Analysis of Utility Wildfire Risk Assessments and Mitigations in California

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Abstract:

Utility-related ignitions have historically been correlated with catastrophic wildfire. First noted in Australia and Southern California, as climate-change related drought has increased catastrophic wildfires from utility ignitions now plague the western US. Regulatory changes now require California utilities to analyze and mitigate wildfire risk. This analysis reviews recent data and risk assessments from Pacific Gas and Electric Company (PG&E), Southern California Edison Company (SCE), and San Diego Gas and Electric Company (SDG&E), California's largest electrical utilities. While utilities have adopted data science methodology, covariates capturing extreme weather effects are missing and tools lack mechanisms to incorporate causal linkage between likelihood and consequence models. Consequently, risk models incorrectly prioritize risk drivers. Additionally, match-drop wildfire spread calculations fail to represent large fires due to limited run time. Risk models also fail to incorporate the health effects of wildfire smoke. Power shutoff is an effective mitigation during extreme weather events, but causes significant public harm. "Hardening" programs, especially undergrounding lines, are effective but their expense threatens public health for the poorest. Accurate balancing of wildfire risks, risk of power loss, and financial impacts on vulnerable populations, in conjunction with application of new technology is required to address the utility wildfire problem.

Keywords: modeling; risk assessment; wildfires; ignition; electric utilities; fire growth; machine learning; wildfire smoke; extreme weather

1. Introduction

While ignition of fire by electrical lines has been a problem that has existed as long as the electrical grid itself, the threat of catastrophic wildfire in general has increased dramatically over the last two decades and has primarily been associated with climate trends and extreme weather events[1,2] Two climactic components related wildfire likelihood and severity are fuel aridity [3] and foehn (Santa Ana, Sundowner, Diablo) winds [4]. Current research does not suggest the intensification of extreme winds in climate change scenarios, but rather suggests possible suppression of wind events, though overall wildfire risk will not be reduced due to the longer wildfire seasons [5, 6].

Extreme winds are a driver of wildfire spread but in the context of electrical distribution and transmission systems they play an additional causal role by initiating a damage event that produces the electrical arc that is the source of wildfire ignition. The common driving mechanism linking the ignition event and conditions favoring explosive wildfire spread create a multiplicative effect that causes electrical wildfires to be overrepresented in lists of the most deadly, destructive, and expensive wildfires in comparison to other ignition sources. Miller et. al. [7] demonstrate that electrically caused fires in Victoria, Australia are over-represented when fire danger is high, and that these fires also are larger and more destructive. Data from the California Department of Forestry and Fire Protection (CAL FIRE) shows the following statistics as of November 2022 for "Top 20" deadliest, most destructive, and largest fires [10, Folder: CALFIRE/].

Table 1 - CAL FIRE "Top 20" deadliest (by fatalities), most destructive (by structures), and largest (by acres burned) as of November 2022 showing relative contribution of electrically ignited wildfires to total numbers and total losses.

Wildfires	Number of Electrical Caused (out of 20)	Fraction of Losses Due to Electrically Caused Wildfires
Deadliest	4	39%
Most Destructive	8	66%
Largest	3	21%

Mitchell 2009 [8] gave the fraction of California wildfires started by power lines as 1% based on CAL FIRE statistics available at that time. CAL FIRE has gone through several iterations of its wildfire data collection process, and currently the fraction of power line fires is considered to be approximately 10% ([10]CPUC/MGRA-R1812005-PD-Cmt]).

In the aftermath of the 2007 Southern California power line firestorm, the California Public Utilities Commission (CPUC) initiated regulatory changes requiring that utilities gather wildfire data, prepare wildfire protection plans, and use CAL FIRE utility wildfire threat maps for mitigation planning. After the power line ignitions during the disastrous 2017-2018 wildfire seasons, which led to over 100 fatalities and led to PG&E's bankruptcy, additional regulatory requirements were put into place including Wildfire Mitigation Plans (WMPs), overseen by the newly constituted California Office of Energy Infrastructure Safety (OEIS). An overview and comparison of the methodology of these plans is given by Zuzinga Vazquez, et. al. [9].

Since 2018, the CPUC has required utilities to develop quantitative risk-based decision making frameworks for evaluating enterprise risk, identifying and prioritizing mitigations, and for operational purposes. Utilities have been required to use a Multi-Attribute Value Function (MAVF) to quantify risks, including safety, economic, and reliability attributes. The risk value assigned to a specific risk event is defined as the product of a "Likelihood of a Risk Event" (LoRE) and "Consequence of a Risk Event" (CoRE) ([10]CPUC/D.18-12-014-Settlement).

The major California utilities have adopted similar models for implementing these requirements. Likelihood of wildfire risk events is determined by analysis of ignition or outage data, while consequence is determined by "match-drop" wildfire spread modeling. This methodology allows risk scores to be calculated for the utility system as a whole as well as for individual components, and allows for the effects of different mitigations to be modelled.

While conceptually sound, there are and have been a number of shortcomings in both the framework and implementation of utility risk models that create biases and lead to both over and underestimations of utility risk. Most seriously, utility risk models underestimate the role of extreme weather events in utility wildfire ignition. Errors in risk estimates can lead to incorrect mitigation and prioritization choices. This paper will discuss shortcomings in electrical utility wildfire risk models and possible remedies.

Using risk based planning allows for cost/benefit optimization. Recent proposals by California utilities have de-emphasized risk-spend efficiencies in favor of undergrounding solutions, which maximize risk reduction but at an extreme cost to ratepayers, which potentially outweigh benefits from improved wildfire safety, with particular impact to low-income populations.

