Sonoma, off the grid: “Socio-economic impact of Public Safety Power Shutoffs in Sonoma County, California”

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Introduction

Over the past decade, the scale and frequency of natural disasters have attracted broad attention. In the US, natural disasters have taken the form of hurricanes and floods on the East and Southern coasts, and wildfires on the West coast. In the fall of 2017, 2018, and 2019, wildfires swept across California, where the dry season is hotter, longer, and drier than ever before. These wildfires displaced thousands of households, and produced smoke that traveled hundreds of miles and impacted millions of people (Manjoo, 2019). Scientists estimate that these conditions are not only the new norm, but will accelerate in the years to come (CAL FIRE, 2019).

In an effort to mitigate fire risk, Pacific Gas and Electric unrolled a statewide Public Safety Power Shutdown (PSPS) program which shuts down electrical transformers during high winds. The cuts power to adjacent areas, but eliminates the possibility of damaged electrical lines sparking fire. In October 2019 PG&E cut power to hundreds of thousands of households for up to 5 days. Although the PSPS events are not a natural disaster, we argue that they qualify as a major climate related. Studies have shown that an outage longer than 24 hours imparts a substantial burden on households, and impedes access to basic necessities (Moreno and Duncan, 2018). Due to their duration and scale, the PSPS events necessitate an analysis of their social, spatial, and economic impact towards better informing policy solutions to mitigate the impact of future shut down.

Our initial research question was: are the frequency and duration of the shutdowns related to income levels? In particular, we were interested in whether the shutdowns disproportionately impacted low income households. We ran a bivariate analysis of household income at the block-group level to both outage duration and fire risk level and found no significant correlation between either variables. This validated the null hypothesis, that there was no income related spatial significance to fire risk or outage occurrence. This tells us that these events are indiscriminate across income levels, but further analysis is required to better understand the proportional impact of outages on income groups.

Research on wealth inequality finds that federal policies contribute to disparate accumulation of assets, where top town policies exaggerate existing wealth gaps through policies that regulate income, investments, inheritances, and interest rates (Alvaredo et al. 2013; Charles and Hurst 2002; Keister 2014; Volscho and Kelly 2012). As a result, the US is already in a state of accelerated inequality, which is further fueled by the growing frequency of climate related events. In "Beyond Disasters: A Longitudinal Analysis of Natural Hazards' Unequal Impacts on Residential Instability," Howell and Elliott found that top down aid processes pose an additional, important, and largely ignored contribution to growth in wealth inequality.

In the KQED segment "Fires Take Disproportionate Toll on Low-Income and Immigrant Communities" Mina Kim investigates the role of natural disasters in exacerbating inequalities. While, natural disasters are seen as a "great equalizer" impacting both rich and poor alike, wealth disparity emerges as a major determinant during recovery. In Mina Kim's interview with Rice Professor, James Elliot, he argues that the ability to withstand long periods of time without power is largely determined by one's access to social, economic, and political resources. Islam and Winkel also argue that the relationship between climate change and social inequality is "characterized by a vicious cycle," where existing inequality causes disadvantaged groups suffer disproportionately. Access to capital and the means to navigate the bureaucratic post-recovery labyrinth often leaves those living precariously before disaster at the edge of homelessness after (Islam and Winkel, 2017).

While there are major differences between the experience of an extended outage and the damages incurred during an extreme weather event, we argue that the two share important underlying attributes. First, they are both increasing in frequency and unpredictability. Second, they are both inherently spatial, our analysis found a positive correlation between fire risk level and outage location and duration. Third, they involve top down actors, through the governments role in regulation, risk, and recovery, and are therefore subject to systematic biases. Therefore, in our conclusion we argue that the longitudinal approach taken by Howell et al. could provide a valuable framework for analyzing prevention strategies like the PSPS.

Background/Literature Review

Disaster Recovery

In 'Damages Done: The Longitudinal Impacts of Natural Hazards on Wealth Inequality in the United States" Howell and Elliott analyze different subpopulations after natural disasters at the intersection of damages from natural hazards and existing social inequalities. They followed a nationally representative sample of respondents ("from the restricted, geocoded Panel Study of Income Dynamics") through time (1999–2013) "as hazard damages of varying scales accrued". Their results indicate a positive correlation between top down assistance after a natural hazard and wealth inequality. They found that wealth inequality, natural hazard damages, and top down recovery assistance are dynamically linked; more FEMA aid an area received, the more inequality grows (Howell and Elliot 2018). Their study focuses on natural disasters that cause damage to property, or material assets, both public (roads, schools, levees, and other infrastructures) and private (residences, businesses, and other physical possessions) (Howell and Elliot 2018). Today, the Disaster Relief Act provides assistance for temporary housing and other forms of immediate relief, the administration of hazard insurance programs, rebuilding damaged infrastructure, and providing low-interest loans to private property and business owners and business owners (Howell and Elliot 2018). These strategies are aimed at restoring and expanding local property and wealth-generation capacities. Today, FEMA distributes billions of dollars of taxpayer money annually to disaster recovery.

Martin and Teles of the Urban Institute identify five ways that households get left behind during disaster recovery. First, damage assessments, used to determine aid eligibility can be inconsistent and incomplete. They are sometimes compromised by property accessibility or the "quality and consistency of inspectors and their techniques." Second, they argue that the FEMA eligibility process disproportionately impacts low-income households because does not account for the disproportionate burden of repair costs on low-income households. FEMA uses property damage assessments to determine long-term, temporary housing needs, but if the property damage falls below the eligibility threshold the household is excluded from the program. Third, the complicated process of, and short window for aid applications can leave less resourced groups behind. Fourth, they identify the gaps in data collection as a limitation for local and federal agencies to assess and provide necessary and proportionate aid to the most vulnerable communities. Finally, they argue that disaster programs are implemented tactically rather than strategically. Disaster programs and data exist independent from the world of urban development, and are not designed to incorporate or be incorporated into housing and community challenges with the expected impact of climate change. Effective disaster recovery requires a knowledge about housing current housing and socio-economic conditions in order to envision reconstruction or relocation (Martin 2018).

Power Outages

Extreme weather events are considered to be the main cause of wide-area electrical disturbances worldwide, causing 80% of the large scale power outages between 2003 and 2012 (Moreno and Duncan, 2018). In "Community resilience to power outages after disaster: A case study of the 2010 Chile earthquake and tsunami" Moreno and Duncan found that in Chile, a series of natural disasters between 2010 and 2017, which triggered numerous widespread power outages, disproportionately affected poor people. They also found that the negative impact of power outages after disasters was higher in low-income communities than high-income communities. The electric power systems is linked to other infrastructure (gas, water supply, telecom, banking and financial services, security services, public health, agriculture, and transit system) and is even more critical during an extreme weather events (Moreno and Duncan, 2018). Electricity is a 'basic' human needs providing the means for "cooking, lighting, and thermal comfort" (Moreno and Duncan, 2018), outages lasting longer than 24 hours become critical because of their impact on access to water, heat, and light (Palm, 2009). Lack of power also becomes a barrier to staying informed, which carries critical importance during extreme weather events.

Outside of disasters, power outages incur a cost on affected households. When households are interviewed, they express a Willingness To Pay (WTP) to prevent a power outage. Lawton, Leora, et al. report that households in the United States are willing to pay $26.27 in 2002 dollars on average (~$37.34 inflation adjusted) to prevent a 12 hour blackout (Lawton, Leora, et al.). Ju-Hee Kim, Kyung-Kyu Lim and Seung-Hoon Yoo in their literature review (Ju-Hee Kim, 2019) state that Hensher et al. found that the WTP for an 8 hour blackout in the united states is $60 (Hensher, 2014), and state that Woo et al. found that the WTP for a 1 hour blackout in Hong Kong is $45 (Woo, 2014). Therefore, a power outage can be seen as a flat income shock to a household, which is expected to have a higher impact on lower income households.

Climate Migration

Resilience must not only consider the adaptation of places that are vulnerable but also the ability to manage migration and resettlement. Last year, the US had more than 1.2 million internally displaced climate migrants, 30 percent of which were the result of wildfires (IDMC). Climate migrants are individuals displaced by conditions related to climate change, whether through evacuations, post disaster buyouts, or independent relocation due to increased risk. In a study on post-disaster migration, Eyer et al. found that permanent resettlement is most likely to occur in the urban areas of neighboring counties (Eyer et al. 2018). Most displaced households after California's 2015 and 2017 fires moved to the neighboring counties and were still living there a year after (Martin 2019). Assessing the consequences of relocation requires addressing the maintenance or breakdown of social ties, and the integration of migrants into new communities. This invites policy makers to consider how to incentivize receiving communities "to prepare for, build capacity for, and integrate newcomers—especially while addressing their own climate-related resource gaps" (Martin 2019).

Data and Methods

Data Collection

On October 8, PG&E announced the implementation of a Public Safety Power Shutoff. They displayed the current status of the power outage event on their "Outage Center" website. The website states that the data is updated every 15 minutes. Using a website scraping script written in python using the Requests package, the current status of the power outage event was collected every minute, to capture any irregularities in update times. This code ran on a Virtual Private Server hosted by OVH, querying the site every minute and saving the downloaded json data file as a text file.

The outage data contains a list of incidents. Each incident contains information such as "cause", "crew current status", "current estimated time of restoration", "estimated customers affected", "hazard flag", "last update time", "outage start time", and the polygon area the outage is affecting.

The census block group outline shapefiles were downloaded from census.gov. The 2019 TIGER/Line shapefiles for California were downloaded. Block groups were used in this project because that is the highest spatial resolution of the median income data that we could collect.

The block group median household income data was downloaded from NHGIS.org, from the 2017 American Community Survey: 5-Year Data. Specifically, we used Source code B19013 and NHGIS code AH1P.

To control for naturally existing fire risk, fire risk maps were downloaded from osfm.fire.ca.gov. Specifically, the Sonoma county State Responsibility Area maps were downloaded. These maps were adopted by CAL FIRE on November 7, 2007.

To account for infrastructure distribution, high voltage power line data was collected from the U.S. Energy Information Administration (EIA). Data was downloaded from the U.S. Energy Mapping System website. Only power lines with voltages between 69 kV and 765 kV are included.

To account for population distribution, household location data was collected from Zillow. Using a website scraping script written in python using the Requests package, addresses in Sonoma county were collected. In addition, the tax assessed value and the estimated housing value was also collected.

Data Curation

Due to the frequency of queries, the power outage data contains multiple duplicate files. Using a MD5 hash of the json data, duplicate files were removed. To translate the json data to a shapefile for analysis in R, the python package pyshp was used. For this project, a couple of assumptions were made. First, shapefiles cannot contain multiple geometry types, so all point location outages were excluded from the output shapefile. While removing the point outages removed 44% of the total outage incidents, it only removed 0.85% of affected households. Second, each power outage incident has a unique ID associated with it, so all of the data was merged along this ID. It was assumed for each outage that the polygon area and the number of affected customers remained constant for each incident. Third, it was assumed all power outages between October 8th to October 14th were due to the public safety power outage, and not due to other events such as wind or lightning.

