# Power Outage Trends in California, Florida, Pennsylvania, and Texas from 2015 to 2023

https://github.com/sarahj-hall/Antonucci_Hall_Huang_Kuehn_ENV872_FinalProject.git

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# 1 Rationale and Research Questions

Electric power outages are costly for both utilities and their customers. Outages disrupt economic activity, and impact critical facilities such as hospitals (Wing et al., 2025). The United States electric grid is increasingly vulnerable to outages due to increasing extreme weather events, such as hurricanes, heatwaves, wildfires, and winter storms, which are increasing in frequency and intensity due to climate change (Wendel, 2024). Because many of these events occur during specific times of the year, understanding weather power outages follow a seasonal pattern is important for planning and resilience. If outages tend to occur in specific months, utilities and communities can better allocate resources, resilience investments, and emergency preparedness.

At the same time, electric utilities have made advancements in system planning, grid hardening, and outage detection (IBM, 2025). Together this raises key questions about whether outages are becoming more or less frequent, whether they show predictable seasonal cycles, and whether their impacts are increasing over time.

To address these questions, this study focuses on Texas, California, Florida, and Pennsylvania. These states represent diverse geographic regions, climates, and electric power systems. For each state, the study examines trends in the number of power outages, seasonality, and severity of outages. Customer weighted hours of outages will be used to quantify the impact of outages, as it combines the number of customers affected with the outage duration.

The research questions of this study are:

- Question 1: How has the number of power outages changed over time?
- Question 2: Is there a seasonal trend? Are certain months more prone to outages?
- Question 3: How has the severity of power outages changed over time?

We hypothesize that (1) the number of power outages have increased over time in response to rising extreme climate events, (2) that each state has distinct seasonal power outage patterns related to its dominant weather hazards, and (3) the severity of power outages have increase over time, which will be reflected in an increase in the customer weighted ours of outages.

# 2 Dataset Information

The Event-correlated Outage Dataset in America by the Pacific Northwest National Laboratory was downloaded from the Open Energy Data Initiative (OEDI) (https://data.openei.org/submissions/6458). The dataset includes an aggregated and event-correlated analysis of power outages in the United States. The specific dataset selected for this analysis is the Aggregated Outage Data which integrates data from the Environment for the Analysis of Geo-Located Energy Information (EAGLE-I), and Annual Estimates of the Resident Population for Counties 2024 (CO-EST2024-POP). The EAGLE-I dataset, provides county-level electricity outage estimates at 15-minute intervals from 2014 to 2023. It encompasses over 146 million customers, but this coverage has increased over time from 137 million in 2018. EAGLE-I only started providing data quality estimates starting in 2018. The Aggregated Outage Dataset provides monthly outage data at the state level, including total number of outages, the maximum duration of outages, and the customer weighted average of outages.

The data was wrangled by combining the yearly data from 2015 to 2023 into one dataframe. The year 2014 was removed from the analysis because it did not have monthly data, only the yearly summary. From this file, four datasets were created by filtering for each state (CA, FL, PA, and TX). For each state, the monthly value equal to 0 was filtered out, which represented the yearly summary. Additionally, a date column was added that combined the monthly and yearly columns into a date object.

This data structure shown in Table 1 applies to all four state datasets. Table 2 summarizes the key statistical characteristics of each datasets.

Table 1: Summary of Outage Dataset Structure

| Variable | Description | Units |
|---|---|---|
| state | Two-letter state abbreviation | N/A |
| year | Year of outage | N/A |
| month | Month of outage | N/A |
| outage_count | Number of outages per month | N/A |
| max_outage_duration | Longest outage duration in a month | Hours |
| customer_weighted_hours | Customer-weighted outage hours | N/A |
| date | Date of outage | N/A |

Table 2: Summary Statistics of CA, FL, PA, and TX Datasets

| State | Outage Count Range | Outage Count Mean | Max Duration Range | Max Duration Mean | Customer Weighted Hours Range | Customer Weighted Hours Mean |
|---|---|---|---|---|---|---|
| CA | 140–2599 | 900.55 | 27.25–609.75 | 131.82 | 491034.75–88045909.75 | 6,151,189 |
| FL | 402–1515 | 970.73 | 11.5–532.75 | 56.80 | 438767.25–532294703.25 | 9,390,167 |
| PA | 336–1312 | 600.20 | 13.5–140.5 | 46.74 | 333846–28965544.5 | 1,970,894 |
| TX | 120–2361 | 1,108.82 | 6–723.75 | 76.26 | 167452–227923742 | 5,712,808 |

# 3 Exploratory Analysis

The exploratory analysis of the data involved initial visualizations of the power outage counts for each state. For each state, a chart was created of power outages from 2015 to 2023 and another chart of power outages by month grouped by year. There was no missing data for any of the states during the time frame, and all outliers were retained because many reflect climate-driven extreme events relevant to our research. These exploratory trends informed the analytical methods used in this study. The presence of visual long-term increases in power outages motivated the use of the Mann–Kendall trend test, while the recurring monthly patterns suggested the need for seasonal decomposition and an ANOVA to test for significant seasonal variations.

#### 3.0.1 California

Initial data exploration of California power outage data suggest a slight increasing trend (Figure 1). Furthermore, Figure 2 shows a clear increase in the number of outages every single month from 2015 to 2023. The monthly plot does not indicate that any particular month consistently experiences a higher number of power outages.

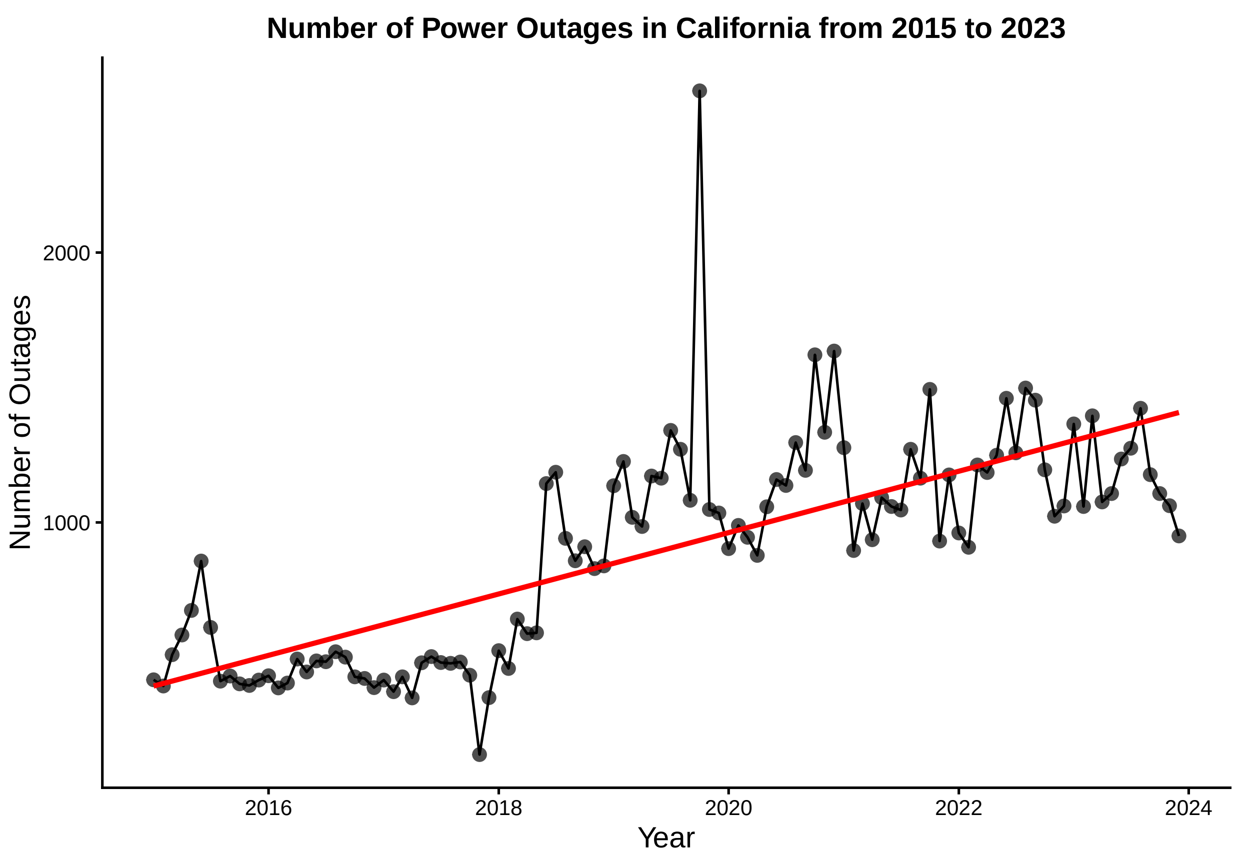


Figure 1: Yearly plot of power outages in California from 2015 to 2023.

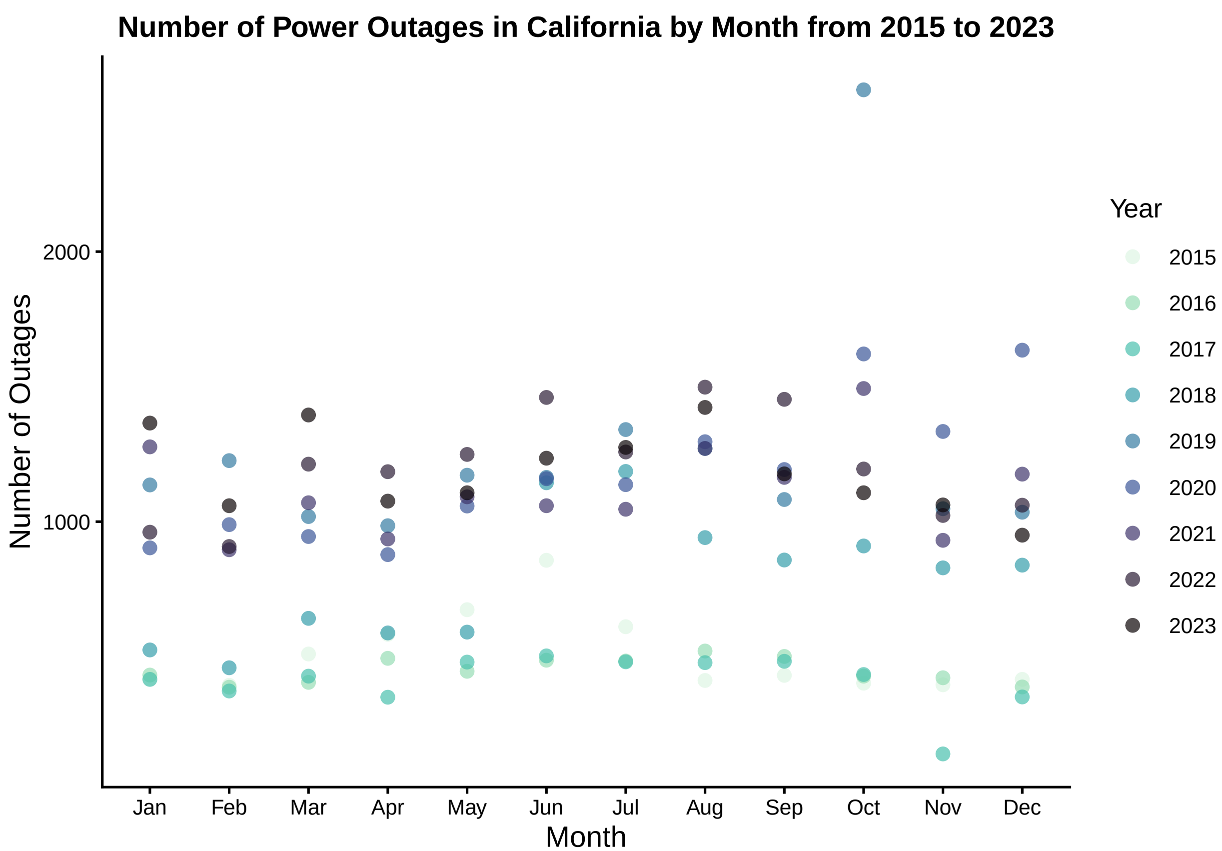


Figure 2: Monthly plot of power outages in California from 2015 to 2023.

#### 3.0.2 Florida

In Florida, the number of outages shows a slight upward trend over the past decade (Figure 3). On a monthly scale, outages consistently rise during the summer months, indicating a seasonal pattern likely driven by weather conditions or increased energy demand (Figure 4). However, when comparing month-to-month patterns across years, no clear year-to-year monthly trend emerges.

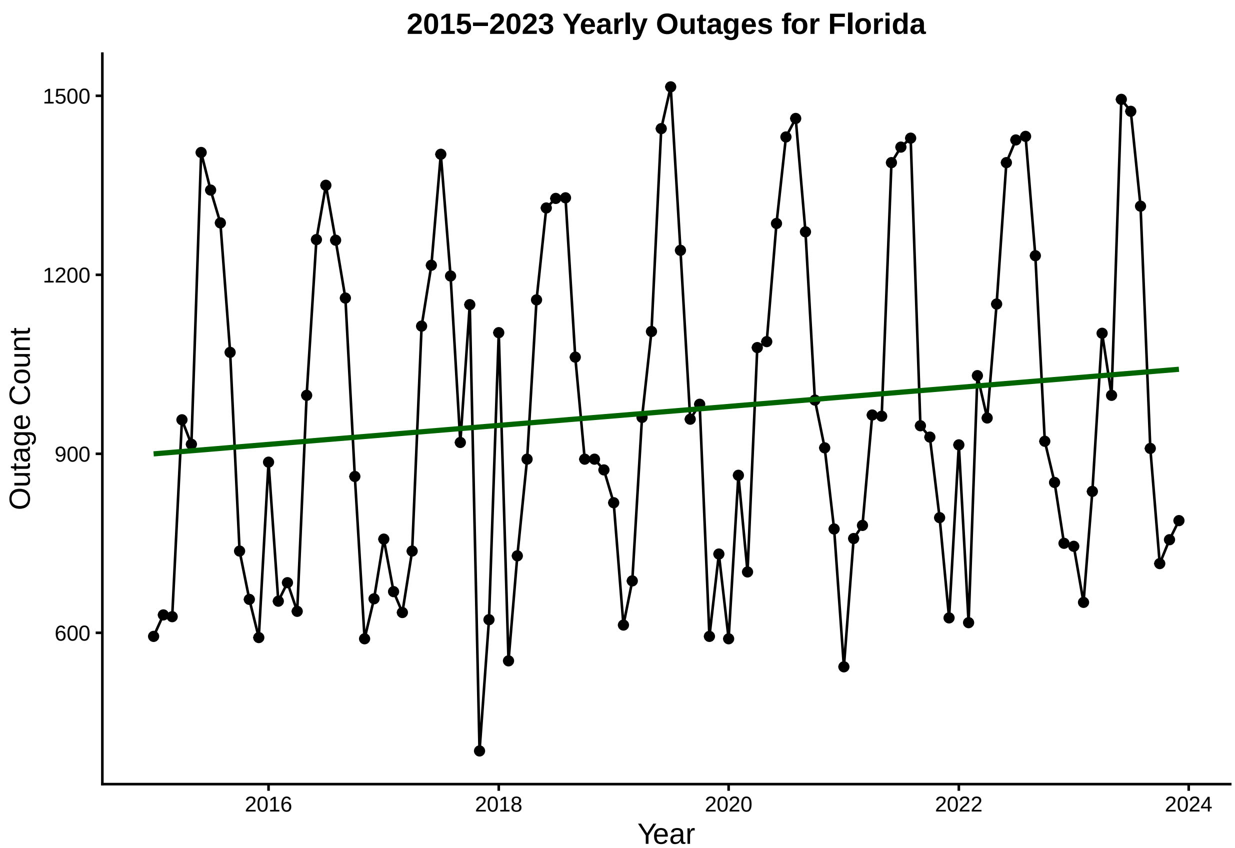


Figure 3: Yearly plot of power outages in Florida from 2015 to 2023.

