Socioeconomic Disparities in Power Outages in Massachusetts

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1 Abstract

Climate change causes changes in weather conditions, thereby increasing power outage frequency. The loss of electricity affects people's physical and economic well being. There is no consensus on whether the existing electricity reliability metrics are correlated to weather. There exists little research on socioeconomic disparities caused by outages, but there exists vast studies on major weather events. This study looks into all weather events from 2013-2021 in Massachusetts and get insights on injustices between communities. To understand this we used customer outage hours as the electricity reliability metric and performed regression splines on the selected four weather variables. Then, we calculated residuals of the generalized additive models on these four weather predictors. Finally, we used this output to analyze how the unexplained variance in the model could be explained by income, population density, and race/ethnicity diversity groups. We concluded that customer outage hours are significantly correlated to the weather predictors and there do exist socioeconomic disparities in Massachusetts.

2 Introduction

Power outages occur can have extreme consequences for the populations which they affect. They most often occur due to weather events such as wind, rain, and abnormal temperature [1]. In the most extreme cases, severe weather conditions such as hurricanes and snowstorms can cause outages for thousands of people[2]. Moreover, climate change is causing more volatile weather and increasing outage frequencies. In the last decade, weather related power outages have increased by 64% in the U.S.[3].

Studying power outages has the possibility to minimize the ramifications of losing power. When a population loses electricity, the community is subject to potential health risks and high costs[4]. A literature review concluded that the loss of power can lead to health risks such as, loss of clean water, food storage, medical technologies, and safety mechanisms[5].

Currently, there are many methodologies used to study the occurrence and frequency of power outages. They are often measured by the system average interruption duration index (SAIDI), which is the average interruption duration of power outages, and the system average interruption frequency index (SAIFI), which is the average frequency of electric interruptions a customer experienced [6]. The differences in methodologies primarily lie in the types of models used and the different variables used/measured in the models. Different models used for outage and damage forecasting have included: SMOTE regression [7], generalized additive models [8], regression trees to ensembles of trees [9], Deep Neural Networks [10], and Monte Carlo sampling technique[11].

There are two major points of consensus in previous studies on power outages. Previous research has largely concluded that weather is a significant predictor of power outages [1, 12] and that power outages lead to high economic costs [13, 14].

Unfortunately, previous literature also lacks consensus. First, there is not a clear consensus on which model is best at predicting frequency nor duration of power outages. Second, there is also disagreement on whether SAIDI or SAIFI are correlated with weather [15, 16].

This study will investigate a sparsely studied subtopic within the domain of power outage research. There is minimal existing research on the demographic inequalities associated with power outages. The majority of existing inequalities research has been conducted on outages caused by major weather events[17, 18, 19]. Lee et al. explain that one barrier to researching demographic implication of non-extreme outages has been difficulty accessing "...fine-resolution data related to the extent and duration of outages for subpopulations." [20] Our research will hone in on these disparities stemming from power outages in Massachusetts.

This paper will explore environmental injustice in Massachusetts and pave the way of exploring the socioeconomic ramifications of power outages in the State of Massachusetts. Thus, our question is: Is there evidence that population density, per capita income, and percentage of White residents determine the severity of power outages? The answers to these questions will provide insight on the disparities which exist within the communities of Massachusetts.

Our work will identify disparities several different methods. First, we will identify the strongest weather predictors of power outages. Then, we will create regression splines for each of those predictors with our power outage metric. Next, with demographic data we will segment the models based on income, population density, and diversity by quantiles to identify statistically significant differences. Finally we will expand our analysis of these differences by looking at a generalized additive model which incorporates all of the regression splines.

3 Data

3.1 Data Sources

We used data from four different sources to compile our joined dataset. First, we downloaded Massachusetts outage data from the Massachusetts Energy and Environmental Affairs Office[21] from 2019 -2021. Their website offers data on outages from three utility companies of Massachusetts. This data includes information on the date and time of the outage, date and time the power was back on, the number of customers affected, if there was failed or damaged equipment, and the weather condition. The weather condition values were consisted of free response answers that contained inconsistencies and missing values that were ultimately unusable for this analysis. Thus, we required our second dataset.

