The Feasibility of Energy Communities for Hurricane Resilience

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ABSTRACT

Climate extremes like hurricanes can devastate vulnerable power lines, resulting in large-scale power outages, e.g., Hurricane Beryl (2024) with 2.6 million customers in Texas, US. In response, peer-to-peer (P2P) energy sharing has emerged as a promising strategy to create energy communities (ECs) that become resilient by adopting distributed energy resources (DERs) to generate and share electricity locally, especially after disasters. We developed a validated high-fidelity model of power systems for 2,640 households, integrating geographical multi-sourced data with probabilistic risk analysis to assess the feasibility of ECs for hurricane resilience. Our study finds that ECs would have experienced shorter outages by 65.8% for Hurricane Isaias (2020) in Absecon City, New Jersey. We then utilized our power risk model to study the financial feasibility of ECs versus other measures (e.g., undergrounding lines) for resilience to future hurricanes in Absecon and compare it to Miami communities, in Florida, exposed to larger hurricanes. We show that benefits are larger in Miami, where ECs can shorten outages by 64.4%, 33%, and 50.54% than no grid upgrade, DERs without P2P sharing (non-ECs), and undergrounding. Battery backups and resilient solar panels enhanced ECs ability to operate in island mode, which would have reduced the percentage of households experiencing outages longer than a day by 74% during Hurricane Isaias (2020). Furthermore, we show that undergrounding results in a negative net present value (NPV) for communities, with households facing a 155% higher cash outflow compared to ECs, where the addition of solar panels reduces energy bills and increases savings. Our study demonstrates the importance of integrating resilience into energy policies, particularly as infrastructure evolves to meet the challenges of a changing climate.

1. INTRODUCTION

Hurricanes can destroy old and vulnerable power lines, causing large-scale cascading power failures [1, 2]. For example, (a) Hurricane Isaias (2020) caused widespread blackouts for more than 3 million customers across five states in the US [3]; (b) Hurricane Ida (2021) caused extensive damage to power infrastructure in Louisiana, leaving 1.2 million customers without power [4]; (c) Hurricane Ian (2022) left 2.7 million customers in Florida without power [5]; (d) more recently, Hurricane Beryl (2024) left more than 2.6 million customers without power in Texas [6]. These blackouts are often prolonged, threatening the health of the affected population as they endure excessive heat after a hurricane [7, 8]. Adding to the distress, the critical interdependence of transport, water pumps, medical facilities, food supplies, and emergency aids with electricity can deprive communities of critical services post-hurricane. Power outages can severely impact vulnerable community members, including households with children, the elderly, and medically fragile populations [9, 10].

Resilient communities must have power systems capable of withstanding extreme weather events and minimizing the extent of cascading power disruptions [11, 12]. In recent years, rooftop solar panels have supplemented the power supply of residential, office, and industrial buildings [13]. The US Energy Information Administration predicts a 75% growth in solar energy production from 2023 to 2025 [14]. Distributed energy resources, such as rooftop solar panels, can generate electricity locally and operate in island mode. Thus, DERs have great potential to enhance community resilience by providing electricity access after a disaster, even when power lines fail [15].

Furthermore, massive governmental and industry investments are targeting integrating DERs at micro-urban scales through microgrids to create energy communities (ECs), an emerging concept in energy markets [16]. In ECs, prosumers - households with energy-generating sources such as rooftop solar panels - sell surplus electricity under peer-to-peer (P2P) sharing to local neighborhoods [17, 18]. One notable example of an energy community (EC) is the Brooklyn Microgrid, which became operational in 2016 [19]. Such ECs are exhibiting resilience after large disasters. In 2017, Hurricane Maria battered Puerto Rico, snapping many power lines and leaving numerous communities without power for several months. In response, communities have turned toward building independent microgrids to solve their energy needs and resilient power infrastructure [20]. To further support these initiatives, the US Department of Energy announced USD 450 million in funding in July 2023 to incentivize the deployment of 30,000 to 40,000 residential solar systems [20].

Currently, there is limited research on the benefits of resiliency with P2P sharing at the community level because most studies have focused on a single or small group (2-3) of households [21–24]. Other studies have not considered the vulnerability of the existing grid [15]. In [25], authors showed increased resilience to power outages at the household level with P2P power sharing during an earthquake, but they did not consider power lines can fail during ground shaking, affecting the power network connectivity of ECs. Analyzing electricity access from solar during hurricanes is also more complex than for earthquakes. Unlike earthquakes, thick optical clouds during hurricanes can significantly hinder the incoming solar irradiance on solar panels [26], further reducing the electrical power generation during the disaster.

To understand the resilience of ECs, this paper develops a high-fidelity outage risk model (Hi-Fi ORiM) for households with rooftop panels, behind-the-meter batteries, and P2P energy sharing to predict electricity access during hurricane emergencies. The model integrates state-of-the-art hurricane hazard [27], vulnerability [28], solar irradiance [29, 30], and network modeling [31] to study ECs during future hurricanes with a probabilistic framework. We combine multiple data streams to create a realistic synthetic network for Hi-Fi ORiM using graph theory (see Methods) [31]. Thus, the Hi-Fi ORiM can assess the failure risk from each component (poles, panels) in the network, as their vulnerabilities vary, and how their failures cascade through the network. We also use high-performance computing to quantify uncertainties in the risk model and thoroughly study the viability of adopting different resilience mitigation strategies, including ECs [32].

Current models that evaluate the viability of DERs in high hurricane hazard areas do not account for solar panel failures, solar irradiance reductions, or the long duration of power recovery during large hurricanes. These factors are crucial for evaluating the ability of DERs to sustain electricity supply during disasters. Existing tools, such as renewable energy integration and optimization tools (REopt) and solar power calculators (PVwatts), do not consider solar panel failure risks, neglecting their repair and replacement costs when optimizing panel and battery size for savings and resilience [33]. Other important studies for hurricane resilience have also neglected such failure risks, in addition to significant solar irradiance decays during hurricanes [34]. Rooftop solar panels can have a 75% failure probability for hurricanes with wind speeds over 90m/s [35]. An example of a failed solar panel in the aftermath of Hurricane Ian (2022) is shown in Supplementary Figure S5. Additionally, in [26], the authors found that solar generation could decrease by more than 70% in Miami-Dade, US, during category-4 hurricanes. Moreover, scholars have mostly considered a particular outage scenario with quick recoveries of 8h to 24h [23, 36]. However, hurricanes can leave populations without power for days to months [10].

Other grid-hardening measures can also increase the resilience of power systems. For example, the resilience of the power grid to hurricanes can be enhanced by undergrounding overhead power lines [37–39]. However, the cost of undergrounding can be high and result in increased consumer electricity tariffs [38]. On the contrary, there is growing literature on the economic and financial benefits, in addition to the environmental ones, that renewables can bring to reduce the billions of dollars in losses caused by power blackouts [21, 36, 40, 41]. Thus, evaluating and comparing the cost of adopting such mitigation strategies to enhance resilience becomes essential.

This paper presents and develops a high-fidelity risk outage model (Hi-Fi ORiM) of a distribution grid serving 2,640 households. We calibrate the model with power outage and recovery data from Hurricane Isaias (2020) to serve as a validated test bed for assessing the resilience of power communities prone to hurricane risks. To evaluate the finances of resilient electricity, we determine the net present value (NPV) of solar panel adoption by considering installation costs, cash flows (amount of electricity sold and bought), and the value of resilience [42]. Traditionally, value of resilience is considered by multiplying the avoided outage duration with the value of lost load (VoLL), expressed in dollars per kWh of unserved load [42, 43]. However, traditional VoLL is limited to qualitative analysis as it is determined through surveys based on the responses to hypothetical conditions provided to the responder. This paper presents a new method to quantify the value of resilience by arranging alternative energy resources during emergencies. Our study compares multiple strategies for resilient electricity: (a) ECs, which involves the adoption of solar panels with P2P sharing; (b) non-ECs, which involves the adoption of solar panels without P2P sharing; and (c) undergrounding of power lines. Additionally, we integrate 5,018 synthetic hurricanes from a state-of-the-art hurricane hazard model to study the resilience benefits against future hurricanes [44]. Our combined approach of state-of-the-art Digital Twin, probabilistic risk modeling, and financial analysis would allow stakeholders such as homeowners, utilities, and local governments to make informed decisions and invest in building a resilient power grid for the future.

2. RESULTS

A. Validated High-Fidelity Outage Risk Model of Power Network

The high-fidelity outage risk model (Hi-Fi ORiM) represents the physical systems of the power grid, enabling simulations of their interactions with natural hazards [31, 45]. This approach assesses the vulnerability of entire power networks by integrating risk modeling for individual components with their interconnections rather than focusing on single components. This method is particularly valuable in scenarios where network dynamics are crucial, such as in power networks. We leveraged high-performance computing (HPC) resources to overcome the computational challenges of running multiple power systems and hurricane scenarios.

We developed Hi-Fi ORiM of the power distribution network serving 2,640 residential consumers in Absecon City in Atlantic County, New Jersey, who could benefit as ECs. We integrated information from publicly available multi-sourced datasets in the model (Figure 1), including limited pole locations from OpenStreetMaps [46], roads and building parcels from New Jersey Open Geographic Information Systems [47, 48], and building footprints from Microsoft [49].

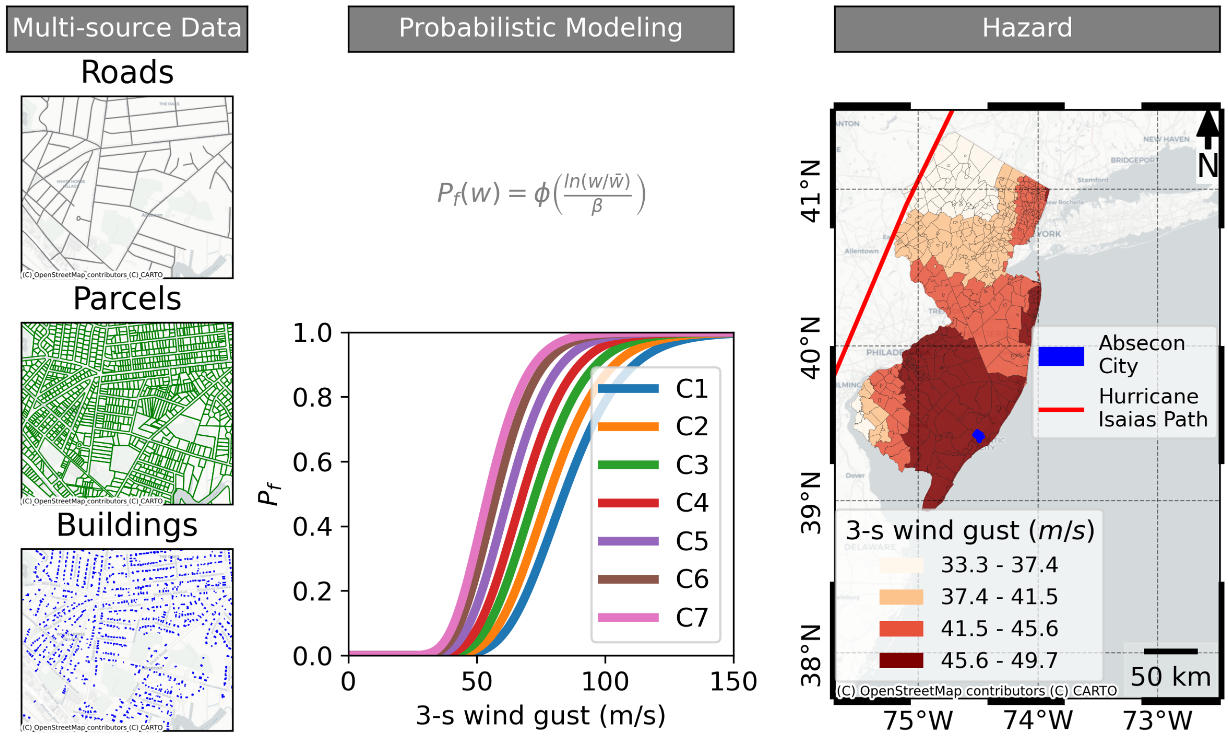

Fig. 1. Hi-Fi ORiM developed using open-source datasets of roads, parcels, and buildings from the New Jersey Geographic Information Network [50]; fragility curves for pole failure probabilities across classes C1-C7, modeled with a log-normal distribution for a median 3-second wind gust ($\bar{w}$) and dispersion (β) [28] (see Methods); and hazard information from 3-second wind gusts during Hurricane Isaias (2020).

Most distribution networks in the US have a radial structure, where the failure of a single overhead pole can cause cascading power failures for all downstream consumers [51]. We developed the Hi-Fi ORiM by reproducing such a radial topology and coupling it with hazard and vulnerability models of the power system's components [31]. The resulting probabilistic risk-network model predicts the damage to the overhead poles from wind hazards, disconnections in the power network due to damages, and the recovery of damaged components back to a fully connected network (see Methods). We only consider wind-driven failures of distribution poles [31] and do not model the compound failures from falling trees on distribution poles due to lack of data [52]. Fragility curves define the wind-dependent failure probabilities for different classes of poles (Figure 1). We used a full circulating [27] and background [53] wind model to capture the complete structure of tropical cyclones to assess realistic hurricane winds. Figure 1 presents all the components to build a Hi-Fi ORiM, including datasets, risk modeling, and hazard information.

