# **Predicting Wind Power Generation**

#### Daniel Kirk-Davidoff

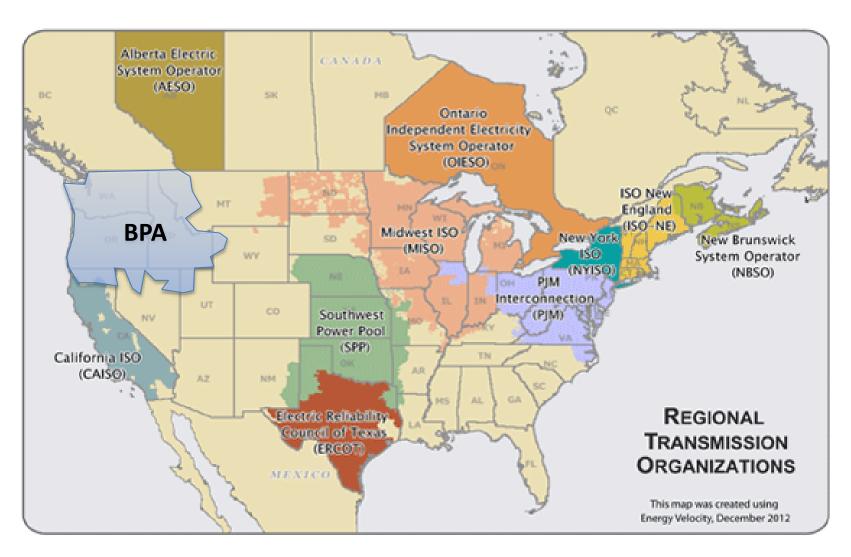
Chief Scientist for Weather and Climate Services

MDA Information Systems LLC

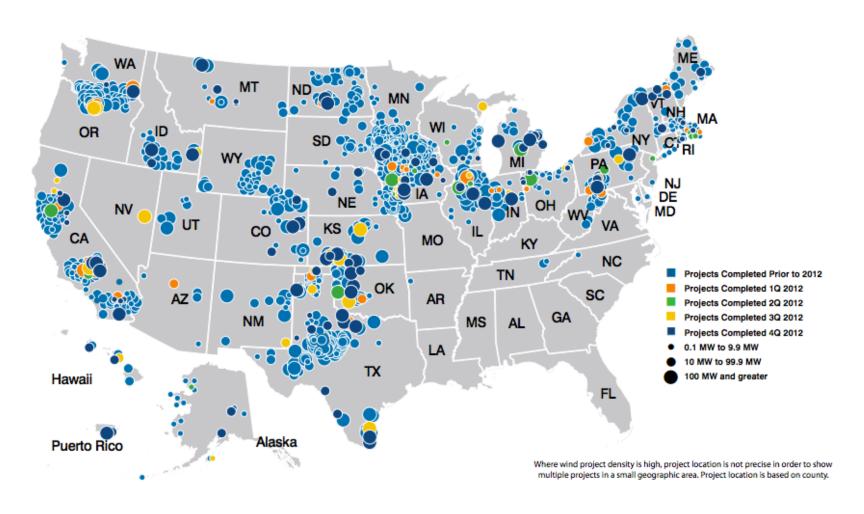
Adjunct Associate Professor of Atmospheric and Oceanic Science

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# US and Canadian RTO/ISO regions

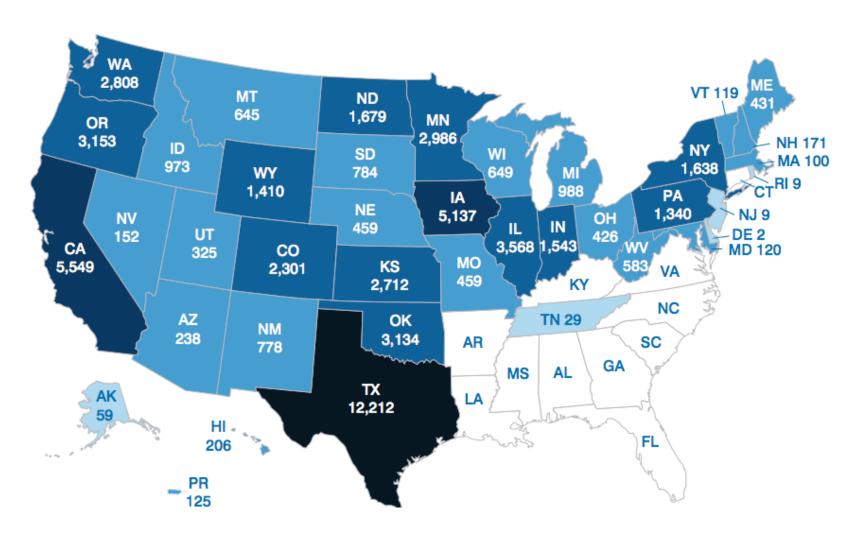


### Wind Farms in the US

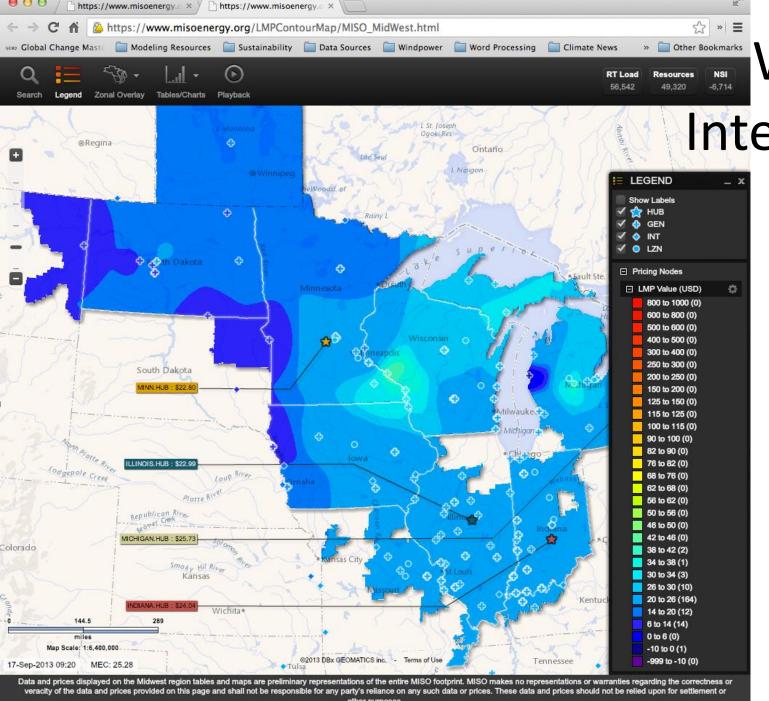


### **Image courtesy of AWEA**

# Installed wind capacity by state



**Image courtesy of AWEA** 

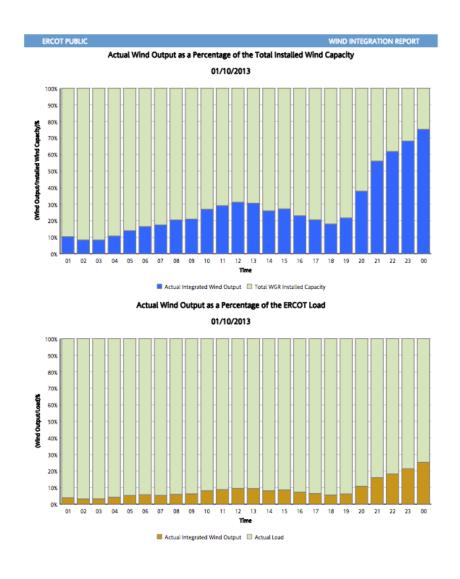


## Wind

Integration

The location marginal price (LMP) of electricity depends on the marginal generation cost, the local demand, and the state of congestion of electrical transmission.

### **Wind Integration**



In ERCOT, wind generation typically averages about 35% of capacity, but can occasionally reach full capacity of 10 GW. Since demand rarely falls below 20 GW, wind typically provides from 10 to 20% of demand.

ERCOT provides weekly "Wind Integration Reports" that show the variability of wind generation and electrical demand over the past week.

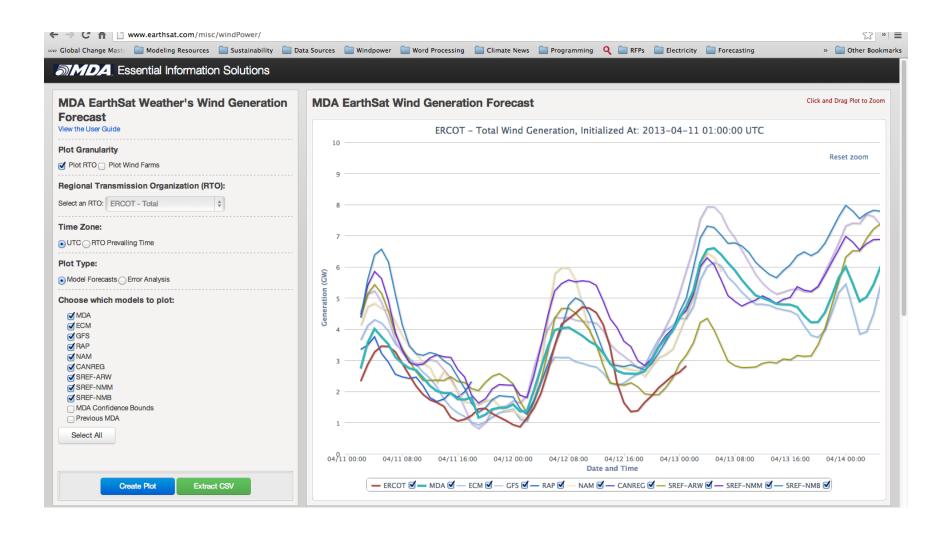
In addition, hourly wind generation data for the past our is available (updated about 5 minutes past the hour) at the ERCOT web site:

http://ercot.com/mktinfo/

# Forecasting wind generation

- 1. Predict wind and air density at turbine location
- 2. Predict power generated by turbine for that wind & air density
- 3. Take into account any operational concerns due to constraints of electrical grid, maintenance of turbines, or meteorological conditions (e.g. icing).

