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ETWG Solar Workshop
Austin, TX
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Current Status and Challenges of Solar Power Production Forecasting

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Overview

- The Solar Power Forecasting Challenge
- Current Forecasting Tools
  - Weeks and Months Ahead
  - Days Ahead
  - Minutes and Hours Ahead
  - Types of Forecast Products
- Forecast Performance Benchmarks
  - Performance metrics
  - Days Ahead
  - Hours Ahead
  - Solar vs. Wind Power Forecasts
- The Road to Improved Forecasts

Solar Power Forecast Challenge

Factors that Affect Solar Power

- **Global Solar Irradiance (~90%),**
- **Temperature (~10%),**
- **Wind (<1%)**
- **Type of Plant**
  - Determines exact impact of all three factors
  - Categories of plants: (1) PV, (2) Concentrating PV, (3) Solar thermal (also concentrating)
  - PV is sensitive to Global Irradiance
  - Concentrating types (thermal and PV) are sensitive to Direct Normal Irradiance
  - Also significant sensitivity variations within basic categories

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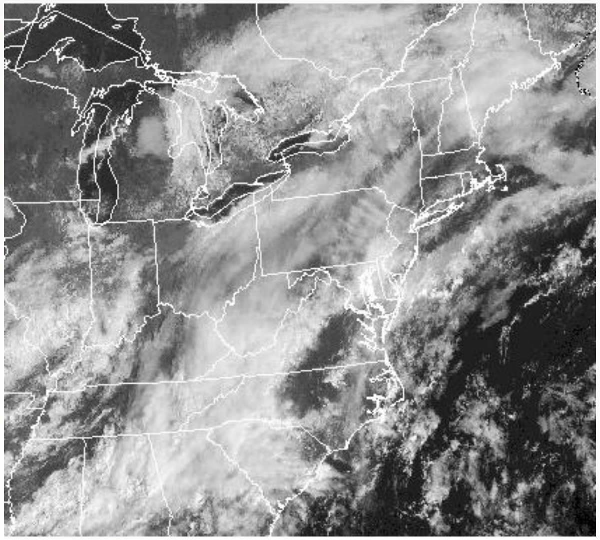
Solar Power Forecast Challenge

Environmental Factors that Affect Solar Irradiance

- **Sun Angle**
  - most significant but completely predictable
- **Cloud Cover**
  - cause of the most variance (~90%)
  - largest meteorological challenge to forecasts
- **Haze, Dust and Smoke Particles**
  - up to 10 % of variance
- **Humidity levels (Water Vapor)**
  - about 1 % of variability
- **Components of Irradiance (diffuse, direct) are affected differently by these factors**



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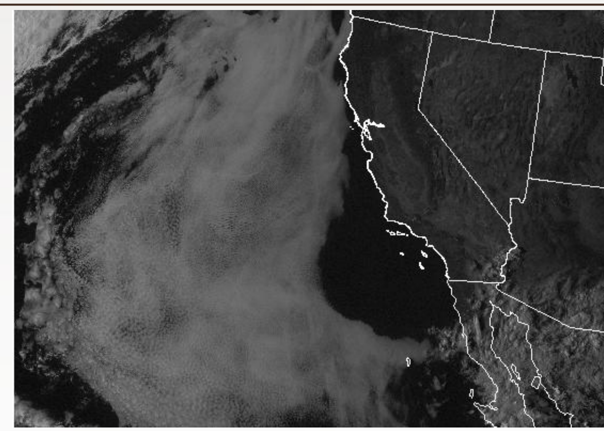
The Challenge – Making the Best Forecast for Various Time Scales

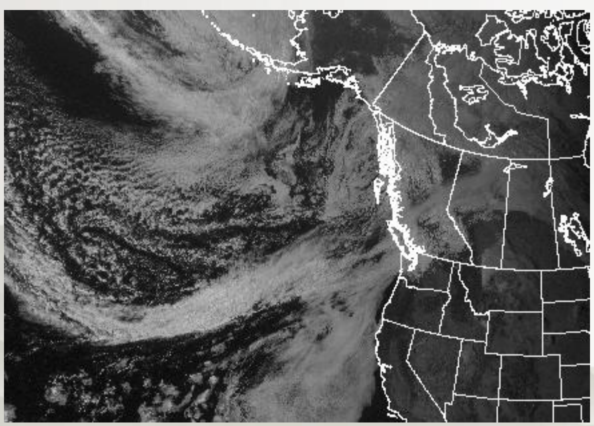
Minutes Ahead

- Cumulus clouds, small-scale cloud structures, fog
- Rapid and erratic evolution; very short lifetimes
- Mostly not observed by current sensor network
- **Tools: persistence, skycams, local irradiance trends**
- Very difficult to beat a persistence forecast
- Need: Data & tools to handle development & dissipation



Hours Ahead

- Frontal bands, mesoscale bands, fog, thunderstorms
- Rapidly changing, short lifetimes
- Current sensors detect existence but not structure
- **Tools: satellite-based cloud advection and NWP**
- Need: Better forecasts of development & dissipation



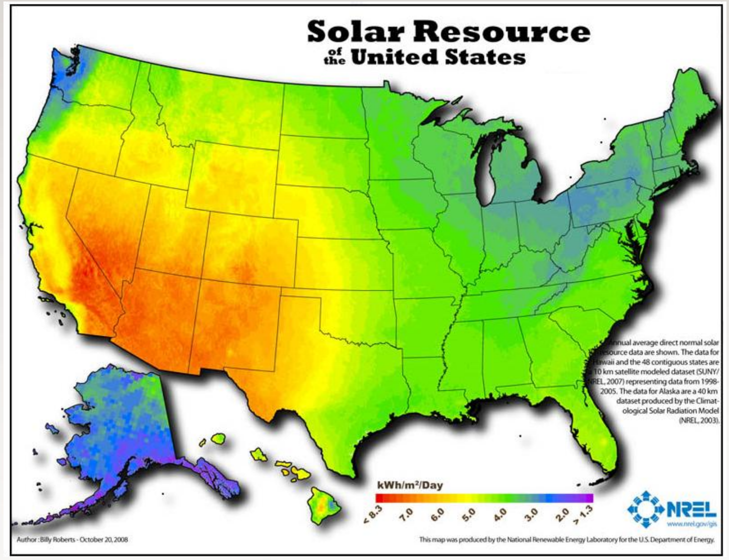
Days Ahead

- "Lows and Highs", frontal systems
- Slowly evolving, long lifetimes
- Well observed with current sensor network
- **Tools: NWP with statistical adjustments**
- **> ~ 10 days**- climatology and climate trends
- Need: better NWP performance & improved MOS

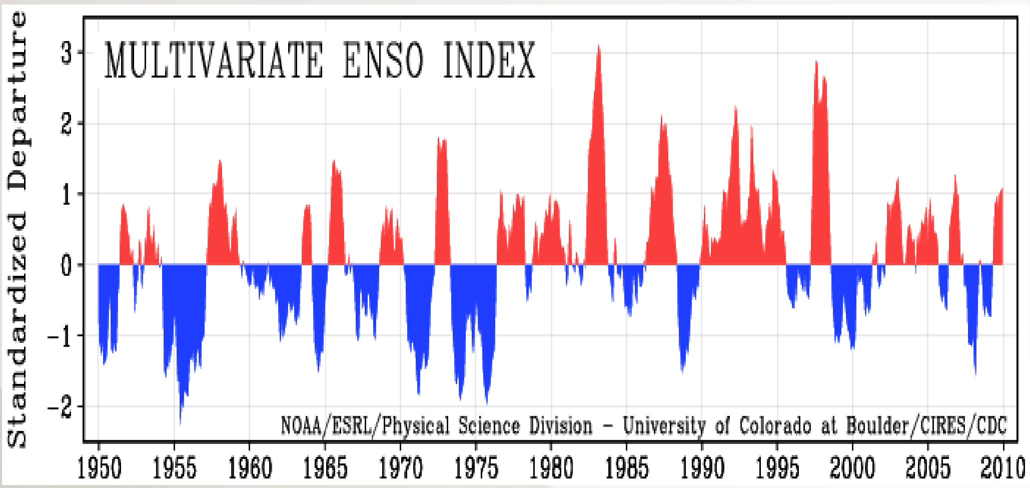
Solar Irradiance Forecasting Tools

Forecasting Techniques – Weeks & Months Ahead

Climatology and Global Circulation Indices



- Climatology
  - Long term characteristics of solar resources by time of day and day of year
  - Often the best forecast for look-ahead periods >10 days



- Statistical links to Global Circulation Indices
  - El Nino (ENSO)
    - Cloudiness and precipitation have significant correlations with ENSO in some areas
  - Madden-Julian Oscillation
  - North Atlantic Oscillation (NAO)
  - Pacific Decadal Oscillation (PDO)

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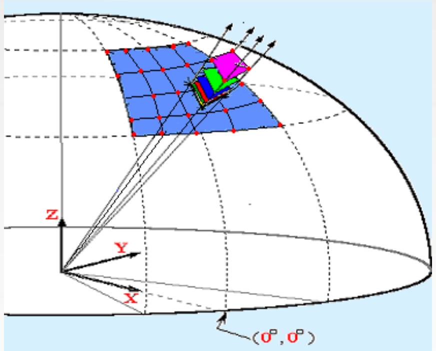
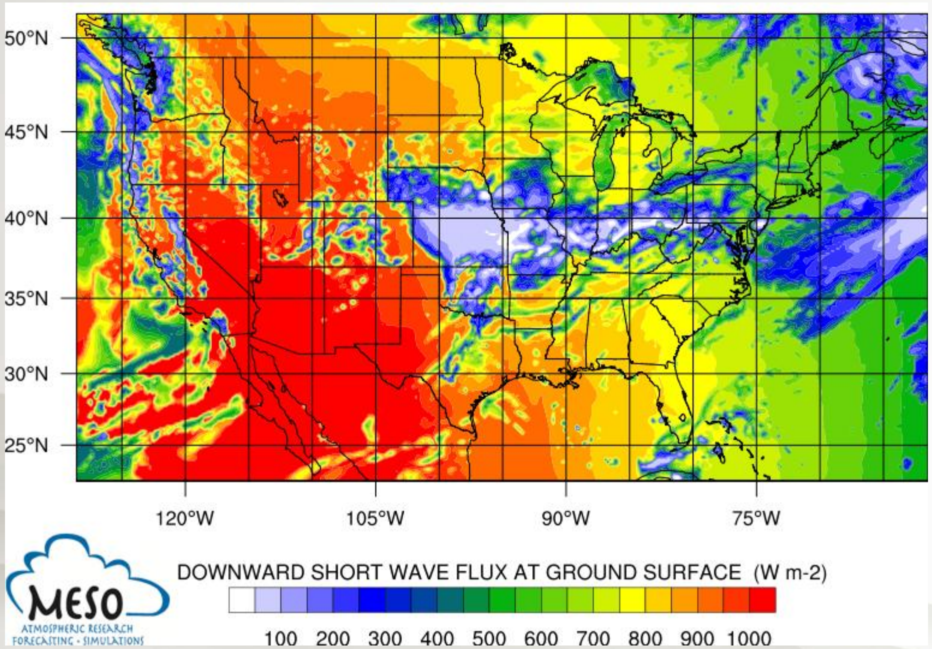
Forecasting Techniques - Days Ahead

Physics-based Numerical Weather Prediction (NWP) Models

- Differential equations for basic physical principles (conservation laws) are solved on a 3-D grid
- Simulates the evolution of the atmosphere over a 3-D volume
  - explicitly predicts a time series of most atmospheric variables including solar irradiance at all grid points in the model domain

$$\frac{\partial u}{\partial t} = m\left(-u\frac{\partial u}{\partial x} - v\frac{\partial v}{\partial y} - \frac{\partial \Phi}{\partial x} - \sigma_p \alpha \frac{\partial p^*}{\partial x} \right) - \dot{\sigma}\frac{\partial u}{\partial \sigma_p} + fv$$





- Initial values for all variables must be specified for all grid cells.
- Boundary values must be specified for all boundary cells (usually from another model with a larger domain)

