PV SoilSayer Soiling Model Validation

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1 Introduction

Soiling of PV panels is the process in which airborne particles deposit and accumulate on the panel surface, reducing solar irradiance received by the panel by absorbing and reflecting a portion of the incident light [1, 2]. In addition to reversible optical losses, soiling can cause permanent damage to PV modules. In cases of omitted cleaning, cemented dust layers can be very difficult to remove, whereas harsh cleaning with brushes can lead to scratching or abrasion of anti-reflective coatings or panel glass. Non-uniform soiling causes partial shading, which can lead to the formation of hot spots (areas of high temperature that result in localized decrease in efficiency and accelerated material degradation). Even with regular cleaning, mechanical loads during cleaning or thermal shocks when hot panels are cleaned with cold water can break solar cells or cause crack formation. Soiling has been estimated to cause an average loss of 3-4% of the global annual energy yield of photovoltaics [3]. Soiling also introduces additional maintenance costs and increases the uncertainty in the estimation of PV performance, leading to higher financial risks and interest rates charged to plant developers [4]. Improving soiling loss predictions will allow to both more-accurately predict system energy production, which will lower financial risk and interest rates, and form more optimal cleaning maintenance schedules to mitigate some of these losses.

The vast majority of previous research into soiling has consisted of observations of the reduction in performance due to dust accumulation as a function of exposure time at a particular location. Many researchers use these observations to derive estimates for annual soiling loss (e.g. 5% per year loss) or constant daily soiling rates (e.g. 0.1%/day). These rough estimates are then used in PV performance modeling and for cleaning schedule guidance [5]. Annual PV soiling losses are generally computed by considering the soiling rate (typically the increase in loss per day) for a site combined with rainfall patterns and manual cleaning events. For example, in 2006, Kimber et al. presented a new model for predicting soiling losses in California as a function of rainfall data and the number of manual cleanings [6]. Their empirical model uses typical meteorological year (TMY) data and hourly soiling rates to predict energy production. They suggested a linear model to represent daily system efficiency reduction due to soiling between rainfalls. When daily rainfall exceeds a threshold value, the soiling loss is assumed to drop to a minimum value. They found that their model is more accurate than using a constant annual soiling loss factor, which is a common approach in the industry. The Kimber soiling modeling approach has become popular in the industry. However, the Kimber model does not consider the influence of site-specific environmental parameters such as air quality, wind speed, and humidity.

One of the most comprehensive studies on the influence of environmental parameters on soiling was performed by Micheli et al. at the U.S. National Renewable Energy Laboratory (NREL), who searched for correlations between soiling and 102 environmental parameters at 20 PV sites [7]. Out of all parameters investigated, they found that the annual average of daily mean particulate matter (PM) and precipitation pattern (quantified by the average length of the dry period) recorded by stations near the PV systems are the best soiling predictors. PM is defined as a mixture of solid particles and liquid droplets suspended in air. There are two types of PM generally reported: PM10 and PM2.5, representing the concentrations of airborne PM less than 10 microns and less than 2.5 microns in diameter in a cubic meter of air, respectively. Note that PM2.5 is a subset of PM10, with these smaller particles typically remaining airborne and traveling longer distances than the larger particles included in PM10 because of their lower mass. PM2.5 is the main cause of haze, which is periodically reduced visibility in urban areas, causing a reduction in solar intensity and alteration of the solar spectrum reaching the ground [8]. The NREL study found no clear conclusion about whether PM10 or PM2.5 was a better predictor of soiling. A separate study performed in the Atacama Desert supports NREL's conclusions, finding that soiling at various sites was strongly correlated with aerosol optical depth, which is known to be correlated to PM [9]. While these works have shown that PM concentration seems to be a good explanation for variation in soiling rates over large distances (geographic location), it has been reported to be inadequate to explain day-to-day variations in soiling rates at a particular location because of other weather conditions [2]. To predict soiling over shorter periods such as weeks, days, or even hours, additional parameters such as wind and humidity are thought to be important [10, 11].

2 Semi-Physical Soiling Model

PV SoilSayer has the option to use a semi-physical soiling model that was developed as part of a research collaboration with Michigan State University. The model is described in detail elsewhere [12] so we only provide a brief summary here. The semi-physical soiling model uses PM10 and rainfall patterns as the dominant soiling predictors, but also adjusts the predictions based on local weather conditions (wind speed and relative humidity) at each site. This model is an improvement over previous academic works [13–15] and describes soiling accumulation as the net of three contributing mechanisms: sedimentation, wind-induced deposition, and resuspension. The net soiling accumulation rate is found by multiplying a weighted sum of the deposition velocities due to sedimentation (v_s) and wind ($v_{d,wind}$) by the particulate matter concentration (PM10) and subtracting the resuspension flux (F_{resusp})

$$\dot{m}_{accum} = P_{10}(v_s + w v_{d,wind}) - F_{resusp} \tag{1}$$

where $w = 0.1$ is a dimensionless fitting parameter controlling the relative effect of wind-induced deposition and sedimentation.

