



## Soiling Issues for O&M of PV Plants

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30 September 2021, Task 13 Focus Workshop on Operation & Maintenance

# Credits for Task13 members



PVPS

## Soiling Losses – Impact on the Performance of Photovoltaic Power Plants

2021

Report IEA-PVPS T13-21:2021

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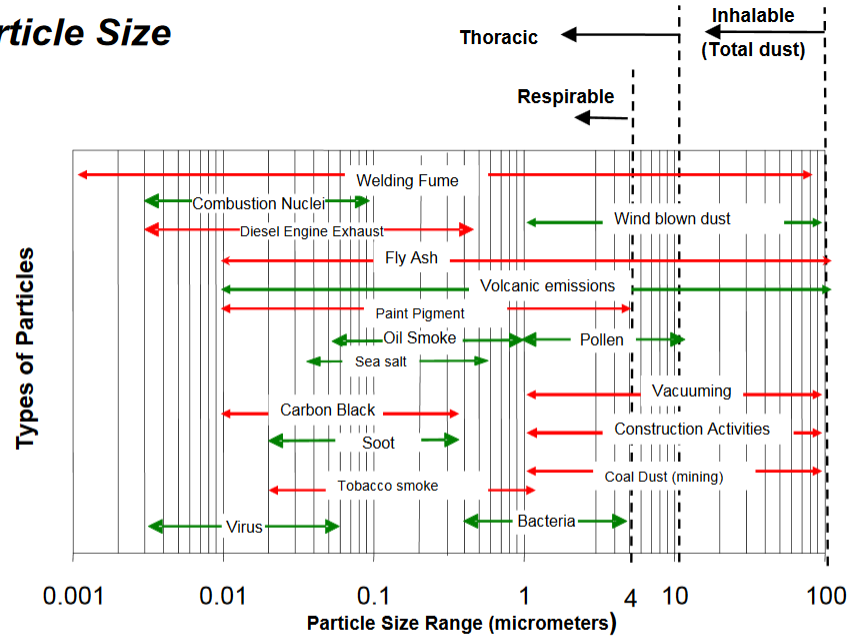
### Editors

Ulrike Jahn, VDE Renewables, Alzenau, Germany

# Sources of Soiling



## Particle Size

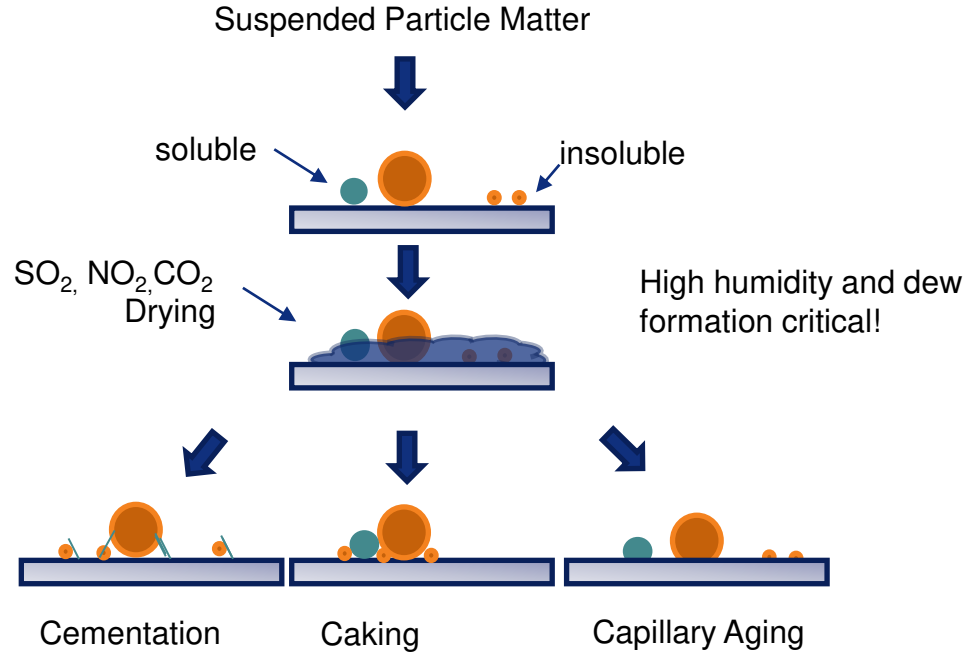
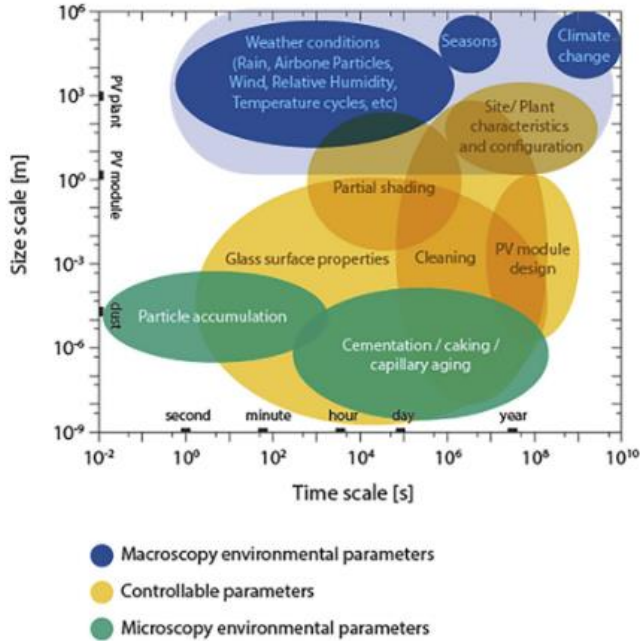


