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LETTER

Smoke from 2020 United States wildfires responsible for substantial solar energy forecast errors

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Abstract

The 2020 wildfire season (May through December) in the United States was exceptionally active, with the National Interagency Fire Center reporting over 10 million acres (>40 000 km²) burned. During the September 2020 wildfire events, large concentrations of smoke particulates were emitted into the atmosphere. As a result, smoke was responsible for ~10%–30% reduction in solar power production during peak hours as recorded by the California Independent System Operator (CAISO) sites. In this study, we focus on a 9 d period in September when wildfire smoke had a profound impact on solar energy production. During the smoke episodes, hour-ahead forecasts utilized by CAISO did not include the effects of smoke and therefore overestimated the expected power production by ~10%–50%. Here we use multiple observational networks and a numerical weather prediction (NWP) model to show that the wildfire events of 2020 had a significantly detrimental influence on solar energy production due to high aerosol loading. We find that including the contribution of biomass burning particles greatly improves the day-ahead solar energy bias forecast of both global horizontal irradiance and direct normal irradiance by nearly ~50%. Our results suggest that a more comprehensive treatment of aerosols, including biomass burning aerosols, in NWP models may be an important consideration for energy grid balancing, in addition to solar resource assessment, as solar power reliance increases.

1. Introduction

Wildfires are some of the most powerful natural disasters on Earth, often leading to devastating effects. There is no doubt that wildland fire activity in the United States (U.S.) has intensified over recent decades [7, 19, 40, 58], and is projected to increase in forthcoming years [3, 60, 63]. These changes are especially concerning for the U.S. wildland-urban interface, which has burgeoned to the tune of approximately 350 000 homes per year over the last two decades [10]. While a primary concern pertaining to wildfire activity is the loss of life and property, air quality effects on human health [14] and solar power forecasting accuracy impacts on grid stability [4] are also greatly affected by biomass burning due to small particles, or aerosols, that comprise smoke emissions.

Biomass burning aerosols in the atmosphere also play an important role in the Earth’s radiation budget [39, 41, 42, 47], as carbonaceous smoke aerosols produced as a result of incomplete fuel combustion absorb and scatter incoming solar radiation [6, 15]. The optical properties of biomass burning aerosols are quite complex, and they are ultimately determined by composition, mixing state, and size properties that continuously evolve during the aerosol lifecycle [9, 27, 34, 50]. Therefore, smoke emissions play a particularly significant role in solar radiation transfer processes. More specifically, direct normal irradiance (DNI)—an important quantity in the context...
of solar energy forecasting—is strongly influenced by smoke properties due to its sensitivity to the aerosol loading [29].

Although fossil fuel combustion comprises a large fraction of global energy production since the industrial revolution, renewable energy methods [24] have existed for thousands of years (e.g. wind for sailing and concentrated solar for furnaces [49]) and are becoming more prevalent [30]. In the U.S., solar energy (combined solar photovoltaics and concentrating solar-thermal power) made up approximately 14% of the renewable energy portfolio as of 2019 [56], and it currently comprises nearly 3% of the total energy production [54]. As of 2019, the Mountain and Pacific Contiguous Census Divisions, as defined by the U.S. Energy Information Administration, were responsible for producing ~50% of the total U.S. solar photovoltaic power, with California alone responsible for nearly 40% of the production [56]. While the unsubsidized levelized cost of energy for utility-scale solar photovoltaics has decreased drastically nationwide from $0.27 kWh$ to $0.046 kWh$ between 2010 and 2020 [53], the U.S. Department of Energy, Solar Energy Technologies Office recently announced a goal to reduce this cost even further to $0.03 kWh$ for 2025 and $0.02 kWh$ for 2030 [55]. It is anticipated that the competitive cost of solar energy will substantially increase its deployment [38], thus requiring a smooth integration into the power grid.

Stable grid integration of solar power depends on quality forecasts of incoming solar, or shortwave (SW), radiation to predict photovoltaic production [8]. An accurate solar forecast requires a realistic depiction of aerosol optical properties—especially during high loading events such as wildfires [43]—because aerosols attenuate incoming SW radiation through absorption and scattering [28, 32]. Therefore, numerical weather prediction (NWP) models are typically employed for day-ahead variable power forecasts [25]. In the context of solar irradiance forecasting, NWP models are advantageous for many reasons [29], including (a) accurate aerosol optical depth (AOD) predictions when applying data assimilation techniques [45, 59] and (b) capturing aerosol radiative feedbacks on the coupled atmospheric system through physics parameterizations [46, 52].

