SOILING FORECASTS FOR CONCENTRATING SOLAR TECHNOLOGIES CONSIDERING PARTIAL CLEANING BY RAIN

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Soiling forecasts for concentrating solar technologies considering partial cleaning by rain
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Images taken at CIEMAT's PSA.

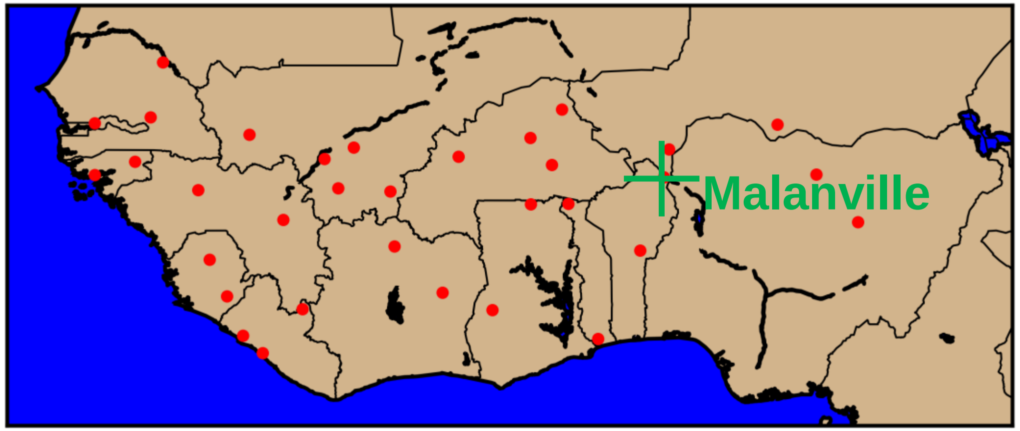
Objectives

- **Create soiling loss forecasts** to enable
  - Improved solar energy yield forecasts
  - Optimized cleaning to reach the best trade-off between the soiling losses & cleaning costs
    - Avoid unnecessary cleanings just before strong rainfalls or strong soiling events
- **Evaluate different soiling forecasts** based on the most recent soiling measurements & different weather forecasts & long-term meteorological data

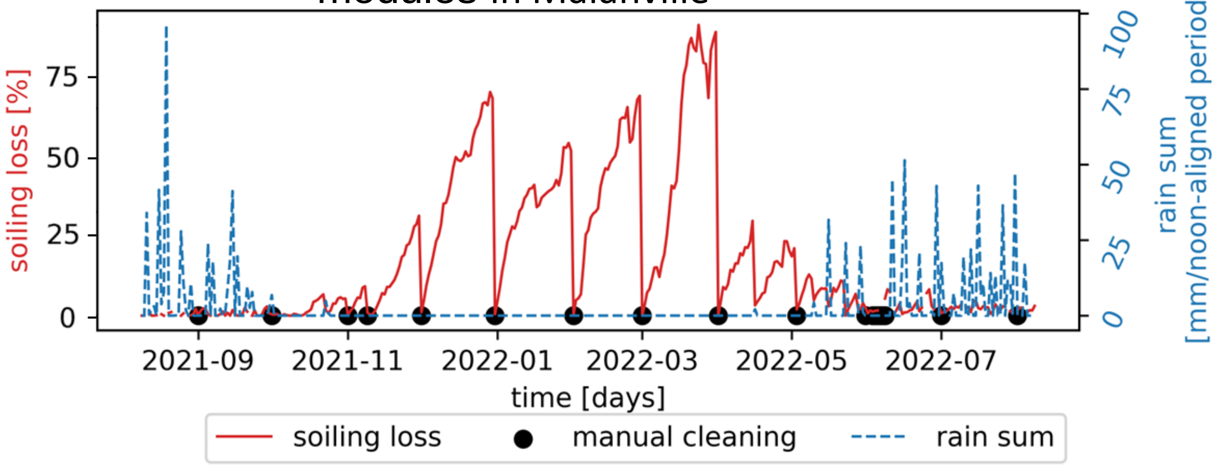
Images taken at CIEMAT's PSA.

