

Opportunities and challenges in PV performance analytics: a case study in module soiling

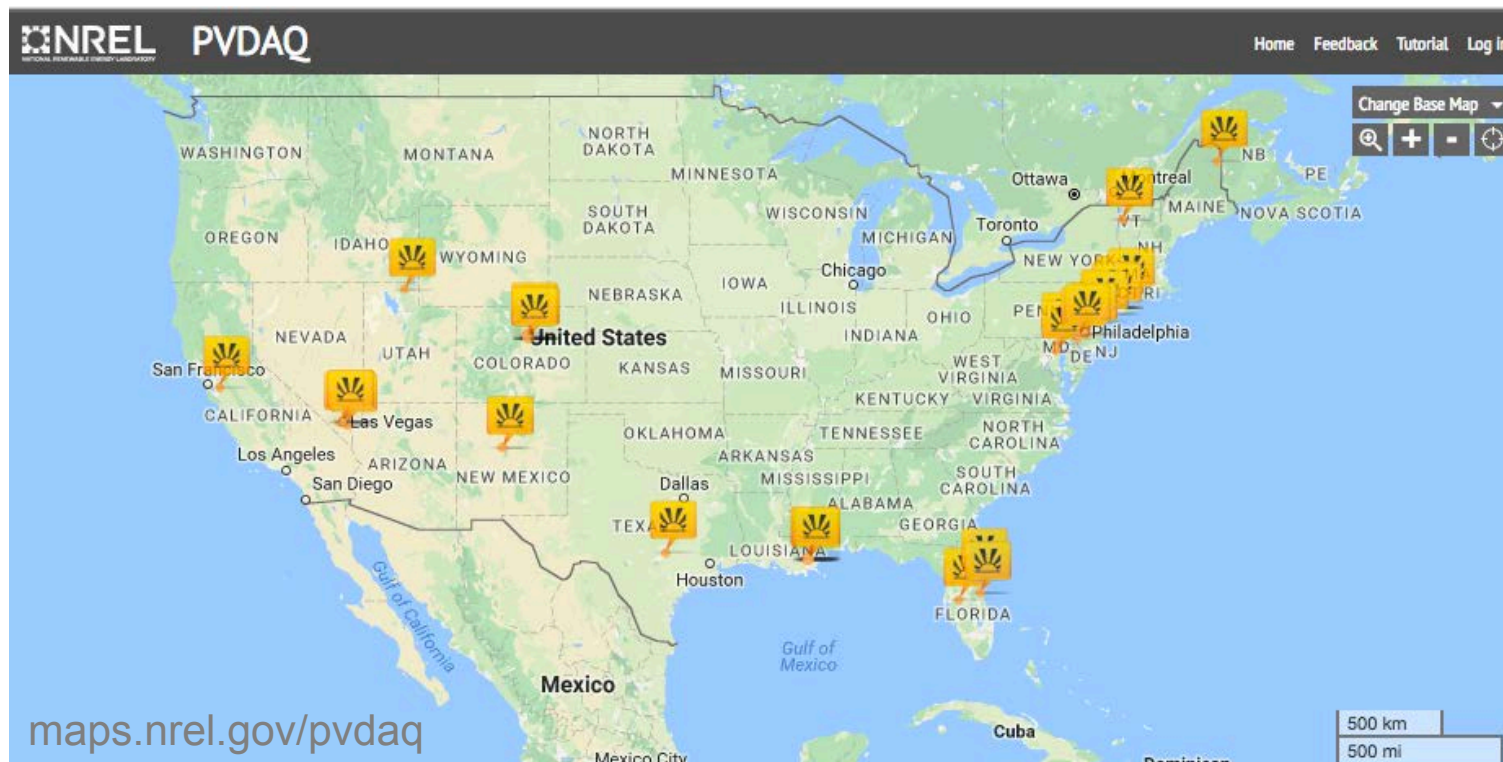
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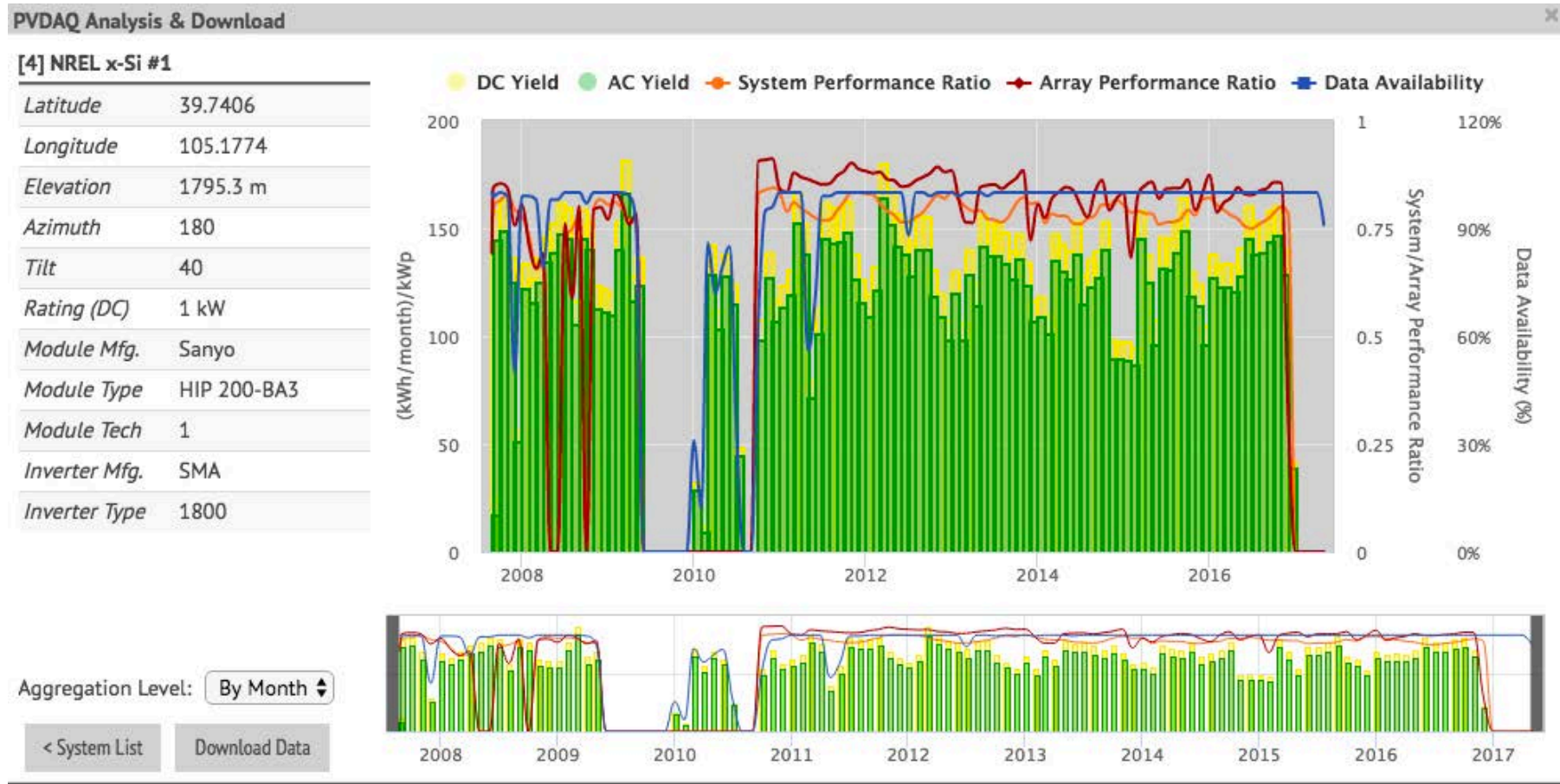
PV data varies in quality and detail

- Sources:
 - Public data sets
 - Research systems
 - Fleet data (asset owners / module manufacturers)



