenarios that may have not yet been observed in history.

Since sampling uncertainty can also impact modeled loss output, Moody's recommends users to consider the full 100,000 years of simulations to analyze exposures for rate making purposes.

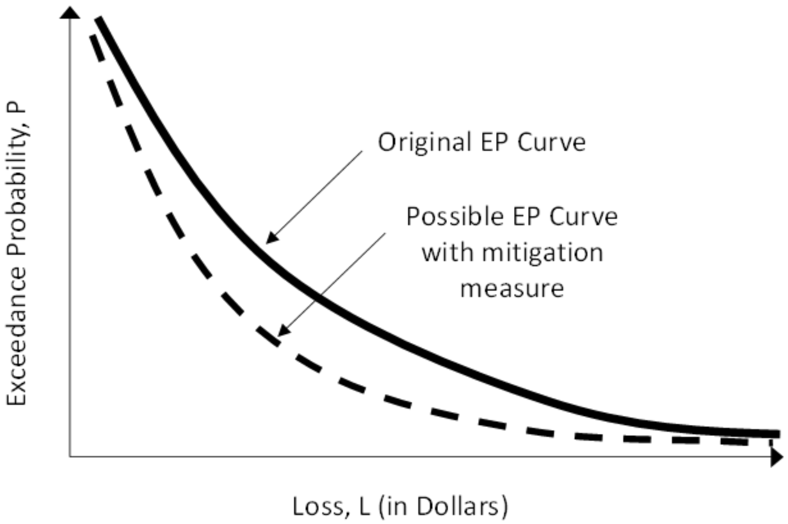
In addition, to achieve convergence in modeled loss costs and probable maximum losses, Moody's recommends users to specify appropriate for number of samples depending on the use case. For instance, for location-level loss costs for use in rate making, the recommended samples is at least 100 when analysis is done using simulated mode. If non-zero deductible (ground loss) is of interest, users can run the analyses in Expected mode that always uses the mean damage ratio instead of sampling the damage ratio.

For historical loss validation exercises, Moody's recommends users to consider up to 1000 samples to obtain robust estimates for individual location-level and event-level loss estimates. For portfolio-level average annual loss and probable maximum losses, the recommended number of samples vary by portfolio size, with 5 or 10 samples providing adequate convergence for the majority of cases.

Impact of mitigation on exceedance probability

Mitigation measures typically decrease the damage potential and therefore reduce the expected loss. Graphically, mitigation shifts the EP curve down and to the left, reducing the AAL (i.e., decreases area under the curve) as depicted in Figure 5 below. Consequently, users can quantify the benefits of mitigation in terms of modeled average annual losses and loss costs – a normalized loss metric defined as the average annual loss per $1000 of coverage (i.e., AAL / Total Insured Value x $1000).

Figure 5. EP curve showing potential benefits of disaster risk reduction



Validation

Moody's uses a variety of techniques to validate catastrophe models during and following model development, wherein each model component as well as overall loss metrics are individually validated. In each case, Moody's assesses the appropriateness of the comparative data and validates model components iteratively as initial comparisons highlight areas requiring refinements or additional research. Moody's catastrophe models maximize the use of available information related to hazard, vulnerability, and historical loss to arrive at best estimates of risk. The resulting model extrapolates far beyond comprehensive and reliable historical records.

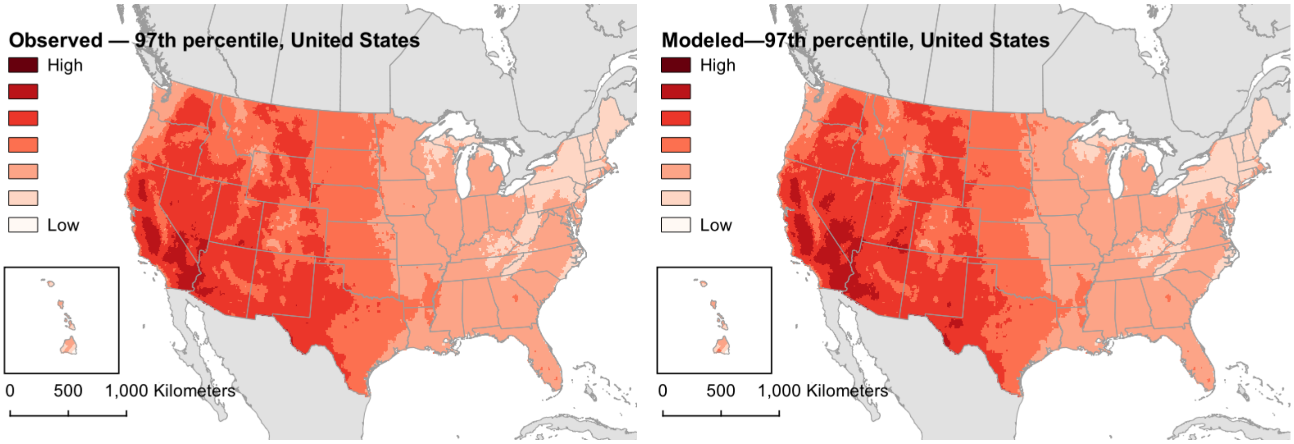
The model was developed in collaboration with and feedback from various independent research entities, including but not limited to: US forest service fire sciences laboratory; California department of Forestry and Fire Protection (CalFire); and the Insurance Institute for Business and Home Safety (IBHS). This collaborative environment ensures state-of-the-art science is used as part of the development.

Moody's validated model outputs for all components: hazard, vulnerability and loss as detailed below

Weather Validation

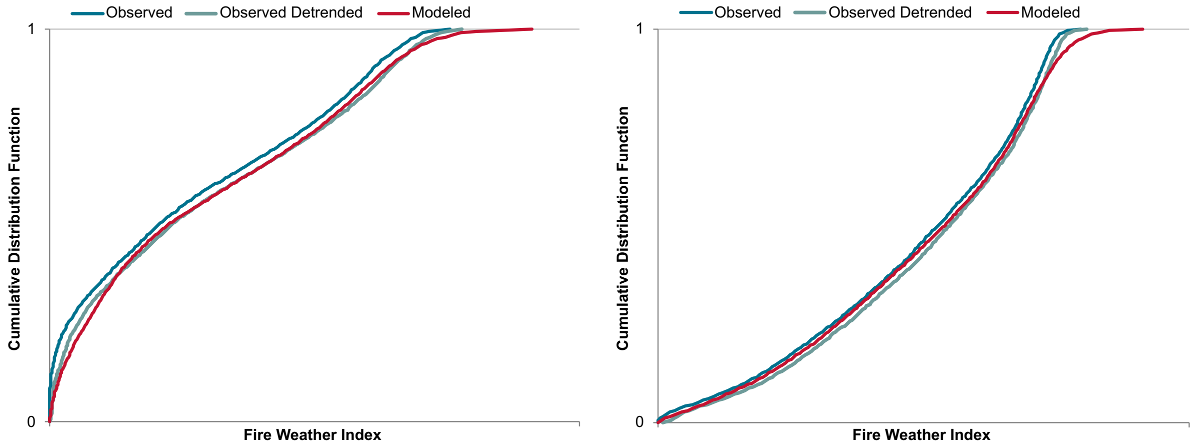
Fire weather simulation validation included comparisons of detrended historical daily ERC-G values from 1981 onwards, after detrending and projection to 2025, with modeled values from the stochastic event set, for a range of different percentiles. The example in Figure 6 shows the comparison for the 97th percentile, representing the severe weather case driving extreme wildfires.

Figure 6. Observed (left) and modeled (right) fire weather (97^{th} percentile)



In addition to validating the spatial patterns, Moody's also compared the distribution of modeled ERC-G values, for each fire weather zone in the U.S., against historical ERC-G from 1981, and the historical ERC-G detrended to 2025 as shown in [Figure 7.](#)

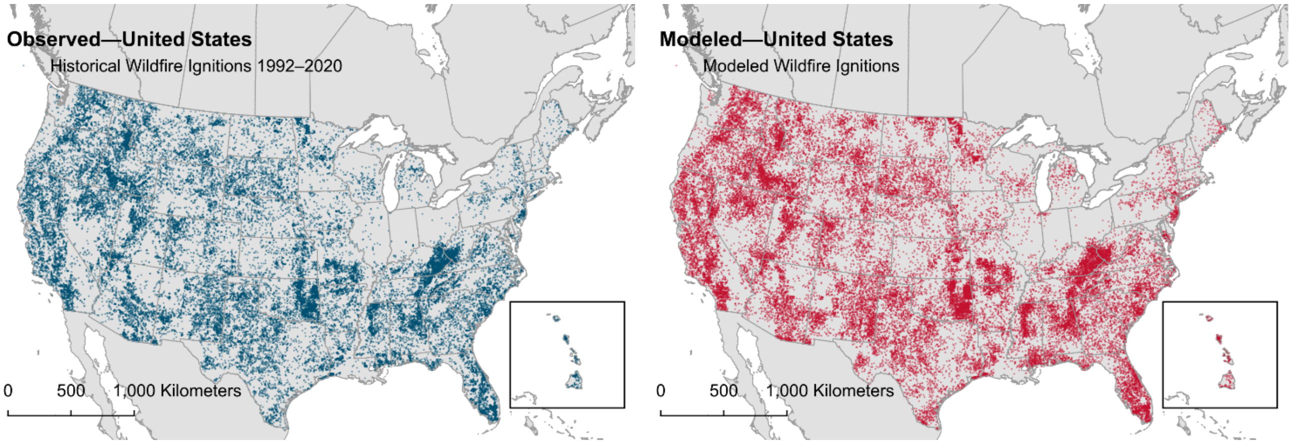
Figure 7. Cumulative distribution functions (CDF) of daily fire weather index for observed (blue), detrended historical (gray), and modeled (red) for select fire weather zones in Northern (left) and Southern California (right)



Ignition validation

To validate that the ignition model is able to adequately reflect observed historical patterns, Moody's used the historical observed fire weather as input to the ignition model and obtained simulated ignitions for the 29-year period 1992-2020. As demonstrated in Figure 8, the simulated ignitions using historical fire weather are well-distributed and within range to the historically reported ignition locations, validating that the ignition model can effectively capture observed spatial patterns of wildfire ignitions.

Figure 8. Reported historical ignitions (left) and modeled ignitions with historical fire weather inputs (right) for the United States of America



Moody's also compared the modeled average annual ignition rates obtained using simulated daily fire weather conditions, aggregated at ZIP code resolution with reported ignitions from 1992-2020. Figure 9 provides a comparison of observed and stochastic modeled ignition rates for the entire U.S., while Figure 10 provides the same for California. In both cases, the model not only shows good agreement with observations, but in general is more comprehensive compared to the limited history.

Figure 9. Observed (left) and modeled (right) ignition rates for the U.S.

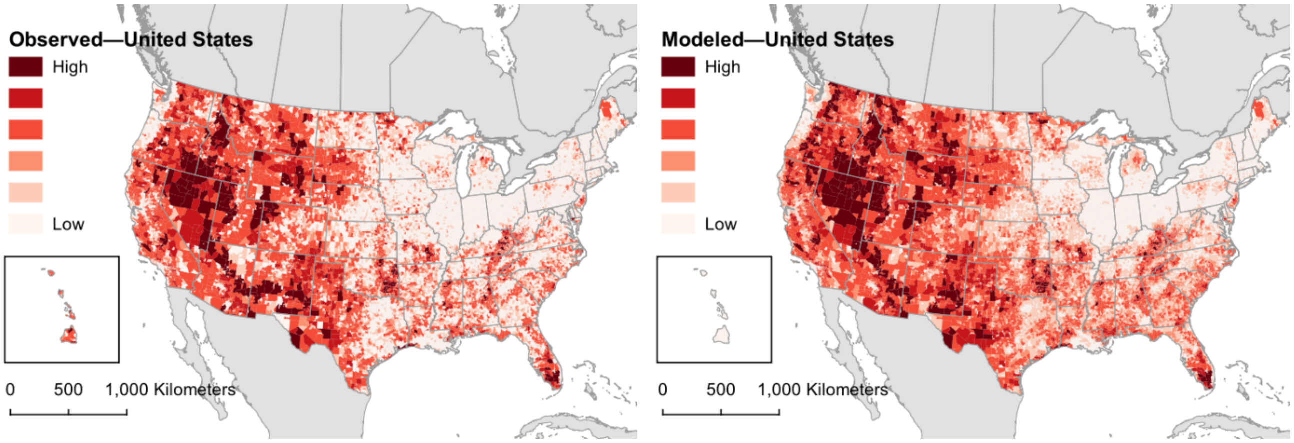
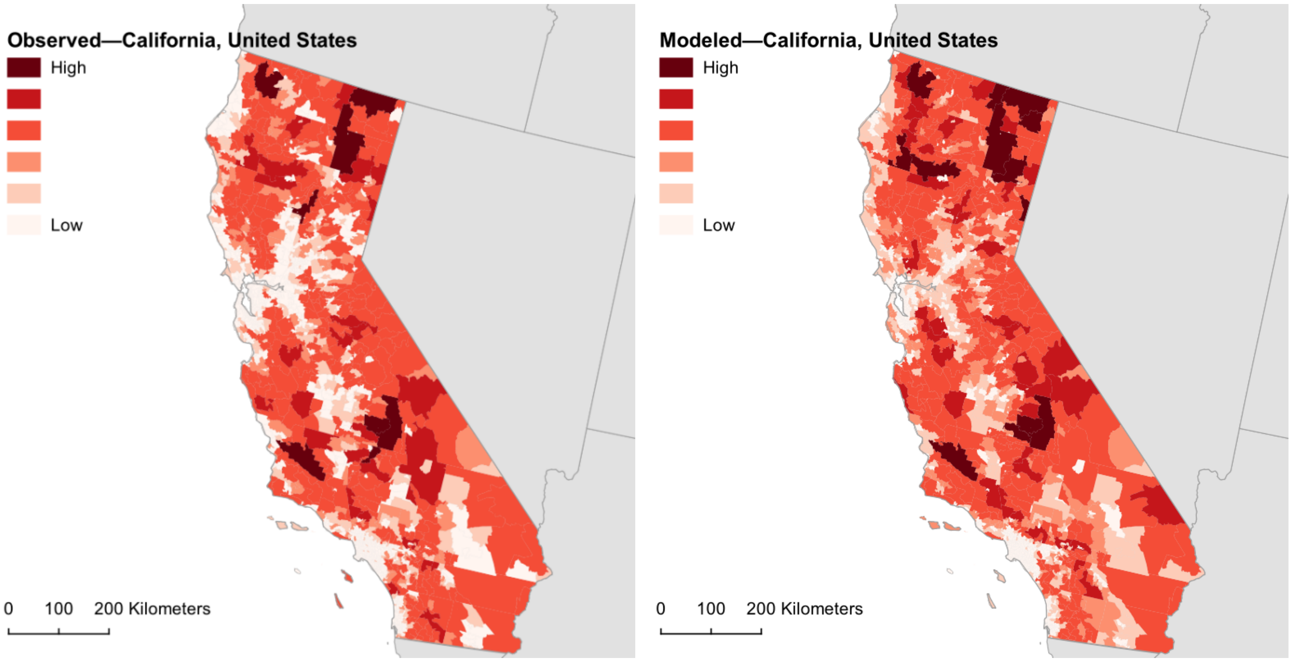
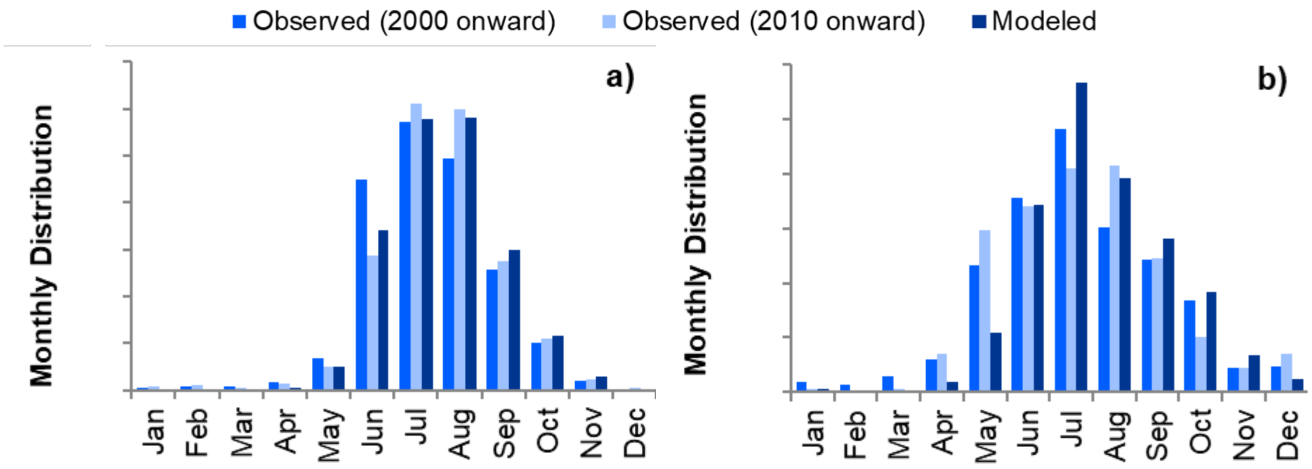


