Assessment of using atmospheric aerosol transport models for predicting the soiling rate in CSP plants

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ABSTRACT

Particle deposition on solar mirrors deteriorates the performance of concentrating solar power (CSP) plants considerably. To save water for cleaning activities and to increase the plant performance, an empirical soiling model was developed by the *German Aerospace Center* to calculate the decline in cleanliness - the soiling rate - of CSP collectors, based on meteorological and aerosol particle input parameters. Until now the model can only be applied to site locations with available measurements of the necessary input parameters. In this work, a new approach is investigated to extend the soiling model application to various locations: aerosol transport models simulate particle concentrations and many other parameters covering large areas, so they can provide the parameters that are needed as soiling model input. To implement this idea while following an integral and gradual process, the soiling model's sensitivity for input data in a different resolution of time and aerosol particle size bins is investigated by adapting ground measurement data. The meteorological and particulate matter parameters provided by two transport models are compared to the ground measurement data. Finally, the data is adapted to the soiling model format, its performance with the new input data is validated and the best available input data source and configuration is determined. The validation of the soiling model for predicting photovoltaics (PV) soiling shows that the soiling model is universally applicable technology-wise too.

1. Introduction

CSP and PV plants are commonly installed in arid or semi-arid regions where the highest levels of direct normal irradiance are provided. At desert locations the aerosol particle concentration, especially the mineral dust load, can be high and particles deposit from the atmosphere onto solar mirrors. The soiling of CSP collectors leads to decreased plant performance and profit and makes cleaning with water necessary. Modelling the soiling losses and applying the best cleaning strategy considering changes in mirror reflectivity, electricity prices, solar irradiance and cleaning costs can increase the profit by 2-3 % [1]. Soiling of PV panels also decreases the PV plant performance, however the effect is slightly less severe for PV as compared to CSP soiling effects [10].

The empirical soiling model developed by DLR for the two locations Plataforma Solar de Almería (PSA) in Spain and Missour (MIS) in Morrocco calculates the daily decline in cleanliness, referred to as soiling rate (SR), based on input parameters such as meteorological data (humidity, wind speed and direction, temperature and surface pressure), particle number concentration, and collector design parameters. The data is obtained with ground measurements at the two locations. The soiling model is validated for the two sites PSA and Missour with available CSP SR measurements. The SR has been measured with the TraCS device, which compares the reflected with the incoming radiation by using two pyrheliometers and tracks the development of their ratio over time [3].

The application of the soiling model to comprehensive areas would enable SR predictions for new favorable CSP plant locations. Medium-range forecasting of SRs can support better strategical cleaning decisions in the operation of CSP plants, with the potential to save up to 70 % of the plant's water consumption [2].

In this work, the possibility of using numerical aerosol transport model data as input for the soiling model is investigated. Aerosol transport models cover large areas, applying grids with varying spatial resolutions, and provide forecasts of particle concentrations and meteorological parameters. Two validated transport models, the NMMB MONARCH Dust model developed by

the Barcelona Supercomputing Center (BSC), and the Copernicus CAMS model by the European Centre for Medium-Range Weather Forecasts (ECMWF), are utilized to generate the necessary input data for the soiling model (see Fig. 1). The NMMB model provides short to medium-range dust forecasts (up to 72 hours) for global and regional domains in three particle size bins with a spatial resolution of 30 km and a temporal resolution of 3 hours [5]. The CAMS model offers forecasts for five aerosol types (sea salt, dust, organic matter, black carbon and sulphate) with a spatial resolution of 80 km and a temporal resolution of 3 hours [6]. The validation of the soiling model with modelled input parameters is implemented for PSA and Missour with TraCS SR measurements.
Validating the soiling model for predicting PV soiling rates with PV soiling measurements recorded at PSA is a step towards the model's future application for this technology. This development is especially interesting against the background of the installed PV capacity which exceeds the CSP capacity by far and an increasing interest in hybrid CSP-PV plants, utilizing the advantages of both technologies. [4]

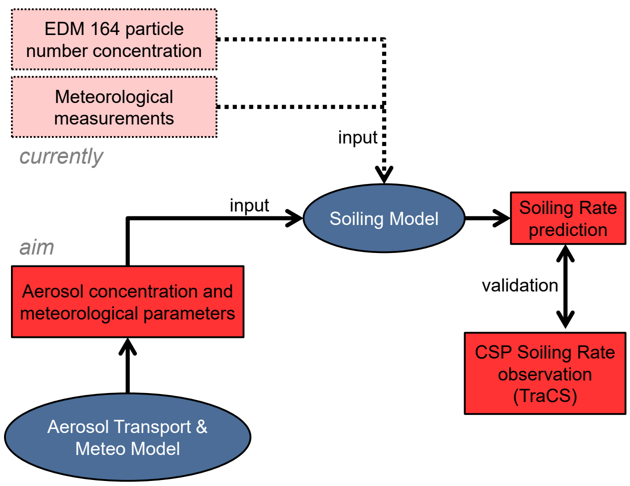

Figure 1. Schematic presentation of substituting input parameters for the soiling model with aerosol transport model data

