FINAL VERSION – PG&E Proprietary - LEGAL REVIEW COMPLETED 7/29/2021

PACIFIC GAS AND ELECTRIC COMPANY

CALCULATING METEOROLOGICAL AND PG&E FIRE RISK

PG&E FIRE POTENTIAL INDEX

July 2021

REV.4

PG&E Emergency Preparedness & Response

PG&E Meteorology and Fire Science

THIS PAGE INTENTIONALLY BLANK

TABLE OF CONTENTS

1 Fire Potential Index Model - FPI

1.1 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 have 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.

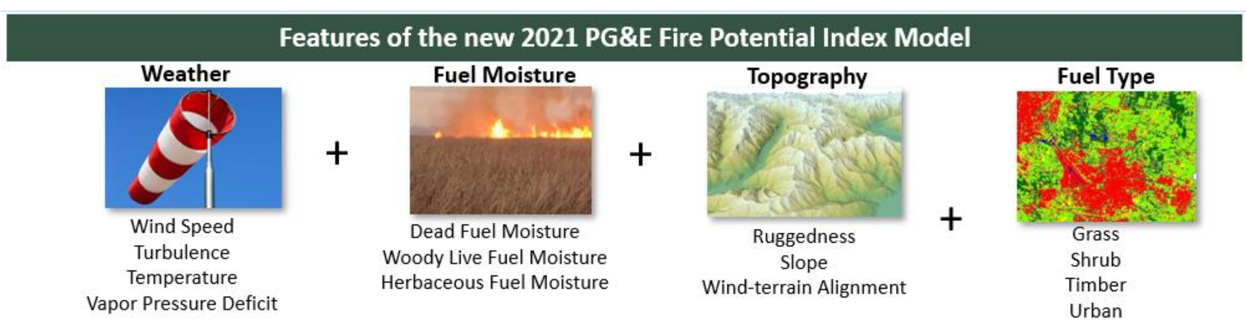

Fig. 1. Features of the 2021 fire potential index model

1.2 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 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.

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.

1.3 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 spreading 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 VIIRS 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. 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. Using these satellite detections, we can more closely match the weather, fuels and topography features that contributed (or not) to the spread of each fire.

