Stochastic Modeling of Solar Generation During Hurricanes

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Abstract The unprecedented growth of solar generation adoption indicates that solar can become a major source of modern and clean energy in just a few decades for our power grids. Despite solar's growing criticality for generation, few studies have proposed models to capture solar generation infrastructure's behavior during natural disasters. Here, we present an integrative methodology to quantify solar generation during hurricanes. The methodology is based on a stochastic model that combines a tropical cyclone hazard model, solar irradiance quantification, solar panel vulnerability, and a model for irradiance decay during hurricane conditions. The irradiance decay model is newly developed through mixed-effect regression on a dataset that merges historical Global Horizontal Irradiance and Atlantic hurricane activity. The proposed stochastic model can be integrated into large grid resilience's models for a wide range of detailed applications that require forecasting power system capacity during storms, such as contingency planning for extreme events. We use the stochastic model to analyze 21 states in the Eastern U.S. for various storms to showcase the methodology's broad applicability. Our results show that for events with return periods of up to 33 years, the loss in generation stems from cloud conditions during hurricanes. However, less frequent events can cause solar panel failure, especially in southern regions of the U.S., triggering complete loss of solar generation. Given that solar generation is expected

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to grow significantly, these results advocate for higher standards in the structural design of solar panels as well as the deployment of storage for disaster resilience.

Keywords Disaster resilience · Solar panels · Hurricanes · Distributed energy resources · Climate Change

1 Introduction

Solar generation is becoming a pillar in modern power systems. Solar energy accounted for nearly 40% of all the new electric generating capacity installed on the U.S. grid in 2019, the highest share in its history (Perea et al., 2019). The rapid adoption of panels to harvest solar energy is transforming key power system features such as its economics, environmental contributions to global warming, and resilience (Moriarty and Honnery, 2016). These new power system features may be a crucial part of our future grids as market and government projections state that solar generation will be 20–30% of the global electricity by 2050 (International Energy Agency, 2014; Shah and Booream-Phelps, 2015; The International Renewable Energy Agency, 2018; Solaun and Cerdá, 2019). Research has already highlighted and projected solar energy’s long-term environmental (Solangi et al., 2011; Creutzig et al., 2017) and economic (Devabhaktuni et al., 2013; Kannan and Vakeesan, 2016) benefits. However, there is significantly less understanding of the resilience benefits of modern power systems with large solar generation shares.

A few recent studies have started to analyze solar infrastructure vulnerability to hazards such as high winds (Goodman, 2015; Watson, 2018; Elsworth and Van Geet, 2020). Yet, to understand modern power grids’ resilience, a holistic framework is needed to integrate solar vulnerability, solar irradiance, and natural hazard models. The lack of such an integration prevents the assessment of solar infrastructure’s actual impact on the power system’s resilience to extreme events and its potential to reduce unmet post-disaster demands and change the extensive vulnerabilities in the grid. Traditional power systems have undergone massive outages during natural disasters due to such vulnerabilities. For example, Hurricane Maria in 2017 left millions of people without power in Puerto Rico (Campbell et al., 2018), and so did the recent 2019-2020 wildfires in California (Abatzoglou et al., 2020; Chediak et al., 2020). Similarly, the recent 2021 Texas winter storm caused 4 million outages during extreme cold temperatures (Penney, 2021).

Current methodologies use risk analysis to assess grid resilience, but they have mainly focused on quantifying the resilience of traditional power systems to natural disasters (Winkler et al., 2010; Ouyang et al., 2012; Guikema et al., 2014; González et al., 2016; Feng et al., 2020). These investigations have built robust power system formulations that analyze the balance between power demand and supply during extreme events. However, they have not accounted for solar energy infrastructure and its ability to produce energy during disasters. Solar generation can increase decentralized generation, a fundamental

paradigm switch where users can generate energy locally, e.g., rooftop solar panels. Accordingly, a new formulation for modeling solar generation during natural hazards is needed to account for the rapid adoption of solar. Only a recent investigation has proposed a framework based on risk analysis to quantify the resilience of modern power systems with rooftop solar panels, but exclusively for earthquake hazards (Patel et al., 2021; Ceferino et al., 2020). As hurricanes pose an enormous threat to urban centers worldwide, this paper applies risk analysis to investigate solar generation during tropical cyclones. Hereafter, we generally refer to tropical cyclones as hurricanes.

Fig. 1: Global horizontal irradiance decay during hurricanes with two snapshots at the same time but in different years. Both plots show the spatial distribution of GHI on August 29th, at 3 pm UTC (or 10 am local time in Louisiana). (a) The plot shows GHI in 2005 during Hurricane Katrina, indicating the hurricane's track, radius of maximum wind, radius at a wind speed of 34 knots, and radius of the outermost closed isobar. (b) The plot shows GHI in 2006 in the same region at the same time. Data retrieved from NREL (Sengupta et al., 2018).

Unlike earthquakes, hurricanes cause wind damage to solar infrastructure and only occur in seasons when solar irradiance and generation are high. Additionally, hurricanes bring environmental conditions that may drastically reduce solar irradiance. Figure 1 exemplifies the effect of hurricanes on the spatial distribution of solar irradiance by showing Global Horizontal Irradiance (GHI) at 3pm UCT (9 am local time) when Hurricane Katrina made landfall in Louisiana as a category 3 event in 2005 compared to the GHI distribution the year after. The comparison shows that the hurricane reduced GHI even for sites that were hundreds of kilometers away from the hurricane center. This observation is consistent with recent findings on GHI decay during past

hurricanes (Cole et al., 2020). Yet, to integrate this observation into a risk analysis framework that assesses solar generation resilience, we lack a predictive model that generalizes GHI reduction under hurricanes, i.e., parametrizing GHI decay with key hurricane features. To fill this research gap, we conduct an extensive data analysis on historical GHI during the hurricane seasons from 2001 to 2017 by combining the hurricane Best Track Database (Landsea and Franklin, 2013) with a GHI database from the National Renewable Energy Laboratory (NREL) (Sengupta et al., 2018). The analysis identifies hurricane features that best predict the intensity and extent of GHI decay. We fit different functional forms for GHI decay during hurricane conditions and highlight the best predictive model.

