Required Model Documentation for the PRID-2025-00001

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1 Notice

This Required Model Information (RMI) document adheres to the stipulations outlined in the California Department of Insurance's (CDI) Pre-application Required Information Determination (PRID) process, which was established in January 2025 under the Catastrophe Modeling in Ratemaking regulation passed in December 2024. This document is intended to support users of Verisk Wildfire Model for the United States, which was reviewed as part of PRID-2025-00001.

Should you have any inquiries regarding the content of this document, please contact the Verisk Extreme Event Solutions Regulatory and Rating Agency Client Services team.

2 Model Highlights

2.1 Wildfire Catastrophe Model Identification

Name of Wildfire Model:	Verisk Wildfire Model for the United States
Wildfire Model Version:	v4.0.0
Available Software Platforms:	Touchstone® 2024 and 2025
Name of Modeling Organization:	Verisk
Street Address:	Lafayette City Center, 2 Avenue de Lafayette, 2nd Floor
City, State, ZIP Code:	Boston, MA 02111
Phone Number:	(617) 267-6645

2.2 Model Facts

Table 1 provides a high-level overview of the Verisk Wildfire Model for the United States.

Table 1. Model Facts

Modeled Countries	United States
Model Domain	Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oklahoma, Oregon, Texas, Utah, Washington, and Wyoming
Modeled Perils	Wildfire, including smoke damage in unburned locations in and around wildfires (i.e., outside burn scars)
Primary Risk Characteristics	Location, Year Built, Occupancy Type, Construction Type, Number of Stories
Secondary Risk Characteristics	Defensible space, Building shape, Roof geometry, Roof covering, Roof detail: roof overhang, Roof detail: fire rating for roof covering, Roof detail: roof vent size, Roof detail: roof vents, Roof attached structure: dormer, Roof detail: soffits, Wall siding, Wall detail: fire rating for wall siding, Surrounding detail: exterior fuel storage, Connection detail: gutter, Connection detail: fences within 5 feet, Firewise USA™ community
Model Resolution	• Wildfire intensity (flame length) is calculated at 90-m resolution • Smoke Potential Index (SPI) is calculated at 1-km resolution

Modeled Parameters	• Total annual area burned (burn scar) by ecoregion (acres) • Ignition location of each fire (longitude, latitude) • Day of year of ignition of each fire • Target burn scar size of each fire (acres) • Smoke damage in unburned areas • Insured and uninsured losses from fire and smoke
Historical Event Set	31 major loss-causing historical events: Oakland Hills, Laguna Canyon, Old Topanga, Cerro Grande, Rodeo-Chediski, Cedar, Old, Witch, Fourmile Canyon, Bastrop County Complex, Waldo Canyon, Black Forest, Valley, Butte, Tubbs, Atlas, Nuns, Mendocino Lake, Thomas, Camp, Woosley, CZU Lightning Complex, Beachie Creek, LNU Lightning Complex, Holiday Farm, Babb, Almeda Drive, Glass, East Troublesome, Marshall, Hermits Peak
Stochastic Catalogs	• 10,000-year catalog • 50,000-year catalog • 100,000-year catalog
Lines of Business	• Residential (Building, Contents, Time) • Commercial/Industrial (Building, Contents, Time) • Mobile home (Building, Contents, Time) • Automobile • Industrial

3 Model Inputs

3.1 Raw Data Inputs

Below is a list of the data inputs used in the construction of the Verisk Wildfire Model for the United States. This list indicates the sources of these data and in the locations where they are used. Data are sourced from a variety of public and private partners and evaluated for their spatial and temporal extents, along with data fidelity and reliability. Within each component of the model, multiple data sources may be used to inform the construction of different variables and in the validation of the model construction. Verisk uses the most up to date information wherever possible at the time of model construction.

California Department of Forestry and Fire Protection (CAL FIRE) Redbooks

Description	CAL FIRE Redbooks provides detailed information about wildfire by jurisdiction such as causes of fires, and estimated financial loss by year. CAL FIRE also provides up-to-date statistics on CA wildfires and CAL FIRE activity, combining state and federal data to track the number of fires and acres burned in California. (***source:*** CAL FIRE Statistics)
Temporal Extent	1991-2022
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Burned Area for Wildland Landscapes, Historical Wildfires, Historical Burn Scar Area

Claims Data

Description	Verisk clients partner with the research teams and offer their claims data for development and validation purposes. The extent and granularity of these vary. Claims data are subject to non-disclosure agreements and cannot be shared with outside parties.
Temporal Extent	through 2021
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal

Use in Verisk Modeling Framework	Model Validation, Estimating Burn Scars of Historical Wildfire Events , Comparison of Modeled Losses to the Target Losses, Comparison of Modeled Losses to the Target Losses, Loss Comparison by Lines of Business (LOB), Loss Comparison by Coverage, Loss Validation by Company, Policy Conditions

Climatic Research Unit Timeseries (CRU TS 4.06)

Description	Gridded weather data variables including cloud cover, diurnal temperature range, frost day frequency, potential evapotranspiration, precipitation, relative humidity, sunshine duration, number of stations contributing to each interpolation, monthly average daily mean, minimum and maximum temperatures, daily average vapor pressure (humidity) and vapor pressure deficit hPa (=mbar). (***source:*** CRU General Information)
Temporal Extent	1901-2022
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Event Generation Overview, Burned Area for Wildland Landscapes, Saturation Vapor Pressure (SVP), Vapor Pressure Deficit (VPD), Seasonal Weather Variables

Ecoregions

Description	Environmental Protection Agency (EPA) Level III Ecoregions are part of a hierarchical framework developed by the United States EPA to classify the ecological regions of the U.S. These regions are delineated based on ecological patterns and are used for environmental management, research, and assessment. The framework consists of four levels, with Level III providing a detailed classification that groups areas with similar ecosystems, including climate, vegetation, soil, water, and wildlife. (***source:*** U.S. Environmental Protection Agency, Level III Ecoregions)
Temporal Extent	April 2013
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Burned Area for Wildland Landscapes, Historical Burn Scar Area, Historical Trends, Estimating Burn Scars of Historical Wildfire Events , Verisk Drought Index, Building Wildfire-Weather Models for Each Ecoregion, Comparisons of Historical Burn Scar Areas with Wildfire-Weather Models, Recasts of Historical Burn Scar Areas , Generating Stochastic Annual Burn Scar Area, Ignition Day Probability , Accounting for Climate Change Overview

ESA WorldCover

Description	ESA WorldCover provides high resolution land use/land cover data. (***source:*** ESA WorldCover)
Temporal Extent	2020 and 2021
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Spread Model Parameters, Surface Fuel, Surface Fuel: Fire Behavior Fuel Models

Fire Occurrence Database (FOD)

Description	A spatial database of wildfires that occurred in the United States from 1992 to 2020. It is the fifth update of a publication originally generated to support the national Fire Program Analysis (FPA) system. The wildfire records were acquired from the reporting systems of federal, state, and local fire organizations. (***source:*** United States Department of Agriculture Forest Service)
Temporal Extent	1992-2020[1]
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Historical Burn Scar Area, Event Generation Overview, Building Wildfire-Weather Models for Each Ecoregion, Ignition Day Probability , Ignition Date and Location, Estimating Burn Scars of Historical Wildfire Events

Geospatial Multi-Agency Coordination (GeoMAC)

Description	GeoMAC was the public face of all wildland fire perimeters. That site was shut down on April 30, 2020 and responsibility for wildfire information was transferred to the National Interagency Fire Center (NIFC). (***source:*** USGS)
Temporal Extent	2000-2020
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Historical Burn Scar Area, Historical Event Losses, Model Validation, Historical Event Losses

[1] Short, Karen C. 2022. Spatial wildfire occurrence data for the United States, 1992-2020 . 6th Edition. Fort Collins, CO: Forest Service Research Data Archive.

Homeland Security Infrastructure Program (HSIP) Gold

Description	The Homeland Security Infrastructure Program (HSIP) Gold database is assembled by the National Geospatial-Intelligence Agency (NGA) in partnership with the Homeland Infrastructure Foundation-Level Data (HIFLD) Working Group for use by Homeland Defense (HD), Homeland Security (HLS), National Preparedness – Prevention, Protection, Mitigation, Response and Recovery (NP-PPMR&R) communities. It is a compilation of 560 of the best available, geospatially enabled baseline infrastructure datasets for all National & Defense Critical Infrastructure Sectors. HSIP Gold data is assembled from federal, state, local government and private sector mission partners. (***source:*** The Homeland Security Infrastructure Program Gold)
Temporal Extent	2005
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Surface Fuel, Surface Fuel: Fire Behavior Fuel Models

LANDFIRE

Description	The LANDFIRE fuels data are one of the Landscape Fire and Resource Management Planning Tools, a joint venture of the USFS and U.S. Department of the Interior.(***source:*** LANDFIRE)
Temporal Extent	LANDFIRE 2022 data (the underlying data used to create the data set was captured in 2020)
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Spread Model Parameters, Ignition Date and Location, Forest Canopy Fuel, Surface Fuel, Surface Fuel: Fire Behavior Fuel Models, Forest Canopy Fuel, Building Data

Monitoring Trends in Burn Severity (MTBS)

Description	MTBS is an interagency program whose goal is to consistently map the burn severity and extent of large fires across all lands of the United States from 1984 to present. This includes all fires 1,000 acres or greater in the western United States and 500 acres or greater in the eastern United States. The extent of coverage includes the continental U.S., Alaska, Hawaii and Puerto Rico. In the western states, the MTBS data set includes fires of at least 1,000 acres (defined as the area within the fire perimeter, which is always larger than the area actually burned) and includes data of ignition, location of ignition, and total area burned for six classes of fire severity. (***source:*** MTBS)

Temporal Extent	1984-2020 (Includes a small number of fires from 2021)[2]
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Event Generation Overview, Burned Area for Wildland Landscapes, Historical Burn Scar Area, Building Wildfire-Weather Models for Each Ecoregion, Ignition Date and Location, Historical Event Losses, Benchmarking Stochastic Losses, Estimating Burn Scars of Historical Wildfire Events

National Agricultural Statistics Service (NASS) Cropland Dataset

Description	The 2019 Cropland data set from the United States Department of Agriculture (USDA) NASS is a research data catalog and repository for public access to data produced during research funded or co-funded by the USDA. (***source:*** Cropland data set from the USDA National Agricultural Statistics Service)
Temporal Extent	2019
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Surface Fuel, Surface Fuel: Fire Behavior Fuel Models

National Interagency Fire Center (NIFC)

Description	The National Interagency Fire Center (NIFC) is the nation's support center for wildland fires and other emergency situations. The partners at NIFC work together to compile information about the current wildfire situation and statistics that encompass lands managed by federal, state, local, tribal, and private agencies. The current wildland fire situation is summarized in the National Fire News and Incident Management Situation Report, produced by the National Interagency Coordination Center. These reports are available daily most of the year, and weekly during the winter months. Wildland fire statistics ranging from the number of fires and acres burned, to federal suppression costs, to the number of lightning-caused fires ignited are updated annually. (***source:*** NIFC)
Temporal Extent	2021-2023
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal

[2] Verisk scientists used the MTBS data set as the primary data source for 1984-2020 fires of at least 1,000 acres in perimeter area, but excluded from analysis and modeling any duplicate entries and especially large fires that were not found in press reports or other data sets. Fire sizes range from 1,000 acres (perimeter area) and larger. The largest fire included in the 2020 1,068,802-acre August Complex in Northern California.

Use in Verisk Modeling Framework	Event Generation Overview, Historical Burn Scar Area, Building Wildfire-Weather Models for Each Ecoregion, Historical Wildfires, Estimating Burn Scars of Historical Wildfire Events

National Land Cover Database (NLCD)

Description	The Multi-Resolution Land Characteristics (MRLC) consortium is a group of federal agencies who coordinate and generate consistent and relevant land cover information at the national scale for a wide variety of environmental, land management, and modeling applications. The creation of this consortium has resulted in the mapping of the lower 48 United States, Hawaii, Alaska and Puerto Rico into a comprehensive land cover product termed, the National Land Cover Database (NLCD), from decadal Landsat satellite imagery and other supplementary datasets. (***source:*** MRLC)
Temporal Extent	2019
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Impervious Surface Area

National Oceanic and Atmospheric Administration (NOAA) North American Regional Reanalysis (NARR)

Description	The North American Regional Reanalysis (NARR) is a model produced by the National Centers for Environmental Prediction (NCEP) that generates reanalyzed data for temperature, wind, moisture, soil, and dozens of other parameters. The NARR model assimilates a large amount of observational data from a variety of sources to produce a long-term picture of weather over North America. Wind speed and direction are key environmental variables that impact wildfire behavior. (***source:*** NOAA Weather Climate Models)
Temporal Extent	1979 – 2014
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Spread Model Parameters, Wind, Local Intensity Input Data, Wind Data

Oak Ridge National Laboratory Building Counts and Location Data

Description	The Oak Ridge National Laboratory collects, curates, and delivers unique geospatial datasets that offer a full picture of human activities, the natural and built environment, and the interactions among them. The USA Structures dataset from the Oak Ridge National Laboratory consists of building footprints (polygons). Verisk researchers converted this dataset into counts of buildings per grid cell. (***source:*** https://disasters.geoplatform.gov/USA_Structures/)
Temporal Extent	2023
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Measure of Access to Suppression Resources, Spread Model Parameters, Building Data

Oak Ridge National Laboratory's LandScan

Description	Oak Ridge National Laboratory's LandScan sets the community standard for global population distribution data. Researchers routinely use the high-resolution database, which won a 2019 Excellence in Technology Transfer award and a 2006 R&D Top 100 award, to estimate populations at risk and to plan, aid, and direct disaster recovery efforts in the wake of earthquakes, tsunamis, hurricanes, and other such events. LandScan uses available data and satellite imagery to map geographic areas and superimpose layers of information at an approximate spatial resolution of 1/1200 decimal degrees. The LandScan datasets have been actively and successfully licensed for 15 years, with updates released annually. (***source:*** https://www.ornl.gov/project/landscan)
Temporal Extent	2020
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Measure of Access to Suppression Resources, Population Density, Building Data

OpenStreetMap (OSM)

Description	OpenStreetMap is built by a community of mappers that contribute and maintain data about roads, trails, cafés, railway stations, and much more, all over the world. Contributors use aerial imagery, GPS devices, and low-tech field maps to verify that OSM is accurate and up to date.(***source:*** OpenStreetMap)
Temporal Extent	Verisk downloaded the Golf course polygons from the OpenStreetMap (OSM) in March 2021. OpenStreetMap data are continuously updated by contributors, therefore there is no fixed vintage.

State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Surface Fuel, Surface Fuel: Fire Behavior Fuel Models

Self-calibrating Palmer Drought Severity Index (scPDSI)

Description	The Self-calibrating Palmer Drought Severity Index (scPDSI) is a variant on the original Palmer Drought Severity Index (PDSI) of Palmer 1965, with the aim to make results from different climate regimes more comparable. As with the PDSI, the scPDSI is calculated from time series of precipitation and temperature, together with fixed parameters related to the soil/surface characteristics at each location. (***source:*** DROUGHT INDICES (scPDSI))
Temporal Extent	1901-2022
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Burned Area for Wildland Landscapes, Drought Index, Accounting for Climate Change Overview, Seasonal Weather Variables, Saturation Vapor Pressure (SVP), Verisk Drought Index,

Tiger Primary and Secondary Road Datasets

Description	Many wildfires are started each year due to direct and indirect human influence (for example, abandoned campfire or power lines). Distance to roadway is considered as a driver of wildfire ignition probability. (***source:*** 2015 Tiger Primary and Secondary Road state-based datasets)
Temporal Extent	2015
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Event Generation Overview, Ignition Location and Spatial Distribution of Fires,

USGS National Elevation Data Set (NED)

Description	The U.S. Geological Survey has developed a National Elevation Database (NED).The NED is a seamless mosaic of best-available elevation data. The 7.5-minute elevation data for the conterminous United States are the primary initial source data. In addition to the availability of complete 7.5-minute data, efficient processing methods were developed to filter production artifacts in the existing data, convert to a consistent datum, edge-match, fill slivers of missing data at quadrangle seams, recast the data to a consistent geographic projection and convert all elevation values to decimal meters as a consistent unit of measure. The USGS Elevation site is located here. National Elevation Dataset Metadata and the data dictionary is located here. (***source:*** USGS EROS)
Temporal Extent	2018
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Topography

Verisk FireLine®

Description	Verisk FireLine considers vegetative fuels, terrain/slope, and road access to understand property-specific risk factors. (***source:*** Verisk FireLine)
Temporal Extent	2019-2022
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Surface Fuel, Surface Fuel: Fire Behavior Fuel Models, Ignition Date and Location

Verisk Industry Exposure Database (IED)

Description	The Verisk United States Industry Exposure Database is a detailed collection of exposure data containing information on insurable properties and their respective replacement values, along with information about the occupancy and physical characteristics of the structures, such as construction types and height classifications. Verisk's Industry Exposure Database provides the foundation for all modeled industry loss estimates. It provides breakdowns of all insurable properties by line of business (LOB), as well as replacement values and policy conditions by coverage for each ZIP code. (***source:*** Industry Exposure Database)
Temporal Extent	2022
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal

Use in Verisk Modeling Framework	Secondary Risk Characteristics for Wildfire, Comparison of Modeled Losses to the Target Losses, Creating Target Losses for the Historical Event Set, Benchmarking Stochastic Losses, Analysis Settings for Touchstone

Verisk Property Claim Services (PCS)

Description	Verisk's Property Claim Services (PCS) offers claims data for all the 56 catastrophic events that happened in the past 50 years in the U.S. Verisk uses claims data to both create damage ratios and validate the models. Claims data helps estimate damage ratios, which indicate the proportion of the insured asset value lost due to a catastrophe, providing insights into the financial impact of future events. It also serves as a real-world benchmark to validate and calibrate the accuracy of models, and help in better risk assessment and management. (***source:*** Verisk PCS)
Temporal Extent	1975-2024
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☒ Temporal
Use in Verisk Modeling Framework	Model Validation, Estimating Burn Scars of Historical Wildfire Events , Comparison of Modeled Losses to the Target Losses, Comparison of Modeled Losses to the Target Losses, Loss Comparison by Lines of Business (LOB)

Wildland Urban Interface (WUI) map from United States Forest Service's (USFS)

Description	The wildland-urban interface (WUI) is the area where houses meet or intermingle with undeveloped wildland vegetation. This makes the WUI a focal area for human-environment conflicts such as wildland fires, habitat fragmentation, invasive species, and biodiversity decline. Using geographic information systems (GIS), we integrated U.S. Census (2010) and USGS National Land Cover Data (2006), to map the Federal Register definition of WUI (Federal Register 66:751, 2001) for the conterminous United States. These data are useful within a GIS for mapping and analysis at national, state, and local levels. (***source:*** The 2010 wildland urban Interface of the Conterminous United States geospatial data sets (Martinuzzi et al., 2015) Statistics)
Temporal Extent	2010
State Specific	☒ Yes ☐ No
Data Type	☒ Spatial ☐ Temporal
Use in Verisk Modeling Framework	Event Generation Overview, Ignition and Burn Footprint, Surface Fuel: Fire Behavior Fuel Models

3.2 Model Variables

Model variables are key components across the different model modules that must be calculated from the raw data listed above in Raw Data Inputs. For each model variable listed below, an understanding is provided about the formulation of the variable, its use in the model and relevant constraints put into place by Verisk.

Historical Burn Scar Area

Source(s)	Monitoring Trends in Burn Severity (MTBS), Fire Occurrence Database (FOD), National Interagency Fire Center (NIFC), Ecoregions, California Department of Forestry and Fire Protection (CAL FIRE) Redbooks
Formulation	The wildfire hazard is related to model pixels (90 x 90 m cells) that burn. For each simulated fire, these pixels are collectively called a burn scar and reflect the area of land actually burned in a wildfire. The burn scar differs from – is smaller than – the area of wildfire that is generally reported (e.g., in wildfire statistical databases and media reports) because a full wildfire footprint (area inside a perimeter) often includes areas that are not burned. Verisk determined relationships between burn scar areas and total wildfire areas reported in wildfire databases through analysis of severity levels in the Monitoring Trends in Burn Severity (MTBS) data set that divides individual fire footprints into fractions of differing burn severity. The MTBS includes six levels of burn severity for fires. Verisk scientists combined fire areal fractions associated with levels 2, 3, and 4 to define the burn scar area of each wildfire. For each ecoregion, a linear equation (capped at a value of 1.0) was determined relating the burn scar fraction of individual historical fires (i.e., the ratio of burn scar area to total reported fire area) to total reported fire area for all MTBS fires. Those equations were then applied to all historical fires in the FOD and NIFC datasets not also included in the MTBS dataset, and combined with Verisk-derived burn scar areas in the MTBS dataset, to create a full Verisk historical ecoregion-based burn scar area dataset.
Use in Model	Event Generation Overview, Estimating Burn Scars of Historical Wildfire Events , Historical Burn Scar Area Estimation, Verisk Drought Index, Annual Total Burn Scar Area under Near-present Climate, Building Wildfire-Weather Models for Each Ecoregion, Comparisons of Historical Burn Scar Areas with Wildfire-Weather Models, Recasts of Historical Burn Scar Areas , Recasts Throughout the Model Domain, Model Validation
Variable Type	☒**Risk-**related ☐ Loss-related ☐ Expense-related

Saturation Vapor Pressure (SVP)

Source(s)	Climatic Research Unit Timeseries (CRU TS 4.06), Self-calibrating Palmer Drought Severity Index (scPDSI)

Formulation	Saturation vapor pressure (SVP) is the maximum amount of water vapor the atmosphere could hold before it is saturated. There are many published approaches to calculating SVP, which is a strong function of air temperature and a weak function of atmospheric pressure (over the normal ranges of atmospheric temperature and pressure). The Verisk model used equations from Alduchov and Eskridge (1996) for saturation vapor pressure over a surface of water.[3] The average daily minimum SVP (in hPa, which is equivalent to mbar) during each month was calculated from the minimum daily average minimum temperature, and the average daily maximum SVP during each day was calculated from the maximum daily average temperature as follows: • Minimum saturation vapor pressure (hPa = mbar) = 6.1413 · $\exp[\frac{(17.625 \cdot T_{min})}{(243.04 + T_{min})}]$ • Maximum saturation vapor pressure (hPa = mbar) = 6.1413 · $\exp[\frac{(17.625 \cdot T_{max})}{(243.04 + T_{max})}]$ • Where T_{min} and T_{max} are the daily average minimum and maximum air temperatures (°C), respectively, from the CRU weather dataset mapped onto the model Ecoregions. The average daily value of saturation vapor pressure during each month in the wildfire model is estimated by averaging the minimum and maximum saturation vapor pressures. This is a coarse simplification because the saturation vapor pressure can vary during a single summer day by a factor of at least three, and the saturation vapor pressure also varies, sometimes considerably, between the days in a month. Nonetheless, for modeling large areas over long time periods with the intent of understanding key drivers of wildfire behavior, this approach, when applied consistently across locations and times, has considerable explanatory power and is a key approach adopted for scientific wildfire research (e.g., Seager et al., 2015).
Use in Model	Vapor Pressure Deficit (VPD), Model Validation
Constraints/ Boundary Implemented	• Tmin and Tmax are the daily average minimum and maximum air temperatures (°C), respectively, from the CRU weather dataset mapped onto the model Ecoregions. • Saturation vapor pressure is strongly and positively related to air temperature. When VPD is zero, the relative humidity is 100%.
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Vapor Pressure Deficit (VPD)

Source(s)	Climatic Research Unit Timeseries (CRU TS 4.06)
Formulation	Vapor Pressure Deficit (VPD) is the difference between Saturation Vapor Pressure (SVP) and Actual Vapor Pressure (AVP). In order to estimate VPD, Verisk researchers used AVP provided in the CRU monthly gridded weather dataset, but the dataset does not include SVP, The SVP was calculated from other variables explained in Saturation Vapor Pressure (SVP) .

[3] At the large spatial scale of the model (and grid size of the CRU dataset) and the averaging of meteorological variables over monthly periods, many approximations to SVP would suffice for the present purpose.

Use in Model	Seasonal Vapor Pressure Deficit (VPD) variables, Verisk Drought Index, Building Wildfire-Weather Models for Each Ecoregion, Seasonal Weather Variables, Event Generation Overview, Accounting for Climate Change Overview
Constraints/ Boundary Implemented	Temperature and precipitation data from 1901-2022 are used.
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Seasonal Weather Variables

Source(s)	Climatic Research Unit Timeseries (CRU TS 4.06), Self-calibrating Palmer Drought Severity Index (scPDSI), Vapor Pressure Deficit (VPD), Ecoregions
Formulation	There are 30 seasonal weather variables considered to develop wildfire-weather relationships, in each ecoregion. These include antecedent precipitation and drought index values for up to two prior years.
Use in Model	Relationship between Weather and Wildfire Area, Historical Trends, Annual Total Burn Scar Area under Near-present Climate, Generating Seasonal Weather Variables , Generating a Recast of Historical Weather to Represent Near-present Climate, Building Wildfire-Weather Models for Each Ecoregion, Comparisons of Historical Burn Scar Areas with Wildfire-Weather Models, Recasts of Historical Burn Scar Areas , Model and Catalog Development
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Seasonal Precipitation Variables

Source(s)	Climatic Research Unit Timeseries (CRU TS 4.06)
Formulation	For each defined season, the average total precipitation in mm is derived. • Autumn/Fall (SON) precipitation, mm/month • Spring (MAM) precipitation, mm/month • Summer (JJA) precipitation, mm/month • Winter (DJF) precipitation, mm/month (Dec is previous year) • precipitation during previous year (12 months), mm/month • precipitation two years ago (12 months), mm/month • Jan-Jun precipitation, mm/month
Use in Model	Historical Trends
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Seasonal Self-calibrating Palmer Drought Severity Index (scPDSI) Variables

Source(s)	Self-calibrating Palmer Drought Severity Index (scPDSI)

Formulation	For each defined season, the average scPDSI variables are defined as: • Autumn/Fall (SON) scPDSI • Spring (MAM) scPDSI • Summer (JJA) scPDSI • Winter (DJF) scPDSI (Dec is previous year) • Apr-Oct scPDSI • scPDSI change from Feb to Aug this year • scPDSI change from last Aug to this Aug • scPDSI change from last Feb to this Aug • scPDSI change from Aug two years ago to this Aug
Use in Model	Historical Trends
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Seasonal Temperature Variables

Source(s)	Climatic Research Unit Timeseries (CRU TS 4.06)
Formulation	For each defined season, the seasonal average temperature variables are defined as: • Autumn/Fall (SON) Tmin, °C • Spring (MAM) Tmin, °C • Summer (JJA) Tmin, °C • Winter (DJF) Tmin, °C (Dec is previous year) • Autumn (fall, SON) Tmax, °C • Spring (MAM) Tmax, °C • Summer (JJA) Tmax, °C • Winter (DJF) Tmax, °C (Dec is previous year) • May-Oct Tmax, °C
Use in Model	Historical Trends
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Seasonal Vapor Pressure Deficit (VPD) variables

Source(s)	Vapor Pressure Deficit (VPD)
Formulation	For each defined season, the seasonal VPD variables are defined as: • Autumn/Fall (SON) VPD, mbar • Spring (MAM) VPD, mbar • Summer (JJA) VPD, mbar • Winter (DJF) VPD, mbar (Dec is previous year) • May-Oct VPD, mbar

Use in Model	Historical Trends
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Verisk Drought Index

Source(s)	Self-calibrating Palmer Drought Severity Index (scPDSI), Historical Burn Scar Area, Ecoregions
Formulation	A Verisk Wildfire Drought Index was developed for each year in each ecoregion in the model based on historical relationships between self-calibrating Palmer Drought Severity Index (scPDSI) values and annual wildfire area. The Drought Index was projected to the near-present climate based on trends in the underlying scPDSI data. There is one Drought Index value for each ecoregion-year combination; it does not vary seasonally during a year. The Drought Index is used by the wildfire spread module as a broad indicator of interannual variation in Fuel Moisture.
Use in Model	Generating a Recast of Historical Weather to Represent Near-present Climate, Fuel Moisture, Drought Index
Constraints/ Boundary Implemented	A drier fuel is more likely to carry a more intense fire. The Verisk wildfire Drought Index has possible values of −2, −1, 0, +1, and +2.
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Annual Total Burn Scar Area under Near-present Climate

Source(s)	Historical Burn Scar Area, Seasonal Weather Variables
Formulation	For each ecoregion, Verisk scientists created a 39-year time series of total annual burn scar area that represents a near-present climate – a burn scar area recast – by using trends and variability in the historical weather data and historical burn scar area data from 1984-2022.
Use in Model	Model and Catalog Development, Generating a Recast of Historical Weather to Represent Near-present Climate
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Surface Fuel

Source(s)	LANDFIRE, ESA WorldCover, National Agricultural Statistics Service (NASS) Cropland Dataset, Homeland Security Infrastructure Program (HSIP) Gold , OpenStreetMap (OSM), Verisk FireLine®, Wildland Urban Interface (WUI) map from United States Forest Service's (USFS)

Formulation	The LANDFIRE fuels data set was modified by Verisk to reflect additional fuels information that had been determined to be critical for fire spread and intensity. • Some land cover types that are identified as burnable in LANDFIRE but that typically do not support wildfire (e.g., golf courses and some kinds of irrigated agriculture may be categorized by LANDFIRE as timber, grass or shrubs but rarely, if ever, burn in wildfires) were designated as unburnable in the modified database. • The designation of some land cover types that may be identified as unburnable in LANDFIRE but that can carry fire was modified in the database (e.g., avocado groves may be categorized by LANDFIRE as unburnable agriculture but have been observed to burn in recent California wildfires). • Fuel category changes – from burnable to unburnable – were made using data from Verisk FireLine® product (2019-2022) because it reflects a more recent view of land use/land cover changes than the LANDFIRE data set. This allows the model to incorporate areas of recent construction in the Wildland Urban Interface (WUI). Each 90-m × 90-m grid cell in the model domain was assigned one of the 40 burnable fuel categories or five unburnable categories as described by Scott and Burgan (2005).
Use in Model	Local Intensity Input Data, Surface Fuel: Fire Behavior Fuel Models, Forest Canopy Cover, Fire Spread in Wildland Areas, Event Generation Overview, Smoke Potential Index (SPI)
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Fuel Moisture

Source(s)	Verisk Drought Index
Formulation	Using the Verisk Drought Index that was developed for each fire ignition event, Verisk scientists assigned values for the individual fuel moisture contents guided by the moisture scenarios described in Scott and Burgan (2005). Using this approach, the fuel moisture conditions in which any given stochastic fire spreads are consistent with the expected large scale environmental conditions for that stochastic year.
Use in Model	Local Intensity Input Data, Fuel Moisture, Surface Spread
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Measure of Access to Suppression Resources

Source(s)	Oak Ridge National Laboratory's LandScan

Formulation	Since wildfires can occur at all times of day, likely suppression activities for both daytime and nighttime cases are accounted for (e.g., schools and commercial businesses tend to have low nighttime population levels but high daytime population levels, whereas residential buildings tend to have low daytime population levels but high nighttime population levels). The model smooths the maximum daytime and nighttime population values because the scale of suppression activities are likely to be slightly larger than the 90-m ⨉ 90-m grid cell.
Use in Model	Population Density, The Fire Spread Algorithm, Fire Spread in Urban Areas, Ignition Probability and Suppression, Fire and Smoke Damage Functions
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Wind

Source(s)	National Oceanic and Atmospheric Administration (NOAA) North American Regional Reanalysis (NARR)
Formulation	For each stochastic fire event ignition, an autoregressive integrated moving average (ARIMA) time series model simulates wind conditions over multiple time scales (i.e., month, day, hour) for each 32-km ⨉ 32-km grid cell in the NARR data set. The model creates typical winds for a given NARR cell for a particular month and time of day; wind speed and direction change every three hours, creating a realistic pattern consistent with historical wind data. The appropriate model is selected based on the location (grid cell) and month. Once an ARIMA model has been selected, the same model is used throughout the event to ensure time series consistency, even if the fire grows into another grid cell or crosses into another month. Thus, the model will represent the monthly conditions at the time of ignition. In addition, the model features downslope wind events that regularly occur in parts of the model domain during certain times of the year (typically autumn/winter). These include Diablo and Santa Ana winds in northern and southern California. The downslope winds increase fire intensity and rate of spread, and limit simulated suppression activities
Use in Model	Event Generation Overview, Ignition Day Probability , Local Intensity Input Data, Wind Data, The Fire Spread Algorithm, Fire Spread in Wildland Areas, Smoke Potential Index (SPI)
Variable Type	☒Risk-related ☐ Loss-related ☐ Expense-related

Smoke Potential Index (SPI)

Source(s)	Surface Fuel, Wind

Formulation	The flame length intensity is calculated within the fire perimeter but soot damage can occur both inside and outside the fire perimeter. The model uses the assumption that damage causing soot outside of a fire's perimeter occurs only within 20 km of the fire perimeter, and within the smoke-damage area, the SPI is calculated on a 1-km $\times$ 1-km grid. The SPI estimated at each SPI grid cell depends on three indices calculated for each smoke-emitting cluster: a soot index fsoot (between 0 and 1), a wind index (which depends on speed and direction between the SPI grid cell and the smoke-emitting cluster) fwind, and a distance index fdist (between 0 and 1). SPI is the sum from each cluster of the product of these three indices: $\text{fsoot} \times \text{fwind} \times \text{fdist}$.
Use in Model	Wildfire Smoke Hazard Model, Fire and Smoke Damage Functions
Variable Type	☐ Risk-related ☒ Loss-related ☐ Expense-related

3.3 Historical Wildfires

The Verisk Wildfire Model for the United States offers a Historical Event Set with 31 major loss-causing historical events. Data for these fires came from National Interagency Fire Center (NIFC) and California Department of Forestry and Fire Protection (CAL FIRE) Redbooks. The Rodeo-Chedeski fire in Arizona is the largest in area in this set (460,000 acres), the Oakland Hills (Tunnel) fire in California is the smallest (less than 2,000 acres). These reported areas are typically with respect to a fire perimeter; the Verisk model is based on burn scars, which cover less area than that reflected by a typical reported fire perimeter.

