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Evaluation of extreme weather impacts on utility-scale photovoltaic plant performance in the United States

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A R T I C L E I N F O

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A B S T R A C T

The global energy system is undergoing significant changes, including a shift in energy generating technologies to more renewable energy sources. However, the dependence of renewable energy sources on local environmental conditions could also increase disruptions in service through exposures to compound, extreme weather events. By fusing three diverse datasets (operations and maintenance tickets, weather data, and production data), this analysis presents a novel methodology to identify and evaluate performance impacts arising from extreme weather events across diverse geographical regions. Text analysis of maintenance tickets identified snow, hurricanes, and storms as the leading extreme weather events affecting photovoltaic plants in the United States. Statistical techniques and machine learning were then implemented to identify the magnitude and variability of these extreme weather impacts on site performance. Impacts varied between event and non-event days, with snow events causing the greatest reductions in performance (54.5%), followed by hurricanes (12.6%) and storms (1.1%). Machine learning analysis identified key features in determining if a day is categorized as low performing, such as low irradiance, geographic location, weather features, and site size. This analysis improves our understanding of compound, extreme weather event impacts on photovoltaic systems. These insights can inform planning activities, especially as renewable energy continues to expand into new geographic and climatic regions around the world.

1. Introduction

The global energy system is undergoing significant changes, both in terms of increasing demand as well as shifts in energy generating technologies to more renewable energy sources [1,2]. Over the last three decades, there has been a 3x fold increase in the contribution of wind, photovoltaics (PV), and other renewable energy sources to the global energy supply [3]. The PV industry, in particular, has seen exponential growth with contributions amounting close to 3% of the world's electricity demand [2]; within the U.S., renewable sources accounted for two-thirds of all new capacity in 2019 [4]. The shift to renewable energy sources reflects the increasing awareness of climate change impacts from fossil-based energy sources and supports the United Nations' Sustainable Development Goals (e.g., Goal 7 - Affordable and Clean Energy) [5].

However, energy generation from renewable sources is not without challenges. For example, researchers have evaluated the impact of flow availability and competing interests for water on the energy production from hydropower plants. Alterations of flow regimes can either positively increase hydropower production or significantly reduce capacity [1]. There are also trade-offs between naturalized flow, energy generation needs, and ensuring habitats are not adversely affected with hydropower generation [6]. Wake effects from upstream wind farms have been shown to significantly reduce monthly power production, resulting in millions of dollars in losses [7]. Short-term enhancements in solar irradiance (i.e., overirradiance) may lead to energy losses at PV plants. Overirradiance events are often of short duration (lasting from one to several minutes), but can have significant impacts on PV operations. For example, short-duration overradiance periods have been shown to overload inverters, especially in low altitude environments [8]. Overirradiance events longer than five minutes in duration have been shown to lead to temperature spikes for fuses, resulting in blown fuses [9].

The resilience of renewable energy systems is further challenged by climate change, which is increasing the frequency and severity of compound, extreme weather events (CEWE). Compound, extreme events are formed when multiple weather variables co-occur or are coupled together [10]. CEWE include storms, hurricanes, and wildfires that are characterized by multiple phenomena, including severe temperature, precipitation, and wind effects that can co-occur and create simultaneous impacts to energy generation [11]. Energy production

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Nomenclature

Abbreviations

CEWE	Compound, extreme weather events
CM	Corrective maintenance
COD	Commerical operation date
GHCN	Global Historical Climate Network
GWAC	Gigawatts in alternating current
GWDC	Gigawatts in direct current
KTI	Key term identification
LIME	Local Interpretable Model-agnostic Explanation
ML	Machine learning
NOAA	National Oceanic and Atmospheric Administration
O&M	Operations & maintenance
PM	Preventive maintenance
PR	Performance ratio
PRISM	Parameter-elevation Regressions on Independent Slopes Model
PV	Photovoltaics
PVCZ	Photovoltaic climate zone
PVROM	PV Reliability, Operations, and Maintenance
RF	Random forest
US	United States

is impacted by CEWE in multiple ways. CEWE have been known to affect resource availability for wind and wave energy generation [12]. Hydropower sites have experienced curtailments and shutdowns due to increased variability in water resources [13]. The close proximity of nuclear power facilities to the coastline has led to increase concern of impacts from sea-level rise [14]. Fuel delivery, flood protections, and operational safety of energy systems are all affected during CEWE conditions [15]. Usage of historical periods as a baseline may lead to underestimates of the likelihood of CEWE in the future [16].

This study focuses on CEWE impacts to PV systems, which are susceptible to local weather conditions [17]. In an analysis of annual performance reports for PV systems, Jordan et al. [18] highlighted a significant reduction in PV performance in Northeastern United States (U.S.) due to Superstorm Sandy. Root cause analyses (RCA) post-hurricanes in the Caribbean have revealed that common damages resulting from hurricanes are wind-blown modules and twisted racking equipment [19]. The distributed nature of these systems, however, was able to mitigate some of the power outages observed across the grid in certain locales [20]. Experimental investigations have also revealed the influence of different PV architectures and module tilt angles on snow-related energy loss. Locations and placement of diode protected strings as well as orientation (i.e., portrait versus landscape) impact the amount of snow coverage on critical components during field testing in Ontario, Canada [21]. Increased tilt angles have been shown to lessen energy production losses from snow events for field sites in Michigan [22] and California [23] in the United States. In addition to tilt angle, air temperature and fresh snowfall also affect the magnitude of snow-related losses [24]. However, it is unclear whether these patterns hold true for other parts of the world that experienced similar, compound extreme weather conditions.

In fact, to date, few studies have analyzed field-collected data (across multiple geographies and metadata characteristics, such as plant size) to systematically quantify the impact of CEWE on PV performance as well as evaluate characteristics that could be contributing to these variations. This is a critical oversight given the increasing trend in weather-driven PV impacts observed within insurance claims. More than 50% of claims at PV facilities are attributed to extreme weather events such as hurricanes, floods, lightning, and hailstorms [25], which has led to some premiums increasing over 400% within an 18-month time frame [26]. Although economic impacts from CEWE are already being felt by the PV industry, quantitative evaluation of impacts to PV production itself are currently lacking. This analysis addresses this knowledge gap by combining field-collected production with operations and maintenance (O&M) data from 800+ PV sites across the United States to quantify PV production impacts due to CEWE.