Figure 10. Observed (left) and modeled (right) ignition rates by post code for California



The time of the year when an ignition occurs influences if and how it spreads to become an event of consequence. To validate the seasonality of the model ignition, Moody's compared the monthly distribution of stochastic fires with observations. Figure 11 shows the seasonal distribution of ignitions in different historical periods compared to the stochastic model for select fire weather zones in Northen and Southern California.

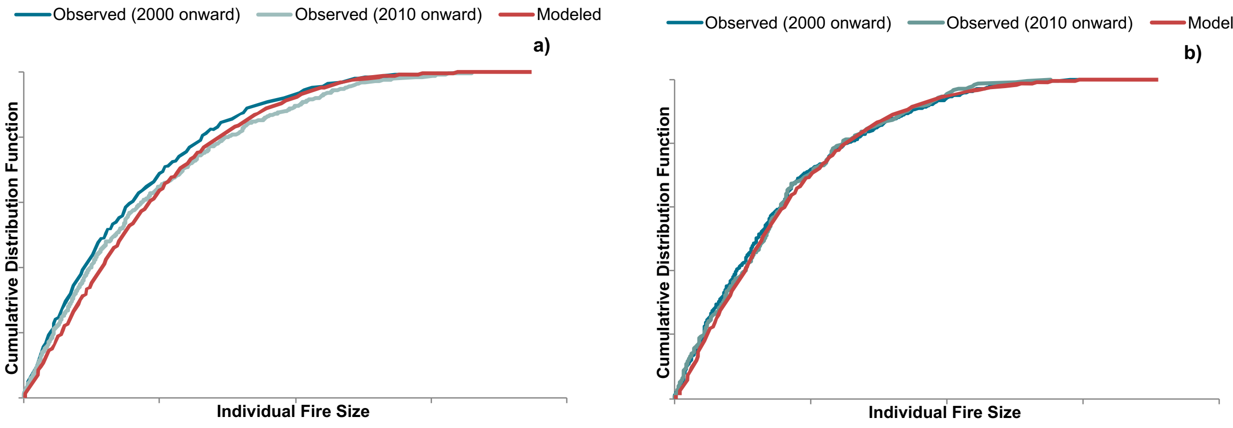
Figure 11. Monthly distributions of fires for Northern (a) and Southern (b) California



Fire Spread (burn area) validation

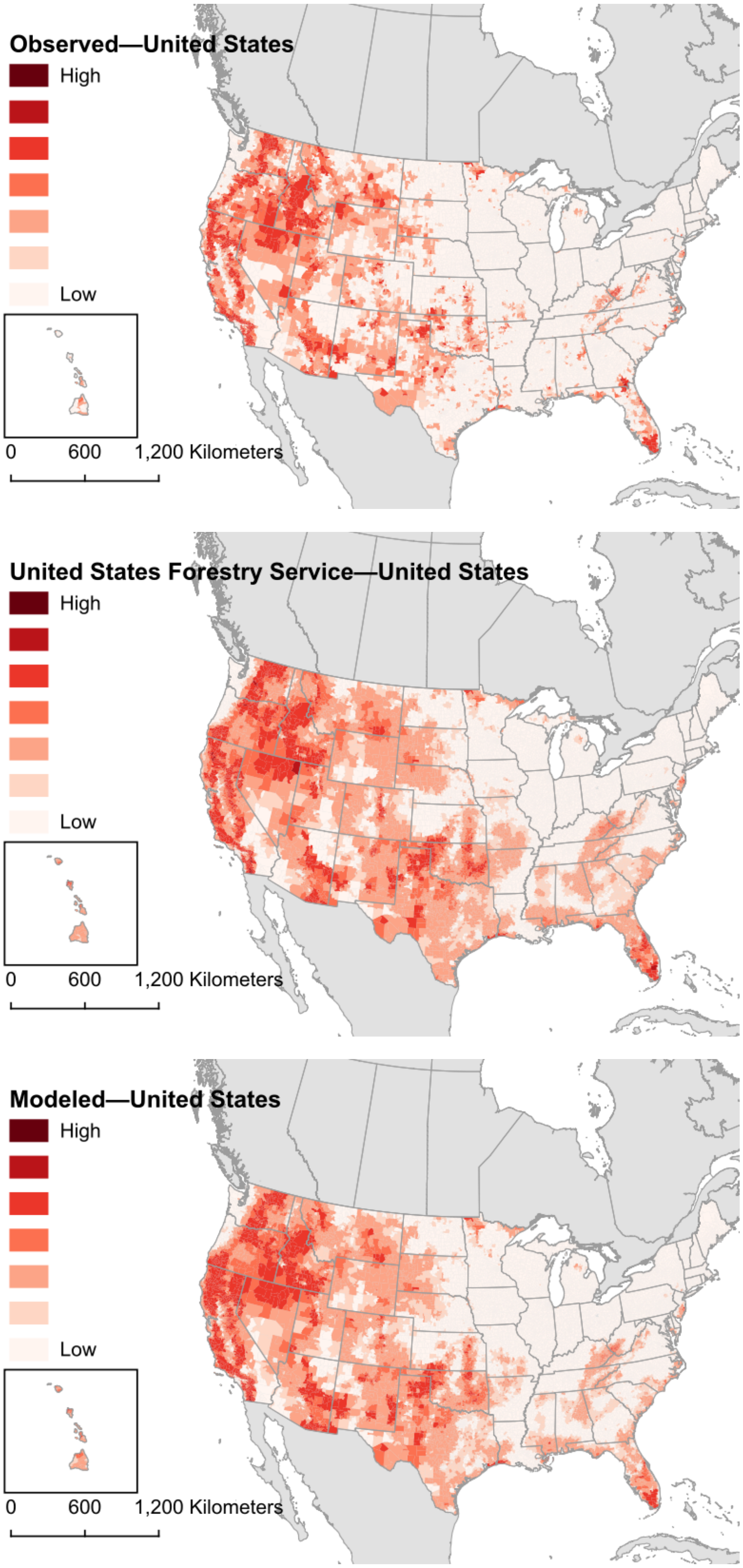
To verify that the model simulates wildfires similar in size and frequency to those observed in history, Moody's compared distribution of historical and stochastic modeled fire sizes for each fire weather zone. The historical fire size distributions are based on the USDA Forest Service's fire occurrence database (Short 2022). Figure 12 presents examples of individual fire size validation for Northern and Southern California.

Figure 12. Comparison of observed and modeled fire size distributions for Northern (left) and Southern California (right)



[Figure 13](#) presents comparisons of average annual burn probability, at ZIP code resolution, across the U.S. modeled domain, between historical observations (1984 onwards) and modeled results. Given the limited historical record, Moody's compared burn probabilities with those from the model developed by the U.S. Forest Service (Dillon et al., 2023).

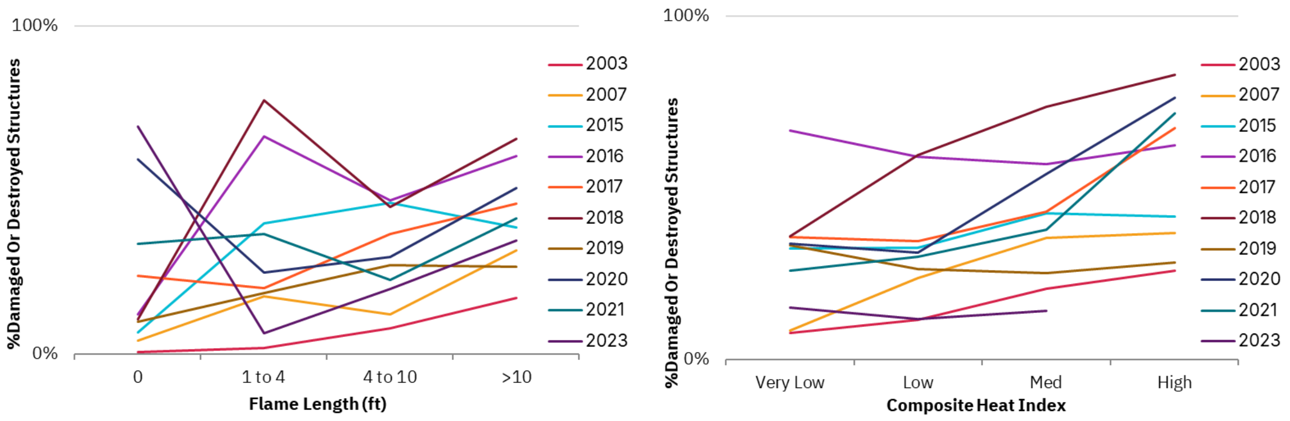
Figure 13. Comparison of postal code burn probabilities for historical (top), US Forest Service (middle), and Moody's stochastic modeled (bottom) for the U.S.



Composite Heat Index validation

Wildfire hazard is complex and flame length may not fully explain observed damage to structures given the environment where these structures are located. Since site-specific hazard characteristics including Distance to vegetation or defensible space, slope of the terrain, and fuel type can influence the likelihood of structure ignition, Moody's developed the composite heat index to provide a more accurate representation of fire behavior vis a vis the affected structures. Figure 14 compares %damaged or destroyed structures plotted against flame length parameter and against composite heat index parameter (that considers distance to vegetation, etc.) for locations affected in 30+ major fires across 10 years. It is evident that the composite heat index parameter can explain the observed damage trends better than flame length alone.

Figure 14. Observed damage for modeled flame length (left) and modeled composite heat index (right)

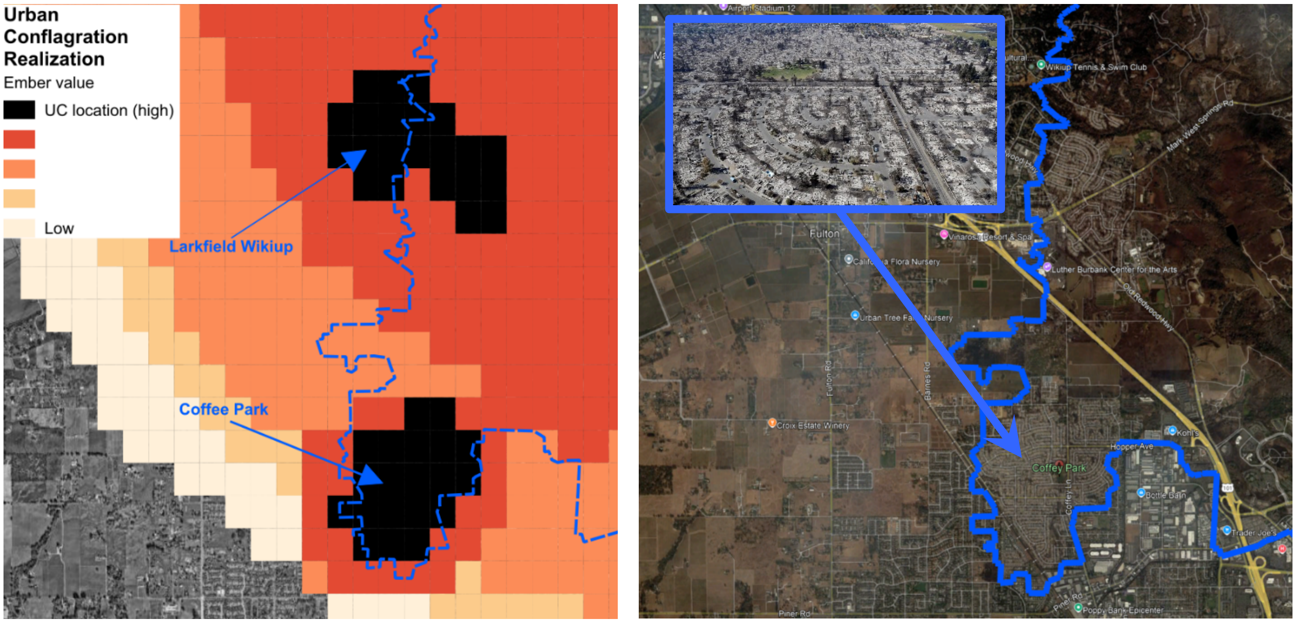


Urban Conflagration validation

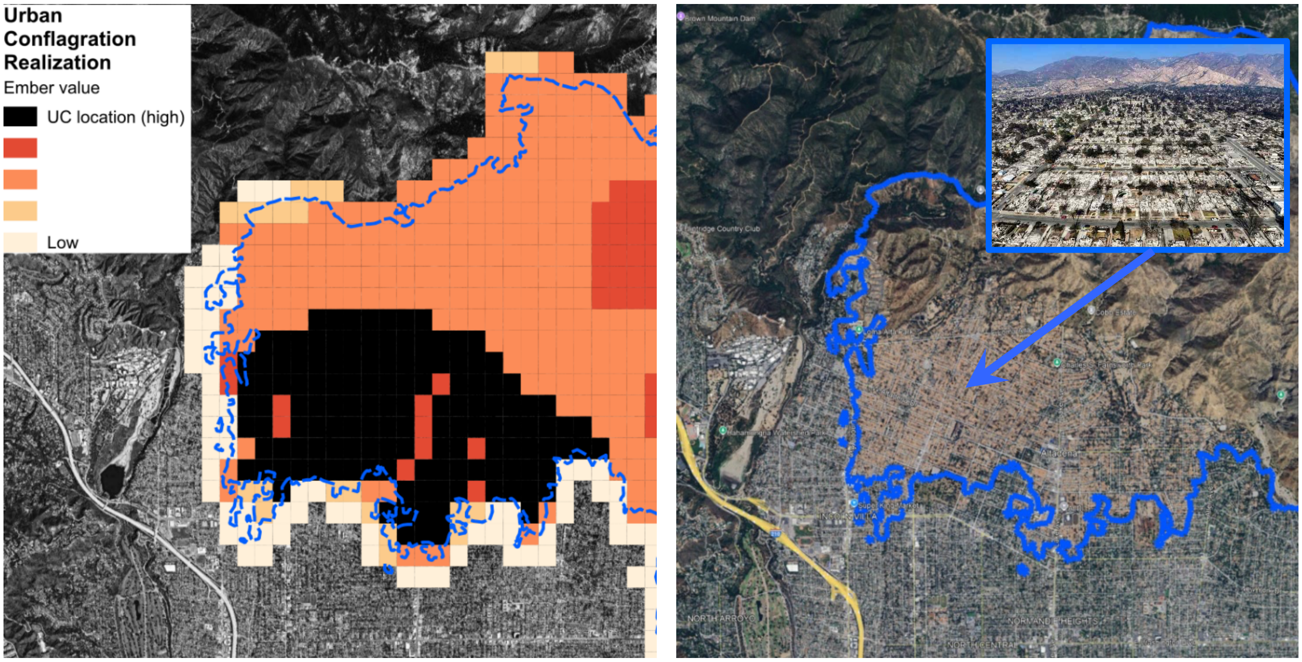
The wildfire urban conflagration model is probabilistic and treats conflagration as a succession of scenarios that need to occur before it is triggered. Moody's ran several thousand realizations of urban conflagration simulations to develop distributions of conflagration extent and severity for different urban environments, wind conditions, and fire suppression scenarios to apply to the stochastic event set when urban conflagration is triggered.

