MAPS OF LONG-TERM SOILING LOSSES IN EUROPE CONSIDERING A PARTIAL CLEANING EFFECT BY RAIN

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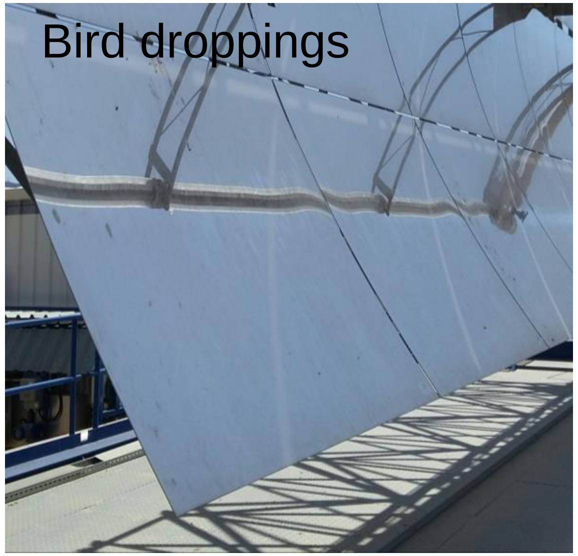
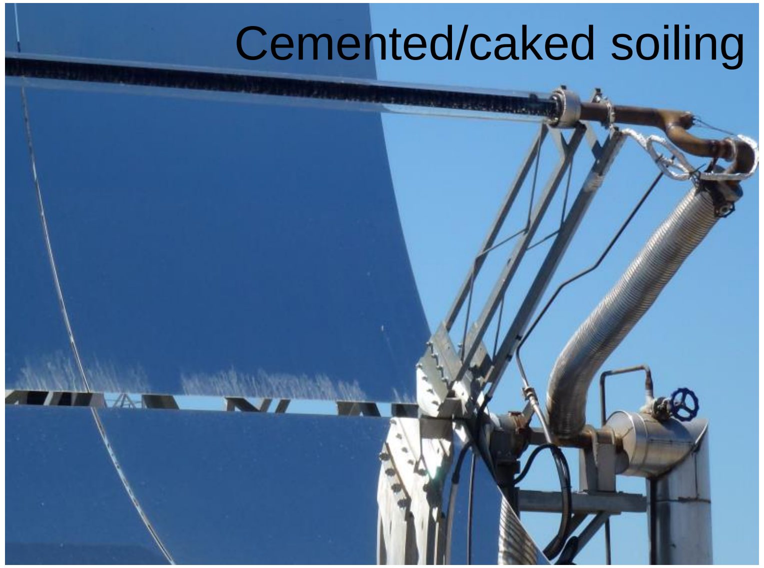
STRUCTURE
Maps of long-term soiling losses in Europe considering a partial cleaning effect by rain

1. Motivation & introduction: Long-term soiling losses & natural cleaning by rain
2. Soiling measurements
3. Soiling models
4. Soiling maps
5. Conclusions

1. Motivation & introduction

- What are the CST soiling losses in Europe if you don’t clean the collectors?
  - Maybe a good question for rainy sites
- How can soiling models be used to answer the question?
  - Rain effect important
  - Rainfall often results only in partial cleaning (Norde Santos et al., 2024)
  - Persistent soiling non-removable by rain can occur





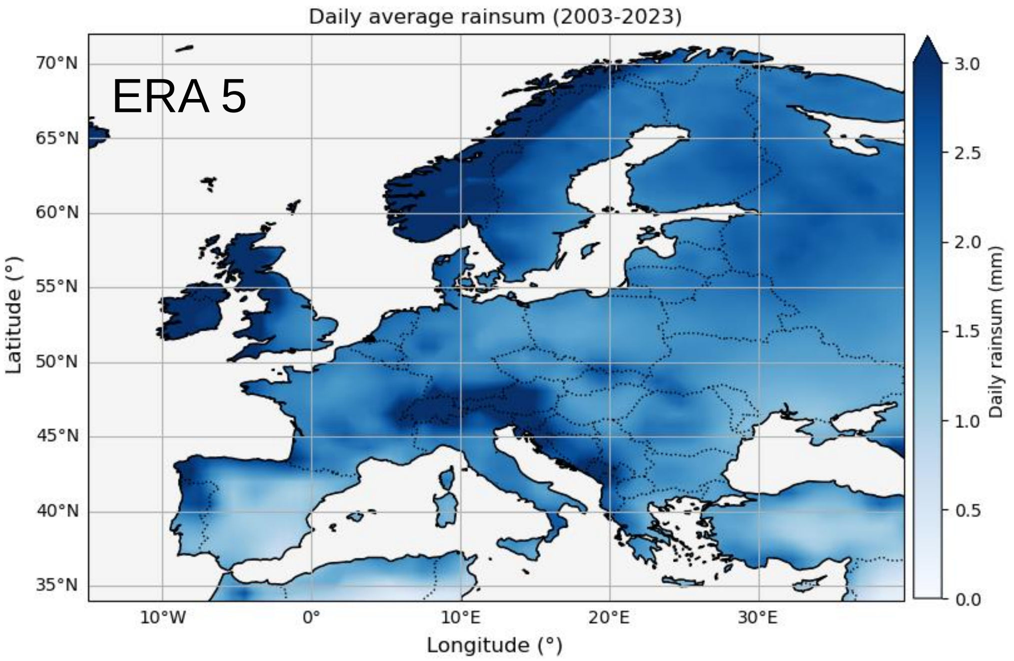
Photos taken at CIEMAT‘s PSA.

