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Quantifying the Power System Resilience of the US Power Grid Through Weather and Power Outage Data Mapping

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ABSTRACT Recent increases in extreme weather events such as severe thunderstorms, floods, and hurricanes are leading to destruction in power system equipment (transmission and distribution poles and lines, substations, power plants, etc.) and are causing widespread prolonged power outages. These outages often cause inconveniences in critical services (health care, transportation, national security, etc.) and significant losses in the economy, leading to human suffering. Therefore, understanding the spatiotemporal correlation of these events with power systems is crucial to planning and for maintaining reliable operation and control under such events. However, developing such correlation requires several datasets, including weather events and power outage datasets, along with coordination from multiple entities (e.g., electric utilities, government agencies, and research organizations). Also, high-resolution data collection is a time-consuming and tedious task because different interest groups are involved in the process. To this end, we propose an automated data framework that maps severe weather events with power outages to quantify power system resilience. This framework uses the publicly available National Weather Service dataset and Oak Ridge National Laboratory's Environment for Analysis of Geo-Located Energy Information (EAGLE-I) power outage dataset to quantify the power system resilience. The proposed work can quantify power system resilience against extreme weather events at the county/state level for different weather event types (e.g., hurricanes, severe thunderstorms, and floods). The outcome of the proposed work will be useful for identifying vulnerability hot spots, developing weather event-based planning strategies (planning strategies might change with events types), developing asset management strategies, and developing predictive analysis tools.

INDEX TERMS Data analytics, EAGLE-I, extreme weather events, power outages, power system resilience, resilience quantification

I. INTRODUCTION

Extreme weather events such as hurricanes, severe thunderstorms, floods, heat waves, and earthquakes have become increasingly frequent and severe in recent years [1]. These events are posing significant operational, control, and planning challenges for the power system worldwide. The power system—as the most complicated and interconnected machine with aging infrastructure in the United States [2]—is highly vulnerable to these events. 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 power generation plants) damage, leading to inconveniences in critical services (e.g., health care, transportation, and national security), severe economic losses, and adverse effects on the well being of the community [3, 4, 5]. Thus, understanding power system resilience, which refers to the ability of the power system to recover from power outages triggered by different weather events in various regions, is crucial. This understanding enables utility companies and emergency responders to plan for and respond to these events more effectively [6, 7].

However, creating a national-scale report on various kinds of weather events causing power outages and restoration time is a challenging and costly task. This process requires a significant amount of time and effort due to the labor-intensive data recording and collection process. Utility companies need to monitor and gather weather and power outage information, and this information from multiple utility companies needs to be gathered, standardized, and processed by a single entity. According to the 2022 annual electric power industry report by the US Energy Information Administration (EIA), 1,700 electric utilities were operating in the United States as of 2020 [8]. To accurately understand power system resilience in terms of various weather events on a national scale at a high-resolution geographic level, such as the county level, it would be ideal for utility companies to actively monitor individual outages and their corresponding restoration times for each weather event. Moreover, the data should be consolidated into a central repository for reporting purposes. However, gathering weather events and their effect on power outages and restoration times nationally is challenging. This undertaking necessitates the involvement of utility companies, which might be required to allocate substantial resources to monitor various weather types and collect detailed information. Implementing such data collection initiatives can be an extra burden for utility companies.

Today, the US Department of Energy (DOE) and the EIA mandate US utility companies to submit their data related to power system resilience [9]. However, the utilities' emphasis is on extreme events only using a generic nationwide threshold (e.g., 50,000 customers affected, 300 MW power loss) or on aggregated data at the utility or state level rather than high-resolution data, such as at the county level, which can omit a considerable number of smaller scale but important events. The effect of the same extreme events can vary significantly in different counties, so the aggregation of data at the utility or state level might obscure important information (e.g., variation of power system resilience in the same state, vulnerability of a county to specific weather event types). Therefore, there is an urgent need for (1) good quality data on weather and power outages for the United States and (2) a reusable automated data framework that combines the best available datasets to enable high-resolution spatiotemporal analysis, allowing for a configurable threshold to detect significant weather events of various scales and types associated with power outages.

To address these needs, this paper leverages the publicly available National Weather Service (NWS) dataset in combination with Oak Ridge National Laboratory's (ORNL's) Environment for Analysis of Geo-Located Energy Information (EAGLE-I) power outage dataset. This work proposes an automated data framework that preprocesses and combines these datasets, detects extreme weather events that cause power outages over a configurable threshold, and quantifies resilience of the US power grids.

A high-level conceptual framework of the proposed work is shown in Fig. 1.

Contributions: The proposed data framework can offer significant insights into improving power grid resilience and emergency response planning, saving time and effort, particularly in regions prone to extreme weather events. The major contributions of this paper can be summarized as follows.

- This work explains publicly available datasets, the NWS dataset, and the EAGLE-I dataset and presents how these datasets can be repeatedly and automatically preprocessed and combined together to quantify power system resilience to weather events in the United States. Mapping of the NWS and EAGLE-I power outage datasets is useful for identifying vulnerability hot spots, developing weather event-based planning strategies (planning strategies might change with event types), developing asset management strategies, and developing predictive analysis tools.
- This work demonstrates how the proposed method can identify critical weather events and their details, which cannot be captured in DOE and EIA reports at higher geographical resolution using a configurable threshold.
- This work also presents a spatiotemporal analysis of power system resilience to various types of weather events (e.g., severe thunderstorms, floods, and hurricanes) through NWS and EAGLE-I power outage dataset mapping. We explored several research topics including (1) the geographical pattern of US power system resilience, (2) a comparison of resilience related to different weather event types, (3) changes in resilience over time, and (4) causes of continued power outages after the end of extreme events.

The remainder of this paper is organized as follows. Section II reviews related work, encompassing an overview of the US power outage related reports, definitions, challenges, and other relevant studies. Section III introduces the datasets used in this study and explains the data processing framework accompanied by a discussion of the underlying assumptions and potential limitations. Section IV provides a national-scale analysis of US power system resilience associated with weather events. Finally, Section V provides concluding remarks with future directions.

II. RELATED WORK

Power system reliability and metrics to measure power system reliability are well defined and widely accepted across

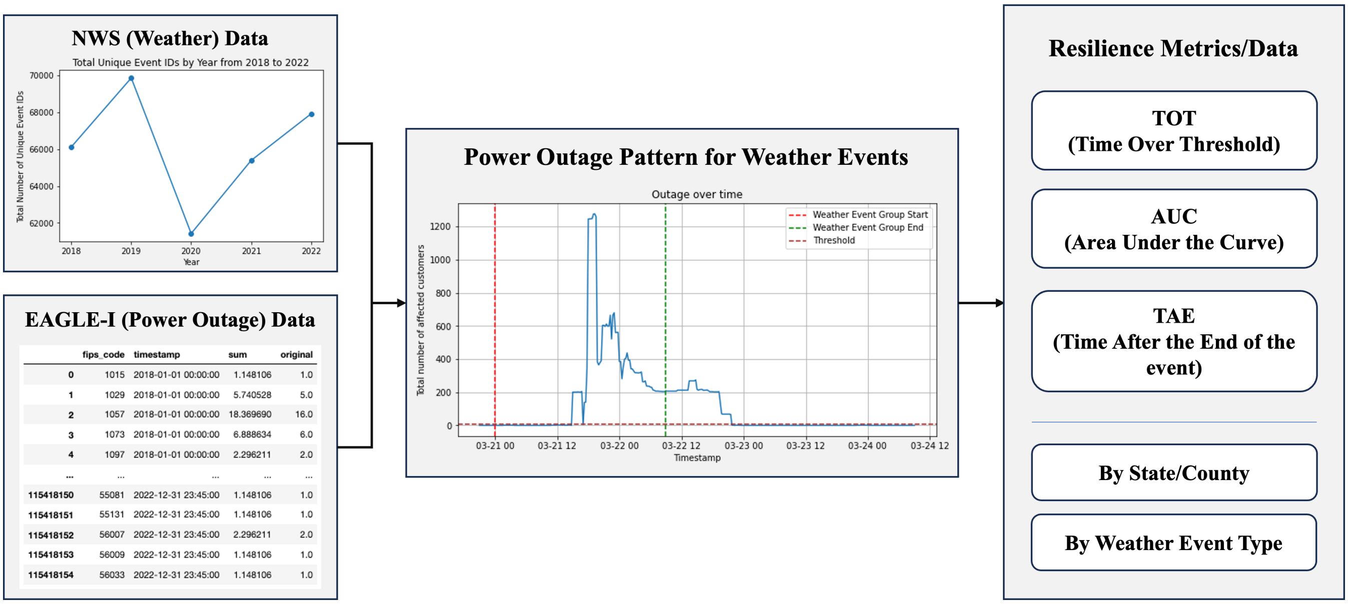

FIGURE 1: High-level conceptual framework of the proposed work.

the industry [10]. Reliability refers to the ability of a power system to deliver power to its customers within accepted standards in a stable manner [11]. Reliability primarily concerns the frequency and duration of outages under *normal conditions* and small disturbances caused by maintenance, or temporary failures. However, unlike reliability, power system resilience definitions have not yet been standardized [4, 7, 12, 13, 14, 15, 16, 17]. Our previous work [4] provides a comprehensive and critical review of power system resilience. In [4], we have thoroughly reviewed the current resilience definition, resilience metrics, resilience evaluation methods, resilience enhancement methods, and power system resilience modeling. Work [4] also presents research gaps and future directions. Therefore, we would like to refer the interested reader to [4] (and [7, 12, 13, 14, 15, 16, 17]) and references and cited articles therein for current power system resilience definitions. In this paper, we follow the power system resilience defined and adopted by the US National Infrastructure Advisory Council (NIAC) and the North America Electric Reliability Corporation (NERC). They define *resilience* of a power system as a power system's ability to withstand, adapt to, and recover from disruptions or unexpected events [18], such as severe weather events or cyber attacks. A resilient power grid system can absorb disturbances and damages so that effects can be limited and recovered from quickly.

In this paper, we particularly focus on the effect of severe weather events on power grid operation. To understand electric outages and power system resilience associated with extreme weather events, having reliable and accurate data is the first step [5]. The DOE collects information on major electric incidents and emergencies for national security, emergency management, and analytical purposes. Balancing authorities, reliability coordinators, and electric utilities are mandated to submit Form DOE-417 to the DOE [9]. Because mandating utility companies to report all power outages and restoration time is impractical, DOE has established various criteria for filing this form. For instance, an uncontrolled loss of 300 MW or more for more than 15 minutes or loss of electric service to more than 50,000 customers must be reported [19].