Next, the paper proposes an integrative framework to quantify solar generation during hurricanes. The framework’s analysis workflow is based on a stochastic model with three sequential steps to combine hurricane hazard, solar vulnerability, and power generation. First, we characterize hurricane hazard using synthetic storm data generated with statistical-deterministic tropical cyclone simulations for the current atmospheric and oceanic environments (Emanuel et al., 2008; Marsooli et al., 2019). Second, we estimate wind damage to panels by computing the storms’ wind fields using a physics-based model (Chavas et al., 2015) and coupling the fields with recently developed wind-based vulnerability functions for solar panels (Goodman, 2015; Watson, 2018). And third, we predict solar generation during storms using our proposed probabilistic model for hurricane-induced GHI decay in order to transform estimates of GHI during normal conditions (Sengupta et al., 2018) to hurricane conditions. Because the proposed GHI decay model is built for different times of the day and throughout the entire hurricane season, our integrative framework quantifies the time-series of solar generation for all the simulated tropical cyclones since their landfall to dissipation.

The presented model provides a fundamental advancement in capturing solar generation during hurricanes. It can be integrated with existing grid models to support key applications for power resilience. For example, our proposed formulation can be combined with power network formulations to assess balances between power demand and supply either in decentralized (Leite Da Silva et al., 2012; Al-Muhaini and Heydt, 2013; Patel et al., 2021) or in centralized grids that have utility-scale solar installations (Winkler et al., 2010; González et al., 2016). Further, it can also be used to support cost-benefit assessments of grid hardening and climate policies for grid resilience (Bennett et al., 2021). Such applications use extensive site-specific datasets to model the grid, power demands, and feasible resilience policies. This paper does not provide such detailed case studies and instead focuses on solar generation during storms.

To showcase the wide and regional applicability of our proposed methodology for capacity modeling, we use the framework to quantify power generation from solar panels during hurricanes at the county level for the entire Eastern U.S., which includes all the U.S. Mainland’s Atlantic Coast. We also discuss regional variations of the contributions of solar panels to power generation.

With this novel model and a geographically extensive case study, this paper lays the groundwork to quantify the resilience of power systems with solar infrastructure to hurricanes.

The rest of the article begins with an statistical analysis of GHI during historical storms. Then, it proposes a probabilistic model for capturing GHI during hurricanes. Next, it introduces a stochastic model to assess solar generation during hurricanes and its application to Eastern US. Finally, the article provides a summary and conclusions of our analysis.

2 Analysis of GHI during historical storms

Hurricane conditions reduce solar irradiance intensity at the ground level over large geographical extents, limiting the ability of PV panels to harvest energy in communities. Figure 1 shows intense GHI decays during Hurricane Katrina in most regions within the radius (R34) at a wind speed of 17 ms^{-1} (34 knots), which reached 262 km. In some regions, intense decays extended to distances similar to the radii of the outermost closed isobar (ROCI), which reached 556 km. While Figure 1 shows only a snapshot for one hurricane demonstrating irradiance decays, we consistently observe the same trend in other hurricanes. In contrast to cloudless conditions of clear skies, which are associated with maximum solar generation, hurricanes cover extensive regions with different cloud structures from the eyewall to the rainbands (Houze, 2010). These clouds absorb and scatter light, reducing direct incident radiation and generally leading to lower GHI and reduced solar panel generation (Xie et al., 2016, 2019). Clouds that have high moisture density and vertical depth, i.e. optically thick clouds, can drastically reduce direct incident radiation (Nouri et al., 2019). Accordingly, hurricanes can significantly and rapidly lessen generation through optically thick cloud structures such as large cumulonimbus. However, hurricanes can also reduce generation significantly even with less optically thick cloud structures like stratiform clouds because they can cover large geographical extents.

To systematically investigate the effect of hurricanes on irradiance, we coupled a large dataset of GHI with historical hurricane data. We used the Physical Solar Model (PSM) version 3 from the National Solar Radiation Database (NSRDB) published by the National Renewable Energy Laboratory (NREL) to extract GHI with high spatial and temporal resolution (Sengupta et al., 2018). The PSM combines satellite-derived atmospheric and land surface properties with radiative transfer models to solve solar radiation through the Earth's atmosphere. The PSM provides solar irradiance at a 4-km horizontal resolution for 30-minute intervals from 1998 to 2017. The PSM enable us to observe the GHI behavior at different timesnaps for different hurricanes since 1998 for multiple sites and under various hurricane conditions.

2.1 Historical hurricane dataset

We compiled hurricane data from the revised Atlantic hurricane database (HURDAT2) (Landsea and Franklin, 2013). The data contain multiple hurricane features and span several decades; however, key spatial information including hurricanes' radii is only available since 1998. The hurricane data include ROCI, the radius of maximum wind (RMW), radius at wind speeds of 17 ms^{-1} (R34, 34 knots) and 33 ms^{-1} (R64, 64 knots), hurricane category, and maximum wind speeds. The hurricane data have a 3-hour temporal resolution, which is coarser than the PSM temporal resolution; thus, we reduced the granularity of the GHI dataset from 30 minutes to 3 hours and matched the hurricane recording times. After performing a preliminary assessment to estimate the geographical extent impacted by the hurricane, we collected GHI records from the 4×4 -km spatial grid within two times ROCI from the hurricane center, which reached several hundreds of kilometers for massive storms.

We analyzed 22 landfalling hurricanes whose geneses were in the North American basin and whose lifetime maximum intensity reached a category of at least 3 to filter out the disproportionately large number of storms that do not reach high intensities. While these events' maximum intensities were high, we tracked them from landfall to dissipation, covering the full range of intensities from high categories until they weakened into tropical depressions. The 22 events had tropical storm winds in their lifespan and nine of them reached a category of 5 (Figure S1).

