Summer Course on Climate and Energy
World Energy & Meteorology Council

Lessons Learned from the Shorter Ranges: Weather Forecasting for Energy Applications

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July 5, 2016

Outline

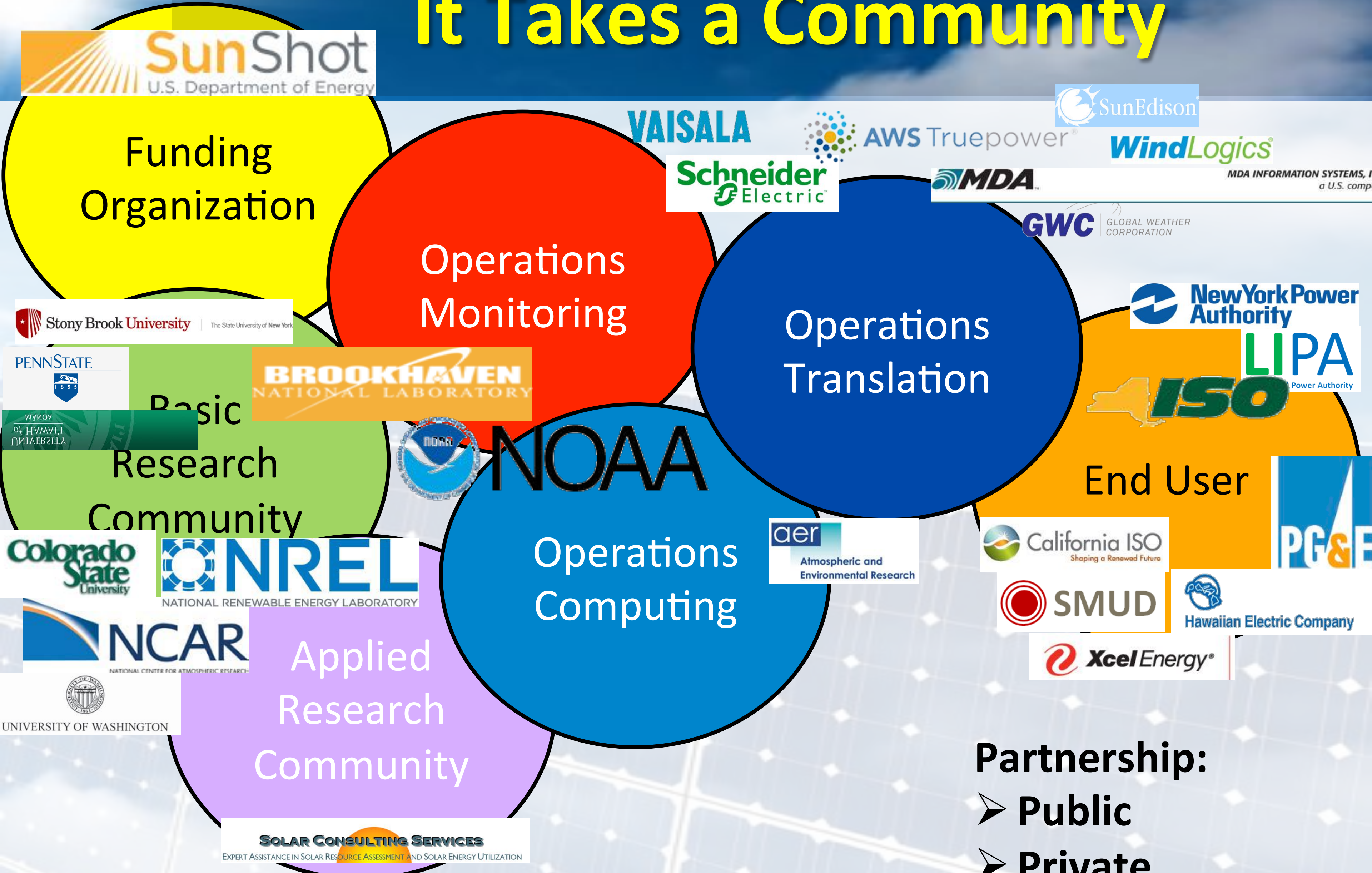
- Stakeholder Needs
- Ingredients
- Forecasting Across Scales
  - Numerical Weather Prediction
  - Data Assimilation
  - Nowcasting (Minutes to Hours)
  - Blending
  - Power Conversion
  - Uncertainty Quantification
  - Extreme Events
- Assessment
- Valuation

Examples:

- Solar Power Forecasting
- Wind Power Forecasting

Theme: Smartly blending data, dynamics, physics, and statistical learning methods

It Takes a Community



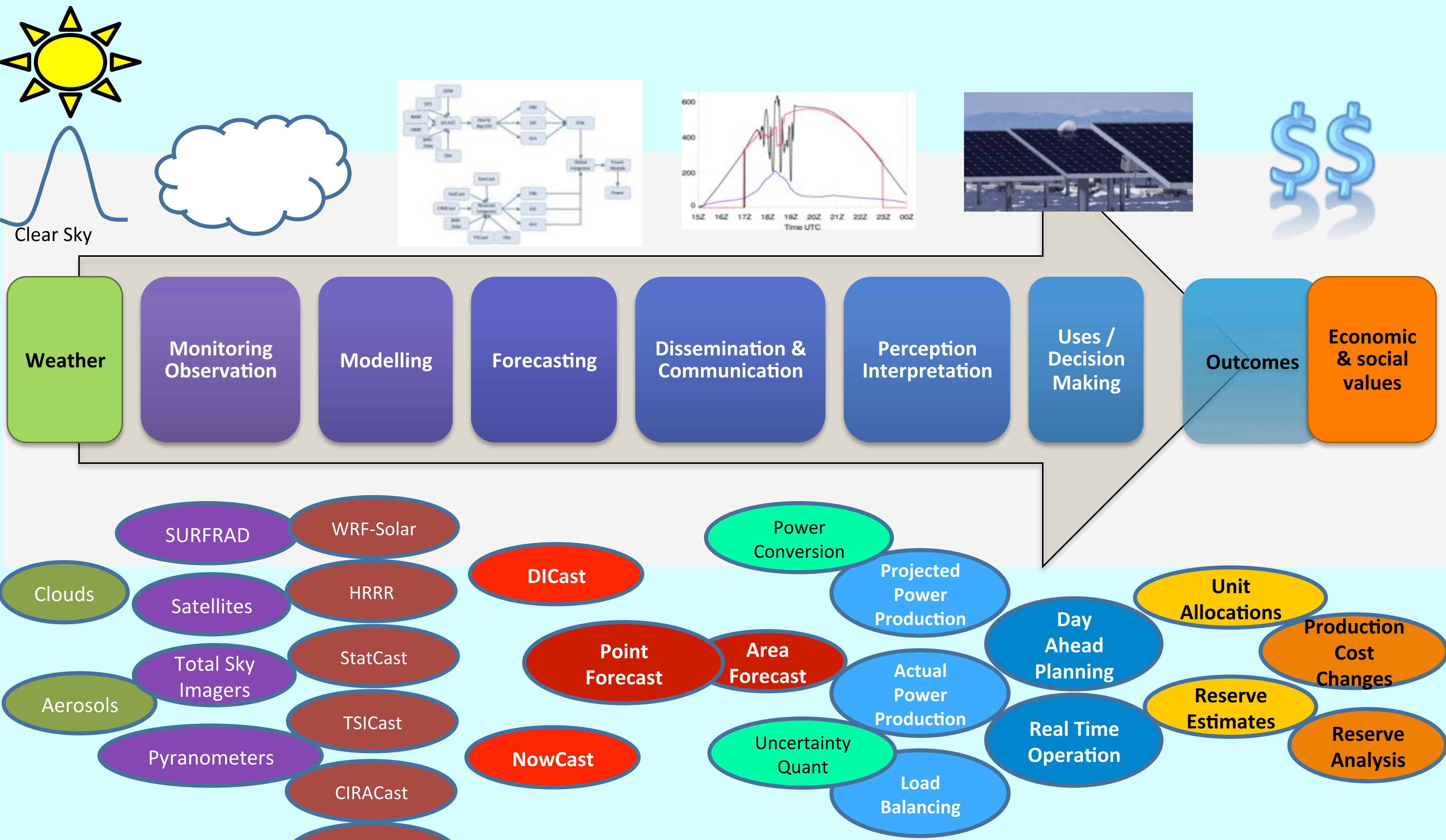
Partnership:

- **Public**
- **Private**
- **Academic**

Industry Needs for Renewable Energy Forecasts

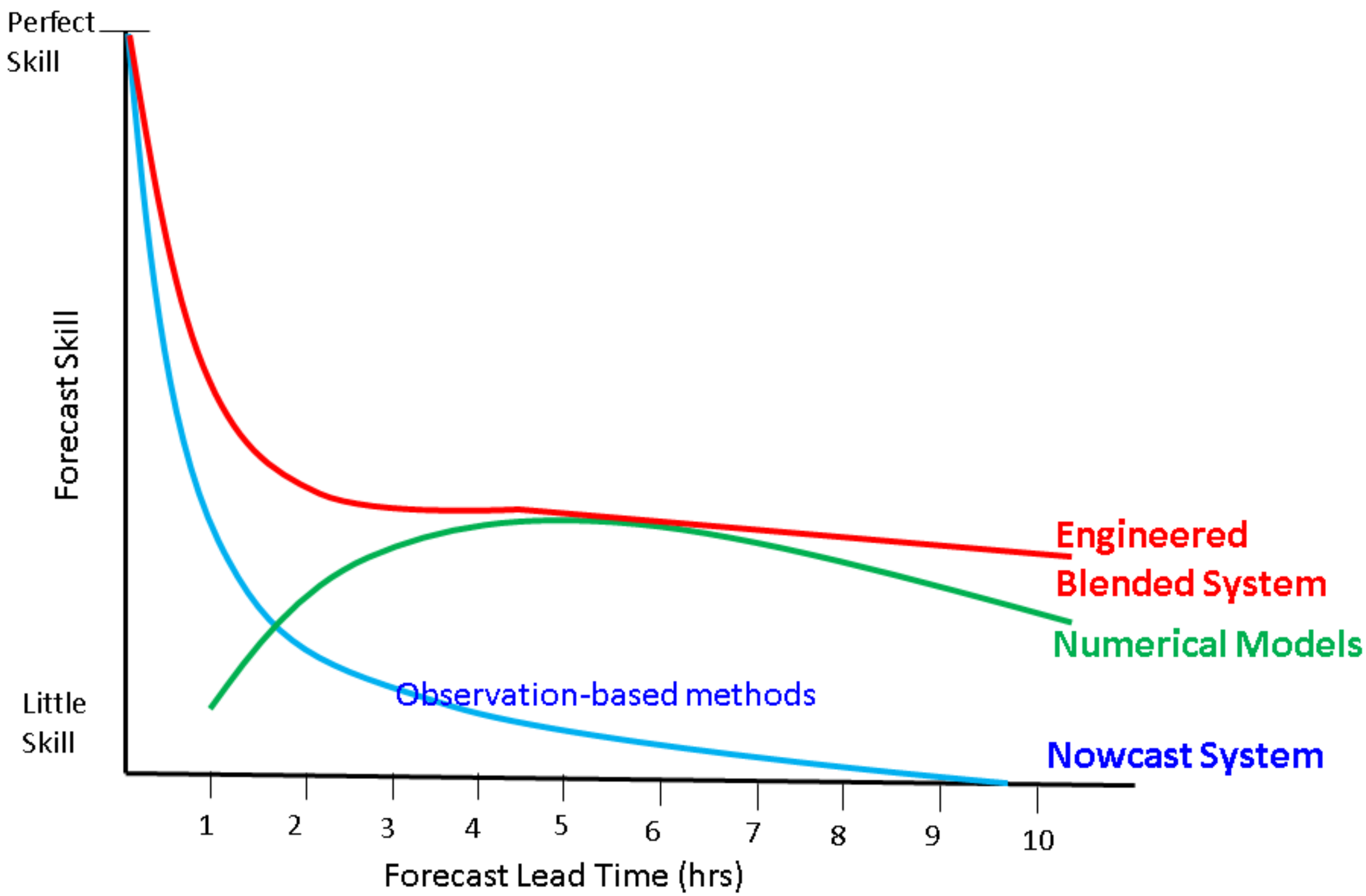
- **Need to predict POWER based on met variables**
  - 80-m wind speed
  - Surface irradiance – GHI, DNI, DIF
- **Time frames for prediction**
  - Long range – weeks –
    maintenance and distribution
  - Medium range – days – hourly
    day ahead trading
  - Nowcast range – hours – 15-min
    grid integration
  - Very short range – seconds to minutes –
    voltage control

Value Chain:
What is the value of solar power forecasting?



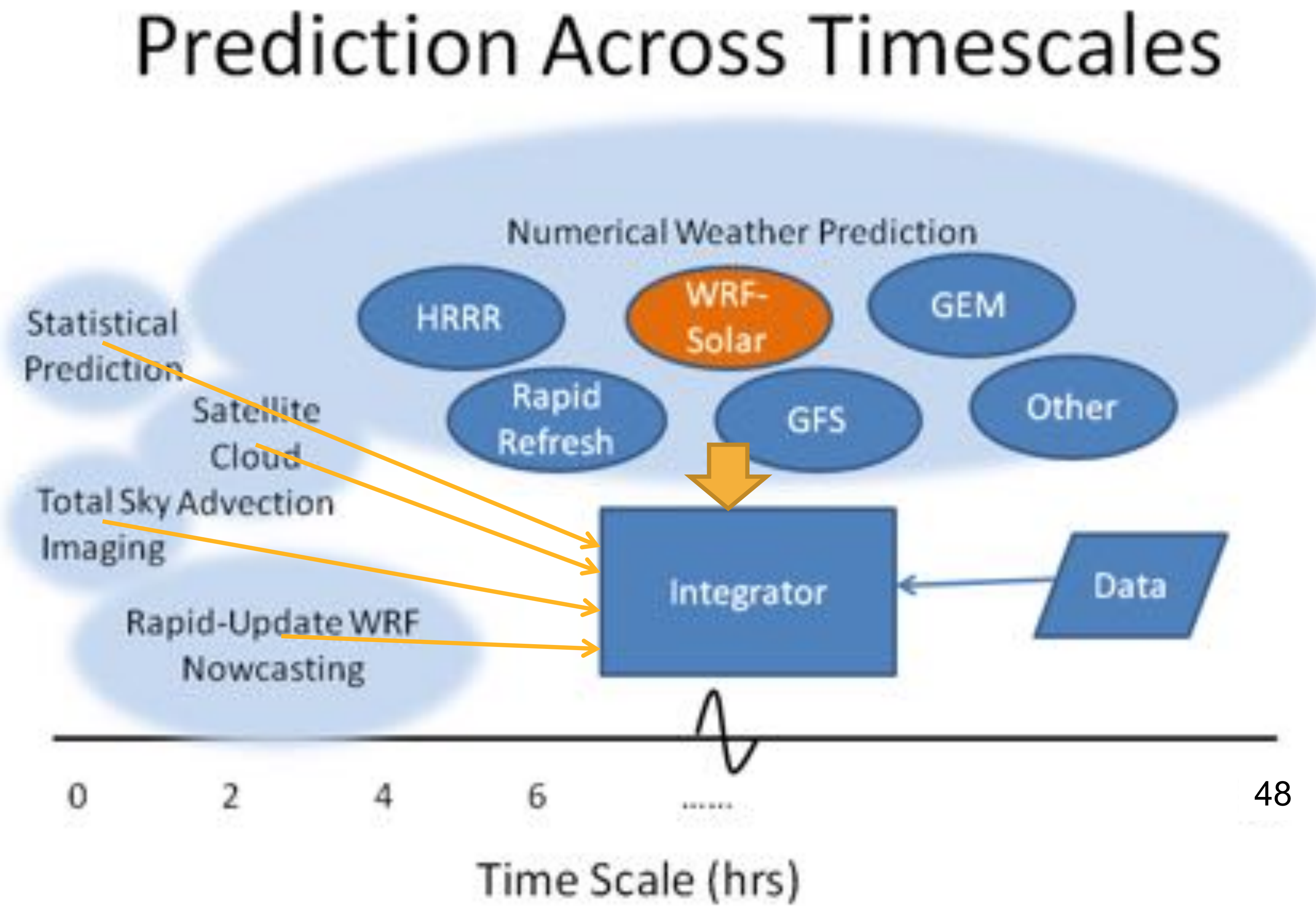
Inspired by Jeffrey Lazo

Meteorological Prediction:

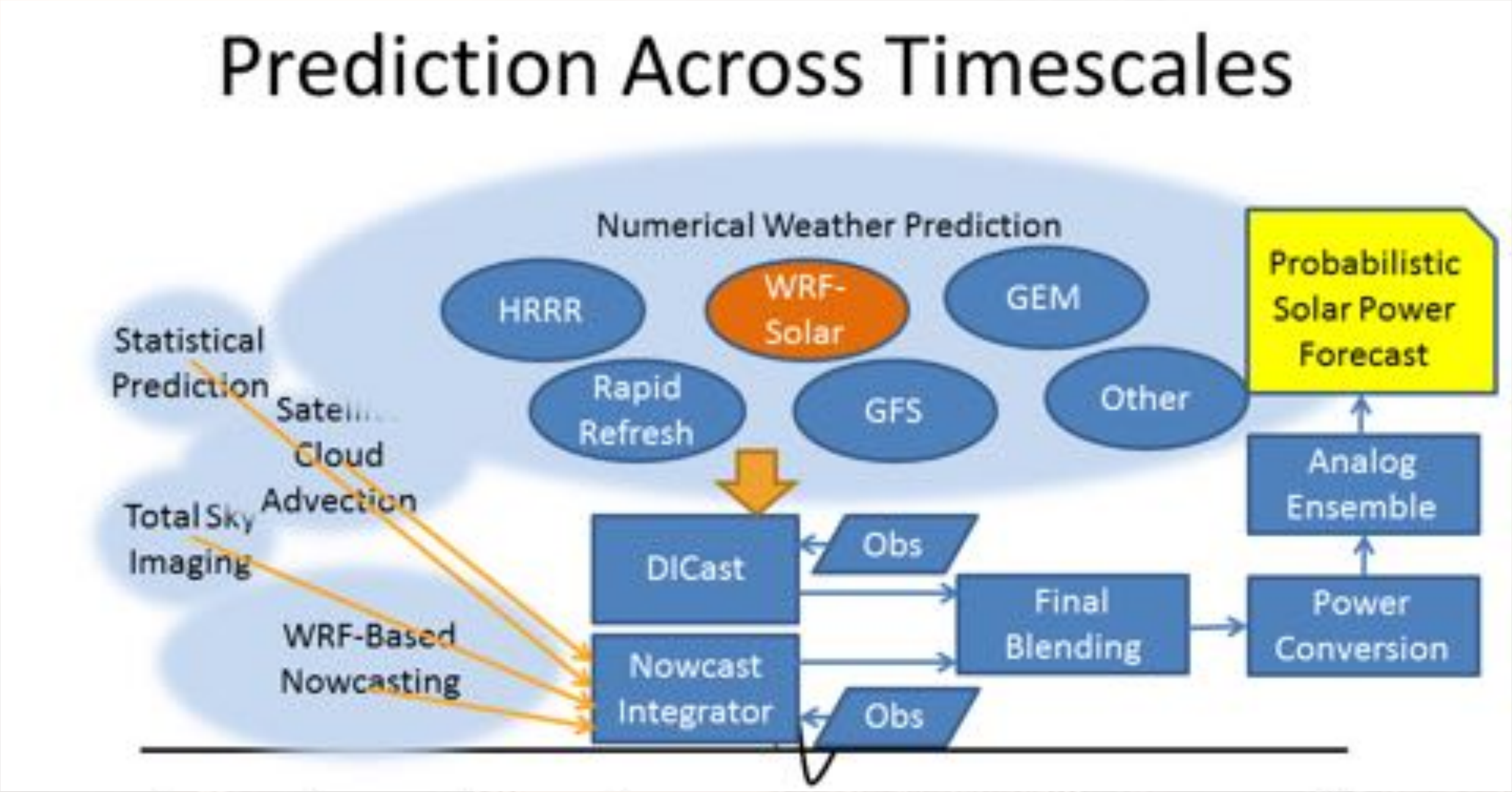


Adapted from Ravela, 2008
Auligne, 2014

Meeting the Needs:
Seamless Approach to Solar Power Forecasting

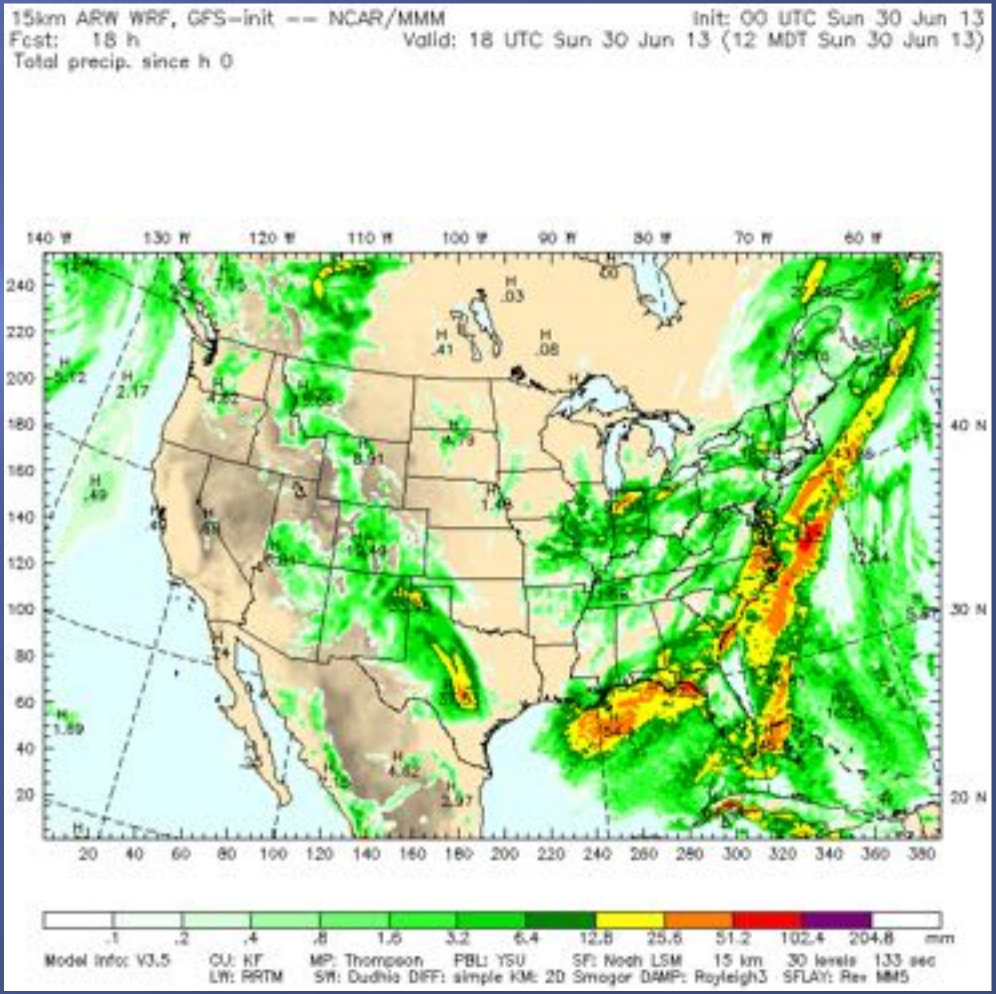


Forecasting System



Atmospheric Modeling Numerical Weather Prediction

- Dynamics
- Physics
- Quality Assurance
- Sensitivity to Initial Conditions
- Preprocessing – Needs for Assimilation
- Postprocessing – Blending Information
- Validation



Dynamic Meteorology

$$\frac{\partial \vec{v}}{\partial t} + \vec{v} \cdot \nabla \vec{v} = -\frac{1}{\rho} \nabla P + g - \nu \nabla^2 \vec{v}$$

$$\frac{\partial \rho}{\partial t} + \nabla \bullet (\rho \vec{v}) = 0$$

$$P = \rho R T$$

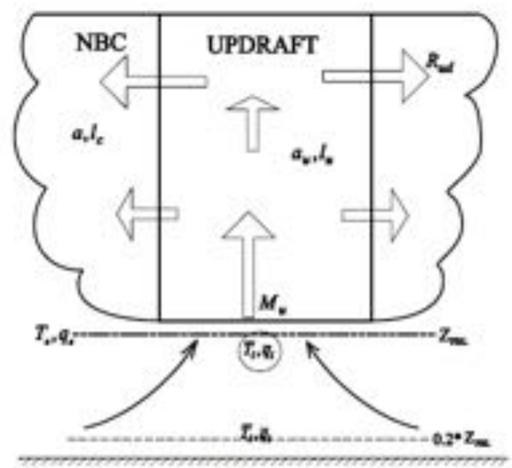
- Numerical methods treat this as an initial value problem
  - Discretize in space
  - Integrate in time
  - Constrained by continuity
  - Related by state eqn
- Nonlinearities make it difficult

Physical Parameterizations

- Various processes that we can't resolve
- Thus, parameterize given
  - Knowledge of physical process
  - Empirics
  - Constants and tuning

PENNSTATE

PSU SCP Schematic



Schematic of the prototype PSU SCP, where a is the neutrally-buoyant cloud (NBC) fraction, l_c is the NBC cloud water content, l_u is the cloud water content in the updraft denoted by subscript u, R_{ud} is the updraft detrainment rate; and Z_{pbl} is the depth of the PBL, etc.

