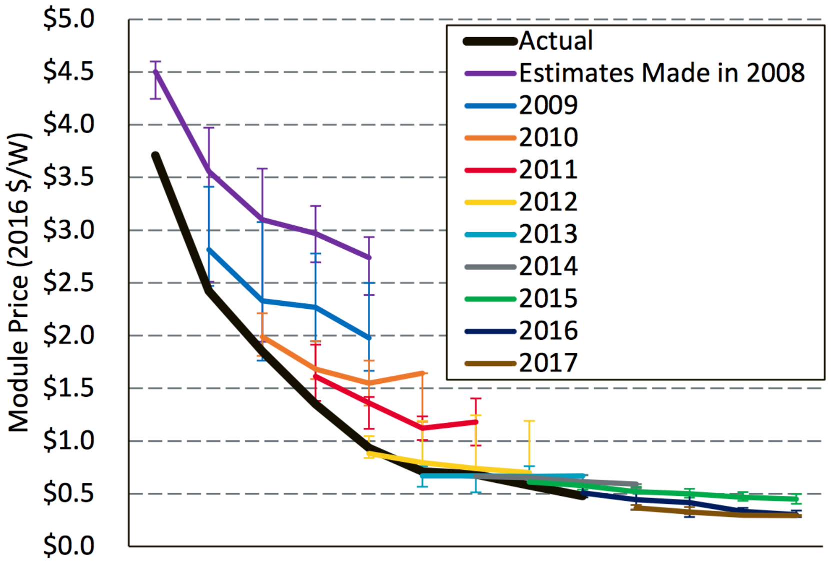
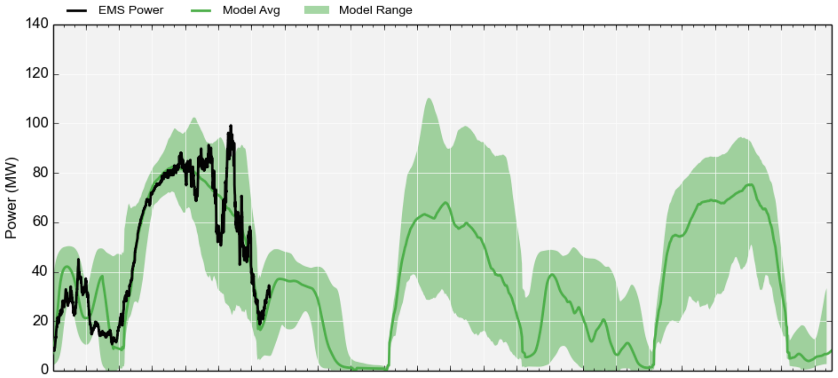
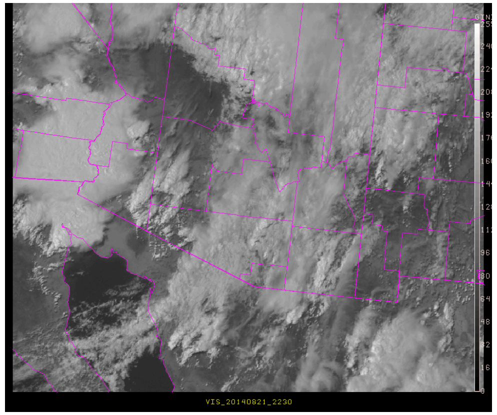
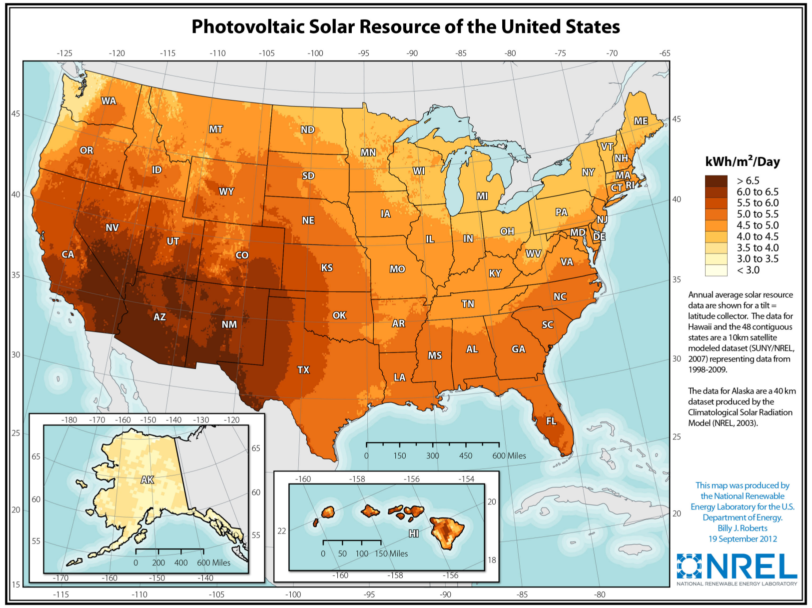
Renewable Energy Forecasting









Will Holmgren

Assistant Research Professor
UA Hydrology and
Atmospheric Sciences

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What kinds of renewable energy forecasts?

- **Technology**
  - Solar
    - PV
    - CSP
  - Wind
  - Biofuels
  - Geothermal
  - Tidal
  - Hydro

- **Time horizon**
  - 1 minute
  - 1 hour
  - 1 day
  - 1 week
  - 1 month
  - 1 season
  - 1 year
  - 1 investment

- **Time resolution**
  - 1 minute
  - 1 hour
  - 1 day
  - 1 week
  - 1 month
  - 1 season
  - 1 year
  - 1 investment

- **Data source**
  - Observational
    - Weather
    - Satellites
    - RADAR
    - Sky cameras
    - LIDAR
  - Modeled
    - Weather
    - Climate
    - Satellite
    - RADAR

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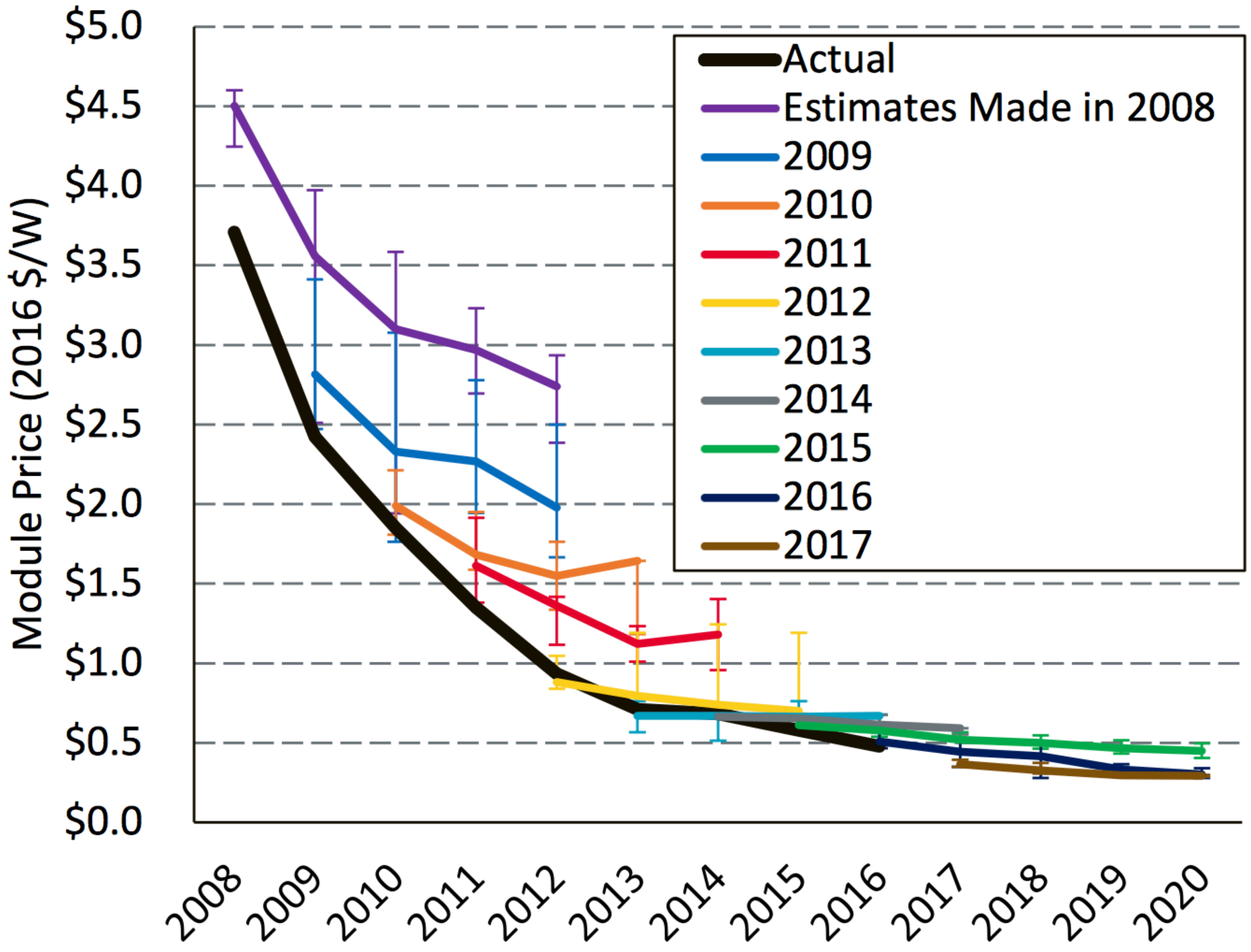
Solar and wind price forecasts



Inputs:

- Price data
- Tariffs
- Innovation rate
- Subsidies (local, state, federal, foreign)
- Regulatory models
- Economic models

Margolis et. al., NREL/Sunshot 2017
NREL/PR-6A20-68425

Solar and wind price forecasts

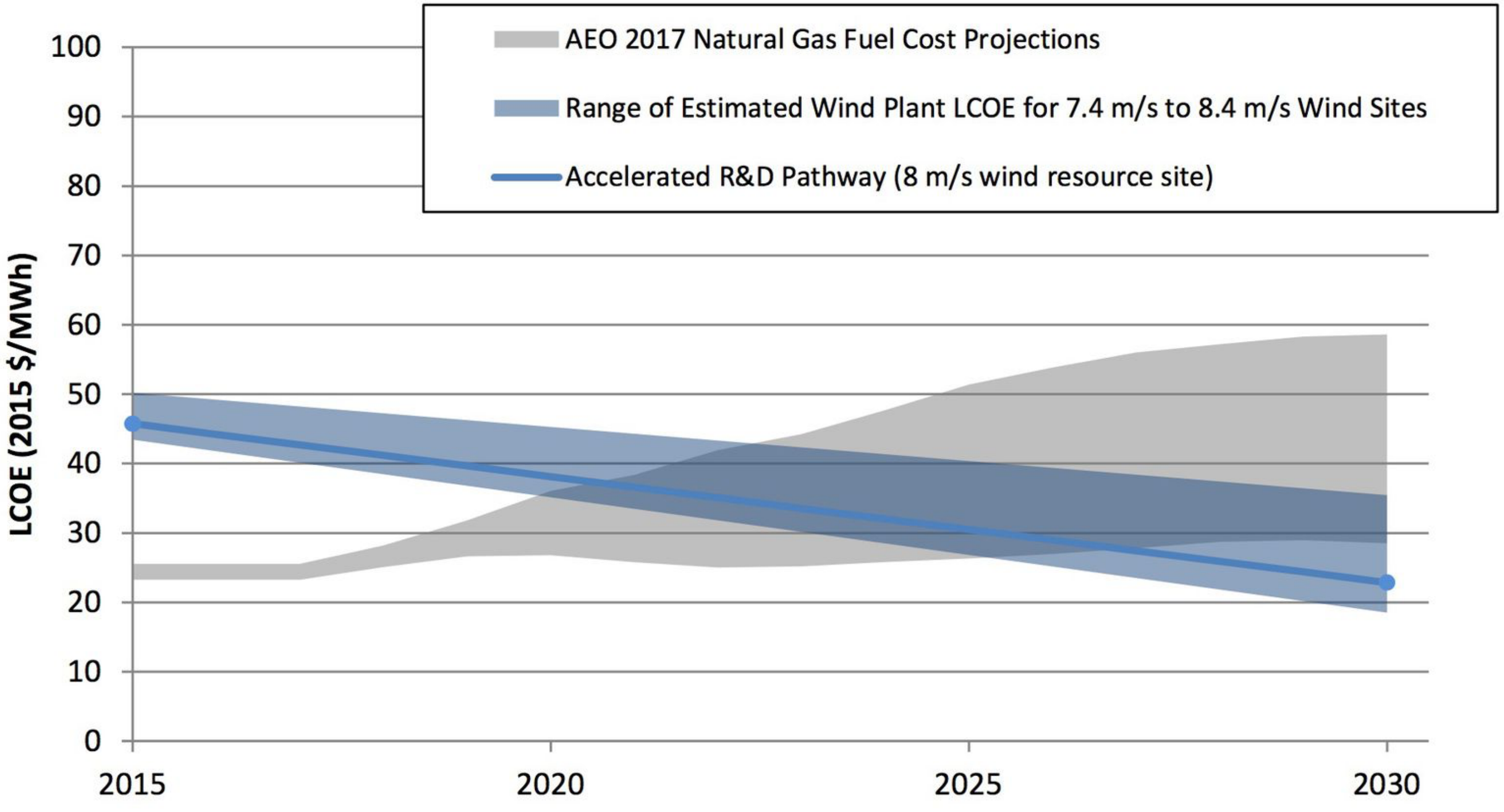


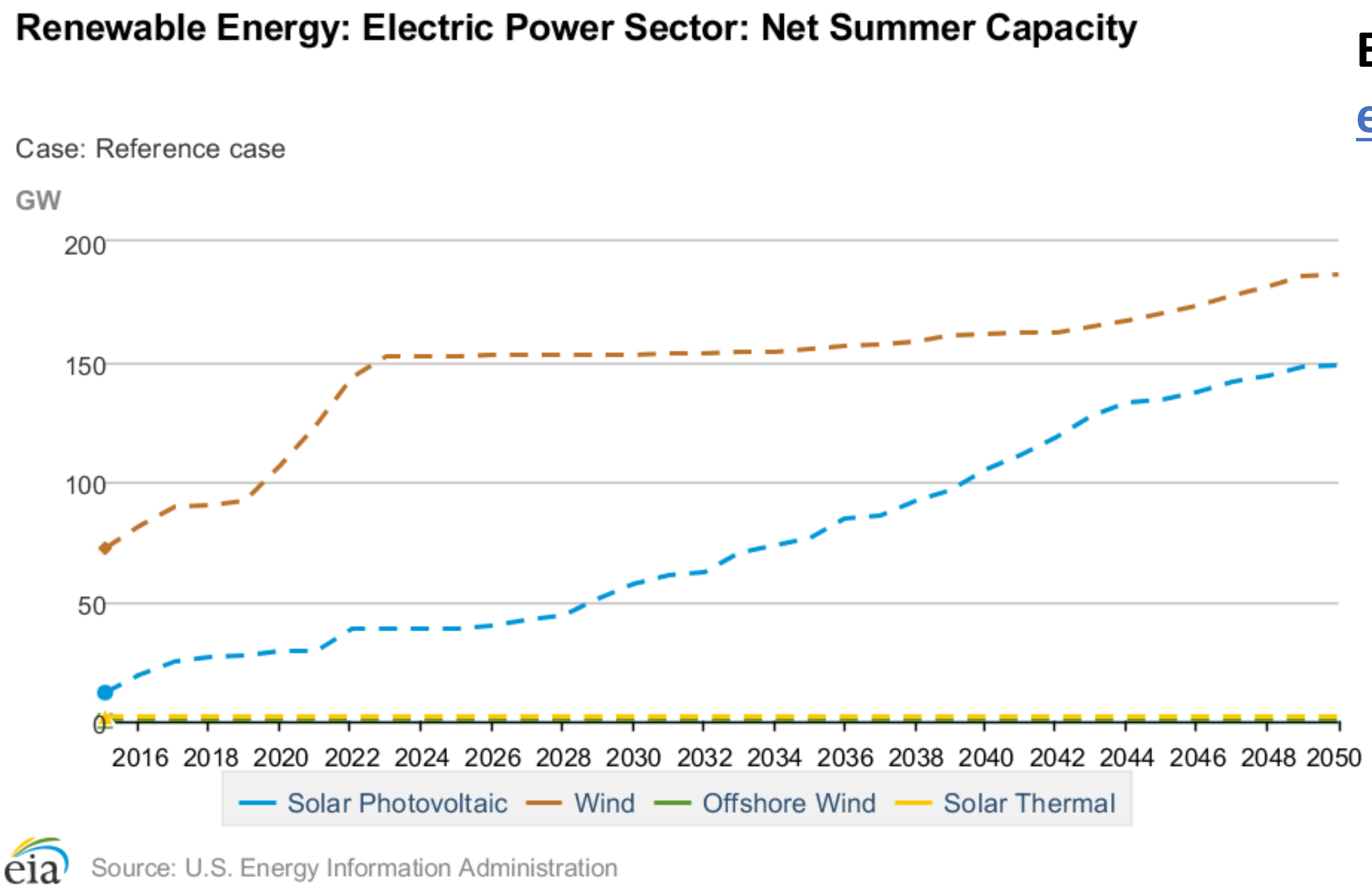
Figure 8. Projected costs for the SMART wind power plant at a range of different wind resource sites using the accelerated R&D pathway relative to future natural gas prices

Inputs:

- Price data
- Tariffs
- Innovation rate (wind and gas)
- Subsidies (local, state, federal, foreign)
- Regulatory models
- Economic models

Dykes et. al., NREL 2017

Solar and wind capacity forecasts



EIA Annual Energy Outlook 2017

[eia.gov](eia.gov)

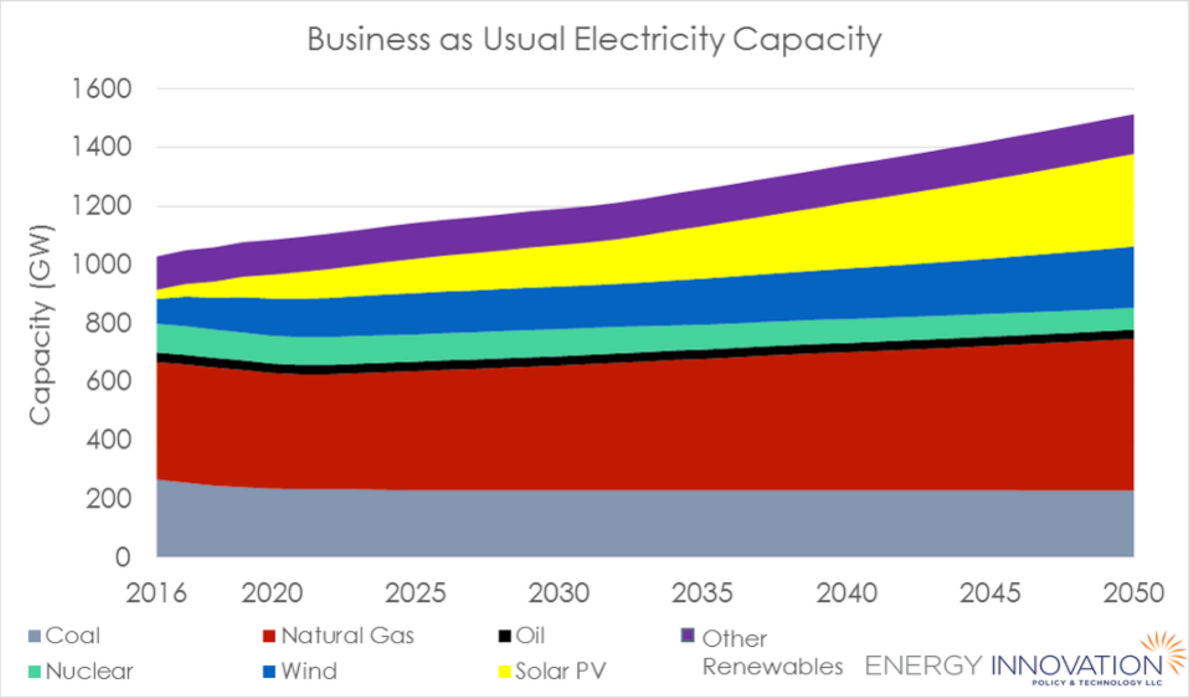
Wind x 2.5?

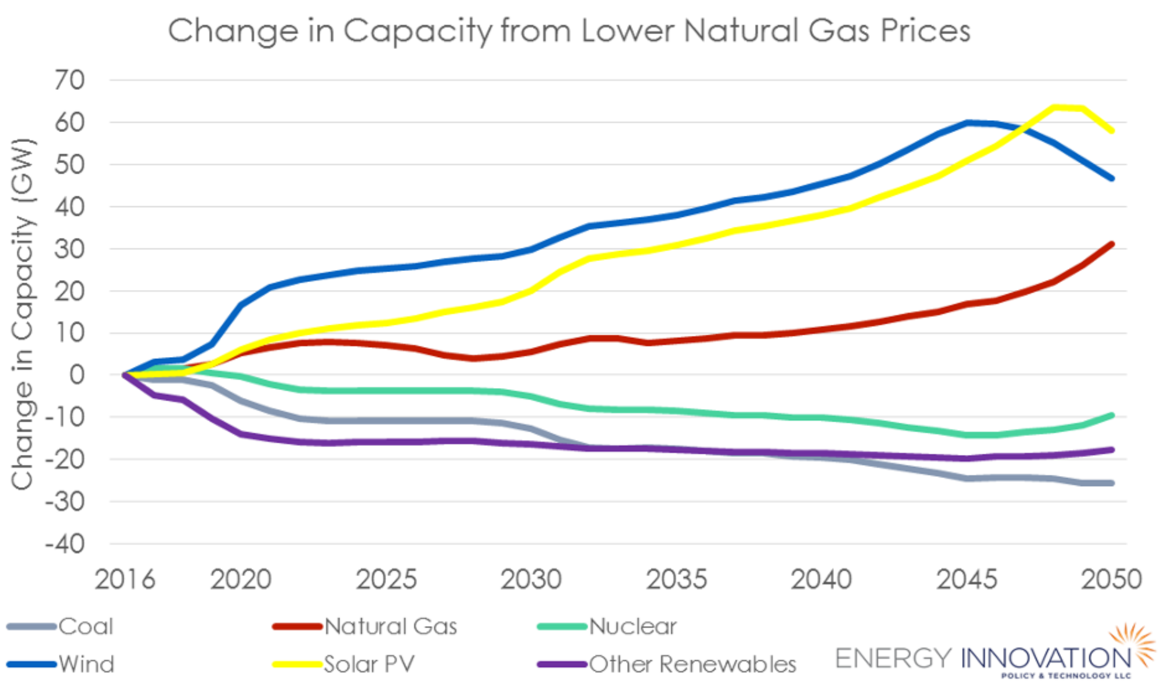
Solar PV x 100!

Solar Thermal and Offshore Wind flat

Solar and wind capacity forecasts

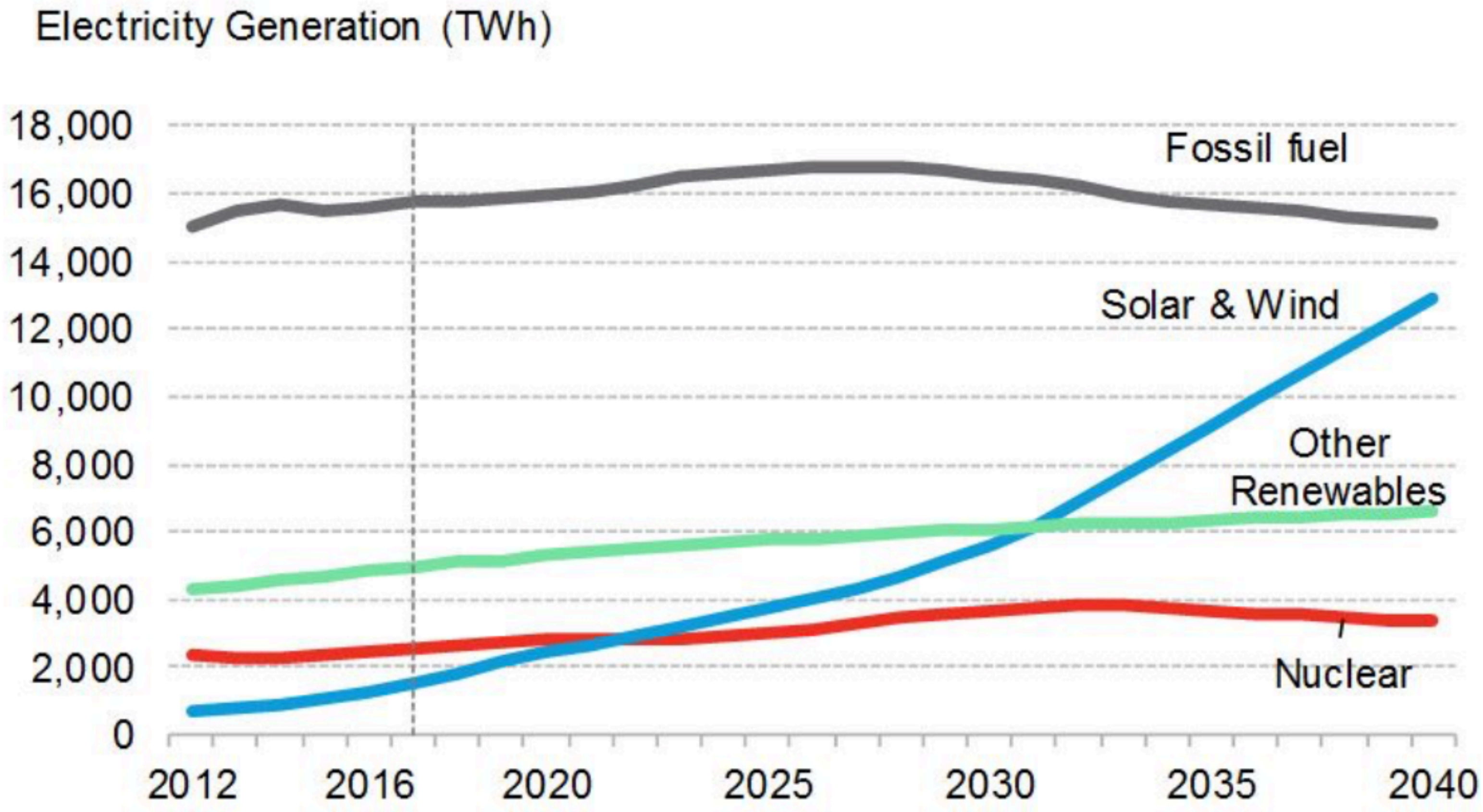
“America's Renewable Electricity Forecast Grows To 2050, Even Under Trump”





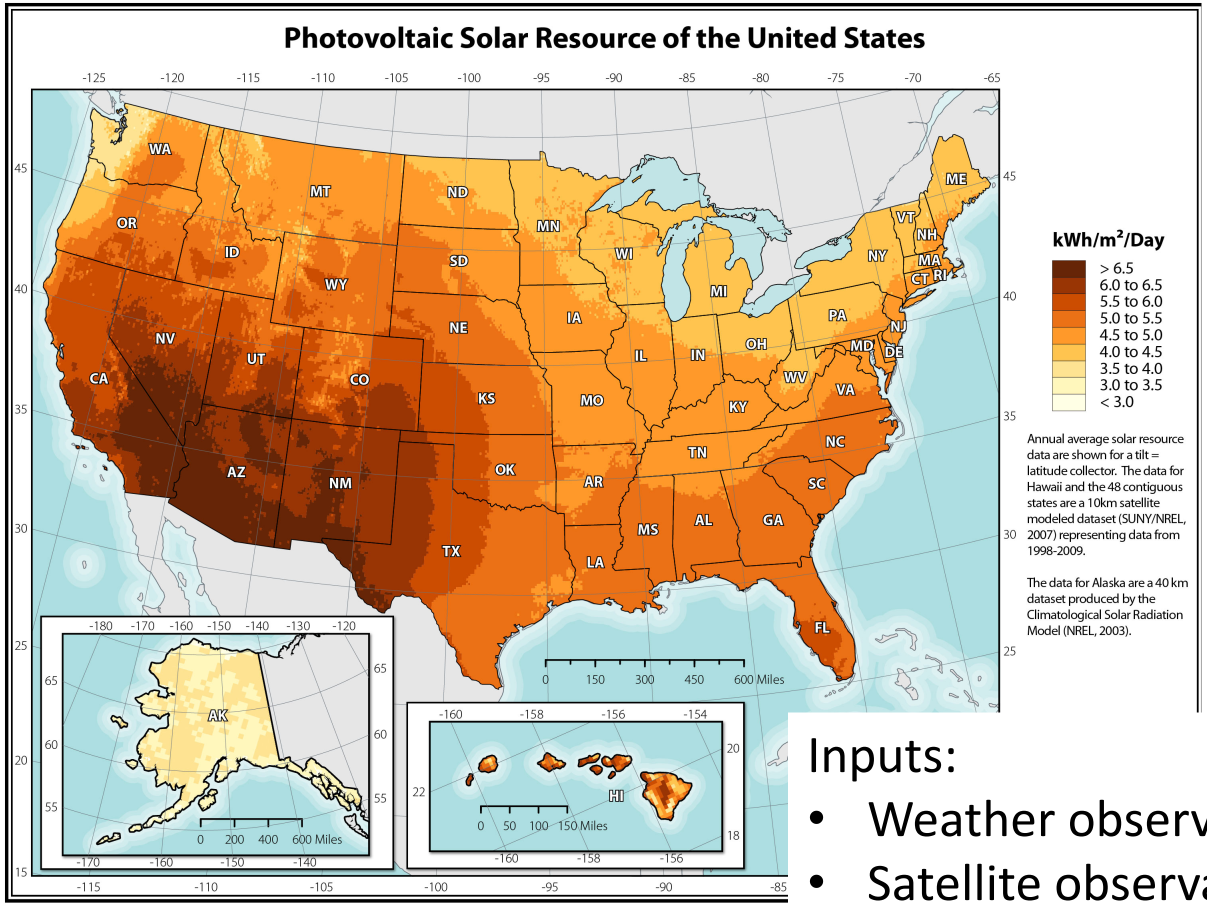
https://www.forbes.com/sites/energyinnovation/2017/05/10/americas-renewable-electricity-forecast-grows-to-2050-even-under-trump

