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IMPROVING RESILIENCE: POWER OUTAGES AND BOIL WATER NOTICES IN TEXAS

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EXECUTIVE SUMMARY

This research explores the link between power outage-related factors and the occurrence of Boil Water Notices (BWNs) in Texas using various statistical methods. The data used in this analysis include Boil Water Notice (BWN) data for the state of Texas from 2018-2023, acquired via a Public Information Request to the Texas Commission on Environmental Quality and Power outage data purchased from poweroutage.us, a website that tracks, records, and aggregates power outages across the United States. The data found in the analysis point to clear and repeated findings of a significant positive relationship between power outages and BWNs and underscores the impact of power disruptions on water supply safety.

Texas water systems face various challenges, including aging infrastructure, extreme weather, and power outages. Emergency Power Systems are recognized best practices for water infrastructure resilience, as highlighted in the U.S. EPA's Power Resilience Guide for Water and Wastewater Utilities and The Department of Homelands Cybersecurity and Infrastructure Security Agency. The economic impact of long-duration, widespread interruptions (LDWIs) in electrical power that disrupt water service impose high economic and social costs that are difficult to quantify (Sanstad et al. 2020). Despite the known vulnerabilities and the passage of Senate Bill 3 (SB3) in 2021 after Winter Storm Uri, Texas infrastructure is still vulnerable to such events with Winter Storm Uri appearing to have had residual effects on the total counts for BWNs for years 2022 and 2023, which were above normal.

Key Findings:

- From January 2018 to July 2023 Texas experienced an average of 2,057 BWNs and 159,810 power outages annually, 85 of which were major power outages affecting 50,000 people or more.
- The findings reveal a clear and significant relationship between the occurrence of power outages and the issuance of BWNs.
- While every power outage has the potential to disrupt water treatment and distribution, leading to BWNs, it is the major outages those affecting 50,000 people or more that have a more considerable influence on the issuance of BWNs. Therefore, in planning and preparedness efforts, special attention should be given to preventing and managing major power outages to mitigate their effect on public water safety.

Policy Recommendations:

1. **Mandatory Backup Generators at Water Treatment Facilities**: To enhance resilience against power outages and reduce Boil Water Notices (BWNs), it is recommended to mandate on-site backup power generation at water treatment and distribution facilities. This addresses the observed strong correlation between power outages and BWNs. This is in line with the current requirements for wastewater treatment facilities in Texas, which

are required to have backup generators.¹ Current optional measures for backup power in emergency preparedness plans may lead to inconsistent preparedness across water systems, impacting service during weather extremes and power outages. Uniform requirements would ensure all systems are equally equipped to maintain continuous service.

2. **Improved Data Reporting and Record Keeping for BWNs**: There is a critical need for detailed information on the causes of BWNs. Current reporting often lacks specificity, with many instances of blank or insufficient descriptions in the Texas Commission on Environmental Quality (TCEQ) data on BWNs. Enhanced reporting protocols should focus on collecting detailed data with more refined categories for the causes and areas affected by BWNs. This will enable a more precise understanding of BWN triggers and support the development of more effective policies and operational responses to safeguard water quality.

¹Texas Administrative Code. Design Criteria for Domestic Wastewater Systems. CHAPTER 217, SUBCHAPTER B, RULE §217.36. <u>https://texreg.sos.state.tx.us/public/readtac\$ext.TacPage?sl=R&app=9&p_dir=&p_rloc=&p_ploc=&pg=1&p_tac=&ti=30&pt=1&ch=21}7&rl=36</u>

INTRODUCTION

The public expects clean water 24/7, 365 days a year, and often safe water is taken for granted. Public water systems provide a lifeline service and are critical to the health and well-being of a community. The loss of power at a water treatment facility results in pump failures, low distribution pressure and a loss of disinfectant residuals, making the water potentially unsafe to drink. This can initiate multiple failures across other sectors that are dependent on a clean water source, such as schools, daycare facilities, health clinics, hospitals, eldercare facilities, and business operations. The economic impact of long-duration, widespread interruptions (LDWIs) in electrical power that disrupt water service impose high economic and social costs that are difficult to quantify (Sanstad et al. 2020), illustrating the need for resilience at Water Treatment Facilities that can withstand events that may result in a power outage.

