# E3 draft results action items

## Fit for purpose

The purpose of the distribution wildfire risk modeling effort is to provide quantitative estimates of wildfire risks posed by grid assets **for use in risk-informed mitigation planning**. Since mitigations are durable and planning operates on an annual cycle, the risks calculated are based on a combination of annual ignition probabilities and location-specific consequence data derived from fire simulations, under dangerous historical wind, heat, and fuel dryness conditions, where the expected count of ignitions multiplied by their expected consequences yields the risk they pose.

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. PG&E also benefits from the subject matter expertise of its work force, with specialized knowledge of equipment, vegetation, wildfire mitigation options, and the service territory, all of which can guide, inform, and help to prioritize the mitigation program.

The primary determinants of the structure of the distribution wildfire risk model are the long-term asset-based planning and prioritization questions being asked of it, the known causes of distribution grid ignitions and how uncommon they are in both time and space, and the character of the data available to train it. The model must operate over annual timeframes, but with sufficient specificity to resolve the relative risks posed by different assets. A large fraction of ignitions is caused by interactions between grid assets and their environment, so environmental data, including data on trees, weather, and climate, must be made available to the model. Furthermore, regardless of cause, ignitions are only viable given available fuels that a dry enough to burn, so modeling "fire conditions" also require the support of environmental data.

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.

There is significant uncertainty in the exact equipment involved in historical ignitions and outages. Ignition locations are approximate and not tied to grid assets and outage locations most reliably record the location of the protective device that actuated. So the model must be robust to uncertainty around the id of the equipment involved and its exact location.

Finally, it is well understood that ignition events are typically associated with outages. It is therefore possible to model ignitions directly or model a broader set of outages and re-scale the results to ignitions. The competing issues are:

(1) **outages are not all equally likely to produce ignitions –** their type, cause, location, failure mode and surrounding environmental conditions all contribute to their propensity to cause ignitions and the

consequences of the ignitions they do start depend on local fuels, dryness, topography, wind, and proximity to infrastructure that can burn. Outages caused by wind, for example, are already associated with one of the ingredients of fire spread. However, winter storms, which often hit coastal locations the hardest and represent the majority of wind-driven outages, pose virtually no catastrophic wildfire risk due to their wet conditions. Models based on outages must attempt to resolve the complex relationship between outages and much rarer ignitions.

(2) **There are significantly fewer ignitions than outages** - directly modeling ignitions bypasses the need to model the complex relationship between outages and ignitions, but the relative sparsity of ignition data raises concerns about the statistical power of 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.).

Both concerns can be expressed in terms of prediction accuracy: Outage-trained models are fit to failures that are related to but distinct from ignitions. Their predictions can be wrong when the conditions that favor outages do not favor ignition. Ignition trained models may lack the training data required to converge to a stable estimate - uncertainties decrease with more training data. Their predictions can be wrong because model fits may include too much stochastic noise to accurately capture the drivers of ignitions. In both cases, the prescription is to train the models and test their performance on out of sample data. Whatever theoretical concerns we have, their impact will be felt through (decreased) prediction accuracy.

Taken altogether, these constraints suggest a model that prioritizes spatial resolution of its results, that can be trained on sparse data (zero inflation and class imbalance), that is robust to spatial uncertainties, and works well with both environmental asset data. These constraints point quite clearly to what we have described as our “where” model. The “where” model starts with a pixelated map of grid locations, with indicators of ignitions (or outages) and environmental and asset covariates available at each location. Both environmental data and asset attributes are spatially correlated, so such an approach is likely to be robust to spatial uncertainties, and the until of analysis is spatial pixels, not assets, so uncertainty in precisely which asset failed does not preclude modeling based on nearby asset attributes. So far, the probability of ignition for each grid pixel could be estimated by a typical classification model, like logistic regression, SVM, or random forest. The possibility of complex interaction between covariates and of over-fitting the training data demand feature generation and some form of feature selection through regularization, and the class imbalance (a model that always predicts “no ignition” will be right most of the time, but totally useless) would appear to demand some form of resampling or weighting scheme.

All these requirements could be met given sufficient time and model complexity. Indeed, there is plenty of cause to keep exploring those options. However, there is a model form well known to ecological modelers that does all of the above (rasterized spatial data, feature generation, regularization, out of sample testing) and re-frames the problem as presence/background rather than presence/absence estimation. This approach is based on constructing empirical distributions of the conditions (I.e. covariate values) associated with the grid pixels that hosted ignitions (or outages) and the distribution of conditions that prevail among all grid pixels. Determining whether a given grid pixel would be expected to be drawn from the ignition distribution is a matter of determining the ratio of the two distributions. That estimation is performed through a maximum entropy optimization that seeks the least unique solution that fits the available data and in so doing, it neatly sidesteps class imbalance and accepts spatial and covariate uncertainties. This approach, called MaxEnt in the literature, is implemented in software called Maxent and Maxent was used to train the P(ignition) portion of the 2021 wildfire distribution risk models (there is one model trained on vegetation-caused events and another trained on conductor-involved events).