2. Material and Methods

The regulatory process in California enables stakeholders or "intervenors" to participate in regulatory proceedings. Parties to proceedings are obliged to provide data to support their filings and applications. Over time, the data provided in utility submissions to regulators has expanded to include infrastructure, outage, damage, maintenance and ignition data. The data and documentation used in this paper were obtained during work on behalf of a party (Mussey Grade Road Alliance of Ramona, California) in wildfire mitigation plan, rate case, and other wildfire safety proceedings. Referenced proceedings include the 2021 and 2022 Wildfire Mitigation Plans filed with the California Office of Energy Infrastructure Safety (OEIS) and General Rate Cases and Rulemakings filed with the CPUC. None of this data was provided under non-disclosure agreement and it is therefore suitable for public dissemination. Results of this paper are based on analysis of PG&E, SCE, and SDG&E data only.

Data and non-academic references in this paper have been made publicly available through Mendeley [10] This data will be referenced by its folder (CPUC, OEIS, CALFIRE, or Data) and identifier (i.e. CPUC/SPD-1). All files and data have full descriptions in the INDEX.xlsx file in the Mendeley site top level folder, including a brief description of analysis performed in the various data files.

Analysis of utility geospatial data was performed with ArcGIS desktop.

3. Results

Analysis was performed on utility wildfire risk models used in the 2021 and 2022 Wildfire Mitigation Plans filed with OEIS (prior to July 1, 2021 the CPUC Wildfire Safety Division) and in CPUC filings supporting SCE, PG&E and SDG&E general rate case proceedings. The utility wildfire risk models are used to inform choice of mitigation and priority of areas for mitigation hence any errors or biases may lead to non-optimal reduction of utility wildfire risk. Analysis performed for MGRA has determined that there are a number of factors contributing to significant inaccuracies in utility wildfire risk analysis. Many MGRA conclusions were validated by regulatory review (CPUC/WSD-019,WSD-020,WSD-021,SPD-1,SPD-2,SPD-9).

Processes or practices developed by the California utilities are either electric utility best practices or have been developed to address the novel challenges posed by California's wildfire crisis.

Therefore, any shortcomings in these models are of general interest wherever utility infrastructure is exposed to extreme weather under conditions conducive to the ignition and propagation of wildfire.

3.1 Limitations of Utility Risk Models

The utility risk models used in 2021-2022 employ a Multi-Attribute Value function to create a unitless representation of risk and use this to compare alternative mitigations. For wildfire risk this function takes the form $Risk = P(ignition) \times \sum w_i C_i$ where C_i is the wildfire consequence for a given attribute i and w_i is the weight of the attribute. Currently the California utilities use three attributes: safety (weighted at 50-60%), financial (weighted at approximately 20-25%), and reliability (also weighted at 20-25%) (OEIS/PGE-2022-WMP, pp. 57-60, OEIS/SCE-2022-WMP, pp.63-68, OEIS/SDGE-2021-WMP, pp. 25-26). Risk is analyzed separately for different causes, equipment components and tranches of similar risk profile, and can be aggregated depending on purpose. Mitigations can affect either probability of the risk event or consequence, and risk can be compared before and after mitigation.

There is a key limitation in this formulation of risk, namely that it assumes that probability and consequence are independent of each other. If there is an external risk driver coupling probability and consequence of ignition, then consequence and ignition must not be calculated independently. Mitchell 2013 [11] discusses how extreme winds are a common-cause risk driver affecting component or tree failure, ignition, and speed of wildfire spread. Nevertheless this dependency is ignored in many of the risk analyses discussed in this paper, leading to spurious results that will be discussed in subsequent sections.

3.2 Biases in Utility Wildfire Spread Modeling

The wildfire spread model used by SDG&E, PG&E, and SCE is Wildfire Analyst by Technosylva [12]. Utilities use this model for "match drop" simulations of ignitions by their infrastructure in all areas of potentially affected landscape, predicting spatiotemporal fire progression and potential damage from each ignition. These simulations are used for 1) operational decisions, specifically whether to de-energize power lines, 2) predicting the risk of loss from an ignition at any specific point of the utility infrastructure, and 3) aggregating all risks from 2 and predicting an overall utility wildfire risk values that can be compared with other enterprise risks.

The accuracy of Technosylva Wildfire Analyst in supporting real-time decision-making during wildfire events is enhanced by the ability to update the fire model with real-time fire and weather data [13]. However, Rate of Spread (ROS) calculations are considered to be highly inaccurate due to uncertainty of local weather conditions (particularly wind) and fuels [14,15,16]. The uncertainty associated with fire size increases with the length of the model run, preventing the accurate prediction of very large fire sizes from initial conditions. For this reason, simulations run for the California utilities adopt a Monte Carlo approach, running thousands of simulations for each potential ignition location (CPUC/SDGE-2022-WMP, p. 103) and limit their fire spread simulations to 8 hours (CPUC/SPD-9, p. 62, SCE-2021-WMP-Rev, p. 62, SDGE-2021-WMP, p. 83). This choice effectively puts a cap on maximum wildfire size. This is shown in Figure 1, which demonstrates that 8 hour Wildfire Analyst simulations rarely produce fires exceeding 10,000 ha to 20,000 ha (Data/SCE-Technosylva-Raw, Data/PGE-Technosylva-Raw).