The 22 hurricanes cover an extensive geographical region of our assessment (Figure 2). These hurricanes have a wide variety of conditions, with maximum wind speeds up to 80 ms^{-1} (category 5), ROCI from 200 km to above 800 km, RMW up to 250 km, and radii at circulating wind speeds of 0 (R0) from 200 km to above 2000 km (Figure S1). HURDAT2 omitted R0, the shortest distance where hurricane circulating wind effects dissipate entirely.¹ Thus, we estimated R0 with a wind profile model that captures the radial structure of tropical cyclones (Chavas et al., 2015).

2.2 Key features for predicting GHI during hurricanes

To characterize GHI decay under different hurricane conditions, we define I^h as GHI during a hurricane. Previous research shows that GHI has strong temporal and spatial variability during normal conditions, i.e., no hurricane (Lehr et al., 2017; Patel et al., 2018). We account for such variability and characterize GHI deviations from normal conditions in the logarithm space as

$$\delta^h = \ln \left(\frac{I^h}{\bar{I}} \right) \quad (1)$$

¹ Notice that there is environmental wind at R0.

Fig. 2: List of hurricanes and their tracks included in GHI decay assessment in the North American basin

where $\bar{I}$ represents the median of the GHI under normal conditions at the same location and at the same time of the year as I^h . Since multiplicative factors capture clouds' effects on solar irradiance, i.e., Beer-Bougner-Lambert law of extinction (Liou, 2002; Xie et al., 2019), we assume δ^h , in the logarithmic space, can capture hurricane effects on GHI. We used 20 years of GHI data to estimate $\bar{I}_{t,j}$ for all the geographical extent covered by the hurricanes using a 3-hour temporal resolution. We used 20 years of GHI data to estimate $\bar{I}$ for all the geographical extent covered by the hurricanes using a 3-hour temporal resolution. We assume that at each time of the day, GHI has approximately the same distribution for a given month. As a result, we used approximately 600 instead of 20 data points to estimate the GHI medians. For example, to estimate GHI at 10 a.m. in June, we lumped the data of its days from 1998 to 2017. We observe that for sites farther from the center of the hurricane, the median of δ^h approaches zero, implying that the site is outside the area where hurricanes reduce GHI, i.e., $\bar{I} = I^h$.

We analyzed GHI during the 22 hurricanes to estimate the samples $\widehat{\delta^h}$ and understand GHI behavior during different hurricane conditions. Because our focus was only on times of the day when communities can generate energy, we only included in our analysis daytime data where and when $\bar{I} > 10 \text{ W-h/m}^2$, which finally resulted in $\sim 28\text{M}$ data points. Figure 3 shows $\widehat{\delta^h}$ as a function of distance from the site to the hurricane's center and category.

Figure 3a shows the relationship between distances to the hurricane center d and $\widehat{\delta^h}$. On average, $\widehat{\delta^h}$ has reduced values for small d and grows steadily up to a plateau close to 0 for d values larger than 600 km. We fitted a line with d below 600 km to account mainly for the sites with significant irradiance decays and found an R^2 of 0.2 (correlation $\rho = 0.45$). We observe that the fitted line is not able to represent the transition between small distances to the plateau for large d where hurricanes have little effect. The observed tran-

Fig. 3: Scatter plots showing relationship between GHI decay and key hurricane features. δ^h during different hurricanes have different color. For each hurricane, the plots show a running average for δ^h using solid lines. The plots also show linear regressions in dotted lines and their corresponding R^2 values when the multi-hurricane data is lumped together. For visual clarity, there are only 50k randomly sampled data points in each plot.

sition is consistent with the spatial distribution of cloud optical thicknesses in hurricanes. Hurricane eyewalls, which surround the hurricane eye typically at 10-50 km from the center (Weatherford and Gray, 1988), are composed of optically thick clouds as a result of high moisture densities and large vertical depths (Kokhanovsky and von Hoyningen-Huene, 2004; John et al., 2020), thus significantly reducing direct incident radiation through high absorption and reflection. Outside the eyewall, clouds' optical thicknesses are high only in rainbands and significantly lower in between them. Outside the regions with rainbands, a regular combination of clear-sky and partially cloudy conditions arise, bringing GHI back to normal levels (Kokhanovsky and von Hoyningen-Huene, 2004; Luo et al., 2008; John et al., 2020). Figure 3a shows that this occurs beyond 600 km from the hurricane center.

Additionally, we find that high hurricane intensity exacerbates GHI decay. To focus on sites with the largest hurricane decay and cover areas within hurricane eyewalls, we analyzed sites located at 100km or less from the hurricane center. Figure 3b shows a decaying trend between hurricane category C and δ^h values, indicating that more intense hurricanes induce larger reductions in solar irradiance. A similar trend is observed between δ^h and maximum winds V (Figure S2a) because V has high colinearity with C as the latter variable is an increasing step function of V . Thus, we see that the linear fit performs very similarly with R^2 of nearly 0.11 ($\rho = -0.34$) in both cases. Lower irradiance levels for higher hurricane categories are also consistent with recent evidence on satellite-derived cloud microphysical features during hurricanes (John et al., 2020). There are larger regions with higher cloud optical thick-

nesses associated with large and thick cloud structures such as cumulonimbus during hurricane maturity and intensification rather than during hurricane development or dissipation.

To investigate hurricane size effect, we evaluated the relationship between different hurricane size metrics and both the intensity and geographical extent of GHI decay. To study whether GHI decays are larger for bigger hurricanes, we analyzed the relationship between $\widehat{\delta^h}$ and ROCI, RMW, and R0, respectively. We observe that hurricane size does not intensify GHI decay as linear fits between the size metrics and $\widehat{\delta^h}$ have low R^2 values of 0, 0.05, and 0.02, respectively (Figure S2).

To study how hurricane size correlates with the geographical extent of GHI decay, we analyzed the relationship between GHI and distance to the storm's center normalized by the hurricane size. We normalized d by four hurricane size metrics, ROCI, RMW, R0, and R34, where R34 is the radius at which the maximum wind speed is 34 knots, the minimum speed for the event to be categorized as a tropical storm. We split the data by hurricane category because C showed predictive power for hurricane decay intensification (Figure 3).

