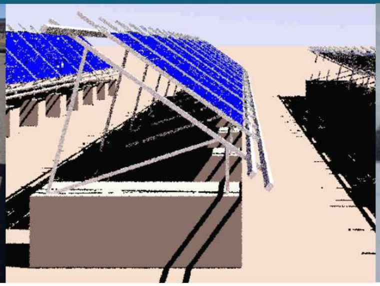
SAND2020-9423C

Challenges Associated with Inconsistent Photovoltaic Degradation Rate Estimations



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SAND2020-

Introduction and hypothesis

- Degradation rate (R_D) is important for predicting lifetime PV performance

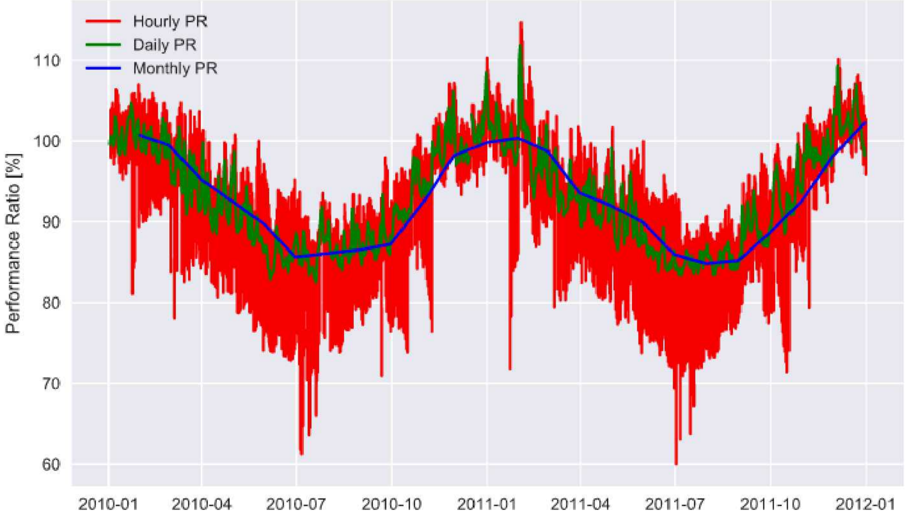
- It is statistically estimated *but* different approaches yield different results and real value is unknown → **Unverified estimates**

- "Several" cycles need to be completed in order to estimate R_D *accurately* and *confidently* → **How many?**

➢Not trivial to answer because:

1) PV output varies seasonally depending on location/climate and module type

2) Normalizations, aggregations, corrections and decomposition models are not perfect and still contain fluctuations



<u>Hypothesis</u>: Location/climate and PV module type are expected to be factors in the accuracy of R_D estimations

Questions to be answered

- How many years of operation are required to accurately estimate R_D?
- How does temperature correction affect the estimations?
- How does aggregation affect the estimations?
- How are these affected at different climates?
- How are these affected by different module types?
- How do different statistical methods perform under all these cases?

Framework for worldwide parametric analysis

Real degradation rate value(s) are unknown

Synthetic datasets of known behavior were generated in order to perform the analysis

30-year hourly weather file from ERA5 → SAPM in *pvlib-python* → Selection of PV modules → Simulation over lifetime → Emulate different degradation rate → Normalization and aggregation

- Nighttime filter only
- Apply OLS, CSD, STL, HW
- Loop for every month

Target: to match the “synthetic” with “estimated” degradation rate within 2% relative

Selected locations based on KGPV Climate Zone

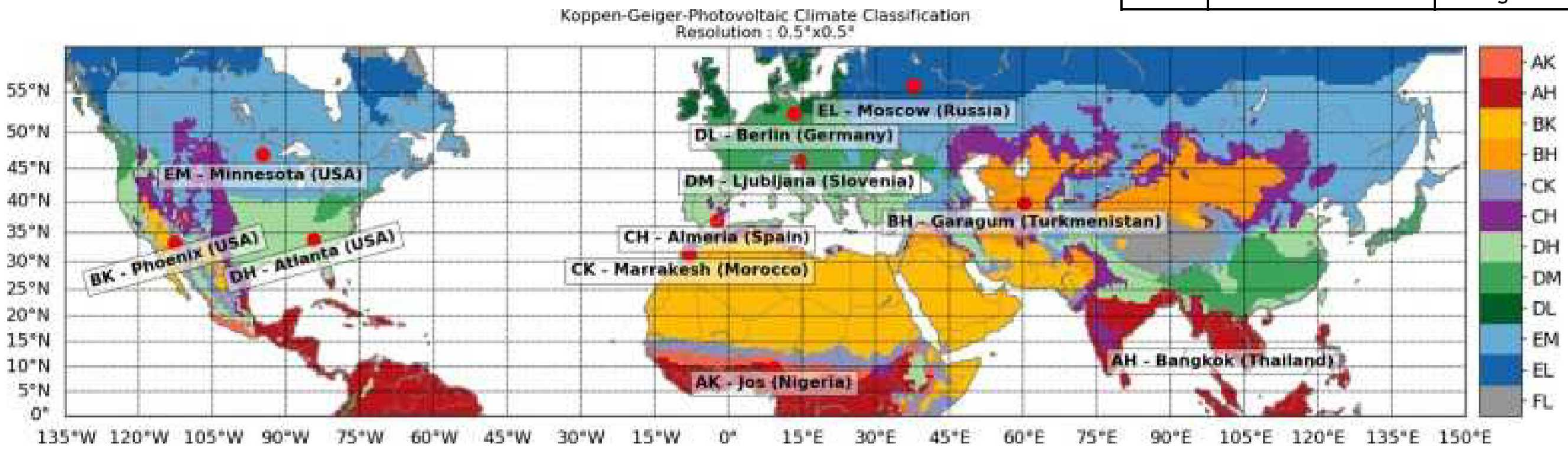
First Letter based on Köppen-Geiger

- Temperature + Precipitation
- A: Tropical, B: Desert, C: Steppe, D: Temperate, E: Cold, F: Polar

Second Letter based on solar irradiation

- L: Low irradiation, M: Medium Irradiation, H: High irradiation, K: Very high irradiation

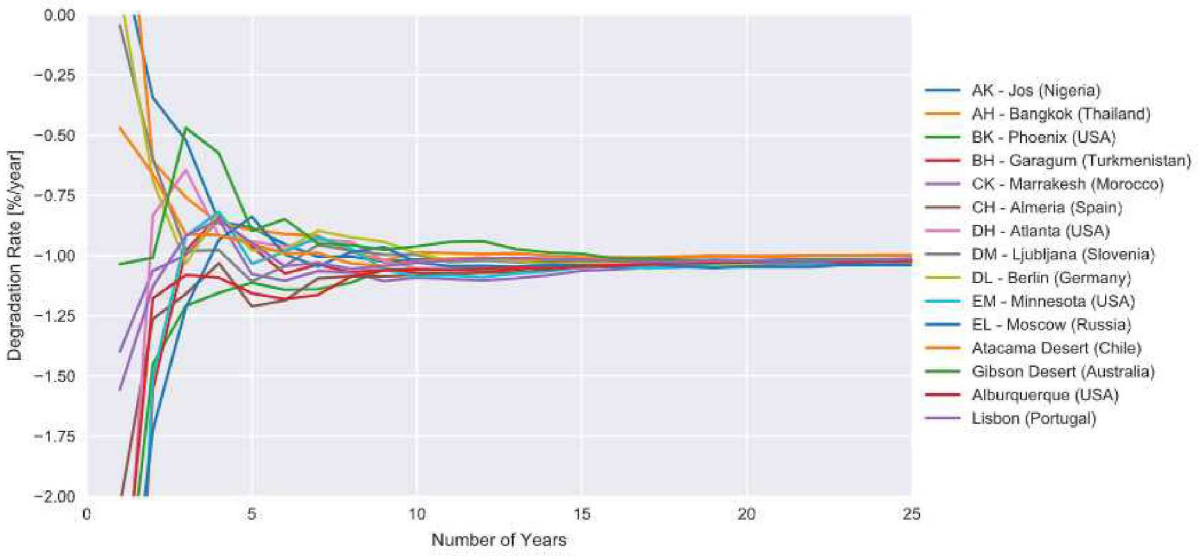
KGPV	City	Country	Latitude	Longitude	Azimuth	Tilt
AK	Jos	Nigeria	9.746418	9.259542	180	30
AH	Bangkok	Thailand	14.079678	100.622890	180	30
BK	Phoenix	USA	33.313361	-112.605852	180	30
BH	Garagum	Turkmenistan	39.784613	60.214470	180	30
CK	Marrakesh	Morocco	31.403721	-7.851913	180	30
CH	Almeria	Spain	37.042022	-2.387938	180	30
DH	Atlanta	USA	33.787074	-84.435500	180	30
DM	Ljubljana	Slovenia	46.057	14.506	180	30
DL	Germany	Germany	52.441759	13.387960	180	30
EM	Minnesota	USA	46.968433	-94.701701	180	30
EL	Moscow	Russia	55.684675	37.714778	180	30
BK	Atacama Desert	Chile	-23.355	-69.919	0	30
BK	Gibson Desert	Australia	-24.455	124.640	0	30
CK	Alburquerque	USA	35.084167	-106.649845	180	30
DH	'Lisbon	Portugal	38.716136	-9.142464	180	30