Table 2. The Historical Event Set Available for the Verisk Wildfire Model for the United States

Fire Name	State	Ecoregion	Year	Acres Burned
Oakland Hills	California	6	1991	1,767
Laguna Canyon	California	85	1993	12,870
Old Topanga	California	85	1993	16,983
Cerro Grande	New Mexico	21	2000	44,164
Rodeo-Chediski	Arizona	23	2002	461,606
Cedar	California	85	2003	263,891
Old	California	8	2003	85,863
Witch	California	85	2007	134,738
Fourmile Canyon	Colorado	21	2010	5,684
Bastrop County Complex	Texas	33	2011	26,250

Fire Name	State	Ecoregion	Year	Acres Burned
Waldo Canyon	Colorado	21	2012	19,561
Black Forest	Colorado	26	2013	10,924
Valley*	California	6	2015	74,045
Butte*	California	5	2015	66,976
Tubbs*	California	6	2017	30,514
Atlas	California	6	2017	40,834
Nuns*	California	6	2017	45,297
Mendocino Lake*	California	78	2017	48,273
Thomas*	California	85	2017	245,302
Camp*	California	5	2018	123,844
Woolsey*	California	85	2018	93,623
CZU Lightning Complex*	California	1	2020	83,681
Beachie Creek*	Oregon	4	2020	185,340
LNU Lightning Complex*	California	6	2020	315,000
Holiday Farm*	Oregon	4	2020	163,153
Babb*	Washington	10	2020	14,489
Almeda Drive*	Oregon	78	2020	3,212
Glass*	California	6	2020	64,472
East Troublesome*	Colorado	21	2020	169,221
Marshall	Colorado	25	2021	6,253
Hermits Peak	New Mexico	21	2022	324,065

Verisk has claims data for the historical wildfire events marked with an asterisk (*) in Table 2.

4 Verisk Catastrophe Modeling Framework

The Verisk Wildfire Model for the United States is a catastrophe model. Catastrophe models are computer programs that mathematically represent the physical characteristics of natural catastrophes, terrorism, and extreme casualty events.

Due to the infrequent nature of severe events like earthquakes, hurricanes and wildfires, historical data often fails to provide a reliable basis for assessing future losses. Consequently, catastrophe models are used to probabilistically simulate a wide range of possible scenarios, capturing the full spectrum of potential events and their impacts. This approach helps organizations prepare more effectively for the financial repercussions of such disasters by generating numerous simulated events and estimating the associated losses based on current scientific data.

The catastrophe modeling framework illustrated in Figure 1 applies to all Verisk property models.

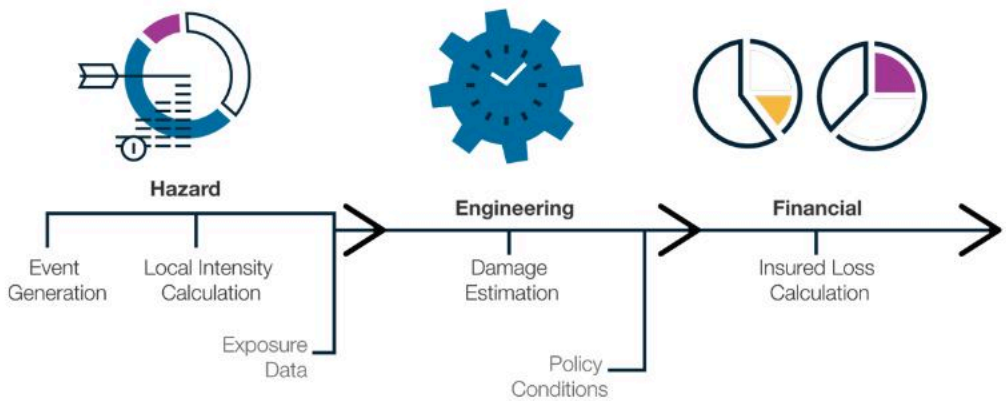

Figure 1. Verisk Catastrophe Modeling Framework

Each component is described in Table 3. The methodologies applied to develop each of these modules are described in the sections below.

Table 3. Components of the Catastrophe Modeling Framework

Module	Model Component	Description
Hazard Module	Event Generation	Large catalogs of simulated events capture the frequency, severity, location, and other characteristics of the entire spectrum of plausible catastrophes.
	Local Intensity Calculation	For each simulated event, the model calculates the intensity of the hazard at each location within the affected area.
Input from insurers	*Exposure Data*	Exposure data are an input from the insurer and captures information about the property, replacement value and physical characteristics. For more information see section User Input

Module	Model Component	Description
Engineering Module	Vulnerability/ Damage Estimation	The measures of intensity of simulated catastrophic events are applied to highly detailed information about the properties that are exposed to them. Equations called damage functions are developed and used to compute the level of damage that is expected to occur to buildings of different types of construction and different occupancies, or usages, as well as to their contents, and to other lines of business, such as marine, large industrial, and auto.
Input from insurers	*Policy Condition*	Policy conditions are inputs from the insurer and captures information about the policy terms and conditions.
Financial Module Overview	Insured Loss Calculation	Policy terms and conditions are applied to estimate insured losses to create probability distribution of loss. This probability distribution of losses, called an exceedance probability curve, reveals the probability that any given level of loss will be surpassed in a given time period—for example, in the coming year. (The probabilities can also be expressed in terms of return periods. For example, the loss associated with a return period of 20 years has only a 5% chance of being exceeded this year, or in one year out of 20, on average.) Loss probabilities can be provided at any geographic resolution—for the entire insurance industry, for a particular portfolio of buildings, or for an individual property.

5 Hazard Module Overview

The hazard component of catastrophe models answers the questions: Where are future events likely to occur? How large, or severe, are they likely to be? And how frequently are they likely to occur? Large catalogs comprising tens of thousands of computer-simulated catastrophes are generated, representing the broad spectrum of plausible events.

For each simulated event, the model calculates the intensity at each location within the affected area. For example, wildfire intensity is measured as flame length.

The hazard components of catastrophe models are built by teams of highly qualified scientists, including meteorologists, climate scientists, seismologists, geophysicists, and hydrologists whose job is to keep abreast of the scientific literature, evaluate the latest research findings, and conduct original research of their own. In doing so, they take a measured approach to incorporating the most advanced science.

The Verisk Wildfire Model for the United States accounts for the increasing size of wildfires in the model domain as a whole (although there are regional variations), shifts in climate patterns and their effects on wildfire area, and increased exposure in wildfire-prone areas (notably the increased exposure in the wildland-urban interface in California).

5.1 Event Generation Overview

The event generation component of the Verisk Wildfire Model for the United States defines the ignition location, the ignition date and time, and the total area of the burn scar. To relate modeled spatial and temporal variation in wildfire activity to key environmental factors that influence wildfire behavior, the model domain is divided into 45 Ecoregions. Within each ecoregion, the biological/ecological systems, climate, and physical properties such as soil and topography are relatively homogenous (at least at a regional rather than local scale), as are the relationships between organisms and their environments (Omernik, 1987). Wildfire-weather relationships, ignition dates, and individual fire size distributions are modeled at the ecoregion level, rather than, for example, within boundaries of ZIP codes, counties, or states. This ecoregion-based approach is used in particular because Verisk scientists (and others) observe ecoregion-dependent consistencies in relationships between weather/climate and the frequency and size of wildfires.

Accounting for key effects of recent climatic change on wildfire frequency, area, and intensity was a key model design criterion. Verisk is committed to representing the norms and variation inherent in climate and their impact on the modeled perils accounting for changes that have already occurred during the historical record. To accomplish this goal, Verisk scientists created time-dependent statistical models of the relationships between weather and wildfire size and frequency in the different Ecoregions using historical data. Recent trends in weather in each ecoregion were extrapolated in time to represent the distribution of environmental conditions affecting wildfire in the current and near-present climate. The wildfire-weather relationship models were then driven by this adjusted distribution of climate to build a view of wildfire risk across the model domain that represents this projected near-present climate.

The following steps outline the process of creating the stochastic wildfire events, more detailed descriptions of each step are in other sections of this document:

1. For each stochastic year and in each ecoregion, Verisk scientists assigned an annual total burn scar area for fires ignited in the ecoregion that is consistent with near-present climate. Each ecoregion-year combination is unique and maintains key correlations in area burned between ecoregions.
2. The annual total burn scar area for fires ignited in each ecoregion was assigned to individual fires of at least 50 acres (burn scar area), each with its own maximum burned area, based upon ecoregion-specific distributions of individual-fire area. These fire area distributions are based upon historical patterns in each ecoregion and recent trends in in sizes of individual fires. Recent trends were considered because in many ecoregions individual fires have become larger, sometimes significantly so, over recent decades.
3. Ignition dates and times were assigned to each fire based on ecoregion-specific ignition date distributions.
4. Ignition locations were assigned to each fire for both natural and human-caused wildfires, proximity to known drivers of ignitions (e.g., population, roads), and availability of enough fuel to meet the target burn scar area.
5. Wildfires were spread from their ignition locations based on stochastic wind, topography, fuel amount and type, and generation and transport of embers. Fires were free to cross ecoregion boundaries when fuel, topography, and wind dictated it.
6. Finally, individual fires were clustered into events based on time and distance between ignition dates and locations based on typical reinsurance terms.

Table 4. Event Generation Data Inputs

Historical Burn Scar Area
Climatic Research Unit Timeseries (CRU TS 4.06) and Vapor Pressure Deficit (VPD)
Surface Fuel
Tiger Primary and Secondary Road Datasets
Wildland Urban Interface (WUI) map from United States Forest Service's (USFS)

5.2 Historical Burn Scar Area Estimation

Typical reports of wildfire area are based on an area within a generalized fire perimeter. In fact, for many small wildfires and most large wildfires, some of the area inside the perimeter does not burn. Because modeled wildfire intensity is based on flame length – which exists only in burned areas (pixels) – Verisk model development and analyses of wildfire data focused on acres that were burned, or burn scar acres.[4] When comparing Verisk wildfire model fire burn scar areas to historical fire reports, burn scars are almost always smaller than total fire area reported.

The model uses several data sets as input, including Monitoring Trends in Burn Severity (MTBS) data set and the Fire Occurrence Database (FOD). The MTBS includes six levels of burn severity for fires greater than at least 1,000 acres; Verisk scientists used levels 2, 3, and 4 (combined) to define the burn scar area of a wildfire.

To estimate burn scar areas for 50-1,000 acre fires, Verisk scientists determined ecoregion- and fire size-dependent statistical relationships between the reported total wildfire size and burn scar size for all wildfires that had a reported perimeter of at least 1,000 acres and applied these relationships to the 50 –1,000-acre fires in the FOD. A similar procedure was applied to historical wildfire data from National Interagency Fire Center (NIFC) for the years 2021 and 2022. After making burn scar corrections to all three historical datasets (MTBS, FOD, and NIFC), Verisk combined the data to create an historical dataset of total annual burn scar area for each of the 45 ecoregions in the model domain for each of the years in the 1984–2022 period: the 1984–2022 Verisk historical ecoregion-based burn scar area database.

Only those fires that had burn scars that were at least 50 acres were used for analyses, modeling, or in the development of ecoregion-specific wildfire-weather models. The fraction of area in the perimeter that is in the burn scar varied between ecoregions (and with fire size) and for the different ecoregions ranged from about 0.7 to about 0.9, with an overall mean value about 0.8.

5.3 Generating Seasonal Weather Variables

Thirty seasonal variables were used to develop models of wildfire-weather relationships in each ecoregion. Extrapolation of the seasonal weather variables using recent trends in the historic data were then used to model wildfire area for the near-present climate. These 30 seasonal variables are available in the Seasonal Temperature Variables, Seasonal Precipitation Variables, Seasonal Self-calibrating Palmer Drought Severity Index (scPDSI) Variables, and Seasonal Vapor Pressure Deficit (VPD) variables sections of the Model Variables.

5.4 Generating a Recast of Historical Weather to Represent Near-present Climate

Wildfire activity in many parts of the model domain is strongly influenced by seasonal weather, and there have been strong trends in many weather variable values in recent decades.[5] Because

4 Because smoke damage to property can occur outside the burn scar, the footprint for model smoke damage is up to 20 km outside of this area (see the Wildfire Smoke Hazard Intensity – Smoke Potential Index in the Local Intensity chapter).

5 There is a large scientific literature base suggesting that future climatic change will increase wildfire area, frequency, and/or intensity. For additional information, see National Research Council 2011. Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia. Washington, DC: The National Academies Press.

a central goal of the Verisk Wildfire Model for the United States is to reflect current and near-present views of risk – that is, to account for the effect climate change is already having on the weather variables that influence wildfire area – observed weather trends were extrapolated. This extrapolation accounts for changes in the long-term averages of observed weather variables but retains the interannual variation which is largely stationary in the observed period.

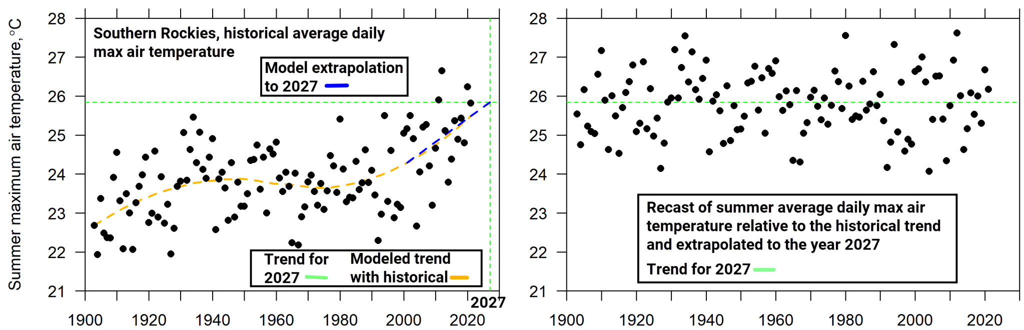

Figure 2. Historical summer (June-August) average daily maximum air temperature in the Southern Rockies (ecoregion 21), and a recast extrapolated to year 2027 (midpoint of 2025-2029)

Although Southern California is a particularly important region with respect to loss-causing wildfires, it is difficult to generalize about future climatic change-driven wildfire changes there (e.g., Dye et al., 2023). Figure 3 shows the average daily maximum air temperature recast to year 2027 in the Southern California/Northern Baja Coast (ecoregion 85). Modest warming is seen in the past two decades with considerable interannual variation in summer daytime maximum temperature. The changes in climate variables have been modest in recent years, making analysis of trends difficult; the main climate factors in southern California in recent decades are the interannual variability in different weather variables rather than strong climate trends.

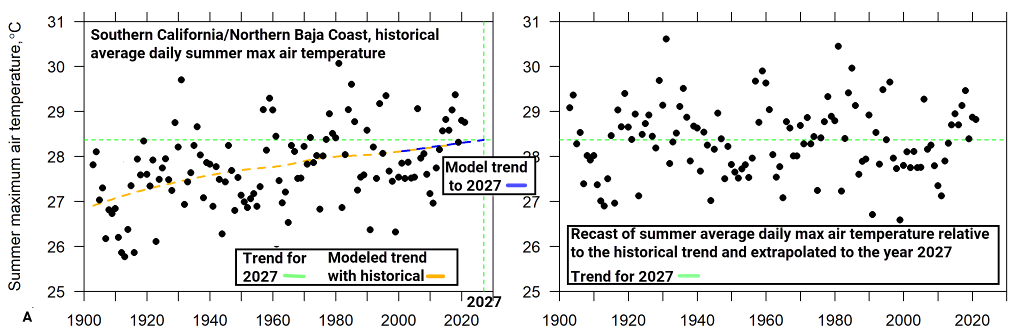

Figure 3. Historical summer (averages for June, July and August) average daily maximum air temperature in the Southern California/Northern Baja Coast (ecoregion 85), and a recast extrapolated to year 2027

5.5 Building Wildfire-Weather Models for Each Ecoregion

Verisk scientists built wildfire-weather models for each ecoregion using a multivariable regression approach. Because ***annual*** variation in wildfire area is typically lognormally distributed, the dependent variable in the wildfire-weather models is $\log_{10}$(acres burned) for each year in each ecoregion. This is standard practice (e.g., Westerling et al., 2003; Littell et al., 2009; Abatzoglou and Williams, 2016; Keeley and Syphard, 2017; Williams et al., 2019) and statistically and ecologically justified.

A step-wise multivariable regression approach with intercept term was used to identify weather variables that are significant drivers of total annual burn scar area in each ecoregion from the 30 seasonal weather variables. In most of the 45 ecoregion-specific wildfire-weather models, total annual area burned was driven by only one or two seasonal weather variables. To avoid model overfitting, no more than four weather variables were used in any ecoregion-specific wildfire-weather model. Model weather variables were chosen based on knowledge of the mechanisms that govern how different weather variables relate to wildfire area in different ecological systems (e.g., summer maximum temperatures in some forest ecosystems, and antecedent precipitation in some water-limited ecosystems). The research team removed potential explanatory variables that were redundant with other variables within a wildfire-weather model (e.g., because daily vapor pressure deficit is causally linked to daily maximum temperature, they were not ***both*** allowed to be included in any model) and variables with no known causal mechanism for influencing wildfire extent in particular ecoregions were also excluded (see Smith, 2018, for related discussion).

Weather and climate play important roles in the interannual variability of area burned by wildfire in some ecoregions but have limited influence in other ecoregions. This is recognized within the wildfire scientific research community and confirmed by independent Verisk research. In the Western United States, interannual variation in wildfire area in forested systems is often more strongly related to interannual variation in weather than is wildfire area in other systems. For example, analyses presented in Williams et al. (2019) indicated that about 52% of the interannual variation in wildfire area in the largely forested North Coast and Sierra Nevada regions of California can be explained by the interannual variation in March-October Vapor Pressure Deficit (VPD), whereas the single best predictor in their analysis (i.e., antecedent standardized precipitation index, SPI) explained less than 4% of interannual variation in wildfire area in the Central Coast and South Coast regions of California.

Consistent with that finding, Verisk scientists found relatively weak relationships between annual total wildfire burn scar areas and weather variables in the Southern California Mountains (ecoregion 8) and Southern California/Northern Baja Coast (ecoregion 85); the Verisk wildfire-weather model for the Southern California Mountains ecoregion is a single-variable model and has an r^2 of about 0.15 and the Verisk wildfire-weather model developed for the Southern California/Northern Baja Coast ecoregion is a two variable model and has an r^2 of 0.29. Those two ecoregions have considerable industry exposure and some of the largest insured wildfire risk in the 13-state model domain.

Recasts of Historical Burn Scar Areas

A key feature of the Verisk Wildfire Model for the United States is its near-present view of risk associated with the changing climate in the Western United States.

For each ecoregion, Verisk scientists created a 39-year time series of total annual burn scar area that represents a near-present climate – a burn scar area recast – by using trends and variability in the historical weather data and Historical Burn Scar Area data from 1984 to 2022. The methodology retained the relative interannual variations in annual total burn scar area within each ecoregion,[6] while accounting for decadal-scale weather trends relevant to the near-present climate. Also, the methodology was designed to maintain the important historical correlations in annual total burn scar area between Ecoregions.

Recasts Throughout the Model Domain

There was wide variation in the impact of climate change on the recasts of historical annual total burn scar areas in different Ecoregions. In seven (of the 45) ecoregions, the climate-change-based recast indicated less risk in the near-present climate relative to the historical period 1984-2020. In the five ecoregions that experienced double digit declines in burn scar area in the climate-based recast, the Historical Burn Scar Area are a small fraction of total ecoregion area so the percentage changes do not mean that there were large absolute shifts in the area burned as a fraction of total ecoregion area. In the other 38 ecoregions, the near-present climate caused small to large increases in annual total burn scar area relative to historical data. The largest ***relative*** increases in average annual total burn scar area were in the Sierra Nevada (ecoregion 5) in eastern California and the Klamath Mountains/California High North Coast Range (ecoregion 78) in northwestern California and southwestern Oregon. Both those ecoregions, and several others with large increases in climate-change related increases in burn scar area, contain significant amounts of forest with strong seasonality of weather, including warm dry summers.

6 Across the full model domain, roughly half of interannual variation in burn scar area is weather-related; the other half is related to other factors, many related to human activities. For individual Ecoregions that fraction varies considerably, with area burned in some ecoregions highly dependent on weather and some largely independent. Both weather-related and non-weather-related interannual variability in wildfire area is included in the model's stochastic catalog of wildfire burn scar areas.

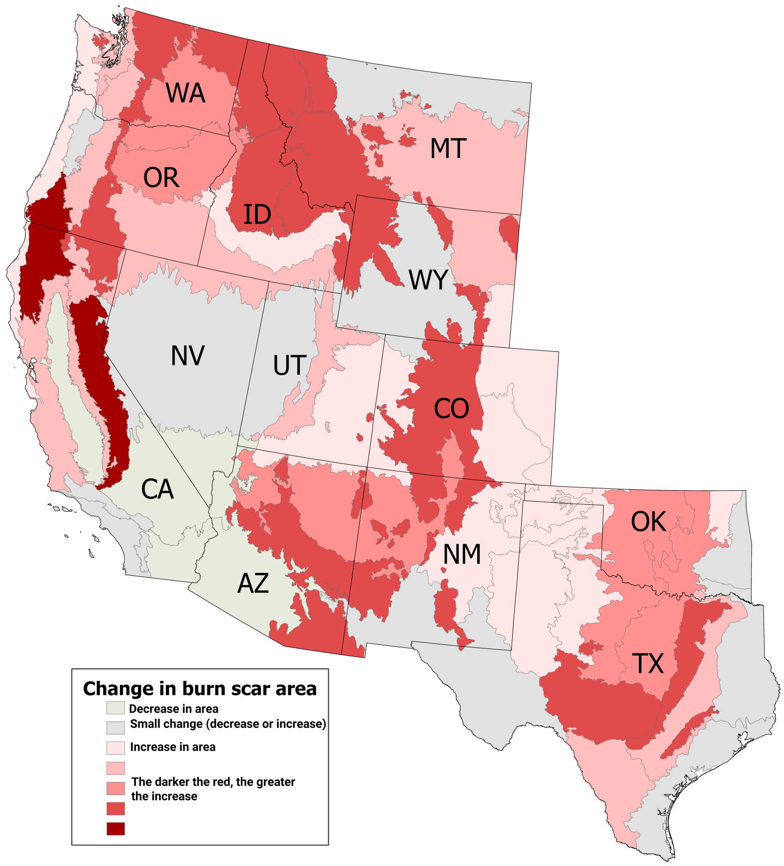

Figure 4. Relative change in average annual total burn scar area in each model ecoregion for near-present climate relative to the historical period 1984–2020.

Generating Stochastic Annual Burn Scar Area

For each stochastic year and in each ecoregion, the model assigns an annual total burn scar area for fires ignited in that ecoregion. The model creates the stochastic realizations of annual burn scar area by perturbing the historical database recast. The stochastic catalog generation process was designed to retain ecoregion-ecoregion correlations while introducing stochastic variation to annual total burn scar area within each ecoregion in each stochastic year. The stochastic catalog is consistent with the recast of historical area burned and therefore consistent with near-present climate; furthermore, it contains extreme events where the total annual area burned in a single ecoregion can be up to double the maximum historical (1984-2022) area burned. The stochastic catalog of wildfire area reflects a probabilistic view of the hazard. Common or typical years are very frequent in the catalog and extreme years are rare.

5.6 Fire Size Distribution

The annual total burn scar area for fires ignited in each ecoregion is further assigned into individual fires of at least 50 acres (burn scar area), each with its own maximum area to burn, based upon ecoregion-specific distributions of individual-fire area. These fire area distributions are based upon historical patterns in each ecoregion and recent trends in sizes of individual fires.

In addition to the general increase in annual total area burned during recent decades, the size distribution of individual fires of at least 50 acres within each ecoregion also changed, in some cases dramatically. In general, the size of fires that exceed the 50-acre burn scar threshold have increased since the 1990s. These changes have been accounted for in the Verisk Wildfire Model for the United States.

Figure 5 shows the exceedance probability of individual-fire burn scar area in four important loss-causing ecoregions: Sierra Nevada, Central California Foothills and Coastal Mountains, Southern Rockies, Klamath Mountains/California North Coast Range. Included in Figure 5 are the exceedance probabilities for historical fires, for fires 2004-2020, and for fires in the catalog (reflecting fire sizes in the near-present climate). Each bar represents the exceedance probability for fires; for example, the leftmost bar is the probability in the historical data set that a fire burn scar area is 100 acres or greater in size. The minimum burn scar size in the historical analysis and the stochastic model is 50 acres and, thus, will have an exceedance probability of 1 (or 100%). In these and all other ecoregions except ecoregion 7 (Central California Valley), the maximum fire size in the stochastic model exceeds the largest fire experienced in the historical fire data sets. The ecoregions shown are 5, Sierra Nevada; 6, Central California Foothills and Coastal Mountains; 21, Southern Rockies; and 78, Klamath Mountains/California High North Coast Range.

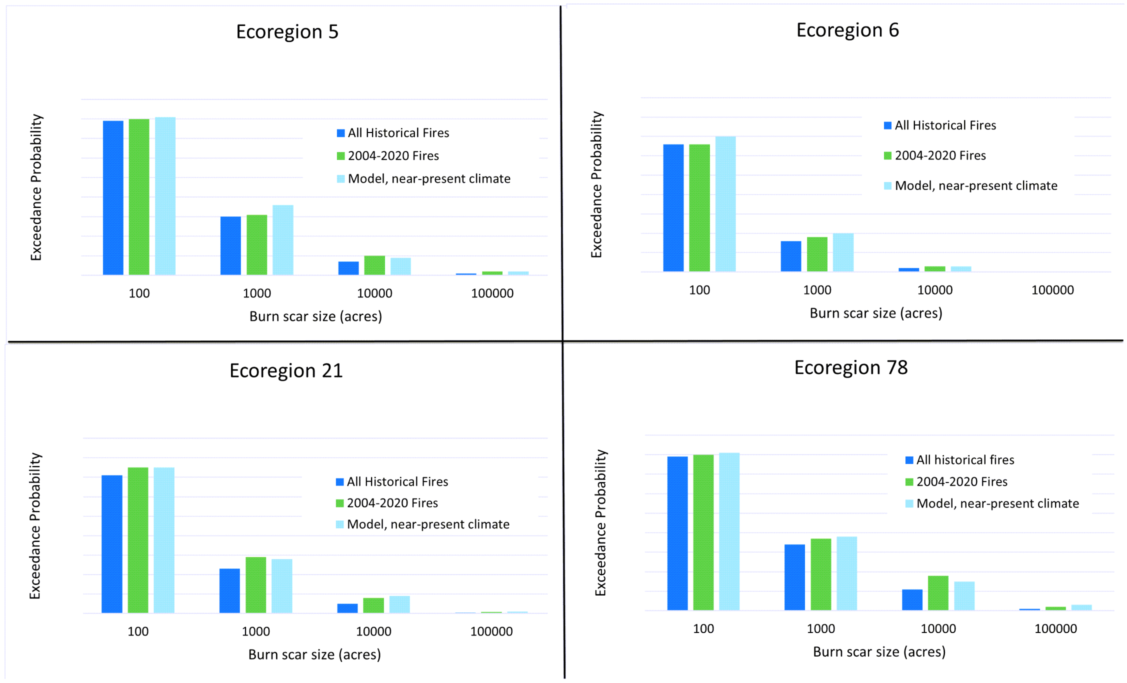

Figure 5. Exceedance probability of individual-fire burn scar area in four important loss-causing ecoregions, for historical fires, for 2004-2020 fires, and for fires in the catalog
The ecoregions shown are Sierra Nevada (5); Central California Foothills and Coastal Mountains (6); Southern Rockies (21); Klamath Mountains/California High North Coast Range (78).

The model's fire-size distributions were developed from an assessment of trends in fire sizes in the long-term history (all fires 1984-2020), more recent history (all fires 2004-2020), ***and*** with consideration for the size of recent especially large fires (2021-2023) relative to the total area in each ecoregion. The consideration for the size of especially large recent fires (2021-2023) is important because of how large individual fires have become in the few years leading up to 2023 (which may limit fuel availability), and because of the extent of areas that were ***not*** recently burned in different ecoregions (which may lead to high fuel loads).

5.7 Ignition Date and Location

Multiple fires can be clustered together by the proximity of their ignition dates and locations, and this is important to many reinsurance contracts.