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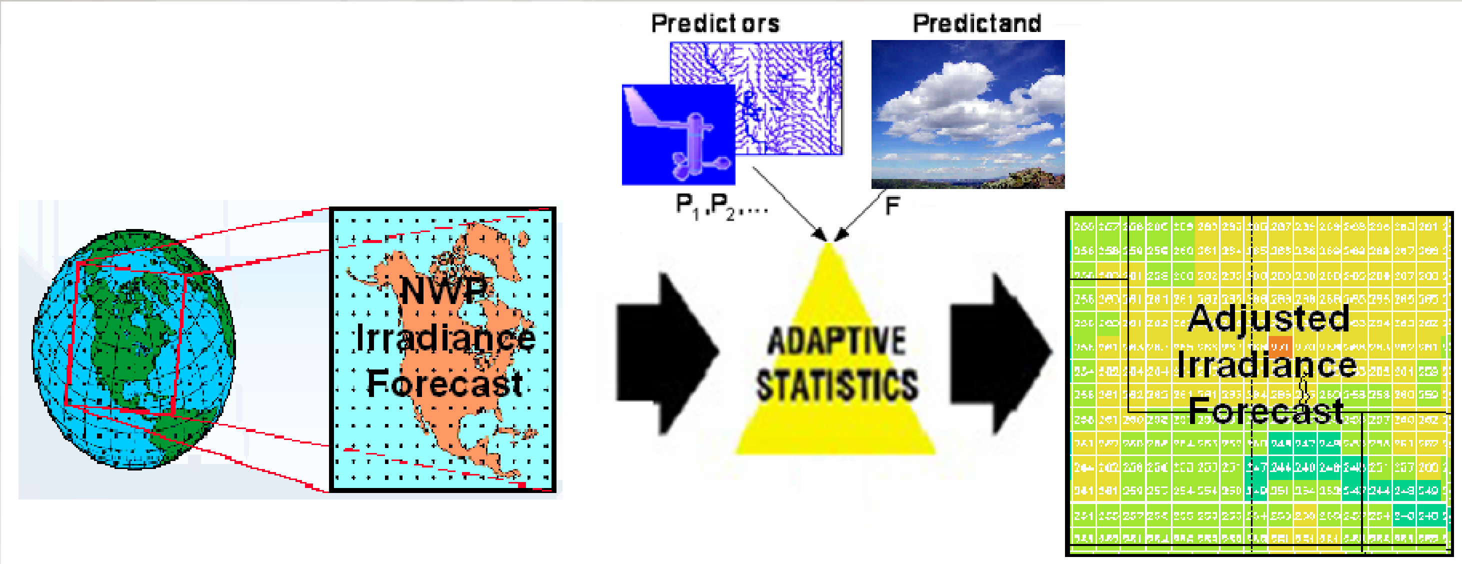
Forecasting Techniques – Days Ahead

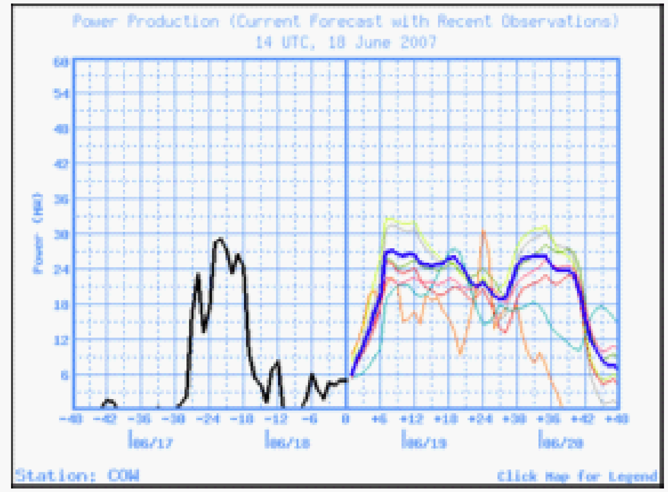
Model Output Statistics (MOS)



- Statistical adjustment to NWP model predictions
  - Account for processes below the resolution of the NWP model
  - Correct for systematic errors caused by the model physics or initialization
- Requires a training sample of concurrent NWP data and measured values of the forecast variable
- Many statistical approaches can be used
  - Statistical models: linear regression, artificial neural networks etc.
  - Training sample strategies: fixed, rolling, regime-based etc.

NWP Ensembles

- Issue: Uncertainty present in any forecast method due to
  - Input data
  - Model type
  - Model configuration
- General Approach: Vary the sources of uncertainty within their range of uncertainty and generate a set (ensemble) of forecasts
- Benefits
  - Ensemble composite typically performs better than any individual forecast over a large sample
  - Ensemble spread provides case-specific measure of forecast uncertainty

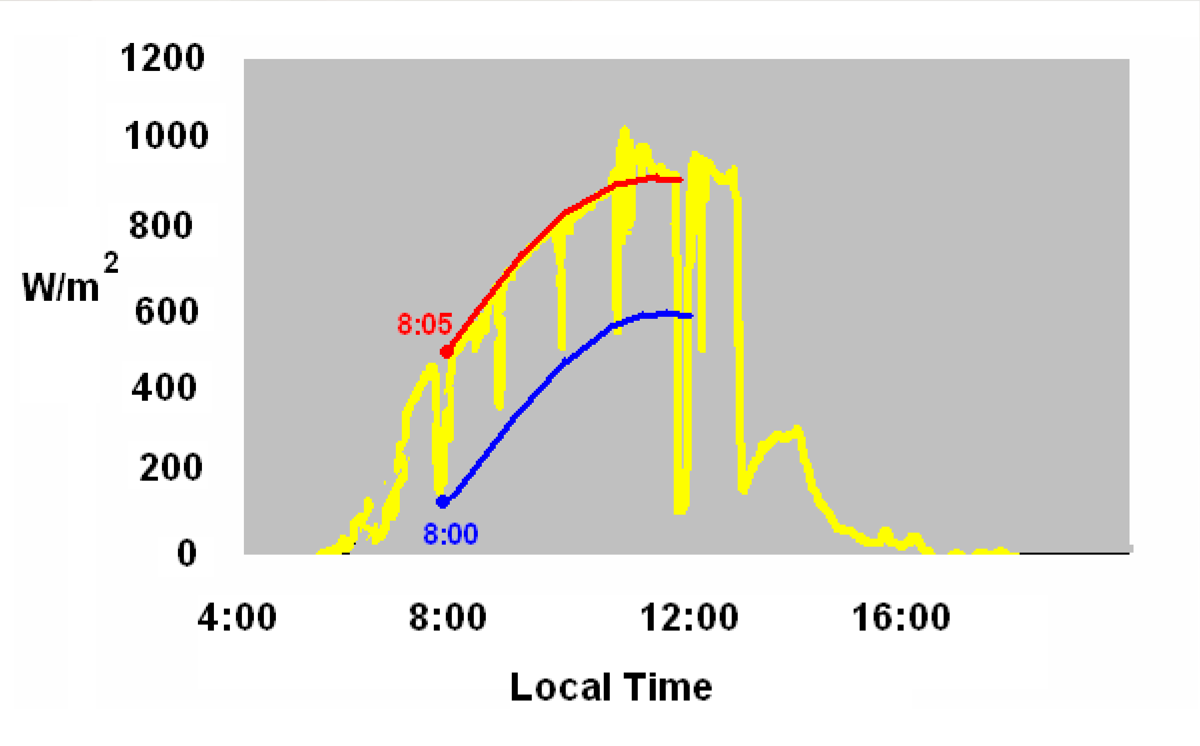


- **Typical Approach 1:** Perturb input data, to produce set of forecasts
- **Typical Approach 2:** Use multiple models or model configurations to produce set of forecasts

Forecasting Techniques - Minutes & Hours Ahead

Persistence and Time Series Methods

- Persistence: Current conditions = forecast
- Usually adjusted for daily solar cycle
- Useful benchmark for other types of forecasts
- Time series methods (e.g. ARIMA) can extend persistence concept by using recent and/or conditional climatological trends

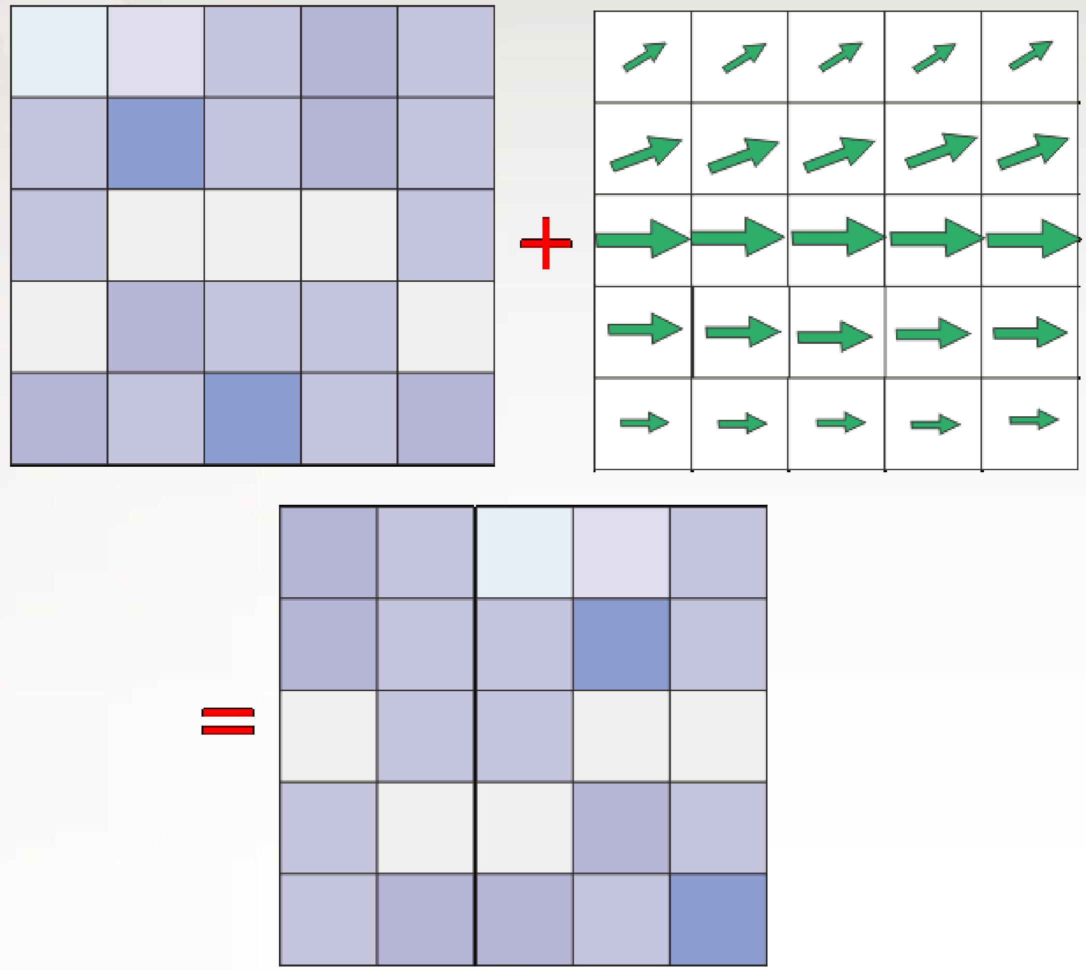


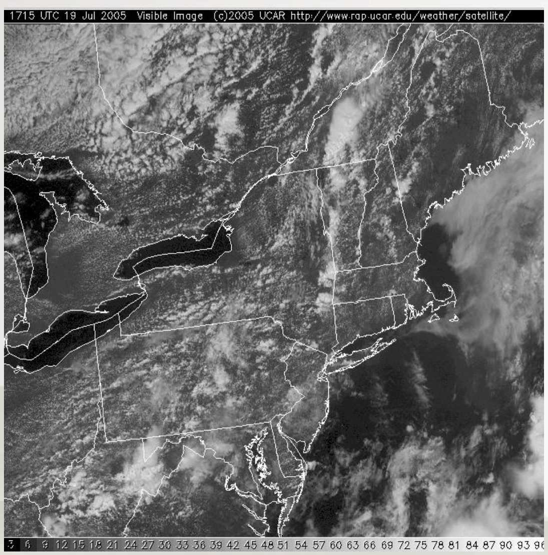
Persistence Irradiance Forecast adjusted for time of day sun angle for 8:00 versus 8:05 AM

Forecasting Techniques - Hours Ahead

Cloud Advection Model

- Obtain initial position of clouds from satellite data
- Obtain wind field from another source (e.g. wind observations from profilers or Doppler radars or NWP model)
- Advect clouds to future positions using wind field