Median household income was merged with the TIGER shapefiles by joining along the census GEOID value.

For the high voltage power line dataset, only lines with status equal to "'IN SERVICE" were included, and all other power lines were removed.

Spatial Exploratory Analysis

The first step in our analysis is to trim the data down to our analysis region, Sonoma County. Using the census block group outlines, we only included data that intersected these block groups.

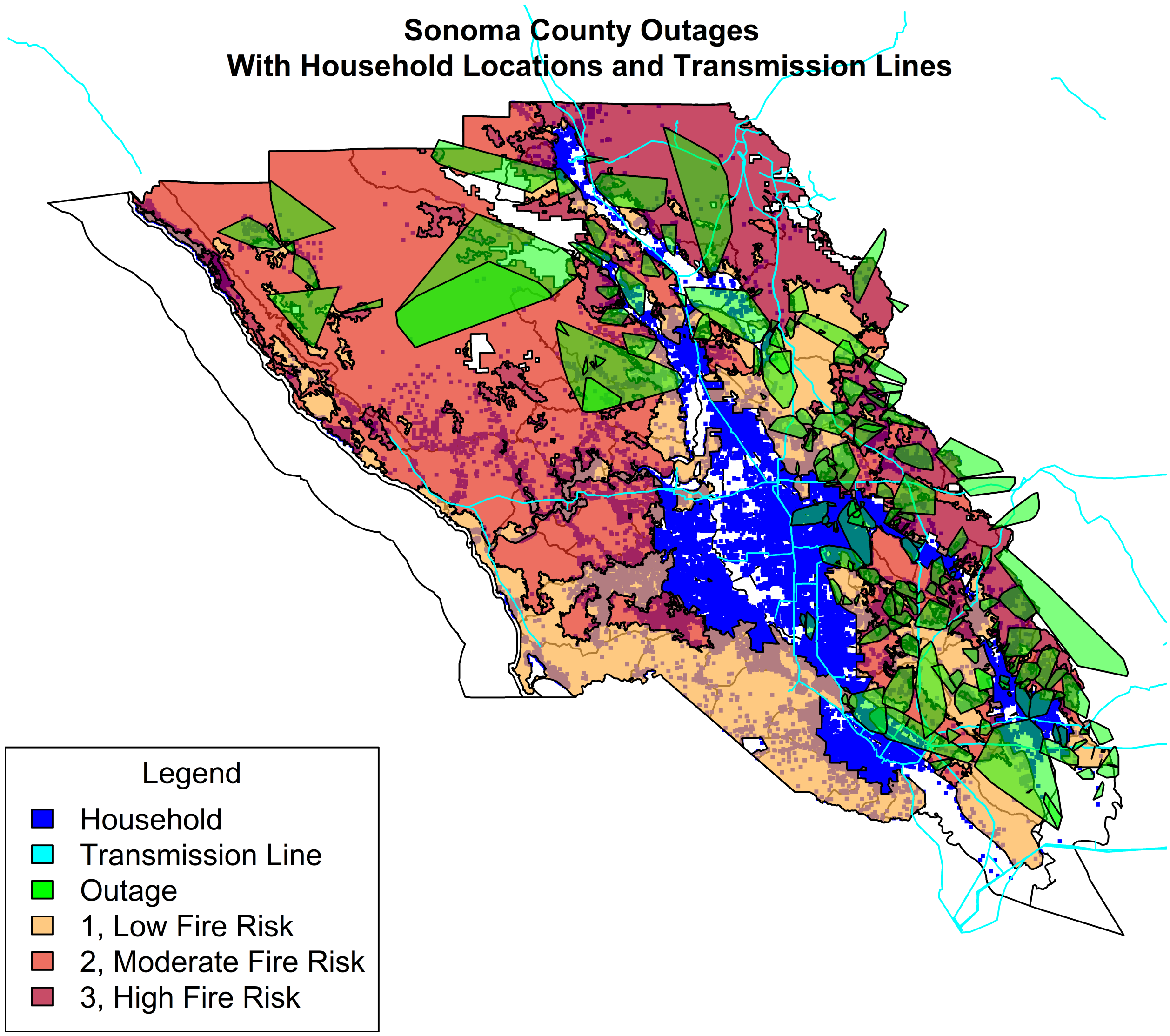

Figure 1: Spatial Context

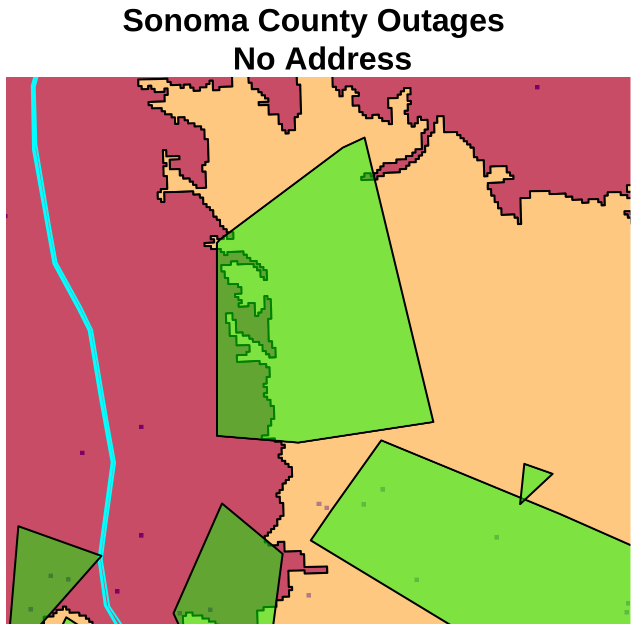

Figure 2: Outage with no address

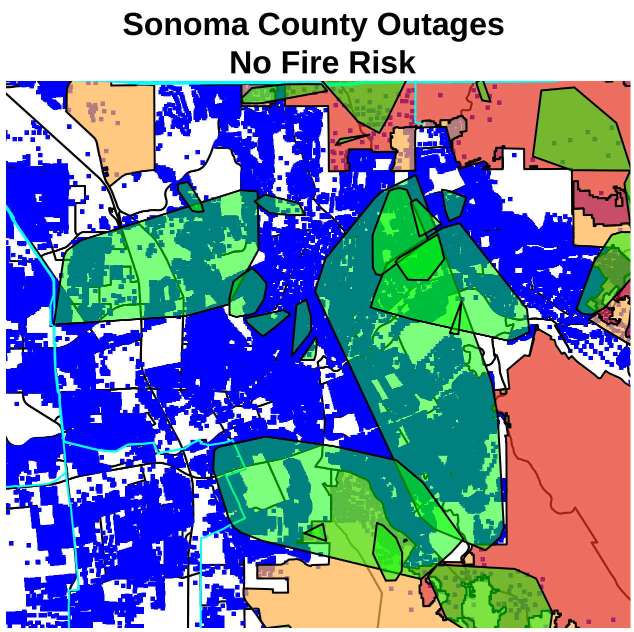

Figure 3: Outage with no fire risk

The next step in our analysis is overlaying and mapping the data of interest to show the spatial context. In figure 1, we overlay the power outages on top of a map of Sonoma County. We also overlay address locations as determined by Zillow, overlay fire risk zones, and overlay high voltage transmission line locations. The purpose of this map is to visually identify any obvious spatial trends. Some discrepancies can be seen on this map. First, it appears not all outage regions have an address inside of it, as shown in figure 2. This could indicate a business location, such as power lines to a farm or timber operation, instead of a household. Second, as expected, it appears most of the outages occur in regions with non-zero fire risk, but some outages did occur in places without any fire risk as shown in figure 3. This indicates that PG&E is using some other criteria besides fire risk in their decisions to shut off power. Third, many outage zones are not overlapping a high voltage transmission line, and it does not appear the entire high voltage line has been shut down. This indicates that PG&E is not just shutting down all power, and is instead actively making choices where to shut off power.

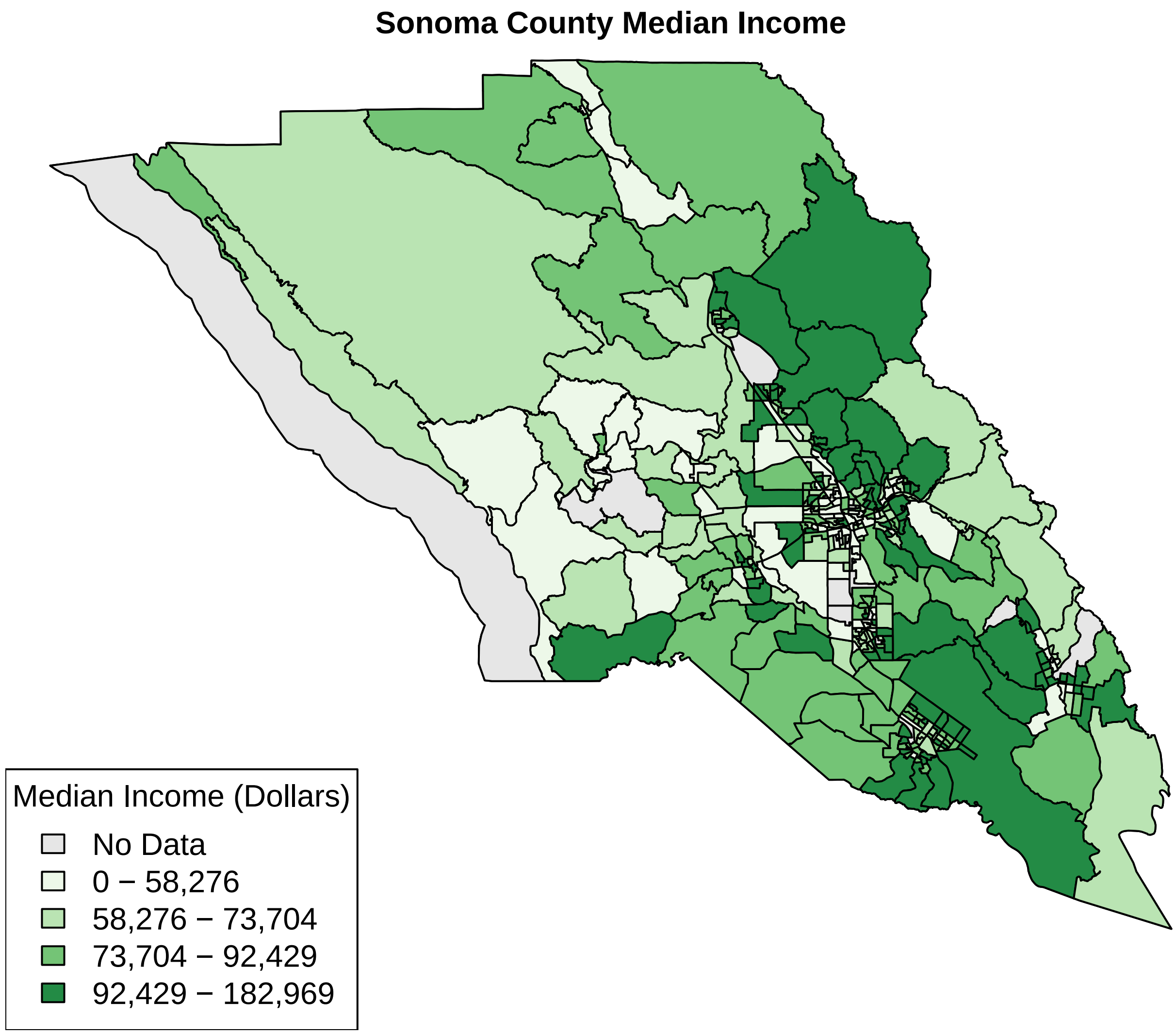

Figure 4: Map of Median Income

In figure 4, the median income data in Sonoma County is mapped. From a visual glance, there appears to be a cluster of high income large rural block groups in the northwest and southwest. Zooming into the city core, there appears to be a clustering of lower income block groups. However, we should be cautious about our visual clustering assessments. Using Moran's I clustering, we can assess if the data is clustered, randomly distributed, or evenly distributed. Using rook contiguity, the following Moran scatterplot was obtained.