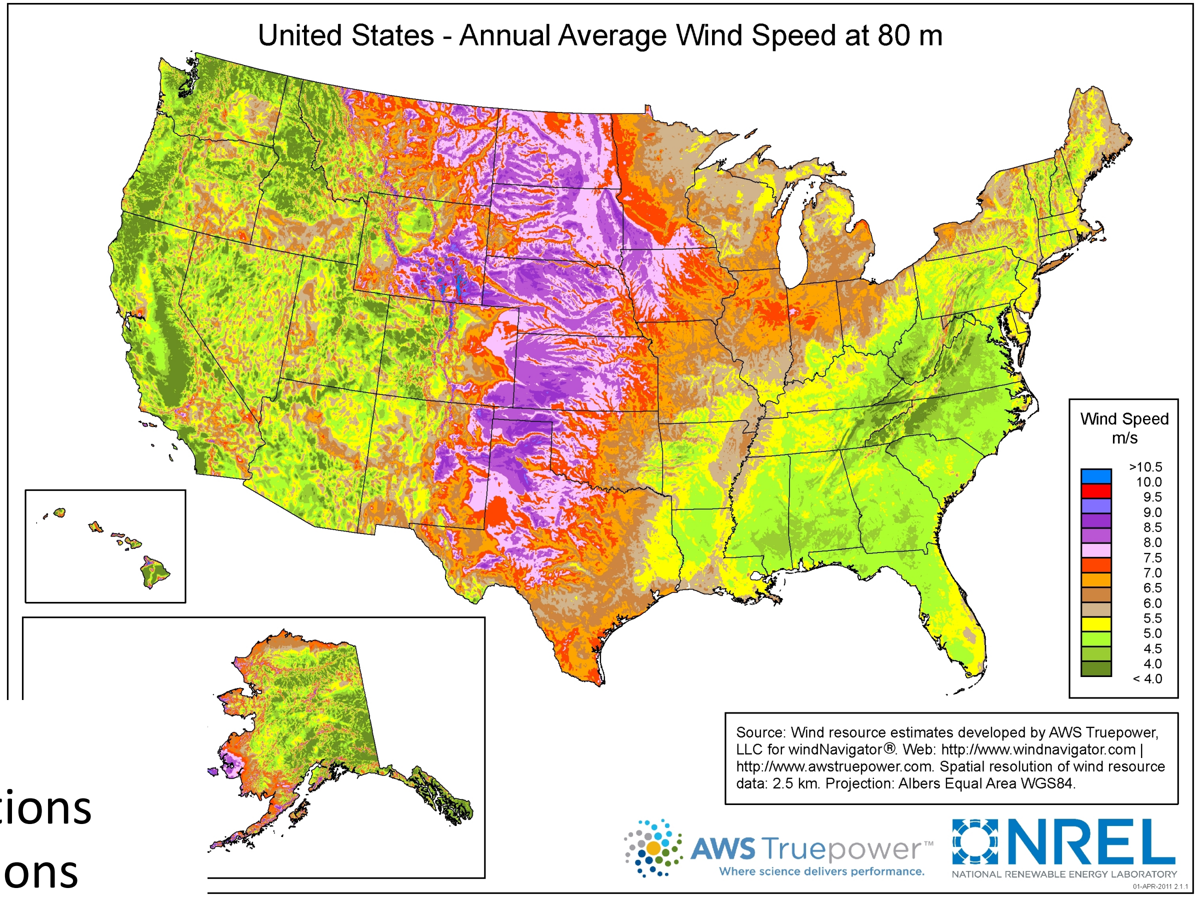
Solar and wind yearly generation forecasts



Source: Bloomberg New Energy Finance, New Energy Outlook 2017

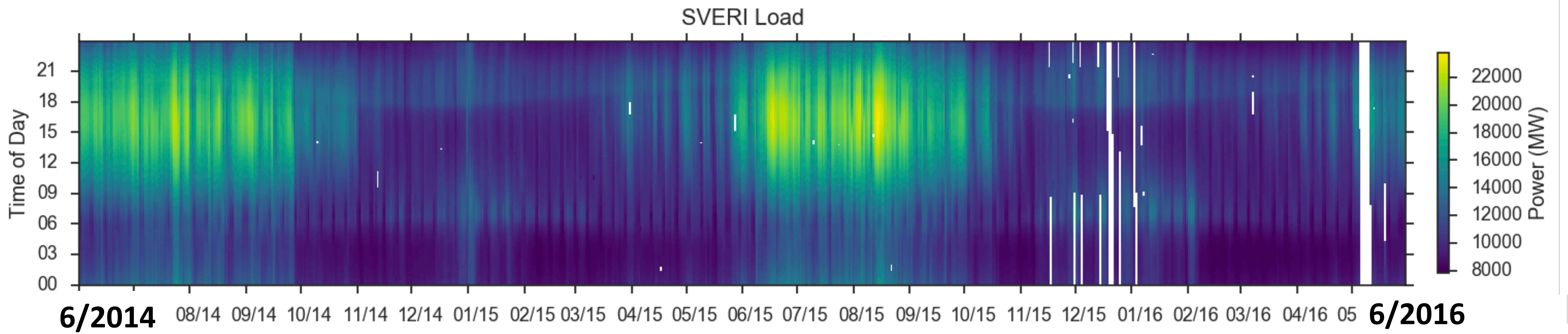
Solar and wind resource assessments

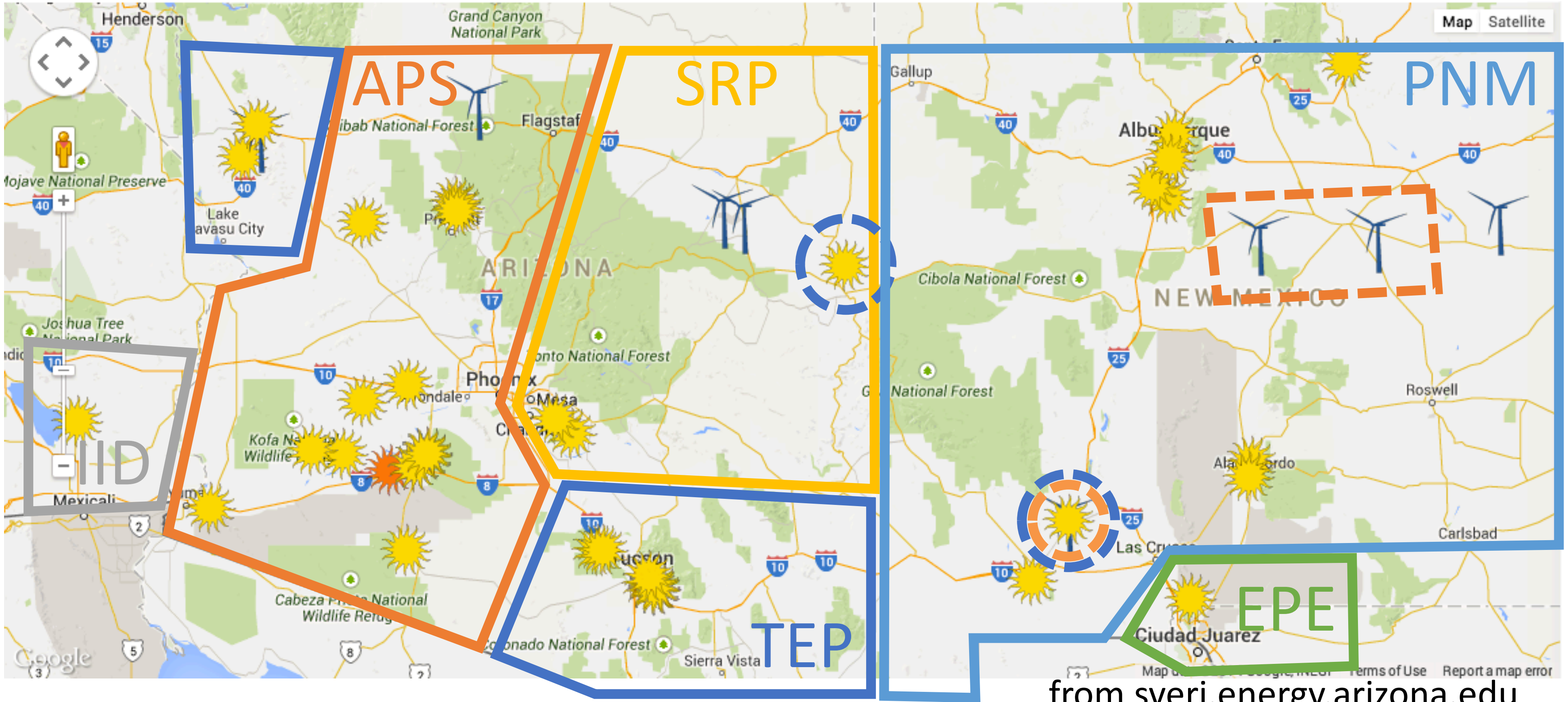




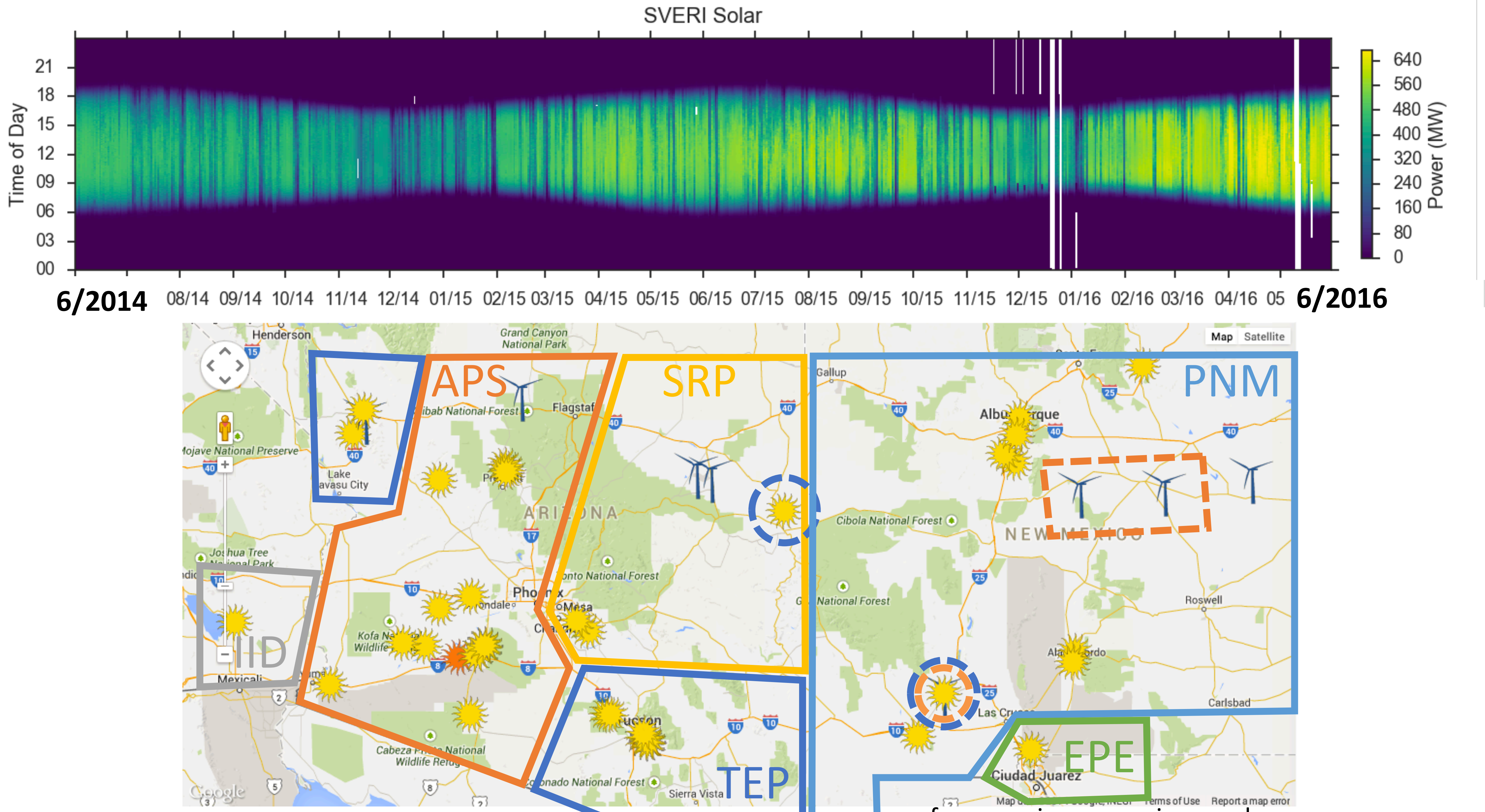
Inputs:

- Weather observations
- Satellite observations
- Weather models
- Weather to power models





from sveri.energy.arizona.edu



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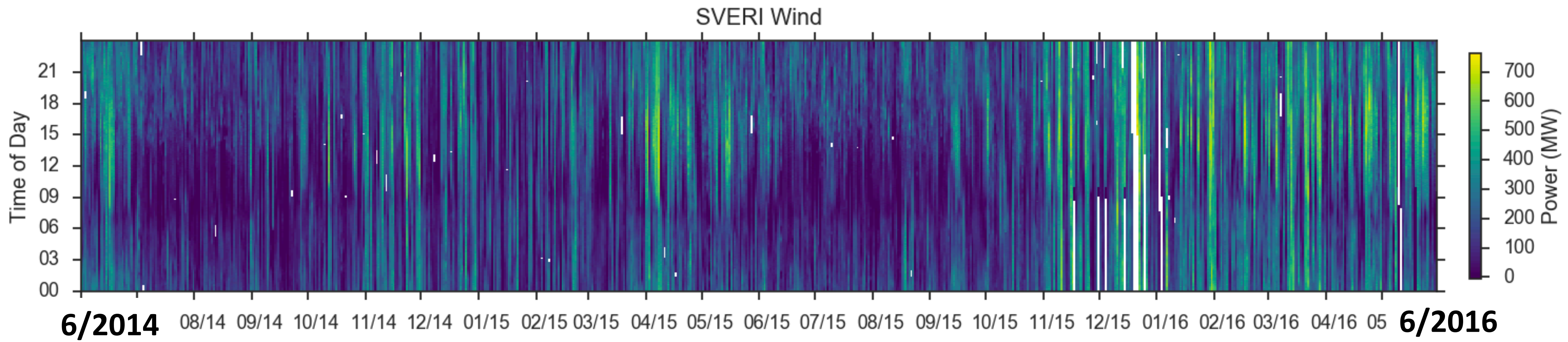

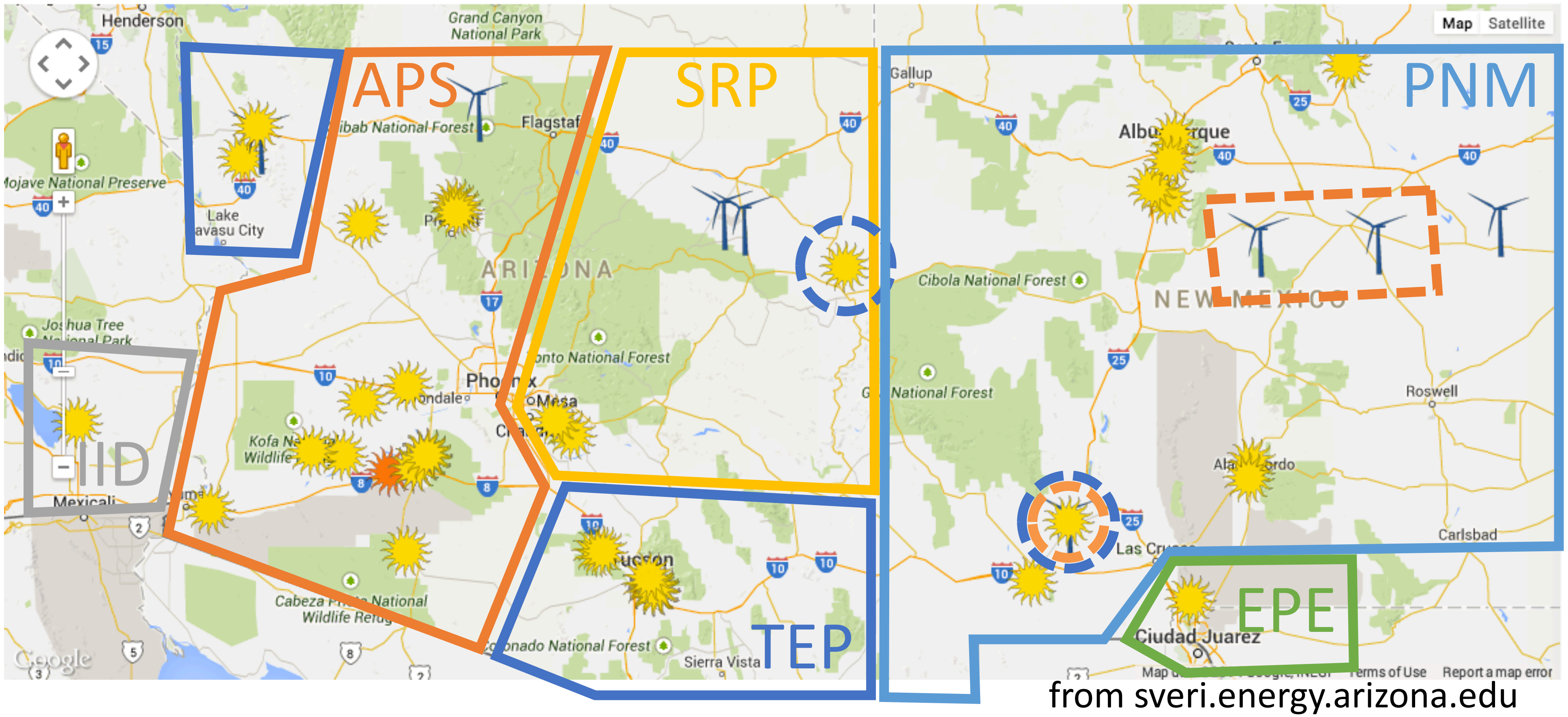

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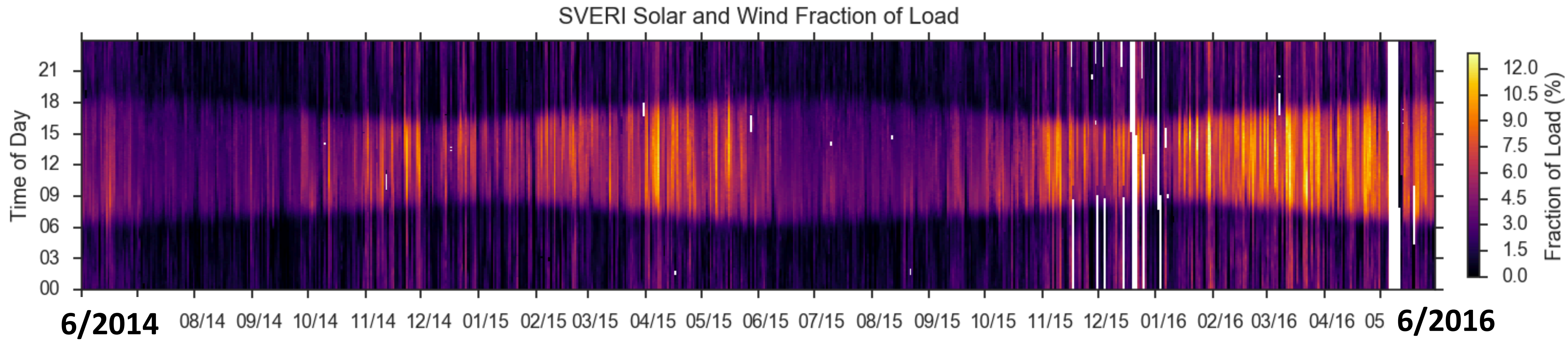

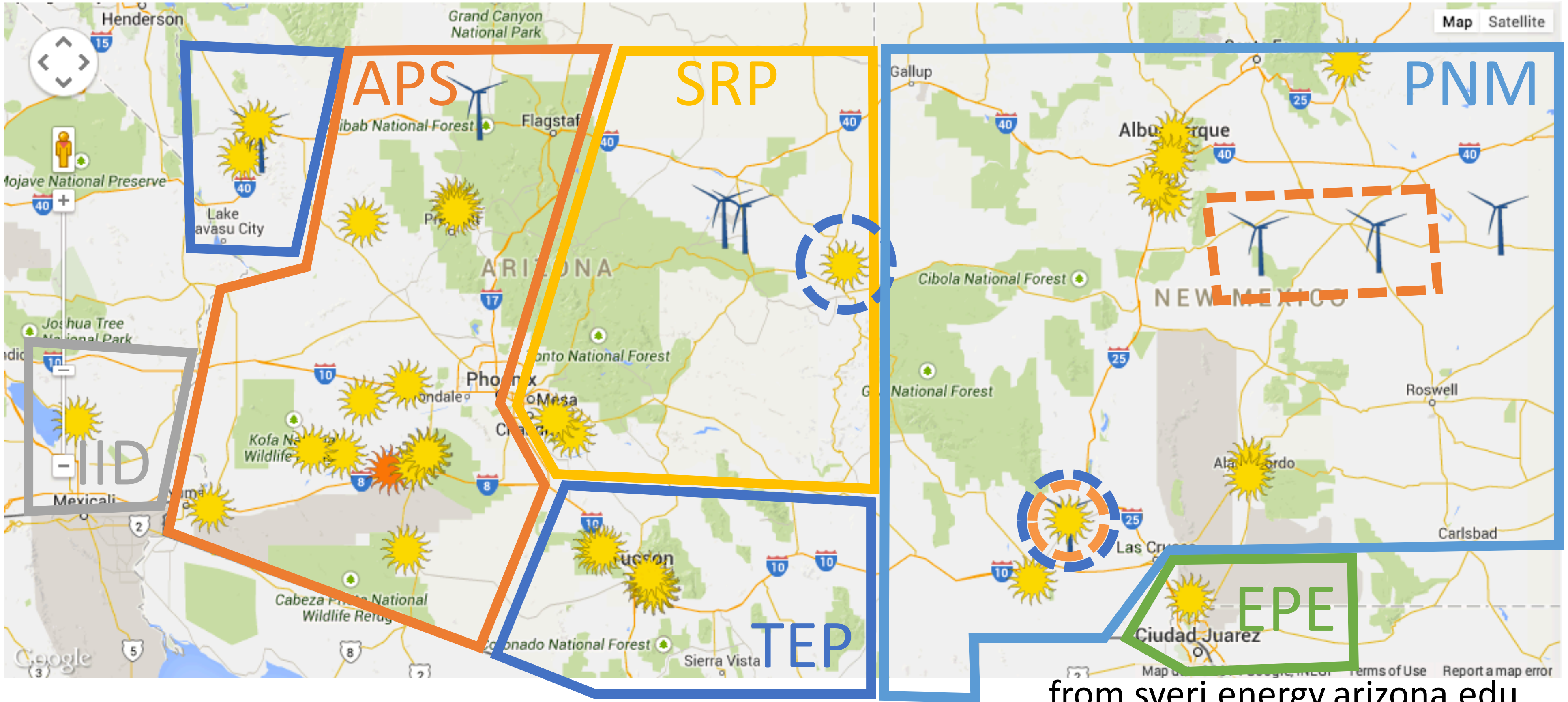

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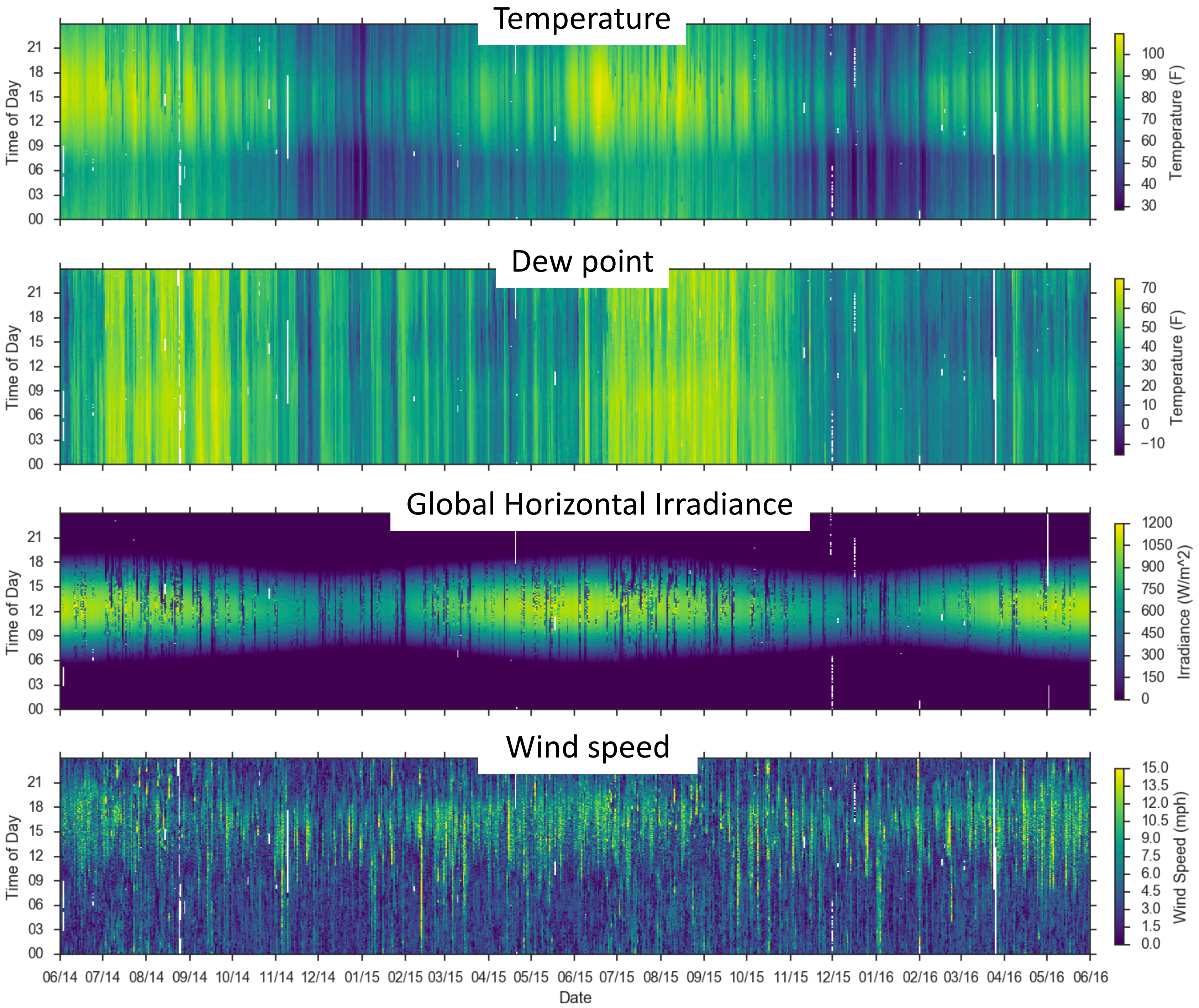
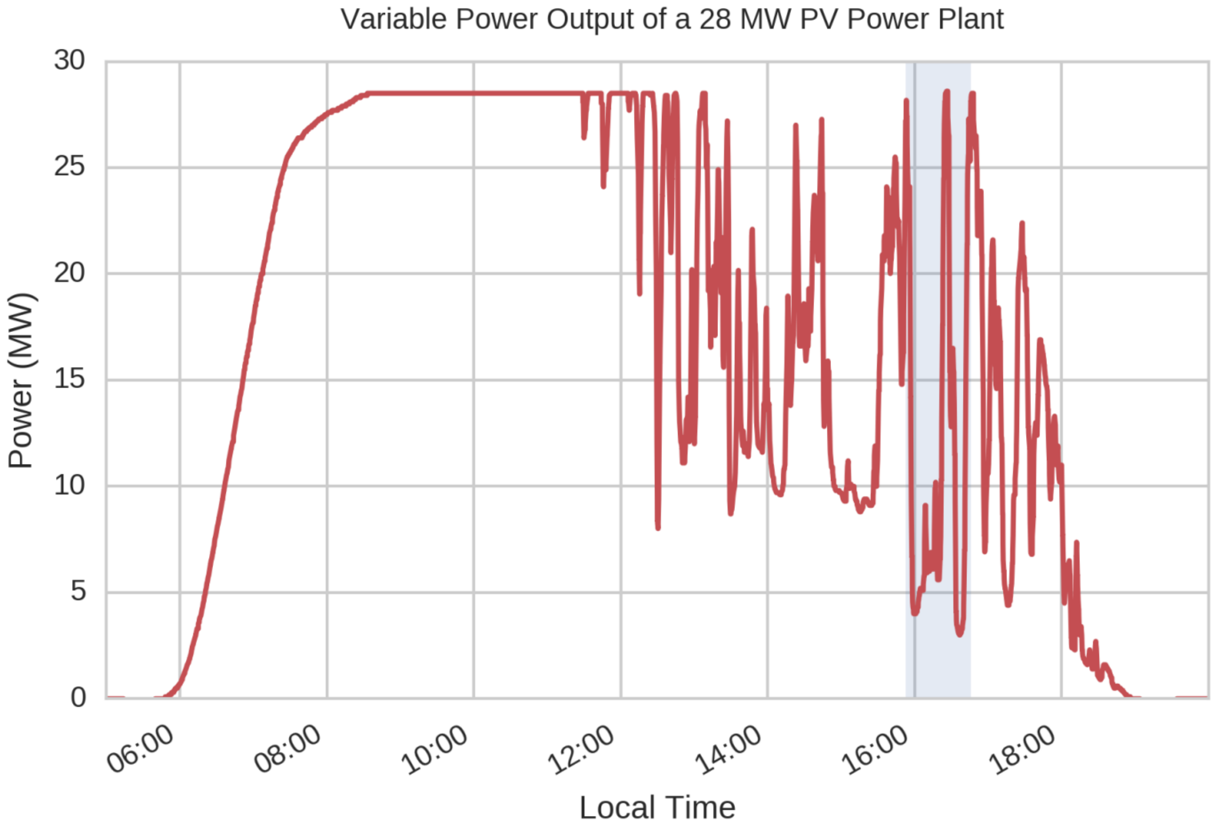


Temperature
Time of Day
00
03
06
09
12
15
18
21
Temperature (F)
30
40
50
60
70
80
90
100
Dew point
Time of Day
Temperature (F)
−10
0
10
20
30
40
50
60
70
Global Horizontal Irradiance
Time of Day
Irradiance (W/m^2)
0
150
300
450
600
750
900
1050
1200
Wind speed
Time of Day
Wind Speed (mph)
0.0
1.5
3.0
4.5
6.0
7.5
9.0
10.5
12.0
13.5
15.0
06/14 07/14 08/14 09/14 10/14 11/14 12/14 01/15 02/15 03/15 04/15 05/15 06/15 07/15 08/15 09/15 10/15 11/15 12/15 01/16 02/16 03/16 04/16 05/16 06/16
Date

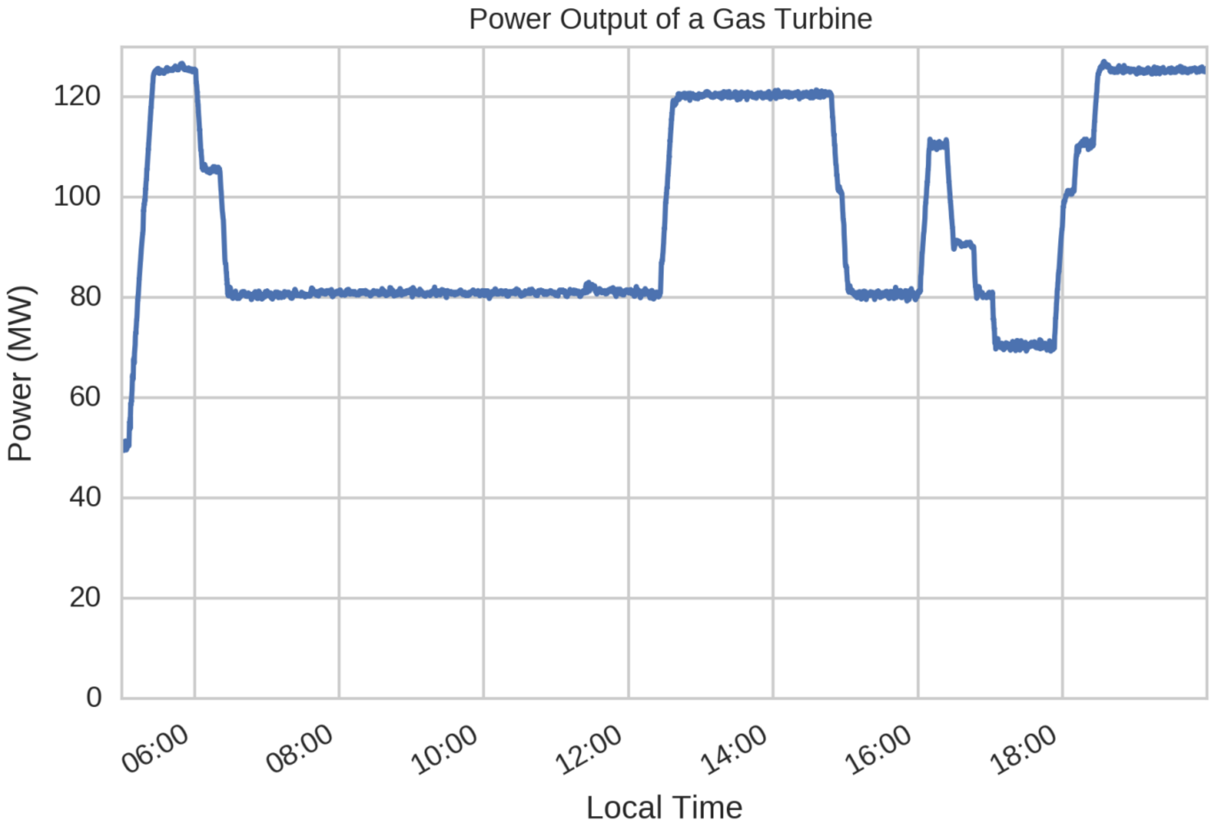
Clouds/wind/weather control the output of solar and wind power plants

