# Simple Model for Predicting Time Series Soiling of Photovoltaic Panels

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*Abstract*—**Results from a model to predict soiling losses of photovoltaic (PV) arrays are presented. The model uses ambient airborne particulate matter concentrations, both $PM_{10}$ and $PM_{2.5}$, the tilt of the PV array including if the array is tracking, and rain data to estimate soiling losses over time. The model uses relationships between average airborne PM concentrations and dust accumulation, rain removal of accumulated dust, and the accumulated dust and transmission loss that have been developed in the literature to estimate soiling losses in a time series. Multiple model runs were performed and were compared with measured soiling data at seven locations. The model was run with both typical Meteorological Year rain data and with recorded rain data from Oregon State University's PRISM database. Each model was run with variable deposition velocities, static deposition velocities, and static settling velocities. When the model was run with recorded rain data and static settling velocities the results matched the general slopes, frequencies, and magnitudes of soiling losses when compared with measured soiling data. Overall, the simple model demonstrates the ability at accurately simulating soiling.**

*Index Terms*—**Air quality, atmospheric modeling, soil, solar energy, surface soil.**

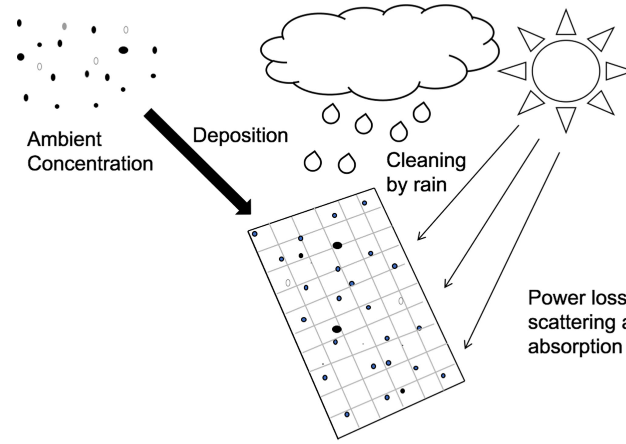


Fig. 1. Framework used for the development of the model. Deposited particulates are assumed to primarily come from measurable airborne concentrations, and that the mass of particulates deposited can predict the fractional power loss of the system. Rain above 1 mm is assumed to completely clean the system.

## I. Background and Introduction

Soiling losses of photovoltaic (PV) systems have been shown to be variable across regions and time [1], [2], [3]. These losses can be a large source of uncertainty in PV system output. Greater understanding and predictability of these losses could result in better understood variability of PV system output, operation, and maintenance costs associated with cleaning system.

Previous studies have found that soiling losses are impacted by the size and chemistry of the deposited particles [4], [5], surface properties of the PV panels [6], [7], and wind speed [8], [9] including resuspension [10] as these parameters are all secondary to the mass of deposited particles [11], [12]. Therefore, in this study, the mass of deposited particles is used as the primary predictor of soiling build up over time.

Several prior studies have built models to predict soiling losses. While these models often do a good job, they are usually made for either a specific location or a solar array and are often complicated [13] and require either large computational power or data sets to create [14].

In this study, we combine several experimentally determined relationships that have shown to be applicable across various geographical areas to create a model that uses widely available data to predict soiling losses on PV systems over time. The results of the model are compared with actual soiling losses from seven installed PV systems across the southwestern United States.

## II. Methods

The model developed in this study calculates particle deposition from the atmosphere, assesses removal by rain, and calculates total accumulated particulate mass. At each time step, the total accumulated particulate mass is then used to estimate the soiling loss. This process allows the evaluation of soiling over time; given time series information about ambient particle concentrations, rainfall, and information about PV array tilt, and tracking. This model is designed to be able to easily build on additional impacts of soiling, such as resuspension from wind, adhesion from dew formation, and surface properties of the PV panel, however these affects are not included in the model at this time.

