Wildfire Consequence Model Version 4

(WFC v4)

Documentation

Prepared By: PG&E Risk and Data Analytics Team

Revision History

Rev	Date	Comment
0	05/28/2024	Initial Release
1	03/12/2025	Added new cover page

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Executive Summary

The Wildfire Consequence (WFC) model is used by PG&E to estimate the expected outcome of a wildfire initiated by an ignition from an electrical grid asset. The model determines outcomes for acres burned, buildings destroyed, and fatalities at the location of every grid asset based on weather, vegetation fuels, and terrain conditions. The predicted outcomes are transformed through a Mult-Attribute Value function (MAVf) to calculate a consequence value. Consequence values are generally higher at locations that are typically dry, windy, in rough terrain, and have an abundance of burnable fuel.

The WFC supports the Wildfire Distribution Risk Model (WDRM) and the Wildfire Transmission Risk Model (WTRM) missions to quantify and categorize wildfire risk from overhead distribution and transmission network assets. The relative wildfire risk results produced by the WDRM and WTRM inform the PG&E Wildfire Mitigation Plan (WMP) as well as specific mitigation program work plans to help realize the company stand, *"Catastrophic wildfires will stop"*.

This document describes WFC version 4 (v4) development by the Risk and Data Analytics (RaDA) team and highlights improvements implemented over its predecessor, WFC v3.4.

WFC v4 Improvements

WFC v4 features several significant improvements to the modeling of wildfire outcomes:

- Improved historical fire data set quality.
    - Increased the number of fires through merging multiple source data sets.
    - Expanded number of years of fire records.
    - Curated fire ignition locations.
- Expanded Technosylva fire simulation time from 8 to 24 hours to improve predictive performance for large fires.
- Introduced Dry Wind Conditions status to help differentiate the highest threat days.
- Developed consequence adjustment models for:
    - Public Egress impact.
    - Wildfire Suppression impact.

WFC v4 Wildfire Consequence Insights

WFC v4 benefitted from several improvements to the consequence model. As a result of the many contributing model improvements, WFC v4 produces consequence values that provide much better performance against historical wildfires in the service territory. However, the updated models also exhibit a flattened set of relative consequence values when compared with WFC v3.4. The flattened consequence results have in turn contributed to a general flattening of the risk profile for the service territory. The most critical insight is that WFC v4 has shifted the WDRM v4 System Hardening composite risk buydown curve, which now requires considerably more primary overhead conductor miles to account for 80% of the High Fire Threat District (HFTD) wildfire risk, increasing from 10,000 miles for WDRM v3 to 14,600 miles for WDRM v4.

While there are many contributing factors for the flattened risk buydown curve, a principal cause has been the WFC v4 model outcome changes driven by improved historical fire datasets, the introduction of public Egress and fire Suppression impacts, the latter is derived from Technosylva's Terrain Difficulty Index (TDI), the implementation of a revised consequence Multi-Attribute Value function (MAVf), and to a minor extent, , 24-hour fire simulations. While the new WFC v4 features have improved performance when compared with v3.4, it has also redistributed consequence, and therefore risk, across the service territory, resulting in a much flatter risk buydown curve.

Future Development Plans

PG&E has historically released new versions of the WDRM, and therefore the WFC, on an annual cycle. In the future, WDRM releases are to be aligned with the Wildfire Mitigation Plan (WMP) filing schedule rather than annually. WDRM v4 is intended to support PG&E's 2026 WMP.

WFC v4 delivered several features planned for 2024 and 2025 development. Future wildfire consequence models will aim to improve on existing features and capabilities while addressing additional unquantified risk. Among existing features and capabilities, the wildfire Suppression and public Egress adjustment impacts delivered for v4 will continue to be refined and several new impact features for vulnerable communities, conflagration, and Wildland Urban Interface (WUI) fire consequence are planned for development. In addition, continual focused efforts are also expected to further improve the capture, detail, maintenance, and curation of data sets used for the consequence models.

1 Introduction

The intent of this document is to present the development, performance, and use of the Wildfire Consequence (WFC) model that supports the wildfire risk predictions provided by WDRM v4 and WTRM v2. Source data, modeling approach, and resulting probability predictions are described in detail.

This document describes WFC version 4 (v4) development by the Risk and Data Analytics (RaDA) team and highlights improvements implemented over its predecessor, WFC v3.4. The document seeks to provide the lay reader with a broad understanding of the WFC model. It is not intended to provide comprehensive working-level mathematical or scientific descriptions of all methods used to produce consequence results.

1.1 Wildfire Consequence Model Overview

The WFC model estimates the probable outcome of a wildfire initiated by an ignition from an electrical grid asset. The model determines outcomes for acres burned, buildings destroyed, and fatalities at the location of every grid asset based on weather, vegetation fuels, and terrain conditions. The predicted outcomes are transformed through a Mult-Attribute Value function (MAVf) to calculate a consequence value. Consequence values are generally higher at locations that are typically dry, windy, in rough terrain, and have an abundance of burnable fuel.

An asset location consequence value combined with a probability of an ignition occurring at an asset location produces an estimate of wildfire risk for the asset. Collections of asset risk values provide the wildfire risk mitigation teams with the crucial data needed to prioritize mitigation work plans.

1.2 WFC Role in Distribution and Transmission Wildfire Risk Models

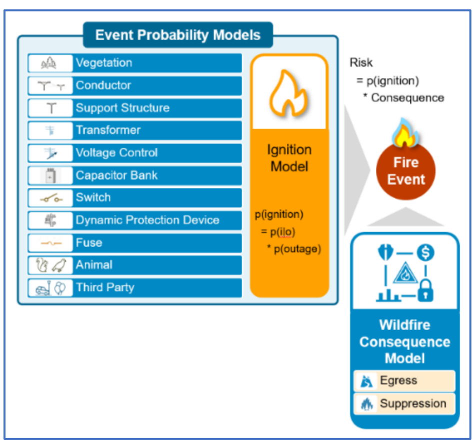

Figure 1 - WDRM Risk Prediction Overview

The Wildfire Distribution Risk Model (WDRM, *Figure 1*) and Wildfire Transmission Risk Model (WTRM, *Figure 2*) are the primary risk models that PG&E uses to to provide insights for prioritizing mitigation work to reduce wildfires initiated by the electric grid. Mitigation program work planners use the WDRM and WTRM results, along with their mitigation program work planning tools to develop work plans that systematically reduce wildfire risk while considering constraints such as budget allocation, human and equipment resource capacity, and regulatory commitments.

The WDRM and WTRM quantify the risk related to PG&E's overhead distribution and transmission equipment assets, which consist of overhead transformers, poles, towers and other support structure parts, lines (conductors), and line-related equipment such as interrupters, switches and fuses. The WDRM and WTRM provide predictions of wildfire risk that occurs during a wildfire season of June 1st through November 30th.

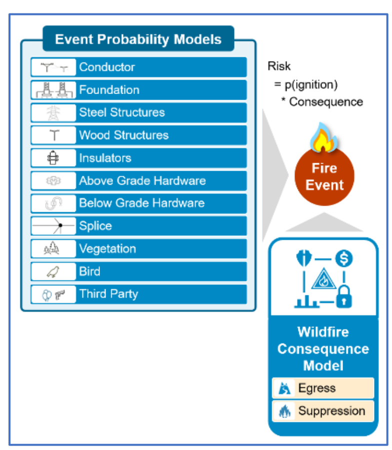

Figure 2 - WTRM Risk Prediction Overview

Wildfire risk is predicted by multiplying two component values. The first component, known as the Likelihood of a Risk Event (LoRE), is the probability of ignition occurring for an asset. The Distribution and Transmission Event Probability Models provide the LoRE values and are described in a separate document. The second component, known as the Consequence of a Risk Event

(CoRE), is the predicted outcome of an ignition event at the location of an equipment asset as estimated by the WFC Model described in this document.

1.3 Document Suite

This document is part of the documentation suite for the Wildfire Distribution Risk Model (WDRM) v4:

- WDRM v4 Documentation
- Wildfire Fire Consequence Model v4 Documentation (this document)
- Distribution Network Event Probability Models v4 Documentation
- RaDA Algorithms and Methodologies

2 WFC v4 Highlights and Evolution

The WFC is continuously improved and expanded to incorporate refreshed and new data sources and to adopt advancements in wildfire simulation. The continuous improvement effort is reflected in the evolution of the WFC version releases. Each new version has advanced the science of wildfire consequence modeling in support of PG&E's stand that catastrophic wildfire will stop.

2.1 WFC v4 Highlights

WFC v4 features several significant improvements to the modeling of wildfire outcomes:

- Improved historical fire data set quality.
  - Increased the number of fires through merging multiple source data sets.
  - Expanded number of years of fire records.
  - Curated fire ignition locations.
- Introduced Dry Wind Conditions status to help differentiate the highest threat days.
- Developed consequence adjustment models for:
  - Public Egress impact.
  - Wildfire Suppression impact.
- Expanded Technosylva fire simulation time from 8 to 24 hours to improve predictive performance for large fires.

2.2 WFC Version Evolution

Assessment of the potential consequence of a wildfire is a rapidly evolving area of practice where improvements are achieved through the adoption of new data and methods. As a result, the WFC model has evolved and improved over time.

Figure 3 provides an overview of Wildfire Consequence Model evolution. As the understanding of ignition consequences has improved, the formulation of model features developed to produce a consequence value has progressed.

Wildfire Consequence Model Evolution

Feature	v1 (2019)	v2 (2021)	v3.4 (2022)	v4 (2023)
Service Scope	HFTD Tier 2/3	HFTD Tier 2/3	Service Territory	Service Territory
GIS Vintage	July 2016	April 2019	January 2022	January 2023
Fuels	2012 LANDFIRE	2020 Fuels Snapshot	2030 Forecast Growth	2030 Forecast Growth
Fire Simulation	6 hours	8 hours	8 hours	24 hours
Historical Fire Locations	No	No	Nearest Asset	At Ignition Location
Model Formulation				
REAX, Vol. & Struct.	✓	x	x	x
Fire Burn Index (FBI)	x	✓	x	x
Acres Burned	x	✓	x	x
Fire Potential Index (FPI)	x	x	✓	✓
Flame Length	x	x	✓	✓
Rate of Spread	x	x	✓	✓
Dry Wind Conditions	x	x	x	✓
Egress Impact	x	x	x	✓
Suppression Impact	x	x	x	✓

Figure 3 - Wildfire Consquence Model Evolution

2.3 Legacy WFC Models

The legacy WFC v2 and v3.4 release data have been archived and are available for version comparison and audit purposes.