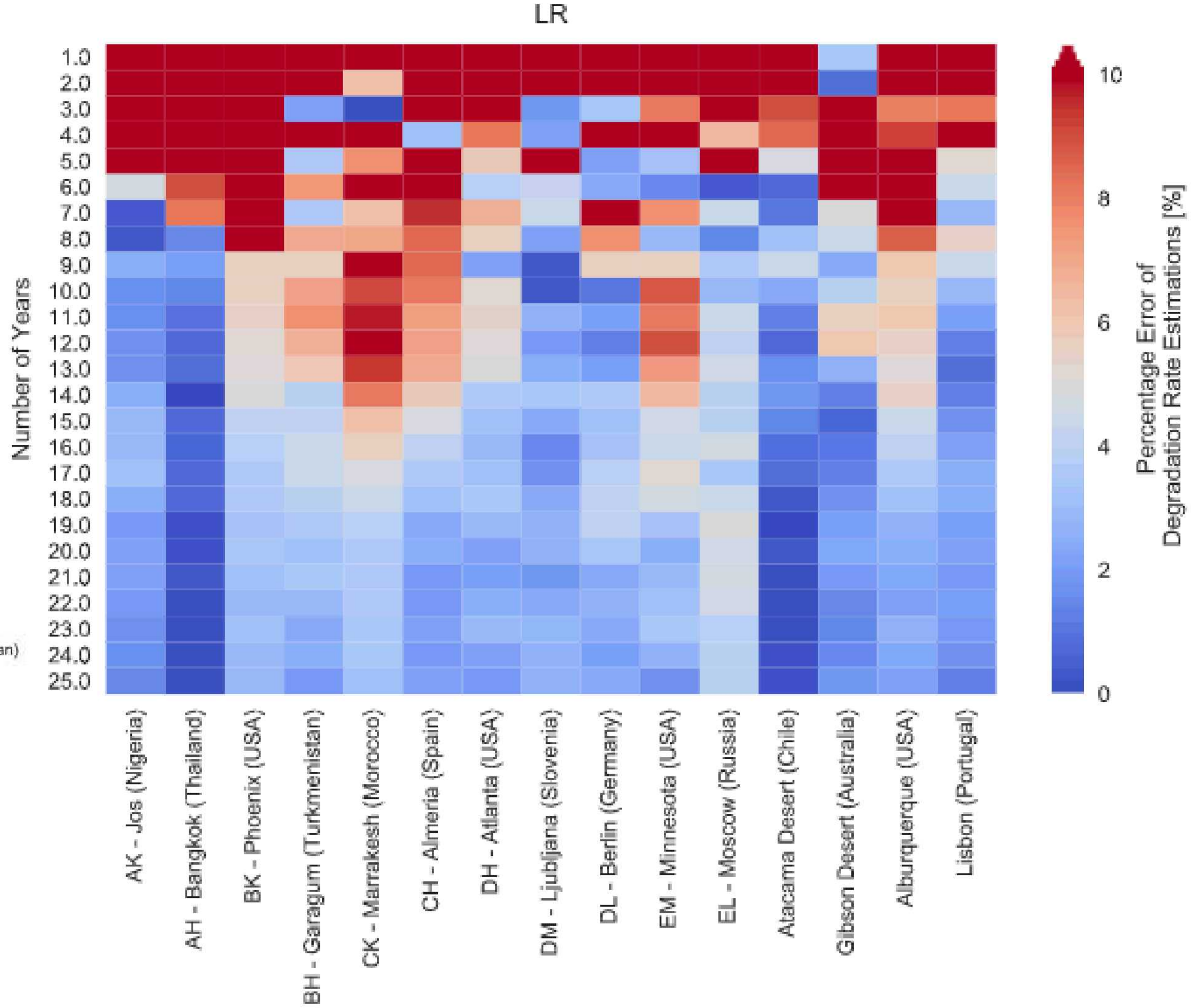


Source: Ascencio-Vásquez et al. (Solar Energy, 2019)

Linear regression (LR) with ordinary least squares (OLS) Case Study: 1%/a, Monthly PR, c-Si

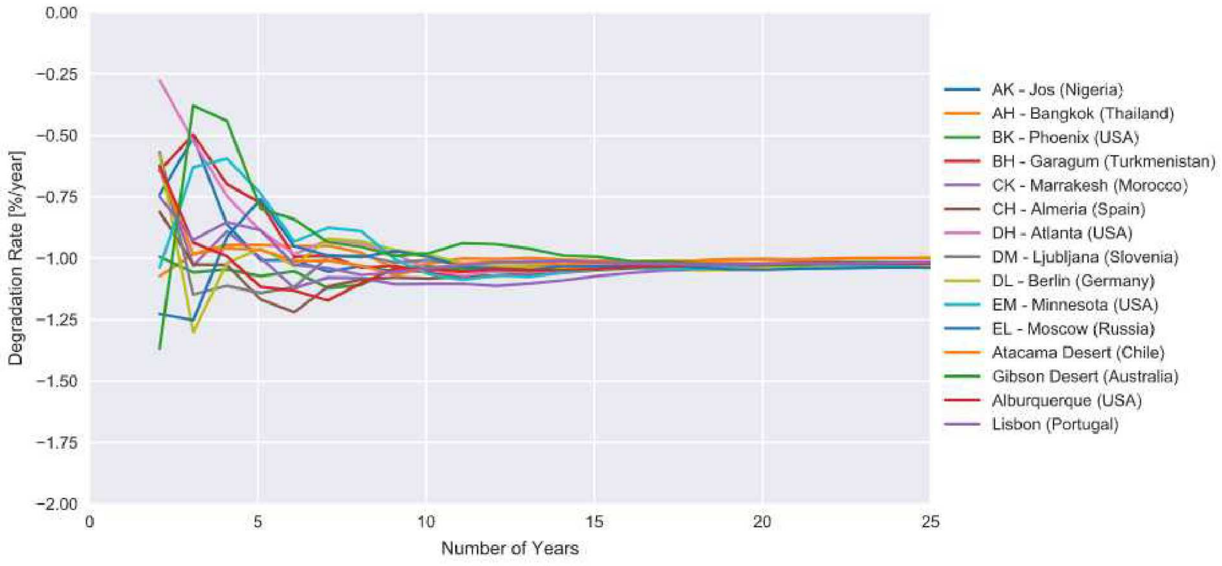
- Highly climate dependent
- Method converges in all climates

