Short-Term Irradiance Forecasting Using an Irradiance Sensor Network, Satellite Imagery, and Data Assimilation

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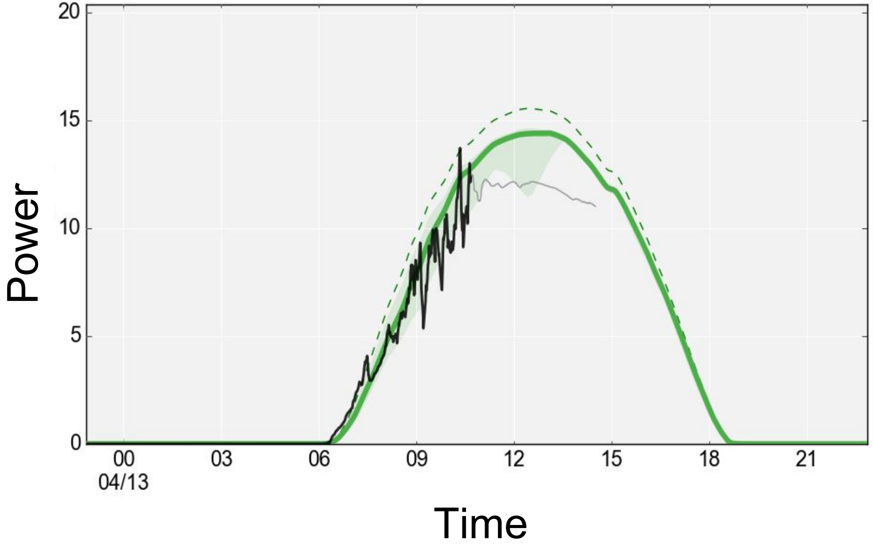
Dissertation Defense

April 14, 2017

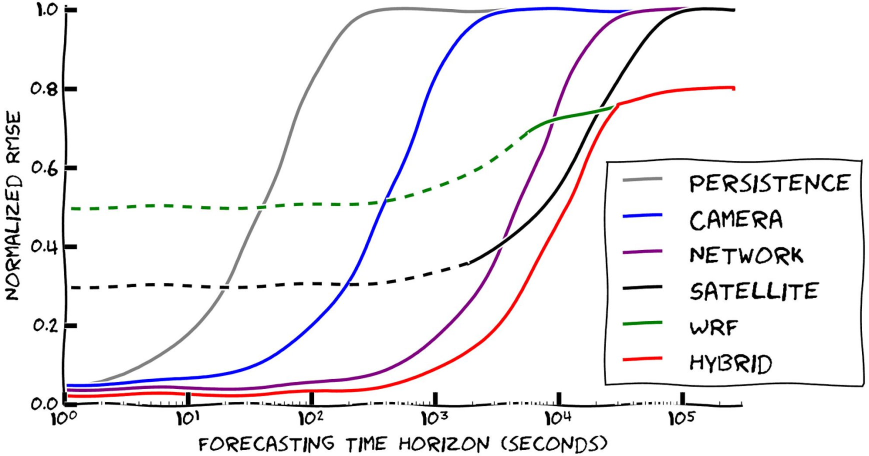
The University of Arizona

Problem & Hypothesis

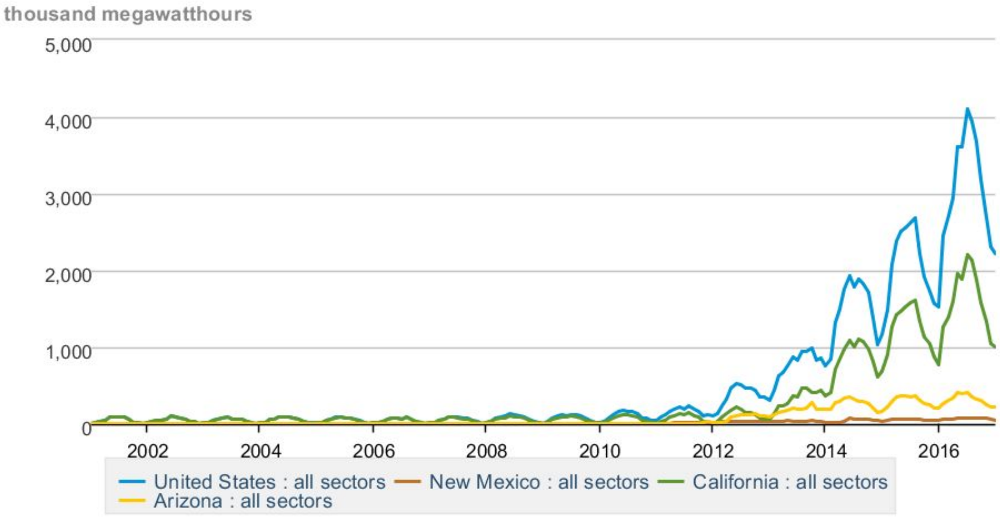
Problem: imperfect solar power forecasts



Hypothesis 1: ground sensors will improve forecasts
Hypothesis 2: hybrid methods will reduce errors



Net generation for all utility-scale solar, monthly



Data source: U.S. Energy Information Administration

BRIEF

CAISO notches record, serving 56.7% of demand with renewable energy in one day

AUTHOR
Peter Maloney
@TopFloorPower

PUBLISHED
March 28, 2017

Dive Brief:

- The California ISO hit an all-time peak percentage, serving 56.7% of demand with renewable energy around 11:19 a.m. on March 23.
- Solar and wind power, combined, also hit a peak on the same day at 49.2% of demand.
- In all, renewable sources produced 186 GWh, representing 33% of the 563 GWh of electricity used on March 23.

Dive Insight:

California is already ahead of its aggressive 50% renewables target and a bill in the state legislature could, if passed, raise the bar to 100% by 2045.

But as renewable energy climbs as a percentage of the state's overall production, some renewable output is going unused.

In a February memo CAISO warned that a “bountiful” hydro conditions and “significant” additional solar installations could result in the curtailment of between 6 GW and 8 GW of renewable capacity this spring.

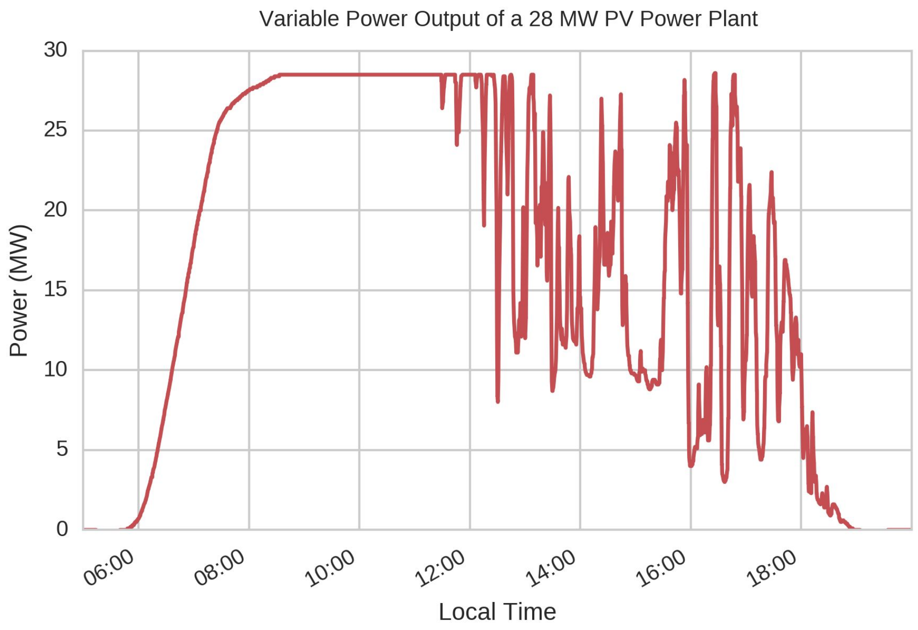
The curtailments could create more opportunities for energy storage that could be used to store unused renewable production for use later in the day when the sun doesn't shine or the wind stops blowing.

California already has some of the largest storage projects in the nation. In February Tesla brought an 80-MWh storage facility online for Southern California Edison and AES Energy Storage and San Diego Gas & Electric

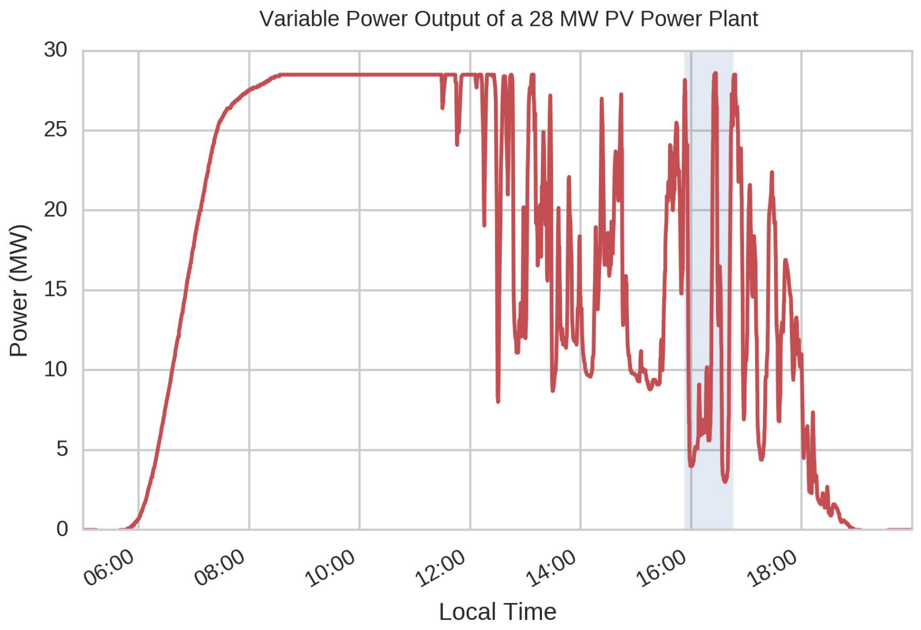
http://www.utilitydive.com/news/caiso-notches-record-serving-567-of-demand-with-renewable-energy-in-one/439085/

Background: Solar Variability

Power from solar plants can be highly variable due to clouds

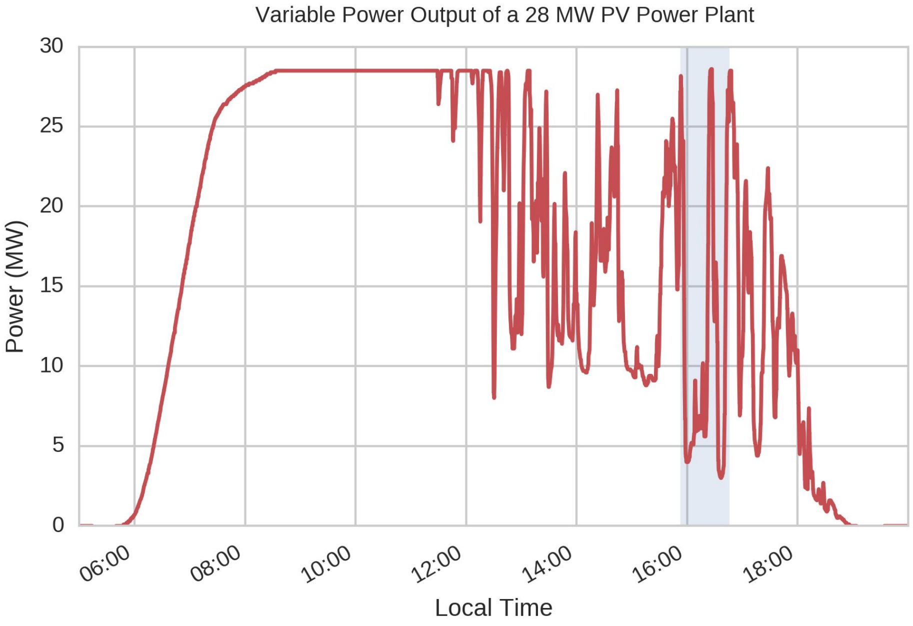


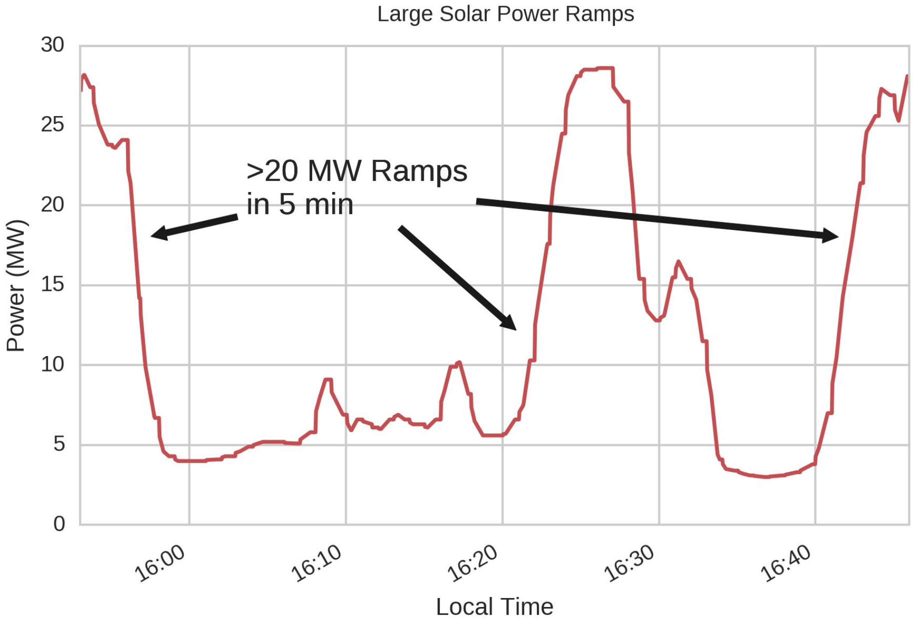
Background: Solar Variability



Background: Solar Variability

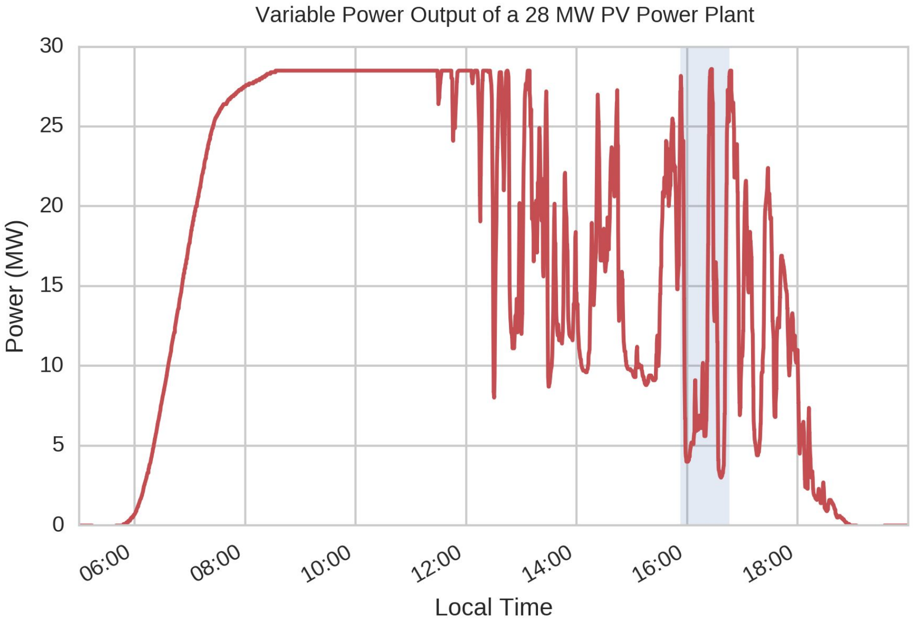
A 20 MW ramp is about equivalent to the demand of 10,000 homes

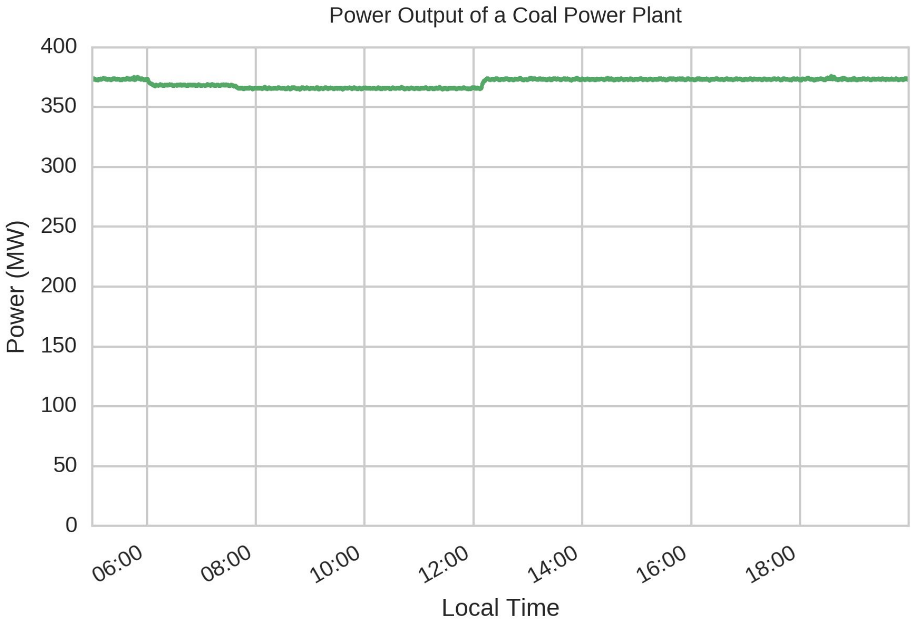




Background: Solar Variability

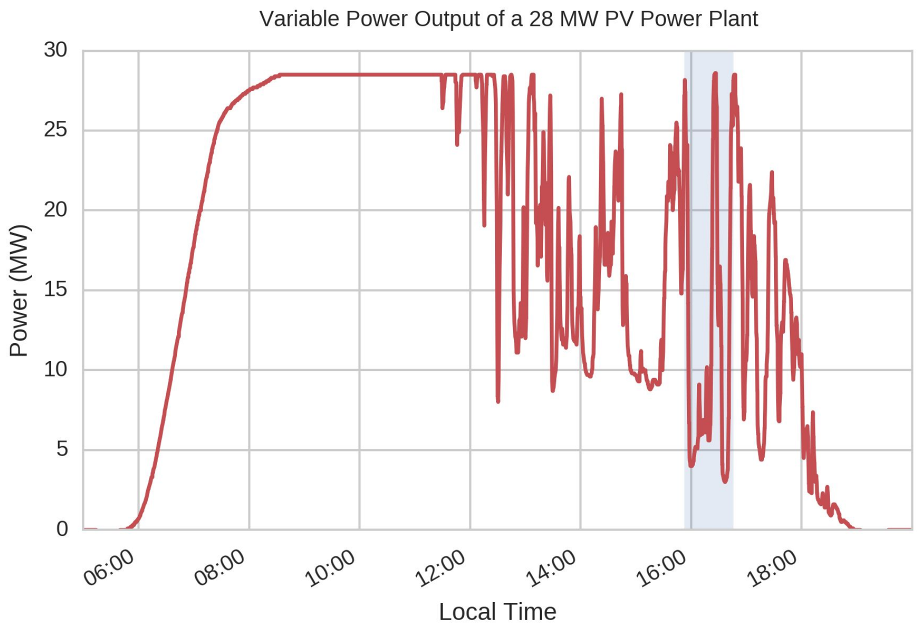
Coal provides base power that cannot change quickly

