PACIFIC GAS AND ELECTRIC COMPANY

CALCULATING METEOROLOGICAL AND PG&E FIRE RISK

PG&E PSPS DECISION-MAKING FOR DISTRIBUTION

July 2021

REV.4

PG&E Emergency Preparedness & Response

PG&E Meteorology and Fire Science

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1 Introduction

1.1 Public Safety Power Shutoff, Extreme Weather and Wildfires

The purpose of the document is to give the reader a deep understanding of the models, tools and methodologies we have developed to make Public Safety Power Shutoff (PSPS) decisions. This document also includes detailed information into how specific models were constructed to understand the increased probability of an ignition event and the potential consequences of a resulting fire.

We developed the PSPS program in 2018 as a response to the continued and growing threat of catastrophic wildfires and as an additional precautionary measure following the 2017 and 2018 wildfires. A PSPS is a proactive de-energization of electric equipment as a measure of last resort to reduce wildfire risk. The most catastrophic fires attributable to PG&E equipment have occurred during dry, offshore wind events called Diablo, Mono, or Santa Ana winds. These wind events helped rapidly spread devastating wildfires such as the Tubbs, Nuns, Atlas, Redwood Valley, La Porte, Cascade, Sulphur, Pocket, Lobo, Camp, and Kinkade fires in Northern California. These events are most frequent from September through mid-November and coincide when live and dead fuel moisture values are near seasonal minimums.

A PSPS will only be considered when dry, gusty winds occur when fuels are dry. These events will likely occur during Red Flag Warnings issued by the National Weather Service. The PSPS program will not eliminate all risk of equipment igniting a wildfire but is aimed at significantly reducing areas with the highest risk when strong winds increase the probability of vegetation and equipment failures as well as contribute to a rapidly spreading wildfire. We have additional programs in place to reduce the overall ignition risk such as enhanced vegetation management, system inspection programs, system hardening, and daily mitigation actions when the fire potential is high. These additional mitigation programs are not discussed in this document.

1.2 Key PSPS Decision Factors

Our PSPS decision making models have evolved since the PSPS program inception in 2018. After each PSPS season, we evaluate the lessons learned from the previous season and work to improve the input data sets, weather prediction, and test new models to better inform when PSPS should be applied. Since 2018, we have conducted PSPS based on risk-informed decisions by evaluating the potential for increased outage activity that may lead to ignitions combined with the potential for large or catastrophic fires. In 2018, we combined outputs from the Storm Outage Prediction Project with a newly developed Fire Potential Index (FPI). This methodology was enhanced in 2019 by developing a granular Outage Producing Wind (OPW)

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model and developing an enhanced FPI model based on logistic regression using historical data. In 2020 we increased the granularity of the core weather model from 3 x 3 km to 2 x 2 km and significantly enhanced the OPW to also provide more granular output. Both the OPW and FPI models were significantly enhanced in 2021 using new datasets, advancements in machine-learning. The OPW output is also translated into an Ignition Probability using outage and ignition causes and their respective ignition to outage rates. This new ignition model is called the Ignition Probability Weather (IPW) model. Additionally, after years of testing fire spread simulations across historical and forecast time-horizons, we added Technosylva fire spread outputs into the PSPS decision making framework in 2021.

This document provides an overview of the 2021 models that are operational as of August 2021. Please note that we will continue to enhance these models in future years.

For 2021, there are three key inputs of the meteorological and fuels analysis to determine PSPS criteria on the distribution system:

- Minimum Fire Potential Conditions (mFPC)
- Catastrophic Fire Probability (CFP_D) comprised of the following:
    - Ignition Probability Weather (IPW)
    - Utility Fire Potential Index (FPI)
- Catastrophic Fire Behavior (CFB) - Technosylva
- Consideration of known high risk vegetation and electric compliance tags

The minimum Fire Potential Conditions (mFPC) are a low-pass weather and fuels filter based on relative humidity values, wind speed and fuel moisture values that must be exceeded for PSPS to be considered. These values were established from an examination of historical fire occurrence in the PG&E territory as well as information published by federal agencies regarding fire behavior and criteria used to issue warnings to the public.

The IPW and FPI models are combined in both space and time to form Catastrophic Fire Probability (CFP_D) output at 2 x 2 km resolution. The CFP_D model provides hourly output and highlights locations that have concurrence of an increased probability for large fires and increased probability of wind-related ignitions on the distribution system. The Catastrophic Fire Behavior (CFB) criteria are used to identify locations that may have lower probability of ignition but could result in fires that are not easily suppressed and have potentially high consequences.

The current PSPS models and general guidance for Distribution is presented below.

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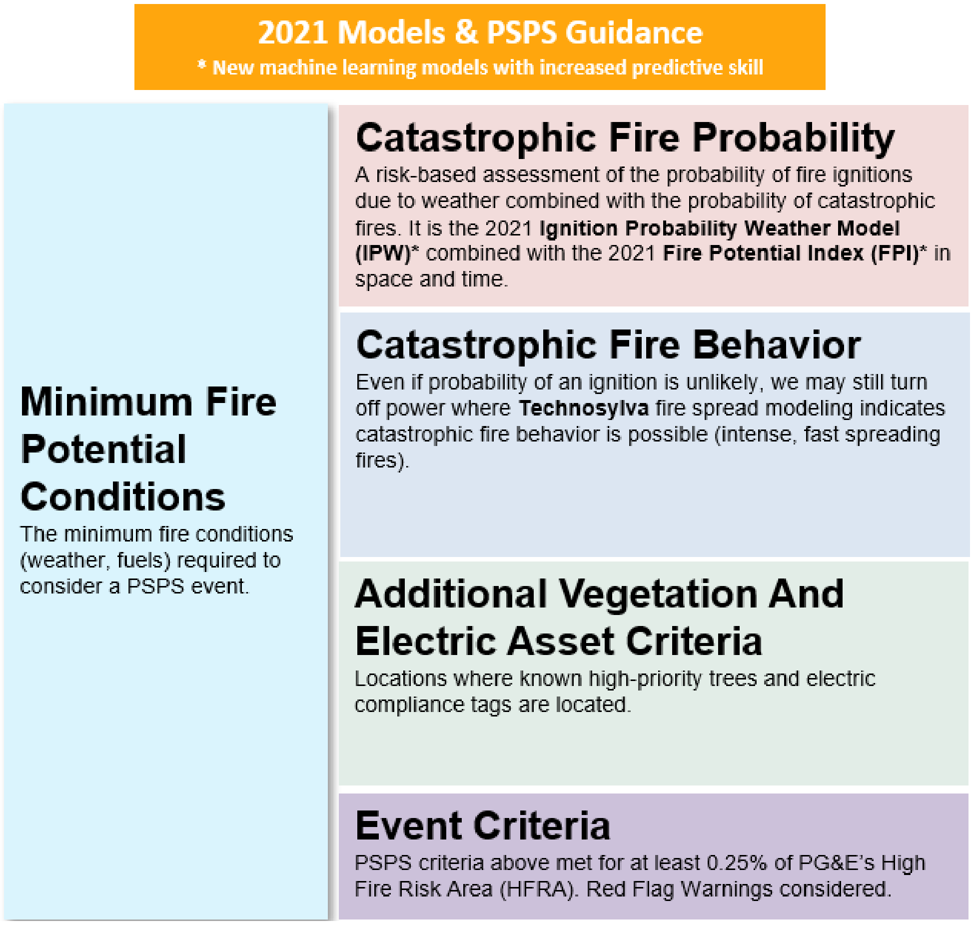

Fig. 1. High level overview of 2021 Distribution PSPS guidance

There are four key inputs of our meteorological analysis to determine PSPS criteria on the Transmission system:

- Minimum Fire Potential Conditions (mFPC)
- Catastrophic Fire Probability (CFP_T) comprised of the following:
    - Transmission Operability Assessment (OA)
    - Utility Fire Potential Index (Utility FPI)
- Catastrophic Fire Behavior (CFB) - Technosylva
- Consideration of known high risk vegetation and electric compliance tags

On Transmission, the same general risk framework is utilized; however, the distribution IPW model is replaced with the Transmission Operability Assessment (OA) model, which provides probability of failure for each transmission structure. For Transmission, the OA and FPI models

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are combined in both space and time to form the Transmission Catastrophic Fire Probability model (CFP_T).

We partnered with a third party, Exponent, to develop the Operability Assessment (OA) model for Transmission. This model combines historical wind speeds for each structure, historical outage activity, and the condition of assets based on inspection programs to help understand the wind-related failure probability of each structure. The model can be driven with forecast wind speeds to output the probability of failure at the structure level.

No single factor drives the determination that a PSPS is necessary, as each situation is dynamic and unique. The main drivers of PSPS are described at a high level above and in more detail in this document. We also carefully review external forecast information from the National Weather Service (i.e., Red Flag Warnings) and other forecast agencies and coordinate with these agencies during high-risk periods to ultimately decide to de-energize portions of the grid for public safety.

1.3 Additional PSPS Decision Factors

Our PSPS models drive every PSPS assessment on the distribution and transmission system and PSPS may be executed when guidance values are exceeded. In addition to the PSPS models, we carefully review an array of available data and federal forecast information to verify that multiple authorities recognize an upcoming or imminent period of risk. These include:

- Red Flag Warnings from the National Weather Service
- High Risk forecasts of Significant Fire Potential from the Geographic Area Coordination Center (GACC)
- Fire weather outlooks from the Storm Prediction Center (SPC), which is part of the National Weather Service (NWS)

During high risk periods PG&E meteorologists participate in daily interagency conference calls that commonly include multiple NWS local offices, the NWS western region headquarters, and representatives from the GACC. This call is hosted by the Northern CA or Southern CA GACC offices. Agreements with CAL FIRE and United States Forest Service (USFS) leadership allow participation on these calls (although our participation does not influence any forecasts issued by these independent agencies). During these calls, the agencies present their expert assessment on the upcoming period(s) and location(s) of risk, wind speeds and fuel moisture levels, and any other relevant factors to consider. We greatly appreciate these conference calls and the opportunity to coordinate with external and independent forecast agencies on upcoming risk periods. During PSPS events, the lead meteorologist for the event, called the

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Meteorologist In Charge (MIC), summarizes these forecasts and discussions for the Officer In Charge (OIC), who ultimately makes the decision to execute a PSPS event. If external agencies are not in agreement with our analysis and do not see an upcoming event as high risk for large fires, the OIC may use this intelligence to decide if PSPS is warranted or not.

In addition to this information, we carefully review and consider the location of existing fires and where new fires are detected using the Satellite Fire Detection & Alerting System (FDAS), which uses data from six NOAA/NASA satellites to detect fires, and other information compiled (such as intel from field observers) by PG&E's Hazard and Awareness Warning Center (HAWC). If an active fire may require active or imminent community evacuations we would consider how best to support those efforts in relation to PSPS decisions.

Below is a list of other sources and tools besides the PSPS models that are considered for PSPS:

1. Fire Weather Watches and Red Flag Warning (NWS - Federal)
2. Significant Fire Potential for Wind (Geographic Area Coordination Center (GACC), Federal)
3. Storm Prediction Center (Federal, part of National Oceanic and Atmospheric Administration (NOAA))
4. Daily Interagency Conference Call with agencies during high risk periods
5. Field Observer information
6. Live weather data from weather stations
7. Location of existing fires
8. New fires detected – Satellite Fire Detection & Alerting System (FDAS)
9. European Centre for Medium Range Weather Forecasts model (ECMWF)
10. North American Mesoscale model (NAM)
11. High-Resolution-Rapid Refresh-Model (HRRR)
12. Global Forecast System (GFS) American global model
13. Other weather models

NOTE: This document represents the current PSPS criteria and is subject to further refinement.

1.4 PG&E's High-Resolution Weather and Fuels Forecasts and Climatology

At this early point in this document, we want to provide the reader with an understanding of core models and datasets used to forecast PSPS events as well as train our PSPS models and discover relationship between environmental factors, outages and fires.

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We partnered with two external experts in Numerical Weather Prediction (NWP) as well as have internal experts with advanced degrees in meteorology to develop historical datasets and forecast models.

In 2014 we partnered with Weather Decision Technology (WDT), which was since acquired by DTN, to deploy the first version of our PG&E Operational Mesoscale Modeling System (POMMS), which is based on the Weather Research and Forecast (WRF) Model. WRF is a mesoscale numerical weather prediction system designed for both atmospheric research and operational forecasting applications. It features two dynamical cores, a data assimilation system, and a software architecture supporting parallel computation and system extensibility. WRF development was a collaborative partnership of the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (represented by the National Centers for Environmental Prediction (NCEP), the (then) Forecast Systems Laboratory (FSL)), the (then) Air Force Weather Agency (AFWA), the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA).

WRF can produce simulations based on actual atmospheric conditions (i.e., from historical observations and analyses) or idealized/forecast conditions. WRF offers a flexible and computationally-efficient platform for operational forecasting that incorporates recent advances in physics, numerics, and data assimilation contributed by developers from the expansive research community. WRF is currently being used operationally at NCEP and other national meteorological centers and in real-time forecasting configurations at laboratories, universities, and private companies.

A second external expert has also been engaged since 2014, Atmospheric Data Solutions (ADS). ADS, led by Dr. [redacted], has extensive knowledge of California fire weather and numerical weather prediction using WRF and he works extensively with the other major CA utilities. We first deployed the high resolution in-house mesoscale forecast model, POMMS, in November of 2014 and continues to improve and build upon the model framework to generate short to medium-term weather, outage, and fire potential forecasts across the PG&E service territory.

POMMS is a high-resolution weather forecasting model that generates important fire weather parameters including wind speed, temperature, relative humidity (RH), and precipitation. Outputs from POMMS are used as inputs to the Nelson Dead Fuel Moisture (DFM) model, and proprietary Live Fuel Moisture (LFM) models developed by ADS to derive key fire danger indicators such as 1hr, 10hr, 100hr, 1000hr DFM, and LFM for multiple species. In late 2018 to 2019, we successfully completed one of the largest known high-resolution climatological datasets in the utility industry: a 30-yr, hourly, 3 km spatial resolution dataset consisting of

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weather, DFM, LFM, NFDRS outputs, and fire weather derivative products such as the Fosberg Fire Weather Index (FFWI).

With this robust weather and fire parameter dataset, we sought to develop outage and fire potential models in 2019 utilizing best-practices deployed in the utility industry, fire science and data science communities. In late 2019 to 2020, we embarked on an intensive effort to improve the POMMS model by increasing the resolution from 3 x 3 km to 2 x 2 km as well as increasing the output accuracy. The 2020 goal was to deploy a more accurate and granular high-resolution model to reduce customer impacts due to Public Safety Power Shutoff (PSPS) in 2020. To achieve this goal, internal numerical weather prediction experts again partnered with external experts, DTN and ADS.

Over the course of half a year from late 2019 to early 2020, nearly 20 different model configurations were tested by internal and external experts to determine the optimal weather model configuration for deployment. This included extensive back-testing and validation of past PSPS events to fine-tune model parameterizations and physics options to achieve the most accurate model possible for deployment. After the optimal model was recommended by external experts DTN and ADS and agreed upon by internal experts, it was deployed in 2020 and utilized during all 2020 PSPS events.

The current POMMS model configuration deployed is WRF model version 4.1.2, which provides data at 2 x 2 km spatial and hourly temporal resolution. Key features added or made default in version 4 of WRF include a hybrid vertical coordinate and a moist potential temperature prognostic variable. A nested grid configuration of 18-, 6-, 2-, and 0.67-km (on demand) grids are utilized. The vertical grid has 51 levels and a 20 hPa top. Adaptive time stepping is used for computational efficiency and the model was configured to run in the AWS cloud across different AWS regions for redundancy. The POMMS forecasts are initialized using ¼° output from the National Centers for Environmental Prediction (NCEP) - GFS model data as well as 1/12° Sea Surface Temperature analyses. The GFS, often referred to as the American Model, is operated and maintained by NOAA’s National Center for Environmental Prediction and is the United States’ flagship global model. Soil moisture cycling and snow cover cycling were added in Q2 2021. Data assimilation (3DVAR) is applied on the outer grid. Data available for assimilation and initialization are taken from MADIS and include conventional surface and upper-air observations, as well as aircraft data and satellite-derived winds. As the NCEP-GFS forecast model is a single point of failure, internal and external experts developed the ability to initialize POMMS with ECMWF in case of a Federal/NCEP data outage. The model domain and nesting configuration is presented below. Each grid is run 4x a day aside from the 0.67 km domain, which is run on-demand during high-risk events.

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In addition to improving the forecast model, a new 31-year climatology dataset was produced by DTN and ADS using this new model configuration at 2 x 2 km resolution. The goal was to create a high-resolution historical dataset with hourly data. The technique to create these high-resolution climatology datasets for study and exploration are widely used in the meteorological industry. In fact, a historical climatology was one of the foundational datasets used by the CPUC and consultants to build the CPUC High Fire Threat District.

This climatology used the NCEP-Climate Forecast System Reanalysis (CFSR) to initialize and force the WRF model. The purpose is to dynamically downscale the coarser CFSR data to the finer 2 x 2 km resolution using the same model physics as we apply in the forecast model.

The CFSR is a third-generation reanalysis product produced from NCEP. It is a global, high resolution, coupled atmosphere-ocean-land surface-sea ice system designed to provide the best estimate of the state of these coupled domains. The CFSR includes (1) coupling of atmosphere and ocean, (2) an interactive sea-ice model, and (3) assimilation of satellite radiances.

DTN created the 31-yr historical weather climatology at 2 x 2 km resolution and hourly time resolution using CFRS and WRF. The output is a massive dataset containing 2 x 2 km resolution data for dozens of weather variables, hourly from 8/1/1998 – 4/1/2021. ADS leveraged this weather climatology to train, test and build DFM and LFM models for multiple plant species. Once final models were set, these models were “backcast” through the climatology to produce DFM and LFM outputs at the same spatial and time resolution as the weather climatology.

This robust dataset serves as the foundation to train and test our new Fire Potential Index and Outage models described in more detail below. For example, the weather and fuel moisture values can be extracted from the location, day and hour of each fire ignition or outage to better understand the contributing causes.

Using the climatology data we can help answer questions such as: *What weather and fuel moisture values are best to predict when large fires will occur or not occur? Are there fuel moisture values above which large fires do not occur? Where do Diablo and Santa Ana winds most frequently develop? Have Diablo wind events increased over the past 30 years? At what wind speeds do we see an increase in outage activity? Is the wind speed to outage relationship hetero- or homogenous across PG&E’s territory?*

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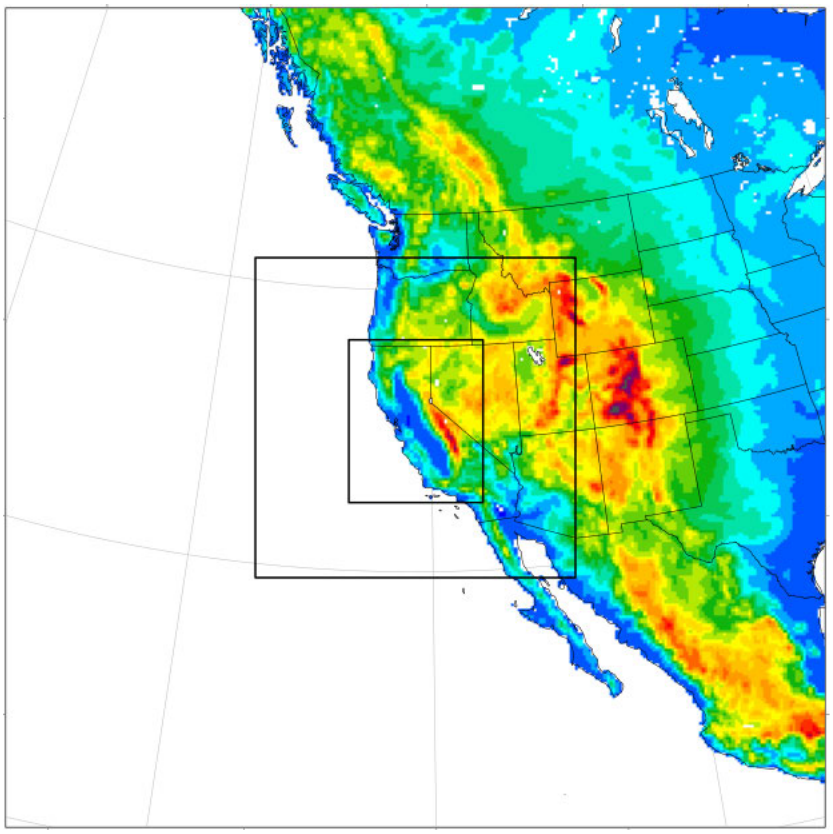

Fig. 2. Operational weather model grid configuration

Table 1. Weather model grid configuration details

Grid number	Grid spacing (km)	Grid extent (nx x ny, staggered)	Width x height (km)
1	18	270 x 270	4842 x 4842
2	6	316 x 316	1890 x 1890
3	2	397 x 481	1188 x 1440
4	0.67	322 x 322	214 x 214

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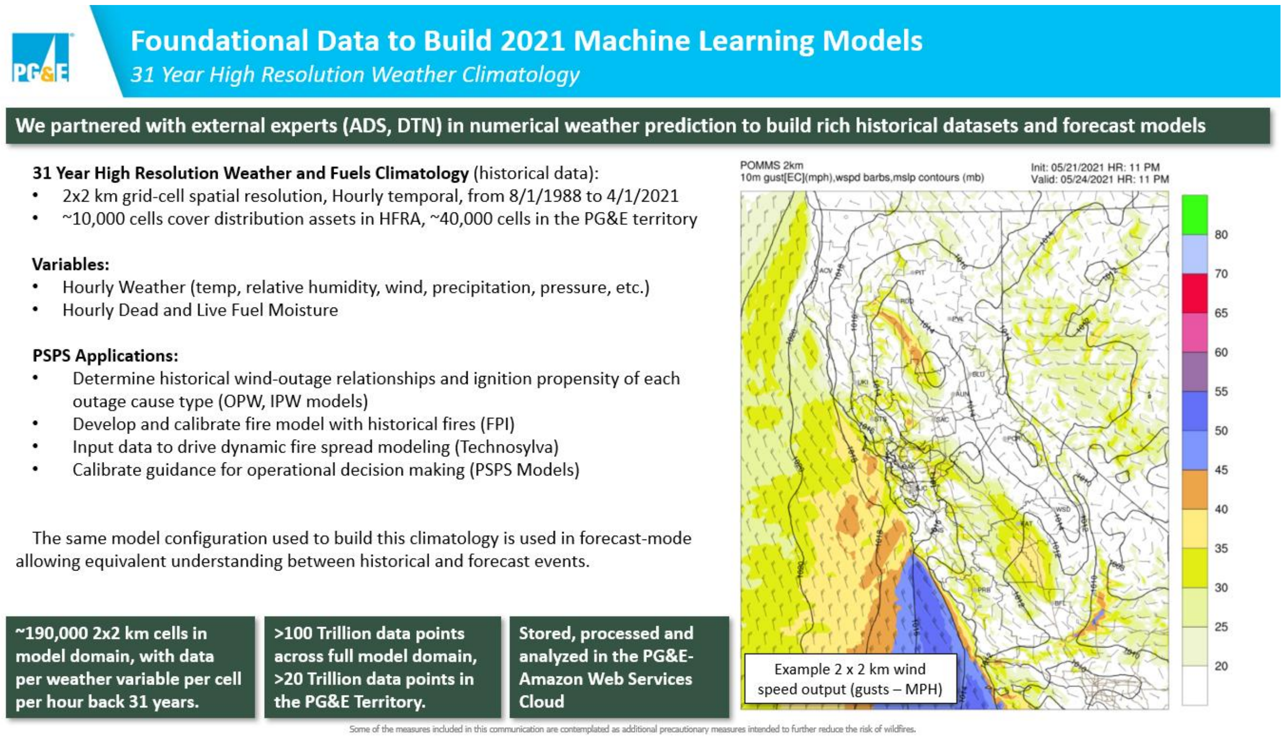

Fig. 3. 31+ year weather and fuels climatology

2 Minimum Fire Potential Conditions

2.1 Introduction

The first step of determining the scope of a PSPS event is evaluating the minimum Fire Potential Conditions (mFPC) in space and time. The mFPC serves as a low-pass weather and fuels filter based on relative humidity values, wind speeds and fuel moisture values that must be exceeded for PSPS to be considered. This ensures that PSPS is only executed during wind events when the atmospheric conditions (RH), and fuels (Live and dead fuels) are dry. These values also add transparency around the conditions and variables we consider for each PSPS event.

These values were established from an examination of historical fire occurrence in PG&E's territory in relation to the weather and fuel conditions surrounding each fire, as well as information published by federal agencies.

In 2020 we received a new historical climatology of weather and fuels at 2 x 2 km resolution and re-evaluated the mFPCs considerations using this new dataset. In 2021, this dataset was extended to include all fires, weather and fuel conditions in 2021 and fires were re-evaluated. The current values considered in the mPFC are discussed below.

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2.2 Application

We conducted a review of National Wildfire Coordinating Group (NWCG) training material and a survey of all large fires in the PG&E territory from 1992 – 2020 and a new dataset combining agency information and daily fire growth determined from satellite that was produced in early 2021 by Sonoma Technology Incorporated (STI). A review of conditions from these fires help determine the minimum fire potential conditions that must be met before PSPS is considered. The Agency fire information was sourced from the USFS fire occurrence database (FPA FOD), while weather and fuels information were sourced from our 31-year climatology (discussed in more detail in the previous section). The STI dataset was created using fire detection data from polar orbiting satellites and provides intelligence on the day to day growth of each fire. This provides additional value over using the USFS fire occurrence dataset alone, which provides data on final fire size. The daily growth metric is important to evaluate as the goal of PSPS is to mitigate those fires that start and then spread rapidly, as opposed to those fires that ignite and only grow large well after the ignition (e.g., Rim fire).

The figure below represents some of the agency training material and validation that was reviewed to establish the mFPCs. A review of past fires revealed, for example, fires that eventually grow larger than 5,000 acres most often occur when Relative Humidity (RH) is less than 20-30% and the 10-hour Dead Fuel Moisture (DFM) is less than 6-8%. This aligns with training material in National Wildfire Coordinating Group material offered in course S-290 (Intermediate Wildland Fire Behavior), where RH and DFM values above 25% and 8%, respectively, would produce “moderate” burning conditions whereas drier conditions would be much more dangerous.

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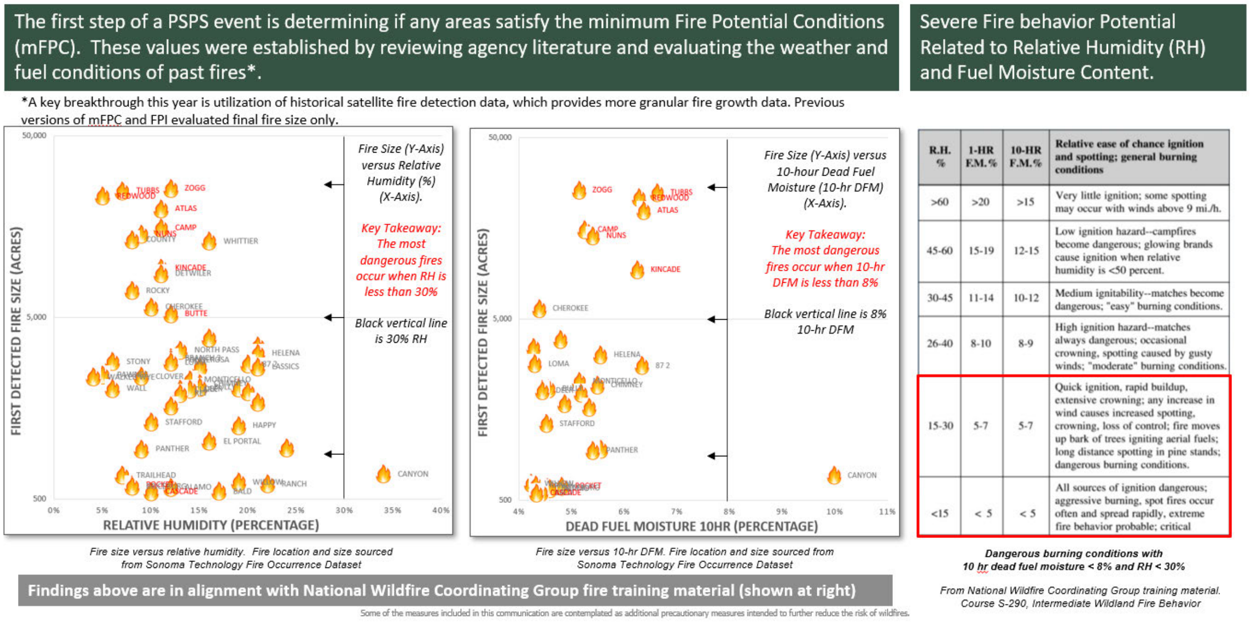

Fig. 4. Minimum fire potential conditions example - relative humidity and 10-hour dead fuel moisture

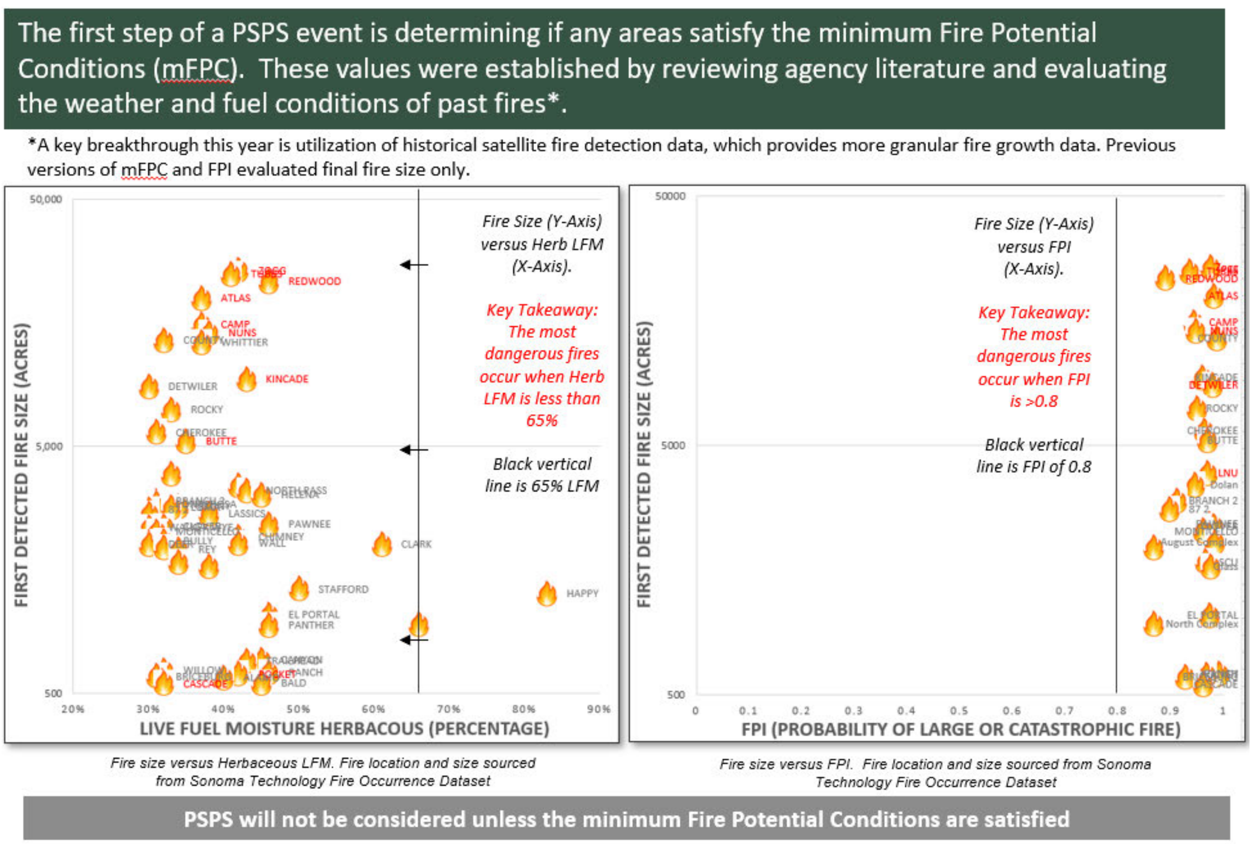

Fig. 5. Minimum fire potential conditions example - live fuel moisture and fire potential index

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Similar analyses were conducted on the 100 hour and 1000 hour DFM time lagged classes to determine when large fires are most likely to occur. Figure 3 below represents large fires through 2020 compared to the 1000 hour DFM values present at the time and location of the incident. There is very low historical precedence based on this analysis for large fires to occur when the 1000-hour DFM is greater than 11% for example.