2.3.1 WFC v2

WFC v2, developed for WDRM v2, used the results of 8-hr fire simulations provided by Technosylva, Inc. directly for determining consequence values. The simulations modeled the consequence of a fire that was initiated on the worst weather day for a location and accounted for the impacts of by fuel availability and terrain. Simulation outcomes for acres burned, buildings destroyed, and population impact were direct inputs to the MAVf calculation that determined consequence values.

2.3.2 WFC v3 and v3.4

WFC v3 and v3.4, developed for WDRM v3, responded to user feedback to deliver three significant improvements.

- High Fire Threat Area (HFRA)/non-HFRA partitioning.
- Historical fire calibration.
- Predicted Destructive conditions.

HFRA/non-HFRA partitioning was added to support the expansion of WDRM v2, which modeled only assets in HFTD, to WDRM v3, which modeled all service territory assets. The partitioning helped the consequence model differentiate the expected impacts of ignitions that occurred outside of the HFRA.

Historical fire calibration was introduced to adjust the 8-hr fire simulations for final fire outcomes. Large fires last much longer than the 8-hr simulation time and therefore burn more acreage, destroy more buildings, and have a larger public impact than the simulation predicts. The calibration improved consequence accuracy and scale of damage while retaining the spatial and temporal coverage of simulations, enabling the prediction of expected fire damages.

Predicted Destructive conditions were added to aid in the explicit identification of catastrophic or destructive wildfire conditions. This feature was aimed at identifying, with a high degree of recall, the conditions which result in catastrophic or destructive wildfires. The Predicted Destructive conditions status was determined from a combination of PG&E Meteorology’s Fire Potential Index and Technosylva’s fire simulation data.

2.4 WFC v4 Model Architecture

The WFC v4 architecture was substantially modified from WFC v3.4 to accommodate WMP 2023 commitments for adding public egress and wildfire suppression impacts to the model. The v4 model consists of four components:

- Base Consequence Model
- Wildfire Suppression Impact Model
- Public Egress Impact Model
- Multi-Attribute Value function (MAVf)

The results of the Base Consequence, Wildfire Suppression, and Public Egress models are joined to determine the combined set of model results for acres burned, structures destroyed, and potential fatalities as shown in *Figure 4*. The combined model outcomes become the inputs into the MAVf to determine the final consequence value.

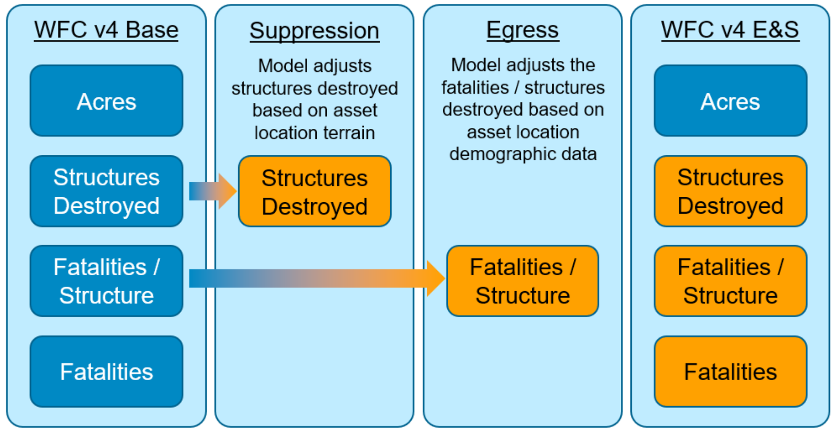

Figure 4 - Wildfire Consequence v4 Model Architecture

2.4.1 Base Consequence Model

The WFC v4 base consequence model is an improved version of the WFC v3.4 that incorporates improved historical fire data and a new Dry Wind Conditions (DWC) feature (Section *3.3.2*). The DWC aided the consequence model to further differentiate relative consequence during Predicted Destructive conditions.

Table 1 - WFC Base Consequence Decision Variables

Decision Variable	WFC v3.4	WFC v4
HFRA Membership	✓	✓
Dry Wind Conditions	X	✓
Predicted Destructive	✓	✓

2.4.2 Wildfire Suppression Impact Model

The Wildfire Suppression Impact Model was investigated and developed in response to a WMP 2023 commitment to consider the effect of wildfire suppression activities on ignition consequence. A major challenge for modeling suppression is the extreme difficulty of understanding historical state, regional, and local responses to ignition events and anticipating how future ignitions will be managed. After extensive research, the fraction of surviving buildings within a burn area was selected as an observable proxy for suppression effectiveness.

The suppression model uses as its primary input a Technosylva product, the Terrain Difficulty Index (TDI). TDI considers several factors including terrain steepness, equipment delivery and set-up, and distance from major roads, that correlate with the relative challenges faced by firefighters when combatting a wildfire event. The suppression model uses the TDI to modify the estimated number of buildings destroyed that was predicted by the base consequence model.

2.4.3 Public Egress Impact Model

The Public Egress Impact Model was researched and developed in response to a WMP 2023 commitment to consider the effect of the ability of the public to leave the path of wildfire on the final consequence of an ignition event. Determining the likely success of egress is a challenge as there is no concrete historical data that can be used to train a model. However, research showed that wildfire fatalities mostly occur inside buildings and the number of fatalities is highly correlated with the number of buildings destroyed. Therefore, the Public Egress Impact Model was built to predict the number of fatalities per building destroyed by a wildfire.

Egress research also revealed a definite bias for those with mobility issues due to age, medical conditions, or vehicle availability as most likely to become wildfire victims. The Egress Impact Model was trained to consider the Access and Functional Needs (AFN) index as a proxy for mobility issues. The model predicts a relatively higher ratio of fatalities to building destroyed in areas where there are higher concentrations of the public characterized as AFN.

The egress impact is interactive with the wildfire suppression impact. If the suppression impact lowers the relative number of buildings destroyed, then it will also lower the expected number of fatalities due to egress issues.

2.4.4 Multi-Attribute Value function (MAVf)

The MAVf transforms the wildfire consequence model outcomes for acreage, destroyed building, and loss of life into a single consequence value. The 2023 Risk Assessment and Mitigation Phase (RAMP) filing implemented a Cost Benefit Approach methodology update to the MAVf that is used for WFC v4. The primary changes to the MAVf are:

- The MAVf output is explicitly one million risk-adjusted 2023 dollars per unit of MAVf.
- The Value of Statistical Life (VSL) is $12.5 million, decreased from approximately $100 million.

Assumptions continued from the prior version of MAVf include:

- $1 million per structure destroyed.
- Suppression cost is $1,157 per acre.
- Serious injury costs are assumed to be 1:1 with fatalities and valued at $3.125 million (0.25 * VSL).
- A non-linear, risk adjustment increases the consequences of more extreme events.

The MAVf update shifts consequence values away from loss of life and increases the importance of buildings destroyed and acreage burned. The shift is partially mitigated by the correlation of loss of life with the number of buildings destroyed. An analysis of the change in MAVf demonstrated minimal change to consequence distribution between WFC v4 and v3.4.

2.5 Performance

WFC v4 benefited from several improvements to the base consequence model as well as the addition of consequence adjustment models for wildfire Suppression and public Egress. As a result of the many contributing model developments, WFC v4 produces consequence values that show a significant improvement in and predicting wildfire outcomes.

2.5.1 Historical Wildfire Performance Improvement

The changes approved and implemented for WFC v4 have been validated through comparison with WFC v3.4. One validation was to look at how proposed changed alter the ability of the consequence model to account for historical wildfires. In general, the expectation is that the higher consequence areas should account for the majority of historical wildfire outcomes.

Figure 5 presents the relative performance for WFC v4 against WFC v3.4 for the three outcomes that are inputs to the consequence MAVf: acres burned, building destroyed, and fatalities. The graphs plot the fraction of historical fires accounted for against the ranked consequence pixel fraction. The rank consequence pixel fraction is determined by first ranking all consequence pixel values from highest to lowest, then finding the fraction of all pixels accounted for when the pixel that represents the ignition point for a historical wildfire is reached. Model performance improves as the resulting curve moves up and to the left.

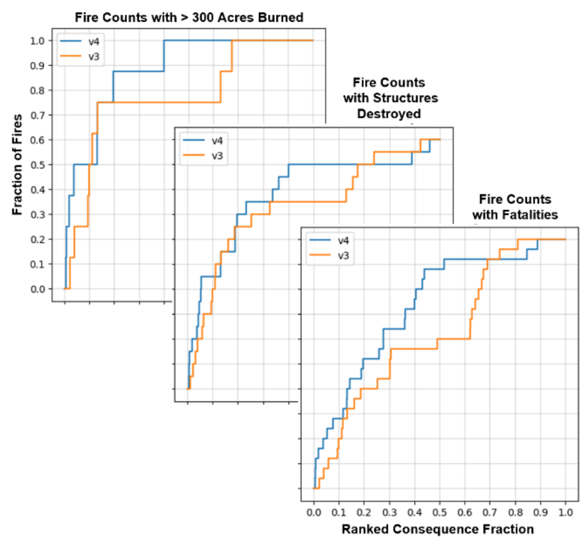

Figure 5 - WFC Historical Wildfire Performance

One way to interpret these graphs is to consider; if an ignition mitigation program were to be implemented in the order of ranked consequence values, how fast would the program reach the ignition points of historical wildfires? The steeper the initial rise of the curve, the quicker the historical ignition points would be mitigated.

WFC v4 outperforms WFC v3.4 for all three historical wildfire outcomes: acres burned, building destroyed, and fatalities. Therefore, the expectation is that WFC v4 will provide improved predictive outcomes for the consequence of ignitions at grid asset locations.

2.5.2 Feature Confusion Matrices

Feature confusion matrices can be used to examine the effectiveness of a feature on predicted outcomes.

