DOE AWARD: **DE-SC0007554**

RECIPIENT: **CLIMATE FORECAST APPLICATIONS NETWORK (CFAN)**

TITLE: **APPLICATION OF GLOBAL WEATHER AND CLIMATE MODEL OUTPUT TO THE DESIGN AND OPERATION OF WIND-ENERGY SYSTEMS**

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Distribution limitations: None

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3. Executive Summary

This project addressed the challenge of providing weather and climate information to support the operation, management and planning for wind-energy systems. The need for forecast information is extending to longer projection windows with increasing penetration of wind power into the grid and also with diminishing reserve margins to meet peak loads during significant weather events. Maintenance planning and natural gas trading is being influenced increasingly by anticipation of wind generation on timescales of weeks to months. Future scenarios on decadal time scales are needed to support assessment of wind farm siting, government planning, long-term wind purchase agreements and the regulatory environment. The challenge of making wind forecasts on these longer time scales is associated with a wide range of uncertainties in general circulation and regional climate models that make them unsuitable for direct use in the design and planning of wind-energy systems. To address this challenge, CFAN has developed a hybrid statistical/dynamical forecasting scheme for delivering probabilistic forecasts on time scales from one day to seven months using what is arguably the best forecasting system in the world (European Centre for Medium Range Weather Forecasting, ECMWF). The project also provided a framework to assess future wind power through developing scenarios of interannual to decadal climate variability and change. The Phase II research has successfully developed an operational wind power forecasting system for the U.S., which is being extended to Europe and possibly Asia.

4. Comparison of actual accomplishments with project goals and objectives

The Phase II research project addressed the challenge of providing weather and climate forecast information to support the operation, management and planning for wind-energy systems. We organized the technical objectives into four thrusts, with each thrust having specific task areas. The actual project work proceeded in a manner to optimize leveraging by other related projects and in response to specific interests expressed among potential partners. The main commercial interest that we have identified for our products is regional or grid-scale forecasts on timescales of 7 to 32 days.

Thrust I. *Weather and climate dynamics of wind power variability*

We have completed all of the tasks under this thrust. However, a major challenge has been to identify suitable data sets for the project; the data sets proposed in the original proposal proved not to be useful beyond the lifespan of the project and commercial providers of hub wind data have all gone out of business. We obtained a limited amount of proprietary hub height wind data, but for the most part relied on conventional meteorological data sets. The interest of our potential clients focused our data analysis on the diurnal cycle and ramp and shut down events. Our primary accomplishment for the climate dynamics analysis was to develop a climatology back to 1950 consisting of the daily values of the weather regime teleconnection indices.

Thrust II. *Prediction of regional wind power*

Based upon interest from our potential clients, this thrust has been the major focus of our Phase II efforts. We have met all of the objectives and completed all tasks in this thrust. The greatest challenge in this thrust was to devise strategies for model calibration, given the paucity of in situ wind data available in real time. We have developed and implemented a model calibration strategy that uses the model reforecast runs, recent model verification statistics against the models own operational analysis, and regional power generation statistics. This calibration strategy was leveraged by our efforts to improve our operational energy demand (temperature) forecast products, which has much better calibration data.

Thrust III. *Interannual and decadal projections of the wind power environment*

This thrust has not met all of the original project objectives, owing to our assessment of the lack of regional predictability of the CMIP5 models. Further, we have not been able to identify any significant commercial interest in extended range projections. Our team published the first comprehensive assessment of the CMIP5 10 year decadal simulations, which show very limited utility at the regional scale. Our seminal research into multi-decadal climate variability has provided a new framework for generating observation-based scenarios of decadal variability (published in *Climate Dynamics*). Curry convened a UK-US Workshop on Climate Science Needed to Support Robust Adaptation Decisions that focused specifically on developing regional climate scenarios for decadal time scales.

Thrust IV. *Decision support tool*

The web-based decision support tool development met all the original project objectives and is fully operational for daily to seasonal forecasts, providing forecast information for each of the wind power generating regions in the U.S. Feedback from our beta-users has provided the basis for improving the utility of the dashboard throughout the span of the project.

5. Summary of project activities

The Phase II work plan was designed around the development of two marketable solutions to address the challenge of providing extended range weather and climate forecast products to support decision making associated with wind power:

i. A real-time, operational forecast service provided on a web-based platform on daily, subseasonal and seasonal time scales.
ii. Scenario analysis of the regional future wind power environment on interannual to decadal scales.

The Phase II research was organized into four interrelated thrusts. Our accomplishments and assessments for each of these thrusts are described below.

Thrust I. Weather and climate dynamics of wind power

The overall objective of this thrust was to prepare a dynamical climatology of variables that characterize the regional wind power environment and its variability in the context of the annual cycle and pervasive weather regimes. A key element of the dynamical climatology analysis is a weather typing approach that is based on an analysis of wind power statistics associated with specific weather regimes and teleconnection patterns.

1. Assemble and evaluate the relevant data sets

Hub height wind data

During Phase I, a cooperative arrangement was reached with AWS Truepower that included provision of wind data. However, much of the data they have access to is constrained by agreements with individual providers, although we did make considerable use of the sodar wind data from the ERCOT region that they provided us.

A survey of commercial wind data providers was performed in preparation of Phase II efforts. We selected Onsemble, which had the largest independent network of real-time wind speed and direction measurements. Their network consists of over 300 hub-height sensors in the 8 major US electrical markets. The data acquired in key locations across the ERCOT region spans both the historic time frame from 2012 forward through the future facing dates for the remainder of 2014. Unfortunately, Onsemble has now gone out of business, as have the other wind data providers that we had previously identified.

In addition to the ERCOT data, an agreement has been entered with Southern Company to receive hub height data from their wind farm locations in the Southern Great Plains. We are receiving near real time data and building a historical data set that will provide a seasonal profile for their specific location to be used specifically in the statistical correction techniques covered further in Thrust II.

During the period from 2008–2013, many government and privately funded projects were undertaken to build valid hub height data sets across the US. At the beginning of Phase II it seemed as if this was actually a growing market segment. However, most government-funded projects have ended and the private market has all but disappeared. The lack of publicly available or commercial hub height wind data has been a significant impediment to the project and its long-term prospects, particularly in terms of demonstrating value to potential customers of our short-range forecasts.

Specifically for ERCOT we have obtained the following power generation data:

- Historical wind farm production data in the ERCOT region from 2004–2012 from NREL project at 1 minute intervals (data obtained from Xcel)
- ERCOT system reports from 2007–2013 on total production and percentage of production generated by wind with intervals varying from 15 minutes to 1 hour (available as a registered user of ERCOT's Planning and Operations website)
- Current ERCOT wind production for the entire region and two core sub-regions at 1 hour intervals (available to US users directly from ERCOT website)

While consistent regional wind farm data is not readily available across all other key regions of the U.S., comparable generation and production data at regional levels can be found in many cases. We completed a survey with respect to quality of data from other Federal Energy Regulatory Commission (FERC) regions such as the Southwest Power Pool (SPP) and the Midwest (MISO) in addition to providers in key wind power regions that are not part of FERC such as the Bonneville Power Authority (BPA). Evaluation was made with respect to items such as:

- Wind based power production at different spatial and temporal resolutions
- Wind production expansion plans
- Wind power excess production capacity exchange with other regions
- Wind production as part of total power and renewable production mixes
- Wind production curtailment orders

While each FERC region has different degrees of readily available data, most have reasonably accessible data that could be utilized in different aspects of our solutions from ranging from forecast enhancement to verification. Additionally, market study efforts during year two led to discovery of contacts within some of these organizations that showed interest in our solutions. This has the potential to lead to strategic partnerships with these organizations as we move beyond Phase II.

Wind farm data

We completed a survey of wind turbines in the ERCOT region, using information obtained from the Public Utility Commission of Texas. A list of wind energy plants in Texas identifies a total generation capacity for Texas of 11,272 MW as of 23 January 2013. The information collected for each wind farm includes location, turbine types and hub height, and number of turbines; a summary of this information was provided in the Phase II Year 1 Report. For each turbine type, we obtained the rated capacity and power curve.

