Analysis of Historical Power Outages of the United States and the National Risk Index

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***Abstract*—Several works have been documented in the literature to study the societal effect of power outages and to analyze their correlation with the Social Vulnerability Index (SVI). However, the relationship between National Risk Index (NRI) and power outages is yet to be explored. This work analyzes the NRI indices such as Risk, Expected Annual Loss, Social Vulnerability, and Community Resilience with several resilience metrics such as event duration, impact duration, recovery duration, impact level, impact rate, recovery rate, recovery to impact ratio, and area under the outage curves to see the correlation of NRI indices with the resilience metrics. The results show that NRI indices such as Risk and Expected Annual Loss increase with the increase of event duration, impact duration, and recovery duration. All Other metrics are indifferent to the change in the Risk and EAL ratings. The results also show that there is no strong relationship between all the metrics and community resilience and social vulnerability. This work also performed the sensitivity analysis of the extreme event selection process. This sensitivity analysis reveals that the way of identifying extreme events has a significant impact on the evaluation of the events.**

***Index Terms*—EAGLE-I, power outage, National Risk Indices, and resilience metrics**

I. Introduction

Extreme weather events have been causing significant disruptions in the power grid system, resulting in widespread power outages and severe infrastructure (e.g., substations, transmission and distribution lines, and generation plants) damage, leading to interruptions in critical services (e.g., health care, transportation, and national security), severe economic losses, and adverse effects on the well being of communities [1]–[4]. Every year, major power outage events result in billions of dollars in losses (25 to 70 billion [5]) to the United States economy. Therefore, analysis of the social, economic, and technical impacts on communities and different regions by extreme weather events is important to strengthen and develop grid resilience while taking the appropriate emergency response. This also aligns with the Department of Energy's (DOE) recent 3.5 Billion dollar announcement for improving the electric grid resilience and reliability against extreme weather events and climate change across the United States as a part of Grid Resilience and Innovation Partnership program [6]. The GRIP projects aim to build community climate resilience by tackling energy reliability and affordability impacted by extreme weather events and climate change.

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To analyze the effect of these major events, the DOE collects power outage data for major power system events [7]. DOE mandates that the utility companies in the United States submit their major power outage information, which DOE publishes in the OE-417 report. Major events are those that cause power outages above 50,000 customers or 300 MW of power demand disruption. Using DOE's major event information, several analyses have been documented in the literature. For example, [8], [9] studied the effect of these events on power delivery in the United States.

In addition to technical analysis of power outages, studying the relations between National Risk Index (NRI) and power outages is important as strong correlations between these two could indicate that counties with higher NRI may also be more prone to longer power outages. Such insights are important for revealing disproportionate burdens and informing policy decisions regarding infrastructure investment, disaster preparedness, and energy policy, ensuring that they address the needs of the most natural hazards prone populations. Some recent works has performed the analysis of power outages and social aspects. For example, work presented in [10] performs socioeconomic vulnerability impact analysis of selected weather-related power outages. The social vulnerability of power outages has been studied in [11]. However, the relationship between the NRI and the power outage is yet to be explored. The NRI covers community resilience and expected annual loss beyond the social vulnerability. Therefore, the relationship between NRI and power outages reveals several aspect of a community and county which may not not be explicitly revealed when considering social vulnerability analysis of the power outages.

In this work, we perform a detailed analysis of power outages and the National Risk Index (NRI) nationwide at county-level resolution. We also performed the sensitivity analysis of the threshold used to identify if a power outage is caused by an extreme event. First, we chooses different percentage of customer impacted as a threshold to identify if an event is caused by an extreme event. Based on the sensitivity analysis of the threshold, we picked a suitable threshold to distinguish the outages caused by the extreme events. Then, we have evaluated the resilience of these outages using the evaluation metrics such as event duration, impact duration, recovery duration, impact level, recovery rate, impact rate, recovery to impact ratio, and area under the curve. Finally, the relationship between these evaluation metrics and the NRI indices such as Risk, Expected annual loss, community resilience, and social vulnerability is examined.