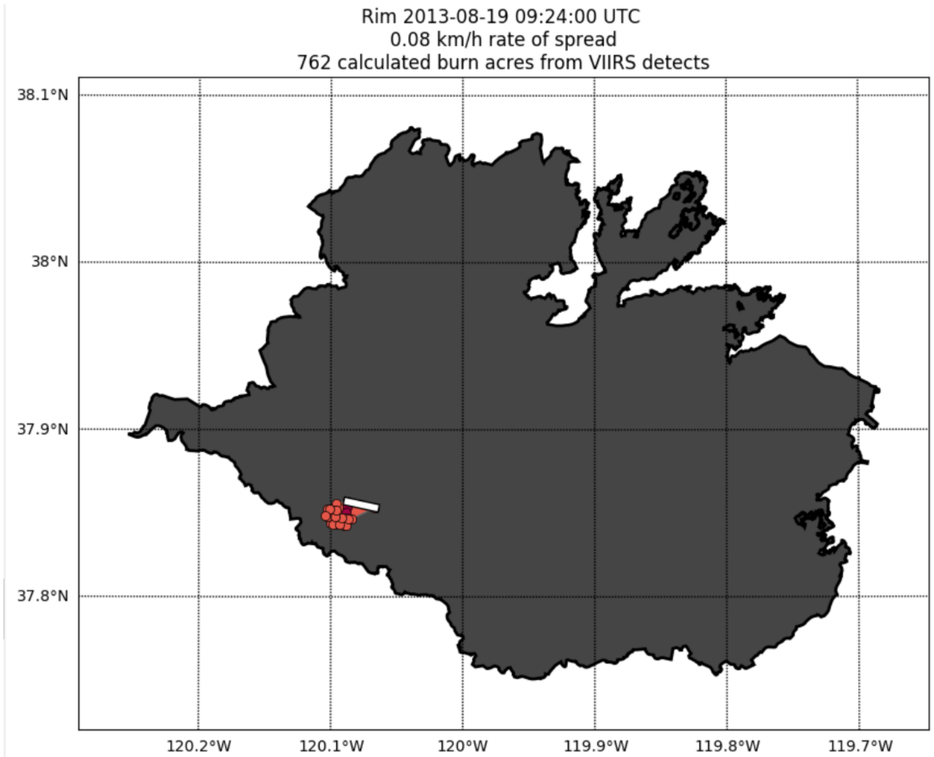

Fig. 2. Satellite fire detections for the Rim Fire

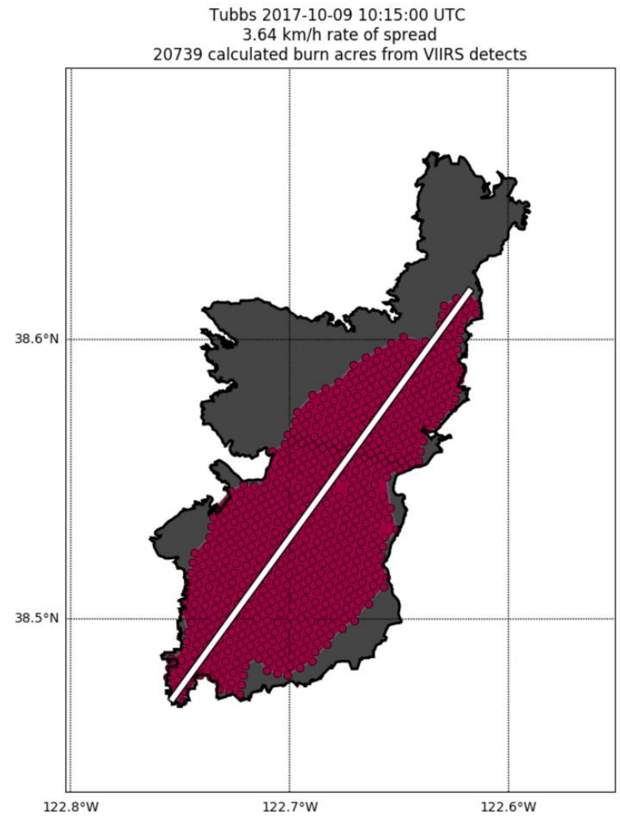

Fig. 3. Satellite fire detections for the Tubbs Fire

1.4 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.