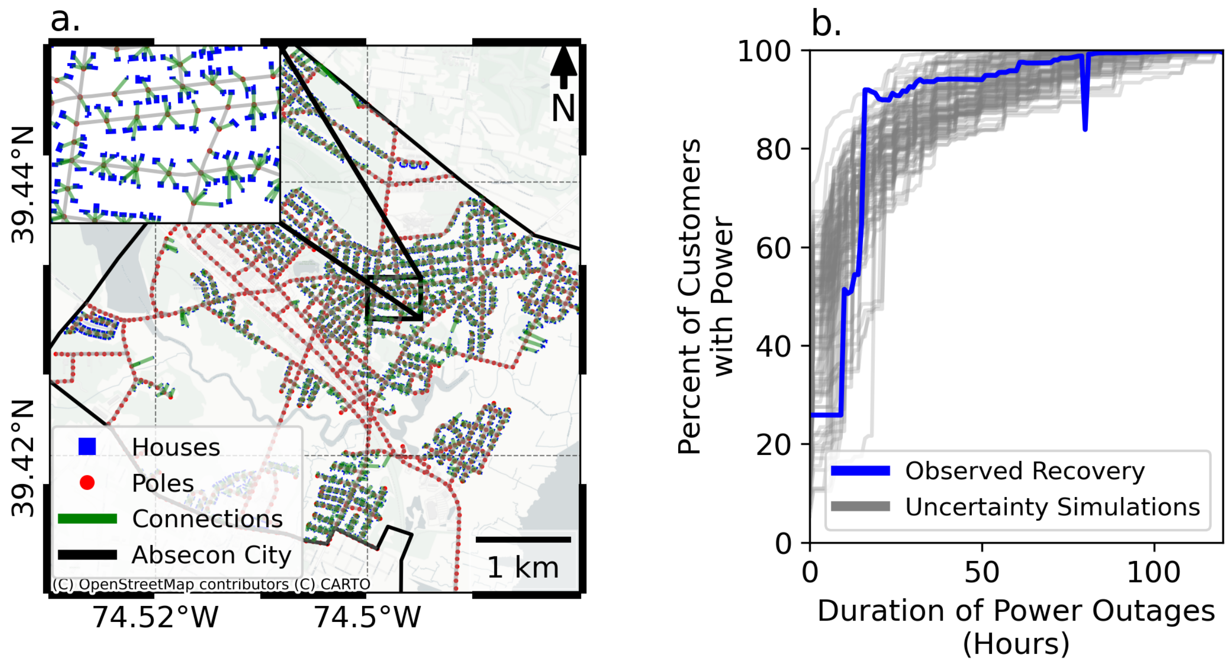

Fig. 2. **a.** Representation of constructed synthetic grid for Absecon City, New Jersey. **b.** Recovery simulations of Hi-Fi ORiM calibrated for the observed recovery during Hurricane Isaias (2020).

Our Hi-Fi ORiM was calibrated using outage and recovery data from Hurricane Isaias (2020) (see Methods) [54]. Isaias carried winds close to 100-year return period events for New Jersey [55]. Even though Isaias transitioned to a tropical storm before hitting New Jersey, it still snapped power lines and destroyed many power poles [56]. Isaias caused economic losses of 4.2 billion and 15 deaths and was responsible for major blackouts across five states in the Northeast United States. One million customers were without power alone in New Jersey, with many suffering power loss for over four days [57, 58].

Our developed Hi-Fi ORiM model, as shown in Figure 2a, can simulate hurricane-induced outages and the post-disaster recovery of the power network with high precision, as demonstrated in Figure 2b. Our model predicts maximum percent outages of 77.42% close to the observed percent outages for 74.15% of consumers. In our synthetic grid, 95% of the customers recover in 61 hours close to 55 hours for the observed recovery of the power grid in Absecon City. Our developed Hi-Fi ORiM model represents a typical suburban power network, making our framework adaptable for assessing the risk of power outages across varying levels of hurricane wind intensity, from low to high.

B. Could we have enhanced electricity resilience during Hurricane Isasias?

We found that communities would have benefited significantly from resilience measures during Hurricane Isaias (Figure 4). To compare the effectiveness of resilience measures, we considered four different cases: (a) No Upgrade, (b) ECs, (c) Non-ECs, and (d) Underground power lines. We ran 400 random simulations of our probabilistic risk model during Hurricane Isaias.

The US is projected to have 55% of its electricity generation through solar energy [59]. In line with this projection, we assumed that 50% of houses in a cluster would adopt solar panels and battery storage of 10 kWh. We grouped the houses into clusters based on Euclidean distance to study the effectiveness of energy sharing (see Methods). The solar panels are sized for net-zero energy consumption, *i.e.*, energy generated by panels equals energy consumed by households. Figure 3a. depicts a network of houses in a power grid without solar panels, where all the houses lose power during hurricane emergencies. In contrast, another network in Figure 3b. has prosumers installing rooftop solar panels. These prosumers can generate electricity or use backup power from a battery during a hurricane emergency. The prosumers gain resilience through solar panels and can enhance the community's resilience by sharing excess electricity in a solar EC.

To model ECs, we extended our Hi-Fi ORiM model (Figure 8). First, we integrated solar panel vulnerability functions into our risk model [35] to predict damage from the hurricane winds [27, 53] We integrated a stochastic model to predict reduced solar irradiance into the Hi-Fi ORiM model, using historical solar data to capture the effect of thick hurricane clouds on solar generation, as shown in Supplementary Figure S4 (see Methods) [26]. Finally, we modeled each household's recovery based on the available solar irradiance and undamaged network components.

To study the effectiveness of undergrounding measures, we assumed that 50% of the most vulnerable power poles are buried. For example, class 7 poles, which have the lowest median wind threshold on the fragility curve (Figure 1), are undergrounded first, followed by the second most vulnerable poles.

Supplementary Figure S7 shows the adoption of solar panels among prosumers across Absecon City for ECs and non-ECs grid hardening configurations, as well as the undergrounding of power poles (lines) to increase resilience against strong winds (see Methods).

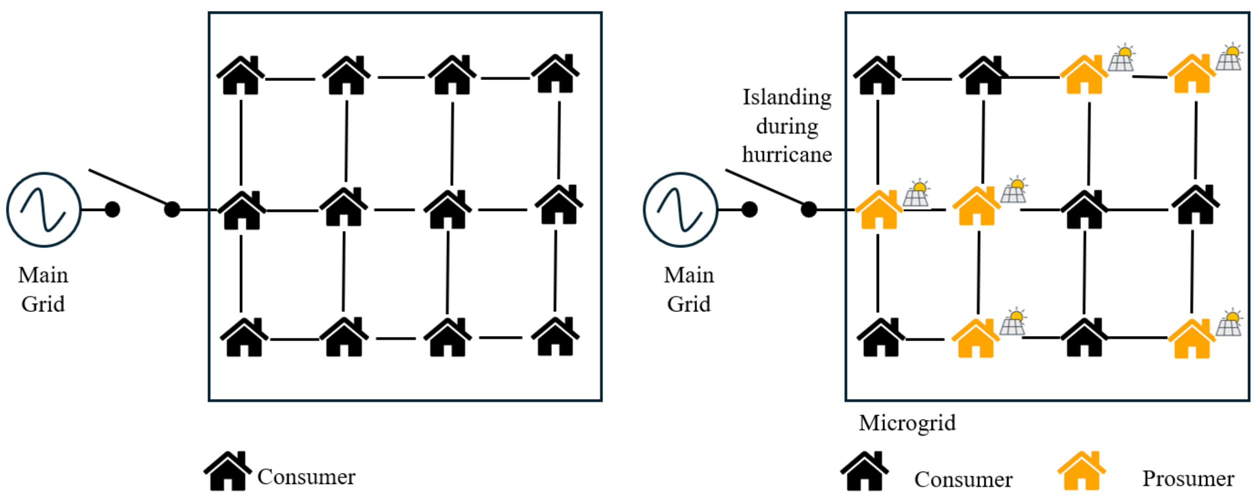

Fig. 3. Schematic Diagram of the P2P energy sharing. The left figure shows the traditional grids where consumers suffer outages during hurricanes due to extensive damage to the power grid, and the right figure shows the adoption of solar panels so that the prosumers can generate electricity in island mode after the hurricane and share excessive energy with consumers (without solar panels) to increase the resilience against power outages.

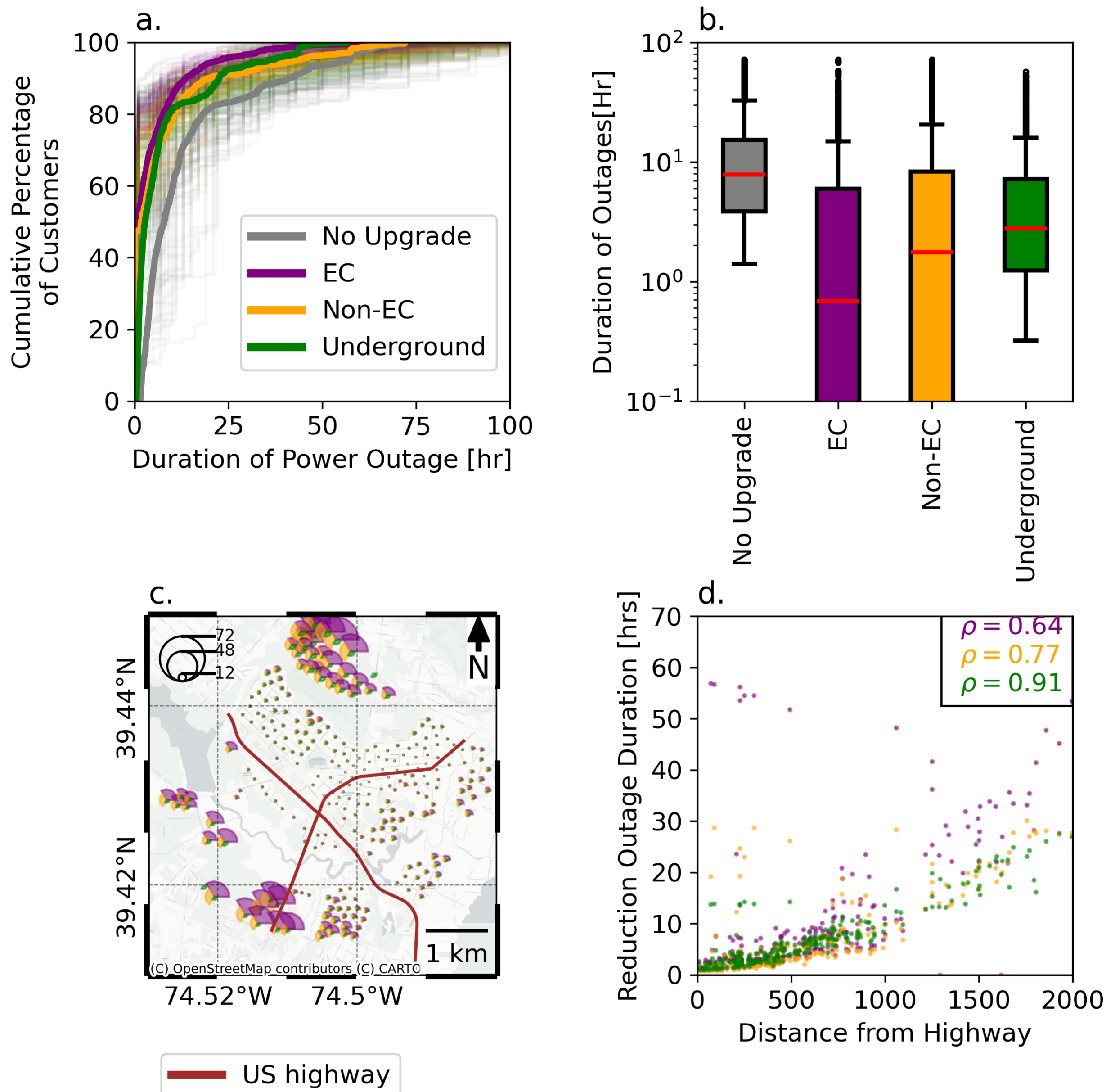

Fig. 4. Simulations for resilient strategies scenarios for the developed Hi-Fi ORiM in Absecon City, New Jersey, during hurricane Isaias (2020). **a.** Cumulative percentage of customers experiencing power outages. **b.** Duration of mean power outages observed for each household under different configurations of Hi-Fi ORiM **c.** Representation of mean reduction in the duration of power outages for a cluster for different resilience strategies compared to the base case of no upgrades. **d.** Scatter plot between the reduced number of outages for a cluster and distance from the US highway.

IEEE Standard 1366-2022 defines reliability indices, such as the System Average Interruption Frequency Index (SAIFI). As reliability only focuses on daily interruptions, utility performance ratings exclude catastrophic events, defined as 'Major Day Events,' such as hurricanes, from SAIFI calculations [60]. Thus, no standard index is defined for measuring the resilience of power systems.

