forcasting forest fires

fantastic fouR: Eli Levine, Hannah Long, Preetha Ramachandran

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Introduction

Climate change represents an existential threat to humanity. Its effects have the potential to dramatically shape life as we know it, creating climate refugees, resource wars, and submerging major cities around the globe. However, unlike previous challenges to our way of life, the threat of climate change will not manifest in a single event, rather in a series of natural disasters that will eventually escalate to a point where we no longer have the resources to manage them. This is being seen already in California as wildfires sweep the state, forcing people to relocate, causing issues with access and use of electricity and causing an estimated $10 billion in damages. Thus, in our project, we plan to determine what are the strongest environmental predictors of forest fires by looking at data from California.

It is important to understand what these predictors are to determine how to prevent short term fires from escalating and to correct these conditions in the long run to see if it is possible to mitigate the threat of these fires going forward. If we know what predictors play a role in a fire, it can help authorities better understand what days or seasons present a higher risk, and thus prepare accordingly. While climate change will continue to affect our way of life, insights into how to manage its consequences and effects will help us plan for both the short term and long term future, at least until policy and research catch up to the severity of the issue.

Thus, the research question we want to answer is: what are the strongest environmental predictors of forest fires in California?

The data we will be using was scraped from CIMIS (California Irrigation Management Information System) weather stations by github user czaloumi using a selenium chromedriver. The dataset was combined with Wikipedia tables listing California fires by county and city to create the Target column, which indicates whether or not there was a fire on a particular day. Additionally, the curator of the dataset adds that this dataset was "used in conjunction to building an XGBoost Classifier to accurately predict probability for fire given environmental condition feature." This user's data contains a mixture of environmental and geospatial data to understand the size and the scope of the forest fires, as well as where the fires seem to be most frequent.

Our Data

There are 128,126 observations in the data set. Each observation represents information on the weather conditions at a given weather station on a specific date.

The response variable we will be investigating is Target, which corresponds to fires on the respective observation date, in the observation region. The Target variable is a binary indicator, with a value of 1 indicating there was a fire and a value of 0 indicating there was not a fire.

Our potential predictor variables are:

`ETo` - The ETo variable measures the average amount of evapotranspiration present in the soil in each of the regions. This means that it is the amount of water transferred to the land by means of plants.

`precip` - The precip variable measurse the long term monthly average amount of precpitation found in the each station's region.

solrad - The solrad variable measures the average amount of solar radiation found in the each station's region.

avgvappress - The avgvappress variable measures the average amount of vapor pressure found in the each station's region.

avgsoiltemp - The avgsoiltemp variable measures the average soil temperature found in the each station's region.

windrun - The windrun variable measures the sum of wind speed over a month.

avgwindspeed - The avgwindspeed variable measures the average wind speed found in the each station's region.

dewpoint - The dewpoint variable measures the average temperature of the dew on the grass in each station over a month long period.

avgrelhum - The avgrelhum variable measures the average relative humidity found in the each station's region.

avgairtemp - The avgairtemp variable measures the monthly average of the air temperature found in the each station's region.

Exploratory Data Analysis

As previously stated, the dataset contains observations of weather conditions and indicates the presence of a fire on a specific date at a certain weather station in California. Each of the stations in our dataset has recorded observations of these weather conditions between 2018 and summer 2020. Because the conditions recorded by one station will likely be similar to those in a nearby station and similar to the recordings the day before, we had to simulate independence by filtering our data.