2. Overview of the methodology for the assessment

The methodology of this work implements several intermediate steps while following the final objective, which is to substitute ground measurement input data with modelled data. This gradual approach is important to justify the final results considering the previously achieved benchmarks as reference points.
The sensitivity of the soiling model concerning its input parameter resolution is tested. Ground measurement data is adapted to the same configuration as the data provided by numerical transport models, which exhibits a lower time resolution and fewer particle size bins than the measured soiling model input data. The loss in information for averaging over periods of 1 hour, 3 hours and 1 day and for summarizing 30 particle size channels to 3 bins and 8 bins is captured and discussed. The soiling model performance with the adapted measurement data is validated and compared to its performance with original input data resolution by calculating the statistical criteria root-mean-square error (RMSE), mean absolute deviation (MAD) and bias. The results are taken as a reference for the ability of the soiling model to digest input data of lower resolution.
Atmospheric aerosol transport models provide meteorological and aerosol particle data like temperature, wind speed, wind direction, surface pressure, relative humidity, particle mass concentration and particle deposition fluxes in several size bins and for varying aerosol types. The simulated values at the two locations PSA and Missour are compared to the measured ground data for these parameters for a period of two years (2017 and 2018). The quality of correlation between the modelled and measured parameters is evaluated with statistical criteria and graphically presented in plots.
The model parametrization is optimized minimizing the RMSE.
To enable a smooth integration of the aerosol transport model data into the soiling model, a novel method to extend the three particle size bins provided by the transport models to 30 size channels used by the soiling model is developed and tested. In the NMMB Dust model, particle mass concentrations of mineral dust are provided in three size bins of 0.2 - 2.5 µm, 0.2 - 10 µm and 0.2 - 20 µm (particle diameters) [5]. The CAMS model provides particle mass concentrations for mineral dust (0.06 - 1.1 µm, 1.1 µm - 1.8 µm, 1.8 µm - 40 µm) and for sea salt aerosol particles (0.06 - 1 µm, 1 - 10 µm, 10 - 40 µm) in three size bins; organic matter, black carbon and sulphate aerosol particles are provided without a specification of size limits [6, 7, 8].
The performance of the soiling model with input data originating from the aerosol transport models NMMB and CAMS is evaluated and compared to its performance with original input data from ground measurements. The validation is implemented for the two locations PSA and Missour with k-fold cross-validation (k = 5) and the average RMSE, MAD and bias and their variation are presented.
Measurements at PSA of the spectrometer EDM 164, a particle counter detecting particle number concentration in 31 size channels from 0.2 µm to 32 µm, are converted into a volumetric size distribution curve, using the effective (medium) diameter of each size channel (see Figure 2) [9].
With the obtained particle volume distribution, for each channel a weighting factor is determined that describes the weight of this channel compared to the rest. These weighting factors, which are specific for each of the mentioned aerosol particle species and size limits provided by the transport models, are then used to convert the particle mass concentrations of the three transport model bins to 30 particle number concentrations, used in the soiling model. The soiling model performance with 3-bin configuration and with the extended 30-bin configuration for transport model data is tested, validated and discussed.

For the application of the soiling model to PV soiling the input data is used in its extended configuration with 30 particle size bins.

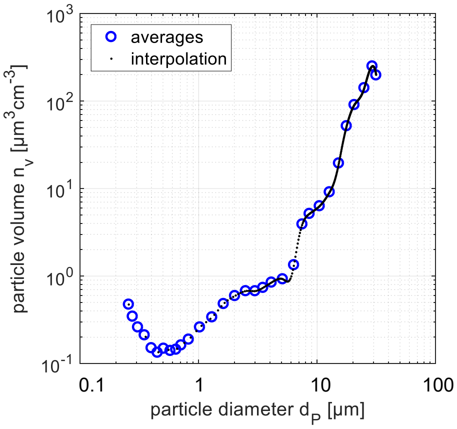

Figure 2. Particle volume size distribution at PSA obtained by averaging minutely particle measurements (01/2017 - 03/2019)

3. Implementation, Results and Discussion

The first three sections of this chapter present results for modelling soiling of CSP collectors, the validation is implemented with the TraCS device at PSA and in Missour. Section 3.4 contains the application of the soiling model to PV modules, validated with the PV soiling measurements at PSA.

3.1 Soiling Model Resolution Sensitivity Analysis

To investigate the soiling model performance for input data with lower resolution, particle size channels are summarized and measurements are averaged over different periods.

The combination of various particle size bins of the ground measurements recorded with the EDM 164 to 3 and 8 size bins according to NMMB model size limits and CAMS size limits (for dust) is implemented. For the summary of various particle number concentrations, the absolute standard deviation (STD) increases. The relative variation, expressed by the ratio of STD and average value, decreases due to the higher average value of summarized particle number concentrations.

Volumetric particle size distribution for the original measurements (EDM 164) and for the adapted data according to NMMB 8, NMMB 3 and CAMS 3 are shown in Figure 3. While the original size distribution is dominated more by large particles and the transition from medium to coarse particles is sharp, the adapted configurations show a more balanced distribution, putting more weight on small particles.