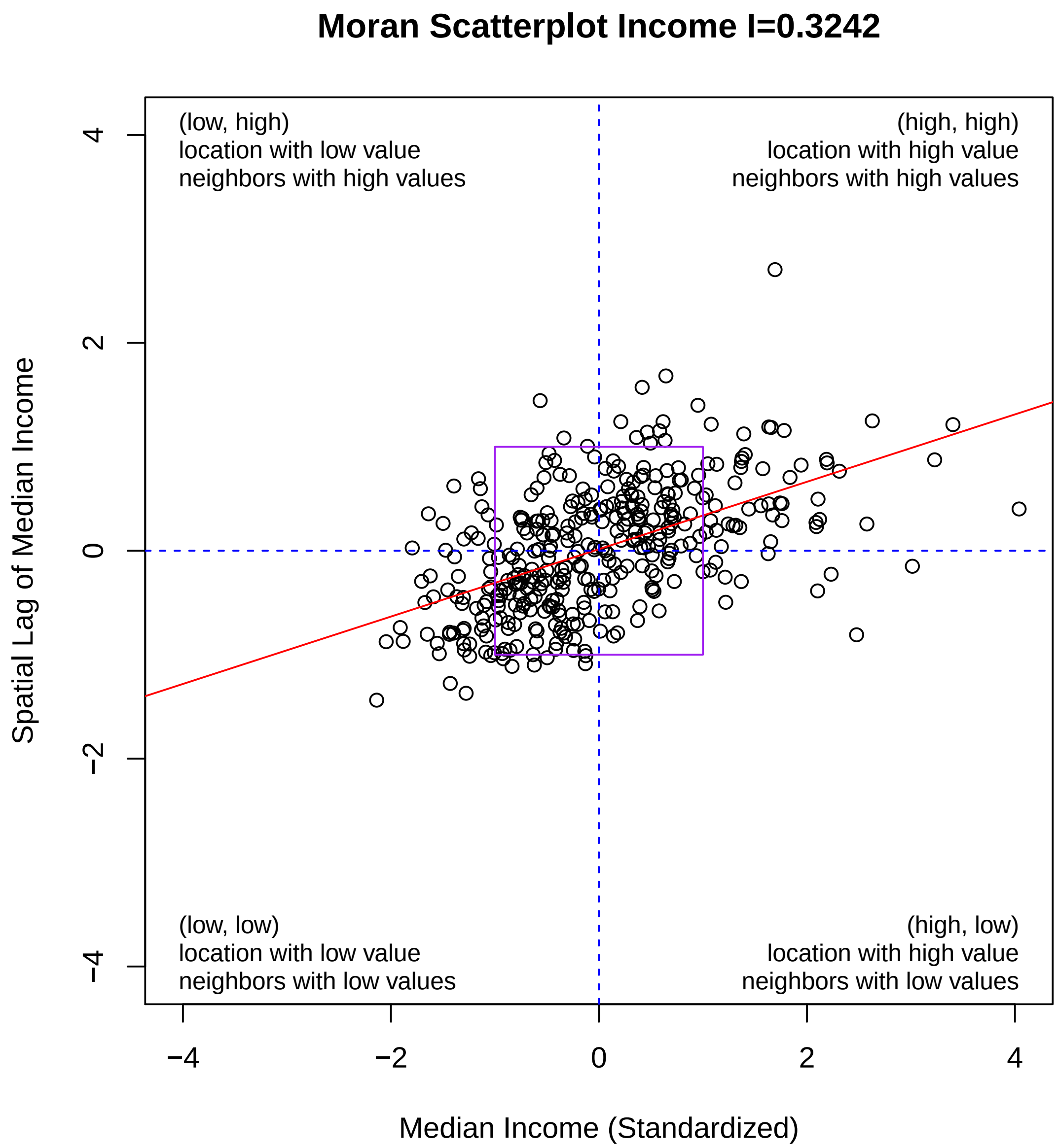

Figure 5: Income Moran Scatterplot

From figure 5, a positive slope is seen. That means that the income data is more clustered compared to a random distribution. In addition, the p value for this fit is very low, indicating that the clustering is statistically significant.

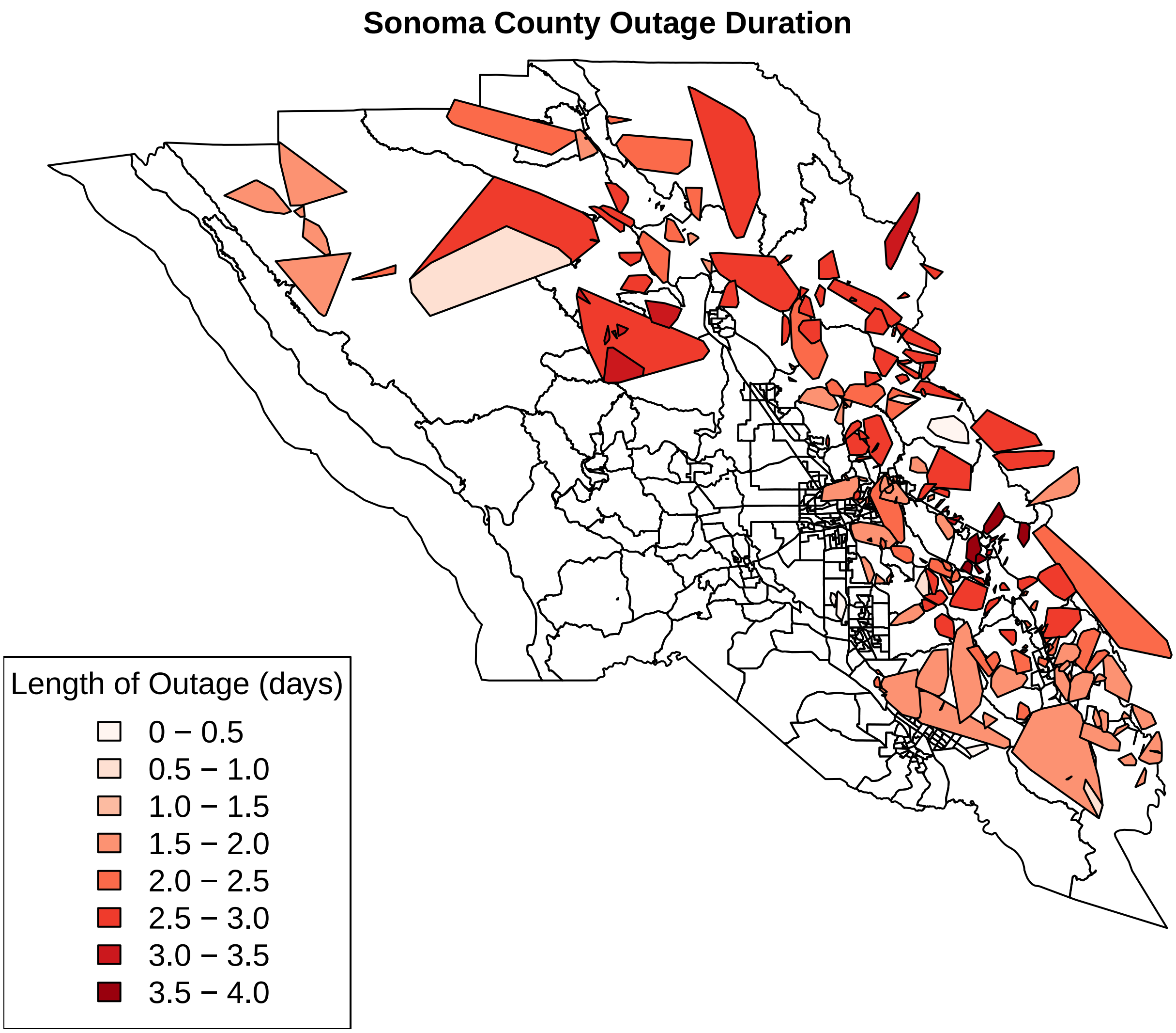

Figure 6: Map of Outage Length

In figure 6, the length of each outage is mapped. It appears that the length of each outage is spatially random, expect for a cluster of long outages in the east. Using Moran's I clustering, we can determine if clustering is present. A distance threshold of 4.19 km was used to construct the neighbor list. This distance is one third of the maximum 1 nearest neighbor distance. This reduced distance was used to reduce the density of neighbors, and isolated outages were removed for the Moran analysis. 12 isolated outages were removed, 5% of the outage dataset.

