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# Transdisciplinary research promoting clean and resilient energy systems for socially vulnerable communities: A review

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ABSTRACT

Extreme weather events caused by climate change can affect the energy sector in different ways. For example, extreme heat, cold spells, strong winds, or flooding may lead to increased energy demand and consumption, reduced energy production, or cause infrastructure failures and outages. Underserved communities are among those most impacted by power outages resulting from extreme weather events due to lower infrastructure investment in the areas where they live. These phenomena encompass a variety of social and technical challenges, for which we propose a new, transdisciplinary framework to explore solutions for providing clean, affordable, and resilient energy systems to vulnerable and at-risk communities. The authors consider a new approach using perspectives from engineering, hazards science, and policy studies to identify and develop solutions for the expansion of the use of solar energy production coupled with increased storage capacities in places where power outages and social vulnerability intersect.

Nomenclature

| Abbreviations and Acronyms | Full Term or Phrase |
|---|---|
| PV | Photovoltaics |
| LCOE | Levelized cost of energy |
| EIA | U.S Energy Information Administration |
| DOE | United States Department of Energy |
| NASA | National Aeronautics and Space Administration |
| RF | Random Forest |
| DT | Decision Tree |
| BGT | Boosted Gradient Tree |
| BART | Bayesian Additive Regression Tree |
| ENS | Ensemble |
| MedVI | Medical Vulnerability Index |
| GIS | Graphic Information System |
| EMS | Emergency Medical Services |
| NREL | National Renewable Energy Laboratory |
| reV | Renewable Energy Potential |

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(continued)

| Abbreviations and Acronyms | Full Term or Phrase |
|---|---|
| SAM | System Advisor Model |
| ITC | Investment Tax Credit |
| EPA | United States Environmental Protection Agency |
| EO | Executive Order |
| kWh | kilowatt-hour |
| MW | Megawatt |

## 1. Introduction

Climate change is increasing the frequency and magnitude of extreme weather events worldwide. In particular, there are more extreme temperatures, heavy precipitation, and worsening droughts in some regions [1]. This phenomenon is having strong effects on communities, especially those that may be more exposed to extreme weather events, either because they are more prone to experience natural hazards or because their socioeconomic characteristics make these communities more vulnerable. Numerous other studies are identifying several patterns that connect impacts from extreme weather events and socioeconomic factors [2].

Extreme weather events are being captured by macroeconomic indicators, suggesting that they are starting to have an impact on both economic growth and national gross domestic product in several countries. Fig. 1 shows the economic impact of weather events and climate disasters in the United States (U.S.) using data from the National Oceanic and Atmospheric Administration [3–5]. Tropical cyclones, severe storms, and drought have had the greatest economic toll, but all of the disaster categories have led to significant loss. In addition to the economic impacts, the increase in global temperature is also affecting the agricultural sector, as crop production has been threatened by extensive droughts. The impact on agriculture, as well as other sectors, can have a domino effect on labor dynamics as several people find themselves with reduced sources of income, making some people more socioeconomically vulnerable as a result of climate-induced extreme weather events [2].

Extreme weather events affect the energy sector in different ways, ranging from increased energy demand and consumption to reduced energy production, infrastructure failure, and grid outages. Each of these is projected to change in frequency and severity in North America given our warming world [6]. Some notable recent examples that show the significant human and economic tolls related to grid outages were Hurricane Maria in 2017 in Puerto Rico [7], Hurricane Michael in 2018 in the Florida panhandle [8], and the Texas power crisis in 2021 due to extreme cold [9]. Oftentimes, vulnerable or marginalized segments of society are most affected by these extreme events due to social inequities and are already struggling to pay their energy bills [10–12].

As extreme weather events become more common and electricity use continues to grow, identifying which areas are most vulnerable to the negative effects of these events becomes crucial to increasing resilience [13]. Resilience represents the ability of a system to absorb and adapt to human-induced or environmental disturbances, ideally by recovering to a stronger condition [14–16]. The approach to developing solutions to these resilience challenges has primarily been focused on the technical elements within engineering [17]. Fig. 2(a) shows the total number of research articles related to each U.S. state for all types of hazards, while Fig. 2(b) shows the distribution of research articles per hazard type for all states.[1] The scholarship efforts regarding power outages for each state do not necessarily mirror the actual economic impacts, shown in 2 (c) for all types of disasters and hazards and 2(d) for tropical cyclones only.[2] When breaking down the distribution of research across various hazard types within each state, it is surprisingly similar, demonstrating a redundancy of existing approaches towards studying this topic. As the authors propose in this review, a more transdisciplinary approach is needed to evaluate the complex relationships between the social and physical sciences to address grid stability in socially vulnerable areas.

One approach to solving this problem lies in expanding the use of photovoltaic (PV) energy production coupled with energy storage in places where power outages and social vulnerability intersect. Not only would this increase energy resilience, especially during extreme weather events, but also has the potential to lower electricity costs for low-capacity communities [20] and reduce air pollution which has been linked to negative health impacts [21]. It can also provide households with the energy required to keep communication and medical devices charged and to provide enough cooling to prevent related medical episodes, such as during Hurricane Irma (2017) where the most common indirect cause of death was exasperation of an existing health issue [22]. However, various challenges remain that need to be addressed to bring forth solutions to improve electric grid reliability and provide clean, affordable, and resilient energy to socially vulnerable communities.

Capital is finite, and PV systems with energy storage (PV + storage) are capital-intensive investments. Often, the communities most vulnerable to grid outages caused by extreme weather events lack the financial resources to build out PV + storage infrastructure [20]. Policies should be put in place to encourage investment in these resources in vulnerable communities. The most effective policies should more precisely identify the locations most at risk in a physical *and* social sense. Additionally, the most appropriate locations for PV + storage are also dependent on technological constraints related to the electric power system (i.e., the grid). Increasingly, research on resilient energy systems such as microgrids identifies the need for more participatory planning with an actively engaged population for where resilient systems will be used [23]. Fig. 2 (e) and (f) include the energy expenditures per capita and estimated potential annual energy production available for rooftop PV in each state. Collectively, this provides an interstate comparison of the financial burden associated with energy consumption and the energy potential for rooftop PV.

Another challenge is related to energy equity, which is the concern for fair and just access to energy services, resources, and benefits across all populations. For example, solar panels provide clean, low-cost electricity, however are more commonly adopted by higher-income households [24], indicating there are still significant energy equity implications to consider during this transition. An equitable approach takes into consideration the different experiences across populations while also actively engaging all impacted communities in the decision- and policy-making process [25]. Energy equity issues stem from a variety of sources, such as high energy prices in low-income areas, or pollution from energy systems inflicted on communities with fewer economic and political resources. Households that are not able to afford their electricity bills face higher rates of energy burdens which may lead to adverse health effects from compromised living standards [26]. Access to clean, distributed energy is one way to significantly improve health outcomes and energy resilience for underrepresented areas [27]; however, careful consideration of program and policy design choices is needed to maximize equity [24]. Similarly, the concept of "equitable resilience" considers unequal access to resilience that goes beyond social vulnerability to also incorporate access to resources, participation into the decision- and policy-making arena, and ability to take part in resilience planning and development [28]. Deployment of more resilient energy solutions, such as PV + storage, requires considerable financial investment, therefore careful study and planning is needed to place

[1] This distribution is relatively consistent across all states.

[2] Tropical cyclones are highlighted here because they have caused the most economic loss and are capable of causing widespread power outages.

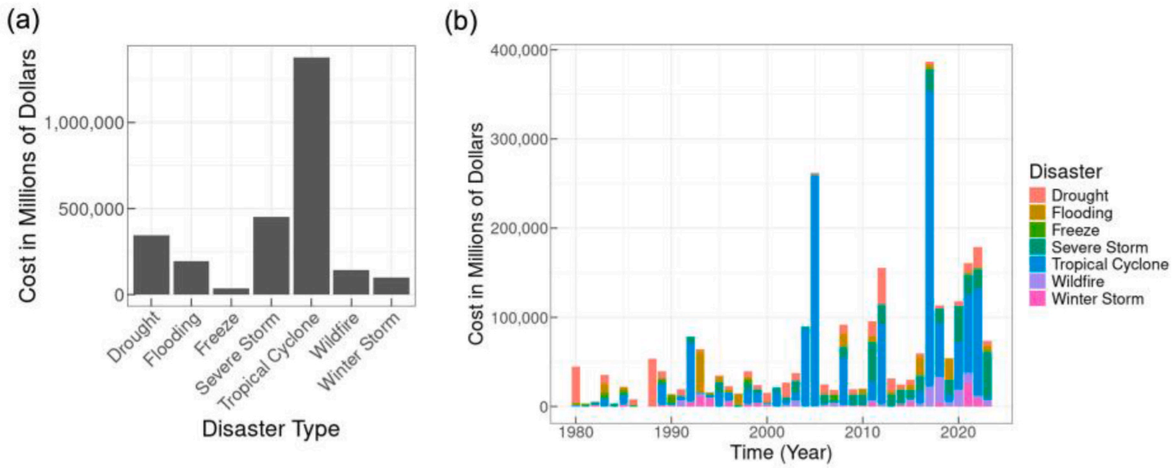


**Fig. 1.** Cost in millions of U.S. dollars of weather events and climate disasters with impacts over one billion U.S. dollars shown as: (a) the total cost per disaster type; and (b) the cost per year for each disaster type. The data source is [3].

these assets where they can benefit communities equitably [20].

