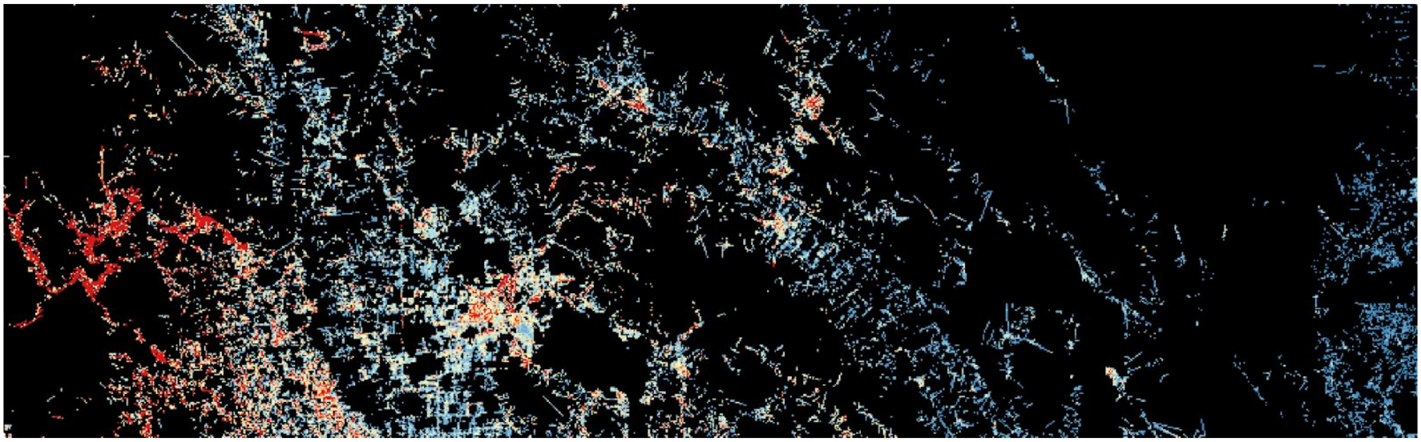

Dx Risk 2021 circuit prioritization: a Maxent approach to calculating annual veg-caused ignition, outage & wiredown probabilities

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Introduction

This document was prepared by the Dx Risk team to support PG&E's upcoming 2021 work plan. We computed a series of event probability scores for each conductor, which were grouped by Circuit ID to predict annual event rates on a per-circuit basis. These event types were vegetation-caused ignitions, outages & wiredowns.

Failure probability scores were modeled using the Maxent approach developed in Phase 1 / Milestone 1. We combined spatially-explicit event data (locations where ignitions, outages & wiredowns occurred) with statewide covariates, which included environmental data (weather, vegetation, topography) and distribution grid properties (e.g. conductor density, jacket type). The model assigns event probability scores to each grid location based on the environmental and grid conditions at that location. Event probabilities for any one asset are typically low as these events are rare; 343 veg-caused ignitions were recorded in 2019 from a network of over 4.5 million conductors. When aggregated across a circuit, the failure probabilities sum to the number of events predicted to occur over a year on that circuit.

Interpreting outputs & performance metrics

Models for ignitions, outages and wiredowns were independently trained and evaluated using AUC, a metric of separability. An AUC score of 0.8 can be interpreted to mean the model is 80% confident it can distinguish between locations where events are and are not likely to occur based on continuous probability scores. We also calculated event 'exposure' scores for each conductor. This was an effort to discriminate, in a binary sense, conductors where events are likely to occur from where they are not. Using an omission rate threshold of 5% we created a 95% confidence area that identifies areas where events could occur. We calculated recall scores to evaluate whether this threshold was well-calibrated; a recall score of 0.96 can be interpreted to mean that 96% of event locations occur within this 'exposure' threshold. Regarding the drivers of model performance, covariates describing the density of fall-in trees, the height of nearby trees, and the number of conductors in an area were consistently the top drivers of model performance.

One key challenge in interpreting this work, and in performing it, is reconciling differences between the gridded predictions and the linear conductor data. We calculated event probabilities using a 100 meter grid, but a grid cell may include multiple conductors. We report normalized probability scores based on the number of conductors per grid cell to avoid double-counting, but this difference manifests elsewhere: while only 40% of the grid *area* may be 'exposed'. 80% of grid *assets* may be exposed when there are multiple conductors in high probability areas.

