eurac research

University of Ljubljana

Performance Loss Rates & Data requirements

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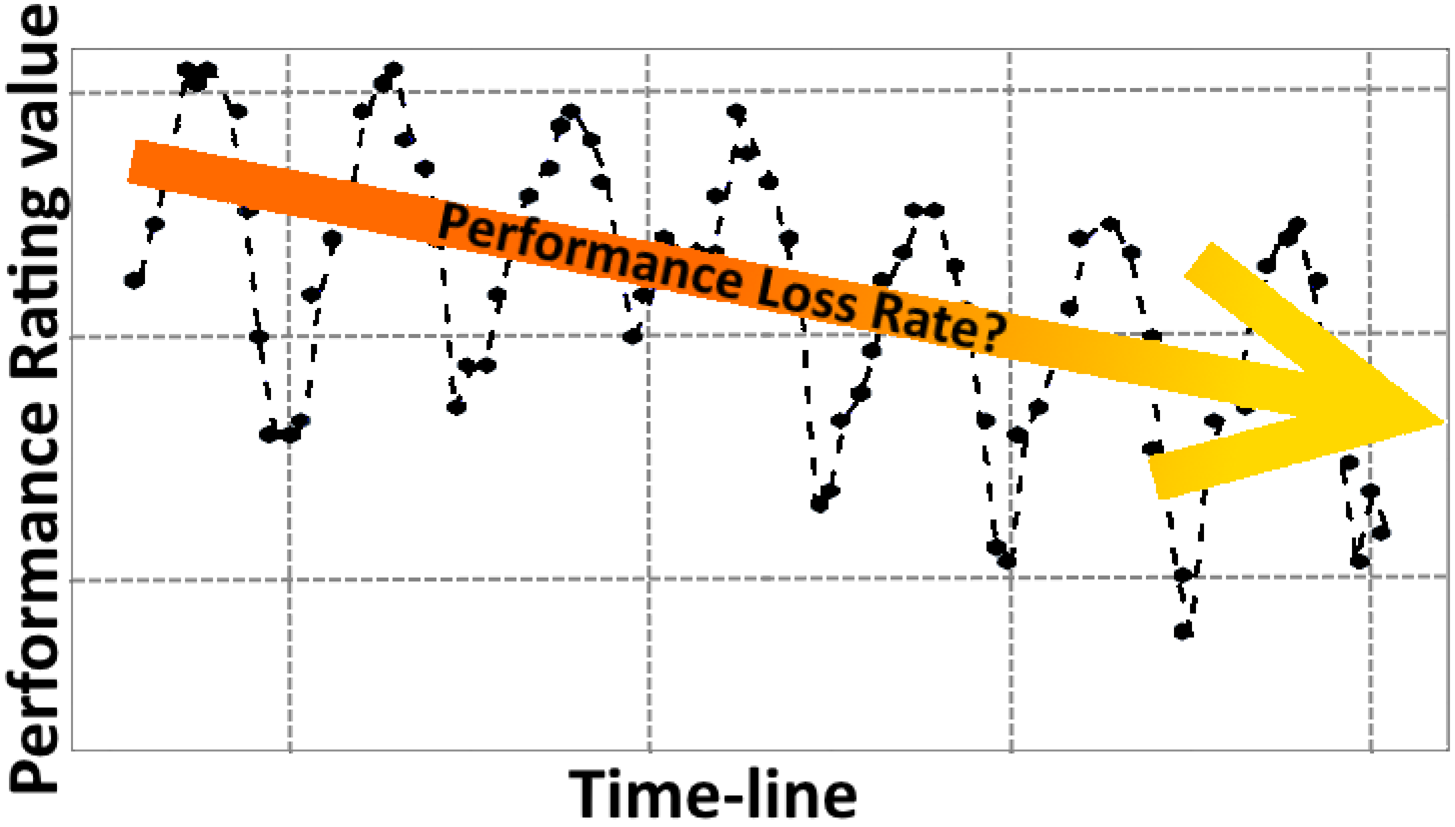
P A R L P V

What is a Performance Loss Rate?

Parameter, which indicates the decline of the power output of a PV system over time



0. Exploratory data analysis for data quality & grading

0.a Data availability

P_{mpp} ; G_{POA} ; T_{mod} ; T_{amb} ; $wind\ speed$

0.b Data quality assessment & grading

Outliers, missing, gaps

1. Input data cleaning/filtering

1.a Data assembly

Data imputation, Timestamp validation

1.b Filter application

P_{mpp} ; G_{POA} ; T_{mod} ; PR ; $clear\ sky$

2. Performance metric selection, corrections & aggregation

2.a Perf. Metric

Predicted Power, Performance Ratio

2.b Temp. corrections

IEC61724-1, UTC

2.c Data aggregation

Daily; weekly; monthly; yearly

3. Timeseries feature corrections

3.a Seasonal decomp.

CSD; STL; HW

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Z-score; Interquartile range

4. *PLR* Result

4.a Statistical models

Regression; YoY

4.b PLR Determination

4.c Assess Confid. Int.

P_{mpp} – PV power in the maximum power point
G_{POA} – irradiance in the plane of array
T_{mod} – module temperature
T_{amb} – ambient temperature
PR – Performance Ratio