BACKGROUND

There are numerous causes of water service interruptions including: aging infrastructure, power outages, extreme weather events, cyberattacks, contamination incidents, vandalism, and fires. In all of these instances, having resilient power is essential to mitigating negative effects on a community. Emergency Power Systems for Critical infrastructure is an established best practices approach to improving reliability for water infrastructure. For example, wastewater treatment facilities in Texas are required to have backup generators.² The U.S. Environmental Protection Agency (EPA), in its Power Resilience Guide for Water and Wastewater Utilities, provides guidance on how a water system can increase power resiliency and protection for utilities to detect, respond to, and recover from physical and cyber threats and attacks, and emphasizes water infrastructure's relationship to other critical infrastructure, like hospitals.³

According to the Office of the Texas State Climatologist at Texas A&M, Texas faces heightened vulnerability to hazards associated with weather and climate events including freezes, heat waves, droughts, floods, and windstorms (Nielsen-Gammon et al. 2021). Winter Storm Uri affected the entire Electric Reliability Council of Texas (ERCOT) grid in February 2021 along with water systems in Austin, Houston, San Antonio, Fort Worth and many other Texas cities (Glazer et al. 2021), and Hurricane Harvey in 2017, caused water system outages affecting almost 1 million Texans (Palin et al. 2018), are two recent examples. Research from the UT Energy Institute and the LBJ School of Public Affairs concludes that it is crucial for Texas to prepare infrastructure for increasing weather extremes (Busby et al. 2021).

Despite the known vulnerabilities, passage of Senate Bill 3 (SB3) in 2021 after Winter Storm Uri, Texas infrastructure is still vulnerable to such events. Tiedman, et al. (2021) suggest that electric grid stability and its risks to water infrastructure are ongoing challenges for the state. SB 3 updated the state water code, mandating the establishment of alternative power to support

³ EPA. Power Resilience Guide for Water and Wastewater Utilities. June 2019. Pg. 3. https://www.epa.gov/sites/default/files/2016-03/documents/160212-powerresilienceguide508.pdf

emergency operations, and required water utilities to provide emergency preparedness plans to be approved by the Texas Commission on Environmental Quality (TCEQ). However, SB 3 does not mandate emergency backup power for drinking water treatment and distribution infrastructure. Instead, utilities are given various options to meet the emergency backup requirements, such as establishing leasing and contracting agreements, emergency mutual aid agreements with other retail public utilities, having alternative electrical feeds, or other alternatives approved by the executive director (TCEQ 2019, Texas State Legislature 2021). Because onsite backup power generation is optional, preparedness and resilience vary significantly across water systems. This inconsistency undermines emergency planning and leads to disparities in service. Without uniform requirements, some systems may be less equipped to handle weather extremes and power outages, affecting their ability to provide continuous service during critical times.

The human and economic costs of water service interruptions are significant. For example, gastrointestinal illness may increase in the aftermath of community-level water service interruptions (Gargano et al. 2015). Service interruptions at drinking water treatment plants in the aftermath of extreme weather events may also pose unique health risks, given the effects of such events on source water quality (Herrador et al. 2021) and health risks from floodwaters (Amaral-Zettler et al. 2008, Kiaghadi and Ritai 2019, Presley et al. 2005). While the full costs associated with drinking water outages are difficult to quantify, research in economics suggests that households and businesses have significant willingness to pay to avoid future short-term water outages and to ensure reliable water supply (Appiah et al. 2019, Rulleau 2020, Brozovic et al. 2007, Akram and Olmstead 2011, Griffin and Mjelde 2000, Hensher et al. 2005, Price et al. 2019).⁴ The direct costs of water service outages to water utilities, themselves, are also significant (Maziotis et al. 2020).