The rest of this paper is presented as follows. Section II provides the overview of the data source and data processing. Section III elucidates power system resilience evaluation metrics and threshold computation. The results and discussion of the proposed work are provided in IV. The paper culminates with section V which provides concluding remarks and insights developed from this work.

II. Data Source and Data Processing

This section provides the source of the data and demonstrates data processing for the proposed work. In this work, we use power outage data from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) platform and NRI data from the Federal Emergency Management system.

A. Power Outage Data: EAGLE-I Data

This work leverages the publicly available power outage data for the United States obtained from the Oak Ridge National Laboratory EAGLE-I platform[1]. EAGLE-I is an interactive geographic information system that allows users to view and map the nation's energy infrastructure and obtain near real-time information updates concerning the electric, petroleum, and natural gas sectors within one visualization platform. The EAGLE-I platform has been collecting county-level power outage datasets based-on voluntary participation from the United States power grid since 2014. EAGLE-I datasets are available for academic research. Because data are more complete from 2018, we use 2018–2022 EAGLE-I data for our analysis. EAGLE-I datasets are collected based on the voluntary participation of utility companies in the United States. The participation of electric utilities has been increasing over the years, making the dataset more reliable and useful. Figure 1 shows the state-wide average coverage ratio. The coverage ratio (ratio between the total number of electric customers who share data to the total number of electric customers) of the EAGLE-I dataset is 0.875.

Figure 2 shows the monthly number of customers affected by power outages (from any cause—weather, operation, cyber, etc.) in the United States from 2018–2022. (Although EAGLE-I started data collection in 2014, data for some states were not available until 2017; therefore, we analyze only the 2018–2022 dataset, complete 2023 data were still not available during this work as well). This figure shows that a maximum number of cumulative power outages occurred in August, followed by September and October. The possible reason for this trend could be that the outages coincide with tropical storms, thunderstorms, and heat waves. This trend could also be the result of more industry demand (as businesses ramp up after summer breaks), pushing the infrastructure capacity limits toward or above the limit boundary.

[1]https://eagle-i.doe.gov/

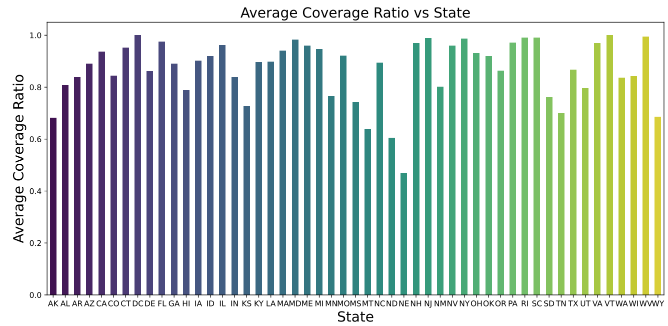

Fig. 1. Average coverage ratio (2018–2022) for different states.

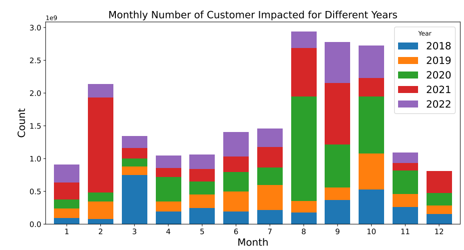

Fig. 2. Number of customers affected by power outages in the United States from 2018–2022 by month.

Figure 3 shows the yearly number of customers affected by power outages in the United States by state from 2018–2022. The figure shows that the maximum number of cumulative power outages occur in Texas, followed by California and Louisiana. A possible explanation for the maximum number of outages in Texas and California could be the significant number of weather events, power grids running near to or above their capacities, and these states being significantly more populous states (more population means more customers could be affected).