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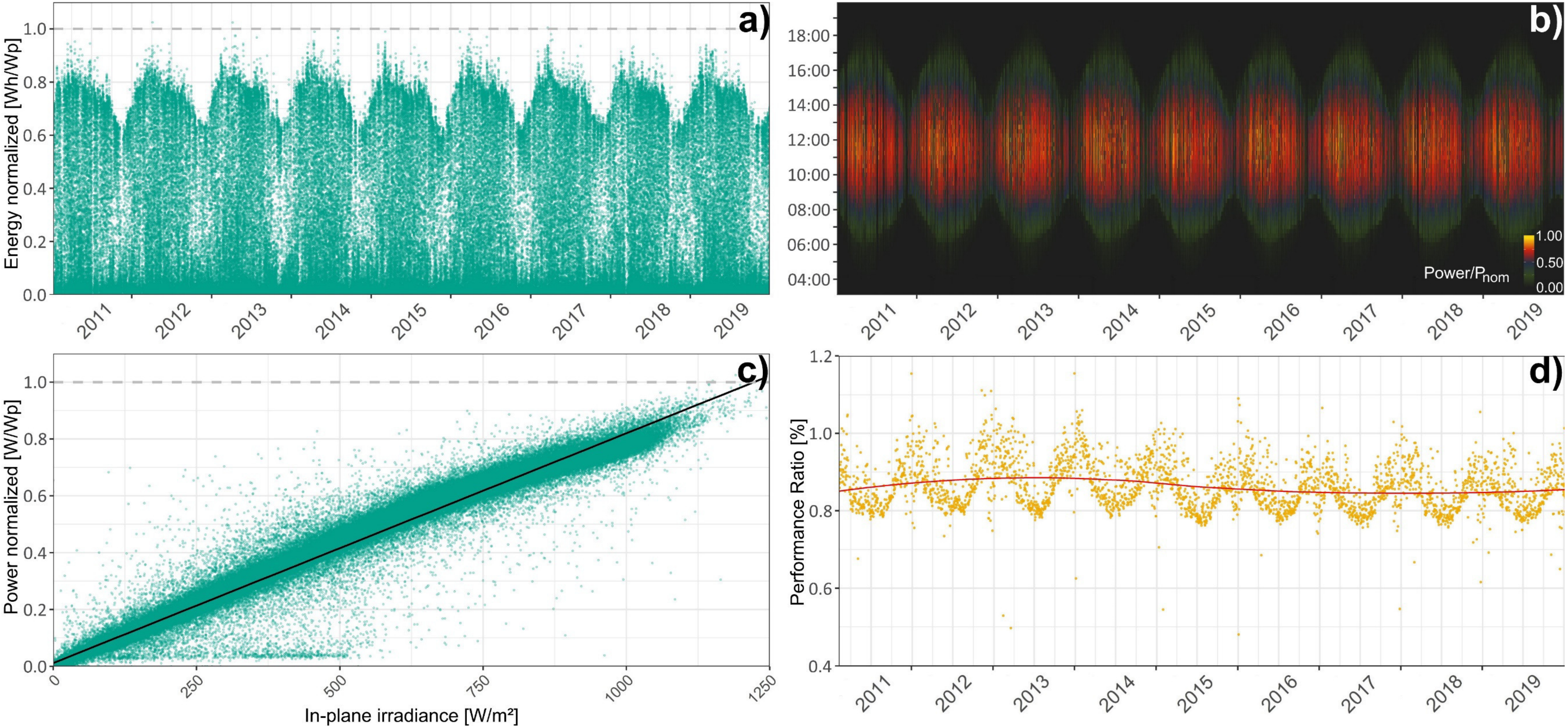
[1] S. Lindig, A. Louwen, D. Moser and M. Topic, "Outdoor PV System Monitoring—Input Data Quality, Data Imputation and Filtering Approaches," Energies, vol. 13 (5099), Sep. 2020.