7

AJ Deng, Dave Stauffer

NCAR

WRF (Weather Research & Forecasting) Model Physics

- Turbulence/Diffusion (diff_opt, km_opt)
- Radiation
  - Longwave (ra_lw_physics)
  - Shortwave (ra_sw_physics)
- Surface
  - Surface layer (sf_sfclay_physics)
  - Land/water surface (sf_surface_physics)
- PBL (bl_physics)
- Cumulus parameterization (cu_physics)
- Microphysics (mp_physics)

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http://www.google.fr/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&ved=0CDcQFjAB&url=http%3A%2F%2Fwww.mmm.ucar.edu%2Fpeople%2Fdudhia%2Ffiles%2Fpresentations%2FWRF_Physics_Dudhia.ppt&ei=mKjQUa3qJa6w4QSdnoDgCw&usg=AFQjCNGb933vSVDkzHeeDRk-

Different Schemes, Different Results

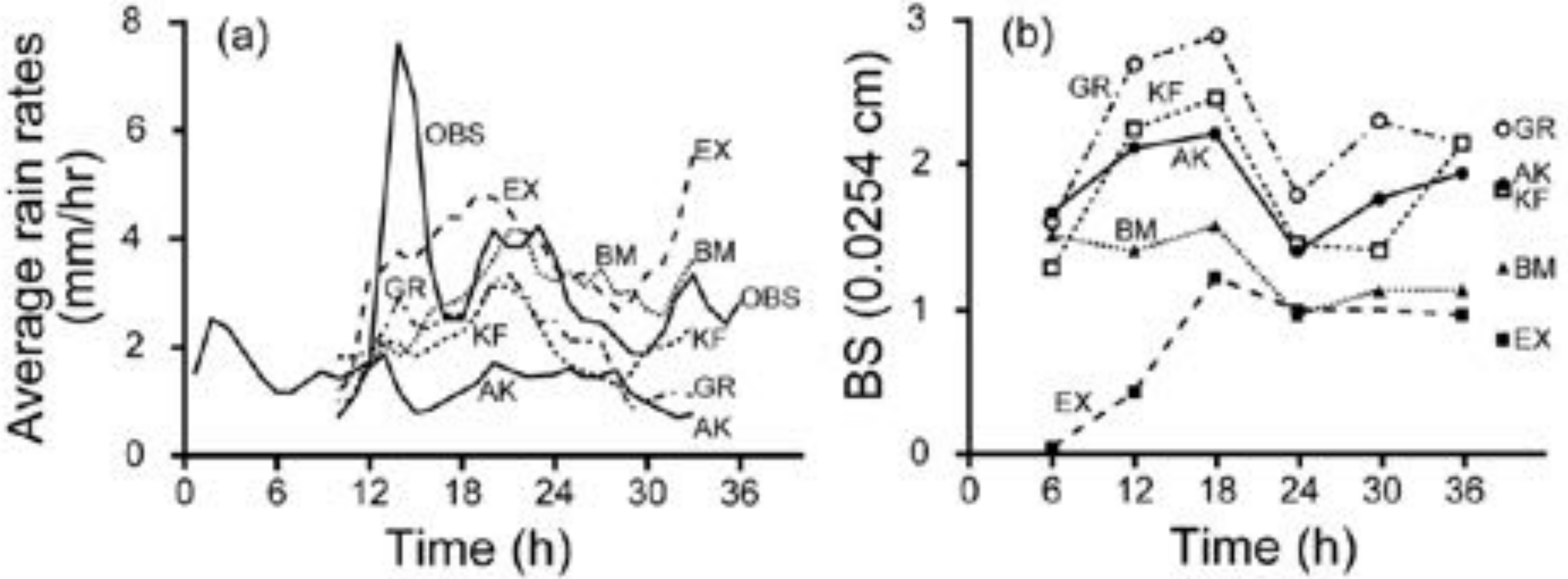

Figure 4. Average rainfall rate, for a spring-season convective event (a), based on observations (OBS) and for five simulations that used different treatments for the convection - four different parameterizations, and no parameterization (EX). Also depicted is the rainfallrate bias score averaged for three warm-season convective events (b), again for each of the four parameterizations and for the use of no parameterization. The four convective parameterizations were the Grell (GR), Kain-Fritsch (KF), Betts-Miller (BM), and Anthes-Kuo (AK) schemes. Adapted from Wang and Seaman (1997).

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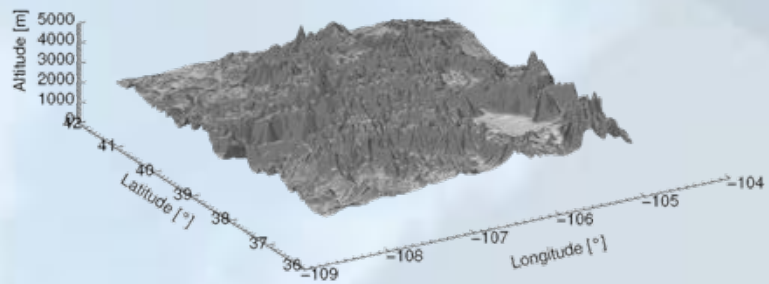
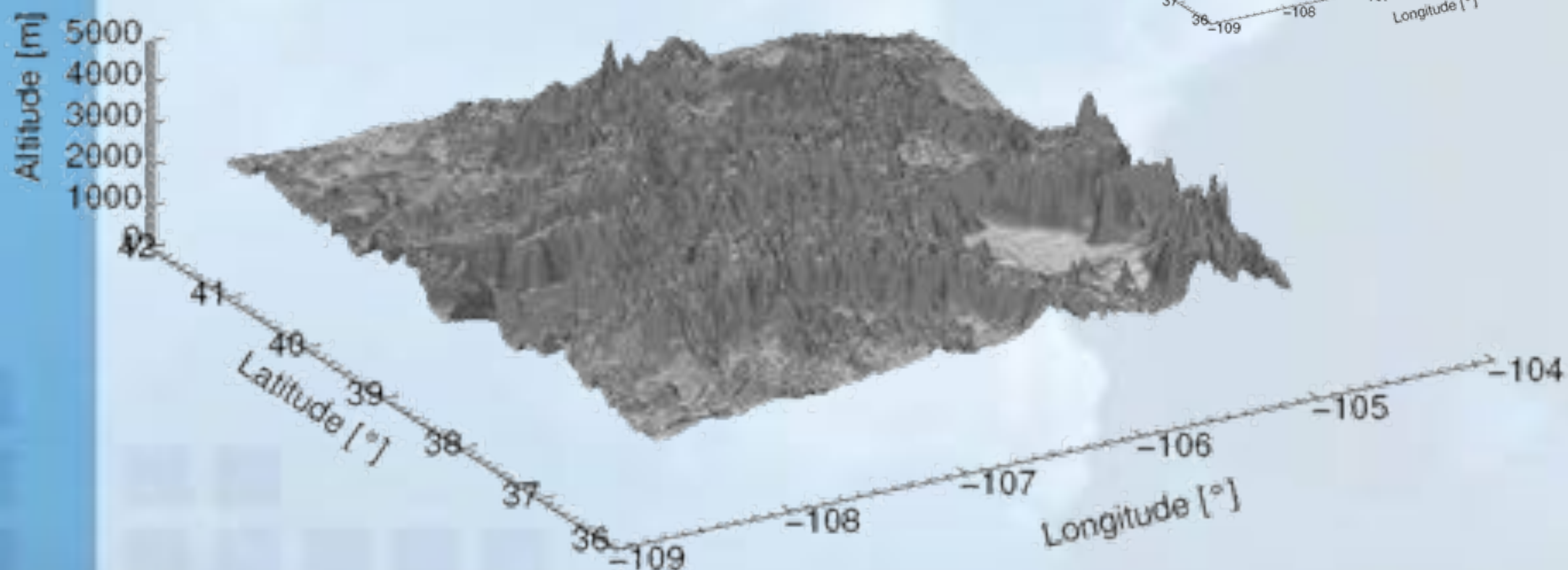
Value of high-resolution regional model

Resolution : 2.4 km

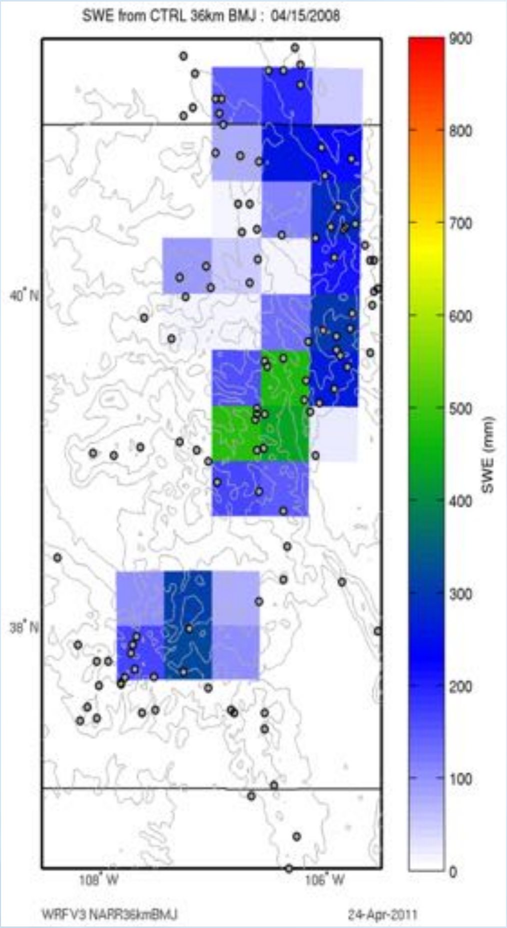


Resolution: 0.0 km

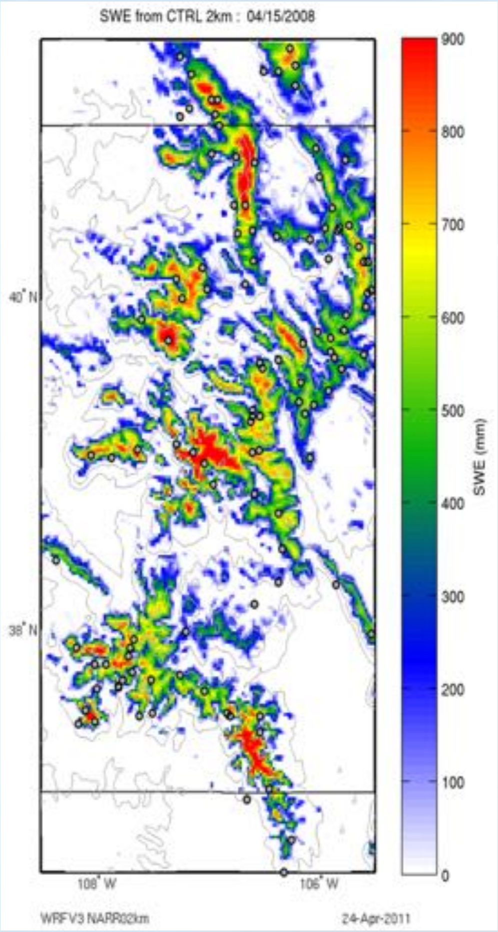


Snowpack in Central Rockies: too little at high elevation and melts three months too early at coarse resolution

36 km



2 km



April 15 snapshot of snow pack at two model resolutions
(Simulation of 2007-2008 water year)

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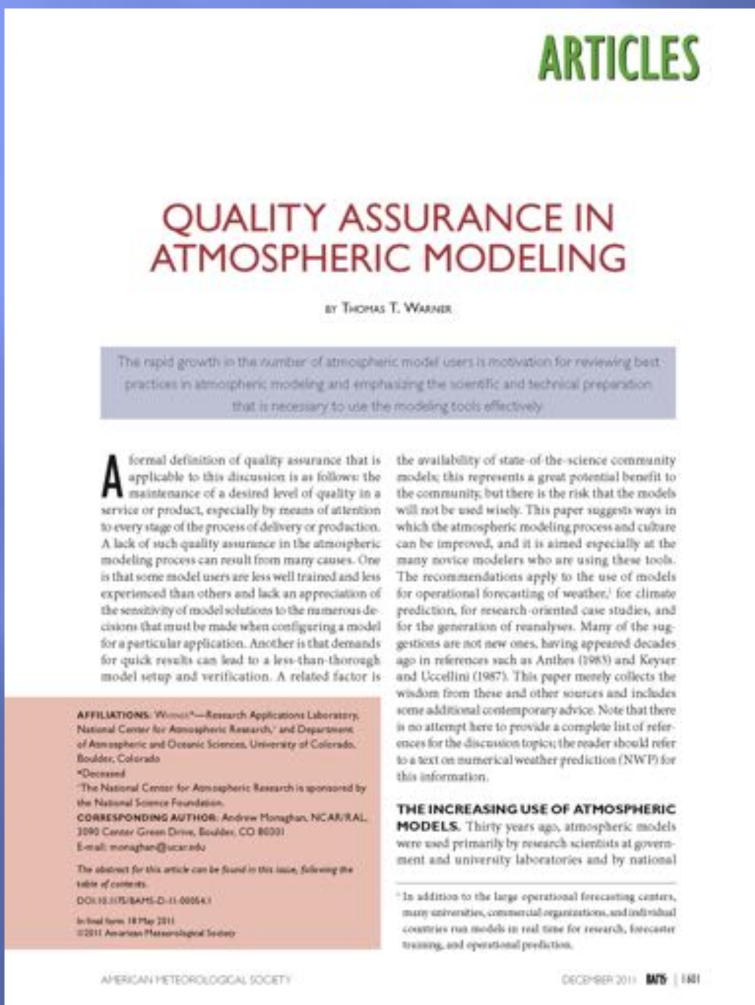
QUALITY ASSURANCE IN ATMOSPHERIC MODELING



ARTICLES

QUALITY ASSURANCE IN ATMOSPHERIC MODELING

BY THOMAS T. WARNER

The rapid growth in the number of atmospheric model users is motivation for reviewing best practices in atmospheric modeling and emphasizing the scientific and technical preparation that is necessary to use the modeling tools effectively.

A formal definition of quality assurance that is applicable to this discussion is as follows: the maintenance of a desired level of quality in a service or product, especially by means of attention to every stage of the process of delivery or production. A lack of such quality assurance in the atmospheric modeling process can result from many causes. One is that some model users are less well trained and less experienced than others and lack an appreciation of the sensitivity of model solutions to the numerous decisions that must be made when configuring a model for a particular application. Another is that demands for quick results can lead to a less-than-thorough model setup and verification. A related factor is the availability of state-of-the-science community models; this represents a great potential benefit to the community, but there is the risk that the models will not be used wisely. This paper suggests ways in which the atmospheric modeling process and culture can be improved, and it is aimed especially at the many novice modelers who are using these tools. The recommendations apply to the use of models for operational forecasting of weather,[1] for climate prediction, for research-oriented case studies, and for the generation of reanalyses. Many of the suggestions are not new ones, having appeared decades ago in references such as Anthes (1983) and Keyser and Uccellini (1987). This paper merely collects the wisdom from these and other sources and includes some additional contemporary advice. Note that there is no attempt here to provide a complete list of references for the discussion topics; the reader should refer to a text on numerical weather prediction (NWP) for this information.

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THE INCREASING USE OF ATMOSPHERIC MODELS. Thirty years ago, atmospheric models were used primarily by research scientists at government and university laboratories and by national

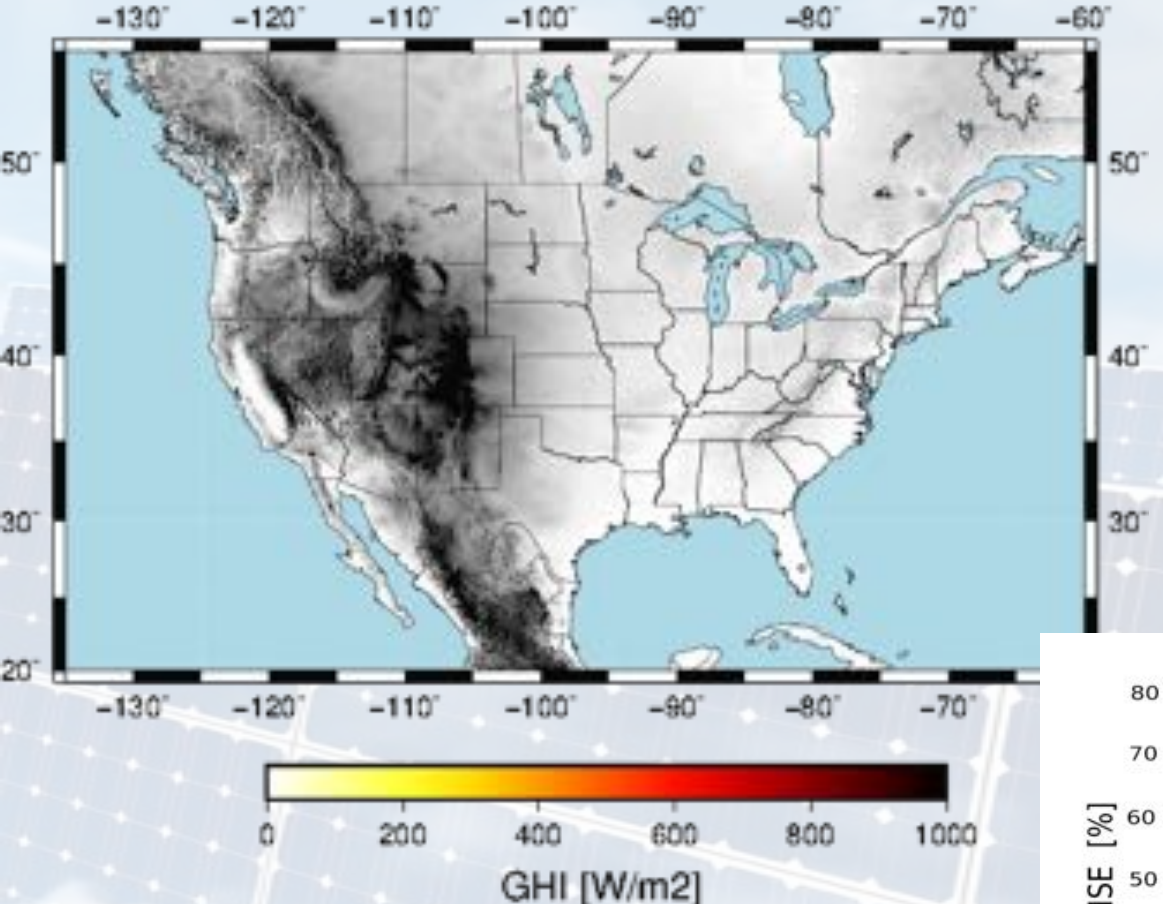
[1] In addition to the large operational forecasting centers, many universities, commercial organizations, and individual countries run models in real time for research, forecaster training, and operational prediction.

Bulletin of the American Meteorological Society

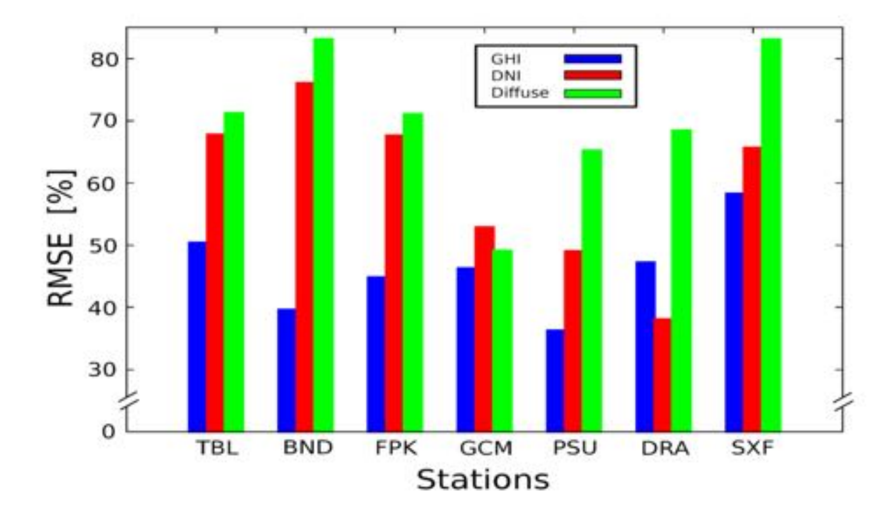
Thomas T. Warner

WRF-Solar

CLOUD-RADIATION-AEROSOL INTERACTION



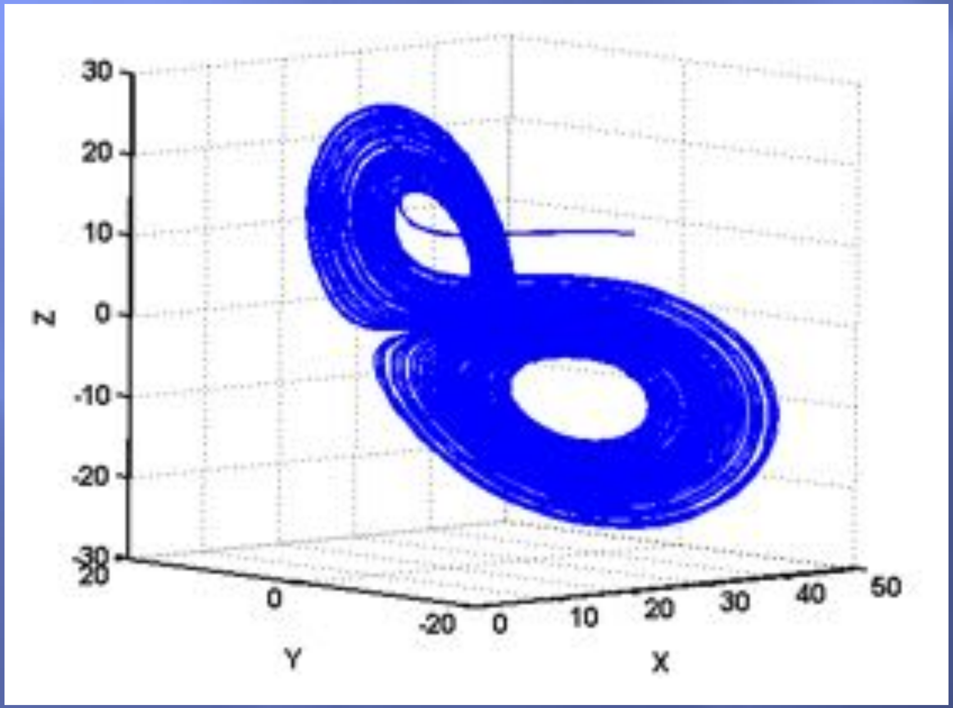
% Improvement over standard WRF



Courtesy: Pedro Jimenez

Fluid Flow is Sensitive to Initial Conditions

$$\frac{\partial \vec{v}}{\partial t} + \vec{v}\cdot\nabla\vec{v} = -\frac{1}{\rho}\nabla P + g - \nu\nabla^2\vec{v}$$



Lorenz (1963)

- Atmospheric flows display sensitivity to initial & boundary conditions and to physics parameterization

⇒ **Chaotic Attractor**

- How do we stay on the correct trajectory?

