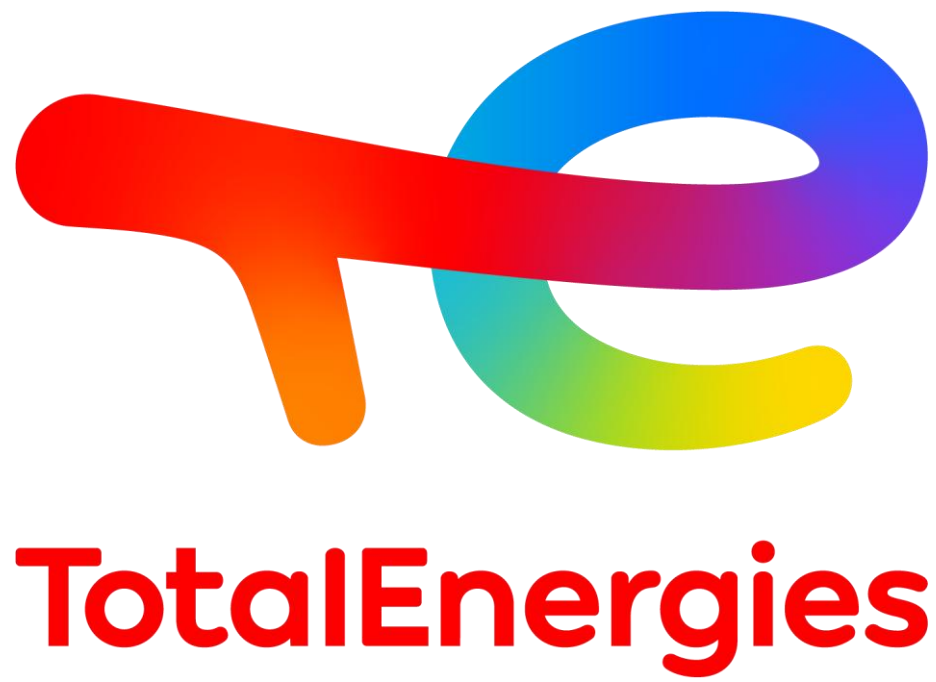


Modeling soiling of photovoltaic systems with atmospheric reanalysis: Supporting site selection and cleaning strategy optimization

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Optimizing photovoltaic plant performance through soiling modeling

Soiling reduces PV output, making accurate modeling essential for site selection, performance optimization, and cost-effective maintenance.