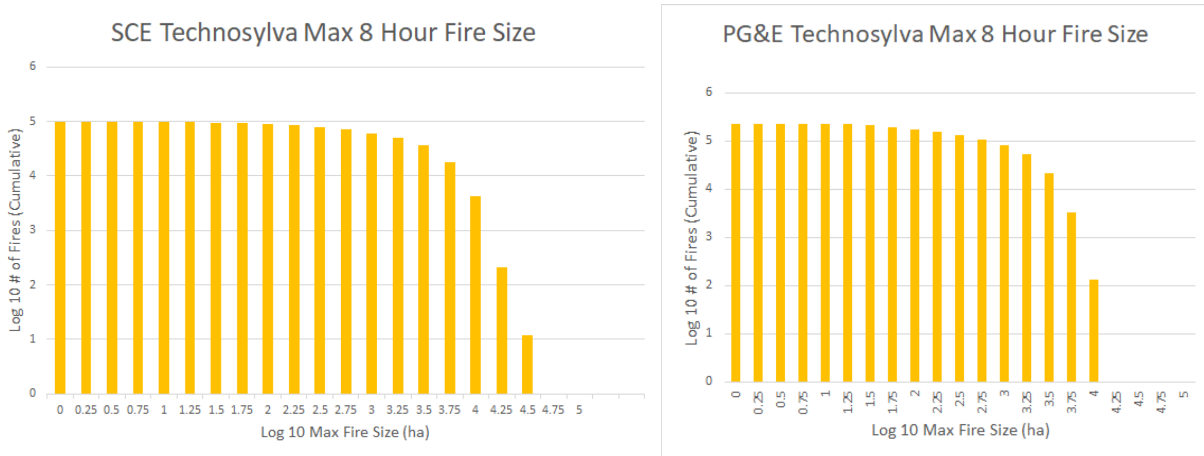

Fig. 1 Raw Technosylva simulation data was provided by SCE and PG&E in response to MGRA data requests, and the logarithm of maximum wildfire size for each set of 8-hour runs was accumulated into histograms. Maximum wildfire sizes rarely exceed 20,000 ha for SCE and 20,000 ha for PG&E.

The limitation of maximum wildfire fire size is problematic. Wildfire sizes follow power law distributions [17, 18, 19]. This has been validated for California wildfires as well [20,21] and Mitchell 2009 [8]. Cumulative size distributions for California wildfires based on CAL FIRE perimeter data are shown in Figure 2 for both non-power line and power line fires (Data/CALFIRE-Perimeter-2019)

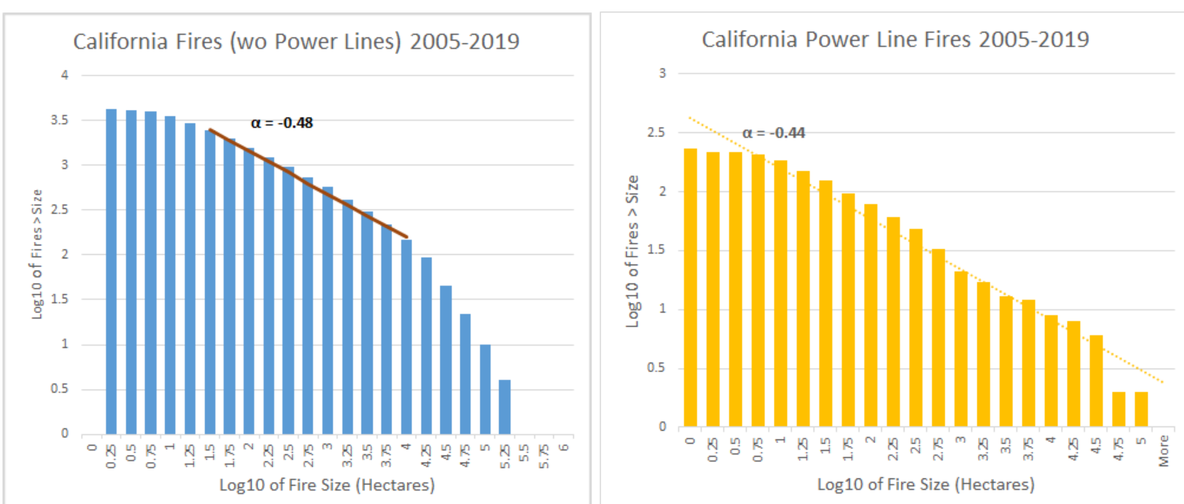

Fig. 2 CAL FIRE perimeter data for wildfires attributed to power line ignitions. 2007 and 2017 fire attributions are corrected with CAL FIRE and CPUC assessments. The trendlines are a guide to the eye, rather than a best fit and shows how power law exponents would appear. Deviations from power law behavior appear above 30,000 acres (without power lines) and 80,000 acres for power line fires.

The power law exponent has not been fit, but lines equivalent to exponents α = 0.48 and α = 0.44 have been added as guides to the eye. Moritz 2005 [20] finds an exponent of 0.5 for wildfires in the Los Padres National Forest in California.

The problem with power laws having exponents less than 1.0 is that their means sizes do not converge as more historical data is collected, potentially making the entire notion of wildfire risk prediction intractable [22]. The danger of ignoring large fires in consequence calculations is amply demonstrated in Figure 3, which uses an identical approach to Figure 2 but calculates cumulative damage per bin.