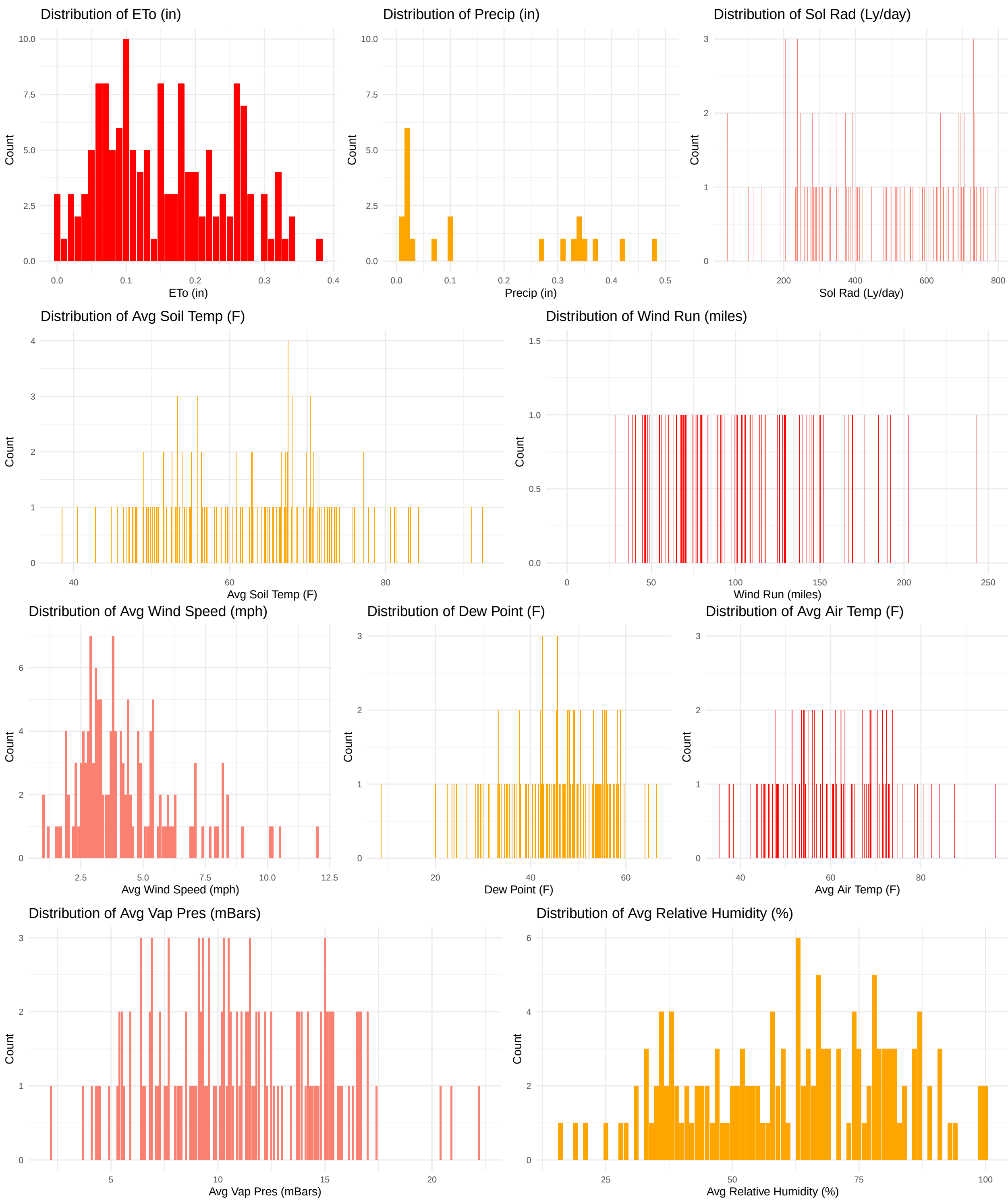
First, observations were grouped by station id number. Next, one day was chosen at random from each of the stations. This gave us 153 observations instead of the original dataset of 128,126 observations.

By reducing the data set to a small training set, we are able to make a model that is a more realistic approximation of the conditions that might cause a fire, sans the correlation that comes with keeping all of the data. Additionally, constructing a model with a random sample of the data allows us to test our final model on a new sample of data to assess its predictive power. What more, taking a smaller, random sample of the data allows us to ensure that randomness is satisfied for our analysis. Finally, taking a random sample would ensure that the data satisfies independence, because whether a fire is reported or not is no longer conditional on surrounding stations, as each station is from different days and from different times of the year. Thus, while the dataset in its entirety does not satisfy independence, our random sample meets this criteria.

Even after reducing our dataset to 153 random observations, it was clear that there was still some stations with missing observations in some variable categories. We decided to use only complete observations in the analysis, and thus, the total number of observations was further reduced to 143.

On surface, it did not appear that the observations with missingness differed systematically from the complete observations; it is thus unlikely that our resulting analysis is biased by the decision to remove the data.

Our first step of our exploratory data analysis was to look at the shape of the distributions of each variable. This would give us a sense about which transformations might be necessary.



Some of the predictor variables in our dataset are not shown here as they were not used for analysis. The plots for these variables can be found in Appendix A along with an explanation for their elimination.

