Resilience of Water Systems After Extreme Weather Events in Texas

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I. Introduction and Summary

The main purpose of this research is to examine the relationship between extreme weather events and water quality violations at public water systems (PWS) in Texas during 2015-2020. The research question examined is: after extreme weather events, is there an increase in water quality violations? Furthermore, the objective was to identify whether public water systems have an increase in violations after a major natural disaster event, the probability of an increase, and the long term effects of a natural weather event on a public water system. For reference, public water systems track the amount of harmful substances in their water supply and must report when they exceed maximum contaminant levels (MCL), set by the EPA. These MCL-violations, which track substances like lead or arsenic, are collected at the federal and state level.

To answer the research questions, I took two main approaches. First, I analyzed the effect of weather events on a county-level. Next, I analyzed the effect of weather events on a watershed-level to see if there was a difference.

My results suggest that while there may be a relationship between extreme weather events in a county and an increase in MCL violations, there is likely no relationship between extreme weather events in a watershed and an increase in MCL violations. While one model on the county-level pointed to a higher probability of MCL-violations in a county after the most extreme weather event in that county, the other model on the county-level suggests that there is not an increase in violations during the month that that extreme weather event hits that county. On the watershed level, the results are even more murky. My first model shows that there is about a 50/50 chance that a violation occurs at a PWS that sources from a watershed after the most extreme weather in that watershed's area. The second model did not converge, suggesting that in months with no extreme weather event in the watershed's area, almost all of the violations occurred.

II. A Literature Review of Modern Texas Water Quality

While Americans expect clean and safe drinking water, the reality is that people across the country do not have access to a public source of clean drinking water. Especially in Texas, where arsenic and nitrates frequently cross the maximum contaminant levels (MCLs) set by the Environmental Protection Agency (EPA). The purpose of this review is to find common issues affecting the drinking water in Texas, especially ones that affect minorities across the state. In this literature review, we mostly found that people without access to public water systems (PWSs) are likely to have both arsenic and nitrate contamination. This review only focuses on the state of Texas. This same group of rural, low-income communities do not respond with bottled water purchases to tier 1 nitrate violations. Bottled water purchases are higher after PWS violations, but purchase of water filters is associated with income. In addition, in the Colonias — settlements without access to basic infrastructure — there is a high reliance on bottled water and a push for reverse osmosis filtration systems.

Arsenic Contamination

In August 2005, the Texas Commission on Environmental Quality commissioned a report from UT Austin's School of Geosciences to evaluate the levels of arsenic contamination in Texas, in response to the EPA standard change, dropping the maximum contaminant level of arsenic in drinking water from 50 ug/L to 10 ug/L (Reedy & Scanlon, 2018, 4). The main conclusion of this report is that arsenic contamination in Texas is not likely anthropogenic because "the lack of correlation between groundwater arsenic concentrations and land use, distance from cotton gins, soil texture, water table depth, and aquifer saturated thickness" (Reedy

& Scanlon, 2018, 29) In addition, the report found that the areas with the highest arsenic contamination (the Southern High Plains and the Southwestern Gulf Coast) have high correlations with the constituents of volcanic ash — vanadium, molybdenum, and boron — in the water (Reedy & Scanlon, 2018, 56). These findings suggest that arsenic contamination is not due to the many industries in Texas that use arsenic compounds (Reedy & Scanlon, 2018, 17).

This report was re-evaluated in 2018 when the UT School of Geosciences released a new assessment of arsenic in the groundwater and water supply systems. This report found that almost 100,000 people live in an area serviced by a non-compliant PWS. This puts Texas only behind California in terms of at-risk population to arsenic levels above MCL (Scanlon et al, 17). These areas corresponded with the areas in the 2005 report, finding that the Southern Gulf Coast and High Plains region housed the most affected populations (Scanlon et al, 4). In addition, the 2018 report found that in the Waco/Trinity area there also were affected populations (Scanlon et al, 4). Also, the report indicates an important fact: "an estimated 2.1 million (M) people out of a population of 44 M people using domestic wells in the U.S. are using groundwater water arsenic exceeding 10 µg/L. Texas ranks 7th in terms of domestic population impacted by arsenic contamination, with ~95,000 people affected" (Scanlon et al, 5). Not only does the arsenic contamination affect people with access to public water systems, it also affects people who rely on domestic systems for water access.