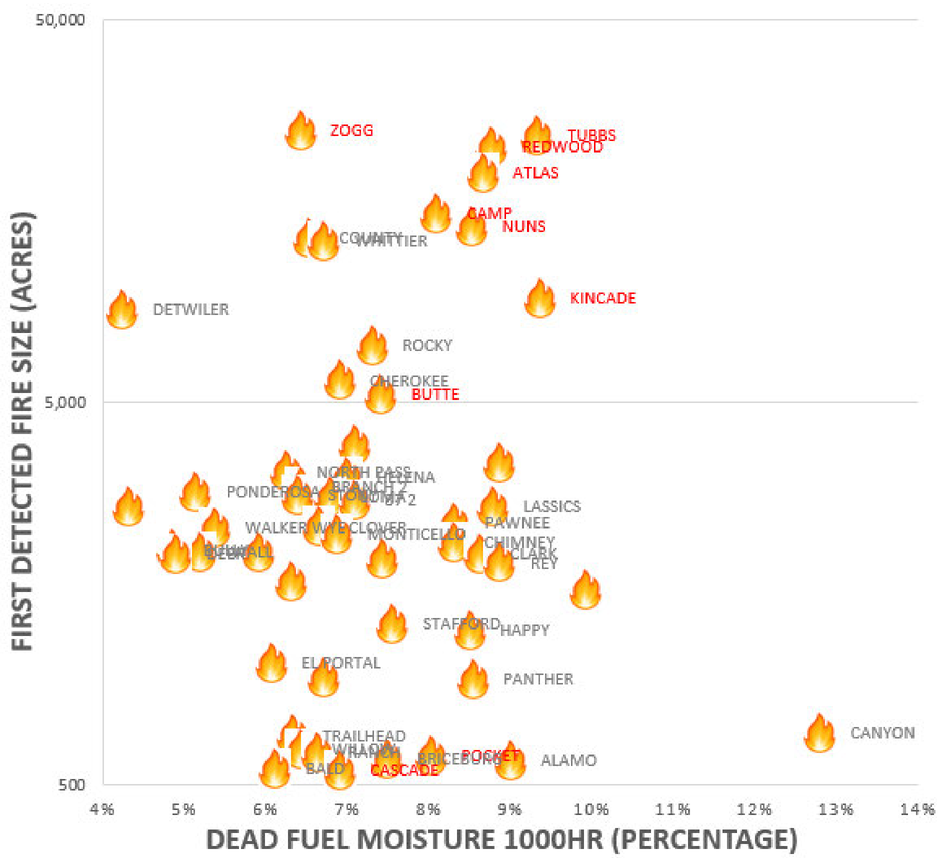

Fig. 6. Minimum fire potential conditions example – 1000-hour dead fuel moisture

In 2021, we also added a minimum requirement for Herbaceous live fuels. Herbaceous fuels are live plants that contain no woody components and include grasses, forbs and ferns for example. Herbaceous fuel moisture follows a seasonal cycle and typically peak in the spring before curing through the summer into fall. In spring the moisture content of these fuels usually exceeds the weight content of the plant material, making them more difficult to ignite and carry fire. This partially explains the seasonal cycle in fire ignitions, where fire ignitions typically do not occur until the seasonal grasses are partially or fully cured. We worked with Technosylva to develop a Herbaceous live fuel moisture model taking advancements of satellite remote sensing. This data was also constructed back to 2000 to perform a comparison against past ignitions and fire events. We found that most catastrophic fires occurred when the Herbaceous live fuel moisture dropped below 50%. For each mFPC criteria, we do not want to

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make it too restrictive and need to allow for some uncertainty. Therefore; we selected a value of 65% to utilize in the mFPC for Herbaceous LFM. This addition was found to help reduce the PSPS footprint in early season Diablo wind events that can occur in May and June when Herbaceous Live Fuels may not be cured enough to ignite and/or carry fire. The timing of curing is of course, dependent on the quantity and timing, or lack thereof, of winter to spring precipitation and snow.

Another important element considered in the minimum fire potential conditions is wind speeds. We recognize PSPS events should not be conducted when gusty winds are not present. To establish a minimum wind speed criterion, we reviewed Red Flag Warning guidance from the National Weather Service (NWS). A Red Flag Warning means warm temperatures, very low humidities, and stronger winds are expected to combine to produce an increased risk of fire danger. Nearly each NWS office utilizes their own criteria, but all offices consider wind speed. The National Interagency Fire Center (NIFC) has compiled a list of RFW criteria utilized by multiple NWS offices around the country. The wind criteria used by the NWS vary widely across NWS offices. Some consider wind gusts over 35 mph, others utilize sustained wind thresholds from 15 – 25, while others use a matrix approach. (https://gacc.nifc.gov/oscc/predictive/weather/myfiles/Watches_and_Warnings_for_California.htm)

The Northern Operations GACC, a federal forecast agency, was also consulted about wind speed criteria used to generate their high-risk forecasts for winds. Based on personal communications with GACC fire weather meteorologists, wind speed criteria generally range from 30 – 40 mph gusts depending on RH and fuel moisture values associated with an event.

The NOAA Storm Prediction Center is another federal forecast agency that generates fire weather outlooks (https://www.spc.noaa.gov/products/fire_wx/). Fire Weather Outlooks are intended to delineate areas of the continental U.S. where pre-existing fuel conditions, combined with forecast weather conditions during the next 8 days, will result in a significant threat for the ignition and/or spread of wildfires (https://www.spc.noaa.gov/misc/about.html#FireWx).

The SPC has published guidance to determine critical fire risk areas for winds. Their guidance is as follows:

- Dry Fuels
- Sustained winds 20 mph or greater (15 mph Florida)
- Relative humidity at or below regional thresholds
- Temperatures at or above 50-60 degrees F, depending on the season
- Concurrency of the above criteria for 3 hours or more

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To align with federal forecast agency guidelines as discussed above, a sustained wind speed value of 19 mph is utilized in the mFPC considered. In 2020, PG&E utilized a minimum sustained wind speed value of 20, but reduced the value to 19 based on a review of the Zogg fire. The Zogg fire was first reported at 2:51 PM PDT on September 27, 2020. It eventually grew to over 50,000 acres, destroyed more than 200 structures and tragically killed four individuals including a minor. We conducted a review of the meteorological conditions near the time of ignition from both observed and model data. The wind speeds at two nearby stations recorded sustained winds of 17 and 10 mph at 1500 on 9/27/2020. The higher speed was recorded at Mule Mountain (MMOC1), which is a Remote Automated Weather Station (RAWS) located about 4 miles to the Northeast to the suspected ignition location. The 10 mph wind speed was recorded at PG&E's Clear Creek (PG732) weather station which was located ~3.8 miles southeast of the suspected ignition location. PG&E's 2 x 2 km weather model revealed stronger wind speeds near the suspected ignition location due to local terrain effects directly to the north, which the model dynamically considers. A review of these modeled values shows that a 19 mph sustained wind speed would have been required to pass the mFPCs. As a result of this finding, PG&E reduced the mFPC wind speed from 20 to 19 mph. Note that in 2020, this area also did not satisfy PSPS criteria for distribution. However, a review of the Zogg fire through the lens of 2021 PSPS criteria reveals it would exceed the 2021 guidance (discussed in more detail later in this paper).

A summary of mFPC is shown in the table below. Identification of these conditions in space and time is the first step in determination of PSPS scope. Additional outage, fire potential and vegetation risk models are then utilized to determine PSPS scope, which is discussed later in this document.

Table 2. Minimum fire potential conditions

Logic	Variable	Sign	Value
&	Sustained Wind Speed mph	>	19
&	Dead Fuel Moisture (DFM) 10hr	<	9%
&	Dead Fuel Moisture (DFM) 100hr	<	11%

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&	Dead Fuel Moisture (DFM) 1000hr	<	11%
&	Herbaceous Live Fuel Moisture	<	65%
&	Shrub (Chamise New Growth) Live Fuel Moisture	<	90%
&	Relative Humidity (RH)	<	30%
&	2021 Fire Potential Index (FPI)	>	0.7

3 Fire Potential Index Model - FPI

3.1 Introduction

To understand the potential for large and catastrophic fires to occur across the PG&E territory, we first developed the Fire Potential Index (FPI) in 2015 and has enhanced the model several times. The latest iteration of the model is called the 2021 FPI model, which reflects the year it was approved.

During each iteration our goal has been to increase the accuracy of the FPI by testing additional model features, model frameworks (e.g., logistic regression versus Random Forest), and improving input datasets. The sections below discuss improvements made across these elements for the 2021 FPI.

At a high level, the 2021 FPI model combines fire weather parameters (wind speed, temperature and vapor pressure deficit), dead and live fuel moisture data, topography and fuel type data to predict the probability of large and/or catastrophic fires. The 2021 FPI was trained on an enhanced fire occurrence dataset that combines agency fire information with sub-daily growth from satellite fire detections.

The FPI is run using the high-resolution weather and fuels coupled model and provides 2 x 2 km forecasts out to 129 hours. The FPI is one of the main components of the PSPS decision making framework. An overview of model features in the 2021 FPI is presented below.

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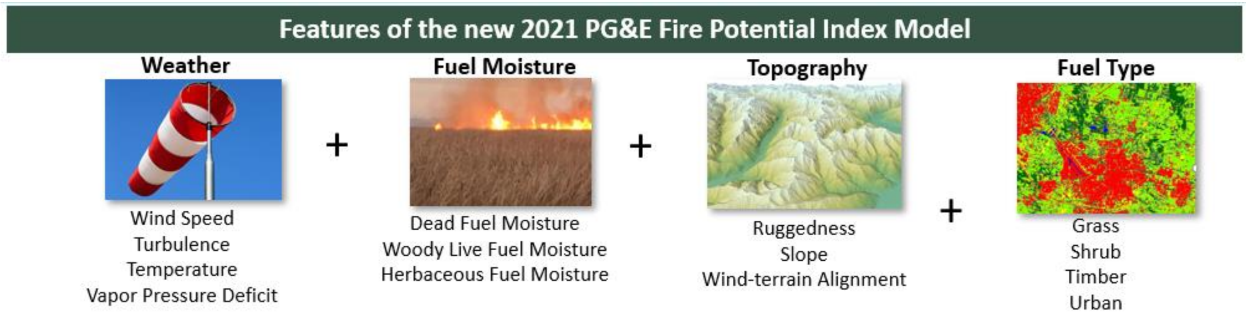

Fig. 7. Features of the 2021 fire potential index model

3.2 Applications

FPI is used as a daily and hourly tool to drive operational decisions to reduce the risk of utility-caused fires. On a day-by-day basis, the FPI informs crews what precautions must be taken to reduce the risk of fire ignitions as directed by utility standard TD-1464S. FPI also informs the potential need and execution for Public Safety Power Shutoff (PSPS). Below is a short history on the FPI evolution since 2015.

We received daily fire danger ratings directly from CAL FIRE up until December 31, 2014 when the service was disabled. In 2015, we evaluated multiple public sources and methodologies for fire danger rating and benchmarked with SDG&E on their deployment of an FPI using high-resolution weather and fuel model data. In addition, PG&E scientists also took instructor-led advanced courses in fire danger rating offered by the National Wildfire Coordinating Group to understand agency best practices and methodologies to evaluate fire danger. The early development work of the FPI and Numeric Weather Prediction (POMMS project) is discussed in detail in PG&E's EPIC 1.05 project report, which can be found here: https://www.pge.com/pge_global/common/pdfs/about-pge/environment/what-we-are-doing/electric-program-investment-charge/PGE-EPIC-Project-1.05.pdf.

The FPI was enhanced in 2019 by coupling the weather and fuels data around the ignition of each fire in the USFS's Fire Program Analysis – Fire-Occurrence Database (FPA-FOD). The end goal was to create an FPI model that could predict, based on forecasted weather and fuels conditions, the probability of a large fire given an ignition. The 2019 Fire Potential Index (FPI) model was a function of several quantifiable factors: The Live Fuel Moisture (LFM), the Nelson Dead Fuel Moisture 10 hour (DFM10hr), the Fosberg Fire Weather Index (FFWI) and Land Use (LU) . As the Live Fuel Moisture (LFM) and the Nelson Dead Fuel Moisture 10 hour (DFM 10hr) decrease (become drier), FPI increases. As the Fosberg Fire Weather Index (FFWI) increases, FPI increases.

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The 2021 FPI model is discussed in more detail below. It represents the next evolution of the FPI that takes advantage of additional model features, an enhanced fire occurrence dataset, and a machine-learning model engine.

3.3 Enhanced Fire Occurrence Dataset

The 2019 version of the FPI was trained with a USFS fire occurrence dataset that provided information on each fire, the ignition location and the final fire size. This provided valuable information to train the 2019 FPI, but we sought to test if FPI performance could be improved by utilizing daily to sub-daily fire growth data. For the purpose of PSPS, we are primarily concerned with those fires that ignite and have a rapid rate of spread shortly after ignition. These fires pose a higher risk to nearby communities than slow spread fires since they may have less time to evacuate. In the PG&E territory, there are several examples of fires that ignite, initially grow slowly but ultimately burn large areas of land after several days or weeks. A couple of examples are the Rim, Rough and King Fires.

To help build an improved fire occurrence dataset, we partnered with Sonoma Technology, Inc. (STI) to combine VIIRS satellite fire detections with agency fire occurrence datasets to derive sub-daily fire growth statistics. VIIRS is a high-resolution instrument aboard a polar orbiting satellite that can detect fires during each pass. The sample rate of VIRRS over CA is at least 2 times per day. By leveraging a GIS platform, STI was able to compile the VIRRS data for each pass to determine the amount of fire growth between each pass. The satellite data was combined with agency records from CAL FIRE’s Fire and Resource Assessment Program (FRAP), ICS-209, GeoMAC, USFS FIRESTAT, and USFS FPA FOD data sets to provide growth metrics for large, named fires.

A few VIRRS satellite detection plots versus final fire perimeter maps are shown below. The first image shown is the Rim fire, which had a slow rate of spread in the first few days after ignition. The next image shown is from the Tubbs fire, which spread catastrophically to the southwest into Sonoma resulting in significant loss of life and homes. The rate of spread after ignition was dramatically different that of the Rim fire and was caused by an unusually strong Diablo wind event. The third image below shows the VIRRS fire detections (points) color coded by time of detection. This provides an example of how the fire spread and direction can be mapped using scan-over-scan detections and that the combined satellite fire detections align well with the final fire perimeter.

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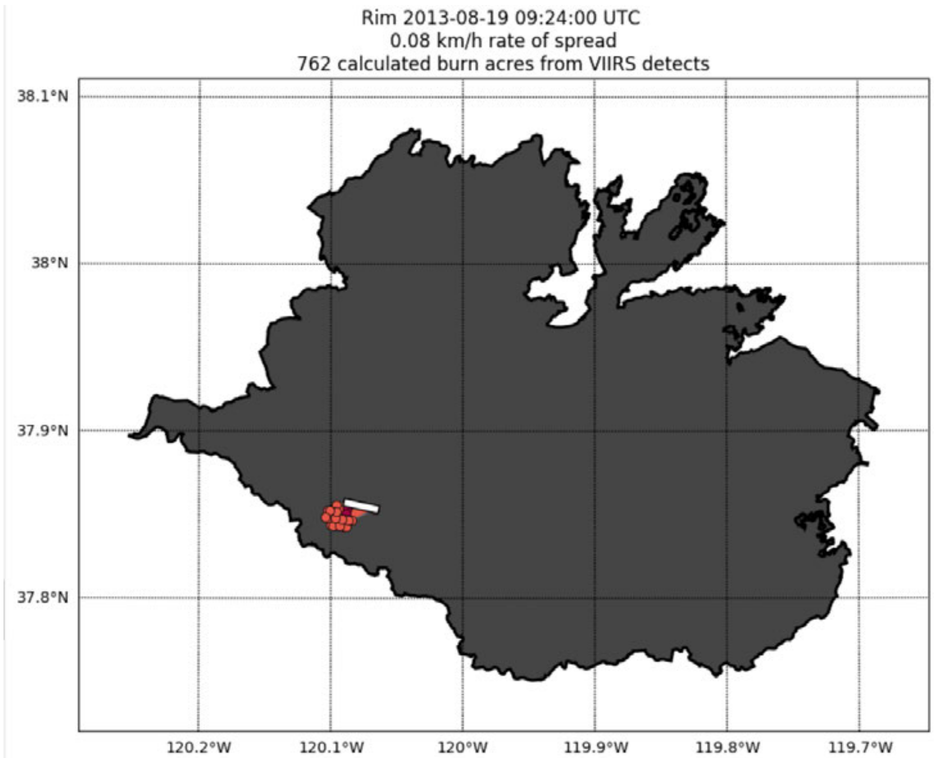

Fig. 8. Satellite fire detections for the Rim Fire

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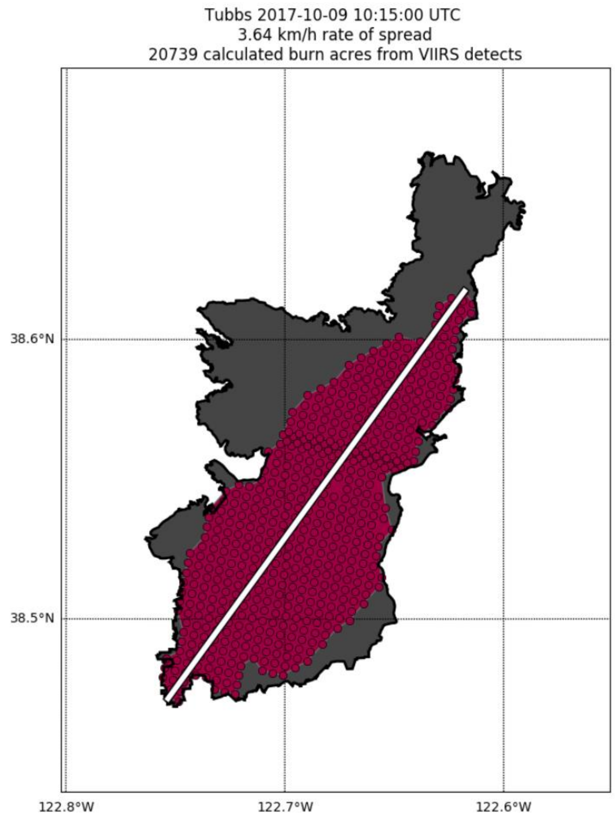

Fig. 9. Satellite fire detections for the Tubbs Fire

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3.4 2021 FPI Model Framework

The 2021 FPI model leveraged the 2 x 2 km weather and fuels climatology as well as the STI enhanced fire occurrence dataset to build the 2021 FPI. The goal of this project was to build a more accurate FPI model that can be used in forecast mode to inform daily and PSPS operations to reduce the risk of utility-caused catastrophic fires.

Data scientists, meteorologists, and fire scientists tested dozens of new model features and various models. Among the model-types tested were logistic regression and multiple machine-learning model types. Model results were tested using a train-test split ratio of 70%-30%. This involved training the models with 70% of the input data and testing predictions with the remaining 30%.

We ultimately chose a Balanced Random Forest Classification Machine Learning model as the final candidate for FPI based on model performance; Random Forest's framework allows collinear features and models non-linearities in their relationships. Model hyperparameters were tuned and the final configuration contains 300 random trees with a tree max depth of 12. The diagram below presents a high-level overview of the FPI Random Forest Classification ML model.

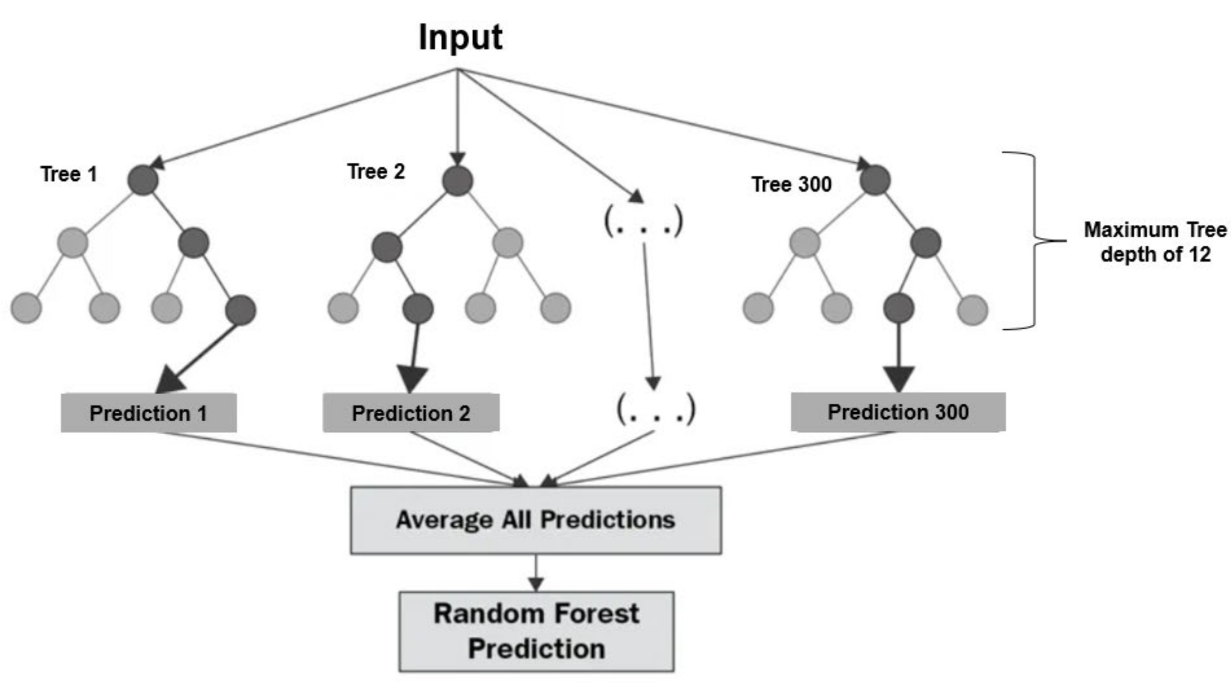

Fig. 10. Fire potential index random forest model

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Based on the input data, described in more detail below, the model predicts how fast a fire will grow shortly after an ignition, should one occur. We utilized the first satellite detection fire growth from the enhanced STI fire occurrence dataset to evaluate fire growth in the first hours after a fire developed. The model output classifications are presented below.

Fire Classification based on first satellite fire detection

- <70 acres (detectable, small)
- 70-500 acres (large)
- >500 acres (catastrophic)

For fires that were observed to grow >500 acres from the first fire detection, they ultimately grow on average, to a final fire size of ~20,000 acres. The first-detect size versus final fire size for each fire in the STI database is presented below. Some of the fires that were observed to grow the fastest based on the first satellite detection are the Zogg, Tubbs, Atlas, Camp, and Kincade, which were all observed to grow >9,000 acres in the first day after ignition.

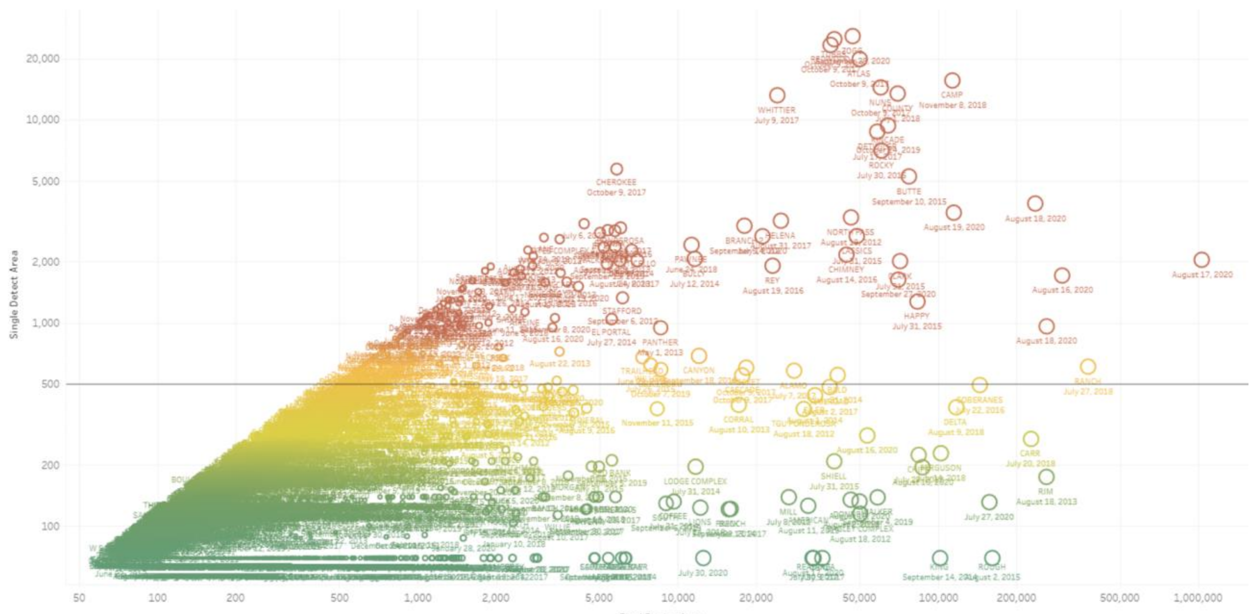

Fig. 11. First-detect fire size versus final fire size from STI fire occurrence database

3.5 2021 FPI Model Features

The list of model features used in the ML FPI model are discussed in this section. These model features can be grouped into four main categories: 1) Weather; 2) Fuel Moisture; 3) Topography; 4) Fuel Type. The ML application has advantages over other models like linear

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regression as the model learns how features may interact non-linearly to contribute to catastrophic fire spread.

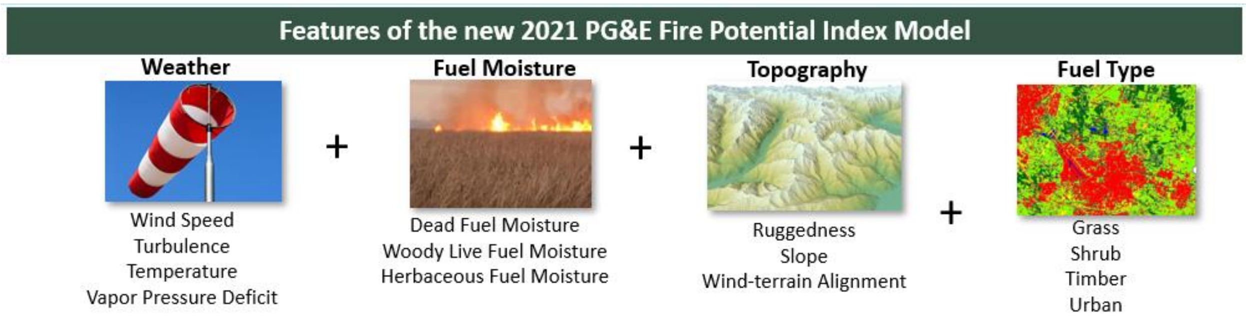

Fig. 12. Features of the 2021 fire potential index model

The weather data is sourced from the 2 x 2 km weather forecast model and 31-year climatology. The source of this information is from a numeric weather prediction expert vendor, DTN. The dead fuel moisture across multiple classes and Live Fuel Moisture – Chamise is sourced from coupling the weather and climatology to models developed by Atmospheric Data Solutions (ADS). New measures of live fuel moistures were added to the 2021 version of the FPI are sourced from Technosylva. These take advantage of remote sensing and a model application to estimate the amount of available moisture in woody and herbaceous plant species.

Topography characteristics were also evaluated for the 2021 FPI and proved skillful. The features included in the 2021 FPI include a measure of terrain ruggedness, which provides a measure of the terrain change in slope and aspect in each 2 x 2 km model grid cell. The slope is also considered and shows to have a positive effect on fire size where there is existence of steep slopes. Finally, a dynamic wind-terrain alignment factor is computed for each hour to provide an assessment of the wind-terrain alignment in each 2 x 2 km grid cell. During Diablo wind events, scientific literature has shown that when the wind flow is perpendicular to terrain features, winds can accelerate down the lee of the terrain feature. During model testing, a similar pattern emerged, which shows that winds that are perpendicular to terrain (upslope or downslope winds) have a positive relationship to fire size compared to terrain-aligned (cross slope) winds.

Finally, a continuous fuel model type is considered in each 2 x 2 km model grid cell. This information is sourced and routinely updated from Technosylva. The fuel model map baseline is the latest iteration from LANDFIRE, but is adjusted to account for recent burn scars and vegetation regrowth after fire that are not considered in LANDFIRE. The native resolution of

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the fuel model map is 30 x 30 m resolution. For each 2 x 2 km model grid cell, the fraction of six fuel model categories is computed to provide the fraction of that area that is urban, grass, grass-shrub, shrub, Timber-litter or Timber-understory. We worked closely with Technosylva fire scientists to consolidate the 50+ fuel model types into these six parent categories.

Each model feature used in the 2021 FPI is presented below.

