Seasonal Trends of Soiling on Photovoltaic Systems

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Seasonal trends of soiling on PV systems

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***Abstract* — This work investigates the seasonal variability of PV soiling losses over a 12-month period for sixteen soiling stations deployed in the USA. A new parameter able to rank the sites according to the cumulative losses occurring over 3- and 6-month periods is presented. The relations between soiling losses and particulate matter are briefly discussed as well. Moving from long-term to shorter-term data increases the complexity of the analysis: monthly correlations are found to have lower accuracy than the longer term ones presented in the literature.**

I. Introduction

Soiling (i.e. accumulation of dust, dirt or particles on a PV surface) can cause dramatic reduction in PV performance [1]. Last year, we presented a preliminary study on the soiling losses of six soiling stations installed in the USA [2]. We showed that the concentrations of airborne particulate matter (PM) and the precipitation pattern were the best soiling predictors. These results were then confirmed in Ref. [3], where performance data of 20 soiling stations were investigated against one hundred parameters. In that work, we found that, when long-term performances of different sites are compared, the correlation between soiling losses and PM has the highest coefficient of determination. Among the meteorological parameters, the average length of the dry period showed the best correlation with the soiling losses, followed by the maximum length of the dry period.

Rainfall patterns and particulate emissions follow seasonal trends that can strongly affect the soiling losses. Indeed, long dry periods can result in higher soiling than that occurring during rainy periods. The identification of seasonal patterns is therefore essential to characterize a site correctly and to determine the most adequate cleaning schedule. The present work aims to investigate, with a systematic approach, the seasonal soiling trends occurring at different sites over a 12-month period and to provide an instrument to quantify the seasonal soiling. In the second part of the paper, an analysis of the causes of seasonal soiling is presented.

II. Seasonal Soiling: Definition and Classification

A. Previous definitions and aim of this work

Seasonality is a concept that has been widely discussed in fields such as meteorology. Colwell [4], using the term "contingency", defined the seasonality as the degree to which time determines states, or the degree to which they are statistically dependent on each other. In this work, the main aim is identifying how much soiling can vary in one year and which factors are driving these changes. Studying the repeatability of seasonality across different years is out of the scope of this paper, which focuses only on 12-month datasets; therefore the term "Variability" has been preferred to "Seasonality" to describe the seasonal trends of soiling independently of their year-to-year recurrence.

A number of works have discussed the seasonal effects of PV soiling. In 2005, Marion et al. [5] considered the effects of a seasonal soiling on the performance ratio. One year later, Kimber et al. [6] showed that PV systems from the Southwest USA had the lowest efficiencies during the summer dry season. El-Nashar [7] investigated the seasonal dust deposition in Abu Dhabi on a thermal solar collector. Caron and Littman [8] found that soiling in agricultural areas was governed by rainfall patterns and by the local seasonal tilling and harvesting activities. These previous works typically discuss the seasonal soiling in a qualitative and often site-specific manner. The goal of this paper, instead, is to provide quantitative instruments to characterize the seasonal soiling losses occurring over a 12-month period. Indeed, the identification of the seasonal soiling trends at a site, and of its atmospheric and pollution data, can help in planning the most adequate cleaning schedule and, thus, to enhance the energy yield while minimizing the maintenance costs.

B. Seasonality Index

A number of indexes have been used in the past to quantify the seasonality of a location. In this work, the "Seasonality Index" (SI), a parameter introduced in 1981 by Walsh and Lawler [9] to describe the degree of variability in monthly rainfall through one year, has been considered. The SI consists of the sum of the absolute deviations of the total monthly accumulated rain from the monthly mean, divided by the total rain accumulated in one year. The authors identified 7 classes, reported and described in Table I. In this work, the SI has been adapted to describe the variability of soiling across a 12-month period and renamed as "Soiling Variability Index" (SVI).