⇒ **Assimilation**

⇒ **Uncertainty Quantification**

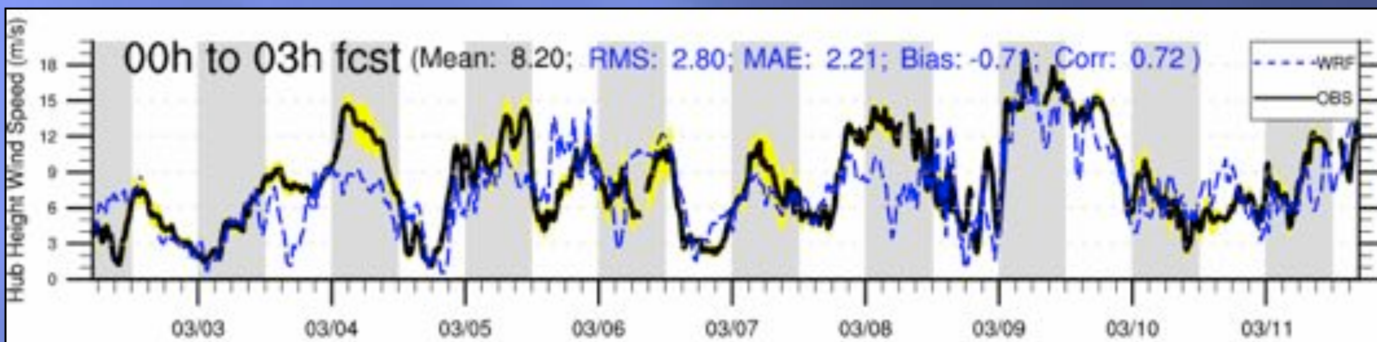
Assimilation provides best ICs

- Data Assimilation – incorporating observations into a model
  - Surface observations
  - Satellite observations
  - Atmospheric profiles
  - Radar observations
  - Data from wind or solar farms
  - Specialized data

Application: Wind Energy Ramping

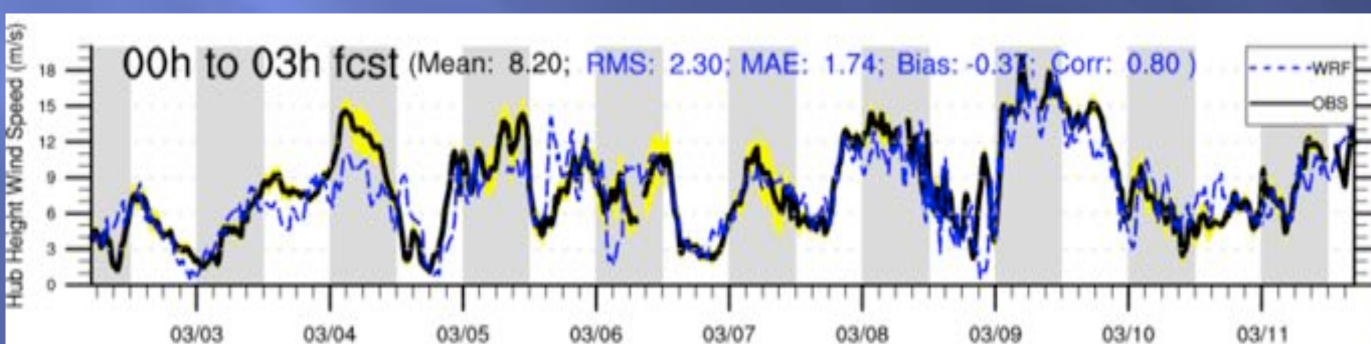
Real Time Four Dimensional Data Assimilation RTFDDA

0-3 hour Wind Energy Predictions



W/O
Farm DATA

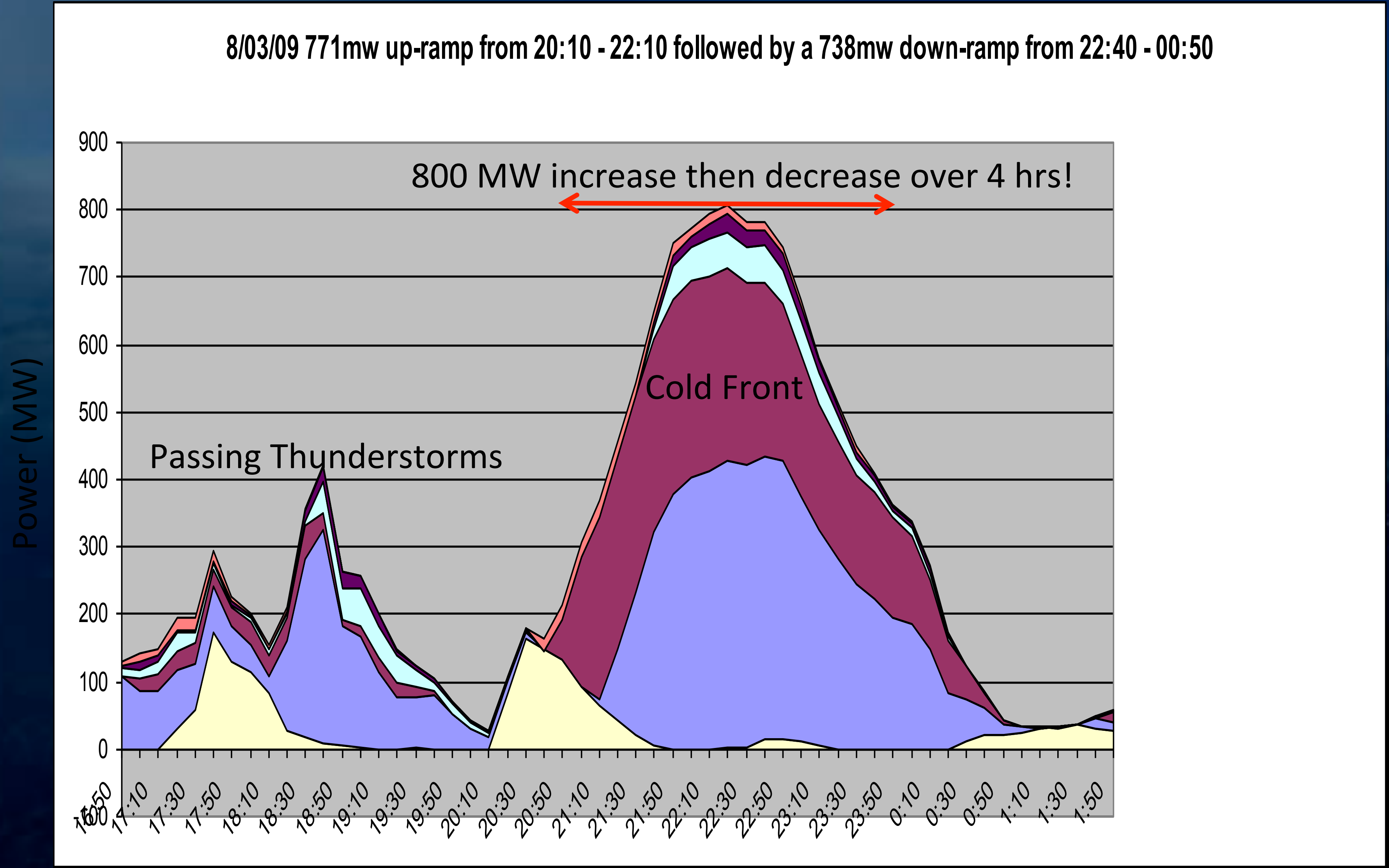
Gain:
17 % in RMS
20% in MAE
11% in Bias



With
Farm DATA

Courtesy: Yubao Liu

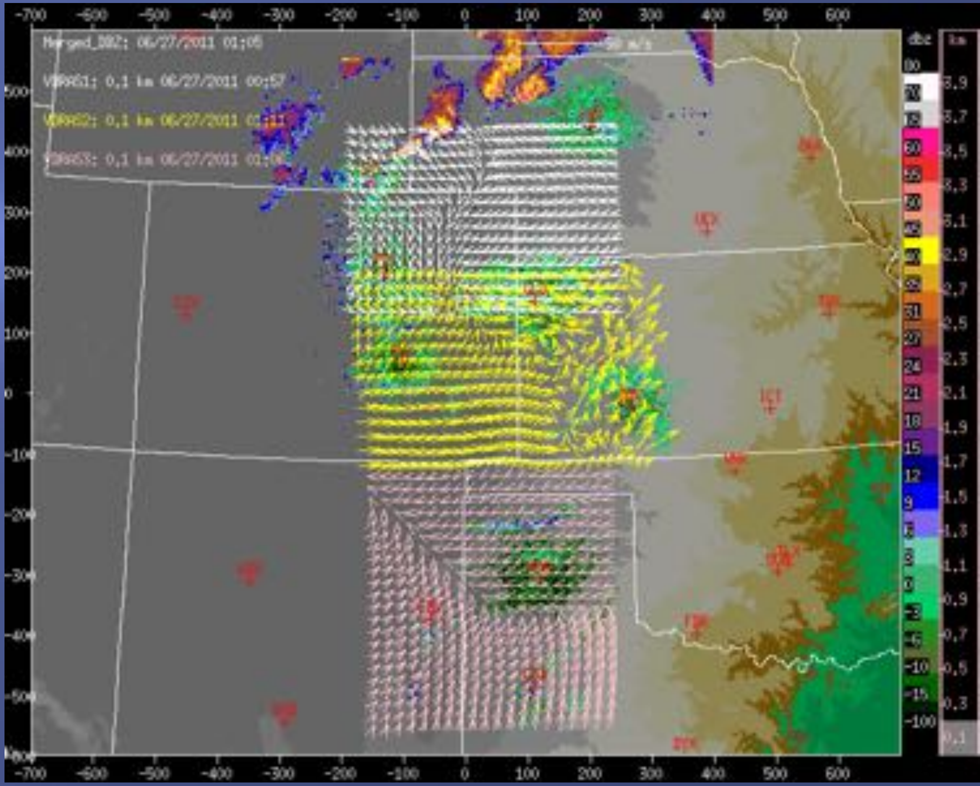
Wind Energy Ramp Event



Assimilation for Nowcasts

Dynamic Assimilation allows recovery of characteristics of realization

- Allows better prediction to meet user needs
- An effective way to deal with sensitivity to initial conditions



Courtesy: Jenny Sun

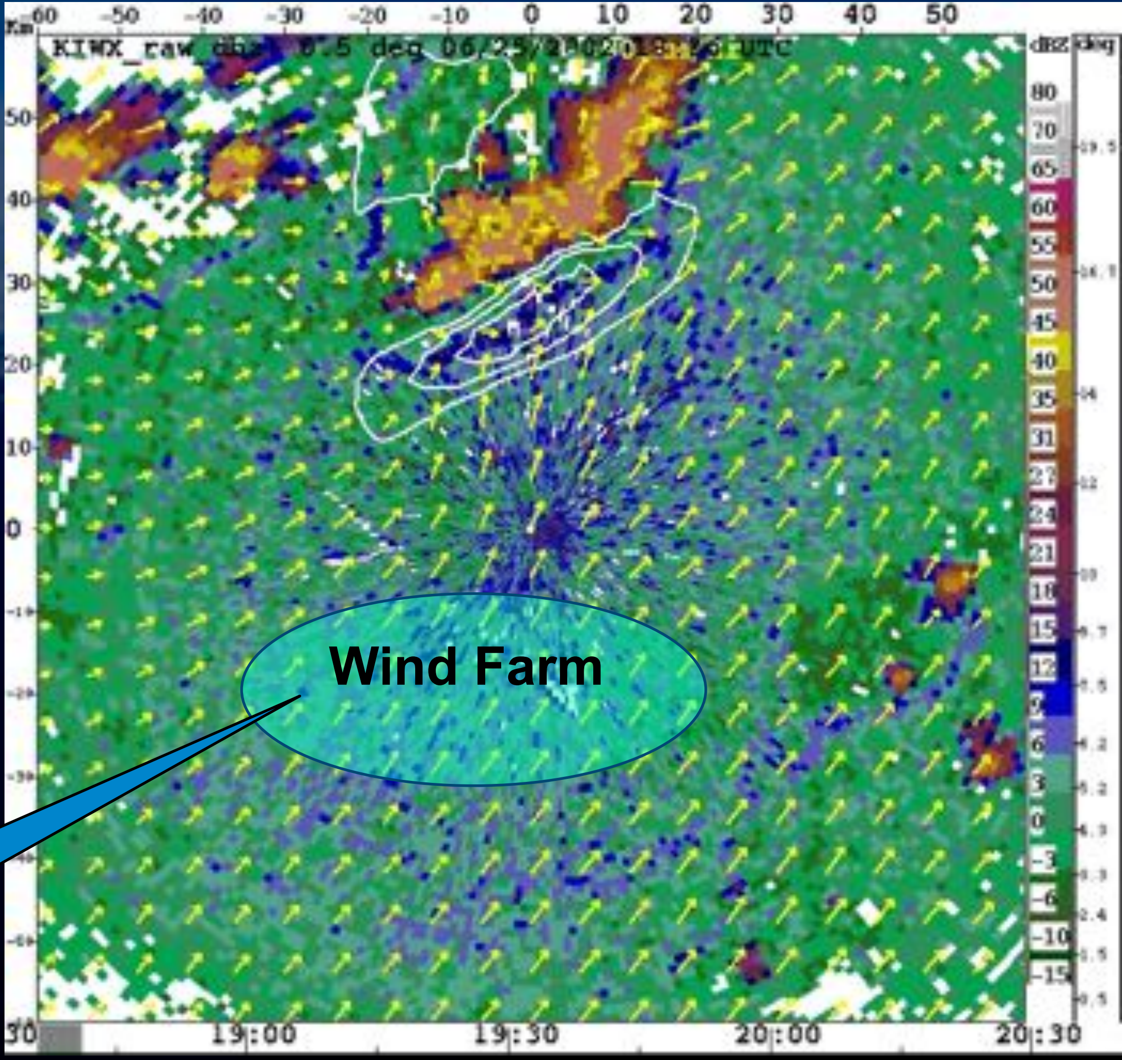
Application: Wind Energy Ramping

Variational Doppler Radar Analysis System

VDRAS

Gust fronts approaching ‘wind plant’

Wind ramp event is imminent



Need to provide time-of-arrival and magnitude of wind energy ramp.

Courtesy: Jenny Sun

NCAR Auto-Nowcasting System

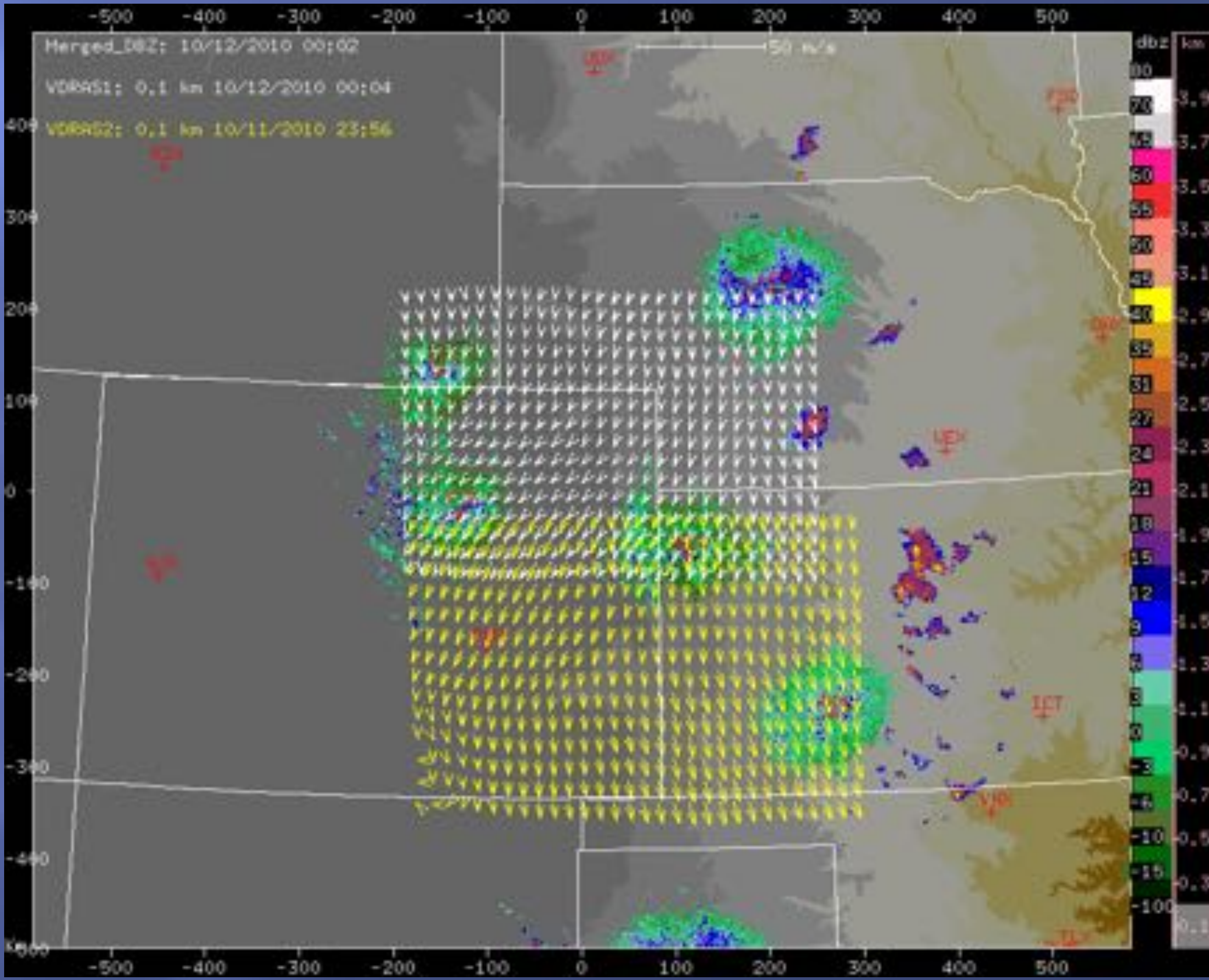
Wind Energy Ramp Event Nowcasting

VDRAS

Variational Doppler Radar Analysis System

+

Expert System (obs-based)



Courtesy: Jenny Sun

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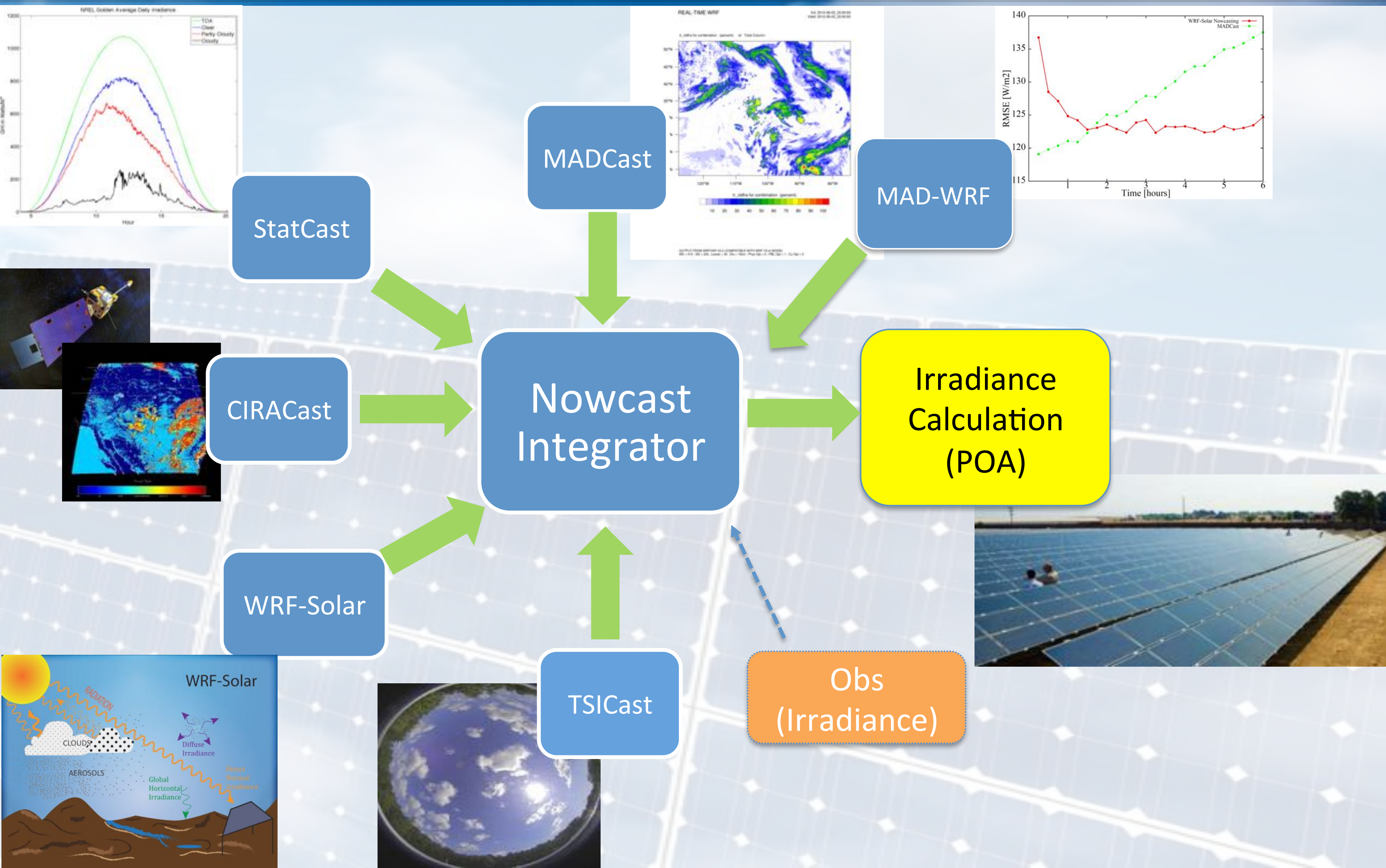
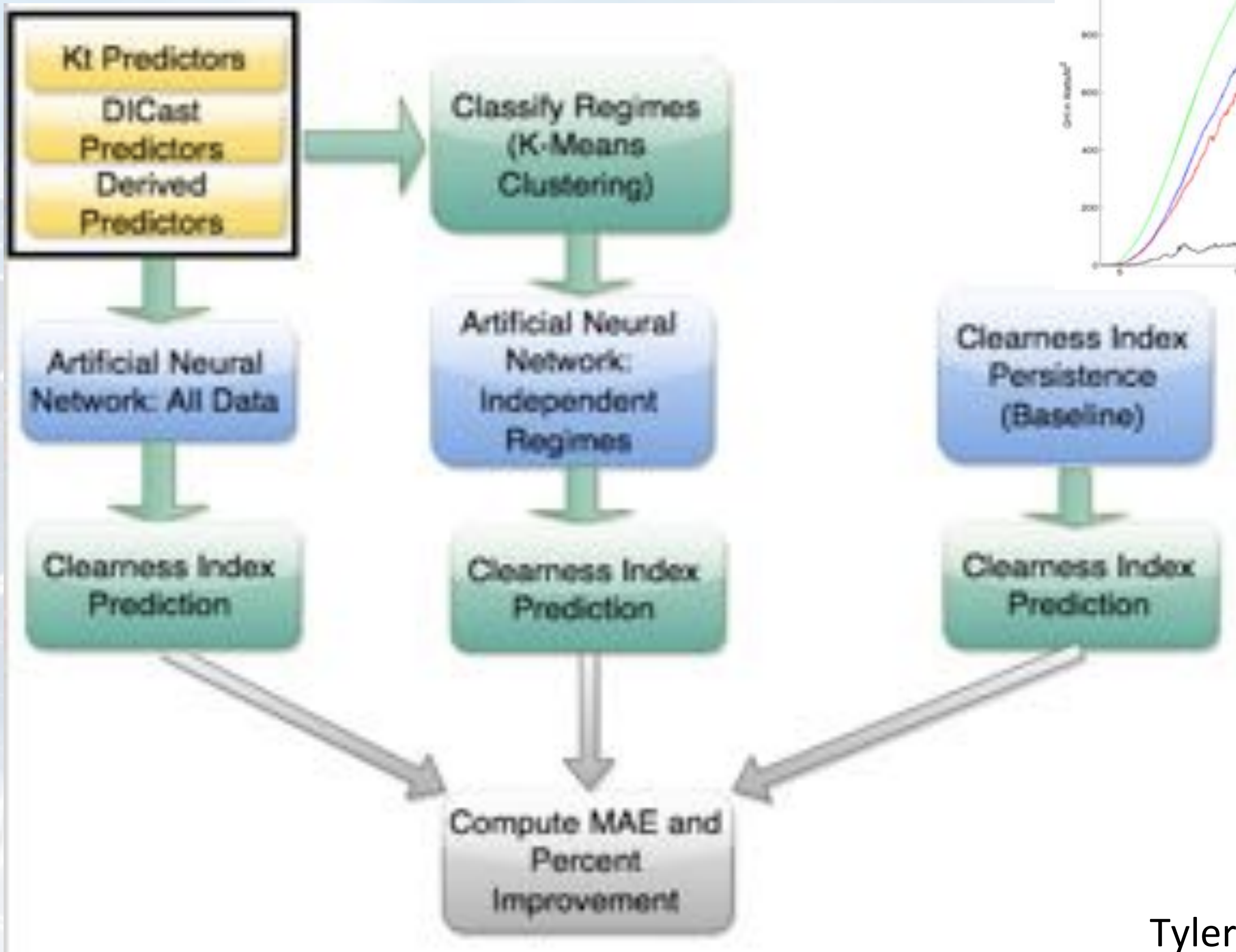
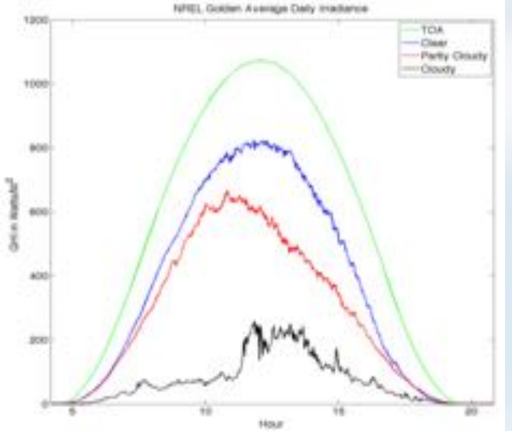
Nowcast System for Solar Power



