Soiling forecasts for cleaning scheduling optimization

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Motivation

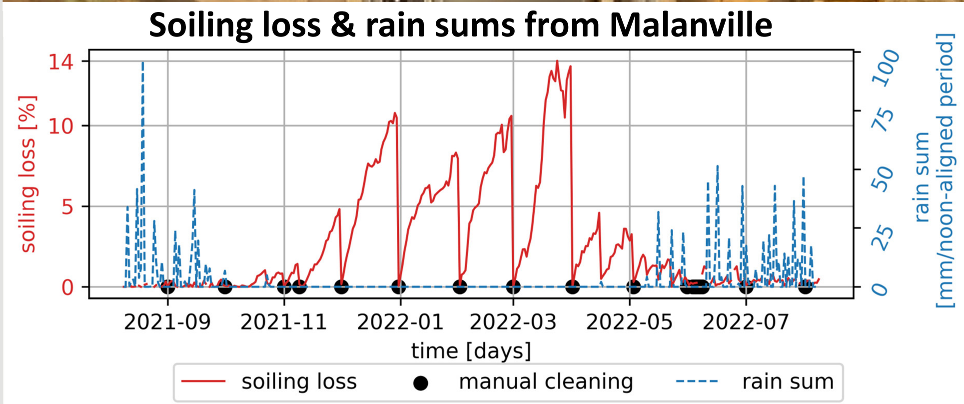
- Soiling = Accumulation of particles + other objects (e.g. leaves, bird droppings) on solar collectors
- Soiling causes a loss of 3%–4% of potential global solar energy production[1], therefore cleaning is important

Objectives

- Create soiling loss forecasts to
  - Predict solar energy yield accurately & to
  - Optimize cleaning to reach the best trade-off between the soiling losses & cleaning costs
    - Not only frequency of cleaning, but also the selection of the cleaning dates must be optimized
    - Avoid unnecessary cleanings just before strong rainfalls or strong soiling events
- Evaluate soiling forecasts based on the most recent soiling measurements & different weather forecasts & long-term meteorological data

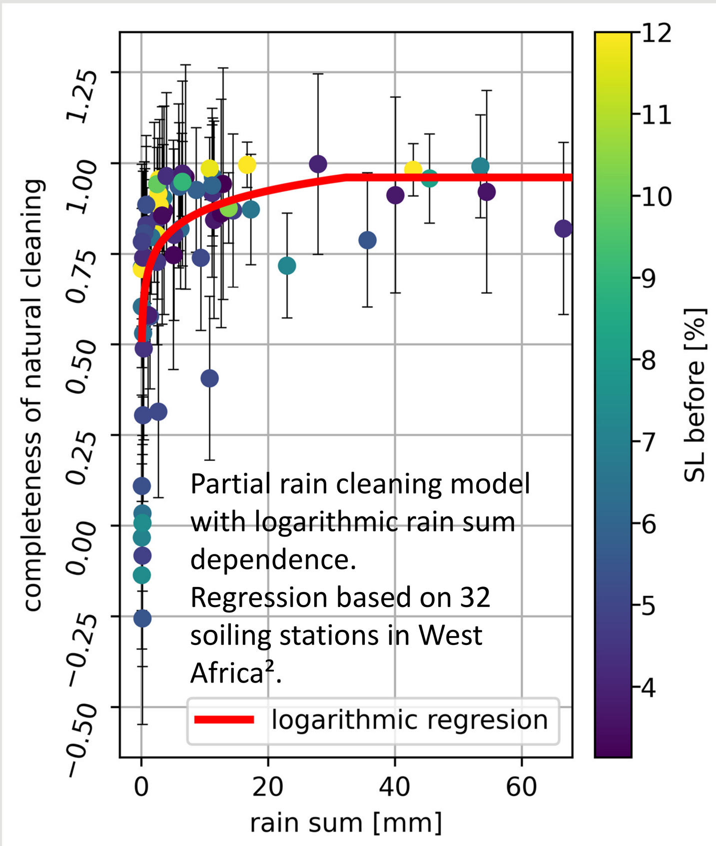
Soiling measurement at the West African Power Pool (WAPP) network station in Malanville, Benin[2]

