Eastern Wind Integration and Transmission Study (EWITS)

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Objectives

AWS Truewind

- Simulate the impact of up to 30% penetration of wind generation in the eastern United States
- Three years: 2004-2006
- 10 minute time resolution
- 300-400 GW (onshore + offshore)
- Focus on transmission constraints, new transmission requirements, and generation reserves
- AWS Truewind role: develop wind plant data sets

AWS Truewind

AWS Scope of Work for EWITS

- Test mesoscale model configurations; select the best one
- Select 600+ GW of onshore and offshore project sites
- Simulate historical 10-minute winds and plant production at all sites for 2004 to 2006
- Simulate forecasts for the same sites
- Synthesize one-minute data for representative periods
- Summarize in Validation (Jul 2008) and Final Project (Nov 2008) reports

Mesoscale Model Validation

- Determine best model and configuration
- Test four configurations of MASS and three configurations of WRF

WRF standard configuration
- No additional observational data
- 28 vertical levels
- 2-way nested horizontal grids
- Yonsei State University boundary layer scheme

MASS standard configuration
- Rawinsonde data
- 25 vertical levels
- 1-way nested horizontal grids
- Turbulent kinetic energy boundary layer scheme

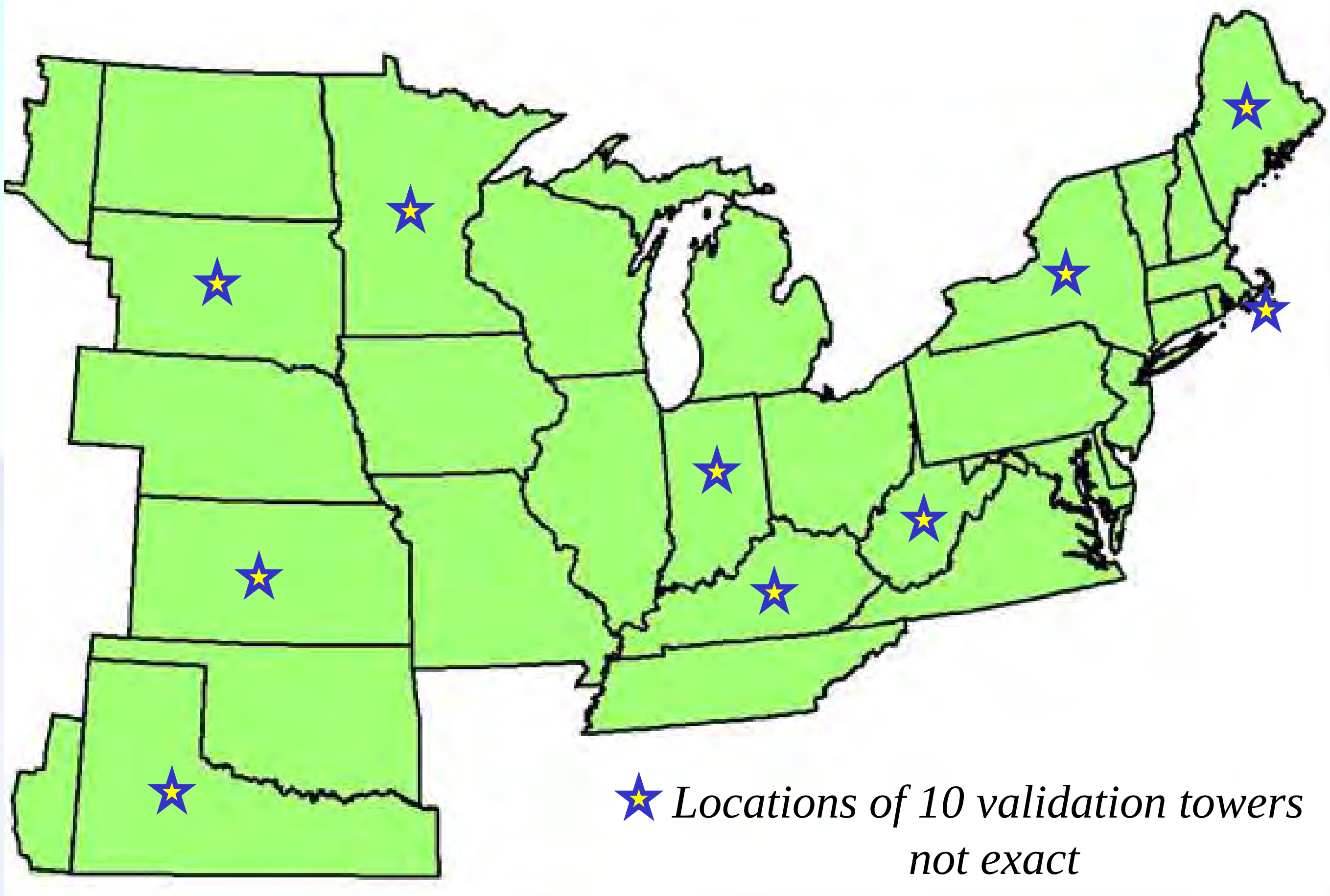
Experiment	Model	Initialization Data, Res	Other
1. MASS/NNGR	MASS 6.8	NNGR, 190 km	
2. MASS/NARR		NARR, 32 km	
3. MASS/NNGR/sfc		NNGR, 190 km	Surface data
4. MASS/NNGR/35 levels		NNGR, 190 km	35 vertical levels
5. WRF/NARR	WRF 2.2.1	NARR, 32 km	
6. WRF/NNGR		NNGR, 190 km	
7. WRF/NARR/MYJ		NARR, 32 km	MYJ PBL scheme

MASS = Mesoscale Atmospheric Simulation System, a proprietary numerical weather model
WRF = Weather Research and Forecasting model, the leading community model
NNGR = NCEP/NCAR Global Reanalysis data; NARR = North American Regional Reanalysis

Mesoscale Model Validation (2)

