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Quantifying Wildfire-Induced Impacts to Photovoltaic Energy Production in the western United States

Samuel D. Gilletly, Nicole D. Jackson, and Andrea Staid
Sandia National Laboratories, Albuquerque, New Mexico, 87123, USA

***Abstract*—Smoke from wildfires results in air pollution that can impact the performance of solar photovoltaic plants. Production is impacted by factors including the proximity of the fire to a site of interest, the extent of the wildfire, wind direction, and ambient weather conditions. We construct a model that quantifies the relationships among weather, wildfire-induced pollution, and PV production for utility-scale and distributed generation sites located in the western United States. The regression model identified a 9.4%-37.8% reduction in solar PV production on smokey days. This model can be used to determine expected production losses at impacted sites. We also present an analysis of factors that contribute to solar photovoltaic energy production impacts from wildfires. This work will inform anticipated production changes for more accurate grid planning and operational considerations.**

***Index Terms*—air quality, wildfires, particulate matter, PM2.5, solar PV generation**

I. Introduction

Wildfire incidents are increasing in both frequency and size throughout much of the western United States [1]. A consequence of these incidents is the reduction in air quality due to increases in dust and other aerosols [2] as well as fine particulate matter concentrations [3] [4], even when accounting for seasonal fluctuations [5]. This is concerning not only for the livelihood of those impacted, but also when it comes to considerations of power grid planning and operations.

The fast-growing solar industry in the western United States (U.S.) plays a large role in electricity production, making wildfire impacts particularly concerning. California, for example, produced 14.2% of in-state electricity with solar photovoltaics (PV) and solar thermal plants in 2019 [6], and at least 50% of its energy is expected to be generated from solar sources in the coming decades [7]. For the period 2013-2017, California annually averaged 8,143 fires and 897,146 burned acres [8]. Therefore, it is crucial that grid operators can plan for these production impacts to better manage resources during what are already some of the most vulnerable times for the electricity sector.

Solar energy production is particularly vulnerable to the wide-reaching second-order effects of wildfires. Smoke from large fires can travel a considerable distance, bringing with it pollution in the form of small particulate matter that obstructs solar radiation and thus PV energy production [9]. Prior work linking air quality to PV performance has been broadly focused on ambient aerosols and is either based on experimental field data [10], laboratory tested modules [11], or global computational models [12]. Ambient aerosols have been estimated to reduce utility-scale PV generation in Korea by 15-24% [13]. Experimental testing of module performance during a wildfire event in Spain resulted in average reduction of 34% [14]. Small PM2.5 particles (fine particulate matter of 2.5 microns or less in diameter) are the primary pollutant in wildfire smoke [15]. Our work presented here seeks to build on these prior efforts by analyzing the impact of PM2.5 due to wildfires on utility-scale and distributed PV energy generation in field-collected data. By understanding the factors that impact production and the degree to which energy production is reduced from wildfires, we can provide better predictive tools for grid planning, thus minimizing costs for grid operators during and after wildfire events. In addition, site owners and operators will be better able to quantify expected losses for improved site management.

Here, we present an analysis with the goal to quantitatively understand the relationships among weather, wildfire-induced pollution, and PV production. To do so, we analyze historical production data from a series of PV plants located in the western U.S. as well as daily particulate matter and weather data. The available production data for many sites overlap with two major wildfire events from 2018: the Mendocino Complex fire during July-September; and the Camp Fire during November. The Mendocino Complex Fire was comprised of the Ranch and River fires and resulted in the combined burning of 459,123 acres [16], [17]. Similarly, the Camp Fire burned 153,336 acres [18]. These fires were near the average annual number of burned acres for the previous five years. While these fires originated in California, they affected much of the western United States. Below, we describe our data fusion process, statistical approach, and resulting predicted solar PV energy production model to understand impacts from wildfire-related PM2.5.