During the course of Phase II, the USGS released a major study that attempted to catalog all US onshore turbines. This study - http://pubs.usgs.gov/ds/817/ and its corresponding web tool - have provided an exceptional resource in efforts to expand our data availability of this type outside ERCOT. We undertook a study to compare existing ERCOT data with the new USGS data for the same region. The resulting correlations were very high and provide confidence that we can keep up to date wind farm/turbine data via this tool while it remains consistently updated.

Reanalyses

For forecast verification and calibration and also climate dynamics studies, the project requires hub height wind data. Because of the limited availability of high quality hub height wind data, both in space and time, we have investigated the use of analysis and reanalysis data sets from Numerical Weather Prediction (NWP) models. The following analysis and reanalysis products have been assessed:

- North American Regional Reanalysis (NARR): provides meteorological data every 3 hours at every 25 hPa on a ~32 km resolution, since 1979.
- MERRA-Land (NASA): provides meteorological data (including 50 m vector winds) every hour on a resolution of 2/3^{o} longitude by 1/2^{o} latitude, since 1979.
- ECMWF operational analyses: provides 100 m vector winds on a 12.5 km resolution, since 2010.
- ECMWF Interim Reanalysis: 100 km horizontal resolution since 1989.
- CFSR reanalysis (NOAA): 0.5^{o} resolution since 1979.

For forecast calibration, 20 years of historical data are required. Higher horizontal resolution is desirable. During Phase I, we used the NARR. We evaluated the (calculated) hub height winds from the analyses/reanalyses against available sodar data in the ERCOT region. While the ECMWF operational analysis verifies very well, we also needed to select one of the reanalysis products that goes back to 1979. Based upon on our evaluation using sodar wind profile observations and wind farm power generation data, we selected MERRA as the basis for forecast calibration and climate dynamics studies.

Figures I.1, I.2 and Table I.1 compare three different sodar sites with the nearest MERRA grid cell. It is seen that the MERRA provides a relatively good characterization of the sodar measurements, with differences attributed to local topography at the sodar sites and the comparison of a grid-scale value to a point measurement.

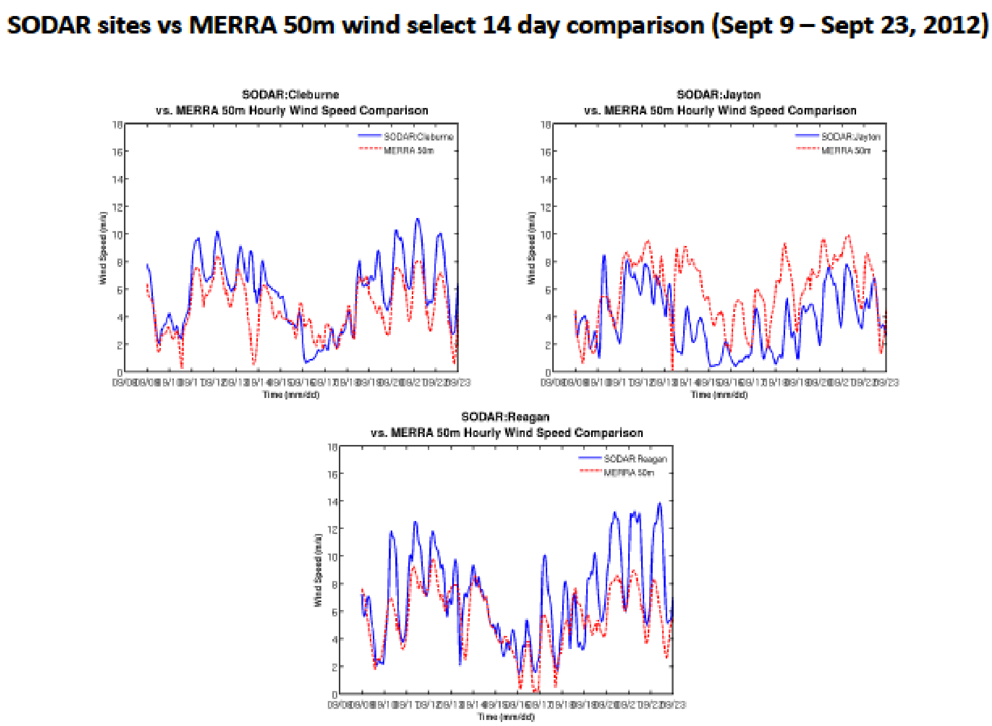

Figure I.1. Comparison of 50 m winds from three sodar sites with the nearest MERRA grid cell for the period 9-23 September 2012.

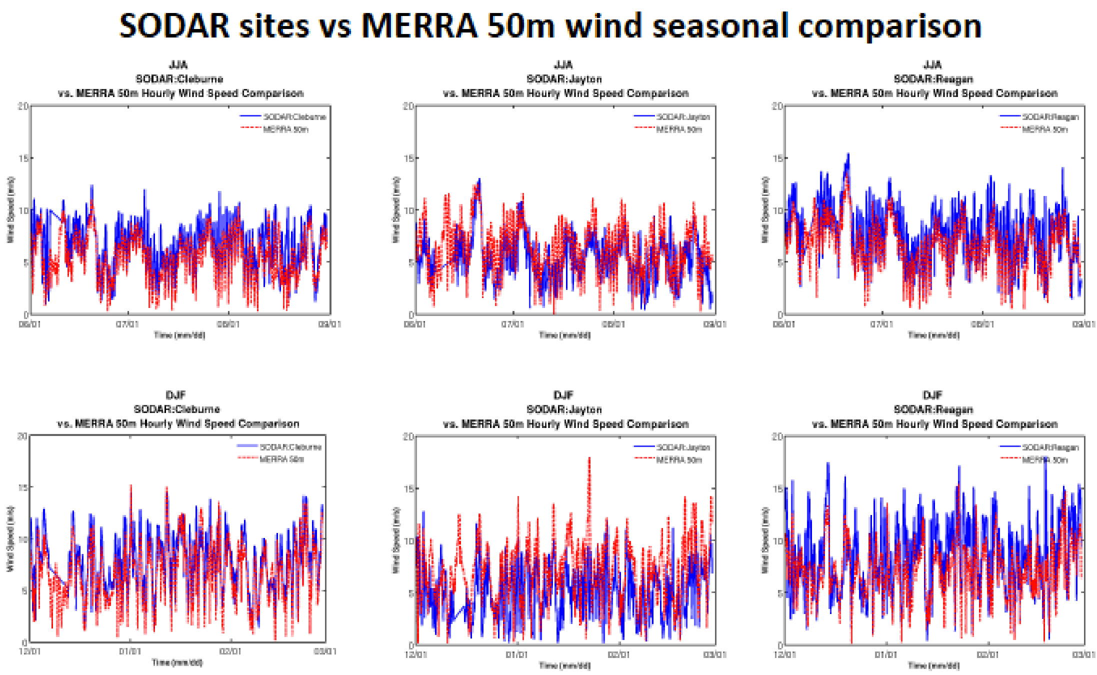

Figure I.2. Comparison of 50 m winds from three sodar sites with the nearest MERRA grid cell for the period 7/21/2011 – 8/31/2012.

Table I.1. Correlation coefficients between 50 m winds for 3 sodar sites and the local MERRA grid cell for 7/21/11 – 8/31/12.

Sodar sites and MERRA 50m wind correlation coefficients

	Full Data Set (7/21/2011 – 8/31/2012)	Seasonal: JJA	Seasonal: DJF
SODAR:Cleburne	0.82	0.75	0.84
SODAR:Jayton	0.57	0.61	0.48
SODAR:Reagan	0.75	0.79	0.73

A more relevant assessment of the utility of the MERRA reanalysis is obtained from comparison with observed wind power generated by a wind farm. Figure I.3 shows 6-hourly farm-level verification of calculated wind power using MERRA for Jan 2012 for the Trent Mesa Wind Project (100.199° W, 32.429° N), located between Abilene and Sweetwater, Texas, in the West Weather Zone of ERCOT. This wind farm uses 100 GE 1.5 MW turbines. Figure I.3 indicates that there is no overall bias in the calculated wind power. Some of the magnitude errors are likely associated with differences in spatial resolution; this verification site represents an area of ~96 km^2 (16x6 km) compared to the MERRA resolution of ~3350 km^2 (50x67 km). Figure I.4 shows the verification for all of 2012.