# Forecasting wind generation



### Numerical Weather Prediction

### Modern weather forecasting is largely a matter of:

- 1. Translating the equations of motion and of conservation of energy and mass into discrete form
- 2. Implementing their solution on computers
- Initializing their solution with data from observation of the atmosphere, land surface and oceans
- Running ensembles of predictions, varying initial conditions and physical parameters within uncertainty
- 5. Performing statistical regressions to link model predictions with observations at locations of interest

# The equations of motion and of state

$$\frac{du}{dt} = \frac{uv \tan \phi}{r} - \frac{uw}{r} - \frac{1}{\rho r \cos \phi} \frac{\partial p}{\partial \lambda} + fv - \hat{f}w + N_{\lambda}$$

$$\frac{dv}{dt} = -\frac{u^2 \tan \phi}{r} - \frac{vw}{r} - \frac{1}{\rho r} \frac{\partial p}{\partial \phi} - fu + N_{\phi}$$

$$\frac{dw}{dt} = \frac{u^2 + v^2}{r} - \frac{1}{\rho} \frac{\partial p}{\partial r} - g + \hat{f}u + N_z$$

$$\frac{d\rho}{dt} + \rho \nabla \cdot \vec{V} = 0$$

$$C_p \frac{dT}{dt} - \frac{1}{\rho} \frac{dp}{dt} = Q$$

 $p = \lambda RT$ 

But note that Q masks a huge amount of complexity! Phase changes of water, radiative transfer (visible, infrared, ultraviolet), thus also ozone chemistry, etc., etc....

# Discretizing the equations

State-of-the-art NWP models are now familiar and widely available software products, available for free download (for example at <a href="wrf-model.org">wrf-model.org</a>). You can run one on your home PC-but it will take a long time. What's under the hood?

#### WRF 3.5 Structure

- MODEL SOLVER
- fully compressible nonhydrostatic equations with hydrostatic option
  - complete coriolis and curvature terms
  - two-way nesting with multiple nests and nest revels
  - one-way nesting
  - moving nest
  - mass-based terrain following coordinate (note that the height-based dynamic core is no longer supported)
  - vertical grid-spacing can vary with height
  - polocidespecification and and polocides.
  - \* Lambert-conformal

  - \* Mercatonumerical details ted)
- Arakawa C-grid staggering
  - Runge-Kutta 2nd and 3rd order timestep options
  - scalar-conserving flux form for prognostic variable
  - 2nd to 6th order advection options (horizontal ap vertical)
  - time-split small step for acoustic and gravity-wave modes:
- small step horizontally explicit, vertically implicit
  - \* divergence damping option and vertical time offcentering
  - \* external-mode filtering option
- lateral boundary conditions
- idealized cases: periodic, symmetric, and open radiative
  - real cases: specified with relaxation zone
  - upper boundary absorbing layer option
- \* increased diffusion
  - \* Raylei **Boundary Conditions**
  - rigid upper lid option
- positive definite and monotonic advection scheme for calars (microphysics species, scalars and tke)
- adaptive time stepping (new in V3.0)
- spectral nudging using gridded analyses (new in V3.1)

**Microphysics** 

- PHYSICS
- microphysics
  - - \* WRF Single Moment (WSM) 3, 5 and 6 class
    - \* Lin et āl.
    - \* Eta Ferrier
    - \* Thompson
    - \* Goddard 6 class
    - Morrison 2-moment
    - WRF Double Moment (WDM) 5 and 6 class
    - \* Thompson scheme from old version
    - \* Milbrandt-Yau double moment
  - cumulus parameterization
- Kain-Fritsch with shallow convection
  - \* Betts-Miller-JanjiConwection
    \* Grell-Devenyi enseConwection
  - \* New Grell 3D ensemble scheme
- planetary borparameterization

- \* Yonsei University (S. Korea) with improved stable BL \* Mellor-Yamada-Janjiconvection
- \* Asymmetric Convective Model (ACM2)
- \* Quasi-normal Psychiatry elements (PRINS \* Level 2.5 and 3 Mellow-Yamada Nakanishi Niino (MYNN) PBI
- \* Boureault-Lacarrere PBL
- \* MRF
- surface laver
- \* similarity theory MM5 may be run with a 1-D ocean mixed laver model
- \* Eta or MYJ
- **Boundary Layer and Land**
- \* ONSE
- urface Parameterizations
- \* slab soil model (5-layer thermal diffusion)
- \* Unified Noah land-surface model
- \* Urban camppy model (works with Noah LSM)
- \* Multi-layer building environment parameterization (BEP, works with Noah, and requires BouLac and MYJ PBL)
- \* building energy model (BEM, works with weak and requires BouLac and MYJ PBL)
- \* RUC LSM
- \* PX LSM
- \* use of fractional sea-ice
- Radiation - longwave radiation
- \* RRTM
- \* CAM
- \* RRTMC
- shortwave radiction
- \* simple MM5 scheme, with Zaengl radiation/topography (slope and shadowing) effects
- \* Goddard
- \* CAM
- \* RRTMG
- single-column mixed layer ocean model
- sub-grid Boundary Layer and Land
- \* constant K diffusion
- \* 2-D Smag Single face Parameterizations
- \* predicted lnE
- \* nonlinear backscatter and anisotropy (NBA) turbulence option for LES (new in V3 2)
- land-use categories determine surface properties
- SST, greenness fraction, seaice and albedo update during long simulations
- analysis nudging, 3 D and surface (new in V3.1)
- observation nudging (new in V2.2)

# Model Implementation Choices

- Parameterizations
- Resolution (horizontal, vertical- higher spatial resolution requires higher time resolution, so doubling horizontal resolution often means multiplying computational time required by ~8).
- Ensemble members: larger ensemble takes more time, but allows greater exploration of possible scenarios (perfect prediction is impossible).

# Model Implementation Choices

At the level of a wind forecasting provider, other choices arise:

- Should we do dynamical modeling at all, or should we just use available forecasts from national and international modeling centers?
- How can we best make use of observations of wind and wind generation?

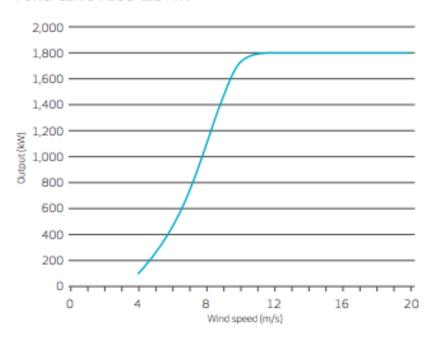
# Wind Power Forecasting

Once the weather has been forecast, how do we turn this into a forecast of wind generation?

- Turbine power curves (official, or empirical)
  - Depend on both wind speed and air density
- Turbine availability
- Curtailment
- Conditions (icing)

### **Power Curves**

#### Power curve V100-1.8 MW

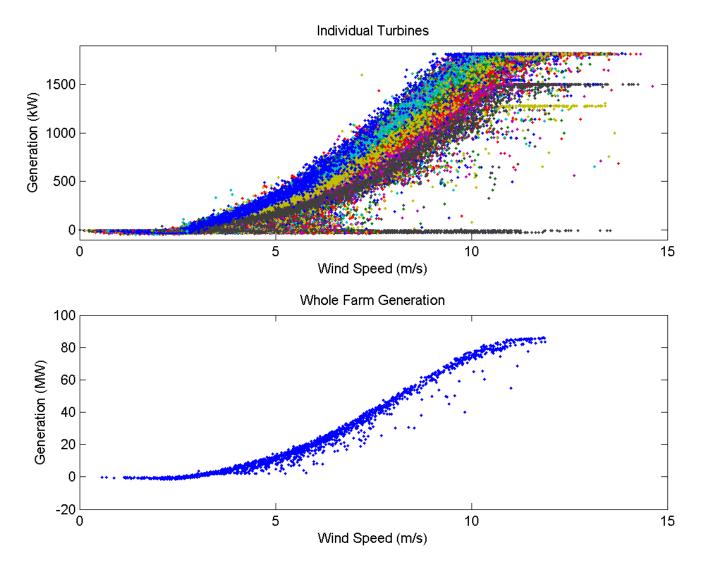




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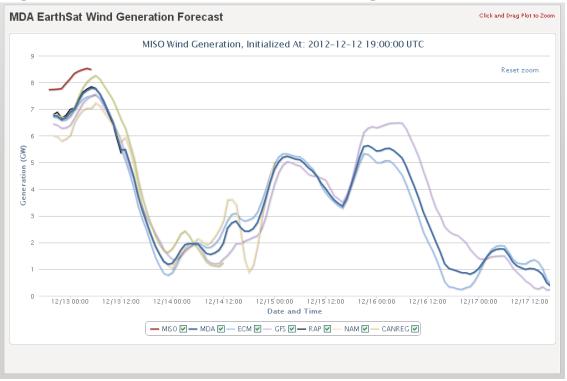
## **Power Curves**