Notes on modeling details:

· The ignitions and wiredown data were filtered by date from 2015-01-01 to 2018-12-31.

· We report the total counts separately for 2015-2018 and 2018-2019 because it appears there were changes in reporting requirements starting some time in 2018 that led to increases in reported ignitions and wiredowns.

· There are separate ignitions databases for 2015-2018 and 2018-2019, and only data from the former were included in model training.

· Ultimately these counts were used to compute **τ**, the Maxent scaling parameter. This corresponds to the average likelihood of observing an event across the whole system, computed as the number of events in a year divided by the area where these events could be observed. Setting this was as much art as science. We erred on the side of using a higher **τ** value using the higher reported event frequencies of the past few years on the assumption that these events still occurred in past years but simply weren't reported.

· Independent model testing has not yet been performed. All reported performance metrics are training metrics.

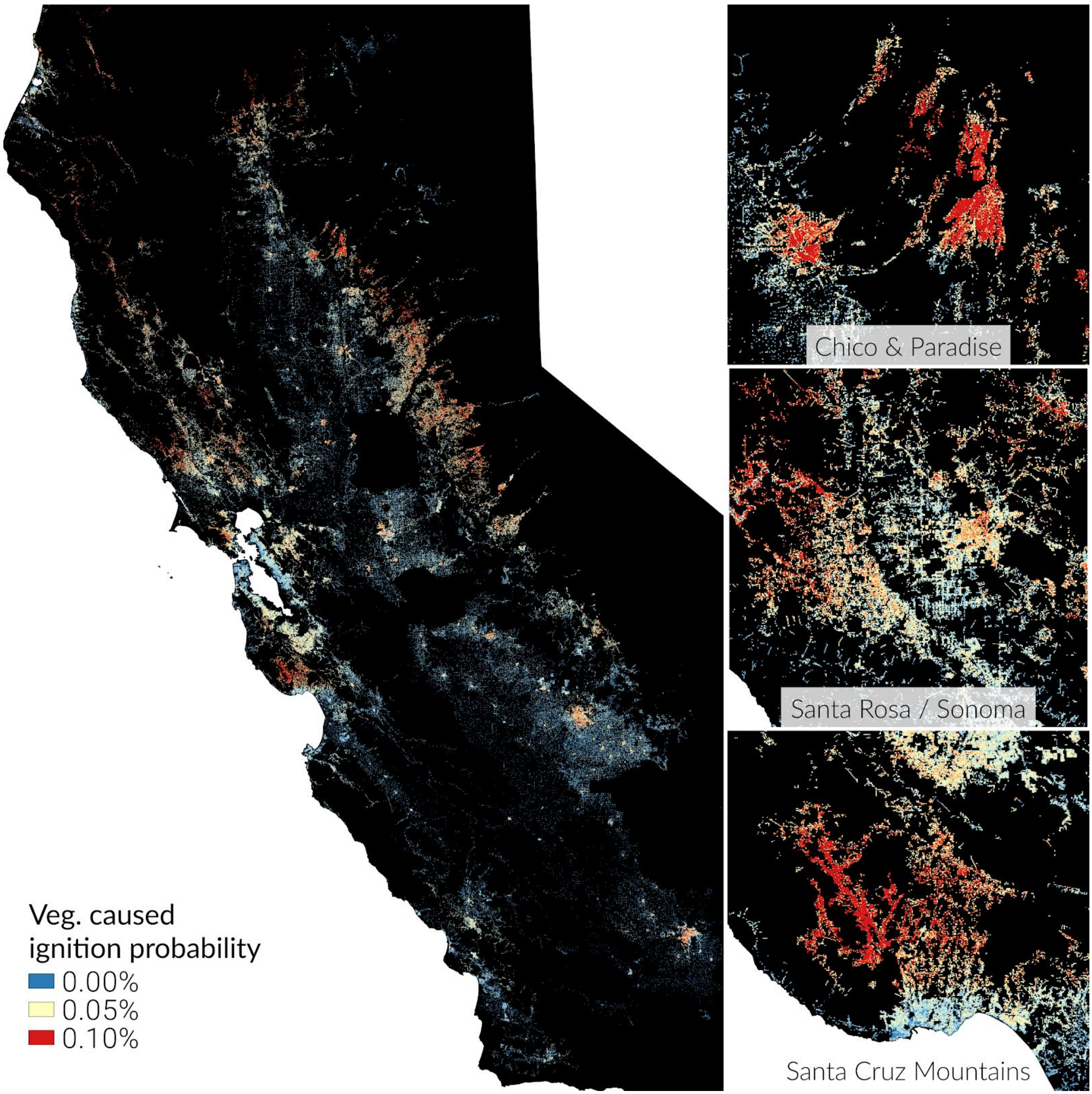
· In the metrics below, percent contribution scores compute how model performance (AUC) changes as a function of randomly altering fitted feature coefficients. Permutation scores are calculated by randomly altering the values of the underlying covariates, not their fitted coefficients, and comparing changes in model performance. Each of these effects are rescaled from 0-100 to estimate relative importance.