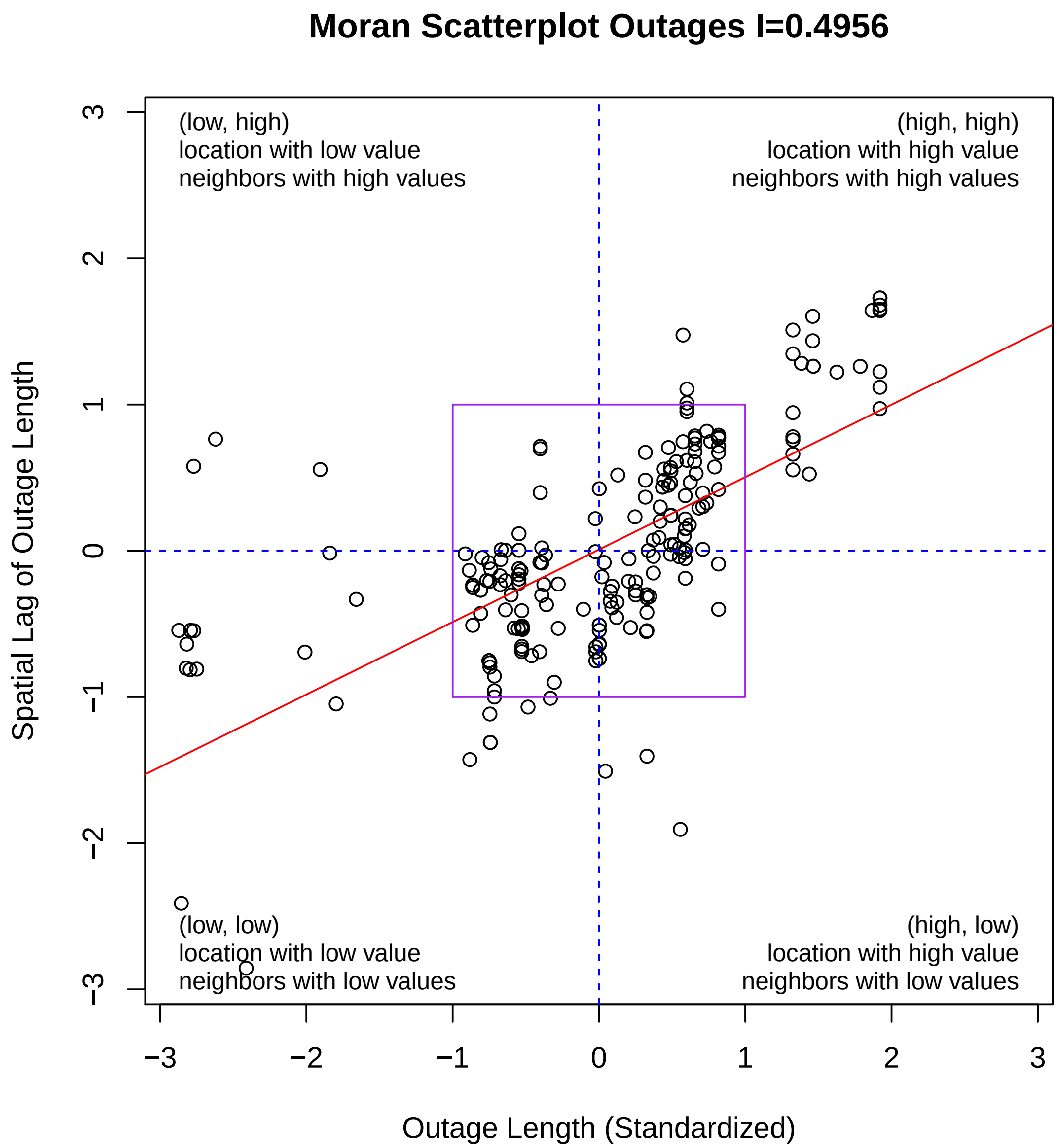

Figure 7: Income Moran Scatterplot

From figure 7, a positive slope is seen. That means that the outage data is more clustered compared to a random distribution. In addition, the p value for this fit is very low, indicating that the clustering is statistically significant. Both power outages and income data show spatial clustering, so median income could possibly explain the spatial clustering of the power outages.

Temporal Exploratory Analysis

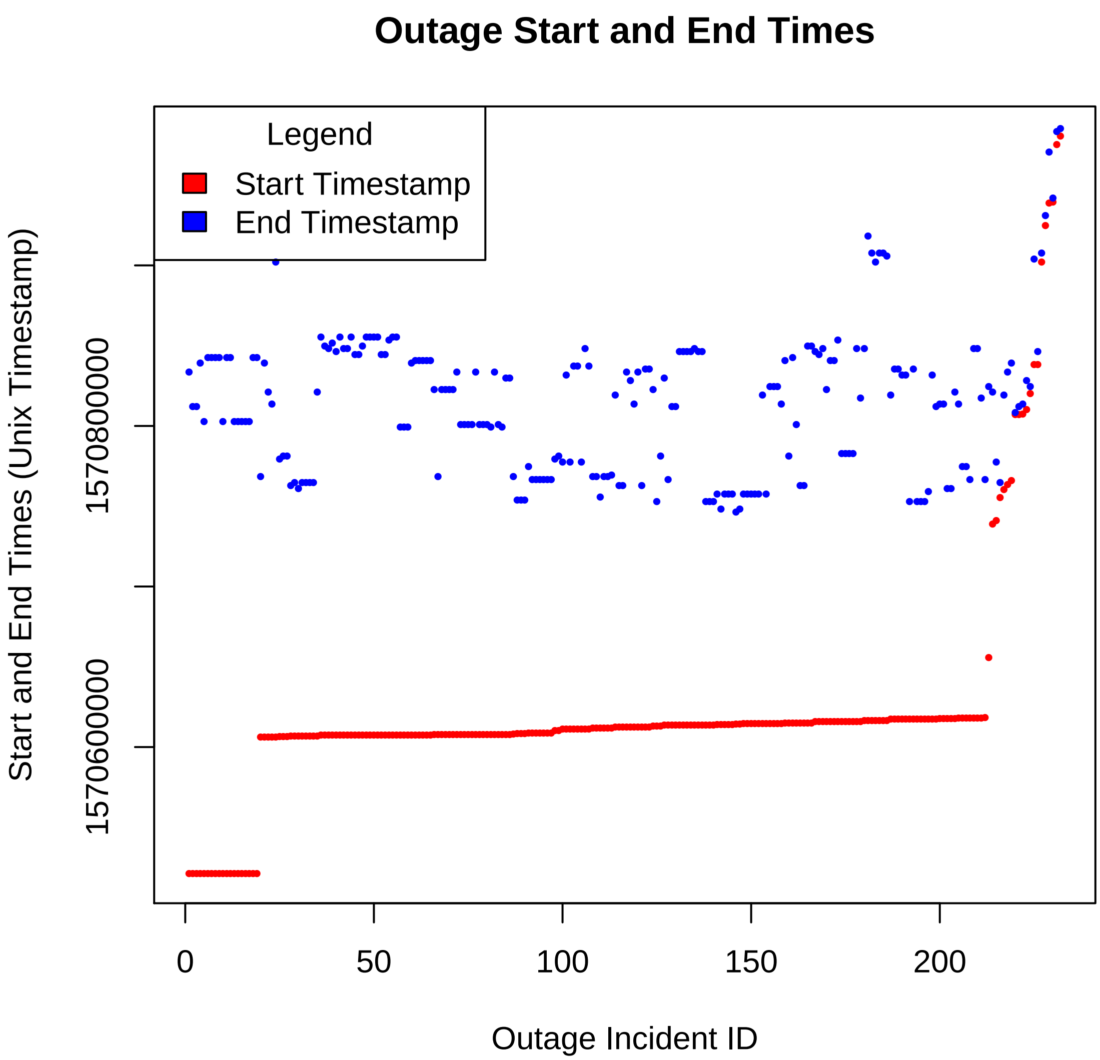

Figure 8: Outage Start and End Times

After getting a glimpse of the spatial relationships between the variables, we need to explore the temporal characteristics of the data. The power outages did not all start at once, and did not all recover at once. Figure 8 shows by ID when each outage started and when each outage ended. Translating from the Unix timestamp, this figure shows some outages started at 00:52 Tuesday Oct 8. Most of the outages started between 00:30 Wednesday Oct 9 and 04:00 Wednesday Oct 9. A few more outages occurred in the following days, which are most likely normal outages due to equipment failure unrelated to the PSPS. In addition, in this figure the outage IDs are sorted by start time. If power was restored in the same order as it was shut off, we would expect the outage end time line to be flat and smooth. However, the apparent random spread in the outage end time indicates that outage start time and outage end time are not correlated with each other. When fitted, the start times and end times only have an R^2 of 0.15, the start time only explains 15% of the variance of the end time. Therefore, two different procedures were used to turn off the power and to turn the power back on.

The PSPS was rolled out in a relatively short period of time, approximately 3 hours. This means PG&E was not monitoring individual neighborhoods for fire risk. They instead looked at very large geographic areas, and made the decision to shut off power for the entire area at once. In contrast, the recovery process spanned a period of approximately 24 hours. PG&E was actively making choices to restore power to different areas, and had to choose an order of restoration. We expect that they would not be using any fire risk metrics in this assessment because the fire risk event had passed. Therefore, we expect that the recovery process was guided by engineering concerns, such as load balancing or current capacity, and by social concerns, such as returning power to population dense areas first or prioritizing populations more likely to file lawsuits. These concerns could cause low income disadvantaged populations to be restored last because these populations are more likely to have older more vulnerable infrastructure and have less ability to hold PG&E accountable for their choices.

Data Merging

To perform the analysis of the data, a common spatial reference frame needs to be used. Each data set was transformed to LongLat coordinates. The data was merged to census block groups because the block groups are contiguous, cover all of Sonoma County, and do not overlap each other. Two methods were used to merge the outage data into the census block groups. The first method was to determine all of the outages that intersected a block group, and then assign an outage length based on the maximum length outage. Figure 9, shows the result of this spatial merging. The city core appears to have shorter outage lengths then the larger rural block groups.

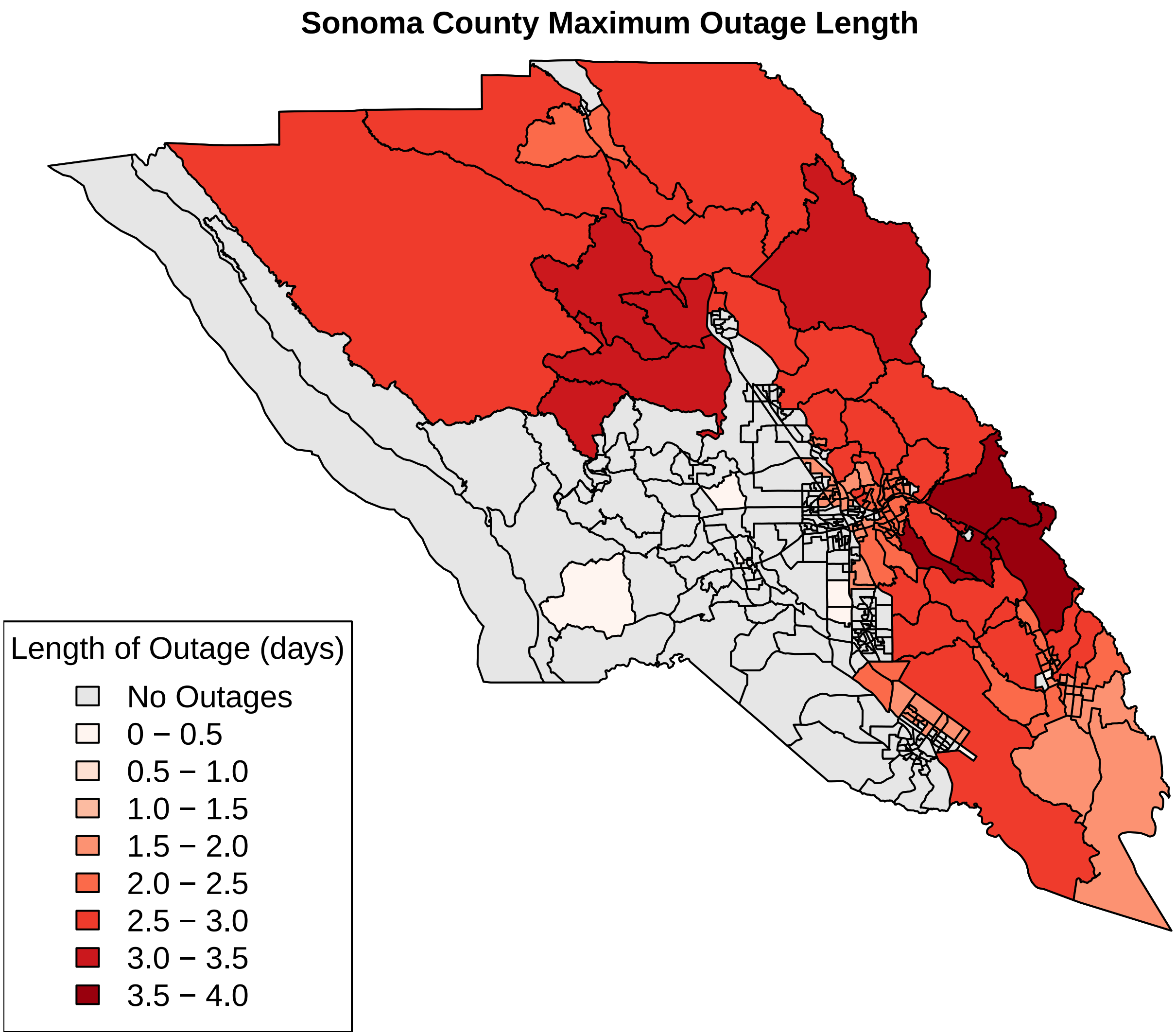

Figure 9: Maximum Outage Length

There were some concerns that the maximum length spatial merge could be sensitive to outliers in the data, so a second method was used to merge outage length to the block groups, an area weighted approach. This approach calculates the average power outage length experienced by a household in the block group.