Winter Storm Uri highlighted vulnerabilities in Texas's critical infrastructure and led to a deeper understanding of the interdependencies within infrastructure systems and the cascading failures that can result from losing power at a water facility.⁵ Adding onsite power resiliency for these assets should continue to be a top priority and is in line with guidance from the EPA, AWWA, and Cybersecurity and Infrastructure Security Agency. According to guidance found in the Cybersecurity and Infrastructure Security Agency (CISA) Resilient Power Best Practices for Critical Facilities and Sites guidebook, "if the loss of a particular infrastructure will likely result in a significant or serious harm to life or economic well-being, then Level 2 or 3 Resiliency may be more appropriate for that infrastructure."⁶ Therefore, the risk planning process should strongly consider requiring critical water plants that perform lifeline functions for an area to meet Level 2 or even Level 3 resilience due to their relationship with other critical facilities.

⁴ The value to households of resilience to large electricity outages has also been estimated (and this may include potential risks to drinking water supply) (Baik et al. 2020).

⁵ Tiedmann et al. Tracking the post-disaster evolution of water infrastructure resilience: A study of the 2021 Texas winter storm. The University of Texas – Austin. January, 19, 2023.

https://www.sciencedirect.com/science/article/pii/S2210670723000288

⁶ Cybersecurity and Infrastructure Security Agency. Resilient Power Best Practices for Critical Facilities and Sites. November 2022. Pg. 13. https://www.cisa.gov/sites/default/files/2023-

^{01/}CISA%20Resilient%20Power%20Best%20Practices%20for%20Critical%20Facilities%20and%20Sites.pdf

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Level 2 Generation System	• Deploy at least two independent generation sources or equivalent so that the site is not dependent upon a common single source of failure.
	 Consider deploying multiple networked smaller generation sources with load shedding rather than deploying two large generators each of which meets maximum load requirements. This can improve fuel efficiency and resiliency as well as reduce costs.
	 Other possibilities to effectively meet the two independent generation sources or equivalent include:
	 Implement two independent connections to two different utility generation sources in addition to having a single backup generation source.
	 Implement a Renewable Energy Hybrid System (REHS), which includes both a renewable and a 24/7 generation source as well as an energy storage system (ESS).
	 Use a single highly reliable power generation source that approximates or is more resilient than two well maintained diesel generators with onsite fuel (e.g., a fuel cell that has been tested to be very reliable).
	 Maintain multiple 24/7 generation sources capable of being operated for the timeframe required with N+1 redundancy (having one more generator than needed).
	 It is recommended that the power generation solution be implemented in an all-hazards resilient island-mode capable microgrid.
Level 3 Generation System	 There should be a means to bypass and isolate any component for repair or replacement without deenergizing critical power to the mission.
	 Consider using multiple types of energy sources, such as diesel and natural gas, which provides better resiliency than using a single type of energy source.
	• The above should be implemented even if there are two independent connections to two different electric utility generation sources.

Source: CISA Resilient Power Best Practices for Critical Facilities and Sites. General Design and Process Best Practices Summary. Pg 18.

METHODS

The data used in this survey include Boil Water Notice (BWN) data for the state of Texas from 2018-2023, acquired via a Public Information Request to the Texas Commission on Environmental Quality. Data cleaning procedures removed duplicate entries of BWN incidents. Power outage data were purchased from https://poweroutage.us/, a website that tracks, records, and aggregates power outages across the United States. These data include outages by county and power supplier from 2017-2023. To match the BWN data, only the years 2018-2023 were analyzed. BWN and power outage data were merged by county and date.

In this study, OpenRefine was used to clean the BWN data and match notices to their underlying cause, such as a broken main pipe or a loss of power from a lightning strike. The statistical analysis software R was used to analyze the data. The analysis includes tabular and visual descriptive statistics, correlations between BWNs and power outages, and several different regression models. Texas county shapefiles were acquired for geospatial analysis in R in order to visualize the geographic distribution of incidents.

RESULTS

The sample includes 12,340 individual BWNs and 958,865 power outages from 2018 to mid-2023. As displayed in **Table 1**, the mean annual number of BWNs in Texas over this period is 2,057 (sd=1,176). The mean annual number of power outages over the same period is 159,810.8 (sd=41,916.42).