Input data availability & quality – Visual check



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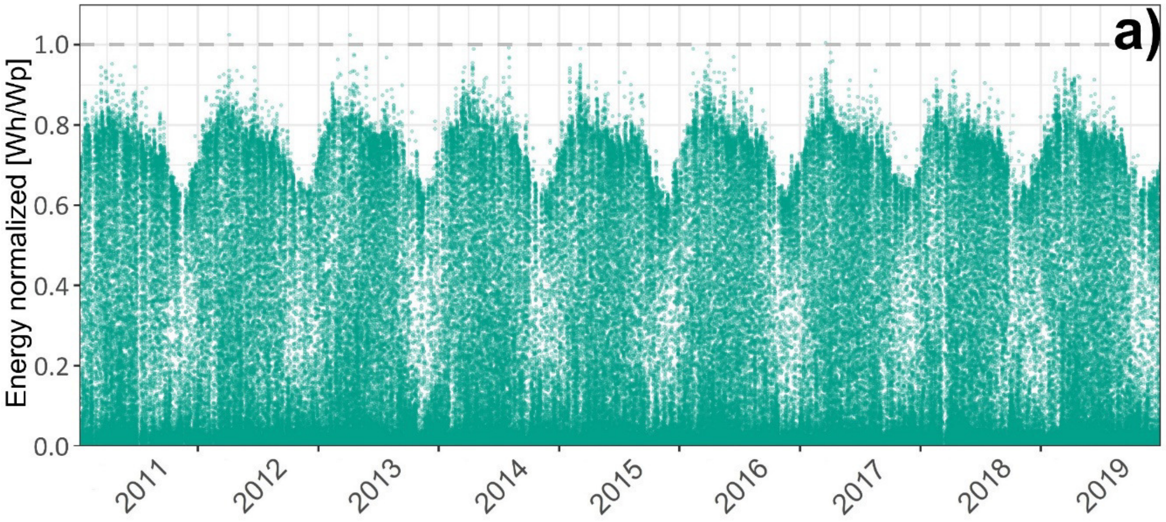
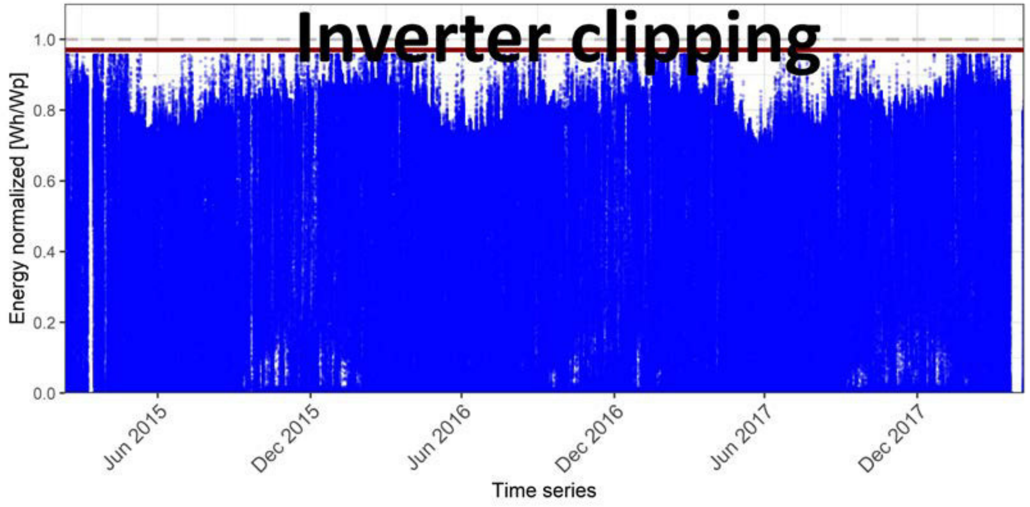
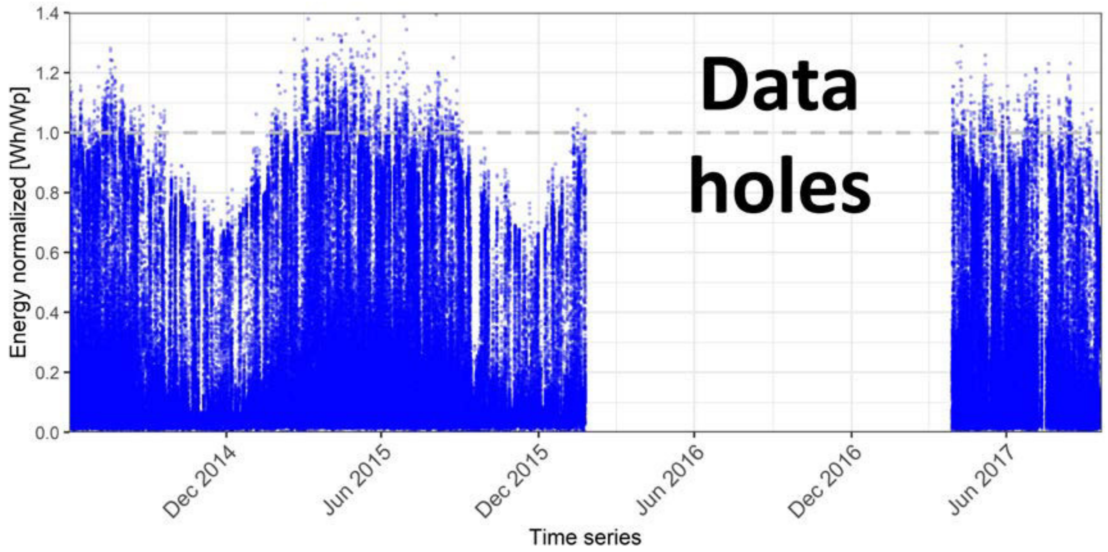
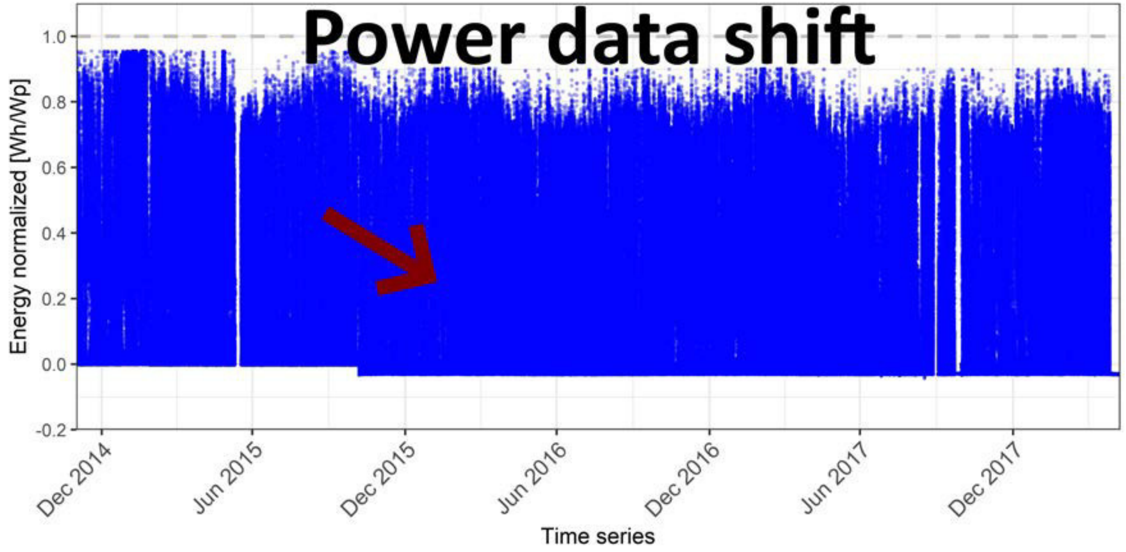
Input data availability & quality - examples









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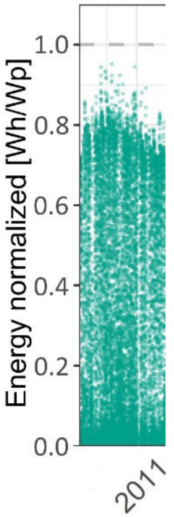