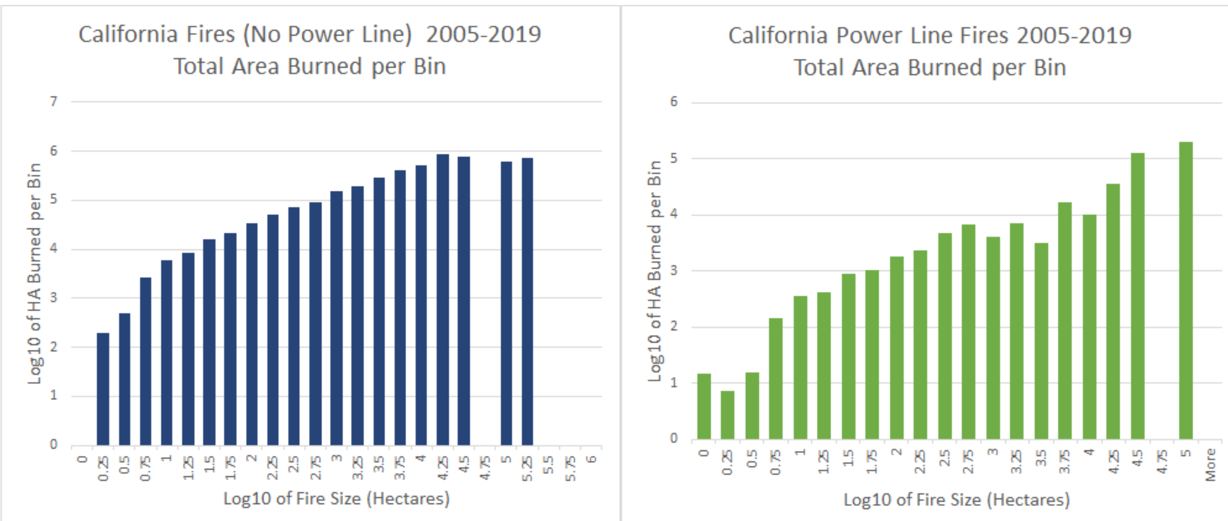

Fig 3 Total area burned per logarithmic bin for California wildfires 2005 to 2019, calculated by multiplying logarithmic mean of bin by number of wildfires in the bin. Power line related wildfires are compared against full sample with non-power line wildfires removed.

The Highly Optimized Tolerance (HOT) suggested by Moritz et. al. [20] suggests that deviations from power law behavior will occur when wildfire sizes become comparable to the size of the contiguous burnable landscape. This enables a cut-off value to be set, preserving the mean and allowing non-divergent risk values to be calculated. In response to regulator and stakeholder input, both PG&E and SDG&E have adopted a Generalized Pareto Distribution (GPD) to describe behaviors of very large wildfires, with a maximum loss cutoff currently set to 5 times the Camp Fire losses, and they performed a sensitivity analysis on the cutoff value. (CPUC/PGE_PL_Whitepaper; CPUC/SDGE-2024-GRC-03-R-Risk, p. RSP/GSF-9). This is applied via a Monte Carlo to their Enterprise Risk Model to ensure extreme fires are incorporated. Southern California Edison uses only Wildfire Analysist outputs for its size estimations.

While the approach taken by PG&E and SDG&E corrects enterprise risk models, their *planning* models, which calculate risk based upon line segment or infrastructure component, and which are used for prioritization of mitigation, are still limited by the maximum wildfire size allowed by the 8 hour simulation. This creates a bias in risk prediction that leads to electrical components closer to population centers (which have higher potential consequences) being rated as having higher risk than remote components. An example is shown in Figure 4, which shows PG&E model estimates near the Sacramento area (Data/PGE-GIS-SegmentRisk). Areas in yellow and orange (higher risk) are clustered close to population centers while remote circuits tend to have lower risk scores. However, many of the great historical wildfires (Witch, Camp, Dixie) started in remote locations and grew to large size before descending onto a broad WUI frontline. A realistic model incorporating catastrophic wildfires would show risk more uniformly distributed across the landscape.