← Environmental / Naturally Occurring Particles →

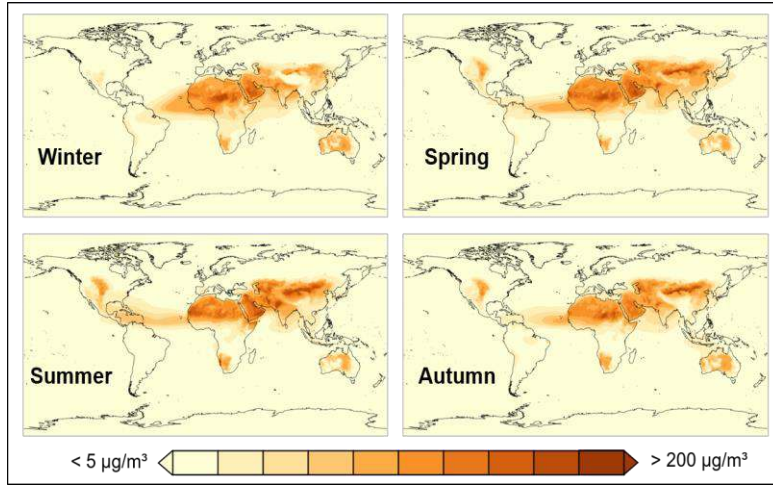
← Workplace / man-made Particles →



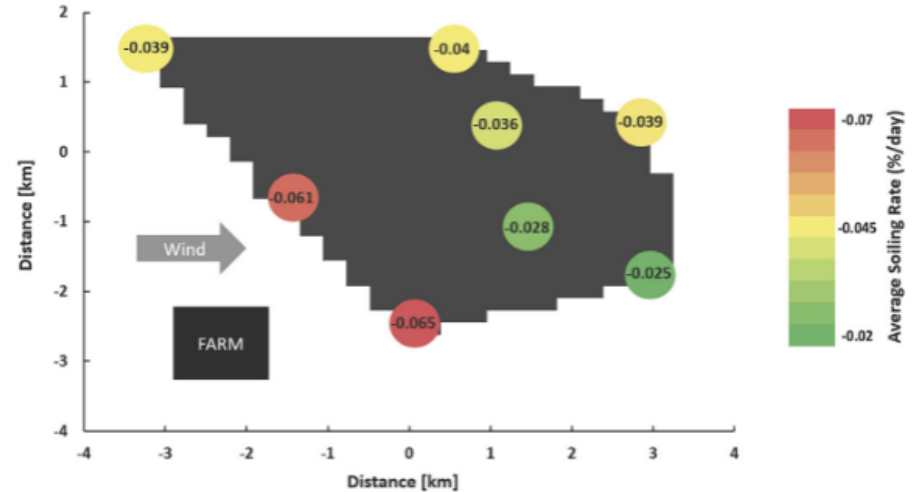
# Basic physical Principles of Soiling



# Spatial and temporal variation of soiling ratios



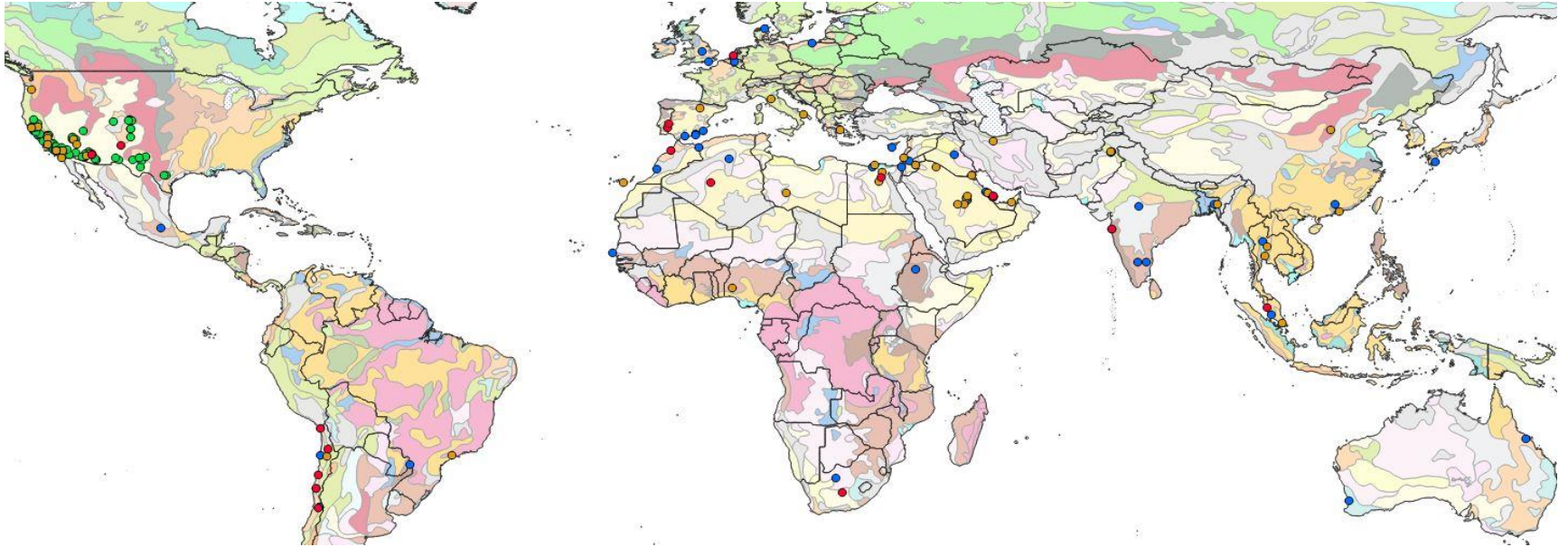
Source: kind permission by Jan Herrmann, University Freiburg