When the distance is normalized by ROCI and R34, we generally observe better fitting performance than for the absolute distance, with improved performance for higher hurricane categories (Figure 4 and S5). We estimated that a linear fit between $R = d/\text{ROCI}$ and $\widehat{\delta^h}$ has an R^2 of 0.38 for category 5, almost twice the value found for absolute distance for all storms (Figure 3a). For $R = d/\text{R34}$, R^2 values show comparably good fitting performance to using ROCI as normalizing distance (Table S1). The slopes of linear fits are steeper for higher categories, further demonstrating that the intensity of the hurricane intensifies GHI decay. As discussed earlier, this feature of GHI decay is driven by optically thicker cloud structures occurring during hurricane maturity and intensification. Distances normalized by RMW and R0 give lower performance, which, however, still illustrate how the effect of the hurricane on irradiance dissipates for large enough values of d (Figure S3 and S4).

The analysis also shows that the regions with GHI decay easily extend beyond RMW and R34 as they only define hurricanes' inner-core circulation (Table S1). In contrast, the regions with significant GHI decay do not reach R0 but are close to being bounded by ROCI. Thus, these observation suggests that the outer structure and radial extent of circulation bounded by ROCI is coupled with the cloud structures absorbing and reflecting light during hurricanes.

Fig. 4: Scatter plot showing relationship between GHI decay and distance normalized by ROCI for multiple categories. For each hurricane, the plots show a running mean for δ^h using solid lines. Linear trends are fitted for R between 0 and 1.2 when the multi-hurricane data is lumped together. There are 10k randomly sampled data points in each plot.

3 Probabilistic modeling of GHI during hurricanes

To leverage well-established mixed-effects regression models (Pinheiro and Bates, 2006), we assume that $\ln(I^h)$ is Gaussian, i.e., I^h is lognormally distributed, during daytime, when generation is not negligible, i.e., $I^h > 0$. Thus

$$\ln(I^h) = \ln(\overline{I^h}) + \epsilon^h \quad (2)$$

where $\bar{I}^h$ is the GHI median, and ϵ^h is a Gaussian random variable with zero mean that accounts for the variability of GHI during hurricanes in the logarithmic space. We also assume that hurricanes reduce median GHI from normal conditions to $\bar{I}^h$ such that in the logarithmic space

$$\ln(I^h) = \ln(\bar{I}) + f(R, C) + \epsilon^h \quad (3)$$

where $\bar{I}$ is the median GHI during normal conditions, and $f(R, C)$ is a reduction factor that is function of the normalized distance to the hurricane's center R and the hurricane category C . f uses both R and C because they demonstrated to have good predictive power for GHI decay in the previous section. Using the expression in Equation 1, then

$$\delta^h = f(R, C) + \epsilon^h \quad (4)$$

Using Equation 4 and the samples of δ^h from our dataset, we conducted a mixed-effect regression analysis to test multiple functional forms $f(R, C)$ and formulate a predictive model for irradiance decay during hurricanes.

3.1 Functional Forms for GHI reduction factors

We tested four different functional forms for $f(R, C)$. These functional forms are shown in Equation 5. All of them include a logarithmic growth as a function of R followed by a plateau when $f(R, C)$ reaches 0. The functional forms include a short-distance correction factor b and a scale factor c that further calibrate the influence of R on the irradiance decay. The short-distance correction factor is added to the value of R so that the logarithmic function approaches the observed values rather than $-\infty$ when the site is close to the center of the hurricane, i.e., $R \rightarrow 0$. The scale factor further normalizes R to define where the plateau is reached.

While all of the functional forms include a slope that varies with the hurricane category ($a_1C + a_2$), they vary in their complexity, differing in the representation of the short-distance correction factor b and the scale factor c . In the functional form f_1 in Equation 5a, b and c remain constant for all hurricane categories. In the functional form f_2 in Equation 5b, b varies with category but c remains constant, and in the functional form f_3 in Equation 5c, b is constant and c varies with hurricane category. In the functional form f_4 in Equation 5d, both b and c vary with hurricane category.

$$f_1(R, C) = \begin{cases} (a_2C + a_1) \times \ln\left(\frac{R+b}{c}\right) & \text{if } R + b < c \\ 0 & \text{if } R + b \geq c \end{cases} \quad (5a)$$

$$f_2(R, C) = \begin{cases} (a_2C + a_1) \times \ln\left(\frac{R+(b_2C+b_1)}{c}\right) & \text{if } R + (b_2C + b_1) < c \\ 0 & \text{if } R + (b_2C + b_1) \geq c \end{cases} \quad (5b)$$

$$f_3(R, C) = \begin{cases} (a_2C + a_1) \times \ln\left(\frac{R+b}{c_2C+c_1}\right) & \text{if } R + b < c_2C + c_1 \\ 0 & \text{if } R + b \geq c_2C + c_1 \end{cases} \quad (5c)$$

$$f_4(R, C) = \begin{cases} (a_2C + a_1) \times \ln\left(\frac{R+(b_2C+b_1)}{c_2C+c_1}\right) & \text{if } R + (b_2C + b_1) < c_2C + c_1 \\ 0 & \text{if } R + (b_2C + b_1) \geq c_2C + c_1 \end{cases} \quad (5d)$$

3.2 Mixed-Effects Regression for GHI decay

We used a mixed-effects regression to capture the main observed features of irradiance decay during hurricanes. Unlike other methods such as fixed-effects regression, this regression allows us to explicitly decompose the random variable ϵ^h in Equation 4 into two independent factors (Pinheiro and Bates, 2006), one factor accounting for the variability between different time steps represented by the random variable η^h and another accounting for the spatial variability at a fixed time represented by the random variable ε^h .

$$\delta^h = f(R, C) + \eta^h + \varepsilon^h \quad (6)$$

Through this explicit decomposition, we properly represent the high GHI temporal and spatial variability structure as extensively discussed in previous research (Lehr et al., 2017; Patel et al., 2018; Mihailović et al., 2021). The mixed-effects regression has both fixed and random components (Pinheiro and Bates, 2006). With the fixed effect component, we capture how hurricanes decrease the (logarithm of) median GHI with the factor $f(R, C)$ (Equation 5). With the random component of the regression, we capture spatial uncertainty at a time step with a within-time random effect ε^h and uncertainty across time steps with a between-time step random effect η^h . The regression assumes that η^h and ε^h are independent. Similar techniques and independence assumptions have been used to model natural disaster intensities with radiating decay. For example, random effect regressions and similar independence assumptions are extensively used to assess ground shaking that propagates from an earthquake epicenter to a large geographical extent (Campbell and Bozorgnia, 2014; Abrahamson et al., 2016).