Table 2 presents the confusion matrix for fatalities against the Predicted Destructive conditions feature. The matrix shows that a fatality is 14 times more likely to occur when Predicted Destructive conditions are present.

Table 2 - Fatalities / Predicted Destructive Confusion Matrix

Fatalities	Non-Predicted Destructive		Predicted Destructive		Ratio
One or more	4	0.103%	22	1.474%	14.3:1
None	3877	99.9%	1471	98.5%	0.99:1

Table 3 displays the confusion matrix for fatalities against the Dry Winds Conditions feature. The matrix reveals that a fatality is 8 times more likely to occur when Dry Wind Conditions are present.

Table 3 - Fatalities / Dry Wind Conditions Confusion Matrix

Fatalities	Non-Dry Wind Conditions		Dry Wind Conditions		Ratio
One or more	12	0.99%	8	8.16%	8.2:1
None	1196	99.0%	90	91.8%	0.93:1

3 Base Consequence Model

The WFC v4 base consequence model is an improved version of the WFC v3.4 that incorporates updated historical fire data and a new dry wind condition partitioning feature. The base consequence model provides foundational consequence values based on ignition location HFRA membership, predicted destructive status, and dry wind condition status.

The base consequence values are adjusted for wildfire Suppression and public Egress impacts to determine final consequence values.

3.1 Key Developments

Several improvements were implemented for modeling the base wildfire consequence model:

- Improved historical fire data set quality.
  - Increased the number of fires through merging multiple source data sets.
  - Expanded number of years of fire records.
  - Curated fire ignition locations.
- Expanded Technosylva fire simulation time from 8 to 24 hours to improve predictive performance for large fires.
- Introduced Dry Wind Conditions status to help differentiate the highest threat days.

These improvements will be described in detail in the following sections on training data and covariates.

3.2 Training Data

A significant effort was made to improve the quality of the historical fire data set used to train the base consequence model. The training data is assembled from three sources:

- NASA Visible Infrared Imaging Radiometer Suite (VIIRS)
- CPUC Safety and Enforcement Division (SED) reports
- CAL FIRE Red Books

A sample of individual wildfire data is provided in Appendix *6.2*, *Table 20*.

3.2.1 Visible Infrared Imaging Radiometer Suite (VIIRS)

VIIRS is a sensor package and data product produced by NASA. It is collected by satellites that pass over the PG&E service territory every 10 to 12 hours. The satellite raw detections for time, intensity, and location are process by third-party vendor Sonoma Technology Inc. (Sonomatech, STi) are processed through analysis into fire records and organized by unique VIIRS Fire IDs.

The VIIRS Fires provides the following crucial information for fires from 2012 to 2022:

- VIIRS Fire ID, derived from geo-spatial clustering
- Initial fire detection
  - Date and time stamp
  - Location
- Fire evolution
  - 10 to 12 hour update frequency
  - Burn area estimate

Satellite monitoring is limited by the need for a fire to endure and reach a certain size for a fire to be detected. Most fires larger than 300 acres persist long enough to be seen from space and therefore appear in the VIIRS data set. Smaller fires, particularly those of less than 10 acres, often do not get added to the VIIRS data set because they are frequently out and cold before a satellite passes over.

Another issue with satellite monitoring is that an initial fire detection often occurs several hours after an ignition due to the satellite pass frequency. Therefore, a fire can already be rather large at the time of detection and the ignition point can be ambiguous in VIIRS. Furthermore, wind can blur the fire footprint, resulting in fire detection well away from the actual combustion area.

3.2.2 CPUC Safety and Enforcement Division (SED)

The CPUC Safety and Enforcement Division (SED) is tasked with investigating the major fires that are suspected to involve an Investor Owned Utility (IOU). The SED produces detailed reports on the ignition locations, times, causes, involved electrical equipment, Supervisory Control and Data Acquisition (SCADA) information, etc. pertinent to determining fire cause. The reports are compiled using information gathered from SED, IOU and fire team sources.

SED fire reports generated since 2015 have been used to supplement the VIIRS data set. Often, the ignition times and locations for larger fires are sourced from SED reports due to VIIRS satellite detection limitations.

3.2.3 CAL FIRE Red Books

The CAL FIRE Red Books are annual publications on the outcomes of major fires that burn more than 300 acres. The recorded fire outcomes of acres burned, structures destroyed, and fatalities are used to calibrate the WFC with historical results.

Unfortunately, using the CAL FIRE Red Book outcomes is a mostly manual process. The CAL FIRE fire IDs must be joined with the Integrated Reporting of Wildfire Information (IRWIN) database to extract ignition locations that can then be matched against VIIRS data.

3.2.4 Lightning Fires

During model development, analysis showed that the expansion of the historical fire training data set included several lightning initiated fires that skewed the consequence model results away from conditions that are expected to have high consequence values. The skewed results were caused by several high impact fires that occurred in the HFRA during non-predicted destructive and non-dry wind conditions which were ignited by lightning strikes.

Lightning fires often occur in highly remote locations and/or during relatively benign conditions. Therefore, in many cases firefighters do not expend significant resources in fighting lightning fires and sometimes make the decision to let the fire burn out naturally. In these cases, the ultimate consequence, especially in terms of acres burned, is larger than what would be expected for an electrical asset initiated fire. As a result, lightning fires in HFRA on non-predicted destructive and non-dry wind condition days have been excluded from the historical fire training data set.

3.3 Model Covariates

3.3.1 Technosylva Wildfire Simulations

Technosylva is a wildfire simulation and analysis company that produces multiple products marketed to fire fighters, the insurance industry, and utilities. PG&E contracts with Technosylva to provide FireSight (formerly WRRM) simulations under different fuel and weather conditions at historical fire and electrical asset locations throughout the distribution and transmission grid networks. The wildfire simulation data is used to as a determinant of Predicted Destructive conditions.

Two substantial updates were requested from Technosylva for producing the wildfire simulation data for WFC v4: localized simulation of historical fires and 24-hr simulation times.

Technosylva wildfire simulations were explicitly requested at the locations for historical fires from the VIIRS dataset for WFC v4. In contrast, WFC v3.4 used a wildfire simulation from the nearest electrical asset within an 8 km radius to any given VIIRS fire ignition location. In many cases the fuel and weather conditions at the nearest asset were significantly different from conditions at the wildfire ignition point, leading to modeling issues for predicting consequence at asset locations. In some cases, for very remote wildfire ignition points, there would be no electrical assets within the 8 km search radius, and therefore the VIIRS fire would not be included in the training set. Sending explicit location and conditions data for historical wildfires to Technosylva for simulation both improved the quality and quantity of returned wildfire simulations for the WFC v4 training data set.

Reviews of WFC v3.4 raised concerns over the 8-hr time duration used for the Technosylva wildfire simulations. Most catastrophic fires last for days and sometimes weeks and at issue was whether or not a longer simulation time would help differentiate when a wildfire was likely to become catastrophic. Technosylva was tasked to produce both 8-hr and 24-hr wildfire simulations in support of WFC v4 development.

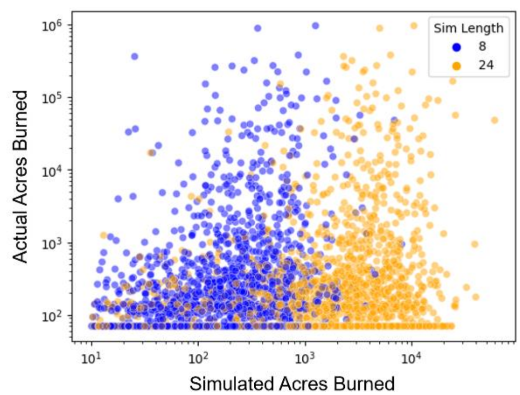

Figure 6 - 8-hr & 24-hr Fire Simulations (log-log scale)

To analyze the impact of 8-hr vs 24-hr simulations, each historic fire from the fire training data set was paired with its 8-hr and 24-hr simulation results. The initial Pearson R correlation results for the 8-hr and 24-hr simulations were very low, only 0.0637 and 0.0795, respectively. Applying a logarithmic transform to the data improved the correlation results for the 8-hr and 24-hr simulations to 0.198 and 0.208, respectively. *Figure 6* presents a log-log plot of the historical fire simulation pairs with 8-hr results in blue (●) and 24-hr results in orange (●). Note that many of the 24-hr simulation pairs are shifted to a larger simulated burn size.

The difference in 8-hr and 24-hr performance becomes clearer when the data pairs are binned as presented in *Figure 7*. The binned plot confirms a general shift to larger simulated burn size for 24-hr simulations. Importantly, the plot reveals a much smoother relationship between simulated and actual burn size for 24-hr simulations.

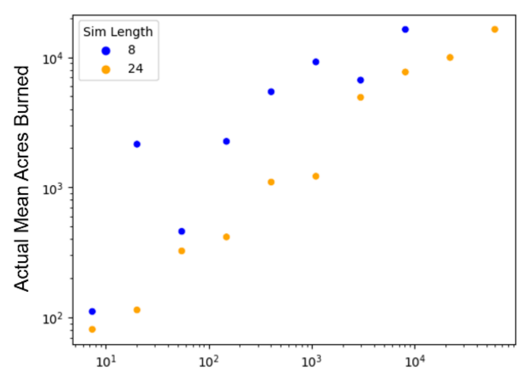

Figure 7 - Binned 8-hr & 24-hr Fire Simulations (log-log scale)

In the end, 24-hr wildfire simulations were chosen to develop the WFC v4 model due to the smoother relationship between simulated and actual burn sizes. However, the overall impact to relative consequence values was minimal.

3.3.2 Dry Wind Conditions (DWC)

A Dry Wind Conditions status was developed for the consequence modeling in response to both internal and external reviews of WFC 3.4 recommending the inclusion of Red Flag Warnings (RFW) issued by the National Weather Service (NWS). RFW warnings are issued by the NWS when there are weather conditions that would intensify fires.