Nitrate Contamination

One discrepancy between the literature is that the reports on arsenic contamination claim that arsenic is the most widespread contaminant in the major aquifers in Texas (Reedy & Scanlon, 2018, 5), while the report from a year prior about nitrate contamination stated, "Nitrate is the most widespread groundwater contaminant in Texas and in the U.S" (Reedy & Scanlon, 2017, 2). Sources of nitrate contamination are both natural and anthropogenic, but the report found that nitrogen levels on the ground do not correspond to groundwater nitrate: “The general lack of correspondence between nitrate loading and groundwater nitrate contamination suggests that soil texture, aquifer status (confined vs unconfined), and water table depths are more important factors controlling nitrate contamination” (Reedy & Scanlon, 2017, 3-4). In conclusion, this report found that 99.13% of PWS systems and 99.96% people served by PWS systems have less than 10 mg/L of nitrate, complying with the EPA nitrate-N MCL (Reedy & Scanlon, 2017, 13). Again, this report finds that rural domestic and irrigation wells have the highest levels of nitrate with almost 70% of samples exceeding the detection levels (Reedy & Scanlon, 2017, 3).

In the Colonias

As discussed in the previous literature, water quality issues happen at a much higher frequency when someone is acquiring water from a domestic system or a well. In some regions of Texas, such as the Colonias where there is little access to clean drinking water, they rely on domestic systems, wells, and bottled water. Both the articles read discussed point-of-use systems in the Colonias. The first study about water treatment systems in the Colonias found that an under-the-sink reverse osmosis unit would be the best option for price and water cleaning ability (Flores, 41). While chemical treatments and point-of-entry systems are the obvious answers, chemical treatments are complicated and need precision and point-of-entry systems are much more expensive. After testing different types of at-home water treatment systems, another thesis agreed that a point-of-use reverse osmosis water treatment system would both solve water quality issues, “e.g. high TDS concentrations or presence of coliforms,” and have a payback period of six-eight months (Ramirez, 19). One caveat to this thesis is that only 20 systems were installed and results are “still pending” on some of these installations (Ramirez, 20). Both of these reports found that a reverse osmosis system would be the best solution to water quality issues for people outside of a traditional PWS, yet admitted that the cost barriers to installing these systems and educating the public are very high.

Public Water Systems

The limitations of a public water system are also present for people within the system. With high costs economically and environmentally, cities like Austin have tried to cut down on water usage through reclaimed water systems. Instead of disposing of wastewater effluent, the University of Texas at Austin has started a program to receive non-potable treated water from the City of Austin wastewater treatment plants (Stillwell et al, 208). This study found that reclaimed water must be analyzed with a clear understanding of municipal energy costs. Places with scarce water or flatter ground might find the energy cost to be worth the benefit of more non-potable water for their municipality. For example, places with desalination plants for drinking water might find sustainable water reuse to be a much cheaper alternative (Stillwell et al, 220). Reclaimed water services can be a good way to resist drought in a local water supply (Stillwell et al, 222). The authors conclude that three things must be practiced for effective water reuse: transparency in energy use calculations, careful comparison to drinking water in non-potable uses, and making sure it is easy for a consumer to use (Stillwell et al, 222). Reclaimed water is one way to address the water shortage problem in public water systems, yet it does not address the issue of violations or lack of data in a PWS.

In the “2015 Onsite Wastewater Installation Assessment Report,” Texas was omitted because the state did not provide detailed enough data about permits or size of onsite sewage facilities (106). While every county responded to the survey conducted, none of the data was included in the national results or could be further analyzed ("Onsite Wastewater," 7). This report is indicative of a larger issue with available data for on-site wastewater systems in Texas.

Bottled Water

The issue of violations in a public water system and how a community responds can be modeled with bottled water sales. One study found that public water system violations with an "immediate health risk" are associated with 14% more bottled water sales (Allaire et al, 2020). The key findings of the report were that communities purchase more bottled water in response to water quality violations, communities become more responsive to the violations after they repeat, and rural, low income communities do not have significant increases in bottled water purchases in response to tier 1 (immediate health risk) nitrate violations. In addition, people are more responsive to pathogens than nitrates: "While Tier 1 pathogen violations are associated with increased sales of bottled water (14.3% ± 5.7 percentage points), nitrate violations are not" (Allaire et al, 20920). The major oversight of this report, however, is one that it acknowledges. It does not take into account any at-home treatment or purchasing of other beverages. Another oversight that might be relevant for Texas is that during hurricane season it is recommended to have large stores of bottled water on hand, thus possibly reducing the bottled water response in Gulf Coast states.

Another more recent article used a household survey in Spain to find consumer motivation behind purchasing bottled water and in-home treatment systems. In this study, they noted that they used sociodemographic data, which is "seldom discussed in the literature" (March et al, 2). In the three models made in this report, they found that perceived water quality was the most important factor in both use of bottled water and in-home water treatments (March et al, 9). In addition, they found taste was often a larger factor in whether someone did not use untreated tap water than safety (March et al, 9). The main factors they found to explain increased bottled water usage were "perception of poor tap water quality, lack of in-home treatment systems, and the presence of children at home" (March et al, 10). Unlike the first report, this one did not find any difference in bottled water purchases based on income; however, this study did not consider the relationship between violations and purchases, only how people purchase bottled water and/or treat tap water in their everyday lives. They did find, however, that the purchase of at-home filters did correlate with income, even though domestic reverse osmosis equipment is cheaper than buying bottled water (March et al, 3). Both bottled water studies found that perception of water quality results in bottled water purchases or in-home treatment, yet neither addressed whether the public's perception aligned with the reality of water quality in their community.