The adaption of the time resolution by averaging over periods of one hour, three hours and one day reduces the variability of parameters, especially if they are strongly fluctuating in their 1-minute resolution. The occurrence of extreme values for meteorological parameters is reduced and the range of values that they take is more limited. Wind speed and wind direction are the most affected variables, with their STD decreasing by about 60 % for daily averages. Parameters that are more constant in general as temperature, relative humidity, and surface pressure are not affected as much by the averaging over time.

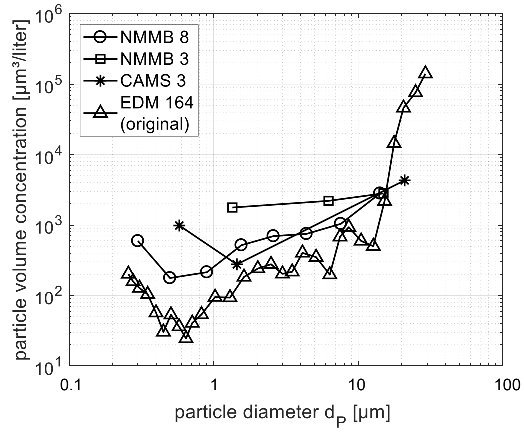

Figure 3. Volumetric particle size distribution of ground observation in different transport model configurations at PSA (01/2017 - 03/2019)

In the observed period (01/2017 to 03/2019) the measured average SR at PSA is -0.33%/day and in Missour -0.47 %/day.

The performance of the soiling model with the adapted ground measurement of varying resolution is validated with five-fold cross-validation, dividing the PSA data set in a training set for the model parametrization and in a test set for the validation. The mean RMSE ± its STD around the mean of the five validation runs on the PSA test set is 0.527 ± 0.298 %/day for the original input data, in Missour the model predicts SRs with RMSE = 0.667 ± 0.011 %/day. The soiling model is underestimating the SR in general with biases of -0.142 ± 0.292 %/day (PSA) and -0.319 ± 0.022 %/day (MIS).

While for the PSA test set the large variation (STD) makes it difficult to testify an impact of the adapted particle size bins on the soiling model performance, in Missour the variation is lower and for input data in the NMMB 3 particle bin configuration, the RMSE increases considerably by 11 %, the MAD is 16 % and the absolute value of the bias is 46 % increased. The CAMS 3 and the NMMB 8 configurations result in a similar range of modelled SRs as the original particle size distribution for both PSA and Missour.

The input data with adapted time resolution has little impact on the soiling model performance with the PSA test set. On the Missour set, the switch from minutely to hourly or three hourly values has little impact on the soiling model performance, while using daily averages results in a 5 % increased RMSE. With averaging input data over increasing time intervals, the model's sensitivity for predicting extreme soiling rates is reduced.

The calculated deposition velocities of particles from the atmosphere adhering on the mirror surface are shown over the particle diameter for varying input parameter resolutions of 1 minute (original), 1 hour, 3 hours and 1 day in Figure 4. The parameter k indicates the number of the set which is used to validate in the k-fold validation process.

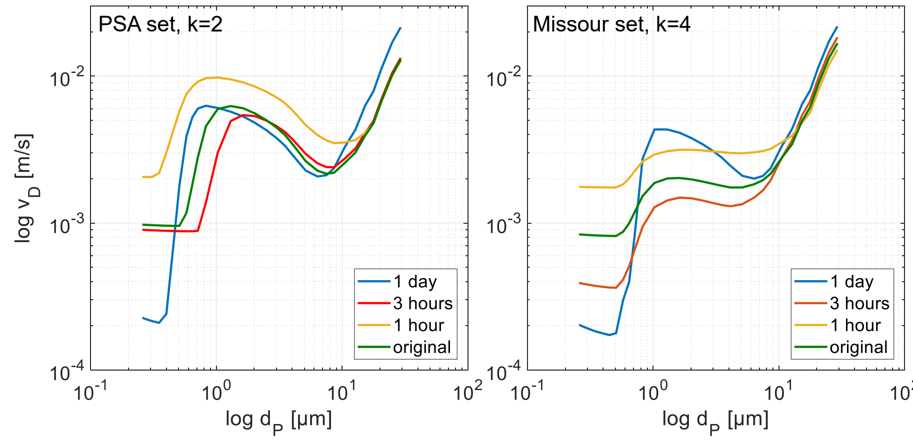

Figure 4. Mean calculated deposition velocity against particle diameter for different time resolutions of input parameters

The daily input parameter resolutions lead to a smaller deposition velocity for fine particles. For medium-sized and large particles the deposition velocity is not considerably influenced by the change of input time resolution.

3.2 Intercomparison of Measured and Modelled Data

To assess the quality of the data provided by transport models, the parameters of the transport models (model data sets) are compared to the ground measurements for the two locations PSA and Missour (reference or measured data sets). The correlation between reference and model parameter is quantified with the Person correlation coefficient (PCC), mean values of the parameters, bias, STD and RMSE.

The intercomparison of the NMMB model with measurement data demonstrates that for some parameters like the temperature ($PCC_{PSA,Temp}$ = 0.6, $PCC_{MIS,Temp}$ = 0.55, shown in Figure 5) and the atmospheric pressure ($PCC_{PSA,press}$ = 0.88, $PCC_{MIS,press}$ = 0.85) the NMMB transport model is able to make predictions with an acceptable correlation to the measured values.