Although the number of customers affected by power outages has changed over the years, drawing conclusions with limited data obtained from scraping utility websites would be premature. Therefore, more data will be required to draw a

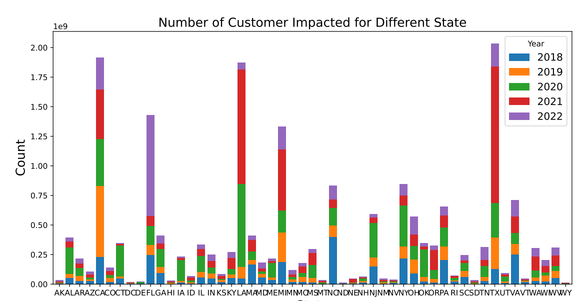

Fig. 3. Number of customers affected by power outages by state from 2018–2022.

concrete conclusion.

B. National Risk Index (NRI) Data

The National Risk Index (NRI) data are obtained from the Federal Emergency Management Agency[2]. A brief overview of the National Risk Index and its relevant terms is provided as follows [12].

a) Risk: Risk has been defined as the probability of an event happening multiplied by the expected consequence if the event happens as shown by Eq. (1). Risk in the NRI has three components: a natural hazard risk component, a consequence-enhancing component, and a consequence reduction component. Expected annual loss (EAL) accounts for the natural hazard risk component.

$$\text{Risk} = \text{Expected Annual Loss} \times \text{Community Risk Factor} \quad (1)$$

$$\text{Community Risk Factor} = f\left(\frac{\text{Social Vulnerability}}{\text{Community Resilience}}\right) \quad (2)$$

b) Expected Annual Loss (EAL): Expected Annual Loss (EAL) is average annual economic loss due to natural hazards each year. EAL is calculated for each type of the hazard for its consequences (e.g. building, population, and/or agriculture) each year. EAL is only calculated for relevant quantity. For example, loss due to draught is relevant for agriculture. For details on calculation of EAL, please refer to [12].

c) Social Vulnerability: NRI leverages the Social Vulnerability Index (SVI) data from the Center for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry (CDC/ATSDR) SVI [13]. The CDC/ATSDR has defined social vulnerability as "Community's ability to prevent human suffering and financial loss in the event of disaster." The main purpose of the SVI is to help communities better prepare before, during, and after hazardous events (extreme weather events, disease outbreaks, and chemical exposure). It provides community-specific and spatially relevant information to health officers and emergency responders.

d) Community Resilience: NRI has adopted the definition of the community resilience from National Institute of Standards and Technology (NIST). NIST defines the community resilience as the ability of a community to prepare for anticipated natural hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions[3]. In National Risk Index, Community Resilience is the consequence reduction risk factor and represents the relative level of community resilience in comparison to all other communities at the same level.

In this work, we have used Risk rating, EAL rating, Social vulnerability rating, and Community resilience rating of NRI for our analysis. These rating range from $0 - 100$.

[2]https://www.fema.gov/flood-maps/products-tools/national-risk-index
[3]https://www.nist.gov/community-resilience

III. Evaluation Method for Power Outages

This section provides overview of power outage evaluation method. Specifically, evaluation metrics for the evaluation of resilience of the power system of the United States is discussed in this section. It also discusses the threshold used to distinguish a certain event as an extreme event.

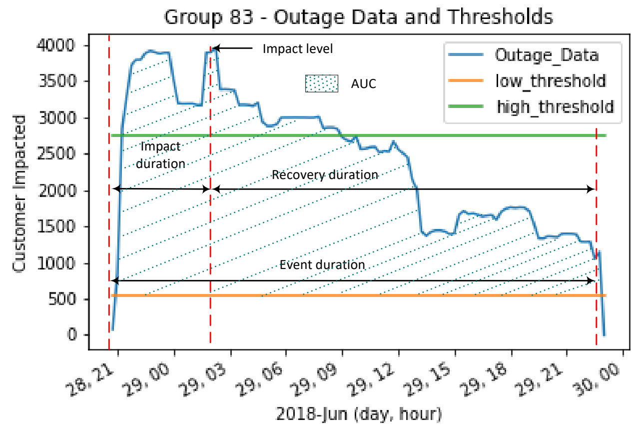

Fig. 4. Power outage curve of an extreme event. Lower threshold is taken as 5% and the higher threshold is taken as 25% in this plot. Please refer to section III-A for details on the evaluation metrics.

