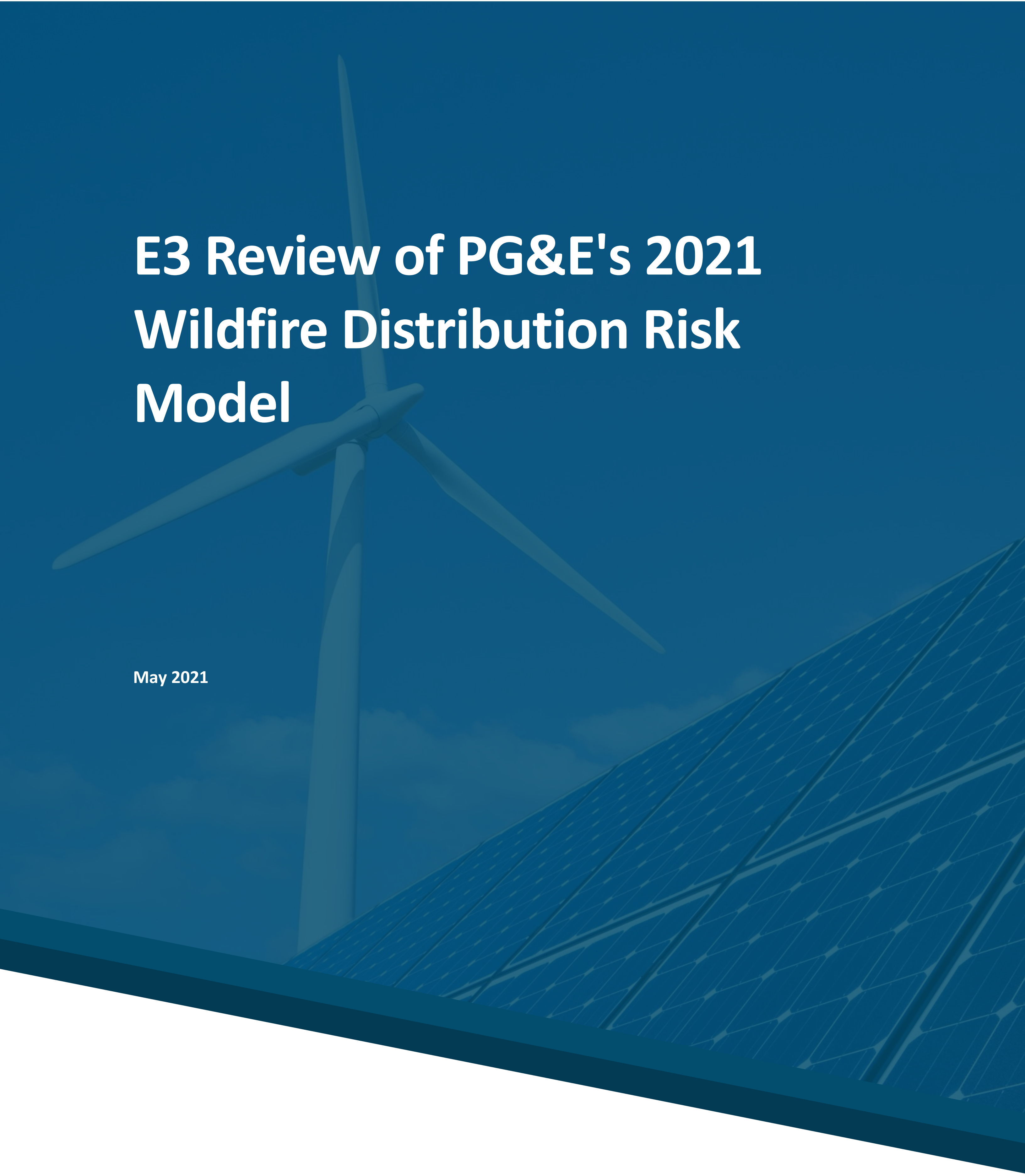

E3 Review of PG&E's 2021 Wildfire Distribution Risk Model

May 2021

Energy+Environmental Economics

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1 Introduction and Executive Summary

1.1 Introduction

Pacific Gas and Electric Company (PG&E) contracted with Energy and Environmental Economics (E3) to perform a review of PG&E's 2021 Wildfire Distribution Risk Model (Distribution Risk Model) and its accompanying documentation. This engagement began in March of 2021 and concluded in May the same year. Our findings are based on review of model documentation produced by PG&E, external documentation on modeling approaches used by the Distribution Risk Model, additional data and documentation sources provided by PG&E upon request, and extensive interviews with PG&E subject matter experts.

The experienced team that we brought to this project included a range of experts in energy and risk modeling who were also familiar with methods and data used in bulk system generation and transmission planning, distribution planning and operations, risk modeling, and machine learning. Moreover, this team has worked extensively on California and PG&E's system in particular and is familiar with the unique challenges and context that define the critical need and value that this work provides. The CV's of the E3 consulting team are attached in Appendix A of this document.

The Distribution Risk Model consists of four sub-models, which were included in our review:

+ **The Equipment Probability of Ignition Model** estimates a spatially differentiated probability of ignitions caused by conductor failures.
+ **The Vegetation Probability of Ignition Model** performs a similar estimation for ignitions caused by interactions of vegetation with PG&E equipment.
+ **The Wildfire Consequence Model** uses spatially differentiated fire simulation data from Technosylva to weight existing California Department of Forestry and Fire Protection (CAL FIRE) consequence data established in the 2020 Risk Assessment Mitigation Phase (RAMP).
+ The fourth sub-model combines the consequence scores with the vegetation ignition probability and conductor ignition probability results to create final risk scores for each spatial coordinate modeled.

The complexity and the range of choices available to the modeling team of each sub-model dictated the extent of our review. Both ignition sub-models employ a novel application of Maximum Entropy (MaxEnt) modeling to estimate ignition probabilities directly from weather, vegetation, and asset data. We spent more effort vetting this unique approach than on other sub-models. Although consequence scoring has a relatively large impact on risk results, the Wildfire Consequence Model is directly fed from the Technosylva fire simulations and CAL FIRE consequence scores. Validation of fire simulations and CAL FIRE scoring was beyond the scope of the review, so a relatively small portion of this document is devoted to the consequence sub-model.

Our review of the Distribution Risk Model focuses on two topics. The first is whether the model and documentation are "fit for purpose." Fitness for purpose requires a clear description of model goals, a rational road map of model development to address changing purpose over time, and evidence that the model is suitable for the questions being asked of it. For the second topic, we focused on intrinsic characteristics of the model, whether the model produces reasonable results, and a discussion of evidence-supported modeling choices.

Although this report was informed by discussions with PG&E staff and several of its contractors, it was not reviewed or edited by PG&E and it only represents the views of its authors. We did present, in PowerPoint form, an initial draft of review findings to PG&E in April of 2021. That presentation is shown in Appendix B. In response to these findings, PG&E provided additional model documentation, including both old and new material. The final review presented in this document includes consideration of these additional materials. Several figures provided in PG&E's response to the draft review appear in this document alongside commentary on why we feel they are essential pieces of model documentation.

This review document is divided into sections aligned with the key review topics. Section 2 assesses the fitness for purpose of the model and the documentation. Section 3 describes our appraisal of the model, key modeling results, and some recommendations that should be considered for model improvement. Section 4 reiterates the review's key findings and conclusions.

1.2 Summary of Findings

Our findings are summarized below:

+ PG&E's Distribution Risk Model is appropriately designed for its stated goals including PG&E's goal to develop a model that provides estimates of risk from ignitions caused by its own equipment. The Distribution Risk Model serves as a useful guide that informs or confirms decisions that subject area experts make to mitigate long term estimates of risk.

+ PG&E's 2021 version of its Distribution Risk Model provides a better predictor of where ignitions could occur and what damages could be expected from those ignitions that its older 2018-2019 model. The improvements are primarily due to the use of more accurate consequence data and a more suitable modeling (MaxEnt) approach.

+ PG&E's approach represents a meaningful step above the industry standard approach used for planning and assessing where to target more traditional grid hardening measures. Mitigating wildfire risk caused by utility ignitions is a rapidly evolving new area that justifies using new data and methods. California utilities are working to create a new industry leading standard as wildfires continue to cause unacceptable levels of damage.

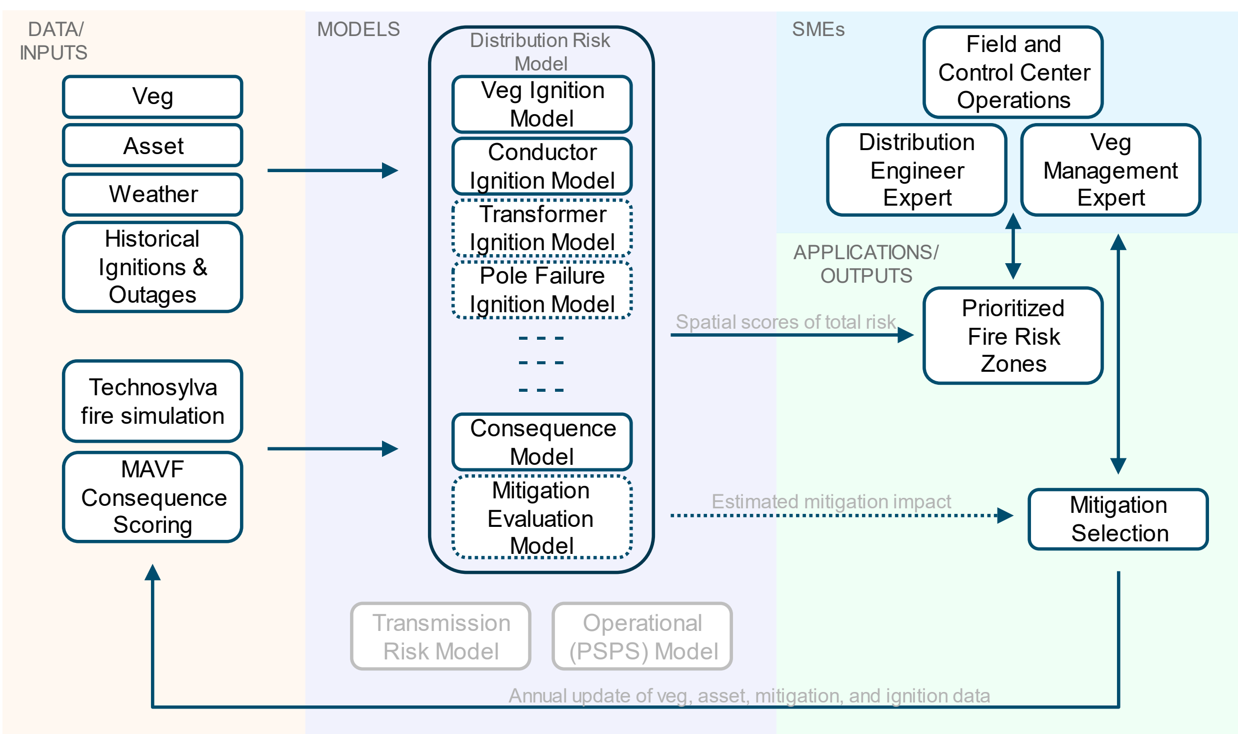
We also note several areas where the Distribution Risk Model could be strengthened:

+ Although PG&E should be commended for quickly developing a model that more accurately estimates ignitions, it could strengthen the critical link that is often required between experts and models to effectively mitigate risk. At this early model development state, there is a lack of close integration between risk models and the asset and vegetation management experts, who continue to be the key decision makers in designing and targeting risk mitigation measures. The goal should be to develop an informed decision-making process where experts use models to make better decisions than they could make on their own.

- The Distribution Risk Model focuses on where PG&E should mitigate risk and its Operational Public Safety Power Shutoff (PSPS) model focuses on where and when to interrupt power to mitigate risk. The PSPS model is beyond the scope of our review, but we believe there should be an explanation of the relationship between the models. This is necessary because investments in long term risk mitigation measures should decrease both wildfire risk and the need for more interruptions. Comparing data and methods from both models or even passing outputs from one into the other might be useful for both PG&E's modeling teams and outside parties with oversight responsibilities.

- We found PG&E's documentation to lack a coherent description of how the family of PG&E's fire risk mitigation models/data work together to address key questions. Figure 1 shows our attempt to describe the process surrounding the Distribution Risk Model in the context of the ecosystem of PG&E wildfire risk mitigation data and models. We include this diagram here because we found it difficult to understand the logical flow from data to models and ultimately to mitigation decisions. We reproduce and describe this figure in detail in Section 2.1.1, but present it here to help orient the reader.

Figure 1. Process Diagram of PG&E's Distribution Risk Model



- In developing a parsimonious model that uses fewer parameters to avoid "overfitting," the modeling team chose to exclude covariates that might be useful in providing more "direct line of sight" to the impact of the actual distribution risk mitigation measures. This model simplification also makes the key risk drivers less intuitive as some of the risk drivers are highly correlated. The impact of the parsimony goal on model accuracy is unclear and led to removal of covariates useful in providing "direct line of sight" to the risk mitigation measures.

- Because utility wildfire mitigation is a new and rapidly evolving topic, there is an obligation to explore many modeling methods before settling on one. The MaxEnt model employed in the ignition probability modeling has several intrinsic traits which *in theory* work in its favor in this problem with relatively sparse and imbalanced (ignition to non-ignition) data. However, this method should be compared to other less parsimonious and less restrictive modeling approaches to be certain that it is the most appropriate approach.

- Apart from commitments to work to both broaden the applications and accuracy, PG&E provides no longer-term roadmap for development of the Distribution Risk Model. It builds models suitable for addressing what it believes are the most important questions in front of it today, with no particular longer-term destination dialogue to identify the best path for model evolution.

- The recent Department of Energy (DOE) work on evolution of the of the Modern Distribution Grid describes the new grid architecture required for the clean energy transition as part of the "crawl, walk or run" phases of development. In assessing PG&E work to date, it is important to remember that while it is on the leading edge, the important work in this new area is just getting started.

2 Fit for Purpose Assessment

PG&E's Risk Modeling framework is a standard approach used by many companies that operate large complicated systems with many potential sources of risk of failure. The approach estimates the probability of an event (ignition) and multiplies it by the consequence of the event to arrive at estimates of expected damages. While the general framework is standard, its approach in estimating ignitions is novel and unique. This uniqueness has generated reasonable questions by reviewers and those tasked with the model's oversight. Our review team had many of the same questions. We offer some answers that were within our scope in this review.

We found it useful as a starting point to compare the attributes of PG&E's new model that they are currently using in 2021 with the one it replaced. In 2018-2019 PG&E used a statistical model that predicted ignitions as a function of a combination of weather, vegetation, and asset data. The 2018-2019 modeling approach was chosen by PG&E to use a widely used regression methodology with plausible explanatory variables. Due to the older models' poor predictive performance, PG&E developed their new machine learning approach based on the conditions that exist at the locations of ignitions like vegetation, asset type and weather.[1]

In making this pivot from a relatively simple model to one using MaxEnt, combined with substantial improvements made to its consequence model, PG&E gained accuracy in the ability to focus its investments in high fire risk zones that it expects will mitigate expected ignitions and their consequence; however, it lost a strong connection to some of the factors that its own experts directly consider in choosing what specific mitigation measures to deploy.

The improvement in accuracy is reflected in both the model's improved statistical performance which has the potential to increase PG&E's ability to more effectively prioritize among competing areas for a constrained risk mitigation budget. In addition to being more accurate, PG&E's new 2021 model, which is directly trained to predict ignitions, avoids the difficult task of linking failures to ignitions. Admittedly, this gain in accuracy comes at the expense of both relying on a much larger data set of outages caused by many factors and being directly linked to many of the outage related mitigation measures.

The change in models is consistent with PG&E's stated purpose of its Distribution Risk Modeling Framework, which is to provide statistically valid information that will help it target its long-term mitigation work in an effort to mitigate overall fire risk caused by PG&E's facilities on its customers.[2] PG&E's stated purposes in making these improvements were to:

1. Provide Situational Awareness of Risk
2. Enable Risk Informed Decision Making
3. Enable PG&E to provide line-of-site on risk reductions from wildfire risk mitigation initiatives.

The modeling improvements in 2021 that we reviewed should improve PG&E's "Situational Awareness" and its ability to make "Risk Informed Decision Making" through better geographic targeting of mitigation

[1] See PG&E's 2020 Ramp Report for Wildfire Risk.
[2] Verbal Interviews

measures. The new framework improves situational awareness because it incorporates consequences that are translated to a multi-attribute risk scoring system applied across all of PG&E. This information, combined with more reliable geographic targeting of ignitions, leads to more informed decision making based on minimizing risk within budget and other limitations.

To see clear evidence of this improvement, we requested that PG&E provide a list showing how its new model changed its geographic targeting of mitigation measures. Although they could not provide this information, PG&E described the internal process in which the model is used. The long-term planning process relies on subject matter experts (SME) to develop risk mitigation measures, and there have been multiple meetings and discussions between the risk modeling team and the SMEs where model results are shared and discussed. However, PG&E does not keep any formal before-and-after record to clearly demonstrate model impact on what is recommended or built. The use of SMEs to develop mitigation measures is consistent with the utility industry standard practice used to develop distribution risk mitigation measures.

PG&E produced several examples that show that its new ignition-trained model is consistent with the SME designation of high fire priority areas. One example, from geographic color-coded map shown in Appendix C of this report, shows that outage-based analysis would overemphasize risk along the coast where there are many outages, but cooler temperatures and lower levels of ignitions lead to lower risk. Conversely, in PG&E inland valley areas where temperatures are much higher during fire season, outages are comparatively low compared to ignitions. Although in its current state, the model doesn't reveal much new information beyond what SMEs already provide, it produces SME-consistent results and is consistent with PG&E's first two stated model purposes.

This version of the model and its "parsimonious" structure does sacrifice PG&E's third goal of "enabling a direct line-of-site on risk reductions from wildfire risk mitigation initiatives." We interpret this goal to mean that to the model supports a direct estimate of a mitigation measure and its impact on risk. Because the model does not include a sufficient number of actual mitigation measures, it is not suited to address the common oversight questions focused on measuring efficacy of one type or location of mitigation compared to another.

PG&E has indicated that it has plans to expand the scope of its model to address some of these questions; the company has already committed to including more mitigation measures in future versions of its modeling. This expansion will include modeling asset failures for transformers and poles for which failure events could directly reflect mitigation measures. We discuss this in more detail in both Section 2.1 (Model Context) below and in Section 2.3 (Roadmap).

We conclude that PG&E's new 2021 Wildfire Risk model is designed to be consistent with its defined, relatively narrow purpose of predicting where on the distribution system PG&E should focus its wildfire mitigation measures.

The lens in which we view the fit for purpose question had the following context: There is only one model, that we are aware of, that attempts to estimate the impact on risk of proposed "grid hardening" related investments. This model was approved by the Florida PUC to authorize grid hardening investments for

Tampa Electric (TECO).[3] Although the model used by TECO goes as far as estimating improved reliability as reduced outage minutes, its methodology is opaque and remains proprietary to Emera, and its focus is on equipment failures not ignitions and subsequent damages. PG&E's Distribution Model addresses entirely new questions with new approaches and is definitely in the "crawl" stage of development. The context questions in the next section summarize the key questions we asked of the PG&E modeling team that helped the E3 review team better understand the specific questions the model was designed to address.

2.1 Distribution Risk Model Context

Existing documentation for the Distribution Risk Model fails to adequately contextualize the modeling effort. Specifically, our recommendation is that the risk modeling documentation needs to better address the following questions:

- How is the model used in the risk decision-making process?
- Where does the Distribution Risk Model exist within the ecosystem of other PG&E risk models?
- What types of wildfire fire events does the model address and not address?
- What factors motivated key changes from the previous model iteration?

We address each of these questions in the following subsections.

2.1.1 How is the model used in the risk decision-making process?

Existing documentation of the risk model provides a risk modeling framework that describes the steps of scoping, data intake, risk identifications, risk assessment, risk management, and risk mitigation.[4] PG&E's illustration of this framework is reproduced in Figure 2.

While this framework contains helpful information, we find it lacks clear process. Based on discussions with PG&E, we constructed the Process diagram in Figure 3, which could serve as a starting point for improved process definition. The diagram shows inputs (data and assumptions) feeding into components of the Distribution Risk Model – which includes existing sub-models as well as planned future sub-models, the latter indicated by dashed outlines. Outputs from the 2021 model help SMEs create a list of prioritized fire risk zones, and future outputs aim to assist subject matter experts' mitigation selection through quantification of anticipated mitigation impacts.

[3] "Tampa Electric's 2020–2029 Storm Protection Plan". 10 Apr. 2020, www.psc.state.fl.us/library/filings/2020/01885-2020/01885-2020.pdf.

[4] See 2021 Wildfire Risk Model Overview v1.pdf, page 11 of 133.

Figure 2. PG&E's Risk Modeling Framework[5]

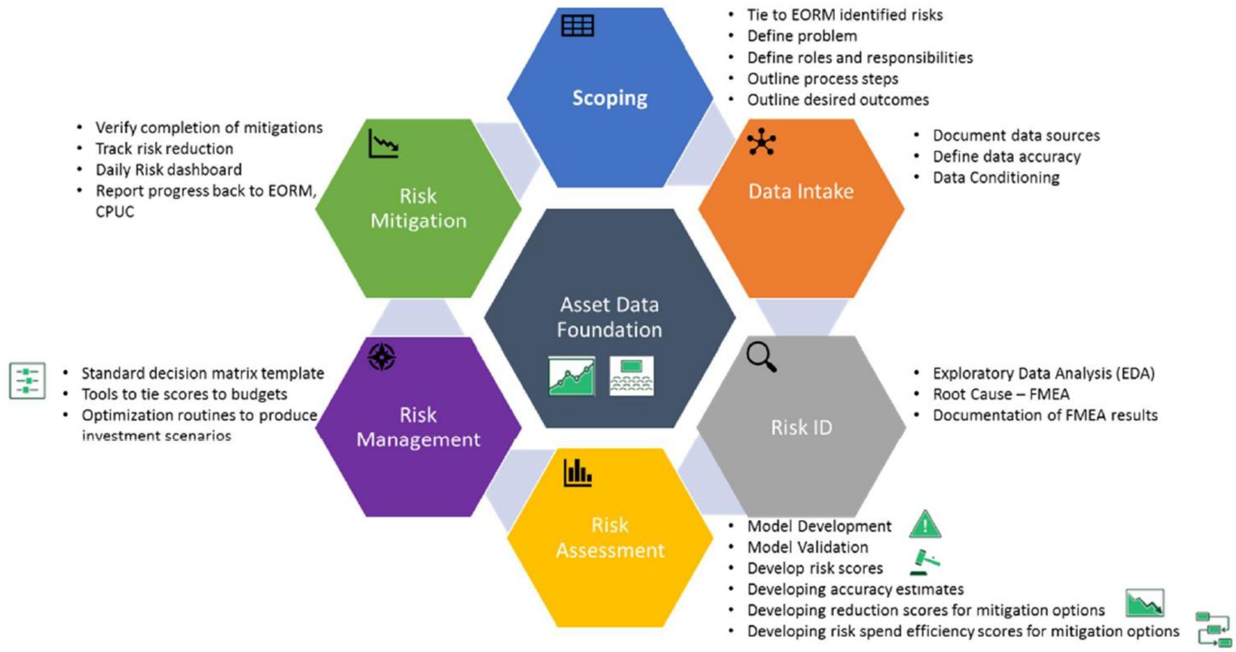
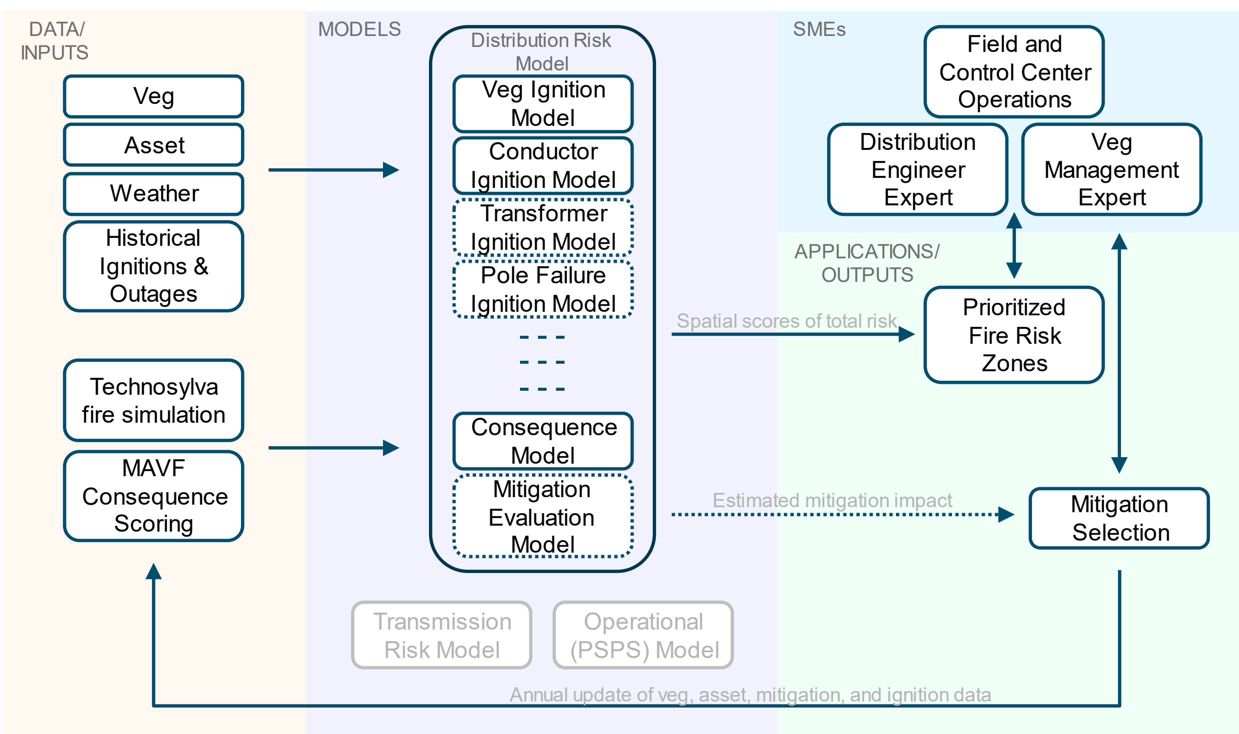


Figure 3. Process Diagram of PG&E's Distribution Risk Model



[5] See 2021 Wildfire Risk Model Overview v1.pdf, page 10 of 133.