Moody's tested the urban conflagration model using several historical wildfire events that experienced urban conflagration, such as the 2017 Tubbs fire, the 2016 Fort Mc Murray fire, the 2020 Almeda fire, the 2021 Marhsall fire, the 2023 Lahaina fire, and the January 2025 Los Angelese fires. Moody's simulated several hundred realizations of the event from ignitions to modeling urban conflagrations. Figure 15 shows the realization where the simulated location, severity, and extent of urban conflagration using the Moody's model closely matched the observed conflagration pattern in the 2017 Tubbs fire (Coffey Park, & Larkfield Wikiup) and the 2025 Eaton fire (Altadena).

Figure 15.(a) Modeled ember footprint depicting simulated urban conflagration in black (left) and observed urban conflagration (right) in 2017 Tubbs fire in Coffey Park and Larkfield Wikiup.



(b) Modeled ember footprint depicting simulated urban conflagration in black (left) and observed urban conflagration (right) for 2025 Eaton fire in Altadena.



Smoke validation

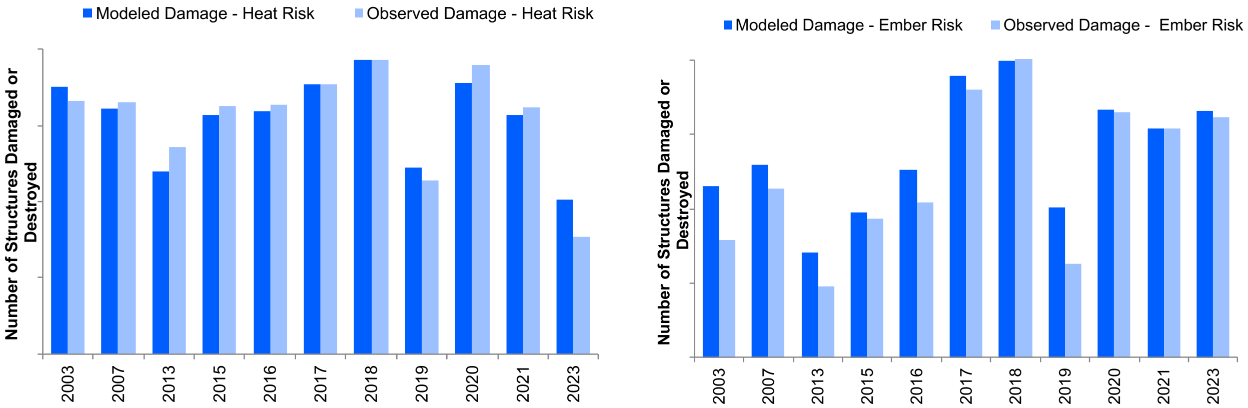
Moody’s validated the smoke hazard module by simulating historical smoke footprints using the same methodology as the stochastic smoke module, such as for the November 2018 Southern California wildfires shown in Figure 16. The satellite images represent a daily snapshot of the smoke plume. The modeled smoke footprint adequately captures the appropriate direction and extent of the damaging smoke plume.

Figure 16. Smoke footprint of Woolsey Fire (2018); left: NASA satellite imagery of wildfire smoke plumes; right: historical modeled smoke footprint

Vulnerability validation

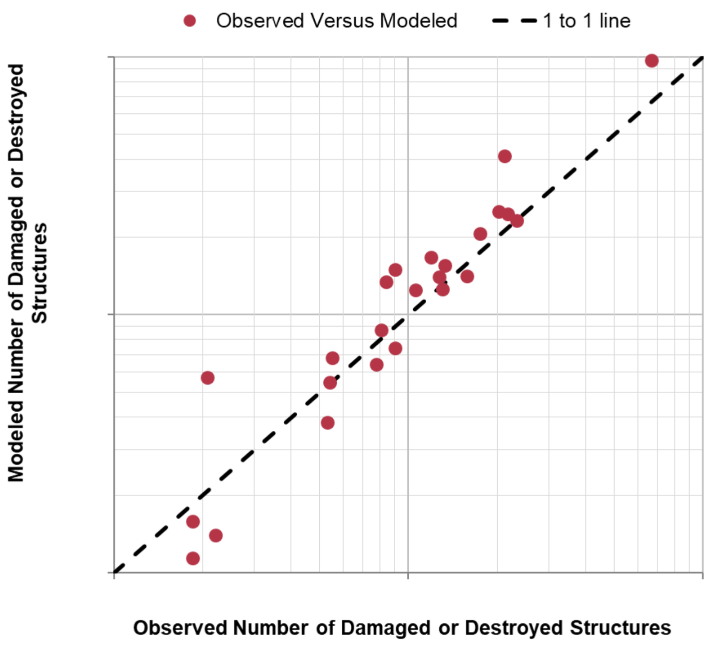
To validate the heat and ember vulnerability functions, Moody’s used detailed exposure, damage, and loss data for key historical events. It is usually challenging to identify the exact cause of structure ignition for affected buildings within the fire footprint (i.e., if ignition was due to heat hazard and flames affecting the structure, or from embers). Consequently, we assumed all reported damaged buildings within the burn footprint to be influenced by heat hazard and all buildings with reported damage outside the burn footprint were likely ember-triggered ignitions. Figure 17 compares reported and modeled number of structure ignitions across the historical fires analyzed. The left plot considers only buildings within the burn area, while the right plot considers structures in areas without burnable fuel (no modeled heat hazard) and only affected by embers.

Figure 17. Comparison of structures damaged and destroyed for heat risk (left) and ember risk (right)



In addition to separate comparisons of structure ignitions for heat and ember hazards, we validated the combined impacts of heat and ember hazards as well with observations from 32 historical events in the U.S as shown in Figure 18 .

Figure 18. Comparison of damaged and destroyed by historical fire for combined heat and ember risk



Loss validation

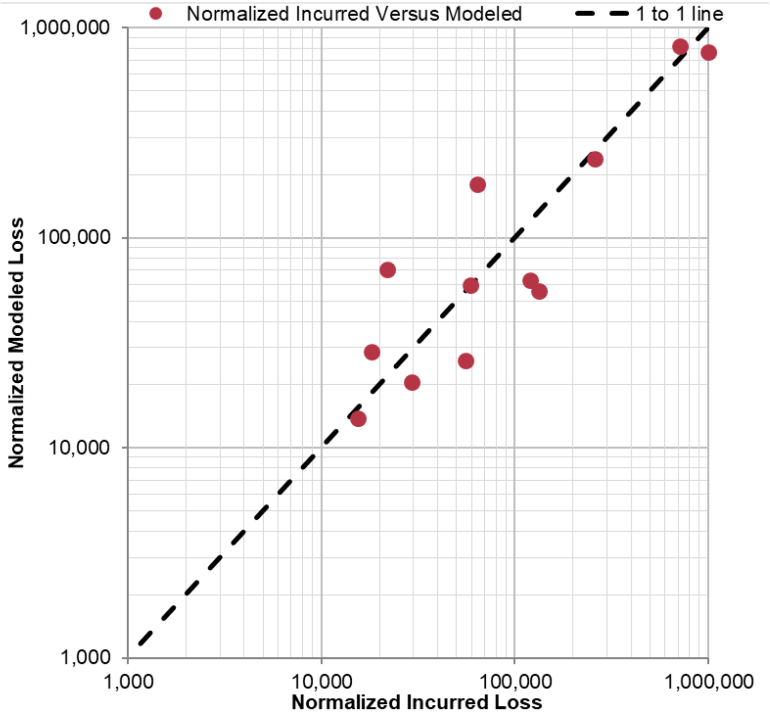
Loss validation tests typically compare modeled losses with observed industry or insurance company portfolio losses across several historical events. The techniques and processes to validate a loss model depend on the availability, quality, and completeness of necessary exposure and claims data for comparison.

Client loss validation

Portfolio loss validation tests use individual insurance company exposure databases as input to produce model losses comparable to the company's actual event loss experiences. The strengths of this test are twofold: (a) it provides multiple data points for each event, as many companies are able to provide such data for a number of events; and (b) all modeled losses are based on exposures at the time of the event, eliminating the need to make trending adjustments to the exposure or actual loss which introduce additional uncertainty, particularly for older events.

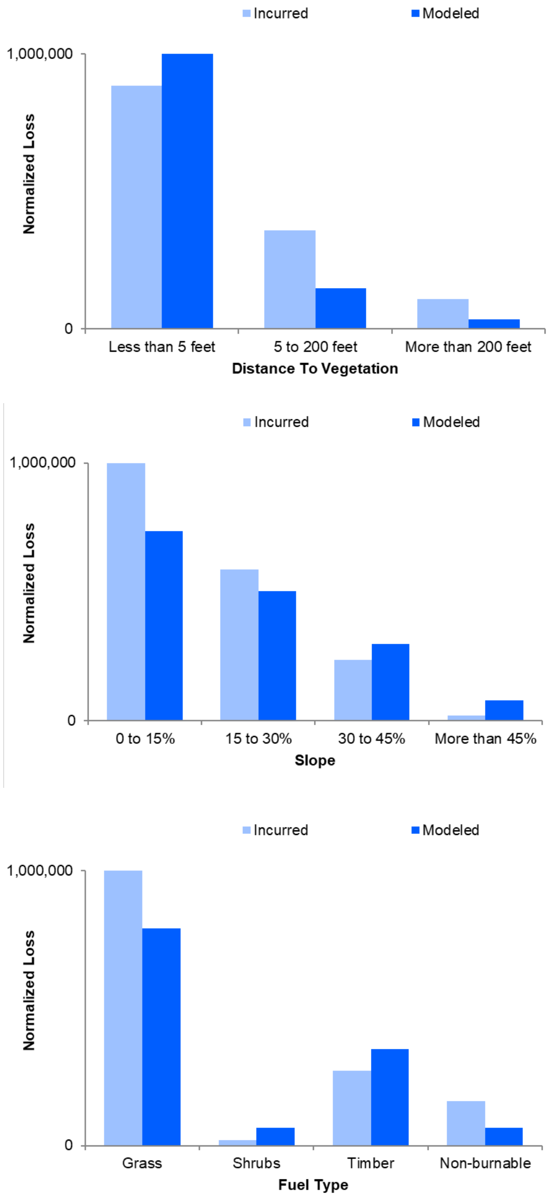
Moody's performed a series of tests to compare recent incurred U.S. losses from client portfolios with those calculated using the exposure data at the time of the event provided by each company. Moody's anonymized the losses by normalizing modeled and incurred losses by a common factor such that the maximum incurred loss equal US$1 million. Figure 19 presents results as a scatter plot. Variations in modeled-to-incurred ratios are expected given the numerous uncertainties in reported losses such as the impact of active suppression for particularly localized portfolios, assignment of claims to individual fire events, or the inclusion of living expenses (ALE) losses in reported claims without adequate corresponding exposure for modeling.

Figure 19. Normalized client loss versus normalized client modeled loss



Moody’s did further validation of portfolio loss results for historical events by comparing modeled and incurred losses by fuel type, distance to vegetation, and slope, as seen in Figure 20.

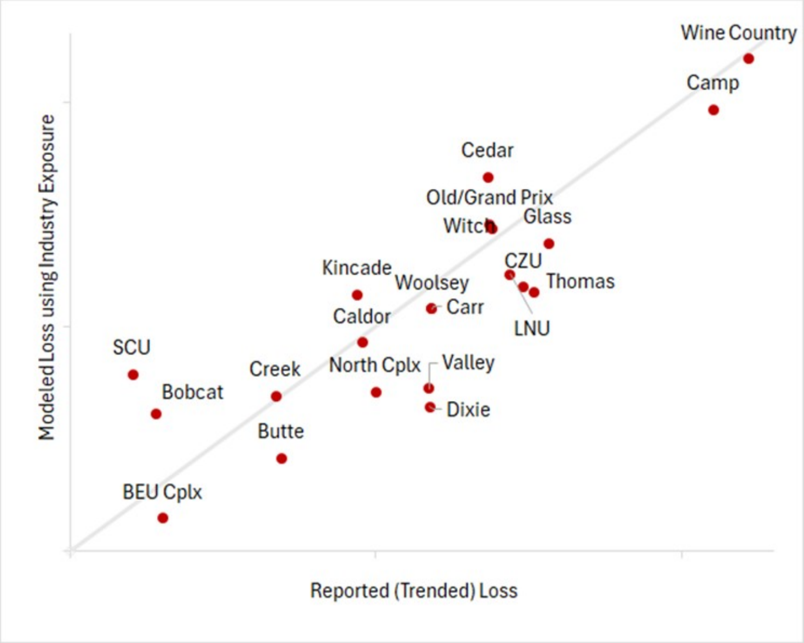
Figure 20. Comparison of normalized observed and modeled across various company portfolio-wildfire event combinations by site-specific hazard characteristics: Distance to vegetation (top), slope (middle), and fuel (bottom)



Industry loss validation

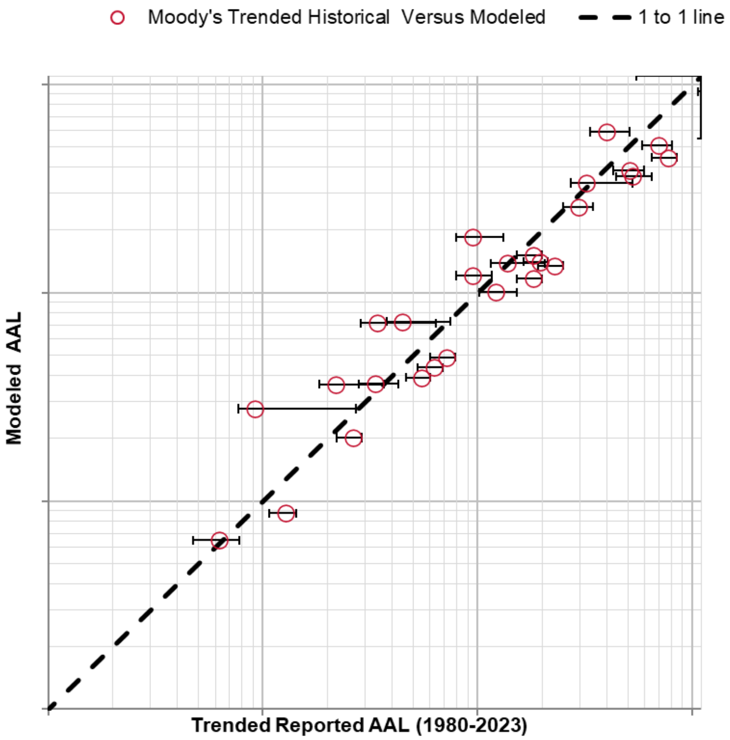
Moody's validated the model's ability to represent industry-level losses for major historical events using modeled losses generated for the industry exposure database and comparing them to trended market-wide reported losses for all lines of business Figure 21 summarizes modeled and trended market-wide California losses for all lines of business for California wildfires with significant losses since 2003.