However, any interruption to the consumers is a disturbance, whether caused by a daily outage or a hurricane. The IEEE Power and Energy Sector (PES) Task Force emphasizes the resilience of power systems as the ability to limit the extent, system impact, and duration of degradation following an extraordinary event such as natural hazards [12]. Thus, we identify the resilience gained from resilience strategies as the reduction in outage durations. Our proposed resilient strategies focus on reducing outage durations by increasing the robustness of power systems through integrating DERs and undergrounding power lines.

Configuration	Outages duration (hours)	Households (%) with long outages [$\geq$ 24 hours]
No Upgrade	13.92 [1.61-59.86]	16.86% [8.41%-31.45%]
ECs	4.76 [0.00-33.11]	4.43% [2.50%-11.33%]
Non-ECs	7.41 [0.00-57.56]	9.05% [4.61%-16.45%]
Underground	7.46 [0.53-43.59]	8.41% [4.50%-20.76%]

Table 1. Mean outage duration of households and households with longer outages for the scenario of Hurricane Isaias (2020)
*95% C.I. in bracket

Our results (Figure 4a-b and Table 1) show that ECs would achieve the highest resilience against hurricanes compared to non-ECs and undergrounding configurations in the scenario of Hurricane Isaias (2020). We found that households in ECs would experience a mean outage duration of 4.76 hours per household, which is 65.80%, 35.76%, and 36.19% shorter than in the no upgrade, non-ECs, and undergrounding cases, respectively. Moreover, 97.5% of households in ECs would have an outage duration of less than 33.11 hours, whereas no-upgrade scenario would be 80.80% longer. Additionally, ECs would have a mean of 4.43% of households experiencing long outages ($>$ 24 hours), which is 73.47%, 51.04%, and 47.32% less than in the no-upgrade, non-ECs, and undergrounding cases, respectively. At the 97.5th percentile, ECs would have 11.33% of households experiencing long outages, which is 177.58% higher in the no upgrade case.

We show the spatial distribution of mean reductions in power outage duration for different resilience strategies across 264 clusters, comprising 2,640 households, in Figure 4c. We observe more significant reductions in outage durations farther from the main highway across all mitigation cases (Figure 4d). For instance, clusters in ECs between 1000 and 1500 meters would observe an average reduction in outage duration of 24.53 hours, three times higher than the reduction for clusters between 500 and 1000 meters. Typically, power grids are restored using a top-down strategy where repair teams reach the poles closer to the main highway first [61, 62]. Thus, households with more remote access through local roads often recover electricity last, especially in radial distribution networks. Our results show that these resilience measures, and especially ECs, can significantly enhance electricity access for such households (Figure 4d).

C. Assessing the effectiveness of resilience measure to future hurricanes

Hurricane Isaias reached a maximum category of 1, but the US is exposed to more significant events, e.g., the recent 2024 category 5 Hurricane Beryl with 165 mph winds [63]. To analyze the benefits of resilience measures comprehensively, we studied multiple realistic hurricane scenarios using state-of-art hurricane hazard models [27]. We analyzed 5,018 landfalling hurricanes that originate in the North Atlantic Basin [64] representing the hurricane hazard under the current climate scenario (Figure 5a). These hurricanes cover approximately $1,485$ years, as about 3.38 hurricanes from the Atlantic Basin make landfall each year [35]. We sampled the hurricanes yearly as a random Poisson process (see Methods). We represent a typical year as the mean of $1,485$ years of simulations. We ran a total of $\sim 4 \times 10^5$ simulations to model outages and recovery in Absecon and Miami.

We also considered a different region from Absecon City to evaluate how resilience measures apply to other US communities exposed to the largest hurricane hazards. To do so, we leveraged our Hi-Fi ORiM model, which represents typical communities with radial distribution lines in the US, to also analyze communities in Miami, Florida (Figure 5a). Miami has recently experienced strong hurricanes *e.g.,* Matthew (2016), Irma (2017), Dorian (2019), Ian (2022) and can experience winds of 62 m/s for a 100-year return period, which is 38% higher than 45 m/s winds for Absecon City. Notice that wooden power poles can sustain winds up to 20 m/s [65]. Thus, wind speeds beyond 20 m/s can make them fail. In Absecon City, only 5.14% simulations exceeded 20 m/s (Figure 5b). In contrast, Miami has 20.18% simulations that exceeded 20 m/s (Figure 5c), highlighting significantly higher hazards due to its different location (Figure 5a).

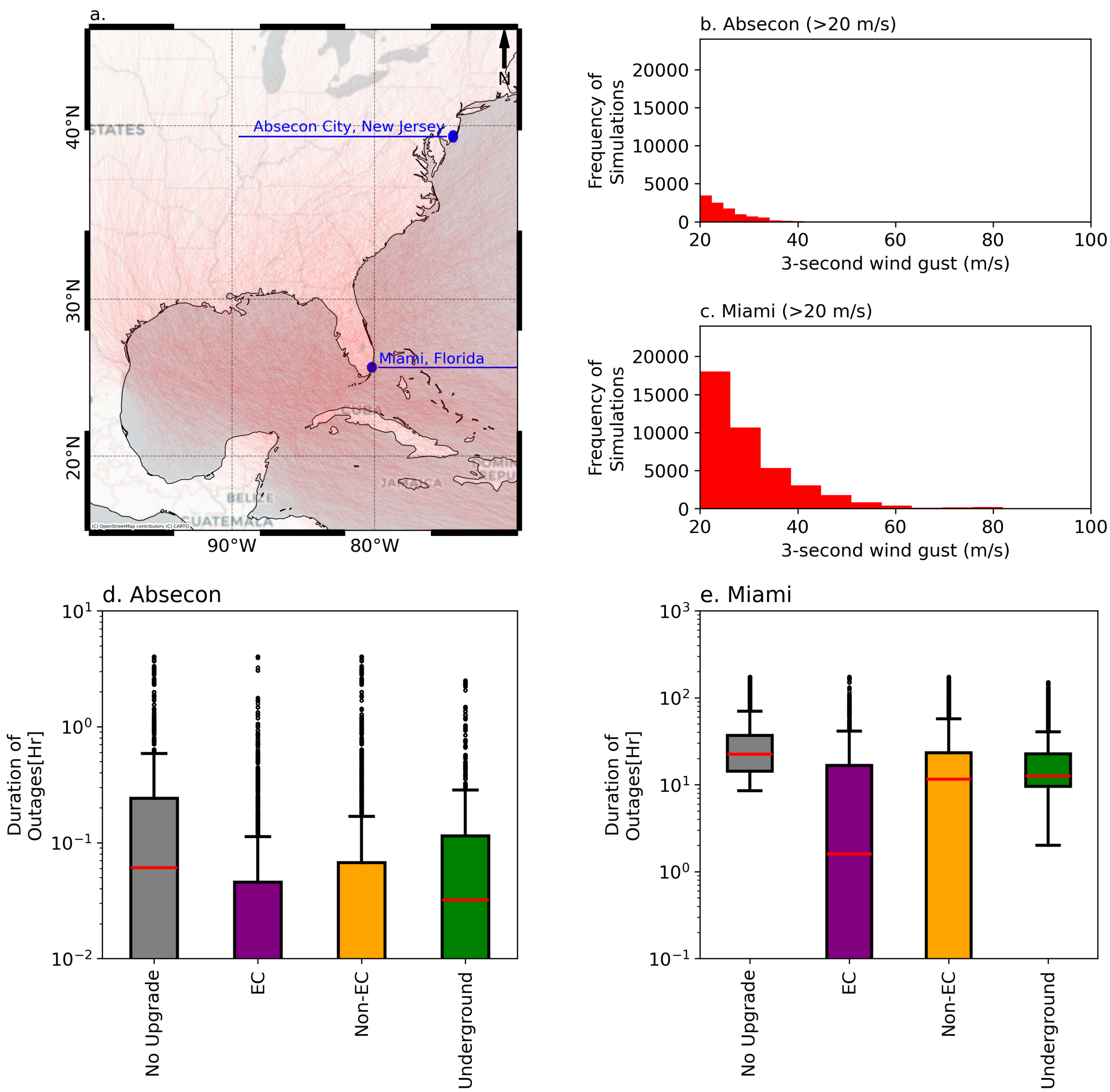

Fig. 5. Simulations for the future (synthetic) hurricanes. **a.** Tracks of synthetic hurricanes in the North Atlantic basin based on the historical climate [44]. **b.** Distribution of wind speeds (>20 m/s) in Absecon City, New Jersey. **c.** Distribution of wind speeds (>20 m/s) in Miami, Florida. **d.** Average duration of power outages observed for each household under different configurations of Hi-Fi ORiM in Absecon City, New Jersey, for 25 years. **e.** Average duration of power outages observed for each household under different configurations of Hi-Fi ORiM in Miami, Florida, for 25 years.

We investigated the same four cases, including a baseline and three resilience measures, under future hurricanes. The average lifetime of a solar project is 25 years. We also assumed that utilities would recover undergrounding costs over 25 years. Thus, we present the average duration of power outages for each house across 25 years with different power grid configurations in Figures 5d-e and Table 2.

Similar to the results for Hurricane Isaias (2020), we found that households will gain more resilience in ECs. From Figure 5d, we observe that the low-wind region of Absecon City would have minimal outages across all the configurations. The observed outages for the high winds region of Miami are ~ 100 times more than the low wind region of Absecon City. In an extreme case, a household can observe an outage of 206 hours (8 days) in Florida. In the aftermath of Hurricane Ian (2022), a category 4 hurricane, nearly 30% of Lee County in Florida consumers were without power after 8 days.

We observe more significant resilience gains for Miami than for Absecon City. For instance, the mean outage durations in Miami decreased from 35.64 hours in the no upgrade scenario to 12.69 hours with ECs, compared to a smaller reduction in Absecon, where the mean outage durations dropped from 0.31 hours to 0.08 hours. The biggest improvement in resilience for Miami is observed with ECs, where we observe a 64.4%, 33.0%, and 50.5% average reduction in outage duration compared to the no-upgrade, non-ECs, and undergrounding cases, respectively. Additionally, 97.5% of households in Miami will observe an average outage duration of less than 80.17 hours, which is 126.32% higher than the outage duration of 130.66 hours for the no upgrade case. Finally, we also observe an increasing reduction in duration with the distance from the highway (Supplementary Figure S9). Like the scenario analysis for Hurricane Isaias, resilience gains are maximized for the population at greater risk of prolonged power outages.

Location	Configuration	Outages duration (hours)
Absecon	No Upgrade	0.31 [0.00-2.90]
Absecon	ECs	0.08 [0.00-0.69]
Absecon	Non-ECs	0.17 [0.00-2.34]
Absecon	Underground	0.08 [0.00-1.45]
Miami	No Upgrade	35.64 [11.42-147.09]
Miami	ECs	12.69 [0.00-80.17]
Miami	Non-ECs	18.95 [0.00-139.43]
Miami	Underground	25.63 [7.40-128.24]

Table 2. Mean outage duration of households (95% C.I. in bracket)

D. Household-scale resilience financing

Here, we quantify the finances for the resilience measure to weigh the cost of investments against the benefits [66]. We evaluate the profitability of prosumers by determining their net present value (NPV) for 25 years, i.e., the solar panel's lifespan (see Methods). We studied the contributions of different components towards NPV: (a) investments and operation costs for panels and batteries (I&O), (b) savings from not purchasing grid electricity, (c) additional state incentives, (d) panel damage from winds, and (e) the avoided costs from shorter/no outages.

Previous research [42] has considered the financial value of resilience measures as the savings from avoided outages based on the value of lost load (VoLL). Historically, the VoLL for residential customers has been estimated using questionnaires based on hypothetical outage scenarios [43].

These questionnaires ask about customers' willingness to pay to avoid outages, but the wide range of options, such as 0 to 50 USD, can lead to underestimations of VoLL as customers tend to choose a lower value. Additionally, these surveys consider outages of up to 16 hours, whereas hurricane-related outages can last up to a week. In contrast, we quantified the value of avoided outages as the savings from not needing alternate energy sources, such as emergency diesel generators, to supply electricity when the grid is down (see Supplementary Text S3). Many communities use generators for days or even weeks as a backup during significant power outages, for example, in Florida after Hurricane Irma (2017) [7]. Thus, we use this avoided cost as a more realistic way to quantify the value of shorter outages during disasters.

We define profitable prosumers as those with a positive NPV and study the effects of state incentives. For brevity, we show results for NPV with state incentives here (Figure 6a) and without them in the Supplementary Information (Figure S11 and S12). Prosumers are more profitable in Miami as Florida receives nearly 25% more solar irradiance than New Jersey (Supplementary Figure S3) [29]. Smaller-sized rooftop solar systems can generate the same amount of solar energy in Florida as larger-sized solar panel systems in New Jersey. Figures 6b-c represent the breakdown of profitable and unprofitable prosumers in Absecon City and Miami. While profitable prosumers have similar I&O costs in Miami and Absecon City, prosumers in Miami have higher savings than those in Absecon City. For example, profitable prosumers in ECs have 29% higher savings in Miami than in Absecon City. We found that 99% of the prosumers are profitable in Miami compared to 92% in Absecon for both ECs and non-ECs.