II. Methods

The evaluation of wildfire-related PM2.5 in this analysis is driven by production, weather, and particulate matter for solar PV sites located in the western United States. Details regarding the datasets used, data processing, and data analysis activities are provided in the following subsections.

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A. Data

We combine historical solar PV energy production data with weather and pollution data with the goal of understanding the impact that nearby wildfires have on site production. This work relies on using diverse datasets, which results in a mismatch in resolutions. Here, we described the datasets used in more detail.

1) Production Data: The utility-scale production data used in the study is provided by Sandia's PV Reliability, Operations & Maintenance (PVROM) database [19]. This repository contains production, operations, and maintenance data from 800+ sites located in the United States. Production data includes time series data for the power and energy generated. Site-level meteorological variables such as plane-of-array irradiance, ambient temperature, module temperature, and wind speed are also available. For this project, we subset PVROM to sites in Arizona, California, Idaho, Oregon, and Utah, and limit the data to April 2018 - July 2019 period. Additional eligibility was based on the availability of historical production that overlapped with the Mendocino Complex and Camp Fires as well as proximity to PM2.5 monitoring stations. These criteria resulted in 68 eligible sites for analysis: 52 utility-scale sites; and 16 distributed sites (see Figure 1 for distribution of site sizes in terms of DC kW). These sites contained over 20,000 days of production data.

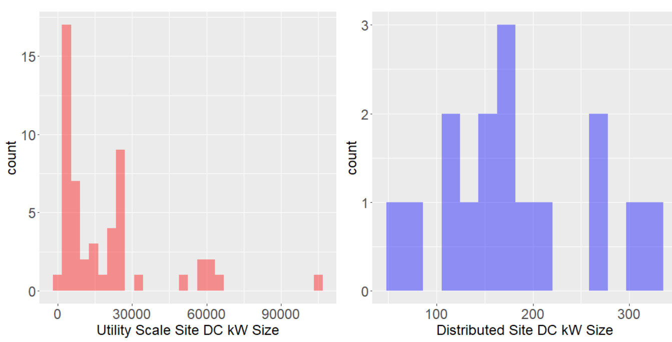

Fig. 1. Histograms of site size in DC kW for utility-scale (left) and distributed (right) sites used in this study.

2) Particulate Matter Data: Fine particulate matter, or PM2.5, is the main source of pollution from wildfires [20]. This particle count data is closely tracked at many sites throughout the U.S. and is openly accessible on the Airnow.gov website [15]. Airnow serves as a central repository for viewing and accessing U.S. Air Quality Index (AQI) data provided in partnership with several government agencies. There are many monitoring stations throughout the country that gather AQI data and report it to the Airnow website. Monitoring stations included in this analysis were identified based on their distance to the nearest solar PV site. If the distance between the solar PV site and closest PM2.5 monitoring station was greater than 30 miles, the solar PV site was removed from the analysis. Based on the locations of the selected solar PV sites, 16 PM2.5 monitoring stations were identified and used in this analysis. The mismatch between the number of solar PV sites and PM2.5 monitoring stations is due a single monitoring station being proximal to multiple solar PV sites. A sample of PM2.5 concentrations in the western U.S. on November 14, 2018 during the Camp Fire wildfire provide a glimpse of the spatial extent and heterogeneity in PM2.5 that can occur during these events (see Figure 2). The black triangle on the plot shows the fire's location. PM2.5 monitoring stations are colored in correspondence with their average daily particle count, which is a function proximity to the fire. At least one monitoring station was found in each state containing a solar PV site.