Comparison of two systems

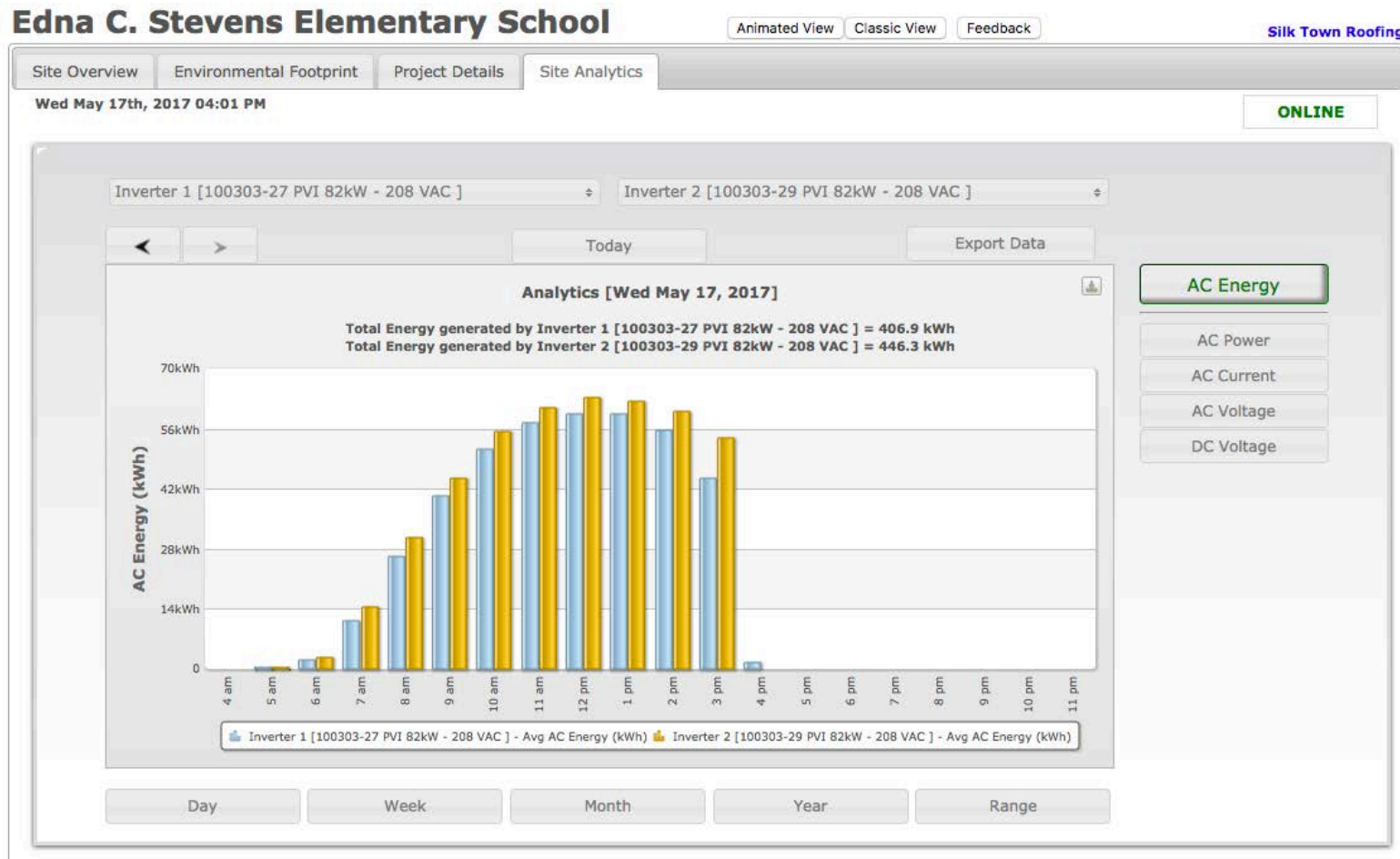
System 1: Research system at NREL



maps.nrel.gov/pvdaq

Comparison of two systems

System 2: Elementary School in Connecticut



www.solrenview.com/SolrenView/mainFr.php?siteId=726

Comparison of two systems

Research system

- Metadata:
 - Location
 - System orientation
 - Module details
 - Inverter details
- Time series:
 - 1-minute
 - AC power/current/voltage
 - DC power/current/voltage
 - Ambient temperature
 - Inverter temperature
 - 3 module temperatures
 - Plane-of-array irradiance
 - DAS diagnostics

Elementary school

- Metadata:
 - Location
 - Module details
 - Inverter details
- Time series:
 - 5-minute
 - AC power/current/voltage
 - DC voltage

Comparison of two systems

Research system

- Metadata:
 - Location
 - System orientation

Elementary school

- Metadata:
 - Location
 - Module details

Challenge:

- **Analytics that enable comparisons between data sets from disparate systems**

- AC power/current/voltage
- DC power/current/voltage
- Ambient temperature
- Inverter temperature
- 3 module temperatures
- Plane-of-array irradiance
- DAS diagnostics

