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Review and Comparison of Methods for Soiling Modeling in Large Grid-Connected PV Plants

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Abstract: Soiling in PV modules is one of the biggest issues affecting performance and economic losses in PV power plants; thus, it is essential to supervise and forecast soiling profiles and establish the best cleaning program. This paper analyzes different methods for soiling modeling in Large Grid-Connected PV Plants and discusses the different factors influencing soiling. Analytical models from environmental conditions are discussed in detail, comparing the proposed model by the authors (SOMOSclean) with another three relevant models from the literature (Kimber, HSU, and Toth), applying them to 16 PV power plants in Spain (total capacity of 727 MWp). Uncertainty between models and sensors is also measured, presenting the numerical results for a period of 2 years. While simpler models may offer straightforward implementation, they often fail to capture the full complexity of soiling dynamics, leading to increased RMSE error.

Keywords: renewable energy; sustainable energy; dust accumulation; energy efficiency; forecasting; photovoltaic power systems; PV cleaning; rain; solar power generation; soiling; soiling model

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1. Introduction

1.1. Motivation

Solar photovoltaic (PV) power once again asserted its dominance as the leading power-generating technology, with a 78% share of all new renewable installations worldwide for the year 2023 [1]. The integration of all this new PV capacity into the grid represents a technical challenge itself [2–4], as does the PV materials disposal [5]. To optimize the cost-effectiveness of PV technology and enhance overall profitability, the solar industry continually explores strategies to maximize efficiencies while minimizing losses and associated costs [6,7].

Among the primary challenges faced by solar installations is the accumulation of dust, commonly referred to as soiling [8]. (See Figure 1). The global impact of soiling on solar power production is significant, with estimates suggesting a reduction of at least 3–4% [9], translating to income losses in the range of 4–7 billion EUR in 2023 [10].

Figure 1. Solar PV panels affected by soiling compared with a clean panel.

1.2. Importance of Soiling Monitoring and Modeling

Given its significant impact, the effective monitoring and prediction of soiling profiles are essential for optimizing cleaning schedules [11–15] and minimizing energy losses. Interest in soiling modeling has exploded in the last few years, and this is evident in the number of publications on the subject. From a systematic search with the keywords "soiling model" and "photovoltaic", the results have gone from virtually no publications in 2000 to more than 100 publications per year from 2022 till now, just regarding soiling modeling (See Figure 2).

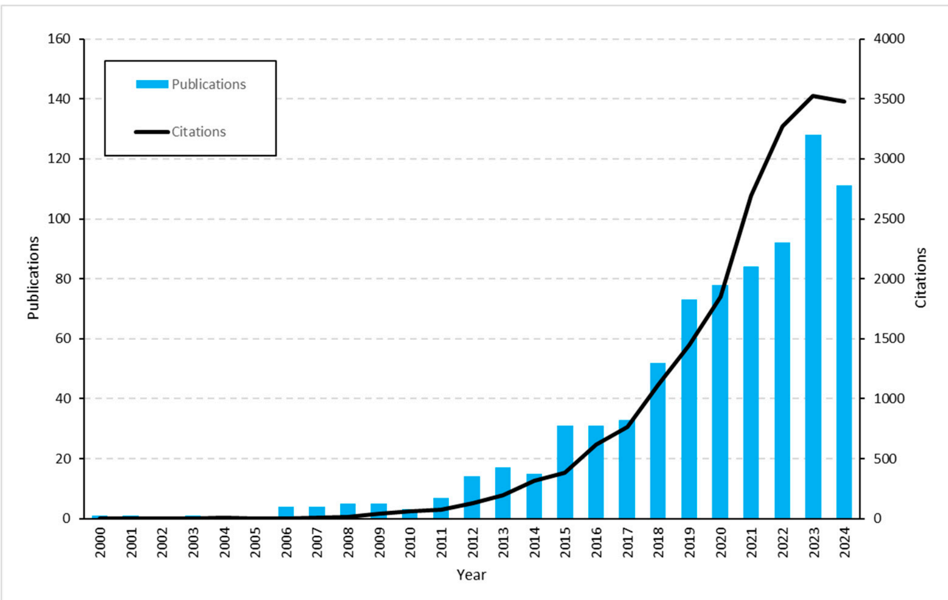

Figure 2. Number of relevant publications and citations since 2000 with the keywords "soling model" AND "photovoltaic".

1.3. Scope of This Paper and Contributions

Building on previous work [16,17], which introduced a model based on environmental conditions, this paper provides a comprehensive analysis of methods for soiling modeling in Large Grid-Connected PV Plants. The study is grounded in three years of monitoring data from 16 PV Plants in Spain, totaling 727 MWp of installed capacity.

The key contributions are the following:

- A systematic review of methods for measuring and modeling soiling in PV power plants, emphasizing their advantages, limitations, and applicability;
- A comparative analysis of four analytical soiling models, evaluated using real-world data from large-scale PV Plants;
- Insights into the main factors influencing soiling accumulation and removal, supporting the development of optimal cleaning schedules and maintenance strategies;
- Quantification of uncertainties in soiling sensors and analytical models, providing a deeper understanding of the reliability of different approaches under varied conditions.

2. Techniques for Measuring Soiling in PV Power Plants: State of the Art

Before going deeper into the analysis of the State of the art, there are some basics regarding soiling metrics. The most frequently used parameter to assess the soiling severity is the Soiling Ratio (*SRatio*). It is expressed as the ratio of the actual power output of a PV power plant under the actual soiling conditions and the power expected in clean conditions [18], as follows:

$$SRatio = \frac{P_{soil}}{P_{clean}} \tag{1}$$

where P_{soil} is the present power output and P_{clean} is the power output expected in clean conditions (all the rest of the weather conditions must be the same). The soiling loss, also known as Soiling Level (SL) in the IEC 61724-1 standard [18] is calculated as $1 - SRatio$. The soiling ratio equals 1 in the absence of soiling (0% soiling loss) and decreases as dust and particles accumulate on the PV modules. In this paper, we use the term Soiling Loss or Soiling Level (*SL*) to denote the percentage of energy losses caused by soiling over a specific period, which, in this case, is measured daily.