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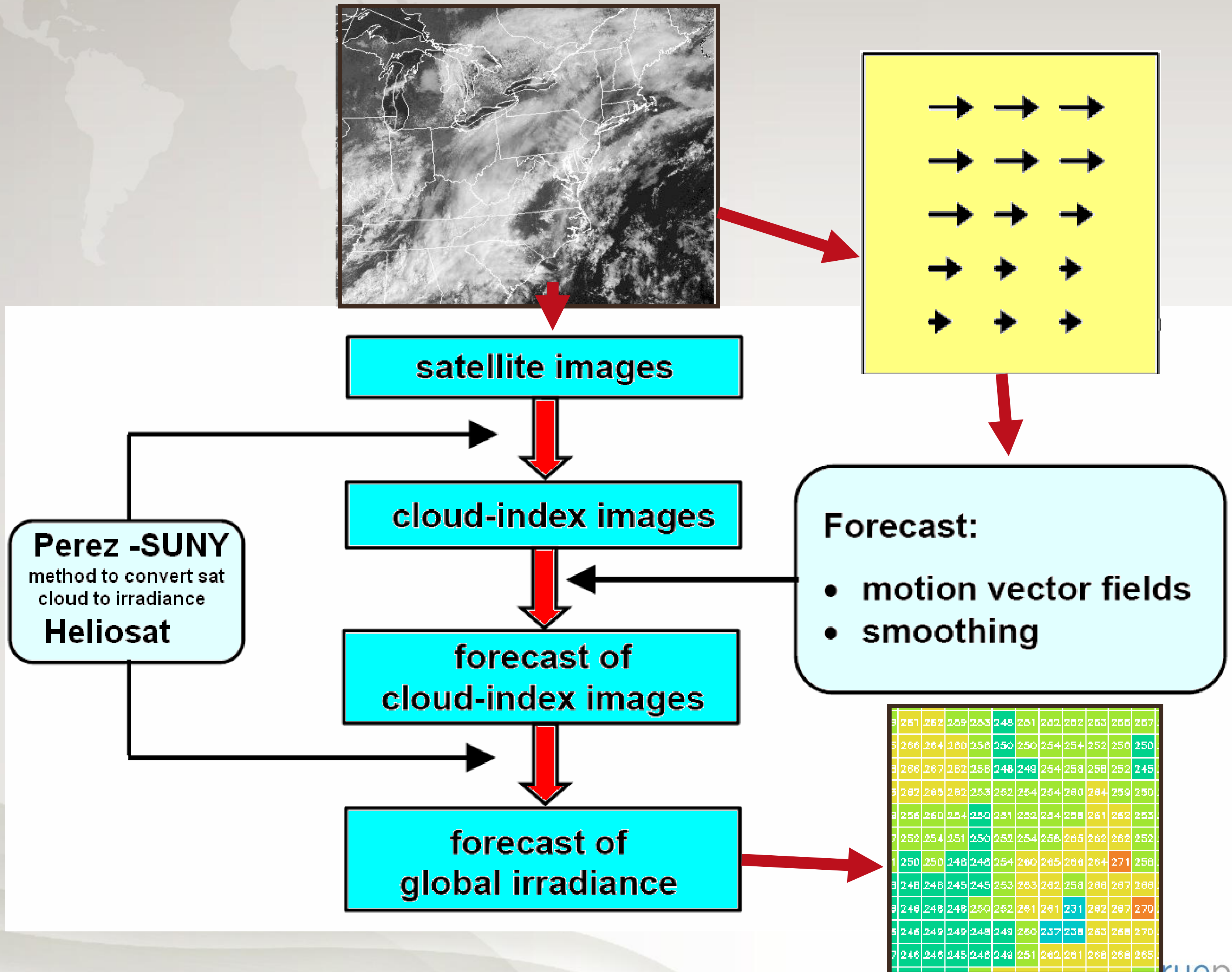
Forecasting Techniques - Hours Ahead

Cloud Vector Motion from Satellite



Forecasting Techniques – Minutes Ahead

SkyCam-Based Methods

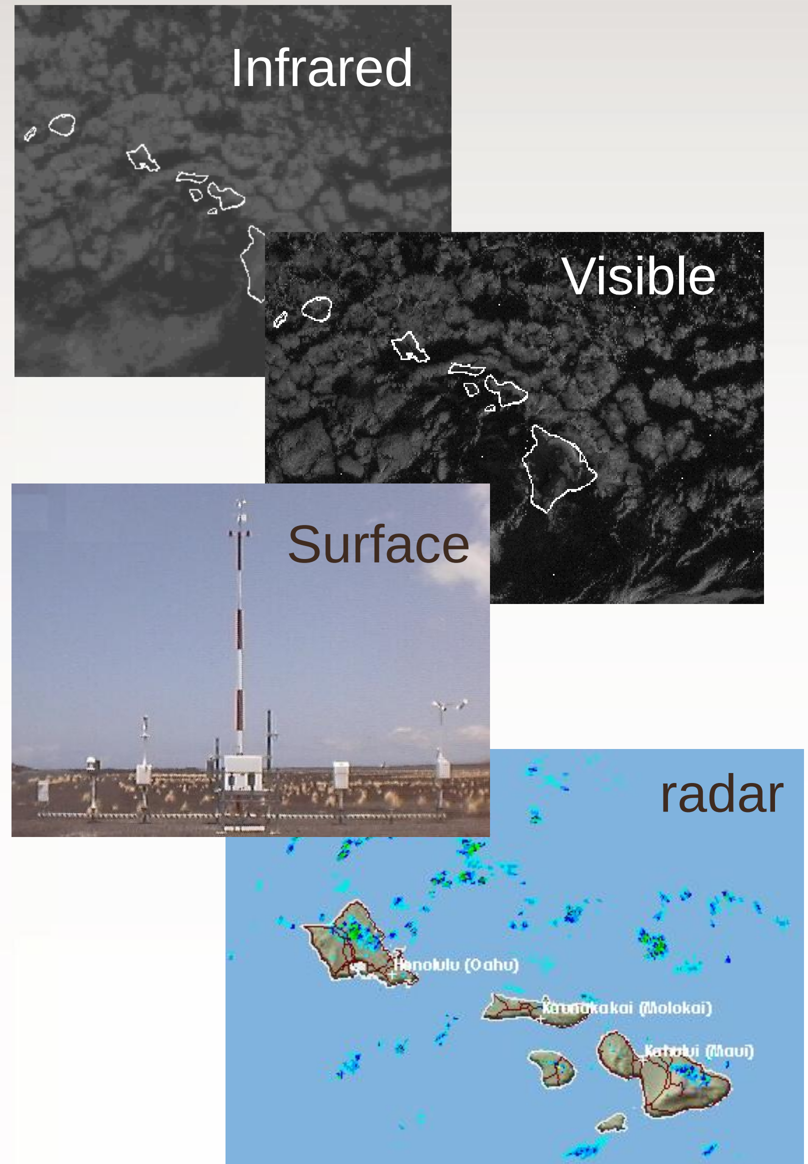
- Cloud motion extrapolation techniques can be applied on minutes ahead time scale using skycam data in place of satellite image data
  - Need source of skycam data
  - Tracks and extrapolates motion of cloud elements
  - Few applications thus far; great potential for 0-1 hour forecasts

Methods

Forecasting Techniques - Hours Ahead

Rapid Update NWP

- Run NWP frequently and at high resolution
  - < 5 km
  - 2 hr or less cycle
- Improve cloud initialization
  - Estimate Cloud top height from infrared satellite imagery.
  - Estimate Cloud coverage from visible satellite imagery.
  - Estimate cloud base height from surface observations.
  - Moisten or dry atmosphere based on knowledge of cloud layers.
  - Locate regions of deep moist air with radar and moisten appropriately
- Improve representation of clouds in the NWP models



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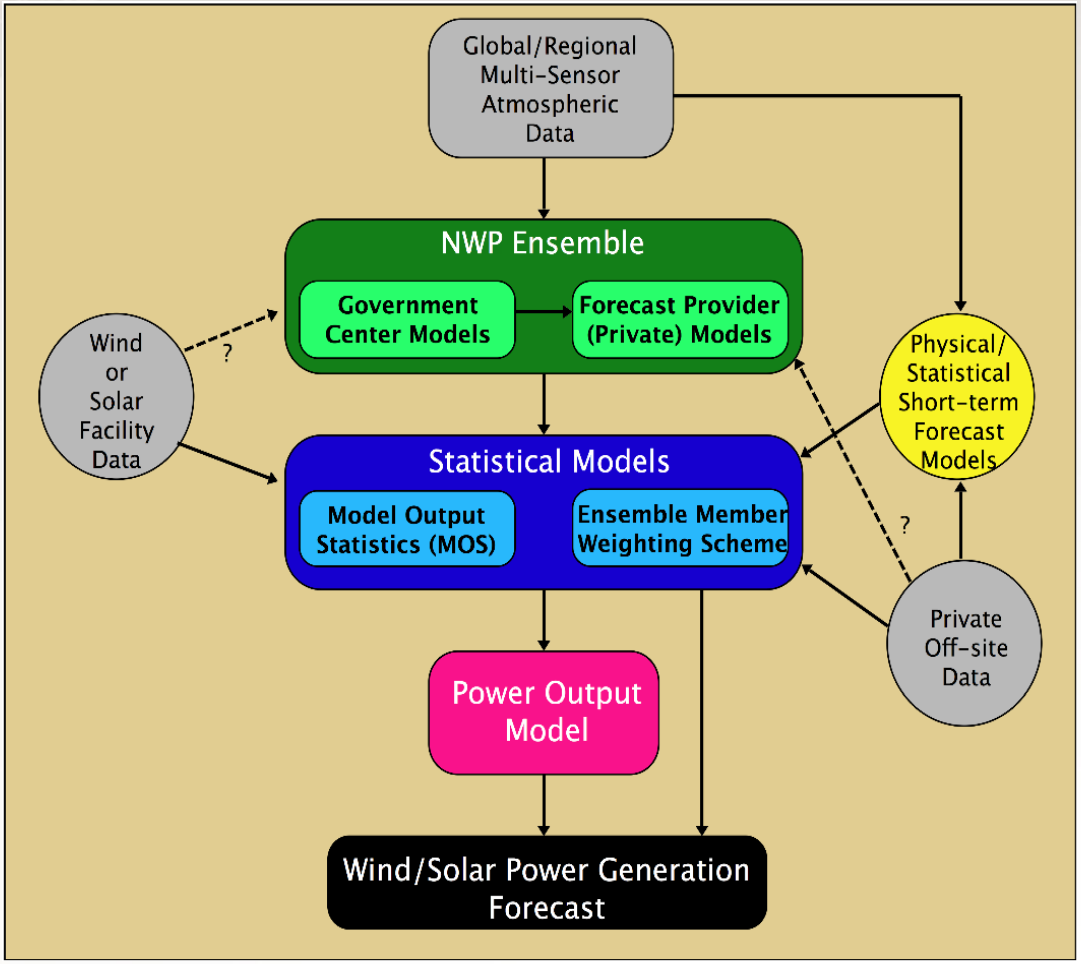
Integrated Solar Forecast System

- Combination of several methods and a variety of input data types
- Ideally: the system seamlessly switches from one technique to another as the look-ahead time increases
- Plant output model must consider the type of solar facility
  - PV, CSP etc
  - Could be a statistical or physics-based model



Types of Forecasts: Deterministic vs. Probabilistic

- **Deterministic**
  - Typically optimized to minimize a performance metric (e.g. RMSE)
  - Deterministic forecasts are simpler to interpret and use
- **Probabilistic**
  - More information than deterministic forecasts
  - The information difference is inversely related to forecast skill
    - At high skill, the difference is small
    - At lower skill levels the information difference is large
  - Studies have demonstrated that a trained user makes better application decisions when using a probabilistic forecast
- **Hybrid**
  - Deterministic time series (but with what performance criterion?)
  - Probabilistic confidence intervals
- **All of these could be in a time-series or event mode**