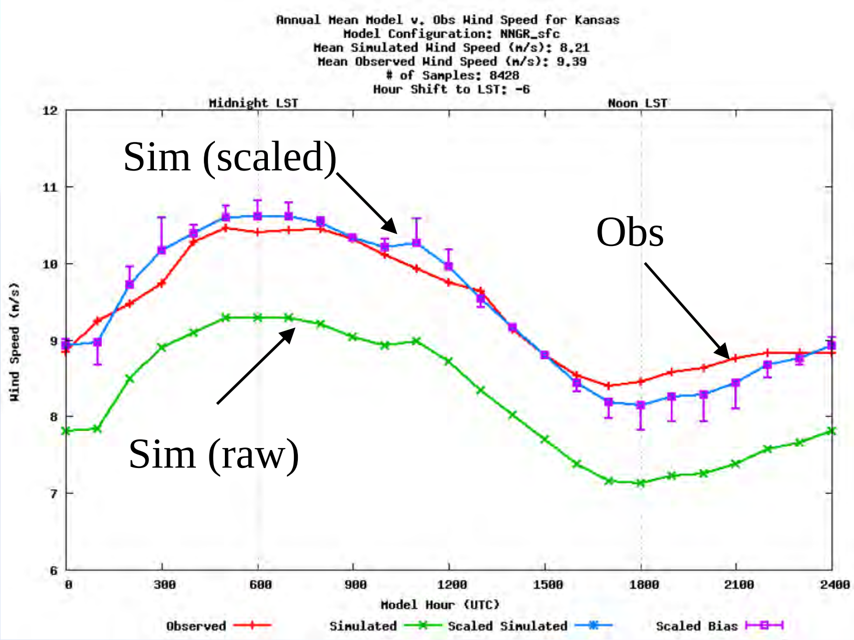
- Generate simulations for 26 two-week periods from 2004-2006 (offshore only 2004) with each model and configuration
- Compare simulated 80-m winds with 80-m data validation towers for 10 sites
- Compute mean bias, mean absolute error (MAE), and scaled mean absolute error (SMAE)
- Derive SMAE using ratio of observed to simulated mean speed over entire period of comparison

