Power Outage Duration in Louisiana by Customer Endpoint and Environmental Conditions

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ABSTRACT
Power outages across the United States are increasing in frequency and duration, raising concern about the resilience of critical infrastructure and the operational stability of regional energy systems. Prior work emphasizes system level reliability and severe weather, with limited insight into how local conditions shape outage duration at the distribution edge. This study identifies key associations of annual power outage duration in Louisiana, operationalized as a household level analog of the System Average Duration Index (h-SAIDI). Event correlated outage records, severe weather reports, and parish-scale indicators were integrated for 63 parishes across five biennial intervals (2014-2022). A Gamma generalized linear model with a log link was used to estimate associations, complemented by spatial and distributional analyses. Results indicated that outage duration reflects the interplay of severe weather factors, customer endpoint conditions, and underlying distribution network and restoration dynamics. Parishes with higher mobile home prevalence and severe weather damage exhibited longer annual outage duration. In contrast, unemployment and lack of vehicle access showed negative associations, consistent with the concentration in urbanized service territories characterized by shorter spans and greater switching options. These findings support targeted local resilience strategies across diverse service territories.

KEYWORDS
Power Outage Duration; Grid Resilience; Energy System Reliability, Severe Weather Events; Customer Endpoint Conditions; Household Infrastructure; Parish-level Analysis; Gamma Regression

INTRODUCTION

Power outages are a persistent and costly challenge across the U.S., prompting growing concern over the resilience of energy systems and the reliability of critical infrastructure.[1,2] Secure, reliable grid operations are essential to limiting disruption, economic loss, and human hardship.[1,3,4] Prolonged outages intensify social hardship by disrupting essential services for extended periods.[5] For example, extended power loss can halt refrigeration, disable medical equipment, and interrupt communication and water systems.[6] Although prolonged outages cannot be entirely avoided, characterizing their distributional patterns and correlates can inform strategies that reduce their consequences and improve resilience.[7,8]

Louisiana consistently records some of the nation's longest outage durations.[9,10] Between 2013 and 2023, the average duration rose 76.4 percent, increasing from 5.5 to 9.7 hours, with the sharpest increase occurring between 2019 and 2020.[10] Prolonged outages are frequently associated with severe weather,[11,12] and the state's electric grid ranks among the least reliable nationally.[11,13] Although Louisiana Public Service Commission (LPSC) regulates utilities statewide,[14] service territories and ownership models vary by parish, producing a patchwork of operators, regulators, and service providers that add operational complexity to the restoration process. The institutional and network heterogeneity, coupled with rising demand,[13] highlight that statewide and utility level metrics do not fully account for how long outages last in specific communities. Parish level evidence on the correlates of outage duration remains limited in the public record, even though parishes exercise meaningful authorities over customer end point electrical codes.[15] The controlled load shed on April 26, 2025 in northwest Louisiana[16] illustrates the value of finer grained outage report documentation and accounting, since restoration timelines were reported at a regional scale without local-specific duration detail.[6]

Prior research on power outages has largely emphasized system-level reliability metrics or utility-wide restoration timelines, often linking outages to broad measures of weather severity. Many studies attribute the majority of outages, often 75% or more, to severe weather events,[17–20] and examine grid level reliability under these stressors.[21–23] Such studies have provided valuable insight into transmission line failures, distribution network resilience, and blackout mitigation.[18,22,24] However, they also tend to treat outages as binary outcomes or rely on national or state averages, masking local variation in the duration. County and parish level studies that do exist often emphasize weather[3] or broad social vulnerability indicators,[5] rather than grid interpretable conditions at the customer endpoint.

This study addresses that gap by examining parish level associations with annual outage duration per household in Louisiana, expressed as a household level variant of the System Average Duration Index (h-SAIDI). Two weather measures were analyzed, severe weather damage and the frequency of events, to capture heterogeneity in local manifestation. To center analysis on the service interface of the distribution grid, three customer endpoint indicators were included for operational salience. The prevalence of mobile homes was used to operationalize household configuration and dispersed siting along radial laterals in rural areas. Mobile homes are the second most common housing structure and the proportion in Louisiana is over twice that of any other state.[25]. Mobile and manufactured homes may contain equipment not designed to withstand severe weather,[26] which could prolong outages. In addition, terrain challenges in rural areas can delay restoration with poles set in marshes and exposure of infrastructure to dense vegetation.[10] Lack of vehicle access captures physical mobility that may limit the ability to obtain alternate resources, maintain communications, or receive emergency services during extended outages.[27] Unemployment serves as a contextual indicator of daytime occupancy and potential patterns in electricity demand or outage reporting,[28] which could indirectly align with outage durations. This is pertinent as Louisiana residential customers use 46.3% more electricity than the average U.S. customer, and most electricity is used in air conditioning (36%), water heating (16%), and space heating (12%).[11] Using five years of outage data, normalized by the number of households, and matched with event-based weather records, the analysis identifies patterns of outage duration that cannot be explained by weather and grid alone.

The rest of the paper is summarized as follows. The next section outlines the data sources, variables, and statistical modelling techniques used to examine parish-level outage duration variation in Louisiana. The results section then summarizes parish level associations for severe weather damage and event frequency, and the three customer endpoint indicators. The discussion interprets the findings in the context of Louisiana service territories and ongoing resilience initiatives. The final section concludes the study with implications for future research.