Utilities control their conventional generators and market purchases

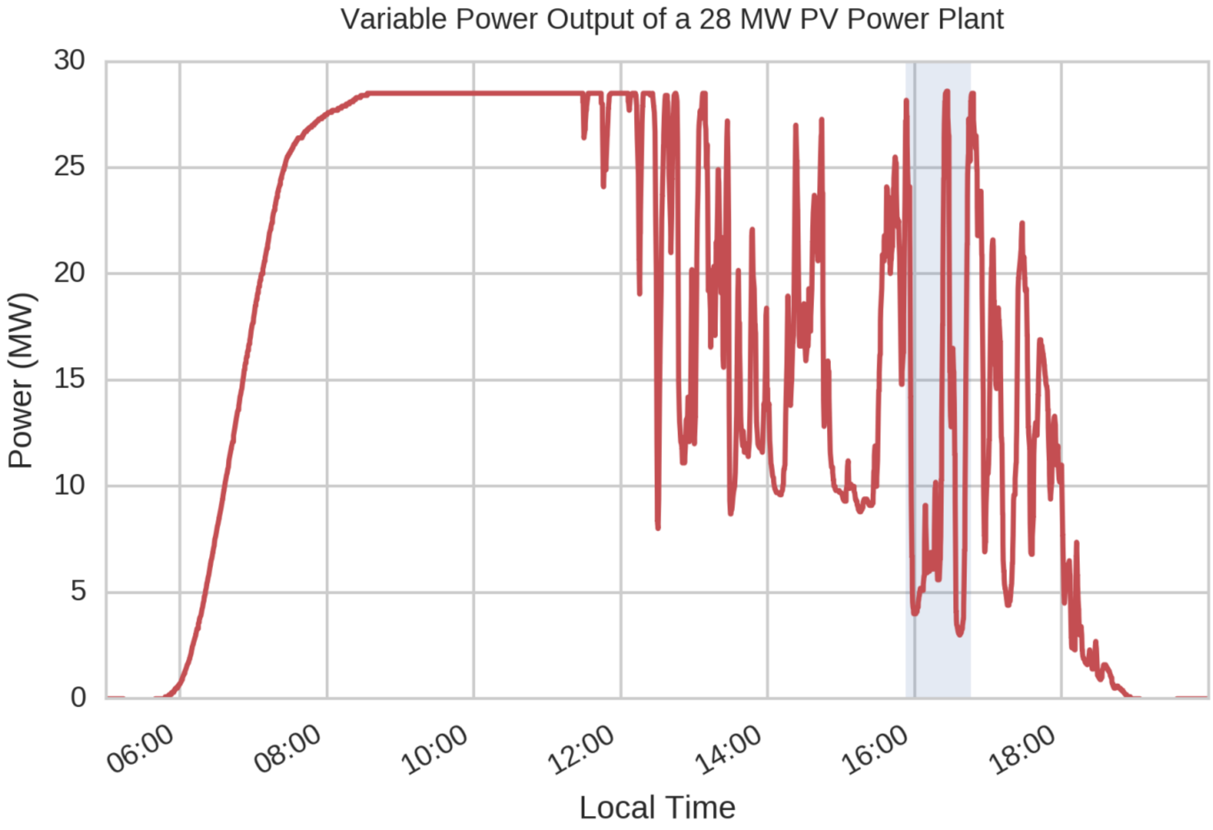
Clouds/wind/weather control the output of solar and wind power plants

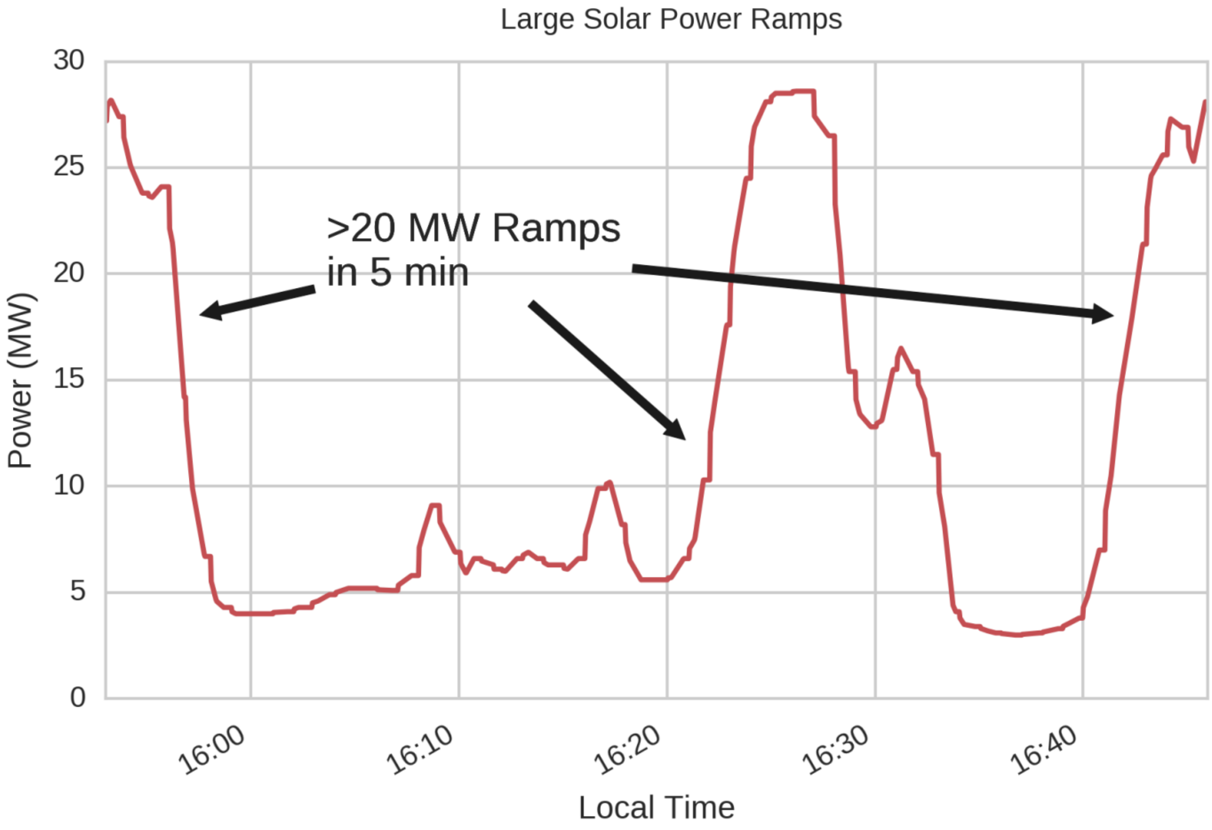


Utilities control their conventional generators and market purchases



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

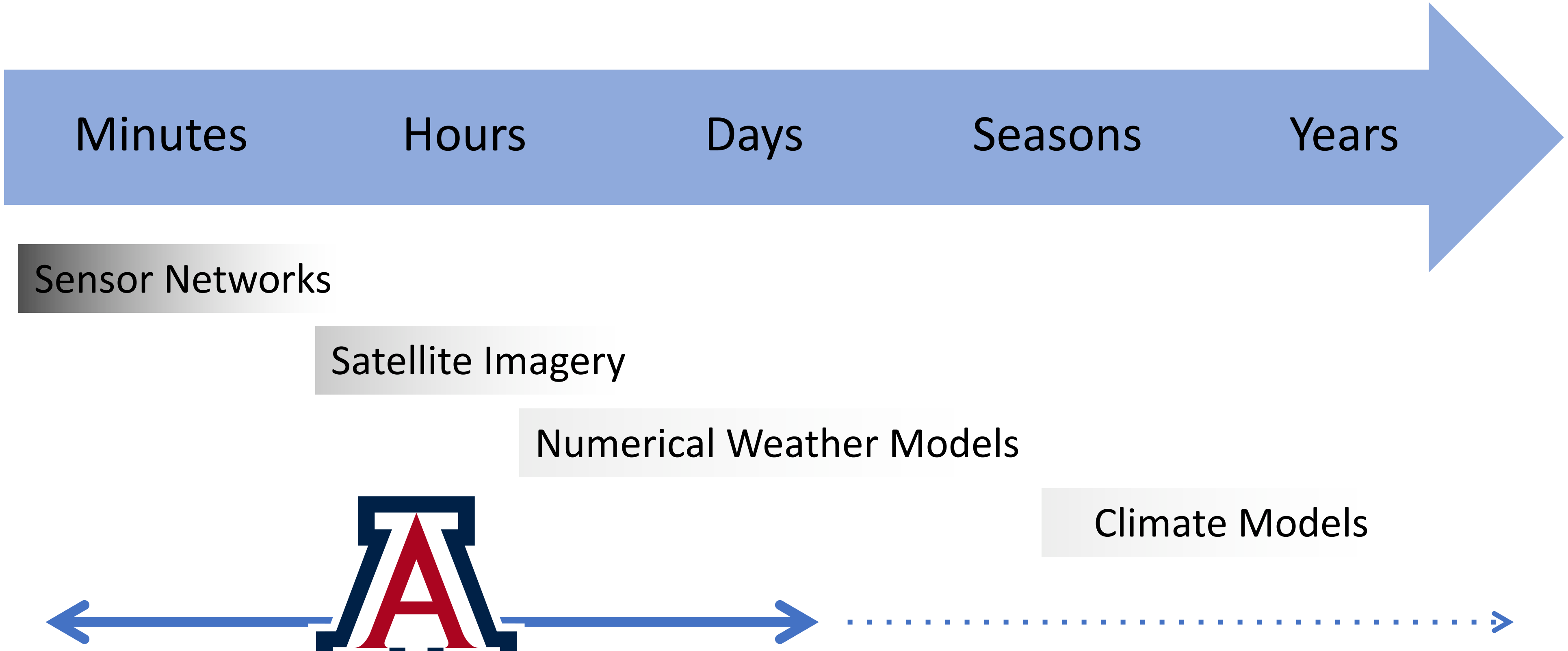




Different utility operations occur on different time scales

New: batteries, demand response, curtailment

Different forecasting methods work better at different time scales



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Renewable energy forecast applications

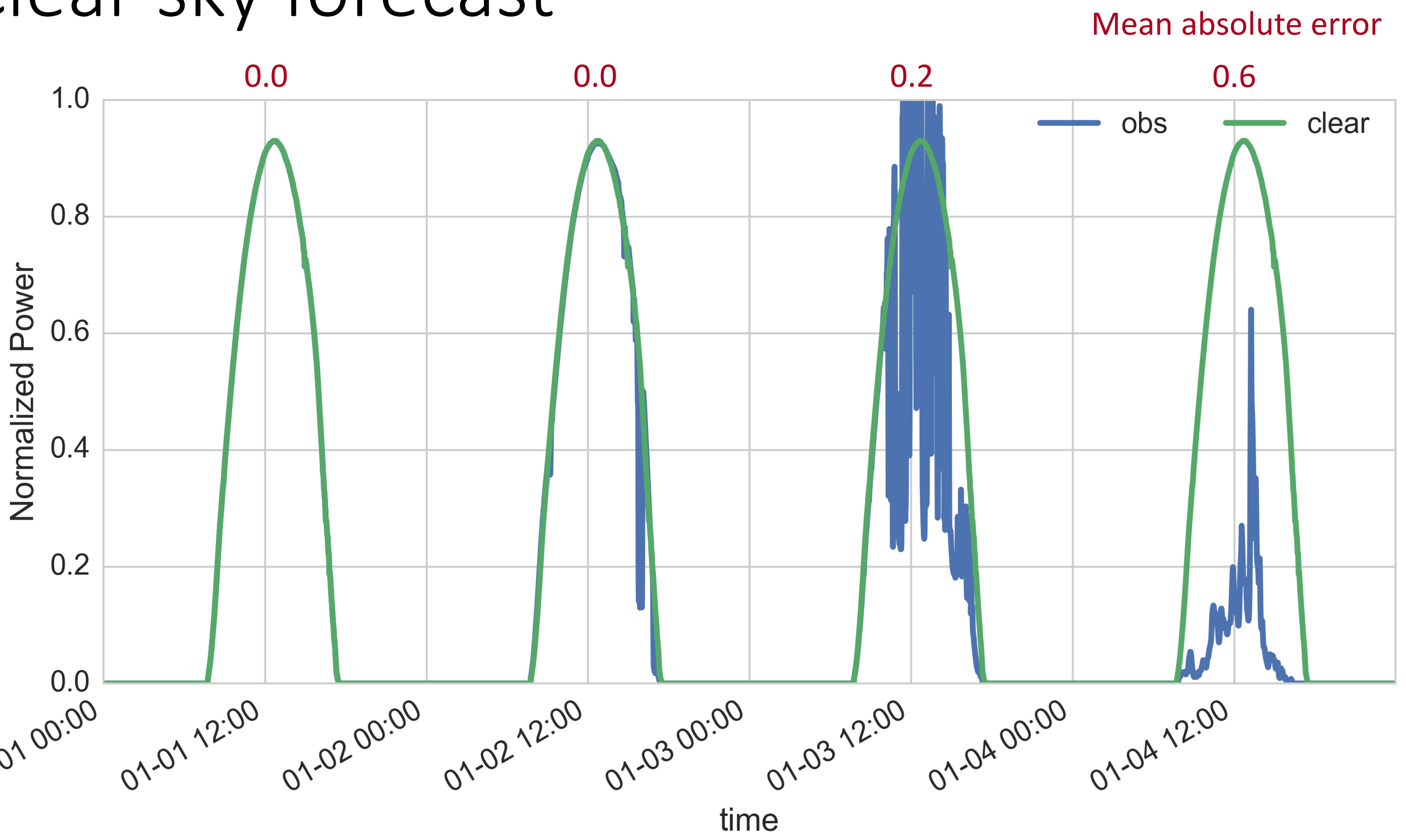
How can forecasts help utilities keep energy costs low and maintain grid reliability?

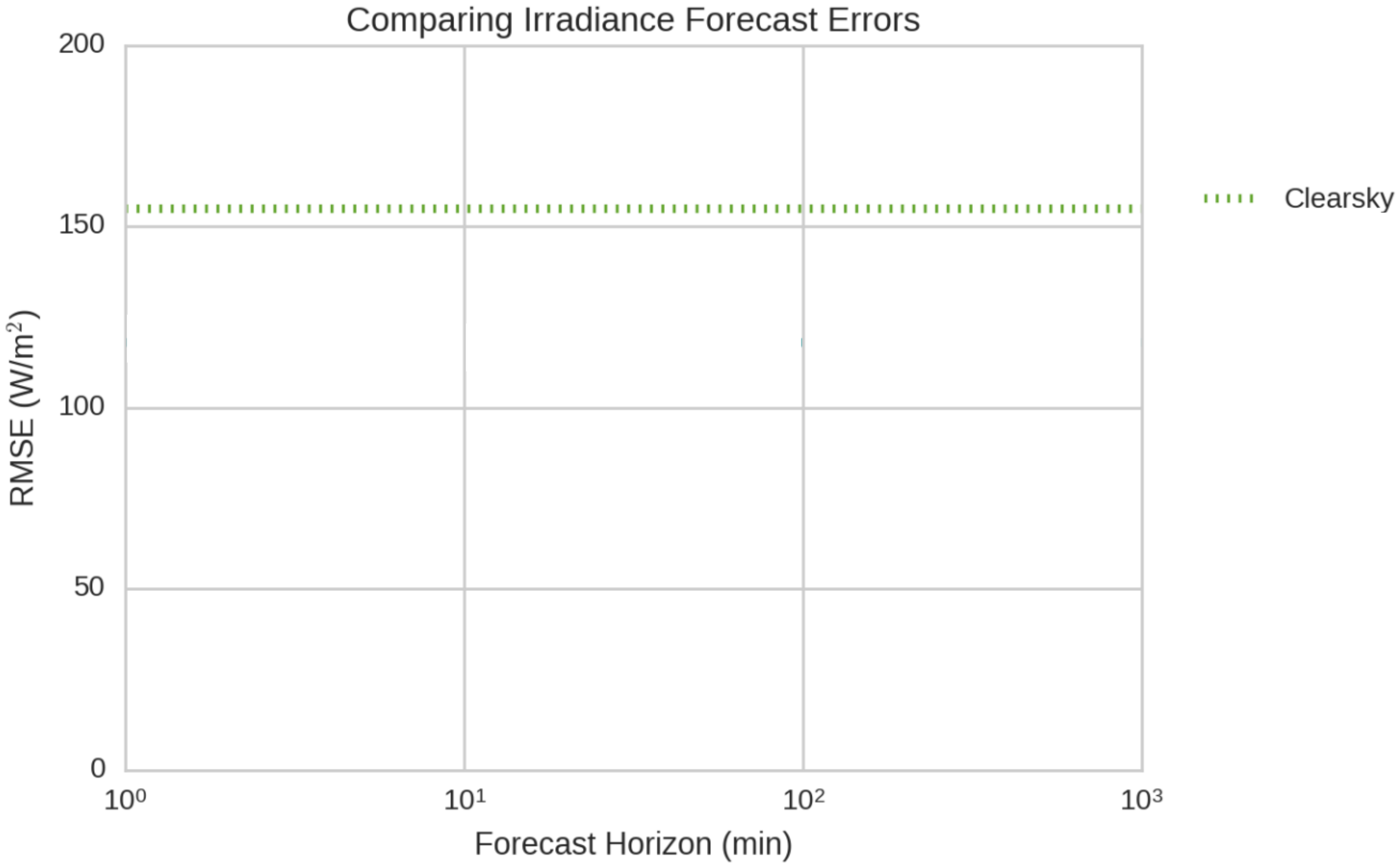
- Improve energy market trading strategies
- Schedule and invest in more efficient generators (e.g. combined cycle vs. combustion turbine)
- Schedule and invest in transmission
- Reduce costs associated with generator starts
- Defer maintenance associated with excessive generator set point seeking
- Optimize the use of battery storage

Simple benchmark forecast methods

1. Clear sky
2. Persistence
3. Clear sky index persistence

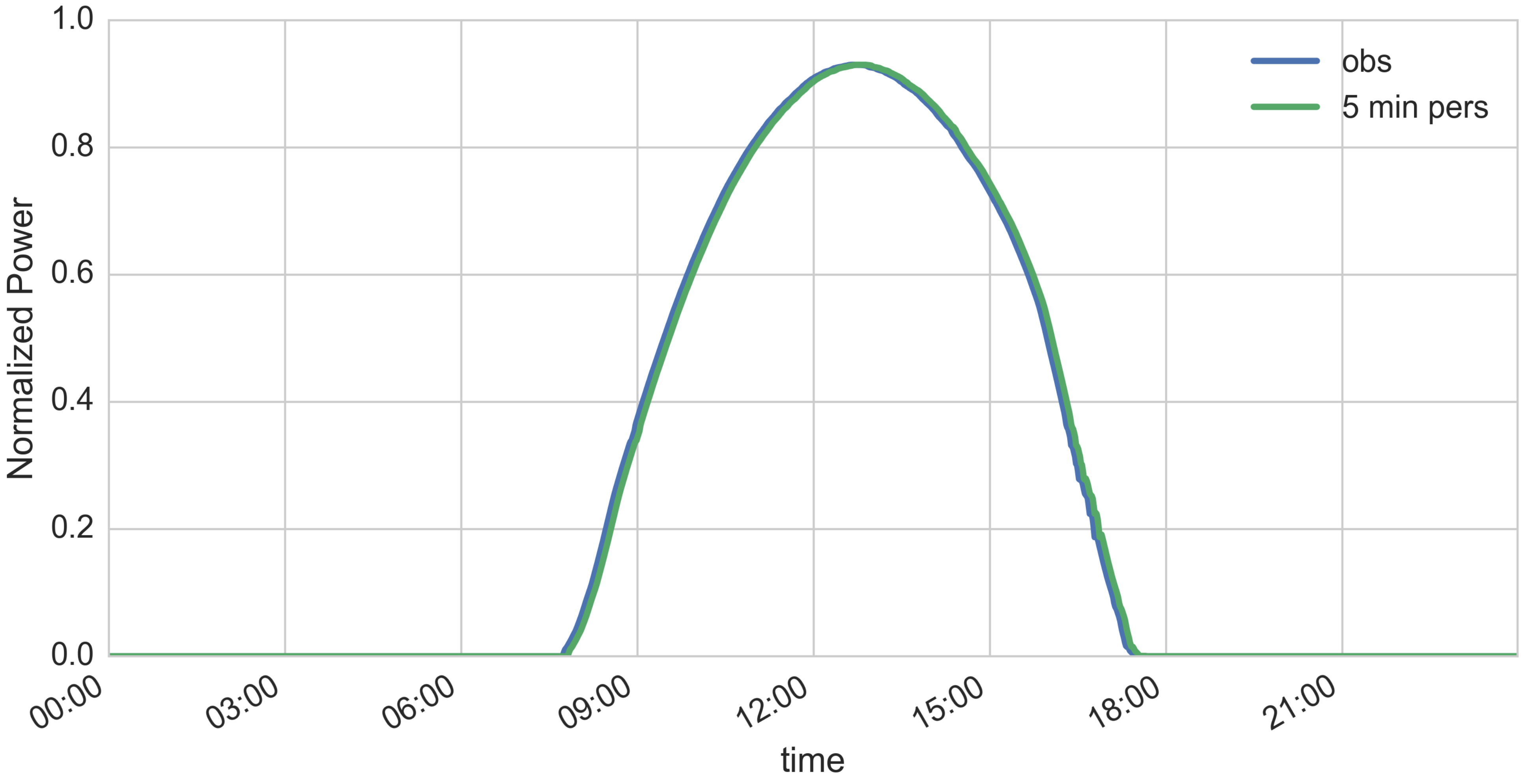
Clear sky forecast





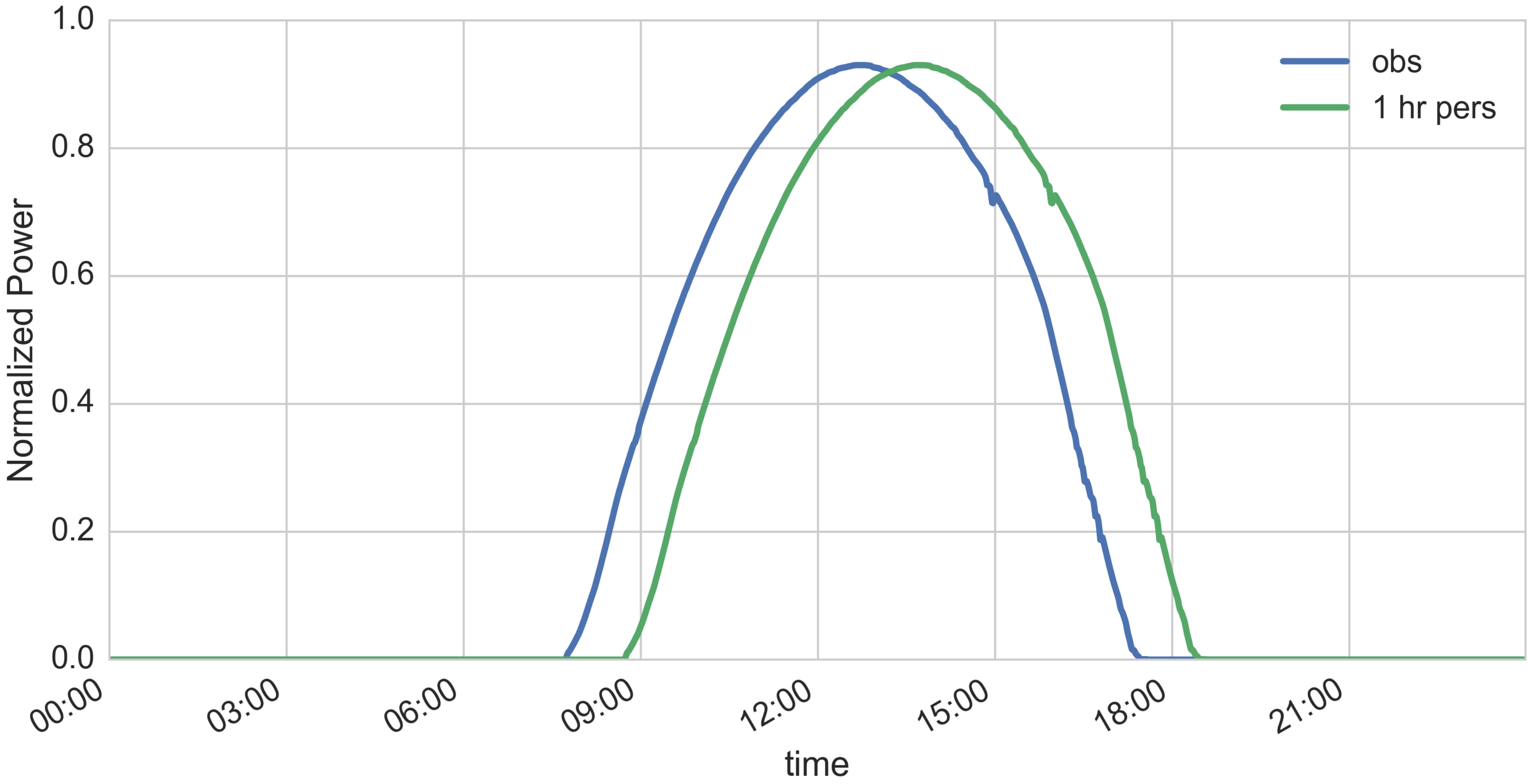
Comparing Irradiance Forecast Errors
200
150
100
50
0
RMSE (W/m²)
10^0
10^1
10^2
10^3
Forecast Horizon (min)
Clearsky

Persistence forecast



The power 5 minutes from now will be the same as it is now $\hat{y}(t_i) = y(t_i - d)$

Persistence forecast

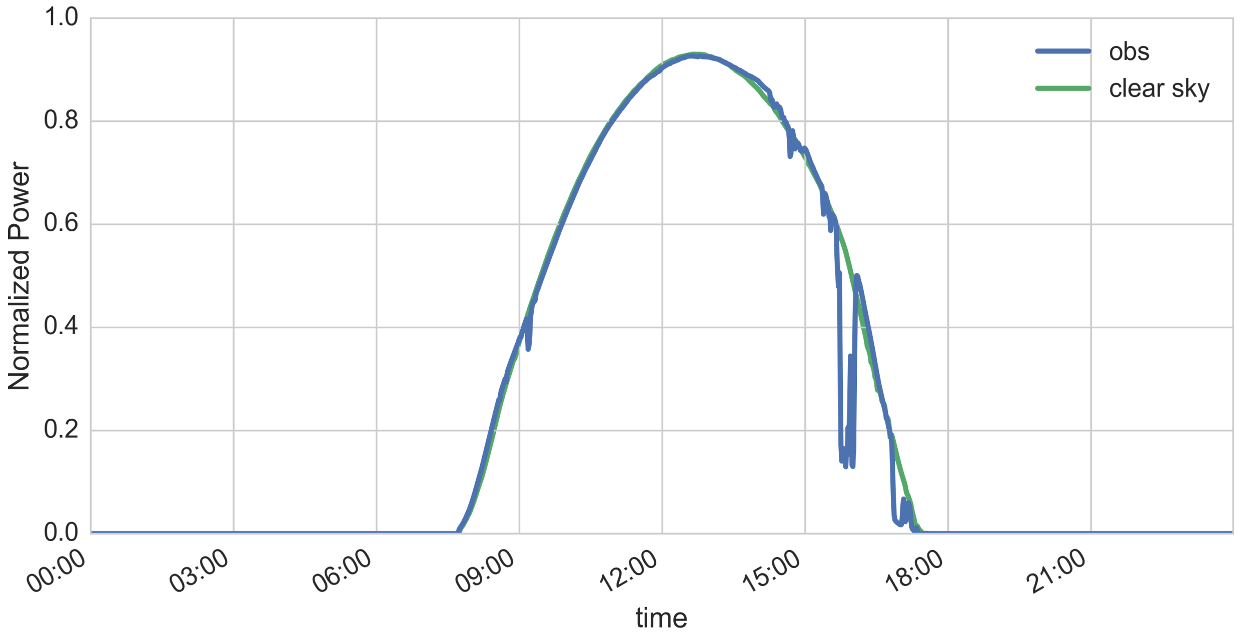


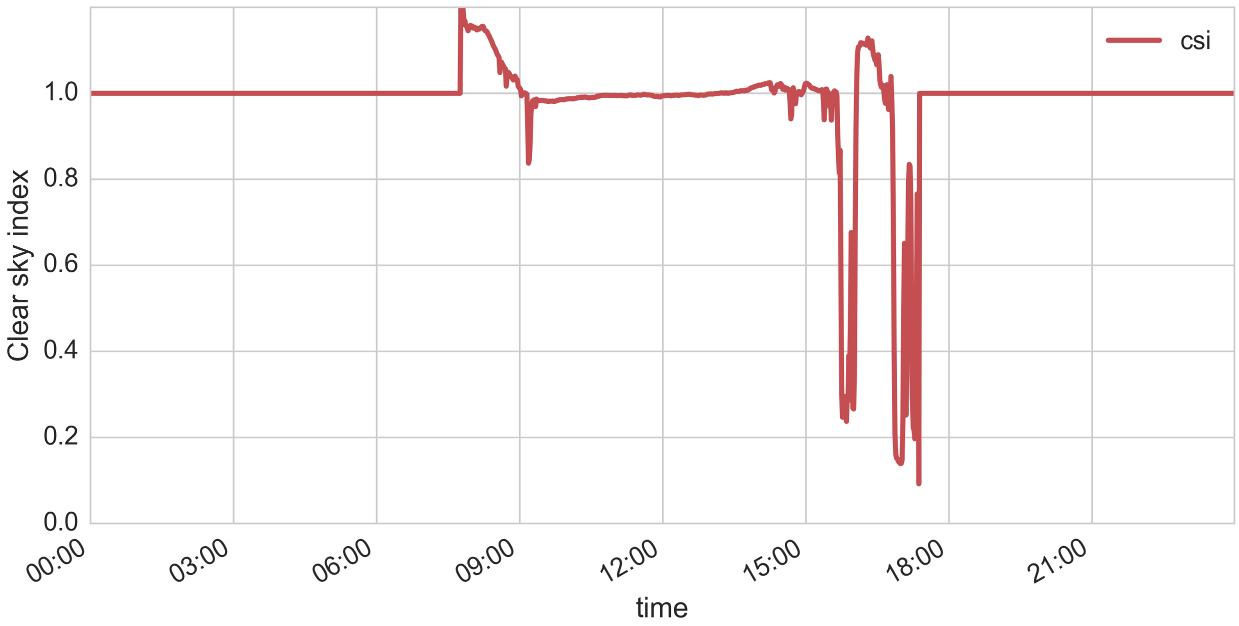
The power 1 hour from now will be the same it is now