The PG&E Enterprise Risk Management (ERM) team shared their research findings with the RaDA team that supported that destructive and catastrophic fires occurred primarily during RFW. A RaDA team analysis uncovered two significant issues with using RFW as a consequence model covariate:

- RFWs are issued for Fire Weather Zones (*Figure 8*) that are defined by an arbitrary mixture of watershed areas, ridgelines, and jurisdictional boundaries such as county lines.
- RFW declaration criteria is not consistent across each Fire Weather Zone and create geospatial discontinuities in RFW data – an RFW declared for one zone while RFW is not declared for a second zone with identical weather conditions. Appendix *6.1 - National Weather Service Red Flag Warning Criteria* provides specific RFW criteria for Fire Weather Zones.

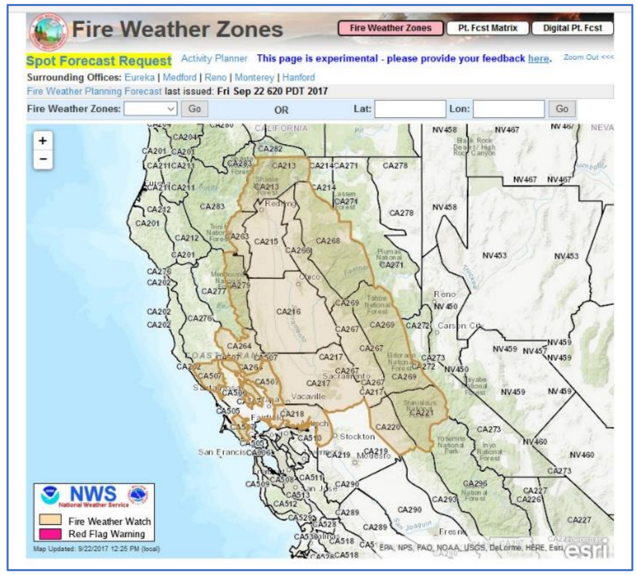

Figure 8 - NWS Fire Weather Zones

The RFW inconsistencies causes problems when trying fit it as a model covariate as the result may be a prediction based on RFW definition rather than the actual local conditions.

To avoid the RFW inconsistency issue, the RaDA team developed DWC as an internal status covariate. DWC is simply a variation of RFW limit criteria applied evenly across the service territory as shown in *Table 4*. The limit criteria for wind speed and relative humidity were aligned with similar criteria used for PG&E Meteorology's Fire Potential Index R-score.

Table 4 - Dry Wind Conditions Criteria

Measurement (daily average)	Limit
Wind Speed	>= 19 mph
10-hr Dry Fuel Moisture	<= 6%
Relative Humidity	<= 30%

3.3.3 Predicted Destructive (PD)

The Predicted Destructive conditions score, originally developed for WFC v3, combines results from PG&E Meteorology's Fire Potential Index R-score (FPI-R) and Technosylva's fire simulation results for Flame Length and Rate of Spread indices. *Table 5* shows the criteria for determining the Predicted Destructive status of a location for any day in the wildfire season.

Table 5 - Predicted Destructive Criteria

Measurement (daily value)	Limit
FPI-R	>= 4
OR	
[Flame Length	>= 5
AND	
Rate of Spread	>= 12**]**

3.3.3.1 Fire Potential Index R-score (FPI-R)

The FPI-R is a critical operation model developed and maintained by the PG&E Meteorology team to assess wildfire conditions.

The Fire Potential Index is modeled at a 2 km by 2km spatial resolution, providing data at hourly intervals for operational uses and daily intervals for planning uses. The daily interval FPI-R data is used for consequence model development.

The FPI-R methodology did not implement any significant updates between WFC v3.4 and WFC v4.

3.4 Base Consequence Table Construction

The base consequence tables are constructed by evaluating each of the historical wildfires that ignited under specific combinations of HFRA status, DWC, and Predicted Destructive (PD) status. These three stratifying variables identify eight distinct regimes for wildfire membership. The eight regimes are referred to using a descriptive shorthand of their respective true or false statuses in the order of HFRA, DWC, PD. Hence, the consequence regime for a location in HFRA, on a day not under Dry Wind Conditions, but on a Predicted Destructive day is referred to as a "T/F/T" regime wildfire.

Within each wildfire regime, the recorded outcome for acres burned, buildings destroyed, and fatalities for each member wildfire are processed through the MAVf function to determine its consequence value. A sample of individual wildfire data is provided in Appendix *6.2*, *Table 20*. The consequence values of all member wildfires are summed and averaged to determine the consequence value for a regime. The WFC v4 base consequence regime values are provided in *Table 6*.

Table 6 - Base Consequence Table

HFRA	Dry Wind Conditions	Predicted Destructive	MAVf
True	**True**	**True**	502
True	**True**	False	1.78
True	False	**True**	180
True	False	False	1.96
False	**True**	**True**	1.80
False	**True**	False	0.46
False	False	**True**	8.64
False	False	False	0.37

3.5 Base Consequence Table Application

The base consequence table is used to assign consequence values for grid asset locations. A grid asset location consequence value is the average consequence value over every fire season day from 2012 through 2022. Each wildfire season is defined as the 183 days from June 1st through November 30th. With 11 wildfire seasons covering 2012 through 2022, daily consequence values can be assigned to a total of 2,013 days.

As an example, take an asset that is located in HFRA. For a low risk day when there is neither Dry Wind Conditions nor Predicted Destructive conditions (T/F/F), the assigned consequence value from *Table 6* is 1.96. However, on higher risk day with both Dry Wind Conditions and Predicted Destructive conditions (T/T/T), the assigned consequence value from *Table 6* is 502. Extending this logic out for a full set of wildfire season days, the average consequence value for an asset location can be calculated as shown in *Table 7*.

Table 7 - Asset Location Base Consequence Value Example

HFRA	Dry Wind Conditions	Predicted Destructive	MAVf	Wildfire Season Days	MAVf Sum
True	**True**	**True**	502	50	25,100
True	**True**	False	1.78	150	979
True	False	**True**	180	550	99,000
True	False	False	1.96	1,263	2,475
Total				**2,013**	**127,554**
Average			**63.4**		

4 Adjusted Consequence

In compliance with WMP 2023 commitments, the potential impacts of suppression efforts and public egress on wildfire consequence predictions were investigated by the RaDA team. Subsequently, consequence impact models were developed for both Wildfire Suppression and Public Egress.

The Wildfire Suppression and Public Egress models impact consequence by adjusting the number of buildings destroyed and fatality rates determined by the Base Consequence model, changing the input values used by the consequence MAVf calculation.

To help explain how the consequence is adjusted for suppression and egress impacts, the Dixie Fire will be used as an example throughout this section. *Table 8* provides a summary of the conditions and outcomes for the Dixie Fire.

Table 8 - Dixie Fire Summary

Statistic	Value
HFRA	True
Dry Wind Condition	False
Predicted Destructive	True
TDI Level	2
AFN Decile	4
Acres Burned	963,309
Buildings Burned	1311
Fatalities	1
MAVf	13106

4.1 Wildfire Suppression Impact Model

The Wildfire Suppression Impact Model was investigated and developed in response to a WMP 2023 commitment to consider the effect of wildfire suppression activities on ignition consequence. A major challenge for modeling suppression is the difficulty of understanding historical state, regional, and local responses to ignition events and anticipating how future ignitions will be managed. Wildfire suppression impacts on consequence need to consider factors such as:

- Policy issues that originate from the responsible management authority for a wildfire location and reflect their mandates, priorities, and objectives for suppression a wildfire.
- The location and availability of firefighting resources that can be allocated during a wildfire. Resource allocation decisions can be affected by concurrent fires or other public needs, accessibility to roads, terrain issues, etc.
- The real-time decision-making by personnel in the field as fire captains with varying degrees of experience evaluate evolving weather conditions, fire conditions, and threats to life and property.

The feasibility of capturing suppression complexities in a model is limited by the usually sparse and often complete lack of availability of data relating each of the factors to actual wildfire outcomes. After considerable exploratory research, the Wildfire Suppression Impact model was developed using the fraction of surviving buildings within a burn area as a proxy for suppression effectiveness.

4.1.1 Key Developments

The crucial development activity for creating a wildfire suppression impact model was the determination to use buildings survival fraction from historical fires as a proxy value for suppression effectiveness.

The primary objective for fighting a wildfire is to protect life and property, with an emphasis on saving lives. Unfortunately, it is difficult to obtain precise data on the successful protection of lives for a given wildfire. However, public egress impact model development, discussed in Section *0*, has established that there is a consistent relationship between lives lost and the number of buildings destroyed by a wildfire. Therefore, success at protecting buildings, in terms of the fraction of buildings undamaged after a wildfire, will also imply success at protecting lives.

The number of buildings destroyed by any given wildfire is publicly available through the annual CAL FIRE Red Books. The number, type and locations of buildings that stood prior to a given wildfire can be obtained from the data records of Open Street Map. From this data the fractional loss of buildings can be determined for historical wildfires.

4.1.2 Historical Wildfire Suppression Outcome Model

4.1.2.1 Model Structure

The historical wildfire suppression outcome general model structure that was explored for developing the wildfire suppression impact model took the form of:

$$Structure\ Loss\ Fraction\ \cong f(Fuels, Terrain, Weather)$$

Where:

Variable	Description
Structure Loss Fraction	Expected fraction loss of buildings due to wildfire
Fuels	Localized fuel information
Terrain	Localized terrain information
Weather	Localized weather at time of wildfire

The modeling structure was based on the original hypothesis that a wildfire in a remote, difficult terrain, with abundant, dry fuels, and with extenuating weather like high wind and temperature would lead to suppression difficulties and therefore more building loss.

4.1.2.2 Training Data

The training data for the historical wildfire suppression outcome model was assembled from two sources:

- CAL FIRE Red Books
- OpenStreetMap

The CAL FIRE Red Books are annual publications on the outcomes of major fires that burn more than 300 acres with recorded fire outcomes of acres burned, structures destroyed, and fatalities.

OpenStreetMap is an open source geographic database that includes a buildings data set with location and structure type information. The data set is used to determine the number of existing structures that existed prior to historical wildfires.

4.1.3 Covariate Selection

4.1.3.1 Covariate Pool

The covariates considered and tested for the historical wildfire suppression outcome model include:

- Fuel conditions from the PG&E Meteorology team, including live and dead 10-hr, 100-hr, and 1000-hr fuel biomass and fuel moisture levels.
- Terrain Difficulty Index (TDI) provided by vendor Technosylva. The TDI is composite index from 1 to 5 that uses local topography and other factors to determine speed and ease of access from public roads and fire line feasibility for service territory equipment asset locations.
- Weather condition assessments from PG&E Meteorology, especially those that pose adverse conditions for suppression, such as relative humidity, wind speeds, etc.