One of the most important covariates in the modeling is causally linked to vegetation-caused events: high spatial resolution tree height data. Trees that are not taller than the lines cannot hit them and trees that are not close enough to the lines cannot hit them. Lidar data is quite useful in this regard, but was not available for use in the 2021 modeling effort. Additionally, even with lidar, it is notoriously difficult to produce accurate tree data across the full territory with regular updates. Instead, we utilized satellite-derived tree height estimates produced using computer vision deep learning algorithms by Salo Sciences (members of the RaDA consulting team). Tree height data with comprehensive coverage and derived data products like fall-in tree coverage, relating line locations and tree heights, was consistently among the most important covariates in the modeling.

The table below summarizes key documents and presentations developed during the exploratory and active modeling phases of the project. They speak to the modeling objectives, exploration of model forms, available data, the performance and interpretation of the MaxEnt approach to spatial modeling, etc. All are available via ESFT.

| | |
|---|---|
| Milestone 1 analysis documentation 2020-02-06.pdf | First major MaxEnt written deliverable. Lots of description around modeling choices.<br>Ends with maps of major early covariates. |
| Dx Risk _ Phase 1 _ Milestone 1.pptx | slide 13: Ignition map<br>slide 14 visual explanation of MaxEnt comparing presence and background distributions of covariates.<br>slide 15 tree height data – very important input<br>slides 18 and 19: intuitive display of high and low probability locations against HFTDs<br>slide 21: ignition probabilities by HFTD tier – higher tier; higher probabilities – intuitive<br>slide 34: green, yellow, red visuals for low, medium, and high risk |
| Lunch and learn presentation.pptx | Slides 13 and 14: concise problem statement |
| DxRisk P1 M3_ Maxent circuit priortization.pdf | Capstone document on MaxEnt applications from the end of our first Phase of work. Visual comparisons of ME fits using ignitions, outages, and wiredown events. Performance metrics for ignitions model predicting ignitions and outage model predicting outages. |
| DxRisk Phase 1 modeling summary.pdf | Capstone visual summary of status of Where (MaxEnt)? When (Arrival Process)? And What (Outage/Ignition event classification)? modeling at the end of our first Phase of work. Get at the choice of MaxEnt for answering the “Where” questions of multi-year system hardening prioritization.<br>Note slide 27, detailing the difference in the timing of when outages and ignitions occur. |

| | |
|---|---|
| VM_ME_model_with_wind.docx | Phase 1 analysis of the impact of mean wind speed (long term average) on ignitions model predictions, with color coded map. |
| SALO fall-in trees.pdf | Visual details on Salo's derivation of our fall-in tree covariate |
| DxRisk Phase 1 Milestone 3_ Overview and Model Specifications.pdf | Synthesis document for all Phase 1 modeling activities, including project goals, features of the data/problem that govern our modeling choices, and "where", "when", "what" model specifications |
| Dx Risk Phase 1, Milestone 2 - Data Exploration and Synthesis.docx | Summary of data sources for modeling and an evaluation of their fitness for our purposes. |
| E3 review new modeling results.pptx | PPT with figures, maps, and discussion relating to the modeling process and the fitness of ignition vs. outage trained models. Developed for this review. Highly relevant. |
| VMD_trees_2019_pz_summary_covariates_e3_hftd_23.csv | Csv "roll-ups" of vegetation-caused results for P(ign), P(outage), consequence (official p(ign) and the results of the models run for the "new modeling results" ppt, and covariate values for all CPZs. |
| 2021 EVM Wildfire Risk Model Results - CPZ exploration tool.xlsx | Color-coded spreadsheet of CPZ level results developed to support the model handoff and discussion with EVM planning experts. |
| 2021 Conductor Wildfire Risk Model Results - CPZ exploration tool - was named conductor_pz_summary_hftd_23_release20201015.xlsx | Spreadsheet summarizing CPZ level modeling results, with their associated covariates, developed to support the model validation and handoff with system hardening experts. |
| EVM-CPZ-analysis for Regional review call.pptx | Summary of top CPZ for each EVM region for discussion with regional heads and other VM experts in the process of validating/improving the model. |
| Keswick 1101 model views.pptx | Circuit zoom looking to explain the high ranking of a specific circuit. Responsive to interest in much more finely resolved pixel-level prediction differentiation. |
| Buck Creek Field Visit 4.16.2021.pptx | Circuit zoom looking to explain the high ranking of a specific circuit. Responsive to interest in much more finely resolved pixel-level prediction differentiation. |

## Ignitions are not proportional to outages

The figures below relate to the use of ignition data in modeling and the performance of those models.