In this review, the case is made for a more transdisciplinary approach to evaluating the challenges and need for resilient energy systems that include multiple perspectives including engineering, computer science, hazards geography, technoeconomic analysis, and public policy. This article reviews relevant work from these various disciplines and proposes a transdisciplinary, geospatial framework focused on equitable grid resilience. Transdisciplinarity refers to an approach that places the interactions among several research disciplines in a holistic and integrated system that results in an evolving and collaborative subdiscipline [29]. Fig. 3 illustrates the key elements of this proposed framework and how each element fits together. This review is organized in the following manner. Section 2 reviews the availability of relevant data sources, analysis and modeling methods, and prior research findings related to connecting extreme weather to power outages in a spatially-resolved manner. This part of the overarching framework, shown on the bottom left of Fig. 3, relies on the use of historical outage and weather data to build models that can predict risk of outages for geographic regions of interest while considering a changing climate. Section 3 covers the links between social and medical vulnerability and power outages. Socioeconomic an medical data can be used to build models for quantifying vulnerability (bottom right of Fig. 3). This can be combined with risk maps to identify geographic regions and, depending on the spatial granularity of the data and models, specific communities that are both at an elevated risk of experiencing outages and socially or medically vulnerable. Section 4 discusses the interventions and technological solutions available to increase energy resilience with an emphasis on the PV and energy storage systems (PV + storage). And finally, section 5 covers the policy implications and potential policy solutions. In the proposed framework, these elements would all be brought together, along with stakeholder feedback, and then used to determine the most appropriate technology and policy solutions in a spatially-resolved, and therefore community-specific manner. There are challenges in working with massive, heterogeneous datasets, but approaches have been developed using high-performance computing and distributed storage [30].

## 2. Extreme weather and power outages

Extreme weather events have become a major cause of electric power outages in recent years. In the U.S., the annual impact of weather-related blackouts (i.e., power outages specifically) ranges from $20 to $55 billion in U.S. dollars [31]. In the U.S., an average of 520 million customers were affected by power outages across 2447 counties between 2018 and 2020; outage data show that about 62 % percent of the outages lasted 8 h or more and were caused by hurricanes, extreme storms, and heat [10]. High winds during hurricanes and storms are considered one of the main causes of wide-area electrical disturbances. For example, Hurricane Sandy (2012) resulted in 8.5 million people being without power, and Hurricane Michael (2018) resulted in 1.7 million people being without power [32,33]. In Florida, hurricane-induced flooding and wind, are the two most frequent causes of power outages [34].

In addition to the wind, other weather drivers result in direct damage to the electricity system infrastructure. Lightning strikes that affectoverhead conductors can result in short-circuit faults, which in turn leads to electrical protection and disconnected lines. Cold waves, heavy snow, and ice accumulation increase the likelihood that overhead lines and towers fail. Under freezing conditions, ice and snow may gather on insulators bridging the insulators and provide a conducting path, resulting in flashover faults. In the winter of 2021, Texas suffered three major winter storms that produced equipment problems (i.e., power equipment in Texas was not winterized) and high demand for electricity. At the peak of the crisis, 4,011,776 customers experienced power outages throughout Texas [35]. Wildfires also impact the power grid, a recent example is the 2021 Colorado wildfire, also known as Marshall Fire, which impacted Xcel Energy's natural gas infrastructure that supports the system in two Counties. High temperatures and heat waves limit the transfer capability of transmission lines and increase the energy losses and the line sagging.

The frequency of power outages caused by extreme weather events is already on the rise, driven by the increasing occurrence of severe weather events and the aging infrastructure of the power grid. 2017 is to date recorded as the costliest Atlantic Hurricane Season since 1851, the year in which losses and damages assessments began to be recorded. 2017 was followed by the 2012 and 2008 seasons which also recorded several weather-related power outages [36]. The increase in consumer power outages, partially due to an increase in extreme weather events [37], also correlate with increases in related health incidents such as increases in carbon monoxide poisoning from generators [38]. As a result, it is important to identify areas that are most vulnerable to power outages due to extreme weather events.

### 2.1. Power outage data sources

In reviewing existing literature pertaining to this issue, there is a dearth of spatially granular data related to power outages. While community aggregated data has been used to reveal disparate impacts during this extreme events such as the Texas winter storms [39–41], there are limited publicly available sources of large-scale power outage data with the type of spatial resolution needed to locate specific communities

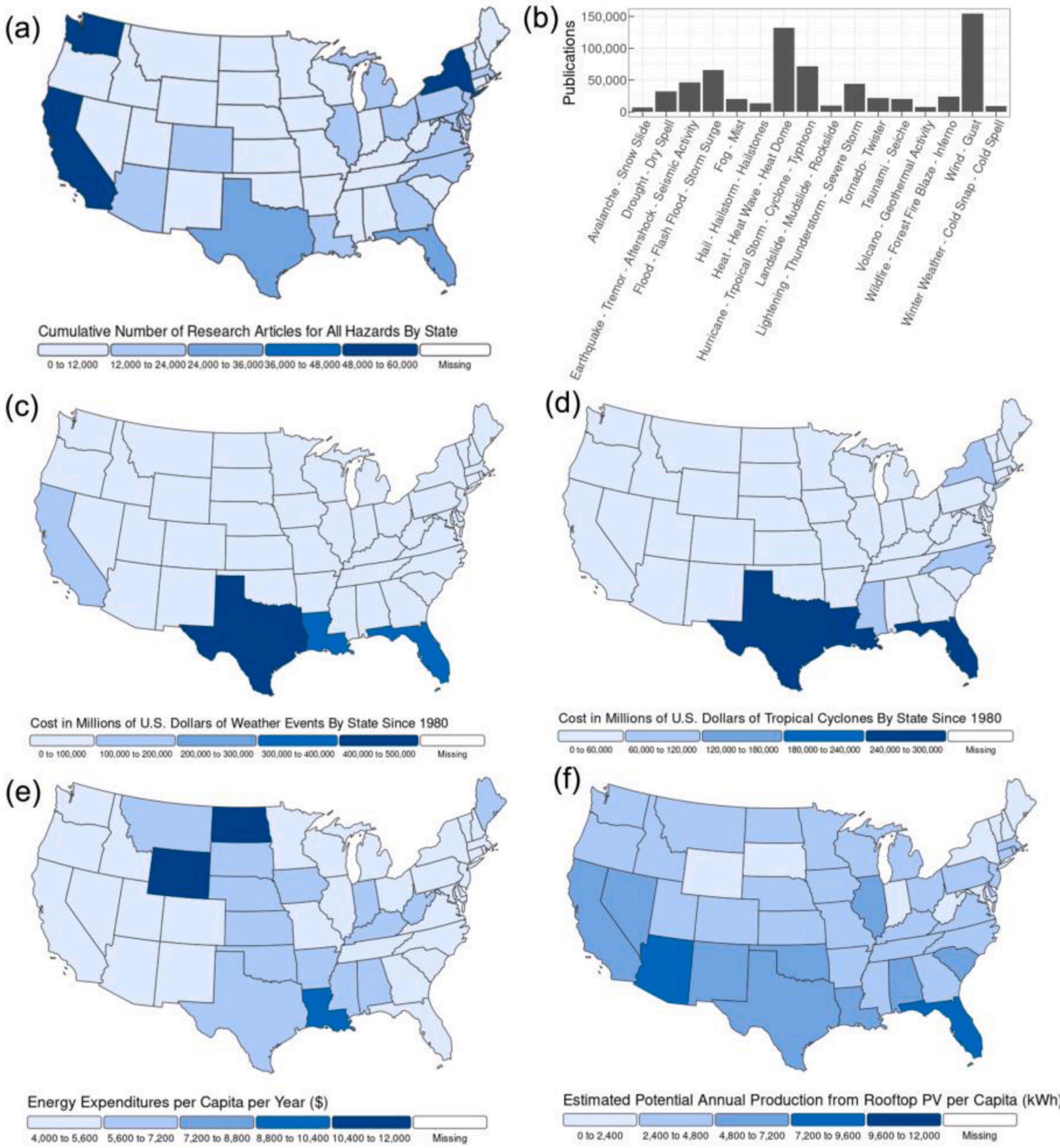


**Fig. 2.** The number of research articles published related to extreme weather and power outages shown: (a) for all hazards as a map of U.S. states all hazards; and (b) for all states, but broken down based on hazard type. Maps of U.S. states showing: (c) the total cost in millions of U.S. dollars of large weather events and climate disasters since 1980 for each state from Ref. [3]; (d) cost in millions for tropical cyclones specifically; (e) annual energy expenditures per capita [18]; and and (e) estimated potential annual production from rooftop PV per capita estimated from Google's Project Sunroof [19].

that have disproportionately experienced outages. This highlights the need for a replicable methods of extracting power outage data on a granular level and public sources of this data.