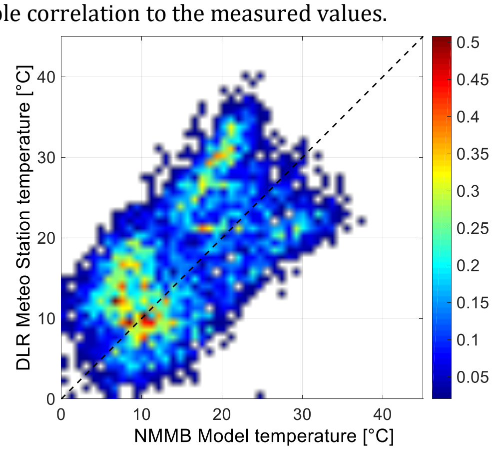

Figure 5. Modelled and measured temperatures at PSA (01/2017 - 03/2019), the colour bar shows the relative occurrence of data points in one pixel

For other parameters, such as wind speed (Figure 6), wind direction, humidity and particle concentrations, the data do not correlate well with DLR measurements. The wind speed correlates with $PCC_{PSA,windsp}$ = 0.22 and $PCC_{MIS,windsp}$ = 0.10, the wind speed's correlation is in a similar range. Especially the mismatch for wind characteristics may originate in topographical terrain conditions influencing these parameters, situated too closely for the model's spatial resolution of 30 km sized grid cells to capture their influence. Both sites at PSA and in Missour are located in mountainous regions, where mountain chains surround the sites or are situated within a few kilometres.

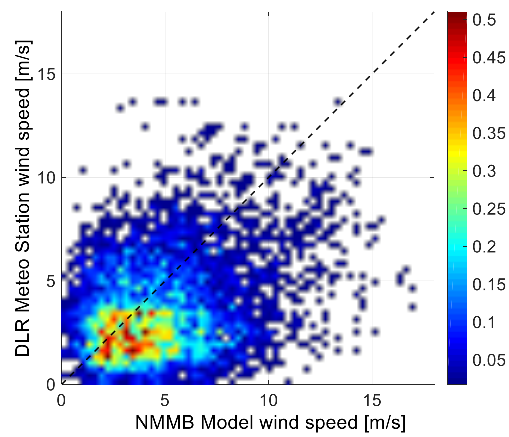

Figure 6. Modelled and measured wind speed at PSA (01/2017 - 03/2019)

A factor degrading the correlation between measured and modelled particle concentrations, which correlate with factors between 0.1 and 0.35 for the different particle size categories, is that only dust aerosol particles are simulated.

Subsequently, the intercomparison of CAMS transport model data and measured data at DLR stations is implemented, yielding slightly better correlations. Correlations of temperature are characterized by $PCC_{PSA,Temp}$ = 0.89 and $PCC_{MIS, Temp}$ = 0.95; surface pressure is correlating with $PCC_{PSA,press}$ = 0.98, $PCC_{MIS,press}$ = 0.88, the wind speed's PCCs are 0.47 and 0.32 respectively. Modelled wind characteristics are in the same range as the recorded values, but their correlation is still minor as compared to the correlation of other parameters. The topographical properties at the sites complicate the simulation of wind speed and direction at exact locations by interpolating spatially between grid points (CAMS spatial resolution: grid cells of 80 x 80 km). The overestimation of the surface pressure might be related to the spatial interpolation too, which is also implemented between vertical model layers. In the processes of soiling model parametrization and fitting, constant offsets in the parameters are resolved and only the linear correlation is of importance for the soiling model operation with transport model data.

The CAMS-DLR correlation of the particle concentrations is improved for some particle size bins compared to the NMMB-generated particle concentrations, now showing correlations of up to 0.54 (for fine PM < 1 µm). Graphical examples of correlation are shown for the temperature (Figure 7) and surface pressure (Figure 8).

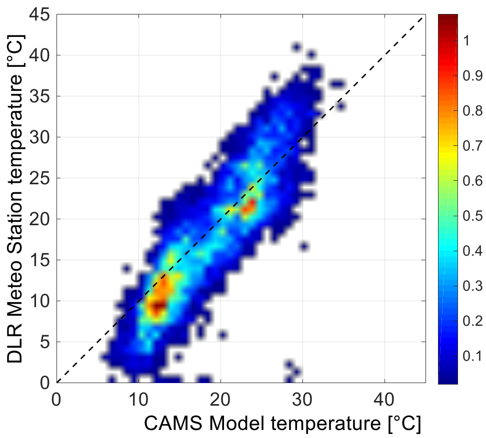

Figure 7. Modelled and measured temperatures at PSA (01/2017 - 03/2019)

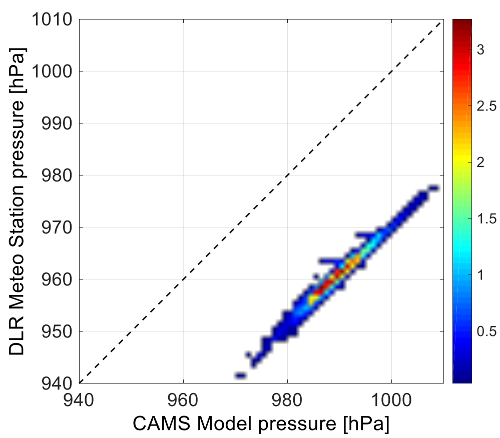

Figure 8. Modelled and measured surface pressure at PSA (01/2017 - 03/2019)

3.3 Soiling Model with Atmospheric Aerosol Model Input

The soiling model with input data generated by the aerosol transport models NMMB and CAMS is implemented for 4 different cases: the two transport models with each two different particle bin modes (three-bin and artificially created 30-bin mode) are tested. The statistical evaluation criteria RMSE, MAD and bias for these configurations and the soiling model performance with original input data (DLR measurements, minutely resolution, and 30 size bins) are presented in Figure 9.