DOE publishes an annual summary report based on the collected data, including the events' dates and times, restoration dates and times, affected areas, event types, demand losses, and the number of affected customers. Because the report relies on manual submissions, the details of each event can vary because there are no strict standardizations or requirements on some of the data fields. For example, some reported events might have restoration times, while others might not. Some reports might include only state-level information and lack country-specific details. Some events lack the number of customers affected. The "event type" column in the published data provides information on whether the reported incident is related to severe weather. However, it lacks further details, such as specifying whether the event was a flood or a thunderstorm. In the 2022 report, 95 severe weather-related events were reported, but this number could have omitted many significant weather-related outage events that were not qualified as "major" events but that created a significant impact, as generalized criteria (e.g., 50,000 customers or 300 MW) might not capture significant impacts on smaller counties [5].

Similarly, the EIA gathers power system reliability data from distribution utilities and electricity power marketers through the EIA-861 form and publishes the annual electric power industry report [8]. This report encompasses statistics such as utility information, operational data, reliability

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indices both with and without major event days, energy efficiency, and more. The EIA report houses a wealth of invaluable information on reliability, featuring metrics such as the customer average interruption duration index (CAIDI), system average interruption duration index (SAIDI), and system average interruption frequency index (SAIFI). It is essential to note, however, that the reliability metrics included in the EIA report do not focus on power system resilience in the face of extreme weather events. Reliability and resilience are two distinct concepts. To assess resilience clearly, we need to analyze the power outages dataset, weather data, and their spatiotemporal relation during extreme weather events. The aggregated data in the Annual Electric Power Industry Report poses limitations in understanding power system resilience. Furthermore, both the DOE and EIA reports rely exclusively on manual efforts by mandating the participation of utilities, a process that can be time-consuming and costly.

The work presented in [5] demonstrates the usefulness of the EAGLE-I power outage data and shows how resilience metrics such as event duration, impact duration, recovery duration, and impact level can be calculated. The authors of [5] used a population-based threshold to identify extreme power outages and conducted a comprehensive analysis of power outages from 2014 to 2021. This analysis illustrated the usefulness of EAGLE-I data in detecting events that could not be found using DOE criteria. The study primarily focused on state-level outage behavior. However, it did not examine different types of weather phenomena (e.g., floods and severe thunderstorms) and their specific effects on power system resilience. Authors in [20] use the power outage dataset from poweroutage.us, which is not freely available. Also, the work [20] analyzes all power outages (customer impact threshold is very small and generic), studies the likelihood of power outage events of certain (e.g. more 1 hour and more 8 hour) duration due to different weather event type, it does not directly calculate the duration of power outages and customer impacted due to an event. Contrarily, we focus on analyzing power system resilience to extreme weather events at both the county and state levels. We also examine the impact of different types of extreme weather events (through weather and power outage data mapping) on the power system resilience, which helps to identify vulnerability hot spots. Information on weather event types is important as power system resilience planning strategies change with the type of weather events. The weather data mapped in the outage data also gives information about whether a power outage continued after the end of an extreme event. Continued power outages after an extreme event could be caused by delays in weather (NWS starts to collect data after weather alerts for extreme events) and power outage data collection (EAGLE-I platform collects power outage data through the utility company's data API or their website). Another possible reason for continued outages after an extreme event signifies weaker and aging power grid infrastructure (important information for asset management). We have quantified the continued power outage duration after the end of an extreme event as one of the resilience metrics for further analysis. Furthermore, information about a weather event will also help in developing the framework to predict power outages in the future against similar events (important for predictive analysis). Moreover, we have also calculated a more realistic threshold value—average power outages from regular causes—to distinguish power outages caused by extreme events from other regular causes (e.g., vegetation and system faults). The extreme event-related power outages determined using this threshold are more realistic than that of the arbitrary 25% value used by [5]. This calculation of threshold value is possible because of the mapping of NWS data on the EAGLE-I dataset, which is lacking in [5].

III. DATA PROCESSING

In this section, we detail two public datasets utilized in our paper, the National Weather Service Data and EAGLE-I data. We are also discussing their contents, basic statistics, and limitations. Additionally, we are explaining how we processed each dataset and mapped them together for the analysis of the impact of weather events on the power system.

A. NATIONAL WEATHER SERVICE DATA

For weather information, we use weather event data collected by the NWS, a US government agency that provides weather, water, and climate data, forecasts, warnings, and impact-based decision support services. Specifically, we used the NWS Valid Time Extent Code (VTEC) archives data processed by the Iowa State University Iowa Environmental Mesonet (IEM). This dataset contains information about the geography and life cycle of weather events that occur in the United States, which include watches, warnings, advisories, and others. VTEC archives the dataset, and its metadata are publicly available in the Shapefile and Keyhole Markup Language (KML) formats. Weather events are classified using a two-character phenomena code (such as FL for flood and SV for severe thunderstorms). IEM daily updates the data at 2:00 a.m. Central time, and the dataset is publicly available. The start and end times of weather events can be modified over time and upgraded to higher-risk events (such as a watch being upgraded to a warning), and the most recent snapshot of the weather events is available in the dataset.

Table 1 displays the selective columns of the NWS VTEC archive dataset. Note that we excluded some of the columns available in the VTEC archive dataset because they are used only for certain types of weather events and are not necessary for our analysis (e.g., HAILTAG column for hail size tag in inches and HV_CAUSE for the cause of flood events). The complete metadata for the dataset is available on the VTEC archive website[1].

To preprocess the dataset, we initially filtered the data using the SIG and STATUS columns. Since our focus is on extreme weather events, we used the SIG column to filter out everything except either warnings or advisories (with

[1]https://mesonet.agron.iastate.edu/info/datasets

TABLE 1: Part of the list of columns of VTEC archive dataset

Column	Description
WFO	A three-character identifier for NWS Offices/Centers.
ISSUED	The timestamp represents the event's start time. During an event's lifecycle, the NWS can update this issued value. This value represents the last known state of the event start time.
EXPIRED	Like the ISSUED column above, this represents the event's end time and is the last updated value.
PHENOM	This is the two-character NWS code for VTEC events. (e.g., TO for Tornadoes, SV for Severe Thunderstorms.)
SIG	This is the one-character NWS code for VTEC significance. (e.g., W for warnings, Y for advisory)
ETN	This is the VTEC event identifier, a unique value for the combination of an issuance center and a continuous spatial region for the event.
GTYPE	Either P for polygon or C for county/zone/parish.
STATUS	The VTEC status code indicates the stage of an event's life cycle. (e.g., NEW for new events, EXP for expired events)
Geometry	Area impacted by the event.

values of "W" and "Y" for the SIG column, respectively). As per the NWS's definition, a warning is issued when a hazardous weather or hydrologic event is happening, imminent, or expected to occur. Similarly, an advisory is issued but with less severity than warnings. Both warnings and advisories can cause significant inconvenience and, if caution is not exercised, can lead to situations that can endanger life or property. Note that we excluded less serious events such as watches and statements but included the ones that were upgraded during the life cycle of those events. We also filtered out data entries whose STATUS column values were "CAN," indicating that the event was canceled and did not actually occur.

As the second step, we converted polygons to counties. The entries in the original dataset have a column GTYPE, which indicates the data entry is either for a county or a polygon. Since EAGLE-I power outage data is county-level data, to more easily join the datasets we converted all polygon-based data into county-based data. Since polygons can cover multiple counties, we identified all the counties that intersect with the polygons and replaced the original data entries with the county geometry.

Following that, we aimed to obtain a unique identifier for each weather event that we could use to identify a weather event with a specific phenomenon type occurring at a particular time frame for its affected regions. However, the original dataset did not have a clear identifier that we could use universally in this manner. Although there was a column named ETN for the event ID, the value was not unique across the dataset. In reality, a weather event is not a discrete object, so there needs to be an assumption to assign an ID to weather an event. Therefore, we assumed that a weather alert can be identified by when, where, and what. We identify weather events with their duration (when), significance, phenomenon type (what), and state (where). Hence, we combined the values of the ISSUED, EXPIRED, PHENOM, SIG, and STATE columns and used them as the ID value for each event. Note that the same event simultaneously happening in multiple states will have multiple identifiers and be considered to be different events. Finally, using the geometry of the counties, we added a FIPS code and STATE column, computed the duration for each event, and added the YEAR column using the value of the ISSUED column.

Table 2 displays samples of the preprocessed dataset. The first two rows represent a gale event (with a PHENOM value of "GL"; see the full list in Table 3) that occurred in January 2018 and affected Delaware and New Jersey. Note that there can be multiple rows with the same event ID if a single event simultaneously affects multiple counties in the same state.

There is always the possibility of errors and missing data when it comes to large datasets, such as the NWS VTEC dataset. The calculated durations of events were unreasonable in some cases. In one instance, the EXPIRED time stamp was earlier than the ISSUED date, resulting in a negative event duration. In another instance, the duration was extremely long—over seven days. Out of a total of 934,185 data rows from 2018 to 2022, 11406 rows (1.2%) had negative durations, and 1,913 rows (0.2%) had durations of more than seven days. We filtered out these outlier cases and retained the remaining 920,858 rows (97.446%). The number of unique EVENT_IDs was 330,670 on the retained data. Fig. 2 displays the distribution of data rows with different event durations. Of the data, 843,401 rows (91.6%) had durations of less than 24 hours, and 56,466 rows (6.1%) lasted between 24 and 48 hours. Events lasting longer than 48 hours were rare.

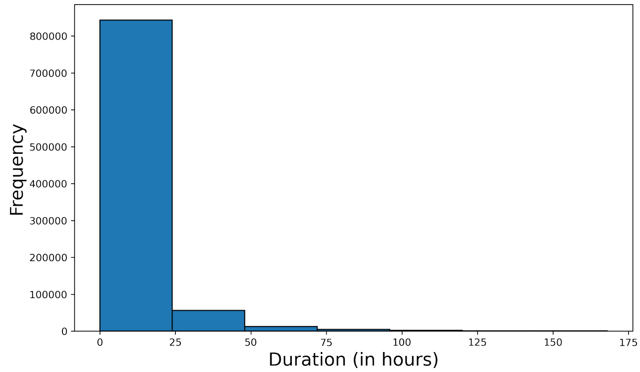

FIGURE 2: Distribution of data rows with different event duration (in hours). There can be multiple rows for the same event, so the numbers indicate the count of rows, not the count of distinct events.