Ignition Day Probability

Each stochastic fire has an ignition date (day of the year) based on 365-day years.[7]

In many locations, wind climatologies are seasonally varying – including the important downslope wind events such as the Diablo and Santa Ana winds in California. These events are

[7] The lack of the 366th day of the year in each leap year was not deemed significant to U.S. wildfire risk analyses.

explicitly accounted for in the model, making ignition date an important predictor of fire intensity and overall burn scar area.

Historical and Stochastic Wildfire Ignition Dates

The simulated ignition date for each fire is based on ecoregion-specific analyses of historical wildfire ignition dates cataloged in the Fire Occurrence Database (FOD) (1992-2020). There are two aspects to the analyses: (1) day-of-the-year ignition probabilities and (2) same-day wildfire ignition probabilities.

Verisk scientists established seasonal patterns of ignition dates by analyzing the Fire Occurrence Database (FOD) to determine the probability of any wildfire igniting on any day of the year. Some Ecoregions were designated to have date windows that do not have any ignitions (for example, during the middle of winter in the Canadian Rockies (ecoregion 41), although fires ignited before these no-ignition windows can still burn into those periods.

Figure 6 shows the modeled stochastic day-of-year ignition probabilities for six ecoregions to illustrate the range of some specific features of wildfire ignition seasonality.

- Ecoregion 4 (Cascades) displays a strong, summer-season distribution of ignition dates
- Ecoregion 6 (Central California Foothills and Coastal Mountains), which is south of ecoregion 4, has a significantly extended 'summer' period of wildfire ignitions
- Ecoregion 8 (southern California Mountains) has an even broader 'summer' wildfire season with a minimum likelihood of ignition in late February
- Ecoregion 25 (High Plains, the ecoregion containing the 2021 Marshall Fire near Boulder, Colorado) has a strong spring and early summer likelihood of ignitions
- Ecoregion 41 (Canadian Rockies) has a narrow summer wildfire season and has no ignitions during the first 70 days of any year nor the last 21 days of any year
- Ecoregion 85 (Southern California/Northern Baja Coast) has peak probability of ignition in the autumn, with minimal likelihood of ignitions in February. Those autumnal and winter ignitions in ecoregion 85 have the possibility of occurring during stochastic Santa Ana wind events, which significantly increases the possibility of significant damage due to large, intense fires.

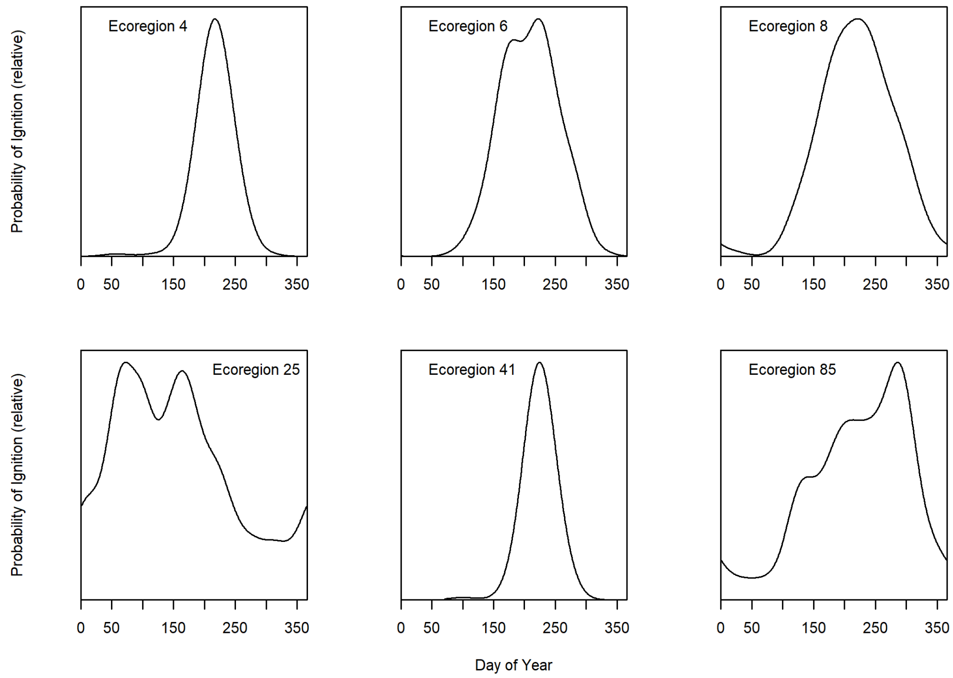

Figure 6. Relative probabilities of a wildfire ignition on an given day of the year (365-day years) for six sample ecoregions
The integral under each of the curves equals one. The ignition probabilities on day 365 and the following year's day 1 do not have a discontinuity.

Many wildfires in the Western United States are ignited on the same day as other wildfire(s) in the same region. The simultaneous ignition of multiple fires within a local area is important because it may mean that (possibly limited) fire-fighting resources must be divided among multiple locations. Same-day ignitions are typical for wildfires started when there is extensive lightning activity across an area or region. Prime examples of this include

- the ~250 wildfires ignited on August 16 and 17, 2020, in the LNU[8] Lightning Complex that subsequently burned over 300,000 acres in wine country area of northern California;
- the many wildfires on August 16 and 17, 2020, in the SCU[9] Lightning Complex that burned nearly 400,000 acres and destroyed over 200 buildings southeast of the San Francisco Bay area;
- the CZU Lightning Complex of multiple fires on August 16 and 17, 2020, in the CZU[10] Lightning Complex that destroyed nearly 1,500 buildings in California's San Mateo and Santa Cruz counties;
- the SQF[11] Complex of two fires on August 19, 2020, that burned near and into Sequoia National Forest in Central California (Tulare County);

8 LNU refers to the local Sonoma–Lake–Napa Unit (LNU) of the California Department of Forestry and Fire Protection.
9 SCU refers to the local Santa Clara Unit (SCU) of the California Department of Forestry and Fire Protection.
10 CZU refers to the local San Mateo–Santa Cruz Unit (CZU) of the California Department of Forestry and Fire Protection.
11 SQF refers to the Sequoia Lightning Complex.

- the 21 wildfires on August 17, 2020, in northern California (Plums and Butte counties) that burned over 300,000 acres, destroyed nearly 2,500 buildings, and caused 16 human fatalities in the North Complex fire;
- the extraordinary August Complex composed of 38 wildfires on August 16 and 17, 2020, that burned over a million acres, killed one firefighter, and destroyed nearly a thousand buildings in northwestern California (Glenn, Lake, Mendocino, Tehama, Trinity, and Shasta Counties).

The Fire Program Analysis Fire Occurrence Database (FOD) was analyzed to determine historical probability of same-day ignitions within each ecoregion (see Figure 7). These ecoregion-specific probabilities were used to assign multiple stochastic fires to a single date within a stochastic year as appropriate. As is clear from these data, wildfires often co-occur within the same ecoregion.

The frequency of same-day ignitions of wildfires for each ecoregion is shown in Figure 7. Within ecoregion 85 (Southern California/Northern Baja Coast)—the rightmost data—23% of historical wildfires of 50 acres or larger were ignited on the same day in the same year as another wildfire and 21% of historical wildfires of 100 acres or larger were ignited on the same day in the same year as another wildfire. All causes of fire are included, not just lightning-caused wildfires.

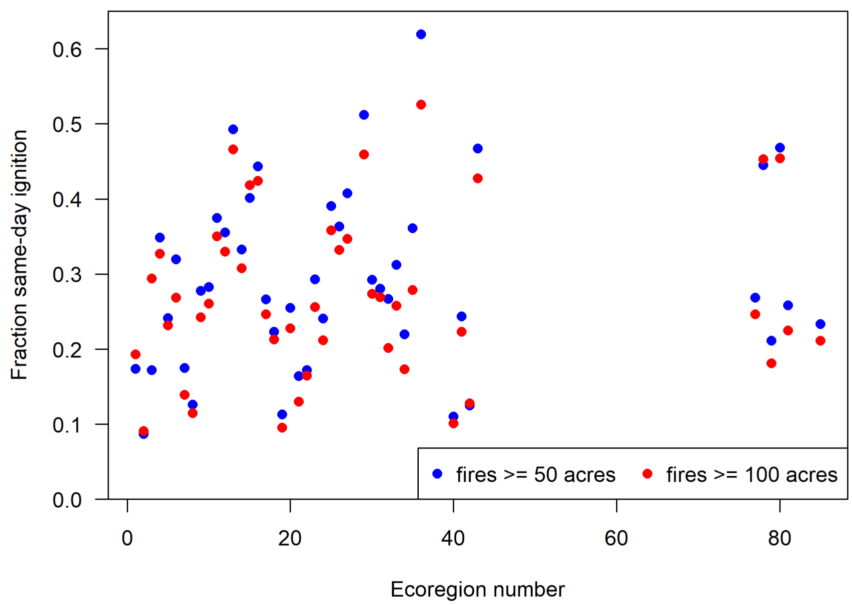

Figure 7. Frequency of same-day ignitions of wildfires of various sizes in each of the model ecoregions

There are gaps on the horizontal axis because not all numbers between 1 and 85 are used to label ecoregions within the 13-state model domain.

Ignition Location and Spatial Distribution of Fires

Wildfires can ignite anywhere there is fuel, but determining the likelihood of ignition and the final growth potential is complex. Adding to the complexity is the variety of ignition sources, both natural and anthropogenic, and the extent to which the different sources control fire activity.

Historical fire ignition location data provide a useful starting point, but data collection limitations and limited time-span of the historical record are significant challenges. For example, while the record of fires greater than 1,000 acres in an ecoregion can be assumed to be reasonably complete in terms of frequency, the possible spatial distribution of such fires is far from complete with only 37 years of Monitoring Trends in Burn Severity (MTBS) data.

Developing Potential Ignition Points

Two sources, the Fire Occurrence Database (FOD) and the Monitoring Trends in Burn Severity (MTBS) data set, were used to create the ignition points for the stochastic catalog.

To avoid double-counting fires that may be present in both data sets, for these purposes Verisk scientists retained only the FOD fires between 50 and 1,000 acres. In addition, to avoid modeling fire ignitions in urban areas, fires in the FOD with ignition points in locations with more than 50% impervious surface area were filtered out. The remaining records are combined with MTBS records to form one data set of historical ignitions.

Because large fires generally occur only where fuel is plentiful and suppression is difficult, and small fires can happen almost anywhere, two ignition point data sets were created:

- a set of ignition points for fires greater than 500 acres (see Figure 8), and
- a set of ignition points for fires with areas between 50 and 2,000 acres (see Figure 9).

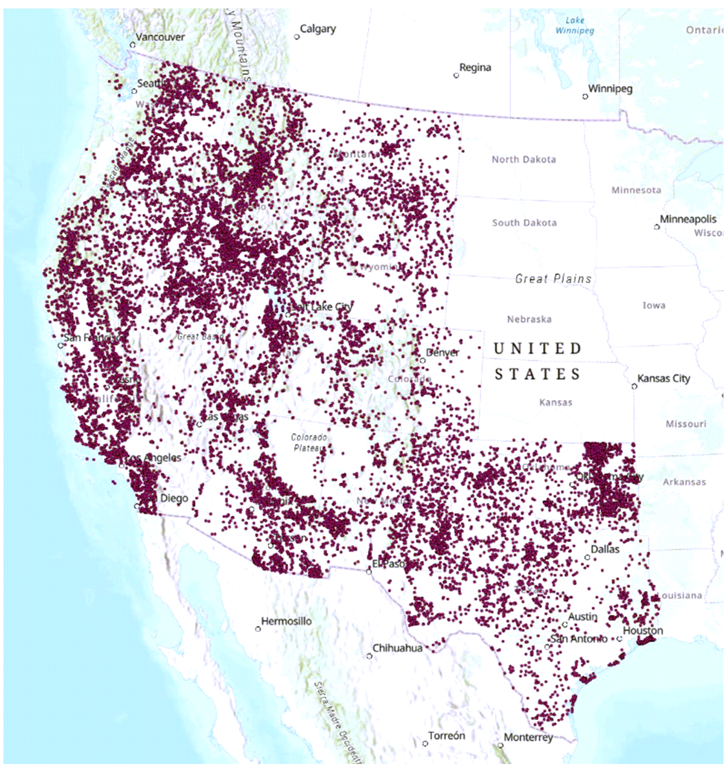

Figure 8. Map of ignition points for fires with fire area greater than 500 acres

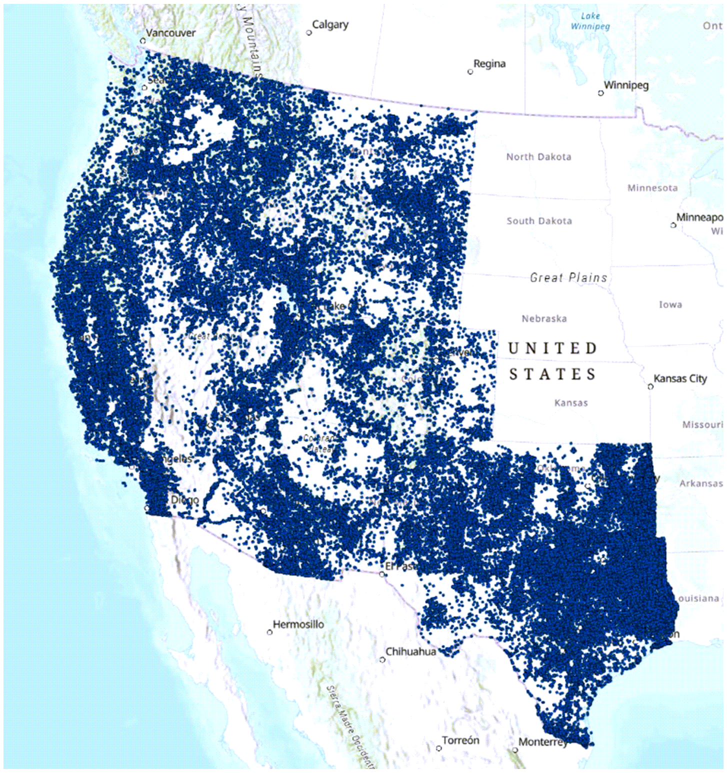

Figure 9. Map of ignition points for fires with fire areas between 50 and 2,000 acres

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The historical fire ignitions from the combined FOD-MTBS data set present an incomplete picture of ignition risk due to the limited temporal history of the data and limitations in reporting in some states. While smoothing can overcome some of these limitations, Verisk scientists developed an ignition location model which incorporates additional data and creates a more robust view of ignition risk. Research into the ignition locations of wildfires suggests there is a significant link between anthropogenic features, such as roads and the wildland-urban interface, and wildfire activity (Faivre et al., 2014 and Syphard et al., 2008). Verisk's ignition location model follows the approach of these researchers.

Gridded ignition counts are predicted by a negative binomial model, based on the following criteria within each 9-km × 9-km ignition grid cell:

- Distance to the nearest road (Tiger Primary and Secondary Road Datasets)
- Wildland Urban Interface (WUI) map from United States Forest Service's (USFS) (location within or near)
- Fuel density
- Impervious surface area

Using this data, the model predicts the number of ignitions within each grid cell, rounded to the nearest integer.

This process is done twice – once using the historical ignitions for fires greater than 500 acres, and once using the historical ignitions for fires less than 2000 acres.

Within each 9-km ⨉ 9-km ignition grid cell, the probability of ignition is assumed to be uniform, with the only restriction being the presence or absence of fuels. This ensures that the ignition location has burnable fuel and that the target fire size area may be met. Viable 90-m ⨉ 90-m cells (the resolution of the fine resolution ignition grid) are those that contain burnable fuels, as classified by the 90-m ⨉ 90-m resolution fuels data. Additionally, to ensure the modeled target fire size will be achieved, the model restricts ignitions to locations where there is sufficient and contiguous fuel to sustain a fire of the required fire size. The area covered by contiguous fuel cells determines where an ignition for a fire of a specified size may ignite; this area is defined where 90-m ⨉ 90-m grid fuel cells are connected to others in at least one of its 8 neighboring cells.

5.8 Defining Stochastic Wildfire Events

Stochastic events in the catalogs are fire clusters. Each cluster includes one or more fires ignited within 300 miles and 10 days of each other. To create these clusters, the model employs an algorithm that conducts two-stage, hierarchical clustering. For each event, the minimum target fire burn scar size is 50 acres.

Spatial clustering

For a given year, a distance matrix (in miles) is calculated for all ignition locations (latitude / longitude) within that year. Each ignition point is assigned to its own cluster and then the algorithm proceeds iteratively, at each stage joining the two closest clusters, continuing until there is a single cluster. At each stage, the distance is recomputed by a dissimilarity update formula, according to the Ward's minimum variance method. Finally, the algorithm returns clusters with a diameter ≤300 miles.

Temporal clustering

Once spatial clustering is complete, a distance matrix (in days) is calculated for all ignition days within a given 300-mile cluster. Using the same method described above, ignition locations within a spatial cluster are subdivided into 10-day clusters.

This process results in clusters of fire ignitions occurring within 300 miles and 10 days of each other. A simplified illustration of this process is presented in Figure 10 and Figure 11.

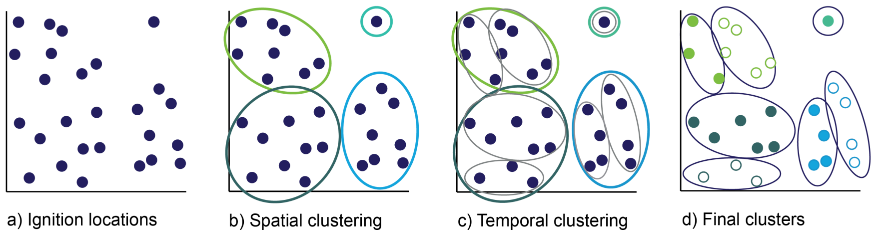


Figure 10. Ignition point clustering

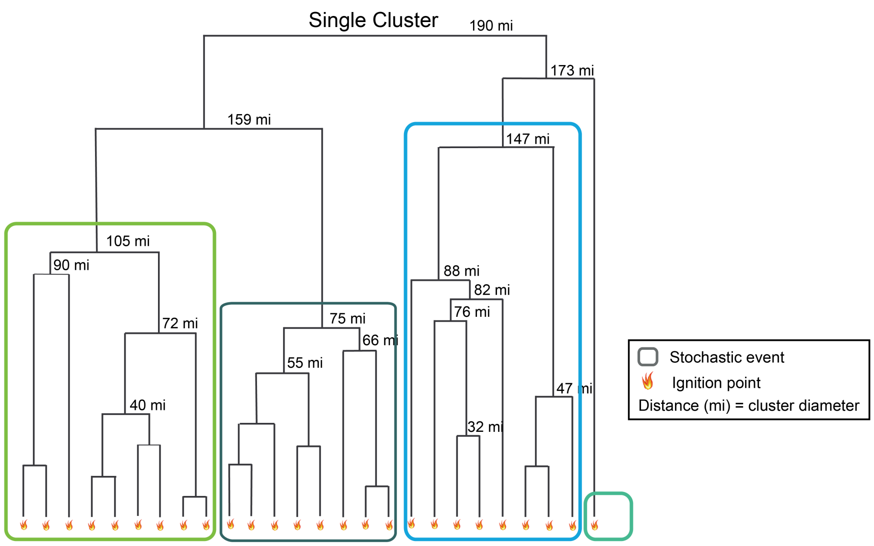


Figure 11. Hierarchical clustering (spatial clustering example)

5.9 Assessing the Stochastic Event Generation

Fire frequency as developed in the 10,000-year run of the model was compared to United States Forest Service Burn Probability index. While these two data sets represent different aspect of wildfire risk and are not directly comparable, clear commonalities in areas of high and low fire risk are apparent.

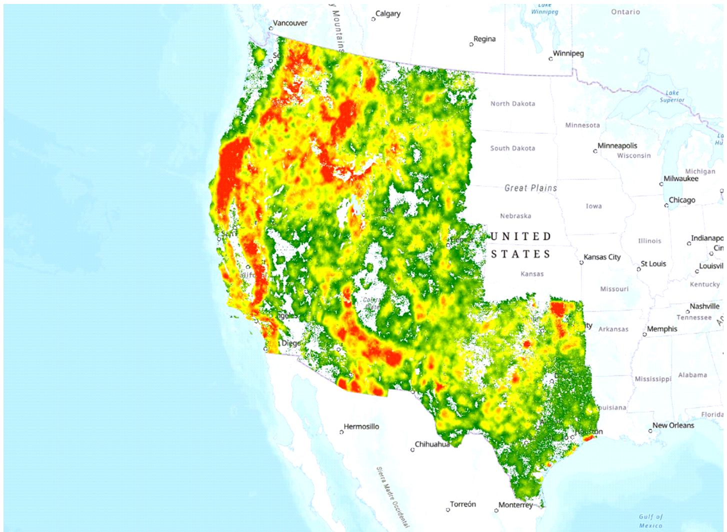


Figure 12. Fire frequency in the 10,000-year catalog

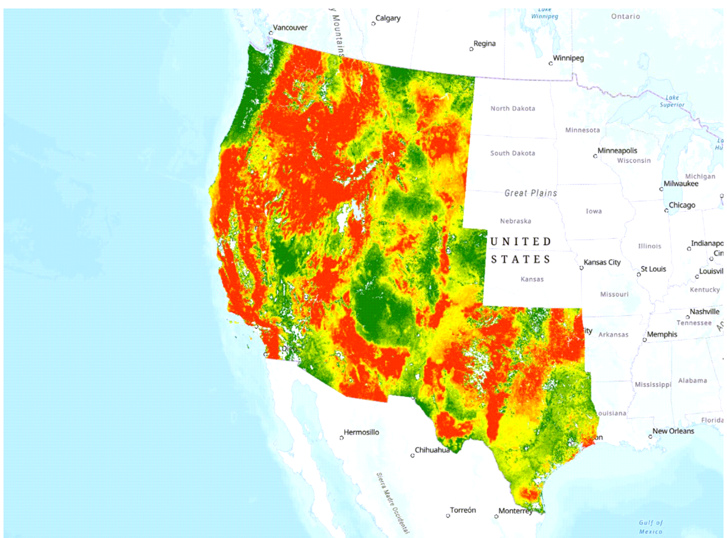


Figure 13. U.S. Forest Service Burn Probability Index

6 Local Intensity Overview

For each simulated event, the model calculates the intensity of the hazard at each location within the affected area.

The local intensity for an individual event in the Verisk Wildfire Model is calculated using a wildfire spread model and a wildfire smoke hazard model. Losses are assumed to be from fire or from smoke, but not from both.

The wildfire spread model employs a cellular automata (CA) algorithm and is designed to create physically realistic wildfire footprints defined by burn scars based on grid cells. This approach distinguishes it from others that rely on vector-based fire perimeters. The intensity of the fire is parameterized by the modeled flame lengths in the grid cells that are burned. The model grid is on an Albers equal area projection domain[12] with a resolution (grid cell size) of 90 m $\times$ 90 m.

The wildfire smoke hazard model calculates damage from smoke; the smoke hazard is calculated using a Smoke Potential Index (SPI), an intensity measure that represents the soot deposition (soot is smoke particles that can deposit on surfaces). SPI depends on amount of fuel burned, average wind speed during the event, and distance of exposure to the burn scar.

6.1 Local Intensity Input Data

The wildfire spread model creates fire intensity footprints by modeling the spread of fire across the landscape. Therefore, the model requires spatial information regarding the characteristics of the landscape that are relevant for fire behavior, such as information regarding wildland and urban fuels (Surface Fuel), terrain (slope and aspect), population density, urbanicity (as measured by impervious surface area, ISA), building characteristics, Wind direct and speed, and Fuel Moisture.

Table 5. Local Intensity Data Inputs

Surface Fuel
Topography
Impervious Surface Area
Measure of Access to Suppression Resources
Oak Ridge National Laboratory's LandScan
Wind
Fuel Moisture
Verisk Drought Index

[12] The Albers projection preserves earth surface area in the projected domain

Surface Fuel: Fire Behavior Fuel Models

The wildfire risk in any given region depends heavily on the type of vegetation present, its density, the amount of moisture it holds, and the readiness and rapidity with which it burns. Given its various characteristics as a fuel source, vegetation is a key input to the spread model. Several factors – the type of vegetation, the condition of the vegetation at any given time, and how dense it is across a slope or level expanse – all affect how readily a fire will ignite and how and where it will spread. See section Surface Fuel.

The LANDFIRE fuels data set was modified by Verisk to create 40 burnable fuel categories that had been determined to be critical for fire spread and intensity, using data from Verisk FireLine® product (2019-2022), ESA WorldCover, Homeland Security Infrastructure Program (HSIP) Gold , OpenStreetMap (OSM), and the 2019 National Agricultural Statistics Service (NASS) Cropland Dataset. The data set was modified to address the following:

- Some land cover types that are identified as burnable in LANDFIRE but that typically ***do not*** support wildfire (e.g., golf courses and some kinds of irrigated agriculture may be categorized by LANDFIRE as timber, grass or shrubs but rarely, if ever, burn in wildfires) were designated as unburnable in the modified database.
- The designation of some land cover types that may be identified as unburnable in LANDFIRE but that ***can*** carry fire was modified in the database (e.g., avocado groves may be categorized by LANDFIRE as unburnable agriculture but have been observed to burn in recent California wildfires).
- Fuel category changes – from burnable to unburnable – were made using data from Verisk FireLine® because it reflects a more recent view of land use/land cover changes than the LANDFIRE data set. This allows the model to incorporate areas of recent construction in the Wildland Urban Interface (WUI).

These fuel categories include sub-types of the greater categories of grass, shrub, mixed grass and shrub, timber understory, timber litter and slash-blowdown fuels. With each fuel type is associated a fuel model, which defines a set of parameter values (e.g., typical fuel size and loads for fine, medium and coarse fuels) that are used in the spread model to calculate fire behavior. Each fuel category has associated alphanumeric and numeric codes; for example, fuel model 121 corresponds to GS1 which represents 'Low Load, Dry Climate Grass-Shrub'. The modified fuel category layer includes two additional unburnable categories for golf courses and irrigated agriculture.

The Urban/Developed category (NB1/91) is considered unburnable within the context of traditional wildfire spread models that use LANDFIRE as an input and has no associated fuel model to evaluate spread rate or intensity. However, the primary purpose of the spread model is to calculate fire intensity at any location in the model domain that may have exposure; in particular, the model must be capable of simulating loss-causing wildfire events that spread from wildland areas into the wildland urban interface Wildland Urban Interface (WUI) and urban areas, including extreme urban conflagration events that start as wildfires. Therefore, Verisk scientists developed and implemented a method of calculating fire spread and intensity in built-up areas as well as wildland areas by including a structure-to-structure fire spread with fuel category NB1/91 that requires building data as input and that is similar to models of fire following earthquake.

Forest Canopy Fuel

The following four categories describe the forest canopy fuel:

- Canopy cover
- Canopy height
- Canopy base height
- Canopy bulk density

Forest Canopy Cover

Forest canopy cover describes the percent of a grid cell's area covered by canopy in a stand of trees. Canopy cover is important in shielding the Surface Fuel from open wind speeds and in determining the transition of a surface fire to a canopy fire. Canopy cover is provided in LANDFIRE as a percent.

Forest Canopy Height

Forest canopy height is the distance from the ground to the top of the canopy. Canopy height is important in determining the canopy wind reduction and is provided in LANDFIRE in meters $\times 10$.

Forest Canopy Base Height

Forest canopy base height is the distance from the ground to the base (bottom) of the tree canopy. Canopy base height is used to determine the intensity/flame height necessary for a surface fire to transition to a canopy fire and is provided in LANDFIRE in meters $\times$ 10.

Forest Canopy Bulk Density

Forest canopy bulk density is the amount of fuel in the canopy by volume. Canopy bulk density is used to determine the spread rate and intensity of a canopy fire and is provided in LANDFIRE in (kg/m^3) $\times 100$.

Topography

Topography creates variation in localized winds, which in turn affects the direction of fire spread. Additionally, fires tend to spread at a faster rate when travelling uphill, as heat from the advancing fire rises, pre-heating fuels uphill.

From the USGS National Elevation Data Set (NED) dataset, Verisk scientists derived slope and aspect. Slope refers to a site's inclination; aspect is the cardinal direction a slope faces. The model uses these characteristics as factors in fire behavior.

Impervious Surface Area

The Verisk Wildfire Model for the United States uses impervious surface area data from the National Land Cover Database (NLCD) 2011 (Xian, et al., 2011), produced by the Multi-Resolution Land Characteristics (MRLC) consortium. This consortium, a group of U.S. federal agencies, generates land cover data at a national scale for environmental, land management, and modeling applications. Impervious surface area is the percentage of an area covered by material that does not allow water to percolate through, usually a manufactured structure (e.g., concrete).

Population Density

The spread model uses population density data from the Oak Ridge National Laboratory's LandScan™ data sets as part of the fire suppression algorithm to provide a probabilistic measure of access to suppression resources (i.e., the higher the population density the greater the likelihood of fire suppression). Since wildfires can occur at all times of day, likely suppression activities for both daytime and nighttime cases are accounted for (e.g., schools and commercial businesses tend to have low nighttime population levels but high daytime population levels, whereas residential buildings tend to have low daytime population levels but high nighttime population levels).

Building Data

The spread model allows buildings to serve as wildfire fuel and for structure-to-structure spread in Wildland Urban Interface (WUI)/built-up areas where the LANDFIRE fuel category is Urban/ Developed.

Wind Data

Wind speed and direction are key environmental variables that impact wildfire behavior.

For each stochastic fire event ignition, an autoregressive integrated moving average (ARIMA) time series model simulates wind conditions over multiple time scales (i.e., month, day, hour) for each 32-km × 32-km grid cell in the National Oceanic and Atmospheric Administration (NOAA) North American Regional Reanalysis (NARR) data set. The model creates typical winds for a given NARR cell for a particular month and time of day; wind speed and direction change every three hours, creating a realistic pattern consistent with historical wind data. The appropriate model is selected based on the location (grid cell) and month. Once an ARIMA model has been selected, the same model is used throughout the event to ensure time series consistency, even if the fire grows into another grid cell or crosses into another month. Thus, the model will represent the monthly conditions at the time of ignition.

Figure 14 shows how a stochastic fire footprint reflects the changes in wind patterns that occur during an event. The color scale represents time since ignition (not intensity). Wind was initially blowing towards the east and the fire spread predominantly in that direction, then the wind shifted northward around the time indicated by the white contour.

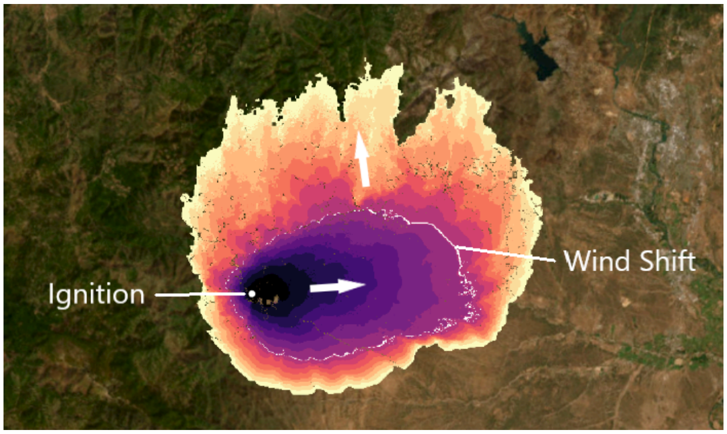


Figure 14. Stochastic fire footprint reflects changes in wind patterns (arrows).
Color scale represents time since ignition (not intensity).