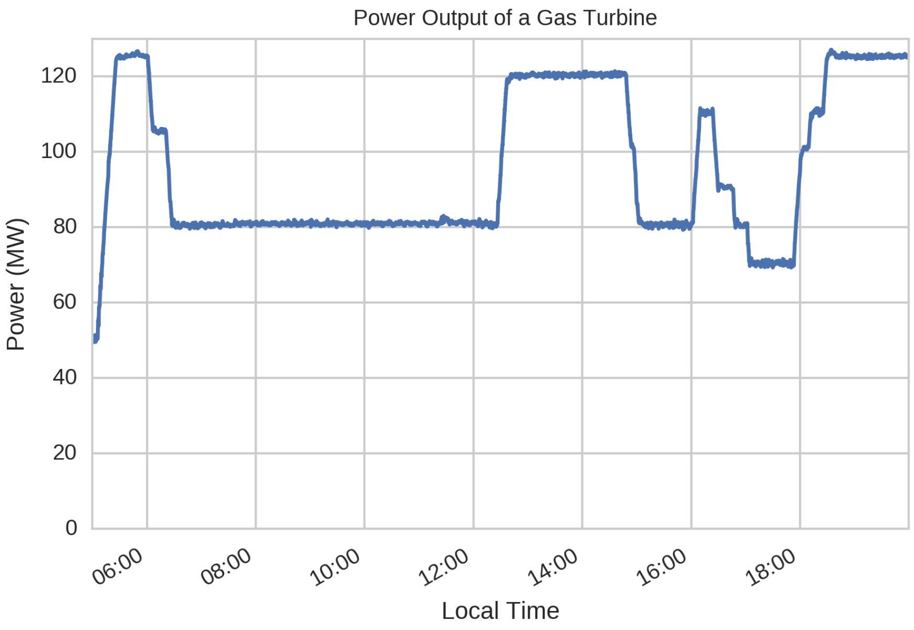




Background: Solar Variability

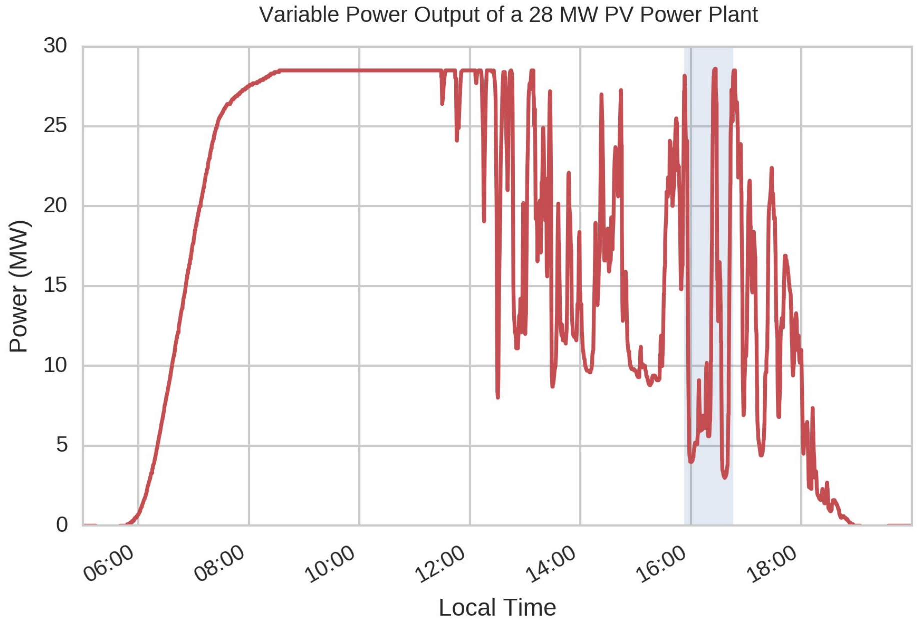
Output from a gas turbine can be ramped quickly. Helps backup solar





Background: Solar Variability

Utilities are accustomed to controlling their generators from a control room

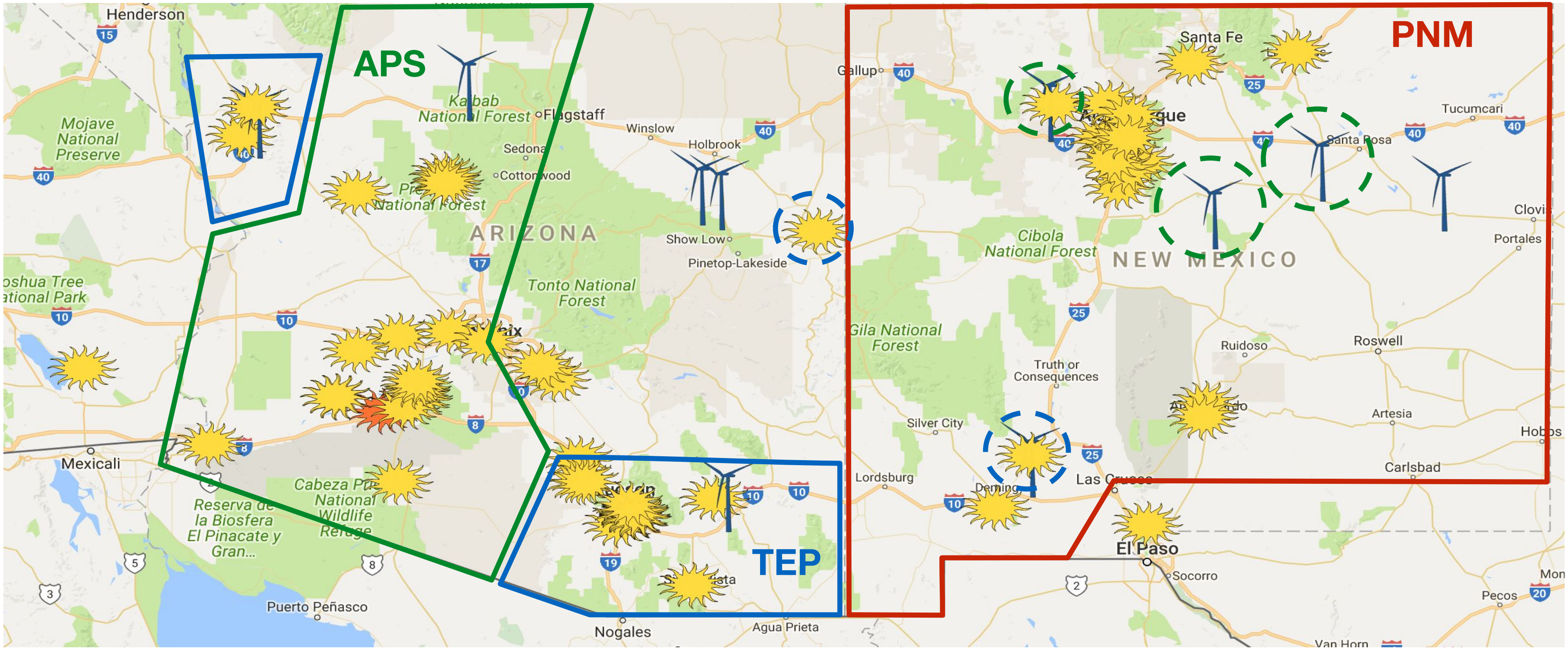


Background: Solar Variability

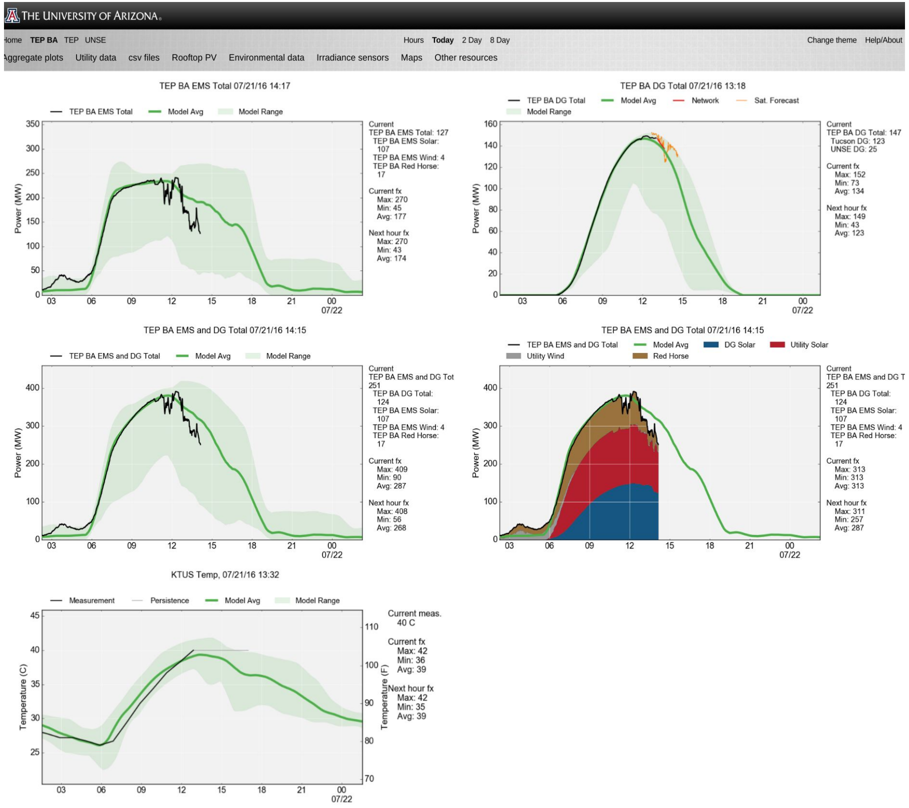
Clouds/weather control the output of solar power plants

Utilities are accustomed to controlling their generators from a control room

UA Forecasting Partners

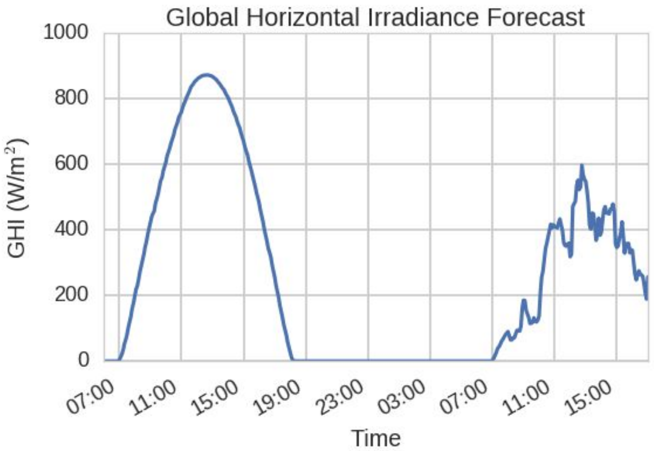


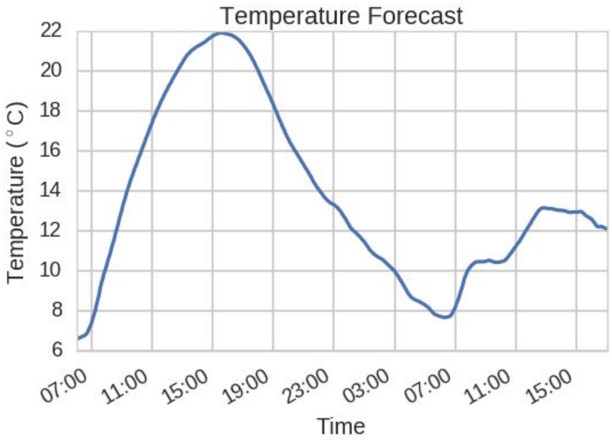
Operational Forecasting for Utilities



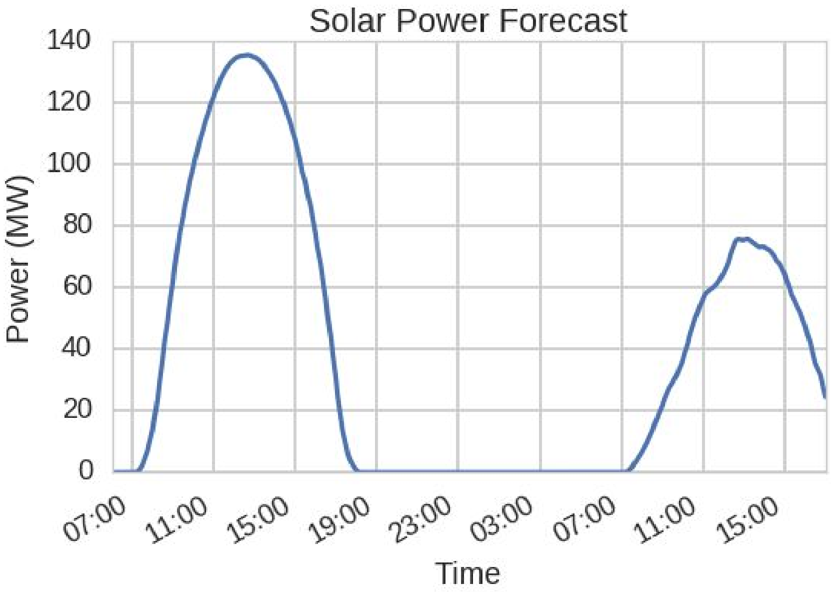
- Our work includes a web page with graphics and information meant to help the utilities understand and use the forecasts
- Also have a HTTP API for programmatic access

Irradiance to Power Conversion

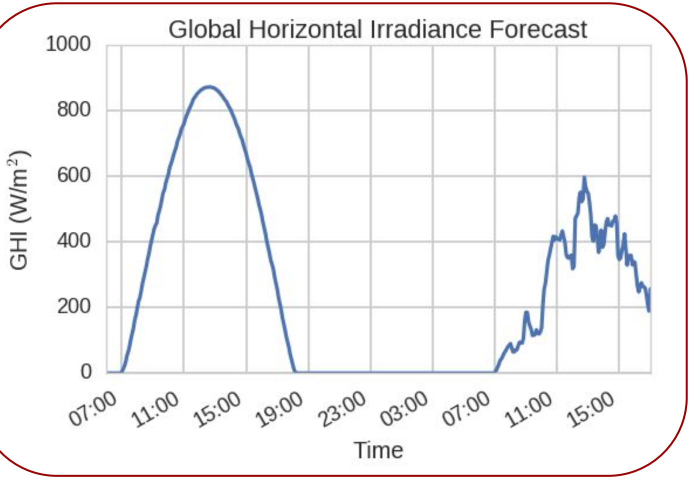




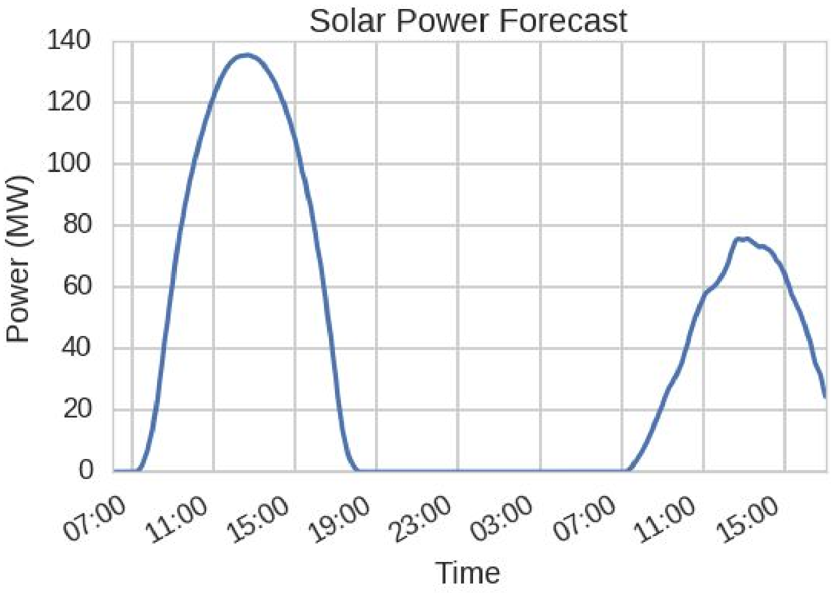
PV System Model →

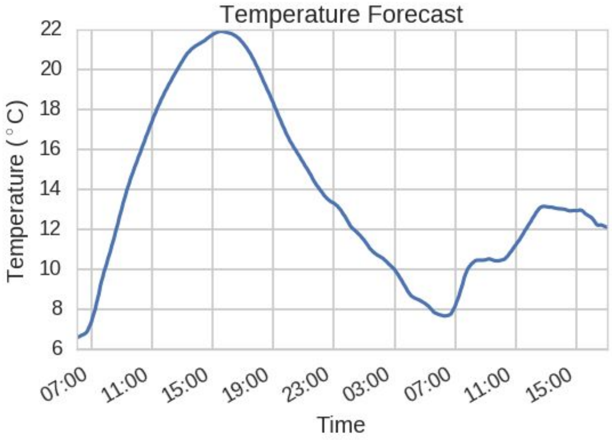


Irradiance to Power Conversion



PV System Model

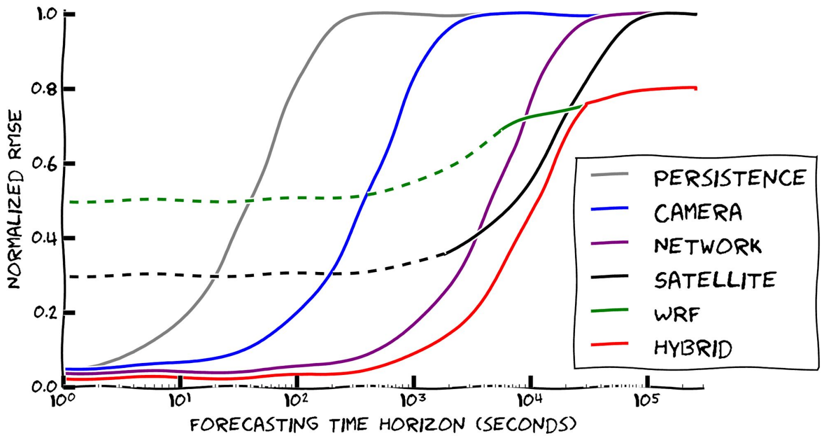




Context & Hypothesis

- TEP, APS, PNM need solar forecasts because variability is an issue
  - Hydrology & Atmospheric Sciences provides forecasts from a weather model (WRF)
  - Physics department explored cloud camera and sensor network approaches

Hypothesis 1: ground sensors will improve forecasts
Hypothesis 2: hybrid methods will reduce errors



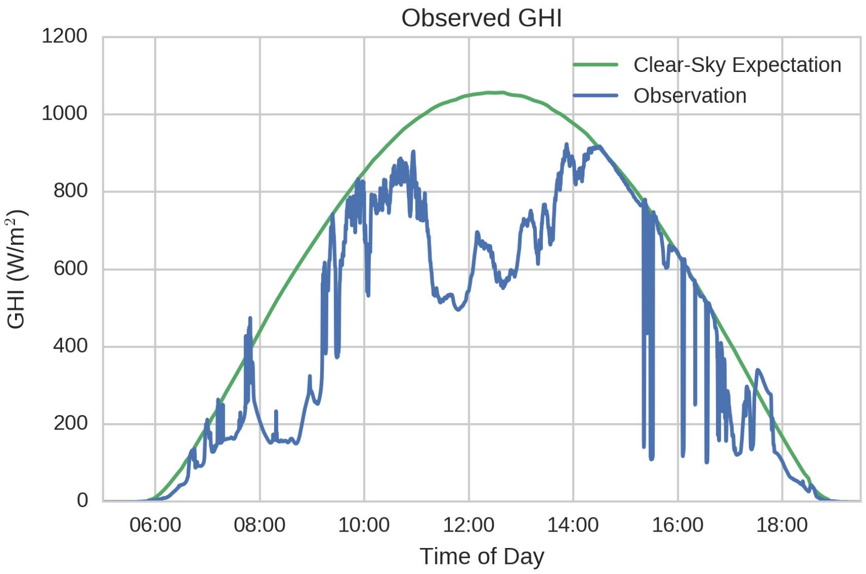
Outline of my work

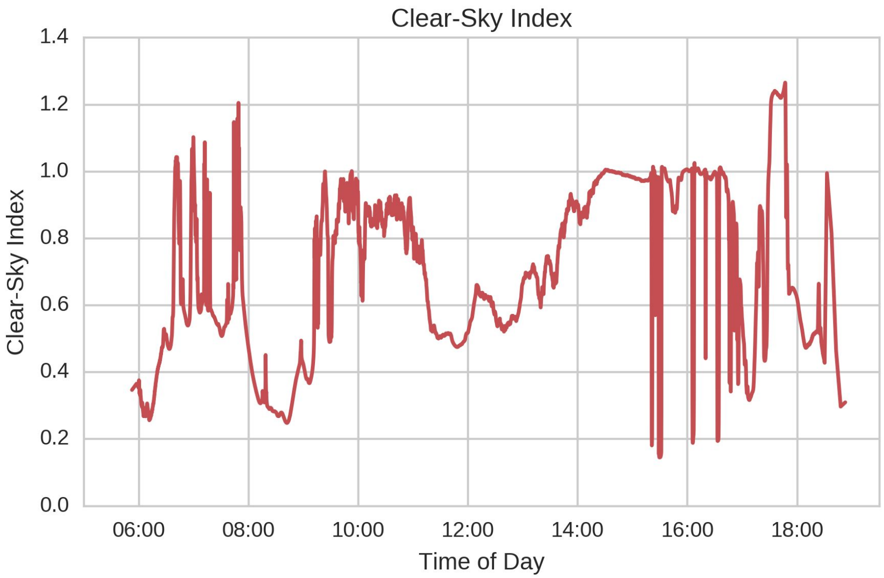
- Benchmark forecasts
- Irradiance network forecasts
- Satellite data assimilation