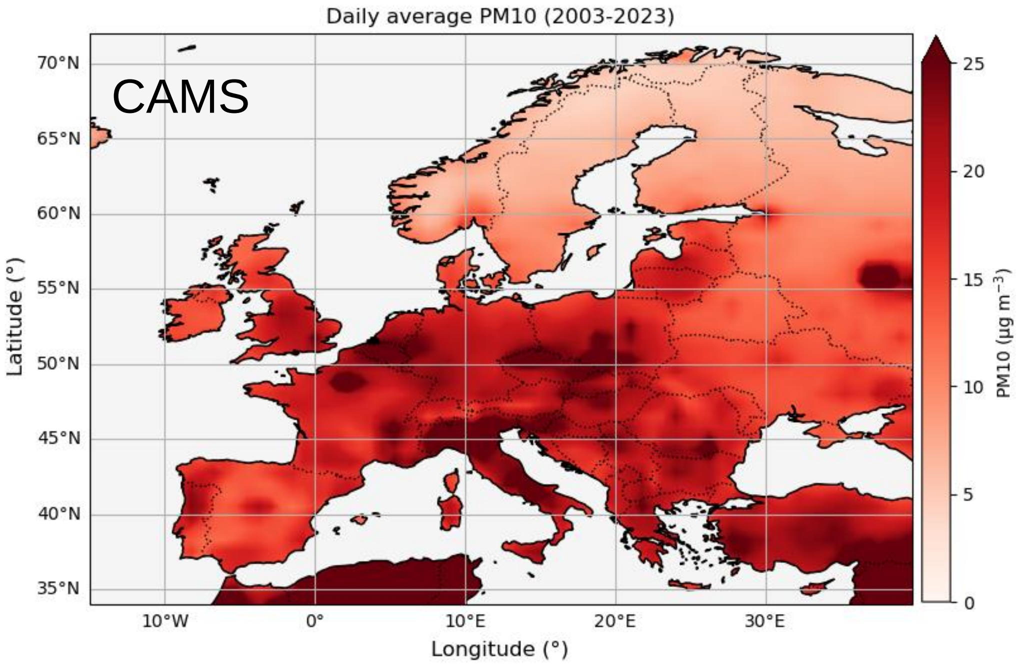
1. Motivation & introduction

- Natural cleaning of collectors by rain usually modelled using threshold approach:

Daily rain sum ≥ threshold → Solar collectors perfectly cleaned Daily rain sum < threshold → No cleaning effect is considered	*Thresholds in literature:* ***0.3 to 20 mm/day***

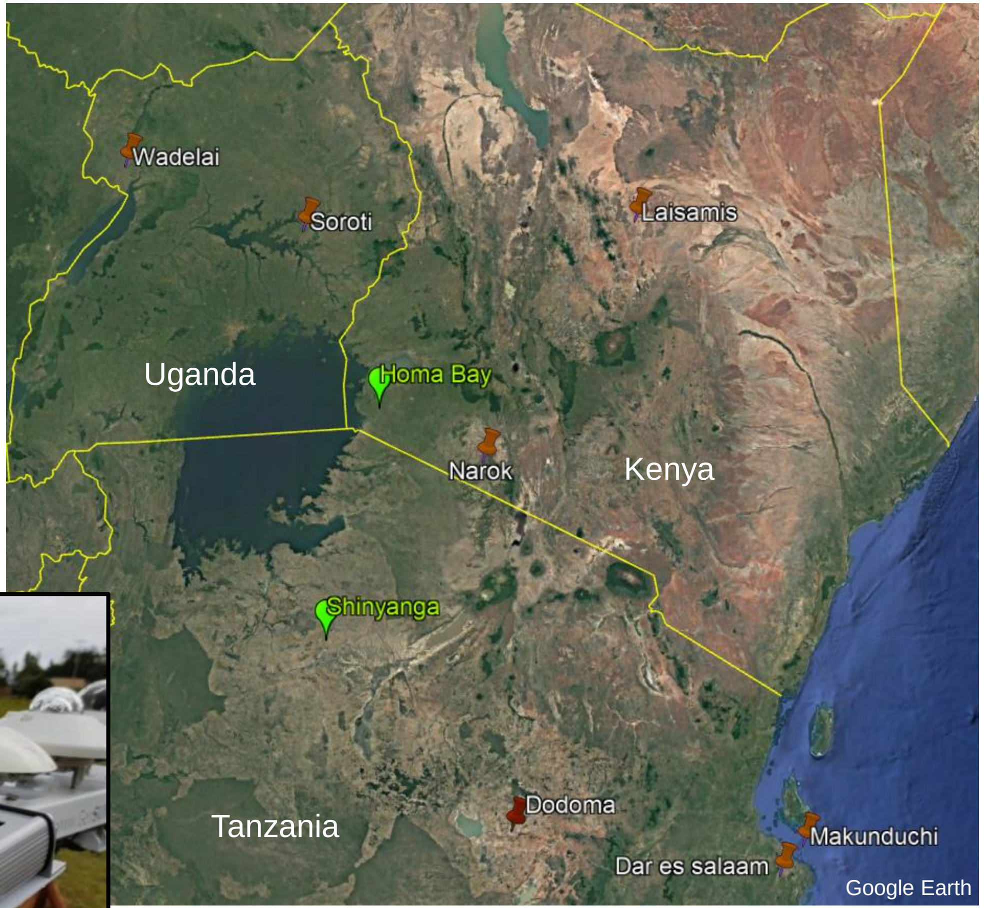
- Actual rain cleaning effect **not perfect & different for different soiling** particles & types
  - PM data does not describe the soiling type
- Soiling models and their input data (**PM & rain**) have high uncertainty
  - World-wide validation of soiling models shows avg. rel. MAD~100% & up to 400% (Pelland et al., 2018)
- **1st task: enhance soiling models & calibrate with long-term soiling data for exemplary soiling types**

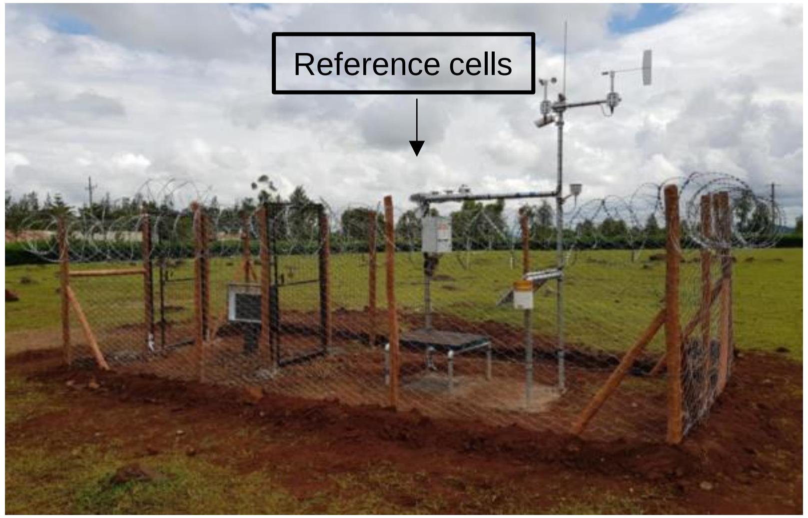




2. Soiling measurements

- Needed long-term continuous soiling measurements without cleaning
- East African Power Pool (EAPP) stations initiated by World Bank with funding from Energy Sector Management Assistance Program (ESMAP)
  - performed by GeoSUN Africa
- 3 tilted reference cells for soiling measurement
  - “clean” reference cell (daily cleaned)
  - “dirty” reference cell (not cleaned during campaign period)
  - “dirty, monthly cleaned” (reference cell cleaned once per month)
- CST soiling losses estimated from the PV soiling losses