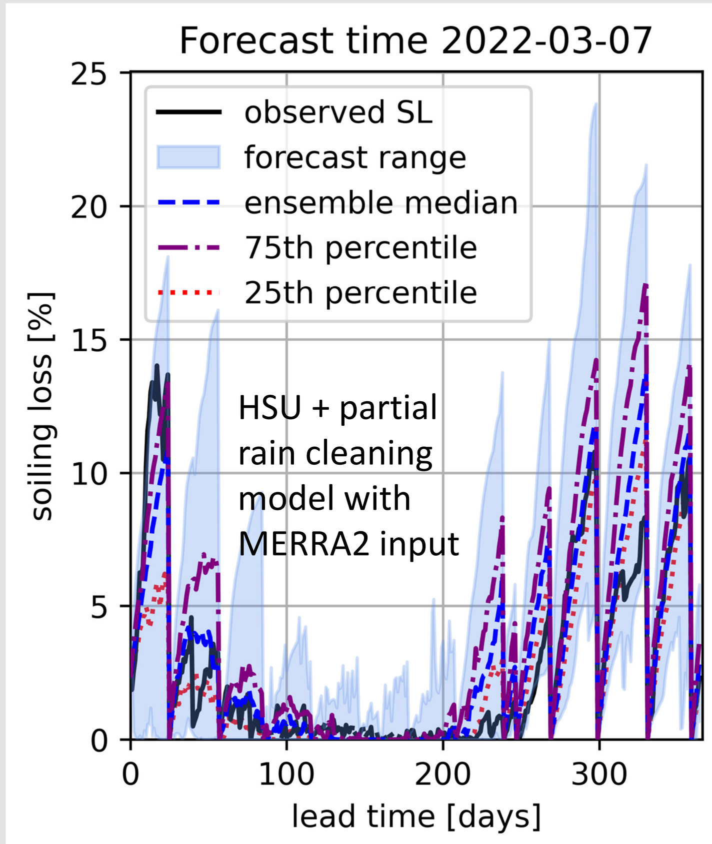
Soiling loss & rain sums from Malanville



Soiling forecasting approaches

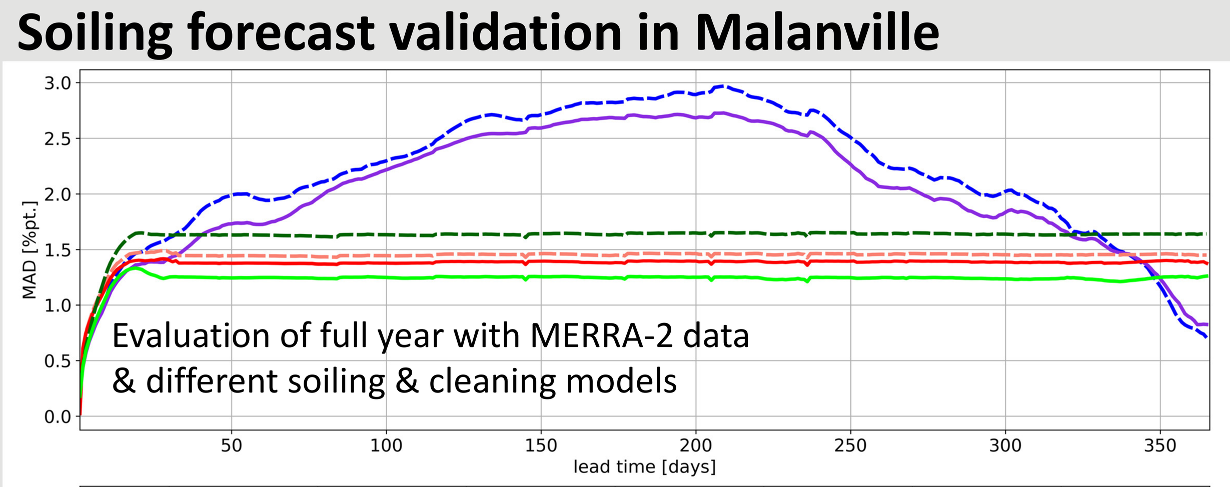
- **Soiling & rain cleaning models**
  - Various options of semi-physical soiling models incl. deposition & natural cleaning tested
  - **Soiling rate models** for days without rain cleaning:
    a) *Persistence*[3]: soiling rate is predicted as the average of the last 20 days without cleaning
    b) *Kimber*[4]: fixed soiling rate of 0.435%/d[5]
    c) *HSU*[6]: soiling rate depending on PM & tilt with settling velocities of 0.0009 m/s for PM2.5 & 0.004 m/s for PM10
  - **Rain cleaning models**
    a) *Full cleaning above threshold of 1 mm daily rain sum; no cleaning otherwise*
    b) *Partial cleaning*[7] *effect with logarithmic rain sum dependence*
- **Input data:**
  - Parameters: particulate matter, precipitation, collector orientation
  - Two input data options:
    I. *MERRA2 data*[8] *of 40 years used as ensemble prediction*
    II. *combination of MERRA2, ECMWF*[9] *and CAMS*[10] *data*
      - First 6 days:
        - all weather parameters except for PM: ECMWF forecast (50 ensemble members)
        - PM: 1st to 5th day: CAMS PM forecast, 6th day: PM from 5th day
      - From day 7 to day 365: MERRA2 data
      - Creation of 200 ensemble members as concatenations of 40 MERRA2 years & 5 members from ECMWF (rain sum closest to avg, lowest, highest, 25- & 75-percentile)

