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Photovoltaic cleaning optimization through the analysis of historical time series of environmental parameters

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ABSTRACT

This work investigates the possibility of using historical environmental parameter data to predict the typical soiling loss profile and the most convenient cleaning schedule for a PV site. The three-year performance of a 1 MW system in Southern Spain is evaluated using different soiling extraction methods. When the rainfall pattern is used to detect natural cleaning events, the best results are obtained if a 1.0 mm/hour threshold is considered. However, despite the optimization, setting a fixed threshold is found to lead occasionally to the over- or under-detection of cleaning events. Similar trends in the modelling results are found if the thresholds are set using the maximum hourly or the cumulative daily rainfall data, but the errors and the optimal values change depending on the rainfall dataset. The study also shows that a soiling extraction method based only on precipitation and particulate matter, calibrated against one year of PV data, is able to generate a soiling profile with a mean absolute error of 0.022 and to recommend a cleaning day within a week of the actual optimal dates. This will make it possible to estimate the soiling losses and the optimal cleaning schedule for a PV site even if no power data are available.

1. Introduction

Soiling consists of the deposition of dust, dirt and particles on the surface of photovoltaic (PV) modules. The layer of soiling reduces the amount of sunlight that reaches the PV cell and that can be converted into electricity (Smestad et al., 2020). It causes significant energy and economic losses worldwide, which can be however diminished through an appropriate soiling mitigation strategy (Ilse et al., 2019).

Currently, cleanings are the most common soiling mitigation strategy. In order to minimize the economic costs of soiling, the number and the timing of the cleanings have to be adjusted to the specific conditions of each site, as cleanings are profitable only if their cost is lower than the revenues made with the recovered energy (National Renewable Energy Laboratory (NREL), 2018). A number of models have been presented in literature to optimize the cleaning strategy (i.e. maximize the soiling mitigation profits) of a site depending on factors as the measured soiling accumulation rate, the cost of cleaning and the electricity price (Besson et al., 2017; Jones et al., 2016; Rodrigo et al., 2020; You et al., 2018).

Key in putting in place an optimal cleaning strategy is understanding the soiling seasonality, as the losses can be more or less severe in specific periods of the year (Javed et al., 2020; Micheli and Muller, 2017; Tanesab et al., 2017). These seasonal soiling trends are the results of the variation of the environmental factors affecting the soiling deposition and removal rates (Javed et al., 2020). Both these processes are indeed caused and influenced by a number of variables, such as rain intensity and frequency, airborne particle concentration, wind speed and direction, and relative humidity (Figgis et al., 2019, 2017; Ilse et al., 2018), which can vary with the seasons and the years. Several models have been proposed in the literature to replicate the soiling loss profile of a site through the analysis of the local environmental parameters (Bergin et al., 2017; Coello and Boyle, 2019; Javed et al., 2017; Toth et al., 2020). So far, these have been used to model past energy loss profiles. However, ideally, they could be used to investigate the typical seasonality of a site and to identify in advance the most profitable cleaning schedule (Micheli et al., 2020a). This information can be of value for PV system operators, as it would make it possible to plan the Operations and Maintenance (O&M) schedule even when no PV data are available, for example during the site selection or the PV installation.

Previous works have either proposed new models for the analysis of soiling based on environmental parameters or investigated the optimal cleaning frequency on past soiling time series. This work, instead, attempts to merge soiling modelling and cleaning optimization to evaluate the seasonality of weather and soiling conditions at a site. This way, the

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Nomenclature

C	Particulate matter concentration [g/m^3]
CC	Cleaning costs [€/kW]
C_w	Specific-cleaning cost [€/kW]
d	Day
d_i	Number of days between *d* and the last rainy day
E_d	Soiling-free DC energy yield on a day d [kWh/kW]
$E_{DC,d}$	Actual DC energy yield on a day d [kWh/kW]
MAE	Mean Absolute Error
n_y	Number of years
p	Electricity price [€/kWh]
$PI_{,d}$	Performance Index on a day *d*
R	Revenues [€/kW]
r_s	Soiling Ratio
t	Conversion factor [s/day]
Z	Data point value
ε_{inv}	Inverter's efficiency
θ	Tilt angle [radians]
ν	Particle deposition velocity [m/s]
ω	Total mass accumulation [g/m^2]

most convenient cleaning strategy of a site can be identified without the need of power data. In this light, past soiling time series are generated using only historical environmental parameter data and are then analyzed to identify the cleaning strategy that would typically generate the most profits.

Differently from previous works, this study is conducted on data sourced from a 1 MW PV system in Southern Spain, rather than from soiling measurement devices. This represents an opportunity to investigate the viability of this approach in a real case scenario. The site experiences markedly seasonal soiling (Micheli et al., 2021a), with most of the losses occurring in the long dry summer. While the most soiling intense season might be easily identified from the weather pattern, the cleaning dates that maximize the soiling mitigation profits are more difficult to estimate. A previous study has shown indeed that, for the investigated site, a delay of 2 weeks in cleaning from the optimal date can reduce the profits by a third, and a month delay might reduce them to zero (Micheli et al., 2021a). So, in addition to the weather seasonality, it is also important to understand the inter-annual variability and the repeatability of the factors affecting soiling. This work aims to address these issues, identifying from the analysis of the weather patterns those cleaning dates that are more likely to generate the maximum profits over the years. This way, ideally, one could evaluate not only the typical impact of soiling, but also estimate the revenues achievable through an optimized cleaning schedule even before the PV system is operational.

A recent work conducted the cleaning optimization using historical rainfall data and assuming the perfect knowledge of the soiling deposition rates (Micheli et al., 2020a). In the present study, also the soiling deposition rate values are estimated from environmental parameters (i.e. airborne particulate data). In this case, the models are calibrated and tested using distinct data series (i.e. a training and a testing set) to evaluate the applicability of this model to fielded PV systems.

The work is structured as follows. The methods used for the calculation of the performance index, the extraction of the soiling losses and the estimation of the cleaning mitigation profits are described in 2. All the results are presented and discussed in 3. In particular, the soiling modelling effort is described in 3.1 and 3.2: the models are calibrated using one year of measured soiling data and their estimations are then tested against the data from the two following years. The cleaning optimization is then performed in 3.3: the optimal cleaning day for the site is identified assuming perfect information first, and then using only historical environmental parameters' data. Last, a discussion on the role of seasonality and on the potential effects of extraordinary events on cleaning optimization is reported in 3.4.