The model starts with the assumption that soiling occurs by particle deposition from the atmosphere, and can be modeled as shown in Fig. 1. Ambient particulate matter concentrations were used as input data and then related to particulate mass

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deposition by

$$m = (v_{10-2.5}C_{10-2.5} + v_{2.5}C_{2.5})t\cos(\theta) \tag{1}$$

where $m$ is mass accumulation per time step in g-m$^{-2}$, $t$ is the time step in seconds, $v$ is deposition or settling velocity in m-s$^{-1}$, $C$ is ambient particulate matter concentration in g-m$^{-3}$, $\theta$ is the PV system deployment angle, the subscript 10–2.5 indicates for the particles from 10 to 2.5 $\mu$m in aerodynamic diameter and the subscript 2.5 is for particles smaller than 2.5 $\mu$m in aerodynamic diameter. The angle is variable for tracking systems and is taken as the average angle over the time step.

Variable deposition velocities were calculated for each particle size using methods described in Sienfield and Pandis [15]. In this model deposition velocity is assumed to be a combination of various resistances to deposit particles

$$v_d = \frac{1}{r_a + r_b} + v_s \tag{2}$$

where $v_d$ is the deposition velocity, $r_a$ is the aerodynamic resistance calculated with (3), $r_b$ is the quasi-laminar layer resistance calculated with (5), and $v_s$ is settling velocity calculated with (6).

The aerodynamic resistance $r_a$ is a piecewise function that is constant for any particle size, thus, $r_a$ only needs to be calculated once. The piecewise function used to calculate $r_a$ is

$$r_a = \begin{cases} \frac{1}{ku_*}[ln(\frac{z}{z_0}) + 4.7(\zeta - \zeta_0)] & \text{if } 0 < \zeta < 1 \\ \frac{1}{ku_*}ln(\frac{z}{z_0}) & \text{if } \zeta = 0 \\ \frac{1}{ku_*}\left[ln(\frac{z}{z_0}) + ln(\frac{(\eta_0^2+1)(\eta_0+1)^2}{(\eta_r^2+1)(\eta_r+1)^2})\right] & \\ +2(\tan^{-1}\eta_r - \tan^{-1}\eta_0) & \text{if } -1 < \zeta < 0 \end{cases} \tag{3}$$

where $k$ is Von Karman Constant, $z$ is the reference height of impaction in m, and $z_0$ is the roughness length in m, which was assumed to be 1 in this model. The variables $\zeta$ and $\zeta_0$ are $z$ and $z_0$ divided by the Monin–Obukhov length, $L$ in m. The variables $\eta_0$ and $\eta_r$ are simplifying variables that are equal to $(1 - 15\zeta_0)^{1/4}$ and $(1 - 15\zeta)^{1/4}$, respectively. Friction velocity, $\boldsymbol{u_*}$, is calculated by

$$\boldsymbol{u_* = \frac{\kappa \bar{u}_x(h_r)}{ln(h_r/z_0)}} \tag{4}$$

where $\boldsymbol{\kappa}$ is Boltzmann's constant and $\boldsymbol{\bar{u}_x(h_r)}$ is the wind velocity at a reference height $\boldsymbol{h_r}$.

The quasi-laminar resistance, $r_b$ was calculated for each particle size bracket. For this study it was assumed there occurs no interception, which reduces $r_b$ to

$$r_b = \frac{1}{3u_* R_1(E_B + E_{IM})} \tag{5}$$

where $R_1$ is the correction factor for the fraction of particles that stick to the surface, $E_B$ is the collection efficiency from Brownian Diffusion, and $E_{IM}$ is the collection efficiency from impaction.

The settling velocity was calculated using

$$v_s = \frac{1}{18}\frac{D_p^2 \rho_p g C_c}{\mu} \tag{6}$$

where $D_p$ is the spherical particle diameter in $\mu$m, $\rho_p$ is the density of particle in kg-m$^{-3}$, $g$ is gravity in m-s$^{-2}$, $C_c$ is the slip correction factor, and $\mu$is the air viscosity in kg-m$^{-1}$ s$^{-1}$. Additional details on the calculation of the variable deposition velocities can be found in [15].