$$\text{Average Household Outage Length} = \frac{\sum_{\text{outages}} (\text{Outage Length}) * (\text{Affected Households}) * \frac{(\text{Block Group Intersection Area})}{(\text{Area of Outage})}}{\sum_{\text{outages}} (\text{Affected Households})}$$

It is assumed that households that lost power are evenly distributed inside each outage polygon. For each outage that intersected a block group, the area of the intersection was measured. The fraction of this intersection area to the whole outage area determines the weight of each outage for the weighted average calculation shown above. Figure 10, shows the result of this spatial merging. The outage lengths determined by this method appear to be more randomly distributed in space.

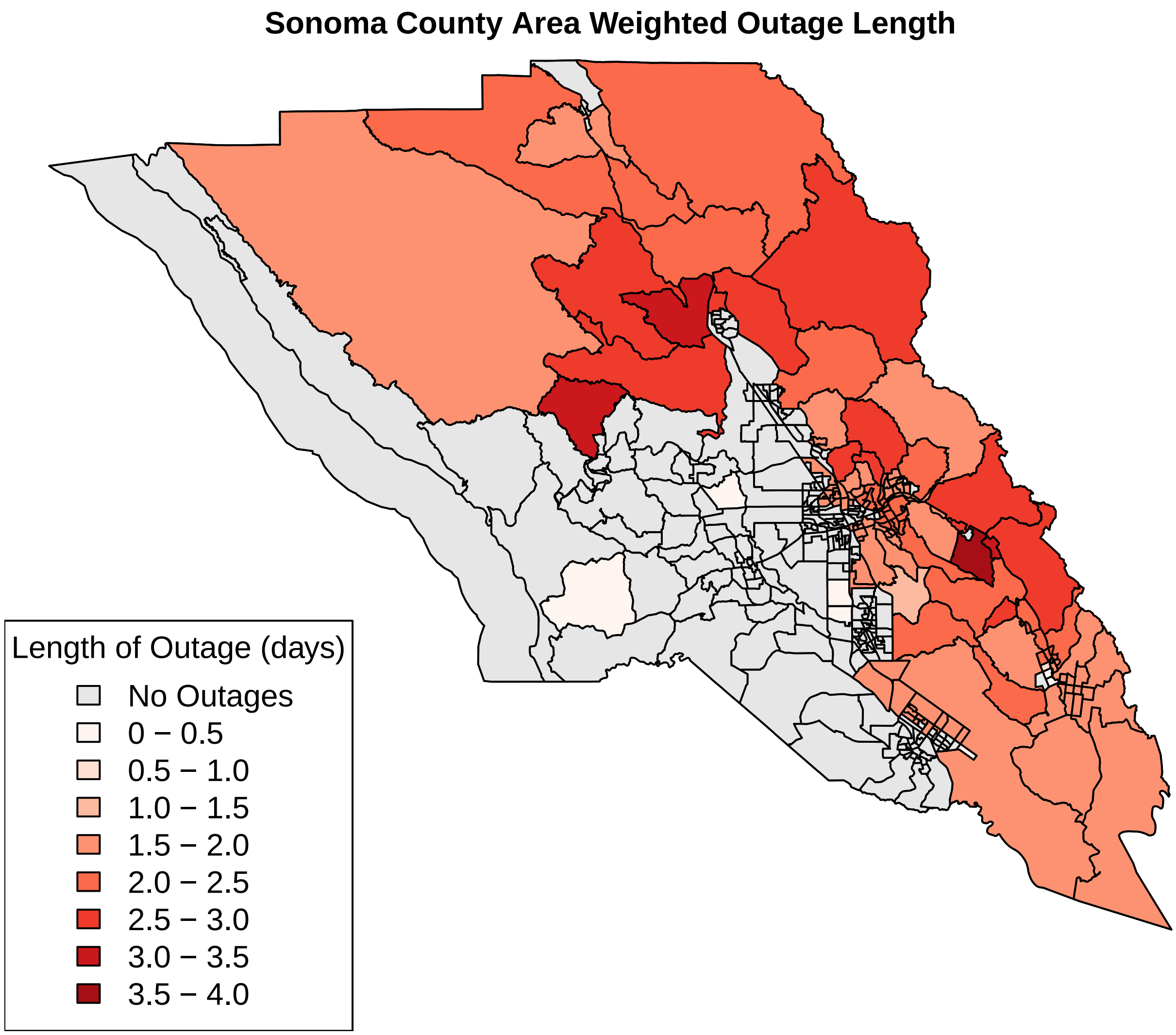

Figure 10: Area Weighted Outage Length

For the fire risk data, an area weighted approach was used to merge it into the block groups.

$$\text{Average Fire Risk} = \frac{\sum \text{(Fire Risk)} * \text{(area of intersection with the block group)}}{\text{(Area of the block group)}}$$

It is assumed that the fire risk is on a linear scale, so high fire risk is only 3 times as risky as low fire risk. Figure 11 shows the result of this spatial merging.