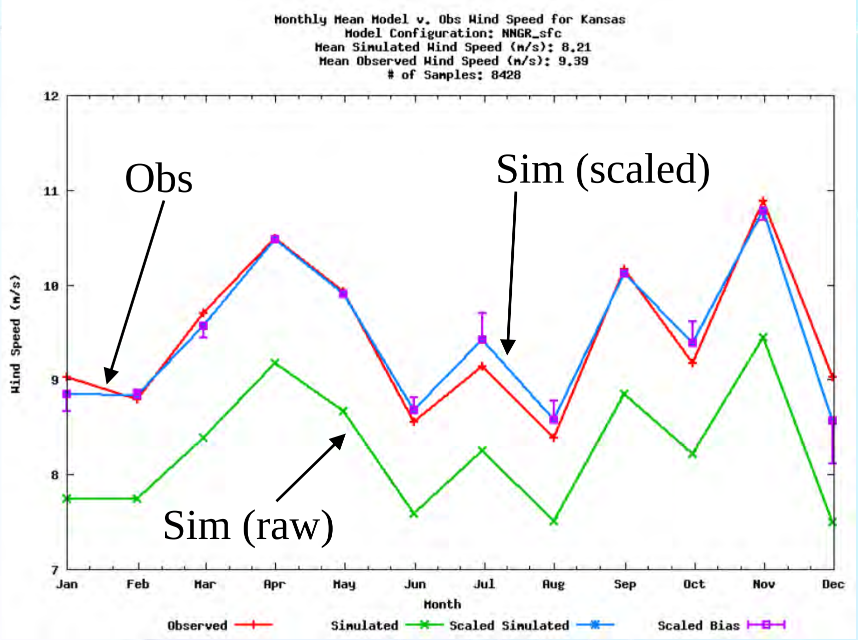
Validation Towers



Validation Example

Kansas



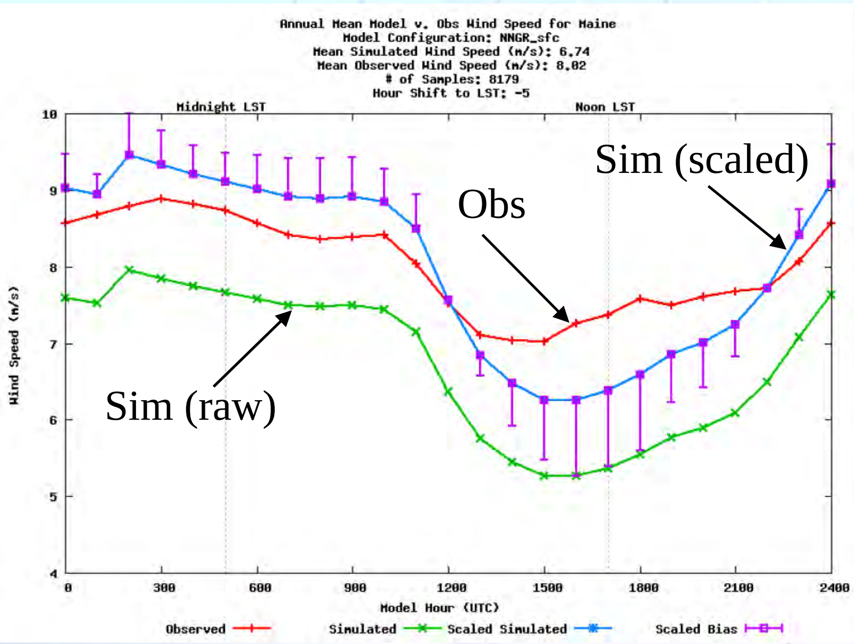


Diurnal

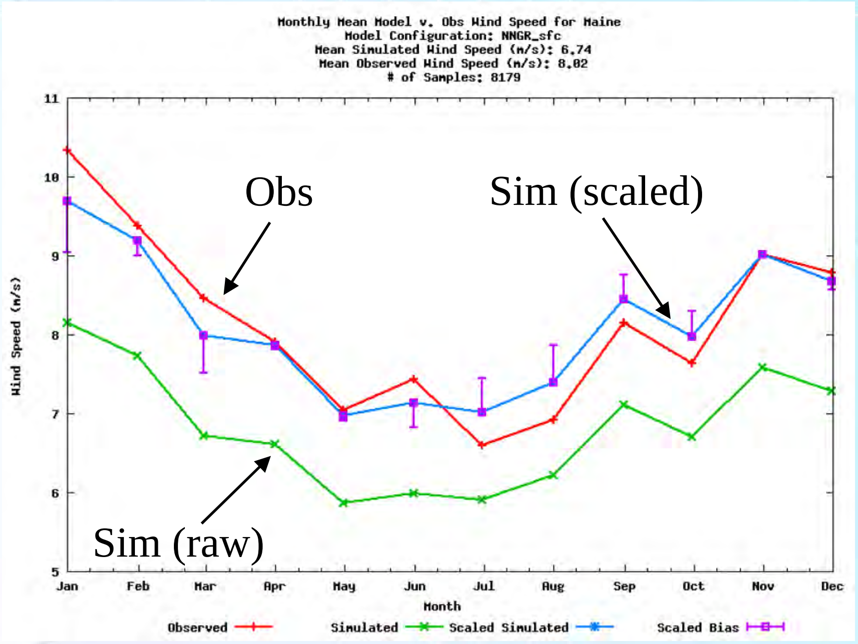
Monthly

Validation Example

Maine

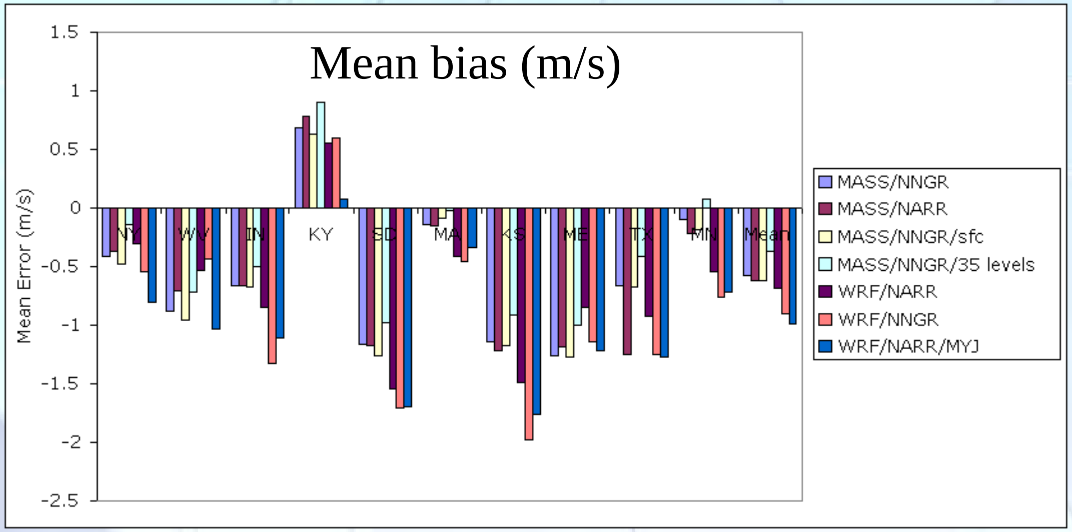


Diurnal

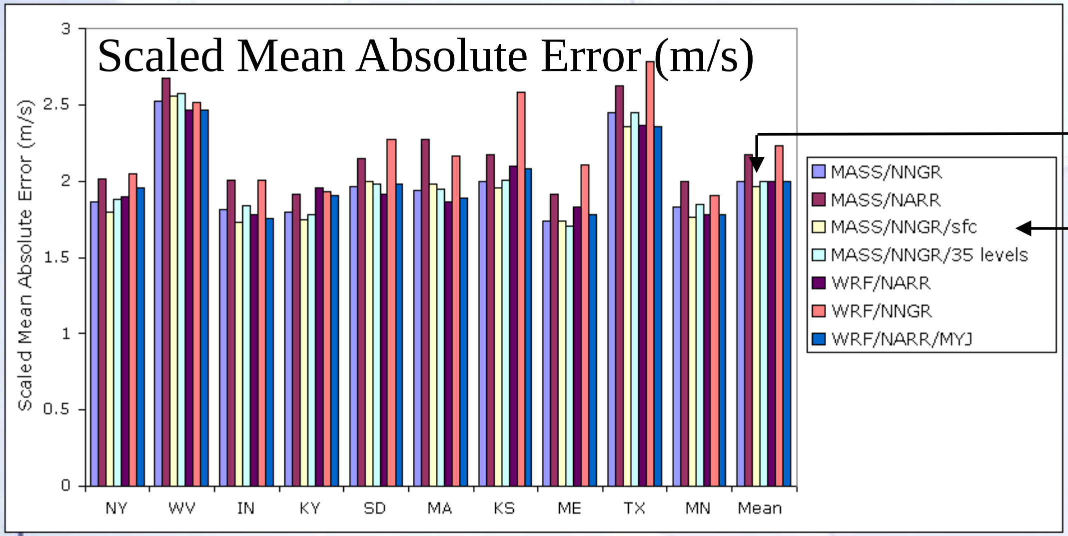


Monthly

Results



Negative bias likely due to towers being on elevated features not resolved by model at the current 2-km grid