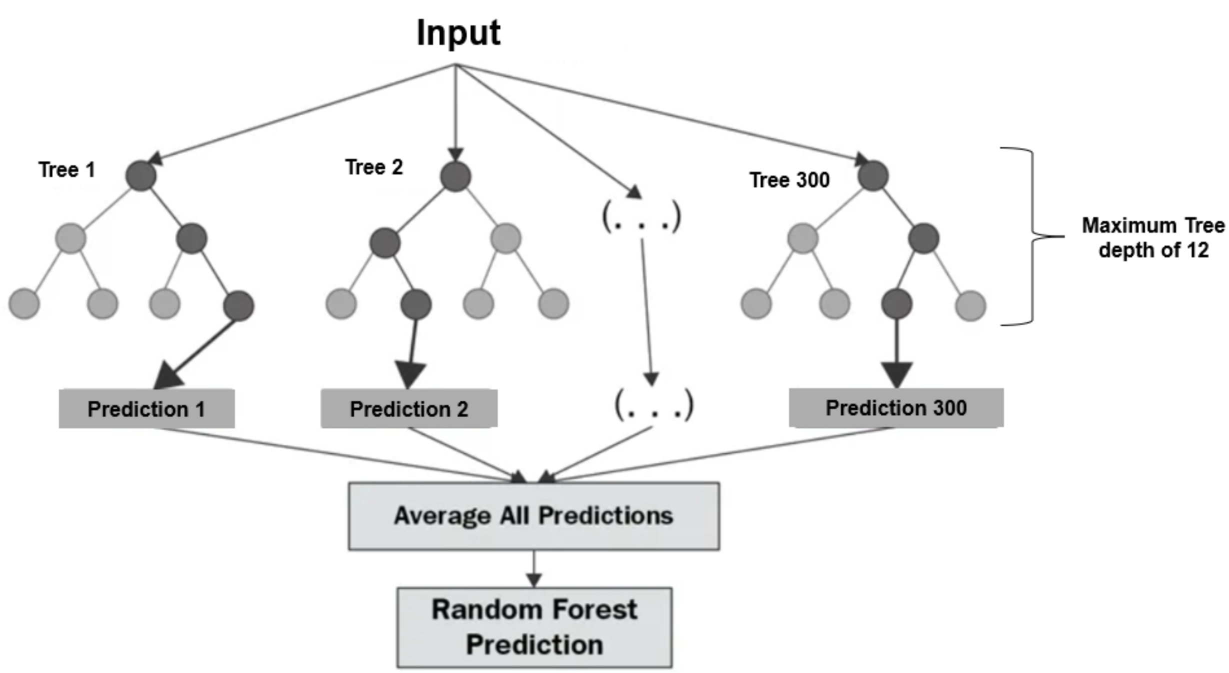

Fig. 4. Fire potential index random forest model

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 (FPI classification only)

- <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.

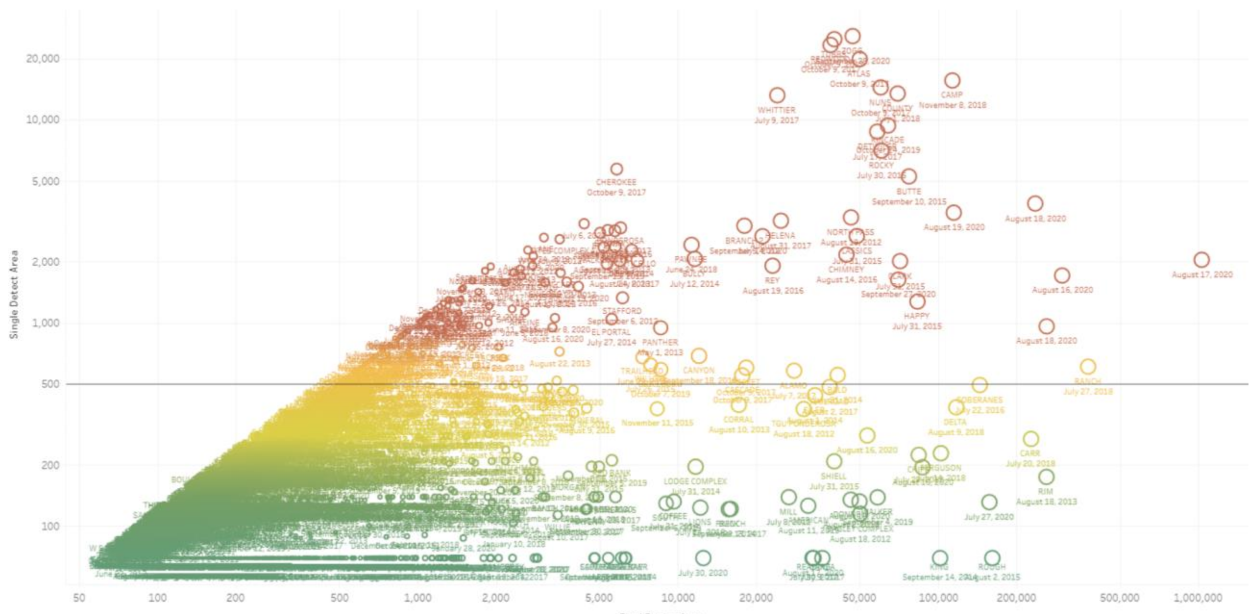

Fig. 5. First-detect fire size versus final fire size from STI fire occurrence database