Table 3. 2021 fire potential index model features

Predictor	Altitude	Description	Source
Temperature	surface	Temperature at the surface in Fahrenheit	POMMS
Wind Speed (sustained)	surface	Wind speed at the surface in mph	POMMS
Wind Speed (sustained)	300 m	Wind speed at 300m above surface	POMMS
Vapour Pressure Deficit	surface	Measure of lack of water vapor relative to saturation in millibars	POMMS
Dead Fuel Moisture - 1000hr	surface	1000-hour fuel moisture content	ADS
Dead Fuel Moisture - 100hr	surface	100-hour fuel moisture content	ADS
Dead Fuel Moisture - 10hr	surface	10-hour fuel moisture content	ADS
Live Fuel Moisture - Chamise New	surface	Live fuel moisture content of Chamise (new growth) species	ADS
Live Fuel Moisture - Herbaceous	surface	Live fuel moisture content of herbaceous species	Technosylva
Live Fuel Moisture - Woody	surface	Live fuel moisture content of woody species	Technosylva
Turbulent Kinetic Energy	50 m	Kinetic energy per unit mass observed in eddies characteristic of turbulent flow in Joules/kg	POMMS
Ustar Friction Velocity	surface	Wind shear stress in velocity terms.	POMMS
Alignment Vector	surface	Alignment between wind direction and terrain	POMMS & DEM
Slope Degree Mean	surface	Slope of terrain averaged over pomms grid cell.	DEM
Terrain Rugged Mean	surface	Measure of ruggedness in pomms grid cell.	DEM
Urban	surface	Proportion of fuel category in pomms grid cell attributed to urban	Technosylva
Grass-Shrub	surface	Proportion of fuel category in pomms grid cell attributed to grass-shrub	Technosylva
Shrub	surface	Proportion of fuel category in pomms grid cell attributed to shrubs	Technosylva
Timber Litter	surface	Proportion of fuel category in pomms grid cell attributed to timber litter	Technosylva
Grass	surface	Proportion of fuel category in pomms grid cell attributed to grasslands	Technosylva
Timber Understory	surface	Proportion of fuel category in pomms grid cell attributed to timber understory	Technosylva

3.6 2021 FPI Model Validation

The 2021 FPI model was validated statistically and climatologically by reviewing results for past fires. Model results were tested using a train-test split ratio of 70%-30%. This involved training the models with 70% of the input data and testing predictions with the remaining 30%. The

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performance metric utilized was the standard Area Under the Receiver Operating Characteristic (ROC AUC), which is widely used to evaluate classification models. AUC is a performance metric designed to test the model's ability to discriminate between cases that were correctly classified (positive examples) and versus non-cases (negative examples). Generally, a AUC score of 1 is a perfect model, while scores near and above 0.70 are considered to have good performance. AUC scores above 0.8 are considered to have excellent performance. A model with no skill has an AUC of less than 0.5. The FPI's catastrophic fire class, a direct input for PSPS operations, yielded a score of 0.88. For comparison, the previous FPI model (2020) yielded a score of 0.71.

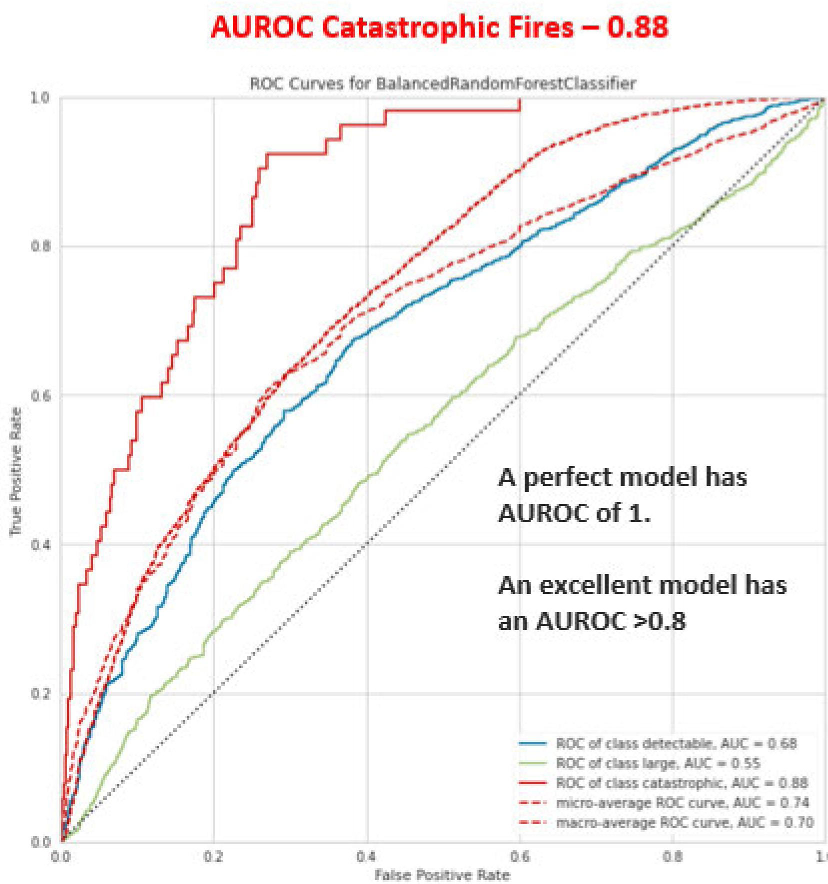

Fig. 13. 2021 fire potential index model skill statistics

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The FPI Probability of Catastrophic fire was evaluated against past catastrophic fires using historical weather data matched in both time and space for each fire. With the class separation at 70 and 500 acres, we found that the model performs well differentiating between the natural categories of fires: large fires with a high rate of spread — typical of wind-driven events, large fires with low to medium rate of spread, and small fires still detectable by satellite.

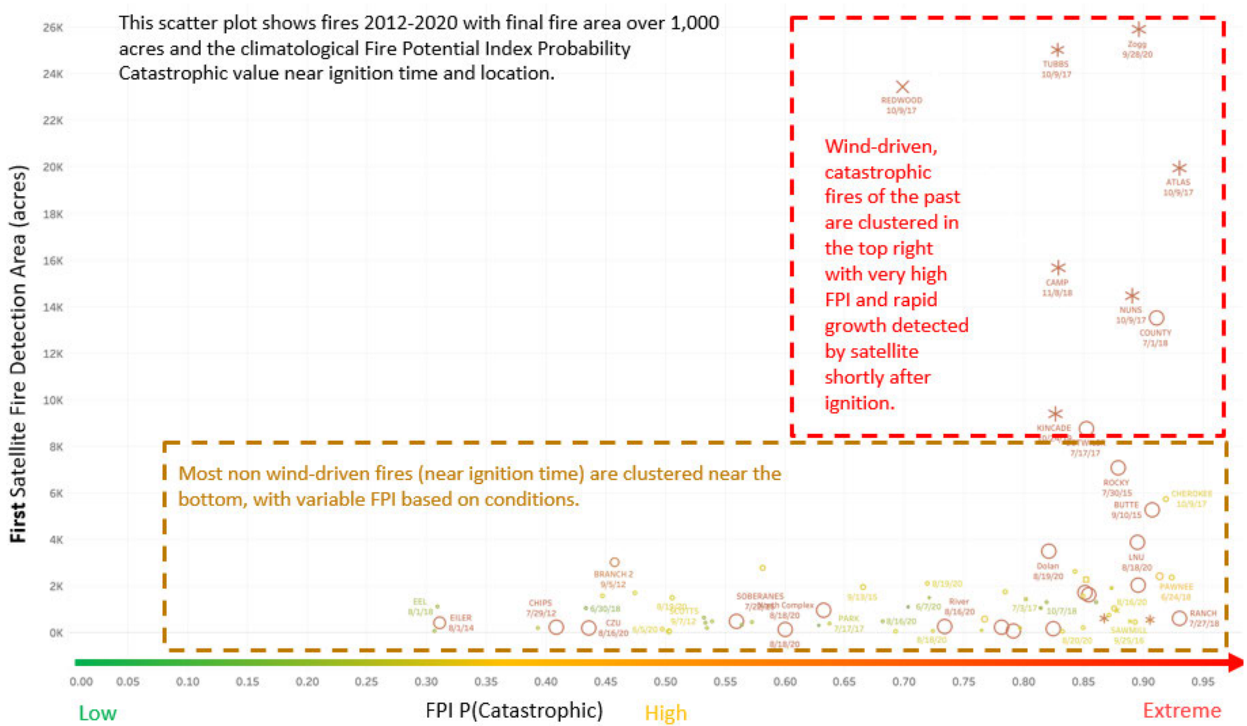

Fig. 14. fire potential index model output for fires >1000 acres from 2012-2020

3.7 FPI - Fire Potential Index Scale

The FPI model outputs the conditional probability from 0 – 100% that a fire will be small, large or catastrophic (three classes) given it is detected by VIRRS. This probability is translated into a fire danger rating scale from R1 (low) to R5 (extreme) based on breakpoints. These breakpoints were established by reviewing FPI percentiles as well as FPI model output for historic fires in the PG&E territory from 2008 – 2020. This method is identical to how numeric outputs of the Energy Release Component or Burning Index from the federal NFDRS are translated to fire

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danger ratings from low to extreme. The fire danger rating scale is shown below; moving up the scale from R1 to R5 increases the forecasted conditional probability that a fire will grow to be larger than 1,000 acres.

Table 4. Fire potential index rating and color scale

R1
R2
R3
R4
R5
R5-Plus

Table 5. Fire potential index scale versus NFDRS rating and color scale

NFDRS SCALE	PG&E FPI SCALE
Low	R1
Medium	R2
High	R3
Very High	R4
Extreme	R5

The FPI assigns a rating of "R5-Plus" when a PSPS event is forecast. This is utilized to not only illustrate that PSPS is possible in these areas, but to differentiate between R5 driven by FPI and R5 coupled with high potential for utility ignitions from the OPW and IPW models.

We run the FPI model hourly on the same model domain as the POMMS weather and IPW model. The FPI probabilities in this hourly output are used as input into the PSPS decision-making framework at a 2 x 2 km resolution. For daily operational decisions, the hourly FPI output is aggregated by geographic areas called "Fire Index Areas (FIAs)" to represent the highest level of fire potential in that area per day – see Figure 7 and Figure 8 for examples, in which each numbered area is a single FIA. FIAs[1] are analogous to Fire Danger Rating Areas (FDRAs) utilized by state and federal agencies to describe a fire danger rating across a static geographic area. These daily ratings are produced daily and are used to mitigate the potential for field activities and events to create a spark that may lead to a wildfire. These mitigation actions are discussed in Utility Standard TD-1464S, "Preventing and Mitigating Fires While Performing PG&E Work".

[1] FIAs were originally developed by the USFS Pacific Southwest Forest and Range Experiment Station (now the Pacific Southwest Research Station) in 1959 and updated in the late 1960s and are still in use today by state (e.g., CAL FIRE) and federal agencies (e.g., USFS). These agencies refer to these areas as Fire Danger Ratings Areas (FDRAs). The FIA boundaries have been adjusted to align with the CPUC HFTD and were expanded to fully encapsulate the PG&E High Fire Risk Area (HFRA). Put simply, the FIAs cover the full extent of the union of the HFTD and HFRA. For more information, see Attachment A: Fire Potential Index Methodology and Background.

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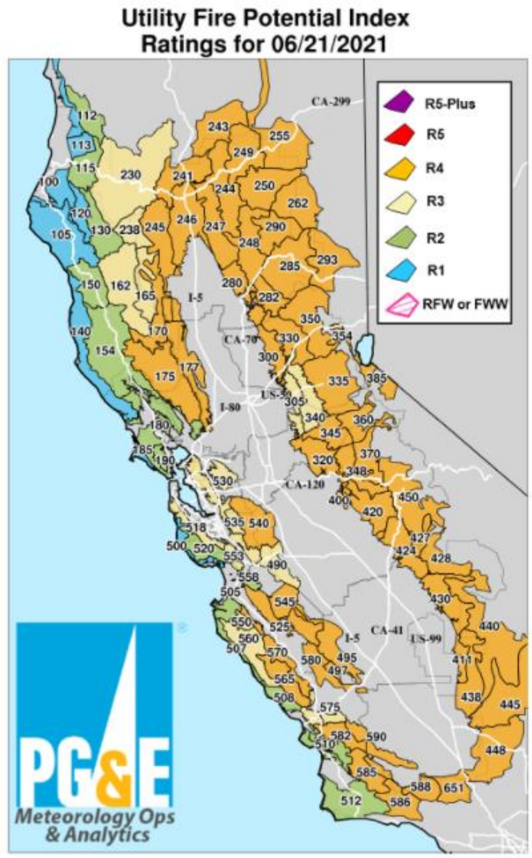

Fig. 15. Example map with fire potential index ratings

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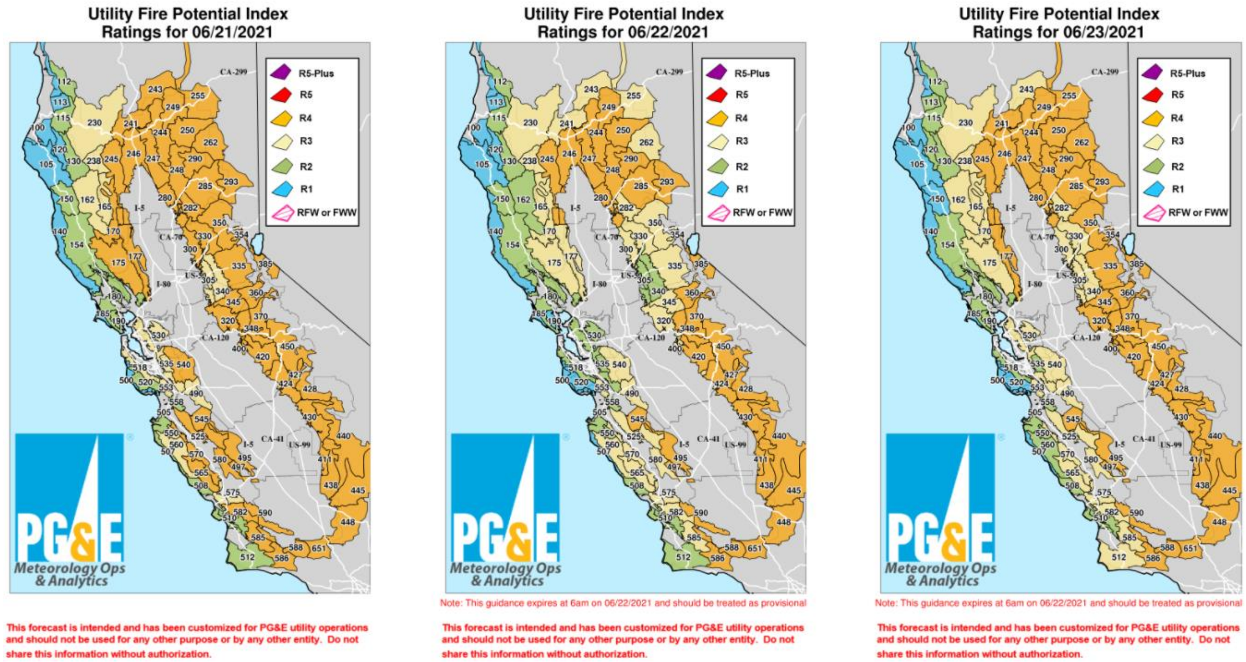

Fig. 16. Example fire potential index three-day forecast

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4 Ignition Probability Weather Model (IPW)

4.1 Introduction

We developed the first iteration of the Outage Producing Wind (OPW) in 2019 for PSPS. This work built upon the decade of work and daily operations of the Storm Outage Prediction Project (SOPP) that is used to forecast the level of outage activity in local regions each day due to any type of weather impact (wind, rain, snow, lightning and heat). These forecasts are used by PG&E staff to adjust staffing levels in advance of weather events. The genesis of the program was the January 8th 2008 winter storm where >1.4 million PG&E customers (>4 million people) lost power.

The goal of the OPW model is to inform on the probability of an outage based on the wind speed. The probability of outage activity was used as a proxy for potential ignition sources during wind events. This offers advantages over selecting a wind-based threshold for PSPS decision making as the probability of an outage can be determined by examining the relationship of wind and historical performance of assets and vegetation in proximity to those assets which varies across the territory. Since tracking of utility-cased ignitions began in 2015, the highest number of daily ignitions occurred during the October 8th, 2019 wind event where several of those ignitions started catastrophic fires that ultimately resulted in devastating loss of life and property.

In 2020 the OPW was enhanced from the ground up. The 2020 OPW model was more granular and had the ability to run on the new 2 x 2 km weather model grid. The model was trained on both sustained and momentary outages as well as damages and hazards found in 2019 PSPS events.

The 2021 OPW and Ignition Probability Weather (IPW) model version represents the next generation of distribution outage and ignition models building on the 2020 OPW 2.0 model. The core model is a new OPW model, that now can forecast outage probability by specific causes. The OPW output is transformed to an ignition probability (IPW) using known outage to ignition ratios for each outage cause.

The 2021 OPW model is trained on windspeeds from our 31 year down-scaled climatology at 2 x 2km resolution and approximately 500,000 sustained and momentary outages occurring on the distribution grid from 2008 to end of 2020. We excluded underground outages and non-weather driven major event days, such as fires and earthquakes from the training dataset. PSPS event damages and hazards were also included in the training set.

The operational application of IPW is forecast four times per day producing hourly outage and ignition probabilities. The model has a forecast horizon of 129 hours ahead at the same 2 x 2 km resolution as the PG&E Operational Mesoscale Modelling System (POMMS), a configuration of Weather Research and Forecasting (WRF) model.

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New 2021 OPW and IPW Model Framework

OPW	Outage Cause		Ignition Rate per Cause	IPW
Probability Outage by Cause Outputs:2x2km, Hourly	P(Vegetation) P(Equipment-Structural) P(Animal-3rd Party) P(Equipment-Electrical) P(Unknown Cause)	➡	Vegetation Equipment-Structural Animal-3rd Party Equipment-Electrical Unknown Cause**	**Probability of Ignition by Cause** Outputs: 2x2km, Hourly

Statistical Evaluation*

Cause	ROC AUC
Vegetation	0.81
Equipment-Structural	0.69
3rd-Party-Animal	0.68
Equipment-Electrical	0.67
Unknown	0.64
No Outage	0.67
Macro Avg. ROC AUC	**0.70**

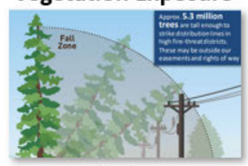
Features of the new 2021 OPW and IPW models

Weather

Wind Speed, Turbulence Temperature, Precipitation Vapor Pressure Deficit

\+

Vegetation Exposure



Aerial Lidar Tree Overstrike in each 2x2 km grid cell.

\+

Local Performance

Outage trends specific to each location through node feature.

Key enhancement: exponentially **weighting recent years more heavily to learn and predict system performance changes** due to vegetation management and system hardening.

$$\mathbf{IPW} = \mathbf{P(Ignition)} = \sum_{\mathbf{type}}^{\mathbf{cause\ types}} \mathbf{P}\left(\mathbf{Outage_{type}}\right) * \mathbf{P}\left(\mathbf{Ignition_{type}} \middle| \mathbf{Outage_{type}}\right)$$

Fig. 17. 2021 outage and ignition probability model framework

4.2 Cause Class Outage and Ignition Model Framework

The enhancements to the 2021 IPW, which is a Machine Learning non-linear model, multi class, exponential time weight ensemble, represent significant enhancements over the 2020 OPW model. The end goal is to help better model ignition probabilities every hour to help inform when PSPS is needed.

The 2021 IPW model engine is a multi-classification Cat Boost Machine Learning model. It is a state-of-the-art model based on decision trees with advanced categorical feature support. The IPW model outputs the probability of 5 outage classes for each 2 x 2 km grid cell based on weather variables, tree overstrike per 2 x 2 km grid cell from aerial LiDAR, and a local "node" categorical variable. The model was tested by first training on every hour and grid cell from 2008-2019 and evaluating performance against 2020. Once performance was quantified, 2020 was incorporated into model training for operational use through 2021.

The model predicts the probability of an outage and ignition across five outage classes. These are: Animal-3rdParty such as cars and balloons; Equipment-Electrical which includes transformers and fuses; Equipment-Structural which includes assets such as poles, cross-arms,

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connectors, conductors, etc.); Vegetation outages; Unknown; and with the final prediction being No-Outage. The cause classes are presented below.

$$cause\ classes = \{\text{Animal} - \text{3rdParty}, \text{Equipment Electrical}, \text{ Equipment Structural}, \text{Unknown}, \text{Vegetation}\}$$

$$class\ \in cause\ classes$$

The weather variables used to train the model include wind speed at 10m & 50m, turbulent kinetic energy at 50m, friction velocity, vapor pressure deficit at 2m, temperature at 2m, and precipitation. The aerial lidar tree overstrike for each tree is summed per 2 x 2 km grid cell to provide the model with a measure of tree density and risk in each grid cell. The “node” is a key categorical variable that allows the model to learn outage trends specific to each location that is not otherwise explained (e.g. due to asset condition, vegetation stress, materials, soils, cars, balloons, animals, and other exogenous factors). The probability of an outage by class by cell per hour can be represented by,

$$P(Outage_{class,cell,hour}) = f(wind\ speed_{cell,hour}, turbulent\ kinetic\ energy\ _{cell,hour}, vapour\ pressure\ deficit\ _{cell,hour}, temperature\ _{cell,hour}\ , lidar\ tree\ overstrike\ _{cell}\ , node).$$

The outage probabilities for each outage class are multiplied by the probability of ignition given outage to determine the utility ignition probability. The IPW model is represented by,

$$IPW = P(utility\ ignition_{cell,hour}) = \sum_{class}^{cause\ clases} P\big(Outage_{class,cell,hour}\big) * P(Ignition_{class}|Outage_{class})$$

The probability of ignition given outage is based on the mean ratio of CPUC reportable ignitions to outages observed from 2015-2020 between May-November excluding weather days that included rain, winter storm, low snow, lightning, for each of those cause classes. This filter provides the summer to fall outage to ignition ratios to apply for the IPW PSPS application. Vegetation cause outage class for example has the highest propensity to cause an ignition.

Distribution Ignition and Outages in HFTD between May-November from 2015-2020 used for the mean outage to ignition ratios are presented in the table below. This dataset was compiled by excluding weather days with Rain, Winter Storm, Lightning, Low Snow as well as excluding some outage cause codes such as Company Initiated (Planned), Wildfire Mitigation, Environmental.

Table 6. Outage and ignition cause classes, counts and percentage of ignitions per outage

Cause Class	Ignition Count	% of Ignitions	Outage Count	% Total Outages	% Ignition per Outage
3rd-Party-Animal	165	23%	3,202	16%	5.15%

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Equipment-Electrical	46	6%	2,988	15%	1.54%
Equipment-Physical	160	22%	3,022	15%	5.29%
Unknown	12	2%	6,712	34%	0.18%*
Vegetation	336	47%	3,844	19%	8.74%
Total of Cause Classes	**719**		**19,768**		**3.6%***

** Note, the mean of 3.64% ignition per outage is applied to probability of ignition given outage for the* ***Unknown*** *cause class in IPW because Unknown ignition causes are not reflective of Unknown outage causes. Unknown outages are due to patrol not conducted and due to patrol unable to determine cause. With ignitions, the ignition is almost always found through patrol, and the cause is more likely to be able to be determined.*

4.3 Time Weighted Ensemble

To address positive and negative trends in grid performance and reliability year-over-year we apply a time-weighted approach to weight current years more heavily in the final model output. The OPW model is 13 outage models trained on each year separately from 2008-2020, and then the class probabilities are combined using a weighted mean with the weight of each model contribution as an exponential weight function (weight $=e^{bt}$ where b is the exponential growth weight we are applying over time in years t from 2008). An optimal b was selected as 0.1 out of a grid search of values based off an evaluation of 2020 prediction using an ensemble model trained with 2008-2019 data. This exponential weighted mean allows changes in local areas to be learned (both negative - increased tree mortality, asset degradation, etc.; and positive – conductor and pole replacement, vegetation management etc.). A schematic and example formula for P(vegetation outage) is presented below.

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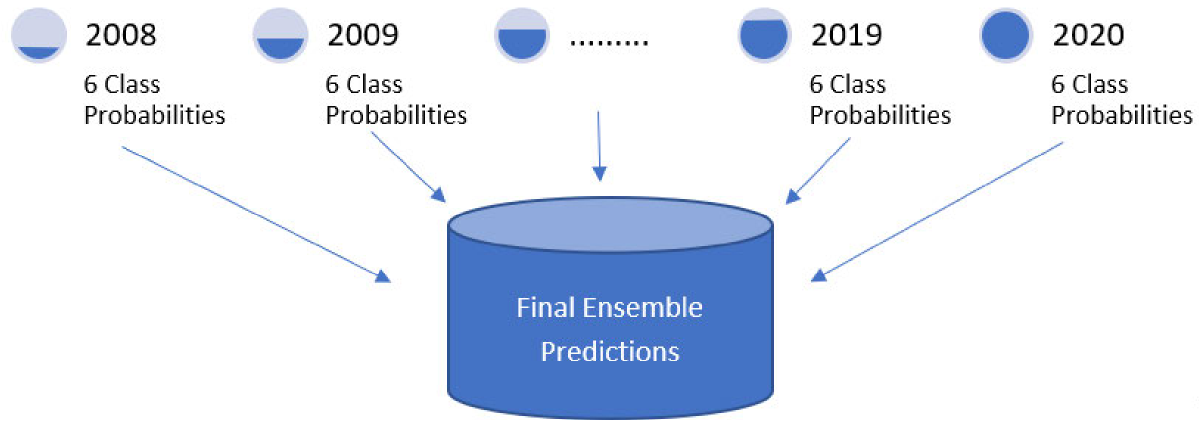

Fig. 18. Outage probability weather model ensemble construction

Ex: Prob(Veg Outage $_{final}$) = w_{2008}Prob(Veg Outage$_{2008}$) + w_{2009}Prob(Veg Outage$_{2009}$)+…+ w_{2020}Prob(Veg Outage$_{2020}$) / Sum(weights)

Details:

- 13 Different Models (one for each year)
- Benefit: A weakness in one model can be offset by another models' strengths
- Applying a weight for each models' prediction
- Weight Formula: wt =e^{bt} where b is the exponential growth weight we are applying over time. b was chosen based off model performance metrics. t is time in years. (t=0, 1, 2, …, 12, 13)

4.4 Model Validation

4.4.1 Statistical Evaluation

The 2021 OPW model was validated statistically and climatologically by testing outage predictions per outage class. The year 2020 and outages from 2020 were withheld from the model training dataset and used to evaluate performance. The performance metric applied was the standard Area Under the Receiver Operating Characteristic (AUROC). The AUROC statistics are presented below for each outage class. A big strength of the model is predicting the probability in vegetation-related outages, which were also found to have the highest outage to ignition propensity. In post-PSPS event patrols, the majority of damages and hazards found to date have been vegetation-related.

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Table 7. Outage probability model skill statistics

Cause	AUROC
Vegetation	0.81
Equipment-Structural	0.69
3rd-Party-Animal	0.68
Equipment-Electrical	0.67
Unknown	0.64
No Outage	0.67
Macro Avg. ROC AUC	**0.70**

4.4.2 Climatological and Event Validation

After constructing the final time-weighted OPW and IPW models, we back casted the data hourly through the 2 x 2 km climatology from 2017-2020. The purpose was to evaluate key historical event days since 2017 against where significant outages and fire ignitions occurred due to weather. We constructed a dynamic IPW event dashboard that allows rapid exploration of model outputs during key days (e.g., 10/8/2017 and 11/8/2018). The dashboard also includes all the 2019 PSPS damages and hazards with ability to filter to see these events.

Operational Meteorologists used the dashboard to evaluate model performance against key historical storm events, evaluating timing of weather onset compared to modeled outage probability increases, and relative magnitude of outage probabilities. We are fortunate to have the experience of an operational Meteorology team that has been forecasting outages and seeking to understand outage drivers as part of its Storm Outage Prediction Project (SOPP) every day for more than a decade. The meteorologists judged the model to perform well in time and space for key weather events.

An example of the dynamic dashboard is presented below. The 2x2 km grid cells on the map are colored by the max IPW of the hours that are filtered. The outage and damage points are colored by cause on the map, the outages will only show for the hours filtered. The data can be explored using the filters to the storm day (or hour) of interest, and other filters spanning weather signal, location.

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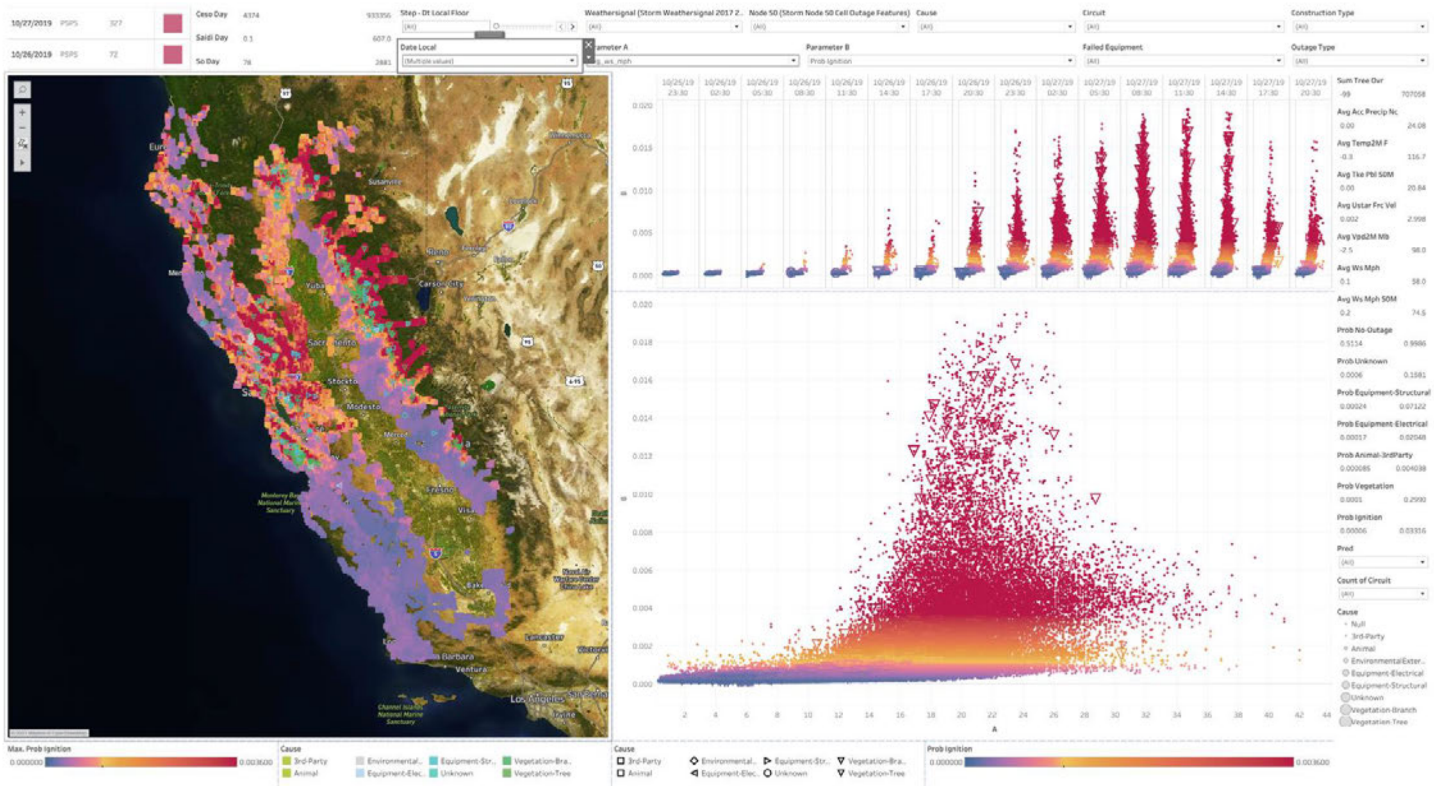

Fig. 19. Outage and ignition probability model event exploratory dashboard example

Output from a few key weather events are presented below. The first case shows model output from the October 8 to 9th 2017 Diablo wind event that caused several catastrophic wildfires to develop. The IPW model well captures both the spatial extent of where the catastrophic fires originated, as well as the timing of peak risk. The second case is from the November 8th 2018 Camp fire. It also shows excellent alignment spatially and temporally.