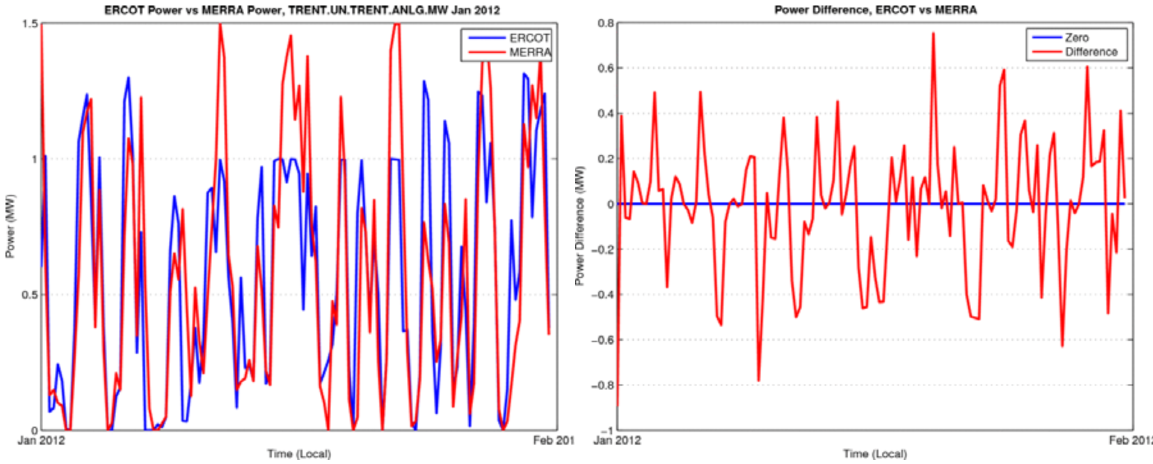

Figure I.3. Comparison of ERCOT power data (normalized to 1.5 MW) from the Trent Mesa Wind Project to power data reconstructed from the MERRA reanalysis dataset in January 2012. Left: ERCOT 1 minute interval data temporally aggregated to 6 hour intervals versus MERRA reconstruction. Right: Differential.

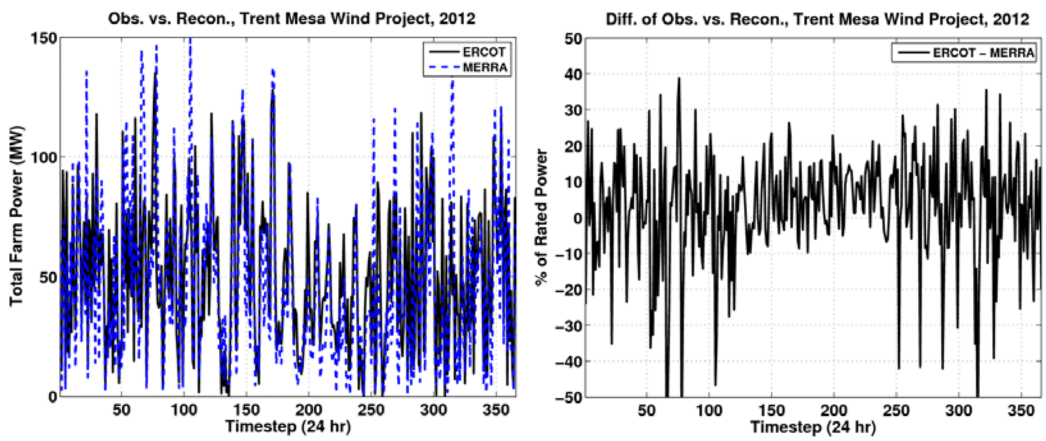

Figure I.4. Comparison of ERCOT power data from the Trent Mesa Wind Project to power data reconstructed from the MERRA reanalysis dataset in 2012. Left: ERCOT 1 minute interval data temporally aggregated to 24 hour intervals versus MERRA reconstruction. Right: Differential.

2. Relate decision relevant variables to the meteorological variables

Since most of these are straightforward, the discussion here focuses on power ramps and upscaling for regional power generation.

Regional upscaling. During Phase II, we developed a power curve for each model grid cell that is weighted by the number of turbines of each type. The wind power in each model grid cell is then determined from the predicted wind speed, the number of turbines in each cell, and the grid power curve. Power is then output as the ratio of the forecasted power to the rated power capacity, for each wind farm, grid cell or region. This upscaling strategy is now operational in our wind power forecasts.

Power ramps. Because of the large diurnal ramp different regions, the statistical post processing filters out the diurnal cycle in wind power production. The diurnal cycle is filtered out using the time series of wind power for the previous 14 days and three predictors [mean, sin($2\pi t$), cos($2\pi t$)]. In context of the temporal resolution of the ECMWF forecasts, we define a ramp to be a change in the regionally averaged power output that is at least 30% of the rated power output and occurs within a time span of 6 hours or less, which insures that power changes are sufficiently rapid and that sufficient ramps are identified for analysis. The relevant characteristics of a power ramp are its magnitude, direction (up or down), timing and duration.

3. *Wind dynamic climatology*

We developed a dynamic climatology of weather regimes as a function of month (annual cycle) and teleconnection patterns to determine any changes in the statistical distribution of the 50 m wind speed associated with these regimes. This analysis provides a key source of information regarding the predictability of wind power in terms of region, season, and weather regime, and also provides a statistical basis for use in the decadal scenarios. The term *weather regime* typically connects the large-scale atmospheric recurring patterns such as the northern hemisphere teleconnections to planetary and synoptic-scale atmospheric dynamics. In general, weather regimes persist for several days to a week, and rapid transitions may occur between them.

The underlying methodology for determining weather regimes for this study uses a k-means cluster analysis of 500 hPa geopotential height anomalies from the ECMWF over the North American for each of the 4 seasons. Several of the cluster patterns resemble combinations between the Arctic Oscillation (AO), Pacific North American pattern (PNA) and North Atlantic Oscillation (NAO) regimes. The next step was to composite the near surface wind speed (50-m) from the MERRA reanalysis for each cluster to assess the impact of a particular large-scale regime onto the hub-height wind speed over South Central US.

The cluster analysis was performed using daily geopotential data for the period 1979–2012 for each of the 4 seasons. The domain for the cluster analysis was selected as 20N–87.5N; 157.5E–360E, to cover North America and the surrounding ocean basins. The 500 hPa geopotential height anomalies were calculated with respect to the daily 1979–2012 long-term climatology. The daily data was smoothed with a seven-day running mean filter to ensure the clustering filters out some of the high frequency signal, and focuses on more robust lower frequency features. A k-means cluster analysis using Euclidean distance was used to identify commonly occurring patterns of 500 hPa geopotential height. The clustering was conducted using the EOF sub-space. The first 10 EOFs were retained as they explain between 81% and 65% of the variance, depending on the season. Note that selecting more modes does not alter the results significantly. The number of clusters was selected using the average silhouette of the data, and based on comparison to previous published studies. Seven clusters were specified for each of all 4 seasons. Results show the geopotential cluster composites computed from the low-pass filtered geopotential height anomalies by averaging all the instances associated with each cluster. Similar composites were conducted for the daily low-pass filtered 50 m wind speed and the AO, PNA and NAO teleconnections.