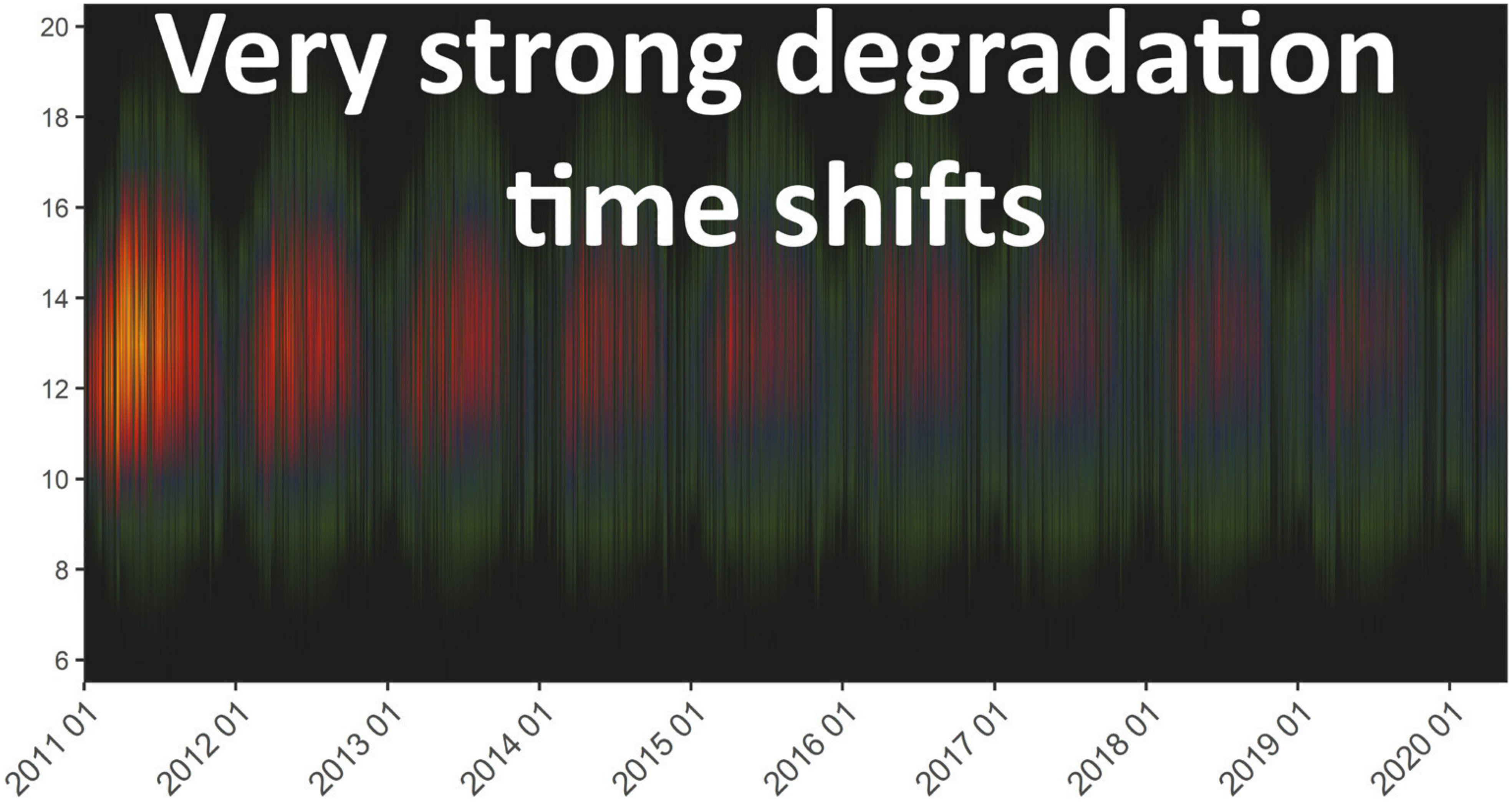

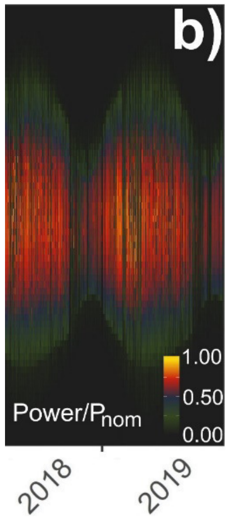

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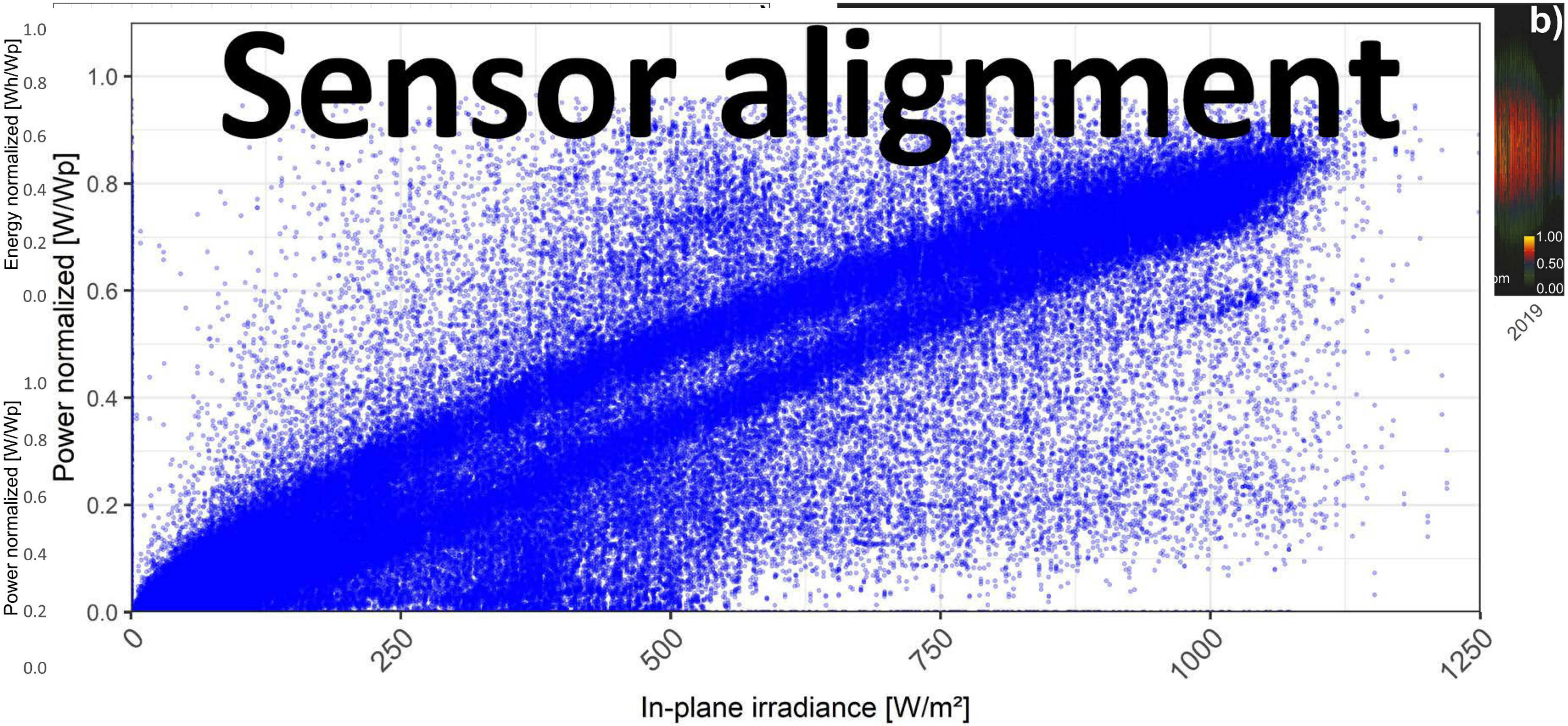