Fig. 3 presents the total number of unique weather events in the preprocessed dataset per year from 2018 to 2022. The highest number of events was observed in 2019, followed

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TABLE 2: Samples of the preprocessed NWS VTEC dataset

EVENT_ID	ISSUED	EXPIRED	FIPS	SIG	PHENOM	COUNTY	STATE	YEAR	DURATION
201801010227-201801011100-GL-W-DE	1/1/18 2:27	1/1/18 11:00	10005	W	GL	Sussex	DE	2018	0 days 08:33:00
201801010227-201801011100-GL-W-NJ	1/1/18 2:27	1/1/18 11:00	34009	W	GL	Cape May	NJ	2018	0 days 08:33:00
201801011327-201801021900-UP-W-MA	1/1/18 13:27	1/2/18 19:00	25007	W	UP	Dukes,MA	MA	2018	1 days 05:33:00
201801011405-201801030000-GL-W-FL	1/1/18 14:05	1/3/18 0:00	12031	W	GL	Duval,FL	FL	2018	1 days 09:55:00

TABLE 3: Phenomena codes and descriptions

Phenomena Code	Description	Phenomena Code	Description	Phenomena Code	Description
AF	Ashfall	HI	Inland Hurricane	SM	Dense Smoke
AS	Air Stagnation	HS	Heavy Snow	SN	Snow
BS	Blowing Snow	HT	Heat	SR	Storm
BW	Brisk Wind	HU	Hurricane	SU	High Surf
BZ	Blizzard	HW	High Wind	SV	Severe Thunderstorm
CF	Coastal Flood	HY	Hydrologic	SW	Small Craft for Hazardous Seas
DS	Dust Storm	HZ	Hard Freeze	TI	Inland Tropical Storm
DU	Blowing Dust	IP	Sleet	TO	Tornado
EC	Extreme Cold	IS	Ice Storm	TR	Tropical Storm
EH	Excessive Heat	LB	Lake Effect Snow and Blowing Snow	TS	Tsunami
EW	Extreme Wind	LE	Lake Effect Snow	TY	Typhoon
FA	Areal Flood	LO	Low Water	UP	Ice Accretion
FF	Flash Flood	LS	Lakeshore Flood	WC	Wind Chill
FG	Dense Fog	LW	Lake Wind	WI	Wind
FL	Flood	MA	Marine	WS	Winter Storm
FR	Frost	RB	Small Craft for Rough Bar	WW	Winter Weather
FW	Fire Weather	SB	Snow and Blowing Snow	ZF	Freezing Fog
FZ	Freeze	SC	Small Craft	ZR	Freezing Rain
GL	Gale	SE	Hazardous Seas		
HF	Hurricane Force Wind	SI	Small Craft for Winds		

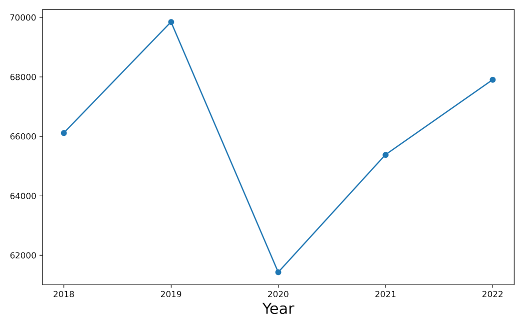

FIGURE 3: Total number of unique event IDs by year from 2018 to 2022.

by a decline in 2020. The number of unique weather events experienced a steady increase from 2020 to 2022.

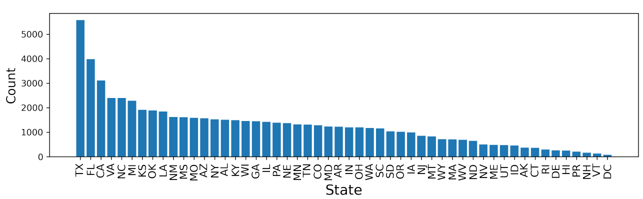

FIGURE 4: Average annual number of unique event IDs by state (from 2018 to 2022).

Fig. 4 presents the average number of unique event IDs per year for each state from 2018 to 2022, sorted from largest to smallest. Although the total number of events per state varied annually, Texas and Florida had the highest average number of events, followed by California. Fig. 5 showcases the top

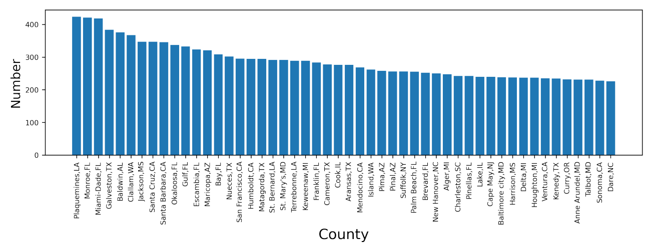

FIGURE 5: Average annual number of unique event IDs by county (top 50, from 2018 to 2022).

50 counties with the highest average yearly total number of events from 2018 to 2022. Notably, Florida had the most number of counties (10) in this top 50 ranking list, followed by California (7). In contrast, Virginia was ranked 4th, but it had nothing on the list. This observation highlights the importance of county-level analysis, as significant findings can be overlooked when data is aggregated at the state level.

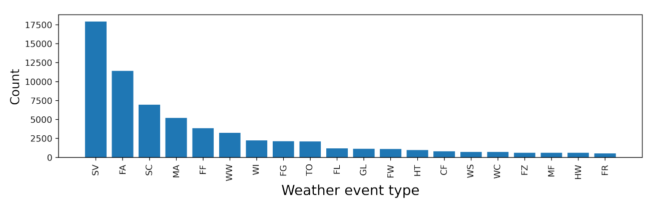

FIGURE 6: Average annual number of unique event IDs by weather event type (top 20, from 2018 to 2022).

Different weather event types exhibit varying levels of prevalence. Fig. 6 displays the average number of unique event IDs per year for each weather event type. Severe thunderstorms (SV) were the most prevalent type of event, followed by flood (FA), small craft (SC), marine (MA), and flash floods (FF).

B. EAGLE-I DATA

For US power outage information, we leverage the data collected by ORNL's EAGLE-I system[2]. EAGLE-I is an interactive geographic information system (GIS) operated by ORNL and sponsored by DOE that enables users to visualize and map the nation's energy infrastructure, including assets at risk such as the electric grid, petroleum, and natural gas infrastructures. The EAGLE-I platform has been collecting US power outage information data since 2014. The historical dataset is available for academic use.

EAGLE-I's electricity outage data comprises records of the total number of customers without power in a geographical district at the county level, along with information about the associated utility company. Note that more than one utility company could report outages for a single county if multiple utility companies serve the county. Thus, we aggregated the data at the county level and calculated the total outage count for each time stamp. Table 4 displays samples of the EAGLE-I power outage data. Each row contains the total number of outages for the county with the FIPS code at the time stamp. More specifically, the number of outages represents the number of customers affected. This outage information is recorded every 15 minutes; however, no data record is available if the outage number is zero. In this example data, the number of customers affected in the county with the FIPS code 9015 was 12 at 2022-01-02 09:30. Although the EAGLE-I power outage data does not track individual power outages and contains only the total number of customers affected in a county at a given time, we can infer restoration times from the records based on certain assumptions by tracking the number of power outages. For example, no data was recorded at 2022-01-02 09:45, indicating that the outages affecting 12 customers were fully resolved within 15 minutes.

The coverage ratio represents the proportion of Eagle-I coverage compared with the total number of customers in the respective state. Over time, the customer coverage provided by the EAGLE-I platform has been expanding, driven by the acquisition of data from more utility companies that serve a wider range of regions. The coverage ratio provides important information about the public reporting of the outage dataset. Fig. 7 displays the maximum national coverage ratio annually from 2018 to 2022, considering all 50 states and Washington, DC. This figure shows the increasing trend of outage data coverage. On average, the coverage ratio was a commendable 0.871. Table 5 shows that EAGLE-I data reporting for all states except Colorado and Kansas from 2018 to 2022 has improved in terms of number of customers. This increased trend of the coverage ratio shows

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

TABLE 4: Samples of EAGLE-I power outage data

FIPS	TIMESTAMP	OUTAGE_SUM
9015	2022-01-02 09:30:00	12
9015	2022-01-02 10:00:00	1
9015	2022-01-02 10:15:00	1
...	...	...
9015	2022-01-02 12:15:00	1
9015	2022-01-02 12:30:00	1
9015	2022-01-02 14:15:00	2

that more power outage data are publicly available every year for academic use. Although the "Total Customers" column shows the total number of customers for 2022, the coverage ratios are calculated based on the number of customers of the specific year.

Because the coverage ratio for EAGLE-I data is not perfectly 1.0, there is a possibility that some customers might experience power outages within regions that fall outside the EAGLE-I scope. This could lead to an underestimation of power outage numbers derived from the data. To address this, we correct the power outage figure by dividing it by the coverage ratio. This adjustment uses the 5-year national average coverage ratio of 0.871. Note that all power outage figures presented in subsequent sections are adjusted to 0.871 coverage ratio numbers.

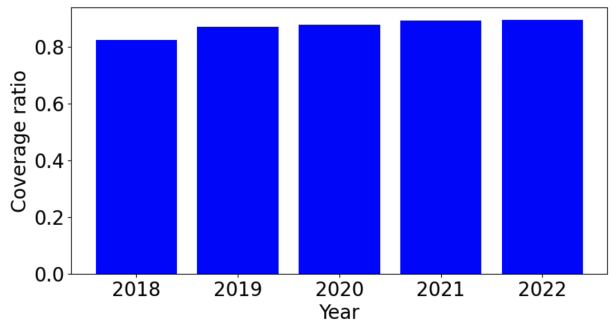

FIGURE 7: Eagle-I coverage ratio for 2018-2022.

C. MAPPING EAGLE-I DATASETS AND THE NWS DATASETS

Our objective is to map the NWS data and EAGLE-I datasets, using the geographical and temporal information from both sources to study power outage data associated with severe weather events. Specifically, we aim to understand how power outages occur and are restored before, during, and after weather events in a given region.