MDA Forecasting – Multi-model Ensembling

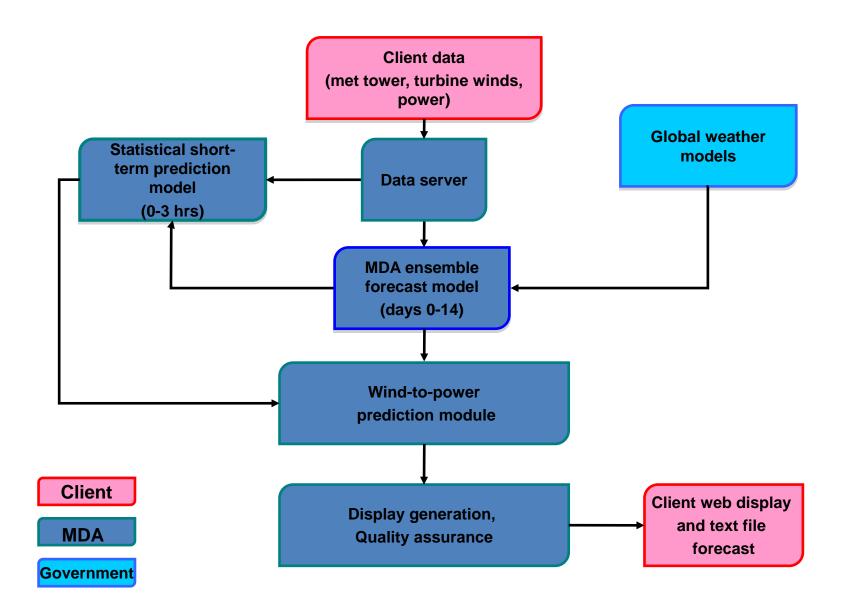
Our forecast is based on an ensemble of NWP models, each of which is interpolated to each wind farm location, run through the appropriate power curve for that farm, and tuned to remove bias evident in the aggregate wind generation data.

The ensemble members are combined using weights calculated from each model's skill.

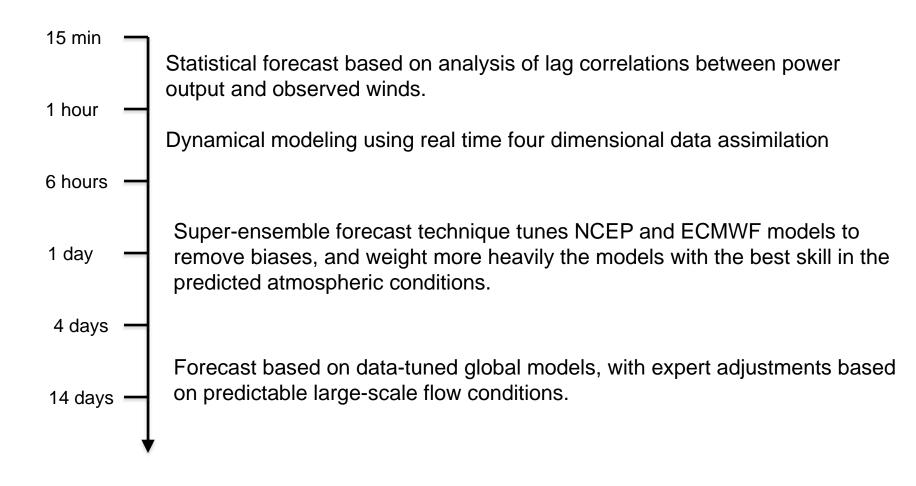


The models can be presented individually, which relays information about the uncertainty in the timing, as well as the magnitude of generation peaks and valleys.

#### Schematic of MDA's modeling system



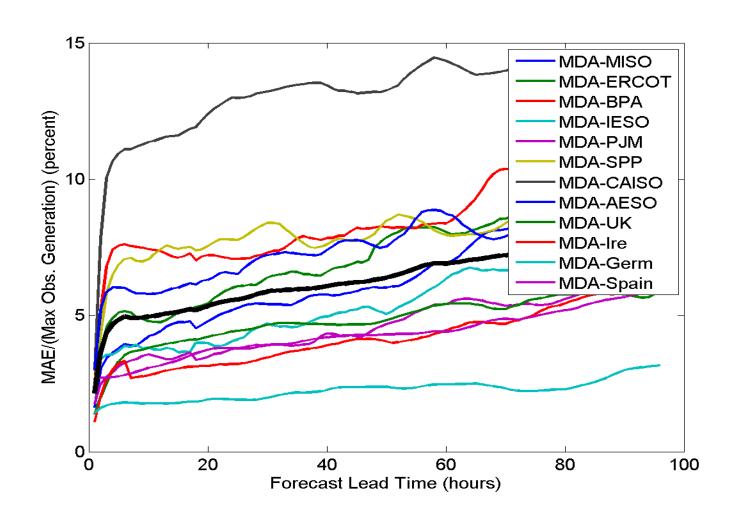
### Forecast Methodology varies with lead time!



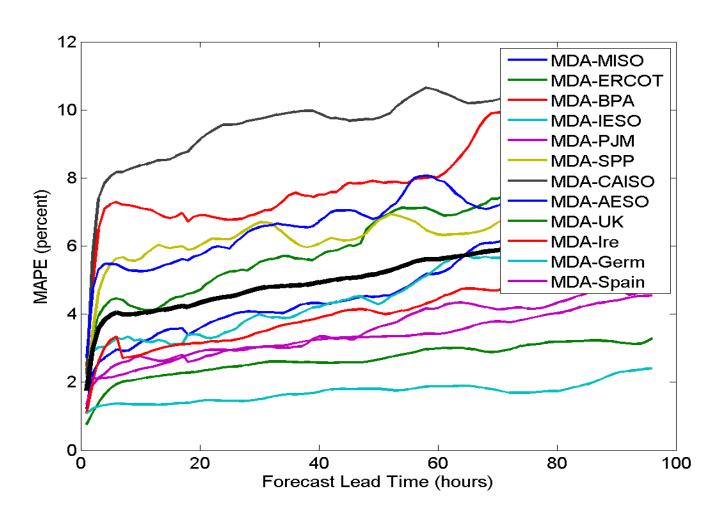
### Summary of our day-ahead forecast skill for RTO markets:

Average Error at 17-42 hours lead time	MISO	ERCOT	PJM	CAISO	ВРА	IESO	UK
MAE (GW)	0.66	0.62	0.43	0.54	0.45	0.12	0.34
2012 Maximum Production (GW)	9.9	9.5	5.1	4.2	4.5	1.7	5.3
%MAE (MAE/Max Production)	6.7%	6.5%	8.4%	12.9%	10%	7.1%	6.4%

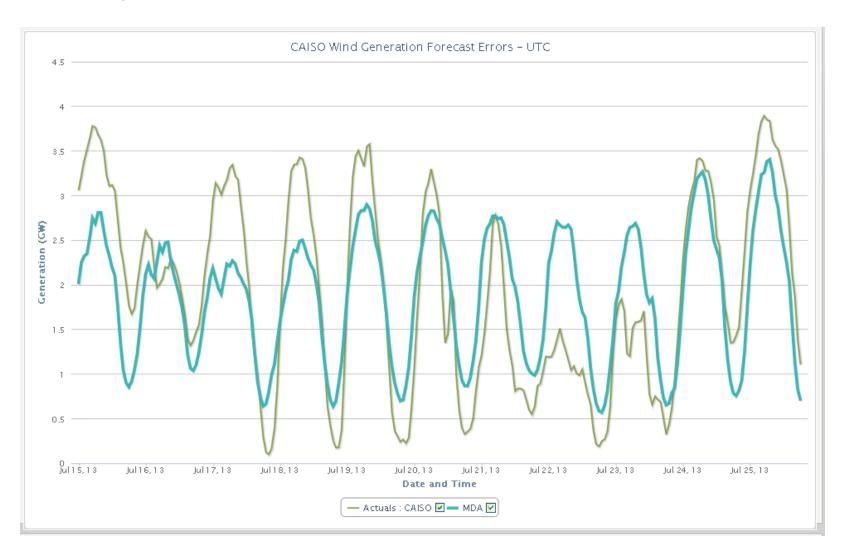
### Summary of our day-ahead forecast skill for RTO markets:



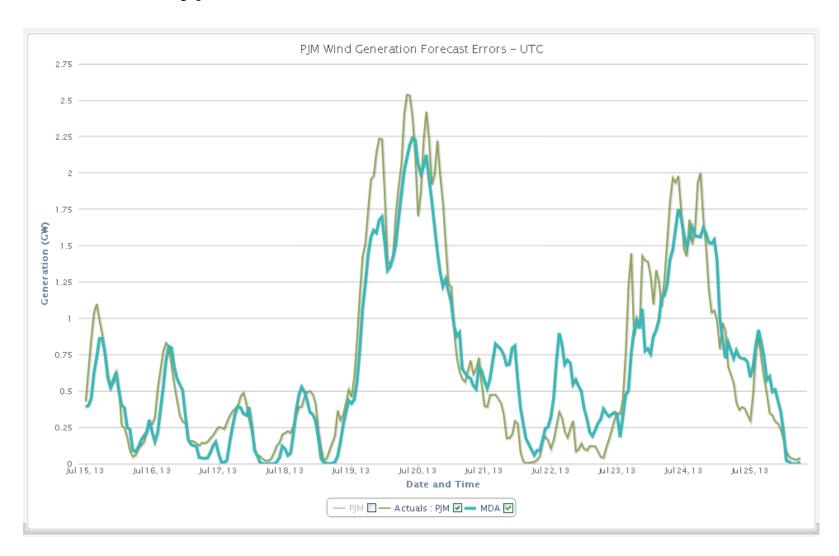
### Summary of our day-ahead forecast skill for RTO markets:



### CAISO, our worst case for recent weeks...



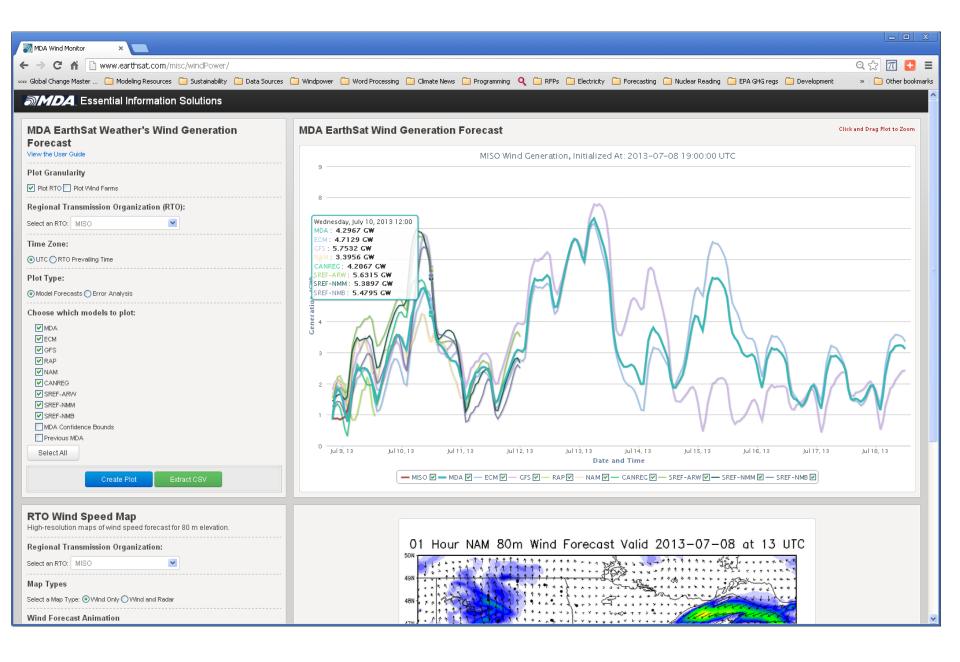
### PJM, more typical of our RTO forecast skill:



# Summary of our day-ahead forecast skill for individual wind farms in AESO, MISO and ERCOT:

Average Error at 17-42 hours lead time	Halkirk (AESO)	Enmax Taber (AESO)	Iowa Farm	Wisconsin Farm	Buffalo Gap (ERCOT)	Papalote 2 (ERCOT)
MAE (MW)	21	12	18	12	13	26
2012 Maximum Production (MW)	150	80	175	150	108	135
%MAE (MAE/Max Production)	14%	15%	10%	8%	12%	14%

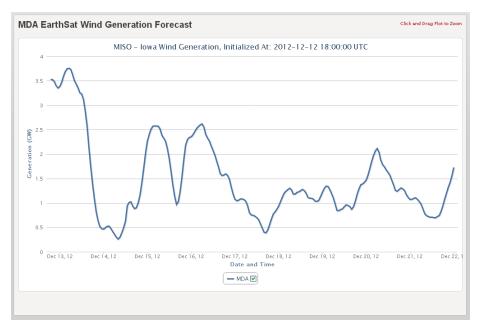


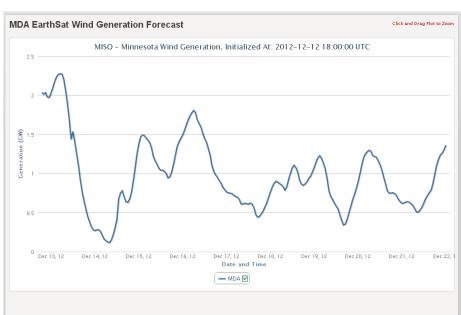


#### Regional WGF within MISO

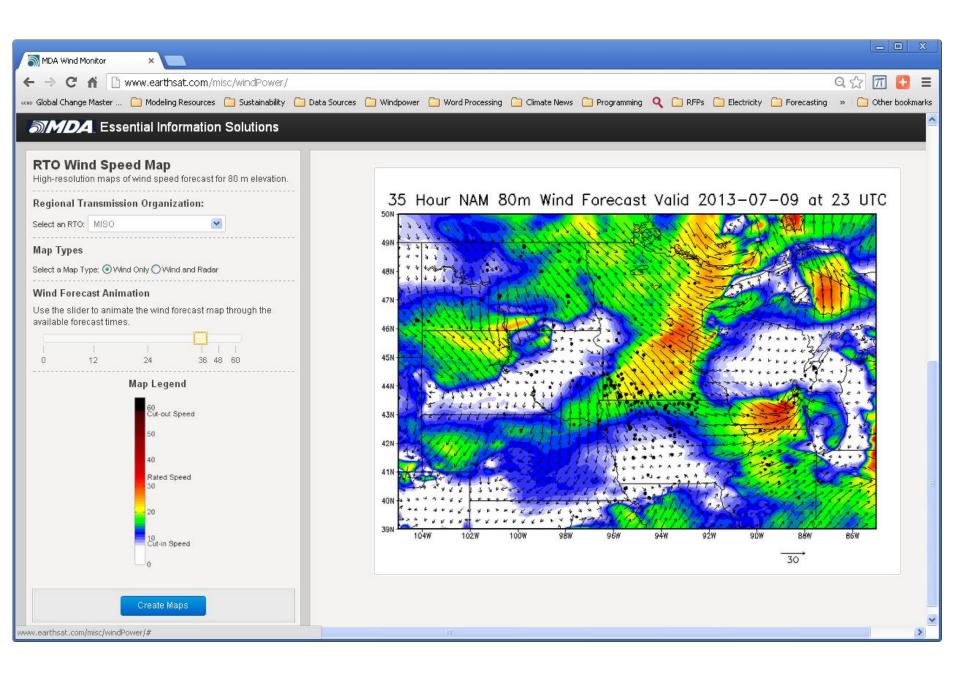


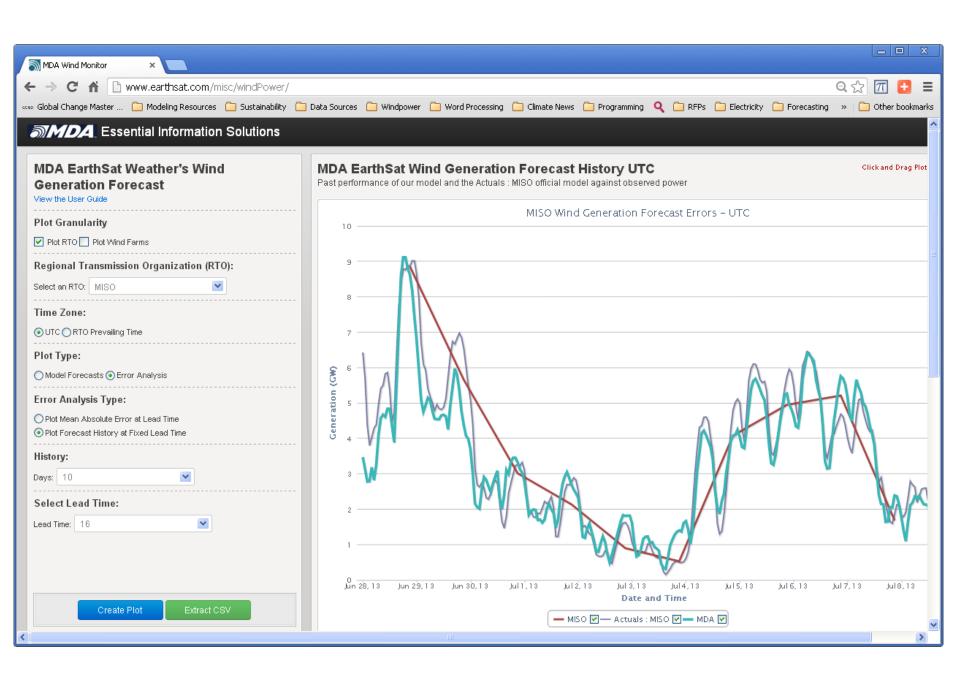
# Menu allows selection of regions within RTO