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

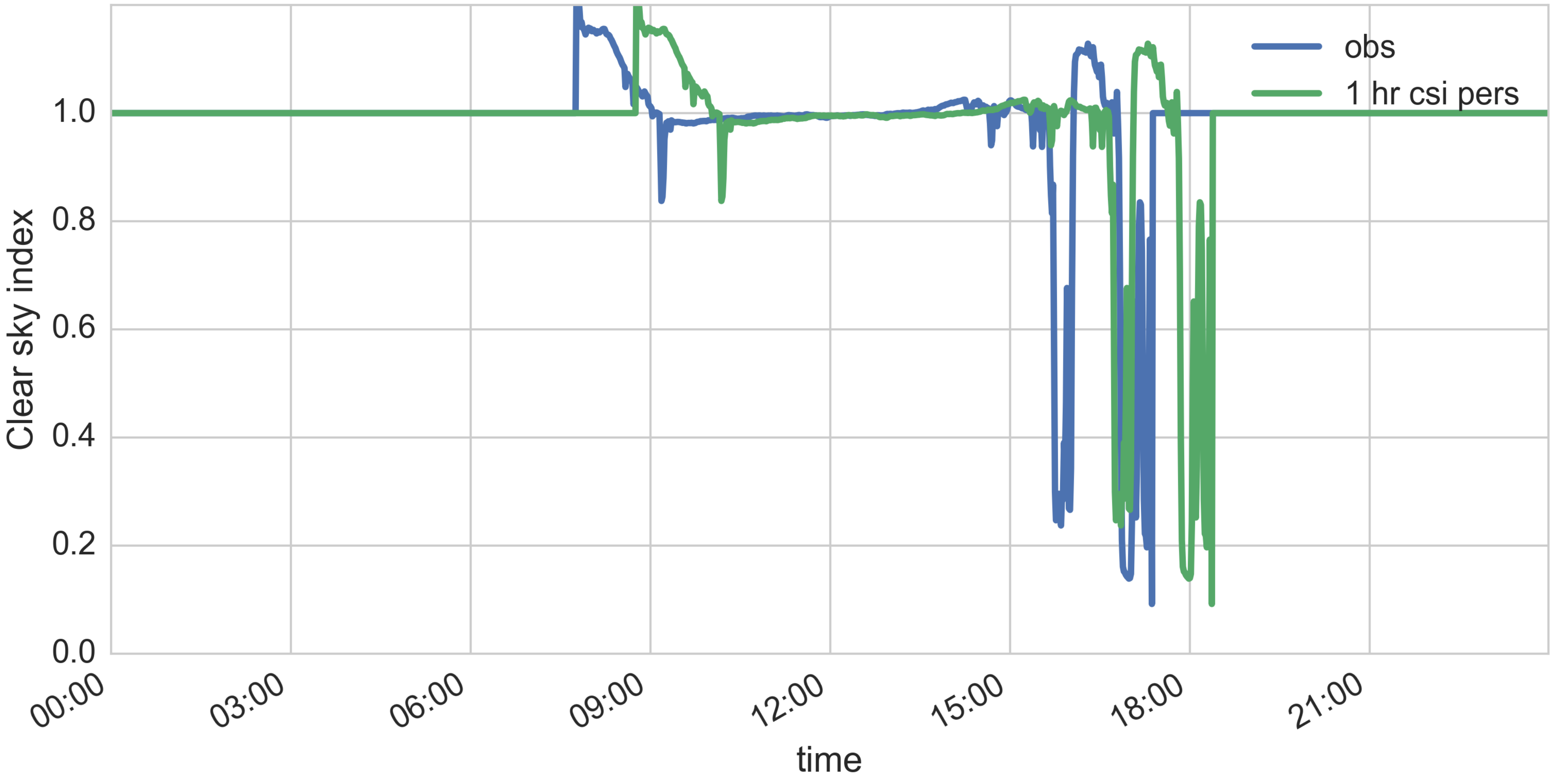
Clear sky index persistence forecast

Clear Sky Index = Observations / Clear Sky Expectation





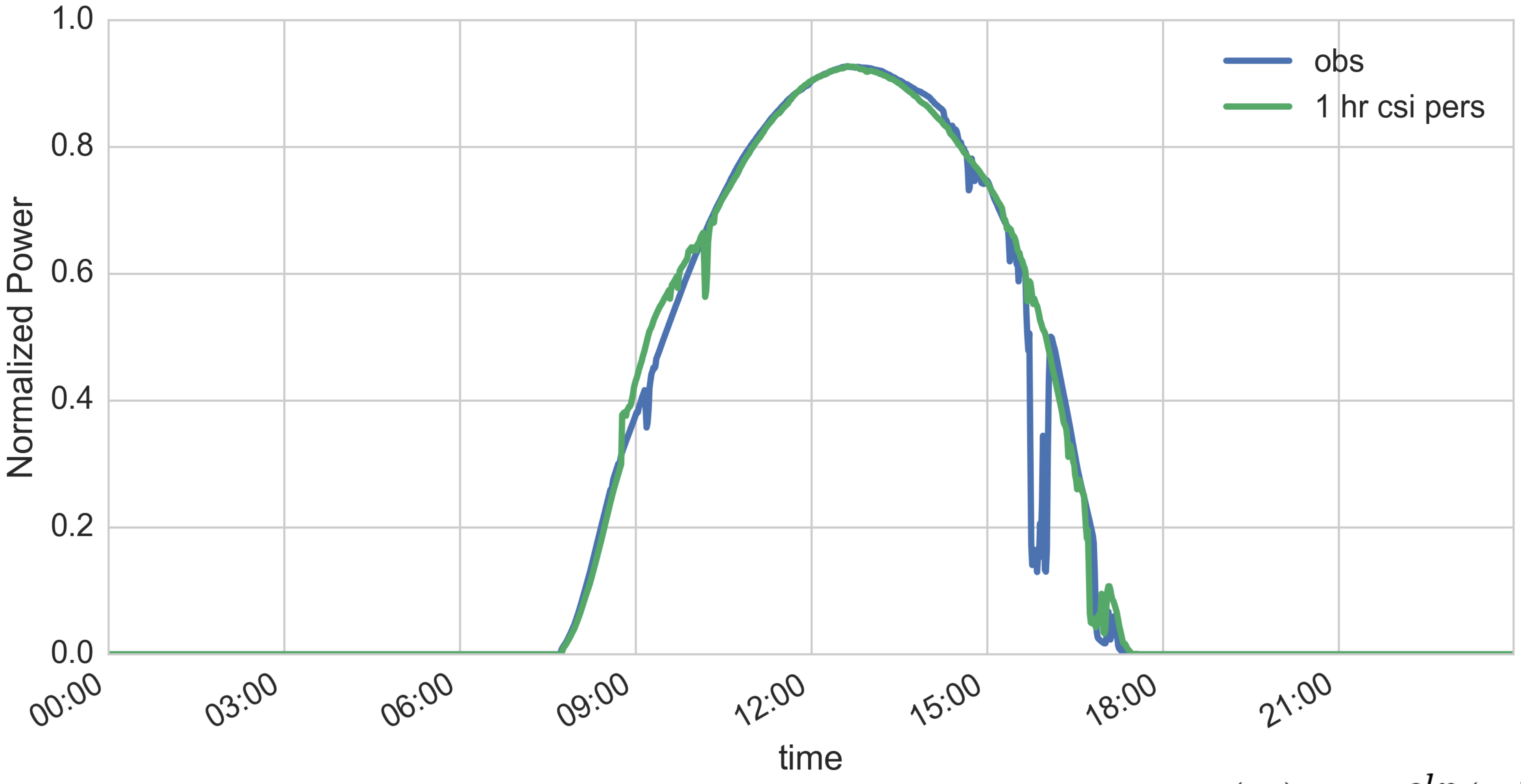
Clear sky index persistence forecast



The clear sky index 1 hour from now will be the same as it now

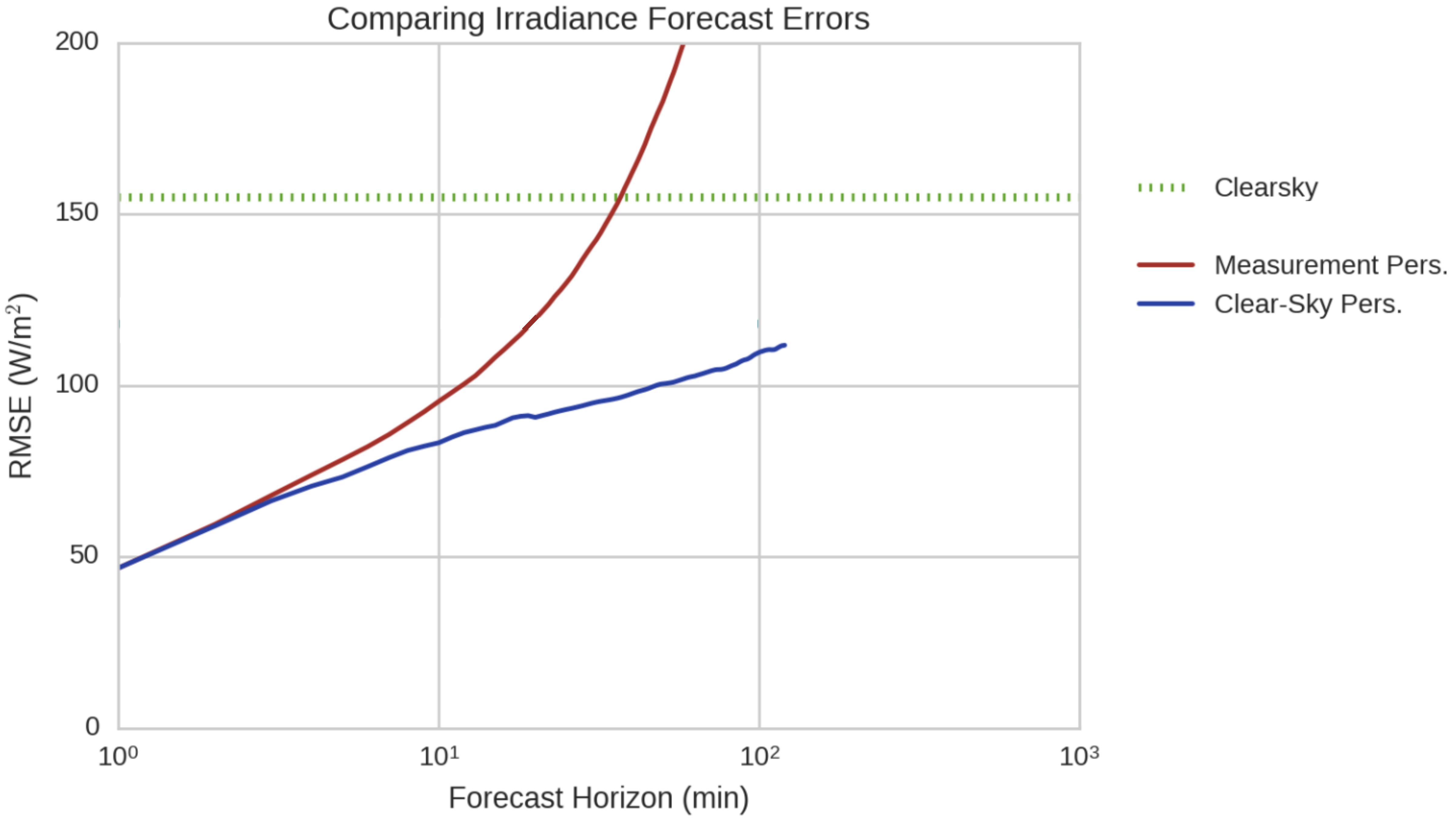
$$\hat{y}(t_i) = y(t_i - d)$$

Clear sky index persistence forecast

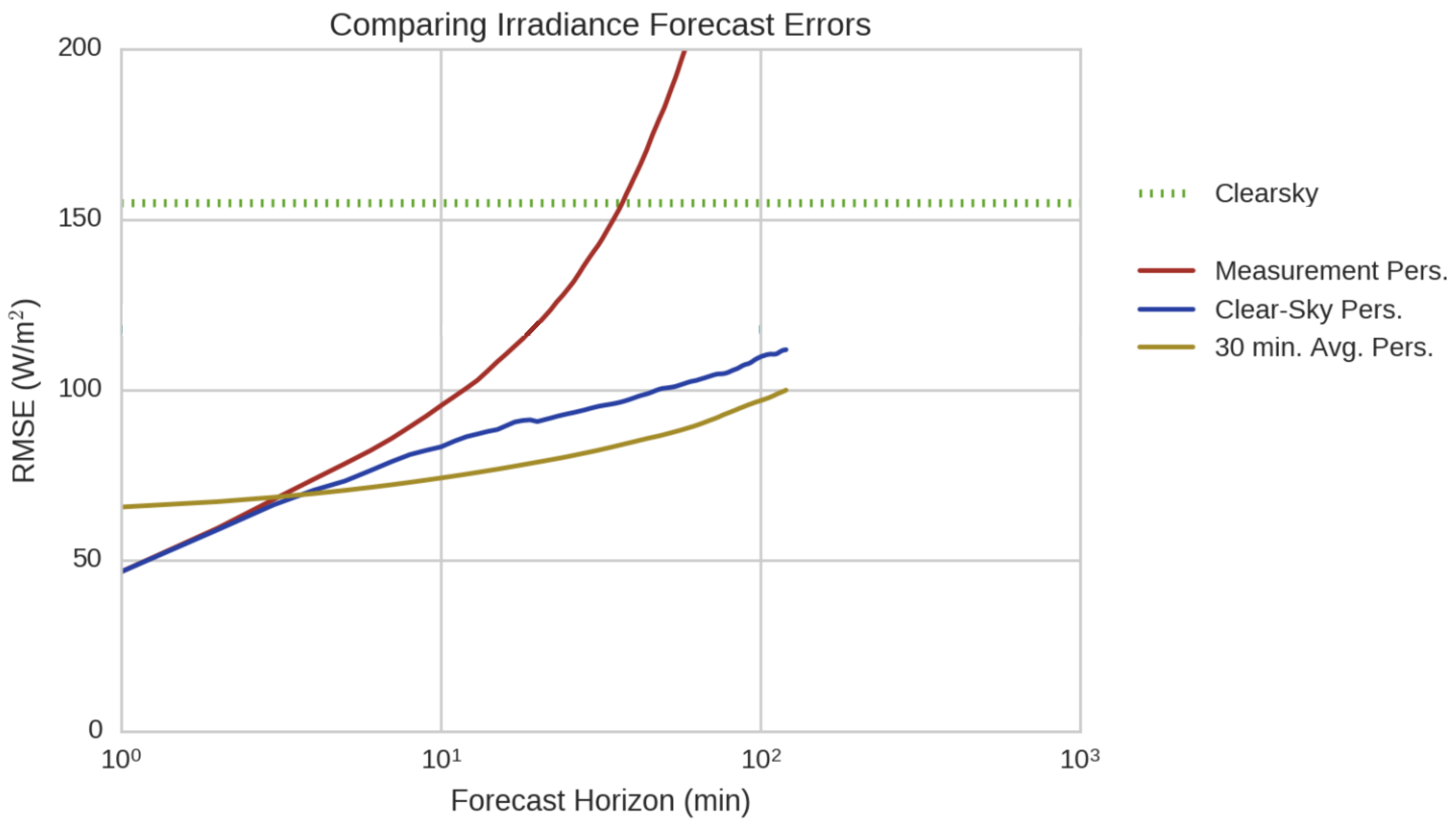


$$\hat{y}(t_i) = y^{clr}(t_i)\ k(t_i - d)$$

The power 1 hour from now will be the same as it now, but account for solar position

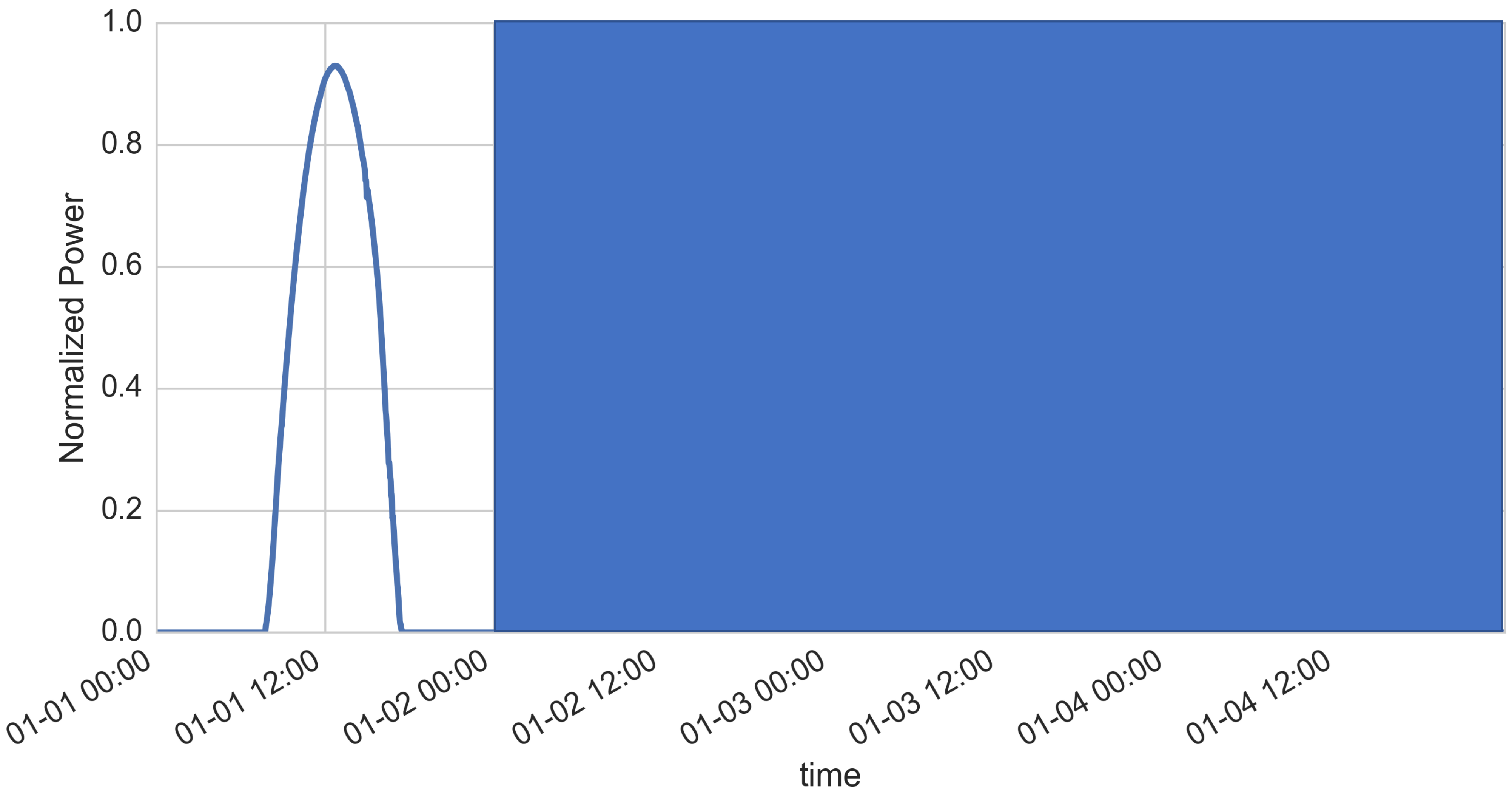


Comparing Irradiance Forecast Errors
RMSE (W/m²)
200
150
100
50
0
10⁰
10¹
10²
10³
Forecast Horizon (min)
Clearsky
Measurement Pers.
Clear-Sky Pers.

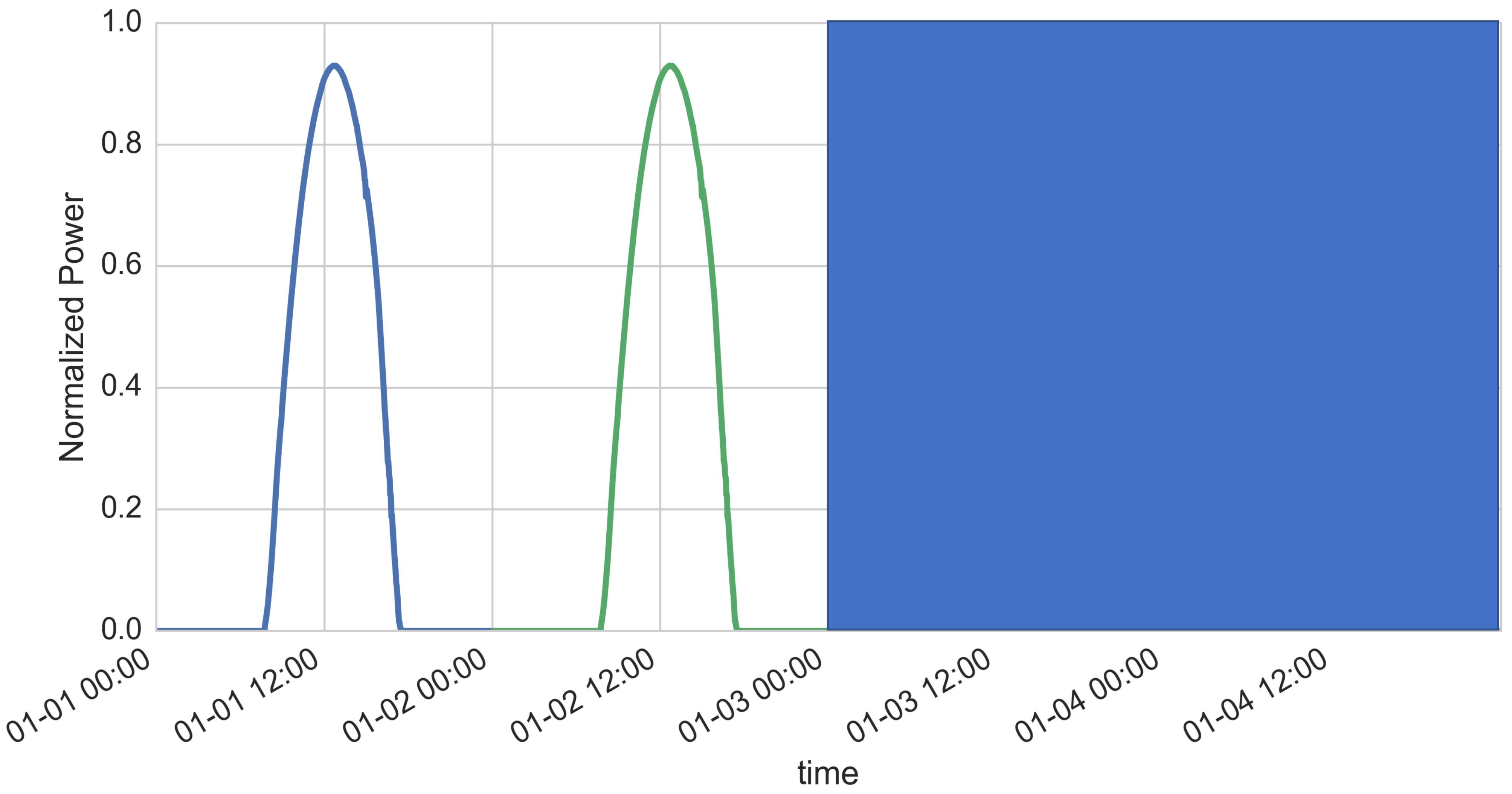


Comparing Irradiance Forecast Errors
RMSE (W/m²)
Forecast Horizon (min)
200
150
100
50
0
10⁰
10¹
10²
10³
Clearsky
Measurement Pers.
Clear-Sky Pers.
30 min. Avg. Pers.