METHODS

Data and variable construction

Power outage data was collected from the Event-correlated Outage Dataset In America, located at located at *https://catalog.data.gov/dataset/event-correlated-outage-dataset-in-america*. The dataset was published by Pacific Northwest National Laboratory (PNNL) and derived from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) Recorded Electricity Outages, located at *https://doi.org/10.6084/m9.figshare.24237376*. The EAGLE-I platform, maintained by Oak Ridge National Laboratory (ORNL), was developed to provide real-time outage information for emergency response, particularly for Department of Energy (DOE) and other government emergency responders.[29] Although not initially intended for retrospective data analysis, the archived EAGLE-I data have since been curated to support post hoc research into power outages and related topics.[30,31] Catahoula Parish was present in the EAGLE-I data, indicating that outages were recorded, however, no corresponding events were included in the merged dataset by PNNL. This suggests that either the recorded outages did not meet thresholds required for event classification or were excluded during event level aggregation. Catahoula was therefore excluded from analysis to preserve data integrity due to the absence of qualifying outage events.

The PNNL merged dataset organizes continuous outage reports into discrete events using thresholds for duration and customer count. Each outage event record includes a start time, duration (in hours), summary statistics describing the number of customers without power (min, max, and mean customers). For each parish-year, the customer outage hours were computed as the product of the outage duration (in hours) for each event and the mean number of customers affected. These values were then summed across all events for the parish year and divided by the total number of households in that parish, resulting in an annual estimate of outage duration per household. This metric is conceptually similar to the System Average Interruption Duration Index (SAIDI), a standard reliability indicator in distributed power systems.[32] According to IEEE Standard 1366, SAIDI represents the average total duration of sustained interruptions experienced per customer over a specified period, calculated as the sum of all customer interruption durations divided by the total number of customers served.[32] Although the IEEE standard differentiates between 'interruption' and 'outage', the term 'outage' is used in this work to remain consistent with the EAGLE-I source dataset, which reports power loss in terms of 'customers out'.[29] In this study, a household-level SAIDI analog was constructed by summing the customer outage hours per parish-year and dividing by the number of households. Given that the majority of customers in Louisiana are residential (87%),[11] and that a 'customer' generally corresponds to a metered household account,[32] dividing by the number of households results an interpretable measure of annual outage duration per household.

Weather event data was collected from the National Centers for Environmental Information (NOAA) Storm Events Database, located at *https://www.ncdc.noaa.gov/stormevents/*, for the same years and locations as the outage data. The database contains significant weather events from January 1950 to April 2025 with enough intensity to cause disruption to commerce, property damage, injury, or loss of life.[33,34] Of the forty-eight possible event types, the Louisiana data contained eight (flash flood, flood, heat, lightning, strong wind, storm surge, and tornado), all associated with power outages in current research[1,12] and Louisiana state level reports.[11] Two variables were derived, the number of severe weather events per parish-year (count), and the total monetary damage (in billions USD), representing event severity. The weather damage variable was scaled in billions to improve interpretability and ensure numerical stability across predictors. This dual representation recognizes that some significant weather events exist without documented damage, and others are associated with unequal levels of damage.

These customer endpoint indicators were derived from the CDC/ATSDR Social Vulnerability Index,[35] which aggregates census-based metrics to assess resilience from disasters. The SVI has recently been used in correlation with power outage data[5,12,36,37] and is recommended for use with EAGLE-I archival data to investigate new outage associations. [38,39] The SVI captures preparedness and evacuation vulnerabilities, such as a lack of transportation or inflexible work schedules, which can hinder disaster preparation and response.[27] The years 2014, 2016, 2018, 2020, and 2022 were selected for analysis due to availability of complete parish-level data when merged with the NOAA and PNNL datasets.[35] Initially, apartment housing (number of units in buildings with 20 or more dwellings) was considered due to its potential to influence grid load concentration and restoration dynamics. However, this variable was excluded from the final model due to high correlation with other structural indicators and low feature importance, discussed in the next section.

The final dataset contained 310 observations for 63 parishes in the state of Louisiana across 5 years. The data was quantitative in nature except for the Parish name and year, which was qualitative. The outcome variable was annual outage hours per household (h-SAIDI), defined as the total number of customer outage-hours per year divided by the number of households in that parish. The covariates included severe weather damage, number of severe weather events, mobile home and unemployment prevalence, and lack of vehicle access. A summary of variable definitions and ranges is provided in **Table 1**.

Variable name	Definition and operationalization	Range and units
Annual outage duration per household (h-SAIDI)	Outcome variable; the total number of customer hours without power within a parish for that year (parish-year) divided by total number of households	0-672.150 (hours/household)
Severe weather damage	Sum of property damage from outage-related severe weather events, per parish-year	0-7.0, in billions USD (nominal)
Number of severe weather events	A count of severe weather events per parish-year (all available for Louisiana: flash flood, flood, heat, hurricane, lightning, strong wind, storm surge, and tornado) per parish-year	0-40, events/year (integer count)
Mobile homes	Number of mobile home units in a parish-year divided by the total households in the parish-year	0.005-0.732 (units/household)
Unemployed	Number of unemployed individuals (civilians age 16+) divided by the total number of households in the parish-year	0.008-0.105 (persons/household)
No vehicle access	Proportion of households without vehicle access in the parish-year	0.009-0.415 (proportion, 0-1)

Table 1. Operationalization of variables.