Figure 21. Comparison of California trended industry losses to modeled losses



Validation of the average annual loss (AAL) explicitly considers the occurrence frequency distribution. Moody's obtained a range of historical benchmark losses from several sources including the California Department of Insurance (CDI), the Californian Department of Forestry and Fire Protection (CAL FIRE), and the National Oceanographic and Atmospheric Administration's (NOAA) Special Hazard Events, etc., to derive market-wide reported loss estimates for the U.S. at County group resolution for entire California. We then compared the calculated market-wide AAL from historical reported losses trended using proprietary methods and compared it with modeled AAL using Moody's industry exposure database. Figure 22 shows a scatterplot of modeled and trended AAL based on historical loss estimates with error bands representing uncertainty in trending reported historical losses to present day. In general, the data representing county-group modeled AAL, are scattered on either side of the 1:1 line indicating good agreement of modeled AAL with historical observations.

Figure 22. Comparison of Trended reported historical losses against modeled industry losses by group of counties



Internal and Independent Reviews

As part of the development process, every component is reviewed by internal technical experts. In addition, the interaction across components and ultimate model loss outputs are extensively reviewed as part of the model calibration and validation process as detailed in the previous section.

Furthermore, Moody's Quality Assurance and Quality control teams use industry standard processes to ensure all its software products deliver results consistent with model requirements. An internal team not involved in the model development also tests the various model engine components, inputs and outputs as part of the 'model certification' process.

The financial model methodologies are actuarially sound and consistent with industry best practices for loss modeling and pricing. The statistics, actuarial science, computer/information science components are built on standard catastrophe modeling frameworks that have been reviewed and certified by regulatory bodies such as the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM) over the past 30 years.

The computational infrastructure adheres to robust software engineering standards and the network architecture and infrastructure meet ISO certification standards.

These frameworks have been widely accepted across multiple perils and regulatory environments, ensuring reliability and regulatory compliance.

Throughout the model development process, Moody’s staff maintained active collaboration with subject matter experts and scientists to ensure the model reflects the latest understanding of wildfire behavior and structural vulnerability. Contributors include scientists from different organizations, including:

Topic experts that the model development team consulted with include

- Mark Finney and colleagues at the Missoula Fire Sciences Laboratory, USDA Forest Service
- Dr. Steve Quarles, formerly Chief Scientist for Wildfire and Durability, IBHS
- Steve Hawks, Assistant Deputy Director of CAL FIRE (Department of Forestry and Fire Protection) and currently Senior Director for Wildfire at IBHS
- Fire Behavior specialists at LANDFIRE
- Specialists on wildfire mitigation programs at several major Utility companies.

These experts provided input on fire spread dynamics, fuel modeling, hazard calibration, structural response to wildfire exposure, and firefighting practices.

The vulnerability model components are based on the same framework and principles developed and used across other peril models for over 30 years, with particular attention to wildfire perils and regulatory environments. Moody’s modelers worked collaboratively with several researchers sharing information on lessons learned from historical wildfires and post-event field reconnaissance.

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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.

Table G-8A

Hazard			
Selected Options		**Notes**	**Import/Analysis log location**
Model Version	RMS - HDv2.0.2	Version 2.0.2 is the latest Wildfire released model and current view of risk	A
Sub-peril options	Fire – Always On	Set to On for Wildfire peril	D
	Smoke - On/Off	Recommended setting is On (Default) for rate filings unless coverage for smoke damage is excluded or not offered.	
Urban Conflagration	On/Off	Recommended setting is On	F
Event Catalogue			
Simulation Set	7 options	"RMS V2.0 Stochastic Rates - Full US" recommended for rate filings. This Period Event Table (PET) represents the complete list of simulated events	G
Simulation Length (Number of Periods)	100,000	100,000-year catalogue recommended for rate filings. Users can select fewer periods to optimize analysis run time and output size for specific purposes.	H
Number of Samples	1 to 1,024 samples	Number of damage ratio samples to be simulated for each location in each wildfire event analyzed. Recommended value varies by resolution of input exposure (location-level vs. aggregate data) and portfolio size in terms of the number of buildings in a portfolio to ensure robust and stable outputs for ratemaking, deductible impact analysis, and notional exposure assessments. For portfolio-level convergence, fewer samples may suffice, but for location-level convergence higher sample counts improve granularity and convergence. Recommendation: • **Analyzing deductible impacts or for notional exposure studies:** Use at least 100 samples per location to achieve convergence in results • **Zero Deductible Analysis:** Expected model output is typically sufficient. In such cases, expected value provides a stable and representative estimate.	I
Hazard Modification			
Distance to vegetation	Users can override model-default value with property-specific input	Nearest distance to burnable vegetation in units at location (building) resolution to indicate the amount of defensible space around the property	User Defined Hazard section

Hazard			
Selected Options		**Notes**	**Import/Analysis log location**
Distance to vegetation units	2 options (ft and metric)	Units of value stored for Distance to vegetation input (feet or meters)	
Distance to vegetation match	3 options	Value to indicate if Distance to vegetation input is model default, user specified, or is not retrieved Match level for Distance to Vegetation field retrieved Value of 0 indicates value not retrieved Value of 1 indicates value set based on hazard lookup Value of 13 indicates user-specified input	
Slope	Users can override the model-default value with property-specific input	Slope of terrain at location (building) resolution as a percentage.	
Slope Match Flag	3 options	Value to indicate if Slope input is model default, user specified, or is not retrieved	
Fuel type	Users can override the model-default value with one of 26 Options	Ranked value of burnable vegetation per Moody's RMS fuel classification at location (building) resolution.	
Fuel Type Match	3 options	Value to indicate if Fuel Type input is model default, user specified, or is not retrieved	
Mechanical Treatment of Fuel	6 options:	Specify risk reduction potential due to mechanical thinning or fuel modification based on severity, extent, and time since treatment.	User Defined Hazard section

Table G-8B.1

Vulnerability			
Option		**Notes**	**Import/Analysis log location**
Vulnerability	3 options	Recommend "RMS Vulnerability Default" for rate filling. Users can select other options depending on their view of risk.	J

Table G-8B.2

Primary Characteristics				
	Selected Options	**User input Required?**	**Unknown calculation**	**Import/Analysis log location**
Occupancy Type	40 Options including: • Unknown • Residential - Single Family • Residential - Multiple Family • Residential - Multi-Family Condo Association • Residential - Multi-Family Condo Unit Owner • Commercial - Temporary Lodging • Commercial - Retail Stores and Entertainment • Commercial - Offices and Professional Services • Commercial- Parking • Commercial – Agriculture • Commercial – Religion • Commercial – Education • Commercial - General Commercial • Commercial - Gasoline Service Stations • Commercial – Restaurants • Industrial - General Industrial • Industrial - Highly Combustible • Industrial - Non-Combustible	Recommended input for rate filling	When any of the primary characteristics are unknown, the model uses region-specific building inventory to construct weighted vulnerability function for loss estimation. When either Occupancy Type or Construction Class inputs are unknown, the model ignores the secondary modifier inputs. So, both these primary characteristics are required to be known for secondary modifiers to be used in the model.	Primary Attributes section
Construction Class	14 options including: • Unknown • Wood Frame • Masonry • Unreinforced Masonry • Reinforced Masonry • Reinforced Concrete • Reinforced Concrete with Concrete Roof Deck • Reinforced Concrete with Wood frame in upper floors • Tilt-up • Reinforced Concrete with Wood or Metal Roof • Steel • Light Metal • Personal Autos • Auto Dealerships	Recommended input for rate filling		Primary Attributes section
Number of Stories	Up to 5 options depending on Occupancy and Construction class input • Unknown • 1	Recommended input for rate filling		

Primary Characteristics				
	Selected Options	**User input Required?**	**Unknown calculation**	**Import/Analysis log location**
	• 2–3 • ≥ 4			
Year of Construction	4 Options: • Unknown • Pre 1996 • 1996–2008 • 2009 or later	Recommended input for rate filling		
Floor Area	• 2 bands for Residential (1–5,000 ft2 and > 5,000 ft2) • 3 bands for Commercial (1–5,000 ft2, 5,000ft2–25,000 ft2 and > 25,000 ft2)	Recommended input for rate filling		

Table G-8B.3

Secondary Modifiers				
	Selected Options	**Default Approach**	**Input method**	**Import/Analysis Log location**
Roof System Covering	15 options: • Unknown • Concrete/clay tiles • Wood shakes • Normal shingle • Concrete roof • Class A Fire Rating • Class B Fire Rating • Class C Fire Rating	Default is unknown, which has no adjustment to “base” vulnerability function obtained based on input primary characteristics	User input at location (building) resolution through exposure data	Secondary Attributes section
Roof Shape	9 options: • Unknown • Flat roof with parapets • Flat roof without parapets • Hip roof with slope less than or equal to 6:12 • Hip roof with slope greater than 6:12 • Gable roof with slope less than or equal to 6:12 • Gable roof with slope greater than 6:12 • Braced gable roof with slope less than or equal to 6:12 • Braced gable roof with slope greater than 6:12			
Roof Age or Condition	5 options: • Unknown • 0–5 years • 6–10 years • 11 years or more • Obvious signs of deterioration and distress			
Roof Vents	6 options: • Unknown • None • Wildfire Resistant Vents • Partially Resistant Vents			
Ember Accumulators	4 options: • Unknown • None to few • Moderate • Abundant			

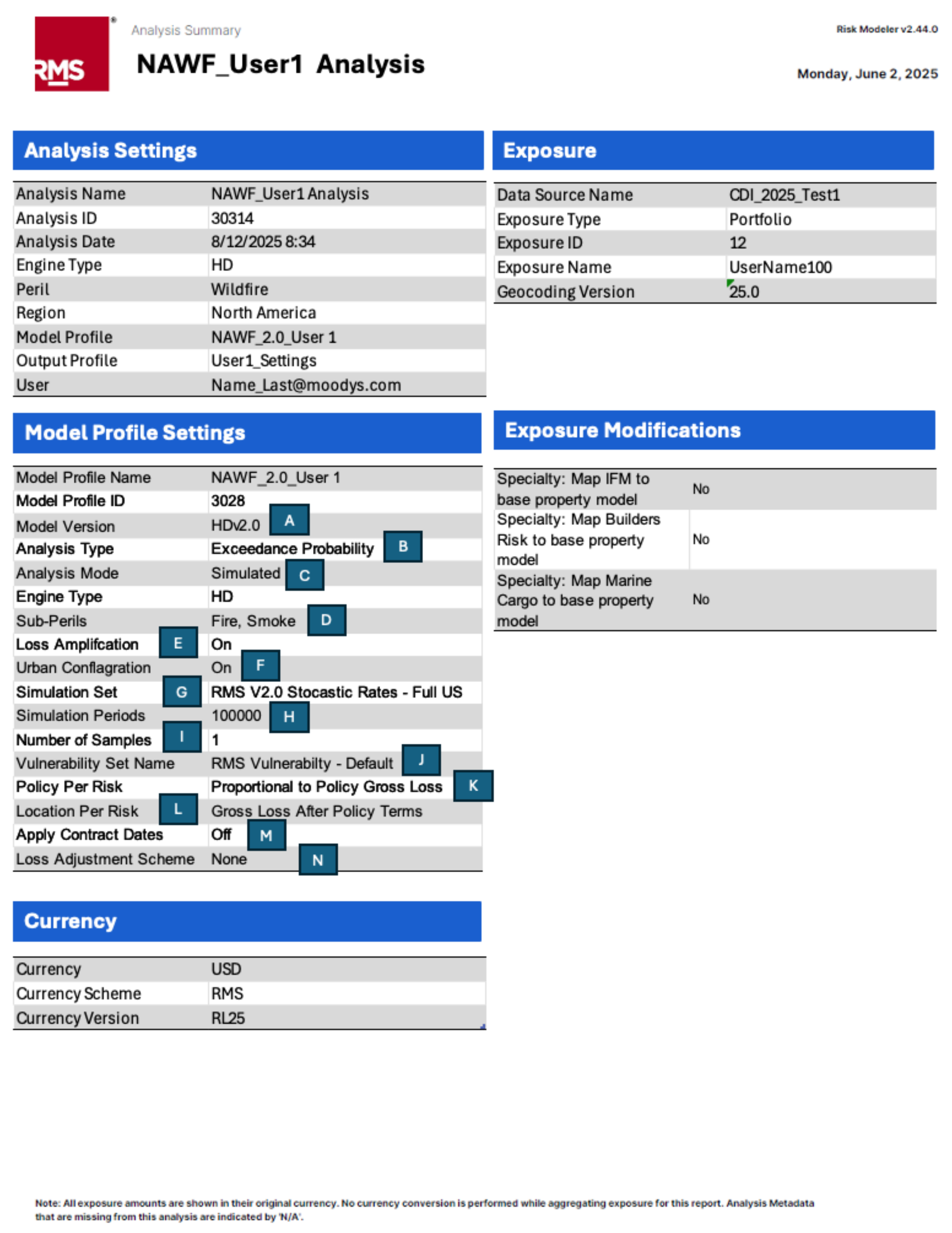
Secondary Modifiers				
	Selected Options	**Default Approach**	**Input method**	**Import/Analysis Log location**
Suppression	4 options: • Unknown • Active Suppression • Passive Suppression • None			
Sprinkler Presence	3 options: • Unknown • Present • Absent			
Construction Quality	4 options: • Obvious signs of deterioration or distress • Certified design & construction • IBHS WF Prepared Home • IBHS WF Prepared Home Plus			
Slope Setback	3 options: • Unknown • Minimal set back • Adequate set back			
Wall Cladding Type	13 options: • Unknown • Brick veneer • Metal sheathing • Wood • EIFS (exterior insulation finishing system) • Impact rated glazing • Stucco • Vinyl siding terminating at least 12” above ground • Wood siding terminating at least 12” above ground and/or with fire retarding treatment			
Residential Appurtenant Structures	16 options: • Unknown • None • Fences / Carport • Attached screen enclosure / Lanai • Detached screen enclosure / Lanai • Skylights			