In conclusion, this literature review begets a few major takeaways. For low-income and/or rural communities, particularly ones like the Colonias, access to clean water is a difficulty. These difficulties arise from both an economic and educational barrier: even if a household could afford a water treatment system, they probably do not know that option is available, how to install it, and which system works best for their water supply. These difficulties are only magnified when a community is located outside of the public water system because arsenic and nitrates are found at much higher levels in water stemming from domestic and irrigation wells. Another major takeaway is that people perceive water quality based on organoleptic attributes like smell and taste, instead of the actual health of the water, especially since bottled water has less disclosure of its ingredients than tap water.

III. Data Cleaning

For the research, the three datasets were used. The Safe Drinking Water Information System (SDWIS) dataset which records the EPA's information on the public water systems, NOAA's storm events dataset that records storms from 1951 to today, and the Texas Center on Environmental Quality dataset on the causes of the violations were all cleaned and appropriately merged. The violations data was merged from the Texas Center for Environmental Quality and the Safe Drinking Water Information System.

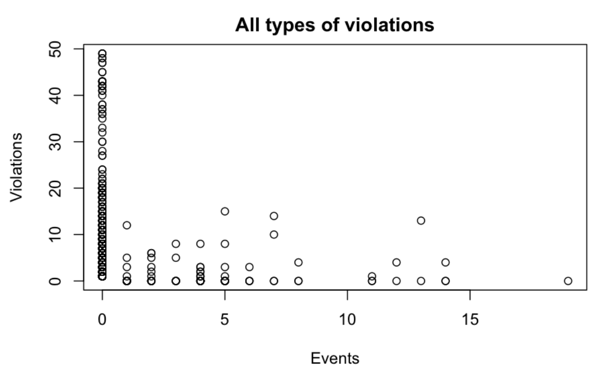
In the cleaning process, I used many packages in R, including dplyr, ggplot2, ggmap, lubridate, tidyverse, and sf. NOAA's storm events dataset did not have an API to quickly aggregate and subset the data, so the researcher downloaded and combined 100 files of different lengths to create the full dataset, then subsetted for Texas and relevant variables. Then, a spatial join was conducted with Texas NOAA subset and Texas FIPS areas to acquire the FIPs code for each county, because the NOAA had irregular data for the FIPS values. This ensured that the FIPS codes existed and matched the 48XXX format of the FIPS code in the SDWIS dataset. In addition, the Property Damage variable was converted from "10K" format to numeric "10000" format. The SDWIS dataset and TCEQ dataset were merged by PWS ID (WSID), which subsetted the dataset to only 2015-2020 data.

For the watershed data, the TCEQ data had to be cleaned again so that it could merge with the SDWIS intakes data. This included removing unnecessary spaces from the WSID data and turning the date functions into date objects. For the merge, a right join was done so that all the intakes data was kept and only the matching violations data was kept in the resulting data. After conducting some graphical and visual analysis, I conducted a full join to merge the surface HUCs data and the intakes data based on PWS ID. See Figures 14 and 15 for visualizations of the spatial join between HUCs and intakes. Then the NA values were removed from the latitude and longitude data for the weather events. After this, identifiers were added to the column names make sure that the HUC id was clear on what it corresponded to. After these steps, a spatial join was conducted between the weather location and the HUC shape objects with a CRS of NAD83. Then, the intakes data frame was merged with a data frame that included the maximum property damage in that watershed. For the second model, the amount of events in each month and the amount of violations and merged them by the month and the year. Then, an indicator variable was made to conduct the logistic regression analysis. 1 for if there were violations in that month and 0 for if there were not any violations.

See the Appendix and Figures Section for graphical representations of the datasets that were formed. To conduct the analysis, four logistic regression models were made.

IV. Statistical Analysis - County-Based Analysis

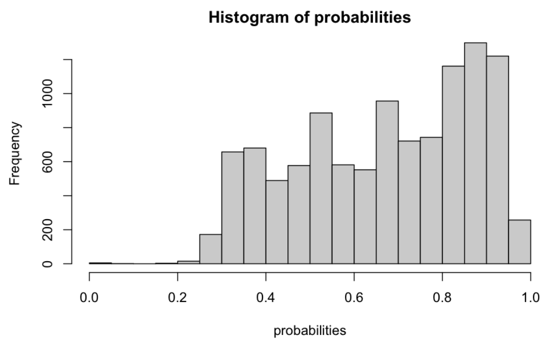
The first model aggregated data by violations per month per county to find the probability that there is a violation given that there is an event. From the first regression model, we find that there is a very low probability that there is a MCL violation in a county when there is an event there that same month.




```
Call:
glm(formula = dummy ~ DAMAGE_PROPERTY_NUM + VIOLATION_YEAR, family = binomial,
    data = merged_df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3908  -0.9678   0.4735   0.8586   1.4027

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)         -1.334e+03  3.376e+01 -39.513  < 2e-16 ***
DAMAGE_PROPERTY_NUM  1.018e-09  2.054e-10   4.954 7.26e-07 ***
VIOLATION_YEAR       6.618e-01  1.674e-02  39.529  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 13901  on 10973  degrees of freedom
Residual deviance: 11910  on 10971  degrees of freedom
  (1713 observations deleted due to missingness)
AIC: 11916
```