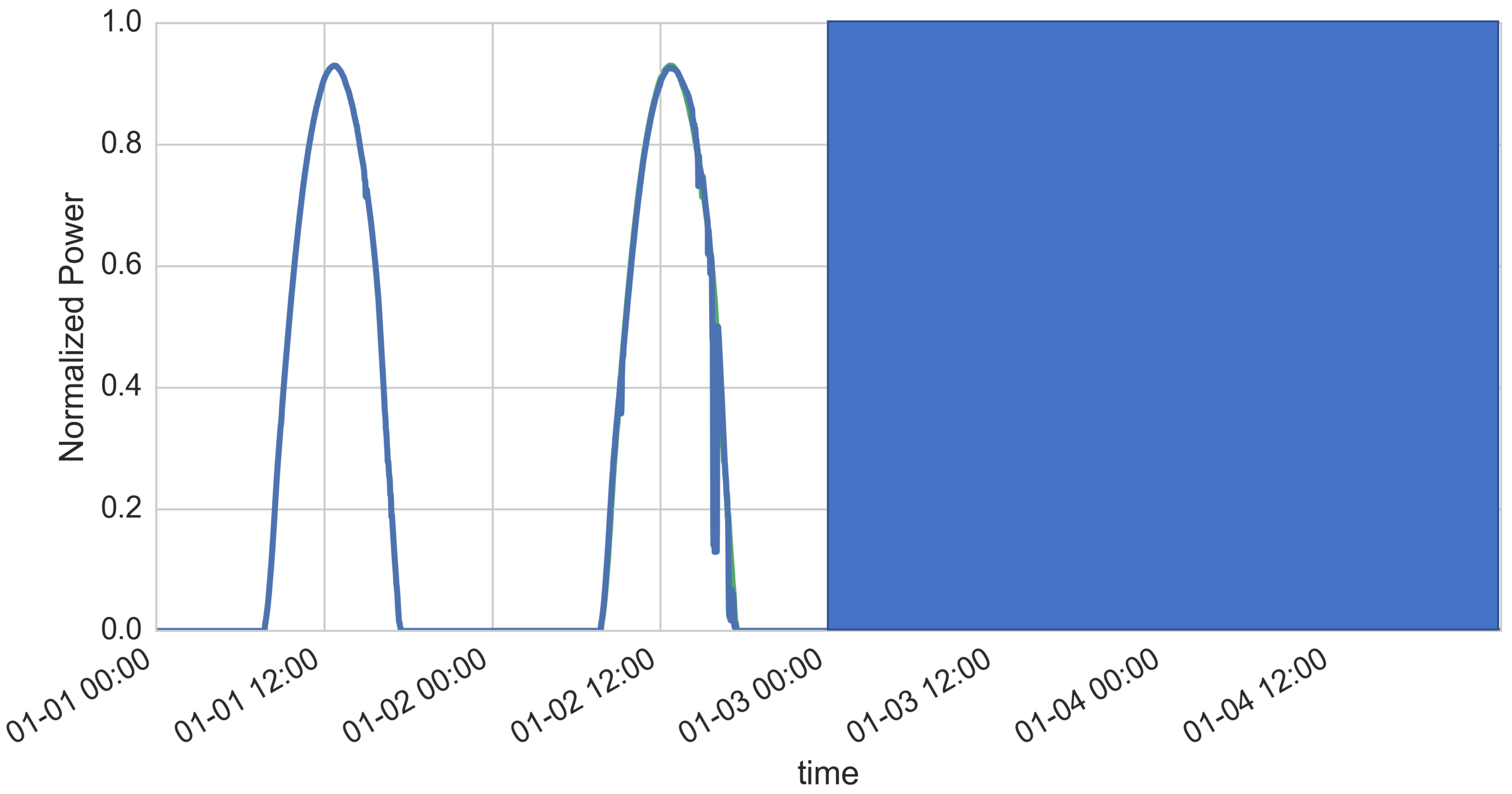
Day ahead persistence forecast



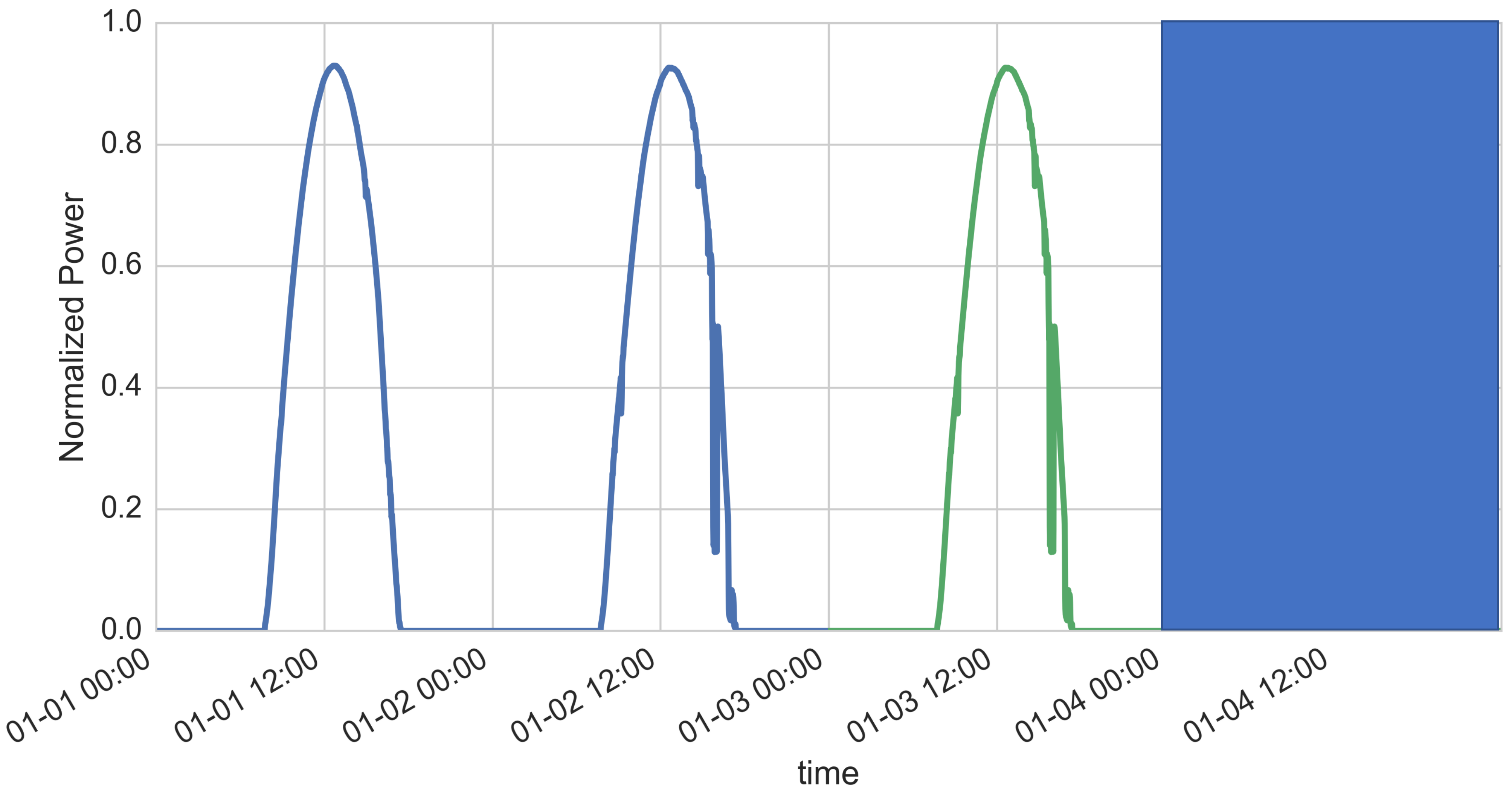
Day ahead persistence forecast



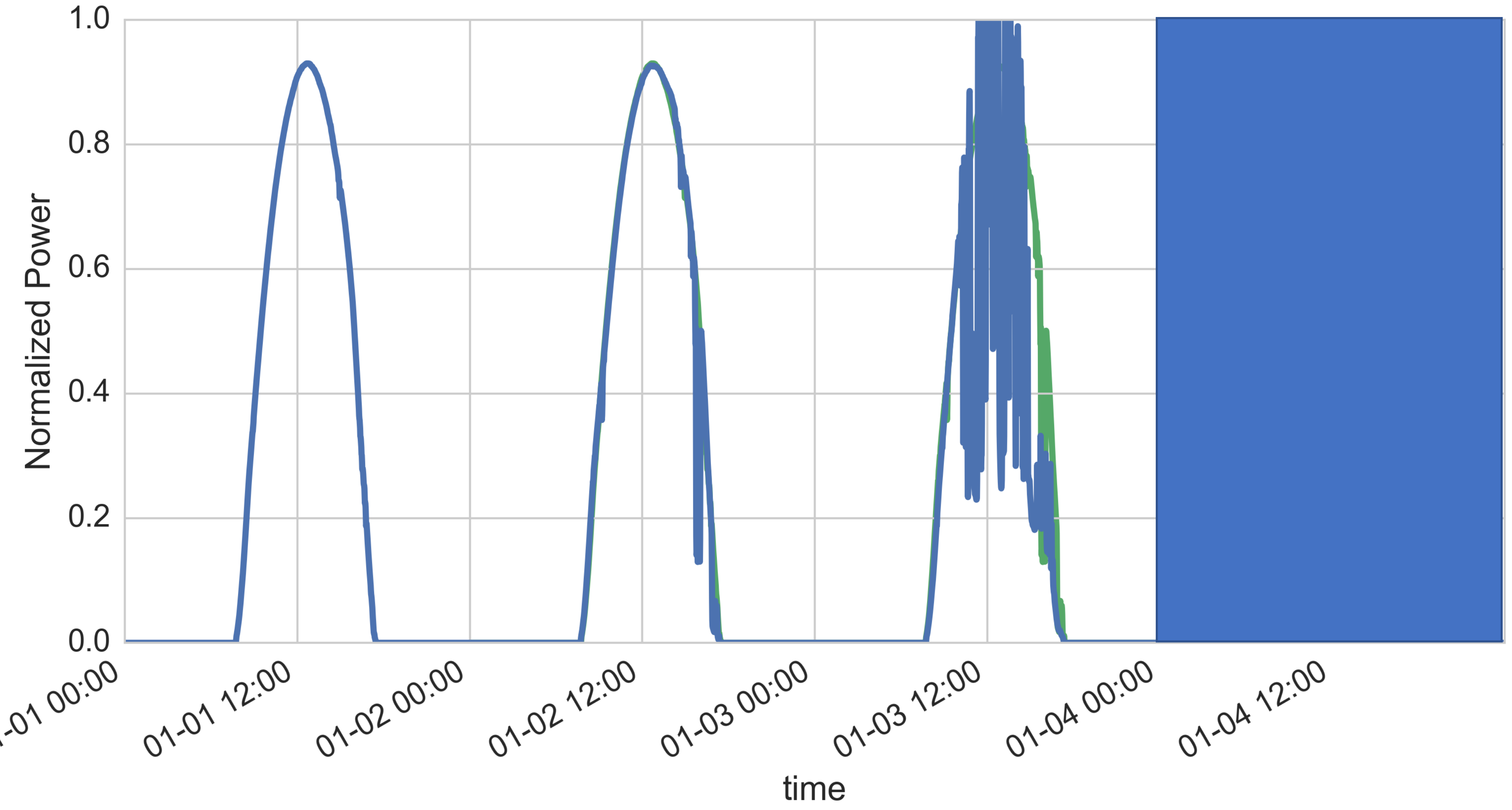
Day ahead persistence forecast



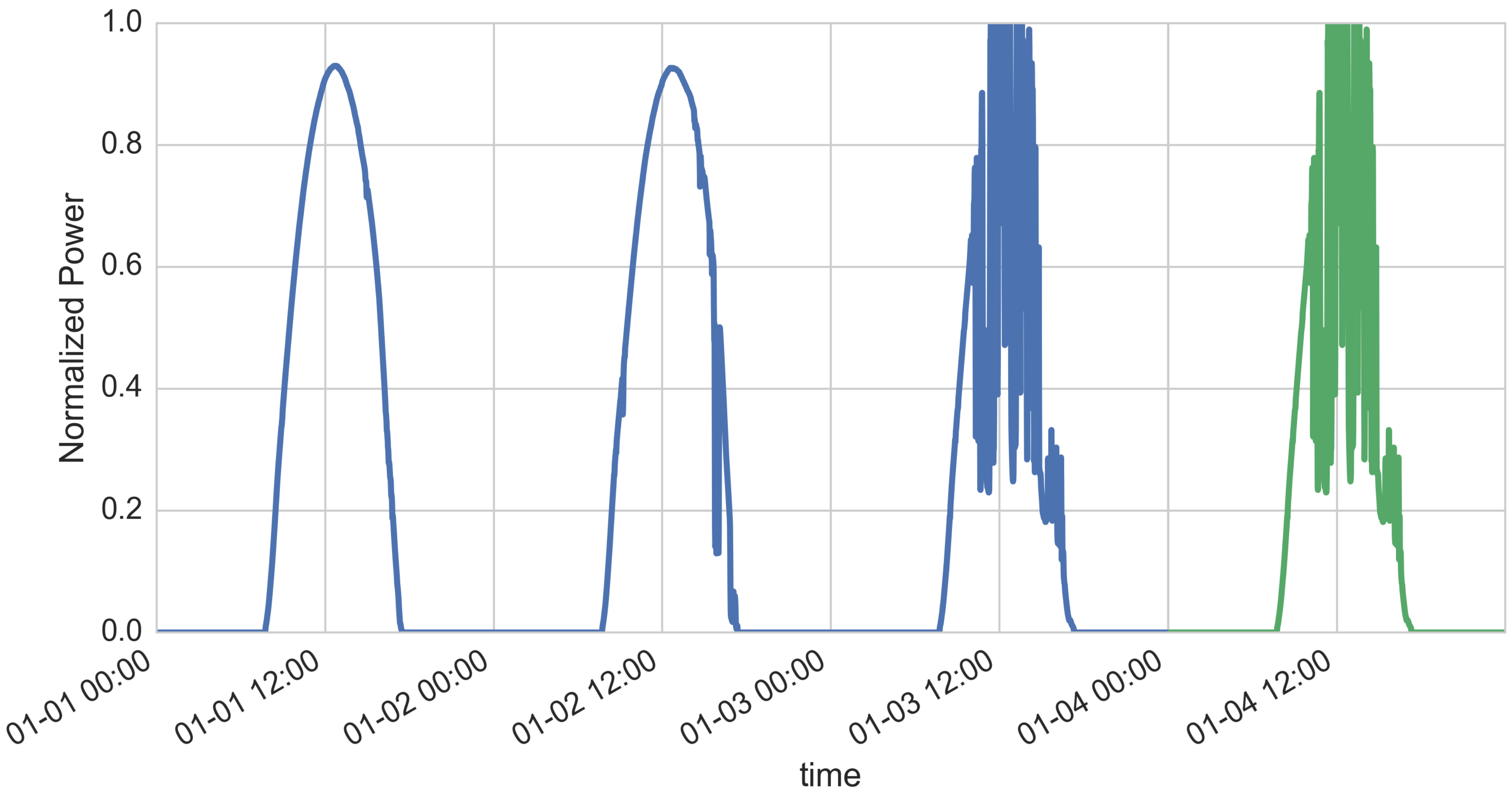
Day ahead persistence forecast



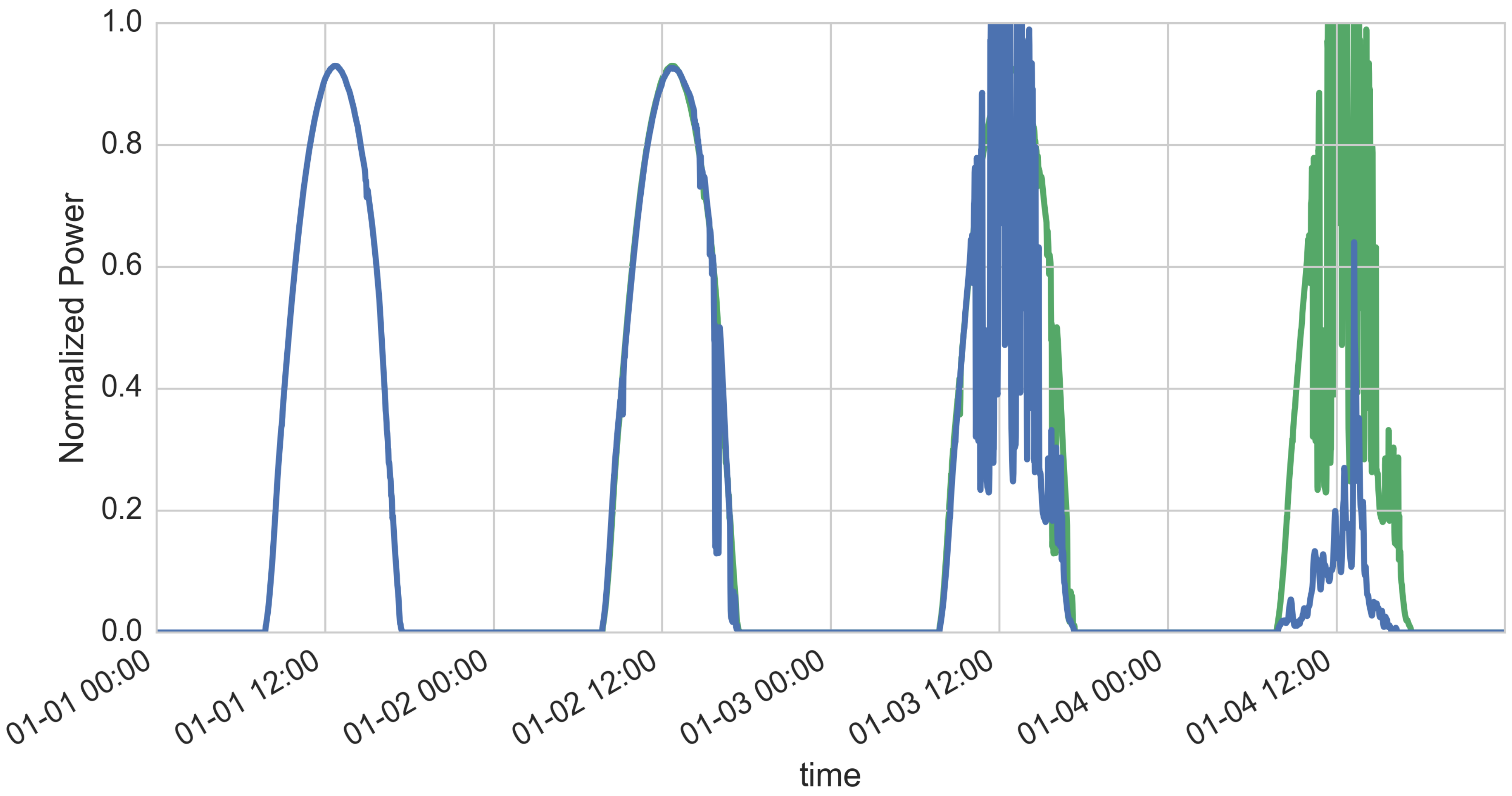
Day ahead persistence forecast



Day ahead persistence forecast



Day ahead persistence forecast



Numerical Weather Prediction at UA

Christopher Marks, Creative Commons

- UA WRF Model highlights
  - 5.4 km outer domain, 1.8 km inner domain
  - Initialized on the 0Z, 6Z, 12Z, 18Z GFS and NAM
  - In summer, 13Z and 15Z RAP initialization

- Local challenges include:
  - Mountains + moisture + heating = monsoon storms
  - Unreliable initialization data from Mexico
  - Extreme planetary boundary layer heights
  - Rapidly changing land/surface characteristics

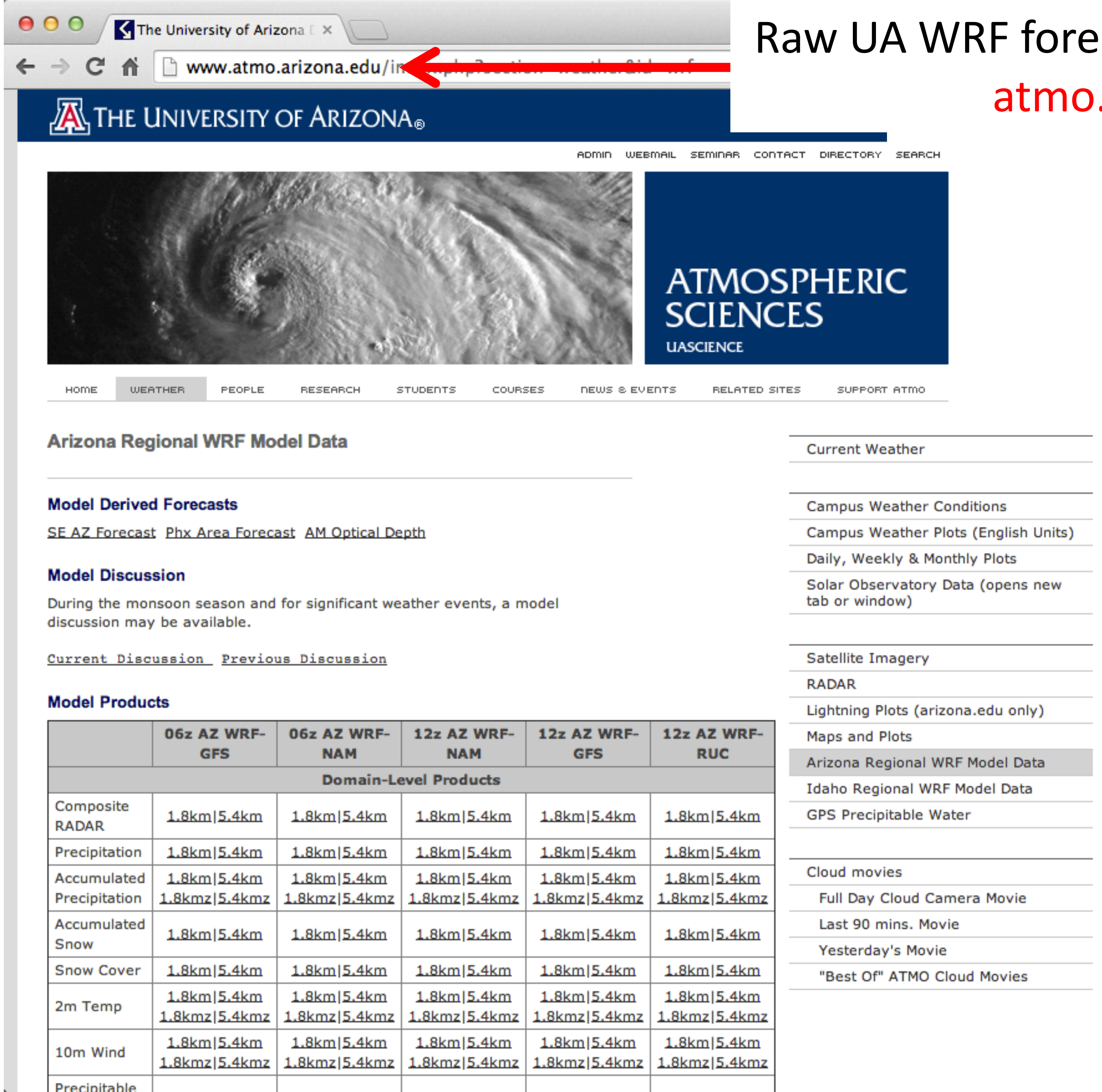
- 1.8 km resolution, 3 minute outputs of:
  - GHI, DNI, 10 m wind, 80 m wind, temp

WRF configuration details:

- RRTMG
- Morrison 2 mom. or SBUYLIN
- Bougeault-Lacarre or ACM2
- Noah LSM

Weather Research and Forecasting (WRF) community model developed at NCAR, NCEP, ESRL, universities, and more

Raw UA WRF forecasts available at
atmo.arizona.edu



WRF details

F = ma

Conservation of mass

2.2 Flux-Form Euler Equations

Using the variables defined above, the flux-form Euler equations can be writt

$$\partial_t U + (\nabla \cdot \mathbf{V}u) - \partial_x(p\phi_\eta) + \partial_\eta(p\phi_x) = F_U$$
$$\partial_t V + (\nabla \cdot \mathbf{V}v) - \partial_y(p\phi_\eta) + \partial_\eta(p\phi_y) = F_V$$
$$\partial_t W + (\nabla \cdot \mathbf{V}w) - g(\partial_\eta p - \mu) = F_W$$
$$\partial_t \Theta + (\nabla \cdot \mathbf{V}\theta) = F_\Theta$$
$$\partial_t \mu + (\nabla \cdot \mathbf{V}) = 0$$
$$\partial_t \phi + \mu^{-1}[(\mathbf{V} \cdot \nabla\phi) - gW] = 0$$

along with the diagnostic relation for the inverse density

$$\partial_\eta \phi = -\alpha\mu,$$

and the equation of state

$$p = p_0(R_d\theta/p_0\alpha)^\gamma.$$

In (2.3) – (2.10), the subscripts x, y and η denote differentiation,

$$\nabla \cdot \mathbf{V}a = \partial_x(Ua) + \partial_y(Va) + \partial_\eta(\Omega a),$$

and

$$\mathbf{V} \cdot \nabla a = U\partial_x a + V\partial_y a + \Omega\partial_\eta a,$$

where a represents a generic variable. $\gamma = c_p/c_v = 1.4$ is the ratio of the heat air, R_d is the gas constant for dry air, and p_0 is a reference pressure (typically right-hand-side (RHS) terms F_U, F_V, F_W, and F_Θ represent forcing terms a physics, turbulent mixing, spherical projections, and the earth's rotation.

2.3 Inclusion of Moisture

Water phase changes

In formulating the moist Euler equations, we retain the coupling of dry air mass to the prognostic variables, and we retain the conservation equation for dry air (2.7), as opposed to coupling the variables to the full (moist) air mass and hence introducing source terms in the mass conservation equation (2.7). Additionally, we define the coordinate with respect to the dry-air mass. Based on these principles, the vertical coordinate can be written as

$$\eta = (p_{dh} - p_{dht})/\mu_d \tag{2.11}$$

where μ_d represents the mass of the dry air in the column and p_{dh} and p_{dht} represent the hydrostatic pressure of the dry atmosphere and the hydrostatic pressure at the top of the dry atmosphere. The coupled variables are defined as

$$\mathbf{V} = \mu_d\mathbf{v}, \quad \Omega = \mu_d\dot{\eta}, \quad \Theta = \mu_d\theta. \tag{2.12}$$

With these definitions, the moist Euler equations can be written as

$$\partial_t U + (\nabla \cdot \mathbf{V}u) + \mu_d\alpha\partial_x p + (\alpha/\alpha_d)\partial_\eta p\partial_x\phi = F_U \tag{2.13}$$
$$\partial_t V + (\nabla \cdot \mathbf{V}v) + \mu_d\alpha\partial_y p + (\alpha/\alpha_d)\partial_\eta p\partial_y\phi = F_V \tag{2.14}$$
$$\partial_t W + (\nabla \cdot \mathbf{V}w) - g[(\alpha/\alpha_d)\partial_\eta p - \mu_d] = F_W \tag{2.15}$$
$$\partial_t \Theta + (\nabla \cdot \mathbf{V}\theta) = F_\Theta \tag{2.16}$$
$$\partial_t \mu_d + (\nabla \cdot \mathbf{V}) = 0 \tag{2.17}$$
$$\partial_t \phi + \mu_d^{-1}[(\mathbf{V} \cdot \nabla\phi) - gW] = 0 \tag{2.18}$$
$$\partial_t Q_m + (\nabla \cdot \mathbf{V}q_m) = F_{Q_m} \tag{2.19}$$

with the diagnostic equation for dry inverse density

$$\partial_\eta \phi = -\alpha_d\mu_d \tag{2.20}$$

s dry air)

$$p = p_0(R_d\theta_m/p_0\alpha_d)^\gamma \tag{2.21}$$

Skamarock et. al. "A description of the Advanced Research WRF Version 3" (2008)

WRF details

3.1.1 Runge-Kutta Time Integration Scheme

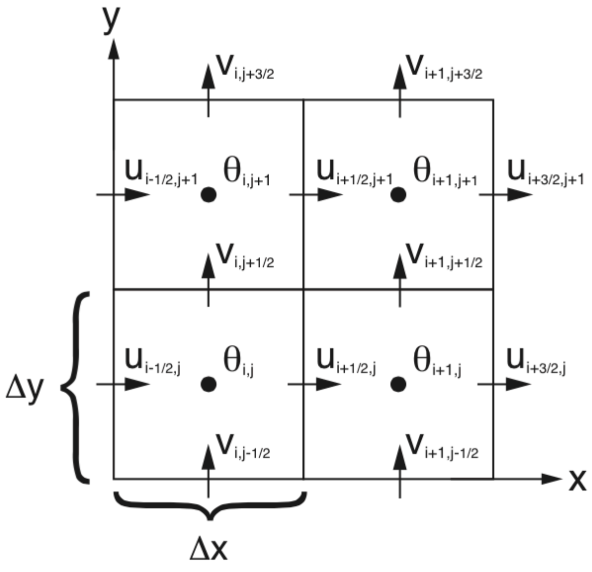
Solve the equations

The RK3 scheme, described in Wicker and Skamarock (2002), integrates a set of ordinary differential equations using a predictor-corrector formulation. Defining the prognostic variables in the ARW solver as $\Phi = (U, V, W, \Theta, \phi', \mu', Q_m)$ and the model equations as $\Phi_t = R(\Phi)$, the RK3 integration takes the form of 3 steps to advance a solution $\Phi(t)$ to $\Phi(t + \Delta t)$:

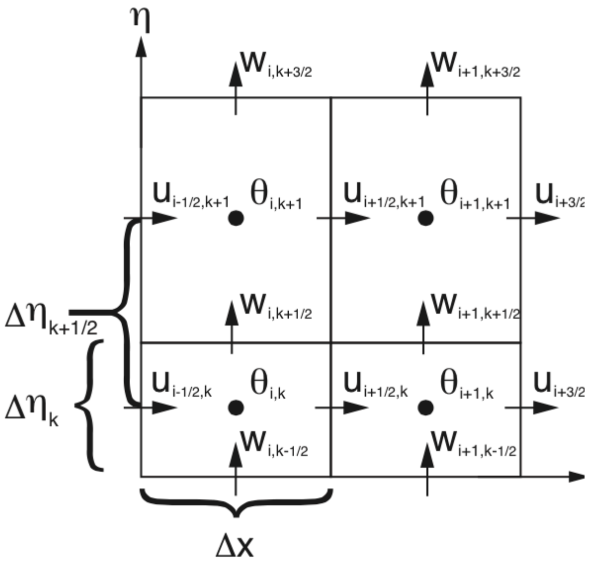
$$\Phi^* = \Phi^t + \frac{\Delta t}{3} R(\Phi^t)$$

$$\Phi^{**} = \Phi^t + \frac{\Delta t}{2} R(\Phi^*)$$

$$\Phi^{t+\Delta t} = \Phi^t + \Delta t R(\Phi^{**})$$

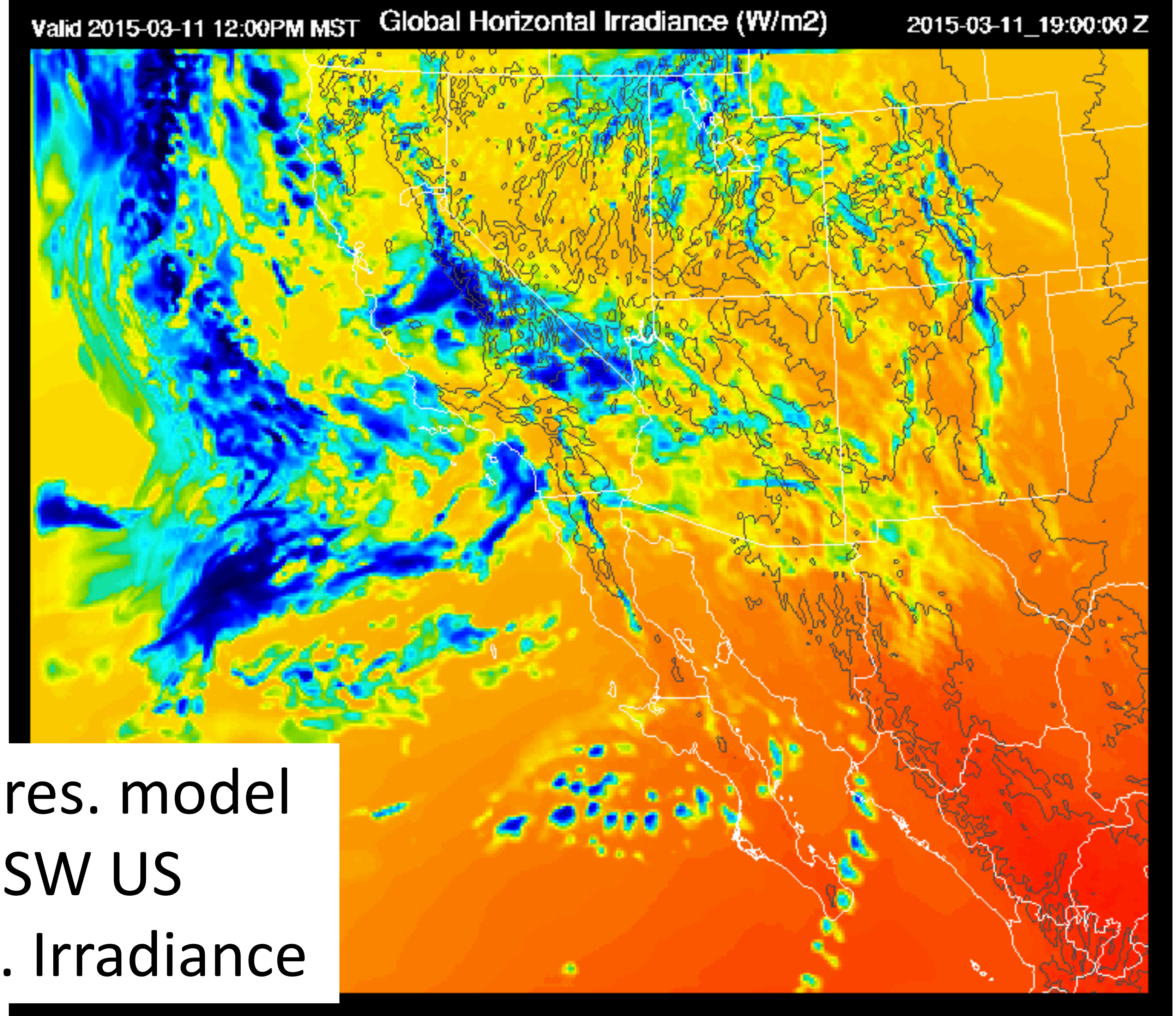


horizontal grid

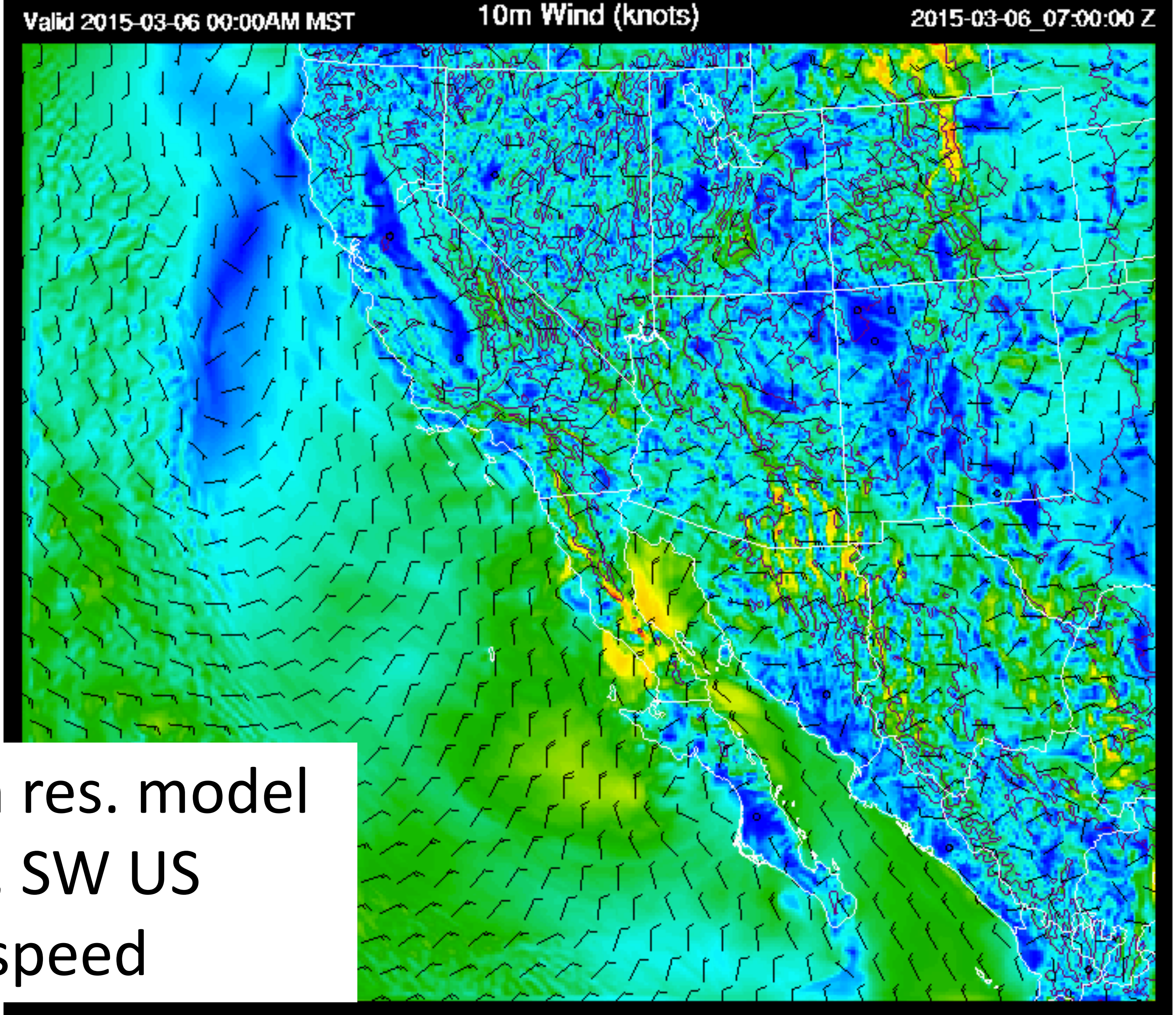


vertical grid

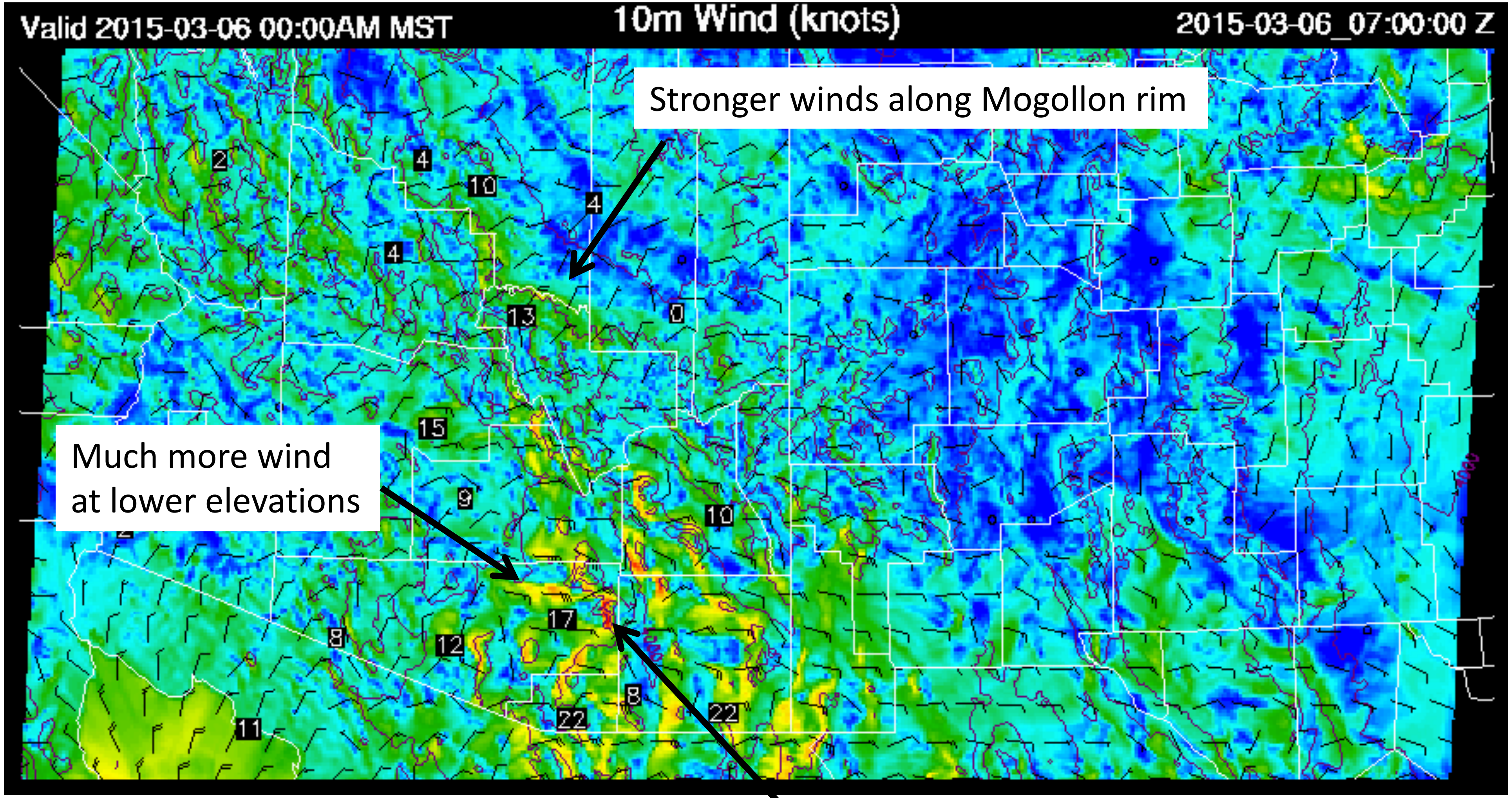
Skamarock et. al. “A description of the Advanced Research WRF Version 3” (2008)