Secondary Modifiers				
	Selected Options	**Default Approach**	**Input method**	**Import/Analysis Log location**
	• Roof-mounted mechanically attached PV array • Combustible fence / detached structure adjacent to primary structure • Combustible fence / detached structure at least 10 ft away from primary structure			
Commercial Appurtenant Structures	12 options: • Unknown • Large signs • Extensive ornamentation • None • Roof-mounted mechanically attached PV array • Large signs and roof-mounted ballasted PV array • Combustible signage / structure adjacent to primary structure • Combustible signage / structure at least 10 ft away from primary structure			
Patio Deck	5 options: • Unknown • No deck present • Wood decking • Non-combustible decking • Fully enclosed non-combustible decking with no flammable / combustible material storage below			
Opening Heat Resistance	7 options: • Unknown • Single-pane windows and glass door – Wildfire vulnerable skylights • Single-pane windows and glass door – Wildfire resistant skylights • Single-pane windows and glass door – No skylights • Double-paned windows and glass door – Wildfire vulnerable skylights • Double-paned windows and glass door - No skylights • All openings compliant with wildfire resistant code			
Accessibility Condition	6 options: • Unknown			

<table>
<tr><th colspan="5">Secondary Modifiers</th></tr>
<tr><th></th><th>Selected Options</th><th>Default Approach</th><th>Input method</th><th>Import/Analysis Log location</th></tr>
<tr><td></td><td>• Community that has implemented wildfire mitigation activities.
• Typical water supply and in-and-out access for fire-suppression activities
• Typical water supply but limited access via single road in-and-out
• Remote location with limited water supply and single access road
• Corner Lots</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>Community Preparedness</td><td>5 options:
• Unknown
• None
• Level 1 Preparedness - Voluntary
• Level 2 Preparedness - Semi mandatory regulations and variable enforcement
• Level 3 Preparedness - Mandatory regulations and enforcement with regular inspection</td></tr>
</table>

Table G-8C

Financial			
Selected Options		**Notes**	**Analysis log location**
Post Event Loss Amplification (PLA)	On/Off, Default is On	Recommend setting to *On* for rate filing	E
Analysis Type	4 options	Use Exceedance Probability for rate filings.	B
Analysis Mode	Simulated or Expected	Recommend *Simulated* mode for rating filing	C
Policy Per Risk	2 options	Recommend *Proportional to Policy Gross Loss* for rate filing	K
Location Per Risk	2 options	Recommend *Gross Loss After Policy Terms* for rate filing	L
Apply Contract Dates	2 Options	Recommend setting to *Off* for rate filing	M
Loss Adjustment Scheme	User defined	Recommend setting to *None* for rate filing	N
Output granularity			
Output Perspective	Portfolio-level	Default setting for rate filing	N/A
Output Perspective	Location-level	Recommended setting for rate filing	N/A



Analysis Summary

Risk Modeler v2.44.0

NAWF_User1 Analysis

Monday, June 2, 2025

Analysis Settings

Analysis Name	NAWF_User1 Analysis
Analysis ID	30314
Analysis Date	8/12/2025 8:34
Engine Type	HD
Peril	Wildfire
Region	North America
Model Profile	NAWF_2.0_User 1
Output Profile	User1_Settings
User	Name_Last@moodys.com

Exposure

Data Source Name	CDI_2025_Test1
Exposure Type	Portfolio
Exposure ID	12
Exposure Name	UserName100
Geocoding Version	25.0

Model Profile Settings

Model Profile Name	NAWF_2.0_User 1	
Model Profile ID	3028	
Model Version	HDv2.0	A
Analysis Type	Exceedance Probability	B
Analysis Mode	Simulated	C
Engine Type	HD	
Sub-Perils	Fire, Smoke	D
Loss Amplifcation	On	E
Urban Conflagration	On	F
Simulation Set	RMS V2.0 Stocastic Rates - Full US	G
Simulation Periods	100000	H
Number of Samples	1	I
Vulnerability Set Name	RMS Vulnerabilty - Default	J
Policy Per Risk	Proportional to Policy Gross Loss	K
Location Per Risk	Gross Loss After Policy Terms	L
Apply Contract Dates	Off	M
Loss Adjustment Scheme	None	N

Exposure Modifications

Specialty: Map IFM to base property model	No
Specialty: Map Builders Risk to base property model	No
Specialty: Map Marine Cargo to base property model	No

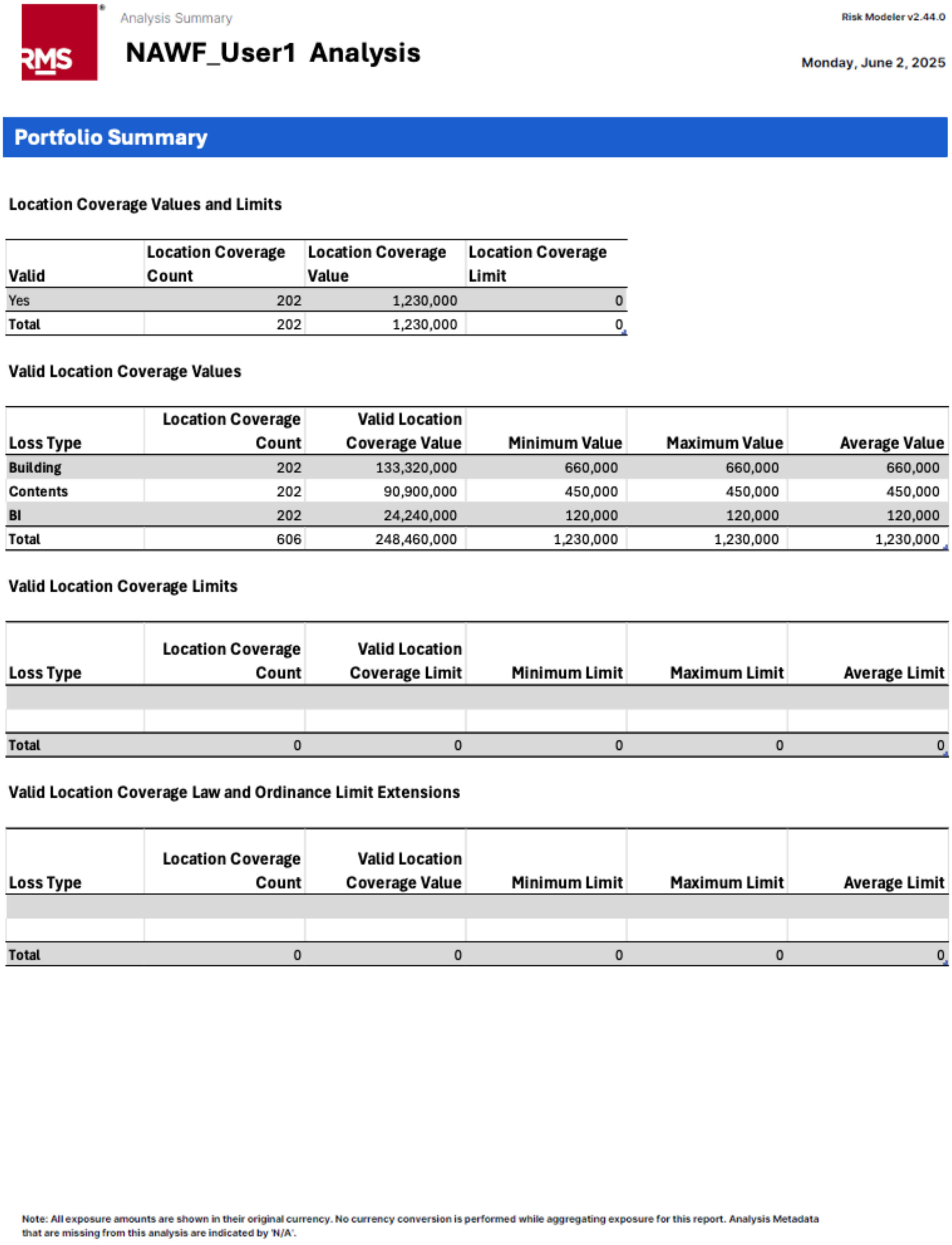
Currency

Currency	USD
Currency Scheme	RMS
Currency Version	RL25

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.

D.

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.



Analysis Summary

Risk Modeler v2.44.0

NAWF_User1 Analysis

Monday, June 2, 2025

Portfolio Summary

Location Coverage Values and Limits

Valid	Location Coverage Count	Location Coverage Value	Location Coverage Limit
Yes	202	1,230,000	0
Total	202	1,230,000	0

Valid Location Coverage Values

Loss Type	Location Coverage Count	Valid Location Coverage Value	Minimum Value	Maximum Value	Average Value
Building	202	133,320,000	660,000	660,000	660,000
Contents	202	90,900,000	450,000	450,000	450,000
BI	202	24,240,000	120,000	120,000	120,000
Total	606	248,460,000	1,230,000	1,230,000	1,230,000

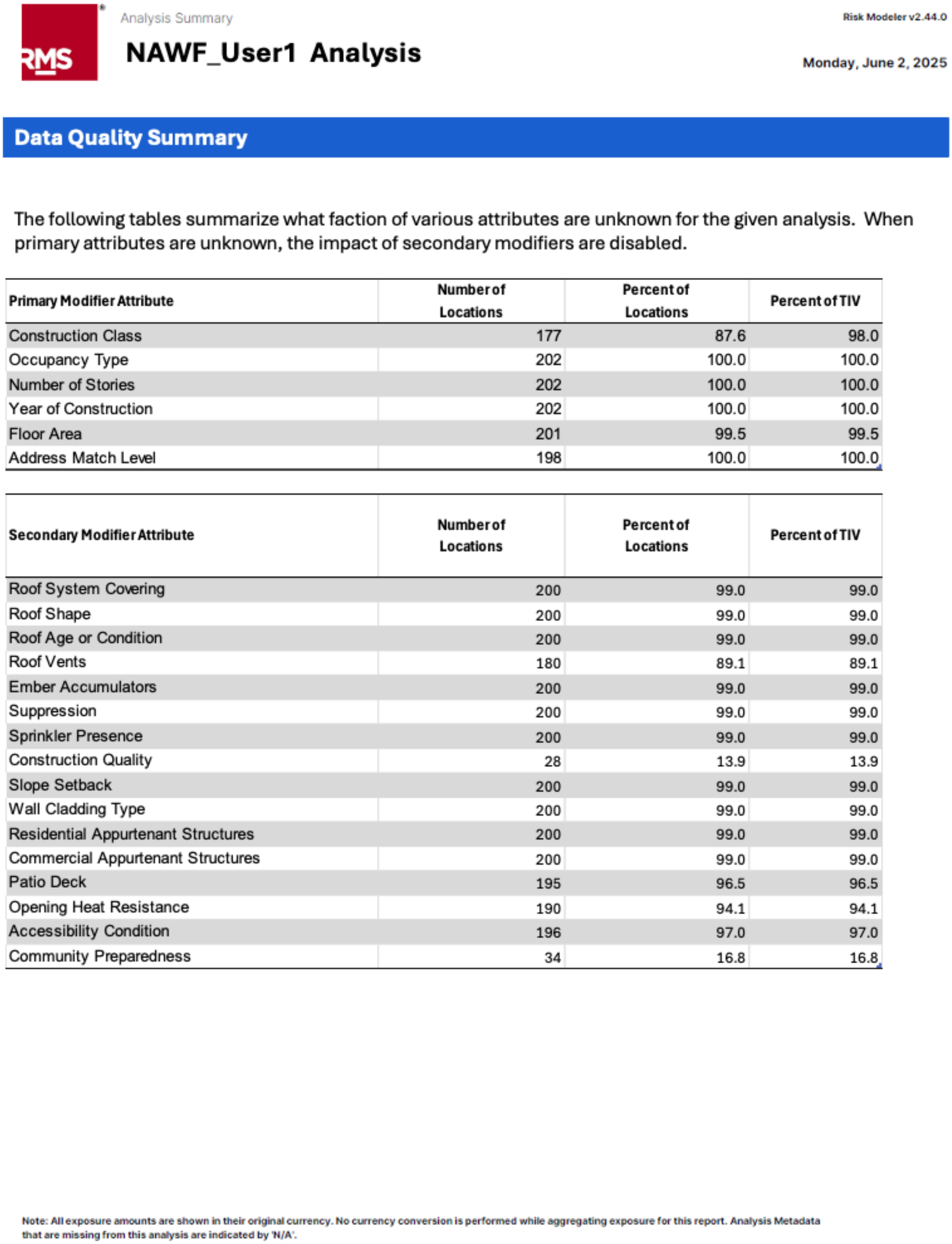
Valid Location Coverage Limits

Loss Type	Location Coverage Count	Valid Location Coverage Limit	Minimum Limit	Maximum Limit	Average Limit
Total	0	0	0	0	0

Valid Location Coverage Law and Ordinance Limit Extensions

Loss Type	Location Coverage Count	Valid Location Coverage Value	Minimum Limit	Maximum Limit	Average Limit
Total	0	0	0	0	0

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.