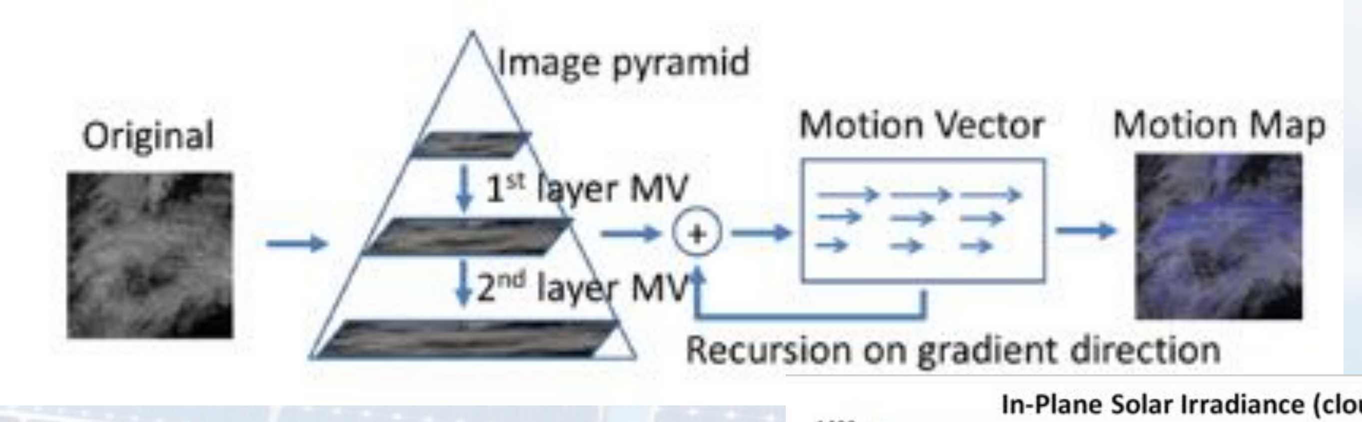
Some Models Employ AI: StatCast

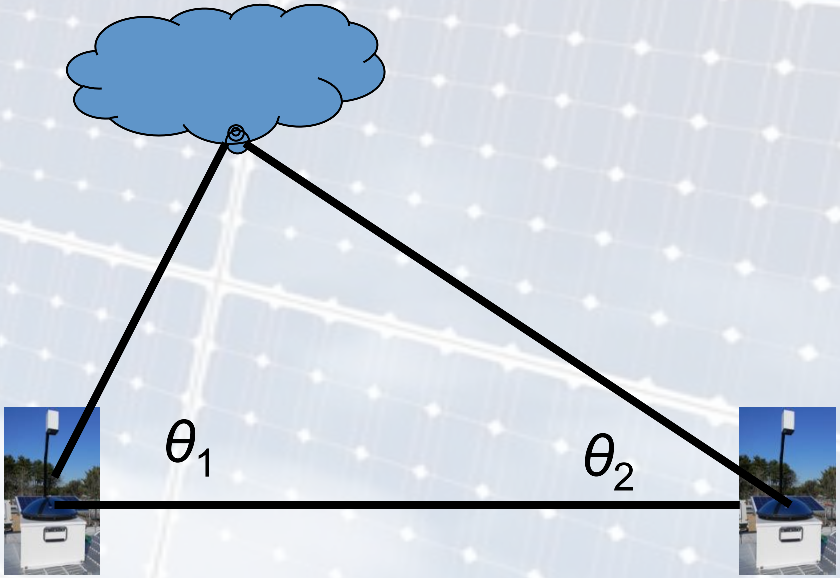


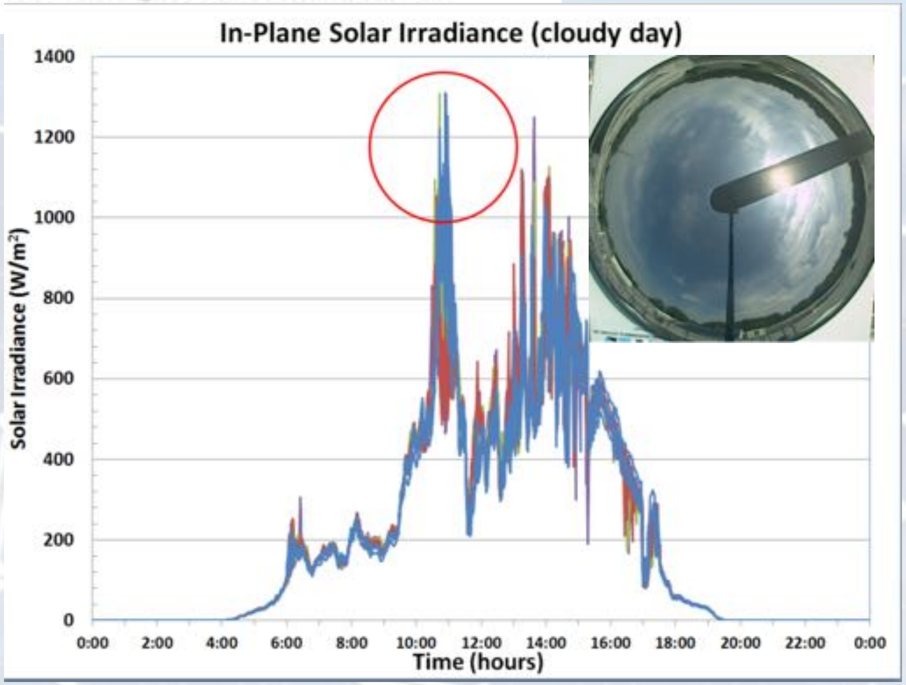


Tyler McCandless

Sky Imager Forecast





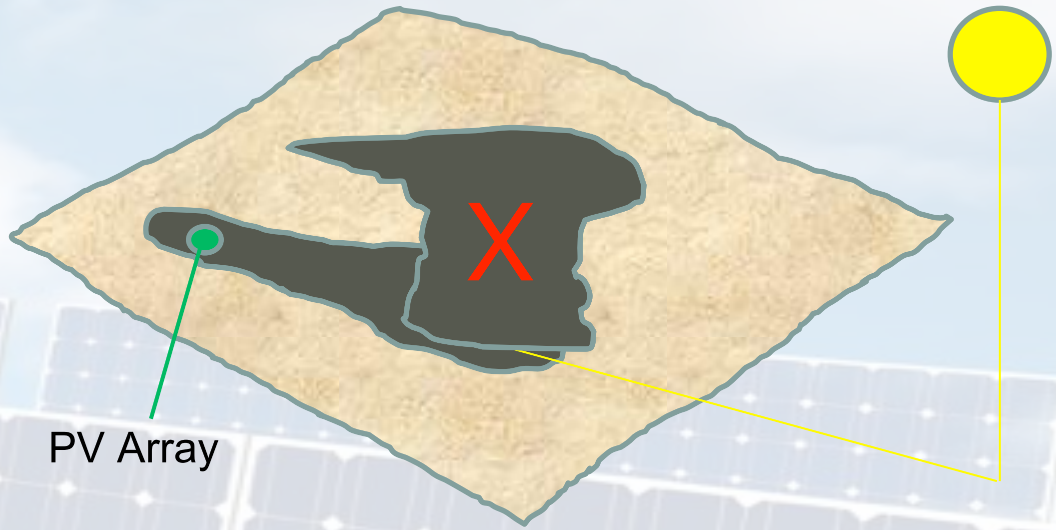


6/19/12

Brookhaven NL

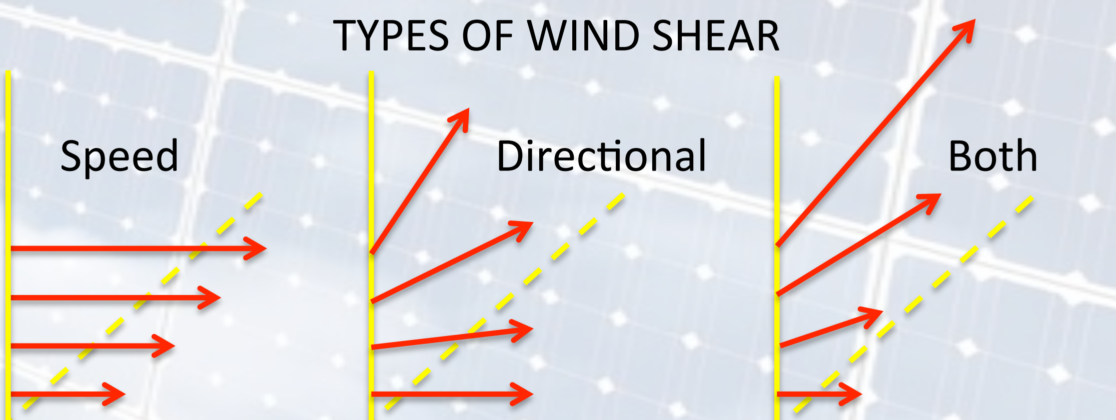
Satellite-Based Forecasting CIRACast - Attention to Details

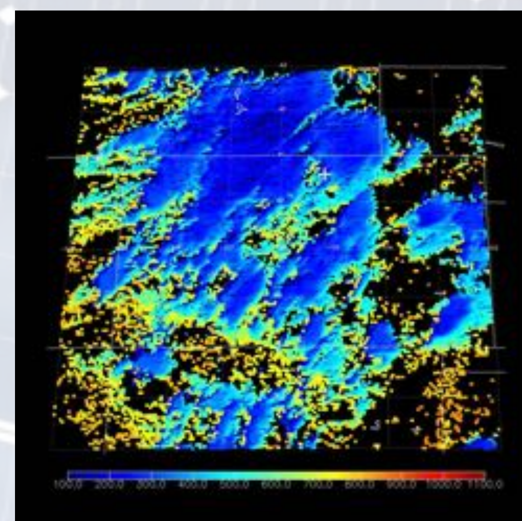
Imagine we are viewing this cloud from the satellite



Without account for sensor/sun geometry, the placement of cloud shadows can be 10's of km in error

Advection of complex cloud layers requires proper account for wind shear



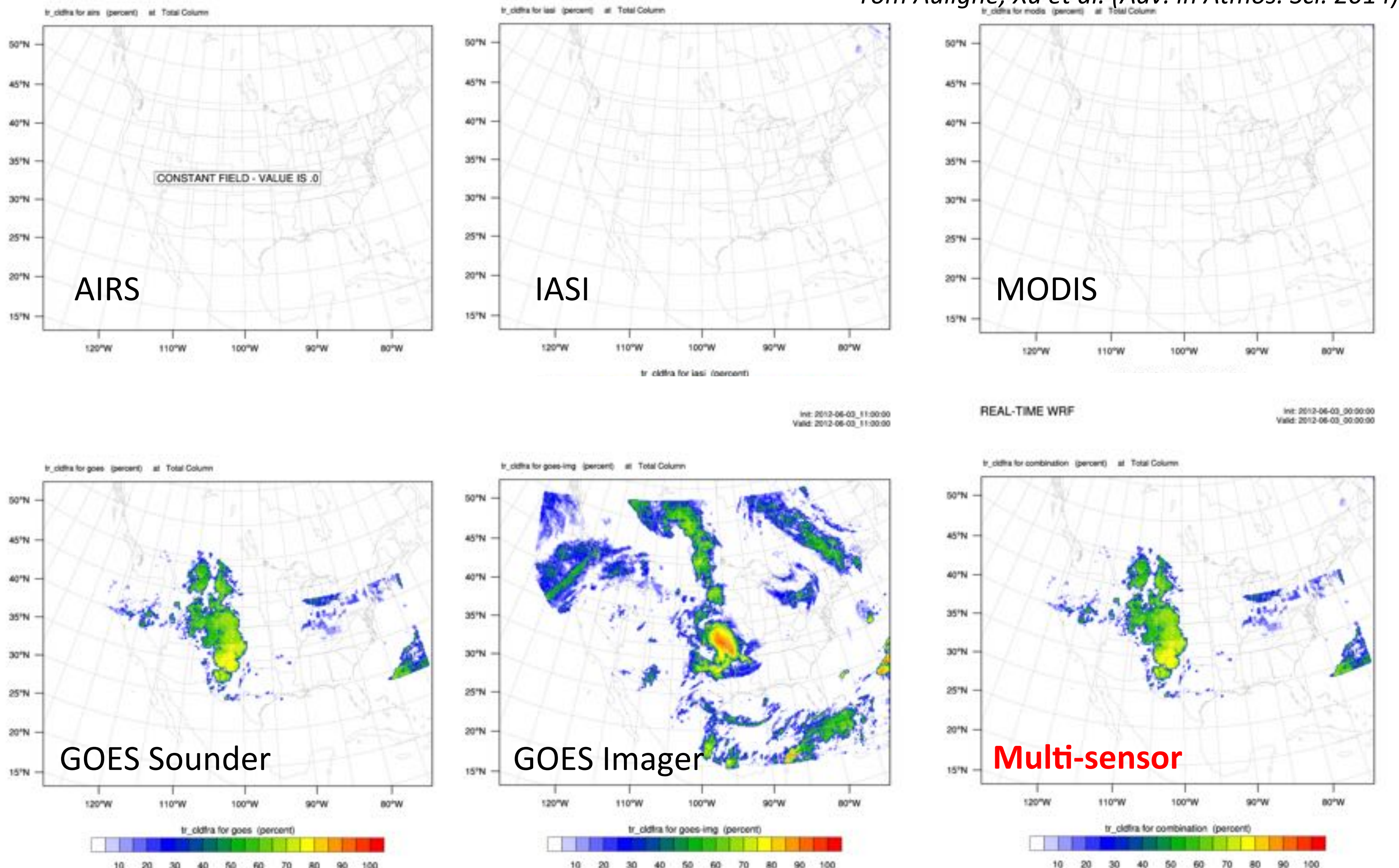


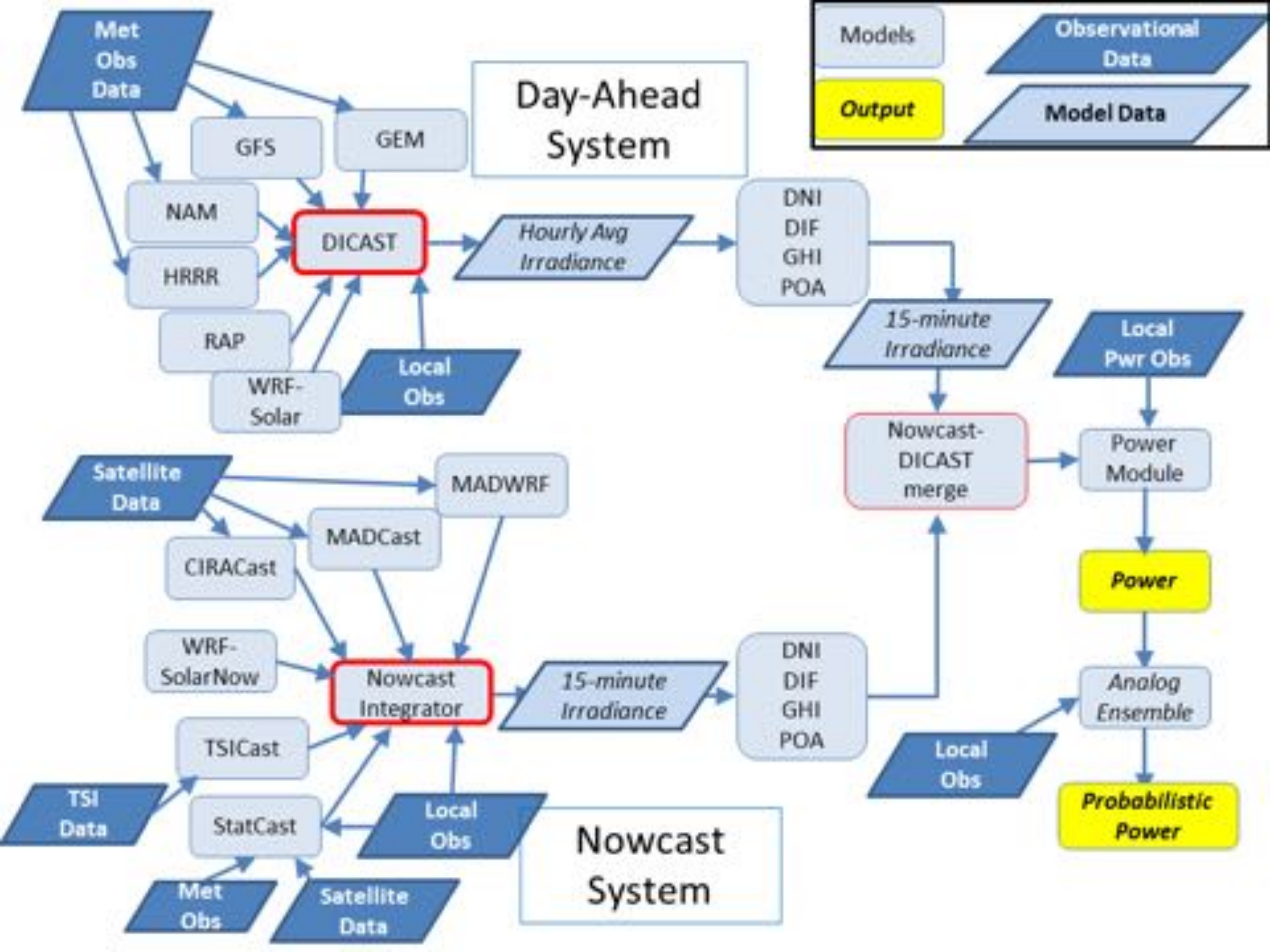
Matt Rogers & Steve Miller: Colorado State University

MADCast

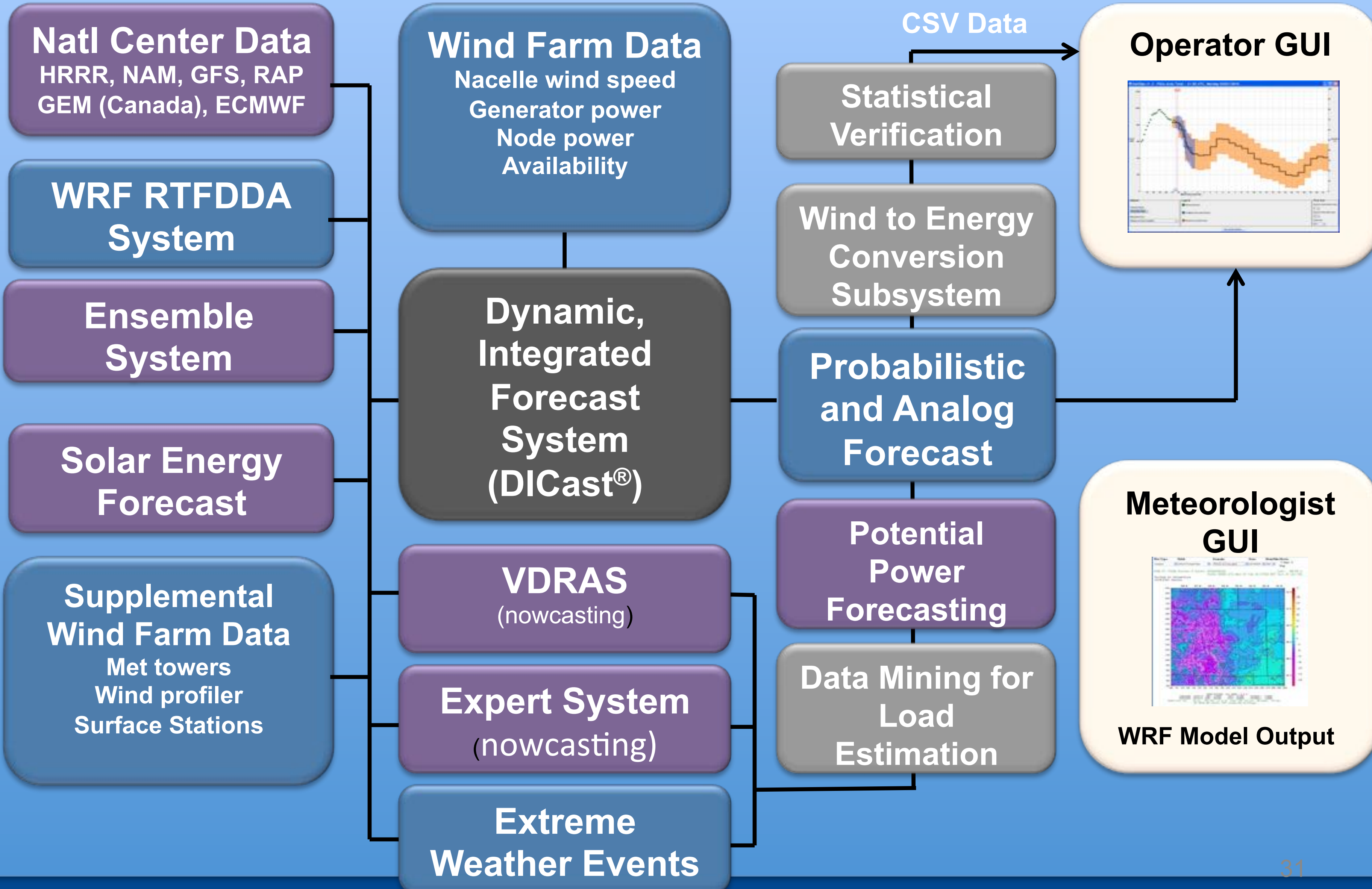
Multi-sensor Advective Diffusive foreCast