It is common for multiple related weather events to occur simultaneously or in close succession within a region, so instead of analyzing each weather event's impact to power systems, we need to identify groups of weather events that are highly relevant. Fig. 8 illustrates four weather events from the NWS dataset spanning the timeline in Tolland County, Connecticut (FIP 9013), from 2022-08-26 19:24:00 to 2022-08-26 21:30:00. FF and SV represent flash floods and severe thunderstorms, respectively, and it is evident that

TABLE 5: EAGLE-I coverage over time (from 2018 to 2022)

State/Territory	Total Customers (2022)	Coverage Ratio					
		2018	2019	2020	2021	2022	Overall Change (2022-2018)
AK	364614	0.67	0.67	0.68	0.68	0.71	0.04
AL	2615212	0.79	0.81	0.81	0.81	0.81	0.02
AR	1630606	0.78	0.83	0.86	0.86	0.86	0.08
AZ	3188212	0.87	0.86	0.9	0.91	0.91	0.04
CA	15666677	0.91	0.93	0.94	0.95	0.95	0.04
CO	2768968	0.88	0.83	0.84	0.83	0.84	-0.04
CT	1680077	0.95	0.95	0.95	0.95	0.96	0.01
DC	317140	1.0	1.0	1.0	1.0	1.0	0.0
DE	499849	0.86	0.86	0.86	0.86	0.86	0.0
FL	10989517	0.97	0.97	0.97	0.98	0.98	0.01
GA	5059196	0.9	0.86	0.88	0.9	0.91	0.01
HI	502534	0.61	0.66	0.67	1.0	1.0	0.39
IA	1601073	0.89	0.89	0.91	0.91	0.91	0.02
ID	904872	0.91	0.92	0.95	0.9	0.91	0.0
IL	5906057	0.92	0.99	0.94	0.98	0.98	0.06
IN	3228957	0.79	0.82	0.86	0.86	0.86	0.07
KS	1980177	0.71	0.74	0.79	0.8	0.59	-0.12
KY	2316157	0.78	0.92	0.92	0.92	0.94	0.16
LA	2400685	0.89	0.89	0.9	0.9	0.91	0.02
MA	3243537	0.89	0.89	0.94	0.99	0.99	0.1
MD	2635074	0.98	0.97	0.98	0.99	0.99	0.01
ME	816054	0.96	0.96	0.96	0.96	0.96	0.0
MI	4933959	0.91	0.96	0.95	0.95	0.96	0.05
MN	2724798	0.71	0.71	0.8	0.8	0.8	0.09
MO	3160891	0.8	0.95	0.95	0.95	0.95	0.15
MS	1546679	0.66	0.74	0.77	0.77	0.77	0.11
MT	634592	0.16	0.75	0.76	0.76	0.76	0.6
NC	5297545	0.82	0.9	0.91	0.92	0.92	0.1
ND	463692	0.51	0.53	0.66	0.66	0.66	0.15
NE	1034499	0.45	0.46	0.48	0.48	0.48	0.03
NH	738754	0.88	0.99	0.99	0.99	0.99	0.11
NJ	4136585	0.99	0.98	0.99	0.99	0.99	0.0
NM	1045100	0.74	0.81	0.82	0.82	0.82	0.08
NV	1390235	0.95	0.95	0.96	0.97	0.97	0.02
NY	8309187	0.98	0.98	0.99	0.99	0.99	0.01
OH	5603381	0.93	0.93	0.93	0.93	0.93	0.0
OK	2047920	0.89	0.9	0.93	0.93	0.94	0.05
OR	2045351	0.75	0.86	0.9	0.9	0.9	0.15
PA	6111114	0.95	0.96	0.98	0.98	0.98	0.03
RI	505947	0.99	0.99	0.99	0.99	0.99	0.0
SC	2800722	0.99	0.99	0.99	0.99	0.99	0.0
SD	475661	0.46	0.87	0.79	0.79	0.89	0.43
TN	3433064	0.55	0.73	0.73	0.73	0.75	0.2
TX	14691490	0.9	0.93	0.63	0.94	0.93	0.03
UT	1252077	0.8	0.8	0.79	0.79	0.8	0.0
VA	3941323	0.96	0.97	0.97	0.97	0.97	0.01
VI	56133	1.0	1.0	1.0	1.0	1.0	0.0
VT	376122	1.0	1.0	1.0	1.0	1.0	0.0
WA	3532113	0.71	0.86	0.87	0.87	0.87	0.16
WI	3068156	0.83	0.84	0.84	0.85	0.85	0.02
WV	1010110	1.0	1.0	1.0	0.97	1.0	0.0
WY	329909	0.62	0.68	0.71	0.71	0.71	0.09

correlated events can occur or co-occur in proximity to one another. We define a *weather event group* as a collection of events occurring in a specific county in which the group encompasses all weather events that overlap in duration with any other events within the group. For example, all events shown in Fig. 8 were grouped together and assigned the same group ID. Additionally, for each weather event group, we calculated the group duration, which is the duration from the start of the first event to the expiration of the last event in the group. We then assigned the type of the longest weather event in the group as the type for the entire weather event group.

Fig. 9 displays a power outage pattern corresponding to a weather event group consisting of events depicted in Fig. 8. The red vertical line signifies the beginning of the weather event group, while the green vertical line indicates its end.

Although we cannot definitively state that the weather events directly caused the power outages, there seems to be a strong correlation between the weather event group and the increase in power outage numbers in this instance, as we observe the increase in power outages immediately after the

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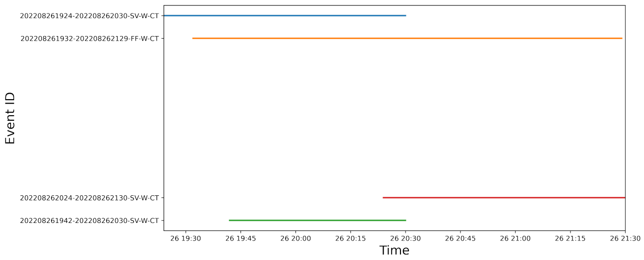

FIGURE 8: Visualization of a weather event group composed of four different weather events.

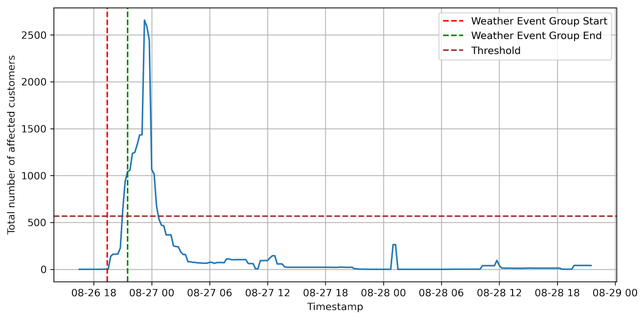

FIGURE 9: Power outage pattern from 3 hours before to 48 hours after a weather event group (FIPS=9013 from 2022-08-26 19:24:00 to 2022-08-26 21:30:00).

beginning of the weather event group.

In Fig. 9, the peak number power of outages reached is 2657; nevertheless, note that the peak number of outages was observed after the weather event group had expired and that the outages persisted many hours. So we need to consider not only power outages during weather events but also power outages after the events. The EAGLE-I data is updated at 15-minute intervals, but there is no guaranteed maximum delay of 15 minutes in the process. The EAGLE-I platform collects power outage data through the utility company's data API or their website, which could result in additional delays on the utility company's end. Another potential reason for observing an increase in power outages after the end of an extreme weather event is that the actual damage might occur after the weather event because of delayed infrastructure damage (probably because of weak and aging infrastructure), flooding aftermath, ice accumulation, and other related factors. We have quantified the continued power outage duration after the end of an extreme event as one of the resilience metrics for further analysis.

Fig. 10 illustrates another power outage pattern for a different weather event group (comprising a single flood event) in Fayette County, Alabama, on May 29, 2018. We observe multiple peak outages before, during, and after the active weather event group. Power outages observed before the active weather alert can still be correlated to the weather alert, as weather events can be unpredictable, leading to delays in issuing weather alerts. Another possible explanation of the

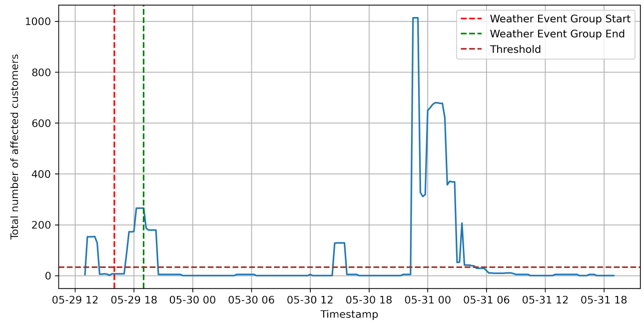

FIGURE 10: Power outage pattern from 3 hours before to 48 hours after a weather event group (FIPS=1057 from 2018-05-29 16:00:00 to 2018-05-29 19:00:00).

outage sometime after (curve at around 05-31 00, as shown in Fig. 10) the end of the event is that the delayed infrastructure damage led to further power outages. We cannot be absolutely certain that power outages occurring before, during, and after weather events are directly caused by these events. However, it is reasonable to assume a connection, especially when we observe an unusually high number of power outages. Both extreme weather events and significant power outages rarely occur. One limitation of our analysis is that it cannot distinguish other causes of power outages (e.g., standalone equipment failures) during extreme weather events. Nevertheless, we believe that such instances are minimal and have a negligible impact on our overall findings.

Power is restored to the majority of customers within 48 hours after an extreme weather event [21]. Thus, we considered any outages that occurred within the time frame of 3 hours before (to accommodate the uncertainty with NWS data recording) to 48 hours after the expiration time of the weather event group to be correlated with the weather event group. In addition, we used this information to calculate the threshold value to distinguish the power outages caused by extreme events vs. power outages caused by other regular events (e.g., load change and system faults). This threshold helps us to determine the accurate power outages caused by extreme events, and it is more realistic than the arbitrary 25% value used by [5]. This calculation of threshold value is possible because of the mapping of NWS data on the EAGLE-I dataset. In this process, a regular outage dataset is created by filtering out all the outage data at the time of extreme weather events and up to 48 hours after the end of the events. The average value of the regular outage dataset is taken as the threshold to distinguish power outages caused by extreme events from outages due to other causes. For example, the horizontal dashed line in Fig. 9 is the threshold line. During extreme events, all the outages above this threshold are considered outages due to extreme events. Outages below the threshold are due to other regular causes and are therefore excluded from the resilience analysis.