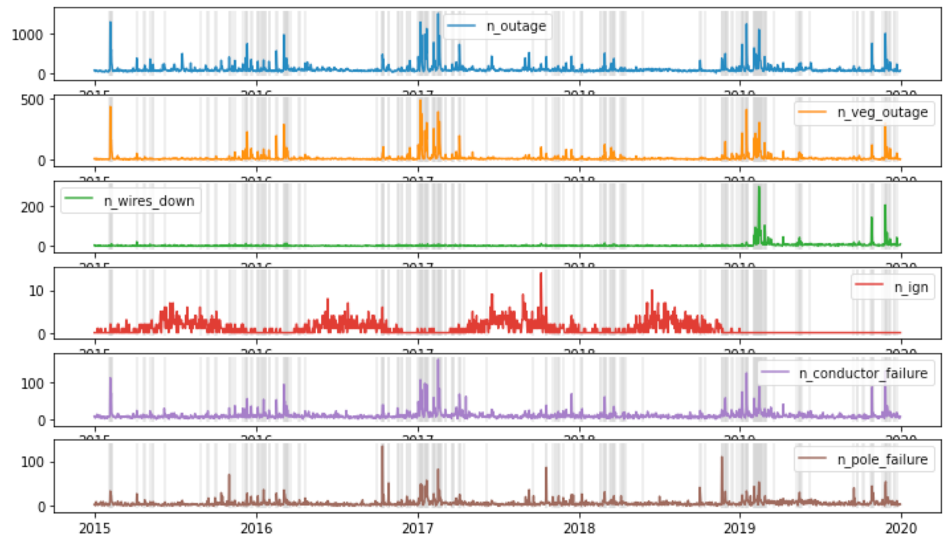



Figure 1: difference in arrival rates of different event types from 2015 to 2020. Note the relative quiet in outages during the summer months when ignitions are the most prominent. (add wind; show how wind colinear with other stuff; better allocation of resources towards high risk areas)

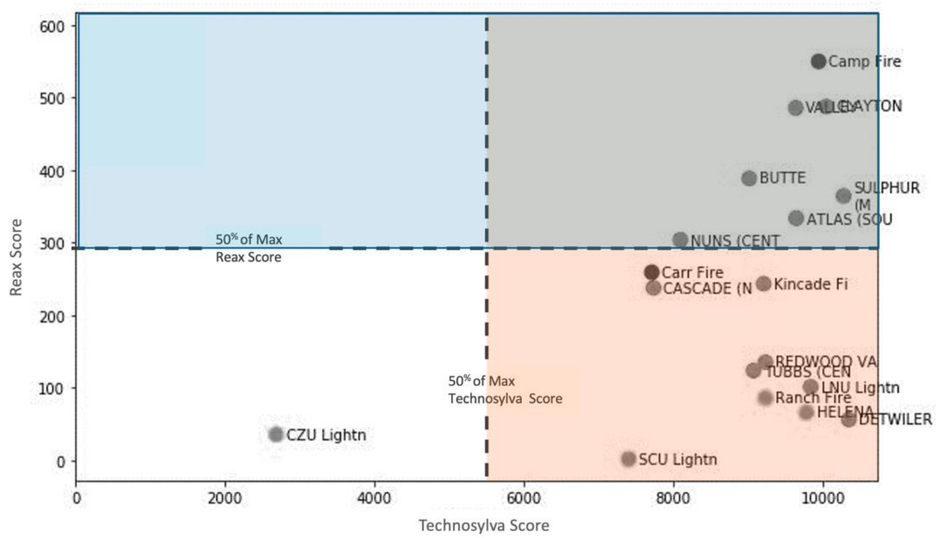
**Model "sees the trees" – what evidence can we provide that the model is not just finding tier 3 but differentiating more finely -** see all the pixel level views of predictions

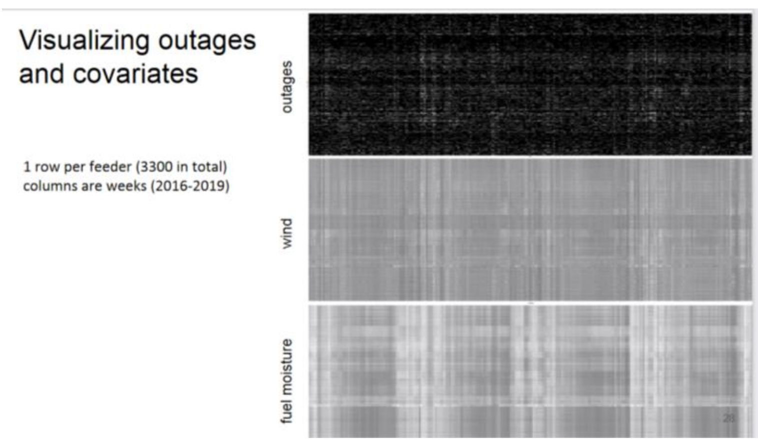
**Planning decisions that are impacted by the "detail experts" - see the "handoff" and "discussion" assets.**

**Schematic diagram of model informing the experts and vice versa**

**Next version of the model – what additional questions are we trying to answer?** Most important: mitigations apply to specific types of ignition causes. Line insulation can prevent both line slap and other sources of phase-to-phase faults, but line spacers prevent only line slap. We are being asked to disaggregate the top-line P(ignition) estimates according to more finely resolved event types. Another example: branch failures vs. trunk failures. To do so, we need to model outages and face the challenge of estimating the probability of an ignition given an outage's characteristics (including type, location, environment, etc.).