2. Methods

2.1. PV performance

The PV system here investigated is located in Granada, Southern Spain. Previous works have made use of data from this plant, to investigate the economic impact of soiling and cleanings (Micheli et al., 2021a; 2020c). While those publications only focused on 2019 data, the present study takes into account the performance of the system since mid-February 2017 to December 2019.

The system has a size of 1 MW and is made of polycrystalline modules oriented south and tilted at 30°. The DC power data used in this work are measured at one of the 100 kW inverters, under the assumption of uniform soiling distribution. The inverter is not subject to clipping. A weather-corrected performance index is extracted using a methodology already employed for the analysis of a utility-scale PV system in Chile (Micheli et al., 2021) through the temperature (King et al., 2004), spectral (Gueymard, 1993; Kasten and Young, 1989) and angular ("ASHRAE standard 93–77," n.d.; Erbs Klein, S. A. & Beckman, W. A., 1983) corrections available in the *pvlib-python* package (Holmgren et al., 2018). With the exception of the locally measured plane-of-array irradiance, hourly weather data have been downloaded from MERRA-2 (Global Modeling and Assimilation Office (GMAO), 2019). Hourly data measured at irradiances outside of the 50 to 1300 W/m^2 range and performance indexes outside of the 0.1 to 1.3 range were discarded, along with any hourly data point outside the two standard deviations (Theristis et al., 2020).

Daily performance index values were calculated considering only the central hours of the day (solar noon ± 1 h) and hours with a POA irradiance > 700 W/m^2. A normalized and corrected performance index was provided to the soiling extraction algorithms described in 2.2 (Fig. 1): the time series was normalized to the 95% percentile and the effect of degradation were removed using the degradation rate identified by the year-on-year decomposition function available on *rdtools* (Jordan et al., 2018; NREL, 2018). Any performance index > 1.0 was set to 1.0. In addition, any daily value on a day *i* outside of two standard deviations of the mean of the values calculated from the data within *i-7* and *i* + *7* was also removed (Micheli et al., 2021b).

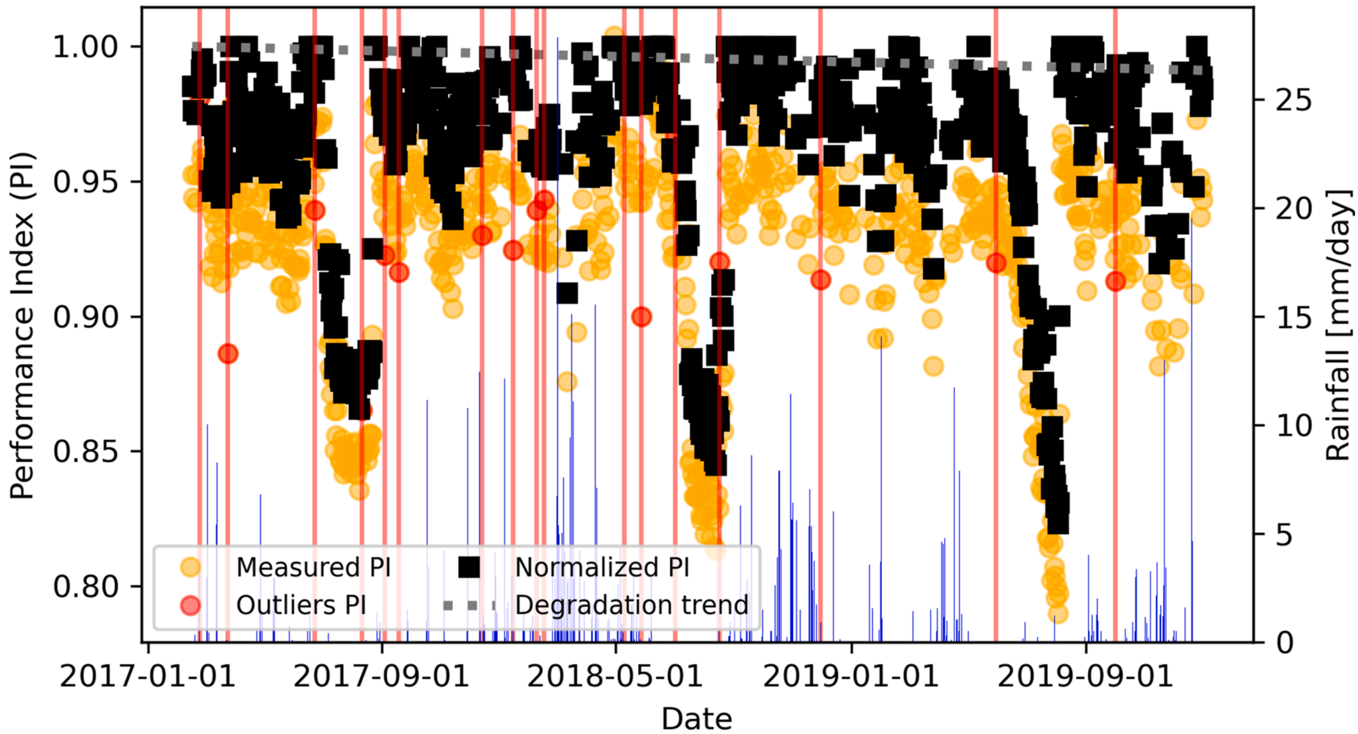

Fig. 1. Performance index profile for the investigated site. Orange round markers: measured performance index. Black square markers: normalized and corrected performance index after the effect of degradation was removed. Red round markers: outliers identified using the two-sigma rule. Grey dotted line: degradation trend. Blue vertical line: precipitation pattern, in mm/day (right y-axis). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.2. *Soiling extraction*

Soiling is quantified using the soiling ratio, defined as the ratio of the actual power output to the expected power output in conditions of no soiling (International Electrotechnical Commission, 2017). The soiling ratio (r_s) has a value of 1 if the PV modules are clean and its value decreases as soiling accumulates on their surface. Soiling loss can be calculated as 1-r_s.

In this work, the soiling ratio has been extracted from the performance index using models based on a two-step process: (i) identification of cleaning events and (ii) modelling of soiling rate in between cleanings. Three soiling extraction models have been employed (described in 2.2.1, 2.2.2, and 2.2.3):

- A Weather-Unaware model (WUM), based on the NREL's Stochastics Rate & Recovery (Deceglie et al., 2018; National Renewable Energy Laboratory, 2018). This approach automatically identifies cleaning events from the PV performance profile, without need of environmental data (i.e. rainfall), and then fits the performance data in between cleanings.
- A Precipitation-and-Performance model (PPM), based on the methodology proposed by Kimber et al. (Kimber et al., 2006). In this case, the cleaning events are determined from the rainfall data, and then the performance data in between rain events of intensity above a predetermined threshold are fitted.
- An Environmental-Parameter model (EPM), based on the method presented by Coello and Boyle (Coello and Boyle, 2019). The soiling profile is generated only using rainfall and particulate matter data, without any PV data in input.