2.1. Soiling Sensors

The use of soiling station with a reference cell is the most accurate, as it directly compares the output of a clean and a dirty cell, following the definition of the IEC 61724-1 [18] but it is necessary not only additional sensors but also to keep clean the reference cell (usually cleaned by hand). There are several commercial solutions for this kind of solutions: Atonometrics [19], NRG [20], DustVue [21], and Kintech [22].

Optical sensors is another good available alternative (Mars [23], DustIQ [24]) as they do not require manual cleaning of a reference cell [25] but require careful calibration for optimal performance. Furthermore, in large PV power plants, the soiling evaluated in a point of the solar field could not correspond to the soiling of the complete power plant.

2.2. Numerical Methods

Calculating soiling losses from PV yield [26–28] is another practical method, particularly for large-scale plants. This approach eliminates the need for additional sensors and can provide plant-wide insights. However, it is affected by other problems in the power plant affecting the performance, such as shading, equipment failures, or module degradation.

Regarding soiling models from environmental conditions, they can be classified in *analytical models* and *Machine Learning* models.

Analytical models [29–37] use mathematical relationships derived from environmental data, such as rainfall, wind, and dust levels, to estimate soiling losses. According to the literature, we have identified four relevant soiling models based on environmental conditions analysis: the Kimber model [29], HSU model [32], Toth model [33], and SOMOSclean model [17]. We will go deeper in these four methos in the next sections.

Machine Learning and Artificial Neural Networks (ANN) models [38–42] leverage advanced algorithms to uncover complex patterns in data but require extensive high-quality training datasets, which can be a limiting factor.

2.3. Image-Based Methods

Recently, numerous methods based on image processing have emerged. They use satellite images [43], surveillance images [44], camera data [45–48], or drone footage [49] to estimate soiling losses. They offer the advantage of being non-invasive and suitable for large-scale applications. However, the reliability of this approach depends heavily on image resolution and the sophistication of image processing algorithms used to analyze the data.

2.4. Summary of Methods to Quantify Soiling

Table 1 summarizes the different methods for determining actual soiling losses, organized into the three categories discussed above. Another possible classification is proposed in [10], including Geospatial Models [50].

Table 1. Methods for determining actual soiling losses in PV Power plants.

Category	Approach	References	Advantages	Limitations
Soiling sensors	(a) Soiling station with clean reference cell	[19–22]	High accuracy	Requires extra equipment and maintenance
	(b) Soiling station with optical sensors	[23–25]	High accuracy (properly calibrated)	Requires extra equipment and complex calibration
Numerical methods	(c) Calculated from PV yield	[26–28]	No extra sensors needed.	Sensitive to plant-specific issues
	(d) Analytical Models from environmental conditions	[17,29–37]	Cost-effective, long-term insights. Representative for large plants	Relies on assumptions
	(e) Machine Learning Models	[38–42]	Can detect complex patterns	Requires high-quality training data
Image-based methods	(f) Estimated from images (satellite data/cameras/drones)	[43–49]	Non-invasive, covers large areas	Accuracy depends on image quality and training data

For large PV Plants, the optimal approach involves combining multiple methods when available and combining direct measurements with specific equipment (a,b) with soiling models based on environmental conditions (d). This hybrid strategy leverages the strengths of each method to achieve more accurate and reliable results.

In order to be able to model the soiling ratio evolution and help the decision-making process of the cleaning schedule, it is very useful to have a model from environmental conditions (type d in Table 1). We will focus on these kinds of analytical models in this article, based on environmental conditions (d).

3. Details of Relevant Analytical Soiling Models Based on Environmental Conditions

3.1. Kimber Model

The Kimber soiling model [29] operates on the assumption that soiling increases linearly during dry periods and is mitigated by rainfall events exceeding a minimum threshold. This straightforward model incorporates three key elements. The *soiling rate* refers to a constant factor determined by the geographical region and the type of soiling environment. The *cleaning threshold* is defined as the amount of daily rainfall required to fully clean the PV system. Finally, the *grace period length* represents the number of days a system remains relatively clean after the last rainfall event that meets the cleaning threshold.

PVlib currently provides a free implementation of the Kimber model using Python [51].

3.2. HSU Model

Another model to assess the soiling severity was presented by Coello et al. in [32], from Humboldt State University (HSU). They use the air particle matter concentration, deposition velocity, rainfall, and the PV system tilt angle as input. The mass accumulation per time step m, in g/m^2 in each dry period is defined as

$$m = (v_{10} \cdot PM_{10-2.5} + v_{2.5} \cdot PM_{2.5}) \cdot t \cdot cos\theta \tag{2}$$

where v is settling or deposition speed in m/s, PM is the ambient particulate matter concentration for each respective aerodynamic diameter in g/m^3, θ is the tilt angle, and t is the time step in seconds.

Once the mass deposited for each time-step is calculated (m), the cumulative sum is applied to obtain a time series of the total mass accumulated on the PV system (ω). The soiling losses (SL) are calculated by

$$SL = 34.37 \cdot erf\left(0.17 \cdot \omega^{0.8473}\right) \tag{3}$$

where ω is the total mass accumulation at time in g/m^2 and erf is the Gauss error function [52]. The rainfall threshold defines when the accumulation is reset.

PVlib currently provides a free implementation of the HSU model using Python [53].

3.3. Toth Model

Another model to forecast daily soiling losses by means of ambient particulate matter concentration and rainfall was published by Toth et al. in [33]. The soiling losses proposed equation is as follows:

$$SL = (A_1 \cdot F_d) + (A_2 \cdot C_d) \tag{4}$$

where F_d is the cumulative sum of fine particles ($PM_{2.5}$) since the first day of data collection and C_d is the cumulative sum of coarse particles (PM_{10}) since the last cleaning event. F_d and C_d use daily averages of particulate matter concentration in each respective day. The model assumes that cleaning events only remove coarse particles ($PM_{10-2.5}$). A_1 and A_2 are constants, fitted through a Truncated Newton Algorithm (TNC). When testing the model in Colorado [33], those constants A_1 and A_2 are 1.8×10^{-5} and 3.5×10^{-5} $m^3/\mu g$, respectively.