Of particular importance are the double-headed arrows between SMEs and prioritized fire risk zones and mitigation selection connecting SMEs to applications/outputs in Figure 3. As with any newly developed model, it is critical that model results be reviewed by SMEs, who can apply their field-based knowledge to vet model results and suggest data improvements. At the same time, the model's ability to leverage machine learning techniques is a powerful tool to add more data-driven methods into SME decision making. A well-defined process for this interaction between model results and SMEs should create a feedback that improves both model predictive power and SME knowledge and assessment.

Existing documentation from PG&E does provide examples of ways in which SME input is used to augment model outputs. PG&E's documentation cites the Vegetation Management Team applying a tree species overlay to the results and notes that the Distribution Asset Strategy team incorporates other data such as terrain, customer locations, and customer counts into their mitigations decisions.[6] Conversations with the Distribution Risk Modeling team indicate that they hope to incorporate these additional data fields from SMEs in future model versions to improve the model predictive power and utility. These examples are valuable, but we hope that documentation for future models can provide a systematic description of this and other pertinent interactions. Ideally, a clear process would exist that provides detail describing how model results feed into SME decision making and how SME knowledge is used to determine future model improvements.

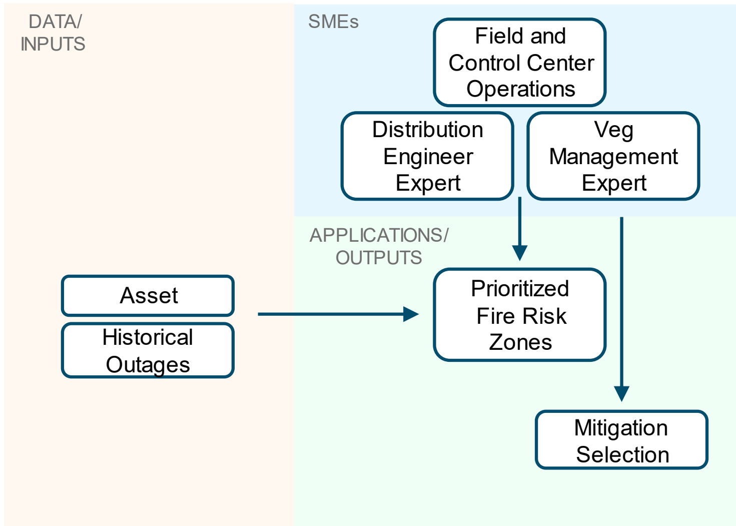
To provide a more complete picture of how PG&E's risk modeling might evolve, this process description could extend to show how proposed mitigation measures are considered within PG&E's capital investment plan. This description would acknowledge the need to balance investment among needs driven by wildfire mitigation, system expansion, lifecycle equipment replacement, replacement of adversely performing equipment, and upgrades to the worst performing circuits. We understand that this broad view is not stated within the requested scope of PG&E's Distribution Risk Model. However, we see value in transparency for the reader regarding assessment of required tradeoffs among these needs and relative scales of investment. We note that the investments driven by wildfire mitigation would come not only from the Distribution Risk Model, but all models within PG&E's wildfire risk modeling ecosystem.

To provide context for the longer-term model goals that might be addressable with all of the models shown in Figure 3 above, we also present Figure 4, which outlines a standard practice process for risk evaluation used in capital investment planning. In addition to having unidirectional flow with fewer inputs, the inputs and outputs that do remain in this process lack the detail and quantity and diversity of data found in PG&E's framework. Asset data frequently includes only fields such as age, life expectancy, ground clearance, thermal ratings, and safety records. Without input from a sophisticated data-intensive model, determination of prioritized zones and mitigations has little transparency and lacks valuable spatial granularity. This standard practice would be insufficient for the questions asked of PG&E's Distribution Risk Model, and the necessary expansion from this simple process to the one outlined by Figure 3 is a large step forward in sophistication and risk assessment. Finally, it is important to remember that the standard approach shown in Figure 4 typically only leads to a qualitative assessment of risk by area and

[6] See 2021 Wildfire Risk Model Overview v1.pdf, page 11 of 133.

across measures suitable for a subjective ranking of projects in a capital budgeting process with no ability to implement multi-attribute risk scoring.[7]

Figure 4. Process Diagram for Typical Risk Assessment



2.1.2 *Where does the Distribution Risk Model exist within the ecosystem of other PG&E risk models?*

The two gray boxes of Figure 3 reference other components of PG&E's wildfire risk modeling ecosystem: (1) the Transmission Risk Model and (2) Operational (PSPS) Model.

Original documentation notes the existence of the Operational Model (referred to as the Large Fire Probability Model (Distribution) or LFP_D), and additional material provided after our draft comments adds some detail:

> *The distribution wildfire risk model is just one part of PG&E's overall wildfire mitigation program. For example, the company has developed a shorter-term operational model that takes the upcoming weather forecast as its main input and supports the determination of when and where PSPS events will be called. The PSPS model can also help to identify circuit segments that could remain fully powered if appropriate switching hardware is installed or mitigation actions are undertaken.*[8]

Though informative, this text only begins to characterize the ecosystem of risk models used by PG&E. A more complete description comparing the temporal and special data used and for what the models are used would increase transparency and understanding. As part of our learning process our team produced Table 1, which lists the models of which we are aware within the ecosystem along with model resolution, purposes, and links to other models. This table has been populated based on model documentation and conversations with the Distribution Risk Model team. Given the unique expertise required for wildfire

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[7] https://www.naesco.org/data/industryreports/DOE-IEEE_Resilience%20Paper_10-30-2020%20for%20publication.pdf
[8] See "E3 validation response_v0.8.docx" page 1.

modeling and the likely use of wildfire risk scores across many risk models, it may be appropriate to break out the Wildfire Consequence Model in its own row, though we have not done so in this version.

If this list were built out to cover all relevant models, it would help those tasked with oversight to understand PG&E's overall view of wildfire risk and how it anticipates mitigating that risk. The finished list of model purposes would ensure a more complete coverage of key questions with minimized overlap and redundant work. Connections to other models should explain data common to multiple models, ways that outputs of multiple models are compared for results validation, and if any outputs of one model become inputs of another model.

Table 1. PG&E Wildfire Risk Models Comparison

Model	Temporal Resolution	Spatial Resolution	Primary Purpose(s)	Connections to Other Models
Distribution Risk Model	Fire season only, all years combined	100m grid along Distribution circuits in v 2 & 3	**Where:** Prioritize protection zones for fire mitigation on D system **What:** Assess likely effectiveness of mitigations (future model version)	
Transmission Risk Model	Fire season only, all years combined	Transmission structure level	**Where:** Prioritize transmission structure assets for fire mitigation	
Operations (PSPS) Model	Fire season only, 5-7 day outlook rerun 1+ times per day	2km grid, HFTD & HFRA zones	**When:** Determine PSPS calls **Where:** Identify circuits where mitigation could prevent future PSPS	

As we understand, each of these models remains siloed and are in relatively early development stage. As such, connections to or consistency with other models has not been considered and additional discussion of connections among models appears in the more forward-looking roadmap discussion of Section 2.3.

2.1.3 What types of wildfire fire events does the model address and not address?

PG&E's wildfire risk model addresses one specific type of wildfire: those resulting from conductor-involved and/or vegetation-caused ignitions on PG&E's distribution system within High Fire-Threat Districts (HFTDs) 2 and 3 during fire season (June 1 through November 30). This seemingly narrow choice is understandable. It is wise to develop a model first on a manageably small subset of total data before expanding, and modeling rare events benefits from creating a dataset that is densely populated with events. And documentation explains that this selection is less narrow than its description implies, noting that "vegetation and equipment failure caused ignitions … represent 38% and 26% of the grid related ignitions respectively"[9] and reinforcing in additional documentation:

> *The outage type most likely to produce an ignition is a wire down event and the most common cause of wire down events is contact from vegetation. Thus the modeling effort for 2021 was focused on vegetation-caused and conductor-involved ignitions - these are among the most highly environmentally interactive ignition types.*[10]

The existing documentation also details the selection of ignition data from 850 to 240 conductor-involved ignitions and from 470 to 220 vegetation-caused ignitions used in the model.[11] This trimming removes events outside of HFTD 2 and 3 and that occur outside of fire season.

As the Distribution Risk Model grows into a role that more directly supports risk mitigation decisions, it will be useful to understand the limits of the model's reach as defined by questions such as:

- What percentage of total wildfires caused by PG&E equipment fall within the Distribution Risk Model purview?
- What percentage of total wildfires in PG&E territory does this represent?
- And how much could that fraction increase with a given model expansion?

Answers to these questions are minimally important given the narrow scope of the current Distribution Risk Model. However, these questions will soon be needed to assess the model's place beside the other wildfire risk models identified in Section 2.1.2, for understanding the role of distribution system wildfire mitigation, and for prioritizing future model modifications.

2.1.4 What factors motivated key changes from the previous model iteration?

Existing documentation contains a section on "Comparison to previous work" that provides a list of the most important improvements made to the Distribution Risk Model between the 2019 version and the 2021 version. These improvements include changes to statistical and machine learning data/methods, wildfire consequence modeling that better predicts historical destructive wildfires, higher spatial granularity, and calibration of risk scoring to system Multi-Attribute Value Function (MAVF) scores.[12] Following this list, the section compares Receiver Operator Curves (ROCs) based on the 2019 and 2021 models to demonstrate the improved model performance of the 2021 model. The list of model improvements is helpful and the ROC demonstration convincing. However, in the interest of contributing to the model roadmap proposed in Section 2.3, we recommend a more thorough section on changes from version to version and the impact of these changes on results.

This revised section would include commentary on why each item in the list of improvements was thought to require an upgrade. These reasons would connect to less-than-satisfying model results or to items in the roadmap's model development plan. Using an example from the above list of improvements, this

[9] See 2021 Wildfire Risk Model Overview v1.pdf, page 7 of 133.
[10] See "E3 validation response_v0.8.docx" page 1.
[11] See 2021 Wildfire Risk Model Overview v1.pdf, page 14 of 133.
[12] See 2021 Wildfire Risk Model Overview v1.pdf, page 33 of 133.

could be an explanation that calibration to MAVF risk scores allows for comparison between risk results of the Distribution Risk Model and other non-wildfire risks quantified by PG&E.

The revised section would also provide evidence that the enacted improvements accomplished their intended goals. For the above list of improvements, one possible example of evidence would be side-by-side 2019 and 2021 model views of quantified risk for a circuit along which the newer model allows for more targeted mitigation measures due to more granular spatial modeling.

Through conversations with PG&E SMEs, we understand that the modeling team building the 2021 Distribution Risk Model had limited access to the 2019 model, making evaluation of individual model improvements difficult. However, we encourage this practice as the model matures and model improvement choices become more nuanced. Verification such as we describe benefits the modeling team by continuing to test their intuition of the model, and benefits stakeholders by attaching measures of accountability to a model development roadmap.

2.2 Evidence of Predictive Power

We requested PG&E provide evidence to answer three questions related to the model's predictive power:

+ Is the model an improvement over the 2019 model in predicting ignitions?
+ Is the model able to correctly identify PG&E assets at risk?
+ Could the model be useful in helping PG&E target mitigation efforts?

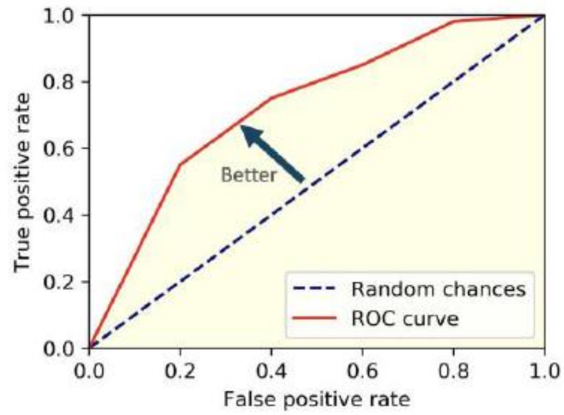
Based on the supplemental documentation PG&E provided, we conclude that the model is an improvement over the 2019 model, that it produces a risk map visually consistent with HFTDs, and that its spatial granularity permits intra-circuit targeting of mitigation measures. In the following subsections, we show the supporting charts and figures provided by PG&E that lead us to these conclusions.

2.2.1 Is the model an improvement over the 2019 model in predicting ignitions?

The predictive power of a binary classification model, such as the 2019 model or MaxEnt, can be shown through ROC curves. ROC curves are standard statistical plots used to illustrate a model's ability to correctly identify binary events (ignition/no-ignition). ROC curves have the true positive rate on the y-axis and the false positive rate on the x-axis. An illustration of an ROC curve is provided in Figure 5. Random guessing will produce a 45-degree dotted diagonal line and an ROC curve that has a high true positive rate (y-axis) for a given false positive rate (x-axis) is better.[13] The shaded portion is the Area Under the Curve (AUC) of the ROC curve. A higher AUC value indicates better predictive power.

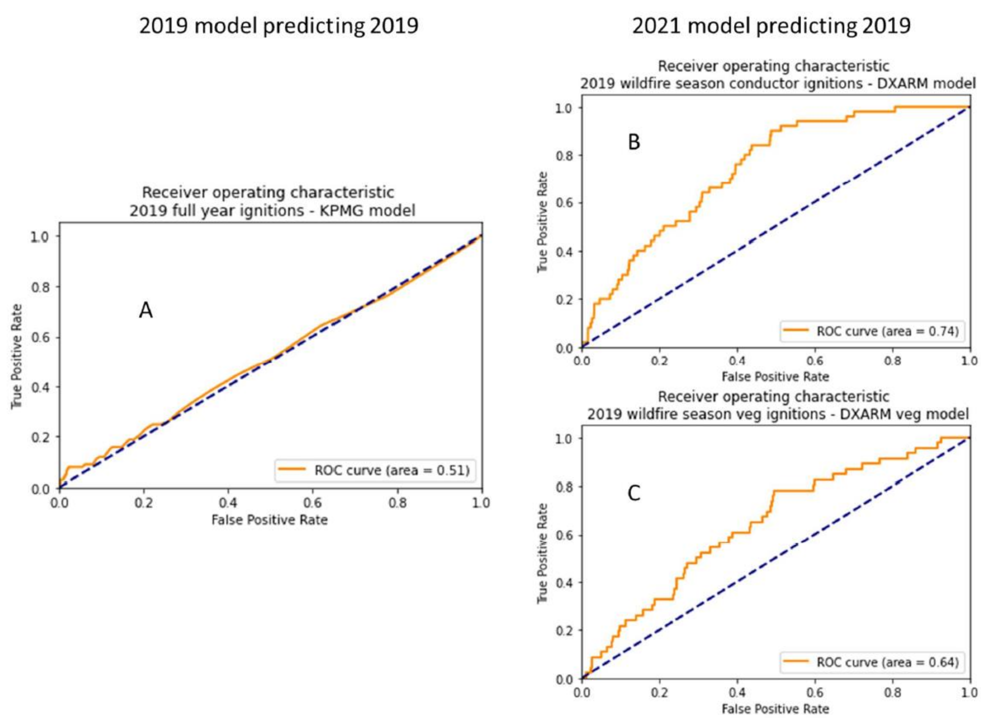
[13] See 2021 Wildfire Risk Model Overview v1.pdf, page 31 of 133.

Figure 5. Illustrative ROC curve



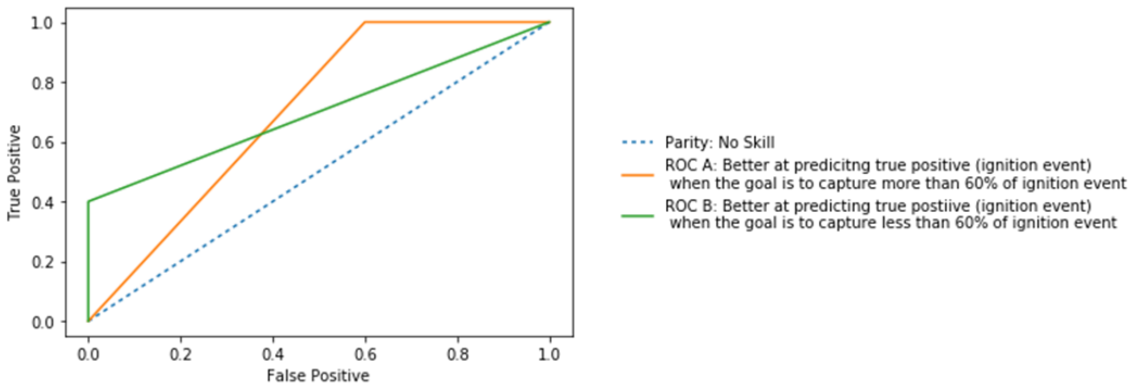
PG&E used the 2019 model to predict ignitions in 2019 and compared it to actual 2019 ignitions (the 2019 ignition dataset was used as an out-of-sample test to evaluate the models' fit). The corresponding ROC curve is shown in orange in the left panel of Figure 6. The AUC value is 0.5, indicating the 2019 model is only as good as a model that randomly guesses. On the right, ROC curves from PG&E's conductor ignition model (right top) and vegetation ignition model (right bottom) are shown. Similar to the 2019 model, both these models were used to predict 2019 ignitions and then compared with actual 2019 ignitions. These models have AUC values of 0.74 and 0.64 respectively indicating they are better than the 2019 model at predicting ignitions.

Figure 6. ROC curves for out-of-sample prediction of 2019 ignition locations, 2021 model (Panel A) vs 2021 Conductor-involved (Panel B) and Vegetation-caused (Panel C)



Despite this, we also point out that the area under curve (AUC) is only part of a larger picture. Two ROCs with the same AUC can look drastically different as shown in Figure 7. For this problem where it is likely that we only mitigated the top few percent of ignition risk first, a curve similar to example B (green line with kink on bottom left-hand corner) would be preferable to one similar to example A, as it would introduce fewer false positives with the same number of true positives.

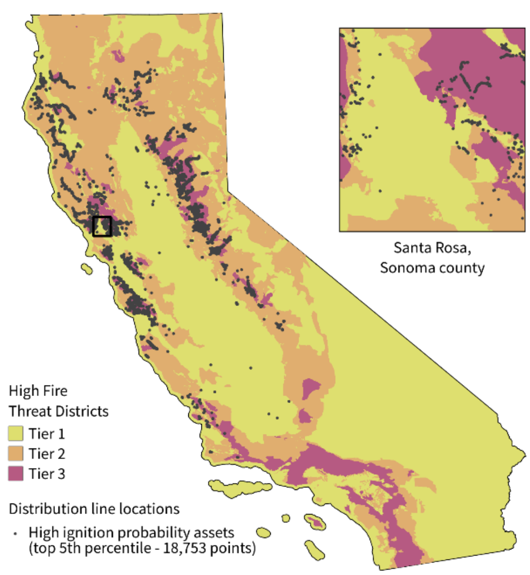
Figure 7 Illustrating how ROC curves with same AUC can have drastically different shapes



2.2.2 Is the model able to correctly identify PG&E assets at risk?

To answer this question, PG&E identified the assets that make up the top 5% of their predicted ignition probability. These are the assets that are predicted by the model to be at high risk of ignition. These assets were then mapped onto California's HFTDs. This map is shown in Figure 8. The high ignition risk assets are shown as black dots. A zoomed in example of Santa Rosa is also shown.

Figure 8. Assets in the top 5% of predicted ignition probability (black dots) and California HFTDs



While some assets that are predicted to be high-risk are identified in Tier 1 HFTDs,[14] the majority of high-risk assets lie in Tiers 2 and 3. Intuitively, we understand that assets in these regions are at high risk of ignition and it is encouraging to see the model confirm this. Accurately predicting ignition locations is important as this might help PG&E's mitigation teams better prioritize areas for deployment.

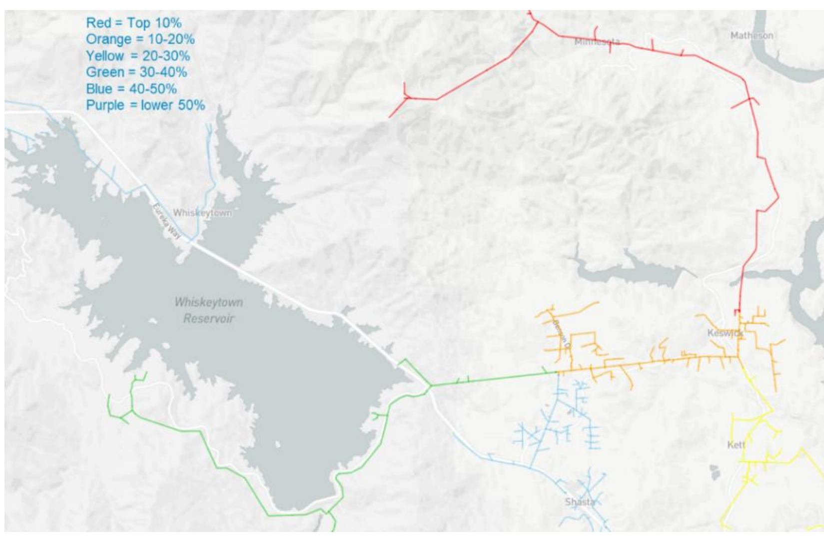
2.2.3 Could the model be useful in helping PG&E target mitigation efforts?

Targeted mitigation efforts require two crucial pieces of data: the asset at risk and the cause of the risk. While knowing the asset at risk helps point to the location the mitigation team needs to be deployed to, the cause of the risk points to the type of mitigation that is needed. For example, branch failure might require one type of mitigation while the presence of large amounts of fuels might require another.

Identifying assets at risk

PG&E provided us with an example of one of their conductors, Keswick 1101, and its predicted wildfire risk. This is shown in Figure 9. The conductor wildfire risk is shown along with risk for each circuit segment. Colors indicate the risk tier of the circuit segments. For example, red indicates that the corresponding circuit segment is in the top 10% of all PG&E assets at risk for wildfire and hence could take precedence over, for example, the blue segments which are at a comparatively lower risk of wildfire, for mitigation deployment.

Figure 9. Conductor risk by circuit segment



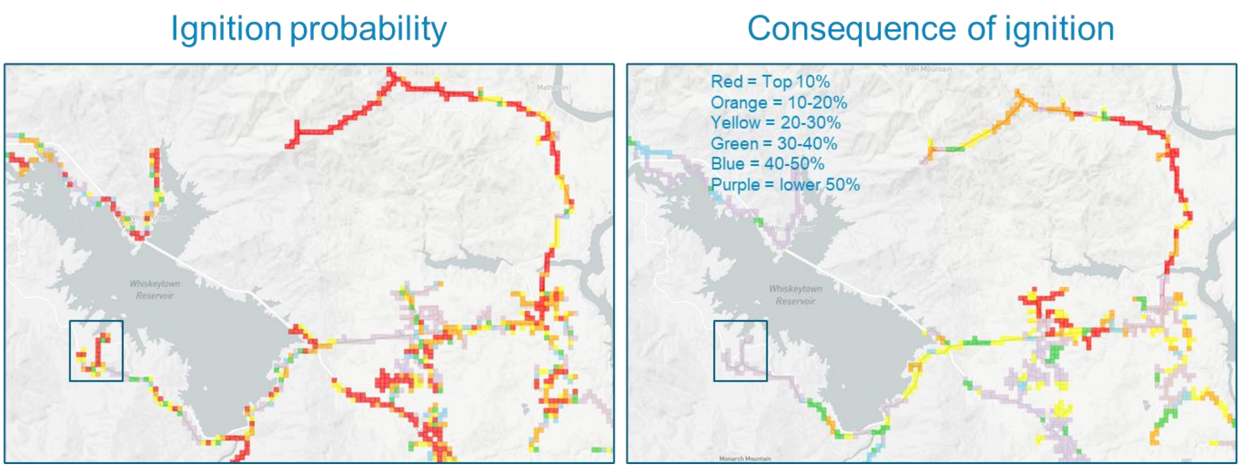
As discussed in Section 3.5.1 this highly granular view of risk was made possible due to the move from Reax to Technosylva fire spread model which allowed PG&E to calculate ignition consequence values at higher resolution.