Measurement data

- 1 year radiation, soiling loss & precipitation measurements from 33 measurement stations of the West African Power Pool network
  - run by Yandalux Solar GmbH and CSP Services GmbH as part of a World Bank Program (ESMAP)
  - PV soiling loss converted to CST soiling loss (see Ruiz Donoso et al. 2025, previous presentation)
- Forecasts created for Malanville, Benin



CST soiling Loss (SL) obtained from two reference PV modules in Malanville[WAPP, 2025]



- Soiled module was cleaned about once a month

Soiling forecasting approaches – part 1: Deposition on days without rain

- Persistence model from (Norde Santos et al., 2022)
  - soiling rate is predicted as the average of the last 20 days without (natural/artificial) cleaning
- Kimber model (Kimber et al., 2006)
  - fixed soiling loss rate of 2.8%/d (**avg. from Niamey in Niger**, NCPRE, (2025)
- HSU model with different settling velocities for different particle diameters (Coello and Boyle, 2019):
  - soiling rate depending on PM & tilt with **default** settling velocities v of 0.0009 m/s for PM2.5 (Particulate matter, d < 2.5µm) & 0.004 m/s for remaining PM10 particles
  - Mass deposition per time step t = $(v_{10-2.5}\,(PM_{10} - PM_{2.5}) + v_{2.5} PM_{2.5}) \cdot t \cdot cos(\theta)$
- Conversion of PV soiling losses to CST soiling losses with scaling factor 6.5 from (Abraim et al. 2023)
  - See previous presentation (Ruiz Donoso et al., 2025 for details)
  - Here accepted as we use the scaling for all tested models & focus on model comparison.
  - In a real CST plant the local CST soiling measurements should be used for a calibration of the forecasts, also reducing the effect of the simple scaling.

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Soiling forecasting approaches – part 2: Natural Cleaning Modeling

Option 1) Full cleaning above **threshold** of 1 mm daily rain sum, no cleaning otherwise

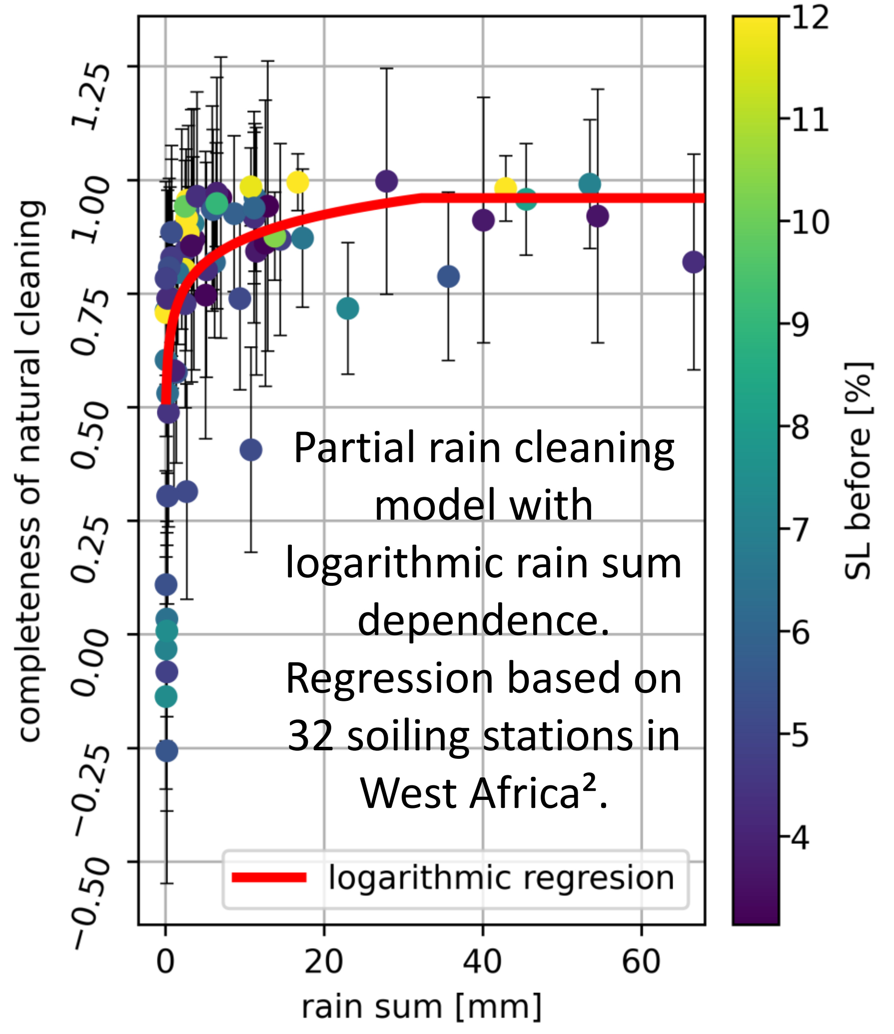
Option 2) completeness of natural cleaning (CNC_{SL}) model (Norde Santos et al., 2024) with **logarithmic** function:

$$CNC_{SL} = \frac{SL_{before} - SL_{after}}{SL_{before}}$$
$$= minimun\ (a \cdot log(rain\ sum) + b\ , CNC_{SL,\ max})$$