Specifically within the U.S., many of the public outage datasets are reported at the county of city level, like data from the U.S. Department of Energy Form OE-417 submission [34] and the more recent EAGLE-I dataset [42,43]. However, in areas that are geographically large, have high populations, and are socioeconomically diverse such as Miami-Dade County in Florida, county or city-wide averages may mask more vulnerable populations at the neighborhood level.

As for private direct access to power outage data, electric utility companies are the primary source of outage data in their transmission area. However, utility companies are disincentivized to share this information if they feel that it may create financial, legal, or public relations liabilities. Another method of accessing the power outage data directly is through smart meter data provided by consumers (e.g. Pecan Street). However, that requires large consumer cooperation and mobilization in order for it to be scalable across many areas.

In the absence of direct power outage data from electric utilities, one option is to process information for data sets whose contents correlate with extreme weather resilience. For example, National Aeronautics and Space Administration (NASA) nighttime satellite imagery can be used for the identification of power outages based on the visibility of lights. This is an indirect method of measuring power outages, however, it can strongly correlate with power outages during extreme weather events. For example, the nighttime images taken via NASA satellite before and after Hurricane Michael in 2018 as depicted in Fig. 4 show the extensive power outages in the area as a result of the storm [44]. There is a clear

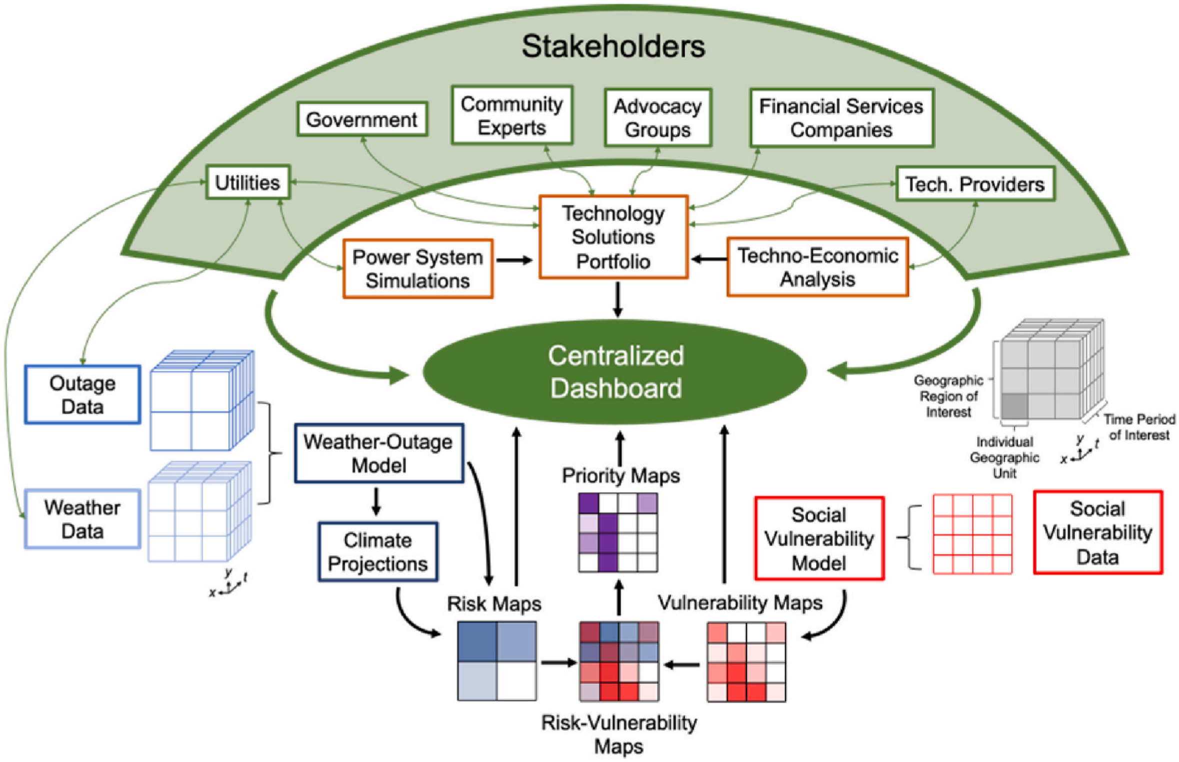


**Fig. 3.** Illustration of the proposed transdisciplinary, geospatial framework for promoting clean, affordable, and resilient energy to socially vulnerability communities.

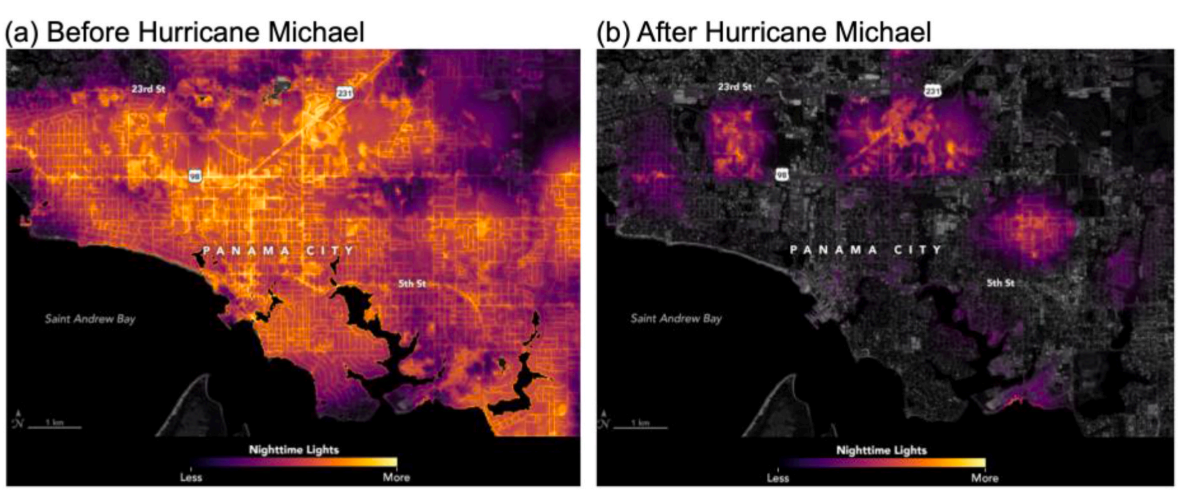


**Fig. 4.** NASA nighttime satellite imagery (a) before and (b) after Hurricane Michael, on October 6, 2018 and October 12, 2018, respectively. Image sourced from Ref. [44].

abundance of areas that experienced a decrease in measurable light.

The limitation of using indirect data sets such as these is that there is a degree of noise that has to be filtered out. In this case, the type and abundance of cloud coverage affects the amount of light shown, therefore another resource is needed to verify cloud coverage at any given pixel during the time that this was taken in order to improve the accuracy. Additionally, other indirect sources for power outage data are not always accessible. For example, it may be possible to conduct a social medias' posts analysis by identifying keywords that may find posts discussing power outages in a given area. This could be possible by making use of tools for social media content analysis (including embed social medias resources such as those available in Facebook) and apply them to individuals and groups (such as, neighborhood Facebook groups) posts. Additionally, another potential source of indirect data is food spoilage insurance claims, however obtaining those claims would involve requesting this information from the company that fulfilled the claims, who may not be willing to cooperate.