· More precise details can be found in the software documentation provided by Phillips, S. J. (2017) A brief tutorial on Maxent. Available at: https://biodiversityinformatics.amnh.org/open_source/maxent/Maxent_tutorial2017.pdf:

> ***Percent contribution:*** *"While the Maxent model is being trained, it keeps track of which environmental variables are contributing to fitting the model. Each step of the Maxent algorithm increases the gain of the model by modifying the coefficient for a single feature; the program assigns the increase in the gain to the environmental variable(s) that the feature depends on. Converting to percentages at the end of the training process, we get the percent contribution."*
>
> *"The percent contribution values are only heuristically defined: they depend on the particular path that the Maxent code uses to get to the optimal solution, and a different algorithm could get to the same solution via a different path, resulting in different percent contribution values. In addition, when there are highly correlated environmental variables, the percent contributions should be interpreted with caution."*
>
> ***Permutation importance:*** *"...for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages."*
>
> *"The permutation importance measure depends only on the final Maxent model, not the path used to obtain it. The contribution for each variable is determined by randomly permuting the values of that variable among the*

training points (both presence and background) and measuring the resulting decrease in training AUC. A large decrease indicates that the model depends heavily on that variable. Values are normalized to give percentages."

Vegetation-caused ignitions



Summary statistics

- Predicted annual ignitions (average): **348.3**
- Observed annual ignitions (2018-2019): 343
- Observed annual ignitions (2015-2018): 119
- Grid area exposed to ignitions: 42.9%
- Grid assets exposed to ignitions: 79.1%
- Top 10 feeders (name, predicted count):
  - APPLE HILL 2102 3.25
  - PLACERVILLE 2106 2.82
  - BRUNSWICK 1106 2.61
  - WEST POINT 1102 2.32
  - PINE GROVE 1102 2.10
  - CAMP EVERS 2106 1.99
  - SHINGLE SPRINGS 2109 1.96
  - MOLINO 1102 1.95
  - NARROWS 2105 1.74
  - HOOPA 1101 1.73

