Collaborative Research on Solar Power Foresting: Challenges, Methods and Assessment

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National Center for Atmospheric Research

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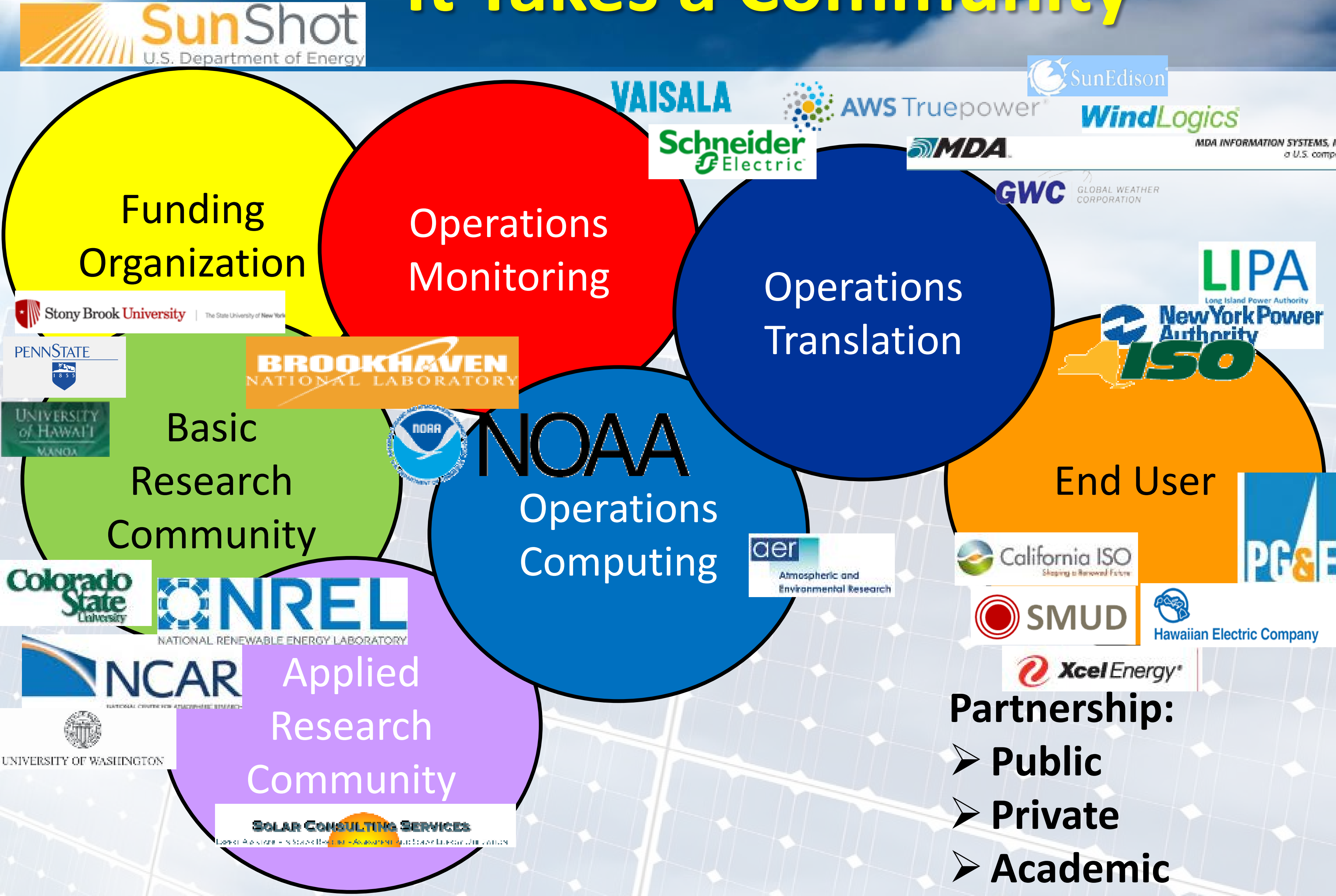
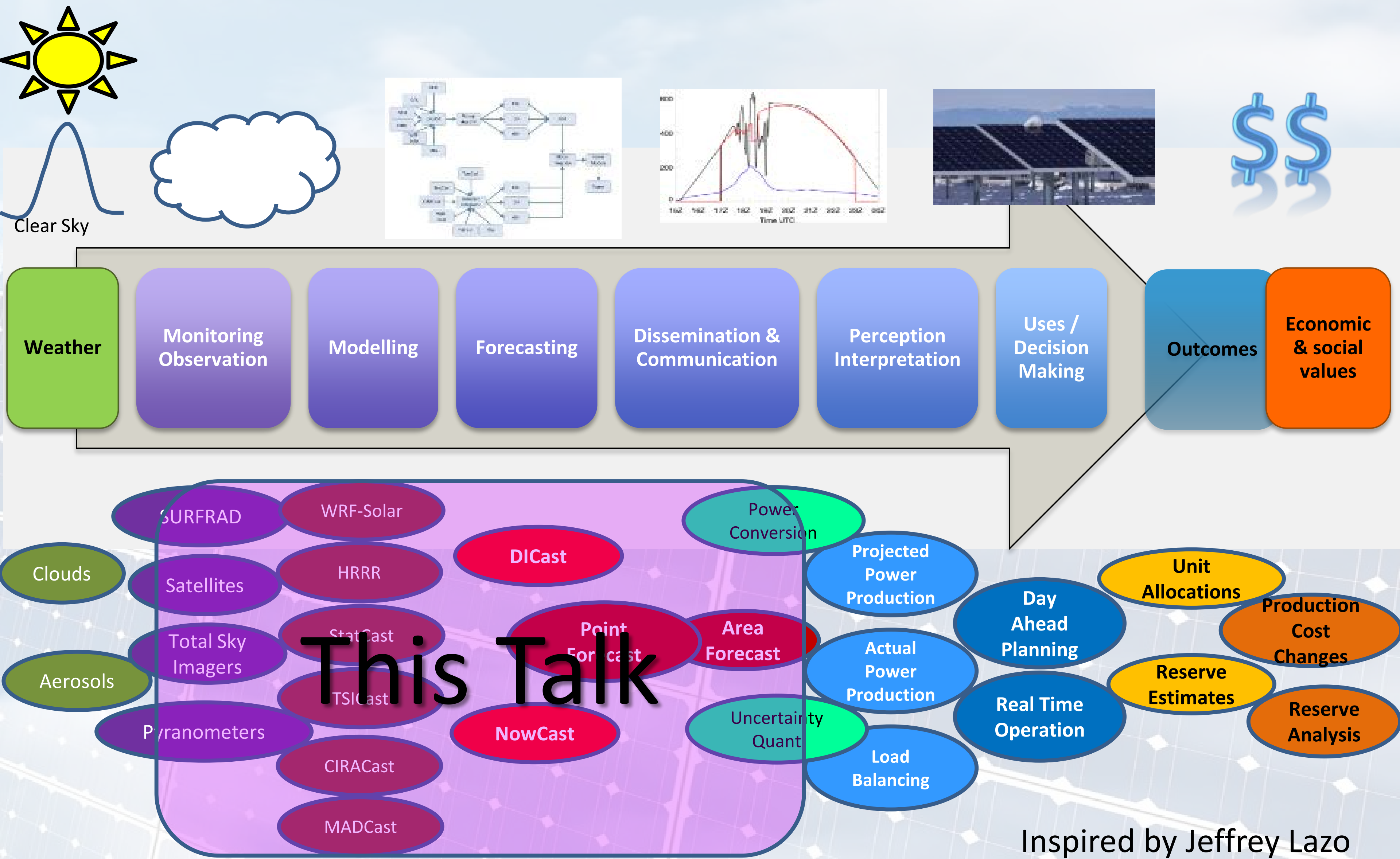
It Takes a Community



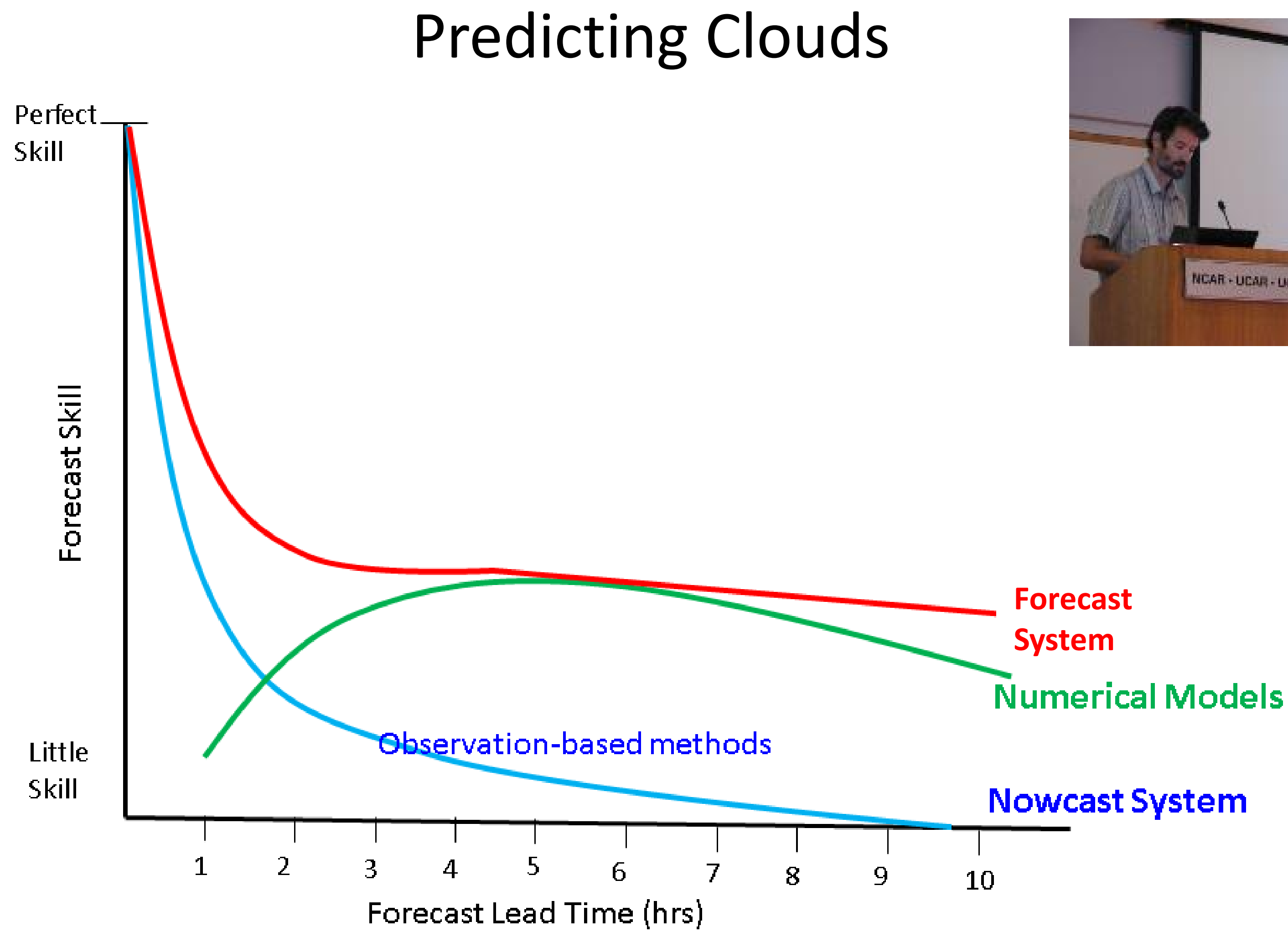
Partnership:

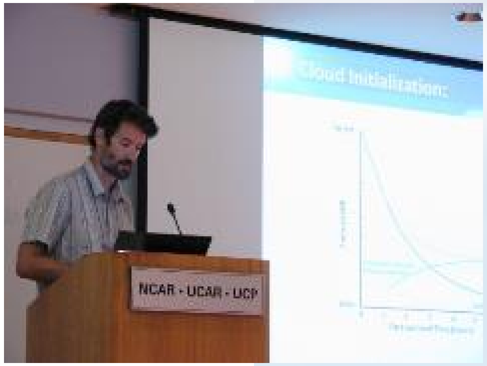
- **Public**
- **Private**
- **Academic**

Value Chain:
Planning toward providing Value



Challenges of Solar Prediction

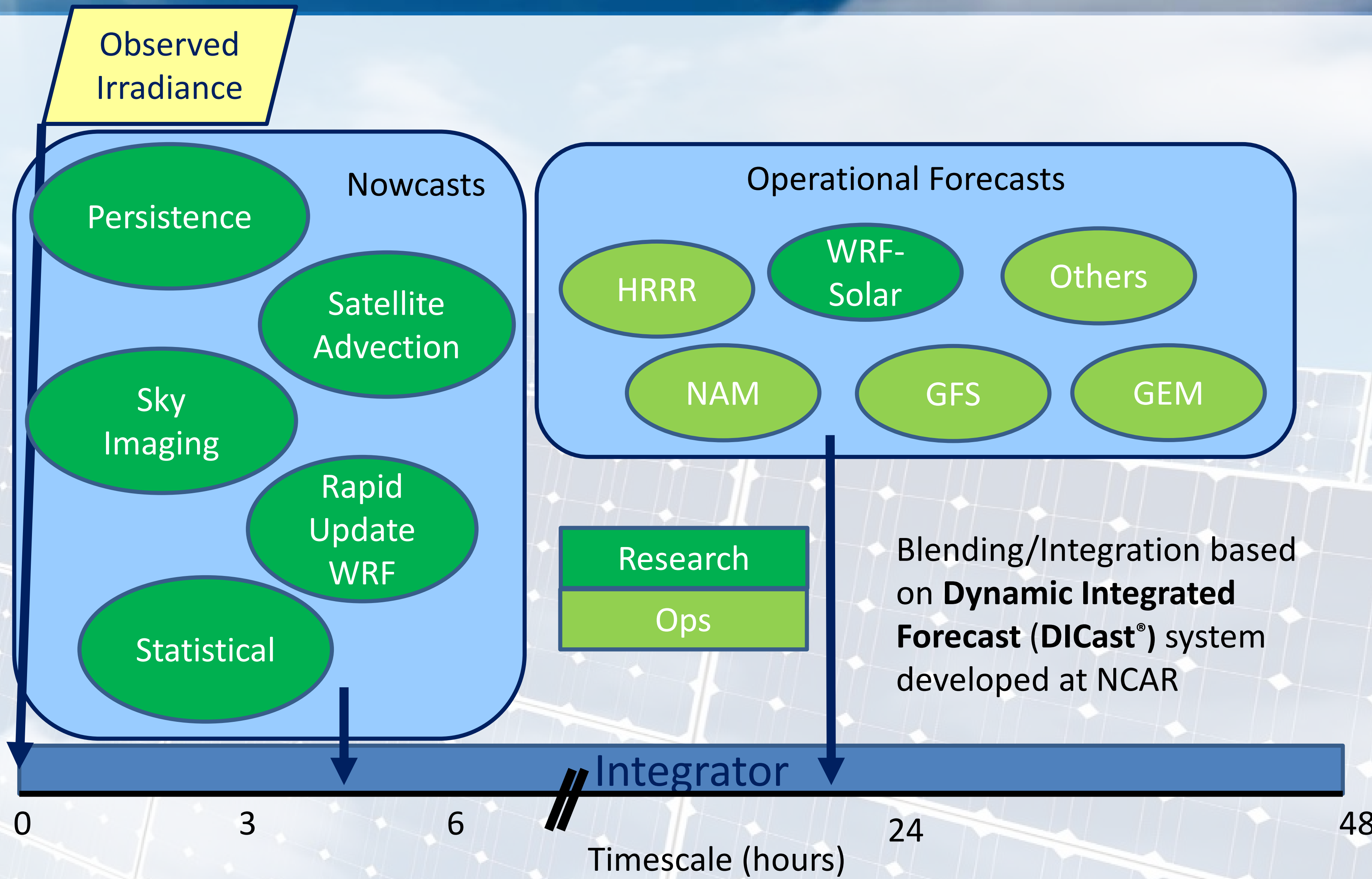




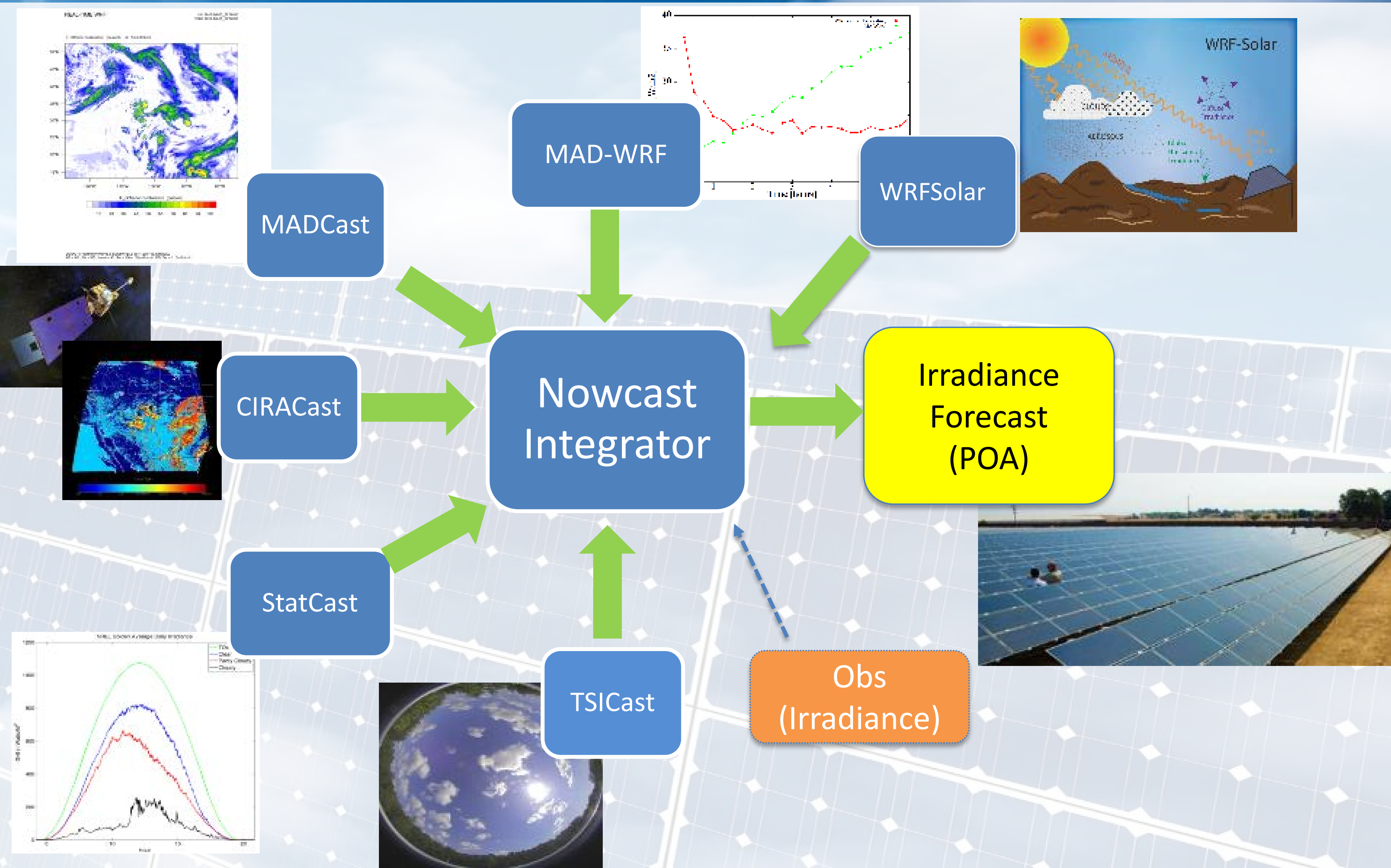
Adapted from Ravela, 2008
Auligne, 2014

DOE SunShot Project

Time Scaled Approach to Power Forecasting

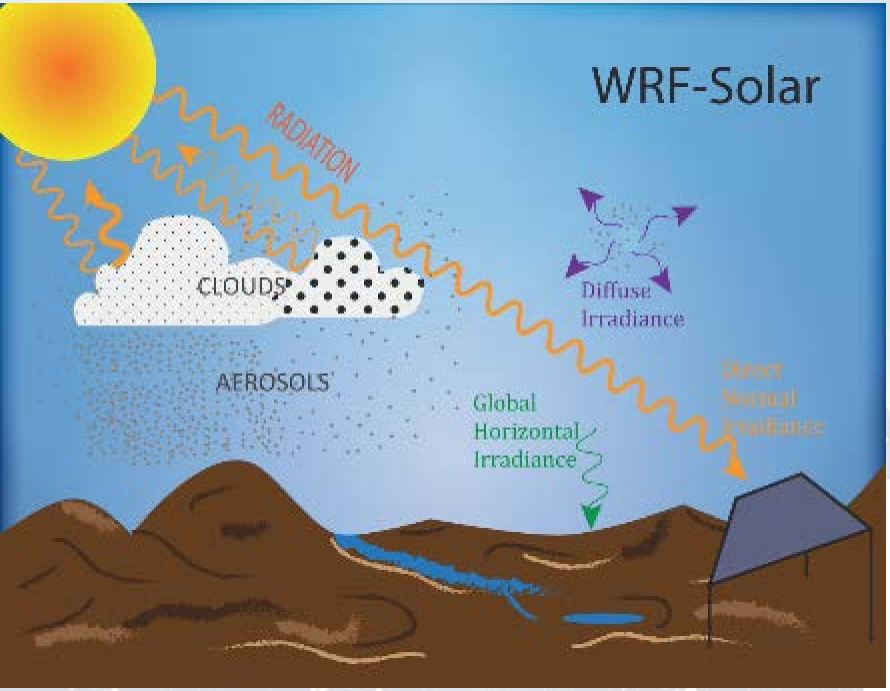


Nowcast System



Numerical Weather Prediction: WRF-Solar

CLOUD-RADIATION-AEROSOL INTERACTION