Analysis Summary

Risk Modeler v2.44.0

NAWF_User1 Analysis

Monday, June 2, 2025

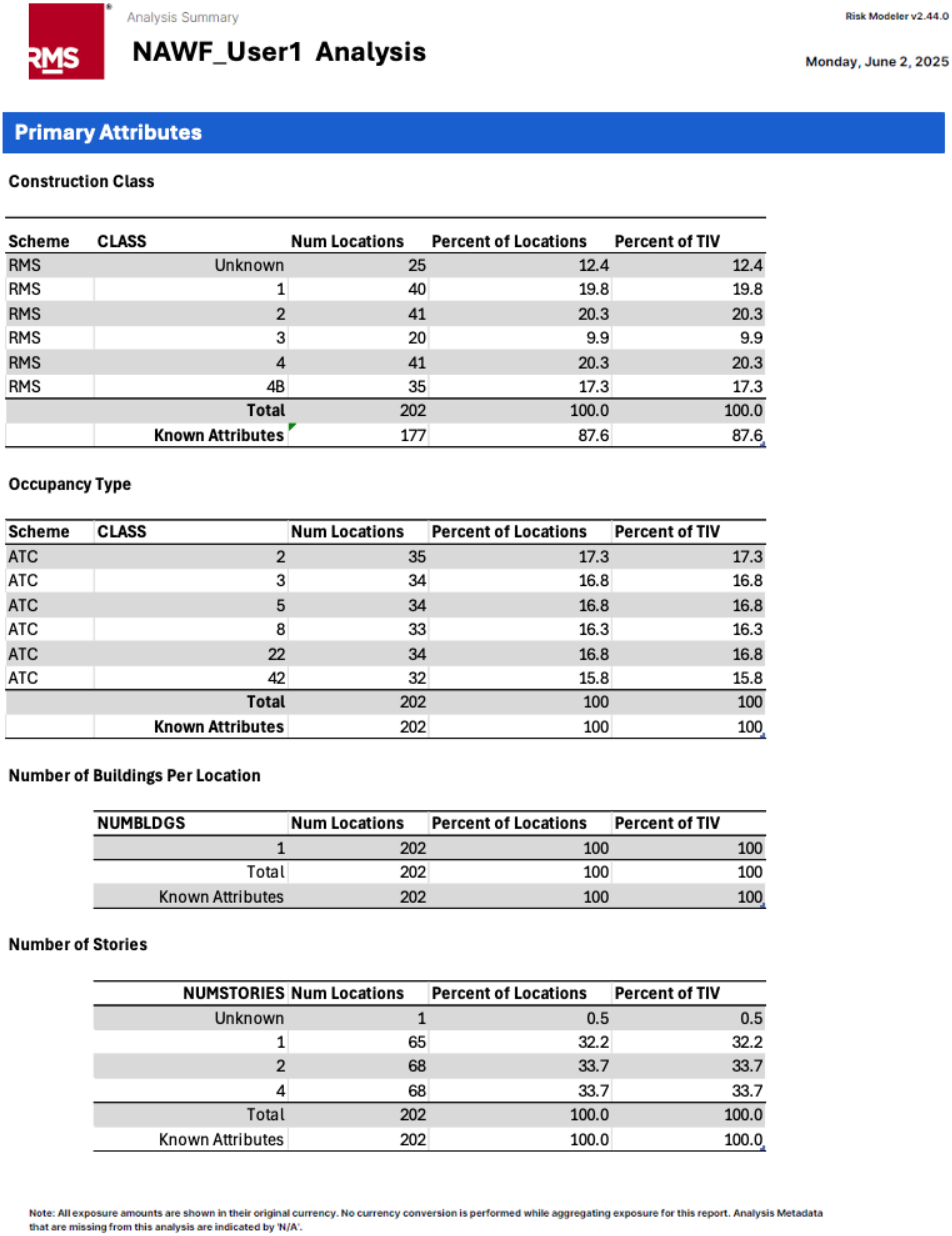
Data Quality Summary

The following tables summarize what faction of various attributes are unknown for the given analysis. When primary attributes are unknown, the impact of secondary modifiers are disabled.

Primary Modifier Attribute	Number of Locations	Percent of Locations	Percent of TIV
Construction Class	177	87.6	98.0
Occupancy Type	202	100.0	100.0
Number of Stories	202	100.0	100.0
Year of Construction	202	100.0	100.0
Floor Area	201	99.5	99.5
Address Match Level	198	100.0	100.0

Secondary Modifier Attribute	Number of Locations	Percent of Locations	Percent of TIV
Roof System Covering	200	99.0	99.0
Roof Shape	200	99.0	99.0
Roof Age or Condition	200	99.0	99.0
Roof Vents	180	89.1	89.1
Ember Accumulators	200	99.0	99.0
Suppression	200	99.0	99.0
Sprinkler Presence	200	99.0	99.0
Construction Quality	28	13.9	13.9
Slope Setback	200	99.0	99.0
Wall Cladding Type	200	99.0	99.0
Residential Appurtenant Structures	200	99.0	99.0
Commercial Appurtenant Structures	200	99.0	99.0
Patio Deck	195	96.5	96.5
Opening Heat Resistance	190	94.1	94.1
Accessibility Condition	196	97.0	97.0
Community Preparedness	34	16.8	16.8

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.



Analysis Summary

NAWF_User1 Analysis

Risk Modeler v2.44.0

Monday, June 2, 2025

Primary Attributes

Construction Class

Scheme	CLASS	Num Locations	Percent of Locations	Percent of TIV
RMS	Unknown	25	12.4	12.4
RMS	1	40	19.8	19.8
RMS	2	41	20.3	20.3
RMS	3	20	9.9	9.9
RMS	4	41	20.3	20.3
RMS	4B	35	17.3	17.3
	Total	202	100.0	100.0
	Known Attributes	177	87.6	87.6

Occupancy Type

Scheme	CLASS	Num Locations	Percent of Locations	Percent of TIV
ATC	2	35	17.3	17.3
ATC	3	34	16.8	16.8
ATC	5	34	16.8	16.8
ATC	8	33	16.3	16.3
ATC	22	34	16.8	16.8
ATC	42	32	15.8	15.8
	Total	202	100	100
	Known Attributes	202	100	100

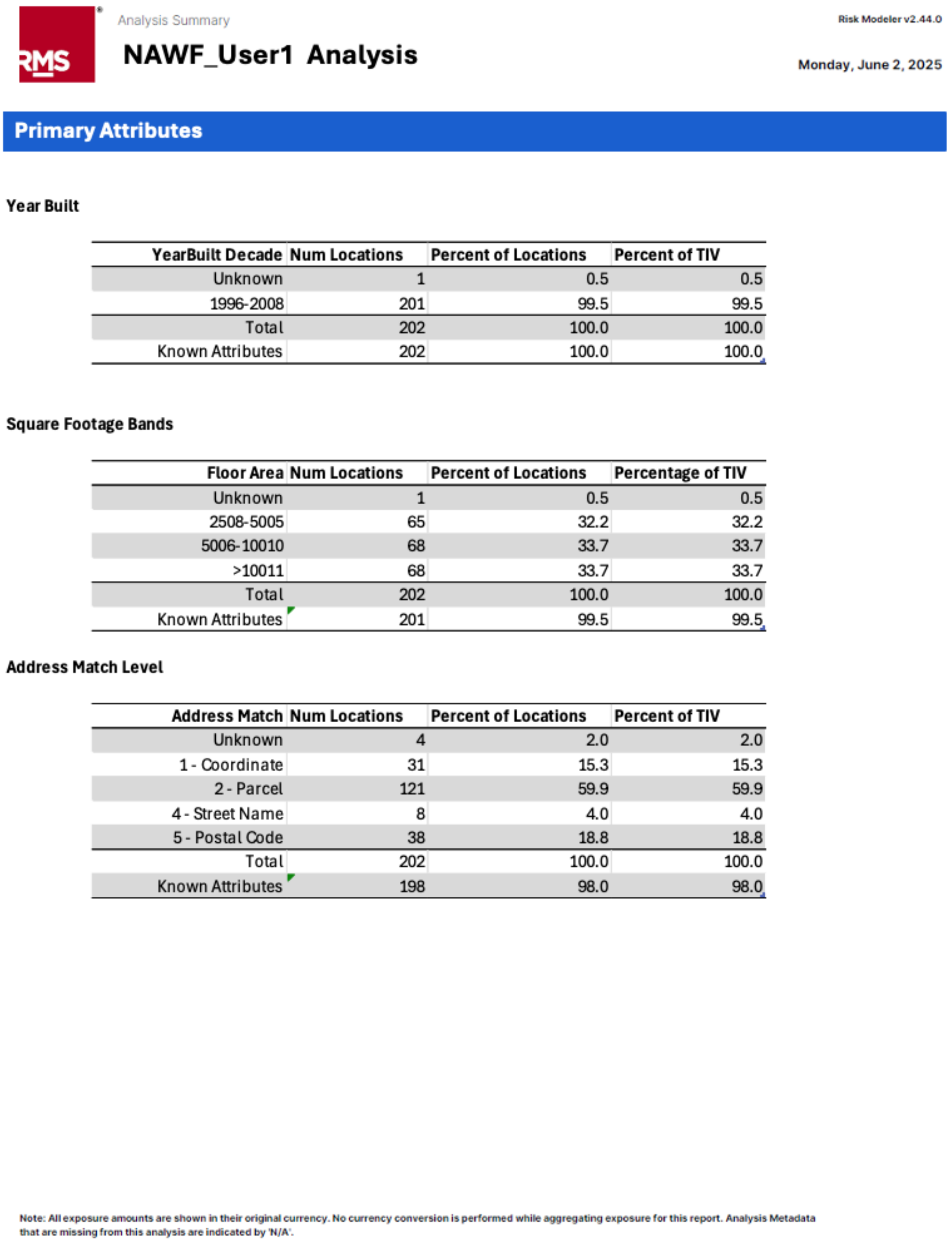
Number of Buildings Per Location

NUMBLDGS	Num Locations	Percent of Locations	Percent of TIV
1	202	100	100
Total	202	100	100
Known Attributes	202	100	100

Number of Stories

NUMSTORIES	Num Locations	Percent of Locations	Percent of TIV
Unknown	1	0.5	0.5
1	65	32.2	32.2
2	68	33.7	33.7
4	68	33.7	33.7
Total	202	100.0	100.0
Known Attributes	202	100.0	100.0

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.



Analysis Summary

NAWF_User1 Analysis

Risk Modeler v2.44.0

Monday, June 2, 2025

Primary Attributes

Year Built

YearBuilt Decade	Num Locations	Percent of Locations	Percent of TIV
Unknown	1	0.5	0.5
1996-2008	201	99.5	99.5
Total	202	100.0	100.0
Known Attributes	202	100.0	100.0

Square Footage Bands

Floor Area	Num Locations	Percent of Locations	Percentage of TIV
Unknown	1	0.5	0.5
2508-5005	65	32.2	32.2
5006-10010	68	33.7	33.7
>10011	68	33.7	33.7
Total	202	100.0	100.0
Known Attributes	201	99.5	99.5

Address Match Level

Address Match	Num Locations	Percent of Locations	Percent of TIV
Unknown	4	2.0	2.0
1 - Coordinate	31	15.3	15.3
2 - Parcel	121	59.9	59.9
4 - Street Name	8	4.0	4.0
5 - Postal Code	38	18.8	18.8
Total	202	100.0	100.0
Known Attributes	198	98.0	98.0

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.

Secondary Attributes

Roof System Covering

Option	Num Locations	Percent of Locations	Percent of TIV
0 - Unkonwn	2	1.0	1.0
1 = Metal sheathing with exposed fasteners	15	7.4	7.4
2 = Metal sheathing with concealed fasteners	15	7.4	7.4
3 = Built-up roof or single-ply membrane roof with gutters	13	6.4	6.4
4 = Built-up roof or single-ply membrane roof without gutters	14	6.9	6.9
5 = Concrete/clay tiles	14	6.9	6.9
6 = Wood shakes	14	6.9	6.9
7 = Normal shingle	13	6.4	6.4
8 = Normal shingle with Secondary Water Resistance (SWR)	13	6.4	6.4
9 = Shingle rated for high wind speeds	13	6.4	6.4
10 = Shingle rated for high wind speeds with Secondary Water Resistance (SWR)	13	6.4	6.4
16 = Concrete roof	13	6.4	6.4
17 = Bermuda-style roof	12	5.9	5.9
20 = Class A Fire Rating	13	6.4	6.4
21 = Class B Fire Rating	13	6.4	6.4
22 = Class C Fire Rating	12	5.9	5.9
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Roof Shape

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Flat roof with parapets	26	12.9	12.9
2 = Flat roof without parapets	26	12.9	12.9
3 = Hip roof with slope less than or equal to 6:12 (26.5 degrees)	24	11.9	11.9
4 = Hip roof with slope greater than 6:12 (26.5 degrees)	25	12.4	12.4
5 = Gable roof with slope less than or equal to 6:12 (26.5 degrees)	26	12.9	12.9
6 = Gable roof with slope greater than 6:12 (26.5 degrees)	25	12.4	12.4
7 = Braced gable roof with slope less than or equal to 6:12 (26.5 degrees)	24	11.9	11.9
8 = Braced gable roof with slope greater than 6:12 (26.5 degrees)	24	11.9	11.9
Total	202	100.0	100.0
Known Attributes	200	99.0	100.0

Roof Age / Condition

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = 0-5 years	52	25.7	25.7
2 = 6-10 years	51	25.2	25.2
3 = 11 years or more	48	23.8	23.8
4 = Obvious signs of deterioration and distress	49	24.3	24.3
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.

Secondary Attributes

Roof Vents

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	22	10.9	10.9
1 = Present (default)	49	24.3	24.3
2 = None	39	19.3	19.3
4 = Wildfire Resistant Vents	41	20.3	20.3
5 = Wildfire Vulnerable Vents	51	25.2	25.2
Total	202	100.0	100.0
Known Attributes	180	89.1	89.1

Ember Accumulators

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = None to few (0-2 accumulator areas)	68	33.7	33.7
2 = Moderate (3-5 accumulator areas)	68	33.7	33.7
3 = Abundant (6 or more accumulator areas)	64	31.7	31.7
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Suppression

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Active Suppression	68	33.7	33.7
2 = Passive Suppression	68	33.7	33.7
3 = None	64	31.7	31.7
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Slope Setback

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Minimal set back	104	51.5	51.5
2 = Adequate set back	96	47.5	47.5
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Sprinkler Presence

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Present	104	51.5	51.5
2 = Absent	96	47.5	47.5
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Secondary Attributes

Wall Cladding Type

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Brick veneer	15	7.4	7.4
2 = Metal sheathing	17	8.4	8.4
3 = Wood	17	8.4	8.4
4 = EIFS (exterior insulation finishing system)	17	8.4	8.4
5 = Impact rated glazing	17	8.4	8.4
6 = Glazing not designed for impact, with gravel rooftop within 1000 ft	17	8.4	8.4
7 = Glazing not designed for impact, without a gravel rooftop within 1000 ft	17	8.4	8.4
8 = Vinyl siding	17	8.4	8.4
9 = Stucco	17	8.4	8.4
10 = None	15	7.4	7.4
11 = Vinyl siding terminating at least 12" above ground	17	8.4	8.4
12 = Wood siding terminating at least 12" above ground and/or with fire retarding treatment	17	8.4	8.4
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Residential Appurtenant structures

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = None	12	5.9	5.9
2 = Fences / Carport	13	6.4	6.4
3 = Attached screen enclosure / Lanai	13	6.4	6.4
4 = Detached screen enclosure / Lanai	13	6.4	6.4
5 = Skylights	13	6.4	6.4
6 = Skylights with impact protection	12	5.9	5.9
7 = Roof-mounted ballasted PV (photovoltaic) array	13	6.4	6.4
8 = Roof-mounted mechanically attached PV array	13	6.4	6.4
9 = Fences/carport and roof-mounted ballasted PV array	12	5.9	5.9
10 = Fences/carport and roof-mounted mechanically attached PV array	12	5.9	5.9
11 = Attached screen enclosure and roof-mounted ballasted PV array	13	6.4	6.4
12 = Attached screen enclosure and roof-mounted mechanically attached PV array	13	6.4	6.4
13 = Detached screen enclosure and roof-mounted ballasted PV array	12	5.9	5.9
14 = Detached screen enclosure and roof-mounted mechanically attached PV array	12	5.9	5.9
15 = Combustible fence/detached structure adjacent to primary structure	12	5.9	5.9
16 = Combustible fence/detached structure at least 10ft away from primary structure	12	5.9	5.9
Total	202	100.0	100.0
Known Attributes	200	99.0	100.0