### *2.2. Parameters that affect power outage*

Power outages often occur due to the complex interaction between various weather variables, vegetation cover, and infrastructure. Most weather-related power outages are caused by falling trees or their limbs affecting electricity distribution lines and poles. Major outages are more often caused by damage to electricity transmission lines [31]. Thus, vegetation management is crucial to reduce the risk of power outages.

This is well reflected in the performance of the weather-outage models; they have shown lower accuracy if vegetation information (usually tree trimming) is not accounted for. The electric system infrastructure (e.g., electric transformers, fuses, reclosers, switches), the number of customers served, and the type of soil have also been found crucial to model power outages. Although the weather-only model has shown lower accuracy than models including infrastructure and vegetation information, they still perform fairly well [45–48].

The relative relevance of the weather variables in the outage-weather model depends on the region [49] and on the type of weather event. In Connecticut [45], concluded that total precipitation, maximum and mean temperature, and mean wind gusts are the most important variables in extra-tropical cyclones while maximum specific humidity, maximum and mean temperature, and maximum soil moisture are the most significant weather variables in thunderstorms. Importantly, models which ignored near-surface parameters were unable to adequately predict outages related to thunderstorms. Staid et al. [50] used tropical cyclone winds to obtain the number of customers without power for each census tract in the Gulf of Mexico and the Atlantic coast of the U.S.

Usually, the set of weather variables also includes precipitation and pre-storm condition indices such as soil moisture at different depth levels [45,47,48], temperature [45,51,52], humidity [45,51], drought [53] and storm intensity classification [45,51], as well as the total number of customers served by the utility in a grid cell and information about tree trimming. It was shown that when the tree-trimming variable is removed from the model, the performance drops, but the model can still predict outages with reasonable accuracy. Finally, results suggested that models which only consider gust wind speed, as is typical for engineering fragility curves, are unlikely to accurately model failures in the power system.

Despite the extensive literature on storm-weather power outage models, some hazards have been widely neglected such as flooding from surge and/or precipitation. Personal communication with utility companies highlighted that flooding is particularly relevant for power outages, especially in hurricaneprone areas [54]. used a hurricane outage model to predict customer outages for Hurricane Sandy in the Northeast of the United States. Although the model did well for many regions, it underestimated customer outages in Connecticut. It was hypothesized that this may have been because storm surge was not included in the model. However [47], found that the storm surge only contributed to a minor fraction of the customer outages in the region while the majority was related to trees interacting with the overhead lines. The existing discrepancy regarding the relative importance of flooding in power outages underscores the need for more comprehensive assessments on the topic.

The above-mentioned weather events cause direct damage to the power system infrastructure, but weather events can also have indirect effects. Sustained heat waves often cause significant changes in the load, comlicating electricity demand predictions. Unanticipated higher demand for space conditioning and refrigeration during heat waves has led to rolling outages in the past. During a heat wave in September 2022, a California grid operator issued a power grid emergency alert to conserve electricity use to prevent outages. In this context [55], found that the cooler demand could be underestimated if only air temperature is accounted for, neglecting the effect of humidity, as it is usually done. They also showed that the relative importance of humidity and temperature varies greatly across a region.

**Table 1**
Summary of machine learning approaches to build weather-outage models.

| Target | Input | Model(s) Tested | Best Model |
|---|---|---|---|
| Number of outages per 2 km grid cell | Weather, grid infrastructure, land cover, vegetation [45] | Decision tree, gradient-boosted tree, random forest, ensemble regression, and BART | BART |
| Count of outages per grid cell (>5 min) [47] | Simulated weather for 89 storms using WRF model variables including wind gust, wind stress, wind at 10 m height, soil moisture, precipitation rate joined with grid information, land cover information | Decision tree, gradient-boosted tree, random forest, and ensemble regression | Ensemble regression |
| Outage duration caused by hurricane [48] | Land use and land cover, hurricane duration and intenstiy, precipitation, soil moisture, wind speed | BART, regression trees, accelerated failure time (AFT) and Cox proportional hazard models (Cox PH) | BART |
| Electricity consumption (GWh/month) [56] | Temperature, precipitation, wind speed, wind gust, visiblity, dew point temperature, and economic data | BART, GLM, GAM, MARS | BART |
| Outage duration [57] | Wind gust, precipitation, ice accretion, land cover, duration of strong winds | AFT | AFT |
| Number of outages [58] | Hurricane characteristics, land cover, non-hurricane climatic data, grid information | GLM, GAM | GAM |
| Major outages at the state level [52] | Socioeconomic data, electricity consumption, state-level climate and weather data, land use data, grid information | SVM, RF | Twostage hybrid risk estimation model |
| Utility-reported power outages for each storm event [59] | Weather data from ERA5 and ERA5-Land, grid information, land cover, tree canopy cover | GBM, RF, optimized model (OPT) | OPT |

### 2.3. Machine learning models

In order to better anticipate and reduce the impacts of weather-induced power outages, several studies have developed forecast models to derive the extent and magnitude of the outages. A summary of these is provided in Table 1. Usually, models are designed to predict the expected number of outages, defined either by the number of customers without power or the number of locations that require manual intervention to restore power. A diverse range of machine learning techniques exists, and they have been applied individually or in conjunction with each other in numerous ways. The most frequent machine learning algorithms used include random forest (RF), decision tree (DT), boosted gradient tree (BGT), an ensemble of models of RF and DT (although ensembles of other models can be found in the literature), and Bayesian additive regression tree (BART) [45,47,48,56]. To a lesser extent, statistical models such as the generalized linear model and the generalized additive model have been also applied to predict power outages [57,58]. Overall, weather-outage models use the same type of input predictors/parameters, which includes information on infrastructure (i.e., a precondition of the power grid), vegetation (e.g., cover, type of vegetation, and trimming), and weather conditions (e.g., wind, precipitation, temperature).

The literature describes a best practice for using machine learning techniques in analyzing impacts on the electric power system. Work from Ref. [47] compared RF, DT, BGT, and an ensemble (ENS) of the three models to predict the number of outages per grid cell in

Connecticut, U.S. for 89 storms including thunderstorms, blizzards, Nor'easters, and hurricanes. Combining magnitude and spatial accuracy, the ENS performed the best, followed by the RF [45]. compared the same set of models (DT, BGT, RF, ENS) in addition to BART, for 76 extra-tropical storms and 44 convective storms in Connecticut. The BART model performed better than others, followed by BGT, ENS, DT, and RF. A similar conclusion was drawn by Ref. [48], who predicted the mean outage duration in the central region of the Gulf of Mexico using data for three different hurricanes. They tested the accelerated failure time regression, cox proportional hazards, BART, and a multivariate adaptive regression spline. They found that the BART model outperformed all other statistical models [56]. tested five different models (generalized linear model, generalized additive model, multivariate adaptive regression splines, ENS-based tree model, and BART) to predict power consumption in Florida, U.S. and found BART to outperform other models. Furthermore [52], developed a two-stage hybrid machine learning model combining support vector machine and RF to predict the extreme outages in the USA at the state level [59]. proposed a framework to classify the severity of an outage event and prediction based on RF, BGT, and ENS (RF + GBT) models for the Connecticut service territory of Eversource Energy. They found that the ENS showed better performance in comparison to single models. Overall, based on the above-mentioned studies, the BART model has been found to yield better outage predictions, followed by ENS.

### 2.4. Climate change impact on power outages: relevance in Florida

Climate change is expected to affect many of the weather variables discussed above and hence will likely also affect the operation and reliability of power systems [60]. For example, there are temperature thresholds above which the operation of transformers and overhead lines is impacted. With the expected continuous increase in the ambient temperature certain elements of the system will likely have to be derated. The same changes in temperature will likely also negatively affect the efficiency of thermal power plants [60]. The continued rise in sea level will threaten coastal assets such as oil and gas pipelines and also facilitate coastal flooding due to elevated base water levels onto which tides and storm surges are superimposed. Changes in rainfall patterns will lead to more flooding in certain areas and more drought periods in others. The former can directly impact power system infrastructure, while the latter affects hydropower generation and the availability of water for cooling purposes in thermal and nuclear power plants [60].