WRF-Solar

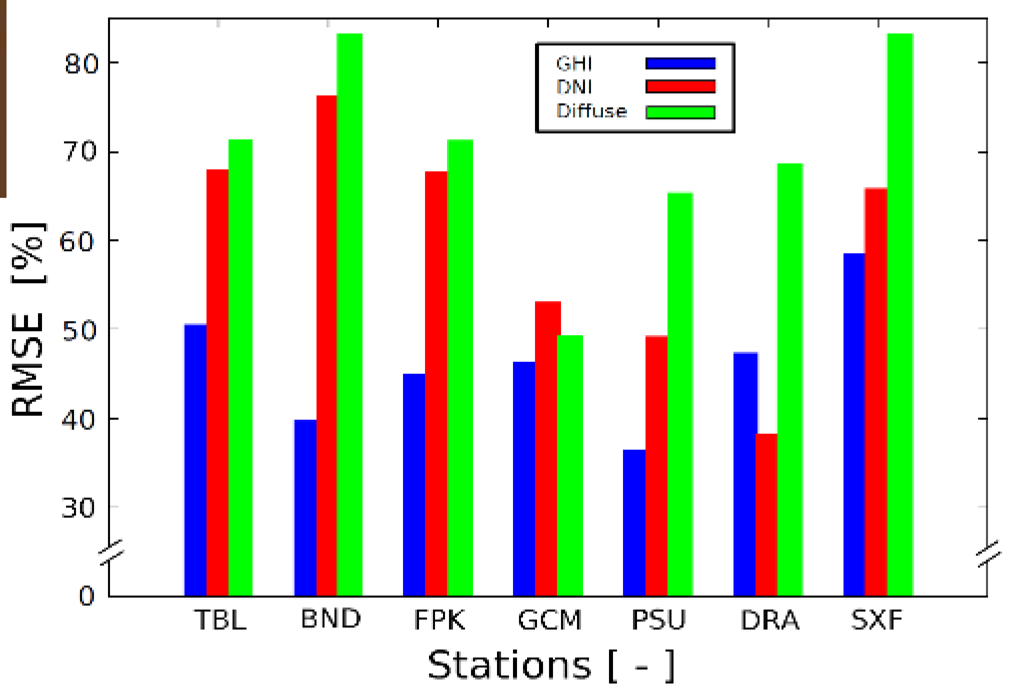
- Include direct & diffuse radiation
- Fully coupled radiation/aerosol/cloud interaction
- Improved cloud physics parameterization
- New shallow convection scheme
- More precise time equation
- Satellite data assimilation

WRF-Solar

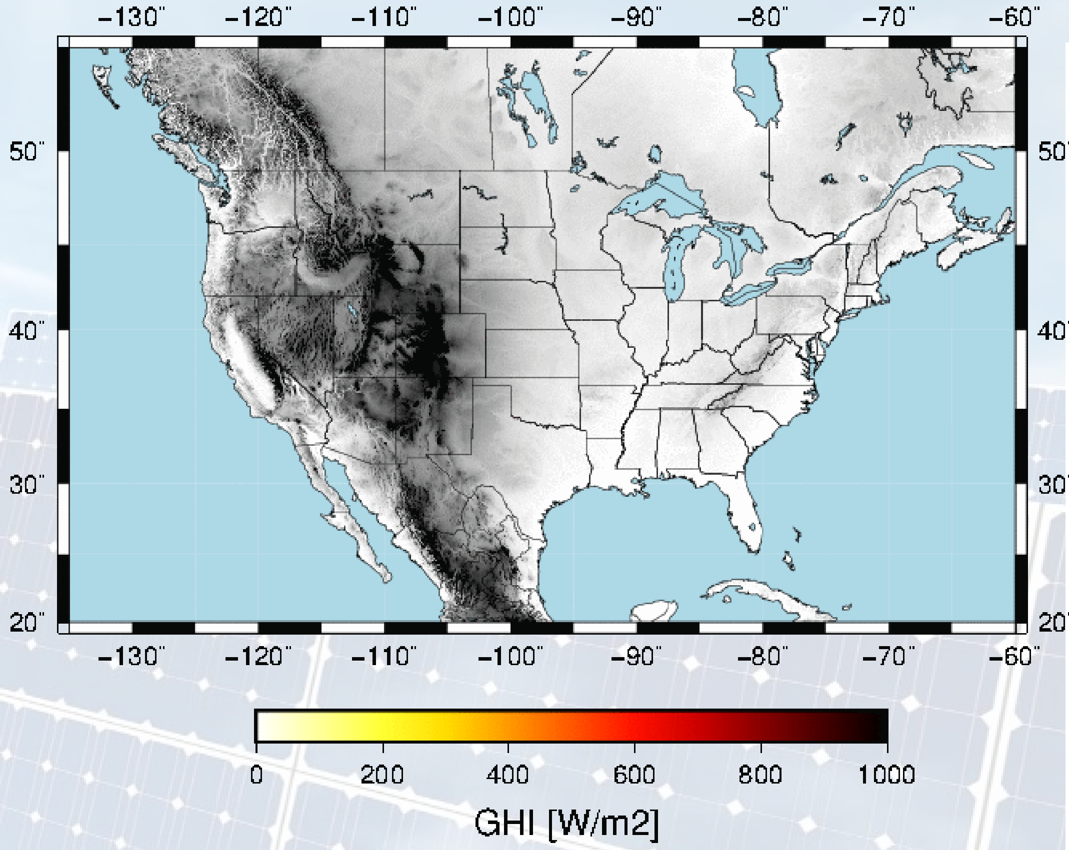
Clear sky analysis shows improvements over standard WRF

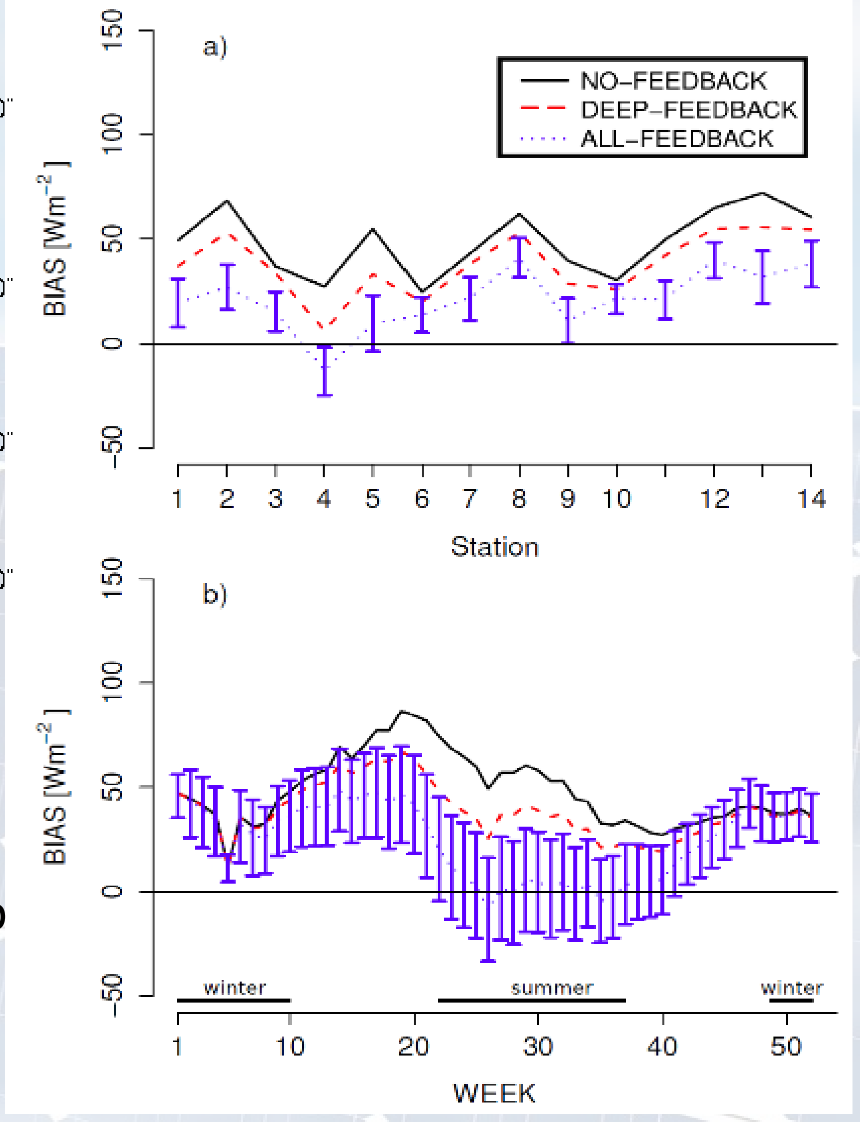
- GHI: 40-58%
- DNI: 40-76%
- DIF: 50-83%

Jimenez, et al., 2016a: BAMS.