UA medium res. model
5.4 km grid, SW US
Global Horiz. Irradiance



UA medium res. model
5.4 km grid, SW US
10 m wind speed

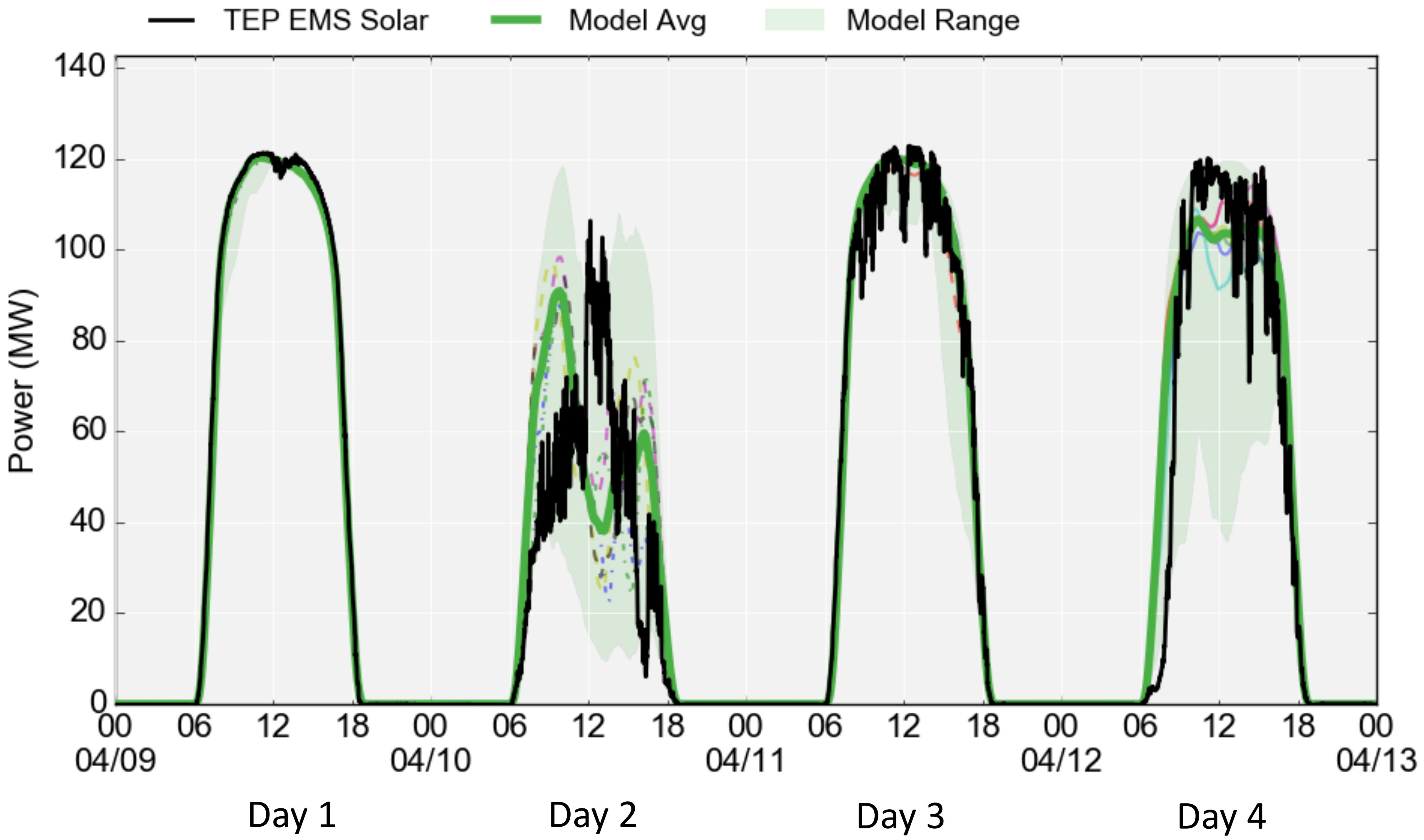


Stronger mountain winds

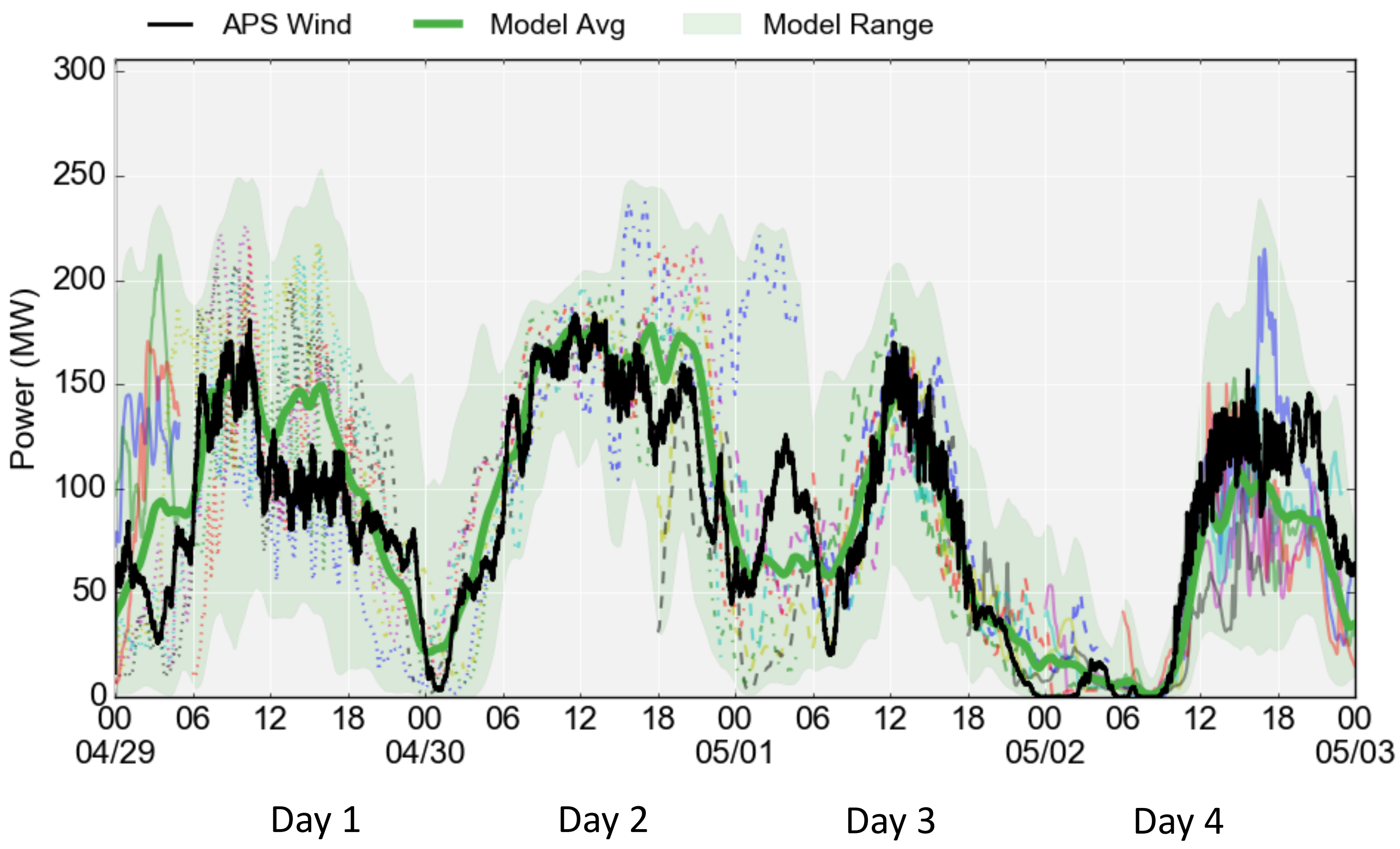
UA high res. model
1.8 km grid, AZ and NM
10 m wind speed

Difference between 5.4 km and 1.8 km domains increases as weather becomes more severe

Solar power forecast from weather model

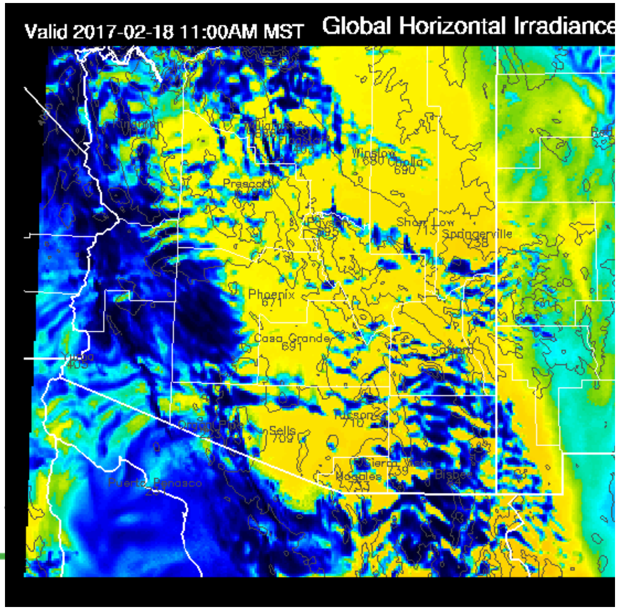


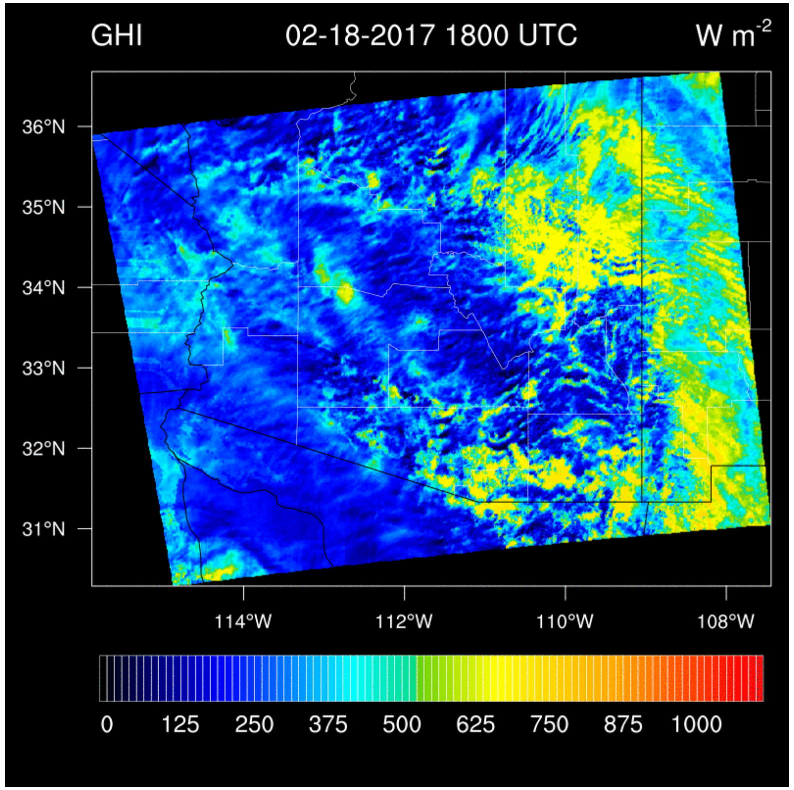
Wind power forecast from weather model



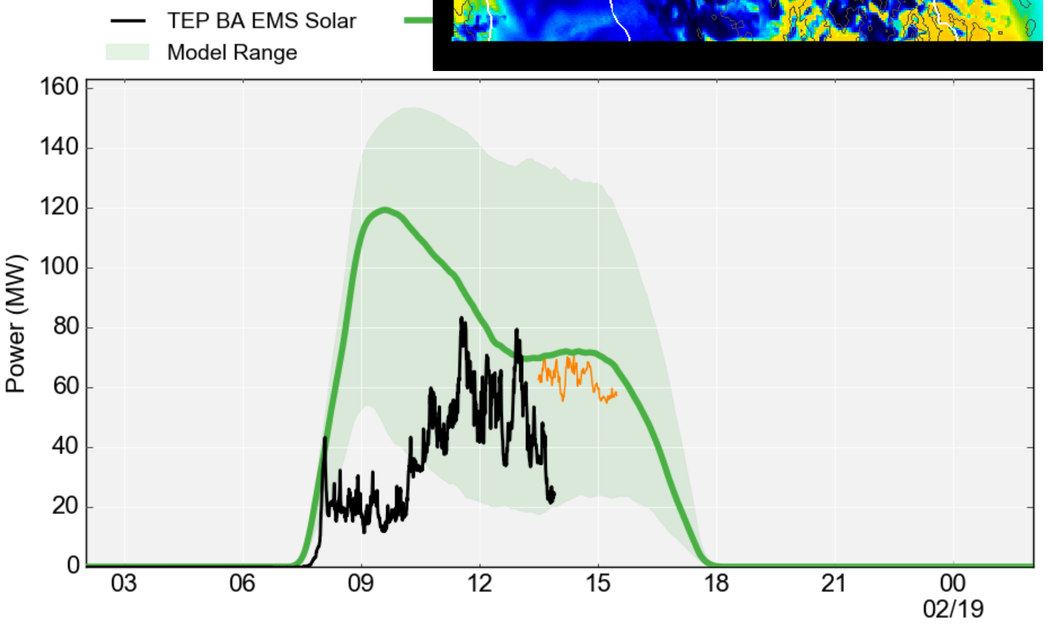
Weather forecasts are not perfect

Forecast irradiance on Feb 18, 2017





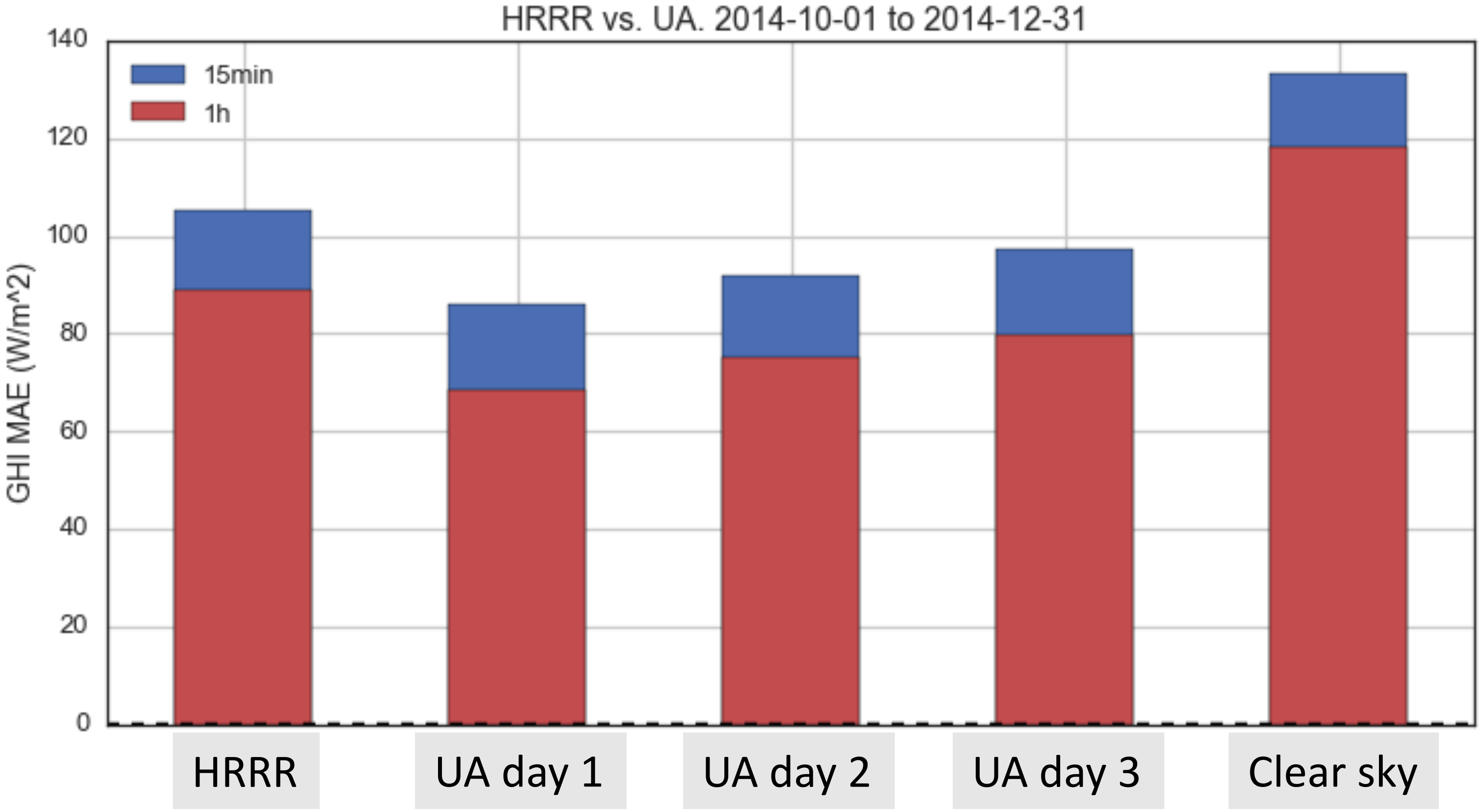
Observed irradiance



Power forecast wrong by 100 MW at 10 AM!

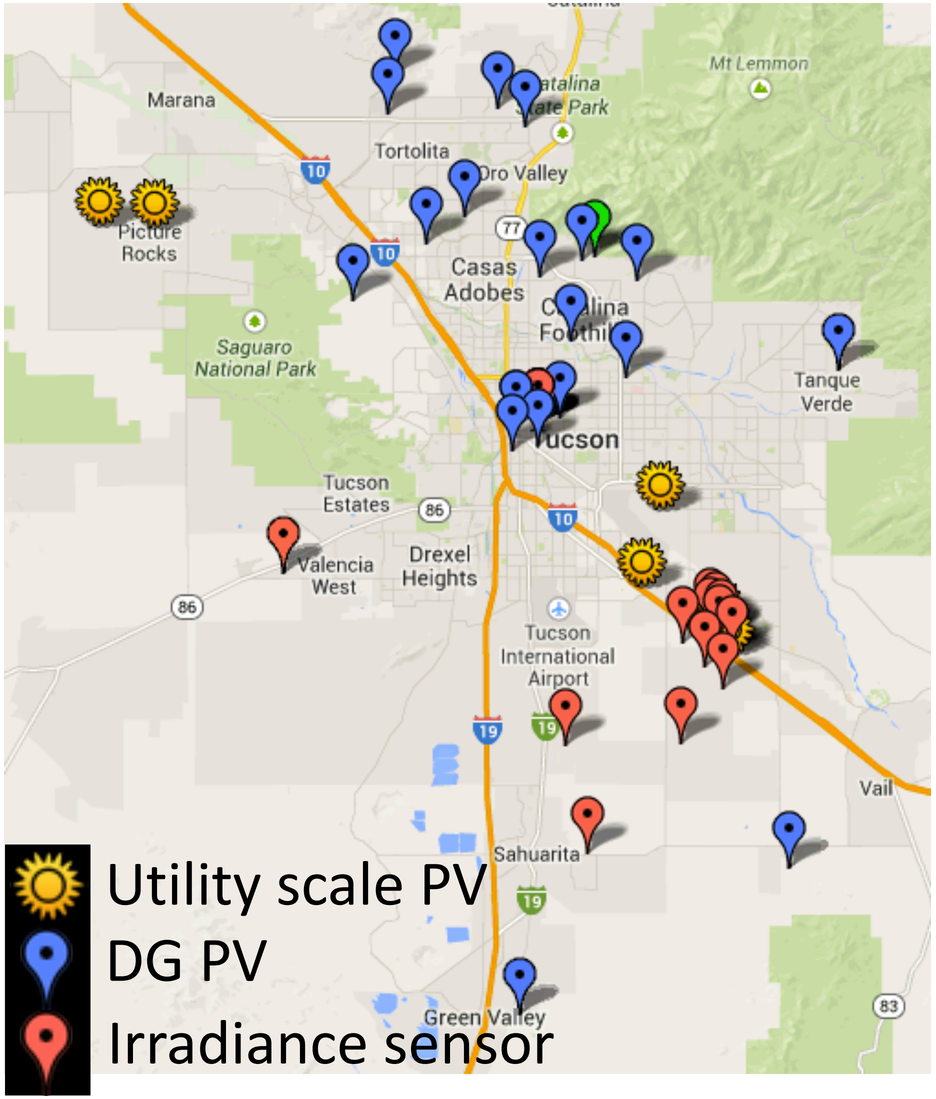
Primary causes of bad forecasts: Initial conditions, microphysics, planetary boundary layer

UA-WRF vs. NWS HRRR Tucson GHI



Limit analysis to large (MAE > 60) errors.
Eliminates clear days.
Helps HRRR, relatively, since it is much worse than UA on clear days.
UA day 3 still outperforming NCEP HRRR

Sensor network forecast

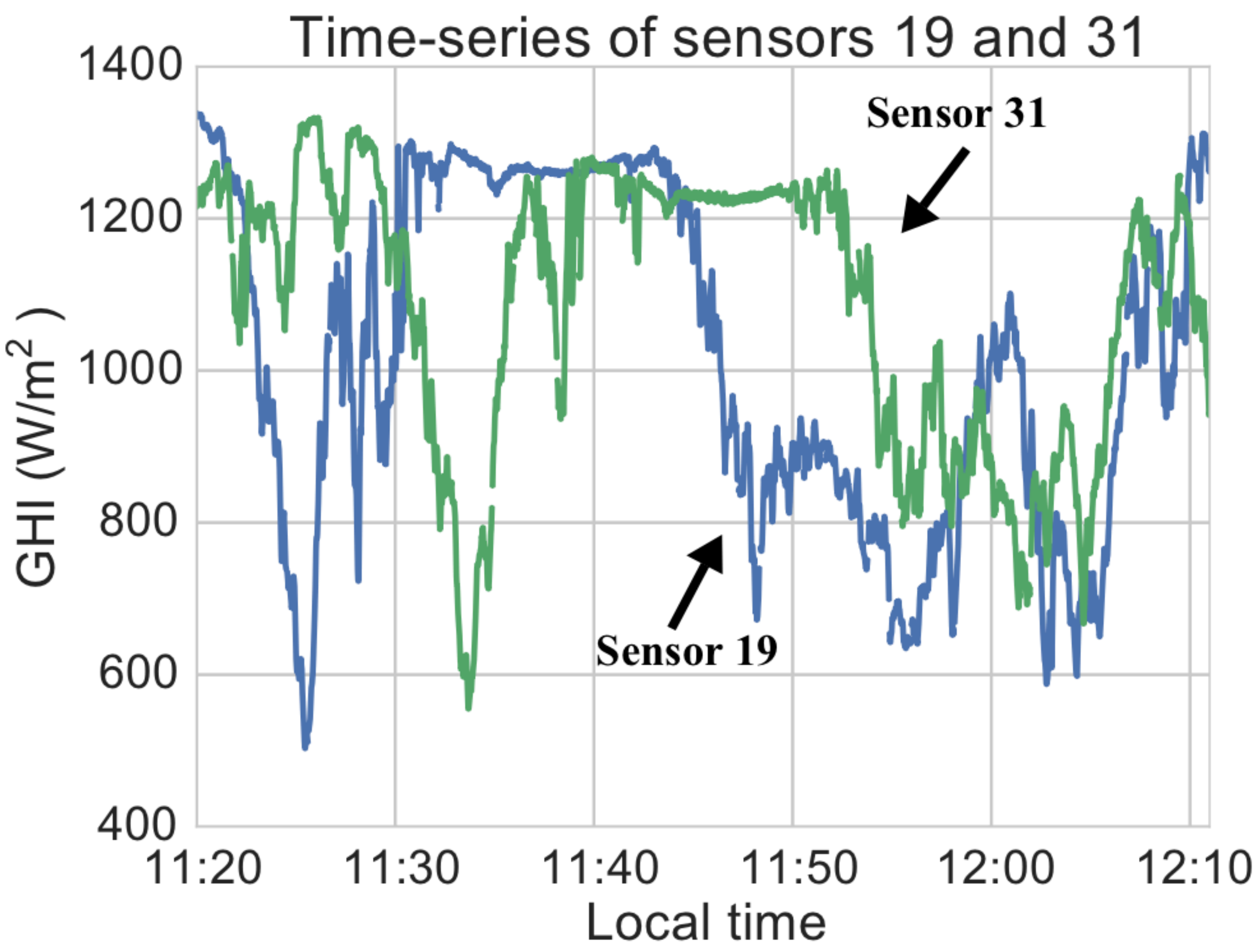


Partnered with local PV installer Technicians for Sustainability to obtain access to real-time (5 min latency) data feeds from residential PV systems.

Prototype: Homebuilt irradiance sensors will cell modems (see A. Lorenzo, AMS 2015).

Network of rooftop solar data and irradiance sensors provides most accurate 30 minute forecasts.

Sensor network forecast

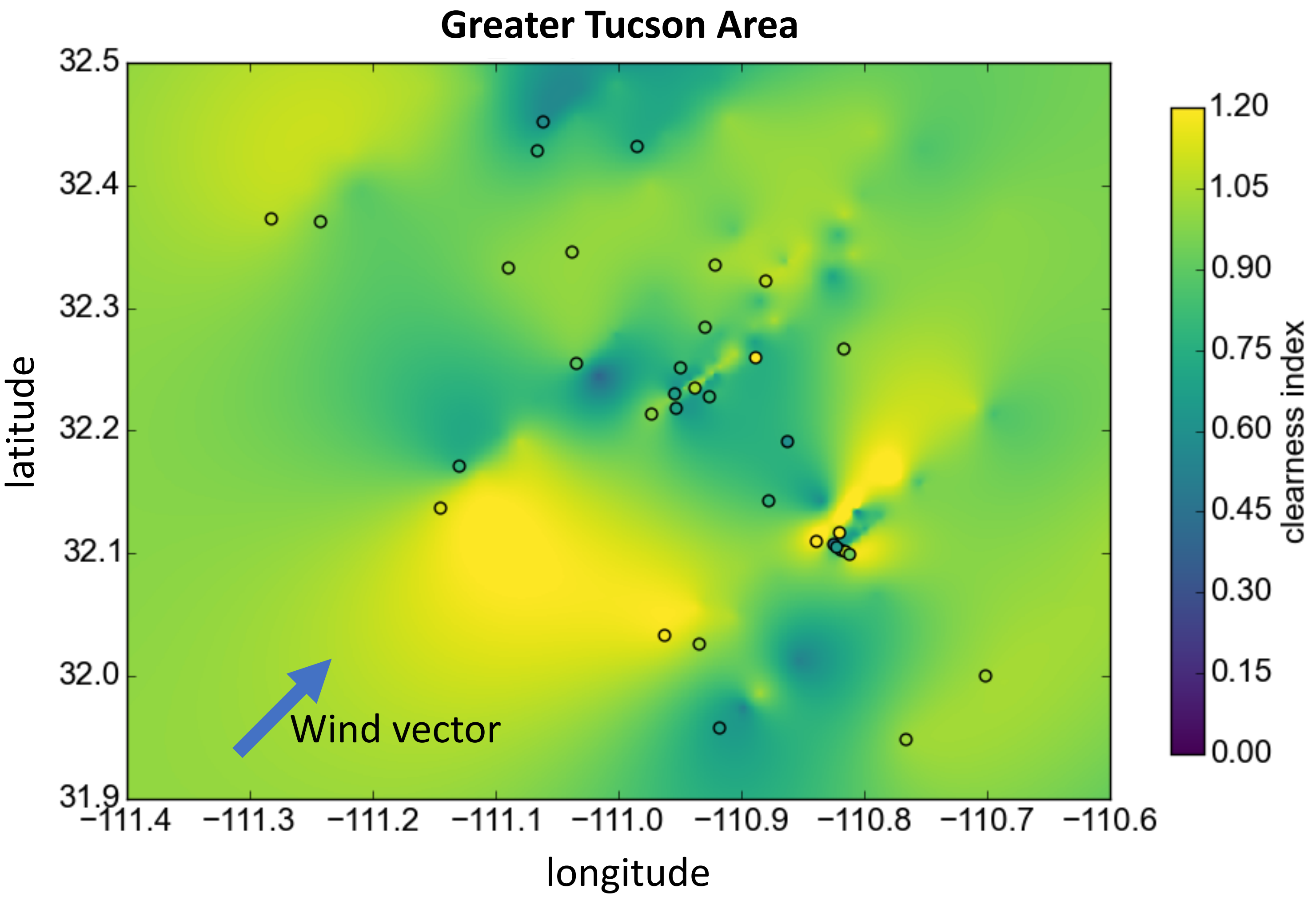


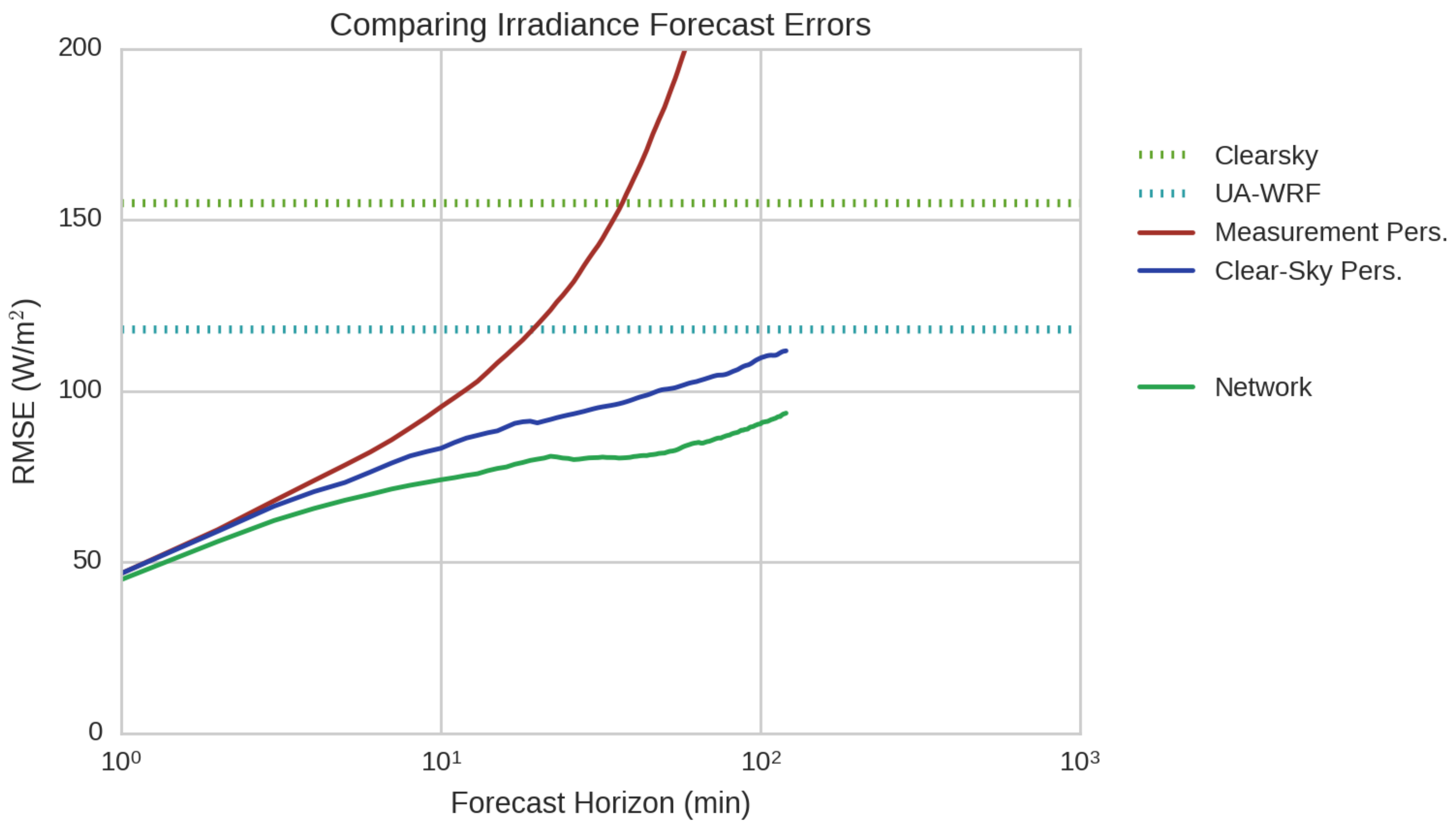
Looks a lot like a persistence forecast!