Secondary Attributes

Commercial Appurtenant structures

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	2	1.0	1.0
1 = Large signs	19	9.4	9.4
2 = Extensive ornamentation	18	8.9	8.9
3 = None	19	9.4	9.4
4 = Roof-mounted ballasted PV array	17	8.4	8.4
5 = Roof-mounted mechanically attached PV array	19	9.4	9.4
6 = Large signs and roof-mounted ballasted PV array	19	9.4	9.4
7 = Large signs and roof-mounted mechanically attached PV array	18	8.9	8.9
8 = Extensive ornamentation and roof-mounted ballasted PV array	18	8.9	8.9
9 = Extensive ornamentation and roof-mounted mechanically attached PV array	18	8.9	8.9
10 = Combustible signage/structure adjacent to primary structure	18	8.9	8.9
11 = Combustible signage/structure at least 10ft away from primary structure	17	8.4	8.4
Total	202	100.0	100.0
Known Attributes	200	99.0	99.0

Patio Deck

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	7	3.5	3.5
1 = No deck present	49	24.3	24.3
2= Wood decking	44	21.8	21.8
3 = Non-combustible decking	51	25.2	25.2
4 = Fully enclosed non-combustible decking with no flammable/ combustible material stored below	51	25.2	25.2
Total	202	100.0	100.0
Known Attributes	195	96.5	96.5

Opening Heat Resistance

Option	Num Locations	Percent of Locations	Percent of TIV
0 = Unknown	12	5.9	5.9
1 = Single-pane windows and glass door; wildfire vulnerable skylights	32	15.8	15.8
2 = Single-pane windows and glass door; wildfire resistant skylights	34	16.8	16.8
3 = Single-pane windows and glass door; no skylights	34	16.8	16.8
4 = Double-paned windows and glass door - Wildfire vulnerable skylights	32	15.8	15.8
5 = Double-paned windows and glass door - no skylights	24	11.9	11.9
6 = All openings compliant with wildfire resistant code	34	16.8	16.8
Total	202	100.0	100.0
Known Attributes	190	94.1	94.1

NAWF_User1 Analysis

Secondary Attributes

Accessibility Condition

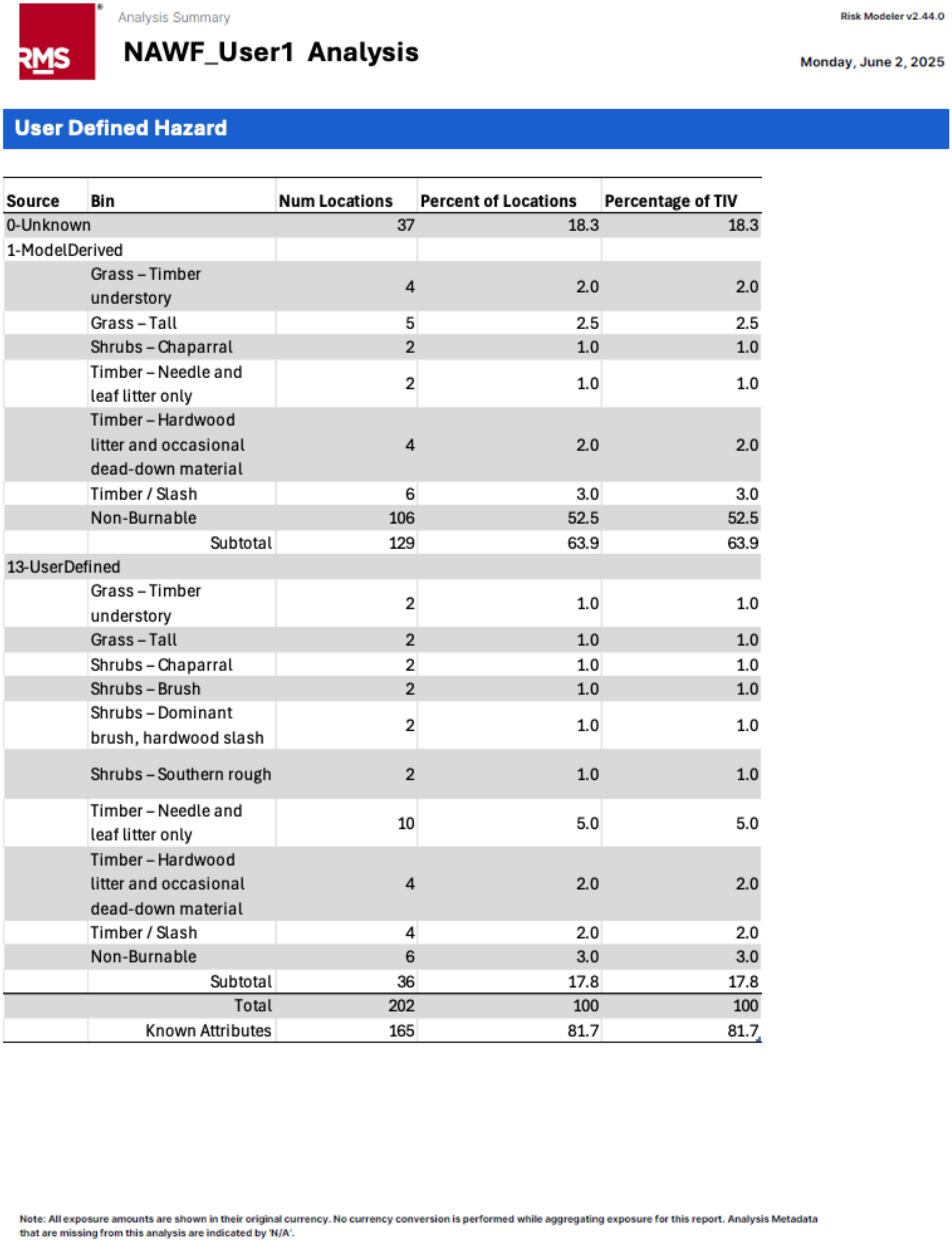
Option	Num Locations	Percent of Locations	Percent of TIV
0=Unknown	6	3.0	3.0
1=Community designed or retrofit to be wildfire resistant/shelter-in-place	49	24.3	24.3
2=Typical water supply and in-and-out access for fire-suppression activities	49	24.3	24.3
3=Typical water supply but limited access via single road in-and-out	47	23.3	23.3
4=Remote location with limited water supply and single access road	51	25.2	25.2
5=Corner Lots	0	0.0	0.0
Total	202	100.0	100.0
Known Attributes	196	97.0	97.0

Construction Quality

Option	Num Locations	Percent of Locations	Percent of TIV
0=Unknown	174	86.1	86.1
1=Obvious signs of deterioration or distress	21	10.4	10.4
9=Certified design & construction	1	0.5	0.5
10=IBHS WF Prepared Home	3	1.5	1.5
11=IBHS WF Prepared Home Plus	3	1.5	1.5
Total	202	100.0	100.0
Known Attributes	28	13.9	13.9

Community Preparedness

Option	Num Locations	Percent of Locations	Percent of TIV
0=Unknown	168	83.2	83.2
1=None	10	5.0	5.0
2=Community designed or retrofit to be wildfire resistant/shelter-in-place	4	2.0	2.0
3=NFPA Firewise USA community	10	5.0	5.0
4=Fire Risk reduction California	2	1.0	1.0
5=Wildfire Adopted Partnership (Colorado)	8	4.0	4.0
Total	202	100.0	100.0
Known Attributes	34	16.8	16.8



Analysis Summary

NAWF_User1 Analysis

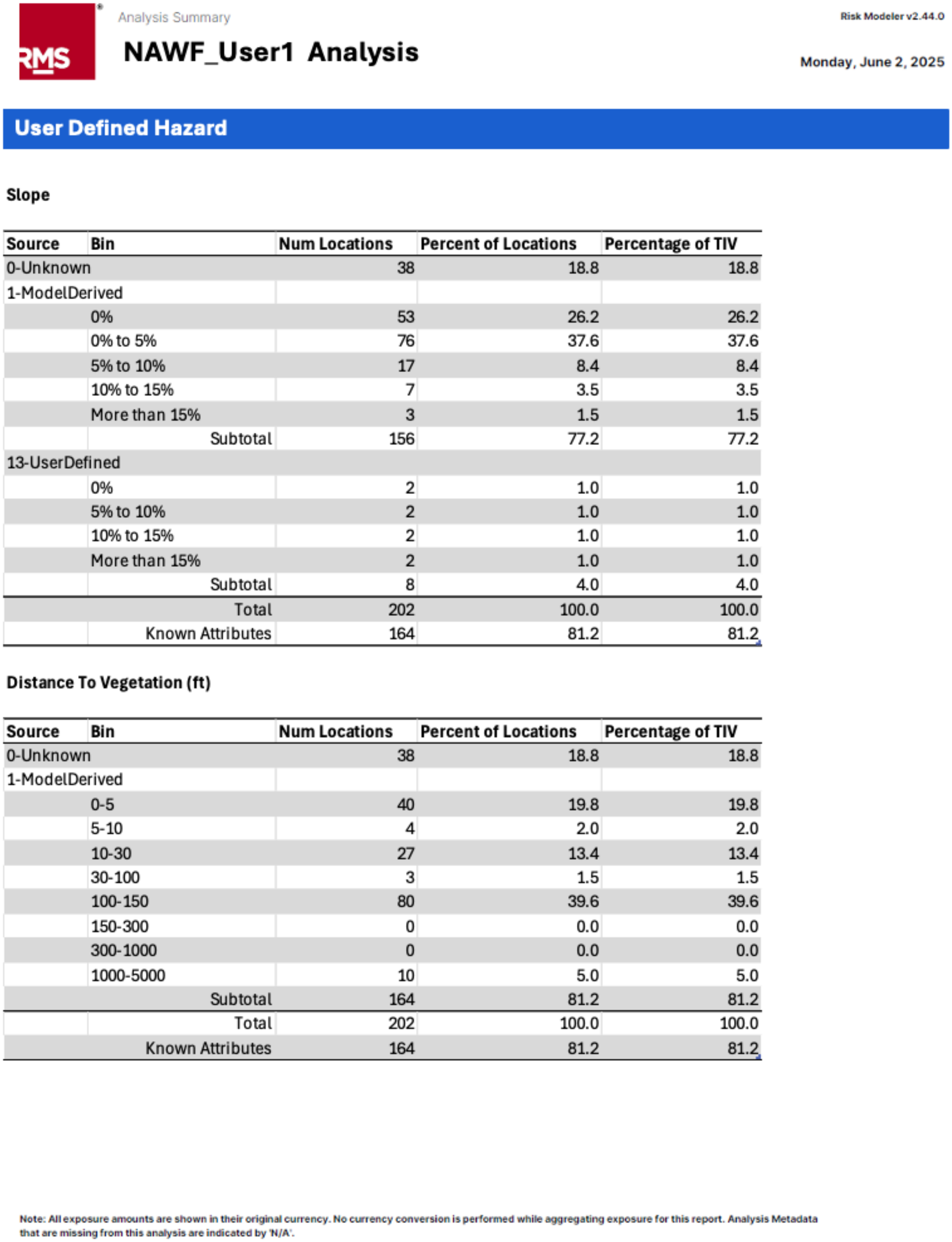
Risk Modeler v2.44.0

Monday, June 2, 2025

User Defined Hazard

Source	Bin	Num Locations	Percent of Locations	Percentage of TIV
0-Unknown		37	18.3	18.3
1-ModelDerived				
	Grass – Timber understory	4	2.0	2.0
	Grass – Tall	5	2.5	2.5
	Shrubs – Chaparral	2	1.0	1.0
	Timber – Needle and leaf litter only	2	1.0	1.0
	Timber – Hardwood litter and occasional dead-down material	4	2.0	2.0
	Timber / Slash	6	3.0	3.0
	Non-Burnable	106	52.5	52.5
	Subtotal	129	63.9	63.9
13-UserDefined				
	Grass – Timber understory	2	1.0	1.0
	Grass – Tall	2	1.0	1.0
	Shrubs – Chaparral	2	1.0	1.0
	Shrubs – Brush	2	1.0	1.0
	Shrubs – Dominant brush, hardwood slash	2	1.0	1.0
	Shrubs – Southern rough	2	1.0	1.0
	Timber – Needle and leaf litter only	10	5.0	5.0
	Timber – Hardwood litter and occasional dead-down material	4	2.0	2.0
	Timber / Slash	4	2.0	2.0
	Non-Burnable	6	3.0	3.0
	Subtotal	36	17.8	17.8
	Total	202	100	100
	Known Attributes	165	81.7	81.7

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.



Analysis Summary

NAWF_User1 Analysis

Risk Modeler v2.44.0

Monday, June 2, 2025

User Defined Hazard

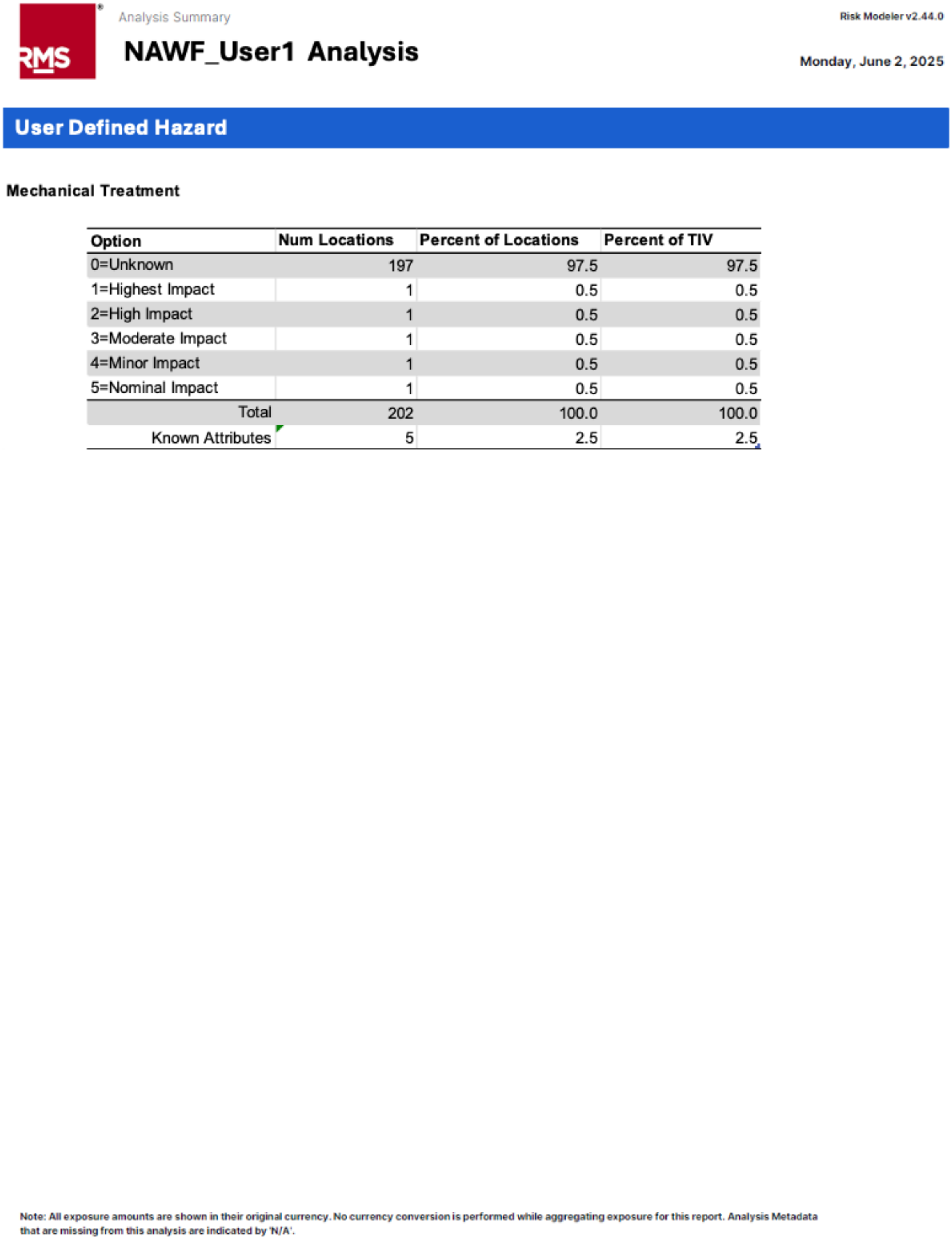
Slope

Source	Bin	Num Locations	Percent of Locations	Percentage of TIV
0-Unknown		38	18.8	18.8
1-ModelDerived				
	0%	53	26.2	26.2
	0% to 5%	76	37.6	37.6
	5% to 10%	17	8.4	8.4
	10% to 15%	7	3.5	3.5
	More than 15%	3	1.5	1.5
	Subtotal	156	77.2	77.2
13-UserDefined				
	0%	2	1.0	1.0
	5% to 10%	2	1.0	1.0
	10% to 15%	2	1.0	1.0
	More than 15%	2	1.0	1.0
	Subtotal	8	4.0	4.0
	Total	202	100.0	100.0
	Known Attributes	164	81.2	81.2

Distance To Vegetation (ft)

Source	Bin	Num Locations	Percent of Locations	Percentage of TIV
0-Unknown		38	18.8	18.8
1-ModelDerived				
	0-5	40	19.8	19.8
	5-10	4	2.0	2.0
	10-30	27	13.4	13.4
	30-100	3	1.5	1.5
	100-150	80	39.6	39.6
	150-300	0	0.0	0.0
	300-1000	0	0.0	0.0
	1000-5000	10	5.0	5.0
	Subtotal	164	81.2	81.2
	Total	202	100.0	100.0
	Known Attributes	164	81.2	81.2

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.