Solar Forecast Performance: Next Day

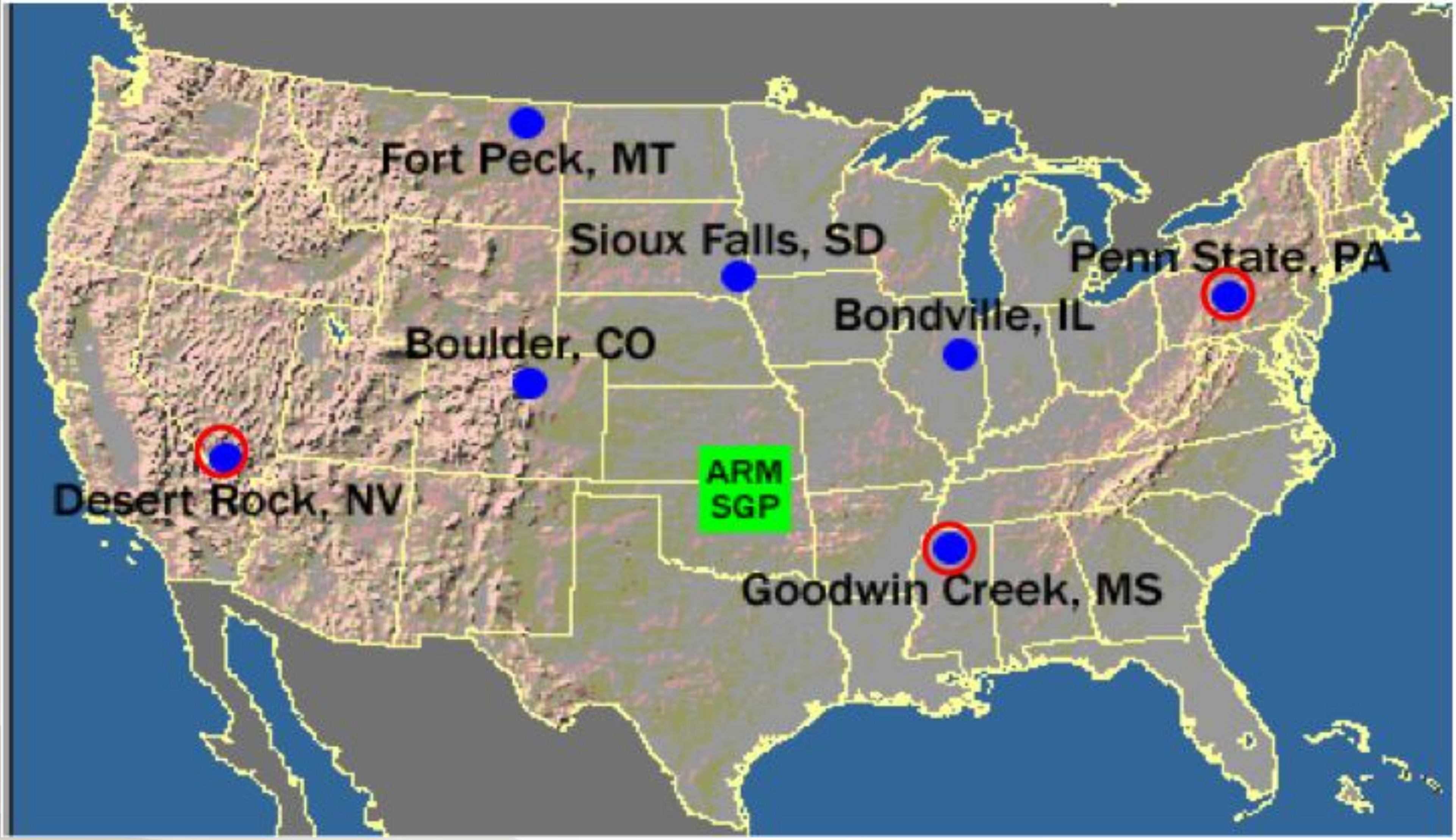
Evaluation Metrics

- **Deterministic**
  - Most widely used: Bias, MAE & RMSE
  - Forecast to observed correlation
  - Error distributions
    - Percentage of time that magnitude of error < threshold
  - Skill Score
    - Percentage improvement of a metric relative to a reference forecast
    - Persistence and climatology are typical reference forecasts
  - Many other possibilities
  - Ideally, metric should measure a user's sensitivity to forecast error
- **Probabilistic**
  - Three key attributes
    - Reliability (most commonly evaluated)
    - Sharpness
    - Resolution
  - Need a measure of all three factors
    - Brier score, Ranked Probability Score (RPSS), etc.

IEA Day-Ahead Forecast Performance Benchmark

- **Background:** Investigation performed in conjunction with the International Energy Agency (IEA) Task 36 NWP Project directed by Richard Perez of the State University of NY at Albany.
  - **Objective:** compare performance of solar irradiance forecasts from different NWP modeling systems
  - Several participants: ECMWF, Environment Canada, SARC, **AWST**, etc.
- **AWST's Sub-project:** Examine performance of solar irradiance forecasts from several mesoscale models and MOS algorithms
- **Evaluation Period:** May 2009 to April 2010
- **Evaluation Approach:** Examine performance statistics (MAE etc.) and analyze specific cases to understand error patterns

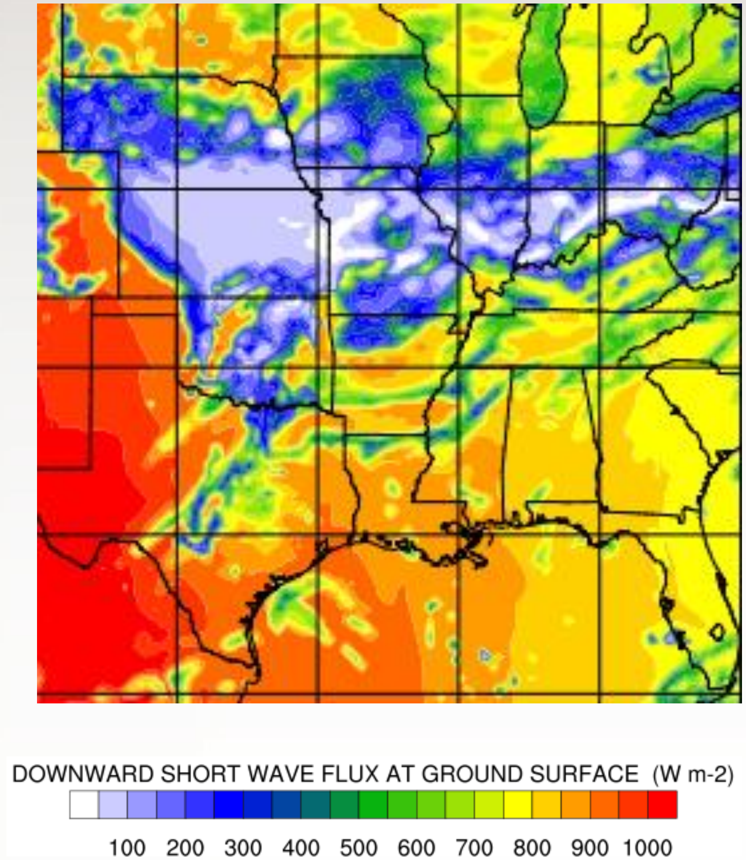
IEA Evaluation Locations: SURFRAD Sites



Forecast Performance – Days Ahead

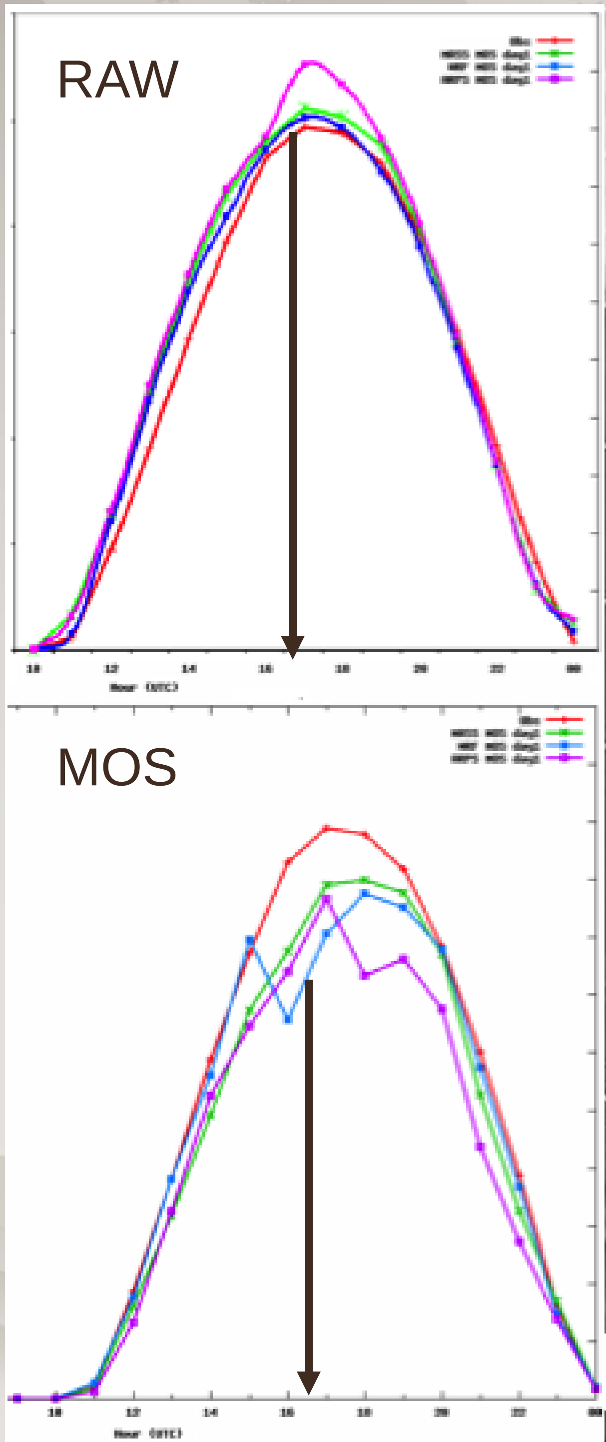
AWST's IEA Project Day-Ahead Experiments

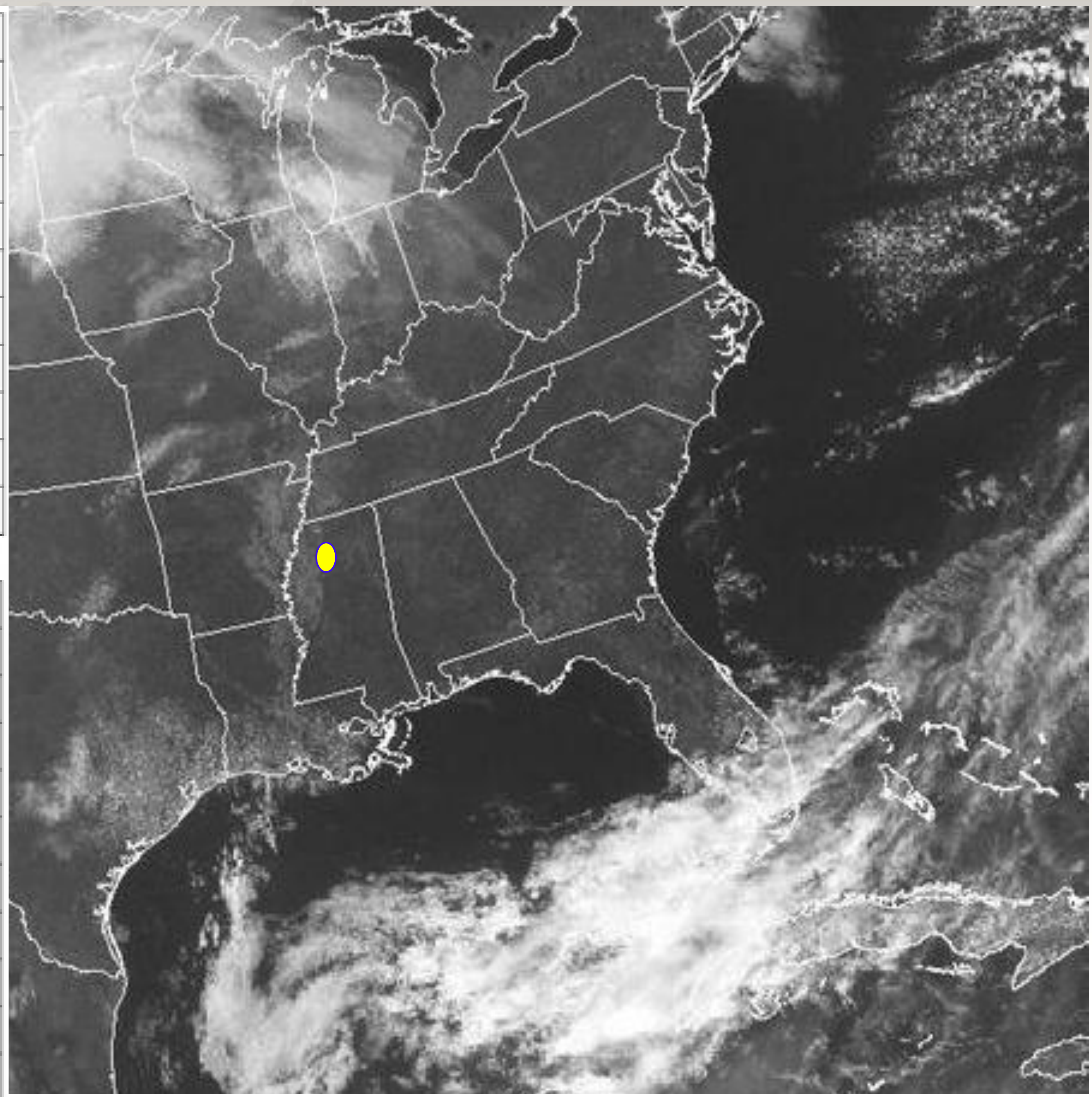
- Three NWP Model Forecasts
  - **MASS:** commercial model (MESO)
  - **WRF**: open source community model
  - **ARPS**: developed at University of Oklahoma
  - Nested grid with 5 km resolution inner grid
  - NOAA's Global Forecast System (GFS) for initial and boundary conditions
  - Forecasts initialized at 0000 UTC each day
- MOS Adjustment for Each Model
  - Screening multiple linear regression
  - Rolling 60-day unstratified sample
  - Predictors are selected output variables interpolated to the forecast location
  - Applied separately to each model's output