The objective of this study is to assess how CEWE impact utility-scale photovoltaic performance in the field. Using the United States as a case study, we are able to address the following questions: (1) How do CEWE differ in impacts to operations and production? and (2) What are the key factors that contribute to low performance during these CEWE? We answer these questions by bringing together three diverse datasets that have not been analyzed concurrently before: text-based maintenance tickets, energy production information, and CEWE characteristics. The use of maintenance tickets is critical to ensuring accurate capture of preventive maintenance (PM) activities that PV owners and operators implement to reduce site impacts. The novelty of this work lies in the fusion of these datasets to effectively identify CEWE of interest for PV and then combine statistical and machine learning (ML) techniques to characterize patterns and conduct associated model validations. Our findings demonstrate specific periods when weather-related performance reductions are present as well as the influence of maintenance practices on performance. These insights expand our understanding of weather-related variations in PV system behaviors, which can be used to inform strategies for reducing production losses and ultimately, increase the affordability to ensure reliable and resilient energy systems.

2. Methods

The evaluation of CEWE impacts in this analysis is driven by O&M tickets for 800+ PV sites from across the United States. A subset of the sites was further evaluated to quantify the impacts on production (Fig. 1). Details regarding the datasets used, data processing, and data analysis activities are provided in the following subsections.

2.1. Datasets

Three datasets were analyzed for this study: (1) O&M tickets, (2) production data, and (3) climate data (Fig. 1). The O&M tickets and performance data are sourced from Sandia's PV Reliability, Operation, and Maintenance (PVROM) database. Initiated in 1999, the PVROM database is a repository of site-level operations and production data to support failure analysis of PV sites [27]. The PVROM database currently consists of 50,000+ O&M tickets collected for 837 sites from 6 industry partners across the U.S. (Table 1). A subset of sites within PVROM also contain production data (Table 1; Figure A2 for spatial distribution).

In total, the sites within PVROM have a capacity of 5.1 gigawatts in DC (GWDC), which represents 14.9% of utility-scale generation in the United States. Commercial operation dates of the sites range from 2008 to 2019 (Figure A1). The database also contains information on plant size, commissioning date, and the array type (fixed vs. tracking) of the sites. Geographically, these sites span 24 U.S. states across multiple NOAA climate regions [28] and PV climate zones (PVCZs) (Figure A2). Developed by Karin et al. [29], PVCZs categorize geographic locations based on module temperature (T zones), specific humidity (H zones), and wind speeds. A comparison of PVCZs to traditional Köppen Geiger classification zones [30] shows that a majority of the sites in PVROM are found in temperate zones (Figure A3).

The industry-provided meteorological data (i.e., irradiance, temperature, and wind speed) were supplemented with open-access weather

Table 1
Summary of the PVROM database.

	O&M Tickets	Production data
Number of industry partners	6	3
Number of sites (Utility-Scale Sites)	837 (547)	186 (129)
Total capacity of sites: GWDC (GWAC)	5.1 (3.9)	1.7 (1.3)
States covered	24	16
PV climate zones	13	11
Commissioning dates	Dec 2008–May 2019	Dec 2008–Dec 2018
Record ranges	Aug 2014–Feb 2020	Dec 2017–Feb 2020
Number of entries	54,000	54,200

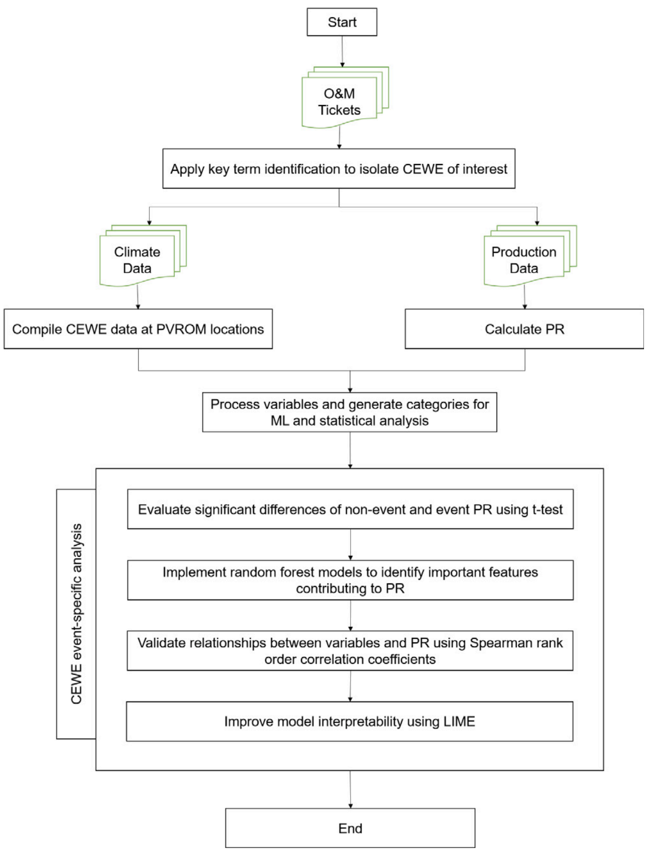

Fig. 1. Overview of the types of data and analytical processes used in this study. Due to the temporal resolution of the weather data, the hourly O&M and production data were aggregated to daily time steps for statistical and machine learning analyses.

data to characterize CEWE conditions at each site. Weather data were retrieved from three open-access repositories: the U.S. National Oceanic and Atmospheric Administration (NOAA) Storm Events database [31], Parameter-elevation Regressions on Independent Slopes Model (PRISM) [32], and Global Historical Climate Network (GHCN) [33]. Data from NOAA, PRISM, and GHCN were retrieved for the years 2008–2020, coinciding with the site commissioning dates (CODs) and available data for O&M and production used in the analysis (Table 1).

2.2. Data processing

2.2.1. O&M tickets

O&M encompasses all activities involved in ensuring maximum production and efficiency of a system. The associated O&M tickets in PVROM capture details about corrective maintenance (CM) associated with repairs for unplanned events as well as PM for routine inspections and servicing of equipment at PV sites [34]. For a given activity, O&M tickets typically contain details about where the event occurred, when it occurred, and what occurred. For CM activities, details regarding repairs made and level of impacts are also captured. Since the O&M tickets contain varying levels of detail and different labels [35], a crosswalk was first conducted to map and identify the most common entries across the partners [36]. The reconciled dataset revealed that, generally, all partners captured information about the site, time, and description of the maintenance activities. These entries were used for subsequent analysis.