4.1.3.2 Fitted Historical Wildfire Suppression Outcome Model

After evaluation, a binomial regression algorithm was selected to model historical wildfire outcomes. The model took the form of:

$$Log\ Odds\ of\ (Fractional\ Structure\ Loss) \cong a * TDI + b * WS + c * LFM + intercept$$

Where:

Variable	Description
Structures Destroyed	Expected number of structures destroyed by wildfire
Structures	Existing structures
LFM	Live fuel moisture of chamise vegetation smoothed to 1 km radius
TDI	Technosylva Terrain Difficulty Index
WS	Wind speed in mph at 300 m above the surface
a, b, c, intercept	Regressed coefficients

Table 9 provides an abridged summary of the model regression results.

Table 9 - Historical Fire Suppression Outcome Model Regression Results

Covariate	Coefficient	P-value
TDI (a)	1.3323	0.000
Wind Speed (b)	0.1100	0.000
Live Fuel Moisture (c)	-0.0774	0.000
intercept	-0.8676	0.000

From the regression results it can be observed that the TDI value is most critical to understanding historical fire suppression in terms of fractional building loss. The TDI coefficient is an order of magnitude more important that LFM and wind speed to modeling the historical wildfires. The model also confirms a common sense understanding of TDI and wildfire suppression, where higher TDI values, and therefore more remote, rugged locations, will result in a higher fraction of wildfire building loss.

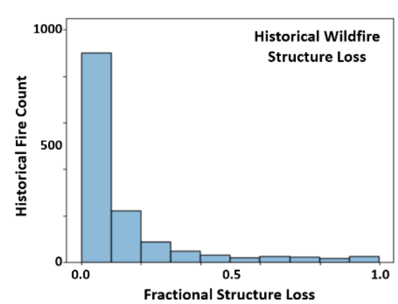

Figure 9 - Historical Wildfire Suppression Outcomes

The historical wildfire suppression model was fit to emulate the known outcomes of historical fires. *Figure 9* displays a histogram of fractional build loss from historical wildfires.

The suppression impact model is built by applying the historical wildfire suppression model to perform a series of what-if predictions at each historical fire location to examine the change in expected outcome in response to evaluating alternative TDI levels, 1 through 5.

Figure 10 visualizes the predicted wildfire outcomes for TDI level 1, 3, and 5. TDI level 1, the lowest level, outcomes skew to dramatically lower fractional structure loss when compared to the historical outcomes. TDI level 3, the middle level, shifts expected consequence significantly higher. Finally, TDI level 5, the highest level, predicts outcomes that are likely to lead to almost complete structure loss for a wildfire.

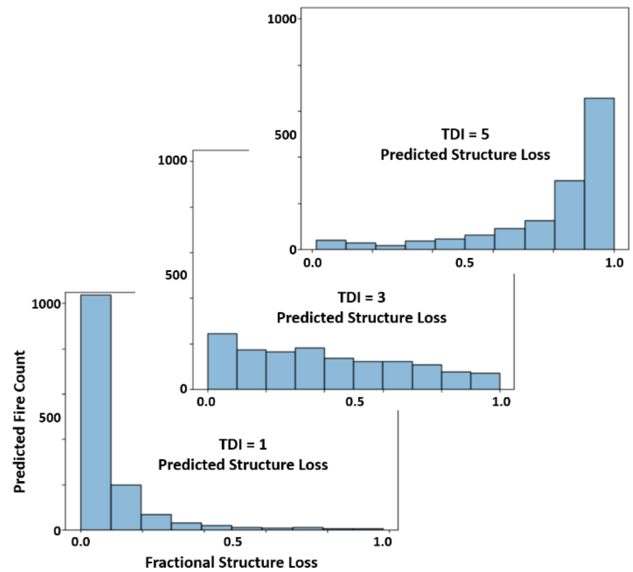

Figure 10 – TDI Level Predicted Wildfire Outcomes

The predicted wildfire outcomes for the alternative TDI levels can also be compared the historical wildfire outcomes by determining their mean consequence values using the MAVf algorithm. *Table 10* reports the mean wildfire consequence values for the historical and predicted wildfire outcomes.

Table 10 - TDI Level Consequence

TDI Level	Consequence
Historical	312.1
1	272.4
2	309.9
3	361.6
4	425.9
5	474.7

As expected, as terrain becomes more rugged and remote and the TDI level increase, the consequence for predicted outcomes becomes more severe.

4.1.3.3 Historical Wildfire Suppression Outcome Model Application

The Historical Wildfire Suppression Outcome Model is applied to each historical fire to examine how TDI level would have impacted the number of buildings destroyed. The integration of suppression data from the analysis of the historical fires to construct a final consequence model is described in Section *4.3*.

Using the Dixie Fire as an example, the suppression model predicts the number of buildings destroyed for the five TDI levels. Referring back to *Table 8*, the Dixie Fire started in an area with a TDI level of 2 and destroyed 1311 buildings. Using the suppression model, it can be estimated how TDI level would have impacted the number of buildings destroyed by the fire, as shown in *Table 11*.

Table 11 - Dixie Fire Suppression Predictions

TDI Level	Buildings Destroyed
Actual	1311
1	531
2	1311
3	3021
4	6082
5	9985

4.2 Public Egress Impact Model

The Public Egress Impact Model was investigated and developed in response to a WMP 2023 commitment to consider the effect of public egress activities on ignition consequence. A major challenge for modeling egress is the difficulty of understanding historical state, regional, and local responses to ignition events and anticipating how future ignitions will be managed. Public egress impacts on consequence need to consider factors such as:

- Policy issues that originate from the responsible management authority for a wildfire location and reflect their mandates, priorities, and objectives for initiating and managing a public evacuation in response to a wildfire.
- Number of egress routes available, volume capacity of egress routes, and public mobility in the predicted path of a wildfire.
- The number of people that choose, or conversely refuse, to follow an evacuation order.
- The real-time decision-making by public safety personnel in response to evolving weather conditions, fire conditions, and threats to life and property.

The feasibility of capturing public egress complexities in a model is limited by the usually sparse and often complete lack of availability of data relating each of the factors to actual wildfire outcomes. After considerable research, the Public Egress Impact model was developed to predict the ratio of the number of fatalities that will occur per number of buildings burned as a proxy for egress effectiveness.

4.2.1 Key Developments

The critical development activity for creating a public egress impact model was the decision to use fatalities per buildings burned ratio as a proxy value for suppression effectiveness. This modeling decision was based on a key assumption that when a building burns due to a wildfire, its occupants must either evacuate or fall victim to the fire.

Several potential contributors to egress impacts were investigated, of which personal mobility and roadway congestion were of particular interest. Interestingly, it was discovered that personal mobility was the much more important quantifiable factor. While roadway congestion is believed to play some role, model regressions failed to find a significant relationship, most likely due the small number of fires with actual roadway fatalities.

4.2.2 Historical Wildfire Egress Outcome Model

4.2.2.1 Model Structure

The historical wildfire egress outcome general model structure that was explored for developing the wildfire egress impact model took the form of:

$$Log\ Odds\ of\ (Fatality\ Fraction)\ \cong f(Road\ Miles\ per\ Capita, Mobility)$$

Where:

Variable	Description
Fatality Fraction	Expected fractional loss of life per buildings burned
Road Miles per Capita	Localized route capacity information
Mobility	Localized public mobility information

The modeling structure was based on the original hypothesis that egress from a wildfire would be dependent on the number, type and capacity of available evacuation routes and the timely ability of the public to leave a threatened area.

4.2.2.2 Training Data

The training data for the historical wildfire egress outcome model was assembled from:

- NASA Visible Infrared Imaging Radiometer Suite (VIIRS)

From the VIIRS data set there were 170 wildfires where there were either burned structures or fatalities recorded. The 170 identified fires became the training data set for the egress model development.

4.2.3 Covariate Selection

With only 170 wildfires available for the training data set, only a limited number of variables could be used for any given model evaluation to prevent regression model overfit. Covariate selection was strongly influenced by exploratory analysis of historical fires such as Tubbs, Nunns, and Camp.

The Camp fire provides an interesting case study[1] for egress:

- 50,000 people in about 25,000 vehicles evacuated Paradise, Concow, Magalia and the surrounding area.
- 19,500 buildings were destroyed.
- 85 fatalities were attributed to the fire.
  - 67 victims were age 64 or above.
  - 73 victims were found in or near their own home, and many had identifiable disability or mobility problems.
  - 5 victims were on foot with no evidence they were ever in a car.
  - Only 9 victims were found in a car or near their car having fled on foot.
- Multiple evacuation routes became completely obstructed.
  - 2 of 4 major routes from Paradise were completely obstructed for most of the evacuation period.
  - Evacuees experienced severe gridlock with many taking over 10 hours to travel just a few miles.
  - 23 burnover events impacted the roadways.
  - 230 vehicles were abandoned major roadways.

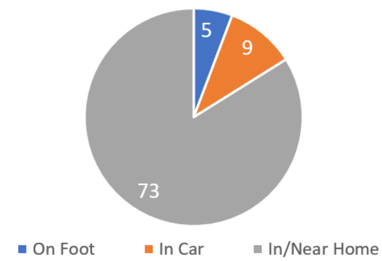

Figure 11 - Camp Fire Fatality Locations

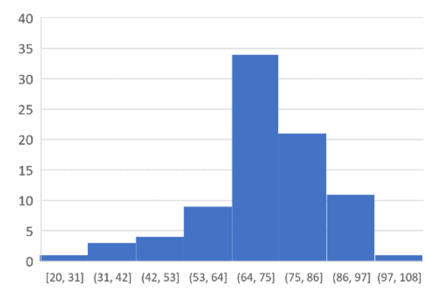

Figure 12- Camp Fire Fatalities by Age

Summarizing, 86% of the Camp fire victims were found in buildings and the overwhelming majority in people in vehicles, 99.98%, reached safety. Roadway egress obstructions did not substantially contribute to fatalities during the largest fire evacuation in California history.