The U.S. Department of Energy in its Regional Vulnerabilities and Resilience Solutions report (2015) [61] indicated that the Southeast region of the country hosts a large amount of energy infrastructure in low-lying coastal plains that are vulnerable to increases in flooding. High winds, coastal erosion, flooding, and large waves from hurricanes and sea level rise-enhanced storm surges threaten oil and gas production, ports, pipelines, refineries, and storage facilities, as well as electricity generation and transmission assets. Higher temperatures and more frequent, severe, and longer-lasting heat waves are also projected for the Southeast, potentially increasing peak electricity demand for cooling while reducing the capacity of the thermoelectric generation and transmission systems needed to meet the increased demand. In this regard, Staid et al. [50] identified the Houston, Texas, New Orleans, Louisiana, and Miami, Florida, metropolitan areas to be heavily impacted even for scenarios of lower-intensity storms. On the contrary, Alemazkoor et al. [62] concluded that hurricane-induced power outage risk under climate change is predominantly driven by the uncertainty in the future frequency of hurricanes. Further research is needed to assess changes in the frequency of extreme events taking into account the uncertainties of projections.

Florida is not exempt from the extreme weather events experienced in the Southeast region. The state encounters various climatic phenomena, heat waves, inland/coastal floods, and strong winds, the latter two often resulting from hurricanes. In addition, the state is experiencing a steep increase in population, which can burden the power system under certain weather conditions such as high temperatures. As mentioned above, the frequency and magnitude of these extreme weather events are expected to change under a warming climate. There have been strong developments in short-term power-outage prediction models, however, the evaluation of the changes in long-term power outages has been limited to the study of hurricane frequency and uncertainties [62] and for changes in the cooling demand [55]. There is a need for infrastructure providers and emergency managers to plan on much longer time scales as recognized by other authors [50], including not only temperature and hurricanes but all other weather parameters that have been recognized to influence power outages.

### 2.5. Local study areas vs. large study areas

As mentioned above, power outages are a function of weather conditions, vegetation cover, and infrastructure, all of which exhibit significant spatial variation. In addition, the impacts of climate change on weather patterns also vary across different regions. Therefore, conducting local studies becomes imperative in order to capture the characteristics of specific areas and deliver more accurate short-term power outage forecasts, as well as long-term projections. By utilizing localized weather-outage models, it becomes possible to forecast weather events in a more realistic manner and gauge the resilience of specific regions against fluctuating weather conditions.

## 3. Social and medical vulnerability

Understanding the needs of vulnerable people is of utmost importance, especially among emergency managers, public health officials, social workers, and social service professionals. However, in cases of disasters or emergencies where sensitive populations may require aid in adequately preparing for, responding to, recovering from, or mitigating hazards, emergency management officials and planners need detailed information to anticipate and meet often very specific needs [63]. From this perspective, vulnerability represents the potential for loss or harm among individuals and communities facing power outages stemming from hazards, disasters, or energy system insecurity, such as those we observed in the Texas 2021 winter power failure [64,65] or those that occur every time a hurricane makes landfall. In hazard literature, the vulnerability concept broadly includes the structural vulnerability of the infrastructure system (power system), often called a biophysical vulnerability, and uneven exposure of individuals and households (to the power system) based on social, political, and economic factors, usually expressed as social vulnerability [66,67]. Generally, social vulnerability refers to those characteristics of a person or group and their situation that influence "their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard (an extreme natural event or process)" [68]. From a practical perspective, understanding social vulnerability determinants means that decision-makers should be able to determine what supplies, equipment, and personnel are needed to respond effectively in emergencies which requires sound knowledge of a region's social, economic, and baseline health conditions.

Consequently, understanding the vulnerability of a population requires a location-based assessment of both socioeconomic sensitivities and special medical needs, which may represent different subpopulations. Although various methods are employed to empirically assess those needs to understand the spatial distribution of vulnerable and marginalized populations, the social vulnerability index (SoVI) is the most popular and widely used in hazard planning, disaster research, and decision-making in emergency management [67]. SoVI models the geographic distribution of vulnerable populations based on 29 different variables that stem principally from vulnerability literature: employment structure, housing, population structure, race/ethnicity, socioeconomic status, and special needs [63]. Using a statistical data reduction approach, these variables are reduced to major components of vulnerability, which can later be mapped using geospatial tools and techniques.

Additionally, supporting the medical and health needs of impacted populations is another challenge to emergency managers during disasters and emergencies. An empirical assessment method called Medical Vulnerability Index (MedVI) is used to understand the medical necessity of an area of interest [69]. MedVI is based on the theoretical framework of social vulnerability and is a companion concept of SoVI utilizing a similar methodological approach. MedVI is constructed from two key concepts; health needs and healthcare access, from medical vulnerability literature and is represented by 36 indicators in four distinct themes: physical health needs, psychological health needs, social health needs, and healthcare access [70,71]. The variables are reduced to major principal components of medical vulnerability using factor reduction technique and have the utility of mapping using a Geographic Information System (GIS) environment.

### *3.1. Social and medical vulnerability and power system failure*

Advanced industrial societies are becoming more technology-dependent and are thus more vulnerable to technology failures. Power systems, one of the critical infrastructures of modern societies, are exposed to various activities such as severe weather, intentional attacks, equipment failures, fuel supply emergency, and islanding [38]. Power system failure is identified as "the single most vulnerable system in our critical infrastructure" [72], and such disruptions and failures will become more frequent with increasing climate extremes and affect more people [38]. Power system failures do not impact individuals equally, and access to proper resources (or lack thereof) can significantly affect how individuals deal with long-duration outages [73]. The relationship between social vulnerability and power outages has recently been explored [10,73–75]. This nascent literature shows that various socio-economic and demographic characteristics play significant roles in increasing health risks, power outage preparedness, and willingness and means to evacuate if necessary [76–80]. These early results highlight a need to identify socially vulnerable groups and medically vulnerable communities so that adequate resources, information, and assistance can be prepared in a more targeted way during such events.

Past studies have shown that differential exposure to such failure dramatically impacts sub-populations. For example, the collapse of the power grid system in 2003 in North America caused ninety excess deaths in New York City, New York, alone, a rise in mortality of 28 %. The death rates were highest for those aged between sixty-five and seventy-four, which shows the differential sensitivity of the population to such events [77]. A study in the Midwest region of the United States indicates that ZIP codes with lower median household income have experienced more power outages during the study period between 2017 and 2022 [81]. Other research found that American Indian populations were positively correlated with average outage duration at the census block group level, showing unequal exposure to such failures [11]. Additionally, the existing literature suggests that power outages have significant health consequences ranging from carbon monoxide poisoning, temperature-related illness, gastrointestinal illness, and cardiovascular, respiratory, and renal disease hospitalizations, especially for individuals relying on electricity-dependent medical equipment [38]. After a 2003 power system failure, hospital emergency department visits and admissions due to respiratory problems increased, especially among women, elderly persons, and people suffering from chronic bronchitis [76]. During a derecho event (destructive thunderstorms) in West Virginia in 2012, utilization of Emergency Medical Services (EMS) and hospital resources increased substantially, from EMS scene responses to inter-facility transfers and standbys increasing by more than 50 percent over the previous year [82]. Thus, power system failure studies should consider factors such as socioeconomic and other social and medical vulnerabilities as well as how community resiliency can mitigate and minimize the adverse impacts of widespread major power outages.

## 4. Technological solutions

The provision of reliable and affordable electricity is essential for economic growth and people's lives. The best way to achieve power grid resilience is through holistic resilience planning [83], as well as continuous advancement of grid technology and diversification of sustainable energy resources.

Technological solutions to achieve resilience proposed in existing literature often require some or all of the following.

- Installation and diversification of additional energy resources;
- Increase of power flow capacity, and reconfigurability of a power system into multiple microgrids [84];
- Optimization, control, and automation to increase flexibility, redundancy, decentralization, self-organization, and coordination [85];
- Implementation through transparency, collaboration, and foresight considerations [85].

Also, every power system has unique features, and hence solutions must be developed for specific communities and their circumstances. And, a combination of tailored solutions should be used to address all potential vulnerabilities.

To achieve resilience of the main grid under extreme weather conditions existing literature suggests the necessity for major generation assets as well as transmission networks need further diversification and decentralization. Examples of these include: (1) hardening grid infrastructure, including transmission line fortification, flood prevention of substations, and transmission capacity enhancement [85]; (2) diversification of generation mix to sustain power generation under supply disruptions and extreme weather conditions; (3) spatial distribution and decentralization of power generation by adding utility-scale wind farms, PV farms, energy storage, and other assets (such as hydrogen); and (4) enhance interconnections among regional grids. At the distribution level, resilience enhancement measures include: (1) underground distribution lines; (2) islandable and interconnected microgrids for local infrastructure needs and critical loads; (3) community PV and energy storage to power communityshared facilities such as a resilience hub; and (4) behind the meter distributed generation, such as rooftop solar and energy storage, coupled with grid-forming inverters (which establish the voltage to supply electricity to individual homes during grid outages) and smart home electricity panels (which enable classification and grouping of various loads in the homes and make them controllable loads). Upon choosing a specific resilience strategy, additional studies should be undertaken to ensure operational reliability, effectiveness, and economic benefits.