$CNC_{SL,max}$ = 1/uncertainty² weighted avg. CNC_{SL} for rain sums above 40mm

$$w_i = \frac{1}{unc^2}$$

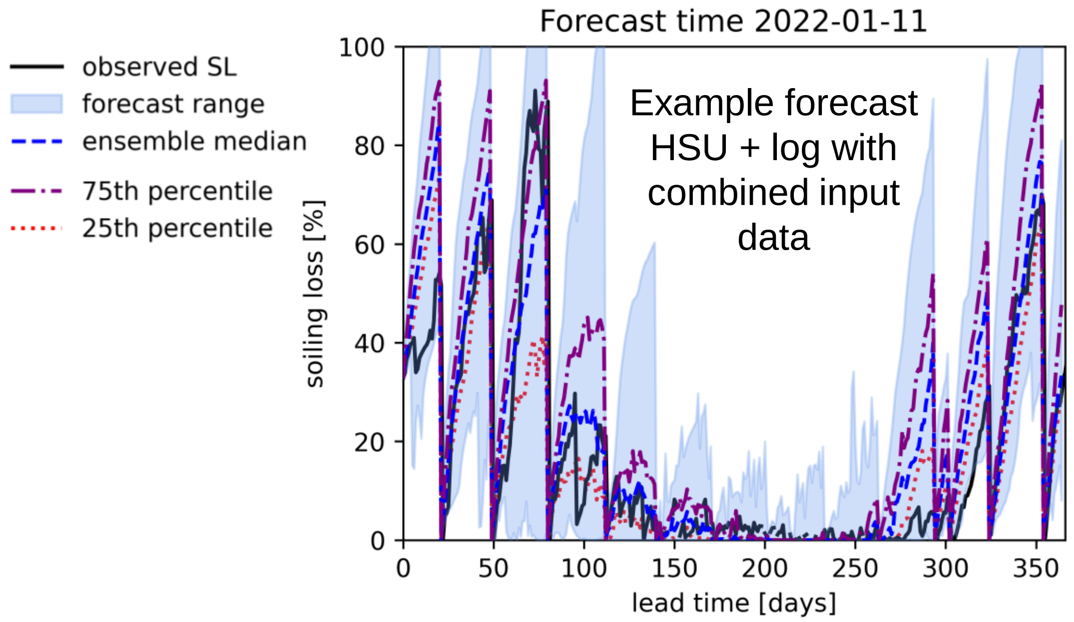
$$CNC_{SL,\ max} = \frac{\sum w_i \cdot CNC_i}{\sum w_i} = \mathbf{0.97}$$



Soiling forecasting approaches: model & input data options

- **Model combination options**
    1. Kimber + rain cleaning threshold model
    2. Kimber + rain cleaning log model
    3. HSU + threshold
    4. HSU + log
    5. Persistence + threshold
    6. Persistence + log

All forecasts are probabilistic due to input data



- **Input options:**
    i. **MERRA2** reanalysis data from 40 years used as forecast with 40 ensemble members
    ii. **ECMWF** Medium Range Ensemble forecast (ENS) for rain + **CAMS** global atmospheric composition forecasts (in case that PM is used by model) + **MERRA2** (200 ensemble members)
        - **First 6 days:**
            - **precipitation:** ECMWF forecast (1st to 6th day) with 5 of 50 ensemble members
                - 5 members with rain sum closest to avg./lowest/highest rain sum & 25%, 75% percentile
            - **PM data:** 1st to 5th day: CAMS PM forecast, separated into PM2.5 & PM10
                - 6th day: PMs from 5th day
        - **From ca. 7 days to 365 days:** MERRA2 data (40 ensemble members)