NWP forecast of solar irradiance

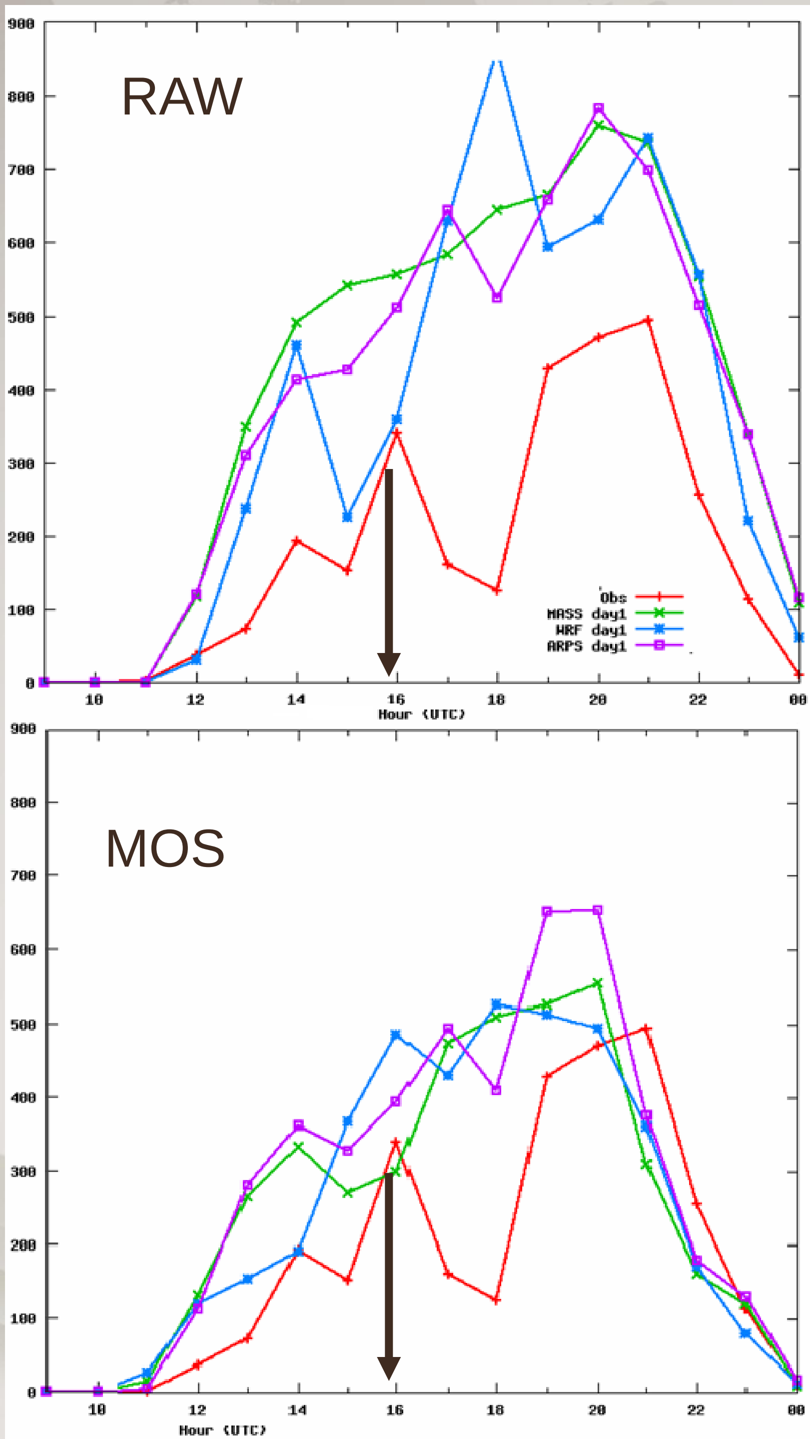
Day Ahead Forecast Example: Clear Day

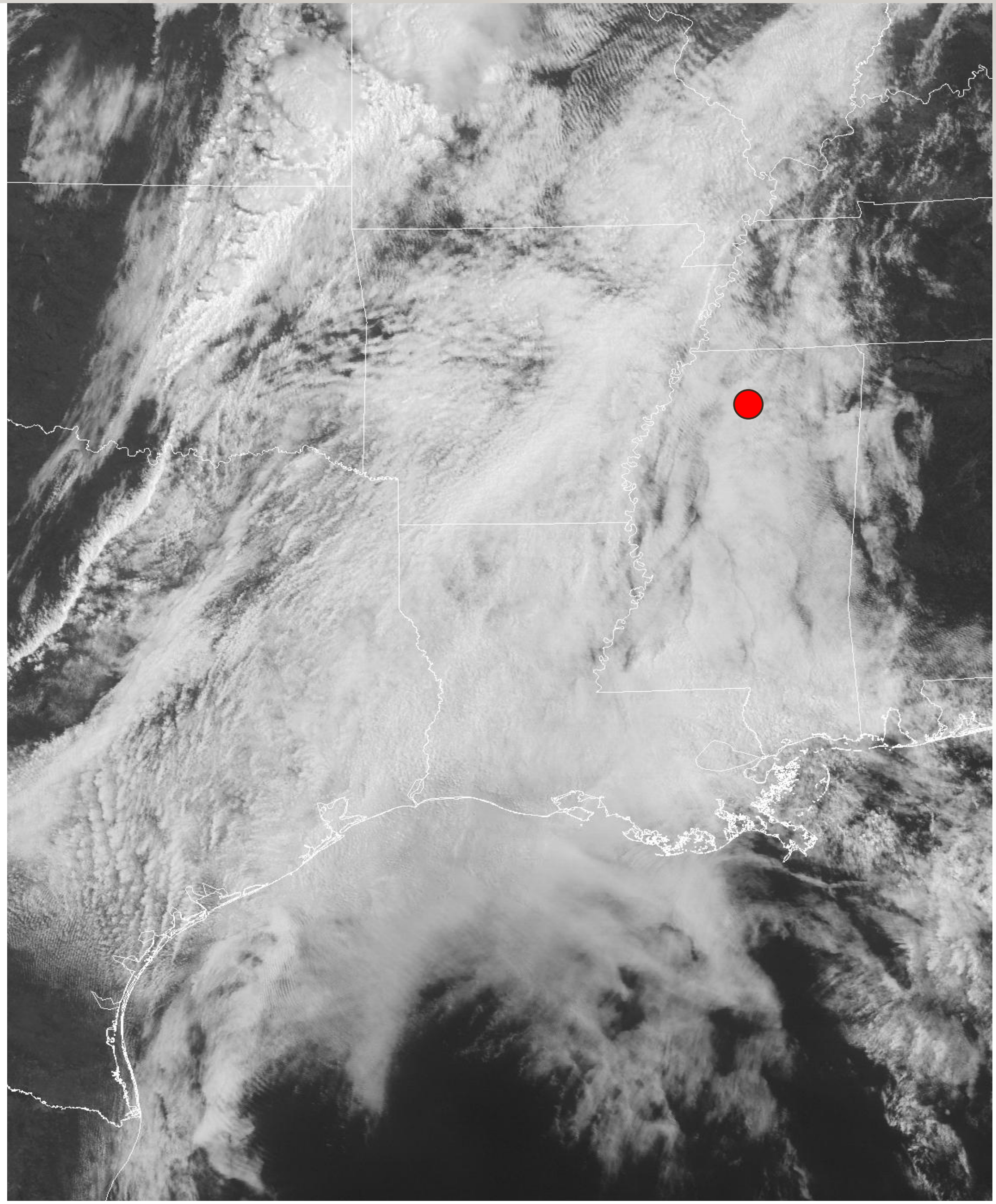




April 29 2010 12:30 PM EDT (1630 UTC)

Day-Ahead Forecast Example: Cloudy Morning





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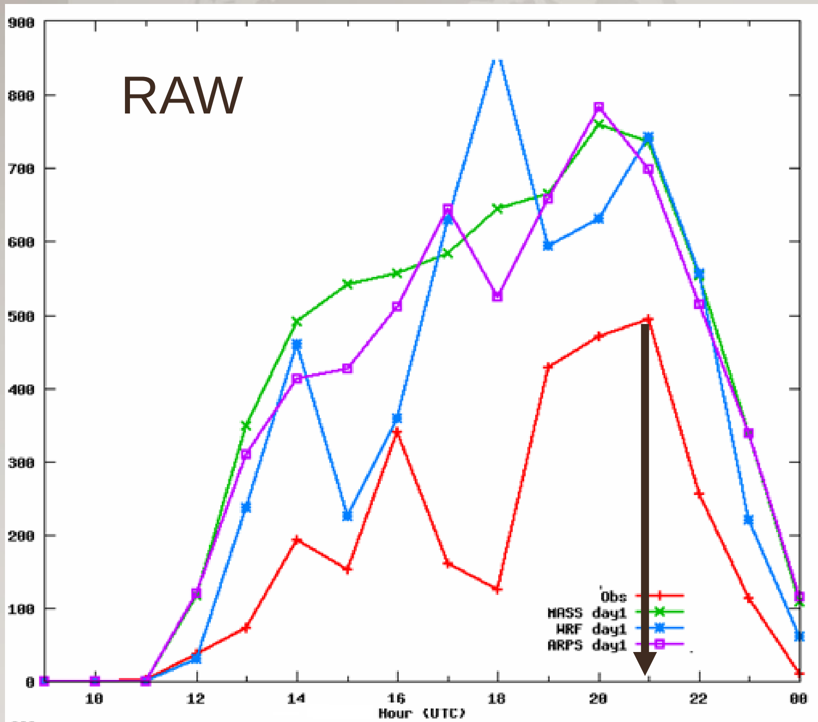
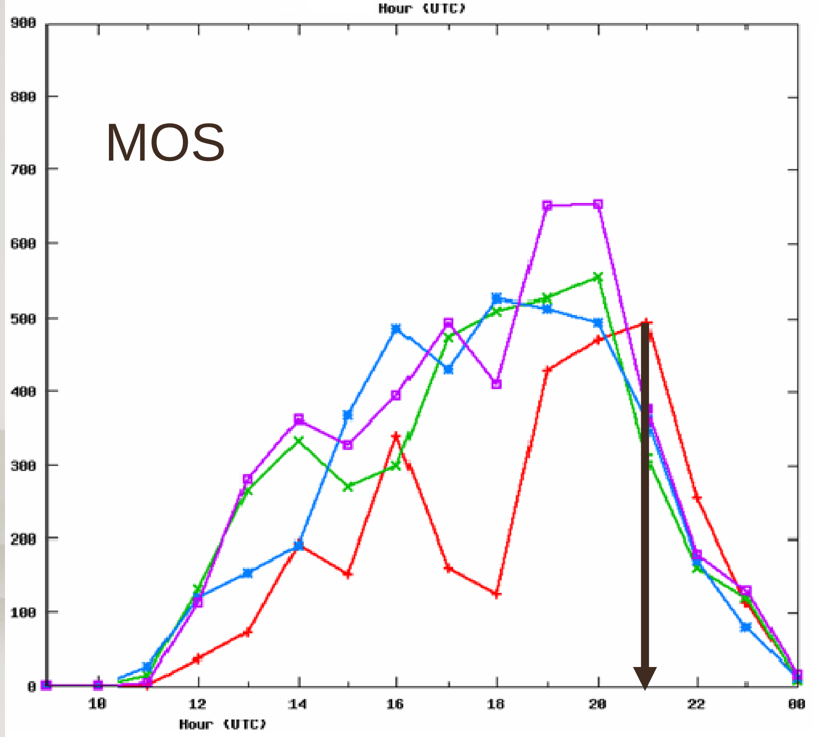
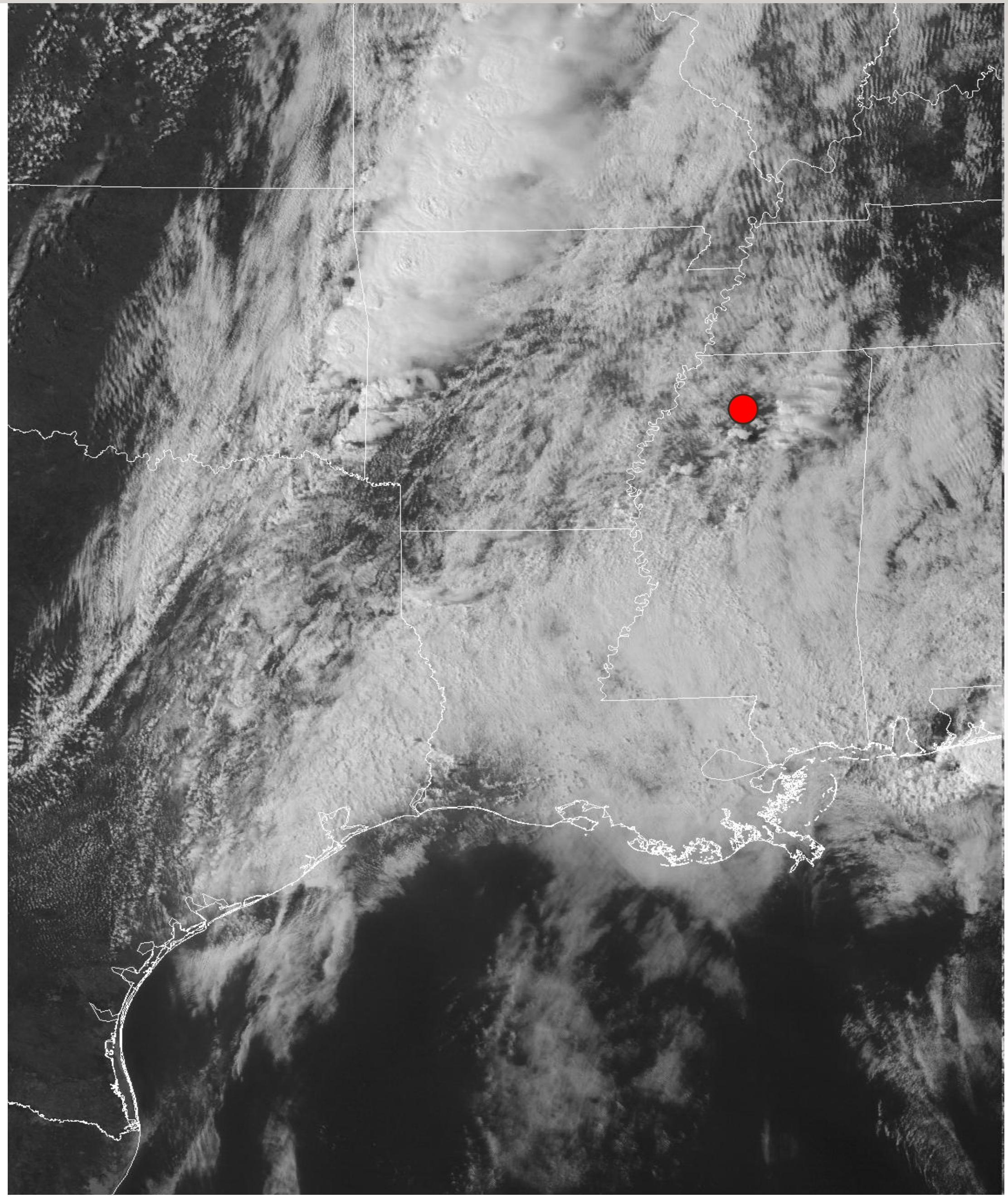
Day-Ahead Forecast Example: Partly Cloudy Afternoon