The second dataset was downloaded from the Global Historical Climatology Network (GHCN) Daily [22]. The GHCN Daily compiles data from the 19 weather stations in Massachusetts, collecting maximum and average values for wind speed, temperature, rainfall, and snowfall.

The third and fourth datasets used were the 2020 census data for Massachusetts[23]. The census datasets used included population density by census block and ethnicity/race percentages by town. We aggregated the density data up to the town level by calculating weighted averages based on the population of each block within a town to compute.

The final dataset we added to our analysis was income for each town by year. The income data was downloaded from the Massachusetts Department of Revenue's Division of Local Services[24] which records the annual per capita income for each town.

3.2 Data Cleaning

We merged the outage data, census data, and income data based on town name. The weather data from the GNHC Daily had missing weather information for towns which did not have weather stations in them. Massachusetts only has 19 weather stations in the state, however, there are 351 towns. Thus, we used ArcGIS Pro to identify the closest weather station for each town. We performed a one to one spatial join so that each outage data point in a town was matched with the nearest weather station, using the "closest" parameter which calculates shortest euclidean distance. We then merged the weather data to outage data by town and date. After merging all datasets, about 3% of the data was dropped due to no recorded weather for certain outages.

4 Methods

4.1 Response Variable Selection

Our goal was to investigate whether the socioeconomic composition of a town impacts the severity of the power outages experienced. The severity of power outages is typically assessed based on three metrics: duration, frequency, and the number of people affected. Measures of power outages used in other literature include SAIDI and SAIFI. These averaging metrics are more informative at describing overall grid reliability rather than the severity of customers' experiences [25]. For example, the SAIDI of an outage which lasts days in a rural area could have the same value as an outage which lasts minutes in a populous city. Moreover, these two metrics are all typically calculated per year. As we wanted to evaluate our analysis at the outage level, a more customer centric metric, we decided to use customer outage hours to measure the impact of an outage. Where customer outage hours is defined by:

$$U_i \times N_i \tag{1}$$

U is the outage duration in hours, N is the number of customers affected for each outage i.

4.2 Feature Selection

Our data had ten weather variables and three demographic variables. As seen in **Figures 14 and 15** in the appendix, the data was not normal, so we could not utilize feature selection methods which rely on linear regression. Instead, we used a random forest to calculate the feature importance for all of our possible predictors. The hyperparameter tuning using 10-fold cross validation can be found in **Figure 16** the appendix.

After the random forest, we looked at correlations between all of the variables. We built our models on the non-highly correlated significant weather predictors and segmented the data for the models based on significant socioeconomic predictors.

4.3 Model Selection

Knowing that our data was non-linear and non-normal, we used natural cubic splines. Natural cubic splines were chosen due to their abilities to model curvature without exhibiting wild tail behaviors at the boundaries in the data. Beyond splines, which analyze one feature at a time, we also used GAMs to model all of our features at once. This GAM was constructed with all four splines.

We created the demographic segmentations of the data for our significant socioeconomic features by splitting each of the features into lower, lower middle, upper middle, and upper quartiles as found in the appendix. It is important to note that the diversity groups were created based on the percent of the town that is white as an inverse measure of diversity.

As the GAM was in five dimensions, it was difficult to interpret disparities by demographic group. To overcome this, we analyzed the demographic segmentation of the data on the residuals of the GAM. The residuals of the model capture the random error term, ϵ. As the GAM is the summation of each individual spline, we can see a piecewise function which represents the equations in between each knot of the spline.

$$S(x) = \begin{cases} S_0(x) = a_0x^3 + b_0x^2 + c_0x + d_0 + \epsilon_0 & t_0 \le x \le t_1 \\ \vdots & \\ S_{n-1}(x) = a_{n-1}x^3 + b_{n-1}x^2 + c_{n-1}x + d_{n-1} + \epsilon_{n-1} & t_{n-1} \le x \le t_n \end{cases} \tag{2}$$