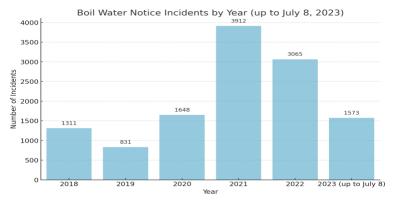
TABLE 1. Univariate Results for Boil Water Notices and Power Outages 2018 to mid-2023

 Descriptive Statistics of BWN Counts by Year

Year	Mean	S	D Min	Мах	Median			
2018 to mid-2023	2056.667	1176.28	4 831	3912	1610.5			
Descriptive Statistics for Annual Power Outages								
Year	Mean	SD	Min	Мах	Median			
2018 to mid-2023	159810.8	41916.42	80192	192351	172589			

Looking at the total counts across the state from 2018 to mid-2023 in **Figure 1**, the sharp rise in BWNs in 2021 can be attributed to Winter Storm Uri, which impacted water delivery systems across the state. Winter Storm Uri also appears to have had residual effects as the total counts for years 2022 and 2023 (given that only six full months are included) were above normal.

FIGURE 1. Boil Water Notice Counts Across Texas 2018 to July 8, 2023



Looking further into the counts for BWNs, **Table 2** reports the average counts per month for each year in the sample. Following the year 2021, 2022 and 2023 both show increases in the statewide mean, standard deviation and median of monthly BWNs.

Year	mean_count	median_count	sd_count	min_count	max_count
2018	109.2500	95.5	64.23412	28	283
2019	69.2500	54.0	43.67468	30	163
2020	137.3333	154.0	74.57557	3	265
2021	326.0000	176.5	625.92622	9	2299
2022	255.4167	243.5	90.10646	166	517
2023	224.7143	239.0	99.91616	22	350

TABLE 2. Descriptive Statistics of BWN Per Month by Year 2018 to July 8, 2023

Nature of Boil Water Notices

To better understand the nature of Boil Water Notices in the State of Texas, R was used to examine how occurrences of Boil Water Notices are broken down. This BWN descriptor has the following categories: low distribution pressure, water outage, disinfectant residual, natural disaster, microbiological, water supply service, other, turbidity, water supply quality, construction, odor, or blank. **Figure 2** summarizes the frequency of BWNs in each of these categories during the study period.

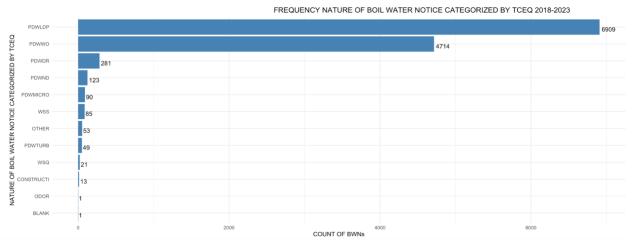
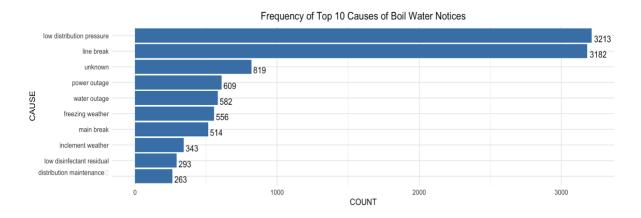


Figure 2. BWN Categories from 2018 to mid-2023.

As seen in **Figure 2.** Low distribution pressure is by far the leading recorded nature of BWNs. We can explore this further by analyzing the underlying cause of BWNs, as seen in **Figure 3.** The TCEQ identify the ultimate cause for the issuance of a BWN only in a "comment" field. Where that field was left blank, the cause is categorized in Figure 3 as "unknown". **Figure 3.** Frequency of Top 10 Causes of Boil Water Notices



Low distribution pressure can be caused by a number of issues such as, power outages, pump failures, leaks in the distribution system, water outages, construction related activities, and high customer demand.