The model also considers the effects of rainfall. There is a consensus in the literature that rain often cleans solar panels; however, a minimum amount of precipitation is needed for effective cleaning. Given the wide variability in the observed effectiveness of panel cleaning by rainfall, our model requires a user input (named *Rainfall Clean Amount*) that specifies the amount of rainfall that results in a perfect or near-perfect clean. The quality of the cleaning effect of rainfall is specified in terms of the soiling loss remaining after a rainfall event with precipitation amount reaching the

Rainfall Clean Amount. We assume that any rainfall less than the Rainfall Clean Amount results in a partial cleaning that is proportional to the rainfall divided by the Rainfall Clean Amount. For example, if 6 mm of rainfall is needed for a clean which leaves 5% soiling loss (Rainfall Clean Quality = 5%), then 2 mm will result in a $0.33 \cdot 0.95 = 31.35\%$ reduction in the soiling amount. Users can also specify different rainfall cleaning thresholds for dry and wet seasons and a minimum hourly rainfall rate threshold needed to result in a cleaning effect. Further details about the rainfall cleaning model parameters are described in the PV SoilSayer user guide.

The losses due to soiling are also influenced by the angle of incidence (AOI) of the incoming solar radiation. Multiple studies [9, 16–20] have found that the losses due to soiling are significantly increased at larger AOIs. The AOI of direct solar radiation depends on the sun's position in the sky and the solar panel tilt angle, which is variable for panels that track the sun (single-axis trackers). On sunny days, losses have been found to be symmetric about solar noon, where they reach a minimum [9, 19]. Changes in angular response are likely due to changes in the optical path length (OPL) of the direct radiation through absorbers and scatterers in the dust layers over the PV module; a shorter OPL (e.g. at noon) leads to less attenuation of direct irradiance that reaches the module surface, while longer OPL leads to more attenuation, enhancing soiling effects [9]. On cloudy days, where global irradiance is mostly composed of diffuse radiation, losses appear to be mostly independent of AOI, probably due to the isotropic nature of diffuse radiation [19]. Since the proportion of diffuse to direct solar irradiance varies from day-to-day, models that attempt to describe the incidence-angle modifier due to soiling need to separately consider diffuse and direct irradiance. PV SoilSayer uses the experimentally-validated models developed by Martin and Ruiz to describe soiling-dependent losses due to incident light that is not perpendicular to the solar panel surface [21–23].

3 Model Validation

The semi-physical soiling accumulation model was validated by comparing its predictions with the results from NREL's study for the 20 sites that was described above. For verification, we selected Site 3 (Calipatria, CA) and 11 (Lamont, CA) from the study, which had less noisy data and more significant observed soiling (many of the sites had yearly average soiling ratios that were greater than 99%). Site 3 is a single-axis tracker, while Site 11 is a fixed tilt (20°) system, so this site selection allowed testing the soiling models for both types of systems. Inputs to the soiling model were daily precipitation data provided in NREL's publication, hourly weather data for the year when the soiling measurements were taken downloaded from NSRDB [24], and monthly average particulate matter data taken from the US Environmental Protection Agency's (EPA) database [25]. The daily precipitation data was converted to an hourly format by dividing by 24. We compared the yearly average soiling rates, which are computed by taking the average of the soiling rates during the dry periods. The soiling rates predicted by the models were similar to NREL's measured values for these sites (between 0.1-0.15%/day).

Additionally, we compared the soiling accumulation time-series. Figure 1a shows the comparison for Site 3 from NREL's study when using unmodified input data, as described above. The predicted soiling rate during the dry period matches the measurements, but there are discrepancies in the effect of rainfall. One possible reason for these discrepancies is that the daily rainfall data lacks information about rain intensity (mm/hr), while the same amount of daily rain can be more or less effective in cleaning depending on its intensity. Secondly, NREL's publication provides rainfall data from an online database (PRISM [26]), instead of measuring it directly at the sites. This could mean that the off-site PRISM data measured a different amount of rain than occurred at the site. For a proof of concept, we adjusted the rainfall amounts of a few rain events where the measured effect of rain was different than predicted (Table 1). Note that we did not change the main rainfall pattern (dates when significant rain of more than 1 mm occurred).

Table 1: Daily rainfall adjustments needed to account for measured soiling ratio time-series for NREL Site 3.

Date	Original Rainfall (mm)	Adjusted Rainfall (mm)
Apr 24	1.04	0.13
Jun 8	0.354	1
Jul 18	3.64	4.64
Sep 7	0.4	0
Oct 15	3.1	7

Figure 1 shows the forecast with these adjustments to the rainfall input data. Changes to decrease rainfall can be justified as follows. The rainfall could have been very light and distributed throughout the day, leading to almost no cleaning effect. For example, often rainfall of less than 0.5 mm/hr does not result in a cleaning effect [27]. However, the dataset does not contain information about rainfall intensity. Changes to increase rainfall can be justified by the chance that the rainfall could have been higher at the site than the PRISM database value or more effective at cleaning than predicted.