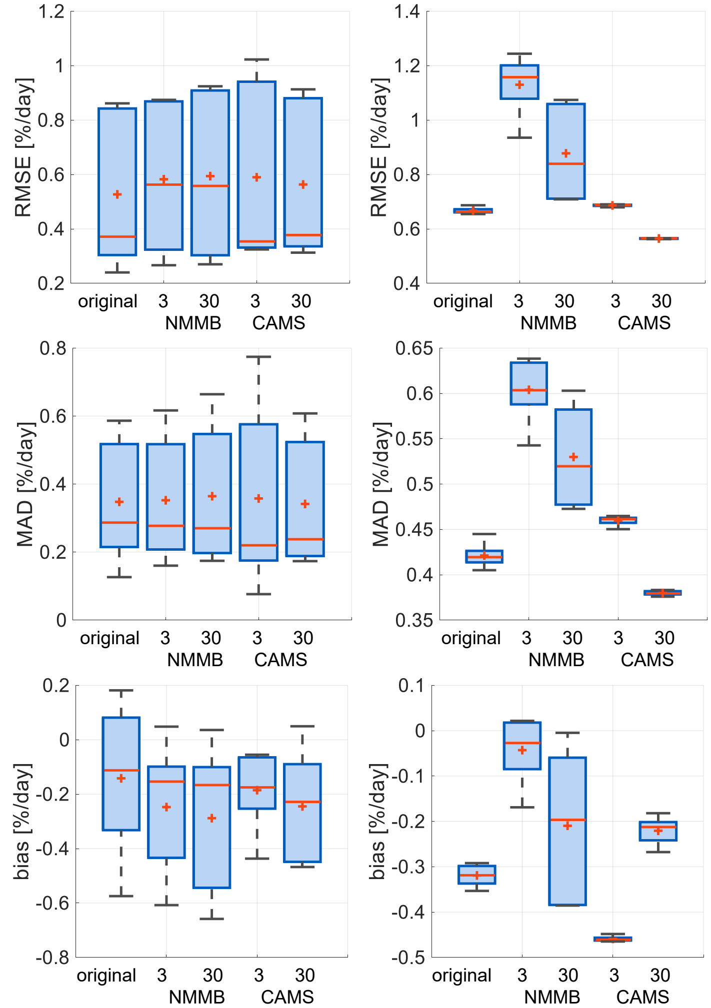

Figure 9. RMSE, MAD and bias of modelled SR compared to measured SR for different input parameter configurations, left: PSA and right: Missour, red central mark: mean of 5-fold validation, red line: median, variation: 50% within blue boxes

Due to the large variation within the five-fold validation, for the PSA test set no general trend is conveyable. For the Missour set, the use of the NMMB 3 transport model data results in an increased RMSE of 1.13 ± 0.117 %/day, using the 30-bin configuration leads to a lower RMSE of 0.878 ± 0.178 %/day. The soiling model with CAMS model data is also performing better when used in 30-bin mode with an RMSE of 0.565 ± 0.002 %/day, which is about 17 % less than the 3-bin mode RMSE. The MADs reveal a similar tendency of the 30-bin mode mitigating the soiling model performance degradation.

The modelled soiling rate is plotted against the observed SR for original and transport model input data in 4 configurations for the PSA test set with k = 3 (k-fold set) in Figure 10 and Figure 12. The same data is shown for the Missour set with k = 1 in Figure 11 and Figure 13. For the PSA test set, the better soiling model performance with CAMS data is noticeable for both bin modes.

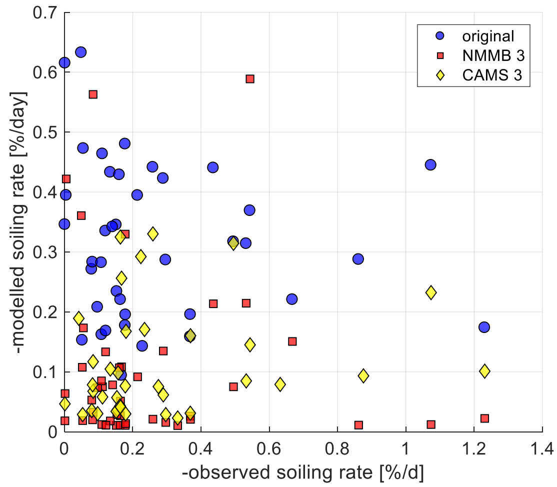

Figure 10. Modelled vs. measured SR for original DLR input and NMMB 3/CAMS 3 input, PSA test, k = 3, in total 57 days