3.4. SOMOSclean Model

The method proposed by the authors, the SOMOSclean (*Soiling Monitoring and Optimization System for Cleaning*) empirical model, was developed by ENEL. A good description of the model can be found in [17]. The model is based on environmental conditions and it approximates the evolution of soiling losses (SL) as a complementary exponential growth, up to a saturation level, according to the following expression:

$$SL = \Delta SL_{sat} \cdot \left(1 - e^{-eqD/k}\right) \tag{5}$$

where eqD is the equivalent time expressed in days, measured from a total cleaning event; ΔSL_{sat} is the maximum saturation level of soiling at the site (which can be adjusted in a range from 20 to 30%), and k the time constant in days that represents the soiling rate.

The model considers that the soiling level is reduced to zero (or to a certain value) when a heavy raining takes place, or an intentional cleaning is performed. Thus, the variable eqD related to day d is calculated as

$$eqD(d) = f * \{eqD(d-1) + 1\} \tag{6}$$

where

- $f = 1$ in case of no events;
- $f = 0$ in case of heavy rain (total cleaning event);
- $0 < f < 1$ in case of partial cleaning, as a function of rainfall;
- $f > 1$ in case of dust event, as a function of PM10 concentration.

The model was validated [17] using 2 years of data from five PV power plants in Spain (with a total peak power of 200 MW). The average of the mean absolute error between the model and the sensors was 0.71%. This difference is lower than the difference between the two sensors installed in the same location, which is 0.98%. It has been observed that dust events are not always registered by the sensors, or they were registered with a delay because they require manual cleaning.

4. Methodology and Comparison

A systematic comparison of the available methods has been performed by using the same input data and with the following considerations.

4.1. Input Variables

The daily precipitation data employed in this study were obtained through the API provided by the AEMET (Spanish National Meteorology Agency) OpenData platform [54].

The PM10 concentration data used in this study have been accessed via API from the European Environment Agency Air Quality Download Service [55].

4.2. Software Implementation

The analysis has been executed using Python (Version 3.12). For Kimber and HSU models, the PVlib specific library has been used [51,53], while the Toth and SOMOSclean models were implemented in specific functions.

4.3. Soiling Sensor Data

In the power plants under study, two soiling sensors were available, so those data have been used to obtain the average value of the plant. Each sensor is a commercial kit composed of two panels, and the soiling ratio output was obtained by a comparison of the output of one panel with that of the clean reference panel (cleaned manually).

It should be considered that the soiling sensor data were not accurate, because sensors required manual cleaning by power plant operators (usually performed weekly) and also because they require a certain level of irradiance, which means that they do not work well in cases of clouds or episodes of very high concentration of particles.

4.4. Cleaning Threshold

The Kimber, HSU, and Toth models are based on a fixed cleaning threshold, so if the raining is higher than that value, it is considered that the soiling goes to zero. The SOMOSclean model also considers partial cleaning with a factor >0. In this case, we have used a cleaning threshold of 6 mm/day for the fixed models and a variable threshold up to 10 mm/day for the SOMOSclean model.

4.5. Results and Discussion

The comparison has been carried out in 16 PV power plants with an overall power of 727 MWp over 2 years. For the discussion, we have chosen the place with a higher quality of sensor data. The main data from the 16 locations are summarized in Table A1 of Appendix A. Following the methodology of previous work [17], we have chosen the PV power plant with higher-quality sensor data (Location 3).

Figure 3 represents the results over 2 years of the four models analyzed, the soiling sensor data, and the main environmental variables (rainfall, PM10 concentration, and manual cleaning dates). We will analyze the behavior of each model in different situations more deeply in the following section.