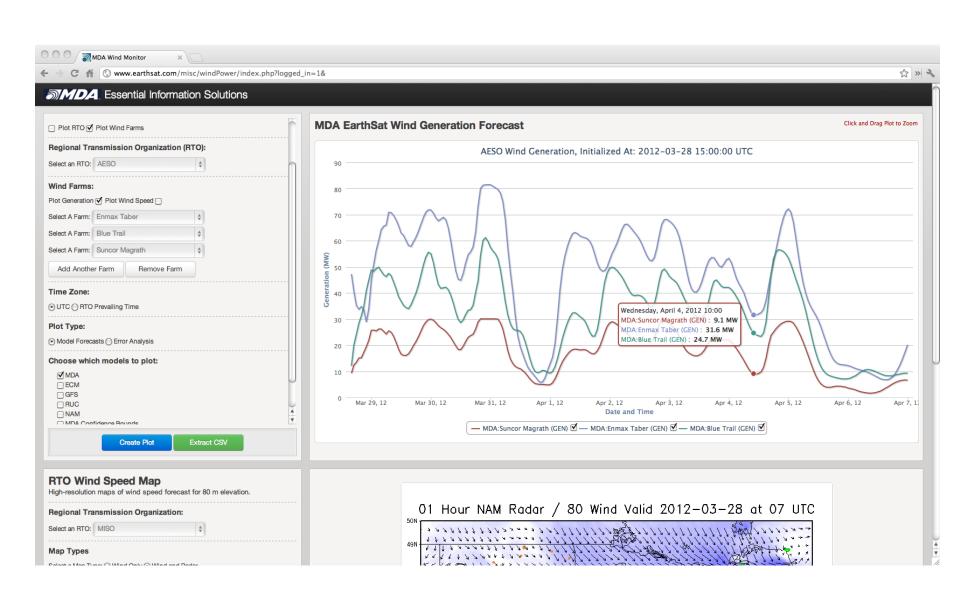


Iowa Minnesota

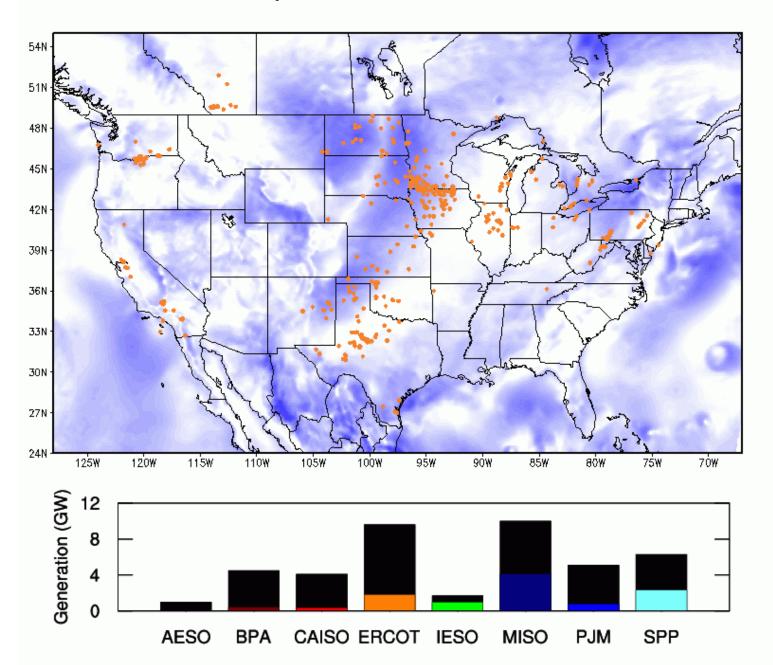








#### Wind Speed Valid 2014-09-13 at 21 UTC

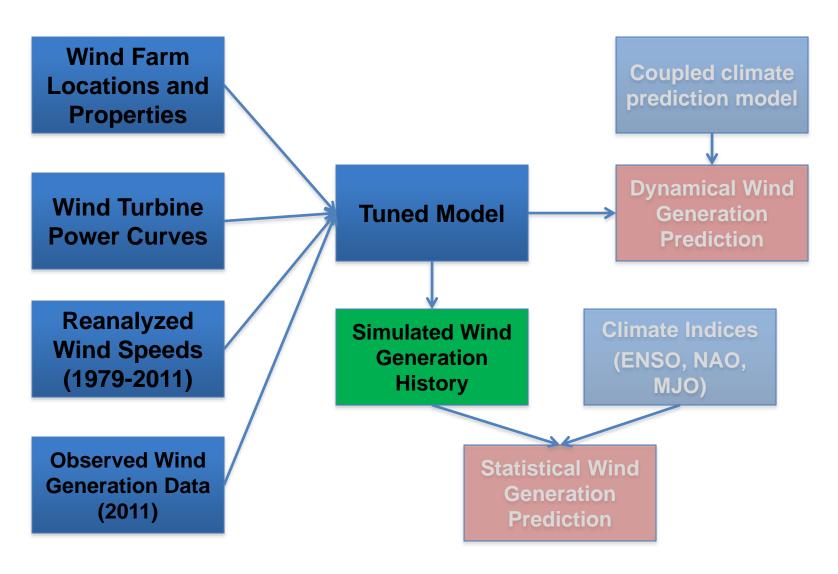


# Generating an historical Wind Index

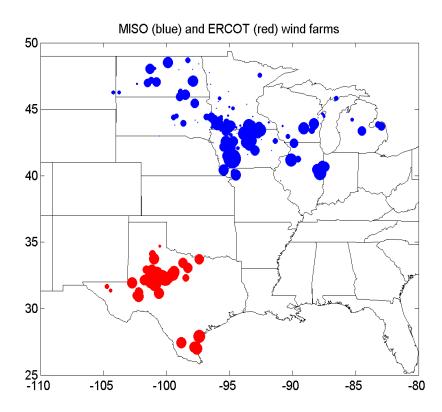
The need: Energy traders and other electrical market participants need a consistent measure of wind generation in real electrical markets that represents the variability in electrical generation associated with weather fluctuations, and not changes in wind generation infrastructure. Such an index allows accurate assessment of the probability distribution of generation over the coming year, month, or week.

The solution: a procedure to generate a virtual history of wind generation for each electrical interconnection for past 30 years using an up-to-date, frozen wind generation infrastructure.

Each year, we will regenerate the 30 year climatology of wind generation that would have resulted from the real wind variations over that period acting on the wind generation infrastructure of the present day.



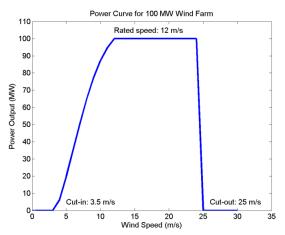
## Wind Farm Locations & Properties



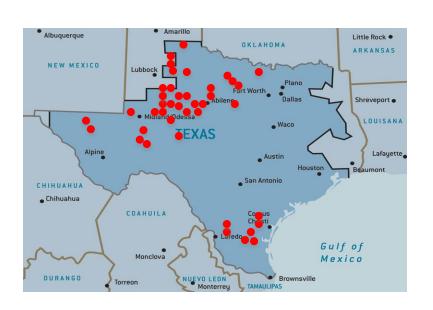
Farm locations and generation capacity are indicated by dots, scaled by size (largest is 444 MW). Total capacities are 8.5 GW in ERCOT, 9.9 GW in MISO

In this study, we will generate simulated historical wind power generation for the MISO and ERCOT transmission organizations.

We use a parametric power curve that allows for arbitrary values of the cut-in, rated and cut-out wind speeds.



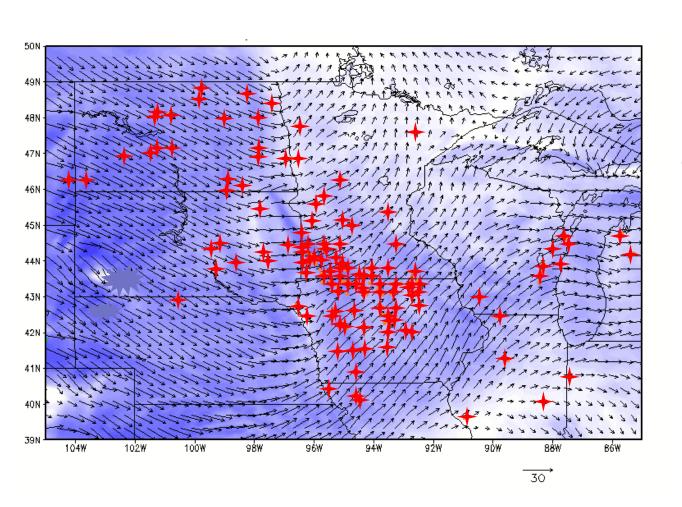
## Wind Farm Locations & Properties



In ERCOT, Wind farms are located primarily in the West Zone, or near the Gulf coast in the South Zone. At present the capacity is divided into 2.3 GW in the South Zone, 0.5 GW in the North Zone, and 7.2 GW in the West zone.

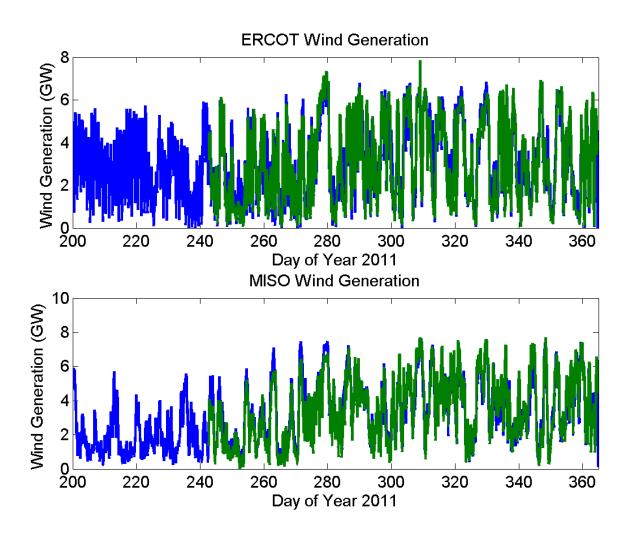
We monitor ERCOT Capacity
Demand Reserve Reports,
which list all generation
facilities in ERCOT by size, to
keep track of where future wind
generation facilities will be
located. Public record
searches allow determination
of the exact locations and

## Reanalyzed Wind Speeds

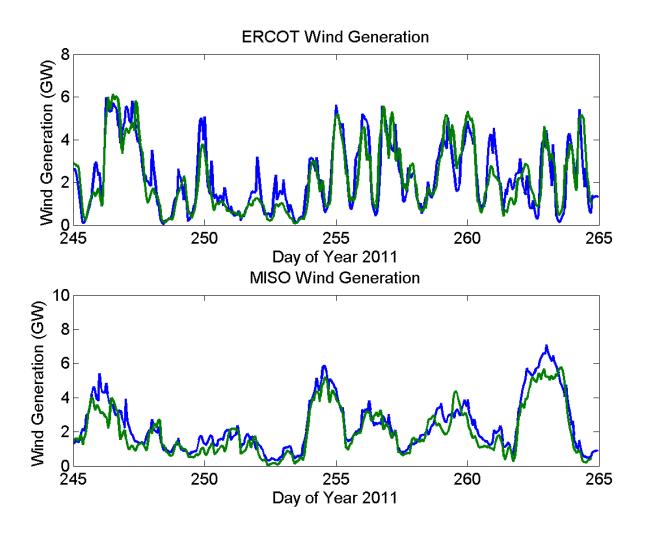


Wind speeds are taken from the CFS Reanalysis, using a weighted average of the 10 m and 0-30 hPa above ground level winds.