III. Soiling Metrics

A. Soiling stations

Among the sites investigated in Ref. [3], this study considers only those sixteen with at least one full year of data available, listed in Table II each per letters A-P. Sites where data have been missing for more than two consecutive weeks have not been included. Four sites had data for more than 2 or 3 consecutive years available: each year has then been analyzed as an independent dataset and numbered under the letter classification. So the total population considered in this work has been of 21 datasets. A soiling station is installed at each site: each station consists of two identical cells, a pyranometer and a weather station. One of the two PV cells is regularly cleaned while the other is allowed to naturally soil. Soiling is quantified using the daily soiling ratio (daily SRatio), determined using the same procedure described in [3]. The daily soiling ratio is calculated using the short circuit currents recorded between 11:00 AM and 1:00 PM and when the plane of array irradiance is higher than 500 W/m^2. Monthly and annual SRatios can be obtained by averaging the daily values.

TABLE I
SEASONALITY INDEX (SI) CLASSIFICATION, AS DESCRIBED IN [9].

SI	Class
< 0.2	Very equable
≥ 0.2 and < 0.4	Equable but with a definite wetter season
≥ 0.4 and < 0.6	Rather seasonal with a short drier season
≥ 0.6 and < 0.8	Seasonal
≥ 0.8 and < 1.0	Markedly seasonal with a longer drier season
≥ 1.0 and < 1.2	Most rain in 3 months or less
≥ 1.2	Extreme, almost all rain in 1-2 months.

B. Quantifying the soiling variability

The "Soiling Variability Index" (SVI) presented in this work has been adapted from the seasonality index (SI). The SI has been originally developed to consider the monthly accumulated rainfall values. So, in order to make it applicable to soiling, the following monthly soiling metric (S_m) has been considered:

$$S_m(m) = \sum_{d=1}^{n_d} \left(1 - dailySRatio(d)\right) \quad (1)$$

where m is the month, d is the day, n_d is the number of days of the m^{th}-month. S_m is not a direct measure of the energy loss, but an indicator of the potential impact of soiling on the energy yield. S_m is 0 if no soiling occurred; otherwise it is always greater than 0. In order not to affect the S_m of months with a reduced number of daily data, a linear regression has been previously conducted to estimate any missing daily value of SRatios. The Soiling Variability Index for a site over a 12-month period is calculated as:

$$SVI(site) = \frac{\sum_{m=1}^{12} \left| S_m(m) - \left(S_{m\_sum}/12\right) \right|}{S_{m\_sum}} \quad (2)$$

where S_{m_sum} is the sum of the monthly Sm. As the original index, no correction has been made to balance the different number of days among the various months. SVI varies between zero (no variability: all the months have the same soiling) to 1.83 (maximum variability: all the soiling is accumulated in one month).

TABLE II
DESCRIPTION OF LOCATION, LAND COVER AND CHARACTERISTIC WEATHER FOR EACH SOILING SITE USED IN THIS STUDY.

Site	Data collection period	County
A	01/15 – 12/15	Colfax, NM
B	01/15 – 12/15	Luna, NM
C	01/15 – 12/15	Imperial, CA
D	07/15 – 06/16	Fresno, CA
E 1	01/14 – 12/14	Los Angeles, CA
E 2	01/15 – 12/15	
F	01/15 – 12/15	Yuma, AZ
G	08/15 – 07/16	San Luis Obispo, CA
H 1	01/14 – 12/14	Pima, AZ
H 2	01/15 – 12/15	
J	06/13 – 05/14	Kern, CA
K	12/14 – 11/15	Winkler, TX
L	05/14 – 04/15	Iron, UT
M	12/13 – 11/14	Kern, CA
N	01/14 – 12/14	Polk, FL
O 1	06/13 – 05/14	Adams, CO
O 2	06/14 – 05/15	
O 3	06/15 – 05/16	
P	01/15 – 12/15	Maricopa, AZ

C. Results

The annual SRatio and the SVI calculated for each site are reported in Table III. For the purpose of operations and maintenance (O&M) decisions it is valuable to understand if a disproportionate amount of soiling occurs in a cumulative period such as the dry season or during other marked periods such as agricultural harvesting. The SVI will provide more practicality if it can distinguish sites with such periods. Therefore the SVI is correlated against a number of variables derived from the monthly soiling metric to investigate the ability of the SVI to determine the seasonal soiling occurring for a number of consecutive months (Table IV). As shown in Fig. 1, for the sites analyzed in this work, the SVI shows a linear relation with the relative cumulative soiling accumulated in the worst (most-soiled) month and in the worst three consecutive month periods. This result suggests that the

SVI could be used to determine high soiling seasons occurring within a 12-month period.

