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Understanding spatio-temporal solar forecasting

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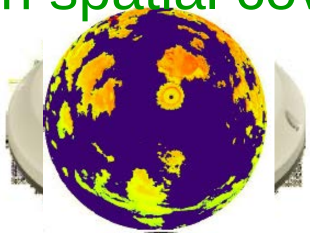
Solar forecasting

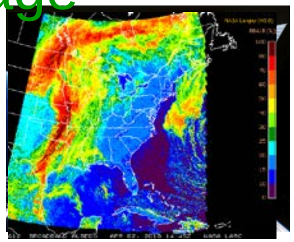
A spatio-temporal approach

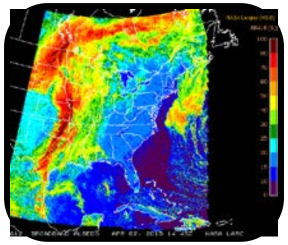
Solar forecasting
The need for spatial information

- Intuitive reasoning: focus on on-site forecasts & observations
  - Forecasts have coarse temporal and spatial resolutions
  - And weather… it moves. So, observations can only do so much

- Maybe we could try checking our surroundings!
  - solar data with spatial coverage

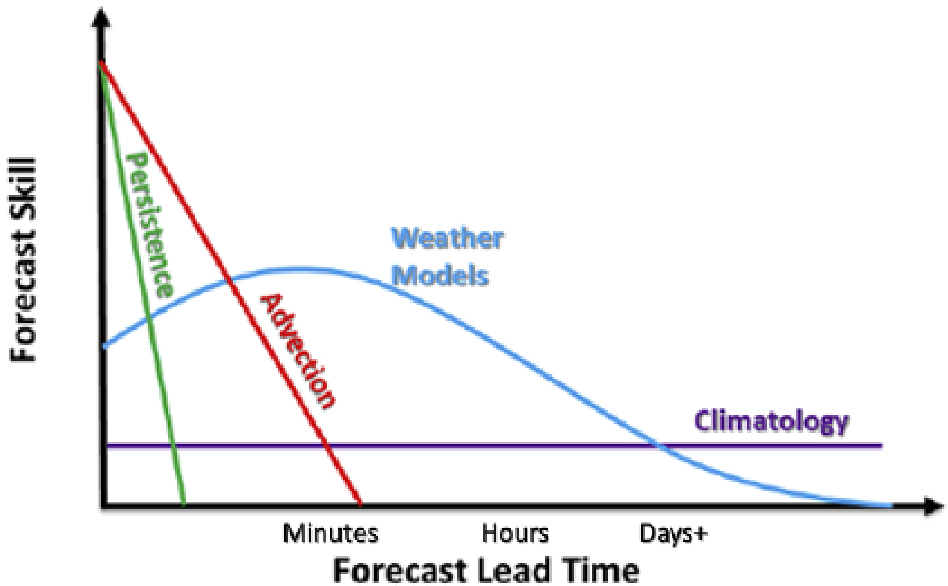






Solar forecasting
There is no absolute best model

NWP



Conceptual skill profile for different forecast approaches

Kleissl, Jan (2013). *Solar Energy Forecasting and Resource Assessment* (adapted)

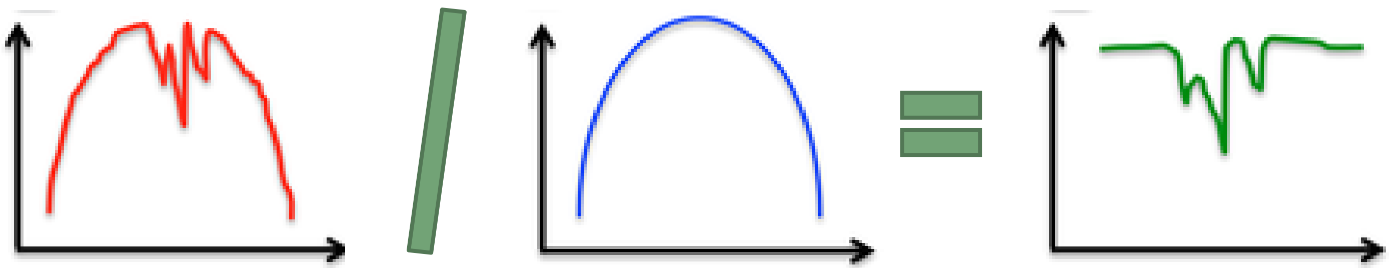
Methodology

How it was set up

Methodology
Data sets

Methodology
Preprocessing

- Removing daily&yearly solar cycle
  - GHI converted to clear-sky index (K)
  - *Ineichen* clear-sky model (Ineichen & Perez, 2002)
    - Based on monthly TL for 2003 parameter from SoDa database*