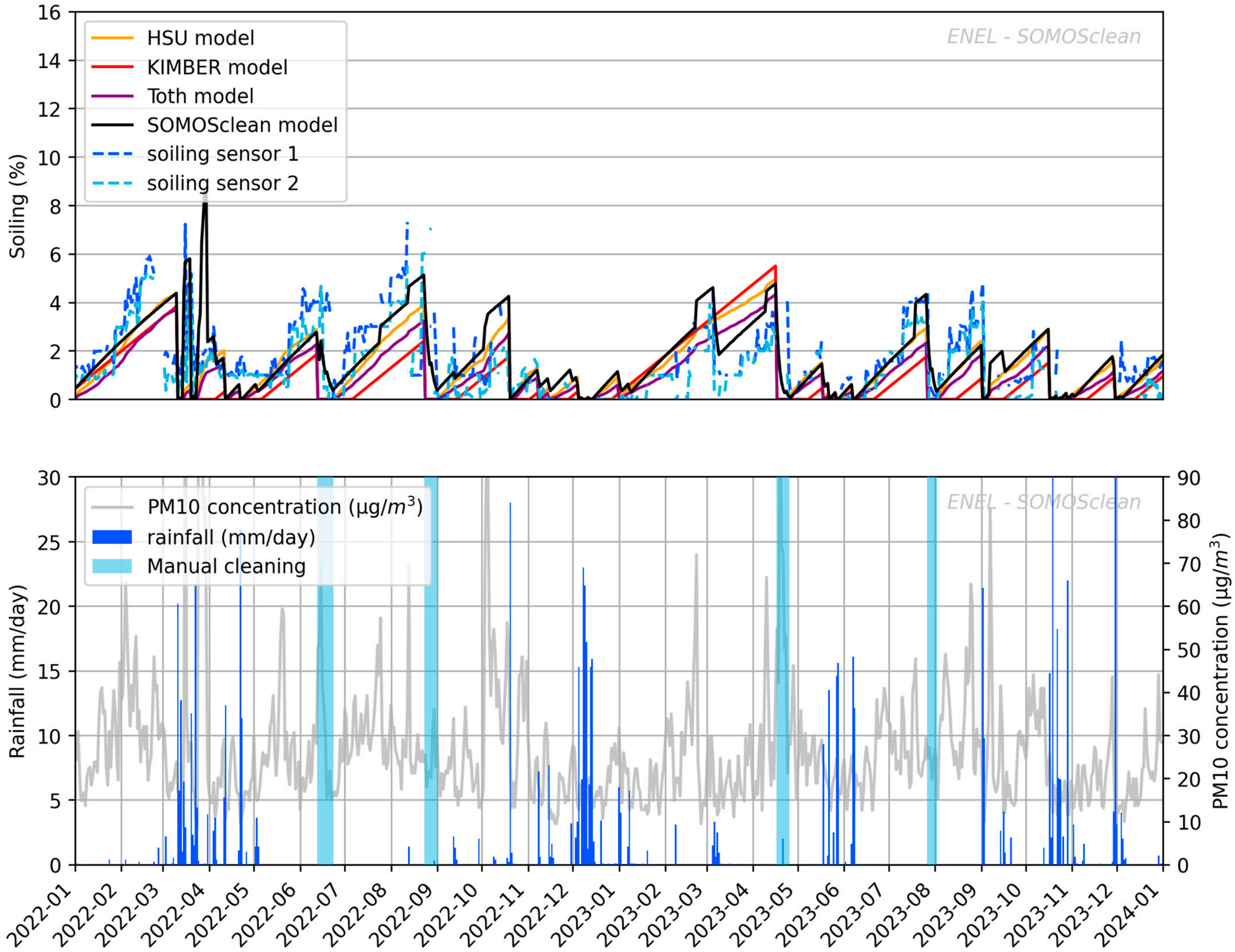

Figure 3. Upper plot: Comparison between different soiling modeling methods applied to a PV power plant (49.5 MWp) in Spain. Lower plot: environmental data for the same period (rainfall and PM10 concentration) and manual cleaning events.

The main differences in these four methods were found in the way of characterization of rain, PM concentration, and manual cleaning. Table 2 summarizes the main characteristics of the four models.

Table 2. Characteristics of soiling models based on environmental data.

Metod	**Characteristics** *Influence of Rain*	*Influence of PM Concentration*	*Manual Cleaning*	**References**
Kimber	Fixed threshold	No	Same as heavy rain	[29]
HSU	Fixed threshold	Yes	Same as heavy rain	[32]
Toth	Fixed threshold	Yes	Same as heavy rain	[33]
SOMOSclean	Variable	Yes	Gradual (for large plants)	[17]

5. Main Factors Influencing Soiling

Rainfall and particle concentration are the two main elements affecting soling losses in power plants, so most models rely on these two measurements to estimate soiling. But this phenomenon is not so simple, and there are a lot of factors affecting soiling [56]: "Normal" behavior (no specific events), rain, cleaning techniques, high particle concentration events, wind, humidity, dew, solar panel tilt angle, type of soil, terrain, vegetation, and birds.

In the next sections, each of these factors will be analyzed more deeply, and how the different methods for estimating soiling will be taken into account.

5.1. "Normal" Behavior

Even in the case of non-specific events (rain, wind, etc.), there is always a certain number of particles suspended in the air, which causes the soiling level to increase little by little.

The behavior of the four models analyzed is very similar, as shown in Figure 4. After heavy rain, the soiling level begins to increase (around 0.065% per day), associated with a normal particle concentration between 15 and 45 $\mu g/m^3$. The deposition velocity can be adjusted in all the models. There is a difference in the Kimber model compared to the rest, which is that it considers that soiling remains at zero for several days after rain.

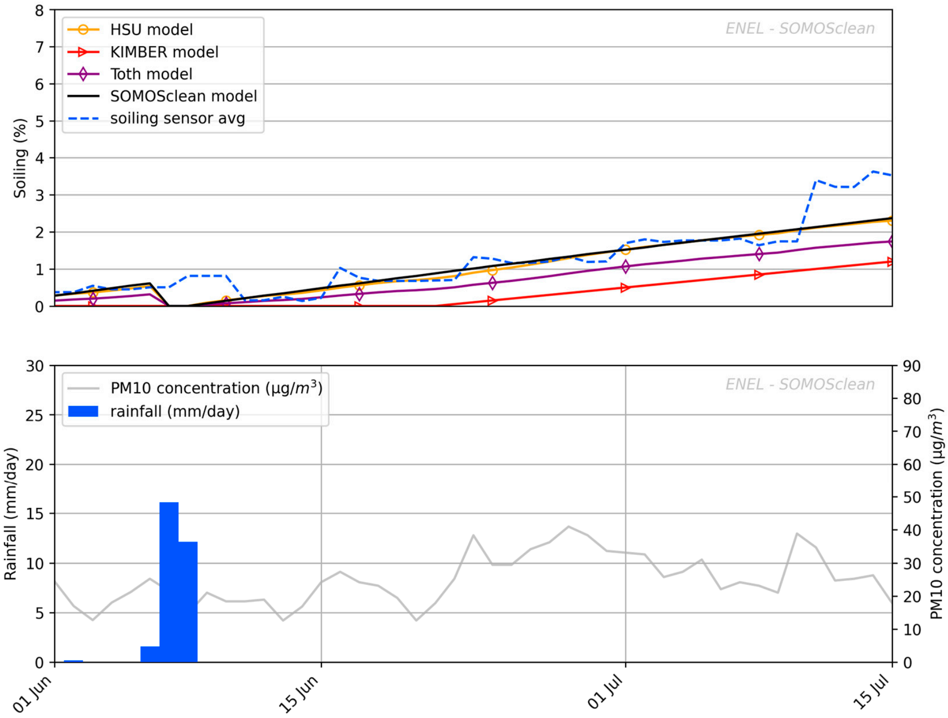

Figure 4. "Normal" behavior. Comparison between different soiling modeling methods applied to a PV power plant (49 MWp) in Spain.

5.2. Rain Effect

The rain helps to clean the solar panels by removing accumulated dirt and dust. Regions with infrequent or light rainfall may experience higher soiling losses compared to areas with regular and heavy rainfall. But also depending on the situation, light rain can contribute negatively to soiling, especially if it follows a dust event, causing the dust to adhere to the panel surface.