- AC power/current/voltage
- DC voltage

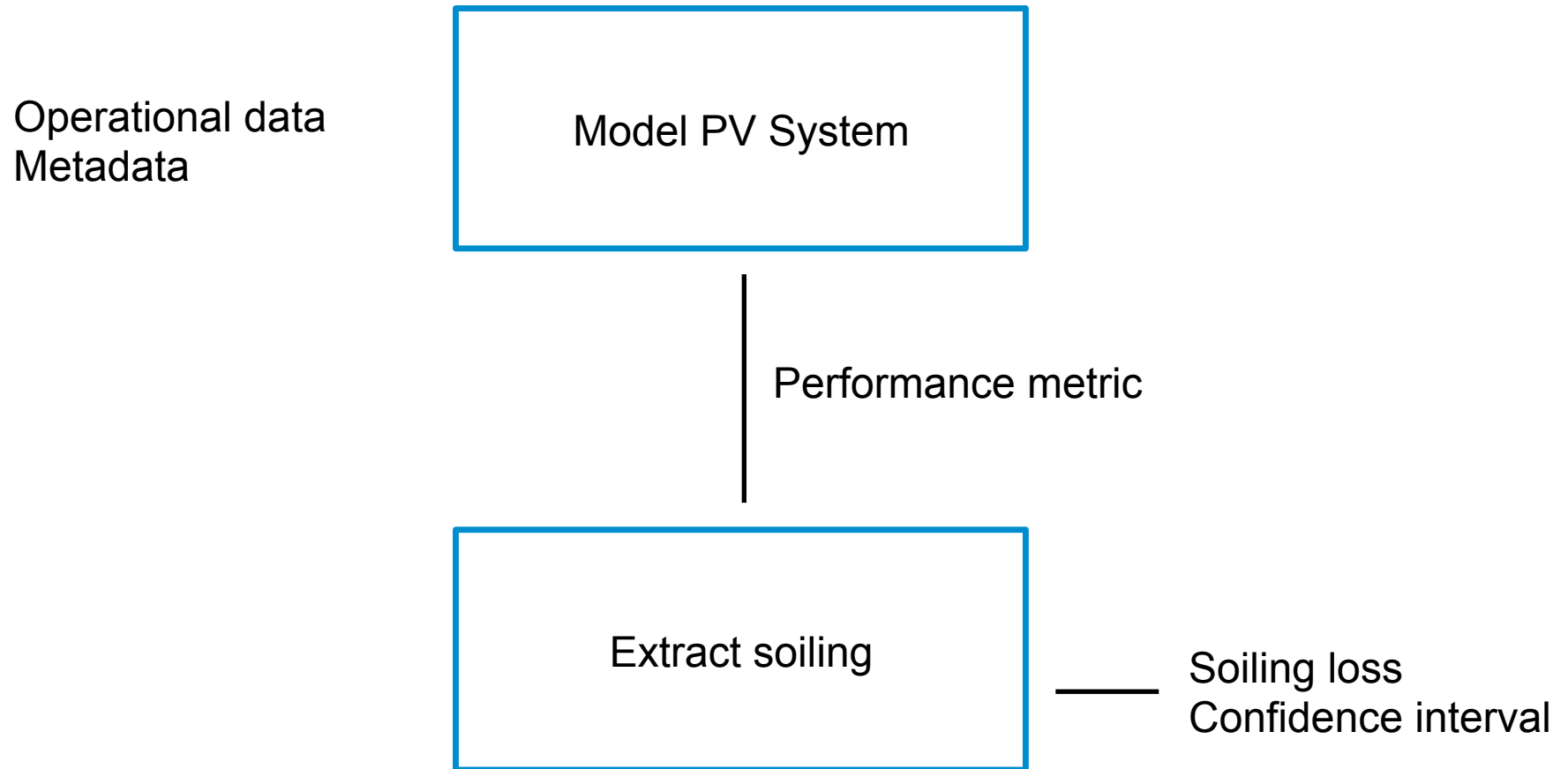
Analytics example: Soiling loss

Goal: Use historical PV data to inform planning

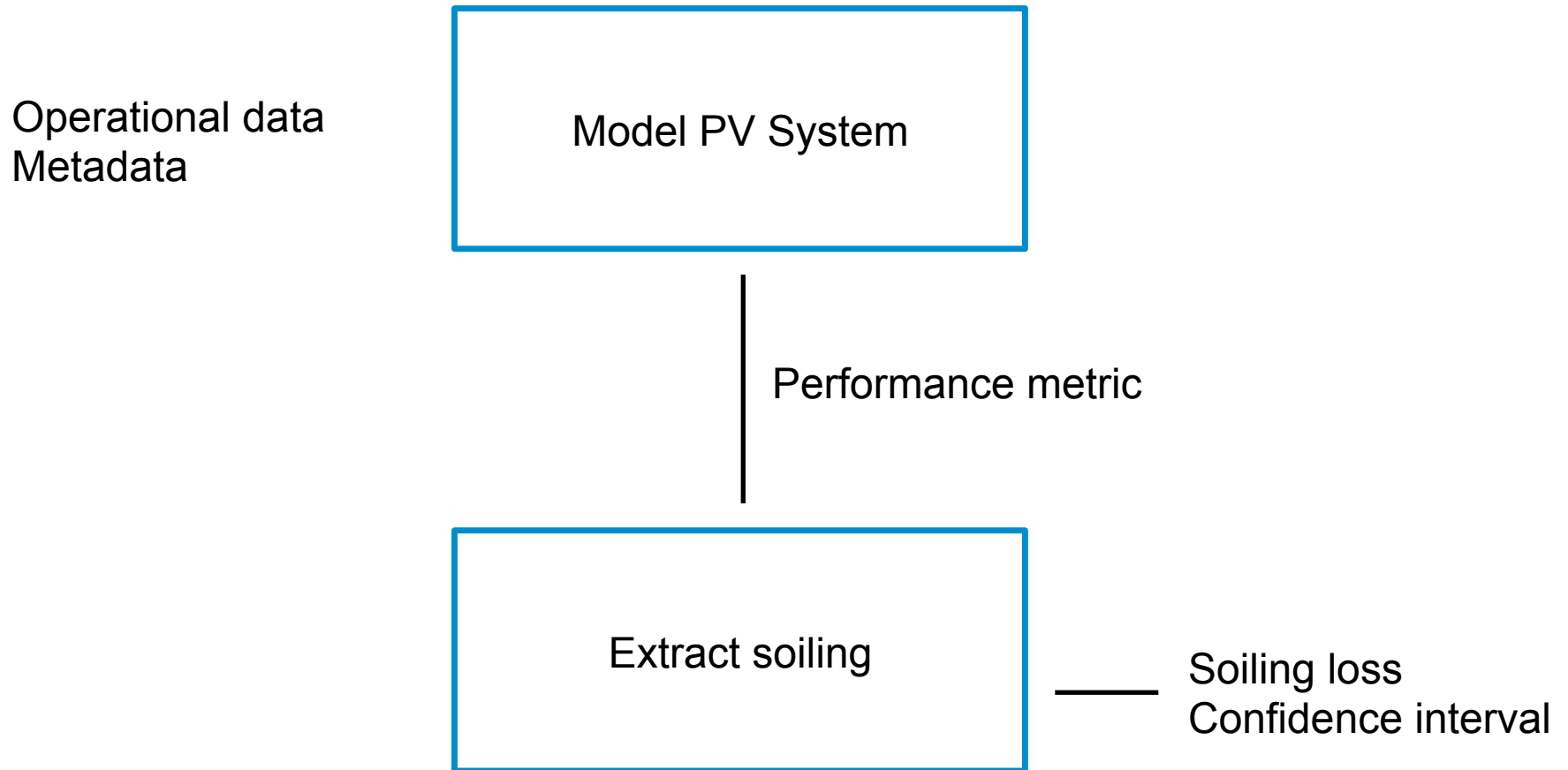
- We're already collecting the data we need, in PV production data
- To unlock the potential:
 - Globally Scalable
 - Statistically rigorous
 - Flexible



