Solar Energy Forecasting Advances and Impacts on Grid Integration

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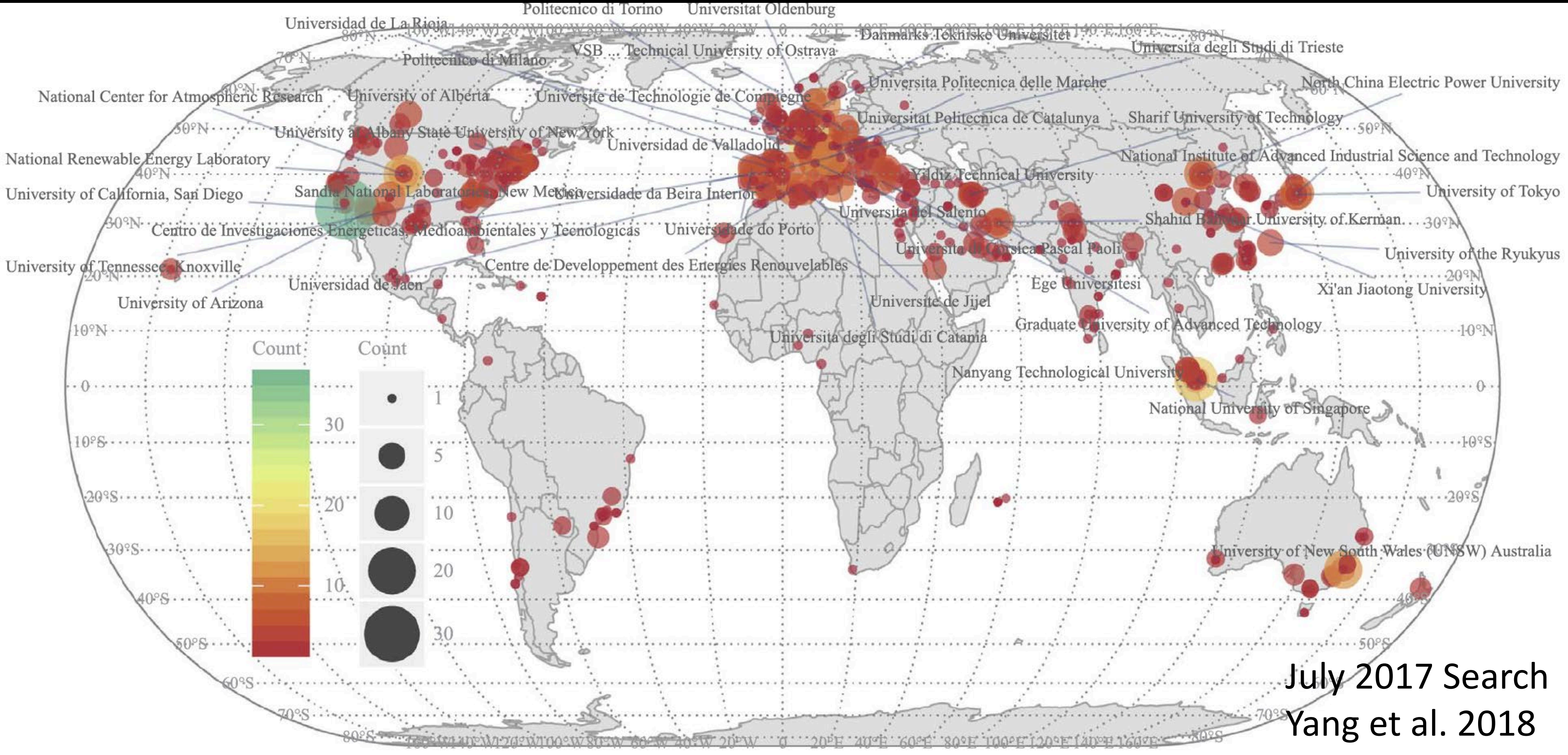
The Solar and Wind Resourcing and Integration Journal

UCSD SRAF

solar resource and forecasting laboratory

Charge

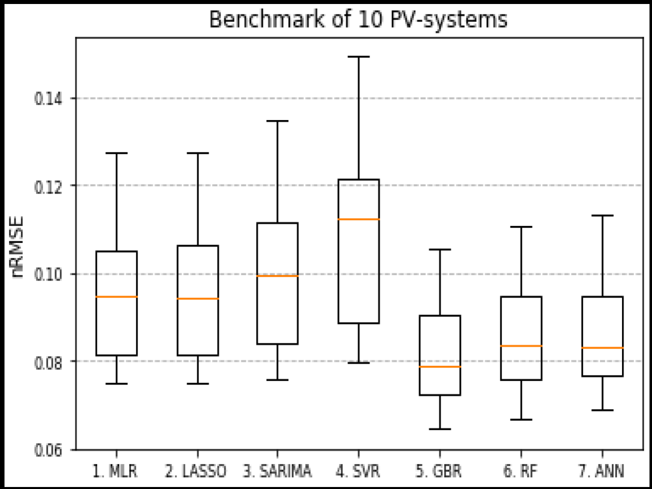
Review progress in solar forecasting since 2016 outside of the DOE Solar Forecasting II work.



July 2017 Search
Yang et al. 2018

What has changed (or not) since 2016?

- NWP:
  - ECMWF still performs best globally
- Satellite:
  - GOES-R
  - Data driven approaches
- Sky imager forecasting deemphasized
- Statistical models:
  - Maxed out forecast skill
  - Ensembling
- More probabilistic forecasting



Lennard Visser, 2019 IEEE PVSC

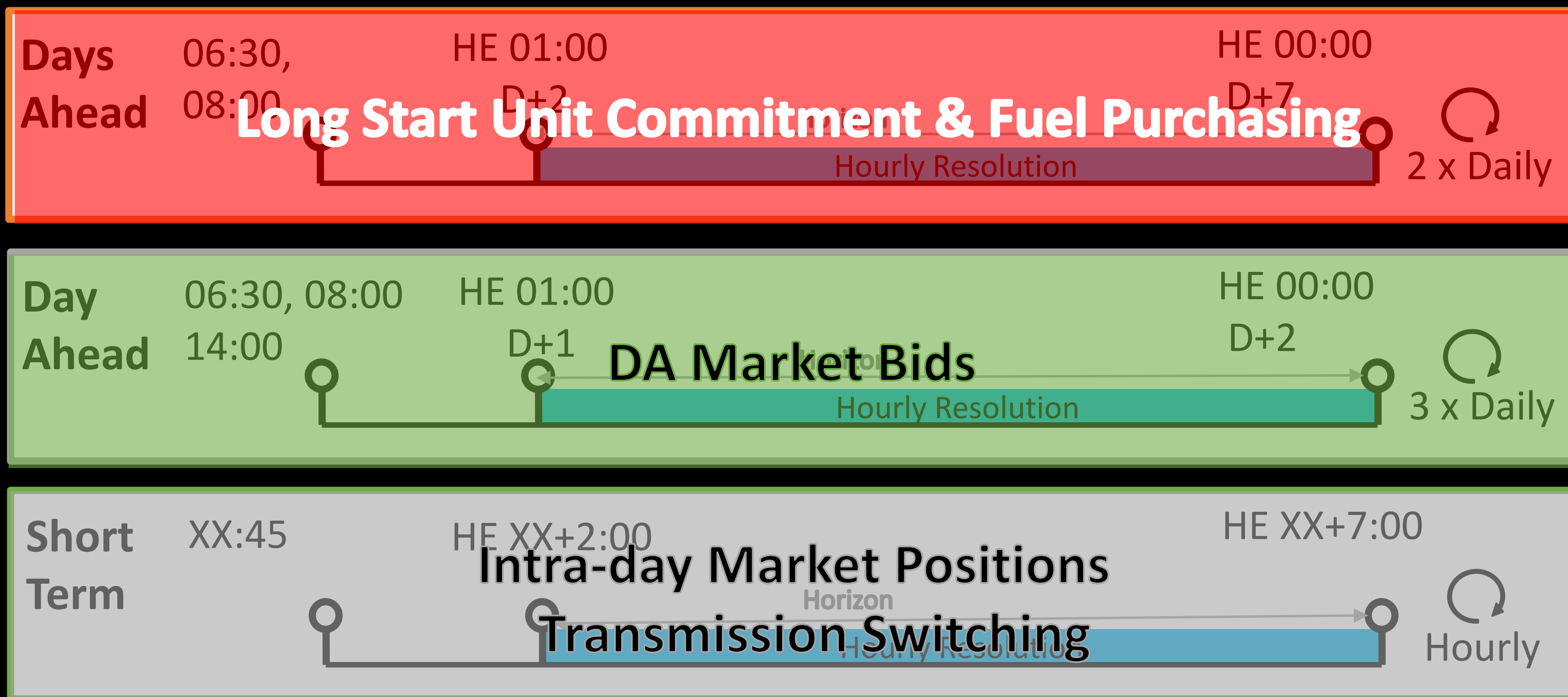
Recent Review Papers

- Yang, D., A guideline to solar forecasting research practice: Reproducible, operational, probabilistic or physically-based, ensemble, and skill (ROPES), J. Renewable Sustainable Energy, 2019.
- Yang, D., et al., Verification of deterministic solar forecasts, Solar Energy, in preparation, 2020.
- van der Meer, D., Widén, J., Munkhammar, J., 2018. Review on probabilistic forecasting of photovoltaic power production and electricity consumption. Renewable and Sustainable Energy Reviews 81, 1484 – 1512.