Our findings show that, on average, the value of resilience, measured as the avoided cost from outages, is about 16% and 23% of I&O costs for profitable and unprofitable prosumers, respectively (Figure 6b-c). These avoided costs are important and can supplement other savings from reduced grid electricity purchases and energy sharing. On average, prosumers have higher profits and savings with ECs configuration than non-ECs. This can be attributed to higher selling electricity costs in local energy markets than net-metering rates. The median NPV with state incentives in Absecon and Miami for ECs is 16% and 7% higher than for non-ECs.

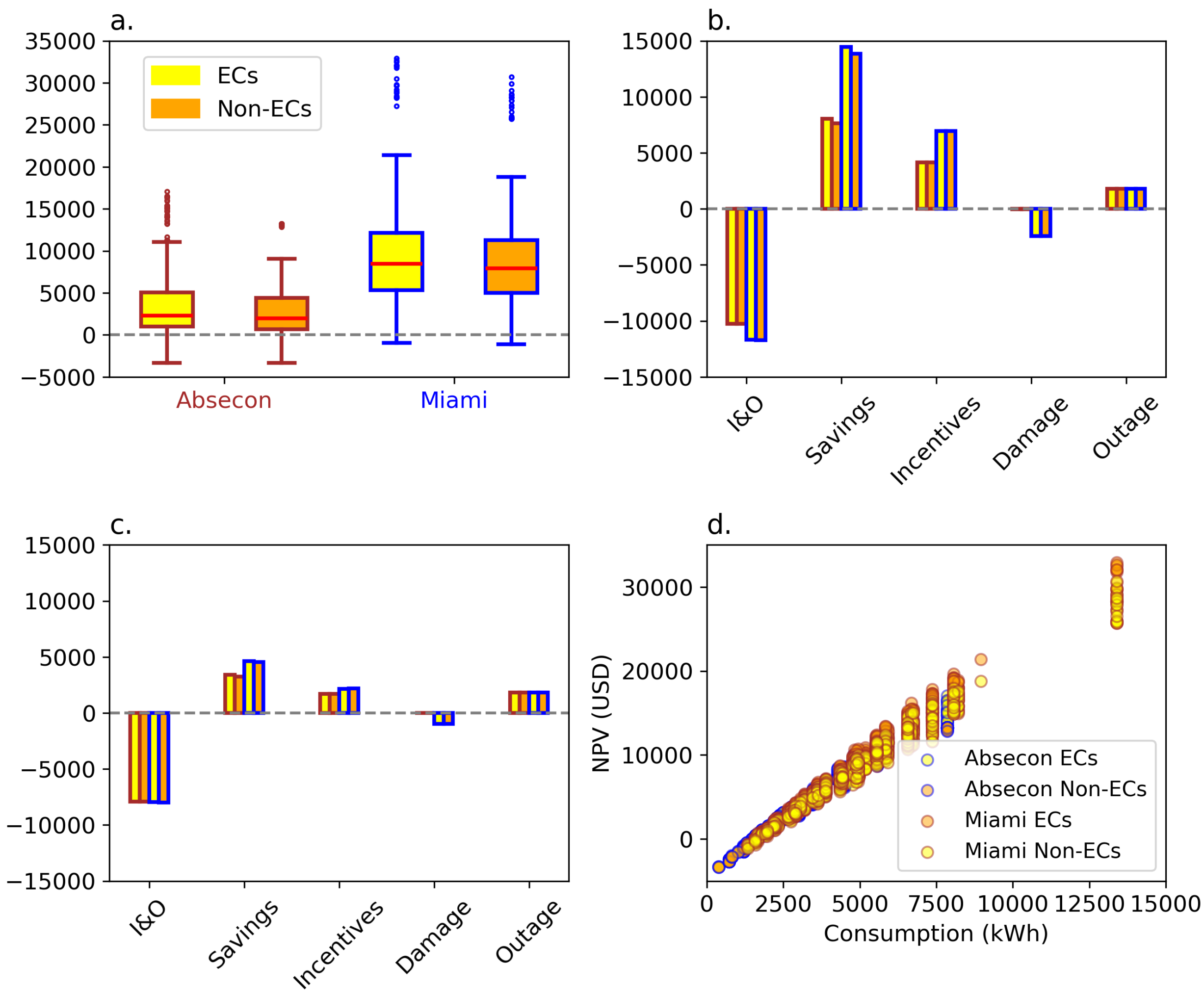

Fig. 6. a. NPV for each prosumer in Absecon City and Miami with state incentives. **b.** Average contributions of different components in NPV for profitable prosumers. **c.** Average contributions of different components in NPV for unprofitable prosumers. **d.** NPV vs. annual consumption for prosumers without state incentives.

We observe from Figure 6d that the NPV for prosumers increases with higher yearly consumption due to more significant savings from self-consumption. For example, in Absecon City, for ECs with state incentives, the mean yearly consumption of houses with positive NPV is 144% higher than that of houses with negative NPV. Similarly, in Miami, for ECs with state incentives, the mean yearly power consumption of prosumers with positive NPV is 141% higher than that of prosumers with negative NPV.

However, even unprofitable prosumers with a negative NPV can still gain significant electricity resilience. For instance, an unprofitable prosumer in Absecon City can still significantly reduce up to 20 hours in outage duration per year. This reduction can be up to 167 hours ($\sim$ 7 days) for an unprofitable prosumer in Miami. We present the cases of unprofitable prosumers with a negative NPV in Figure 6c. We find that lower savings (*e.g.*, 57% for unprofitable prosumers in Miami versus 123% for profitable ones) contribute to a negative NPV. Solar panels are sized for net-zero energy consumption, and we assumed a constant battery size of 10kWh for all prosumers, leading to higher ratios of I&O costs versus savings for smaller households. While batteries could be smaller to reduce I&O costs [23], households would also lose resilience to more extended outages, e.g., outage lasted days for Hurricane Isaias [3]. Given these financial challenges, further research is essential to better quantify the value of resilience that could significantly boost the adoption of solar panels.

Meanwhile, to support solar adoption, incentives such as the 30% Solar Investment Tax Credit (SITC) towards residential solar installations [67] and Successor Solar Incentive (SuSI) Program [68] by NJ Clean Energy Programs can reduce the financial burden on households. As shown in Figure 6d, state incentives can cover up to 40% and 60% of I&O costs for the profitable prosumers in Absecon City and Miami. These incentives can significantly benefit the prosumers in low irradiance regions, such as Absecon City, and could be crucial in helping unprofitable prosumers move toward profitability. This is evident as there are only 26% profitable prosumers in Absecon City without state incentives for ECs, while 80% profitable prosumers in Miami. These incentives will also attract more solar panel adoption where net-metering rates are at wholesale rates, *e.g.,* in New Jersey [69], or where net-metering is expected to decrease to wholesale rates, *e.g.,* in Florida with the introduction of House Bill 741 [70].

Finally, we found that damage costs are negligible in Absecon City's low-wind region. In contrast, in Miami's high winds region, the average damage cost over 25 years equals 21% of average I&O costs. Miami's high-wind region experiences an annual mean panel failure rate of 3.3×10^{-2}, 21 times higher than 1.5×10^{-3} in Absecon. Despite this higher failure rate, solar panels can still provide resilient electricity; for instance, when the chance of a panel failure is 3%, a class 7 pole has a 38% chance of failure. The rate of solar panel damage was determined through hurricane simulations and panel fragility assessments. Damage costs were calculated by multiplying the failure rate by the cost of installing a new panel (see Methods). The "Solar Under Storm" report, based on observations from hurricanes Irma and Maria in 2017 and Dorian in 2019, suggests using vibration-resistant module bolted connections to enhance resilience. This would increase installation costs by approximately 5%, which is still significantly lower than the 21% damage cost [13]. Our results show Miami has more profitable prosumers even with approximately 100 times higher damage costs than Absecon City because of higher solar irradiance. This highlights the need for policies that not only incentivize solar adoption but also ensure resilience, enabling robust solar energy even in high wind risk areas like Miami.

E. Community-scale resilience financing

The cost of installing new rooftop solar panels is covered by the individual house installing the panels. However, the economic cost of undergrounding power lines is passed on to all the consumers [38], requiring a financial analysis at the community scale, e.g., Florida Senate Bill 796 (2019) [71] (see methods). For a clean investment comparison of undergrounding versus ECs, we analyzed NPVs at the community level, aggregating the cash flows for the 2,640 households.

At the community level, investments in ECs in Absecon City and Miami have positive aggregated NPVs (Figure 7a). This positive NPV results from savings for the prosumers and reduced bills for households without solar panels, who purchase electricity from prosumers at reduced prices. Similar to NPV for individual prosumers, the NPV of the community in Miami is 188% higher than the community in Absecon City with solar EC configuration.

In contrast, households primarily experience cash outflow during undergrounding due to increased consumer bills needed to cover the cost, even though there is added value in resilience. To cover the cost of undergrounding, households might observe an annual increase of up to 42%, with the value of resilience being negligible in Absecon and only accounting for 0.3% of consumer energy bills in Miami. Thus, we observe negative NPVs for the undergrounding of power lines in both Absecon City and Miami in Figure 7a.

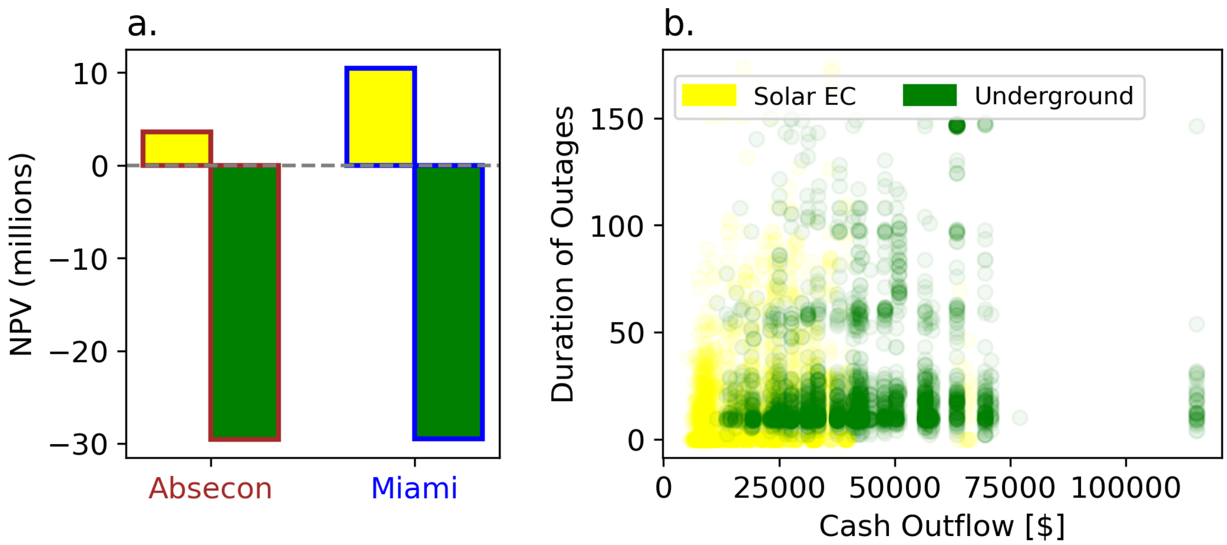

Fig. 7. Community-Scale Results. **a.** Community-wide NPV for adoption of solar panels in ECs and undergrounding cases. **b.**Scatter plot for the duration of outages and net cash outflow for ECs and undergrounding cases in Miami, Florida.

To compare each household's total spending, we calculated the net cash outflow over the next 25 years for solar EC and undergrounding in the Miami region, including state incentives. We calculated the net cash outflow because NPV includes savings that do not generate any cash inflow. Although Absecon City had 92% profitable prosumers, close to 99% in Miami, we focused on Miami due to its high wind region, where solar power significantly enhances community resilience. We present the distribution of cashout flow and duration of outages for EC and undergrounding cases for 2,640 households in Miami in Figure 7b. We observe a cluster of households in the community with less than 50 hours of outages for ECs. In contrast, the undergrounding case has a higher duration of outages. We observe that close to 16% of customers would experience more than 50 hours of outages in undergrounding case, whereas less than 8% would experience the same duration in ECs. Battery backup, combined with more resilient solar panels, enhances the capacity of ECs to operate in island mode. However, undergrounding 50% of power poles can still result in network disconnections where poles remain above ground, leading to prolonged outages. The average cash outflow of households in ECs is USD 16998.77 $[7593.40 - 36012.95, 95\%\text{CI}]$ while the average cash outflow in the undergrounding case is 155% higher at USD 42552.67 $[19164.34 - 69465.29, 95\%\text{CI}]$. Thus, ECs can gain more electricity resilience with lower net cash outflows than undergrounding case.

3. DISCUSSION

We developed a high-fidelity outage risk model (Hi-Fi ORiM) of a power distribution network serving a city with 2,640 households. This model leverages multi-source datasets on roads, buildings and power network and integrates state-of-the-art hurricane hazard model [27] to predict failures of power network components, cascading outages, and recovery after hurricanes. We calibrated the model to accurately reproduce outages from Hurricane Isaias (2020) in New Jersey [72], achieving a 77.42% peak outage prediction compared to the actual 74.15% outages. Our validated risk model represents a typical radial US power network. Thus, we used it as test bed for evaluating outage risks and the feasibility (e.g., costs and benefits) of resilience measures across varying hurricane conditions.