Model performance

- AUC - 0.73
- Recall - 0.98
- Precision - 0.65

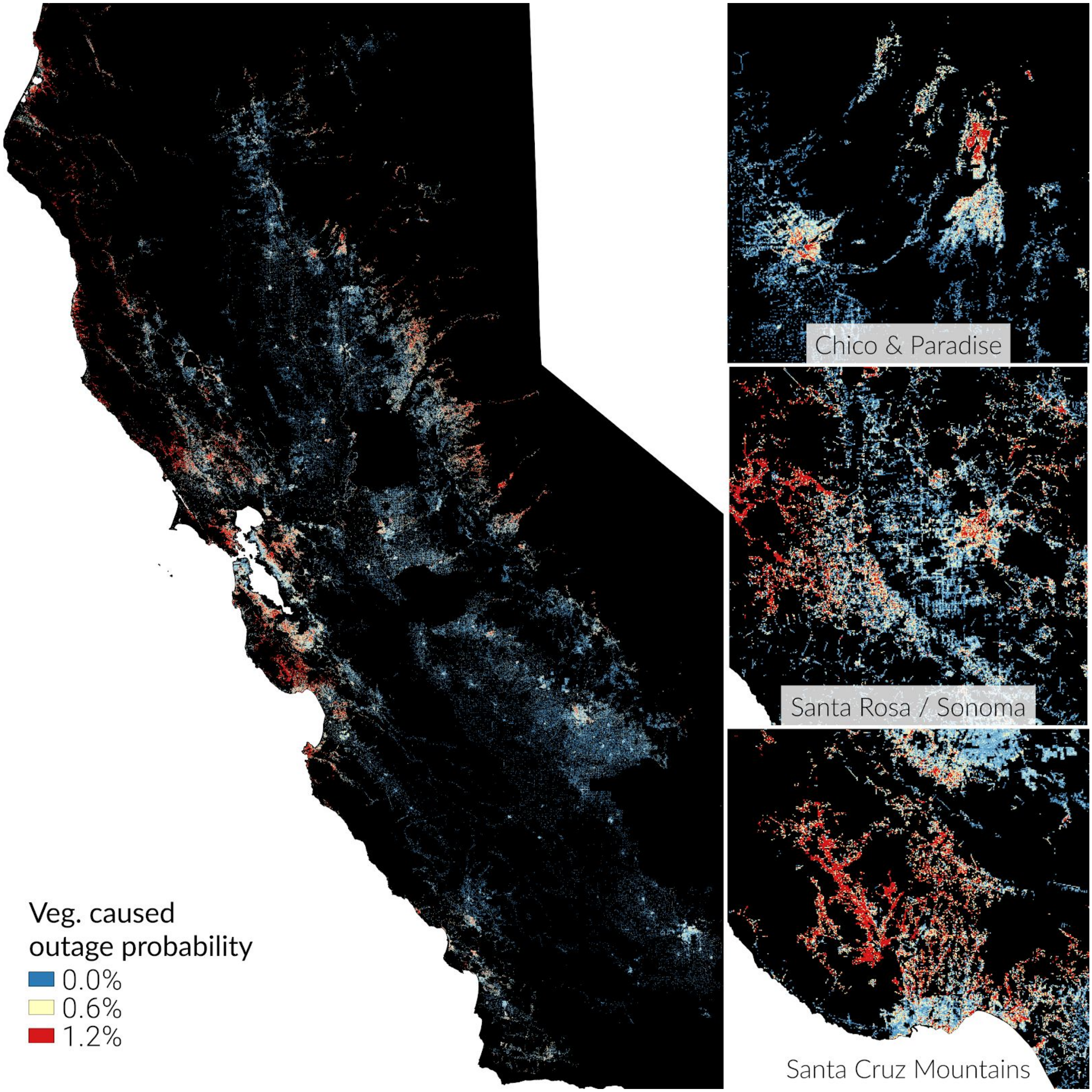
Event data

- 461 ignition locations
- Time frame: 2015-2018
- Filtered by: ‘Contact from Object’ == ‘Vegetation’
- Removed points with spurious lat/lon
  - Outside continental US
  - Greater than 400m away from any conductor

Variable importance rankings

Variable	Percent contribution	Permutation importance
tree-fall-in	32	9.1
tree-height-max	25.2	21.9
conductor-count	8.7	13.3
vapor-pressure-deficit-avg	8.1	15.6
hftd	5.4	2.1
precipitation-avg	4.8	10.3
impervious	3.7	10.9
specific-humidity-avg	3	1.2
canopy-stress	3	1.9
temperature-avg	2.7	2.5
1000-hour-fuels-avg	1.1	1.6
tree-height-avg	0.9	4.1
100-hour-fuels-avg	0.6	0.9
local-topography	0.5	1.5
energy-release-avg	0.3	2.2
burn-index-avg	0	0.7

Vegetation-caused outages



Summary statistics

- Predicted annual outages (average): **3,499.4**
- Observed annual outages (2015-2018): 3,471
- Grid area exposed to veg-caused outages: 36.7%
- Grid assets exposed to veg-caused outages: 80.0%
- Top 10 feeders (name, predicted count):
  - CAMP EVERS 2105 36.79
  - MOLINO 1102 36.19
  - CAMP EVERS 2106 34.78
  - MONTE RIO 1113 29.67
  - MONTE RIO 1111 25.35
  - BIG BASIN 1101 24.99
  - FORT BRAGG A 1102 23.31
  - EL DORADO PH 2101 22.82
  - PINE GROVE 1102 22.16
  - ARCATA 1122 22.12