Correlation Results

One approach to understanding the relationship between power outages and BWNs in Texas is to calculate a Pearson correlation coefficient, which measures the strength and direction of a linear relationship between two variables. Given that power outages may lead to BWNs, one would expect that coefficient to be positive. **Table 3** reports Pearson correlation coefficients, and these results suggest that there is a statistically significant relationship between BWNs and four power outage statistics: total power outages, major power outages (those affecting 50,000 or more customers), the maximum number of customers experiencing an outage, and the total number of hours that customers are out of power. The correlations are positive, but small.

TABLE 3. Correlation between Power	Outages and Boil Water Notices 2018-July 8, 2023
Correlation Between Power Outages and BWNs	

	Variable	Correlation	PValue
cor	Power_outages	0.0361173	<0.001***
cor1	Major_outages	0.1242422	<0.001***
cor2	CustomersTracked	0.0020380	0.8
cor3	MaxCustomersOut	0.1240917	<0.001***
cor4	CustomerHoursOutTotal	0.1305211	<0.001***
cor5	CustomerHoursTrackedTotal	0.0020314	0.8

Multivariate Regression Analysis

Another approach a linear regression analysis to explore the relationship between the various factors tracked in the power outage data (Power Outages, Major Outages, Customers Tracked, Max Customers Out, Customer Hours Out Total, and Customer Hours Tracked Total). The model revealed positive, statistically significant relationships for three predictors (**Table 4**): total Power Outages, Major Outages, and Max Customers Out.

Looking at **Table 4**, power outages, while having a relatively small coefficient in the model, still significantly affects the likelihood of BWNs being issued. The data suggests that each additional power outage is associated with a slight increase in the number of BWNs. This relationship is statistically significant despite the small size of the coefficient, meaning that even minor increases in power outages can be expected to lead to more BWNs. The impact of major outages on BWNs is more pronounced. The estimated effect of major outages is larger (1.477) than that of general power outages, indicating that BWNs are more sensitive to major outages. When a major outage occurs, the model predicts a more substantial increase in BWNs than what would be expected from a non-major power outage. This is not only statistically significant but also suggests that major outages are a critical factor to consider when assessing the risk and potential number of BWNs. The factor labeled MaxCustomersOut, represents the maximum number of customers experiencing an outage, also shows a significant relationship with BWNs, albeit with a smaller effect size than that of major outages. This indicates that as more customers are affected by an outage, the number of BWNs tends to increase, but not as dramatically as it does with major outages.

Supplementary models Poisson and Negative Binomial (NB), detailed in the appendix, also offer an examination of the factors contributing to BWN occurrences. While the linear regression might suggest the direction and magnitude of the relationship between predictors and BWNs, the Poisson and NB models provide insights into the actual frequency of BWN occurrences, accommodating the count data's dispersion. These models demonstrated similar results.

TABLE 4. Linear Regression between Power Outages and Boil Water Notices 2018-July 8,2023

Linear Regression Model Coefficients

	Estimate	Std. Error	t value	Pr(> t)	Signif
(Intercept)	0.4897747	0.0693177	7.0656504	0.0000000	***
Power_outages	0.0042817	0.0009735	4.3981263	0.0000110	***
Major_outages	1.4772622	0.3840069	3.8469675	0.0001201	***
CustomersTracked	0.0005132	0.0007934	0.6468079	0.5177660	
MaxCustomersOut	0.0010642	0.0003200	3.3260337	0.0008830	***
CustomerHoursOutTotal	0.0000014	0.0000241	0.0561856	0.9551947	
CustomerHoursTrackedTotal	-0.0000215	0.0000331	-0.6513607	0.5148234	

CONCLUSIONS AND POLICY RECOMMENDATIONS

Considering the results of the statistical analysis as a whole, the repeated findings of a significant positive relationship between power outages and BWNs underscores the impact of power disruptions on water supply safety. This finding aligns with the hypothesis that power outages impair water treatment and distribution systems and increase the risk of water contamination. The results also highlight the importance of considering the maximum number of customers affected by outages in predicting BWNs. Larger-scale outages, potentially affecting critical infrastructure, may have more impact on water safety than the total duration of outages or the total number of customers monitored. While every power outage has the potential to disrupt water treatment and distribution, leading to BWNs, it is the major outages — those affecting 50,000 people or more — that have a more considerable influence on the issuance of BWNs. Therefore, in planning and preparedness efforts, special attention should be given to preventing and managing major power outages to mitigate their effect on public water safety.