4.2.3.1 Covariate Pool

The Camp Fire case study led to considering personal mobility proxy covariates for the historical wildfire suppression outcome model:

- Census data on older resident demographics.
- PG&E data on Medical BaseLine needs (MBL) customer fraction.
- PG&E data on Access and Functional Needs (AFN) customer fraction.
- Road congestion.

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[1] A Case Study of the Camp Fire - Notification, Evacuation, Traffic, and Temporary Refuge Areas (NETTRA), July 18, 2023

Census data and MBL, while producing modest relationships for the historical fires, were rejected as covariates. Census data is not available with enough fine granularity to predict with spatially. The percentage of MBL customers in the PG&E service territory, 5.8%, was too sparsely distributed to be useful as a covariate.

Potential road congestion, which is often suggested as a covariate by subject matter experts such as firefighters and wildfire analysts, was also rejected as a variable mostly due to lack usable information pertinent to modeling. A road availability proxy value available from Technosylva was tested but resulted in unstable regressions with poor covariate significance. While there may be a relationship between road congestion and wildfire fatalities, a means to successfully model the relationship eluded the development for this version of Egress impact modeling.

AFN was selected as a covariate for the Egress model. AFN is an all-encompassing term for any PG&E customer who:

- Classified as MBL
- Has a mobility issue.
- Is hearing-impaired.
- Is visually impaired.
- Is a life support customer.
- Self-identified as vulnerable.
- Over the age of 65.

Approximately 33% of the PG&E customer base has an AFN status. Therefore, AFN provides a much more detailed view of demographic impacts that could influence wildfire evacuation. Even so, modeling results between AFN and wildfire fatalities were modest, but stronger than for the rejected covariates.

The AFN value used for modeling fraction fatalities is processed from PG&E premises service point data. Information about the service point is rasterized and then blurred with a gaussian convolution using a standard deviation of 10 km. The intent of the gaussian convolution is to approximate the spatial alignment of a source consequence model to the population that could be within range of a life-threatening fire. For the egress model the distance of 10 km was used based on the common day-one burn length for fatal fires.

The blurred AFN value also makes use of a regularization factor to handle population sparsity and calculation float errors. Many service points are remote, impact a very small number of premises and people, which makes a localized AFN value difficult to accurately assess. The regularization effectively limits the minimum value of the blurred AFN value to the territory-wide AFN mean value. For more densely populated areas with greater than one person per square kilometer, the regularization contribution is negligible.

4.2.3.2 Fitted Historical Wildfire Egress Outcome Model

After evaluation, a binomial regression algorithm was selected to model historical wildfire outcomes. The model took the form of:

$$Fractional\ Fatalities\ \cong a * AFN + b * WS + intercept$$

Where:

Variable	Description
Fractional Fatalities	Expected fractional number of fatalities from wildfire
AFN	Blurred Access and Functional Needs value
WS	Wind speed in mph at 300 m above the surface
a, b, intercept	Regressed coefficients

Table 12 provides an abridged summary of the historical wildfire egress model regression results. *Figure 13* illustrates the relative change in fatality rate as a function of AFN fraction deciles. The table has been normalized to the 5th decile result.

Table 12 - Historical Egress Outcome Model Regression Results

Covariate	Coefficient	P-value
AFN (a)	3.0006	0.000
Wind Speed (b)	0.0133	0.000
intercept	-7.2095	0.000

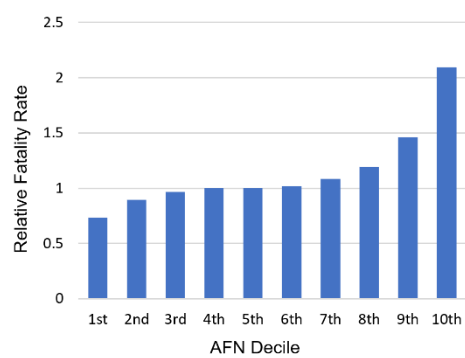

Figure 13 - Fatality Rate - AFN Relationship

4.2.3.3 Historical Wildfire Egress Model Application

The Historical Wildfire Egress Outcome Model is applied to each historical fire to examine how AFN decile level would have impacted the number of fatalities. The integration of egress data from the analysis of the historical fires to construct a final consequence model is described in Section *4.3*.

Using the Dixie Fire as an example, the egress model predicts the number of fatalities for the ten AFN deciles. Referring back to *Table 8*, the Dixie Fire started in an area with a TDI level of 2, an AFN decile level of 4, and resulted in 1 fatality. Using the egress model, it can estimated how AFN level would have impacted the number of buildings destroyed by the fire for a given TDI level, as shown in *Table 13*.

Table 13 - Dixie Fire Egress Predictions

AFN Decile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Fatalities	2.3	2.8	3.1	3.2	3.2	3.2	3.4	3.8	4.6	6.6

4.3 Adjusted Consequence Methodology

Base consequence for any specific fire season day, as discussed in Section *3*, is determined from a combination of location HFRA membership, Dry Wind Conditions, and Predicted Destructive conditions. These three stratifying variables identify eight distinct regimes for wildfire consequence. The eight regimes are referred to using a descriptive shorthand of their respective true or false statuses in the order of HFRA, DWC, PD. Hence, the consequence regime for a location in HFRA, on a day not under Dry Wind Conditions, but on a Predicted Destructive day is referred to as "T/F/T".

The consequence adjustment methodology expands each of the eight base consequence regimes from a single consequence value to a 5 by 10 matrix of consequence reflecting the TDI level and AFN Decile for a location. The matrixed consequence values are determined by first applying the Suppression Impact Model described in Section *4.1*, then the Egress Impact Model described in Section *0*.

Figure 14 provides an overview of how Suppression and Egress impact the predicted outcomes that are input to the MAVf to determine a consequence value for a location on a particular day.

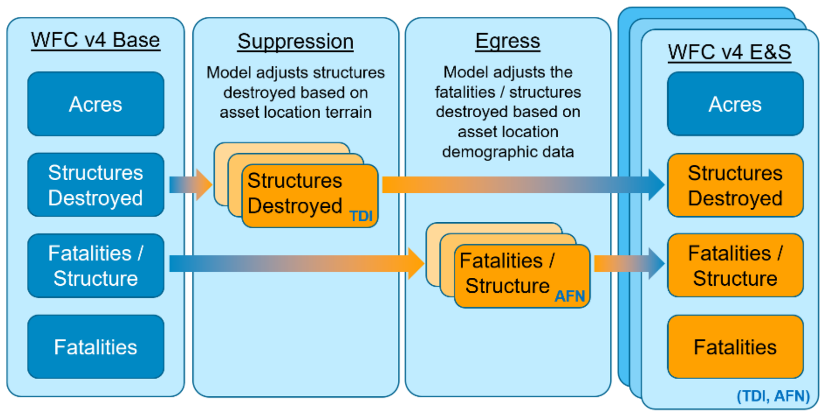

Figure 14 - Overview of Wildfire Consequence with Suppression and Egress Impacts

4.3.1 Consequence Regime Table Construction

The consequence regime tables are constructed by evaluating each of the historical fires that ignited under the specific regime conditions. The Dixie Fire example is a fire that started in HFRA, without Dry Wind Conditions, on a Predicted Destructive day (T/F/T). Using the Suppression and Egress Impact Models, the number of buildings destroyed for a given TDI level and the expected fatalities based on AFN Decile can be predicted, resulting in the matrix of hypothetical outcomes shown in *Table 14*.

Table 14 - Dixie Fire Predicted Suppression & Egress Outcomes

TDI Level	Structures Destroyed	Expected Fatalities by AFN Decile									
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
1	531	0.9	1.1	1.2	1.3	1.3	1.3	1.4	1.5	1.9	2.7
2	1311	2.3	2.8	3.1	3.2	3.2	3.2	3.4	3.8	4.6	6.6
3	3021	5.4	6.5	7.0	7.3	7.3	7.4	7.9	8.7	10.6	15.2
4	6082	10.8	13.1	14.2	14.7	14.7	14.9	15.9	17.5	21.4	30.7
5	9985	17.7	21.5	23.3	24.1	24.1	24.5	26.1	28.7	35.1	50.3

The predictions are converted into consequence values using the MAVf function, producing the *Table 15* matrix.

Table 15 - Dixie Fire Predicted Suppression & Egress MAVf Consequence

TDI Level	AFN Decile									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
1	7145	7153	7156	7158	7158	7159	7162	7167	7181	7212
2	13180	13199	13208	13212	13212	13214	13222	13235	13268	13344
3	26419	26463	26484	26493	26493	26497	26516	26618	26898	27560
4	50410	50741	50894	50963	50965	50999	51140	51369	51933	53265
5	81348	81892	82143	82256	82260	82315	82547	82923	83848	86036

This process is repeated for each historical fire recorded for a consequence regime. Finally, the consequence values for each TDI – AFN combination are averaged across all of the regime historical fires, resulting in a final consequence matrix as shown in *Table 16* for the T/F/T regime. Note that as the majority of historical fires in the T/F/T regime are not catastrophic that, unlike the Dixie Fire, the average consequence values are much lower.

Table 16 - T/F/T Consequence Regime Table

TDI Level	AFN Decile									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
1	45	45	45	45	45	45	45	45	46	47
2	98	99	99	99	99	99	99	100	101	104
3	217	218	219	219	219	219	220	221	224	231
4	409	412	414	414	414	415	416	418	424	438
5	621	626	628	629	629	630	632	636	644	666

The T/F/T consequence regime Suppression and Egress impacts relationship can also be visualized graphically, producing the plot shown in *Figure 15*. Note that the plotted point colors are coordinated with the row colors of *Table 16* above. On the plot it is easy to understand how both TDI Level and AFN Decile impact the relative consequence value for a consequence regime.

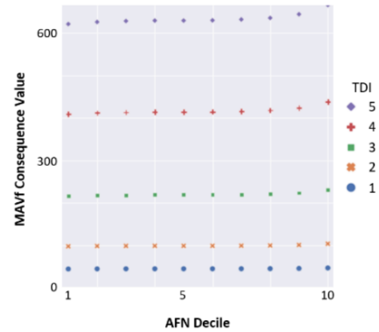

Figure 15 - T/F/T Consequence Regime

Figure 16 below displays the four consequence regimes generated for WFC v4 for assets located inside the HFRA for the four possible combinations of Dry Wind Conditions (DWC) and Predicted Destructive (PD). The y-axis is the consequence value range is different for each regime, with three orders of magnitude difference between highest and lowest consequence values.