Here, we ask the critical question: during a large-scale wildfire event, what is the quantitative impact of smoke emissions on solar energy forecasting? To address this fundamental question, we undertake a multifaceted approach that fuses both national scale observational networks and an NWP model. We will demonstrate the smoke effects during extreme wildfire conditions that plagued the Western U.S. in 2020. While recent studies examined the reduction in solar energy during to the 2020 wildfires [20, 22, 61], to the authors’ best knowledge, this is the first study to investigate explicitly the impact of wildfire smoke on solar energy forecasts using a mesoscale NWP model.

2. Data and methods

In this section, we describe the data sets and techniques used to examine the role of smoke as it pertains to aerosol loading, solar irradiances, and solar energy production.

2.1. Solar and aerosol measurements

The Surface Radiation Budget Network (SURFRAD) and Solar Radiation (SOLRAD) stations used in this study are located throughout the U.S. and provide surface solar irradiance data including global horizontal irradiance (GHI) and DNI at 1 min intervals. The SURFRAD stations also report AOD at 1 min intervals; however, these data are less continuous than the irradiance data due to clouds contaminating some of the samples. We use all valid data during the 9 d period, which are publicly available through the National Oceanic and Atmospheric Administration (NOAA) Global Monitoring Laboratory (GML). Valid data are determined by the quality control flags reported by NOAA GML. SURFRAD and SOLRAD station locations are shown in figure S1(B) (available online at stacks.iop.org/ERL/17/034010/mmedia), and more information is listed in tables S1 and S2, respectively.

Additional AOD measurements shown here are from AErosol RObotic NETwork (AERONET) stations. Specifically, we use Level 2.0 data which are quality-assured; according to the National Aeronautics and Space Administration (NASA), the data are calibrated pre- and post-field, automatically cloud cleared, and manually inspected before becoming publicly available (https://aeronet.gsfc.nasa.gov/new_web/data_description_AOD_V2.html). Measurements at AERONET sites are taken across a range of wavelengths. Because the instruments do not directly measure AOD at 550 nm, we use the measured AOD at 500 nm, along with the Ångström Exponent at 440–675 nm, to calculate AOD at 550 nm. This calculation allows us to better compare with the Weather Research and Forecasting (WRF) model output, which diagnoses AOD at 550 nm. AERONET station locations are shown in figure S1(B), and additional information is listed in table S3.

2.2. WRF model configuration

To complement the observations, we use the WRF model [48]. Our developments are part of the WRF-Solar version 2 modeling framework, which builds on the widely-used WRF-Solar version 1 modeling package [29]. The WRF model setup used for the simulations presented herein follow the WRF-Solar reference configuration (https://ral.ucar.edu/projects/wrf-solar). Notable deviations from the reference configuration include a two-domain structure, with the
outer (inner) domain using a horizontal grid spacing, \( \Delta x = 9 \text{ km} \) (figure S1(B)). Moreover, we use a parent-child time step ratio of 2, as well as horizontal diffusion in \( x-y-z \) physical space in the inner domain to reduce errors associated with turbulent mixing in complex terrain. Meteorological forcing is provided by the National Centers for Environmental Prediction operational Global Forecast System on a \( 0.25^\circ \times 0.25^\circ \) latitude-longitude grid. Nine simulations are conducted for a total of 36 h each, with the first 12 h of each simulation discarded as spin-up. The first and last simulations begin at 00 UTC on 7 September 2020 and 00 UTC on 15 September 2020, respectively.

For this study, we conduct WRF model simulations using two different aerosol forcing data sets: a climatology derived by [52] from multiyear global simulations [18] using the Goddard Chemistry Aerosol Radiation and Transport (GOCART) model [23] and a reanalysis from the Goddard Earth Observing System, Version 5 (GEOS-5) [51]. Aerosol concentrations vary monthly in the former data set, while the latter data set varies every three hours. The GEOS-5 modeling system assimilates bias-corrected AOD from the MODerate resolution Imaging Spectroradiometer aboard Aqua and Terra, the Advanced Very High Resolution Radiometer, the Multi-angle Imaging SpectroRadiometer, and ground-based AERONET sites [44]. Both GOCART and GEOS-5 provide three-dimensional aerosol mass mixing ratios. Two-dimensional aerosol emission fluxes are provided by GEOS-5; however, when using GOCART forcing, WRF assumes fixed aerosol emission fluxes following the Thompson–Eidhammer aerosol-aware microphysics parameterization [52]. Other aerosol analysis products, such as the Navy Aerosol Analysis and Prediction System (NAAPS [13]), may be used in lieu of GEOS-5 so long as they provide sufficient aerosol information for the Thompson–Eidhammer microphysics parameterization.