Figure I.5 a-d provide analyses for each of the 4 seasons of the most significant clusters. For each season, the 2 or 3 dominant clusters are shown, with the geopotential pattern for North America and wind anomalies for the ERCOT region. The scatterplots are interpreted as follows, using DJF as an example. The figure NAO vs. AO provides the average NAO and AO magnitudes of all days corresponding to each cluster. For example, Cluster 7 (C7 - in red) is associated with strong negative AO (-2.7) and strong negative NAO (-0.75). In contrast cluster 6 (C6) - orange is associated with weak positive AO (0.2) and strong positive NAO (0.2). It appears that the greatest influence on ERCOT wind speeds is represented by medium to strong PNA patterns in association with weak AO. In contrast, the NAO or strong AO do not seem to influence the ERCOT winds in a consistent manner. In general, we see negative PNA and a weak positive AO is associated with strong winds over ERCOT region, and positive PNA is associated with weaker than normal ERCOT winds.

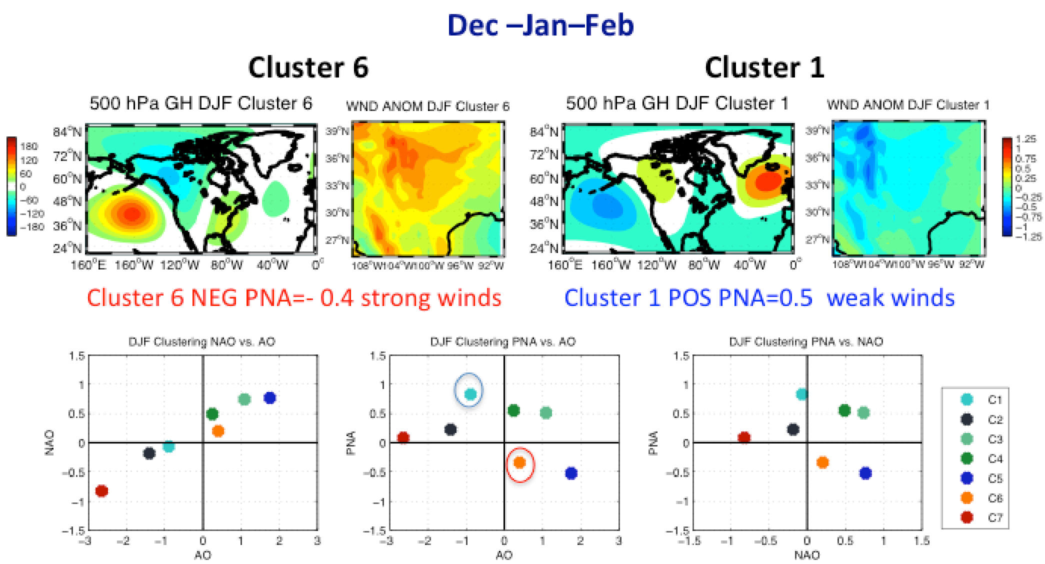

Figure I.5 a): Selected k-means composite clusters (6 and 1) patterns of 500-hPa geopotential height anomalies (m) over the N. Am. As well as 50-m wind speed (m/s) over the south central US encompassing the ERCOT region and composite mean AO, NAO and PNA indices of the all days included in each of the seven clusters (bottom panels 1 through 3 as labeled). The clusters were computed for the Northern Hemisphere winter season.

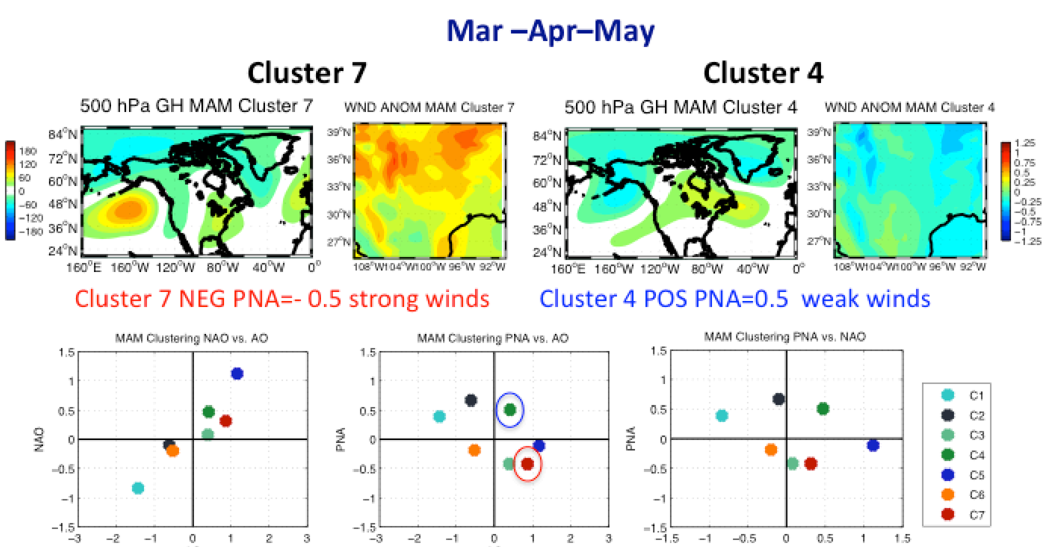

Figure I.5 b): Same as a) but for the MAM period, with the top panels depicting clusters 7 and 4.

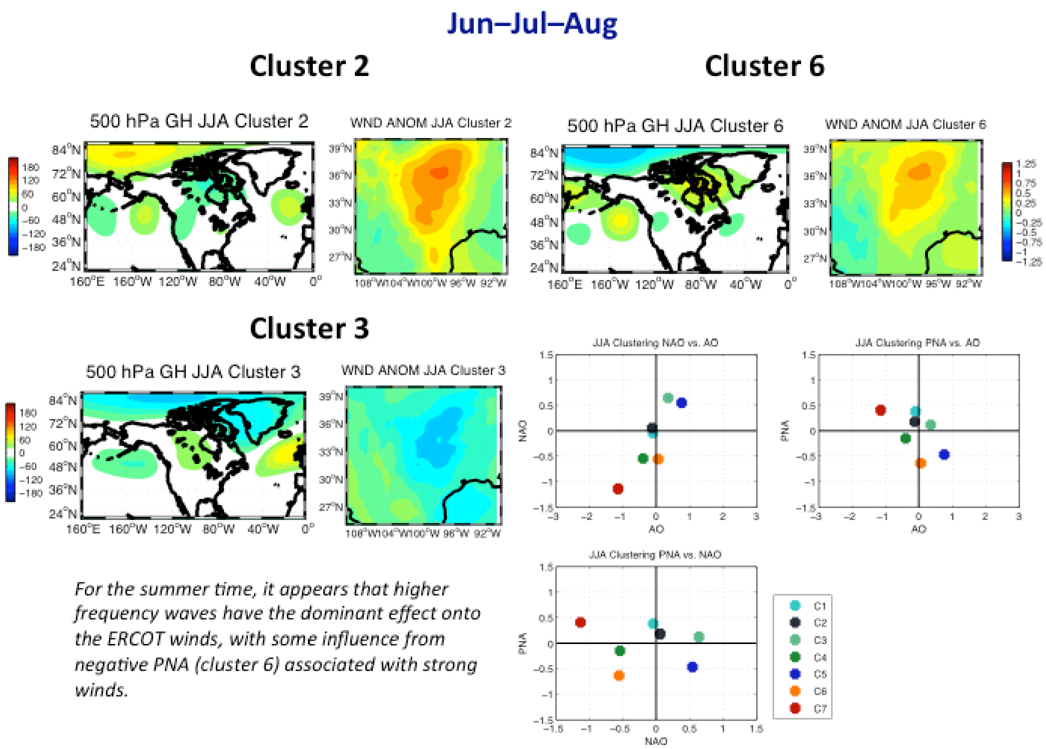

Figure I.5 c): Same as b) but for the June through August period. Clusters 2, 3 and 6 were included.