Two part calculation

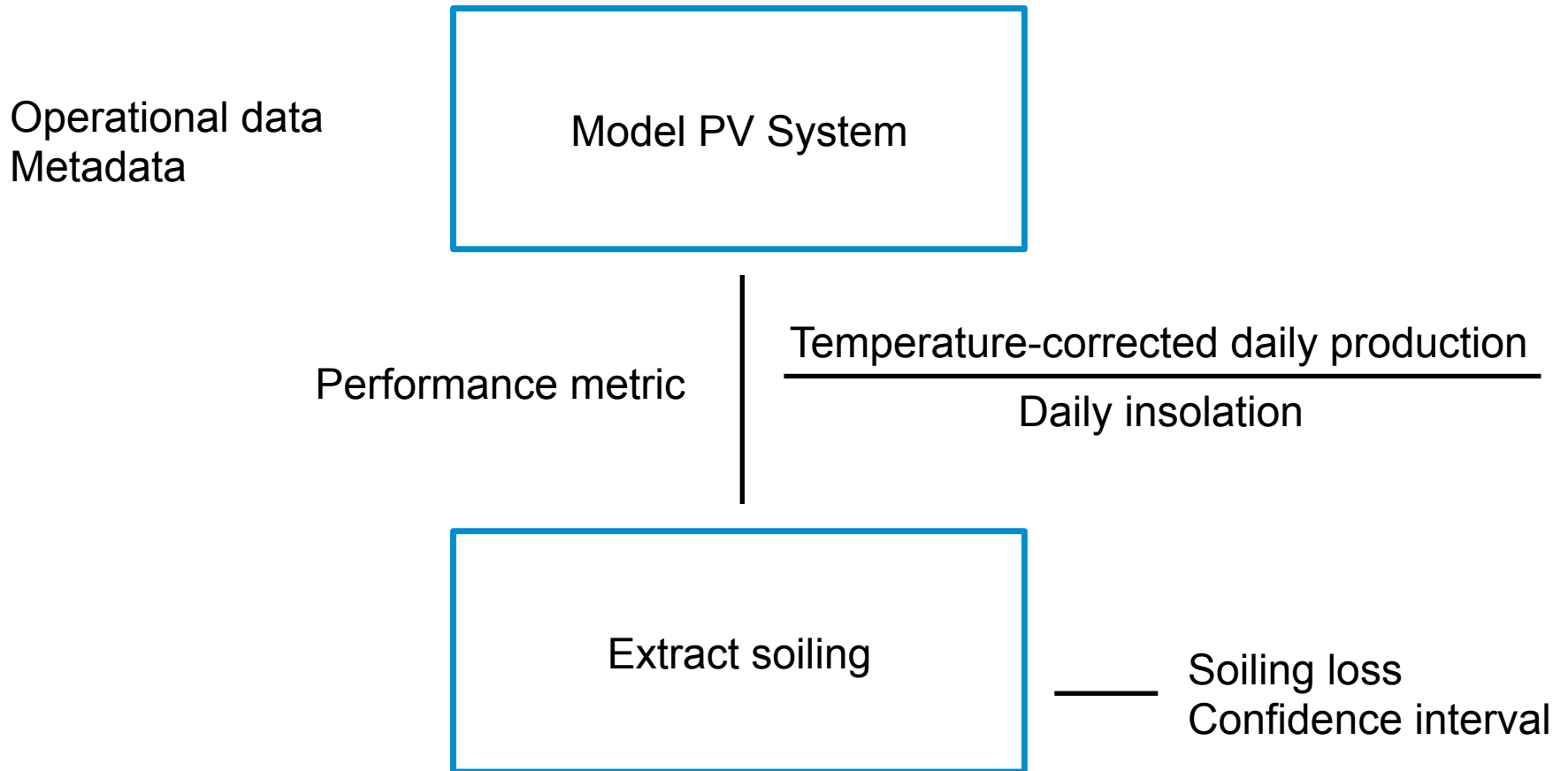


Two part calculation



Extraction should handle varying detail/quality in data and model

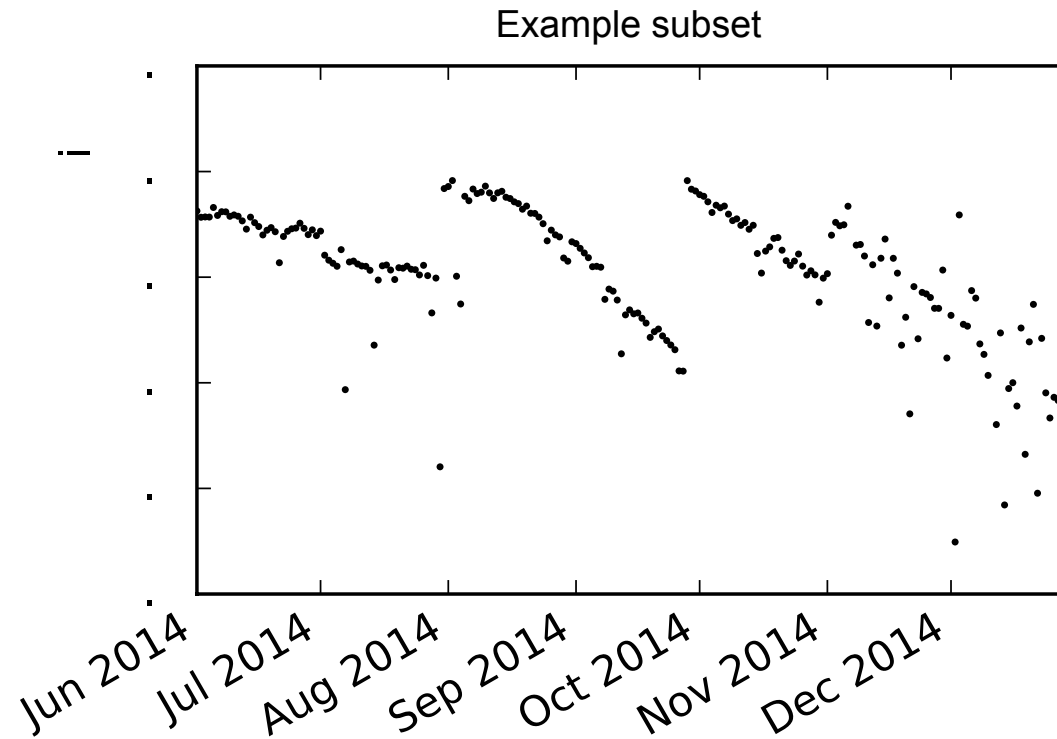
Performance metric



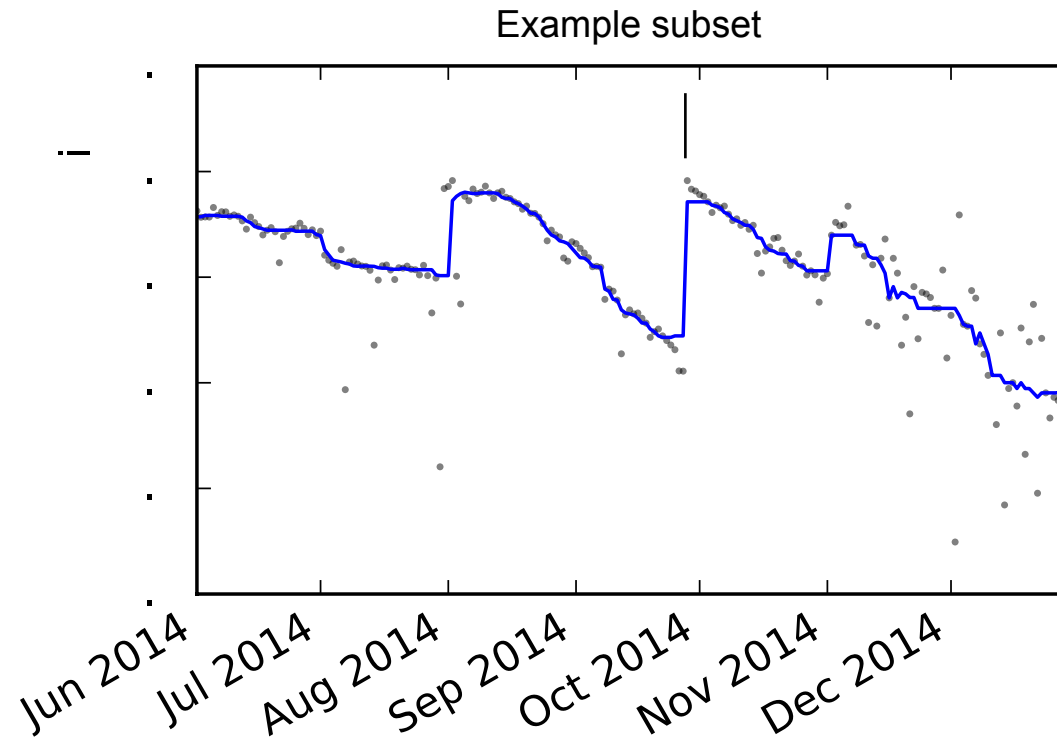
Steps

1. Detect cleaning events
 - This divides data into intervals
2. Fit the slope for each interval
 - Yields a daily soiling derate
 - Also get an uncertainty in each slope
3. Calculate and apply derate to daily insolation
4. Compare raw and derated insolation of period of interest
5. Use slope uncertainties in Monte-Carlo to estimate uncertainty

