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The impact of air pollutant deposition on solar energy system efficiency: an approach to estimate PV soiling effects with the Community Multiscale Air Quality (CMAQ) model

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Abstract

Deposition and accumulation of aerosol particles on photovoltaics (PV) panels, which is commonly referred to as “soiling of PV panels,” impacts the performance of the PV energy system. It is desirable to estimate the soiling effect at different locations and times for modeling the PV system performance and devising cost-effective mitigation. This study presents an approach to estimate the soiling effect by utilizing particulate matter (PM) dry deposition estimates from air quality model simulations. The Community Multiscale Air Quality (CMAQ) modeling system used in this study was developed by the U.S. Environmental Protection Agency (U.S. EPA) for air quality assessments, rule-making, and research. Three deposition estimates based on different surface roughness length parameters assumed in CMAQ were used to illustrate the soiling effect in different land-use types. The results were analyzed for three locations in the U.S. for year 2011. One urban and one suburban location in Colorado were selected because there have been field measurements of particle deposition on solar panels and analysis on the consequent soiling effect performed at these locations. The third location is a coastal city in Texas, the City of Brownsville. These three locations have distinct ambient environments. CMAQ underestimates particle deposition by 40% to 80% when compared to the field measurements at the two sites in Colorado due to the underestimations in both the ambient PM₁₀ concentration and deposition velocity. The estimated panel transmittance sensitivity due to the deposited particles is higher than the sensitivity obtained from the measurements in Colorado. The final soiling effect, which is transmittance loss, is estimated as $3.17 \pm 4.20\%$ for the Texas site, $0.45 \pm 0.33\%$, and $0.31 \pm 0.25\%$ for the Colorado sites. Although the numbers are lower compared to the measurements in Colorado, the results are comparable with the soiling effects observed in U.S.

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1. Introduction

1.1 The soiling of photovoltaic panels

Soiling of photovoltaic (PV) panels, which is the process by which airborne particles deposit and accumulate on solar panels, impacts the performance of the PV energy system. The deposited particles on the panel absorb and backscatter part of the incident solar radiation, thereby reducing the panel energy transmittance. The performance loss due to the soiling of panels, referred to as the soiling effect, varies by environment. In sunny, arid, dusty regions such as the Middle East and India, the power losses have been reported to be between 20% to 70% (Elminir et al., 2006; Hasan and Sayigh, 1992; Hegazy, 2001; Said, 1990; Sayigh et al., 1985), while in locations with frequent precipitation or low ambient particle concentration, the energy loss is typically below 5% (Hottel and Woertz, 1942; Sarver et al., 2013). A recent study reports a 2.8% reduction in energy transmittance for every g/m^2 of particulate matter deposited on the solar panel based on observations from five locations across the continental U.S. (Boyle et al., 2017). In addition to spatial variation, the performance loss can vary when deposited particles on the panel accumulate over time and then get removed by wind, precipitation, or other manual cleaning mechanisms and changes according to system's specifications, such as panel material, tilt angle (Sarver et al., 2013; Maghami et al., 2016; Ahmed et al., 2013).

It is desirable to determine the expected soiling effect at a given location because the effect decreases the system energy production by decreasing the solar panel transmittance while also increasing the uncertainty in system performance. The National Renewable Energy Laboratory (NREL) has generated a map that highlights soiling effect information from parameters of fielded PV panels at >80 locations across the U.S where there is ongoing soiling measurements or past measurements (National Renewable Research Laboratory). However, because soiling rate varies across time due to changes in the environment, a map showing soiling rate base on past or on-going measurements may not serve well the need in predicting soiling effect. Past modeling efforts include prognostics models that predict the soiling effect based on physical parameters such as wind speed, temperature, and radiation (Chokor et al., 2016). The suitability of these models is unfortunately often limited to a specific location. Other attempts include more advanced data sciences. For example, an artificial neural network (ANN) approach was applied to model PV panel cleanliness in a field at Doha Qatar (Javed et al., 2017). Although the ANN model is theoretically applicable to any place, it is still constrained by the availability of high quality measurement data in practice. There are multiple factors impacting the soiling effect, such as site-specific environment (e.g., significant emission sources and wind erosion), meteorological parameters, and the PV system specifications. Micheli and Muller (2017) quantified the strength of the correlation between the soiling effects and 102 environmental or meteorological parameters across 20 sites located in eight states of the U.S. In addition to meteorological parameters (such as precipitation frequency, accumulated precipitation, and wind speed), air pollution data (such as mean PM_{2.5} and PM₁₀ concentrations within certain distances of the site), site environment specification parameters (such as distance from a highway, distance from dirt roads, distance from the ocean, and the wind erosion index), hazard related parameters (such as fire risk regime), panel characteristics (e.g., tilt

angel, angle between wind direction, and panel surface) and land use related parameters. The results showed that the annual average of daily mean particulate matter (PM) concentration recorded by monitoring stations deployed near the PV systems is the best predictor of soiling effect, implying that ambient air quality has a significant impact on solar panel efficiency. In addition, among different meteorological parameters precipitation pattern was also found to be the most relevant because the average length of dry periods had the best correlation with the soiling ratio.

Despite numerous studies on the soiling issue by the solar energy research community in past decades, a comprehensive review by the National Renewable Energy Laboratory (NREL) pointed out that the fundamental processes related to particle deposition and their effect on energy transfer are still not fully understood (Sarver et al., 2013). The purpose of this study is to design and examine an approach to estimate the soiling effect by utilizing PM dry deposition estimations from air quality model simulations and available optical properties. The Community Multiscale Air Quality Modeling System (CMAQ) used in this study is a state-of-the-art air quality model that undergoes continuous development and updating by the U.S. Environmental Protection Agency (U.S. EPA) and is routinely used for air quality forecasts, regulation, and research purposes (U.S. EPA. Office of Research and Development, 2017; Byun and Schere, 2006). The results from the analysis are evaluated at three continental U.S. locations. These locations include an urban site, Commerce City, Colorado (CC); a suburban site, Erie, Colorado (ER); and a coastal city site, Brownsville, Texas (BV). The sites in Colorado (sites CC and ER) were selected because there have been past studies that conducted field measurements of particle deposition on solar panels and analysis of the consequent soiling effect at these locations (Boyle et al., 2014, Boyle et al., 2015), while the site in Texas (site BV) was chosen since the soiling effect estimated for BV in this study would be incorporated into an energy economic assessment project for the city. As a port city, BV is different from CC and ER in terms of weather and emission sources of particles, providing a case to test the proposed approach in a different environment. While there are multiple factors impacting the particle deposition estimates, we focus on the impact of land-use type by analyzing three sets of simulations based on different surface roughnesslength, which is the sole relevant land-use type parameter for particle deposition simulation. The evaluation conducted for the three sites with three different roughness length assumptions will provide a synthesis on how the choice of land-use type could impact atmosphere-surface particle exchange in general and how the presented approach could be applied to estimate soiling effects in practice.