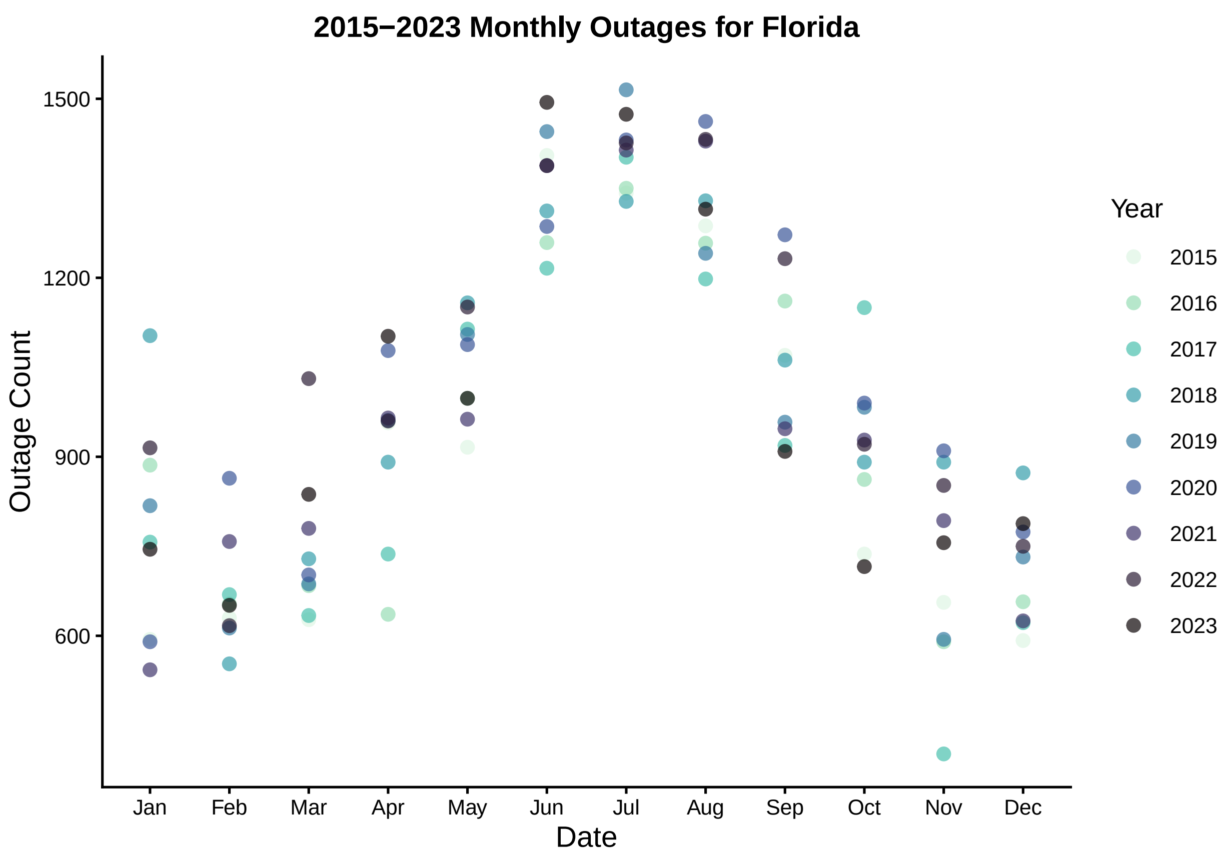


Figure 4: Monthly plot of power outages in Florida from 2015 to 2023.

### 3.0.3 Pennsylvania

From the initial data exploration of Pennsylvania, it is clear that power outages have gradually increased over the past decade (Figure 5). On a monthly basis, there is a noticeable rise in outages during the summer months, suggesting a seasonal pattern likely related to weather or energy demand (Figure 6). Overall, the data points to both long-term growth in the number of outages and predictable seasonal fluctuations.

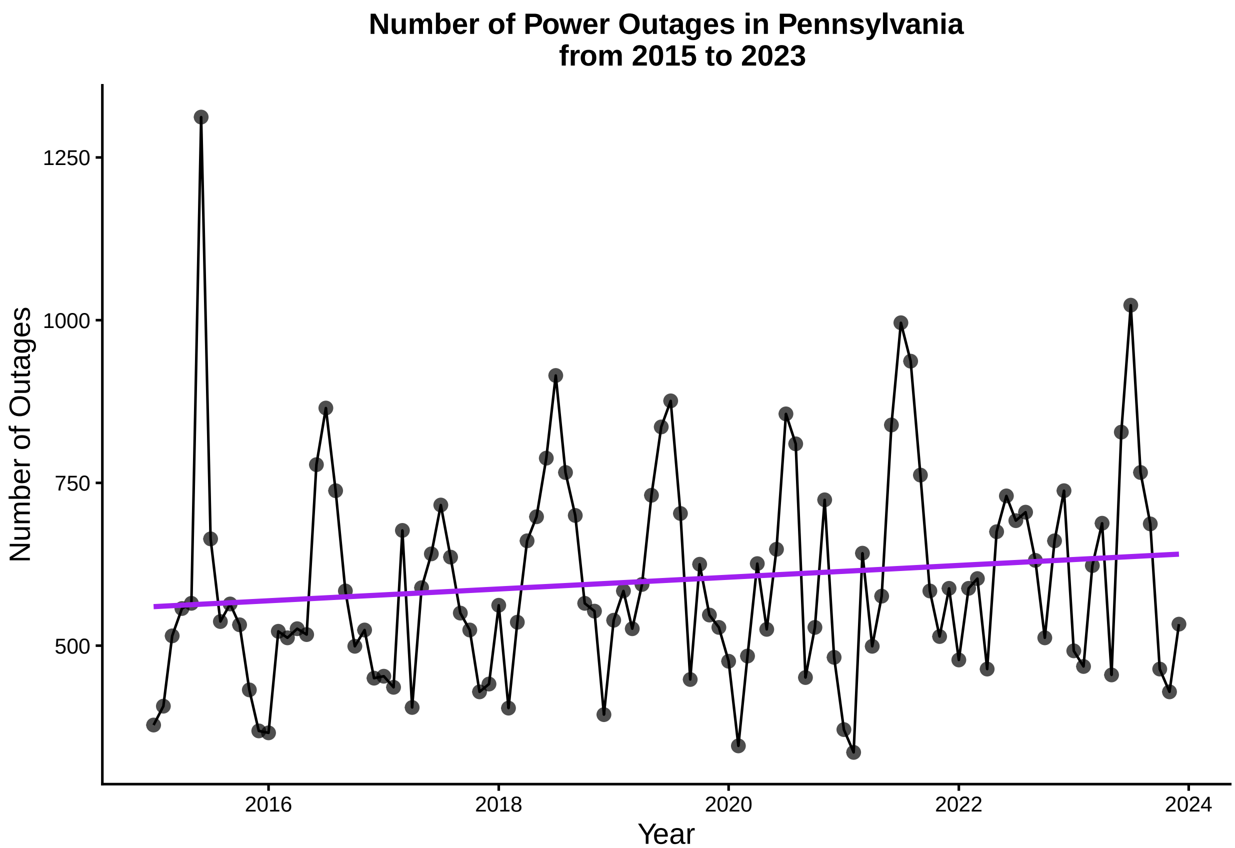


Figure 5: Yearly plot of power outages in Pennsylvania from 2015 to 2023.

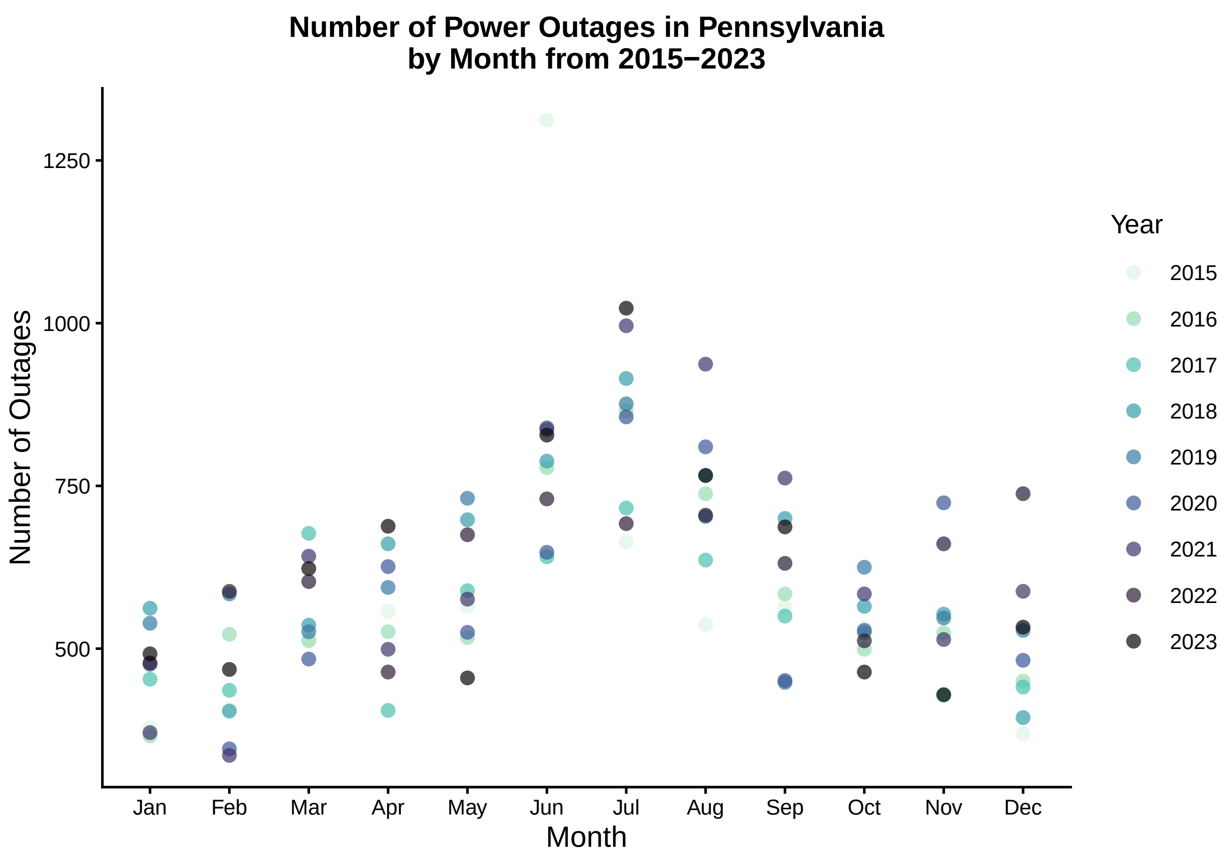


Figure 6: Monthly plot of power outages in Pennsylvania from 2015-2023.

### 3.0.4 Texas

From this yearly plot of power outages in Texas from 2015 to 2023, we can observe a general increasing pattern of power outages between this time period, aside from the temporary drop between 2016-2018 (Figure 7). By looking at this graph, we are also observing a pattern of spikes around May or the early summer months and could indicate a seasonal pattern (Figure 8).

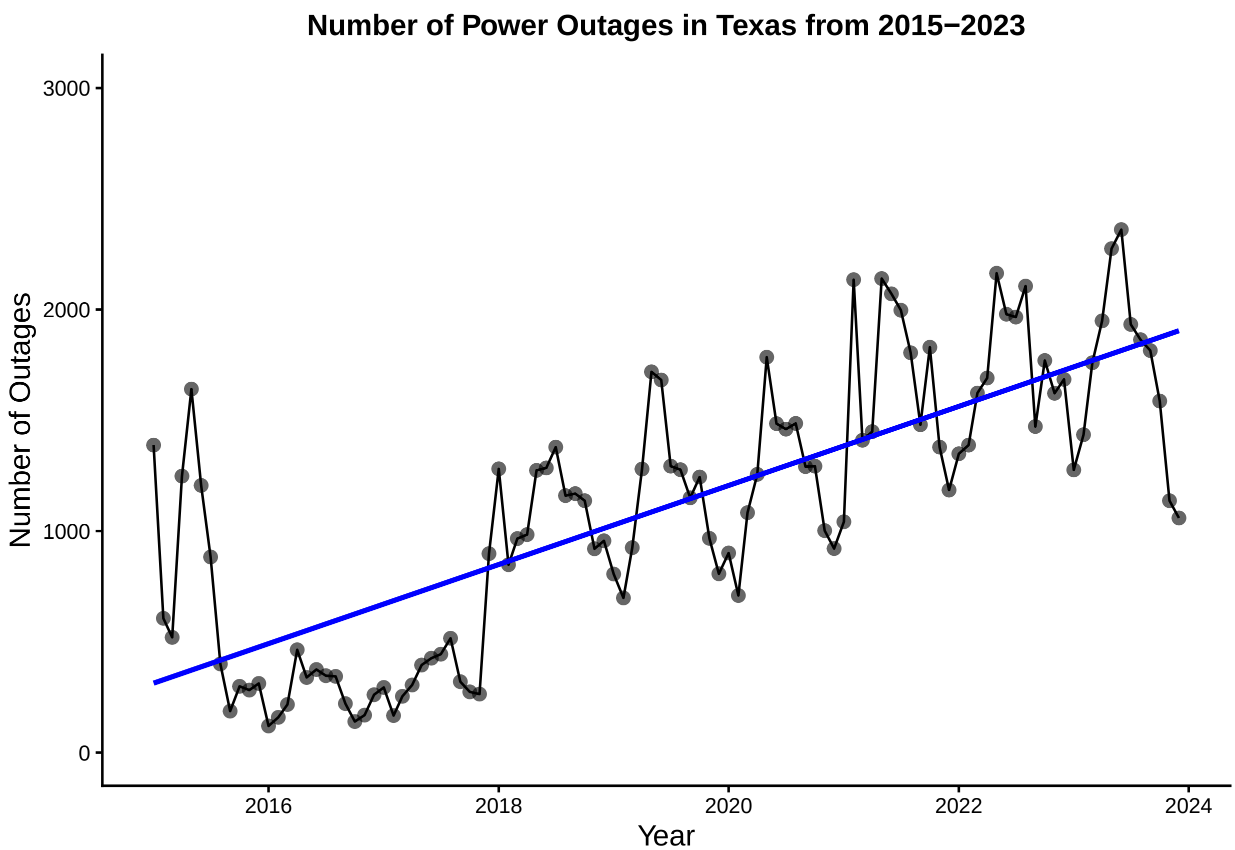


Figure 7: Yearly plot of power outages in Texas from 2015-2023.