Clear-Sky Index

Clear-Sky Index = Observations / Clear-Sky Expectation

$$k(t) = y(t)/y^{clr}(t)$$





Terms

$$y(t_i) \equiv \text{observation at time } t_i$$

$$\hat{y}(t_i) \equiv \text{forecast at time } t_i$$

$$y^{clr}(t_i) \equiv \text{clear-sky expectation at time } t_i$$

$$k(t_i) \equiv \text{clear-sky index at time } t_i$$

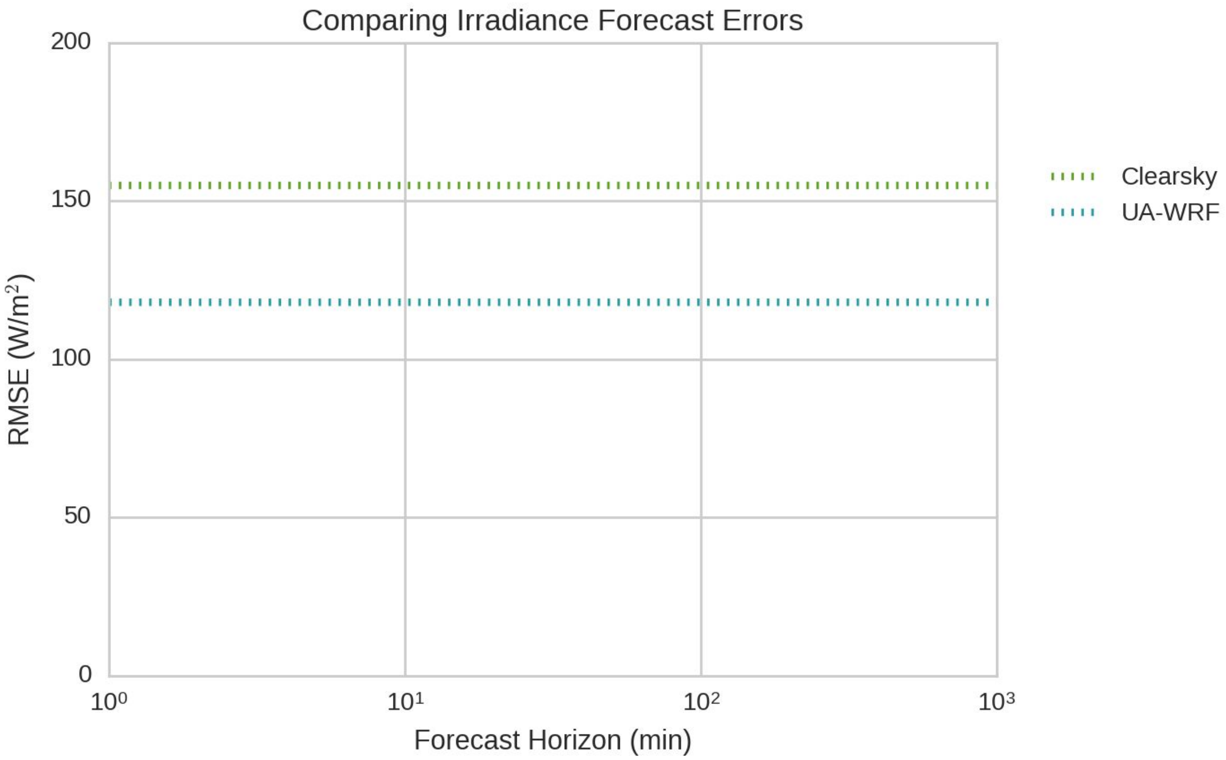
$$d \equiv \text{delay or forecast horizon}$$

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}\left[\hat{y}(t_i) - y(t_i)\right]$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}(t_i) - y(t_i)\right|$$

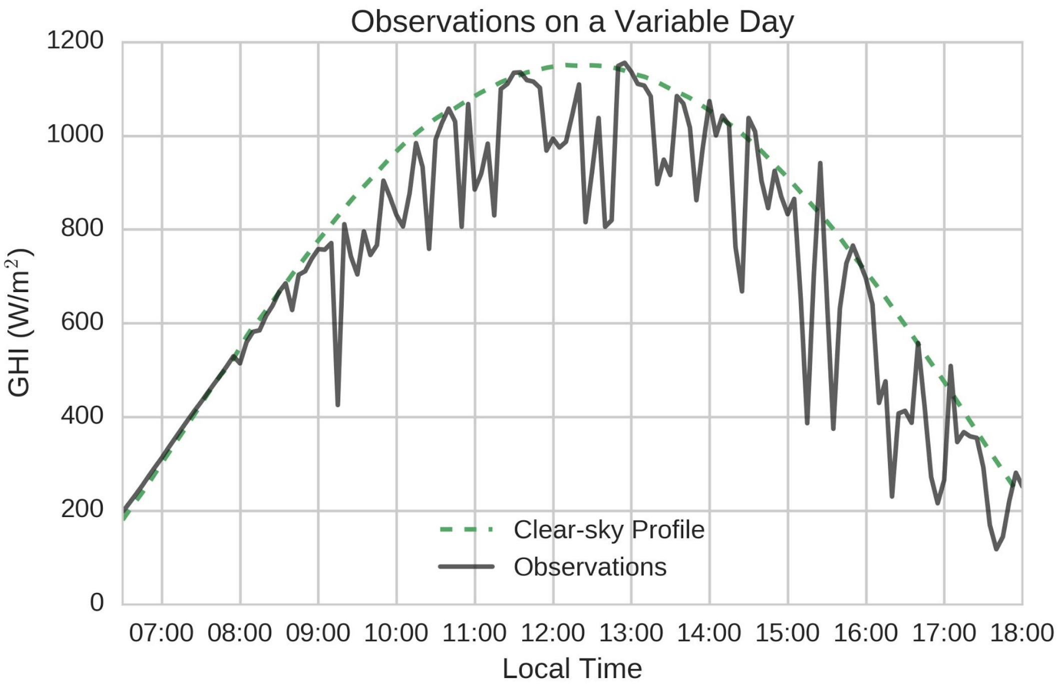
$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\hat{y}(t_i) - y(t_i)\right]^2}$$

Benchmarks



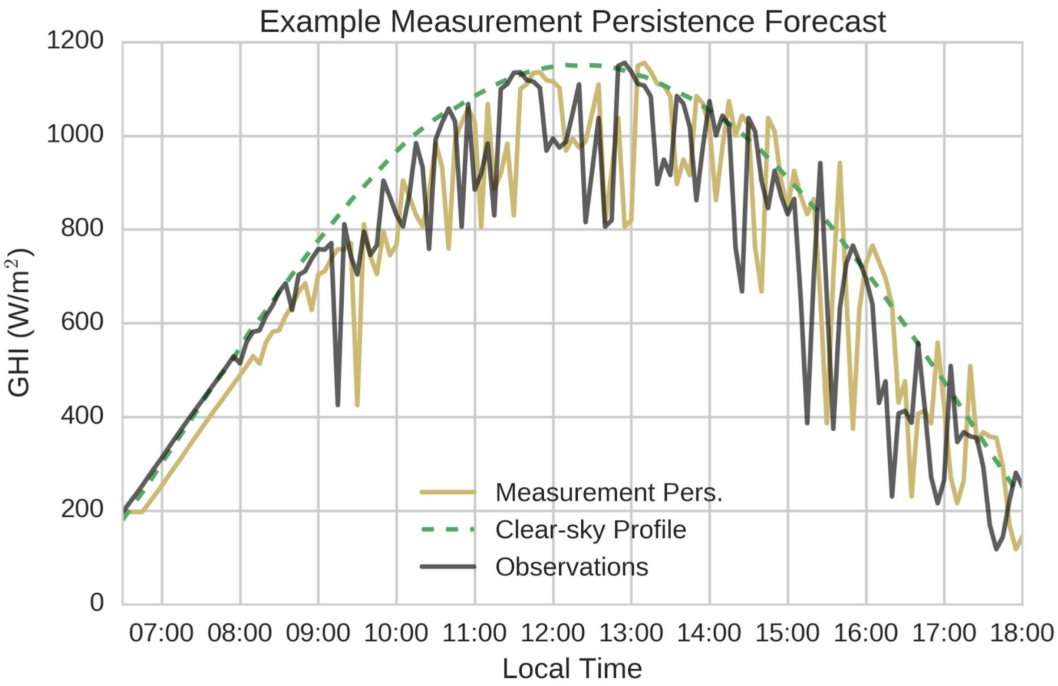
Comparing Irradiance Forecast Errors
200
150
100
50
0
RMSE (W/m2)
10⁰
10¹
10²
10³
Forecast Horizon (min)
Clearsky
UA-WRF

Persistence Forecasts



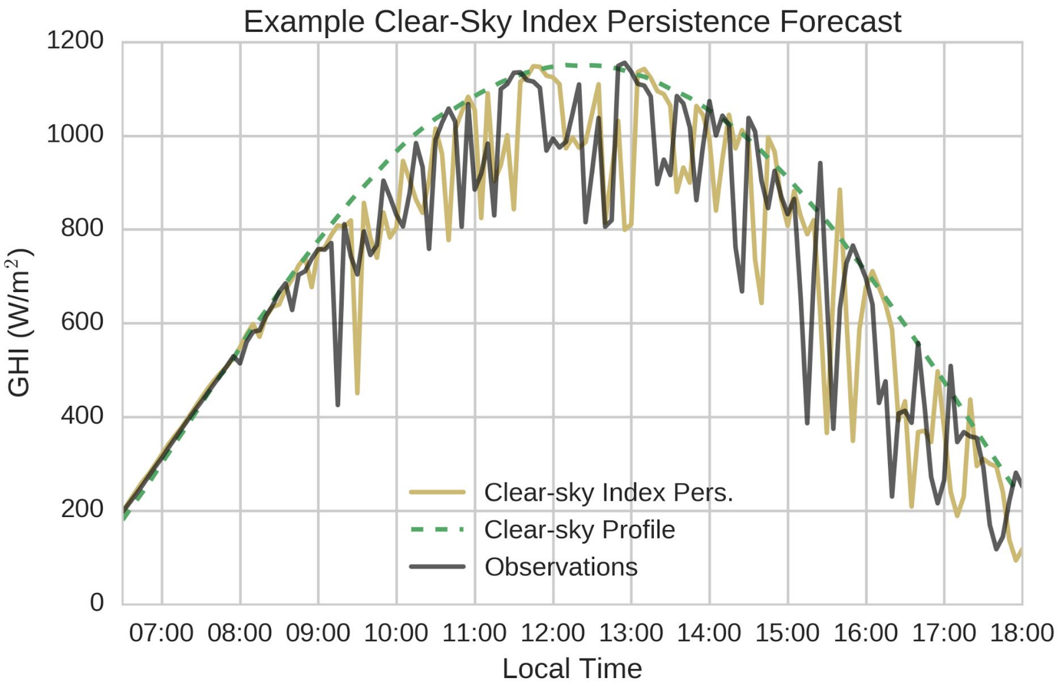
- Forecast assuming a quantity doesn’t change, e.g.
  - “the power output tomorrow will be the same as today”
  - “the GHI in 15 minutes will be the same as it is now”

Persistence Forecasts



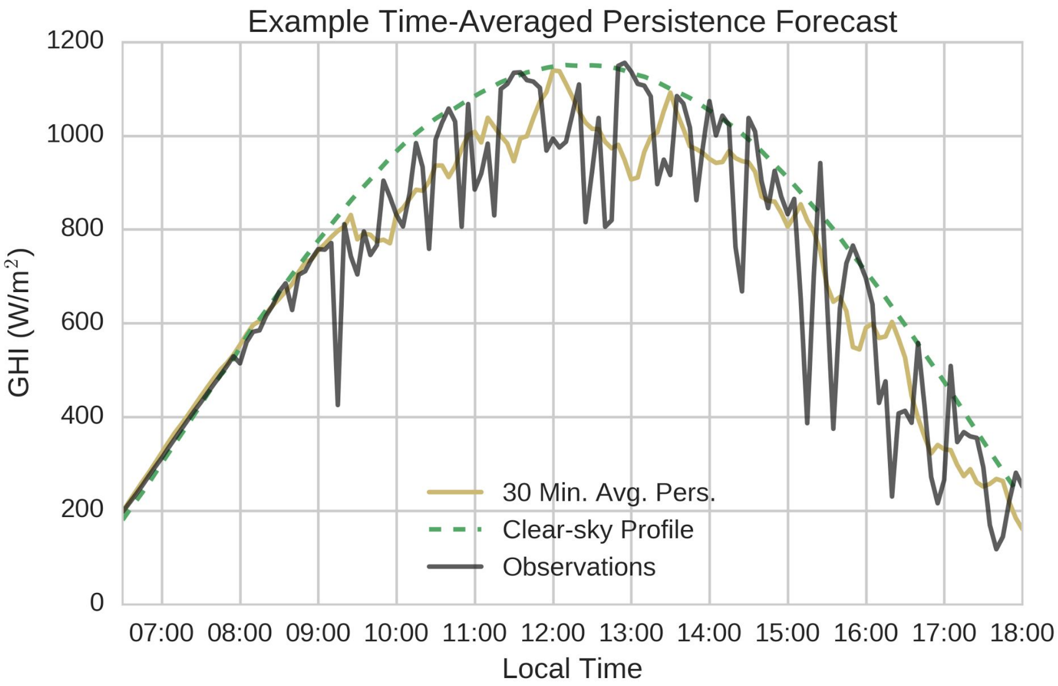
$$\hat{y}(t_i) = y(t_i - d)$$

Persistence Forecasts



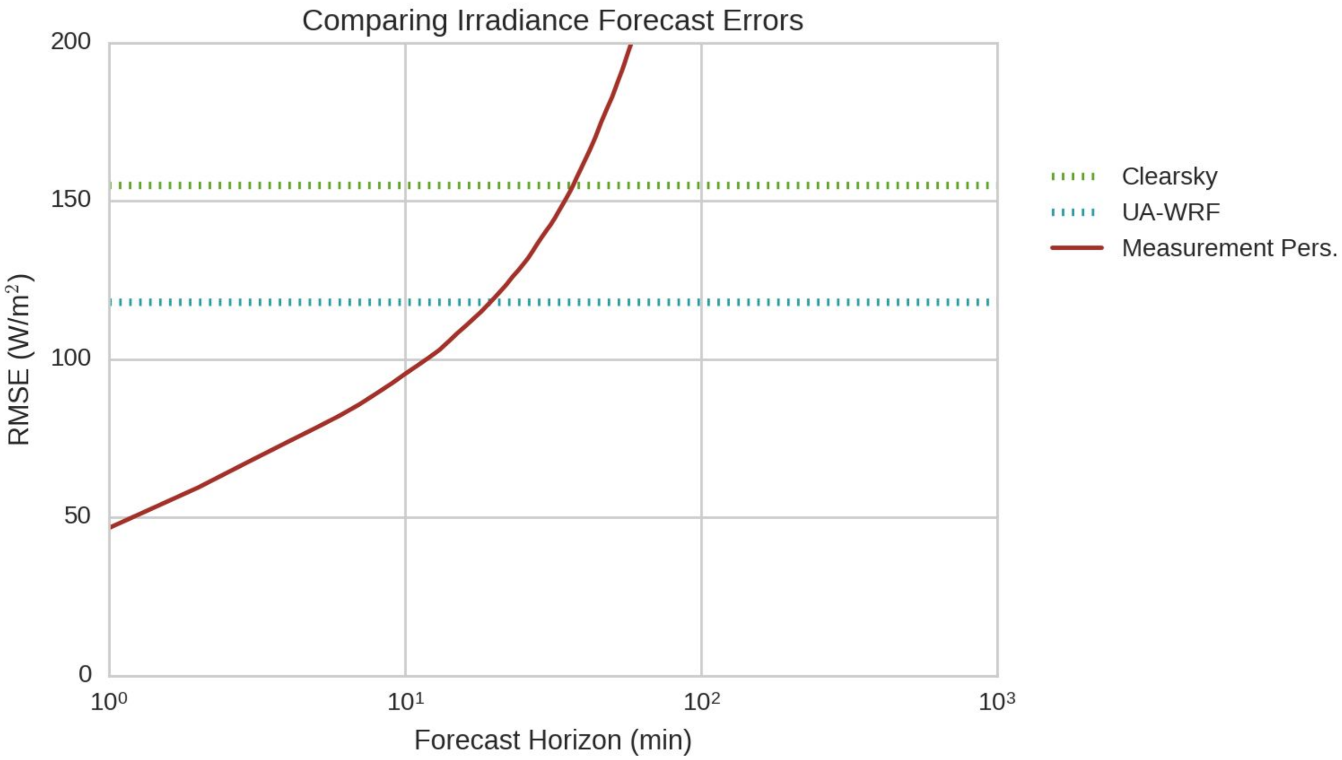
$$\hat{y}(t_i) = y^{clr}(t_i)\ k(t_i - d)$$

Persistence Forecasts



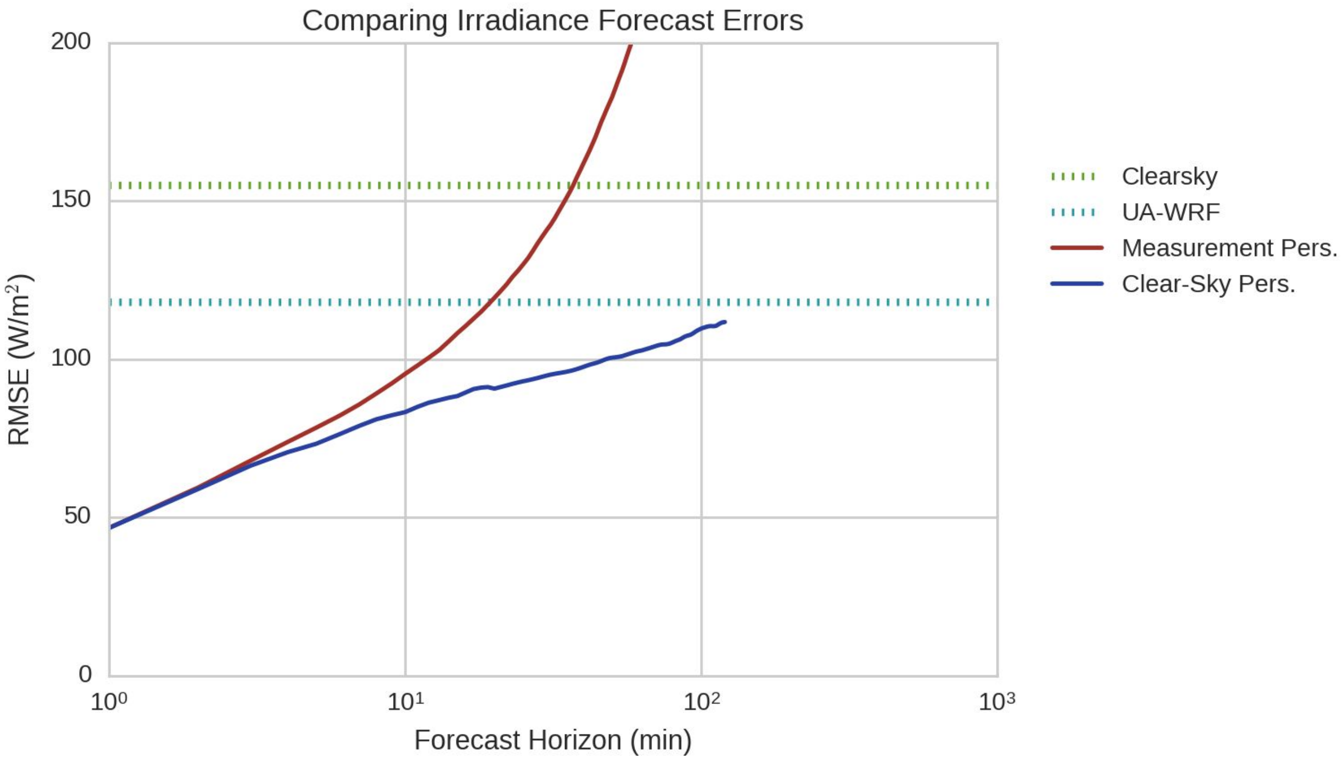
$$\hat{y}(t_i) = y^{clr}(t_i)\ \bar{k}(t_i - d)$$

Benchmarks



Comparing Irradiance Forecast Errors
200
150
100
50
0
RMSE (W/m²)
10⁰
10¹
10²
10³
Forecast Horizon (min)
Clearsky
UA-WRF
Measurement Pers.