2.2.1. *Weather-unaware model*

Cleanings are detected by identifying positive shifts in the performance index profile that are larger than a fixed threshold. The original equation sets a cleaning event when the shift is larger than the upper fence of the distribution of the absolute values of the differences between neighbor values (Deceglie et al., 2018). A later work reported the identification of false cleanings if the equation was not tuned according to the noise of each individual site (Skomedal et al., 2019). In order to address this issue, false cleaning events were removed in (Micheli et al., 2021) if, after fitting, they did not produce a shift in the modelled soiling ratio larger than a predetermined value. A similar approach is used in this case, with false cleaning events removed if they do not produce any positive shift in the modelled soiling ratio. In addition, a cleaning event occurring on July 14, 2018 is manually removed.

Subsequently, any period in between cleaning events of at least 7 days is fitted using piecewise regression (Micheli et al., 2021b; 2020b). If a change point occurs within seven days of a cleaning event, line regression is used instead. In both cases, the fitting is forced to restart from a soiling ratio of 1, assuming a full recovery after each cleaning. If the R^2 of the fitted data is lower than 0.1 (Micheli et al., 2017a; 2017b), a flat profile is assumed.

The WUM has been chosen as reference model to evaluate the performance of the EPM. This is motivated by the fact that the WUM does not require in input any weather data and therefore does not assume only rainfalls as natural cleaning agents. On the other hand, though, it does not make it possible to model historical soiling profiles if PV power data are not available. Therefore, it cannot be used to evaluate the seasonality of the site and to recommend a typical cleaning date if long-term PV data are not available, which is the aim of this study.

2.2.2. *Precipitation-and-performance model*

Compared to the previous approach, in this case cleanings are identified using the rainfall pattern (Kimber et al., 2006). This model requires the preliminary identification of a cleaning threshold, which defines the minimum amount of rain needed to clean the PV modules (Kimber et al., 2006). Various thresholds have been used in the literature varying from 1 mm/day (Besson et al., 2017; Caron and Littmann, 2013) to >5 mm/day (Hammond et al., 1997; Toth et al., 2020; You et al., 2018). In some cases, the threshold was set on the maximum hourly rain intensity, rather than on the daily accumulated values (Bergin et al., 2017; Li et al., 2020; Valerino et al., 2020). While in most cases, the threshold was arbitrary set, Toth et al. (Toth et al., 2020) selected its value so that it optimized the soiling extraction. The same approach is used in this study: the cleaning threshold is set so that it minimizes the modeling error (3.1). In addition, compared to previous works, both hourly and daily thresholds are evaluated.

It should be noted that a recent study has proposed a relation between the intensity and the cleaning effect of a rain event (Javed et al., 2020). Despite that, the present work assumes a fixed and binary threshold (clean vs. no clean), in agreement with the original model (Kimber et al., 2006). This choice is justified by the soiling profile of the investigated site, which, as shown in previous publications (Micheli et al., 2021a; 2020c), experiences most of the losses in the dry summer and some significant rainfalls at the end of it, which typically wash off soiling completely. Because of this long dry and soiling intense period and because of the limited losses in the rest of the year, assuming perfect cleanings and a fixed cleaning threshold is found to be sufficient for the cleaning optimization and forecast purposes of this work.

Once the cleaning events are identified, the same fitting procedure as in WUM is employed to generate the soiling profile.

2.2.3. Environmental-parameter model

In this case, the soiling profile is modelled as a function of the cumulative sum of the particulate matter since the last rainfall event (Coello and Boyle, 2019). The particulate matter measures the concentration of suspended particles in a 1 m^3 of air. It is commonly expressed using the PM_{10} and the $PM_{2.5}$, which consider particles of diameter < 10 μm and < 2.5 μm respectively. The concentration of coarse particles only, $PM_{10\text{-}2.5}$, can be calculated as the difference of PM_{10} and $PM_{2.5}$.

The model is based on the method proposed by Coello and Boyle (Coello and Boyle, 2019). The soiling ratio on a day *d* is calculated using an equation proposed by (Hegazy, 2001):

$$r_s(d) = 1 - 0.3437 \bullet \mathrm{erf}\left(0.17 \bullet \omega(\mathrm{d})^{0.8473}\right) \tag{1}$$

where ω is the total mass accumulation, in g/m^2, calculated as:

$$\omega(d) = \sum_{d_i=0}^{d-i} \left(v_{10-2.5} \cdot C_{10-2.5}(d_i) + v_{2.5} \cdot C_{2.5}(d_i)\right) \bullet \mathrm{t} \bullet \cos(\theta) \tag{2}$$

where d_i is the number of days elapsed since the last rainy day *i*, *v* is the particle deposition velocity in m/s, *C* is the daily average particulate matter concentration in g/m^3, *t* is the factor used to calculate the daily values and θ is the tilt angle (30°).

In their work, Coello and Boyle (Coello and Boyle, 2019) found the best modelling results by using referenced static settling velocities for $v_{10\text{-}2.5}$ and $v_{2.5}$. Therefore, even in this work, constant values have been considered throughout the years. Differently, though, these have been determined by fitting the model to the measured soiling data, similarly to the approach used in (Toth et al., 2020).

The aim of this work is a first attempt to develop a tool for future cleaning optimization, rather than for the estimation of current or past measured soiling losses. So, the aforementioned model has been selected for its simplicity, as it makes use of rain, PM_{10} and $PM_{2.5}$ data only, and because it was validated against the largest number of sites. Despite that, other models have been presented in literature (Bergin et al., 2017; Coello and Boyle, 2019; Guo et al., 2015; Javed et al., 2017; Toth et al., 2020; You et al., 2018) and could be applied for the same purpose. These should be investigated in future.

2.2.4. Removal of artificial cleaning

An artificial cleaning was performed by the O&M team on August 5, 2019. In order to analyze the costs and benefits of different cleaning schedules, it is necessary to estimate the full extent of the soiling losses occurring at the site in conditions of no soiling mitigation. This means that the effect of the artificial cleaning has to be removed. Differently from the previous studies (Micheli et al., 2021a; 2020c), in this case, the correction is applied to the performance data, rather than to the extracted soiling loss profiles. This choice is motivated by the fact that, in this work, different soiling extraction approaches are tested. This way, their outputs can be directly compared without the need of additional processing which could have biased the comparison.