Tom Auligne; Xu et al. (Adv. in Atmos. Sci. 2014)

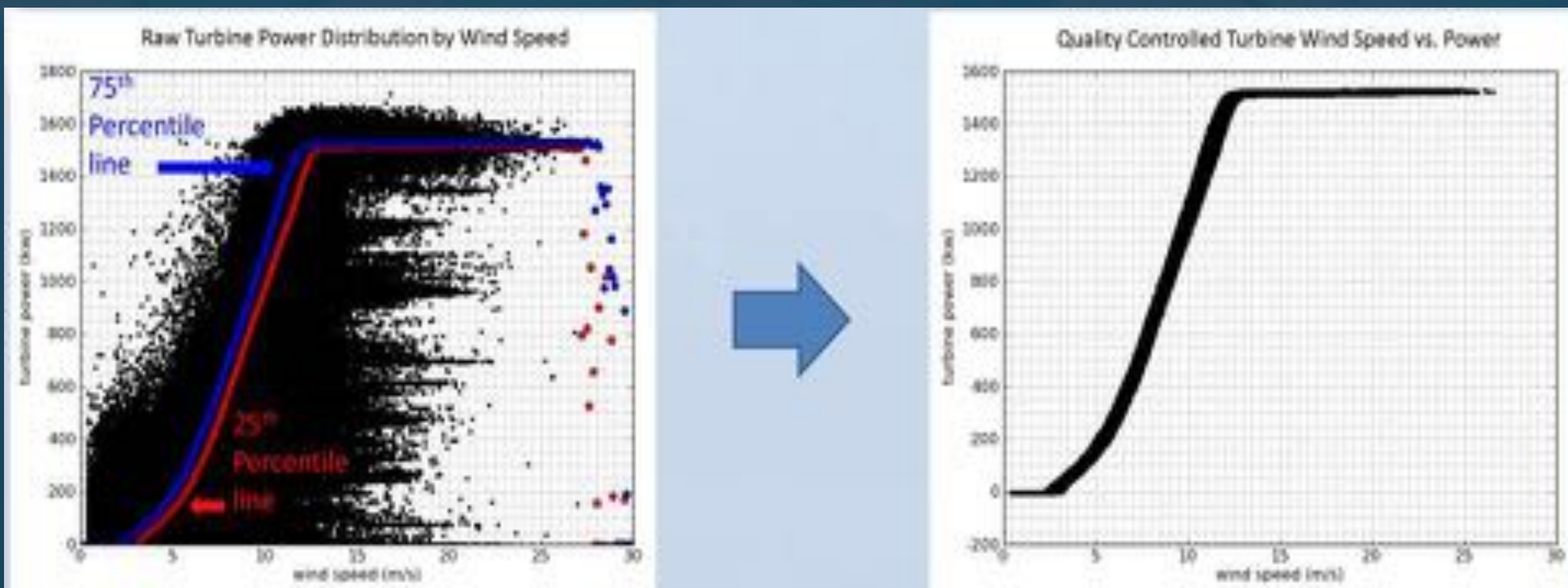



Models
Observational Data
Output
Model Data
Met Obs Data
GFS
GEM
Day-Ahead System
NAM
DICAST
HRRR
RAP
WRF-Solar
Local Obs
Hourly Avg Irradiance
DNI
DIF
GHI
POA
15-minute Irradiance
Local Pwr Obs
Nowcast-DICAST merge
Power Module
Power
Satellite Data
MADWRF
MADCast
CIRACast
WRF-SolarNow
Nowcast Integrator
15-minute Irradiance
DNI
DIF
GHI
POA
Analog Ensemble
Local Obs
TSICast
TSI Data
StatCast
Local Obs
Met Obs
Satellite Data
Nowcast System
Probabilistic Power

Variable Energy Forecasting System



Customized Power Conversion Curves



Observation-based power curves represent the site better than manufacturers' power curves

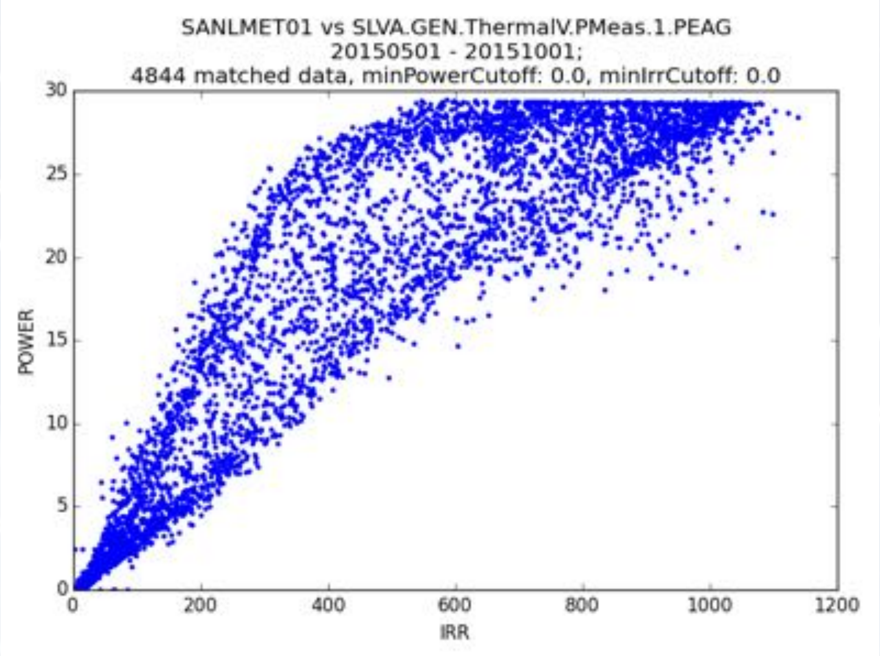
Gerry Wiener

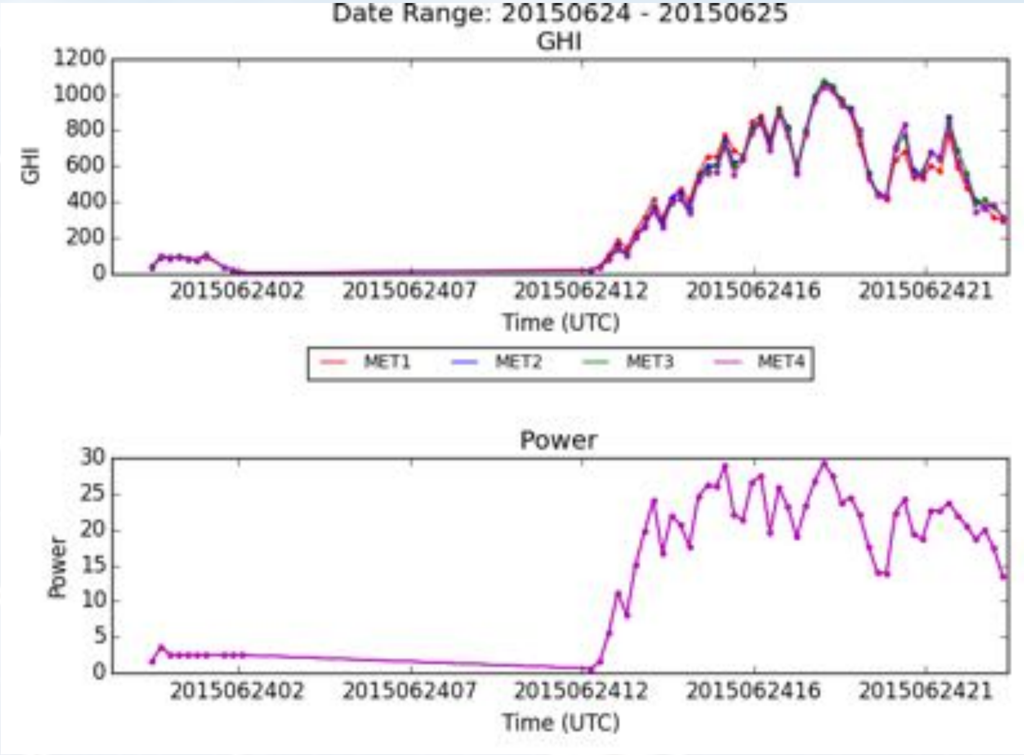
Power Conversion

Empirical Power Conversion: Regression Tree - Cubist

Example for single axis tracking PV plant

Pattern depends heavily on time of day, AM takes higher route; PM more linear route

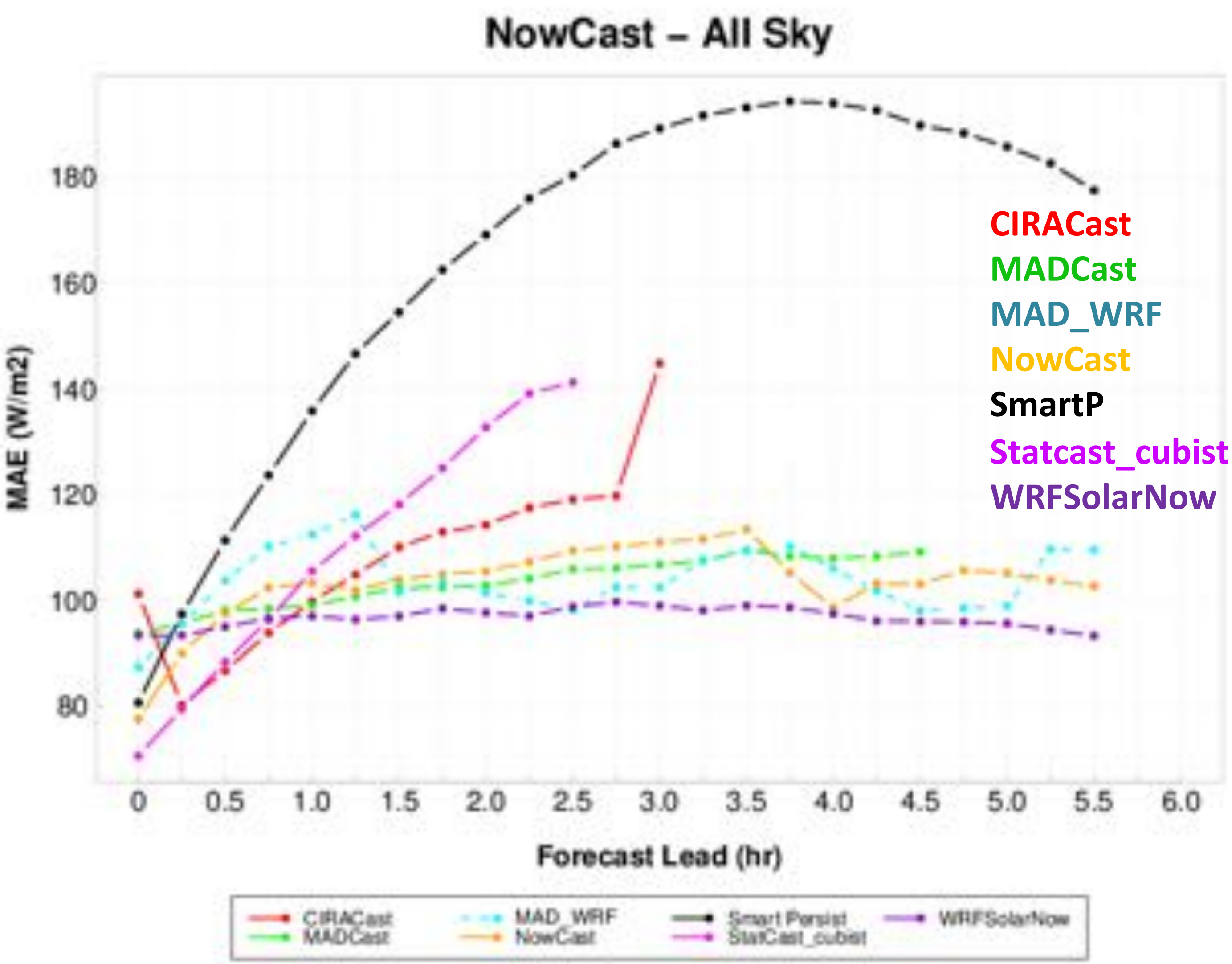




Quantify Value - Metrics

	Model-Model Comparison	Economic Value
Base	• Mean Absolute Error • Root Mean Square Error • Distribution (Statistical Moments and Quantiles) • Categorical Statistics for Events	• Operating Reserves Analysis • Production Cost
Enhanced	• Maximum Absolute Error • Pearson's Correlation Coefficient • Kolmogorov-Smirnov Integral • Statistical Tests for Mean and Variance • OVER Metric • Renyi Entropy • Brier Score incl. decomposition for probability forecasts • Receiver Operating Characteristic (ROC) Curve • Calibration Diagram • Probability Interval Evaluation • Frequency of Superior Performance • Performance Diagram for Events • Taylor Diagram for Errors	• Cost of Ramp Forecasting Tara Jensen

NowCast Performance

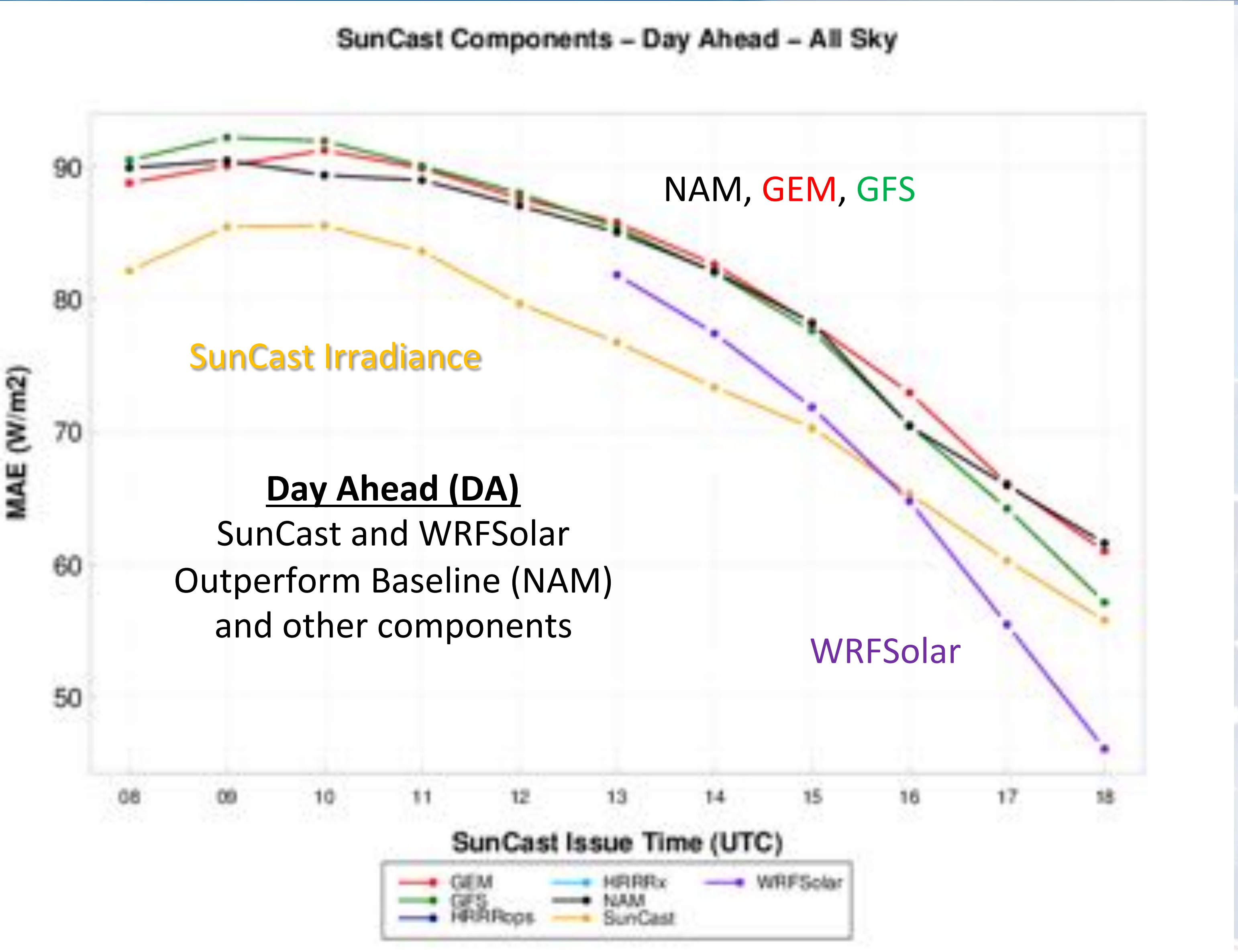


Aggregated over All Issue times and All Sky Conditions

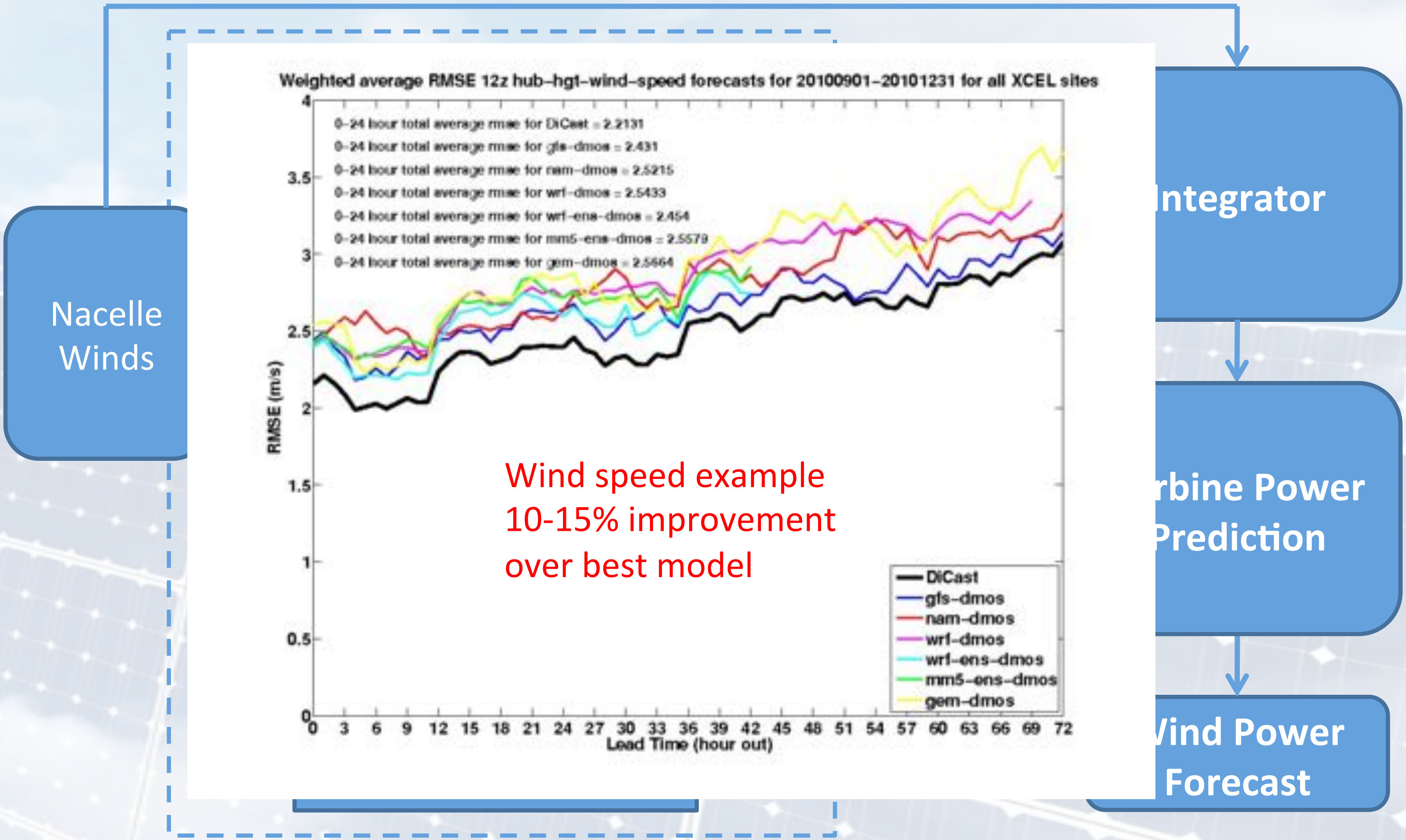
Component performance varies by lead time

All Compontents have lower MAE (greater skill) after 30 minutes into forecast (lead time)

SunCast Performance – Day Ahead



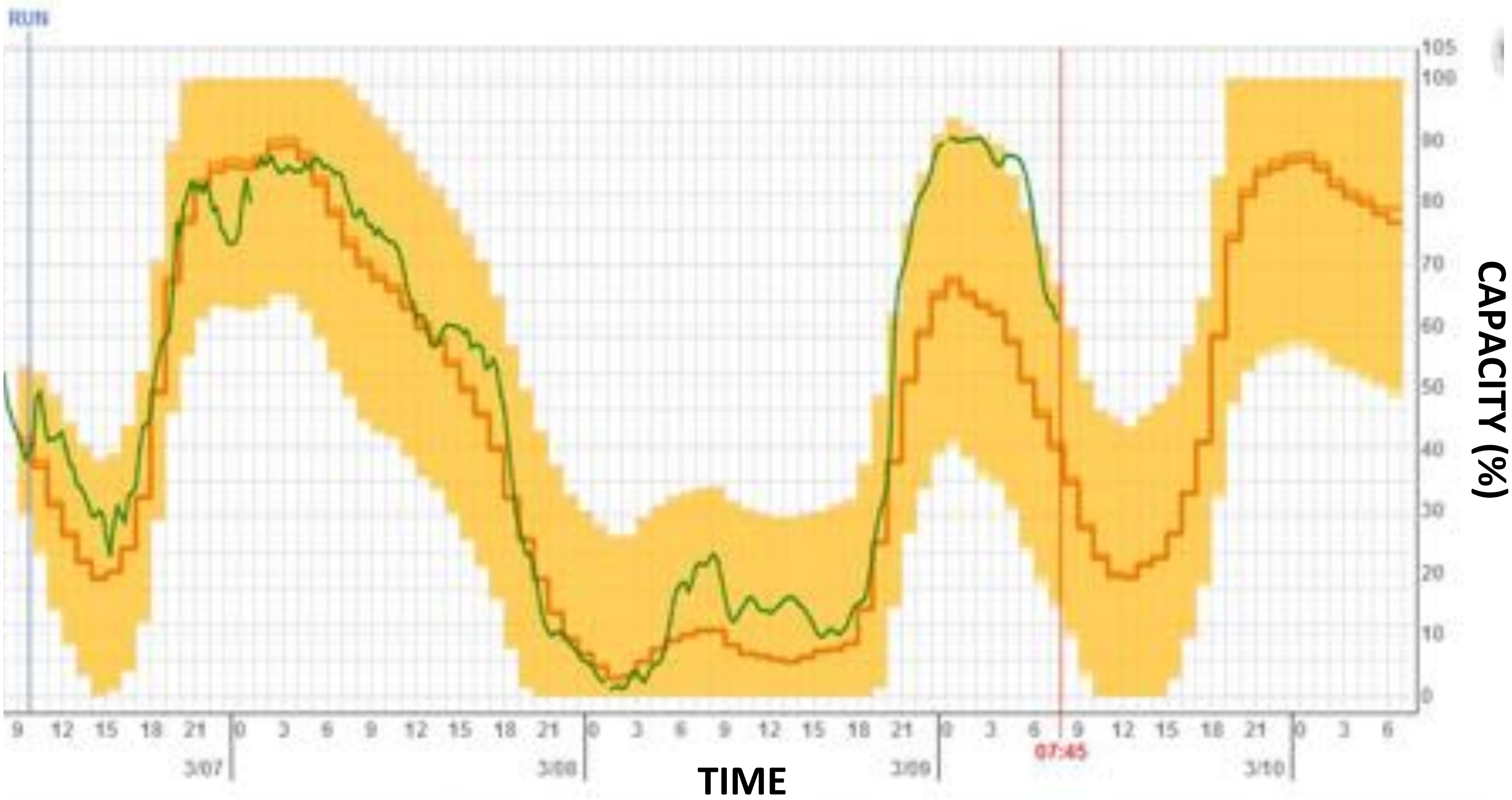
Dynamic Integrated Forecast System (DICast)