Data visualization

Prior to statistical modeling, patterns in the outcome variable were examined to better understand temporal. **Figure 1** shows parish level patterns in mean versus median annual outage duration (h-SAIDI), highlighting important differences in outage profiles across the state.

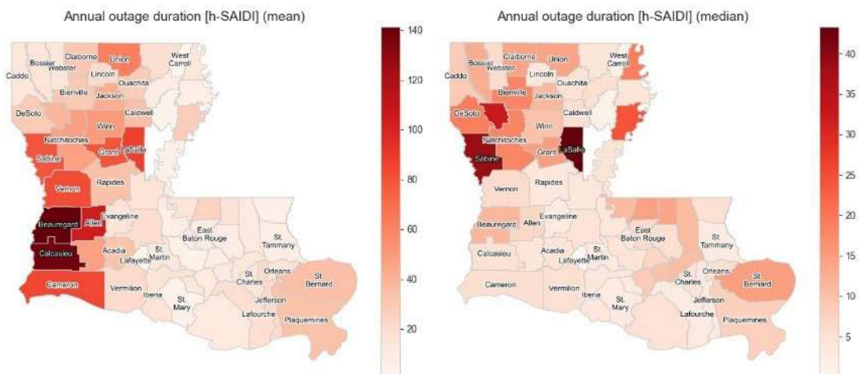

Figure 1. Mean (left) and median (right) annual outage duration per household (h-SAIDI) by parish.

In **Figure 1**, darker shading indicates higher values. Large mean-median gaps illuminate parishes where annual outage durations are driven by infrequent extreme events, whereas high values in both metrics indicate consistently prolonged outages across the year. Parishes such as Cameron, Allen, Calcasieu, Beauregard, and Vernon exhibit exceptionally large percentage gaps, indicating that infrequent but severe outage events dominate annual totals despite most outages being much shorter. In contrast, parishes with both high mean and median values, including LaSalle, Natchitoches, and Sabine, point to persistent reliability issues in which extended outages are common rather than exceptional. Quantifying these disparities helps distinguish areas where resilience strategies should focus on mitigating rare high impact events from those requiring systemic reliability improvements to reduce consistently long interruptions.

Building on the multi-year means and medians in **Figure 1**, the ten parishes with the highest mean values were further examined. **Figure 2** plots mean, median, and maximum annual outage hours per household (h-SAIDI) for the top ten parishes by maximum value, allowing a view of chronic outage prevalence versus acute spikes.

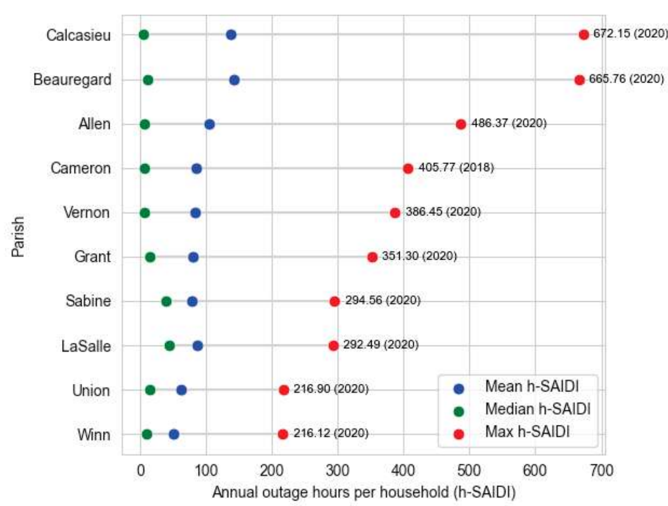

Figure 2. Comparison of mean, median, and maximum annual outage duration (h-SAIDI) for the top ten parishes with the largest single year values.

As seen in **Figure 2**, Central Louisiana parishes experience both acute outage events as well as high median and mean values. The maximum value is Calcasieu, meaning the average household in Calcasieu Parish experienced a total of 672 hours without power in 2020, equivalent to approximately 28 days over the course of a year, aggregated across all events. Structural hotspots appear to be LaSalle, Sabine, Grant, Allen, And Beauregard, where there is an overlap of high mean, median, and max. **Figure 2** also shows that all except one of the extreme outage events occurred in 2020. The surge in 2020 aligns with an unprecedented sequence of severe weather events, including deadly tornadoes and several hurricanes. During the Easter tornado outbreak April 12-13, approximately 140 tornadoes caused 32 fatalities and over 250 injuries across ten states.[40] At least eight tornadoes affected northeast Louisiana on Easter Sunday, with approximately 458 homes damaged and 23 destroyed in Ouachita Parish. On August 27, Hurricane Laura made landfall in Cameron Parish as a Category 4 hurricane.[41] Hurricane Delta compounded the damage of Laura, followed by Zeta in southeastern Louisiana.[42] The cumulative impact of these disasters led to extensive grid disruption and prolonged power outages.

To further examine this pattern, a prominence-based peak detection filter (threshold ≥ 0.15) was applied to normalized customer outages in 2020. As shown in **Figure 3**, the most pronounced spikes occur in parishes such as Allen, Beauregard, and Calcasieu, reinforcing the severity of storm related disruption.