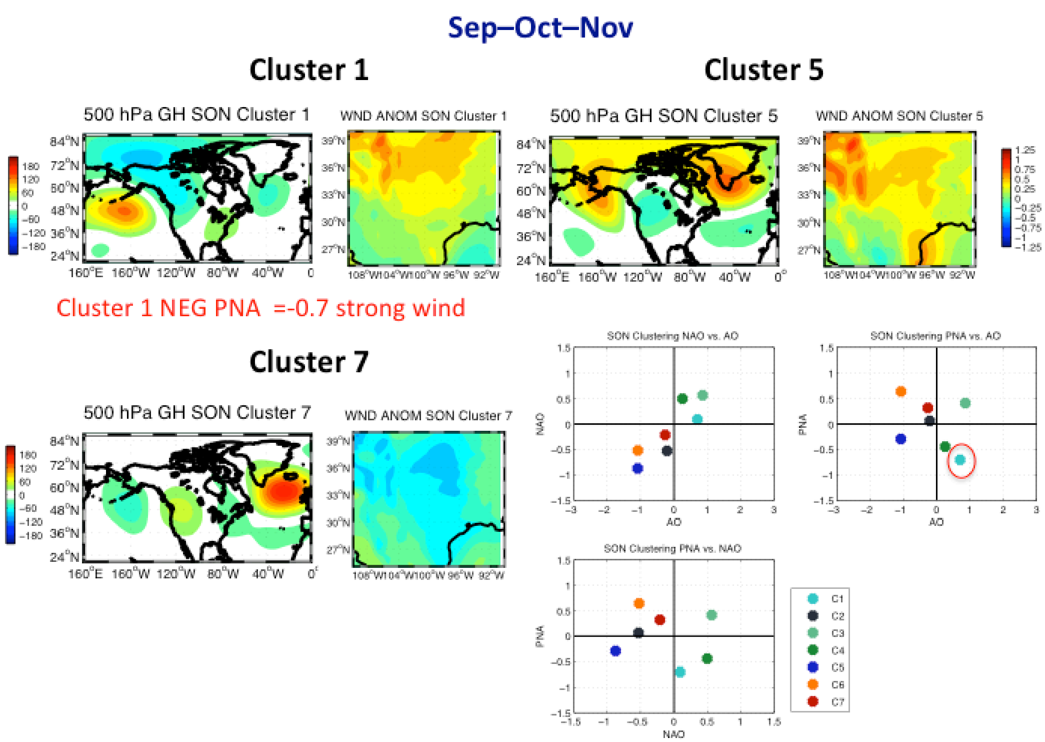

Figure I.5 d): Same as c) but for the September through November period. Clusters 1, 3 and 7 were included.

Consistent with previous analyses based on near-surface observations or radiosonde data, there are strong teleconnections between the leading modes of large-scale climate variability and both near-surface and midtropospheric wind speeds over the contiguous US. Two recently published papers are also significant in this regard. Pryor and Ledolter (2010) and Schoof and Pryor (2014) examined the relationship between the annual 90th percentile wind speeds at multiple levels in the lower troposphere and NAO, PNA, and ENSO and found that regionally averaged wind speeds exhibited significant differences with the phase of at least one mode in all regions of the contiguous US. Identification of strong statistical relationships between near-surface and lower troposphere wind speeds and large-scale modes of climate variability suggests that low frequency variability associated with these climate modes could be used to estimate low frequency wind variability using large-scale circulation features simulated by climate models.

Thrust II. Prediction of regional wind power

For predictions on timescales from days to seasons, CFAN's operational wind power forecasts are based on the European Centre for Medium Range Weather Forecasting (ECWMF) ensemble weather forecast system, including the following products:

- *Deterministic atmospheric model*: 1-10 days at 0.125^{o} x 0.125^{o} horizontal resolution, available twice daily at 3-hour intervals to 144 hours, and at 6-hour intervals at beyond 144 hours.
- *Atmospheric Ensemble Prediction System*: 51 ensemble members, 1-15 days at 0.25^{o} x 0.25^{o} resolution to 10 days and 0.5^{o} x 0.5^{o} resolution beyond 10 days. Available twice daily at 6-hour intervals.
- *Monthly forecasting system*: 51 ensemble members, 1-32 days at 0.5^{o} x 0.5^{o} resolution. Output variables include wind velocities at 10 m, 1000 hPa and 925hPa, available twice weekly at 6-hour intervals.
- *Seasonal forecasting system*: 41 ensemble members, 1-7 months at 1.5^{o} x 1.5^{o} resolution. Output variables include 10 m wind velocities, available once per month at 6-hour intervals.

1. Produce probabilistic forecasts

CFAN is producing probabilistic forecasts for ERCOT (Texas), Southern Plains, Northern Plains, Midwest and West Coast (Northwest and California) regions. We are also producing operational forecasts of wind power and temperature anomalies for the continental U.S. and offshore regions. A large-scale ramp forecast product is operational for ERCOT. Monthly wind anomalies out to 7 months are produced for the continental U.S. and Europe. Weather regime forecasts are operational, for 1-15 days, 15-32 days, and out to 7 months. The login information for DOE users is as follows:

<< Confidential information
Site: http://cfan.eas.gatech.edu/BETA/wd.php
User: DOE
Pass: Phase!!2015
ends here >>

Operational environment

During 2013, CFAN made a major shift in its computing environment that was designed to make it more robust and geared for true operations. Despite the bandwidth benefit of being located historically in Georgia Tech facilities, the technical staff was geared only for traditional work-week support. By entering into a long-term strategic agreement with The Weather Companies, we were able to make a major leap forward in our operational environment. Our production environment server gained a 16-fold increase in processing capability and a doubling in our development environment, which can also serve as a production backup. This redundancy has also been added to web distribution environment as well. This computing environment is supported by a 24x7 operational staff that serves a large global user community.

Regional, daily wind power forecasts

Probabilistic wind and power forecasts out to 15 days are now available for the following regions:

- ERCOT
- Northern Great Plains
- Southern Great Plains
- Midwest
- Northwest
- California

Each of these locales is divided into zones based upon concentrations of wind farms and meteorological regimes (Figure II.1 shows the zones for each of these regions).

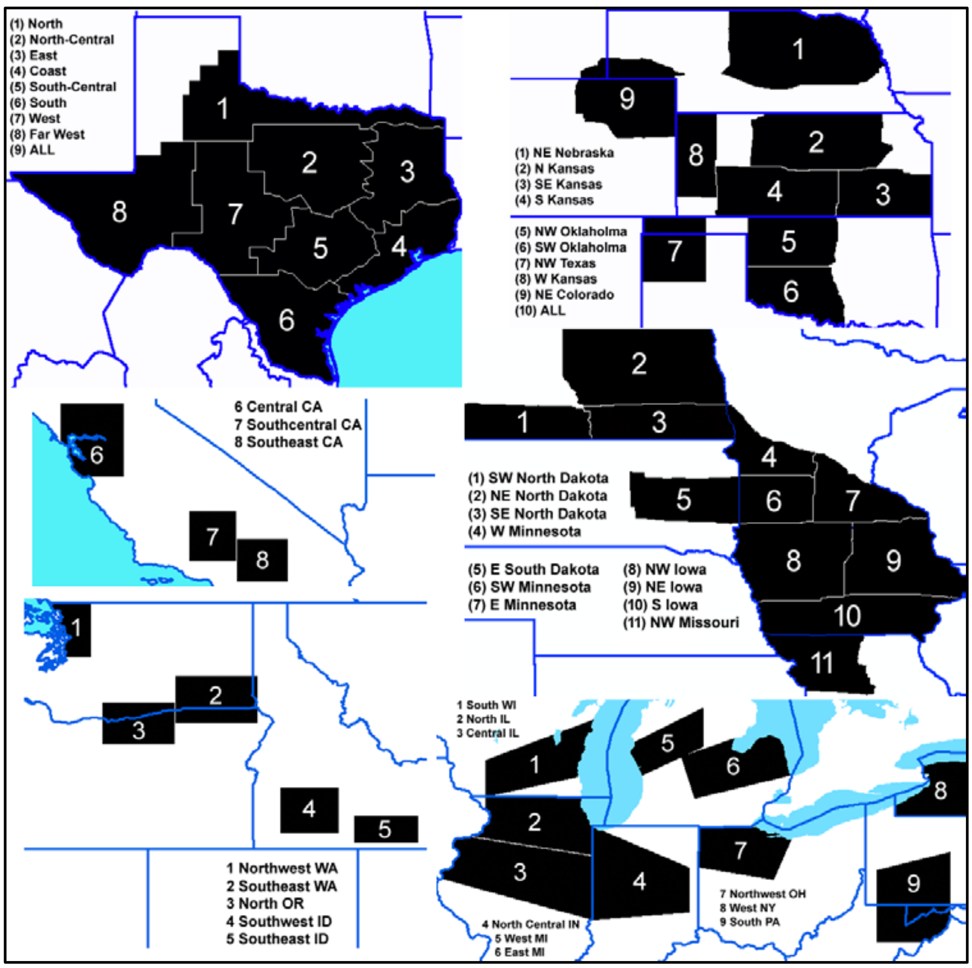

Figure II.1. Forecast region / zone maps for the currently forecasted areas - ERCOT (upper left), Northern Plains (upper right), California (middle left), Southern Plains (middle right), Northwest (lower left), Midwest (lower right).