The correction, described in 3.1, is performed by reducing the performance index by a fixed offset for all the days following the cleaning event and until the first day with rain of intensity above the threshold. The offset is set equal to the positive shift in soiling ratio caused by the cleaning. The correction requires, first, to identify the correct cleaning threshold (3.1).

2.3. Cleaning optimization method

The cleaning optimization is conducted in few steps. First, the historical soiling profiles are estimated using rainfall and particulate matter data from 1980 to 2016. Second, the optimal cleaning day is calculated: this is the cleaning date that minimizes the average soiling loss (i.e. maximizes the average soiling ratio) if one cleaning was performed every year on this same date. Third, the profits obtained in 2017, 2018 and 2019 for cleaning on the optimal date are calculated. These are compared with the profits obtained by using the WUM-generated soiling profile (considered as reference and optimal case scenario).

The cleaning profits are calculated from the difference of revenues (*R*) and cleaning costs (*CC*), as in (Besson et al., 2017). The revenues are calculated as:

$$R = p \bullet \varepsilon_{\mathrm{inv}} \bullet \sum_{\mathrm{d}=1}^{\mathrm{D}} \mathrm{E_d} \bullet \left(\mathrm{r_{s,1}(d)} - \mathrm{r_{s,0}(d)}\right) \tag{3}$$

where *p* is the electricity price, ε_{inv} is the inverter's efficiency, E_d is the DC soiling-free energy yield on the day *d* in conditions of no soiling and $r_{d,1}$ and $r_{d,0}$ are soiling ratio values on day *d* if one cleaning per year and if no cleaning is performed respectively. The optimal cleaning day is the one that returns the maximum value of $\sum_{d=1}^{D}(r_{s,1}(d) - r_{s,0}(d))$.

Fixed values are considered for the electricity price and the inverter's efficiency, equal to 0.06 €/kWh and 95% respectively. The soiling-free energy yield is calculated as:

$$E_d = \frac{E_{DC,d}}{PI_d} \tag{4}$$

where $E_{DC,d}$ is the measured DC energy yield and PI_d is the performance index found on the day *d*. Any missing soiling free daily energy yield value is estimated through the linear interpolation function in the *NumPy* package for Python 3.7.0 (Harris et al., 2020a).

The cleaning costs have been calculated as:

$$CC = n_y \bullet \mathrm{CC_w} \tag{5}$$

where n_y is the number of years considered in the calculation and CC_w is the specific-cleaning cost. This last value has been set equal to 0.62 €/kW, as reported in previous works for the same site (Micheli et al., 2021a; 2020c). A single yearly cleaning scenario is considered in this work, as it was previously found in (Micheli et al., 2021a) to be the most profitable soiling mitigation strategy for the site.

It has to be acknowledged that the methodology proposed in this work, partially built on previous models, makes use of some assumptions that should be addressed in future works. The AC energy is calculated from the DC energy data, assuming a constant 95% inverter efficiency. Similarly, the electricity price and cleaning costs are fixed: their variation can affect the costs and benefits of the soiling mitigation strategies. In addition, as done previously (Micheli et al., 2020a), the identification

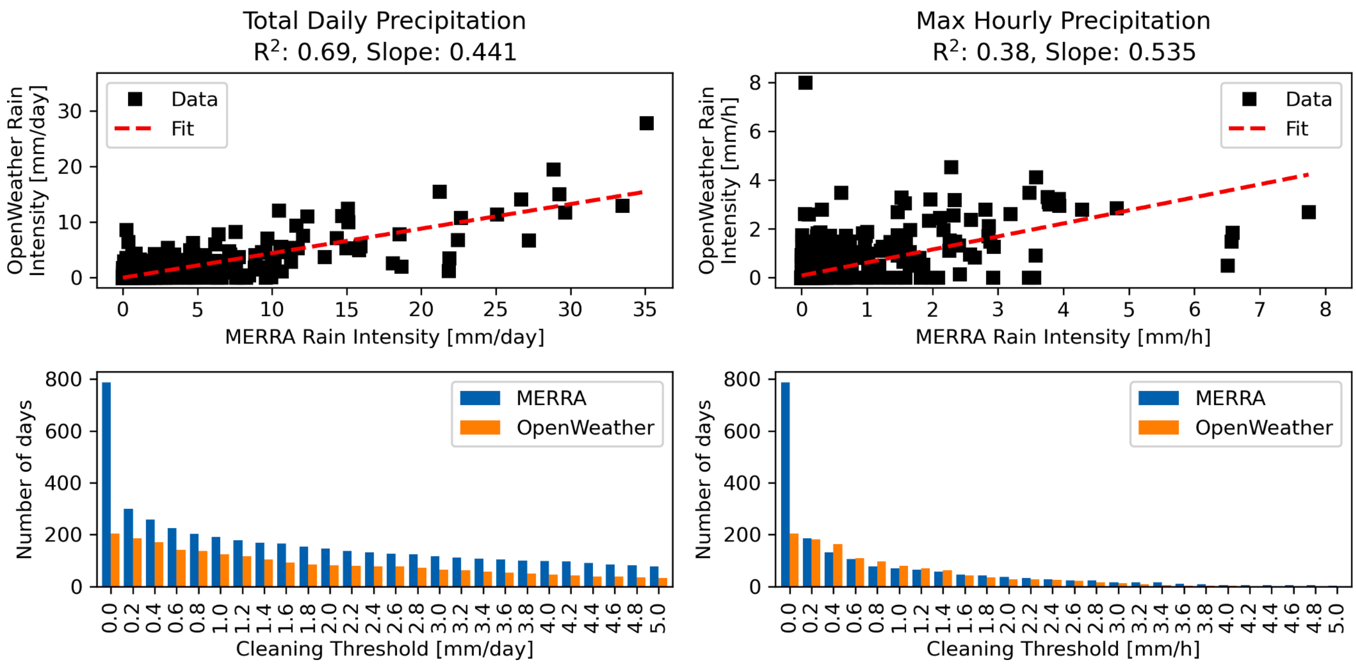

Fig. 2. Comparison of MERRA-2 and OpenWeather rainfall data considering the 2017 to 2019 period. Daily values are shown on the left, hourly values are shown on the right.

of the optimal cleaning day is based on the soiling profile only, and does not consider the variability of the irradiance. As mentioned, the work is conducted under the assumption of soiling uniformly distributed over the PV plant. Last, natural cleanings in this work are always modelled to restore the soiling ratio to 1, as previously done by several authors (Coello and Boyle, 2019; Kimber et al., 2006; Toth et al., 2020). However, some studies have suggested that the cleaning effectiveness of rainfalls might change depending on the rain intensity (Javed et al., 2020; Li et al., 2020; You et al., 2018).