Benchmarks



Comparing Irradiance Forecast Errors
200
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100
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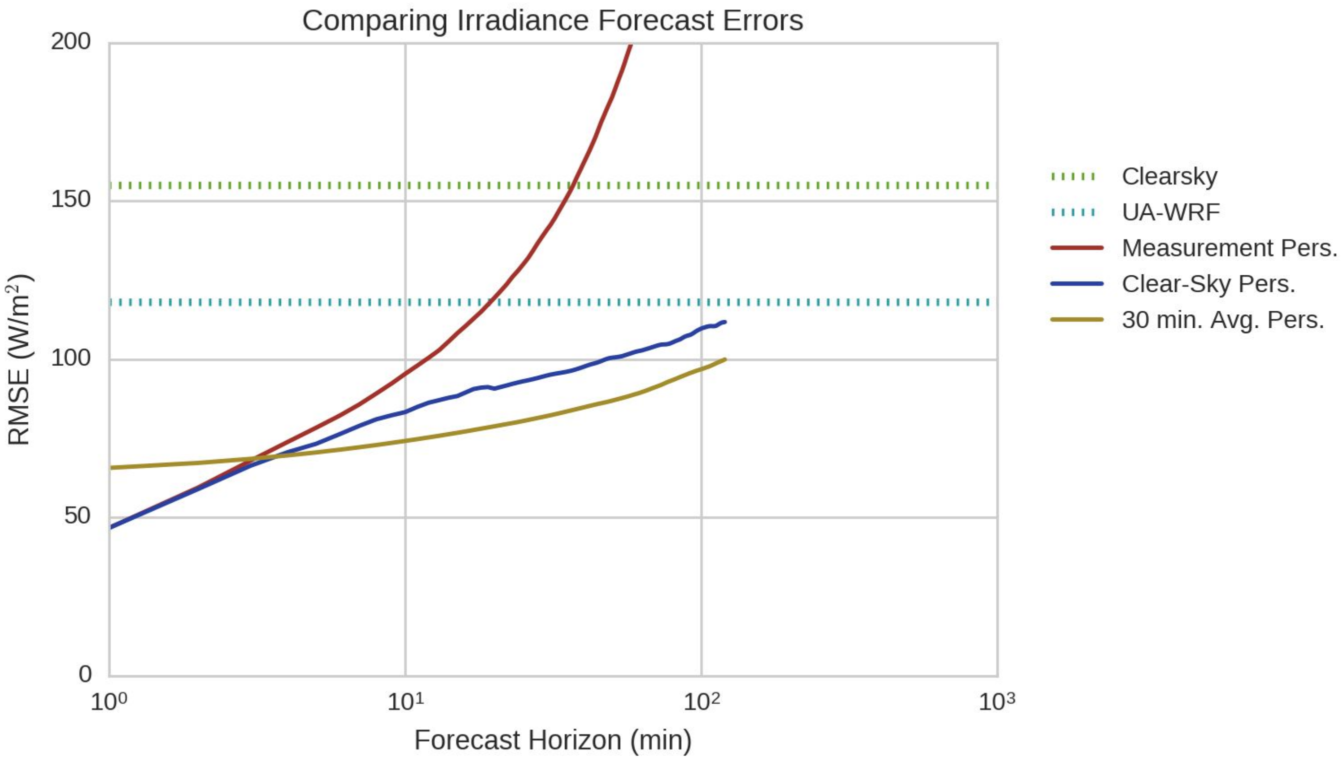
0
RMSE (W/m²)
10⁰
10¹
10²
10³
Forecast Horizon (min)
Clearsky
UA-WRF
Measurement Pers.
Clear-Sky Pers.

Benchmarks

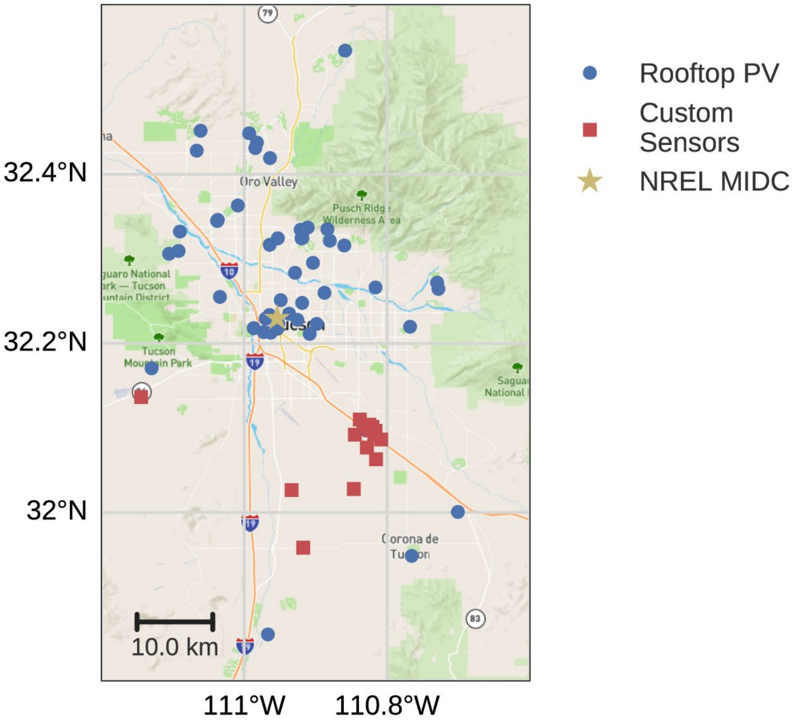

Comparing Irradiance Forecast Errors
200
150
100
50
0
RMSE (W/m²)
10⁰
10¹
10²
10³
Forecast Horizon (min)
Clearsky
UA-WRF
Measurement Pers.
Clear-Sky Pers.
30 min. Avg. Pers.

Outline of my work

- Benchmark forecasts
- Irradiance network forecasts
- Satellite data assimilation

Irradiance Sensor Network

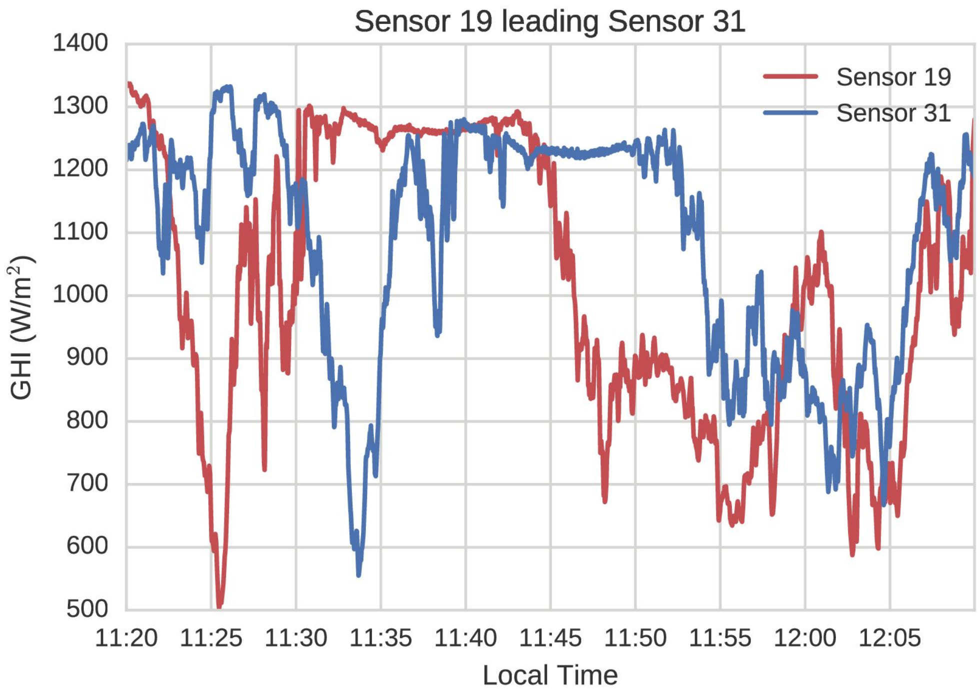
- Custom sensors
  - Inexpensive ($500)
  - Solar panel + battery power
  - GSM modem to transmit data in real-time
  - Built and deployed in 2014
- Rooftop PV power data
  - 5 minute average power
  - Proxy for irradiance
  - Thanks to Technicians for Sustainability!



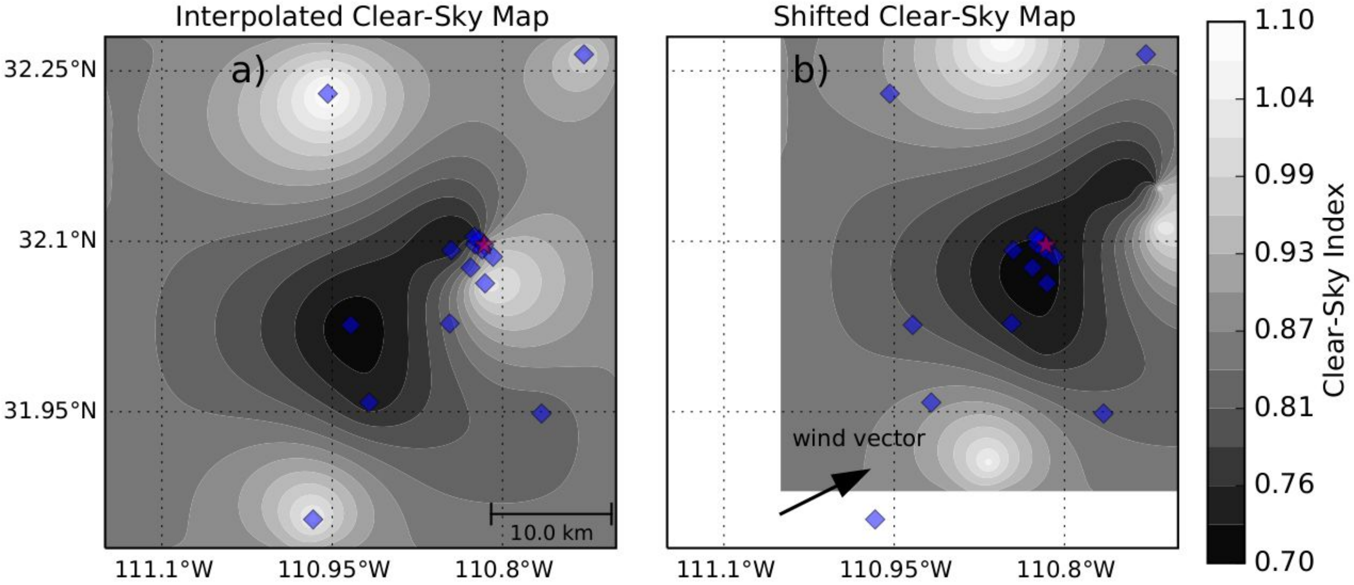
A. T. Lorenzo, W. F. Holmgren, M. Leuthold, C. K. Kim, A. D. Cronin, and E. A. Betterton, "Short-term PV power forecasts based on a real-time irradiance monitoring network," in 2014 IEEE 40th Photovoltaic Specialist Conference (PVSC), 2014, pp. 0075–0079.

Network Forecasts: Basic Premise

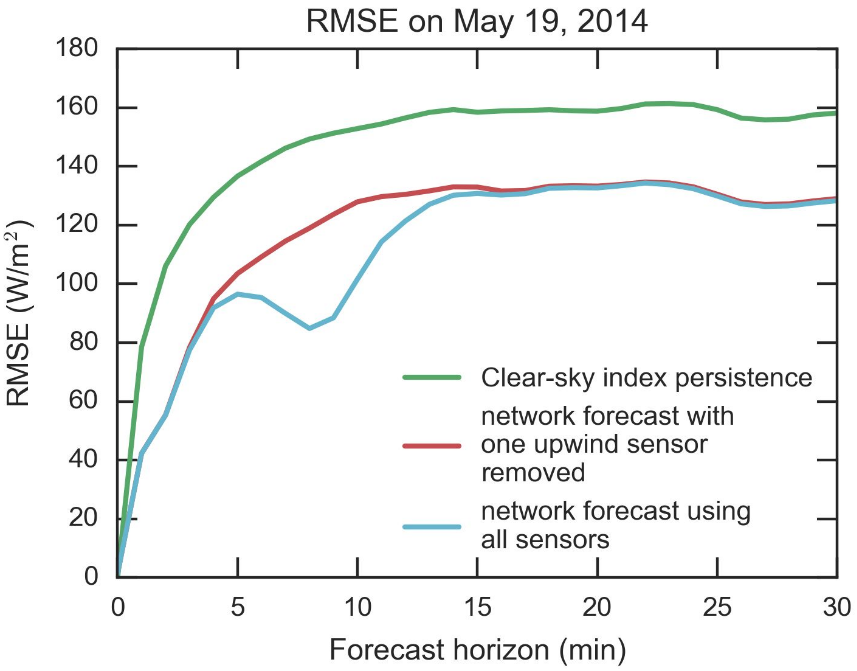
- One sensor predicts the output of another
- Map cloud field with enough sensors



Network Forecasts: Implementation



Network Forecasts: Results



- 20% improvement over clear-sky index persistence on average for 3 months of data
- Surprise: this 20% improvement was seen even at 2 hours
- Comparing only RMSE is not enough

Taylor Diagram

$$\mathrm{RMSE}^2 = \sigma_f^2 + \sigma_r^2 - 2\sigma_f\sigma_r R + \mathrm{MBE}^2$$

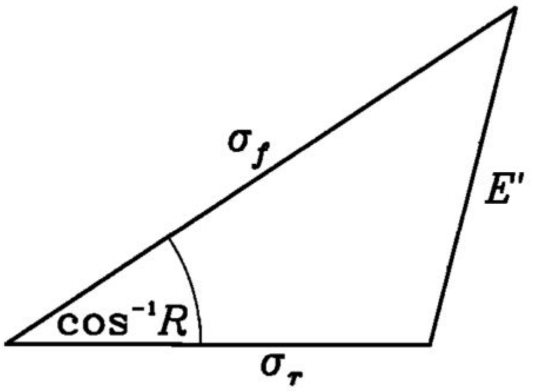
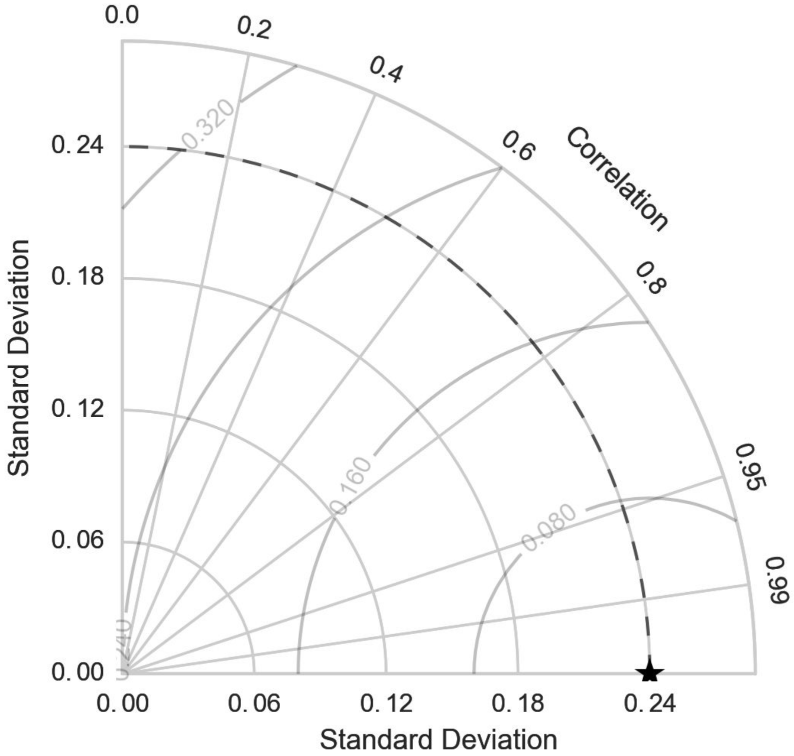
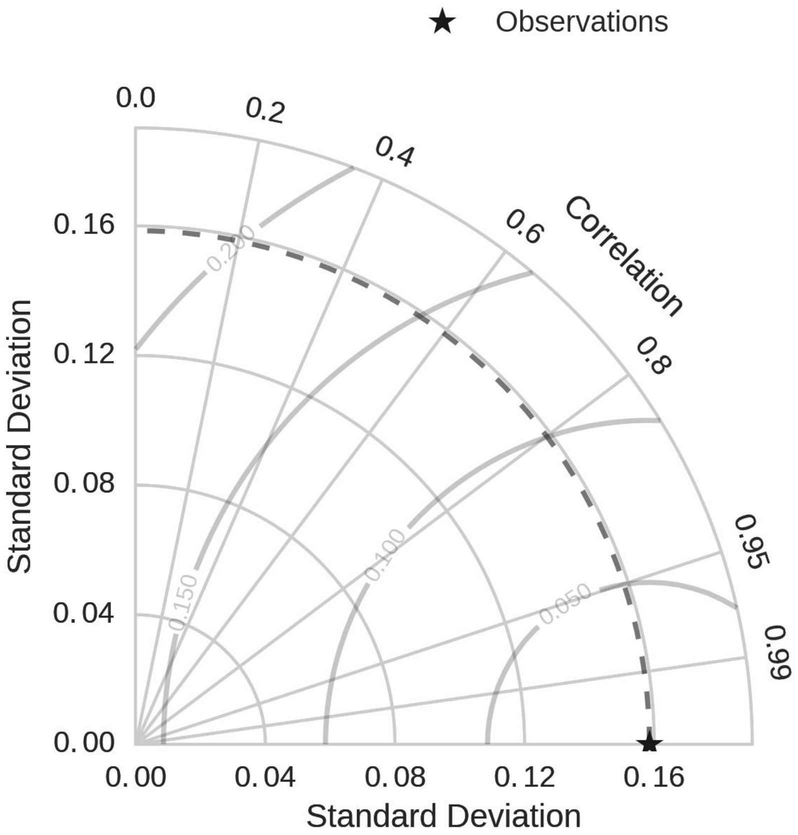


Figure 1. Geometric relationship between the correlation coefficient R, the centered pattern RMS error E', and the standard deviations σ_f and σ_r of the test and reference fields, respectively.