Using key term identification (KTI), O&M tickets were consistently classified into corresponding weather events. KTI uses Boolean logic to identify whether a description contains one or more words of interest. This approach is especially powerful in situations where data is not well categorized [37]. A list of weather-related key terms was compiled from existing weather lists (Table A1). KTI was then implemented using regular expressions pattern matching in R to identify tickets that contains entries matching entries within the key term list (Table A2). The subset of O&M tickets containing the key terms was then reviewed manually to remove non-relevant tickets (e.g., non-weather tickets for sites containing "snow" or "fire" in their name) and to categorize the tickets into coherent event categories capturing PM and CM activities (e.g., pre- and post-inspection for hurricanes). There is significant overlap between some of the weather phenomena. For example, lightning and high winds can occur during both storms or and hurricanes. To address this overlapping issue, the O&M tickets were grouped into relevant CEWE parent categories prior to data analysis (Table A6).

For the statistical and ML analyses, the O&M tickets were summarized into daily entries to enable merging with the production and climate datasets. Only O&M tickets that met data quality standards (i.e., complete start and end dates and end dates occurring after start dates) were retained. The resulting O&M data was then grouped together by site and day for the period to generate a single daily entry for each site that identified the combination of assets affected, the total number of active tickets, and the estimated level of production impact.

2.2.2. Production data

The production data contains time series of the amount of energy generated as well as site-level weather data (e.g., plane-of-array irradiance, module temperature, ambient temperature, and wind speed). The production data (captured at either 5-min or 1-hour intervals) was aggregated to daily time steps and evaluated using the performance ratio (PR). A common industry metric, PR captures energy losses by comparing measured output to expected output. PR is calculated following IEC 61724 [38]:

$$PR = \frac{E_M/P_0}{G_i/G_{i,ref}} \tag{1}$$

where E_M is the measured output, P_0 is the DC array power rating, G_i is plane-of-array irradiance, and $G_{i,ref}$ is the reference plane of array irradiance (assumed to be 1 kW m^{-2}).

For a daily reporting period, the reference yield in the PR equation is equivalent to the number of sun hours at the reference irradiance. In addition to evaluating numerical PR values, each site's PR time series was also binned into equal-sized low, medium, and high categories (using the "bin" function in the OneR package [39]) to support ML analyses.

2.2.3. CEWE data

Daily time series capturing the duration and intensity of weather events were constructed for each site through comparison of event bounding areas with site locations (NOAA) or interpolation (PRISM and GHCN). To identify whether a given event occurred at a site, a boundary box was created for each event (using either county-level or latitude–longitude information, whichever was available) and compared to a given site's location. A binary variable was then constructed to indicate the presence of a given weather event at each site. Since the hurricane data from NOAA did not capture details for inland sites, an additional binary variable was constructed for each site to capture whether a hurricane was active within the state for a given day (see Table A3). Where available, a continuous variable capturing event durations (minutes per day) was constructed based on the event beginning and end information provided in the NOAA dataset.

Weather events are inherently complex and may in reality be compound in nature (e.g. a storm could be comprised of heavy rain, high winds and lightning) [10,11,40]. Therefore, and in addition to the general presence of an event, information regarding rainfall, wind, and irradiance characteristics were generated. Site-level values for rainfall and snowfall were generated through spatial interpolation using the akima [41] and interp packages [42] for PRISM and GHCN data, respectively. An additional variable was created to capture net daily snowfall by using melting factors to modify the amount of snow that is present on a site [43].

Variables were also generated to capture the number of days between a weather event and the day of observation. These "nearest" variables (e.g. nearest snow, nearest hurricane, nearest storm) were constructed to capture impacts to plant performance that may occur after (i.e., lag) a weather event has taken place. In the absence of an event ever occurring at a site, we use the site's commissioning date as an approximation of when the last observed event took place. In addition to continuous variables, the weather data was binned into either binary or categorical features to capture impact of relative event magnitudes on energy production (Table A4). The binning was conducted for each site to normalize for local variations in feature occurrence (i.e., thresholds for high wind conditions may vary depending on the specific site).

2.3. Data analysis

Data analysis activities focused on: (1) identification of primary weather events impacting PV sites, (2) evaluation of production performance during weather events, and (3) implementation of ML to gain insights into underlying drivers influencing variations in production impacts. It should be emphasized that ML was not used for prediction, but rather used to characterize and understand relationships between the many variables that could impact PV site performance.

After using KTI, a Pareto analysis was conducted to evaluate the relative frequency of weather events and identify the relevant CEWE influencing PV operations. In addition to evaluating seasonal and geographical prevalence, contextual details captured in the descriptions of issues within the O&M tickets were reviewed for common themes and patterns. Results are presented in an aggregated format, with respect to either climate zones or state-level features, to reveal spatial and temporal variations in observed patterns. Information about prominent weather events gleaned from the O&M tickets was then used to refine the pertinent weather signals to narrow the production performance impacts analysis. Specifically, the O&M tickets were used to identify the specific CEWE data collected and analyzed.

An integrated panel of weather, production, and O&M data was used to understand differences in performance metrics due to CEWE. The inclusion of the specific owner-operator variables within the analyzed dataset helps to account for variations in O&M documentation styles and activities, which can vary from partner to partner (e.g., systematic implementation of pre- and post-inspections after hurricanes may be conducted by one partner but not another). Some of the variables (e.g., state) are common across all weather events analyzed while others are specific to a weather event (e.g., cumulative snow) (see Table A4).

Boxplot visualizations were used to compare PR during event and non-event periods. T-tests were implemented to evaluate statistical significance between these two categories using a 95% confidence interval. For each CEWE, variations in production impacts were further evaluated using ML (Fig. 1). Random forest (RF) algorithms were used to evaluate PR (i.e., "y" variable) as a function of CEWE data, maintenance activities, and site characteristics (i.e., "x" variables). The RF algorithm, which use a bagging method to train the model [44], was selected for this analysis because of their ability to significantly outperform regression-based methods within unbalanced datasets [45]. RF analysis was implemented using caret package in R [46]. Each panel was split 70/30 into training and testing datasets. The PR categories were equally distributed to both the training and testing datasets to ensure a balance of potential classifications. Validation of the random forest model patterns was conducted using Spearman correlations, which evaluate the monotonic nature of relationships and thus, do not assume normal distribution of variables.