- Seasonal and intra-day variation

- Spatial variation within one plant
- Each plant is different

# Global soiling publications



## Harmonized World Soil Database

FAO/IIASA/ISRIC/ISS-CAS/JRC, 2008. Harmonized World Soil Database (version 1.0).  
FAO, Rome, Italy and IIASA, Laxenburg, Austria



# Inhomogeneous soiling and IR imaging

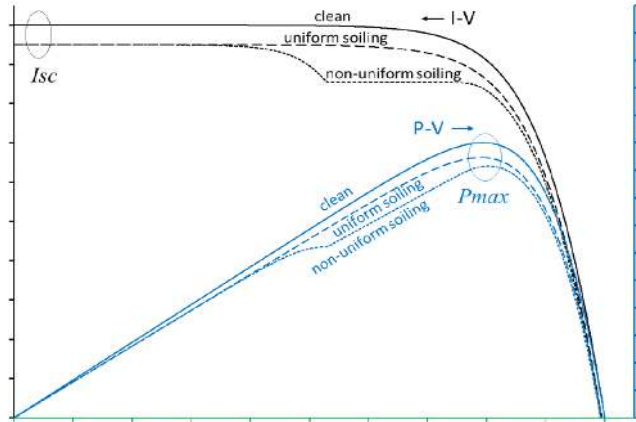


Figure 2-1: Illustration of soiled PV module and corresponding I-V & P-V curves

**Most commonly used metric:**

$$\text{SRatio} = P_{\text{max\_soiled}} / P_{\text{max\_clean}}$$



## Part 1: Monitoring – Soiling

- Defines terms
- Measurement principles (MPP,  $I_{sc}$ -based, clean vs. soiled)
- Sampling intervals per accuracy classes
- Number of sensors per plant size
  - (e.g. 6 sensors for  $300 \text{ MW} \leq \text{plant size} \leq 500 \text{ MW}$ )
- Data analysis (“daily average, filter outliers” etc.)
- Recommends rain gauge, but states that having soiling measurements gives direct result
- states that snow loss may be detected by soiling sensor unless mounted atypically for array



# Monitor Soiling: Overview of Sensors



Soiling Sensors					
Manufacturer	Atonometrics	Atonometrics	Campbell Scientific	<del>Kipp and Zonen</del>	NRG Systems
Model name	Soiling Measurement System	Mars Soiling Sensor	CR-PVS1	Dust IQ	Soiling Measurement Kit
Method	Short-circuit current and power	Optical (image processing camera)	Short-circuit current	Optical (LED)	Short-circuit current
Module power range	Up to 450 W	Not applicable	Up to 300 W	Not applicable	3 panels of 15 W each
Power supply	10 to 30 VDC or 100 to 240 <u>VAC</u>	10 to 30 VDC	16 to 32 VDC	12 to 30 VDC	5 to 15 VDC
Output options	Ethernet	RS-485, Ethernet	RS-232	RS-485	Available upon request
Approximate Cost: Euro / USD	€ 6078 / \$ 6900	€ 2600 / \$2950	€ 2334 / \$ 2649	€ 3807 / \$ 4320	Available upon request