TABLE III
ANNUAL SRATIO, SOILING VARIABILITY INDEX AND UNCERTAINTY SVI FOR THE SITES INVESTIGATED IN THIS STUDY. UNCERTAINTY IS CALCULATED AS REPORTED IN SECTION III-D.

Site	SRatio	SVI	Uncertainty
A	>0.99	0.8	18%
B	0.98	0.1	36%
C	0.97	0.4	4%
D	0.98	0.4	4%
E 1	0.99	0.6	12%
E 2	0.99	0.7	6%
F	>0.99	0.4	36%
G	0.98	1.0	3%
H 1	0.99	0.5	10%
H 2	>0.99	0.2	43%
J	0.92	0.5	1%
K	0.99	1.1	12%
L	>0.99	1.0	15%
M	0.99	0.6	5%
N	0.99	0.4	12%
O 1	0.98	0.6	6%
O 2	0.99	0.3	13%
O 3	0.99	1.0	6%
P	0.99	0.4	30%

TABLE IV
PARAMETERS USED TO DESCRIBE SOILING VARIABILITY OF A SITE. THE PERCENTAGES REPRESENT THE R^2 OBTAINED WHEN THEY ARE RELATED TO THE SOILING VARIABILITY INDEX.

Parameter	Description	R^2
Months to 50%	Number of months needed to achieve the 50% of the total Sm	82%
Max monthly Sm	Max Sm registered in one month	73%
Max 3-month Sm	Max Sm when three consecutive months are considered	82%
Max 6-month Sm	Max Sm when six consecutive months are considered	37%

The datasets analyzed in this work fall into five of the seven categories given in Table I. The behavior of 19 datasets as divided into the SVI categories is as follows:

- SVI < 0.2: seasonal variability in soiling is not present or negligible in these datasets. Indeed, the variation of monthly SRatio is very limited (< 1%) and the losses are equally distributed during the year (about 50% of the losses recorded in the worst 6 months).
- 0.2 < SVI < 0.4: these datasets are affected by limited seasonal soiling, with 60 to 70% of their soiling losses occurring in 6 months.
- 0.4 < SVI < 0.6: seasonal soiling can have a non-negligible impact, since the value of the monthly SRatio can vary up to 15% during the year. 70 to 80% of the total losses occur in 6 months.
- 0.6 < SVI < 0.8: datasets with high variability in soiling. Most of the losses occur in 3 to 4 months and 85 to 90% of soiling is experienced in 6 months.
- SVI > 1: soiling in these datasets has extreme variability. Around 30% of soiling occurs in the worst month and almost all the losses (> 95%) take place in 6 months.

These results should be extended and refined through the analysis of more datasets.

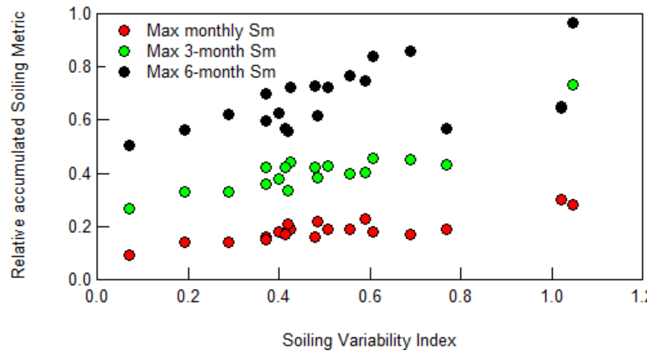

Fig. 1. The relative accumulated soiling metric in 1 month, 3 month and 6 month period plotted against the soiling variability index of each site. The parameters are described in Table IV.