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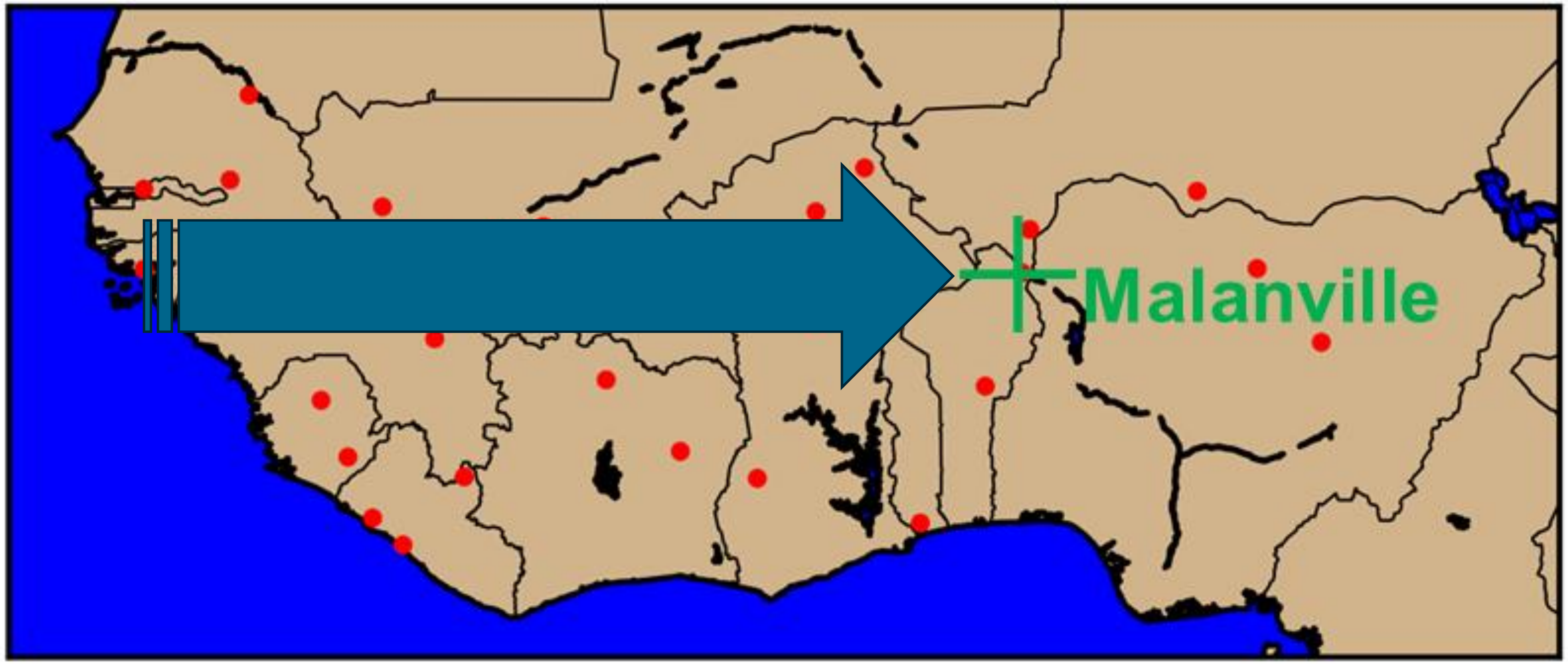