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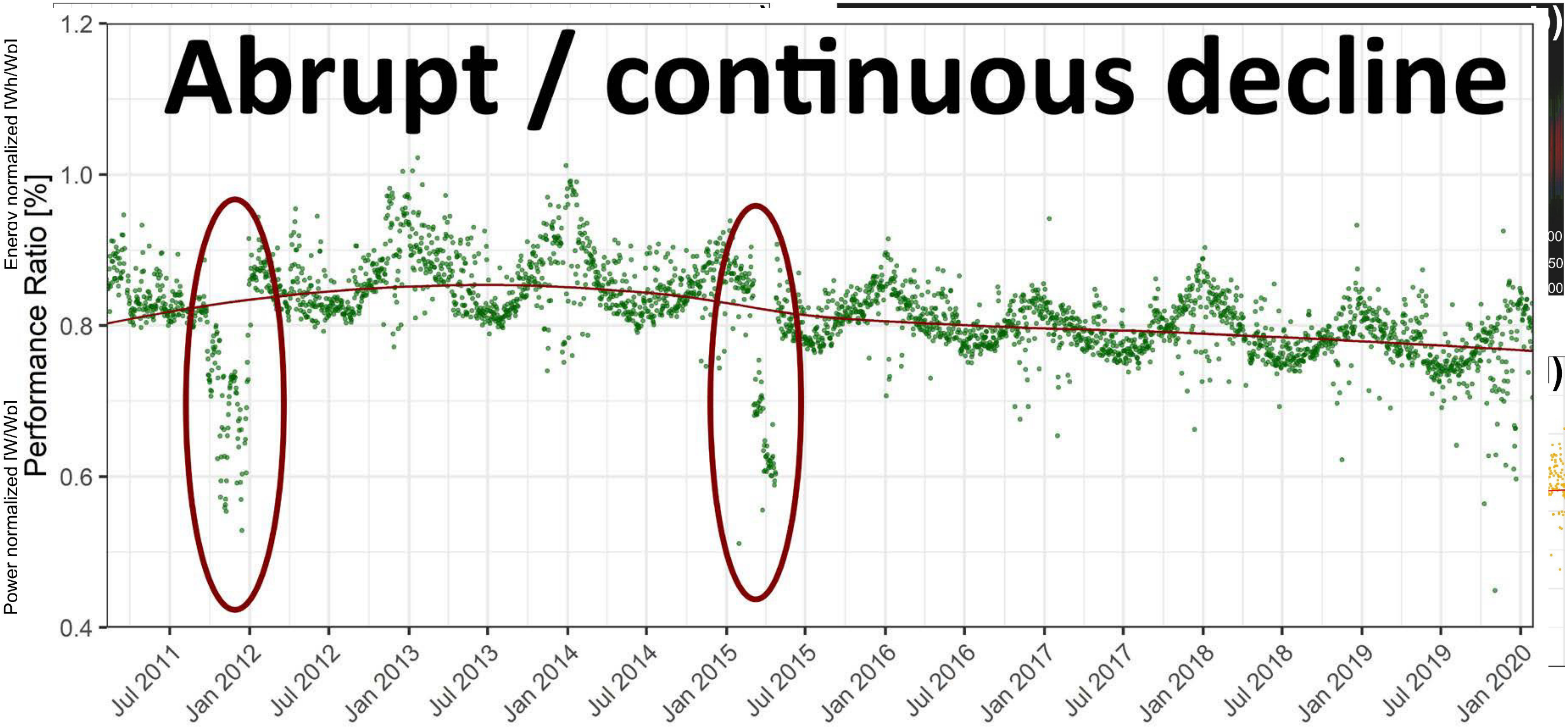