Winds are interpolated to wind farms locations

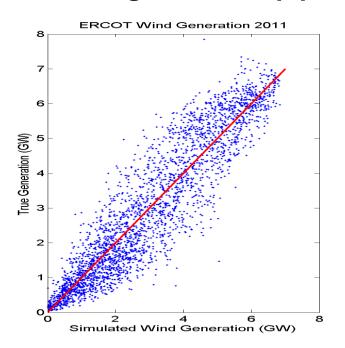


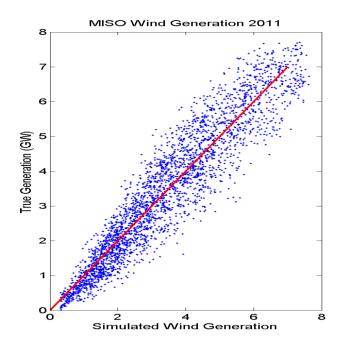
These plots show hourly wind generation for the ERCOT and MISO interconnection s. Blue shows the simulated wind generation, green shows the actual generation. The agreement is quite good: correlation coeffcients are 0.91 and 0.94 for **ERCOT** and

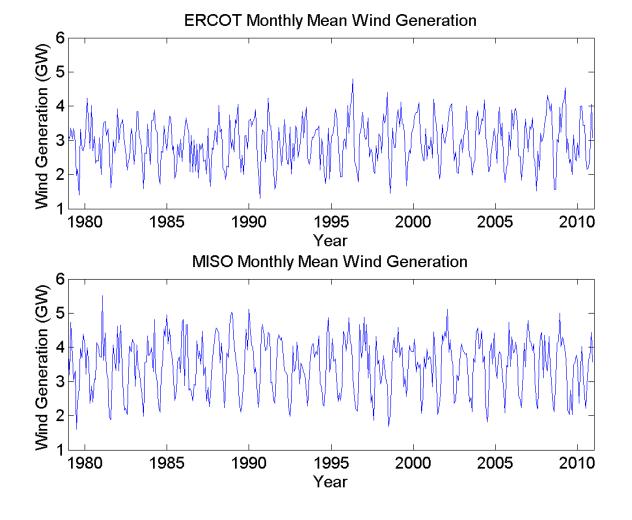


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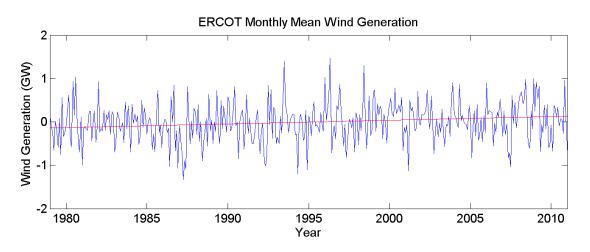
Scatterplots show the high correlation between the simulated and actual wind generation values during the overlap period.

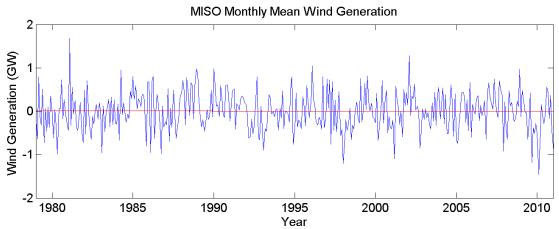






Here are the full 30 year histories, smoothed to monthly means for clarity.

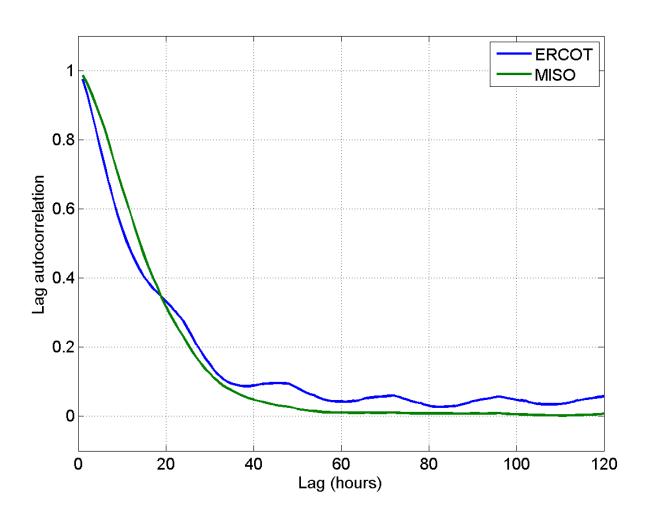




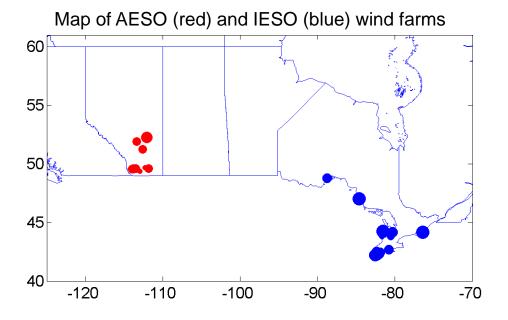
In these plots the annual cycle has been removed, to show the anomalous monthly mean generation in each interconnection.

A small, but significant trend of 85 MW/decade is evident in the ERCOT history, while the MISO history shows no significant trend.

# Climatology of Historical Wind Generation



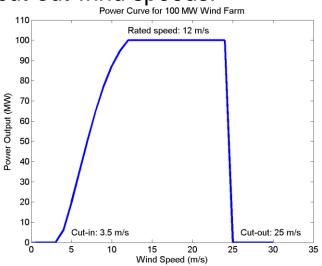
This figure shows the decay of autocorrelation of the ERCOT and MISO generation, with the seasonal and diurnal cycles removed. **Autocorrelation** falls to near zero within 5 days, suggesting that long-term prediction will be challenging.

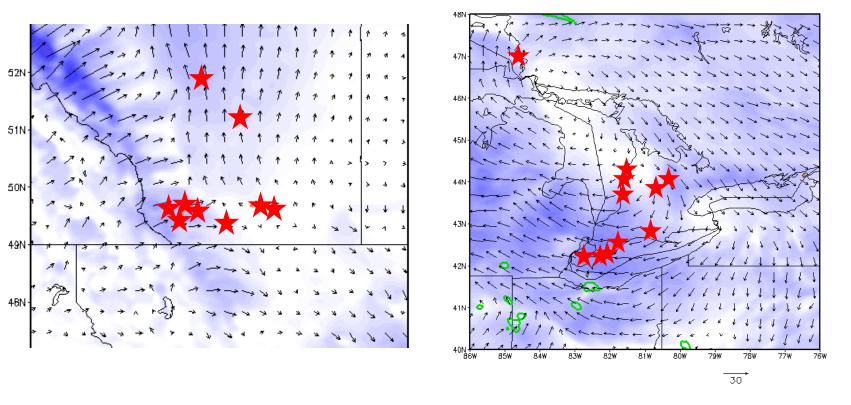


Farm locations and generation capacity are indicated by dots, scaled by size (largest is 197.8 MW). Total capacities are 1.1 GW in AESO, 2.0 GW in IESO

In this study, we will generate simulated historical wind power generation for all the US and Canadian transmission organizations.

We use a parametric power curve that allows for arbitrary values of the cut-in, rated and cut-out wind speeds.

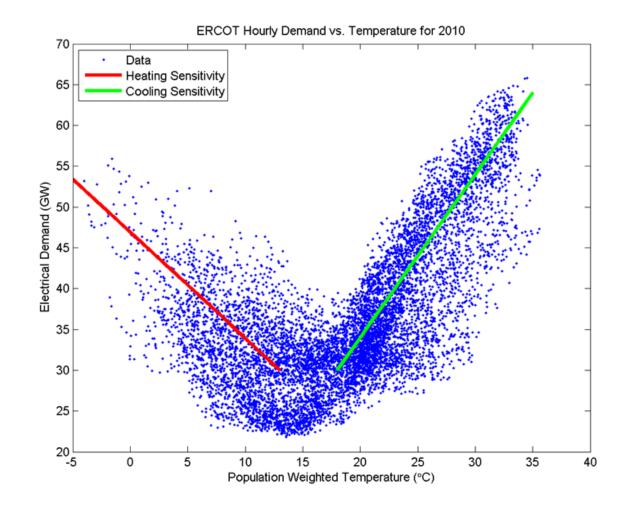


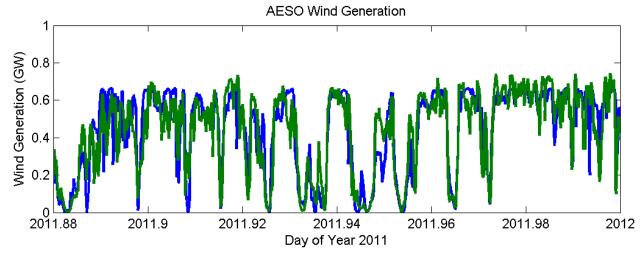


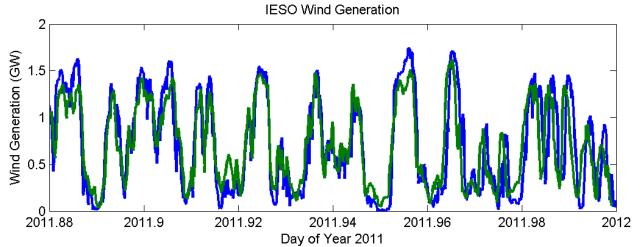
Wind speeds are taken from the CFS Reanalysis, using a weighted average of the 10 m and 0-30 hPa above ground level winds.