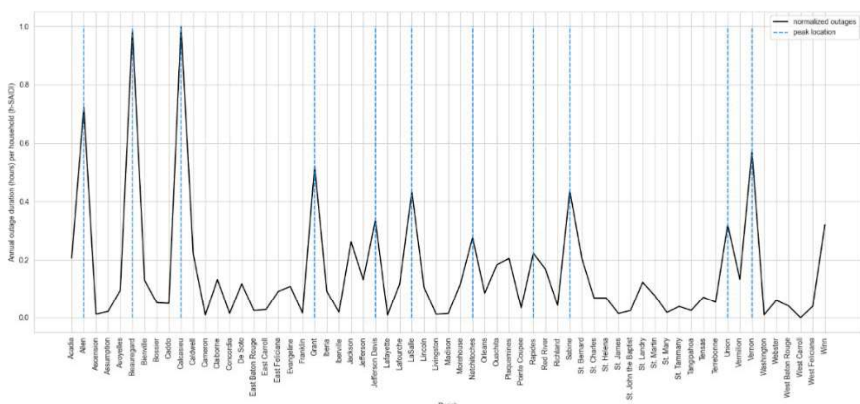

Figure 3. Customer outages per year with prominence filter = 0.1.

Interestingly, not all high-exposure areas exhibited elevated outage severity. As shown in **Figure 4**, Bossier Parish experienced the highest number of severe weather events in 2020 but reported few outages and minimal damage. This contrast suggests that outage duration reflects not only reflects severe weather damage or event frequency, but also by underlying system conditions and recovery capacity.

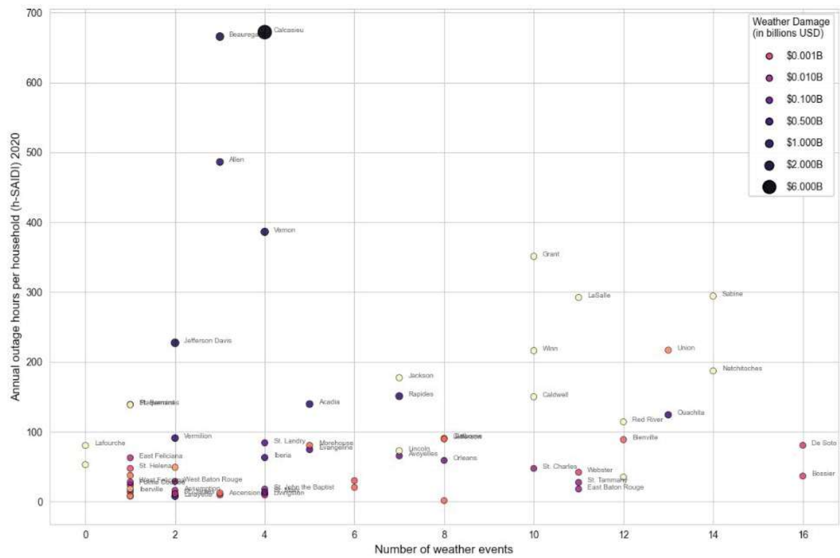

Figure 4. Annual outage hours per household vs number of weather events in 2020 (colored by damage).

Dimension reduction and descriptive statistics

All analyses were conducted in Python 3.12 using scikit-learn and `statsmodels` libraries unless otherwise specified. A Lasso regression regularization technique with standardized values was used to reduce dimensionality by identifying redundant or irrelevant features. This technique aligns well with linear regression models and penalizes less informative variables. The resulting feature weights ranked from highest to lowest were: weather damage (42.067), mobile homes (11.865), unemployed (-8.538), no vehicle (-7.898), number of weather events (7.773), and apartment (-3.415). Weather damage and mobile homes emerged as dominant linear features, while unemployed and no vehicle access were negatively associated with power outage burden. For robustness, a random forest regressor was used to compute permutation-based feature importances. As shown in **Figure 5**, the random forest confirmed weather damage as the most influential feature across both linear and nonlinear models, and suggested that the influence of mobile home prevalence was more linear than nonlinear in nature.

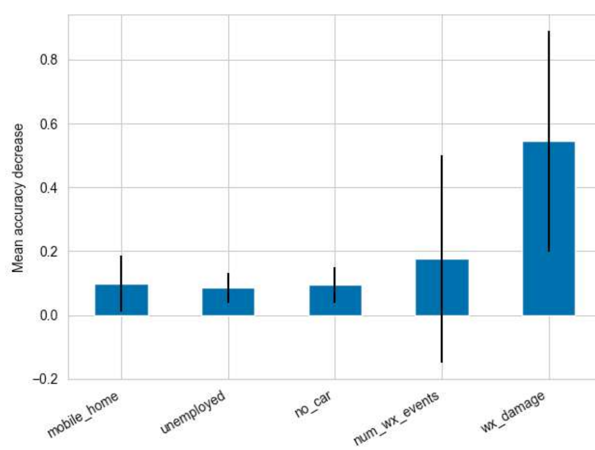

Figure 5. Permutation feature importances.