Although the ARIMA model is practical and efficient for creating realistic wind time series with conditions that do not deviate significantly from typical monthly and diurnal variability in the NARR wind data, extreme fire behavior is most frequently associated with strong downslope wind events (e.g., Chinook winds on the eastern slopes of the Rocky Mountains or Santa Ana winds in southern California). To allow for these events to be represented more explicitly in the stochastic catalog, the model includes a downslope wind feature for wind time series generation. Using the observed downslope wind climatology developed by Abatzoglou et al. (2021) as a guide for location, seasonality, and frequency of events, stochastic fire events that occur in areas susceptible to downslope winds may be labeled as a "downslope wind event" depending on the time of year of ignition. In such cases, the wind time series used in the spread model simulation is drawn from a distribution that is more representative of observed downslope wind events than is available in the NARR data set because the NARR data set, in general, is too coarse to resolve the extreme wind speeds often observed in downslope wind systems.

Fuel Moisture

The moisture content of vegetation impacts its likelihood of burning and the intensity with which it does burn, along with the rate at which the fire spreads through the fuel.

The spread model requires input on the moisture content of dead fuels (of several different size classes) and live fuels (herbaceous and woody). Each of these different Fuel Moisture content values responds to different environmental drivers, ranging from hourly changes in weather conditions to seasonal growth cycles.

Dead fuel is described in terms of the amount of time required for the fuels to come to equilibrium with its environment, assumed to be a function of the fuel's diameter: 1-hr (fuels < 1/4 inch diameter), 10-hr (1/4 inch to 1-inch diameter), or 100-hr (>3 inches diameter). That is, 1-hr fuels change with environmental conditions quickly, whereas 100-hr fuels change more slowly. Dead fuels exposed to rain or high humidity will have a high moisture content, whereas dead fuels exposed to high winds and low relative humidity will have a low moisture content.

Moisture values in live fuels, however, are primarily controlled by the growing cycle of the vegetation – moisture content is typically highest during the spring when fresh foliage is developing, remains relatively high through the growing season, and then becomes cured in the winter months. Because live fuel moisture responds to changes in the soil, and does not respond quickly to changes in the air, for a stochastic year in which the region of ignition is significantly drier/wetter than normal, the fuel moisture content values will be lower/higher than normal.

Using the Verisk Drought Index that was developed for each fire ignition event. Verisk scientists assigned values for the individual fuel moisture contents guided by the moisture scenarios described in Scott and Burgan (2005). Using this approach, the fuel moisture conditions in which any given stochastic fire spreads are consistent with the expected large-scale environmental conditions for that stochastic year.

Figure 15. Pinyon pine and juniper forest in Nevada with low percentage of dead fuels
By Famartin - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=29072733

Figure 16. Pinyon pine and juniper forest in New Mexico with high percentage of dead trees
By Craig D. Allen, USGS, 2002 https://www.nps.gov/articles/pinyon-juniper-woodlands-ecosystem-drivers-disturbance-succession.htm

6.2 The Fire Spread Algorithm

The simulation method used in the wildfire spread model is a cellular automata (CA) algorithm that draws from several previous studies of CA models for wildfire spread (i.e., Berjak and Hearne, 2002; Rui et al., 2018; Jiang et al., 2021). The model uses a discrete rectangular grid on an Albers equal-area projection of the model domain and employs a rule-based CA technique combined with expert knowledge of fire behavior to determine how fire spreads from one grid cell to another. The spread model is based on a fundamental, but very general, CA method that allows for flexibility in simulating fire spread through and between wildland and urban landscapes based on specific models for fire spread in wildland areas; in urban areas; and where they meet at the United States Forest Service's (USFS) wildland-urban interface of the conterminous United States. This method also enables realistic spatial representation of fire intensity while achieving computational efficiency.

The essential properties of a CA algorithm are the definition of the state of a cell and a local rule, or transition function, that updates this state from one time interval to the next. In the wildfire spread model's CA algorithm, the model domain is divided into square cells of uniform size (90 m), each of which contains a state attribute, ***S***. The state of cell (***i***, ***j***), at time ***t*** changes discretely with time depending on its own state and that of the eight cells that surround it – commonly known as the Moore neighborhood of (***i***, ***j***) – expressed generally in terms of the transition function, ***f***, as

$$S_{i,j}^{t+\Delta t} = f\left(S_{i,j}^{t}, N\right)$$

where Δt is the model time step and N refers to the states of each of the eight cells in the Moore neighborhood of (***i***, ***j***). Each cell state variable can take one of three values: $S_{i,j}$=0 (unignited), $S_{i,j}$=1 (active burning), and $S_{i,j}$=2 (extinguished).

Figure 17 illustrates the grid configuration for the Moore neighborhood of cell (***i***, ***j***); when cell (***i***, ***j***) is ignited, the spread rate, ***R***, in each of the eight Moore neighborhood directions is calculated. The calculation of these directional spread rates for any given cell depends on the wind and the nature of the fuel in the cell; in particular a different method is used for wildland and urban/developed fuel types.

- The spread rate, R, to the north of the cell is R_N or $R_{i,\,j+1}$
- R to the north-east is R_{NE} or $R_{i+1,\,j+1}$
- R_E is to the east, or $R_{i+1,\,j}$
- R_{SE} is the south-east, or $R_{i+1,\,j-1}$
- and so on...

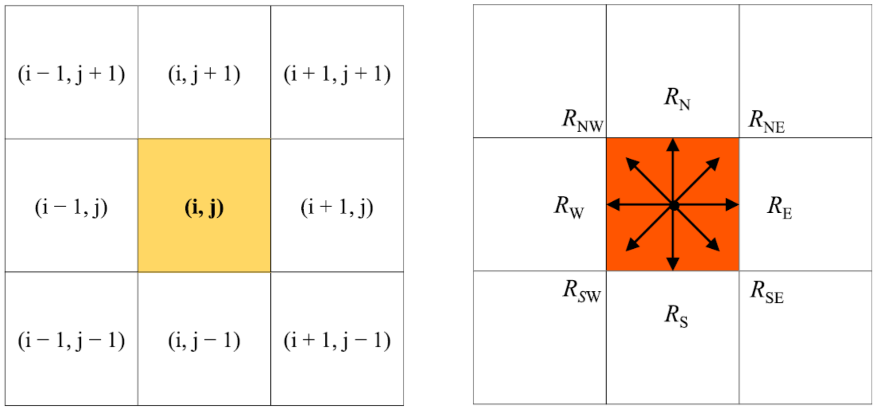


Figure 17. The grid configuration for the Moore neighborhood of cell

The model calculates the spread rate in each of the Moore neighborhood directions beginning in the grid cell that contains the ignition location. The simulation proceeds by evaluating the transition function to determine changes to the state variable in each of the Moore neighborhood cells of the ignition cell. When one of those neighborhood cells meets the conditions for ignition as defined below, its state variable is changed from 0 to 1 to denote active burning. In this manner, the fire spreads from cell to cell, whereby all cells that are actively burning can contribute to the ignition of all the neighborhood cells via the transition function.

All events simulated by the model have an associated size (area); the event will continue until the target size (area) is reached or until no cells are actively burning. An event may burn out before its target size (area) is reached if it runs out of fuel and/or is suppressed.

Fire Spread in Wildland Areas

The model calculates the spread rate as a function of the Wind and the Surface Fuel in the cell. In wildland areas, the model employs the spread equations of Rothermel (1972) to determine when the fire moves from one grid cell to the next. The modes of fire spread include:

- Surface
- Surface to canopy
- Canopy

  These modes of spread form a hierarchy — the fire is assumed to start as a surface fire, and if certain criteria are met, it will transition to a canopy fire. Fuel type and wind speed determine which burning cells create firebrands. For these cells, firebrands are lofted into the air, facilitating the ignition of spot fires ahead of the fire front.

Surface Spread

To calculate the rate of surface spread, the model relies on Rothermel's surface spread equations (Rothermel, 1972), which are based on fuel model inputs, fuel moisture, wind conditions at midflame height, and terrain.

Surface to Canopy Spread (Tree Torching)

For each cell ignited by a surface fire, the model calculates fireline intensity[13] based on the rate of spread, fuel consumption, and heat yield. When the fireline intensity reaches a certain threshold (based on canopy base height for the location), it is possible for the fireline to move vertically to the tree canopy, engulfing a tree's crown in flames. The model determines when this transition is appropriate based on the work of Scott et al. (2001), which links Rothermel's (1972) surface spread equations and van Wagner's (1977) crown fire transition criteria.

Canopy Spread

Once a fire has moved into the canopy of a single tree, it is possible for the fire to begin spreading from tree canopy to tree canopy as an active canopy fire (or crown fire). Conditions such as high wind speeds, a high percent canopy cover, and high crown bulk density promote the development into an active canopy fire. Crown fires are an important consideration in wildfire modeling, as they are harder to control – their spread rate is considerably faster than surface fires and are associated with higher intensity fires.

The spread model calculates fire intensity at each time step to determine if a certain cell will experience tree torching. If tree torching occurs, the canopy structure of the cell experiencing tree torching and the surrounding cells are used to determine if the fire will spread as an active canopy fire. For each cell, the model calculates two different spread rates, one for the surface and one for the canopy. The spread rate in a cell is either the surface spread or the canopy spread, whichever is larger.

Fire Spread in Urban Areas

In traditional wildfire modeling, "urban/developed" is considered an unburnable fuel category (Scott and Burgan, 2005). Unfortunately, experience indicates this is not always the case. For example, the community of Mountain Springs in Colorado Springs, Colorado (appearing as gray to indicate "urban", in Figure 18) suffered almost all of the losses from the 2012 Waldo Canyon fire. Therefore, the model allows fires in areas categorized as unburnable urban/developed if there are any structures in that cell. If there are structures, the fire spreads based on the algorithm for fire spread in urban areas. If there are no structures (e.g., a parking lot) then the fire doesn't spread, and the flame length is zero.

[13] Frontal fire intensity (or Byrams fire intensity) was defined by Byram (1959) as the rate of heat output per length of fireline.

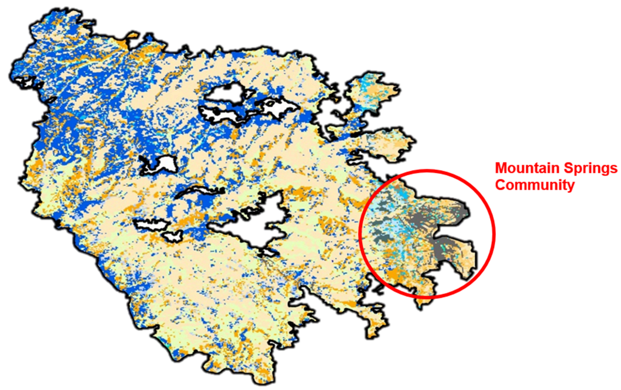


Figure 18. 2012 Waldo Canyon fire perimeter and underlying fuels

In the model, wildfire penetration into the built environment is a function of the impervious surface area and suppression activities.

In cases where suppression is effective, fires will spread up to areas of high impervious surface area; the fire perimeter stops at the edge of the urban area. Once fire has penetrated the built environment, however, it may spread using buildings as fuel. While the rate of spread of fire in wildlands employs the spread equations of Rothermel (1972), the rate of structure-to-structure spread is estimated following the approach of Hamada (1951), who modeled the spread of fire following earthquake.

Building are also an important source of embers that may propagate and ignite non-adjacent cells, starting spot fires that are a critical component for urban fire spread in conjunction with spread between adjacent structures.

Figure 19 shows an example of a stochastic fire in which embers ignited cells outside of the original fire perimeter and spread independently, related to the impervious surface area.

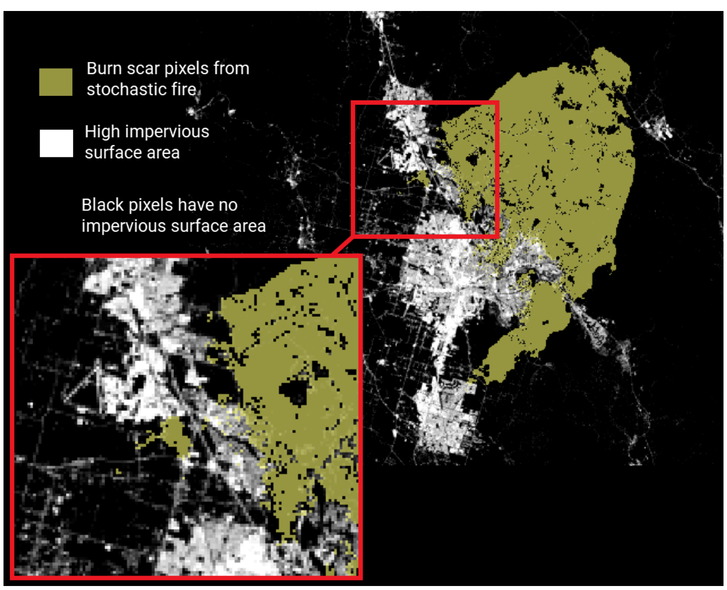


Figure 19. Spot fire ignitions

Figure 20 shows an example of how a stochastic fire can spread into developed areas and lead to urban conflagration; this penetration into developed areas depends on several factors, including the wind speed, impervious surface area, and suppression.

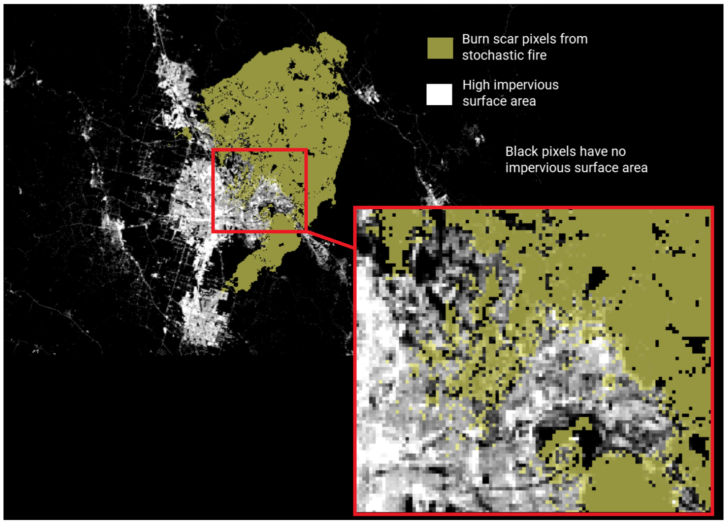


Figure 20. Urban fire spread

Figure 21. The 2018 Camp Fire in California destroyed the community of Kilcrease Circle in the town of Paradise, and left the immediate surrounding forest largely untouched.
Source: Keeley, J.E., Syphard, A.D. Twenty-first century California, USA, wildfires: fuel-dominated vs. wind-dominated fires. ***fire ecol*** **15**, 24 (2019). https://rdcu.be/dzsql, from a Maxar company satellite image from Nov 2018.

Figure 22. Avista Adventist Hospital in Louisville as the Marshall Fire approached on Dec. 30, 2021
Source: Centura Health Avista Adventist Hospital

Ember Generation and Spot Fires

Based on findings in Sardoy et al. (2008), the spread model considers only short distance firebrands (< 1 km) for the ignition of spot fires. This study found, based mostly on numerical simulations, that there is a bimodal distribution for firebrand travel distance – one long distance, and one short distance, and that most fire brands in the long distance category (typically > 1 km) reached a charred state by the time they landed and were not likely to ignite a spot fire. Alternatively, almost all firebrands in the short distance category landed in a smoldering or flaming state, and thus were likely to ignite spot fires.

In the spread model, each ignited cell is evaluated in terms of its ability to produce firebrands. This assessment is based on the presence of a canopy or urban fire, a cell's fuel type and wind speed. If a determination is made that the cell produces firebrands, the embers are distributed log-normally, where the mean and standard deviation of the distribution are a function of the type of plume (buoyancy- or wind-driven), the intensity of the fire, and the open wind speed. Given that winds are responsible for transporting the fire brands to their landing location, the model assumes fire brand trajectory is centered around the prevailing wind direction. To account for local variation in wind and other unknowns, the trajectory is allowed to uniformly vary in a 60-degree arc around the wind direction (30 degrees on either side).

Due to the shape of the lognormal distribution, many spot fires do not exceed the bounds of the origin cell, and thus do not impact the advancement of the fire. For a firebrand traveling beyond its cell of origin, whether or not it ignites the landing cell is made based on available fuel conditions.

Figure 23 is an example showing spot fires caused by embers contributing to wildfire spread. Ember ignitions are shown by the red pixels.

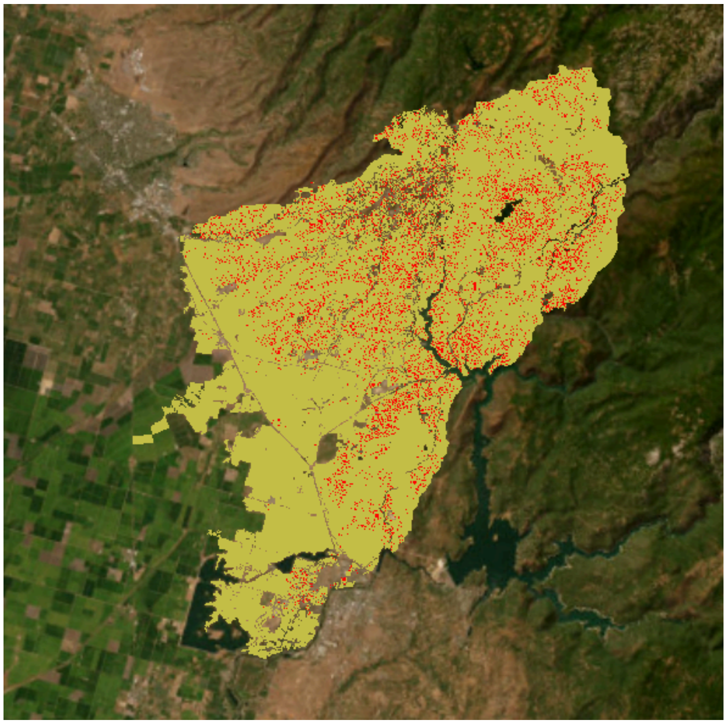


Figure 23. Spot fires caused by embers

Ignition Probability and Suppression

Community-based suppression is an important control in terms of evaluating how far a fire will be allowed to penetrate into the urban environment. Highly populated areas are more likely to be prioritized for fire suppression efforts than scarcely populated areas. During a fire, firefighters try to "hold a line" to fight fires. They create a firebreak (e.g., backburn) or use an existing environmental structure (e.g., a road) and attempt to stop the fire from spreading beyond that location. Although it is impossible to model the specific method firefighters will employ in each situation – such as cutting roads for fire breaks, igniting backfires, dropping fire retardants – the model simulates where these resources are most likely to deployed.

To model this behavior, the spread model considers population data on a 90-m × 90-m grid. Since wildfires can occur at all times of day, both daytime and nighttime population are considered (e.g., schools and commercial businesses tend to have low nighttime population levels but high daytime population levels, whereas residential buildings tend to have low daytime population levels but high nighttime population levels). The model smooths the maximum daytime and nighttime population values because the scale of suppression activities are likely to be slightly larger than the 90-m × 90-m grid cell. Based on the smoothed population of a cell, the model evaluates the likelihood that a fire entering that cell would be suppressed. If a cell is in a "suppressed" state, it cannot be ignited.

The probability of a given cell's being "suppressed" is dynamic and may change through the course of an event. Multiple factors affect suppression probability – fire intensity, wind speed, and condition of neighboring cells. Suppression is more likely to fail during high intensity events.

Fire Intensity

Flame length – the distance between the flame tip and the midpoint of the flame depth at the base of the flame – is commonly used as an observable measure of fire intensity. If there is no wind and the terrain is flat, flame length and flame height are the same. Under windy conditions or on a slope, the flame length and height can be different (see Figure 24). The larger the flame length, the higher probability that a structure will burn.

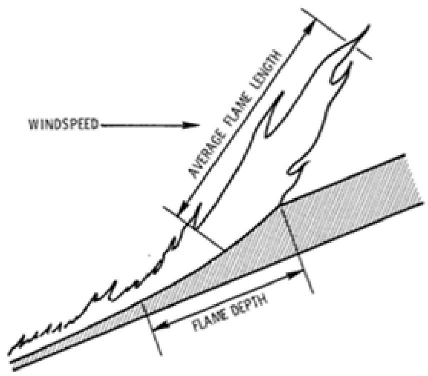


Figure 24. Flame dimensions, showing dependence on wind and slope of the terrain
Source: Rothermel, R. C., 1983.

Figure 25 shows contours for specified flame lengths (in feet) and their corresponding intensities (in BTU/ft/sec) relative to heat output per area and rate of spread (BTU/ft^2 and 'chains'/hr[14], respectively).

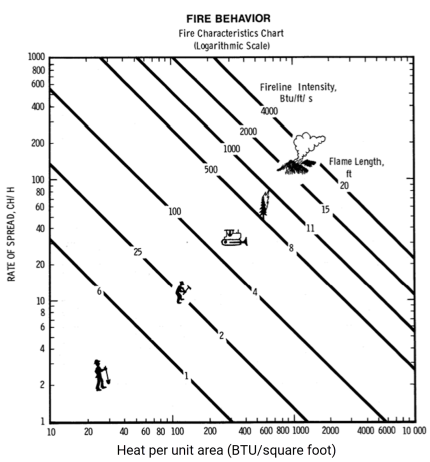


Figure 25. Fire behavior chart, showing contours of fireline intensity (in BTU/ft/sec) relative to heat output per unit area and rate of spread for given flame lengths, on log-log scale.
Source: source: Rothermel, R. C., 1983.

[14] A 'chain' as a unit of measurement is 66 ft

Table 6. Typical fire suppression efforts for given flame length and fire intensity

Flame length	Fireline intensity	Interpretation
<4 feet	< 100 BTU/ ft/sec	Hand tools at the head or the flank of the fire
4 -8 feet	100-500 BTU/ft/sec	Too intense for hand tools, heavy equipment such as bulldozers, plows and aircraft.
8-11 feet	500-1,000 BTU/ft/sec	Torching, crowning and spotting are likely, control efforts at the fire head are likely ineffective
>11 feet	>1,000 BTU/ft/sec	Torching, crowning and spotting and major fire runs, control efforts at the fire head are ineffective
Source: Andrews, P. L., and Rothermel, R. C., 1981		

6.3 Wildfire Smoke Hazard Model

The model calculates damage from smoke as well as from direct flame (fire damage); because damage from flames is more severe than damage from smoke, losses to buildings are assumed to be from fire or from smoke, but not from both. The smoke hazard is calculated using a Smoke Potential Index (SPI), an intensity measure with arbitrary units that represents the soot deposition (soot is smoke particles that can deposit on surfaces). SPI depends on amount of fuel burned, average wind speed during the event in different directions, and distance of exposure to burn scar.

Smoke Production Calculation

As a first step in smoke hazard intensity calculation, the model calculates the total amount of smoke produced by a fire. Only a small fraction of this total amount of smoke produced is expected to cause smoke damage because the majority of the smoke disperses in the atmosphere.

Smoke Potential Index (SPI)

The flame length intensity is calculated within the fire perimeter but soot damage can occur both inside and outside the fire perimeter. The model uses the assumption that damage-causing soot outside of a fire's perimeter occurs only within a certain distance of the fire perimeter, and within the smoke-damage area.

7 Damage Estimation Overview

The measures of intensity of simulated catastrophic events are applied to highly detailed information about the properties that are exposed to them. Equations called damage functions are developed and used to compute the level of damage that is expected to occur to buildings of different types of construction and different occupancies, or usages, as well as to their contents, and to other lines of business, such as marine, large industrial, and auto.

The damage functions of the Verisk Wildfire Model for the United States include:

- Shape of the building damage function based on claims data from recent fires.
- Separate damage function for appurtenant structures.
- Contents damage function based on claims data.
- Time element damage function based on industry loss (data) contribution by coverage.
- Compliance with building code updates to California after year built 1997 that are based on the hazard zonation and in all other states & some specific counties based on the adopted codes.
- Claims-based damage function for smoke sub-peril.

The damage estimation component of the Verisk Wildfire Model for the United States translates wildfire intensity into expected damage, which includes property damage and business interruption losses for residential properties, manufactured homes (mobile homes), commercial and industrial assets, and automobiles caused by fire and smoke. Smoke damage both within and beyond fire perimeters is modeled explicitly.

7.1 Building Classification and Resistance to Wildfire Damage

The building components and features that affect an exposure's vulnerability to wildfire can be divided into two broad categories of attributes:

- **Primary:** Characteristics such as the occupancy, construction type (material), height, and age of the building
- **Secondary:** Characteristics that define the building envelope and the building's environs - roof cover type, wall siding material, glass type used in windows, roof attachment features, and the surrounding landscaping.

Wildfires ignite structures in three ways:

- Ember accumulation
- Direct contact with flames
- Radiant heat

Of these modes of ignition, ember accumulation is a major source of ignitions of homes and other properties. Embers (see Figure 26) can travel with the wind as far as a kilometer, resulting in fire ignition well beyond the main burning area.

Figure 26. Fire and embers, 2017 Thomas fire, Los Padres National Forest, California
Source: https://www.flickr.com/photos/usforestservice/albums/72157688491050272

Damage from flames always begins with penetration of the building envelope. The flammability of a structure's exterior surfaces or attached structures, such as the roof, wall-siding, deck, and fence, are critical factors in determining a structure's vulnerability to fire. Historically, damage by flames show a strong binary pattern. Homes that suffer damage are generally a complete loss – they burn to the ground – whereas others survive completely intact. These surviving structures, however, are often found to be contaminated by smoke and soot, especially those within a fire perimeter. Therefore, wildfire damage within burn scar is either minimal (smoke/soot damage) or complete (total loss), with very little in between. Smoke can travel far, and the model calculates smoke damage up to a certain distance outside of a fire's perimeter.

Effect of Building Height on Peril

The number of stories in what are classed as low-rise, mid-rise, high-rise and tall buildings depends on the occupancy class of the building, shown in Table 7.

Table 7. Height classes per occupancy type

Occupancy	Low-Rise	Mid-Rise	High-Rise	Tall
Single/ Multi-Family Residential	1	2	3	4 & Above
Commercial / Industrial & Services	1 to 3	4 to 7	8 to 25	26 & Above
Height classes do not apply to infrastructure (200 series construction codes) and large industrial (400 series occupancy) type exposures.				

In general, a 1 to 3 story rise building is considered the most vulnerable since it tends to accumulate more combustible debris, such as pine needles, dead leaves, etc., and embers are more likely to accumulate on them. Ember ignition is the major causal factor of houses being destroyed by wildfires.

Figure 27. Typical California ranch

Long overhangs (with or without soffits) also referred to as wide eaves, are observed in wildfire events (as well as lab experiments) to increase the vulnerability of 1-story buildings (Figure 28 shows a ranch house with a ~2-ft overhang without a soffit). Wide eaves such as these create a cave-like volume that traps any hot air from burning wood chip mulch, low bushes and other vegetation around homes that have been ignited by embers. In Figure 29, a 1-story building is on fire after the fire had "jumped" onto the roof. Multi story (4+ story) buildings have much smaller probability of having cave-like eaves because the eaves are higher above the ground.

Figure 28. An open eave with no soffit

Figure 29. A Spring Valley house is consumed by flames in the Ranch fire in Lake County, California in 2018

Residential Buildings

The predominant construction type for residential buildings in the United States is wood frame construction (see Figure 30). As illustrated in Figure 31, masonry construction is also widely used in certain regions, though considerably less than wood frame. Other construction types are negligible.

Common roof covers for residential buildings include asphalt shingles, clay and concrete (RC) tiles, slate, and wood shingles.

Exterior wall siding materials for residential buildings primarily include vinyl, metal, wood, fiber, stucco, and masonry.

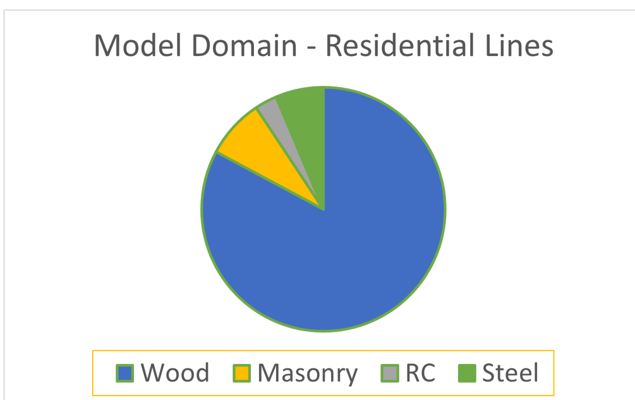


Figure 30. Residential construction distribution in the model domain

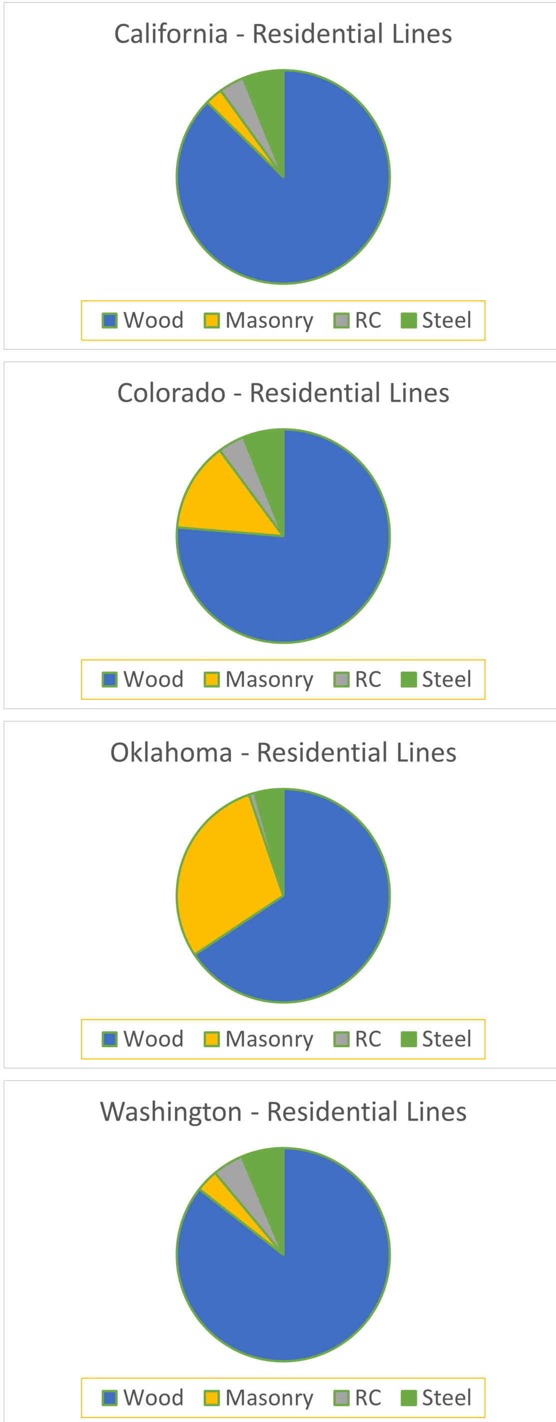


Figure 31. Residential construction distribution in California, Colorado, Oklahoma, and Washington

Residential houses are typically built using light-frame construction following commonly accepted engineering practices.