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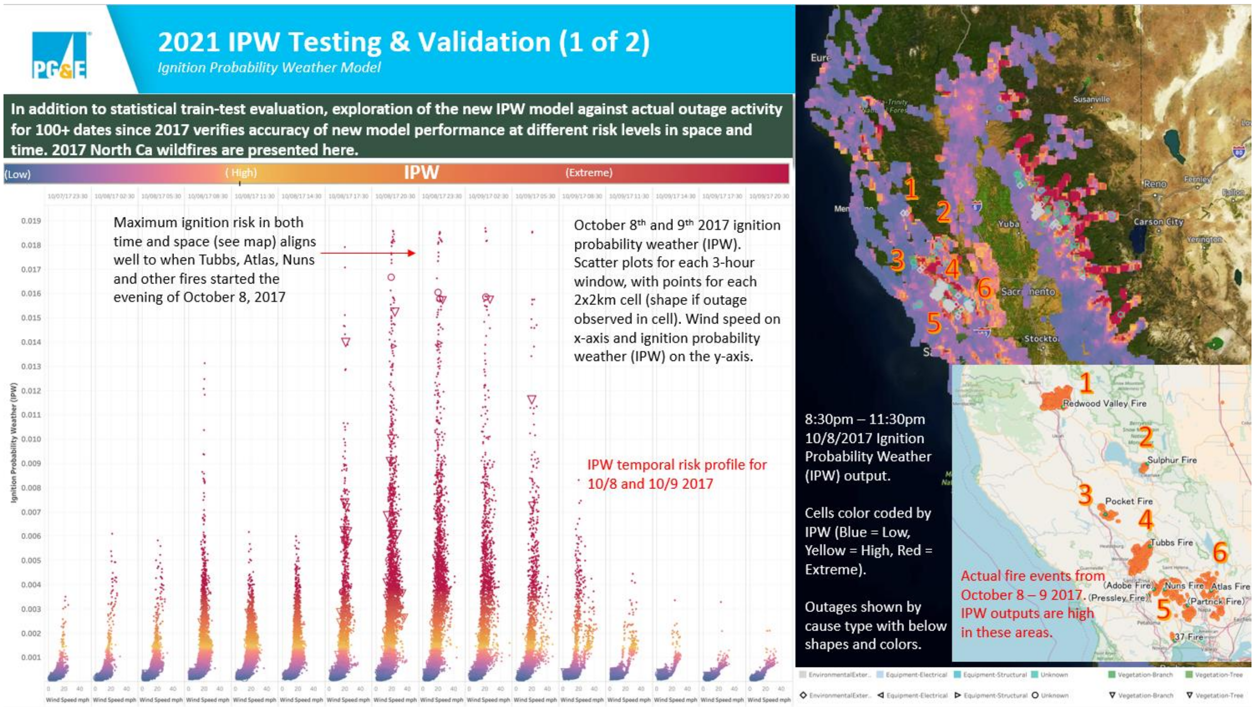

Fig. 20. Ignition probability model event output for October 8 and 9, 2017

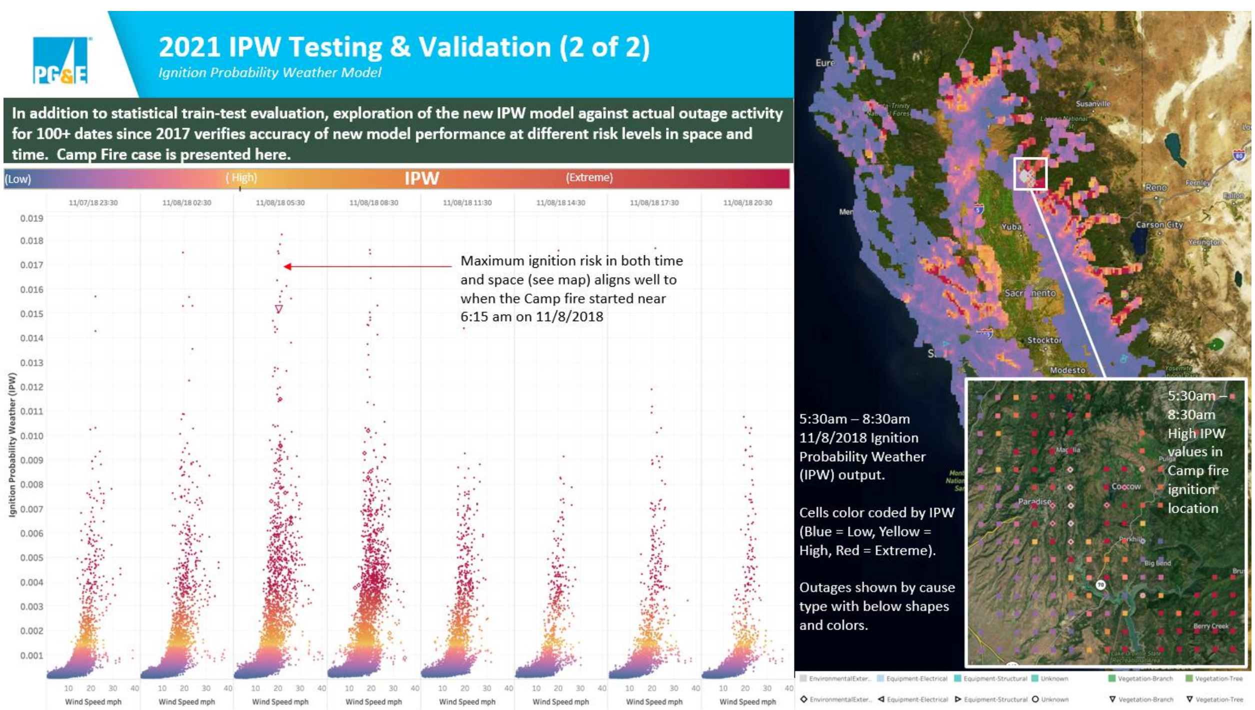

Fig. 21. Ignition probability model event output for November 8, 2018

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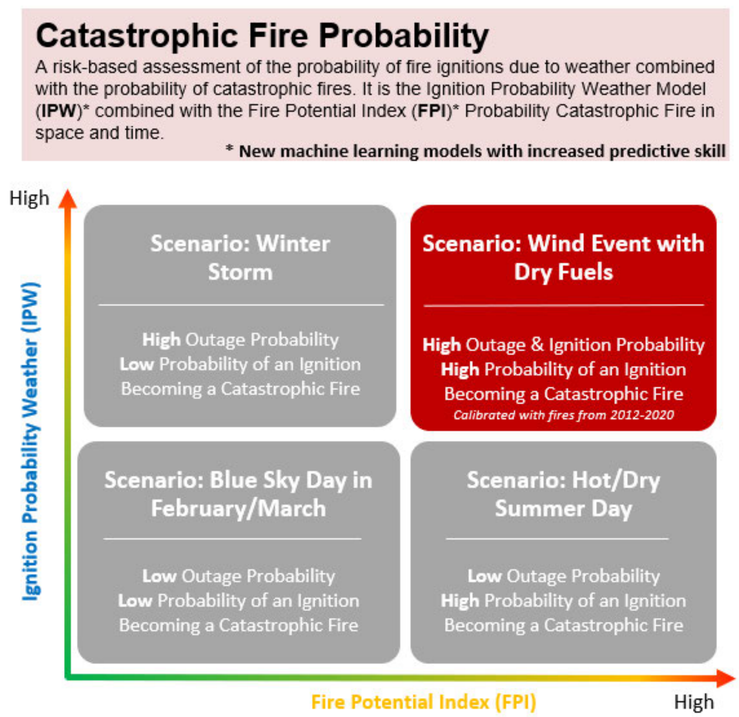
5 Distribution Catastrophic Fire Probability Model (CFP_D)

The Distribution CFP_D model is one of the main pathways for recommending if a segment of a distribution line should be considered to be deenergized for public safety. CFP_D is a risk-based assessment of the probability of fire ignitions due to weather combined with the probability of catastrophic fires. It is the product of the 2021 Ignition Probability Weather Model (IPW) and the 2021 Fire Potential Index (FPI) in space and time. A conceptual diagram of the CFP_D is presented below.



$$CFP_D = P(\text{Ignition}) * P(\text{Catastrophic Fire} \mid \text{Ignition})$$

Fig. 22. Catastrophic probability model conceptual framework

The CFP_D outputs are on the same 2 x 2 km grid spacing as the IPW and OPW and have been back cast from 2008 – 2020 and are also produced in forecast mode and used to determine when and where PSPS should occur.

6 Catastrophic Fire Behavior

6.1 Introduction

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We developed the minimum fire potential conditions as well as the Catastrophic Fire Probability model for Distribution, CFP_D, as the main driver of PSPS scope. These models identify the lines with the highest concurrent risk of wind-related outage and ignition probability and high FPI.

In 2020 we introduced an evaluation of “Black Swan Guidance” to review locations that may have a low probability of an outage, but environmental conditions that can lead to significant fires, recognizing that not all outage and ignition events can be perfectly predicted. This allowed capturing potential outage and ignition events that are much rarer and difficult to forecast but have very high expected consequence. These potential outage pathways include for example animal contacts, 3rd party contacts, foreign debris contacting lines (e.g., metallic balloons), etc or unknown equipment or tree-related deficiencies. For example, a review of 2020 (Jan through August 15, 2020) CPUC-reportable fire ignitions originating from PG&E assets showed that approximately one third of ignitions were caused by third-party or animal contacts.

As documented in PG&E’s 2020 and 2021 WMPs, we have been evaluating how to incorporate dynamic fire spread simulations into PSPS decision making. We have been working with a global leader in fire spread technology since 2018 to this end: Technosylva. Their technology has been adopted by several IOUs as well as state fire agencies including CAL FIRE. For PSPS events in 2021, the Black Swan Guidance has been replaced with forecast outputs from Technosylva. This capability allows evaluation of areas for their potential to ignite catastrophic wildfire that are difficult to control. This section provides an overview of the Catastrophic Fire Behavior consideration for PSPS decision making.

6.2 Technosylva Technology Overview

We have partnered Technosylva to test and deploy cloud-based wildfire spread model capabilities to better understand the technology and test integration into current decision support frameworks, such as PSPS. Each day, we deliver our high-resolution 2 x 2 km weather and fuels model data sets to Technosylva, who then perform over 100 million fire spread simulations every three hours out ~4 days. These simulations provide fire spread outputs (e.g., potential number of acres burned, population impacted, flame length and rate of spread) and can be visualized per overhead circuit in forecast mode to determine the highest risk circuits every 3 hours. Example forecast output from a Technosylva application called Wildfire Analyst Enterprise (WFA) is shown below.

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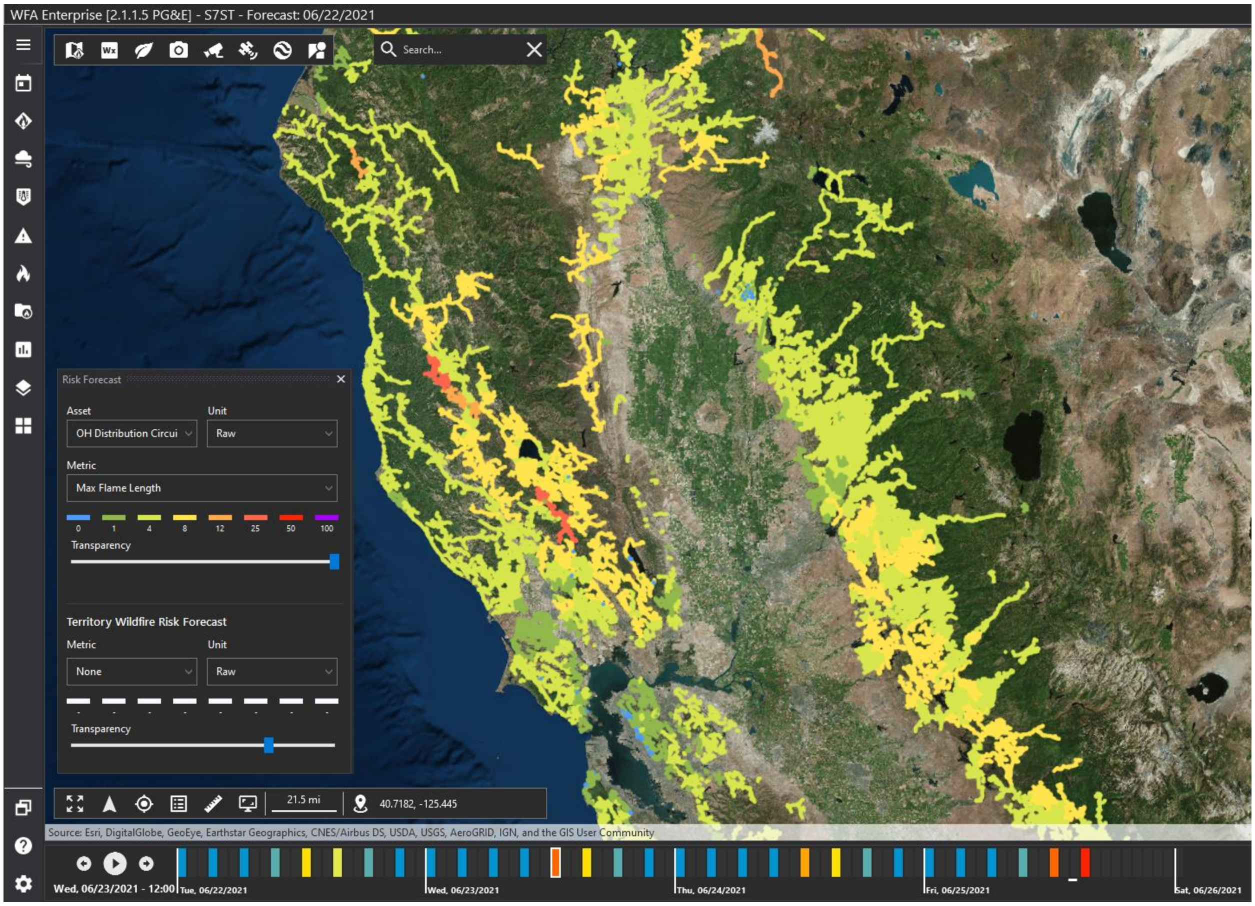

Fig. 23. Example output from Technosylva wildfire analyst software

WFA also gives users the ability to simulate fires on-demand. This involves selecting a location on a map, the start time of ignition and the simulation duration in hours. The Technosylva wildfire spread model uses the dynamic weather forecast of wind and fuel moisture to model how the wildfire may spread. This model framework and technology is also being utilized by other Investor-Owned Utilities in California, as well as California Department of Forestry and Fire Protection (CAL FIRE). This technology produces forecasts of ~100 million virtual fires daily across the PG&E territory in forecast mode, simulate fires on demand as they start, simulate hypothetical fires based on PSPS damage and hazard reports.

Importantly, Technosylva also can simulate billions of historic fires using a climatology of weather, fuel moistures and fuel model datasets. As described in the following section, these historic simulations were used to validate the Technosylva model and select the right output metrics for the PSPS application.

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6.3 Catastrophic Fire Behavior Guidance

6.3.1 Creating a Climatology of Catastrophic Fires

To test and evaluate fire spread output metrics for the PSPS application, we created the largest known climatology of fire spread simulations. First, we conducted a review of past weather days and selected 574 cases from 2000 – 2020 to simulate fires on. These included a mixture of worst-case fire days, Diablo wind-event days, PSPS days, days where catastrophic fires occurred and some typical hot and dry summer days. Next, we delivered our 2 x 2 km hourly weather, dead fuel moisture from the 31-year climatology for each day, so that each fire spread simulation can take advantage of dynamic hour-by-hour data. Technosylva also utilized their historical woody and herbaceous live fuel moisture model, which was reconstructed back to 2000 for this analysis. For the state-of-the-fuels, we opted to use a pre-fire fuel model map where recent burn scars were replaced with the pre-fire fuel model map. This was done to verify the model against past catastrophic fire incidents. Note that in the forecast application of WFA as well as the fuel model map that is a feature of the FPI model, we use the current fuel model map, which includes recent fire disturbances.

Finally, for each day, fires were simulated every 200 m along overhead assets on distribution and transmission in the entire CPUC HFTD as well as surrounding burnable areas.

6.3.2 Fire Behavior Characteristics and Suppression

We worked closely with Technosylva scientists to test and identify the optimal metrics to utilize for PSPS decision making. One lesson learned from evaluating outputs from WFA since 2018 is that the fire spread model tends to overpredict fire spread and impacts in grass-land areas compared to historical fires, and this is primarily driven by a lack of fire suppression effects in the core model. Fire suppression is extremely hard to predict due to the dynamic nature of resources available to respond to each incident and their effectiveness. There are many human elements and decisions that are involved in the response to each incident including how and where to apply mitigations, which present numerous challenges to directly model. Grass fires are also relatively easier to control compared to timber and brush fires due to low flame lengths and heat output and can most often be attacked at the flaming front of the fire to stop forward spread. Grass fires, left unmitigated, can grow large as WFA often suggests, but rarely do so as fire suppression efforts are typically successful. Thus; we explored additional metrics in WFA to identify those fires that would present control challenges due to the fire behavior characteristics.

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The USFS Rocky Mountain Research Station, a federal hub of wildfire research, has published documentation that relates the observed and modeled fire behavior to the type of fire suppression efforts that may be effective or ineffective. Andrews, *et al.,*2011 published a fire characteristics chart, also known as a "hauling chart", that presents fire behavior characteristics (e.g., rate of spread, flame length) with fire suppression interpretations ranging from fires that can be attacked by persons with hand tools to fires for which control efforts are ineffective.

The surface fire behavior chart reproduced from Andrews, *et al.,*2011 is shown below as well as a table relating the surface fire flame length to suppression interpretations. Their data show that for fires with flame lengths of less than 8 feet, suppression efforts using hand-line or equipment such as aircraft or dozers can be effective. For flame lengths of greater than 8 and 11 ft, their data suggests that control efforts at the flaming front of the fire will probably be ineffective to completely ineffective, respectively.

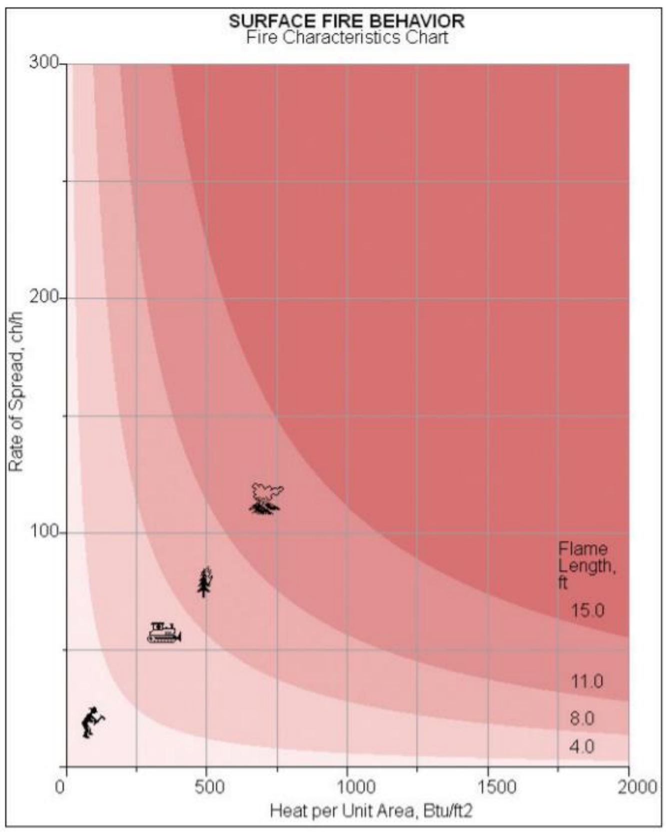

Fig. 24. The surface fire behavior fire characteristics chart comparing rate of spread, heat per unit area, and flame length for calculated or observed fire behavior (Andrews and Rothermel 1982) versus indication of fire suppression. Reproduced from Andrews, et al.,2011.

Figure NN: The surface fire behavior fire characteristics chart is used to plot rate of spread, heat per unit area, and flame length for calculated or observed fire behavior (Andrews and

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Rothermel 1982). Figures on the chart are an indication of fire suppression effectiveness related to flame length.

Table 8. Relationship of surface fire flame length and fireline intensity to suppression interpretations. Reproduced from Andrews, et al.,2011.

Flame length		Fireline intensity		Interpretation	
ft	m	Btu/ft/s	kJ/m/s		
< 4	< 1.2	< 100	<350		• Fires can generally be attacked at the head or flanks by persons using hand tools. • Hand line should hold the fire.
4 – 8	1.2 – 2.4	100 – 500	350 – 1700		• Fires are too intense for direct attack on the head by persons using hand tools. • Hand line cannot be relied on to hold the fire. • Equipment such as dozers, pumpers, and retardant aircraft can be effective.
8 – 11	2.4 – 3.4	500 – 1000	1700 – 3500		• Fires may present serious control problems—torching out, crowning, and spotting. • Control efforts at the fire head will probably be ineffective
> 11	> 3.4	> 1000	> 3500		• Crowning, spotting, and major fire runs are probable. • Control efforts at head of fire are ineffective.

6.3.3 Fire Behavior Sensitivity Studies

Using Andrews, *et al.,*2011 as a guide, we explored the fire climatology constructed on 574 selected days from 2000 – 2020 that contained billions of virtual fires. A dynamic dashboard was constructed to allow for rapid iteration and exploration of results from 2017 – 2020 initially, before the full dataset was utilized in final PSPS sensitivity studies due to the immense size of the fire climatology.

An example of this dashboard is presented below. On the right, the analyst can apply filters on the following metrics: Area, Fire volume, Flame length, Rate of Spread, Buildings impacted, Population impacted, or Buildings plus population impacted. Once the filters are set, the entire dashboard dynamically updates. The map on the left shows each fire simulation from 2017 – 2020 that pass each filter, while the center table presents a sorted list of days with the number of simulations passing each filter ranked from high to low. The scatter plot on the bottom can be customized by the user by selecting variables for the x and y-axis. The dashboard has more advanced functionality that allows the user to view outputs daily as well as view outputs from individual simulations using a mouse-hover feature.

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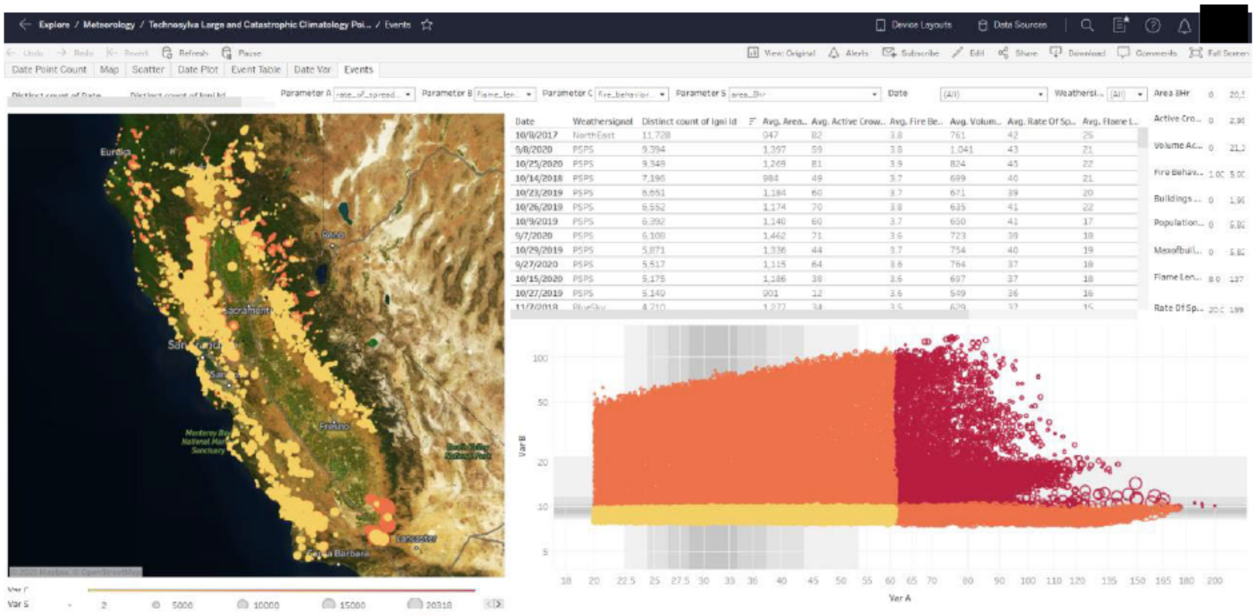

Fig. 25. Example image from historical fire simulation dashboard

To illustrate the challenge previously identified with suppression and grass-land fires, the image below presents the dashboard results for fires filtered only on fire size >10,000 acres and above and Rate of Spread >20 chains / hr (~0.25 mph). The location of these incidents occur in grass land areas along the west side of the Sacramento Valley, the Altamont Pass area east of Livermore where there is a wind farm, and other grass-land areas adjacent to the southern San Joaquin Valley. The event-day ranking also shows numerous “Blue-Sky” days, where no adverse weather was observed. This clearly shows that selecting a metric based solely on fire size simulated over an 8 hr period would result in identification of grass-land areas, which is not aligned with where catastrophic fires have occurred in the past.

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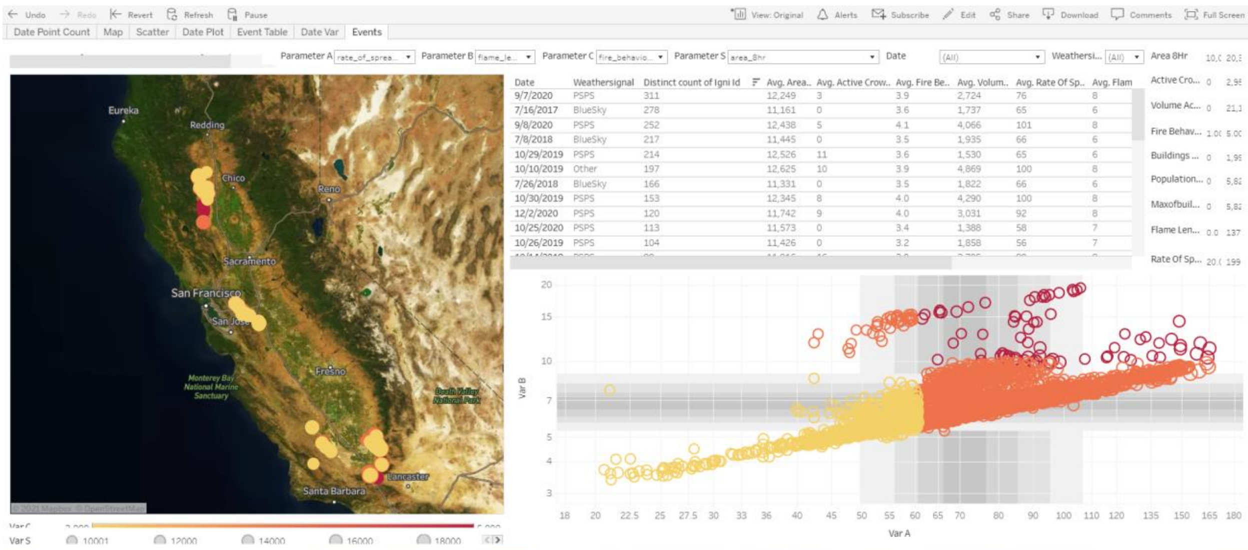

Fig. 26. Image from fire simulation dashboard showing 8-hour fire simulations > 10,000 acres

Below is another example from the dashboard by applying filters only on flame length > 20 ft and Rate of Spread >20 chains / hr (~0.25 mph). The locations shift dramatically from grass-land areas to shrub and timber and more closely aligns to locations where recent catastrophic fires have been observed. The event list also shows the highest risk day was 10/8/2017, where numerous catastrophic wildfires resulted from a strong Diablo wind-event. The next 11 dates correspond to PSPS event days where lines were proactively deenergized due to strong winds.

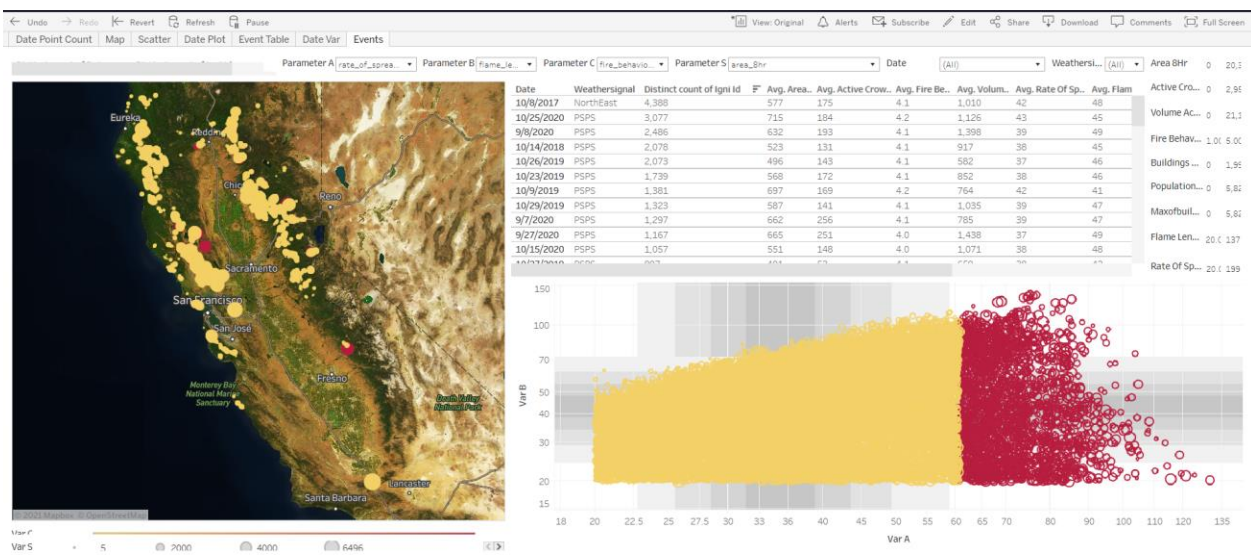

Fig. 27. Image from fire simulation dashboard showing fires >20-feet flame length

The dashboard was also utilized to view outputs on days where catastrophic fires occurred. These dates included the 10/8/2019 North California wildfire siege events, the 2018 Camp Fire, 2019 Kincade Fire and 2020 Zogg fire. Results utilizing filters on flame length > 8 ft and Rate of

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Spread > 20 chains / hr (~0.25 mph) and area burned ≥ 100 acres are presented below for each day. We found that the model does well as identifying areas where past catastrophic fires have occurred by evaluating the fire behavior/characteristics. These results were shared with Technosylva scientists as well as scientists from SCE and SDG&E during joint IOU task force meetings and very positive feedback was received on our methodology and results.