Figure 1. Model 1 Plot and Output.

The second model found the probability that a violation occurs before or after the most damaging event in that county, using the predictors of property damage amount, violation year, amount of facilities at PWS and amount of site visits during violation year. From the second regression model, we find that there is a high likelihood that a MCL violation occurs after the most damaging weather event in that county. These two regression models are contradictory and led to more research.




```
predicted.classes
 after event before event
        8375         2599
>
```

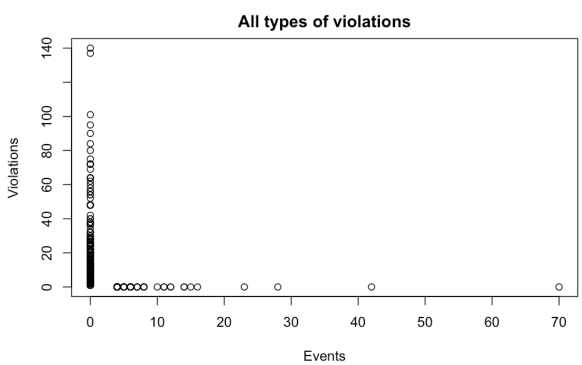
Figure 2. Model 2 Histogram and Predictions.

In particular, the research changed its focus to where the PWSs get their water intake from and figuring out if weather events over the intake source have a large effect on the amount of water quality violations.

V. Statistical Analysis - Watershed-Based Analysis

After analyzing on a county-level and receiving mixed results, the research moved to address the question of HUC-based analysis instead of county-based analysis. In this method, the HUC, or hydrologic unit code, is used to compare weather events by watershed and public water systems by intake site. I used HUC codes at the Watershed 5th Level, which means that the watershed typically is from 40 to 250K acres or 62 to 390 mi² (West Virginia Dept. of Environment). To conduct the analysis, two more logistic regression models were made.

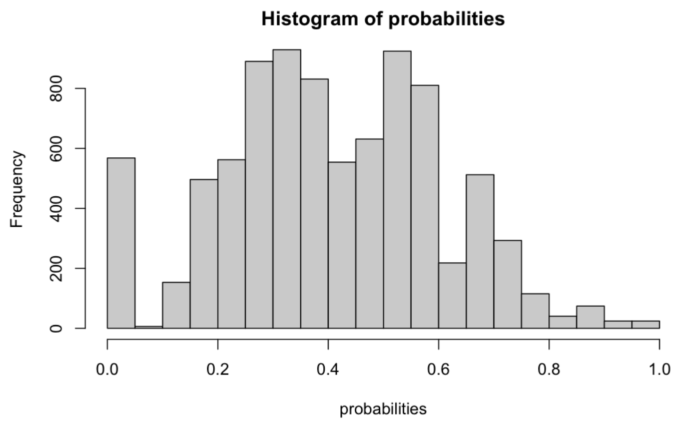
The first model aggregated data by violations per month per HUC to find the probability that there is a violation given that there is an event in the HUC where the PWS intakes its water from. From this regression model, we find that there is no chance that there is a MCL violation in a HUC when there is an event there that same month. In fact, the algorithm did not converge and if we inspect the plot, it is clear that in months with no event in the HUC, almost all of the violations occurred. A few events occurred in the same months as violations, but not enough to fit an algorithm or to discuss these cases as any more than outliers.




```
Warning: glm.fit: algorithm did not converge
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Call:
glm(formula = Vio.dum ~ Events, family = binomial, data = count_df)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-9.024e-06   3.121e-06   3.121e-06   3.121e-06   3.121e-06

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    26.05    9047.38   0.003    0.998
Events        -12.49    3733.49  -0.003    0.997

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 7.0952e+02  on 1034  degrees of freedom
Residual deviance: 1.4201e-08  on 1033  degrees of freedom
AIC: 4

Number of Fisher Scoring iterations: 25
```

Figure 3. Model 1 of Logistic Regression on HUCs.