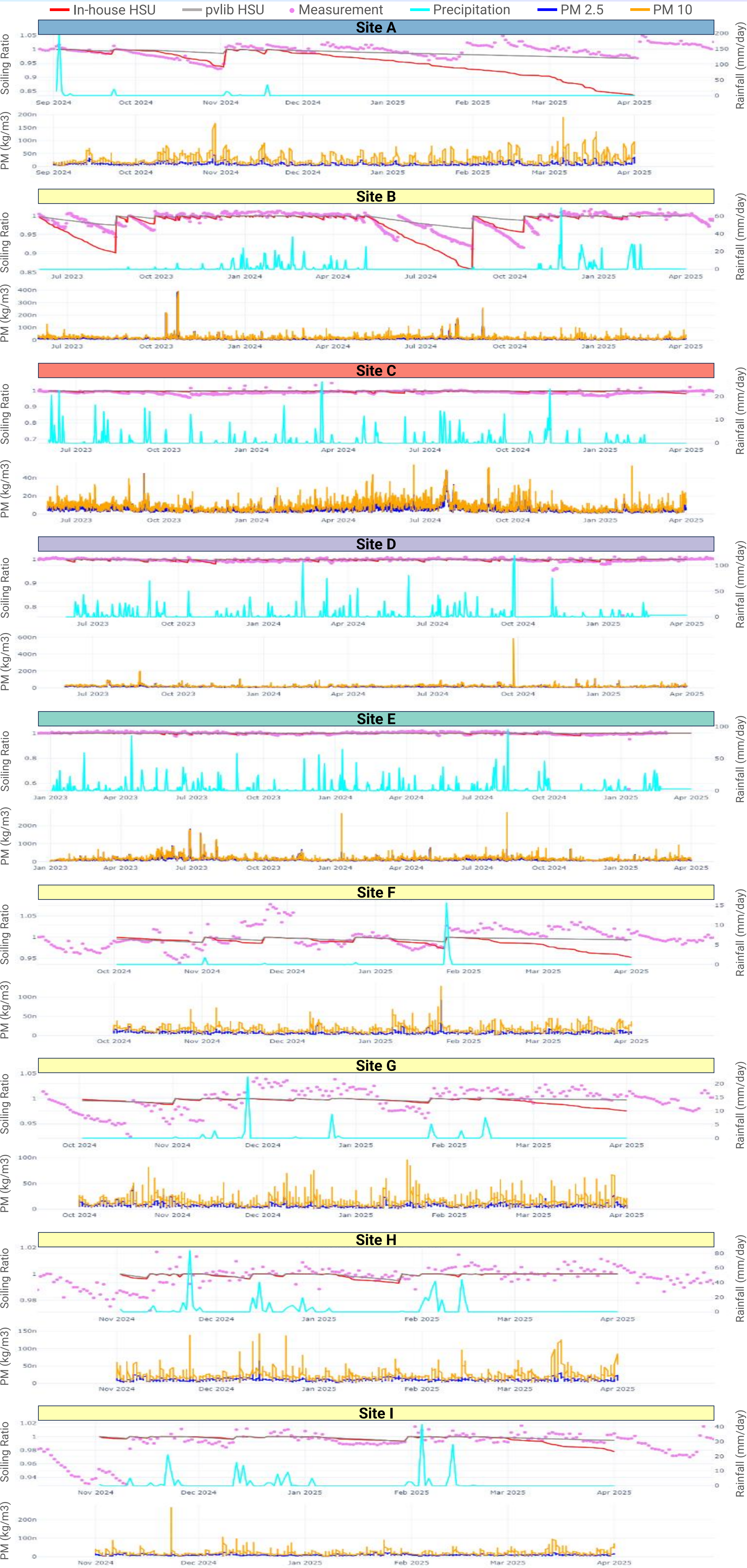
- Objectives:**
- **PV site prospection:** Identify optimal locations and estimate energy loss from soiling
 - **Cleaning strategy:** Balance cleaning costs with energy recovery to reduce the levelized cost of PV electricity

- Reliable soiling estimates improve:**
- Economic forecasting and competitive bidding
 - O&M contract negotiations and cleaning equipment selection (e.g., cleaning robots)