Model performance

- AUC - 0.82
- Recall - 0.96
- Precision - 0.80

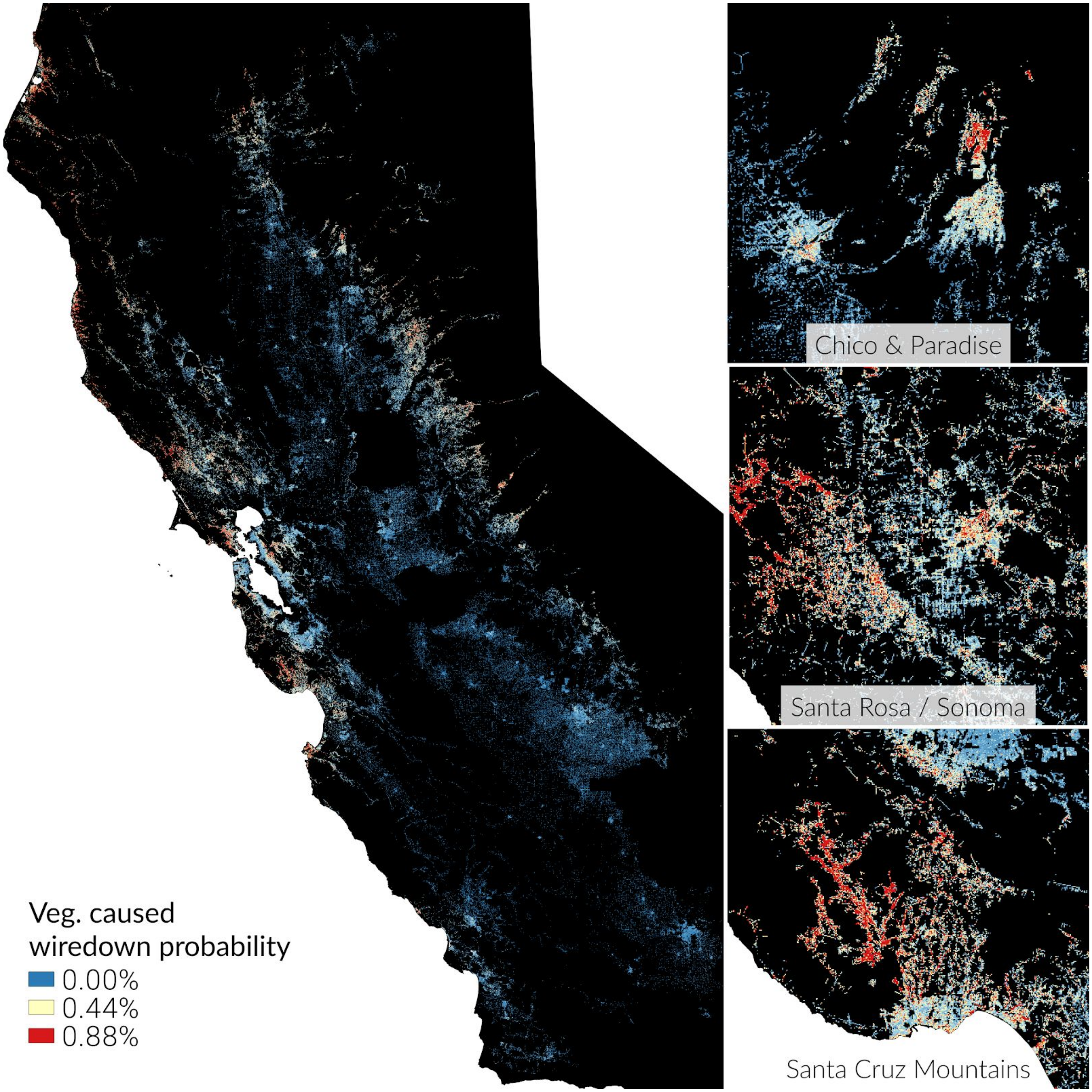
Event data

- 12,885 outage locations
- Time frame: 2015-2018
- Records from the Veg. Outages database
- Removed points with spurious lat/lon
  - Outside continental US
  - Greater than 400m away from any conductor