Nevertheless, the threshold value is configurable, and, depending on the analytic purposes, the same threshold can

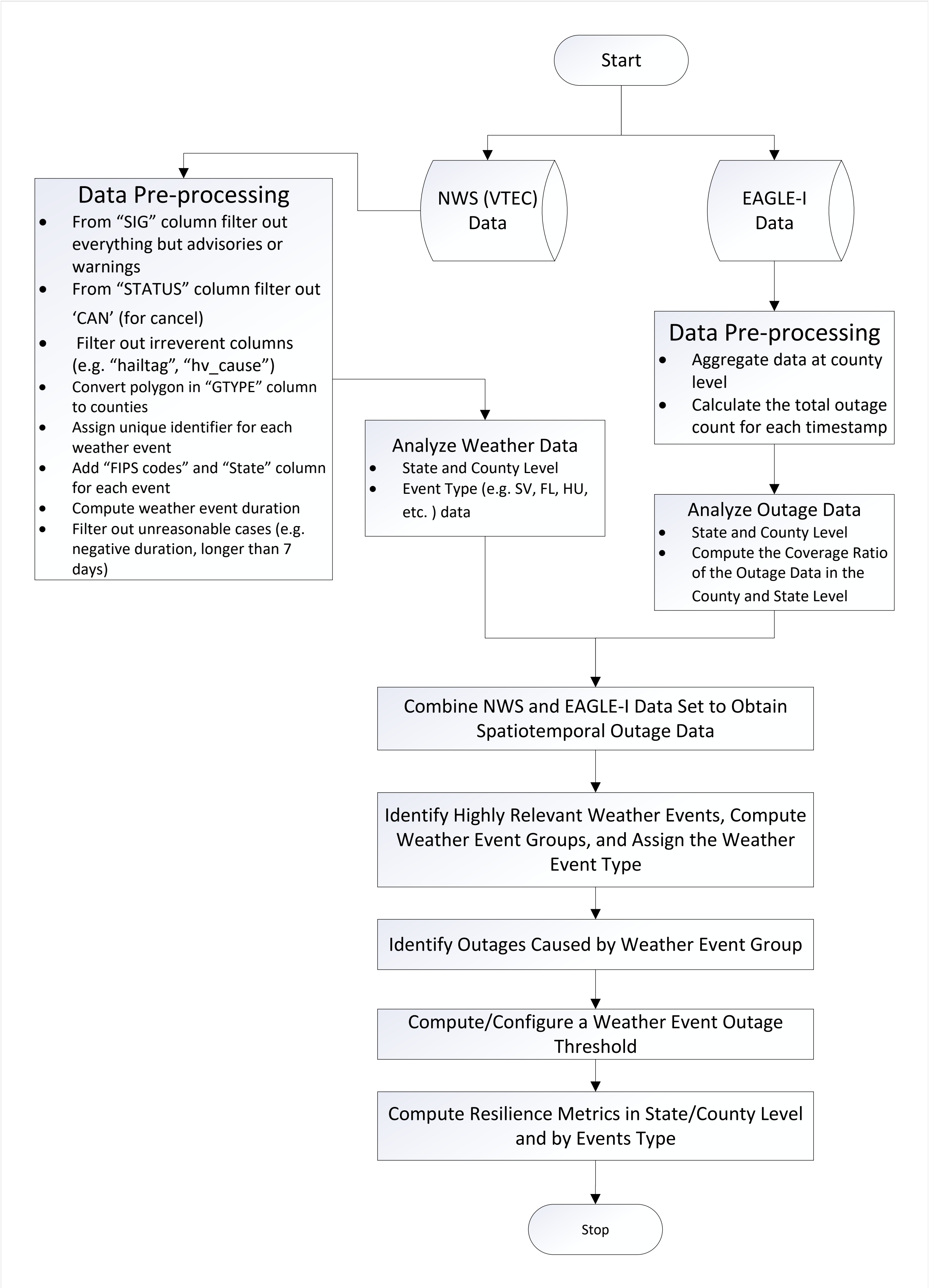

FIGURE 11: Flowchart of the Proposed Approach.

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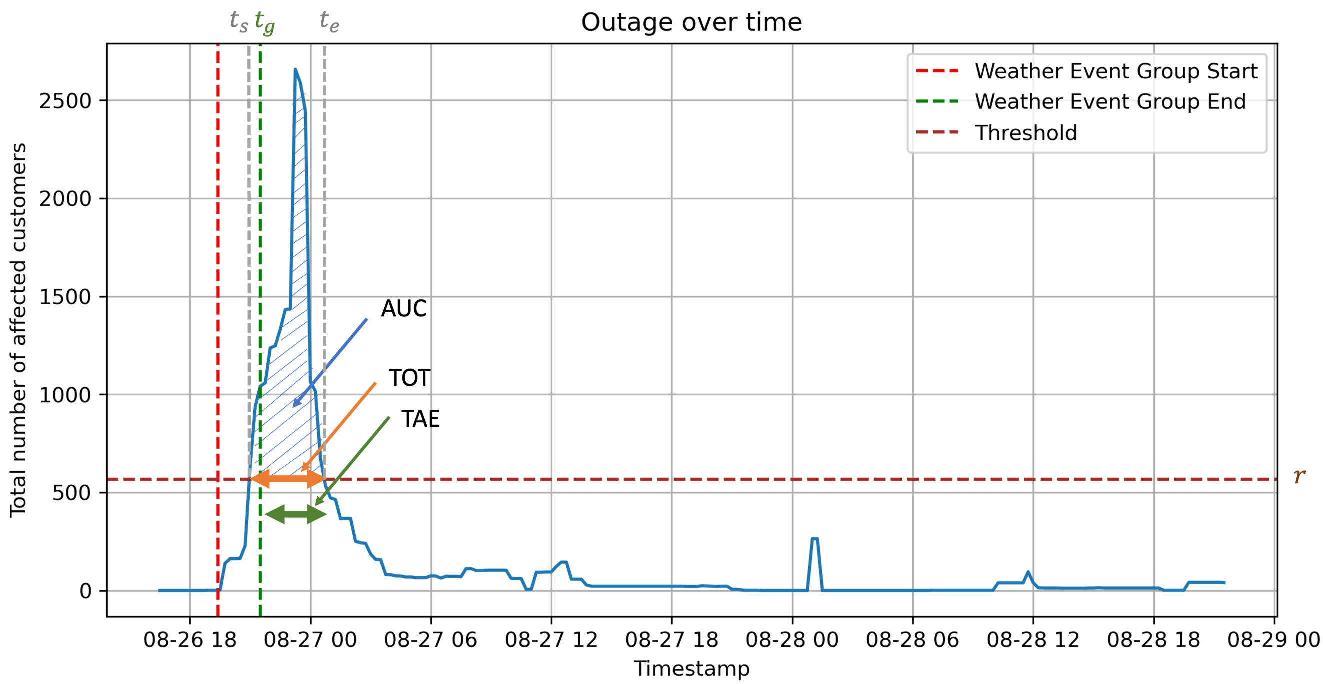

FIGURE 12: Visual representation of power system resilience metrics – AUC, TOT, and TAE – for Tolland County in Connecticut during the period from 2022-08-26 19:24:00 to 2022-08-26 21:30:00.

be used for all counties. If we use a lower threshold, more power outages will be related to extreme weather.

The proposed approach can be summarized through a flow chart, as shown in Fig. 11.

IV. RESILIENCE ANALYSIS

This section provides an assessment of the resilience of the US power systems to extreme weather events using the proposed automated data framework. This section provides details on resilience metrics, an overall annual trend in terms of the proposed metrics, state and county-level analysis, and the specific impact of weather event types on power systems.

A. POWER SYSTEM RESILIENCE METRICS

To provide a numerical assessment of the US power system, quantification metrics are necessary. Although there are several power system resilience quantification metrics in the literature, they have not yet been standardized or universally accepted [4, 14]. Several efforts have been made, for example, [4, 12, 15, 16, 17, 22], to capture the resilience features (e.g., withstand, adapt, and restore or recover) for the assessment of power system resilience. Motivated by these conventions, we propose the following resilience metrics to study and quantify the power system resilience against extreme weather events.

In order to define power system resilience metrics, we first define the terms used in across definitions.

- t_s denotes the start time when the total number of affected customers first exceeds the threshold.
- t_e represents the end time when the total number of affected customers drops below the threshold
- t_g is the time denoted by the green vertical line (end of weather event)
- r represents the threshold value.
- $f(t)$ is the total number of affected customers as a function of time at t.
- T is the total number of customers.

Now, the power system resilience metrics used in this paper are defined as follows.

- **Power outage time over threshold (TOT)**: TOT represents the duration for which the total number of affected customers remains above the set threshold. This is visually indicated by the length of time the curve remains above the red horizontal line in Fig. 12. Formally, TOT is defined as $(t_e - t_s)$.
  TOT provides information about the duration of power outages experienced by customers due to extreme events. Lower TOT represents better resilience because it means that it takes less time to recover from power outages triggered by a weather event.
- **Power outage area under curve (AUC)**: TOT gives information about the duration of outages; however, it does not convey information about the number of customers affected. To account for the number of customers affected, along with the total outage time, we calculated the area under the curve as another quantification metric. AUC is the area under the curve above the dotted threshold outage line, as shown in Fig. 12.

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AUC is defined as $\int_{t_s}^{t_e}(f(t)-r)\,dt$, where $f(t)$ is the total number of affected customers as a function of time at t. AUC is measured in customers-minutes. Lower AUC represents better resilience, as it means the power system can reduce the number of affected customers more quickly in case of power outages triggered by a weather event. To compare the AUC at the state and county levels and by event type, AUC is normalized—outage impact per customer in minutes—(sum of the area under the curve for each event divided by the total number of customers). Formally, the equation becomes $AUC_{normalized}=\frac{AUC}{T}$, where T is total number of customers. The unit for the normalized is in minutes.

- **Power outage time after the end of the event (TAE)**: TAE is calculated to determine how long a power outage event continues after the end of an extreme weather event. A power outage after the end of an event could be caused by a delay in weather and power outage data collection. Another important reason for continued power outage after an event signifies how quickly the system is bouncing back. A system's response depends on several factors (e.g., system condition and available resources), an important one being the physical condition of the grid. Physically weak and aging infrastructures have more probability of failure resulting in longer response time due to repair and installation requirements. Therefore, TAE gives some perspective on the physical condition of the power grid and hardening requirements. TAE does not include the immediate (within the event duration) recovery response. Formally, TAE is defined as $(t_e - t_g)$. Lower TAE represents better resilience, as power outages continue for a shorter time after extreme weather events. TAE is measured in minutes.

Both TOT and AUC information are important to determine the extent of the effects on customers. There are four conditions for customer impacts: (1) low TOT and low AUC signify that very few customers were impacted and that they experienced shorter power outage durations (this is characteristic of a more resilient power system); (2) low TOT and high AUC signify that many customers were impacted for a shorter duration of time; (3) high TOT and low AUC signify that a few customers experienced prolonged power outages; and (4) high TOT and high AUC signify that a large number (widespread) of customers experienced prolonged outages (this indicates a less/poor resilient power system).

Note that the time difference between TOT and TAE gives information about the capability of a utility company to immediately restore power to customers (by repairing the damaged infrastructure, etc.) during the extreme event and to what extent other interrelated networks (communication and road network) are damaged. High TOT-TAE indicates, to some extent, damage to the electrical infrastructure (e.g., distribution and transmission poles and lines), the severity of the event, damage to the interrelated infrastructures (e.g., road network and communication network), and unprepared or resource-scarce utility company.