The values used for the static deposition velocities were obtained from research which observes deposition velocities at different meteorological conditions. Values of 9.17 and 1.5 cm-s$^{-1}$ were mean observed deposition velocities for $PM_{10-2.5}$ and $PM_{2.5}$ [16]. The model was also run by settling velocities in place of deposition velocities. The values used for settling velocities of 0.4 and 0.09 cm-s$^{-1}$ for $PM_{10-2.5}$ and $PM_{2.5}$ were used from a model developed by Sehmel for the aerodynamic diameters of 10 $\mu$m and 2.5 $\mu$m, respectively [17].

Daily average ambient particle concentration data was obtained from the Environmental Protection Agency [18], for the year 2015. These data were used to calculate mass deposition using (1). Once the mass deposited for each time-step was calculated, this mass deposition was added to the prior mass accumulation to find the current total mass accumulation. This was repeated for each time-step to obtain a time series of the total mass accumulated on the PV system.

Several works have shown that various amount of rain will clean panels [2], [3], [19] and in this study 1 mm of precipitation is used as the cleaning threshold. If more than 1 mm of rain is recorded in a time step then the panels are assumed to be completely cleaned, and the total mass accumulation at that time is set to zero.

After the total deposited mass was calculated the transmission loss was calculated by

$$1 - SR = 34.37\,\mathrm{erf}(0.17\omega^{0.8473}) \tag{7}$$

where $SR$ is the soiling ratio (or one minus the transmission loss), and $\omega$ is the total mass accumulation in g-m$^{-2}$ at that time. This relationship was fit to experimental data by Hegazy [11] and has been shown to agree with soiling losses in other areas [12].

The model was designed as a predictive model that can use hourly rain data from the Typical Meteorological Year 3 dataset (TMY3) [20]. The model was also run using daily recorded rain obtained from PRISM Climate Data at Oregon State University for the year 2015 [21]. Since there is not a dataset that contains predicted and/or typical values for ambient PM concentrations, for both the TMY3 and PRISM simulations, the recorded ambient PM concentration data recorded in 2015 was used.

Modeled soiling ratios were compared with actual soiling ratios for the year 2015 that have been published for 19 sites [22]. Seven of those sites were chosen for comparison sites. These sites were chosen for their length of available data and variety of soiling losses. Three of the seven sites are located in Arizona in Yuma, Pima, and Maricopa counties. The remaining four sites are located in central/southern California in Imperial, Riverside, Fresno, and San Luis Obispo counties. The Yuma, Maricopa,