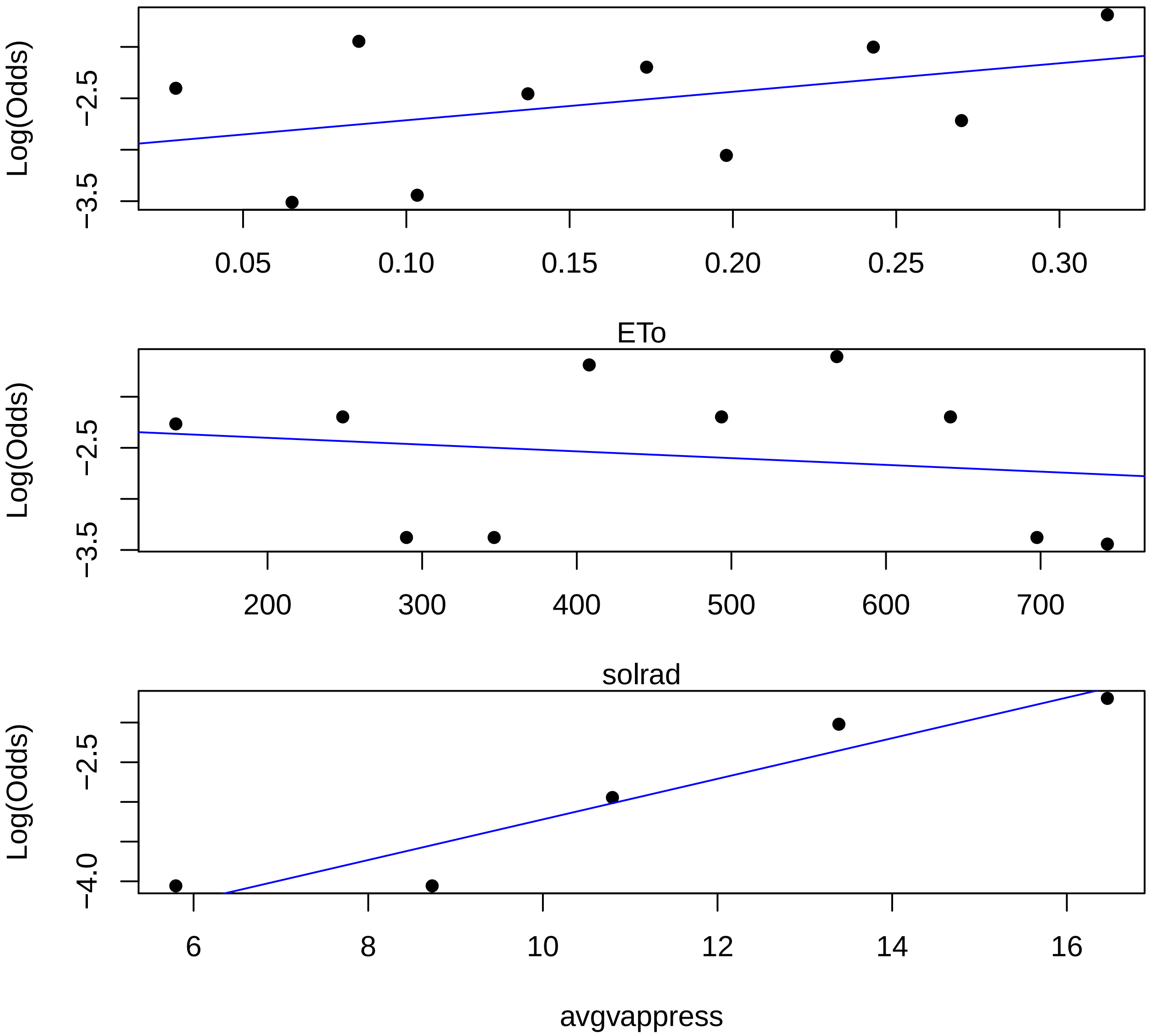
Precipitation and average wind speed appear to be right skewed, ETo is roughly trimodal, average relative humidity is bimodal, and dew point is roughly left skewed. Across the board, the histograms are far from normal, the multiple peaks and unique spreads and distributions are likely due to limited data points, a hypothesis made clear by the low counts shown on each graph.