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

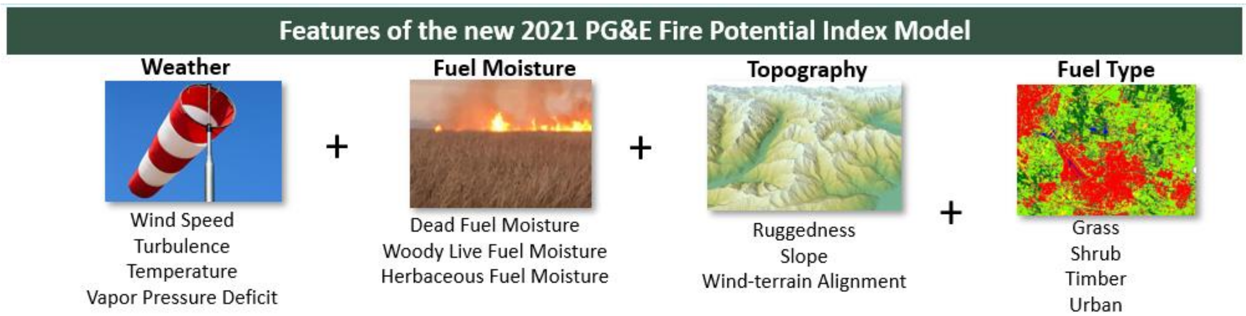

Fig. 6. Features of the 2021 fire potential index model

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 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 1. 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

1.6 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 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.

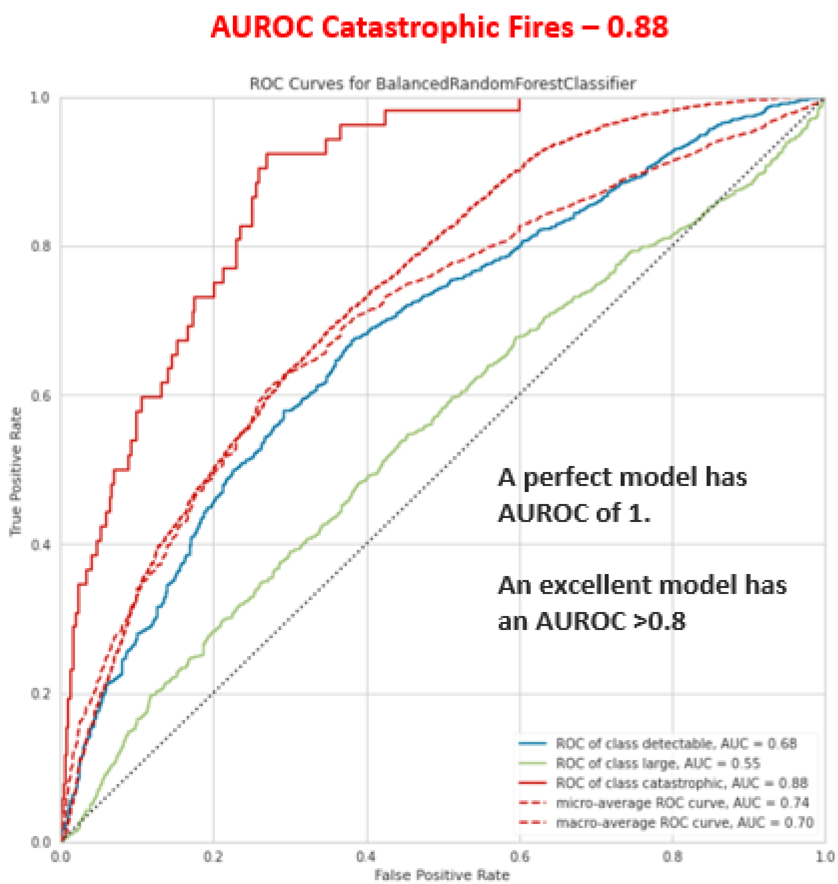

Fig. 7. 2021 fire potential index model skill statistics

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.