Figure II.2 is an example of 15-day wind power forecasts (initialized 1/26/2014) for individual zones in 3 separate regions along with forecasts (initialized 4/30/2015) for zones from the latest regions added to the operational product in year 2 of the project. The forecasts display outputs derived from both the ECMWF high resolution deterministic as well as ensemble based forecasting systems.

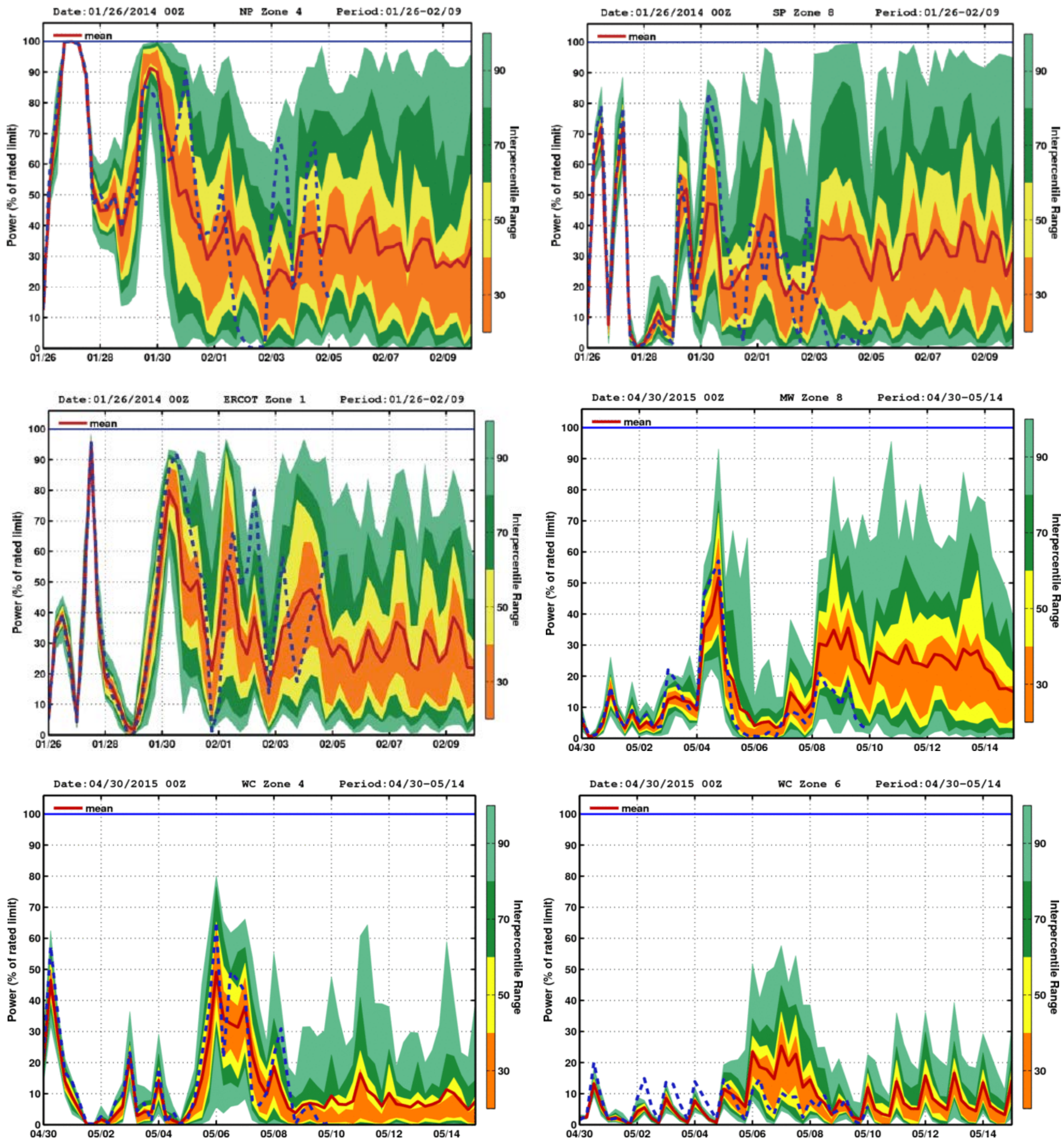

Figure II.2. 15 day forecasts initialized 1/26/14 for: West Minnesota (upper left); west Oklahoma (upper right); and north Texas (middle left). 15 day forecasts initialized 4/30/15 for: Western New York (middle right); Southwest Idaho (lower left); and Central California (lower right).

U.S. wind power anomaly and population weighted energy demand products - daily

Figure II.3 shows an example of a wind power forecasts anomaly at 96 hours after the initiated forecast date of 2/15/15. The forecast covers a 6 hour period and in this case reflects the contrast of synoptic scale features with a large frontal boundary moving across the eastern US.

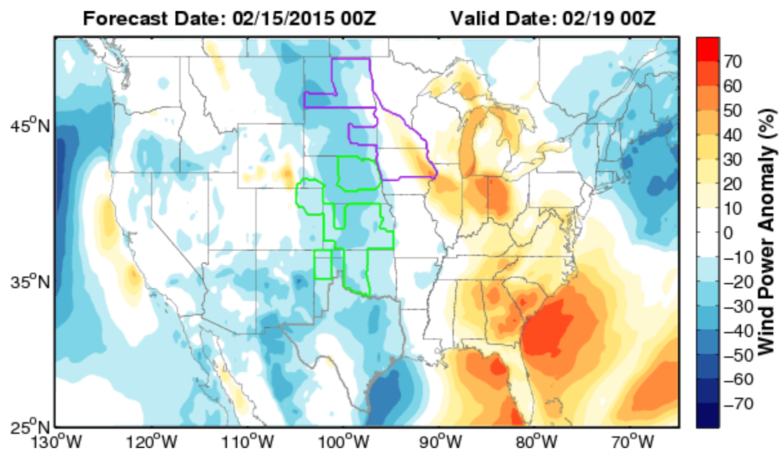

Figure II.3. Example of the operational wind power anomalies generated at 6-hr resolution through 240 hrs. Forecast is initialized 2/15/15 and the time horizon is at 96 hours. The region outlined in black denotes ERCOT, green indicates the Southern Plains, and purple denotes the Northern Plains.

The anomaly forecasts use the ECMWF ensemble predictions of the 100 m total wind field and calculate the wind power using the GE 1.5 S power curve for each grid point location. The calculation is completed at each grid point and for each ensemble separately before calculating the mean ensemble power. The grid point wind power projections are calibrated using the ECMWF hindcasts for the 100 m total wind. The climatology is determined by averaging the last 20 years and 5 ensemble members (total sample size: 100 members). Finally, the wind power anomalies are determined by removing the climatology from the ECMWF ensembles. The anomalies are then scaled by $1.5*10^{-4}$ to derive the probability (in %) for each grid point.

Analogously, Figure II.4 shows an operational forecast of population weighted energy demand based on temperature anomalies.