[14] This indeed might be true and in fact, we consider this a strength of this modeling approach – having the ability to identify high-risk assets outside HFTD Tiers 2 and 3.

Understanding cause of risk

Now that the asset at risk has been identified, the cause needs to be understood so that the appropriate team can be dispatched. Continuing with the Keswick 1101 conductor example from above, PG&E provided us with maps that show the two components that make up the total wildfire risk – Ignition Probability and Consequence of Ignition. Maps showing these individual components for each "pixel" of the asset location are shown below in Figure 10.

Figure 10. Ignition probability and Consequence values



There are some pixels that have a higher probability of ignition, but a lower consequence score and this brings the total risk of that circuit segment down. For example, consider the ignition probabilities and consequence values of the circuit segment in the inset. Now consider the corresponding total risk of that segment as shown in Figure 9. A higher ignition probability does not indicate a higher total risk – this distinction is important because with limited resources, efforts need to be directed towards assets that have the greatest total risk. Pixels in these maps can be examined to understand the drivers behind the total risk – Do tall trees in this location result in a high probability of ignition? Or is it buildings or fuel presence that result in a high consequence score? Understanding these drivers could lead to a more targeted allocation of resources for mitigation.

In summary, given that the model is successful in both identifying the asset at risk and in helping PG&E understand the cause of the risk, we believe that the distribution risk model is useful in helping target mitigation efforts.

2.3 A Risk Modeling Road Map

Existing model documentation includes a list of planned improvements for the next model iteration. These improvements focus on improving predictive power and expanding the model's scope to include the stated goal of enabling line-of-site for risk mitigation initiatives. These improvements focus solely on the model's immediate future while avoiding the consideration of mid- and long-term challenges and opportunities for integration.

We understand that PG&E has not been asked to create a roadmap for model development and acknowledge that one has not been essential in the early stages of model development. The urgency to produce a continuous stream of useful and responsive models is of primary importance, but it is difficult to prioritize among many modeling choices and changes unless the team knows what new questions they are being asked to answer. As such, we believe that roadmap construction may begin with those tasked with oversight. They could consider the entire risk modeling ecosystem and prioritize the questions that they would like to see answered. This first step opens an engagement between modelers and overseers out of which comes a map of planned evolution for the models to make the ecosystem suitable for addressing the questions.

Given the early stages of the modeling process, the lack of a roadmap should not be viewed as a shortcoming so much as an opportunity for growth with future model versions. We view a roadmap as a fundamental component of model design based on its ability to align visions and create accountability.

The most important piece of the proposed roadmap is the list of future questions for the Distribution Risk Model and other wildfire risk models to answer. Clear definition of questions creates alignment of PG&E's modeling team with the rest of the company and external parties regarding model purpose. This purpose guides the model development plan, from data improvements to model upgrades and validation steps. Having an overseer-endorsed list of questions to guide model growth creates transparency for all stakeholders. This clearer delineation of model scope would also curtail the potential for misuse of the model.

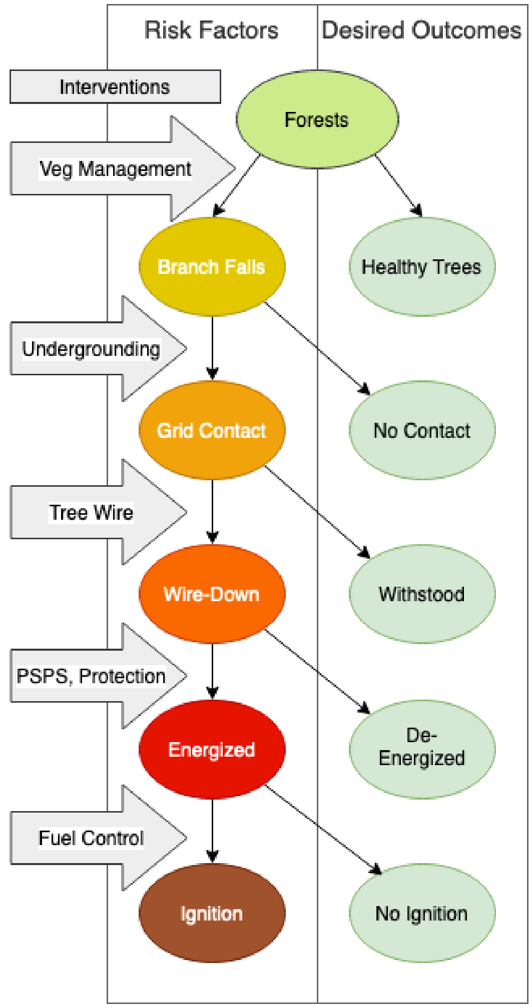
In the first section below, we take a sample guiding question as a test case and walk through how asking this question unfolds a multitude of model development needs. The question is the very next one being asked of the Distribution Risk Model: what are the expected reductions in risk associated with a variety of mitigation measures that could be applied in a given location? After, we note several likely targets for data improvement and model integration with other models/workstreams that should appear in a roadmap in the context of ongoing model maintenance and improvement.

2.3.1 Quantification of Mitigation Measure Impact

As we have stated, the current model is fit for the narrow purpose of determining where on the distribution system PG&E should prioritize wildfire mitigation efforts. Current documentation explains the intention to expand this purpose to include quantification of how different mitigation measures can reduce wildfire risk in a given location. This undertaking is substantial; entailing progress along and coordination between many threads.

Comparison among mitigation tactics requires that a large diversity of possible solutions be placed on similar footing. For example, Figure 11 shows a sample of potential interventions and places each in the sequence from tree contact to fire ignition. Interventions vary widely in longevity, level of effort, area impacted, and inconvenience to customers. Beyond the items shown in the figure, we anticipate a need to evaluate more innovative mitigation measures as well. Comparison among measures carrying such disparate levels of familiarity and types of impact will be a challenging task.

Figure 11. Sample Wildfire Prevention Interventions and Impacts on Risk Factors



A roadmap guides the development on an organized process for this which is curated as a roadmap. Ideally, such process includes identification of new or improved data that is required, engagement with SMEs to work out characterization of various interventions in the model, proposals for small scale testing of novel technologies to better understand their capabilities, and avenues for feedback from data and SMEs to assess actual performance relative to expected. We note that the feedback in the last step may not be quantifiable, due to the rare nature of wildfire events, but encourage some form of assessment. Having this process spelled out benefits PG&E by allowing them to set reasonable expectations for outcomes and timing, and it benefits the CPUC and other parties by providing accountability through a detailed schedule or even predetermined reporting.

There are of course many directions to go for potential mitigation framework but working with the foundation of the ignition probability model, a practical first step is to vary the input feature value for each ignition location and observe how ignition probabilities change with respect to that. This would at least pin down the physical features to tackle such as tree height or location, even though it does not directly raise measures. More involved frameworks such as reinforcement learning[15] can also build on top of current ignition model as a more systematic solution.

Asking this first question opens the door for bigger picture questions as well. Today there is no shortage of high-priority mitigation locations, and it is likely that at least one of the available interventions in a given high risk location will reduce risk appreciably. If the available budget for risk mitigation grows over time as climate change continues to increase risk the models are going to be tasked with calculating net benefits for each proposed mitigation measure. Though this hypothetical time seems far off today, a roadmap could seed an important engagement between utilities and regulators on the topic of eventual standards, supported by analysis of costs and benefits, for wildfire prevention.

2.3.2 Ongoing Model Maintenance and Improvement.

Presentation of a roadmap creates an opportunity to make plan for incremental model improvements and to make explicit linkages with new sources, company experts, and other workstreams. It is reasonable that this integration be deprioritized during early phases of model development, but it should be included as a model matures as a part of regular maintenance and improvement. Here we highlight a number of key areas for model improvement that have not been problematic historically but will have increasing importance in years to come.

- PSPS event calls introduce a disruption into the data set for ignition events – there is no obvious way to determine what ignitions may have occurred if a PSPS event were not called. Data from 2019 and beyond contains these calls, so PG&E needs to determine a method for accommodating new data years that does not implicitly assume several, or an increasing number, of PSPS events every summer.

- The impact of climate change on local and global weather creates a shifting landscape for wildfire risk. Because of this change, use of historical weather in the model may not accurately predict future event hotspots. Also, changing weather means that the existing HFTD map may not always provide an appropriate spatial screen for wildfire risk. PG&E should devise a method to include climate impacts in their input weather data. Given the model's ability to approximately reproduce HFTDs, PG&E and the CPUC may want to consider incorporation of model results into design of future HFTD maps.

- In existing documentation, PG&E notes the availability of LiDAR data on vegetation and their intent to incorporate this data into the next model version.[16] Documentation also notes the use of a tree species overlay to inform develop work plans and a desire to include similar data in future modeling. It would be helpful to create a list of future data improvements, including these and other needs, accompanied by likely sources for the new data, timelines for incorporation into the model, and rationale for the additions.

[15] Sutton, Richard S., and Andrew G. Barto. Reinforcement learning: An introduction. MIT press, 2018.
[16] From 2021 Wildfire Risk Model Overview v1.pdf, page 64 of 133.

- Table 1 and the accompanying discussion in Section 2.1.2 describe the need to connect the Distribution Risk Model to other models in the wildfire risk ecosystem. The roadmap should describe how these models evolve over time to form an integrated family of models with tight coordination to be able to address a broad set of policy, safety, and prudency questions. To this end, the roadmap should identify for all known questions asked of the model ecosystem which model(s) are or will be fit to address them. Furthermore, the roadmap should contain a plan for coordination among the models, from shared inputs and interim results to outputs that benchmark against one another.

- As described in Section 2.1.1, the connection between SMEs and the Distribution Risk Model should be strengthened. The plan for model improvement should contain a path to finding the ideal interaction process between SMEs and wildfire risk models to allow for augmentation of SME knowledge with model results and improved model inputs based on SME expertise.

From our conversations with PG&E's modeling team, we understand that some of these items are already in progress. We would like to see these challenges and others included in a roadmap to improve process transparency.

3 Model Methods Assessment

In this section, we take a closer look the methodology of PG&E's Distribution Risk Model. Specifically, we delve into the two components of risk estimation: probability of event – in this case ignition – and consequence of the event. PG&E models probability of ignition using their MaxEnt model and uses Technosylva's fire simulation model to simulate fire spread and calculate the resulting consequence of ignition.

We first conduct a brief review of contemporary risk estimation practices to highlight how PG&E's methodology compares to that of industry peers. In that review, we find a need for risk modeling choices to be a data-driven process that recognizes the uniqueness of a given utility and their key risk factors.

Bearing in mind the need to make data-driven modeling choices, we explore key decisions in PG&E's event probability modeling. We dedicate subsections to three key questions:

+ Why was a non-standard model such as MaxEnt chosen to model events?
+ Why did PG&E choose to focus on ignitions as opposed to outages?
+ Are modeling simplifications made by PG&E reasonable and data-driven?

Overall, we believe that PG&E has leveraged available data appropriately, allowing it to guide modeling decisions and including the most important physical indicators in the ignition probability model. We come to this conclusion based on interviews with the modeling team and requests for them to provide supporting documentation for the above questions. Without this additional material, we found the lack of data exploration within the original documentation failed to support PG&E's modeling choices.

At the end of this section, we address the consequence component of risk calculation. We offer light commentary on the choice to use Technosylva's fire simulation software but note that review of the simulation approach is outside the scope of this document. We discuss possible complications of PG&E's method to translate simulation results into consequence scores and suggest improvements to this process to reduce sensitivity of key results tied directly to the targeting of mitigation measures were not the result of small changes in assumptions or simulation outcomes.

3.1 Common practices in risk estimation

The general framework PG&E uses to estimate total risk is similar to the other CA Investor Owned Utilities' (IOUs') risk estimation framework – total risk is defined as the product of the Probability of ignition and Consequence of the ignition. As described earlier, MaxEnt is a non-traditional choice to model event probabilities – we deem this divergence reasonable due to the novelty of the problem and the characteristics PG&E's data.

There is a nascent body of literature describing methods to assess risks and the impacts of mitigation measures with respect to grid hardening. For example, Tampa Electric Co. (TECO) characterizes hurricane risk as the product of the probability of a hurricane damaging power equipment structures and the consequence of those damages.[17] The American Petroleum Institute (API) recommends this approach as the U.S. standard for security risk assessments on petroleum and petrochemical facilities.[18] Most of this work focuses on lowering the risk of grid failures in weather related events. What makes PG&E's problem in this application novel and challenging is that risk events have only recently begun to occur with regularity or frequency. This gives rise to the sparsity of rare events data and an extremely skewed balance between risk events and non-events. This data sparsity and imbalance issue drives the choice among suitable models.

Statistical models trained with sparse and imbalanced data is an emerging area in statistics. This emerging nature combines with the magnitude of wildfire damages and alarming growth rate of wildfire frequency to necessitate novel approaches, both in risk modeling and mitigation strategy. Most utilities use qualitative measures of risks; approaches used to rank projects vary to suit utilities' individual circumstances. Quantitative assessment should be no different: a common risk framework is prudent, but exact alignment on approach is unrealistic. Of the California IOUs, PG&E has the largest balancing area, most geographic diversity, and has experienced the most wildfire events. These challenges and increased wildfire data present a unique opportunity to explore novel modeling approaches.

3.2 The choice to use a MaxEnt model

PG&E used a maximum entropy or MaxEnt model to predict the probability of ignition in grid "pixels" of PG&E service territory. MaxEnt is a non-traditional statistical model (compared to models such as logistic regression models or random forests, which are more widely used) and we requested that PG&E present documentation to support this choice. PG&E acknowledged that there were two main factors that drove their decision to choose MaxEnt.

1. Although typical classification models like logistic regression, random forests, or Support Vector Machine (SVM) models can be used to predict the probability of ignition, there is a possibility of over-fitting training data which would require time-intensive modeling work involving what experts call *feature generation and feature selection through regularization*. Additionally, class imbalance in the data would have demanded some form of resampling or weighting. PG&E acknowledged that given enough time, traditional classification models could be adapted to PG&E's specific requirements. However, MaxEnt is a model that already possesses most of the capabilities described above and is well-established albeit only within the ecological modeling community.
2. PG&E chose to only focus on vegetation and conductor involved ignitions for the 2021 wildfire risk model. For the next round of modeling, PG&E has committed to expanding the modeling to include more asset types such as transformers and poles. While MaxEnt is more suitable for

[17] "Tampa Electric's 2020–2029 Storm Protection Plan". 10 Apr. 2020, www.psc.state.fl.us/library/filings/2020/01885-2020/01885-2020.pdf.

[18] Moore, David A. "Security risk assessment methodology for the petroleum and petrochemical industries." *Journal of Loss Prevention in the Process Industries* 26.6 (2013): 1685-1689. Also see, https://www.naesco.org/data/industryreports/DOE-IEEE_Resilience%20Paper_10-30-2020%20for%20publication.pdf for a much broader description of quantitative and qualitative approaches to estimating risk for the purpose of grid hardening.

ignitions involving environmental data such as climate, trees and weather, asset failure-caused ignitions might be better modeled by different algorithms. To this end, PG&E is exploring other models for future work.

Given that MaxEnt is a nonstandard approach used primarily in the ecology field, we use the following sections to present a "lay-man" explanation of MaxEnt, followed by discussion of why maximizing entropy is a reasonable modeling choice for this problem. We compare MaxEnt with more traditional statistical models from a theoretical standpoint, and conclude with observations about the actual MaxEnt results.

3.2.1 Understanding the MaxEnt Ignition Model

The MaxEnt model is trying to identify drivers of ignition events, by comparing the occurrence of these drivers in ignition and non-ignition locations. From this perspective, the MaxEnt model shares similar underlying ideas with other models. Ultimately, a MaxEnt model is a regression model, and it is much closer to linear regression models than a weather-based ignition simulation, for example.

we requested PG&E's modeling team to provide a more layman's explanation of the MaxEnt model. Their response appears in Appendix C. To supplement PG&E's explanation, we provide our own description of the maximum entropy algorithm through the set of questions and brief answers below:

+ What is information entropy?
    - Informational entropy is the amount of information or uncertainty in a system. A roll of the dice has higher entropy than a coin toss since it has six possible outcomes rather than two.
+ How to maximize entropy?
    - A more uniform system would have higher entropy. So, most of the time if you want to maximize entropy, you should make the system more uniform. For example, compare a perfectly balanced coin with a coin that always lands on heads. The second coin has a fixed outcome and thus has no entropy or uncertainty.
+ Why maximize entropy?
    - The reason to maximize entropy is related to making things uniform. If we know nothing about the hypothetical coin, we assume its outcome is 50-50 heads or tails. In the wildfire problem, if we have no strong evidence to suggest humidity suppresses fire, then the model would assume higher humidity has no impact on ignition probability. Essentially, these assumptions are embedded in the approach and provide another way of avoiding over-fitting of the model to a sparce and unbalanced data set.
+ How to maximize entropy in this problem?
    - We must have some constraints to maximize entropy. If we try to maximize entropy with no constraint, the model would always say no variable has any impact, since that would leave us with the largest amount of uncertainty.

+ What are these constraints?

- The constraints are constructed based on augmented input variables that experts call features. For example, first order and second order power of wind speed could be two features. The constraints, without exception, are always bound by the rule that for any feature, its mean in the ignition data over its mean in non-ignition data must be equal to the same ratio calculated from the entire training set. For example, if the mean wind speed in ignition events equals the mean wind speed in non-ignition events, then the model, while maximizing entropy, must make sure that this ratio remains one for all ignition vs non-ignition events.

3.2.2 Comparing MaxEnt with other methodologies

We asked PG&E's modeling team to provide supplemental information on how MaxEnt compares to other models and received Table 2 in response.

Table 2. PG&E's comparison of MaxEnt with other Modeling choices.

	Spatial models			Asset models	
		SVM, kernel machines	Logistic regression, random forest, etc	Logistic regression, random forest, etc.	Arrival process or survival models
Model requirements	MaxEnt	Pixel	Pixel classification	Asset classification	Asset-based
Handles sparse Data	x (regularized fit robust to over-fitting)	x (empirical question)	x (limits number of parameters; risk of over-fitting)	x (limits number of parameters; risk of over-fitting)	Not well
Handles zero inflation	x (filter to grid/HFTD pixels)	x (filter to grid/HFTD pixels)	x (filter to grid/HFTD pixels)	? (trickier than pixels)	? (trickier than pixels)
Handles class imbalance	x (ratio of distributions is presence-only model)	x (bootstrapping or class-specific weights - tougher than presence only)	x (bootstrapping or class-specific weights - tougher than presence only)	? (imbalance is worse for assets)	? (imbalance is worse for assets)
Models assets or fine locations	x	x	x	x	NO
Models time step varying conditions	NO	NO	NO	NO	x
Good with environmental causes	x	x	x	x (environment near asset can be regressors)	x
Good with asset attribute causes	OK	OK	OK	x	x
Robust to uncertainty in locations	x (prevailing conditions define distributions)	x	x (prevailing conditions dominate model fits)	NO	NO
Robust to uncertainty in equipment locations	x	x	x	NO	NO
Provides probability output	x (through tau adjustment)	NO	x	x	x (probability of failure by count)

We agree with PG&E's assessment that many other categories of models excel at spatial modeling. With a combination of the right modeling choice and data engineering, they can all overcome data sparsity, imbalance, and zero inflation issues.

In our view three characteristics of MaxEnt distinguish it from other models: (1) parsimony, (2) strong regularization, and (3) inhomogeneous Poisson Distribution. These distinguishing characteristics should provide the reasoning to choose or reject use of MaxEnt.

Parsimony

MaxEnt is a parsimonious model, which means that it uses few parameters to do its fitting. This parameter reduction tends to increase explain-ability and generalizability; however, it may reduce predictive power. The loss of parameters may also obscure the connection between potential mitigation levers and their impacts as we described earlier.

For each feature created for the MaxEnt model, there would be one constraint, which ends up becoming one parameter in the ending model. Given one hundred features, the MaxEnt model would only have one hundred parameters, compared to what can frequently be thousands of parameters in a random forest approach and sometimes millions in a specialized deep learning neural network. According to PG&E's modeling team, vegetation and conductor ignition model have fewer than one hundred parameters.

The MaxEnt modeling approach has a cost. Statistical models are often straddling the balance between explain-ability and predictive power. More parameters generally lead to more predictive power while reducing explain-ability and sometimes generalizability as well.

A parsimonious model in a low-parameter space is more suitable when there is less data. In the case of PG&E's models, there are roughly 300 ignition events for each problem, which would be a small number to use for characterization of tens of thousands of parameters. The choice of MaxEnt is suitable for the given the small sample size of trainable data.

Another cost is the potential loss in flexibility associated with MaxEnt's parsimony. From what we understand, each input is augmented into roughly six different features. Therefore, the probability distribution conditioned on each input has only six degrees of freedom. More complex models generally provide hundreds if not thousands of degrees of freedom, resulting in more pliable distributions. Too much flexibility may cause an over-representation of gating effects, but six degrees of freedom may be too few to represent continuous effects.

Regularization

Regularization refers to the model's ability to overlook pseudo-patterns and avoid over-fitting on training data. A model with strong regularization generalizes better and is more likely to retain its performance in real life, which we argue is the case for MaxEnt.

MaxEnt's regularization comes from two different aspects: First, it inherently assumes a fixed shape distribution (inhomogeneous Poisson distribution) for every feature. This fixed shape reduces the likelihood that the model will overfit to specific features. Second, adjacent cells must have similar ignition probability. This prevents overfitting to specific events or locations.[19] We believe that the built-in regularization of the MaxEnt model makes it a suitable candidate for this physical problem.

Distribution

From this specific MaxEnt formulation, the optimizer would always give rise to an inhomogeneous Poisson distribution for the ignition probability.[20] It is less important what this distribution exactly is than the very fact that there is a parametrized distribution. Nevertheless, we briefly explain the Poisson distribution for completeness.

It may be reasonable to characterize wildfire as a Poisson process; ignitions follow physical principals, and under certain conditions the probability to catch fire has a constant mean rate of occurrence. However, Poisson processes apply to independent events, whereas wildfire events are dependent: When one location suffers an ignition event, the fire exhausts burnable material, thereby reducing the chances of another even in the near future.

Beyond the suitability of the Poisson distribution specifically, the predefined nature of the ignition distribution may be limiting. For most machine learning models, such as artificial neural networks and random forests, the distributions of results are amorphous and non-parametric.

If the Poisson distribution is an apt representation of ignition events, there are benefits to having a fixed distribution including that the model would generalize well. As time and resources permit in the future, comparison of MaxEnt against an amorphous higher-dimensional machine learning alternative would help indicate the reasonableness of this distribution assumption.

In summary, the theoretical foundation of the MaxEnt model is sound and it appears to be suitable for PG&E’s ignition problem. However, both parsimony and the inhomogeneous Poisson distribution within the MaxEnt model could be as either positive or negative attributes. In the future, we recommend that PG&E provide a comparison between the MaxEnt model and a garden variety machine learning model such as artificial neural network to know with certainty if MaxEnt’s unique properties are working in its favor.

In addition to exploring the statistical properties that show that MaxEnt is suitable to model ignitions, below, we present some modeling results that convince us that MaxEnt is able to capture the physical nature of the ignition problem well.

[19] By coincidence, training data may include a location that has an ignition event abutting a location that does not. This does not necessarily mean the two locations are different; it is more likely a product of pure chance. A model without regularization would try to decipher the difference between these two adjacent locations, which is not desirable.

[20] The Poisson distribution expresses the probability of independent and discreet events occurring over a fixed interval of time when they have a known and constant mean rate of occurrence. The Poisson distribution is often used to model arrival type event, such as arrival of phone call, taxis, or in this case wildfire.

3.2.3 MaxEnt model provides physical and intuitive results

Statistical models often provide good predictive power but suffer from questioning on whether they can capture physical events. Here we show examples in which we find that the MaxEnt model provided intuitive and physical findings that suggest that the model is picking up physical rules of the grid.