Each piece of the function has an ϵ_n, and this error term is mathematically equivalent to the residuals. The residuals are given by:

$$Y_i - Y_{pred_i} \tag{3}$$

By studying the residuals of the model, we are looking at the portion of customer outage hours which cannot be explained by the weather predictors. We call the residuals the corrected customer outage hours. The residuals of a model should be random and uncorrelated with features of the model. We conducted a ordinary least squares (OLS) regression with the corrected customer outage hours as the response and a weather feature of the GAM. If there is correlation between the residuals and a feature of the model, there must be unexplained variance. If there was more unexplained variance, that signifies that the GAM built with the weather predictors does not predict power outages equitably as there must be other factors explaining the outages. More unexplained variance for certain socioeconomic groups would show a disparity.

4.4 Model Hyperparameter Tuning

Each spline was fit using five-fold cross validation on the degrees of freedom which directly impacts the number of knots the patsy library uses to create each spline. The one standard error rule was also used to limit the degrees of freedom from being too large as small increases in the number of knots caused our splines to overfit. The search space for degrees of freedom is shown in **Figure 17** of the appendix.

For the GAM, we used the optimal degrees of freedom found for each spline through cross validation and the one standard error rule. No further hyperparameter tuning was done for the GAM.

5 Results

5.1 Feature Selection

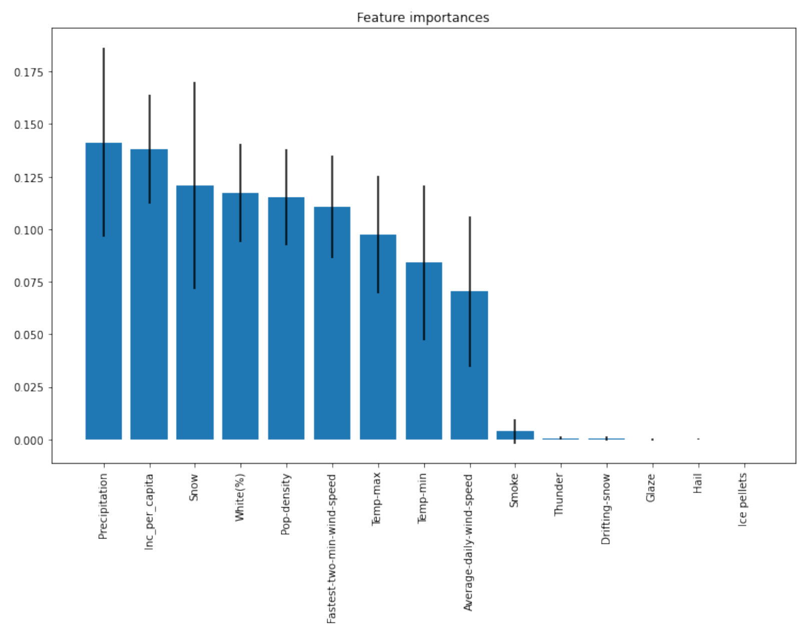

Figure 1: Random Forest Feature Importance

The random forest, **Figure 1**, reported nine variables as being important predictors for our response variable, customer outage hours. Six were weather predictors, and three were socioeconomic variables. We built our models on only the weather predictors and then segmented the data based on socioeconomic predictors.