The original Thompson–Eidhammer scheme has two different aerosol categories, cloud condensation nuclei (‘water-friendly’) and ice nucleating particles (‘ice-friendly’), whose number concentrations are treated prognostically. The water-friendly category is made up of sea salt, sulfate, and organic carbon aerosol, while the ice-friendly category is made up of dust. As an original contribution to the work presented here, we have added an additional prognostic aerosol category to the Thompson–Eidhammer parameterization: black carbon. This additional aerosol category is necessary because BC is strongly absorbing, compared to the other categories which are strongly scattering. Therefore, we consider only sea salt, sulfate, organic carbon, dust, and BC from the GOCART and GEOS-5 models. For each of these five aerosol types, we generate initial and lateral boundary conditions for the model simulations. The aerosol fields are converted from mass mixing ratio to number concentration after assuming a lognormal size distribution. The GEOS-5 aerosol emissions of organic carbon and BC are separated between anthropogenic and biomass burning sources. The biomass burning aerosol are distributed evenly in all grid cells that fall within the planetary boundary layer vertical column, while all other aerosol are emitted in the lowest model grid box.

In our WRF simulations, the aerosol direct radiative effect is represented by calculating AOD at 550 nm. The AOD values are a function of aerosol number concentration and aerosol extinction coefficient, the latter of which is determined through a look-up table that is generated at the beginning of the simulation. The aerosol optical properties are calculated via the Mie Theory [62] and stored in the look-up table. The ice-friendly and BC aerosol categories follow the core–shell assumption (perfectly coated, externally-mixed dry aerosol), while the aerosols comprising the water-friendly category are assumed to be internally mixed [52]. For each of the three aerosol classes, inputs to the Mie optical calculations include hygroscopicity, refractive indices, and geometric standard deviation. The refractive indices, as well as the aerosol distribution properties, for BC follow [16]. Our simulations do not consider BC to be microphysically active (i.e. BC may not serve as cloud condensation nuclei or ice nuclei), and removal of BC occurs through only wet scavenging.

### 2.3. California Independent System Operator (CAISO) data

We utilize freely available reports (www.caiso.com/) from the CAISO to link the smoke plumes to solar energy losses. The CAISO variables used in this study, Real-Time Dispatch (RTD) and Hour-Ahead Scheduling Process (HASP), are reported at 5 and 60 min intervals, respectively. The RTD represents the amount of solar power produced by each site and available for release prior to any potential curtailments. The HASP is a real-time energy market optimization that issues pre-dispatch instructions for energy bids. Renewable forecast information, which is updated every 5 min using NWP guidance along with persistence and corrective machine learning techniques, inform the HASP.

### 3. The Western U.S. wildfires of 2020

In this study, we will focus on a 9 d period (7–16 September 2020) of particularly smoky conditions that resulted from intense wildfire activity across the Western U.S. In California, 9 of the state’s top 10 most destructive wildfires (in terms of acres burned) occurred between 2012 and 2021, with the 2020 wildfire season featuring 5 of them [12]. The most notable 2020 event was the August Complex, which over the course of approximately 3 months consumed more than 1 million acres (>4000 km² and nearly 1% of...
California's land) and destroyed over 900 buildings. Nine other California wildfires topped the 100,000 acres burned mark in 2020, with an additional 13 fires burning more than 25,000 acres [1]. In Colorado, the state endured three of the most intense wildfires to date, each burning more than 100,000 acres: Pine Gulch (139,007 acres or ∼653 km²; ∼0.21% of Colorado's land), East Troublesome (193,812 acres or ∼784 km²; ∼0.29% of Colorado's land), and Cameron Peak (208,913 acres or ∼845 km²; ∼0.31% of Colorado’s land) [40]. By their containment dates, the latter two wildfires became the two largest in Colorado state history. Oregon experienced record-breaking conditions as well: during the Labor Day fires, more than 11% of the Oregon Cascades ecoregion burned, surpassing the sum of acres burned over the previous 36 fire seasons [2].