Tools

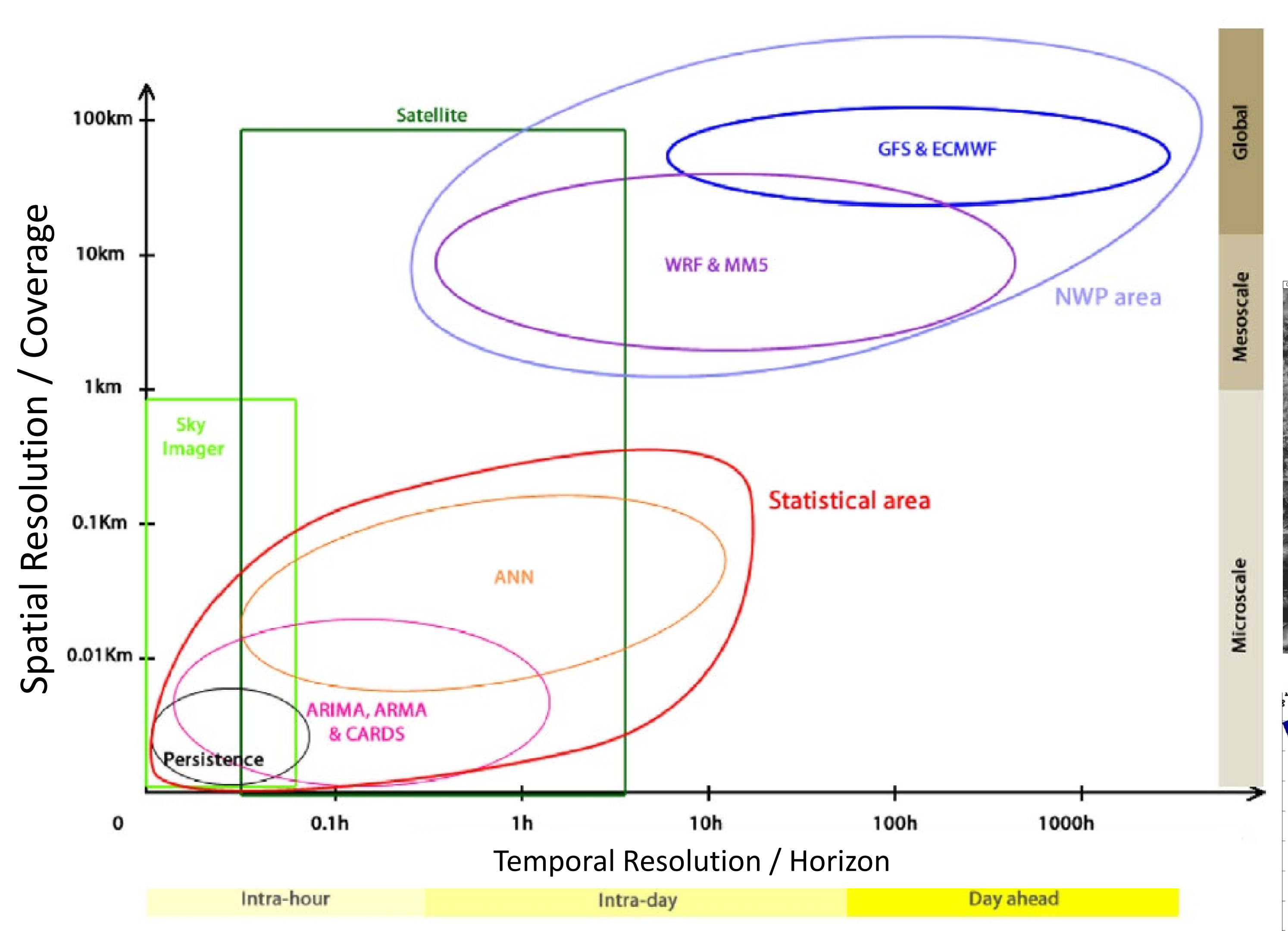
- Quality Control Method for PV data:
  - Killinger, S., Engerer, N., Müller, B., 2017. QCPV: A quality control algorithm for distributed photovoltaic array power output. Solar Energy 143, 120–131. http://dx.doi.org/10.1016/j.solener.2016.12.053.
- Quality controlled datasets with code:
  - OpenSolar: Promoting the openness and accessibility of diverse public solar datasets, C Feng, D Yang, BM Hodge, J Zhang, Solar Energy 188, 1369-1379
  - SolarData package update v1. 1: R functions for easy access of Baseline Surface Radiation Network (BSRN), D Yang, Solar Energy 188, 970-975

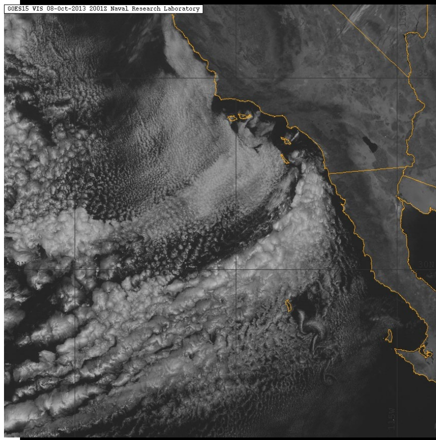
Time Horizons for Energy Markets

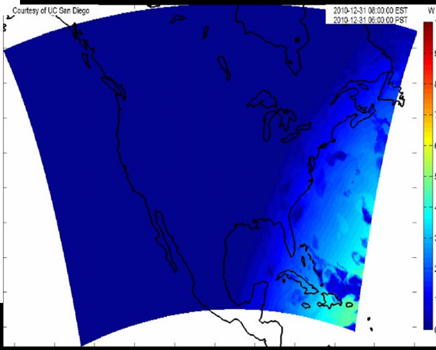


Lannoye, Tuohy, EPRI (2015)

Solar Forecast Types and Horizons







Diagne *et al.*, 2013, Inman *et al.*, 2013

Outline

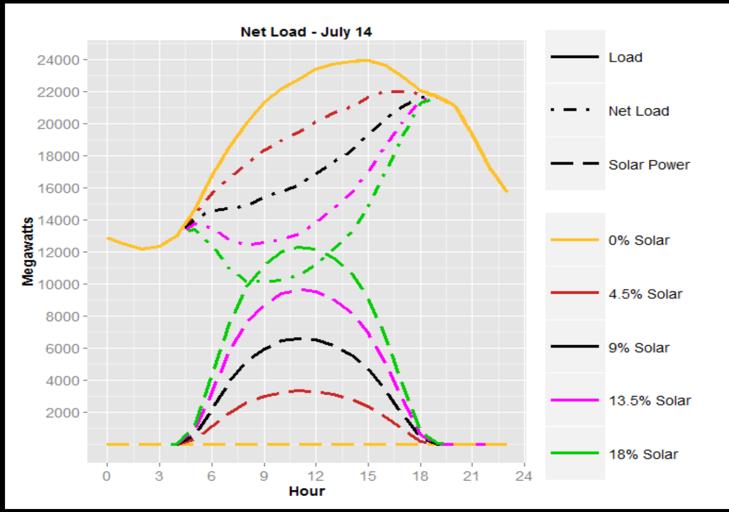
- Value of Solar Forecasting Case Study
  - Day-ahead forecast for unit commitment
- Advances in Solar Forecasting Techniques
- Solar Forecast Publishing Paradigm with Example
- Conclusions and Future Directions

Value of Day-Ahead Solar Forecasting

- What is the value of improving DA solar power forecasts?
- And what are the impacts on bulk power system operations?

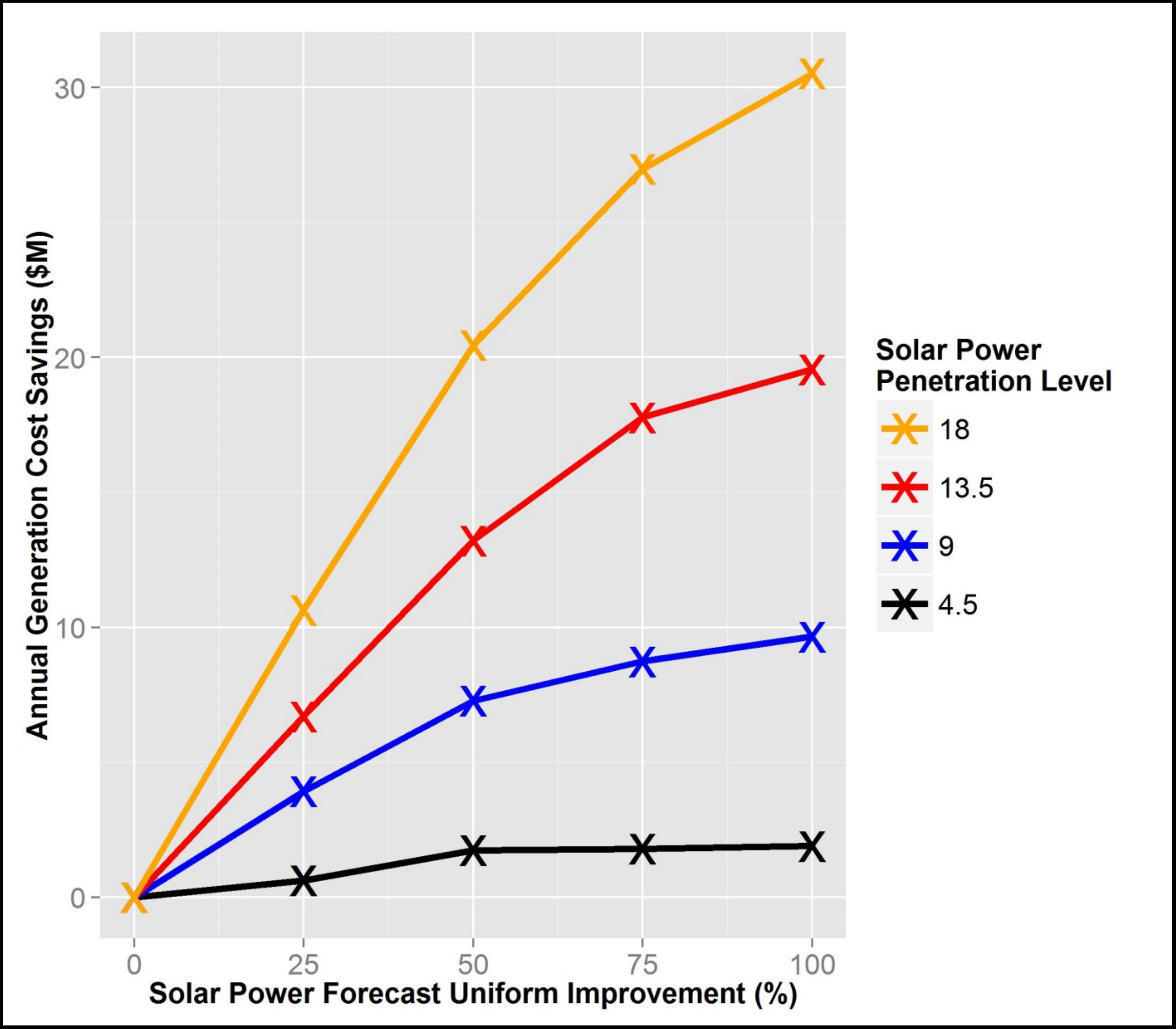
Scenarios for each solar energy penetration level (4.5% / 9.0% / 13.5% / 18.0%)

- DA forecasts: 25% uniform improvement
- DA forecasts: 50% uniform improvement
- DA forecasts: 75% uniform improvement
- DA forecasts: 100% uniform improvement