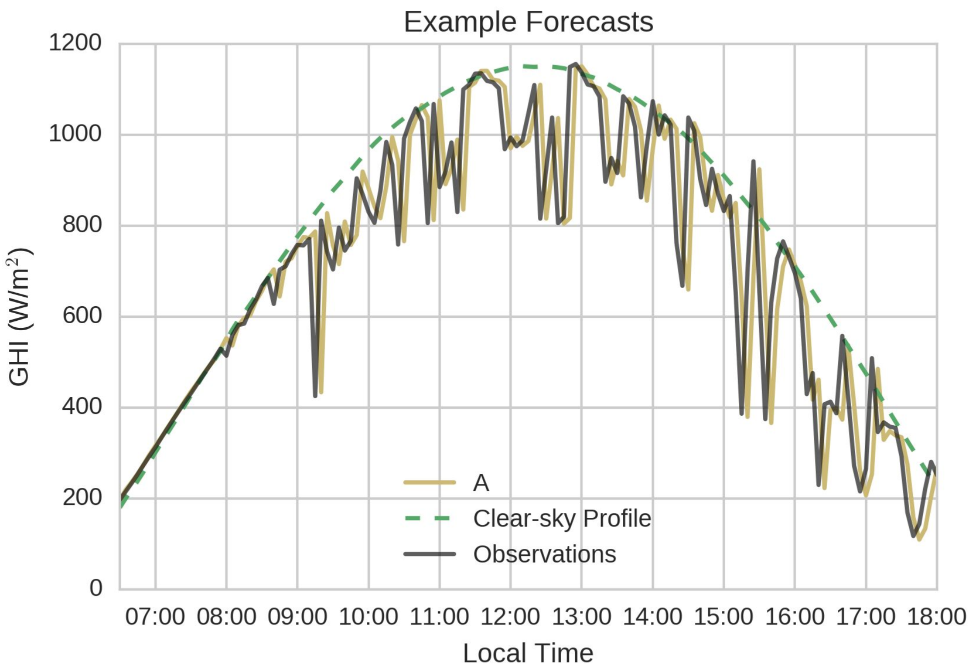


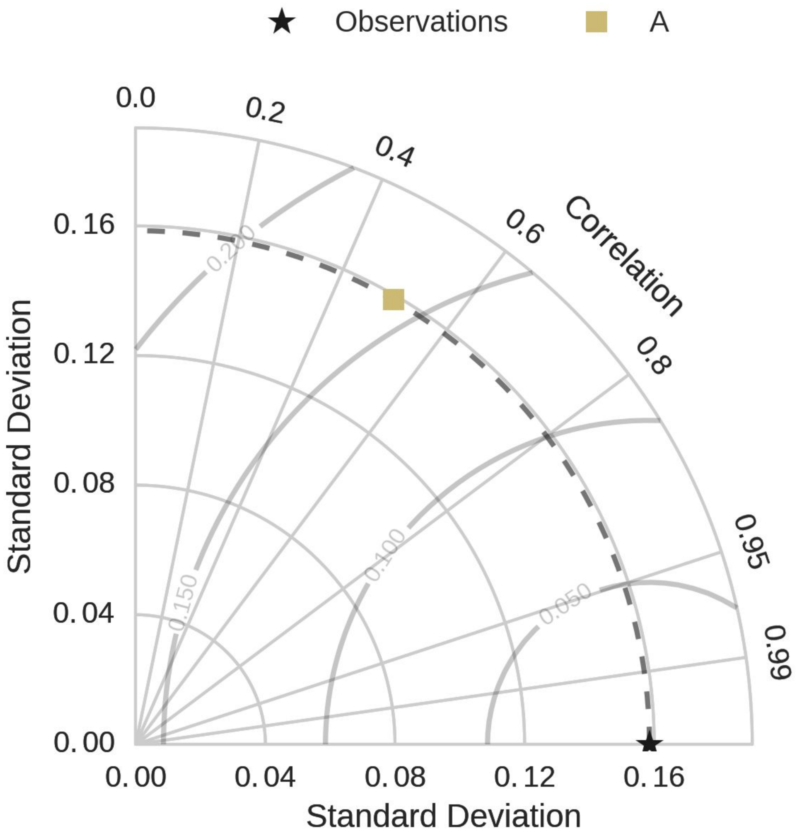
Source: Taylor, 2001 doi: 10.1029/2000JD900719

Taylor Diagram

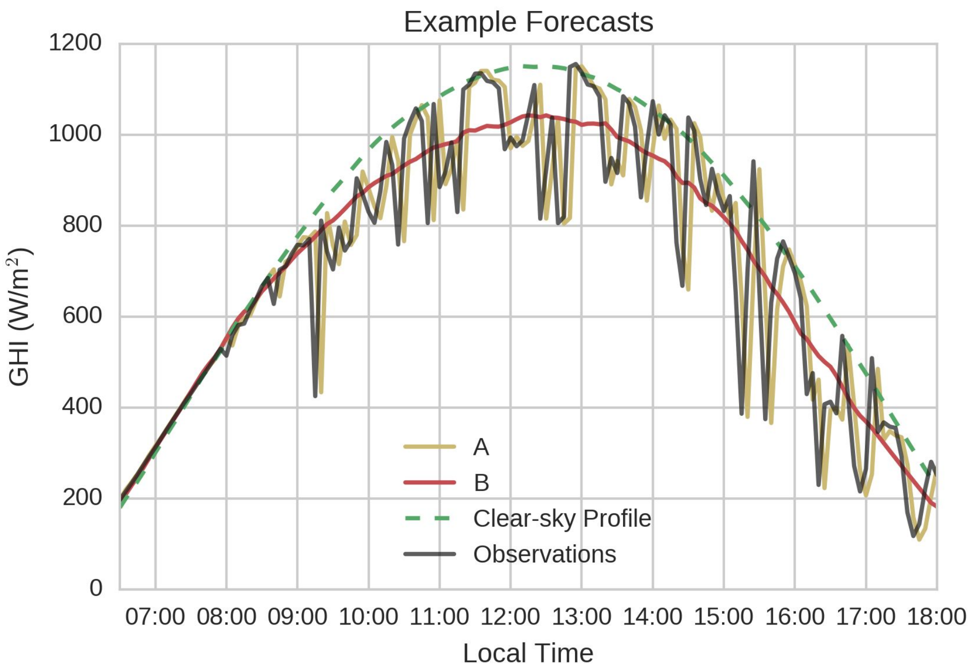


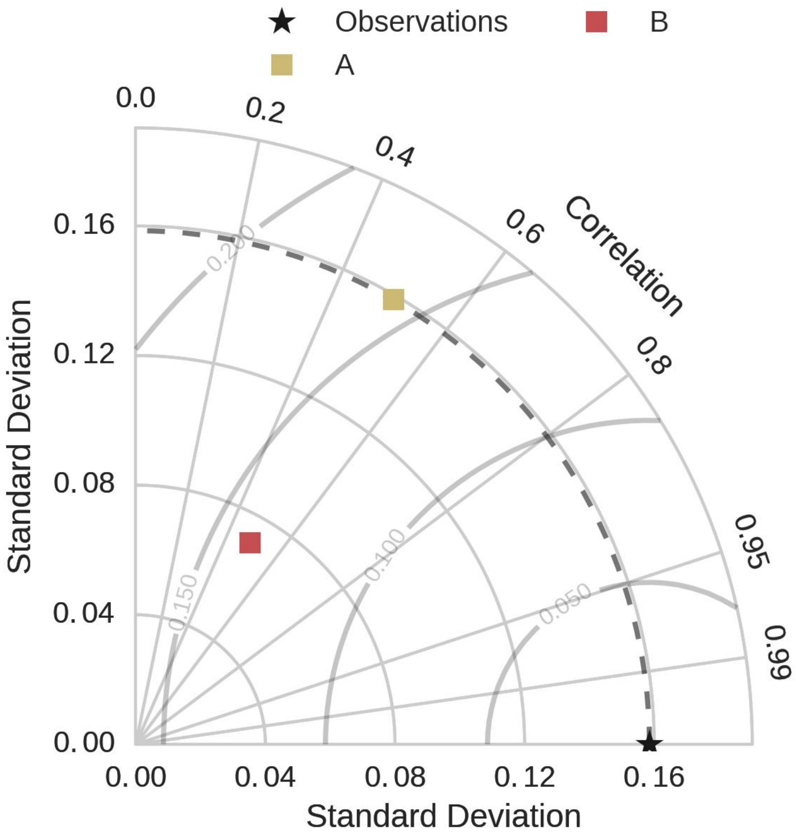
Taylor Diagram



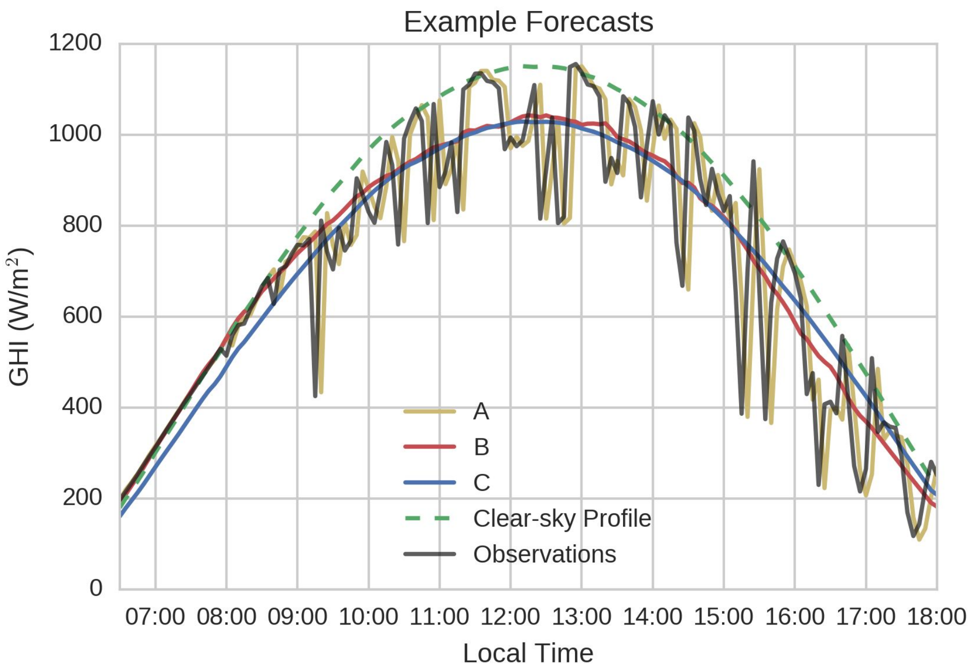


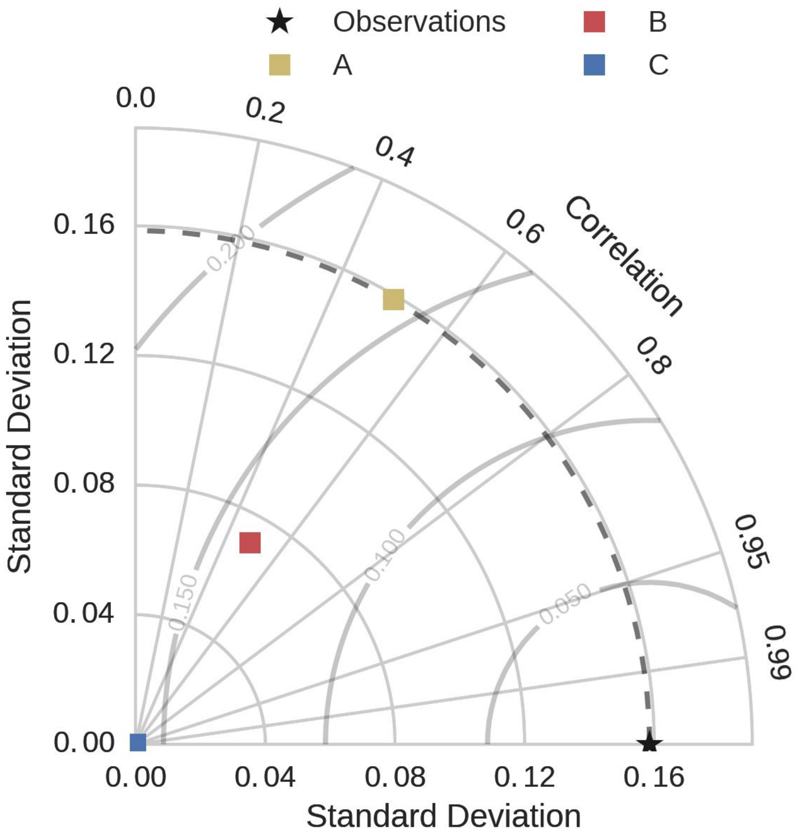
Taylor Diagram



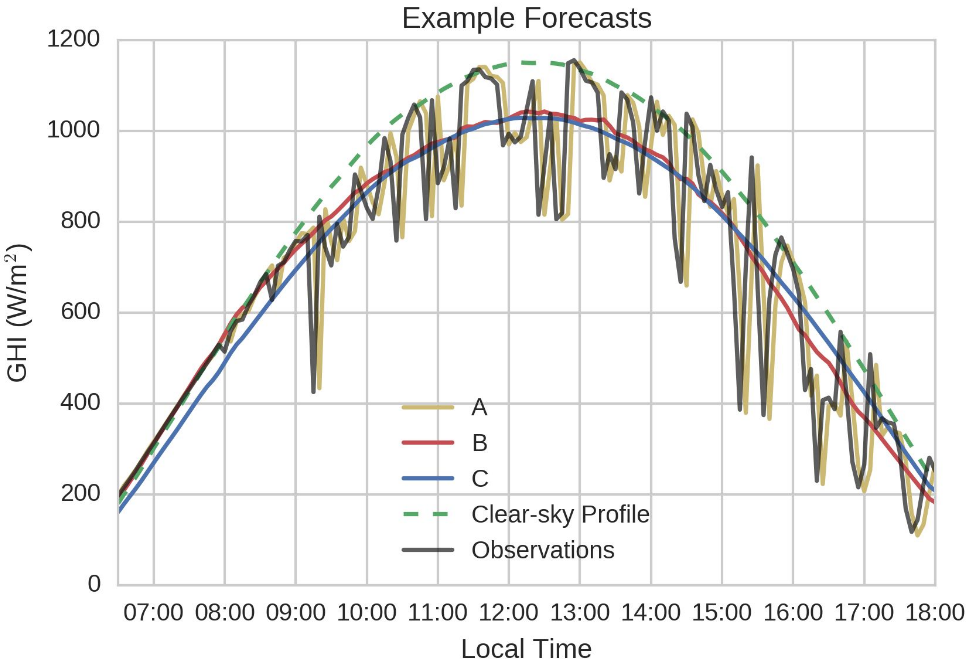


Taylor Diagram



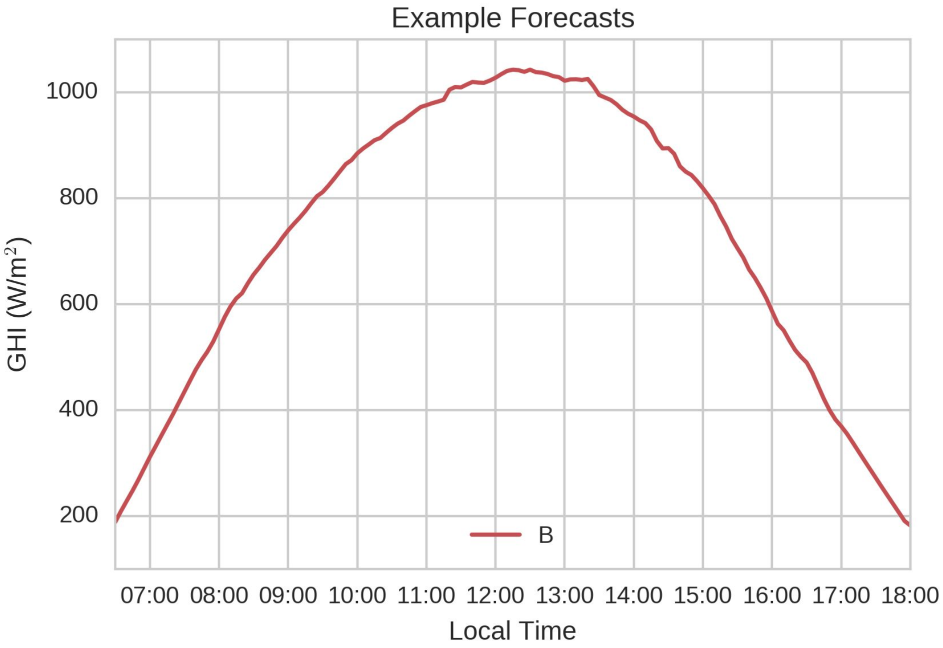


Taylor Diagram



	A	B	C
MBE	0.00	0.02	0.01
MAE	0.10	0.09	0.12
RMSE	0.16	0.13	0.16
Correlation	0.49	0.53	–
Std. Dev.	0.15	0.07	0.00

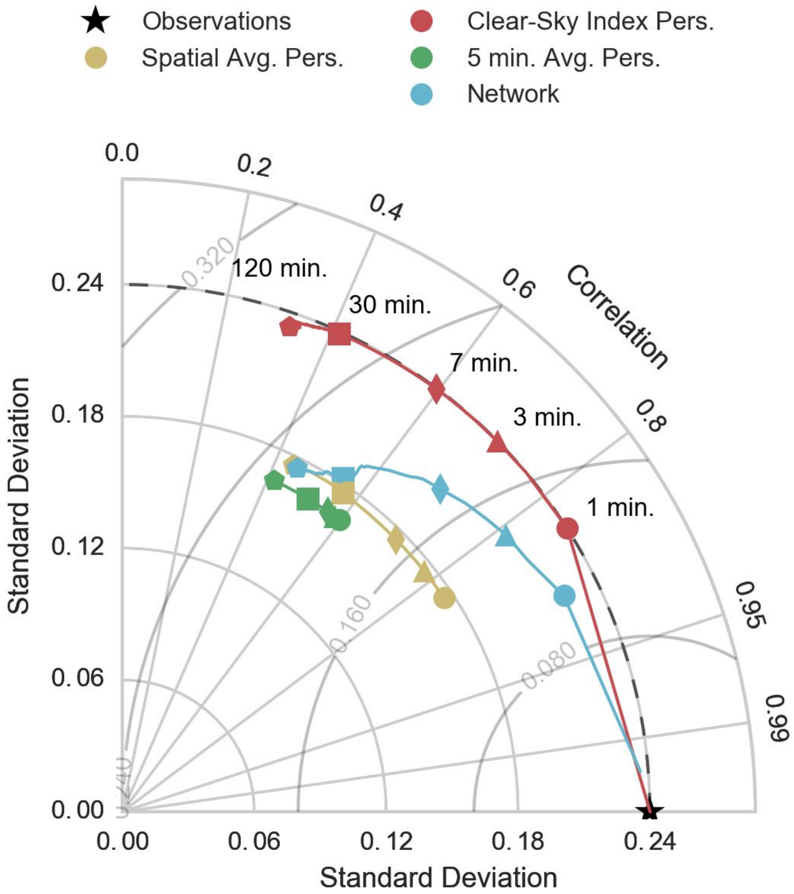
Taylor Diagram



- How the forecast will be used is important to assessing forecast quality
- Analyzing only RMSE may not be enough

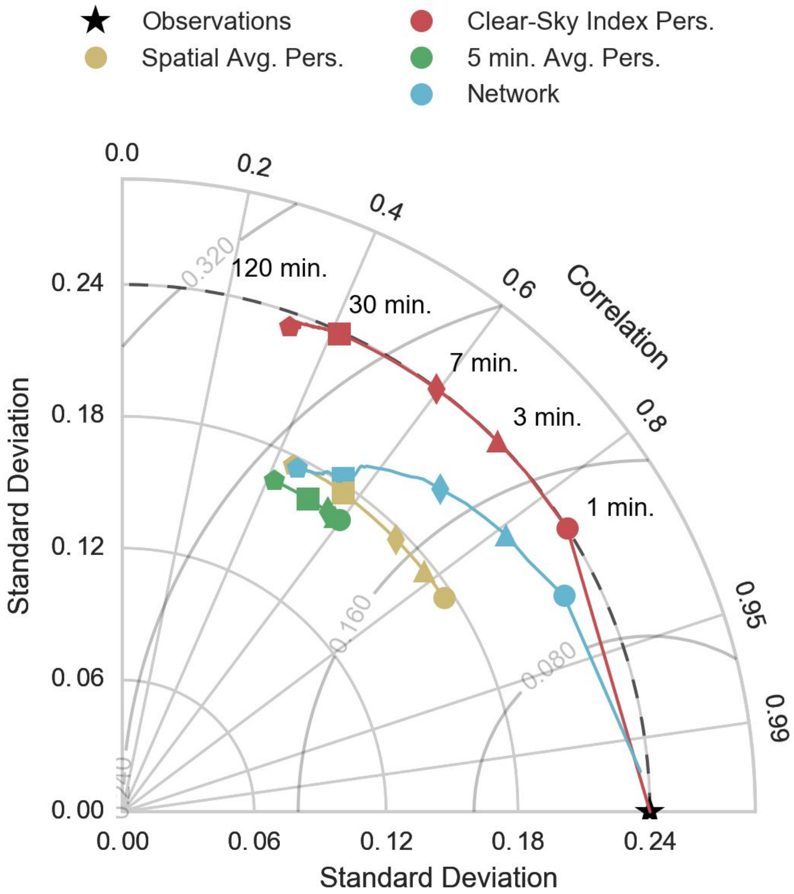
Taylor Diagram for Network Forecasts

- Network forecasts may have larger RMSE at some time horizons, but they better capture the observed variability