From the technical perspective, renewable energy resources such as PV and wind are highly variable, and there is a limit on how many variable resources can be incorporated into a distribution network without violating operational voltage limits. Determination of the limit, referred to as hosting capacity analysis [86], can be done using power system simulations. Typically, distribution networks would experience voltage issues when the renewable penetration level exceeds 20 %. There are several ways to increase the penetration level and maintain a stable and admissible voltage profile across the distribution network.

The first is the incorporation of battery-based energy storage to smooth out the PV production variability (i.e., PV + storage), often called PV smoothing, and the trade-off is the cost. The others are cooperative controls of both reactive power and active power (the latter of which can be accomplished by either storage control or load control or both). To achieve a high level of resilience, it is desirable to raise the PV penetration level to the maximum base load, i.e., at or over 100 % penetration so that the excess PV generation during the PV peak hours can charge the storage devices within the network. To enable such extreme penetration, the so-called control enable hosting capacity analysis should be carried out, and a distributed cooperative control needs to be implemented to coordinate the control actions among the distributed energy resources. Both of them are embedded in the open-source software package MA-OpenDSS [87].

The control-enable hosting capacity determination is a two-stage greedy search algorithm to find realistic worst-case scenarios (in terms of operational voltages) for 100 %–200 % PV penetration, considering both the location and the size of the PVs in the primary and the secondary nodes of a feeder [88]. In the first stage, the worst-case scenario is found by considering PV locations only in the primary nodes. In the second stage, the worst-case PVs from the parent primary nodes are redistributed further down throughout the secondary children's nodes by taking into consideration the size of the PVs. The PVs distributed in the secondary nodes are assumed to not exceed twice the amount of the total load in the secondary node, and any remaining PVs are left on the parent primary node. The process is repeated feeder by the feeder, and the worst-case scenarios for all the feeders are combined to obtain the worst-case scenario for each system. This two-stage greedy search approach reduces the search computational time which, otherwise, would have been intractable for $n!$ combinations required for a feeder with $n$ nodes. Once the worst-case scenarios are identified, the second algorithm of distributed cooperative controls can be applied to perform reactive power compensation so all the feeders in the distribution network can be operated adaptively and autonomously to ensure all voltages are within the operational range (0.95–1.05 per unit).

In Fig. 5, the first sub-figure shows a sample 100k-node system for which the greedy search algorithm determines the worst PV distribution of 100 % penetration. The distribution network voltage profile of the worst-case PV penetration without and with cooperative distributed reactive power control are shown as the second and third sub-figures, respectively. Upon completing control-enabled hosting capacity analysis, the planner can choose multiple configurations of PV and energy storage to perform techno-economic analysis and in turn, make decisions.

A holistic resilience plan and the use of modern grid technologies, like those described previously, enable the integration of PV systems with and without storage. PV systems are inherently clean (i.e., no direct emissions), not subject to fuel supply issues and price volatility, and provide numerous environmental and public health benefits compared to fossil fuel resources [89–91]. Like virtually any technology, the adoption of PV is strongly linked to its economic competitiveness compared to competing options. Technoeconomic analysis plays an important role in evaluating PV systems and PV + storage systems in comparison to fossil fuels, as well as other alternative sources of energy. Often, the levelized cost of energy (LCOE) is one of the key metrics being calculated. The usefulness of LCOE is that it provides a means of comparing different energy generation resources against each other and against, in this case, typical retail electricity rates.

A variety of tools and methods exist for this type of analysis, and they are often dependent on a wide variety of factors. LCOE itself can be simply described as the lifetime cost of the energy system divided by the total energy produced over the life of the system. For a PV or PV + storage system, the majority of the cost is paid at the beginning of the system's life in the form of hardware costs and soft costs (e.g., design, installation, permitting, financing, sales, overhead). The typical warrantied lifetime for PV modules and many of the other components is in the range of 25–30 years normally, so there are naturally some operations & maintenance costs incurred, but these are relatively low for most PV systems.

Ground-mounted utility scale PV systems without energy storage have the lowest LCOE due to lower hardware and installation costs driven by economies of scale and have the largest market share [92], compared to residential and commercial rooftop. The total installation cost per watt (W) for utility scale PV are around \$1.3/W in the U.S. [92], compared to around \$2/W for larger non-residential PV and closer to \$4/W for residential PV [93] depending on the state. However, utility scale PV does not provide distributed resilient power to communities in the case of an outage because it is reliant on transmission and distribution infrastructure. Nor does residential PV if some type of energy storage option, like batteries, is not included. Grid-connected inverters without storage shut down when power from the utility is lost, in order to comply with interconnection standards aimed at preventing unintentional islanding [94–96]. There are various ways to assess the value of backup services to residents, such as using estimates of current electricity rates or what residents are willing to pay to keep their power on. While the average U.S. residential price of electricity is approximate \$0.14/kWh, studies have found that residents are willing to pay between \$0.3/kWh to \$1.2/kWh for backup services to maintain full or partial electric services during a blackout [97]. Achieving LCOE values below \$0.14/kWh is already achievable in the U.S. and abroad [98], even for residential PV + storage systems [99], although these system will always have a higher LCOE than utility scale systems at less than \$0.04/kWh currently in the U.S [92].

In addition to costs, the energy yield of the PV over the life of the system is also critical being the denominator in the LCOE equation. Yield is driven be a variety of factors, including location's expected incident solar irradiance over time (i.e., solar irradiation) and local climate (e.g., ambient temperature), the specific mounting configuration and resulting microclimate, and the specific PV cell and module technology used. Locations with high irradiation are critical, because the output power and therefore yield are directly proportional to irradiance and irradiation, respectively. The power decreases slightly as the PV cell and module operating temperature increase, and the resulting temperature coefficient is strongly dependent on the PV cell technology and module design. The local climate, microclimate, and module selected will also impact the performance loss rate (i.e., degradation rate) of the system

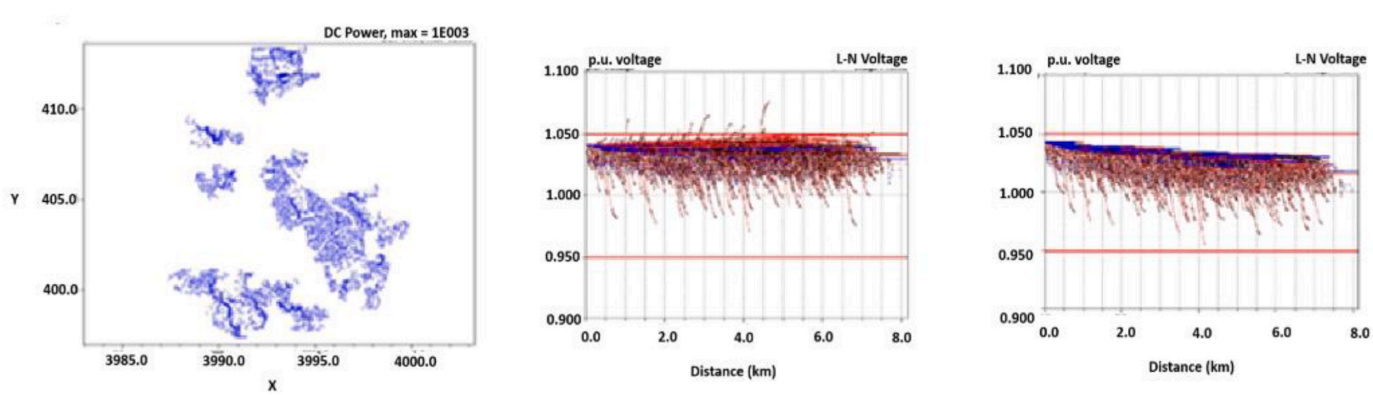


**Fig. 5.** An 100k-node system: 12 feeders, 53,011 buses, 124 + $j$41 MVA total load.

[100].

A variety of reliability and durability issues have been studied in fielded PV systems and many resolved over the years for older technologies [101–111], but questions remain for newer technologies [112–123]. Additionally, component failures require additional human intervention and add cost. And finally, extreme weather itself can also have an impact on PV system performance [124], although snow loading [125] and hail [126,127] appear to have a larger impact on PV system performance than things like tropical cyclones. Manufacturing metrology and field inspection techniques and analysis methods have been developed to monitor PV performance and identify defect and problems related to manufacturing issues, degradation processes, or extreme weather events [128–139]. A variety of modeling and simulation tools have been developed by the PV R&D community to calculate the expected performance of PV systems using these various inputs, including tools using physical and analytical models (e.g., pvlib [140–142], System Advisor Model [143], PySAM [144], PVsyst [145]) and newer data-driven models [146].