2.4. Precipitation and particulate matter data

Hourly rainfall data downloaded from two datasets have been used: OpenWeather (openweathermap.org) and MERRA-2 (Global Modeling and Assimilation Office (GMAO), n.d.). The daily values are obtained as sum of the hourly values.

The data reported by the two sources have been compared (Fig. 2). It is found that the two datasets show some significant differences in the rainfall patterns. MERRA-2 tends to have a larger number of rainy days (lower plot of Fig. 2), especially if no minimum threshold is set. A coefficient of determination of 0.69 is found between the total daily intensities reported for the two sites, when data from the same days are compared. This lowers to 0.38 if the hourly values are considered instead. This result suggests that calibration will have to be conducted on each site to identify the correct cleaning threshold, as even the data source might affect its value. For this reason, in the next section (3.1), the soiling extraction models are calibrated against the data from both OpenWeather and MERRA-2. Additional studies should be conducted in future on this, adding also local rainfall measurements and other datasets.

The PM_{10} and $PM_{2.5}$ concentrations have been calculated from aerosol concentration parameters, downloaded from MERRA-2 (Global Modeling and Assimilation Office (GMAO), 2020), using the equations in (Provençal et al., 2017), proposed for a previous version of the dataset. It is acknowledged that finer procedures are available for the calculation of the particulate matter, and should be tested in the future (NASA, n.d.). The daily PM_{10} and $PM_{2.5}$ concentrations have been calculated as average of the hourly values.

2.5. Fitting functions and errors

The soiling extraction is performed using the the *curve_fit* function of the *SciPy* library for Python 3.7.0 (Jones et al., 2001). The piecewise regression function in the *NumPy* library (Harris et al., 2020a) is employed with the same initial guesses and parameters' boundaries as in (Micheli et al., 2021b).

The fitting of the EPM model is performed by using the *LMFIT* package (Newville et al., 2014). This is chosen because it allows setting non-constant boundaries: $v_{10-2.5} \geq v_{2.5} \geq 0$. These boundaries make it possible to model deposition velocities for coarse particles larger than for finer particles. The initial values are set equal to the observed deposition velocities reported in (Coello and Boyle, 2019): 0.4 cm/s and 0.09 cm/s for $v_{10-2.5}$ and $v_{2.5}$ respectively.

The Mean Absolute Error (MAE) is used to assess the quality of the modeled soiling profiles and is calculated as:

$$MAE = \sum_{d} \left| Z_{mod,d} - Z_{meas,d} \right| \quad (6)$$

where $Z_{mod,d}$ is the modelled value of the $Z_{meas,d}$ measured data point on each day *d*. The MAE has the same units as the investigated parameter and its value grows with the magnitude of the error. A MAE of 0 is found if the modelled data have the same values of the measured data.

3. Results

In order to replicate a real case scenario, the available data are divided into a training dataset (based on 2017 data) and a test dataset (based on 2018 and 2019 data). The training dataset is used to calibrate the models, while the test dataset is used to validate their performance.

First, the PPM is employed to identify the correct rainfall threshold and, subsequently, to remove from the performance index the effects of the artificial cleaning (3.1). Then, the soiling profile is extracted through the EPM, by using the previously found cleaning threshold, and compared with the WUM estimation for the 2018 and 2019 data (3.2). The results of cleaning optimization are presented in 3.3. Last, the findings, the potentials and the limits of the presented study are discussed in 3.4.

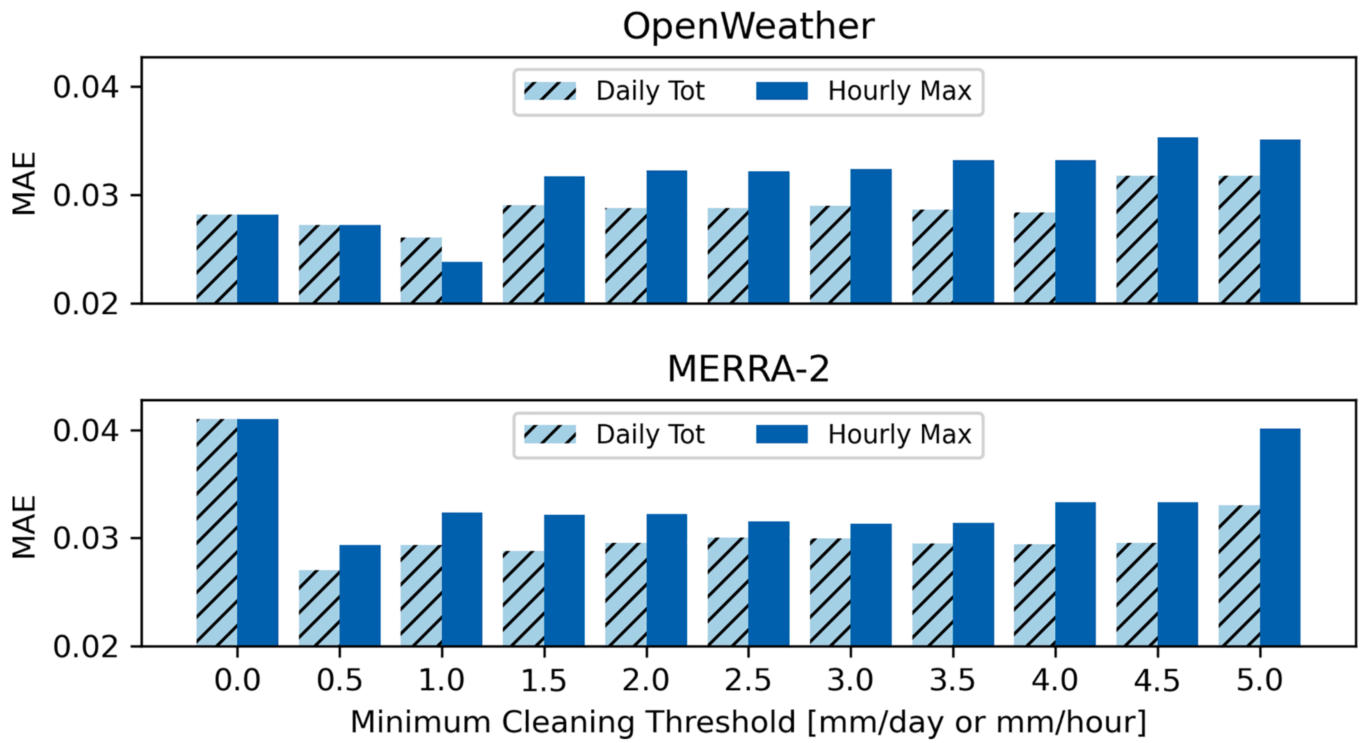

Fig. 3. Mean Absolut Error between measured and PPM modelled soiling ratio for different cleaning thresholds, considering only 207 data. The rainfall data from OpenWeather (upper plot) and MERRA-2 (lower plot) have been considered.