# Can Soiling be predicted? – Soiling models



Lead Author	Model Class	Year	Aim	Key Parameters	Main Findings	Reference
Kimber	Linear	2008	Extracting soiling loss from PV performance data.	PV Performance Ratio, Rainfall	The model generates a soiling profile based on the rainfall pattern and on the soiling rate recorded during the longest dry spell. It requires the identification of a minimum cleaning threshold, and of the length of dry period.	A. Kimber, L. Mitchell, S. Nagrali and H. Wenger, 'The Effect of Soiling on Large Grid-Connected Photovoltaic Systems in California and the Southwest Region of the United States', in 2008 IEEE 4th World Conference on Photovoltaic Energy Conference, Waikoloa, HI, 2008, pp. 2291-2295, doi: 10.1109/WCPVCEC.2008.279090.
Qasem	Semi-Physical	2012	Modelling soiling loss profile using weather data.	Ta, WS, WD, dust, RH, rainfall	A model is developed to estimate the dust accumulation based on weather conditions and to convert this into an electrical loss based on the PV module characteristics and on the dust spectral transmittance.	H. Qasem, T. R. Betts, and R. Gottschalla, 'Soiling Correction Model for Long Term Energy Prediction in Photovoltaic Modules', New York: IEEE, 2012.
Boyle	Linear	2015	Modelling a daily soiling profile measured at five U.S. Locations	TSP	A linear model is developed where the transmittance loss rate is a function of TSP and of the exposure time.	L. Boyle, 'don't soil your chances with solar energy experiments' of natural dust accumulation on solar modules and the effect on light transmittance...
Guo	Linear & Semi-Physical	2016	Modelling a daily soiling profile of a soiling measurement system in Qatar.	WS, PM10, RH	A multi-linear and a semi-physical models are developed and compared. Both models were found to return estimation with < 10% uncertainty when used to estimate the daily soiling loss profile.	Guo B, Javed W, Khan S, Figgis B, Mirza T. Models for Prediction of Soiling-Caused Photovoltaic Power Output Degradation Based on Environmental Variables in Doha, Qatar. ASME 2016 10th Int. Conf. Energy Sustain., 2016, p. 1-8. https://doi.org/10.1115/ES2016-69390.
Bullucsa	ANN & Linear	2016	Soiling loss is estimated from particle size composition	Particle size	Multi-linear regression and ANN are used to estimate the soiling losses based on particle size composition of the soil. ANN are found to perform better.	S. Bullucsa, F. Mani, and R. Kumar, 'Modelling of soiled PV module with neural networks and regression using particle size composition', Sol. Energy, vol. 123, pp. 115-120, Jan 2016, doi: 10.1016/j.solener.2016.11.012.
Javed	ANN & Linear	2017	Modelling a daily soiling profile of WS, WD, Ta, RH. Previous day PM10, WS, RH, Wind Gust frequency and exposure time	WS, WD, Ta, RH, PM10, WS, RH, Wind Gust frequency and exposure time	A 10-input ANN model was able to significantly model the soiling loss trends, returning better results than a multi-linear approach based on the same inputs. PM10, WS and RH were found to be parameters better correlated with soiling.	W. Javed, B. Guo, and B. Figgis, 'Modeling of photovoltaic soiling loss as a function of environmental variables', Solar Energy, vol. 157, pp. 397-407, Nov. 2017, doi: 10.1016/j.solener.2017.08.046.
Bergin	Semi-Physical	2017	Modelling the profile of a soiling measurement in India	PM components concentrations	The soiling profiles is modelled based on the concentration of each PM10 and PM2.5 components. The model is able to predict the soiling loss for each specific component's absorption and scattering efficiency.	Bergin MH, Greenwald R, Xu J, Berta Y, Chappelow VL. Influence of aerosol dry deposition on photosynthetically active radiation available to plants: A case study in the Yangtze delta region of China. Geospat. Res Lett. 2011;28:360-3. https://doi.org/10.1029/2010GL013461

Michel	Linear	2017	Ranking the average soiling losses of 20 soiling station in the USA.	PM10, PM2.5, Rainfall	PM10, PM2.5 and rainfall are found to be the best soiling predictors, out of 104 potential variables, when the average losses of different sites are compared.	Michel, L. Muller M. An investigation of the key parameters for predicting PV soiling losses. Prog Photovoltaics Res Appl. 2017;25:261-267. https://doi.org/10.1002/pp.2850.
Figgis	Linear	2018	Modelling soiling deposition and resuspension	WS, PM10	Multilinear relations are proposed to estimate soiling accumulation, deposition, resuspension and rebound rates.	Figgis B, Guo B, Javed W, Abul S, Bessouba Y. Dominant environmental parameters for dust deposition and resuspension in desert climates. Aerosp Sci Technol. 2018;79:269-282. https://doi.org/10.1016/j.ast.2018.1452473.
Cordero	Linear	2018	Modelling soiling rates in Chile	AOD	A linear correlation is found in between AOD and soiling rates. Ground-measurements, overestimated satellite derived data.	Cordero RR, Damiani A, Lopez D, Macdonald S, Jorquera J, Sepulveda E, et al. Effects of soiling on photovoltaic (PV) modules in the Atacama Desert. Sci Rep. 2018;8:1-14. https://doi.org/10.1038/s41598-018-32011-8.
You	Semi-Physical	2018	Modelling the soiling loss profile for seven cities worldwide	PM50-20, WS	The soiling accumulation is calculated from the local conditions.	You S, Lim YJ, Dai Y, Wang CH. On the temporal modelling of solar photovoltaic soiling: Energy and economic impacts in seven cities. Appl Energy. 2018;228:1136-46. https://doi.org/10.1016/j.apenergy.2018.07.020.
Zhou	Semi-Physical	2019	Modelling soiling loss based on particle deposition estimation	PM, Rainfall	The soiling losses are estimated using a Community Multiscale Air Quality (CMAQ) model. The estimated PV panel transmittance are lower compared to onsite measurements.	L. Zhou et al., 'The impact of air pollutant deposition on solar energy system efficiency: An approach to estimate PV soiling effects with the Community Multiscale Air Quality (CMAQ) model', Sol. Total Environ, vol. 651, pp. 458-465, Feb. 2019, doi: 10.1016/j.solener.2019.08.194.
Michel	Linear	2019	Rank the severity of the average soiling losses of 41 soiling stations in the USA using environmental parameters.	PM10, PM2.5, Rainfall	The work confirms that PM10 and PM2.5 are the best soiling predictors, followed by parameters describing the average and maximum length of the dry periods. Although, Desatle that, it found that the results could be significantly affected by the environmental parameters sourcing and processing method.	Michel, M. G. Desatle, and M. Muller, 'Predicting photovoltaic soiling losses using the best environmental parameters: An update', Progress in Photovoltaics: Research and Applications, vol. 27, no. 3, pp. 210-219, Mar. 2019, doi: 10.1002/pp.3079.
Shao-souh	Linear & ANN	2019	Modelling the soiling loss from a PV installation in the UAE	Irradiance, Rainfall, Exposure time	A multi-linear and an ANN models were used to estimate the performance of a soiled PV module, with no significant difference between their results.	S. Shao-souh, R. Dhauadi, and I. Zulkarnain, 'Using Linear Regression and Back Propagation Neural Networks to Predict Performance of Soiled PV Modules', Procedia Computer Science, vol. 155, pp. 463-470, 2019, doi: 10.1016/j.procs.2019.08.066.
Michel	Geo-spatial	2019	Estimating average soiling loss from nearby data, site's characteristics	Nearby soiling data, site's characteristics	The average soiling loss of a site can be estimate using soiling data from nearby sites by using spatial interpolation.	Michel, L. Desatle, WS Muller, M. Mapping Photovoltaic Soiling Using Spatial Interpolation Techniques. IEEE J Photovoltaics. 2019;9:272-7. https://doi.org/10.1109/JPHOTOV.2019.28272548.
Larabi	ANN	2019	Modelling the soiling rate of a site in Morocco	Irradiance, WS, WD, Ta, RH, Rainfall	A 6-35-1 ANN model is implemented and validated. A sensitivity analysis shows that relative humidity, first, and second wind	Larabi, B. May Izou, O. Dahlou, D. Bassam, A. Flota-Batuellos, M. Bahdad, A. Artificial neural network modeling and sensitivity analysis for soiling effects on photovoltaic panels in Morocco. Superlattices Microstruct.