We studied resilience measures through four cases: a) No Upgrade, b) ECs, c) Non-ECs and d) Undergrounding power lines. First, we analyzed how these resilience measures would have enhanced electricity access for communities in Absecon City after Hurricane Isaias. We found that ECs would have provided the most significant gains, with only 4.43% households facing outages longer than 24hrs compared to 16.86%, 9.05%, and 8.41% for no upgrade, non-ECs, and undergrounding cases, respectively.

We then investigated the benefits of these resilience measures for future hurricanes through state-of-art disaster risk modeling. For a comprehensive analysis of hurricane conditions, we extended our case study in Absecon City to include Miami, which, unlike Absecon City, is one of the US regions facing the most significant hurricane hazards. Due to the higher hurricane hazards, our predictions showed Miami could experience outage durations up to 100 times longer than Absecon City.

We observed modest resilience gains in Absecon City for future hurricanes due to the lower likelihood of experiencing many events like Hurricane Isaias. However, Miami is exposed to stronger and more frequency hurricanes that can cause large-scale outages, and thus, we found significant resilience gains. We predicted that Miami ECs would have average outage durations 64.4%, 33.0%, and 50.5% shorter than those in the no-upgrade, non-EC, and undergrounding cases, respectively. We have already seen DERs can enhance electricity access after previous disasters. Hurricane Ian in 2022 caused widespread outages, leaving 2.6 million households in Florida without electricity. Nevertheless, Babcock Ranch, a small community in the state, maintained power for 2,000 households using its solar panels [5]. Similarly, after the Tohoku Earthquake in 2011, the Sendai Microgrid continued to supply electricity through solar panels and batteries [73]. These findings highlight the need for greater investment in DERs to bolster community resilience against disasters. While the energy policies are shifting towards clean energy goals [74], they should also focus on disaster risk management.

Next, we assessed the financial feasibility of implementing such resilience measures. We found that the avoided costs from preventing outages are 18% and 23% of the investments and operations (I&O) costs of these measures for profitable and unprofitable prosumers, respectively. To estimate these avoided costs, we calculated the expenses of arranging alternate energy sources, such as diesel generators, to access electricity during an outage. This approach results in different costs than the typical small values of lost load (VoLL) from consumer surveys [43], traditional VoLL estimates are not suited for disaster scenarios. Traditional VoLL underestimates the costs of outages, which are based on hypothetical short outage scenarios [43]. We observe that unprofitable prosumers can significantly reduce outage duration during hurricanes. This suggests that their financial feasibility might be underestimated Given these findings, future research should focus on quantifying the true value of avoiding outages after disasters, as these prosumers might actually be profitable when considering the broader economic benefits of resilience, especially for vulnerable groups relying on electric medical equipment.

We also found that prosumers in Miami would observe a 21 times higher failure rate for solar panels than prosumers in Absecon due to their higher wind hazards. Extensive structural surveys after Hurricanes Irma (2017), Maria (2017), and Dorian (2019) found many rooftop panels experienced failures in racks and clips attaching the panels to the racks in the Caribbean Islands [13]. These surveys suggested vibration-resistant module bolted connections to improve resilience against storm winds. Overall, the projected increase in solar installation cost is about 5% to gain resilience through stronger structural systems. This projected cost is less than the expected damage cost for solar panels in Miami for the next 25 years, which is 21% of I&O costs, including solar panels and battery, and damage cost might be an even higher proportion of only solar panels costs.

We found that prosumers can be profitable with higher savings and incentives and that solar adoption can also help the community become resilient. State incentives could be crucial in determining consumers' willingness to adopt solar panels, especially in low-irradiance regions such as New Jersey. Without state incentives, we found that the percentage of profitable prosumers in Absecon City reduces from 92% to 26% for ECs as those incentives can cover up to 40% of I&O cost. The reduction in profitable prosumers in Miami is not as drastic as in Absecon City, as regions in Florida receive 25% more year-round consistent solar irradiance than in New Jersey. Moreover, prosumers in ECs can earn more profit by selling excess solar power to local neighborhood energy markets at higher selling costs than net-metering costs.

Unlike solar adoption, where only prosumers bear installment costs, undergrounding costs are distributed among all households in the community. Therefore, we calculated the NPV for the entire community for both ECs and undergrounding cases. ECs had a positive NPV for both Absecon City and Miami, but the NPV was negative for the undergrounding case for both locations. Consumers do not benefit financially from undergrounding, except for the added resilience, as it mainly leads to increased electricity bills to cover the costs. We also compared the net cash outflow (NCF) and duration of power outages for ECs and undergrounding cases in the Miami region for 25 years. The average NCF in undergrounding is 155% higher than in ECs. Moreover, more than 16% of the consumers would observe more than 50 hrs for power outage duration compared to less than 8% of the consumers in ECs. Thus, adopting solar panels in the P2P sharing setting not only increases the community's resilience benefits but also proves more profitable.

Finally, our study also has some limitations. Our Hi-Fi ORiM captures the structural failures of the power grid components during hurricanes. However, this study does not consider the synchronization of DERs with the main grid as required in IEEE Standard 1547-2018 [75]. Future studies could address this limitation, as well as other requirements, such as voltage regulations, since we only focus on the connectivity of power system components. Additionally, future research could explore the value of inverters and the costs associated with operating a microgrid, especially as additional operators might be required.

4. METHODS

A. High-Fidelity Outage Risk Model (Hi-Fi ORiM)

Researchers have developed probabilistic and machine-learning models to predict power outages during a storm [51, 65, 76, 77], but these models only provide point estimates of the total number of outages in a city and cannot quantify the risk at the component level for a power grid. Another stream of literature has focused on developing synthetic grids to model the risk of natural disasters to power networks as individual components have different hazard-dependent failure probabilities [2, 31, 38, 78]. We developed a high-fidelity outage risk model (Hi-Fi ORiM) for the power network to model hurricane risk to individual components (*e.g.,* poles, solar panels) at the residential level. Our Hi-Fi ORiM was further employed to analyze mitigation strategies, such as rooftop solar adoption and undergrounding power lines.

For this Hi-Fi ORiM model, we used open-source data for Absecon City, New Jersey, to create a power network. We calibrated our Hi-Fi ORiM against outages recorded during Hurricane Isaias (2020) by PowerOutage [72], as shown in Figure 2. To develop the synthetic power grid, we calculated an average distance of approximately 60 meters between power poles, based on the limited number of poles available in OpenStreetMap data [46]. We then used the roads shapefile from New Jersey Geographic Information Network (NJGIN) [47] to place poles along five classes of roads: US highways, state highways, county routes, other county roads, and local roads, excluding ramps and inaccessible roads (see Supplementary Text S1, Table S1, and Figures S1-S2). For simplicity, poles were positioned along the center of roads, and for two-way roads (*e.g.*, US and state highways), poles were placed on only one side. We obtained the locations of 2,640 residential buildings from New Jersey parcel data [48] and assigned each building to the nearest pole like a typical radial power grid. The power network can be represented as a graph $G = (N, E)$ where poles and houses are nodes (N), and connections between poles and from pole to houses are edges (E).

We captured the damage to the power distribution network through failures of power poles from hurricane winds. The probability of pole failure is hazard-dependent, i.e., it changes with the wind and is represented through fragility curves for different classes of the pole (Figure 5c) obtained from [28]. The fragility curves are represented as.

$$P_f(w) = \phi\left(\frac{ln(w/\bar{w})}{\beta}\right) \tag{1}$$

where $P_f(w)$ is the probability for an observed 3-second wind gust of $w\ ms^{-1}$, $\phi(.)$ is the standard normal distribution, $\bar{w}$ is the median of fragility curves (*i.e.*, $P_f(\bar{w}) = 0.5$), and β is the dispersion parameter. The parameters $\bar{w}$ and β vary depending on the class of the pole (Figure 1).

We used the tropical cyclone model from [27] to determine axis-symmetric winds and the background wind model from [53] to capture the complete wind structure. The historical hurricane paths are available from IBTRACS [79]. In [80], the authors emphasized the importance of using a complete wind structure, as excluding the background winds can result in underestimating wind hazards and, hence, an underprediction of risk from wind storms.

In [31], authors calibrated their synthetic grid for the poles of age 50 and 60 as most of the power distribution systems in the United States are old. We assumed a uniform age of 50 years for all poles in our synthetic power distribution network. We iteratively selected the class of pole for each road class from the seven available pole classes (Figure 1). We performed 1.6×10^6 iterations to select the combination of the class of poles, which minimizes the error on the predicted percentage of outages for our synthetic network with actually observed outages.

We obtained the observed percent of customers without power from PowerOutage[72]. PowerOutage reports the outages for all types of customers, including industrial, commercial, and residential. Since our focus is on residential customers, we matched only the percentage of customers without power, not the total number of customers affected. Additionally, PowerOutage compiles reports from utilities, which can delay the reporting of power outages [72]. Therefore, we assume that maximum outages occur initially and persist until a reported decrease in outages. To simulate total outages, we disconnected the network at identified failure points, forming subnetworks. Since transmission networks are predominantly aligned with US highways, we assumed that the subnetwork along the highway with the highest node density would retain power. The proportion of outages is given as.

$$O_{ratio} = \frac{\sum_{i=1}^{N_b} b_{oi}}{N_b} \tag{2}$$

where O_{ratio} is the percent of customers without power, $b_{oi} = 1$, if a building is disconnected from the supply network otherwise 0, and N_b is the total number of buildings. The final selection for pole classes was as follows: US and State Highways were assigned class 7 poles; County Routes were assigned class 3 poles; Other County Roads were assigned class 4 poles; and Local Roads were assigned class 5 poles.

We further calibrated our synthetic power distribution network to model the recovery time of failed poles. We assumed that repair teams would initially focus on main highways before progressing to local roads for restoration. In a radial network, this top-down strategy is expected to facilitate the rapid recovery of many buildings [62]. Therefore, we assigned recovery times to poles based on their distance from the US highway, formulated as follows.

$$t_{recovery} = floor\left(\frac{d}{100}\right) * t_1 + t_2 \tag{3}$$

where $floor(.)$ is the greatest integer operator, d is the distance of a pole from the US highway in meters normalized with 100 meters, t_1 follows a truncated normal distribution as $t_1 \sim N(\bar{t}_1, \bar{t}_1/2)$, $t_1 \in (0, 2\bar{t}_1)$, and t_2 represents an initial time to start any repair work which also follows a truncated normal distribution, $t_2 \sim N(\bar{t}_2, \bar{t}_2/2)$, $t_1 \in (\bar{t}_2/2, 3\bar{t}_2/2)$. We calibrated $\bar{t}_1$ and $\bar{t}_2$ to represent the recovery during Hurricane Isaias (2020) (Figure 2b). Since recovery time depends on the number of failed poles, which is influenced by wind gusts in future hurricanes and constrained by the limited number of crews [62, 81], we scale $\bar{t}1$ for a future hurricane, given as.

$$\bar{t}_{1\text{ future}} = \frac{w_{\text{future}} \cdot \bar{t}_1}{w_{\text{Isaias}}} \tag{4}$$

where w_{future} is the 3-second wind gust of a future hurricane, and w_{Isaias} is the observed 3-second wind gust during hurricane Isaias.

We performed 400 uncertainty simulations for the scenario of hurricane Isaias and 4×10^5 uncertainty simulations for future hurricanes. Each simulation begins by disconnecting the failed poles. Based on the recovery times, poles are reconnected to their original adjacent poles every hour. The simulation continues until all nodes in the original power network are fully restored.

B. Future Hurricanes

The 5,018 landfalling synthetic hurricanes chosen for this study consider the current climate scenario according to the National Center for Environmental Prediction (NCEP) reanalysis [44]. The synthetic storm generative model involves three steps: random seeding for storm genesis, a beta-advection tropical cyclone motion model, and storm development based on environmental factors [44]. We show tracks of all synthetic hurricanes in Figure 5a.

On average, 3.38 landfalling hurricanes are expected per year in the US. Thus, the simulation of 5,018 hurricanes corresponds to 1,485 years. We perform Monte-Carlo Simulations (MCS) [82] to determine the number of hurricanes in a year, assuming their occurrence follows a Poisson process, given as.

$$P(k) = e^{-\lambda} \frac{\lambda^k}{k!} \tag{5}$$

where $\lambda = 3.38/yr$ is average hurricane occurrences per year, and $P(k)$ is the probability of k number of hurricane events in an year. We randomly sampled without replacement yearly hurricanes for 1485 years from the dataset of 5018 synthetic storms. We represent a typical year with an average of 1485 years of simulation.