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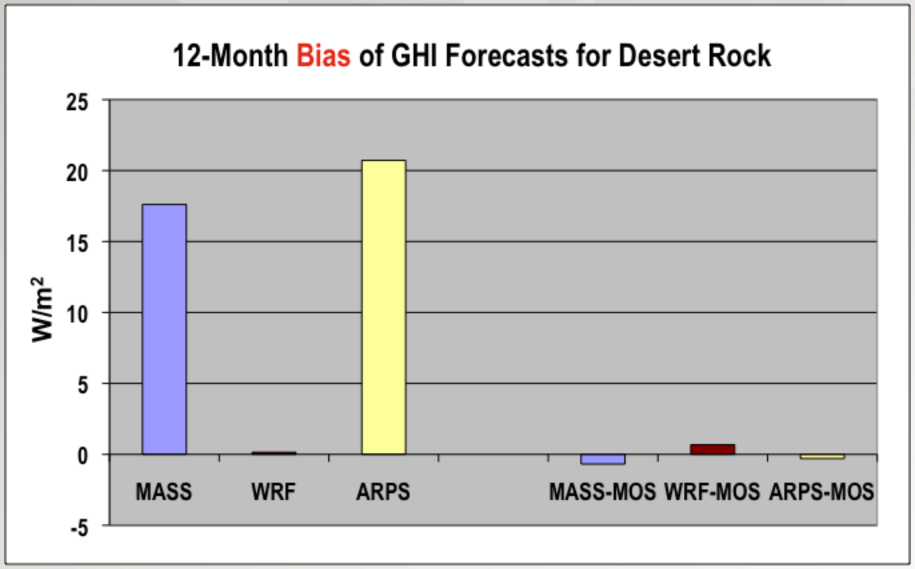
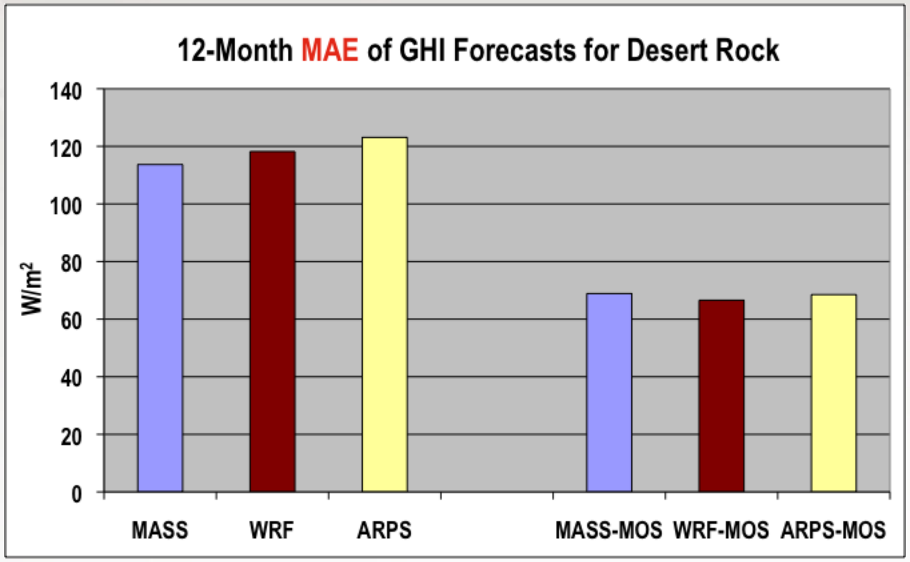
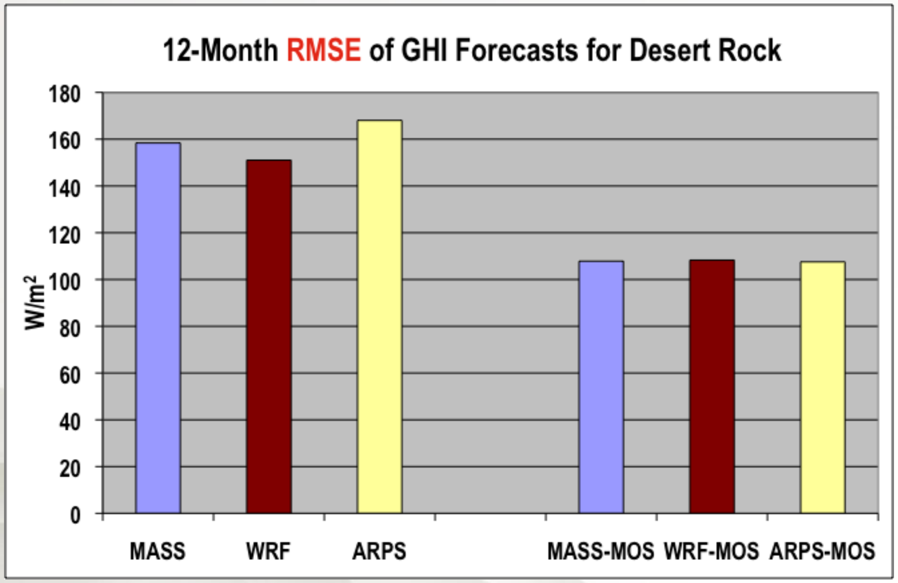
12-Month Bias, MAE and RMSE for Desert Rock Day-ahead Forecasts







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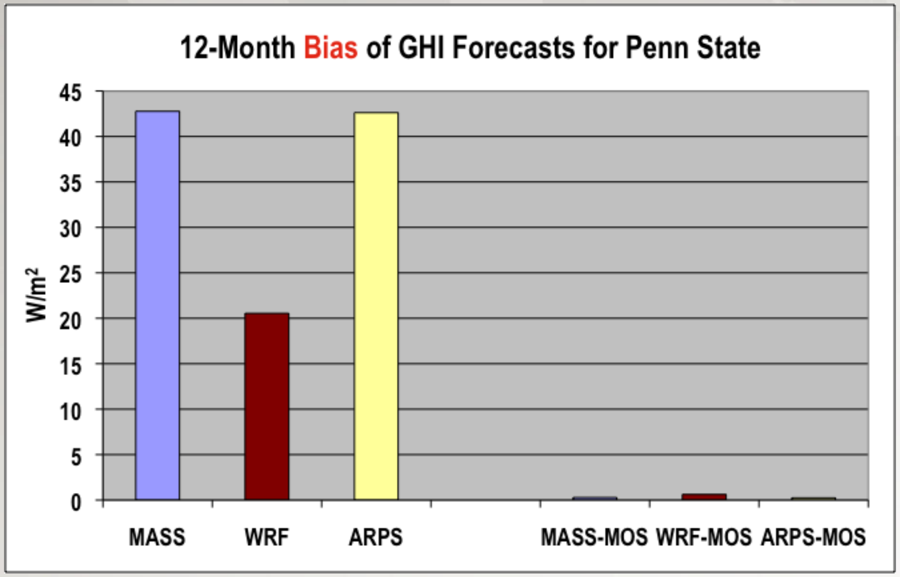
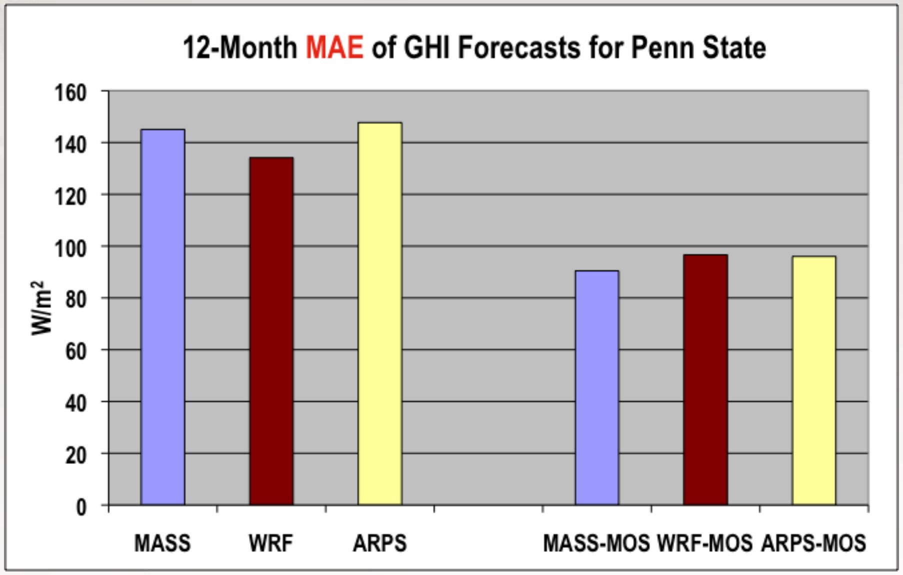
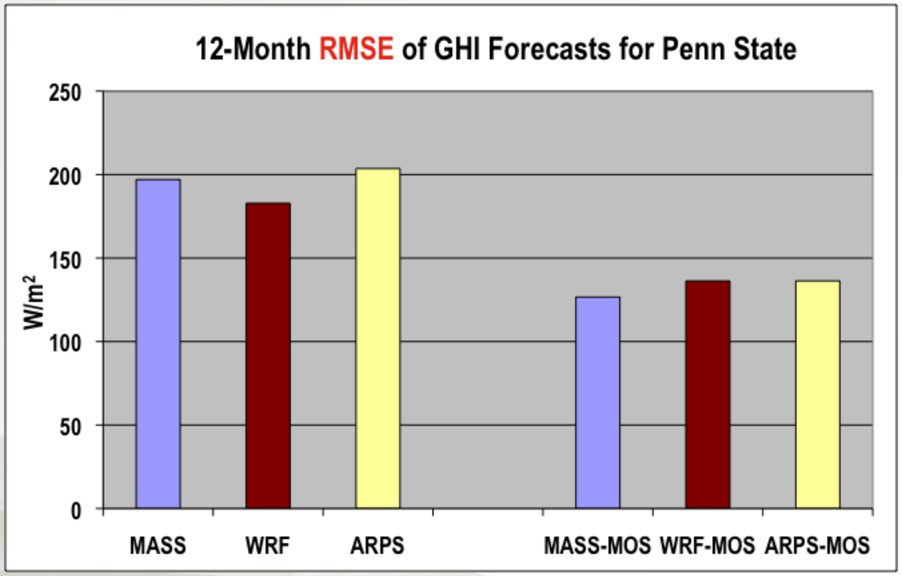
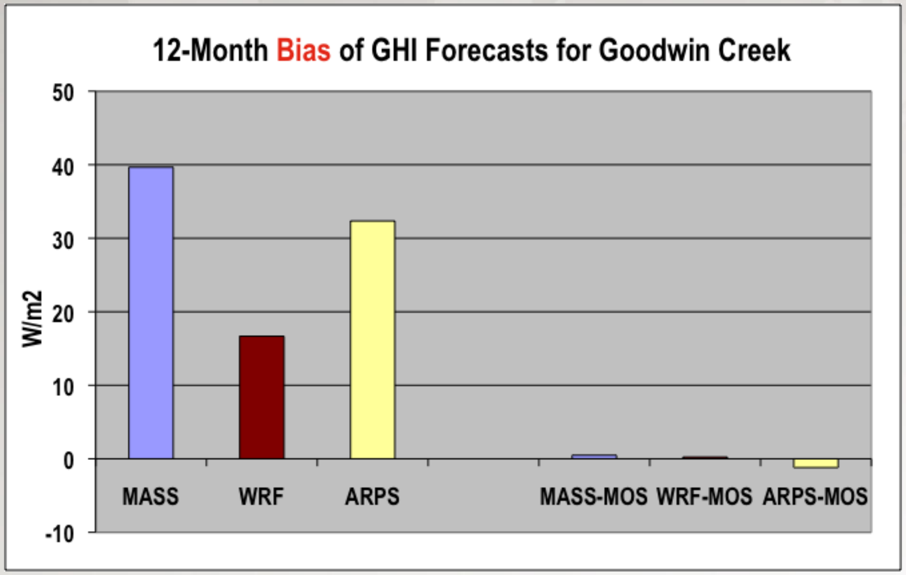
12-Month Bias, MAE and RMSE for Penn State Day-ahead Forecasts