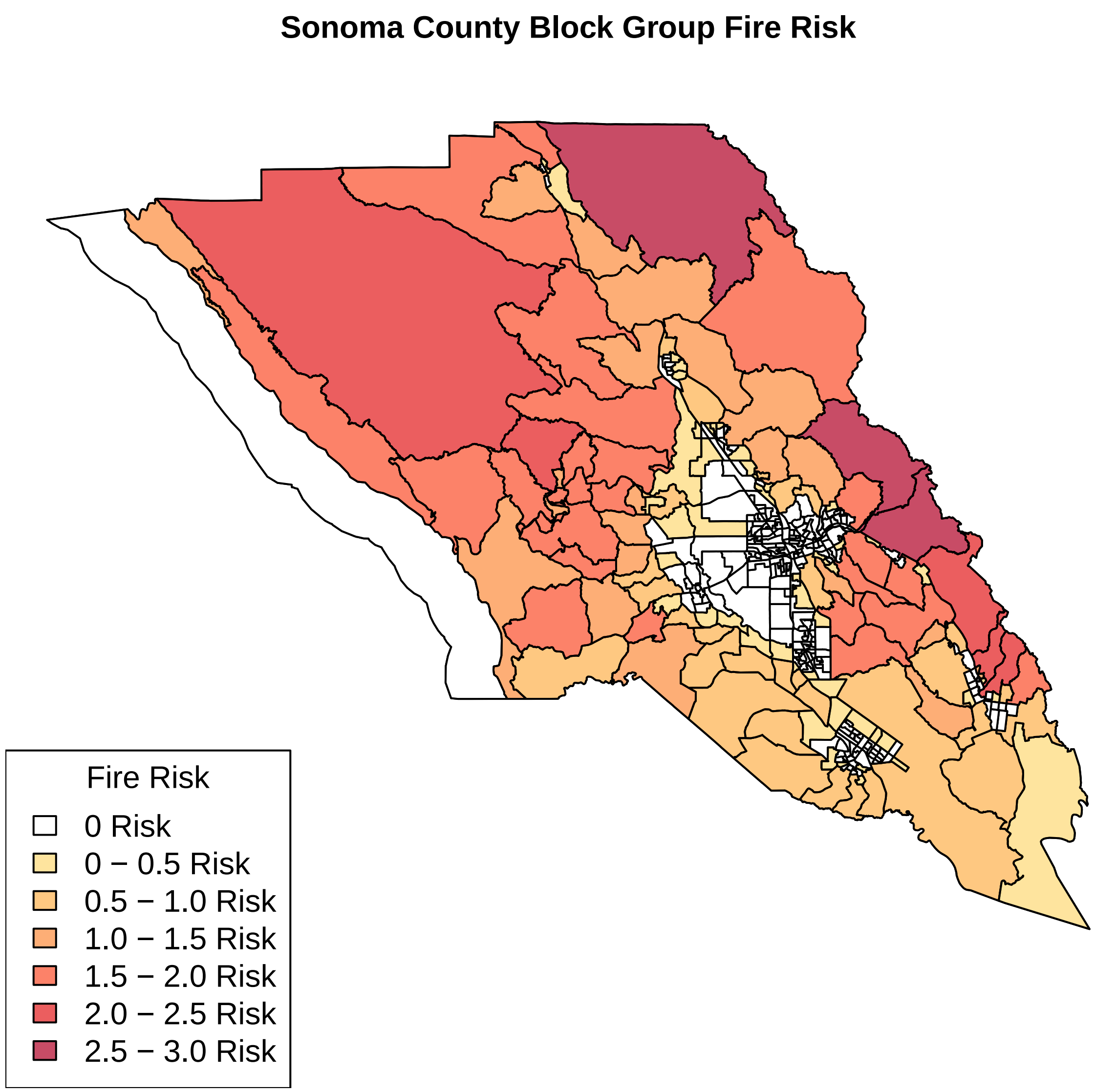

Figure 11: Block Group Fire Risk

Results

Income vs Outage Duration

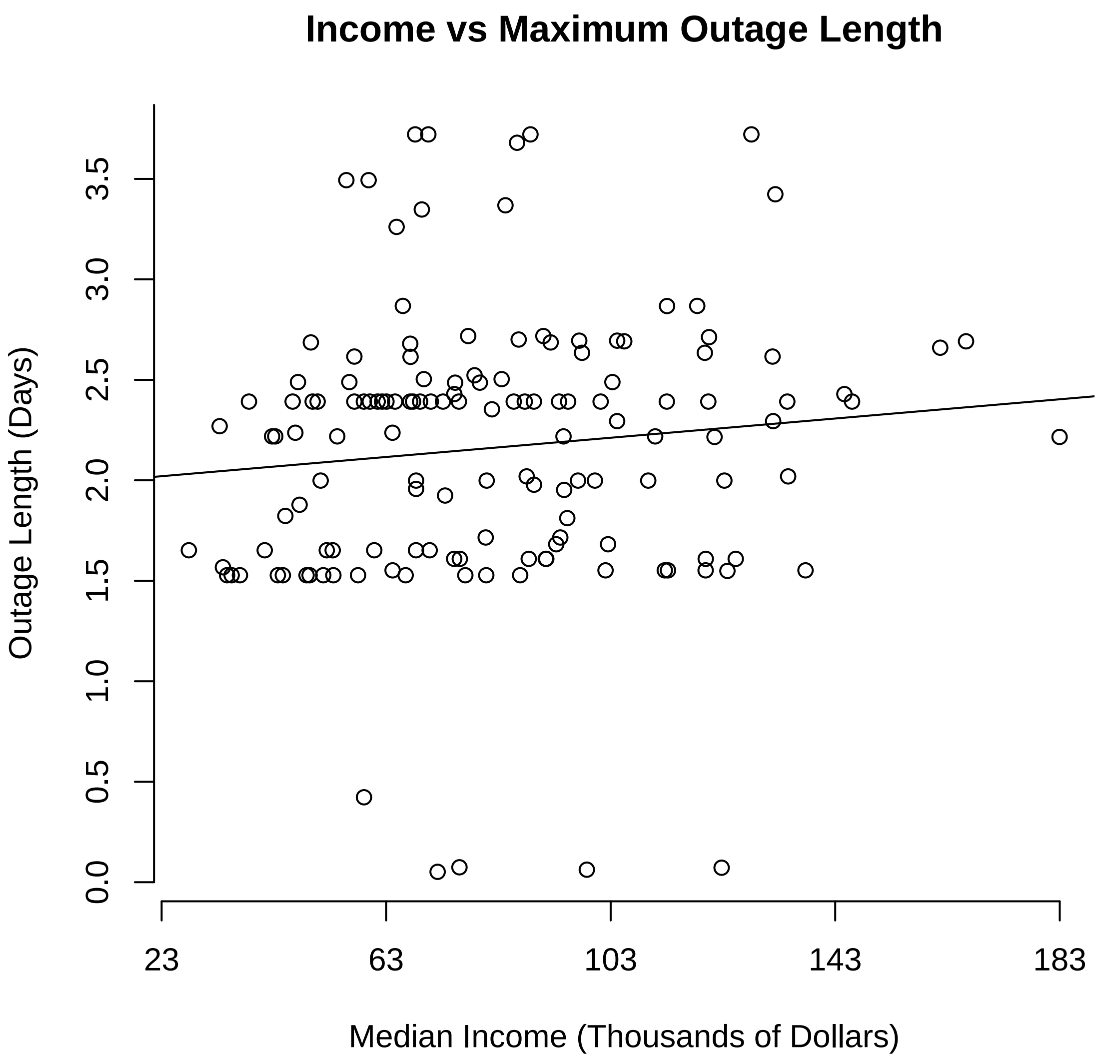

Figure 12: Income Vs Maximum Outage Length

To assess our research question of whether power outages disproportionately affect lower income households, we can plot median income vs outage duration for each block group. Figure 12 shows the relationship between income and the maximum length of a power outage. From the plot, there is no observable trend. The p value exceeds 0.05 indicating that there is no trend. And the R^2 value is 0.01157, indicating that income does not explain any variance in the power outage duration.

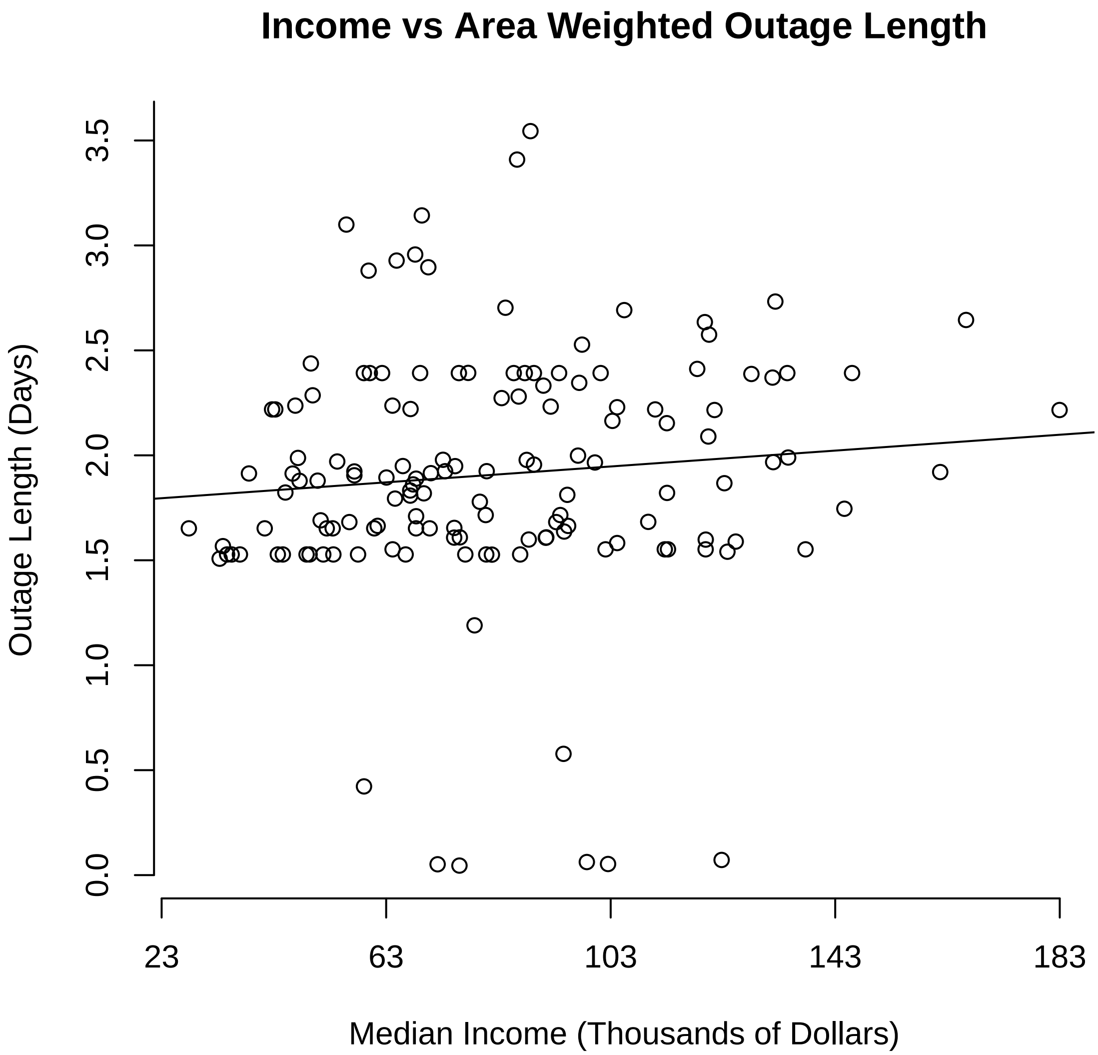

Figure 13: Income Vs Area Weighted Outage Length

If we look at area weighted outage duration instead in figure 13, the conclusion is the same. The p value exceeds 0.05 indicating no trend, and the R^2 is 0.009578, indicating that income does not explain outage duration.

Therefore, we cannot reject the null hypothesis, so outage length and income are not related to each other.

Customers Affected vs Outage Duration

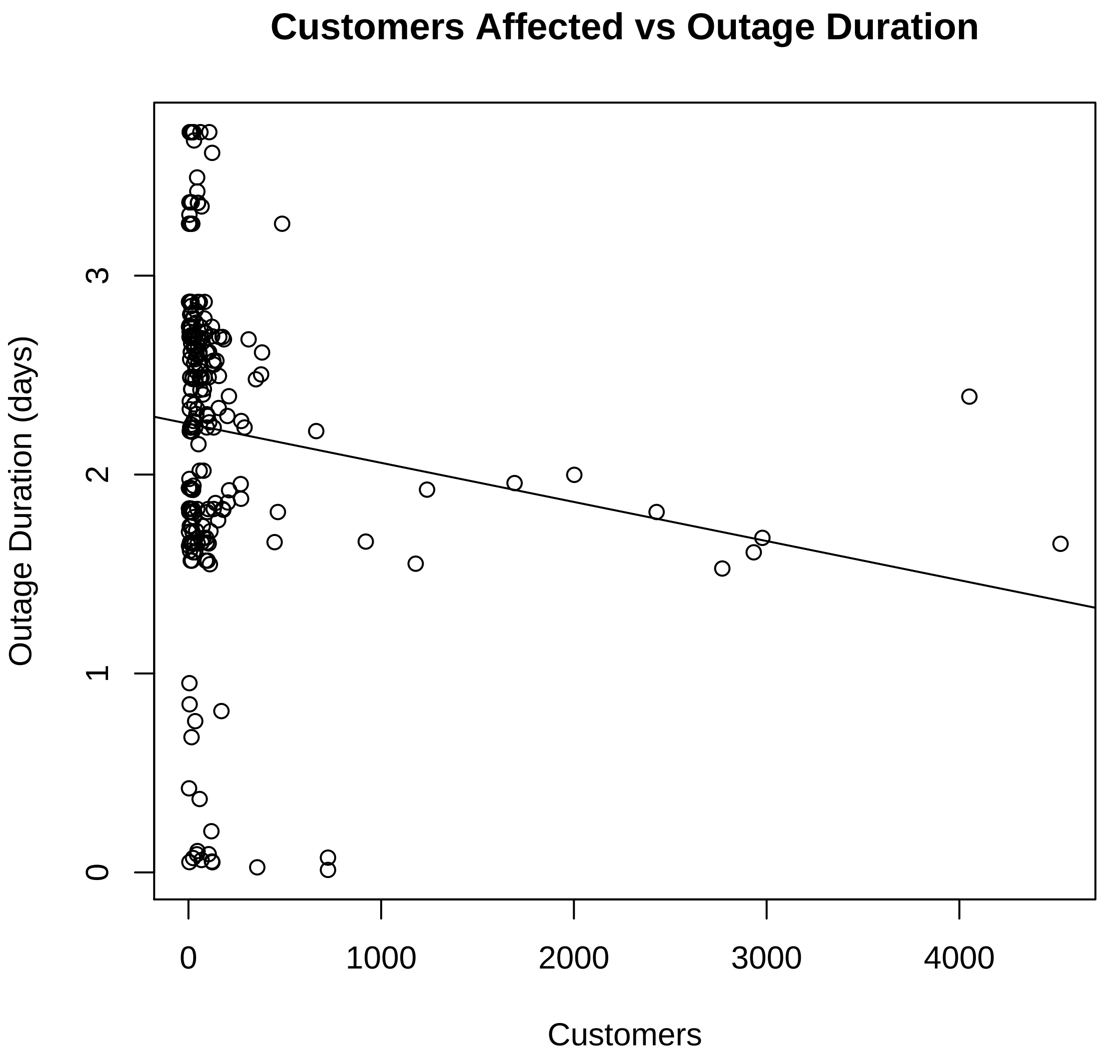

Figure 14: Outage Count Vs Outage Duration

We can consider other criteria that PG&E uses when restoring power. One possible criteria is to restore power to locations with more households. Figure 14 shows the relationship between customers affected and the duration of the power outage. A significant negative trend at p = 0.03323 is found, indicating that outages with more people are turned back on sooner. However, the R^2 is very poor at 0.01956, which means customers affected is not a good predictor of outage length.