Carlo Brancucci Martinez-Anido et al, 2016

Value of DA Solar Power Forecasting Improvement for ~20 GW ISO New England

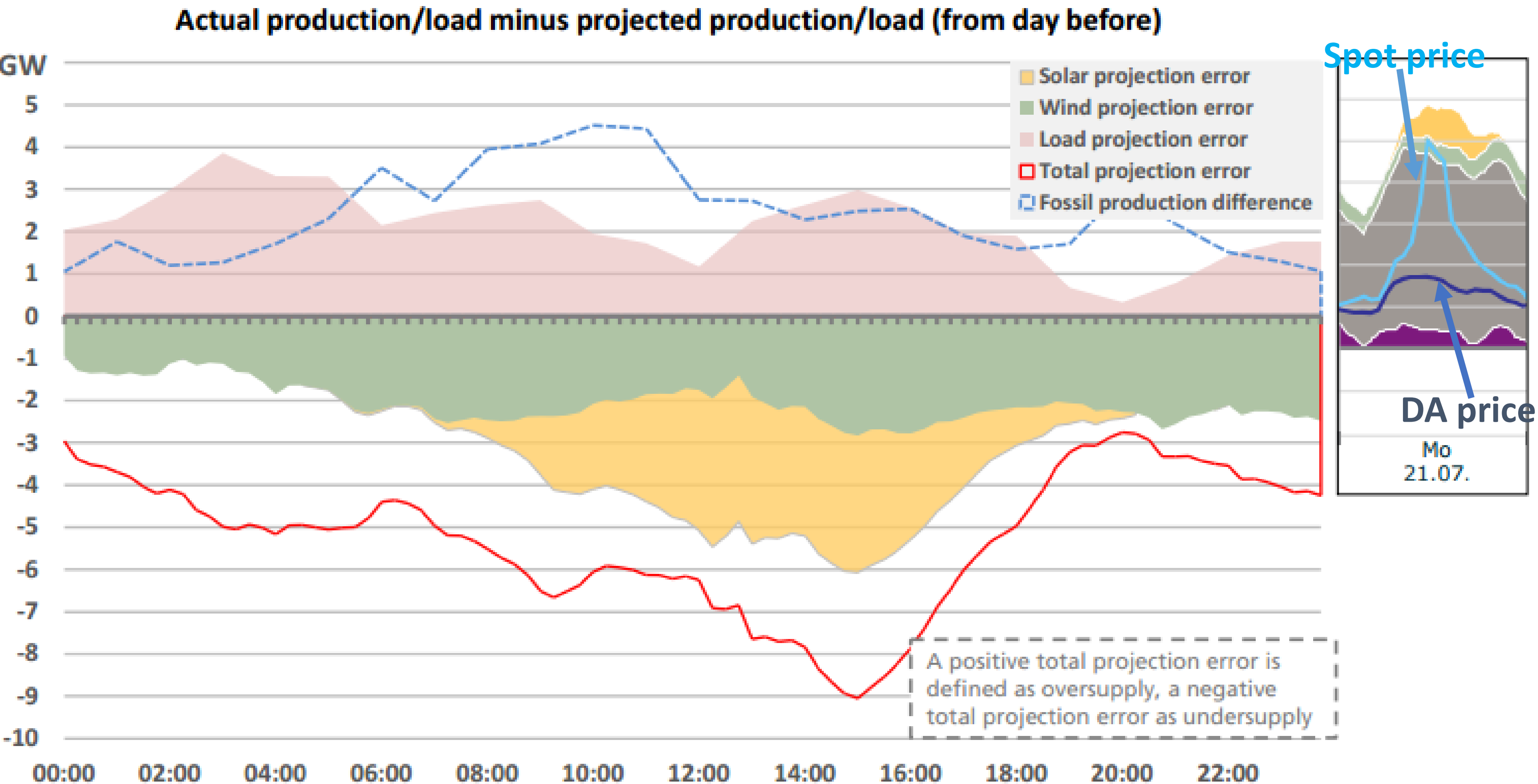


and in reality …

Impact of DA Forecast Errors on Intraday Spot Pricing in Germany

Analysis of the high Intraday prices on 21.07.2014

Overforecast Event



Source: Johannes Mayer, Fraunhofer Institute for Solar Energy Systems; Data: EEX, Entso-E

Back to month chart

Back to week chart

Fraunhofer ISE

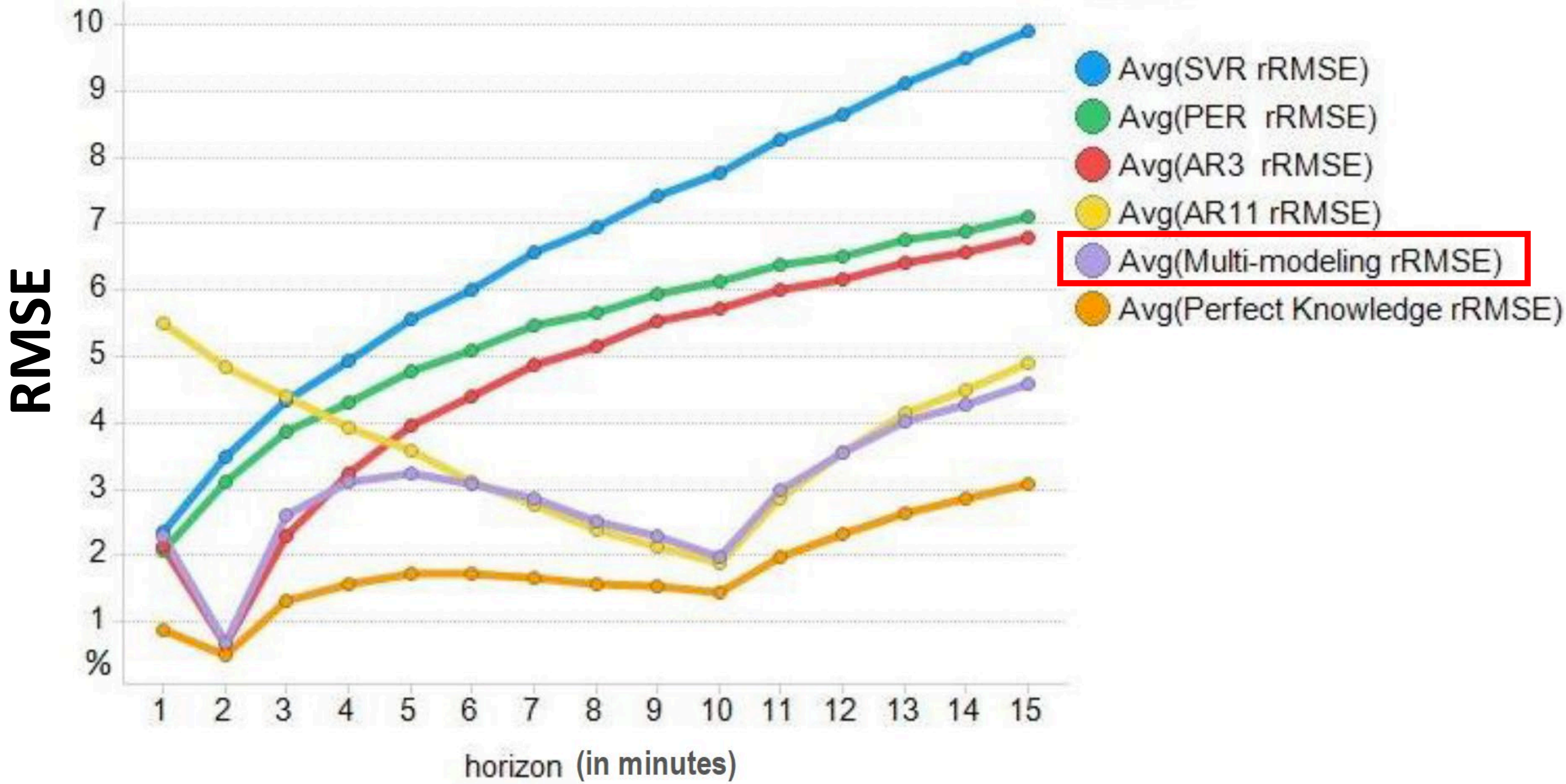
Progress

Literature Review Outside the US

Sanfilippo et al. (2016)

Ensembling

Combining different models – Supervised Classification



Srivastava and Lessmann (2018)

Deep Learning Methods

As an example, Long Short Term Memory (LSTM) slightly outperforms Feed Forward Neural Network (FFNN) and Gradient Boosting Regression (GBR).

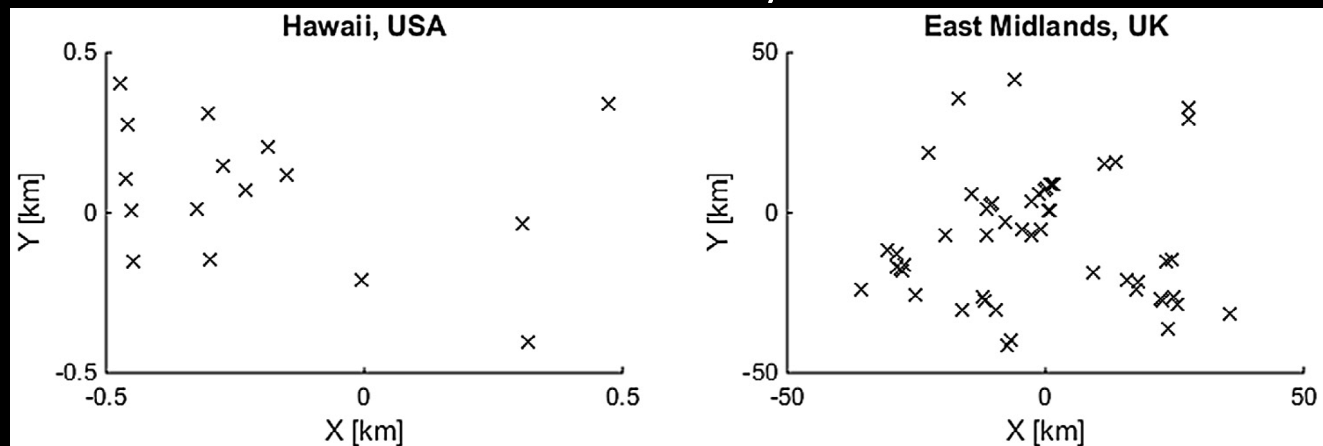
Country	Forecast Skill:RMSE			RMSE			
Location	**FFNN**	**GBR**	**LSTM**	**FFNN**	**GBR**	**LSTM**	**Pers**
Germany							
Hohenpeissenberg	54.1	54.5	**55.3**	30.03	29.79	**29.26**	65.48
Netherlands							
Cabauw	48.2	48.3	**53.1**	28.06	28.05	**25.42**	54.20
De Bilt	53.1	55.3	**55.4**	24.96	23.81	**23.76**	53.22
Austria							
Grossenzersdorf	**56.1**	49.9	55.8	**26.84**	30.67	27.04	61.19
Sonnblick	42.0	**44.2**	40.8	36.27	**34.89**	36.98	62.50
Wien	49.9	45.9	**55.6**	31.59	34.07	**27.94**	62.99
France							
Carpentras	57.4	59.2	**62.1**	26.87	25.70	**23.90**	63.05
Palaiseau	48.5	**53.5**	44.8	29.30	**26.46**	31.38	56.89
Spain							
Santander	53.7	53.0	**55.4**	31.43	31.93	**30.34**	67.95
La Coruna	44.0	47.6	**48.0**	33.34	31.21	**30.92**	59.50
Alicante	46.6	46.0	**46.9**	27.16	27.47	**26.98**	50.85
Madrid	49.5	**54.6**	53.1	25.43	**22.83**	23.60	50.31
Switzerland							
Basel	51.9	53.5	**58.0**	28.59	27.63	**24.99**	59.45
Zurich	50.2	53.7	**54.5**	30.61	28.46	**27.97**	61.52
Geneva	52.4	53.8	**53.8**	28.95	28.12	**28.07**	60.82
Davos	**52.2**	52.1	51.4	**32.12**	32.20	32.69	67.19
USA							
Desert Rock	37.6	42.0	**45.3**	29.38	27.29	**25.77**	47.07
Bondville	41.4	47.0	**49.5**	43.85	39.67	**37.78**	74.86
Fort Peck	37.7	39.7	**43.6**	37.00	35.82	**33.49**	59.36
Goodwin Creek	50.3	56.7	**57.9**	36.47	31.76	**30.89**	73.39
Penn State	50.0	53.0	**54.8**	38.71	36.39	**35.02**	77.48