Winds are interpolated to wind farms locations (shown as red stars on these figures).

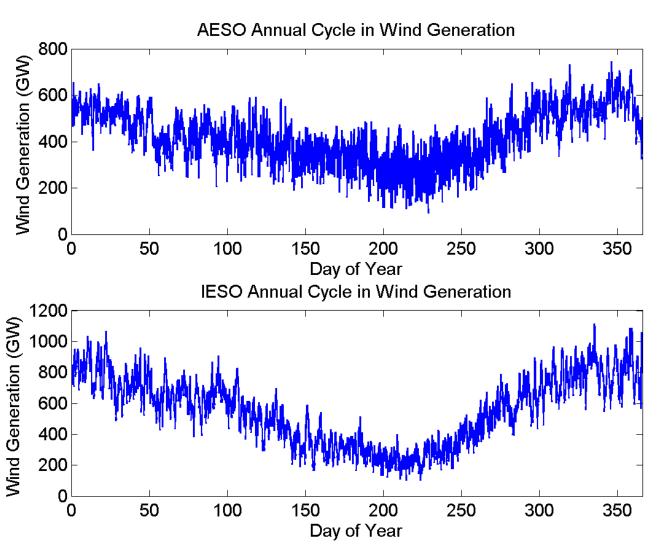
We can also simulate the weather-dependent part of electrical demand using reanalysis temperature data (weighted by population) and actual demand data. Of course we could just use actual demand data as well, but we want to isolate the contribution of weather variability here.





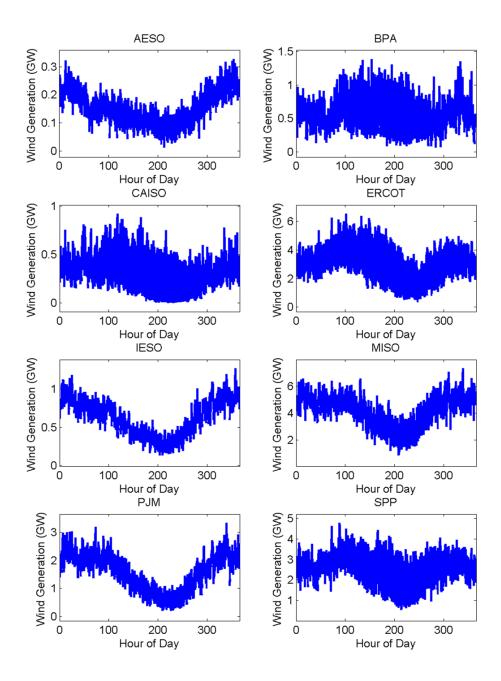


These plots show hourly wind generation for the **AESO** and **IESO** interconnections. Blue shows the simulated wind generation, green shows the actual generation. The agreement is reasonably good: correlation coeffcients for both RTOs are r = 0.87.



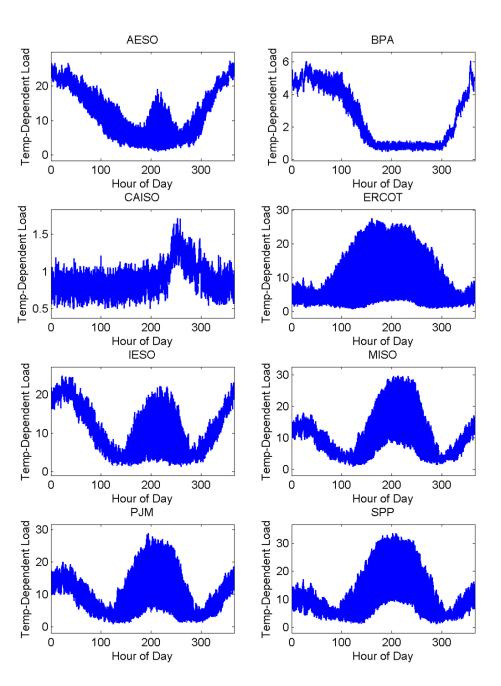
Here we show the average of 32 years of simulated wind generation history, by hour of year.

This shows well the change in the amplitude of the diurnal cycle, as well as the change in daily mean generation through the seasonal cycle.



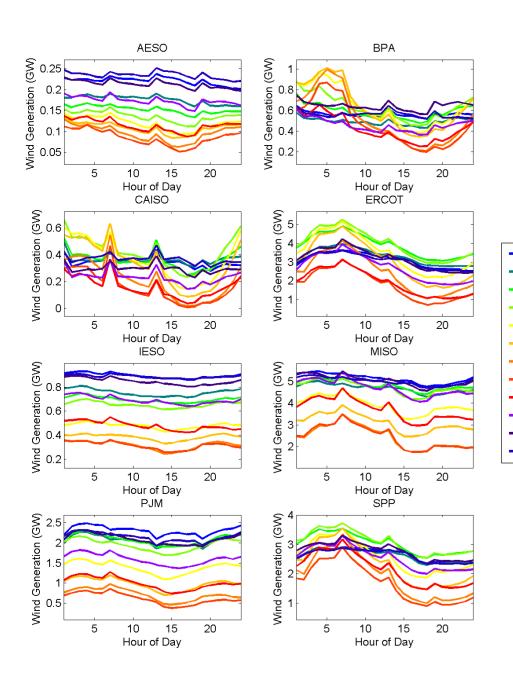
Here we show the average of 32 years of simulated wind generation history, by hour of year.

This shows well the change in the amplitude of the diurnal cycle, as well as the change in daily mean generation through the seasonal cycle.



Here we show the average of 32 years of simulated temperature-dependent electrical demand, by hour of year.

This shows well the change in the amplitude of the diurnal cycle, as well as the change in daily mean generation through the seasonal cycle.



Here we show the diurnal cycle of simulated wind generation in each month of the year, for each RTO. Diurnal cycles are notably stronger in many (but not all) regions. The phase of the diurnal cycle is fairly consistent through the year.