MAVF CoRE vs Reax Structures (10km Max) of destructive fires



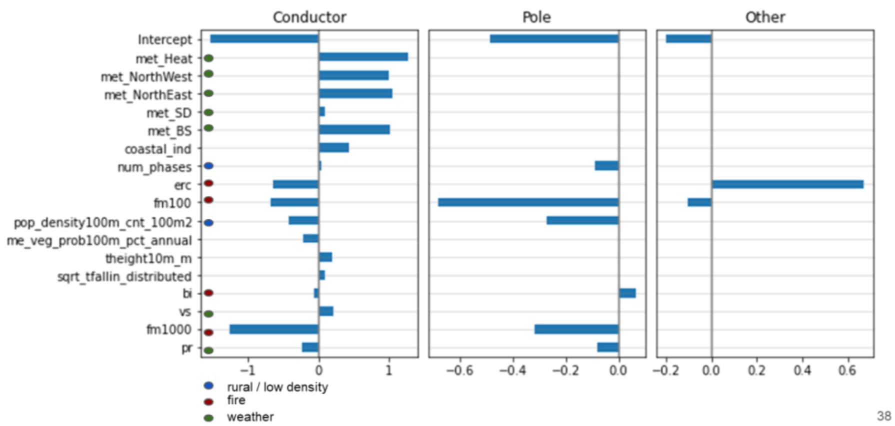



Figure 2: Outage to ignition classification model performance by equipment type. Depends on equipment type involved. For conductors, ignitions are more likely during heatwaves, in wind, and on sunny days, and less likely as fuel moisture and population density increase.

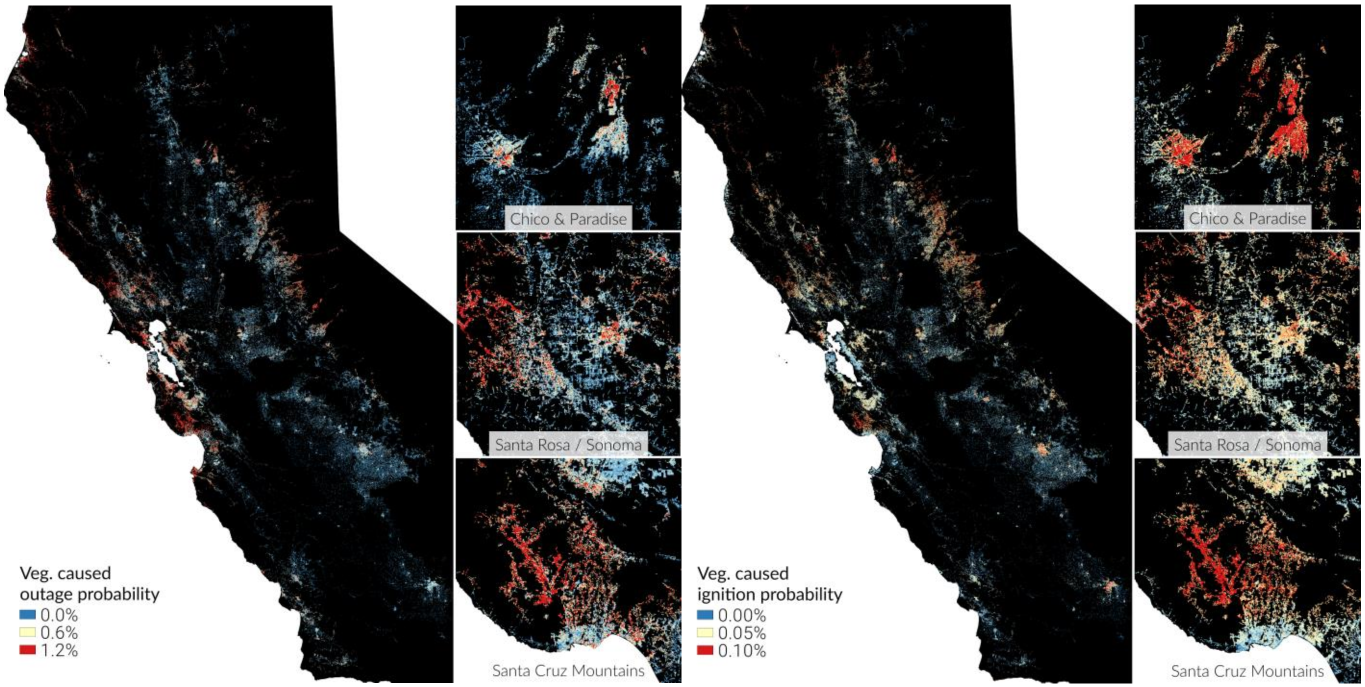



Figure 3: MaxEnt outage (left) vs. ignition (right) predictions.