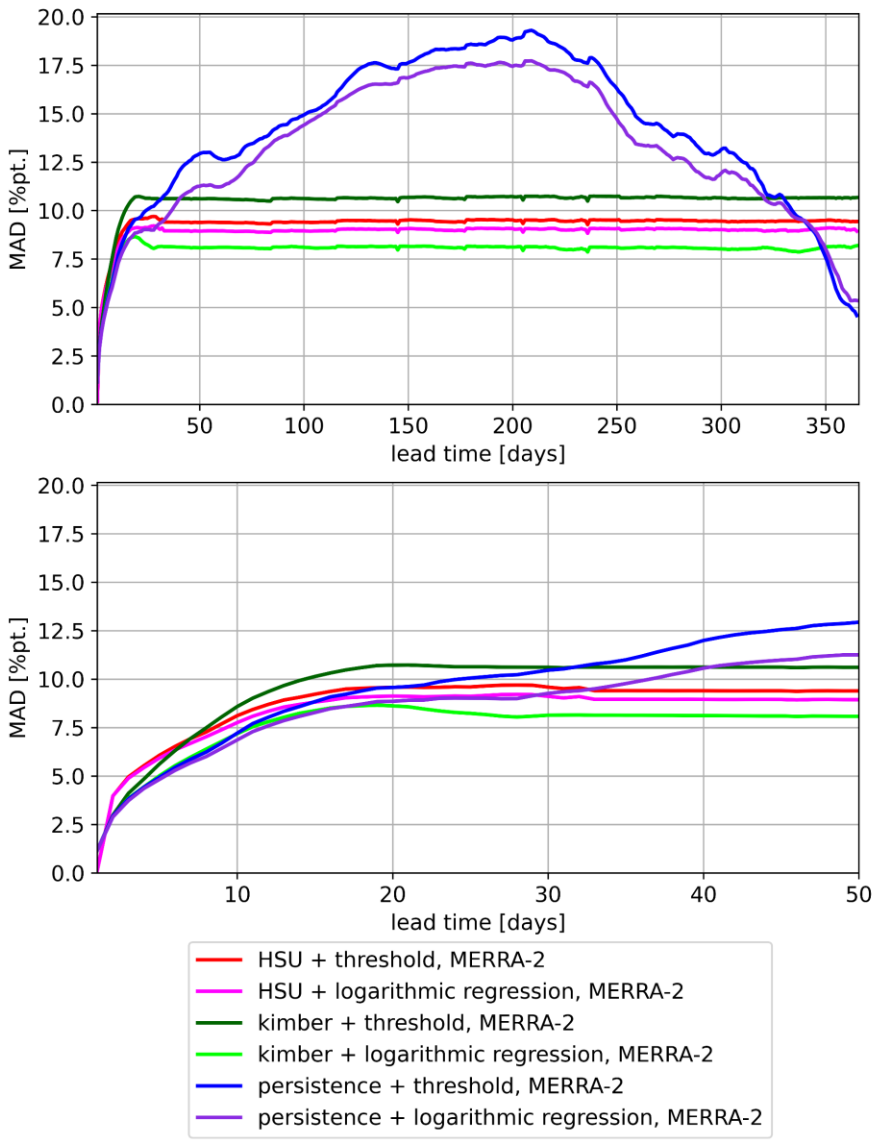
Case study & validation in Malanville, Benin