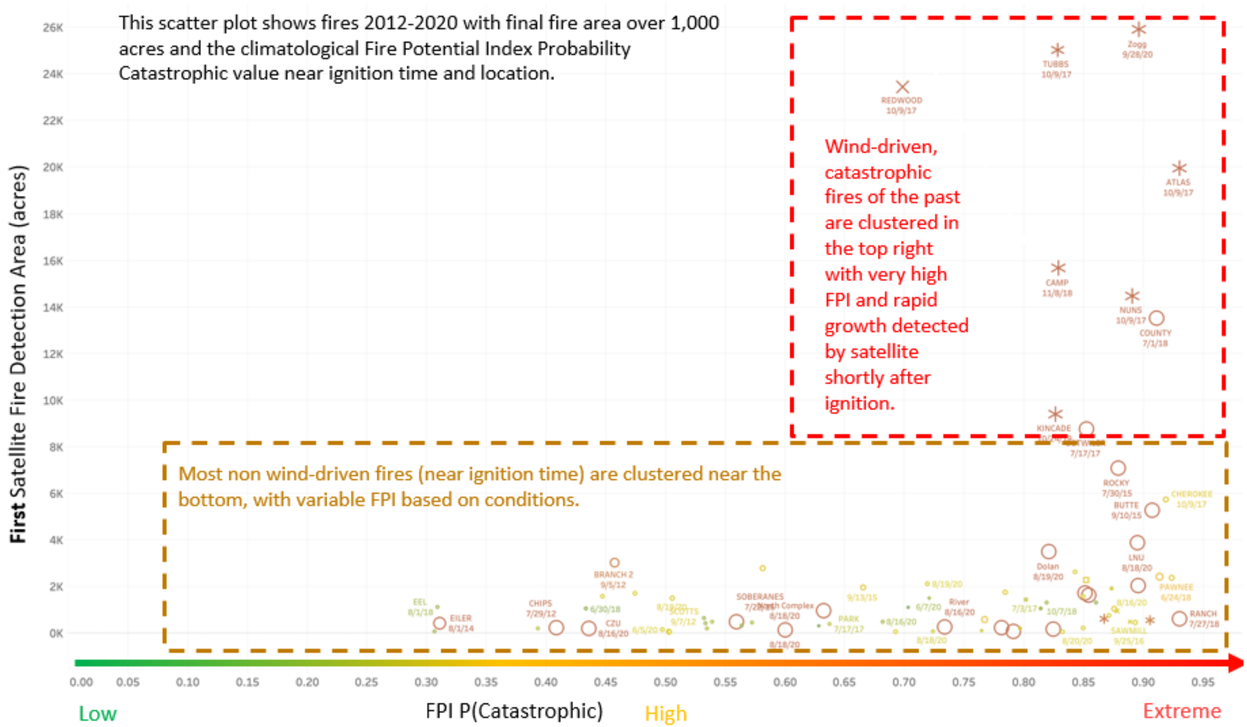

Fig. 8. fire potential index model output for fires >1000 acres from 2012-2020

1.7 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 climatological breakpoints. These breakpoints were established by reviewing climatological percentiles as well as FPI model output for historic fires in the PG&E territory from 2008 – 2020. This method is identical to how raw numeric outputs of the Energy Release Component or Burning Index from the federal

National Fire Danger Rating System are translated to fire danger ratings from low to extreme. Our methodology mirrors agency best practices taught in instructor-led courses in fire danger applications offered by the National Wildfire Coordinating Group

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 more rapidly shortly after ignition.

Table 2. Fire potential index rating and color scale

R1
R2
R3
R4
R5
R5-Plus

Table 3. 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

[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.

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”.