Step 1: Detect cleaning events

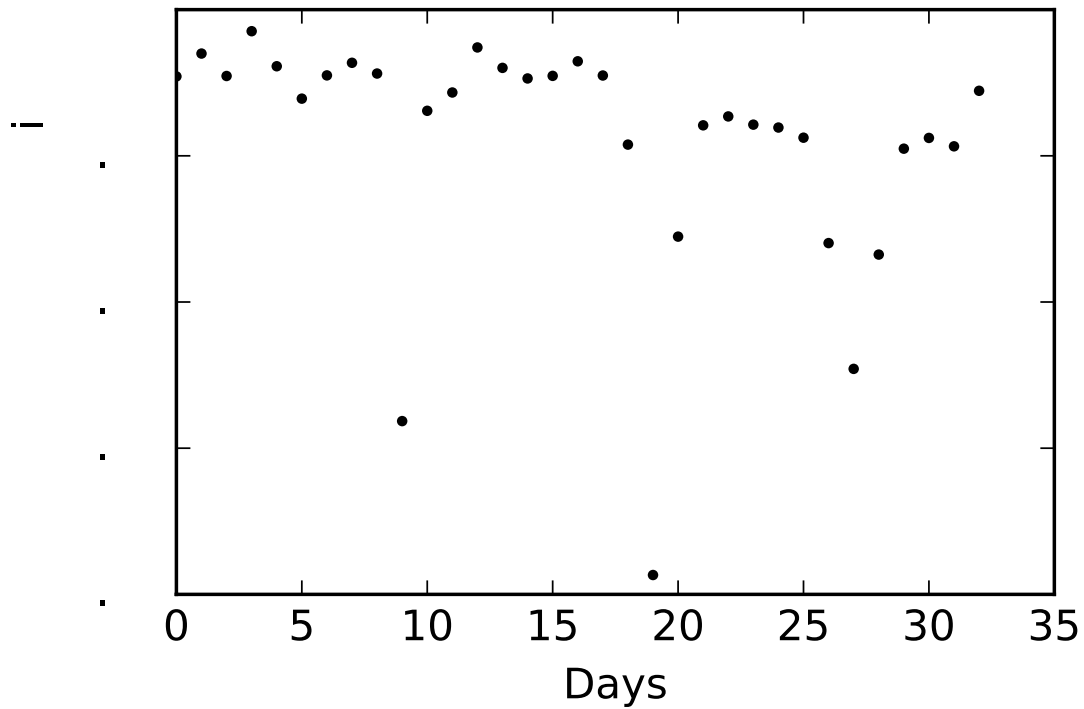


Step 1: Detect cleaning events

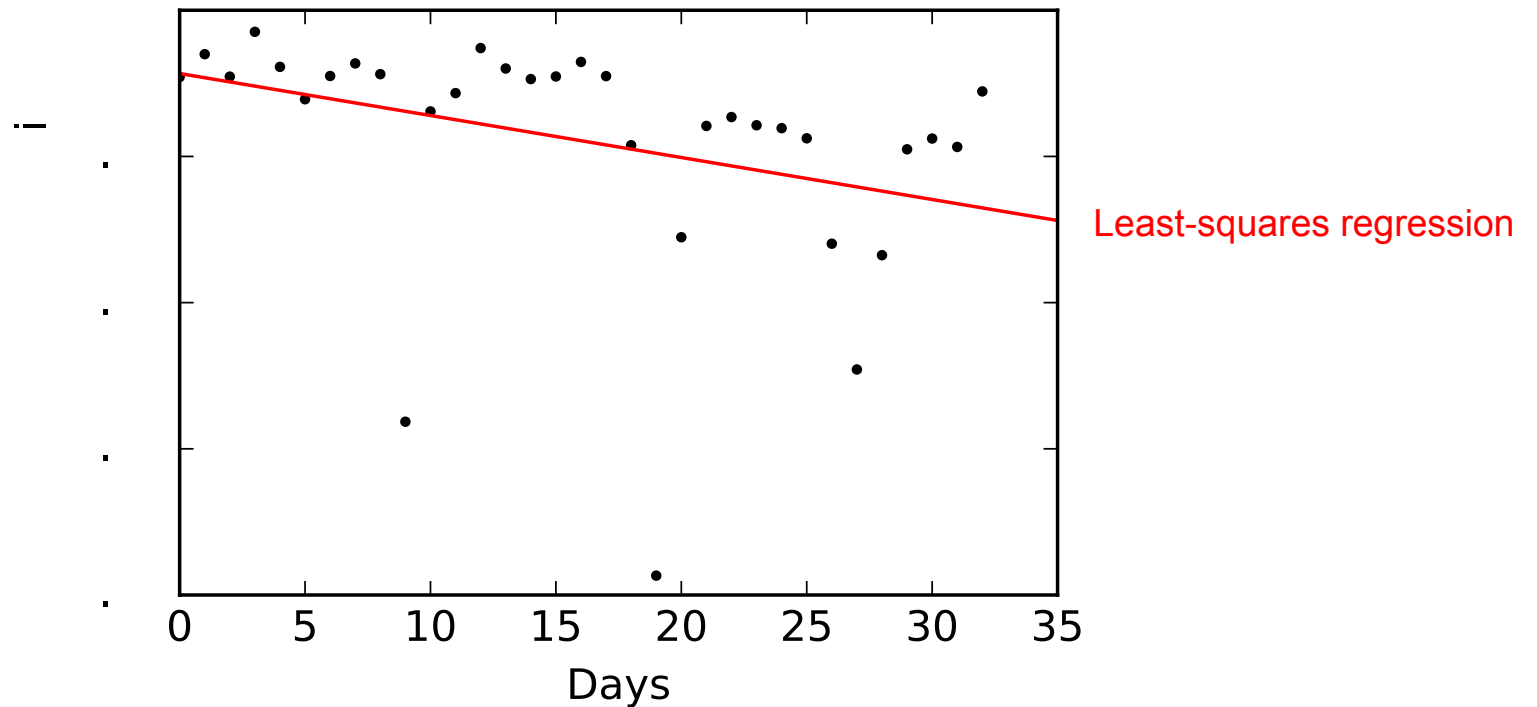


- Apply rolling median
- Detect upward steps
- **No need for precipitation data**

Step 2: Extract slope for each interval

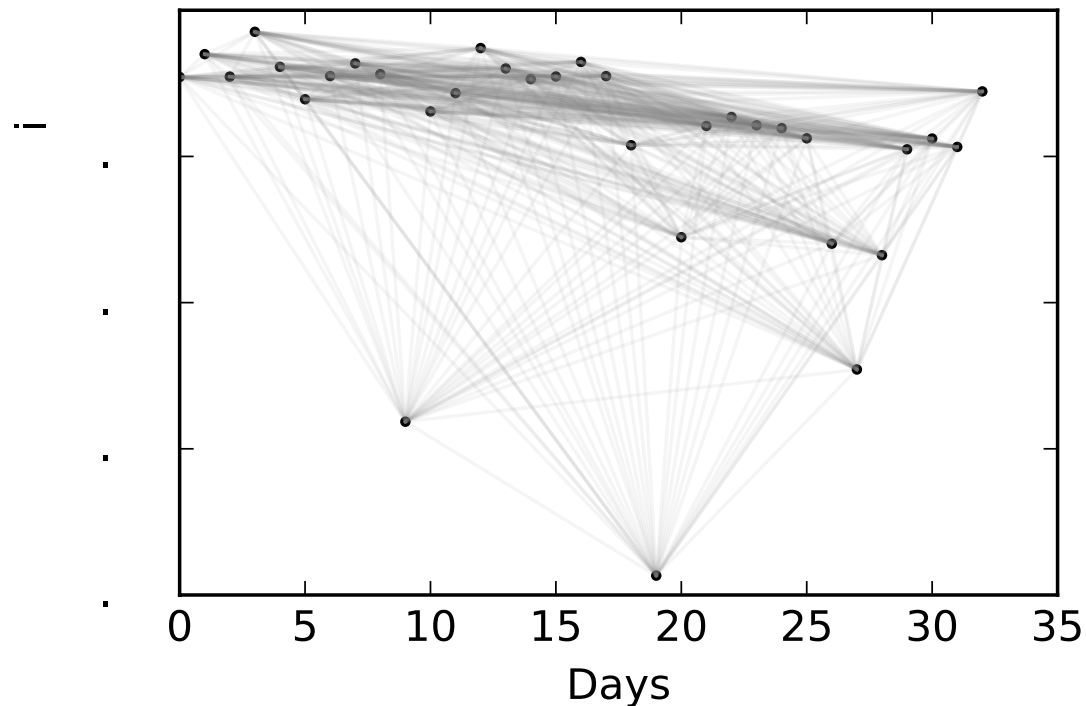


Step 2: Extract slope for each interval



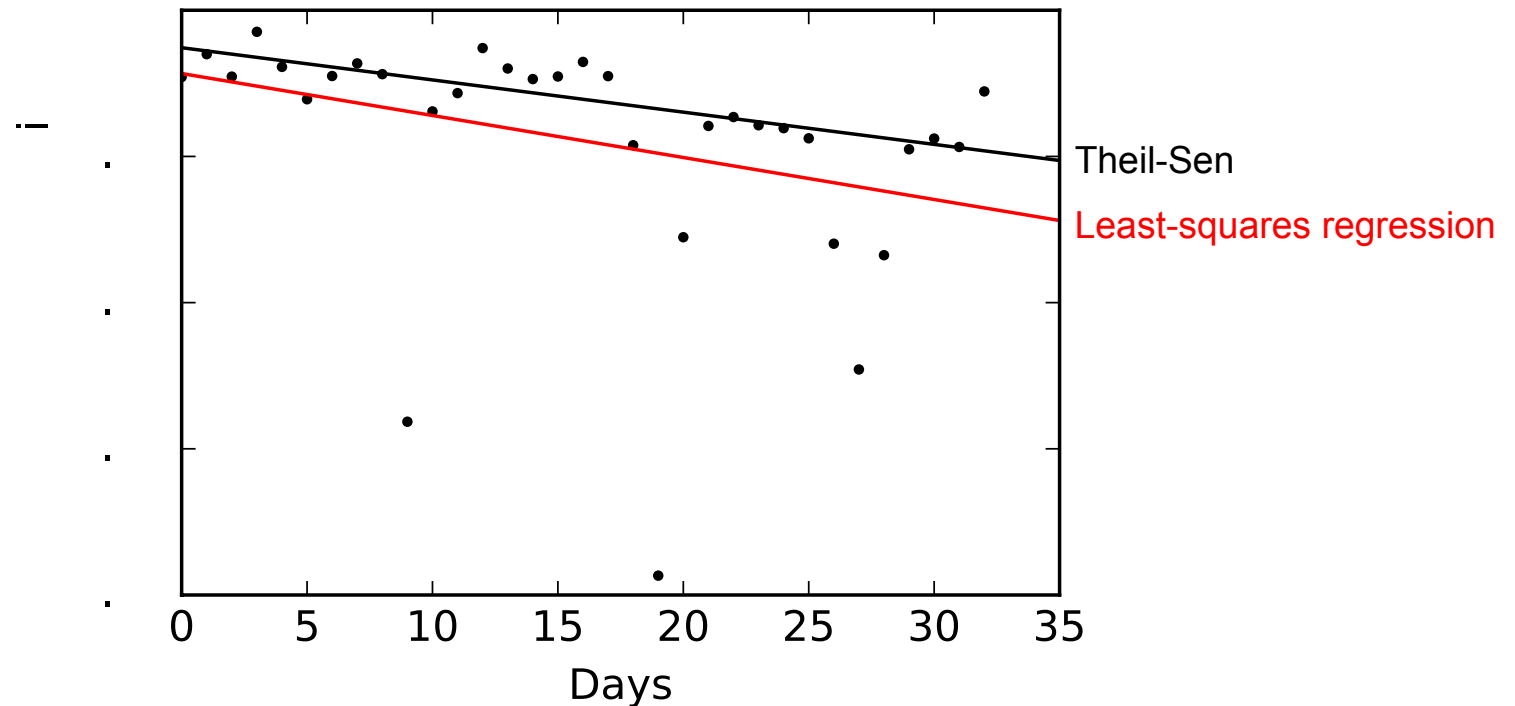
- Robust slope estimation needed for anomalous data