- Values with GHI<50 W.m-2 were removed

*www.soda-pro.com

- multivariate linear regression (ARX)

$$K_A(t+1) = \underbrace{m_1 \times K_A(t-\ldots)}_{\text{AR component}} + \underbrace{m_2 \times K_B(t-\ldots) + \ldots}_{\text{Spatial information}}$$

- Data is split into training/testing sets

	Hawaii (NREL)	Oklahoma (NREL)	Oklahoma (Mesonet)
Training size	7 months	2 years	12 years
Testing size	1 year	1 year	2 years

Methodology
Performance assessment

- For each data set forecasts were done for
  - every individual sensor/grid point
  - a specific range of horizons

- Forecast skill
  - improvement over baseline model
  - FS (%) = $RMSE_{ARX}$ / $RMSE_{baseline}$ x 100

- Baseline: smart persistence
  - $GHI_A(t+1) = K_A(t) \times CS_A(t+1)$

Results

What did we find

Results
Spatial patterns and local climate

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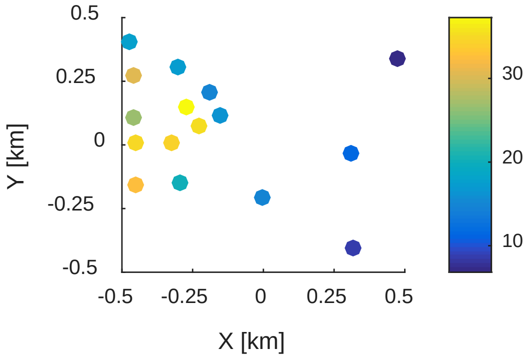
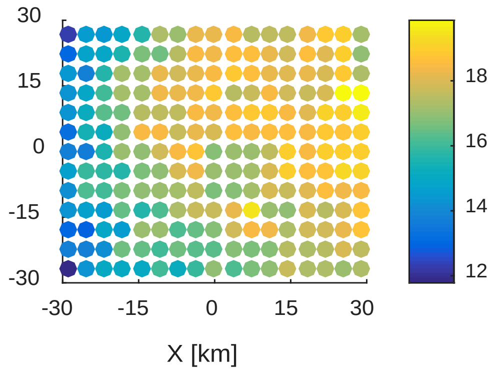
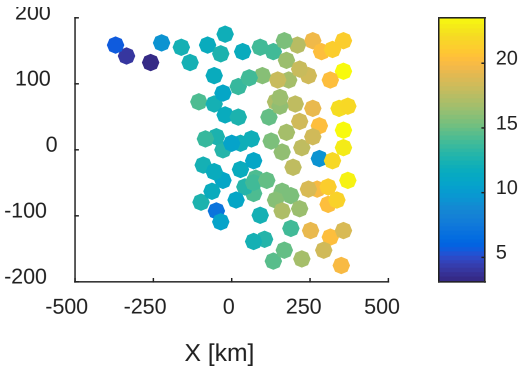
<u>Hawaii</u>
10 s horizon



<u>Oklahoma</u>
30 min horizon



<u>Oklahoma</u>
24 h horizon



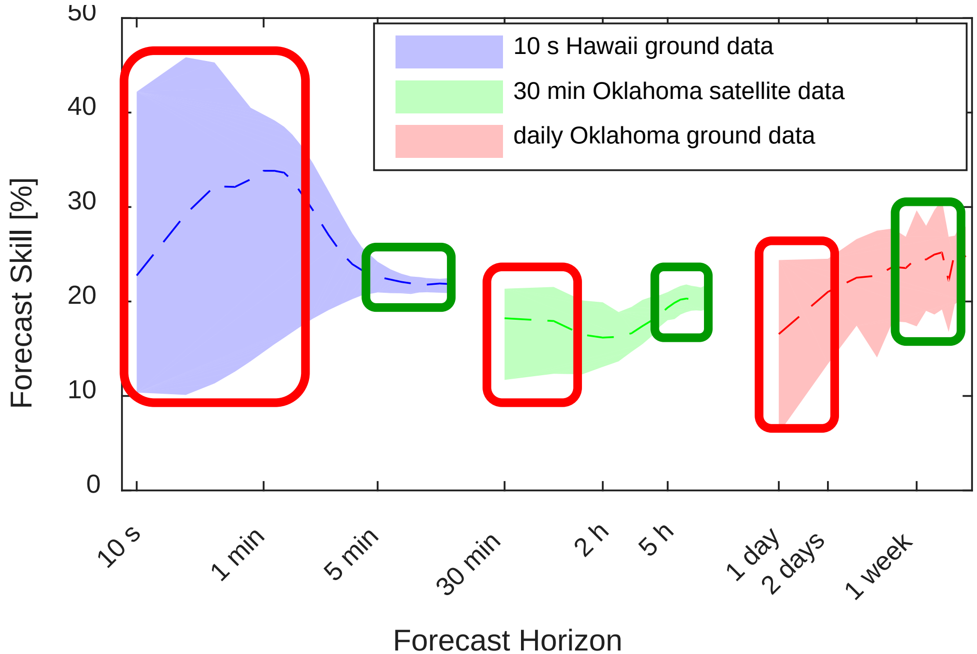
Local wind patterns
(Hinkelman 2013)