3.1. *Cleaning threshold & O&M cleaning correction*

The cleaning threshold corresponds to the minimum rain intensity needed to clean the PV modules (Kimber et al., 2006). In order to find its correct value, several soiling profiles are extracted using the PPM, each considering a different threshold. The process is repeated, with an approach similar to that in (Toth et al., 2020), varying iteratively the minimum cleaning threshold in between 0.0 and 5.0 mm/hour, at 0.5 mm/hour steps, and in between 0.0 and 5.0 mm/day, at 0.5 mm/day steps. Then, the MAE is calculated for each modelled profile compared to

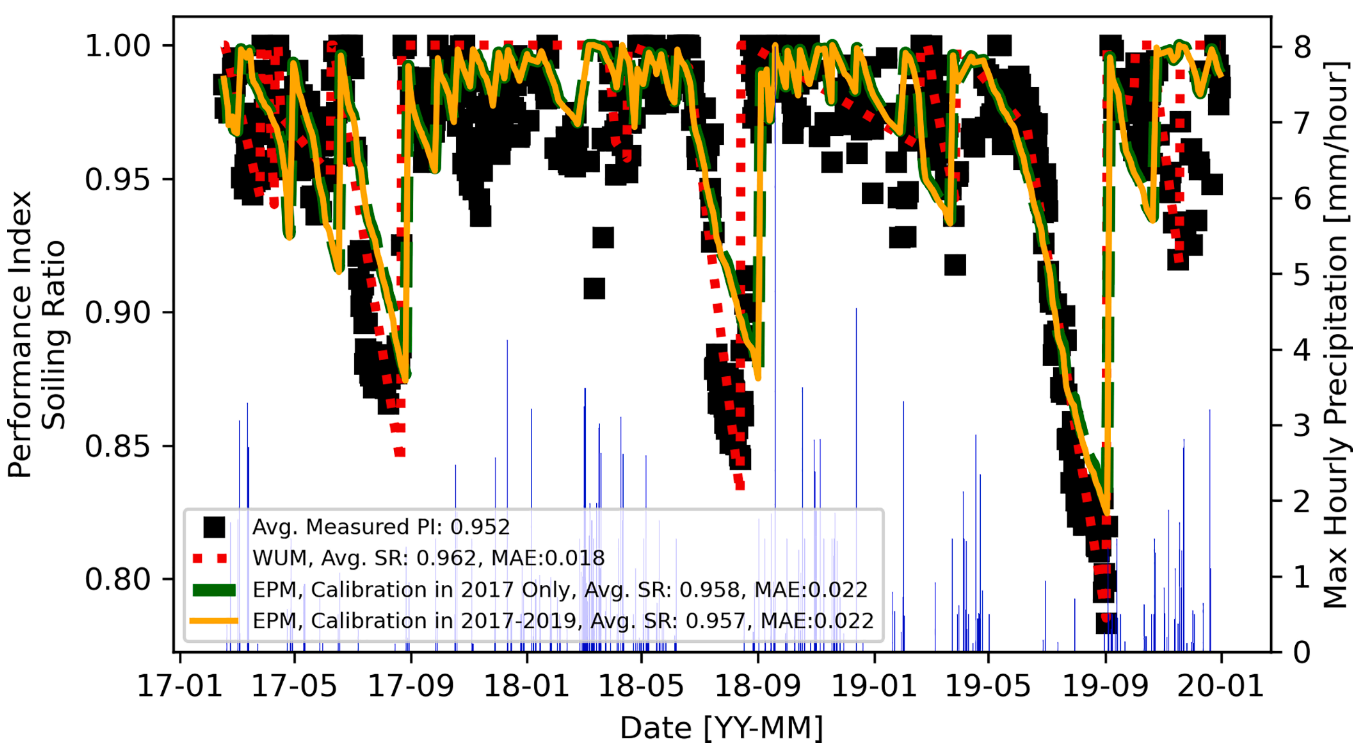

Fig. 4. WUM and RPM modelled soiling ratio profiles vs. measured performance index. Vertical bars represent the maximum hourly precipitation per day (right y-axis).

the measured performance index, considering only the 2017 data. The analysis is repeated for both the MERRA-2 and the OpenWeather data.

The results in Fig. 3 show that, as expected, the modelling error changes with the cleaning threshold. In addition, different results are returned for the two rainfall datasets. The error for MERRA-2 is maximum if no threshold is considered, consequence of the high number of days with low rainfall values shown in Fig. 2. Interestingly, the overall daily and hourly thresholds follow similar trends. For MERRA-2, the minimum errors are found for thresholds of 0.5 mm/day and 0.5 mm/hour. For OpenWeather, the minimum errors are found for thresholds $\leq$ 1.0 mm/day and $\leq$ 1.0 mm/hour. The fact that the hourly and daily values are the same in OpenWeather is probably due to the weather pattern of the site. Indeed, 62% of the rain events of intensity $\geq$1 mm/day registers also a maximum hourly precitation $\geq$ 1 mm/hour. This percentage raises to 85% if a maximum hourly threshold >0.5 mm/hour is considered.

Overall, the minimum error is found for OpenWeather for a threshold of 1.0 mm/hour. These are therefore the dataset and the cleaning threshold used in the rest of the work. The identification of this minimum cleaning threshold makes it possible to correct the effects of the artificial cleaning performed at the site by the O&M team on August 5, 2019. The first rain event of intensity > 1.0 mm/hour occurs on September 4, 2019: if the O&M cleaning had not been performed, the dry summer soiling dry period would have prorogated until this date. The performance index data is therefore corrected accordingly, extending the soiling deposition previously interrupted on August 5, 2019, until September 4, 2019.

3.2. Soiling extraction

Once the cleaning threshold is defined, soiling is then extracted with the EPM, providing in input both the rainfall and the particulate matter time series. The fitting returns significance only for the $PM_{10\text{-}2.5}$ coefficient ($v_{10\text{-}2.5}$ = 1.20 cm/s), setting instead $v_{2.5}$ = 0.0 cm/s. This is probably due to the fact that the $PM_{10\text{-}2.5}$ and $PM_{2.5}$ series are found not to be independent of each other in this case. Indeed, if the daily values are correlated, the R^2 is 0.985. This depends on the methodology employed to process the particulate matter data (Provençal et al., 2017). In addition, it is not expected to be necessarily true for different sites, and might change also depending on the source of particulate matter data.