Step 2: Extract slope for each interval



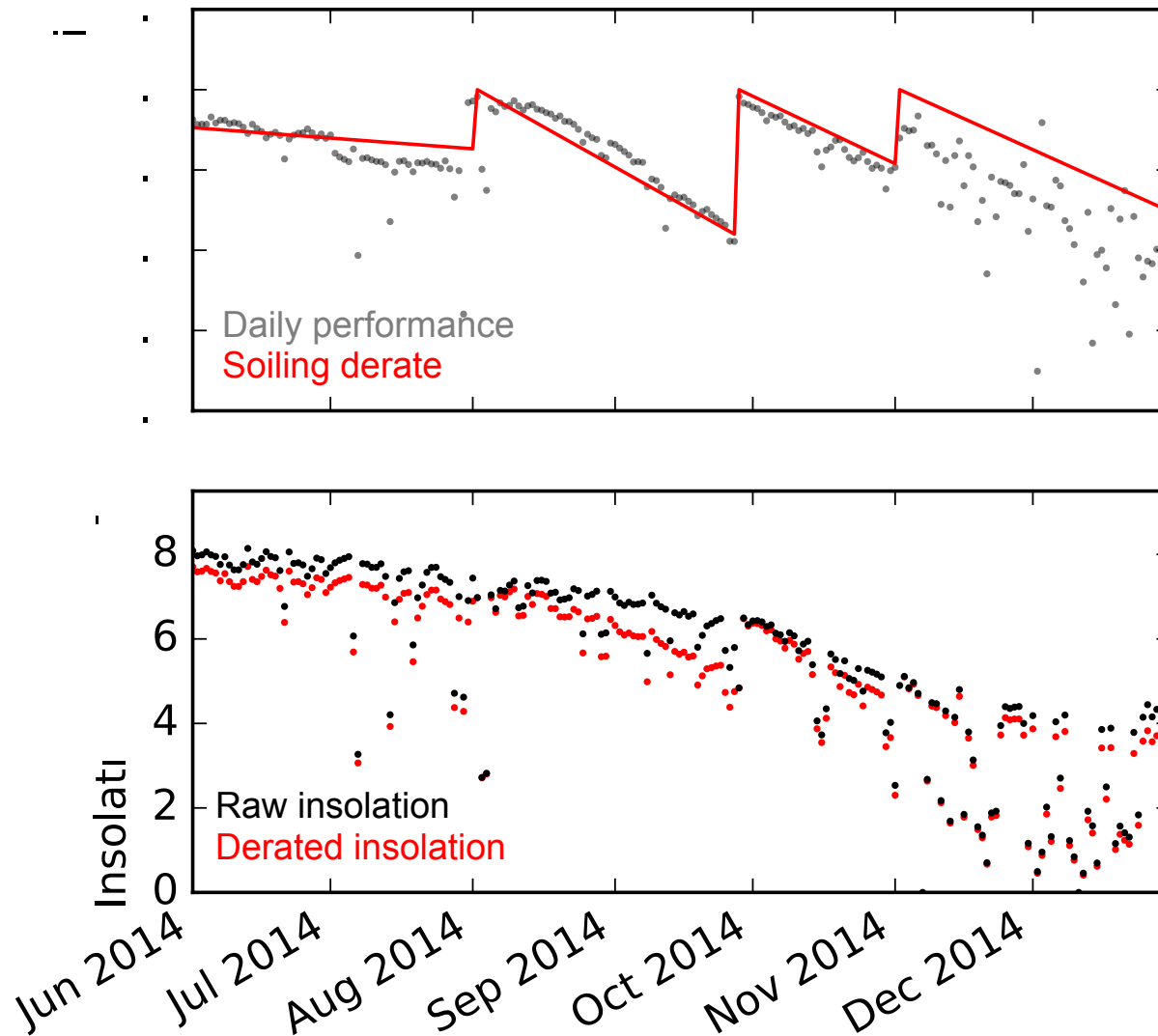
- Robust slope estimation needed for anomalous data
- Solution: Theil-Sen estimator
 - Consider lines between all pairs, take the median slope

Step 2: Extract slope for each interval

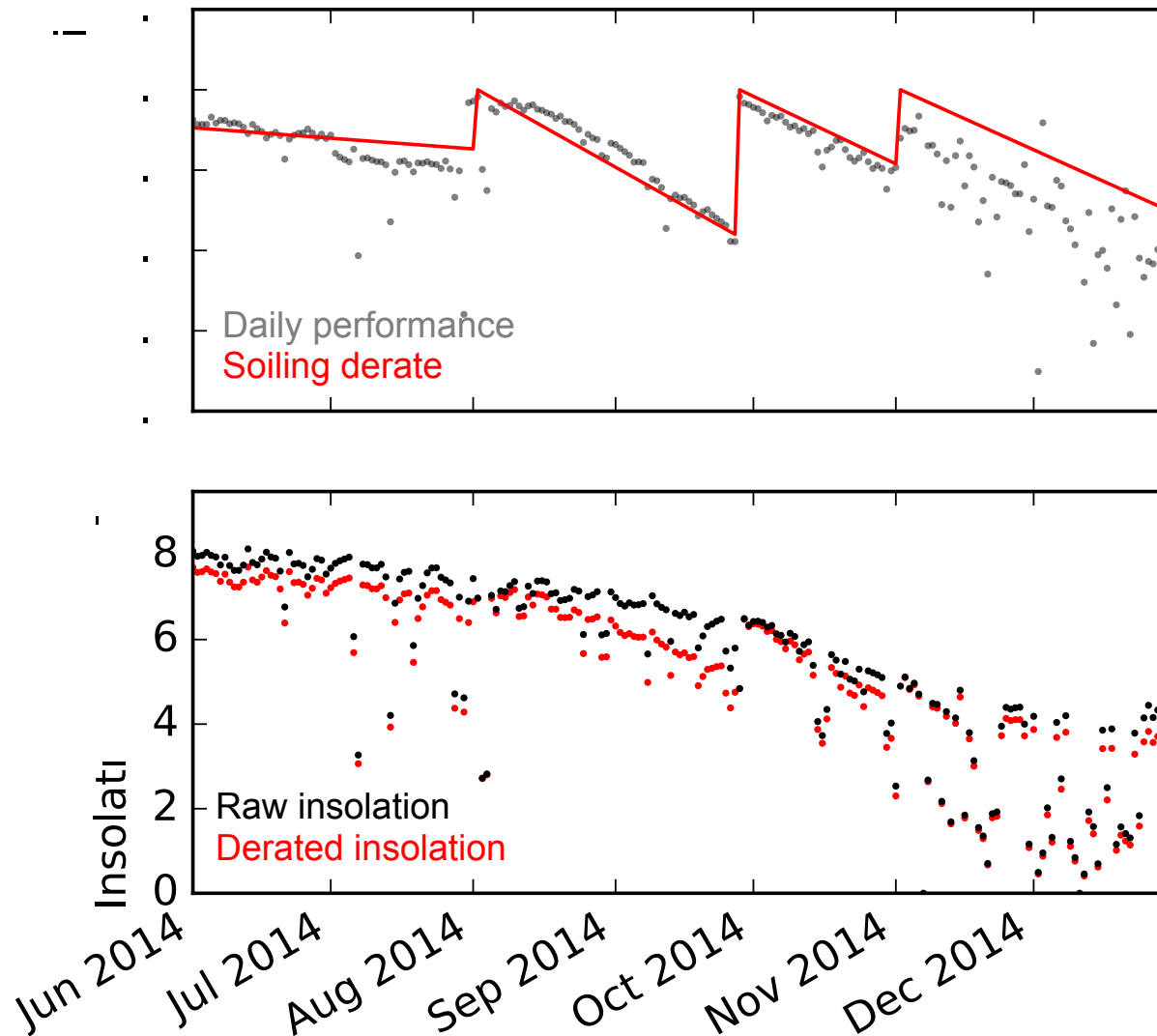


- Robust slope estimation needed for anomalous data
- Solution: Theil-Sen estimator
 - Consider lines between all pairs, take the median slope