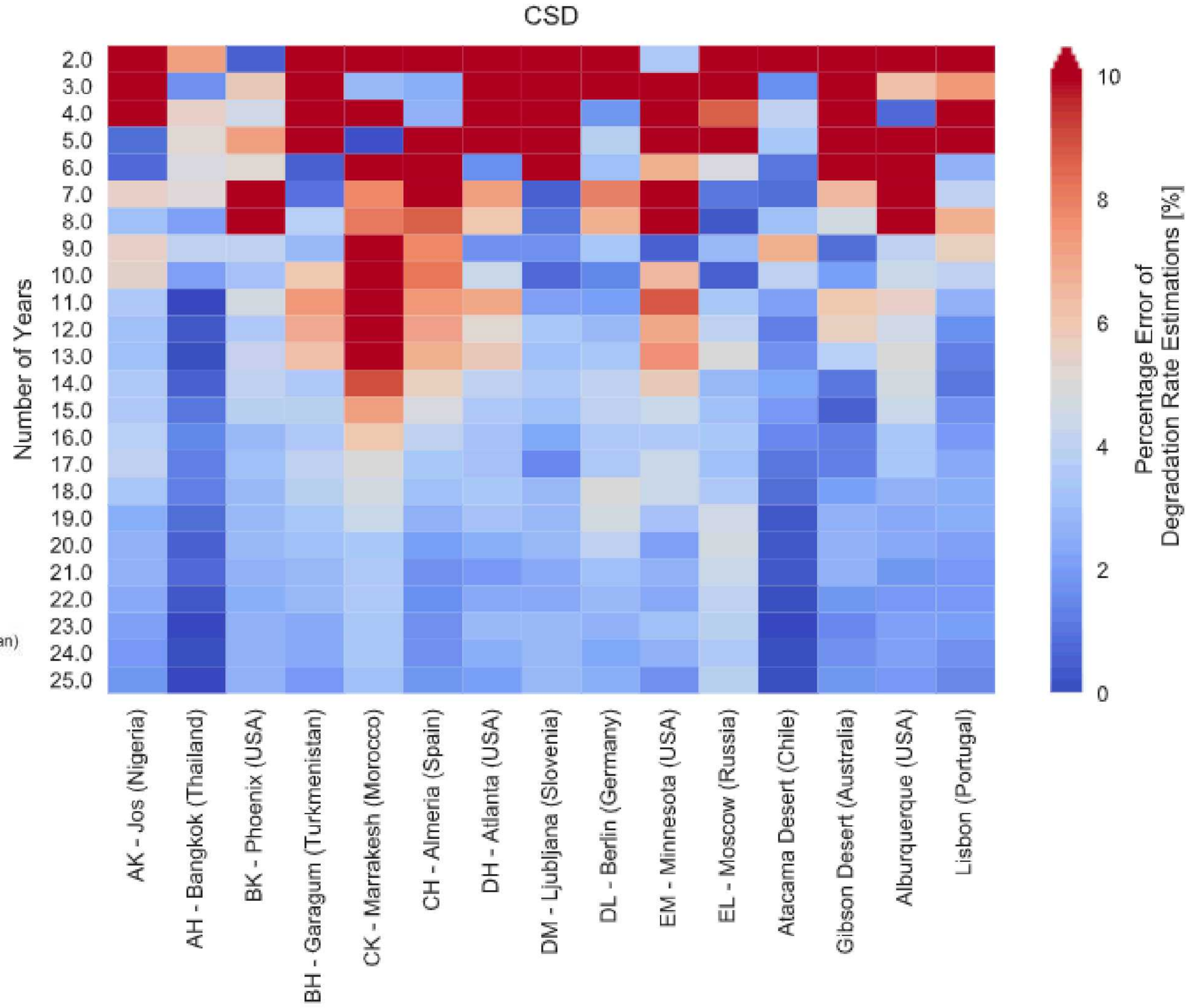




Classical Seasonal Decomposition (CSD) Case Study: 1%/a, Monthly PR, c-Si

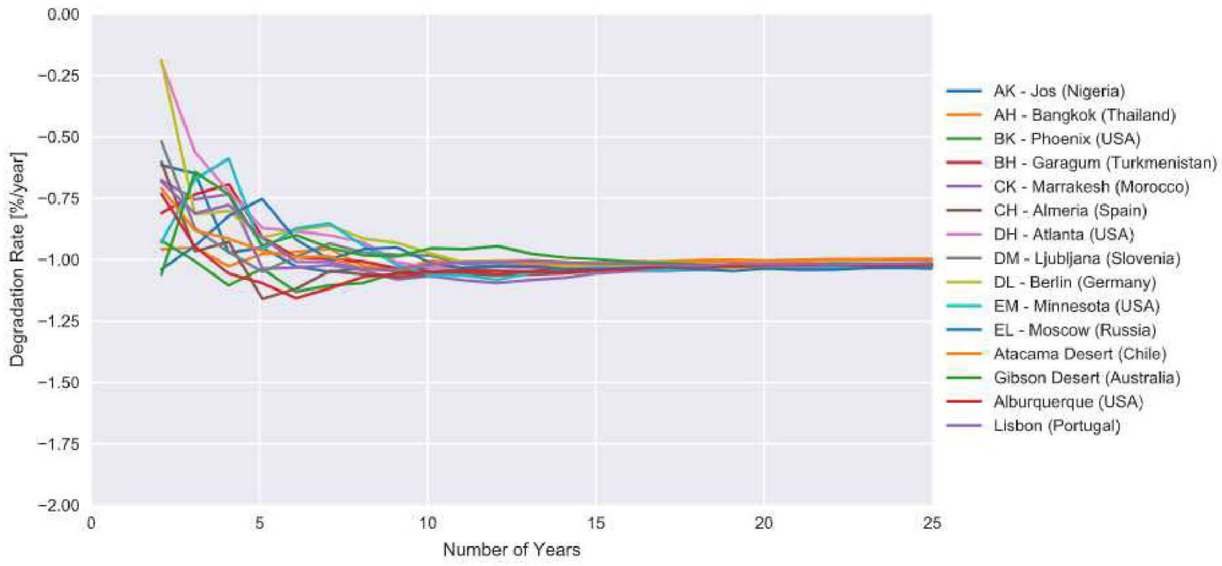
- Possible to apply after 24 months of data
- Highly climate dependent
- Method converges in all climates
- Requires more data to converge

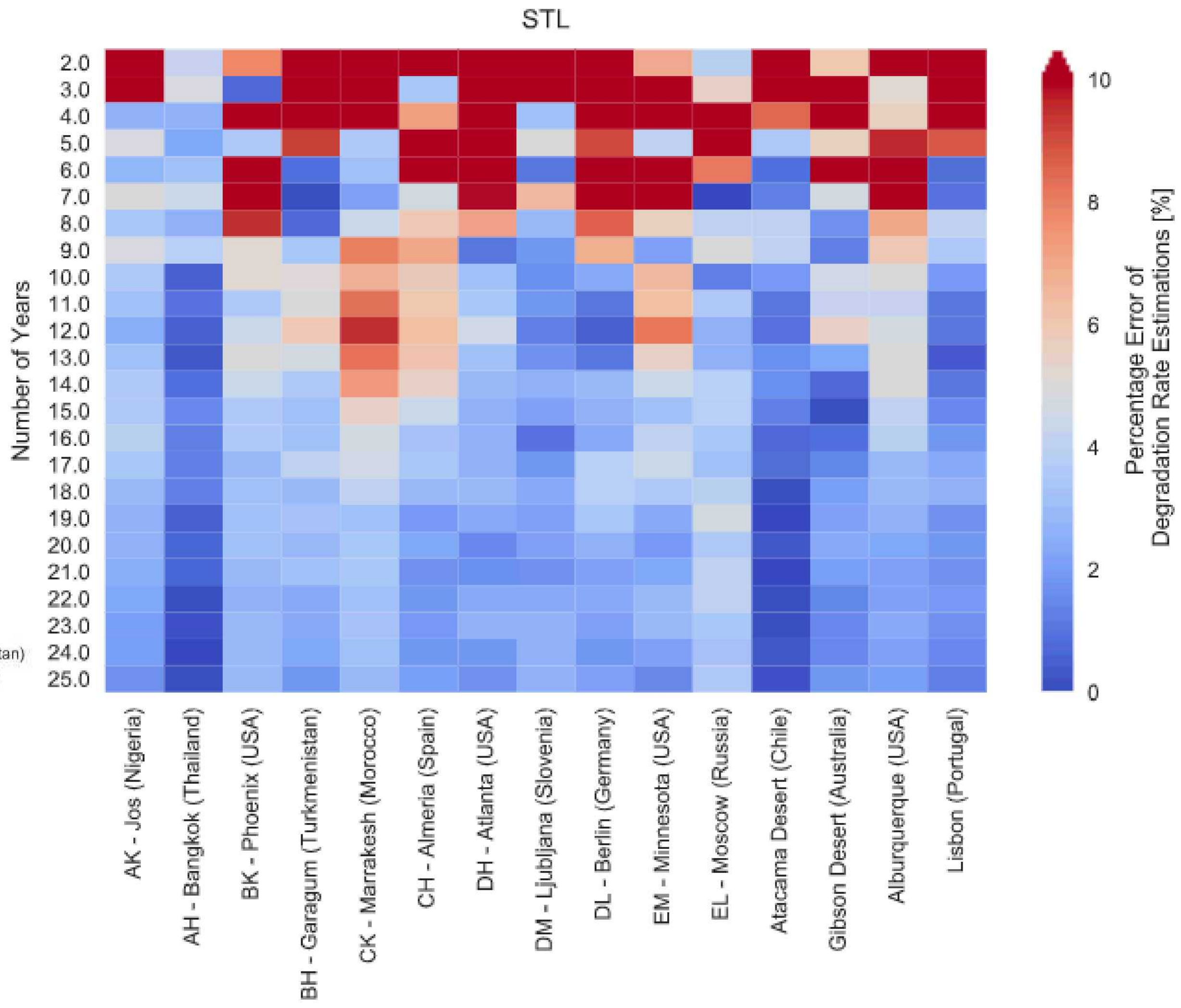




Seasonal and Trend Decomposition using LOESS (STL) Case Study: 1%/a, Monthly PR, c-Si

