Evaluating Undergrounding Decisions for Wildfire Ignition Risk Mitigation across Multiple Hazards

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***Abstract*—With electric power infrastructure increasingly susceptible to impacts from climate-driven natural disasters, there is an increasing need for optimization algorithms that determine where to harden the power grid. Prior work has primarily developed optimal hardening approaches for specific acute disaster scenarios. Given the extensive costs of hardening the grid, it is important to understand how a particular set of resilience investments will perform under multiple types of natural hazards. Using a large-scale test case representing the Texas power system, this paper aims to understand how line undergrounding investment decisions made for wildfire ignition risk mitigation perform during a range of wildfire, hurricane, and wind events. Given the varying geographical spread and damage profile of these events, we show that investment decisions made to address one type of natural disaster do not necessarily improve broader resilience outcomes, supporting the need for co-optimization across a range of hazards.**

***Index Terms*—Resilience planning, wildfires, line undergrounding, multi-hazard outages.**

I. Introduction

The power grid faces increased frequency of weather-related power outages as climate change worsens [1]. For instance, extreme weather related outages have had an average annual cost of \$127.4 billion from 2019 to 2024 in the United States [2]. Sustained power outages, largely attributable to extreme weather events [3], had an annual cost of over \$40 billion in 2015, a 25% increase from 2002 [4]. Parallel to the frequency and severity of natural disasters, investments in climate resilience are growing. A 2024 Biden-Harris initiative announced \$2 billion for improved resilience to mitigate impacts from hurricanes, tornadoes, wildfires, and other extreme weather events [5]. This investment is part of a larger \$100 billion in spending on power infrastructure, resilience, and clean energy [6]. The initiative in [5] specifically includes funding for projects in Texas, which has seen power outages from hurricanes [7], wildfires [8], ice storms [9], and strong winds [10]. One study found the system average interruption duration index (SAIDI) in the West South Central region (including Texas) increased 6% annually from 2000 to 2015, a finding which is "correlated with high wind speeds" [11]. As such, Texas provides an interesting case study due to its large geographic area and exposure to a wide variety of extreme weather events that are sometimes localized within a given region but can extend across large portions of the state.

As investment for climate resilience expands, researchers are investigating methods to optimally design and operate transmission-scale infrastructure [12], [13]. Prior research, e.g., [14], considers long-term investment planning with Texas case studies; however, this research largely considers random outages without using actual geographic weather data. Research has also been performed investigating cascading failures from line outages under extreme hurricane events in Texas, suggesting power lines be hardened or undergrounded to remove the likelihood of failure [15]. Many research efforts have evaluated optimal infrastructure decisions for specific climate-related resilience including winterization of generators in Texas with consideration for equity [16] or winterization through mobile battery systems on a reduced Texas system [17]. Similarly, reference [18] considers equitable line undergrounding for wildfire ignition risk mitigation. Research in [19] investigates large-scale battery installation to support both wildfire-related power outages and nominal operations.

Outside of Texas, researchers have considered power system planning in climate-related contexts. Reference [20] investigates expansion planning for transmission systems under increasing temperatures in Arizona. Reference [21] develops a multi-stage stochastic distribution expansion model for resilience under hurricane-related vulnerabilities. Likewise, reference [22] formulates a capacity expansion planning model for hurricane resilience in Puerto Rico. Additionally, reference [23] proposes a three-stage robust transmission expansion problem under climate uncertainty in Chile.

Wildfires pose a unique climate event since power infrastructure can not only be damaged by active wildfires but also can ignite wildfires under conditions of high temperatures, high winds, and low humidity [24]. To combat this, utilities conduct Public Safety Power Shutoff (PSPS) events to mitigate wildfire ignition risk, but these events can lead to load shedding for consumers [25]. Distributed energy resources are one solution evaluated in [26]. Similarly, networked microgrids are explored in [27]. Line undergrounding for PSPS events has also been extensively explored [28]–[30]. Undergrounded lines effectively remove the risk of igniting a wildfire while allowing these lines to continue transmitting power. Undergrounded lines are also less susceptible to other extreme events, such as winds, hurricanes, or active fires.

This paper evaluates the performance of climate resilience investment decisions developed for a specific type of extreme weather event under other types of natural disasters. In particular, we consider real, extreme weather-driven power outage data associated with a large-scale and realistic synthetic transmission grid geolocated in Texas [31]. We evaluate how line undergrounding decisions made to mitigate wildfire ignition risk impact power outages under three types of extreme weather events: hurricanes, wind, and active wildfires from actual 2021 data. To the best of our knowledge, this is the first power systems paper to analyze the impacts of infrastructure investments made to mitigate one hazard in the context of a range of other hazards for a large-scale realistic test case.