ESMAP
Energy Sector Management Assistance Program

EAPP

GeoSUN AFRICA

2. Soiling data: PV to CST conversion & model calibration

- Simplification with high uncertainty contribution: CST soiling losses estimated from PV soiling losses by scaling them with factor 6.5 (Abraim et al., 2022)
  - 6.5 = fixed tilt PV to mirror (TraCS) soling loss conversion from paper + 1 for absorber soiling loss

- Simplification accepted for our study because
  - Soiling models should always be **calibrated for specific soiling type, CST collector & site** of interest due to high model & input data uncertainty.
    - **Hence, soiling maps can only be examples for given soiling types & CST collectors.**

Photos taken at CIEMAT's PSA.

2. Soiling models: Original HSU model applied to CST

(Coello and Boyle, 2019) + (Abraim et al., 2022)

- Daily accumulated mass m_i on collector after $(i-i_0+1)$ timesteps of duration t

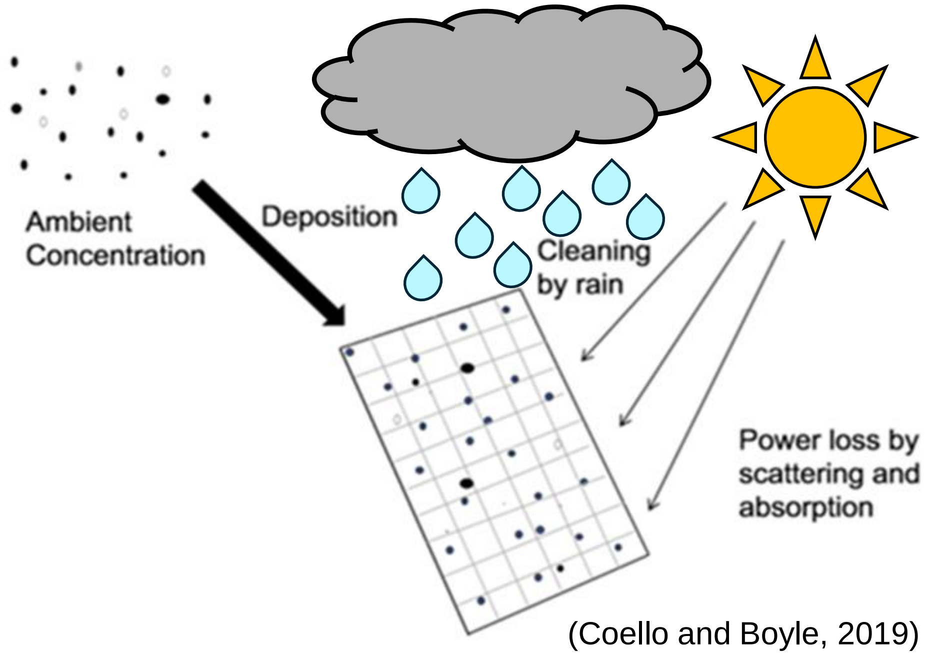
$$m_i = \begin{cases} \sum_{k=i_0}^{i} v_d \cdot PM_{10}(k) \cdot t \cdot \cos(\theta(k)) & if\ daily\ rainsum < threshold \\ 0 & if\ daily\ rainsum \geq threshold \end{cases}$$

- Soiling loss (limited to max. 100%)

$$SL_i = 34.37\% \cdot \mathrm{erf}\left(0.17 \cdot m_i^{0.8473}\right) \cdot 6.5$$

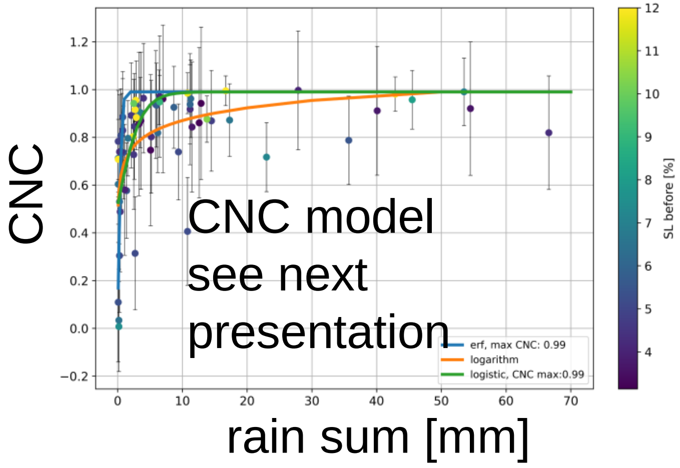
- Calibration parameters
  - Daily rainsum cleaning threshold (CT)
  - Deposition velocity v_d

- Input variables
  - CAMS EAC4 PM_{10} concentration
  - ERA5 precipitation



(Coello and Boyle, 2019)

2. Soiling models: Modified HSU model



- Completeness of natural cleaning

$$CNC_i = \frac{m_{i-1} - m_i}{m_{i-1}} = a \cdot \log(rainsum) + b \qquad \text{(limited to max of 0.97)}$$

- Persistent mass (non-removable by rain) accumulated on collector

$$\omega_i = \chi \cdot \sum_{k=i_0}^{i} v_d \cdot PM_{10}(k) \cdot t \cdot \cos(\theta(k))$$

- Daily accumulated mass on collector panel

$$\boxed{m_i = \begin{cases} (1 - CNC_i) \cdot m_{i-1} & if\ \ rainsum > 0\ and\ (1 - CNCi) \cdot m_{i-1} > \omega_i \\ \omega_i & if\ rainsum > 0\ and\ (1 - CNC_i) \cdot m_{i-1} \leq \omega_i \\ \sum_{k=i_0}^{i} v_d \cdot PM_{10_k} \cdot t \cdot \cos(\theta) & if\ rainsum = 0 \end{cases}}$$