Combine data from many sensors using statistical methods

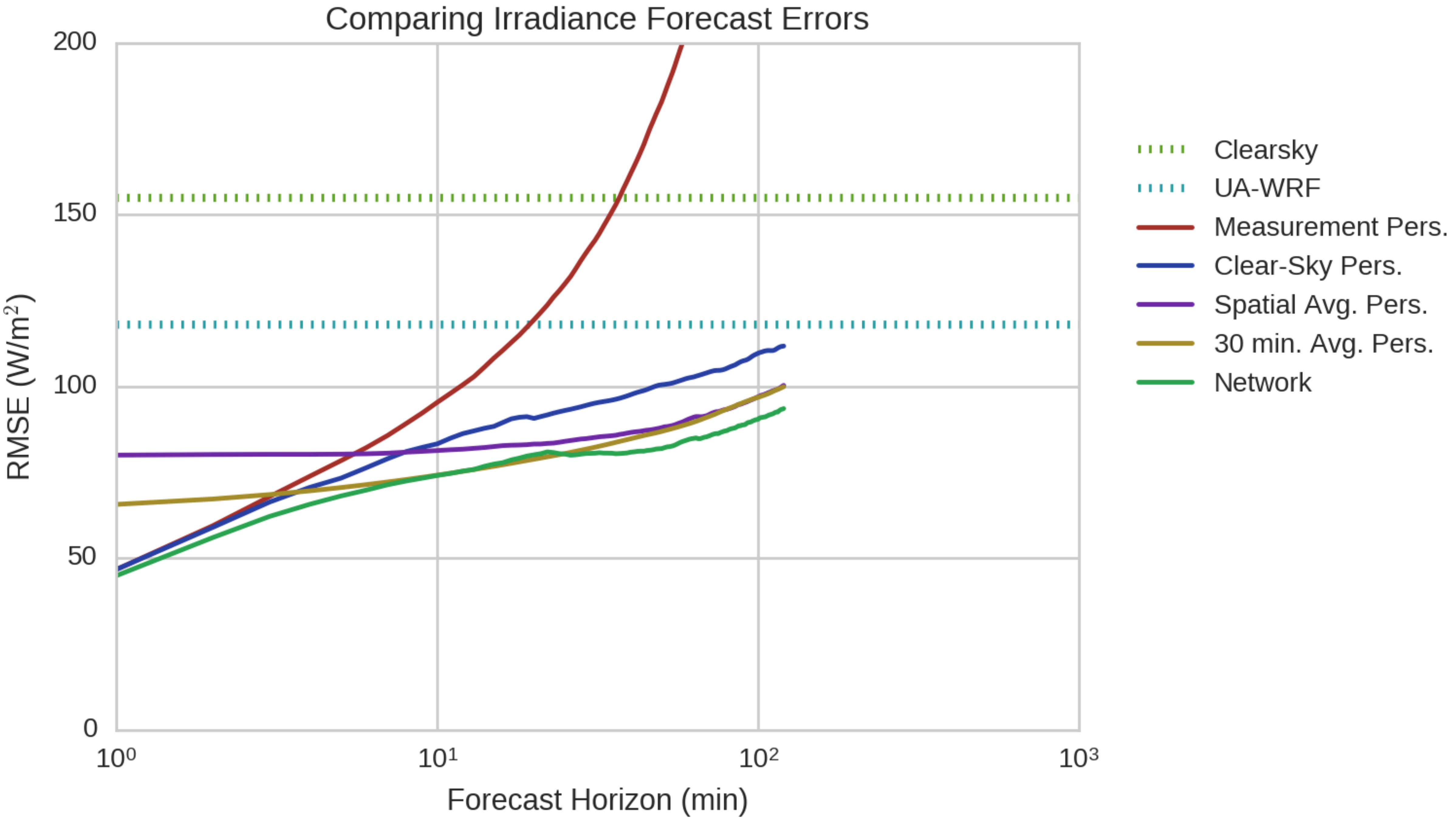
Lorenzo et. al., Solar Energy 2015

Sensor network interpolation





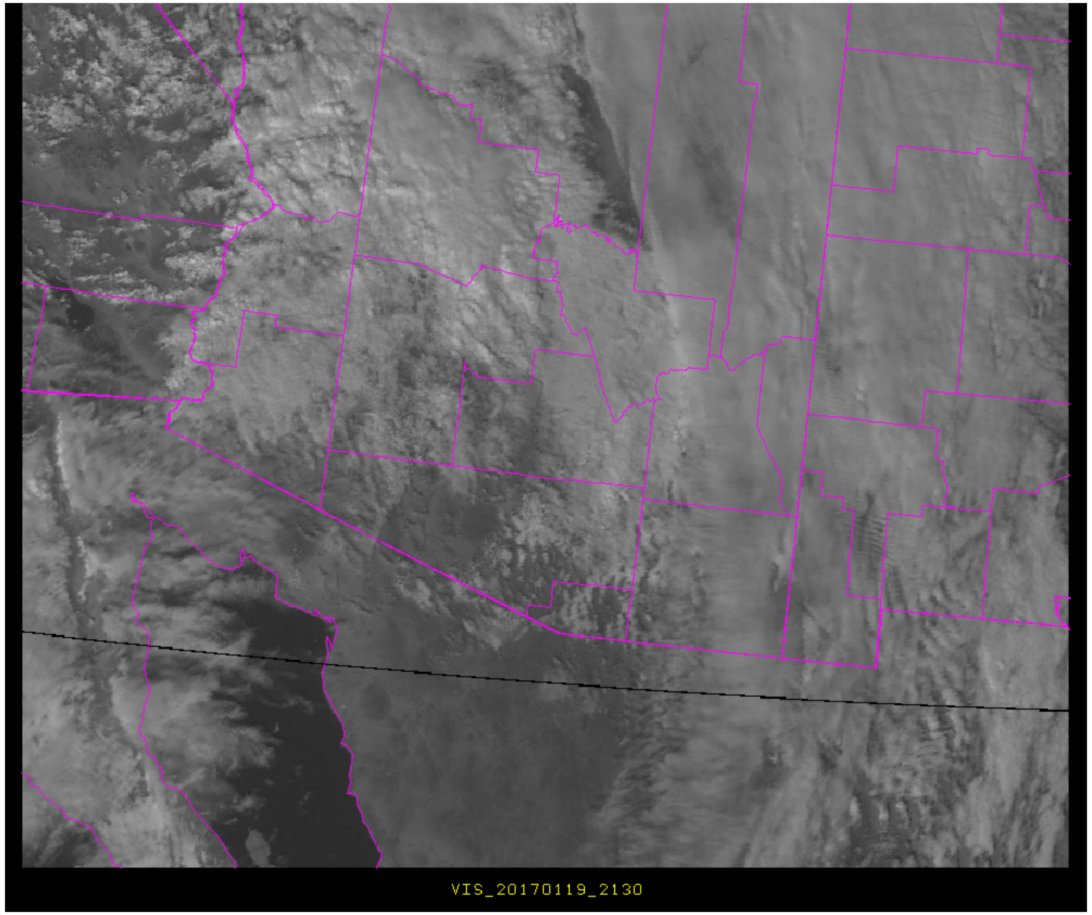
Comparing Irradiance Forecast Errors
RMSE (W/m²)
Forecast Horizon (min)
200
150
100
50
0
10⁰
10¹
10²
10³
Clearsky
UA-WRF
Measurement Pers.
Clear-Sky Pers.
Network



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

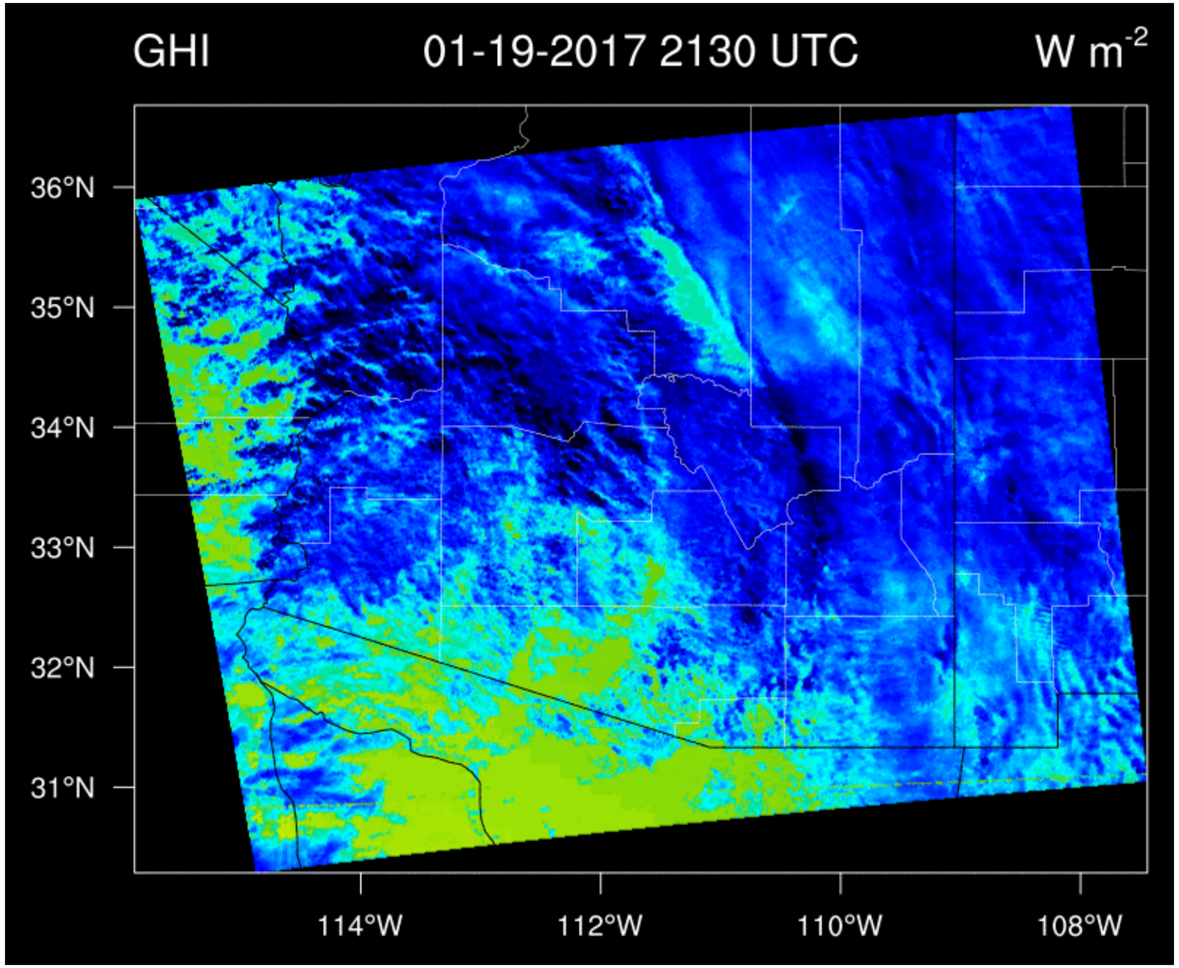
Satellite Derived Irradiance

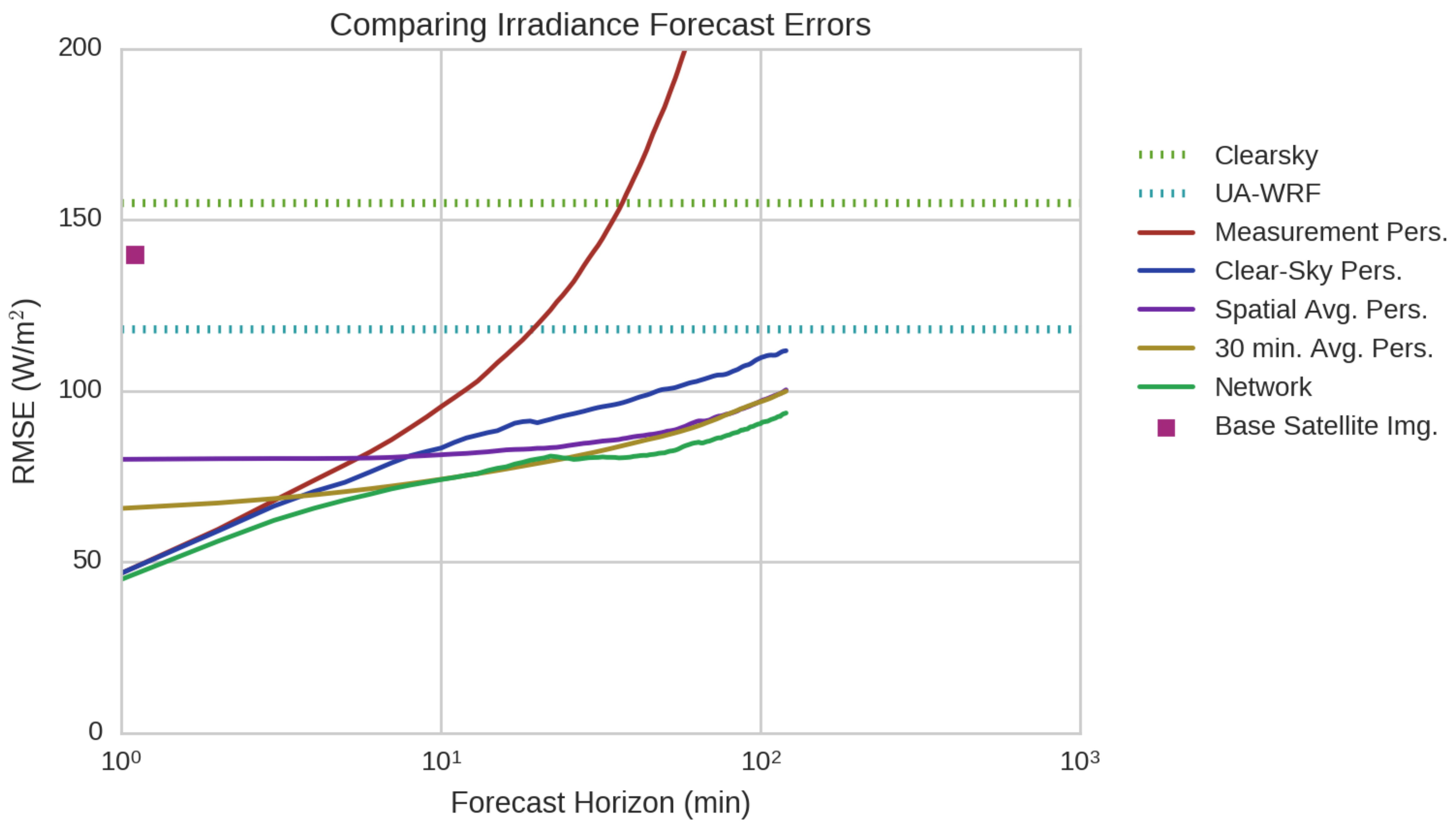
Light reflected from the tops of clouds



model

Light that gets through clouds





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.
Spatial Avg. Pers.
30 min. Avg. Pers.
Network
Base Satellite Img.

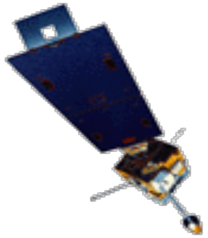
Ground irradiance data to improve satellite irradiance estimates

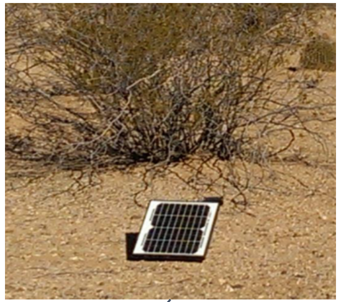
Satellite irradiance estimates rely on algorithms that convert the observation (light reflected by cloud tops) into transmitted irradiance.

Use ground PV and irradiance data to improve estimates

Unique method developed at UA

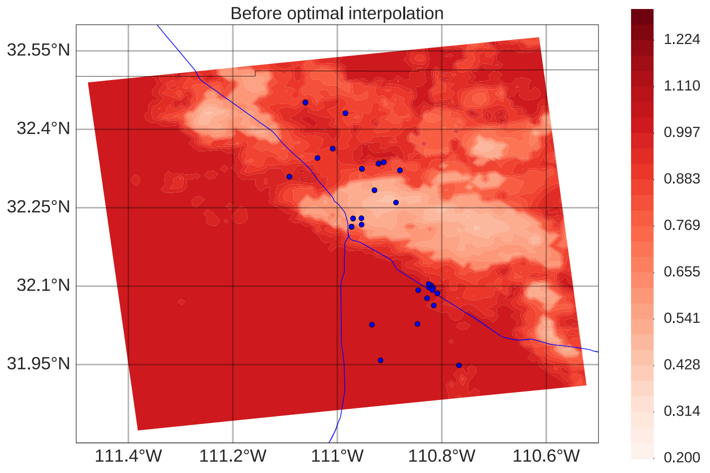
Published in Solar Energy (Lorenzo 2017)

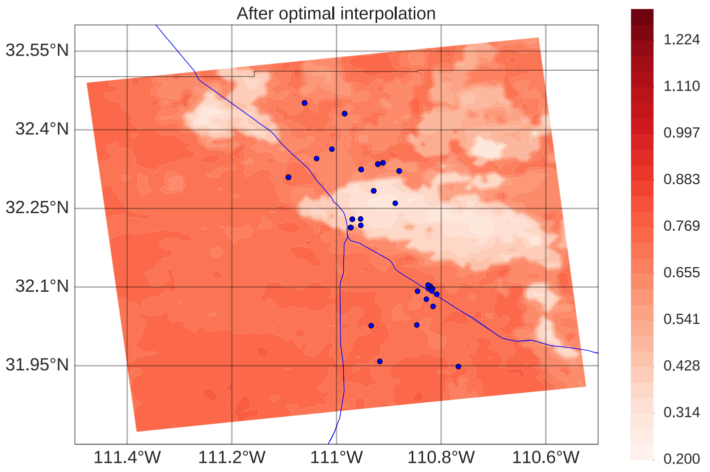


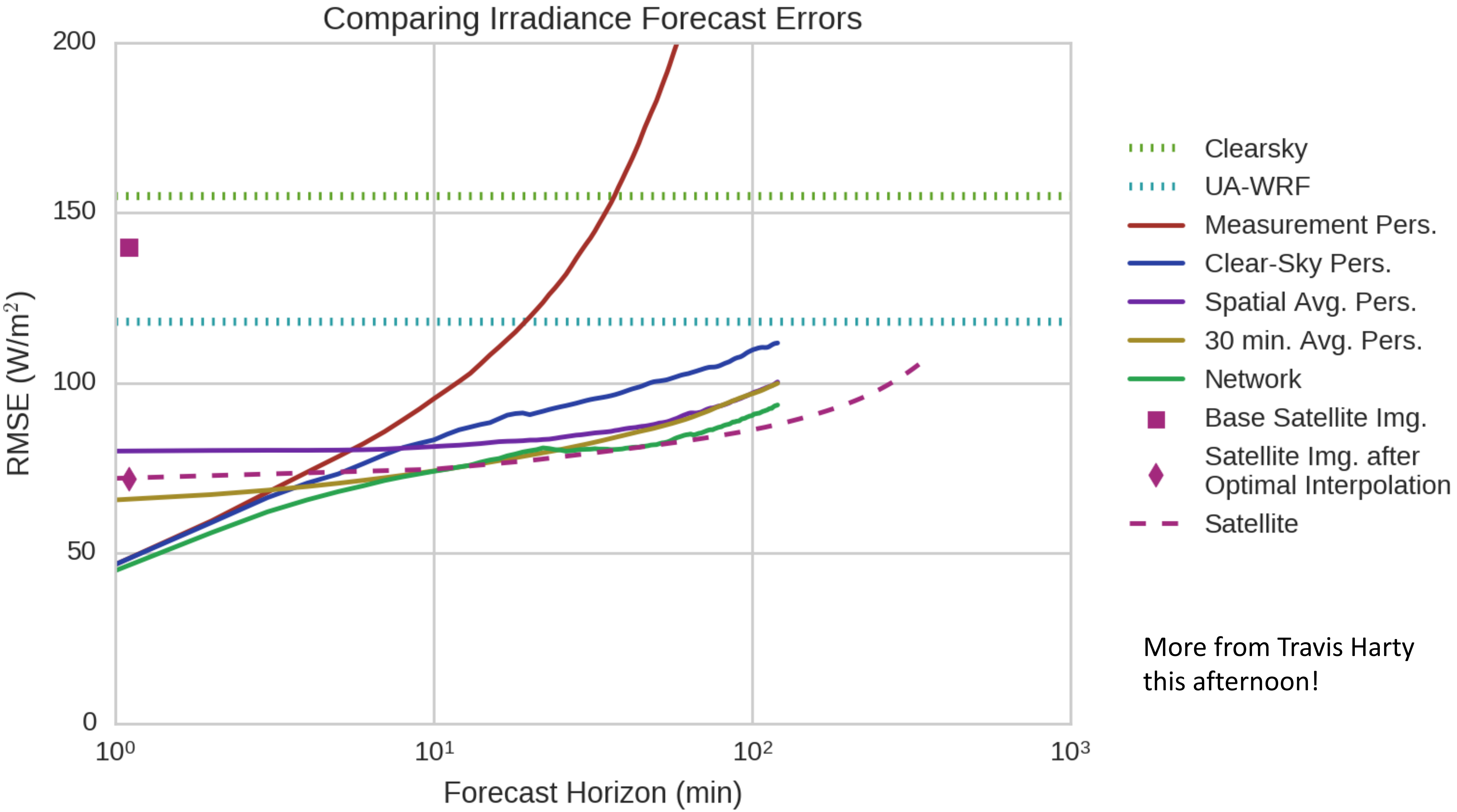


Optimal Interpolation

Better satellite-derived estimate of GHI







More from Travis Harty this afternoon!

Taylor diagram: RMSE is not enough

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

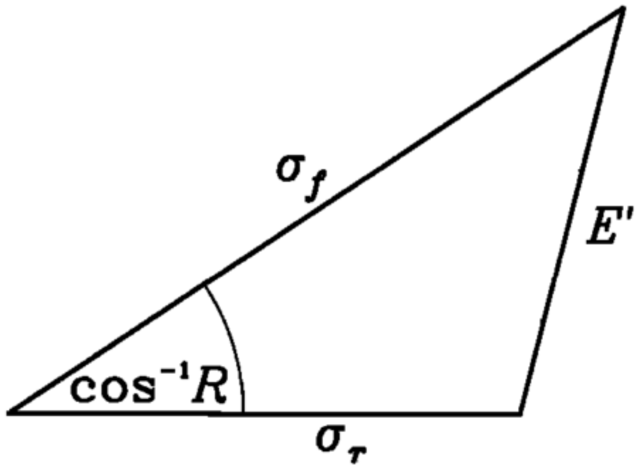
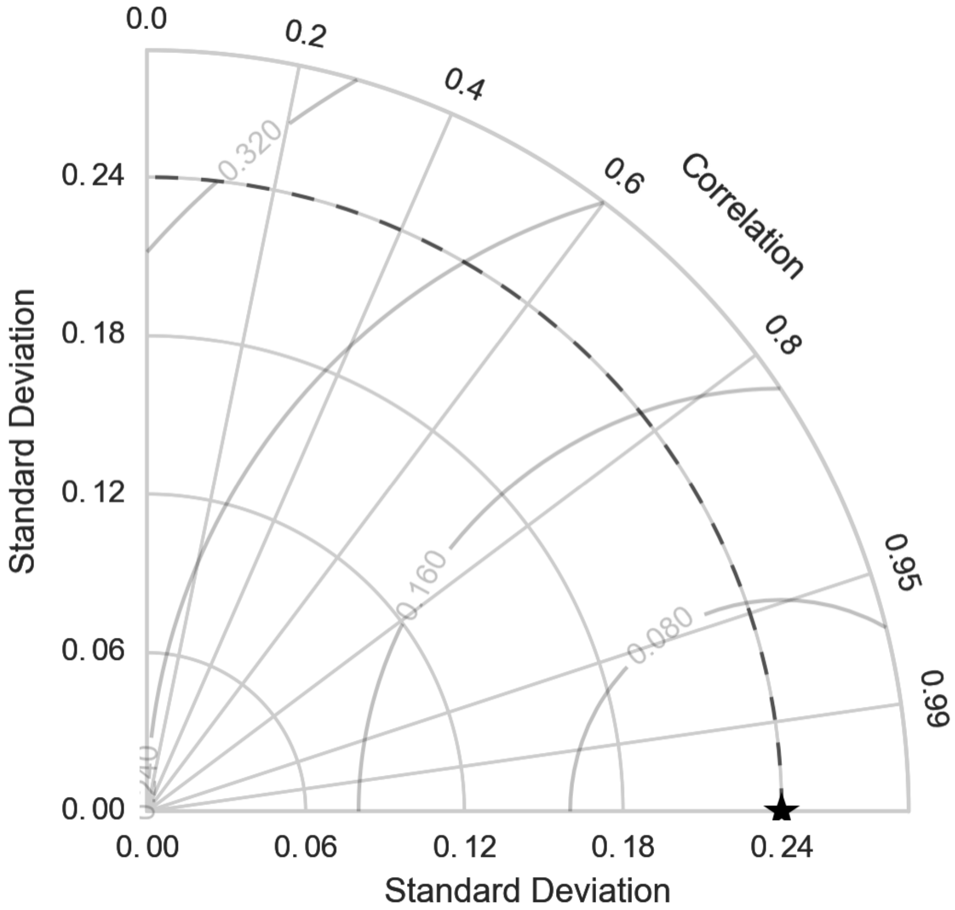
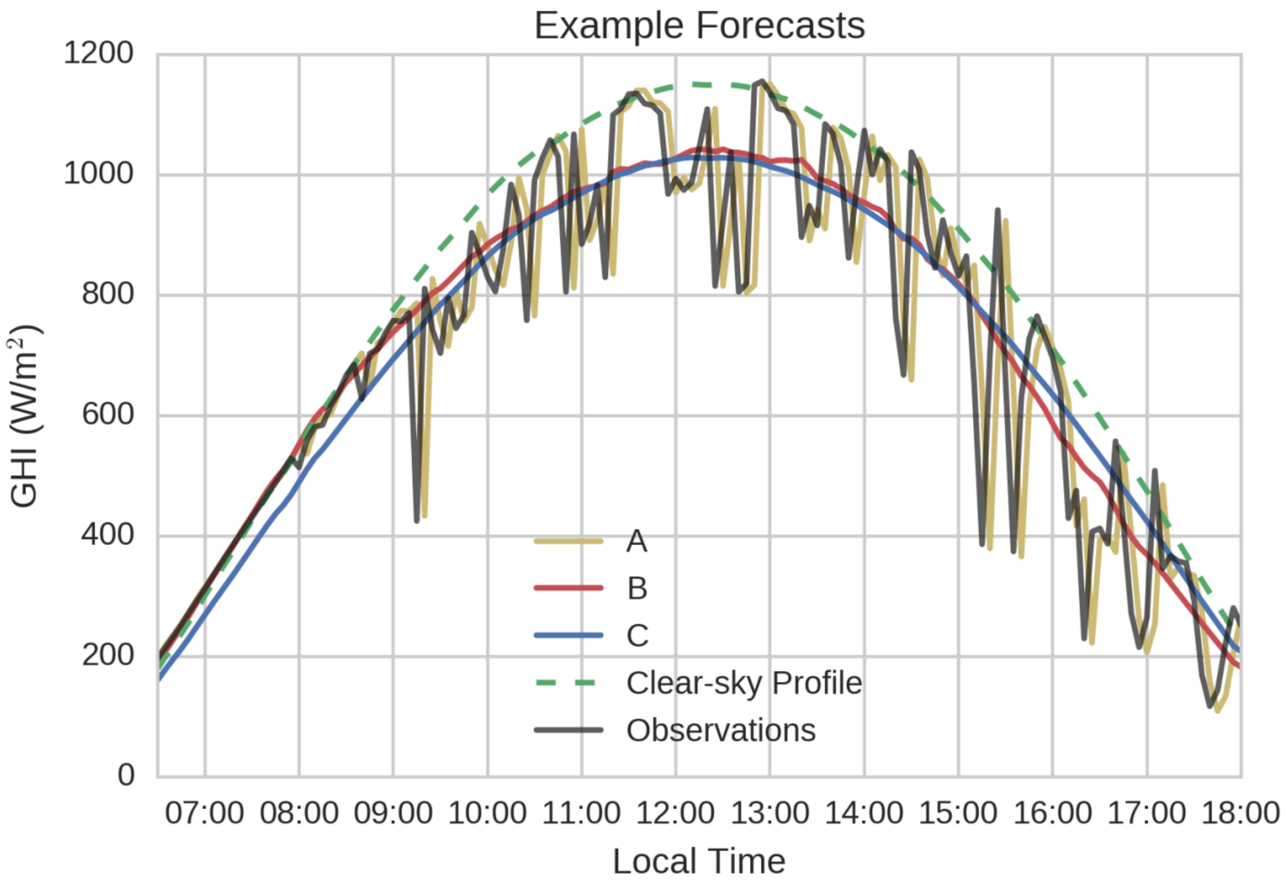


Figure 1. Geometric relationship between the correlation coefficient R, the centered pattern RMS error E', and the standard deviations σ_f and σ_r of the test and reference fields, respectively.