The second model found the probability that a violation occurs before or after the most damaging event in the intake HUC of the public water system, using the predictors of property damage amount, violation year, amount of facilities at PWS and an interaction between population/damage amount. From the second regression model, we find that there is almost an equal likelihood that a MCL violation occurs before or after the most damaging weather event in that county. In fact, our prediction algorithm found that 64.9% of the violations would have occurred before the event, which is the opposite of what we found when we did this same analysis on the county level.




```
Call:
glm(formula = dummy ~ DAMAGE_PROPERTY_NUM + VIOLATION_YEAR +
    POPULATION + Number.of.Facilities + DAMAGE_PROPERTY_NUM:POPULATION,
    family = binomial, data = merged_df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5054  -0.9616  -0.8339   1.1361   1.6134

Coefficients:
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -6.432e+02  3.116e+01 -20.644   <2e-16 ***
DAMAGE_PROPERTY_NUM           -1.473e-09  1.297e-10 -11.353   <2e-16 ***
VIOLATION_YEAR                 3.188e-01  1.545e-02  20.639   <2e-16 ***
POPULATION                    -1.442e-08  2.900e-07  -0.050    0.960
Number.of.Facilities           4.003e-04  8.649e-04   0.463    0.643
DAMAGE_PROPERTY_NUM:POPULATION -3.776e-15  7.395e-15  -0.511    0.610
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 11693  on 8653  degrees of freedom
Residual deviance: 10683  on 8648  degrees of freedom
AIC: 10695

Number of Fisher Scoring iterations: 7
```

```
predicted.classes
 after event before event
        3034         5620
```

Figure 4. Model 2 of Logistic Regression on HUCs

VI. Discussion

My results suggest that while there may be a relationship between extreme weather events in a county and an increase in MCL violations, there is likely no relationship between extreme weather events in a watershed and an increase in MCL violations. This is an unexpected result. I expected to find that extreme weather events had a large effect on both the watershed that a public water system intakes from and the county where the public water system is located. Instead, I found that there is a high probability that an MCL violation will occur after an extreme weather event in the county where the PWS is located, but not after an extreme weather event in the watershed where the PWS intakes from.

There are a few reasons why this might be the case. One might be that extreme weather events with significant amounts of damage in a county might also damage the facilities of the public water system itself. Another might be that extreme weather events can possibly cause rain or debris to get into the water supply, either at the facility or in exposed pipes that might have broken during a storm or flood event. These would all be situations in which an extreme event would affect a county and the location of the PWS but would not affect the intake from the watershed. Another possibility might be that water is filtered when it is taken into the PWS from a watershed, so any possible violations might not come from the water intake itself but from external sources.

This begs the question of infrastructure and repairs for public water systems. For infrastructure that is already patchwork and underfunded, resilience measures are not always a high priority. This research suggests that the administrators of public water systems should verify their infrastructure is resilient to storms and that any kind of water-related event has no ability to penetrate the water supply from outside.

VII. Appendix & Figures

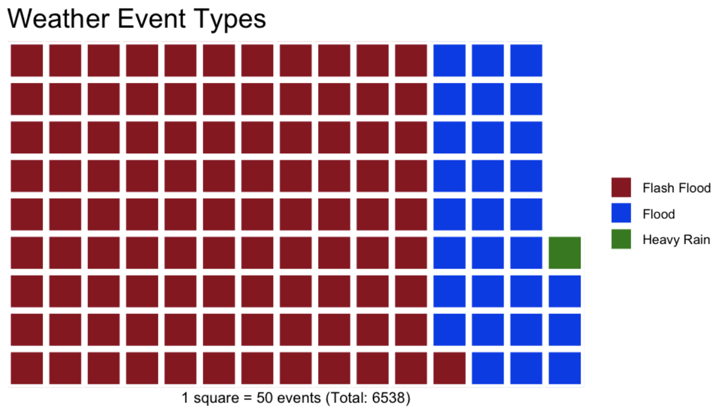


Figure 5. Waffle Plot of Types of Weather Events with Property Damage ≥ $1 million, showing that the events with this much damage are mainly flash floods, floods, or heavy rain. Importantly, hurricanes are not shown because there were not 50 events in this time period.

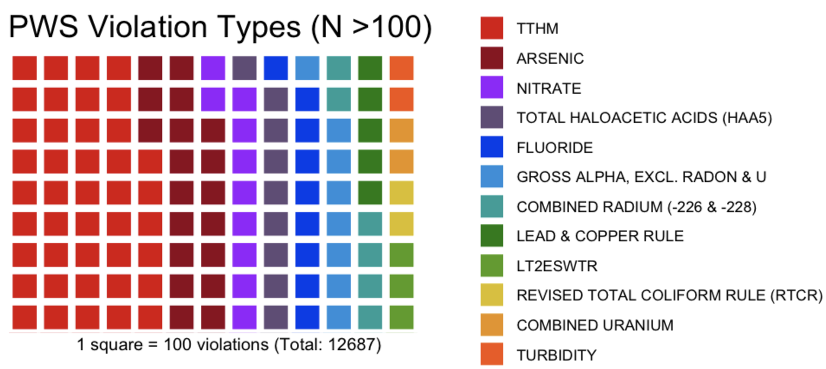


Figure 6. Waffle Plot of Public Water System Violations, showing the different types of violations and how many occur in Texas.