A. Evaluation Metrics

Evaluation metrics such as provided by [3] are used for evaluation of the resilience of the power system of the United States. We have also leveraged the area under the curve (AUC) developed in our previous work [14] to account the duration of the power outage and the customer impacted together. Please refer to Fig. 4 to visualize some of these metrics in an outage curve. These metrics are computed only of the extreme events obtained based-on the threshold calculated as described in III-B. Note that all of these metrics are quantified based-on the lower threshold as the baseline customer outage level.

- Event Duration (T_e): Time between the start (based on the lower threshold) and end of an extreme event as shown in Fig. 4.
- Impact Duration (T_i): Time between the start of an event and time when it impacts maximum number of customers as shown in Fig. 4.
- Recovery Duration (T_r): Time between when an even impacts maximum number of customers and end of the event as shown in Fig. 4.
- Impact Level (I_L): Maximum number of customer impacted due to an extreme event as shown in Fig. 4.
- Recovery Rate (R_r): This is the ratio of the Impact level to the Recovery duration.
- Impact Rate (R_i): This is the ratio between the impact level to the impact duration.
- Recovery/Impact Ratio (R_ri): This is the ratio between the recovery duration to the impact duration.
- Area Under the Curve (AUC): Area under the power outage curve, it includes both the number of customers

impact and the duration of the outages due to an extreme event as shown in Fig. 4.

B. Threshold Computation

Before evaluating the resilience of power outages, it is necessary to distinguish if the outage is caused by an extreme event using a certain threshold. This is because generally the power system resilience is considered to account for longer outage duration of widespread nature caused by the extreme events such as hurricane, tornado's, flooding, and cyber-attack. Although clearly not distinguished, this work assumes to considers the power outages cause by extreme weather events. If we do not consider a threshold, there can be many insignificant events which are not worth investigating from the available resource prospective at least at the national scale.

The threshold calculation follows similar procedure as that of [3]. There are two thresholds in this process, the high threshold is to identify if an outage is related to an extreme event and the lower threshold to make a baseline for evaluation metrics calculation. Figure 4 shows these thresholds in a power outage curve.

Similar to [3], we started the threshold computation by taking 25% of total customer outages as the higher threshold to distinguish if an event is an extreme event and 5% of the total customer outages as the lower threshold as a baseline to calculate the evaluation metrics. One of the problems with this way of calculating the threshold is that in some counties (e.g. Harris counties in Texas), it ignores more than $50,000$ customers because the 25% of total customers is more than $50,000$ customers outage in those counties. Note that DOE (OE-416) considers more than $50,000$ customers impact for more than 1 hours as a major event. To incorporate the (OE-416) criteria of $50,000$ customers impact and improve the limitation of [3], we have modified 25% of the customers outage to $50,000$ or 25% as threshold to identify an extreme event. The lower threshold is also modified to 20% of the higher threshold to account for the change in criteria of the high threshold calculation.

The sensitivity analysis of the threshold is necessary to know if the selected threshold is accurately capturing the extreme events. The sensitivity of this way of calculating the threshold is evaluated below.

1) Sensitivity of Threshold: We perform the sensitivity analysis of the high threshold by varying it (a threshold that determines whether an outage is due to an extreme event) from 5% to 25%. The variation of the number of extreme events due to variation of high threshold value is as shown in Fig. 5. Figure 5 shows that the number of event is significantly high when the high threshold is 5% (which is also a low threshold) as compared to 10%, 15%, 20%, or 25%. The change of number of event is not much from $15-25\%$. From Fig. 5, we can say that the threshold value somewhere between $15-20\%$ would be a good balance between not ignoring the resilience events as minor events and not including small event as large events. The average of the metrics obtained by varying the

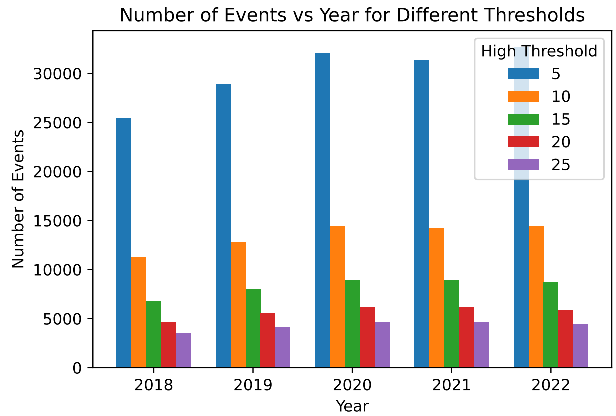

Fig. 5. Number of events in different years varies as higher threshold for event detection ranges from 5% to 25% of total customer impacted.