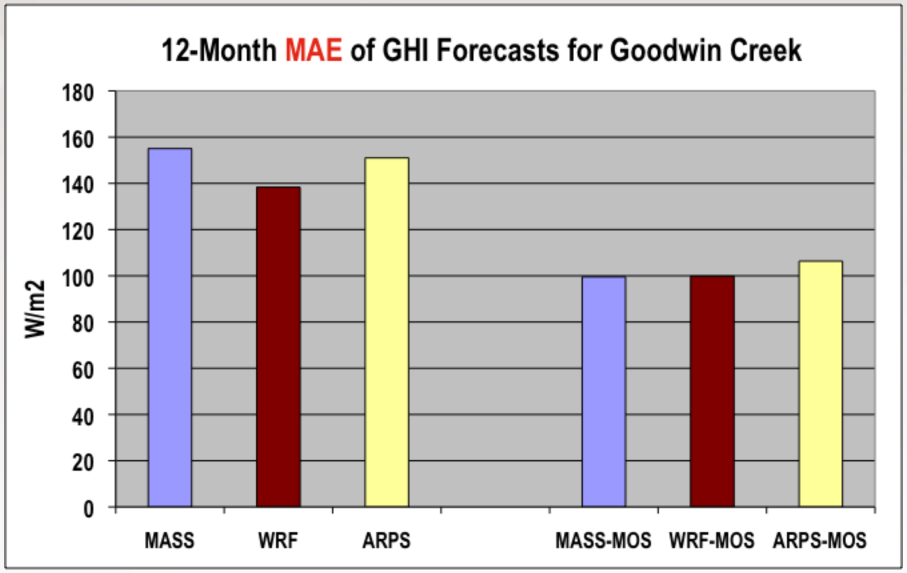


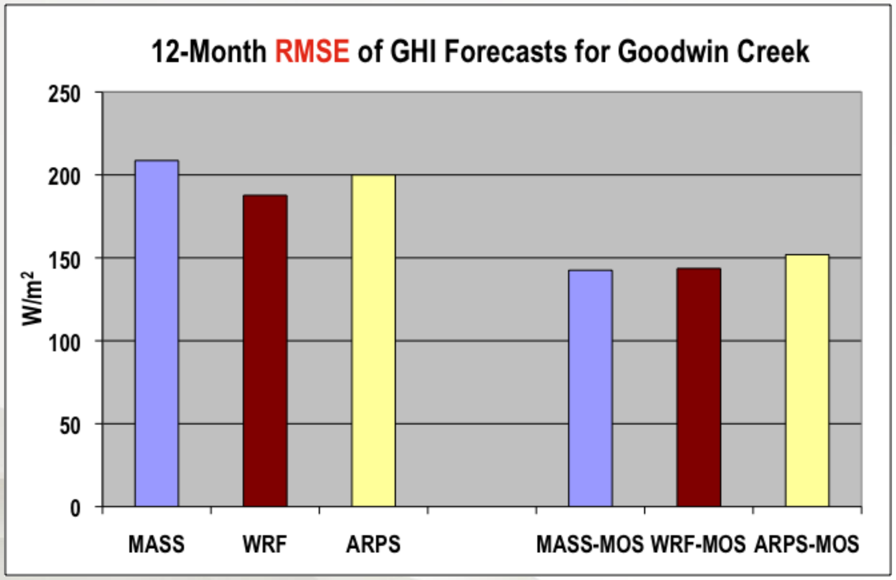




12-Month Bias, MAE and RMSE for Goodwin Creek (Raw and MOS)







12-Month Day-Ahead GHI Forecast Performance Statistics

		RAW NWP			MOS-ADJUSTED NWP		
		MASS	WRF	ARPS	MASS	WRF	ARPS
Bias	DRA	17.61	0.15	20.71	-0.68	0.68	-0.30
	PSA	42.77	20.54	42.62	0.28	0.62	0.24
	GWN	39.66	16.68	32.35	0.49	0.24	-1.19
MAE	DRA	113.69	118.19	123.10	68.88	66.57	68.52
	PSA	145.04	134.12	147.69	90.44	96.63	96.01
	GWN	155.05	138.33	151.00	99.53	99.80	106.35
RMSE	DRA	158.36	151.04	168.04	107.83	108.30	107.54
	PSA	196.98	182.82	203.60	126.64	136.31	136.32
	GWN	208.63	138.33	199.94	142.49	145.55	151.90

Best Performance

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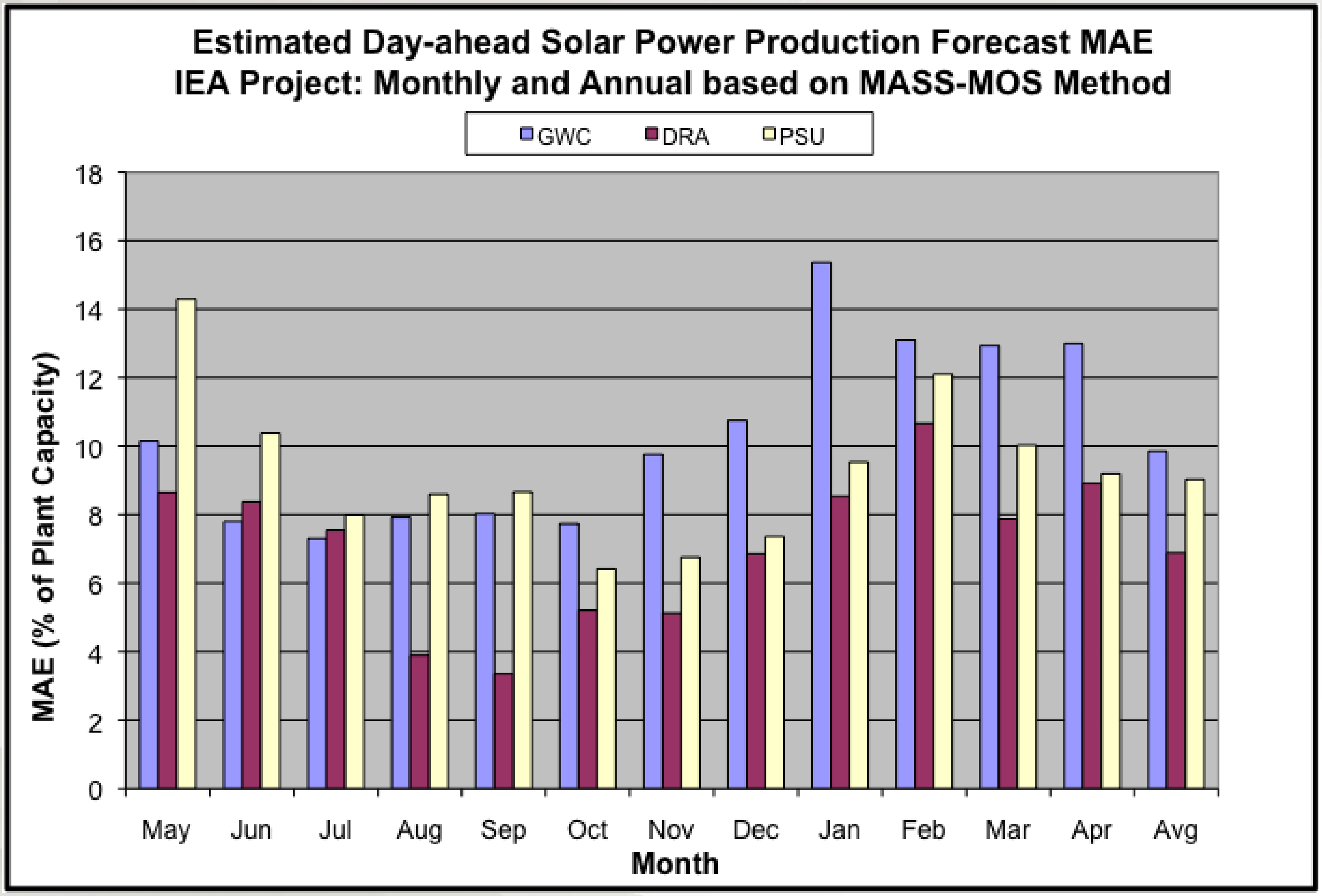
Estimated Solar Power Forecast Performance

- Output model (from AWST data)
- Output model applied to measured and forecasted GHI values
- MAE for all hours of the day with non-zero measured average GHI (daylight)



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Solar Forecast Performance: Hours Ahead

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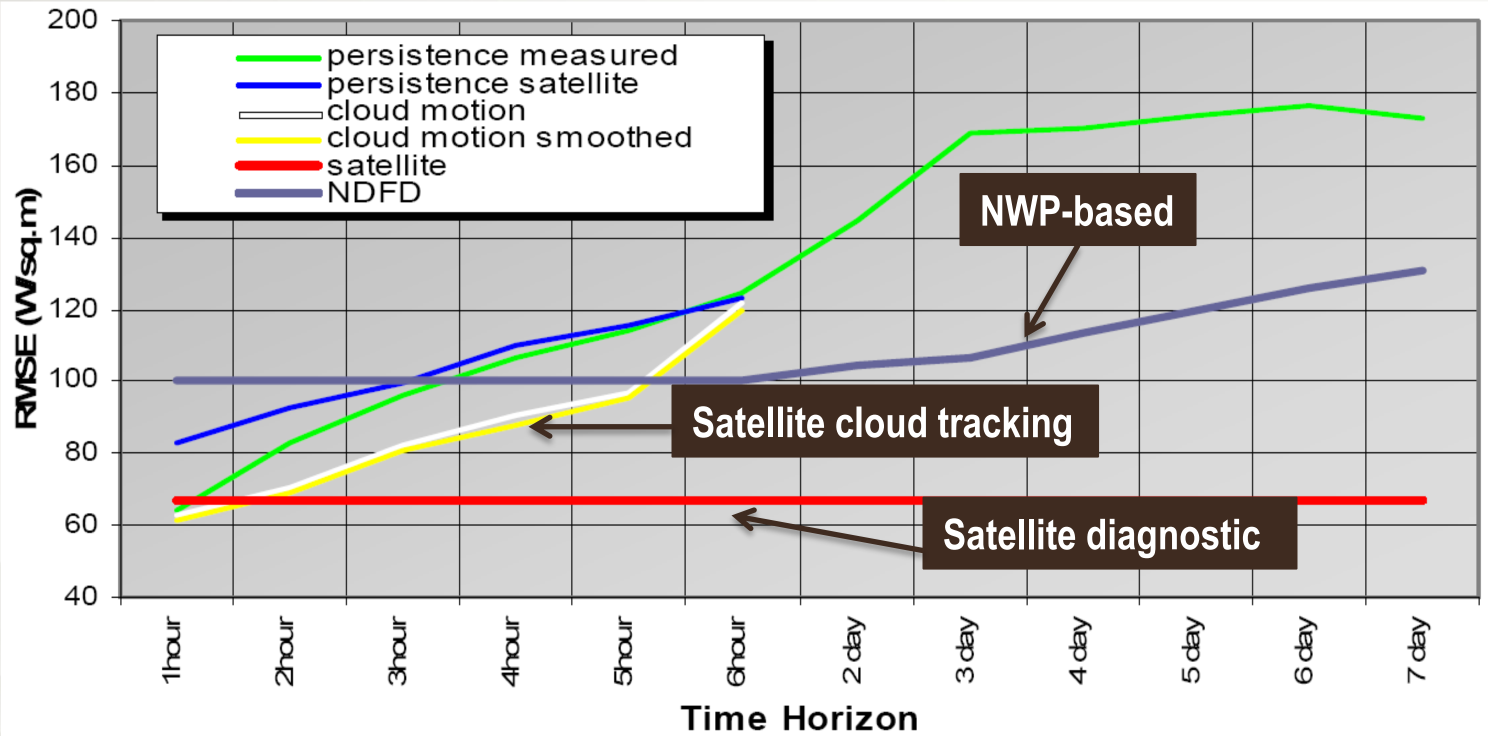
Short-term GHI Forecast Benchmark (U Albany)