The decision tree-based method used in RFs is especially suited to capture nonlinear interactions between independent variables. However, the resulting trained model is hard to interpret since it only generates importance features but not necessarily whether they are a contributing (positive feature weight) or diminishing (negative feature weight) factor. Thus, we complement the RF analysis with local interpretable model-agnostic explanation (LIME) analysis, which provides explainability to the RF models by training a regression model for each CEWE [47]. Specifically, we implement LIME on the trained RF model (using the lime package in R [48]) to identify which features contributed to low plant PR during each of the CEWE analyzed. The key output from LIME is an explanation that contains plain text describing which aspect of a feature was important ('feature description') and an associated value ('feature weight') that quantifies how influential the feature is for a given observation. These explanations were aggregated across all observations to determine features that contributed to low plant PR for each CEWE. The feature description contains two parts: the feature as identified from RF; and either the discrete variable or threshold (if drawn from a continuous feature) that contributes to the feature weight. These feature characteristics are drawn from the datasets used in the study.

3. Results

KTI analysis revealed that 12% of O&M tickets referenced either ambient or extreme weather conditions (Fig. 2; see Table A5 for additional details about the distribution of records by number of tickets, sites, and states affected for each event). Hurricanes, snow, and storms were the dominant CEWE discussed while lightning, fire, and flood events were mentioned less frequently (Fig. 2). Most fire-related tickets either discussed PM-related activities (e.g., checking of fire extinguishers) in fall and winter months or CM-related activities arising from equipment-triggered (e.g., fuses and terminations) fires throughout the year. Since only one O&M record discussed an environmental cause of fire (arising from a tree falling onto a transmission line), fires were excluded from the production analysis. Lightning- and flood-related tickets were grouped into relevant CEWE parent categories (see 2.2.1).

Some of the tickets contained more than one weather-term (Table A6). For example, the term "storm" was used colloquially to refer to hurricane- (55%) and snow-related (9%) events while lightning, flood, and wind impacts were often discussed in the context of both hurricanes and storms (Table A6). In the following sections, the specific O&M impacts from snow, hurricane, and storm weather events and associated production impacts are discussed in greater detail.

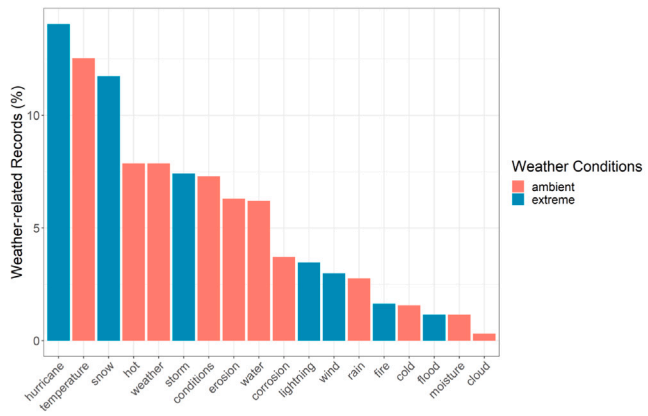

Fig. 2. Frequency analysis of key weather terms in the O&M tickets. Hurricanes, snow, and storms are the dominant compound, extreme weather events discussed in the O&M tickets.

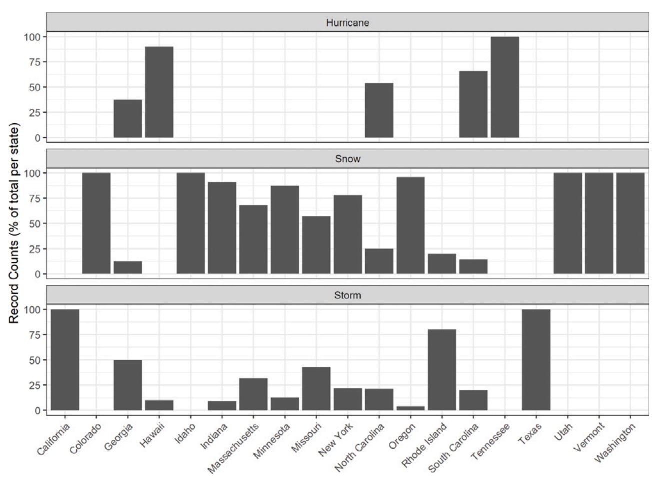

Fig. 3. Distribution of compound, extreme weather events by state.

3.1. Hurricane

Hurricane-related O&M tickets are, unsurprisingly, concentrated in Hawaii and in the eastern United States (Fig. 3). These tickets can be organized into three categories: preparation-related activities (10%), post-event inspections (61%), and post-event damages (29%). Preparation activities mostly involved stowing of trackers, taking plants offline, surveying sites for loose debris, and strapping down modules. A few tickets captured instances where pre-hurricane inspections identified issues such as remote access for trackers not working, inverters not sealed, or improper data backups. The most common findings from post-inspections were no damages (21%) followed by module damages (12%), plant offline due to tripping or grid-related issues (10%), offline inverters (9%), and communication loss (8%), with a majority of sites (61%) observing multiple issues. Flood-related tickets predominantly discussed moisture ingress issues (e.g., water within an inverter), erosion on site, or trackers being stuck in flood stow mode. Most of the preparation and inspection activities occurred in September and October, but sometimes the documentation of the issues extended into later months (e.g., discussion of associated repairs from Hurricane Matthew in May; Figure A4). Analysis of O&M tickets for hurricane-related activities identified four hurricanes that affected PVROM sites: Dorian, Florence, Irma, and Michael (see Table A3 for a summary of these hurricanes). Only Hurricanes Florence and Michael overlapped with production data available for this analysis.

Production analysis indicates that, in total, PR for hurricane days are on average 12.6% lower than non-hurricane days ($p < 0.001$) (Fig. 4A). During the month of September, there is a statistically significant 22.2% reduction PR ($p < 0.001$) and greater variance compared to non-hurricane days. For October, the only other month with hurricane activity in our panel, we find a nominal (1.1%) but statistically insignificant increase in average performance during hurricane days.