2. Methods

2.1 Description of CMAQ model, particle dry deposition process, and modeling setup

The Community Multiscale Air Quality (CMAQ) Model is a computational tool for both air quality management and atmospheric research (U.S. EPA. Office of Research and Development, 2017; Byun and Schere, 2006). The model represents atmospheric processesincluding emissions from anthropogenic and biogenic sources, meteorological transport, atmospheric chemical reactions, radiation, cloud processing, and deposition. Dry depositionis the exchange process of pollutants from the Earth's atmosphere to its surface in

the absence of precipitation (Pryor et al., 2008; Petroff et al., 2008). The parameterizations of dry deposition velocity in the CMAQ model are represented by electrical resistance analogs. In case of aerosols, the resistances consist of aerodynamic resistance R_a and quasi-laminar boundary layer resistance R_b (Pleim and Ran, 2011).

The aerodynamic resistance R_a describes the turbulent flux at a distance above the surface where turbulent flux cannot penetrate. The flux is modeled by means of turbulent surface layer similarity theory since the momentum goes to zero at some finite height, known as the roughness length (z_0), which depends on the characteristics of the surface (e.g. vegetation, building type, or water). The equation for R_a is:

$$R_a = \frac{\varphi_{hn}}{u_* k} \left[\ln\left(\frac{z}{z_0}\right) - \delta_h\left(\frac{z}{L}, \frac{z_0}{L}\right) \right] \quad (\text{Equation 1})$$

where φ_{hn} is the non-dimensional temperature profile constant for neutral conditions, δ_h is the stability correction function for heat, L is the Monin-Obukov length scale, u_N is the surface friction velocity, and k is the von Karman constant. The roughness length z_0 modifies R_a by impacting the surface friction velocity u_N . z_0 is included in the set of surface characteristic parameters that correspond to each land-use type. CMAQ has 40 land-use types defined for the U.S. domain, with a resolution of 30 m based on the National Land Cover Database (NLCD) (Homer et al., 2015).

The quasi-laminar boundary layer resistance, R_b , describes the diffusion flux by considering the Brownian diffusion, interception, and surface inertial impaction, all of which are dependent on the particle diameter (D_p). For example, Brownian diffusion dominates for particles in the nano size range ($D_p < 100$ nm) while the inertial impaction dominates in the super micron range ($D_p > 1$ μ m). The minimum aerosol dry deposition velocity is therefore found for particles between 0.1 and 1 μ m size range. The equation for R_b is:

$$R_b = \left[F_f u_* (Sc^{-\frac{2}{3}} + E_{im} + E_i + E_{in})^{-1} \right] \quad (\text{Equation 2})$$

where F_f is an empirical correction factor to account for increased deposition in convective conditions as suggested by Binkowski and Shankar (1995), Sc is the Schmidt number for aerosols defined as $Sc = \nu/D_b$, where D_b is Brownian diffusivity which is a function of particle diameter. The interception collection efficiency, E_{in} , depends on the characteristic size of microscale structures such as the size of the leaves, however it is not considered in the CMAQ model due to the much larger model scale (~4–20 km). E_{im} is the impaction efficiency and is also a function of aerosol size.

The CMAQ model represents the final aerosol dry deposition with the two resistances as a function of particle diameter, D_p , as:

$$V_d(D_p) = \frac{V_g}{1 - \exp(-V_g(R_a + R_b))} \quad (\text{Equation 3})$$

where the gravitational settling velocity V_g is:

$$V_g = \frac{\rho D_p^2}{18\mu} C_c \quad (\text{Equation 4})$$

where ρ is the aerosol particle density, μ is air dynamic viscosity, and C_c is the Cunningham slip correction factor to account for the drag of small particles. CMAQ uses modal size distribution to describe aerosol population, therefore an integrated V_d is computed for each mode by integrating the equations over each log-normal size distribution as described by Binkowski and Shankar (1995) and Feng (2008). The final deposition flux is computed as the product of the deposition velocity and aerosol concentration at the surface layer.

The uncertainty associated with aerosol dry disposition flux simulated by CMAQ therefore consists of two parts. One part comes from the estimation of turbulent flux, for which the temperature profile, surface friction velocity, and the surface roughness height parameter are the relevant factors. Another part of the uncertainty comes from the particle concentration and particle number size distribution as the quasi-laminar boundary resistance depends on the particle size, and the overall dry deposition velocity takes an integration over the particle size distribution.

2.2 Description of the CMAQ model setup and simulations

In this study, the CMAQ model version 5.2 is used to simulate the full-year 2011 for a domain covering the continental U.S. with $12 \text{ km} \times 12 \text{ km}$ horizontal grid cells, 35 vertical layers with varying thickness from the surface to 50 hPa, and an approximate midpoint of 10 m for the lowest surface model layer. The year 2011 was chosen because there are deposition measurements available for the evaluation needed in this study, it is a base year for the EPA's National Emission Inventory (NEI) (U.S. EPA, 2011), and has the most intensive emission information available as compared to other base years. The initial and boundary conditions for the simulation are provided by a 2011 hemispheric GEOS-Chem (Bey et al., 2001) simulation, and the meteorological input data are provided by the Weather Research and Forecast (WRF) model version 3.7 (Skamarock et al., 2008) simulation. Aerosol size distribution in the model is represented by three log-normal modes, which are Aitken mode with mean diameter at $0.06 \mu\text{m}$, accumulation mode with mean diameter at $0.28 \mu\text{m}$, and coarse mode with mean diameter at $6 \mu\text{m}$. The particle composition consists of sulfate, nitrate, ammonium, black carbon, 20 organic compounds, 8 metallic compounds (iron, silicon, aluminum, titanium, calcium, magnesium, manganese, and potassium), anthropogenic emitted coarse particles, coarse windblown soil dust, and remaining unspecified $\text{PM}_{2.5}$ mass. Model input, mechanism options, and model settings are listed in Table S1.

As will be discussed further in Section 3.1, uncertainty in the modeled particle deposition comes from the meteorology input (temperature and surface friction velocity), the surface roughness length parameter (land-use information), and the simulated aerosol concentration and size distribution. The uncertainties associated with the input meteorology and simulated aerosol concentration are not easily quantifiable due to the uncertainties in other models and the complex interplaying atmospheric processes modeled in CMAQ, therefore we focus on the impact of surface roughness length in this study because it is the sole input environment

characteristic parameter that is directly related to the particle deposition velocity estimation. Three different deposition estimates are modeled by CMAQ to qualitatively understand how the land-use type may impact solar soiling effects through the input parameter, surface roughness length. Three CMAQ simulations have been designed: 1. “REGULAR” is the regular CMAQ deposition output, which is calculated based on the area-weighted average surface characteristic parameters over all land-use types that present in a model surface grid. 2. “MOSAIC” is the deposition calculated for the specific land-use type that is consistent with the location of solar panel installation in this study using the 40 m -resolution NCLD land-use data base. 3. “SMOOTH” is the same as MOSAIC except that the CMAQ simulation is conducted with the surface roughness length for the grid cell set as 0.005 m, which represents a smooth surface like a solar panel (Table S2).