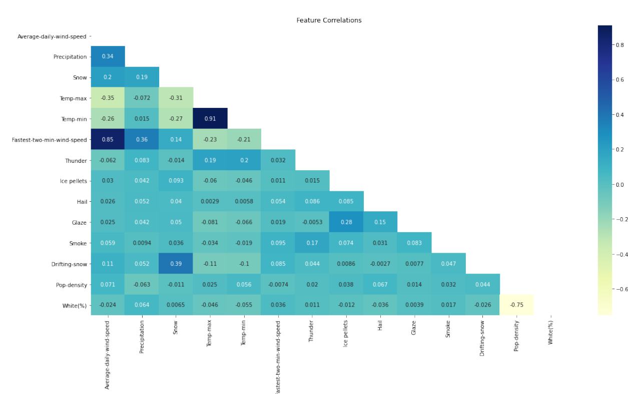

Figure 2: Feature Correlation Matrix

Figure 2 depicts the correlations between all of the features. The minimum temperature was highly correlated with the maximum temperature (correlation of .91). Additionally, the second highest correlation, was between the fasted two minute wind speed and the average daily wind speed (correlation of .85). Because of these correlations, we only kept the maximum temperature and the fasted two minute wind speed in our models.

5.2 Natural Cubic Splines

From **Figure 3**, the precipitation, wind speed, and temperature maximum splines show the upper income group splitting to lower customer outage hours compared to the other income groups around 80 mm, 16 meters/sec and -2 °C to 23 °C respectively based on 95% confidence intervals. The spline regressing against snowfall showed overlap in the groups 95% confidence intervals except between 0 mm of snow to just over 400 mm of snow, where customer outage hours for the upper income group was lower than that of other income groups.

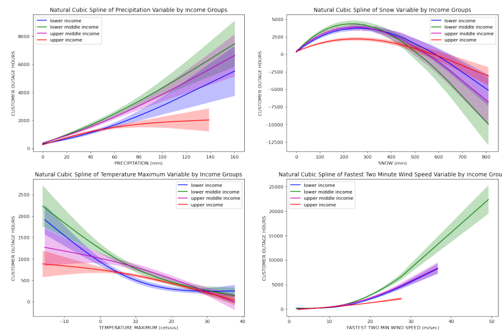

Figure 3: Natural Cubic Splines by Income Group

From **Figure 4**, the precipitation, wind speed and maximum temperature splines show the highest diversity group had the lowest customer outage hours around 38 mm to 77 mm, 14 meters/sec, and -6 °C to just around 20 °C respectively based on 95% confidence intervals. Wind speed splits off at 15 meters/sec for low diversity groups and these groups had the highest amount of customer outage hours. For snowfall splines, from 0 mm to just over 300 mm of snowfall, high diversity groups experience the lowest amounts of customer outage hours. Meanwhile, from about 160 mm to about 530 mm of snowfall, low diversity towns experience some of the highest amounts of customer outage hours.

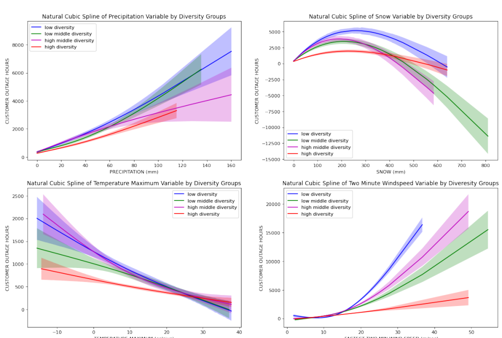

Figure 4: Natural Cubic Splines by Diversity Group

In our last group of splines, we regress with the data split by population density groups shown in **Figure 5**. The precipitation plot shows that the low density group has the lowest customer outage hours except for the range of precipitation between 120 mm and 140 mm based on 95% confidence intervals. The wind speed plot shows that at 18 meters/sec, the high density towns show the lowest amount of customer outage hours based on its 95% confidence interval. The regression on snowfall, displays no significant difference in customer outage hours for two middle density groups. While low density towns and high density towns exhibit similar behavior at the left tail,high density towns exhibit higher customer outage hours than low density towns starting at 280 mm of snow. The maximum temperature plot shows a general decreasing trend in customer outage hours as the maximum temperature increases for all density groups. The two middle density groups show no significant difference in customer outage hours. The low density group and the high density group also show no difference in customer outage hours at the extremes of maximum temperature values. However between -11 °C to 19 °C, high density groups exhibited higher customer outage hours than low density groups.