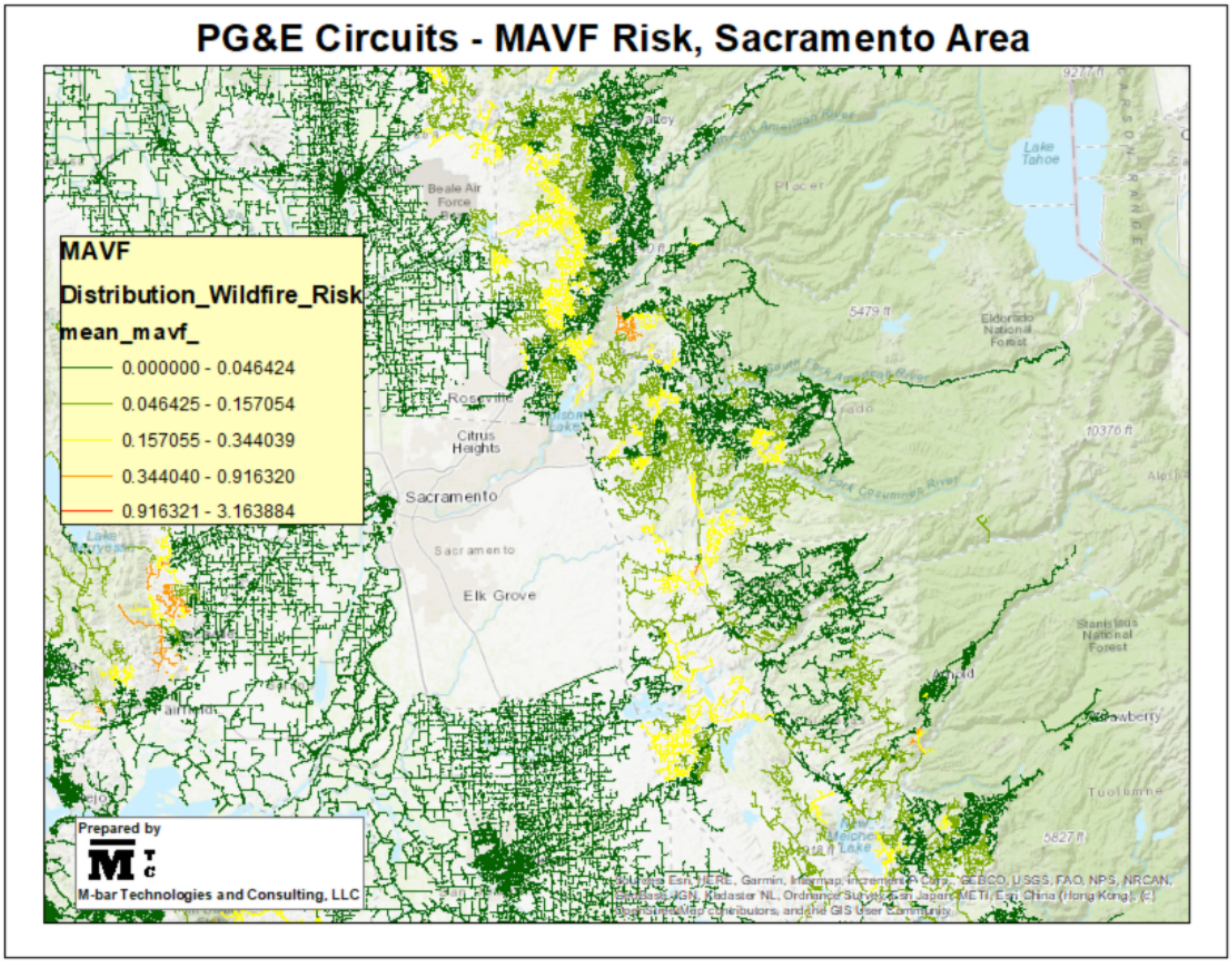

Fig 4 PG&E Wildfire Distribution Risk Model (WDRM) v2 risk estimates for circuits in the Sacramento/Lake Tahoe area. Green areas. Note that the areas of greatest risk tend to be greater nearer population centers, and drop to lower values for more remote areas.

3.3 Limitations in Utility Probability of Ignition (PoI) Machine Learning Models

As per regulatory requirements put in place over the last decade, California electrical utilities are now required to collect and provide extensive metrics on ignitions, outages, inspections, maintenance, and other infrastructure-related items. The goal of collecting metrics is to allow the prediction of potential future ignitions and to allocate resources to prevent ignitions from occurring. As the field of data science has developed, the electric utilities have recruited data scientists to help with this task. Both outage and ignition data may be used for ignition risk estimation. Outages provide a much larger data set for use in modeling but also require a Bayesian approach to calculating ignition probability: $PoI = (PoF \times PoI_F)/PoF_I$, where PoI is the probability of ignition, PoF is the probability of failure, PoI_F is the conditional probability of ignition given a failure, and PoI_F is the conditional probability of failure given ignition, equal to 1 (OEIS/SDGE-2022-WMP, p. 87). SDG&E applies a regression model to determine likelihood of ignition (Id., p. 86-92), while SCE uses a machine learning (ML) utilizing a Random Forest Classifier for PoI (OEIS/MGRA-2021-WMP-App, pp. 131-3/296), and PG&E uses a Maximum Entropy (MaxEnt) classifier (OEIS/PGE-2021-WMP, p. 97). Both the SCE and PG&E analyses use a wide variety of geospatial attribute data for their predictive models. However, both of these analyses use aggregated weather data (means, maxima, and exceedance frequency) (Id., Op. Cite) and therefore have no means to discriminate for transient extreme conditions. An independent review sponsored by PG&E at the request of regulators notes that "The current formulation cannot incorporate short but intense events" and that "[t]o properly incorporate this impact, the temporal resolution would allow either incorporation or exclusion of the events from the training data set" (OEIS/PGE-E3-Review). Consequently, both SCE and PG&E models find that wind-related variables have low predictive value for ignition. PG&E's 2021 WMP finds that the number of "gusty summer days" with wind speeds in excess of 32 km/h has a 6% permutation importance for vegetation ignitions and that average wind speed has a permutation importance of only 0.9% (OEIS/PGE-2021-WMP, pp. 164-165). SCE's analysis in 2022 also finds that aggregated wind variables have relatively low predictive value, with yearly maximum windspeed ranking 12th of 50 variables for contact from object and log of wind force ranking 19th of 50 variables for equipment failure (CPUC/MGRA-SCE-RAMP-Cmt, pp. 41-43/44.) Utilities have demonstrated that these analyses are skillful at predicting geographic dependence of ignition probability, but have not demonstrated that these predictions apply specifically to the locations of ignitions of catastrophic wind-driven fires.

3.4 Biases in Combining Probability and Consequence of Ignitions

SDG&E, SCE and PG&E employ a technique that further couples the probability of outage/ignition component to the consequence component when computing risk scores. The Wildfire Analyst match drop simulations are run with WRF data from hundreds of historical "worst case" weather days (OEIS/SDGE-2022 WMP, p. 101, OEIS/SCE-2022-WMP, p. 470; CPUC/MGRA-PGE-GRC23-Testimony, pp. 106-107/208) in order to optimize computing resources. However, this introduces bias if there is no attempt to correct for the fact that certain types of outages that lead to ignition are more likely during "worst case" weather conditions (such as equipment failure and vegetation contact) and others are less likely (such as "external agent" contact – animal, vehicle, balloons, or third parties). This will lead to an artificial amplification in the predicted risk associated with drivers <u>uncorrelated</u> with extreme weather. This effect is evident in Table 2, which shows that a significant fraction of ignitions are predicted from external agents such as vehicles, balloons, animals, and vandalism in the SCE and SDG&E data models.