## Different types of models (n>15):

1. Linear Regression Models
2. Semi-Physical models
3. ANN
4. Geospatial models

# Mitigation: preventive and corrective measures

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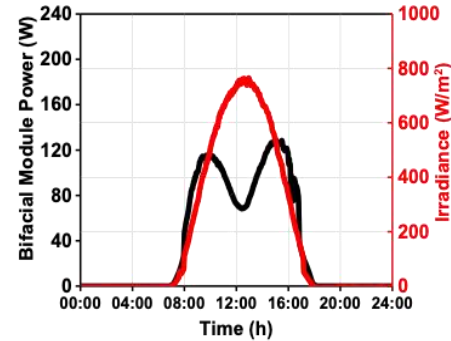
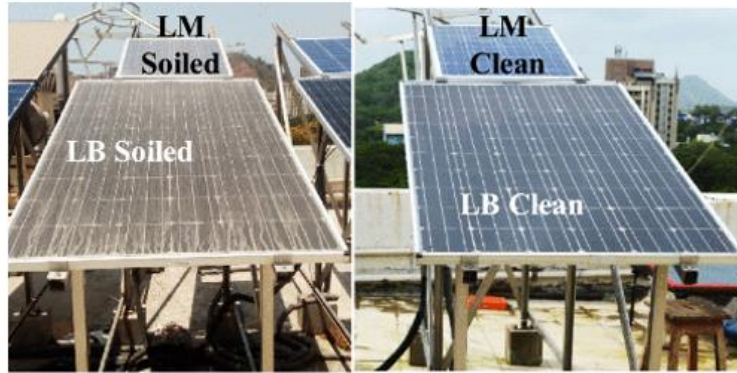
Preventive measures fall rather into the responsibility of EPCs:

- site- and module selection,
- anti-soiling coating applications,
- site adaption

whereas corrective measures fall into the competence of O&M:

- choosing the right cleaning technology and schedule

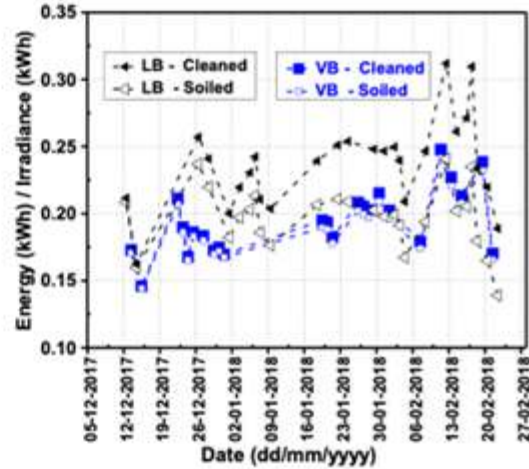
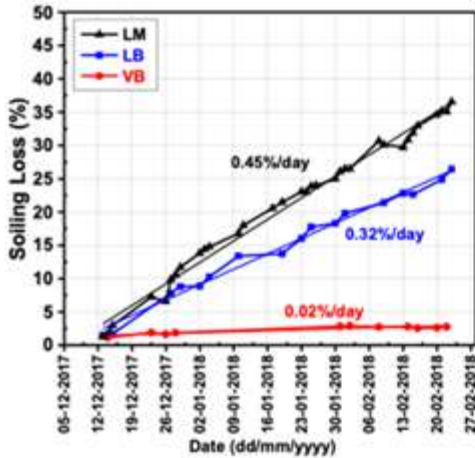
# Mitigation System Design: Vertical Bifacial E/W