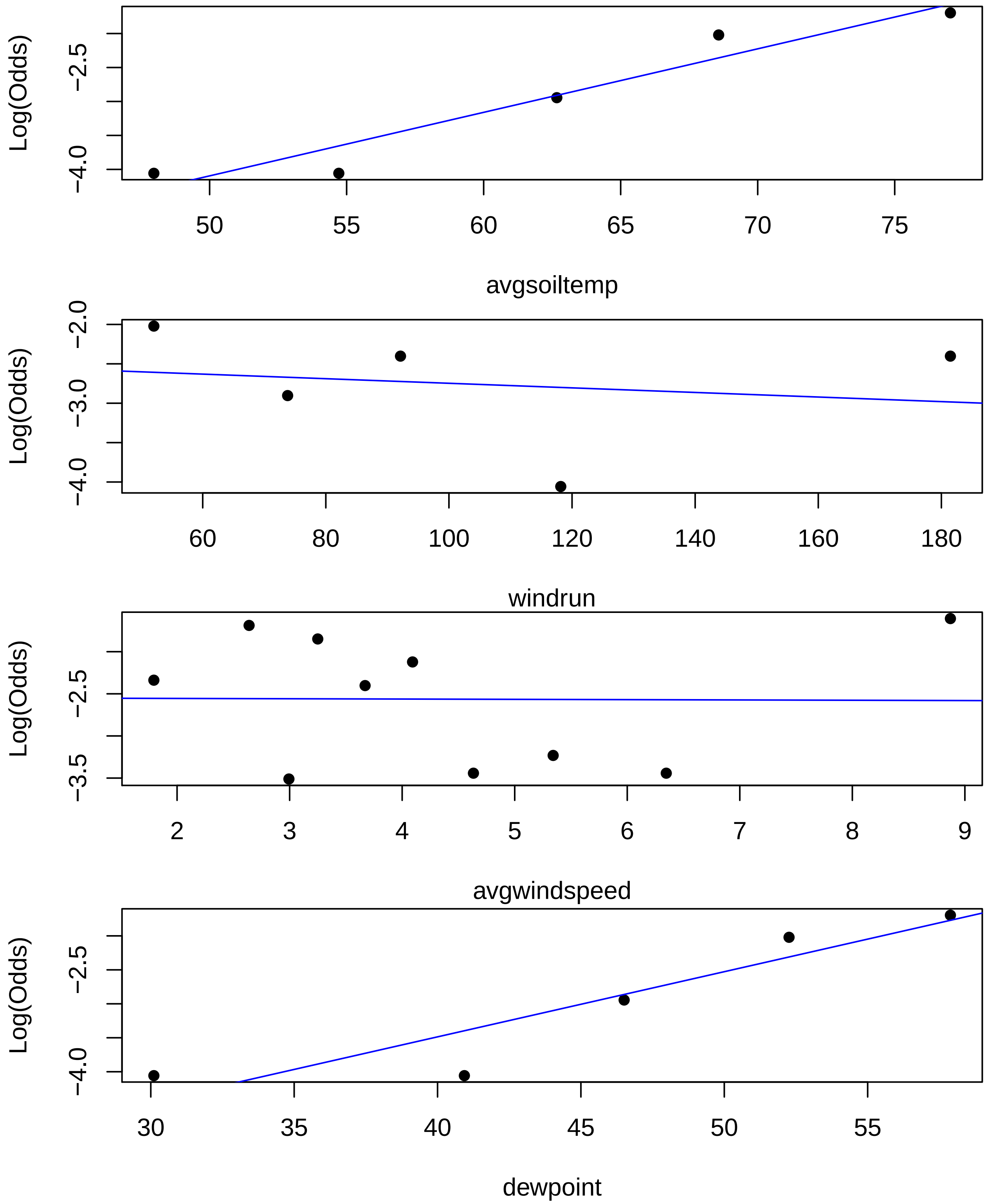
Methodology

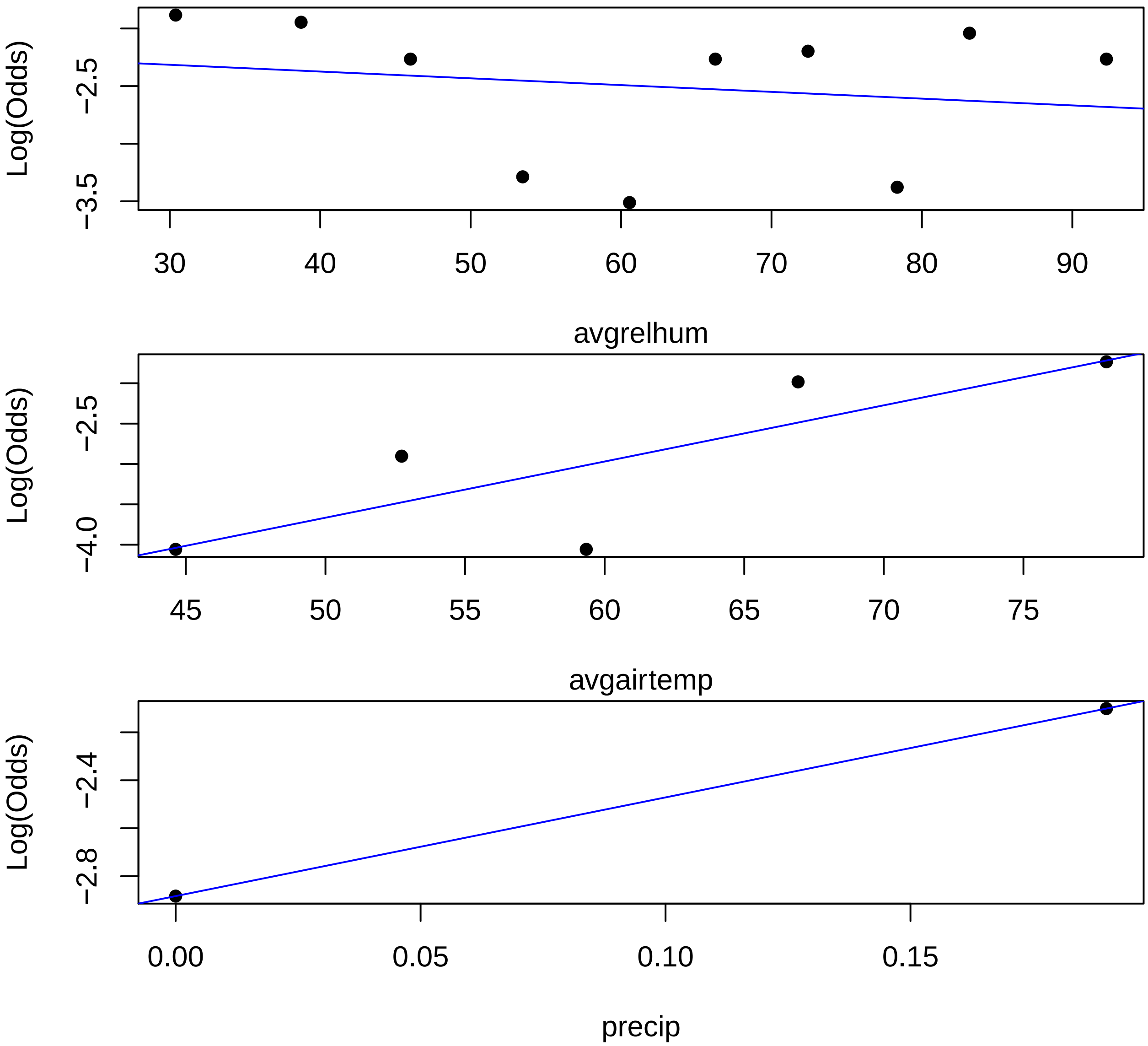
We are trying to predict the presence of a fire with a binary response variable, Target (which indicates the presence or non presence of a fire); therefore we will use a logistic regression for our analysis.

However, to be able to use logistic regression we need to check the conditions, and ensure that the data satisfies linearity, randomness and independence.

To check linearity, we will make an empirical logistic regression plot for each of the predictor variables.




Log(Odds)
−4.0
−2.5
50
55
60
65
70
75
avgsoiltemp
Log(Odds)
−4.0
−3.0
−2.0
60
80
100
120
140
160
180
windrun
Log(Odds)
−3.5
−2.5
2
3
4
5
6
7
8
9
avgwindspeed
Log(Odds)
−4.0
−2.5
30
35
40
45
50
55
dewpoint



After looking at these graphs, it is apparent that average wind speed, and average relative humidity do not follow a linear relationship. Furthermore, linearity is only satisfied for precipitation when there are only 2 groups. This means that a linear model might not be an appropriate estimation for precipitation.