Table 2 – Percentage of enterprise ignition risk represented by different risk drivers as per SCE and SDG&E's 2022 Wildfire Mitigation Plans (OEIS/SDGE-2022-WMP, p. 46; OEIS/SCE-2022-WMP, pp. 55-56; OEIS/PGE-2022-WMP, p. 61, OEIS/MGRA-2022-WMP Comments, pp. 32-34. PG&E's analysis is limited to National Weather Service Red Flag Warning (RFW) days. All PG&E external agent contact (vehicle, balloon, animal, other) is listed under "Other Contact".

Ignition Driver	**Percentage**		
	SDG&E	SCE	PG&E (RFW)
Vehicle	17	7	
Balloon	17	13	
Veg Contact	15	11	59
Other Contact	8	6	4 (all external)
Animal	5	13	
Wire Contact	3	5	1
Vandalism	2	5	0
Equipment	33	42	33

Table 2 shows that SCE and SDG&E show relatively large contributions from external agent contact (39% and 47% of enterprise wildfire risk, respectively), while PG&E estimates only 4% of risk from external agents. PG&E, in response to stakeholder input and internal analysis, restricted its data set to risk events occurring during National Weather Service Red Flag Warning days (OEIS/PGE-2022-WMP, p. 87). The dramatic difference between the SCE and SDG&E risk estimates on the one hand and PG&E risk estimates on the other demonstrates the effect of using "worst case" weather conditions for fire spread modeling of historical ignitions without adjusting for the conditional probability that a specific risk driver occurs on a "worst case" weather day.

Major utility wildfires rarely result from external agent ignitions. Most utility ignitions during fire weather events result from vegetation contact and equipment failure (Mitchell, 2013 [11]). SCE and PG&E provided lists of major utility caused fires (>100 acres for SCE, >500 acres for PG&E) between 2015 and 2020 (Data/SCE-Ignitions-2015-2020, OEIS/PGE-2022-RN-Rsp, pp. 1-13). These were analyzed using a Pearson Chi-squared goodness of fit (with/without Yates correction) to compare them against the utility-prediction probabilities for different ignition drivers. To improve statistical power the SCE and PG&E datasets were combined and driver categories of "external agent" (balloon, vehicle, animal, 3rd party), and "non-agent" (vegetation and equipment failure) were used for binning. The analysis demonstrates that the utility ignition cause hypotheses of Poisson-distributed ignition times for catastrophic wildfires can be excluded with statistical significance (Data/Ignition-Risk-Rankings).

Table 3 - Statistical analysis of combined SCE and PG&E ignition data binned into Agent (balloon, 3rd party, vehicle, and Non-Agent (vegetation, equipment) to improve statistical power. Probabilities were calculated with the Excel function CHISQ.DIST.RT, using 2 degrees of freedom.

Driver	Observed	Expected	Chi2	Yates
Non-Agent	31	24.09	1.98	1.71
Agent	4	10.91	4.38	5.03
Total	35	35	6	7
P - Chi2	0.01168126			
P - Yates	0.00943576			

This is not to imply that agent-related causes cannot cause catastrophic fires. However, wind related drivers have been observed to be the predominant contributor to utility risk as represented by historical losses, as would be expected from physical models. Accurate risk models must correctly take geographic dependency of wind-related drivers into account.

3.5 Utility Operational Models and Wind Speed

Despite the fact that utility ignition models used for risk planning show little to no dependency on wind, utility operational models, which use much of the same analytical infrastructure and are used for planning de-energization during high wind events, include a parameterization of outage and ignition dependency on wind. All three utilities have identified results similar to those shown in Mitchell 2013 [11], namely that outage probability is a strong function (polynomial or exponential) of wind speed. (OEIS/SDGE-2022-WMP, p.129-132; OEIS/PGE-2022-WMP, pp. 93-94, OEIS/ MGRA-2021-WMP-Cmts, pp. 27-30).

It is also noteworthy that utilities use only aggregated historical weather data for planning and mitigation. Real-time weather data is used only as an input to operational planning, specifically for de-energization.

3.6 De-Energization as Mitigation and Risk, and Resulting Risk Estimation Bias

In general, only utility equipment that is energized can produce a fault that ignites a wildfire. Therefore, de-energization (called "Public Safety Power Shutoff" or PSPS by California utilities and regulators) during extreme fire weather has been shown to be an effective wildfire preventative measure. However, loss of electrical power has severe safety and economic impacts, and has a strong negative connotation with the public and regulators.

The efficacy of de-energization was examined by the CPUC's Safety and Enforcement Division (SED) which contracted with Technosylva to run its Wildfire Analyst [12] simulations using input data from post-de-energization damage surveys [23]. These datasets comprise utility damage and object contacts noted by utilities after the windstorm and reported to the CPUC. Weather simulations for the model uses both measured and predicted data to predict the course of fire events ignited at the damage point. Simulations model a 24 hour spread. While these fire spread models are problematic for several reasons – they lack a suppression component, only building exposure and not loss is modeled, inaccuracies cascade and multiply over the course of the calculation – they nevertheless demonstrate a likely answer to the contrafactual question

“What would have happened if utilities had not heavily utilized de-energization during the October 2019 weather events?”