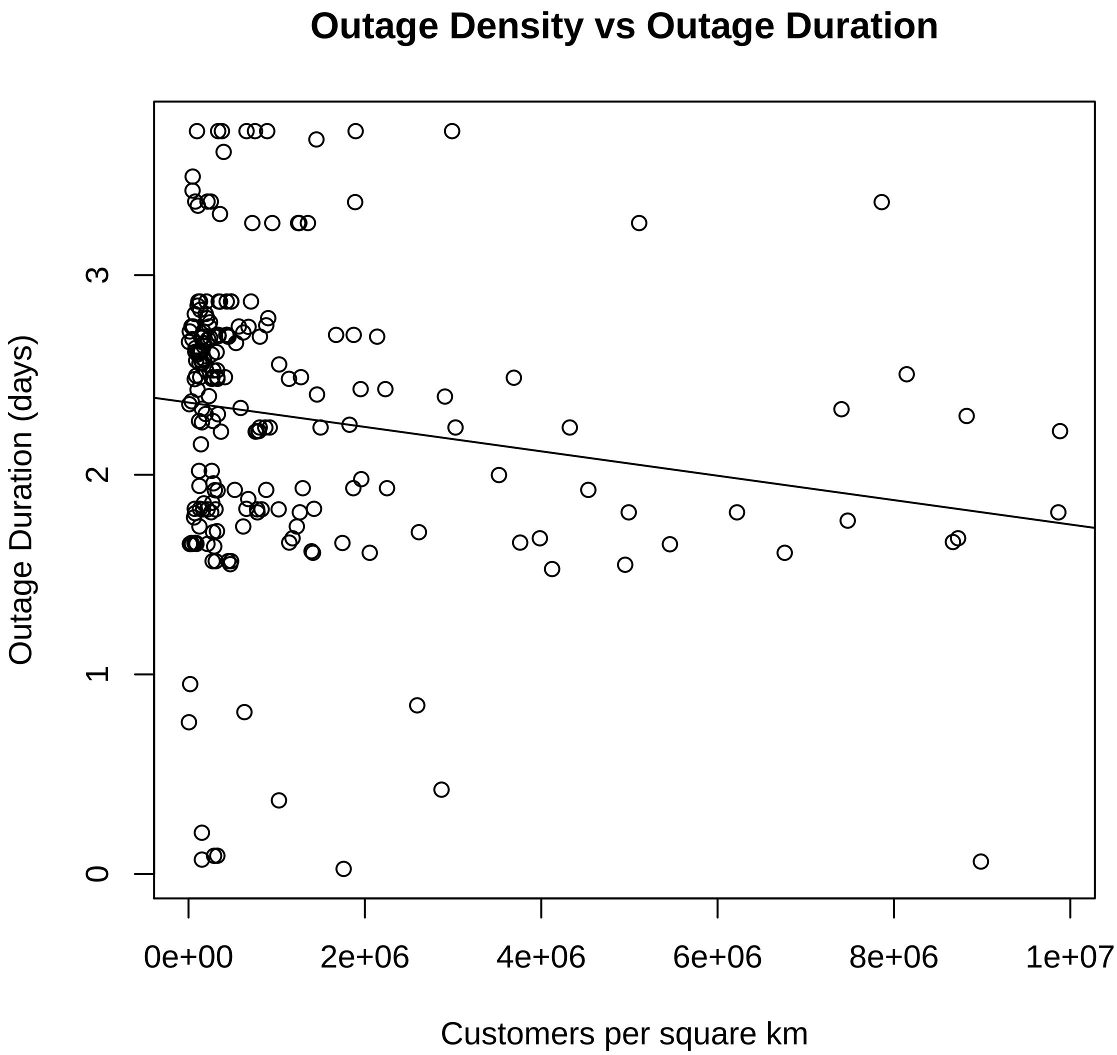

Figure 15: Outage Density Vs Outage Duration

We can also look at the spatial density of affected households. Figure 15 shows the relationship between customers affected per square km and the duration of the power outage. A significant negative trend at p = 0.01287 is found, reinforcing the previous finding that outages with more people are turned back on sooner. However, the R^2 is very poor at 0.02883, which means customers affected per square km is not a good predictor of outage length.

Fire Risk vs Outage Duration

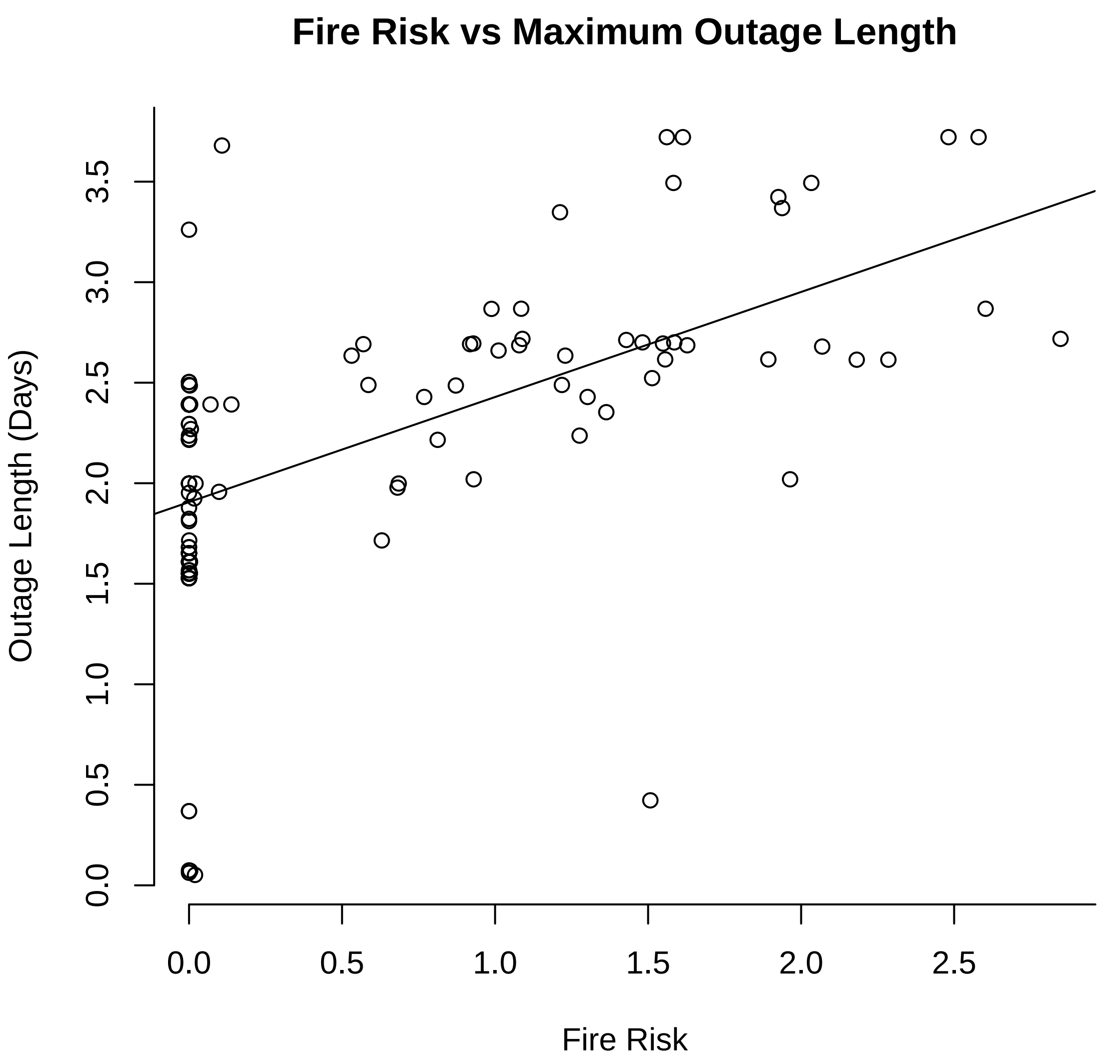

Figure 16: Fire Risk Vs Outage Max Length

Fire risk could be a criteria used by PG&E to turn the power back on. Earlier it was discussed that it is likely that the recovery could only start once the fire risk had passed for the entire region, but it is possible that PG&E can monitor local fire risk conditions to determine when to safely turn power back on for individual outage events. Figure 16 shows the relationship between the block group fire risk and the block group maximum outage length. A significant trend is detected, and the R^2 is 0.3034, indicating much better predictive power.