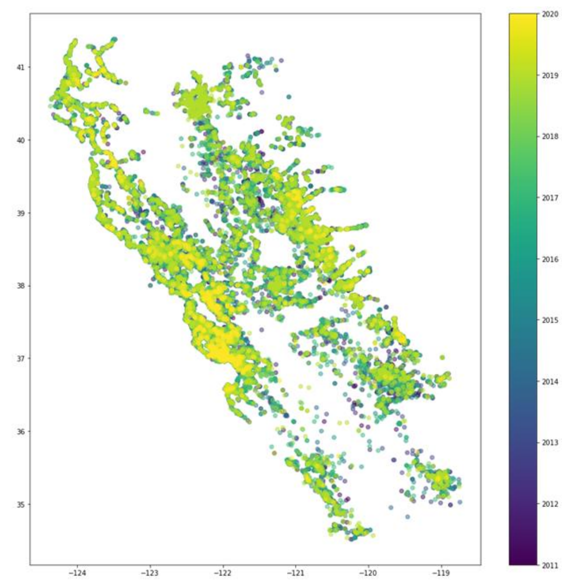



Figure 4: Vegetation-caused outages 2011-2020

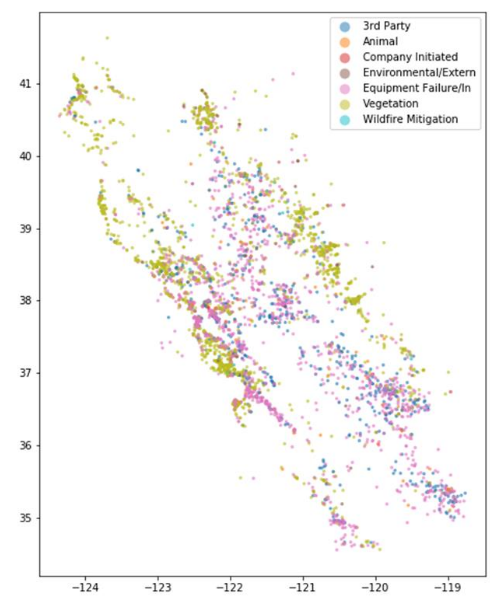



Figure 5: wiredown events (highly correlated with ignitions) by cause type. Note spatial heterogeneity.

| left | right | matches | n_left | n_right | pct_left | pct_right |
|---|---|---|---|---|---|---|
| **outages** | wires_down | 10772 | 707312 | 10812 | 1.5 | 99.6 |
| **outages** | veg_outage | 62341 | 707312 | 76389 | 8.8 | 81.6 |
| **outages** | ign | 1267 | 707312 | 1351 | 0.2 | 93.8 |
| **wires_down** | veg_outage | 2342 | 10812 | 76389 | 21.7 | 3.1 |
| **wires_down** | ign | 198 | 10812 | 1351 | 1.8 | 14.7 |
| **veg_outage** | ign | 385 | 76389 | 1351 | 0.5 | 28.5 |

Table 1: Proportion of events that are also another type. 0.2% of all outages are ignitions 0.5% of vegetation-caused outages are ignitions and 1.8% of wires down are ignitions.

## Physical interpretation

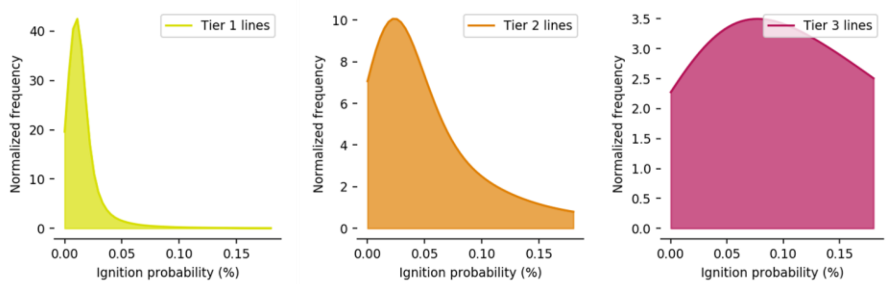



Figure 4: MaxEnt prediction of P(ignition) higher in HFTD tiers 2 and 3 (earlier model of entire grid, not just restricted to the HFTDs