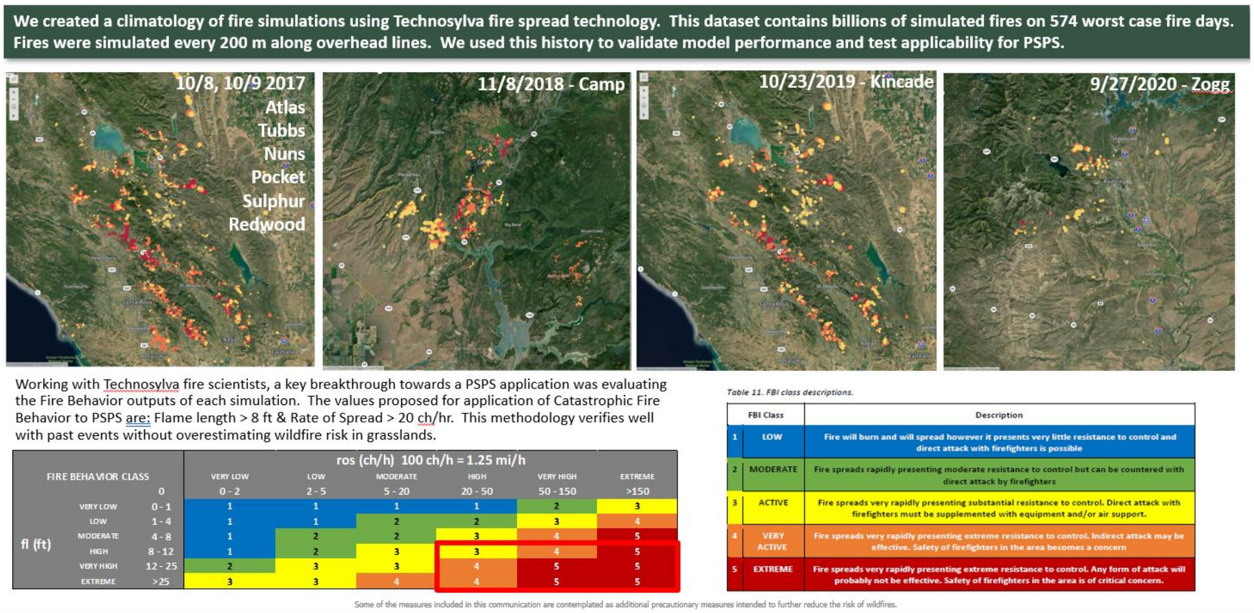

Fig. 28. Example verification of historical catastrophic fires

6.3.4 Catastrophic Fire Behavior Guidance

By leveraging a robust climatology of fire spread simulations from 2000 – 2020, published agency literature, workshops with Technosylva fire scientists, and sensitivity studies, we established Catastrophic Fire Behavior (CFB) guidance to apply for PSPS decision making starting August 1, 2021. This guidance takes advantage of the fire behavior outputs from Technosylva WFA to identify locations where fires are less probable to be contained should a fire ignition occur. The final CFB guidance selected and approved is presented in the image and table below and aligns with USFS published research.

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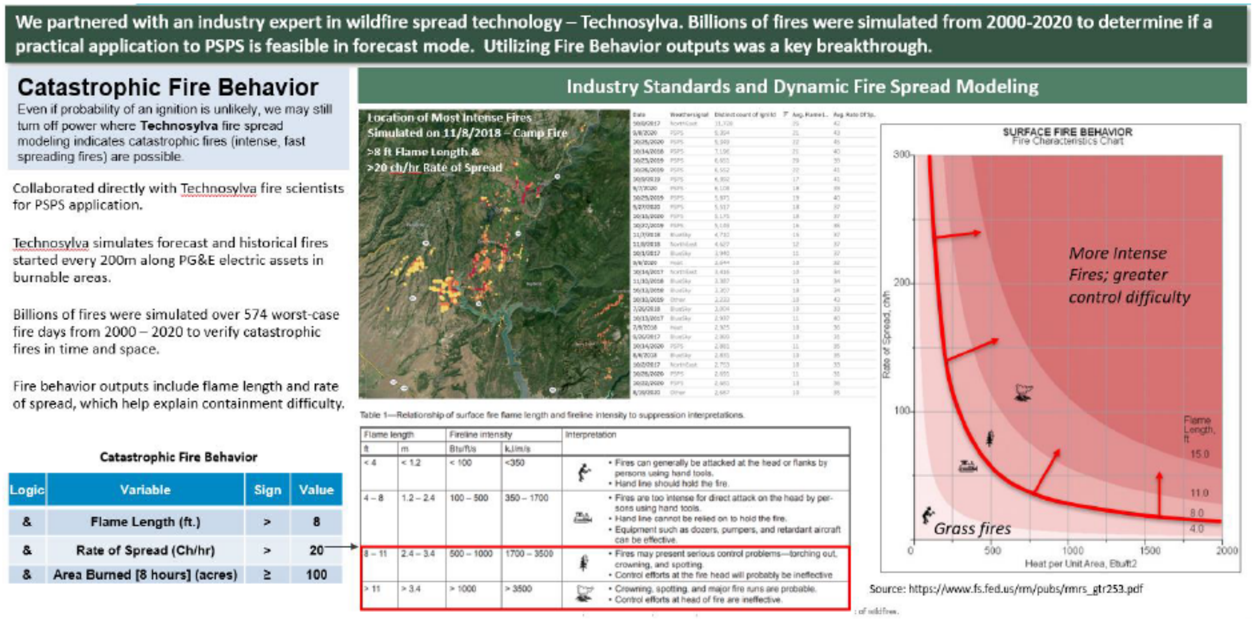

Fig. 29. 2021 PSPS guidance - catastrophic fire behavior

Table 9. 2021 PSPS guidance - catastrophic fire behavior

Catastrophic Fire Behavior Guidance:	Sign	Value
Flame Length	>	8 ft
Rate of Spread	>	20 chains/hr
Area Burned in 8 hours	≥	100 acres

7 2021 Distribution PSPS Guidance

7.1 Sensitivity Studies

To establish PSPS guidance we performed numerous sensitivity studies in backcast mode for calibration and validation. In 2021 this involved running 63 different versions of the combined PSPS guidance through hourly historical data to calibrate PSPS guidance. Through this “lookback” analysis we can evaluate the potential size, scope and frequency of PSPS events

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(customer impacts), the days PSPS events would have occurred as well as if historic fires caused by utility infrastructure would have been deenergized.

This is a very time consuming and computational expensive process but a critical step to ensure the most catastrophic incidents of the past are being identified by CFP_D guidance whilst considering the significant impacts to customers from PSPS across multiple dimensions (duration and frequency). This helps ensure that future PSPS events will capture conditions similarly present during the most catastrophic fires of the past while also balancing impacts to customers.

To accomplish this, we utilize cloud computing resources to run PSPS model guidance for every hour at every 2 x 2 km grid cell across the historical dataset to determine the number of times and locations PSPS guidance is exceeded. Each grid cell exceeding guidance is then grouped into events to determine the location and size of each PSPS event given the weather and fuels present at that time under the parameters of the study version. This allows us to determine if the right synoptic-driven events (e.g., Diablo wind events) are being identified, and if historical fires attributable to PG&E equipment may have been mitigated.

We also created a dynamic dashboard where PSPS guidance sensitivity studies could be also be conducted rapidly and to visualize impacted areas. An example of this dashboard is presented below. Guidance parameters can be adjusted to evaluate, for example, the difference between a CFP_D value of 9 or 10. Outputs include an extent analysis that can be filtered by event, circuit-by-circuit outputs, a timeseries and event magnitude visualization, as well as multiple dimensions per event (e.g., date, duration, customers impacted, circuits impacted, etc). The dashboard only includes data from 2017 through 2020 due to data-size limitations. Once a set of guidance values is ready for a final sensitivity analysis, it is then run hour-by-hour from 2008 – 2020 to obtain a wider view of impacts over time.

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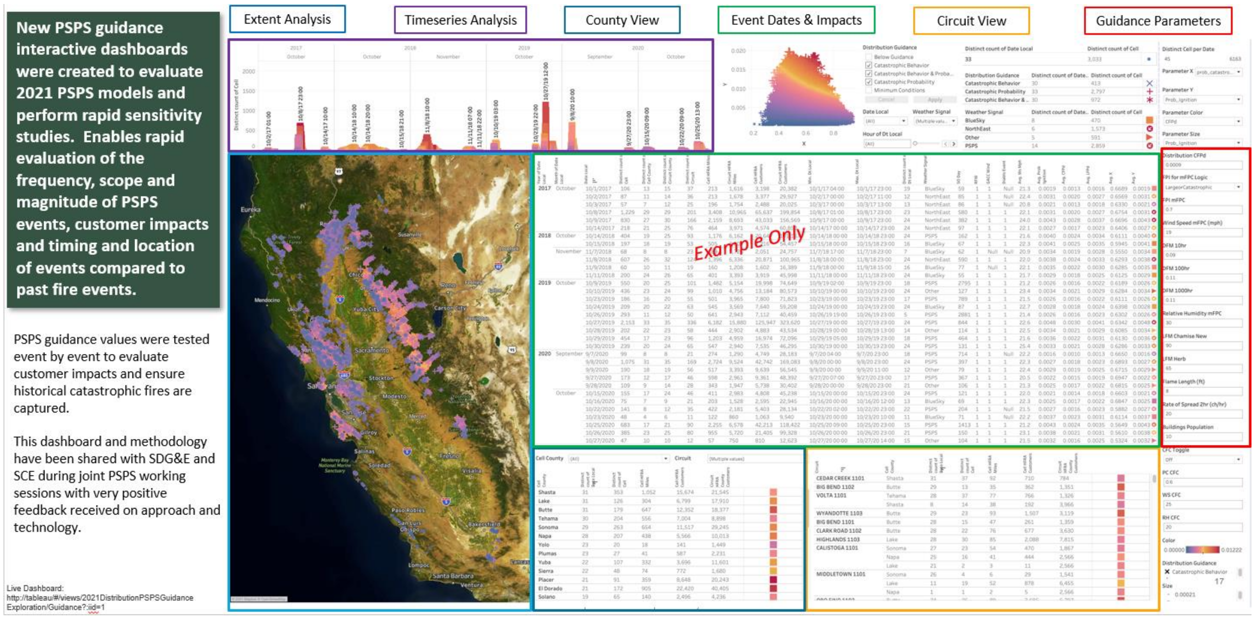

Fig. 30. Example PSPS guidance exploratory dashboard

7.2 Validation of Wind-Driven Fires

To evaluate if CFP_D captures large, catastrophic *wind-driven* fires, we built a verification dataset by extracting the IPW, FPI and CFP_D for all fires that have occurred in the PG&E territory. An example image from this analysis is shown below. Note that many large catastrophic fires attributable to PG&E equipment are located in the upper right portion of the image. This indicates these fires have concurrence in space and time of large FPI values and IPW on the distribution system due to the wind speeds present. Note also there are many large fires that have low IPW values. Large fires are possible without the presence of strong wind speeds in CA and are fuels- or plume-dominated. This has been discussed extensively in the academic literature (Keeley and Syphard, 2019). An examination of some of those incidents like the Butte, Carr and Mendocino-Complex fires revealed that winds associated with these events were not extraordinary. The purpose of PSPS is not to mitigate the risk of all fires, but to mitigate the risk of the most extreme cases where winds can drive a fire so rapidly that evacuation of populations and egress is significantly challenged.

Based on the historical review of incidents, verification of event dates and the guidance sensitivity and calibration analysis, a CFP_D value of 9 was chosen as the quantitative guidance value to consider for PSPS on the distribution system. This guidance represents >99th percentile conditions when evaluating hours exceeding guidance versus hours below guidance across the historical dataset.

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The CFP_D guidance value of 9 is shown in the image below respective to recent large fires since 2012. Any fires above the 9 line indicate PSPS would have been executed had these models and guidance been in use during these historic events if they also met the minimum fire potential conditions. The historical results show that had this model been deployed and implemented since 2012, the new PSPS protocols would have prevented >21,000 structures from being destroyed and 102 fatalities from fires igniting during high wind conditions. The 2 fatalities and majority of structures from fires that would not have been captured through PSPS are from the 2015 Butte Fire that ignited during low winds speeds. There were no Federal warnings in effect at the time, including Red Flag Warnings.

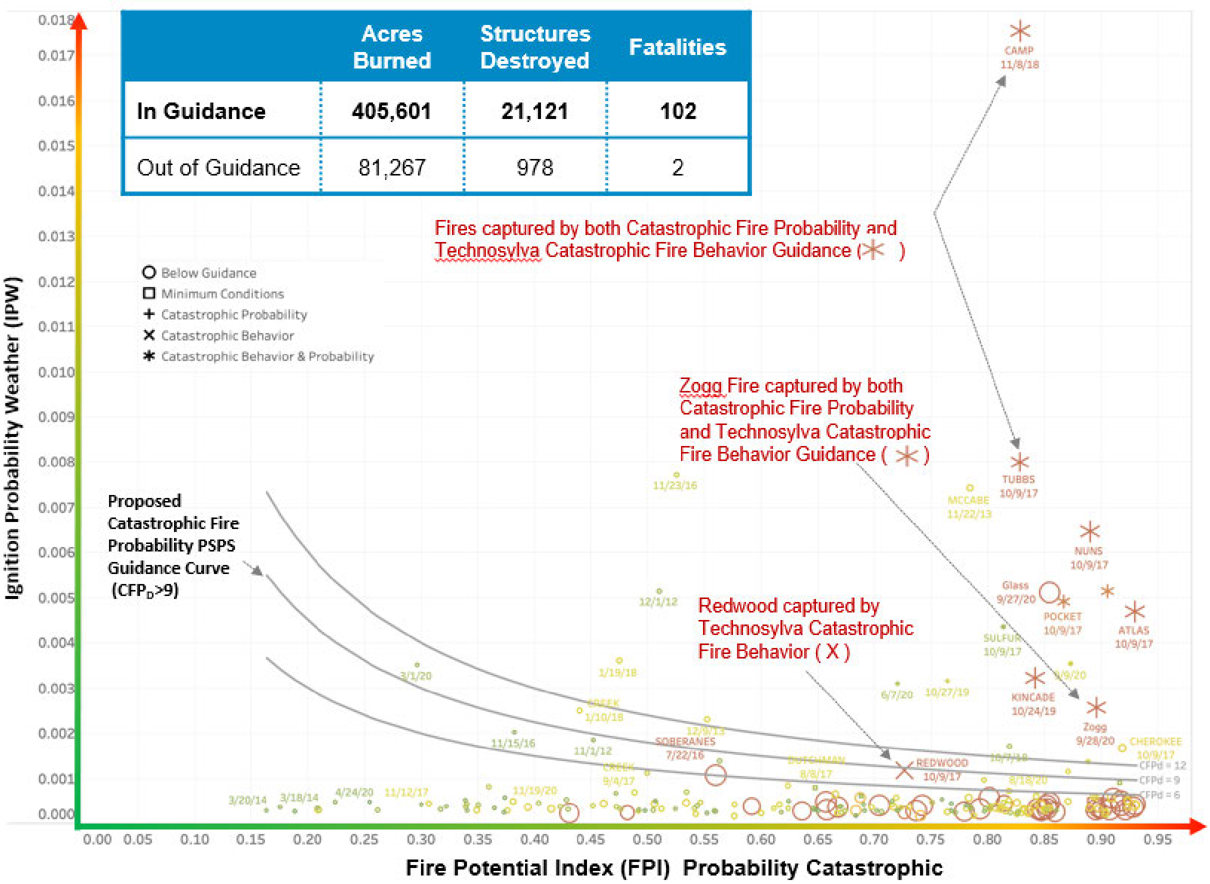

Fig. 31. 2021 PSPS guidance verification of historical catastrophic fires

7.3 2021 Distribution PSPS Guidance

The remaining sections in this document provide detailed information on the data, models and sensitivity studies that were used to construct the 2021 Distribution PSPS model framework.

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This guidance was reviewed in several sessions with the Chief Risk Officer and was approved by the Wildfire Risk Governance Committee on June 4, 2021 for operational use on August 1, 2021.

The full objective PSPS guidance for Distribution is presented in the image below. If the minimum fire potential conditions are met, then either the CFP_D, CFB, or high priority electric assets or vegetation can bring an area into scope for PSPS.

As we model these PSPS criteria in over 10,000 2 x 2 km model grid cells every hour there are times where a single grid cell or few exceed guidance for a short period of time. A review of these showed that they often occur during hot and dry periods during a routine sea breeze and typically not when Red Flag Warnings or other Federal fire warnings are in effect. To help identify events, both through historical lookbacks and in forecast mode, we define an event as meeting PSPS criteria for 25 grid cells out of 10,000 concurrently. This represents 0.25% of grid cells that contain assets. This grid cell criteria will be leveraged with Red Flag Warnings and other federal warning criteria to ensure that PSPS is utilized during high risk wind events only. This is consistent with academic literature (E.g., McClung and Mass, 2020), where Diablo wind events were only identified in their study if the criteria were met for several consecutive hours.

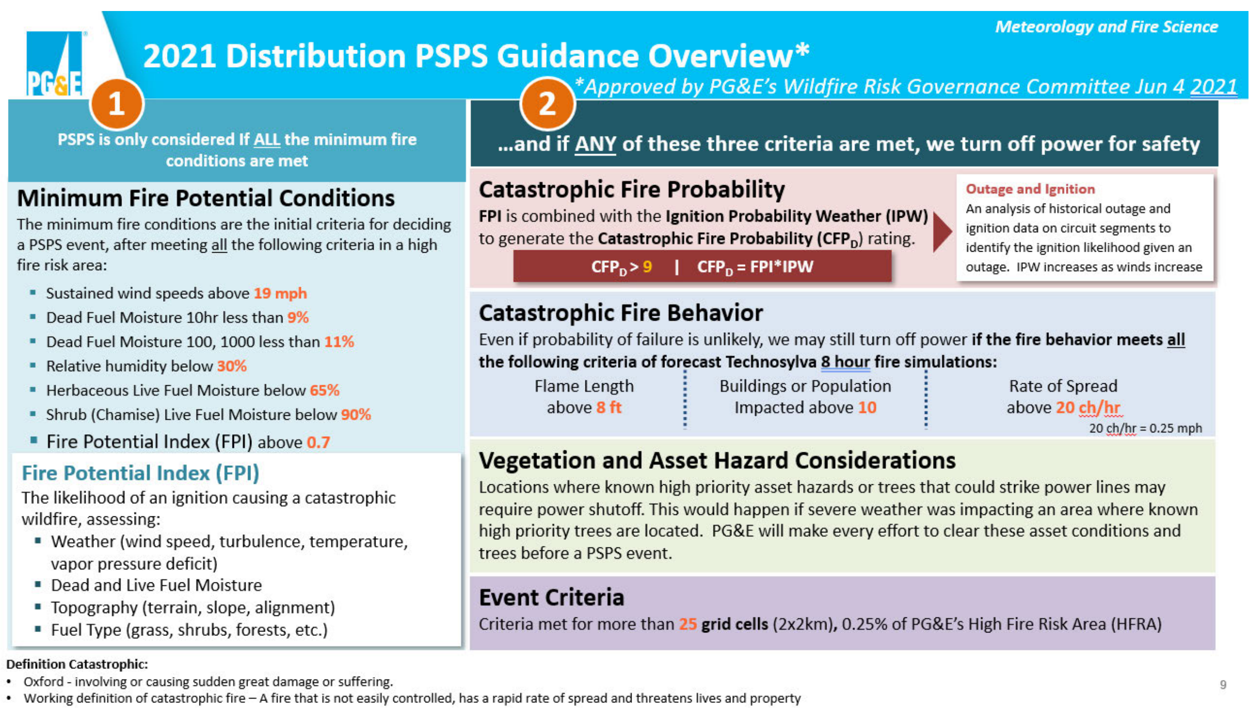

Fig. 32. 2021 distribution PSPS guidance overview

7.4 Expected Customer Impacts

Through the sensitivity study and historical lookback process, described above, we evaluated

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customer impacts due to PSPS through multiple dimensions (size, scope, duration, and frequency). The following tables and images show output from the last four years of the lookback study (2017 – 2020) for the approved PSPS Distribution guidance.

We expect that had these models been in effect at the start of 2017 that there would have been 19 PSPS events with ~72 million customer-hours. The customer impact study also shows that the by reducing the guidance value below a CFP_D of 9, the expected % of ignitions mitigated through PSPS does not change significantly, while customer impacts increase significantly.

The remaining images show the annual number of expected events versus actual events and previous versions of PSPS guidance (2020 and 2020+vegetation considerations). In addition, the circuit and county impacts from 2017 – 2020 are provided to show geographic areas at higher risk of PSPS. These generally align well with where Diablo wind events are most probable to occur: in the Northern Sierra and elevated terrain of the North Bay.

We ran dozens of sensitivity studies to study the impacts of PSPS. Below are final PSPS guidance levels for consideration based on the main PSPS criteria – Catastrophic Fire Probability (CFP_D = IPW*FPI)

2017-2020 Guidance Study Catastrophic Fire Probability (CFP_D)	% Ignitions Mitigated by PSPS of Expected Ignitions meeting Fire Potential Conditions. (4 Year)	PSPS Event Count (4 Year)	% Difference - PSPS Event Count (4 Year)	Total Customer Hours*** (4 Year)	% Difference - Total Customer Hours*** (4 Year)	Total Customers* (4 Year)	% Difference - Total Customers* (4 Year)	Avg. Event Duration** [hours]	% Difference - Avg. Event Duration**	Avg. Event Customer* Impact	% Difference - Avg. Event Customer* Impact	Max. Event Customer* Impact	% Difference - Max. Event Customer* Impact
>13	92.5%	16	-16%	64,135,738	-11%	1,505,288	-9%	39	5%	94,080	8%	314,201	-5%
>12	93.2% (+0.7)	18	-5%	65,588,598	-9%	1,543,264	-7%	37	0%	85,737	-2%	317,510	-4%
>11	94.2% (+1)	18	-5%	67,238,751	-7%	1,569,329	-5%	37	0%	87,185	0%	320,658	-3%
>10	94.2% (+0)	18	-5%	69,940,821	-3%	1,603,797	-3%	38	3%	89,100	2%	324,721	-1%
>9	96.4% (+2.2)	19	-	72,359,026	-	1,654,555	-	37	-	87,082	-	329,434	-
>8	96.6% (+0.2)	20	5%	73,742,772	2%	1,692,405	2%	35	-5%	84,620	-3%	330,082	0%
>7	96.6% (+0)	20	5%	78,140,155	8%	1,750,644	6%	37	0%	87,532	1%	330,432	0%

Catastrophic Fire Probability >9 is recommended for operation in Fall 2021 based on the balanced evaluation of historical fires, expected ignitions mitigated, and PSPS event dates and customer impacts. Further steps down in guidance show a diminishing rate of additional HFRA expected ignitions mitigated by PSPS, while adding PSPS customer hours impacted.

Customer counts* are distribution service points and are estimated at ***circuit level counting all customers with HFRA* *secondary transformers on a circuit, and do not include customer impacts from Transmission PSPS.*
******Event Duration*** *is from the start to the end of the fire weather event and does not include restoration.*
****Customer Hours impacts is based on event* ***duration*** *multiplied by the* ***customer count*** *for each event.*

Fig. 33. 2021 distribution PSPS guidance results from sensitivity analysis

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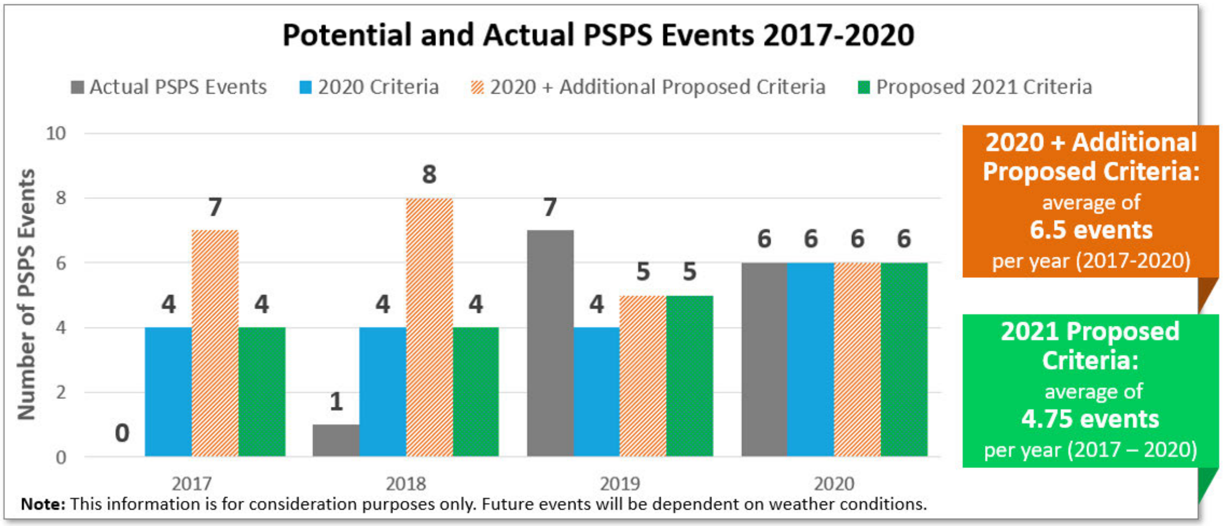

Fig. 34. 2021 PSPS guidance frequency of events compared to previous PSPS model versions

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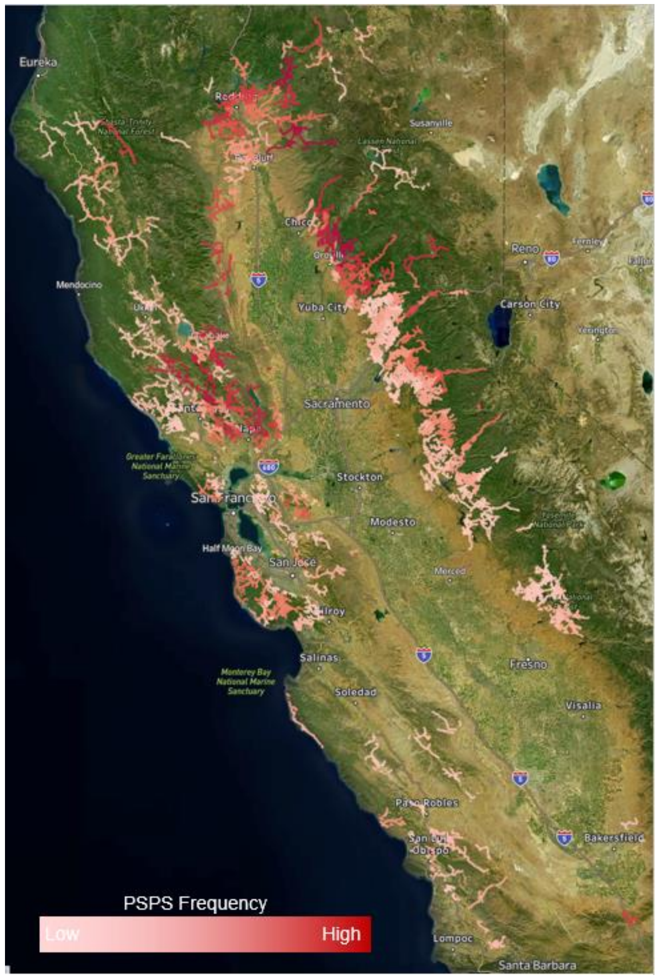

Fig. 35. 2021 distribution PSPS guidance circuit impact frequency

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Fig. 36. 2021 distribution PSPS guidance county impact frequency

7.5 PSPS Model Calibration and Verification

We performed extensive model calibration and verification of the PSPS guidance using several internal and external datasets. The goal of this analysis was to first determine if the right weather events are being captured (e.g., Diablo wind events), and second to determine if lines that have been implicated in historic catastrophic fires would have been identified by guidance.

We used the following datasets in this analysis.

- National Center for Environmental Prediction (NCEP) North American Regional Reanalysis Archive (NARR) synoptic weather maps [external]
- Climatology of Diablo wind events [internal]
- Historical fire occurrence data compiled by federal agencies [external]
- Hourly high-resolution wind maps from the climatology data set [internal]
- Distribution and transmission outage history [internal]
- Red Flag Warnings from the NWS [external]
- High Risk of potential large fires due to wind from the GACC [external]

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- The weather signal database [internal]
- Exploratory and dynamic dashboards created with internal and external data [internal]

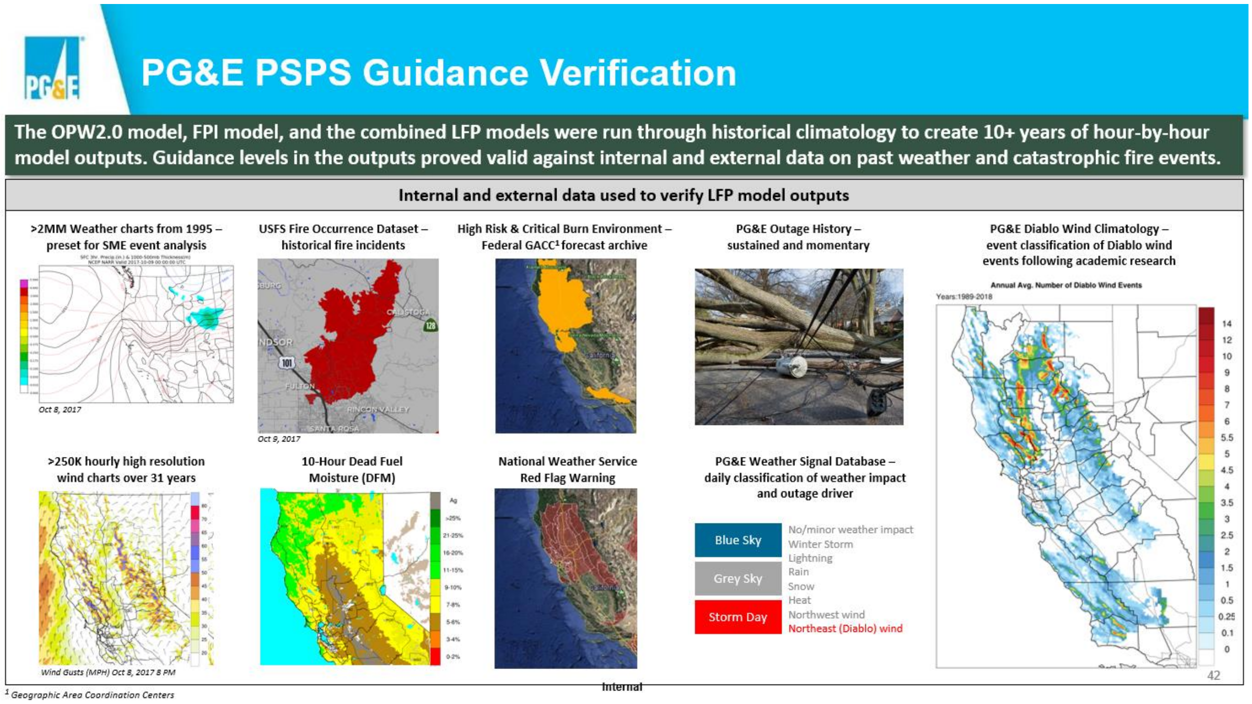

Fig. 37. Datasets used to verify 2021 PSPS guidance

7.5.1 National Center for Environmental Prediction (NCEP) North American Regional Reanalysis Archive (NARR) synoptic weather maps

The NARR is NOAA-NCEP's high resolution assimilated dataset. It provides a best guess at the gridded state of the weather in 4 dimensions (x,y,z,t). The NARR assimilates a large quantity of surface-based observations, satellite data, profiler information and more to generate the long-term state of the weather every 3 hours at approximately a 32 km resolution.