Manufactured (mobile) homes

In the Verisk Wildfire Model for the United States, manufactured homes are addressed as a separate construction classification. Although the design and construction of single family homes are based on local or state building codes, the design and construction of manufactured homes is regulated and governed federally by the U.S. Department of Housing and Urban Development (HUD), pursuant to the 1974 National Manufactured Housing and Construction Safety Standards Act.

The HUD code defines a manufactured home as a structure that is transportable in one or more sections, and is at least 8 body feet wide or 40 body feet long during transport. When onsite, it is at least 320 square feet, built on a permanent chassis, and designed to be used as a dwelling with or without a permanent foundation, when connected to utilities (24 CFR 3280.2 and 24 CFR 3285.5). This class does not include modular homes. Unlike manufactured homes, modular homes are designed and constructed according to the local building codes. Verisk includes modular homes in the classification for single family homes.

A manufactured home is less expensive than a light-frame construction single family house, and its value depreciates upon leaving the factory. In comparison with standard home construction, mobile homeowners typically have less control over building materials, landscaping, fire insurance or other safeguards against wildfire. Building materials of manufactured homes are generally of lower quality than constructed dwellings. Many manufactured homes use asphalt shingles or TPO (thermoplastic polyolefin) as the roof cover. Both materials are flammable, making manufactured homes vulnerable to wildfire.

Commercial and Industrial Buildings

Commercial and industrial exposures include a greater variety in construction than residential properties. The commercial/industrial occupancy class in the 13 western states of the model domain consists almost half as wood construction, with the remainder consisting of masonry, concrete (RC) and steel constructions.

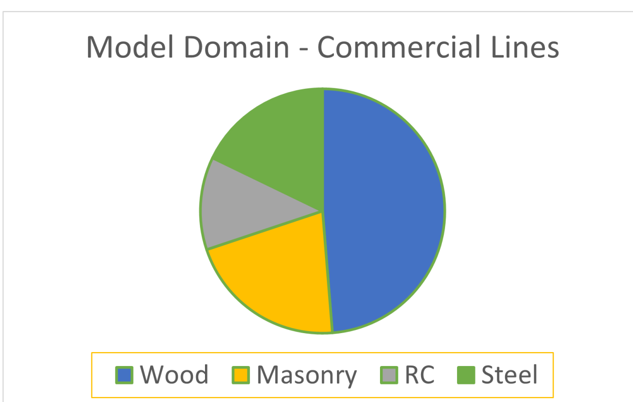


Figure 32. Commercial construction distribution in the Western United States

Although wood frame buildings are in both residential and non-residential occupancies, non-residential wood frame construction is different from residential dwellings in several ways – design and construction methodology, construction materials, and surrounding environments.

Wood frame construction is common for low- to mid-rise non-residential buildings, such as hotels, religious buildings, stores, and multi-unit apartment buildings. Rather than conventional light-frame construction, building codes often require engineered methods for the design and construction of these buildings. Engineered methods include allowable stress design (ASD) and load resistance factor design (LRFD).

The materials used as roof cover for non-residential buildings are significantly different from those used in residential construction. Due to the large size of a non-residential building and the functionality requirements of the roof, these structures typically have a flat roof with built-up cover as opposed to a pitched roof. One advantage of a flat roof is that it provides great space for mechanical equipment, such as cooling or ventilation systems, solar panels, etc.

For non-residential buildings, it is commonly preferred to use low-maintenance and long-lasting cladding materials such as stone, stucco, brick veneer, fiber cement, glass, metal, mortar, and thermal insulation composite systems. Most of these materials are not flammable.

Throughout most of the United States, non-residential buildings usually are separated from residential structures depending on local zoning requirements. Building codes for these structures require large parking lots. Typically places of assembly, such as a church or theater, need to provide one parking space for every 5 seats or every 40 square feet of interior space.

Appurtenant Structures

It is possible to have damage only to the appurtenant structures and no damage to the main building or structure (rock tunnel with toll booth as an example of such case). In these cases, there will be no content damage or business interruption losses because those depend on there being a main building damage ratio.

Region and Age Variability

Newer buildings may be less vulnerable from wildfires than older buildings because of state, county or regional building codes.

Several building codes including the International Wild-Urban Interface Code (from 2003 to 2018), the California Building Code and California Fire Code (2007 & 2010) and the Standard for Reducing Structure Ignition Hazards from Wildland Fire (NFPA 1144) affect newer buildings in the 13-state model domain.

In California, local, state and federal responsibility area zones were mapped to moderate, high and very high hazard levels as shown in figure below. California Building Code construction class A, B, & C requirements were mapped to the hazard levels. For example, the vulnerability for same flame length intensity in the very high hazard zone is lower than in the high hazard zone because of the higher level of code requirements in the very high hazard zone.

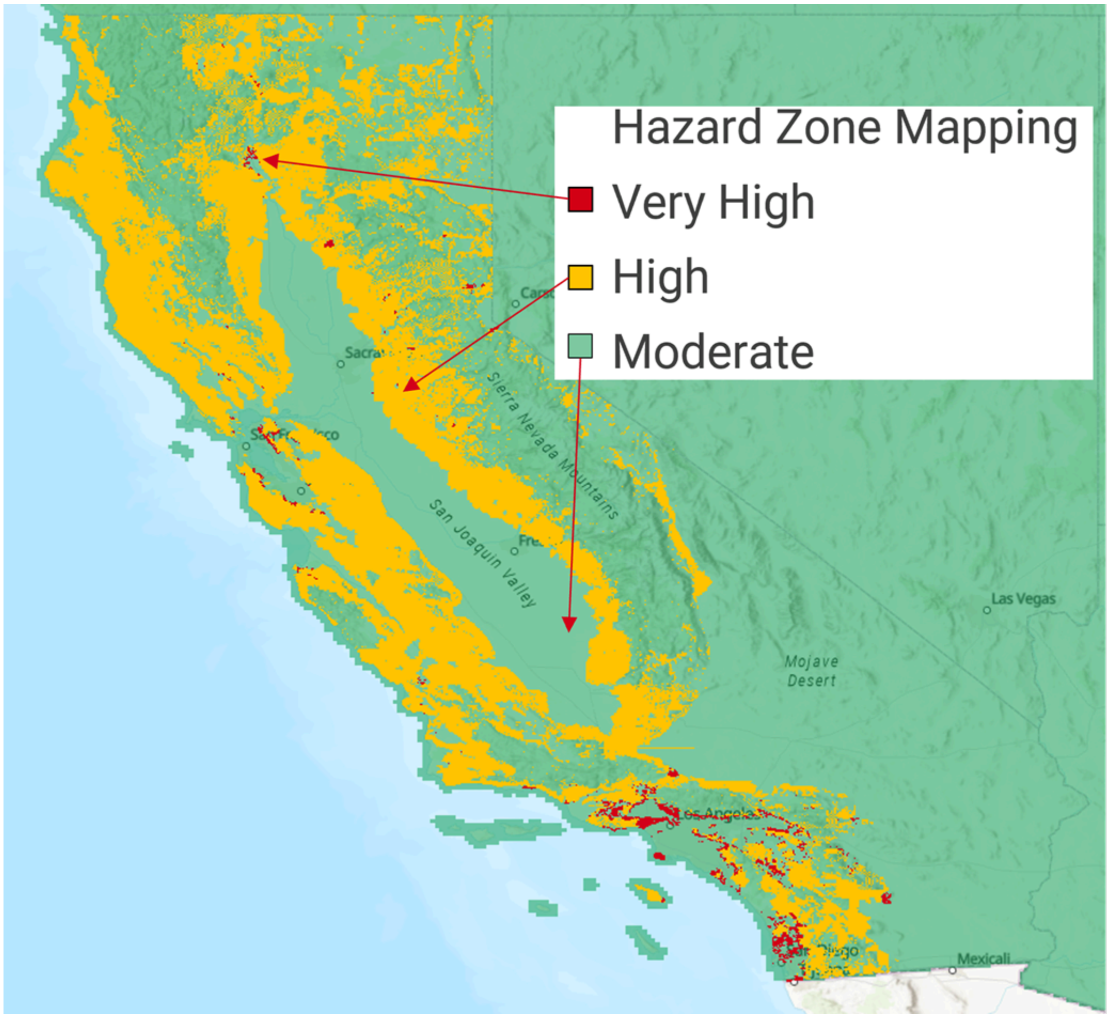


Figure 33. Moderate, high, and very high hazard levels for California

The hazard mapping presented in Figure 33 is used only for understanding building characteristics due to building codes, and does not relate to the representation of the hazard in the model.

California, Colorado, Montana, Nevada and Utah have adopted state-wide wildfire code requirements for new construction, and some counties have adopted codes. If both the state and county have region-specific vulnerability, the model applies the county-specific vulnerability first. For example, the state of Colorado as well as Boulder County in Colorado have state-wide wildfire code requirements; the model applies the specific vulnerability for Boulder County first. The following specific counties have adopted wildfire codes (listed by state):

- Pima, AZ
- Boulder, CO
- Pueblo, CO
- Boise, ID

- Douglas, NV
- Washoe, NV
- Bernalillo, NM
- McCurtain, OK
- Austin, TX
- Chelan, WA
- Douglas, WA
- Kittitas, WA
- Yakima, WA
- Teton, WY

Unknown Characteristics

Based on the building replacement values of known occupancies and constructions in Verisk's Industry Exposure Database, the weights of unknown types of indices are pre-calculated.

In general, unknown height is similar to the vulnerability for low-rise residential, and commercial is more likely to be in the mid-rise height class. Furthermore, the construction of steel and concrete (RC) type indicate taller buildings in the unknown weight calculation mix.

7.2 Secondary Risk Characteristics for Wildfire

Secondary risk characteristics (SRC) are features of a building and its environment that significantly impact the building's vulnerability to damage during an event. The SRCs are important contributing factors to losses sustained by residential, commercial, and industrial properties.

For any feature and option from a Secondary Risk Characteristic that is viewed as worse (making building more vulnerable) than the base damage functions, a higher relativity score is assigned to that building and vice versa for any viewed as making a building less vulnerable.

Safer from Wildfires

"Safer from Wildfires" in California was created by an interagency partnership between Insurance Commissioner Ricardo Lara and the emergency response and readiness agencies in Governor Gavin Newsom's administration. There are ten steps outlined in the program and under the regulation effective October, 2022, associated with this program, insurers are required to give discounts for every action take under the Safer for Wildfire steps. The 10 steps are:

- **Class-A fire rated roof** – Most roofs qualify including asphalt shingles, concrete, brick, or masonry tiles, and metal shingles or sheets. Wood shake shingles are not Class A fire-resistant rated. The Office of the State Fire Marshal maintains a list of tested and approved materials.

- **5 foot ember resistant zone, including fencing** – Removing greenery and replacing wood chips with stone or decomposed granite 5 feet around your home prevents fire from getting a foot in the door. Replacing wood fencing connecting to your home with metal is critical because it can act like a candle wick leading fire straight to your home.
- **Ember- and fire-resistant vents** – Installing 1/16 to 1/8 inch noncombustible, corrosion-resistant metal mesh screens over exterior vents can keep wind-blown embers out of your house.
- **Non-combustible 6 inches at the bottom of exterior walls** – Having a minimum of 6 vertical inches measured from the ground up and from any attached horizontal surface like a deck can stop embers from accumulating and igniting your walls. Noncombustible materials include brick, stone, fiber-cement siding or concrete.
- **Enclosed eaves** – Installing soffits under your eaves can prevent heat and embers from getting trapped and igniting. When enclosing eaves, non-combustible or ignition resistant materials are recommended.
- **Upgraded windows** – Multi-paned windows are more resistant to breaking during a wildfire, which helps keep flames from entering. Multi-paned glass or added shutters all qualify.
- **Cleared vegetation, weeds and debris from under decks** – Noncombustible materials like concrete, gravel, or bare soil are permitted.
- **Removal of combustible sheds and other outbuildings to at least a distance of 30 feet** – These include sheds, gazebos, accessory dwelling units (ADUs), open covered structures with a solid roof, dog houses and playhouses.
- **Defensible space compliance** – following state and local laws requiring defensible space including trimming trees and removal of brush and debris from yard. See CAL FIRE's defensible space page and your local city or county for details.
- **Being safer together** – Safer from Wildfires recognizes two community-wide programs, Firewise USA and Fire Risk Reduction Communities as small as 8 dwelling units or as big as 2,500 can create an action plan and start being safer together. Firewise USA is a nationally recognized program with proven results, sponsored by the National Fire Prevention Association.

The Verisk Wildfire Model for the United States secondary risk characteristics can be used to understand the relative impacts of these steps on your book of business, when the features are coded into the exposure data. Following is a comparison of the Safer from Wildfires features and the SRC features available in the Verisk Wildfire Model for the United States:

Class-A fire-rated roof: The Safer from Wildfires program requires a Class-A fire-rated roof, which includes materials like asphalt shingles, concrete, brick, masonry tiles, and metal. Wood shake shingles do not qualify. The Verisk Wildfire Model also recognizes the importance of roofing materials in wildfire vulnerability but goes further by considering a broad range of fire-resistivity in different roof materials rather than a strict classification and accounts for 11 different type of roof material. In addition, the Verisk model accounts for roof geometry, roof shape, roof attached structures such as chimneys, A/C unit, skylights, parapet walls, dormer.

The 5-foot ember-resistant zone: for the 5-foot ember-resistant zone, Safer from Wildfires recommends removing vegetation and replacing combustible materials near the home, as well as replacing wood fencing connected to the house with metal to prevent fire from spreading. The Verisk model considers only the section of fencing attached to the building and evaluates different fencing materials and their impact on wildfire risk.

Ember- and fire-resistant vents: The Safer from Wildfires specifies the use of 1/16 to 1/8-inch noncombustible metal mesh screens to prevent ember entry. The Verisk model, accounts for roof vents with 1/8-inch or smaller mesh as wildfire-resistant but does not explicitly include the 1/16-inch mesh size.

Non-combustible 6 inches at the bottom of exterior walls: The Safer from Wildfires recommends at least six vertical inches of fire-resistant material like brick, stone, fiber-cement siding, or concrete. While the Verisk model considers types of wall siding, there is no explicit characteristic for the 6in bottom clearance.

Enclosed eaves: The Safer from Wildfires advises installing soffits made of non-combustible or ignition-resistant materials to prevent embers from accumulating. The Verisk model accounts for this by incorporating roof overhang (eaves) and soffit design into its damage function.

Upgraded windows: The Safer from Wildfires highlights multi-paned glass and shutters as effective ways to reduce wildfire risk. The Verisk model similarly considers glass type and skylights, noting that skylights can create additional vulnerabilities by allowing embers to enter.

Cleared vegetation, weeds, and debris from under decks: The Safer from Wildfires recommends using noncombustible materials like gravel, concrete, or bare soil. The Verisk model accounts for this under defensible space Zone 1, recommending that no vegetation be within five feet of the building.

Removal of combustible sheds and other outbuildings: The Safer from Wildfires mandates that structures like sheds, accessory dwelling units (ADU)s, and gazebos be placed at least 30 feet away from the home. The Verisk model considers external fuel storage, such as sheds and propane tanks, but focuses on those within five feet of the building.

Defensible space compliance: the Safer from Wildfires requires adherence to state and local laws for vegetation management. The Verisk model incorporates defensible space zones (1–3) based on FEMA's definitions, considering their impact on wildfire spread. The FEMA defensible zones share the same fundamental objectives as CAL FIRE's defensible space guidelines: reducing wildfire risk by creating buffer zones around structures, managing vegetation by reducing density and minimizing flammable materials near buildings, and enhancing structural protection by clearing debris from roofs and gutters, keeping flammable objects away from structures, and using fire-resistant materials whenever possible.

Community-wide mitigation efforts: The Safer from Wildfires promotes Firewise USA™ and Fire Risk Reduction Communities, where groups of homes work together to reduce fire risk. The Verisk model assumes that properties in Firewise USA™ communities have a defensible space equivalent to 100 feet, unless a greater defensible space is specified. Then the specified vulnerability will be used for loss calculations.

In addition to the above mentioned SRC features, the Verisk Wildfire Model for the United States accounts for wall siding, building shape and gutters.

7.3 Wildfire Mitigation Credits

Verisk leverages publications and studies on the effectiveness of wildfire mitigation measures from these sources, combined with in-house structural engineering expertise and building damage observations from historical wildfires, to establish an expert opinion regarding the impact of wildfire mitigation measures on the vulnerability of structures exposed to wildfire risk.

The academic sources upon which the Verisk Research team bases its fundamental understanding of wildfire risk mitigations—particularly with respect to defensible space and Firewise Community participation—include the Forest Stewards Guild, the National Institute of Standards and Technology (NIST), and the Institute of Catastrophic Loss Reduction (ICLR). The wildfire team employ data from many sources, both public and private, including data from sources such as the Insurance Institute for Business and Home Safety (IBHS), and insurance claims data in the building of the model. Staff have also participated in damage surveys to better understand wildfire risk.

Building components and features that affect an exposure's vulnerability to wildfire can be divided into two broad categories of attributes – primary and secondary. Primary characteristics that define the exposure include occupancy, construction type (material), height and age of the building. The building's location and age play a crucial role in determining its susceptibility to wildfire risks implicitly implying mitigation activities. Structures erected in areas designated as high-risk zones according to building codes tend to have more stringent design standards, making them better equipped to withstand wildfires compared to similar buildings located in low-risk regions. Secondary characteristics are those that define the building envelope and the buildings environs – roof cover type, siding material, glass type used in windows, roof attachment features, and the surrounding landscaping. In total six secondary features are included in the model, including two specific to wildfire (defensible space and Firewise USA™ communities).

In the Verisk Wildfire Model for the United States, exposures input by the user to the model without specified features assume default vulnerabilities. That is to say, an average building for the exposure area is defined in the model. This default vulnerability is based on Verisk's understanding of the built landscape. All building/exposure characteristic options further defined by the user augments this understanding of the default vulnerability, making it more or less damageable in the face of the named peril. Consider a user input of an exposure with unknown roof characteristics. The model the assumes average roof characteristics. However, specifying shingle types can reduce or increase the vulnerability of the structure in the model and result in different loss estimates for a defined insurance policy. Adjustments are made to the mean damage ratio – a metric which defines the average damage to a structure across the intensity of the peril (in the case of wildfire, this intensity measure is flame length).

The Verisk Wildfire Model for the United States uses actuarially sound methods, data and assumptions in the estimation of wildfire losses. The relationship among the wildfire characteristics are logical. Loss costs decrease as vulnerability features strength increase, other factors held constant. For example, switching from a wood shingle roof to an asphalt roof is going to decrease a loss cost.

Age, construction, year built, and number of stories can have up to 20% impact on losses depending on, but not limited to, the combination of characteristics, coverage, and location. Defensible space can have up to a 40% impact, Roof types can have a up to 30% impact and Windows can have up to 10% impact on losses depending on, but not limited to, the combination of characteristics, coverage, location, and glass type.

The Verisk Wildfire Model for the United States account for community-level and property-level mitigation efforts as explained below:

Firewise USA Community-Level Mitigation Efforts

The Firewise USA program is a National Fire Protection Association (NFPA) program, co-sponsored by the USDA Forest Service, U.S. Department of the Interior, and the National Association of State Foresters. Among numerous requirements, recognition as a Firewise community requires a community wildfire risk assessment, which provides residents with critical wildfire information about their community. Community members are responsible for maintaining wildfire safety standards in common areas, but they are also educated about fuel management best practices that they can implement on and around their own homes.

The Verisk default behavior in the Verisk Wildfire Model for the United States is to assume the exposure is not part of a Firewise USA Community. If the exposure is designated as being a Firewise USA community the model assumes both that the defensible space must be at least 100ft (or greater if input by the user), assumes the structure is in good condition, and yields a reduction to the mean damage ratio for the structure. The Firewise designation includes evaluating:

- Vegetation
- Topography
- Wind severity
- History of wildfires
- Building materials: roofing material choices, soffit vent, siding, skirting
- Attachments: decking and decking material choices, windows, roof/gutter debris, gutter types
- Within 0-5ft of structure: materials and vegetation
- Within 5-30ft of structure: vegetation and condition of surrounding surfaces
- Within 30-100ft (200ft where applicable): vegetation and condition of surrounding surfaces
- Common areas: proximity to wildland and other fuel sources, management plans therefore.

Property-Level Mitigation Efforts

Defensible Space

Defensible space is the area between the structure and an oncoming wildfire, where landscaping has been managed to alter or cut off the fire's path, with the intent of increasing the structure's probability of survival.

Verisk categorizes defensible space into 3 zones. Enacting defensible space around an exposure in the Verisk Wildfire Model for the United States yields reductions to the mean damage ratio in all cases – implying that the default is anticipated to have no defensible space. Reductions in vulnerability are given by zonal region, which are defined in accordance with FEMA definitions.

Verisk Defensible Space - Zone 1

Zone 1 is defined as the distance of 0 to 30 feet from the structure. Ground-level fuels—dead plants, grass, weeds (vegetation), dry leaves, twigs, pine needles, and combustible debris—should be removed within 0 to 5 feet, and significantly controlled from 5 to 30 feet from a structure. If present, this type of material should also be removed from the roof and rain gutters. Zone 1 should be free of all firewood piles, construction material, propane tanks, or other combustible materials. If a fence is attached to the building, the section of the fence within Zone 1 must be constructed of non-flammable material.

Verisk Defensible Space - Zone 2

Zone 2 is the distance of 30 to 100 feet from the structure. Fire-resistant plants and materials should be used in this zone as much as possible. Species of trees/shrubs should be slow-growing and deciduous (e.g. maple, poplar), and materials such as rock, brick, gravel, and stone are ideal for patios, decks, and walkways. Vertical and horizontal space between vegetation should also be maintained to reduce the potential spread of fire.

Verisk Defensible Space - Zone 3

Verisk defines Zone 3 as 100 to 200 feet from the structure. Fuel management in Zone 3 is only needed when a high wildfire hazard level exists. A high hazard level may be due to the presence of continuous forest vegetation or special topography where fuels are not sufficiently reduced in Zone 2. Special topography conditions include a steep slope, narrow draw, or small canyons – all features that increase the ignition potential of a structure.

7.4 Fire and Smoke Damage Functions

Damage functions are the core of the damage estimation component of the model. Wildfire damage functions estimate the damage to buildings using flame length as the intensity parameter to produce a mean damage ratio (MDR) for any given intensity. Flame length is defined as the distance between the tip of the flame and the ground, midway in the zone of active combustion (see Figure 34).

Figure 34. Firefighter making firebreaks during the Black Forest fire, Colorado
Source: http://www.af.mil/News/Photos/igphoto/2000041046/, modified by Verisk

Fire Damage Functions – Buildings

The wildfire damage function for buildings (see Figure 35) provides an estimation of mean damage at given flame length. This is a claims-driven damage function. The curve shown is for a typical 2-story, single-family residential building with wooden construction. In claims data, structures start to experience losses at short flame lengths (< 1 foot). Typically, low damage is expected in this range as short flames can be suppressed by household hand tools such as shovels and garden hoses. When the flame length is in the mid-range (2 to 6 feet), heavy equipment and professional firefighters are needed to suppress the fire. In this situation, the efficacy of fire suppression is uncertain, as it is highly dependent on the weather conditions and fire suppression resources. If the flame length exceeds 8 feet, the fire is often deemed not suppressible. The damage quickly increases to near complete loss (> 75%) at flame lengths above 8 feet.

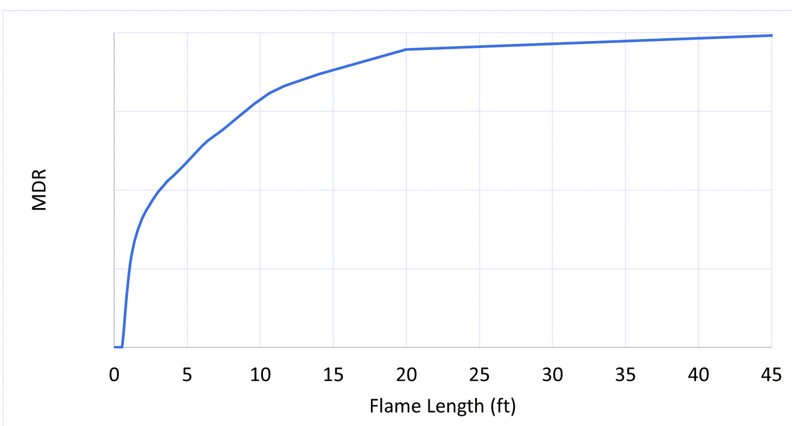


Figure 35. Mean Damage Ratio (MDR) for buildings vs flame length

The estimated mean damage ratio includes minor damages, such as melting and exterior damage, to severe damage, such as structural damage due to heat and fire reaching interior of the building. Depending on the flame length, the probability of each type of damage varies. Figure 36 shows the damage ratio distribution for a 5% mean damage ratio (MDR). There is a spike at total damage on the right and minor damages represented on the left.

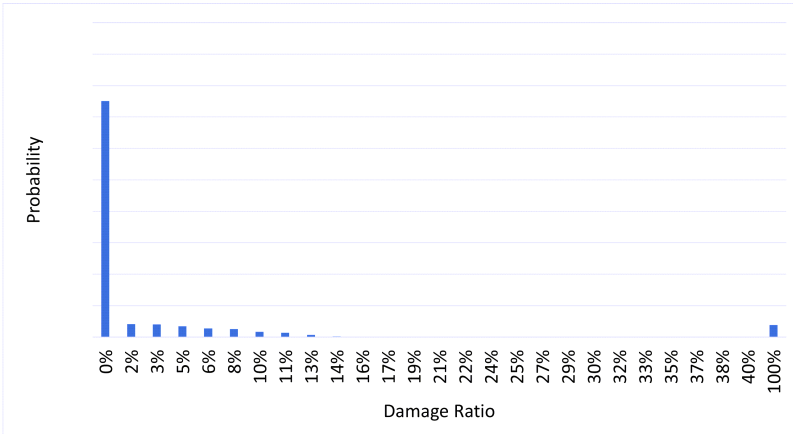


Figure 36. Damage distribution for a 5% MDR

Fire Damage Functions – Contents

Contents inside a building start to be damaged after a fire burns through the building envelope. Given this correlation, contents damage is modeled as a function of building damage.

Smoke Damage Functions – Buildings and Contents

Smoke damage can occur due to deposition of soot and ash on the exterior and interior of the building as well as on contents. The loss is incurred due to the associated cleaning or repainting costs for building surfaces and for replacement of contents damaged beyond repair.

Large Industrial Facilities

Large industrial facilities are treated the same as industrial occupancies. They do not have further dependency on construction class. They are expected to have the same vulnerability as steel or concrete construction industrial occupancy with low-rise height class.

Infrastructure

Most of the infrastructure type exposure is assigned a modifier to relativity based on Verisk's expert judgement since it is not possible to validate each of these assets. In general, the vulnerability of non-combustible and non-heat damageable assets is lower, and the vulnerability of chemically active or easily heat damageable assets is higher.

Time Element Losses, Additional Living Expenses (ALE) and Business Interruption (BI)

In addition to direct economic losses from physical damage to buildings and contents, loss of building functionality due to excessive damage, lack of access, or safety concerns can lead to further monetary losses. Monetary losses that can arise from loss of use are also known as Time Element losses. For residential properties, these losses may be incurred for temporary lodging or relocation expenses and are referred to as Additional Living Expenses (ALE). For other lines of business, such as commercial and industrial, monetary losses incurred from loss of use are referred to as Business Interruption (BI) losses.

Combined Building and Contents Damage Functions for Time Element Loss

The time element loss is calculated as a function of the number of days required to repair or rebuild the structure or replace damaged contents. The number of days required to bring a property back to the usable condition is a function of the extent of both building and contents damage. However, the degree to which both of these types of damage contribute to the overall duration of downtime (measured in days) depends on the severity of the damage. For example, when damage to the building is relatively minor, the majority of downtime is related to re-supplying the contents so that the building regains functionality. However, when building damage is more severe, the time required for extensive repair or reconstruction typically outweighs the time required to replace the damaged contents.

Additional Living Expenses

The Verisk additional living expenses (ALE) damage functions take into account the time that people may need to stay in a hotel or elsewhere while their home is repaired. It also takes into consideration any necessary time taken off work due to their inability to get to their place of employment, or necessary time spent with contractors.

Business Interruption

Downtime, or the number of days before a business can return to full operation, is the primary parameter for estimating business interruption (BI) losses. The methodology used for estimating BI losses, as illustrated schematically in Figure 37, uses an event tree approach, incorporating the latest research and findings from an extensive analysis of claims data (including but not limited to wildfire).

For each damage state, a probability is assigned to two possible outcomes:

- Continued operations
- Cessation of operations at the location

If operations cannot continue at the location, a probability is assigned to whether the company will relocate. These probabilities vary by occupancy. For example, while relocation is feasible for an office, it is not for a hotel. Thus, the two occupancies will take different paths to recovery, and hence will have different downtimes in the event of business interruption.

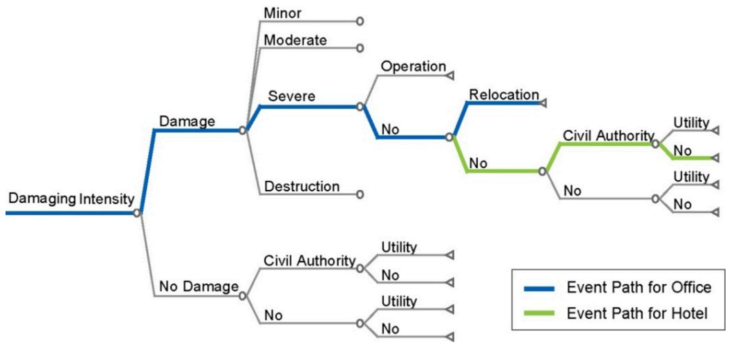


Figure 37. Hypothetical event tree of BI estimation for an office and a hotel

Downtime is calculated for each stage of the damage assessment and recovery process. The first stage is the time before repairs can get underway (pre-repair). Damage must be assessed, repair costs negotiated with contractors, and the building permit obtained. The next stage is the repair time. Some businesses choose to relocate rather than wait for repairs, but relocation takes time as well. Once repairs are completed, revenues may not resume immediately at the pre-disaster level; it may take some time to regain market share, or to rebuild a labor force that may have been dislocated.

In the Verisk model, the estimated number of days needed to restore the business to full operation depends on the level of damage sustained and occupancy class.

Buildings with significant architectural complexity will take longer to repair. Warehouses can be quite large, but repairs are likely to take place quickly because of their architectural simplicity. Hotels are not only typically larger than offices, but can take more time to repair due to the more complex and higher quality of interior finishing.

Some types of businesses, such as hospitals, are more resilient than others and may be able to restart operations before repairs are complete, or they may have had disaster management plans in place, allowing them to relocate some operations quickly. For other businesses, such as hotels, location is so critical that relocation is not an option. Since many parameters (such as building size, complexity, and business resiliency) that are critical to determining business interruption are generally not available for input into the model, occupancy class is used as a proxy to measure these parameters.

Occupancy is also used to estimate the probability that there may be business interruption at a dependent building within the damage footprint—such as the supplier of a necessary manufacturing input—that will exacerbate BI losses at the principal building. Estimation of the impact of damage to the dependent building(s) on the principal building requires knowledge of the location and the degree of interdependence between dependent and principal buildings. Since this level of detailed information is generally not available, logical assumptions are made to estimate the impact of the dependent building(s) on the principal building's downtime. The methodology for estimating BI losses relies in part on loss experience data and in part on expert judgment in the face of limited available exposure information.