The 2020 wildfire season across the Western U.S. was undoubtedly one for the record books, largely due to exceptionally warm and dry atmospheric conditions [26] in addition to favorable regional wind patterns [2]. According to [26], 2020 ranked as the season with the second highest burned area and vapor pressure deficit—a measure of aridity—across the West over the last 36 years. While the 2020 fires burned primarily from July through November, an exceptionally active period plagued a large portion of the U.S. in early and mid September. During this time, the Fire Weather Index [57] reached extreme levels (defined as exceeding the local 90th percentile) across 85% of forested regions in the Western U.S. [1]. Coincident with the extreme Fire Weather Index, [1] note that the U.S. Preparedness Level, which indicates the amount of national resources committed to wildfire response, was elevated to a maximum value of 5 for a 44-day period from August into September.

The expansive smoke plumes in September could be seen clearly from satellite observations across the U.S. Pacific Northwest, California, Utah, and Colorado (figures S2(A)–(C)). On 7 September, a low pressure system was centered over Ontario and lifting off to north and east [33], leaving a large region of cloud cover blanketing the north central U.S. (figure S2(A)). Meanwhile, high pressure was positioned over the southwestern U.S. with westerly flow aloft, also confirmed by the smoke plume orientation in figure S2(A). By 11 September, low- and mid-level offshore flow dominated across the Western U.S., acting to increase fire activity and smoke production (figure S2(B)). The scene on 15 September featured a broad zone of high pressure in the central and southern U.S. and subsequently weak flow (not shown). Relatively strong, zonal flow stretching from California into the upper Midwest and Canada allowed for the transport of aged wildfire smoke; faint signatures of smoke plumes extending into the Northeast U.S. are seen in the satellite imagery (figure S2(C)).

Forward trajectories from HYSPLIT, launched at different locations where wildfires actively burned between 11 September and 15 September, illustrate clearly the smoke transport from the Western U.S. across the country into the Northeastern U.S. (figure S1(A)). Particulate matter measurements from ground stations stations in the Western U.S. registered extended exceedances during the 9-day period (figure S3(A)), leading to extreme exposures over Oregon and Washington (figure S3(B)) for several vulnerable populations (supplementary information). The smoke plumes were observed as far away as Leipzig, Germany on 11 September, where co-located ground-based and spaceborne lidars sampled the biomass burning aerosol that were lofted into the free troposphere [5], likely due to intense convection associated with cumulonimbus flammagenitus, or pyrocumulonimbus [21]. Moreover, the High-Resolution Rapid Refresh (HRRR) Smoke modeling system (https://rapidrefresh.noaa.gov/hrrr/HRRRSmoke/) predicted smoke plume transport within the U.S. reasonably well during this period (not shown).

4. Results

4.1. Aerosol loading is captured by the model

Particles contained in smoke plumes control the aerosol loading and play a critical role in the energy budget. Figure 1(A) presents a comparison of the observed and modeled AOD at 550 nm wavelength for all available sites composited over the 9-day period. Surface measurements are from SURFRAD and AERONET instrument sites. WRF model simulations using the two different aerosol forcing data sets perform very differently. The simulations using GOCART aerosol show little spread while strongly underestimating the measured AOD at both SURFRAD and AERONET sites (coefficient of determination, $r^2$ of 0.037 and 0.025, respectively). Meanwhile, the simulations forced with GEOS-5 aerosol fields yield much better agreement with the measurements with $r^2$ of 0.488 and 0.369 for SURFRAD and AERONET, respectively.

Time series plots for individual AERONET stations confirm that the GOCART climatological aerosol field does not reproduce the temporal AOD variability (figure 1(B)). Using a monthly AOD climatology, which is the industry standard practice, is therefore inadequate to represent the aerosol loading during wildland fire events. In general, the WRF simulations with GEOS-5 aerosol capture well the timing and magnitude of both low and high AOD periods. Perhaps the substantial differences between the two sets of simulations is not surprising; however, these results highlight the need to realistically represent the aerosol state during biomass burning periods in order to accurately forecast the aerosol loading.
4.2. California energy market operations

The magnitude of AOD plays a critical role in determining the amount of SW energy that reaches the Earth’s surface. Under typical atmospheric conditions during the middle of September, CAISO reports a peak in solar power production of ~9555 MW across their three utility service areas (figure 2(A)). However, due to the smoke plumes persistent over the region during 7, 8, 10, and 11 September, solar power production was reduced compared to typical conditions by approximately 10%–30% during peak production hours (here considered 19–23 UTC or 12–16 Pacific Daylight Time (PDT)). Our findings agree well with those from previous studies focused on wildfire smoke impacts on solar reduction [22, 36], including during the 2020 season in the Western U.S. [20, 61]. In contrast, 9 September and the 12–16 September period featured solar production much closer to what is expected under typical conditions (less than 7% reduction) because the smoke plumes were transported out of the region.