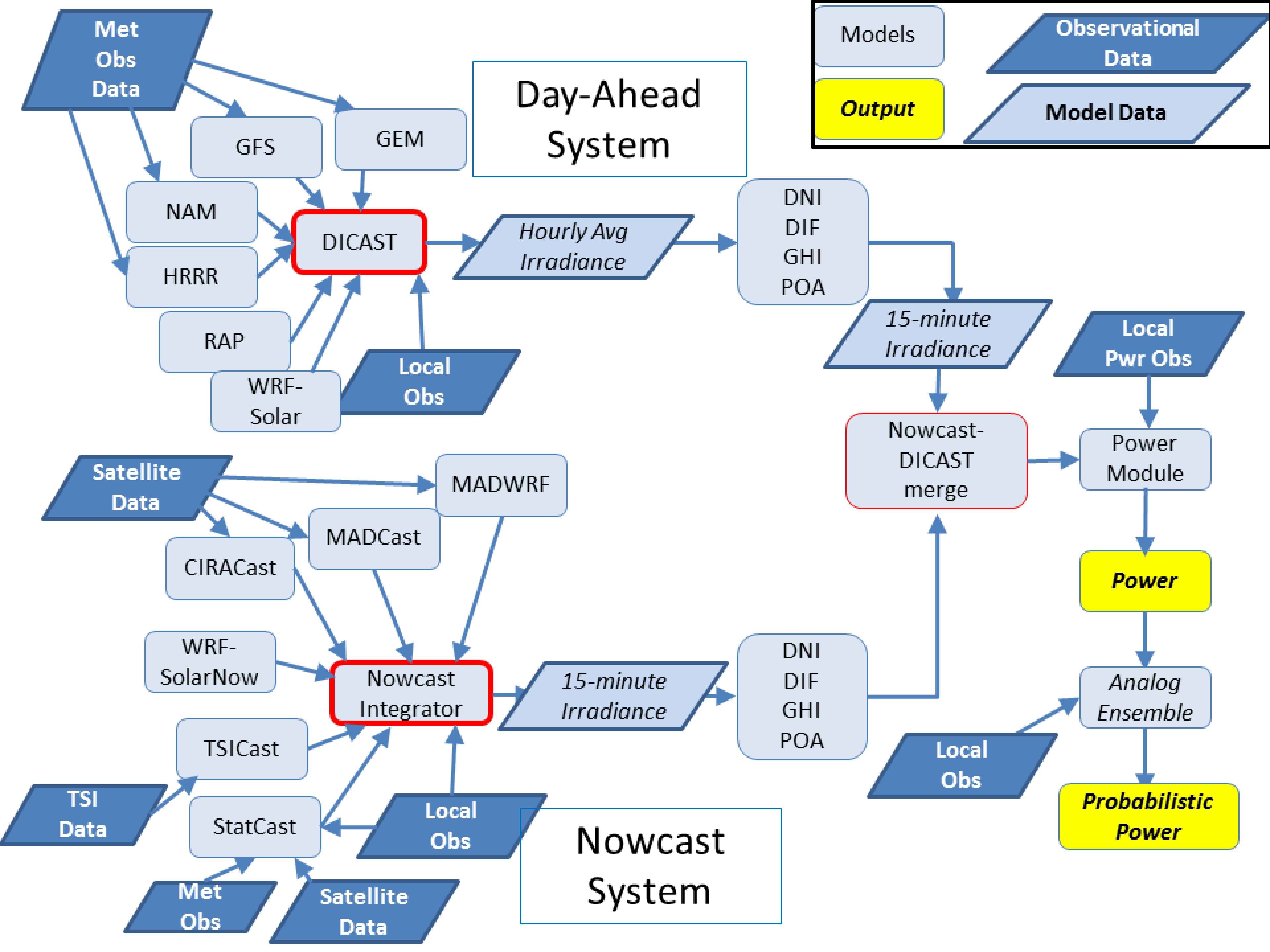
WRF-Solar: Results





WRF-Solar - All sky analysis shows engaging shallow convection scheme in addition to deep convection results in 55% improvement in GHI bias error

Jimenez, et al., 2016b: MWR.

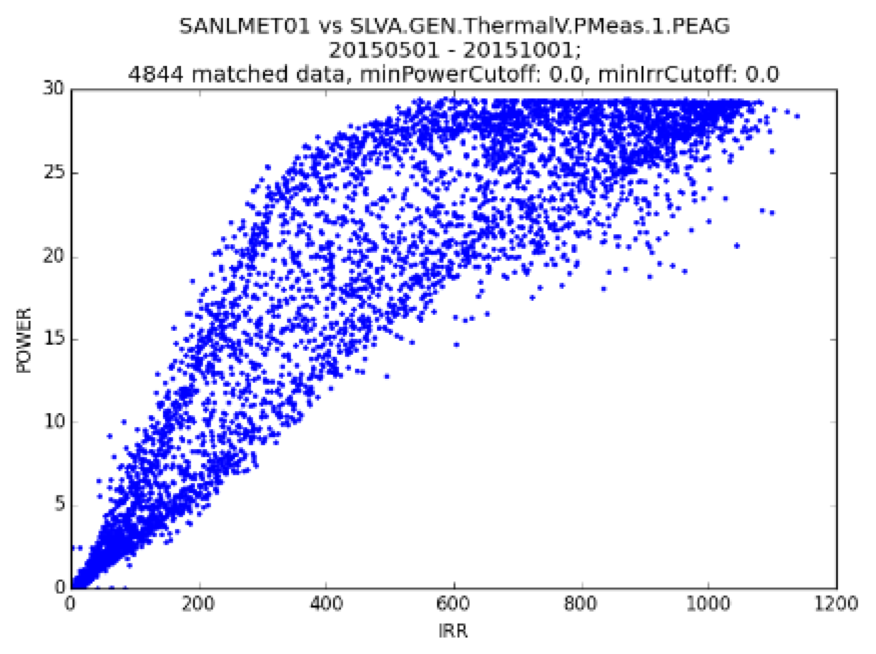

Models
Output
Observational Data
Model Data
Day-Ahead System
Met Obs Data
GFS
GEM
NAM
HRRR
RAP
WRF-Solar
DICAST
Local Obs
Hourly Avg Irradiance
DNI
DIF
GHI
POA
15-minute Irradiance
Local Pwr Obs
Nowcast-DICAST merge
Power Module
Power
Analog Ensemble
Local Obs
Probabilistic Power
Satellite Data
MADWRF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