In terms of existing rooftop PV system installations in the continental U.S., California is the leader in the total number of installations. In terms of the annual potential energy production from rooftop PV, estimates from tools like Google's Project Sunroof indicate virtually all U.S. states have significant potential [19]. Open tools and databases like Project Sunroof, DeepSolar [147], and the U.S. Large-Scale Solar Photovoltaic Database [148] enable people to locate existing PV systems and identify suitable locations for adding PV, a shown in Fig. 6. These tools, when used in conjunction with the grid planning tools described previously, can assist in efforts to promote clean, affordable, and resilient energy systems.

Ongoing research aims to develop innovative machine learning and optimization algorithms that address outage forecast for specific communities, their technology solution of PV + storage, resilient enhancement of distribution network, and their technoeconomic analysis and optimization. While the algorithms must be generic, scalable, and computationally efficient, the technology solution and its corresponding technoeconomic analysis are community dependent because physical location, power system topology, physical attributes of the distribution network, and load/generation distribution all play their roles. In

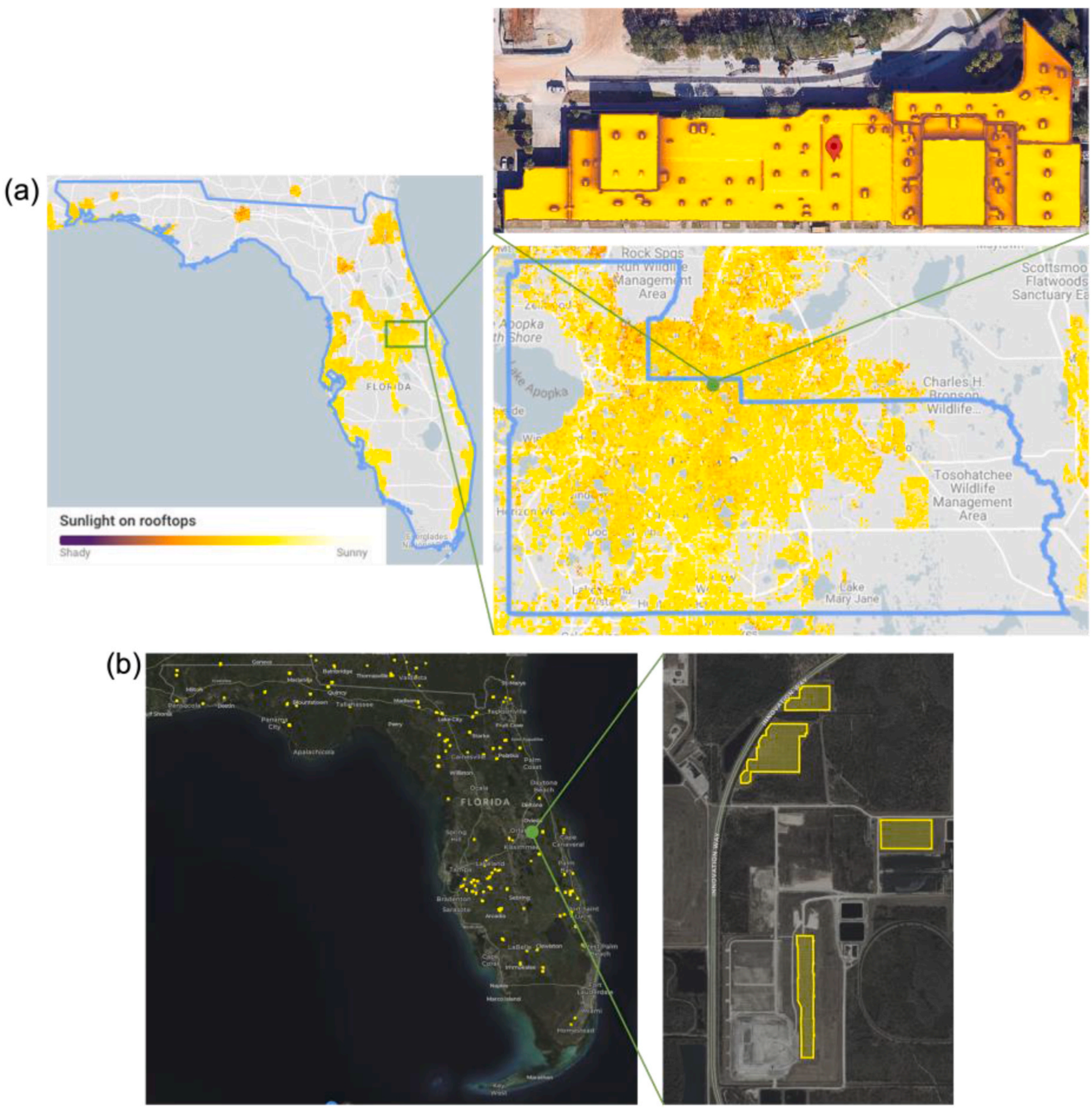


**Fig. 6.** (a) Example of Google's Project Sunroof highlighting suitable rooftops for PV in Florida, Orange County, and a specific building in downtown Orlando [19]. (b) Example of the U.S. Large-Scale Solar Photovoltaic Database showing Florida and a specific large, utility-scale PV system near Orlando [148].

Ref. [149], a stochastic machine learning framework is developed to forecast outages in specific distribution networks, and the framework is shown to have transfer learning capability. In Ref. [150], a novel scheme is presented to achieve resilience of distribution networks in a time shared manner and by using relatively small distributed energy resources but adding a small number of circuit reclosers that enable segmentation and dynamic microgrids. And, PV + storage can further enhance the resilence solution as PV not only reduce local energy needs but also potentially charge the battery storage systems and in turn extend their operational periods [151].

## 5. Policy solutions

Individuals and communities play an important role in building community resilience. As distributed energy resources become more common, and consumers transition to prosumers that contribute to the design and supply of the electricity grid, the models for how resilient grids are governed and incentivized are changing [152,153]. Traditionally, electricity is provided through centralized electric utility providers connected to large power plants that generate electricity that is transmitted across the grid to consumers. However, smallscale PV systems (less than 1 MW in size) in the United States have grown by over 800 % since 2014 from 5000 MW to almost 48,000 MW by December 2023, dramatically increasing the amount of distributed resources on the grid [154].

This growth in small-scale PV in the US is attributed to lower PV module hardware and soft costs (e.g. installation, financing, etc.), as well as state and federal clean energy incentives and policies to reduce the cost of adding solar arrays [155,156]. One example is the federal residential solar investment tax credit (ITC), which provides solar PV owners a tax credit for up to 26 % of the cost of a new residential solar array in their federal income taxes, greatly reducing the installation cost of a new PV system (Table 2). The Inflation Reduction Act of 2022 raises this tax credit to 30 % for installations between 2022 and 2032 and is expected to continue promoting solar growth in the U.S [157].

Despite the recent growth in small-scale PV and cost reduction trends, studies show that small-scale solar is still in the early phase of demand, with only 2.2 % of homeowners across the United States with solar PV systems on-site [167]. Capital costs for installing distributed energy resources remain one of the top barriers to more wide-scale adoption. State adoption rates for rooftop solar range from 23.6 % in Hawaii and 11 % in California to almost no rooftop solar in states such as North and South Dakota and West Virginia [154]. While some of these variations are attributed to access to solar resources and electricity prices, state and local policies significantly impact the accessibility and affordability of distributed, customer-side solar [164,165,172].

In an effort to decarbonize the electric grid, some states have put into place renewable or clean energy targets, such as Renewable Portfolio Standards present in 30 states plus the District of Columbia. Renewable Portfolio Standards set targets for renewable energy contributions to the overall electricity grid mix in that state. The literature is mixed on the degree of effectiveness of Renewable Portfolio Standards on growing solar capacity in the U.S [163–166]. While these may not directly lead to compensation for rooftop solar homeowners [165], renewable energy targets have generally driven other state policies meant to encourage PV growth [164].

One such policy is net metering, which compensates PV owners for any excess electricity generated by their solar array that is exported to the grid, usually on a per-kilowatt-hour basis [167]. As of 2022, 33 states offer some form of net metering credits, however, the rate of compensation (typically retail rate or less), capacity caps, or other rules may impact their effectiveness [165,167]. Much of the literature agrees that net metering has had a substantial impact on distributed solar growth in the U.S. [164,165], perhaps as much as a doubling of small-scale PV capacity between 2008 and 2018 [167].