VB: Vertical Bifacial  
LB: Latitude tilt Bifacial  
LM: Latitude tilt Monofacial

A Study by  
Anil Kottantharayil and colleagues, India

# Mitigation System Design: Vertical Bifacial E/W



Latitude tilt Bifacial cleaned: always higher  
Latitude tilt Bifacial soiled: initially higher, after ~7 weeks lower than Vertical Bifacial (VB)

# Mitigation: Cleaning Methods



## Manually, semi-automatic, fully-automatic





# Mitigation: Cleaning Methods

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- Manual devices, dust brooms, water brushes, nozzles (see module datasheet for max pressure!)
- Truck-mounted devices
- Semi-automatic systems use portable robots which can be manually moved from row to row. (battery-powered or wired, rail-mounted, frame-mounted or freely movable)
- Fully automatic systems: regularly clean one row of modules. These systems are often solar-powered, and they can be rail-mounted, frame-mounted or freely movable.

# Mitigation: Cleaning per Weather condition



Weather/Area	Cleaning technique applied
Desert	Vibration of surface and aerodynamic streamlining
Dry	Electrostatic biasing, autonomous robotic cleaning, sprinkler
Rainy, humid	Special techniques are not required, but can be combined with anti-reflective coating
Cold, moist	Autonomous/robotic cleaning, sprinkler, and anti-reflective coating
Snow	Stowing/inverting, anti-reflective coating
Hot, arid, sunny	Electrostatic biasing, autonomous/robotic cleaning, sprinkler
Cloudy, shaded	Autonomous/robotic cleaning, sprinkler, aerodynamic streamlining

Adapted from S. Mondal, A. K. Mondal, A. Sharma, V. Devalla, S. Rana, S. Kumar and J. K. Pandey, "An overview of cleaning and prevention processes for enhancing efficiency of solar photovoltaic panels," *CURRENT SCIENCE*, vol. 115, no. 6, p. 13, 2018

# Generic « Best Time to Clean »

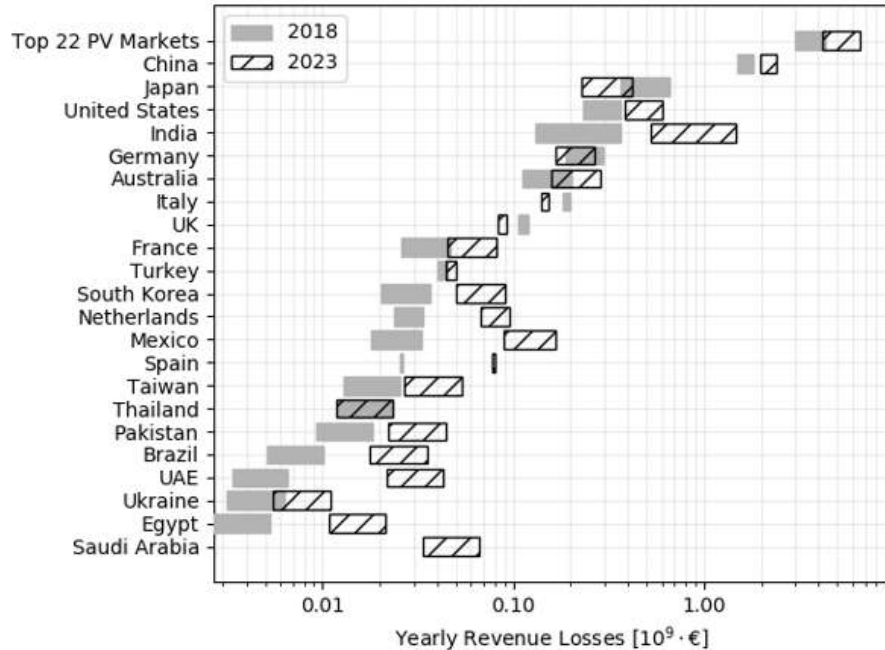


→ balancing the total cost of cleaning against the cost of energy lost to soiling.

Jones (2016)

- Cost of cleaning operation at the start of the interval ( $C_c$ )
- The value of the energy lost due to soiling over the interval between cleans ( $V_L$ )
- The value of energy sold over the interval ( $V_S$ )
- The power loss due to soiling ( $L_s(t)$ )
- The power generated by the plant without soiling ( $P(t)$ )
- Electricity Tariffs ( $R(t)$ )

# Global economic Impact of Soiling



Estimate:

2018:

- loss ~ 3% to 4% of annual PV energy
- Economic loss ~ 3 - 5 billion €

2023:

- increase up to 4% to 5% and 4 to 7 billion €

Factors:

- Installation in high-insolation regions → Soiling
- reduced price of electricity: less revenue
- Same soiling, more efficient modules: larger energy losses