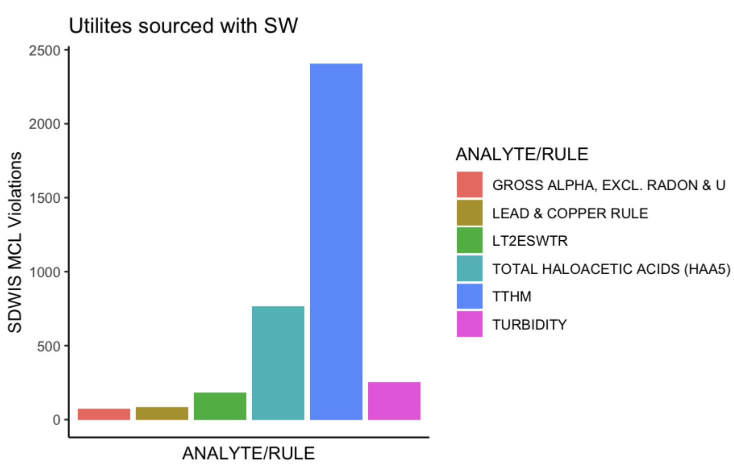


Figure 7. Bar chart of the Maximum-Contaminant Levels Violations of Utilities that are sourced with Surface Water.

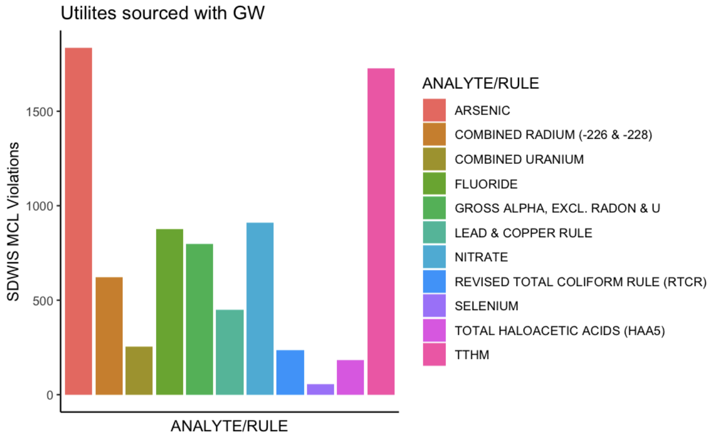


Figure 8. Bar chart of the Maximum-Contaminant Levels Violations of Utilities that are sourced with Groundwater.

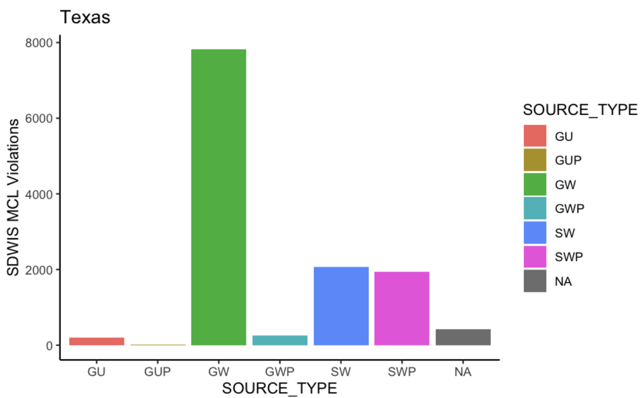


Figure 9. Bar chart of the Total Maximum-Contaminant Levels Violations, split by Water Source, in Texas.

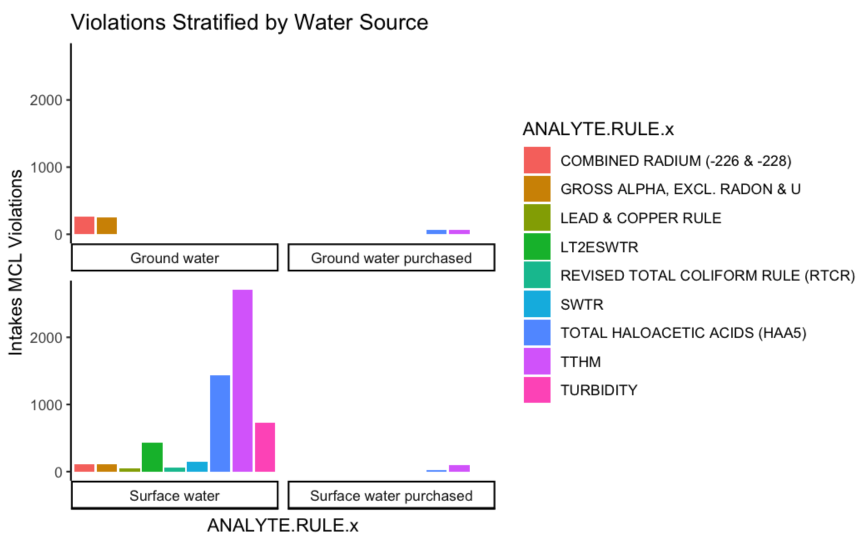


Figure 10. MCL Violations Stratified by Water Source.