D. Soiling variability index vs. soiling ratio

The determination of O&M decisions cannot leave aside the absolute impact of soiling. Indeed, conducting cleaning at a high-seasonal variation but low-soiling site might not be cost effective. Therefore, the analysis of site soiling should take into account both the SVI and the annualized SRatio. Indeed, despite being able to identify sites with distinct periods of high relative cumulative losses (Fig. 1), the SVI is not able to distinguish high vs. low soiling loss sites. The SVI would rate similarly a site with high soiling losses and a site with low soiling losses if both of them show the same distribution over the year. This is the case of Site C and Site P (Fig. 2), where 20% of the losses occur in the worst month and 30 to 40% occur in the 3 worst consecutive months. The SVI of these two sites is similar (0.40 vs 0.42), even if the annual SRatios are strongly different (0.97 vs 0.99). Another interesting case is Site A, with very low soiling losses (monthly SRatio ≥ 0.99) and a high variability, because more than 40% of the losses are concentrated in 3 months. Despite the high SVI, this seasonal pattern would have a very limited impact on the PV system, since the absolute soiling losses are negligible at any time of the year.

A way to quantify the actual magnitude of seasonal soiling is by considering the impact of the uncertainty on the soiling measurement through a Monte Carlo computation. Indeed, the daily soiling ratios measured at the soiling stations are subject to uncertainties [10] and the uncertainty can be particularly significant for low soiling ratio sites. In order to estimate the uncertainty in SVI, each dataset has been modified, generating daily SRatio values equal to:

$$SRatio^*(d) = SRatio(d) \cdot (1 + x^* 0.005) \qquad (3)$$

being SRatio*(d) the new daily soiling ratio value in input for a *d* day, and x a randomly generated number, regenerated on each day, with a value between -1 and +1. SRatio*(d) is set to be always ≤ 1. In this approach a fixed 5% uncertainty on the daily SRatio value has been considered. For each site, the dataset is regenerated 1000 times and, each time, a new SVI is calculated. The results of this analysis (Table III) show that the uncertainty on SVI tends to increase with the soiling ratios, going from values of 1% to 42%.

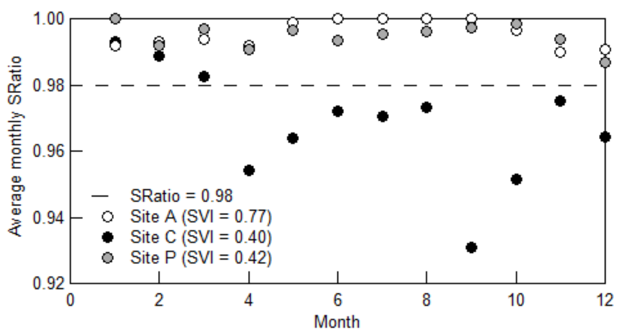

Fig. 2. Average monthly SRatios of Site A, C and P. Site A has high seasonality and low soiling losses. Site C has intermediate seasonality and high losses. Site P has intermediate seasonality and low losses. Months are numbered 1 to 12, from the start of the data collection to the end, so there is not necessarily correspondence between the number and an actual month.