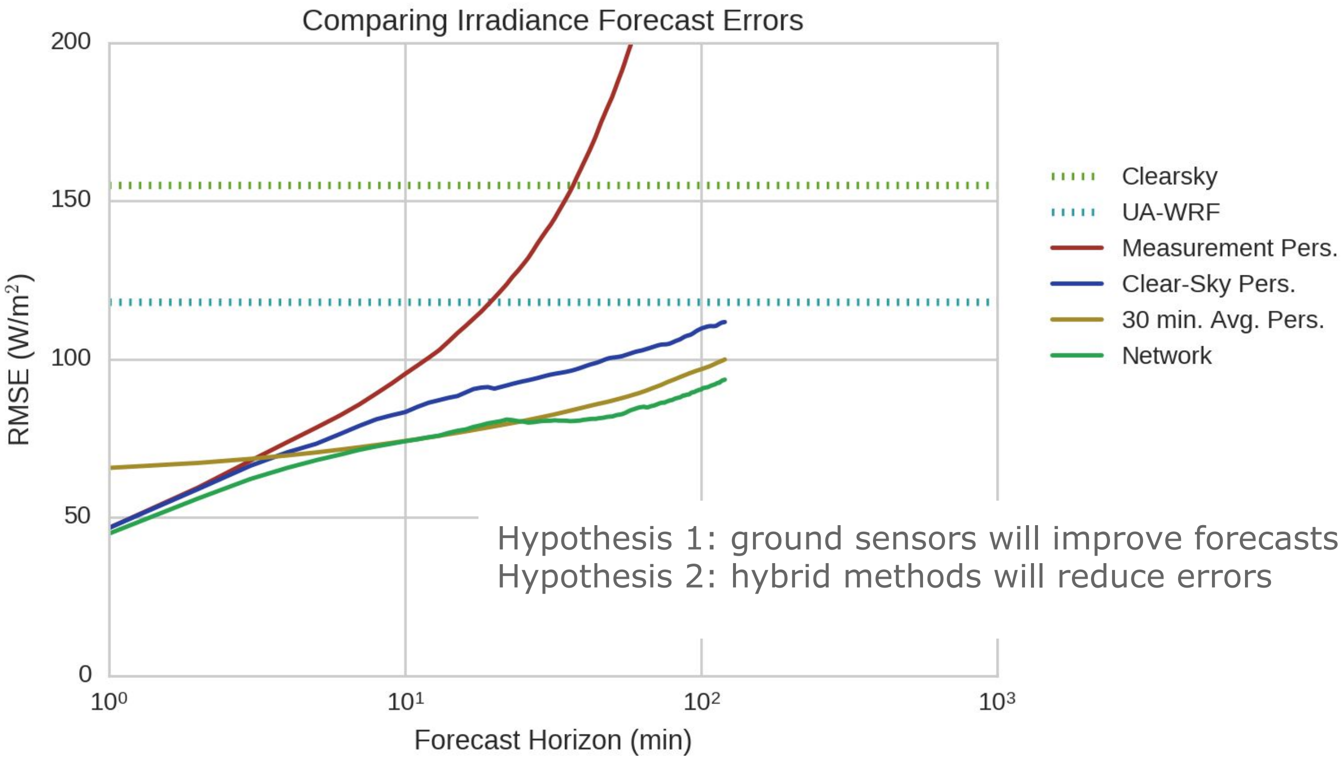


Published work on irradiance network

A. T. Lorenzo, W. F. Holmgren, and A. D. Cronin, “Irradiance forecasts based on an irradiance monitoring network, cloud motion, and spatial averaging,” *Sol. Energy*, vol. 122, pp. 1158–1169, 2015.

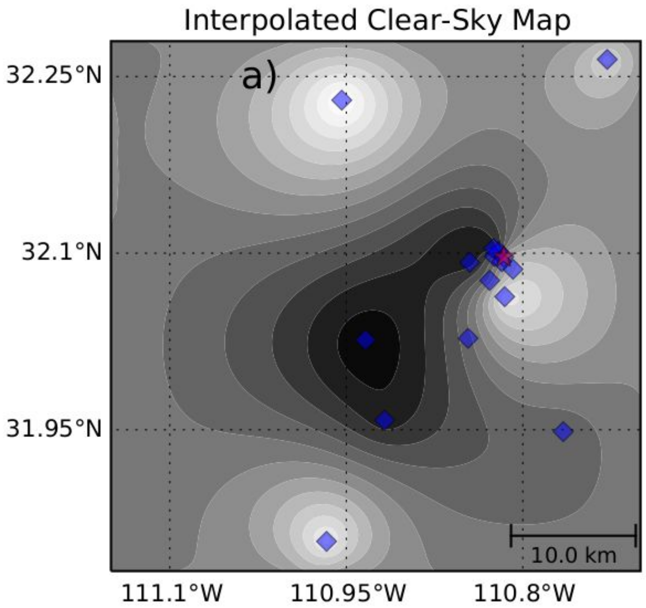


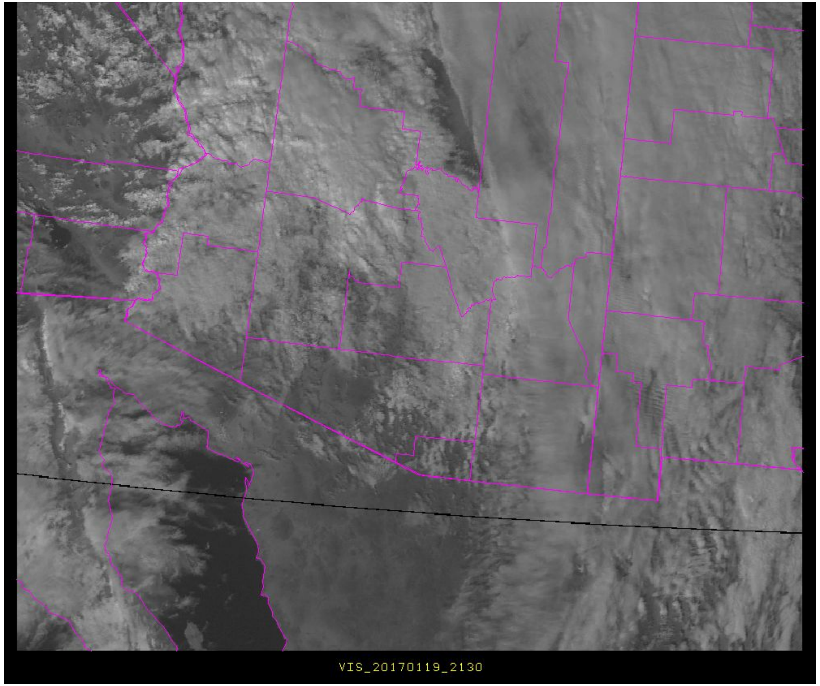
Network Forecasts: Results



Hypothesis 1: ground sensors will improve forecasts ✔
Hypothesis 2: hybrid methods will reduce errors

Network Forecast: Limitation





Strengths & Weaknesses

Irradiance Sensors

- Strengths
  - High accuracy
  - High temporal resolution
- Weaknesses
  - Low spatial coverage
  - Expensive to deploy and maintain

Satellite Imagery

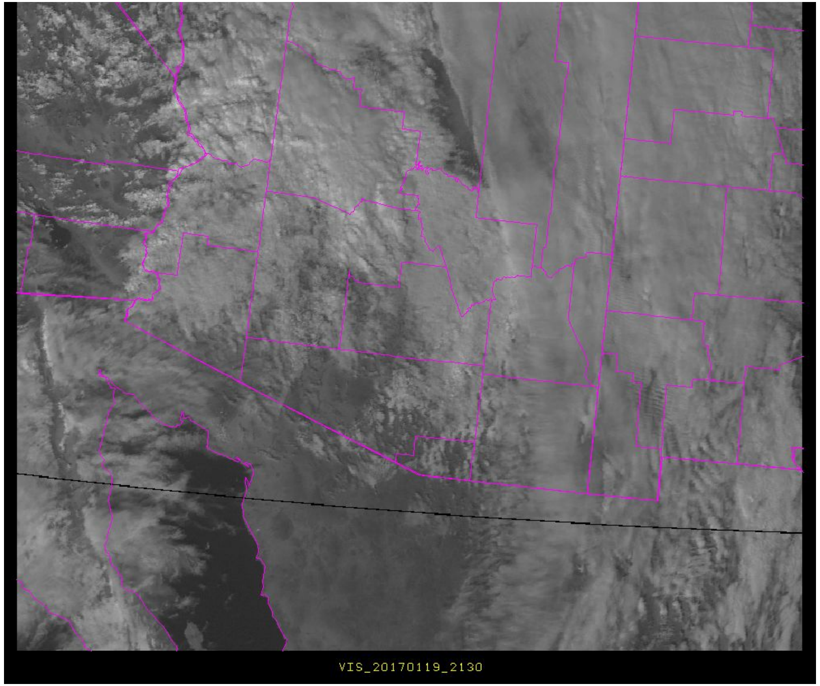
- Strengths
  - Broad coverage
  - Freely available
- Weaknesses
  - Errors introduced because GHI is a derived quantity
  - Low temporal resolution

Outline of my work

- Benchmark forecasts
- Irradiance network forecasts
- Satellite data assimilation

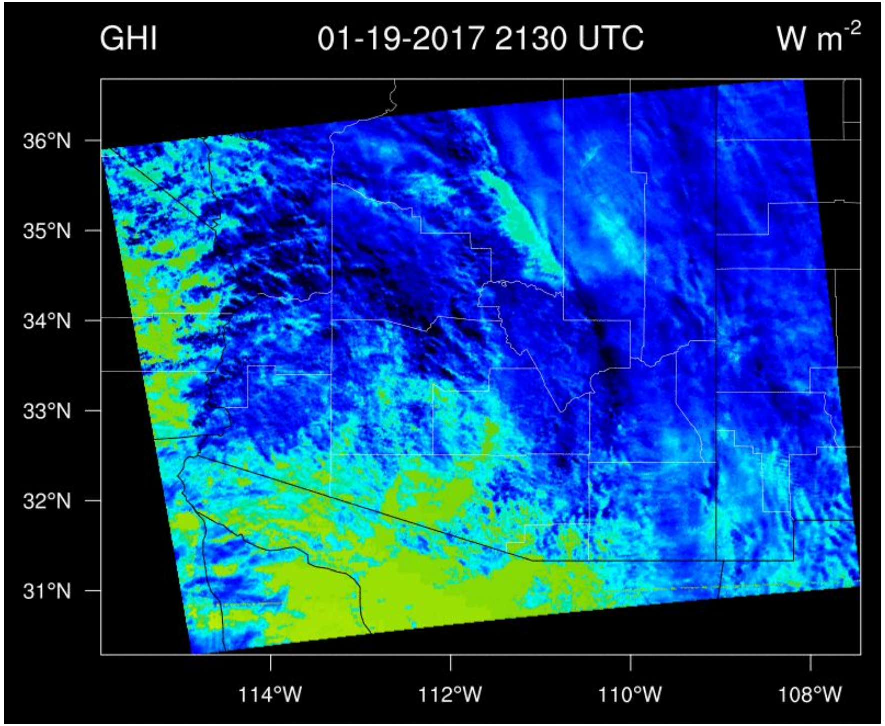
Satellite Derived Irradiance

Light reflected from the tops of clouds

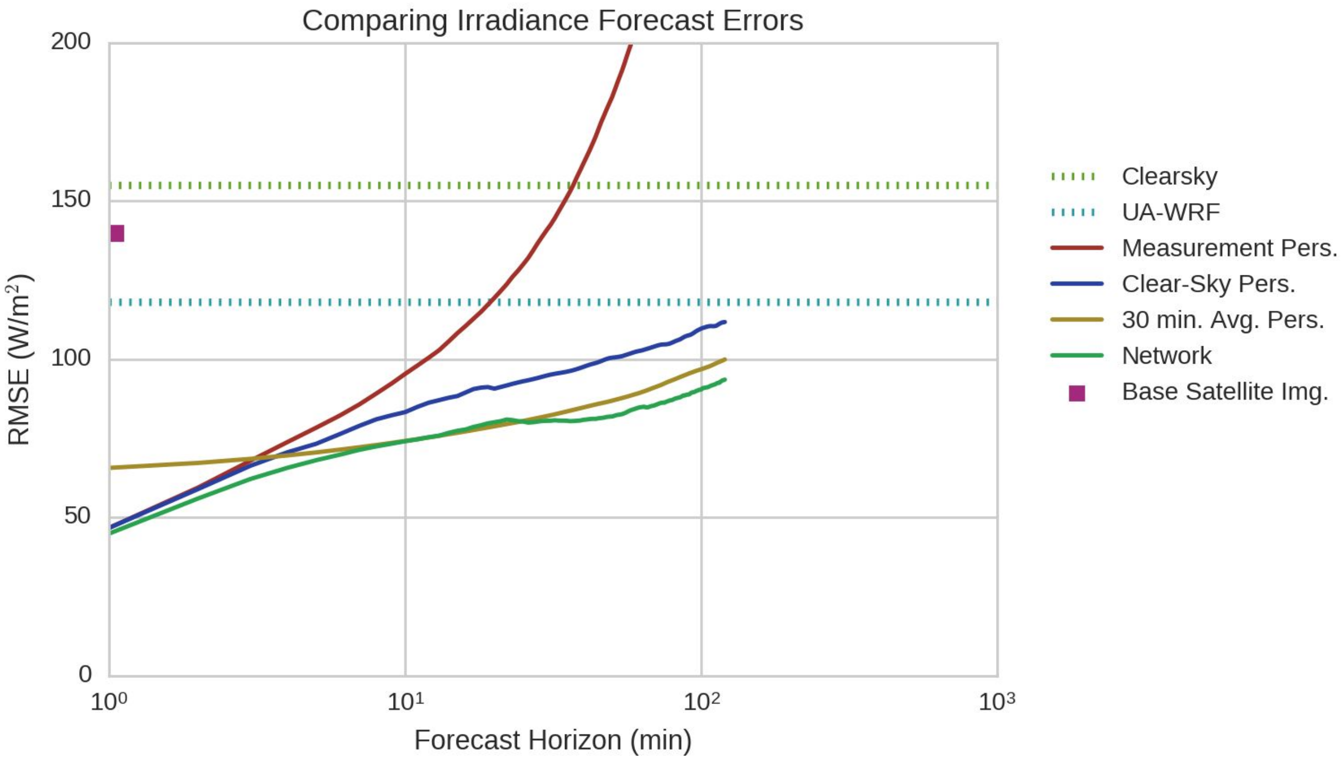


model

Light that gets through clouds

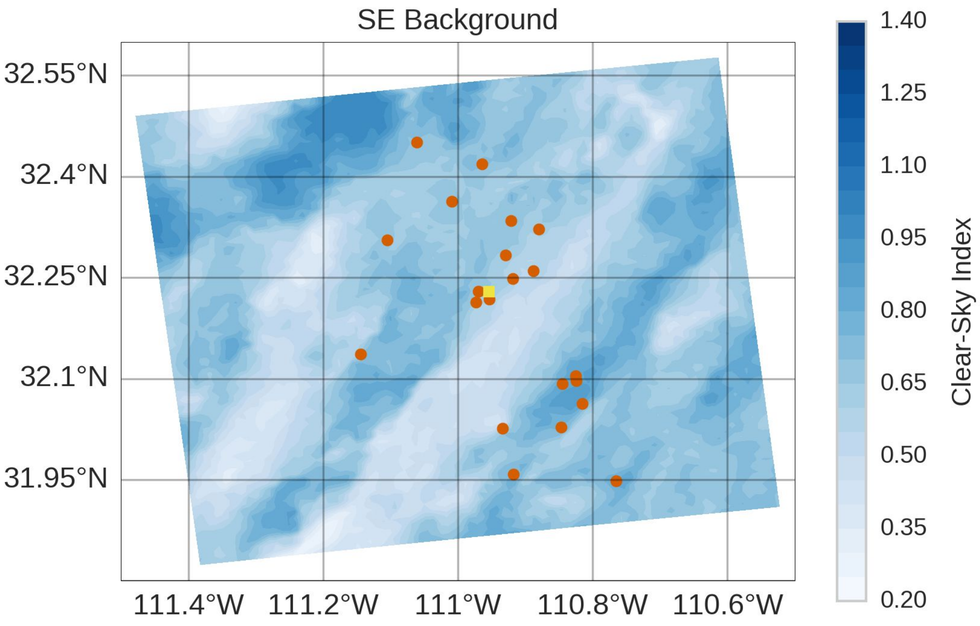


Satellite GHI Error

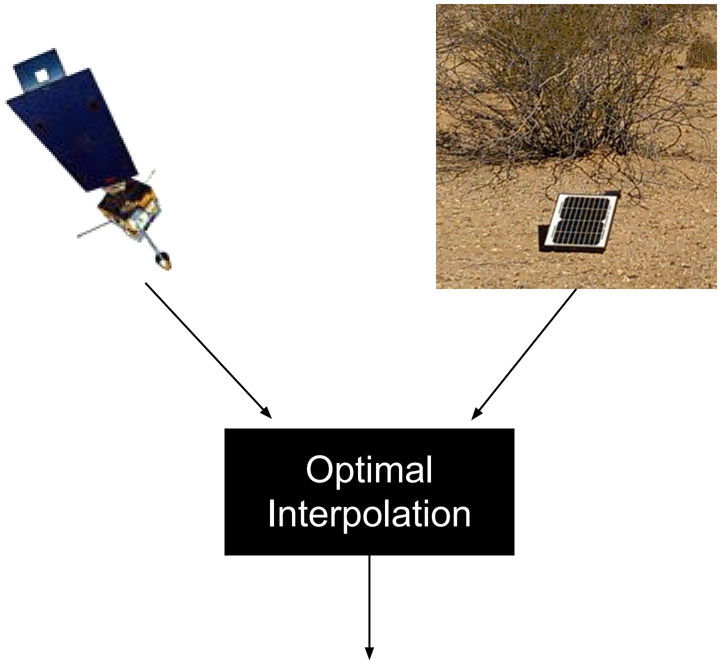


Satellite-derived GHI estimate

- Two conversion models:
  - **SE**: A semi-empirical model that applies a regression to data from visible images
  - **UASIBS**: A physical model that estimates cloud properties and performs radiative transfer
- Nominally 1 km resolution
- Using 75 km x 82 km area over Tucson



Optimal Interpolation

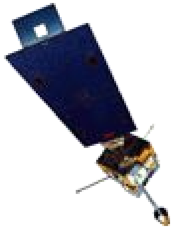


Better satellite-derived estimate of GHI

- Bayesian technique derived by minimizing the mean squared distance between the field and observations
- Is the best linear unbiased estimator of the field
- Same as the update step in the Kalman filter

Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

Optimal Interpolation



Optimal Interpolation

Better satellite-derived estimate of GHI

Satellite Derived Irradiance:

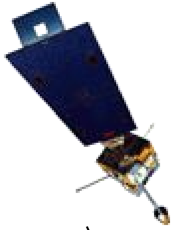
$$\mathbf{x}_b = \mathbf{x}_t + \mathbf{g}$$
$$\mathbf{g} \sim N(\mathbf{0}, \mathbf{P})$$

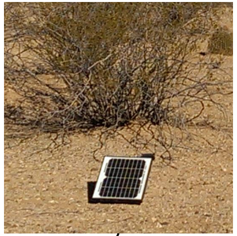
Observations:

$$\mathbf{y} = \mathbf{y}_t + \mathbf{e}$$
$$\mathbf{e} \sim N(\mathbf{0}, \mathbf{R})$$

Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

OI Algorithm





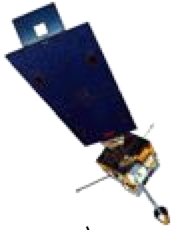
Maps points from satellite image to observations