2.3 Method in estimating soiling effects from deposition

The method used for estimating the soiling effect is based on Bergin et al. (2017), which considers the different optical properties associated with particles of different composition and sizes. Based on the CMAQ aerosol size distribution, two particles sizes are defined for the calculation. One is the fine particle, which is the sum of Aitken mode and accumulation mode and designated in this manuscript as PM_{2.5} (particles with diameter under 2.5 μm); another is the coarse particle, which corresponds to coarse mode defined in the model and designated as PMC (particles with diameter between 2.5 μm and 10 μm). The total particle concentration would be the sum of PM_{2.5} and PMC and is designated as PM₁₀ (particles with diameter under 10 μm). Six particle compositions, which are black carbon (BC), organic matter (OM), dust, sea salt (SEA), ionic particles (ION, the sum of sulfate, ammonium, and nitrate) and other unspecified particles (UNSPEC), were derived based on CMAQ simulated aerosol species (Table S3). The model simulates BC and OM only in the fine particle mode.

With information on particle deposition simulated by the CMAQ model, the sensitivity of solar panel transmittance (T) to accumulated PM mass on the panel, i.e., the change in solar panel transmittance, ΔT , per unit mass accumulated on the panel (g m^{-2}), is calculated as:

$$\text{Sensitivity} = \frac{\Delta T}{PM} = - \frac{1}{\sum PM_{i,j}} \sum_{j=1}^2 \sum_{i=1}^6 (E_{abs,i} + \beta_j E_{scat,i}) PM_{i,j} \quad (\text{Equation 5})$$

$E_{abs,i}$ and $E_{scat,i}$ are the mass absorption and scattering efficiency associated with particle composition, i , respectively; β_j is the upscatter fraction of particles in fine (PM_{2.5}) or coarse mode (PMC); $PM_{i,j}$ is the accumulated particle composition, i , in either size mode, j . The optical properties associated with these compositions are listed in Table S4. The upscatter fraction, β_j , is taken to be 0.3 for fine particles and 0.02 for coarse particles (Wiscome and Grams, 1976). The E_{scat} and E_{abs} for BC are 1.0 and $0.02 \text{ m}^2 \text{ g}^{-1}$, which are based on a measurement study made in the Gobi Desert region of China (Xu et al., 2004) and airborne dust measurements made over the Pacific Ocean (Yang et al., 2009). OM and ionic particles are assumed to be primarily scattering with negligible absorbing effect so that E_{scat} and

E_{abs} are 4.0 and 0.0 $\text{m}^2 \text{g}^{-1}$ based on a measurement study made in Atlanta (Carrico et al., 2003). SEA particles are assumed to be primarily scattering with negligible light absorbing effect with E_{scat} and E_{abs} as 1.5 $\text{m}^2 \text{g}^{-1}$ and 0 $\text{m}^2 \text{g}^{-1}$ based on the study by Hess et al. (1998). As will be discussed in Section 3.2, the UNSPEC particles could be primarily from road salt, vehicle abrasion, or emissions from coal combustion. Particles emitted from coal combustion consist mainly of sulfate and carbon. Coal fly ash contains particles coated with trace elements including silicon, aluminum, calcium, etc. (Lee, 2011). The chemical composition of particles emitted from vehicle abrasion could consist mainly of trace metals from the brake, rubber from tires, and road erosions, therefore the optical property of particles from this source is hard to estimate. The optical property of road salt could be similar to sea salt. Therefore, optical properties between sea salt particles and ionic particles are used for UNSPEC particles for analysis in this study, with E_{scat} and E_{abs} as 2.0 $\text{m}^2 \text{g}^{-1}$ and 0 $\text{m}^2 \text{g}^{-1}$. It should be noted that the optical properties assigned here are one of the major uncertainty sources to the estimation of transmittance sensitivity and transmittance loss.

The soiling effect, which is the percentage change in transmittance, T , is calculated with the transmittance sensitivity and total particle mass, PM_{tot} , accumulated on the panel as:

$$\Delta T = \text{Sensitivity} * PM_{\text{tot}} \quad (\text{Equation 6})$$

Several assumptions were made when determining the amount of PM accumulation on the solar panel. First, it was assumed that the panels are horizontally installed and that 100% of deposited PM is collected on the panel. Second, assuming there is no manual cleaning of solar panels in practice in the U.S., and assuming rain is the only cleaning mechanism, the scenario is further simplified that the accumulated PM on the panel drops to zero after each rain event. Precipitation data from the WRF simulation is used to determine rain events. Daily accumulated precipitation of 0.3 mm or less is not counted as a rain event, assuming that this amount of precipitation is not sufficient to wash off the accumulated dust on the solar panel (Ahmed et al., 2013). The transmittance sensitivity and soiling effects (change in transmittance) presented in this study are calculated based on yearly or monthly mean PM mass accumulation level, which is calculated as a yearly sum or monthly sum of PM deposition divided by number of non-precipitation days in the year or month.

2.4 Description of evaluation sites and data sets

While the full model evaluation for CMAQ version 5.2 is not available, the published evaluation of CMAQ version 5.1 (Appel et al., 2017) can serve as a good reference for the general CMAQ performance in simulating ambient particle concentrations and compositions over the continental U.S. The updates since version 5.1 that are related to this study include new sources of secondary organic aerosols (Murphy et al., 2017; Pye et al., 2017) and improvement in wind-blown dust emission calculation (Foroutan et al., 2017). However, to provide a robust analysis of the proposed soiling effect estimation approach in this study, the input precipitation and wind speed data from WRF simulation and CMAQ simulations of ambient PM concentration and deposition will be first evaluated against observations from the three selected locations (BV, CC, and ER) before proceeding to soiling effect calculation.

A list of available observation datasets is presented in Table S5. The daily precipitation records from the counties where the three sites (BV, CC, and ER) are located were retrieved from the National Climatic Data Center, operated by the National Oceanic and Atmospheric Administration, through the Climate Data Online portal (National Oceanic and Atmospheric Administration & National Centers for Environmental Information). Observed monthly precipitation frequencies are compared with the input precipitation data by the WRF model. The simulated daily ambient PM_{2.5} and PM₁₀ concentrations at each site (BV, CC, and ER) are compared against observations from monitoring sites included in the Air Quality System (AQS; <https://www.epa.gov/outdoor-air-quality-data>) network (U.S. EPA, 2018). The AQS network contains ambient air pollution data including PM_{2.5} and PM₁₀ collected by U.S. EPA, state, local, and tribal air pollution control agencies from thousands of monitors. There are no particle composition measurements available at the three sites on which this study focuses. However, there are several EPA Chemical Speciation Network (CSN) and Integrated Monitoring of Protected Environments (IMPROVE) network sites in Colorado and Texas that provide daily average concentrations of speciated PM composition, typically every third day (Solomon et al., 2014). The CSN sites are primarily located in urban or suburban areas, while IMPROVE network sites are primarily located in rural areas. The deposition measurements from a specific solar panel soiling study (Boyle et al., 2014; Boyle et al., 2015) will be used to evaluate the simulated particle depositions at sites CC and ER. The deposition measurements were collected using glass plates deployed horizontally, 55 cm above the ground, and covered with a small roof to prevent cleaning by precipitation. The plates were cleaned and weighed before each deployment, and the plates were deployed for lengths ranging from one to five weeks, with the typical deployment being two or four weeks. After deployment the plates were weighed again, and the difference between the weights was taken as the mass of accumulated dust on the plate. The measurements at CC were collected on the roof top of a one-story elementary school located in a mixed industrial and residential area, while the location where measurements at ER were collected is surrounded by farmland. Surface roughness length is one of the parameters defined with each land-use type. Table 1 presents the actual land-use type within a 100 m radius from the site of solar panel installation (Boyle et al., 2015), the top five land-use types by area for the modeled grid cells covering the county where the three evaluation sites are located, the surface roughness length associated with each land-use type.