The amount of rain needed to clean a solar panel depends on various factors such as the amount of dust already deposited on the panel, the kind of dust particles, or the presence of very adherent dirt (such as bird droppings). Also, the rain rate and intensity are important to the effectiveness of cleaning the panel (it does not have the same effect of 0.25 mm/h for 24 h or 6.0 mm in a few minutes).

The Kimber, HSU, and Toth models are based on a fixed cleaning threshold, so if the rainfall is higher than that value, it is considered that the soiling goes to zero. The SOMOSclean model also considers partial cleaning, resulting in a better characterization of rain (See Figure 5).

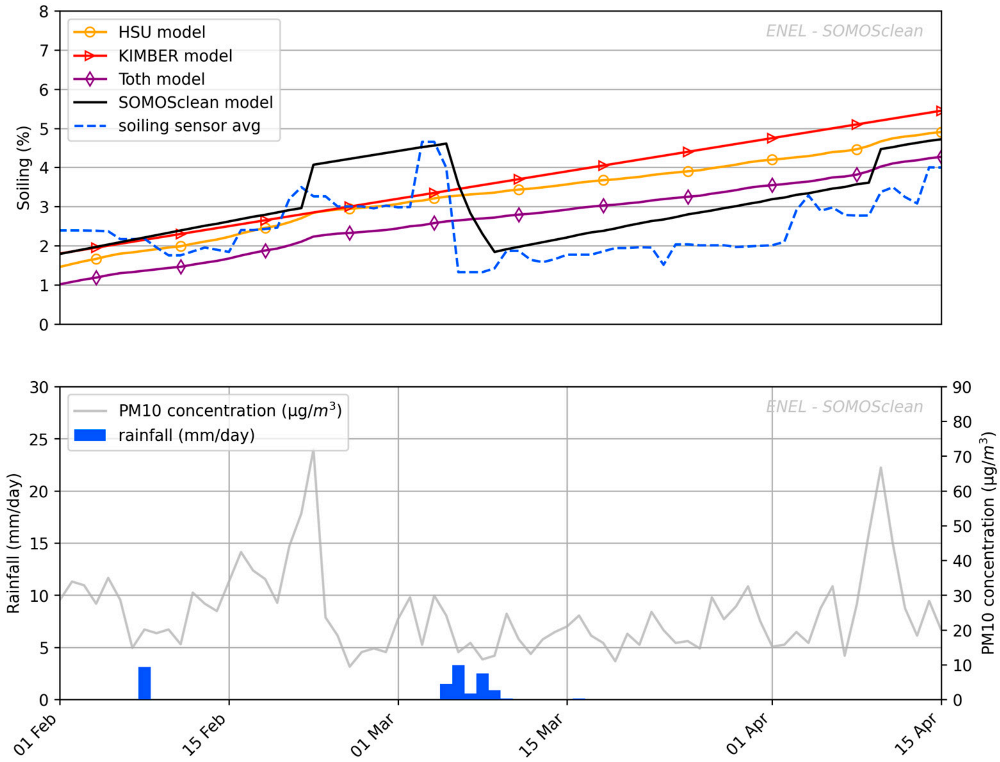

Figure 5. Partial rain effect. Comparison between different soiling modeling methods applied to a PV power plant (49 MWp) in Spain.

Most of the models also consider that over a certain threshold, the cleaning is perfect but it has been observed that the effect of heavy rain does not always succeed in cleaning the panels, especially when surfaces are extremely unclean (with very adherent dirt or with bird droppings).

5.3. Cleaning Techniques

In small PV Plants, manual cleaning is relatively easy to characterize, as the soiling level (SL) is reset to 0% after the cleaning; it is similar to the effect of heavy rainfall. On the other hand, in large PV Plants, the cleaning process can take several weeks. During this time, some panels are cleaned earlier than others, leading to varying degrees of soiling across different areas of the plant.

As shown in Figure 6, the Kimber, HSU, and Toth models do not have a special consideration for these cleanings in large plants. However, the models would fit well if a different soiling value was considered for each zone of the plant, which can be useful in some cases. SOMOSclean has a different approach, calculating the degree of soiling in the whole plant (for instance for soiling losses calculation), with a gradual decrease from day to day.

In the case of robotic or automated cleaning [57], an estimation area by area should be conducted and probably, the soiling after the cleaning should not go to zero but to a residual value (around 0.5–1%). In the case of the SOMOSclean model, this can be modeled through a *factor* $\neq 0$.

A good review of cleaning mechanisms in the literature can be found in [58,59], including semi-automated cleaning, robot-based, electrostatic-based cleaning techniques, and also preventive actions such as specific anti-soiling coatings [60–62].