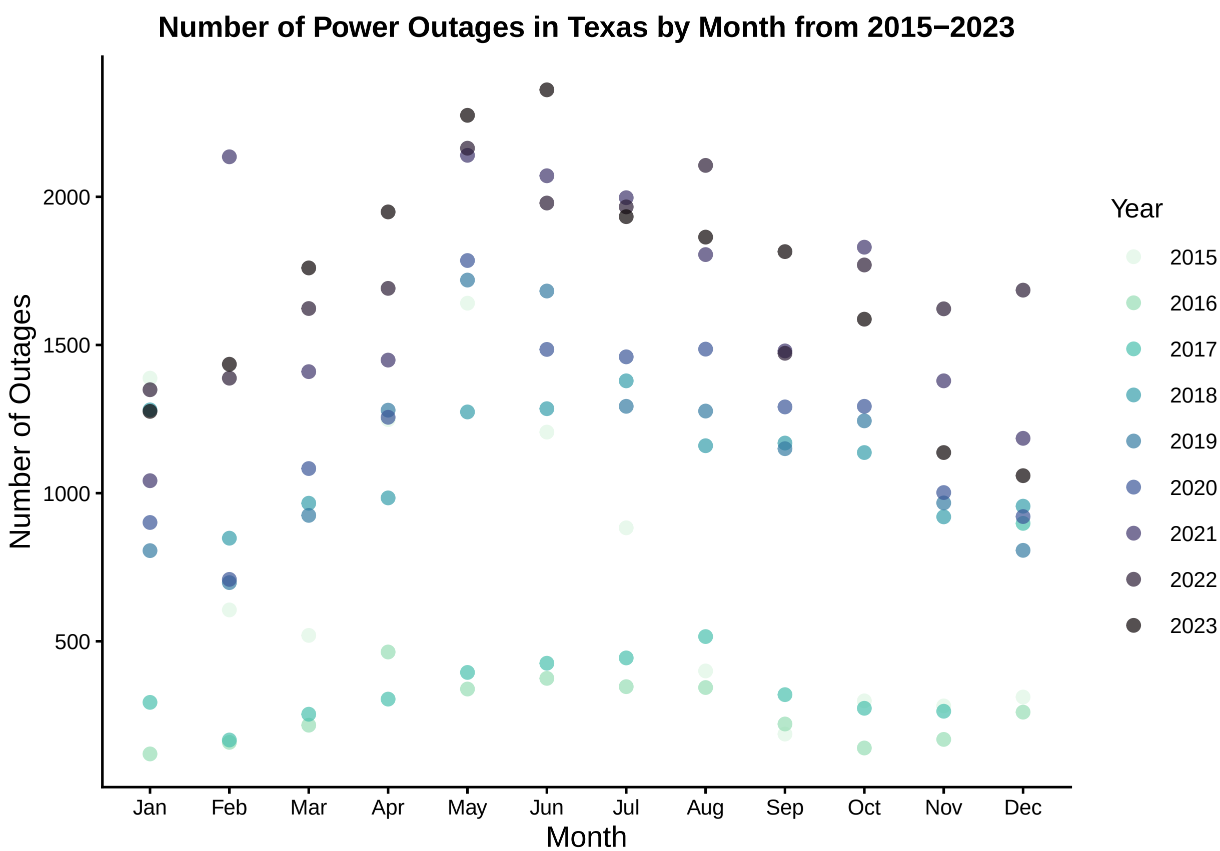


Figure 8: Monthly plot of power outages in Texas from 2015 to 2023.

# 4 Analysis

The power outage datasets for each state were analyzed by creating time series objects of the power outage count data. The time series objects were decomposed to separate the trend, seasonality, and remainder. New data frames were created with these three time series components. A non-seasonal power outage count component was created by subtracting the seasonal component from the trend and remainder components. This nonseasonal components was graphed along with the observed power outage count to display the visual fit of the trend. Mann-Kendall tests were performed on the nonseasonal component to statistically analyze the trends, providing the trend direction and statistical significance.

The seasonal component was isolated and graphed by grouping the yearly values (2015-2023) by month. This shows how the seasonal component changes over the year, allowing for the months with a high count of power outages to be identified. To statistically analyze the seasonality of power outages, a one-way ANOVA test was performed to see if power outage counts varied significantly across months.

To investigate the severity of power outages, time series objects were created of the customer weighted hours data. The customer weighted hours' time series objects were also decomposed to separate the trend, seasonality, and remainder of each dataset. A non-seasonal power outage count component was created by subtracting the seasonal component from the trend and remainder components. This nonseasonal components was graphed along with the observed customer weighted hours to display the visual fit of the trend. Mann-Kenndall tests were performed on the nonseasonal component to statistically analyze the trends, providing the trend direction and statistical significance.

## 4.1 Question 1: How has the number of power outages changed over time?

### 4.1.1 California

Figure 9 displays the decomposed time series of the number of power outages in California from 2015 to 2023. There appears to be clear seasonal trend, which is analyzed further in Section 4.2.

A MannKendall non-seasonal trend analysis was applied to the California power outage count dataset with the seasonal component removed, a significant overall increase in power outages over time is observed (MannKendall; tau = 5.437e-01, $p < 2.2e\text{-}16$). This supports the hypothesis that the number of power outages are increasing. Figure 10 visualizes the trend compared to the observed number of power outages in California. The red line represents the overall increasing trend.

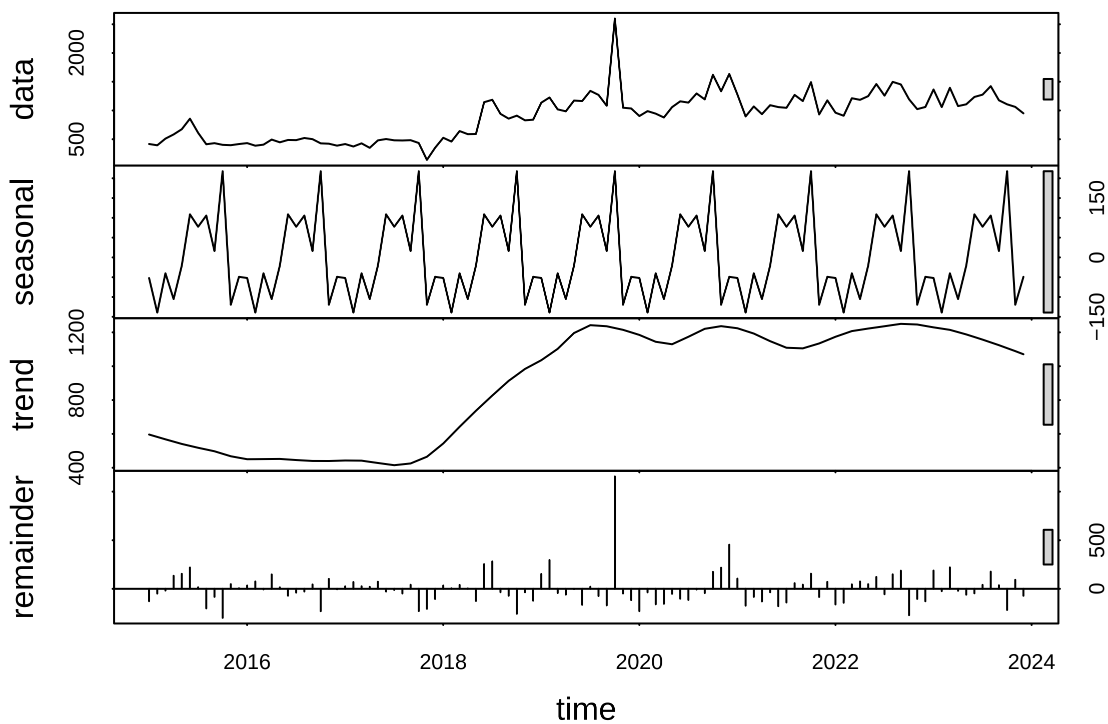


Figure 9: Decomposed components of the California power outage count time series.

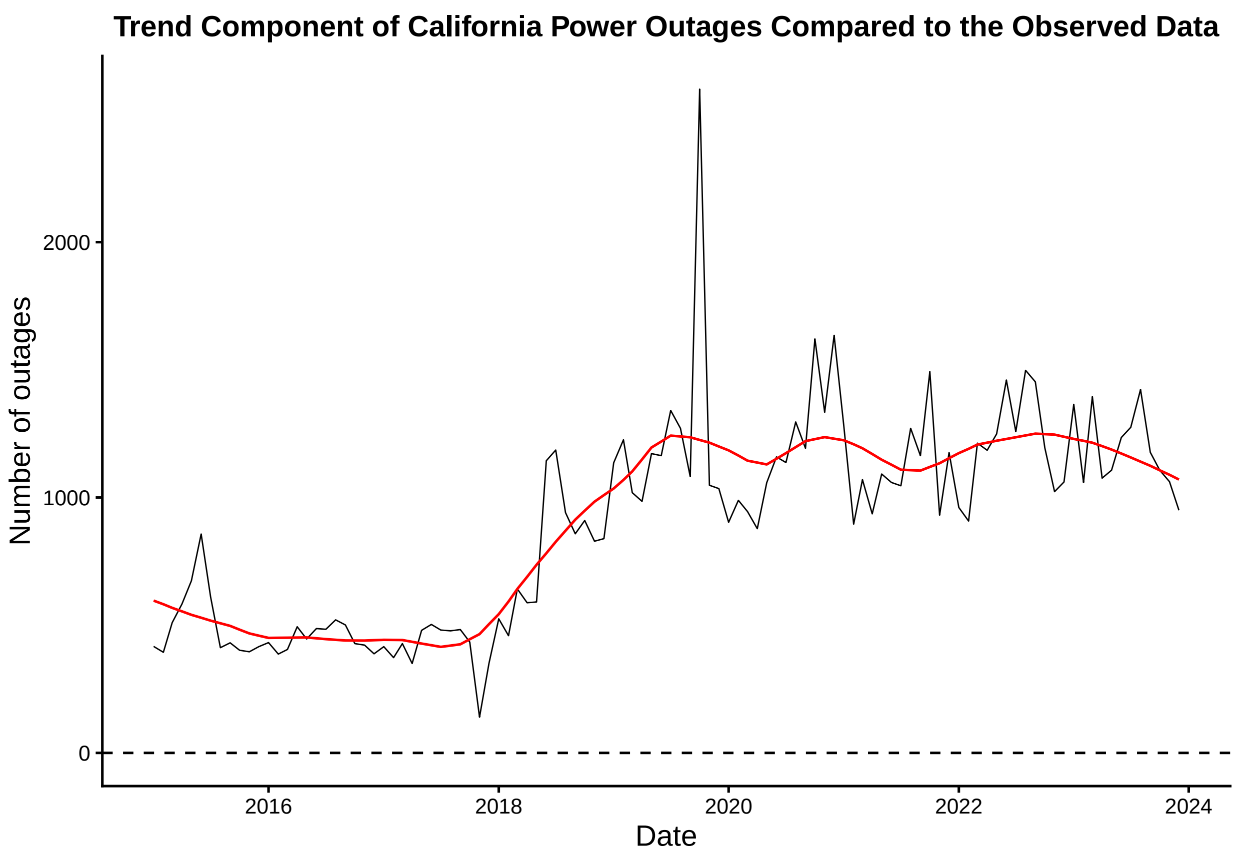


Figure 10: Trend versus observation of power outages in California (2015-2023).

### 4.1.2 Florida

Figure 11 shows the time series analysis for outage occurrences across Florida from 2015 to 2023. While a clear pattern of seasonality is evident within the time series, applying a non-seasonal Mann-Kendall test will determine if outage count across the years has a significant trend. The results of the test confirm that there is a statistically significant increase in outages in Florida (tau = 2.426865e-01, p = 0.0001997), independent from seasonality changes. Figure 12 shows the increasing trend.

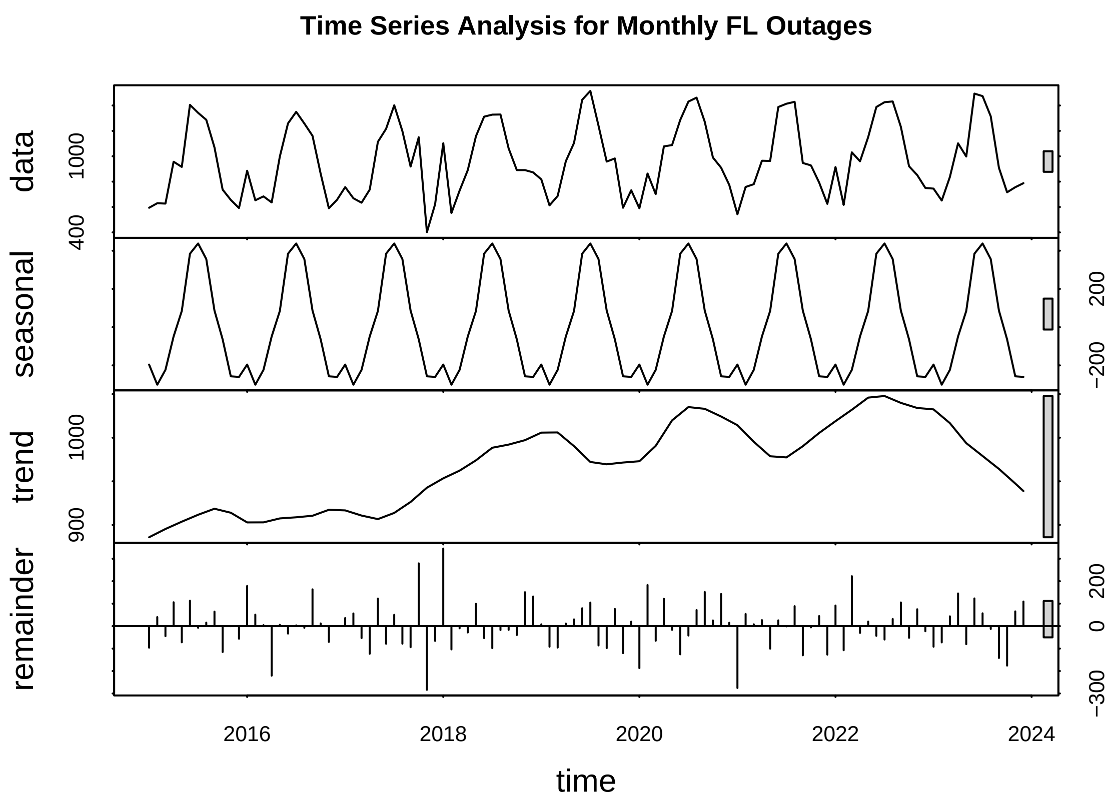


Figure 11: Decomposed components of the Florida power outage count time series.