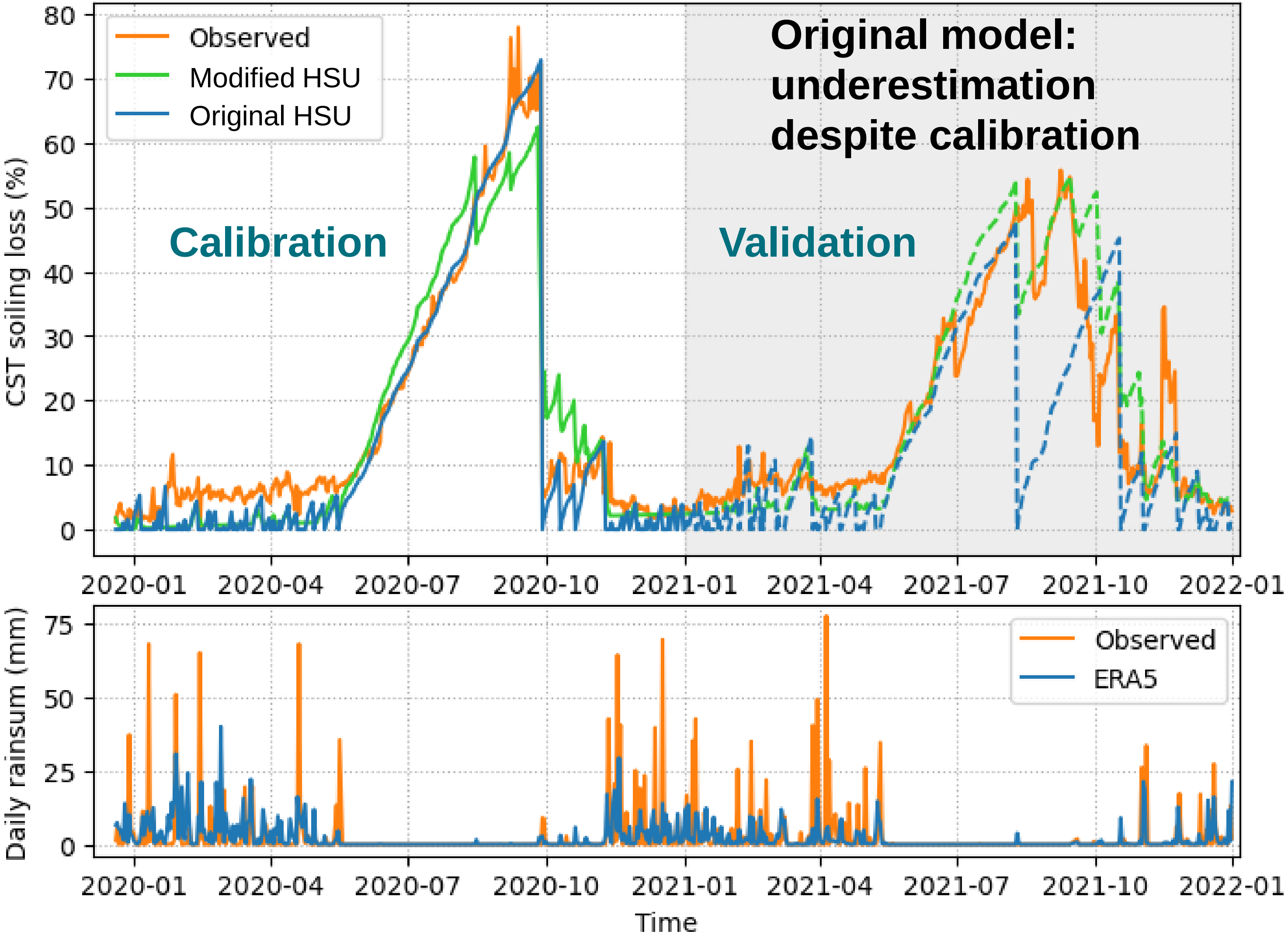
- Soiling loss (limited to max. 100%)

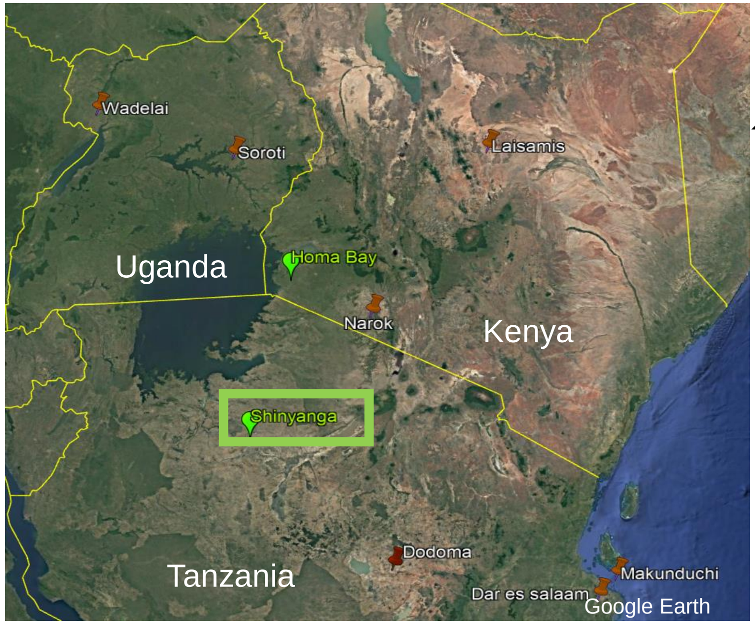
$$\boxed{SL_i = 34.37\% \cdot \mathrm{erf}\left(0.17 \cdot m_i^{0.8473}\right) \cdot 6.5}$$

- Calibration parameters
  - a, b for completeness of natural cleaning
  - Percentage of daily-accumulated persistent mass χ
  - Deposition velocity v_d

- Input variables (same as for original model)
  - CAMS PM_{10} concentration
  - ERA5 precipitation