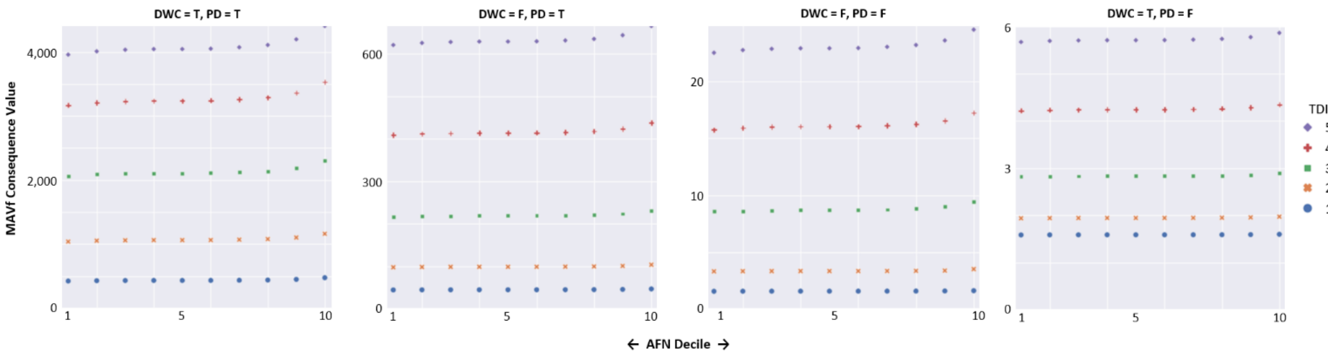

Figure 16 - Consequence Regimes for HFRA Asset Locations

Figure 17 displays the four consequence regimes generated for WFC v4 for assets located outside the HFRA for the four possible combinations of Dry Wind Conditions (DWC) and Predicted Destructive (PD). The y-axis consequence value range is different for each regime, with an order of magnitude difference between highest and lowest consequence values.

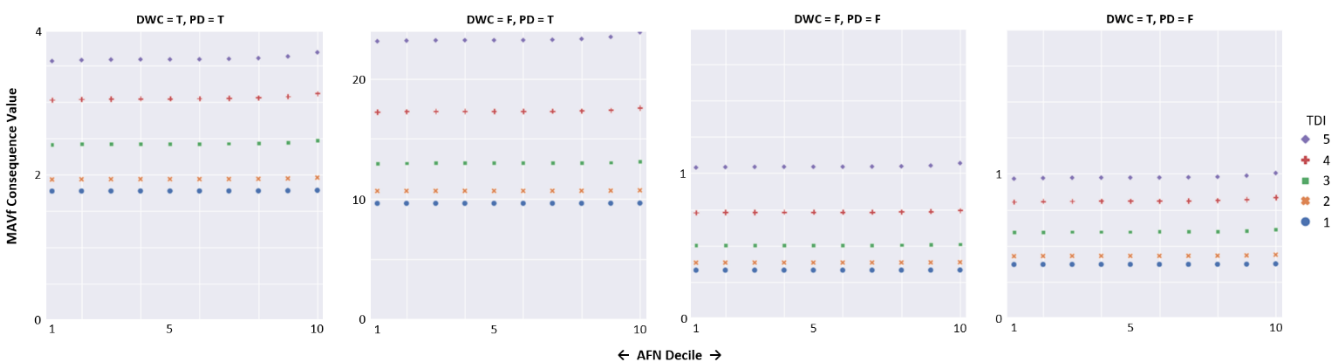

Figure 17 - Consequence Regimes for non-HFRA Asset Locations

Note that, as expected, there is a considerable disparity between high consequence regime values for HFRA versus low values for non-HFRA asset locations for similar Dry Wind Conditions and Predicted Destructive states.

4.3.2 Consequence Regime Table Application

Like the base consequence table, the consequence regime tables are used to assign adjusted consequence values for grid asset locations. A grid asset location adjusted consequence value is the average adjusted consequence value over every wildfire season day from 2012 through 2022. Each wildfire season is defined as the 183 days from June 1st through November 30th. With 11 fire seasons covering 2012 through 2022, daily consequence values can be assigned to a total of 2,013 days.

As an example, take an asset that is located in HFRA, has a TDI level of 2, and is at the 4th AFN decile. For a day where with no Dry Wind Conditions but with Predicted Destructive conditions, the assigned adjusted consequence value is 99, which can be confirmed by checking *Table 16*. However, on higher risk day with both Dry Wind Conditions and Predicted Destructive conditions, the assigned adjusted consequence value would be 1,000. Extending this logic out for a full set of wildfire season days, the average consequence value for an asset location can be calculated as shown in *Table 17*.

Table 17 - Asset Location Adjusted Consequence Value Example

HFRA	Dry Wind Conditions	Predicted Destructive	TDI Level	AFN Decile	Adjusted MAVf	Fire Season Days	MAVf Sum
True	**True**	**True**	2	4	1063	50	53,150
True	**True**	False	2	4	1.94	150	291
True	False	**True**	2	4	99	550	54,450
True	False	False	2	4	3.35	1,263	4,231
Total						2,013	113,122
Average							**56.2**

Referring back to the asset location base consequence example value provided in *Table 7* of Section *3.5*,the Egress and Suppression adjustments for TDI level and AFN decile have modified the average asset location consequence from a base value of 63.4 to an adjusted value of 56.2. This is a contributing factor to the flattening of the overall risk curve for WDRM v4.

4.4 Adjusted Consequence Impacts

As described previously, adjusted consequence values are determined as an extension of the base consequence regimes. Therefore, an examination of the adjusted and base consequence values was performed to understand and validate the consequence adjustment for wildfire Suppression and public Egress.

Figure 18 provides a view into where the adjusted consequence shifted values relative to the base consequence in the western Sierra Mountains. Most notable are the easily distinguished yellow circuit lines indicating a significant relative consequence increase for the more remote and rugged valleys. The increase largely reflects the wildfire Suppression impact and reflects the higher TDI levels assigned to these areas. Conversely, foothill areas, especially those with significant populations, generally have lower relative consequence due to proximity to firefighting resources and better access to for initial ignition response.

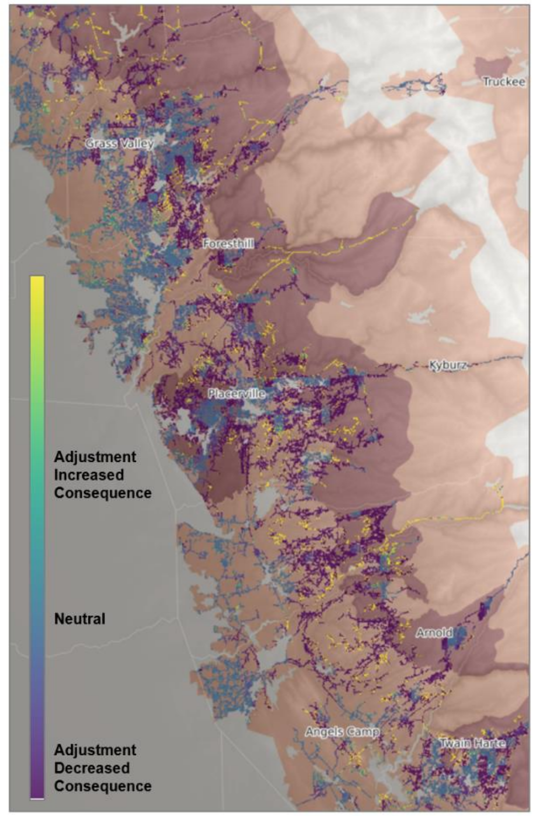

Figure 18 - Relative Adjusted Consequence Differential

The WFC model directly supports the WDRM, so consequence model changes are typically analyzed using aggregations of consequence pixel values to System Hardening's mitigation work planning unit, Circuit Segments (CS). *Figure 19* is a plot of adjusted versus base consequence rankings (highest rank is 1) for the top 2,500 circuit segments. On this plot the blue diagonal line represents where the CS consequence ranks are the same for both the adjusted and base values. Any point above the blue diagonal represents a CS where the adjusted consequence rank is lower than the base consequence rank, while any point below the diagonal represents a CS where the adjusted consequence rank is higher than the base consequence rank. Note that the CS point color represents the length of the CS with longer CS represented by darker points.

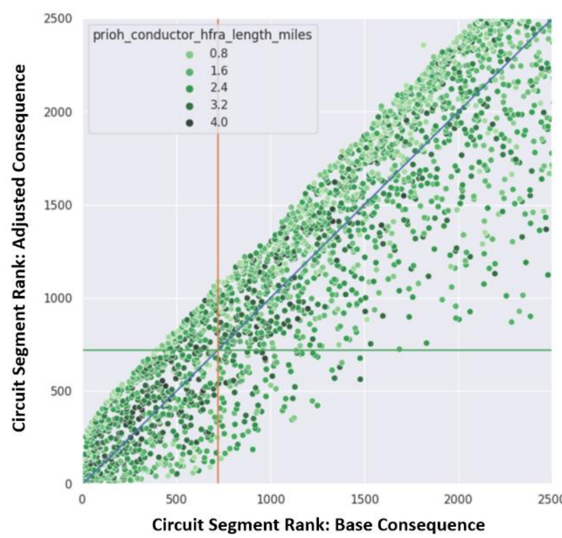

Figure 19 - Adjustment Impact on Circuit Segment Consequence

Keep in mind that a consequence rank change could be the result of two different reasons. First, the change could be due to a significant delta between the adjusted and base consequence value. Second, while the adjusted and base consequence values may be almost the same, other closely ranked circuit segments may have seen very significant changes that shifted the relative rankings.

Another consequence validation analysis was to look at how the adjusted and base consequence model values impact the System Hardening risk buydown curve. The risk buydown curve provides an estimate of many miles of primary overhead conductor must be undergrounded or harden to mitigate wildfire risk for the distribution grid.