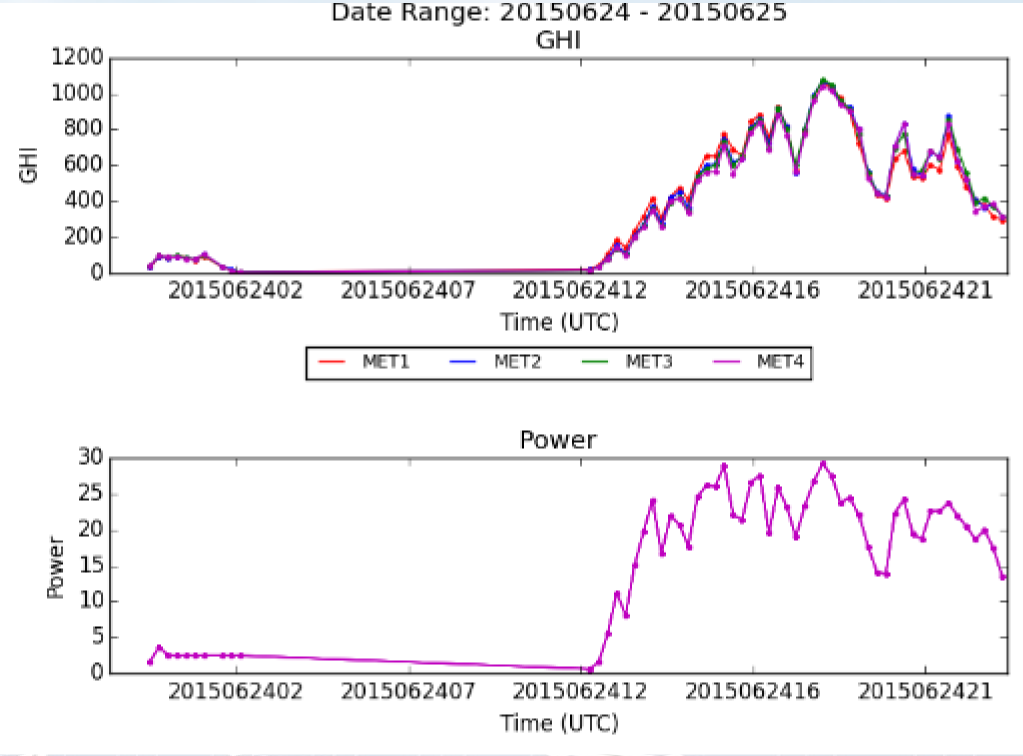
Power Conversion

Empirical Power Conversion: Regression Tree - Cubist

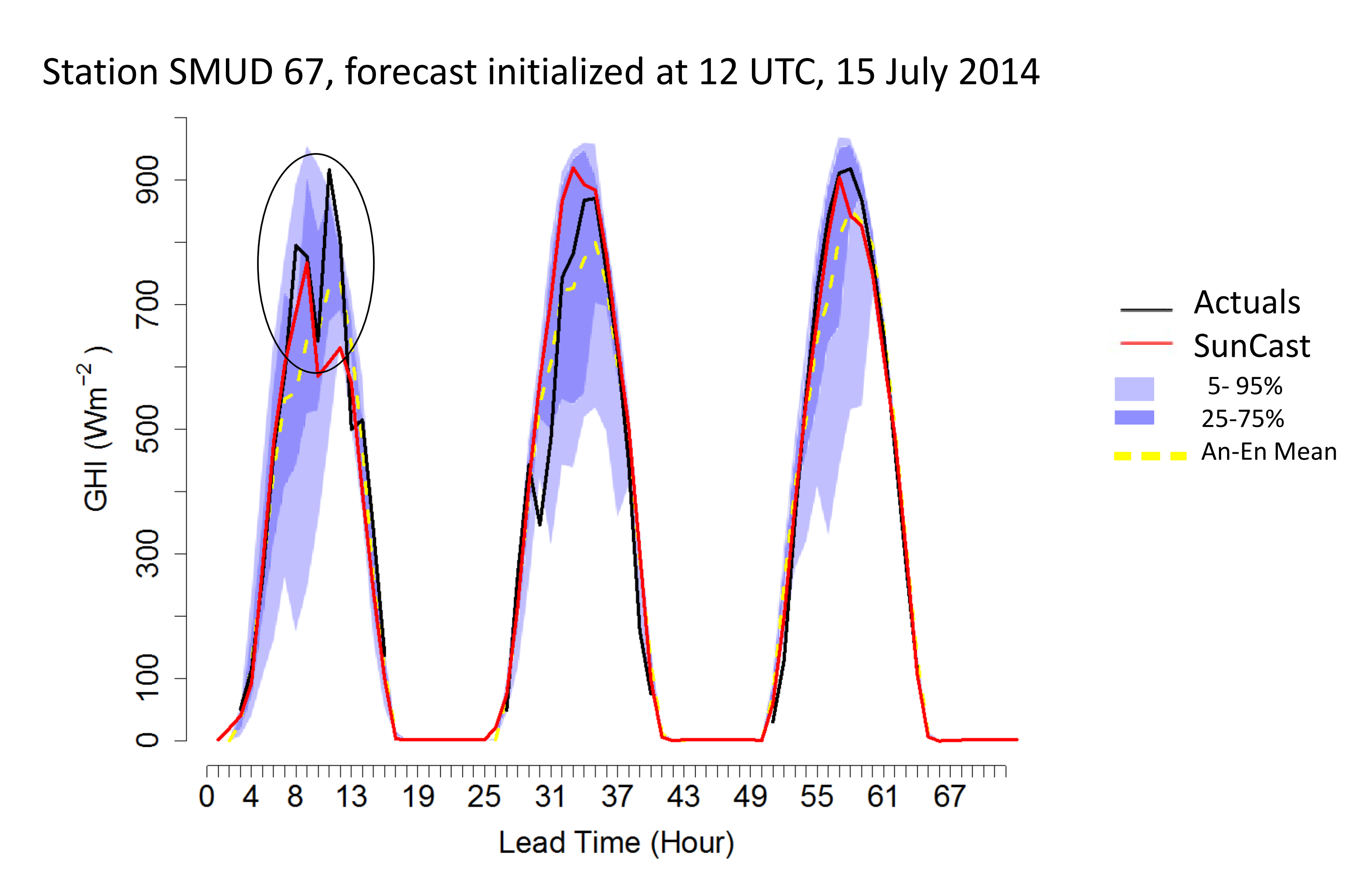
Example for single axis tracking PV plant

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



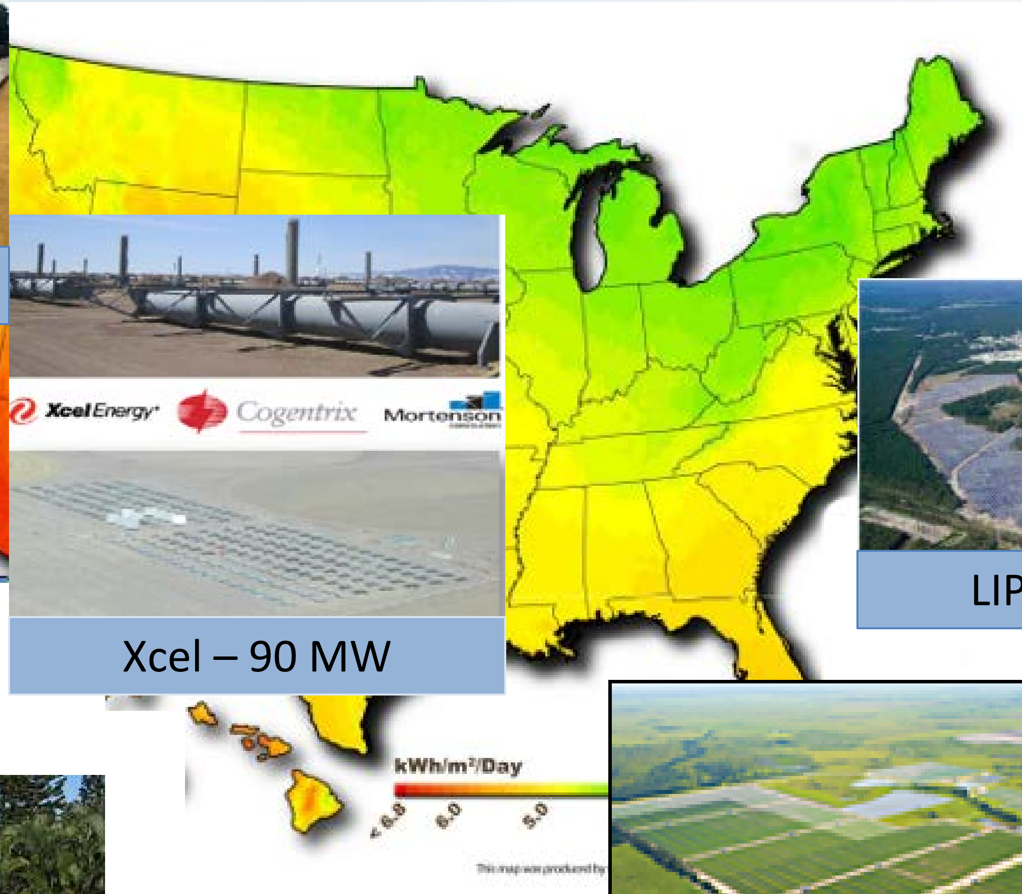


Uncertainty Quantification
Analog Ensemble Approach



SunShot Operationalization

SMUD – 100 + 50 MW



Xcel – 90 MW

LIPA – 32 MW

SCE – 350 Comm + 325Q + 1000 Dist MW

HECO– 43 MW

DeSoto Plant – 25 MW

SunShot Evaluation System

SunCast NowCast and Components
StatCast
CIRACast
MADCast
WRFSolarNow
NowCast
SmartPersistence

SunCast and Components
GEM
GFS
NAM
HRRRops
HRRRx
WRFSolar
SunCast

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)