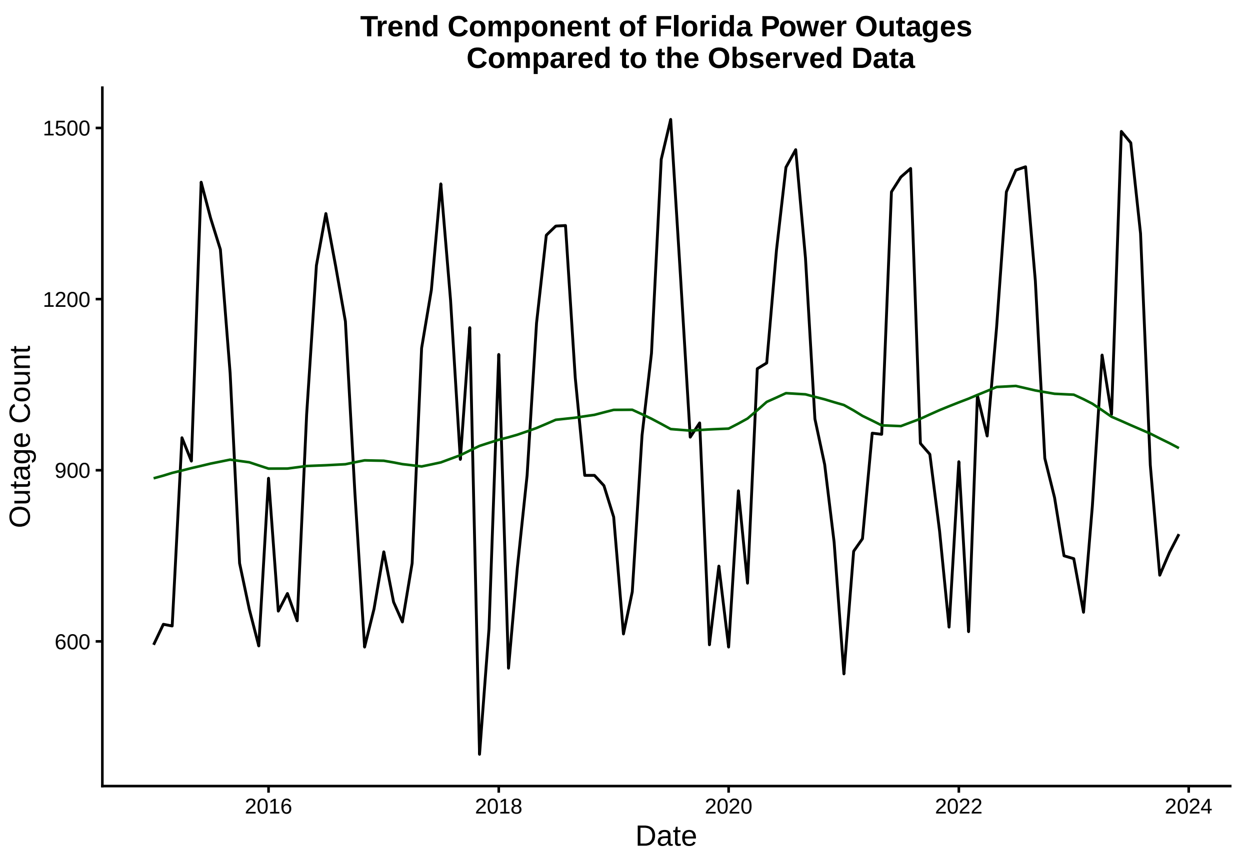


Figure 12: Trend versus observation of power outages in Florida (2015-2023)

#### 4.1.3 Pennsylvania

After removing the seasonal component from the Pennsylvania outage time series, the Mann–Kendall trend test revealed a significant positive trend (z = 3.02, n = 108, p = 0.002), indicating that the number of outage has increased slightly from 2015 to 2023. This result supports the hypothesis that outages have become more common during this time, independent of seasonal patterns. The decomposed time-series visualization shows this trend clearly, revealing that even after accounting for monthly fluctuations, the long-term component continues to rise (Figure 13). Figure 14 reveals the trend of the power outages with the seasonality element removed compared to the observed data.

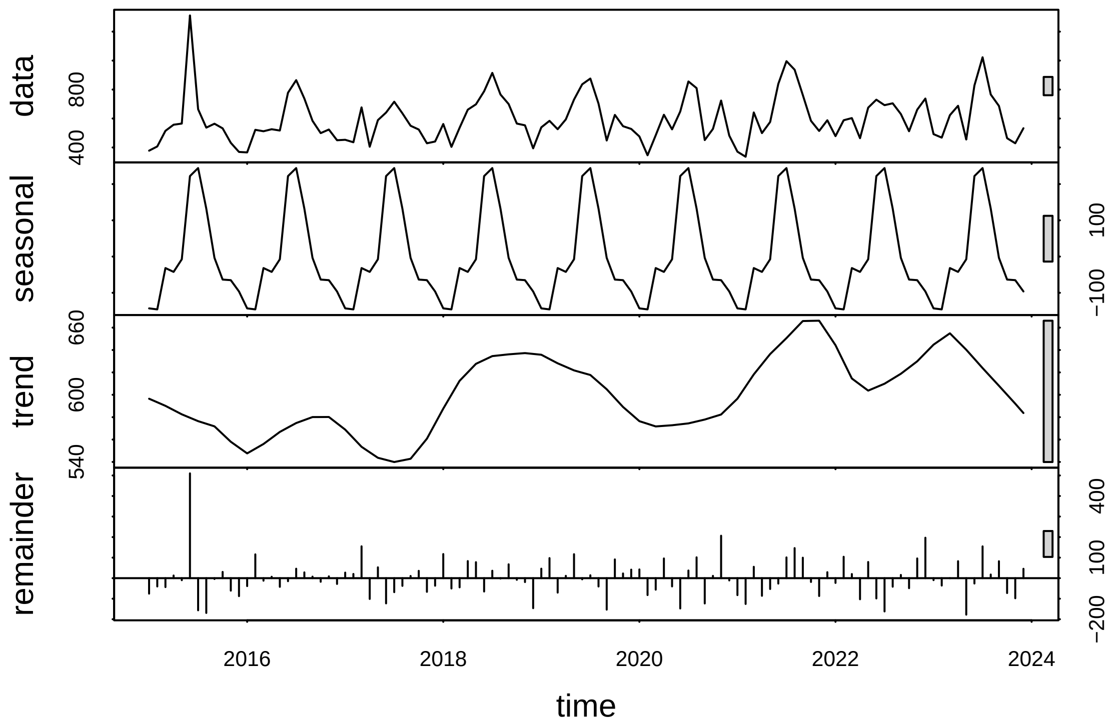


Figure 13: Decomposed components of the Pennsylvania power outage count time series.

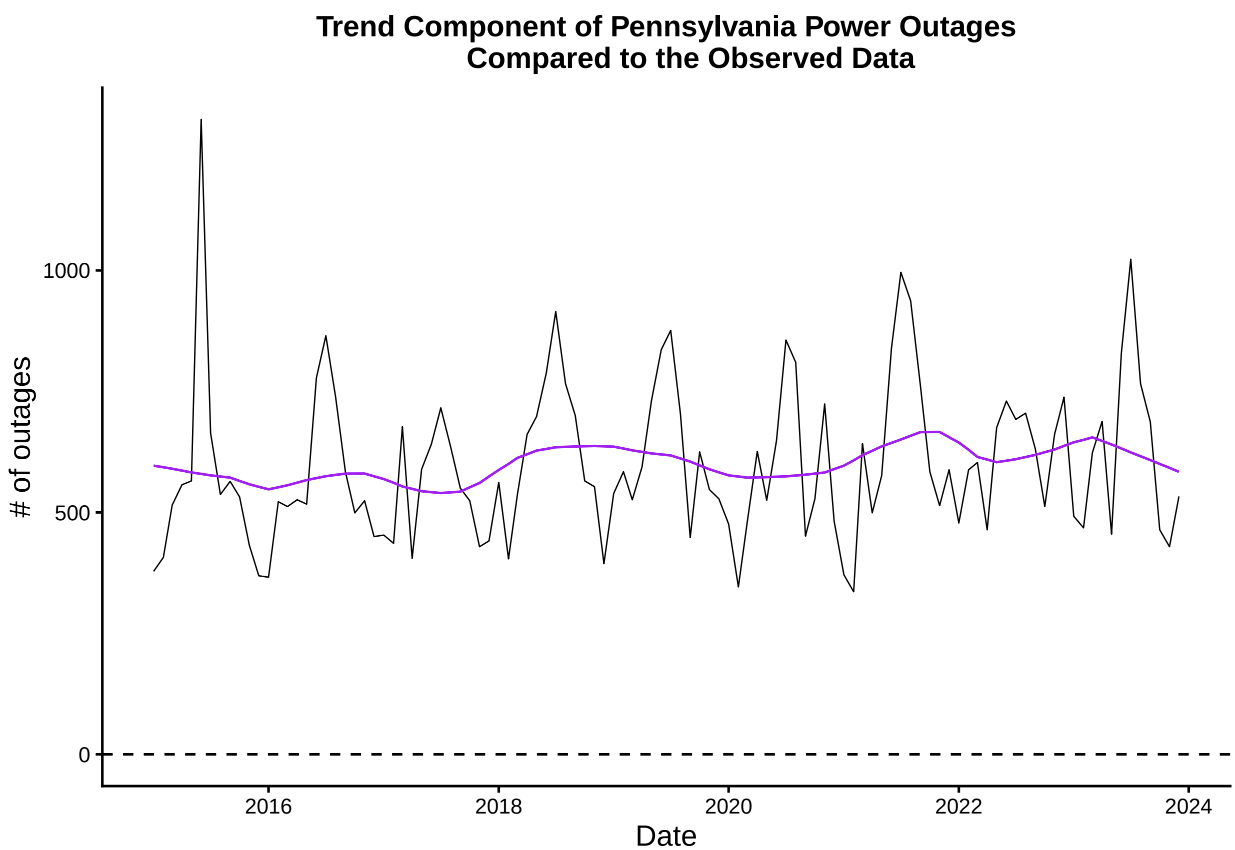


Figure 14: Trend versus observation of power outages in Pennsylvania (2015-2023).

### 4.1.4 Texas

Figure 15 shows the decomposed components of the Texas power outage count time series from 2015–2023. With a very small p-value (2.22e-16), the result indicates an upward trend, and it is statistically significant. After removing the seasonal component and rerunning the test, the Mann–Kendall results (z = 9.9423, n = 108, p-value < 2.2e-16) still show a highly significant positive trend. This confirms our earlier visualization that the increase in outage counts persists even after accounting for the influence of seasonal weather patterns. Figure 16 shows the overall trend without seasonality of power outages in Texas compared to the observed data.

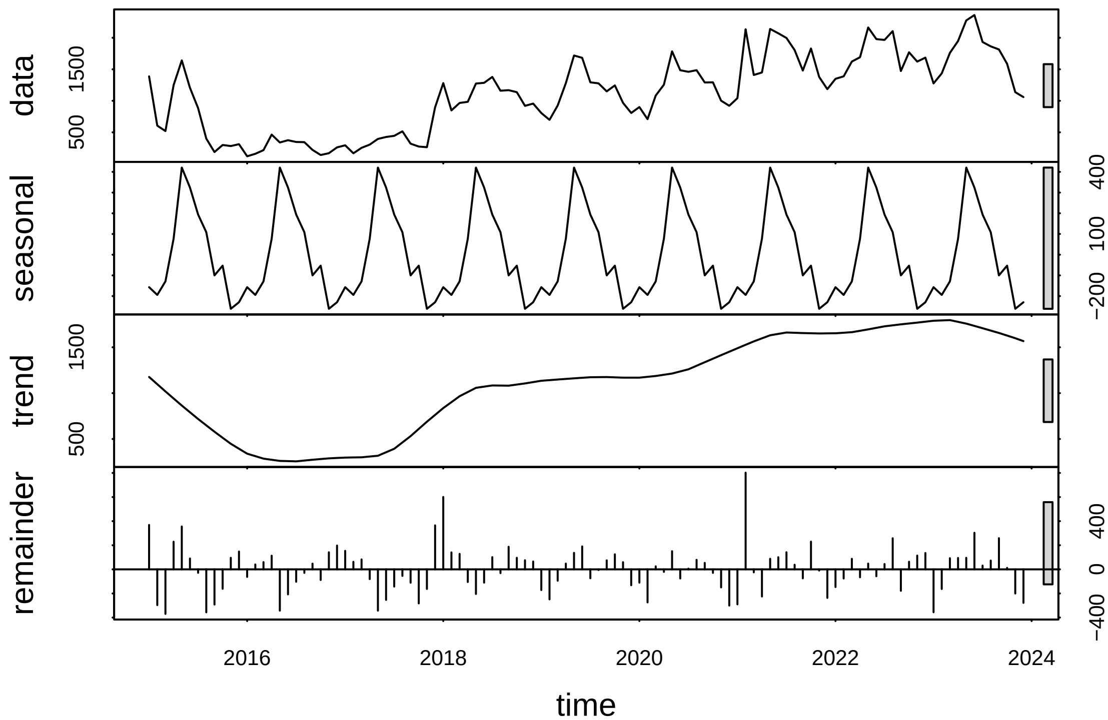


Figure 15: Decomposed components of the Texas power outage count time series.

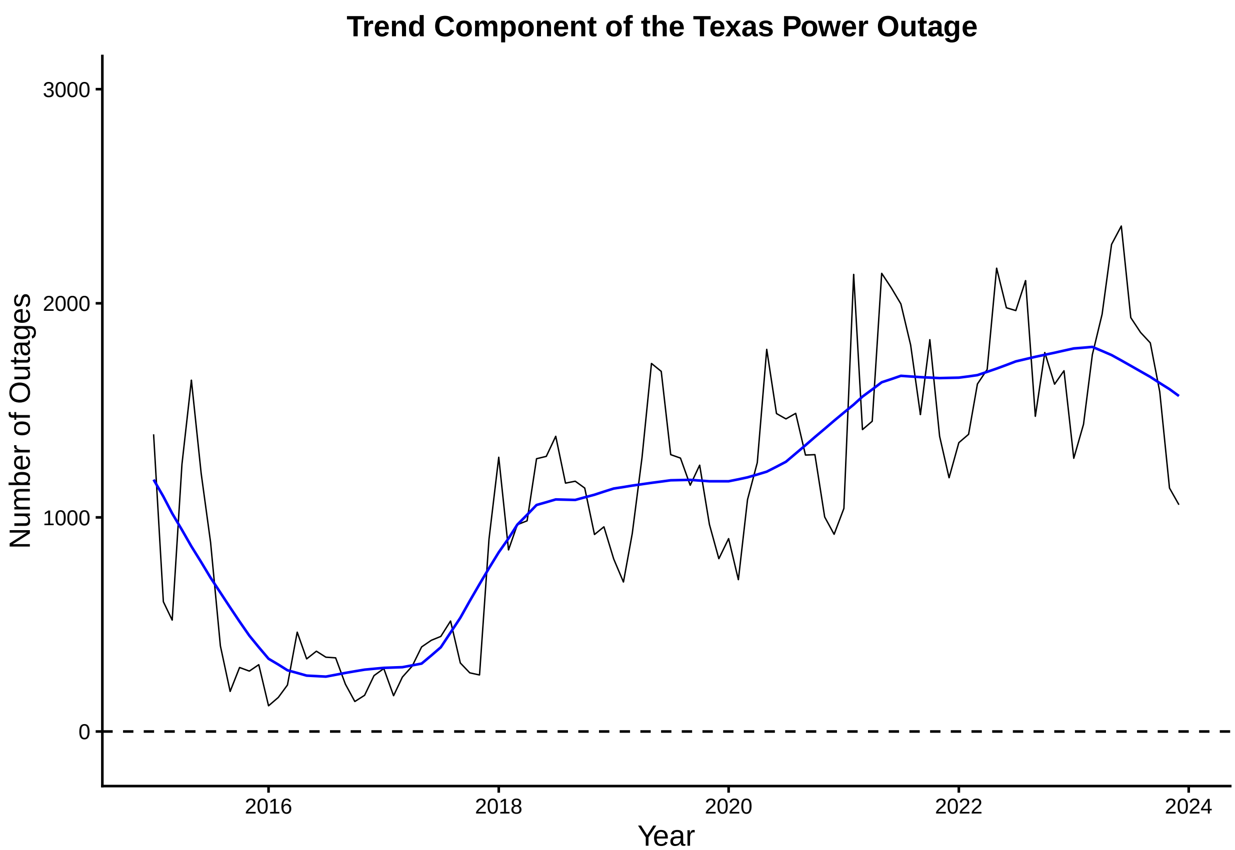


Figure 16: Trend versus observation of power outages in Texas (2015-2023).