- Possible to apply after 24 months of data
- Highly climate dependent
- This method does converge
- More robust in shorter time periods





Holt-Winters (HW)
Case Study: 1%/a, Monthly PR, c-Si

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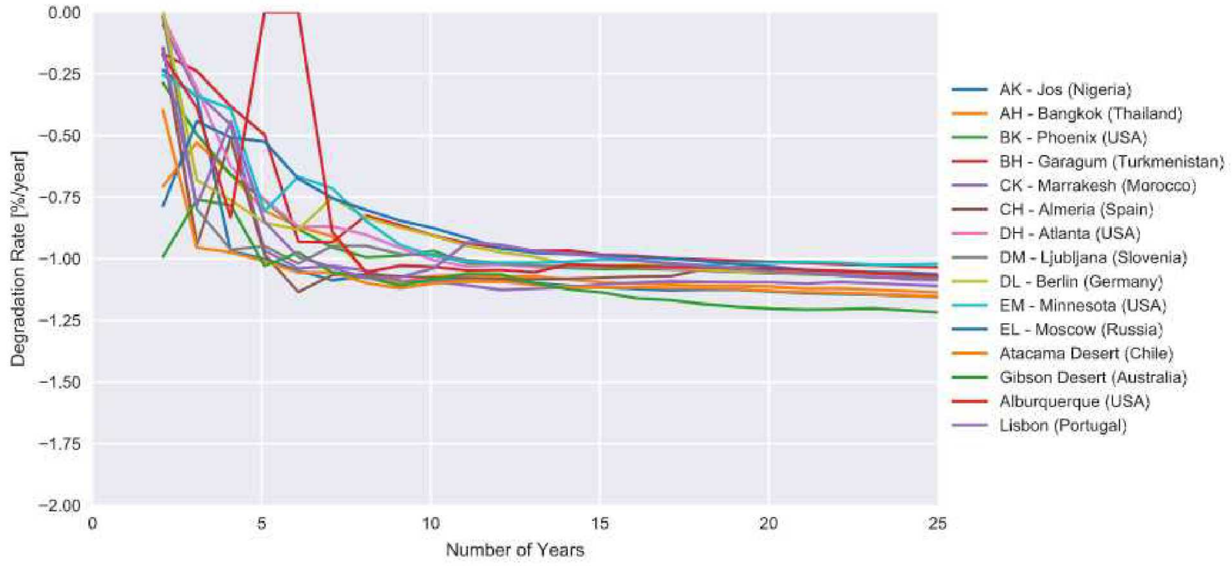
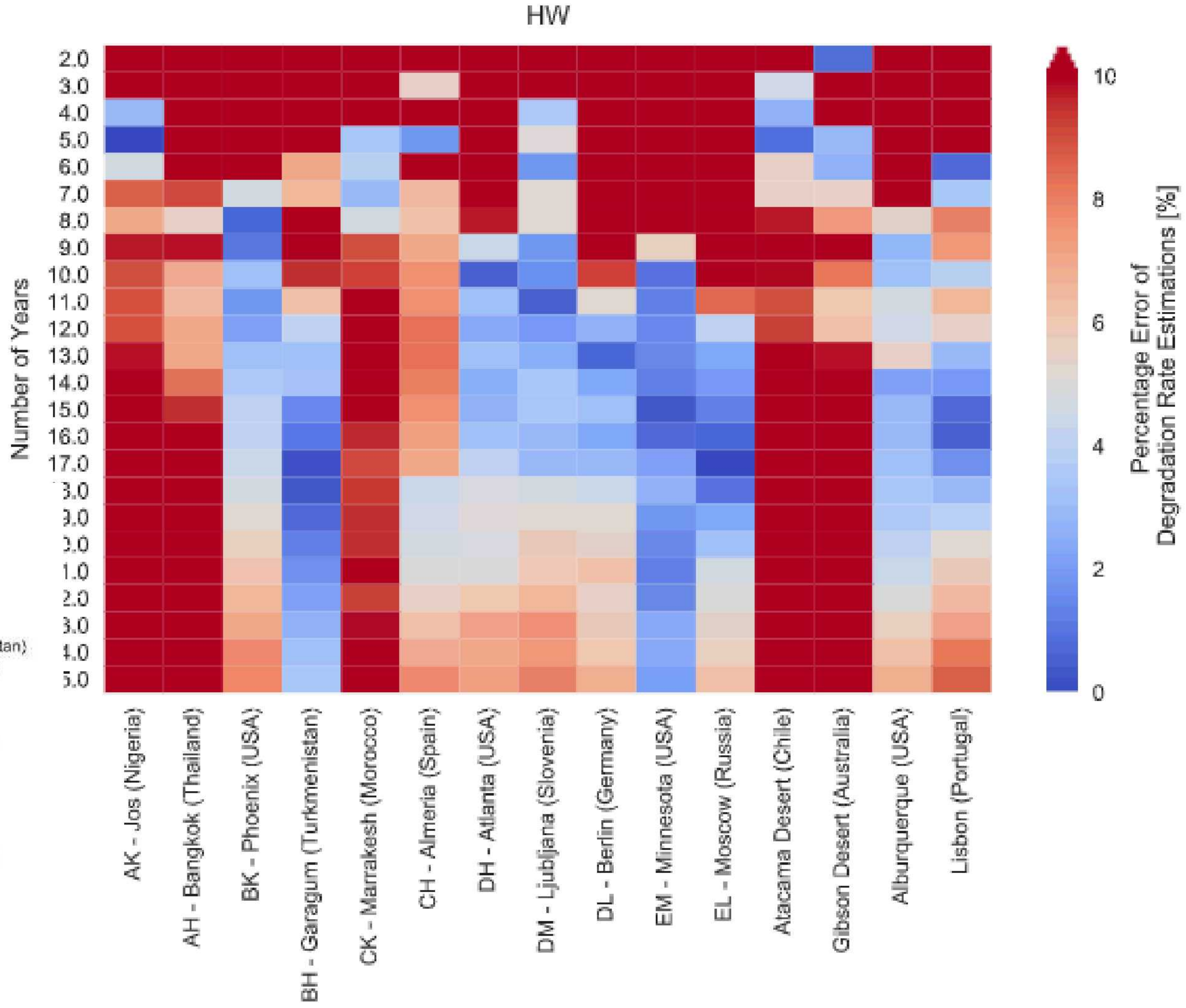
- Possible to apply after 12 months of data
- Highly climate dependent
- This method does not converge at all times
- Statistical methods seem to fail sometimes…