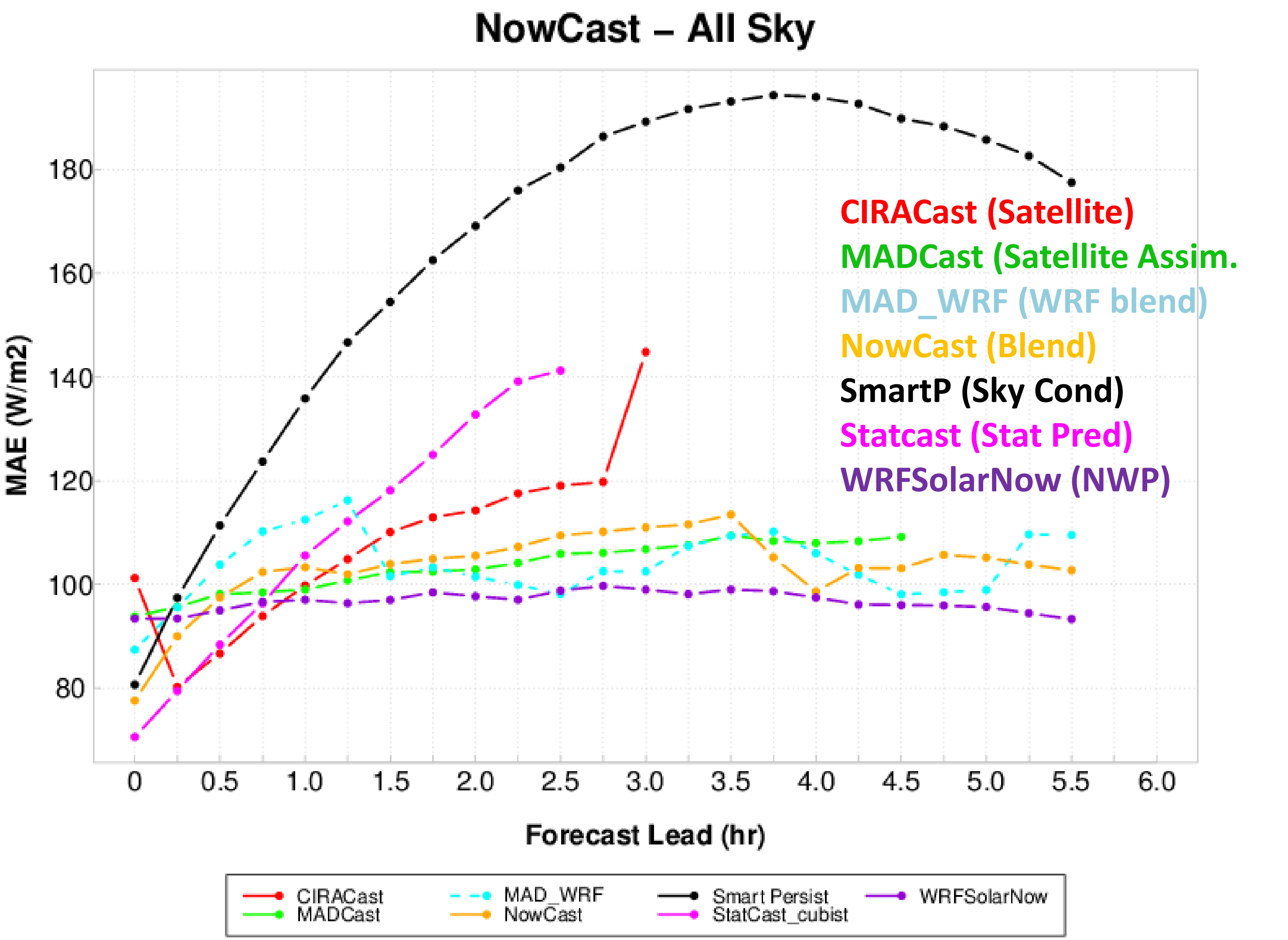
METViewer Database and Display

Available for advanced users on Web

Plots of
Time Series
Threshold Series
SkyCondition Series
Box Plots

Data for analysis

NowCast Performance



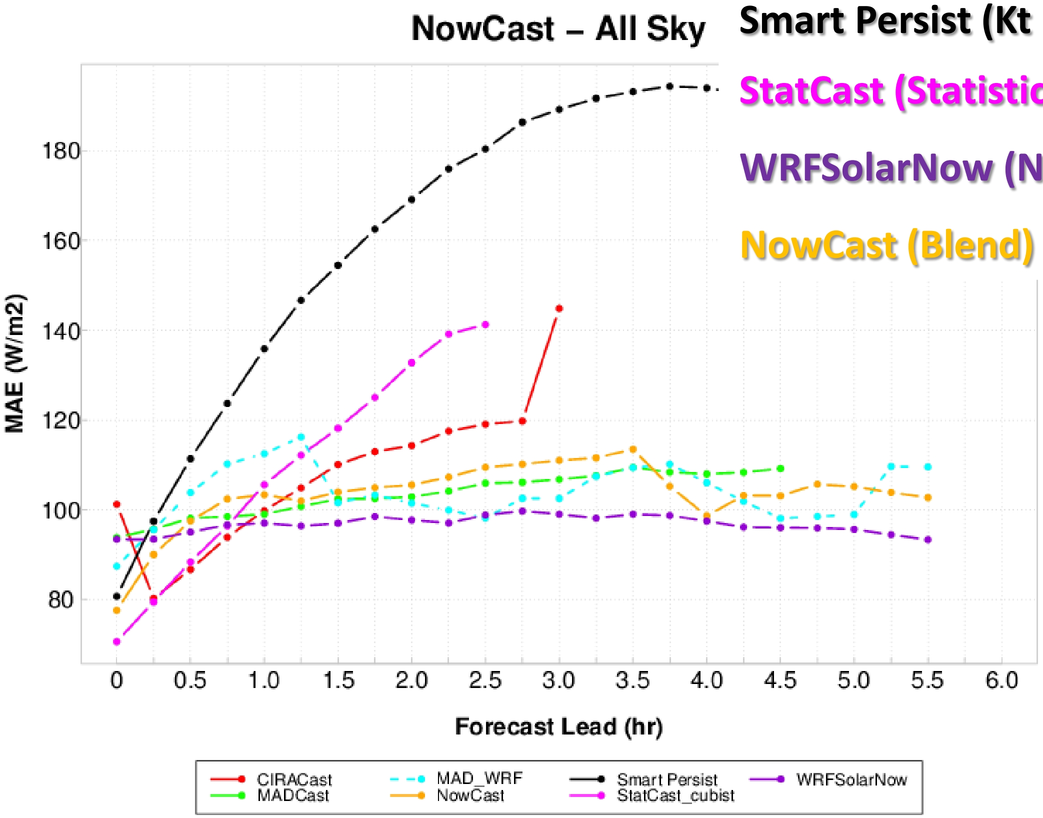
Aggregated over All Issue times and All Sky Conditions

Component performance varies by lead time

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

NowCast Performance

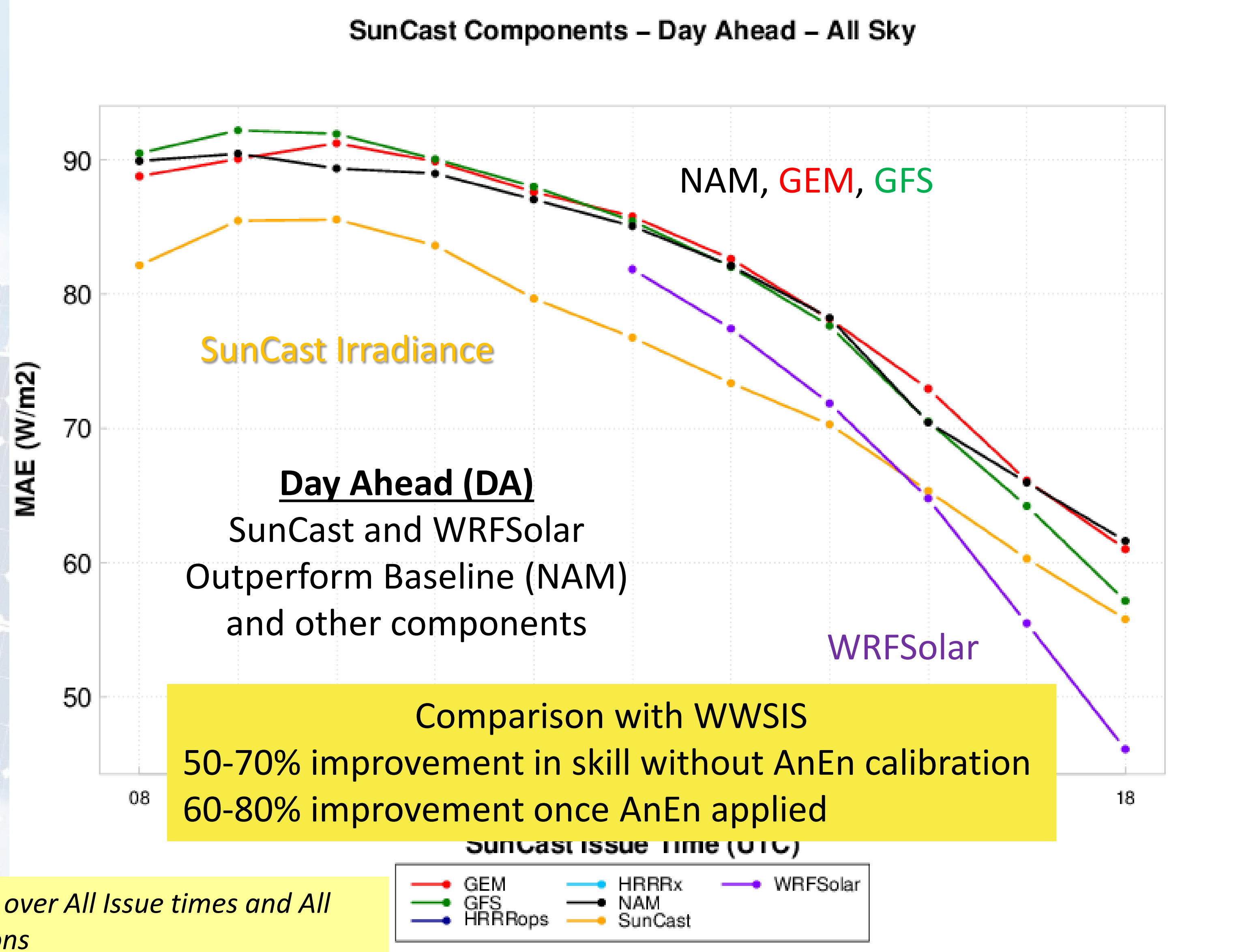
Component	Rank			
	0-1hr	1-3hr	3-6hr	all
CIRACast (Satellite)	**2**	5	n/a	5
MADCast (Satellite Assim.)	5	3	4	4
MAD_WRF (NWP blend)	6	**2**	3	**2**
Smart Persist (Kt Persist)	7	7	5	7
StatCast (Statistical Pred)	**1**	6	n/a	6
WRFSolarNow (NWP)	3	**1**	**1**	**1**
NowCast (Blend)	4	4	**2**	3



WRFSolarNow – Ranked 1
NowCast – was optimized in 2014 when some components not available in final form

Aggregated over All Issue times and All Sky Conditions

SunCast Performance – Day Ahead



Day Ahead (DA)