While these findings provide insights into the drivers of BWNs, it is crucial to acknowledge the limitations of this study. The results are dependent on the accuracy and completeness of the data used, and the model's assumptions. Future research could explore more granular data on outage causes, such as severe weather, and their direct impact on water systems. The paragraphs that follow offer several policy recommendations that emerge from this study.

Require Backup Generators at Water Treatment Facilities: Implement mandatory requirements for on-site backup power generation at water treatment and distribution facilities. This will enhance the resilience of these systems against power outages and reduce the incidence

of BWNs. The repeated findings of a significant positive relationship between power outages and BWNs, and guidance from EPA and CISA demonstrate the necessity of requiring back-up power generation at water treatment facilities instead of giving utilities options to meet resiliency requirements. Because onsite backup power generation currently is optional to meet the requirements of emergency preparedness plans to be approved by the Texas Commission on Environmental Quality (TCEQ), preparedness and resilience vary significantly across water systems. This inconsistency can undermine emergency planning and lead to disparities in service. Without uniform requirements, some systems may be less equipped to handle weather extremes and power outages, affecting their ability to provide continuous service during critical times.

Enhanced Data Reporting and Record Keeping: A major issue during this research was in the lack of detailed information regarding the causes of BWNs, which is crucial for understanding their drivers. In many instances, the description column in the raw data set provided by TCEQ, which is meant to provide more detail regarding a BWN's cause, was left blank. In many instances the information provided was insufficient to assign a specific cause. To address these issues, the reporting protocols for BWNs should be updated. Enhanced data collection should focus on gathering granular details about causes and affected areas. Implementing these measures will facilitate a more accurate and comprehensive understanding of BWN triggers, ultimately aiding in the development of more effective policy and operational responses to ensure water safety.

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APPENDIX:

Poisson Regression Analysis

TABLE 5. Poisson Regression Analysis between Power Outages and Boil Water Notices 2018-July 8, 2023

Poisson Regression Model Coefficients

	Estimate	Std. Error	z value	Pr(> z)	Signif
(Intercept)	-0.5819868	0.0199662	-29.148632	0.0000000	***
Power_outages	0.0052301	0.0002583	20.245042	0.0000000	***
Major_outages	0.4476215	0.0289477	15.463133	0.0000000	***
CustomersTracked	0.0004204	0.0001788	2.350531	0.0187467	*
MaxCustomersOut	0.0004062	0.0000555	7.313811	0.0000000	***
CustomerHoursOutTotal	-0.0000204	0.0000042	-4.860667	0.0000012	***
CustomerHoursTrackedTotal	-0.0000176	0.0000075	-2.363120	0.0181218	*

A Poisson regression analysis was also performed, treating BWNs as a count variable. The results indicated significant effects for all the predictors in the model. Power Outages (Estimate = 0.0052, p < 0.001), Major Outages (Estimate = 0.4476, p < 0.001), Customers Tracked (Estimate = 0.0004, p = 0.0187), Max Customers Out (Estimate = 0.0004, p < 0.001), Customer Hours Out Total (Estimate = -0.00002, p < 0.001), and Customer Hours Tracked Total (Estimate = -0.00002, p = 0.0181) were all significant predictors.

The positive coefficients for Power Outages, Major Outages, Customers Tracked, and Max Customers Out indicate that higher values of these variables are associated with an increase in BWN counts. Conversely, Customer Hours Out Total and Customer Hours Tracked Total showed a negative relationship with BWN counts.

The model's overdispersion test yielded a value of 14.0756, suggesting the presence of overdispersion and indicating that the Poisson model might not be the best fit for this data.