3. Results

3.1 Evaluation of CMAQ model concentration

All meteorology parameters, such as temperature, wind, and humidity impact the particle dry deposition through emissions, transport, surface exchange, and chemical and microphysical processes. As has been pointed out by Micheli and Muller (2017), precipitation frequency is the most relevant factor among all meteorology parameters that impact the dry deposition estimation and our estimation of particle accumulation level on the solar panel, because more frequent precipitation is related to more frequent cleaning and therefore less particle accumulation. Fig. 1 compares the monthly precipitation frequencies applied in the model and the observations at the three sites during 2011. At BV, the model underestimates the precipitation frequency from June to November with the highest

underestimation of 7 times in September; the model overestimates the precipitation frequency in January, February, April, and May. The highest overestimation of 7 times is seen in January. The comparison in precipitation frequency between the model and observations does not show a clear trend at CC. The largest discrepancies are in August and October, with an overestimation and underestimation of five times, respectively. At ER, the model precipitation is consistently more frequent than observations except for months from October to December. The overall overestimation in precipitation frequency at CC should result in less particle dry deposition and less particles accumulated on solar panels.

Surface friction velocity u_N is another meteorology parameter that impacts the deposition velocity calculation. According to Eqs. (1), (2), (3) in Section 2.1, the higher the u_N , the smaller the aerodynamic resistance, R_a , and quasi-laminar boundary layer resistance, R_b , and the smaller R_a and R_b result in faster deposition velocity. However, there are no measurements available for u_N at the three sites. Therefore, the surface wind velocity is instead compared between observations and the WRF model wind speed at 10 m because the surface friction velocity is positively correlated with surface wind speed (Patil et al., 2016). As can be seen in Fig. S1, the WRF model reconstructs the wind speed variation well at BV and CC, though the magnitude is underestimated at both sites. The annual normalized mean bias for wind speed is -10.76% at BV and -36.93% at CC. At ER, the WRF model wind speed fails to capture the large variability in observed wind speed and has an annual normalized mean bias of -14.15% . In summary, the wind speed at the three sites is underestimated, with the wind speed at CC having the largest negative bias, which could potentially contribute negative bias to the CMAQ simulation of deposition velocity.

3.2. Evaluation of modeled particle accumulation

The simulated ambient $PM_{2.5}$ and PM_{10} are compared to observations from the AQS network, from which one AQS observation site is located for BV, CC, and ER each. The model simulated $PM_{2.5}$ concentration generally compares well with the daily AQS observed concentration at BV, although the concentration is overestimated in the spring (Fig. 2), while the model consistently overestimates $PM_{2.5}$ at the two locations in Colorado. The overestimation is as much as 100% for several days in the spring at both the CC and ER sites and in autumn and winter at CC. The annual normalized mean model bias (NMB) for $PM_{2.5}$ is 74% at CC (the highest of the three sites) and 15% at BV (lowest of the three sites) (Table 2). Seasonal NMB values can be found in Table S6. The model generally underestimates PM_{10} concentrations across the three locations. The underestimation is largest in the summer, with NMBs ranging from -37 to -46% across the three sites. The annual NMB for PM_{10} ranges between -14% and -18% , with the largest bias again for the CC site and the smallest for the BV site. Considering the overestimation in $PM_{2.5}$, the actual underestimations in coarse particles (diameter between $2.5\ \mu m$ and $10\ \mu m$) should be larger than the underestimation in total particle mass indicated by PM_{10} . In other words, the simulated PM has higher fractions of fine particles than observed due to the overestimation in $PM_{2.5}$ and underestimation in PM_{10} . The simulated ratio of $PM_{2.5}/PM_{10}$ is the highest at CC (0.7) and the lowest at ER (0.59), compared to the highest ratio observed ratio of 0.48 at BV and the lowest of 0.35 at CC.

The simulated PM_{2.5} compositions are compared to particle speciation measurements from CSN and IMPROVE networks. In Colorado, there are five CSN sites (located in or around the Denver area) and eight IMPROVE sites (spread across the state) with available data in 2011, while in Texas there are three CSN sites (located in the eastern half of the state) and two IMPROVE sites (located in the western half of the state) available. For the sites in Colorado, total annual PM_{2.5} mass for 2011 is overestimated for both networks, with a mean bias (MB) of 1.93 μgm^{-3} (NMB = 22.8%) for the CSN sites and a MB of 0.30 μgm^{-3} (NMB = 11.5%) for the IMPROVE sites. The overestimation of total PM_{2.5} mass is primarily driven by overestimations of elemental carbon (EC), OM, and soil (dust) at the urban CSN sites and OM at the rural IMPROVE sites, which is consistent with recent studies using the CMAQ modeling system (Appel et al., 2017).

The composition of coarse particles (PMC) at BV clearly reflects the coastal environment, since sea salt (SEA) is a major component in the modeled PMC (Fig. S2). In addition, part of the coarse ionic particles may contain sulfate aerosol derived from the oxidation of dimethyl sulfide emissions from the ocean. The major component in the modeled coarse mode particles at CC and ER is UNSPEC particles. UNSPEC constitutes the dominant portion of PM emission in the NEI and it consist primarily of the directly emitted anthropogenic PM that is not chemically speciated in the NEI. Based on measurement studies conducted in Colorado, the UNSPEC particles could be primarily from road salt, vehicle abrasion, or emissions from Colorado coal combustion (Clements et al., 2014; Moreno et al., 2011; Moreno et al., 2013; Pakbin et al., 2011). Past studies have reported that CMAQ overestimates the UNSPEC particle mass (Appel et al., 2013), thereby indicating the model underestimates other sources of coarse particles. So, for this study, the model overestimates PM_{2.5} concentration due primarily to an overestimation in organic aerosols, underestimates PMC concentration due to missing sources, and underestimates PM₁₀ concentration.