Table 2 displays descriptive statistics and Pearson correlation coefficients for the variables, including the dependent variable annual outage duration per household. As expected, the dependent variable showed strong correlation with weather damage, and significant correlations with other predictors. The independent variables were weakly correlated, with the exception of a modest negative association between no vehicle access and the number of weather events. To further evaluate predictor independence, a variance inflation factor (VIF) test was performed. The mean VIF for the model was 1.339, with the highest being 3.702 for the unemployment variable. All VIF values were well below the common threshold of ten, suggesting that multicollinearity was not a concern.[43]

Variables	Mean	Std. Dev.	1	2	3	4	5	6
1 **Annual outage duration per household (h-SAIDI)**	29.453	76.619	1.00					
2 **Mobile home**	0.259	0.126	0.15**	1.00				
3 **Unemployed**	0.037	0.013	-0.15***	-0.09*	1.00			
4 **No vehicle**	0.141	0.120	-0.13**	-0.02	-0.11*	1.00		
5 **Num weather events**	4.784	5.531	0.10*	-0.03	-0.18***	0.05	1.00	
6 **Weather damage**	0.074	0.463	0.53***	-0.08	-0.04	-0.10*	0.01	1.00

Table 2. Descriptive statistics and Pearson correlation coefficients (n = 320). *p < 0.10; **p<0.05; ***p<0.01

The descriptive statistics indicate a right skew in the annual customer outage hours per household, with several parish-years exhibiting extreme values relative to the mean. This distribution reflects the cumulative nature of outage durations and the varying scale of service interruptions across Louisiana parishes over time.

While **Table 2** reports bivariate Pearson correlations, these measures do not account for interrelationships among the variables in the study. Several variables are moderately correlated, and examining them in isolation could obscure or inflate their apparent relationships with the outage duration per household. To address this, a generalized linear model (GLM) with a Gamma distribution and log link was estimated, appropriate for the positive, right-skewed distribution of annual outage duration per household. The GLM quantifies the statistical association of each variable with annual outage duration per household while adjusting for the others, providing partial association estimates that are robust to multicollinearity and more accurately reflect the complexity of the observed patterns.

RESULTS

The GLM was implemented with a Gamma distribution, log link, and heteroskedasticity-consistent (HC3) standard errors using Python version 3.12 and the `statsmodels` package version 0.14.1. Model estimation used iteratively reweighted least squares (IRLS), a standard maximum likelihood estimation technique for GLM that accounts for non-normally distributed outcomes and applies link functions to transform the expected value of the dependent variable. The Gamma-log specification models the logarithm of the expected outcome, enabling multiplicative interpretation of predictor effects while ensuring strictly positive predicted values. This modeling approach complements the correlation analysis by identifying which associations remain statistically significant in a multivariable structure and by estimating their relative magnitudes after adjusting for other variables in the model. **Table 3** presents the estimated coefficients, standard errors, and significance levels for each explanatory variable.

Variables	Coef.	Std. Error	z stat	p value
1 **Intercept**	2.916***	0.462	6.312	0.000
2 **Mobile home**	2.281**	0.851	2.680	0.007
3 **Unemployed**	-19.568*	8.255	-2.239	0.018
4 **No vehicle**	-2.329*	0.901	-2.208	0.010
5 **Num weather events**	0.068**	0.020	3.310	0.001
6 **Weather damage**	1.999***	0.233	9.179	0.000

Table 3. Summary of coefficients and significance levels from the GLM for annual outage duration per household in Louisiana. *p < 0.05; **p<0.01; ***p<0.001

The model achieved a Cox-Snell pseudo R^2 of 0.225, indicating moderate fit. McFadden's pseudo R^2 was 0.032, consistent with conservative fit statistics in Gamma GLMs with high-dispersion outcomes. The Pearson chi-squared statistic of 1070 with 304 degrees of freedom, resulting moderate dispersion with a factor of approximately 3.52. Robust standard errors were used to account for heteroskedasticity. Five high outage parishes (Allen, Orleans, Evangeline, and Jefferson parishes in 2020, Cameron parish in 2018) are largely responsible for the dispersion value. Allen parish in 2020 is the largest outlier, with observed outage hours greater than thirteen times higher than the fitted value. Attempts to fit a more flexible Tweedie GLM resulted in inferior model fit (Pearson chi-square value of 6100, lower log-likelihood), suggesting the Gamma distribution remained the best option for this dataset. Model interpretation thus focused on coefficients and directionality of effects.

As shown in **Table 3**, all predictors were statistically significant at the 0.05 level of significance. Weather damage and prevalence of mobile homes were the strongest predictors, corresponding to multiplicative increases in expected annual outage hours per household of approximately 7.38 times and 9.78 times, respectively. In a Gamma log model, each coefficient in the model represents the natural log of the multiplicative change in the expected value of outages per household for a one unit increase in that predictor, which makes the multiplicative factor e^{β}, therefore $e^{1.999} = 7.38$ and $e^{2.281} = 9.78$. Unemployment rate and proportions of households without vehicles were both negatively associated with outage rates. Each additional extreme weather event corresponded to an approximate 7.0% increase in expected annual outage hours per household ($e^{0.068} – 1$). .

DISCUSSION

Weather damage exhibited the largest positive association with annual outage duration per household (coef. = 1.99, $p < 0.001$), indicating that parishes experiencing greater financial loss from severe weather events also tended to experience longer cumulative outages. The number of severe weather events was also positive but substantially smaller in magnitude (coef. = 0.068, $p = 0.001$). Because coefficients are on the link scale of the Gamma GLM, magnitudes are not comparable across differently scaled covariates; the consistent result is that weather damage is more salient than the frequency of events. **Figure 6** shows the same pattern spatially and reveals a geographic contrast. The year 2020 was selected because it exhibits the largest aggregate weather damage and the widest cross-parish dispersion, maximizing contrast for assessing associations between severe weather and outage durations.