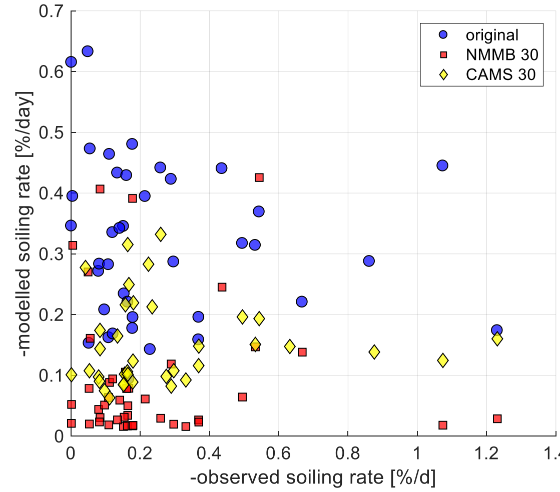

Figure 12. Modelled vs. measured SR for original DLR input and NMMB 30/CAMS 30 input, PSA test, k = 3, in total 57 days

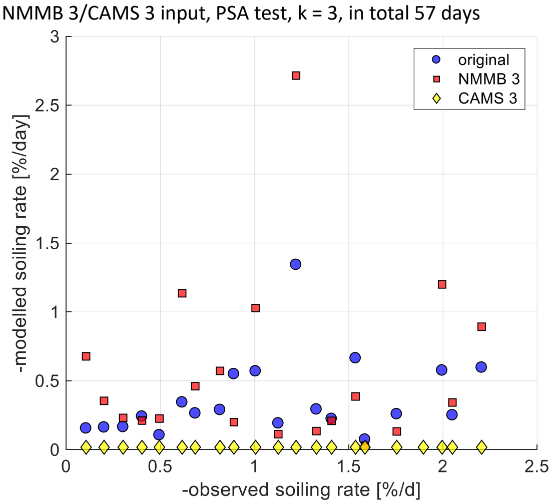

Figure 11. Modelled vs. measured SR for original DLR input and NMMB 3/CAMS 3 input, MIS, k = 1, in total 310 days

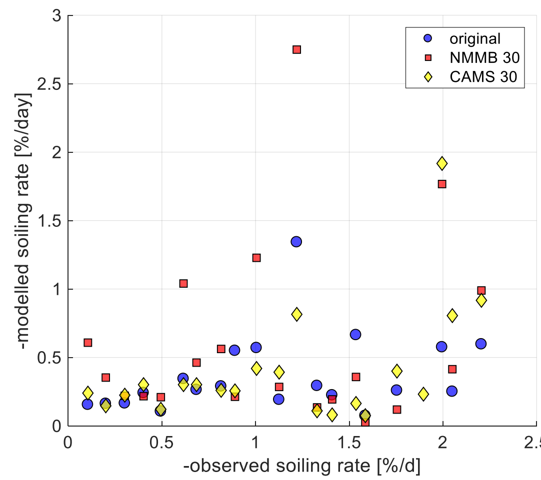

Figure 13. Modelled vs. measured SR for original DLR input and NMMB 30/CAMS 30 input, MIS, k = 1, in total 310 days

In the presentation for the Missour set, the SR underestimation for using CAMS in its 3-bin configuration is distinct (confirmed also by the low bias of around - 0.45 %/day). A substantial improvement is achieved for using the CAMS 30-bin configuration (Figure 13). It is evident that the soiling model accuracy even with original ground measurement data is still low, as the spread of markers and the SR underestimation show, especially in Figure 11 and 13.

The ranges of modelled SRs change when using transport model input data. Small SRs are modelled more frequently and high SRs are not modelled as often compared to using original input data. The modelled SRs at PSA, for example, go up to 0.75 %/day with original input, while for NMMB 30 input SRs values are only modelled up to 0.6 %/day, for CAMS up to 0.4 %/day.

Considering the available options for input data sources, using the CAMS transport model in its extended 30-bin mode achieves the best results for the soiling model performance. Using the NMMB transport model data as input results in a slightly degraded model performance, characterized by a higher RMSE and a higher MAD. Regarding the overall weaker correlation of NMMB model data with DLR measurements at PSA and in MIS, that emerged from the data intercomparison (3.2), this might be the main reason for the observed lower soiling model performance with this input data.

The artificial generation of particle bins based on the volumetric particle distribution curve measured at PSA leads to better results. Applying this method to CAMS data allows utilizing its full potential and the overall weaker performance of NMMB data in the soiling model can be enhanced by it.

3.4 Application of the Soiling Model to Photovoltaics

Soiling of glazing surfaces is not a process that is exclusive to CSP collectors. PV modules also undergo a decrease in cleanliness over time when they are exposed to the environment. Both technologies experience optical losses due to diffuse reflection, scattering, and absorption of incoming light. Aerosol particles that adhere to the transmitting glass layer of the module scatter the incoming light in all directions, but mostly forward, and reduce the electricity output and cell efficiency. The effect that a soiled glass layer has on the output of a PV system is generally smaller than the equally soiled CSP mirror has on the CSP system output. In CSP systems, the incoming light has to be reflected quite precisely within a small acceptance angle to reach the absorber and to be utilized for the heat transfer to the fluid. Light which is scattered by soiling particles to other directions than the acceptance angle (around 25 mrad ≈ 1.5° for a parabolic *EuroTrough* collector) is lost, unlike in a PV system, where forward scattered light is still transmitted and reaches the PV cell within an acceptance angle that is by far wider than the CSP acceptance angle (can be up to 150°, depending on the incidence angle of the sun). [10]

At PSA, the soiling rate of PV modules is measured by comparing the short circuit current of a soiled PV cell with the one of a regularly cleaned cell, the reference PV cell and calculating the daily change of this cleanliness ratio. PV SR measurements for 240 days between April 2018 and February 2019 are available. The mean SR during this time is -0.071 %/day.