By a very small margin, MASS/NNGR/sfc had the lowest overall SMAE

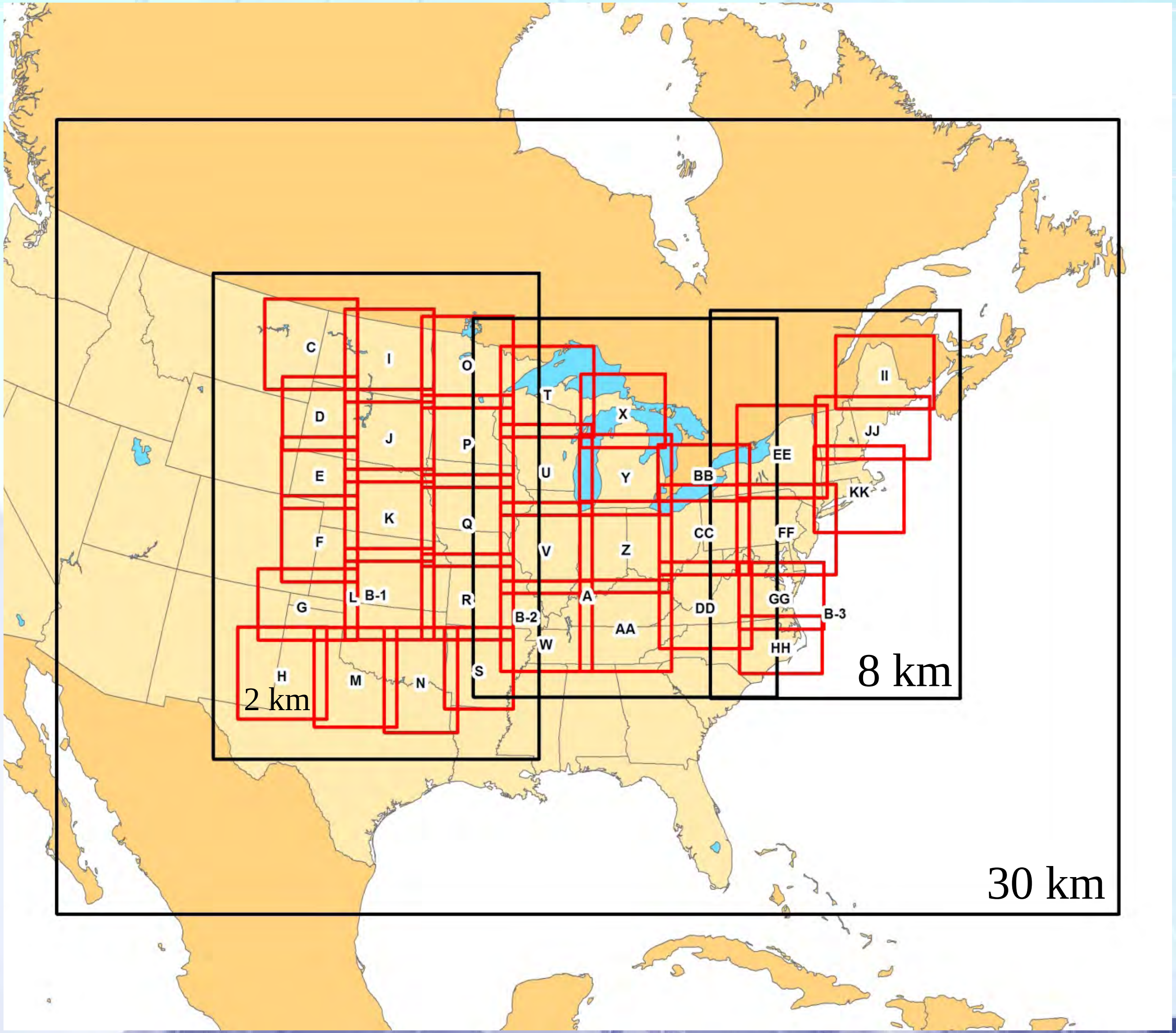
Main Mesoscale Simulations

- Mesoscale runs carried out over period from May – Sep 2008
- Simulations covered 3-yr period (1 Jan 2004 – 31 Dec 2006)

Model configuration for simulation runs

Model	MASS v. 6.8
Initialization data source	NNGR
Data assimilated (30- and - km grids only)	Rawinsonde, standard surface observations
Sea-surface temperatures	MODIS (1-km satellite based)
Terrain and land cover (2-km grid only)	USGS 40-m CDED and 30-m LULC
Cumulus scheme (30- and 8-km grids only)	Kain-Fritsch
Spin-up	12 hours before start of valid run
Duration	15-16 days (e.g. 1-15 Jan)
Output frequency	10 minutes
Variables stored	U, V, T, p, turbulent kinetic energy at five heights T_s, p_s, humidity, radiation, precipitation

Mesoscale Model Grids



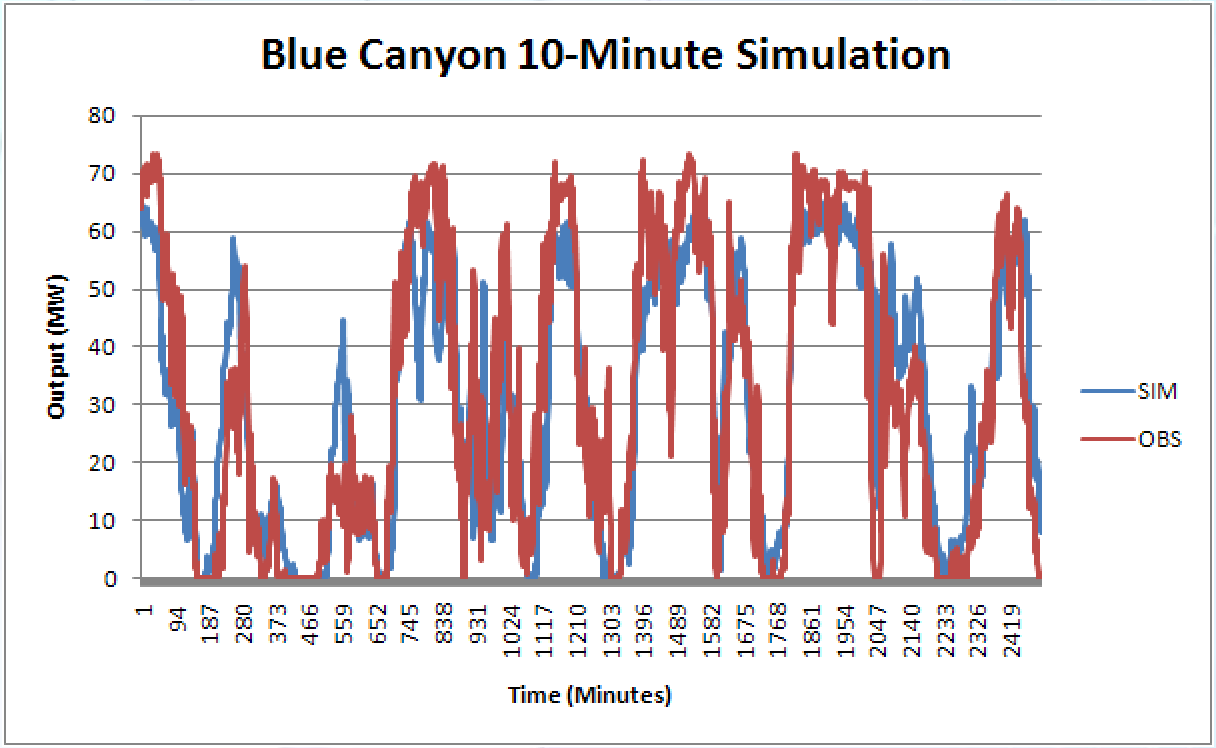
Wind Plant Output Generation

- Power conversion process details
  - Adjust for expected speeds based on AWS 200-m maps
  - Correct for long-term mean from AWS 20-km windTrends data
  - Composite power curve for site IEC class (standard air density)
  - Air density, turbulence (both from simulated values)
  - Account for high-speed shut downs
  - Introduce wake and non-wake losses (total loss ranging from 12-20%)
  - Time filter to replicate the “spatial smoothing” of the output of a real wind plant