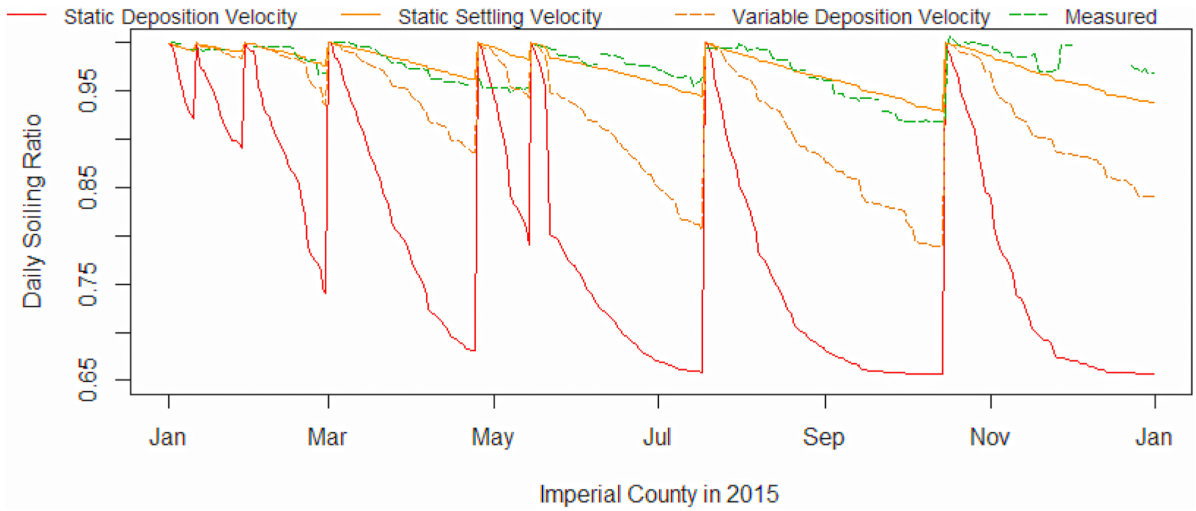


Fig. 2. Model results when using static settling velocity, static deposition velocity, and variable deposition velocity compared with measured soiling losses for a site located in Imperial County California in 2015.

Pima, and San Luis Obispo sites have low soiling with less than 4% maximum losses, and Imperial, Riverside, and Fresno had higher soiling ratios with more than 4% maximum soiling losses [22]. This model was in no way based on information from these sites, and they are used only to show how the model may compare to real-world soiling data which use appropriate ambient PM data and rainfall data for these sites.

## III. Results and Discussion

First the model was run to compare variable deposition velocity, static deposition velocity, and static settling velocity. The outputs were compared with measured soiling data at the seven comparison sites. An example of this is shown in Fig. 2 for Imperial county and indicates that the static settling velocity resulted in the most accurate outputs. The static settling velocity model has a similar slope to the measured soiling, when the static and variable deposition velocity model over estimates the soiling losses by a factor of 10 and 5, respectively. While only one example of this behavior is presented, this pattern occurs at the other six sites. For this reason, static settling velocities are suggested as the best to predict soiling losses and were used in the rest of the analysis presented here.

The model results presented in Fig. 3 used static settling velocities, and matched the duration and magnitude of the soiling events recorded in the actual soiling data which use the recorded rain data from the PRISM database. When the model results are compared with the PRISM and TMY3 data it is clear that rain is a dominate factor in soiling events because the severity and frequency of large soiling events are dictated by the frequency of rain.

As seen in Fig. 3 the TMY3 and PRISM model runs produce different results, as expected. The results generated by both rain data sets have the same slopes for soiling losses because they use the same PM data that drives the downward slope. Where the models differ is the occurrence of rain and therefore cleaning events. This again suggests rain is a driving factor in the model. In most instances in Fig. 3, the PRISM outputs closely match the patterns seen in the measured soiling data as this rain data is the actual rain for this time period. The TMY3 data shows different cleaning patterns, but still captures the overall level of soiling for most of these sites, which indicates that the model could be used to predict future soiling losses using this dataset. This displays the model's ability to accurately predict soiling losses given accurate rain data.

To further demonstrate the model's dependency on rain data, the cleaning threshold required for the model to clean the system was varied to 0.5 and 5 mm from the 1-mm threshold the model uses. The cleaning threshold sensitivity analysis, presented as Fig. 4, was performed on the static setting velocity model for Imperial County with PRISM rain data. It can be seen in Fig. 4 that the output of the model differs greatly depends on the cleaning threshold. When the threshold is a lower value, such as 0.5 mm, the model experiences more frequent cleaning events. While in contrast, when the threshold is greater, such as 5 mm, the model experiences less frequent cleaning events.

The PRISM model runs presented outputs that both fit and diverge from soiling seen in the high and low soiling sites. Imperial County is an example of the model that accurately simulates soiling at a high soiling site, while there is some disagreement in the model for Fresno County. Yet, in the case of Fresno County, the measured soiling loss data experienced a cleaning event in September 2015 that resulted in reduction of the soiling losses that was not simulated in the model. The model performs well at modeling soiling losses at San Luis Obispo and Pima county, both sites with low soiling. Although, both rain models over estimated soiling losses in Yuma County, which is also a low soiling site.