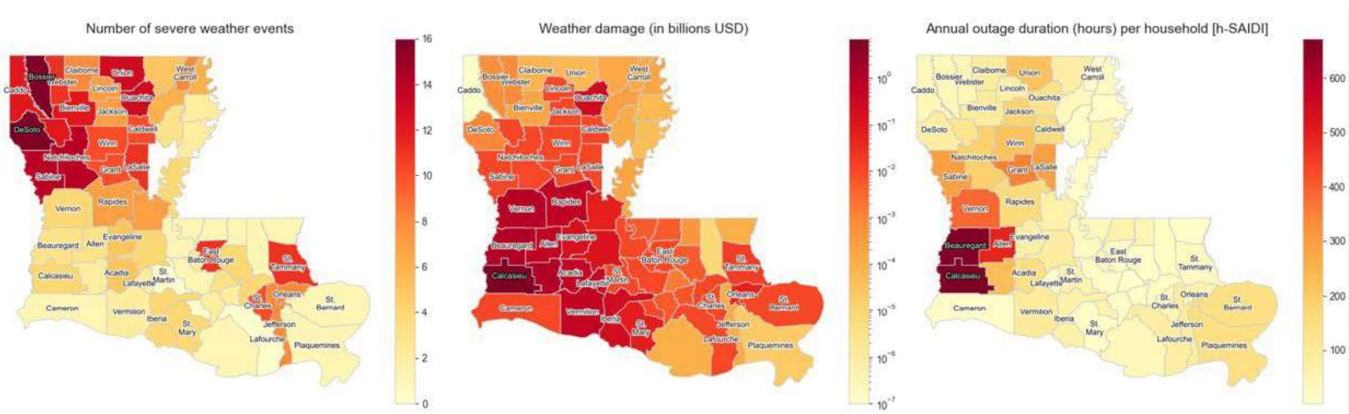

Figure 6. Severe weather factors associated with annual outage duration per household (h-SAIDI), 2020.

In **Figure 6**, high damage areas co-locate with elevated h-SAIDI, whereas high event counts alone do not imply long outages. In the northwest, for example, Bossier Parish records many events but comparatively low damage and short outage duration. That geography aligns with institutional anchors and recent resilience activity. For example, Barksdale Air Force Base's energy resilience efforts include reducing energy consumption, addressing waste, upgrading or replacing systems, retrofitting fixtures and controls, and implementing backups and redundancy.[44,45] Louisiana's new Hubs for Energy Resilient Energy Operations (HERO) is seeding additional capabilities (e.g., a deployable battery hub in Bossier City) alongside pilots in Baton Rouge, Lafayette, New Orleans, and elsewhere.[46] In the Baton Rouge-Lafayette corridor, Louisiana State University (LSU)-led efforts on resilience further situate those metros as nodes of planning and restoration capacity, which is consistent with locales in **Figure 6** that show damage but relatively modest h-SAIDI.[47]

The prevalence of mobile homes was the second largest positive association with annual outage duration in the model (coef. = 2.281, $p = 0.007$). Concentrations of mobile homes imply differences in grid service configuration and restoration logistics, including exposed connection points, and vegetation proximity,[10] which can increase the time required to restore power. In addition, mobile homes may not be readily accessible by interstate or public transportation, and clustered in communities, which may increase the number of households experiencing and reporting outages.[48] **Figure 7** shows an overlay of mobile home prevalence with the contemporaneous outage hours per household (h-SAIDI). The year 2020 is retained for temporal correspondence with **Figure 6**, since mobile home prevalence varies little across years, and parish means and medians show a similar pattern.

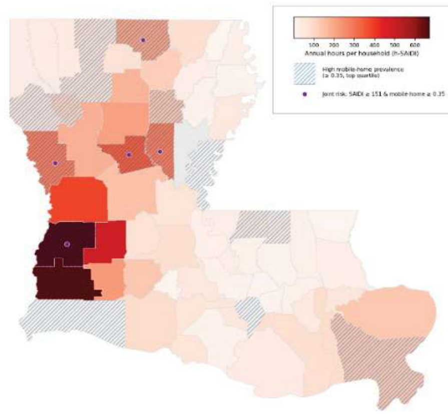

Figure 7. Annual outage duration (h-SAIDI) and mobile home prevalence in Louisiana parishes, 2020.

Figure 7 shows a clear concentration of higher annual outage hours per household in a west-central and southwest corridor, including Calcasieu, Cameron, Beauregard, Allen, and Vernon, with adjacent parishes also elevated. The striped overlay marks parishes in the upper quartile of mobile-home share, and the purple markers identify those in which both outage duration is high and mobile home share meets the threshold indicated in the legend. Jointly elevated parishes form a defensible priority set for reliability improvements and response and restoration investments. These could include hardening feeder lines, sectionalizing and switching, vegetation management, subsidizing repairs and mobile home upgrades and assisting communities with resources such as generators.[49]

The negative association of unemployment with annual outage duration (coef. = -19.56, p = 0.018) was unexpected. One possible explanation is that it is attributable to network design and restoration logistics rather than household occupancy. Five year median maps show higher unemployment concentrated along the Interstate-10 and Mississippi corridor and adjacent urbanized parishes where more dense service areas exist (**Figure 8**). Restoration may proceed faster where distribution feeders are shorter, redundancy is greater, and repairs restore service to more customers per action.[5,50] Rural cooperative territories, by contrast, rely on long radial systems through difficult terrain, and comparable work restores fewer households and prolongs duration.