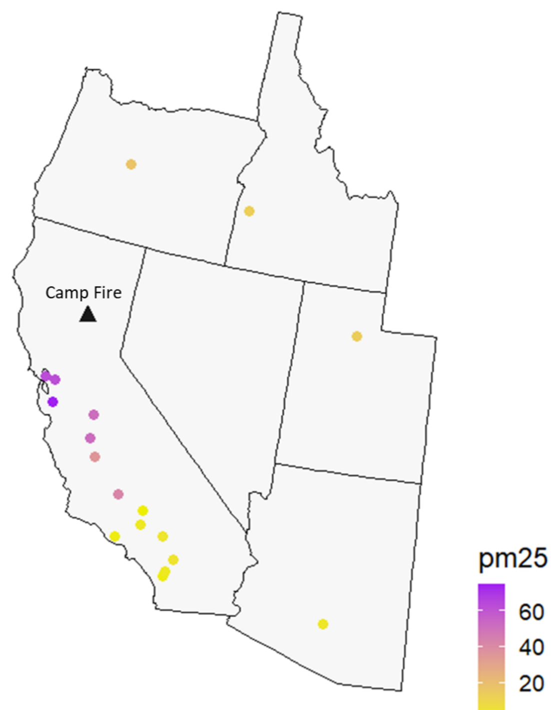

Fig. 2. Average daily PM2.5 concentration at monitoring stations during the Camp Fire Event on Nov. 14, 2018. Each location represents a PM2.5 station used in this study.

We obtain historical hourly PM2.5 data for the period April 2018 - July 2019 in units of $\mu g/m^3$ (micrograms per cubic meter of air) from each identified monitoring station to measure the impact of smoke. We assume that the PM2.5 data at the monitoring station is equivalent to the concentration at the PV solar site. A representative time series of PM2.5 at a solar PV site shows minimal increases in PM2.5 during the Mendocino Complex Fire but elevated concentrations during the Camp Fire (see Figure 3).

3) Historical Weather Data: The NASA Prediction of Worldwide Energy Resource (POWER) Project is a repository of global solar and meteorological data that is of general interest to the energy community [21]. For this project, we collected daily historical mean temperature at 2 meters (T), wind at 10 and 50 meters (W10M, W50M), precipitation (P), and insolation clearness index (CI) data at the solar PV site

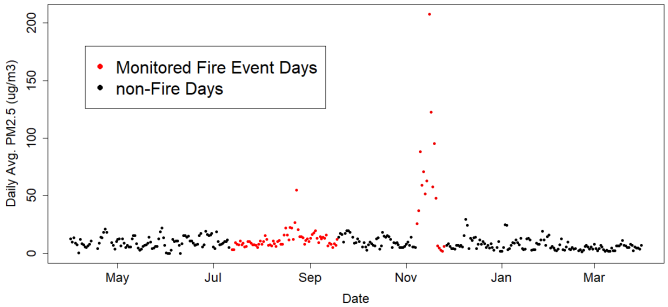

Fig. 3. Time series of PM2.5 for a solar PV site near the San Francisco Bay area in California.

for the time period of interest. We include these additional explanatory variables to help improve both predictive model fit as well as isolate the effects of the PM2.5 variable, which is of primary interest.

B. Data Processing

The data processing took place in two parts. First, all data was coerced into a consistent time scale. Then, the energy generation data was normalized to provide a common scale across all solar PV sites. The three datasets (i.e., solar PV energy generation, PM2.5 data, and weather data) were fused together to form a cohesive data panel. Additional details regarding the data processing are below.

1) Time scale consistency: The unprocessed production, weather, and PM2.5 data was available in two levels of temporal precision. The PV site energy production and PM2.5 data were recorded hourly, whereas the NASA POWER weather data was available at the daily time scale. We chose the daily time scale to achieve temporal consistency across all three datasets.

For production data, daily values were obtained for each site through two steps. First, any negative hourly values were removed. The remaining hourly observations were then limited to only hours occurring between sunrise and sunset. The daily total energy production for the site was obtained by summing across all remaining hours for the day. Days where there was measured irradiance but no production for at least one hour during the middle of the day were removed from analysis. Additionally, there were four sites that consistently had abnormally small production values even after aggregation; they were excluded from the study.