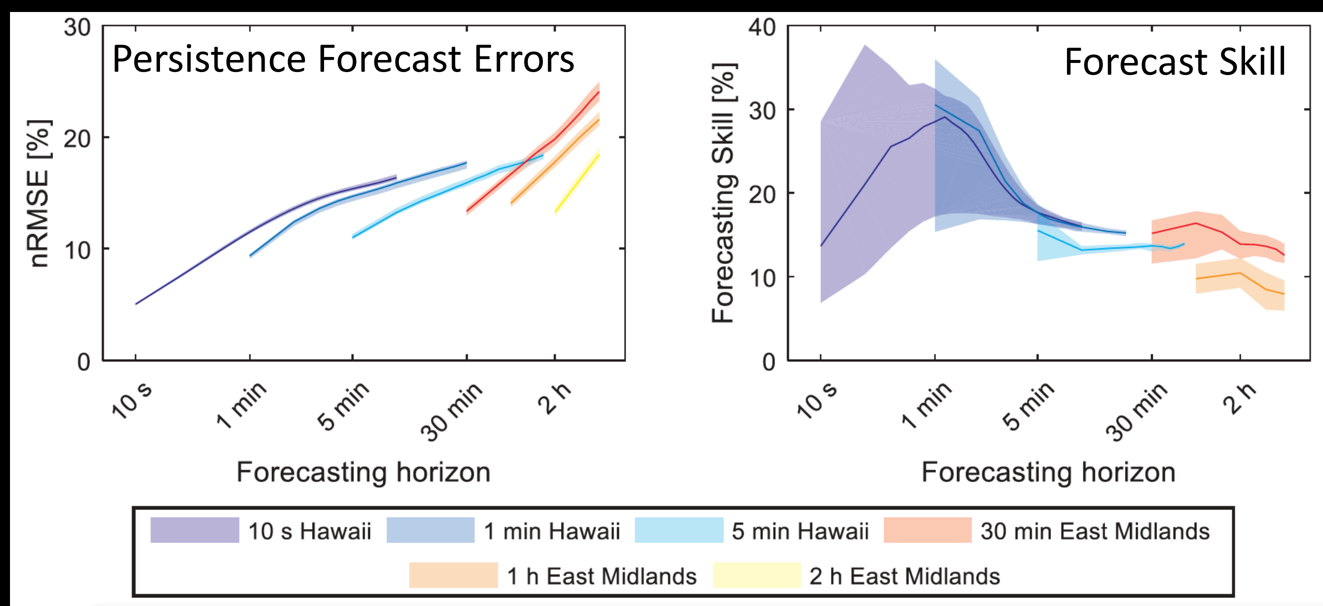
Amaro e Silva & Brito (2018)

Spatio-temporal forecasting with sensor networks

- Linear regression (ARX)
- No regime (wind direction) dependence
- Results confirm the (maybe) obvious.

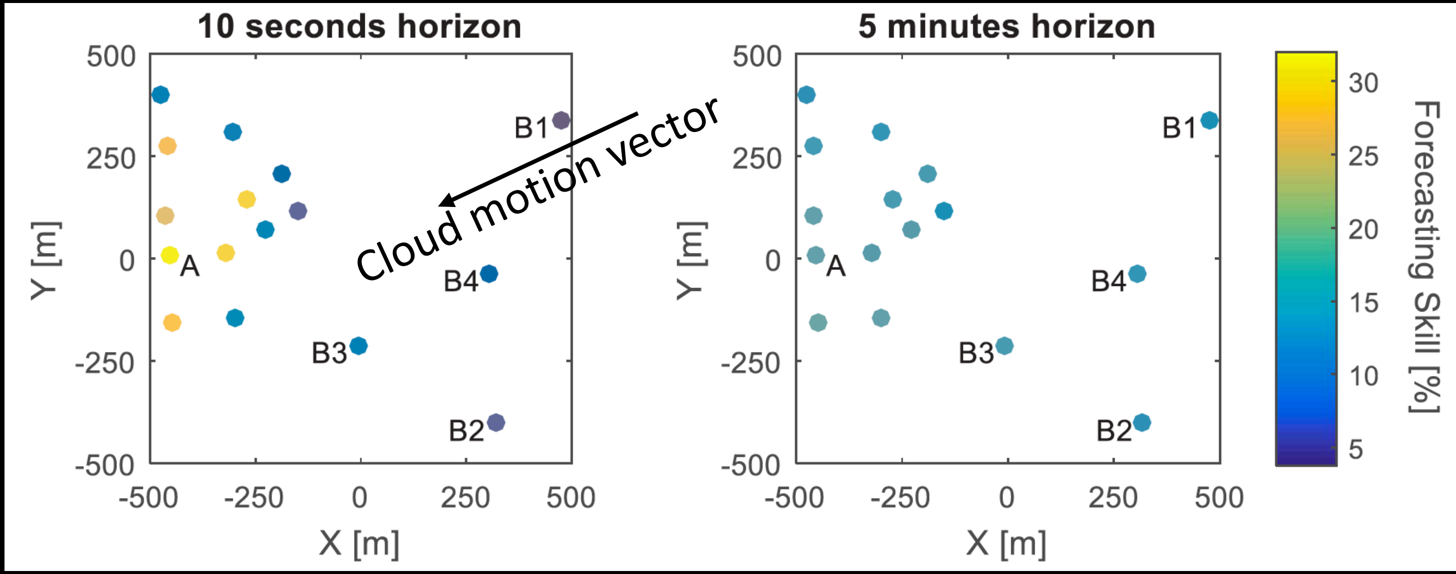
Network Layout

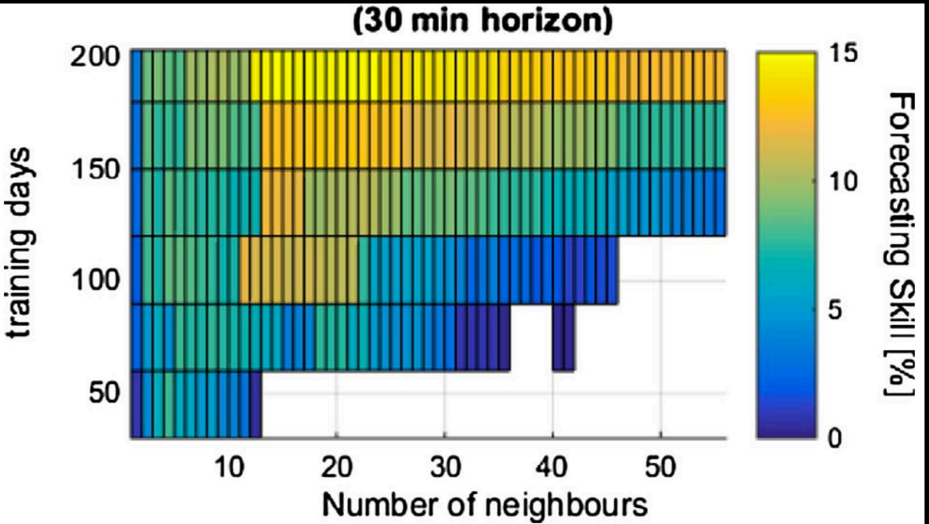




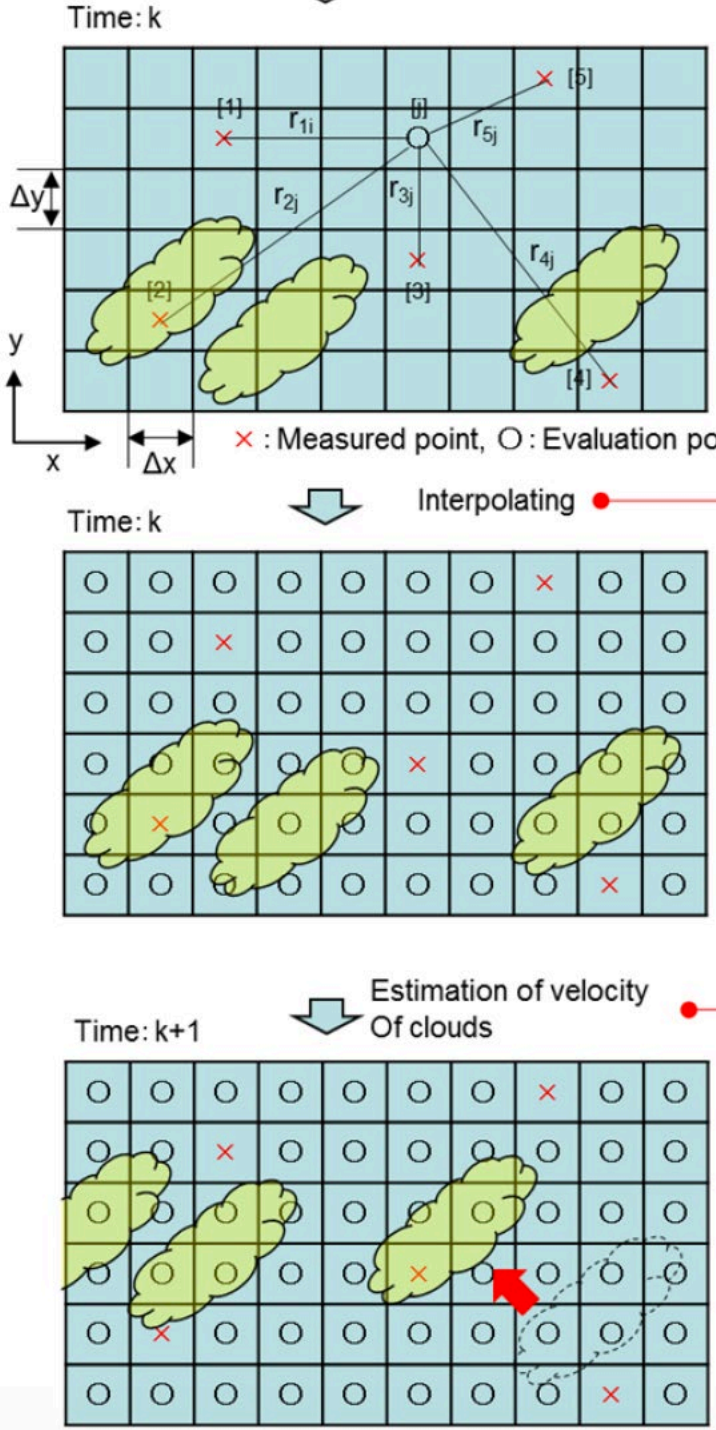
Amaro e Silva & Brito (2018)