SunCast and WRFSolar Outperform Baseline (NAM) and other components

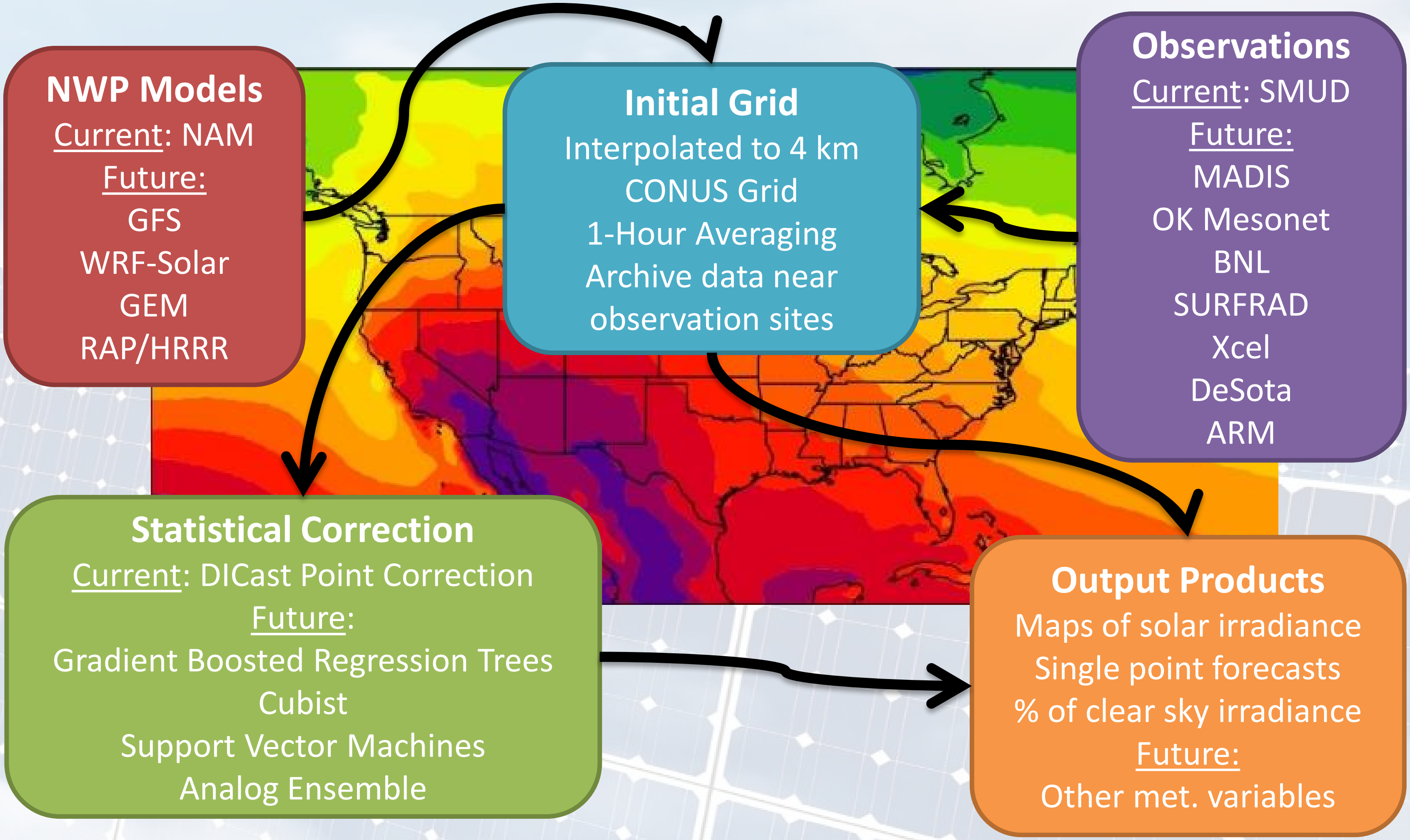
Comparison with WWSIS

50-70% improvement in skill without AnEn calibration

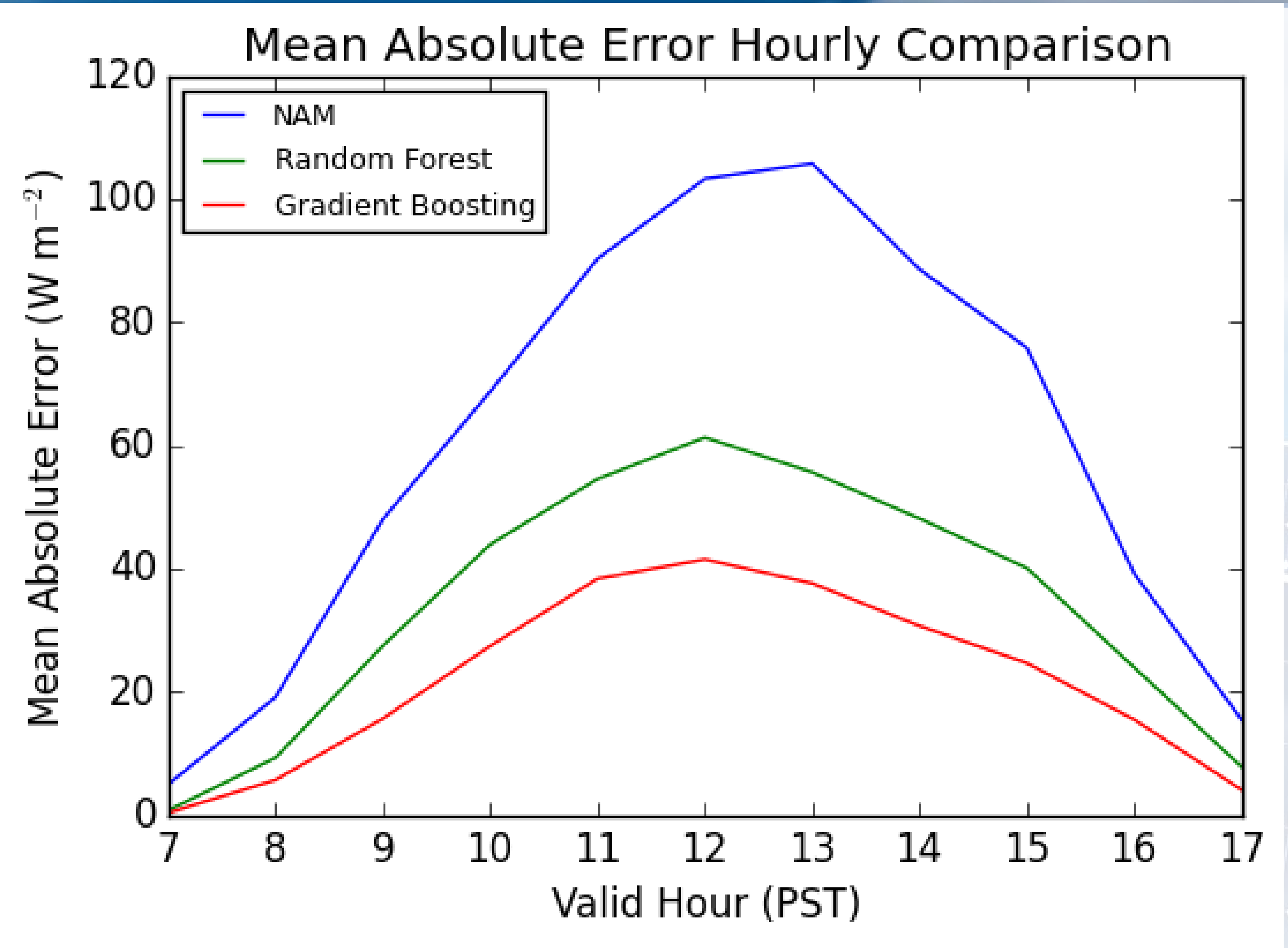
60-80% improvement once AnEn applied

Aggregated over All Issue times and All Sky Conditions

Gridded Atmospheric Forecasting System GRAFS-Solar: Framework



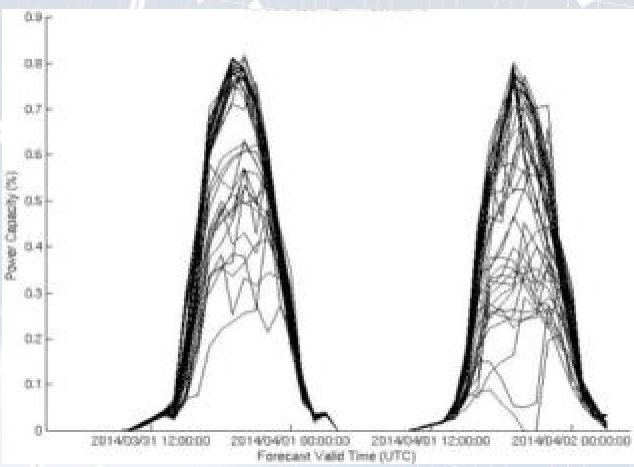
GRAFS: Machine Learning Enhancements

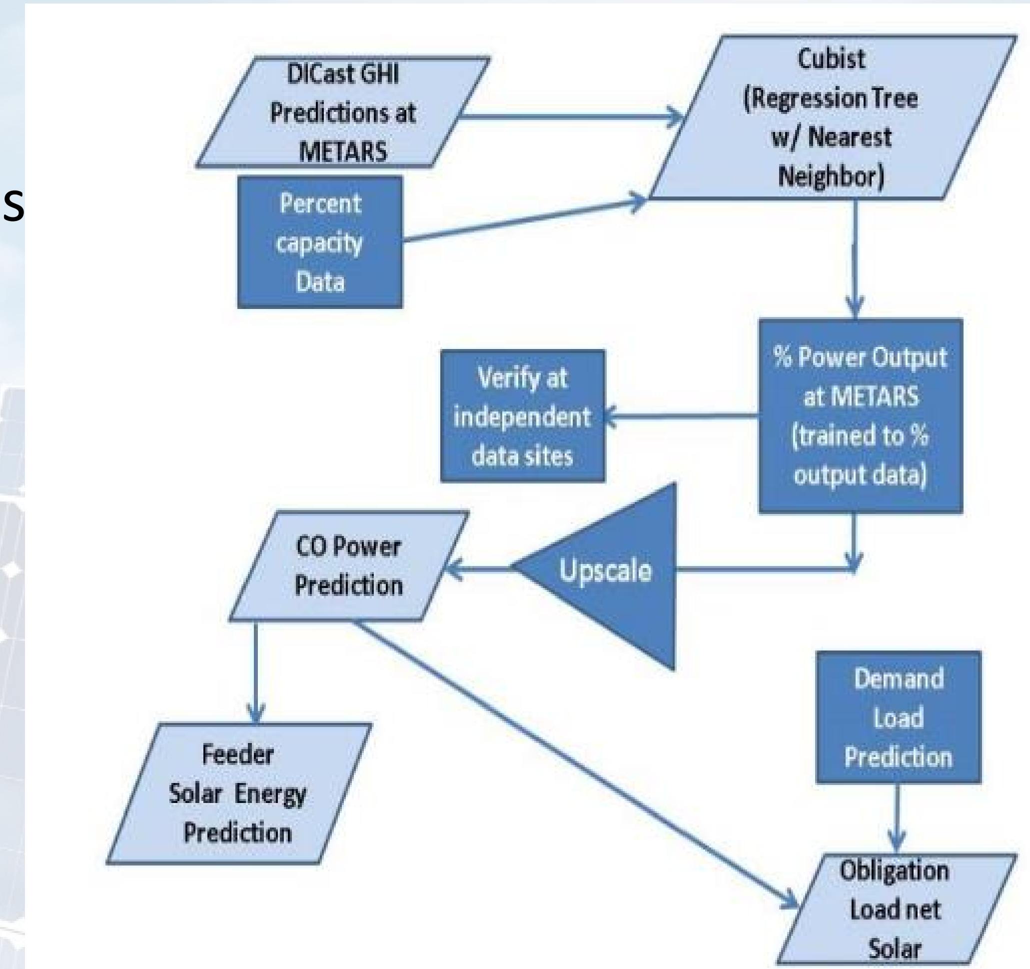


Statistical correction after initial grid formed decreases errors drastically

Distributed Solar Forecasts

- Built system to forecast solar power and upscale to CO, plus provide info for feeders
- Solar forecast to impact load forecast – will allow to grow with increased deployment

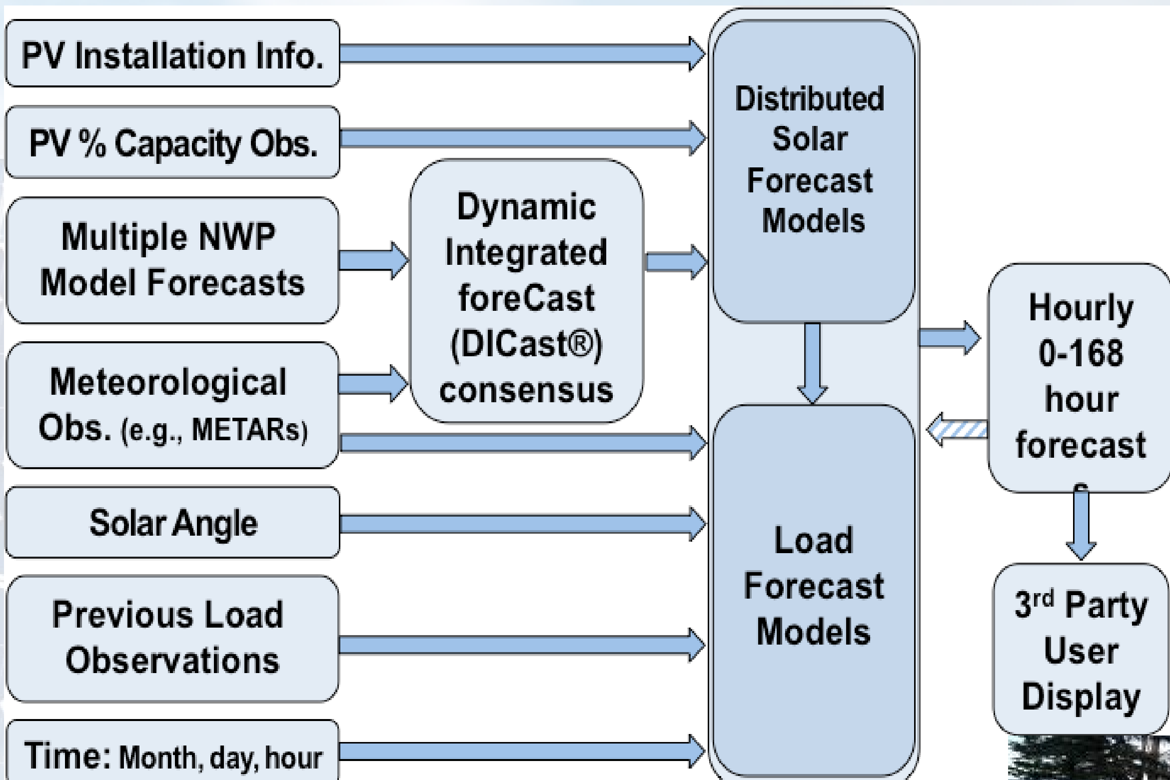




At Trading Decision Time (4-5am) forecasts show nRMSE values to be under 3%

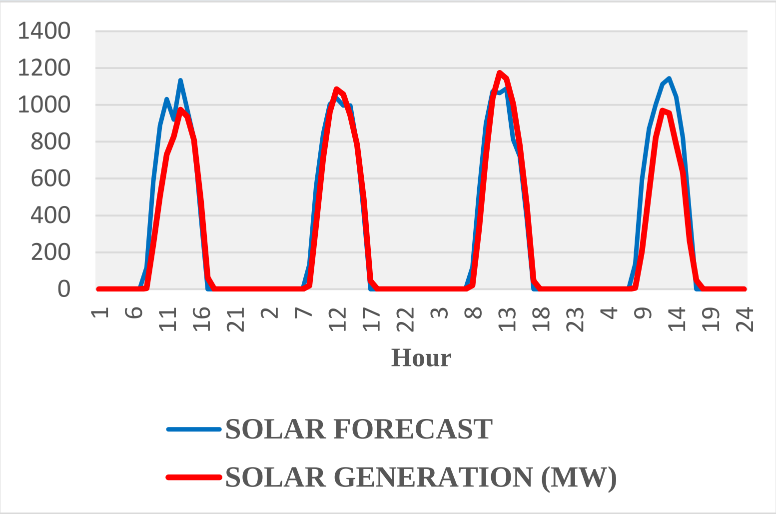
Load + DPV Forecasting System

Merge Load Forecast with Distributed Solar Power Forecast to determine Net Load



A base percent capacity increases, the DPV forecast becomes more important to the load forecast,

Valuation

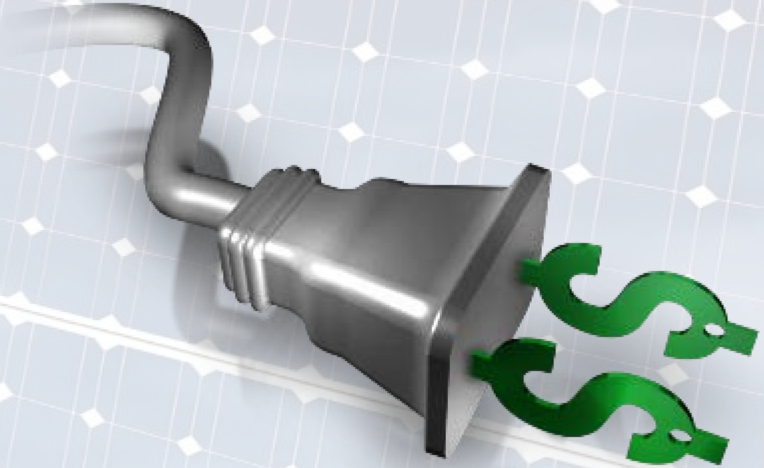


<u>Production Cost Modeling</u>

- 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



Scientific Lessons Learned

- **Blending**
  - Use component systems together with machine learning
  - Use a base NWP model enhanced and tuned for the purpose (WRFSolar)
  - Include multiple NWP models (Operational Models)
- **Improving upon persistence**
  - Use methods trained on *in situ* observations (e.g. TSICast, StatCast)
- **Satellite based cloud advection**
  - Useful, but can challenging (CIRACast)
  - Combined with NWP can be even more powerful (MADCast, MAD-WRF)
- **NWP**
  - The source of aerosol data and shallow cumulus parameterizations are important (WRF Solar)
- **Predictability**
  - There are limits to predictability due to the chaotic nature of atmospheric flow and sensitivity to initial conditions.

Scientific Lessons Learned

- **Empirical power conversion**
  - Works best with well documented, clean data
  - However, it’s viable even when data limited.
- **Analog ensemble**
  - Improves the deterministic blended forecast