Analysis Summary

Risk Modeler v2.44.0

NAWF_User1 Analysis

Monday, June 2, 2025

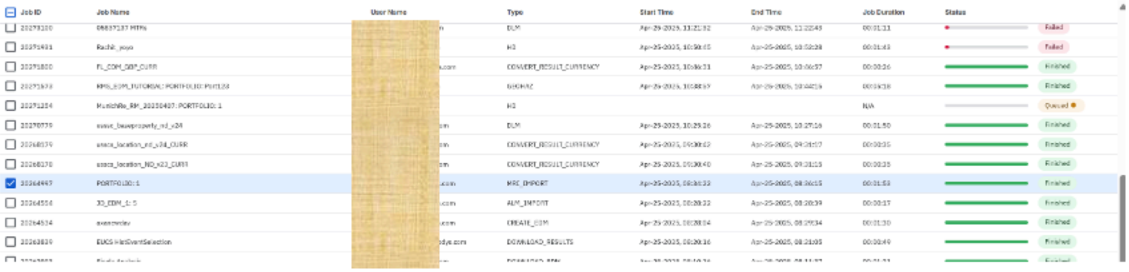
User Defined Hazard

Mechanical Treatment

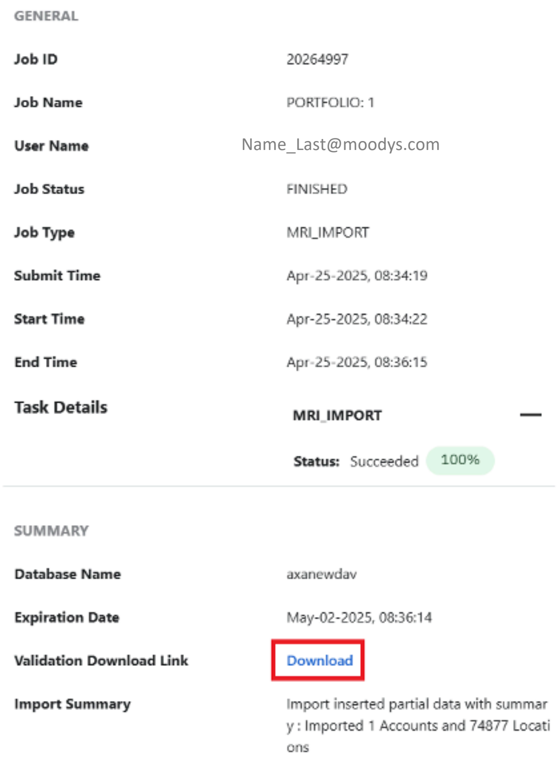
Option	Num Locations	Percent of Locations	Percent of TIV
0=Unknown	197	97.5	97.5
1=Highest Impact	1	0.5	0.5
2=High Impact	1	0.5	0.5
3=Moderate Impact	1	0.5	0.5
4=Minor Impact	1	0.5	0.5
5=Nominal Impact	1	0.5	0.5
Total	202	100.0	100.0
Known Attributes	5	2.5	2.5

Note: All exposure amounts are shown in their original currency. No currency conversion is performed while aggregating exposure for this report. Analysis Metadata that are missing from this analysis are indicated by 'N/A'.

Sample Validation Log for Import Issues:



☐ Job ID	Job Name	User Name	Type	Start Time	End Time	Job Duration	Status
☐ 20273100	09837137 MTRs	[redacted]	DLM	Apr-25-2025, 11:21:32	Apr-25-2025, 11:22:43	00:01:11	Failed
☐ 20271931	Rachit_yoyo	[redacted]	HD	Apr-25-2025, 10:50:45	Apr-25-2025, 10:52:28	00:01:43	Failed
☐ 20271800	FL_EDM_GBP_CURR	[redacted]	CONVERT_RESULT_CURRENCY	Apr-25-2025, 10:36:31	Apr-25-2025, 10:36:57	00:00:26	Finished
☐ 20271573	RMS_EDM_TUTORIAL: PORTFOLIO: PORT123	[redacted]	GEOHAZ	Apr-25-2025, 10:38:57	Apr-25-2025, 10:44:15	00:05:18	Finished
☐ 20271254	MunichRe_RM_20250407: PORTFOLIO: 1	[redacted]	HD			N/A	Queued ●
☐ 20270779	axaxc_bauproperty_nd_v24	[redacted]	DLM	Apr-25-2025, 10:25:26	Apr-25-2025, 10:27:16	00:01:50	Finished
☐ 20268379	axaca_location_nd_v24_CURR	[redacted]	CONVERT_RESULT_CURRENCY	Apr-25-2025, 09:30:42	Apr-25-2025, 09:31:17	00:00:35	Finished
☐ 20268378	axaca_location_ND_v23_CURR	[redacted]	CONVERT_RESULT_CURRENCY	Apr-25-2025, 09:30:40	Apr-25-2025, 09:31:15	00:00:35	Finished
☑ 20264997	PORTFOLIO: 1	[redacted]	MRI_IMPORT	Apr-25-2025, 08:34:22	Apr-25-2025, 08:36:15	00:01:53	Finished
☐ 20264554	JD_EDM_1: 5	[redacted]	ALM_IMPORT	Apr-25-2025, 08:20:22	Apr-25-2025, 08:20:39	00:00:17	Finished
☐ 20264534	axanewdav	[redacted]	CREATE_EDM	Apr-25-2025, 08:28:04	Apr-25-2025, 08:29:34	00:01:30	Finished
☐ 20263839	EUCS HistEventSelection	[redacted]	DOWNLOAD_RESULTS	Apr-25-2025, 08:20:16	Apr-25-2025, 08:21:05	00:00:49	Finished



GENERAL

Job ID	20264997
Job Name	PORTFOLIO: 1
User Name	Name_Last@moodys.com
Job Status	FINISHED
Job Type	MRI_IMPORT
Submit Time	Apr-25-2025, 08:34:19
Start Time	Apr-25-2025, 08:34:22
End Time	Apr-25-2025, 08:36:15
Task Details	**MRI_IMPORT** — **Status:** Succeeded 100%

SUMMARY

Database Name	axanewdav
Expiration Date	May-02-2025, 08:36:14
Validation Download Link	Download
Import Summary	Import inserted partial data with summary : Imported 1 Accounts and 74877 Locations

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44296
Location data rejected during import due to DataType issue
4/25/2025 1:35:32 PM
Location
44297
Location data rejected during import due to DataType issue
4/25/2025 1:35:32 PM
Location



44298
Location data rejected during import due to DataType issue
4/25/2025 1:35:32 PM
Location
44299
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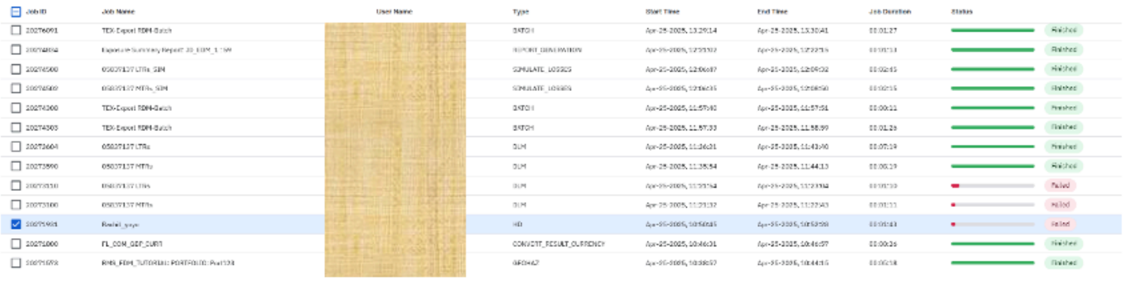
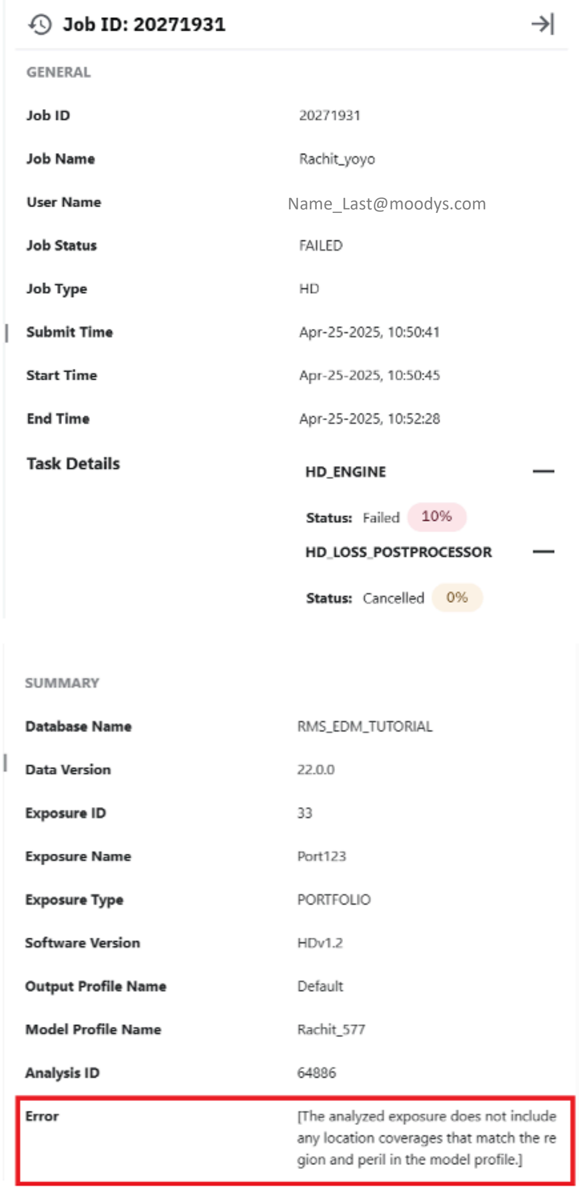
Sample Error for Analysis Failure:



☐ Job ID	Job Name	User Name	Type	Start Time	End Time	Job Duration	Status
☐ 20276091	TEX-Export RDM-Batch	[redacted]	BATCH	Apr-25-2025, 13:29:14	Apr-25-2025, 13:30:41	00:01:27	Finished
☐ [illegible]	Exposure Summary Report [illegible]	[redacted]	REPORT_GENERATION	[illegible]	[illegible]	[illegible]	Finished
☐ 20274500	05037137 LTRs_SIM	[redacted]	SIMULATE_LOSSES	Apr-25-2025, 12:06:47	Apr-25-2025, 12:09:32	00:02:45	Finished
☐ [illegible]	05037137 MTRs_SIM	[redacted]	SIMULATE_LOSSES	[illegible]	[illegible]	[illegible]	Finished
☐ 20274300	TEX-Export RDM-Batch	[redacted]	BATCH	Apr-25-2025, 11:57:40	Apr-25-2025, 11:57:51	00:00:11	Finished
☐ 20274303	TEX-Export RDM-Batch	[redacted]	BATCH	Apr-25-2025, 11:57:33	Apr-25-2025, 11:58:59	00:01:26	Finished
☐ 20273604	05037137 LTRs	[redacted]	DLM	Apr-25-2025, 11:36:21	Apr-25-2025, 11:43:40	00:07:19	Finished
☐ 20273590	05037137 MTRs	[redacted]	DLM	Apr-25-2025, 11:35:54	Apr-25-2025, 11:44:13	00:08:19	Finished
☐ [illegible]	[illegible] LTRs	[redacted]	DLM	[illegible]	[illegible]	[illegible]	Failed
☐ 20273100	05037137 MTRs	[redacted]	DLM	Apr-25-2025, 11:21:32	Apr-25-2025, 11:22:43	00:01:11	Failed
☑ 20271931	Rachit_yoyo	[redacted]	HD	[illegible]	[illegible]	[illegible]	Failed
☐ 20271000	FL_COM_GDP_CURR	[redacted]	CONVERT_RESULT_CURRENCY	Apr-25-2025, 10:46:31	Apr-25-2025, 10:46:57	00:00:26	Finished
☐ [illegible]	RMS_EDM_TUTORIAL: PORTFOLIO: Port123	[redacted]	[illegible]	[illegible]	[illegible]	[illegible]	Finished



Job ID: 20271931

GENERAL

Job ID	20271931
Job Name	Rachit_yoyo
User Name	Name_Last@moodys.com
Job Status	FAILED
Job Type	HD
Submit Time	Apr-25-2025, 10:50:41
Start Time	Apr-25-2025, 10:50:45
End Time	Apr-25-2025, 10:52:28
Task Details	**HD_ENGINE** **Status:** Failed 10% **HD_LOSS_POSTPROCESSOR** **Status:** Cancelled 0%

SUMMARY

Database Name	RMS_EDM_TUTORIAL
Data Version	22.0.0
Exposure ID	33
Exposure Name	Port123
Exposure Type	PORTFOLIO
Software Version	HDv1.2
Output Profile Name	Default
Model Profile Name	Rachit_577
Analysis ID	64886
Error	[The analyzed exposure does not include any location coverages that match the region and peril in the model profile.]