Figure 12. Maximum tree height and modeled ignition probability showing parallel in distribution[21]

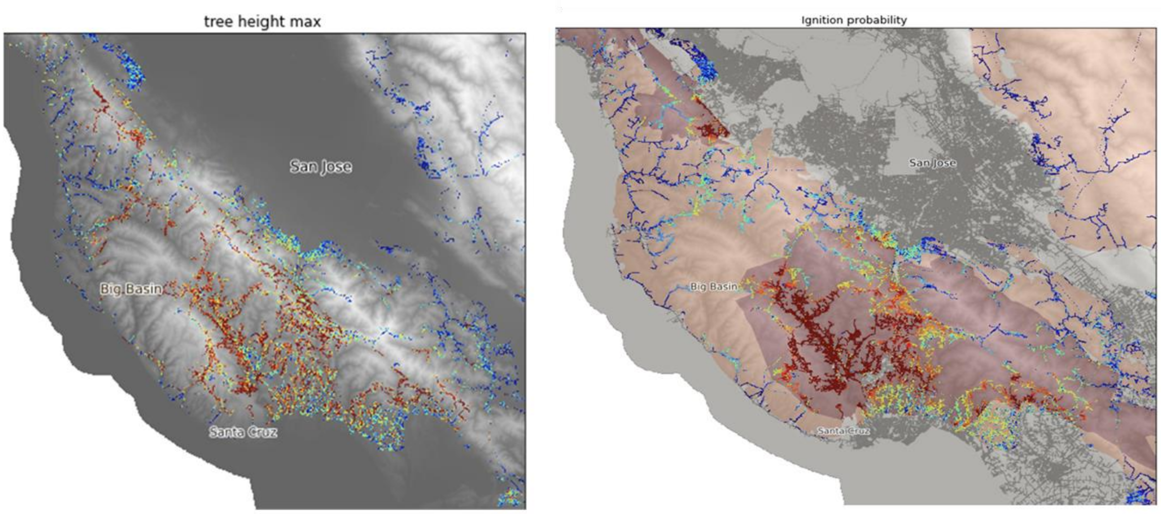
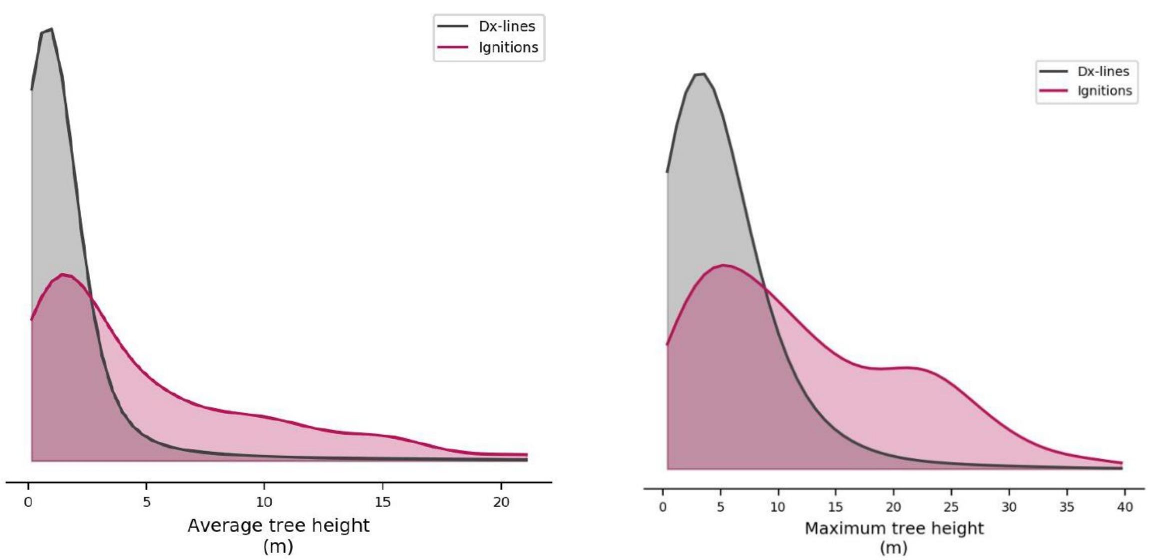


FIGURE 26 - PER-PIXEL MAXIMUM TREE HEIGHT - RED IS HIGHER, BLUE IS LOWER

FIGURE 28 -IGNITION PROBABILITY RESULTS PER PIXEL, RED IS HIGHER, BLUE IS LOWER. GREY LINES ARE GRID-PIXELS OUTSIDE HFTDS, TRANSLUCENT ORANGE AND RED AREAS ARE HFDT TIERS 2 AND 3 RESPECTIVELY.

Figure 13. Ignition and background distributions for average and maximum tree height[22]



[21] From 2021 Wildfire Risk Model Overview v1.pdf, pages 54 and 56 of 133.

[22] From 2021 Wildfire Risk Model Overview v1.pdf, page 112 of 133.

In Figure 12 and Figure 13, we reproduce images from PG&E's documentation that we find especially convincing. Visually, Figure 12 confirms the intuition that tree height directly impacts the ignition probability, specifically that higher tree heights lead to higher ignition risks in PG&E's Santa Cruz, Big Basin areas. Similarly, the surge in ignition probability around 25-meter tree height seen in Figure 13 coincides with the height of most power lines. These examples showcase MaxEnt's ability again to learn physical rules and give us relative confidence that the use of MaxEnt in the Distribution Risk Model allows the model to capture physical and intuitive mechanisms.

3.3 Model training on outages or ignitions

As ignition events are typically associated with outages, one method to predict ignitions is to model a broad set of outages (as opposed to modeling ignitions directly) and then re-scale the results to ignitions. Directly modeling ignitions bypasses the need to model the complex relationships between outages and ignitions, but the smaller ignition dataset raises concern about the statistical power of the models trained on them. If there are too few ignitions to deliver a good model fit, it will fail to accurately predict on out of sample data (new locations, future years, etc.). [23]

After reviewing the wildfire risk model documentation, we requested additional material from PG&E to support their choice to instead model ignitions directly. The supplemental charts and documents we received confirm that, given the availability and quality of data, modeling ignitions directly out-performs modeling outages in PG&E's service territory. Below, we explore this choice in greater detail. Then we provide a brief explanation of data resampling that could improve either an outage- or ignition-based model.

3.3.1 Temporal and spatial distributions of outages and ignitions

Figure 14 shows outages and ignitions within PG&E's HFTDs from 2015. There is poor temporal correlation between outages and ignitions. Most of the outages (blue) occur on storm days (grey bars) while most of the ignitions (red) occur on non-storm days. It can further be seen that outages that involve either vegetation (orange) or conductors (purple) – the ones on which the 2021 wildfire risk model focuses – are poorly correlated with ignitions (red). These conclusions are unsurprising. Winter storms tend to cause outages, but not fires.

While Figure 14 shows the temporal distribution of historical vegetation-caused outages and ignitions, Figure 15 shows their spatial distribution through kernel densities. These charts show the geographic concentration of historical outages and ignitions in each "pixel" of the map. All vegetation caused outages across the year are shown in purple, green indicates the subset of fire season outages, and red shows historical ignitions.

[23] See "E3 validation response_v0.8.docx" page 2.

Figure 14. Chronological events in PG&E service territory from 2015 to 2020. Total outages are shown in blue and ignitions in red. Outages, wire-downs, conductor-, and pole-failures are shown in orange, green, purple, and brown, respectively

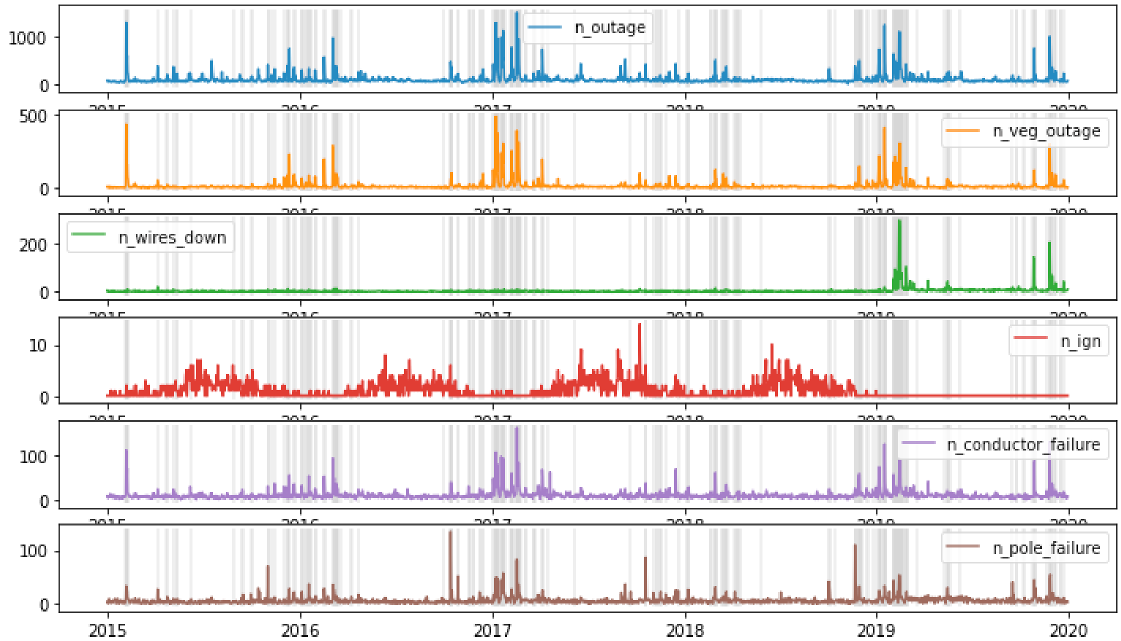
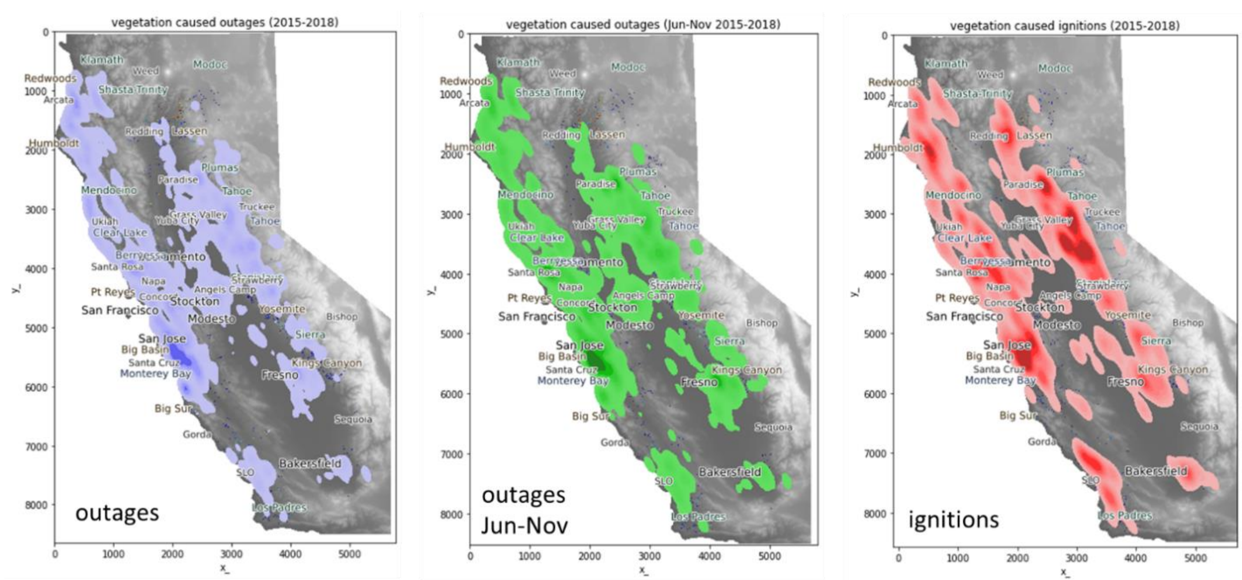


Figure 15. Kernel densities of vegetation-caused outages and ignitions. Left to right: vegetation-caused outages, vegetation-caused outages in summer, and vegetation-caused ignitions.



There is understandably significant overlap between the areas covered by historical vegetation-caused outages and ignitions. While there are some areas that had a greater incidence of both outages and ignitions such as near Big Basin and Santa Cruz, the areas where the greatest number of ignitions are not the same as the areas with the greatest number of outages.

The lack of good correlation between outages and ignitions as evident from the temporal and spatial charts presented above supports PG&E's choice to model ignitions directly. If there was very little data available to statistically model ignitions, outages could be used as a reasonable proxy instead. Based on the initial results presented by PG&E it is reasonable for PG&E to have made the switch from outages to ignitions using a statistical model such as MaxEnt.

3.3.2 Ignition- vs outage-based model performance

In Section 2.2, we presented evidence of the 2021 wildfire distribution model's predictive power. Supplemental documentation provided by PG&E to E3 helped establish that the new model is an improvement over the 2019 model, capable of identifying PG&E assets at risk, and capable of helping PG&E target mitigation efforts.

In this section, we ask if the model's focus on ignitions leads to improved predictive power compared to a model trained on outages. We requested PG&E to present evidence of this comparison, with a focus on two questions:

+ Does an ignition-trained model predict ignitions better than an outage-trained model?
+ Does an ignition-trained model identifying areas at risk for ignition that an outage-trained model fails to identify?

Whether a model is trained on outages or ignitions, its precision can be measured by how well the model predicts ignitions on out of sample data (data not used for training the model: new locations, future years etc.). In response to our request, PG&E conducted new work and provided us with AUC values of two MaxEnt models, trained respectively on 2015-2018 vegetation-caused outages and ignitions and then used to predict vegetation-involved ignitions. These AUC values were calculated by 4-fold cross-validation with 25%/75% train test splits in which 25% of events at random were held for testing. Table 3 shows the AUC values and indicates that the MaxEnt ignition model is slightly better at predicting ignitions than the (best) MaxEnt outage model.

Table 3. AUC values of MaxEnt model trained on outages vs ignitions.

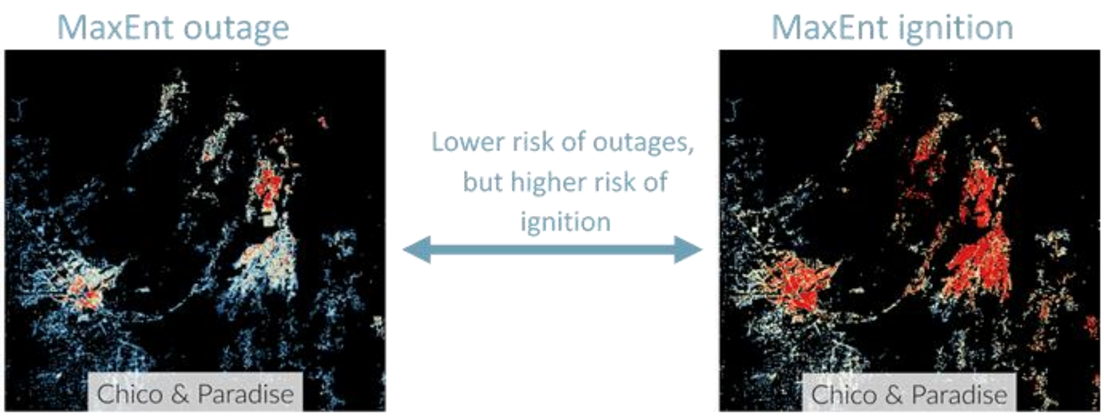
Model	AUC
Vegetation ignitions (Jun-Nov), Best effort outage-based model	0.658
Vegetation ignitions (Jun-Nov), Official ignition-based model	0.684

PG&E also presented evidence that a MaxEnt model trained on ignitions provides different predictions of ignition locations than a MaxEnt model trained on outages. In Figure 16, the MaxEnt model trained on outages (left) identifies risk of outages in Chico & Paradise. On the right, the MaxEnt model trained on ignitions shows a comparatively higher probability of ignition (evidenced by the red color on the right vs the mix of yellow/blue/red on the left). This higher ignition probability prediction aligns with historical events such as the deadly Nov 2018 wildfire that destroyed Paradise and its surrounding areas. In fact, since 1999, there have been 13 large wildfires within the perimeter of the 2018 camp fire which clearly indicates that this region has a higher probability of ignition.[24] Examples such as these, where model prediction is supported by historical data, helps to validate PG&E's choice of modeling ignitions directly.[25]

Combined with a better AUC score for the ignition-based model, this more intuitive result coming from the ignition-based model supports the use of the ignition-based model. This evidence may indicate that predicting ignitions directly provides physically accurate spatial results that are absent from an outage-based model, which is likely overstating ignition probability in areas prone to outage but not ignition.

As previously noted, the decision to model outages or ignitions directly should consider how results will be used in addition to how well the model performs. As PG&E moves to include mitigation measure impacts in the Distribution Risk Model, the more direct connection between mitigation and equipment failure may support use of an outage-based model despite the lower AUC.

Figure 16. Pixel prioritization with MaxEnt trained on outages (left) vs ignitions (right)



3.3.3 Data resampling to improve model performance

As previously discussed, training a model on ignitions (or to a lesser extent outages) means using a sparse and imbalanced data set. While MaxEnt has features to help deal with sparse data, the issue can be addressed more directly through data resampling.

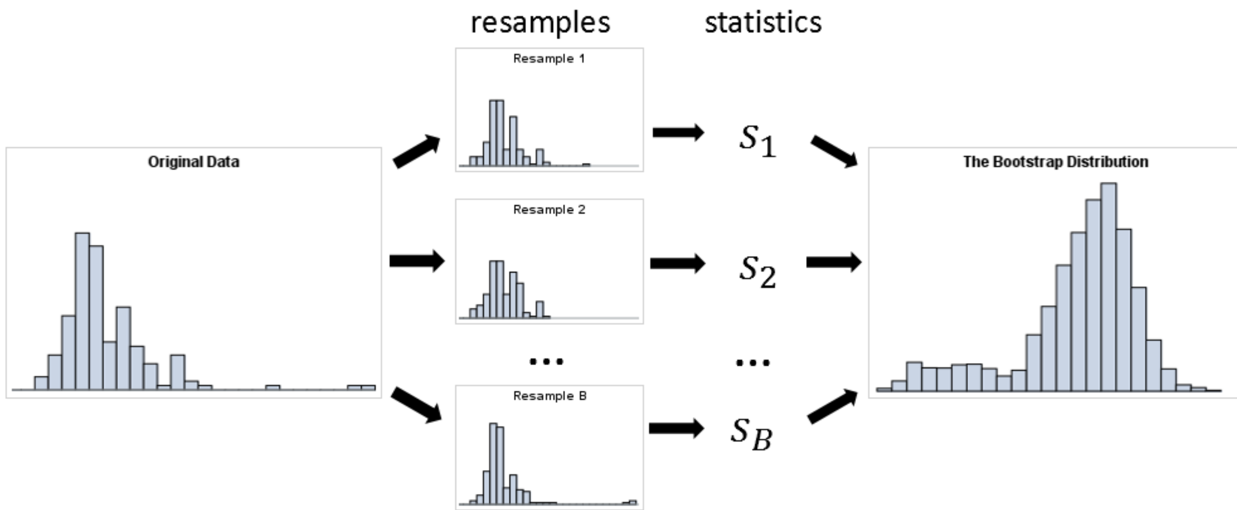
Data resampling here refers to the practice of preparing data for an optimizer such as MaxEnt by resampling. Bootstrapping is one of the simplest and widely used of the resampling method; it can be implemented by redrawing the data points from the original training set uniformly with repetition[26]. For instance, an original data set with samples [1,2] can become [1,1] [1,2] or [2,2].

[24] Gafni, Matthias. "Rebuild Paradise? Since 1999, 13 Large Wildfires Burned in the Footprint of the Camp Fire." The Mercury News, 3 Dec. 2018, www.mercurynews.com/2018/12/02/rebuild-paradise-since-1999-13-large-wildfires-burned-in-the-footprint-of-the-camp-fire/.

[25] The map of PG&E's full service-territory where ignition model differs from outage model predictions is in Appendix C.

26 Davison, Anthony Christopher, and David Victor Hinkley. Bootstrap methods and their application. No. 1. Cambridge university press, 1997.

Figure 17. Graphical illustration of the boot-strapping process.[27]



The benefit to bootstrapping is linked to the pseudo pattern concept. Resampled training data is likely to retain the true pattern, while a pseudo pattern arises through sheer coincidence would likely disappear. Bootstrapping is normally used together with model ensemble techniques, such as creating multiple trained models and using their average ignition probability prediction to be the final answer. As pseudo patterns are a prevalent in scarce data sets, we believe that data resampling and application of a model ensemble could make the model results generalizable across a wider geographic area and ultimately across more risk mitigation solutions.

3.4 Prudency of chosen model simplifications

As we have previous stated, building a model of a physical system requires a series of tradeoffs in which developers value accuracy of their representation against practical concerns such as time to create a model, time to run a model, error introduced through added complexity, data availability, how results will be used, and others. Simpler models are easier to understand and interpret, so a frequent goal is to develop the simplest possible model that can attain a correct enough conclusion.

Here we explore some key simplifications made by the Distribution Risk Model to assess the prudency of these choices. We consider the practical elements that appear to drive each decision and discuss whether these decisions are meaningfully reducing the value of the model and its results. The key choices we isolate are:

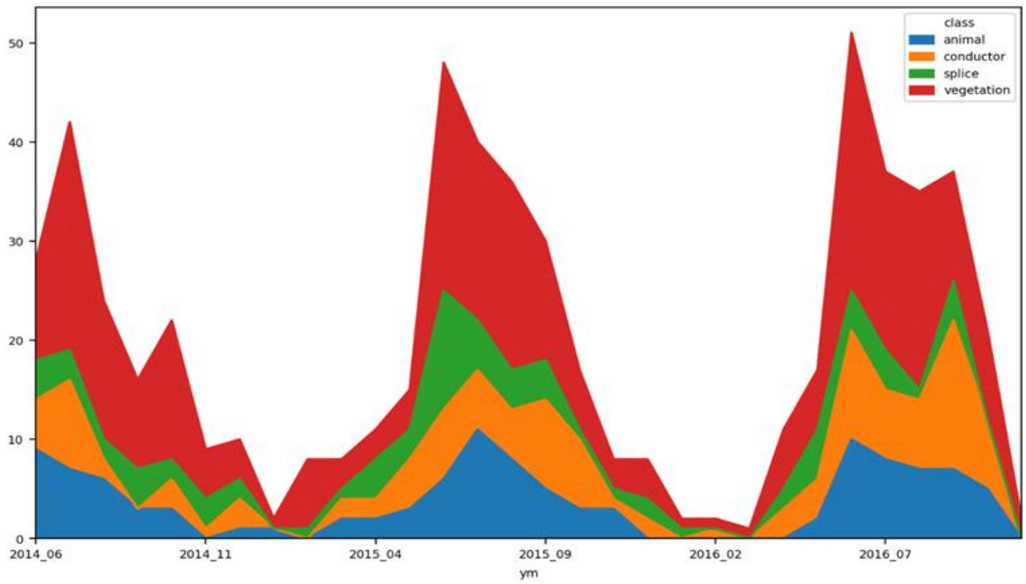
- modeling only ignitions caused by vegetation and conductors
- restricting the model domain to HFTDs during fire season
- removing the temporal dimension from the model
- using feature selection to pare down the number of variables.

[27] https://blogs.sas.com/content/iml/2018/12/12/essential-guide-bootstrapping-sas.html

3.4.1 The choice to model vegetation- and conductors-involved ignitions only

As described in Section 2.1.3, the 2021 wildfire risk model focuses only on vegetation- and conductor-involved ignitions. This choice has clear motivation: wire-down events are likely to produce ignitions and the most common cause of wire-down events is contact from vegetation. Figure 18, obtained from PG&E in response to our draft comments, shows historical number of ignitions by type. For a first pass model looking to capture most events with the fewest causes, a focus on these categories is reasonable.

Figure 18. Historical ignitions (2014-2016) by ignition type.



Worth mentioning is the large overlap between these categories. PG&E notes that "vegetation-caused ignitions involving conductors - wires down in particular - are the vast majority of ignition events used to train both models."[28] The coupled nature of these types of events means that the vegetation and conductor models have similar data needs. This makes the incremental cost low to creating two models instead of one, which also supports the case for focusing first on vegetation and conductor events.

For the next iteration of the Distribution Risk Model, PG&E has described their goal of broadening the breadth and depth of events being considered. They aim to disaggregate probability of ignition within the vegetation model by specific causes such as branch failures versus trunk failures.[29] Beyond vegetation and conductor ignitions, PG&E has also committed to expanding the modeling to include more asset types such as transformers and poles.[30] While MaxEnt is suitable for ignitions involving environmental data such as climate, trees and weather, asset failure-caused ignitions might be better modeled by different algorithms. Exploration of different modeling methods should be conducted for these additional event types.