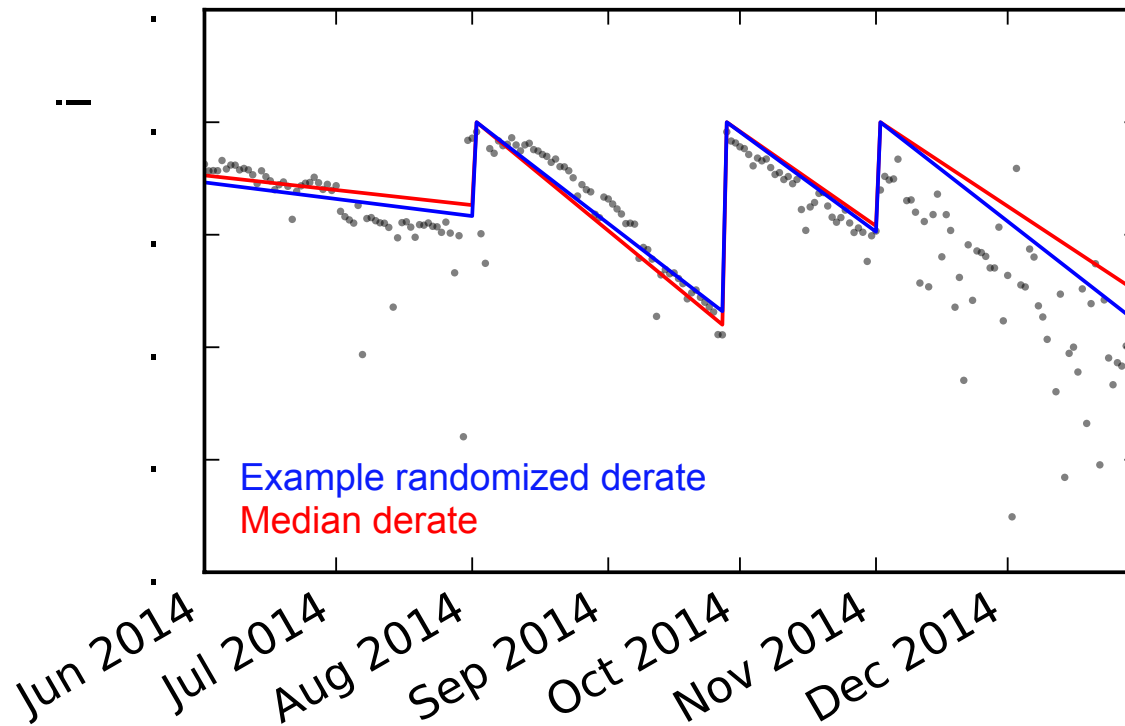
Step 3: Derate insolation



Step 4: Integrate and compare insolation



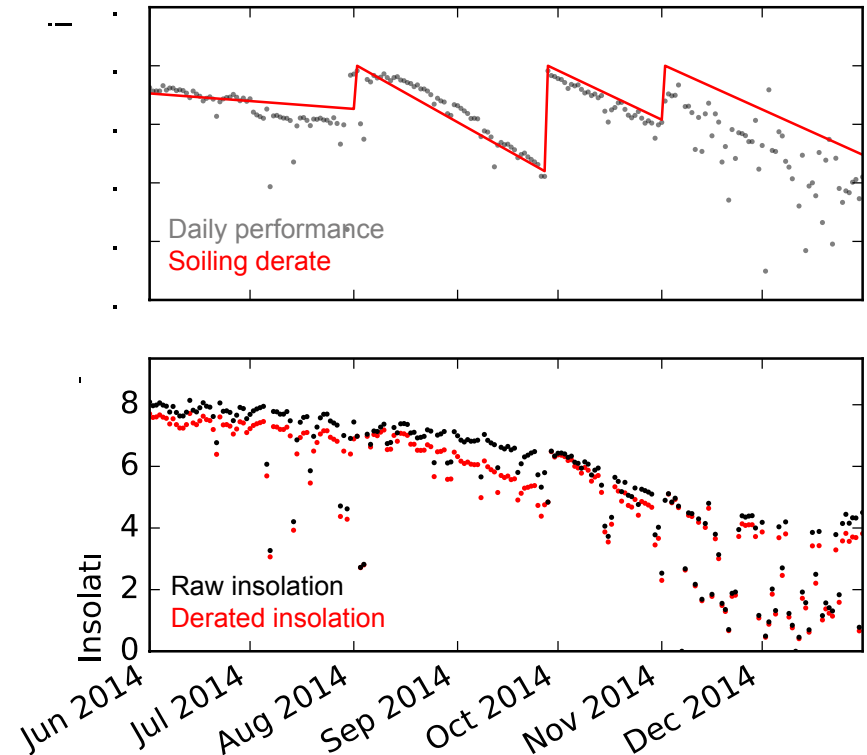
Step 5: Monte Carlo for Uncertainty



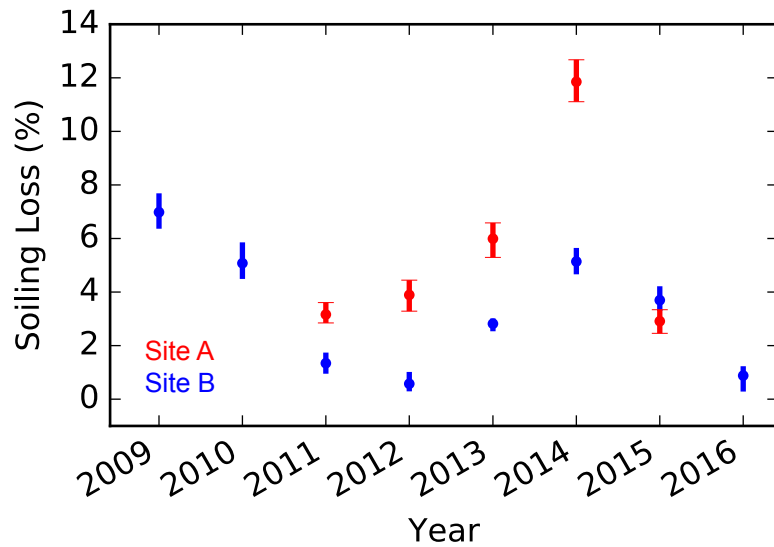
- Use the confidence interval for the slope
- Recalculate 1000s of randomized derate profiles
- Look at the distribution of integrated losses

Steps

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 - Also get an uncertainty in each slope
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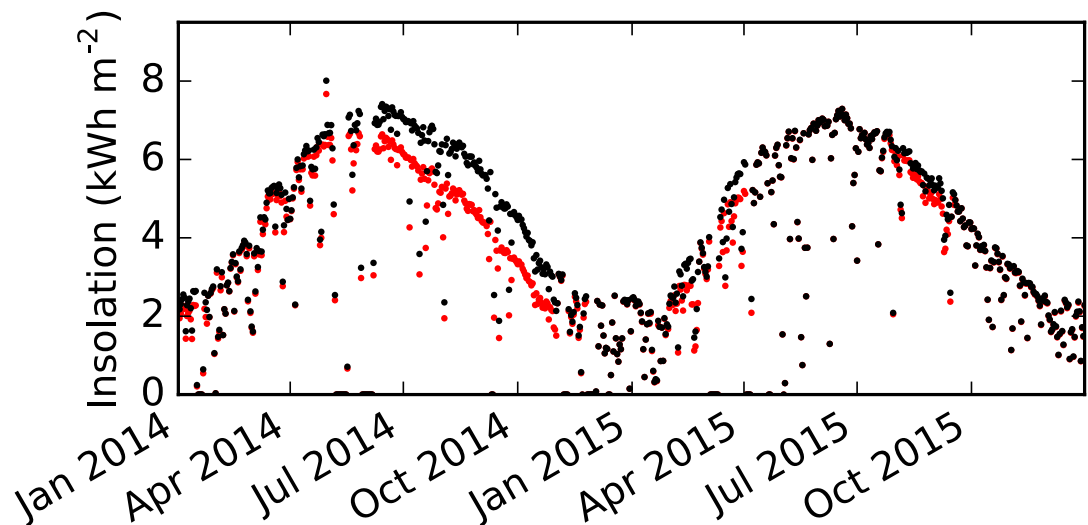
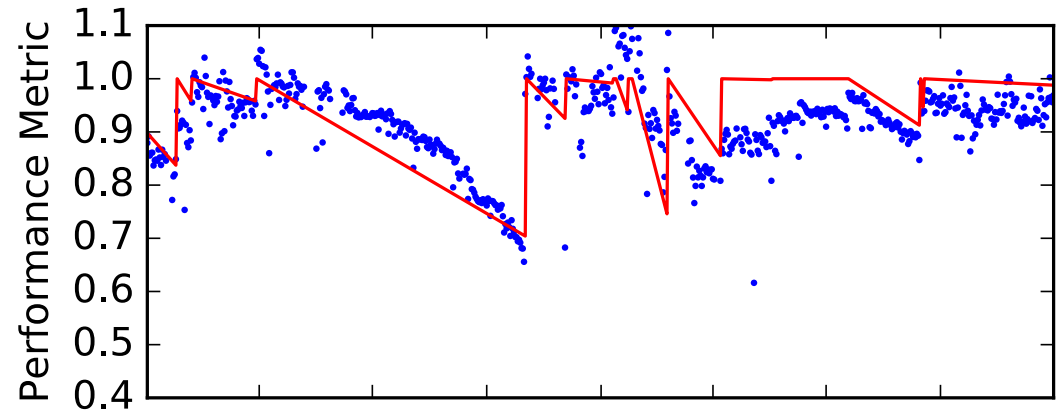