C. Solar Analysis

We used global horizontal irradiance (GHI), measured in watts per square meter units, to determine the total solar potential. We obtained the historical GHI from the National Solar Radiation Database, maintained by the National Renewable Energy Laboratory (NREL), which provides data at a spatial resolution of $4km \times 4km$ and a temporal resolution of 30 minutes [29]. We averaged GHI over a window of 1 hour to obtain hourly GHI and used nearest-neighbor interpolation to assign GHI to the solar energy-generating building. While historical irradiance is available for the case of Hurricane Isaias (2020) scenario to measure the solar potential, we used solar irradiance for future hurricanes introduced by [26], which is given as.

$$I^h = \bar{I} \times e^{f(R,C)} \tag{6}$$

where I^h is the reduced irradiance during hurricane, $\bar{I}$ is the spatiotemporal average of the observed irradiance, and $f(R,C) \leq 0$, is a function of the ratio of hurricane's distance-to-site (d) to the radius-of-closed-isobars ($ROCI$) where winds are zero, $R = d/ROCI$ and category of a hurricane (C) as can be found in [26]. To calculate $\bar{I}$, we used the GHI at an hourly scale during 2020 and averaged the irradiance at each hour across all days to get the $\bar{I}$ for a typical 24-hour day of a month. We determined the start of outages and corresponding solar irradiance (I^h in Eq. 6) by using the location and month of the year for each hour from each synthetic hurricane's genesis to its complete dissipation.

To share solar energy in ECs, we clustered houses using a k-means clustering algorithm based on Euclidean distance, with the average cluster containing ten houses. Refer to Supplementary Figure S8 for the distribution of the number of houses clustered together for energy sharing. We assumed that 50% of households in a cluster adopt solar panels and behind-the-meter batteries. Like overhead power lines, solar panels installed on rooftops are exposed to high hurricane winds. In [35], authors developed data-driven fragility models of the rooftop-mounted panels to the hurricane winds, represented similar to Eq. 1 with parameter $\varpi = 80\ m/s$ and $\beta = 0.32$.

We ran simulations for any pole and solar panel failures in our Hi-Fi ORiM during a hurricane. If a solar panel is damaged during a hurricane, only behind-the-meter power will provide the power during the disaster, and there will be no solar generation for that panel. Energy sharing during a disaster is only possible if none of the poles connecting houses in a cluster are damaged and all houses belong to the same disconnected subnetwork; otherwise, houses with solar panels will use the generated solar power for themselves. Also, during an emergency, households with solar panels first consume energy for themselves and then share any surplus equally with those without solar panels. We assume a simple power balance for household energy sharing but with no transmission losses [81]. Our study does not consider the failure of lines due to overloading [18], which could be addressed in future studies. Figure 8 outlines our approach to determining generated power.

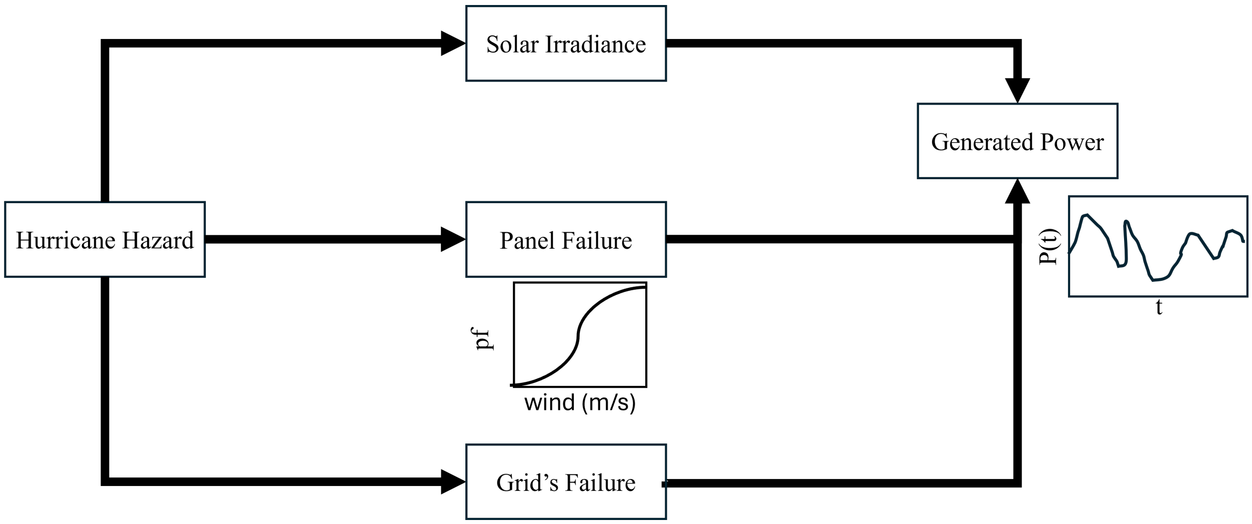

Fig. 8. Framework for evaluating the available energy during and after the hurricane. First, we get the cloud cover and winds during a hurricane. Then, we determine any failures for power poles and solar panels from hurricane winds. Finally, we determine the generated power during and after a hurricane.

We assumed that solar panels are made of standard crystal silicone with an energy conversion efficiency of 19% [33]. Further energy conversion losses could happen due to system losses such as soiling, shading, and wiring issues. Hence, we considered further system losses of 14%. Finally, we considered an AC-to-DC conversion ratio of 96%. Thus, the total available solar energy was calculated by multiplying GHI with the energy conversion efficiency, system losses, and AC-to-DC conversion factors [58].

For this study, rooftop solar panels are sized according to the net-zero energy efficiency criterion, meaning the total energy generated equals the total consumption by a house [25]. We also constrained the panel size not to exceed the roof area. We used open-source building footprints provided by Microsoft [49] to determine roof size.

Real-time electrical energy consumption data for individual buildings is not publicly available. However, NREL's ResStock provides a simulated dataset for thousands of residential load profiles across various climate zones in the United States [83]. These datasets are validated against the US Energy Information Administration's survey on residential energy use [84]. The load profile dataset includes buildings with different floor areas, construction years, and types, such as single-family and multi-family residential buildings.

We considered diverse load profiles since larger households typically consume more electricity, and newer houses might use electrical heating systems, unlike older buildings that often have gas-fired heaters [85]. The load profiles are available at the census block level across the US. Since our study focuses on residential buildings, we filtered the load profiles for single-family and multi-family residences based on census block, building area, and construction year. We obtained the construction year and number of floors from parcel data [48] and multiplied the number of floors by the building footprints [49] to calculate the total floor area for each building. Based on the different combinations of building floor area and year of construction (see Supplementary Text S2, Tables S2-S3, and Figure S6), we obtained consumption profiles for our synthetic grid at an hourly scale for a typical year.

D. Undergrounding

Undergrounding power lines can be an effective resilient strategy to hurricanes, as it reduces the exposure to the high hurricane winds [2, 39, 81]. Thus, we also investigated underground energy as an alternative to adopting solar energy to reduce cascading power blackouts during extreme weather events. We assume that 50% of the power lines to estimate the resilience gained with the undergrounding strategy. To understand the effect of undergrounding, we assume that power poles are undergrounding in the decreasing order of vulnerability. For example, class 7 poles are the most vulnerable (Figure 1), so they are assumed to be underground first. The poles for the underground power lines were assigned a zero probability of failure, *i.e.*, $P_f(w) \rightarrow 0$ in Eq. 1. The failure analysis and recovery for the rest of the poles in the synthetic grid are similar to methods for the synthetic grid without undergrounding.

E. Economics of resilience

Net present value (NPV) has been used to define prosumers' profitability. A positive NPV represents profit, while a negative NPV represents prosumers' losses. NPV is presented as.

$$NPV = -I_0 + \sum_{n=1}^{Lifetime} \left(\frac{CF}{(1+r)^n} \right) \tag{7}$$

where I_0 is the initial investment to install solar systems and behind-the-meter battery, the project's lifetime is 25 years, r is the discount rate, and CF is the cash flow, which is given as.

$$\begin{aligned} CF = -C_{O\&M} - C_D - C_B(n = 11\, or\, n = 21) + P_{pv\rightarrow self} \times C_{grid} \\ + P_{pv\rightarrow grid} \times C_{net-meter} + P_{pv\rightarrow local} \times C_{local} \\ + P_{localpurchase} \times (C_{grid} - C_{local}) + D_{avoid-outage} \times C_{outage} \end{aligned} \tag{8}$$

where $C_{O\&M}$ is the cost of operation and maintenance, C_D is the cost of damage determined by multiplying the average failures of solar panels multiplied by the cost of installing a new panel, C_B is the cost of behind-the-meter battery assuming lifetime of a battery is 10 years, $P_{pv\rightarrow self}$ is the self-consumption of solar power, $P_{pv\rightarrow local}$ is the surplus power sold locally, $P_{pv\rightarrow grid}$ is the surplus power sold to the grid, $P_{localpurchase}$ is the locally purchased electricity at the time of underproduction of solar power, C_{grid} is the cost of grid purchased electricity, $C_{net-meter}$ in the incentive from net-metering, C_{local} is the local sell price of electricity, $D_{avoid-outage}$ is the duration of avoided outages, and C_{outage} of avoided outage. Thus, $P_{pv\rightarrow self} \times C_{grid}$ represents the savings from self-consumption, $P_{pv\rightarrow grid} \times C_{net-meter} + P_{pv\rightarrow local} \times C_{local}$ represents the incentives from P2P sharing and net-metering, and $P_{localpurchase} \times (C_{grid} - C_{local})$ represents the savings by avoiding to the purchase the electricity from grid. We studied the case of ECs and non-ECs to understand the profit of selling electricity locally.

We calculated the cost of avoided outages by considering the reduction in outage duration with the adoption of solar panels in an average year (out of 1485 years of simulation). For our analysis, we determined the value of resilience by calculating the cost of an alternative energy source: a rental diesel generator. Consequently, the reduction in outages is rounded up to the nearest integer number of days to determine the rental cost for the diesel generator as the cost of avoided outages.

We also evaluate the NPV for the community in the solar EC community and undergrounding configurations of our synthetic power grid. We assume that the customers bear the cost of undergrounding, and the utility recovers the cost over the next 25 years. Thus, we distribute the cost to the customers uniformly based on their annual consumption to their electricity bills, which is represented as.

$$\Delta C_{grid,underground} = \frac{I_{underground} - O_{underground}}{25 \times \sum P_{consumer}} \tag{9}$$

where $\Delta C_{grid,underground}$ is the increase in the bill of consumers, $I_{underground}$ is the cost of undergrounding, $O_{underground}$ is the reduction in operation cost of power lines after undergrounding, and $P_{consumer}$ is the energy consumption of each consumer. We use Eq. 7 and cash flow for undergrounding is.

$$CF_{underground} = -(C_{grid} + \Delta C_{grid,underground}) \times P_{consumer} + C_{outage,underground} \tag{10}$$

where $C_{outage,underground}$ is the cost of saved outages with the undergrounding risk mitigation strategy. We also compute the net cash outflow (NCF) for the mitigation strategies of solar EC and undergrounding. For undergrounding, NCF is given as.

$$NCF_{underground} = (C_{grid} + \Delta C_{grid,underground}) \times P_{consumer} \tag{11}$$

For solar EC, NCF is different for prosumers and consumers. For a prosumer, NCF is given as.

$$\begin{aligned} NCF_{solar,prosumer} = I_0 + C_{O\&M} + C_D + C_B(n = 11\, or\, n = 21) - P_{pv\rightarrow self} \times C_{grid} \\ - P_{pv\rightarrow grid} \times C_{net-meter} - P_{pv\rightarrow local} \times C_{local} \\ + P_{local purchase} \times C_{local} + P_{grid purchase} \times C_{grid} \end{aligned} \tag{12}$$

NCF for a consumer is given as.

$$NCF_{solar,prosumer} = P_{local purchase} \times C_{local} + P_{grid purchase} \times C_{grid} \tag{13}$$

The Supplementary Text S3 provides all cost details used in the above calculations. Supplementary Figure S10 presents an example of generated energy, energy sold, and energy purchased from the grid for a house with solar panels.

DATA AVAILABILITY

References for all the open-source data have been provided in the main manuscript, and data is available from authors upon reasonable request. Power outage data was obtained from PowerOutage [72]. We have also made available made the developed Hi-Fi ORiM risk model available at the NSF's DesignSafe respository at [86].

CODE AVAILABILITY

The code for hurricane risk simulation for the developed Hi-Fi ORiM is deposited to NSF's DesignSafe repository at [86]. Please contact the corresponding author for any queries related to the code.

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COMPETING INTERESTS

The authors have no competing interests.

AUTHORS CONTRIBUTION

P.A. and L.C. conceptualized the Hi-Fi ORiM and hurricane risk analysis framework. P.A. curated the data and ran the simulations under the guidance of L.C. P.A. drafted the manuscript with contributions and editing from L.C.