3.3. Evaluation of modeled particle accumulation

The estimated mean daily PM₁₀ deposition amount, deposition velocity, and fraction of fine particles in the total deposition (PM_{2.5}/PM₁₀ ratio) are presented in Table 3. All estimated daily deposition amounts are lower than the measured daily PM accumulation amounts at CC and ER in Colorado, with the underestimation ranging from 40% (ER) to 80% (CC). Several reasons for the discrepancy are 1) that the observations could be biased high due to possible contamination during sample deployment and transportation (Boyle et al., 2015); 2) underestimation of ambient PM₁₀ concentration as discussed in the previous section; 3) underestimation of simulated deposition velocity due to possible underestimation in surface friction velocity, as explained in Section 3.1; and 4) underestimation of deposition velocity, which results from the overestimation of the PM_{2.5}/PM₁₀ ratio in concentration (Table 2). The deposition velocity of fine particles can be up to two orders of magnitude slower than that of PMC particles (Seinfeld and Pandis, 2006). Therefore, for equal ambient PM₁₀ concentrations, a higher fraction of fine particles in the ambient concentration would lead to lower calculated PM₁₀ deposition. A similar analysis to Boyle et al. (2014) is conducted to derive the deposition velocity of PM₁₀ by fitting a least square regression to the average model PM concentration and model daily deposition amount (Fig. S3). The

deposition velocities derived from the linear regression in Fig. S3 are listed in Table 3. Deposition velocities at CC and ER are up to 80% less than the velocity derived from the measurements. There are no deposition measurements available at BV, however the BV estimated deposition amount and velocity are likely more accurate than CC and ER due to more accurate $PM_{2.5}/PM_{10}$ ratio and mass concentrations simulated by the model as well as a possibly more accurate model surface friction velocity at that site.

SMOOTH gives the lowest deposition velocity with roughness length set close to 0 m. A smooth surface has less deposition due to the decrease in particle impaction and interception. For urban land-use types, which have high roughness lengths, the model estimates high deposition velocities (MOSAIC at BV and CC). Because the land-use type “Grass Herbaceous” has a low roughness length that is closer to the roughness length of a smooth surface than to the grid average roughness length, the MOSAIC deposition velocity is closer to the SMOOTH velocity (Table 3). The grid cells covering BV have a relatively diverse land-use type classification. The “Urban” land-use type at BV covers only 21% of the total area (Table 1). The average roughness length for the grid cell is therefore much lower than the roughness length of typical urban land-use types, resulting in the REGULAR deposition to be only 60% of the MOSAIC deposition. Conversely, the urban land-use type covers 54% of the grid cell area for CC, resulting in a REGULAR deposition velocity much closer to the MOSAIC velocity (14% difference). MOSAIC velocity at CC is the output for the land-use type “Grassland Herbaceous,” but that type covers only 6% of the grid cell area. The average roughness length of model grids is weighted higher due to the dominant “Urban” land-use type (44%) and leads to a higher REGULAR deposition velocity estimation than MOSAIC by 47%.

The simulated composition of accumulated fine and coarse particle concentration based on simulation REGULAR is presented in Fig. 3. The composition is consistent across the three estimations because the differences in deposition estimation are only related to the particle size. The concentration of fine particles is much less than coarse particles; the highest $PM_{2.5}$ fraction was 5.5% for the SMOOTH estimation at CC (Table 3). This fraction is likely overestimated due to the overestimation in fine particle fraction in the ambient concentration. In addition, the accumulated PM mass on the solar panel has a seasonal variation that is closely related to the precipitation frequency. At BV, the mean particle accumulation amount is high from April to June due to high ambient particle concentrations in the spring and early summer, as well as less frequent precipitation. At CC and ER, the particle accumulation level is low in the winter due to snow, while also being low in July and August due to frequent rain events.

3.4. Transmittance sensitivity and the soiling effects

Fine particles have a greater influence on panel transmittance due to their larger upscatter fraction (0.3) versus coarse particles (0.02), with the calculated sensitivity showing a clear dependence on the fine particle fraction in the accumulated particle mass (Fig. 4). The annual transmittance sensitivities averaged over the three estimations are $6.67 \pm 1.11\%$, $9.45 \pm 2.63\%$, and $9.58 \pm 2.10\%$ for BV, CC, and ER, respectively. This sensitivity is high compared to the sensitivity obtained from field measurements at CC and ER ($4.1 \pm 1.36\%$)

(Boyle et al., 2015). The estimated sensitivity is not off the reasonable range as a sensitivity between 12 and 17% was estimated based on measurements from an arid region of northwestern India (Bergin et al., 2017). It should be noted that there are large uncertainties associated with both the composition and optical properties of the particle deposition simulation.

The change in solar panel transmittance shows a strong correlation with the deposition amount (Fig. 5). Despite the transmittance sensitivity from SMOOTH being the highest, the final SMOOTH change in transmittance is the lowest at the three sites due to a low-level of particle accumulation on the panel. The impacts of soiling effect are minor at CC and ER, with annual changes averaged over all three estimations of $0.45 \pm 0.33\%$ and $0.31 \pm 0.25\%$, respectively. The transmittance loss measurements by Boyle et al. (2015) has a large variation between -2% to 11% , with most measurements falling between 0% – 5% , which is generally larger than the transmittance loss estimated for CC and ER in this study. The discrepancy is most likely due to the lower particle accumulation level estimated based on the simulation (Table 3). In addition, the possible positivity bias in deposition should partly explain the discrepancy too. The highest transmittance losses are in March, June, and November, corresponding to periods of relative high levels of particle accumulation on the panel at CC and ER. The annual mean transmittance loss at BV is $3.17 \pm 4.20\%$, comparable with measurement studies conducted in other parts of the U.S. (Hottel and Woertz, 1942; Maghami et al., 2016; Ryan et al., 1989). The large standard deviation is due to the high transmittance loss from April to June, when the deposited particles accumulate to their highest level during the year. The calculated transmittance loss for these months range from 5.42% to 16.17% , depending on which deposition estimation is chosen.

4. Conclusion

Three sets of particle dry deposition estimations from the CMAQ model are evaluated and used to estimate solar PV panel soiling effects at three locations in U.S. The three estimates differ by the assumed roughness length, which impacts the deposition velocity calculation. SMOOTH estimation assumes near-zero surface roughness in calculation and provides the lowest annual mean daily deposition at all three sites, with $25.69 \pm 22.49 \text{ mg m}^{-2} \text{ day}^{-1}$, $7.20 \pm 6.88 \text{ mg m}^{-2} \text{ day}^{-1}$, and $7.02 \pm 6.77 \text{ mg m}^{-2} \text{ day}^{-1}$ at BV, CC and ER. MOSAIC is good for environment specific applications as it has the most relevant set of surface characteristics for the deposition calculation. MOSAIC gives the highest annual mean daily deposition as $62.86 \pm 55.06 \text{ mg m}^{-2} \text{ day}^{-1}$ and $15.31 \pm 15.75 \text{ mg m}^{-2} \text{ day}^{-1}$ at BV and CC. REGULAR is based on regular CMAQ simulations, in which the weighted average surface roughness length of each model grid is used to calculate deposition velocity. REGULAR gives the highest annual mean daily deposition as $10.98 \pm 11.52 \text{ mg m}^{-2} \text{ day}^{-1}$ at ER. All three particle dry deposition estimates are lower compared to the field measurements at CC and ER, with the underestimation ranges between 40% and 80% . The reasons include 1) underestimation in ambient total particle concentration with annual normalized mean bias around -17% , and 2) underestimation in deposition rates due to underestimation in surface wind speed input and more frequent precipitation input.