The RF model for hurricane events has an accuracy of approximately 69% (see Table A8 for the complete confusion matrix). The top 5 variables contributing to the RF model predictions are plant age, rain, hurricane, and low irradiance (Fig. 5; see Figure A6 for complete list of features). Mean winds categorized in the high and medium bins were also important features. Operator-estimated production impact levels, affected assets, ticket minutes were identified as minor variables of importance. Spearman correlation also highlight rainfall, windspeed, and O&M tickets as statistically significant metrics (see Table A7).

Days with low irradiance, which can be attributed to cloud cover during hurricanes, is the most influential feature in supporting the RF models' ability to successfully identify low performance days (Fig. 5; see Figure A6 for complete list of features). Other notable features were a site being located in the Southeastern United States, days since either Hurricane Florence or Michael, and being classified as a medium size site based on PV capacity. Interestingly, low rainfall and low wind speeds contributed more to low performance during hurricanes (Fig. 6; see Figure A7 for full list of explanations). With regards to plant age (the most important variable in the RF model), the LIME results suggest a critical age range of 19–34 months for supporting the classification of low performance during hurricanes (Figure A7).

3.2. Snow

Snow-related impacts were documented in almost all states analyzed, except California, Hawaii, Tennessee, and Texas (Fig. 3). Most discussions of snow events relate to production and underperformance at the site, module, and inverter levels, primarily in May (Figure A4). A majority of the tickets capture low or no production issues (61%), followed by specific assets being offline (12%). Tracker-related issues ranged from lack of charging and communications to being stuck or erroneous triggering of snow mode. Preventive activities such as installing plywood, clearing vegetation, and disabling/increasing settings were used to reduce nuisance alarms for snow-related sensors.

Multiple racking damages were also documented (9%), including downed, slipped, or fallen modules; sinking racks; tilted or leaning racks; and wires becoming loose. Although sites across all climate zones experience snow issues (Figure A5), none of the partners utilize snow removal on modules, opting to wait for the snow to melt away from the panels. A few tickets did discuss snow clearing of roadways (mostly in Minnesota, Idaho, and Oregon) to note site access issues following a snowstorm. Snow-related delays in ongoing site activities (e.g., inspections, repairs, and vegetation removal) were also noted. Power being lost at the site due to utility issues were also captured in the some of the tickets, including the occurrence of a snow-related car accident at a local utility pole.

A comparison of monthly distribution of PR indicates that days with fresh daily snowfall (i.e., snow days) have lower performance and show more variance compared to non-snow days (see Fig. 4B). When controlling for the month, the period of October through April resulted in statistically significance differences in PR ($p < 0.001$). PR for snow days are on average 54.5% lower ($p < 0.001$) than non-snow days across all performance days. April (−68%), December (−61.8%), January (−57.1%), and February (−56.4%) show the largest reduction in PR during snow days for our study period.

The RF model for snow events has an accuracy of approximately 64% (see Table A8 for the complete confusion matrix). The contribution of each variable's importance in generating the predictions indicates that the top five features are plant age in months, low irradiance,

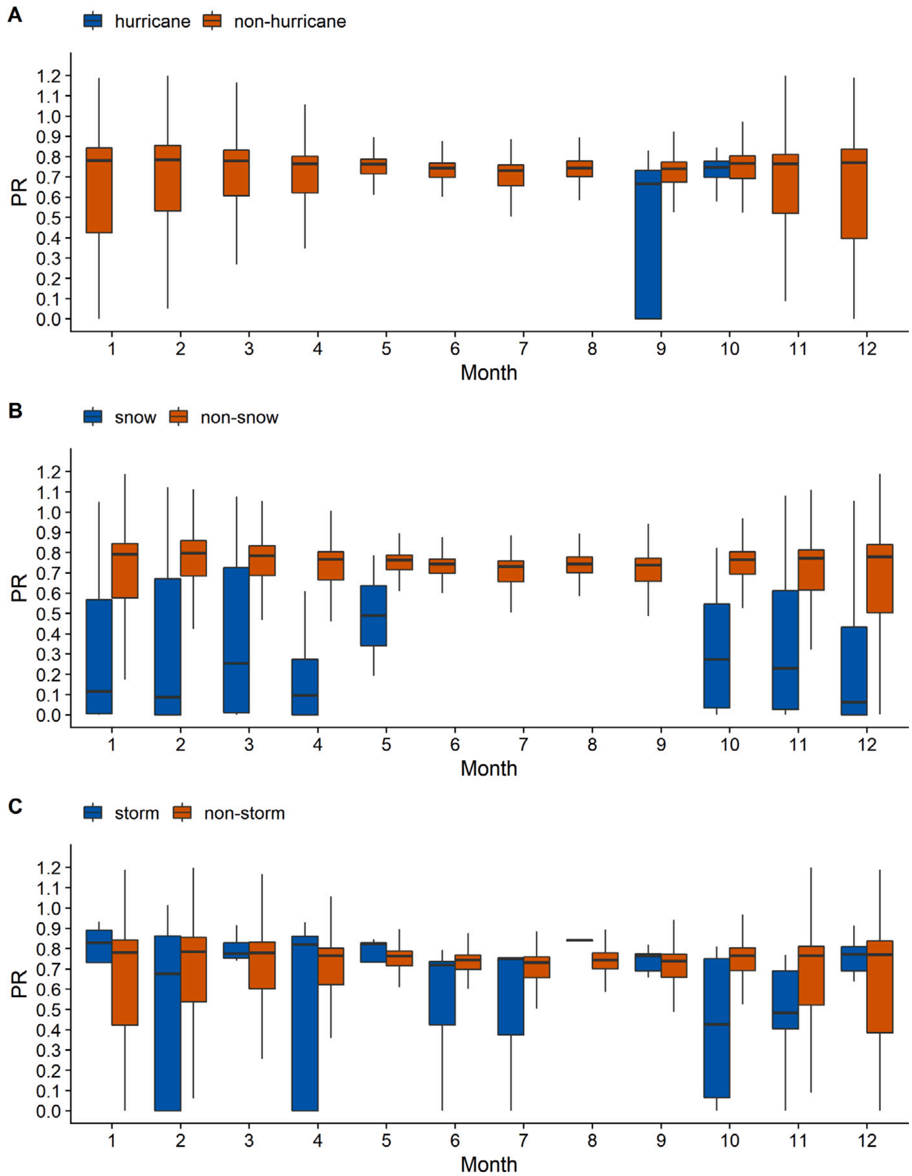

Fig. 4. Distribution of performance ratio (PR) by month for event versus non-event days for (A) hurricanes, (B) snow, and (C) storms.

cumulative snow, and the PVCZ zones (Fig. 6; see Figure A8 for full list of features). Thermal zone T4 was identified as being in the bottom half of features for the final RF model. No operator or O&M-related variables emerge as important features for the RF model for snow events. These patterns are consistent with Spearman correlations, which showed significant correlations with snowfall and irradiance values (Table A7).