Jan Feb

Mar Apr

May

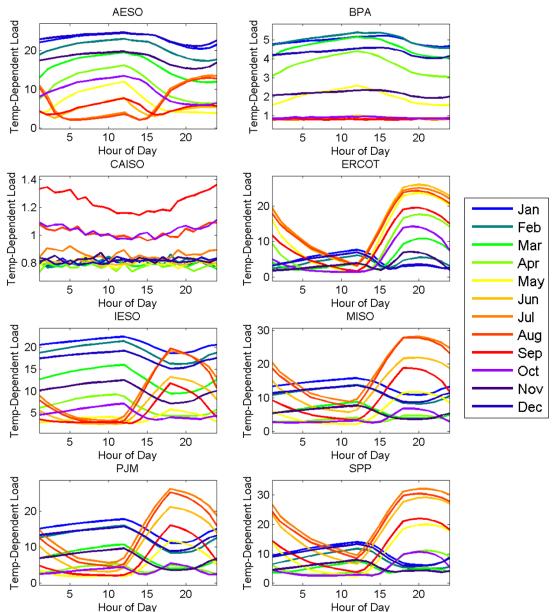
Jun

Jul

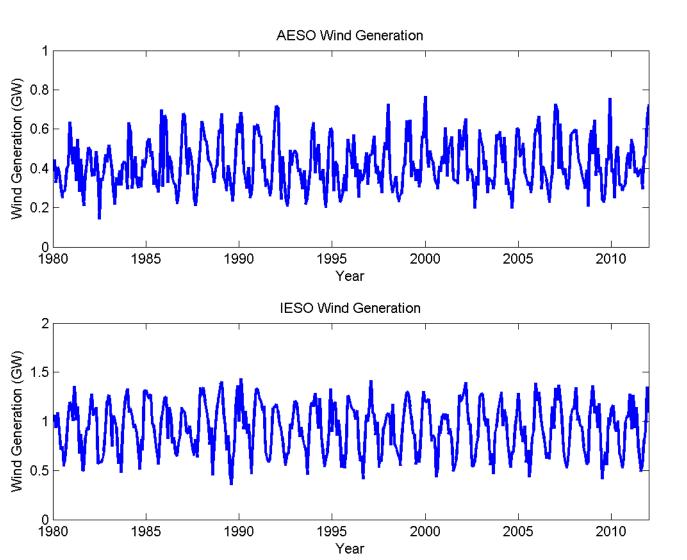
Aug Sep

Oct Nov

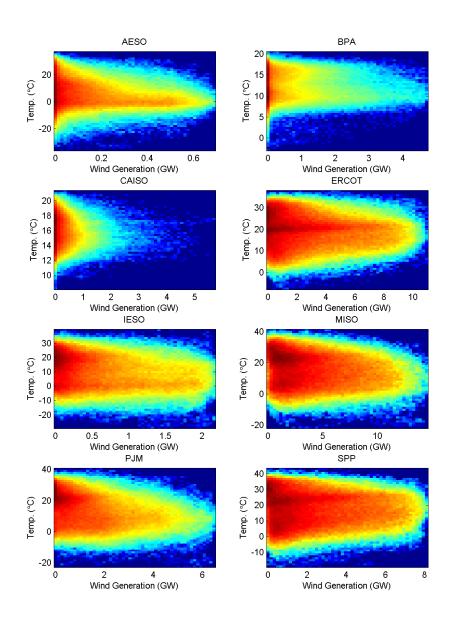
Dec



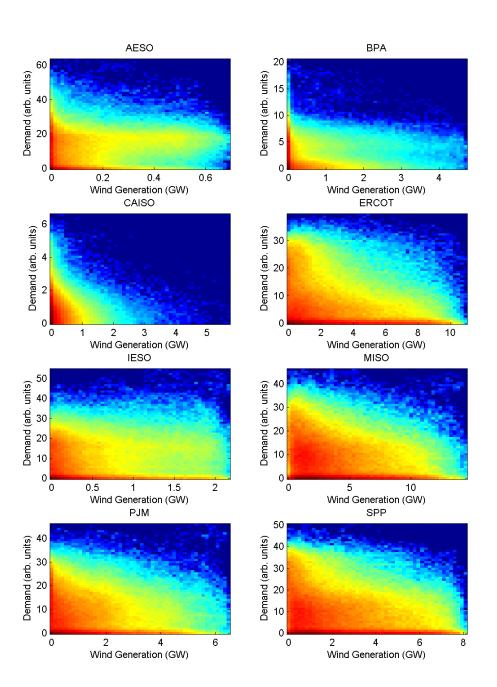
The diurnal cycle of population-weighted temperature-related electrical demand (in arbitrary units). The phase of the cycle shifts dramatically over the year (heating demand versus cooling demand).



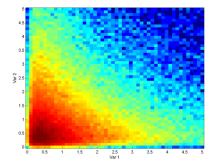
Here are the full 30 year histories, smoothed to monthly means for clarity. Note the higher interannual variability in AESO, while IESO has a more regular seasonal cycle.



Here we show two-dimensional histograms of wind generation (horizontal axis) and raw temperature (vertical axis). Alberta is an interesting case: down to zero, winds tend to increase, but very low temperature events are also associated with low wind.

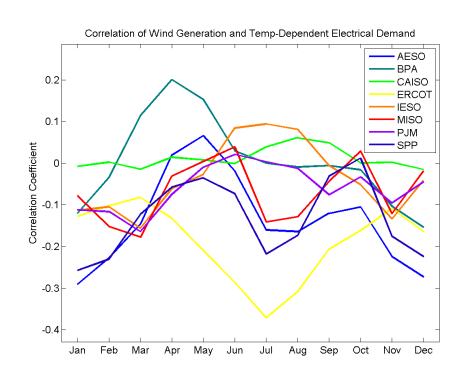


Here we show two-dimensional histograms of wind generation (horizontal axis) and temperature-dependent electrical demand (vertical axis). For reference, the same map for two log-normally distributed random variables is shown below. Some of the relationships (MISO) are "worse" than random, in the sense of preferentially low generation during times of high demand and vice versa, while others are "better" (AESO, PJM).



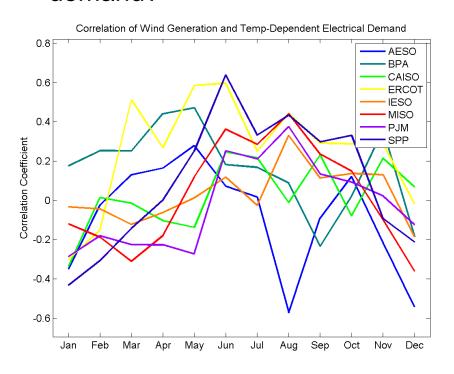
## Correlation of unfiltered variations by month

Most of this is diurnal and synoptic variability



## Correlation of interannual variations (low-pass filtered)

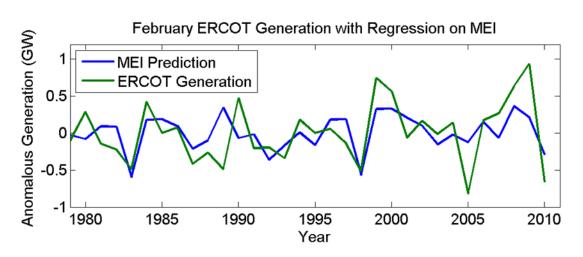
We can also ask, are months with low wind generation associated with low electrical demand?



### **ENSO** and Wind Generation Variability

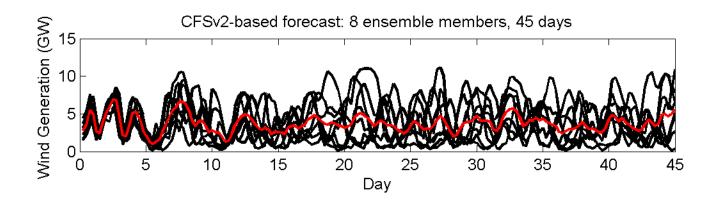
Seasonal analysis of MEI correlations shows that January, February and April wind generation anomalies have the most robust relationship with the MEI (in both regions, for these months, La Niña years are windier than El Niño years). In addition, MISO generation shows a significant negative correlation with the MEI in August.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ERCOT	-0.42	-0.58	-0.07	-0.45	-0.35	-0.04	0.38	0.11	-0.04	-0.21	-0.18	-0.15
MISO	-0.34	-0.46	-0.01	-0.47	-0.19	-0.23	0.19	-0.43	-0.29	-0.09	-0.40	0.04



February ERCOT generation appears to be tolerably well predicted by a regression on MEI.

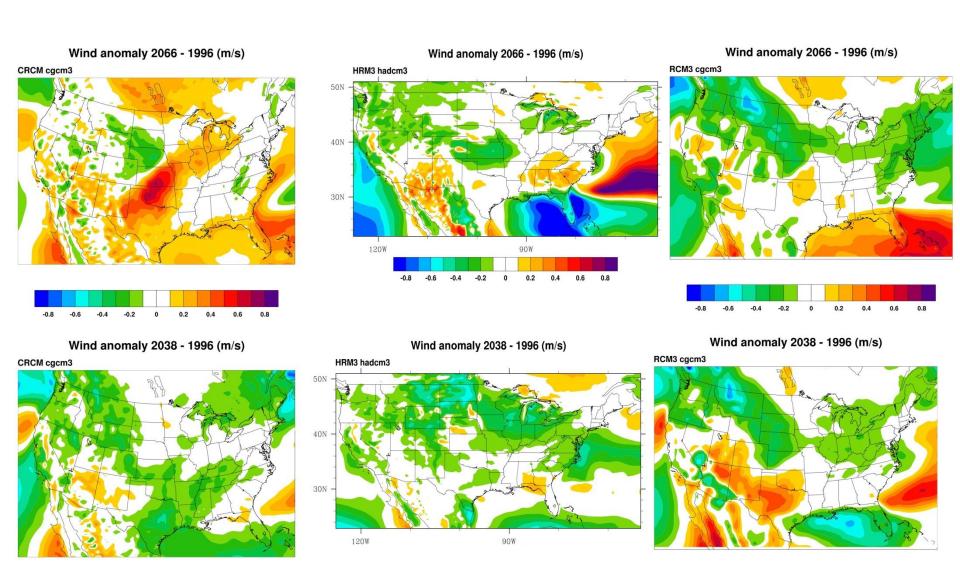
## Coupled model long lead-time forecast of wind generation



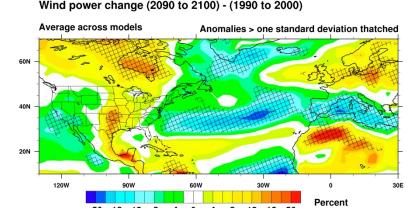
Sample forecast for MISO Wind Generation, starting from January 25, 2013 and using 8 ensemble members. Ensemble spread suggests some skill in the initial two weeks. Skill at long range is yet to be demonstrated.

#### The Impact of Anthropogenic Global Warming on the Wind Power Resource

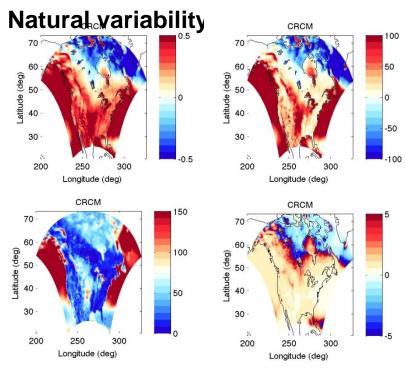
#### NARCCAP predicted wind speed changes for three RCMs:



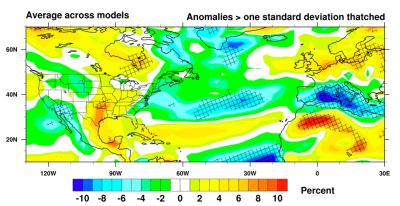
#### **IPCC** model results



## Speed changes versus power changes;



#### Wind power change (2050 to 2060) - (1990 to 2000)



#### **Conclusions**

- AGW is, in several models, associated with significant changes in wind power, relative to both model spread and model variability.
- Model spread is very significant: the signal is more like the precipitation signal in this sense than the temperature signal.
- In the ensemble mean power typically increases in the Midwest and decrease over the coastal Atlantic, but there are models that strongly disagree.
- Inter-annual and decadal variability is also substantial
- High resolution modeling shows significant (with respect to interannual variability) small scale spatial variability in long-term trends

## Thank you! Questions?