Table 4 shows a summary of the Technosylva simulations, showing how many acres would be burned, displaced population, and how many houses impacted had all potential fires due to damage and contact with de-energized equipment occurred and had outcomes similar to the simulation [23].

Utility	Dates	Potential Ignition Evts	Population	Buildings	Acres burned (ha)
PG&E	Oct 9-12, 2019	114	36,015	18,819	11,279
PG&E	Oct 26-29, 2019	422	421,271	257,570	1,236,859
PG&E	Numerous, 2019	4	400	47	284
SCE	Numerous, 2019	54	55,982	25,434	148,028
SDG&E	3 weather events Oct-Nov 2091	13	34,471	35,122	132,444

Only damages deemed capable of supporting a wildfire ignition were included in the analysis. The projected damages are inaccurate due to lack of any fire suppression component, the assumption that all damage would have produced an outage capable of igniting a wildfire, some fires might extend beyond the 24 hour runtime, and divergence due to uncertainties in the initial conditions. Nevertheless, these demonstrate that a major power line firestorm event would have been likely in 2019, much like in 2017 or 2007, had utilities not resorted to widespread outages. The only catastrophic utility fire occurring during this period was the Kincade fire, which originated from a transmission circuit that had not been de-energized (CAL FIRE/Kincade-Fire-2019).

While de-energization is effective in preventing wildfire ignition, it itself causes great public harm [24]. Currently, there is no generally agreed mechanism for assigning this harm [25], and each utility assesses harm using its own methodology. The CPUC recently decided (CPUC/D.22-12-027, pp. 38-41, CPUC/ D.22-12-027-AppC) that utilities should work with the ICE calculator tool [26] group to devise a common mechanism to determine monetized losses from de-energization. However, additional mechanisms to quantify the risk of power shutoff to the public during extreme fire weather conditions (loss of communications, secondary fires, evacuation traffic disruption, inadequate post-event inspection) have yet to be quantified.

A complete risk analysis must incorporate both the comprehensive harm of power shutoff and its benefits in terms of avoided wildfires.

One final note on utility models and de-energization: Because de-energized equipment can experience neither a fault nor an ignition, the historical record for outages and ignitions will be missing the areas and times during which lines were de-energized. To the extent that these historical records are used to project future risk, the results of the subsequent analysis will be biased, with commonly de-energized areas appearing to have lower risk than they actually do. So far only PG&E has introduced a correction to this bias, in which it incorporates its post-shutoff damage events into its event history (CPUC/PGE-GRC23-WP4, p. WP 4-53).

3.7 Wildfire Smoke Effects

Over the last decade, wildfire smoke has become known as a major health risk that leads to morbidities and fatalities, particularly due its PM2.5 particulate component [27]. Evidence points to PM2.5 particulates from wildfire being significantly more dangerous than PM2.5 particulates from other sources [28]. Utility risk estimates fail to adequately take this risk into account, though rough approximations indicate that wildfire smoke risk may cause more morbidities and fatalities than direct exposure to wildfire.

SDG&E initiated the attempt to incorporate wildfire smoke risk into its regulatory proceedings by estimating a "fatalities per acre" equivalency. An equivalent analysis was performed by the author using more recent references (O'Dell, et al.[27], Liu, et. al [29]) and yielded equivalent proportionalities of one fatality per 445 hectares and 4,654 hectares burned, respectively (CPUC/SDGE-RAMP-SPD-Report, pp. 220-221/295). SCE was also requested to perform a risk analysis using an equivalency of one fatality per 465 hectares and one per 4411 hectares. According to SCE's weighting of risk, for fatality rates greater than one fatality per 1,600 acres burned, wildfire smoke would provide the greatest contribution to wildfire safety risk (CPUC/MGRA-SCE-RAMP-Cmt, pp. 7-9). However it is important to emphasize that 1) wildfire fatality and morbidity numbers are highly uncertain [30] and wildfire smoke affects populations depending on the ambient weather conditions at the time. A more useful and accurate estimation of utility wildfire smoke risk will require the development of new methodologies that can estimate plume dispersal and perform population impact analyses based upon epidemiological studies.

3.8 Utility Wildfire Mitigations

Aside from shutting off the power, utilities utilize a number of mitigations in order to reduce wildfire ignition risk [31], including enhanced inspections of vegetation and equipment, (OEIS/SDGE-2022-WMP, pp. 244-304) vegetation management, (OEIS/PGE-2022-WMP, pp. 631-704) and "grid hardening".

While there are many possible components to "grid hardening" the most effective at scale are "covered conductor" and "undergrounding". The three utilities in question have performed a common study of "covered conductor", which in their case comprises a three-layer polymer and semiconductor extrusion over the conductors (CPUC/SDGE-2022-WMP, pp. 213-214). Analysis by utility subject matter experts concludes that covered conductor reduces overall wildfire ignition risk by 65% compared with bare conductor (Id., pp. 562-639/699). As of September 2022, SCE had deployed 4,025 km of covered conductor, (CPUC/SCE-RAMP-SPD-Report, p. 104/142) with 688 km of circuits completely covered (CPUC/MGRA-SCE-RAMP-Cmt, pp. 33-34/44). While the overall fault rate is reduced by approximately the predicted value (Op. Cite), its observed rates for ignitions and "wires down" is reduced to a lower value than would be accounted for by a 65% reduction in risk. For the period January 2019 through September 2022, at SCE's ambient ignition rate the mean of predicted ignitions would be 5, while 0 have been observed, and the predicted mean of "wires down" events would be 26, with 3 observed (Data/SCE-CC-Eff). This indicates that the prediction that covered conductor will reduce ignitions by 65% may be an underestimate, and this should be re-evaluated after further deployment and field experience.