3. Soiling model calibration: Shinyanga
Removable soiling type



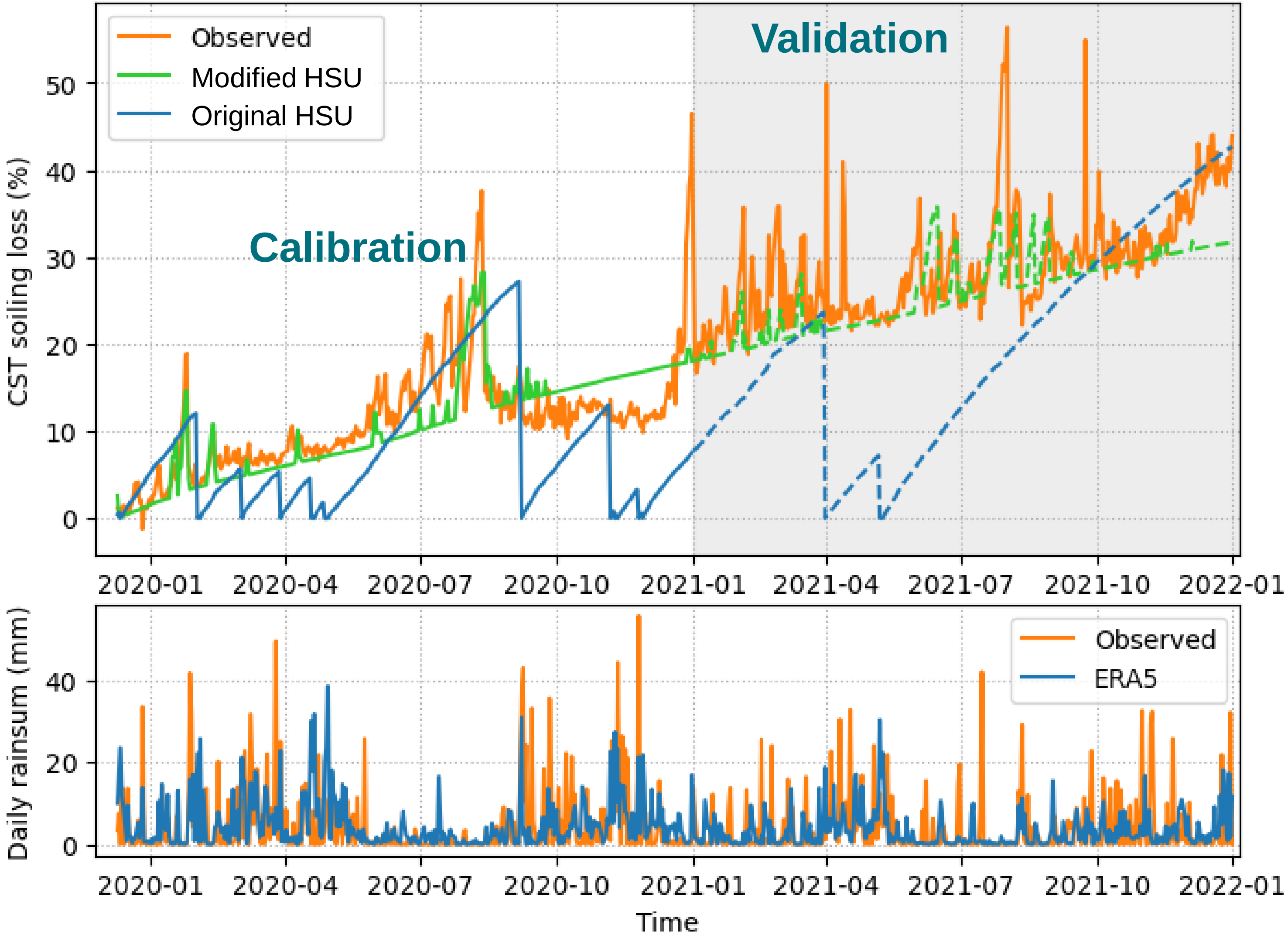


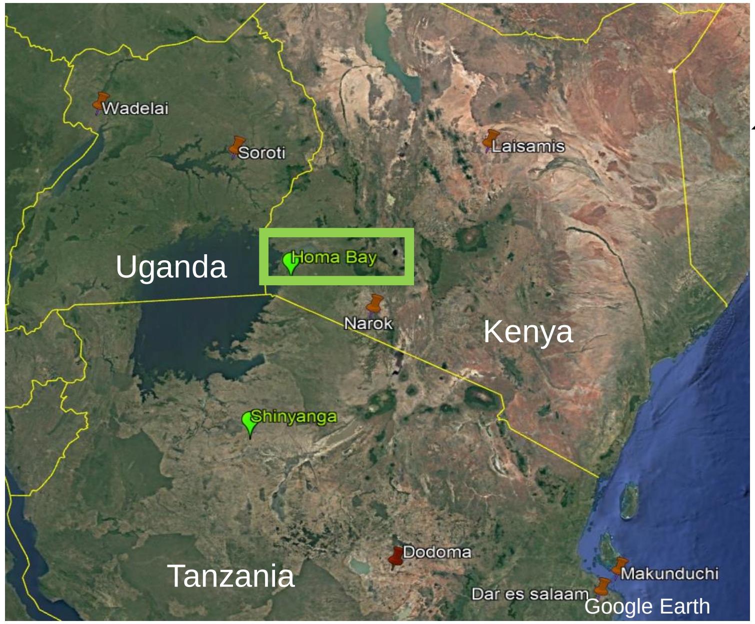
	HSU original CT = 2.6 mm/day; v_d = 0.009m/s		
	RMSE	MAE	Bias
Calibration	3.8%	3.0%	-2.3%
Validation	12.3%	7.5%	-4.7%

	HSU modified a=0.10, b=0.23, v_d=0.011m/s, χ=0.5%		
	RMSE	MAE	Bias
Calibration	6.2%	4.7%	-1.0%
Validation	7.3%	4.9%	0.7%