The annual mean transmittance sensitivity averaged across the three estimations is $6.67 \pm 1.11\%$, $9.45 \pm 2.63\%$, and 9.58 ± 2.10 for BV, CC, and ER, respectively. The final estimation on soiling effects, which is the transmittance loss, shows stronger correlation to the total particle deposition than to the calculated transmittance sensitivity. The monthly variation in transmittance loss coincides with the variation in dry deposition that is impacted by precipitation and snow scavenging. The annual mean transmittance loss at BV is $3.17 \pm 4.20\%$. The mean transmittance losses at CC and ER, $0.45 \pm 0.33\%$ and $0.31 \pm 0.25\%$ respectively, are smaller than measurements conducted at the sites. The estimated transmittance losses at three sites are comparable with measurement studies conducted in other parts of the U.S.

The surface roughness length parameter, or land-use type definition, is just one factor contributing to the total uncertainty of the soiling effect estimation. As has been discussed in the method part of the deposition modeling approach, aerosol concentration, size distribution and composition, meteorology, and related boundary layer stability are all important factors that have crucial impact on the final results. In addition, the optical properties of different aerosol particles add another aspect of uncertainty on top of the uncertain particle deposition estimation. Therefore, further exploring the role of deposited particle chemical composition, size distribution, concentration, and optical properties is valuable for the Solar PV community to address the issue of soiling.

Finally, the results in this study also have implications on the potential feedback between air quality and the solar energy system. Short-term events like wildfires, which significantly deteriorate air quality, will have a larger impact than the normally assumed transmission loss on the solar energy system, and therefore are worth considering in the PV energy system performance modeling.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

- Ahmed Z, Kazem HA, & Sopian K (2013). Effect of dust on photovoltaic performance: Review and research status. *Latest Trends in Renewable Energy and Environmental Informatics*, Kuala Lumpur, 2013, pp.193–199.
- Appel KW, Pouliot GA, Simon H, Sarwar G, Pye HOT, Napelenok SL, Akhtar F, and Roselle SJ (2013) *Geosci. Model Dev*, 6: 883–899. doi:10.5194/gmd-6-883-
- Appel KW, Napelenok SL, Foley KM, Pye HOT, Hogrefe C, Luecken DJ, Bash JO, Roselle SJ, Pleim JE, Foroutan H, Hutzell WT, Pouliot GA, Sarwar GS, Fahey KM, Gantt B, Glliam RC, Heth NK, Kang D, Mathur R, Schwede DB, Spero TL, Wong DC, and Young JO (2017) Description and evaluation of the Community Multiscale Air Quality (CMAQ) modeling system version 5.1. *Geosci. Model Dev*, 10: 1703–1732. doi:10.5194/gmd-10-1703-2017 [PubMed: 30147852]

- Bergin HM, Choroi C, Dixit D, Schauer JJ, and Shindell DT (2017) Large reductions in solar energy production due to dust and particulate air pollution. *Environ. Sci. Technol. Lett*, 4 (8): 339–344, DOI: 10.1021/acs.estlett.7b00197
- Bey I, Jacob DJ, Yantosca RM, Logan JA, Field BD, Fiore AM, Li Q, Liu HY, Mickley LJ, and Schultz MG (2001) Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation, *J. Geophys. Res.*, 106: 23073–23096.
- Binkowski FS, Shankar U (1995) The regional particulate matter model — part I: model description and preliminary results *J. Geophys. Res.*, 100 (1995), pp. 26191–26209.
- Boyle L, Flinchbaugh H, and Hannigan M (2014) Ambient airborne particle concentration and soiling of PV cover plates. 2014 IEEE 40th Photovoltaic Specialist Conference (PVSC), Denver, CO, 2014, pp. 3171–3173.
- Boyle L, Flinchbaugh H, and Hannigan MP (2015) Natural soiling of photovoltaic cover plates and the impact on transmission. *Renew. Energ.*, 77: 166–173.
- Boyle L, Burton PD, Danner V, Hannigan MP, King B (2017) Regional and national scale spatial variability of photovoltaic cover plate soiling and subsequent solar transmission losses. *IEEE J. Photovoltaics*, 7 (5) (2017)
- Byun D, and Schere KL (2006) Review of the Governing Equations, Computational Algorithms, and Other Components of the Models-3 Community Multiscale Air Quality (CMAQ) Modeling System, *Appl. Mech. Rev.* 59, 51.
- Carrico CM, Bergin MH, Xu J, Baumann K, Maring H (2003) Urban aerosol radiative properties: measurements during the 1999 Atlanta Supersite Experiment. *J. Geophys. Res.*, 108 (D7), p. 17
- Chokor A, Asmar ME, Lokanath SV (2016) A review of photovoltaic DC systems prognostics and health management: Challenges and Opportunities. Annual Conference of the Prognostics and Health Management Society
- Clements N, Eav J, Xie M, Hannigan MP, Miller SL, Navidi W, Peel J, Schauer JJ, Shafer MM, and Jana BM (2014) Concentrations and source insights for trace elements in fine and coarse particulate matter. *Atmospheric Environment*. 89: 373–381. [10.1016/j.atmosenv.2014.01.011](https://doi.org/10.1016/j.atmosenv.2014.01.011).
- Clements N, Eav J, Xie M, Hannigan MP, Miller SL, Navidi W, Peel J, Schauer JJ, Shafer MM, and Jana BM (2014) Concentrations and source insights for trace elements in fine and coarse particulate matter. *Atmospheric Environment*. 89: 373–381. [10.1016/j.atmosenv.2014.01.011](https://doi.org/10.1016/j.atmosenv.2014.01.011).
- Costa SCS, Diniz ASAC, and Kazmerski LL (2016) Dust and soiling issues and impacts relating to solar energy systems: literature review update for 2012–2015. *Renew. Sust. Energ. Rev.* 63: 33–61.
- Elminir HK, Ghitass AE, Hamid RH, El-Hussainy F, Beheary MM, and Abdel-Moneim KM (2006) Effect of dust on the transparent cover of solar collectors. *Energy Convers. Manag.* 47: 3192–3203.
- Folye K, Roselle SJ, Appel W, Bhawe P, Pleim JE, Otte TL, Mahur R, sarwar G, Young JO, Gilliam RC, Nolte CG, Kelly JT, Gilliam A, and Bash JO. (2010) Incremental Testing of the Community Multiscale Air Quality (CMAQ) Modeling System Version 4.7. *Geosci. Mod. Dev.* 3(1): 205–226.
- Foroutan H, Young J, Napelenok S, Ran L, Appel KW, Gilliam RC, and Pleim JE (2017), Development and evaluation of a physics-based windblown dust emission scheme implemented in the CMAQ modeling system, *J. Adv. Model. Earth Syst.*, 9: 585–608, doi: 10.1002/2016MS000823. [PubMed: 30245776]
- Hasan A, and Sayigh AAM (1992) The effect of sand dust accumulation on the light transmittance, reflection, and absorbance of the PV glazing In: Sayigh AAM (Ed.), *Renewable Energy, Technology and Environment*. Pergamon Press, Oxford, pp. 461–466.
- Hegazy AA (2001) Effect of dust accumulation on solar transmittance through glass covers of plate-type collectors. *Renew. Energy*, 22:525–40.
- Hess M, Koepke P, and Schultz I (1998) Optical properties of aerosols and clouds: The software Package OPAC, *Bull. Am. Meteorol. Soc.*, 79: 831–844;
- Hottel H, and Woertz B (1942) Performance of flat-plate solar-heat collectors. *Trans. ASME*, 64.
- Maghami MR, Hizam H, Comes C, Radzi MA, Rezadad MI, and Hajighorbani S (2016). Power loss due to soiling on solar panel: A review. *Renewable and Sustainable Energy Reviews*, 59: 1307–1316.
- Micheli L, and Muller M (2017) An investigation of the key parameters for predicting PV soiling losses. *Prog. Photovolt: Res. Appl.*, 25: 291–307. doi: 10.1002/pip.2860.