IV. Particulate Matter and Seasonal PV Soiling

A. Data sourcing

The investigation described in the previous section has been focused on the analysis of the performance data recorded at different stations. The results presented so far could not be used for the prediction of future soiling variability at a site. Seasonality is generally determined using multi-year datasets. Lacking such long soiling datasets, the prediction of seasonal soiling relies on the identification of its correlation with other more widely available parameters. In our previous work [3], we showed the relations among the mean soiling ratios and a number of meteorological and environmental parameters on a multi-month time scale. In this section, we briefly discuss the relations between soiling and one of the most impactful parameters among those investigated in [3], the particulate matter, on a short-term scale. The investigation here is limited to the PM_{10} data, calculated from the closest monitoring stations and from the stations located within 50 and 100 km from each site. Daily PM data have been downloaded from the US Environmental Protection Agency databases [11]. PM values for each site have to be determined from nearby monitoring stations, by using an inverse distance weighting algorithm [12]. Daily PM data are more challenging to process than yearly ones: PM concentrations are recorded by each station at different time intervals and some of the stations have data missing for some time periods. In the present approach, the daily concentration of a site is calculated as the average of the measurements available from the nearby stations, weighted according to the distance and the spatial distribution of the stations active on that day. The rainfall data used in this analysis have been sourced from the PRISM database [13].

B. Impact of airborne particulate matter

An R^2 of 0.39 is found if the monthly accumulated daily losses, measured through the S_m, are compared against the accumulated daily PM_{10} concentrations (Fig. 3a). This value can be increased to 0.47 if monthly data are replaced with data accumulated in three consecutive months (Fig. 3b). Data occurring for dry periods longer than 90 days are marked in white, since they appear to have a different trend. Indeed, without those data, the R^2 would raise to 0.63.

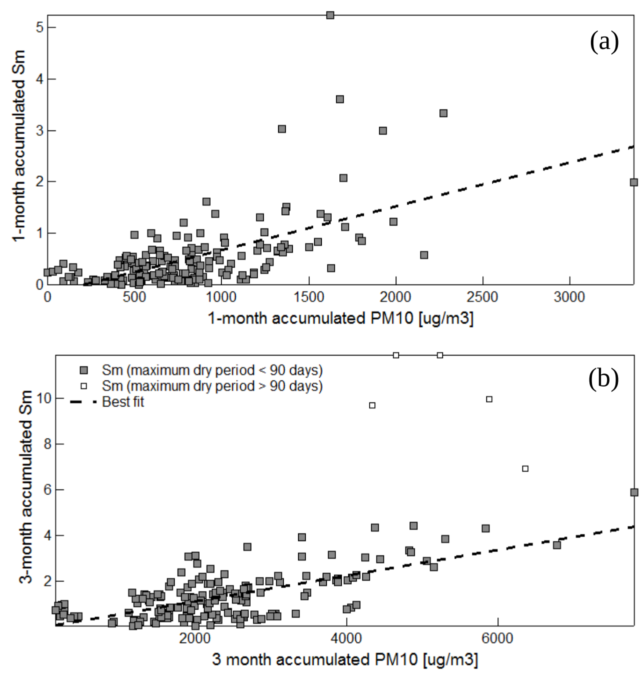

Fig. 3. (a) S_m accumulated each month plotted against the PM_{10} concentration accumulated in the same month. (b) S_m accumulated in three months plotted against the PM_{10} accumulated in the same time period. The maximum length of the dry period counts the number of days elapsed since the last rainfall and, thus, can be higher than the number of days in a month. Data occurring for dry periods longer than 90 days are marked in white.

The lower R^2 registered for PM_{10} in this investigation compared to the previous study [3] are probably due to a number of reasons. First, when short time periods are considered, the variability of a number of parameters becomes more relevant than for annual or longer time periods. Indeed, the complexity of correlating short term PM10 concentrations and PV soiling has already been discussed in literature [14], [15]. For example, the seasonal behavior is expected to be strongly affected by the rainfall pattern and by the distribution of the dry periods, in particular. This is confirmed by a visual analysis of the soiling profile of Site D, in Fig. 4: the daily SRatios are higher when precipitations are more frequent, between November and May. Second, the discontinuity problems with daily PM10 registered by the EPA monitoring stations result in increased uncertainty: the results of this analysis could be enhanced by using alternative data process approaches. Third, the EPA monitoring stations might not be able, in some cases, to register the local seasonal PM10 trend of a site. For example, Site P is surrounded by agricultural fields outside of Denver while the PM stations are within the suburban Denver landscape (Fig. 5). In this case the PM stations will not be able to record the effects of the rural activities that are affecting the site during the harvesting/tilling seasons.