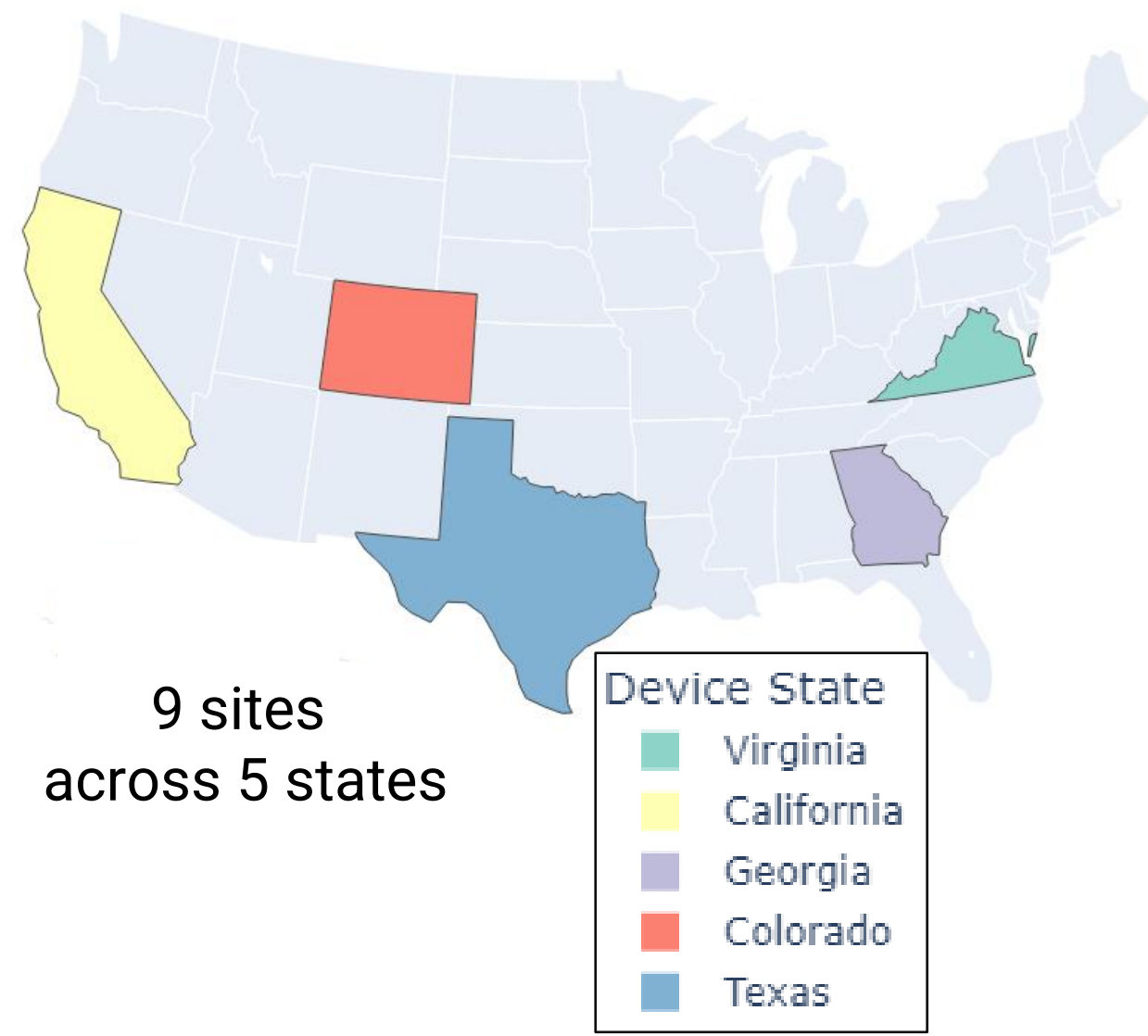
To minimize costly measurement campaigns, this study evaluates semi-empirical dry deposition models, and their implementations, for generating soiling loss time series without ground data. While these models, including the HSU soiling model^[1] in *pvlb* Python library, have been published^{[1][2][3]} and discussed^[4], comprehensive validation across diverse locations remains limited.