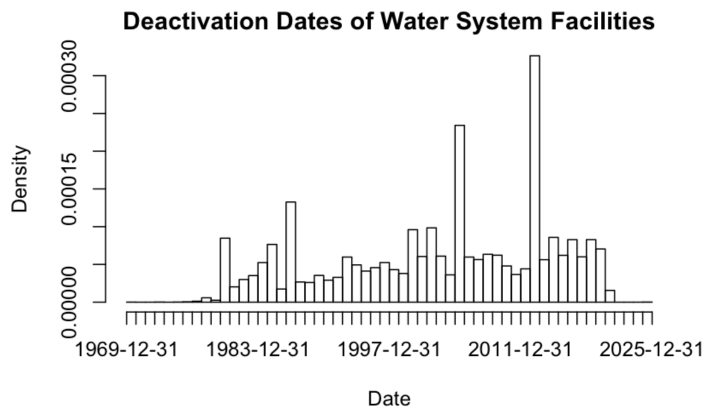


Figure 11. Deactivation Dates of Water System Facilities.

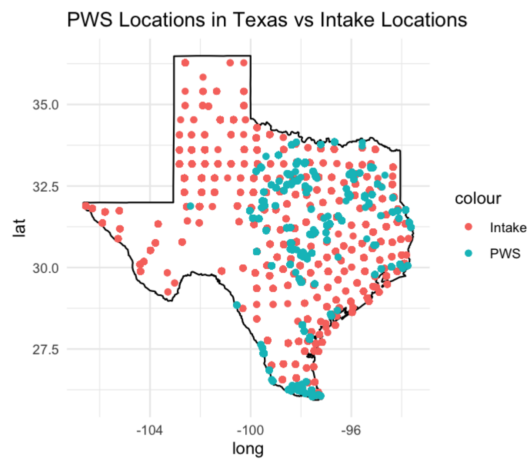


Figure 12. Public Water System Locations In Texas, Compared to Intake Locations, Keeping the Intakes with an Unidentified Source In The Map

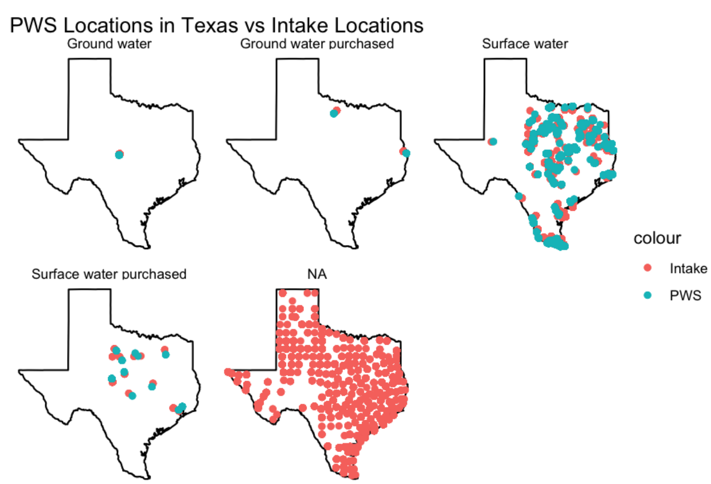


Figure 13. Public Water System Locations In Texas, Compared to Intake Locations and Stratified by Water Type

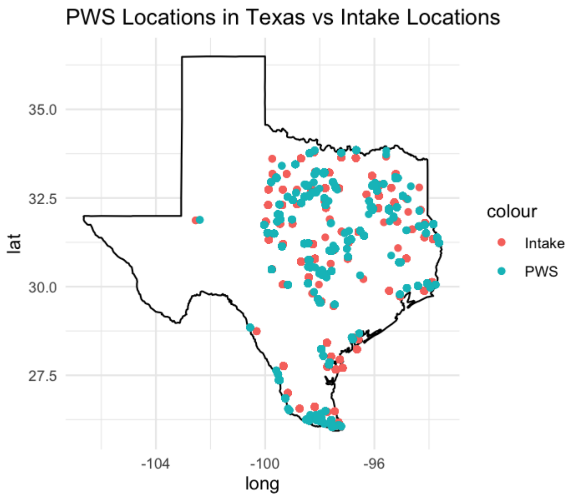


Figure 14. Public Water System Locations In Texas, Compared to Intake Locations with Intakes with Unknown Water Sources Removed