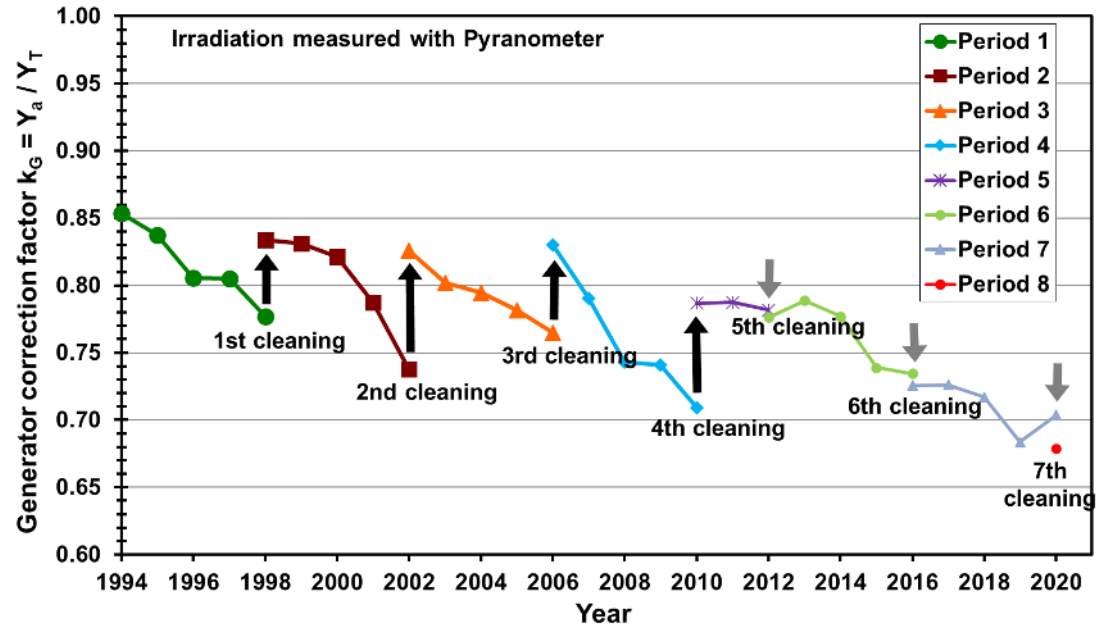
Based on optimal cleaning schedule scenario  
In a real world: even higher losses

# Use case Soiling in temperate climates



- Thomas Schott, Rosmarie Neukomm, CH
- Main pollution is a railway line (Bern-Zürich) at a distance of less than 100 m of the PV system.
- natural rainfall > 1'000 l/m<sup>2</sup>a
- Nat. cleaning considered to be sufficient BEFORE installation of the plant.

**PV-System Tiergarten West, BFH-TI, Burgdorf:**  
Trend of the generator correction factor in summer (April-September)

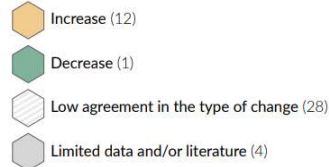


# An outlook: IPCC projections

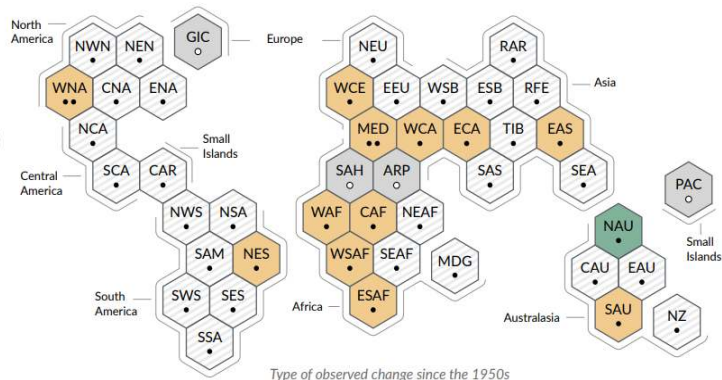
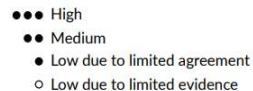


c) Synthesis of assessment of observed change in **agricultural and ecological drought** and confidence in human contribution to the observed changes in the world's regions

**Type of observed change**  
in agricultural and ecological drought

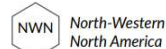


**Confidence in human contribution**  
to the observed change



Type of observed change since the 1950s

Each hexagon corresponds to one of the IPCC AR6 WGI reference regions



IPCC AR6 WGI reference regions: **North America:** **NWN** (North-Western North America), **NEN** (North-Eastern North America), **WNA** (Western North America), **CNA** (Central North America), **ENA** (Eastern North America), **Central America:** **NCA** (Northern Central America), **SCA** (Southern Central America), **CAR** (Caribbean), **South America:** **NWS** (North-Western South America), **NSA** (Northern South America), **NES** (North-Eastern South America), **SAM** (South American Monsoon), **SWS** (South-Western South America), **SES** (South-Eastern South America), **SSA** (Southern South America), **Europe:** **GIC** (Greenland/Iceland), **NEU** (Northern Europe), **WCE** (Western and Central Europe), **EEU** (Eastern Europe), **MED** (Mediterranean), **Africa:** **MED** (Mediterranean), **SAH** (Sahara), **WAF** (Western Africa), **CAF** (Central Africa), **NEAF** (North Eastern Africa), **SEAF** (South Eastern Africa), **WSAF** (West Southern Africa), **ESAF** (East Southern Africa), **MDG** (Madagascar), **Asia:** **RAR** (Russian Arctic), **WSB** (West Siberia), **ESB** (East Siberia), **RFE** (Russian Far East), **WCA** (West Central Asia), **ECA** (East Central Asia), **TIB** (Tibetan Plateau), **EAS** (East Asia), **ARP** (Arabian Peninsula), **SAS** (South Asia), **SEA** (South East Asia), **Australasia:** **NAU** (Northern Australia), **CAU** (Central Australia), **EAU** (Eastern Australia), **SAU** (Southern Australia), **NZ** (New Zealand), **Small Islands:** **CAR** (Caribbean), **PAC** (Pacific Small Islands)