- Moreno T, Querol X, Alastuey A, Reche C, Cusack M, Amato F, Padolfi M, Pey J, Richard A, Prevot ASH, Furger M, and Gibbons W (2011) Variations in time and space of trace metal aerosol concentrations in urban areas and their surroundings. *Atmos. Chem. and Phys.*, 11: 9415–9430.
- Moreno T, Karanasiou A, Amato F, Lucarelli F, Nava S, Calzolari G, Chiari M, Coz E, ARinano B, Lumberras J, Borge R, Boldo E, Linares C, Alastuey A, Querol X, and Gibbons W (2013) Daily and hourly sourcing of metallic and mineral dust in urban air contaminated by traffic and coal-burning emissions. *Atmos. Environ* 68: 33–44.
- Murphy BN, Woody MC, Jimenez JL, Carlton AMG, Hayes PL, Liu S, Ng NL, Russell LM, Setyan A, Xu L, Young J, Zaveri RA, Zhang Q, and Pye HOT (2017) Semivolatile POA and parameterized total combustion SOA in CMAQv5.2: impacts on source strength and partitioning. *Atmos. Chem. Phys. Discuss.*, 10.5194/acp-2017-193, in review, 2017.
- Pakbin P, Ning Z, Shafer MM, Schauer J, and Sioutas C (2011) Seasonal and spatial coarse particle elemental concentrations in the Los Angeles area. *Aerosol Sci. Technol.*, 45: 949–963.
- Petroff A, Mailliat A, Amielh M, and Anselmet F (2008) Aerosol dry deposition on vegetative canopies. Part I: Review of present knowledge. *Atmos. Environ* 42: 3625–3653.
- Pitchford M, Malm W, Schichtel B, Kumar N, Lowenthal D, and Hand J (2007) Revised Algorithm for Estimating Light Extinction from IMPROVE Particle Speciation Data, *J. Air Waste Manag. Assoc.*, 57: 1326–1336. [PubMed: 18069456]
- Pleim J and Ran L (2011). Surface Flux Modeling for Air Quality Applications, *Atmosphere*, 2: 271–302. doi:10.3390/atmos2030271.
- Pryor SC, Gallagher M, Sievering H, Larsen S, Barthelmie RJ, Birsan F, Nemitz E, Rinne J, Kulmala M, and Grönholm T (2008) A review of measurement and modelling tools for quantifying particle atmosphere-surface exchange. *Tellus*, 60B: 42–75.
- Pye HOT, Murphy BN, Xu L, Ng NL, Carlton AG, Guo H, Weber R, Vasilakos P, Appel KW, Budisulistiorini SH, Surratt JD, Nenes A, Hu W, Jimenez JL, Isaacman-VanWertz G, Misztal PK, and Goldstein AH (2017) On the implications of aerosol liquid water and phase separation for organic aerosol mass, *Atmos. Chem. Phys.*, 17: 343–369, doi:10.5194/acp-17-343-2017. [PubMed: 30147709]
- Ryan C, Vignola F, and McDaniels D (1989) Solar cell arrays: degradation due to dirt. In: *Proceedings of the American section of the international solar energy society*. 234–237.
- Said SAM (1990) Effects of dust accumulation on performances of thermal and photovoltaic flat-plate collectors. *Appl. Energy*, 27:73–84.
- Sarver T, Al-Qaraghuli A, and Kazmerski LL (2013) A comprehensive review of the impact of dust on the use of solar energy: History, investigations results, literature, and mitigation approaches. *Renewable and Sustainable Energy Reviews* 22: 698–733.
- Sayigh AAM, Al-Jandal S, and Ahmed H (1985) Dust effect on solar flat surfaces devices in Kuwait In: Furlan C, Mancini NA, Sayigh AAM, Seraphin BO, editors. *Proceedings of the workshop on the physics of nonconventional energy sources and materials science for energy*, ICTP, Trieste, Italy 1985 p. 353–67.
- Seinfeld JH and Pandis SN (2006) *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*, 2nd ed., Wiley Interscience.
- Skamarock WC, Klemp JB, Dudhia J, Gill DO, Barker DM, Duda MG, Huang X-Y, Wang W, and Powers JG (2008) A description of the advanced research WRF version 3, NCAR Tech Note NCAR/TN 475 STR, UCAR Communications, pp. 125.
- Solomon PA, Crumpler D, Flanagan JB, Jayanty RKM, Rickman EE, and McDade CE (2014) U.S. National PM2.5 Chemical Speciation Monitoring Networks—CSN and IMPROVE: Description of networks. *J. Air Waste Manag. Assoc.*, 64: 1410–1438. [PubMed: 25562937]
- U.S. EPA (2016) U.S. Technical Support Document (TSD) Preparation of emissions inventories for the Version 6.3, 2011 Emissions Modeling Platform. <https://www.epa.gov/air-emissions-modeling/2011-version-63-technical-support-document>
- U.S. EPA (2017) Office of Research and Development. (2017, June 30). CMAQ (Version 5.2). Zenodo. 10.5281/zenodo.1167892
- U.S. EPA (2018) Air Quality System Data Mart [internet database] available at <http://www.epa.gov/ttn/airs/aqsdatamart>. Accessed May 7, 2018.

Yu P, Toon OB, Bardeen CG, Mills MJ, Fan T, English JM, and Neely RR (2015) Evaluations of tropospheric aerosol properties simulated by the community earth system model with a sectional aerosol microphysics scheme, *J. Adv. Model. Earth Syst.*, 7: 865–914, doi:10.1002/2014MS000421. [PubMed: 27668039]

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Figure 1.

Daily observed concentration from AQS network and model concentration for PM_{2.5} (left column) and PM₁₀ (right column).

Figure 2.

Seasonal stacked bar plots of $PM_{2.5}$ composition from CMAQ simulation (color filled bars) and from CSN sites observations (empty bars) in the western or southern part of U.S. The individual $PM_{2.5}$ composition (in order from bottom to top) are ionic particles (ION, red), dust (yellow), organic matter (OM, green), black carbon (EC, black) and all other composition (OTHER, purple).

Figure 3. Seasonal stacked bar plots of coarse mode (PMC) particle composition from CMAQ simulation at three sites. The individual PMC composition (in order from bottom to top) are ionic particles (ION, red), dust (yellow), sea salt (SEA, light blue), and other unspecified particle composition (UNSPEC, purple).