#maybe move this to EDA where we actually do this process We took a random sample of the days in our data set. This also supports independence. Our cleaning of the data to include a random sample of days and stations. ##

We then began to construct prediction models. We first started with a main effects model containing all possible predictors.

term	estimate	std.error	statistic	p.value
(Intercept)	10.675	35.013	0.305	0.760
ETo	188.028	87.104	2.159	0.031
solrad	-0.084	0.032	-2.581	0.010
avgvappress	-1.638	2.454	-0.667	0.505
avgsoiltemp	0.372	0.158	2.359	0.018
windrun	5.004	2.377	2.106	0.035

term	estimate	std.error	statistic	p.value
avgwindspeed	-121.460	57.515	-2.112	0.035
avgrelhum	-0.430	0.305	-1.411	0.158
precip	2.630	7.298	0.360	0.719
dewpoint	1.961	1.527	1.284	0.199
avgairtemp	-1.239	0.678	-1.827	0.068

Because the only significant term in the model is the term for average soil temperature (the only term with an associated p.value of less than 0.05), we suspected multicollinearity. We used vif to further investigate this idea.

	x
ETo	213.555
solrad	137.988
avgvappress	96.436
avgsoiltemp	6.590
windrun	27969.818
avgwindspeed	28326.883
avgrelhum	102.907
precip	1.497
dewpoint	156.484
avgairtemp	184.489

We removed the variable representing the sum of wind speed over the month (windrun) due to its multicollinearity with average wind speed, as indicated by the large and similar vif values for both. Average relative humidity and dewpoint were removed as well due to multicollinearity with average vapor pressure and average air temperature, respectively. We then constructed a new model (main_fire_model) without the aforementioned variable.

term	estimate	std.error	statistic	p.value
(Intercept)	-5.392	7.582	-0.711	0.477
ETo	66.411	47.197	1.407	0.159
solrad	-0.031	0.015	-2.075	0.038
avgvappress	0.432	0.316	1.365	0.172
avgsoiltemp	0.218	0.082	2.650	0.008
avgwindspeed	-0.430	0.429	-1.003	0.316
precip	1.430	4.442	0.322	0.747
avgairtemp	-0.203	0.180	-1.128	0.259

	x
ETo	104.092
solrad	49.728
avgvappress	4.094
avgsoiltemp	4.308
avgwindspeed	2.944
precip	1.245
avgairtemp	23.040

Because the remaining vif values are 1) dissimilar from each other or 2) generally small, we can conclude that we have removed highly correlated variables from analysis.

Next, using backwards selection from main_fire_model, we constructed new_fire_model.

```
## Start:  AIC=46.99
## Target ~ ETo + solrad + avgvappress + avgsoiltemp + avgwindspeed +
##     precip + avgairtemp
##
##                Df Deviance    AIC
## - precip        1   31.089 45.089
## - avgwindspeed  1   32.148 46.148
## - avgairtemp    1   32.402 46.402
## <none>              30.992 46.992
## - avgvappress   1   33.309 47.309
## - ETo           1   33.524 47.524
## - solrad        1   38.263 52.263
## - avgsoiltemp   1   39.324 53.324
##
## Step:  AIC=45.09
## Target ~ ETo + solrad + avgvappress + avgsoiltemp + avgwindspeed +
##     avgairtemp
##
##                Df Deviance    AIC
## - avgwindspeed  1   32.167 44.167
## - avgairtemp    1   32.436 44.436
## <none>              31.089 45.089
## - avgvappress   1   33.329 45.329
## - ETo           1   33.528 45.528
## - solrad        1   38.297 50.297
## - avgsoiltemp   1   39.509 51.509
##
## Step:  AIC=44.17
## Target ~ ETo + solrad + avgvappress + avgsoiltemp + avgairtemp
##
##               Df Deviance    AIC
## - avgairtemp   1   32.579 42.579
## - ETo          1   33.563 43.563
## - avgvappress  1   33.573 43.573
## <none>             32.167 44.167
## - solrad       1   39.933 49.933
## - avgsoiltemp  1   40.605 50.605
##
## Step:  AIC=42.58
## Target ~ ETo + solrad + avgvappress + avgsoiltemp
##
##               Df Deviance    AIC
## - avgvappress  1   33.599 41.599
## - ETo          1   33.874 41.874
## <none>             32.579 42.579
## - avgsoiltemp  1   40.961 48.961
## - solrad       1   42.532 50.532
##
## Step:  AIC=41.6
## Target ~ ETo + solrad + avgsoiltemp
```

```
##
##               Df Deviance    AIC
## - ETo          1   34.678 40.678
## <none>             33.599 41.599
## - solrad       1   43.297 49.297
## - avgsoiltemp  1   50.269 56.269
##
## Step:  AIC=40.68
## Target ~ solrad + avgsoiltemp
##
##               Df Deviance    AIC
## <none>             34.678 40.678
## - solrad       1   49.448 53.448
## - avgsoiltemp  1   61.224 65.224
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-15.2290556	3.5724080	-4.262967	0.0000202	-23.5649146	-9.1682137
solrad	-0.0118340	0.0037360	-3.167531	0.0015374	-0.0205131	-0.0053647
avgsoiltemp	0.2580629	0.0646067	3.994368	0.0000649	0.1472155	0.4076018

AIC	BIC
40.678	49.566

write out new_fire_model here

We then decided to try out variable transformations to potentially bolster the predictive power of our model.

From a theoretical perspective, it is likely that our response variable, the log likelihood of a fire, and one of our predictors, average temperature of the dew on the grass (dewpoint), have a curvilinear relationship. A low value for dewpoint could be recorded by a particular station as a result of firefighting efforts while a high value for dewpoint could be the result of a fire.

To test if this might be the case, we added a quadratic transformation of dewpoint as a predictor to our main effects model and fit a new model.

term	estimate	std.error	statistic	p.value
(Intercept)	56.625	46.019	1.230	0.219
ETo	186.740	84.868	2.200	0.028
solrad	-0.083	0.032	-2.602	0.009
avgvappress	-7.723	6.523	-1.184	0.236
avgsoiltemp	0.374	0.159	2.350	0.019
windrun	4.937	2.384	2.071	0.038
precip	2.378	7.374	0.323	0.747
I(dewpoint^2)	0.047	0.035	1.327	0.185
avgairtemp	-1.142	0.643	-1.775	0.076
avgwindspeed	-119.824	57.703	-2.077	0.038
avgrelhum	-0.379	0.286	-1.324	0.185