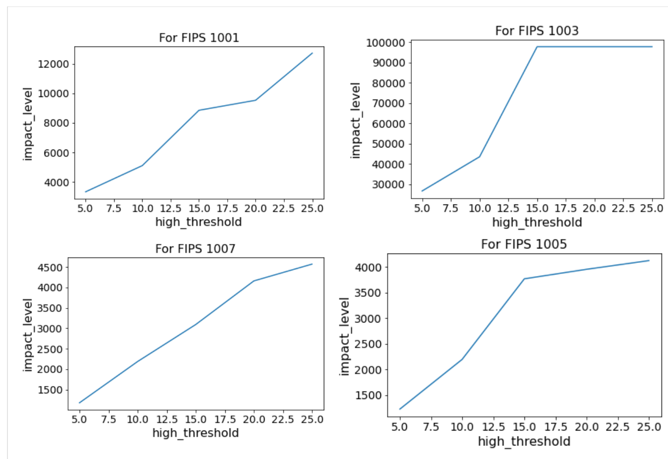

Fig. 6. Impact level as threshold varies from 5% to 25% of total customers impacted for some of the FIPS.

threshold per Federal information processing standard (FIPS) for 2018-2022 is calculated. The event duration and impact level metrics with variation of the threshold is as shown in Fig. 6 and Fig. 7. These curves can be interpreted as follows. For event duration, if the event duration is monotonically increasing, then we are not loosing the important events; if event duration is flattening after a certain threshold, the good threshold would be one where the flattening starts, and if the curve tend to decrease at a certain threshold point, then it means we are loosing potentially significant events that have a longer outage duration. Further details of the threshold analysis is not provided here and is left for our future research.

To be more conservative about the size of the event, we are using 15% or $30,000$ customers impacted as the high threshold to identify the extreme events for our analysis. The lower threshold is still the 5% of total customer or $10,000$ customers impacted (20% of $50,000$).

Note that since we are analyzing the threshold to distinguish the outages due to extreme events, it needs to have weather magnitude on it to compute threshold more accurately. Some of it has been explored in our previous work [14]. However,

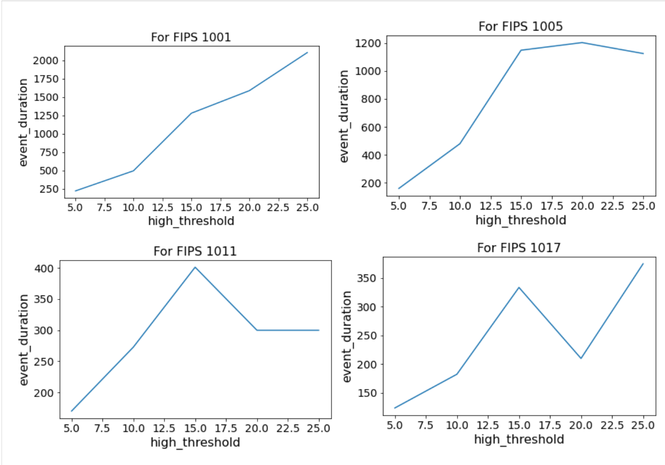

Fig. 7. Event duration as threshold varies from 5% to 25% of total customers impacted for some of the FIPS.