Bill Myers

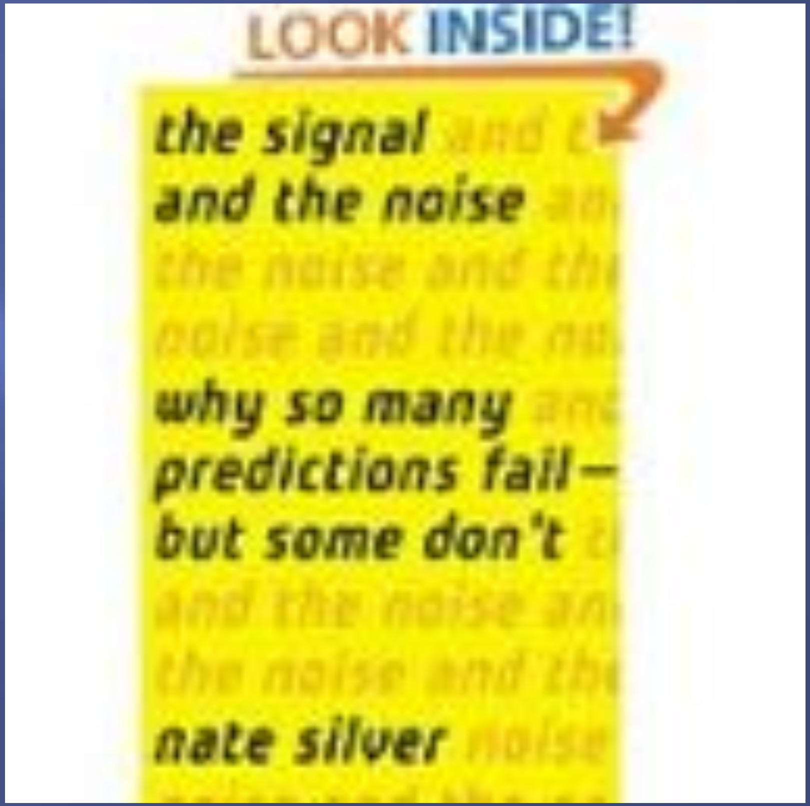
DICast System Blends Output from Several Numerical Weather Prediction Models

Public Service of Southwestern Public Service Company
Total Power, 03/08 Ramp



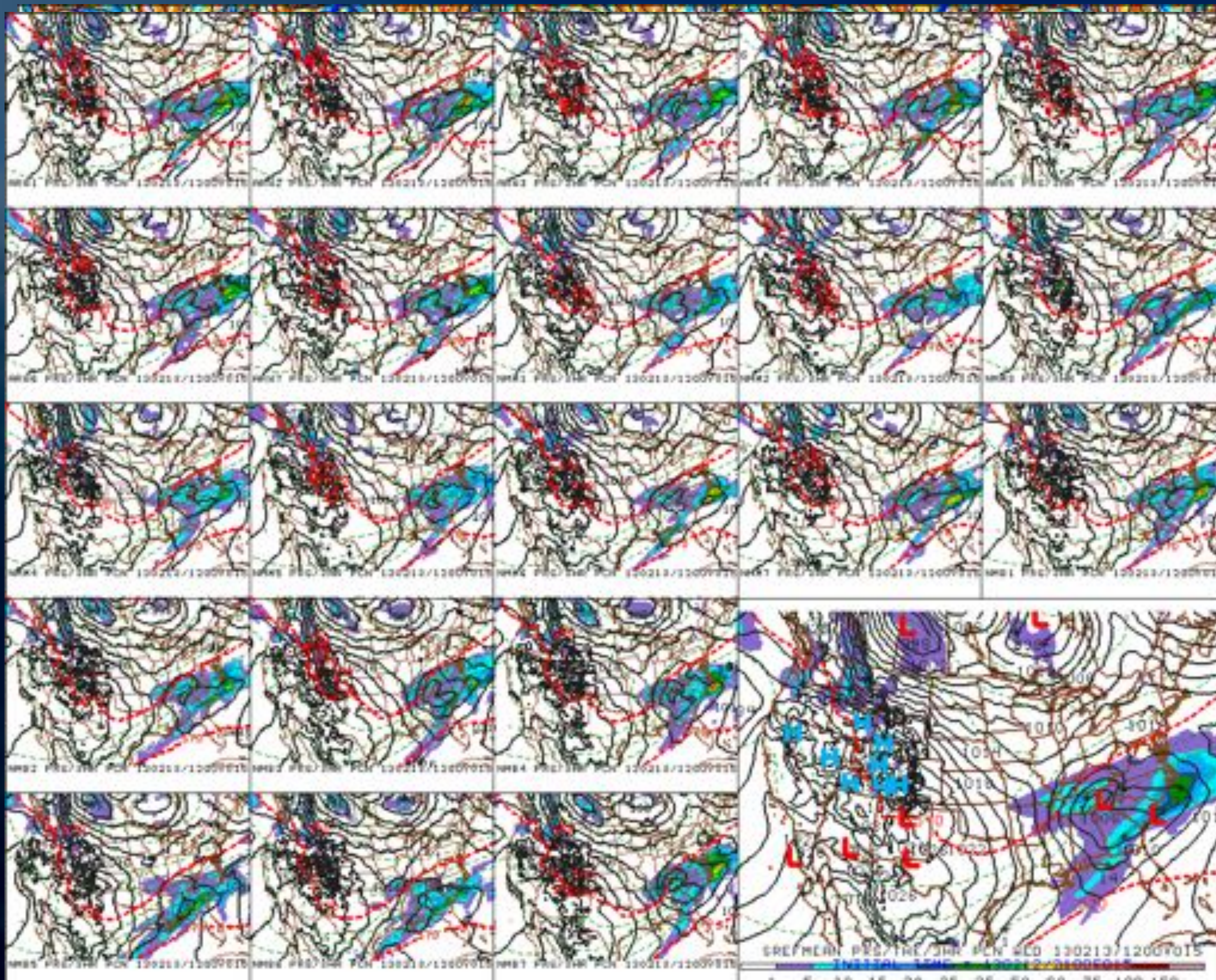
Probabilistic Prediction

- Recent emphasis in popular scientific literature to emphasize probabilistic approach
- Nate Silver thinks meteorologists are ahead of the rest:
  - Embrace uncertainty
  - Quantify it
  - This produces better deterministic forecasts as well

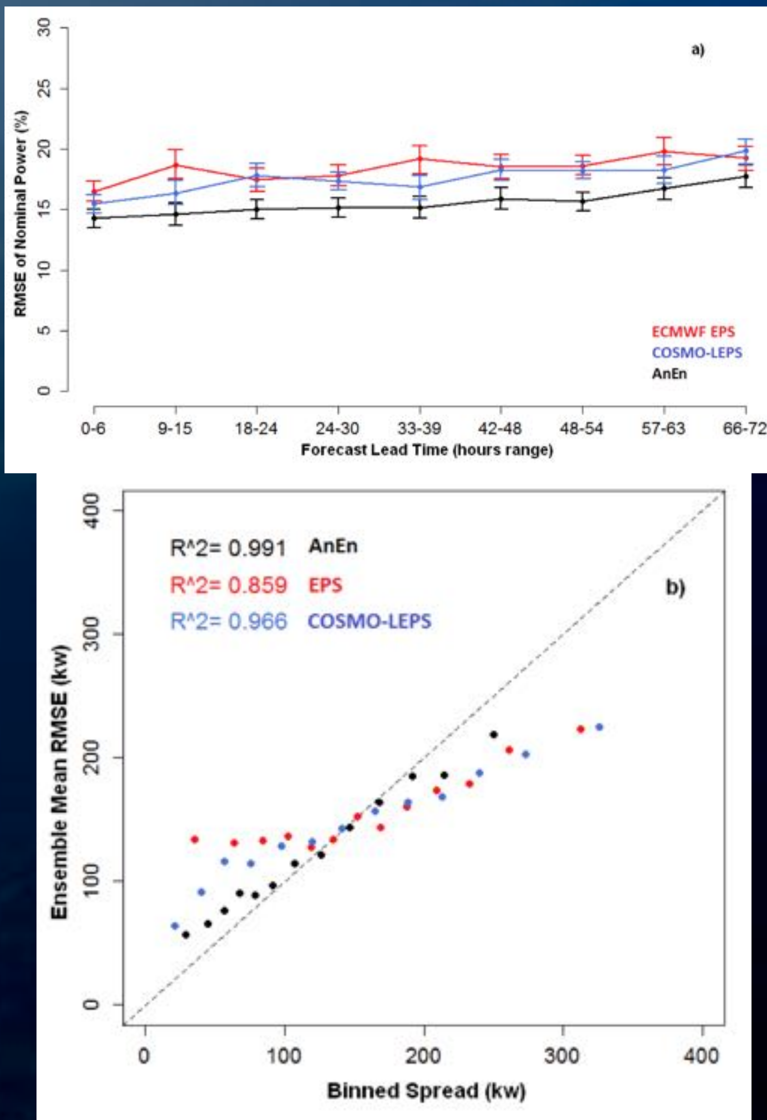


NCAR

Ensemble Prediction



What if we had only one member? Analog Prediction

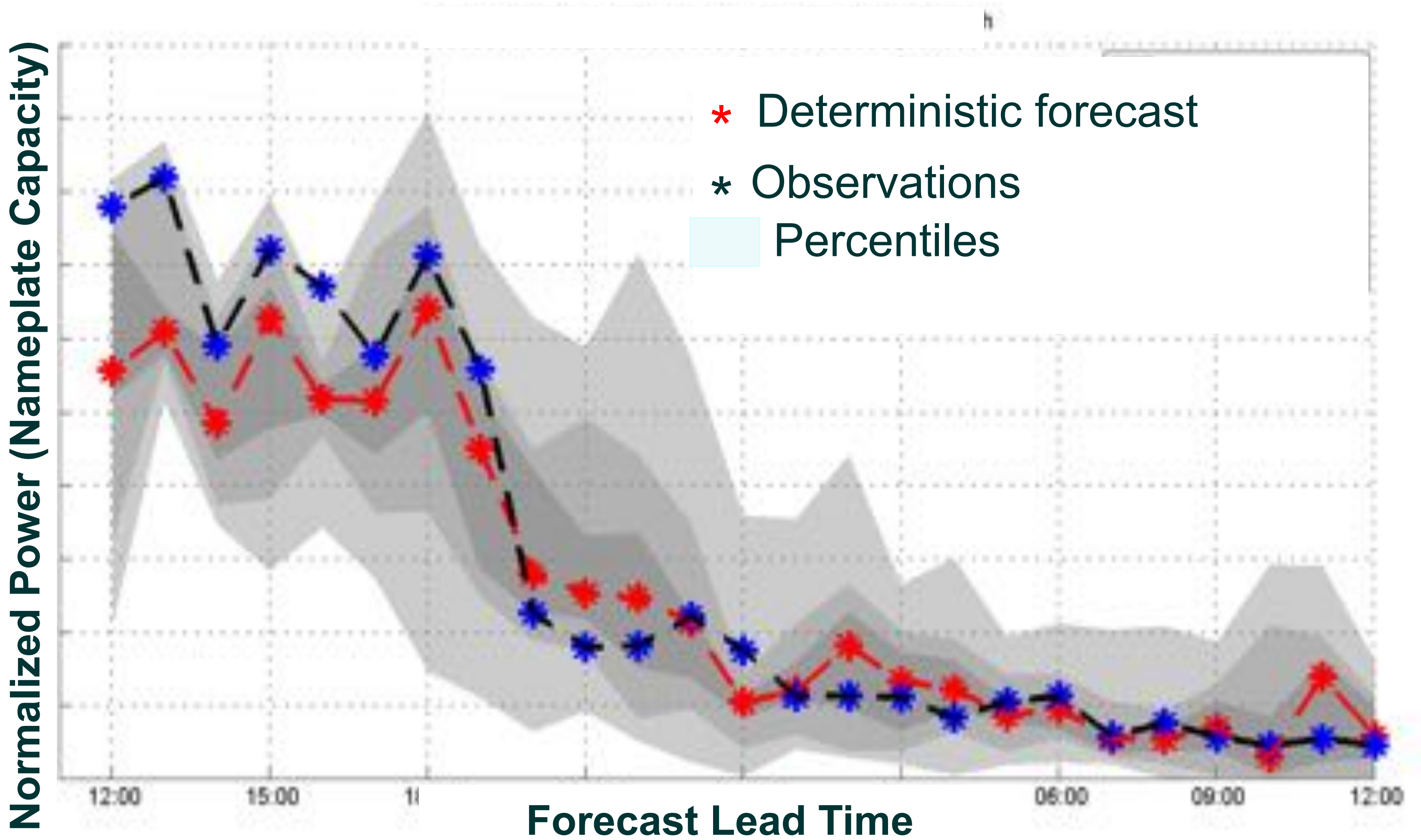


Analog Ensemble Method

- Statistical learning method to calibrate model output and provide probabilistic information
- Based on observed past model-observation pairs
- Algorithm search for analogs and clusters them
- Shown to perform at least as well as full NWP ensemble systems

Luca Delle Monache & Stefano Allasandrini

Probabilistic Power Prediction With Analog Ensemble Method

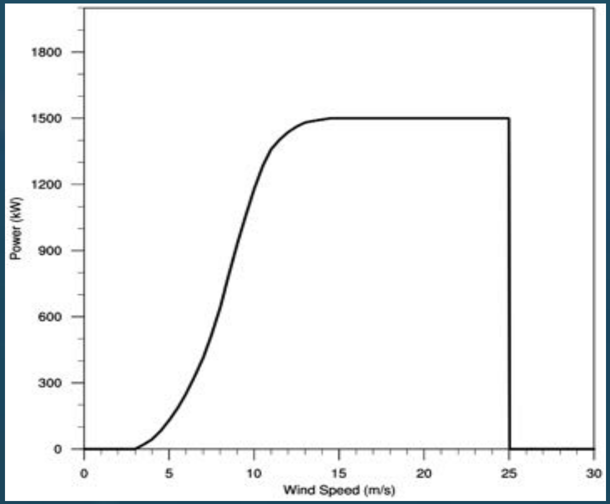


Icing Forecasting System ExWx Provides Categorical Forecast of Icing

- Predicting wind turbine icing is critical for power trading on open market and short term load balancing.
- In order to successfully develop a robust wind turbine icing forecasting system, a truth dataset must be developed.
- Limited documentation of icing events and monitoring equipment make identifying icing after the fact difficult.
- Plus, there is a “Big Data” problem.

Datasets For Icing Forecast

Power Data



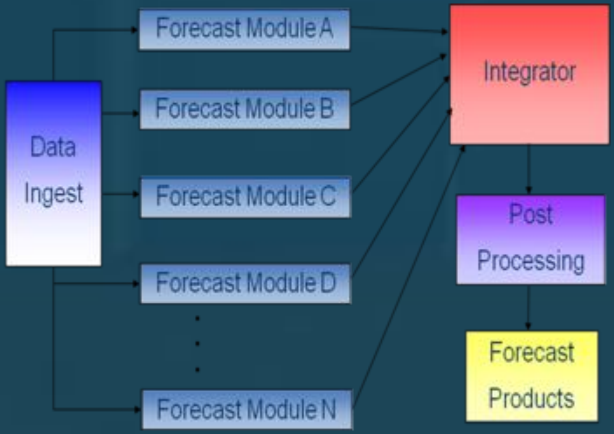
Sensor Data

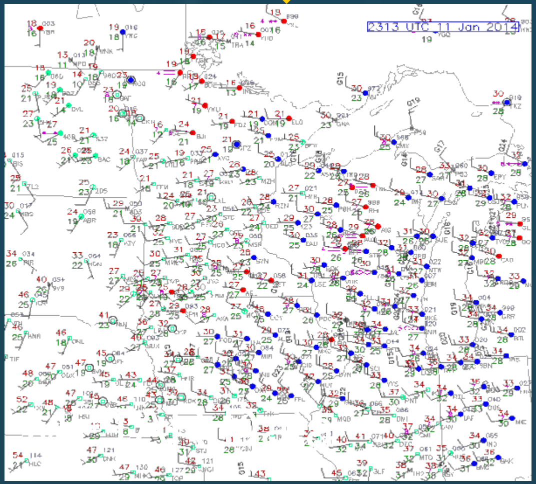
http://www.newavionics.com/Images/9734_410x359.jpg

PRIMARY

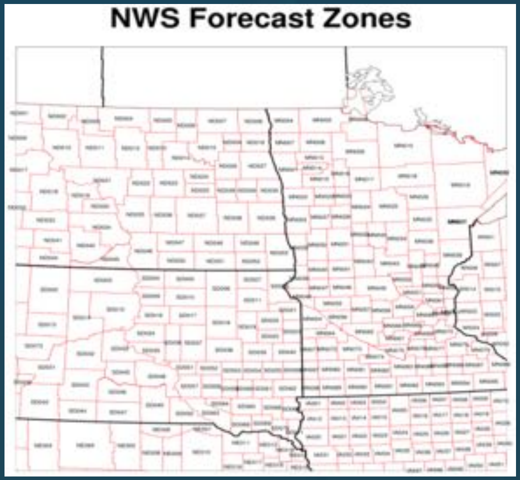
SECONDARY

DICast Data

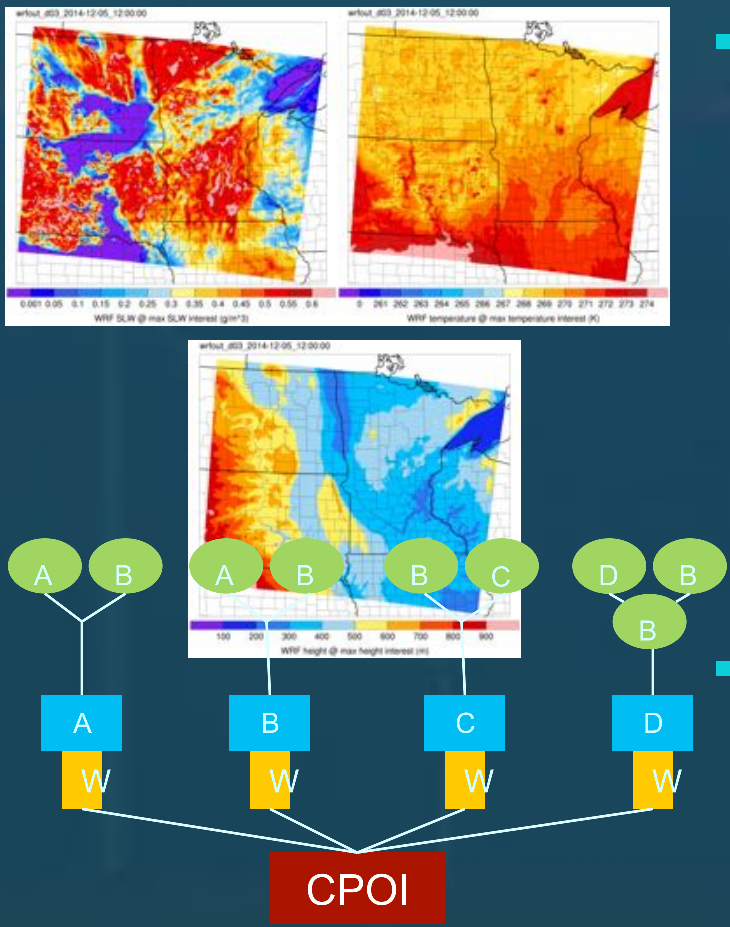




NWS Data



ExWx Uses WRF-RTFDDA and DICast Blended NWP Output to Compute Icing Potential



- **WRF icing potential**
  - Evaluates all WRF model levels < 1km
  - Combines model level height, model predicted supercooled liquid water, and temperature at each level using fuzzy logic maps (configurable)
  - Final potential at each WRF grid point is the maximum of the icing potential at each level < 1km
- **DICast icing potential**
  - Conditional probability of icing (CPOI) deterministic forecast from DICast
  - Combines five NWP model solutions
  - Typically one site per farm, more in some cases

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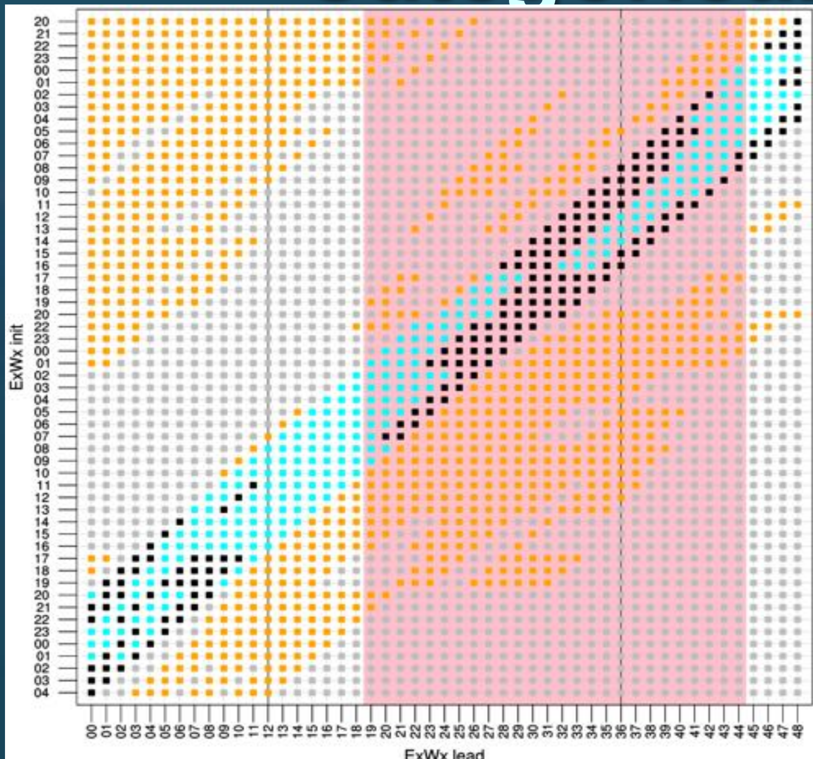
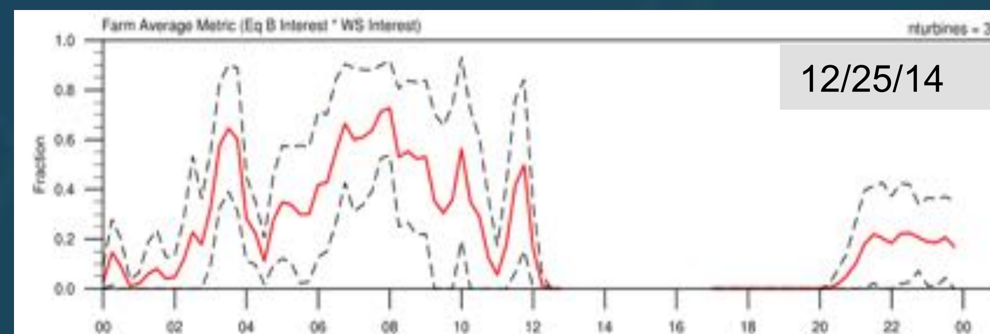
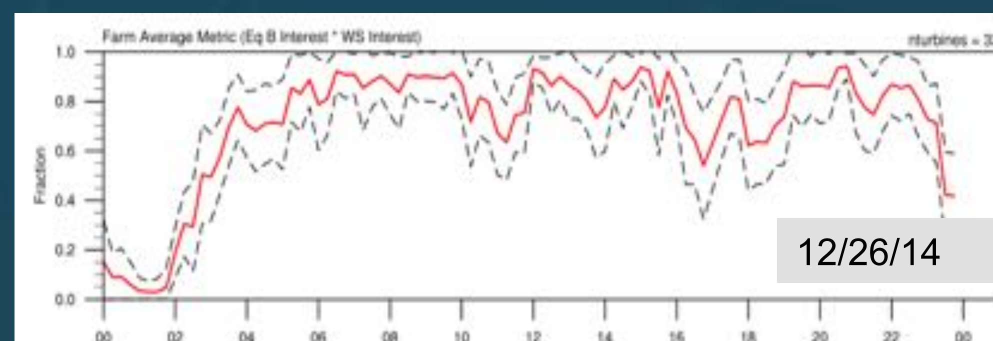
Icing Forecasting System Provides Categorical Icing Forecast