II. Data

In this paper, we evaluate real-world data from 2021 geolocated in Texas for wildfires, hurricanes and wind based events. We augment and evaluate this data with an undergrounding plan devised to reduce load shed during PSPS events for wildfire ignition risk mitigation.

A. Outage Data

County-level grid outage information (i.e., number of customers affected) was obtained from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) dataset [32] for the year 2021. The outage information was converted to an hourly resolution and further refined to identify discrete, multi-hour outage events. The outages were paired with weather event data from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) storm event database [33]. For this work, we consider three weather-based hazards: wind (i.e., high winds, strong winds, and thunderstorm winds); hurricanes; and wildfires. The combined data provides information on the average and maximum number of customers affected during an outage, total duration, and binary indicators for the presence of a storm event.

B. Undergrounding Plan

We consider wildfire ignition risk mitigation via the undergrounding investment plan from [18]. In this paper, a budget of \$1 billion USD is used to underground transmission lines in Texas to minimize the amount of load shedding associated with PSPS events. The authors in [18] found the undergrounding investment plan to reduce the load shed from PSPS events by over 70%. These events proactively de-energize transmission lines that are at high risk for igniting wildfires through faults caused by certain extreme weather conditions [34]. While expensive, undergrounding transmission lines allows power to continue flowing while removing the risk of that line igniting a fire. The planned lines for undergrounding are shown as the bold blue lines in Fig. 1, largely in the northwest region of Texas. For more information on how these lines are optimally selected for undergrounding, see [18].

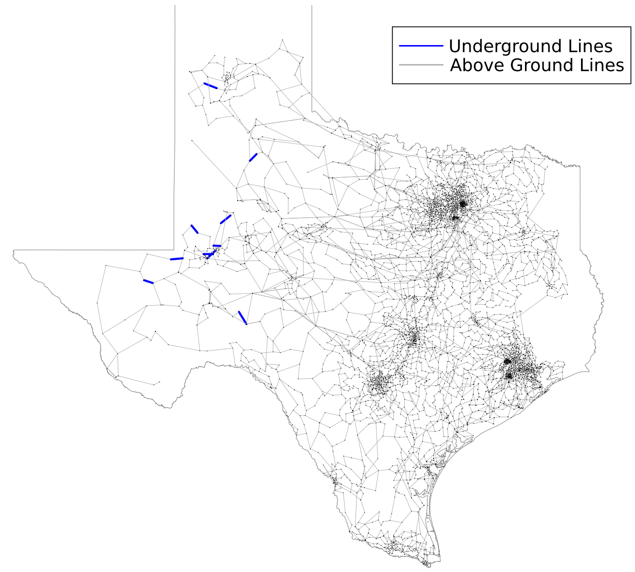

Fig. 1: A map of the line undergrounding plan considered in this paper based on [18]. Grey lines show above ground transmission lines (at risk for outages). Bold blue lines represent planned transmission lines for undergrounding.

C. Test Network

The Texas7k network, a realistic synthetic transmission network developed by Texas A&M PERFORM group is used in this research [31]. This synthetic network provides a realistic transmission system covering the areas served by ERCOT [35]. This network includes 6717 buses and 9140 transmission lines.

III. Methodology

We generate 100 outage scenarios for each day of the year for the three discussed hazards: wildfires, hurricanes, and wind events. We evaluate the load shed in a pre-resilience case, i.e., when all outaged lines are unable to transmit power. We also evaluate the post-resilience case where the undergrounded lines that would otherwise have been outaged remain energized and can transmit power.

A. Scenario Development

Using the combined datasets, we generated 100 different outage scenarios per event type per day. The dataset provides the fraction of customers experiencing load shed in each county as well as a binary hazard indicator. We take the following approach to determine the sets of line outages for each event in each scenario:

1) $\rho_{d,c} = \sum_{t \in \mathcal{T}} \rho_{d,c,t}$ — the outage probability proxy for a county $c \in \mathcal{C}$ on day d where $\rho_{d,c,t}$ is the proportion of customers experiencing an outage in county c at time t on day d.
2) $o_{l,d,k}$ — a random outage number for each line $l \in \mathcal{L}$ in scenario k chosen from a beta prime distribution with a mean value of 0.01 [36], [37].