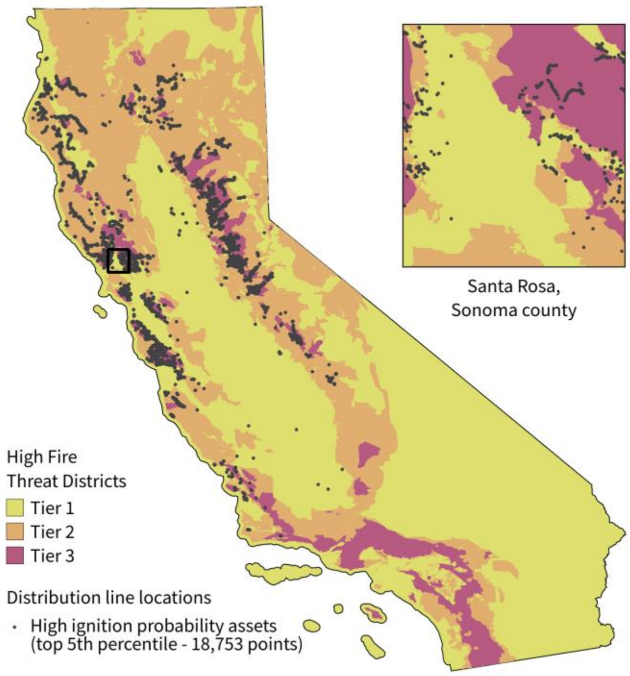



Figure 5: Top 5% of P(ignition) predictions closely align with the HFTD tier 3 zones in northern CA and the sites of many prominent fires.

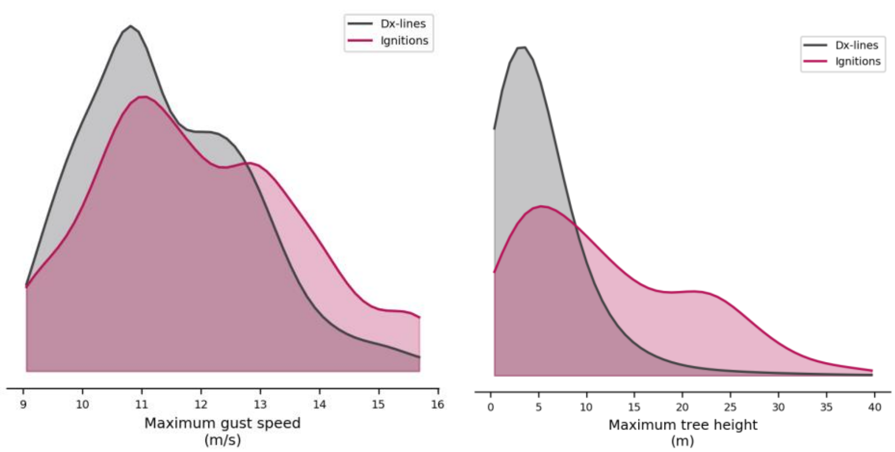



Figure 6: Ignitions associated with higher annual max gust speeds and taller trees

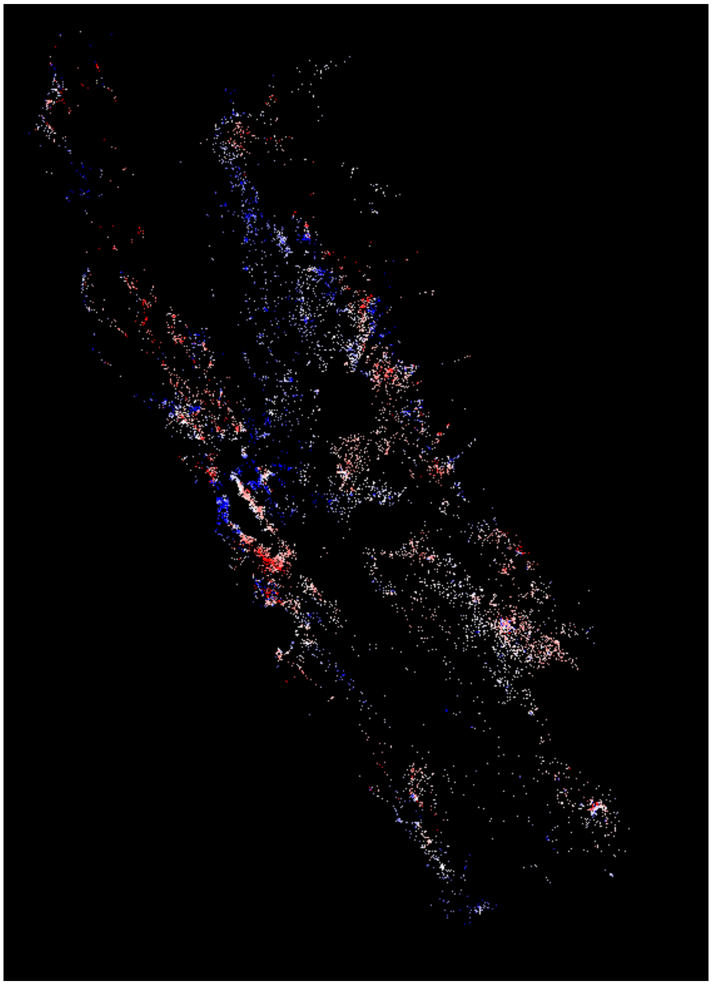


Figure 7: Locations where the prevailing wind covariate increase (red) and decreases (blue) P(ignition)