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[28] From 2021 Wildfire Risk Model Overview v1.pdf, page 35 of 133.
[29] From 2021 Wildfire Risk Model Overview v1.pdf, page 65 of 133.
[30] From 2021 Wildfire Risk Model Overview v1.pdf, page 65 of 133.

3.4.2 The choice to limit the domain to HFTDs during fire season

In the documentation, PG&E pointed out that they further filtered the trainable ignition events to limit them only to the HFTD area and only during the fire season. As noted in Section 2.1.3, this cuts down the conductor and vegetation ignition data sets to under 300 points each that are used to train the model.

This reduced data set is another product of balancing: training on a broader data set might decrease specificity of the model, but it would also allow the model to see more data and become more general.

Equally important to the question of whether training on a larger but potentially more sparse data set improves predictive power is understanding if this limited domain confines model results to be based on too small a region. With climate change shifting weather in time and space, there is likely value in removing constraints on the model domain to allow for risk mitigation prioritization with a wider scope. We understand that PG&E has plans to extend the spatial domain to include all High Fire Risk Areas (HFRAs) but that data availability outside of HFTDs and HFRAs may prevent easy expansion beyond these boundaries.

3.4.3 Collapse of the temporal dimension

PG&E's modeling team noted two fundamental reasons for removing the temporal dimension from the Distribution Risk Model: the model has a long term planning focus and it is difficult to model temporal sequences within the MaxEnt framework.

The first point is consistent with the model's purpose as evaluated in Section 2, and so this modeling simplification is reasonable. For the second point, we recommend that PG&E reconsider the merits of this choice. The original formulation of MaxEnt does not stipulate having no temporal dimension. Having this dimension would suggest unstacking annual ignition and non-ignition events into daily or even hourly resolution. This broader formulation has the potential to introduce more non ignition events into the training data set, but MaxEnt's presence only modeling should still work well.

In fact, introducing the temporal dimension might be a necessity to improve the accuracy in wildfire prediction and ability for this model to interact with the PSPS model. The current formulation cannot incorporate short but intense events. For example, PSPS calls would greatly reduce the ignition probability within a region but only for a very short time period. To properly incorporate this impact, the temporal resolution would allow either incorporation or exclusion of the events from the training data set. With temporal resolution, weather related variables such as wind might gain a more explanatory power. Annual average wind speed contributes little to ignition, but we would expect hourly wind speed would have a larger influence.

3.4.4 The usage of feature selection process

Feature selection is a common process for statistical problems that removes variables or inputs in the hope of making the model more explainable and generalizable, while avoiding causing any decrease in accuracy. The ignition probability model used by PG&E also employed the feature selection process, and in this process, removed several wind-related variables in the conductor involved ignition model.

We agree with the motive behind the feature selection process, however it is important to point out the context that modern machine learning algorithm routinely uses thousands of features without running any feature selection process. The key here is regularization. As described in Section 3.2.2, MaxEnt is a parsimonious and strongly regularized model. Because of this, we do not find the feature selection process to be necessary and imagine its omission would not alter results.

A related topic here is the importance of wind as a feature. Within the automatic variable selection process of the MaxEnt package, several wind-related features were removed in the conduction related ignition model. This seems to imply that wind is inconsequential in the current MaxEnt model, while in fact, wind is consequential but in a less direct form.

In conversation, PG&E correctly pointed out that the wind features explanatory power maybe have been transferred to highly correlated features, such as tree height. Therefore, its importance is not directly visible in the jack-knife plots.[31]

3.5 The Wildfire Consequence Model

The Wildfire Consequence Model produces consequence scores, consistent with the Multi-Attribute Value Function (MAVF) scoring system, which are multiplied by the ignition probabilities at each grid point to calculate risk. Because the consequence scores are unique to locations but not to the distribution system itself, the consequence scores determined by the consequence model could be used across all models in the wildfire risk modeling ecosystem. In fact, we understand that the Transmission Risk Model is now starting to use these scores. For now, though, the consequence model remains housed within the Distribution Risk Model. Due to the scale of consequence values, this component has the single largest impact on the final risk scores.

In spite of the importance of consequence scores to risk scores, our review of the Wildfire Consequence Model is limited. The single most important component of the consequence model is the fire simulation software itself. Review of the Technosylva fire simulation approach was not included in the scope of our review, as this review should only be appropriately performed by forest fire experts. We do offer commentary on the advantages of using Technosylva simulations based on the strengths of the tool described to us in interviews with PG&E's Distribution Risk Model team.

The next most important component of the determination of MAVF wildfire scores, is also out of scope – those scores are determined as a part of the CPUC RAMP proceeding. The consequence model component that remains for our review is the assignment of MAVF scores to fire simulations, which we review below. We also discuss the calibration of risk scores to ensure alignment with the total distribution wildfire risk stated in PG&E's Wildfire Mitigation Plan (WMP).

[31] From 2021 Wildfire Risk Model Overview v1.pdf, pages 32 through 33 of 133.

3.5.1 Technosylva for fire simulation

One of the most significant changes to the Distribution Risk Model from the 2019 version to the current version is the use of fire simulation data from Technosylva instead of REAX. Based on conversations with PG&E's modeling team, we understand this change to be driven primarily by the data available to Technosylva. The data includes fine grain structure density information (as opposed to census block averages) which allows for better spatial resolution. The data also include more up to date fuels characterization that better captures ladder fuels – burnable vegetation that allows a fire to progress in steps from a spark to a large wildfire. Another driving factor in this choice was the emerging consensus among the IOUs to use Technosylva for statewide consistency. The simulation software does not include any representation of fire suppression efforts, which is a potentially impactful but understandable omission – attempts to include this impact would be just as likely to introduce error as add value.

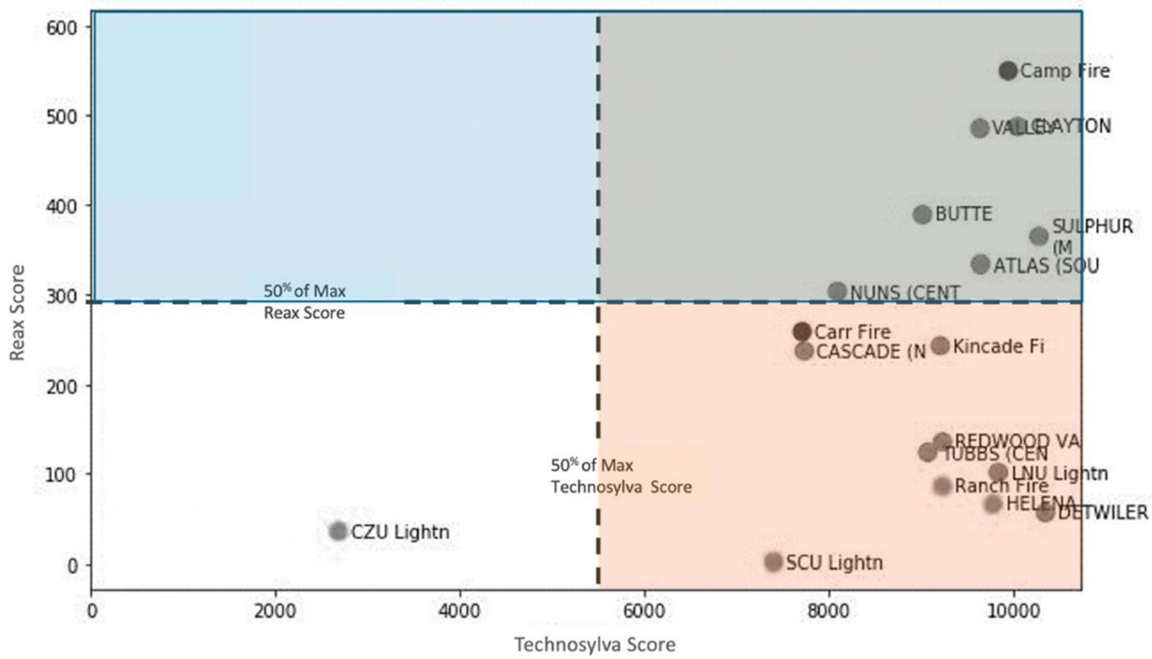
Higher spatial resolution in consequence scoring is an upgrade. Due in part to the consequence ranking method used in the 2019 model version (see Section 3.5.2) and in part to the spatial coarseness of the REAX simulations, the 2019 model version used consequence scores that were uniform within each circuit. With the switch to Technosylva simulations, the model is able to access consequence scores on a 200m grid which are later matched to the 100m ignition probability grid. This upgrade allows for more sophisticated risk prioritization within circuits. As demonstrated by Section 2.2.3, this resolution improves PG&E's ability to target risk mitigation.

We cannot speak with expertise to the importance of ladder fuels in fire simulations, or more broadly to the merits and weaknesses of simulation methods used by REAX and Technosylva. Given the nascency of wildfire simulation, we do expect significant innovation and improvement in the near term. It will be important for PG&E to monitor and incorporate advances in wildfire simulation to keep its risk modeling on the leading edge.

PG&E has noted that statistically significant empirical validation of wildfire simulation is difficult, and so simulation review largely relies on subject matter expert appraisal of model design.[32] However, they do offer a helpful graphic reproduced in Figure 19 to gauge the model's ability to note dangerous conditions in locations of historically dangerous fires. The chart presents the REAX and Technosylva scores for fire simulations in locations of historically destructive fires. A data point's horizontal position indicates how destructive Technosylva scored a fire in that location, while the vertical position indicates how destructive REAX scored a fire in the location. The clustering of points on the right-hand side of the figure is convincing evidence that Technosylva simulations are able to reproduce dangerous fires in areas known to be historically dangerous. We do not believe this to be caused by Technosylva scoring all fires as dangerous – the data we have seen indicate that the vast majority of simulations achieve scores that would fall in the left-hand side of the figure.

[32] See 2020 General Rate Case Phase I Application 18-12-009 Data Response to PubAdv_160-Q03, page 1.

Figure 19. Comparison of REAX and Technosylva scores for notable wildfires[33]



One limitation noted in PG&E's documentation is that Technosylva fire simulations use an 8-hour fire duration, which may understate the consequence of large fires.[34] The rationale for this choice is explained in an email from Technosylva to PG&E. We reproduce the most relevant points of that email here.[35]

- *A standard 8-hour duration is used for all fire spread simulations conducted using historical data (climatology) for WRRM analysis, and also for daily risk forecasting with FireCast*
- *This duration represents a typical first burning period of a fire, consistent with response and suppression efforts.*
- *Based on calibration performed using 30 years of historical fires, and more importantly during the 2020 fire season working with CAL FIRE, the Technosylva fire spread model performs very well matching observed conditions during the first burning period. This also represents a time window where weather prediction is most accurate to observed and expected conditions.*
- *Using a consistent duration, rather than a duration probability based on weather conditions, allows for consistent, comparable, and repeatable results across the entire service territory. Risk scores can be compared despite different fuels and ecosystems.*
- *Generally, it is believed that using a shorter duration, i.e. such as 2-4 hours, does not provide the window of time when fires may escape initial attack and begin to actually*

[33] See 2021 Wildfire Risk Model Overview v1.pdf, page 132 of 133.
[34] See 2021 Wildfire Risk Model Overview v1.pdf, page 133 of 133.
[35] See email "Response to 8-hour simulation duration question" from David Buckley dated 5/12/2021

impact people. Using a duration longer than 8 hours, introduces a small margin of error in the input data.

In addition to these points, the translation from simulation into consequence scores described below includes a mechanism to compensate for the possibility of a simulation being cut off before it has reached its full potential. Specifically, the translation uses fire behavior index – a combination of flame length and rate of spread – as one of the criteria to classify the wildfire's intensity. This allows a fire that has not yet reached its full potential to be classified more severely based on the potential for further spread at the end of the 8-hour simulation.

3.5.2 Translation of fire simulations into consequence scores

The 2019 model version did not translate fire simulation results to MAVF consequence scores. Instead, simulation results were binned into 11 categories. These binned scores allowed for ranking of consequence and risk within the model but disconnected the model's wildfire risk scoring from scoring used to assess risk elsewhere in the utility. The tradeoff of using the MAVF scoring system is that consequence scores vary by four orders of magnitude – this large range in scores gives the consequence values a large impact on total risk. We do not view this large impact as undue but note that there may be times when probability of ignition alone, or consequence alone, is a more useful model output than total risk.

The translation of fire simulations into consequence scores is a simple one: Each simulation is categorized as a *small*, *large*, or *destructive* fire based on the burn area, number of structures destroyed, and the fire burn index. Then a fraction of *destructive* fires is recategorized as *catastrophic* based on a heuristic rule. Finally, MAVF scores are assigned to each category (*catastrophic* ~13,000, *destructive* ~7,000, *large*/*small* ~0).[36] This process repeats for 452 simulations at each location based on the weather conditions from the 452 worst historical fire weather day at the location.[37] The average MAVF consequence score across the 452 scores for each location is carried forward.

To design a complex method of assigning scores to simulations would state false precision, ignoring the large uncertainty present in the output metrics of the fire simulations. We view the simplicity of this scoring method as a necessity but see room for improvement. In conversation, PG&E's modeling team notes that they are working on refining this translation with the help of experts at Technosylva. Hoping to add to this refinement, the following paragraphs suggest improvements to reduce sensitivity to uncertain simulation results and to demystify simulation results.

PG&E observes that fire categorization is sensitive to the parameter values they chose for fire burn index, acres burned, and structures destroyed.[38] Knowing this and considering the uncertainty in simulation outputs, we recommend future versions of PG&E's scoring system should attempt to be more continuous than discrete. This could be done by designing a multidimensional interpolation scheme to bridge

[36] Exact categorical MAVF values vary by HFTD and Red Flag Weather as well, but the variation due to those considerations is insignificant compared to the total score.
[37] This weather day selection process is described in Appendix C
[38] See 2021 Wildfire Risk Model Overview v1.pdf, page 133 of 133.

between the points defining each fire category. This interpolation would reduce sensitivity to the chosen cut-offs between categories by allowing the uncertain simulation results to sit on a gradual spectrum instead of in sharply defined buckets.

Instead of defining the final consequence scores only by the averages at each location, uncertainty bands should be taken from the distribution formed by the 452 scores at each location. This uncertainty would flow through to provide error bars around the risk calculated for each grid point, which provides an additional metric to consider as priority locations are determined. Given the inexact nature of simulation results and the magnitude of their impact, we view the incorporation of this uncertainty as essential. In conversation, the PG&E modeling team has stated their intent to use high, medium, and low scores to capture this uncertainty in the next model version.

Finally, we suggest that in the future PG&E explore ways to demonstrate the importance of key variables used in the fire simulations to build intuition through the connection of simulation results to observable data. In the same way that the vegetation probability of ignition model identifies tree height and other variables to be strong indicators, the wildfire consequence model should identify the variables associated with high consequence. In addition to helping build intuition for those using the model, this output would serve as another checkpoint between model results and SMEs. As an example, it would be intuitive and instructive to see the magnitude and role that windspeed plays in determining fire severity.

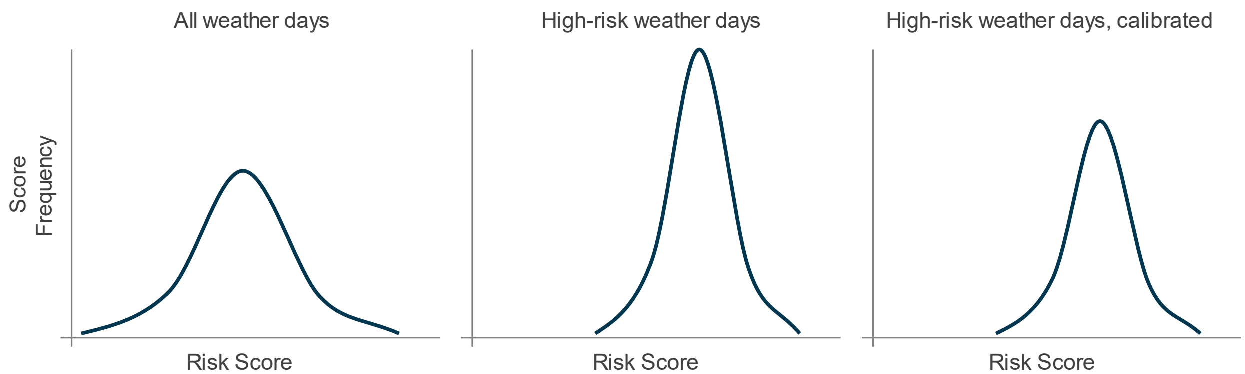
3.5.3 Rescaling of risk scores

PG&E notes that the use of the worst weather days to seed fire simulations results in a total risk across the service territory that is overstated.[39] In conversation, they have told us that simulating a mix of high-risk and low-risk weather days is difficult because the fire simulation software is built specifically for high-risk weather conditions. To make sure that the wildfire risk results are comparable to other risk metrics, the modeling team designed a calibration step that ensures that total risk output by the Distribution Risk Model is equal to the distribution wildfire risk reported in the WMP.

We view this rescaling as an important step. However, there is potential that the process of simulating high-risk days and rescaling creates a distorted distribution of risk across all simulations. We provide an illustrative example of this possibility in Figure 20. The horizontal axes in the figure indicate risk score assigned to a given simulation, and the vertical axes indicate the number of simulations with that risk score. The total risk would be sum of the risk score times the frequency at each point along the curve (mathematically, this would be expressed as $\int x\, f(x)\, dx$).

[39] See 2021 Wildfire Risk Model Overview v1.pdf, page 131 of 133.

Figure 20. Illustrative example of distribution distortion due to oversampling high-risk days



The first panel of the figure shows a theoretical risk distribution produced based on simulations using all weather days. The curve in the second panel is a theoretical distribution produced by only simulating high-risk days. The right-hand boundary of the distribution does not change from the first panel, but the distribution is weighted towards higher risk scores, creating a total risk higher than that of the first panel's distribution. In the third panel, the high-risk distribution has been scaled down to match the total risk of the distribution in the first panel. However, the distribution itself is more compact and weighted towards higher risk than the distribution in panel one.

The example provided by the figure is purely hypothetical. The day selection and risk calibration processes give us reason to believe it is representative of the of the entire distribution, but distortion of the distribution is possible, and the severity of the distortion is unknown. Because the right-hand tail of the distribution is not moved further right (i.e., the distortion does not inflate the severity of risk conditions, only the frequency with which they occur), we do not believe the oversampling of high-risk days is a high priority issue. Ranking of priority zones determined by the model is unlikely to be impacted, and the large magnitude of wildfire consequence means that uncertainty around simulations probably outweighs the possible errors in risk scores due to oversampling. This issue is unlikely to be impacting mitigation targeting in a meaningful way today.

4 Conclusions

Over the course of three months, E3 conducted a review of PG&E's 2021 Wildfire Distribution Risk Model. The review consisted of a high-level assessment of the model's fitness for purpose, evidence, and context as well as a more detailed review of modeling methods. Broadly, we found the model to be fit for the purpose of estimating spatially granular risk from ignitions caused by a subset of PG&E distribution equipment located in high wildfire risk zones.

Our findings are based on a combination of existing model documentation, weekly discussion with PG&E risk modeling team and the incremental evidence that PG&E provided directly to use in response to our questions.

We also note that utility wildfire risk modeling is, by necessity, a rapidly emerging topic ripe for novel approaches but also in need of a model development roadmap to chart the path ahead for future model goals, improvements, and integration with other models and processes at PG&E.

The following bullets restate the most valuable findings from our review:

+ The model is fit for the relatively narrow purpose it was designed for, which was to help focus PG&E's long term mitigation efforts towards reducing the impact of ignitions on customer and societal damages.

  The ecosystem in which PG&E's 2021 Distribution Risk Model is used is important in looking at the future role for this model.

+ There is no industry standard approach that performs well under today's rapidly evolving conditions. Clear evidence of this is the relatively poor performance of PG&E's 2019 version of the Risk model, which was not fit for purpose and the company quickly developed a new model that is more accurate and represents a meaningful step forward in utility risk assessment.

+ The new model improves the 2019 model on several fronts when it comes to predictive power:
  1. It is able to predict ignition locations better;
  2. it is better able to identify PG&E's assets at high risk of ignition;
  3. and, it appears to have the potential to also be more useful in targeting mitigation efforts as experts begin to use it to supplement and expand their mitigation work.

+ The choices to train the ignition probability models directly on ignitions and to use the MaxEnt method are reasonable for the current model's goals. However, this approach is somewhat disconnected from the levers associated with mitigation efforts selected by PG&E experts. We hope to see testing of other model approaches as the purpose of the model expands to ensure that a wide range of solutions are considered for this novel problem. In discussions with PG&E they appear to have similar goals.

+ There is a need to develop a roadmap where the models (Risk, Operations, Expert) work together to address the key questions and make better mitigation decisions consistent with best practices from experts, data, and models. The roadmap should also be guided by future questions for the model ecosystem as determined by those tasked with oversight of PG&E.

We acknowledge this model as an early but critical step in the ongoing development of wildfire risk assessment and mitigation. The model accomplishes its stated goals, but expectations for future model goals have not been clearly set. A roadmap is needed to ensure that planned model developments fit into the long-term aspirations for this model and into PG&E’s larger process for mitigation of all risk. This big picture planning and coordination is necessary to reduce wildfire risk across PG&E’s territory as efficiently and effectively as possible.

Appendices

A. CVs of E3 Team

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ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Managing Partner

Dr. Orans founded Energy and Environmental Economics, Inc. (E3) in 1989. An economist and engineer, he has focused throughout his career on the challenges facing the electricity industry. He is a trusted advisor to a broad range of clients that have included government agencies, utilities, system operators, regulators, independent power producers, energy technology companies, public interest organizations, and investors. He has led E3 teams on numerous high-impact and high-profile projects that have required both rigorous technical analysis and the ability to effectively distill actionable insights to help E3's clients make informed decisions as they develop innovative projects, programs, or policies.

Dr. Orans' pioneering work in utility planning has centered on the design and use of area and time-specific (ATS) marginal costs for both pricing and evaluation of grid infrastructure alternatives. This seminal work has led to detailed area costing applications in pricing, marketing, and planning for many utilities throughout North America. He is an expert in designing wholesale transmission tariffs and has served as an expert witness in regulatory proceedings on retail rate design and wholesale transmission pricing, including for Canada's three largest utilities: BC Hydro, TransEnergie, and Ontario Power Generation.

Dr. Orans provided his expertise to California's energy and environmental regulators in evaluating the operational challenges, feasibility, and cost consequences of a higher Renewables Portfolio Standard (RPS) in California by 2030.[1] Additionally, in consultation with advisors to California's Governor and principals and staff from the energy agencies and the CAISO, Dr. Orans and E3 staff developed a set of technology deployment scenarios that meet California's goal of reducing greenhouse gas (GHG) emissions to 80 percent below 1990 levels by 2050.[2] This analysis leveraged E3's California PATHWAYS model, an economy-wide, infrastructure-based GHG and cost analysis tool that captures interactions among the buildings, industry, transportation, and electricity sectors in a low-carbon future.

Dr. Orans has also guided E3's national deep decarbonization analysis, most notably in the influential report *Pathways to Deep Decarbonization in the United States*.[3] Co-authored with Lawrence Berkeley National Laboratory (LBNL) and Pacific Northwest National Laboratory (PNNL), its principal finding is that multiple pathways exist to achieving deep decarbonization by midcentury at manageable cost. The report was published for the Deep Decarbonization Pathways Project (DDPP), an initiative led by the United Nations Sustainable Development Solutions Network (SDSN) and the Institute for Sustainable Development and International Relations (IDDRI) to explore how countries can transform their energy systems by 2050 to achieve needed greenhouse gas reductions. These models continued to be used by

[1] https://www.ethree.com/projects/modeling-californias-50-percent-renewables-portfolio-standard/ and subsequent analysis of the decarbonization pathways sponsored by California's state agencies.
[2] https://ethree.com/public_projects/energy_principals_study.php
[3] http://unsdsn.org/wp-content/uploads/2014/09/US_DDPP_Report_Final.pdf

leading jurisdictions in Hawaii, New York, California and Minnesota to facilitate the transition to clean energy.

Dr. Orans is a respected thought leader who is often asked to share his expertise and vision for the energy industry. He regularly publishes in refereed journals and has twice taught a graduate course on electric utility planning at Stanford University and continues to give guest lectures. He received his Ph.D. in Civil Engineering from Stanford University and his B.A. in Economics from the University of California at Berkeley.

DEPARTMENT OF ENERGY Washington, DC
Lead Consultant 1989 – 1990
Dr. Orans was the lead consultant on a cooperative research and development project with the People's Republic of China. The final product was a book on lessons learned from electric utility costing and planning in the United States.