3. Soiling models optimization: Homa Bay
Persistent soiling type

Original model: underestimation despite calibration

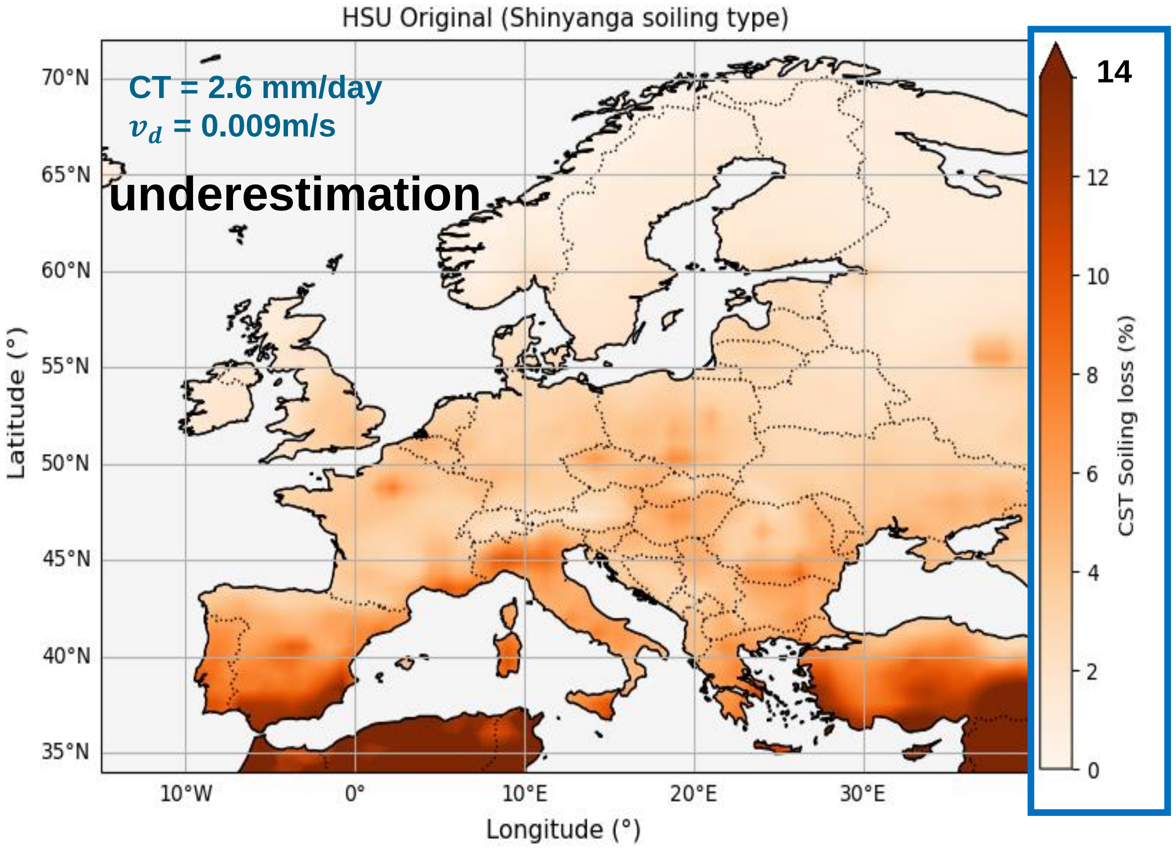


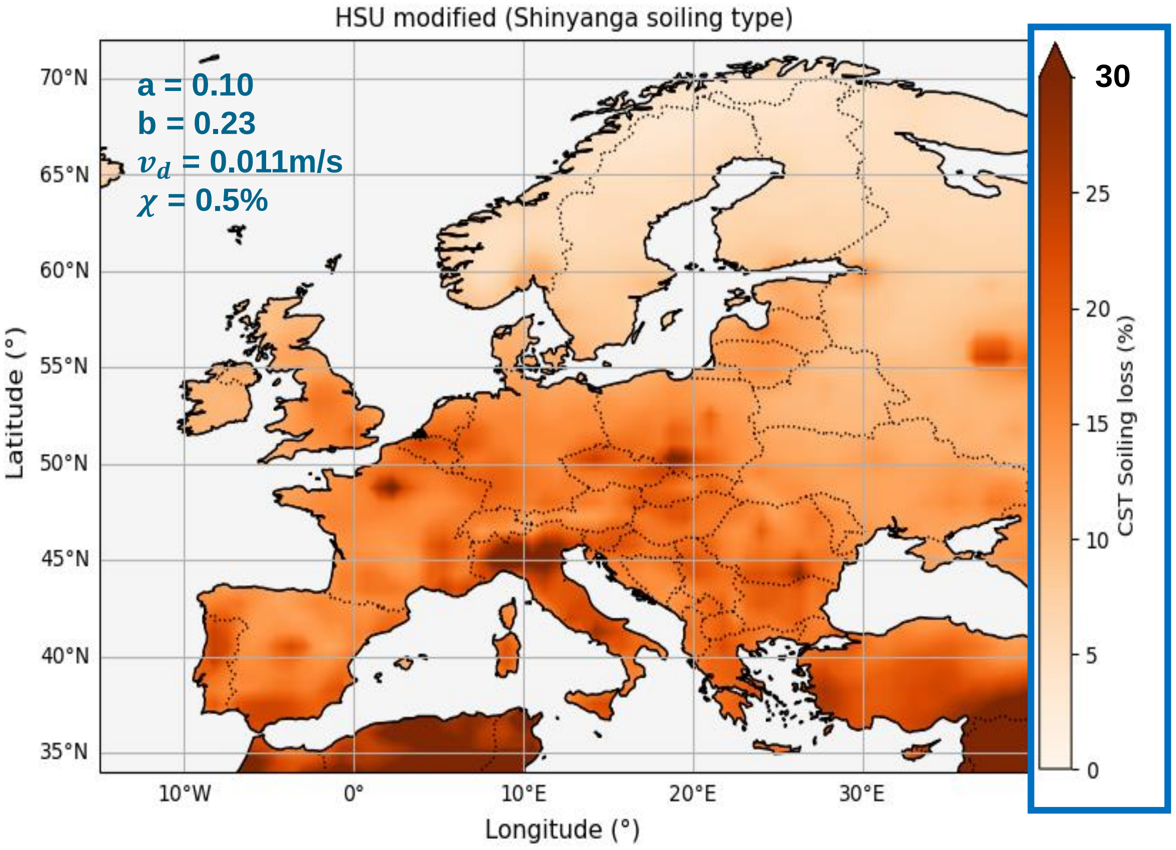


	HSU original CT = 18.3 mm/day, v_d = 0.0007m/s		
	RMSE	MAE	Bias
Calibration	7.6%	6.0%	-3.6%
Validation	13.5%	10.5%	-9.2%

	HSU modified a = 0.3, b=0.08, v_d = 0.007m/s, χ=2,5%		
	RMSE	MAE	Bias
Calibration	4.4%	3.1%	-0.6%
Validation	6.0%	4.0%	-2.9%