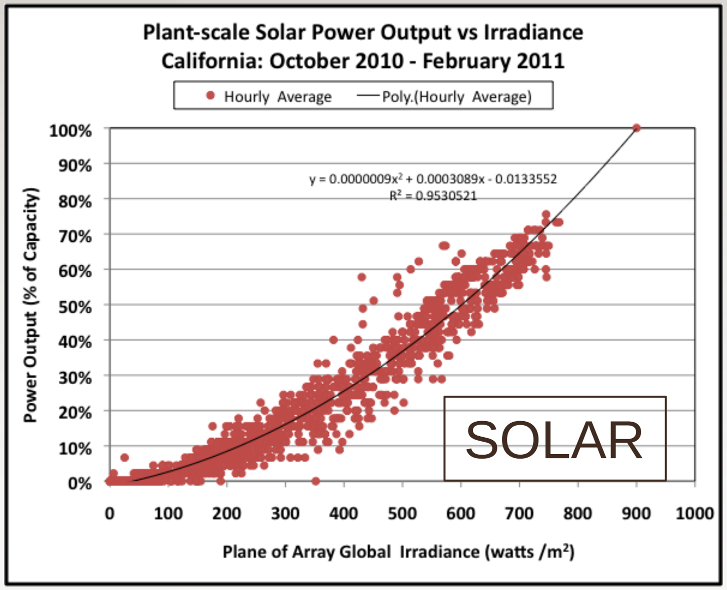
- Period: August 23, 2008 to January 31, 2009 (drier season)
- Composite RMSE for 6 sites
  - Fort Peck, MT, Boulder, CO, Sioux Falls, SD, Bondville, IL, Goodwin Creek, MS, State College, PA
- 5 forecast methods
  - NDFD (NWP-based), persistence satellite, persistence measured, cloud vector motion, cloud vector motion smooth

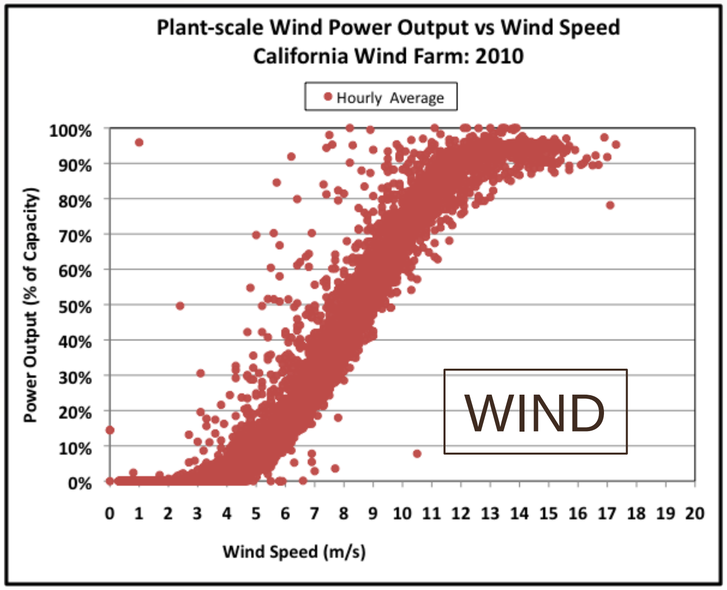


Forecast Performance: Solar vs. Wind

Solar vs. Wind Forecasting

- Location Attributes
  - Utility-scale solar plants are sited in sunny areas
    - Less variable than an average site
  - Wind plants are sited in windy areas
    - More variable than an average site
- Power System Attributes
  - Solar generation has a quasi-linear relationship to irradiance
  - Wind generation is a function of wind speed cubed between start-up speed and rated capacity
- Forecast Input Data
  - Dominant factor is cloud coverage and density which can be spatially observed via satellite and sky-cams
  - Wind speeds patterns can't be as easily observed





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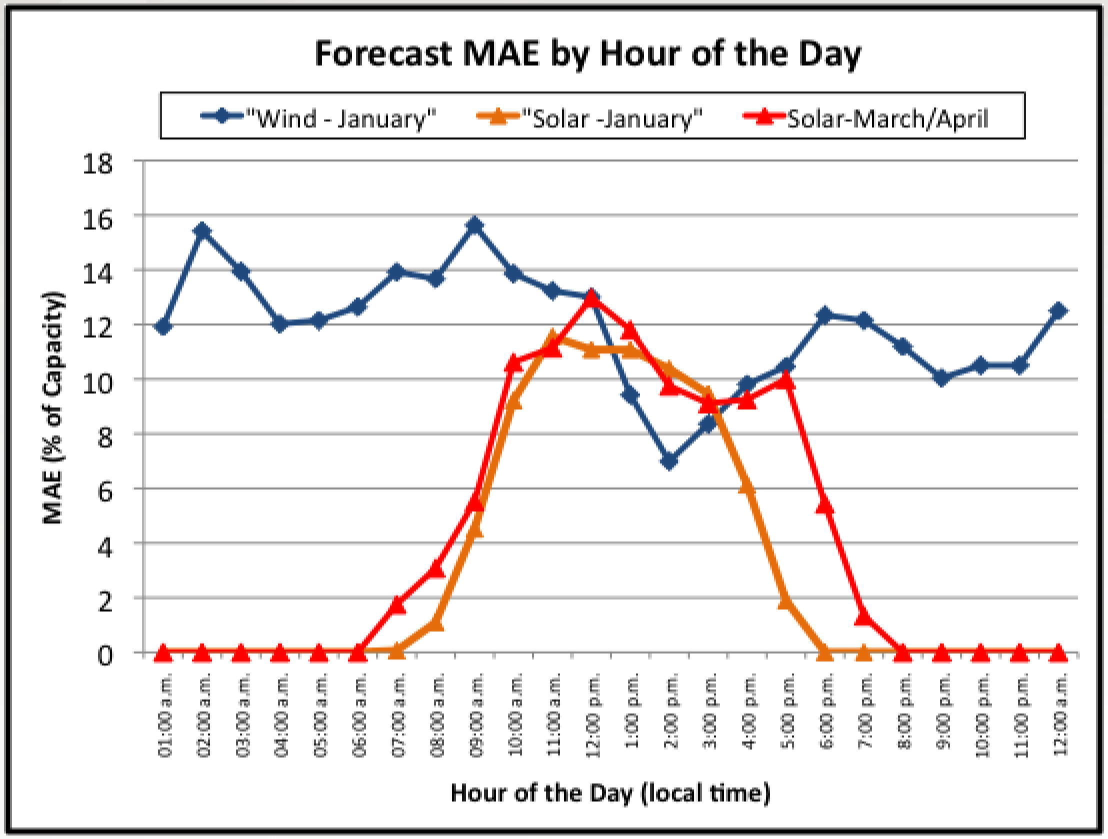
Solar vs. Wind Forecasting Performance: An Arbitrary Real Word Comparative Example

- Wind: ~ 80 MW facility in the ERCOT control area
- Solar: ~ 5 MW facility in central California
- Monthly MAE (% of capacity)
  - Wind: 11.8% (all hours)
  - Solar:
    - For a relatively cloudy time of year
    - 3.1% (all hours)
    - 6.9% (daylight hours)
    - 10.7% (10 AM – 3 PM)



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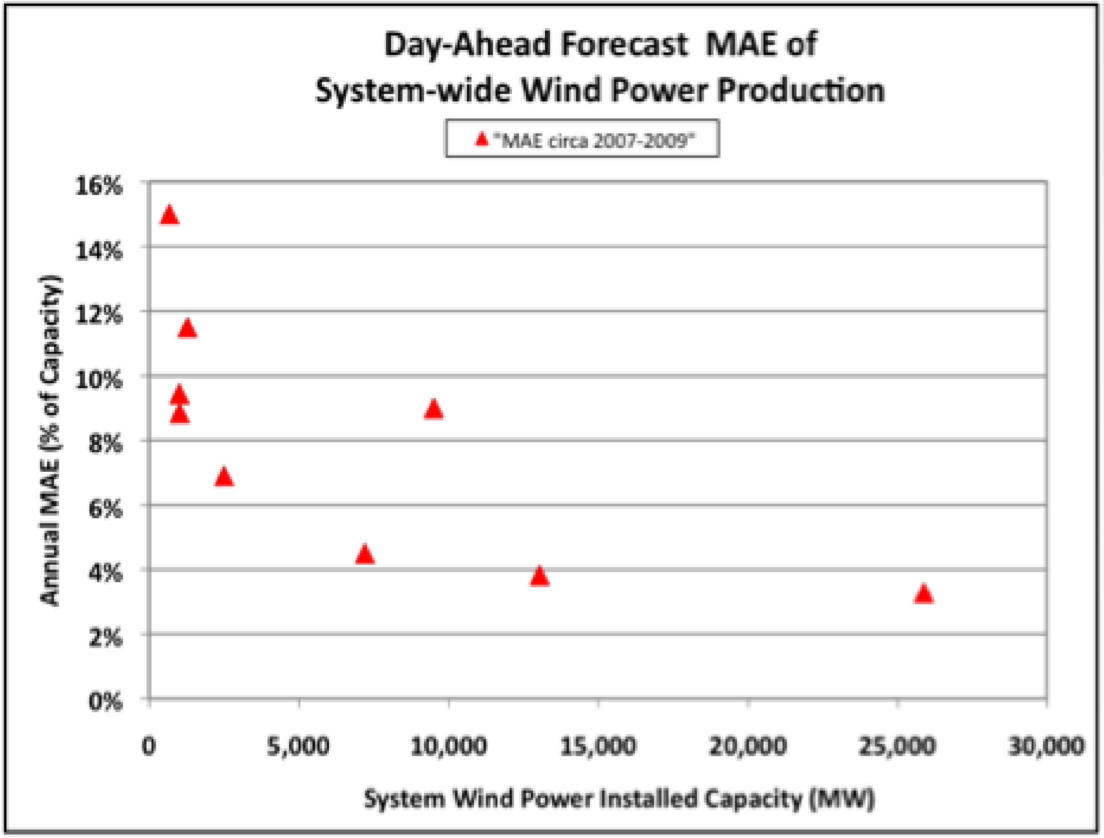
Solar Forecast Performance: Impact of Aggregation

- Impact of aggregation on solar forecast performance has not been thoroughly analyzed
  - Penetration of solar power production is low in most areas
  - Limited data available
- Impact of aggregation is substantial for wind
- What will be the impact of aggregated wind and solar on forecasts of combined generation?



Impact of aggregation on day-ahead wind forecast MAE

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The Road to Increased Forecast Value

Future Prospects:
How can forecast value be increased?

- Improve forecast performance
  - Days ahead
    - Gradual improvement in global/regional NWP model performance due to additional global data, data assimilation system improvements and refinements to NWP models
    - Further near-term improvement due to more sophisticated correction of NWP's systematic errors and statistical weighting of NWP ensemble members – probably diminishing returns soon
  - Hours and minutes ahead
    - Use of customized rapid update NWP
      - Improve cloud initialization and cloud submodels
    - Refinement of satellite-based cloud element tracking methods
      - Techniques to account for cloud development and dissipation
      - Higher resolution satellite-image data
    - Application of skycam-based cloud tracking for 0-1 hr ahead forecasts
    - More sophisticated time series forecasting techniques with off-site data

Future Prospects:
How can forecast value be increased?

- **Develop Distributed Solar Generation Forecast Tools**
  - Inventory of solar generation sites
    - System attributes
    - Operating condition
  - Data from the sites?
  - NWP and satellite-based methods can be easily adapted for this application
  - Statistical schemes need site data (power output or irradiance)
- **Make more effective use of forecast information**
  - Use of probabilistic forecasts
    - Substantial amount of information is discarded when ONLY deterministic information is provided
    - Research studies in other (non-energy) applications have indicated that trained users make better application decisions when using a probabilistic forecast
  - Better forecast integration with decision-maker's procedures

Summary

- State-of-the-art forecasts are generated with a combination of statistical, pattern-recognition and physics-based forecast tools and a variety of input data types
- Relative performance of the forecasting tools varies with look-ahead time – best current tool for each look-ahead range:
  - Weeks / months ahead: statistical links to global indices (e.g. El Nino)
  - 6 hours – 10 days ahead: Statically adjusted ensemble of NWP
  - 1 – 6 hours ahead: Satellite-based cloud motion extrapolation
  - 0 – 1 hour ahead: Sky-cam based cloud motion extrapolation
- “Typical” day-ahead forecast errors for an individual facility:
  - GHI: 75 watts/m^2 to 175 watts/m^2
  - PV plant power output: 8-13% of capacity during peak generation hours
  - Overall performance is better for sunnier sites
- Potential for improvement in the near-term is highest for minutes and hours ahead forecasts