#### 4.1.5 Comparision between States

Figure 17 visualizes each state's non-seasonal power outage time series trend. Red represents California, green is Florida, purple is Pennsylvania, and blue is Texas. All states are seeing a significant increasing trend of power outages, this confirmed both visually and through each state's Mann–Kendall results (CA: p $< 2.2e\text{-}16$, FL: $p = 0.0001997$, PA: $p = 0.002$, TX: $p < 2.2e\text{-}16$). These results supports our first hypothesis that power ouotages are becoming more frequent. California and Texas are experiencing the greatest increase, while Pennsylvania and Florida are experiencing more gradual increases in comparison. Towards the end of the time period, California and Texas also overall have more power outages than Florida and Pennsylvania, with Pennsylvania seeing overall the lowest amount of power outages.

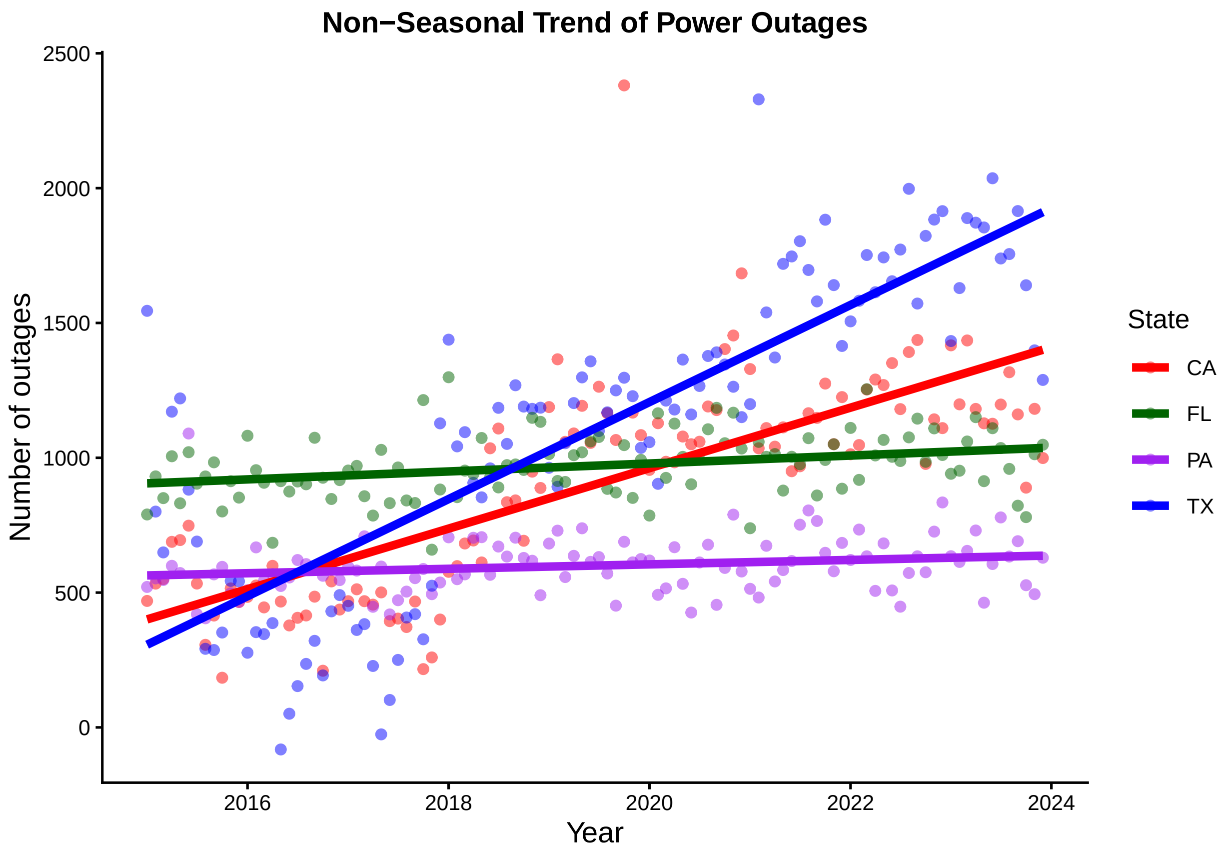


Figure 17: Non-seasonal trend of power outages in California, Florida, Pennsylvania, and Texas.

### 4.2 Question 2: Is there a seasonal trend? Are certain months more prone to outages?

#### 4.2.1 California

Figure 9 displays a clear seasonal pattern in the decomposed time series of the number of power outages in California. The seasonal component was isolated and grouped by year to show the seasonal cycle of power outages in California in Figure 18. The seasonal cycle highlights a potential pattern of power outage counts rising in the summer months, peaking in October. However, despite the visual pattern, the number of power outages in California was not significantly different among the months (ANOVA; df = 11, F = 0.704, p = 0.732). This result does not support the second hypothesis that each state has distinct seasonal power outage patterns related to its dominant weather hazards.

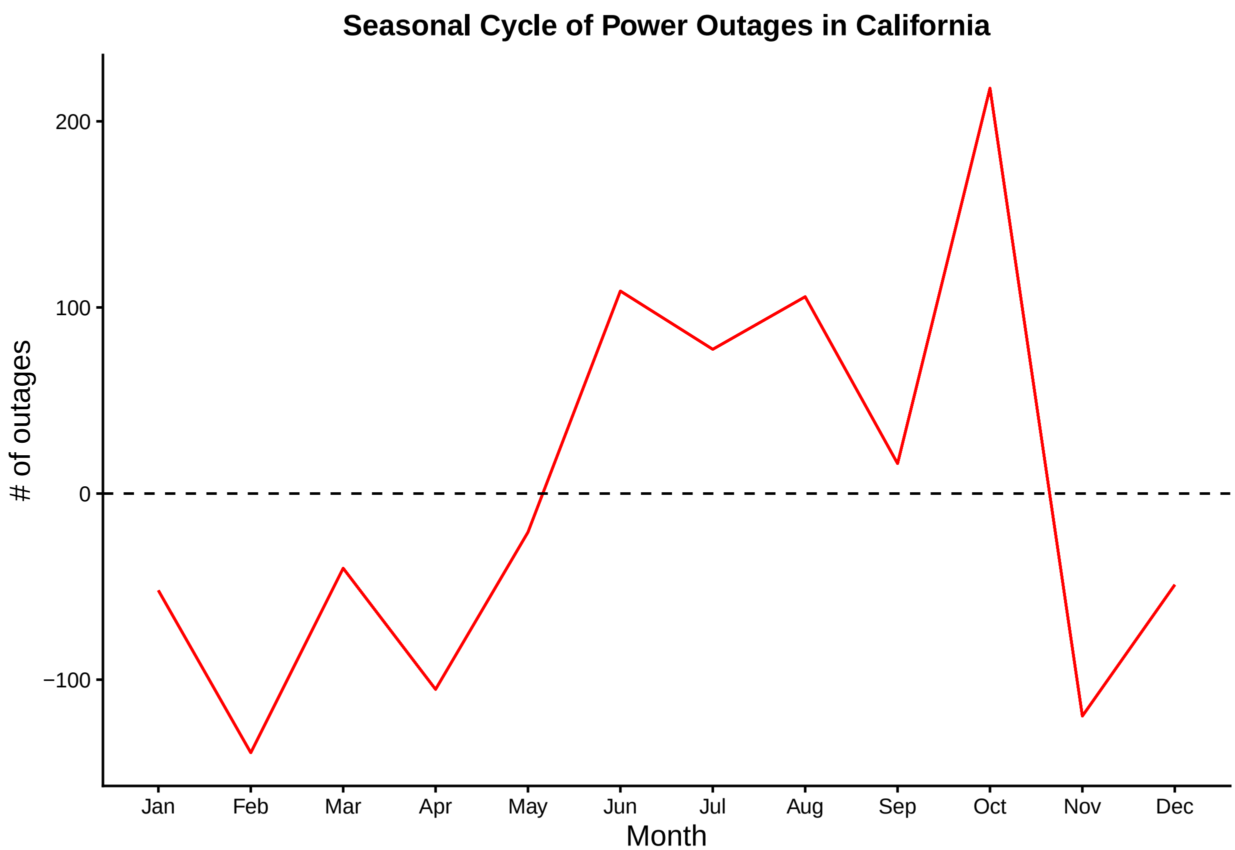


Figure 18: Seasonal component of the California power outage time series analysis where yearly data is grouped by month.

### 4.2.2 Florida

Results from the time series for outages in FL displayed a pattern of seasonality. To further analyze the strength of that trend, months of every year were aggregated to show a cumulative trend across 2015 to 2023 in Figure 19. A clear normal distribution shows a concentration of outage occurrences in summer months, and a significant decline in winter months. The June to September seasonal peak coincides with the Atlantic Hurricane season. An ANOVA test statistically confirms that outage counts between months vary significantly, following a seasonal trend (Df = 11, F-value = 43.28, $p < 2e\text{-}16$). This supports the second hypothesis that each state has distinct seasonal power outage patterns related to its dominant weather hazards.

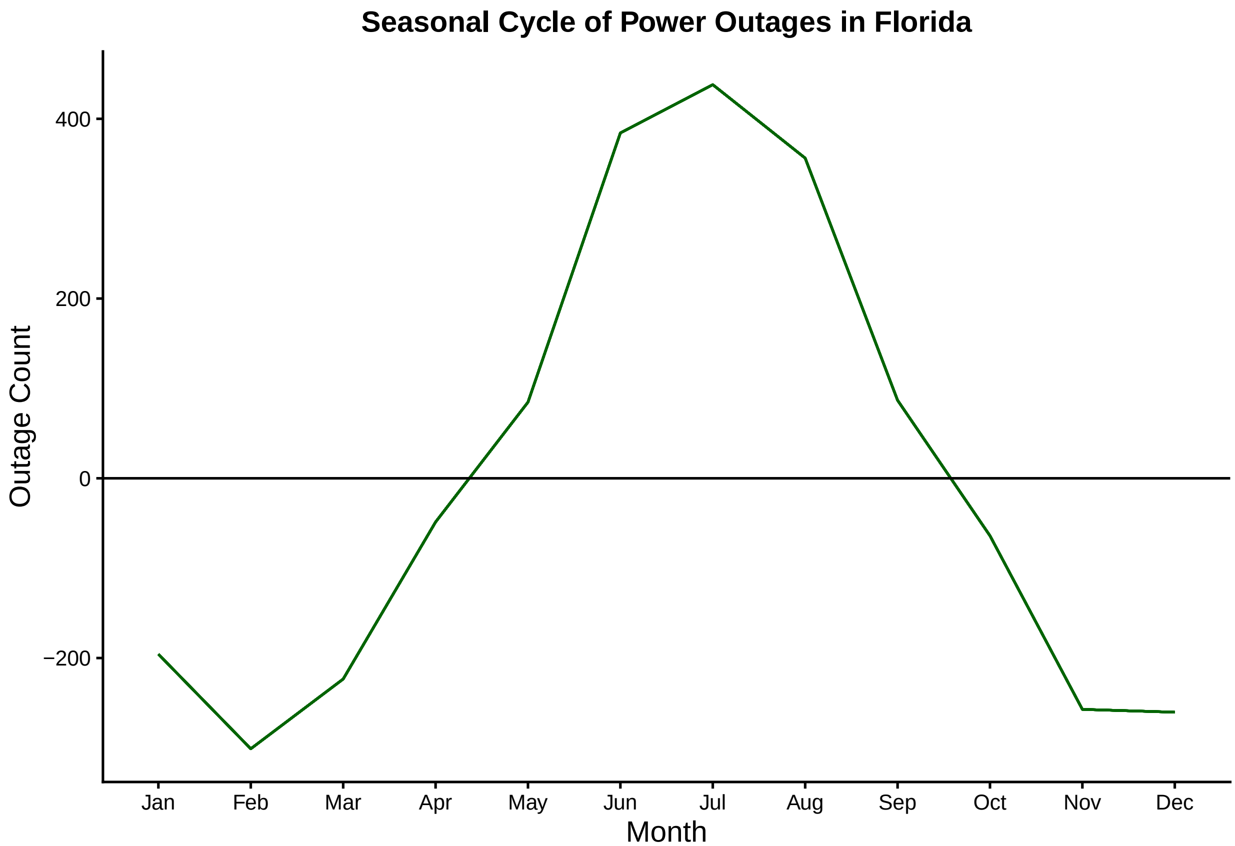


Figure 19: Seasonal component of the Florida power outage time series analysis where yearly data is grouped by month.

#### 4.2.3 Pennsylvania

The Mann–Kendall seasonal trend test for Pennsylvania outage counts indicated a significant seasonal signal in the data (tau = 0.20, p = 0.009), demonstrating that outage frequencies vary across months. This finding supports the hypothesis that outages are not evenly distributed throughout the year but instead follow a seasonal pattern. The visualizations further highlight this pattern, showing clear peaks in June, July, and August, when outage counts are highest (Figure 20). Together, these results suggest that summer months consistently experience elevated outage activity, potentially driven by seasonal weather conditions or increased energy demand. The number of outages in Pennsylvania was significantly different among the months (ANOVA; df = 11, F =12.1, $p < 7.54e\text{-}15$). This supports our alternative hypothesis that outages are not evenly distributed throughout the year but instead follow a seasonal pattern.