Observed changes in global droughts and human contribution, IPCC report 2021: the problem will become worse in sunbelt regions



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# Matching Soil type against soiling publications

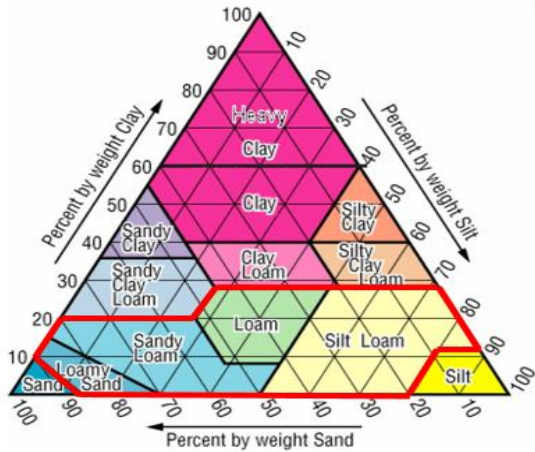
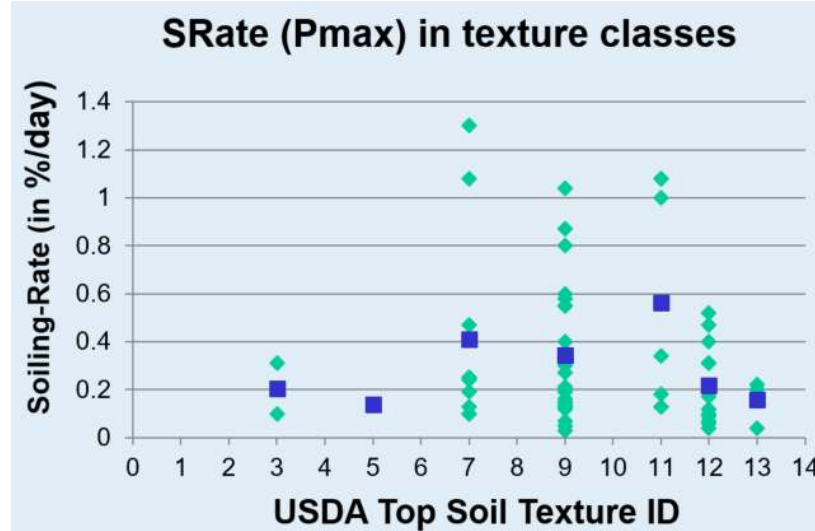


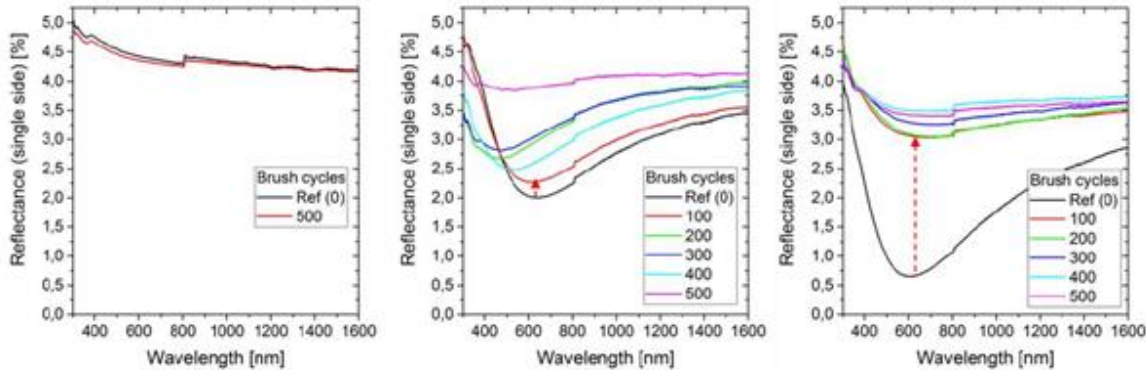
Image source U.S Department of Agriculture, Public domain



1	clay(heavy)
2	silty clay
3	clay (light)
4	silty clay loam
5	clay loam
6	silt
7	silt loam
8	sandy clay
9	loam
10	sandy clay loam
11	sandy loam
12	loamy sand
13	sand

Image Source: ISE

# PV Module cleaning tests



Spectral reflectance of 3 glass types:

- float glass without ARC,
- float glass with ARC
- structured glass with ARC - after up to 500 linear abrasion test cycles with a brush according to ASTM D2486



Laboratory car wash for testing the scratch resistance of coatings in accordance to ISO 20566