This dataset is widely utilized in the meteorological modeling community to evaluate the synoptic or larger scale drivers of weather events. We have acquired the NARR archive back to 1995 and produced over 2 million maps that can be utilized to study past events. They are also useful to study the antecedent conditions leading up to the event such as the extent (or not) of precipitation events and heat waves, for example.

Example images are shown below for weather events that contributed to large fires. Black lines on the images are isobars or constant lines of sea level pressure, while the shading represents the precipitation accumulation over a three-hour period. The dashed lines are the 1000-500

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mb thickness values in meters to help meteorologists understand atmospheric conditions aloft. The first image shown is from the October 2017 Northern California wildfire event. The isobars indicate there is surface based high pressure northeast of CA and lower pressure along the CA central coast. This pattern is indicative of a Diablo Wind event, where the pressure differential drives a northerly to northeast winds across Northern CA. In addition, when the wind direction aligns near-orthogonally to CA ridgelines, critical layers aloft may develop, leading to downward momentum transfer and downslope wind-storms. As winds are typically descending with height from the upper great basin down to the foothills in CA, the air undergoes compressional effects which cause it to warm and lower relative humidities. These synoptic to small scale features associated with Diablo Winds make them particularly challenging.

The figures following the first are taken from similar cases of interest. When the large fire probability models are run through the climatology, each event identified was compared against the NARR archive to determine the large scale atmospheric features present for each event. Other data was utilized to evaluate each event further.

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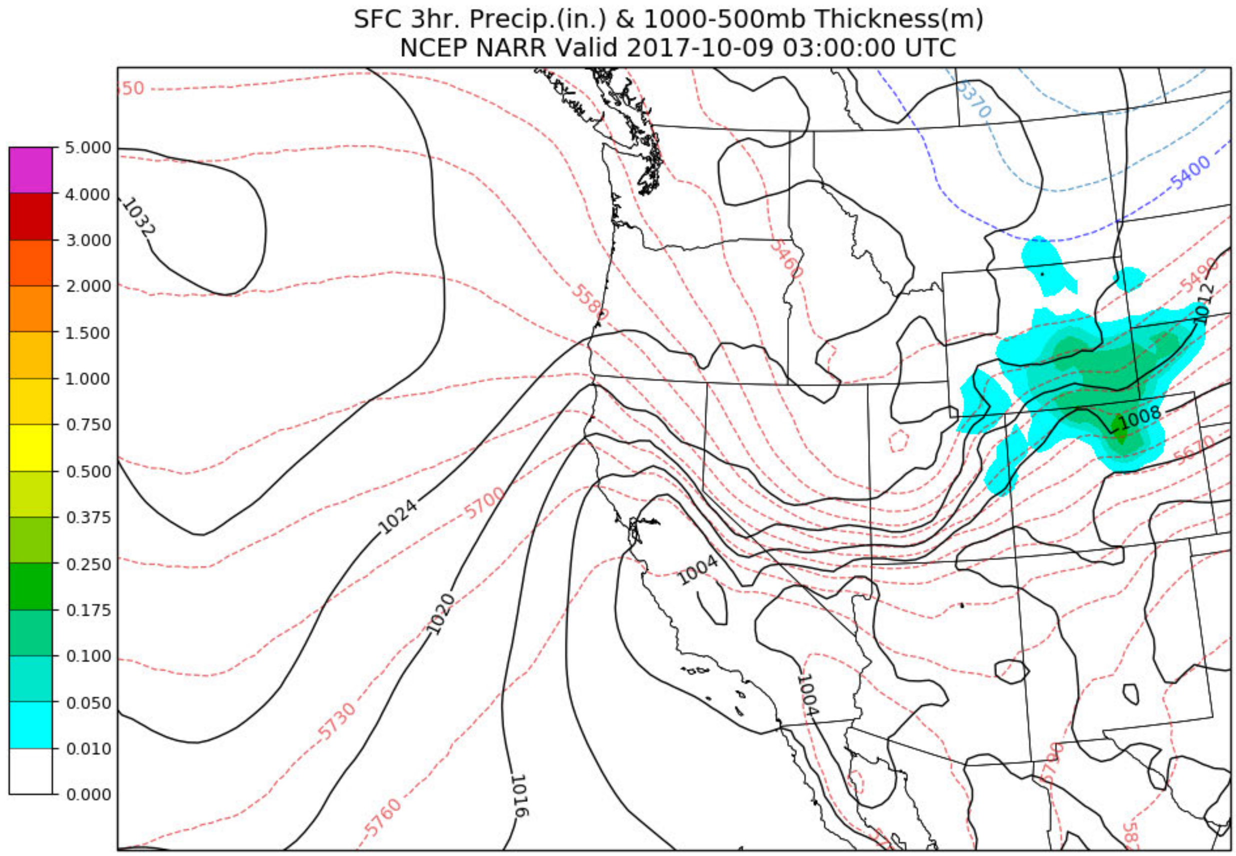

Fig. 38. NARR surface map for October 9th, 2017 at 0300 UTC. (Diablo Wind event. Black lines – isobars, shading – precipitation accumulation over 3 hours).

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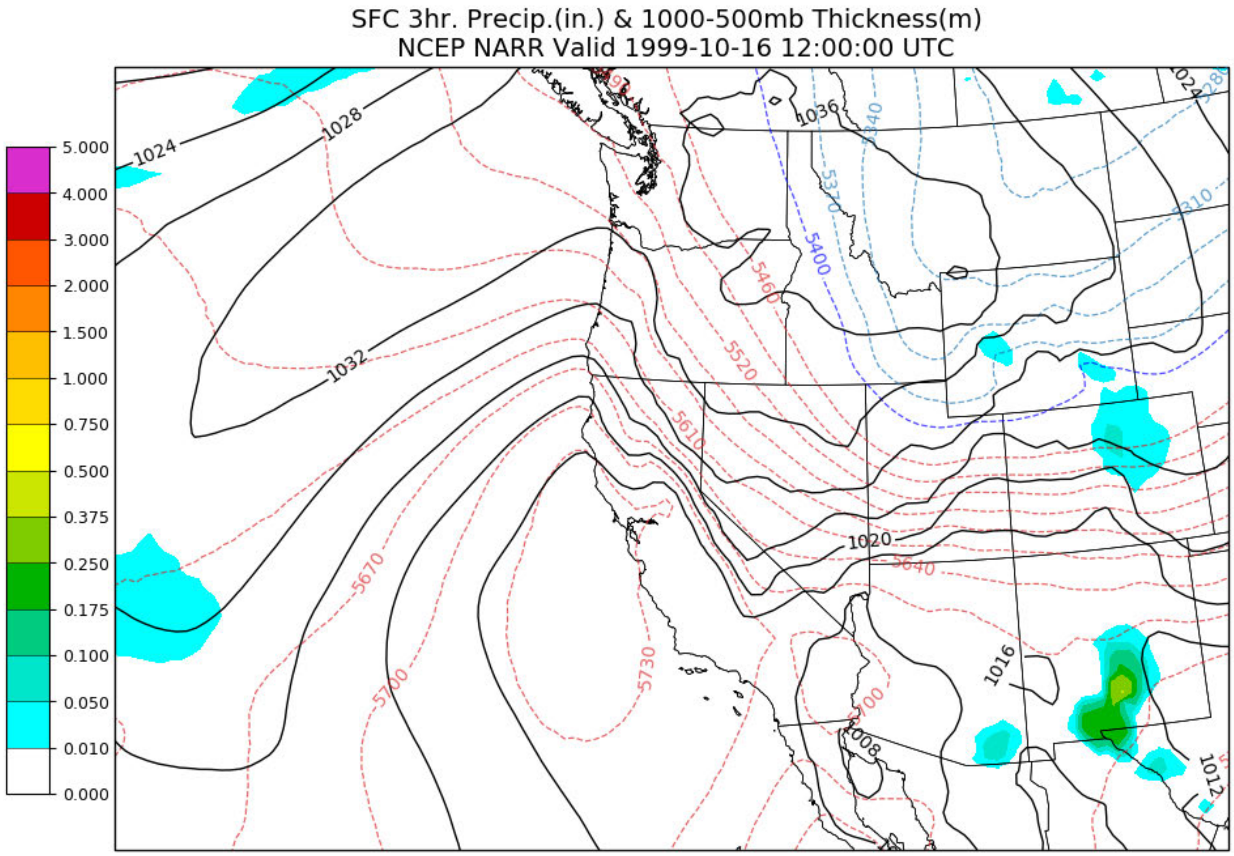

Fig. 39. NARR surface map for October 16th, 1999 at 1200 UTC. (Diablo Wind event. Black lines – isobars, shading – precipitation accumulation over 3 hours).

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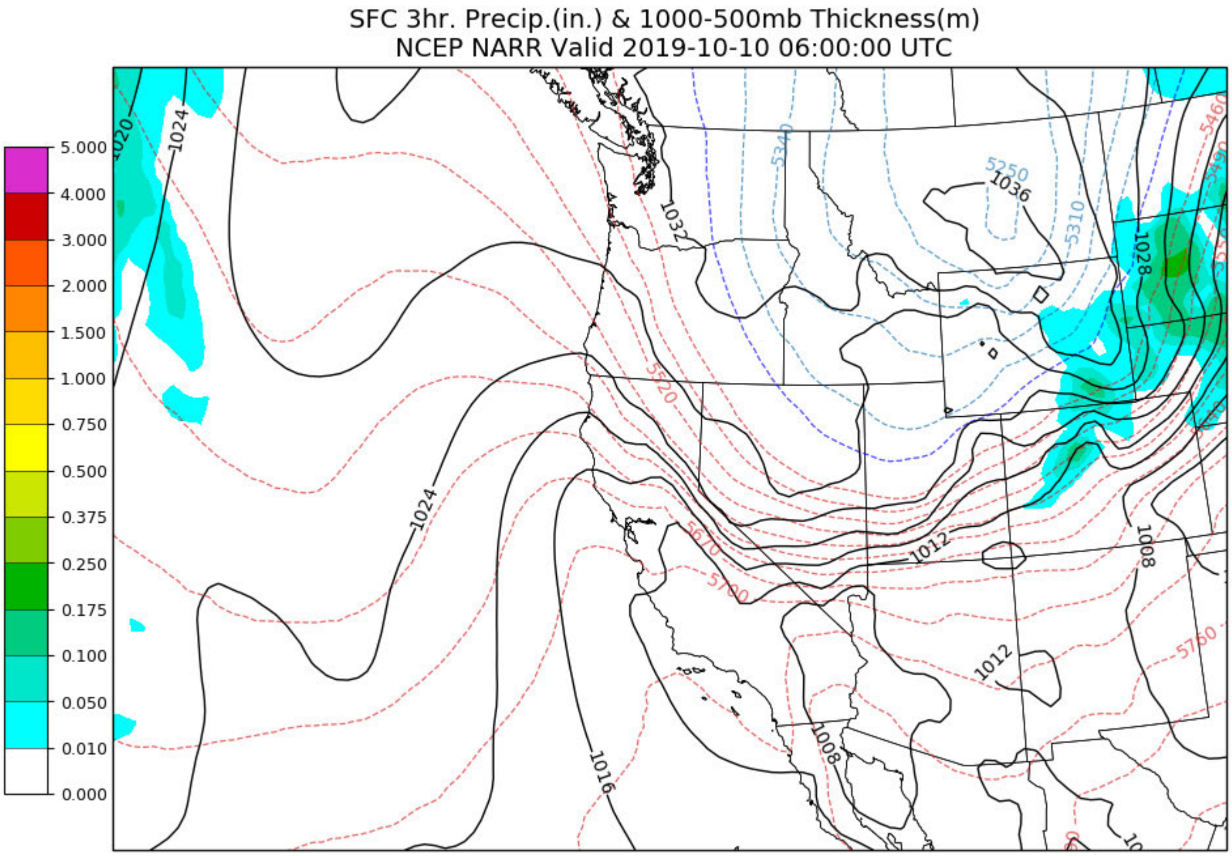

Fig. 40. NARR surface map for October 10th, 2019 at 0600 UTC. (Diablo Wind event. Black lines – isobars, shading – precipitation accumulation over 3 hours).

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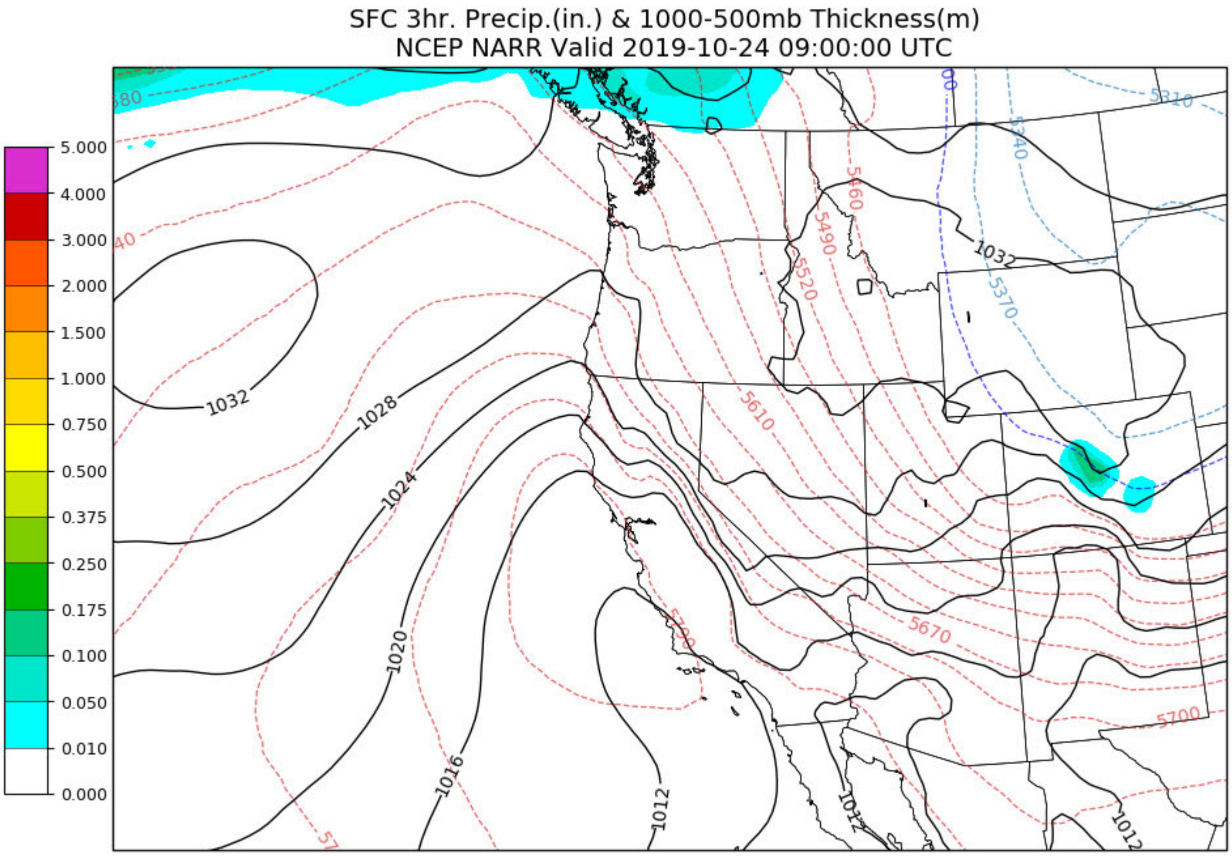

Fig. 41. NARR surface map for October 24th, 2019 at 0900 UTC. (Diablo Wind event. Black lines – isobars, shading – precipitation accumulation over 3 hours).

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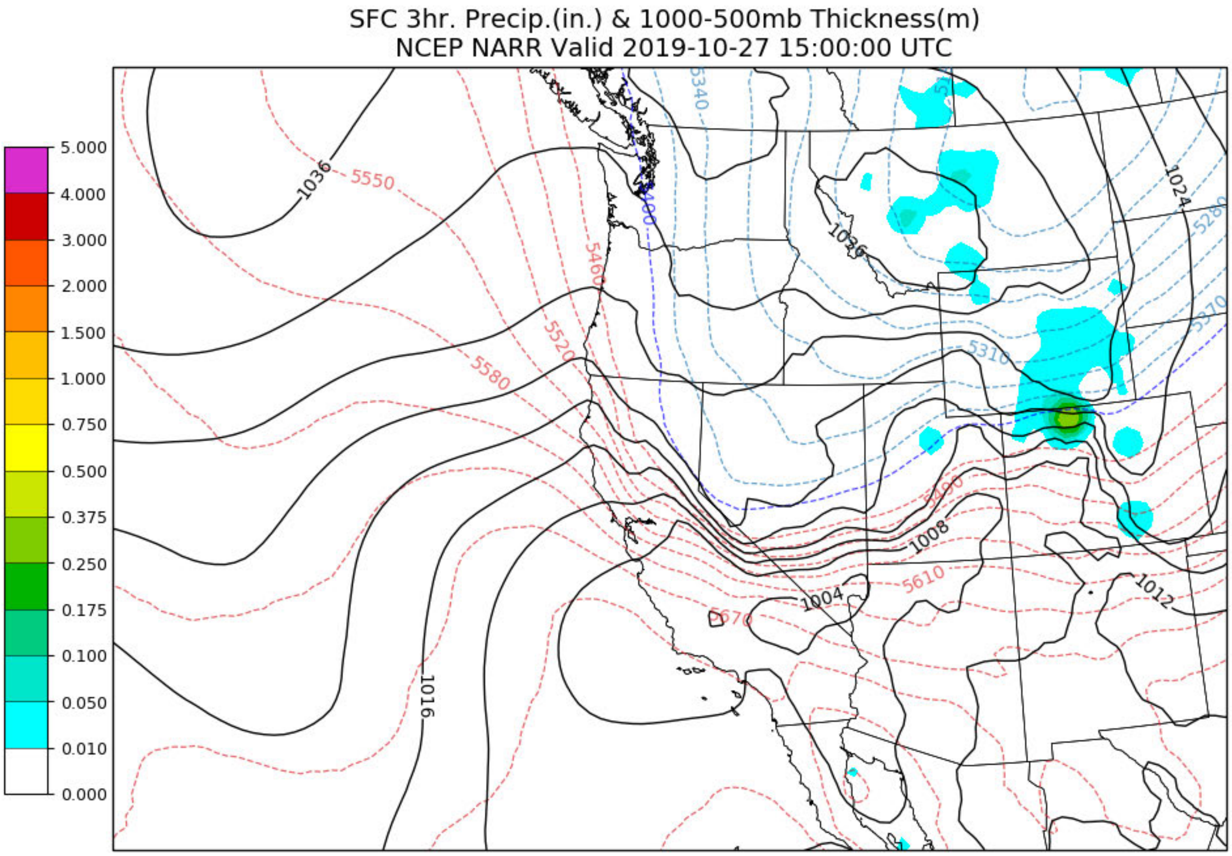

Fig. 42. NARR surface map for October 26th, 2019 at 1500 UTC. (Diablo Wind Event. Black lines – isobars, shading – precipitation accumulation over 3 hours).

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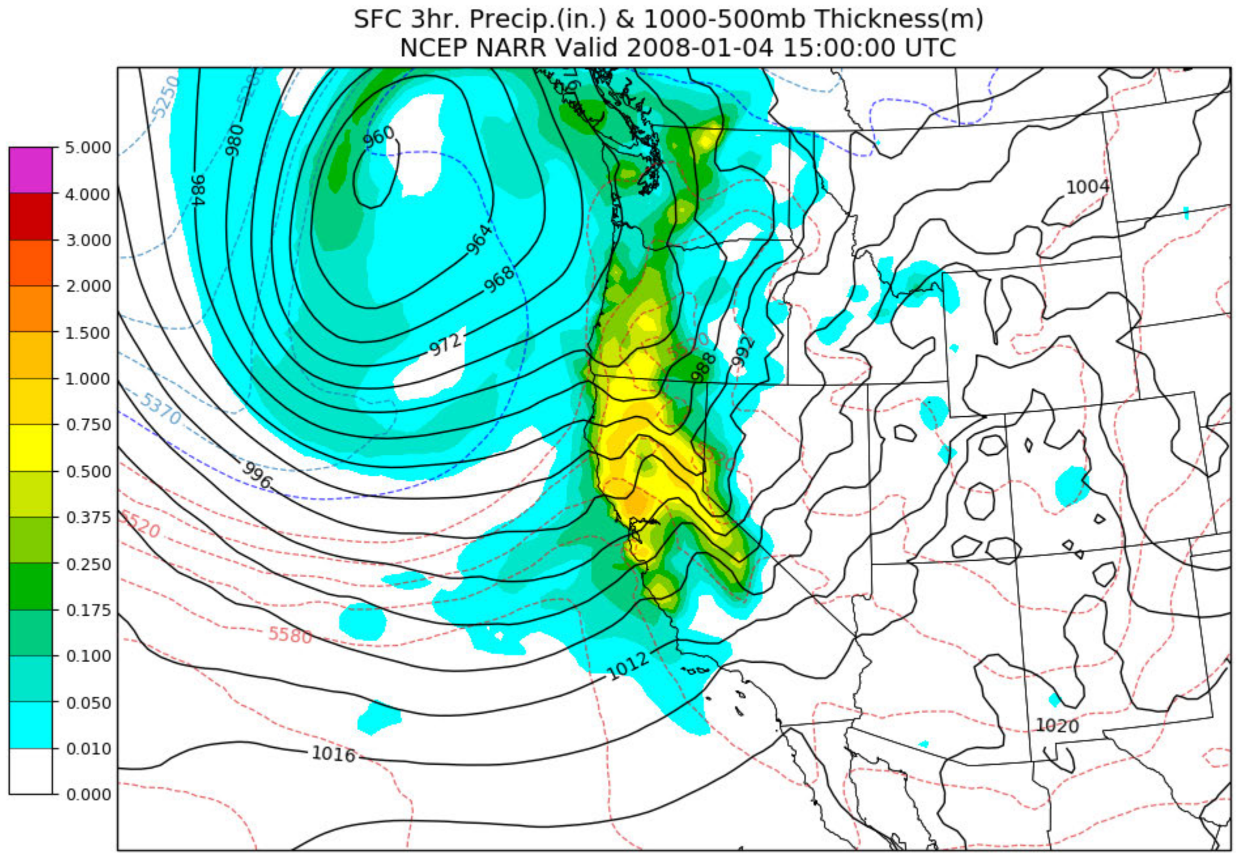

Fig. 43. NARR surface map for January 4th, 2019 at 1500 UTC. (Major Winter Storm. Black lines – isobars, shading – precipitation accumulation over 3 hours).

7.5.2 Climatology of Diablo wind events

Diablo wind events have caused or contributed to some of the most catastrophic fires in Northern CA such as the Oakland Hills fires, the October 2017 fires, Camp and Kincade.

We leveraged the latest academic research on these events that used surface-based observations in order to create a climatology of Diablo wind events (McClung and Mass, 2020). We adapted the criteria stated in this research and processed it hour-by-hour through the 31-year weather climatology to determine the frequency, magnitude and timing of Diablo winds.

The criteria applied are as follows:

- Windspeeds > 20 mph (gusts >34 mph)
- RH < 25%

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- Wind direction north to northeast (offshore)
- 1000 hr Dead Fuel Moisture < 11%

The output of this analysis was a 31-year calendar of Diablo wind events experienced in the PG&E territory. The figure below presents the location where these events were found to be most frequent.

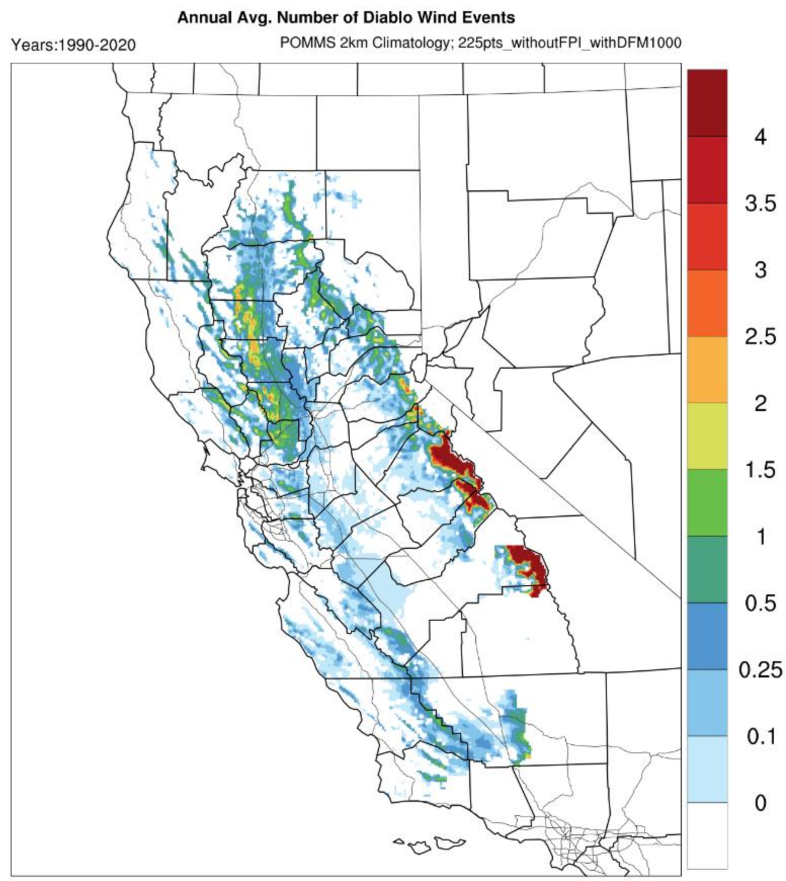

Fig. 44. Diablo wind event frequency analysis

The graph below shows the month by month frequency of Diablo events. These events peak in the fall and coincide when fuels are typically at their driest levels. This combination of a wind event on top of dry fuels is what makes these events particularly dangerous.

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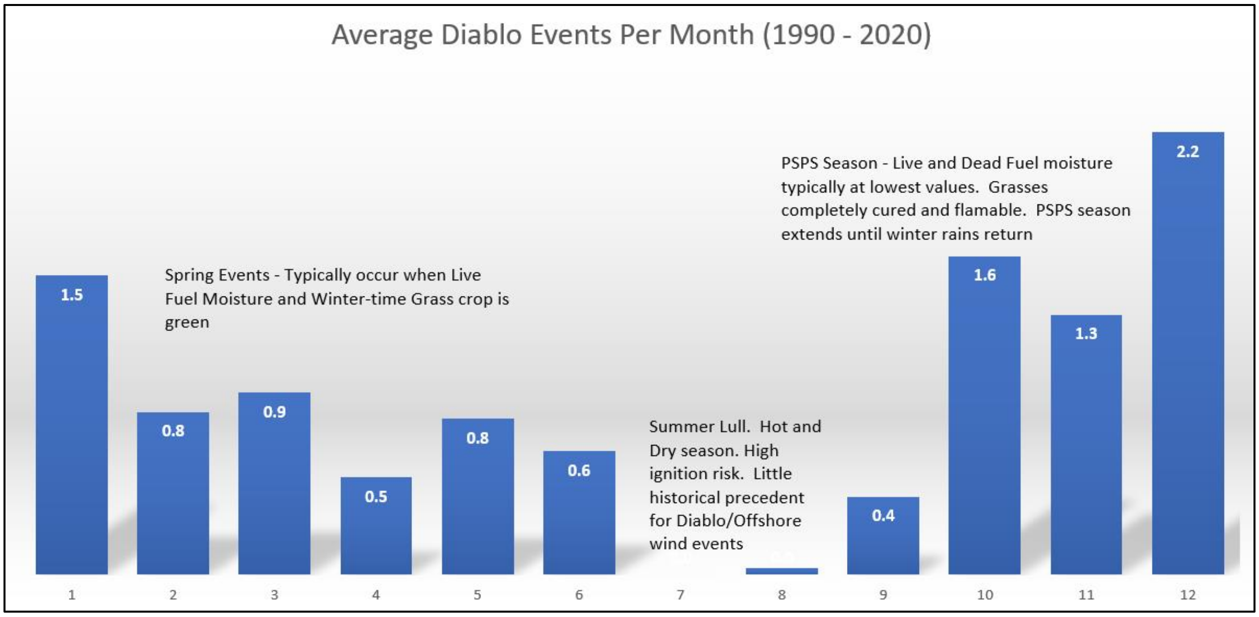

Fig. 45. Diablo wind event frequency analysis timeseries

As it relates to PSPS directly, the strongest Diablo wind events were evaluated to verify if PSPS guidance also selects these days for potential PSPS. Using the days identified by PSPS guidance and the Diablo event list, a high-level comparison was completed to evaluate overlap of the events. Any events that did not meet PSPS guidance were evaluated further using additional data sources described in this section. For example, the NARR archive proved useful, as antecedent conditions such as rainfall before an event and the magnitude of the event could be evaluated.

7.5.3 PG&E's weather signal database

PG&E's Meteorology team built and continues to maintain a 'weather signal' database that flags each day starting Jan 1, 1995 to present that has experienced any weather-related outages on distribution and the main weather driver (e.g., heat, low-elevation snow, northeast wind, winter storm etc.). If distribution outage activity is not driven by weather, the day is classified as a "Blue Sky" day, meaning that weather was not a main driver of outage activity.

This is a simple but very powerful dataset that combines weather and distribution outage activity that allows rapid filtering of events based on the main weather drivers. To validate PSPS guidance, we used a combination of "Northeast" wind days and "Blue-Sky" days. Our definition of a Northeast wind day is as follows: "Weather type used when strong offshore (northerly or northeast winds) result in elevated outage activity. This includes Diablo and Santa Ana wind events. An example are the classic offshore winds events where surface high pressure develops in the Upper Great Basin."

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The definition of a Blue Sky day is as follows: "Blue Sky Day is defined the same as a non-weather impact day (no or very limited impacts due to weather)".

The PSPS guidance was validated against all Northeast wind days in the database. This is similar, but complimentary to the Diablo event analysis as it also accounts for outage activity observed on those days. Events were also compared against Blue Sky days to ensure that PSPS would not be recommended for a high percentage of non-weather-impact days where little to no outage activity was observed.

7.5.4 Red Flag Warnings from the NWS

We also validated PSPS guidance against Red Flag Warnings (RFWs) from the NWS. A Red Flag Warning means warm temperatures, very low humidities, and stronger winds are expected to combine to produce an increased risk of fire danger. These RFWs were collected for the past 6 years (2015 – 2020) in shapefile format and used to evaluate the timing and spatial extent of historical RFWs against PSPS guidance.

It should be noted that each NWS office in the PG&E territory has different RFW criteria and the issuance of a RFW is somewhat subjective, making direct and quantifiable comparison challenging. However, we used this dataset to evaluate if RFWs were issued when PSPS guidance is met or not. It should be noted that RFWs are expected to occur more frequently and cover a broader area than PSPS.