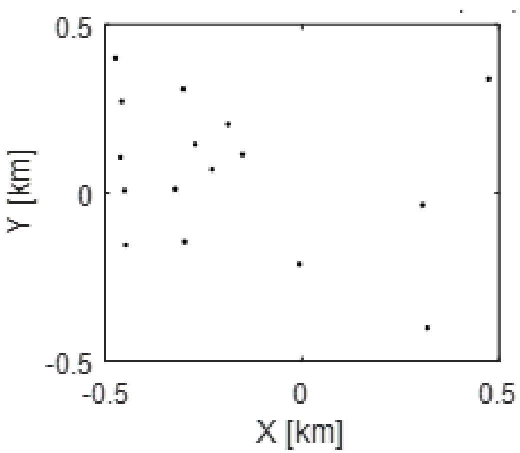
Local wind patterns
(OK Climatological Survey)

Weather systems progression
(Hocker et al. 2008)

Regression can detect spatial patterns <u>solely by correlations</u>!

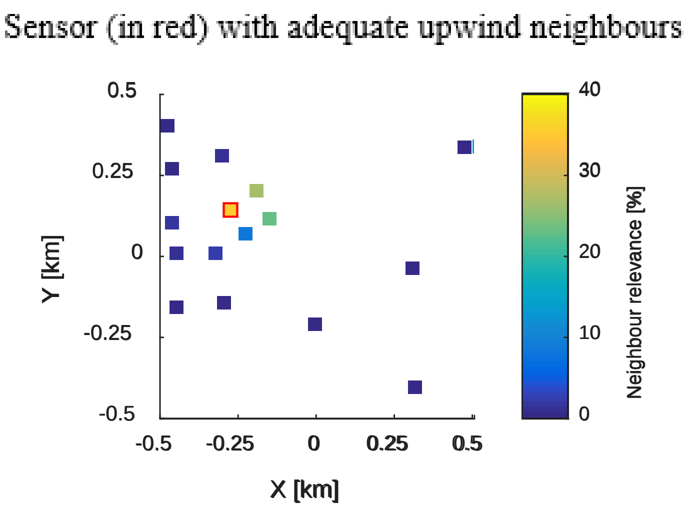
Results
Forecast skill

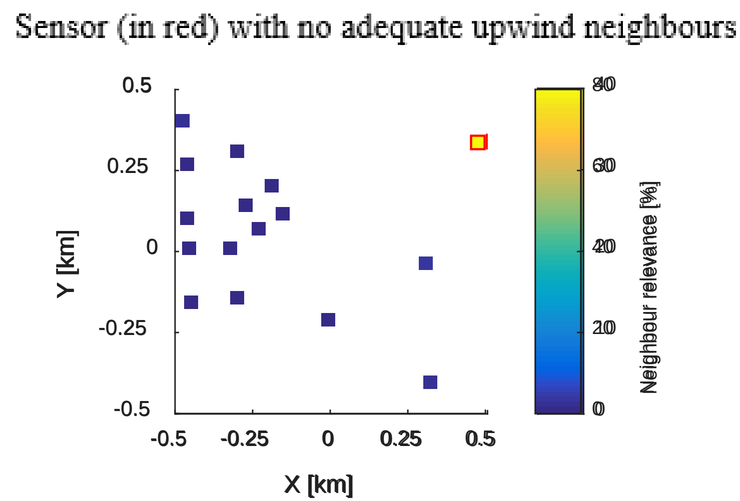




For each set, <u>shorter horizons show higher variability</u> among sensors/grid points