For the PM2.5 data, daily data was calculated as a weighted average. The weights were based on the theoretical clear sky direct normalized irradiance at each site. The hourly clear sky irradiance for each day is calculated for the exact location of the site using the *pvlib* python package [22]. Next, the hour is given a weight that is the percentage of the daily irradiance that occurs during the given hour. These weights are then used to calculate a daily weighted average of PM2.5 for the site. This weighting scheme results in a daily average PM2.5 with each hour of PM2.5 data having an impact on the daily average proportional to that hour's irradiance. Smoke that occurs during hours of no measured irradiance (e.g., nighttime) have no impact on daily average PM2.5 calculations. Similarly, smoke that occurs during times of high irradiance (e.g., midday) have the largest impact on PM2.5 daily averages. A sample time series of hourly irradiance and weighted PM2.5 shows periods of low and high irradiance and fluctuating levels of PM2.5 (see Figure 4). In this example the unweighted average PM2.5 measurement for that day is 51.83. However, the weighted irradiance average is 47.99. Days that have higher contrasts of smoke during the night and day will have larger differences in this calculation.

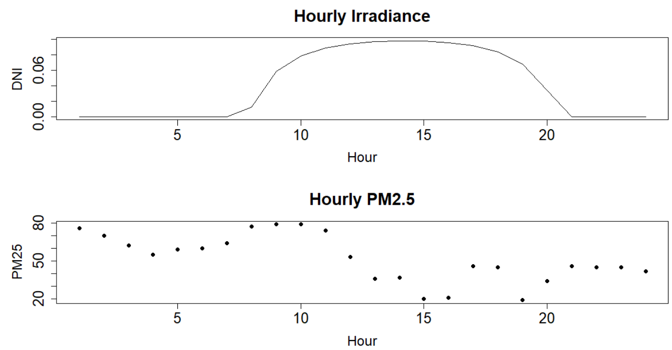

Fig. 4. Sample time series of hourly irradiance (top) and PM2.5 (bottom) data used to calculate the daily weighted average PM2.5 calculations.

The weighting process is applied to all days and sites used in this study. There is significant variability in the average daily PM2.5 for the region during the study period (see Figure 5). The two prominent fire events during this period result in elevated PM2.5 concentrations for the region. While the Mendocino Complex Fire had a longer duration than the Camp Fire, it has lower average PM2.5 concentrations.

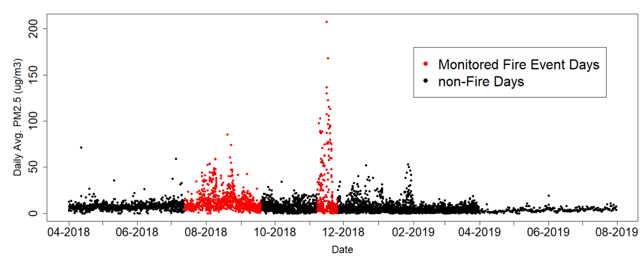

Fig. 5. Average daily PM2.5 concentration across all monitoring stations used in this study.

2) Energy Production Normalization: A normalization of the energy production data is needed due to the differing sizes of sites used in this study (see Figure 1). The daily IEC clear sky production is calculated for every site and day using the *pvOps* python package [23]. Each site's daily production is normalized by dividing the observed production by the IEC clear sky production. A sample hourly time series demonstrates the difference between the observed and IEC clear sky energy production (see Figure 6). The normalization procedure results in all sites, regardless of size, having a production value on the same scale for analysis.

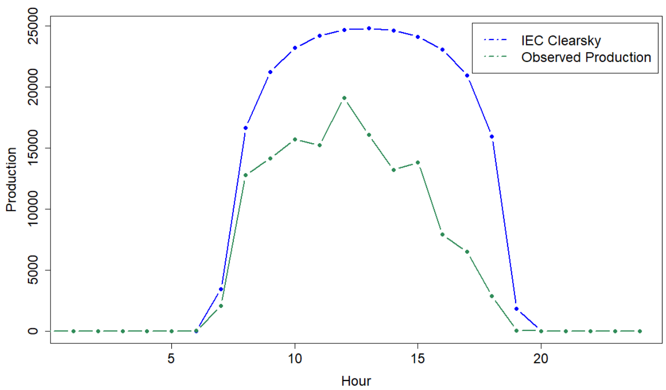

Fig. 6. Sample time series of observed & IEC clear sky energy production.