4. European maps, example 1: Removable soiling type from Shinyanga 1st year calibration

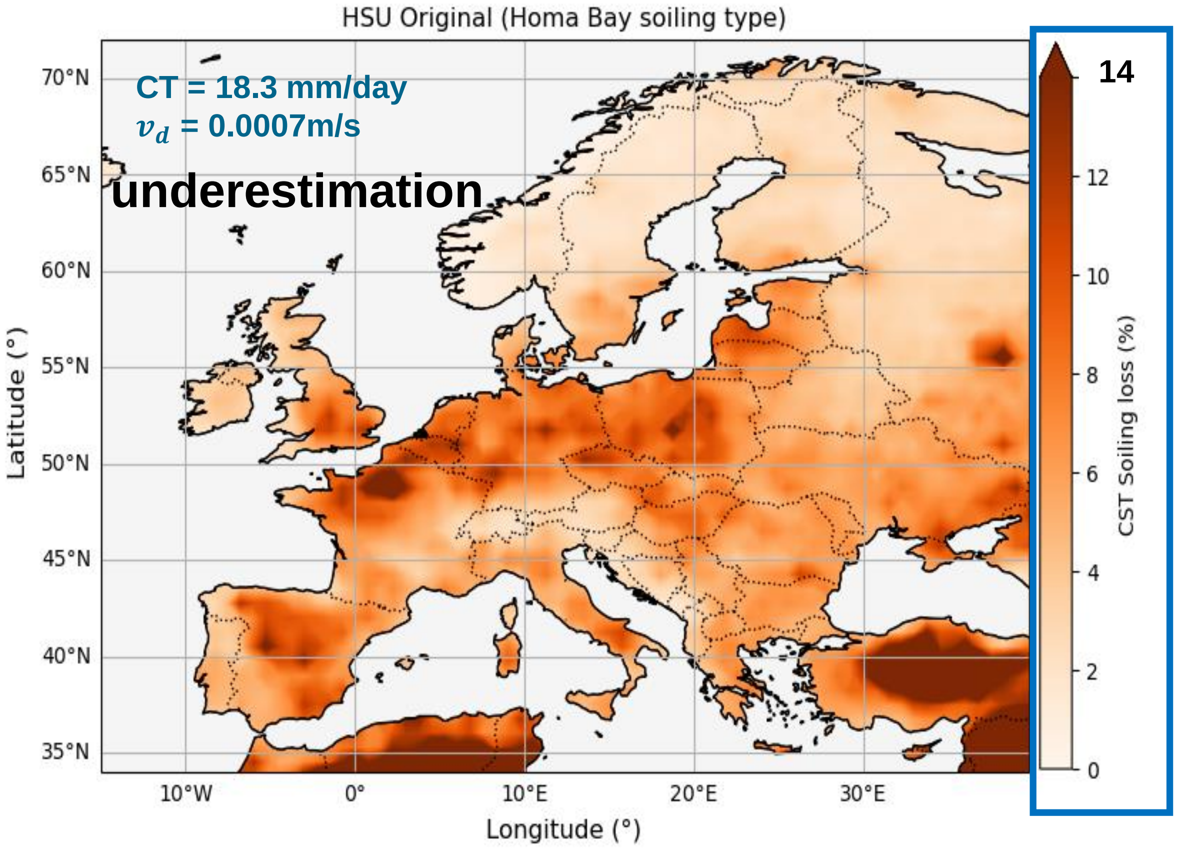


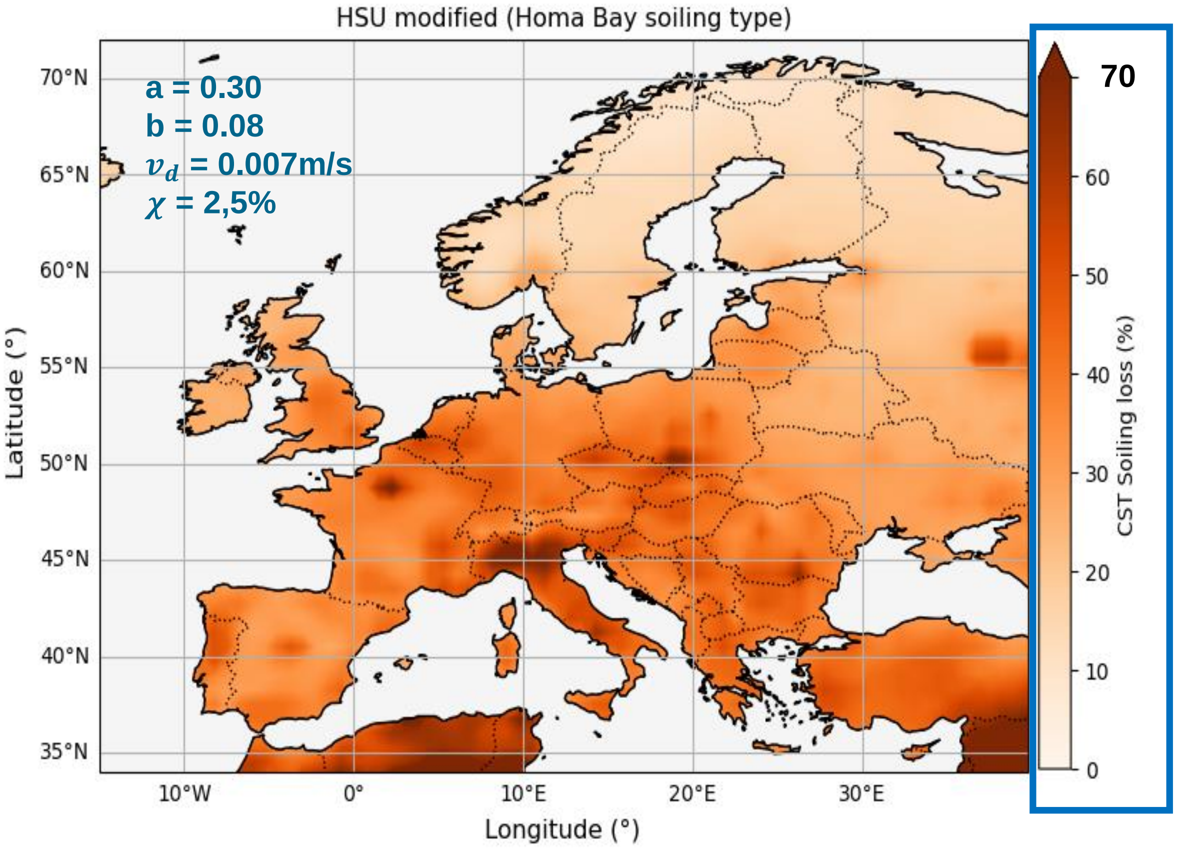


Average soiling losses in Europe for operation from **2003 to 2023 without cleaning**

	HSU original CT = 2.6 mm/day, v_d = 0.009m/s	**HSU modified** a = 0.10, b = 0.23, v_d = 0.011m/s, χ=0.5%
European average (%)	3.1	12.2
German average (%)	3.4	15.8
Andalusian average (%)	11.4	20.2