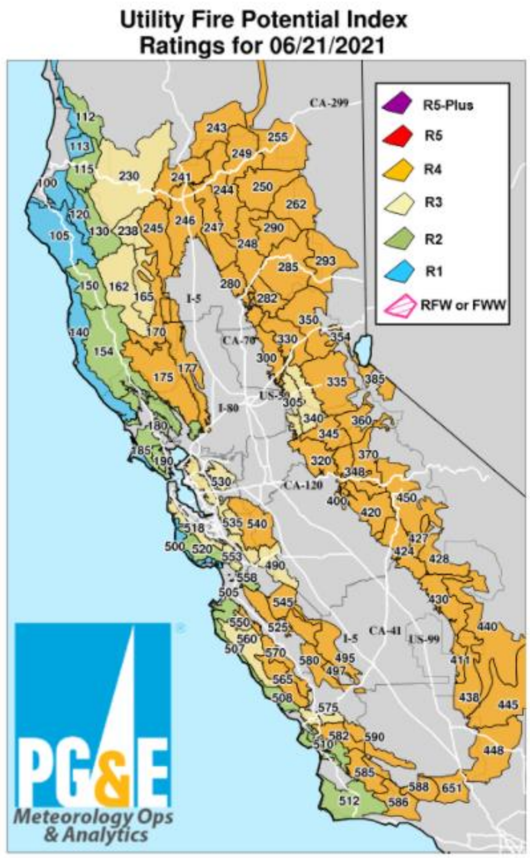

Fig. 9. Example map with fire potential index ratings

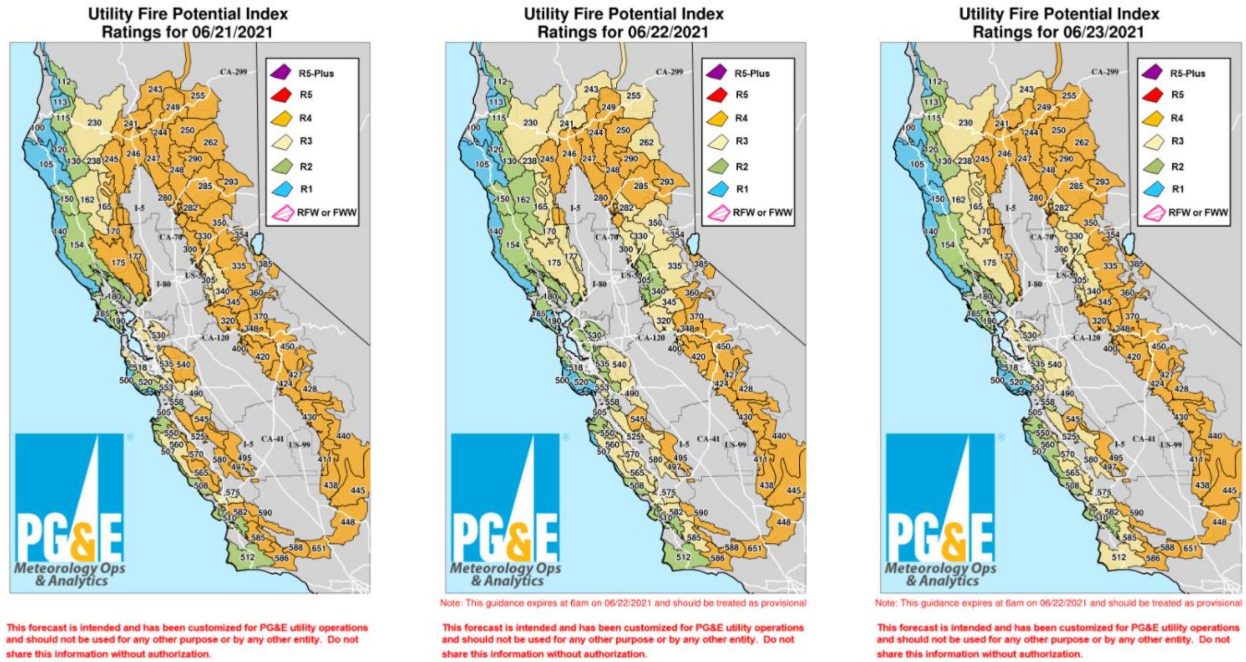

Fig. 10. Example fire potential index three-day forecast