LIME analysis indicated that days identified as having low irradiance are the leading feature contributing to a successful identification of low performance days in the RF model (Fig. 6; see Figure A9 for full list of explanations). Other notable feature descriptions supporting low performance predictions were a site being in either thermal zone T4 or humid zone H3, having cumulative snow of at least 904 mm (35.6 inches), and plant age > 57 months (Fig. 6). Low performance was also observed across multiple locations, from the Northeast to the Southwest United States (Figure A9). Although Spearman correlations showed a significant correlation between PR and duration of snow tickets, no significant features related to O&M tickets are present in either the RF (Figure A8) or LIME (Figure A9) models.

3.3. Storm

Storm-related tickets are present in 13 of the 19 states with CEWE-related tickets (Fig. 3). Tickets about storm-related events primarily occur during the months of February and July–August (Figure A4). Storm-related tickets often discuss lightning and flood-related characteristics associated with impact (Table A6). The most common issues observed during storms are related to tripping of devices (from lightning), either at the inverter-level (23%) or at the site-level from reclosers (16%) or grid outages (7%). Other issues captured in the O&M tickets relate to civil issues (e.g., erosion), module damage from high winds, stalled trackers, and underperforming combiners. Unlike hurricanes, preparation activities for storms are limited; only 7 tickets note stowing of trackers in advance of a storm. There were also a few tickets that noted that site-related impacts were assumed to be due to current storm conditions, but post-event inspections revealed a different cause (e.g., inverter being offline due to a faulty wire). The most common response activity for storm-related impacts are to reset equipment (especially for tripping-related events) followed by repair, power cycling, and replacement. Only two storms are named in the

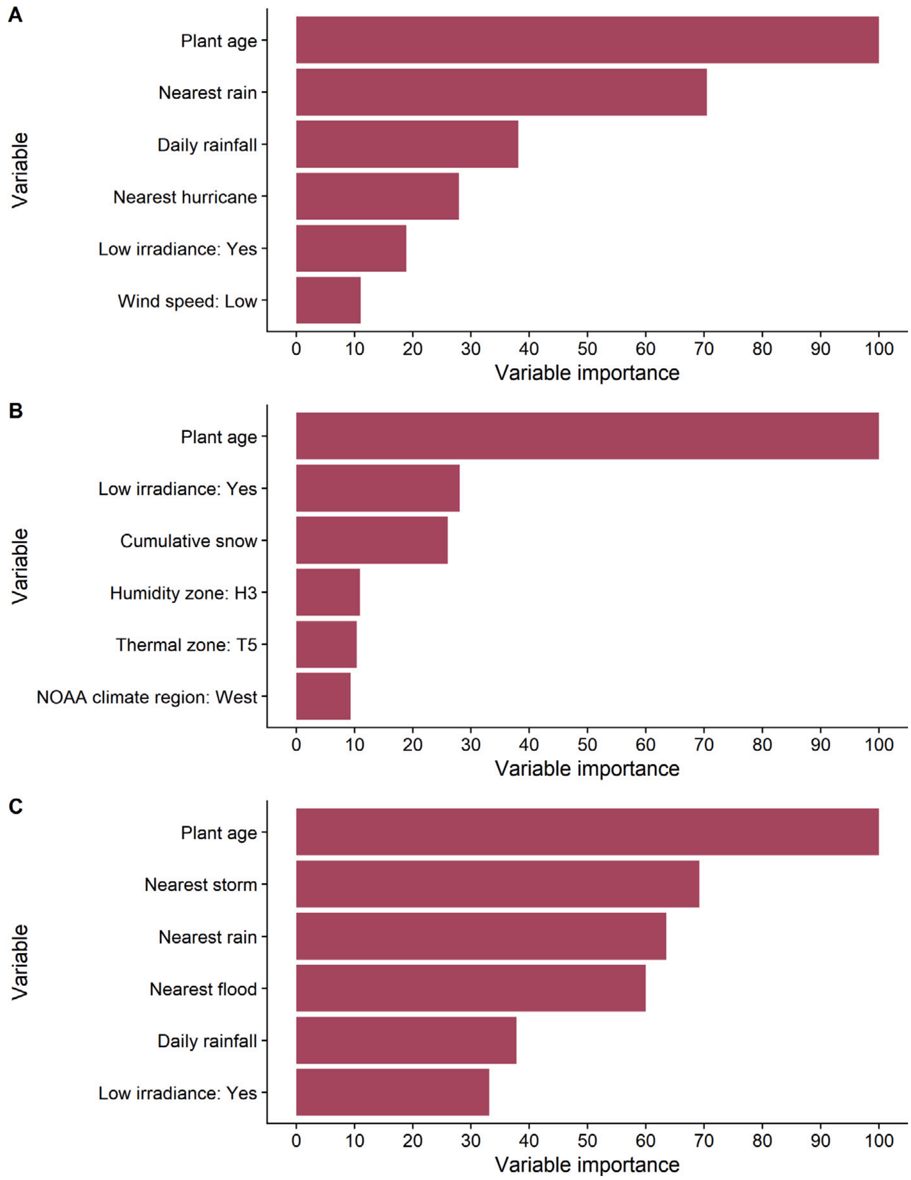

Fig. 5. Most important features explaining performance ratio in random forest models for (A) hurricanes, (B) snow, and (C) storms.

O&M descriptions, Michael and Imelda, both of which are represented in the storm weather dataset.

Production analysis revealed that non-storm days show less variance compared to storm days (Fig. 4C). On average, there is a statistically insignificant difference of 1.1% in PR for storm days versus non-storm days ($p = 0.7695$). Similarly, the months with the largest reductions in PR are also statistically insignificant between storm days and non-storm days: October (−38.0%), February (−27.1%), November (−20.3%), July (−16.2%), and June (−15.4%). We do find statistically significant ($p < 0.001$) differences in PR for storm days compared to non-storm days during March (24.4%), August (25.3%), and December (25.6%).