Spatio-temporal forecasting with sensor networks





- Most skill
  - at downwind sensors
  - at the "right" time horizons
- Importance of training days and numbers of neighbors.



Advection Equation with Cloud Thinning / Thickening applied to Ground Data

■ **Estimation of cloud dynamics:**

$$\frac{\partial I}{\partial t} + u\frac{\partial I}{\partial x} + v\frac{\partial I}{\partial y} = \omega \qquad \text{-2)} \quad \text{:Advection equation}$$

where, I: irradiation, t:time, x, y: coordinates,
ω: increase-decrease rate of clouds
u,v: speeds of x-, and y-direction

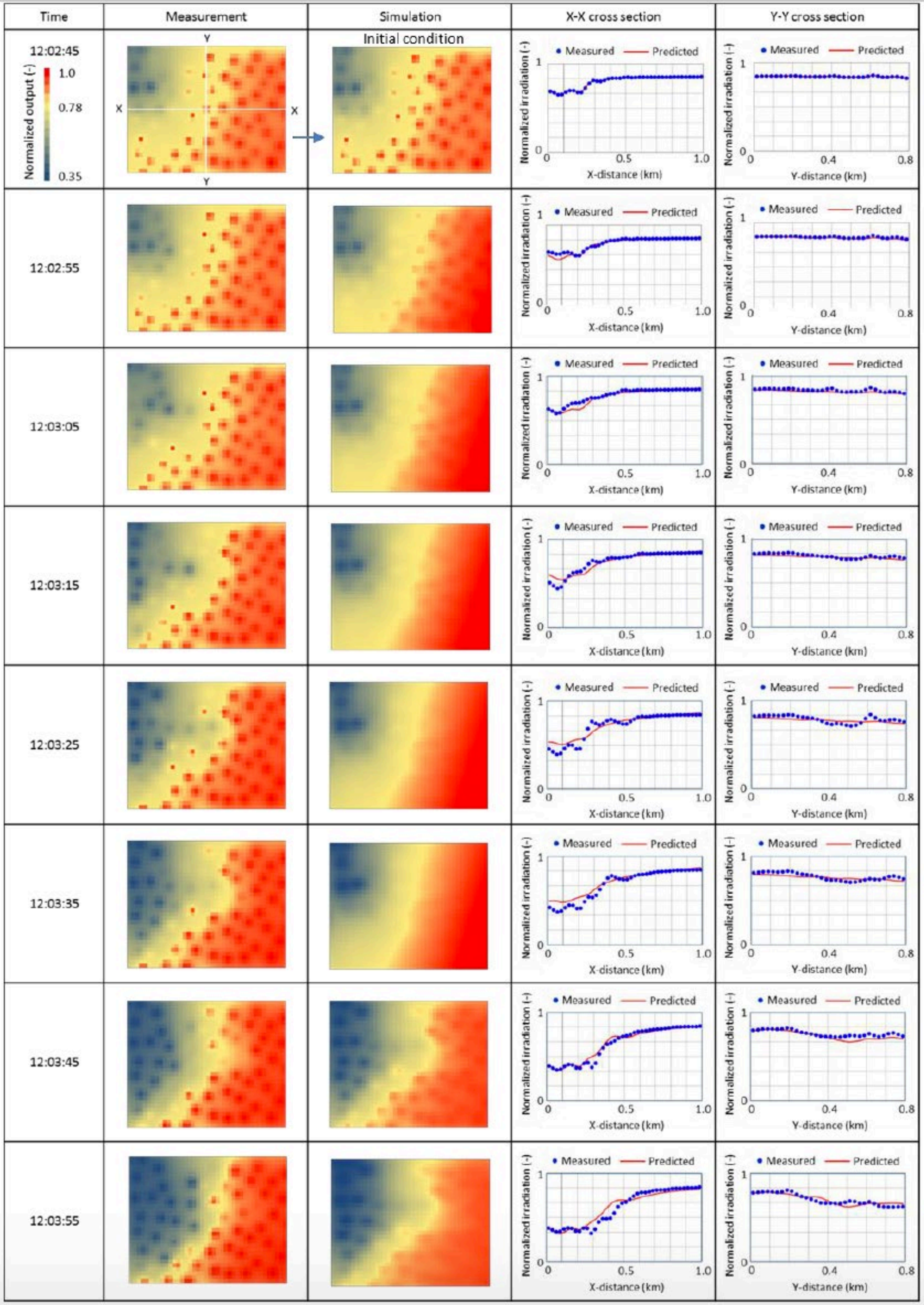
u, v, and ω were assumed as follows:

$$u = C_1 x + C_2 y + C_3$$

$$v = C_4 x + C_5 y + C_6 \qquad \text{-3)}$$

$$\omega = C_7 x + C_8 y + C_9$$

Inage, SI, Solar Energy, 2016, Development of an Advection Model for Solar Forecasting based on Ground Data First Report: Development and Verification of a Fundamental Model



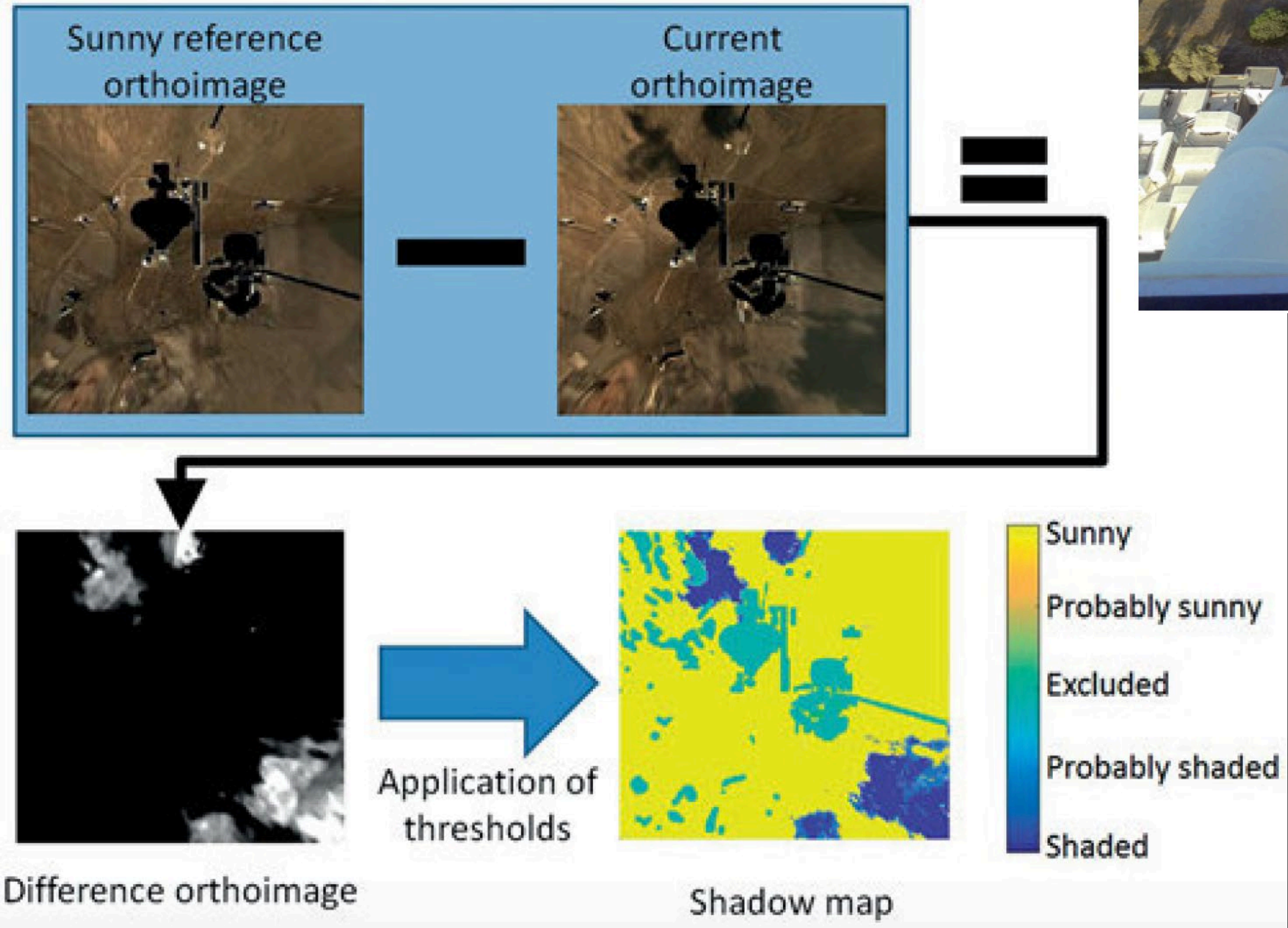
Advection Equation Results

- Achieved very high forecast skill of 80%.
- But:
    - Anecdotal validation
    - Future data may have been used as boundary condition