- Note no missing data-wherever DICast was missing the WRF is used exclusively (and vice-versa)
- Threshold of 0.5 is configurable based on experience of operators
- <u>Event well forecast by ExWx!!!</u>





ExWx icing potential forecasts for all ExWx runs affecting the event window (8 hours centered on 00Z)

- Icing potential < 0.5 inside window
- Icing potential > 0.5 inside window
- Icing potential > 0.5 outside window
- Icing potential < 0.5 outside window

Wind Power Forecasts Resulted in Savings for Ratepayers

Forecasted MAE 2009	2014*	Percentage Improvement	Savings
16.83%	10.10%	40%	$49,000,000

*Data through November, 2014

Also: saved > 267,343 tons CO_2 (2014)

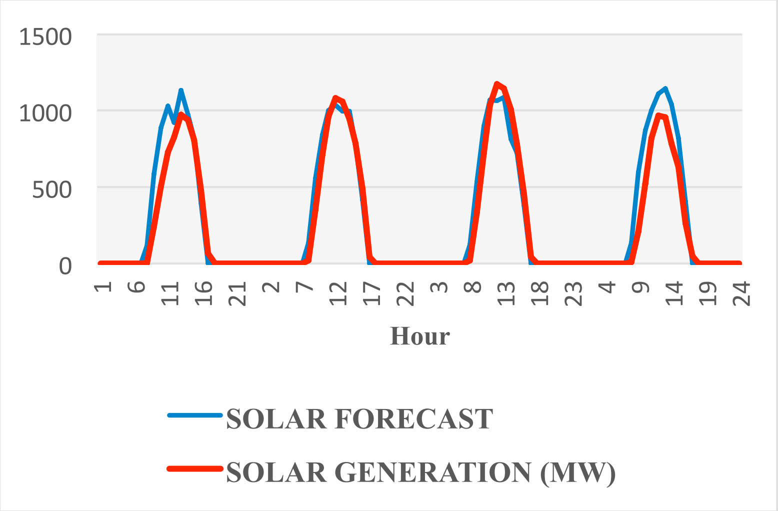
Drake Bartlett, Xcel

Valuation

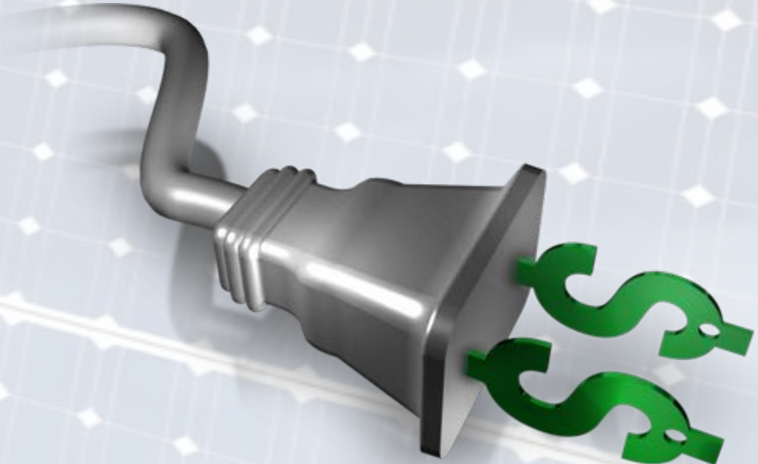
<u>Production Cost Modeling</u>

- Accomplished by Utility Partner – Xcel

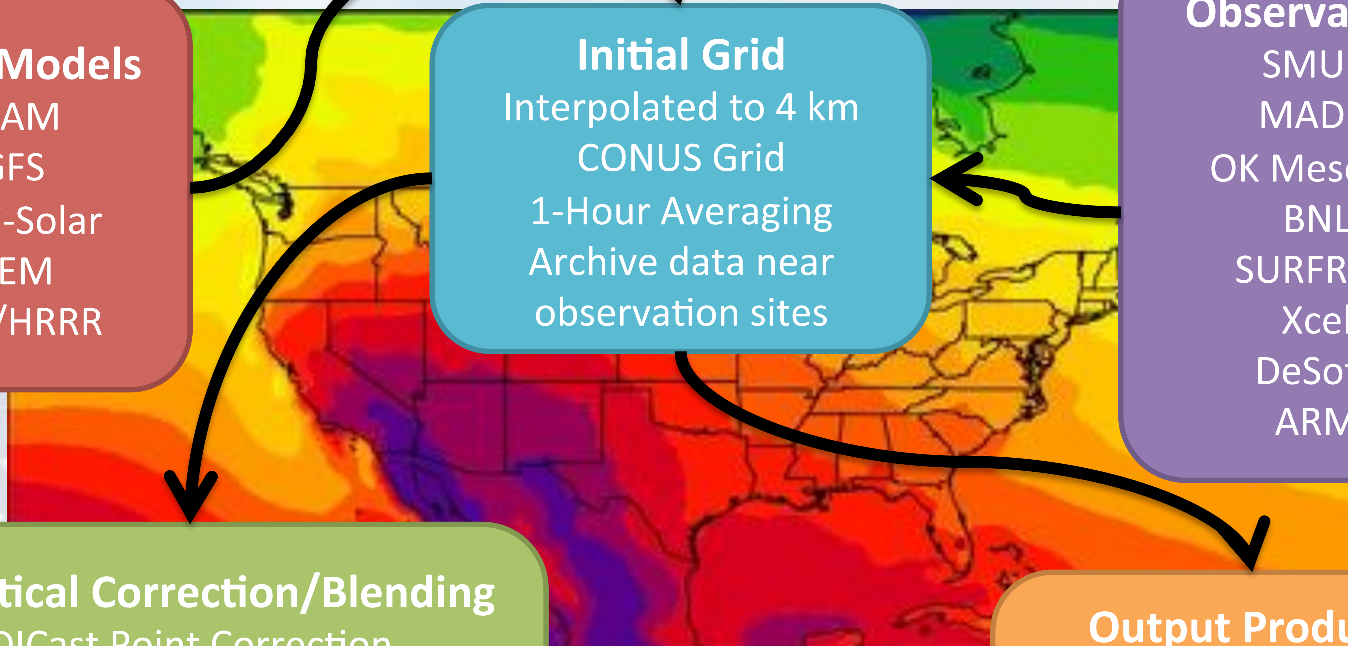
  Value of 50% Forecast Improvement: $820,000 (2024 – increased utility scale capacity)



- Upscaled by NCAR (Lazo)
  - Annual National Savings: $10 – $21M / year (2015-2024)
  - 26 year savings: $455M



Gridded Atmospheric Forecasts: GRAFS-Solar



NWP Models
NAM
GFS
WRF-Solar
GEM
RAP/HRRR

Initial Grid
Interpolated to 4 km
CONUS Grid
1-Hour Averaging
Archive data near
observation sites

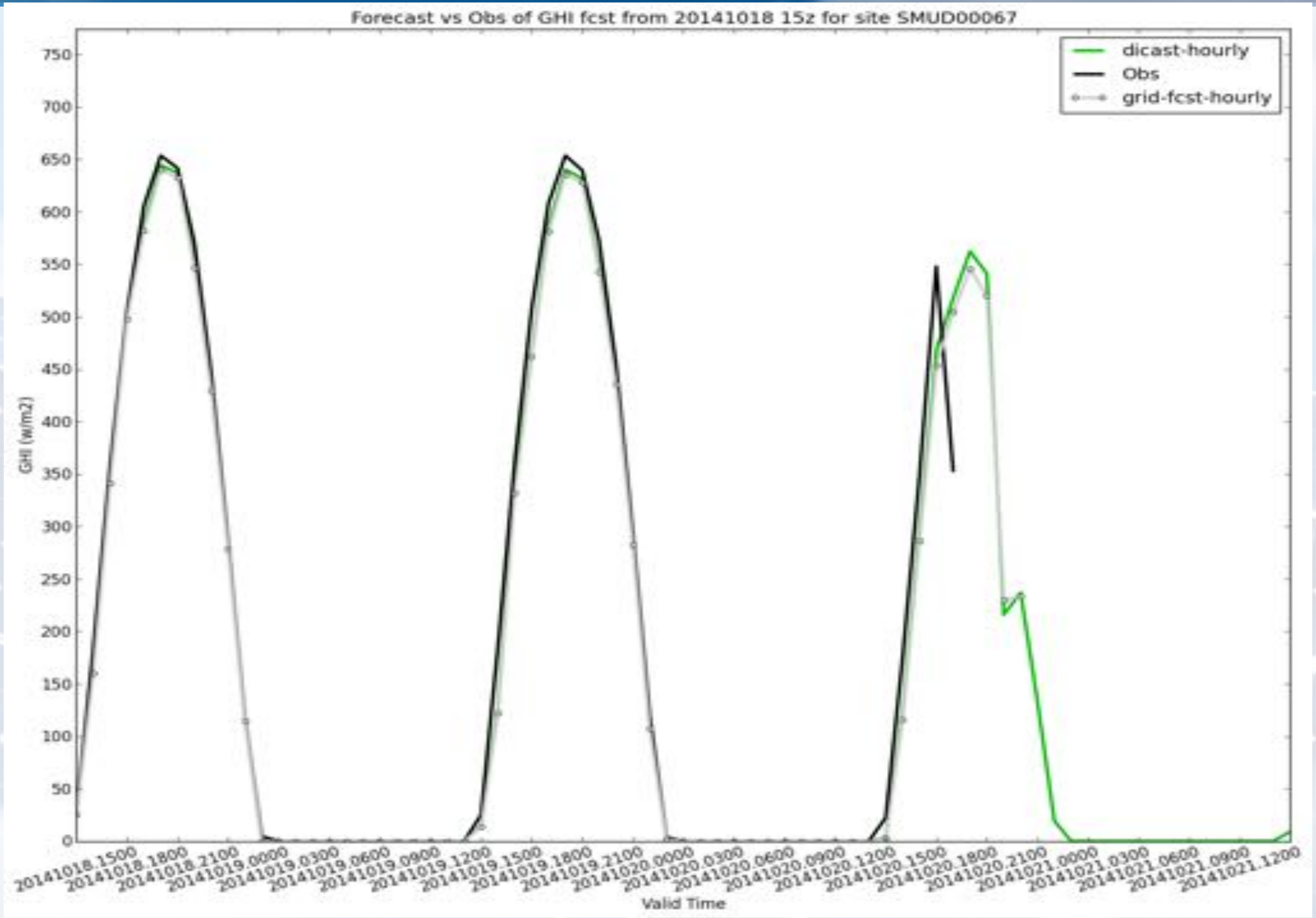
Observations
SMUD
MADIS
OK Mesonet
BNL
SURFRAD
Xcel
DeSota
ARM

Statistical Correction/Blending
DICast Point Correction
Gradient Boosted Regression Trees
Cubist
Random Forests
Analog Ensemble

Output Products
Maps of solar irradiance
Single point forecasts
% of clear sky irradiance
Future:
Other met. variables

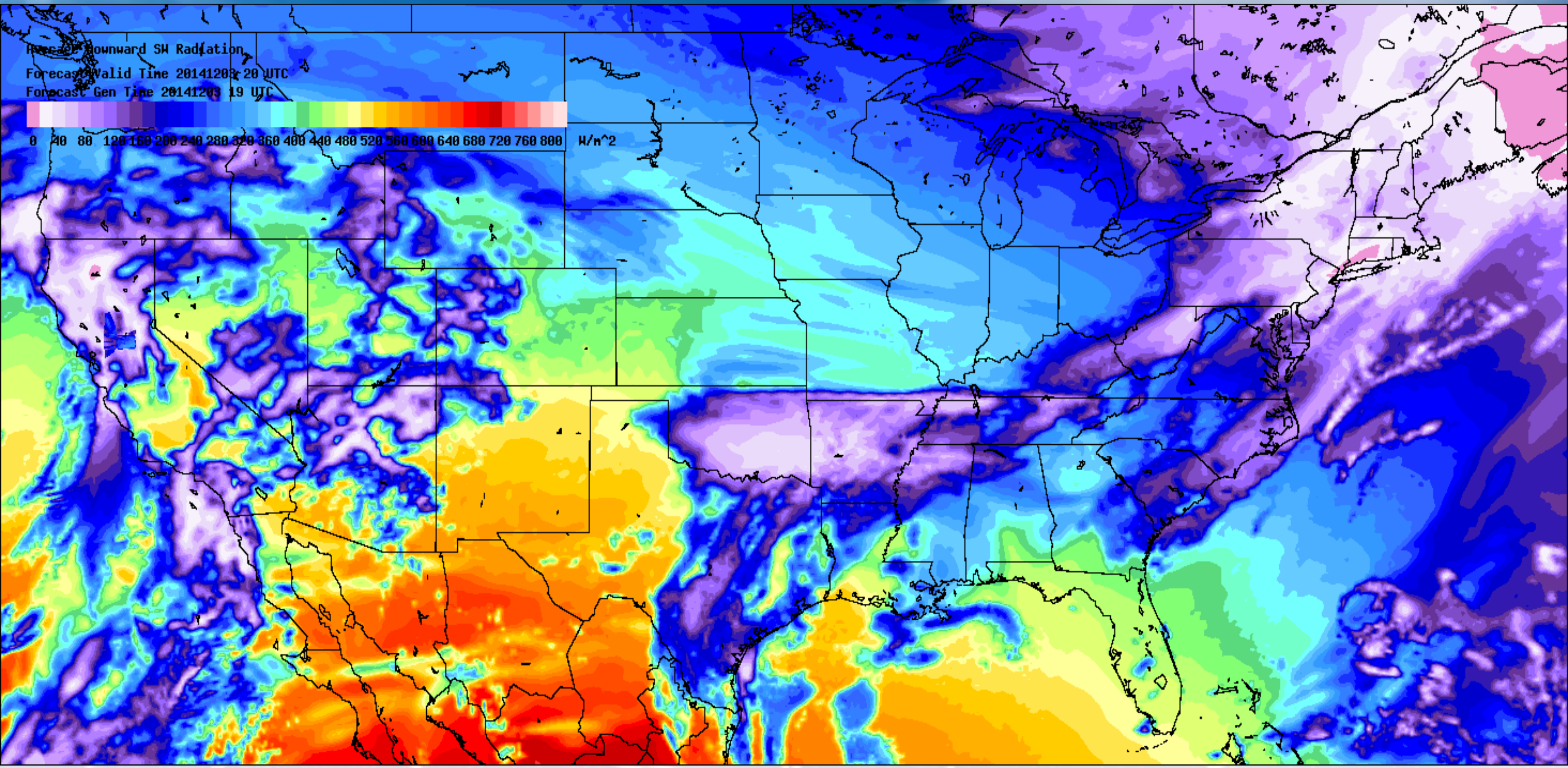
NCAR

Grid Forecast Timeseries: Sunny Day



DICast Correction

GRAFS

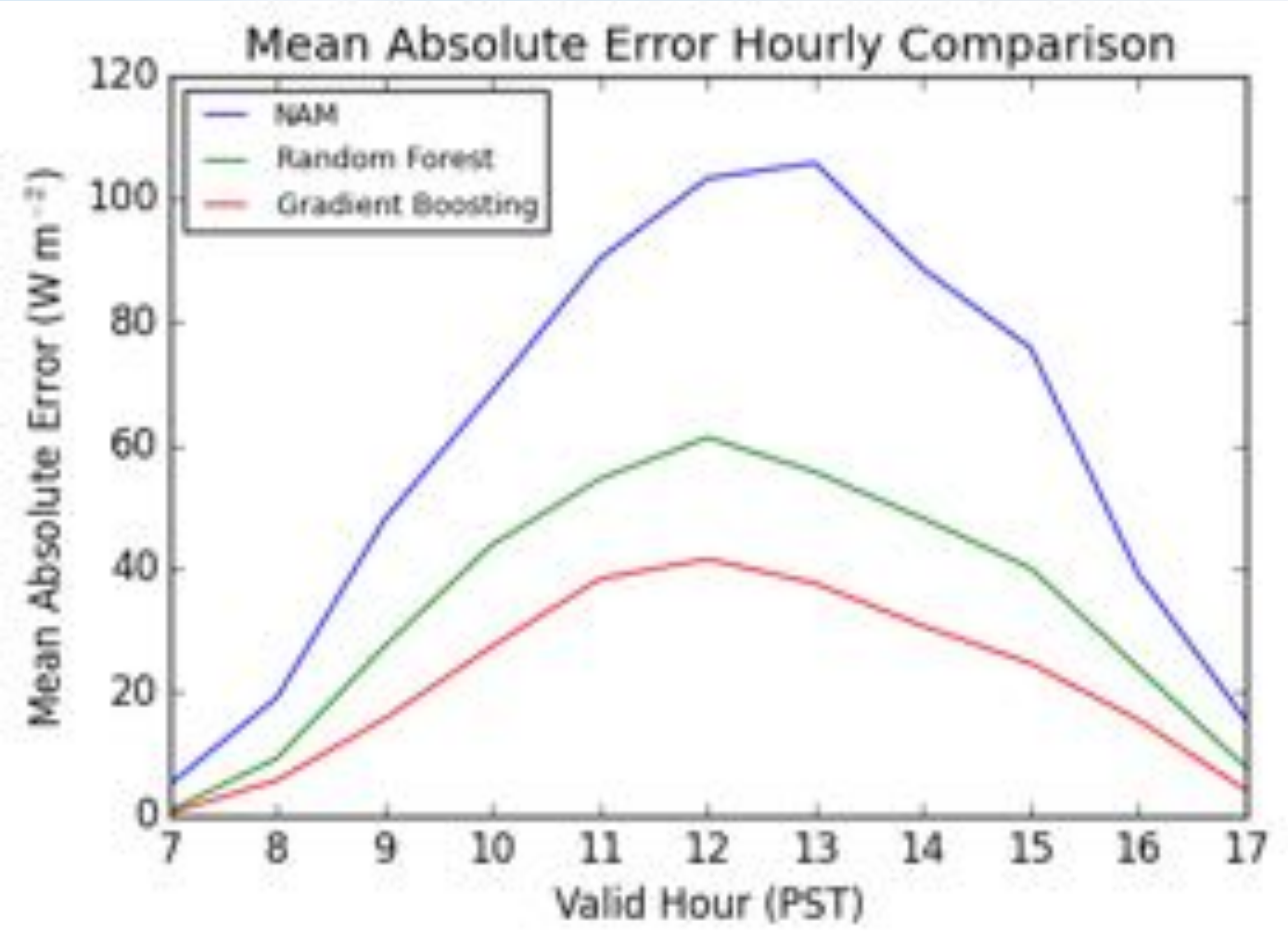


- A new forecast is generated every hour
- Individual images are generated for each lead-time
  - Currently hourly out to 60 hours.

NCAR

GRAFS

AI methods at SMUD Sites



NCAR

Summary

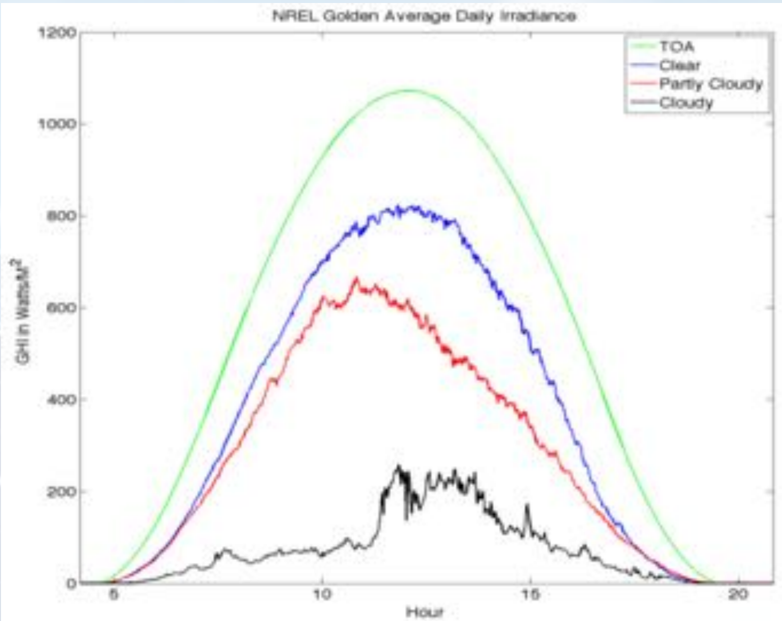
Theme: Smartly blending data, dynamics, physics, and statistical learning methods

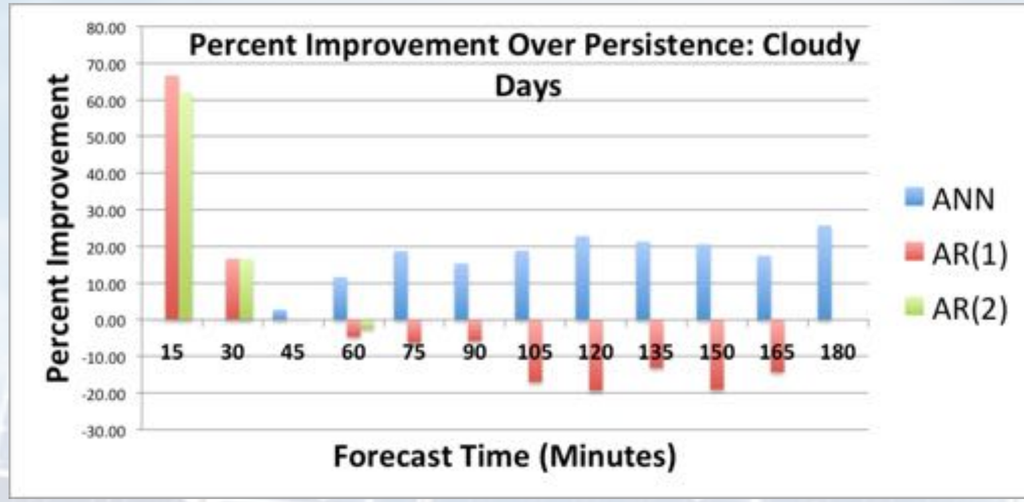
- We need good models of the dynamics & physics
- We need high quality data to assimilate
- Statistical learning (artificial intelligence) can add value and help to determine the characteristics of the physics
- Specialized applications may require specialized forecasts