The so-calibrated model is then employed to replicate the full PV performance time series, going from 2017 to 2019. The results are reported in Fig. 4 and are compared with those obtained using the WUM. The models return average soiling ratios of 0.958 and 0.962 for the 2017 to 2019 period, slightly higher than the value of the normalized performance index (0.952). EPM overestimates the minimum average soiling ratio by almost 5 $\%_{abs}$: 0.828 vs 0.783. In line with these results, the minimum modelling error is found for WUM, whereas the EPM return an error 20+% higher.

If the EPM model is recalibrated using all the available data (2017 to 2019), no significant improvement can be found. In this case, $v_{10\text{-}2.5}$ would be set to 1.23 cm/s, with $v_{2.5}$ still at 0.0 cm/s (Fig. 4).

It should be noted that the EPM models the 2018 summer cleaning with a 3-week delay compared to the WUM. This is due to the fact that the effects of a 0.5 mm/hour event occurred in correspondence to the WUM cleaning is not detected by EPM because it is lower than the threshold. This result confirms that a fixed threshold might not be correct in some occasions, even if contributing to good long term soiling loss estimates. Indeed, two events of larger intensities in summer 2019, i.e. 0.9 mm/hour (30 June) and 0.7 mm/hour (31 July), did not had any cleaning effect on the modules and are correctly discarded thanks to the threshold. Previous studies (Gostein et al., 2015), indeed, have reported that rainfalls of the same intensities can clean the modules in a season, but have no effect in others. This finding suggests that additional studies should be conducted on cleaning effectiveness of rainfalls and on the cleaning thresholds.

The 0.022 MAE represents the minimum error achievable using the selected EPM method, for the investigated soiling time series. Part of the uncertainty, as also proved by the WUM error, is due to the quality of the PV performance data, which can be expected to be noisier than the measurements of soiling stations and detectors. Despite that, the results suggest that a model only based on particulate matter and rainfall provides a good estimation of the soiling trends at the investigated site, as the three long dry summers are correctly identified. However, in future, the addition of other environmental parameters, such as wind speed and humidity (Figgis et al., 2017), along with more flexible cleaning identification and modelling procedures, could improve the quality of the modeling.

In this work, the model required at least one year of PV data to be calibrated. In reality, if the deposition velocities could be estimated from environmental data or from referenced values (Coello and Boyle, 2019), no calibration would be needed. This means that it would be possible to estimate the soiling losses even before the installation of the PV system, under the assumption of a known cleaning threshold.

3.3. Cleaning optimization

In this section, the EPM is used for cleaning optimization purposes and compared with the results obtained by the WUM. Two cases are simulated. First, perfect information are assumed: the optimization is conducted by feeding the EPM with the actual environmental data for the 2017 to 2019 period. Second, the optimization is conducted using only the historical time series of particulate matter and rainfall.

The results of the cleaning optimization conducted using the 2017–2019 data are shown in Table 1. The estimations of the WUM are used as baseline to evaluate the EPM's results. For all the available years, the EPM identifies dates that are within three days of those recommended by the reference method (WUM). It should be noted that the different cleaning dates returned by the two methods for the summer 2018 do not affect significantly the cleaning optimization in this case. This is due to the fact that, according to the WUM, soiling starts accumulating at a significant rate about 2 weeks after the date in which the EPM summer dry period starts. In this case, this difference balances the previously reported EPM cleaning detection delay.

No significant difference can be found in terms of the "actual" profits returned by the two models. These are calculated by applying to the WUM profile the cleaning dates found by each method. Slightly differences are found instead between the expected and the actual profits: this means that using the EPM can lead to cleaning profit estimations different from the "actual" values. It should be noted that, even if the cleaning day is correct, a wrong estimation of the cleaning profits can potentially affect the cleaning decision, as it might call as profitable an actually non-profitable cleaning and vice versa.

In addition, the EPM allows generating soiling profiles for all the years in which rainfall and particulate matter data are available. This makes it possible to evaluate the seasonality of soiling at the site even if no PV data are available and anyway over time periods longer than those in which PV data are typically available. The cleaning optimization can therefore be performed "in advance" by identifying which day minimizes the average modelled historical soiling loss series if the system is cleaned every year on that same date. For the given site, the optimal cleaning date corresponds to the 22nd of July. This is about a week from the WUM recommended cleaning dates for 2017, 2018 and 2019. This approach would have returned soiling mitigation profits (1.7 €/kW) about 5% smaller than those found for perfect information over the three year period and shown in Table 1. Ideally, if short-term forecasts were available, these could be used in conjunction with the measured real time data to adjust the prediction maximizing the soiling mitigation profits. This possibility should be investigated in future.

Table 1
Energy and economic analysis of the soiling profile extracted by using the EPM and WUM methods. The EPM “Actual” profits are calculated applying to the WUM soiling profile the EPM recommended cleaning day. Since it is used as reference, the WUM expected profit coincides with the actual profits. In all cases, perfect knowledge on the soiling-free energy output is assumed.

	Weather-Unaware Model			Environmental-Parameter Model			
Year	Estimated Soiling Losses [€/kW]	Recommended Cleaning Day	“Actual” Profit [€/kW]	Estimated Soiling Losses [€/kW]	Recommended Cleaning Day	Expected Profit [€/kW]	“Actual” Profit [€/kW]
2017	2.2	17-Jul	0.4	2.7	17-Jul	0.3	0.4
2018	1.7	16-Jul	0.3	1.7	19-Jul	0.5	0.3
2019	3.5	16-Jul	1.1	3.7	13-Jul	1.2	1.1