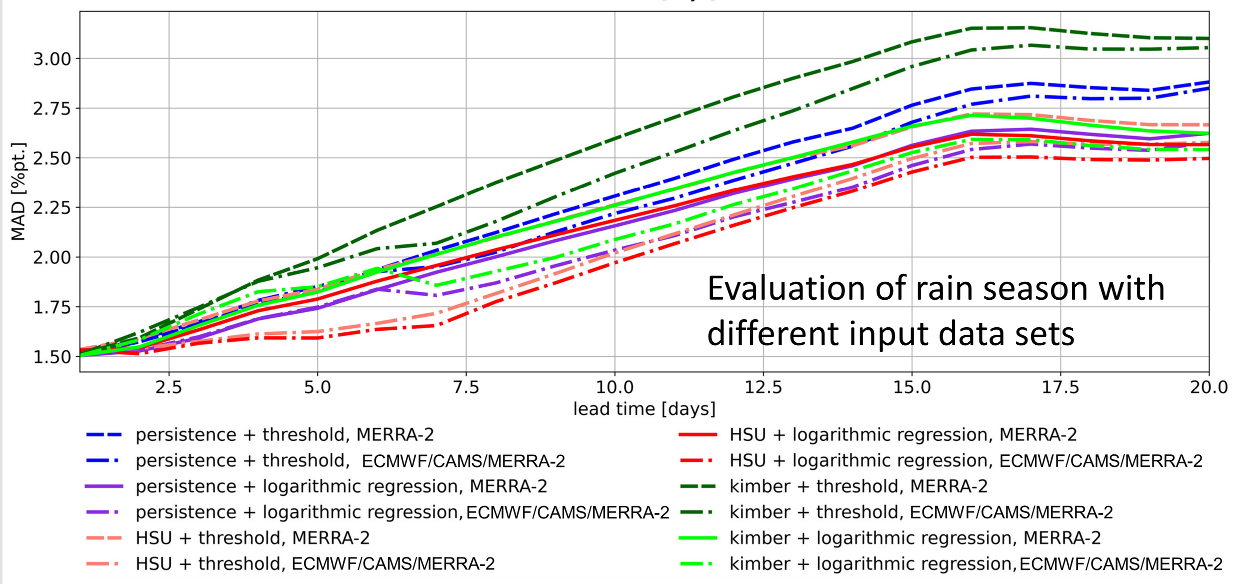




- **Case study**
  - Apply & evaluate the forecasts for Malanville (Benin)
  - There, soiling was measured for more than one year
  - Forecasts for the case study were created with a horizon of one year

Soiling forecast validation in Malanville





Evaluation of different soiling & cleaning models with MERRA2 data:

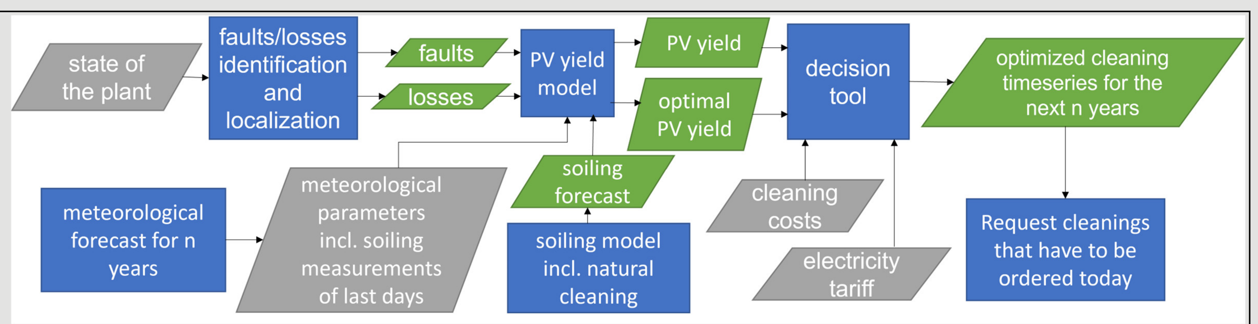
- *Kimber & HSU models outperform persistence most of the time*, except:
  - with forecast lead time of ~1 year (persistence benefits from seasonal effect)
  - during the first days (all forecasts benefit from application of latest measurement data)
- Kimber combined with logarithmic regression achieves the best performance for many lead times
  - This can change if the Kimber model's fixed soiling rate is less adequate for the site of interest
- In the first days, HSU + logarithmic rain cleaning model performs best
- Using *the logarithmic rain cleaning model improves the soiling forecast* compared to using the same models with a cleaning threshold

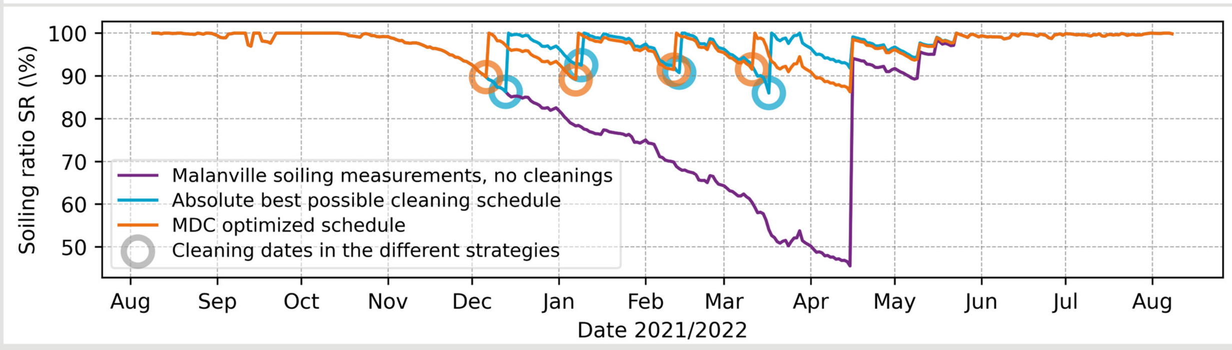
Evaluation of the effect of using additional CAMS PM & ECMWF precipitation data:

- *CAMS & ECMWF data can reduce the forecast errors in some cases*, e.g. rainy period (April - September)
- Considering also the dry period, an overall increase of the errors was found using the additional data. The MERRA2 ensemble seems to describe the weather conditions quite well.
- Especially in the first 7 days, the HSU model using CAMS and ECMWF performs considerably better than the other combination of models and datasets.

Cleaning optimization

- Cleaning schedule optimizer based on a Markov Decision Chain (MDC) approach[11,12] for an exemplary PV plant in Malanville, Benin.
- Optimizer is executed every day in the morning with most recent forecasts (MERRA2, partial cleaning)
  - It derives the time plan of cleaning tasks for the next year resulting in the largest economical yield
  - Only the suggested cleaning tasks that have to be ordered on the current day are actually considered
  - The actually scheduled cleaning tasks form the cleaning timeseries that is used for the evaluation of the economic and energetic effect of the optimization
- Compared to a PV system that is not cleaned
  - 9.7 % net income increase
  - 12.1 % energy generation increase





Conclusion & outlook

- Results highlight the potential of soiling forecasts and cleaning schedule optimization to improve yield predictions, and the actual economic & energetic yield of PV systems
- Calibration of soiling models to site or soiling type is important for accuracy
- More complex models and further data sets may be useful depending on the data quality and season. However, this is not guaranteed as the 40 year ensemble from MERRA2 already provides valuable information, and all data/model uncertainties are high
- If a PV system is meant to be cleaned less frequently than once per year the forecast horizon would have to be increased. Additionally, the soiling model would have to include the long-term build-up of soiling due to particles that cannot be easily removed by rain.

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