The normalization process resulted in some days being problematic. All days which had a normalized production greater than 1.2 (i.e., 120% of IEC clear sky) were removed from analysis. This threshold was based on discussions with industry and resulted in the removal of four sites that consistently had abnormally large normalized production values. There are additional abnormal production values in the data. However, we did not remove additional problematic data to minimize assumptions.

C. *Data analysis*

Regression models were the primary data analysis method used is this study. In particular, we focus on modeling the relationship between smoke (i.e., PM2.5) and solar PV production. All available data, across all sites, was included in the model analysis to have the largest data set possible to measure key relationships. Two quantitative methods were employed to assess model performance: R^2, and the root mean square error ($RMSE$). An iterative process was used to consider different combinations of explanatory variables while attempting to maximize R^2, minimize $RMSE$, and retain variables that were statistically significant (95% confidence interval).

III. Analysis & Results

A. *Regression Model Selection*

The initial regression model was based on regressing PM2.5, temperature at 2 meters, wind speed at 10 and 50 meters, precipitation, and insolation clearness index. There is a seasonal component to solar PV production. The temperature variable was used to account for this as it tracked this variability closely. Some possible variable interactions were investigated. These interactions were excluded as they were found to be statistically insignificant.

There was still a large amount of variability in the data. A site-specific variable (i.e., a site adjustment factor) was introduced to improve model fit. This variable was significant and improved model fit. However, it resulted in the model no longer capturing any temperature effects. As a result, temperature was therefore removed from the model in favor of the site adjustment variables. The significance of the site adjustment variable indicates that there are some inherent differences in production across sites, even after normalizing the production data.

The final selected model achieved $R^2 = .6732$, indicating that the model explains 67.32% of the variability in the daily production at the solar PV sites. In addition to the site adjust variables, PM2.5, insolation, precipitation, and wind speed were found to be statistically significant (see Table I for a summary of the final model). We only present a few site adjustment variables for illustrative purposes.

TABLE I
Regression model parameter summary. Only three site adjustment parameters are included for comparative purposes.

Parameter	Estimate	Std. Error	t value	P value
Intercept	0.0659	0.0073	9.0490	<2e-16
PM2.5	-0.0019	0.0001	-19.5190	< 2e-16
Insolation CI	0.8614	0.0066	131.3980	< 2e-16
Precipitation	-0.0030	0.0002	-12.3460	< 2e-16
Wind Speed 10M	0.1025	0.0026	39.6450	< 2e-16
Wind Speed 50M	-0.0710	0.0019	-36.6450	< 2e-16
Site C2S101	0.0393	0.0075	5.2110	< 2e-7
Site C2S106	0.0007	0.0076	0.0960	0.9235
Site C2S107	-0.0751	0.0076	-9.9380	< 2e-16

Separate parallel regression lines for every site have been incorporated. This site variable is specific to these sites, but it is not requirement to use the model for prediction. Two approaches can be taken. With no site information, a site effect of zero can be assumed. Alternatively, access to some site production information enables the site effect to be measured.

Model assumptions are satisfied based on residual analyses (see Figure 7). Studentized residuals are residuals where the model is fitted to all data except for that observation. The distance between the observed and the model's predicted value is calculated. This aids in preventing anomalous observations from pulling the model towards them and therefore reducing their residual value. The fitted versus residual plot should display no apparent trend (i.e., appear to be a random cloud of points) if the model fits the data well. Most points behave in this manner, but there appears to be a diagonal line cutting off the points on the left side of the plot. This line is associated with the zero cut-off for observed production and not a problematic trend. The Q-Q plot should roughly display as a straight line, and these results suggest that the normality assumption of the residuals has been satisfied. Thus, no transformations or additional variables are required to have confidence in model results.