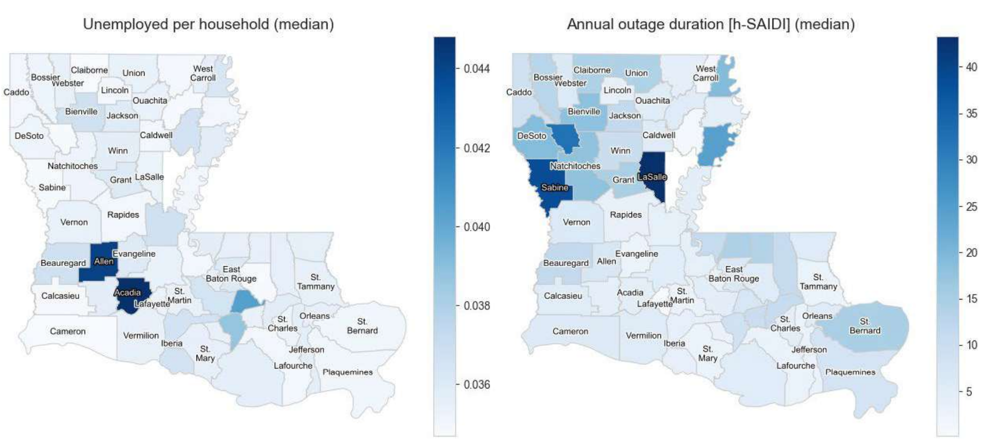

Figure 8. Five year median comparison of unemployed and annual outage duration per parish.

Two descriptive checks support this interpretation. First, a cross-sectional plot of parish medians shows a weak negative correlation between unemployment and the annual outage duration per household (**Figure 9a**; r = -0.11). Second, stratifying by utility company class[51] and comparing with a Mann-Whitney U test shows substantially higher median annual outage hours in cooperative territories than those that are investor owned (**Figure 9b**).

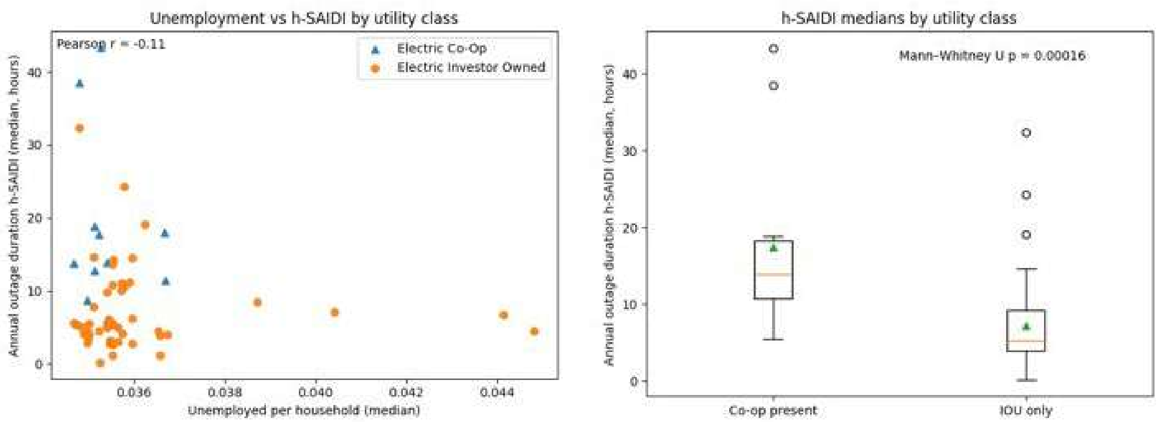

Figure 9. (a) Cross-sectional correlation of unemployment vs h-SAIDI (medians), coded by utility class; (b) Annual outage duration (h-SAIDI) medians by utility class.

For further testing, the unemployed variable was decomposed into a between-parish component and a within-parish component (annual deviation from the median). The within-parish plot of Δunemployed and Δh-SAIDI and a locally weighted scatterplot (LOWESS) smoothing function[52] (**Figure 10a**) exhibits only a shallow downward trend. Stratifying by weather damage tertiles produces similarly weak gradients (**Figure 10b**). Taken together, the checks suggests that unemployment functions as a contextual proxy for utility operational network characteristics rather than household daytime occupancy.

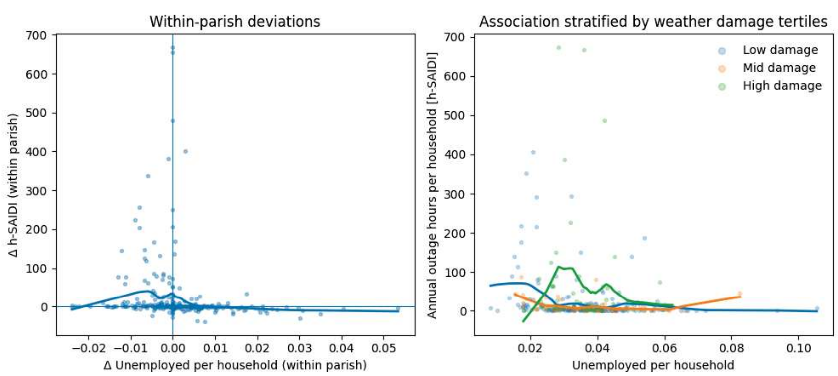

Figure 10. (a) Within parish deviations after subtracting the mean (2014-2022); (b) Stratified association by weather damage.