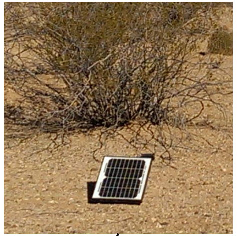
Better GHI estimate

$$\mathbf{x_a = x_b + W(y - Hx_b)}$$

Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

OI Algorithm





Maps points from satellite image to observations

Better GHI estimate

$$x_a = x_b + W(y - Hx_b)$$

$$W = PH^T(R + HPH^T)^{-1}$$

Need to a way to estimate these error covariances

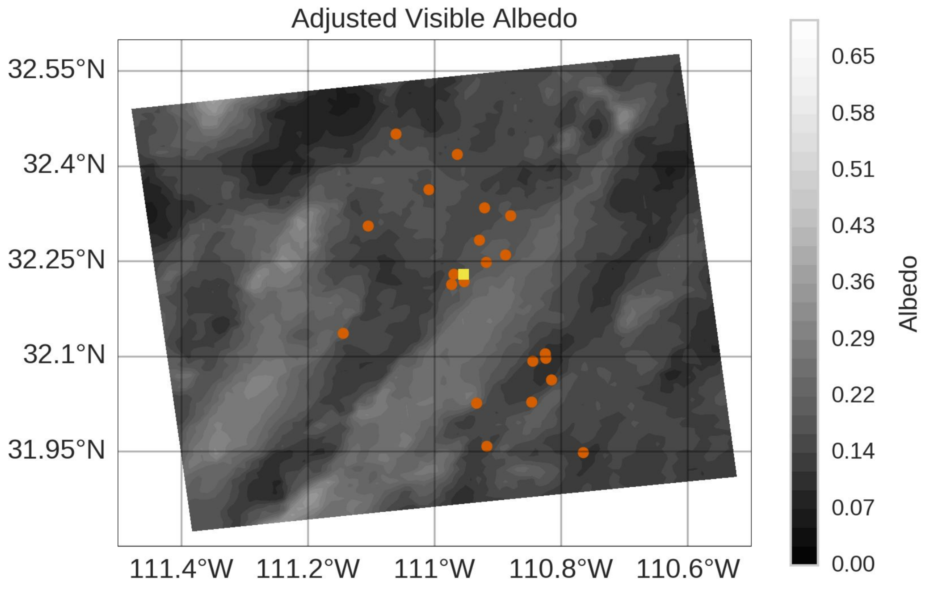
Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

Error Covariances: P and R

- Decompose **P** into diagonal variance matrix and correlation matrix:

$$\mathbf{P} = \mathbf{D}^{1/2}\,\mathbf{C}\,\mathbf{D}^{1/2}$$

- Prescribe a correlation between image pixels based on the ***difference in cloudiness*** to construct **C**
- Compute **D** from cloud free training images
- Assume observation errors are uncorrelated and estimate **R** from data



OI Parameters

$$\mathbf{P} = \mathbf{D}^{1/2}\mathbf{C}\mathbf{D}^{1/2}$$

$$\mathbf{D} = d\mathbf{D}'$$

$$C_{ij} = k(r_{ij})$$

Correlation Functions that I studied

$$k(r) = \begin{cases} 1 - \frac{r}{l} & r < l \\ 0 & r \geq l \end{cases}$$

$$k(r) = \exp\left(-\frac{r}{l}\right)$$

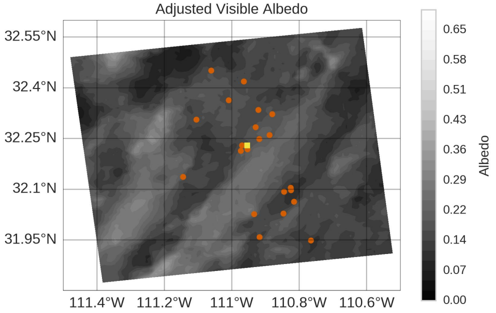
$$k(r) = \exp\left(-\frac{r^2}{l^2}\right)$$

Distance Metrics that I studied

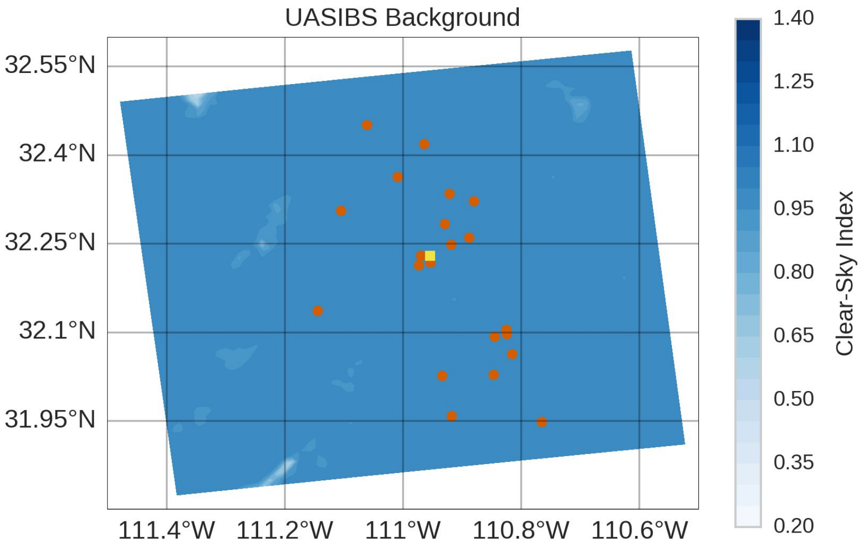
$$r_{ij} = |z_i - z_j|$$

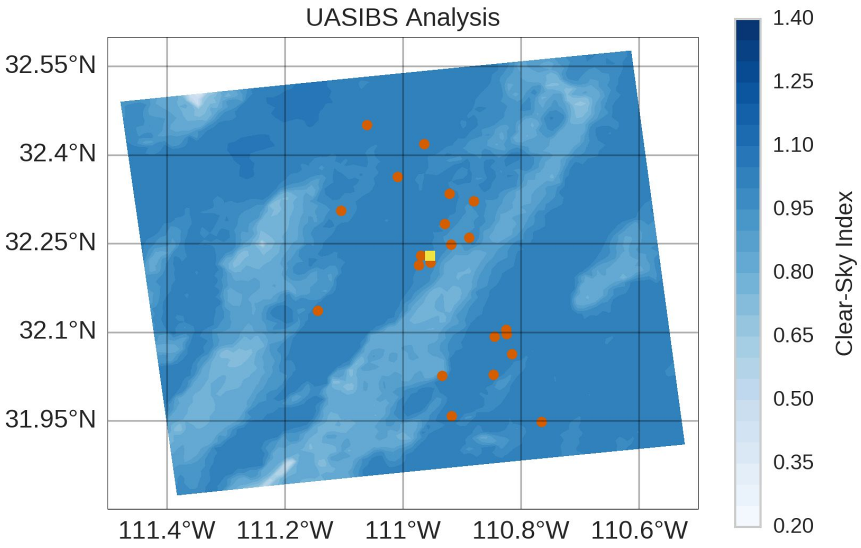
$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

500 training images * 2 models * 6 fold cross validation * 50 height adj. * 2 corr. methods * 3 corr. fcns. * ~10 corr. lengths * ~10 inflation params = 200 million OI analyses

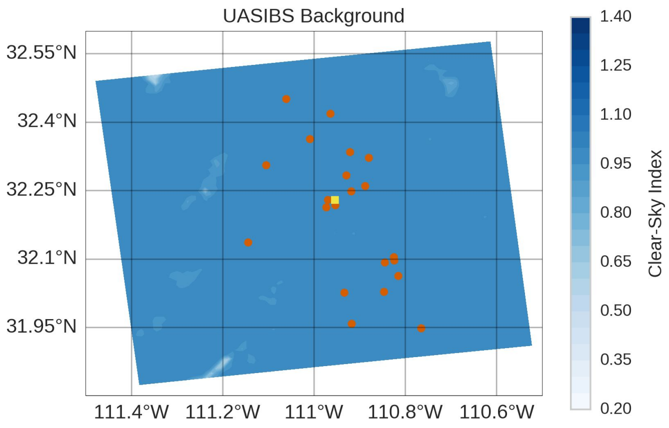

Adjusted Visible Albedo
32.55°N
32.4°N
32.25°N
32.1°N
31.95°N
111.4°W 111.2°W 111°W 110.8°W 110.6°W
0.65 0.58 0.51 0.43 0.36 0.29 0.22 0.14 0.07 0.00
Albedo

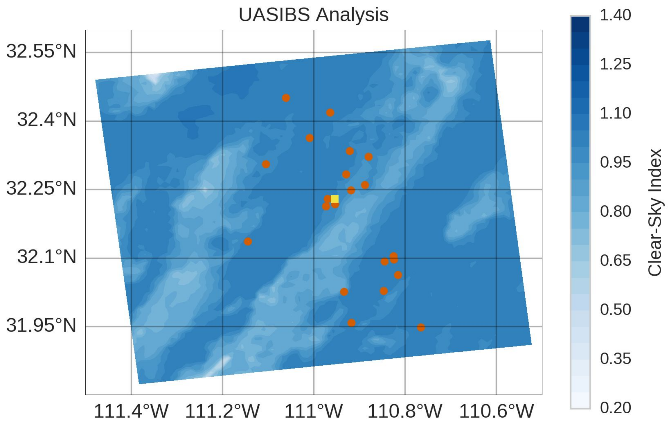
OI in action

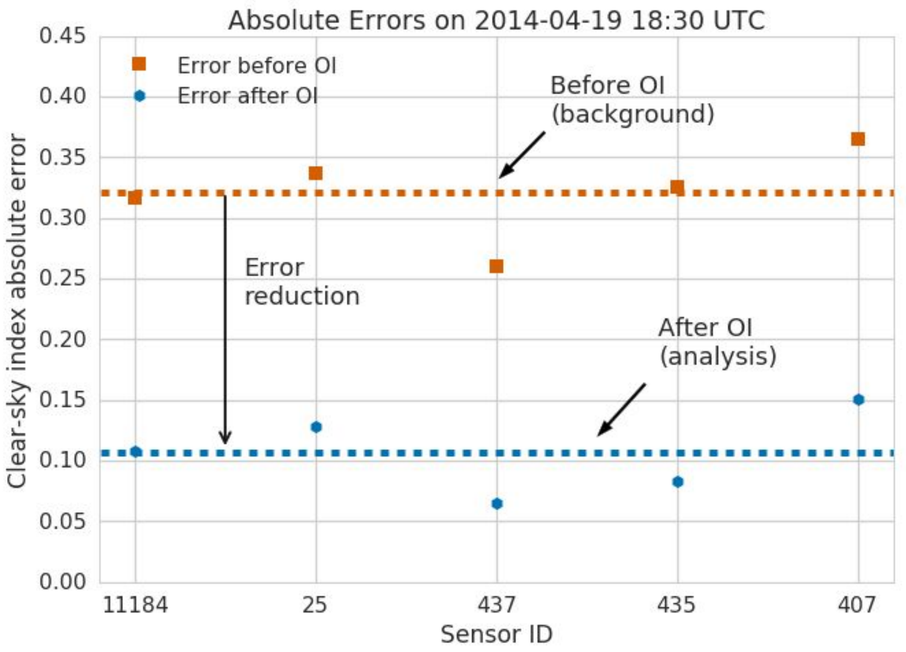

UASIBS Background
32.55°N
32.4°N
32.25°N
32.1°N
31.95°N
111.4°W 111.2°W 111°W 110.8°W 110.6°W
1.40 1.25 1.10 0.95 0.80 0.65 0.50 0.35 0.20
Clear-Sky Index

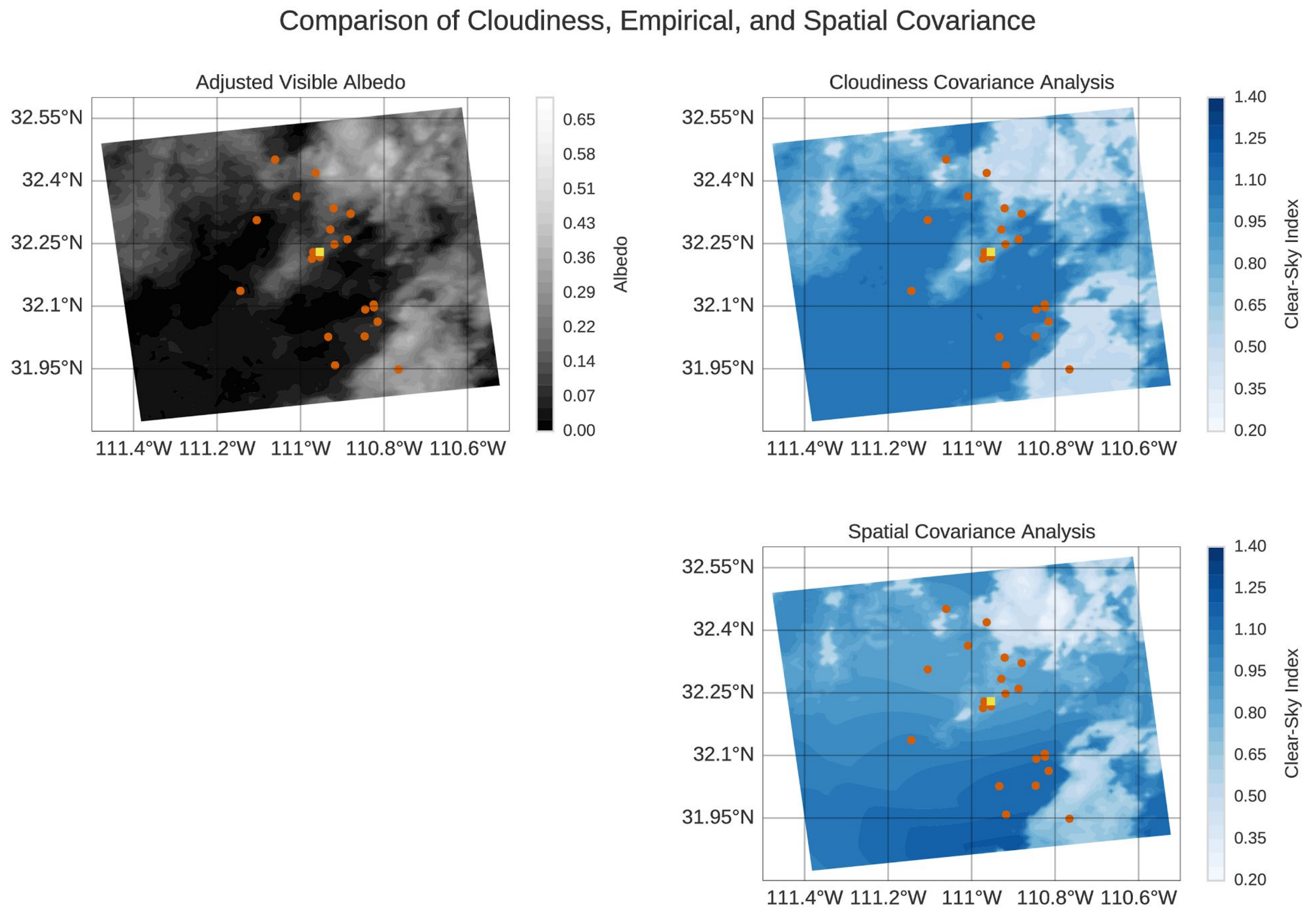

UASIBS Analysis
32.55°N
32.4°N
32.25°N
32.1°N
31.95°N
111.4°W 111.2°W 111°W 110.8°W 110.6°W
1.40 1.25 1.10 0.95 0.80 0.65 0.50 0.35 0.20
Clear-Sky Index

Results (one image)

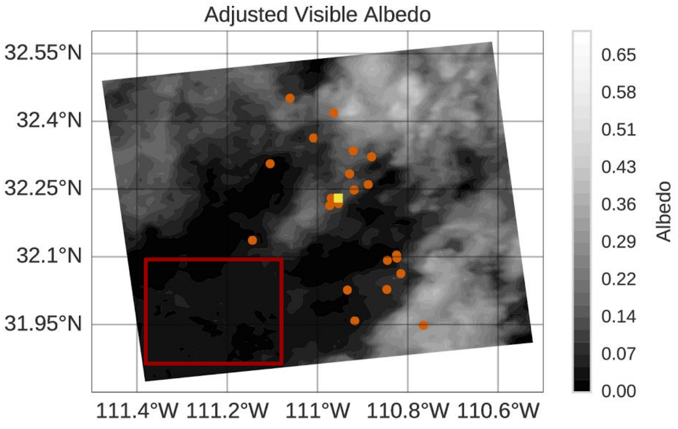


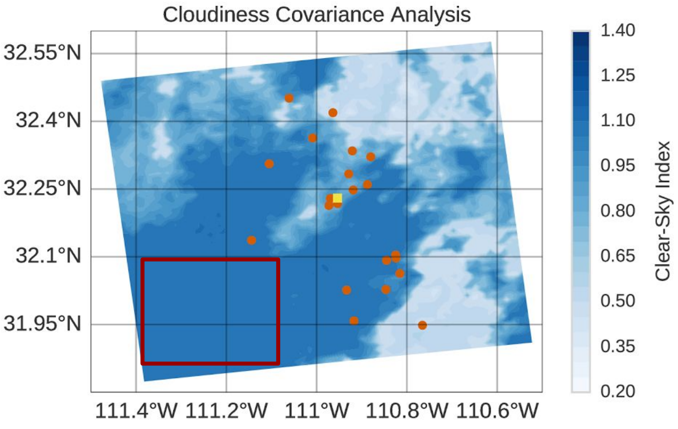




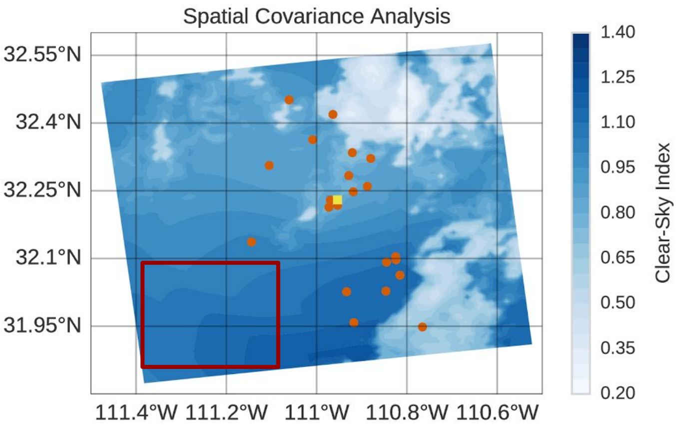

Comparison of Cloudiness, Empirical, and Spatial Covariance
Adjusted Visible Albedo
Cloudiness Covariance Analysis
Spatial Covariance Analysis
32.55°N
32.4°N
32.25°N
32.1°N
31.95°N
111.4°W 111.2°W 111°W 110.8°W 110.6°W
Albedo
0.65 0.58 0.51 0.43 0.36 0.29 0.22 0.14 0.07 0.00
Clear-Sky Index
1.40 1.25 1.10 0.95 0.80 0.65 0.50 0.35 0.20

Comparison of Cloudiness, Empirical, and Spatial Covariance

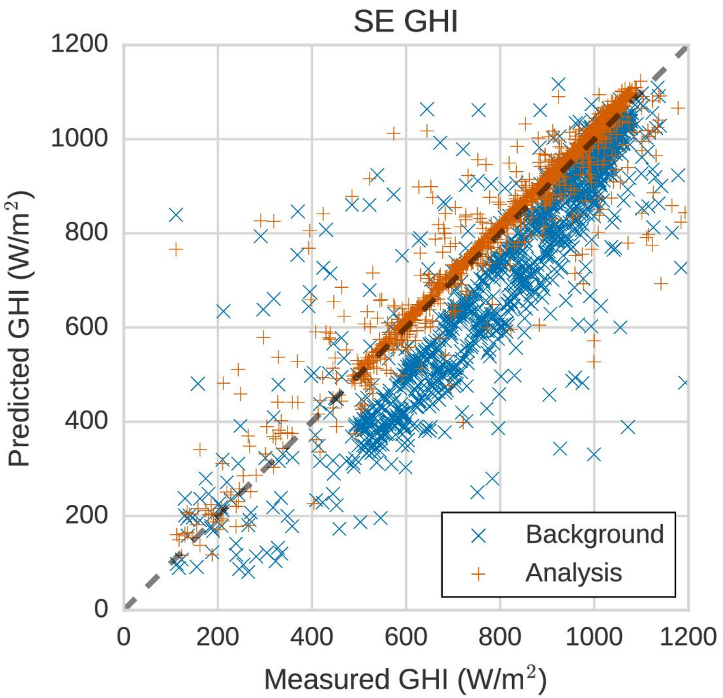




- No clouds in satellite albedo image
- No clouds in analysis using cloudiness correlation ✔
- Clouds with a smooth gradient in analysis using spatial correlation ✖