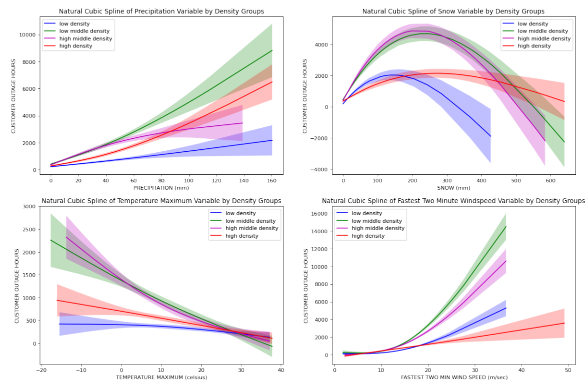

Figure 5: Natural Cubic Splines by Population Density Group

The test MSE's for all splines can be found in the appendix.

5.3 Generalized Additive Model

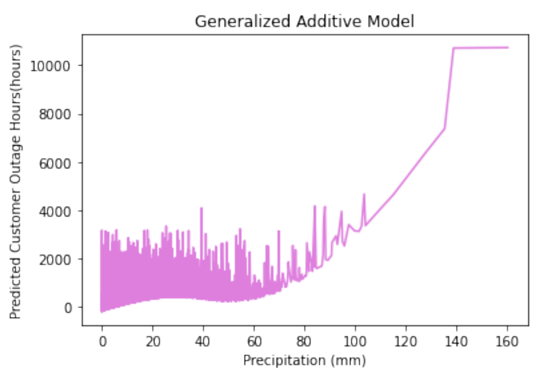

Figure 6: GAM plotted against precipitation

Figure 6 shows one example of the GAM plotted against precipitation. The GAM plotted against the other three predictors (**Figures 24, 25, and 26)** can be found in the appendix. Because the GAM is fit in five dimensions, these models are highly variable and uninterpretable for analysis on socioeconomic differences.

5.4 Residual Regression

Figures 7 and 8, **Figures 9 and 10** , **Figures 11 and 12** display the results of the OLS regression broken down by income, diversity, and population density groups respectively. The plotted 95% confidence intervals prove that there are statistically significant disparities between the two lower income groups and the two lower diversity groups with their respective other groups. The upper middle and upper income and diversity groups have overlapping confidence intervals, therefore we cannot say there is a disparity between the groups. Population density groups tell a similar story, but the plotted 95% confidence intervals prove that there is a significant disparity between the low population density group from the rest of the density groups. The low middle, high middle, and high density groups have overlapping confidence intervals, therefore we cannot say there is a disparity between the groups.

In all three regressions **Figures 8, 10, 12**, the groups whose confidence intervals did not overlap had higher magnitude slopes.

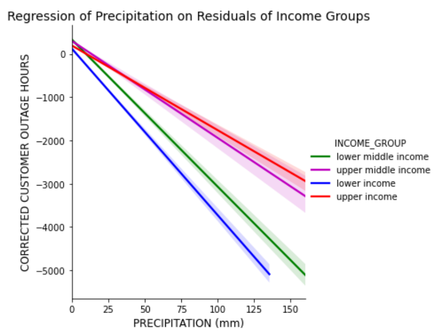

Figure 7: Income Residuals

INCOME_GROUP	slope
lower income	-37.588253
lower middle income	-33.832727
upper income	-20.186655
upper middle income	-25.269751

Figure 8: Income Regression Coefficients

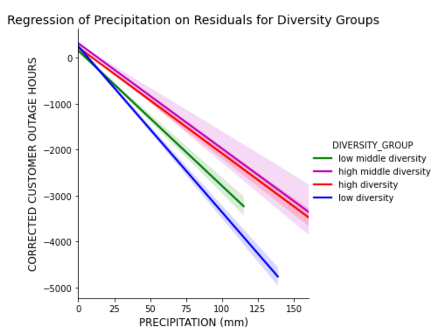

Figure 9: Diversity Residuals

DIVERSITY_GROUP	slope
high diversity	-19.738206
high middle diversity	-28.404387
low diversity	-36.437508
low middle diversity	-30.231503