There are additionally a variety of technical innovations being researched by utilities that may drastically reduce the potential for ignition. Generally these share the characteristic of reducing the available energy in the line before an arc can be generated capable of sustaining ignition. PG&E claims that a simple change to its fault trip triggering threshold using its existing equipment (which calls "EPSS") allowed it to cut wildfire ignitions by a third (OEIS/PGE-2022--WMP, p. 55), though it also severely impacted its customer service with 600 unplanned outages affecting 650,000 customers [24, p. 32]. An example of more advanced technologies is REFCL (Rapid Earth Fault Current Limiter), which was developed in Australia [32] and is currently being deployed and tested by both PG&E and SCE. While these technologies may not address all fault scenarios (such as phase-to-phase contact), in combination with other mitigation such as covered conductor they may provide protection approaching that of placing conductors underground.

3.9 Undergrounding and Affordability Impacts

Placing conductors underground virtually eliminates the potential for wildfire ignition. The reason that this mitigation hasn't been widely deployed is expense. The cost of undergrounding currently averages $1.9 million per kilometer, depending on specific circumstances, making it far more costly than other mitigations such as covered conductor (OEIS/SDGE-2022-WMP, p. 672/699). With nearly 40,000 miles (64,000 km) of conductor in wildfire prone areas [24, p. iii] the cost of using undergrounding as a primary mitigation in California could cost over $US 100 billion. Consequently, when undergrounding as a mitigation is compared via its risk-spend efficiency against other mitigations, it fares poorly.

Nevertheless, in June of 2021, PG&E announced plans to rely primarily on putting conductors underground as its primary mitigation strategy and expenditure, announcing a target to complete 10,000 miles of undergrounding in 10 years (CPUC/PGE-2022-WMP, p. 5). SCE and SDG&E have also announced plans to expand their undergrounding programs. And the State of California in 2022 passed legislation (Senate Bill 884)[33] which expedites the review process for utility undergrounding plans.

If major undergrounding plans move forward unprecedented costs may fall on utility ratepayers, and these costs could potentially have significant public health effects.

It is well known that income affects life expectancy, for example a US study shows men in the 20% household income percentile have a life expectancy of 77.5 years and men in the 80% percentile have a life expectancy of 85 years [34]. A naive example of the effect of $300 per year utility rate increase on the 20-40% household income quintile , with a low-income population of 10 million, could result in the loss of 380,000 years of life or the equivalent of 5,000 75 year life spans (OEIS/MGRA-2022-WMP-Cmts, pp. 58-60). While this is purely a thought experiment – there are for instance programs to help low income California with energy bills – it demonstrates clearly that societal cost of mitigations cannot be decoupled from wildfire mitigation programs without shifting the risk from residents of the Wildland Urban Interface to low income ratepayers.

4. Conclusions

Significant progress has been made in quantifying and analyzing utility wildfire risk over the past decade, a period that has also seen some of the most catastrophic power line fires in history, particularly in California. The goal of understanding utility wildfire risk is to understand where and under what conditions are utility-sparked ignitions likely to occur and spread into catastrophic wildfires. With this knowledge, the most cost-effective mitigations can be chosen and applied to the riskiest circuits first. However, a number of mistakes have compromised the initial effort to estimate wildfire risk in California and lessons from these mistakes should inform future work both in California and elsewhere. Primarily, the physical process coupling utility faults to rapid fire spread should be incorporated into risk models. The power of data science modelling is compromised in a process with temporal dependencies if none of the covariates adequately capture these dependencies. In the current case, data models tell us that there is a substantial risk of catastrophic fires from animals, balloons, and vehicles, whereas these are relatively minor contributors during extreme wind events, when the vast majority of catastrophic fires actually occur.

Another shortcoming in models results from limitations in fire spread modeling, which lead to fires much smaller than those that have historically been responsible for most losses. This leads to a perceived risk that is greater near population centers (the consequence target) and lesser deeper into the wildlands. This ignores a common mechanism for catastrophic fire growth, where remote ignitions deep in the wildlands (Witch (2007), Cedar(2003)) are fanned by winds and descend many hours later onto the Wildland Urban Interface in a long destructive front.

Based on current modeling, utilities are already deploying a number of mitigation methods to reduce wildfire risk, and have begun to heavily rely on de-energization. While effective in preventing large fires, harm from de-energization has yet to be fully incorporated into risk estimations, and these measures have proven unpopular among regulators and the public. The effects of wildfire smoke have only now begun to be incorporated into utility risk models, but a scientifically supportable methodology has yet to be developed.

Fortunately, the California utilities continue to improve their risk models at the behest of regulators, stakeholders and on their own initiative. Development of risk modeling that takes into account extreme wind drivers that couple ignition probability and fire spread must be completed, and models also need to include catastrophic fires that have historically been the cause of most losses. Research and development on technologically based innovations must be accelerated. In the meantime, utilities should tune their de-energization thresholds to optimize the risk/benefit balance for the population. Risk models should also be expanded to include wildfire smoke and the effects of utility rates on the population. Finally, abandoning risk modeling and mitigation planning to adopt a comprehensive undergrounding program threatens to shift risk from the Wildland Urban Interface onto other vulnerable segments of the population. Achieving the long term goal of reducing utility wildfire risk requires a comprehensive wildfire risk model that balances the needs of all Californians. Such a model would be applicable to similar areas around the globe where utility-ignited wildfires are a threat.

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