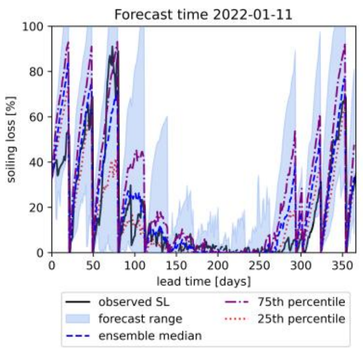
Case study & validation in Malanville
Evaluation of different soiling & cleaning models with MERRA2 data
MAD

- Results shown for mean absolute deviation (MAD) of the avg of all ensemble members
- “Persistence+log” & “Persistence+threshold” are
  - among the best models up to day 18 (persistence benefits from soiling rate & clear dry / rain seasons)
  - better than other models for forecast lead time of ~1 year (persistence benefits from seasonal effect)
- Although HSU takes into account the MEERA2 PM data it performs worse than “Kimber + log” in terms of MAD
  - Effect of bias -> calibration of forecast with on site data some time after starting forecast for the site could be helpful
- conclusions similar for RMSD, less advantage for “Kimber + log”
- ***logarithmic** rain cleaning model improves all soiling forecasts compared to threshold*

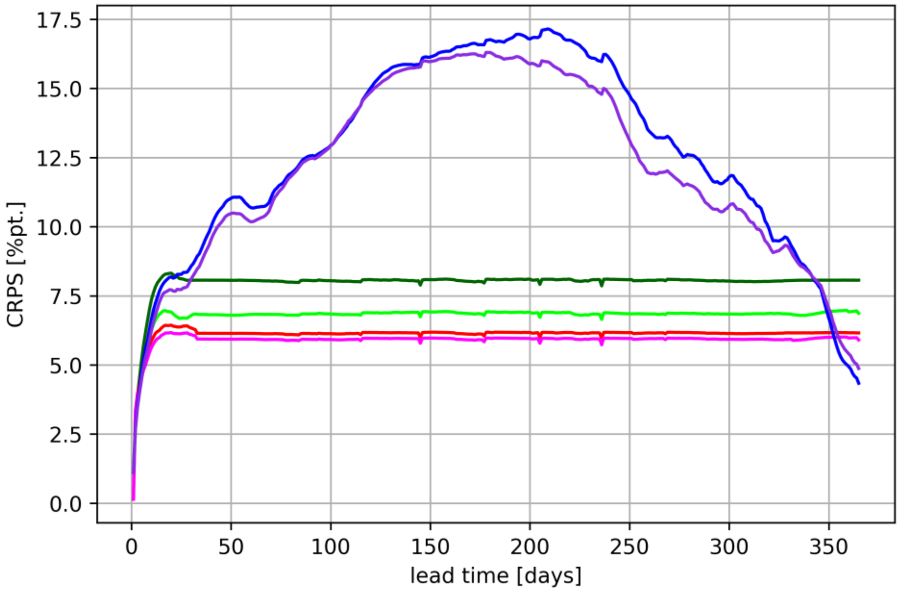


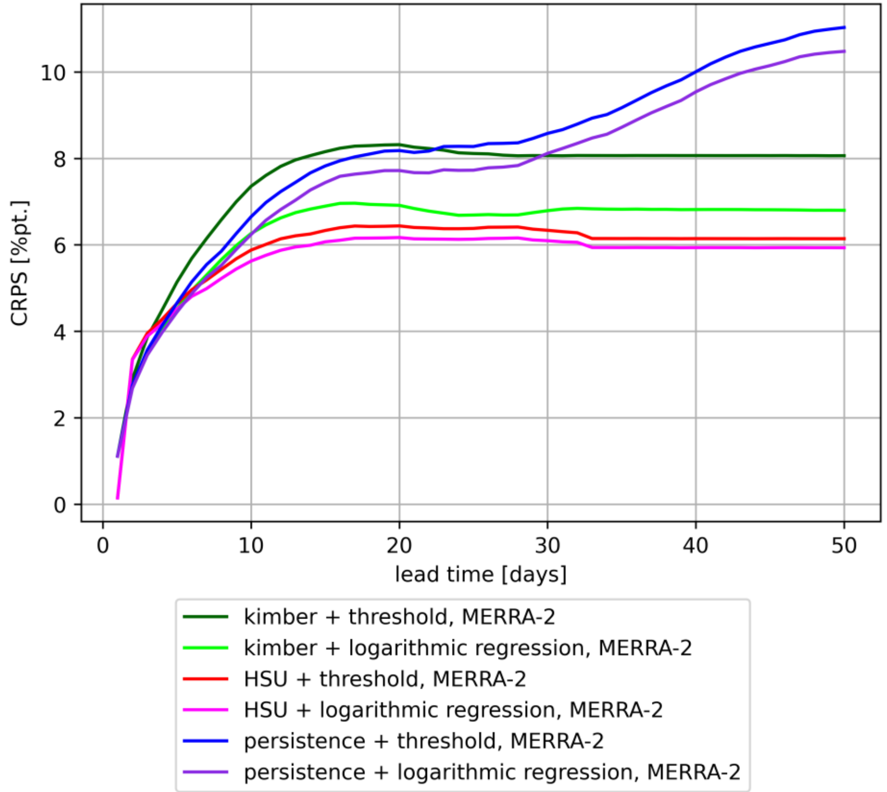
Case study & validation in Malanville
Evaluation of different soiling & cleaning models with MERRA2 data: CRPS

- CRPS = Continuous Ranked Probability Score
  - Common error metric for evaluation of probabilistic forecasts that describes also if the predicted distributions are good
  - CRPS is negatively oriented (smaller CRPS = better)
  - same unit as the forecasted variable
  - converts to MAD for deterministic forecasts