Figure 10: Diversity Regression Coefficients

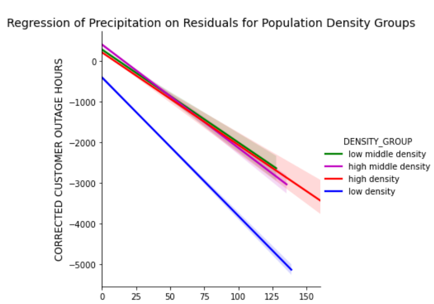

Figure 11: Population Density Residuals

DENSITY_GROUP	slope
high density	-23.365802
high middle density	-25.847983
low density	-34.424966
low middle density	-24.587817

Figure 12: Population Density Regression Coefficients

6 Discussion

Our results from the random forest, natural cubic splines, and residual regressions indicate that income, race/ethnicity, and population density affect the severity of the power outages a population will experience. The higher magnitude slopes of the low and lower middle income groups, the low and low middle diversity groups, and the low population density group demonstrate that these communities have a more unexplained variance in the weather GAM model. Because these groups are statistically different, we can conclude that the weather features are not the only outage predictors in lower income, lower diversity, and rural areas.

We were surprised to find that lower diversity towns had more unaccounted variance after accounting for weather. This finding would benefit from further analysis on the possible interaction between population density and diversity.

This analysis has several limitations. The first limitation we faced was a result of each dataset used in the analysis being in a different level of resolution. We needed to aggregate the data to town level.

Another significant limitation in this analysis was missing data. Our weather features included many missing values with about 83.7% of the snow feature being Nan values in the weather data. These missing values were filled in by taking the average snowfall for each month of each year. As can be seen in **Figures 3, 4, and 5**, the splines for the snow variables take a sharp downward slope around 200 mm resulting in negative customer outage hours predicted in the upper snowfall range. In our dataset the snowfall maximum value was 810 mm and our customer outage hours minimum was zero. We suspect the right hand tail behavior is a result of both the method used to fill missing values and the limited data points at higher snowfall ranges. In future iterations of this analysis the snow data should be filled in with a more nuanced technique or excluded altogether due to substantial missing data.

A further limitation to this analysis was missing outage data. We did not have access to outage data for 40 towns whose power is supplied by municipality power. According to a Mood's median test, these excluded towns have a significantly higher median per capita income than the included towns. Future versions of this analysis should strive to include outages from these 40 towns for a more accurate analysis in quantifying disparities in electricity reliability.

7 Conclusion

Overall, we can see that weather is a significant predictor of customer outage hours. We also conclude that there are disparities in customer outage hours experienced by communities of different diversity, income, and density levels. This is meaningful because the customer outage hours experienced bring physical and economic consequences for those affected. Due to the higher magnitude of unexplained power outages for lower income and rural towns, our results suggest that there should be further research into the explanation behind outages in those communities.

8 Acknowledgements

This work was supported by professor Deborah Sunter at Tufts University. Professor Sunter provided Massachusetts outage data from 2013-2018 which was downloaded from the Massachusetts Energy and Environmental Affairs Office.