Business Interruption for Various Occupancy Classes

The functional relationship between building damage and loss of use is based upon published construction and restoration data along with expert engineering judgment. Figure 38 shows the relationship between repair time, or downtime, and the geometric mean of building and contents damage, for a variety of occupancy classes. Note that the model includes business interruption damage functions for all occupancy types in Touchstone. Touchstone Re users can run business interruption losses for occupancies that belong to the commercial and industrial classes.

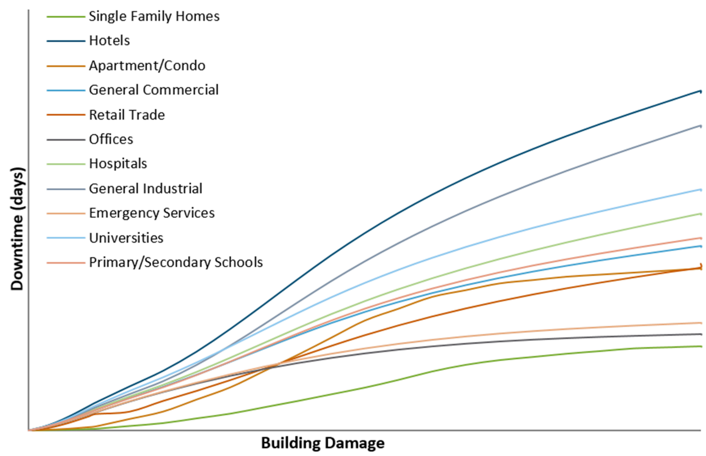


Figure 38. Business interruption damage functions for different occupancy classes

8 Financial Module Overview

Policy terms and conditions are applied to estimate insured losses to create probability distribution of loss. This probability distribution of losses, called an exceedance probability curve, reveals the probability that any given level of loss will be surpassed in a given time period—for example, in the coming year. (The probabilities can also be expressed in terms of return periods. For example, the loss associated with a return period of 20 years has only a 5% chance of being exceeded this year, or in one year out of 20, on average.) Loss probabilities can be provided at any geographic resolution—for the entire insurance industry, for a particular portfolio of buildings, or for an individual property.

The financial components of catastrophe models are developed by statisticians and actuaries with the expertise to analyze the impact of highly complex policy terms for portfolios that may span multiple regions and be exposed to multiple perils.

Verisk's Next Generation Financial Module, first released in Touchstone 2023, introduced a fully probabilistic, transparent, and flexible framework designed to improve how catastrophe risk is financially quantified. The financial module is applied across all perils and regions, including wildfire, to provide more realistic and granular financial loss estimates. This financial modeling architecture enables Verisk model users to more accurately model the losses for single locations, better account for dependencies and correlations in loss accumulation, and more realistically capture the application of complex policy terms.

As a part of the development and release of Verisk's Next Generation Financial Module, considerable information was provided to the market and the public about different financial concepts and how those are handled in the platform.

- Next Generation Financial Modeling for Residential and Small Business Lines describes how financial modeling is done in Touchstone for residential and small business lines. This includes information about loss distributions across perils and coverage types in the financial module framework.
- Modeling Fundamentals: Understanding Uncertainty describes how uncertainty is accounted for in the Verisk financial module of Touchstone. Primary uncertainty are data quality, data completeness, and incomplete scientific understanding of the natural phenomenon being modeled. Secondary uncertainty is the uncertainty associated with the damage and loss estimation should a given event occur.
- Next Generation Modeling: Loss Accumulation describes how loss accumulation works in the Verisk financial module and its relation to uncertainty. Modeling the dependencies in loss accumulation is a component of Verisk's overall strategy of propagating and reporting all modeled uncertainty, due to the central role that loss accumulation plays in a catastrophe modeling platform.
- The remaining articles are theoretical documents exploring fast and accurate algorithms for adding together probability distributions for many correlated exposures.
- Bivariate Copula Trees for Gross Loss Aggregation with Positively Dependent Risks
- Geospatial Metrics for Insurance Risk Concentration and Diversification
- Direct and Hierarchical Models for Aggregating Spatially Dependent Catastrophe Risks

- [Split-Atom Convolution for Probabilistic Aggregation of Catastrophe Losses]
- [Using Intraclass Correlation Coefficients to Quantify Spatial Variability of Catastrophe Model]

8.1 Insured Loss Calculation

In this component of the Verisk Wildfire Model for the United States, ground-up damage is translated into financial loss. Insured losses are calculated by applying policy conditions to the total damage estimates resulting from the damage estimation module. Policy conditions may include franchise deductibles, coverage limits, loss triggers and risk-specific reinsurance terms.

8.2 Aggregating Losses Probabilistically

Post-disaster surveys and actual claims data reveal an inherent variability in wildfire damage. Loss estimates generated by the Verisk Wildfire Model for the United States capture this variability by accounting for both primary and secondary uncertainty. Primary uncertainty derives from the uncertainty associated with the stochastic event generation process, while secondary uncertainty describes the uncertainty in damage resulting from a given event. This secondary uncertainty captures the uncertainty in the local intensity estimation and in vulnerability of exposures.

The uncertainty in the local intensity of the hazard can be attributed to unmodeled phenomena, local site factors, as well as the spatial resolution of calculated intensity. The inherent randomness in building ignition constitutes the primary source of building damage uncertainty. Although a building is as strong as its weakest characteristic against fire ignition, given the same level of modeled intensity, a building will likely survive if ignition sources do not accumulate around the vulnerable area.

The model calculates damage using damage functions that provide, for a given event intensity, a mean damage ratio (MDR) and a probability distribution around the mean that captures the variability in damage. For the Verisk Wildfire Model for the United States, a distribution combined with empirically derived probabilities of 0% and 100% damage levels is used to model the uncertainty around the mean damage.

The damage functions are used to produce, for each event, a distribution of ground-up losses by location and coverage. Limits, deductibles and reinsurance are applied in the financial module to the ground-up loss distribution to produce gross and net loss estimates. Note that insured losses can accumulate even if the mean damage ratio is below the deductible, because some structures are damaged above the mean damage ratio and the deductible. The distributions are applicable to the analysis of a single exposure and in this case usually have a high degree of uncertainty. The individual distributions are combined to obtain the portfolio distribution, where the uncertainty is lower.

The financial model aggregates losses probabilistically at various levels. Ground-up, coverage-level damage distributions are typically aggregated parametrically. However, after location and policy terms are applied, the distributions cannot be represented parametrically. Further aggregation is achieved statistically using numerical algorithms.

The financial module within Verisk's software applications supports a wide variety of location, policy and reinsurance conditions. Location terms can include limits and deductibles by site or by coverage. Supported policy terms include blanket and excess layers, minimum and maximum deductibles, and sublimits. Reinsurance terms include facultative certificates and various types of risk-specific and aggregate treaties with occurrence and aggregate limits.

8.3 Demand Surge

Evidence from major catastrophic events in past years suggests that after a major event, increased demand for materials and services to repair and rebuild damaged property can put pressure on prices, resulting in temporary inflation. This phenomenon is often referred to as demand surge and it results in increased losses to insurers.

Demand surge is the sudden, and usually temporary, increase in labor and materials costs driven by high demand following a catastrophe that has caused widespread property damage. An affected area might also experience increased demand for services and resources (e.g., transportation, equipment, and storage). The greater and more widespread the damage, the greater the resulting demand surge and insured losses.

Scarce resources can also increase the time required to repair or rebuild. Such delays may affect business interruption losses and living expenses. Infrastructure damage, delayed building-permit processes, and a shortage of available building inspectors also increase time-element loss. These factors can result in insured losses that exceed expectations for a particular event and portfolio.

Verisk has related the amount of demand surge in a particular event to the amount of total industry-wide insurable losses from the event. The factor is dependent on coverage. A table incorporated into the software contains the corresponding demand surge factors, by coverage, for different levels of industry-wide losses. For a given event, the demand surge factors by coverage are applied to the corresponding ground-up losses, based on the industry-wide loss for that event. Policy conditions are then applied probabilistically. The sum of these losses by coverage yields the total event loss with demand surge included.

Demand surge effects are expected to be small when included in a wildfire analysis. Very few individual stochastic fire events meet the default threshhold for adding demand surge, and the number does not greatly increase when temporal aggregation is considered. Simply put, wildfires are more of a frequency issue than a severity issue.

Demand surge does not have built-in regional differences regarding the threshhold or factors applied to losses. There will be regional effects of demand surge because it occurs where the catastrophes occur. For example, a desert region would be expected to experience less effect from demand surge applied to wildfires than a WUI region would because the events where there is ample fuel will be larger and more likely to meet or exceed the threshhold.

9 Model Validation

Verisk catastrophe models are validated. Every component is verified against data obtained from historical events. In addition, when all the components come together, the final model output is expected to be consistent with basic physical expectations of the underlying hazard, and unbiased when tested against both historical and real-time information.

9.1 Historical Event Losses

Estimating the losses for the Historical Event Sets involved estimating the burn scar sizes for these events more accurately than available through available data sets, and then estimating the historical losses.

Estimating Burn Scars of Historical Wildfire Events

To evaluate modeled losses, Verisk scientists estimated the burn scar areas for historical fires by processing data from the Monitoring Trends in Burn Severity (MTBS) data set for most of the events; for more recent events, Verisk scientists used satellite images to create additional burn scars following the MTBS methodology.

To do this, Verisk scientists computed the difference between the pre and post fire normalized burn ratio (dNBR) computed from the Landsat satellite data near infrared (NIR) and Shortwave Infrared (SWIR) bands.

Areas with dNBR less than 0.1 were classified as unburned (or burned in prior wildfire events) and removed from the identified extent of the burn scar. Areas with a dNBR above 0.1 were classified as burned and included in the burn scar.

Since dNBR is a measure of fire severity, and strictly a measure of intensity, Verisk used an algorithm to study the burned areas and fire intensity. The algorithm looks at what kind of fuel were in each spot and how fast the wind was blowing during the fire.

This intensity of the fire (i.e. flame length) is used to calculate the modeled losses referred to in the following sections.

Verisk scientists used Geospatial Multi-Agency Coordination (GeoMAC) fire perimeters to verify the extent and location of burn scars (see Figure 39).

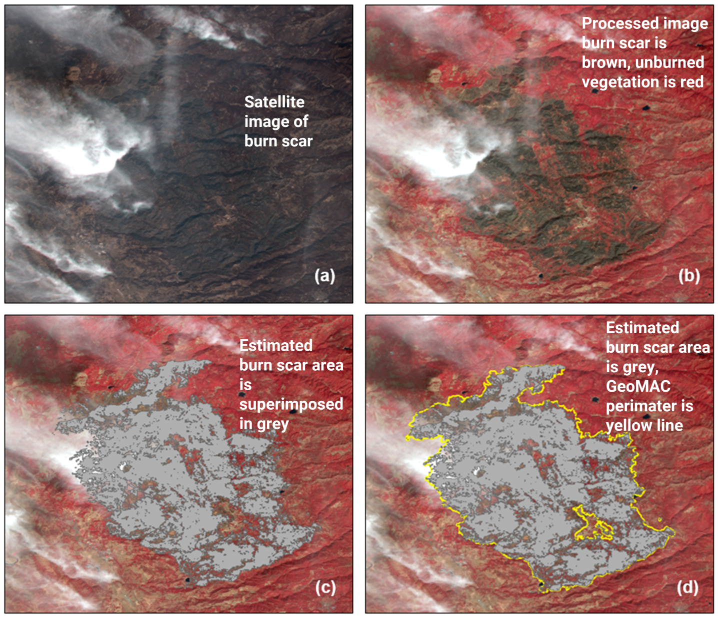


Figure 39. Landsat 8 images of the 2015 Butte fire (California) burn scar captured on January 12, 2016 , and estimated burn scar area.

Creating Target Losses for the Historical Event Set

To evaluate modeled industry-level losses for fires in the Historical Event Set, reported losses must be adjusted to 2022 values. Capturing the change in exposure into previously unoccupied wildland gets less reliable with older events. Therefore:

- for events between the 1991 Oakland Hills fire to the 2015 Valley fire, adjusted losses are 70% of the total replacement values within burn scar in Verisk Industry Exposure Database (IED) vintage 2022 (approximately based on the ratio of total loss reported to total replacement value for recent wildfire loss events);
- for events that occurred more recently (2017-2022), reported losses are adjusted to account for inflation, shifts in median home values, and changes in the number of housing units by adjusting Verisk Property Claim Services (PCS) values.

Comparison of Modeled Losses to the Target Losses

The broad assumption of 70%, can lead to a very high losses compared to reported PCS losses. Figure 40 shows the modeled losses vs target losses for the events in the Historical Event Set. In Figure 40, the grey horizontal lines indicate the range of reported losses from different sources. The blue circles on the grey lines indicate the trended loss values on horizontal axis, and modeled loss on vertical axis on a log-log scale. Overall, there is a good agreement between the targets and modeled losses, however, the modeled losses are typically lower than target. The modeled losses represent damage to residential, mobile home, commercial, and automobile lines of business, as well as coverages of building, contents and business interruption or time element losses. They do not include demand surge, nor extra expenses such as debris removal, additional living expenses (ALE), and guaranteed replacement cost (GRC). These factors can contribute a significant portion of the reported loss (up to 20%) and can vary significantly from event to event based on location, frequency of events and magnitude. (For the Nuns fire, PCS did not report loss data separately but included it with the Tubbs fire; therefore, the Nuns and Tubbs fires are combined in the comparison.)

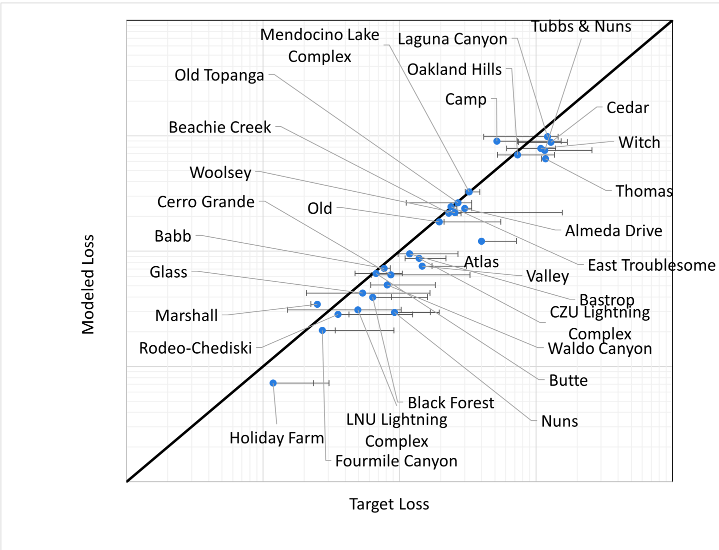


Figure 40. Verisk modeled loss validated using reported ranges of losses for the 31 historical events

Loss Comparison by Lines of Business (LOB)

Figure 41 shows loss breakdown by lines of business for reported and modeled losses; data were provided by Verisk Property Claim Services (PCS) for historical events that occurred after 1999.

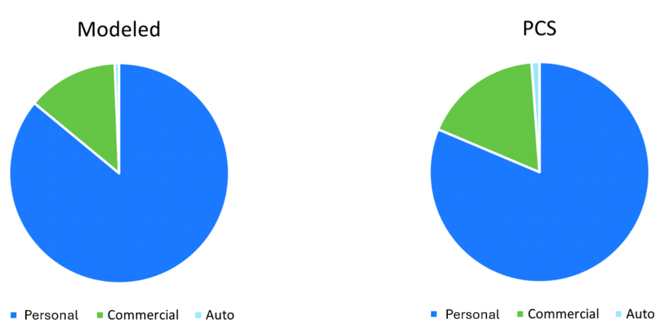


Figure 41. Comparison of loss breakdown by lines of business between reported and Verisk modeled losses

Loss Comparison by Coverage

Loss contribution by coverage is only available in some of the claims data studied (~40%). The available claims loss data by coverage compares well with the model's total historical loss by coverage as shown in the Figure 42.

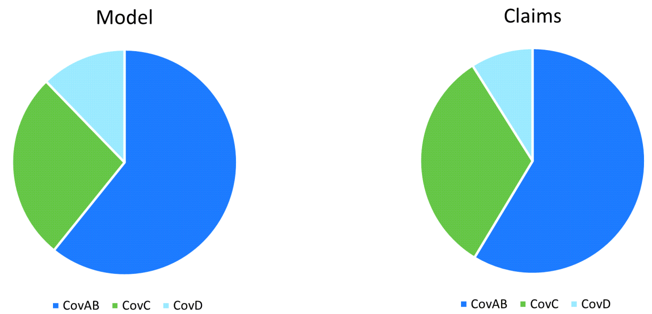


Figure 42. Loss comparison by coverage

Loss Validation by Company

Figure 43 shows that claims data and modeled losses show reasonable agreement – the data shown are for recent historical events using exposures and claims data from four companies. It should be noted that the model losses exclude demand surge, whereas demand surge may be included in the company claims.

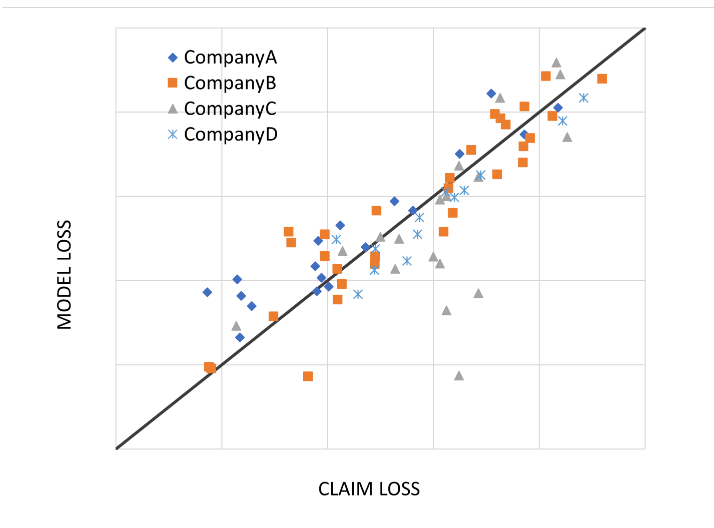


Figure 43. Company loss comparison

Smoke Contribution to Loss

Smoke loss was calculated for the 31 historical events using the smoke intensity and smoke damage functions described in the Damage Estimation Chapter. The smoke contribution varies from negligible to up to 17% based on direction of wind towards or away from exposure; the average smoke contribution was about 2.5%, however, a reported loss from PCS does not typically provide the breakdown between fire and smoke for an event. When reported, the range of smoke contribution to total loss in claims from companies varied similarly from 1% to 13%.

Benchmarking Stochastic Losses

Verisk researchers benchmarked the predicted frequency of losses resulting from simulated wildfires in the stochastic catalog. Verisk researchers validate the reasonableness of modeled frequencies against actual loss experience; however, due to the unique characteristics of wildfires, historical loss data are often incomplete and unreliable. Furthermore, the change in exposure can be dramatic. Figure 44 shows an example of dramatic exposure change within the perimeter of an older fire. This unnamed wildfire[15] likely did not cause any significant damage to buildings and other properties. The exposure changed dramatically between May 1993 and May 2022.

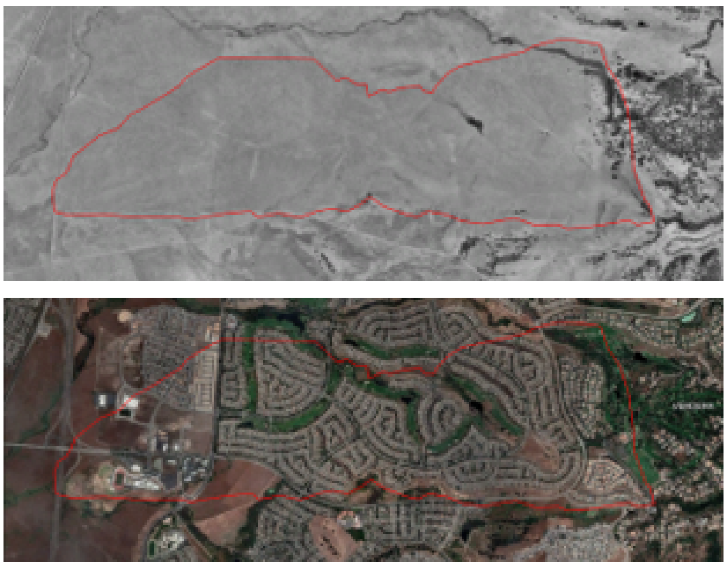


Figure 44. Satellite images from May 1993 (top) and May 2022 (bottom) and the perimeter of an unnamed 1992 wildfire in Northern California, showing dramatic exposure change within the fire perimeter.

California

California had two consecutive high loss years in 2017 and 2018 with events such as Tubbs, Atlas, Nuns and Camp. Figure 45 illustrates the model EP curve in light blue color in California for both aggregate and occurrance losses. The horizontal red and dark blue lines show trended reported losses from Verisk PCS for Tubbs, Atlas, and Nuns fires in 2017 and Camp fire in 2018).

[15] fire id: ca3885512126919920820 in MTBS database

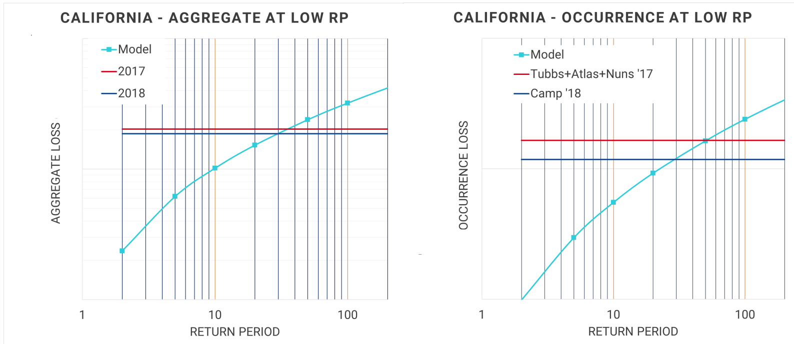


Figure 45. California exceedance probability curves for occurrence and aggregate modeled losses for 10,000-year stochastic catalog compared with 2017 and 2018 values (Tubbs, Atlas and Nuns fires in 2017, and Camp fire in 2018).

Considering the large area and regional variations within the state of California, the view of risk is often assessed individually in northern and southern California. This geographical split is indicated for clarity in Figure 46, which illustrates EP curves with near-climate losses in light blue and historical climate losses in dark blue, shown separately for Northern California and Southern California.

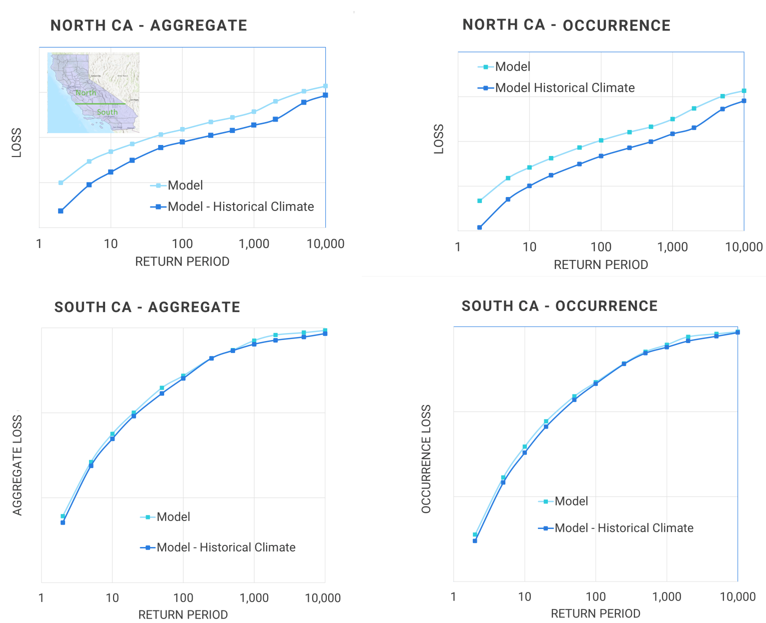


Figure 46. Aggregate and occurrence losses in northern and southern California from the model, and the model with no climate trending (historical climate)

10 Accounting for Climate Change Overview

Verisk's atmospheric peril models are designed to estimate risk of loss to insured properties in the ***near-present climate***. Where significant shifts in the distribution of a hazard have occurred over the course of the instrumental record, and where the shifts are deemed highly likely to persist given the latest understanding of the processes by which climate change interacts with that hazard, Verisk scientists represent such changes in the modeled event sets. Generally, model development teams continuously evaluate models against new data as they become available, as well as in light of ongoing developments in science. The focus on near-present climate is thus a natural part of Verisk's ongoing processes of model vetting and update scoping. Representation of any changes in the underlying climatological distributions of modeled hazards that may have occurred is also an extension of the basic catastrophe risk modeling principle that risk estimates should be locally unbiased.

In the case of wildfire, the state of scientific understanding strongly supports the explanation that climatic trends in weather variables are key to trends in the wildfire peril in the Western United States (e.g., Abatzoglou & Williams, 2016; Westerling, 2016; Williams & Abatzoglou, 2016; McKenzie & Littell, 2017; Wehner et al., 2017; Littell, 2018; Littell et al., 2018; Williams et al., 2019; Goss et al., 2020; Keeley et al., 2021; Dong et al., 2022; Jones et al., 2022; Shi & Touge, 2022, 2023; Abatzoglou et al., 2023). Over the course of the development of the hazard model for the Wildfire Model for the United States, Verisk scientists paid particular attention to recent, ongoing trends in temperature extremes (especially summer daily maximum temperature), precipitation, atmospheric vapor pressure deficit (Vapor Pressure Deficit (VPD) especially during the fire seasons), and the Self-calibrating Palmer Drought Severity Index (scPDSI). Identification of the driving weather variables for wildfire, and their trends, was carried out independently for each ecoregion in the 13-state model domain over the period of record.

10.1 Historical Trends

Verisk scientists extensively researched the historical trends associated with wildfire activity and the weather variables related to wildfire activity in the 13-state model domain, through internal analyses and scientific literature review.[16] Three aspects of the relationship between annual wildfire area and weather/climate were found to be critical to the representation of wildfire responses to climate change in the model domain: (1) the geographical variation of the impact that weather has on the interannual variation in wildfire (2) the increase or decrease in total annual wildfire burn scar area over the past several decades in many ecoregions of the model domain, and (3) the trends, over the past several decades, in weather variables in some ecoregions in which the weather variables have an important relationship with burn scar area.

[16] e.g., Abatzoglou & Williams, 2016; Westerling, 2016; Williams & Abatzoglou, 2016; McKenzie & Littell, 2017; Wehner et al., 2017; Littell, 2018; Littell et al., 2018; Williams et al., 2019; Jones et al., 2022; Shi & Touge, 2022, 2023

Wildfire Annual Total Burn Scar Area

The trends in annual total wildfire burn scar area varied geographically, in both strength and direction, during the historical period 1984-2022[17] according to the Theil-Sen estimator (see Table 8). Within the model domain, 19 ecoregions had statistically highly significant positive trends in annual total burn scar area during the 39-year historical period in the Verisk Historical Event Set. Several of those positive trends were strong and in Ecoregions with significant insurable exposure, including the Sierra Nevada (ecoregion 5) and Klamath Mountains/California High North Coast Range (ecoregion 78) in northern California. Two of the ecoregions had statistically highly significant negative trends in annual total burn scar area: the Central California Valley (ecoregion 7) in California and South Central Plains (ecoregion 35) in eastern Texas and southeastern Oklahoma. Five other ecoregions had moderately significant increasing trends. Positive trends (slopes) indicate increasing wildfire burn scar area over time since 1984.

Trends were estimated using the Theil-Sen estimator (the median of the slopes of all the lines through all the pairs of points in the time series), which is relatively insensitive to outliers. On the other hand, wildfire outliers (on the large side) have potential to lead to catastrophic losses and are therefore often the most important events in the Western United States.

Table 8. Trends in total annual burn scar area over the historical period 1984-2022, by ecoregion

Ecoregion number and name		Slope
1	Coast Range	n.d.
2	Puget Lowland	n.d.
3	Willamette Valley	n.d.
4	**Cascades**	**positive**
5	**Sierra Nevada**	**positive**
6	Central California Foothills and Coastal Mountains	n.d.
7	**Central California Valley**	**negative**
8	Southern California Mountains	n.d.
9	**Eastern Cascade Slopes and Foothills**	**positive**
10	**Columbia Plateau**	**positive**
11	**Blue Mountains**	**positive**
12	Snake River Plain	n.d.
13	Central Basin and Range	n.d.
14	Mojave Basin and Range	n.d.
15	**Northern Rockies**	**positive**
16	Idaho Batholith	positive
17	**Middle Rockies**	**positive**
18	Wyoming Basin	n.d.

[17] The annual total wildfire burn scar area in the Verisk Historical Event Set is for burn scars of at least 50 acres.

Ecoregion number and name		Slope
19	**Wasatch and Uinta Mountains**	**positive**
20	Colorado Plateaus	n.d.
21	**Southern Rockies**	**positive**
22	Arizona/New Mexico Plateau	positive
23	**Arizona/New Mexico Mountains**	**positive**
24	Chihuahuan Deserts	n.d.
25	High Plains	positive
26	**Southwestern Tablelands**	**positive**
27	**Central Great Plains**	**positive**
29	**Cross Timbers**	**positive**
30	**Edwards Plateau**	**positive**
31	**Southern Texas Plains**	**positive**
32	**Texas Blackland Prairies**	**positive**
33	East Central Texas Plains	n.d.
34	Western Gulf Coastal Plain	n.d.
35	**South Central Plains**	**negative**
36	Ouachita Mountains	n.d.
40	**Central Irregular Plains**	**positive**
41	Canadian Rockies	n.d.
42	Northwestern Glaciated Plains	n.d.
43	Northwestern Great Plains	positive
77	**North Cascades**	**positive**
78	**Klamath Mtns/California High North Coast Range**	**positive**
79	Madrean Archipelago	positive
80	Northern Basin and Range	n.d.
81	Sonoran Basin and Range	n.d.
85	Southern California/Northern Baja Coast	n.d.

Vapor pressure deficit

Several previous studies (e.g., Williams et al., 2019) and Verisk research indicate that Vapor Pressure Deficit (VPD)[18] averaged over several periods (e.g., June-August, May-October, March-October, etc.) is strongly positively related to wildfire area in many regions of the model domain, especially in forested ecosystems with strong seasonal patterns in weather (e.g., cool winters and warm summers) and wildfire activity (e.g., wildfire activity largely confined to the warm

[18] Vapor pressure deficit (VPD) is the difference between saturation vapor pressure (Saturation Vapor Pressure (SVP): the amount of water vapor the atmosphere can hold when it is water-saturated) and actual vapor pressure (AVP. the actual vapor pressure or actual amount of water vapor in the atmosphere) (VPD = SVP – AVP). Saturation vapor pressure is strongly (exponentially) and positively related to air temperature. When VPD is zero, the relative humidity is 100%]

summer periods). This is important to the Verisk Wildfire Model for the United States because VPD has been increasing significantly during the past 50 years in several model ecoregions, and many of the forests in the model domain are sensitive to summer VPD. These recent trends in VPD indicate that wildfire area may increase to the extent that VPD continues to increase in the near-present climate. See section Seasonal Vapor Pressure Deficit (VPD) variables.