The specific optical properties of CSP and PV technologies result in different soiling rates; CSP SRs measured with the TraCS device are approx. 8 times higher than measured PV SRs (Figure 14) [10].

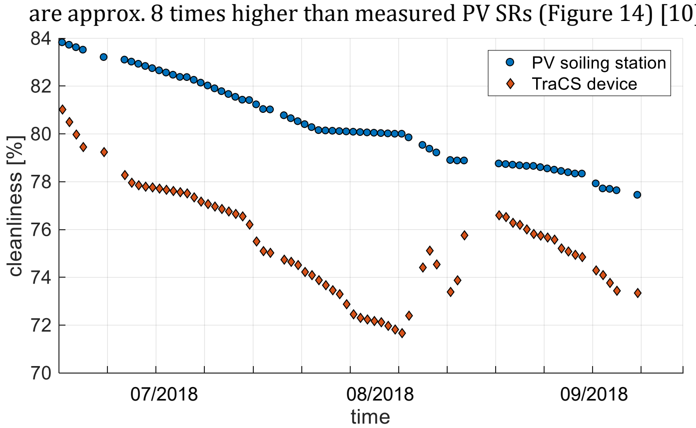

Figure 14. Comparison of CSP and PV soiling at PSA, July to September 2018

The soiling model converts the projected particle surface coverage into the cleanliness by fitting linearly through the correlation of surface coverage and measured soiling rate, thus with measured PV SRs, the soiling model should be able to capture the comparably lower SRs of this technology. [11]

The statistical evaluation of the PV SR modelling compared the measured PV SR yields the following results (Table 1):

Table 1. Statistical evaluation: means and standard deviation (STD) of RMSE, MAD, bias for the 5-fold validation on the PSA test set, all values in %/day

RMSE	STD_{RMSE}	MAD	STD_{MAD}	bias	STD_{bias}
0.0939	0.0510	0.0638	0.0276	-0.0417	0.0349

Like in its application to CSP soiling, the soiling model tends to underestimate the SR of PV, indicated by a negative bias. The values for RMSE and MAD are relatively large compared to the low average measured PV SR.

The modelled PV SRs are plotted against the measured SRs of the PV module. Exemplarily two results of the five-fold cross-validation are presented (k = 2 and k = 4), also to show the variation that occurs using this validation method. The test set is switched chronologically in each step of the validation so that in total 5 different sets of 48 daily soiling rates are used to validate the soiling model. Depending on the selected set, the observed soiling rates vary: in the test set for k = 2 observed PV soiling rates range from 0 %/day to 0.2 %/day, for k = 4 observed daily soiling rates range up to 0.08 %/day.

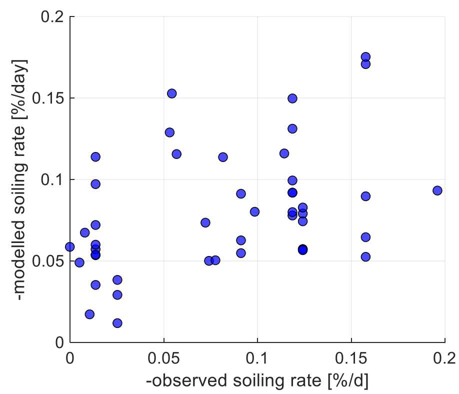

Figure 15. Modelled vs. measured PV soiling rates at PSA, 04/2018-02/2019, PSA test with k = 2, in total 48 days with SRs are plotted

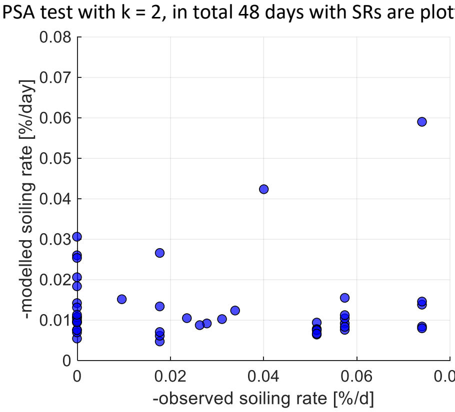

Figure 16. Modelled vs. measured PV soiling rates at PSA, 04/2018-02/2019, PSA test with k = 4, in total 48 days with SRs are plotted

Generally, the modelled soiling rates are in the same range as the measured soiling rates, thus it can be conducted that the soiling model can predict the quantitatively lower soiling rates that occur in PV soiling. The discrepancy between modelled and observed soiling rates occur for example when the same soiling rate values are measured multiple times, as for k = 4 the observed soiling rates 0 %/day, 0.018 %/day, 0.052 %/day, and 0.057 %/day. The accumulated observations originate from the data post-processing which includes manual fitting of raw cleanliness curves. The decline of PV cleanliness curves is very flat so the manual fitting is implemented over many days with a linear fit, resulting in a constant soiling rate. The soiling model does not simulate the soiling rates accordingly constant.