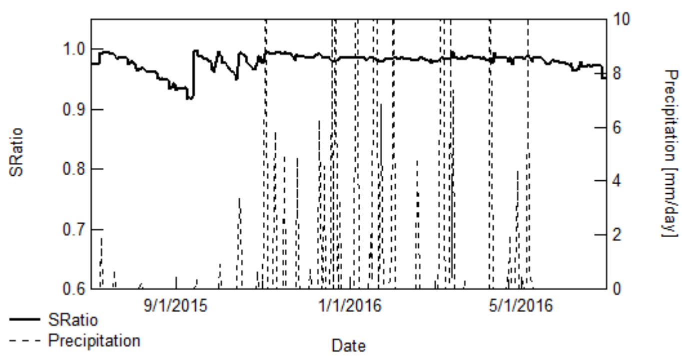

Fig. 4. SRatio profiles of Site D.

V. Conclusions

This paper presents the initial results of an investigation on seasonal PV soiling. The daily soiling performance of sixteen soiling stations installed in the USA has been analyzed and compared.

The first part of the work has been focused on the definition and the identification of seasonal soiling trends. A new parameter, seasonal variability index (SVI), obtained by adapting the seasonality index, has been introduced to quantify the seasonal behavior of soiling over a 12-month period. This parameter provided a means to classify the datasets investigated in this study in five groups depending on the number of months in which most of the losses are experienced. The SVI is a valid instrument for the characterization of soiling variability but cannot distinguish sites with high or low soiling losses, since it is based on the analysis of the relative cumulative losses only. A Monte Carlo computational approach has been used to investigate the impact of soiling station measurement uncertainty on the SVI. The results show that stations at low soiling loss sites can have disproportionately higher uncertainty in the SVI. In this sense, the high uncertainty in the SVI signals that the SVI has low usefulness, which is consistent that there is low practical value in calculating an SVI when the annual soiling losses are lower than 1%.

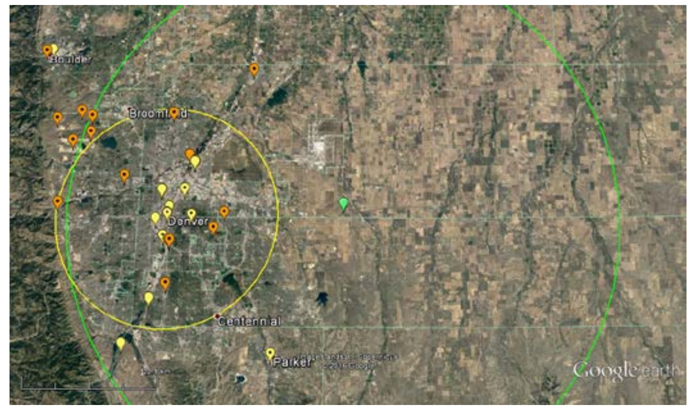

Fig. 5. Aerial view of Site O, in Colorado. The green mark indicates the location of the site; the orange and yellow marks represent the PM_{10} and $PM_{2.5}$ monitoring stations available nearby. The green circle delimitates the area within 50 km from the site. A yellow 20-km circle is represented around the Denver metro area (centered at lat. 39.742043 and long. -104.991531): it can be seen the monitoring stations are concentrated in the urban areas.
Source: 39.75685 & -104.62025. Google Earth, 12/30/16. 01/19/17.

In the second part of the paper, the relations among short-term soiling, particulate matter and rainfall patterns have been investigated. This kind of study is required in order to be able to predict the seasonal behavior of soiling at a site. The correlations among monthly soiling and pollution data have been found to have lower accuracy that those reported previously for longer-term data. These results have been enhanced when the soiling period increased from one month to three months: an R^2 as high as 0.63 was obtained between 3 month cumulative soiling and PM_{10} values. A number of factors that can have impacted this correlation have been listed and should be investigated in future to enable the prediction of seasonal soiling trends.

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