```
## Start:  AIC=41.11
## Target ~ ETo + solrad + avgvappress + avgsoiltemp + windrun +
##     precip + I(dewpoint^2) + avgairtemp + avgwindspeed + avgrelhum
```

```
##
##                 Df Deviance    AIC
## - precip         1   19.211 39.211
## - avgvappress    1   20.750 40.750
## <none>               19.111 41.111
## - I(dewpoint^2)  1   21.289 41.289
## - avgrelhum      1   21.489 41.489
## - avgairtemp     1   24.509 44.509
## - windrun        1   26.776 46.776
## - avgwindspeed   1   26.880 46.880
## - ETo            1   28.559 48.559
## - avgsoiltemp    1   32.017 52.017
## - solrad         1   36.476 56.476
##
## Step:  AIC=39.21
## Target ~ ETo + solrad + avgvappress + avgsoiltemp + windrun +
##     I(dewpoint^2) + avgairtemp + avgwindspeed + avgrelhum
##
##                 Df Deviance    AIC
## - avgvappress    1   21.181 39.181
## <none>               19.211 39.211
## - avgrelhum      1   21.675 39.675
## - I(dewpoint^2)  1   21.748 39.748
## - avgairtemp     1   24.681 42.681
## - windrun        1   26.871 44.871
## - avgwindspeed   1   26.971 44.971
## - ETo            1   28.618 46.618
## - avgsoiltemp    1   32.303 50.303
## - solrad         1   36.556 54.556
##
## Step:  AIC=39.18
## Target ~ ETo + solrad + avgsoiltemp + windrun + I(dewpoint^2) +
##     avgairtemp + avgwindspeed + avgrelhum
##
##                 Df Deviance    AIC
## - avgrelhum      1   21.967 37.967
## <none>               21.181 39.181
## - I(dewpoint^2)  1   23.504 39.504
## - avgairtemp     1   24.757 40.757
## - ETo            1   28.920 44.920
## - windrun        1   29.290 45.290
## - avgwindspeed   1   29.363 45.363
## - avgsoiltemp    1   34.968 50.968
## - solrad         1   36.608 52.608
##
## Step:  AIC=37.97
## Target ~ ETo + solrad + avgsoiltemp + windrun + I(dewpoint^2) +
##     avgairtemp + avgwindspeed
##
##                 Df Deviance    AIC
## <none>               21.967 37.967
## - I(dewpoint^2)  1   24.701 38.701
## - avgairtemp     1   25.610 39.610
## - ETo            1   29.928 43.928
```

```
## - windrun        1   30.862 44.862
## - avgwindspeed   1   30.946 44.946
## - avgsoiltemp    1   36.340 50.340
## - solrad         1   36.909 50.909
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-6.727	8.645	-0.778	0.437	-25.007	10.901
ETo	157.331	75.853	2.074	0.038	39.359	352.290
solrad	-0.070	0.029	-2.400	0.016	-0.147	-0.026
avgsoiltemp	0.434	0.180	2.414	0.016	0.169	0.924
windrun	5.255	2.506	2.097	0.036	1.418	11.731
I(dewpoint^2)	0.002	0.002	1.312	0.189	0.000	0.007
avgairtemp	-0.374	0.233	-1.606	0.108	-0.932	0.009
avgwindspeed	-127.386	60.670	-2.100	0.036	-284.273	-34.577

AIC	BIC
37.967	61.669

Adding the quadratic transformed variable, AIC has a three point improvement over new_fire_model, but BIC is larger. Because we have no preference for a parsimonious model (what is indicated by a lower value of BIC), we decided to keep the quadratic term for dewpoint. Thus, our current model is:

$$\hat{Target} = -6.727 + 157.331 ETo + -0.070 solrad + 0.434 avgsoiltemp + 5.255 windrun + 0.002 (dewpoint^2) + -0.374 avgairtemp - 1$$

Next, we explored potentially meaningful interaction terms. We ultimately chose to test the only interaction term which seemed meaningful: ETo*avgwindspeed. We inferred that large amounts of water transferred to the land by means of plants (ETo) and high wind speed would (jointly) significantly increase the log likelihood of a forest fire because a lot of fast-moving wind may spread the water and thus make it harder for a fire to develop in the area, and, on the other end of the spectrum, easier for a fire to begin in a region with less plant based transpiration.