Key Contribution: We present a cross-site validation of the HSU model for soiling loss estimation, comparing the *pvlb* implementation (with default parameters, run via the PVRADAR Python package) against an in-house implementation. The validation uses proprietary Soiling Ratio (SR) data from diverse climates to assess the models' accuracy and practical applicability.

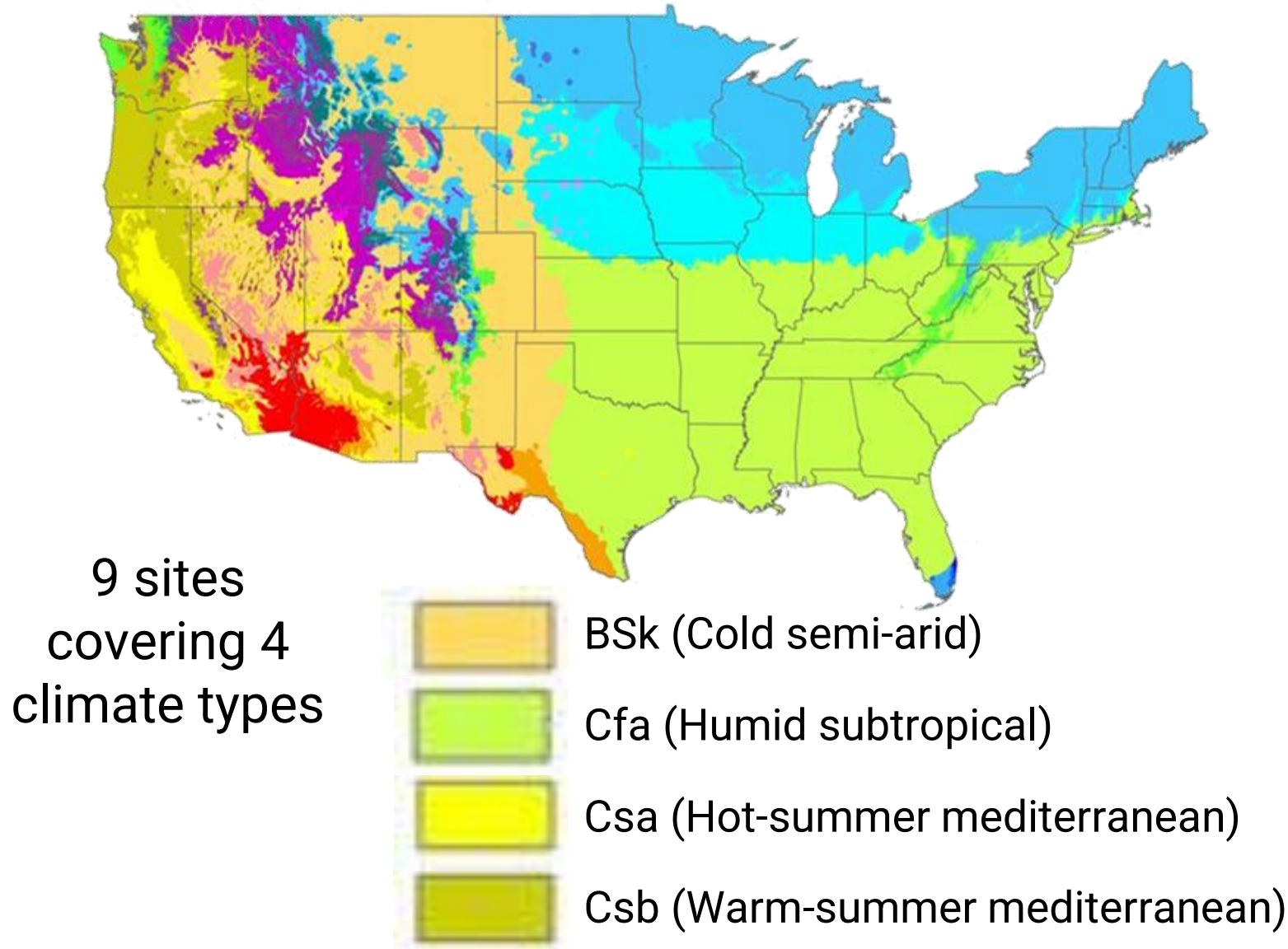
Soiling ratio, rainfall & particulate matter per site