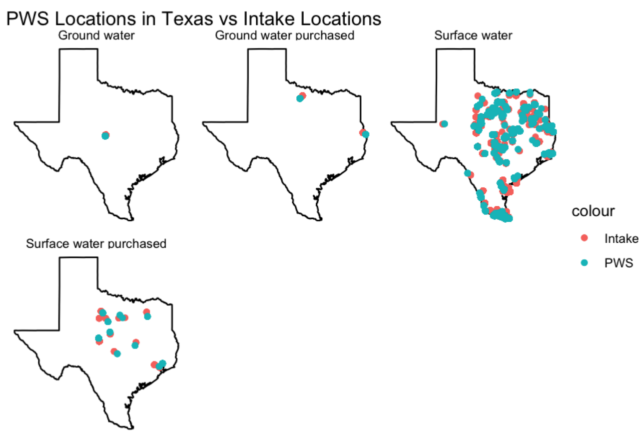


Figure 15. Public Water System Locations In Texas, Compared to Intake Locations and Stratified by Water Sources, with Intakes with Unknown Water Sources Removed

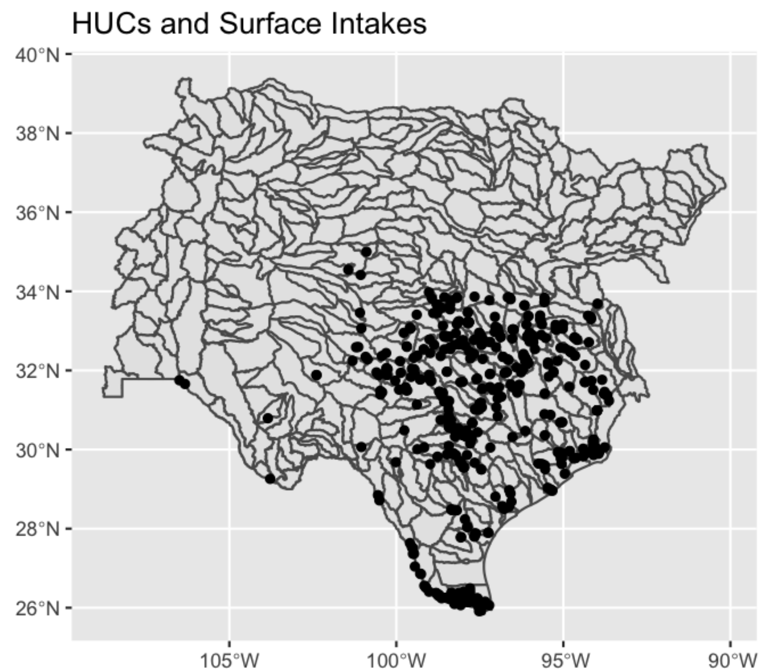


Figure 16. Map of HUCS and Surface Intakes in Texas

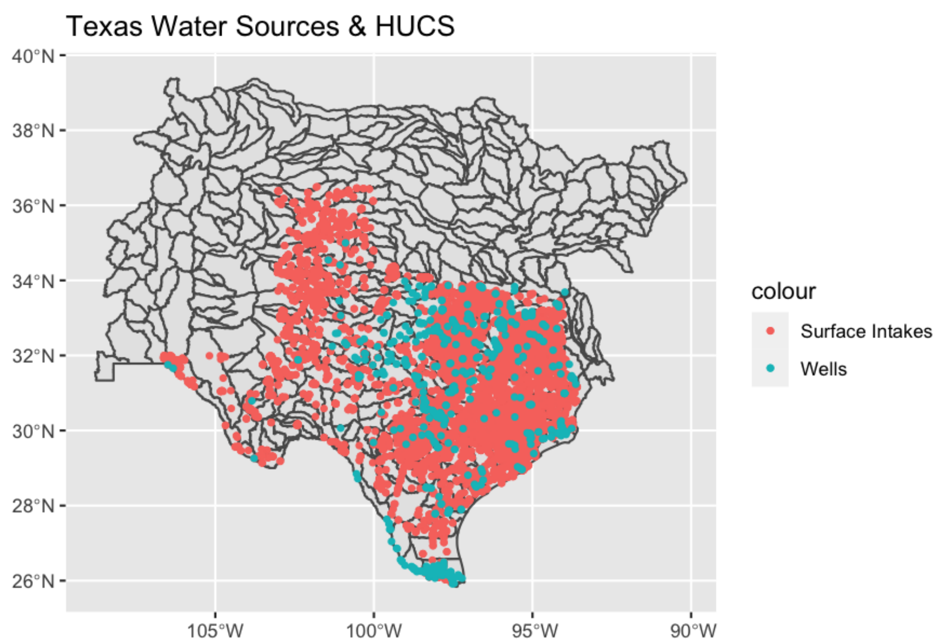


Figure 17. Map of HUCS, Wells and Surface Intakes in Texas

VIII. References

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