Similarly, the results showed negative association with lack of vehicle access (coef. = -2.32, $p = 0.010$). This could also be explained by concentrations of carless households in urban areas[48] where grid topology and operations favor faster restoration. A violin plot of medians with 95% bootstrap percentile confidence intervals (B=3000 resamples) shows a marked increase in the proportion of households without a vehicle in 2022 (**Figure 11**).

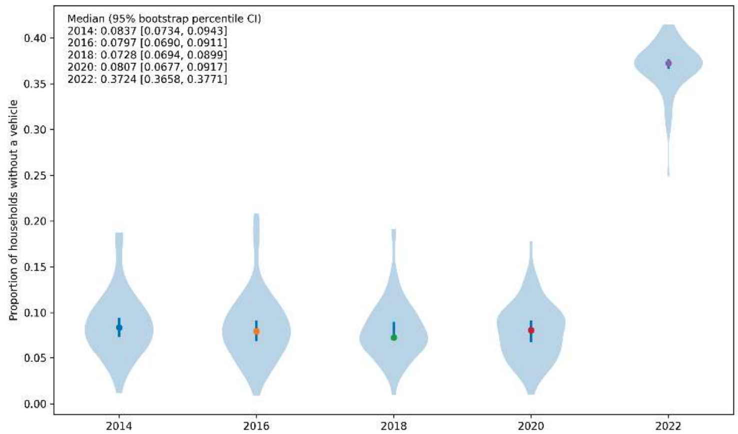

Figure 11. Violin plot by year with medians and 95% bootstrap percentile confidence intervals.

The medians of the parish distributions in **Figure 11** for 2014-2022 were 0.0837, 0.0797, 0.0728, and 0.0807, and 0.03724, respectively. Across years, distributions differ significantly by a Kruskal-Wallis H test (H=151.12, *df*=4, *n*=310, $p = 1.17 \times 10^{-31}$) with a large effect size $\varepsilon^2 = 0.482$.[53] The 2022 median is 0.0373 [0.365, 0.377], whereas 2014-2020 medians cluster near 0.08, indicating a substantial left shift in the cross section. The apparent 2022 divergence may reflect compounding factors between 2020 and 2022, including pandemic-era economic dislocation, changes in household composition, and recovery dynamics following the severe 2021 hurricane season. Weather damage, displacement, and relocation into denser housing, often in urban areas with lower vehicle ownership, could have shifted parish level rates upward. Importantly, this shift does not alter the association with outage duration; rather, it reinforces that no vehicle access likely proxies distribution network density and restoration dynamics, instead of household mobility.

Overall, the results show that severe weather and customer endpoint conditions jointly structure outage duration at local scale. The strongest positive association of severe weather damage with outage duration is consistent with reliability theory, where restoration time reflects actual failure, not a count of events.[54] This explains cases like parishes with many events but low damage that do not experience long durations. The customer endpoint conditions at the household level add explanatory power beyond severe weather. Mobile homes emerge as the second largest correlate, which supports a distribution edge perspective of slower restoration times with longer feeders and slower sectionalized restoration. The negative associations for no vehicle access and unemployment are consistent with spatial concentration of these indicators in urbanized service territories characterized by shorter spans, higher meshing, and switching operations reduce duration.

CONCLUSIONS

This study examined parish-level outage duration per household in Louisiana by integrating event correlated outage records, severe weather measures, and customer endpoint indicators across 63 Louisiana parishes from 2014 to 2022. Outage durations were not uniformly distributed, even among parishes with similar counts of severe weather events, indicating substantive local variation consistent with difference in distribution network characteristics and conditions at the service interface. A Gamma regression model with a log link and robust errors was used to estimate associations, complemented by spatial and distributional summaries and nonparametric checks. Damage from severe weather was identified as the strongest positive correlate of the household level outage duration, while event frequency was not consistently aligned with duration. The prevalence of mobile homes was positively associated with outage duration; unemployment and lack of vehicle access were negatively associated, consistent with the operational advantages of robust distribution networks.[55]

This study findings contribute to ongoing grid resilience efforts by indicating where targeted actions are likely to reduce long durations. High priority areas are those where severe weather damage and mobile home prevalence coincide along long radial feeders; actions include added sectionalizing and reclosers, vegetation management, and conductor and pole upgrades, with selective consideration of microgrids. In regions with high unemployment or limited vehicle access, complementary strategies include pre-positioned backup power sources, walkable access to relief sites, and shared service centers with refrigeration or charging capabilities. Standardized sub-parish outage reporting would improve accounting that supports resilience investment decisions Future work should incorporate operational utility data such as feeder topology, switching and outage management logs, vegetation cycles, and asset age, extend analysis to sub-parish circuits and event level timelines, compare provider classes, and evaluate targeted interventions longitudinally.

DISCLAIMER STATEMENT

The views expressed in this document are those of the authors and do not reflect the official policy of the U.S. Naval Academy, Department of the Navy, the Department of Defense, or the U.S. Government

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PRESS SUMMARY

Power outages are lasting longer and occurring more frequently across the United States, raising concerns about the reliability of regional energy systems. While previous studies have focused on severe weather and overall grid performance, few have examined how customer endpoint conditions shape outage duration at the distribution edge. This study analyzed data from 63 parishes in Louisiana and found that severe weather damage and prevalence of mobile homes were strongly associated with of higher outage duration, whereas unemployment and limited vehicle access showed negative associations. These findings highlight the importance of planning for resilience by accounting for both severe weather and localized customer endpoint conditions.