Validation Sites

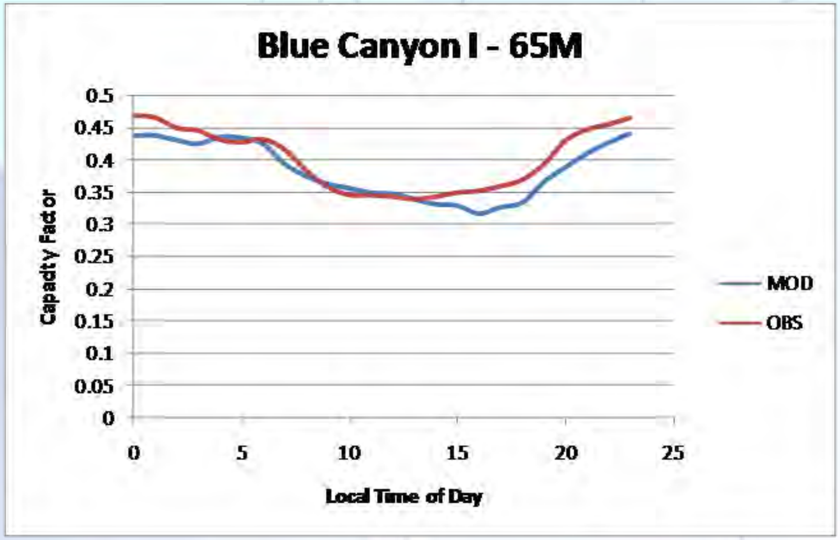
Plant Name	State	Rated Capacity (MW)	Turbine Type	Hub Height (m)
Blue Canyon I	Oklahoma	74.25	NM72 (1.65MW)	67 m
Lake Benton	Minnesota	103.5	Zond 750	51.2 m
Storm Lake I	Iowa	112.5	Zond 750	63 m

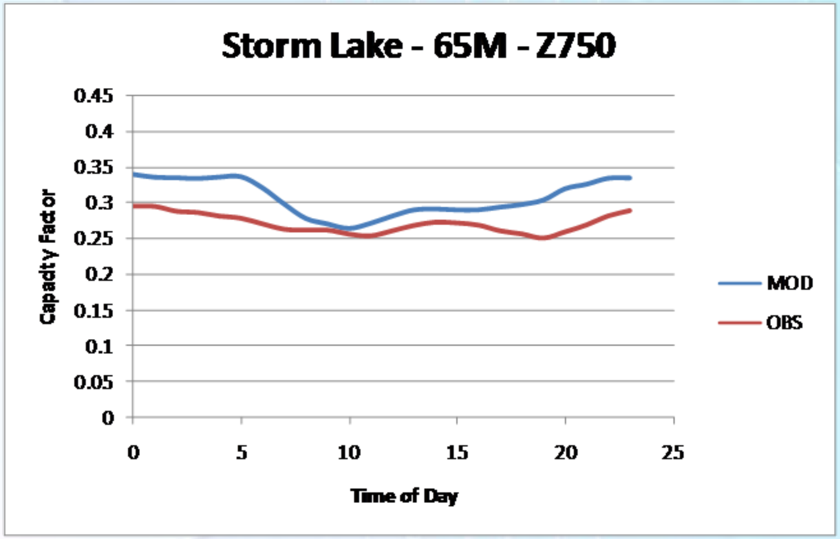
Validation Example



Validation Example (2)

Diurnal Mean Capacity Factor

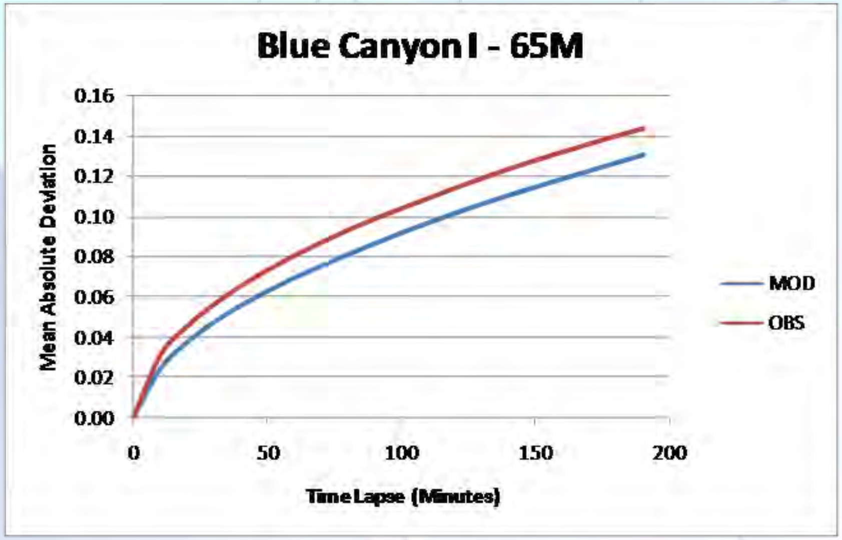


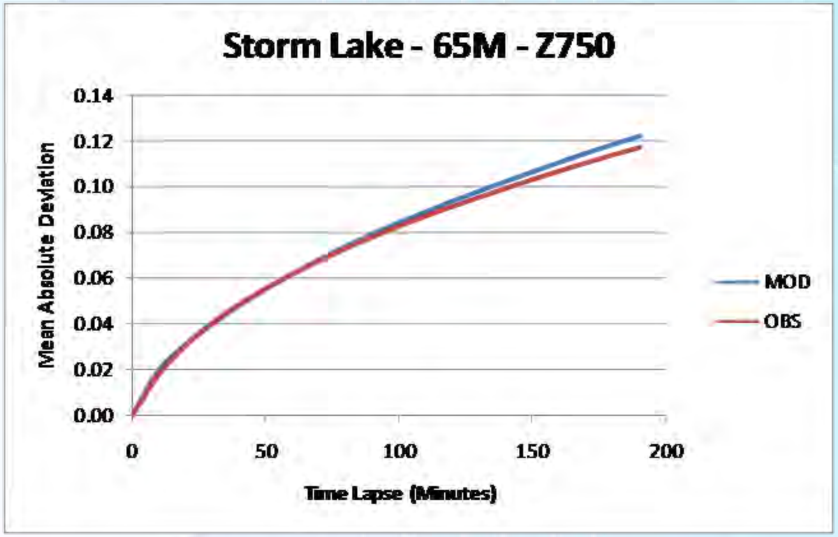


- Use correct power curve at each project, adjust simulated speeds/diurnal correction to actual hub height, and adjust rated capacity to match actual – result is similar diurnal trends
- Predicted output at Blue Canyon below observed – likely related to underestimate of mean wind speed in AWS map
- Predicted output at Storm Lake above observed – likely related to poor availability and other operational problems