The RF model for storm events has an accuracy of approximately 73% (see Table A8 for the complete confusion matrix). The top 5 variables based on importance are plant age in months, nearest storm events, and total rain (Fig. 5). Operator variables capturing production level impacts, affected assets, and length of tickets are present within the variable importance plot of the RF model (Figure A10). Inverters, the overall facility, and other unspecified assets also have nominal importance in the RF model for storms (Figure A10). These patterns are consistent with Spearman correlation results, which show a statistically significant correlation between PR and storm characteristics and O&M tickets (Table A7).

The LIME analysis also highlights the important contributions from weather, O&M activities, and site features to driving low performance (Fig. 6; see Figure A11 for full list of explanations). Having a day partially occupied with O&M ticket activity was the most influential variable in describing low performance due to storms. Other highly influential features were whether a day had a storm or flood as well as low irradiance. The LIME results show increased importance of inverters and facilities as affected assets in understanding low performance outcomes. O&M tickets describing production impact levels as ‘partial’ and ‘unknown’ are influential in understanding low performance days (Fig. 6; see Figure A11 for a full list of explanations).

4. Discussion

This analysis identifies that the three primary CEWEs impacting PV plant production across the US are hurricanes, snow, and storms. The coupled analysis of production and weather data showed lower and more variable performance across weather events. Snow events demonstrated the largest performance reductions, followed by hurricanes and

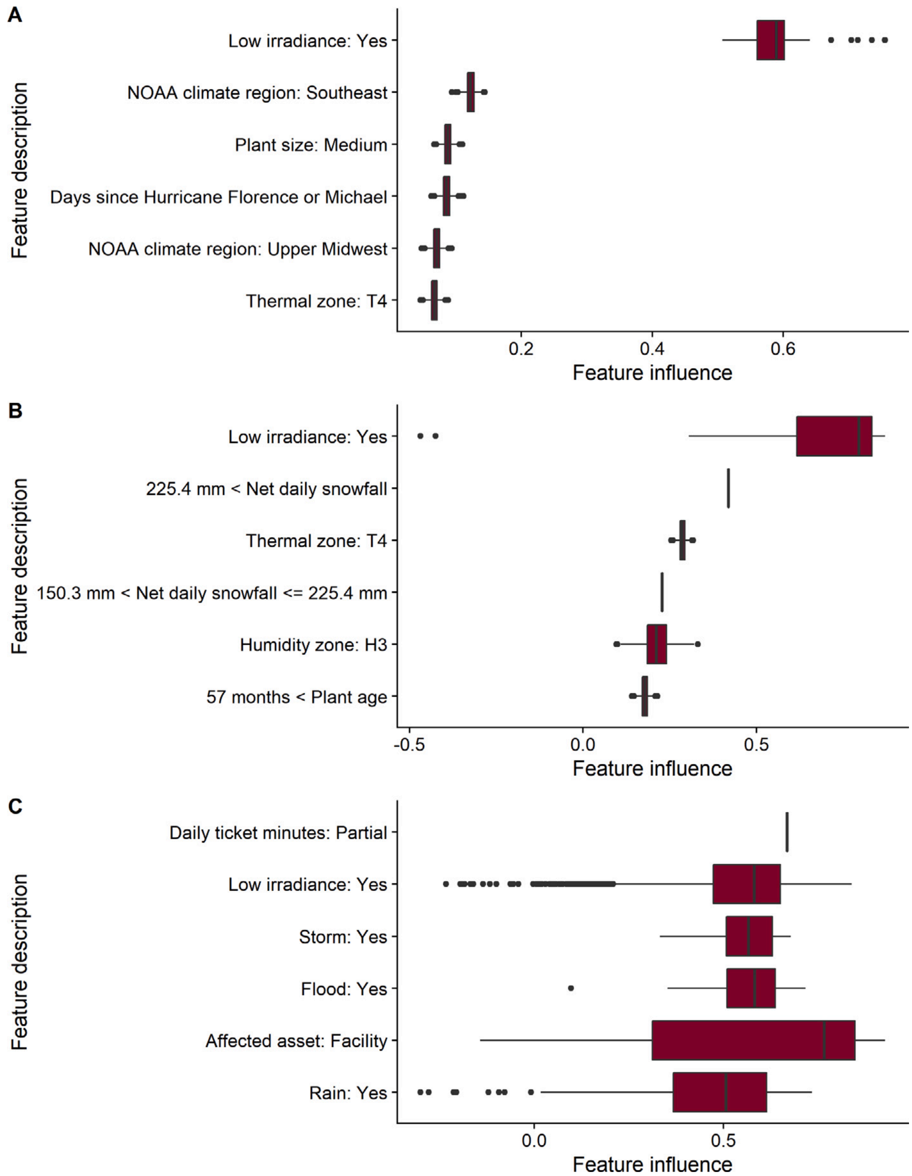

Fig. 6. LIME explanations for low performance in the trained random forest models for (A) hurricane, (B) snow, and (C) storm events. Numerical thresholds are generated by LIME based on the data used in the analysis.

storms (Fig. 4). The ML analyses identified that the primary drivers for these reductions span from weather features to site location and other site characteristics. Influential variables identified through ML in this study are similar to those identified based on other datasets [49].

Low performance for all three CEWE events was driven by low irradiance (Fig. 6). This is unsurprising given that irradiance, which is analogous to clear sky potential, directly reflects the reliance on solar radiation for PV energy generation [50]. In addition, associated event characteristics (e.g., wind speeds, snow depth, and rainfall amounts) emerged as significant features for low performance. These features are consistent with performance ratio impacts found when evaluating the open solar performance and reliability clearinghouse database [49], snow loss prediction models within the field [51], and simulated energy production during hurricanes [50]. However, different features do emerge across the CEWE ML analyses, reflecting geographic variations and site features. For example, hurricane impacts were primarily felt in the Southeast and Upper Midwest (Figure A7) while storm impacts are concentrated in the Upper Midwest and Southwest (Figure A11) and snow impacts are present throughout the United States (Figure A9). The increased prevalence of snow tickets in May (Figure A4), however, likely reflects unexpected conditions compared to typical seasonal patterns. Although different regions generally develop local adaptations to differing snowfall amounts, the presence of snow-driven low performance across the different regions of the country likely reflects the consistent lack of maintenance activities for snow; most PV operators do not remove snow from modules.