Questions

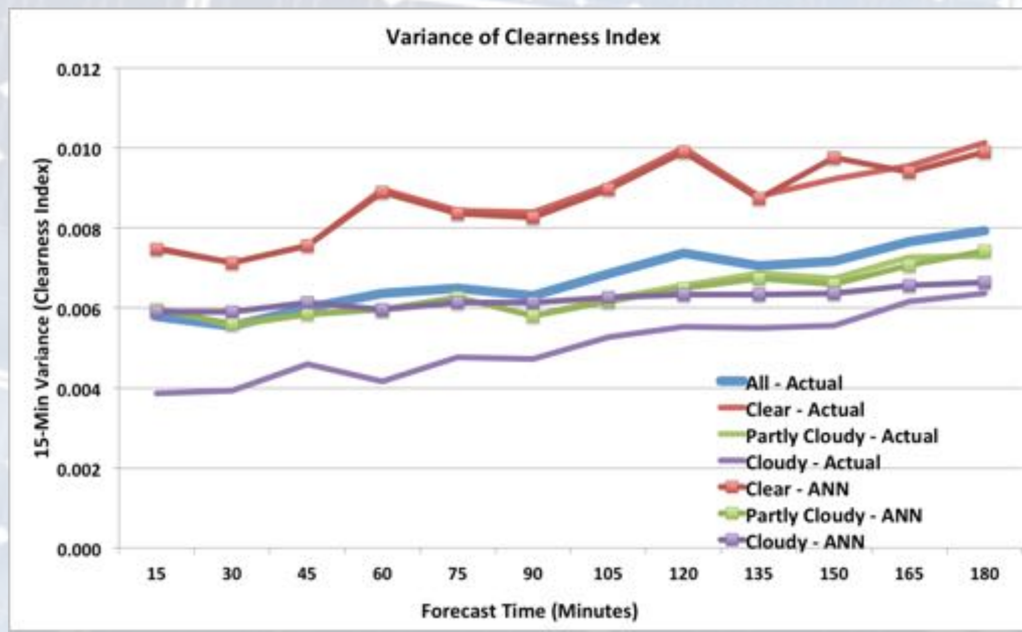
Supplementary Slides

StatCast



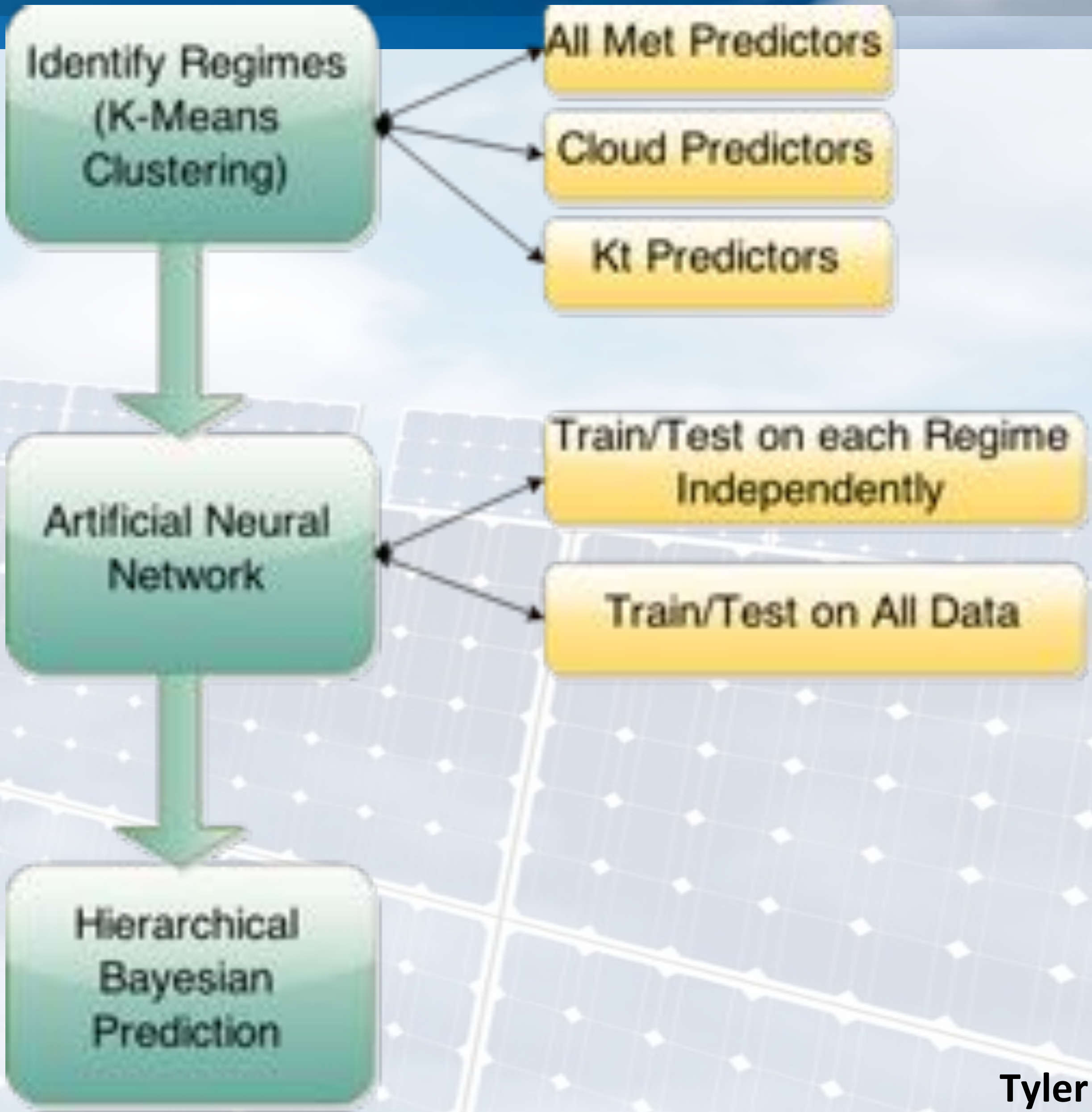


- Forecast Clear Sky Index
- Separate into:
  - Clear
  - Partly Cloudy
  - Cloudy



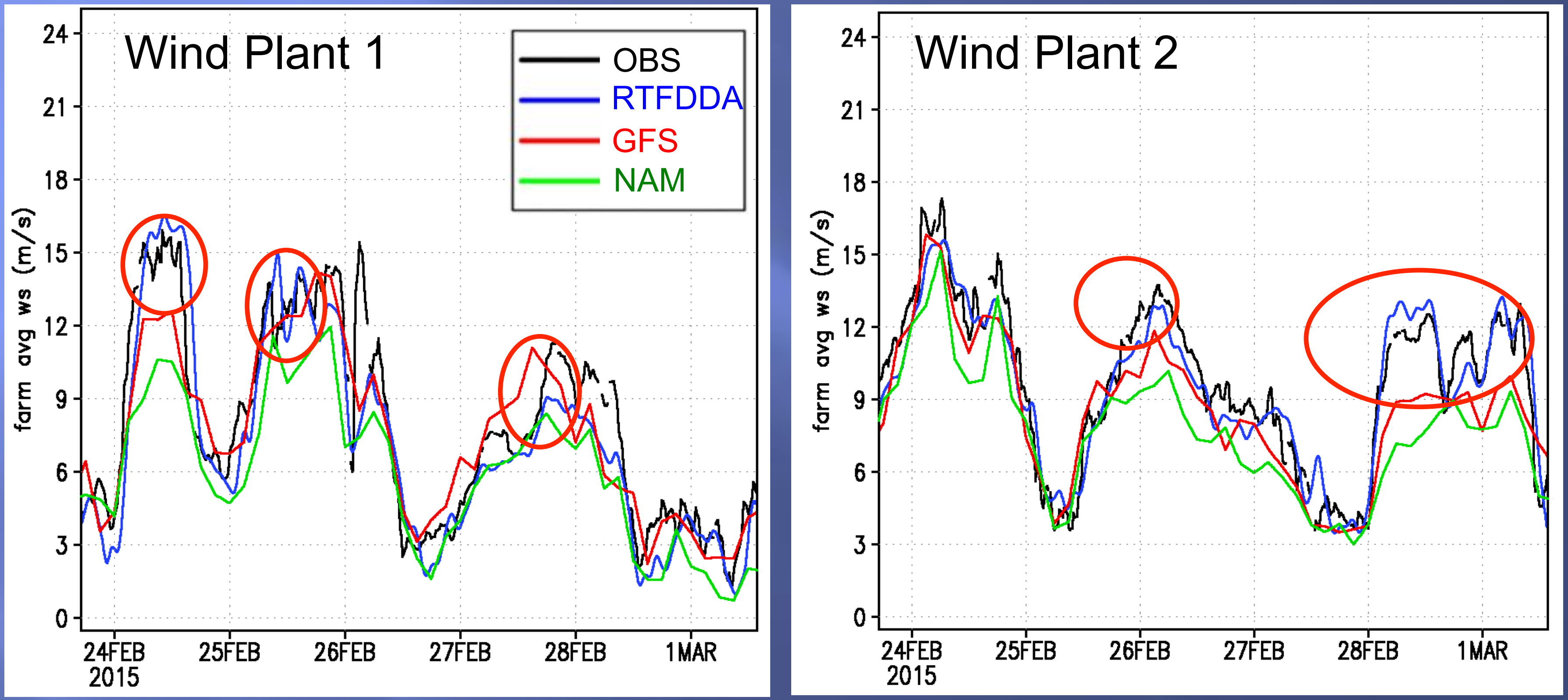
Tyler McCandless

Regime-Dependent Statcast



Tyler McCandless

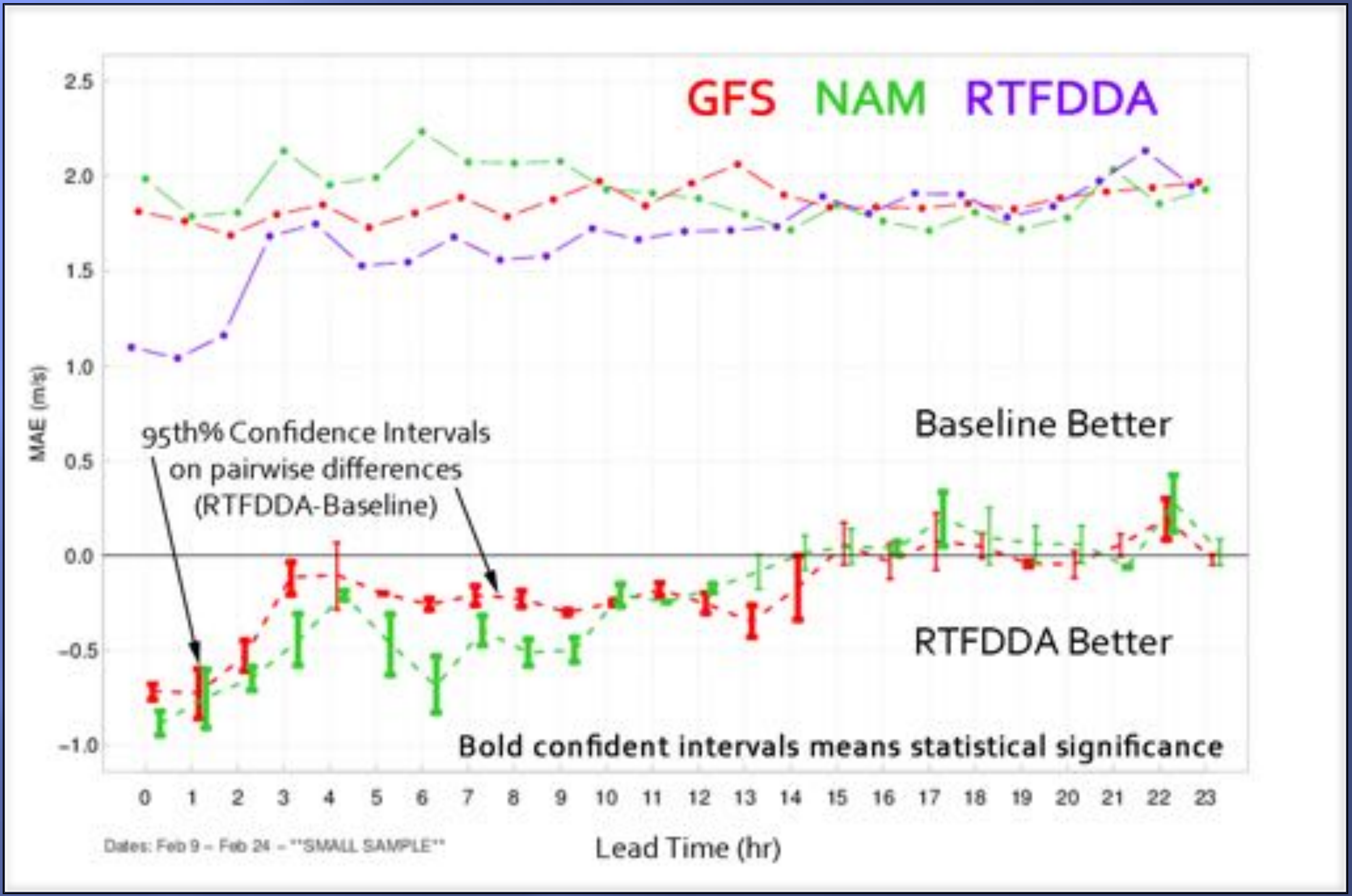
WRF-Real Time 4D Data Assimilation (RTFDDA) Assimilates Wind Farm Data



- WRF RTFDDA exhibits exceptional capability for forecasting wind ramps in term of their timing, rates and magnitudes.
- Rapid cycling (hourly) WRF RTFDDA is recommended where 0 - 6h ahead wind ramp prediction is critical.

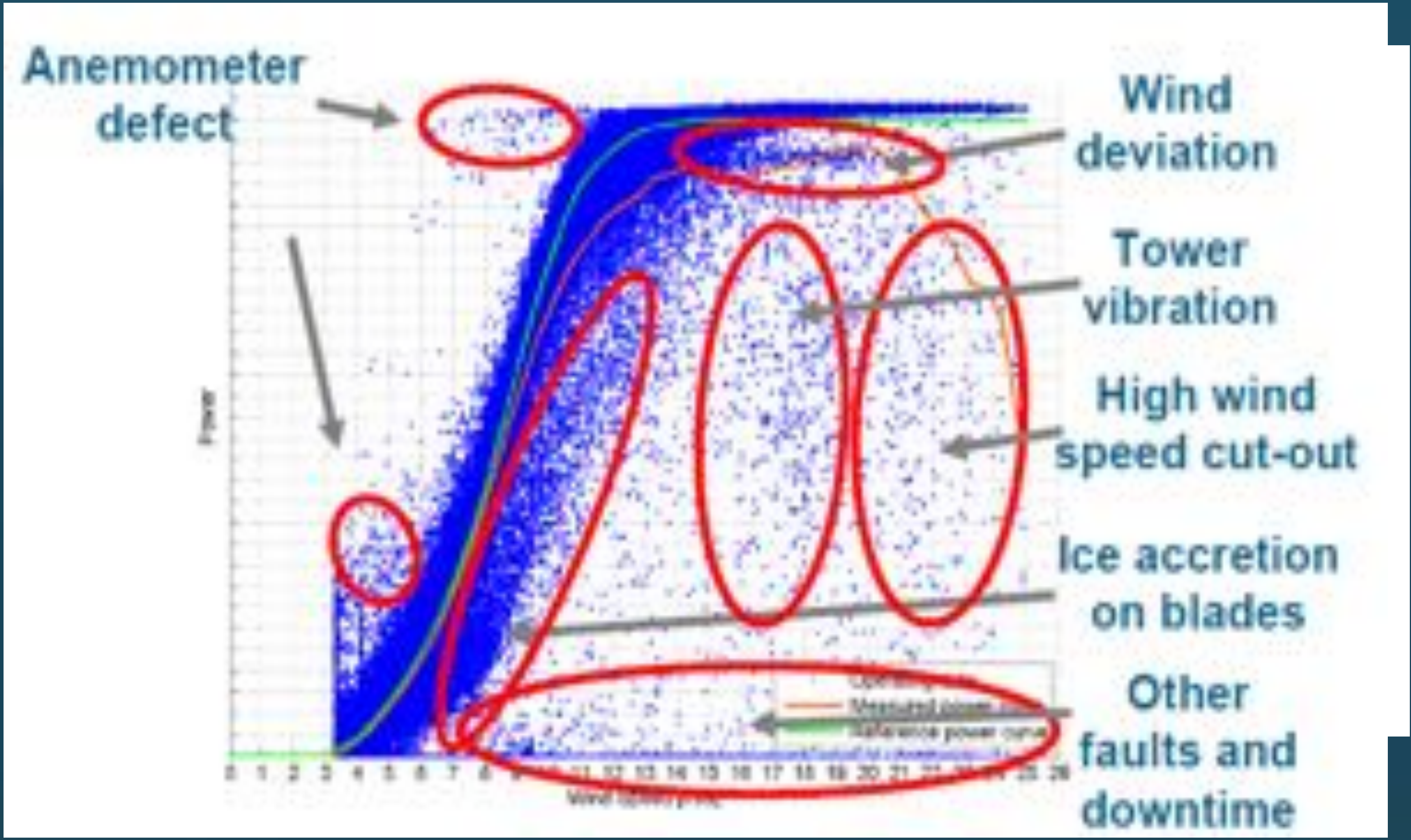
Courtesy: Yubao Liu

WRF- RTFDDA Improves Short Term Forecasts (0-9h)



Courtesy: Tara Jensen, Yubao Liu

Empirical Power Conversion Curves



Not Straightforward!

Gerry Wiener

Operationalization

SMUD – 100 + 50 MW

SCE – 350 Comm + 325Q + 1000 Dist MW

Xcel – 90 MW

LIPA – 32 MW

HECO– 43 MW

DeSoto Plant – 25 MW

Evaluation System

NowCast and Components
- StatCast
- CIRACast
- MADCast
- WRFSolarNow
- NowCast
- SmartPersistence

DICast and Components
- GEM
- GFS
- NAM
- HRRRops
- HRRRx
- WRFSolar
- DICast

Final Products
- Power
- AnEn Members
- Probabilitistic Forecasts

KT - Sky Condition Values; Capacity for Normalization

Matched Pairs
Forecast and Observed Values matched up in Space and Time

MET
Model Evaluation Tools

MODEL EVALUATION TOOLS (MET) Continuous Stats (e.g. MAE, RMSE, Dist. Of Errors, Brier Skill Score)

MODEL EVALUATION TOOLS (MET) Categorical Stats for Ramps (e.g. Probability of Detection, Frequency Bias)

METViewer Database and Display

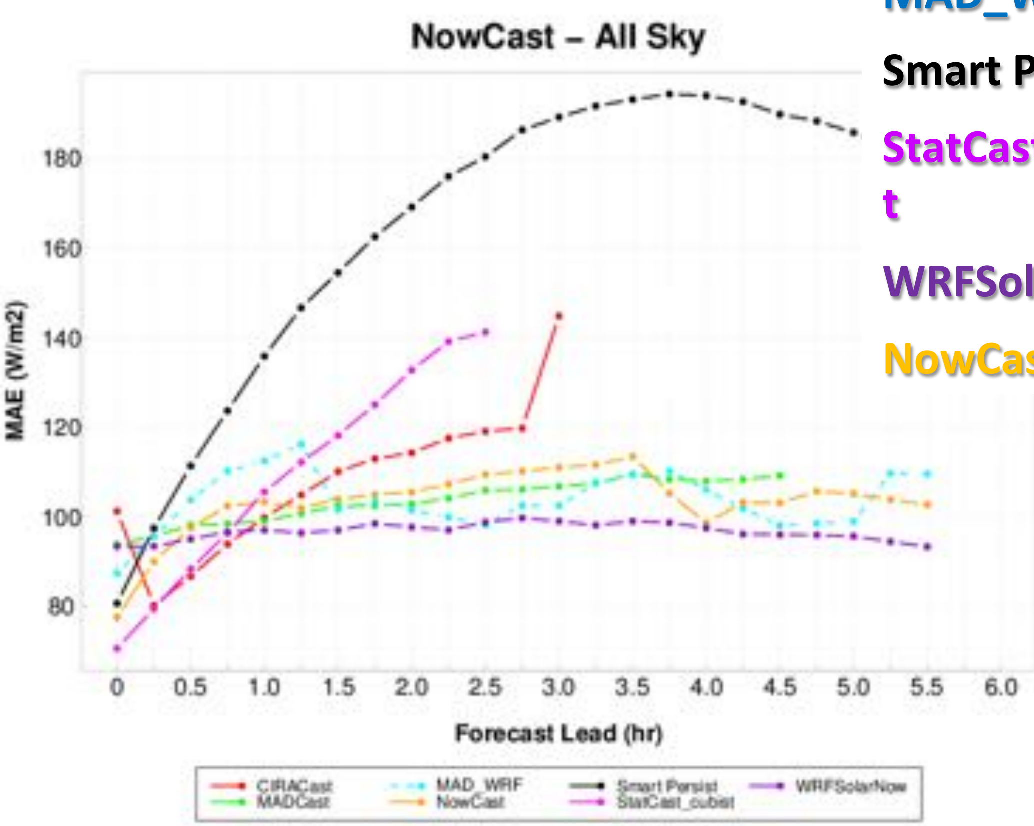
Available for advanced users on Web

Plots of
Time Series
Threshold Series
SkyCondition Series
Box Plots

Data for analysis

NowCast Performance

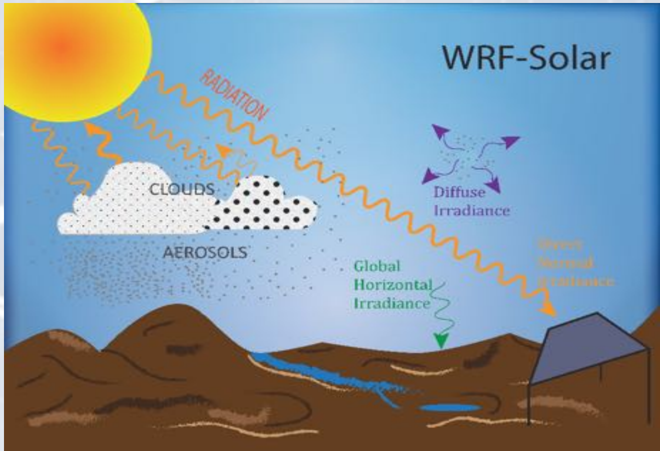
Component	Rank			
	0-1hr	1-3hr	3-6hr	all
CIRACast	**2**	5	n/a	5
MADCast	5	3	4	4
MAD_WRF	6	**2**	3	**2**
Smart Persist	7	7	5	7
StatCast_cubist	**1**	6	n/a	6
WRFSolarNow	3	**1**	**1**	**1**
NowCast	4	4	**2**	3



WRFSolarNow – Ranked 1
NowCast – was optimized in BP2

Some Highlights

- WRF-Solar improved on Standard WRF by 20-80%
- WRF-Solar also important component of NowCast system, often best component
- StatCast-Cubist can improve upon smart persistence by 37-62% - short range (0-3 hr)
- TSICast better than persistence first 15 min – 29-34%
- Cloud advection and assimilation methods predict ramps well – Nowcast with WRF-Solar-Now
- Nowcast improvement 45-53% MAE averaged all conditions, all sites
- Saw 47% improvement in prediction at Xcel sites, despite 2016 harder to predict (El Nino)
- DICast® improves on best forecast
  10-28% MAE
- AnEn improves by another 16-96% MAE
- SunCast improvement 90% MAE (SMUD)



Recommendations for Solar Fcsting

- Blend various component models or systems together with machine learning.
- Use a base NWP model enhanced and tuned for the purpose.
- Include multiple NWP models.
- It is possible to improve upon persistence, even at the very short-range by using methods trained on *in situ* observations.
- Satellite based cloud advection is useful, but tricky.
- NWP can be combined with satellite data via assimilation for nowcasting.
- The analog ensemble approach is helpful for both improving the deterministic blended forecast as well as for producing a probabilistic prediction.
- An empirical power conversion method
viable, even where data limited.
- Enhanced metrics necessary.