Validation Example (3)

Mean Absolute Deviation (MAD) of
Capacity Factor (CF) from time T to T+ΔT



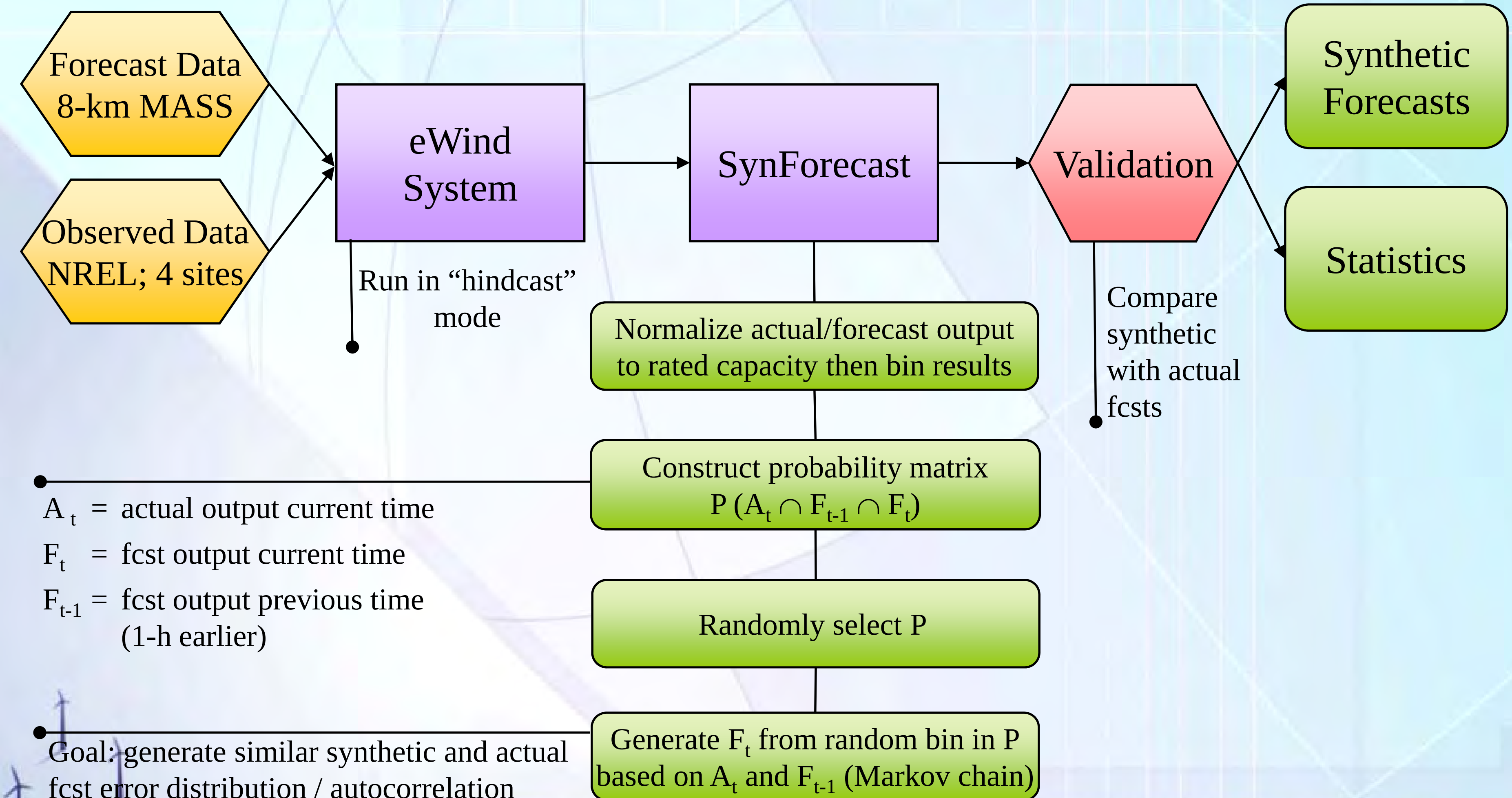


- As with diurnal output, ramp rates as measure by the MAD of CP are similar
- Predicted output below observed at Blue Canyon (and Lake Benton not shown) but judged satisfactory for the study to proceed

Synthetic Forecast Process

- Produce hourly forecasts for three time horizons: next day (ND), 6 h, and 4 h
- Use actual forecasts (eWind) and observed plant output to develop probability matrices
- Step forward in time using Markov chain
- Generate forecasts using actual plant data (4 sites; 2004-2006)
  - Trent Mesa (west Texas)
  - Blue Canyon I (southwest Oklahoma)
  - Lake Benton (southwestern Minnesota)
  - Storm Lake I (northwestern Iowa)

Synthetic Forecast Process



A_t = actual output current time

F_t = fcst output current time

F_{t-1} = fcst output previous time (1-h earlier)

Goal: generate similar synthetic and actual fcst error distribution / autocorrelation

Synthetic Forecast Validation

- Correlation of real and synthetic fcsts with obs very similar
- RMS errors also show remarkable similarities
- RMS error depends, in part, on plant output
- More productive plants experience higher errors as a function of rated capacity because they spend more time in the steeply sloping portion of power curves