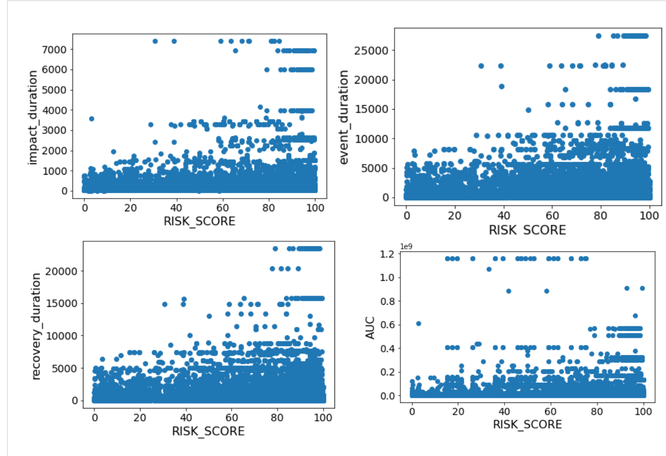

Fig. 8. Correlation of power outage Vs Risk Rating. Only Impact duration, Event duration, Recovery duration, and Area under the curve are shown.

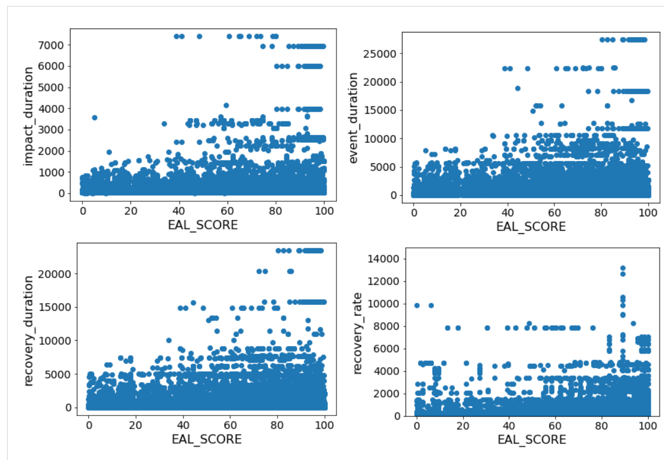

Fig. 9. Correlation of power outage Vs EAL Rating. Only Impact duration, Event duration, Recovery duration, and Recovery rate are shown.

it needs further investigation and is left as future research.

IV. Results and Discussion

This section provide the correlation analysis of the power outages and the various NRI indices.

A. Power Outage vs Risk

The power outage events captured with 15% of customers impacted as high threshold is plotted against the Risk rating as shown in Fig. 8. Figure 8 shows that there is positive correlation between the risk rating and the impact duration, event duration, and recovery duration. In other words, in high risk areas if there is a power outage event, it takes longer time to reach the time at which maximum number of customer are impacted (impact duration); similarly, it takes longer duration to recover the impacted customers; and therefore, resulting longer event duration as well. However, Risk rating seems (not all metrics are shown in Fig. 8, only AUC is shown) to be indifferent against other metrics (AUC, impact level, impact rate, recovery rate, recovery to impact ratio).

B. Power Outage vs Expected Annual Loss

The power outage events is plotted against the Expected Annual Loss rating as shown in Fig. 9. Figure 9 shows that there is positive correlation between the EAL rating and the impact duration, event duration, and recovery duration. In other words, for areas with high expected annual loss due to natural hazards, the impact duration, event duration, and recovery duration are high as well. However, Risk rating seems (not all metrics are shown in Fig. 9, only recovery rate is shown) to be indifferent against other metrics (AUC, impact level, impact rate, recovery rate, recovery to impact ratio).

C. Power Outage vs Social Vulnerability

The results for different resilience metrics of the power outage events against the Social Vulnerability rating are presented in Fig. 10. Figure 10 shows that there is no clear correlation between the Social Vulnerability rating and the resilience metrics. This shows power outage is indifferent to the Social Vulnerability rating. Although only the Impact duration, Event duration, Impact rate, and recovery impact ratio are shown in Fig. 10, other metrics are also indifferent to the Social Vulnerability rating.

D. Power Outage vs Community Resilience

The evaluated resilience metrics of power outage events of the United States are plotted against the community resilience rating and are shown in Fig. 11. Figure 11 shows that there is no clear correlation between the community resilience rating and the resilience metrics. This shows power outage is indifferent to the community resilience rating. Although only the Impact duration, Event duration, Recovery duration, and Impact level are shown in Fig. 11, other metrics are also indifferent to the community resilience rating.