3) For each line l, we compare $o_{l,d,k}$ to $\rho_{d,c}$, $\forall c \in \mathcal{C}_l$, the set of counties intersected by line l. If $o_{l,d,k} < \rho_{d,c}$, line l is outaged (included in the set $\mathcal{L}^{\text{out}}_{d,k}$) for the corresponding day.

	Avg Outages	Max Outages	Days	Scenarios
Wildfire	13.2	20	2	109
Hurricane	900.3	1230	2	200
Wind	24.7	303	86	6239

TABLE I: Statistics for line outages co-occurring with the three examined types of weather events. The average outages column indicates the average number of lines outaged across all scenarios on all days (excluding scenarios with no outages) for each event type. The max outages column indicates the maximum number of lines outaged across all scenarios on all days. The days column indicates the total number of days where any outages occur. The scenarios column indicates the number of scenarios across all days where any outages occur.

Table I shows summary statistics that capture the average and maximum number of line outages are across all scenarios and days. Only scenarios with at least one line outage are counted when finding the average. Wildfires see relatively few lines outaged, with roughly 13 lines outaged on average across the scenarios. Hurricanes see an order of magnitude more outages with over 900 lines being outaged on average across the scenarios. Wind scenarios occur much more often than both hurricanes and wildfires and much more extensively throughout the year, causing almost twice the number of line outages on average.

We see extensive outages co-occurring with hurricanes, specifically on September 13/14th. On these days, a large portion of the synthetic transmission network is outaged. Similarly, wildfire outages also only occur on two days (April 10th and December 10th). However, there are only reported power outages in a few counties, leading to very few lines being impacted in our scenarios. Wind-related events occur much more sporadically throughout the year, impacting dozens to hundreds of lines, during related power outages.

B. Power System Model

To evaluate the load shedding in each scenario on each day, we run a Bθ DC-OPF model with an objective to minimize total network load shed. We define $\mathcal{L}^{\text{out}}$ as the set of outaged lines on a given day and scenario for the outage types discussed. We model hourly operations on each day, with hourly demand information adapted from [38]. The mathematical model is shown in Model 1, $\forall d \in \mathcal{D}, \forall k \in \mathcal{K}$, where $\mathcal{D}$ is the set of days and $\mathcal{K}$ is the set of scenarios.

Objective 1a minimizes the sum of load shed across all buses and time periods. Equation 1b constrains the power generation ($p^i_{g,t}$) to be between the lower and upper limits for each generator $i \in \mathcal{G}$, the set of all generators. Equation 1c constrains the load shed ($p^n_{ls,t}$) to be nonzero and less than the load demanded ($p^n_{d,t}$) at the same time and for each bus $n \in \mathcal{N}$, the set of buses. Equation 1d ensures the power flow

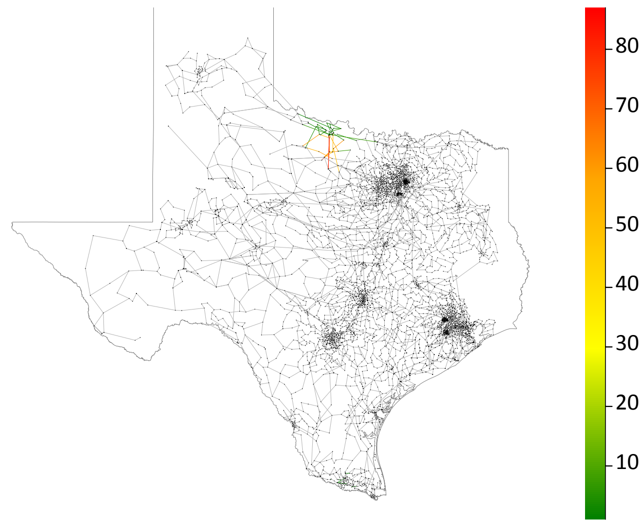

Fig. 2: A map showing line outages which co-occurred with wildfires. The most-outaged line (in red) is shutoff 87 times across all days and all scenarios while the least-outaged line (in green) was only outaged 1 time.