Kuhn et al. (2019), 10.1127/metz/2019/0954

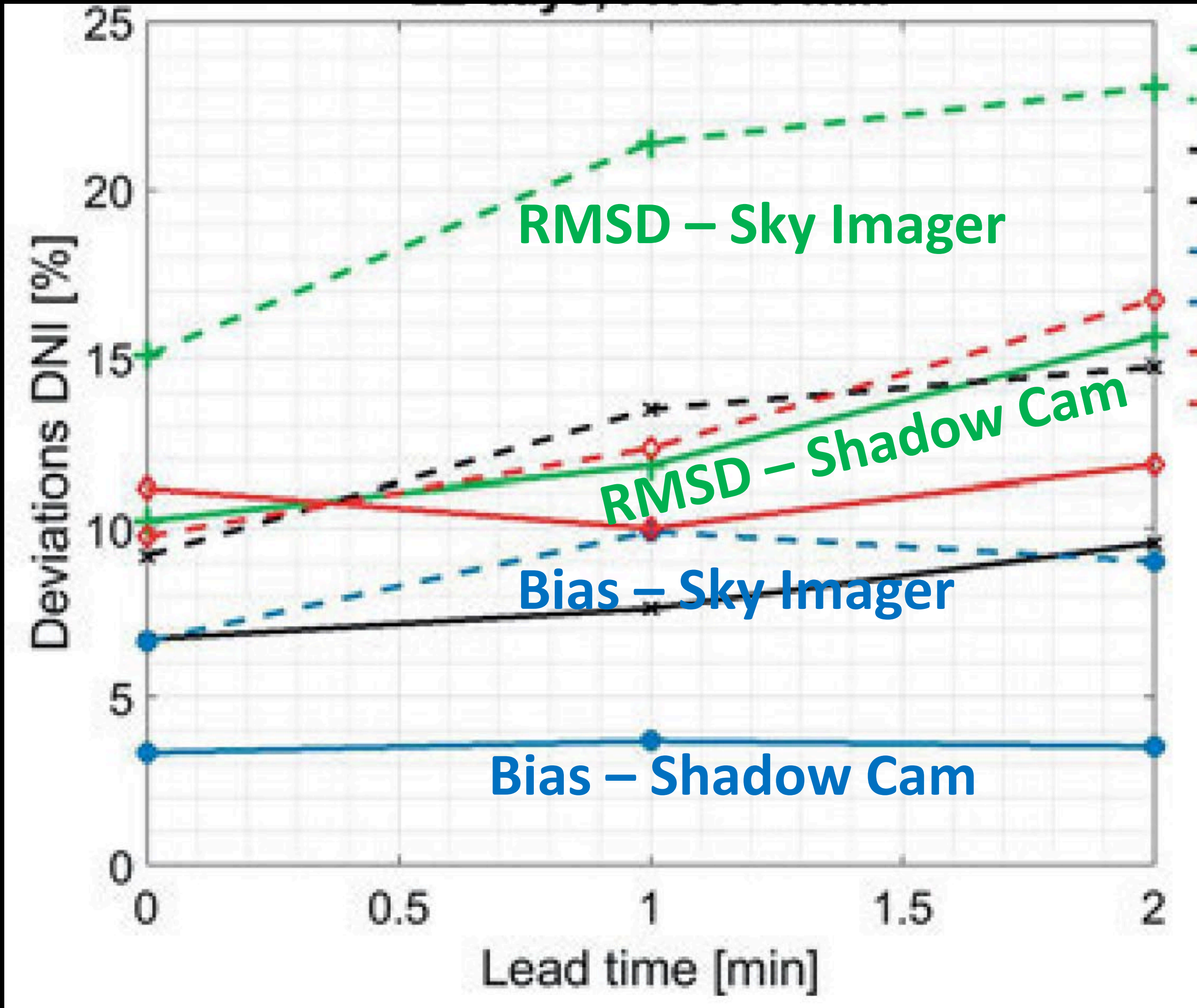
Shadow Camera Forecast System – aka the downward-looking sky imager

- 6 shadow cameras



Shadow Camera Forecast System – aka the downward-looking sky imager

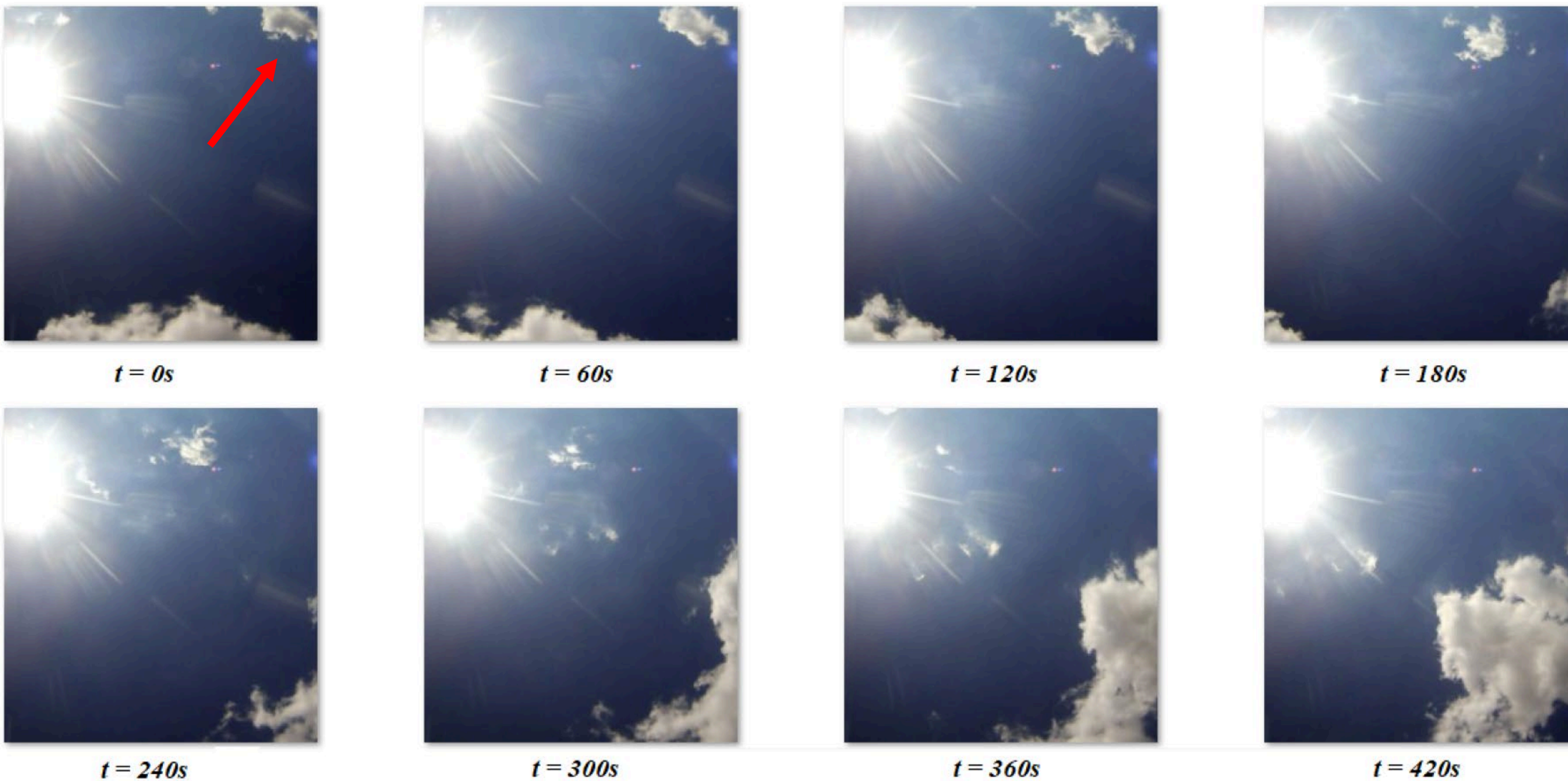
- Shadow camera system outperforms sky imager
- Paper also contains innovative cloud tracking approach



Manning and Baldick, JRSE (2019)

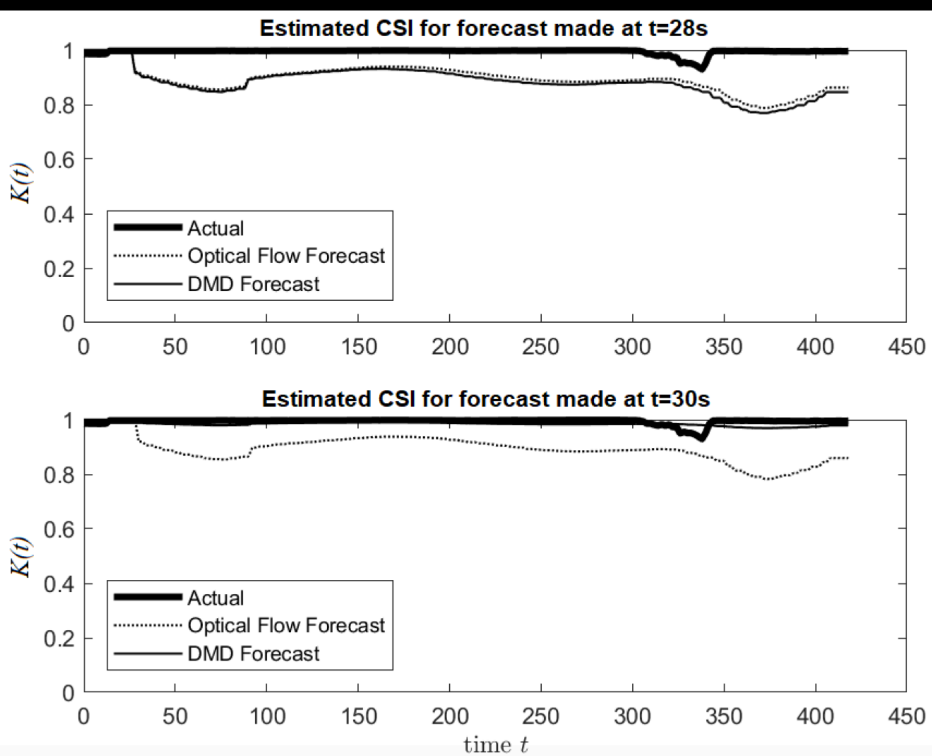
Data-Driven Approaches: Imager forecast including cloud dynamics