REFERENCES

1. Adam B. Smith. U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268). *National Centers for Environmental Information*, 2020. doi: 10.25921/STKW-7W73. URL https://accession.nodc.noaa.gov/0209268.
2. Kairui Feng, Min Ouyang, and Ning Lin. Tropical cyclone-blackout-heatwave compound hazard resilience in a changing climate. *Nature Communications*, 13(1):1–11, 2022. ISSN 20411723. doi: 10.1038/s41467-022-32018-4.
3. Mihir Zaveri and Ed Shanahan. Isaias Hits NY Area: 2.5 Million Lose Power and One Is Killed, 2020. URL https://www.nytimes.com/2020/08/04/nyregion/isaias-ny.html. The New York Times, Accessed: 2024-08-30.
4. American Journal of Transportation. Hurricane Ida caused at least 1.2 million electricity customers to lose power, 2021. URL https://ajot.com/news/hurricane-ida-caused-at-least-1.2-million-electricity-customers-to-lose-power. Accessed: 2024-08-30.
5. Maria Cortes, Prateek Arora, Luis Ceferino, Haitham Ibrahim, Denis Istrati, Dorothy Reed, David Roueche, Amir Safiey, Tori Tomoczek, Ioannis Zisis, Mohammad Alam, Tracy Kijewski-Correa, David Prevatt, and Ian Robertson. StEER - Hurricane Ian, 2022. URL https://doi.org/10.17603/ds2-kc9k-s242. Accessed: 2024-08-30.
6. Alejandra Martinez and Emily Foxhall. Texas attorney general investigating centerpoint energy after hurricane beryl's long-lasting power outages. URL https://www.texastribune.org/2024/07/25/texas-power-grid-puc-centerpoint-hurricane-beryl/. Accessed: 2024-08-31.
7. Paul M. Chakalian, Liza C. Kurtz, and David M. Hondula. After the Lights Go Out: Household Resilience to Electrical Grid Failure Following Hurricane Irma. *Natural Hazards Review*, 20(4): 05019001, 2019. ISSN 1527-6988. doi: 10.1061/(asce)nh.1527-6996.0000335.
8. Kairui Feng, Min Ouyang, and Ning Lin. Hurricane-blackout-heatwave compound hazard risk and resilience in a changing climate. *Nature Communications*, 13:4421, 2022. doi: 10.1038/s41558-023-01596-6. URL https://www.nature.com/articles/s41558-023-01596-6.
9. Luis Ceferino, Judith Mitrani-Reiser, Anne Kiremidjian, Gregory Deierlein, and Celso Bambarén. Effective plans for hospital system response to earthquake emergencies. *Nature Communications 2020 11:1*, 11(1):1–12, 8 2020. ISSN 2041-1723. doi: 10.1038/s41467-020-18072-w. URL https://www.nature.com/articles/s41467-020-18072-w.
10. Diana Mitsova, Ann Margaret Esnard, Alka Sapat, and Betty S. Lai. Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma. *Natural Hazards*, 94(2):689–709, 2018. ISSN 15730840. doi: 10.1007/s11069-018-3413-x. URL https://doi.org/10.1007/s11069-018-3413-x.
11. National Academies of Sciences, Engineering, and Medicine. *Enhancing the Resilience of the Nation's Electricity System*. National Academies Press, July 2017. ISBN 978-0-309-46307-2. doi: 10.17226/24836.
12. Aleksandar M Stankovi, Kevin L Tomsovic, Fabrizio De Caro, Martin Braun, Joe H Chow, Ian Dobson, Joseph Eto, Blair Fink, Christian Hachmann, David Hill, Chuanyi Ji, James A Kavicky,

Victor Levi, Chen-Ching Liu, Lamine Mili, Rodrigo Moreno, Mathaios Panteli, Frederic D Petit, Giovanni Sansavini, Chanan Singh, Anurag K Srivastava, Kai Strunz, Hongbo Sun, Yin Xu, and Shijia Zhao. Methods for Analysis and Quantification of Power System Resilience. *IEEE TRANSACTIONS ON POWER SYSTEMS*, 38(5), 2023. doi: 10.1109/TPWRS.2022.3212688. URL https://doi.org/10.1109/TPWRS.2022.3212688.

13. Laurie Stone. Solar Under Storm Part II: Designing Hurricane-Resilient PV Systems, 2020. URL https://rmi.org/solar-under-storm-part-ii-designing-hurricane-resilient-pv-systems/. Accessed: 2024-09-03.
14. Katherine Antonio. Solar and wind to lead growth of U.S. power generation for the next two years, 2024. URL https://www.eia.gov/todayinenergy/detail.php?id=61242. Accessed: 2024-09-03.
15. Chen Chen, Jianhui Wang, Feng Qiu, and Dongbo Zhao. Resilient Distribution System by Microgrids Formation after Natural Disasters. *IEEE Transactions on Smart Grid*, 7(2):958–966, 3 2016. ISSN 19493053. doi: 10.1109/TSG.2015.2429653.
16. Gavin Newsom, David Carter, Doug Saucedo, Jim Zoellick, Charles Chamberlin, Marc Marshall, Steve Shoemaker, Greg Chapman, Jana Ganion, Peter Lehman, Pramod Singh, Jamie Patterson, Fernando Piña, and Drew Bohan. Demonstrating a secure, reliable, low-carbon community microgrid at the blue lake rancheria. Technical report, California Energy Commission, 2019. URL https://www.schatzcenter.org. CEC-500-2019-011.
17. Chao Long, Jianzhong Wu, Chenghua Zhang, Meng Cheng, and Ali Al-Wakeel. Feasibility of Peer-to-Peer Energy Trading in Low Voltage Electrical Distribution Networks. *Energy Procedia*, 105:2227–2232, 5 2017. ISSN 1876-6102. doi: 10.1016/J.EGYPRO.2017.03.632.
18. Prakhar Mehta and Verena Tiefenbeck. Solar PV sharing in urban energy communities: Impact of community configurations on profitability, autonomy and the electric grid. *Sustainable Cities and Society*, 87:104178, 12 2022. ISSN 2210-6707. doi: 10.1016/J.SCS.2022.104178.
19. Esther Mengelkamp, Johannes Gärttner, Kerstin Rock, Scott Kessler, Lawrence Orsini, and Christof Weinhardt. Designing microgrid energy markets: A case study: The Brooklyn Microgrid. *Applied Energy*, 210:870–880, 1 2018. ISSN 0306-2619. doi: 10.1016/J.APENERGY.2017.06.054.
20. U.S. Department of Energy. Puerto Rico Grid Recovery and Modernization, n.d.. URL https://www.energy.gov/gdo/puerto-rico-grid-recovery-and-modernization. Accessed: 2024-08-30.
21. Kate Anderson, Nicholas D. Laws, Spencer Marr, Lars Lisell, Tony Jimenez, Tria Case, Xiangkun Li, Dag Lohmann, and Dylan Cutler. Quantifying and Monetizing Renewable Energy Resiliency. *Sustainability 2018, Vol. 10, Page 933*, 10(4):933, 3 2018. ISSN 2071-1050. doi: 10.3390/SU10040933. URL https://www.mdpi.com/2071-1050/10/4/933/htmhttps://www.mdpi.com/2071-1050/10/4/933.
22. Huangjie Gong and Dan M. Ione. Improving the Power Outage Resilience of Buildings with Solar PV through the Use of Battery Systems and EV Energy Storage. *Energies 2021, Vol. 14, Page 5749*, 14(18):5749, 9 2021. ISSN 1996-1073. doi: 10.3390/EN14185749. URL https://www.mdpi.com/1996-1073/14/18/5749/htmhttps://www.mdpi.com/1996-1073/14/18/5749.
23. Travis Simpkins, Kate Anderson, Dylan Cutler, and Dan Olis. Optimal sizing of a solar-plus-storage system for utility bill savings and resiliency benefits. *2016 IEEE Power and Energy Society Innovative Smart Grid Technologies Conference, ISGT 2016*, 12 2016. doi: 10.1109/ISGT.2016.7781237.
24. Jian Zhou, Stamatis Tsianikas, Dunbar P. Birnie, and David W. Coit. Economic and resilience benefit analysis of incorporating battery storage to photovoltaic array generation. *Renewable Energy*, 135:652–662, 5 2019. ISSN 0960-1481. doi: 10.1016/J.RENENE.2018.12.013.
25. Siddharth Patel, Luis Ceferino, Chenying Liu, Anne Kiremidjian, and Ram Rajagopal. The disaster resilience value of shared rooftop solar systems in residential communities. *Earthquake*

Spectra, 37(4):2638–2661, 2021. ISSN 87552930. doi: 10.1177/87552930211020020.
26. Luis Ceferino, Ning Lin, and Dazhi Xi. Stochastic modeling of solar irradiance during hurricanes. *Stochastic Environmental Research and Risk Assessment*, 36(9):2681–2693, 9 2022. ISSN 14363259. doi: 10.1007/S00477-021-02154-2/FIGURES/6. URL https://link.springer.com/article/10.1007/s00477-021-02154-2.
27. Daniel R. Chavas, Ning Lin, and Kerry Emanuel. A model for the complete radial structure of the tropical cyclone wind field. Part I: Comparison with observed structure. *Journal of the Atmospheric Sciences*, 72(9):3647–3662, 2015. ISSN 15200469. doi: 10.1175/JAS-D-15-0014.1.
28. Yousef Mohammadi Darestani and Abdollah Shafieezadeh. Multi-dimensional wind fragility functions for wood utility poles. *Engineering Structures*, 183:937–948, 3 2019. ISSN 0141-0296. doi: 10.1016/J.ENGSTRUCT.2019.01.048.
29. Manajit Sengupta, Yu Xie, Anthony Lopez, Aron Habte, Galen Maclaurin, and James Shelby. The National Solar Radiation Data Base (NSRDB). *Renewable and Sustainable Energy Reviews*, 89: 51–60, 6 2018. ISSN 1364-0321. doi: 10.1016/J.RSER.2018.03.003.
30. Luis Ceferino, Ning Lin, and Dazhi Xi. Modeling Solar Generation during Hurricanes. *Environmental Science and Technology*, pages 1–28, 2021.
31. Chengwei Zhai, Thomas Ying jeh Chen, Anna Grace White, and Seth David Guikema. Power outage prediction for natural hazards using synthetic power distribution systems. *Reliability Engineering and System Safety*, 208(October 2020), 2021. ISSN 09518320. doi: 10.1016/j.ress.2020.107348.
32. Huangjie Gong. Models and Optimal Controls for Smart Homes and their Integration into the Electric Power Grid. *Theses and Dissertations–Electrical and Computer Engineering*, 1 2022. doi: https://doi.org/10.13023/etd.2022.053. URL https://uknowledge.uky.edu/ece_etds/179.
33. Aron P. Dobos. *PVWatts Version 5 Manual*, 2014. URL https://www.nrel.gov/publications.
34. Will Gorman, Galen Barbose, Juan Pablo Carvallo, Sunhee Baik, Chandler Miller, Philip White, and Marlena Praprost. County-level assessment of behind-the-meter solar and storage to mitigate long duration power interruptions for residential customers. *Applied Energy*, 342: 121166, 7 2023. ISSN 0306-2619. doi: 10.1016/J.APENERGY.2023.121166.
35. Luis Ceferino, Ning Lin, and Dazhi Xi. Bayesian updating of solar panel fragility curves and implications of higher panel strength for solar generation resilience. *Reliability Engineering & System Safety*, 229:108896, 1 2023. ISSN 0951-8320. doi: 10.1016/J.RESS.2022.108896.
36. Nicholas D. Laws, Kate Anderson, Nicholas A. DiOrio, Xiangkun Li, and Joyce McLaren. Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings. *Renewable Energy*, 127:896–909, 11 2018. ISSN 0960-1481. doi: 10.1016/J.RENENE.2018.05.011.
37. Arkaprabha Bhattacharyya, Soojin Yoon, and Makarand Hastak. Optimal strategy selection framework for minimizing the economic impacts of severe weather induced power outages. *International Journal of Disaster Risk Reduction*, 60:102265, 6 2021. ISSN 2212-4209. doi: 10.1016/J.IJDRR.2021.102265.
38. Zhecheng Wang, Michael Wara, Arun Majumdar, and Ram Rajagopal. Local and utility-wide cost allocations for a more equitable wildfire-resilient distribution grid. *Nature Energy 2023 8:10*, 8(10):1097–1108, 8 2023. ISSN 2058-7546. doi: 10.1038/s41560-023-01306-8. URL https://www.nature.com/articles/s41560-023-01306-8.
39. Julian Stürmer, Anton Plietzsch, Thomas Vogt, Frank Hellmann, Jürgen Kurths, Christian Otto, Katja Frieler, and Mehrnaz Anvari. Increasing the resilience of the Texas power grid against extreme storms by hardening critical lines. *Nature Energy 2024*, pages 1–10, 3 2024. ISSN 2058-7546. doi: 10.1038/s41560-023-01434-1. URL https://www.nature.com/articles/s41560-023-01434-1.
40. Salim Moslehi and T. Agami Reddy. Sustainability of integrated energy systems: A performance-based resilience assessment methodology. *Applied Energy*, 228:487–498, 10 2018.

ISSN 0306-2619. doi: 10.1016/J.APENERGY.2018.06.075. URL https://asu.pure.elsevier.com/en/publications/sustainability-of-integrated-energy-systems-a-performance-based-r.