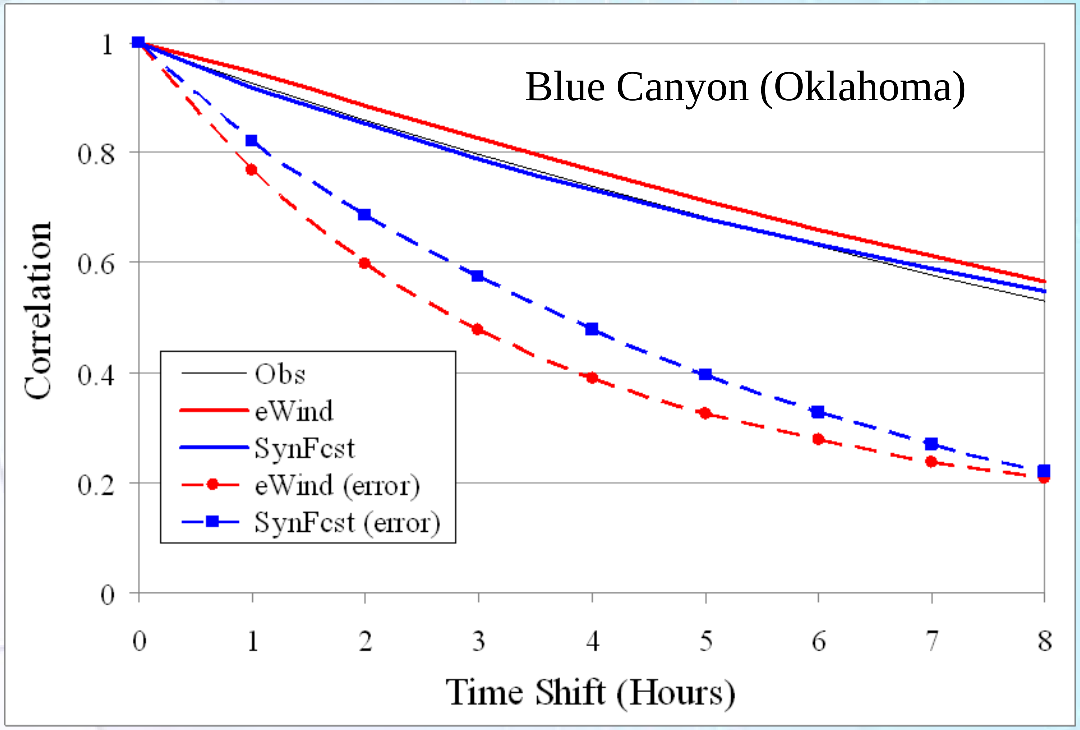
Correlation eWind and SynFcst with actual output
Root Mean Square (RMS) forecast error for eWind and SynFcst

	Correlation (Pearson r)		RMS Forecast Error (CF)	
Plant	eWind	SynFcst	eWind	SynFcst
Trent Mesa	0.77	0.77	0.20	0.20
Blue Canyon I	0.77	0.73	0.21	0.22
Storm Lake I	0.79	0.81	0.16	0.16
Lake Benton	0.72	0.71	0.19	0.19

Synthetic Forecast Validation (2)

- Observed output strongly autocorrelated over first several hours
- Actual and synthetic forecasts show similar trends
- Forecast (eWind) error autocorrelation is lower than output
- SynFcst captures this pattern quite well
- SynFcst output slightly less correlated than eWind in time
- SynFcst output errors slightly more correlated than eWind in time

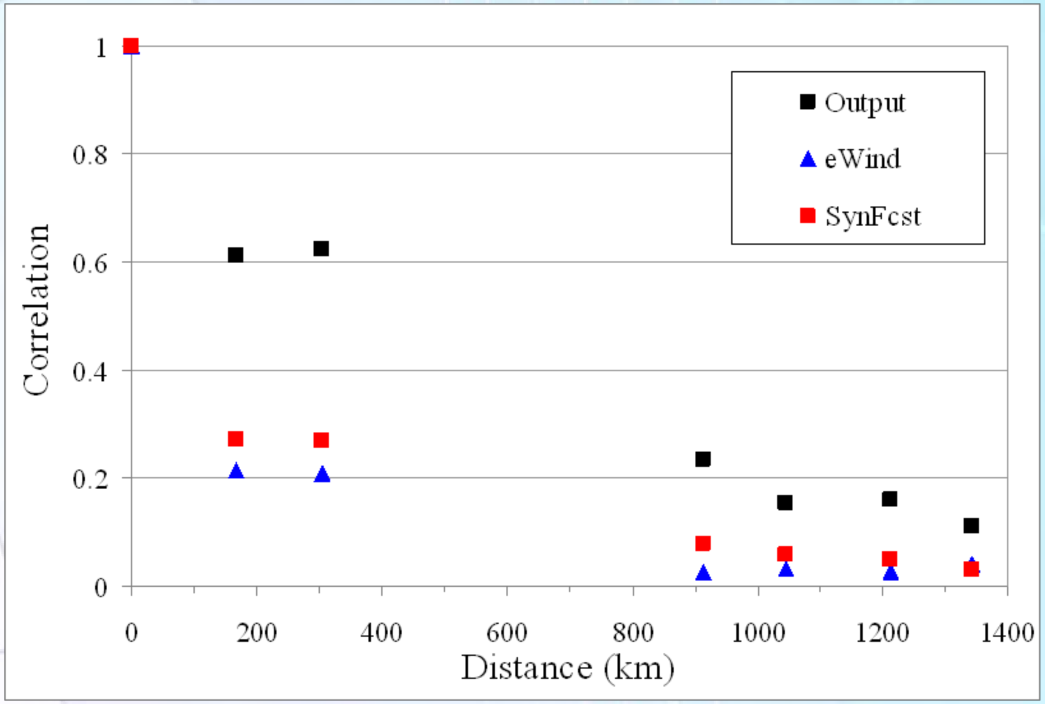
Autocorrelation of observed and forecast output and errors in forecast output