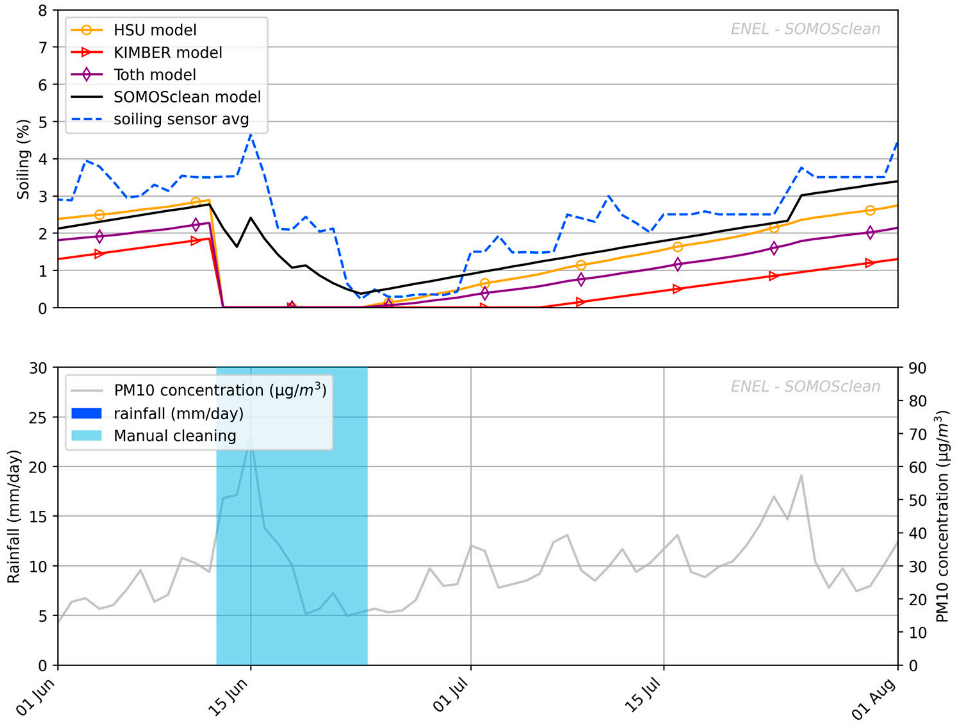

Figure 6. Manual cleaning. Comparison between different soiling modeling methods applied to a PV power plant (49 MWp) in Spain.

5.4. High Particle Concentration Events

Figure 7 represents the behavior of the four soiling models analyzed, under a dust event that occurred in Spain, in March 2022 [63]. The dust concentration in the same locations went up to 1000 $\mu g/m^3$, extremely high values, which had not been observed in the current century [64].

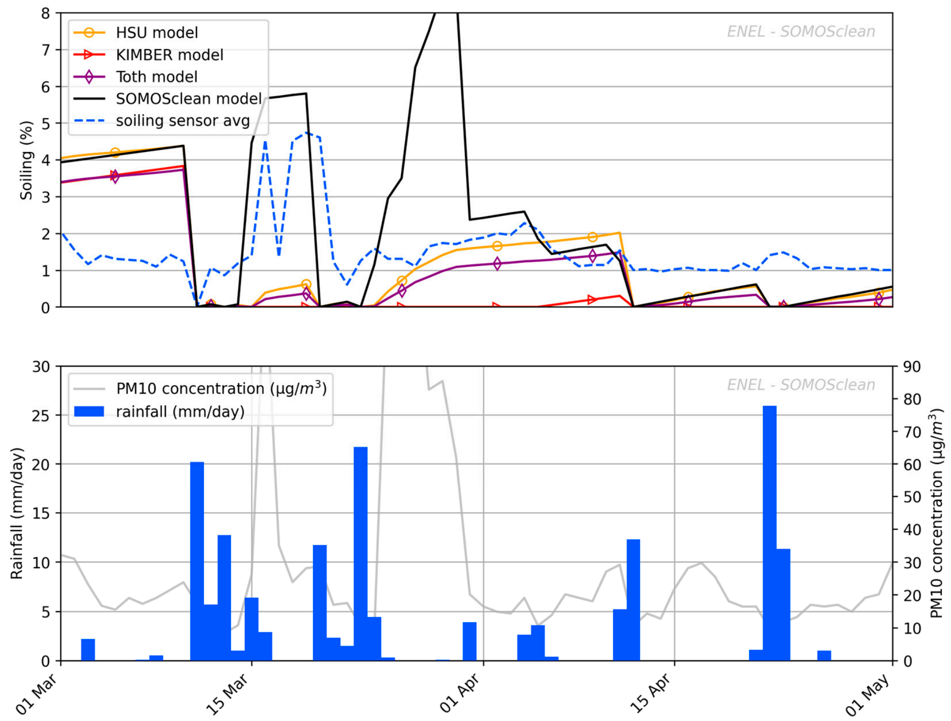

Figure 7. Dust concentration effect. Comparison between different soiling modeling methods applied to a PV power plant (49 MWp) in Spain.

By comparing the behavior of each model to this type of event, we found that the KIMBER model is the simplest one, and it does not consider PM10 concentration, so it cannot model the effect of high concentrations of particles. HSU and Toth's model behavior are very similar, increasing the soiling rate deposition, but in a very smooth way.

The SOMOSclean model considers particle concentrations as events when the concentration is above a certain threshold, increasing the effect through a factor (proportional to the particle concentration value) [17].

Another effect can be observed in Figure 7, specifically regarding how soiling sensors respond to these types of events. During the first dust event, a delay between the event and the sensor output is observed, both in the increase due to high PM10 concentration and in the cleaning caused by rainfall. The second dust event was not even recognized by plant sensors. This can be attributed to two main factors. First, soiling sensors require a certain level of irradiance to function properly, making them less effective in conditions with cloud cover or extremely high particle concentrations. Second, most sensors rely on the manual cleaning of the reference cell, meaning that an increase in soiling is not recorded until the reference cell has been cleaned.

However, soiling sensors are essential in most cases, to have a comparison measurement (even if delayed) because the real effect of this type of high particle concentration event can be very different depending on the conditions.

The models analyzed consider particle concentration but not wind or humidity, which, of course, have a considerable influence. Also, the type of pollutant (i.e., composition, color, diameter, etc.) is very important, since equal amounts of various kinds of dust particles may cause completely different effects. There are several studies analyzing the dust deposition phenomenon: influence of particle size, chemical and mineralogy composition, or deposition time [65–68].

5.5. Wind

Another important factor in particles deposition is the wind. It aids in the transfer of dust particles from one location to another by traveling thousands of kilometers. While low wind speeds encourage dust collection, high wind speeds have the capacity to clear dust from the PV surface.

None of the soiling models analyzed take into account wind speed, an aspect to be considered in future work.

5.6. Humidity

Relative humidity plays a significant role in how dust accumulates on solar panels, as it affects how dust particles stick to the surface. Low relative humidity can cause static electricity buildup, which attracts and holds dust particles on the surface of solar panels. In a humid environment, the deposition velocity of particles with different sizes increases as compared to dry deposition. This is due to the size increment of a particle in humid conditions [69].

None of the soiling models analyzed consider relative humidity, an aspect to be considered in future work.

5.7. Dew

Dew formation occurs when the temperature of a surface, such as a PV panel, drops below the dew point temperature of the surrounding air, causing water vapor in the air to condense into liquid water droplets on the surface.