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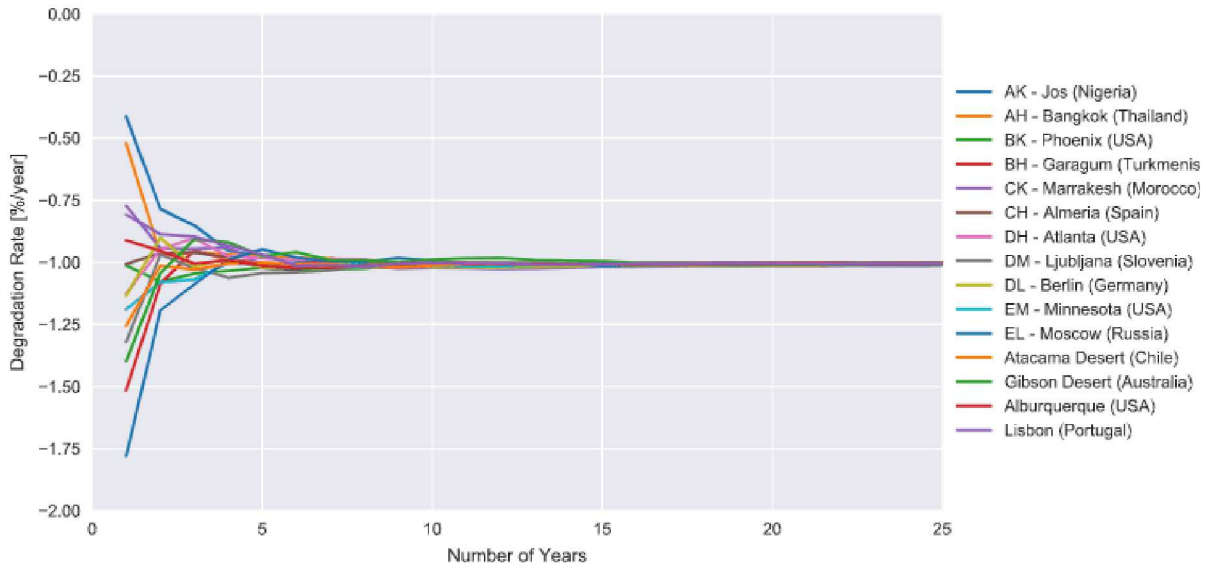
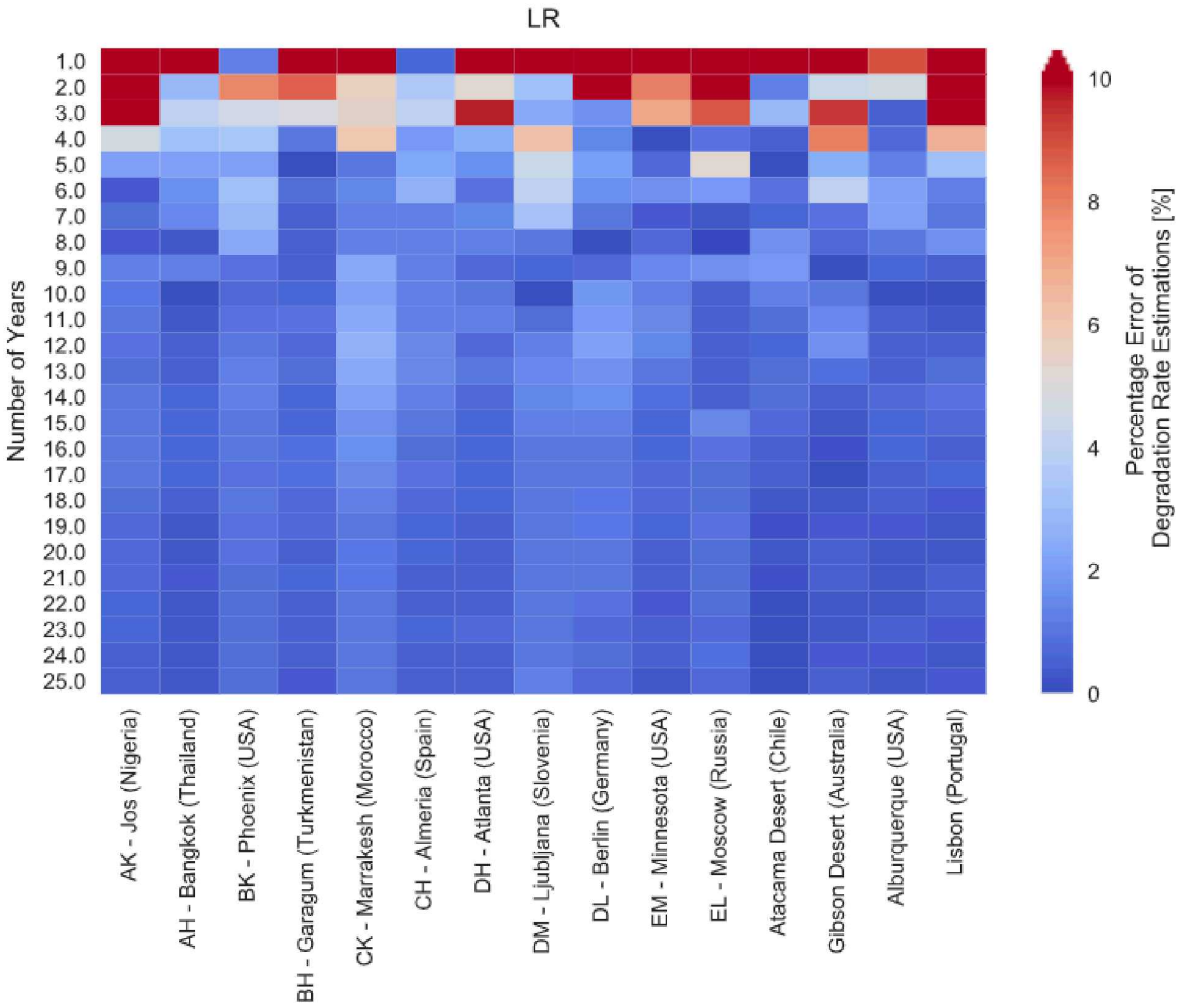
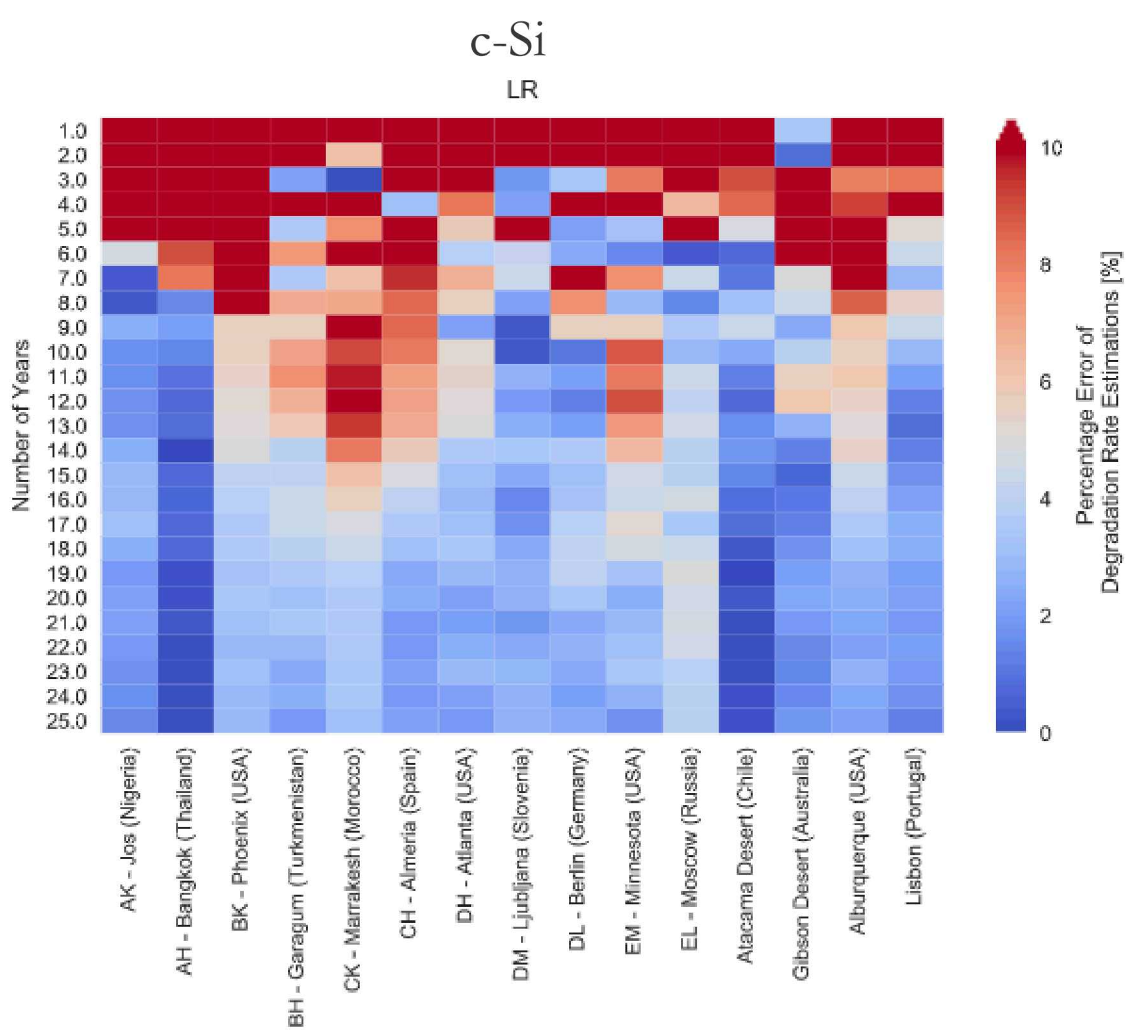
Temperature correction with linear Regression (LR) Case Study: 1%/a, Monthly PR_{TC}, c-Si