We lumped all hurricane data to fit the parameters of $f(R, C)$. Notice that for a fixed time t , an observation of δ^h at site j ($\delta_{t,j}^h$) is the sum of η_t^h , $\varepsilon_{t,j}^h$ and $f(R_{t,j}, C_t)$. As η_t^h only captures temporal uncertainty, at a fixed time t , it takes the same value for all sites. $\varepsilon_{t,j}^h$ captures spatial uncertainty, thus at

fixed time t , it varies for each specific site j . Similarly, while C_t varies at each time step t , $R_{t,j}$ also varies for each site j . Thus, for each observation

$$\delta_{t,j}^h = f(R_{t,j}, C_t) + \eta_t^h + \varepsilon_{t,j}^h \quad (7)$$

As described previously, we estimated $\delta_{t,j}^h$ for around ~ 28 M observations corresponding to multiple time steps and sites of GHI recordings during the 22 hurricanes in the NREL dataset. We preprocessed the data by removing sites at long distances from the hurricane center, where hurricanes did not have significant effect on GHI. We then balanced the observations across the hurricane categories and distances from the center to the sites (see subsection 3.1 in Supporting Information). Following these constraints, we used ~ 0.75 M data points for the analysis.

We estimated the model parameters using maximum likelihood estimation (MLE) for the non-linear mixed-effects regression with a Matlab package. The package uses an expectation-maximization algorithm to solve for the parameters of the fixed component in Equation 5 while accounting for the unobserved component of the regression in Equation 7 (Lindstrom and Bates, 1990). We fitted the parameters for the four models considering the four previously analyzed normalization radii, ROCI, RMW, R0, R34.

3.3 Best-Fitted functions for GHI decay

We conducted mixed-effect regressions for all 16 combinations of functional forms $f(R, C)$ and normalizing radii. We report all fitted parameters in the Supplementary Information. Additionally, we estimated the Akaike information criterion (AIC) (Akaike, 1974) to evaluate the regressions' relative statistical performance. The model with f_4 and $R = d/\text{ROCI}$ exhibits the best performance. We find that the selection of the functional form f did not modify the regression statistical performance to the degree of the selection of the normalizing radius. The performance of ROCI is followed by R34, and ROCI and R34 performed significantly better than RMW and R0 (see Figure S6-S7 and Tables S2-S5).

Figure 5 shows the best fit, that is, f_4 and $R = d/\text{ROCI}$, for different categories. The plot shows how GHI decays during hurricanes, with stronger effects closer to the hurricane center and for higher hurricane categories. These observations are consistent with the presence of optically thick cloud structures close to the hurricane center and during hurricane maturity and intensification as noted previously. The regression also shows that the decay consistently extends up to sites that are ~ 1.3 times ROCI from the hurricane center, confirming the observation that the cloud structures and radial extent of hurricane circulation defined by ROCI are strongly coupled with the hurricane mechanism for high light absorption and reflection. Because this threshold (~ 1.3) does not change significantly for different categories, hurricanes with low categories can cover more extensive regions with clouds that reduce GHI than

hurricanes with high categories as long as they have larger ROCI. However, the level of the decay will be smaller for lower categories.

Fig. 5: Fitted f_4 (Equation 5d) as function of $R = d/\text{ROCI}$ that tracks GHI decay during hurricanes. This fit has the best AIC performance out of the 16 combinations of normalizing radii and functional forms tested.

4 Modeling solar generation during hurricanes

We propose an integrative stochastic model that couples our proposed GHI decay model with synthetic hurricane simulations and a fragility function for rooftop solar panels. We used a synthetic dataset with 5018 physically possible landfalling storms in the U.S. generated from a statistical-deterministic tropical cyclone (TC) model (Marsooli et al., 2019). The model accounts for current climate conditions (observed from 1980 to 2005) according to the National Centers for Environmental Prediction (NCEP) reanalysis. As a result, the 5018 synthetic storms roughly correspond to 1485 years of simulation. The model consists of three parts: a random seeding genesis model, a beta-advection TC motion model, and a dynamical TC model that captures how environmental factors influence the TC development. The model outputs TC locations, maximum sustained winds and radii of maximum winds in 2-hour intervals.

Additionally, at each time step, we estimate R_0 based on both the radius of maximum wind and maximum wind using a TC wind field profile model that connects the inner storm structure to the outer structure (Chavas et al., 2015). We estimate ROCI using the expression $\text{ROCI} = 0.18 \times R_0 + 226$ (km), which was obtained conducting a regression on the 22 historic TC described previously. Wind fields are estimated by combining axisymmetric winds circulating counterclockwise from the TC wind profile model (Chavas et al., 2015) and the estimated background wind field (Lin et al., 2012). Previously, this synthetic storm model has been extended to quantify TC surge hazard (Lin and Shullman, 2017; Marsooli et al., 2019) and TC rainfall hazard (Emanuel,

2017), demonstrating its versatility for multiple hurricane hazard assessments. Here, we extend the applicability of the TC model to quantify solar generation during hurricanes.

4.1 Fragility function of solar panels

We used a fragility function with a lognormal shape (Figure 6) developed according to current structural design standards for solar panels (Goodman, 2015). The fragility function assesses the probability of panel's structural failure p as

$$p = \Phi\left(\frac{\ln(w) - \ln(\bar{w})}{\beta}\right) \quad (8)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, w is the wind that the solar panel experiences, and $\bar{w}$ and β equal 58 ms^{-1} (3-second maximum wind) and 0.3, respectively (Figure 6).