In order to further assess the model, statistical evaluations were performed. Since soiling is a phenomenon that compounds over time, the daily change in soiling between the model and the comparison data were taken, and these daily differences were

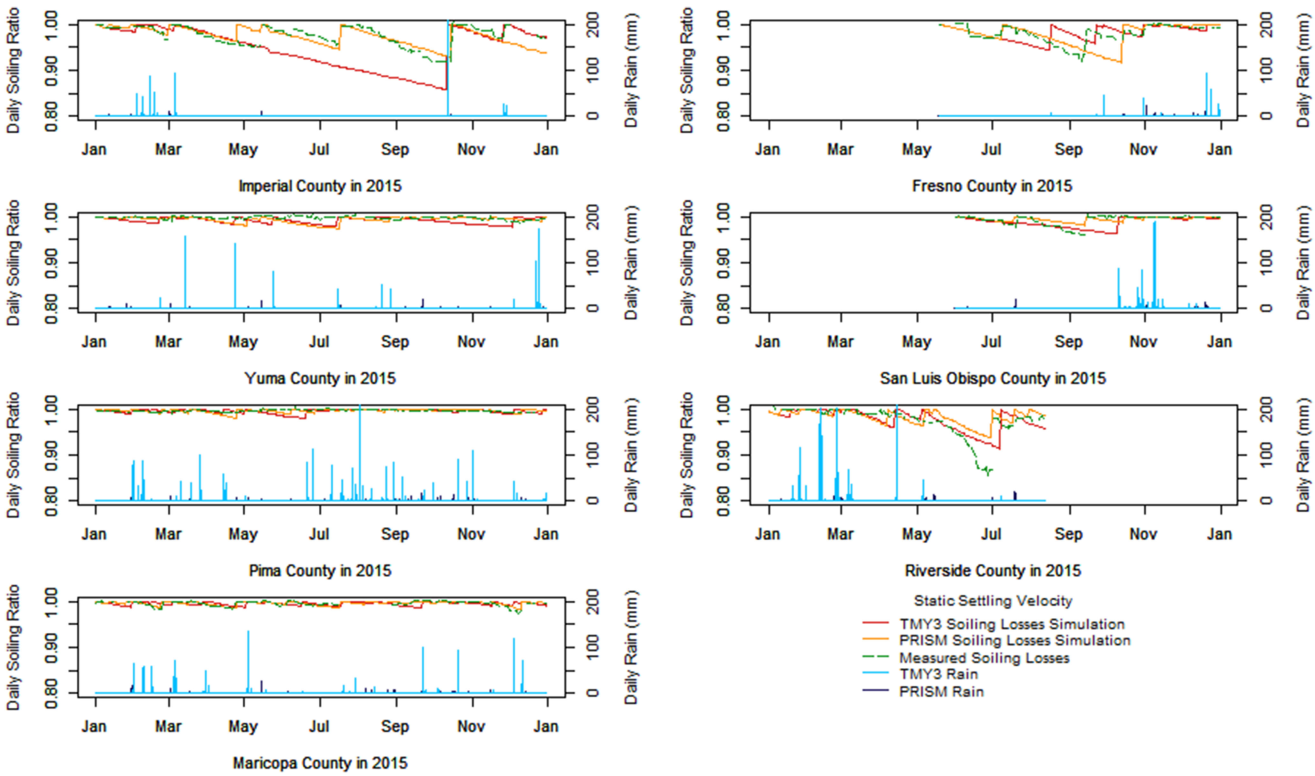


Fig. 3. Simulations results run using static settling velocities with TMY3 (typical rain data, not related to 2015) and PRISM (actual data near the sites for 2015) rain data compared with measured soiling ratios for seven locations in the southwestern United States.