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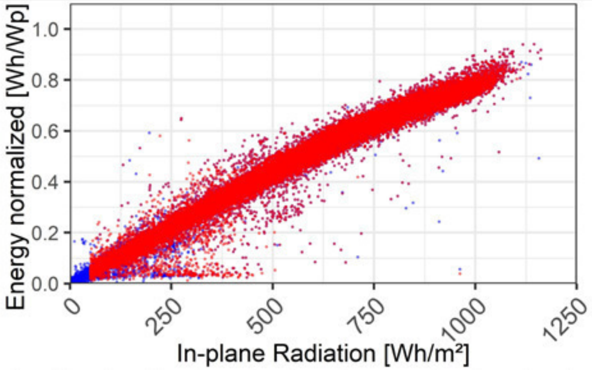
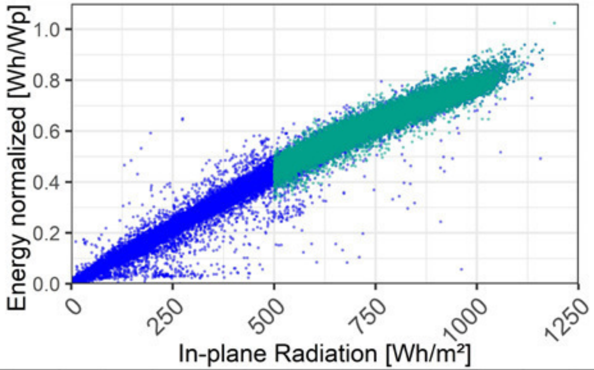
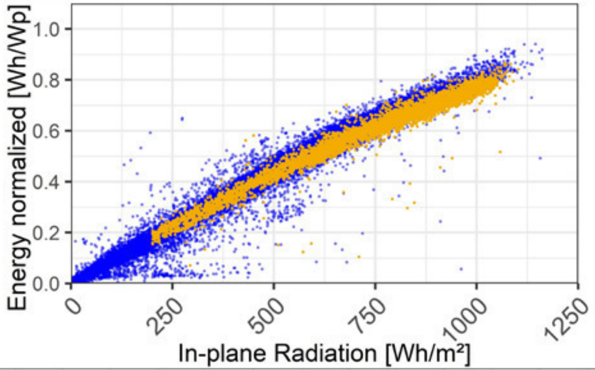
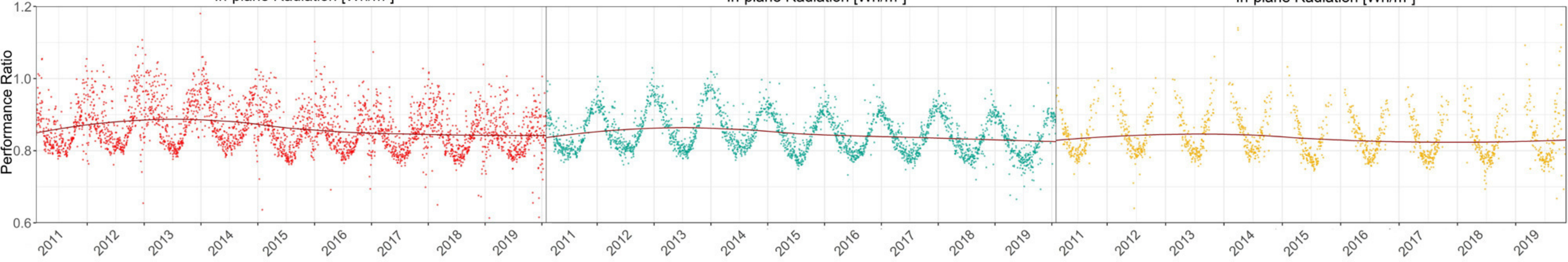
Data filtering

Filter 1 - IEC Standard filter	Filter 2 - Own filter PLR calculations	Filter 3 - clear-sky filter RdTools
$0.01*P_{nom}$ < power < $1.02*P_{nom}$ 50 W/m² < G_{POA} < 1200 W/m² Filter ratio: 78.4%	$0.01*P_{nom}$ < power < $1.02*P_{nom}$ 500 W/m² < G_{POA} < 1200 W/m² ±2 standard deviations around monthly PR mode Filter ratio: 34.6%	200 W/m² < G_{POA} < 1200 W/m² Sensor irradiance and modelled clear-sky irradiance agree within 15% window Filter ratio: 3.8%









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Performance Losses of systems in Pearl PV DB

Pearl PV DB[3]:

- Collection of over 8,000 system data sets
- Only power data available in 10 min resolution
- Most datasets 3 years or less

[2] S. Lindig, J. Ascencio-Vasquez, J. Leloux, D. Moser, and M. Topic, "Climate Related Dependence of Performance Losses of over 3,500 PV Systems," in37th EUPVSEC Proceedings, Sep. 2020.
[3] A. Reinders et al., "Development of a big data bank for PV monitoring data, analysis and simulation in COST Action 'PEARL PV'," in *46th IEEE Photovoltaic Specialists Conference*, Chicago, Jun. 2019.

Data input

- 10 min power time series
- Monthly ERA5 in-plane irradiation[4]