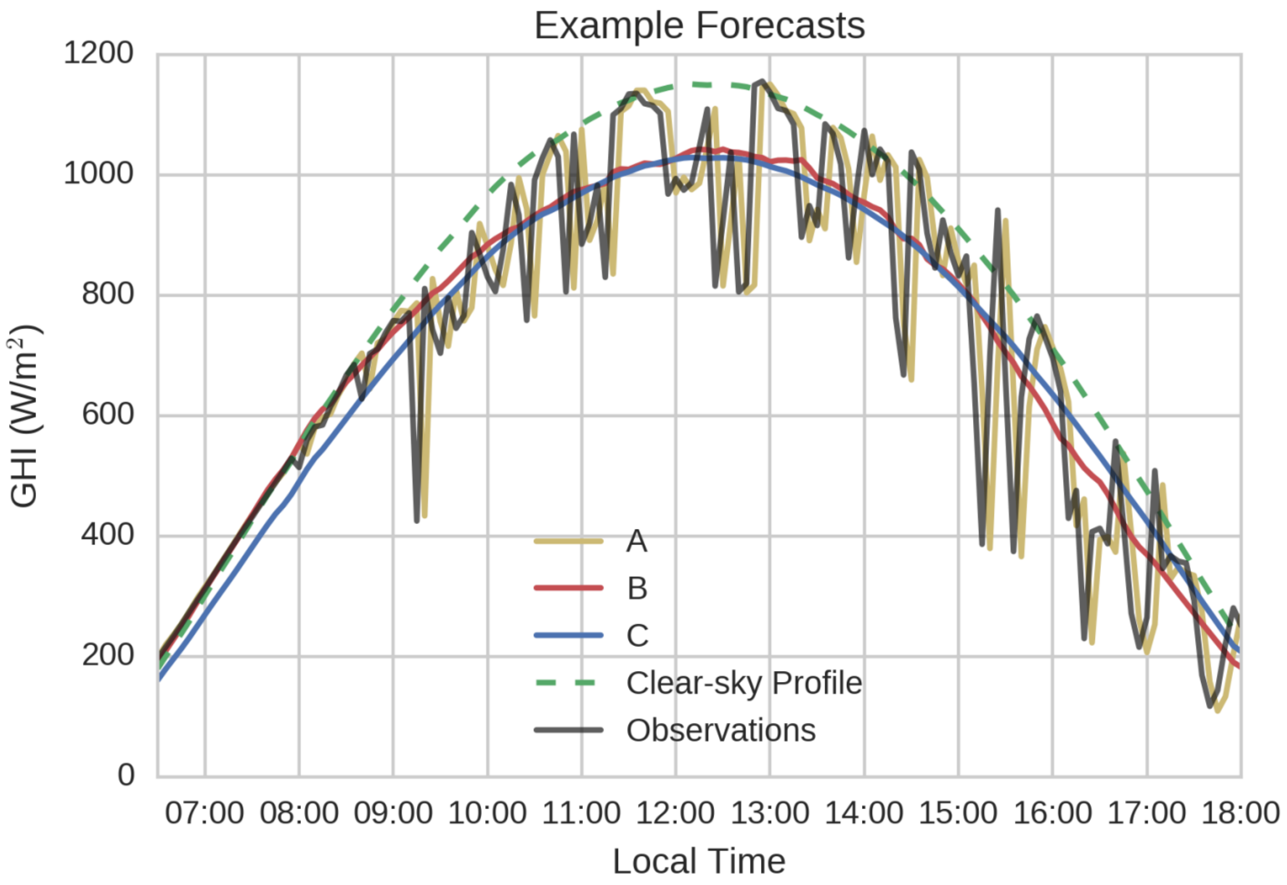


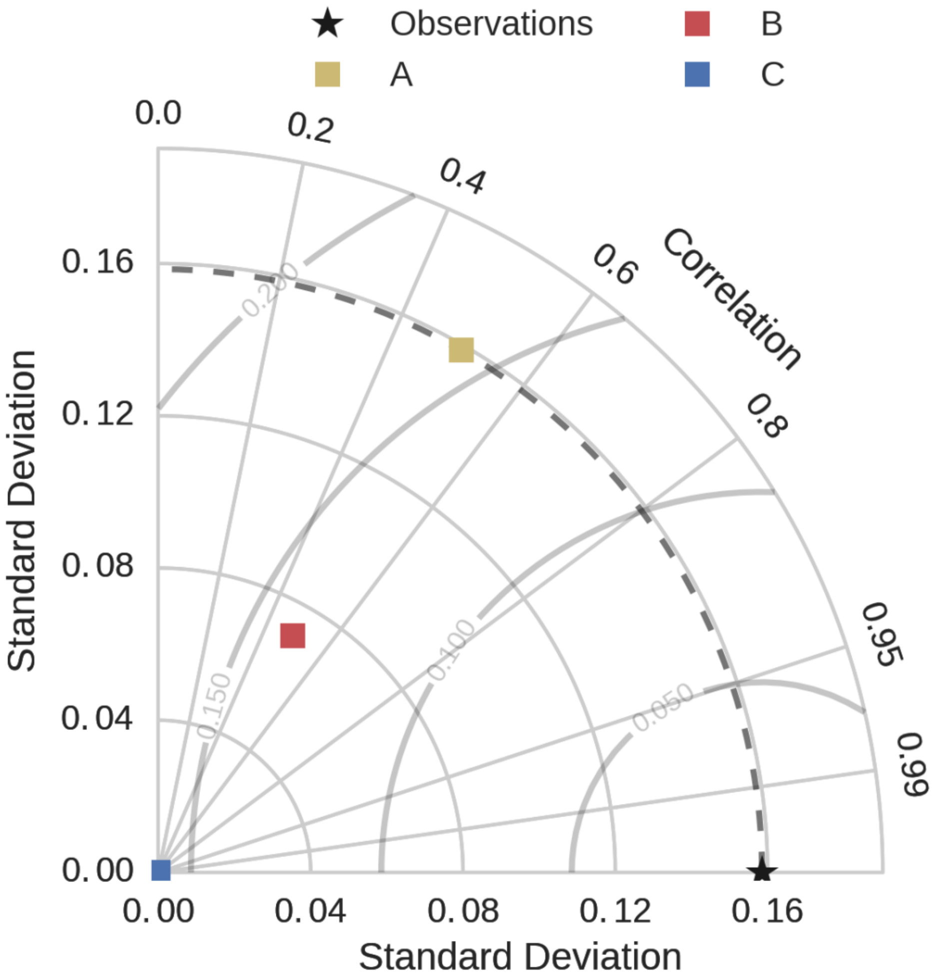
Taylor diagram: RMSE is not enough



	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: RMSE is not enough



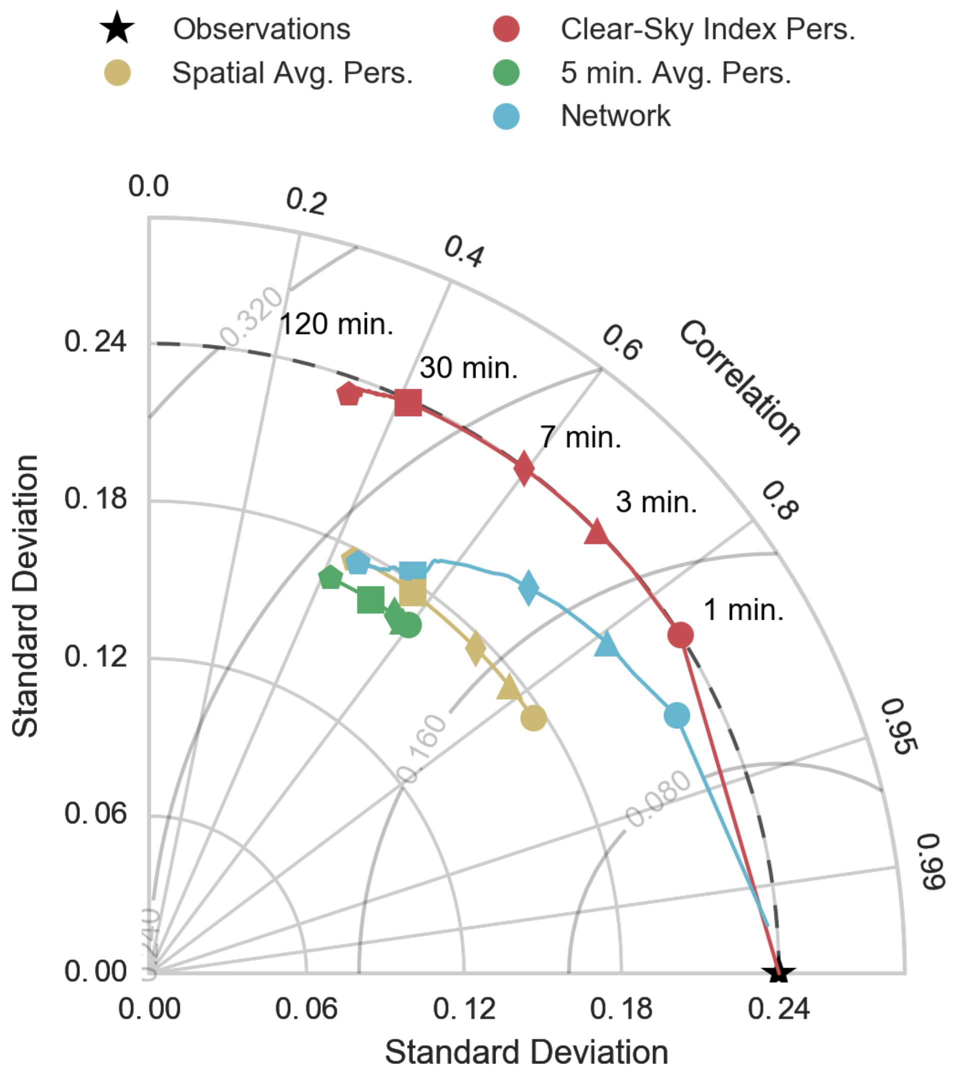


Taylor diagram: RMSE is not enough

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

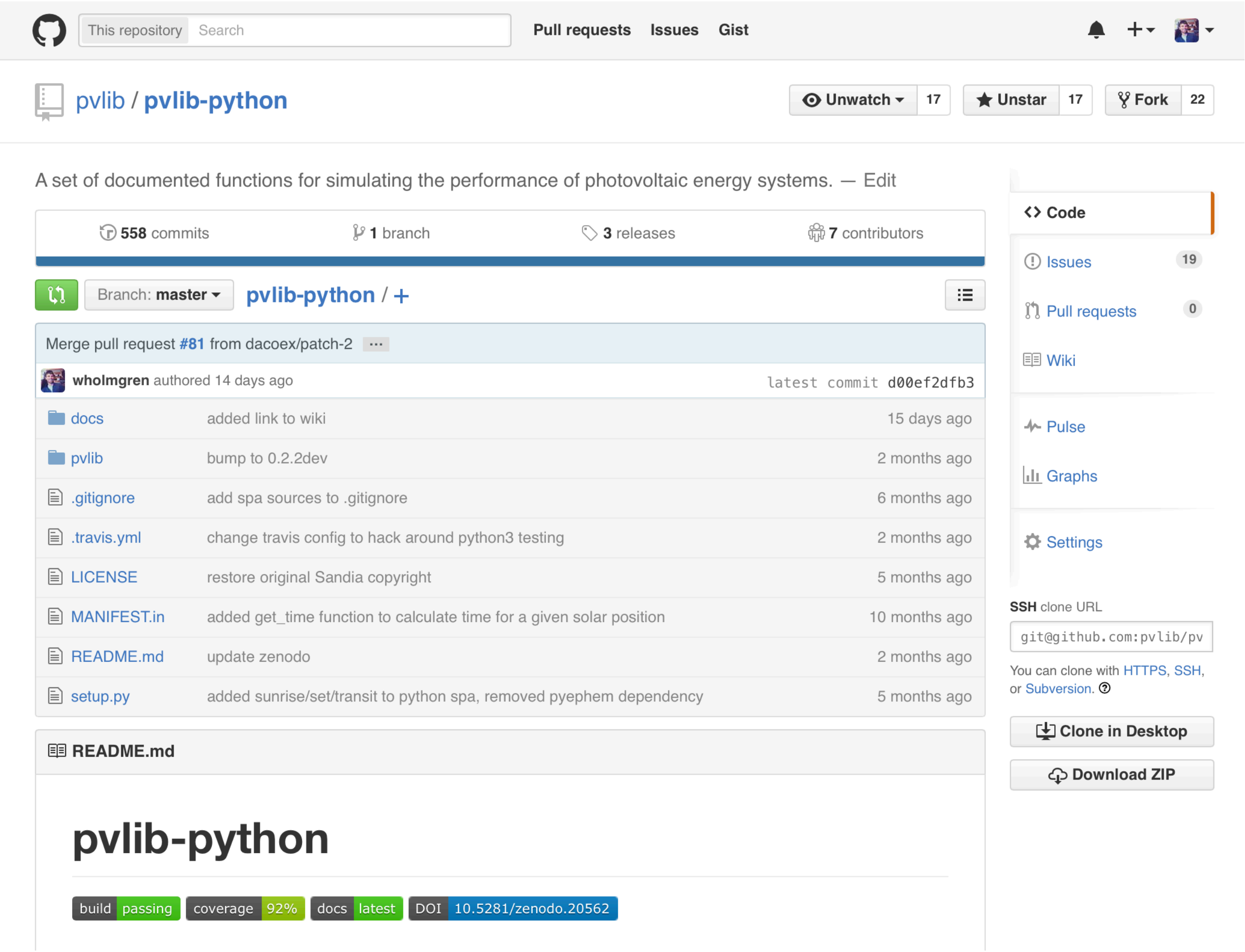
The best forecast has

1. The lowest error AND
2. The same variance as the observed signal



PVLib Python

- Tool for modeling solar power systems
- Foundation of the UA power forecasts
- Open source
- Descendant of Sandia's PVLIB MATLAB
- Primarily coordinated by Will, with contributions from across the world.
- Solar power forecast module funded by EPRI and Southern Company
- github.com/pvlib



PVLIB Python statistics

Known users include:

1. Sandia National Lab
2. NREL
3. Sun Power
4. First Solar
5. NCAR
6. Fraunhofer ISE
7. Sunshine Analytics
8. Solar City
9. Itron
10. PV Performance Laboratories
11. Reiner Lemoine Institute
12. Strata Solar Services
13. Stuart Bowden (ASU)

Unwatch 41 | Unstar 104 | Fork 139

As of October 18, 2017…

Issues: 42 Open ✓ 162 Closed

Pull requests: 5 Open ✓ 178 Closed

934 commits | 4 branches | 18 releases | 28 contributors | BSD-3-Clause

PVLib Python forecasts

The problem: weather forecast data is a mess!

Model	GHI	DNI	Cloud cover
GFS, 0.5 deg	3/6 hr mixed interval average	None	3/6 hr mixed interval average
NAM, 12 km	1 hr for 36 hrs 3 hr for 84 hrs	None	1 hr for 36 hrs 3 hr for 84 hrs
RAP, 13 km	None	None	1 hr instant
UA-WRF, 1.8 km	3 min. instant	3 min. instant	None

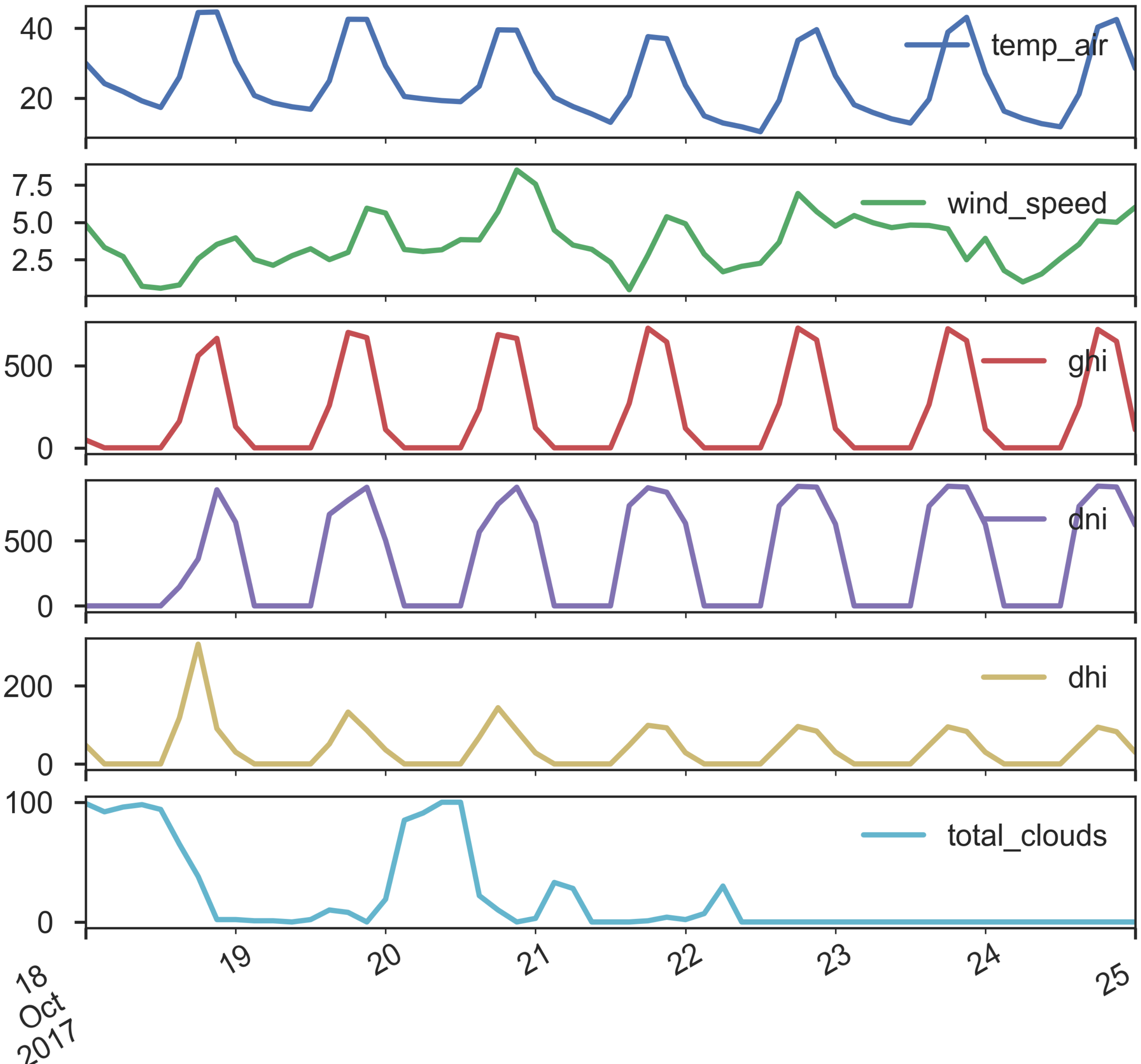
A solution: standardized data processing in PVLib Python

PVLib Python forecasts

Get relevant weather forecast data in 5 lines of code

```
from pvlib.forecast import GFS, NAM, RAP, HRRR

lat, lon = 32.2, -110.9

start, end = pd.Timestamp('20171018'), pd.Timestamp('20171025')

fx_model = GFS()

fx_data = fx_model.get_processed_data(lat, lon, start, end)
```

PVLi

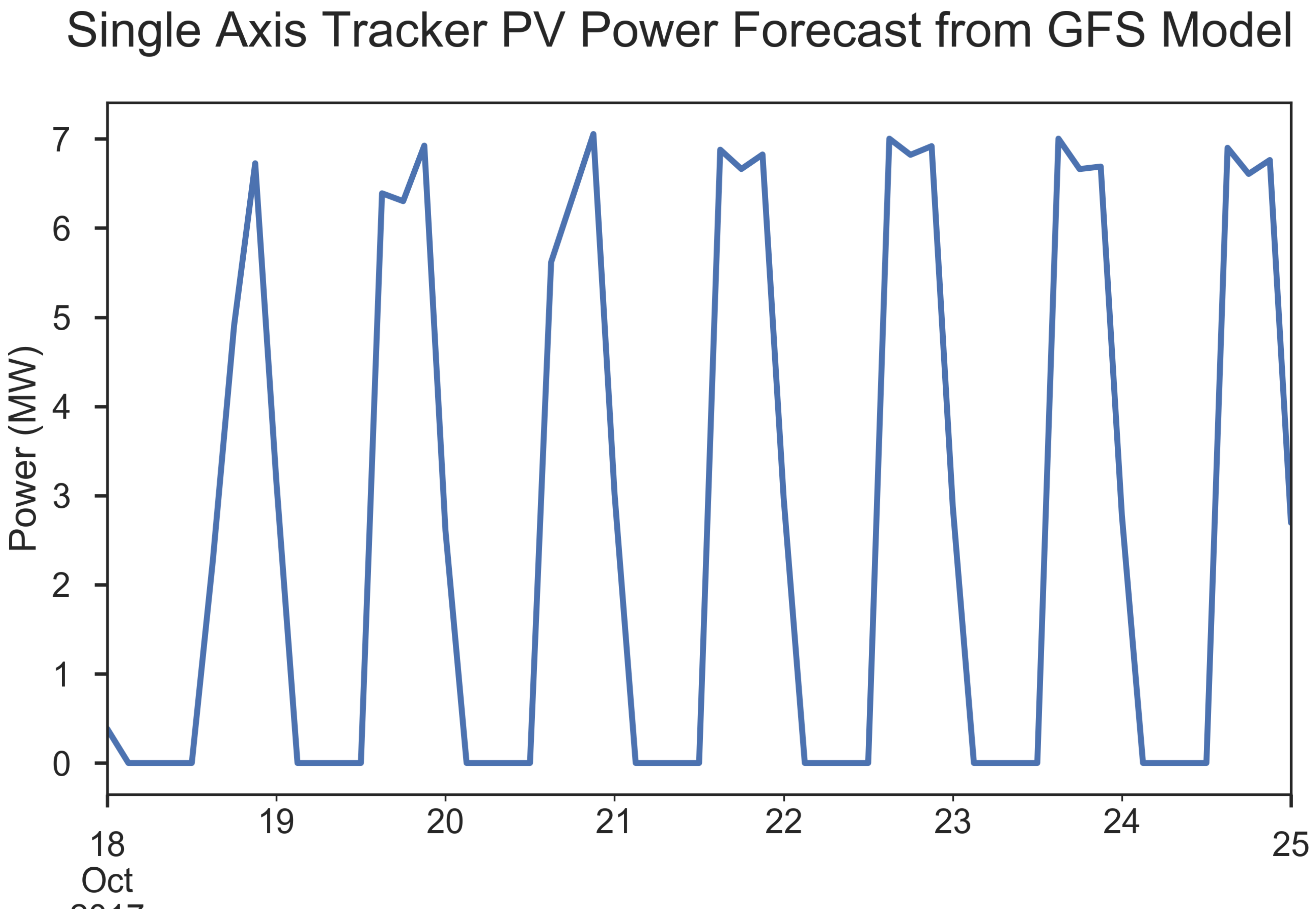



```
lat, lon =
start, end                                   1025')

from pvlib

fx_model =

fx_data =                                    d)
```

PVLib Python forecasts

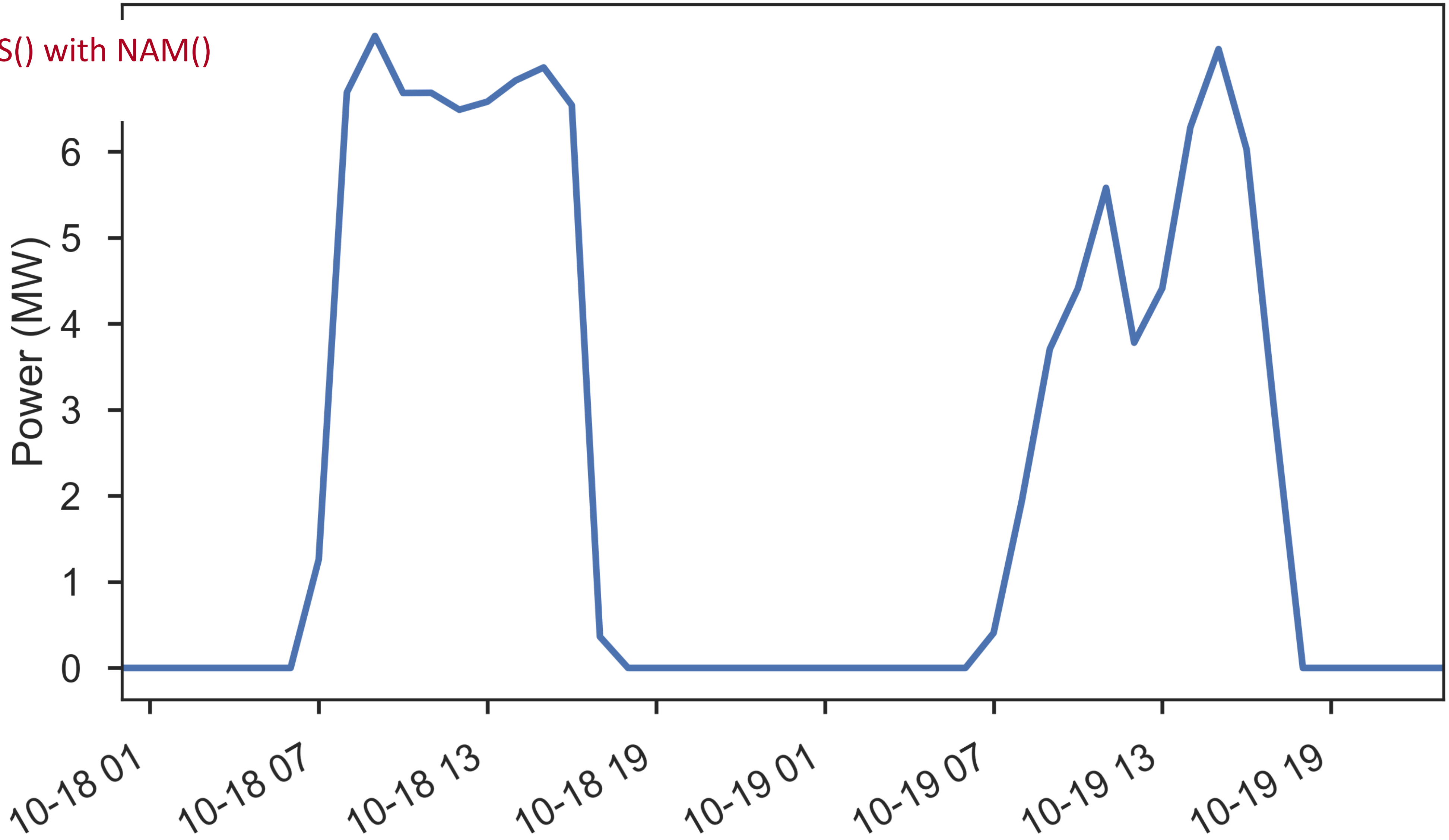
Convert your weather forecast into a power forecast in 5 lines of code

```
module_parameters = {'pdc0': 10.0, 'gamma_pdc': -0.0035}

system = SingleAxisTracker(module_parameters=module_parameters)

location = Location(lat, lon)

mc = ModelChain(system, location, **model_parameters)

mc.run_model(times=fx_data.index, weather=fx_data)
```


Single Axis Tracker PV Power Forecast from GFS Model
Power (MW)
0
1
2
3
4
5
6
7
18
Oct
19
20
21
22
23
24
25

Single Axis Tracker PV Power Forecast from NAM Model

Replace GFS() with NAM()
Rerun code

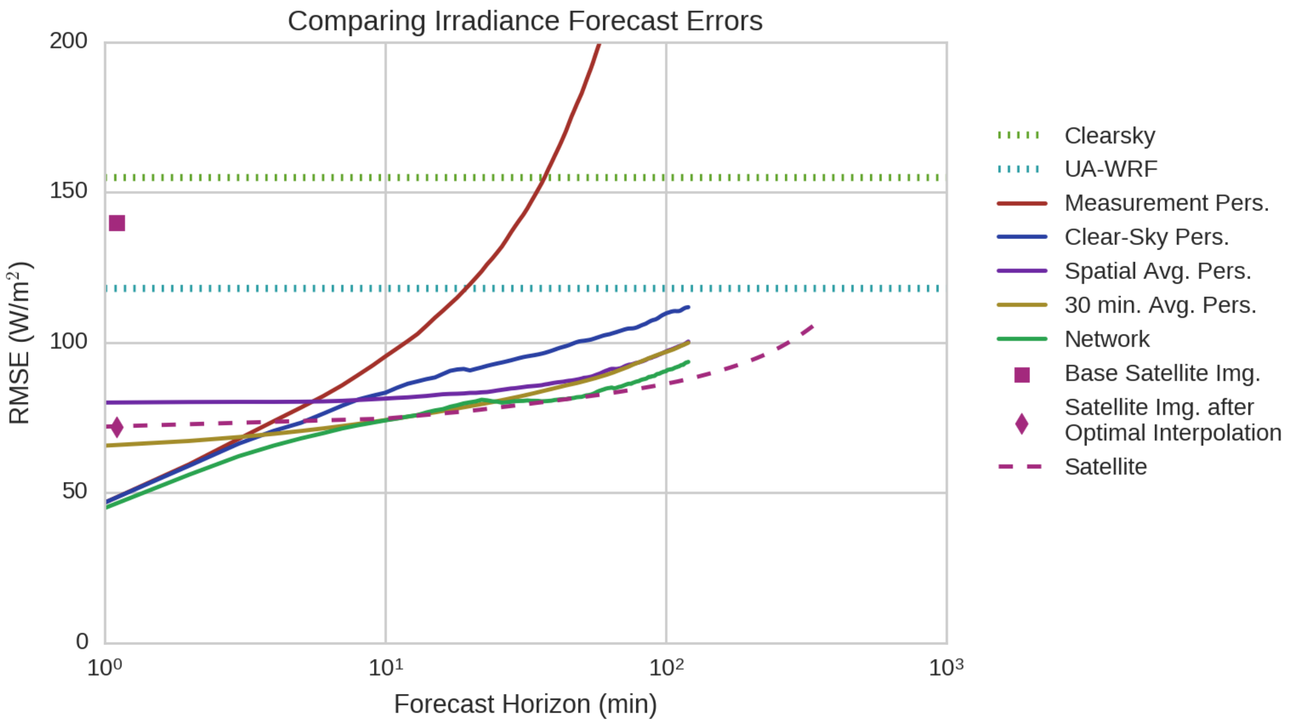


You too can be a forecaster!

1. Define your forecast problem
2. Determine what's "good enough"
3. Select an appropriate forecast method and data set

If working in solar…

4. Use PVLib Python or PVLib Matlab for PV modeling
5. Help me make PVLIB better for everyone



Thanks to our funding agencies

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SRP

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Arizona Department of Environmental Quality