9 Appendix

9.1 Testing for Normality

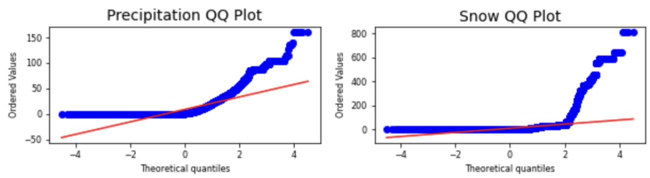

Figure 13: QQ Plots for Precipitation and Snow

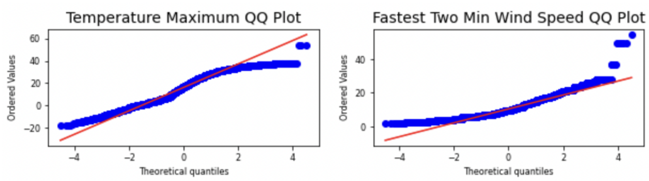

Figure 14: QQ Plots for Temperature Max and Fastest 2 Minute Wind Speed

```
PRECIPITATION:
ShapiroResult(statistic=0.6288862824440002, pvalue=0.0)

SNOW:
ShapiroResult(statistic=0.23575669527053833, pvalue=0.0)

FASTEST TWO MIN WIND SPEED:
ShapiroResult(statistic=0.9450325965881348, pvalue=0.0)

TEMPERATURE MAXIMUM:
ShapiroResult(statistic=0.9672042727470398, pvalue=0.0)
```

Figure 15: Shapiro-Wilk Test for all 4 Predictors

9.2 Hyperparameter Tuning

Hyperparameter	Minimum Value	Maximum Value
Number of Trees in Forest	10	100
Maximum Leaf Nodes of each Tree	3	100
Maximum Depth of each Tree	1	10
Minimum Samples Required to Split Leaf Nodes	1	30
Minimum Samples Required for Leaf Nodes	2	20

Figure 16: Hyperparameter Search Space for Random Forest Model

Hyperparameter	Minimum Value	Maximum Value
Degrees of Freedom	3	11

Figure 17: Hyperparameter Search Space for Cubic Splines and Generalized Additive Model

9.3 Socioeconomic Feature Group Cutoffs

```
Lower Income Score: 5545 - 25457
Lower_Middle Income Score: 25458 - 32107
Upper_Middle Income Score: 32108 - 43399
Upper Income Score: 43399 - 386499
```

Figure 18: Income Quartiles Cut Offs

```
Lower Population Density Score: 55.92 - 793.81
Lower_Middle Population Density Score: 793.82 - 2115.4
Upper_Middle Population Density Score: 2115.5 4601.17
Upper Population Density Score: 4601.18 - 57121.5
```

Figure 19: Population Density Quartiles Cut Offs

```
Lower Diversity Score: 0.16 - .82
Lower_Middle Diversity Score: 0.83 - .89
Upper_Middle Diversity Score: 0.9 .92
Upper Diversity Score: 0.93 - 0.97
```

Figure 20: Diversity Quartiles Cut Offs

9.4 Spline MSE's by Demographic Feature

```
LOWER INCOME MSE PRECIPITATION is:  9725784.50
LOWER MIDDLE INCOME MSE PRECIPITATION is:  17380614.52
UPPER MIDDLE INCOME MSE PRECIPITATION is:  11618896.27
UPPER INCOME MSE PRECIPITATION is:  6370298.43

LOWER INCOME MSE SNOW is:  9673299.85
LOWER MIDDLE INCOME MSE SNOW is:  17397606.94
UPPER MIDDLE INCOME MSE SNOW is:  11724358.37
UPPER INCOME MSE SNOW is:  6442654.15

LOWER INCOME MSE TEMP_MAX is:  9770031.86
LOWER MIDDLE INCOME MSE TEMP_MAX is:  17529461.44
UPPER MIDDLE INCOME MSE TEMP_MAX is:  11805575.64
UPPER INCOME MSE TEMP_MAX is:  6451798.23

LOWER INCOME MSE FASTEST_TWO_MIN_WIND_SPEED is:  9591239.21
LOWER MIDDLE INCOME MSE FASTEST_TWO_MIN_WIND_SPEED is:  17140938.23
UPPER MIDDLE INCOME MSE FASTEST_TWO_MIN_WIND_SPEED is:  11511595.84
UPPER INCOME MSE FASTEST_TWO_MIN_WIND_SPEED is:  6367808.28
```