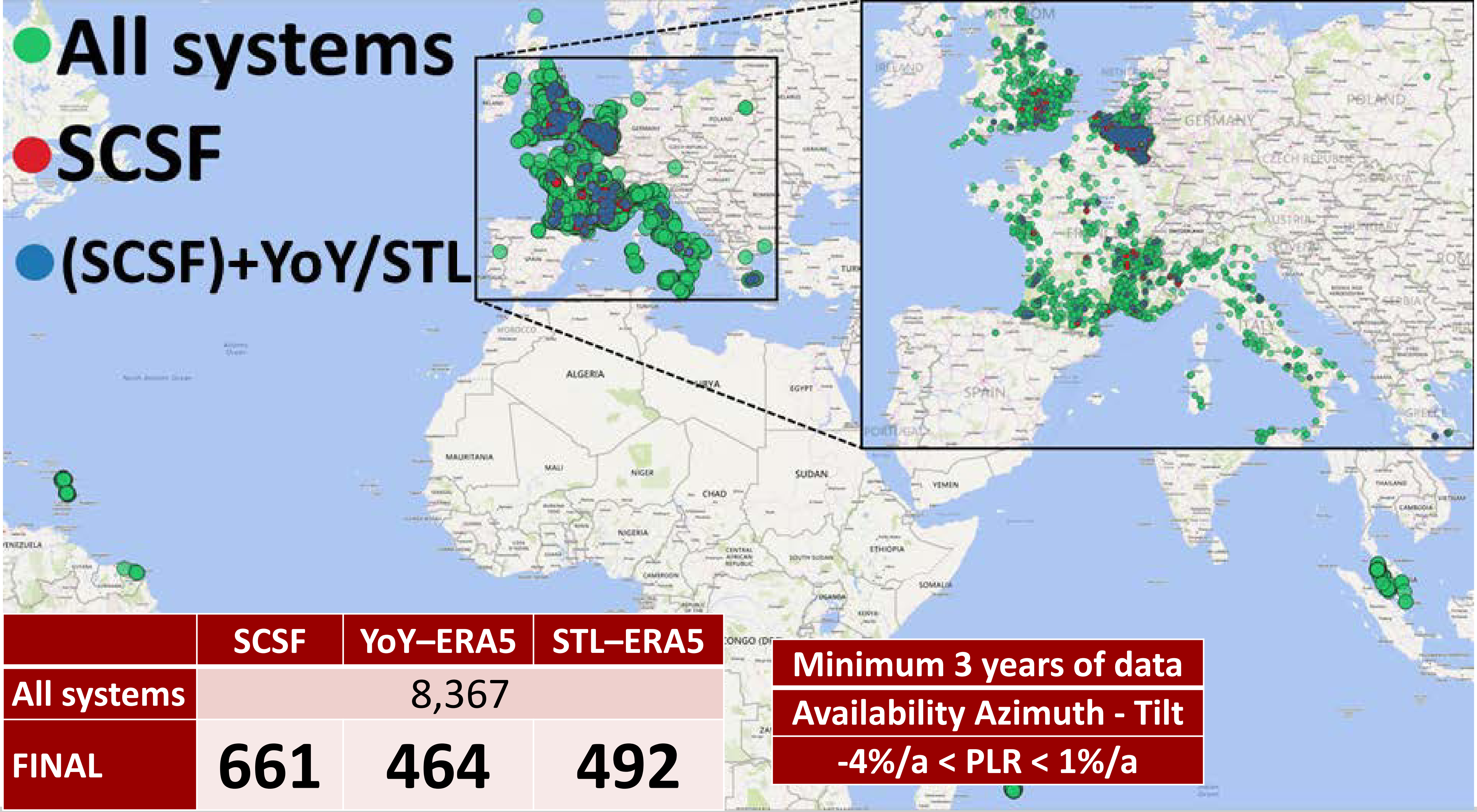
Outlier filtering

- SCSF: clear-sky modelling
- YoY & STL: ±2σ around $\overline{\mathrm{PR}}$
  - Filling with 6 month rolling mean

Metric selection & PLR calculation

- SCSF on daily clear-sky energy[5]
- YoY on monthly PR[6]
- STL on monthly PR[7]

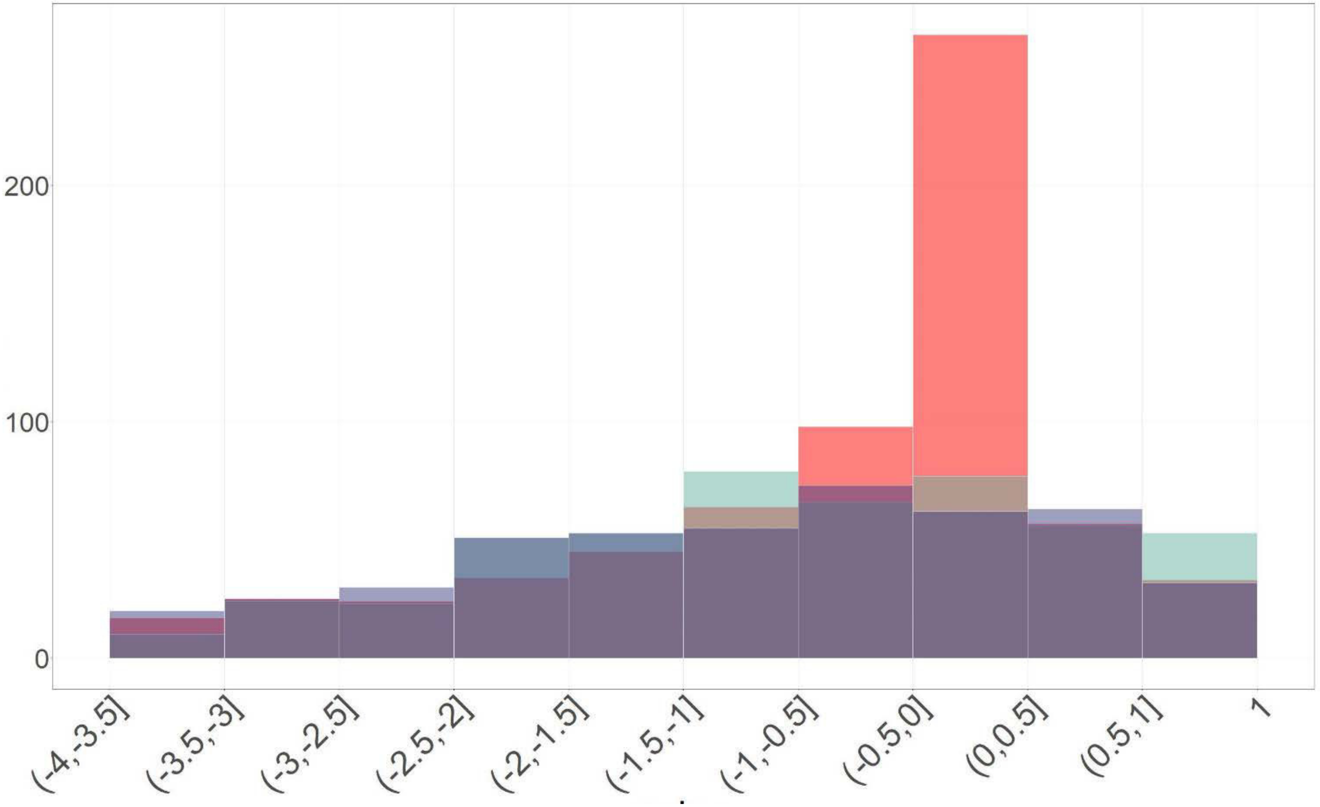
[4] Copernicus Climate Change Service (C3S) ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service Climate Data Store (CDS) 2017.
[5] B. Meyers, et al, "Signal Processing on PV Time-Series Data: Robust Degradation Analysis Without Physical Models," IEEE Journal of Photovoltaics, 2019.
[6] D. Jordan, et al, "Robust PV Degradation Methodology and Application," IEEE Journal of Photovoltaics, 2017.
[7] R. B. Cleveland et al., "STL: A Seasonal-Trend Decomposition Procedure Based on LOESS," *Journal of Official Statistics,* 1990.