***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*

See companion deck slides 3 and 4. On slide 3, you will find vegetation-caused outage points (blue) and ignition point (red) for all year (left) and June-Nov (right). Recall that our modeling concern is whether outage and ignitions share the same spatial patterns. When they do not, an outage-trained model will be more likely to prioritize locations/assets that correlate with outage risk rather than ignition risk, diluting the prioritization of wildfire risk. Referring to the map on the left, it is clear that outages do not share the same spatial patterns as ignitions. One of

**Commented [BS1]:** Produce maps outages and ignitions for both actuals and predictions.

the most prominent effects is the greater prominence of coastal outages from winter storms. There are also outages from snow/ide loading in the Sierras. We might conclude that only fire-season outages should be examined to isolate more plausible wildfire failure causes. The map on the right shows better spatial alignment between fire-season outages and ignitions, but the relative density of the two event types still differs.

Referring to slide 4, which presents kernel density estimates for ignitions (left), outages(center), and fire-season outage (right), it is straight forward to identify locations where ignitions occur with relatively higher density than summer outages. See for example the central sierras and north and south coasts. In a nutshell, we understand that "ignition conditions" require an outage to take place with small fuels available and those available fuels to dry enough to favor propagation. Fuel availability and dryness are not direct drivers of outages and thus spatial predictions of outage probabilities, even in the summer, offer a clouded view of where reportable ignitions should be expected.

We expect that a non-trivial model that expresses the relationship between outages and ignitions based on locations and conditions could correct models trained on (far more prevalent) outage data and are currently pursuing such a strategy. The development of such a model was ruled out due to lack of available development time during the modeling for the 2021 deliverables, so the team focused on modeling ignitions directly to avoid biasing results away from locations lacking ignition supporting conditions. This decision was supported by mitigation subject matter experts concerned about having their work directed to low impact outage-drive locations.

See also earlier work visualizing outage and ignition rates in time series.

***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*

**Commented [BS2]:** Outage and ignition data with only locational information guided choice of model which manages presence only data challenge well. Outline identification of need for spatial model. Provide Phase 1 report.

Future improvement in outage and ignition data that is associated with the failed asset will allow for potentially use of other model approaches.
Discuss planned data improvements (LiDAR, etc)

See Phase 2 report for our assessment of all available data, as diagramed below. See also the MaxEnt methods document for a discussion of the factors that led to its selection.

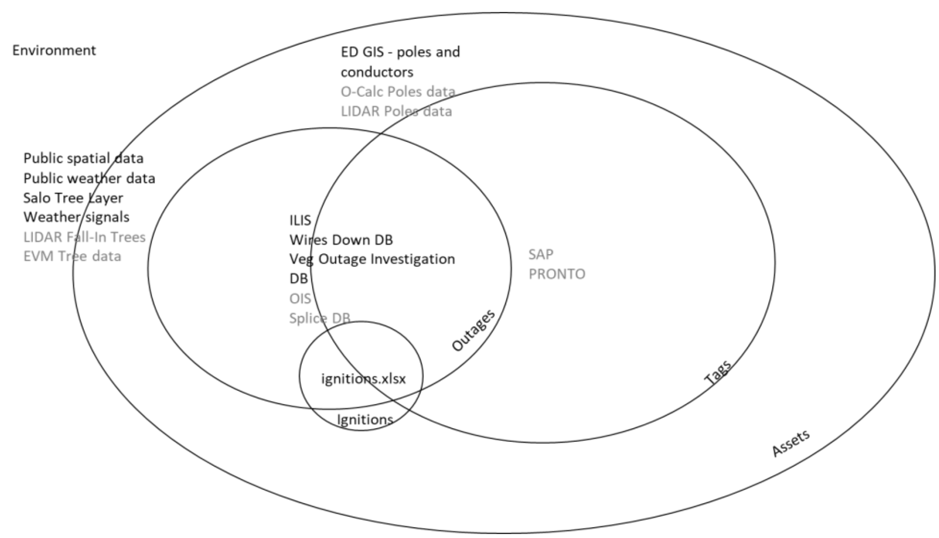


Figure 8: Visual summary of data sets available to the modeling team and cataloged during Milestone 2 of the project.

***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*

Supporting ppt, slides 5-12. Trained 4 different vegetation-caused ignition/outage model specifications using 4-fold 75%/25% train/test splits, always testing on out of sample ignitions. All models focused on HFTDs 2 and 3. The official vegetation-caused ignition model for 2021 was trained using "core" and "fire susceptibility" covariates, combine as "official covariates". Models include: (1) outage from all year; core covariates (2) Jun-Nov outage; core covariates (3) Jun-Nov outages; official covariates (4) Jun-Nov ignitions; official covariates (official model with different training data). Ignition model out-performs best effort outages model with ROC-AUC, with % of correct ignition predictions within the first 20% of ranked grid pixels, and with precision recall, but the two are fairly close.

The qualitative differences between the two models are: ignitions model more concerned in the Sierra Foothills, and North Bay hills and less concerned along the coast and in urban areas.