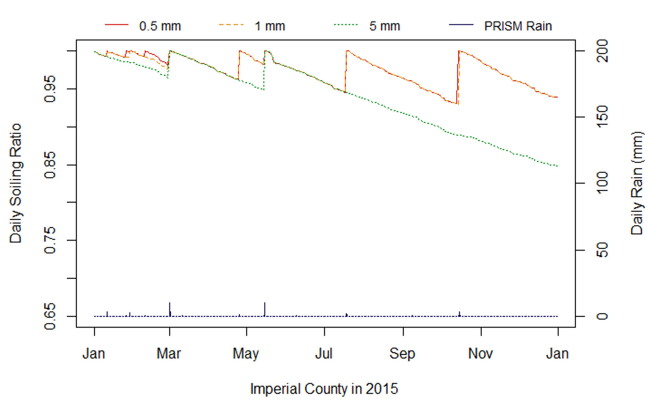


Fig. 4. Cleaning threshold sensitivity analysis compared with the chosen cleaning threshold of 1 mm to a lower value of 0.5 mm and a greater value of 5 mm for the static settling velocity model for Imperial County with PRISM rain data.

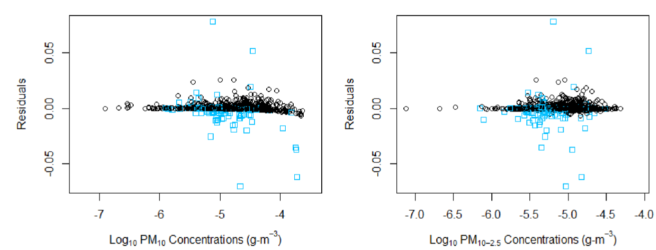


Fig. 5. Residuals between the compilation of differenced variable deposition velocity simulation data from each site and the differenced measured data for ambient $PM_{10}$ and $PM_{10-2.5}$ concentrations where the square data points are time-steps that experienced rain.

used for analysis. Residual plots were generated for the difference between the differenced simulation data and the differenced measured data to see if there is a dependency on $PM_{10}$ and $PM_{10-2.5}$ in the model.

The residual plots between the PRISM static settling velocity differenced data for all of the seven sites and the differenced measured data are presented in Fig. 5. The residual plot presented shows there is homoscedasticity within the residuals. There are outliers in the residuals that are a result of the cleaning of the system from a rain event. Data points that experienced rain at the beginning of the time-step are presented as squares. These results further emphasize that rain events drive the model's accuracy.

A linear regression model was run between the differenced simulation data and the differenced measured data for all of the seven sites combined. The slope from the linear model was checked for statistical significance compared with zero. Since there are outliers in the data due to the rain events, the time-steps that experienced rain were excluded from this analysis. The linear regression compilation of the PRISM static settling velocity models and the measured soiling data including and excluding rain time-steps are shown in Fig. 6.

The linear regression excluding the data that experienced a rain event yields a slope of 0.4 that is significantly different

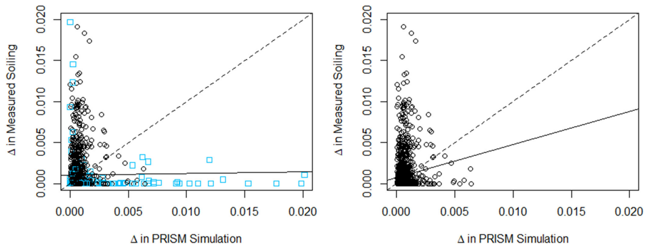


Fig. 6. Linear regression models (solid line) for the complication of the PRISM static settling velocity models and the measured soiling data including (left) and excluding (right) rain time-steps seen as square points along with a 1:1 line (dashed line).