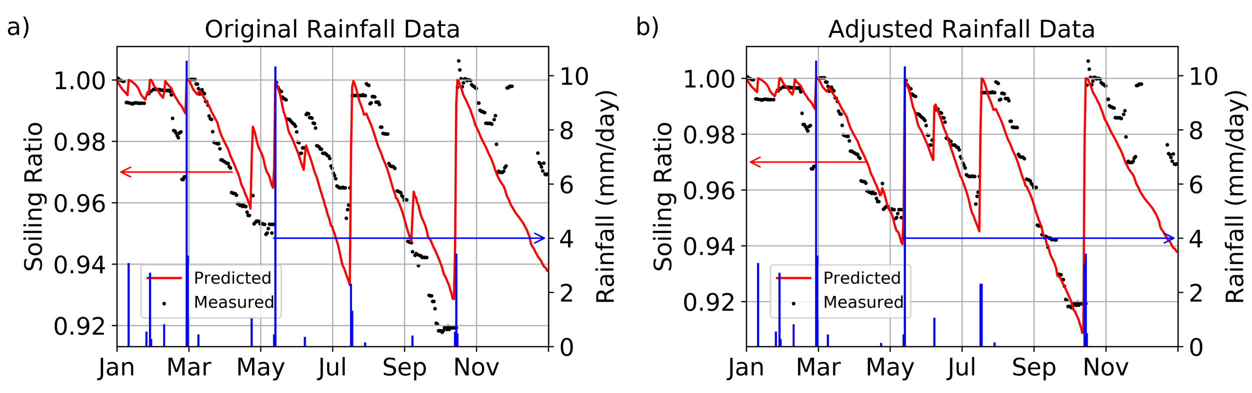

Figure 1: Comparison of model predictions with NREL Site 3 (Calipatria, California) when using precipitation data provided by NREL (a) and when using modified rainfall data (b).

We repeated the same validation approach for NREL Site 11 (Lamont, CA) with the results without and with adjustment to the rainfall shown in Figure 2. With this site, we had to add a few partial rainfall clean events to account for the measured increases in the soiling ratio that did not correspond to any recorded rainfall. The changes to rainfall are listed in Table 2.

Table 2: Daily rainfall adjustments needed to account for measured soiling ratio time-series for NREL Site 11.

Date	Original Rainfall (mm)	Adjusted Rainfall (mm)
Apr 29	0	0.25
May 24	0	0.75
Aug 15	0	0.2
Oct 8	0.65	2.3

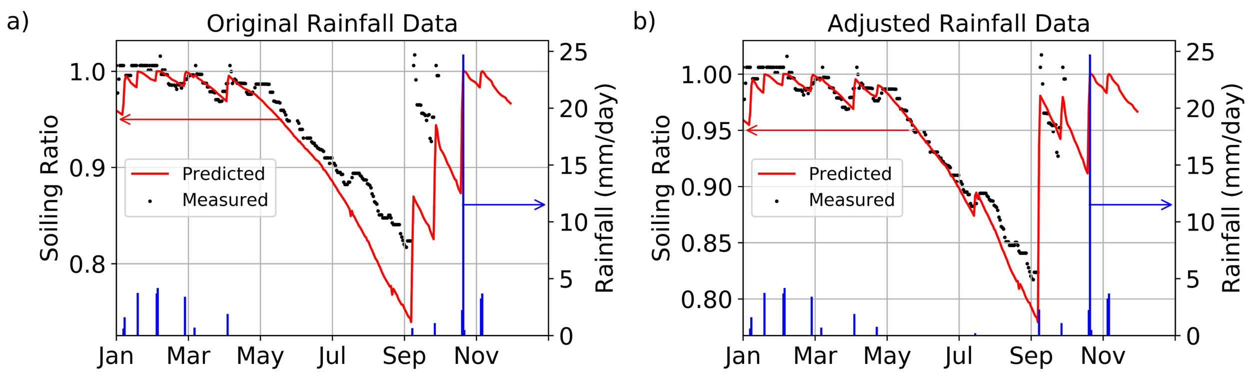

Figure 2: Comparison of model predictions with NREL Site 11 (Lamont, California) measured data when using precipitation data provided by NREL (a) and when using modified rainfall data (b).

4 Conclusion

In conclusion, model validation showed an excellent agreement between measured and predicted dry period soiling rates but a difficulty in predicting the effectiveness of rainfall in cleaning the panels. Modifying the rainfall to change its effectiveness in cleaning allowed to account for most of the discrepancies between measured and predicted data. This demonstrates the need for reliable hourly rainfall data measured on-site and further research into understanding rainfall's effectiveness in cleaning panels as a function of the rain intensity and amount. PV Soilsayer with the semi-physical soiling model described here is expected to help PV system developers, maintainers, engineers, and researchers have a better understanding of soiling losses at their current and potential future sites, as well as have access to easier-to-use and more-accurate soiling analysis tools.

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