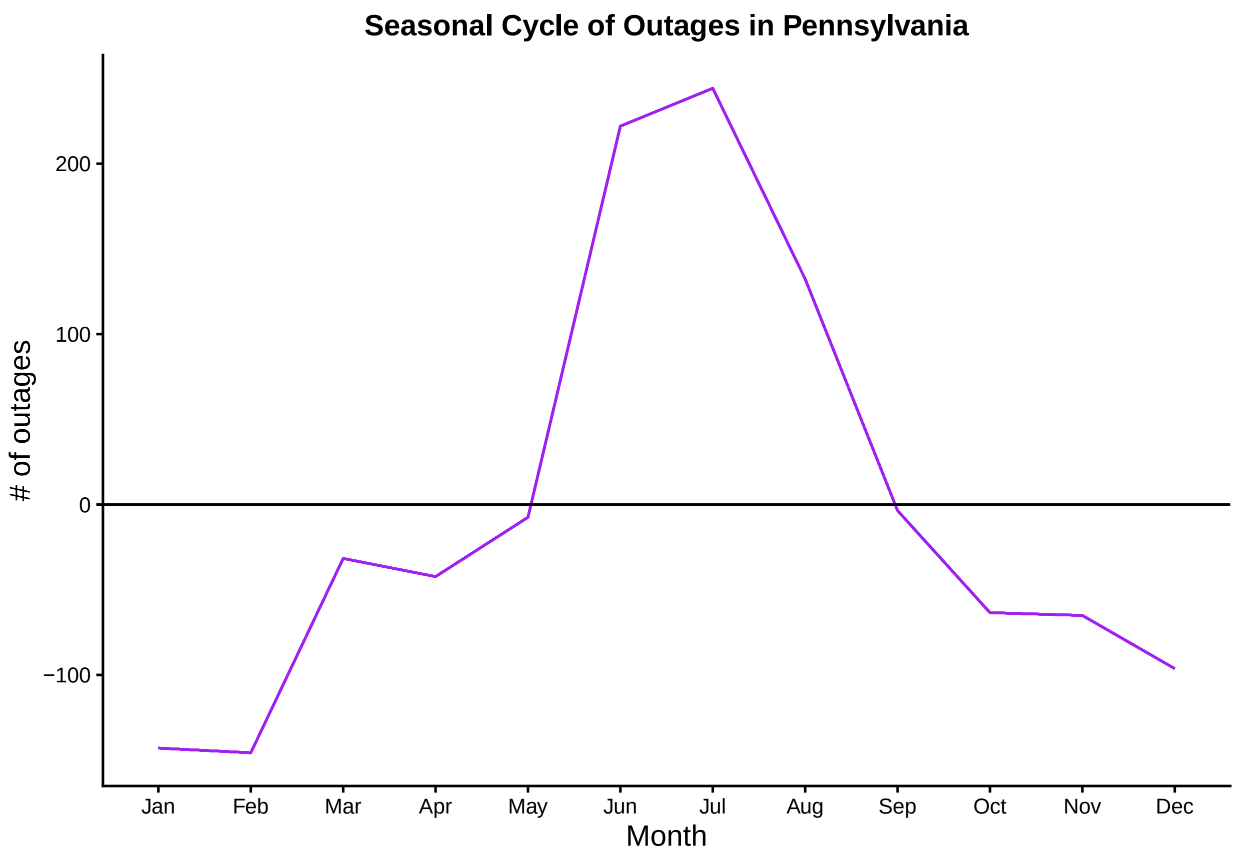


Figure 20: Seasonal component of the Pennsylvania power outage time series analysis where yearly data is grouped by month.

#### 4.2.4 Texas

By observing Figure 21 alone, there's a visible seasonal trend with a sudden peak in May. However, after running an ANOVA test, the results (df = 11, F = 1.215, p = 0.288) shows a high p-value (>0.05). This result suggests that despite the peak in May in Figure 21, the number of Texas power outages during 2015-2023 was not significantly different between different months based on outage counts alone.

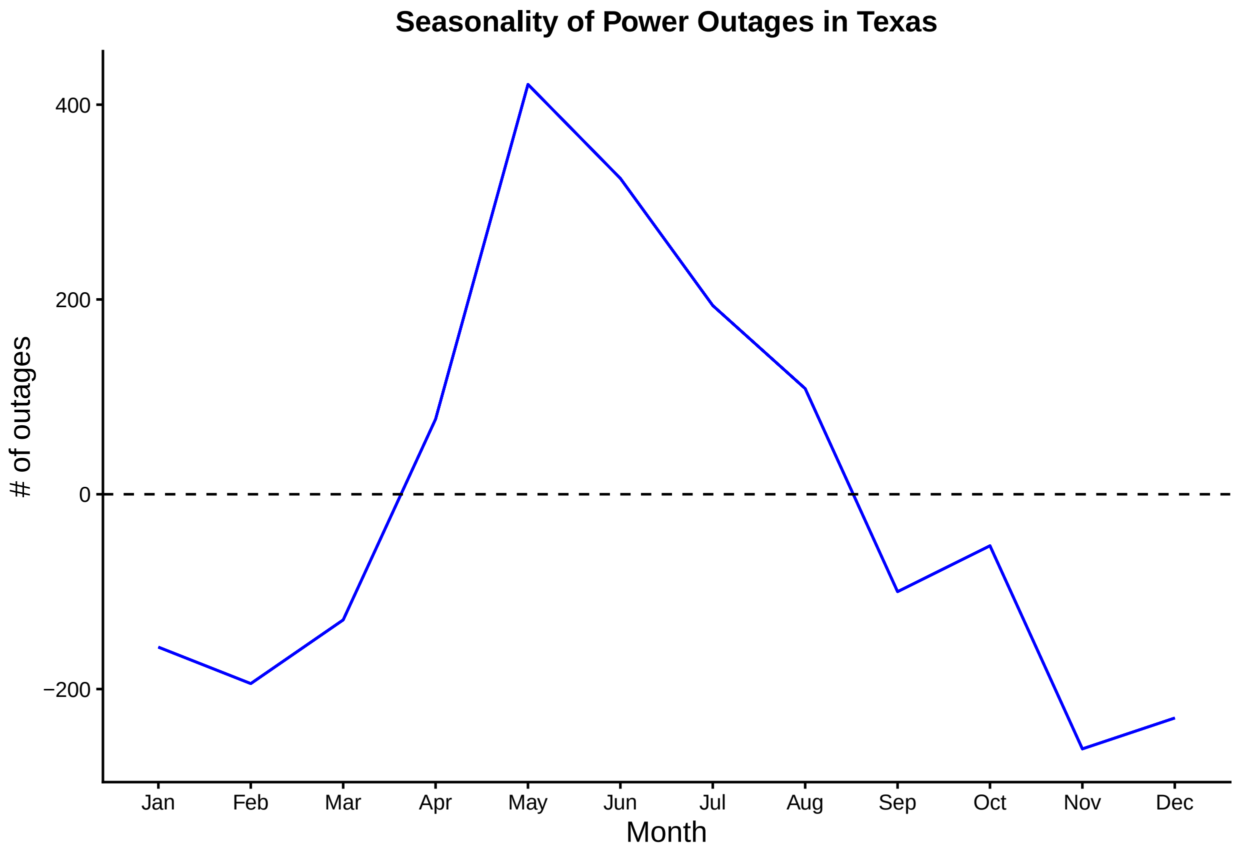


Figure 21: Seasonality component of the Texas power outage count time series analysis where yearly data is grouped by month.

#### 4.2.5 Comparision between States

Figure 22 displays the seasonal cycle for each state. This was created by aggregating the monthly power outage data of every year to show cumulative trend across 2015 to 2023. Florida and Pennsylvania have very similar seasonal patterns, with a outages concentrated in the summer months (peaking in July), and declining sharply in the winter months. Texas appears to peak earlier in May, while California has a less discernible trend, with a peak in October.

ANOVA tests show that California and Texas both have high p-values (CA: $p < 0.732$, TX: $p<0.288$), suggesting that there's no seasonal trend in the number of power outages in these two states. However for Florida and Pennsylvania, the ANOVA results (FL: $p < 2e{-16}$, PA: $p < 7.54e{-15}$) suggest a seasonal pattern in power outages.

These results provide partial support for our second hypothesis. Florida and Pennsylvania clearly demonstrate seasonal outage patterns linked to their dominant weather hazards, while California and Texas do not show significant seasonality. Further analysis is needed to quantify the relationship between climate-related extreme events and power outages.

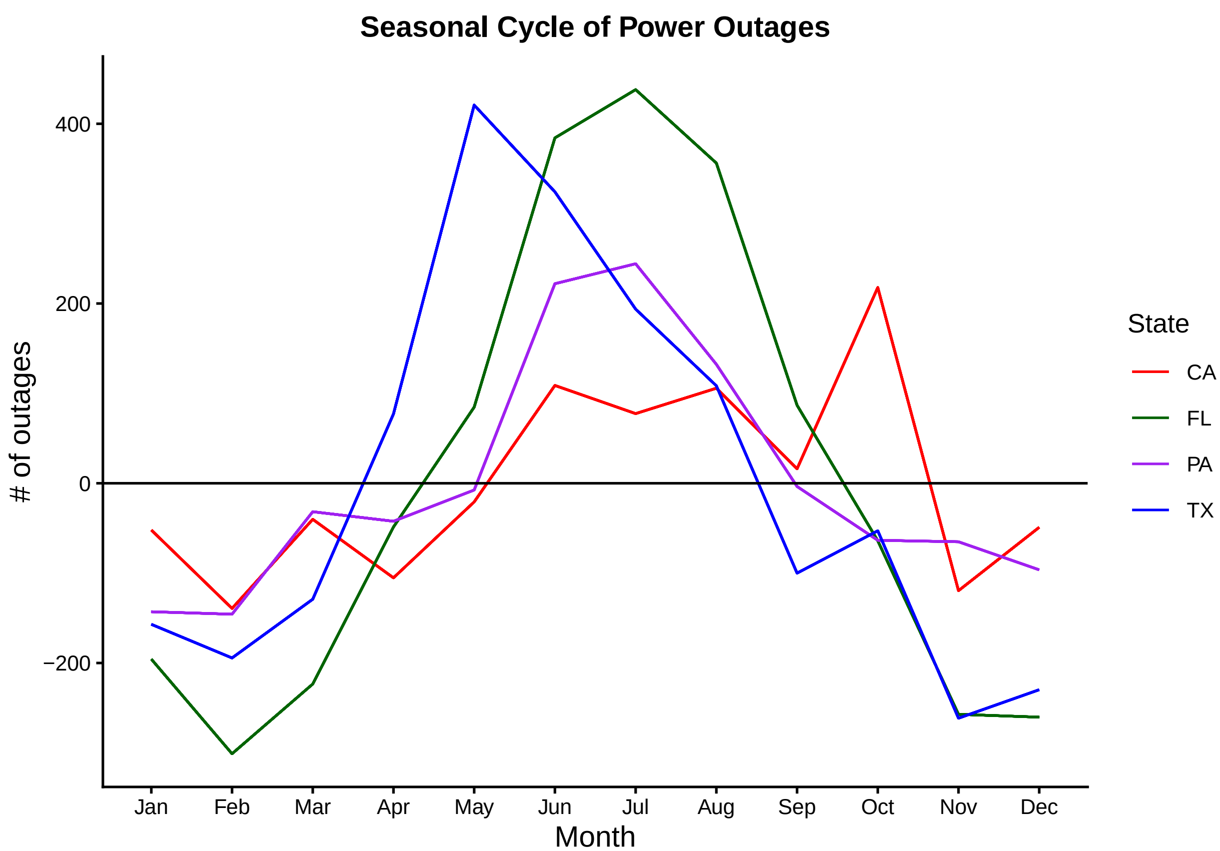


Figure 22: Seasonal cycle of power outages in California, Florida, Pennsylvania, and Texas (2015-2023 combined).

## 4.3 Question 3: How has the severity of power outages changed over time?

### 4.3.1 California

Figure 23 displays the decomposed time series of the California customer weighted hours from 2015 to 2023. After removing the seasonality component the Mann-Kendall trend test suggests that there is a significant increase in the overall customer weighted hours of power outages in California (MannKendall; tau 3.513e-01 = p < 7.178e-08), and thus supporting the third hypothesis that the severity of power outages is increasing.

Of note is that the customer weighted outage hours appears to be dominated by infrequent extreme weather events. In Figure 24 there are clear spikes that correlate with extreme events, such as the 2019 Public Safety Power Shutoffs conducted by California PG&E to prevent wildfire during strong windstorms, and Atmospheric River events in early 2023 (Maxouris, 2019; NASA, 2023). Future analysis should graph customer weighted hours with these events to present the correlation.

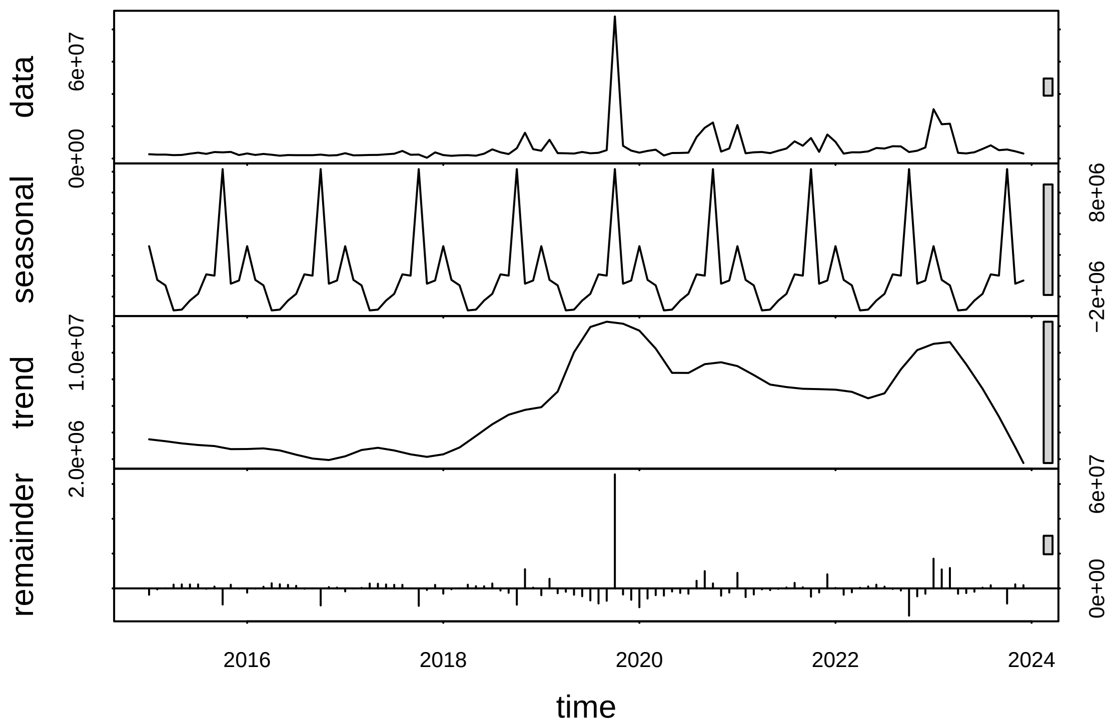


Figure 23: Decomposed trend of customer weighted outage time in California

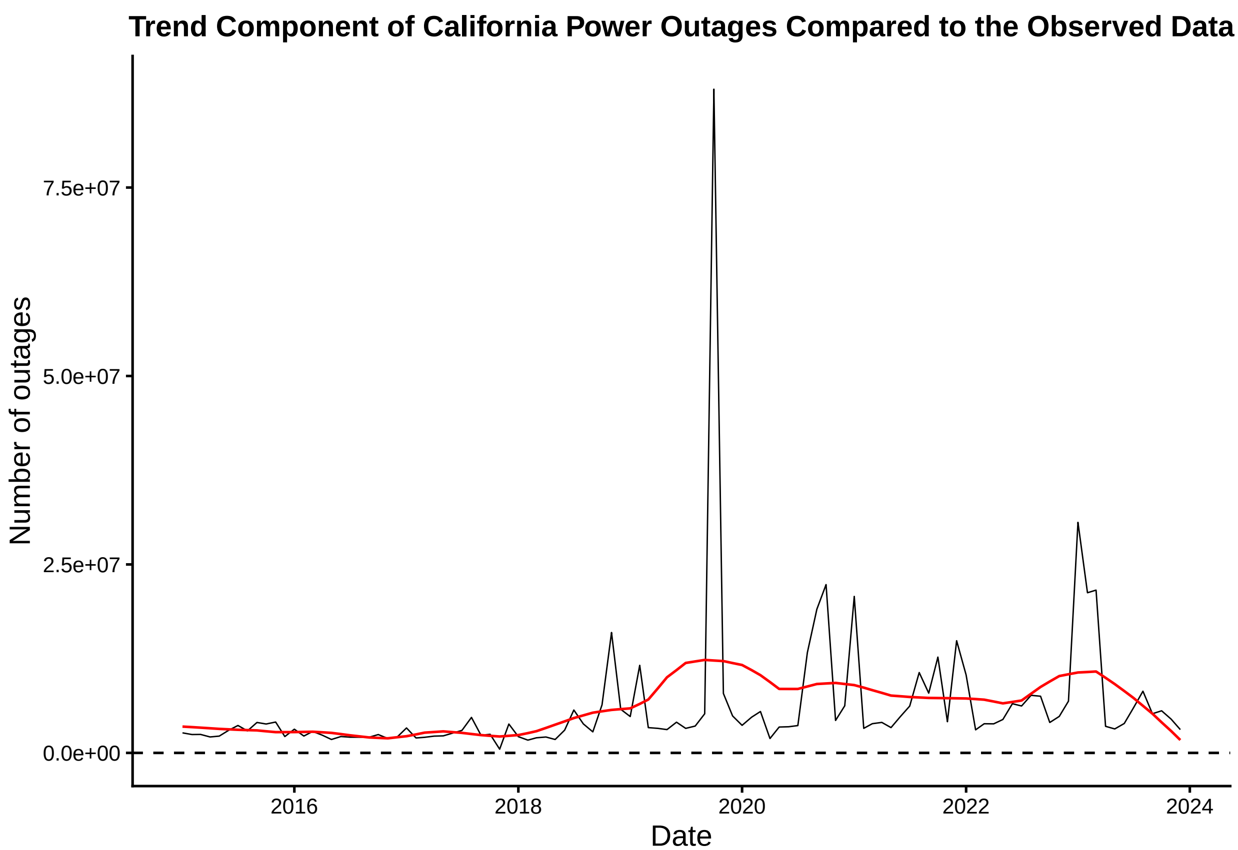


Figure 24: Trend versus observation of customer weighted hours in California (2015-2023).