All of the resilience metrics are quantified for each weather event group occurring within a county. For our analysis, we measured the duration of power outages over the threshold within a time window spanning from 3 hours before to 48 hours after weather event groups. This is because power outages might start before weather events and can persist afterward, as depicted in Fig. 9 and Fig. 10. (Note that an actual power outage due to an event does not occur before an event; nevertheless, because of the uncertainty in the NWS data collection, outages are seen before the start of the events in the outage datasets.)

B. ANNUAL TREND ANALYSIS

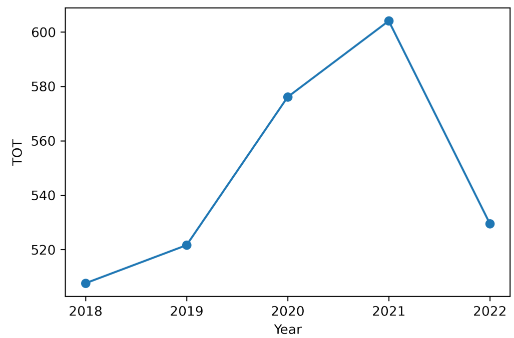

FIGURE 13: Annual average TOT from 2018 to 2022 (in minutes).

Fig. 13 illustrates the changes in the yearly average TOT (in minutes) associated with weather events. We observe a continual increase from 2018 (507.654) to 2021 (604.016–peak value in the given range) and a decrease in 2022 (529.568). The 5-year average was 548.192.

Fig. 14 illustrates the changes in the yearly average AUC—outage impact per customer in minutes—(the sum of the area under the curve for each event divided by the total number of customers) associated with weather events. We observe the average AUC (normalized) as 2.767 in 2018, 0.537 in 2019, 1.351 in 2020, 0.847 in 2021, and 0.650 in 2022. The 5-year average was 1.184 outage impact per customer in the United States.

Fig. 15 illustrates the changes in the yearly average TAE (in minutes) associated with weather events. We observe a continual change from 2018 to 2022. The 5-year average TAE is 24.385 (minutes after the end of the events).

These figures show that there are no specific trends in terms of all the compared metrics.

As seen in Fig. 3, the number of weather events occurring in 2020 was the lowest, suggesting that there is no direct correlation between the number of weather events and the measured resilience metrics of the US power systems. Many other factors could have influenced this result, such as the size of weather events, the age of infrastructure, and maintenance practices.

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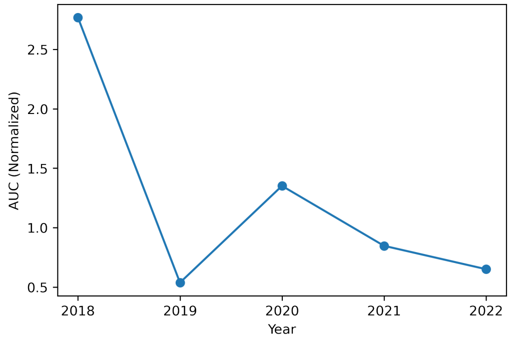

FIGURE 14: Annual average AUC (normalized) from 2018 to 2022 (in minutes).

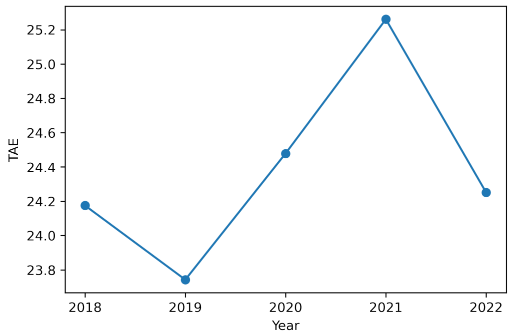

FIGURE 15: Annual average TAE from 2018 to 2022 (in minutes).

C. STATE AND COUNTY LEVEL ANALYSIS

Geographical regions experience different extreme weather patterns, and their varying infrastructure strengths and resistance may impact power system resilience. Thus, it is important to understand the resilience of different geographical locations at the county and state level. The impact of weather events on these levels, based on the proposed metrics, is presented as follows.

1) Power outage time over threshold

The blue bar in Fig. 16 depicts a comparison of the average TOT (sum of TOT of each event divided by the total number of events) across various US states and territories. California (CA) demonstrates the highest value of 1021.229, followed by West Virginia (WV) of 787.459, Michigan (MI) of 780.362, and Pennsylvania (PA) of 761.096. These results show that events in these states are causing longer outages. Conversely, the states with the lowest average TOT are Wyoming of 291.217, Rhode Island (RI) of 330.837, and Iowa (IA) of 338.314, indicating shorter outage duration per event in these states. Although TOT provides information about how long it takes for a power system to return to pre-event status after an extreme weather event, it alone cannot provide information about the power system resilience level because it does not properly incorporate the number of customers. California has the most customers, which could be the reason for the longer outage duration (outage impact per customer is analyzed with the AUC in the following section). The red bar chart in Fig. 16 represents the number of events exceeding the dotted outage threshold line in each state. A higher number indicates more events exceeding the outage threshold to extreme weather events.

We did not observe a strong correlation between the number of reported cases exceeding the threshold line and the average TOT values. For instance, Washington (WA) had less threshold exceeding cases (2579), yet it had a high average TOT of 753.175, ranked at 5 out of 51 districts. States with high average TOT but low case numbers exceeding the threshold line—such as WA, OR, and HI— indicate that the events in these states are more impactful (i.e., have longer outages). Conversely, we noticed the high number of cases exceeding the threshold line in Texas (TX) with 33644 cases, Florida (FL) with 15549 cases, and Georgia (GA) with 13426 cases. However, their respective average TOT values: 587.168, 547.479, and 396.860, respectively, are either comparable with or lower than the overall average TOT value of 548.192. This means the the events in these states are less impactful (i.e., have shorter outages).

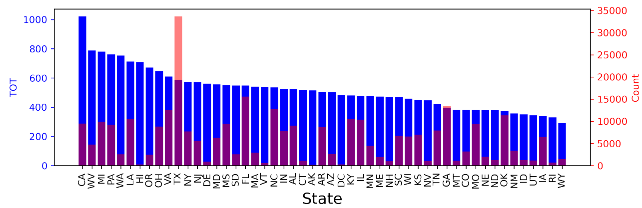

FIGURE 16: Average TOT by state.

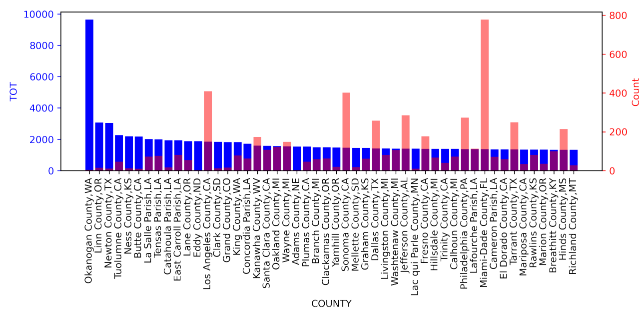

FIGURE 17: Average TOT by county. (Top 50)

Fig. 17 presents the top 50 counties with the highest average TOT. Okanogan County (WA) topped the list with an average TOT value of 9640.000, followed by Linn County (OR), with 3073.928, and Newton County (TX), with 3045.000. The number of cases exceeding the threshold line in these counties was relatively low, with 3, 14, and 11 cases, respectively, indicating that power outages exceeding the threshold due to weather events were infrequent in these areas. However, when such events occur, they tend to result in prolonged outages.

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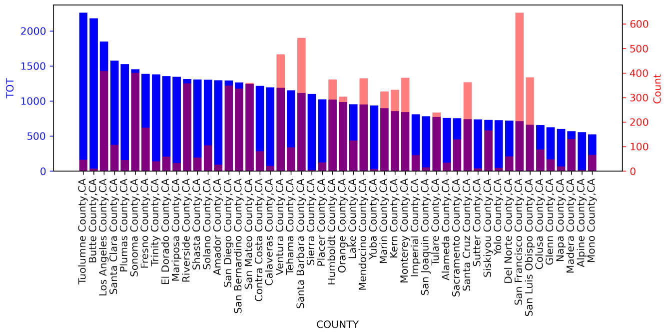
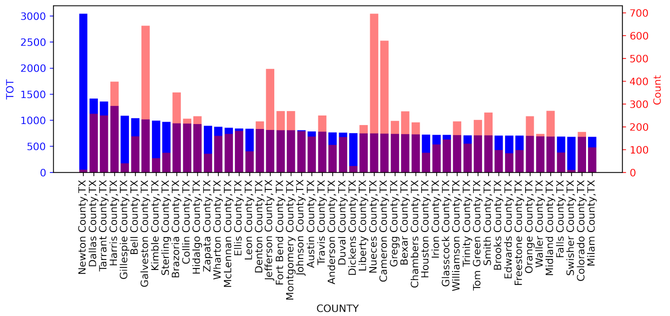
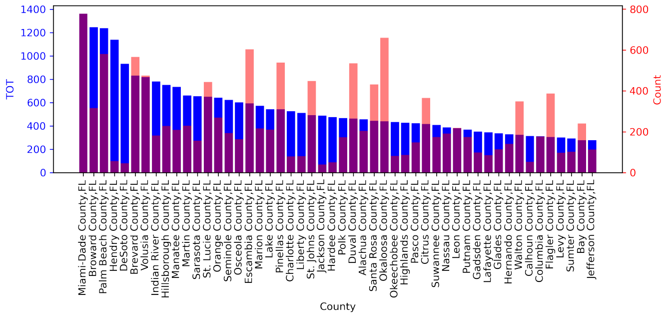


(a) CA



(b) TX



(c) FL

FIGURE 18: Average TOT by county.

Fig. 18 shows the average TOT of counties in CA, TX, and FL. As we can see, even within the same state, the variation of average TOT values is high. On average at the state level, CA had a higher TOT value compared with both TX and FL; however, there are many counties in TX and FL, which have higher average TOTs than those of counties in CA. This confirms that not only state-level resolution but also higher resolution analyses are needed.

In this work, we have compared the outage duration without incorporating the magnitude of the events (e.g., wind speed and flooding magnitude for flood); however, to compare the events more precisely, it is important to incorporate event's magnitude in the resilience metric. This will be our future research work.

The state- and county-level results are presented in the US map in Fig. 19 and Fig. 20, respectively.