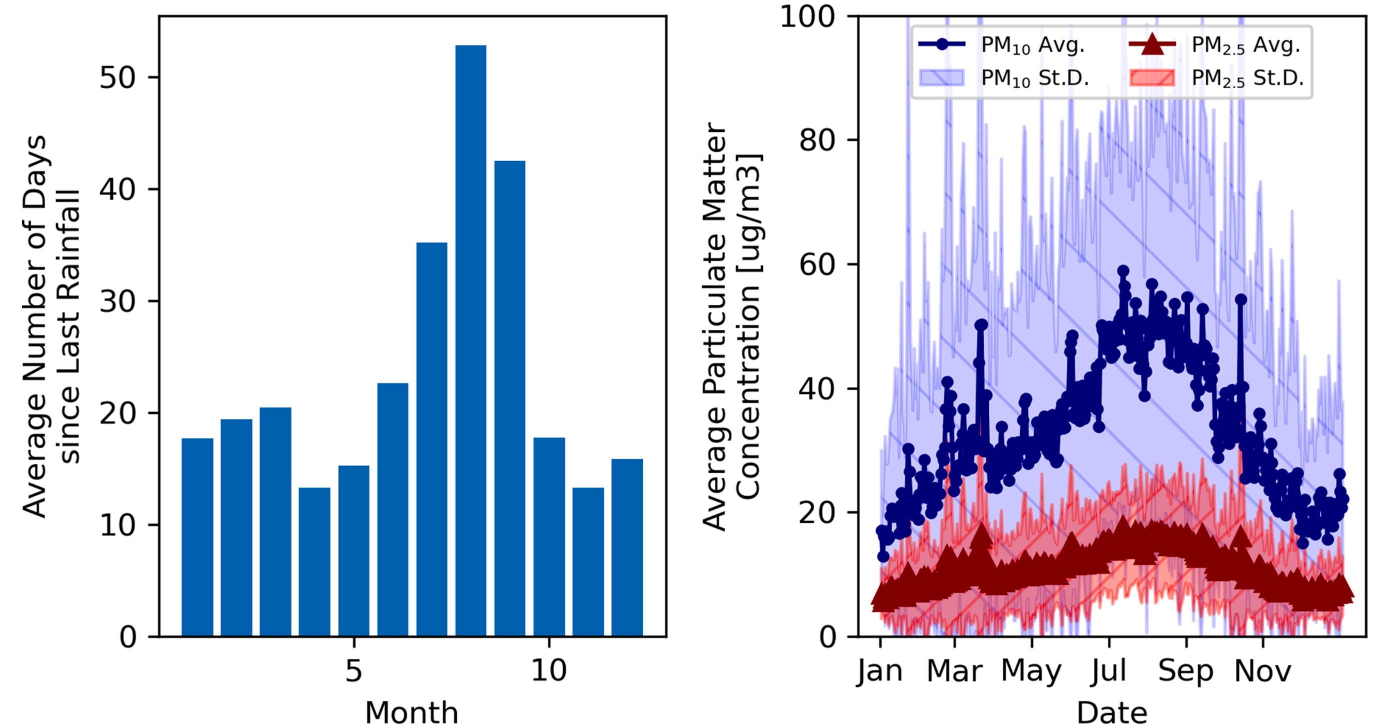

Fig. 5. Left plot: monthly average number of days since the last rainfall. Right plot: daily average particulate matter concentrations and standard deviation. The values are calculated from data from 1980 to 2019.

3.4. Discussion

The results of the cleaning optimization suggest that, for the given site, it is possible to identify in advance the typical cleaning day. This is a useful information, as it allows planning the cleaning schedule of the site in advance, at a minimum expense in terms of profits. The advanced cleaning optimization is made possible by the marked seasonality of the investigated site. Indeed, a prolonged dry season occurred in most of years since 1980. The dry periods in August and September are on average twice as long as compared to the rest of the year (left plot of Fig. 5). In addition, also the peak in particulate matter concentrations is generally reached in between July and September (right plot of Fig. 5). The combination of infrequent rainfall and high-suspended particle concentrations cause the high soiling losses that are typically experienced in summer at the site and their yearly repeatability makes the advanced cleaning optimization possible.

So, the methodology proposed in this work can be expected to identify successfully in advance the optimal cleaning strategy if employed for sites with a similarly clear seasonality. However, it should be noted that, for 7 of the 40 yearly soiling profiles generated using the environmental data in between 1980 and 2019, the optimal cleaning day is detected in a season other than summer. Indeed, exceptional natural or man-driven events can vary the soiling deposition rates: the region in which the site is located is, for example, exposed to episodic Saharan dust intrusions that can take place also in the winter months and cause significant losses (Conceição et al., 2018). In addition, unexpected dry spells or unusually rainy summer days or seasons can make the actual soiling losses and optimal cleaning dates deviate from the expectations. This means that advance-cleaning optimization should be combined with an accurate and continuous activity of soiling monitoring and analysis, as exceptional conditions can lead occasionally to significantly different yearly soiling profiles.

Future works should be conducted in more locations to further validate and tune the proposed methodology. Both soiling station and PV performance data should be analyzed, to understand and correct the effect of the signal noise on the cleaning optimization. In addition, as mentioned in 2, several assumptions had to be made in this work and should be addressed in future.

4. Conclusions

This work presents the results of the optimal cleaning schedule prediction for a 1 MW PV site in Southern Spain. The optimization is conducted by modelling soiling loss profiles using historical weather data only, analyzing the seasonality and the inter-annual variability of the factors affecting soiling.

Soiling modelling is conducted considering rainfall data originated from two distinct sources and considering different time intervals and minimum cleaning threshold values. It is found that the modelling error changes depending on both the cleaning threshold and the rainfall dataset. No significant differences are found, instead, between the modelling errors calculated for thresholds expressed as maximum hourly intensity or total daily intensity. Overall, the best results for the investigated sites are found for a cleaning threshold of 1 mm/hour. As it is shown in the paper, however, despite the optimization, a constant threshold might lead to the over- or under-detection of some cleaning events. Future studies should consider the possibility of a variable threshold, and of a rain intensity-dependent cleaning effectiveness.

A referenced weather-data-only based soiling extraction method is used to generate soiling profiles for the site using only rainfall and particulate matter data. This is calibrated using one year of PV performance data and returns a minimum mean absolute error of 0.022 for the investigated three-year period. No significant improvement is found if, instead, the model is calibrated using the full tree years of data.

When provided with perfect information, this model is able to identify most profitable cleaning dates within three days of those identified using the reference soiling extraction method. In addition, based on historical weather data only, the model predicts that the cleaning should be conducted every year on July 22nd to maximize the soiling mitigation profits. This date would have led, for the three years under investigation, to soiling mitigation profits only 5% lower than those calculated using perfect information.

This case study demonstrates the possibility of using historical weather data to predict the optimal cleaning schedule, at least for PV sites with a marked seasonality. Despite that, it is recommended to use this method in combination with monitoring systems and, if available, forecasts to address any exceptional event that can cause an unexpected variation in the soiling deposition rate or in the natural cleaning frequency.

Assumptions and limitations of the study are described in the paper, along with future research opportunities. The study, indeed, should be repeated for a larger number of sites, under a variety of soiling conditions. In addition, future cleaning optimization studies should take into account also the variability of electricity prices and cleaning costs, as these can affect the optimal cleaning frequency, fixed to one per year in the present work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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