### 4.3.2 Florida

Figure 25 visualizes the time series analysis for customer weighted hours in Florida from 2015 to 2023. The results of the non-seasonal Mann-Kendall test returned a non-significant increasing trend in customer weighted duration (tau = 7.961e-02 p-value = 0.223). This does not support the third hypothesis that power outages are increasing in severity. The customer weighted hours dataset appears to be dominated by extreme weather events. For example, in Figure 26 there is a big peak in later 2017, which coincides with Hurricane Irma which impacted 64% of customers in the state (EIA, 2017). Additionally, there is another peak in late 2022, which coincides with Hurricane Ian which also caused wide-spread power outages (NASA, 2022).

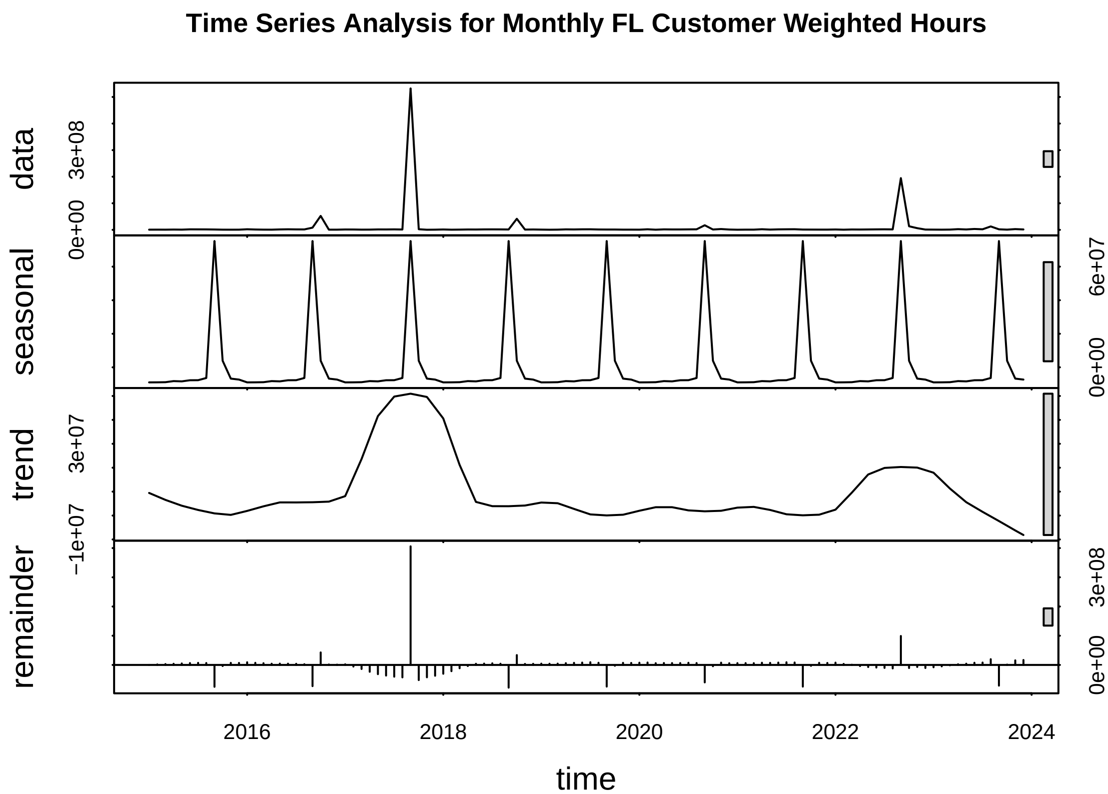


Figure 25: Decomposed trend of customer weighted outage time in Florida.

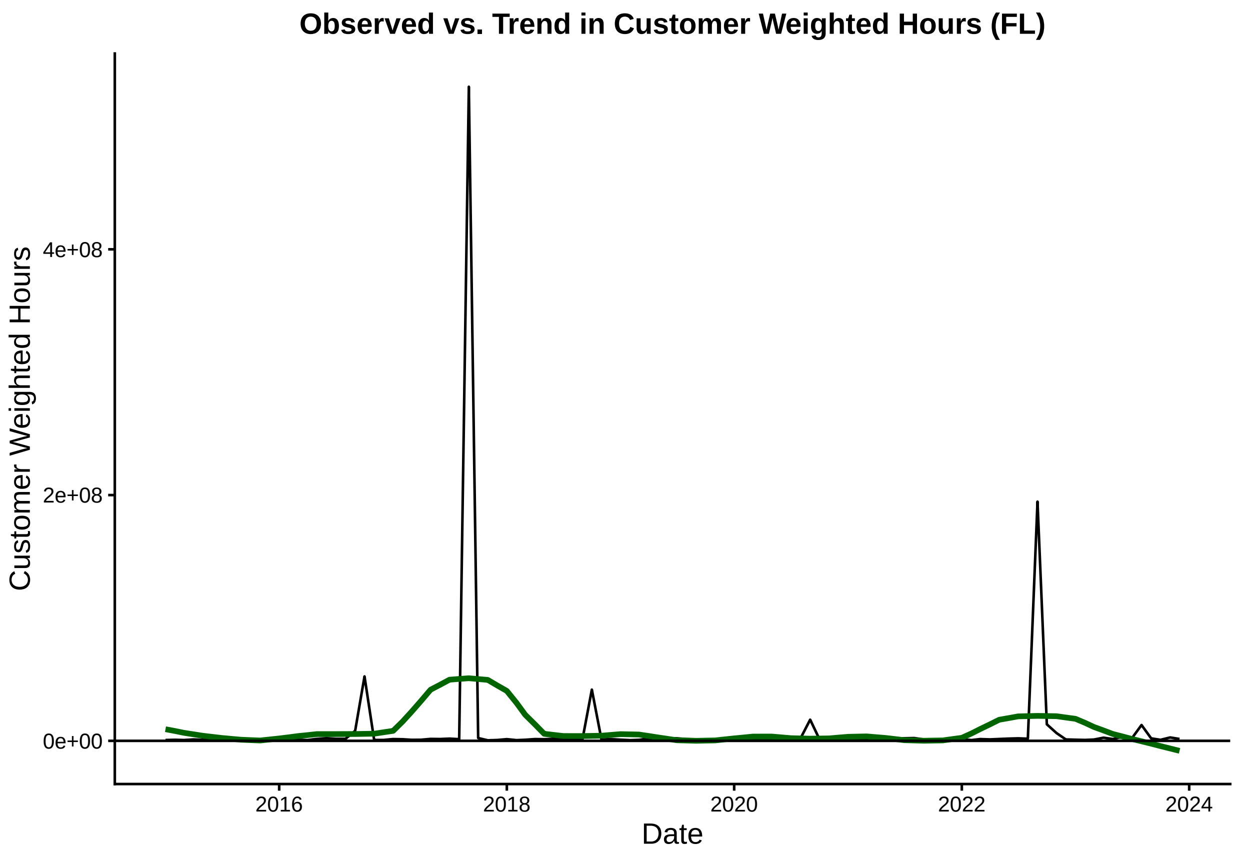


Figure 26: Trend versus observation of customer weighted hours in Florida (2015-2023)

#### 4.3.3 Pennsylvania

Figure 27 visualizes the time series analysis for customer weighted hours in Pennsylvania from 2015 to 2023. The results of the non-seasonal Mann-Kendall test returned a non-significant increasing trend in customer weighted duration (tau = 1.232e-01, p = 0.0591). Overall, these results suggest that while outage counts are increasing and show clear seasonality, there is not a significant increase in the impact on customers. Figure 28 shows the non-seasonal trend compared to observed data. This displays how sensitive the customer weighted hours data is to extreme weather events. There is a big peak in early 2018, which correlates with two big Nor'easter storms hitting the region and causing wide-spread power outages (CNN, 2018). There are also two smaller peaks in 2020 which likely correlate with Tropical Storm Isaias high winds and flooding (NWS, n.d.).

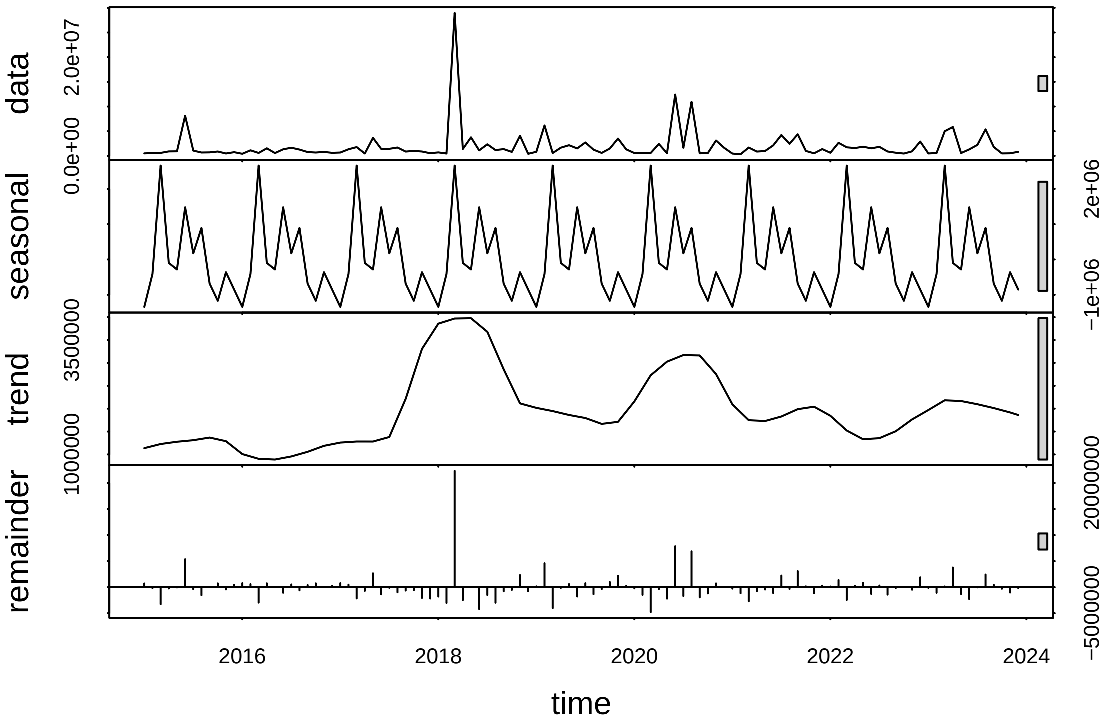


Figure 27: Decomposed trend of customer weighted outage time in Pennsylvania.

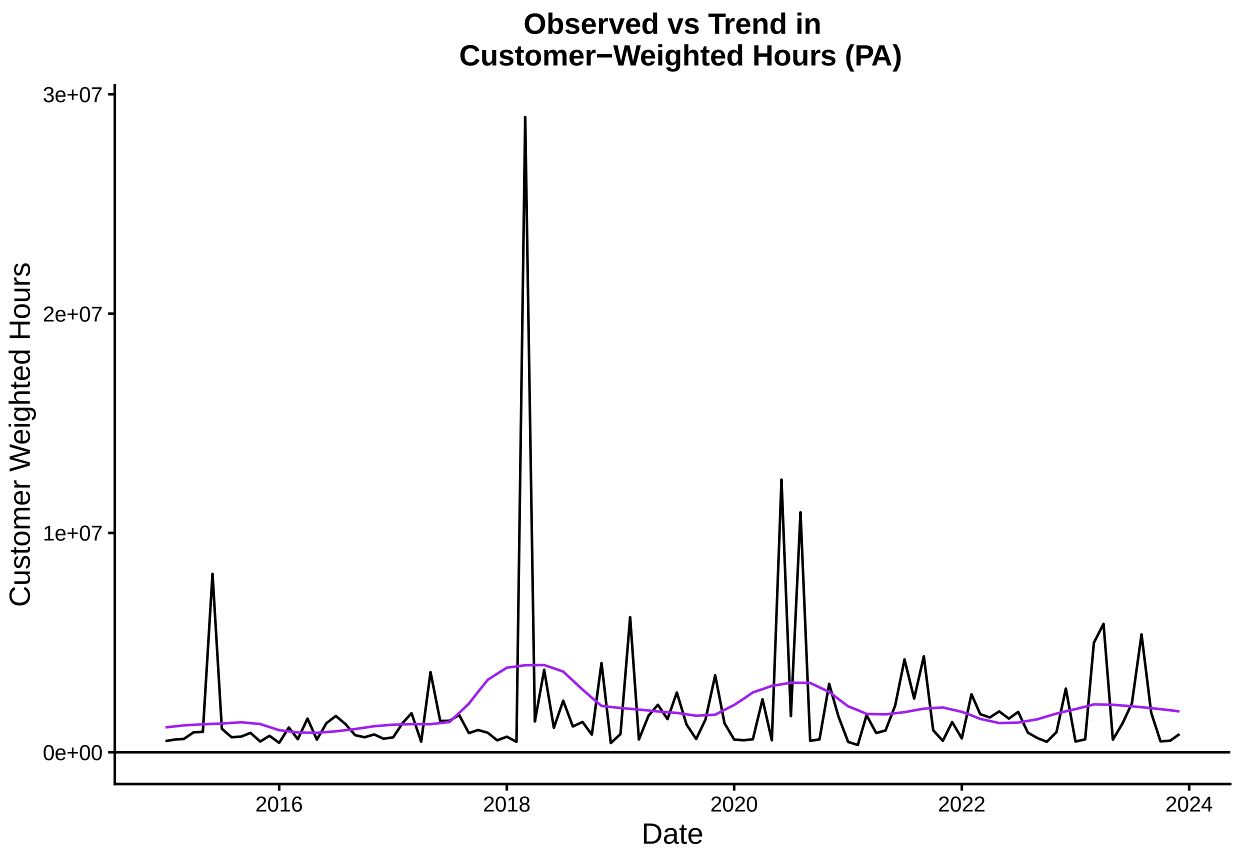


Figure 28: Trend versus observation of customer-weighted hours in PA (2015-2023).