Variable importance rankings

Variable	Percent contribution	Permutation importance
tree-fall-in	47.7	27.7
tree-height-max	25.3	43.1
conductor-count	13.9	16.4
specific-humidity-avg	4.3	4.7
vapor-pressure-deficit-avg	3.5	3.7
temperature-avg	3.2	0.9
precipitation-avg	0.8	1.4
operating-voltage	0.7	1.6
local-topography	0.3	0.3
tree-height-avg	0.2	0.2
canopy-stress	0.1	0
jacket-type	0	0

Vegetation-caused wiredowns



Summary statistics

- Predicted annual wiresdown (average): **2,721.9**
- Observed annual wiresdown (2018-2019): 2,718
- Observed annual wiresdown (2015-2018): 690
- Grid area exposed to wiresdown: 36.7%
- Grid assets exposed to wiresdown: 73.2%
- Top 10 feeders (name, predicted count):
  - MOLINO 1102 27.28
  - FORT BRAGG A 1102 25.45
  - BIG RIVER 1101 22.38
  - MONTE RIO 1113 22.27
  - CAMP EVERS 2105 21.58
  - ARCATA 1122 20.86
  - MONTE RIO 1111 20.75
  - BRUNSWICK 1106 20.06
  - CAMP EVERS 2106 19.62
  - APPLE HILL 2102 19.59

Model performance

- AUC - 0.82
- Recall - 0.96
- Precision - 0.73

Event data

- 1,844 wiredown locations
- Time frame: 2015-2018
- Filtered by 'Basic Cause' ∈
  - 'Vegetation'
  - 'Environmental/Extern',
  - 'Environmental/External'
- Removed points with spurious lat/lon
  - Outside continental US
  - Greater than 400m away from any conductor

Variable importance rankings

Variable	Percent contribution	Permutation importance
tree-fall-in	46.5	28.6
vapor-pressure-deficit-avg	15.6	16.6
tree-height-max	15.2	19.8
temperature-avg	6.9	4.4
precipitation-avg	5.2	15.1
conductor-count	5.2	5.8
operating-voltage	3	2.5
specific-humidity-avg	0.9	1.3
local-topography	0.7	0.8
tree-height-avg	0.5	4.9
canopy-stress	0.2	0.2
jacket-type	0	0

CSV data

A tally of expected failure counts produced with this approach has been shared along with this document.

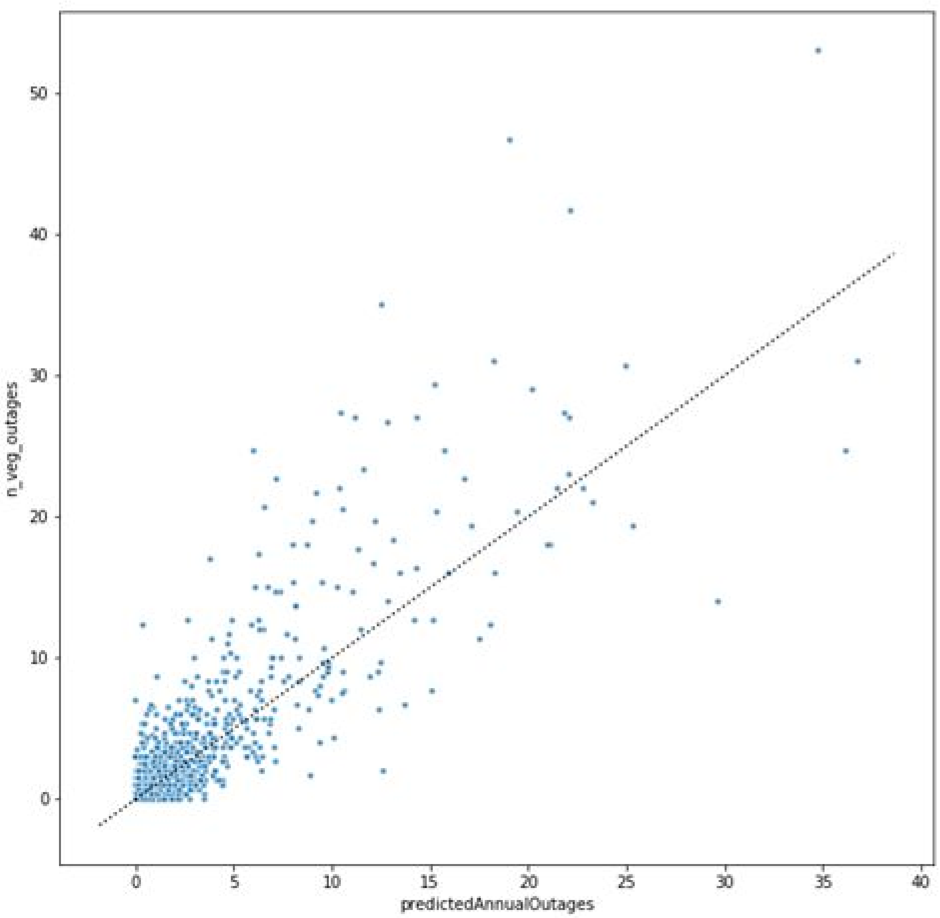
column	**description**
lineMiles	the sum of conductor line miles on the circuit
conductorCount	the number of conductors on the circuit
nPrimary	the number of primary conductors on the circuit
nSecondary	the number of secondary conductors on the circuit
predictedAnnualIgnitions	the sum of expected ignitions across all conductors in a circuit. These were calculated on a raster grid.
predictedAnnualWiresdown	the sum of expected wiredown counts across all conductors in a circuit
predictedAnnualOutages	the sum of expected veg-caused outage counts across all conductors in a circuit
predictedAnnualUnknownOutages	the sum of expected unknown-cause outage counts across all conductors in a circuit
pctExposedIgnitions	the percent of all conductors flagged as 'exposed' to veg-driven ignitions – based on the omission rate calculation (used in recall score assessment)
pctExposedWiresDown	the percent of all conductors flagged as 'exposed' to veg-driven wiredowns
pctExposedOutages	the percent of all conductors flagged as 'exposed' to veg-driven outages