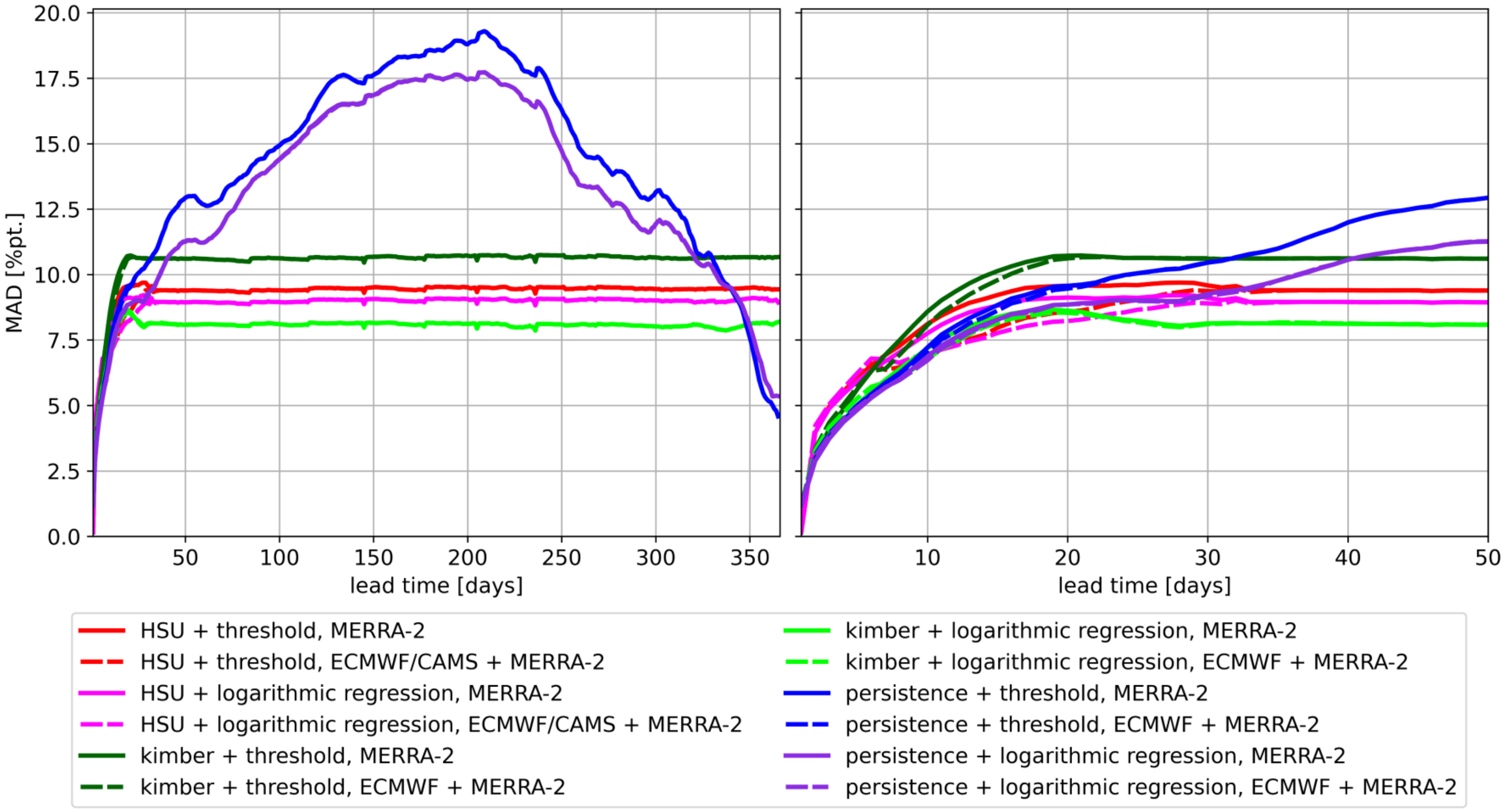
- More pronounced deviations of models & now advantage for HSU models after day 8
  - Although avg. of ensemble is worse than “Kimber+log” in terms of MAD, predicted distributions fit better to observations





Effect of using additional CAMS PM and/or ECMWF rain data

- Only minor benefit with additional data for MAD
  - & only in first weeks
- Small additional improvement for CRPS for days 8-30
- MERRA2 ensemble seems to describe avg. weather conditions quite well for Malanville



Summary

- Soiling loss forecasts can be created with various models
- Partial cleaning modelling improved all forecast models
- More complex deposition models & forecast data might be useful, but not always
    - Persistence deposition + probabilistic partial cleaning forecast performed best up to ~day 18 in the case study
    - forecasts with 40 year reanalysis data ensemble from MERRA2 reach similar or even better MAD than those using also ECMWF rain forecasts & CAMS PM forecasts
        - Advantage found in terms of predicted distributions (CRPS)
    - Calibration of soiling models is relevant for forecast accuracy
- Estimate of forecast errors of soiling loss MAD ~10% compared to up to 90% soiling loss in the data set
    - promising for application for cleaning schedule optimization & improved yield predictions

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Thank you for your attention!
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