We have considered using the timing and spatial extent of RFWs directly for PSPS guidance; however, the spatial extent of these warnings are expansive and would produce untenable customer impacts. For example, during the October 26 – 27th PSPS event that lead to a large PSPS event of almost 1MM PG&E customers, the number of PG&E customers under a RFW was estimated at ~2.2MM. See image below that shows the extent of the RFW for that event.

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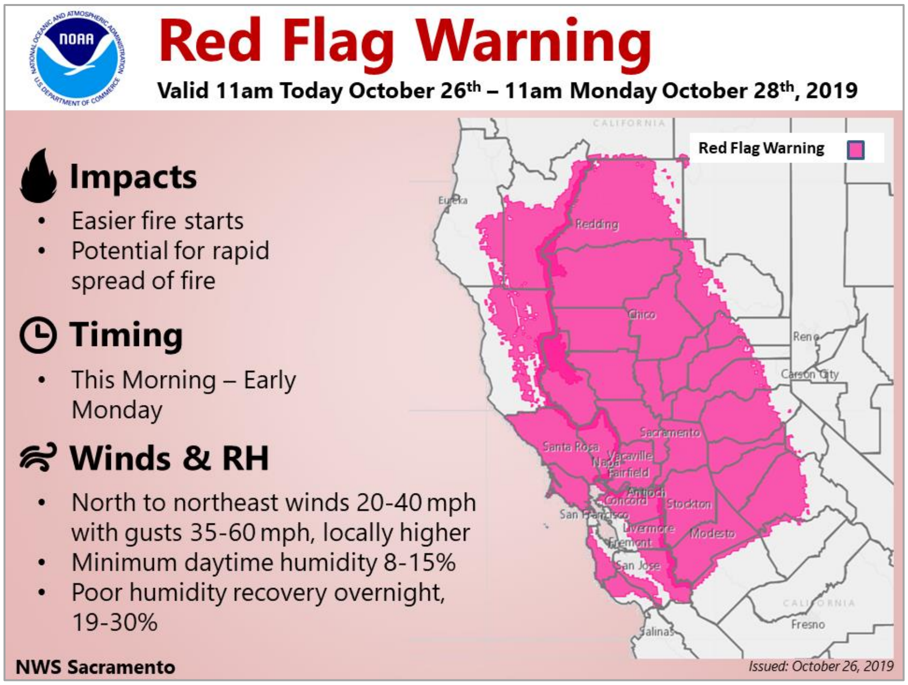

Fig. 46. Red flag warnings issued October 26, 2019

7.5.5 High Risk of potential large fires due to wind from the GACC

We also validated PSPS guidance against historical "High Risk" days from the Federal Geographic Area Coordination Centers. The GACCs issue High Risk Day alerts when fuel and weather conditions are predicted that historically have resulted in a significantly higher than normal chance for a new large fires or for significant growth on existing fires. Examples of critical weather conditions are high winds, low humidity, an unstable atmosphere and very hot weather. GACC uses an Orange box with a symbol representing the weather condition responsible for the critical burn environment (e.g, W – Wind).

Similar to the RFW analysis, we used this dataset to evaluate if High Risk days were issued when PSPS guidance is high. It should be noted that High Risk Days are expected to occur more frequently and cover a broader area than PSPS.

We also considered using the timing and spatial extent of High Risk days directly for PSPS guidance; however, the spatial extent of these warnings are expansive and would produce untenable customer impacts. For example, during the October 26 – 27th PSPS event that lead to a large PSPS event of almost 1MM PG&E customers, the number of PG&E customers under High Risk from the GACCs was estimated at ~3.8MM. See image below that shows the extent of High Risk for that event (see Red outline).

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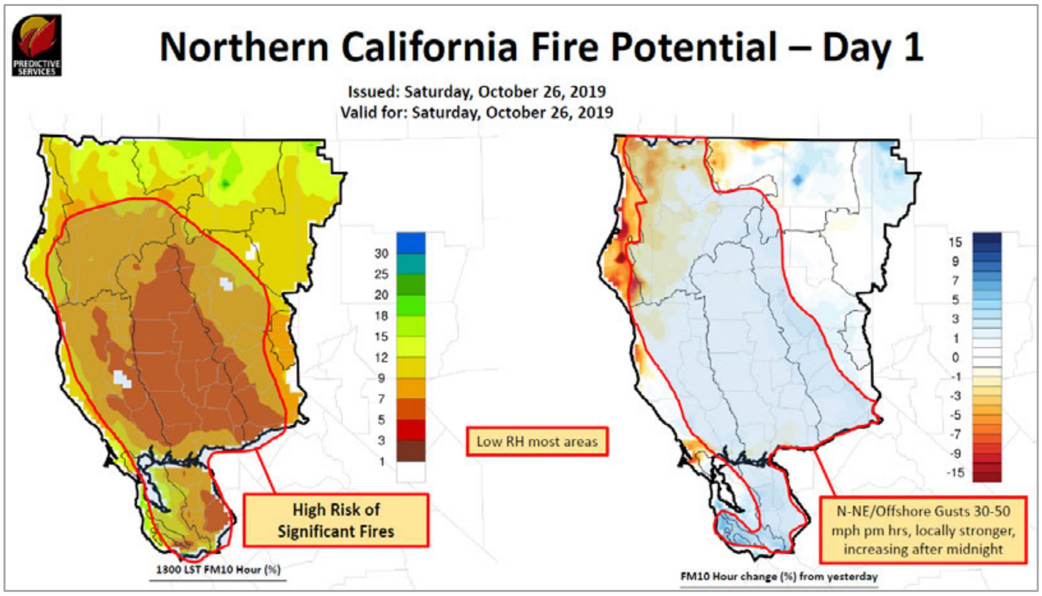

Fig. 47. High risk of significant fires issued October 26, 2019 from the GACC

7.5.6 Hourly high-resolution wind maps from PG&E climatology data set

We created hourly maps from the 30-yr high resolution climatology and web-based application to display any hour across the past 30 years. There are over >250,000 images for any parameter available, such as wind speed.

For each event that meet PSPS guidance in the climatology, these maps were evaluated by a meteorologist to better understand the nature of the event, wind speeds, antecedent conditions, and the spatial extent of strong winds. An example of the front-end application is shown below as well as some example hourly wind maps that are available for historical events. Importantly, forecast wind speeds are available in the same exact format allowing operational meteorologists to put forecast events in perspective with historical events using the same model.

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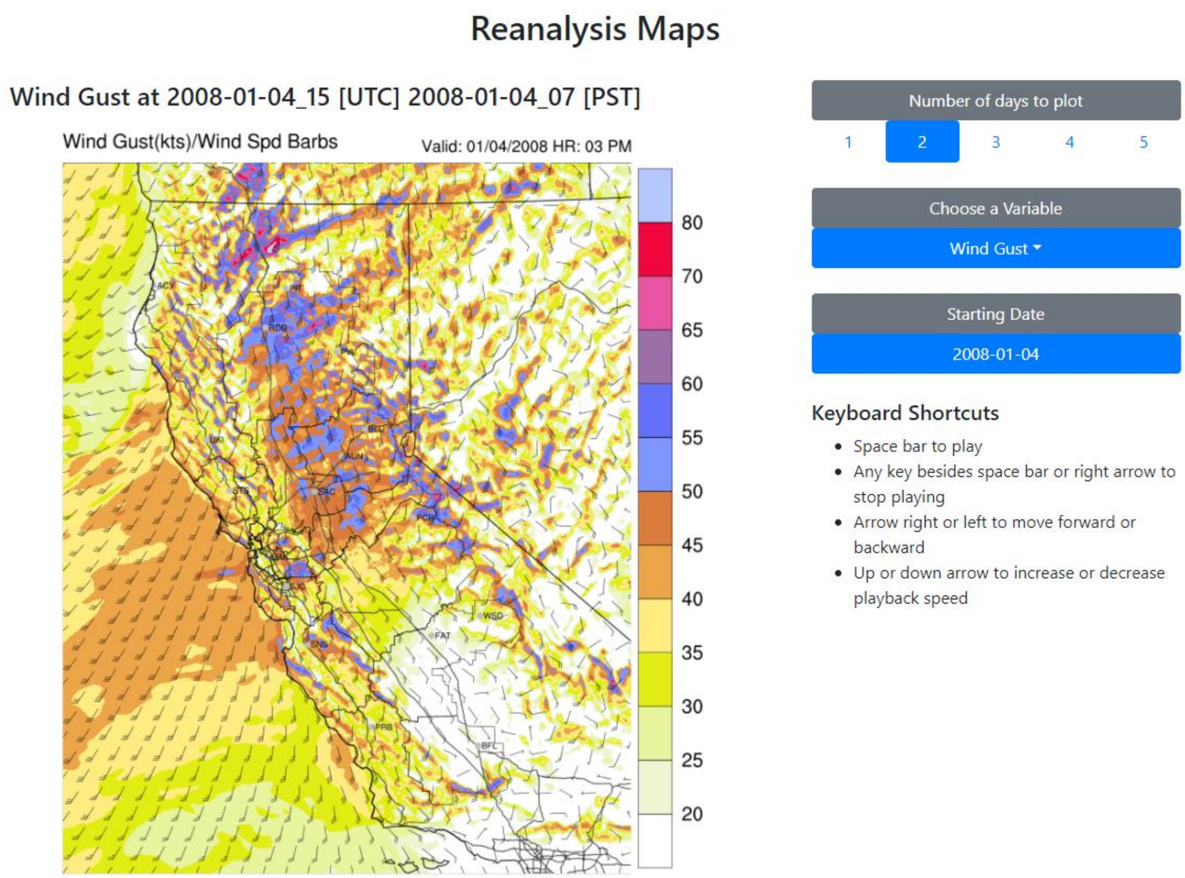

Fig. 48. Web based application to visualize hourly data from climatology

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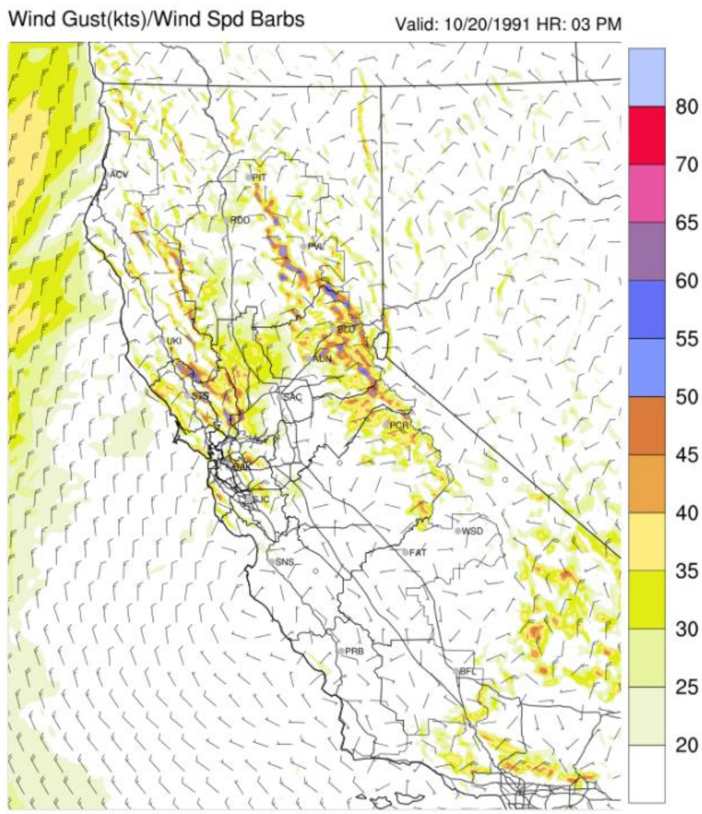

Fig. 49. Example image from 1991 Tunnel fire (Time is shown in UTC)

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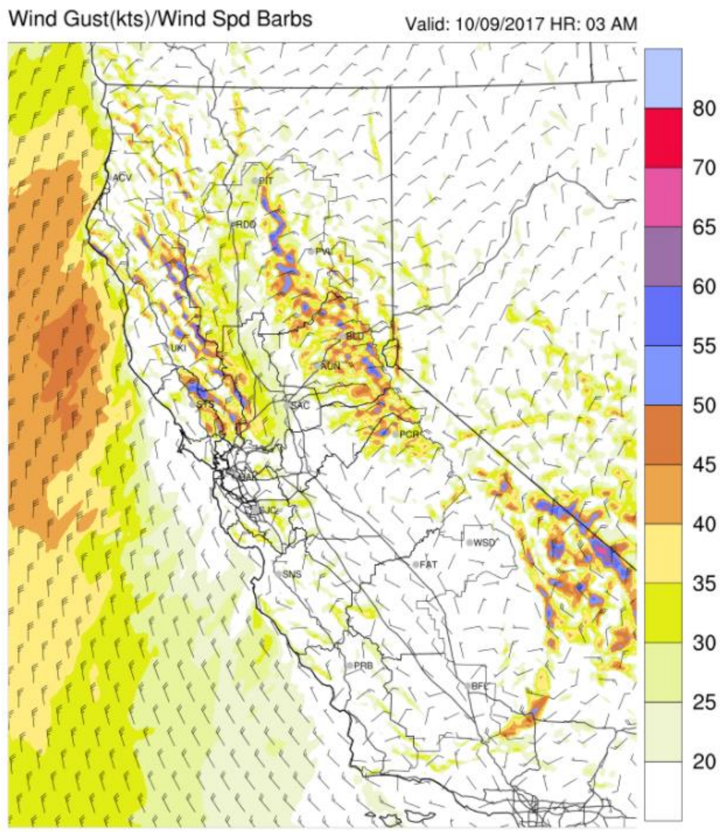

Fig. 50. Example image from October 2017 Northern CA wildfires (Time is shown in UTC)

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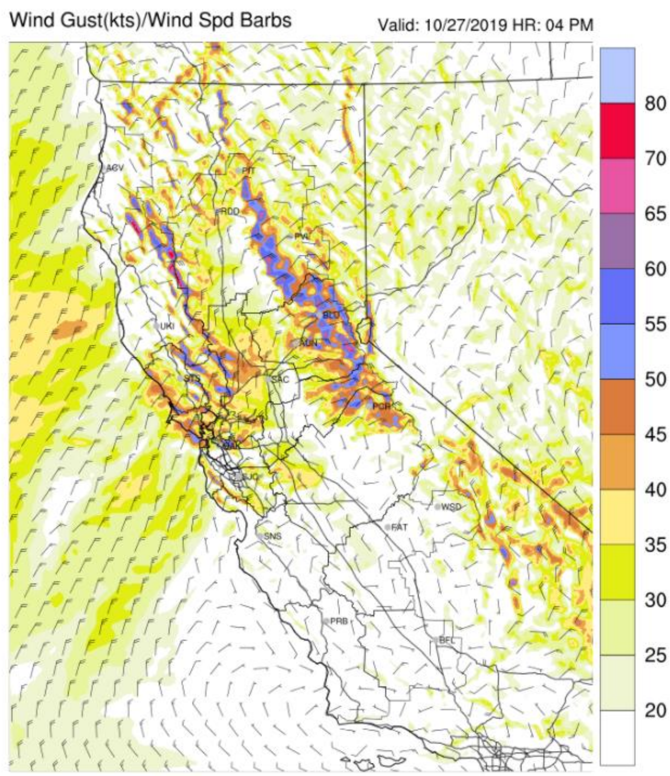

Fig. 51. Example image from October 26 – 28 2019 PSPS event (Time is shown in UTC)

7.5.7 Detailed Event Dashboards

Meteorologists and data scientists utilized the data sources described above to evaluate historical events hour by hour to verify the locations and times that are being flagged as meeting PSPS guidance.

These dashboards are very useful to determine if historical fire events would have been flagged by PSPS guidance. A few example dashboard images are presented below. The first image is the IPW exploratory dashboard that shows the predicted IPW values with actual outage activity overlaid (dots). Meteorologists evaluated these data hourly to verify model performance of the IPW model and suitability for operations. Another dashboard example is presented below for the Camp fire. The PSPS guidance can be evaluated spatially using the dashboard map integration, while the size and timing of the event can be evaluated using the timeseries integration.

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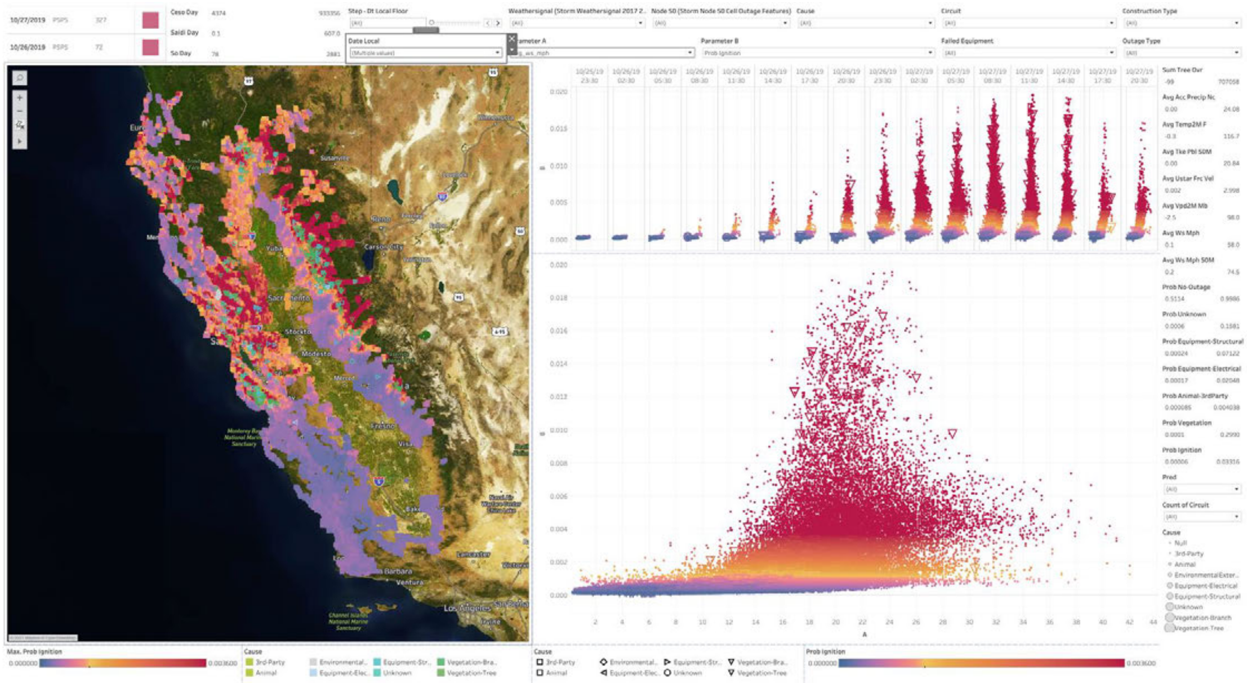

Fig. 52. Example image from the IPW exploratory dashboard

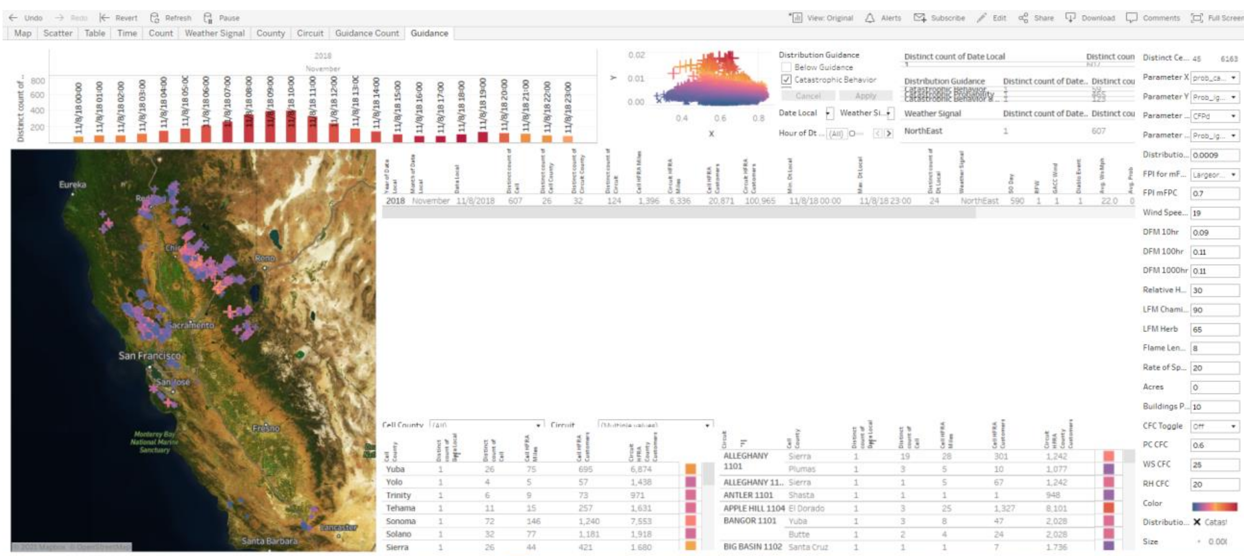

Fig. 53. Example dashboard image from Camp Fire event (11/8/2018)

7.6 PSPS Data Flow and Event Scoping using ArcGIS Pro

This section gives a high-level overview about the PSPS cloud-based operational data flow as well as how PSPS events are scoped using advanced GIS technology.

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PG&E's high-resolution weather model is run in the Amazon Web Services (AWS) cloud. The data are delivered to the AWS computing environment for post processing. The weather model data arrives to an ingest AWS-S3 bucket and are then transferred internally to PG&E AWS development (dev), quality assurance (qa), and production (prod) environments. Once the data arrives, data processing jobs are triggered that take the weather data and run downstream models such as LFM, DFM, CFP and IPW. Once the data are processed they are delivered back to the S3 bucket. After this post-processing, scripts on AWS write the data to a PostgreSQL database. These PostgreSQL databases have been linked dynamically with ArcGIS Pro such that the latest model data can be visualized in ArcGIS Pro in relation to assets, Red Flag Warnings and other relevant data.

An image showing the high-level data flow in AWS is presented below.

Figure 29 – High Level Overview of PG&E AWS PSPS Dataflow

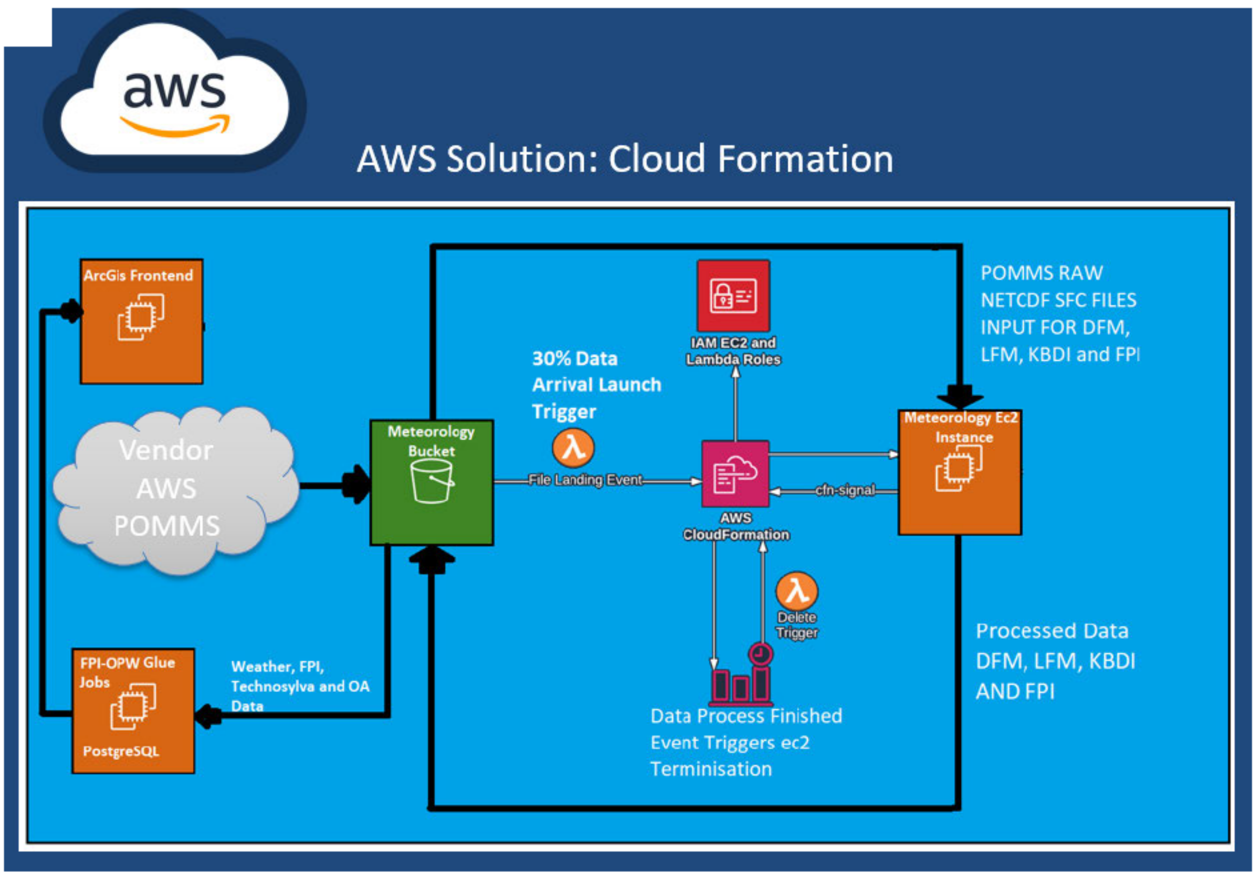

Fig. 54. PG&E AWS weather data pipeline overview

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The PostgreSQL databases on AWS have been linked dynamically with ArcGIS Pro such that the latest model data can be visualized in ArcGIS Pro in relation to assets, Red Flag Warnings and other relevant data. ArcGIS Pro is the latest professional desktop GIS application from Esri. During a potential PSPS event, meteorologists can view the PSPS guidance and other model data at the native format of the weather model for each consecutive model run. Grid points that exceed PSPS guidance are visualized and grouped into Time-Places (TPs) by operational meteorologists that are staffing the EOC. These are generated by a lead meteorologist while at least one other meteorologist participates in real-time to provide a layer of quality control.

Once the TPs are created, they are output and written to a PostgreSQL database, which can then be read by multiple applications. One of those applications is the PSPS viewer, which translates the PSPS guidance footprint into an electrical footprint and identifies the devices that need to be operated in order to deenergize each TP should conditions warrant. An example image from ArcGIS Pro below and shows the weather and model data available for each grid point.

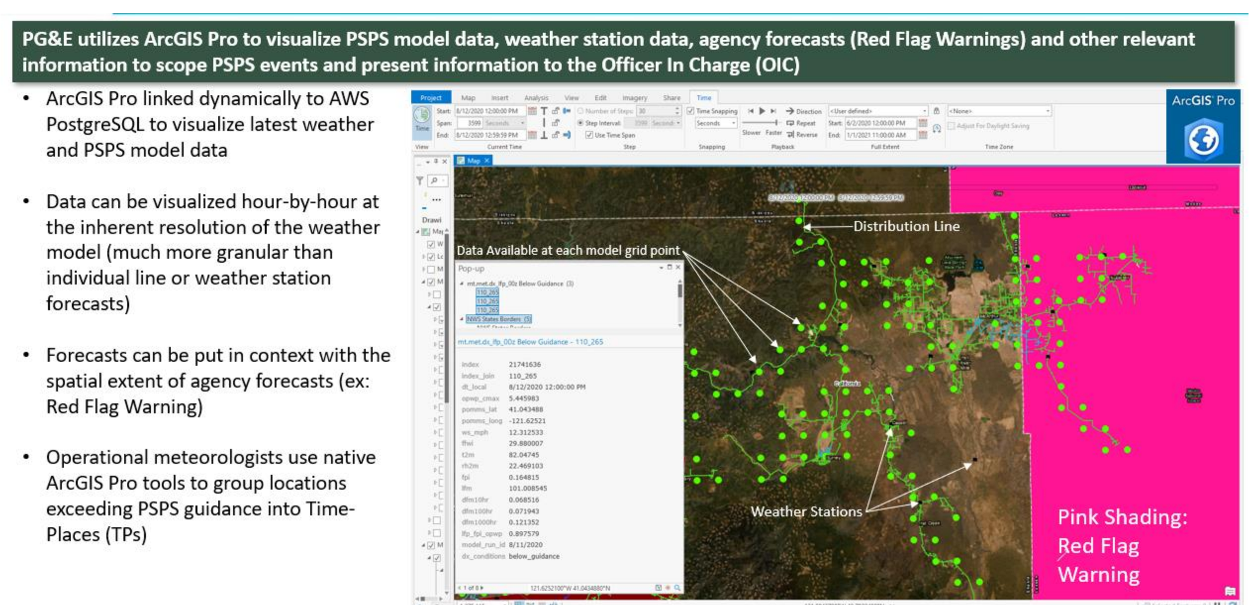

Fig. 55. Example ArcGIS Pro PSPS data integration and map interface

Meteorologists review the last two to four high-resolution model simulations to ensure that the forecast model has shown consistency across those results and to ensure the underlying model data used to scope an event is not an outlier or anomaly. Meteorologists also review other independent forecast models such as the HRRR, California and Nevada Smoke and Air Committee (CANSAC), NAM, GFS, ECMWF and others as needed to verify that there is consensus in results between the relevant fire and weather forecasts and model platforms.

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Meteorologists also review federal and state agency forecasts to verify alignment in their identification of risk areas and timing.

All this information is used to identify the scope and timing of a potential PSPS to address the highest fire and outage risk areas in PG&E's service territory. This scope determines which areas might need to be de-energized to prevent ignition of potentially catastrophic fires, with the PSPS start time set by the time when high wind and outage risk is forecasted to begin. This information is passed to the EOC Planning and Intelligence section as input to the PSPS viewer to determine the electric lines and assets within the PSPS footprint, the customers affected, and critical facilities at risk.

Depending on timing of this initial scoping process relative to the planned time of PSPS de-energization (which may differ for different areas of the service territory depending on localized weather and threat conditions), this process may be completed multiple times as new forecast information becomes available and if forecast conditions change. The scope of the event is continually refined and reviewed for each future time period until PSPS is executed. PSPS events are driven by weather and are thus extremely dynamic, which may lead to scope changes as the onset of an event draws closer. PG&E holds a series of decision-making meetings throughout this process, which trigger events that include opening the EOC, sending customer notifications, and in-event PSPS decisions. In these meetings, meteorology presents all factors considered in drafting the scope of the event to the OIC, to inform their decision to execute the PSPS. Meteorology briefings typically include the driving factors such as fuel moistures, wind speeds and humidity, external forecast information, information received on interagency calls, and other information as requested. The PSPS model output and timing and real-time weather information are presented -- typically on an hour-by-hour basis -- to show how the event is expected to play out given current weather and risk information, so the OIC can make the final PSPS scoping and execution decisions based on the best available information.