To determine if this interaction term is statistically significant, we added it to the model with the quadratic dewpoint term (shown above) and conducted a drop-in-deviance test between the model with and without the interaction term.

term	estimate	std.error	statistic	p.value
(Intercept)	-7.071	8.901	-0.794	0.427
ETo	141.203	90.262	1.564	0.118
avgwindspeed	-123.252	59.778	-2.062	0.039
solrad	-0.066	0.031	-2.119	0.034
avgsoiltemp	0.422	0.177	2.387	0.017
windrun	5.076	2.474	2.052	0.040
I(dewpoint^2)	0.002	0.002	1.223	0.221
avgairtemp	-0.341	0.257	-1.325	0.185
ETo:avgwindspeed	1.244	3.990	0.312	0.755

Resid..Df	Resid..Dev	df	Deviance	p.value
135	21.967	NA	NA	NA
134	21.874	1	0.092	0.761

The p-value of the drop-in-deviance test is 0.761, much greater than our alpha level of 0.05, which suggests that the data do not provide sufficient evidence to suggest that the interaction term is statistically significant. Thus, we will not include the interaction term in our final model.

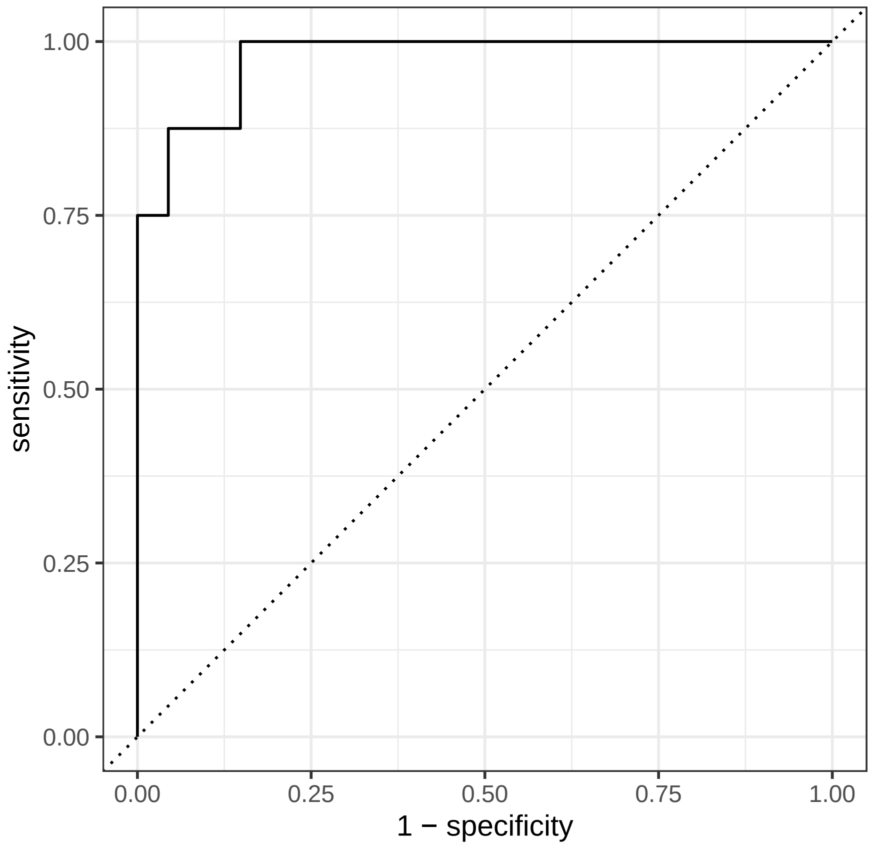
After all these analyses/tests, our final model is:

term	estimate	std.error	statistic	p.value
(Intercept)	-6.727	8.645	-0.778	0.437
ETo	157.331	75.853	2.074	0.038
solrad	-0.070	0.029	-2.400	0.016
avgsoiltemp	0.434	0.180	2.414	0.016
windrun	5.255	2.506	2.097	0.036
I(dewpoint^2)	0.002	0.002	1.312	0.189
avgairtemp	-0.374	0.233	-1.606	0.108
avgwindspeed	-127.386	60.670	-2.100	0.036

$$Tar\hat{g}et = -6.727 + 157.331(ETo) - 0.070(solrad) + 0.434(avgsoiltemp) + 5.255(windrun) + 0.002(dewpoint^2) + -0.374(avgairte$$

Conclusion

To test our model, we first constructed an ROC curve to identify a prediction threshold.



From this ROC curve, we selected a prediction threshold of 0.193, identified by minimizing 1-specificity while maximizing sensitivity. Because there is greater risk in failing to predict a fire (type 2 error), we were less interested in the false positive rate as opposed to high sensitivity.

.threshold	specificity	sensitivity	false_rate
0.193	0.956	0.875	0.044

Target	pred_resp	n
1	fire	6
1	no fire	2
0	fire	6
0	no fire	129

The confusion matrix indicates that the model correctly predicts the presence or non presence of a fire in 135/143 cases or 94.41% of the time at a threshold level of 0.193.

To truly test our model, we randomly selected a new set of observations from our original dataset and assessed the model's predictive power on the new data points.