V. Conclusion

This work studied how power outages are related to the National Risk Index (NRI). In this work, the NRI indices

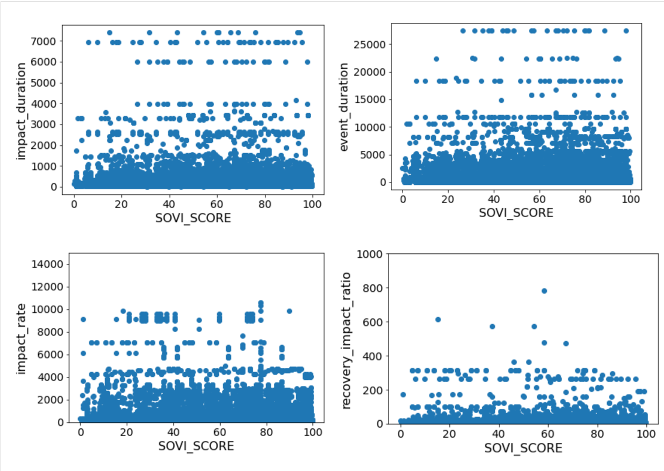

Fig. 10. Correlation of power outage Vs Social Vulnerability Rating. Only Impact duration, Event duration, Recovery duration, and Impact level are shown.

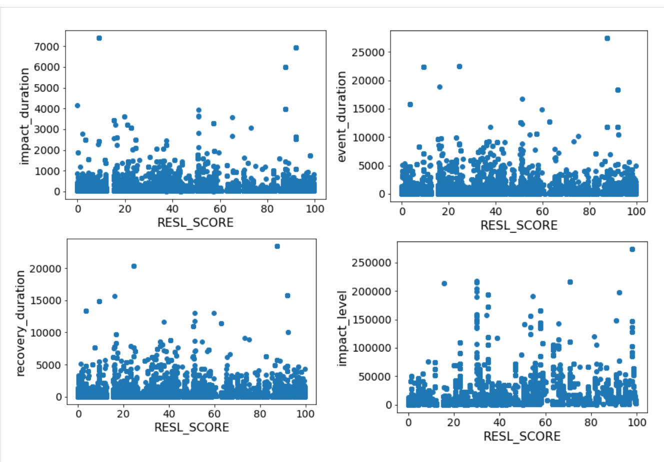

Fig. 11. Correlation of power outage Vs Community Resilience Rating. Only Impact duration, Event duration, Recovery duration, and Impact level are shown.

such as Risk, Expected Annual Loss, Social Vulnerability, and Community Resilience were analyzed with several resilience evaluation metrics such as event duration, impact duration, recovery duration, impact level, impact rate, recovery rate, recovery to impact ratio, and area under the outage curves to examine the correlation of NRI indices with the resilience metrics. The results showed that NRI indices such as Risk and Expected Annual Loss increased with the increase of event duration, impact duration, and recovery duration. All other metrics were indifferent with the change of the the Risk and EAL ratings. The results also showed that there was no strong relationship between all the metrics and community resilience and the social vulnerability. Since Risk is a function of EAL and the latter two components, the correlation between outages and Risk may be driven primarily by the risk of natural hazard exposure (i.e., EAL alone).

Our results are indicative of the interpretability, limitations, and implications for use of SVI and community resilience indices in energy policy, infrastructure investment, and resilience planning. Due to complex social-technical interactions, a county's social vulnerability can be counteracted by the ability to adapt and recover (i.e., resilience), while it still faces human burdens and susceptibility to weather-related outages that such indices may not entirely capture [15], [16]. These findings highlight the research need to better capture the relationships between hazards, outages, and community impacts, particularly in respect to community resilience relative to the duration of weather events and outages. Further work can also explore whether correlations arise using different spatial scales, geographical subsets, and alternative metrics for social vulnerability and community resilience that are more closely related to power outages due to natural hazards.

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