Application: annual variation

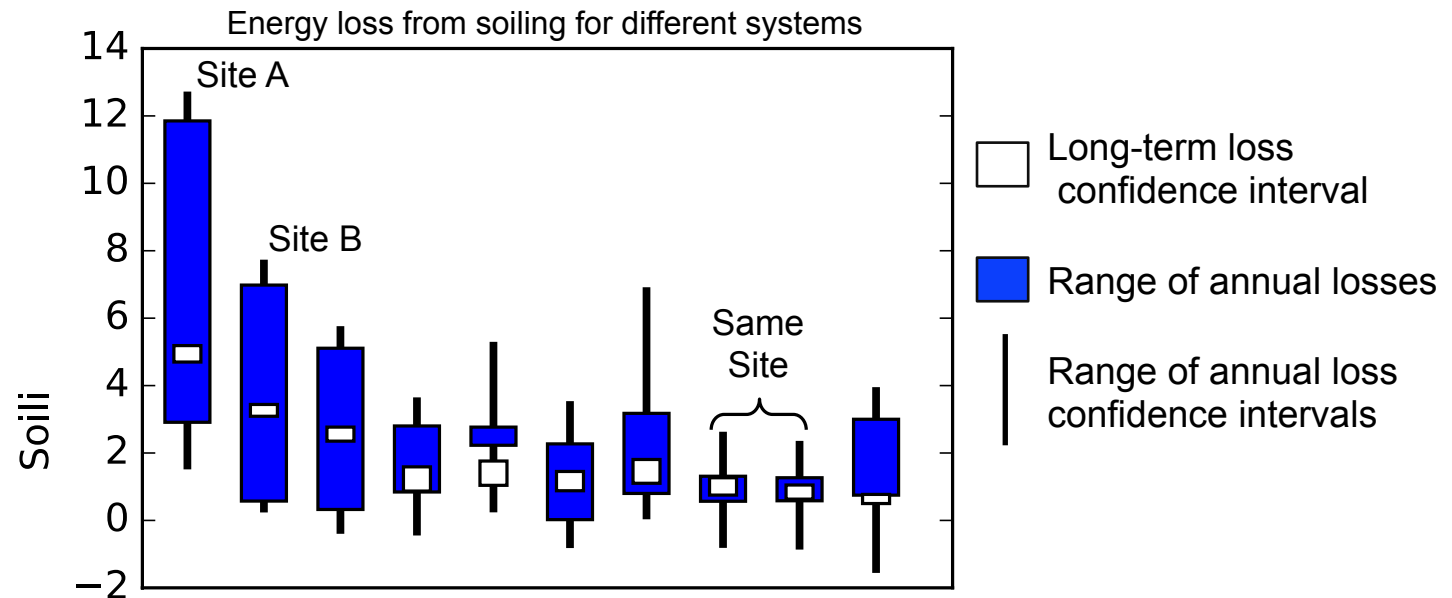


We observe substantial year-to-year variations

Comparison of 2014 and 2015 time series for site A



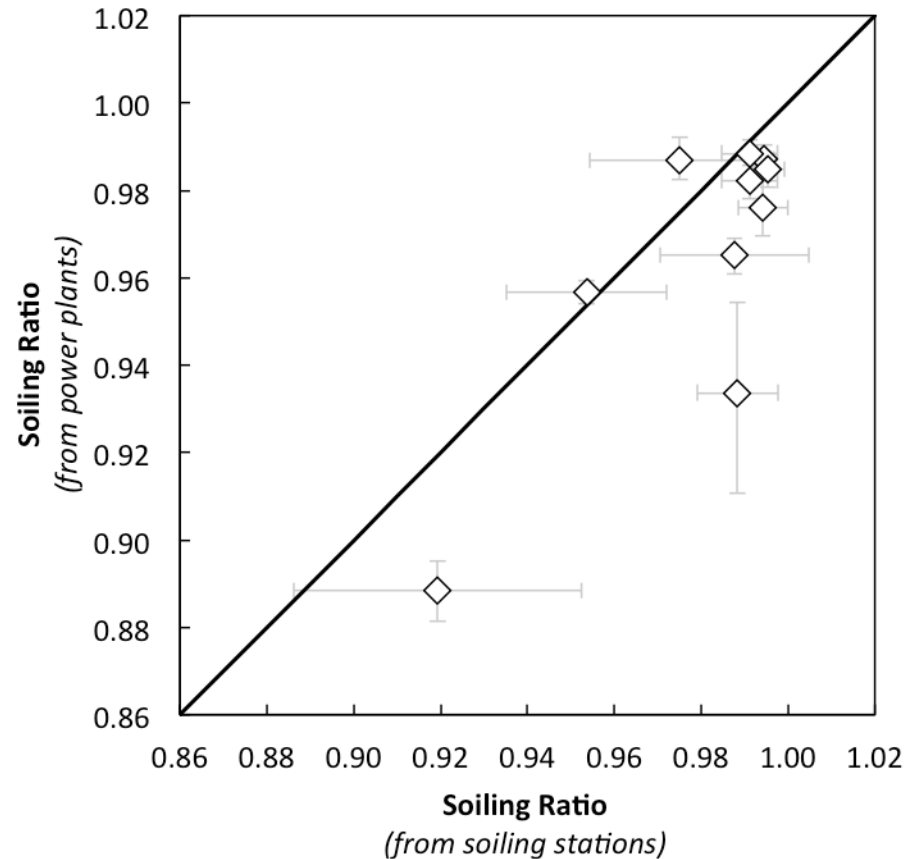
Annual vs. long-term loss



- Year-to-year variation can be large relative to long term losses
- There may be no such thing as a “typical soiling year”
 - Perhaps we should quantify the worst-case year?

Validation

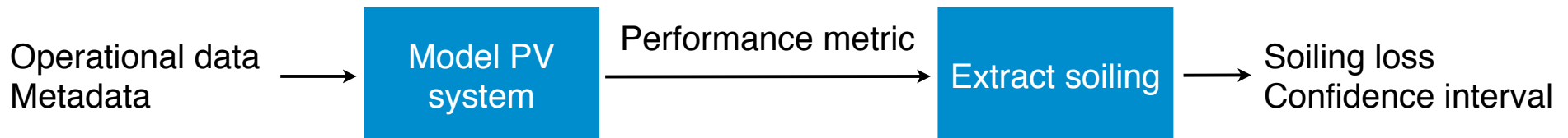
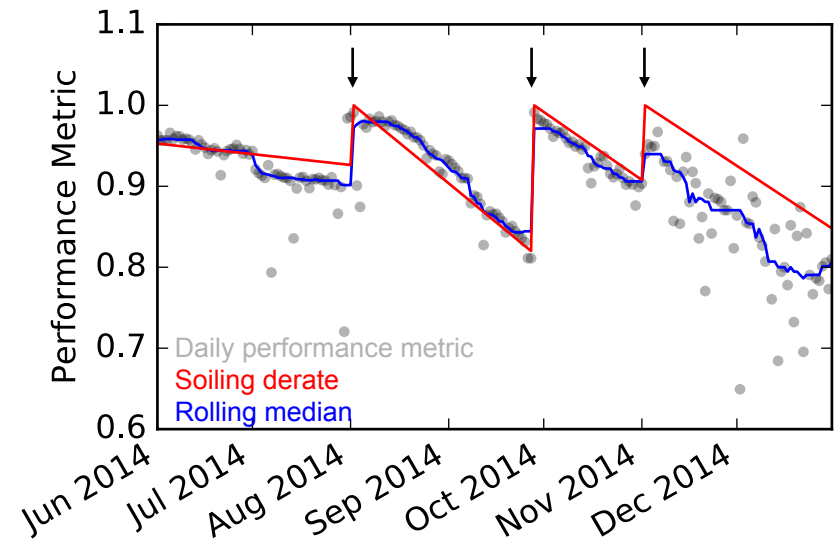
- Comparison with data from soiling stations show general agreement
- Different assumptions about precipitation and cleaning explain discrepancies



Recommendations for PV analytics

PV field performance data has varying quality and detail

- Decouple the system modeling for the analysis
 - Provides generality and flexibility
 - Minimize the inputs required to the analysis step
- Use methods that are robust to outliers
 - Reduces need for hands-on analysis
- Emphasize confidence intervals



Acknowledgement

- Thank you to Greg Kimball (SunPower), and Sarah Kurtz (NREL) for insightful conversations
- Further reading:
 - “A Scalable Method for Extracting Soiling Rates from PV Production Data,” Michael G. Deceglie, Matthew Muller, and Sarah Kurtz, PVSC 2016.
 - “Quantifying Year-to-Year Variations in Solar Panel Soiling from PV Energy-Production Data,” Michael G. Deceglie, Leonardo Micheli, and Matthew Muller, PVSC 2017 (forthcoming)

NREL is a national laboratory of the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, operated by the Alliance for Sustainable Energy, LLC

This work was supported by the U.S. Department of Energy under Contract No. DE-AC36-08GO28308 with the National Renewable Energy Laboratory. Funding provided by U.S. DOE Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Program.