Dew can contribute to soiling by acting as a solvent that dissolves and carries atmospheric contaminants onto the surface of PV panels. As dew droplets form overnight, they can pick up airborne particles such as dust, pollen, and pollutants, depositing them onto the panel surface as the dew evaporates during the day.

But, according to the observations, the effect of dew at night is not always negative. When dew and light rain are combined, the panels do clean more easily, although the rain threshold that would normally be necessary to clean the panels is not reached. This is explained because in this case, the dew "softens" the dirt, making it easier to be washed away by the rain. In this case, the orientation of the panel plays an important role, as we will see in the following section.

5.8. Solar Panel Tilt Angle

The tilt angle and orientation of solar panels also affect soiling levels. Panels with a steeper tilt angle may be less prone to soiling as rainwater can help wash away contaminants more effectively. Experiments has been carried out for testing different stow positions during the night: 0°, 30°, 90°, and 180° [70]. The effect of gravity on dust removal is analyzed in [71], proposing an optimal tilt angle to provide a better daily performance.

Regarding the soiling models, the HSU model considers the tilt angle as an input but as a fixed parameter it is not valid for solar tracking systems. This is also an interesting aspect to be considered in future work.

5.9. Type of Soil, Terrain, Vegetation, and Birds

There are other location-dependent characteristics influencing the deposition on the panels and therefore the efficiency of solar PV Plants, such as dust from agriculture or industry (i.e., tractor movement). In this sense, the type of terrain and vegetation plays a fundamental role. Pollen, moss, and bird droppings [72] are other examples that can substantially influence soiling, depending on the location of the PV plant.

6. Measuring Uncertainty Between Models and Sensors

6.1. Metodology and Soiling Sensors Considerations

In order to evaluate the uncertainty between the models and the sensors, we chose different metrics [73]: the coefficient of determination (R2), which is used to evaluate the linear relationship, the Root Mean Square Error (RMSE), and the Mean Absolute Error (MAE), which measures the average error between the measured and the simulated data.

$$R2 = 1 - \frac{\sum\left(y_{ref} - y_i\right)^2}{\sum\left(y_{ref} - \overline{y}_i\right)^2} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{ref} - y_i\right)^2} \tag{8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_{ref} - y_i\right| \tag{9}$$

where y_{ref} are the actual observations (reference values obtained from the sensors) and y_i are the values estimated from the models.

Before analyzing the metrics of the different models, it is important to consider that soiling sensors inherently exhibit delays or output errors due to their specific characteristics. These delays occur because soiling sensors require a minimum level of irradiance to function effectively, which limits their performance under cloudy conditions or during episodes of extremely high particle concentrations. Additionally, many sensors depend on the manual cleaning of the reference cell, meaning increases in soiling are not detected until this cleaning takes place. Errors may also arise from issues such as calibration inaccuracies or communication failures.

Due to those characteristics, we compared 7 day averages, considering an average delay of 2 days in sensor outputs. So, the reference values were taken as actual observations to compare the models, which are calculated as follows:

$$y_{ref} = \frac{\sum_{1+2}^{7+2}\frac{\left(y_{sensor1\_raw} + y_{sensor2\_raw}\right)}{2}}{7} \tag{10}$$

Additional considerations regarding the interpretation of soiling sensor values are as follows. If no valid output is available from one of the sensors during a 7-day period, the other sensor is used as the reference. However, if neither sensor provides valid output during this period, the data for that timeframe are excluded from the metrics calculation. When calculating the metrics for each sensor, missing data are replaced with the most recent valid data available. It is also worth noting that the high particle event in March 2023 was excluded from the comparison, as it was not properly detected by the sensors.

6.2. Results and Discussion

The results of the evaluation are presented in Table 3 and in Figure 8. The input data correspond to the Location 3, chosen for the comparison of previous sections (See Figure 3) as the quality of the sensors data were the best over the different locations.

Table 3. Evaluation metrics of the 4 models analyzed (7 day average value comparison, over 105 weeks).

Method	Soiling (%) Mean	Count (n. of Weeks with Valid Data)	R2	RMSE	MAE
Reference values (average of soiling sensors)	1.41%	99	1.0	0.0	0.0
Sensor 1	1.92%	85	−0.218	1.288	0.763
Sensor 2	1.15%	99	0.886	0.394	0.301
Kimber	0.88%	105	−0.351	1.356	1.035
HSU	1.04%	105	0.233	1.022	0.740
Toth	1.39%	105	0.239	1.018	0.734
SOMOSclean	1.56%	105	0.380	0.919	0.694

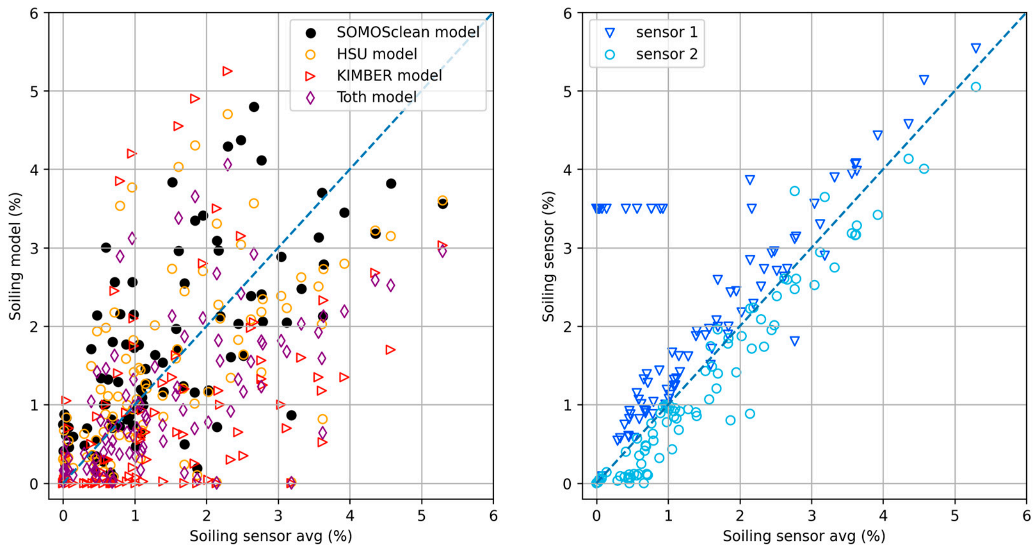

Figure 8. Regression plot of 7-day values of soiling (%). Each point represents the 7 day average value compared versus the average values of both soiling sensors.