The primary goal of this analysis was to measure the impact of smoke on solar PV energy production. Maximizing R^2 increases confidence in a model's ability to predict this relationship. The overall model ($R^2 = .6732$) is a good result as the weather predictors were not obtained at the site but

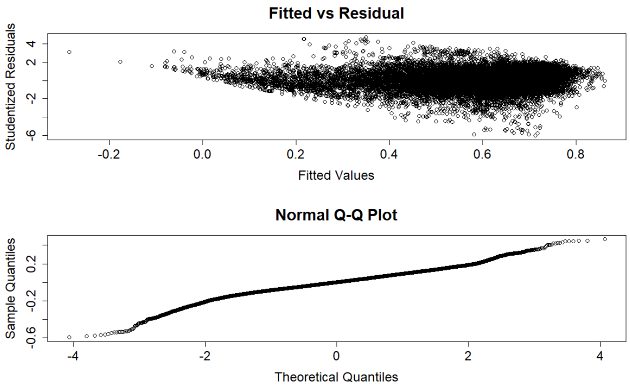

Fig. 7. Residual analysis plots.

rather come from satellite measurements. Additionally, the final selected model has $RMSE = 0.099$. This indicates that there will be, on average, an approximate difference of 0.099 normalized kWh ($\sim$ 10% of daily site production) between the estimated and true daily energy generation for predicted observations. $RMSE$ appears to be significantly better than the R^2. This is likely caused by a small portion of the data being significantly different than the model (outlier candidates). These outliers result in increased data variability not explained by the model, which more adversely effects the R^2 metric than the $RMSE$ metric.

B. Model Analysis

The PM2.5 variables regression parameter estimate is -0.0019. Thus, as daily average PM2.5 increases by one $\mu g/m^3$, the normalized production is expected to decrease by approximately 0.0019. On days when PM2.5 reaches $50-200\mu g/m^3$,the model predicts a 9.4% to 37.8% reduction in normalized production, respectively. Similarly, normalized production is anticipated to decline as precipitation and wind speed at 50m increase by 0.0030 and 0.0710, respectively. Conversely, normalized production is predicted to increase by 0.8614 and 0.1025 due to a one unit increase in insolation and wind speed at 10m, respectively.

The site variables (only 3 of 68 displayed; see Table I)) indicate an adjustment factor for the linear model, and no change in the PM2.5 and weather parameter values. For example, site C2S101 (arbitrary ID), has an adjustment estimate of 0.0393, which indicates that normalized production for this site is expected to be 0.0393 higher than other sites. It should be noted that not every site correction is significant. In these cases, there is effectively no correction (zero effect).

A visual comparison between the observed normalized and predicted production data shows both clustering around a 1:1 fitted line as well as significant numbers of outliers (see Figure 8). There is a clear linear trend between predicted and observed values, but some additional trends are also present. There are a significant number of points in the lower right quadrant of the graph with high predicted values and low observed values. Some of these could be anomalies where some production was not observed or some site operations resulted in reduced production. There are some days during which the model predicts negative production when production is observed to be near zero. Negative production is infeasible. These days are likely the result of rare events where several weather variables that all negatively impact production are observed simultaneously. In these instances, the model would round normalized energy production to zero.

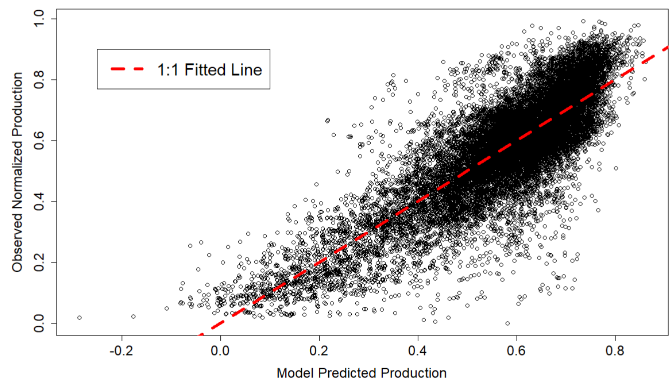

Fig. 8. Predicted versus observed normalized production across all sites used in this analysis.