Fig. 6: Fragility function relating wind speed with probability of solar panel failure according to current structural design standards (Goodman, 2015). The Saffir-Simpson Hurricane Wind Scale was converted from 1-minute sustained wind to 3-second gusts using empirical relationships (Vickery and Skerlj, 2005).

While the fragility function was derived for rooftop solar panels, wind tunnel experiments suggest that these fragility functions can be applicable to ground-mounted solar panels (Goodman, 2015; Watson, 2018), like the ones installed in large arrays by utility companies. The sources of uncertainty in these fragility functions stem from the stochasticity in the relationship between wind velocity and pressure, and the aleatory components in the assessment of panels' material strength and construction quality.

The wind measure in the fragility function was transformed from 3-second gust to 1-minute sustained wind speeds to make it compatible with the synthetic hurricane data using an empirical formula (Vickery and Skerlj, 2005).

Hurricanes of category 3, starting at maximum wind speeds of 50 ms^{-1} (3-second gusts of 60 ms^{-1}), can induce failure with a likelihood higher than 50% (Figure 6).

4.2 Stochastic modeling of cumulative solar generation during hurricanes

We use stochastic modeling to estimate solar generation and solve the problem with Monte Carlo simulation. The analysis uses H realizations of hurricanes and estimates solar generation for each site j (out of N sites of interest) during multiple time steps t . First, the panel damage state s is represented by a Bernoulli distribution. s takes the value of 1 if the hurricane causes solar panel failure due to extreme wind conditions or 0 otherwise. Thus,

$$s \sim \text{Bernoulli}(p) \quad (9)$$

where p is estimated from Equation 9 for $\max_t(w)$, the maximum wind that the solar panel at site j experiences throughout a storm. Then, for a site j , a realization $\tilde{s}_j$ is sampled from Equation 9. Next, we explicitly model the panel failure time because this key variable will account for the energy that the panel will be able to generate before becoming nonfunctional. If there is panel failure, i.e., $\tilde{s}_j = 1$, we model failure time τ with the probability density function $g_\tau(t)$. To account for higher likelihoods of failure when winds are more intense, we consider that $g_\tau(t)$ is proportional to the time-varying failure likelihood due to different wind conditions at the site throughout the hurricane. As the model is discrete in time, $g_\tau(t)$ is a categorical distribution, and thus, $g_\tau(t) \propto p_{t,j}$, where $p_{t,j}$ can be estimated from Equation 10. Accordingly, at site j , a realization $\tilde{\tau}_j$ is sampled from $g_\tau(t)$ if $\tilde{s}_j = 1$, or it is assigned ∞ if $\tilde{s}_j = 0$, i.e., when the hurricane does not cause panel failure. At each time step t , the panel's time-varying functionality status $\tilde{x}_{t,j}$ is estimated as

$$\tilde{x}_{t,j} = \begin{cases} 0 & \text{if } t > \tilde{\tau}_j \\ 1 & \text{if } t \leq \tilde{\tau}_j \end{cases} \quad (10)$$

After assessing solar panel functionality, samples of GHI realizations are computed. Thus, following Equation 3,

$$I^h = \bar{I} \times e^{f(R,C)+\epsilon^h} \quad (11)$$

In the logarithmic space, ϵ^h accounts for spatiotemporal variability in GHI during hurricanes. Under our initial assumption that hurricanes only modify the GHI logarithmic mean, ϵ^h remains the same as normal-conditions ϵ . Thus

$$I^h = \bar{I} \times e^{f(R,C)+\epsilon} \quad (12)$$

Following the lognormality assumption for GHI under normal conditions, I^h can be estimated by transforming GHI during normal conditions to GHI during hurricane conditions

$$I^h = I \times e^{f(R,C)} \quad (13)$$

Based on the assumption that hurricanes only modify the GHI logarithm mean, Equation 13 enables us to leverage well-defined GHI normal condition statistics throughout the entire U.S. (Sengupta et al., 2018) with a clean and simple formula to find decayed GHI during hurricanes. For each site j and time t , a realization of GHI during normal conditions ($\tilde{I}_{t,j}$) is sampled and adjusted to hurricane conditions using $f(R_{t,j}, C_t)$ as

$$\tilde{I}_{t,j}^h = \tilde{I}_{t,j} \times e^{f(R_{t,j}, C_t)} \quad (14)$$

Next, the power generated at time t and site j , $\tilde{q}_{t,j}$, is estimated per area of installed solar panel A with efficiency E , the ratio between the amount of electricity the panel produces and the amount of solar energy it absorbs from the sun. Thus

$$\tilde{q}_{t,j} = \tilde{I}_{t,j}^h \times \tilde{x}_{t,j} \times A \times E \quad (15)$$

Finally, the cumulative energy $\tilde{Q}_{t,j}$ generated is updated by adding the product between $\tilde{q}_{t,j}$ and dt , the interval between time steps.

$$\tilde{Q}_{t,j} = \tilde{Q}_{t-1,j} + \tilde{q}_{t,j} \times dt \quad (16)$$

5 Solar generation in the East Coast of the U.S. during hurricanes

We use our integrative framework to estimate the distribution of cumulative solar generation during hurricanes in 1217 counties of 21 states with high hurricane risk in the East Coast of the U.S. The 5018 synthetic hurricanes described previously were included in the assessment ($H = 5018$). We used the counties' centroids as sites of interest ($N = 1217$) and conducted the analysis for unitary area of installed solar panel ($A = 1 \text{ m}^2$) and for an efficiency of 19% ($E = 0.19$), representative of the efficiency of commercial rooftop systems such as LG solar panels.