Results
Neighbors relevance





10-minute horizon
10-second horizon

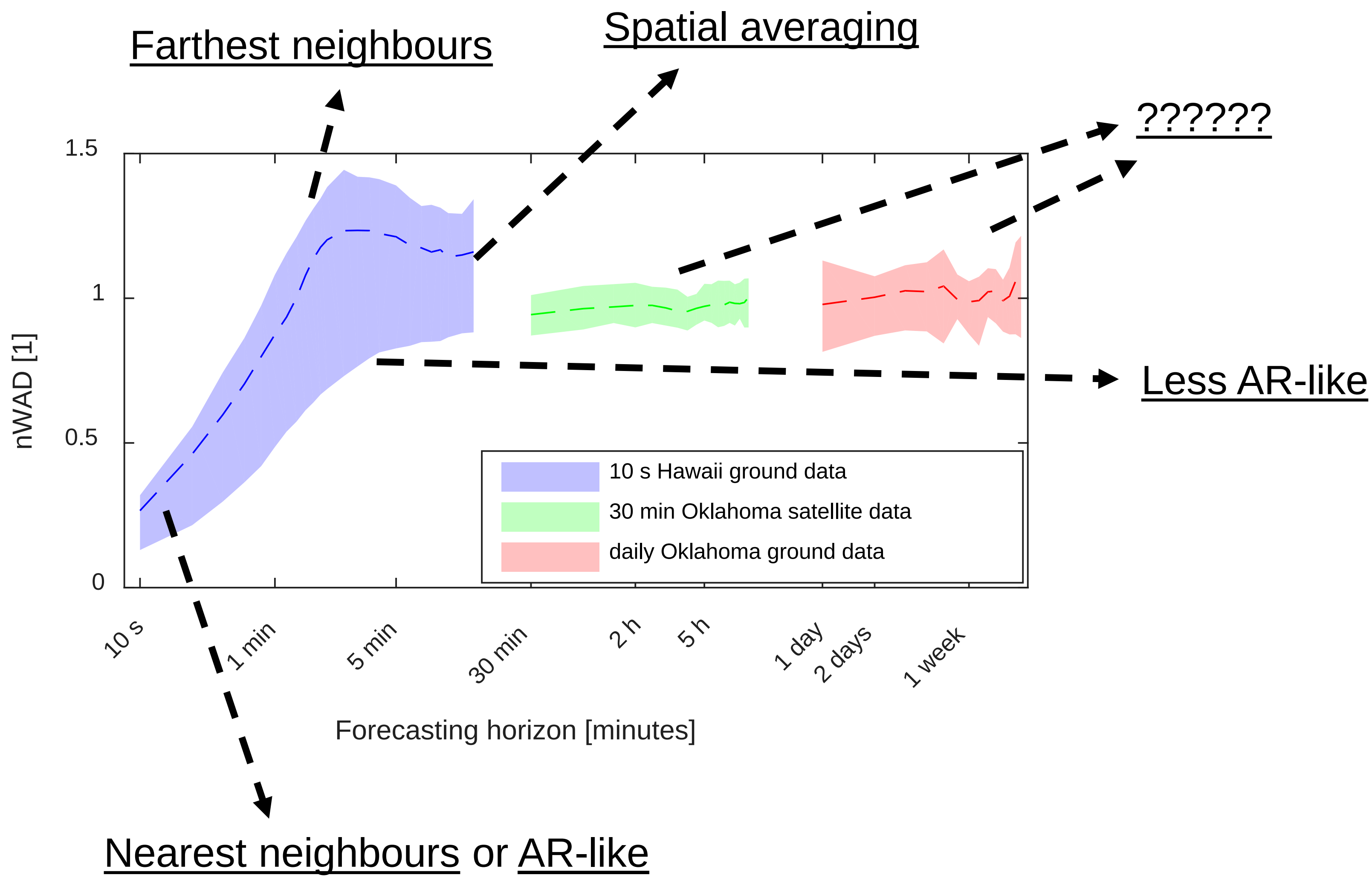
- Regression coefficients also show spatial pattern
- Inadequate spatial information => model AR-like
- If horizon is > spatial coverage => model spatial average-like

Results
nWAD parameter

- normalized Weighted Average Distance
  - Average neighbor distance weighted by their regression coefficient
  - Normalized by the regular average distance

- In short:
  - nWAD<1, nearer neighbours
  - nWAD=1, all neighbours
  - nWAD>1, farther neighbours

Results
nWAD profile



Final remarks

- Linear regression is capable of detecting spatial patterns
  - Each location has its predominant dynamic
- Spatially denser sensors with higher-frequency sampling
  - Higher performance potential but more location dependence
- Longer timescales require wider spatial coverage

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