Summer daily maximum air temperature

Trend analyses by Verisk scientists indicated summer (June to August) average daily maximum air temperature (T_{max}) increased in all 45 model ecoregions during the period 1970-2021. The summer T_{max} increased by more than 0.5 °C over that period in all but four ecoregions, exceeding 1.0 °C in nearly all cases and approaching 2.0 °C in many ecoregions. In four ecoregions T_{max} increased by less than 0.5 °C over that period, including the two ecoregions with the majority of insurable exposure in Southern California: the Southern California Mountains and the Southern California/Northern Baja Coast ecoregions.

Verisk scientists determined that T_{max} is associated with burned area in five of the ecoregions, and built those ecoregion-specific wildfire-weather models with summer T_{max} as an input variable. In all five cases, total annual wildfire burn scar area was positively related to summer T_{max}. This implies that wildfire area might increase if summer T_{max} is increasing as a component of climate change, and vice versa. In four of these wildfire-weather model cases, however, the net effect of climate change on wildfire area was found to depend on multiple factors, not just summer T_{max}, and therefore summer T_{max} was one of multiple weather variable inputs to the ecoregion-specific wildfire-weather models.

Precipitation

Precipitation during the previous year can be important to wildfire area in water-limited ecosystems by enhancing plant growth and therefore increasing the amount of potential fuel. Verisk scientists found that in seven ecoregions, wildfire area was ***positively*** related to the previous year's total precipitation. This implies that over multi-year periods wildfire area might increase if total annual ecoregion precipitation is increasing as a component of climate change, and vice versa. In all seven of these ecoregions, however, the previous year's total annual precipitation was found to be one of multiple weather variables associated with wildfire area; in these ecosystems, the net effect of climate change depends on multiple factors, not just total annual precipitation.

Precipitation during the current summer (June to August) – as contrasted with total annual precipitation during the previous year – was associated with wildfire extent in six ecoregions. In all six, wildfire area was ***negatively*** related to summer precipitation during that same year. This negative relationship between summer precipitation and wildfire area was earlier observed by Littell et al. (2009) and is most easily understood as a consequence of the amount of water in fuel during the summer fire season. Fuel with higher water content is more difficult to ignite, and if ignited, burns with less intensity than a comparable but drier fuel.

Self-Calibrating Palmer Drought Severity Index

Wildfire area in the Western United States has been related to drought indices in previously published research (e.g., Littell et al., 2009), and Verisk research found the same for recent decades in the model domain. Summer (June-August) Self-calibrating Palmer Drought Severity Index (scPDSI) is associated with wildfire extent in four of the model's ecoregions. In all four ecoregions, a smaller (more negative) value of the summer sc-PDSI (which indicates dryness[19]) was positively related to total annual wildfire burn scar area. This indicates the positive effect of dry summer fuel on wildfire activity in these ecoregions, probably related to high summer VPD and/or relatively limited summer precipitation, although the sc-PDSI integrates multiple ecosystem water balance components (precipitation, runoff, recharge, potential evapotranspiration, actual evapotranspiration, and others) over a longer time period (i.e., the index involves longer term lags in relative moisture conditions than just immediate summer values). The index is also related to multi-decadal history of water balance in different ecosystems/ecoregions rather than being a simple physical measurement of a contemporary state variable such as air temperature (see Welles et al., 2004). See section Seasonal Self-calibrating Palmer Drought Severity Index (scPDSI) Variables.

10.2 Model and Catalog Development

Catalog development is explained in Event Generation Overview section of the model documentation. For detailed information refer to this section in the Hazard Module.

10.3 Model Validation

The Verisk Wildfire Model for the United States was built to reflect the wildfire peril within the context of the near-present climate; that is, the model reflects present risk rather than summarizing history because wildfire history in the western United States does not reflect present risk, in part because of ongoing climatic changes. As such, stochastic model outcomes cannot be directly validated by comparisons to historical data because of the strong trends in both weather and wildfire activity in the historical period that may continue through the near-present climate period. That is, the modeled peril reflects the expected climatologies across the model domain during the 2025-2029 period, and these are expected to differ from those in the (recent) historical period.

Correlations in Annual Total Burn Scar Area between Ecoregions

Interannual variation in total annual burn scar area is positively correlated between some ecoregions, negatively correlated between others, and uncorrelated for still others. Positive correlations in total annual burn scar area can be expected among ecoregions that (1) are in

[19] For the self-calibrating Palmer Drought Severity Index, more positive values indicate more moisture and more negative values indicate more drought

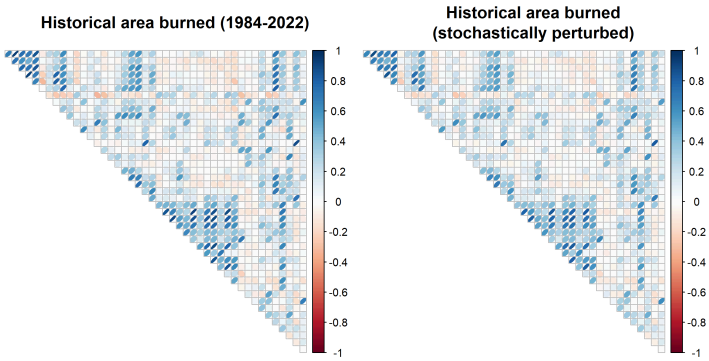
close geographic proximity and therefore experience similar weather, (2) have similar vegetation and ecological characteristics, and (3) have similar wildfire-weather relationships. In ecoregions with positive correlations in interannual variation in annual total burn scar areas, interannual variation in insured losses might also be correlated. This can be an important consideration in diversification of risk.

Figure 47 shows the correlations between interannual variation in each ecoregions' annual total burn scar areas in the Verisk historical (1984–2022) wildfire database (n = 39 historical years) and that same Verisk historical area data stochastically perturbed (n = 100,000 stochastic years). Figure 48 shows the correlations between ecoregions' annual total burn scar areas in the same Verisk historical wildfire database (n = 39 historical years) and in the stochastic catalog of annual total burn scar area reflective of the near-present climate (n = 100,000 stochastic years).

In Figure 47 and Figure 48, positive correlations in interannual variation in wildfire area between ecoregions are in blue and negative correlations are in red, according to the scale shown to the right of each panel; also, the narrower an ellipse, the stronger the positive or negative correlation. The columns and rows reflect each ecoregion in the model domain arranged by ecoregion number. Consecutively numbered ecoregions tend to be near each other, and therefore clusters in the figures sometimes correspond to geographic clustering, but that is not always so.

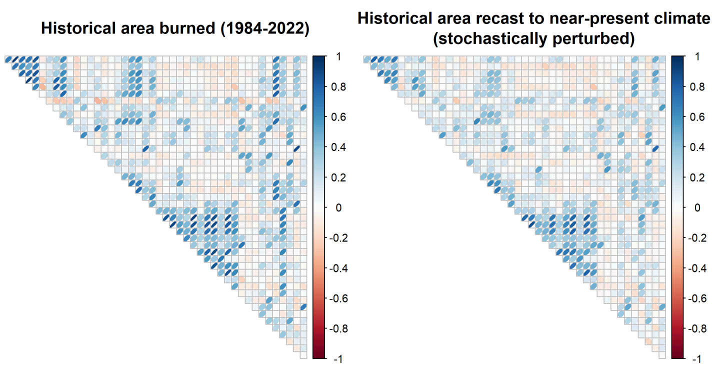
The modeling process of stochastically perturbing the ecoregion-based annual total burn scar areas reflective of the near-present climate principally retained the historical correlations among ecoregions – as illustrated by a comparison of the left and right panels in Figure 48. This comparison shows that the process used by Verisk to stochastically perturb historical wildfire area data retains geographic correlations in the underlying input data.

It is key to note that some of the historical correlation strengths (positive and negative) weakened to a small degree in the 100,000-year catalog of burn scar area in the Verisk Wildfire Model for the United States as a result of recasting the historical fire data into the context of the near-present climate. This was expected, and due at least in large part to differences in projected climatic changes between ecoregions (i.e., differences in climatic change trends in different regions) and to differences in the wildfire-weather relationships in different ecoregions. Nonetheless, the groupings of positive correlations, negative correlations, and lack of correlation between ecoregions in the 39-year historical database was broadly retained in the near-present climate-based recast of historical burn scar data and the resulting 100,000-year stochastic catalog of total annual burn scar areas.



The rows and columns represent each of the model's ecoregions. Positive correlations between ecoregions are in blue and negative correlations are in red. The 'narrowness' of each ellipse is related to strength of correlation (narrow means strong correlation), either positive or negative.

Figure 47. Correlations between ecoregions' annual total burn scar areas in the Verisk historical (1984–2022) wildfire database (n = 39 historical years), and in the historical area data stochastically perturbed (n = 100,000 stochastic years)



Details are the same as previous figure. The left panels in the two figures are identical for uniform comparison purposes.

Figure 48. Correlations between ecoregions' annual total burn scar areas in the Verisk historical (1984–2022) wildfire database (n = 39 historical years), and in the stochastic catalog of annual total burn scar area in the Verisk Wildfire Model for the United States reflecting the near-present climate (n = 100,000 stochastic years)

Summary

There are strong historical relationships between climate and wildfire burn scar area in many parts of the Western United States. Moreover, there is good understanding of the mechanisms involved that are associated with both amount of fuel available to burn during a year or season and its relative flammability. The latter issue is related to fuel moisture content, which in turn is related to seasonal weather. There also have been strong trends in some climate variables that are known to affect wildfire activity (i.e., burn scar area) in parts of the Western United States. In other parts of the Western United States, however, there are only weak relationships between climate and wildfire burn scar area and/or the climate variables related to wildfire area have not changed or changed only marginally in recent decades. That is, both relationships between climate and wildfire activity, and recent trends in climate variables that affect wildfire activity, are geographically disparate. As a result, changes in expected effects of the near-present climate on wildfire area relative to historical activity vary significantly as represented by the Verisk model across the 13-state domain (Figure 49).

Many of the ecoregions experiencing increased annual burn scar area in response to the near-present climate contain high-elevation forested ecosystems that are sensitive to dry summers during which fuel becomes especially flammable. Some areas with decreases in modeled wildfire activity relative to the historical record are water-limited arid/desert areas growing less potential fuel under the current unprecedented drying. Ecoregions with small changes in annual total burn scar area from the historical record either contain ecosystems that are relatively insensitive to climate or have fire activity driven mainly by climate variables that have not significantly changed in recent decades, or both.

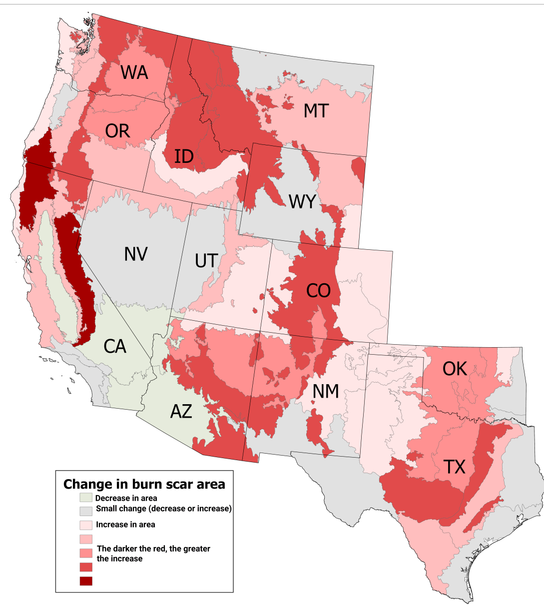


Figure 49. Relative change in average annual total burn scar area in each model ecoregion for the near-present climate relative to the historical period 1984–2020.
The near-present climate in the context of this model is ~2025-2029.

11 Modeling in Touchstone

11.1 User Input

As mentioned in the Verisk Catastrophe Modeling Framework, exposure data and policy conditions are information provided by the insurers. These details must be included in the input for each location to enable analysis at that location.

Table 9. Inputs by Insurers

Data Input	Description
Exposure Data	Information about the property, replacement value and physical characteristics, is provided by the insurer.
Policy Conditions	Policy terms and conditions are provided by the insurers

UNICEDE®

UNICEDE is managed and maintained by Verisk Analytics and is a globally accepted industry data format to standardize insurance data exchange. The format is used by primary insurers, reinsurers, and reinsurance intermediaries with Touchstone, Touchstone Re, and CATRADER applications. For more information visit https://unicede.air-worldwide.com/.

Exposure Data

Verisk's risk modeling platform, Touchstone, requires insurers to provide the primary risk characteristics which are described below as part of their exposure data.

1. **Location of the Building:** A complete address of the building including number, street name, city, ZIP code and state results in more accurate estimation of the loss.
2. **Age of the Building:** The year of construction, which can influence the building's vulnerability to hazards due to changes in building codes and construction practices over time.
3. **Height of the Building:** The number of stories or overall height, which can impact the building's exposure to different types of hazards (e.g., wind load for tall buildings in hurricanes).
4. **Construction Type:** The materials and methods used in constructing the building (e.g., wood frame, masonry, steel), which affect its resilience to various hazards.
5. **Occupancy Type:** The use of the building (e.g., residential, commercial, industrial), which can influence both the vulnerability and potential economic impact of a hazard event.

These characteristics are critical in determining the building's vulnerability to different types of natural disasters and are key inputs in catastrophe modeling for risk assessment.

Secondary risk characteristics (SRCs) are optional inputs. Touchstone assumes unknown input for all SRCs unless the insurer choses the correct input for each category.

ZIP Codes in the United States

Accurate model output is highly dependent on the correct location information. ZIP code is one of the supported geographical resolutions by Touchstone. During analysis in Touchstone if Disaggregation is selected, the aggregate County, City or Zip codes exposures are automatically disaggregated to a 1-km grid, based on industry exposure weights, by line of business.

The Verisk ZIP Code update is a biennial update. Touchstone 2024 includes a ZIP All database vintage April 2022. Touchstone 2025 includes a ZIP All database with vintage April 2024.

Lines of Business

At Verisk, exposures are organized into Lines of Business (LOBs) which are specific to country and peril type. The following lines of business are included in the Verisk Wildfire Model for the United States:

- Residential: Building, contents, and time
- Commercial/Industrial: Building, contents, and time
- Mobile home: Building, contents, and time
- Automobile
- Industrial

When exporting loss results users must map user-specified lines of business (LOBs) in the data to Touchstone-supported industry LOBs.

Policy Conditions

Insured losses are calculated by applying policy conditions to the total damage estimates resulting from the damage estimation module. Policy conditions may include franchise deductibles, coverage limits, loss triggers, and risk-specific reinsurance terms.

Estimates of physical damage to buildings and contents are translated into estimates of monetary loss. These, in turn, are translated into insured losses by applying insurance policy conditions to the total damage estimates. Probabilities are assigned to each level of loss.

The model's damage functions are developed by highly trained structural engineers. They incorporate published research, the results of laboratory testing, the findings from on-site damage surveys, as well as detailed Claims Data provided by insurance companies.

Policy conditions are inputs from the insurer and captures information about the policy terms and conditions. Touchstone will treat locations with unknown (blank) deductibles as if they have a zero dollar deductible.

11.2 Analysis Options in Touchstone

The analysis options available in Touchstone are provided in Form G-8: Wildfire Catastrophe Model Settings and Input.

11.3 List of Common Model Outputs

Table 10. List of Common Model Outputs

Output	Description
Average Annual Loss	Average annual losses (AAL) by line of business, by coverage, by geographical area or by user defined category. "Average loss" is the long-term average loss, on either an aggregate or occurrence basis. It is calculated by using either the aggregate total losses or maximum occurrence losses for all the simulated years and then dividing by the number of years in the simulation.
Exceedance Probability (EP) Curve	Exceedance probability represents the probability that a certain level of loss or hazard event will be exceeded in a given time period, usually one year. It is often expressed as a percentage or a fraction. The EP curve is a ranking of event losses and is used to quantify a complete risk profile. In general: Exceedance probability of the nth highest loss = n/ [years in simulation] **Example:** An Average Exceedance Probability (AEP) of 1% for a $1 million loss indicates there is a 1% chance that a loss of $1 million or more will occur in any given year.
Loss Return Period	The return period is the inverse of the annual probability of occurrence of an event. For example, a return period of 100 years means that there is a 1% chance (1/100) of an event of that magnitude or greater occurring in any given year. Loss Return Period = 1/(Exceedance Probability) **Example 1:** A 100-year wildfire means there is a 1% probability in any given year that a wildfire of certain magnitude will occur. **Example 2:** in terms of insurance claims, a return period of 200 years for a $1 billion loss indicates there is a 0.5% chance of experiencing a loss of at least $1 billion in any given year.
Occurrence Loss	An annual occurrence loss is the largest loss caused by a single simulated event in a given year.
Aggregate Loss	An annual aggregate loss is the sum of the losses caused by all simulated events in a given single year
Ground Up Loss	Ground-up loss is the total amount of loss that is covered by an insurance policy. Ground-up loss does not include deductibles paid by the insured, nor does it include liabilities ceded to a reinsurance company.
Gross Loss	The amount of a ceding company's loss irrespective of any reinsurance recoveries due.

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Output	Description
Tail Value at Risk (TVaR)	TVaR is a quantification of the shape of your EP distribution beyond a certain threshold. It is an average of all simulated losses beyond a specified threshold. This is also a direct output from Touchstone. TVaR can be used to compare the relative risk between two exposure portfolios. In general, a portfolio with a bigger TVAR value is riskier. Further, the TVaR value can be used as a basis for portfolio optimization. Mitigating the TVaR value by eliminating certain contracts or policies that contribute disproportionally to your total TVaR value can help to lower your TVaR as well as the AAL for the entire portfolio. **Example:** if the losses exceed the 95th percentile threshold, what would be the expected average loss.
Event Footprint	For each individual event, our software provides detailed graphical and other key information about the event.
Estimates of Uncertainty	The EP Curve with Secondary Uncertainty analysis feature in Touchstone allows users to display additional uncertainty. However, the user should be aware that the financial module always accounts for secondary uncertainty in loss calculations. The difference is constructed using the secondary uncertainty around each event, whereas the Standard EP Curve uses the mean of each event distribution.
Event Loss Summary Detail Table	The Event Loss Summary Detail Table in the Touchstone user interface (or export) displays more detailed information about each of the events generated by the standard (probabilistic) loss analysis. This information allows users to assess the impact of large loss scenarios on a portfolio level and to dig into what type of event can cause that size of losses to a portfolio. By default, the table displays stochastic events; however, you can also view historical and world scenario event losses by selecting them in the Events Detail section of the ribbon.
Annual Aggregate EP Curve	The aggregate EP curve provides loss distribution for the combined potential loss in any given year
Occurrence EP Curve	The occurrence EP curve provides loss distribution for the largest potential loss in any given year

11.4 Supported geographic resolutions

The following geographic resolutions are supported for the Verisk Wildfire Model for the United States in Touchstone:

- County
- Zip code
- Complete address (street, city, and state)
- User-specified latitude and longitude

11.5 Modeling aggregate data

Touchstone can be run with **Disaggregation** turned on or off. During analysis in Touchstone if **Disaggregation** is selected, the aggregate County, City or Zip codes exposures are automatically disaggregated to a 1-km grid, based on industry exposure weights, by line of business.

11.6 Construction and occupancy classes, year built and height bands, and relative vulnerabilities

The vulnerability of a structure depends on its construction and occupancy class combination as well as its age and height. With the goal of enabling clients to code their exposure data as specifically as possible, the Verisk Wildfire Model for the United States supports 125 construction classes (including 20 marine asset classes) and 123 occupancy classes (including 12 marine storage classes). Of the occupancy classes, 62 are classes for industrial facilities.[20]

Descriptions of the supported construction and occupancy classes are available in the ***Touchstone Exposure Data Validation Reference***.

11.7 Secondary risk characteristics

For additional details, see Secondary Risk Characteristics for Wildfire section.

11.8 Damage functions for unknown characteristics

Often a characteristic of a building (e.g., its construction or occupancy class, height, etc.) is unknown. In these cases, Touchstone uses a composite damage function based on Verisk's Industry Exposure Database. For a given unknown characteristic, the unknown damage function represents a weighted average of the damage functions of the different classes that are in the Verisk Industry Exposure Database, with weights determined by the relative share of total insurable value of each class. The Verisk Wildfire Model for the United States supports damage functions for risks with unknown characteristics at the state level.

[20] The industrial facilities set of occupancy classes refers to the 400-series, are large, complex facilities comprising many components.

11.9 Supported policy conditions

The financial module in Touchstone allows for the application of a wide variety of location, policy, and reinsurance conditions. Location terms may be specified to include limits and deductibles by site or by coverage. Supported policy terms include blanket and excess layers, minimum and maximum deductibles, and sublimits. Reinsurance terms include facultative certificates and various types of risk-specific and aggregate treaties with occurrence and aggregate limits.

12 Appendix 1

12.1 Scientific Literature

The following reference materials have been used in the development and refinement of the Verisk Wildfire Model for the United States.

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13 Appendix 2

13.1 Vulnerability Function Flowchart

Add the flowchart on vulnerability function development.

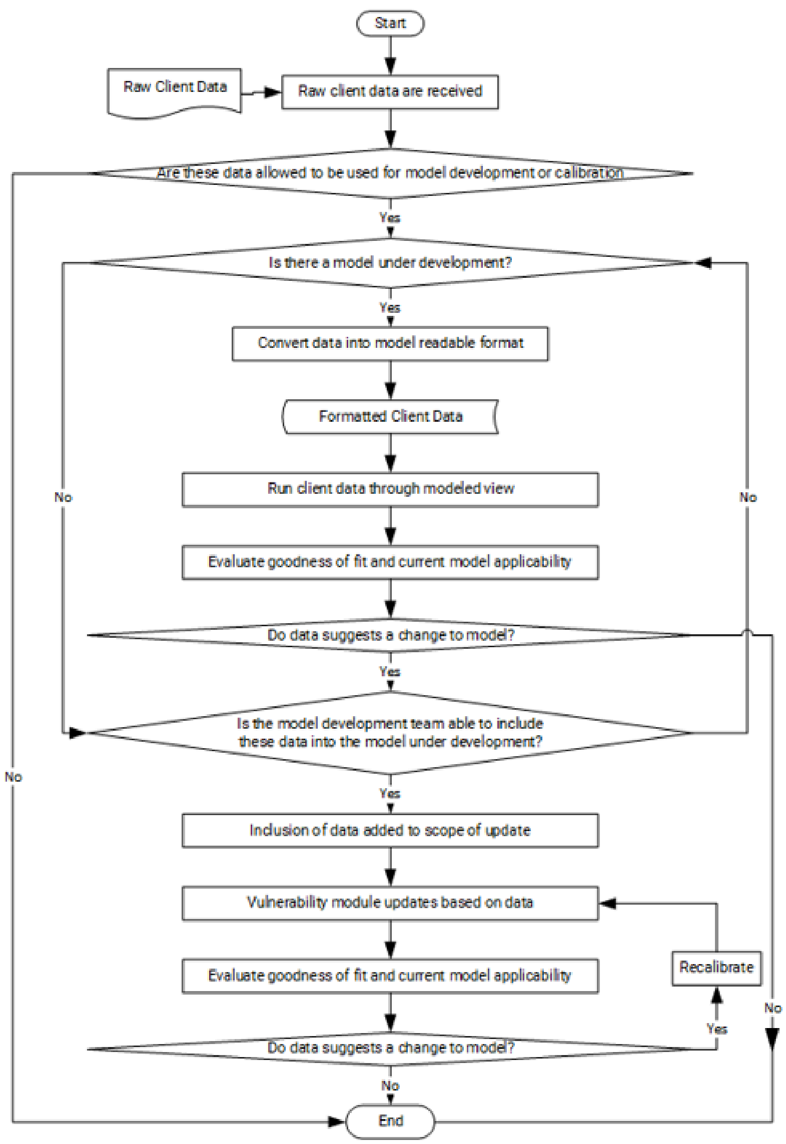


Figure 50. Process to Include Client Data

14 Appendix 3

14.1 Version Control

The Verisk Wildfire Model for the United States is implemented in our software platform, Touchstone. Verisk generally produces one major release of Touchstone annually (e.g. Touchstone 2024, Touchstone 2025).

Any revision that results in a change in any California residential wildfire loss cost or probable maximum loss level results in a new model version number. The Verisk Wildfire Model for the United States version definitions are predefined and follow typical versioning methodology, including:

- Major Version (two digit)—Incremented when model components, such as the catalog, hazard, intensity, or vulnerability modules, are updated. A single major version increment is sufficient in cases when multiple components are updated during a release cycle.
- Minor Version (two digit)—Incremented when data files, such as the physical properties or industry exposures, are updated but the model components remain unchanged. If data files are changing simultaneously with a major version update, the minor version number does not need to be incremented.
- Build Version (two digits)—Incremented when data file, model component, or loss-impacting software bugs have been identified after the release of our client software products.

The internal software version definitions are predefined and follow typical software versioning methodology, including:

- Major Version (two digit)—Incremented when new or revised models are implemented into the software application. Also introduces database, engine, and other significant changes to the software.
- Minor Version (two digit)—Incremented when new or revised models, functionality enhancements, and other various software upgrades are introduced. Most often, this service pack is released in the fall.
- Update to Minor Version (one digit)—Incremented in cases when bug fixes are necessary and have been identified after the release of our client software. The need to increment this version number is most often identified externally by a client and incrementing this digit indicates that a service pack or Hot Fix was released.
- Build Version (two digit)—Incremented in cases when bug fixes are necessary and these changes have been identified prior to a release of our client software.
- Build Date (Eight digit—yyyymmdd)—Incremented each time significant changes are made to the source code and the software is compiled. The build date will change most frequently. A new build date is introduced every time the version number changes.

- Client Request for Custom Update (alpha character)—An alpha-character suffix designates a custom version of Verisk software. For example, it is used when a client requests an update to be compatible with their technical environment.

15 Appendix 4

15.1 Form G-8: Wildfire Catastrophe Model Settings and Input

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.

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

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.

Form G-8.A

An example Import Log, along with annotated images supporting the data presented, is provided below:

```
*********************************
            **      Touchstone 2024      **
            *********************************

            ********** Log header **********
            Description:    [Import] initiated by [AIR-WORLDWIDE\I44919] on [CCSG22TS4HN1]
            Time Submitted: [2025-07-09 10:58:54,337]
            Time Started:   [2025-07-09 10:58:54,383]
            Time Ended:     [2025-07-09 11:00:13,591]
            Duration:       [00:01:12]
            Status:         [Completed]
            Owner:          [AIR-WORLDWIDE\I44919]
            Platform Name/
            Identification: [Touchstone 2024]
            DataImport Version: [12.2.0.1]


            ********** Log Data Source Information **********
            Import Type: [CSV]
            Import Date Format: [Default]
            Data Source: [\\CCSG22TS4HN1\AIRWork\IMPORT\1153.Form G-8 geocode
 input.csv]
```

```
            Data Tables: [1153.Form G-8 geocode input.csv
 1153.Map_53a8ce22-91f2-4d04-9512-1e2bea4c5def 1153.Default_39517b83-9302-4954-
b87e-a3723c1cf331 1153.Form G-8 geocode input.2025-07-09T105853.csv ]
            Delimiter: [,]
            Text Qualifier: [Double Quote]
            Has Header: [Y]

            ********** Log Import Options **********
            Destination Database        : [GP_Geocode_Test_EXP]
            Destination SQL Server       : [CCSG22TS4DB1\PRIMARYSQL]
            Target Type                 : [Exposure Set]
            Target Name                 : [GP_Geocode_Test]
            Contract Type               : [Primary]
            Mapping Set                 : [GP_Geocode_Test]
            Continue Geocode with Import Errors: [Y]
            Duplicate Contract          : [Skip+Error]
            Location Error              : [Reject Location]
            Fail After                  : [Unlimited]
            Max Errors                  : [0]
            Existing Geocode            : [Preserve user-supplied and premium geocodes]
            Geocoder                    : [AIR Geocode]
            User-supplied Geocode Match Level Mapping Set : [None]
            Include Decommissioned Offshore Platforms : [No]
            Min HPC Cores               : [1]
            Max HPC Cores               : [4]
            Job Priority                : [Normal]
            Job Scheduled Time          : [Execute Immediately]
            Premium Geocoding Batch Size:         [40000]
            Premium Geocoding Internal Batch Size: [4000]
            Currency                    : [USD]

            Auto Exposure View: Yes
            Project Name: [CDI_PRID_Touchstone_Demo]
            Exposure View Name: [GP_Geocode_Test]
            Generate Exposure Summary: [Yes]



            ----> Executing Advance Geocoding Plan


            ----> Executing Advance Geocoding Plan


            ----> Executing Advance Geocoding Plan


            ----> Executing Advance Geocoding Plan


            ----> Executing Advance Geocoding Plan


            ----> Executing Advance Geocoding Plan


            ********** Log Summary Statistics **********
            Elapsed Time: [00:00:01:09]
            Total No. of records: [1024]
```

```
No. of records successfully processed: [1024]
Percentage of records successfully Imported: [100.00%]



********** Log Detailed Statistics **********
Summary of Property Records Imported: |
No. of Contracts                    : |[512]|
No. of Locations                    : |[512]|
No. of Location Details             : |[512]|
No. of Sublimits                    : |[0]|
No. of Layers                       : |[0]|
No. of Treaty                       : |[0]|
No. of Facultative                  : |[0]|
No. of Step Functions               : |[0]|
No. of Location Groups              : |[0]|


Summary of Property Records     NOT IMPORTED: |
No. of Contracts               NOT IMPORTED: |[0]|
No. of Locations               NOT IMPORTED: |[0]|
No. of Location Details        NOT IMPORTED: |[0]|
No. of Sublimits               NOT IMPORTED: |[0]|
No. of Layers                  NOT IMPORTED: |[0]|
No. of Reinsurance Treaty      NOT IMPORTED: |[0]|
No. of Reinsurance Facultative  NOT IMPORTED: |[0]|
No. of Reinsurance (Unknown)    NOT IMPORTED: |[0]|
No. of Step Functions          NOT IMPORTED: |[0]|
No. of Location Groups         NOT IMPORTED: |[0]|


Summary of Property Exposure Data            : |
Total of Replacement Value A Imported        : |[307,200,000.00]|
Total of Replacement Value A Not Imported    : |[0.00]|
Total of Replacement Value B Imported        : |[30,720,000.00]|
Total of Replacement Value B Not Imported    : |[0.00]|
Total of Replacement Value C Imported        : |[230,400,000.00]|
Total of Replacement Value C Not Imported    : |[0.00]|
Total of Replacement Value D Imported        : |[61,440,000.00]|
Total of Replacement Value D Not Imported    : |[0.00]|
Total of Replacement Value Imported          : |[629,760,000.00]|
Total of Replacement Value Not Imported      : |[0.00]|
Total Number of Risks Imported               : |[512]|


Geocode Statistics :|
GeoCoding Elapsed Time: [00.00:00:34]

[384] locations records required geocoding
[128] locations records user retained geocodes
[0] locations records geocoded using premium geocoding
[264] locations records were successfully geocoded using default geocoding
[120] location records were not geocoded

Summary of Geocode Match Level :|
[0] address(es) are matched at the Point level
[48] address(es) are matched at the Exact Address level
[0] address(es) are matched at the ZIP9 Centroid level
```

```
[72] address(es) are matched at the Relaxed Address level
[96] address(es) are matched at the Postal Code Centroid level
[24] address(es) are matched at the City Centroid level
[24] address(es) are matched at the County Centroid level
[0] address(es) are matched at the Cresta Centroid level
[0] address(es) are matched at the Subarea 2 level
[0] address(es) are matched at the Area Centroid level
[0] address(es) are matched at the Country level
[0] address(es) are matched at the Disaggregated level
[128] address(es) are matched at the User Supplied level
[0] address(es) are matched at the Wind Turbine CRESTA level
[120] address(es) are not matched
[0] address(es) were not geocoded due to errors

Summary of Premium Geocoding Geocode Levels :|

Summary of User Provided Geocode Match Level :|
[512] Address(es) have no provided match level

Summary of user provided Verisk BINS :|

********* Error Summary **********
******** Business Errors *********
********** Data Errors ***********

************ Warnings ************
```

```
********************************
**      Touchstone 2024       **
********************************

********** Log header **********
Description:    [Import] initiated by [AIR-WORLDWIDE\I44919] on [CCSG22TS4HN1]
Time Submitted: [2025-07-09 10:58:54,337]
Time Started:   [2025-07-09 10:58:54,383]
Time Ended:     [2025-07-09 11:00:13,591]
Duration:       [00:01:12]
Status:         [Completed]
Owner:          [AIR-WORLDWIDE\I44919]
Platform Name/
Identification: [Touchstone 2024]
DataImport Version: [12.2.0.1]


********** Log Data Source Information **********
Import Type: [CSV]
Import Date Format: [Default]
Data Source: [\\CCSG22TS4HN1\AIRWork\IMPORT\1153.Form G-8 geocode input.csv]
Data Tables: [1153.Form G-8 geocode input.csv 1153.Map_53a8ce22-91f2-4d04-9512-1e2bea4c5def 1153.Default_39517b83-9302-4954-b87e-a3723c1cf331 1153.Form G-8 geocode
input.2025-07-09T105853.csv ]
Delimiter: [,]
Text Qualifier: [Double Quote]
Has Header: [Y]

********** Log Import Options **********
Destination Database          : [GP_Geocode_Test_EXP]
Destination SQL Server        : [CCSG22TS4DB1\PRIMARYSQL]
Target Type                   : [Exposure Set]
Target Name                   : [GP_Geocode_Test]
Contract Type                 : [Primary]
Mapping Set                   : [GP_Geocode_Test]
Continue Geocode with Import Errors: [Y]
Duplicate Contract            : [Skip+Error]
Location Error                : [Reject Location]
Fail After                    : [Unlimited]
Max Errors                    : [0]
Existing Geocode              : [Preserve user-supplied and premium geocodes]
Geocoder                      : [AIR Geocode]
User-supplied Geocode Match Level Mapping Set : [None]
Include Decommissioned Offshore Platforms : [No]
```