However, some electric utilities are seeking state regulations to slow the transition to more distributed generation sources [168], oftentimes by pursuing alternative or reduced forms of net metering [169]. The goal of the utility is to reduce the degree of compensation to the homeowner for distributed generation supplied back to the grid. Utilities and state regulatory agencies may also add additional and unnecessary equipment requirements for rooftop solar in interconnection regulations, citing safety or other reasons, which can add additional and unnecessary costs across the country [173].

In addition to generation-related policies, programs to reduce the installation, financing, and permitting soft costs for distributed solar have had mixed success in incentivizing solar adoption. Some solutions discussed by Ref. [156] to reduce small-scale solar PV soft costs include using quote platforms, which are third-party systems to collect and compare multiple PV quotes in a standardized, online format. Customer aggregation such as through microgrids or community solar projects typically reduces transaction costs through interconnection among many or one small-scale PV source. According to Ref. [20], particular design elements of community solar projects including the ownership model, rate design, and subscriber enrollment play an important role in the success of these programs in expanding solar adoption and localized access to clean energy benefits.

Another possible solution to incentivize the adoption of distributed energy resources is by promoting the benefits of grid resilience. Not only is distributed solar a cleaner energy resource with lower carbon dioxide and traditional pollutants, but microgrids and small-scale networks of distributed generation coupled with energy storage can also enhance

**Table 2**
Summary of policy incentives aimed at lowering the cost of PV systems.

| Policy | Description | Level of Government | Primary Benefits | Primary Drawbacks |
|---|---|---|---|---|
| Investment Tax Credit | Tax credit for up to 26 % cost of new residential solar array | Federal | Reduces overall investment cost making it cost-competitive with other generation sources [158], extended recently in the Inflation Reduction Act 2022 and expected to continue improving cost competitiveness of solar [157,159] | Most clean energy tax credits have gone to higher-income households [160,161], scheduled sun setting of the policy creates some uncertainty [158] |
| Renewable Portfolio Standards | Sets targets for renewable energy contributions to the grid | State | More stringent RPS leads to higher renewable capacity growth [162,163], encourages other state policies that more directly incentivize PV growth [164] | Not a direct compensation for rooftop solar homeowners [165], impact of RPS smaller in longer time series, and smaller compared to federal policy impact [166] |
| Net Metering | Compensates residential solar homeowners for generation exported to the grid | State/Utility | Reduces the payback time for covering solar investment costs [164,165] | Limitations such as lower rates of compensation or caps reduce degree of effectiveness [165,167–169], paid for in part by low-income ratepayers without solar [170,171] |

electrical grid resilience [174,175]. [174] use a discrete choice experiment in a survey of over 900 New Yorkers to determine that respondents would typically be willing to pay an additional $14 per month of their electricity bill for a microgrid system with higher service levels and greater reliability. However, literature on resilient energy systems also considers lifecycle questions regarding the environmental sustainability of materials used in PV + storage microgrids. Batteries and other energy storage material production and disposal are under the attention of scientists and policymakers [88,176,177]. Despite this, there is good agreement in the literature that solar panels and energy storage can have a powerful impact on climate mitigation and adaptation [178].

Despite policies that are working to reduce the capital costs of cleaner and more resilient, small-scale energy systems, the financial system and debt-based approach towards energy transitions are preventing even larger-scale deployment of these technology solutions [170,179]. For socioeconomic and medically vulnerable populations, who particularly stand to benefit from better grid resilience with distributed solar, the high investment cost for the technology can make it more difficult to attain. Numerous studies show that rooftop solar adopters tend to have higher incomes [180,181], live in White-majority census tracts [182], and have higher levels of education [181]. However, declining costs of solar [181], and some energy justice programs [182] are beginning to improve more equitable solar adoption across demographics.

Solar plus storage microgrids present an opportunity for greater sustainability towards climate mitigation, as well as more resilient energy solutions able to withstand the consequence of the changing climate. Therefore, if policymakers could transform from the financial market regulations perspective, more private entities and citizens would be able to *step in* and foster the energy transition via renewable energies [179].Based on a review of the literature, support for pro-solar policies such as net-metering [167], community shared solar programs [20], and energy justice programs [26] are promising avenues for improving more equitable access to clean energy resources. In order to develop a robust, community-based energy resilience plan, significant engagement with multiple communities, technology, and local government partners and community members is needed to develop effective and fair programs and incentives. Co-production of knowledge using direct feedback from community members has the potential to produce more effective solutions to complex and wicked environmental problems [183] and energy justice challenges [26]. However, more research is needed on the specific policy designs and implementation strategies that work best to improve solar adoption inequities and access to the benefits of affordable clean energy technology [170,182].

## 6. Conclusion

Climate change is exacerbating the number and magnitude of extreme weather events that are affecting communities worldwide. Compounding risks are disrupting efforts communities are making toward disaster risk reduction, sustainable development, and energy security and transition. Because of financial and infrastructural limitations, underserved communities, especially in coastal areas, are disproportionately affected by disasters resulting from climaterelated natural hazards. Power outages often occur in areas where there is a high reliance on the 'traditional grid' and little or no penetration of renewable energies, including solar PV. Indeed, 'traditional' sources of energy have proven to be less resilient to the effects of today's extreme weather events characteristics and this is creating a compounding effect on underserved communities who already struggle because of socioeconomic disadvantages.

Our study was motivated by the need to provide an overview of both the literature and the scientific efforts aimed at developing solutions to grid resilience challenges due to a changing climate. Thus, power outage modeling does not always accounts for climate change-related impacts that may affect a location in the future. Based on our study, research on short-term power outage forecast models under current climate conditions is ongoing, but there is a lack of focus on long-term climate-induced changes in power outages. From our review, weather parameters in long-term weather-outage models in addition to hurricane and temperature data are needed. Similarly, the relevance of flooding overall, and surge along the coastal regions, are parameters that, given climate change and its impact on characteristics of storms, should be included as well. This review reveals the necessity to evaluate the impacts of the uncertainties of each weather variable in the long-term weather-outage projections in order to assess the long-term changes in weather-related power outages to better plan a more resilient power grid. This is particularly important for vulnerable underserved communities where energy transition and access to multiple sources of energy appears to be a pathway to strengthen their resilience to climate-induced extreme weather events.

Numerous technical solutions to improve grid resilience using cleaner energy sources exist, and research in this field is focused on the increased need for diversification, decentralization, and integration of major generation assets. However, technical challenges still remain regarding complementary renewable energy technologies such as energy storage, as well as the study of integration algorithms for intermittent renewable sources of electricity. Ongoing research is focusing on the development of machine learning and optimized algorithms that can better forecast power outages in a given community. These algorithms can be scalable and computationally efficient but must be kept generic in order to do so; additionally, technological solutions and related economic analyses depend by a variety of factors, including the physical location of the system, the power system topology, the physical attributes of the distribution network itself, and the generation/load distribution of it. Further, the cost of these technologies, necessary upgrades, and transmission infrastructure makes this more challenging, especially for socially vulnerable populations that traditionally are not first-adopters in cleaner and more resilient energy technology.

Despite the resilience-related benefits to underserved communities, promotion of renewable resources as an alternative to traditional sources of energy still faces resistance in the energy transition. For example, electricity providers are considered about the loss of profit to more distributed solar PV. Furthermore, there is little data availability, especially granular data, that would help identify populations more subject to power outages in order to focus policy efforts where a higher number of people and/or underserved communities are most affected by those outages. Last but not least, policymakers should focus on providing solutions that would enable the energy market to overcome the current debt-based approach in favor of different types of incentives. In order to implement effective policies that favor energy security in underserved communities in the aftermath of extreme weather events, policymakers should access data about power outages at a more granular level that is currently available.

There had been recent progress on promoting energy equity in the U. S. at the federal level within the timeframe this study was conducted (2022-2023). For example, the Executive Order on Advancing Racial Equity and Support for Underserved Communities Through the Federal Government (EO 13985, January 20, 2021), federal agencies that promote clean energy are pursuing more transdisciplinary initiatives to promote equitable solutions to climate change. The U.S. Department of Energy (DOE) was moving forward with a set of initiatives and research projects funding aimed at promoting renewable energy use in socially vulnerable communities. The U.S. Environmental Protection Agency (EPA) was focusing its efforts on equity making sure that communities and other relevant stakeholders are involved in the decision-making process. While these federal efforts are currently under review in early 2025, state and local governments may build off of these initiatives to continue their efforts at a more local scale.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

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