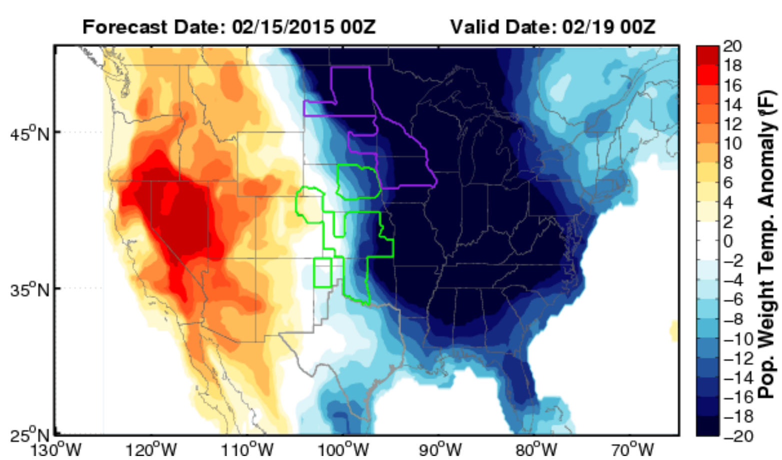

Figure II.4. Example of the population-weighted temperature anomalies generated at 6-hr resolution through 240 hrs. The forecast is initialized 2/15/15 and reflects the forecast at 96 hours.

The population data set used is from the 2010 Census Data. Gridded population estimates valid for 2010 were obtained from Colombia University's Gridded Population of the World: Future Estimates. This population dataset contains a low-resolution version of the UN-adjusted population count grids in ASCII format. The raster data are at 0.25 degrees (15 arc-minutes) resolution for the continental U.S.

Using the ECMWF ensembles and the 2m surface temperature along with the ECMWF hindcasts, the surface temperature anomaly per ensemble is determined. Next, the temperature anomaly for each ensemble member is then scaled by population. The scaling occurs by grid point in which for each grid point the locus of points that fall within 75 km of a grid point are identified. Then each grid point is weighted by the population of the grid point normalized by the total population of all grid points that fall within this radii, and the results are aggregated to determine the final anomaly. The procedure acts as a smoother to the spatial anomaly fields but also tends to amplify the raw temperature anomalies especially in regions where the anomalies occur in regions of high population density.

The temperature-based demand forecasts are often used as a primary indicator of the demand side need for power generation. When used in the conjunction with the wind anomaly forecast, a user can gain a better understanding of where wind power will or could fit into the overall power generation mix at forecast intervals over the next 10 days.

ERCOT Wind Ramp Outlooks - daily

Figure II.5 is an example of a wind ramp risk outlook for ERCOT Zone 7. These high resolution point forecasts are an example of extreme event forecasts. The forecasts highlight exposure to pronounced anomalies expected at windfarm level resolution.

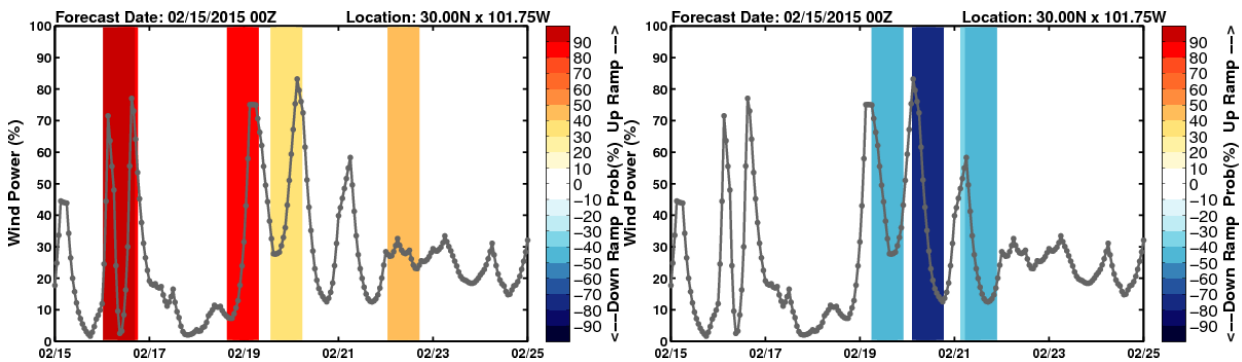

Figure II.5. Ramp risk forecasts initiated on 2/15/15 for the next 10 days at 30Nx101.75W.

A ramp is forecast to occur when the variation is high and steep enough compared to the normal variation for a location. We define the variation as 30% of the nominal wind power for a grid point. We classify ramps based on their support, timing, and intensity. These forecast help both wind energy suppliers and users in anticipating anomalies outside what would be typically consider a normal diurnal variation window.

Weather regime forecasts - weekly

We have implemented operational probabilistic weather regime forecasts for 1-32 days using the ECMWF monthly forecast product. The Arctic Oscillation (AO) index is developed by projecting the 1000 hPa daily geopotential anomalies poleward of 20°N onto the loading pattern of the AO. This pattern represents the leading Empirical Orthogonal Function (EOF) of the monthly mean 1000-hPa height anomalies poleward of 20°N. The other weather regimes loading patterns are determined by applying a

Rotated Principal Component Analysis (RCPA) analysis to the monthly standardized geopotential height anomalies at 500 hPa. This analysis yields 10 weather regimes, of which we use the following: North Atlantic Oscillation, East Atlantic, East Atlantic/Western Russia, Scandinavia, Polar Eurasia, West Pacific, East Pacific-North Pacific, Pacific North American. This method of calculating the weather regime indices follows closely the method used by NOAA CPC. These patterns have varying degrees of influence on weather behavior across the different regions of the U.S. Typically the values help in diagnosing prolonged (3+ days) variances from normal that can be expected to impact a given region and its meteorological environment.

Recent forecasts for the Arctic Oscillation (AO) and Pacific/North American pattern (PNA) are shown below in Figure II.6.

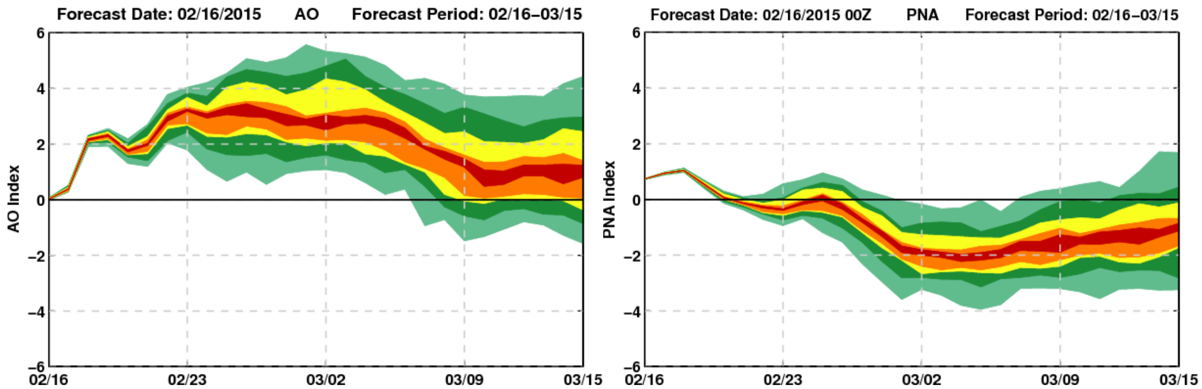

Figure II.6. 32 Day Probabilistic forecasts of: Arctic Oscillation (AO; left) and 32 day forecast of the Pacific/North American pattern (PNA; right).

Subseasonal and seasonal forecasts

Subseasonal forecasts (out to 32 days) of wind power (% of rated limit) are provided for the ERCOT region (9 zones plus entire region).