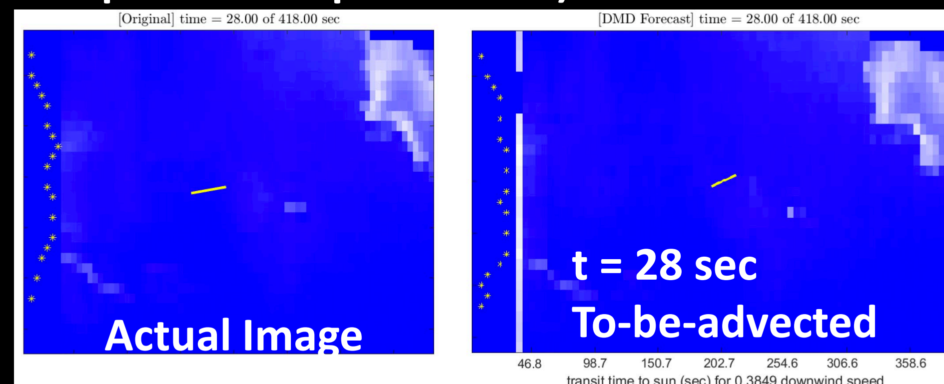
- Dynamic Mode Decomposition

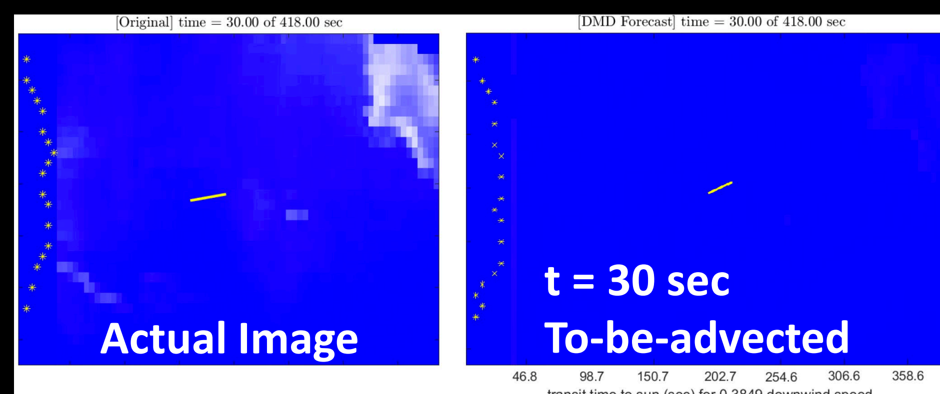


Data-Driven Approaches Applied to Imagery

- Cloud dynamics successfully represented
- Other approaches exist (e.g. Koopman operator)



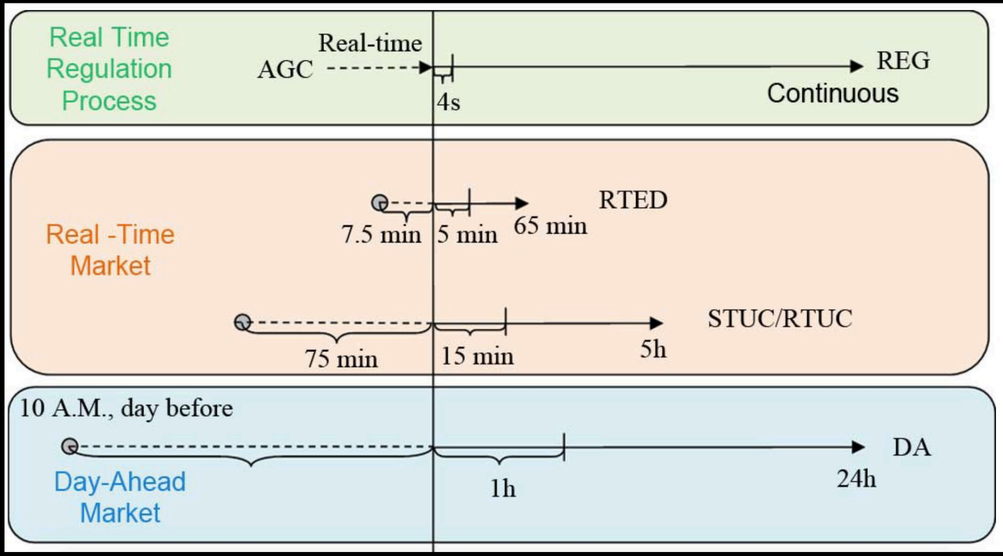




Solar Forecast Publishing Paradigm and Example

ROPES

Aside: Classifying time–scales in forecasting



Makarov et al., 2011

- The quadruplet (H,R,L,U)
  - H: forecast horizon
  - R: resolution
  - L: lead time
  - U: update rate
- Examples:
  - CAISO Day-ahead market: (H24h, R1h, L14h, U24h)
  - CAISO Short-term unit commitment: (H5h, R15min, L75min, U1h)
  - Real-time economic dispatch: (H65min, R5min, L7.5min, U5min)

A paradigm shift in (solar) forecasting - ROPES

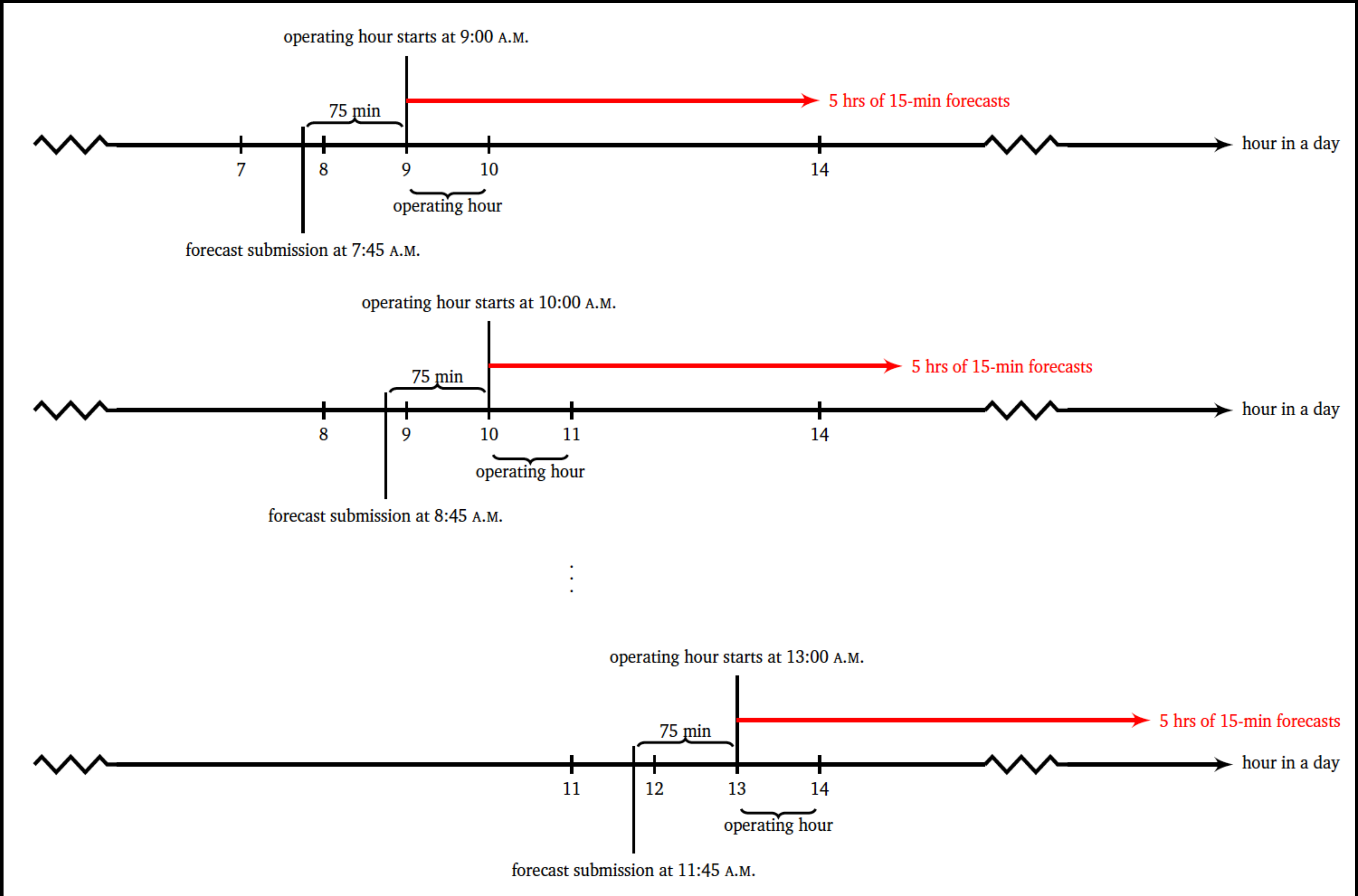
1. **R**eproducible: Code and data please!!
2. **O**perational: Every detail matters. One needs to follow the grid forecast submission requirement exactly.
3. **P**robabilistic or **P**hysically-based: Simple point forecasting using ML algorithm will no longer be accepted.
4. **E**nsemble: Cooperative or competitive ensemble. No hybrid please!!
5. **S**kill: Forecasts need to be verified through skill metrics against benchmarks, e.g., forecast skill using smart persistence, or CRPS skill score.

Yang D. A guideline to solar forecasting research practice: Reproducible, operational, probabilistic or physically-based, ensemble, and skill (ROPES). Journal of Renewable and Sustainable Energy. 2019 Mar 23;11(2):022701.

Example: **Yang**, Wu, Kleissl (IJF, 2019)

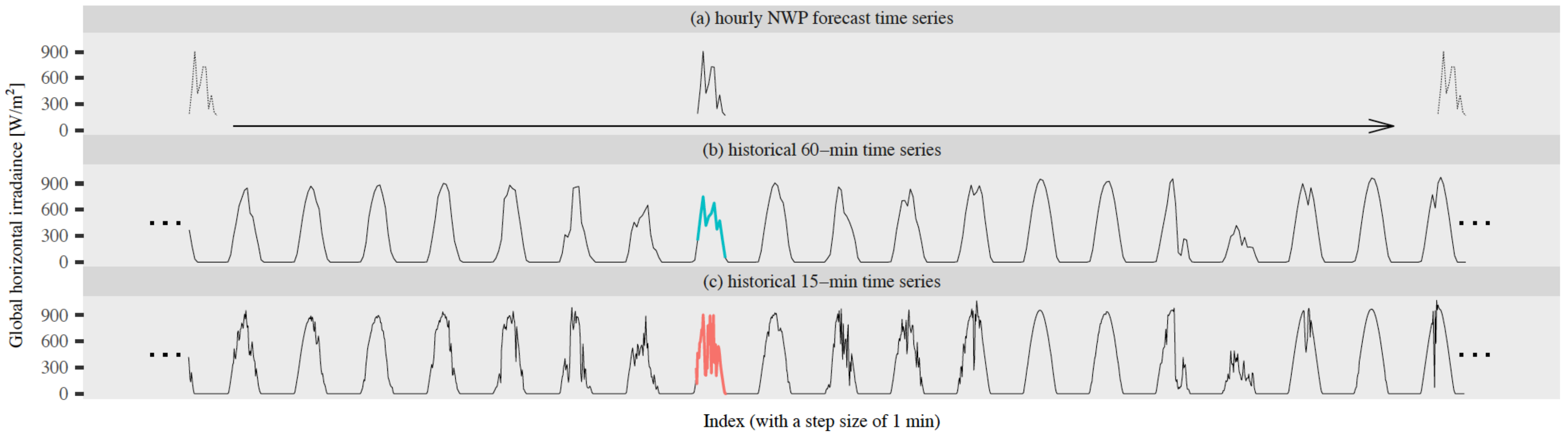
1. Reproducible: Sure, all code is online.
2. Operational: CAISO Hour-Ahead.
3. Probabilistic or Physically-based: Both!
4. Ensemble: Target the “strong” ensembles, i.e., multi-modeling and analog ensemble.
5. Skill: Smart persistence and persistence ensemble.