5.1 Time series of solar generation during hurricanes

We assessed cumulative solar energy generation for four days during a hurricane emergency using time steps of 2 hours. In Figure 7, we show a subset of cumulative generations $\tilde{Q}_{t,j}$ for four coastal counties exposed to high hurricane hazard, Galveston (TX), Miami (FL), New Hanover (NC), and New York (NY). Each curve depicts how much energy a stakeholder will harvest since a

hurricane hits land. Thus, for $t = 0$ at landfall, we set $\tilde{Q}_{0,j}$ to 0 for all sites j . The gray curves show the sample simulations of cumulative solar electricity generation per square meter of installed solar panels. The cumulative generation estimates represent GHI levels during the hurricane season (often during summer) and incorporate GHI decay as a result of hurricane cloud conditions and the potential failure of solar panels due to wind damage. For reference, the plots include cumulative solar generation from median GHI conditions during normal summer and winter seasons, respectively, in dashed and dotted lines. The curves are wavy as GHI varies at different times of the day, i.e., the curves are flat at nights. Additionally, we evaluated the extreme hurricane conditions that led to low electricity generation in these counties and characterized them through return periods. While return periods are commonly used to describe the occurrence probability of hazards (e.g., hurricane intensity) (Rouge et al., 2006), in this application, we estimate return periods of cumulative solar generation, our metric for solar generation resilience. For a certain generation level, we estimated its return period as the division between the number of equivalent years of hurricane simulation (1485) and the number simulated events with same or worse generations. These estimated return periods represent the average time between storms under which cumulative solar generation is below specific values. Storms that cause lower solar generations will have longer return periods.

Counties are more frequently affected by storms whose induced GHI decays are not intense and which do not cause major panel damage. Most simulations show that cumulative generations for these very frequent events (with return periods shorter than 3 years) are spread around the summer median (gray curves shown in Figure 7). Events with longer return periods (above 3 years) are often driven by stronger storms. For example, reductions in generation with 10-year return periods are caused by hurricanes that reach a category of at least 3 in 14% of counties. Yet, reductions with 1000-year return periods are caused by at least category-3 hurricanes in 42% of counties. These less frequent events will significantly affect cities' abilities to harvest solar power through both strong GHI decays due to optically thick clouds absorbing and reflecting light and extreme winds leading to solar panel damage and failure. Note that cloud conditions of category-5 hurricanes drastically reduce the median GHI by 74%, i.e., $f_4 = -1.34$, even at distant sites 0.5ROCI away from the hurricane center (Figure 5). A few realizations that show cumulative generation becomes flat (e.g., generation for return period of 333 years in Figure 7c) indicate that the solar panel failed, reducing generation capacity to zero.

Cole et al. (2020) noted that GHI decayed to 18-60% from clear-sky GHI during 18 previous hurricanes. These events made landfall as large cyclones and lasted 44 hours, on average, with extreme wind conditions. During the 72 hours following the hurricanes, GHI decayed to 46%-100%. Our results for extreme events give comparable solar generation decays (Figure 7), indicating consistency with the observations by Cole et al. (2020) when the solar panel infrastructure is not damaged. For example, in New York, where simulations did not show solar panel failure, we observe that estimates of solar generation

are within the range estimated by Cole et al. (2020) (Figure 7d) for the similarly large hurricane intensities (with return periods from 3 to 1000 years). In our simulations, 33% of these extreme hurricanes had a category of 3. Consistent with these simulations, 28% of events in the set of extreme hurricanes analyzed by Cole et al. (2020) had a category of 3.

Fig. 7: Simulations of cumulative generation from solar panels in four different counties through different hurricane conditions for four days. Only 50 out of the 5018 simulations are shown in gray curves in the plot for visual clarity. For reference, the cumulative of median solar generation during normal conditions (without hurricanes) in the months of January and July are shown. For comparison, the range of expected solar generation during hurricanes estimated by Cole et al. (2020) (44 hours and 4 days after landfall) are shown.

Figure 7 also demonstrates how different geographical locations have different risks of reduced solar generation. The results indicate that in New York City, NY, an event with a 1000-year return period will not lead to solar panel failure, but due to hurricane clouds, generation would be similar to the one during the winter. In contrast, in New Hanover, NC, an event with a 1000-year (or 333-year) return period will lead to complete loss of generation triggered by solar panel failure almost as soon as the hurricane makes landfall. Miami-

Dade, FL, and Galveston, TX, face higher risk as even an event with a 100-year return period can reduce their solar generation capacity to negligible levels. Furthermore, this analysis was conducted for a unitary area ($A = 1\text{m}^2$) and a standard panel efficiency ($E = 0.19$). However, these observations can be generalized to different panel areas and efficiencies because they report relative rather than absolute generation losses during storms.

5.2 Spatial analysis of solar generation resilience to hurricanes

To comprehensively visualize the spatial distribution of risk of losing solar generation, Figure 8 shows cumulative solar generation at day 4 after landfall for multiple return periods as a percentage of the median generation during the summer. The plot shows that solar generation during an event with a 3-year return period will be reduced by around 25% on average for the counties in the analysis, with slightly higher reductions in Mid-Atlantic and the northern region of the South Atlantic. For example, the average reductions in New Jersey and South Carolina were 27% and 26%, respectively. Average reductions for events with 10-year and 33-year, 100-year, 333-year, and 1000-year return periods were 40%, 50%, 59%, 72%, and 82%, respectively. While events with return periods of 33 years and lower are thoroughly controlled by GHI decay during cloud conditions, as noted earlier, events with 100-year return period can bring generation to zero due to solar panel failure, especially in counties in the southern states, e.g., Texas, Louisiana, and Florida. Events with 333-year return periods lead to panel failures in counties that are even a hundred kilometers away from the coastline. Events with 1000-year return periods will expand the regions with panel failures triggering complete reduction of solar generation in almost entire states, e.g., 100% in Florida and 96% in Louisiana. These results show that northern and southern states undergo significant reductions in solar generation even for less frequent events (31% in Florida versus 40% in New Jersey for 10-year return period). However, rarer events will disproportionately exacerbate the generation reduction in the southern states as solar infrastructure fails at higher rates.