Figure 4.

Monthly stacked bar plots of mean $PM_{2.5}$ (plot a, d, g) and PMC (plot b, e, h) accumulation amount with composition information from CMAQ simulation at three sites based on Estimation REGULAR. The individual $PM_{2.5}$ composition (in order from bottom to top) are ionic particles (ION, red), dust (yellow), organic matter (OM, green), black carbon (EC, black) and all other composition (OTHER, purple). Bar plots WRF-modeled monthly number of precipitation events (plot c, f, i) at three sites.

Figure 5. Monthly estimation of solar panel transmittance sensitivity to soiling effect (plot a, c, e), mean fine particle fraction in total accumulated mass on the solar panel (plot b, d, f) at three sites based on three deposition estimations and model precipitation frequency.

Figure 6. Monthly estimation of mean PM_{10} accumulation amount (plot a, c, e) and transmittance change (plot b, d, f) at three sites based on three deposition estimations and model precipitation frequency.

Table 1.

Land use type at three locations and available observations.

Site	Land use type where panels are installed	Top five land types presented in the model grid cells (percentage) ^c	Observation data sets
Brownsville, Texas (BV)	Urban ^a	Urban (21%) Cultivated crops (17%) Shrub scrub (11%) Emergent herbaceous wetland (11%) Woody wetland (9%)	Daily PM _{2.5} and PM ₁₀ concentration from AQS network
Commerce City, Colorado (CC)	Urban ^b	Urban (54%) Cultivated crops (27%) Grassland herbaceous (11%) Pasture hay (3%) Woody wetland (2%)	Daily PM _{2.5} and PM ₁₀ concentration from AQS network On-site deposition measurements
Erie, Colorado (ER)	Grassland herbaceous ^b	Urban (44%) Cultivated crops (38%) Grassland herbaceous (6%) Pasture hay (5%) Woody wetland (2%)	Daily PM _{2.5} and PM ₁₀ concentration from AQS network On-site deposition measurements

^aThe economic assessment of roof top solar panel project targets on the residential area of Brownsville, therefore urban land use is designated as the actual land use where panels are installed.

^bLand use type from NLCD [Boyle et al. 2015].

^cLand use data from NLCD. Urban land use type includes four NLCD land use types: Developed, low intensity, Developed, middle intensity, Developed, high intensity and Developed, open space.

Table 2.

Particle composition derived from model aerosol species.

Composition	Fine particle mode (<2.5 µm)	Coarse particle mode (2.5 – 10 µm)
Sea salt (SEA)	Inferred from Aitken and accumulation mode aerosols species chlorine, sodium, calcium, and magnesium.	Inferred from lumped aerosol species ASEACAT and coarse mode chlorine
Ionic particles (ION)	Sum of Aitken and accumulation modes aerosol species sulfate, nitrate and ammonium	Sum of coarse mode aerosol species sulfate, nitrate and ammonium
Organic matter (OM)	Sum of 35 aerosol species classified as organic matter	None
Black carbon (BC)	Sum of Aitken and accumulation mode of elemental carbon	None
Dust	Inferred from aerosol species aluminum, silicon, calcium, iron and titanium [Foroutan et al., 2016]	Inferred from lumped aerosol species ASOIL and coarse mode chlorine
Other unspecified particles (UNSPEC)	The difference between the sum of all aerosol species and sum of the five particles listed in this table in Aitken and accumulation modes.	The difference between the sum of all aerosol species and sum of the five particles listed in this table in coarse mode.

Table 3.

Optical properties for six particulate matter compositions.

Optical Properties	SEA	ION	OM ^b	BC ^b	DUST	UNSPEC
E _{scat} [m ² /g]	1.5	4.0	4.0	0.0	1.0	1.0
E _{abs} [m ² /g]	0.0	0.0	0.0	8.0	0.02	0.02
β^a	0.02 / 0.3	0.02 / 0.3	0.3	0.3	0.02 / 0.3	0.02 / 0.3

^a. 0.02 for coarse mode particles, 0.3 for fine mode particles.

^b. Organic matter and black carbon are simulated only in fine particle mode.

Table 4.

Simulated and observed mean PM_{2.5} and PM₁₀ concentrations, annual normalized mean bias (NMB) and ratio of PM_{2.5} to PM₁₀. Standard deviations are shown in brackets.

Site	PM _{2.5} Obs.	PM _{2.5} Mod.	Annual PM _{2.5} NMB	PM ₁₀ Obs.	PM ₁₀ Mod.	Annual PM ₁₀ NMB	PM _{2.5} /PM ₁₀ Obs.	PM _{2.5} /PM ₁₀ Mod.
BV	10.69 (5.22)	12.32 (8.71)	15.23%	22.41 (8.00)	19.32 (11.26)	-13.80%	0.48 (0.14)	0.64 (0.10)
CC	8.09 (4.95)	14.07 (8.31)	74.01%	24.10 (11.40)	19.88 (10.67)	-17.52%	0.35 (0.18)	0.70 (0.11)
ER	7.06 (4.66)	9.75 (5.52)	37.99%	19.95 (10.23)	16.77 (9.03)	-15.95%	0.38 (0.18)	0.59 (0.15)

Table 5.

Modeled and observed average daily deposition amount, fitted deposition rates, fraction of fine particles in the deposited mass at three locations. Standard deviations are shown in brackets.

	Site	REGULAR	SMOOTH	MOSAIC	Observation
Daily PM₁₀ deposition amount [mg m⁻² day⁻¹]	BV	36.90 (33.26)	25.69 (22.49)	62.68 (55.06)	Not available
	CC	12.61 (13.05)	7.20 (6.88)	15.31 (15.75)	47.30 (18.10)
	ER	10.98 (11.52)	7.02 (6.77)	7.49 (7.33)	19.3 (11.3)
PM₁₀ Deposition Velocity [cm s⁻¹]	BV	2.54 (0.16)	1.71 (0.11)	4.22 (0.26)	Not available
	CC	0.77 (0.16)	0.50 (0.08)	0.90 (0.19)	2.50 (1.01)
	ER	0.81 (0.12)	0.55 (0.07)	0.58 (0.07)	2.01 (1.09)
Fine particle fraction in deposited mass (PM_{2.5}/PM₁₀)	BV	0.024 (0.017)	0.028 (0.020)	0.020 (0.015)	Not available
	CC	0.035 (0.023)	0.055 (0.037)	0.031 (0.021)	Not available
	ER	0.034 (0.024)	0.048 (0.034)	0.046 (0.032)	Not available

Table 6.

Roughness length (m) used for three estimations at three sites.

Site	REGULAR	SMOOTH	MOSAIC
BV	0.22	0.005	0.3~1.0 ^a (Urban)
CC	0.33	0.005	0.3~1.0 ^a (Urban)
ER	0.27	0.005	0.07 (Grassland)

^aEstimation MOSAIC at BV and CC is estimated based on “urban” land use type, include NLCD land use types “Developed, open space”, “Developed, low intensity”, “Developed, middle intensity”, and “Developed, high intensity”, which are assigned with roughness length 0.3, 0.4, 0.6, and 1.0 m.