Operational Forecast



Example: Yang, Wu, Kleissl (2019)

- Given the horizon of 7 h, only satellite and NWP will work. So we use:
- North American Mesoscale (NAM) forecast system.
  - NAM forecasts contains 4 daily runs. 12:00 run out to 36 h covers the entire operating day
- Is NAM good enough? No. So let 's ensemble it and post-process it. (time series ensemble + model output statistics)
- The native day-ahead forecasts has a 1-h resolution, we need to downscale it!
  - Distance profile - the fastest Euclidean-distance-based pattern matching tool.
  - Ensemble the top-n matches to form a prediction interval (PI).



Ensembling

- Component models (N = 140)
  - MOS Bias correction
  - Seasonal exponential smoothing (ETS)
  - …
- How to ensemble?
  - Averaging, trimmed square, ordinary least square (OLS), etc.
  - OLS worked best
- Downscale:
  - Pattern matching algorithm

Procedure PMA (*history*, *query*)

$n \leftarrow \texttt{len}(history)$

$m \leftarrow \texttt{len}(query)$

$\boldsymbol{\Sigma} \leftarrow \texttt{mvss}(history)$ #Moving sum-of-squares

$\mathbf{Q}_{\downarrow} \leftarrow \texttt{rev}(query)$ # Reverse *query*

$\mathbf{Q}_{\downarrow}[m+1:n] \leftarrow 0$ # Pad the reversed *query* with 0's

$dots \leftarrow \texttt{ifft}(\texttt{fft}(history) * \texttt{fft}(\mathbf{Q}_{\downarrow}))$ #Conv. between *history* and $\mathbf{Q}_{\downarrow}$

$result \leftarrow \texttt{sqrt}\left(\texttt{sum}\left(\mathbf{Q}_{\downarrow}^{2}\right) + \boldsymbol{\Sigma} - 2 * dots[m:n]\right)$ # Eq. (8)

return *result*

Deterministic Forecast Results

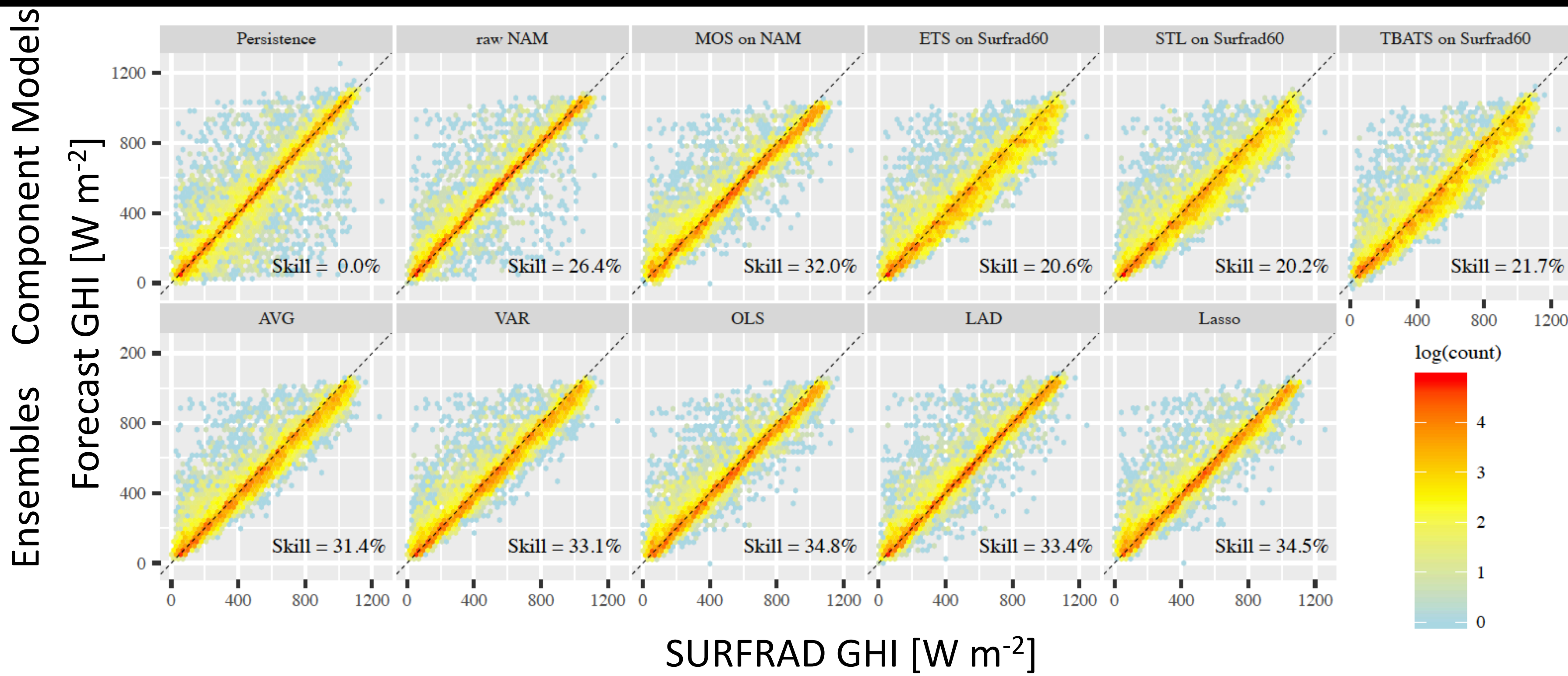
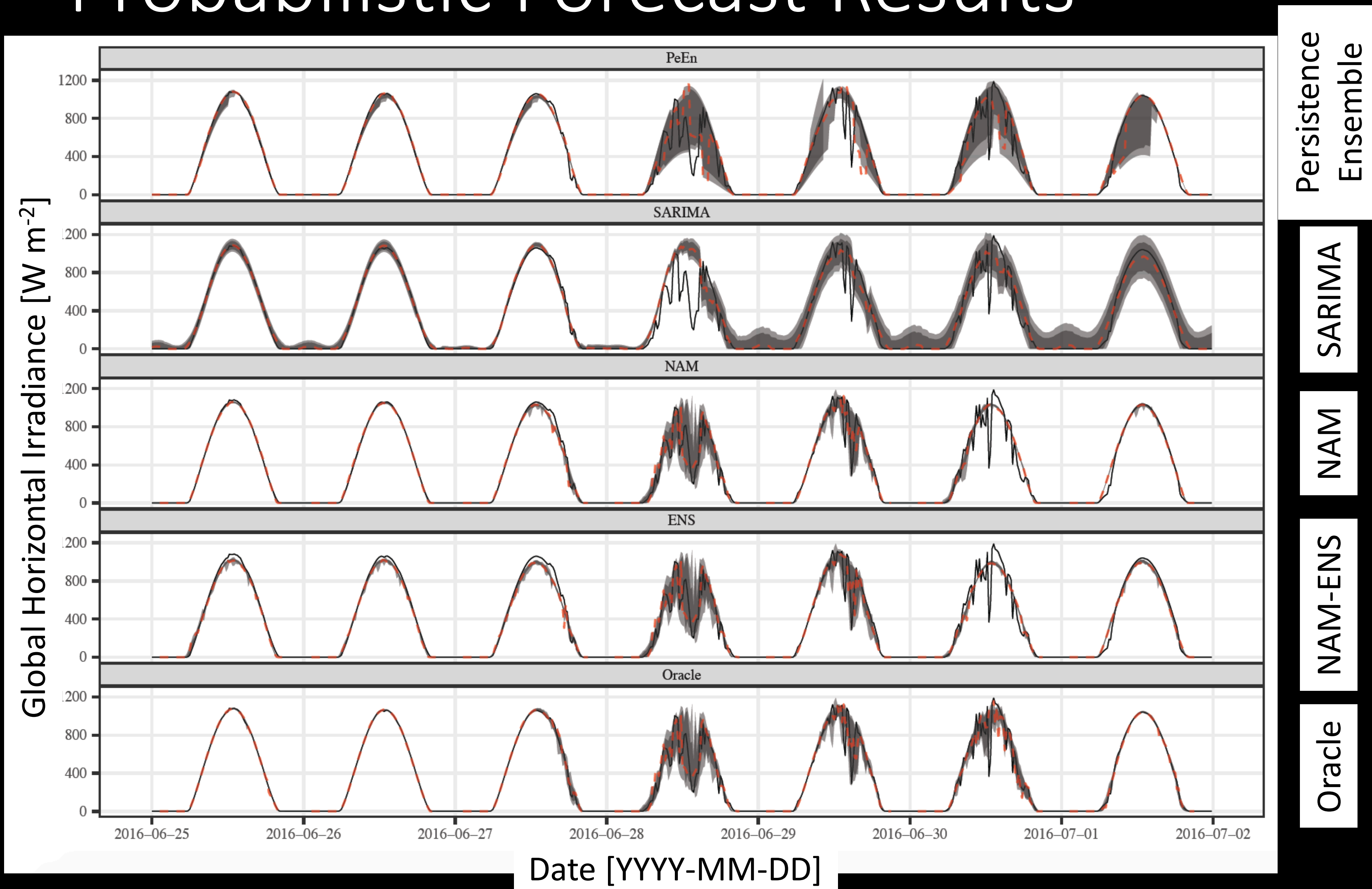


Figure: The forecast $(\mathscr{H}^{24h}, \mathscr{R}^{1h}, \mathscr{L}^{12h}, \mathscr{U}^{24h})$ versus measured GHI at Desert Rock $(-116.02°, 36.62°)$. The component models are arranged in the top row, whereas the ensembles are in the bottom row. Hexagon binning is used for visualization. For a higher contrast, the color scheme is based on the logarithm of bin frequency.

Probabilistic Forecast Results



Conclusions and Future Directions

- Solar forecasts have great value for power grid operations
- Forecast paradigm: ROPES
- Satellite data are underexploited.
  - Coupled data driven – physics models
- Lack of work on longer forecast horizons (weeks to months)