41. S. Ong, P. Denholm, and N. Clark. Grid parity for residential photovoltaics in the united states: Key drivers and sensitivities. Preprint, National Renewable Energy Laboratory (NREL), 2012. URL https://www.osti.gov/bridge. NREL/CP-6A20-54527, Presented at WREF 2012.
42. Kate Anderson, Amanda Farthing, Emma Elgqvist, and Adam Warren. Looking beyond bill savings to equity in renewable energy microgrid deployment. *Renewable Energy Focus*, 41: 15–32, 6 2022. ISSN 1755-0084. doi: 10.1016/J.REF.2022.02.001.
43. U.S. Department of Energy. Valuation of energy security for the united states (full report). Technical report, U.S. Department of Energy, 2017. URL https://www.energy.gov/sites/prod/files/2017/01/f34/Valuation%20of%20Energy%20Security%20for%20the%20United%20States%20(Full%20Report)_1.pdf. Accessed: 2024-08-30.
44. Reza Marsooli, Ning Lin, Kerry Emanuel, and Kairui Feng. Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nature Communications 2019 10:1*, 10(1):1–9, 8 2019. ISSN 2041-1723. doi: 10.1038/s41467-019-11755-z. URL https://www.nature.com/articles/s41467-019-11755-z.
45. Enrico Cicalò, Mara Balestrieri, Michele Valentino, Francesca Maria Ugliotti, Anna Osello, Muhammad Daud, and Ozan Onur Yilmaz. Enhancing Risk Analysis toward a Landscape Digital Twin Framework: A Multi-Hazard Approach in the Context of a Socio-Economic Perspective. *Sustainability 2023, Vol. 15, Page 12429*, 15(16):12429, 8 2023. ISSN 2071-1050. doi: 10.3390/SU151612429. URL https://www.mdpi.com/2071-1050/15/16/12429/htmhttps://www.mdpi.com/2071-1050/15/16/12429.
46. OpenStreetMap contributors. OpenStreetMap. URL https://www.openstreetmap.org/#map=5/38.007/-95.844. Accessed: 2024-08-30.
47. New Jersey Geographic Information Network. Nj geographic information network: Roads dataset, . URL https://njgin.nj.gov/njgin/edata/roads/. Accessed: 2024-08-30.
48. New Jersey Geographic Information Network. Nj geographic information network: Parcels dataset, . URL https://njgin.nj.gov/njgin/edata/parcels/index.html. Accessed: 2024-08-30.
49. Microsoft. microsoft/USBuildingFootprints: Computer generated building footprints for the United States, 2018. URL https://github.com/microsoft/USBuildingFootprints. Accessed: 2024-08-30.
50. New Jersey Geographic Information Network. Nj geographic information network: Nj office of geographic information systems (njogis), . URL https://njgin.nj.gov/njgin/about/ogis/. Accessed: 2024-08-30.
51. Prateek Arora and Luis Ceferino. A Quasi-Binomial Regression Model for Hurricane-Induced Power Outages during Early Warning. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 10(2):04024027, 6 2024. ISSN 23767642. doi: 10.1061/AJRUA6.RUENG-1215/SUPPL{_}FILE/SUPPLEMENTAL{_}MATERIALS{_}AJRUA6.RUENG-1215{_}ARORA.PDF. URL https://ascelibrary.org/doi/abs/10.1061/AJRUA6.RUENG-1215https://ascelibrary.org/doi/10.1061/AJRUA6.RUENG-1215.
52. Prateek Arora and Luis Ceferino. Probabilistic and machine learning methods for uncertainty quantification in power outage prediction due to extreme events. *Natural Hazards and Earth System Sciences*, 23(5):1665–1683, 5 2023. ISSN 16849981. doi: 10.5194/NHESS-23-1665-2023.
53. Ning Lin, Kerry Emanuel, Michael Oppenheimer, and Erik Vanmarcke. Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change*, 2(6): 462–467, 2012. ISSN 1758678X. doi: 10.1038/nclimate1389.
54. Andy Latto, Andrew Hagen, and Robbie Berg. National hurricane center tropical cyclone report: Hurricane isaias. Technical report, National Hurricane Center, June 2021. URL

https://www.nhc.noaa.gov/data/tcr/AL092020_Isaias.pdf.

55. American Society of Civil Engineers. ASCE 7 Standard: Minimum Design Loads and Associated Criteria for Buildings and Other Structures, n.d. URL https://www.asce.org/publications-and-news/asce-7. Accessed: 2024-08-30.
56. Jim Giuliano. Review and assessment of electric utility performance: August 4, 2020, tropical storm isaias weather event. Technical report, New Jersey Board of Public Utilities, 2020. URL https://www.nj.gov/bpu/pdf/boardorders/2020/20201118/6A%20-%202020%20Tropical%20Storm%20Isaias%20BPU%20Staff%20Report.pdf. Division of Reliability and Security.
57. U.S. Department of Energy. OE-417 Electric Emergency Incident and Disturbance Report Form. URL https://www.oe.netl.doe.gov/OE417/Form/Home.aspx. Accessed: 2024-08-30.
58. Prateek Arora and Luis Ceferino. Could rooftop solar panels and storage have enhanced the electricity resilience during Hurricane Isaias (2020)? *14th International Conference on Applications of Statistics and Probability in Civil Engineering*, (2020), 2023.
59. U.S. Energy Information Administration. Annual Energy Outlook 2022. URL https://www.eia.gov/outlooks/aeo/data/browser/. Accessed: 2024-08-31.
60. IEEE Standards Association. IEEE Standard 1366-2022: IEEE Guide for Electric Power Distribution Reliability Indices, 2022. URL https://standards.ieee.org/ieee/1366/7243/. Accessed: 2024-08-30.
61. Hao Wu, Xiangyi Meng, Michael M. Danziger, Sean P. Cornelius, Hui Tian, and Albert László Barabási. Fragmentation of outage clusters during the recovery of power distribution grids. *Nature Communications 2022 13:1*, 13(1):1–7, 11 2022. ISSN 2041-1723. doi: 10.1038/s41467-022-35104-9. URL https://www.nature.com/articles/s41467-022-35104-9.
62. Tara Walsh, Thomas Layton, David Wanik, and Jonathan Mellor. Agent Based Model to Estimate Time to Restoration of Storm-Induced Power Outages. *Infrastructures 2018, Vol. 3, Page 33*, 3(3):33, 8 2018. ISSN 2412-3811. doi: 10.3390/INFRASTRUCTURES3030033. URL https://www.mdpi.com/2412-3811/3/3/33/htmhttps://www.mdpi.com/2412-3811/3/3/33.
63. NOAA Research. Hurricane Beryl: An opportunity for collaborative research, 2024. URL https://research.noaa.gov/2024/07/24/hurricane-beryl-an-opportunity-for-collaborative-research/. Accessed: 2024-08-30.
64. Kerry Manuel, Ragoth Sundararajan, and John Williams. Hurricanes and Global Warming: Results from Downscaling IPCC AR4 Simulations. *Bulletin of the American Meteorological Society*, 89(3):347–368, 3 2008. ISSN 0003-0007. doi: 10.1175/BAMS-89-3-347. URL https://journals.ametsoc.org/view/journals/bams/89/3/bams-89-3-347.xml.
65. Seth David Guikema, Roshanak Nateghi, Steven M. Quiring, Andrea Staid, Allison C. Reilly, and Michael Gao. Predicting Hurricane Power Outages to Support Storm Response Planning. *IEEE Access*, 2(September 2015):1364–1373, 2014. ISSN 21693536. doi: 10.1109/ACCESS.2014.2365716.
66. Kate Anderson, Eliza Hotchkiss, and Caitlin Murphy. Valuing resilience in electricity systems: Quantifying, valuing, and monetizing its impact on system resilience. *Renewable Energy*, 2018. doi: 10.1016/j.renene.2018.05.011. URL https://doi.org/10.1016/j.renene.2018.05.011.
67. U.S. Department of Energy. Homeowner's guide to the federal tax credit for solar photovoltaics, n.d.. URL https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics. Accessed: 2024-08-30.
68. New jersey's clean energy successor solar incentives (susi) program: Administratively determined incentive (adi) program revised srec-ii incentive levels. Technical report, New Jersey Clean Energy Program, 2023. URL https://njcleanenergy.com/renewable-energy/programs/susi-program/adi-program.

69. New Jersey Clean Energy Program. Net Metering and Interconnection. URL https://www.njcleanenergy.com/renewable-energy/programs/net-metering-and-interconnection. Accessed: 2024-08-31.
70. Florida Senate. House Bill 741 (2022) - Net Metering, 2022. URL https://www.flsenate.gov/Session/Bill/2022/741. Accessed: 2024-08-30.
71. Florida Senate. Senate Bill 796 (2019) - Public Utility Storm Protection Plans, 2019. URL https://www.flsenate.gov/Session/Bill/2019/796. Accessed: 2024-08-30.
72. POWEROUTAGE.US. Poweroutage.us, 2020. URL https://www.poweroutage.us. Accessed: 2024-08-30.
73. Microgrids for Disaster Preparedness and Recovery, 2020. URL https://preparecenter.org/wp-content/sites/default/files/microgrids_for_disaster_prep_and_recovery.pdf. Accessed: 2024-09-03.
74. Federal sustainability plan: Catalyzing america's clean energy industries and jobs. Technical report, Office of the Federal Chief Sustainability Officer, 2021. URL https://www.sustainability.gov/pdfs/federal-sustainability-plan.pdf. Accessed: 2024-08-30.
75. IEEE Standards Association. IEEE Standard 1547-2018: IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces, 2018. URL https://standards.ieee.org/ieee/1547/5915/. Accessed: 2024-08-30.
76. Roshanak Nateghi, Seth Guikema, and Steven M. Quiring. Power Outage Estimation for Tropical Cyclones: Improved Accuracy with Simpler Models. *Risk Analysis*, 34(6):1069–1078, 2014. ISSN 15396924. doi: 10.1111/risa.12131.
77. Sara Shashaani, Seth D. Guikema, Chengwei Zhai, Jordan V. Pino, and Steven M. Quiring. Multi-Stage Prediction for Zero-Inflated Hurricane Induced Power Outages. *IEEE Access*, 6: 62432–62449, 2018. ISSN 21693536. doi: 10.1109/ACCESS.2018.2877078.
78. Adam B. Birchfield, Kathleen M. Gegner, Ti Xu, Komal S. Shetye, and Thomas J. Overbye. Statistical Considerations in the Creation of Realistic Synthetic Power Grids for Geomagnetic Disturbance Studies. *IEEE Transactions on Power Systems*, 32(2):1502–1510, 2017. ISSN 08858950. doi: 10.1109/TPWRS.2016.2586460.
79. Kenneth R. Knapp, Michael C. Kruk, David H. Levinson, Howard J. Diamond, and Charles J. Neumann. The international best track archive for climate stewardship (IBTrACS). *Bulletin of the American Meteorological Society*, 91(3):363–376, 3 2010. ISSN 00030007. doi: 10.1175/2009BAMS2755.1.
80. Prateek Arora and Luis Ceferino. A performance-based probabilistic framework to model risk to power systems from hurricanes. *14th International Conference on Applications of Statistics and Probability in Civil Engineering*, 2023.
81. Min Ouyang and Leonardo Dueñas-Osorio. Multi-dimensional hurricane resilience assessment of electric power systems. *Structural Safety*, 48:15–24, 2014. ISSN 01674730. doi: 10.1016/j.strusafe.2014.01.001. URL http://dx.doi.org/10.1016/j.strusafe.2014.01.001.
82. Christopher Z Mooney. Introduction In: Monte Carlo Simulation. *Monte Carlo Simulation*, pages 1–5, 1997. URL http://methods.sagepub.com/book/monte-carlo-simulation/n1.xml.
83. Eric J. H. Wilson, Andrew Parker, Anthony Fontanini, Elaina Present, Janet L. Reyna, Rajendra Adhikari, Carlo Bianchi, Christopher CaraDonna, Matthew Dahlhausen, Janghyun Kim, Amy LeBar, Lixi Liu, Marlena Praprost, Liang Zhang, Peter DeWitt, Noel Merket, Andrew Speake, Tianzhen Hong, Han Li, Natalie Mims Frick, Zhe Wang, Aileen Blair, Henry Horsey, David Roberts, Kim Trenbath, Oluwatobi Adekanye, Eric Bonnema, Rawad El Kontar, Jonathan Gonzalez, Scott Horowitz, Dalton Jones, Ralph T. Muehleisen, Siby Platthotam, Matthew Reynolds, Joseph Robertson, Kevin Sayers, and Qu Li. End-use load profiles for the u.s. building stock: Methodology and results of model calibration, validation, and uncertainty

quantification. Technical report, National Renewable Energy Laboratory (NREL), Golden, CO (United States), March 2022. URL https://www.osti.gov/servlets/purl/1854582/.
84. U.S. Energy Information Administration. Hurricane michael caused 1.7 million electricity outages in the southeast united states, oct 2018. URL https://www.eia.gov/todayinenergy/detail.php?id=37332. Accessed: 2024-08-30.
85. Philip R. White, Joshua D. Rhodes, Eric J.H. Wilson, and Michael E. Webber. Quantifying the impact of residential space heating electrification on the Texas electric grid. *Applied Energy*, 298:117113, 9 2021. ISSN 0306-2619. doi: 10.1016/J.APENERGY.2021.117113.
86. Prateek Arora and Luis Ceferino. Hurricane risk analysis of power failures, 2024. URL https://doi.org/10.17603/ds2-a510-6f83.