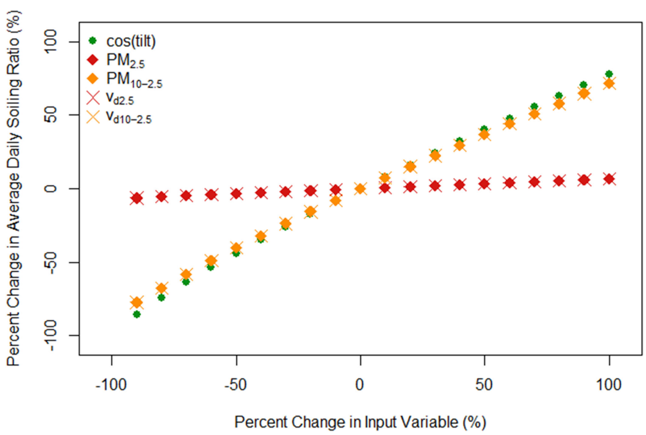


Fig. 7. Sensitivity analysis of the parameters cosine of the PV system tilt, and setting velocity and ambient concentrations for $PM_{10-2.5}$ and $PM_{10}$ for the static settling velocity model for Imperial County with PRISM rain data.

from zero ($p = 7.28 \times 10^{-5}$). This indicates that this model is generally predicting soiling loss rates below the actual soiling loss rate, but is a statistically significant predictor of soiling losses.

An additional sensitivity analysis was performed on the static settling velocity model for Imperial County with PRISM rain data. The variables tested were the cosine of the PV system tilt, the settling velocity, and ambient concentrations for $PM_{10-2.5}$ and $PM_{2.5}$. The variables were varied from − 100% to + 100% of the original value used in the model and the average daily soiling rate percent change was calculated (Fig. 7). It should be noted that in the sensitivity analysis for the ambient concentration of $PM_{10-2.5}$, the value was varied after the $PM_{2.5}$ concentration was subtracted from the $PM_{10}$ concentration to obtain $PM_{10-2.5}$ concentration. Similarly, the $PM_{2.5}$ concentration was not varied until after the subtraction step during the sensitivity analysis for $PM_{2.5}$ concentration.

The sensitivity analysis demonstrated varying the settling velocity and the ambient concentration of $PM_{2.5}$ resulted in the same change in average daily soiling rate. This behavior is also seen in the sensitivity analysis for $PM_{10-2.5}$. This behavior is a result of the settling velocity and the ambient concentration being multiplied together in (1) to calculate mass deposition. It is observed a greater percent change is seen in the average daily soiling rate when $PM_{10-2.5}$ is varied compared with $PM_{2.5}$. This is an indicator that $PM_{10-2.5}$ has a much greater effect on the models soiling estimation than $PM_{2.5}$. The percent change in the output when the cosine of the PV system tilt varied is slightly greater than the outputs percent change when $PM_{10-2.5}$ is varied. This further supports the argument that $PM_{10-2.5}$ has more weight over the soiling estimation than $PM_{2.5}$ since the cosine of the PV system tilt is multiplied by the sum of $PM_{10-2.5}$ and $PM_{2.5}$ terms in (1). These results also indicate that the most important data for this model is $PM_{10}$ along with rain data.

## IV. Conclusion

Overall, the model developed in this study has shown an ability to accurately predict soiling losses at the comparison sites. Additional work has been needed to determine if this model will apply to more diverse geographical areas. The model performed well using settling velocities to calculate mass deposition and recorded rain data gave accurate results for soiling losses at seven different locations. The simulation model using TMY3 data has given reasonable predictive soiling losses for a typical rain year. The model demonstrated strong dependency on the frequency and magnitude of rain the PV system experiences.

The simple static deposition velocity model built in this study requires only time series of ambient $PM_{10}$, $PM_{2.5}$, and rain; and the angle of deployment of a PV panel to accurately predict long-term time series soiling for a PV array. The model built in this study does not include many factors that have been shown in the literature to impact soiling. Including rebound and resuspension of particles from wind [23], cementation and dew formation [24], and PM larger than 10 $\mu$m in aerodynamic diameter [25]. Future work could involve including these mechanisms, to increase the accuracy of the model, especially in short time periods, and verify the model's usefulness is more diverse geographical areas.

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