Model 1 Bθ DC-OPF

$$\textbf{min} \sum_{t\in\mathcal{T}} \sum_{n\in\mathcal{N}} p^n_{ls,t} \tag{1a}$$

$$\textbf{s.t.} \quad \forall t \in \mathcal{T},$$

$$\underline{p}^i_g \leqslant p^i_{g,t} \leqslant \overline{p}^i_g \qquad \forall i \in \mathcal{G} \tag{1b}$$

$$0 \leqslant p^n_{ls,t} \leqslant p^n_{l,t,d} \qquad \forall n \in \mathcal{N} \tag{1c}$$

$$f^\ell_t = 0 \qquad \forall \ell \in \mathcal{L}^{\text{out}}_{d,k} \tag{1d}$$

$$-\overline{f}^\ell \leqslant f^\ell_t \leqslant \overline{f}^\ell \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}^{\text{out}}_{d,k} \tag{1e}$$

$$\underline{\delta}^\ell \leqslant \theta^{n^{\ell,\text{fr}}}_t - \theta^{n^{\ell,\text{to}}}_t \leqslant \overline{\delta}^\ell \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}^{\text{out}}_{d,k} \tag{1f}$$

$$f^\ell_t = -b^\ell(\theta^{n^{\ell,\text{fr}}}_t - \theta^{n^{\ell,\text{to}}}_t) \qquad \forall \ell \in \mathcal{L} \setminus \mathcal{L}^{\text{out}}_{d,k} \tag{1g}$$

$$\sum_{\ell\in\mathcal{L}^{n,\text{fr}}} f^\ell_t - \sum_{\ell\in\mathcal{L}^{n,\text{to}}} f^\ell_t = \sum_{i\in\mathcal{G}^n} p^i_{g,t} - p^n_{l,t,d} + p^n_{ls,t} \ \forall n \in \mathcal{N} \tag{1h}$$

(f^ℓ_t) is zero for any line $\ell \in \mathcal{L}$, the set of outaged lines. For any lines that remain operational, equation 1e constraints the power flow to be between the lower and upper limits. Equation 1f constrains the voltage angle difference across a line to be within the lower and upper bounds. Equation 1g models the Bθ power flow approximation for each line. Finally, equation 1h models the power balance constraints. For the post-resilience results discussed in Section V-B, the set of outaged lines is defined as $\mathcal{L}^{out} \setminus \mathcal{L}^{ug}$ where $\mathcal{L}^{ug}$ is the set of undergrounded lines shown in Fig. 1.

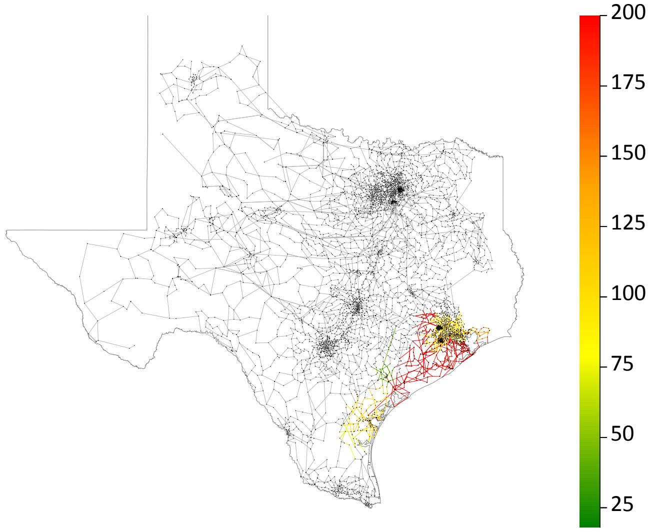

Fig. 3: A map showing line outages which co-occurred with hurricanes. The most-outaged line (in red) is shutoff 200 times across all days and all scenarios while the least-outaged line (in green) was only outaged 18 times.

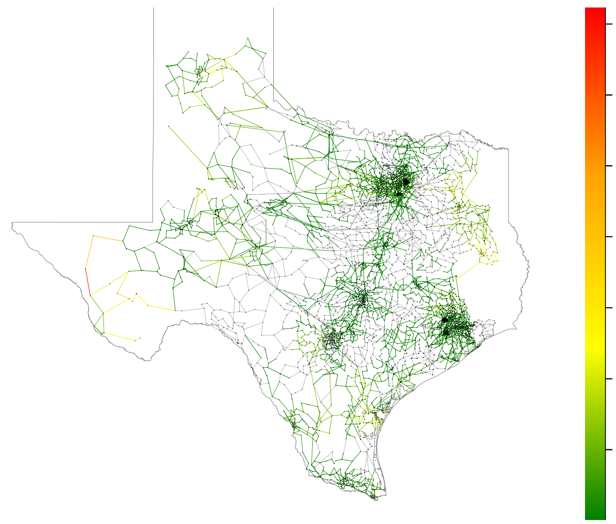

Fig. 4: A map showing line outages which co-occurred with wind hazards. The most-outaged line (in red) is shutoff 723 times across all days and all scenarios while the least-outaged line (in green) was only outaged 1 time.