### 4.3.4 Texas

Figure 29 shows the decomposed components of the Texas customer weighted outage hours time series from 2015–2023. A non-seasonal Mann–Kendall tau of 3.281e-01 indicates a strong positive monotonic trend in customer weighted outage hours with seasonality removed. With a very small p-value (4.882e-07), this upward trend is statistically significant. This supports the third hypothesis that power outages are increasing in severity.

The customer weighted hours dataset appears to be dominated by extreme weather events. In Figure 30 there is a a clear peak in 2021 which coincides with the Texas power grid failure during Winter Storm Uri, where almost 4.5 million customers were without power at the peak of the event (FERC, 2021).

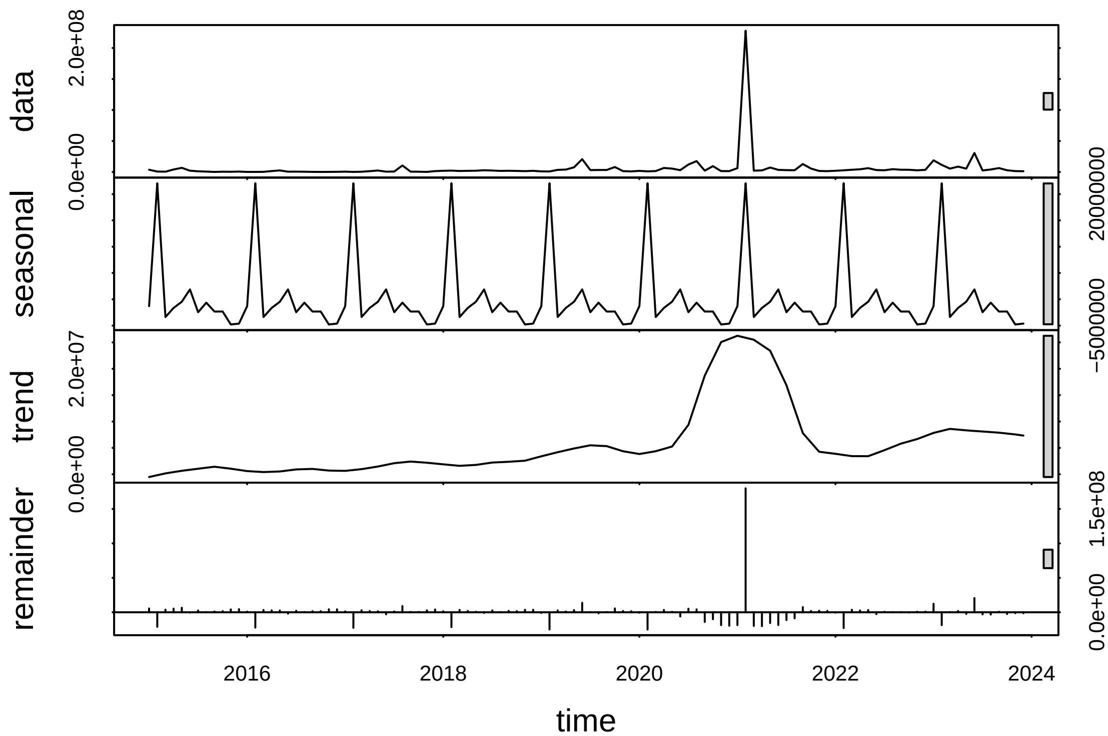


Figure 29: Decomposed trend of customer weighted outage time in Texas

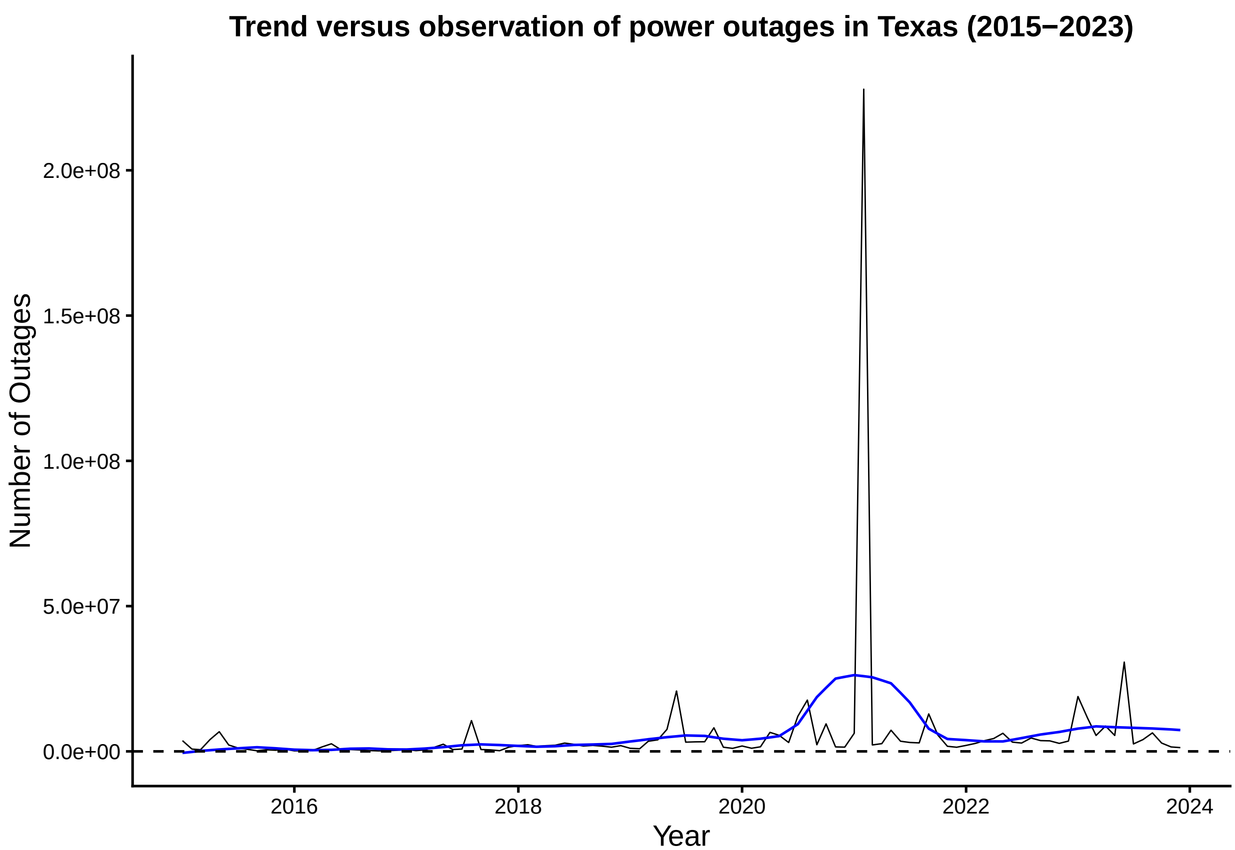


Figure 30: Trend versus observation of customer weighted hours in Texas (2015-2023).

### 4.3.5 Comparison between States

This plot shows the non-seasonal pattern of customer-weighted outage hours for four states from 2015–2023 (Figure 31). It should be noted that the y-axis is adjusted and some outliers are not graphed to allow for a clear visual of the trend lines. Overall, California and Texas both show a similar strong upward trends, indicating that total customer-weighted outage has increased significantly since 2015. Non-seasonal Mann Kendall test support this with both states having significant p-valus. (CA: $p < 7.178e\text{-}08$, TX: $p = 4.882e\text{-}07$). These results support the third hypothesis that the severity of power outages are increasing. The rise in customer weighted hours in California could be a result of California's increasing risk of high-wind and wildfire events. Texas increase in customer weighted hours could be caused by winter storm impacts and high summer demands.

While Florida has the highest overall customer weighted outage hours, it's increasing trend was insignificant (FL: $p = 0.223$). Pennsylvania remains the lowest out of all four states, and it's increasing trend was also insignificant (PA: $p = 0.0591$).

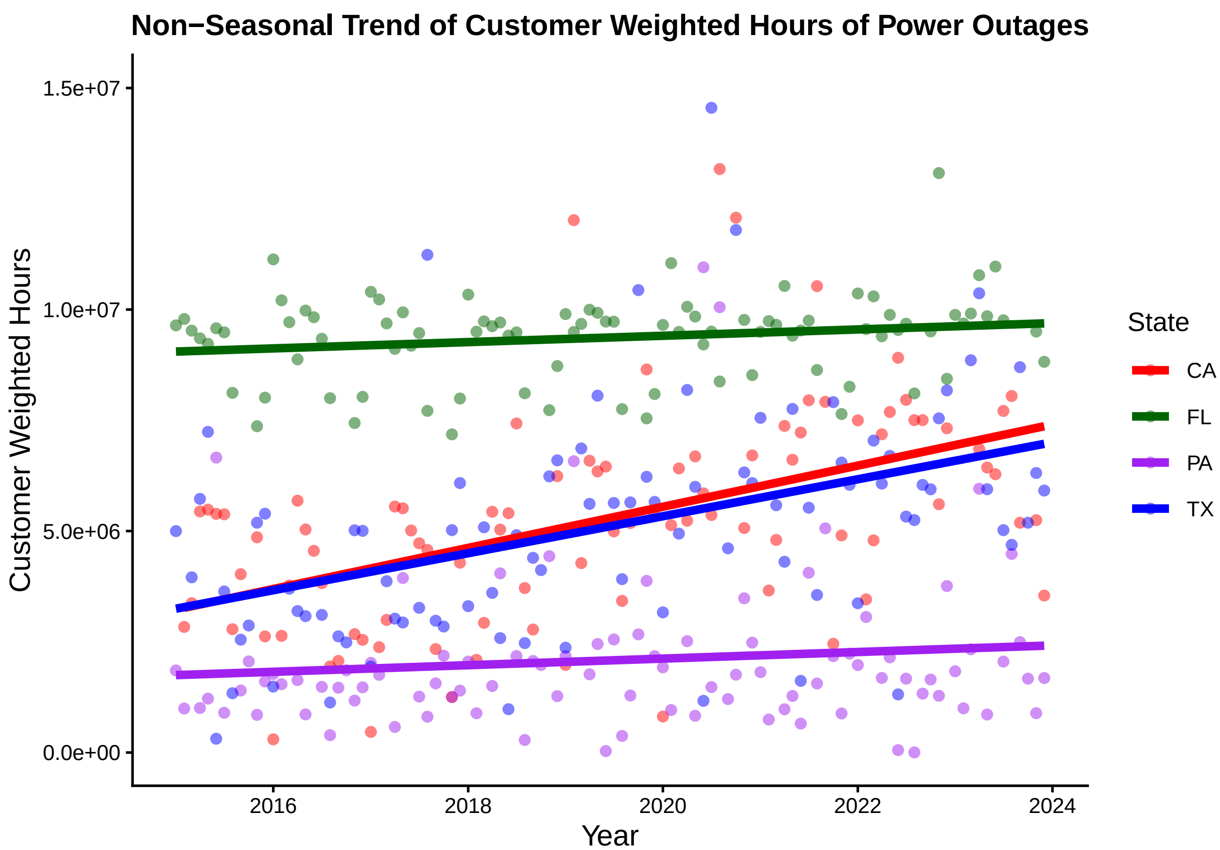


Figure 31: Non-seasonal pattern of customer-weighted outage hours for CA, FL, PA, and TX from 2015–2023. Note that some outliers are removed from view.

# 5 Summary and Conclusions

In California, both the frequency of power outages and the total customer impact is trending from 2015 to 2023, indicating that Californians are experiencing more outages and that these events are affecting larger numbers of customers than in previous years. The time series analysis revealed a potential seasonal cycle, with outages typically rising during the summer months and often reaching their highest levels in early fall. However, statistical testing reveled that there is not a significant difference between power outages across the months.

In Florida, power outages have gradually increased over the past decade, with a clear seasonal pattern. Outages typically rise during the summer months, a time where Florida experiences extreme heat, storms, and high electricity demand. In contrast, the winter months see far fewer disruptions. Although the exact monthly pattern shifts slightly from year to year, the overall seasonal cycle remains consistent. Long-term patterns show that Florida is experiencing more outages over time, indicating that both environmental pressures such as an increase in storms and growing energy demand may be contributing to the steady upward trend.

After accounting for seasonal patterns, the analysis shows that the number of power outages in Pennsylvania has increased from 2015 to 2023. Outage counts display a clear seasonal trend, with the highest numbers occurring in the summer months of June, July, and August. In contrast, customer-weighted hours do not show a strong seasonal pattern, but there is a slight upward trend over time, indicating that the impact of outages on customers is also gradually increasing. Overall, while outages are becoming more frequent and seasonally concentrated, the effect on customers is rising more moderately.

After running ANOVA and MannKendall tests, the results show that there's an overall increasing trend of power outages in Texas from 2015-2023. The customer weighted outage hours take into account the amount of customers impacted by these outages, which also shows an increasing trend over the study period. However, it is surprising that despite the visual season trend, Texas does not have a seasonal trend of power outages.

After comparing outage patterns across all four states, Florida and Pennsylvania show clear seasonal patterns in power outages, with events concentrated in the summer,especially July, and dropping sharply in winter. Texas peaks earlier in May, while California has no strong seasonal pattern, though outages rise somewhat in October. ANOVA results confirm this; Florida and Pennsylvania have extremely low p-values, indicating strong seasonality, while California and Texas have high p-values, indicating no statistically significant seasonal trend. These patterns may relate to regional climate factors. Florida and Pennsylvania face strong summer energy demand and storms, Texas experiences diverse weather but no consistent seasonal driver, and California's fire season varies widely year to year.

From 2015 to 2023, customer-weighted outage hours show a strong upward trend in both California and Texas, indicating growth in the scale of outages. California's rise is likely tied to increasingly severe wildfires, while Texas's growth may reflect the combined effects of winter storms and heavy summer electricity demand. Florida, although having the highest overall outage hours, shows only a mild upward trend. Pennsylvania has the lowest outage numbers among the four states and is experiencing only a slight gradual increase over time.

To strengthen the project in the future, further analysis could directly quantify the relationship between climate-related events and the trend in power outages. This could include directly modeling the customer weighted hours with known climate events. The exploration of severity of power outages could also be improved by exploring other variables, such as the duration of outages with a minimum threshold of customers impacted. This would help reduce noise from minor outages and focus the severity metric on if there is a general trend in power outage duration.

Furthermore, we could include more a nuanced perspectives by incorporating socioeconomic data to examine the broader impact that power outages could have on a community. It would be interesting to inspect spatial data and identify areas in a state that are most vulnerable to power outages.

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