During energy utility operations, CAISO utilizes renewable forecast information in multiple real-time market updates throughout the day. The two real-time market updates highlighted in this article are the HASP and RTD. Examining the difference between the RTD and HASP, with a negative value indicating less-than-expected solar power production, provides insight into the solar power forecast error (figure 2(B)). During 7, 8, 10, and 11 September, from 17–01 UTC (10–18 PDT), the mean RTD-HASP percentage difference is approximately −27%, with a difference peaking around −40% and −50% in the morning and late afternoon/evening hours, respectively. The sharp drop-off in power production during the later daylight hours coincides with the largest ramp in energy demand.

4.3. Solar energy forecast improves by nearly 50%

The CAISO HASP solar power errors during intense wildfire conditions provide motivation for incorporating an accurate treatment of smoke particles in
Figure 2. (A) Time series of solar power RTD from CAISO for the event time period (dark blue lines) and September climatology (years 2018–2020; light blue lines). (B) Time series of solar power RTD minus HASP from CAISO averaged over 7, 8, 10, and 11 September (black line). The time offset is shown relative to 21 UTC (14 PDT), which is approximately the time of peak solar power production. Gray shading represents the range of values across the 4 d average. The CAISO region is labeled in figure S1(B).

Figure 3. Time series of (A) global horizontal irradiance (GHI) and (B) direct normal irradiance (DNI) biases (calculated as model minus observations). Observations represent the composite of all SURFRAD and SOLRAD project sites from 7–16 September 2020. The time offset is shown relative to local solar noon. Model simulations using GOCART and GEOS-5 forcing are represented by black and light blue lines, respectively. The locations of SOLRAD stations are shown in figure S1(B).

operational models. Due to the improved accuracy of AOD predictions (figure 1), we find commensurate improvements in the forecast of solar irradiances during the 9 d period of active wildfires in the Western U.S. (figure 3). Comparisons of all-sky GHI and DNI between measurements and WRF-Solar
are displayed in figures 3(A) and (B), respectively. For GHI and DNI, composite bias improvements of \(\sim 48\%\) and \(\sim 49\%\), respectively, are realized when using the GEOS-5 aerosol forcing compared to the GOCART aerosol forcing (table S5). Composite mean absolute error improvements are smaller (\(\sim 29\%\) and \(\sim 44\%\) for GHI and DNI, respectively); however, improvements exceed 50\% at some individual sites—especially those impacted by biomass burning plumes—averaged across the 9 d period (table S6). The largest bias improvements in GHI occur during the late morning and early afternoon hours, while those for DNI are realized across the early morning and late afternoon hours (not shown).

5. Discussion and conclusions

Wildfire activity, and specifically intensity, has increased in recent years, raising concerns as the wildland-urban interface continues to expand. Smoke emitted from wildfires and subsequently advected by atmospheric wind patterns presents a direct impact on daily human life. Exposure to smoke remains a leading concern in the context of air pollution due to the compounding effects that can be devastating to human health. To explore the potentially detrimental effect of biomass burning emissions on air quality, we focus on the intense wildfire activity in September 2020 across the Western U.S. Our results find that a large region in the U.S. Pacific Northwest was subject to extreme PM\(_{2.5}\) conditions, including several vulnerable populations. While the U.S. Pacific Northwest has seen a recent upward trend in PM\(_{2.5}\) concentrations due to the uptick in wildfire activity and related emissions [35], wildfires will likely continue to be a main pollution source in many geographical regions [31], especially since PM\(_{2.5}\) effects may be felt 100s of miles downwind of source locations [37].

Due to the abundant smoke emissions during the September 2020 period of biomass burning examined here, impressive aerosol loading was observed across the country and captured quite well by the global GEOS-5 model. As a result of the large aerosol loads, smoke particles produced by the 2020 wildland fires also had a profound influence on solar energy production. Across the state of California, solar power potential was reduced by approximately 10\%–30\% on days influenced by smoke plumes compared to solar power potential under typical atmospheric conditions. To illustrate the benefit of including wildfire smoke emissions on day-ahead solar forecasts, we use WRF-Solar, a state of the science NWP model. Initializing the WRF-Solar model with GEOS-5 aerosol fields, compared to using a climatological aerosol data set, leads to bias improvements of nearly 50\% when forecasting solar irradiance quantities GHI and DNI.