U.S. States with SR measurement devices



Köppen climate types of the contiguous U.S.



Scope & Methodology

HSU model Core Assumptions:

- Semi-empirical dry deposition model with no rebound or re-suspension
- Rain events clean the surface when precipitation exceeds a defined threshold

Key Inputs:

- Particulate Matter (PM) 2.5 and 10 concentrations^(a)
- Precipitation data^(b) and Rain cleaning threshold, user-defined (1 mm/day here)
- Environmental parameters impacting particle transport and deposition rate: wind speed, T & z0^(a)

^(a): MERRA-2 data used here
^(b): NOAA data used here

Key differences between in-house & pvlb implementations:

Feature	In-house HSU	pvlb HSU
PM data resolution	Hourly (3-hourly MERRA-2 values set constant)	Hourly (interpolated from 3-hourly MERRA-2)
PM2.5 estimates	Simplified equation proposed by MERRA-2	Only smallest bins for DU (with 0.58*DU003) & SS
Deposition velocity	Dynamic: varies with environmental conditions	Constant (unless specified)
PM2.5 velocity	Higher on average	Lower on average
PM10 velocity	Similar on average	Similar on average

Implications: The in-house implementations adapts to local air quality and weather conditions, which helps to capture transient or intense soiling events more effectively

Results & Discussion

In-house HSU implementation vs. Ground Truth

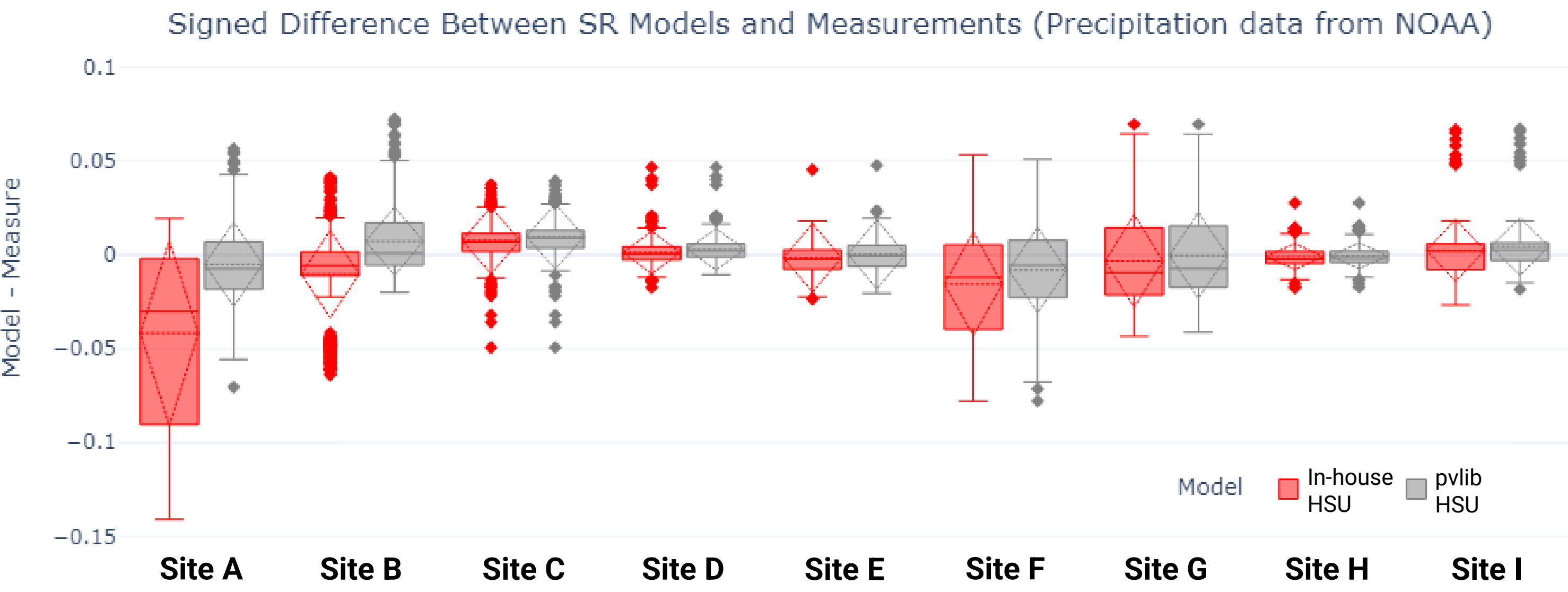
- SR time-series align well with measured soiling trends
- Seasonal variations are generally captured
- SR reset events are sometimes missing due to use of NOAA station rainfall data, which may not always reflect site-level precipitations

In-house HSU vs. pvlb HSU implementations

- **In-house better captures notable soiling events**, primarily due to its **dynamic deposition velocity** and **higher PM2.5 deposition rates**, which allow sharper responses to environmental changes
- **Pvlb HSU tends to underestimate soiling**, so its predictions remain **closer to clean baseline levels** even when rainfall events are missed
- This causes **in-house performance to suffer more from missing rain data**—when a local rain event goes undetected, the in-house model continues to accumulate soiling more realistically, but lacks a reset

Takeaway:

- **Both implementations perform similarly overall**
- While both are affected by rainfall data quality, in-house's higher sensitivity to soiling accumulation makes the absence of accurate rain data more visible in its results



Model limitations & Future directions

Challenges:

Current models face limitations in all key processes: **deposition**, **resuspension**, and **optical attenuation**:

- Incorporating wind direction into deposition and resuspension fluxes may improve accuracy
- Refining optical models, particularly its impact on electrical output, may enhance predictive power*

*Empirical correlations, such as those in the HSU model, relate soiling to power loss, but may need refinement to better generalize beyond their original design sites.

What's next:

Evaluate models performance at all sites with SR data, identify sources of error, refine existing models, and explore both new models and alternative data sources to improve accuracy and broaden applicability

References

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- [2]: S. You, Y. J. Lim, Y. Dai, C. H. Wang, "On the temporal modelling of solar photovoltaic soiling: energy and economic impacts in seven cities", Appl. Energy 2018, 228, 1136. DOI:10.1016/j.apenergy.2018.07.020
- [3]: C. S. Saiz, J. P. Martínez, N. M. Chivelet, "Influence of Pollen on Solar Photovoltaic Energy: Literature Review and Experimental Testing with Pollen", Appl. Sci. 2020, 10, 4733. DOI:10.3390/app10144733
- [4]: J. G. Bessa, L. Micheli, J. Montes-Romero, F. Almonacid, E. F. Fernández, "Estimation of Photovoltaic Soiling Using Environmental Parameters: A Comparative Analysis of Existing Models", Adv. Sustainable Syst. 2022, 6, 2100335. DOI: 10.1002/adsu.202100335

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