Other physical features that emerged during the ML and LIME analyses include the size and age of a PV plant as well as specific features affected. Plants that were between 19–34 months in age were more adversely affected by hurricanes while storms and snow event-related impacted were greater in plants greater than 55 months in age (Fig. 6). These variations could reflect impacts of both improved technologies over time and degradation having greater impacts on plant performance during extreme weather events as systems age. Medium-size plants were also more likely to have low performance during hurricane events (Fig. 6). This could reflect the higher likelihood of medium-size sites of being connected to the grid via lower voltage distribution circuits, which would make them more susceptible to utility-related outages than larger sites that might be tied into higher-voltage transmission circuits. The storm analysis, on the other hand, revealed that inverters were the most likely asset to be affected during this CEWE (Figure A11). This is likely attributed to nuisance alarms for ground faults from nearby lightning events [35]. Storm events, however, can also have positive impacts on PR. Although there is significant variability in PR for storms, in many cases, there was actually an increase in PR observed from storms (Fig. 4). This could be likely due to rainfall washing away soiling on the modules, thereby leading to an increase in energy production [52]. Additional analyses, with a finer time interval resolution, would allow verification of possible causal connections. For example, NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) provides global climate gridded data from 1980 to the present that could be used to generate hourly climate data to further distinguish weather phenomena occurring during production and non-production periods [53].

The combination of production analysis and weather data with associated O&M tickets provided valuable insights into operator practices and adds context to the presence of weather events. These tickets enabled targeted identification of the primary CEWE affecting sites found in PVROM as well as the damage associated from these events (e.g., broken modules from hurricanes). However, this approach is not without limitations, since lack of weather events described within maintenance tickets could reflect a data collection issue rather than lack of a weather event impact. For example, hail-related damage is one of the leading drivers for insurance claims in PV [25] while recent wildfires in California have reduced solar generation by as much as 30% [54]. Inclusion of other weather-related datasets (e.g., particulate matter-2.5) could help elucidate impacts from wildfires, hail, winter storms, and flooding impacts [40,55]. Improvements can also be made to better incorporate the compound nature of these events. For example, hurricanes are currently categorized by weather agencies based on the magnitude of sustained wind speeds but not by increased rainfall and storm surges that typically accompany these events. Alternative metrics that incorporate parameters such as sea-level pressure, wind speed, and rainfall may better predict the potential damage from these events, especially to fielded PV systems. Future work could consider using these metrics to provide a more robust weather event scenario that more clearly distinguishes between storms, tropical storms, and hurricanes. An additional limitation results from the poor labeling of extreme weather events within the O&M tickets. While we are able to draw some correlations between operator variables and performance ratio (see Table A7), the labeling issues does affect our ability to extend the analysis to determine causality.

The study analyses could also be improved by expanding the amount of production and operational data analyzed. There is significantly more data in terms of sites, states represented, and dates available in the operations data compared to the production data. The limited production data therefore results in the exclusion of potentially impactful events such Hurricane Irma and Superstorm Sandy from the performance ratio analysis. The data limitations also affect the thresholds determined by LIME as they are based exclusively on the dataset used in this analysis. Additional work is needed to understand the sensitivity of these thresholds for the critical parameters identified in this study. This could be done through expansion of the current methods to consider feature similarity for medium and high class performance (Table A8) or by evaluating additional algorithm types, such as support vector machines and deep neural networks [50]. Inclusion of cost information from the operational databases would also provide additional insights into impacts beyond low performance (such as damages to equipment noted above) that would help inform planning investments ways to further reduce economic losses arising from CEWE to PV plants. Finally, given the increase of battery storage systems [50], evaluation of how these technologies and demand side management moderate extreme weather impacts should be evaluated in future work.

While this study encompassed PV sites in multiple U.S. states, further analyses are warranted to identify to validate and extend these initial findings to include sites located in other countries that may be subject to similar compound, extreme weather events, such as monsoon storms in India and Brazil [56] or blizzards in Europe [10]. This can only done through collaborative data sharing within the solar industry. For example, the United States Department of Energy currently supports repositories such as the PV Fleet Performance Data Initiative and the Open Solar Performance and Reliability Clearinghouse. International working groups such as the Photovoltaic Collaborative to Advance Multi-climate Performance and Energy Research (PV CAMPER) are working on advancing such international collaborations [9]. While these repositories are oriented towards production data, this analysis highlights that O&M data should also be captured to provide context to the production patterns. A central repository of O&M data could also help improve the standardization of O&M data across the industry and assist with optimizing operations planning. The expansion of production data time series and the inclusion of more sites will provide more robust information regarding extreme weather impacts and associated regional variations.

5. Conclusion

This study demonstrates the value in integrating weather, performance, and operations & maintenance data for evaluating compound, extreme weather events impacts to PV production. Specifically, the multi-year and multi-site assessment approach used in this study enabled us to evaluate fluctuations in site performance within the field, taking into account both variations in local weather events and site maintenance practices. The results indicated that snow events adversely impacted plant performance (54.5%), more so than hurricanes (12.6%) and storms (1.1%). Our analysis also generated insights into drivers of solar generation losses during extreme weather events, such as geography and weather characteristics (e.g., net snowfall greater than 225 mm) as well as plant characteristics (e.g., differing plant ages and sizes that are most vulnerable). Study limiting factors, such as the spatial and temporal resolution of analyzed production data as well as details captured within operations & maintenance data, could be addressed in future work through incorporation of additional weather and cost-based datasets for these and emerging weather concerns (e.g., wildfires).

Although this analysis was limited to sites within the United States, these findings would be generally applicable to PV sites in any region that may be subject to similar compound, extreme weather events, such as monsoon storms in South Asia and blizzards in northern latitudes. Furthermore, the methods presented in this work (centered on data fusion and machine learning/model interpretability analyses) introduce a new capability to further current methods for gaining operational insights into complex weather phenomenon that could be leveraged by other renewable energy sectors. Given the increased sensitivity of renewable energy generation to local weather, improved understanding drivers of low performance during compound, extreme weather events is critical to better protect and adapt these fast-growing sectors to ensure an overall resilient energy system.

CRediT authorship contribution statement

Nicole D. Jackson: Data collection, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Thushara Gunda:** Conceptualization, Data collection, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Supervision.

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 statement

Anonymized PV O&M, production, and weather data used for the machine learning and model interpretability analyses are available for public download at: http://dx.doi.org/10.25984/1812011.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117508.

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