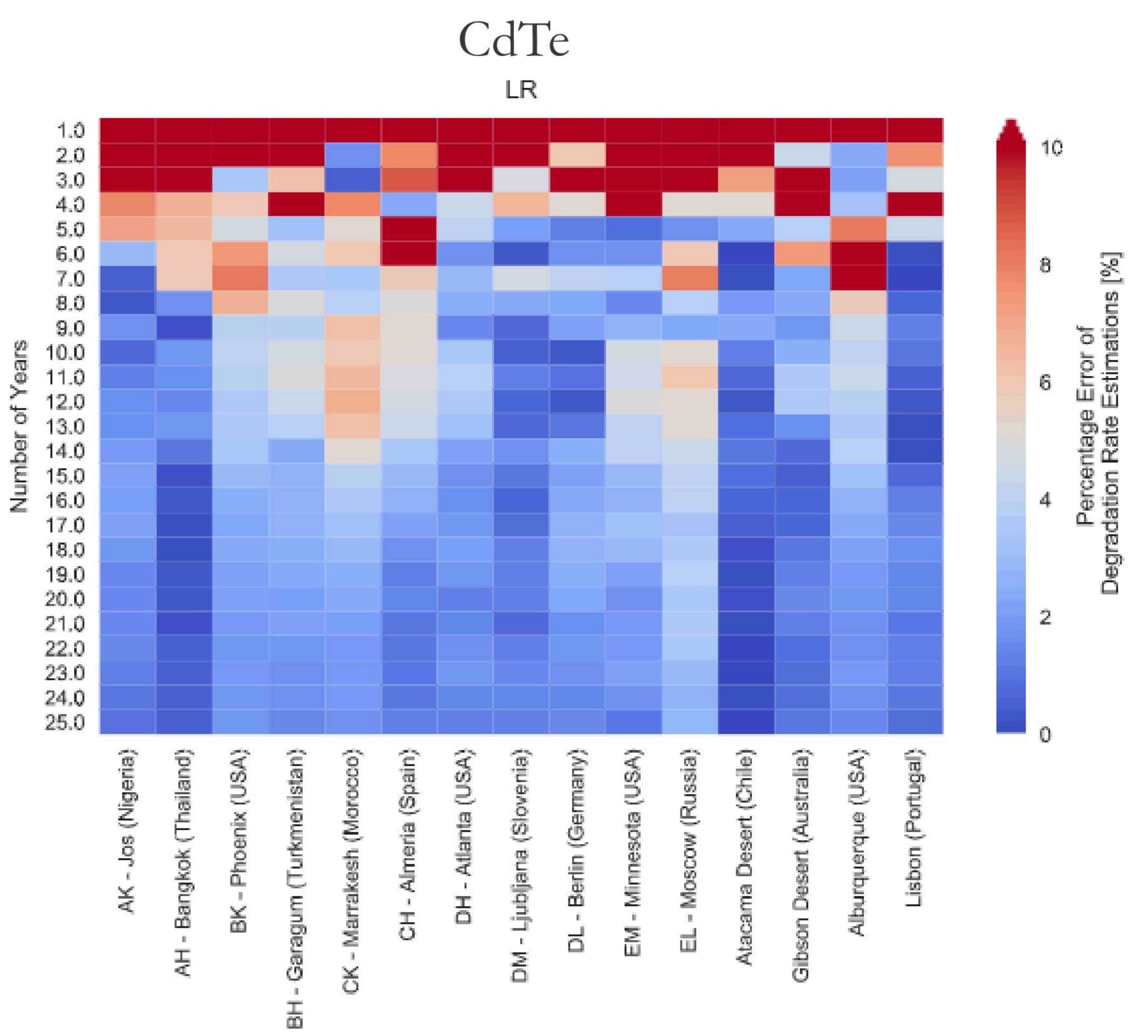
- Highly climate dependent
- Method can get to convergency in all climates
- Temperature correction gives great improvements





Technology comparison
Case Study: 1%/a, Monthly PR, Linear regression





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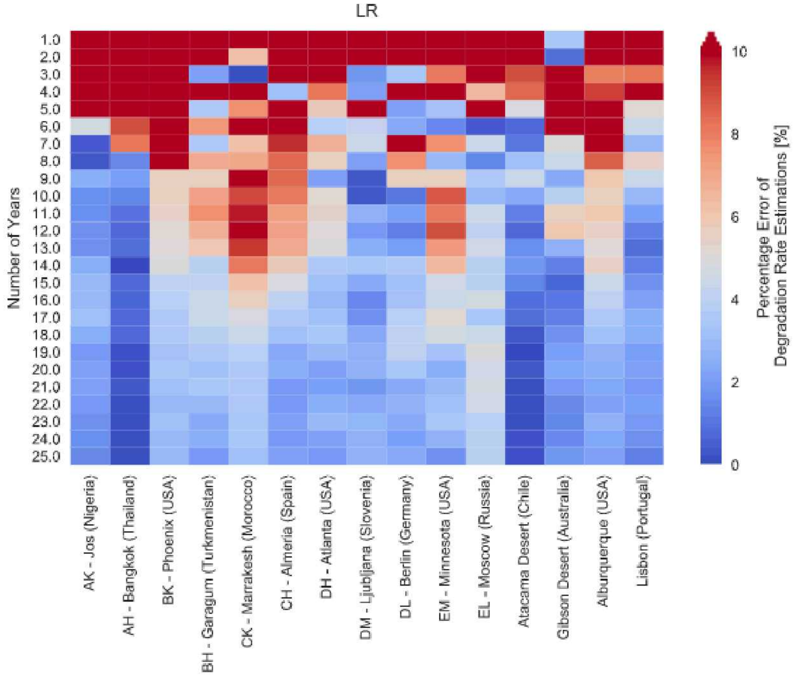
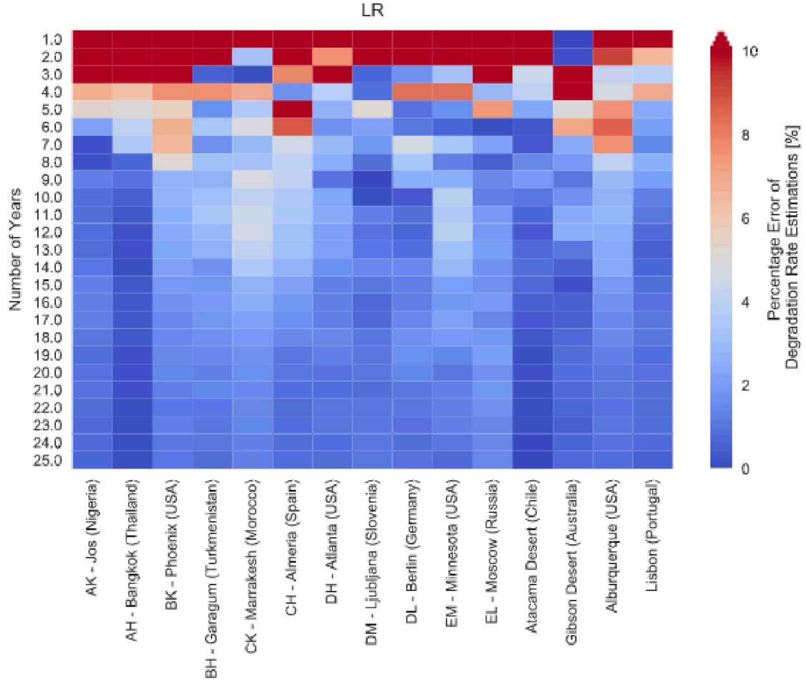
Magnitude of degradation rate
Case Study: Monthly PR, c-Si, Linear regression