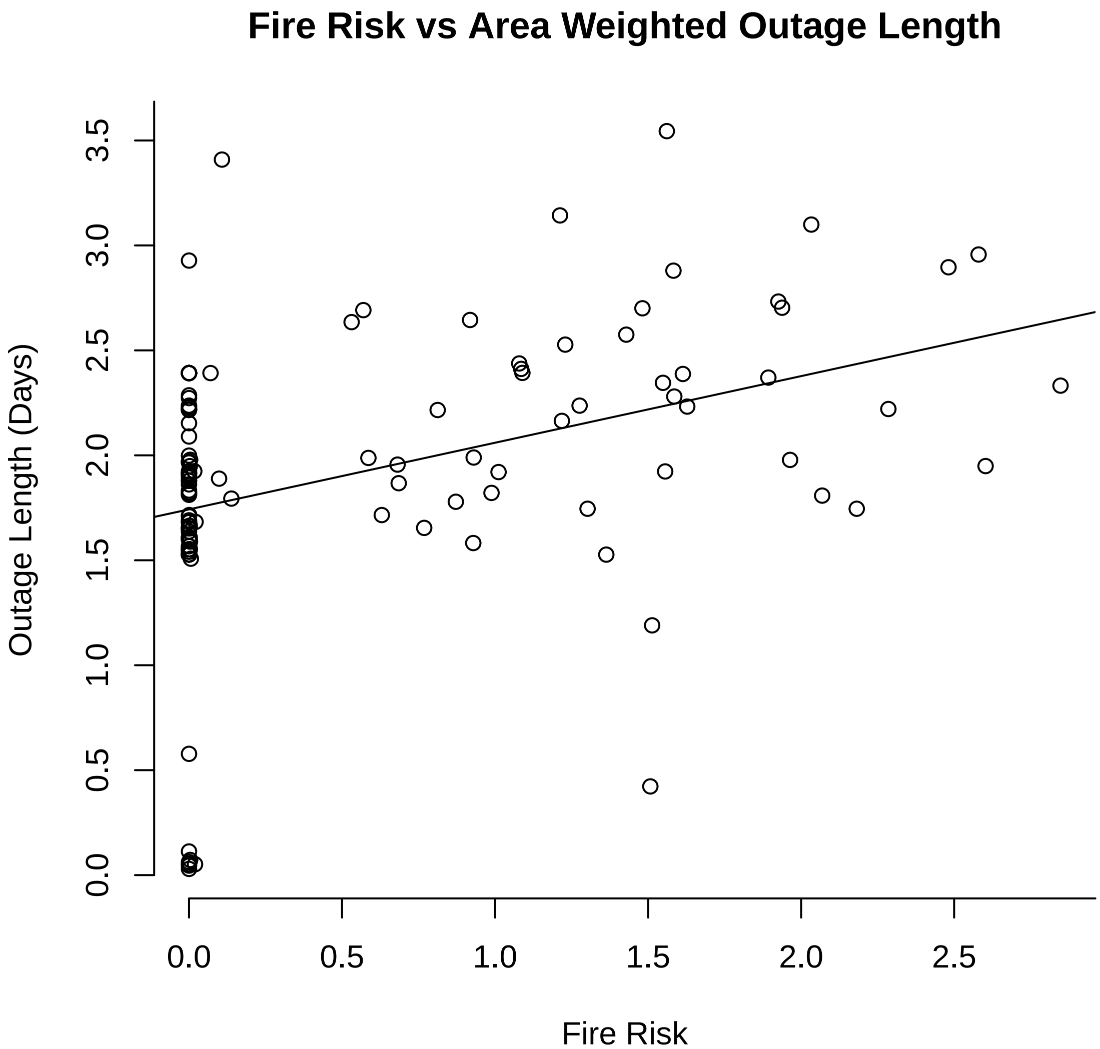

Figure 17: Fire Risk Vs Outage Area Weighted Length

Figure 17 shows the relationship between fire risk and area weighted outage length. A significant trend is also shown, but the R^2 value of 0.1432 is worse than the maximum outage length relationship.

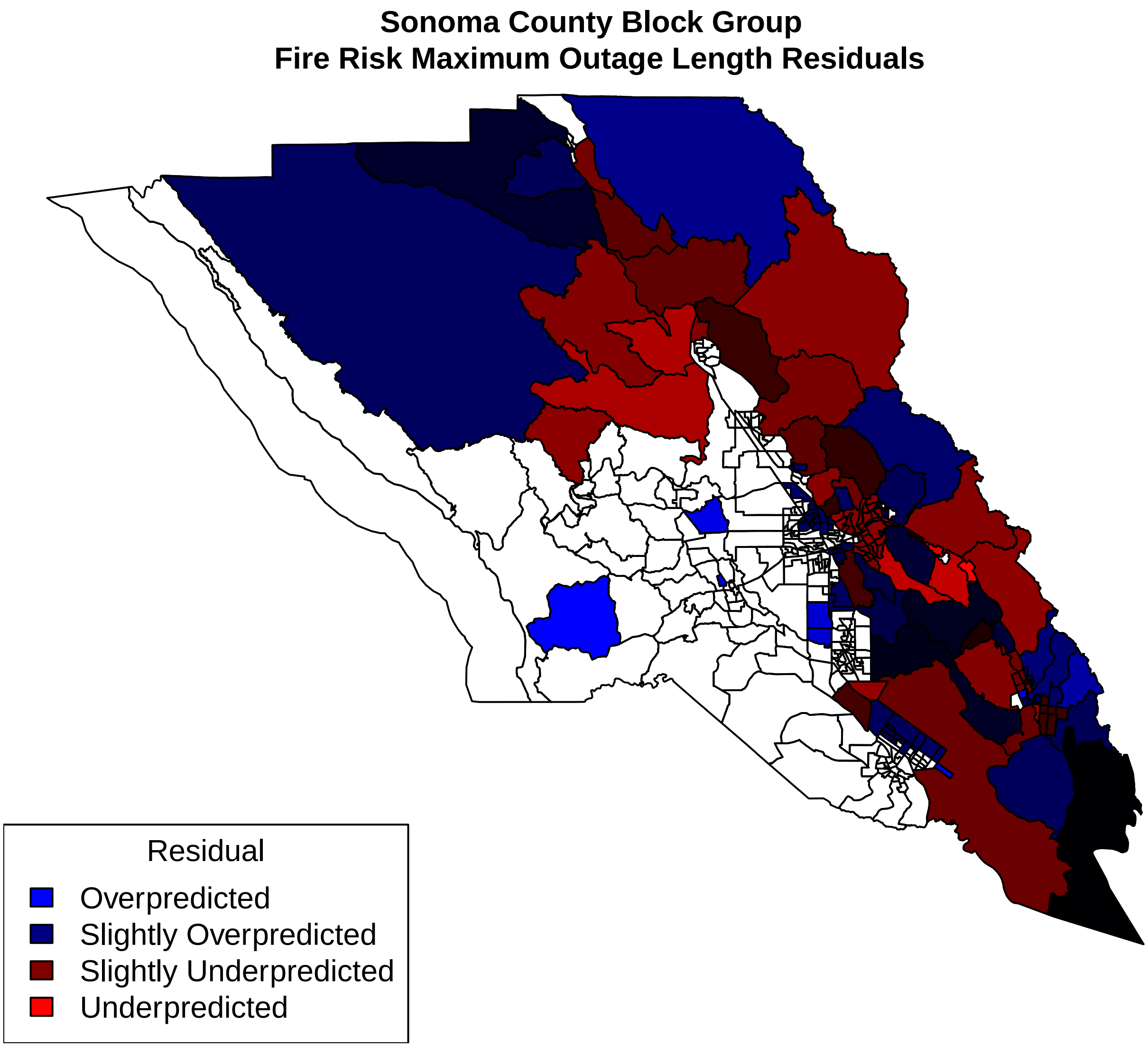

Figure 18: Fire Risk Vs Outage Max Length Residuals

We can assess the residuals of the fire risk prediction of maximum outage length. Figure 18 maps where fire risk is not an accurate predictor of outage length. Obvious spatial clustering of the residuals is observed, suggesting some spatial autocorrelation of outage length. A possible explanation of this autocorrelation is power repair crews starting their repairs and inspections in rural areas, and moving inward to the dense city cores, but we do not have data supporting this claim.

Discussion and Conclusion

Discussion

Overall, our hypothesis that median income affects the duration of the PSPS is not true. PG&E's method for restoring power after a PSPS is not correlated with median income. It is observed that a slight trend exists between the number of affected households and the duration of the PSPS. Of the analyzed factors, the geographic fire risk is the most significant factor determining the length of the PSPS.

Future work could apply more sophisticated statistical models. Instead of looking at univariate regressions, multivariate regressions could be used instead. The spatial autocorrelation effects of repair and inspection processes can be explicitly modeled using spatially lagged variables. The regressions could be weighted by population to more accurately capture trends. Future discussions with PG&E could illuminate some inconsistencies in the power outage data, such as outages with no mapped addresses or households, and explanations for overlapping outage zones.

Shortcomings

One of the shortcomings of our research is that we used household income as the sole indicator of wealth. Wealth is the measured value of assets minus liabilities (Howell et al 2018). It is accumulated in the short term through wages and other forms of income, in the long term through returns on investments, and across lifetimes through intergenerational transfers (Howell et al. 2018). Our research uses 5- year income estimates at the Census block group level from, limiting the study to an understanding of wealth as short term accumulation. We chose this as an initial variable because of the ease of data access at the desired administrative unit. We also recognized that the inequitable appreciation of real estate markets is a source of unequal returns to households (Howell et al, 2018). A future path of inquiry is to investigate the scraped 2019 Zillow home value data. This data would need to be cross referenced with another data set, such as census data, to validate the dataset. Once validated, Zillow home value data can be used as a proxy for access to capital funds, and can be used to evaluate real estate appreciation.

Our research, like most on natural hazards, used a single case to analyze inequality after an extreme event. Howell and Elliot, in contrast, used longitudinal, population-centered approach, because it links data from broad sample to information on local experiences and across durations of time. This allowed them to analyze how "damages influence wealth trajectories differently for different segments of the population, net of a wide array of other individual, family, household, and contextual factors." (Howell and Elliot, 2018). In 'Extending the Boundaries of Place,' Siordia and Matthews argue that multilevel models offer statistical advantages over conventional single-level approaches. The conventional two-level model situates an individual in a single context, which is too reductive when analyzing socio-spatial significance: “If an analytical model is seeking to examine pathways and exposures linking people to place then it would seem that several functionally meaningful units reinforce this relationship” (Siordia and Matthews). They argue that the emphasis on boundaries undermines the spatial and temporal scales of human behavior. Our study was limited by both administrative boundaries and limited variables. However, when we found no significant relationship between household income or home value and fire risk / outage severity, we decided not to pursue further measures of wealth or vulnerability. Applying a longitudinal- population centered approach could provide a more contextually nuanced analysis of the impact of PSPS on wealth over the next decade to better understand how it shapes access and advantage.

Another set of variables that would be valuable to include in an analysis of the PSPS impact is community resilience. Community resilience is “the ability of a social system to respond and recover from disasters and includes those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-event” (Cutter et al. 2008). Empirical studies addressing community resilience during long outages have found that people rely heavily on community networks (Moreno and Duncan, 2008). In complement to Howell and Elliot’s strategy, a field study of community networks could help assess resilience strategies going forward.

Conclusion

Looking at the short term, there are several strategies that policy makers could implement to mitigate the effects of future PSPS on vulnerable populations. Moreno and Duncan argue that “satisfying people’s basic needs and reducing the level of uncertainty and insecurity after an outage could contribute to lessening the public’s level of discomfort and discontent.” Providing more information about the estimated duration of an outage and supplying alternatives “such as: backup generators, battery torches, portable chargers, camping stoves and heaters” (Moreno and Duncan, 2018), would mitigate the impact of an extended outage on vulnerable households. Purchasing a generator is a financial burden that many households can’t take on. Access to an alternative source of energy is therefore a clear indicator of the impact that wealth has on the experience of an outage. Publicly subsidized collectively owned generators could provide a one short term solution to increasing access to alternative sources of energy during an outage. In the long term, a dynamic restructuring of infrastructure and residential settlement patterns is necessary if people want to continue to live in regions with a high probability of weather related events. This would require a dynamic approach in both strategy and tactics. In the era of climate consequences, public policy, urban design, and infrastructure engineering must be intricately engaged. On the public policy side, research, resources and assistance needs to be engaged for both communities experiencing climate disasters and those poised to receive climate migrants. This is also tied to urban design strategies, where relocating entire communities through large scale buyouts is necessary to clear the urban wild interface where properties are both the most vulnerable and worsening the spread of wildfires (and in the case of hurricanes, rewilding the currently occupied floodplain is a strategy towards mitigating the severity of flooding). In terms of infrastructure, one solution currently being debated is a state buyout of the power grid. This would certainly improve accountability and potentially reduce corruption, but it would not address the risk that the existing grid poses. During fire seasons, Northern California receives a significant amount of sunlight (according to a rooftop analysis by Google's project sunroof), a municipal solar power system could be an effective alternative to a distributed power grid, effectively eliminating any impact of the PSPS.

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