  - Produces a probabilistic prediction
- **Metrics**
  - Industry standard metrics are good
  - Enhanced metrics help better understand performance
  - Economic value assessments are challenging due to proprietary processes

What has a big impact?

- **Availability and quality of data**
  - Critical issue for any forecasting system.
  - Quality of the data and the metadata often does not meet our expectations and needs
  - Each utility measures a different type of irradiance measurement
    - Some use GHI, while others use POA, or DNI for concentrated systems
    - Critical metadata is not always shared / available
    - Makes it difficult to engineer the systems.
  - Historical data often unavailable.
    - Statistical learning methods require historical data for training the system
    - Where it does not exist, those techniques cannot be employed.
  - Standardized data format would greatly benefit all who deal with such data.

What is left to do?

- Work toward better 0-2 hour prediction using observational methods
- Improve physical models with better representation of aerosol loading, cloud properties including thickness, height, advection and dispersion
- Better understand and predict the impacts of contaminants on the solar panels such dust and snow and ice (including when and how it melts off)
- Continue to explore statistical methods like gradient boosted regression and deep data-mining techniques
- Optimize power conversion and probability forecasts using Analog Ensemble and other methods
- Have more time to work with utility partners:
  - Tailoring information and metrics to their needs
  - Understanding the value of forecasts
  - Understanding what types of forecasts are needed to maximize utility of storage

Summary:

- Solar Power Forecasting advancing rapidly - **SunCast**
- Advanced NWP part of blended forecasting system **WRF-Solar**
- Distributed Generation forecasting can be fed to Load forecast - **DGL**

- **GRAFS** is a new community gridded forecasting system being developed
- **Final outcome:** to advance solar energy through better, more economical grid integration

NCAR

Question?

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Thank You

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