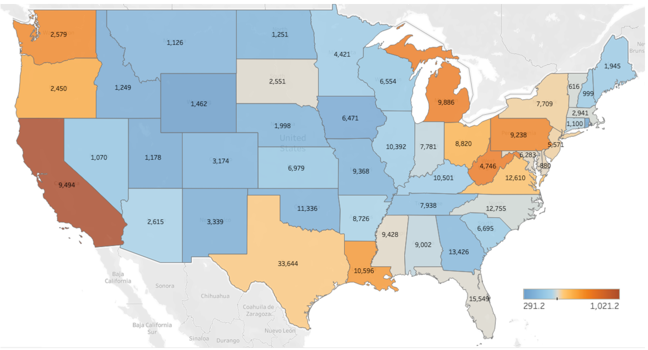


FIGURE 19: Average TOT by state.

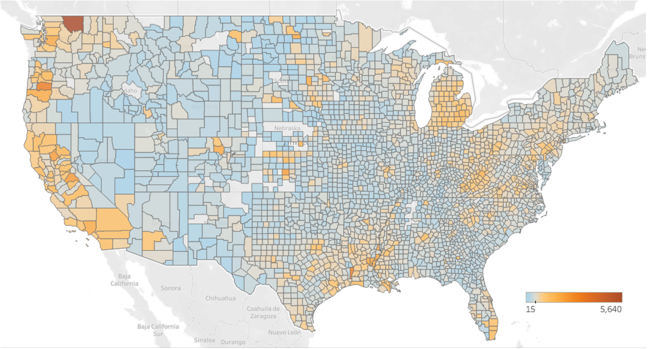


FIGURE 20: Average TOT by county.

2) Power outage area under curve

Table 6 provides the average AUC—outage impact per customer in minutes—(sum of AUC for each event divided by the total number of customers) by state associated with extreme weather events. This table indicates that the outage impact per customer in minutes (normalized average AUC) is highest in North Carolina, followed by Virginia, Louisiana, Texas, and so on. This shows that the individual customers in North Carolina are the most heavily affected, indicating poor power grid resilience in terms of AUC. On the other hand, customers in Washington, DC, Delaware, and Maryland are the least affected, indicating relatively better power system resilience in terms of the AUC metric.

Table 7 provides the average AUC—outage impact per customer in minutes—(sum of the AUC for each event divided by total number of customers) by county (50 counties with the highest AUC) associated with extreme weather events. This table indicates that Waynesboro (VA) has seen the most per-customer impact, followed by Buena Vista (VA), Henderson (NC), Lexington (VA), and so on.

Although at the state level, Virginia seems to be the worst performing state, this is mostly driven by three counties/cities (Waynesboro City, Buena Vista City, and Lexington City) because the average outage impact per customer of the rest of the counties is only 0.446 minutes. This indicates that Waynesboro City, Buena Vista City, and Lexington City need special attention to improve the power system resilience of the state of Virginia. Similarly, if we look at one of the less impacted states, for example, North Dakota, the average outage impact per customer is only 0.294, but Eddy County in North Dakota is 6th among all the counties in the United States, demanding special attention in terms of outage impact per customer in minutes. Therefore, it is important to perform a granular analysis of the outages to better prepare the most impacted areas.

TABLE 6: Normalized AUC (outage impact per customer in minutes) and number of events exceeding threshold by state

State/Territory	AUC (Normalized) Average	Event Counts
NC	11.333	12148
VA	10.106	12601
LA	0.899	10596
TX	0.860	33644
MI	0.627	9886
VT	0.606	616
WV	0.596	4746
ID	0.587	1249
ME	0.563	1945
MS	0.536	9428
MT	0.500	1126
SD	0.488	2551
AR	0.401	8726
RI	0.368	681
WY	0.365	1428
CA	0.350	9454
KY	0.348	10501
MA	0.327	2941
CT	0.308	1100
NY	0.299	7709
ND	0.294	1251
WI	0.276	6554
WA	0.262	2579
AL	0.260	9002
IA	0.258	6471
GA	0.252	13426
OR	0.243	2450
KS	0.232	6979
MN	0.226	4421
NH	0.221	999
OH	0.216	8820
IN	0.207	7781
NE	0.199	1998
OK	0.195	11336
PA	0.189	9238
NJ	0.186	5571
MO	0.174	9368
AK	0.166	202
SC	0.153	6695
IL	0.152	10392
FL	0.151	15549
NV	0.148	1068
HI	0.132	304
TN	0.127	7938
NM	0.126	3339
CO	0.126	3174
UT	0.121	1178
AZ	0.102	2615
MD	0.074	6283
DE	0.042	880
DC	0.016	288

TABLE 7: Normalized AUC (outage impact per customer in minutes) and number of events exceeding threshold by county/city (top 50 counties/cities in terms of AUC)

County/City	AUC (Normalized) Average	Event Counts
Waynesboro city,VA	2038.581	48
Buena Vista city,VA	944.644	21
Henderson County,NC	728.582	153
Lexington city,VA	151.798	14
Jeff Davis County,TX	71.633	46
Eddy County,ND	49.068	2
Alamance County,NC	21.997	135
Niobrara County,WY	20.111	19
Brewster County,TX	16.574	105
Butte County,ID	14.931	15
Vance County,NC	14.713	95
Edwards County,TX	13.757	84
New Hanover County,NC	12.981	673
Hamilton County,NY	11.360	49
Pamlico County,NC	11.026	102
Clay County,GA	10.711	26
Bandera County,TX	10.201	47
Calaveras County,CA	10.170	21
Lac qui Parle County,MN	8.698	9
Terrell County,TX	8.639	41
Hyde County,NC	8.598	141
Caswell County,NC	8.585	53
Jones County,NC	8.475	46
Presidio County,TX	8.359	53
Wahkiakum County,WA	8.217	4
Tuolumne County,CA	6.662	46
Moore County,NC	6.416	78
Kinney County,TX	5.920	33
Lunenburg County,VA	5.787	38
Alpine County,CA	5.649	4
Plumas County,CA	5.207	45
Real County,TX	5.084	50
Amador County,CA	4.995	26
Sutton County,TX	4.847	53
Morton County,KS	4.836	14
Robertson County,TX	4.814	88
Gillespie County,TX	4.699	39
Madison County,TX	4.626	77
Mason County,TX	4.582	39
Lafourche Parish,LA	4.510	113
Cottle County,TX	4.357	16
Alcona County,MI	4.342	27
Meagher County,MT	4.331	14
Chatham County,NC	4.293	148
Jackson Parish,LA	4.090	113
Union County,NM	4.021	18
Foard County,TX	3.977	33
Ogemaw County,MI	3.955	42
Schleicher County,TX	3.942	26
Cameron Parish,LA	3.934	71

3) Power outage time after the end of the event

The blue bar in Fig. 21 depicts a comparison of the average TAE (sum of TAE of each event divided by the total number of events in minutes) across various US states and territories. The bar chart shows that Hawaii has the highest TAE, followed by California, Washington, DC, Florida, Delaware, and so on. Idaho, Montana, North Dakota, Rhode Island, and Iowa are among the lowest TAE states. These results indicate that it takes the longest amount of time (despite of having very few events exceeding the threshold line) to repair the infrastructure in Hawaii and the shortest amount of time in Idaho.

The blue bar in Fig. 22 depicts a comparison of the average TAE (sum of TAE of each event divided by the total number of events in minutes) across the top 50 counties in the United States. The bar chart shows that Gregory County (SD), Graham County (AZ), Broward County (FL), Tripp County (SD), and Miami-Dade County (FL) have the highest

TAE. These results indicate that it takes longer (despite of having very few events exceeding the threshold line) to repair the infrastructure in these counties.

Longer TAE means more damaged electrical infrastructure and possibly other correlated infrastructure (e.g., communication and road network); however, we cannot ignore the magnitude of the events in each case. Therefore, our future work is to incorporate the magnitude of the event in the resilience metrics calculations.

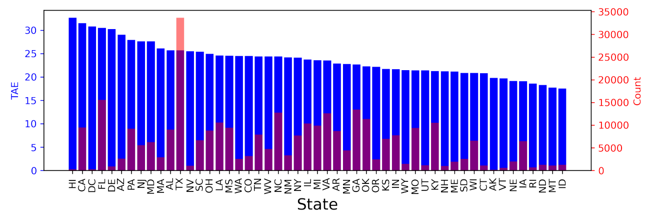


FIGURE 21: Average TAE by state.

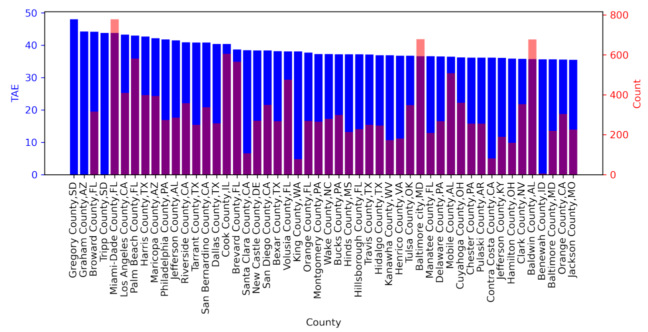


FIGURE 22: Average TAE by county. (Top 50)

D. WEATHER IMPACT ANALYSIS

This section provides an analysis of how different weather event types impact power systems in terms of the proposed metrics.

1) Power outage time over threshold

Fig. 23 depicts the average TOT for major weather event group types in the United States. Extreme wind (EW) ranked first with a value of 11741.667, followed by tropical storm (TR) at 5574.711, storm (SR) at 1488.041, ice storm (IS) at 1212.437, and blowing dust (DU) at 1192.161. If we ignore the magnitude of the weather event type, these weather event types are causing longer outages.

We observe that weather event types with high average TOT values (more impactful) are less frequent in terms of the number of events exceeding the threshold line (the red bar shows the number of events). On the other hand, severe thunderstorms (SV) were the most frequent cause of TOT (in terms of the number of events exceeding the threshold line); however, the average TOT for SV is 632.940, which is lower than many other less frequent weather event types.

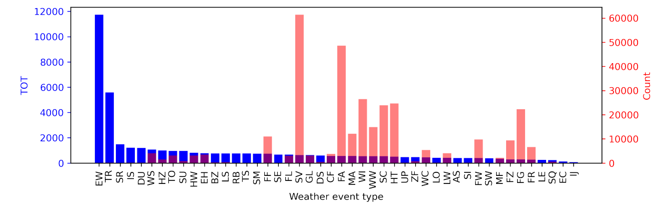


FIGURE 23: Average TOT by weather event type. Refer to Table 3 for descriptions of weather event types.