Touchstone's default behaviors are:
- Do not geocode locations with provided Latitude/Longitude values
- Use the built-in geocoding system for all other locations

```
Min HPC Cores                  : [1]
Max HPC Cores                  : [4]
Job Priority                   : [Normal]
Job Scheduled Time             : [Execute Immediately]
Premium Geocoding Batch Size:          [40000]
Premium Geocoding Internal Batch Size: [4000]
Currency                       : [USD]

Auto Exposure View: Yes
Project Name: [CDI_PRID_Touchstone_Demo]
Exposure View Name: [GP_Geocode_Test]
Generate Exposure Summary: [Yes]


----> Executing Advance Geocoding Plan


----> Executing Advance Geocoding Plan


----> Executing Advance Geocoding Plan


----> Executing Advance Geocoding Plan


----> Executing Advance Geocoding Plan


----> Executing Advance Geocoding Plan


********** Log Summary Statistics **********
Elapsed Time: [00.00:01:09]
Total No. of records: [1024]
No. of records successfully processed: [1024]
Percentage of records successfully Imported: [100.00%]

********** Log Detailed Statistics **********
Summary of Property Records Imported: |
No. of Contracts                    : |[512]|
No. of Locations                    : |[512]|
No. of Location Details             : |[512]|
No. of Sublimits                    : |[0]|
No. of Layers                       : |[0]|
No. of Treaty                       : |[0]|
No. of Facultative                  : |[0]|
No. of Step Functions               : |[0]|
No. of Location Groups              : |[0]|

Summary of Property Records     NOT IMPORTED: |
No. of Contracts                NOT IMPORTED: |[0]|
No. of Locations                NOT IMPORTED: |[0]|
No. of Location Details         NOT IMPORTED: |[0]|
No. of Sublimits                NOT IMPORTED: |[0]|
No. of Layers                   NOT IMPORTED: |[0]|
No. of Reinsurance Treaty       NOT IMPORTED: |[0]|
No. of Reinsurance Facultative  NOT IMPORTED: |[0]|
No. of Reinsurance (Unknown)    NOT IMPORTED: |[0]|
No. of Step Functions           NOT IMPORTED: |[0]|
No. of Location Groups          NOT IMPORTED: |[0]|
```

This section counts the number of errors encountered during the import process.

```
Summary of Property Exposure Data                : |
Total of Replacement Value A Imported            : |[307,200,000.00]|
Total of Replacement Value A Not Imported        : |[0.00]|
Total of Replacement Value B Imported            : |[30,720,000.00]|
Total of Replacement Value B Not Imported        : |[0.00]|
Total of Replacement Value C Imported            : |[230,400,000.00]|
Total of Replacement Value C Not Imported        : |[0.00]|
Total of Replacement Value D Imported            : |[61,440,000.00]|
Total of Replacement Value D Not Imported        : |[0.00]|
Total of Replacement Value Imported              : |[629,760,000.00]|
Total of Replacement Value Not Imported          : |[0.00]|
Total Number of Risks Imported                   : |[512]|
```

This section sums the total insured value of all successful and all unsuccessful imports.

```
Geocode Statistics :|
GeoCoding Elapsed Time: [00.00:00:34]
```

```
[384] locations records required geocoding
[128] locations records user retained geocodes
[0] locations records geocoded using premium geocoding
[264] locations records were successfully geocoded using default geocoding
[120] location records were not geocoded

Summary of Geocode Match Level :|
[0] address(es) are matched at the Point level
[48] address(es) are matched at the Exact Address level
[0] address(es) are matched at the ZIP9 Centroid level
[72] address(es) are matched at the Relaxed Address level
[96] address(es) are matched at the Postal Code Centroid level
[24] address(es) are matched at the City Centroid level
[24] address(es) are matched at the County Centroid level
[0] address(es) are matched at the Cresta Centroid level
[0] address(es) are matched at the Subarea 2 level
[0] address(es) are matched at the Area Centroid level
[0] address(es) are matched at the Country level
[0] address(es) are matched at the Disaggregated level
[128] address(es) are matched at the User Supplied level
[0] address(es) are matched at the Wind Turbine CRESTA level
[120] address(es) are not matched
[0] address(es) were not geocoded due to errors

Summary of Premium Geocoding Geocode Levels :|

Summary of User Provided Geocode Match Level :|
[512] Address(es) have no provided match level

Summary of user provided Verisk BINS :|

********* Error Summary **********
******** Business Errors *********
********** Data Errors ***********

************ Warnings ************
```

Match level is a measure of how precisely the geocoder reported the Latitude/Longitude for a location.

Match level meanings are defined in the accompanying document.

Figure 51. Annotated Import Log

Note: When users import data to Touchstone:

1. The order of the rows in the import source does not affect the analysis results.
2. Adding or removing policies from the import data does not affect the results for the unchanged policies.

Table 11. Touchstone Geocode Match Levels for Non-Street-Level Address Data

Resolution Level	Geocode Matching Level on the UI	Geocode Match Level Code	Enhanced Geocode Match Level Code	Description
Highest resolution	Postal Code Centroid	POST	POST	Touchstone geocodes the exposure at the centroid for the corresponding postal area.
⇑	City Centroid	CITY	CITY	Touchstone geocodes the exposure at the centroid for the corresponding city.
⇑	CRESTA Centroid	CRES	CRES	Touchstone geocodes the exposure at the centroid for the corresponding CRESTA area.
⇑	County Centroid	CNTY	SUBA	Touchstone geocodes the exposure at the centroid for the corresponding county.
⇑	Country	COUN	COUN	Touchstone geocodes the exposure at the centroid for the country.

Resolution Level	Geocode Matching Level on the UI	Geocode Match Level Code	Enhanced Geocode Match Level Code	Description
Lowest Resolution	None	NONE	NONE	Touchstone cannot determine the geocode.

Table 12. Touchstone Geocode Match Levels for Street-Level Address Data

Resolution Level	Geocode Matching Level on the UI	Geocode Match Level Code	Enhanced Geocode Match Level Code	Description
Highest resolution	Point	PT	PT	The highest resolution geocoding available because it is obtained from GPS or satellite images directly on the building. Since this data is obtained as part of the on-site commercial building inspection process, point matches are available only in some commercial building records via augmentation.
⇑	Parcel	PRCL	PRCL	Touchstone places the geocode at the centroid for the land parcel of a given property. This level is the second highest available geocoding resolution. No interpolation is required because each parcel centroid in this parcel-level dataset has a specific address for matching. This level of resolution is only available in some commercial building records via augmentation.
⇑	Address (Exact)	ADDR	SEGI	Street Segment Imputed: Touchstone finds the address in a street segment that has a geocode for the endpoints. All key street components match to expected values and acceptable city/state or zip code values. Touchstone calculates (interpolates) the relative location of the address between the segment endpoints.
⇑	Relaxed	RLXA	SEGI	Street Segment Imputed: Touchstone imputes a geocode from a matched street segment. However, if the street number is out of range or if some of the key street components, such as street name, directional(s), or street type, are changed during the street validation match, then the highest possible Geo. Match Level Code is a "Relaxed" match.

Resolution Level	Geocode Matching Level on the UI	Geocode Match Level Code	Enhanced Geocode Match Level Code	Description
⇑	Address (Exact)	ADDR	BLCK (Zip9 Centroid)	The streetseqnumstart and streetseqnumend of the street segment are the same (Zip9 Single Address).
⇑	Address (Exact)	ADDR	BLCK (Zip9 Centroid)	The address is found in a street segment, but the street segment has no geocodes available. However, a Zip9 Centroid is available.
⇑	Relaxed	RLXA	BLCK (Zip9 Centroid)	Only a Zip9 is included, or the Zip9 cannot be validated.
⇑	Relaxed	RLXA	STRI	Street Imputed: The address is not found in a street segment, but the address is between the start and end range for the matched street. Touchstone calculates (interpolates) the location of the address between the street endpoints.
⇑	Relaxed	RLXA	STRC	Street Centroid: The street number is not available on the input address, but the street is short enough to have a useful centroid. The house number could be missing from or incorrect in the input address.
⇑	Postal Code Centroid	POST	POST	The street address is not found, and street centroid is not available, or the street is too long to have a useful centroid. Touchstone returns a population-weighted zip code centroid if one is available.
⇑	City Centroid	CITY	CITY	The street address is not found, and street centroid is not available, or the street is too long to have a useful centroid. In addition, Touchstone does not have Zip5 data for this location. That is, no postal centroid is available. Touchstone returns a city centroid.
⇑	County Centroid	CNTY	SUBA	Touchstone places the geocode at the center of the county (from the Area Code database). In this case, no postal or city centroid information is available.
⇑	Country	COUN	COUN	Touchstone places the geocode at the center of the country.
Lowest Resolution	None	NONE	NONE	Touchstone cannot determine the geocode.

Table 13. Touchstone Geocode Match Levels for User Supplied Geocodes

Geocode Matching Level on the UI	Geocode Match Level Code	Enhanced Geocode Match Level Code	Description
User Supplied	USER	USER	The user has provided the geocode. The accuracy of this type of geocode depends upon the precision of the user supplied data.
None	NONE	NONE	Touchstone cannot determine the geocode.

An example of an analysis log, along with annotated images supporting the data presented in Tables G-8.A, G-8.B, and G-8.C, is provided below.

```
***********************
        **  Touchstone 2025  **
        ***********************



        o Analysis Header Info

        Analysis Type:            Detailed Loss Analysis
        Express Analysis:          No
        Analysis Name:
Form_A1A3_Miti_Residential_Notional_10K_Smoke_andWF
        Template Name:             AIR Default Loss Template
        Analysis SID:            32
        Result SID:             2
        Activity ID:            31
        HPC Job ID:             130
        Description:            N/A
        User:                AIR-WORLDWIDE\i36730
        Time Submitted:           06/12/2025 12:39:10
        Time Started:           06/12/2025 12:39:10
        Time Ended:            06/12/2025 12:56:53
        Duration:             00:17:35
        Status:              Completed



        o Error/Warning Summary


        o Fatal Error

        None

        o Ignorable Errors

        None
```

```
o Exposures Modelled

Total
100% Replacement Value
100% Locations



o System Info

System Version:               13.0.0.1773
Platform Name/
Identification:               Touchstone 2025
SQL Server Name:              CCSG22TS6DB1\PRIMARYSQL
HPC Head Node:                CCSG22TS6HN1


o Analysis Target Info

Analysis Target Type:         Portfolio
Analysis Target Name:         Form_A1A3_Miti_Residential_Notional
Exposure View Filter:         Not Applied

Exposure Set(s):              Database : Exposure Set Name
--------   ------------------
CK_Test_EXP : Form_A1A3_Miti_Residential_Notional

Analysis Statistics:          Analyzed
--------
Policy Count:                 5094
Total Location Count:         508420
Property Location Count: 508420
Workers Location Count:  0
Disaggregated Location Count: 0
Layers Count:                 0
SubLimits Count:              0
Reinsurance Count:            0
Total Replacement Value:      625,356,600,000

o Event Set Options

Event Set Name:               10K US AP (2025) - Standard
Event Set Type:               Stochastic
Event Filter:                 Off
Year Filter:                  Off
Location Filter:              Off
Rule Filter:                  Off
Demand Surge:                 On
Custom Demand Surge(US-derived):      No
Custom Demand Surge(Country-specific):      No
Country-specific Demand Surge Options:      Construction Cost Inflation Percentage-
N/A
Countries/ Regions Supporting Country-specific Demand Surge-  N/A
Exposure Exclusions for the Country-specific Demand Surge-    N/A

Perils:                       Other Perils -     Smoke
Other Perils -     Wildfire
```

Hazard Models: Model: Model Version: Catalog: Catalog Version: Events: Scenarios:
Verisk Wildfire Model for the U.S. 5 4.0.1 Verisk Wildfire Model for the U.S. 05.00.1209 7173209 10000

o Financial Model Options

Disaggregation: Off
Average Properties: Off
Invalid Con/Occ Pairs: Ignore

o Reinsurance Options

Program Name: N/A
Order of application of Fac: Do not apply
FAC Reinsurance Count: 0
Treaty Reinsurance Count: 0

o Custom Model Options

Custom Model: N/A

o Output Options

Loss Perspectives: Ground Up
Gross

Event Losses By: Portfolio
Geography: Event Total
Summary (AAL Only): Location Summary

Sub Peril: Off

Save By Treaty: Off
Save By Facultative: Off

Loss Details: Coverage

Auto Export CLF: No
Save By Zone: False
Zone By Peril: False
Retain Annual EP By Zone: False

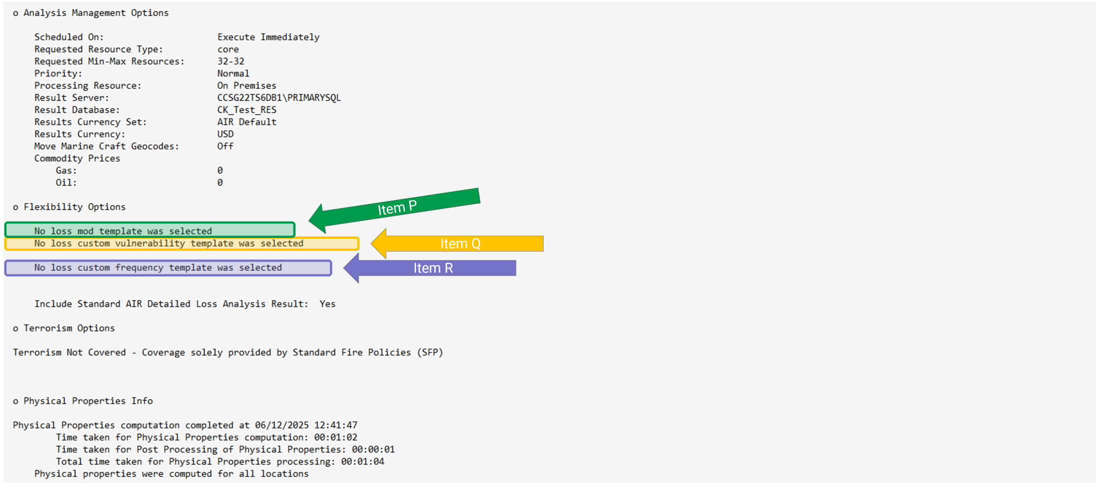
o Analysis Management Options

Scheduled On: Execute Immediately
Requested Resource Type: core
Requested Min-Max Resources: 32-32
Priority: Normal
Processing Resource: On Premises
Result Server: CCSG22TS6DB1\PRIMARYSQL
Result Database: CK_Test_RES
Results Currency Set: AIR Default
Results Currency: USD
Move Marine Craft Geocodes: Off
Commodity Prices

```
Gas:                    0
Oil:                    0

o Flexibility Options

No loss mod template was selected
No loss custom vulnerability template was selected

No loss custom frequency template was selected


Include Standard AIR Detailed Loss Analysis Result:  Yes

o Terrorism Options

Terrorism Not Covered - Coverage solely provided by Standard Fire Policies (SFP)



o Physical Properties Info

Physical Properties computation completed at 06/12/2025 12:41:47
Time taken for Physical Properties computation: 00:01:02
Time taken for Post Processing of Physical Properties: 00:00:01
Total time taken for Physical Properties processing: 00:01:04
Physical properties were computed for all locations
```

```
***********************
**  Touchstone 2025  **
***********************


o Analysis Header Info

    Analysis Type:                  Detailed Loss Analysis
    Express Analysis:               No
    Analysis Name:                  Form_A1A3_Miti_Residential_Notional_10K_Smoke_andWF
    Template Name:                  AIR Default Loss Template
    Analysis SID:                   32
    Result SID:                     2
    Activity ID:                    31
    HPC Job ID:                     130
    Description:                    N/A
    User:                           AIR-WORLDWIDE\i36730
    Time Submitted:                 06/12/2025 12:39:10
    Time Started:                   06/12/2025 12:39:10
    Time Ended:                     06/12/2025 12:56:53
    Duration:                       00:17:35
    Status:                         Completed


o Error/Warning Summary

        o Fatal Error

                None

        o Ignorable Errors

                None

o Exposures Modelled

    Total
    100% Replacement Value
    100% Locations


o System Info

    System Version:                 13.0.0.1773
    Platform Name/
    Identification:                 Touchstone 2025
```

```
    Identification:                  Touchstone 2025
    SQL Server Name:                 CCSG22TS6DB1\PRIMARYSQL
    HPC Head Node:                   CCSG22TS6HN1

o Analysis Target Info

    Analysis Target Type:            Portfolio
    Analysis Target Name:            Form_A1A3_Miti_Residential_Notional
    Exposure View Filter:            Not Applied

    Exposure Set(s):                 Database : Exposure Set Name
                                     --------   ------------------
                                     CK_Test_EXP : Form_A1A3_Miti_Residential_Notional

    Analysis Statistics:             Analyzed
                                     --------
        Policy Count:                5094
        Total Location Count:        508420
             Property Location Count: 508420
             Workers Location Count:  0
        Disaggregated Location Count: 0
        Layers Count:                0
        SubLimits Count:             0
        Reinsurance Count:           0
        Total Replacement Value:     625,356,600,000

o Event Set Options

    Event Set Name:                  10K US AP (2025) - Standard          Item A
    Event Set Type:                  Stochastic
    Event Filter:                    Off                                  Item B
    Year Filter:                     Off
    Location Filter:                 Off
    Rule Filter:                     Off
    Demand Surge:                    On                                   Item C
    Custom Demand Surge(US-derived):       No
    Custom Demand Surge(Country-specific):      No
    Country-specific Demand Surge Options:      Construction Cost Inflation Percentage-              N/A
                                     Countries/ Regions Supporting Country-specific Demand Surge-   N/A
                                     Exposure Exclusions for the Country-specific Demand Surge-     N/A

    Perils:                          Other Perils -      Smoke            Item D
                                     Other Perils -      Wildfire

                                                                                      Item E
    Hazard Models:                          Model:   Model Version:   Catalog:                            Catalog Version:   Events:    Scenarios:
    Verisk Wildfire Model for the U.S.      5        4.0.1            Verisk Wildfire Model for the U.S.  05.00.1209         7173209    10000

o Financial Model Options

    Disaggregation:                  Off                                  Item F
    Average Properties:              Off                                  Item G
    Invalid Con/Occ Pairs:           Ignore                               Item H

o Reinsurance Options                                                     Item I

    Program Name:                    N/A
    Order of application of Fac:     Do not apply
    FAC Reinsurance Count:           0
    Treaty Reinsurance  Count:       0

o Custom Model Options

   Custom Model:                     N/A                                  Item J

o Output Options

    Loss Perspectives:               Ground Up                            Item K
                                     Gross

    Event Losses By:                 Portfolio                            Item L
    Geography:                       Event Total
    Summary (AAL Only):              Location Summary                     Item M

    Sub Peril:                       Off                                  Item N

    Save By Treaty:                  Off
    Save By Facultative:             Off

    Loss Details:                    Coverage

    Auto Export CLF:                 No
   Save By Zone:                     False                                Item O
   Zone By Peril:                    False
   Retain Annual EP By Zone:         False

o Analysis Management Options

    Scheduled On:                    Execute Immediately
    Requested Resource Type:         core
    Requested Min-Max Resources:     32-32
    Priority:                        Normal
    Processing Resource:             On Premises
    Result Server:                   CCSG22TS6DB1\PRIMARYSQL
    Result Database:                 CK_Test_RES
    Results Currency Set:            AIR Default
    Results Currency:                USD
    Move Marine Craft Geocodes:      Off
```



```
o Analysis Management Options

    Scheduled On:                   Execute Immediately
    Requested Resource Type:        core
    Requested Min-Max Resources:    32-32
    Priority:                       Normal
    Processing Resource:            On Premises
    Result Server:                  CCSG22TS6DB1\PRIMARYSQL
    Result Database:                CK_Test_RES
    Results Currency Set:           AIR Default
    Results Currency:               USD
    Move Marine Craft Geocodes:     Off
    Commodity Prices
        Gas:                        0
        Oil:                        0

o Flexibility Options

    No loss mod template was selected
    No loss custom vulnerability template was selected

    No loss custom frequency template was selected


    Include Standard AIR Detailed Loss Analysis Result:  Yes

o Terrorism Options

Terrorism Not Covered - Coverage solely provided by Standard Fire Policies (SFP)



o Physical Properties Info

Physical Properties computation completed at 06/12/2025 12:41:47
        Time taken for Physical Properties computation: 00:01:02
        Time taken for Post Processing of Physical Properties: 00:00:01
        Total time taken for Physical Properties processing: 00:01:04
    Physical properties were computed for all locations
```


Figure 52. Annotated Analysis Log

Table 14. Form G-8.A, Hazard

Hazard		
Option	**Notes**	**Analysis Log Location**
Event Set	There are three event sets in Touchstone which contain the Wildfire Model: • 10K US AP (2025) - Standard • 50K US AP (2025) - Standard • 100K US AP (2025) - Standard • Older versions have the same names but different years in the parentheses.	Item A
Event Set Filter	Default: None. This option allows the user to select only certain events.	Item B
Perils	For Wildfire, only "Wildfire" and "Smoke" are relevant options.	Item D
Region	United States	Item E
Model	AIR Default is the only model supplied by Verisk to clients.	Item J
Custom Frequency	Default: None. Only available to clients who license Model Builder.	Item R

Form G-8.B

Table 15. Form G-8B.1, Vulnerability

Vulnerability		
Option	**Notes**	**Analysis Log Location**
Disaggregation	Default: On. When turned on, the Disaggregation Financial Settings parameter distributes aggregate (coarse resolution) location data down to a finer resolution to locations where exposures are likely to be located based on lines of business represented in Verisk's Industry Exposure Database. This process enables the loss engine to apply policy terms appropriately across an entire (distributed) region, rather than applying them only across the centroid of the region; this generates more accurate loss results for risk locations with poor quality data because it avoids analysis of aggregate exposures at a single-point location.	Item F
Average Properties	Default: Off. This is a feature for other models in the platform and does not affect loss outcomes event if "On."	Item G
Custom Vulnerability	Default: None. Only available to clients who license Model Builder.	Item Q

Table 16. Form G-8B.2, Primary Characteristics

Primary Characteristics				
Characteristic	**Option**	**User Input Required?**	**Unknown Calculation**	**Input Method**
Construction	Construction class codes help to determine the vulnerability of your risks to various perils. Touchstone provides a set of construction class codes that describe the building material and/or type of construction used in risks.	Yes	When the construction and occupancy codes for a location are both "Unknown", Touchstone assigns the occupancy code "General Commercial." For an exposure of known occupancy but unknown construction and height, Touchstone uses a damage function that is a weighted average of the damage functions for the same occupancy class corresponding to all combinations of construction and height classes statewide.	User input through exposure data

Primary Characteristics				
Characteristic	**Option**	**User Input Required?**	**Unknown Calculation**	**Input Method**
Occupancy	The primary Residential occupancy codes define the type of activity carried out in the risks included in a record.	Yes		User input through exposure data
Stories	Integer between 0 and 999, inclusive.	Yes	Treated as weighted mixture of locations with similar construction & occupancy.	User input through exposure data
Year Built	Integer between 0 and Current Year, inclusive.	Yes	When the year built of the structure is not known, Touchstone calculates an unknown year built damage function by applying a statewide building stock data-weighted distribution to the corresponding damage functions for each year built.	User input through exposure data

Table 17. Form G-8B.3, Secondary Characteristics

Secondary Characteristics and Mitigation Features			
Characteristic	**Default/Unknown Calculation**	**Input Method**	**Options**
Defensible space	Treated as zero feet.	User input through exposure data	Location surrounding detail fields
Firewise USA™ community	Treated as "No".	User input through exposure data	Location surrounding detail fields
Glass type	Treated as "Tempered".	User input through exposure data	Location wall detail fields
Roof attached structure	Treated as "No Attached Structure".	User input through exposure data	Location connection detail fields
Roof covering	Treated as "Asphalt shingles" for wooden and masonry residential buildings.	User input through exposure data	Location roof detail fields

Secondary Characteristics and Mitigation Features			
Characteristic	**Default/Unknown Calculation**	**Input Method**	**Options**
Fire rating for roof covering	Treated as "Class B" for applicable Roof Coverings.	User input through exposure data	Location roof detail fields
Wall siding	Treated as "Aluminum/ vinyl siding" for wooden residential buildings.	User input through exposure data	Location wall detail fields
Fire rating for wall siding	Treated as "Class B" for applicable siding types.	User input through exposure data	Location wall detail fields
Building shape	Treated as "Rectangle".	User input through exposure data	Location building detail fields
Roof geometry	Treated as "Gable end without bracing" for any wooden construction and masonry residential buildings.	User input through exposure data	Location roof detail fields
Skylight	Treated as a weighted mixture of "No Skylights" and "Operable" damage functions.	User input through exposure data	Location roof detail fields
Soffits	Treated as "Aluminum/ Vinyl - continuous vents"	User input through exposure data	Location roof detail fields
Roof overhang	Treated as "Overhang/ Rake <8 in."	User input through exposure data	Location roof detail fields
Roof vents	Treated as "Roof Vents (Turbines, Goose Neck, Ridge Vents, etc.)"	User input through exposure data	Location roof detail fields
Roof vent size	Treated as weighted mixture of "⅛ in. or Smaller Mesh" or "Wildfire Resistant and ¼-in." or "No Mesh"	User input through exposure data	Location roof detail fields

Secondary Characteristics and Mitigation Features			
Characteristic	**Default/Unknown Calculation**	**Input Method**	**Options**
Deck	Treated as "No Deck"	User input through exposure data	Location connection detail fields
Gutter	Treated as "Gutter with guard/cover" for all constructions and occupancies.	User input through exposure data	Location connection detail fields
Fences within 5 feet	Treated as weighted mixture of "No fences", "Non combustible" and "Combustible".	User input through exposure data	Location connection detail fields
Exterior fuel storage	Treated as weighted mixture of "No Exterior Fuel Storage" and "Exterior Fuel Storage"	User input through exposure data	Location surrounding detail fields

Form G-8.C

Table 18. Form G-8C, Financial

Financial		
Option	**Notes**	**Analysis Log Location**
Deductible	Default: Zero. Deductibles are part of the Location file imported by the user. Details of the ways these may be coded are available at Terms (location terms)	N/A
Demand Surge	Default: With. The demand surge analysis option inflates loss results to reflect the increased cost of labor and materials following a major catastrophe. As the industry loss rises, so will the cost to repair and replace properties damaged in the event; the greater the industry loss for an event, the greater the Demand Surge factor used in the calculations. Touchstone comes with a standard demand surge curve for the U.S. which is automatically applied.	Item C

Financial		
Option	**Notes**	**Analysis Log Location**
For Invalid Con/Occ Pairs	Default: Ignore. A location that has an invalid construction/occupancy combination (e.g. manufactured home construction with an occupancy of automotive manufacturing) will be included or excluded in a loss analysis depending on the user's selection. If the Ignore option is chosen, the location will not be analyzed. If the Use System Default option is chosen, the software will convert the invalid codes into an unknown construction and general commercial occupancy.	Item H
Reinsurance	Default: None	Item I
Loss Perspectives	Options (On/Off): Ground Up, Pre-Layer Loss, Net of Pre-CAT, Retained, Gross, Post-CAT Net	Item K*
Save Loss By	Options (Select One): Portfolio, Contract, Layer, Line of Business, Location, Geography, User Defined Field This setting determines the level of granularity at which information about loss costs is saved.	Item L*
Summary (AAL Only)	Options (On/Off): Contract Summary, Location Summary	Item M*
Additional Details	Options (On/Off): Coverage, Sub-Peril, # Claims, Injury Type, MAOL, EP by Peril, EP by Model	Item N*
Zone Output	Options (On/Off): Zone	Item O*
Loss Modification Factor	Default: None. Users can apply different loss modification factors directly to ground-up losses in order to perform sensitivity analyses on their potential portfolio losses.	Item P

* This option determines output granularity and does not impact loss estimates.

About Verisk

Verisk Analytics (Verisk) provides risk modeling solutions that make individuals, businesses, and society more resilient to extreme events. In 1987, a Verisk subsidiary founded the catastrophe modeling industry and today models the risk from natural catastrophes, terrorism, pandemics, casualty catastrophes, and cyber incidents. Insurance, reinsurance, financial, corporate, and government clients rely on Verisk's advanced science, software, and consulting services for catastrophe risk management, insurance-linked securities, longevity modeling, site-specific engineering analyses, and agricultural risk management. Verisk (Nasdaq:VRSK) is headquartered in Jersey City, New Jersey with many offices throughout the United States and around the world. For information on our office locations, visit https://www.verisk.com/about/locations/.

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