IV. Event Overlap

For the line undergrounding plan outlined in Section II-B, we find there are no lines that are undergrounded for wildfire ignition risk mitigation that are outaged during the hurricane events or the active wildfire events from this study. For the wildfire events, the ignition risk data used for the undergrounding decisions comes from the United States Geological Survey's Wildland Fire Potential Index [39] which indicates where a significant fire is likely to *start*. In contrast, the combined EAGLE-I and NOAA NCEI storm events dataset used for these outage scenarios show where *active* wildfires are co-occurring with impacted power system operations. For the evaluated time period, outages from active wildfires are observed in the central-north part of the state (Fig. 2), which does not overlap with the lines chosen for undergrounding. Similarly, for hurricanes, the lack of overlap can be explained by the geographic disparity between where lines are undergrounded due to high wildfire ignition risk (northwest Texas in Fig. 1) and where the hurricane event captured by this research impact power infrastructure (southeast Texas in Fig. 3).

Outage events co-occurring with wind events examined in this paper span a wide geographic area (see Fig. 4). Some of the lines outaged from wind events overlap with those in the undergrounding plan. Of the 6,239 total scenarios with wind-related outages across the year-long time period examined, 252 scenarios involve lines that are undergrounded, or roughly 4% of the wind-related outage scenarios. There are 12 total outage scenarios that are fully prevented, since all involved lines are undergrounded, representing less than 0.2% of wind-related outage scenarios. Load shedding outcomes from pre- and post-undergrounding are discussed in Section V.

V. Results

In this section, we show load shed outcomes for winds, hurricanes, and wildfire related outages without line undergrounding investments. As discussed in Section IV, there are no impacted lines in the hurricane or wildfire scenarios that are undergrounded in the wildfire ignition risk mitigation undergrounding plan. Thus, in Section V-B, only results from wind events are shown to highlight the reduction in load shed when lines are undergrounded. Note that the figures in this section have different scales on the vertical-axis to better show detail for specific weather-based hazards. Load shed values in this sections are given in megawatt-hours (MWh).

A. *Pre-Resilience Outages*

As discussed in Section II-A, active wildfires caused very few impacts to the power grid during the evaluated time period. We see this again in Fig. 5 which shows around 1,000 MWh of load shed or less on December 10^{th} and even less on April 10^{th}. This constitutes less than 0.1% of the total demand across the network on December 10^{th}. Likewise, we only see load shed with hurricanes on September $13/14^{\text{th}}$, aligning with the limited line outages discussed in Section II-A. In Fig. 6, we see that the hurricane-related outage events cause significant load shed, with the average load shed across the scenarios approaching 300,000 MWh on September 14^{th}. This

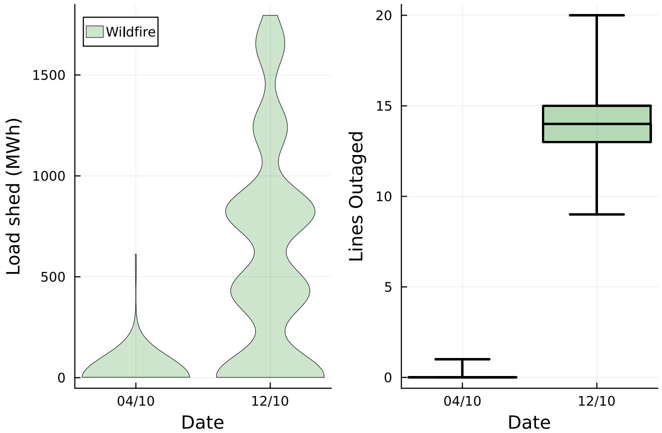

Fig. 5: Violin plots show the daily load shed across scenarios on the two impacted days under the wildfire events. Box plots indicate the number of outaged lines co-occurring across the scenarios on a given day.