There remain many uncertainties and challenges that should be addressed for more accurate solar forecasting as it pertains to smoke. For example, while the overall bias in AOD seems small in figure 1(A), there is still a lot of scatter, which suggests large short-term biases in AOD and thus solar energy production. We hypothesize that a major contributing factor pertains to predicting future fire behavior (e.g. occurrence, growth/reduction of existing fires, and emission rates). Another issue is related to AOD: it is important for the wavelength dependence of AOD to be correct because this parameter is needed to compute the effect of aerosol on shortwave radiation.

As highlighted in this study, the considerable reductions in solar irradiances due to intense aerosol loading during the 2020 Western U.S. wildfires likely represent a relatively infrequent scenario. Over the course of an entire burning season, the effects of a week-long period of very smoky conditions may not seem so deleterious to the power grid. Nevertheless, a direct consequence of climate change is continued extreme biomass burning, which may lead to more frequent and intense smoke events, similar to the case highlighted here. In fact, a 2013 study reported that, based on an ensemble of global climate models, wildfires may triple in number by 2050 leading to substantially higher organic and black carbon concentrations [63]. In general, we recommend that accounting for the effects of smoke in solar energy forecasts is needed to soften the blow of a poor forecast on the nationwide energy grid balancing. Future studies should estimate the potential economic burden of a poor solar power forecast due to wildfire smoke.

Even though our study focuses on the short-term benefits of including smoke in NWP forecasts, the longer-term implications of smoke on solar energy production cannot be ignored. Solar energy deployments are expected to increase to address climate mitigation; however, some fraction of the expected solar power production will be offset by smoke events. Therefore, future solar power resource assessments should consider the potential impact of smoke, which is not necessarily a local solar energy problem confined to the Western U.S. because smoke may be transported far downwind. While the impact on solar energy downwind will be smaller, it is likely still important due to the direct relationship between AOD (a column-integrated quantity) and incoming surface solar radiation. Global and regional climate models, spanning a range of future climate scenarios, should be utilized to better understand smoke effects on solar power production as deployments expand in the 21st Century.

In the U.S., efforts are ongoing to enhance operational smoke modeling capabilities. Most notably, NOAA operates HRRR-Smoke, which is based on the WRF model and assimilates several data sources. The operational version of the HRRR-Smoke model includes PM\(_{2.5}\) forecasts and is therefore useful for a range of applications, including predicting high
impact air quality events. Despite the many advancements made within the HRRR-Smoke framework, we believe that further developments should focus on strengthening the link between fire weather and solar energy forecasts. For instance, fire radiative power from spaceborne instruments is assimilated into HRRR-Smoke to estimate smoke emissions and injection height; however, these data are rather sparse spatially (∼1 km) and temporally (∼6–12 h), so the model would benefit in the future from higher resolution retrievals. The model forecast of biomass burning emissions and transport is tied closely to these satellite measurements. Therefore, coupling the HRRR-Smoke NWP model to a wildfire behavior model (e.g. similar to WRF-Fire [17]) to improve predictions of fire evolution, such as the growth or decay of existing fires, would greatly improve smoke emission and transport forecasts, likely benefiting solar energy predictions. Finally, in the operational HRRR-Smoke model, biomass burning emissions are not yet linked to cloud formation. We emphasize here that incorporating aerosol-radiation-microphysics interactions may be critical for accurately estimating solar energy potential on hour- and day-ahead time scales.

By and large, the topic of wildfire smoke emissions and related effects connects several scientific domains including fire, meteorology, forestry, air quality, and renewable resources. In practice, tackling this challenge bridges several operational mission spaces: fire behavior analysis (e.g. U.S. Forest Service and fire departments), weather forecasting (e.g. NOAA), and renewable energy (e.g. plant and grid operators and energy markets). We believe that the framework presented in this study will greatly enhance short term solar energy outlooks during future wildfire smoke events. Nonetheless, this research addresses just one component of a complex, multifaceted problem. Ultimately, a convergent approach likely will be required whereby experts in different disciplines collaborate and interact with all of the stakeholders to develop effective solutions.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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