Predicted vs. observed counts

With a model that assigns an annual probability of failure (from 0 to 1) to each small set of grid components, the expectation value of the annual count of failures on a feeder can be computed as the sum of the expected count of failures across all of its components. A simple example with three components that can only fail once, with a 50% chance of failure each, would have an expected failure count of 0.5 each and produce and expected count of 0.5 + 0.5 + 0.5 = 1.5 failures.

The above calculation is a simplification of what we are actually doing. Recall that we are not modeling assets directly. We are modeling grid pixels that still have outage rates are so sparse in both space and time that no individual "grid pixel" has a large probability of annual failure. It is the nature of probabilities that an event with a tiny probability of happening over the course of a year, which is itself the integral of smaller probabilities on finer timescales, could happen 0, 1, 2, 3 or more times, but with a small annual rates, the average rate of failures over each feeders pixels might be expected to be 1 in 100 years or more. If you use a Poisson distribution to model such rare events, the difference between 1*p(y=1) and sum(p(y>=i) * i) for 1 to infinity is something like 0.0001, or 1 in 10,000. In other words we have taken a small shortcut by equating E[fail] for one year with p(fail). We might casually say that we are taking the sum of probabilities across all of a feeder's components, but we are actually implicitly converting to E[fail] for each pixel in a feeder and summing them. It is true that if we were modeling a less sparse occurrence, we could not take this shortcut.

What the ME model in particular is doing with each failure is recording the covariate values at that time/location and adding them to the distributions of values for observed failures. To the model it is irrelevant where they came from. So if you have many failures in the exact same spot, that signal boosts the probabilities of all pixels with similar values, with no particular affinity for the original location. So in the hypothetical case where a single asset repeatedly fails, say n times, that "count" will be spread across environmentally similar pixels, resulting in an expected increase in E[fail] of n. The expected failure counts for this work were calculated in this manner and can be compared to historical rates of outages of different types.



The figure above plots a point for every feeder with the model prediction of the expected failure counts on the x-axis and the 2015-2018 mean count of outages with vegetation listed as their cause on the y-axis. The dotted line runs through the points where the two numbers are equal (perfect prediction). Feeders above the line suffer more outages than predicted and feeders below the line suffer fewer than predicted. Feeders that fail more often than the model predicts are likely to have exacerbating factors beyond the ones used to train the model influencing their outcomes.