ELECTRIC POWER RESEARCH INSTITUTE Palo Alto, CA
Consultant 1987 – 1989

Dr. Orans developed the first formal economic model capable of integrating DSM into a transmission and distribution plan; the case study plan was used by PG&E for a $16 million pilot project that was featured on national television and the approach and method was published by EPRI and used by several leading utilities to integrate efficiency and other distributed resources into their distribution planning processes.

PACIFIC GAS & ELECTRIC COMPANY San Francisco, CA
Research and Development Department 1984 – 1991

Dr. Orans's first application of his targeted evaluation approach shows that targeted, circuit-specific, localized generation packages or targeted DSM can in some cases be less costly than larger generation alternatives. PG&E used the new approach to develop a 500kW photovoltaic (PV) facility at their Kerman substation. This is the only PV plant ever designed to defer the need for distribution capacity.

Corporate Planning Department *1986-1992*

Dr. Orans was the lead consultant on a joint EPRI and PG&E research project to develop geographic differences in PG&E's cost-of-service for use in the evaluation of capital projects. The approach was filed and adopted by the California Public Utilities commission. He also designed and implemented the first version of the shared savings DSM incentive mechanism that was ultimately used for all investor owned utilities in California and is still used today**.**

Rate Department Economist *1981-1985*

As an economist at PG&E, Dr. Orans was responsible for the technical quality of testimony for all electric rate design filings. He was also responsible for research on customers' behavioral response to conservation and load management programs. The research led to the design and implementation of the first and largest residential time-of-use program in California and a variety of innovative pricing and DSM programs.

Education

Stanford University — Palo Alto, CA
Ph.D., Civil Engineering

Stanford University — Palo Alto, CA
M.S., Civil Engineering

University of California — Berkeley, CA
B.A., Economics

Citizenship

United States

Refereed Papers

1. *Orans, R., F. Kahrl, and D. Aas (2017) "Envisioning the Electric Utility in 2030: 'Fat' or 'Skinny'?" Public Utility Fortnightly, March 2017.*

2. *Li, M., R. Orans, J. Kahn-Lang and C.K. Woo (2014) "Are Residential Customers Price-responsive to an Inclining Block Rate? Evidence from British Columbia, Canada," The Electricity Journal, 27(1), 85-92.*

3. *Orans, R., A. Olson, J. Moore, J. Hargreaves, R. Jones, G. Kwok, F. Kahrl and C.K. Woo (2013) "Energy Imbalance Market Benefits in the West: A Case Study of PacifiCorp and CAISO," The Electricity Journal, 26(5), 26-36.*

4. *Woo, C.K., I. Horowitz, B. Horii, R. Orans, and J. Zarnikau (2012) "Blowing in the wind: Vanishing payoffs of a tolling agreement for natural-gas-fired generation of electricity in Texas," The Energy Journal, 33:1, 207-229.*

5. *Mahone, A., B. Haley, R. Orans, J. Williams (2011) "Electric Vehicles and Gas-Fired Power: A Strategic Approach to Mitigating Rate Increases and Greenhouse Price Risk," Public Utilities Fortnightly (Dec 2011) 42-50, available at: http://www.fortnightly.com/exclusive.cfm?o_id=918*

6. *Alagappan, L., R. Orans, and C.K. Woo (2011) "What Drives Renewable Energy Development?" Energy Policy, 39: 5099-5104.*

7. *R. Orans, F. Pearl, A. Mahone (2010) "A Modest Proposal: After Cap and Trade," Brookings Institute.*

8. *Orans, R., C.K. Woo, B. Horii, M. Chait and A. DeBenedictis (2010) "Electricity Pricing for Conservation and Load Shifting," Electricity Journal, 23:3, 7-14.*

9. *Olson A., R. Orans, D. Allen, J. Moore, and C.K. Woo (2009) "Renewable Portfolio Standards, Greenhouse Gas Reduction, and Long-line Transmission Investments in the WECC," Electricity Journal, 22:9, 38-46*

10. *Orans, R., M. King, C.K. Woo and W. Morrow (2009) "Inclining for the Climate: GHG Reduction via Residential Electricity Ratemaking," Public Utilities Fortnightly, 147:5, 40-45.*

11. *Woo, C.K., E. Kollman, R. Orans, S. Price and B. Horii (2008) "Now that California Has AMI, What Can the State Do with It?" Energy Policy, 36, 1366-74.*

12. *Orans, R., S. Price, J. Williams, C.K. Woo and J. Moore (2007) "A Northern California - British Columbia Partnership for Renewable Energy" Energy Policy, 35:8, 3979-3983.*

13. *Lusztig, C., P. Feldberg, R. Orans and A. Olson (2006) "A Survey of Transmission Tariffs in North America," Energy - The International Journal, 31, 1017-1039.*

14. *Woo, C.K., A. Olson and R. Orans (2004) "Benchmarking the Price Reasonableness of an Electricity Tolling Agreement," Electricity Journal, 17:5, 65-75.*

15. *Orans, R., Woo, C.K., Clayton, W. (2004) "Benchmarking the Price Reasonableness of a Long-Term Electricity Contract," Energy Law Journal, 25: 2, 357-383.*

16. *Orans, R., Olson, A., Opatrny, C. (2003) "Market Power Mitigation and Energy Limited Resources," Electricity Journal, 16:2, 20-31.*

17. *Woo, C.K., D. Lloyd-Zannetti, R. Orans, B. Horii and G. Heffner (1995) "Marginal Capacity Costs of Electricity Distribution and Demand for Distributed Generation," The Energy Journal, 16:2, 111-130.*

18. *Pupp, R., C.K. Woo, R. Orans, B. Horii, and G. Heffner (1995) "Load Research and Integrated Local T&D Planning," Energy - The International Journal, 20:2, 89-94.*

19. *Chow, R.F., Horii, B., Orans, R. et. al. (1995) "Local Integrated Resource Planning of a Large Load Supply System," Canadian Electrical Association.*

20. *Feinstein, C., Orans, R. (1995) "The Distributed Utility Concept," The Annual Energy Review.*

21. *Woo, C.K., R. Orans, B. Horii and P. Chow (1995) "Pareto-Superior Time-of-Use Rate Options for Industrial Firms," Economics Letters, 49, 267-272.*

22. *Woo, C.K., B. Hobbs, Orans, R. Pupp and B. Horii (1994) "Emission Costs, Customer Bypass and Efficient Pricing of Electricity," Energy Journal, 15:3, 43-54.*

23. *Orans, R., C.K. Woo, R. Pupp and I. Horowitz (1994) "Demand Side Management and Electric Power Exchange," Resource and Energy Economics, 16, 243-254.*

24. *Woo, C.K., R. Orans, B. Horii, R. Pupp and G. Heffner (1994) "Area- and Time-Specific Marginal Capacity Costs of Electricity Distribution," Energy - The International Journal, 19:12, 1213-1218.*

25. *Orans, R., C.K. Woo and B. Horii (1994) "Targeting Demand Side Management for Electricity Transmission and Distribution Benefits," Managerial and Decision Economics, 15, 169-175.*

26. *Orans, R., C.K. Woo and R.L. Pupp (1994) "Demand Side Management and Electric Power Exchange," Energy - The International Journal, 19:1, 63-66.*

27. *Orans, R., Seeto, D., and Fairchild, W., (1985) "The Evolution of TOU Rates," Pergamon Press.*

Research Reports

1. *R. Orans, Woo, C.K., L. Alagappan, M. Madrigal, Creating Renewable Energy-Ready Transmission Networks, World Bank, September 2010*

2. *CPUC Staff, Olson, A., Orans. R., 33% Renewables Portfolio Standard Implementation Analysis Preliminary Results, California, June 2009.*

3. *Orans, R., Olson, A., Load-Resource Balance in the Western Interconnection: Towards 2020, Western Electricity Industry Leaders Group, September 2008.*

4. *Orans, R., Olson, A., Integrated Resource Plan for Lower Valley Energy, December 2004.*

5. *Orans, R., Woo C.K., and Olson, A., Stepped Rates Report, prepared for BC Hydro and filed with the BCUC, May 2003.*

6. *Woo, C.K. and R. Orans (1996) Transmission: Spot Price, Reliability Differentiation and Investment, report submitted to Ontario Hydro.*

7. *Orans, R., Woo, C.K., and B. Horii (1995) Impact of Market Structure and Pricing Options on Customers' Bills, Report submitted to B.C. Hydro.*

8. *Horii, B., Orans, R., Woo, C.K. (1994) Marginal Cost Disaggregation Study, Report submitted to PSI Energy.*

9. *Woo, C.K., L. Woo and R. Orans (1995) Rationing and Area-Specific Generation Costs, Report submitted to Pacific Gas and Electric Company.*

10. *Orans, R., Woo, C.K., and C. Greenwell (1994) Designing Profitable Rate Options Using Area - and Time-Specific Costs, Report No. TR-104375, Electric Power Research Institute.*

11. *Singer, J., Orans, R., Energy Efficiency Lending, A Business Opportunity for Fannie Mae, Report submitted to Fannie Mae.*

12. *Orans, R., Feinstein, C., et. al. (1993) Distributed Utility Valuation Study, submitted to the Electric Power Research Institute, the National Renewable Energy Laboratory, and PG&E.*

13. *Orans, R., Pupp, R. (1993) Menomonee Falls Case Study, Submitted to Wisconsin Electric Power Corporation.*

14. *Orans, R. and C.K. Woo (1992) Marginal Cost Disaggregation Study, Report submitted to Wisconsin Electric Power Corporation.*

15. *Orans, R., C.K. Woo, J.N. Swisher, B. Wiersma and B. Horii (1992) Targeting DSM for Transmission and Distribution Benefits: A Case Study of PG&E's Delta District, Report No. TR-100487, Electric Power Research Institute.*

16. *Orans, R., Swisher, J., Duane, T. (1989) Lessons Learned from U.S. Electric Utilities, Prepared for the Department of Energy for the People's Republic of China.*

17. *Orans, R. (1989) Area-Specific Marginal Costing for Electric Utilities: A Case Study of Transmission and Distribution Costs, Ph.D. Thesis, Stanford University.*

18. *Orans, R. (1987) The Risk of Sales Forecasts: Controllable through Indexation and Careful Disaggregation, Submitted to Stanford University and Pacific Gas and Electric Company.*

19. *C.K. Woo and R. Orans (1983) Transferability of Other Utilities' Time of Use Experiments to PG&E's Service Schedule D-7, Pacific Gas and Electric Company Reports filed with the California Public Utilities Commission.*

Conference Papers

1. *Orans, R. (2011) "Getting to 2050, Pathways to Deep Reductions in GHG Emissions," CFA Society Presentation, San Francisco, CA, October 25, 2011.*

2. *Orans, R. (2010) "Renewable Resource Opportunities in the West," Law Seminars International, British Columbia, August 2010.*

3. *Orans, R. (2009) "California's 33% RPS Implementation Plan," Law Seminars International, San Francisco, September 2009.*

4. *Orans, R. (2009) "Comparable Treatment of Resource Options," FERC Technical Conference, Phoenix, AZ, September 2009.*

5. *Orans, R. (2008) "A GHG Compliant World in 2050," Law Seminars International, San Francisco, CA, September 2008.*

6. *Orans, R. (2007) "Gaps in State Energy Policy Coordination: A View from the Cheap Seats," CFEE, Napa, California, September 2007.*

7. *Orans, R. (2004) "Evaluating Generating Resources based on an Equivalent Reliability Methodology," 2nd Annual Resource Planning Symposium, January 2004, Vancouver, Canada.*

8. *Martin, J., Orans, R., Knapp, K. (2000) "DG Economics and Distribution Rate Design," Western Electric Power Institute, Distributed Generation and the Utility Distribution System Conference, Reno, NV, March 22-23, 2000.*

9. *Orans, R. (1997) "Getting the Transmission Prices Right," Facilitating Cross Border Trade, New Mexico.*

10. *Orans, R. (1997) "Deregulation on the Mainland: What is Happening and What is Not," PCEA Conference, Hawaii.*

11. *Swisher, J., Orans, R. (1995) "A New Utility DSM Strategy Using Intensive Campaigns Based on Area Specific Costs," ECEEE 1995 Summer Study.*

12. *Orans, R., Greenwell, C. (1995) "Designing Profitable Rate Options Using Area and Time-Specific Costs," Prepared for EPRI, Annual DSM Review, Dallas, Texas.*

13. *Orans, R. (1995) "Integrated Local Area Planning," Prepared for NELPA and presented in Calgary.*

14. *Orans, R. "Local Area Planning for Profit: Annual Review of Distributed Resource Studies," Prepared for EPRI, Lake George, New York.*

15. *Orans, R., C.K. Woo, B. Horii and R. Pupp (1994) "Estimation and Applications of Area- and Time-Specific Marginal Capacity Costs," Proceedings: 1994 Innovative Electricity Pricing, (February 9-11, Tampa, Florida) Electric Research Power Institute, Report TR-103629, 306-315.*

16. *Heffner, G., R. Orans, C.K. Woo, B. Horii and R. Pupp (1993) "Estimating Area Load and DSM Impact by Customer Class and End-Use," Western Load Research Association Conference, September 22-24, San Diego, California; and Electric Power Research Institute CEED Conference, October 27-29, St. Louis, Missouri.*

Andrew DeBenedictis, Ph.D.

One Broadway, 14th Floor, Cambridge, MA 02142 617.203.7689
andrew@ethree.com

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Director

Dr. DeBenedictis rejoined E3 in 2018. He works in E3's Boston office, where he helps clients in New England and elsewhere work towards a cleaner, more efficient energy sector. A member of E3's DER team, Dr. DeBenedictis helps clients develop grid modernization plans, including cost benefit analyses and business cases for investments, to accommodate the challenges of a two-way decarbonized grid. He also uses E3's extensive modeling capabilities to analyze the potential for and impacts of building electrification, including likely technology uptake given customer economics under a range of policy mechanisms including incentives and mandates.

Outside of the DER team, he enjoys working with clients to formulate broad decarbonization strategies through many avenues. Examples include Clean Energy Standards (CESs) designed to meet state carbon reduction targets, Performance Incentive Mechanisms (PIMs) to promote cross-sectoral decarbonization, and Integrated Resource Plans (IRPs) that balance clean energy, reliability, and affordability goals to plan utility investments.

Dr. DeBenedictis originally worked at E3 for five years before attending graduate school. During that time, he contributed to E3's landmark study, published in the journal *Science,* that analyzed the technology path to deep decarbonization by 2050. He also helped the California Public Utilities Commission develop a successor to its net energy metering (NEM) tariffs, helped to design a robust resource adequacy modeling platform, and conducted extensive rate design analysis for large commercial and industrial customers.

Dr. DeBenedictis received a Ph.D. and M.S. in Physics from Tufts University, and a B.A. in Physics and Astronomy from Bowdoin College.

PHYSICS AND ASTRONOMY DEPARTMENT Medford, MA
Tufts University – Research Assistant 2013 – 2018

- Developed Mathematica-based finite element model with adaptive moving mesh to solve shape/field coevolution problems
- Created C-based finite difference model to investigate liquid crystal behavior between patterned substrates
- Shared research findings through presentations and posters at more than 10 conferences
- Collaborated on research with peers and faculty from Tufts University Department of Mathematics, UNSW Chemical Engineering, UC Merced Department of Physics, UPenn Materials Science and Engineering, and Sheffield Hallam University Materials and Engineering Research Institute

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. (E3) San Francisco, CA

Consultant 2008 – 2013

- Supported projects involving resource planning, rate design, cost-effectiveness evaluation, and modeling future emissions scenarios
- Designed several quantitative models utilized in public proceedings and for utility planning
- Managed projects totaling over $1 million in contracted funds
- Clients included British Columbia Hydro (BCH), the California Public Utilities Commission (CPUC), the California Independent Systems Operator (CAISO), Lower Valley Energy (LVE), Pacific Northwest Generating Cooperative (PNGC), and Lawrence Berkeley National Laboratory (LBNL)

PHYSICS AND ASTRONOMY DEPARTMENT Brunswick, ME
Bowdoin College – Research Assistant 2007 – 2008

- Created Mathematica computer programs to calculate parameters for and investigate various string theory configurations

RESEARCH EXPERIENCE FOR UNDERGRADUATES (REU) East Lansing, MI
Michigan State University – Research Assistant Summer 2007

- Built FORTRAN computer program to model bulk-heterojunction polymer solar cells to optimize cell efficiency

Education

Tufts University Medford, MA
Ph.D., Physics 2018
Burlingame Fellowship 2017

Tufts University Medford, MA
M.S., Physics 2015
Provost Fellowship 2013 – 2015

Bowdoin College Brunswick, ME
B.A., Physics and Astronomy (Highest Honors) 2008
Sarah and James Bowdoin Scholar (Dean's List) 2004 – 2005, 2005 – 2006, 2007 – 2008

Selected Publications

- Xia Y., **DeBenedictis A.**, Kim D.S., Chen S., Kim S.U., Cleaver D.J., Atherton T.J., Yang, S. *Programming emergent symmetries with saddle-splay elasticity*. Nature Communications (2019), 10, 5104
- **DeBenedictis A.**, Rodarte A.L., Hirst L.S., Atherton T.J. *Modeling deformation and chaining of flexible shells in a nematic solvent with finite elements on an adaptive moving mesh*. Physical Review E (2018), 97:3, 032701.

- Dahiya, P., **DeBenedictis A.**, Atherton T.J., Caggioni, M., Prescott, S.W., Harteld, R.W., Spicer, P.T. *Arrested coalescence of viscoelastic droplets: triplet shape and restructuring*. Soft Matter (2017), 13, 2686-2697.
- **DeBenedictis A.**, Atherton T.J. *Shape minimisation problems in liquid crystals*. Liquid Crystals (2016), 43:13, 2352-2362.
- **DeBenedictis A.**, Anquetil-Deck C., Cleaver D.J., Emerson D.B., Wolak M., Adler J.H., Atherton T.J. *Competition of lattice and basis for alignment of nematic liquid crystals*. Physical Review E (2015), 92:4, 042501.
- **DeBenedictis A.**, Haley B., Woo C.K., Cutter E. *Operational energy-efficiency improvement of municipal water pumping in California.* Energy (2013), 53:5, 237-243.
- Williams J., **DeBenedictis A.**, Ghanadan R., Mahone A., Moore J., Morrow W., Price S., Torn M. *The Technology Path to Deep Greenhouse Gas Emissions Cuts by 2050: The Pivotal Role of Electricity.* Science (2012), 335:6064, 53-59.
- **DeBenedictis A.**, Hoff T.E., Price S., Woo C.K. *Statistically adjusted engineering (SAE) modeling of metered roof-top photovoltaic (PV) output: California evidence*. Energy (2010), 35:10, 4178-4183.
- Orans R., Woo C.K., Horii B., Chait M., **DeBenedictis A.** *Electricity Pricing for Conservation and Load Shifting*. Electricity Journal (2010), 23:3, 7-14.

Citizenship

United States

Saamrat Kasina, Ph.D.

One Broadway, 14th Floor, Cambridge, MA 02142 415.391.5100, ext. 327
saamrat@ethree.com

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Managing Consultant

Dr. Saamrat Kasina focuses on issues related to resource planning and market design and also conducts sophisticated benefit-cost analysis at the distribution level, supporting utility initiatives related to grid modernization and distributed energy resources (DER) in the U.S. and abroad. His work includes supporting a Northeastern utility's grid modernization filing, advising multiple utilities on joining the Western Energy Imbalance Market, and developing Integrated Resource Planning models for several Community Choice Aggregators (CCAs) in California. Dr. Kasina joined E3 upon receiving both his Ph.D. in Environmental Engineering and his Master of Science in Engineering from Johns Hopkins University. Select projects at E3 include:

- Developed a grid modernization roadmap to support National Grid's Advanced Metering Functionality (AMF) and Grid Modernization Plan (GMP) filings in Rhode Island. Led benefit/cost analysis of AMF and GMP proposals.
- Developed Integrated Resource Planning models for two California-based CCAs to support their strategic planning processes
- Worked with a team of developers and utility personnel to investigate the economic benefits of flexibly operating solar power plants: allowing them to dispatch on a sub-hourly basis and provide grid reliability services. The study received a "Top Innovator 2018" award from *Public Utilities Fortnightly*.
- Co-led a study for one Southwestern utility and provided modeling support for another to quantify the prospective economic benefits of joining the Western Energy Imbalance Market (EIM)
- AURORA modeling to assist a renewable energy developer in evaluating the future of California's energy market
- Assisted in asset evaluation for a power producer in the Western U.S. and analyzed the impacts of regulations on their market position
- Helped develop a set of long-term investment decisions to support the islands of Hawaii in achieving their goal of reaching 100 percent renewable energy using RESOLVE, E3's resource planning model.
- Identified current market and planning practices in the Indian electricity sector as part of an advisory report to state electricity regulators.

JOHNS HOPKINS UNIVERSITY – Doctoral Program Baltimore, MD
Select projects 2012 – 2017

Non-cooperative multi-regional transmission and generation planning Sep 2015 – July 2017

- Modeled strategic interaction between intra-regional stakeholders in transmission and generation investment models as Mathematical Programs with Equilibrium Constraints (MPECs)

- Quantified the value of cooperation in planning to adjacent ISOs by solving Equilibrium Problems with Equilibrium Constraints (EPECs)

Unit commitment approximations for capacity investment models July 2013 – July 2017

- Developed a tight linear approximation of the Unit Commitment MIP model
- Bridged long-term transmission planning and short-term operations using the UC approximation

Benefits of additional decision stages in Multi-Stage Stochastic Transmission planning 2014 – 2015

- Developed a multi-stage, stochastic transmission and generation co-optimization investment model to quantify the benefits of additional decision stages
- Applied mathematical decomposition techniques to solve this large-scale Western Electricity Coordinating Council (WECC) model

Education

Johns Hopkins University Baltimore, MD
Ph.D., Environmental Health and Engineering 2017

Johns Hopkins University Baltimore, MD
M.S.E., Environmental Economics and Management 2011

Indian Institute of Technology Guwahati, India
Bachelor of Technology, Biotechnology 2010

Selected Presentations

1. Kasina, S., "Non-cooperative Multi-Regional Transmission Planning," Nashville, Tenn. *INFORMS.* November 2016.

2. Kasina, S., "Unit Commitment Approximations for Resource Planning," University of Washington, Seattle, Wash. *Seminar for the Next Generation of Researchers in Power Systems*. September 2015.

Publications and Reports

1. Kasina, S., B.F. Hobbs. "An Equilibrium Model for Non-cooperative Multiregional Transmission Planning." *European Journal of Operations Research* 285.2 (2020): 740-752

2. Wang, S., Zheng, N., Bothwell, C., Xu, Q., Kasina, S., Hobbs, B.F., "Crediting Variable Renewable Energy and Energy Storage in Capacity Markets: Effects of Unit Commitment and Storage Operation" *IEEE Transactions on Power Systems*, (In review)

3. Nelson, J., S. Kasina, J. Stevens, J. Moore, A. Olson, M. Morjaria, J. Smolenski, J. Aponte. "Investigating the Economic Value of Flexible Solar Power Plant Operation," Energy and Environmental Economics, Inc. (E3), October 2018. (White paper.)

4. Hobbs, B. F., S. Kasina, Q. Xu, S. W. Park, J. Ouyang, J. Ho, P. Donohoo-Vallett. "What is the Benefit of Including Uncertainty in Transmission Planning? A WECC Case Study." In Tung X. Bui & Ralph H. Sprague Jr., Eds., *"HICSS,"* IEEE Computer Society, pp. 2364-2371. 2016.

5. Ho, J., B. F. Hobbs, P. Donohoo-Valett, Q. Xu, S. Kasina, S. Park, Y. Ouyang. "Planning Transmission for Uncertainty: Applications and Lessons with the Western Interconnection." Report prepared for the Western Electricity Coordinating Council (WECC). July 2015.

6. Munoz, F. D., B. F. Hobbs, J. L. Ho, S. Kasina. "An Engineering-Economic Approach to Transmission Planning Under Market and Regulatory Uncertainties: WECC Case Study." *IEEE Transactions on Power Systems*, Vol. 29, No. 1, pp. 307-317. January 2014.

7. Munoz, F. D., B. F. Hobbs, S. Kasina. "Efficient proactive transmission planning to accommodate renewables." *IEEE 2012 Power and Energy Society General Meeting*, pp. 1, 7, 22-26. July 2012.

Citizenship

India

Yuchi Sun, Ph.D.

44 Montgomery Street, Suite 1500, San Francisco, CA 94104 415.391.5100, ext. 442
yuchi@ethree.com

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Senior Consultant

Dr. Yuchi Sun joined E3 after completing his Ph.D. degree at Stanford University. His research focused on using modern machine learning algorithms to mitigate uncertainty in short-term solar production, and on quantifying the value of accurate solar forecasts. Other research projects addressed using CO_2 electrolysers as seasonal storage devices, carbon capture and sequestration, and GHG accounting of global oil fields.