A time series for the study domain provides a comparison between the observed normalized and predicted production data for sample site (see Figure 9). Additionally, this graphic displays both fire events in red. Overall, the predicted production follows the observed production well. There is one notable exception in late June where the observed production is quite lower than expected. There is a clear reduction in production during both of the fire events present in both the observed and predicted normalized production. The first fire event appears to have a more pronounced reduction in production in late August. This corresponds with the site's observed peak PM2.5. There is also a significant reduction in production during the Camp Fire event in November present in this graphic, this is in correspondence with the very high rates of PM2.5 during the month of November in 3. The high rates of variability in the normalized production after the Camp Fire event is due in large part to clouds and precipitation. There is a possible interaction between lower rates of precipitation leading up to and during fire events that could have some impact on solar production during this time which is not explored here.

IV. Discussion

A statistical model can capture the basic relationship between air quality, which serves as a proxy for wildfire impacts, and the energy production of a nearby solar PV site. Additionally, while we find that PM2.5 plays a large role, other variables also factor in when it comes to capturing performance impacts during non-wildfire time periods, and our model can account for these changes. For example, the model is still able to capture the daily production fluctuations in the

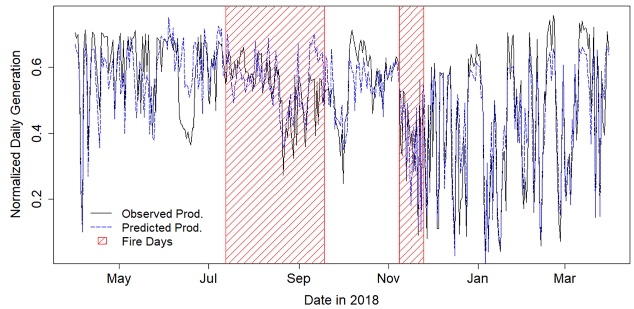

Fig. 9. Predicted versus observed normalized production for a solar PV site near the San Francisco Bay area in California.

days following the end of the fire event when PM2.5 levels have largely returned to normal.

There are several limitations to this analysis and possible next steps. In the data, there is no way to distinguish between either the impacts of smoke on production due to the blocking of solar irradiance or ash soiling on PV panels. This includes no ability to measure or determine the possible lingering effects of ash soiling after smoke has cleared, either on panels or other site instruments. Most of the smoke impact observed in this analysis is believed to come from smoke blocking solar irradiance. Several sites were removed from analysis for problematic data. Future work could refine the process for defining normal and abnormal behavior alike to remove only specific days as opposed to a site's full time series. Additional weather data or site-specific geographical features could be considered to further refine the model, both improving its predictive power and refining smoke impact quantification. Further testing of model performance could be done using site production validation data that was not used in fitting the model.

V. Conclusion

Wildfires are becoming increasingly common and increasingly severe, requiring better planning for all levels of potential impact. One growing consideration is the impact of wildfire-induced pollution on solar PV production. We show here that high levels of PM2.5 in the atmosphere play a large role in disrupting energy production at affected PV sites, and we have developed a statistical model to better understand the strength of this relationship, as well as the degree to which other weather parameters factor affect PV energy generation. The regression model identifies a reduction in solar PV production between 9.4% to 37.8% on smokey days. This model can be used in conjunction with historical smoke data or smoke spread models to predict solar PV losses associated with wildfires for PV sites. Predicting loses can help with both long term prediction as well as short term emergency response planning. For advanced planning and operational support, this type of model can be combined with mature products that forecast smoke movement and air quality impacts to determine which set of PV sites will be impacted by wildfire smoke and to what degree.

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