	SCSF	YoY–ERA5	STL–ERA5
All systems	8,367		
FINAL	661	464	492

- Minimum 3 years of data
- Availability Azimuth - Tilt
- -4%/a < PLR < 1%/a

Performance Losses of Pearl PV database



	SCSF	YoY	STL
$\overline{PLR}$	-0.74 %/a	-1.13 %/a	-0.97 %/a
$\widetilde{PLR}$	-0.4 %/a	-1.00 %/a	-0.90 %/a

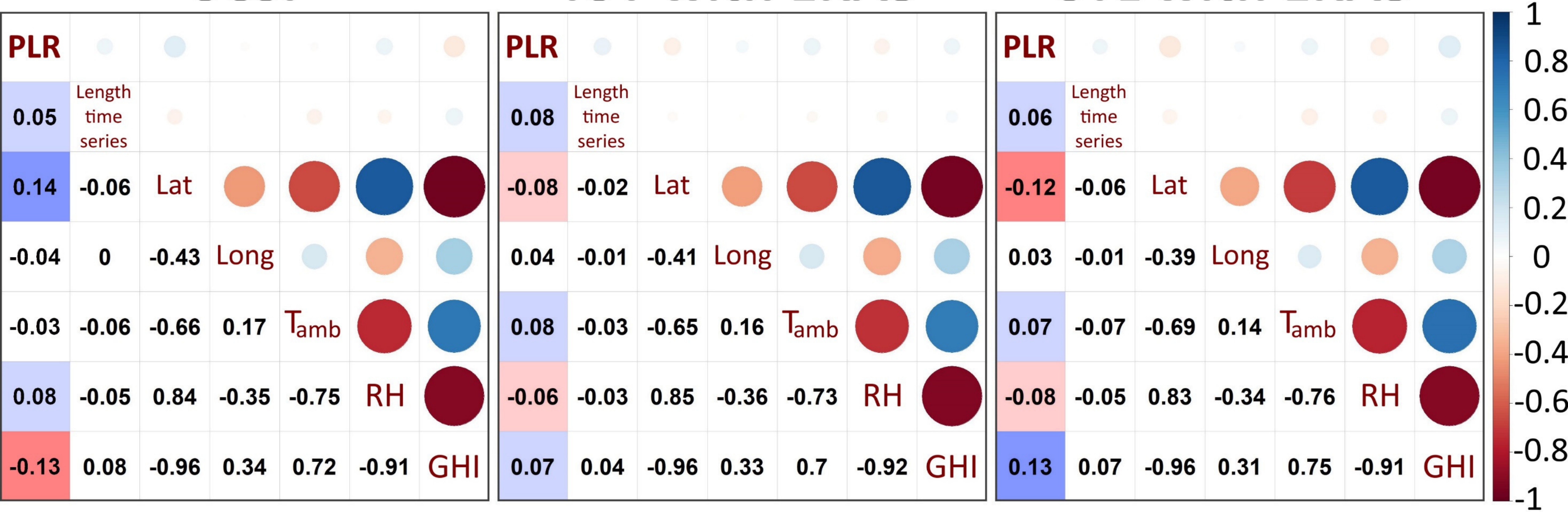
	Jordan[8]	Kiefer[9]
$\overline{PLR}$	-0.8 - -0.9 %/a	-0.7 %/a
$\widetilde{PLR}$	-0.5 - -0.6 %/a	

[8] D. C. Jordan, et al, "Compendium of photovoltaic degradation rates," Progress in Photovoltaics Research and Application, vol. 24, no. 7, pp. 978-980, 2016.

[9] K. Kiefer, et al, "Degradation in PV Power Plants: Theory and Practice," in 36th EU PVSEC, Marseille, 2019.

Performance Losses of Pearl PV database

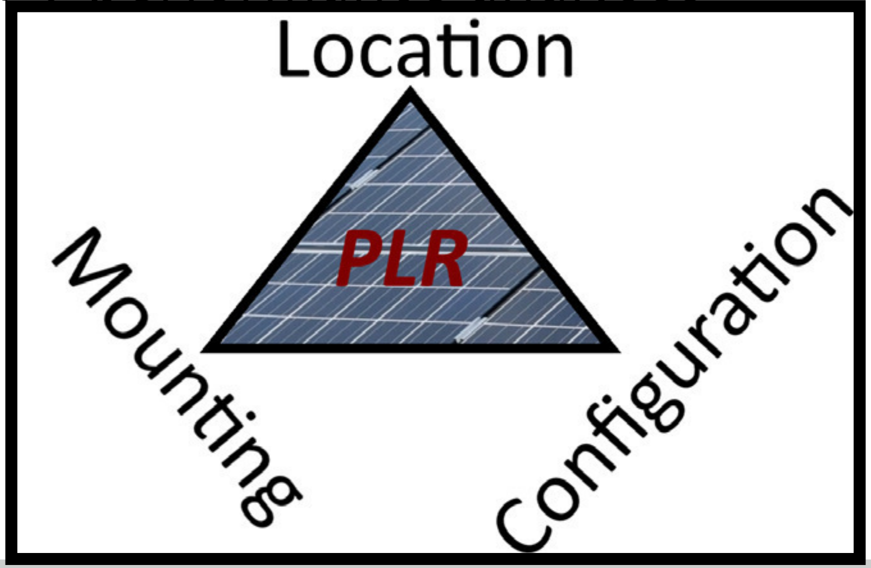
SCSF | YoY with ERA5 | STL with ERA5



Summary

PLR is an important parameter to assess the **health status of a PV system**

- Calculating PLR values is not straightforward
  - Many variables have to be considered
  - The length and quality of the PV system time series is the most important characteristic of PV performance analyses



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Thank you for your attention

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie GA No 721452.