Dr. Sun works primarily in E3's resource planning practice. As an E3 summer associate in 2018, his projects involved integrated resource planning and the evaluation of resource procurement proposals for various utilities. He is especially experienced with capacity expansion optimization and operational reliability analysis, and with using and developing E3's RESOLVE and RECAP models. Dr. Sun also has experience in siting renewable resources, valuation of renewable and fossil power plants, and simulation of power system operation.

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Summer Associate June – August 2018

- Supported the capacity expansion planning of an integrated utility
- Improved the functionality of E3's long-term planning model (RESOLVE) and reliability model (RECAP)
- Participated in other projects, including market research, internal model testing, database building

BOSCH RESEARCH AND TECHNOLOGY CENTER Palo Alto, CA
Battery System Intern June – August 2017

- Modeled battery performance and internal state with machine learning algorithms (NN and LSTM-RNN)
- Modeling approach delivered comparable accuracy faster than traditional electrochemical models

STANFORD UNIVERSITY Stanford, CA
Teaching Assistant Autumn 2014 and Winter 2016

- Assisted courses Energy 293A (Solar Cells) and Energy 291 (Energy Systems Optimization)
- Responsibilities included holding office hours, grading homework, and instructing students

WORLD RESOURCE INSTITUTE (CHINA OFFICE) Beijing, China
Intern Analyst Summer 2012

- Participated in developing carbon reduction plan for Chengdu (Capital city of Sichuan Province)
- Calculated greenhouse gas emissions from different industrial sectors in Chengdu

Research Projects

- **Short-term Solar Forecast with Convolutional Neural Network** Jun. 2016 – Aug. 2019
  Build a machine learning model to predict solar power with cloud images and other features. Identify and predict cloud movement with camera images at 5- to 15-minute time scale.
- **Performance of a CO2 - reduction Based Seasonal Storage System** Sep. 2015 – Jun. 2016
  Calculated the mass and energy balance of a CO2 electrochemical reduction system. Compared the energy and cost performance of the system to other long-term storage solution.
- **Exergetical Life Cycle Analysis of CCS Enabled Coal Fired Power Plant** Jun.2014 – Aug.2015
  Provided a new perspective on CCS technology by accounting the life cycle exergy input/output. Constructed a detailed CCS system model with an emphasis on material cost.
- **Carbon Emissions of Petroleum Production in Global Oilfields** Sep.2013 – Sep. 2014
  Calculated the GHG emission from oil production in thirty major oilfields across the globe. Accounted for vastly different oil production technology and indexed them.
- **Development of a Carbon Footprint Calculator on Android Platform** Jun.2011 - Sep.2011
  Titled Mr. Carbon (available on Google Play, Search Mr. Carbon). Developed a methodology to calculate direct and indirect carbon footprint for Chinese citizens. 1st place in The Seventh Environmentally Friendly Technology Competition sponsored by HACH

Publications

1. **Sun, Yuchi**, Vignesh Venugopal, and Adam R. Brandt. "Short-term solar power forecast with deep learning: Exploring optimal input and output configuration." *Solar Energy* 188 (2019): 730-741.
2. **Sun, Yuchi**, Gergely Szűcs, and Adam R. Brandt. "Solar PV output prediction from video streams using convolutional neural networks." *Energy & Environmental Science* 11.7 (2018): 1811-1818.
3. Brandt, Adam R., et al. "Energy return on investment (EROI) for forty global oilfields using a detailed engineering-based model of oil production." *PloS one* 10.12 (2015): e0144141.
4. Brandt, Adam R., **Yuchi Sun**, and Kourosh Vafi. "Uncertainty in regional-average petroleum GHG intensities: countering information gaps with targeted data gathering." Environmental science & technology 49.1 (2014): 679-686.

Education

Stanford University Stanford, CA
Ph.D., Energy Resources Engineering August 2019

Stanford University Stanford, CA
M.S., Energy Resources Engineering August 2015

Tsinghua University Beijing, China
B.S., Energy Resources Engineering; B.A., English June 2013

Jessie Knapstein

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jessie.knapstein@ethree.com

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. San Francisco, CA
Managing Consultant

Ms. Knapstein joined E3 in 2019, where she helps utilities, system operators, and state agencies meet climate goals. She joined E3 from Pacific Gas & Electric, where she led efforts to prepare for climate-related impacts and conducted analysis of climate and energy regulation and legislation. Previously, Ms. Knapstein worked for the U.S. Department of Energy on funding and commercializing energy efficient building technologies. Ms. Knapstein holds an M.S. in Energy and Resources and a Master of Public Policy degree from the University of California, Berkeley and a B.A. in Business Administration, with a minor in Physics, from the University of Florida.

PACIFIC GAS & ELECTRIC COMPANY San Francisco, CA
Expert Analyst, Climate Resilience and Climate Policy June 2018 – September 2019
Senior Analyst, Climate Resilience and Climate Policy June 2017 – June 2018

- Managed integration of climate risk into company-wide investment strategy
- Analyzed risks and recommended mitigations related to climate change
- Conducted technical, economic, policy assessments of climate and energy regulation and legislation
- Contributed to cross-cutting proceedings including integrated resources plan (IRP), rate design, building decarbonization, low carbon fuel standard (LCFS), and renewable fuel standard
- Represented PG&E at CPUC, CEC, CARB, EPA, and elsewhere

NATURAL RESOURCES DEFENSE COUNCIL (NRDC) San Francisco, CA
Energy Policy Fellow September 2016 – May 2017

- Produced building decarbonization policy analysis used to support drafting of "SB 1477: Low-emissions Buildings and Sources of Heat Energy," signed into law in September 2018

THE CALIFORNIA PUBLIC UTILITIES COMMISSION (CPUC) San Francisco, CA
Graduate Student Researcher January 2016 – June 2016

- Analyzed GHG tracking, climate credit funding, and compliance under AB 32
- Analyzed self-generation incentive program (SGIP) for GHG emission reductions and fraudulent incentive claims

EDISON ELECTRIC INSTITUTE (EEI) Washington, DC
Research Assistant May 2015 – August 2015

- Wrote briefs on flexible generation and advanced metering infrastructure (AMI) deployments

CENTRO MARIO MOLINA Berkeley, CA
Energy and Climate Policy Consultant December 2014 – May 2015

- As part of a team of student consultants, developed an analysis of renewable portfolio standard (RPS) best practices in the context of Mexico's recent energy reform. Compared the ability of various RPS design strategies to provide the stability necessary to develop large amounts of renewable capacity in country with only a nascent clean energy industry.

U.S. DEPARTMENT OF ENERGY (DOE-EERE) Washington, DC
Energy Analyst June 2012 – September 2014

- Managed contractor/lab team, platform rollout, stakeholder engagement, marketing, and education for the largest public database of building energy data with >1M unique records (Buildings Performance Database). Managed design of complimentary data specification and schema for energy application interoperability.
- Managed peer review, selection, funding and commercialization of emerging tech grants
- Managed 6 annual innovation teams with $40K budget (Better Buildings), concluding in White House presentations to investors
- Managed 5 emerging tech grants annually with a budget of $400K, one achieving 30% energy savings for air conditioning units

U.S. HOUSE OF REPRESENTATIVES Washington, DC
Energy and Environment Intern February 2012 – June 2012

- Authored white papers for senior staff ("Grid Modernization in New Mexico," "Opportunities in Solar Energy Zones") used to petition the Bureau of Land Management for preferential energy development specifications and permitting

SCOPEINSIGHT/NEWFORESIGHT Utrecht, The Netherlands
Consultant October 2011 – March 2012

- Supply chain emission reductions and sustainability consulting for clients including Nestle, Hershey's, Mars, flower and fish distributors
- Developed international market-research database and commercialization plan for platform to align sustainable farms with interested funders, banks, and NGOs; secured $2M from the Government of the Netherlands for prototype

GAINESVILLE REGIONAL UTILITIES (GRU) Gainesville, FL
Finance Intern December 2009 – May 2010

- Assisted in roll-out of feed-in-tariff program and managed and tracked assets

Education

University of California, Berkeley Berkeley, CA
M.S., Energy and Resources 2017
Master of Public Policy 2016

University of Florida — Gainesville, FL
B.A., Business Administration, Minor in Physics — 2011

Academic Appointments

U.C. BERKELEY – RENEWABLE AND APPROPRIATE ENERGY LABORATORY — Berkeley, CA
Graduate Student Researcher — January 2016 – May 2017

- California Energy Commission grantee: Climate Adaptation, Risk Planning for Investor Owned Utilities
- Polled IOU, ISO, CCA stakeholders on climate change risk and adaptation practices for grid infrastructure

U.C. BERKELEY – ENERGY AND CIVILIZATION — Berkeley, CA
Graduate Student Researcher and Instructor — June 2016 – December 2016

- Designed course, recruited speakers, and created course content; taught 50 students

UNIVERSITY OF NEW SOUTH WALES – CLIMATE CHANGE RESEARCH CENTRE — Sydney, Australia
Visiting Research Scholar and Lecturer — June 2016 – August 2016

- Researched renewable energy technology learning curves and knowledge spillovers
- School of PV and Renewable Energy Engineering (SPREE) lecturer

UC BERKELEY - ENERGY AND SOCIETY — Berkeley, CA
Graduate Student Instructor — August 2015 – December 2015

- Taught discussion sections to 100 students covering interdisciplinary energy topics

UNIVERSITY OF FLORIDA - SOIL AND WATER SCIENCE LABORATORY — Gainesville, FL
Bioenergy Research Assistant — July 2010 – January 2011

- Conducted food-waste chemical-oxygen demand audit for anaerobic digesters

Citizenship

United States

Joseph Farella

33 Irving Place, New York, NY 10003 415.391.5100
joe.farella@ethree.com

ENERGY AND ENVIRONMENTAL ECONOMICS, INC. New York, NY
Managing Consultant

Joe Farella joined E3 in 2020. Joe has more than 30 years' experience as a manager, supervisor, operator, and engineering in the utility industry, including the generation, transmission, and distribution fields. He was instrumental in transitioning grid and market operations at National Grid from the New York Power Pool to the New York Independent System Operator (NYISO) and has held management roles in generating station maintenance and engineering, substation design, transmission control center operations, grid modernization, and DSO development. As Manager of EMS Development, Joe was responsible for all aspects of the design and implementation of a state-of-the-art SCADA & energy management system (EMS) for the National Grid NY & NE jurisdictions. Most recently, he served as Manager of Grid Modernization, where he chaired and/or served on several NYISO and NY Joint Utility committees and working groups whose primary focus was the integration of DER into grid and market operations.

NATIONAL GRID Syracuse, NY
Control Center Operations, Manager Grid Modernization 2006-2020

- Responsible for integrating new technologies and programs into the transmission and distribution control centers primarily associated with DER and state programs
- Chaired and participated in multiple NY Joint Utilities, NY Independent System Operator (NYISO) and NYS Department of Public Services working groups and committees responsible for shaping the integration of renewables into existing and new markets to support the NY's Reforming the Energy Vision (REV) initiatives
- Primary team member of the NY Public Service Commission (PSC) Market Design and Integration Working Group, integrating renewable resources into wholesale and distribution markets
- Responsible for multi-disciplined presentations about various DER grid and market operations topics to NYPSC, NY Joint Utilities, and NYS Stakeholders
- Member of multi-disciplined team responsible for drafting of NY's REV Distributed System Implementation Plan (DSIP) filing and the NY Joint Utilities Supplemental DSIP filing, in response to a NYS PSC Order
- Responsible for development and implementation of the Control Center Technology Roadmap, which defines current and future tools to support and manage the electric system
- Project manager for the delivery of the National Grid US Energy Management System, a very large-scope, multi-regional project

Manager, NY Transmission Control Center 2004-2006

- Supervised 12 operators charged with monitoring and controlling transmission assets to maintain transmission security and system reliability, in accordance with NERC, NPCC, state, and local standards and guidelines

- Maintained NERC Certified System Operator Reliability credential since 2004
- Authorized and coordinated scheduled and non-scheduled outages of company transmission and generation equipment
- Performed real-time and contingent analysis using load flows applications in EMS security software

Power Operations Engineer 1998-2004

- Served in various NYISO working groups and committees through transition of the New York Power Pool (NYPP) to the NYISO
- Assisted power control system operations and billing/scheduling departments in the transition from the New York Power Pool to the NYISO by developing procedures and providing training
- Provided daily support to power control operations staff, including technical support, procedure development, and updates

System Operator 1997-1998

- Monitored and controlled bulk transmission and cross-state power flows; maintained bulk power substation security
- Developed and coordinated hourly interchange schedules with other utilities, forecasted customer load demand, and brokered sale and purchase of energy
- Authorized and coordinated scheduled and non-scheduled outages of company transmission and generation equipment

NIAGARA MOHAWK POWER CORP Lycoming, NY
Engineering Supervisor, System Support / Test 1992-1997

- Managed a staff of ten engineers at Nine Mile Point #1 Nuclear Generating Station
- Responsible for plant maintenance planning and scheduling
- Provided technical support for the operations and maintenance departments
- Responsible for root cause evaluations of personnel errors and equipment failures, including corrective and preventive actions
- Developed, reviewed, and approved plant modifications to ensure compliance with codes, standards, and licensing basis
- Conducted peer evaluations of other utilities for benchmarking and assessments
- Authored safety evaluations according to 10CFR50.59
- Responsible for identifying adverse trends in plant equipment and systems, initiating corrective actions

Supervisor, Instrument and Control 1989-1992

- Supervised and inspected the work of technicians responsible for installation and maintenance of instrument and control equipment
- Verified all work was completed and consistent with applicable codes, standards, regulations, and state and federal licensing requirements

Project/Design Engineer 1985-1989

- Designed, installed, and tested modifications for plant systems, including protective relaying
- Developed schedules and budgets for design and installation of various modifications

Education

Clarkson University Potsdam, NY
B.S., Electrical Engineering – Power Systems 1985

Committee Service

- Chair of NY Joint Utilities Working Groups for Monitoring and Control and NYISO-Joint Utilities Coordination
- Joint Utilities Distributed System Platform (DSP) Steering Committee
- NYISO Operating Committee
- NYISO Billing and Accounting Working Group
- NYISO Metered Data Working Group
- Joint Utilities of NYS
- Institute of Nuclear Power Operations (INFO) Peer Audit Team

Citizenship

United States

B. PowerPoint Summary of E3 Review

This presentation was given to PG&E's Risk Modeling team in two sessions on April 27 and April 28, 2021. They were asked to comment on our findings and to correct any errors in our understanding.

E3 Review of PG&E's 2021 Wildfire Risk Model

Draft 1

April 27, 2021

Energy+Environmental Economics

Ren Orans, Managing Partner
Andrew DeBenedictis, Director
Jessie Knapstein, Managing Consultant
Saamrat Kasina, Managing Consultant
Yuchi Sun, Senior Consultant
Joe Farella, Senior Managing Consultant

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Approach & Methodology

+ **E3 has produced the following assessment of PG&E's 2021 Wildfire Distribution Risk Model ("Risk Model")**
    - The assessment is based on review of documentation and interviews with PG&E's subject matter experts over the first quarter of 2021
+ **The assessment focuses on two broad questions**
    - Whether the model is "fit for purpose" and has a rational road map development plan
    - Whether the existing or next version of PG&E's modeling approach can be easily improved
+ **The assessment places more emphasis on PG&E's calculation of ignition probability than on the wildfire consequence scoring**
    - We view this as the key distinguishing feature of PG&E's approach which makes it stand out as a driving factor perhaps more than it should

The need for improved documentation

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Model documentation is poor

+ **Current documentation is not adequate to determine if model is fit for purpose**
  - Risk Model approach is theoretically appropriate, but more thorough supporting evidence is needed

+ **Documentation improvements should focus on three areas**
  - Context
  - Evidence
  - Road mapping

As part of its review, E3 would like to help the PG&E Risk Modelling Team recast the documentation in a way that provides a more useful product for outside parties

Context: A brief history of risk assessment at the CPUC shows increasing role of wildfire risk

- 2014 – Risk-Based Decision-Making Framework (RDF) incorporated RDF into the Rate Case Plan for the General Rate Cases (GRCs)
- 2015 – Present - CPUC requires IOUs to apply the RDF through two new filings, which feed into the GRC applications:
  - Safety Model Assessment Proceeding (S-MAP)
  - Risk Assessment Mitigation Phase (RAMP)
- 2019 – Wildfire Mitigation Plans
- 2020 – Further Develop a Risk-Based Decision-Making Framework for Electric and Gas Utilities

Key Take away: PG&E used to have a failure-based model, and it was inadequate in helping them focus on the appropriate long term risk mitigation measures

Context: Explain PG&E's risk modeling ecosystem and define the Risk Model's place in that ecosystem

- **Documentation does not provide a problem statement the Risk Model seeks to solve (i.e. "where on the distribution system should PG&E prioritize wildfire mitigation efforts?")**
  - Difficult to know what applications are in-scope and out-of-scope for the Risk Model
  - This lack of clarity will lead to the CPUC and others at PG&E asking the model to answer questions outside where it can reasonably be expected to contribute
- **PG&E has several risk modeling efforts underway in different groups – readers need to understand what questions each model tries to answer and how the different models interact with and benchmark to each other**
  - Wildfire Transmission Risk Model
  - PSPS model
  - …

Data → Models → Key questions & Applications

Data
- Vegetation
- Assets
- Ignitions
- Consequence

- Interviews

Long Term Ignition Risk Model

- Expert Opinion Model

Applications: The Where Questions
- 2021: Prioritize locational investments to mitigate damages
- 2022: ?

- The What Questions

Narrowness of model scope leaves key questions unanswerable

+ **Regulators prefer a process that relies minimally on "expert opinion"**
+ **Effectiveness of mitigation measures cannot be assessed by the Risk Model (currently)**
  - Tradeoff between "quick & cheap" vs. "deep & expensive" options
  - What mitigation method is most appropriate in a given area?
  - How effective has a mitigation action been at reducing wildfire occurrence or damage?
    - This sort of counterfactual EM&V analysis of rare and sparse events is difficult for any model even with lots of data and a stationary baseline. PG&E has sparse data a quickly moving baseline and multi-dimensional problem
+ **Temporal questions also remain out of scope**
  - When is a wildfire most likely to occur at a given location?
  - Connecting the Risk Model to the PSPS model might eventually be able to address this question

Impact

Likelihood

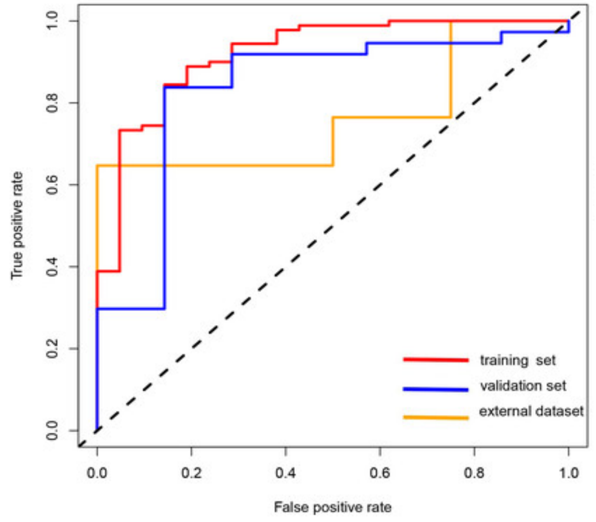
	Negligible	Minor	Moderate	Significant	Severe
Very Likely	Low	Moderate	High	High	High
Likely	Low	Moderate	Moderate	High	High
Possible	Low	Low	Moderate	Moderate	High
Unlikely	Low	Low	Moderate	Moderate	Moderate
Very Unlikely	Low	Low	Low	Moderate	Moderate

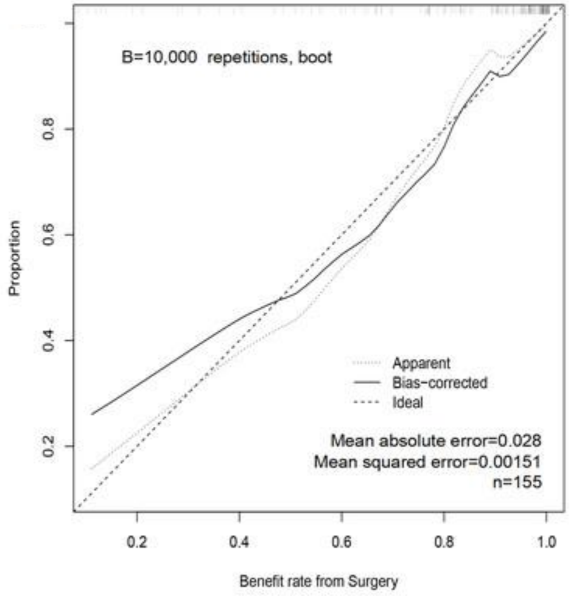
Wildfire likelihood and impact make modeling mitigation assessment more valuable

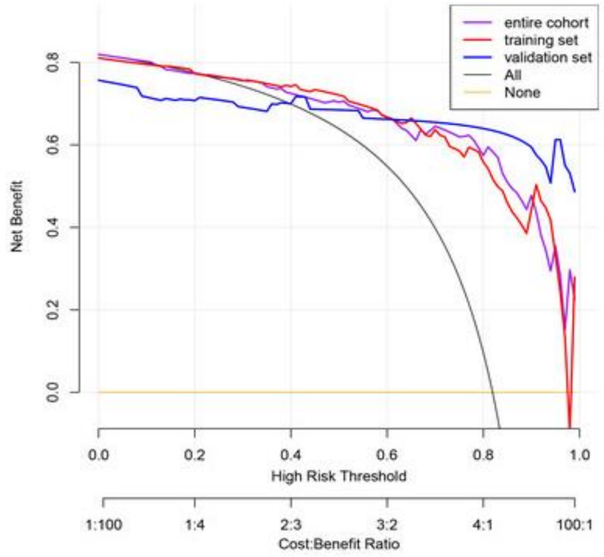
Evidence: Develop analysis and documentation to support PG&E's modeling approach

+ **Given the novel modeling techniques used in the Risk Model and the unconventional decision to model rare ignition events instead of outages, documentation should provide ample evidence that these design choices improve on the model's predictive power**
  - Specifically, PG&E should develop for comparison a more conventional model version that trains on outages and then applies a probability of ignition given outage
+ **Given the number of changes made in updating the model from the previous version to the current version, a similar comparison should be made to historical predictive power**
  - Proves to the reader that additional effort to refine data and methods produces a more than marginal improvement

Need transparent measures of improvement







Evidence: A lack of evidence limits E3's ability to state support for the Risk Model

- **PG&E's method and data represent a likely improvement over historical modeling and current alternatives**
  - However, current documentation does not provide adequate evidence to verify this improvement
- **E3 can only say that the model is fit for purpose in theory without seeing evidence that it works better than an alternative**
  - Ideally, PG&E would provide requested evidence before we create a public-facing review
    - Evidence could be included as an appendix to that review, or could be released separately beforehand by PG&E
    - If PG&E has already moved beyond this model version, public review could be withheld for the next model version, which would include adequate evidence

Road mapping: Share a plan for how PG&E expects to continue model development in the coming years

+ **The CPUC will want a clear plan with justified prioritization and milestones for multiple years instead of a list of features for next year**
+ **Connect the increasing amounts of data through to the models and that enable the Company to accurately answer more questions**
+ **Having a clearer plan gives PG&E a timeline for answering key follow-up questions to the current Risk Model**
    - When new features will be added?
    - What are plans for future data improvements?
    - How will results be benchmarked against other models and actual data?
    - What additional applications will be unlocked by new features and data?
+ **A model roadmap also improves accountability, which ratepayers and commissioners will be eager to have**

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Long Term Ignition Risk Model
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Applications: The Where Questions
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Independent outside review of Risk Model

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PG&E's broad approach to risk quantification is novel and consistent with best practices, but details differ

- **All IOUs follow the same general method of calculating Total risk**
  - Total Risk = Probability of ignition x Consequence
- **IOUs differ in methods for estimating ignition probability**
  - PG&E models probability of ignition directly using Max Ent
  - SCE's trains its model on outage data and then multiplies by probability of spark and fire to find probability of ignition (for now, all sparks were estimated to lead to fires)
  - SDGE's model uses Monte Carlo simulations (not machine learning) to estimate ignitions[1]
- **Anecdotally, all CA IOUs have moved to consequence modeling using Technosylva fire simulations**
  - Limited available documentation from SCE and SDG&E does not indicate if translation of fire simulations to consequence scores is consistent across the IOUs