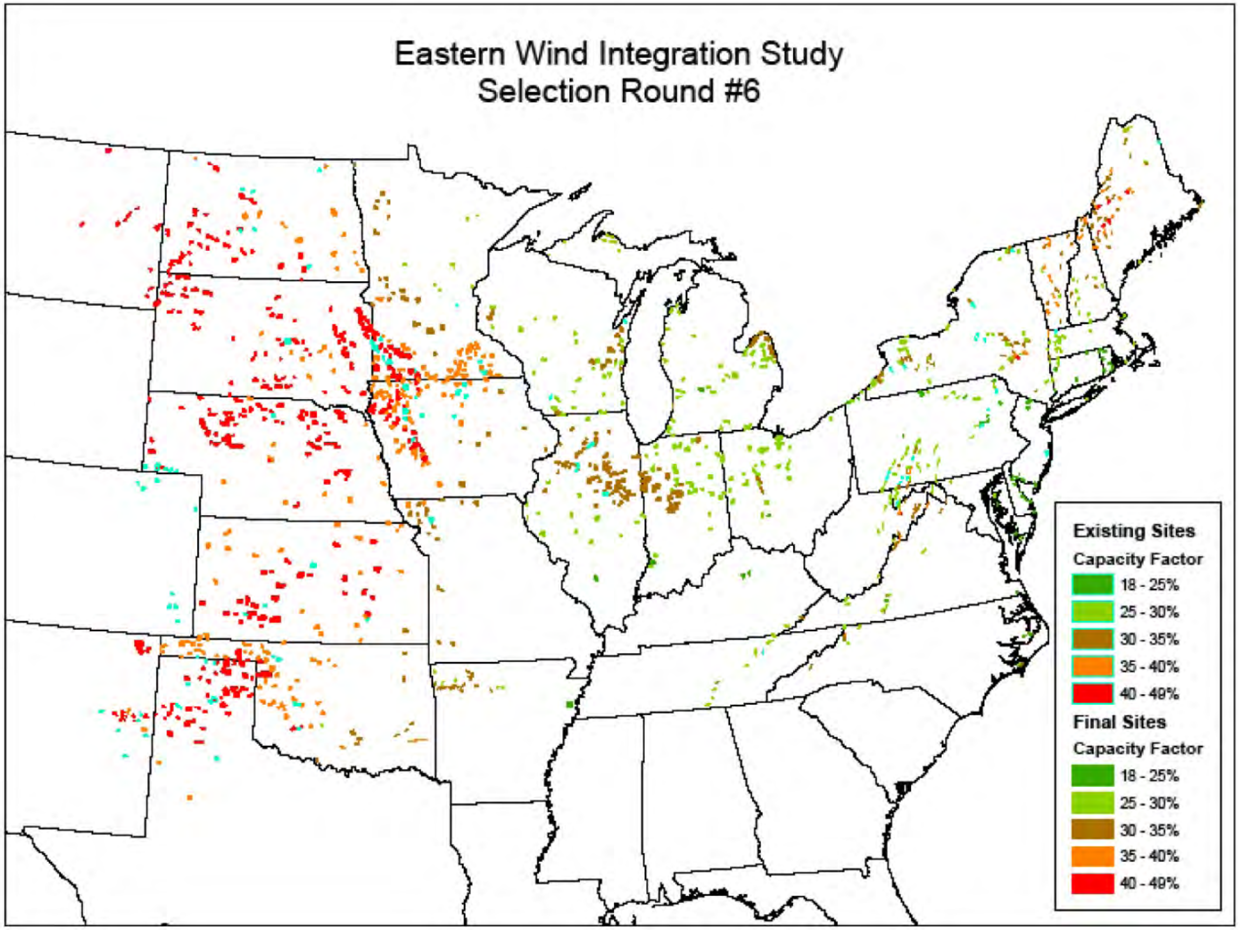
Synthetic Forecast Validation (3)

- Correlation of site output decreases with separation distance
- Correlation of errors with distance smaller than output
- SynFcst and eWind show similar decrease of error correlation with distance
- SynFcst error correlations are higher than eWind indicating a tendency to overestimate aggregated (regional) errors

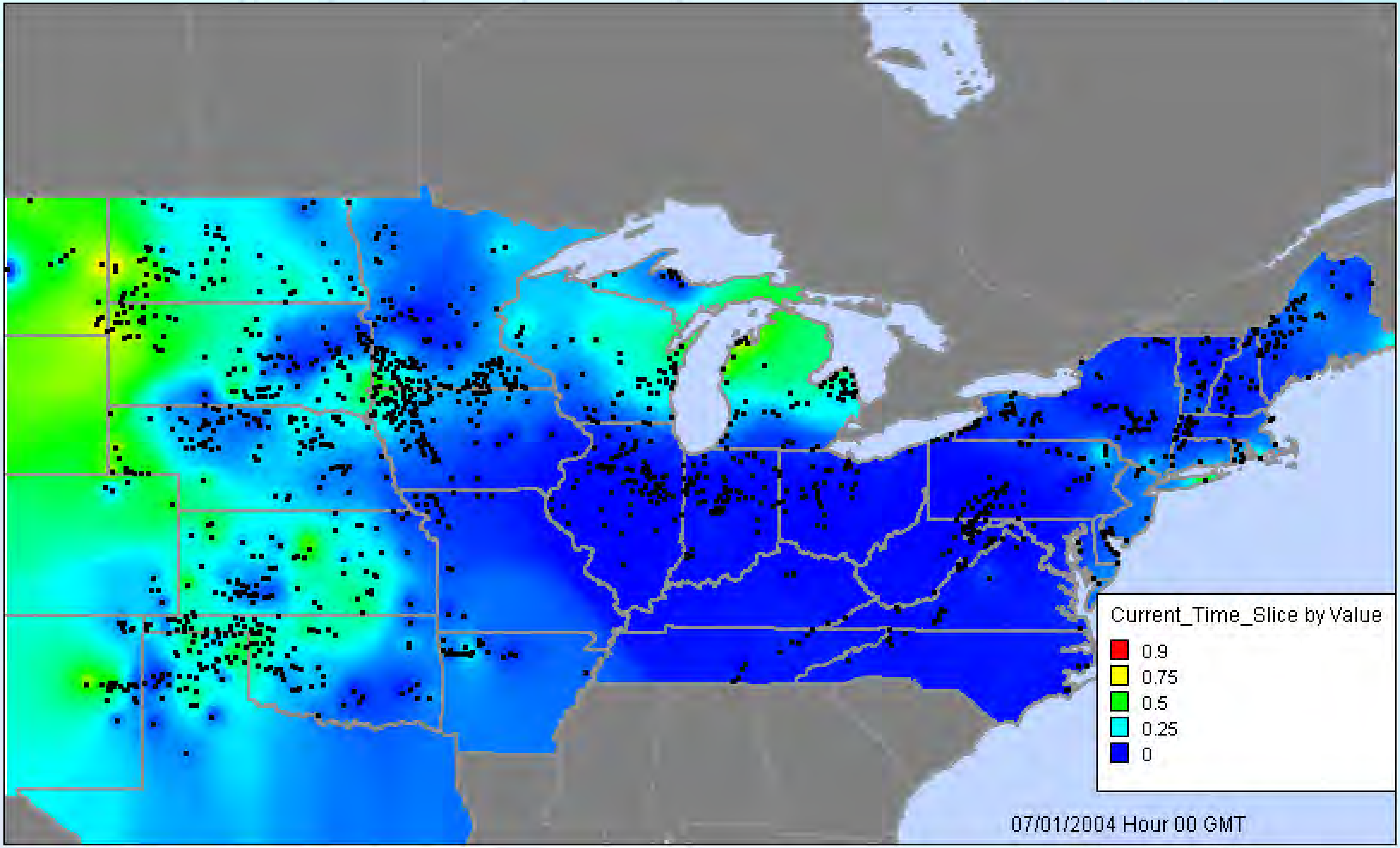
Correlation of output and forecast errors as a function of distance between project pairs



Onshore: Selected Sites



July Movie


Current_Time_Slice by Value
0.9
0.75
0.5
0.25
0
07/01/2004 Hour 00 GMT

December Movie