4. European maps, example 2: Persistent soiling type from Homa Bay 1st year calibration





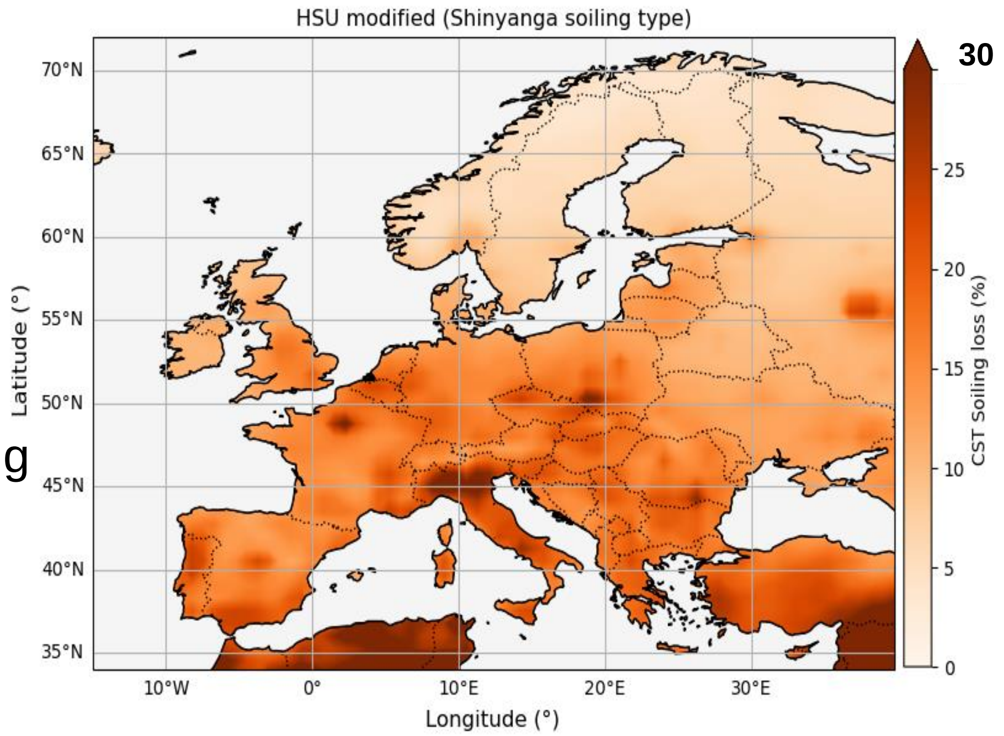
Average soiling losses in Europe for operation from **2003 to 2023 without cleaning**

	HSU original CT = 18.3 mm/day, v_d = 0.0007m/s	**HSU modified** a = 0.30, b = 0.08, v_d = 0.007m/s, χ=2,5%
European average (%)	5.1	29.2
German average (%)	7.9	38.4
Andalusian average (%)	7.3	38.1

If soiling not removed well by rain => Germany > Andalusia

5. Conclusion and outlook

- Maps illustrate two examples of possible long-term soiling losses
  - Indicate importance of partial cleaning & persistent soiling for losses & model accuracy
- The uncertainty of modelled long-term soiling losses is high & hence introduces a significant uncertainty in yield assessments if no or very infrequent cleaning is planned
  - Plan sufficient cleaning frequency, as this reduces not only losses, but also model uncertainty
  - Current models should be calibrated for the site of interest
- Not cleaning a CST collector leads to high losses even for rainy regions
  - E.g. 20a avg. loss: 16-38 % Germany, 20-38 % Andalusia
- **Outlook**
  - Evaluate also other less extreme cleaning frequencies & optimize cleaning schedules
  - Collect & test with long-term CST soiling measurements
  - Improve soiling models (e.g. better consider aging of soiling layer, bird droppings, lichen, moss, …)



Thank you for your attention!
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References

- Pelland et al. "Testing global models of photovoltaic soiling ratios against field test data worldwide." 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC). IEEE, 2018.
- Fernandez Solas, et al. (2025) Photovoltaic soiling loss in Europe: Geographical distribution and cleaning recommendations. Renewable Energy, 239. Elsevier. doi: 10.1016/j.renene.2024.122086. ISSN 0960-1481.
- Bellmann, et al. (2020) Comparative modeling of optical soiling losses for CSP and PV energy systems. Solar Energy, 197, Seiten 229-237. Elsevier. doi: 10.1016/j.solener.2019.12.045. ISSN 0038-092X.
- WAPP, West African Power Pool. URL: https://www.ecowapp.org/en/news/measurement-summary-solar-development-sub-saharan-africa. (accessed: January 27 2025).
- Norde et al. (2022), “Soiling Persistence Model as Benchmark for Soiling Forecasts of Solar Collectors”, EUPVSEC conference Milan, Italy.
- Kimber et al. (2006), The Effect of Soiling on Large Grid-Connected Photovoltaic Systems in California and the Southwest Region of the United States. Proc. IEEE 4th World Conference on Photovoltaic Energy Conference, Vol. 2, Waikoloa, Hawaii, May 2006.
- NCPRE, (2025) National Centre for Photovoltaic Research and Education. SERIIUS Soiling Rate of the World. IIT Bombay. https://www.ncpre.iitb.ac.in/ncpre/pages/seriius-soiling-rate-of-the-world.php Accessed July 2, 2025.
- Coello and Boyle (2019). Simple model for predicting time series soiling of photovoltaic panels. IEEE Journal of Photovoltaics, 9(5):1382–1387, 2019. ISSN 2156-3381. doi: 10.1109/JPHOTOV.2019.2919628.
- Norde Santos et al. (2024) Cleaning of photovoltaic modules through rain: Experimental study and modeling approaches. Solar RRL, 8(24):2400551, 2024. ISSN 2367-198X. doi:10.1002/solr.202400551. Copernicus Atmosphere Monitoring Service (2021): CAMS global atmospheric composition forecasts. Copernicus Atmosphere Monitoring Service (CAMS) Atmosphere Data Store, DOI: 10.24381/04a0b097 (Accessed on 16.06.2025)
- Abraim et al. (2022). Techno-economic assessment of soiling losses in CSP and PV solar power plants: A case study for the semi-arid climate of Morocco. Energy Conversion and Management 270. 116285. https://doi.org/10.1016/j.enconman.2022.116285

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