1. Q10, 2021 WMP WSD DR 03

Decision to predict ignitions directly is non-standard

- **More standard approach would be to predict equipment failures and then estimate the probability of ignition given a failure**
  - Failures provide a larger dataset for model training, but this extra data may serve to emphasize drivers of failures that do not necessarily lead to ignitions
    - E.g. outages are common in coastal regions and dense forest where ignition is unlikely due to moisture and lack of starter fuel
  - Estimating the probability of ignition given a failure is difficult and should be modeled using <u>spatial</u> vegetation data
  - Alignment with other utility approaches has value
- **Based on interviews with subject matter experts, E3 finds the Risk Model has the following costs and benefits compared to the industry standard approach:**
  - + Bypasses the translation of failures to ignitions by focusing directly on ignitions
  - – Smaller dataset of ignitions is used in favor of much larger failure data set
  - – Approach is less directly tied to mitigation measures than failures

Focus on vegetation and conductor sub-drivers is good for testing, but expansion is necessary

- **The Risk Model predicts distribution system ignitions due only to vegetation and to conductor failures**
  - SCE and SDG&E model ignitions from all assets
- **Focusing on vegetation and conductor-caused ignitions helped PG&E analyze large drivers of ignitions in the context of a new ignition model methodology**
  - Vegetation caused 38% and equipment failure caused 26% of ignitions (Page 7 of Risk Model Documentation)
  - This choice limits scope and applicability; an expanded model will cover more modes of failure and can begin to answer questions about prioritization order of mitigation measures

A note on ongoing refinements to modeling efforts

- **For the next version of the Risk Model, PG&E is working on a composite model approach**
  - This approach will expand the list of sub-drivers being modeled and apply different modeling methods as appropriate for different types of ignition events
    - Includes training models on outage data and then applying a conditional probability to get to ignition
  - Also refines existing models to address “double-counting” ignitions – where both vegetation and conductors are involved
- **E3 agrees with this direction for future modeling**
  - Allow for direct comparison between different models to ensure that the best model approach is used for each sub-driver

Need to be clear about data limitations and how that impacts model use and results

+ Critical datasets: Vegetation, Ignition, and Asset

- All critical datasets limited to HFTDs with the possibility for later expansion
- LiDAR and most recent inspection data not in use now but planned for next version
- Vegetation data
  - LiDAR data availability limits quality of vegetation and equipment data outside of HFTDs
- Ignition data
  - Started recording nonreportable ignitions only in 2018 (charring and scorching fires that don’t spread)
  - 2019 data used to validate model, but also includes PSPS events which makes comparison tricky
  - How will this be dealt with going forward? PSPS will increase sparsity of ignition data
- Quality of asset data and initiatives to improve collection are not discussed

The parsimony of the Max Ent model has advantages and disadvantages

- **Statistical models straddle the balance between explain-ability and predictive power; more parameters generally lead to more predictive power while reducing explain-ability**
- **Max Ent is a parsimonious model, meaning that it enforces strong rules and has smaller number of parameters**
  - The Max Ent Models used here have less than a hundred parameters compared to tens of thousands of parameters for higher dimensional ML models (Random forest, MLP, etc.)
- **Advantages:**
  - A parsimonious model in a low parameter space is suitable with less data (e.g. 300 ignition events) – a model cannot characterize tens of thousands parameters with only 300 data points
  - Provides better explain-ability
  - The inhomogeneous Poisson distribution rising from the Max Ent formulation is a strong assumption but might be more suitable than the more amorphous non-parametric distribution from higher dimensional ML models
- **Disadvantages:**
  - There is likely some loss in flexibility from modeling the distribution associated with the Max Ent's parsimony
  - Gating effects are likely over-represented while the continuous effect may be under-represented

Underemphasis on wind is counterintuitive

- **Though resampling through jack-knife results do not show much wind as a key driver of ignitions, it is E3's opinion that wind might still be consequential in the Max Ent model**
  - Negative correlation with tree height, which is strongly conducive to fire
  - Dilution and masking of key variables across multiple features
  - Difficulty capturing the tail event of high wind
- **Results of the vegetation model suggest that wind is important, just less so than tree height, fuel availability, and dryness**
- **Impacts of different wind variables offer compelling proof that average wind speed is less telling than maximum speed and gustiness**

Complexity of consequence method is inconsistent with importance of consequence scores

+ **Assignment of consequence scores to fire simulations is the most impactful model step in determining risk, but the method is simplistic**
  - Each simulation categorized as *small*, *large*, or *destructive*
  - Some fraction of *destructive* fires recategorized as *catastrophic* (in HFTD: 86% during RFW, 63% otherwise)
    - This method could lead to a site with FBI = 3 fires being characterized the same as a site with FBI = 5 fires (unless RFW is very different between the two)
  - MAVF score assigned (*catastrophic* ~13,000, *destructive* ~7,000, *large/small* ~0)
    - It would be useful to display some characterizations of the averages and ranges of scores across the state to convince the reader that this tri-modal scoring method returns reasonably smooth results
+ **Simplicity may be necessary for such an uncertain metric, but sensitivity analysis should be conducted to test the impact of small changes in base assumptions**

Unclear if the calibration methods accurately capture spatial consequence

+ **Technosylva consequence data is primarily used to weight existing CALFIRE consequence data established in the 2020 RAMP**
+ **Technosylva simulations struggle to produce reasonable results on benign days, therefore the worst 452 wildfire weather days were modeled**
  - Unclear how the resulting spatial distribution of consequences maps to the territory and whether this is accurate outside of those 452 days
+ **Technosylva consequence data is calibrated to 2020 RAMP consequence data using HFTD indicator, location specific RFW, and fire severity**
  - Unclear how these two models actually work together
  - Unclear how statistical extracts from each model are applied to create total consequence at each location

Suggested Improvements

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The Risk Model should be contextualized among other related models and CPUC proceedings

+ **Identify all models in PG&E's risk modeling ecosystem**
  - Clearly state what questions are in-scope and out-of-scope for each model
  - Explain what inputs are shared among models, how/why model designs differ, and how outputs are benchmarked across all models to ensure consistency
+ **State what aspects of consequence scoring are inherited from elsewhere (CPUC or PG&E) versus unique to the Risk Model**

Data
- Vegetation
- Assets
- Ignitions
- Consequence

- Interviews

Long Term Ignition Risk Model

- Expert Opinion Model

Applications: The Where Questions
- 2021: Prioritize locational investments to mitigate damages
- 2022: ?

- The What Questions

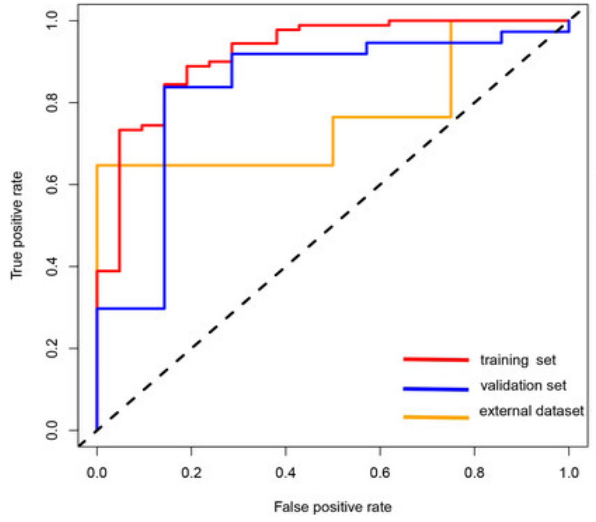
Documented data exploration should motivate the need for a model and guide the approach

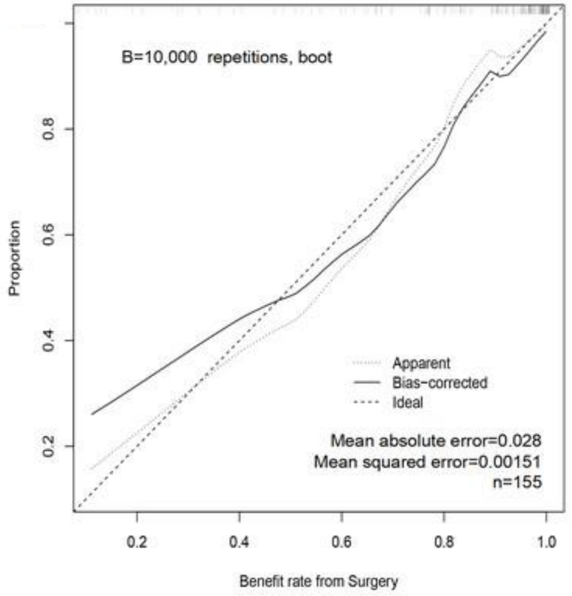
+ **Compare maps of outage and ignitions to note differences and likely explanations**
  - Proves that outage and ignition have a poor or at least spatially uneven correlation, which helps justify a focus on ignition
+ **Explain data available to use in model**
  - Guides choice of Max Ent or other modeling approach
  - Points to holes in data that should be a focus of future data collection

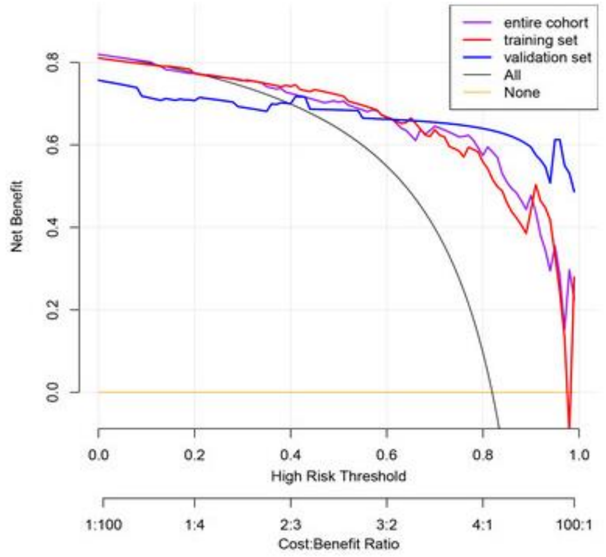
Comparing results with data and other models gives credence to modeling approach

- **Create an outage-based model to compete against the ignition-based model**
  - Compare results to identify/prove the best model for PG&E’s available data
- **Compare results of current Risk Model to historical Risk Model to showcase added value of recent modeling and data incorporation**
  - Comparison of Technosylva model over previous REAX model is convincing, but this is only one component
- **Present more thorough comparison of out-of-sample (2019 ignitions) and the modeled ignition probability map**
  - ROC curve alone is helpful, but additional evidence adds value
- **Include zoomed-in results from two or three pixels to better showcase spatial resolution**
  - Explain the implications of the modeling results for PG&E’s assets in those pixels

Need transparent measures of improvement







Emphasize results conformity with physics and intuition to make readers more comfortable with statistical model

+ **Avoid messaging that wind is inconsequential in ignition modeling**
  - Due to difficulty disentangling wind from other variables, making the claim definitively is challenging
  - As PG&E has seen, stating that wind is unimportant raises red flags among stakeholders that make communication of other ideas difficult
+ **Put intuitive findings in the forefront to assure the audience that this model is physical and conforms to expectations**
  - E.g. Fig. 26 and Fig. 28 show great parallel, and Fig. 61 showcases Max Ent 's ability to learn a physical rule

Example 1: Parallel between Figs. 26 and 28

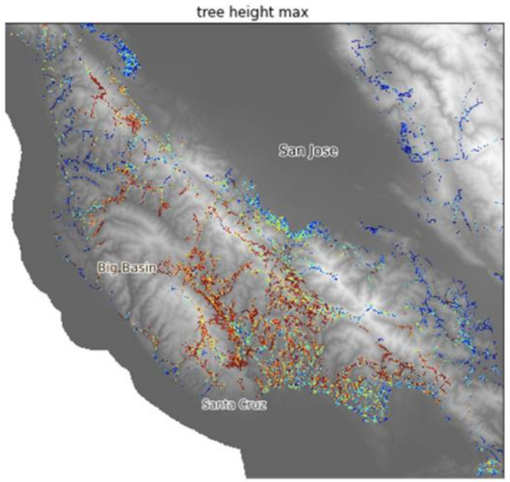


FIGURE 26 - PER-PIXEL MAXIMUM TREE HEIGHT - RED IS HIGHER, BLUE IS LOWER

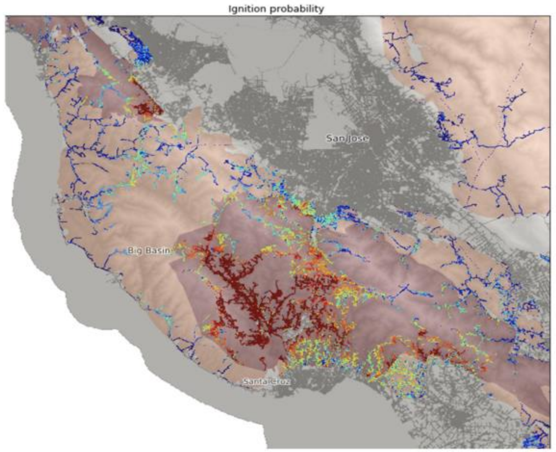
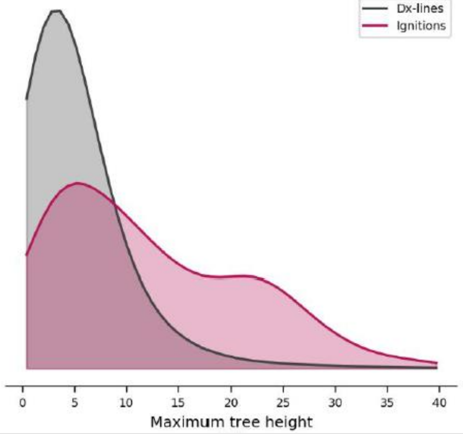


FIGURE 28 -IGNITION PROBABILITY RESULTS PER PIXEL, RED IS HIGHER, BLUE IS LOWER. GREY LINES ARE GRID-PIXELS OUTSIDE HFTDS, TRANSLUCENT ORANGE AND RED AREAS ARE HFDT TIERS 2 AND 3 RESPECTIVELY.

Example 2: The 25-meter probability surge for tree height in ignition event



Increased evidence around consequence and risk results is needed to connect model to application

+ **State early and clearly that consequence is the most impactful component of risk**
  - This point is already mentioned, but emphasis is needed to counter the volume of documentation spent on probability of ignition, which may imply the opposite relationship
+ **Present evidence to suggest that 8-hour fire simulations do not produce meaningfully different results than longer simulations**
+ **Explore ways to show importance of variables in *risk* (not just ignition)**
  - Including consequence may visually promote the role wind and avoid questions from reviewers

Adding a model development roadmap to documentation previews PG&E's risk assessment priorities

+ **Create a roadmap that gives future goals and ties the Risk Model to other models. Consider including:**
    - A process to understand effectiveness of vegetation management and system hardening, and steps to feed this understanding back into the Risk Model for evaluation of mitigation measures
    - A plan to evaluate how changing trends in local and global weather patterns may impact areas of ignition risk
    - A plan for tying the Risk Model to other models (i.e. Are model results benchmarked against each other? Are some model outputs used as inputs elsewhere?)
+ **In considering current and future model applications, identify decisions for which ignition probability or consequence scoring is alone more useful than risk**
    - This may help drive equitable investment if risk scoring is found to favor wealthier areas

Model methods seem sound, but some data and analysis additions may be useful

+ **Consider adding more data fields for equipment characterization**
  - Explore use of thermography and equipment loading
+ **Use data bootstrapping to reduce class imbalance**
  - Useful for methods that model ignitions or outages
+ **Conduct uncertainty analysis around consequence scoring**
  - At a minimum, show uncertainty in risk scores based on range around averages at each simulation location

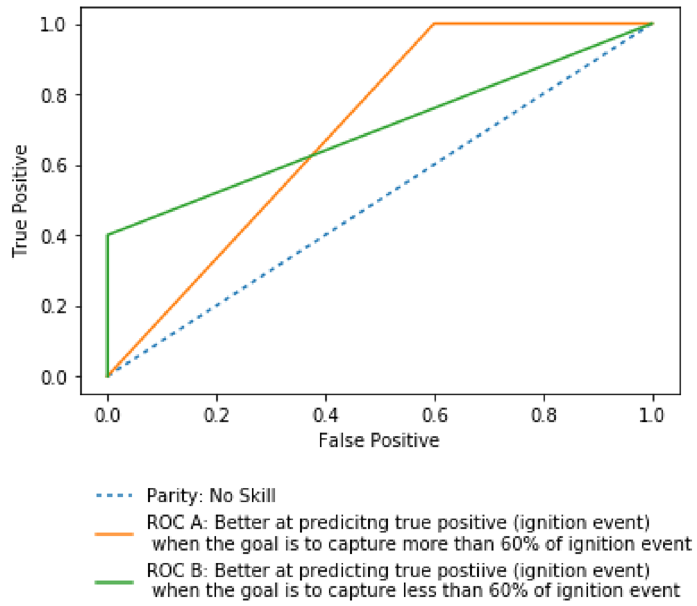
Evaluation of model results should expand

+ Consider removing the variable selection process and use all variables

- Removing some of the variables introduced one of the most controversial decision within this method, which is removing wind for the conductor model. E3 agrees with the reasoning but believes that including the variable will not decrease the predictive power.
- Max Ent is a parsimonious and strongly regularized model, even with the total set of variables it should still be easy to avoid over-training. It is recommended to include all variables and observe how does the ROC change. E3 predicts no substantial change

+ Consider assessing model predictive power based on both the shape and area of ROC curves

- The area under curve (AUC) is only part of a larger picture. Two ROC with the same AUC can look drastically different.
- For this problem where the outcome of a false-negative drastically outweighs a false-positive, a curve similar to example A would be preferable to one similar to example B, which has the same AUC.



Conclusions

Energy+Environmental Economics

Risk Model assessment conclusions

- **The Risk Model approach is *theoretically* sound and makes good use of available data**
  - Comparison to an industry standard model approach is needed
  - Model documentation fails to provide evidence that model performance is improved by design choices
- **The Risk Model is designed to answer only a narrow set of questions**
  - Model documentation does not clearly state what questions are in-scope and out-of-scope for the model
- **Identified model improvements should improve performance and broaden applicability**
  - Model documentation does not provide a longer view of model evolution and how the model will integrate with other PG&E risk models
- **Some modeling method improvements could improve performance and robustness**
  - Data bootstrapping
  - Uncertainty analysis of consequence scoring

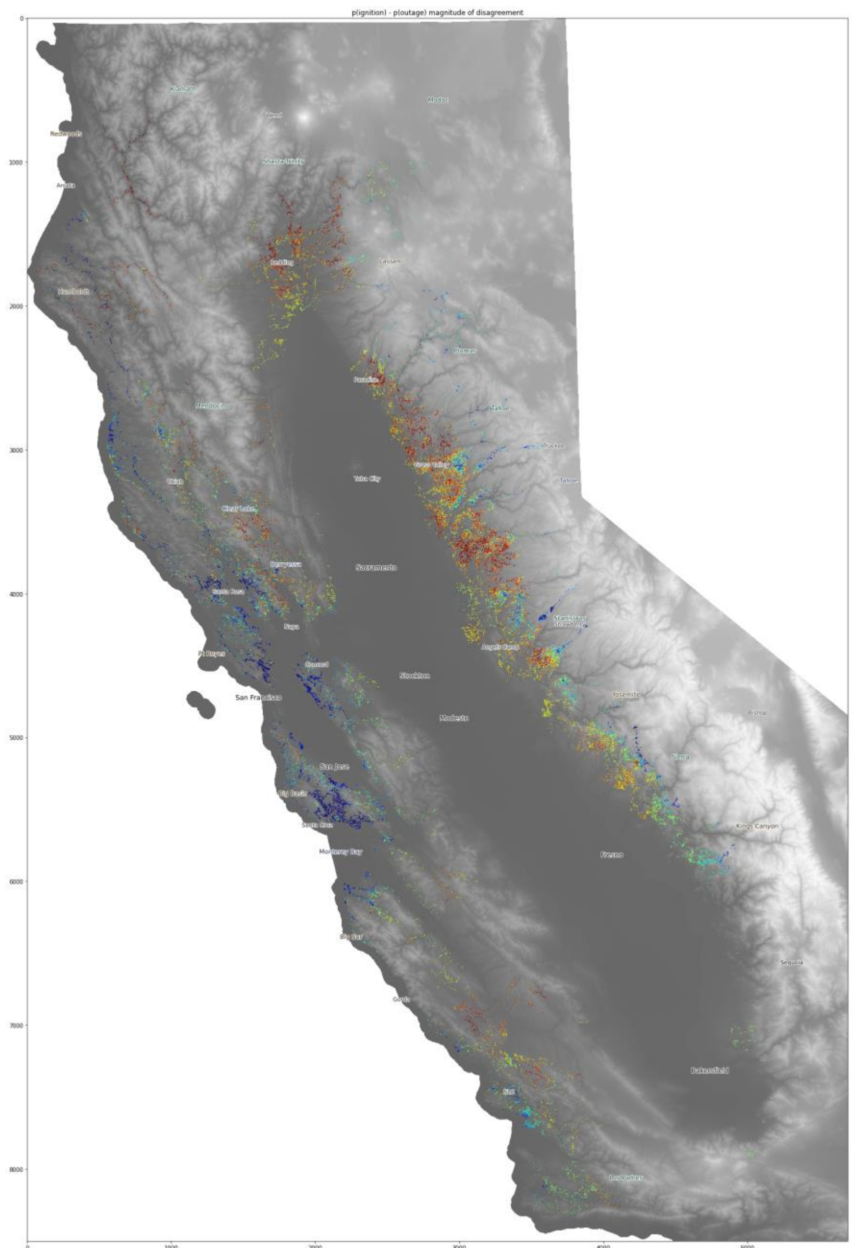
Next Steps

+ **Risk Modelling Team to produce evidence required for fit-for-purpose assessment**
  - What is reasonable timing for this?
  - Ideally, Risk Modelling Team develops roadmap also
+ **Simultaneously, E3 will develop its independent review**
  - Modelling approach is fit for purpose
  - Provides reliable results that are better than its own previous models
  - Includes rational roadmap for product development
  - *Timing and claims contingent on first bullet*

C. Additional documentation and evidence provided by PG&E

Different ignition probability output by ignition-trained vs outage-trained model

Map of PG&E’s service territory where the MaxEnt ignition model differs from MaxEnt outage trained model. Shown below is P(ignition)-P(outage). Red indicates a higher probability of ignition than outage.



Layman's explanation of MaxEnt from PG&E

Distributions are smoothed out histograms whose total area is equal to 1 used in statistics. The goal of a MaxEnt model is to compare the statistical distribution of environmental conditions and asset characteristics associated with ignition locations (i.e. the distributions of tree heights, conductor sizes, rainfall averages, fuel dryness, etc.) to the distribution associated with all locations along the distribution grid, also called the background. To the extent those distributions have statistically significant differences, the model can use values associated with any given location to assign a probability that that location would be a place where ignitions will occur in the future. For example if the fraction of vegetation caused ignitions near trees taller than 15 meters is 10x larger than the fraction of randomly selected distribution grid locations near trees that tall, then, all else being equal, locations with trees taller than 15 meters will be predicted to be roughly 10x more likely to experience ignitions.

The key step to differentiating "ignition occurrence conditions" from "background conditions" is to calculate the ratio of the ignition location distribution and the background distribution. This ratio is also known as the relative occurrence rate or the MaxEnt "raw output". To do this, the distribution of ignition occurrence conditions must be estimated based on the limited number of values at the known ignition locations. Those values will be consistent with many different potential distributions so the question is which one to use.

"Maximum entropy" in this context refers to the goal of maximizing the relative information entropy of the estimated ignition occurrence distribution compared to the background distribution, while still properly characterizing the rate of occurrence of values observed at ignition locations. The higher the relative entropy, the more similar the two distributions will be.

So in layman's terms, the MaxEnt model estimates the distribution of environmental conditions associated with ignitions in a manner that requires it to be as similar to the conditions found elsewhere on the grid as possible while still accurately characterizing the rate of occurrence of values observed at ignition locations. The similarity is quantified through a value know as relative information entropy, which gives this method its name.

Selection method for high fire risk days used in Technosylva simulations

Summary and Methodology to compile this dataset: The list of historical days will be used by Technosylva (TS) to simulate fires to understand where the most catastrophic fires tend to be across the PG&E territory. These data are used in the distribution risk model and will also be used to calibrate a consequence component of PG&E's PSPS model if possible and valuable. These data were compiled by leveraging multiple sources and expert review. First, the historical list of days that were first determined by REAX were retained for fidelity with past efforts. This analysis involved ranking days by using the Fosberg Fire Weather Index applied against the North American Regional Reanalysis. Next, PG&E meteorologists added days where Diablo Winds occurred, by leveraging a Diablo Wind analysis from PG&E's 30 year climatology. PG&E then validated the list to ensure that historical PSPS days and "northeast" outage days were captured, by using PG&E's weather signal database. The date list were then compared with a fire occurrence dataset that contained the start date and final fire size for large historical fires. All dates were a >50,000 acre fire occurred were added, and additional days were added after an expert review. Finally the list were reviewed and validated before the analysis began. The list of days contains a mix of traditional hot and dry days and strong Diablo and Santa Ana wind event days.