The soiling model can be used to predict soiling rates for PV modules with a model performance that is similar to its application on the CSP soiling rate calculation.

4. Conclusion

Several research approaches intend to model soiling rates based on combining and interpolating ground measurements to soiling maps and by using GIS and a soiling potential model [12, 13, 14, 15, 16]. In this work, an approach using a soiling model with input data obtained by numerical transport models is pursued in order to achieve more exact and spatially more comprehensive soiling data. Data generated by two different transport models, NMMB and CAMS, in each two configurations, 3 and 30 particle size bins, are used as soiling model input.

Among the four different options, using the CAMS transport model in the extended 30 particle size bins configuration achieves the best results. The obtained soiling rate predictions are closest to the soiling model performance which can be achieved with original input data.

The performance of the soiling model on the PSA test set with transport model input data is slightly decreased as compared to the soiling model performance with original input data, but a general trend is not conveyable because of the variation in the validation results. For the Missour set, using NMMB 3 transport model data results in an about 70 % increased RMSE compared to using ground measurement data as soiling model input. The use of NMMB data with 30 size bins leads to a less increased RMSE which is only 30 % higher than the RMSE achieved with ground measurement data. Modelled soiling rates for Missour with CAMS 3 input data underestimate the observed soiling rate but a substantial improvement can be achieved for using the 30 artificially generated particle size bins. This shows that the novel method for artificial generation of particle size bins based on the particle size distribution curve of PlaSolA has the potential to solve the challenge of the generally low number of particle size bins provided by aerosol transport models.

A general tendency of the soiling model to underestimate the soiling rate, characterized by a negative bias, is present for original input data and continues if transport model data input is used.

The soiling model sensitivity analysis for the soiling model behaviour with adapted in-situ measurement data showed the influence of temporal and particle size input parameter resolution on the soiling model performance. Generally, the frequency of extreme values for meteorological and aerosol particle concentration parameters is reduced for averaging over increasing time intervals and especially daily averaging can lead to inaccurately modelled soiling rates. Changing the number of particle size bins from 30 to 3 bins or 8 bins leads to a similar range of modelled soiling rates as the original particle size distribution, with exception of the NMMB 3 modification which underestimates the soiling rate considerably.

The comparison of aerosol transport model data to ground measurement data at Plataforma Solar de Almería (Spain) and in Missour (Morocco) shows that the NMMB model can make predictions which correlate well with the measured values for temperature and pressure. For other parameters, however (wind speed, wind direction, humidity, $PM_{2.5}$, PM_{10}, and PM_{20}), the simulated data does not correlate well with DLR measurements. This may be due to topographical terrain conditions influencing these parameters situated too closely for the model's spatial resolution – grid cell sizes of about 30 km – to capture their influence. Another degrading factor is that NMMB's only simulates dust aerosol particles. The change from 3 to 8 particle size bins might improve the correlation in the future.

The data provided by the CAMS transport model correlates better with DLR measurements. Temperature, pressure and relative humidity correlate almost linearly. Modelled wind speed and wind direction are in the same range as the recorded values but the linear relation between model and reality for these parameters is not distinct which might again be the result of the spatial model resolution (even less with 80 km grid cells). Topographical properties at the sites, as mountain chains surrounding the PlaSolA and the mountainous region in Missour, complicate the estimation of wind characteristics with spatial interpolation between grid points.

The application of the soiling model to PV soiling shows that it can model the quantitatively lower PV SRs. This is especially interesting because PV and CSP continue to coexist and complement each other increasingly in the form of hybrid plants, incorporating the advantages of both technologies. The soiling model predicts soiling rates for PV modules with a model performance that is similar to its application on the CSP soiling rate prediction.

The results of this thesis show that it is generally possible to use transport model data in combination with a soiling model to predict soiling losses. Several steps for improving the soiling model results were identified. A challenge is the currently low accuracy of the soiling model even when operated with ground measurement data. In the future, the utilized transport models should be assessed with regard to which aerosol types their output includes. If more aerosol species are provided within the aerosol transport model output, like in the CAMS model, the soiling model performance is better. With additional information of eight instead of three particle size bins in the NMMB model, a further improvement is probable, especially when the generation of 30 artificial size bins is adapted following the method introduced in this work. Regarding the low correlations between modelled and measured wind characteristics, consulting other sources for wind data as wind maps used for the wind energy industry might be a solution, since they reproduce the influence of topographical features close to the sites more accurately. [17]

The next important step is the further improvement of the soiling model. Then, ways to create a soiling map and soiling forecasts based on using aerosol transport model data as input can be pursued. Future research approaches should include methods for processing the large data volume and for automatization at an early stage. The here presented validation of using numerical aerosol transport models – considering also their performance – as input for the empirical soiling model opens up the possibilities of compiling soiling maps covering comprehensive areas and enables forecasting of soiling rates for exact locations without taking ground measurements.

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