These results have different implications for decentralized (e.g., residential rooftop panels) and centralized solar generation (e.g., large ground-mounted panel arrays by utility companies) during hurricanes. Households with rooftop solar panels still rely on the vulnerable main grid if their inverters are placed in the grid and not at their homes. When households or commercial buildings adopt a combination of solar panels and storage units, inverters are placed at within the buildings, outside the main grid; thus, consumers acquire independence from the grid and can work on island mode when the grid is out (Cook et al., 2020; Patel et al., 2021). Yet, as discussed previously, the reduced generation during the first four days after the hurricane will force reduced consumption. These reduced capacity can be particular unacceptable for critical infrastructure such as hospitals or fire stations needing to operate at full capacity during and after the storm. Additionally, surges in energy demands in

Fig. 8: Cumulative generation from solar panels for different levels of hurricane conditions at day four since landfall as a percentage of the median cumulative generation during the summer (July). Different levels of cumulative generations are characterized by different return periods, i.e., average time between storms that cause same or lower generation.

households from possible heatwaves (Zhao et al., 2018; Baldwin et al., 2019) following hurricanes can even be life-threatening if energy is not sufficient due to hurricane effects (Feng et al., 2020).

Turning to large centralized generation, such reductions in capacity can be extremely dangerous for community safety during an after a hurricane. In our assessment, we used fragility functions for rooftop solar panels, thus our results are representative of distributed generation. However, similar solar generation losses might be found in ground-mounted solar panels adopted by utility companies as the vulnerability of rooftop and ground-mounted might be comparable (Goodman, 2015; Watson, 2018). In that case, even the 20% reduction in a scenario with 3-year return period can pose significant threat to the cities as solar panels become the pillar of power systems. Texas lost 30% of its capacity due to a winter storm in 2021 that froze energy generating infrastructure, triggering more than 4 million outages and leaving Texans exposed to extreme cold temperatures without energy (Penney, 2021). As we transition towards cleaner energy, utility companies and cities must be aware of the risk their energy generation faces and prepare to accommodate demands during emergencies.

6 Conclusions

This paper has proposed the first framework to evaluate solar generation during hurricanes. The framework integrates four key pieces: hurricane hazard analysis, solar irradiance modeling, solar panel vulnerability, and a newly developed model to assess irradiance decay resulting from hurricane cloud conditions. The framework focuses on quantifying solar generation resilience rather than grid resilience. However, it allows for its integration with existing power grid models to assess the reliability of entire power systems with solar generation infrastructure and test strategies and policies to enhance resilience to hurricanes.

The integrative framework has been presented through a stochastic model that estimates time-series of solar generation during hurricanes. While the integrative stochastic modeling is a key contribution from this article, our scope also includes developing a model to capture irradiance decay during hurricanes, a crucial piece of the framework, which to the authors' knowledge, has not been developed before. The irradiance decay model is based on an extensive assessment of GHI under 22 landfalling storms in the North American basin, which reached a category of at least three during their lifetime. The dataset conclusively shows that hurricanes reduce GHI throughout their tracks. We confirmed that the distance from a site to the hurricane and its category are key predictors of irradiance decay. We argue that the mechanism driving the decay is the formation of optically thick clouds in the eyewall, which often become thicker during hurricane intensification. These optically thick clouds, with high moisture density and vertical depth, reduce direct incident radiation by light absorption and reflection.

We fitted four functional forms that vary in complexity to represent irradiance decay using a mixed-effects regression. Multiple category-dependent features controlling the intensity and shape of decay were tested, and the best functional form was selected using AIC to demonstrate its suitable statistical performance. ROCI is shown to be a good size metric for normalizing the distance in the functional forms of irradiance decay.

Next, we described a stochastic model to quantify solar generation during hurricanes. To showcase its broad applicability, we used the model to assess 1217 counties belonging to 21 states in the entire Eastern region of the U.S. Our results show that solar generation during most storms with return periods shorter than three years will be reduced by up to 25%. Events with return periods of 10 years and 33 years will reduce generation more significantly, by 40% and 50%, on average, respectively. Optically thick clouds that reflect and absorb light are the drivers of such reductions. Rarer events with return periods of 333 and 1000 years will reduce generation to a higher degree, in 72% and 82%, respectively. While in the northern states, these extreme events will reduce generation due to optically thick clouds, they will likely trigger solar panel structural failure due to strong winds in the southern states. As a result, southern regions face a higher risk of losing power generation, as northern regions can still generate at a reduced level if the panel has not failed.

Finally, our results suggest that the predicted solar generation loss might be unacceptable for a hurricane emergency. The Texas winter storm reduced the generation capacity by 30% and triggered 4 million outages, exposing Texans to extreme cold weather without electricity. In a solar-based grid, we predict similar reductions (20-37%) for hurricanes that recur relatively frequently (each 3-10 years). While building structurally stronger panels will help prevent failure during the most extreme events (return periods of 333 and 1000 years), stronger panels will not prevent generation loss due to hurricane cloud conditions.

To be more resilient, communities will need a combination of higher structural standards, appropriate contingency planning, and strategic deployment of storage. Contingency planning requires other power generation sources that remain functional during the storm to compensate for solar generation loss. Additionally, if used strategically, storage, especially at the decentralized generation level, can provide energy security while electricity generation is recovered and the transmission and distribution lines are repaired. Solar generation is expected to become a pivotal source for our future power systems. At the same time, hurricanes are projected to be stronger in the future climate (Knutson et al., 2020). Thus, our results show that for communities to rely on solar generation, a combination of higher standards for solar panel structural design, contingency planning, and strategic deployment of storage are required to deliver critical power during hurricane emergencies.

Declarations

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Conflict of interest

The authors declare that they have no conflict of interest.

Availability of data and material

The GHI data are publicly available and were obtained from the NREL website (<https://www.nrel.gov/gis/solar.html>) using the corresponding API. The historical hurricane data are publicly available and were obtained from the National Hurricane Center website (<https://www.nhc.noaa.gov/data/>). The parameters for the fitted GHI decay model, Figures S1-S7 and Tables S1-S6 are provided in the Supplementary Information in <https://tinyurl.com/29wktr7u>.

Code availability

The code with the model implementation from this paper is available upon request to the corresponding author.

Author contributions

L.C. and N.L. conceptualized the model for GHI decay and the framework for assessing solar generation during hurricanes. L.C., N.L., and D.X. curated the data for irradiance during storms, processed wind fields, and fitted the statistical models for the GHI decay model. L.C., D.X., and N.L. conducted the framework's application to the Eastern United States using synthetic hurricanes. L.C. drafted the manuscript with contributions and edits from all the authors.

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