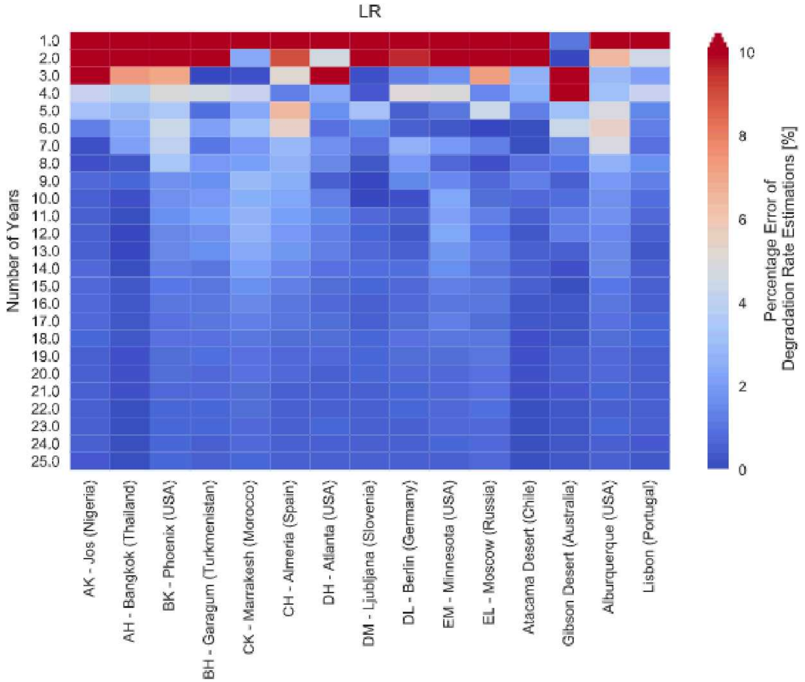
1%/a



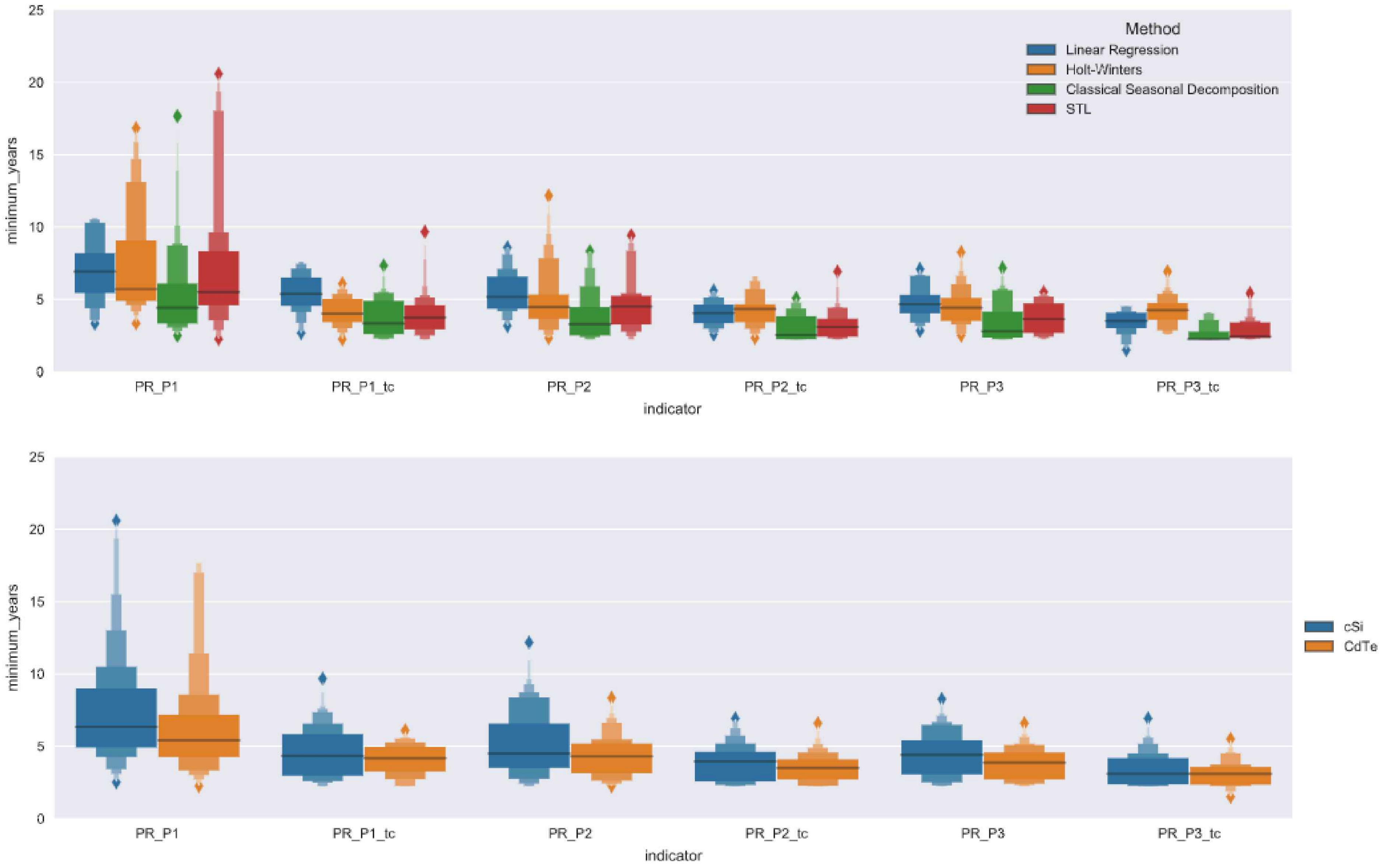
2%/a



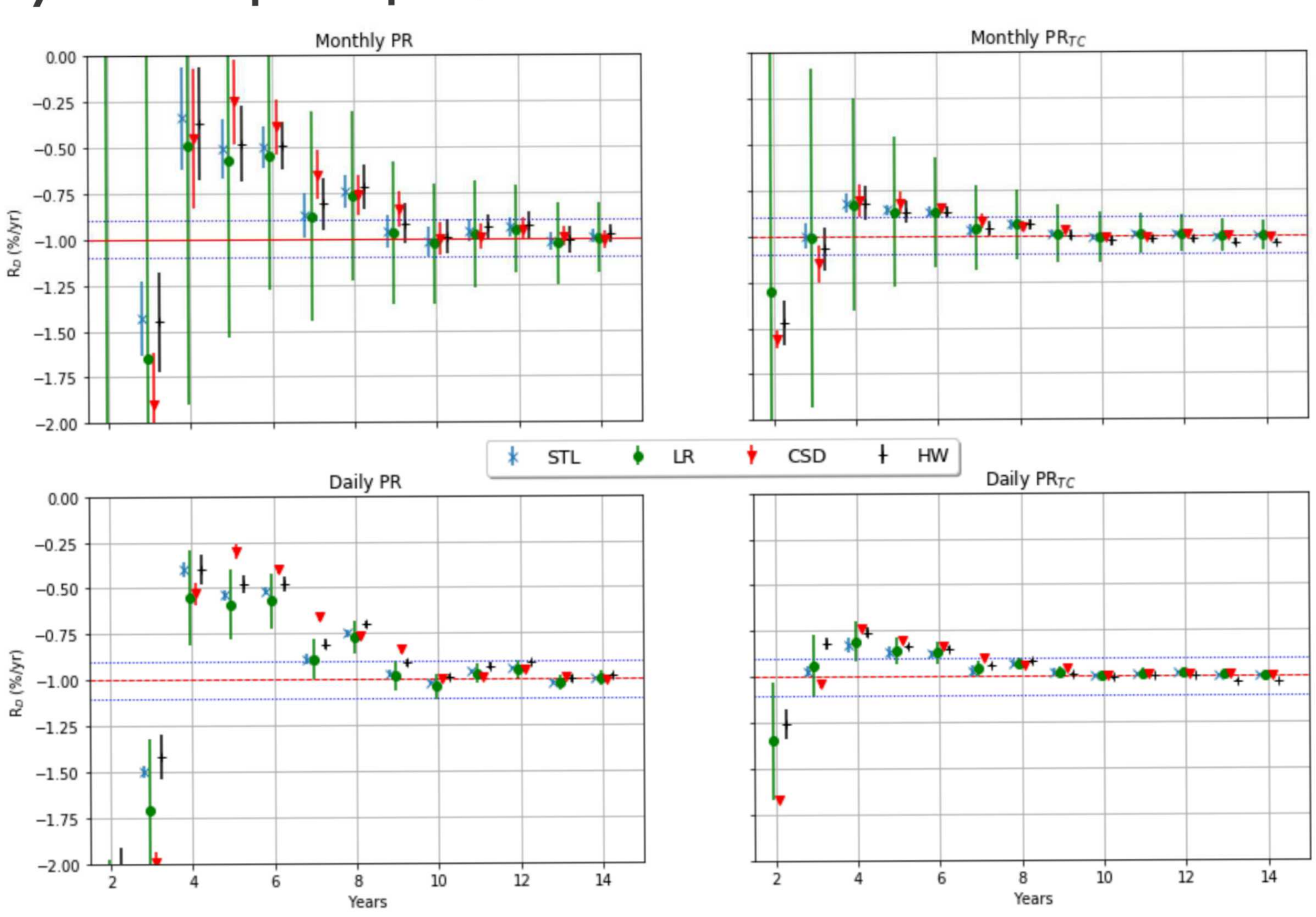
3%/a



Boxenplots: Monthly data, 2% threshold, all locations



Confidence intervals, aggregation, temperature correction Case Study: Albuquerque, c-Si

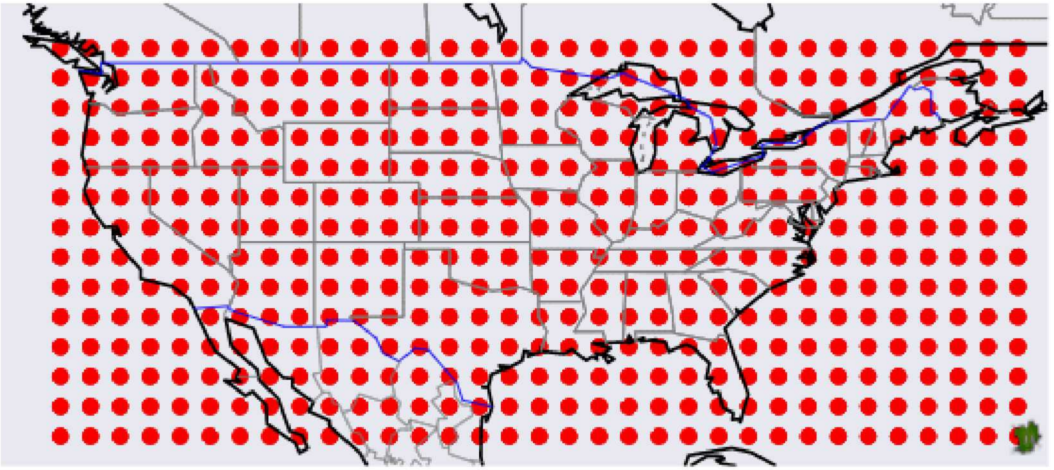


Degradation Rate Estimations
Large geographical regions

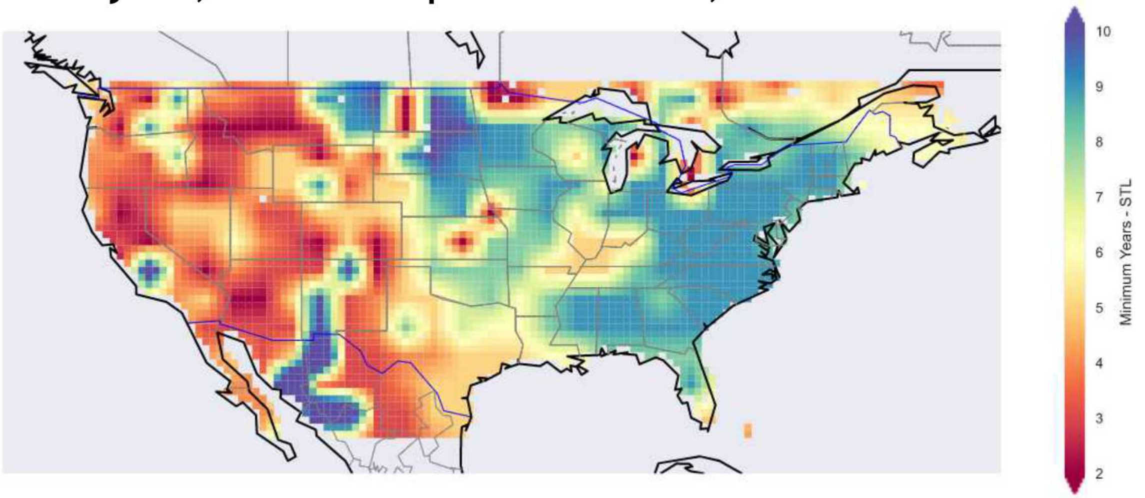
Spatial Grid : 2°x2° Latitude, Longitude

Minimum years will depend on the selected threshold value and method, but also the weather conditions (irradiance, temperature, etc) and seasonal index.

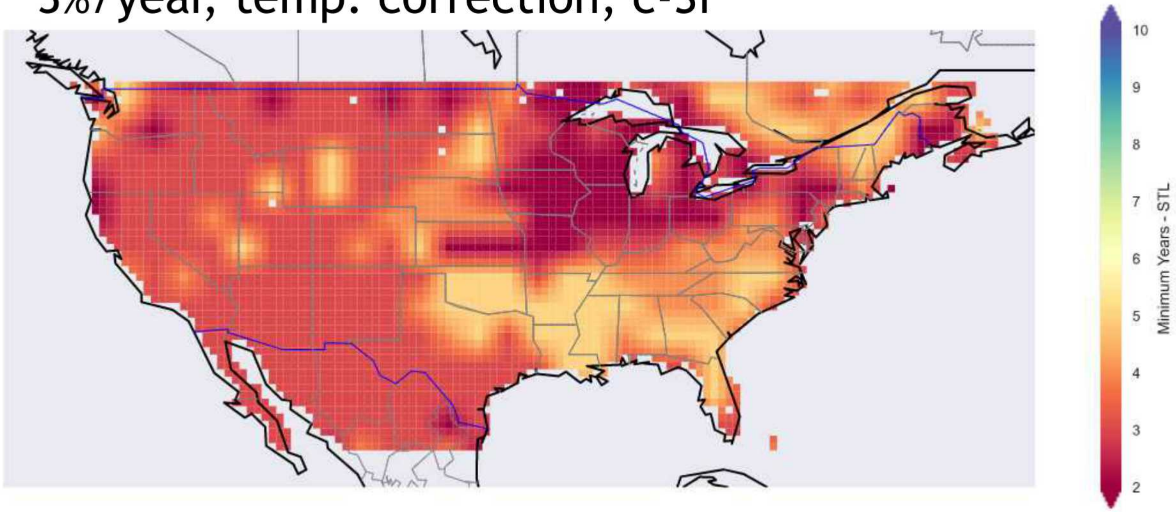
Bilinear interpolation to smoothen results



3%/year, Non- temp. correction, c-Si



3%/year, temp. correction, c-Si



Conclusions and future work

- True hypothesis: Climate/location and PV technology indeed affect the R_D accuracy
- Faster convergence in degradation rate estimation is achieved when:
  - Degradation rates are larger (e.g. >> 1%/year)
  - PV technology exhibits low seasonal performance (e.g. thin-films vs crystalline silicon)
- Confidence interval is as important as the degradation rate estimations
- Confidence intervals are reduced with temperature correction and finer aggregation
- Future work will investigate additional metrics, methods and larger geographical regions

Thank you for your attention!

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