Figure 21: Income MSE's

```
LOWER DIVERSITY MSE PRECIPITATION is:  15968231.67
LOWER MIDDLE DIVERSITY MSE PRECIPITATION is:  13798459.94
UPPER DIVERSITY MSE PRECIPITATION is:  15914845.68
UPPER MIDDLE DIVERSITY MSE PRECIPITATION is:  4598342.42

LOWER DIVERSITY MSE SNOW is:  15982293.79
LOWER MIDDLE DIVERSITY MSE SNOW is:  13883164.39
UPPER MIDDLE DIVERSITYMSE SNOW is:  15914630.34
UPPER DIVERSITY MSE SNOW is:  4654937.14

LOWER DIVERSITY MSE TEMP_MAX is:  16176116.25
LOWER MIDDLE DIVERSITY MSE TEMP_MAX is:  13982188.23
UPPER MIDDLE DIVERSITY MSE TEMP_MAX is:  16001096.32
UPPER MSE TEMP_MAX is:  4679671.67

LOWER DIVERSITY MSE FASTEST_TWO_MIN_WIND_SPEED is:  15421005.83
LOWER MIDDLE DIVERSITY MSE FASTEST_TWO_MIN_WIND_SPEED is:  13697676.95
UPPER MIDDLE DIVERSITY MSE FASTEST_TWO_MIN_WIND_SPEED is:  15701788.62
UPPER DIVERSITY MSE FASTEST_TWO_MIN_WIND_SPEED is:  4619300.91
```

Figure 22: Diversity MSE's

```
LOWER DENSITY MSE PRECIPITATION is:  4910824.27
LOWER MIDDLE DENSITY MSE PRECIPITATION is:  17857405.32
UPPER MIDDLE DENSITY MSE PRECIPITATION is:  15937911.55
UPPER DENSITY MSE PRECIPITATION is:  5252088.97

LOWER DENSITY MSE SNOW is:  4887869.03
LOWER MIDDLE DENSITY MSE SNOW is:  17885758.61
UPPER MIDDLE DENSITY MSE SNOW is:  15979967.24
UPPER DENSITY MSE SNOW is:  5331482.00

LOWER DENSITY MSE TEMP_MAX is:  4930993.30
LOWER MIDDLE DENSITY MSE TEMP_MAX is:  17997000.89
UPPER MIDDLE DENSITY MSE TEMP_MAX is:  16085817.39
UPPER MSE TEMP_MAX is:  5352891.14

LOWER MSE FASTEST_TWO_MIN_WIND_SPEED is:  4855199.24
LOWER MIDDLE MSE FASTEST_TWO_MIN_WIND_SPEED is:  17537329.30
UPPER MIDDLE MSE FASTEST_TWO_MIN_WIND_SPEED is:  15695909.00
UPPER MSE FASTEST_TWO_MIN_WIND_SPEED is:  5286036.48
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Figure 23: Population Density MSE's

9.5 GAM plots for other 3 predictors

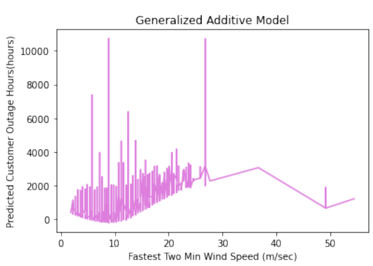

Figure 24: GAM plotted vs. Fastest 2 min wind speed

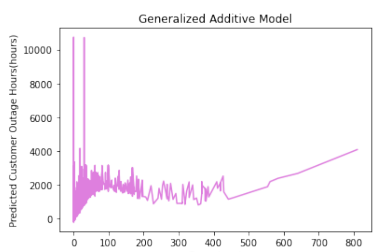

Figure 25: GAM plotted vs. Snow

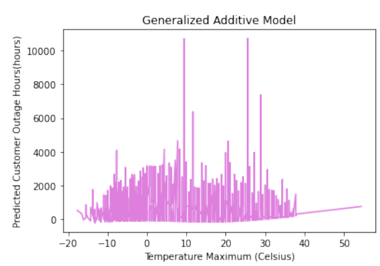

Figure 26: GAM plotted vs. Temp Max

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