Target	pred_resp	n
1	fire	5
1	no fire	3
0	fire	8

Target	pred_resp	n
0	no fire	126

On the new, randomly selected test dataset, the confusion matrix indicates that the model correctly predicts the presence or non presence of a fire in 131/142 cases or 92.25% at a threshold level of 0.193.

Discussion

Since fire_model3 appears to be our strongest model, that means that ETo, solrad, avgsoiltemp, windrun, I(dewpoint^2), avgairtemp, avgwindspeed are the most significant environmental predictors of forest fires in California. While this might mean that monitoring these three will provide a reduction strategy to fires, it creates some ethical questions. ETo, ethylene oxygen, is a flammable colorless gas that cannot be simply removed from the atmosphere without introducing another agent. Furthermore, managing average temperature also provides a number of practical issues, as does managing soil temperature. Thus, our model suggest that it is likely too late to be able to do anything effectively to prevent or can firefighting measures only be reactive from this point forward.

The reliability and validity of our data certainly comes into question. As previously stated, a single data point was randomly chosen from each station (as the data spans multiple years and the goal was to reduce multicollinearity as much as possible). However, this method is not foolproof. Stations that are spatially close together and whose randomly selected dates are close together are not screened for in our data selection process. With more time, this data selection process would be further refined to ensure data points are as independent as possible.

Additionally, we only considered one potentially meaningful interaction term, ETo*avgwindspeed, throughout our analysis. In an expanded version of this project, we would potentially explore more interaction terms, as this single term was ultimately left out of the model.

Though we considered both AIC and BIC throughout our analysis, we were partial to BIC, favoring a parsimonious model. The result is our final model with only three terms. With more time, we could construct 1) a model with AIC selection criterion and 2) a model with BIC selection criterion and compare the two on a new randomly selected set of data points to identify which has greater prediction accuracy.

Appendix

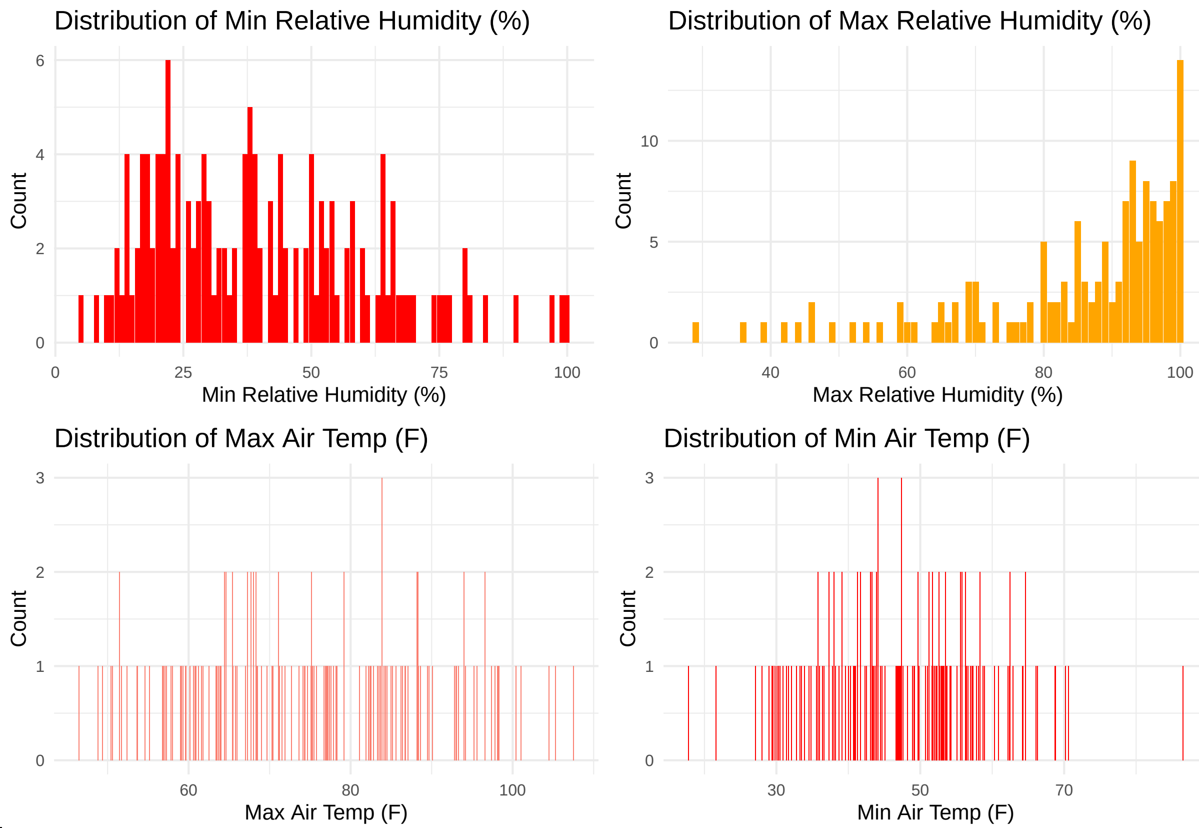


FIGURE A

To reduce multicollinearity, we decided to eliminate these variables from our analysis. For example, the dataset included the average, minimum and maximum value for a number of variables, including relative humidity and air temperature. We determined that the daily averages for these variables were likely the most relevant value for each condition recorded by each station with regards to predicting fires.