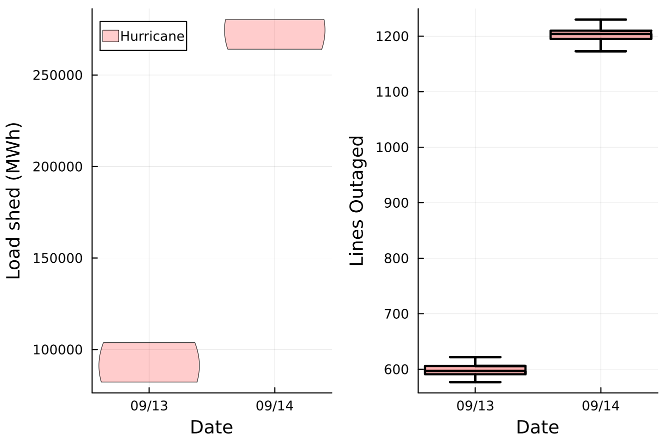

Fig. 6: Violin plots show the daily load shed across scenarios on the two impacted days under the hurricane events. Box plots indicate the number of outaged lines co-occurring across the scenarios on a given day.

constitutes nearly 25% of the total demand on that day. Although the region impacted by the hurricane is a relatively small portion of Texas, as seen in Fig. 3, the large number of line failures leads to widespread impacts across the network. On September 14th, there are roughly 1200 lines outaged, comprising over 10% of the synthetic transmission network, as can be seen in the box plots in Figure 6 Fig. 7 shows that load shed throughout the considered time period varies from nearly zero to the order of 30,000 MWh of load shed on days with wind-related outages. Figure 7 shows a subset of days with outages co-occurring with wind hazards. The maximum load shed that occurs is on October 28th, representing less than 3% of the demand on that day.

B. Post-Resilience Outages

Wind-related line outages were the only type that intersected with the set of underground lines for wildfire ignition risk mitigation as discussed in Section IV. In Figure 7, we show the

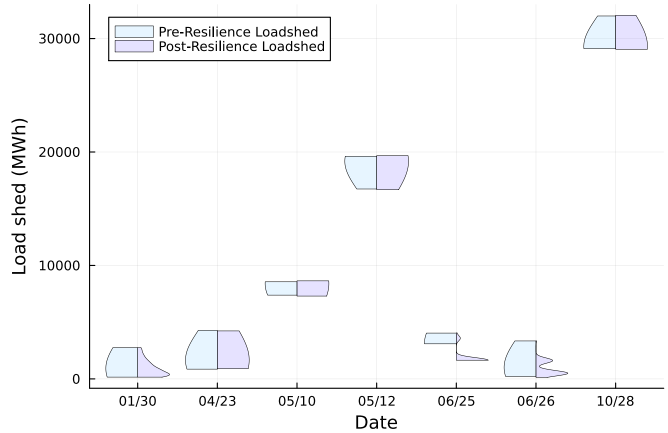

Fig. 7: Violin plot showing the total amount of daily load shed across wind events on a subset of days. The left side shows pre-contingency load shed and the right side shows post-contingency load shed.

post-contingency load shed on the right side of the violin plots. Only three days saw load shed reduction when considering the lines undergrounded to support PSPS events: January 30th, June 25th, and June 26th. The average decrease in load shed per scenario after considering undergrounded lines is 25MWh, 1250MWh, and 135MWh across the three days respectively.

VI. Conclusion

This paper compared line outage profiles of three types of extreme weather events based on real-world data correlated with a realistic synthetic transmission grid geolocated in Texas. Using an optimal power flow formulation, we computed the load shed during every hour of each day of 2021 with 100 scenarios per day. This provides a baseline to compare load shed results after we consider certain lines to be undergrounded and protected from the considered weather events.

Line undergrounding decisions were based on their effectiveness in reducing load shed from PSPS events that mitigate the risk of wildfire ignitions from power infrastructure. While these undergrounding decisions improve resilience outcomes in this specific context [18], we find that they yield very small improvements for the other extreme events evaluated in this work, namely, active wildfires, hurricanes, and wind. The first two of these event types had no overlap between their associated line outages and the lines that were undergrounded for wildfire ignition risk mitigation. The third, wind events, had some overlap but only saw meaningful reduction in load shed on three days out of the year.

Thus, while the line undergrounding decisions are effective at reducing load shed for PSPS events that mitigate wildfire ignition risk, this paper shows that resilience investments planned and optimized to aid in a specific climate events can have negligible impacts on reducing climate impacts more broadly. This motivates further research on *co-optimizing* infrastructure investments across a number of different geographically varying extreme weather events.

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