***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*

See zoomed in PPTs. Also note that

**Present evidence to suggest that 8-hour fire simulations do not produce meaningfully different results than longer simulations**

[JET]

## Emphasis / future documentation structure

***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.*

[we didn't say it was inconsequential, are following advice RE emphasis for next year, FAQ section on wind, high rank in EVM; wind dominates consequence, but not all ignitions]

***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*

[we appreciate this input for our future documentation – feel free to reference those figures and additional intuitive support in your work]

***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*

[we agree; will do in the future; scatter plot – risk vs. consequence; we interpret the dominance as some landscapes are more primed for fire through dryness, fuels, exposure to wind – for example, the 2020 lightning strikes showed how viable ignitions were in landscapes throughout CA]

***Explore ways to show importance of variables in risk (not just ignition). I*** *ncluding consequence may visually promote the role wind and avoid questions from reviewers*

[CPZ csv with covariates and risk components provided]

**Commented [BS3]:** Produce ROC curves to measure predictive power of outage and ignition trained models in predicting ignitions.

**Commented [BS4]:** Zoomed in views of the actual ignitions and probabilities map. Provide views of circuit and circuit segment views of locations, ie, Vaca, Middletown, Keswick,

**Commented [BS5]:** Check with TS and Meteorology on sensitivity analysis on longer simulations. Larger uncertainties.

**Commented [BS6]:** Highlight locations in documentation where call out importance of wind in the model. Knit together to show that wind not inconsequential and better understand it's role. Strengthen role of wind in consequence and overall risk. Explore season weather data and consequence scores to see if pattern that supports the importance of wind.

**Commented [BS7]:** Provide narrative to support the figures more clearly to non-statistical reader. (Also in Phase 1 report).

**Commented [BS8]:** Provide additional narrative with charts from documentation.

**Commented [BS9]:** CPZ level summaries with average covariate values. SH spreadsheet for Brad. Develop scatterplots for variables from spreadsheet. Check with meteorology for wind conditions on worst weather days.

***Use data bootstrapping to reduce class imbalance. Useful for methods that model ignitions or outages***

[different cure for the same symptom; we work with presence only and compare distributions; imbalance undermines prediction and prediction is good; background locations are sampled in MaxEnt - however, we are now reporting cross validated performance data]

***State what aspects of consequence scoring are inherited from elsewhere (CPUC or PG&E) versus unique to the Risk Model***

[JET - MAVF already quantifies risk (defines risk units) and identifies tranches of risk associated with wildfire. EORM performs these top-down calculations and it is desirable to have our work tie in with and normalize to EORM's reported risk scores]

***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*

[Yes this is a case where a modeler could impose model structure not required for overall fit. Indeed those variables did not produce over-fitting when included]

## Continuous improvement

***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*

[2019 model delivered results only; cannot be re-run. So all comparisons to it require analysis of 2019 predictions at the CPZ level. These were performed 2019 vs. 2021 using ROC/ AUC for Vegetation-caused and Conductor-involved; Figure 17. 2019 model not significantly different from chance; 2021 model much improved.] [JET]

***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*

[maps of CPZ p(ign) with points] [Monday discussion with Paul] - it * might * work out to map the 2019 CPZ results. Hasn't yet been pursued.

***Consider adding more data fields for equipment characterization.*** *Explore use of thermography and equipment loading*

[we have and are trying for more: specific targets for 2022 models are lidar, better outage locations, more accurate ids on failed equipment, better meteorology data]

## Future modeling

***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.*

***Create a roadmap that gives future goals and ties the Risk Model to other models. Consider including:***

**Commented [BS10]:** No class imbalance as MaxEnt is presence only. Provide MaxEnt algorithm from MaxEnt experts on how bootstrapping works.

**Commented [BS11]:** Outline MAVF from CPUC and then PG&E MAVF version. Also, catastrophic, and destructive fire definitions. Begin with what provided in documentation.

**Commented [BS12]:** Figure 17 of documentation Produce ROC curves again and tighten narrative for E3

**Commented [BS13]:** Produce map of actual ignitions with probabilities.

**Commented [BS14]:** IR, distribution loading example. Pole model use of pole loading data and transformer model use of electrical loading.

**Commented [BS15]:** Combine with request from Sumeet for all PG&E risk model view. Show plan for increasingly coordinated plan. How use models to measure progress on risk reduction. (JET)

**Commented [BS16]:** Also the PG&E all model view. Need to clarify how these constraints are evident in the current model. For example, how to forecast climate change instead of current fuels. Perhaps tie model to climate variables that are anticipated to change over time.

- *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*

***Conduct uncertainty analysis around consequence scoring.*** *At a minimum, show uncertainty in risk scores based on range around averages at each simulation location*

***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.*

**Commented [BS17]:** Provide information on inspection use of only consequence.

**Commented [BS18]:** Plan to develop ranges and/or error bars for model outputs.

**Commented [BS19]:** Review and report back on how interpret characterization of model ROC curves. Show that supports top 20% workplan.