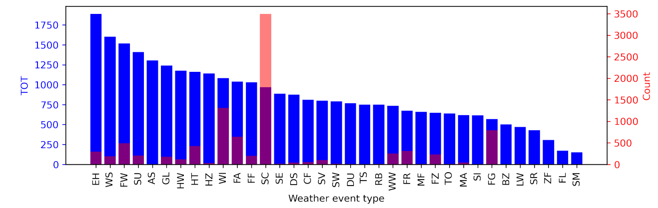


FIGURE 24: Average TOT by weather event type for California. Refer to Table 3 for descriptions of weather event types.

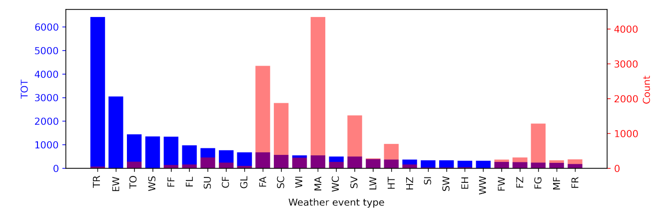


FIGURE 25: Average TOT by weather event type for Florida. Refer to Table 3 for descriptions of weather event types.

Fig. 24 and Fig. 25 provide the average TOT by weather event type for California and Florida. These figures show that the most impactful in terms of TOT weather event is extreme heat (EH) in the state of California and tropical storm (TR) in Florida. This suggests that California needs to put more emphasis on developing strategies against EH while Florida needs to develop strategies against TR to improve TOT. Note that although there is some observation that less frequent events tend to have more impact in terms of the duration of power outages, less frequent events are not always the more impactful cases. Since the impact of weather event type heavily depends on the magnitude of the event types, the magnitude of the event types needs to be incorporated in the power outages to properly compare the impact of weather events on power systems. This will be our future research work.

2) Power outage area under curve

Table 8 provides the average AUC—outage impact per customer in minutes—(sum of AUC for each event divided by the total number of customers) by weather event types. This table shows that extreme wind (EW) seems to be most impactful in terms of normalized AUC, followed by wind storm (WS), flood (FL), tropical storm (TR), and so on.

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TABLE 8: Normalized AUC (outage impact per customer in minutes) and number of events exceeding the threshold by weather event type. Refer to Table 3 for descriptions of weather event types.

Weather Event Type	AUC (Normalized) Average	Event Counts
EW	39.835	9
WS	28.780	3987
FL	22.244	2980
TR	17.736	156
HZ	3.689	1450
SR	1.931	74
IS	1.423	158
WW	1.329	14811
TO	1.154	3119
WC	1.147	5302
FF	1.041	10921
DU	1.023	155
SV	0.911	61328
HW	0.851	3117
FA	0.699	48385
SU	0.697	791
BZ	0.668	266
ZF	0.578	746
WI	0.548	26360
CF	0.502	3729
LS	0.347	344
MA	0.341	12128
FR	0.333	6605
FZ	0.314	9284
GL	0.291	3087
EH	0.274	3449
FW	0.263	9715
HT	0.260	24618
DS	0.227	445
UP	0.191	195
LW	0.188	4050
SC	0.186	23857
LO	0.151	114
SI	0.098	130
FG	0.098	22294
SQ	0.096	555
SE	0.085	64
MF	0.082	2173
SW	0.068	109
AS	0.063	109
SM	0.034	34
LE	0.024	11
RB	0.014	7
TS	0.010	2
EC	0.003	1
IJ	0.000	1

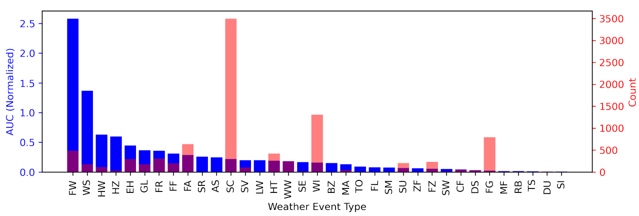

FIGURE 26: Normalized AUC by weather event type for California. Refer to Table 3 for descriptions of weather event types.

Fig. 26 and Fig. 27 provide the normalized AUC by

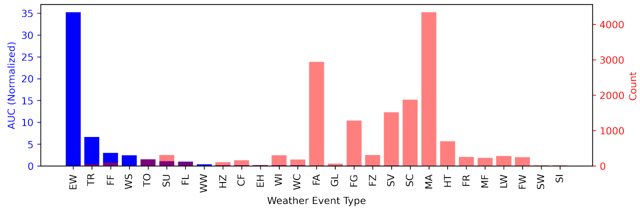

FIGURE 27: Normalized AUC by weather event type for Florida. Refer to Table 3 for descriptions of weather event types.

weather event type for California and Florida. These figures show that the most impactful weather event in terms of normalized AUC is fire weather (FW) in the state of California and extreme wind (EW) in Florida. This suggests that California needs to put more emphasis on developing strategies against FW while Florida needs to develop strategies against EW to improve AUC.

As mentioned previously, the magnitude of events needs to be incorporated into these assessments, and this will be our future research work.

3) Power outage time after the end of the event

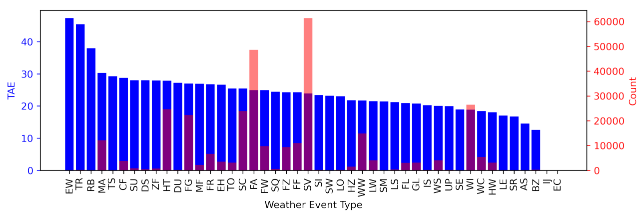

FIGURE 28: Average TAE by weather event type. Refer to Table 3 for descriptions of weather event types.

The blue bar in Fig. 28 depicts a comparison of the average TAE (sum of the TAE of each event divided by the total number of events in minutes) by weather event types. The blue bar chart shows that extreme wind (EW) is most impactful in terms of average TAE followed by tropical storm (TR), small craft for rough bar (RB), marine (MA), and so on. This shows that the power outage continues for longer duration after an extreme wind. Extreme wind causes several types of damage to power system infrastructure, leading to longer power outages. The presence of vegetation exacerbates the situation as extreme wind causes vegetation damage, which could damage the power system infrastructure.

Fig. 29 and Fig. 30 provide the average TAE by weather event type for California and Florida. These figures show that the most impactful weather event in terms of TAE is blowing dust (DU) in the state of California and extreme wind (EW) in Florida. This suggests that California needs to put more emphasis on developing strategies against DU while Florida needs to develop strategies against EW to improve TAE.

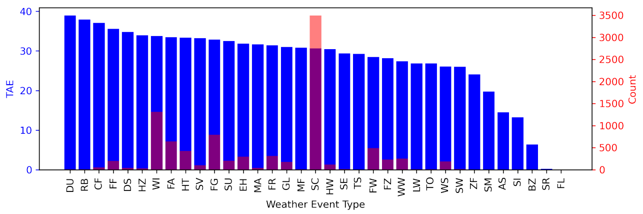

FIGURE 29: Average TAE by weather event type for California. Refer to Table 3 for descriptions of weather event types.

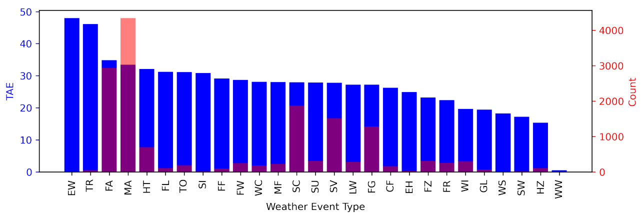

FIGURE 30: Average TAE by weather event type for Florida. Refer to Table 3 for descriptions of weather event types.

V. CONCLUSIONS

This paper presents an automated data framework to analyze the resilience of power systems against extreme weather events. For this work, 2018 to 2022 data was collected from the NWS dataset and the ORNL EAGLE-I power outage dataset to conduct a thorough power resilience analysis from various perspectives. Our methodology involved preprocessing, error handling, grouping near-time weather events, mapping the EAGLE-I power outage dataset on the NWS dataset, configuring the outage event threshold, and quantifying the resilience of the power system against extreme weather events. We defined TOT, AUC, and TAE as the metrics to uncover significant disparities in resilience associated with various types of extreme weather events and across diverse geographic locations.

Through this proposed approach we analyzed the effect of extreme weather events on power systems at the state and county levels. The analysis shows that states are impacted differently in terms of the defined metrics. For example, California is the most impacted in terms of TOT followed by West Virginia and Michigan. On the other hand, in terms of normalized AUC (outage impact per customer in minutes), North Carolina is the most impacted state followed by Virginia, Louisiana, and Texas. However, when we look from the perspective of TAE, Hawaii, California, Washington, DC, Florida, and Delaware are among the most impacted states. Therefore, there is no single trend that follows all the metrics together. County-level analysis shows that power system resilience varies significantly in terms of presented metrics. County- and city-level granularity is crucial to better understanding the unique resilience challenges faced by individual communities. Many of these results could be driven by factors such as varying extreme weather patterns, diverse geographical patterns, differing infrastructure strengths, or resistance levels. These aspects are worth investigating, and we will investigate them in our future work.

This work also analyzed the impact of different weather event types on power systems. Weather events such as extreme wind, winter storms, and fire weather need to be concerned more in terms of TOT as their average TOT was very high. Similarly, extreme wind, winter storms, and floods, were most impactful in terms of normalized AUC (outage impact per customer in minutes). In terms of TAE, extreme wind is most impactful, followed by tropical storms, small craft for rough bar, and marine. This shows that extreme wind challenges power systems most in terms of all the quantified metrics. Note that the magnitude of the events are not incorporated properly in this study.

Our automated data workflow has the added advantage of not requiring active utility company participation, which can often be a significant barrier to data collection in this field. This approach could pave the way for more extensive and more frequent analyses of power outages caused by extreme weather events, ultimately aiding in improving power grid resilience and reducing the societal and economic impacts of power outages. Also, the proposed approach is useful for identifying vulnerable hot spots (helpful for asset management) to know the impact of specific event types, which is important for developing planning strategies and the predictive analysis framework.

For future work, we will develop a framework to incorporate the magnitude of weather events to better analyze the specific impacts across different states and counties. The magnitude of weather event types needs to be normalized and incorporated into the quantification metrics to further analyze their impact. For example, the analysis of hurricane categories can be considered in the analysis of power system resilience related to hurricanes. Further, various meteorological variables such as temperature, wind speed, and precipitation will be considered for a more detailed analysis of power system resilience. Another important perspective of this research is analyzing the impact of climate change on power outages, as is studying the impact on maintenance schedule. These analyses will become more useful and trustworthy in the future as the coverage of EAGLE-I data increases.

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