7. Conclusions

In this paper, the effect of the most important environmental parameters on soiling losses has been analyzed, comparing the behavior of four different analytical models: Kimber [29], HSU [32], Toth [33], and SOMOSclean [17] models. While simpler models may offer straightforward implementation, they often fail to capture the full complexity of soiling dynamics, leading to increased RMSE error.

The behavior of the models is very similar in "normal" conditions (without specific atmospheric events). The main input variable to all of the models is the rainfall, considering that most of them have a fixed threshold and perfect cleaning, while SOMOSclean models it in a different way, allowing partial cleaning. The influence of the PM10 concentration is also different in each model: the Kimber model, the simplest one, does not consider the influence of particle concentration. The HSU and Toth models consider them in a similar way, while the SOMOSclean model responds better to high particle concentration events.

It has been stated that soiling sensors usually have an intrinsic delay or output error, so it is important to consider it when analyzing the numerical results. When comparing 7-day values over more than 2 years in a 49.5 MWp PV plant, the better model was SOMOSclean with an MAE (Mean Absolute Error) of 0.694. HSU and Toth's models are very similar with an MAE of 0.740 and 0.734, respectively, and the Kimber model has the greatest MEA with 1.035. However, the four methods can be a good tool to estimate soiling when there is no other alternative, or to compare soiling sensor values and help the decision-making process.

Roadmap for Future Research

While this study highlights key factors influencing soiling, such as wind, humidity, and dew, these variables are not fully accounted for in the analytical models evaluated. Future research should focus on refining these models to incorporate additional environmental variables and improve their predictive accuracy.

Moreover, integrating analytical models with emerging machine-learning techniques and image-based approaches could offer significant advancements. This combination has the potential to enhance soiling predictions by leveraging the strengths of data-driven algorithms and remote sensing technologies, ultimately contributing to more efficient maintenance strategies and higher PV plant performance.

8. Patents

The method presented in this paper has been submitted to be patented (Redondo Cuevas M. Method for modeling the degree of soiling of photovoltaic panels and optimization of cleaning Spanish Patent Application number P202230237).

Author Contributions: Conceptualization, M.R.; methodology, M.R. and C.A.P.; software, M.R. and F.R.; validation, V.D. and A.M.; formal analysis, M.R. and A.M.; investigation, M.R.; resources, A.M.; data curation, M.R., F.R. and V.D.; writing—original draft preparation, M.R.; writing—review and editing, M.R., C.A.P., F.R., V.D. and A.M.; visualization, M.R. and V.D.; supervision, V.D. and A.M.; project administration, M.R.; funding acquisition, A.M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Authors Marta Redondo, Antonio Moset, Fernando Rodríguez and Vicente Donate were employed by Enel Green Power Iberia. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

In this section, the data of the 16 PV power plants are compared to choose the better location for the analysis presented in this paper. For each PV power plant, the following figures are indicated in Table A1.

- Capacity (MWp): Nominal Peak Power;
- SL avg (%): Average values of soiling sensors measurements;
- Date since: Date with the availability of sensor data;
- Sensors % availability: % of days with at least one sensor valid output;
- R2: Coefficient of determination between sensor 1 and sensor 2;
- MAE: Mean Absolute Error between sensor 1 and sensor 2.

Table A1. Location of 16 PV Plants and sensor quality measurements comparison. Better figures regarding availability, R2, and MAE are highlighted with a tick symbol.

Location	Province	Capacity (MWp)	SL Avg (%)	Date Since	Sensors % Availability	R2 (S1 vs. S2)	MAE (S1 vs. S2)	Comments
Location 1	Murcia	84.71	2.26	1 January 2022	80.4	0.104	✔ **0.81**	
Location 2	Sevilla	49.90	2.39	1 January 2022	✔ **94.7**	✔ **0.549**	✔ **0.79**	
Location 3	**Sevilla**	**49.48**	**1.52**	**1 January 2022**	✔ **88.1**	✔ **0.631**	✔ **0.73**	✔ Higher R2 and lower MAE
Location 4	Málaga	43.24	1.53	2 January 2022	✔ **93.4**	−0.663	1.72	
Location 5	Málaga	43.24	1.55	1 January 2022	✔ **93.2**	0.356	✔ **0.90**	
Location 6	Badajoz	49.91	0.79	1 January 2022	✔ **93.4**	−0.570	1.19	
Location 7	Baleares	13.32	1.32	1 January 2022	69.2	0.169	1.09	
Location 8	Sevilla	22.48	1.28	1 October 2022	53.6	0.158	1.23	
Location 9	Huelva	30.44	1.82	1 November 2022	43.2	0.830	0.35	Sensor data availability <50%
Location 10	Badajoz	49.56	0.61	31 December 2022	40.1	0.000	N/A	Sensor data availability <50%
Location 11	Badajoz	48.99	2.51	31 December 2022	38.3	−0.221	2.20	Sensor data availability <50%
Location 12	Badajoz	46.59	0.73	31 December 2022	38.9	−2.945	1.37	Sensor data availability <50%
Location 13	Badajoz	47.46	1.61	31 December 2022	26.7	−1.430	0.97	Sensor data availability <50%
Location 14	Badajoz	49.87	2.20	31 December 2022	38.6	0.000	N/A	Sensor data availability <50%
Location 15	Badajoz	47.88	2.35	31 December 2022	42.3	0.358	1.20	Sensor data availability <50%
Location 16	Badajoz	49.87	5.14	31 December 2022	42.8	0.000	N/A	Sensor data availability <50%

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