Negative Binomial Regression

TABLE 6. Negative Binomial Regression analysis between Power Outages and Boil Water Notices 2018-July 8, 2023

Negative Binomial Regression Model Coefficients

	Estimate	Std. Error	z value	Pr(> z)	Signif
(Intercept)	-0.6772126	0.0451477	-14.9999359	0.0000000	***
Power_outages	0.0055291	0.0006232	8.8723217	0.0000000	***
Major_outages	-0.2433068	0.2240632	-1.0858849	0.2775299	
CustomersTracked	0.0003426	0.0004957	0.6909891	0.4895724	
MaxCustomersOut	0.0009997	0.0002000	4.9985172	0.0000006	***
CustomerHoursOutTotal	0.0000224	0.0000148	1.5121652	0.1304918	
CustomerHoursTrackedTotal	-0.0000144	0.0000207	-0.6973793	0.4855655	

Due to overdispersion observed in the data found in the Poisson Regression, a Negative Binomial Regression Model was utilized to investigate the relationship between various power outage metrics and the incidence of Boil Water Notices (BWNs) across different Texas by county and Month-Year. The Negative Binomial Regression was used to better handle the variability in the count of Boil Water Notices (BWNs). Negative Binomial Regression Model showed that more power outages tend to lead to more BWNs. The numbers tell us this relationship is strong and statistically certain. When more customers are affected by power outages, it's more likely that there will be BWNs. The statistics confirm this is a significant and reliable finding.

ADDITIONAL MAPS AND FIGURES

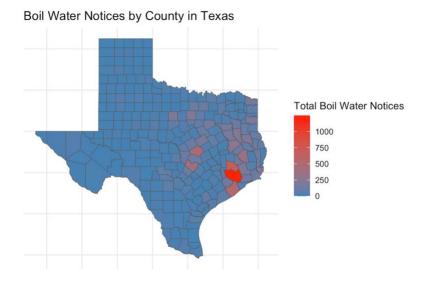
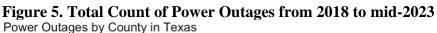


Figure 4. Total Count of Boil Water Notices from 2018 to mid-2023



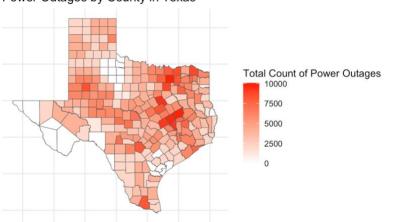


Figure 6. Total BWNs by TCEQ Region from 2018 to mid-2023

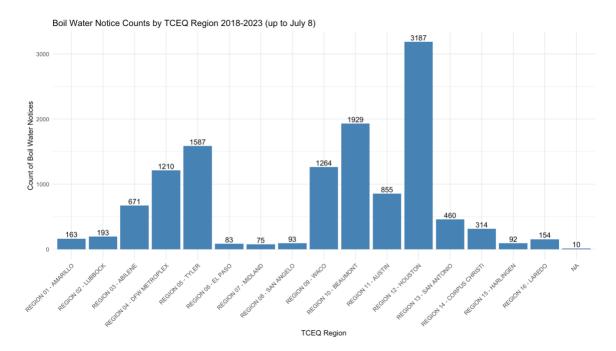
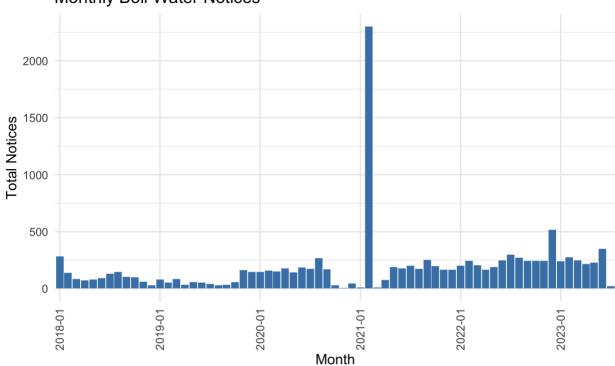


Figure 6. Boil Water Notices from 2018 to mid-2023.



Monthly Boil Water Notices