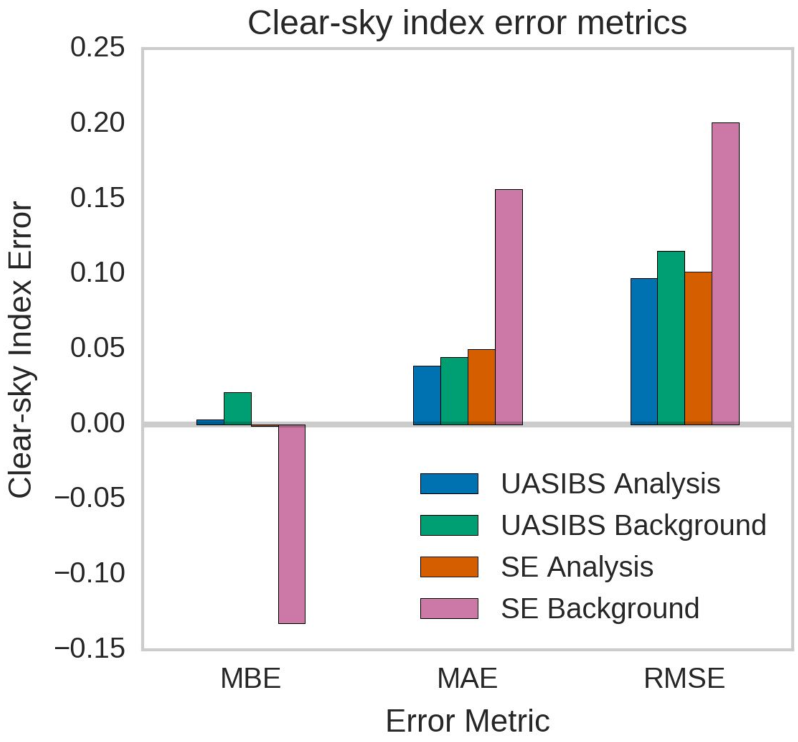
Predicted vs Measured Scatterplot



- Dashed 1-to-1 line indicates perfect model
- Background is biased with time of day dependence
- Analysis removes bias and time dependence

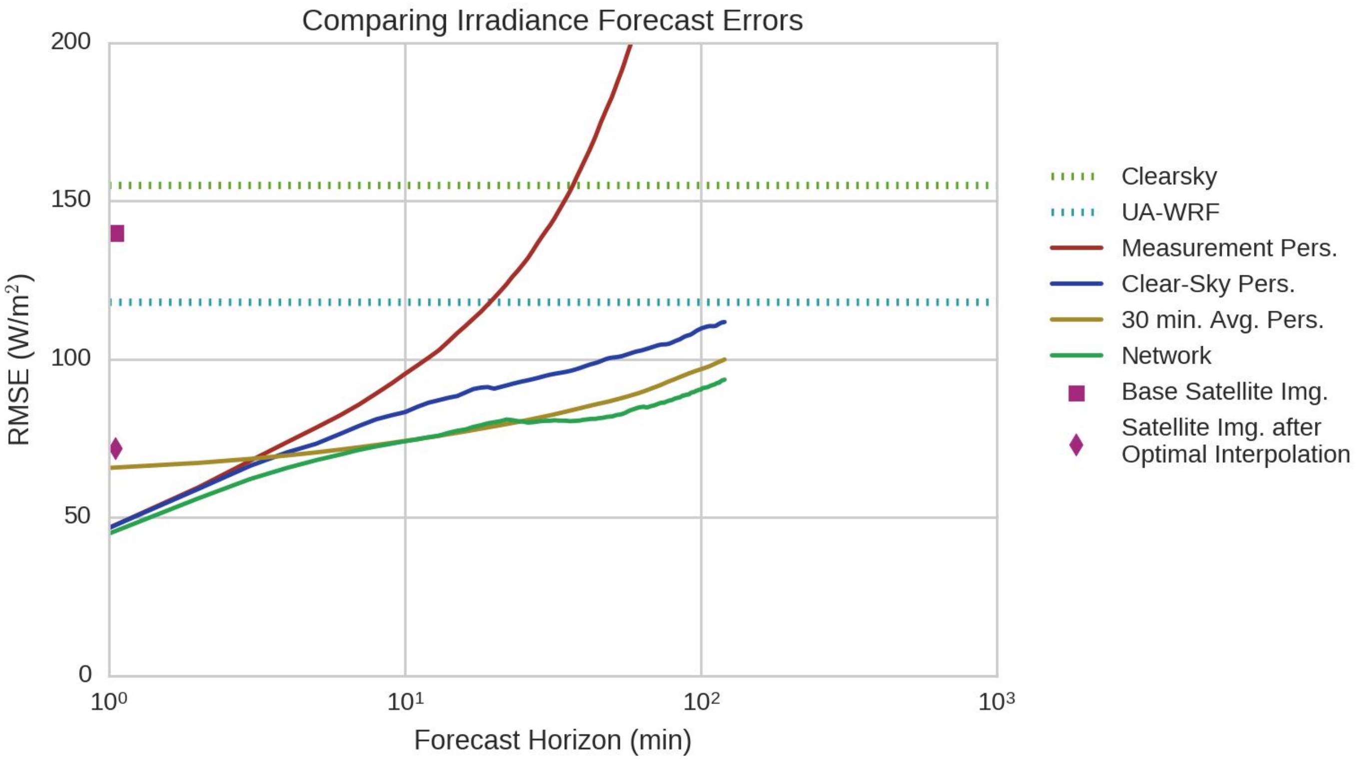
Optimal Interpolation Results

- 900 verification images analyzed
- Six-fold cross-validation over sensors performed
- The large bias for the empirical model was nearly eliminated
- RMSE reduced by 50%

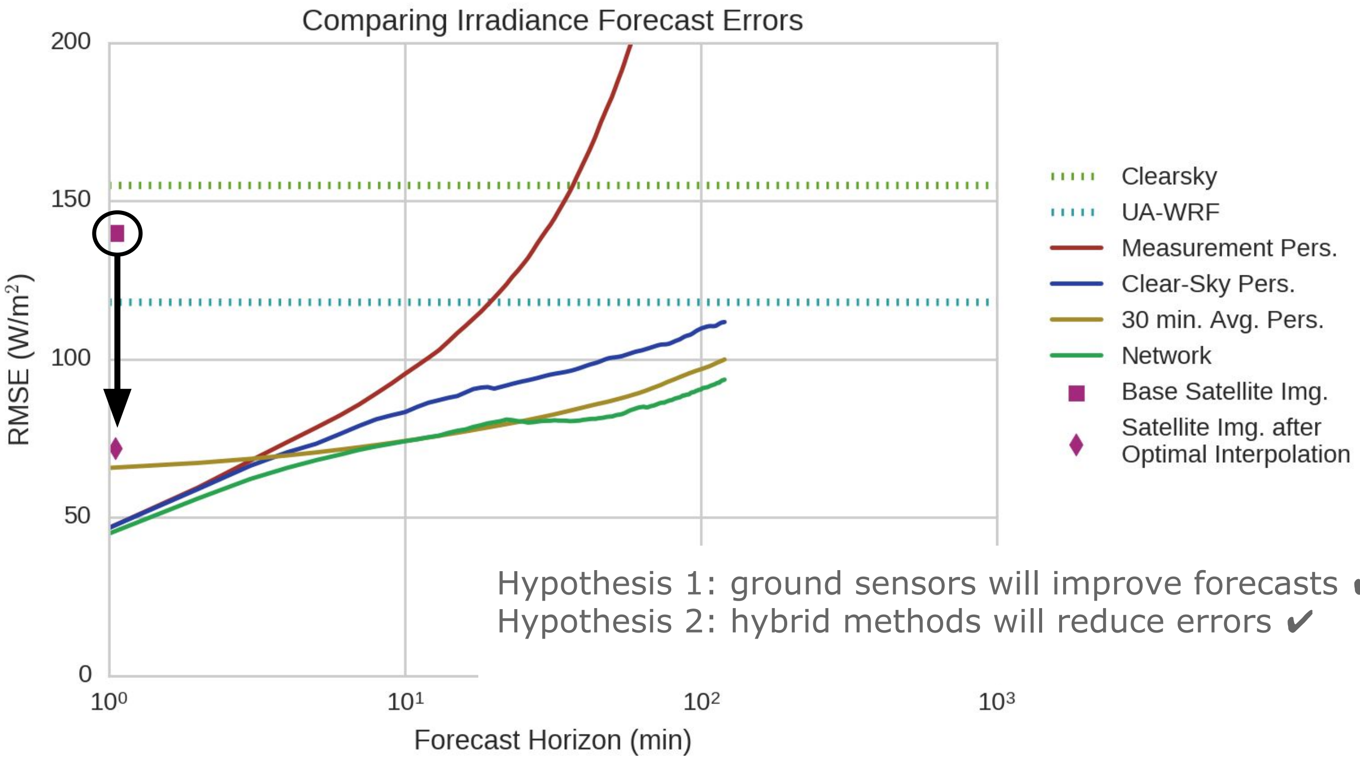


A. T. Lorenzo, M. Morzfeld, W. F. Holmgren, and A. D. Cronin, "Optimal interpolation of satellite and ground data for irradiance nowcasting at city scales," *Sol. Energy*, vol. 144, pp. 466–474, 2017.

Improved Satellite GHI Error

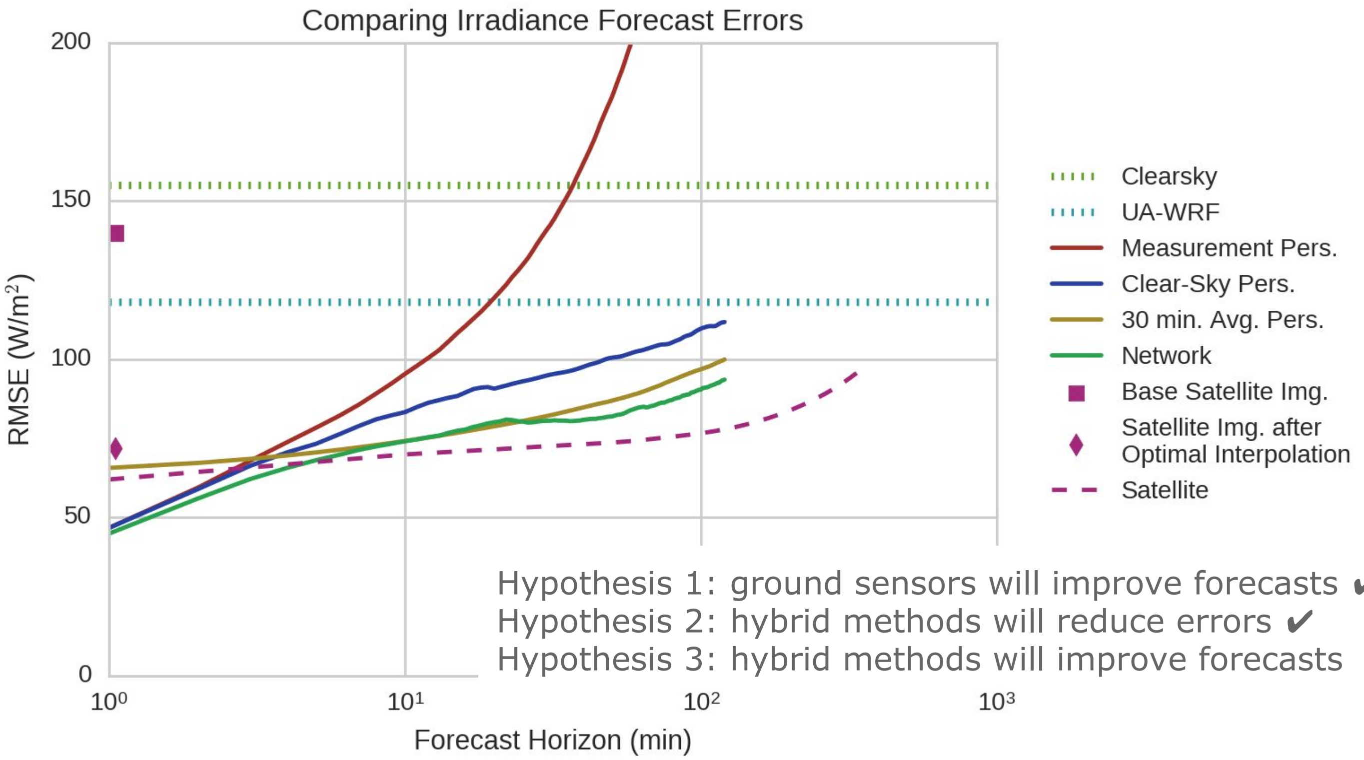


Improved Satellite GHI Error



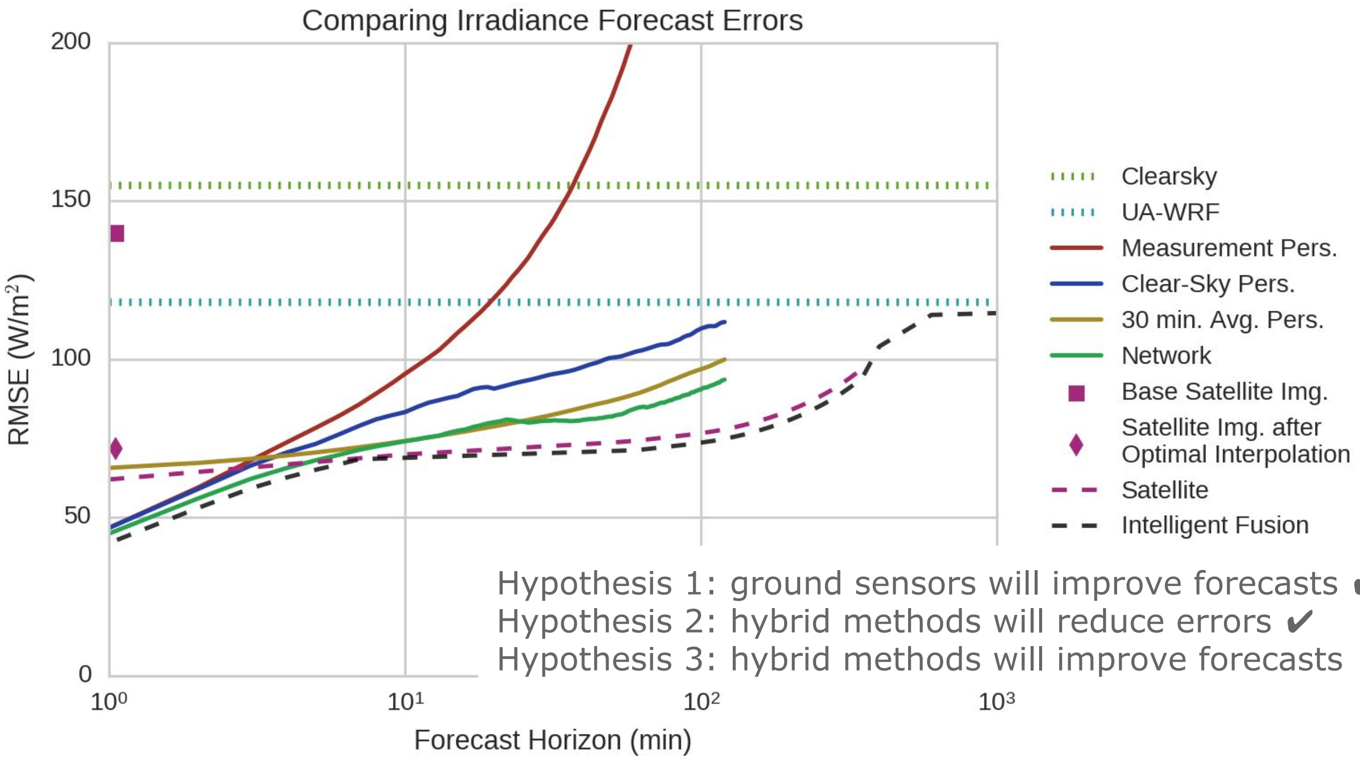
Hypothesis 1: ground sensors will improve forecasts ✔
Hypothesis 2: hybrid methods will reduce errors ✔

Future Work: Satellite Forecast



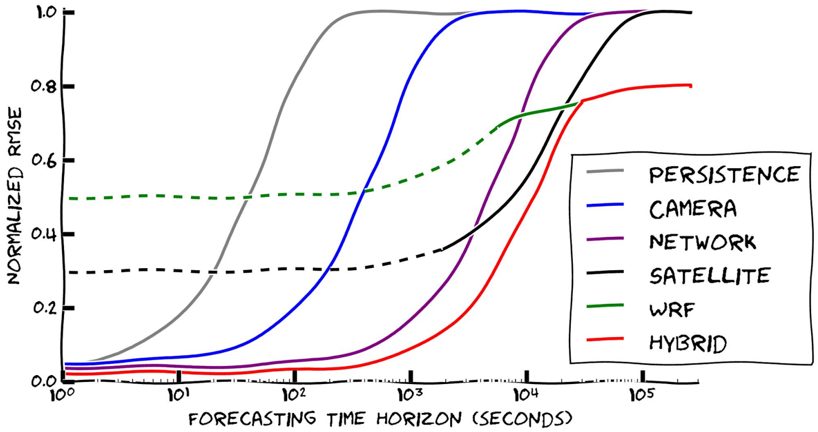
Hypothesis 1: ground sensors will improve forecasts ✔
Hypothesis 2: hybrid methods will reduce errors ✔
Hypothesis 3: hybrid methods will improve forecasts

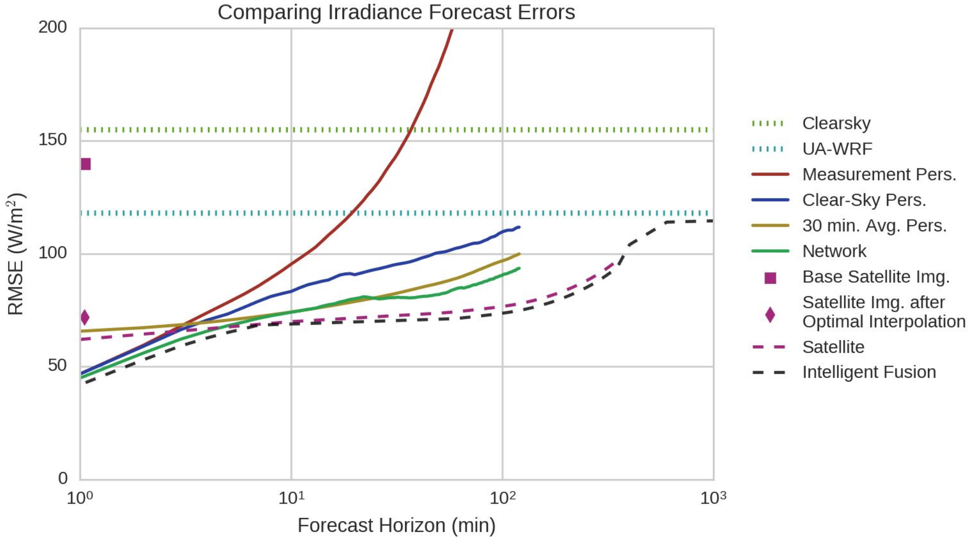
Future Work: Fusing together forecasts



Hypothesis 1: ground sensors will improve forecasts ✔
Hypothesis 2: hybrid methods will reduce errors ✔
Hypothesis 3: hybrid methods will improve forecasts

Hypothesis & Results





Summary

- Designed and deployed irradiance sensor network,
- Used ground sensors to make short-term forecasts that are superior to WRF or persistence,
- Combined sensor data with satellite images to improve irradiance nowcasts.

Thank you!

- Alex Cronin
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- Mike Eklund
- Ardeth Barnhart
- Travis Harty
- Rey Granillo

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