Figure 20 contrasts the buydown curves for adjusted and base consequence. The introduction of the wildfire Suppression and public Egress flattened the risk buydown curve when compared with base consequence. The significance of the flattened curve is that it will take more miles of mitigated risk to achieve reduction targets. The base consequence curve estimates that it will take about 7,500 miles of work to mitigate 60% of wildfire risk, whereas the adjusted consequence curve estimates that it will require 10,000 miles of work to mitigate the same amount of risk. This was not the original expectation for adding the wildfire Suppression and public Egress impacts, resulting in additional efforts to validate the results and confirm the model development.

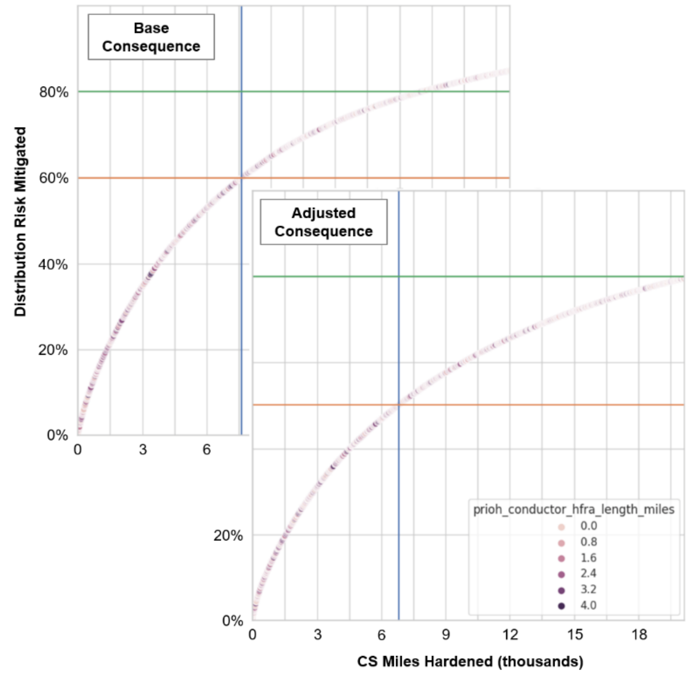

Figure 20 - System Hardening Risk Buydown

5 Future Plans

PG&E has historically released new versions of the WDRM, and therefore the WFC, on an annual cycle. In the future, WDRM releases are to be aligned with the WMP filing schedule rather than annually. Therefore, the next version of the WFC is expected to be released to coincide with a new version of the WDRM in support of the 2026 WMP.

Figure 21 presents an overview of the 3-year Wildfire Risk Products Plan, with planned improvements for the WFC highlighted in blue. The Egress and Suppression impacts delivered for v4 will continue to be refined and several new impact features for vulnerable communities, conflagration, and Wildland Urban Interface (WUI) fire consequence are planned for development. In addition, continual focused efforts are also expected to further improve the capture, detail, maintenance, and curation of data sets used for the consequence models.

Products	2026 WMP	Future WMP

Event Probability Models	• Data Quality Improvement
	• Model Refresh / Calibration
	• Asset Models – Distribution
	  • Switches
	  • Fuses
	  • Capacitor Banks
	  • Voltage Regulators
	• Asset Health – Tags
	• Work Plan Model Causality
	• Animal/Third Party – Distribution
	• Vegetation
	  • Tree Mortality
	  • Time Series Update
	• Insulator Contamination Update
		• Data Quality Improvements
		• Model Refresh / Calibration
		• Full Year Models
		• Asset Model – Distribution
		  • Secondary Conductor
		• Underground Assets
		• Lightning
		• Seismic – Distribution
		• Third Party – Transmission

Risk Models	• WDRM v4 • WTRM v2 • Public Safety Risk Model v2 • Reliability Risk Model v1 • Integrated Grid Planning	• WDRM Update • WTRM Update • Risk Mitigation Automation • Risk Reduction Reporting
Consequence Models	• Wildfire Consequence v4 • Wildfire Egress Impact • Wildfire Suppression Impact • Public Safety Consequence v2 • Reliability Consequence v1	• Wildfire Consequence Update • Conflagration • Vulnerable Communities • WUI Population Growth

Figure 21 - Wildfire Risk Products Plan

6 Appendix: Special Topics

6.1 National Weather Service Red Flag Warning Criteria

Red Flag Warnings (RFW) are issued for a Fire Weather Zone (*Figure 22*) by the National Weather Service (NWS) when there are weather conditions that would intensify fires. As noted in Section *3.3.2* on the Dry Wind Conditions covariate, the criteria to declare a Red Flag Warning varies by Fire Weather Zone.

Table 18 and *Table 19* provide a summary of the different limit criteria in effect for the NWS Fire Weather Zones.

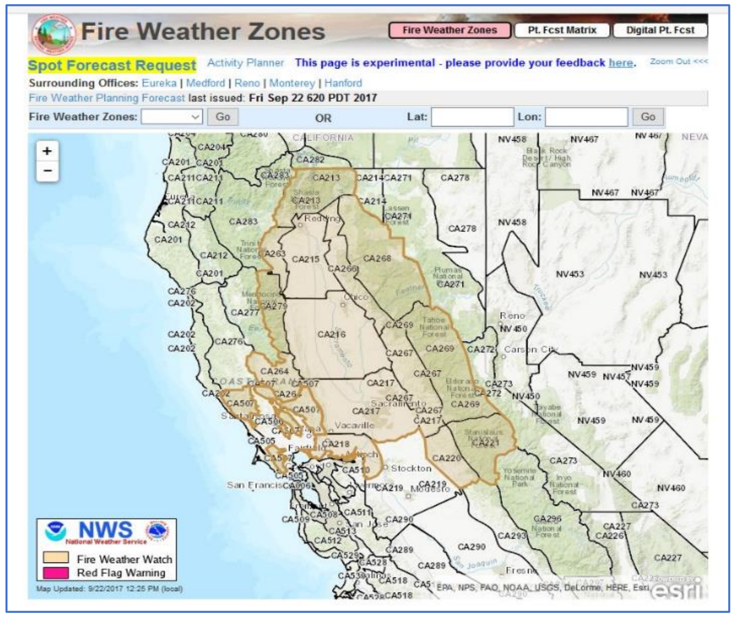

Figure 22 - NWS Fire Weather Zones

Table 18 - NWS Fire Weather Zone RFW Limit Criteria

Zones	Description	Criteria
226-228, 230, 232, 260-262	Southern California desert area excluding the Colorado River Valley	Relative humidity <= 15% and wind gusts >= 35 mph for 3+ hours
229,231	Colorado River Valley	Relative humidity <= 15% and sustained winds (@20 ft) >= 20 mph or frequent gusts >= 35 mph for 3+ hours
298, 299, 259	Antelope Valley and SE Kern County deserts	Relative humidity <= 15% and sustained winds (@20 ft) >= 25 mph for 8+ hours
234-258, 288-297	Southern California from mountains westward	EITHER Relative humidity <= 15% and sustained winds >= 25 mph or frequent gusts >= 35 mph for 6+ hours OR Relative humidity <= 10% for 10+ hours
214, 270-273, 278, 284, 285	Northern California East of Cascade/Sierra Crest and Western Great Basin including the Modoc Plateau	TAHOE MANAGEMENT BASIN Wind gusts >= 30 mph And relative humidity <= 20% For 3+ hours REMAINDER Wind gusts >= 30 mph And relative humidity <= 15% For 3+ hours
201-213, 215-221, 263-269, 274-277, 280-282	Northern California West of the Cascade/Sierra Crest	Reference *Table 19 – NorCal Fire Weather Zone RFW Limit Criteria Matrix*

Table 19 – NorCal Fire Weather Zone RFW Limit Criteria Matrix

Criteria	Sustained Wind Speeds			
Relative Humidity	6-11 mph	12-20 mph	21-29 mph	> 30 mph
Daytime Minimum : 29-42% Nighttime Maximum : 60-80%				RFW
Daytime Minimum : 19-28% Nighttime Maximum : 46-60%			RFW	RFW
Daytime Minimum : 9-18% Nighttime Maximum : 31-45%		RFW	RFW	RFW
Daytime Minimum : < 9% Nighttime Maximum : < 31%	RFW	RFW	RFW	RFW

6.2 Wildfire Consequence Training Data

Table 20 provides a small sample of wildfire data use for training the consequence models. It combines information from the VIIRS satellite detections as well as CALFIRE Red Book reports. Also included are the latitude/longitude coordinates given to Technosylva for creating wildfire simulations at the actual fire locations.

Table 20 - Wildfire Consequence Traing Data Sample

VIIRS					Technosylva		CALFIRE					
Fire ID	Start Time	First Detection Latitude	First Detection Longitude	Final Detection Area	Simulation Latitude	Simulation Longitude	Name	Acreage	Structures Destroyed	Structures Damaged	Fatalities	MAVf
2017_1106	2017-10-09 03:15:00-07:00	38.3737	-122.25684	49849	38.373799	-122.257	('ATLAS (SOUTHERN LNU COMPLEX)',)	51624	783	120	6	1931
2017_1107	2017-10-09 03:15:00-07:00	39.31841	-123.21579	38557	39.323005	-123.132	('REDWOOD VALLEY\n(MENDOCINO LAKE COMPLEX)',)	36523	543	41	9	1624
2017_1128	2017-10-09 03:15:00-07:00	38.33153	-122.46737	60202	38.428266	-122.549	('NUNS (CENTRAL LNU COMPLEX)',)	44573	1355	172	3	5261
2017_1136	2017-10-09 03:15:00-07:00	38.53556	-122.68947	39811	38.600649	-122.62	('TUBBS (CENTRAL LNU COMPLEX)',)	36807	5636	317	22	40243
2018_1369	2018-11-08 11:50:00-08:00	39.77267	-121.55362	113229	39.814389	-121.434	('CAMP',)	153336	18804	754	85	151388
2020_1480	2020-08-17 02:12:00-07:00	39.69898	-122.73410	1027832	39.698192	-122.734	('AUGUST COMPLEX',)	889467	34	4	1	2666
2021_1331	2021-07-14 02:06:00-07:00	39.87496	-121.38244	945313	39.875	-121.382	('DIXIE',)	963309	1311	94	0	13106