8 Triggers for EOC Activations for PSPS

8.1 EOC Readiness Posture

The PSPS models provide forecasts out at least ~100 hours and are based on the POMMS model. The meteorology team also uses several forecast models in order to determine the potential for elevated outage potential and fire potential beyond 100 hours, to give advanced warning of when PSPS might be needed. These models include but are not limited to: the European Centre for Medium-Range Weather Forecasts (ECMWF), American Global Forecasting System (GFS), and the Canadian Meteorological Centre/Global Environmental Multiscale

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(CMC/GEM). If these weather models indicate potential for strong and dry winds to develop 4 to 7 days ahead, PG&E moves into an EOC Readiness Posture to prepare for possible Emergency Operations Center (EOC) activation. This pre-EOC activation typically will occur more than 72 hours before the start of a potential event.

Note: Movement into Readiness Posture is not a requirement for PG&E to activate the EOC.

8.2 EOC Activation

Typically within 72 hours before the start of the event, the EOC is activated if there remains a reasonable chance that PSPS may be executed. The decision to activate the EOC is made by the OIC, who is presented with data from our PSPS models as well as any external Federal risk information available at the time. Once the EOC is activated it will remain staffed 24/7 through the end of the event.

9 Monitoring Real-Time Conditions with Weather Stations and Field Observers

9.1 Weather Stations

We have aggressively installed weather stations to monitor fire weather conditions since 2018. As of July, 2021, we have installed more than 1100 weather stations that report wind speed, wind gust, temperature and relative humidity every ten minutes. These stations are utilized in real-time to support confirm/abort/delay decisions before each area is deenergized for PSPS. The stations are also used to support every all-clear decision to ensure conditions have returned to a safe level to begin the restoration process.

The figure below shows our internally developed weather station monitoring tool. Each station and geographic area (called restoration zones) are color coded based on the weather components of the minimum Fire Potential Conditions (mFPC) from low to high (green to red).

Data from each weather station can be viewed individually or all stations in a restoration zone can be viewed at the same time and sorted from highest to lowest wind speed. The table view presents data over a 24 hour period and is valuable to visualize trends for all weather stations in each restoration zone. This functionality is shown in the upper right-hand portion of the image. This tool leverages the >1000 weather stations we have deployed as well as Remote Automated Weather Stations (RAWS), and NWS stations. PG&E's weather stations utilize the Campbell Scientific EE181-L air temperature and relative humidity sensor and the RM Young 05103L wind speed and direction sensor.

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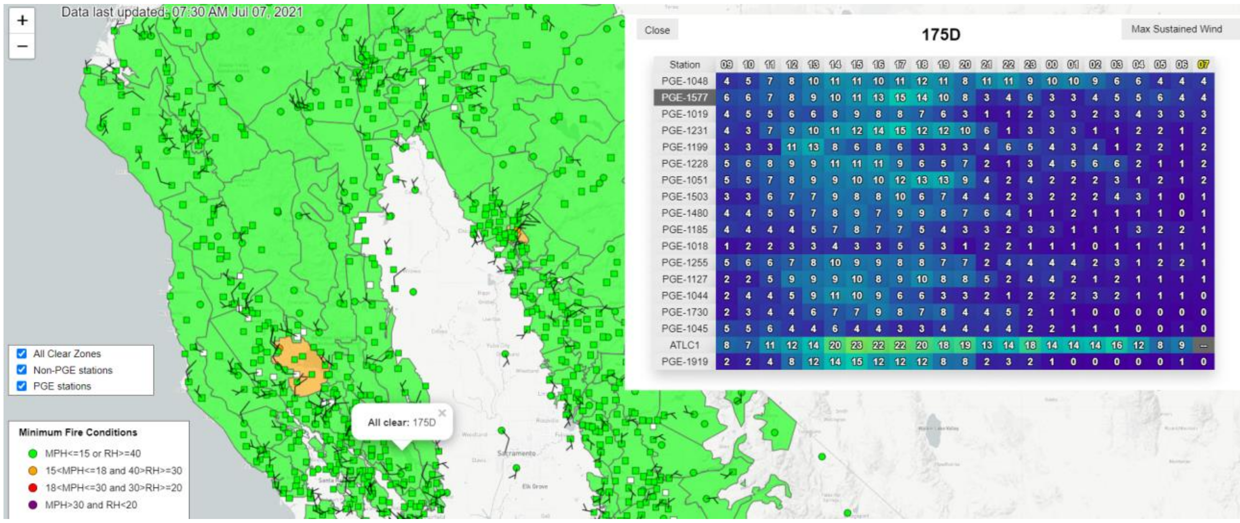

Fig. 56. Snapshot of real-time wind monitoring tool

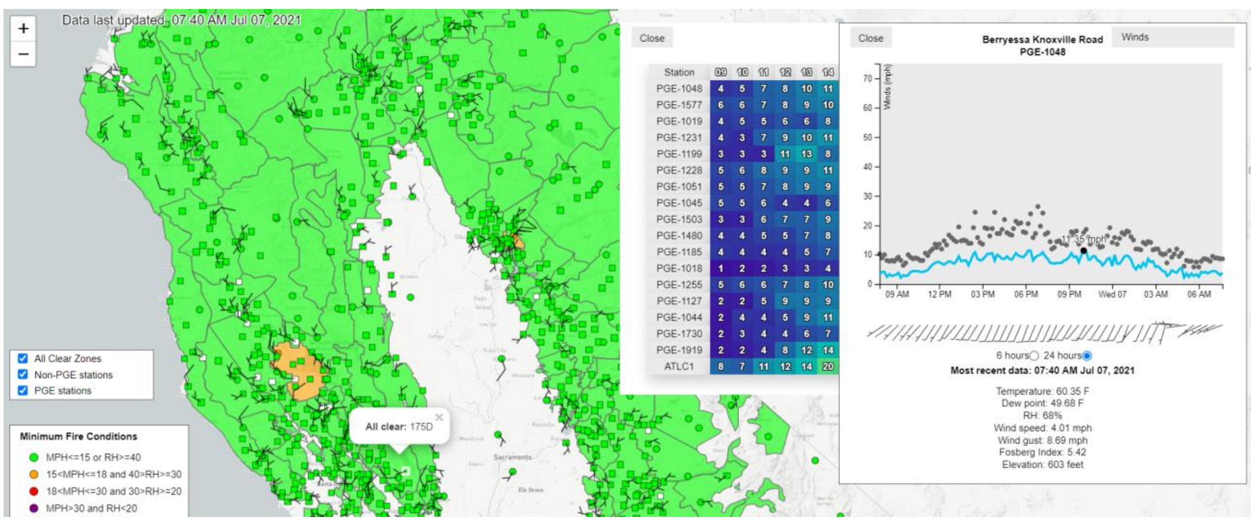

Fig. 57. Snapshot of Real-Time Wind Monitoring Tools

9.2 Pressure Gradients

In order to track the onset and strength of a weather event, meteorologists use an automated tool to track wind speeds in real-time (collected from field weather stations across the service territory) and observed versus forecast pressure gradients from multiple forecast models. Figures 37, 38, and 39 show examples of the operational tool and snapshots from the October 26th, 2019 PSPS event. Black dots represent weather station observations while solid lines represent forecast model data. Note that ECM is the ECMWF model, NAM is the North

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American Mesoscale model, HRRR is the High-Resolution Rapid Refresh model, POMMS is the PG&E high resolution forecast model, and GFS is the American global model. The pressure gradient force ultimately drives wind speeds and is therefore a proven meteorological metric for operational meteorologists in the National Weather Service. Pressure gradient tracking allows meteorologists to determine forecast model alignment and if a weather event is materializing under or over forecasted predictions. Meteorologists also track wind speeds in real time using internally developed tools and/or publicly available web applications like Mesowest and the NWS Weather and Hazards data viewer.

In Figures 37, 38, and-39 black circles respresent actual station observations while solid lines represent model forecasts.

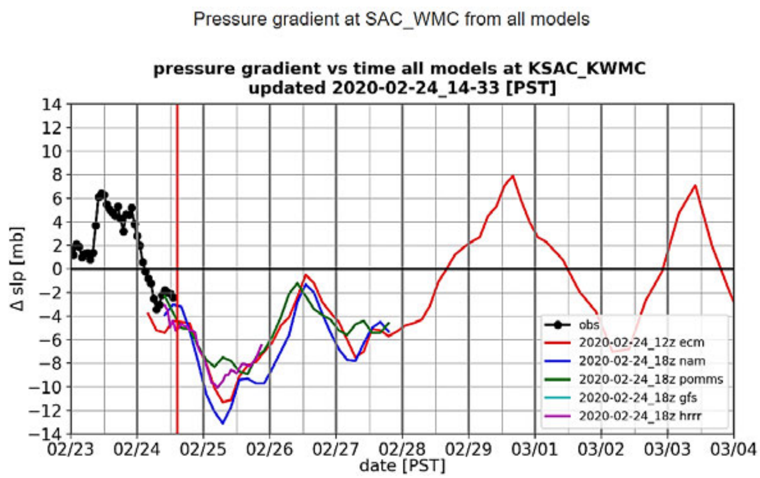

Fig. 58. Data Snapshot of real-time pressure gradient tracking tool taken 2/24/2020

Figure 13 shows the forecasted difference in pressure from KSAC (Sacramento airport) to KWMC (Winnemucca, NV). The solid lines represent weather model forecast data from multiple sources, while the black dots are actual observations. The tool compares the latest forecast model data available from each weather model, but each model can be selected individually to show how the model has changed over time. A strong negative KSAC-KWMC is indicative of an east-to-west or offshore pressure gradient that is typically present in Diablo wind events. A strong negative KSAC-KWMC gradient was observed in the October 8-9, 2017 fire event for example.

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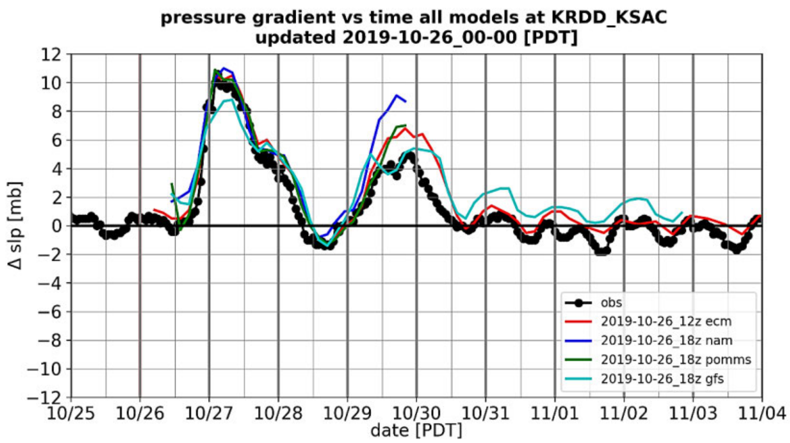

Fig. 59. Pressure gradient tracking tool taken 10/26/20219. Pressure Gradient Between Redding (KRDD) and Sacramento Airport (KSAC)

Figure 14 shows the forecasted difference in pressure from KRDD (Redding airport) to KSAC (Sacramento airport) for the October 26th, 2019 PSPS event. Again, solid lines represent weather model forecast data from multiple sources, while the black dots are actual observations. All forecast models were aligned that a strong KRDD-KSAC or north to south pressure gradient would develop that would produce strong northerly winds. The forecasted KRDD-KSAC and other pressure gradients were expected to be stronger than those observed on October 8 - 9 2017, indicating a very strong event. The observed KRDD-KSAC gradient was recorded at 10.6 mb, which were calculated as a 1 in 15 year event using historical KRDD-KSAC data. KRDD recorded a peak wind gust of 66 mph during the event as a result of the extreme gradient. Figure 15 below presents a similar view of the October 26th, 2019 PSPS event but with the KSAC-KWMC gradient. Over 20 station gradient pairs can be visualized on demand, using this automated tool.

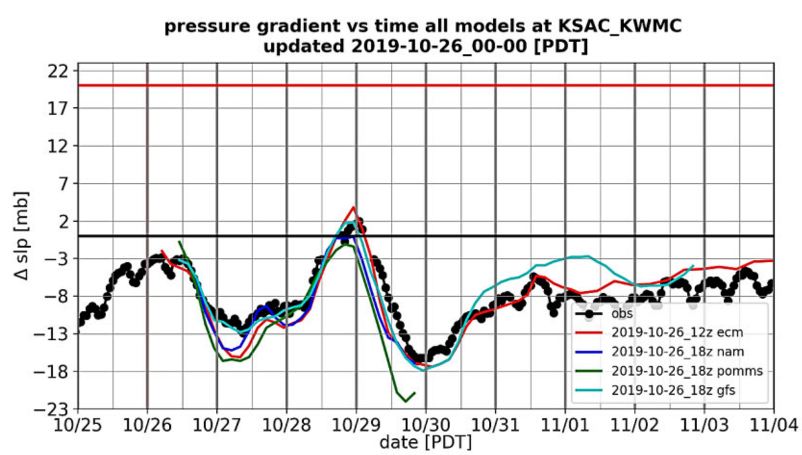

Fig. 60. Pressure gradient tracking tool taken 10/26/20219. Pressure Gradient Between Winnemucca (KWMC) and Sacramento Airport (KSAC)

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9.3 Field Observers

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We have established a Hazard and Awareness Warning Center (HAWC) that monitors fires 24/7 and coordinates response. The HAWC plays a key role in addressing the challenges of weather and climate-driven extreme weather events that may pose a threat to customer and community safety. The HAWC serves as a coordination, facilitation and communications hub for wildfire activities, including using weather data to monitor fire threats. In the event of a potential fire threat or actual fire, HAWC coordinates and mobilizes response efforts with appropriate field personnel, first responders, media, local government, and other safety officials. The HAWC operates on a 24-hour basis and is staffed with experienced personnel knowledgeable in electric operations, safety, engineering, meteorology, fire science and other areas. The HAWC staff includes field teams of Public Safety Specialists who train first responders and local agencies on how to safely respond to emergencies associated with electric and gas facilities.

During PSPS events, the HAWC manages the location and information obtained from field observers. This data is compiled and reported into to EOC for PSPS decision making purposes. More on this process is described below.

Fig. 61. Hazard and Awareness Warning Center (HAWC) formerly the Wildfire Safety Operations Center (WSOC)

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We collect real-time field observations of weather conditions across our service territory, with particular attention to conditions on any circuits identified to be within a forecasted fire and outage risk area that could turn into a PSPS event. We can collect data remotely from a fleet of weather stations and supplement this with human observers where needed. These individuals are members of PG&E's Safety and Infrastructure Protection Team (SIPT) that report to the HAWC. They are given specific observation and reporting positions to provide field information on the presence of adverse conditions, before forecasted PSPS de-energization timing, and to verify the weather "all-clear" that marks the start of post-PSPS circuit patrols, repair and re-energization. The HAWC works with the meteorology team to place observers in strategic locations where forecasted risk is elevated and is not currently covered by an automated weather station.

Field Observers will note hazards related to wind conditions that could lead to outages and/or ignitions. On-the-ground, real-time field observations provide qualitative and quantitative information (such as the presence of flying debris, trees/branches down, conductor movement, ground-level wind speed, relative humidity (RH) and temperature) about the presence of adverse conditions and the possible need to trigger a PSPS event sooner than expected or stand down a PSPS event. The observers update conditions using the SIPT Viewer (see example data entry table in Figure 41), that is available in real-time in the HAWC and EOC. Figures 41 - 43 show snapshots from the SIPT viewer and include the field observer form that is filled out, a map showing the geographic location of the observer and his or her observations and a dashboard of all recent observations. If no mobile connection is available, Field Observers radio in observations to the HAWC, which will manually enter the data into the dashboard.

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Fig. 62. Example data entry application image for SIPT viewer

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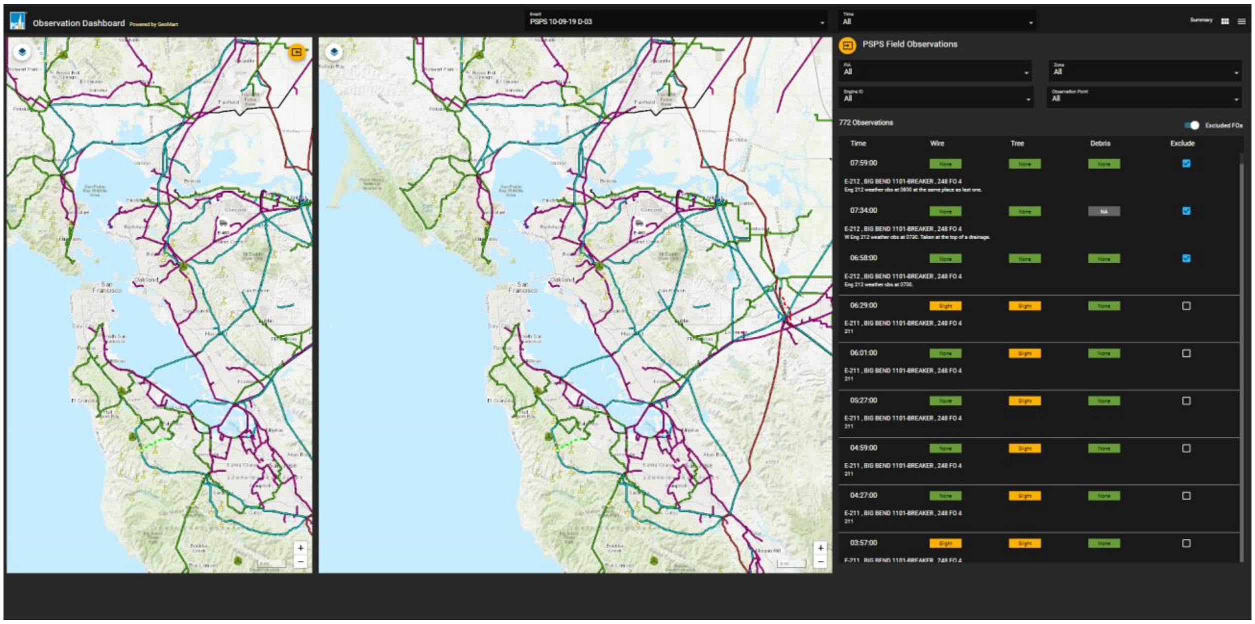

Fig. 63. Example SIPT dashboard

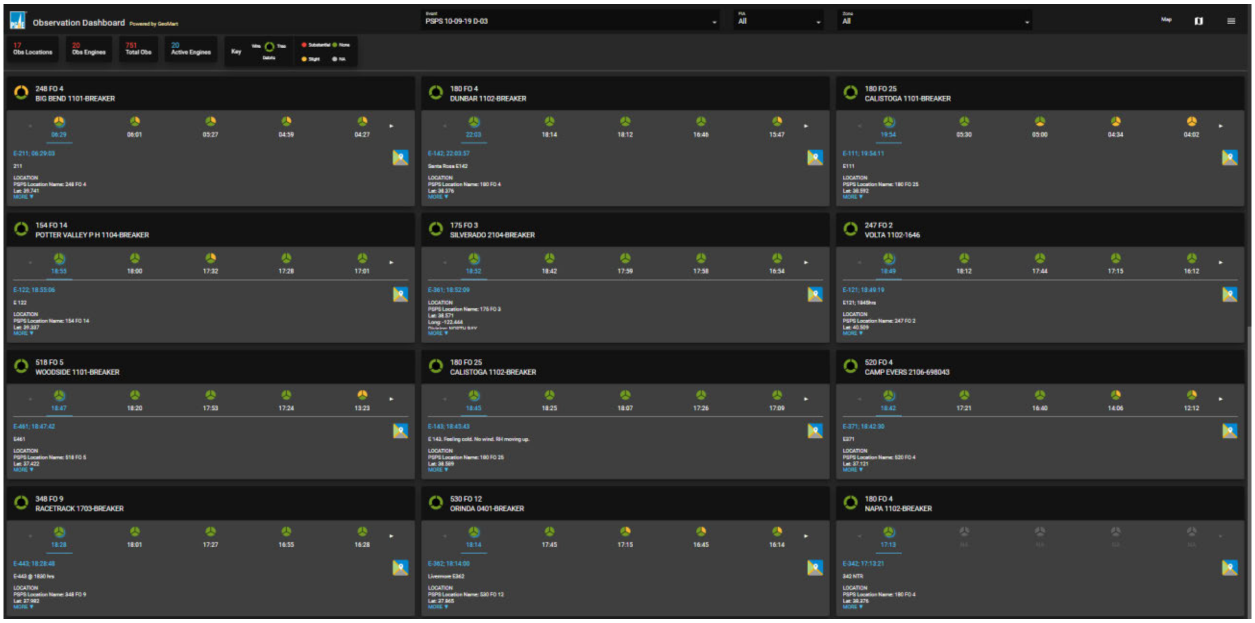

Fig. 64. Example SIPT dashboard - summary view

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10 Post PSPS Weather Event: Example of Damages and Hazards

10.1 Introduction

After the OIC declares the weather all-clear for a portion of the PSPS area, crews patrol lines for damage and hazards before restoring power to customers. Each instance of a damage or hazard found during an event is documented for further analysis. This information is evaluated against the final scope of the event to compare where damages and hazards occurred and where they did not – in other words, did high winds cause damages in the area that was taken out of service by the PSPS, or did the PSPS scope mis-identify the high-risk areas where a wind-caused equipment outage might have created an ignition and wildfire? This information is valuable but is only a part of the picture of outage and ignition risk that was mitigated by PSPS. For example, a vegetation strike[2] on lines and line-to-line contacts often may often not produce equipment damage, but could have created a spark had those lines remain energized. This includes tree branches that may have broken off a tree, impacted the line(s) temporarily, then fall to the ground before a patrol is conducted. A high-level analysis of outage activity with a "patrol-nothing found" cause was conducted to determine the approximate percentage of outages that produce no damage. This ratio was found to be ~25% of outages.

PG&E records actual damage and hazards to PG&E assets in three categories:

- Asset damage – PG&E asset/equipment that was damaged due to the wind event where no evidence of vegetation causing the damage was found
- Vegetation damage – PG&E asset/equipment that was damaged due to the wind event where evidence of vegetation causing the damage was found

[2] There are three ways that vegetation can contact a power line. "Grow-ins" occur when vegetation grows up into a power line; this is why utilities maintain wide rights-of-way around lines and conduct vigorous tree-trimming and right-of-way clearing. "Drop-ins" occur when untrimmed branches or leaves grow taller than the line and hang over it, and can drop into the line under high wind or ice conditions; these can also be prevented by aggressive tree-trimming and vegetation management. "Blow-ins" occur when high winds break and carry limbs or vegetation from distant areas into a power line. This is more of a problem when there are more dead trees near a line but outside the utility's authorized vegetation management perimeters, since limbs from dead trees break off more easily and can be carried farther because they are lighter (containing less moisture). Utility vegetation management programs can mitigate "grow-ins" and "drop-ins" but cannot mitigate the threat of "blow-ins".

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- PSPS Hazard – An instance where an asset was not damaged but could have potentially caused arcing or a fire had the line been energized (such as a branch laid across multiple phases of a circuit)

Figures 46, 47, and 48 are example images of damage and hazards identified in 2019 post-PSPS patrols. Additional images can be found in PG&E's public 10-day PSPS report to the CPUC.

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Fig. 65. Example of damage to electric lines from fallen tree

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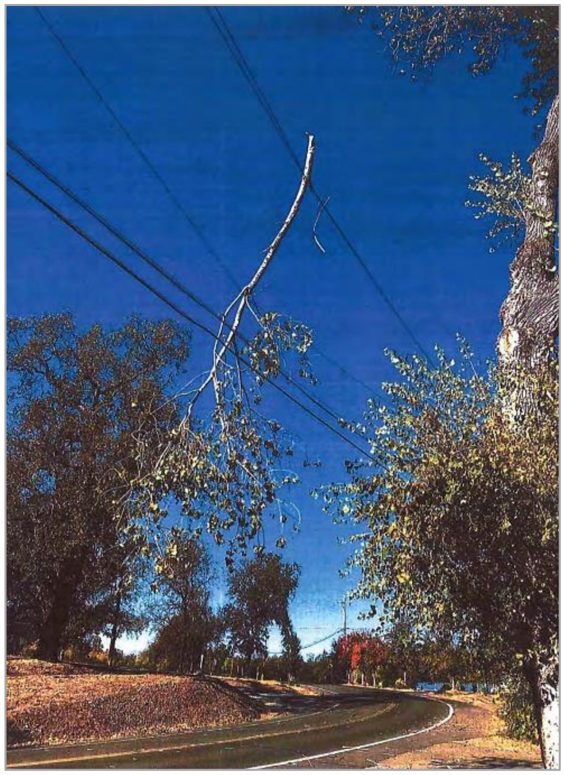

Fig. 66. Example of branch blown into electric line

Fig. 67. Example of branch blown into electric line

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Figures 49 and 50 are examples from two of the largest PSPS events conducted in 2019 . They show the PSPS footprint in blue and damage/hazards found in post-PSPS patrols (marked by the orange triangles). During the October 9 – 12 PSPS event, PG&E's North Coast section was not within the PSPS scope but was deenergized because the PSPS deenergized transmission lines that feed this location from the northern Sacramento Valley. During the largest PSPS event in PG&E's history, October 26, 2019, more than 550 cases of line damage and hazards were found, most due to tree contacts that could have caused ignitions and wildfires. This event was stronger than the October 8-9, 2017 Diablo wind event that caused numerous fires including the Tubbs, Nuns, Redwood Valley and Atlas fires.

Figures 49 and 50 show that the PG&E equipment damages found after these two PSPS events are concentrated immediately within the footprints of these PSPS events (with few exceptions). Furthermore, no wildfires sparked by PG&E equipment contacts or failures occurred within these areas and time periods. These results indicate that our use of advanced meteorology techniques to identify and target high fire risk conditions and areas, and the use of PSPS de-energizations to prevent wind-caused ignitions from utility facilities, prevented many potential ignitions that could have grown into catastrophic wildfires.

While we recognize that PSPS de-energizations impose great burden and disruption upon affected customers, we know that catastrophic wildfires can have worse outcomes for customers and for overall public safety. We are working to use the meteorology tools and processes described above to improve the accuracy and precision of PSPS scoping and duration, to affect as few customers as necessary for as little time as possible without compromising public safety from catastrophic wildfires.

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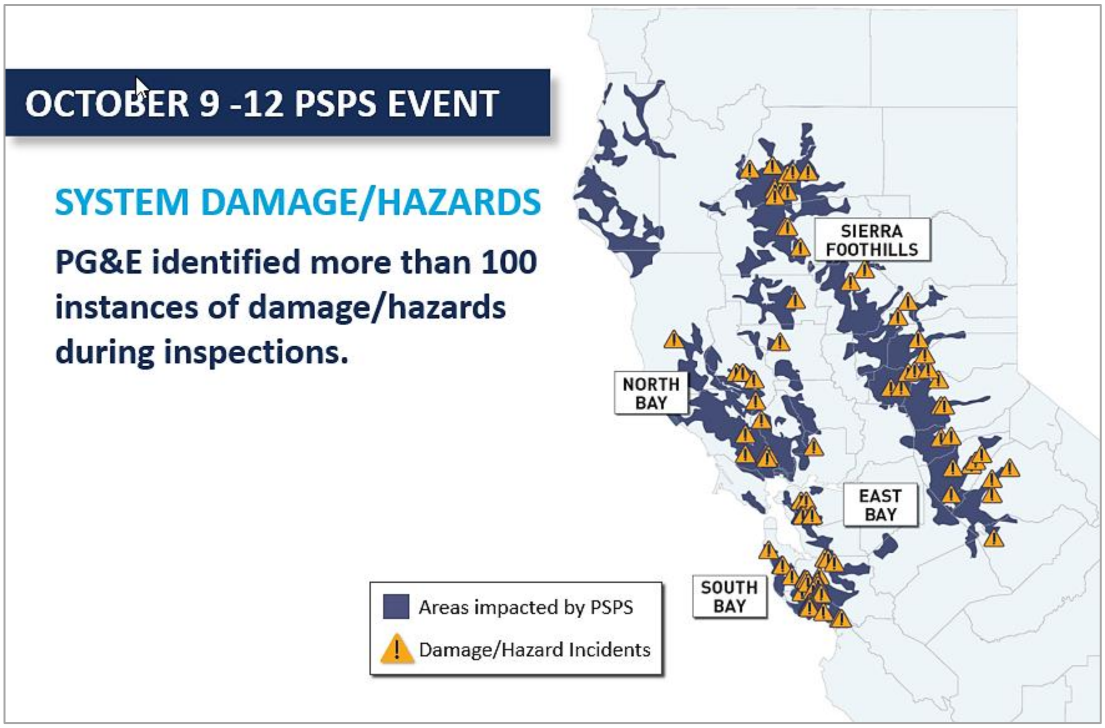

Fig. 68. System Damage/Hazards from the October 9-12, 2019 PSPS Event

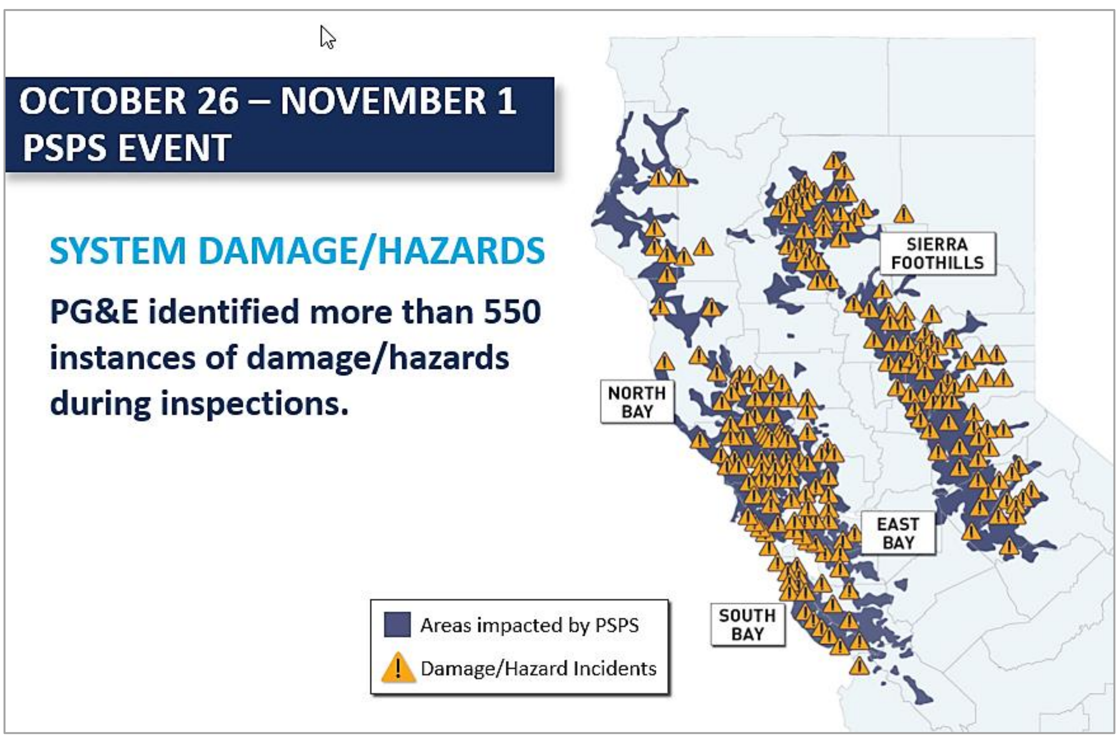

Fig. 69. System Damage/Hazards from the October 26 – November 1, 2019 PSPS Event

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