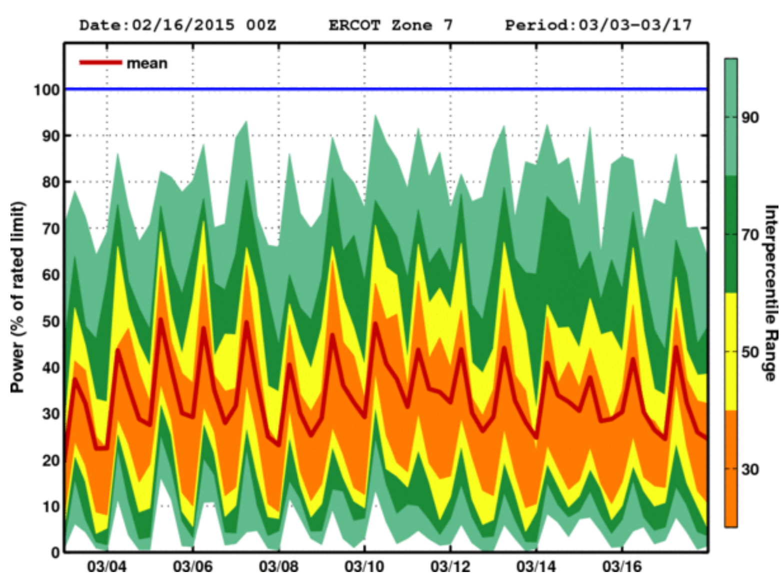

Figure II.7. 32 Day probabilistic outlook for Zone 7 in ERCOT.

Seasonal gridded forecasts of continental wind anomalies (continental U.S. and Europe) are provided out to 7 months for monthly averaged wind anomalies, although there is limited skill beyond one month.

The example shown in Figure II.8 demonstrates high overall power availability during the forecast period. Yet high amounts of uncertainty exist when compared with the projections seen in figure II.6 for the influential teleconnection regimes.

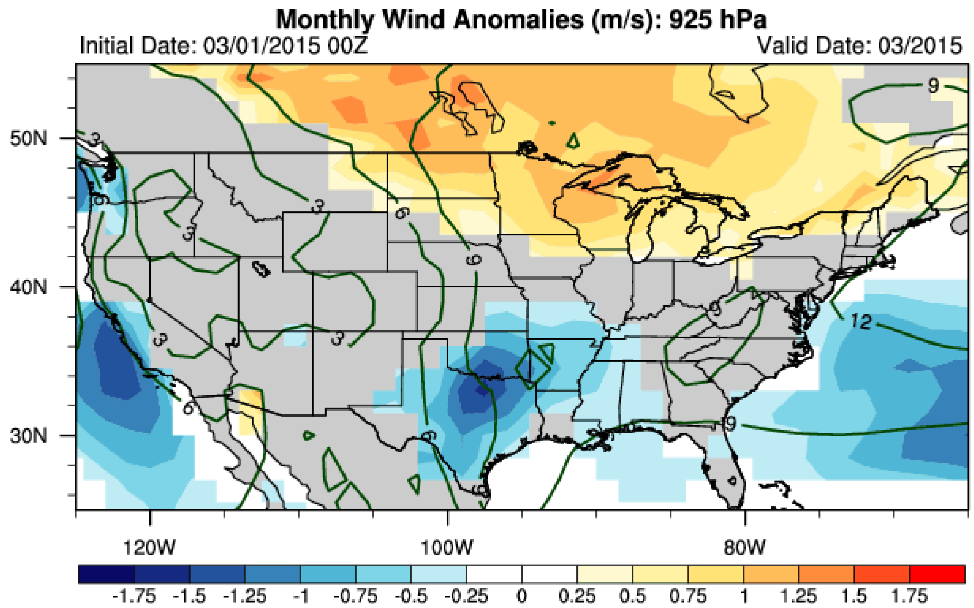

Figure II.8. Monthly average for March showing negative wind anomalies for ERCOT and the West Coast while the Northern Plains and Midwest can expect enhanced wind production.

A major study is being undertaken on seasonal predictability of ENSO and the SOI (Southern Oscillation Index), which is the principal basis for any predictability of winds beyond 45 days. Figure II.9a shows the long-term variability of March SOI autocorrelation for different lag months using a 15-year sliding window. Figure II.9b shows the same but starting in June. Together the figures show generally short-term persistence in the boreal spring and generally longer persistence from summer onwards. But there is also coherent interdecadal variability added to this seasonal behavior. For example, Figure II.9a indicates that there was an increase in spring persistence between 1946–1956, with the initial March persistence signal projectioning more like the summer. June persistence shows interannual/interdecadal variability as well (Fig. II.9b).

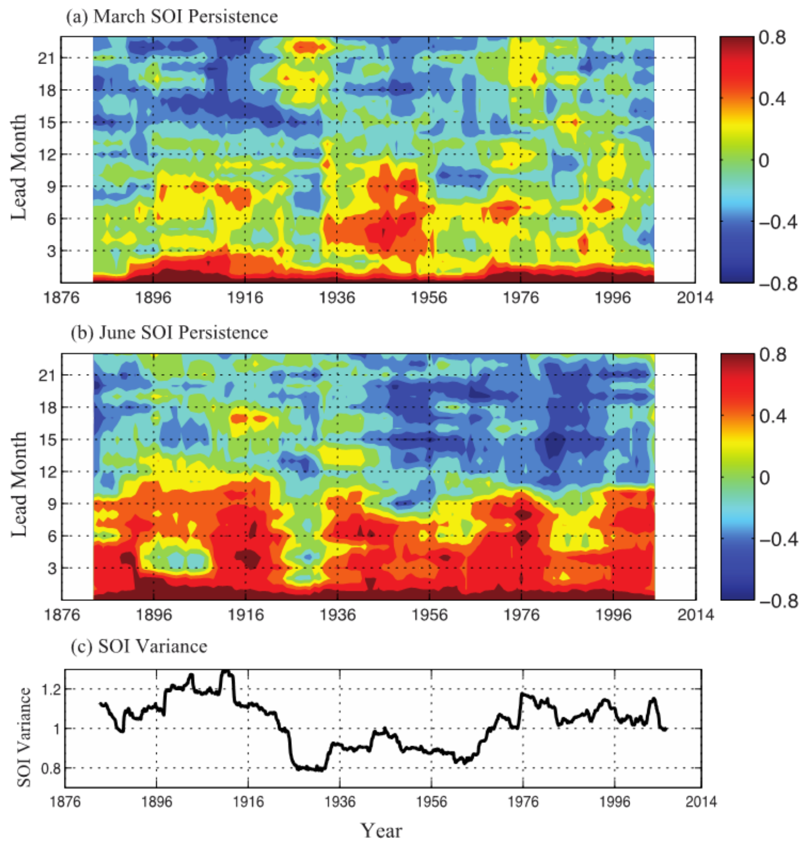

Figure II.9. Interannual variability of (a) March and (b) June SOI persistence for the period 1876–2014. Persistence is calculated as lagged autocorrelation for lag months 1 to 24. A sliding window of width 15 years was used to compute the correlations. The x-axis marks the center of the 15-year window, while the y-axis represents the lagged months.

Products under development

While the STTR project has formally completed, based on feedback from our BETA users we continue to undertake enhancements to our operational suite of forecast products.

We have developed the capability for providing 'point' forecasts of wind speed and wind power on the scale of an individual wind farm. Effective forecasts require a real-time stream of hub height wind observations (as well as detailed information about the wind turbines). We are developing a beta version in conjunction with Southern Company.

We are evaluating new zones for the Wind Ramp forecasts. This high-resolution type forecast has been well received by a wide variety of user types; however the production cost is high. Evaluations will be made on the most prominent regions in the overall US wind energy production profile. This type of product could also be developed for individual wind farms as part of a suite of 'point' products.

In addition, CFAN is in the process of developing a gridded 0.5^{o} resolution, 100 m wind forecast product for the continental U.S., Europe and eastern Asia, focusing on the subseasonal time scale (3-4 weeks). This product is being developed to the specifications of Weather Systems International (WSI; a subsidiary of The Weather Companies), under CFAN's license and product development agreement with WSI. This product is targeted at energy traders and the financial sector. It is likely this project will lead into the expansion of other portions of the existing suite into the European domain.

2. Statistical post processing and ensemble interpretation

The most challenging and time-consuming aspect of this project has been statistical post processing, and we continue to evaluate and improve our techniques for statistical post processing.

Regional average power production

An example of the difference between the original area-averaging with the upscaling scheme is illustrated in Figure II.10. Depending on the distribution of wind speeds across the domain, the new scheme may predict more or less power than the original scheme.

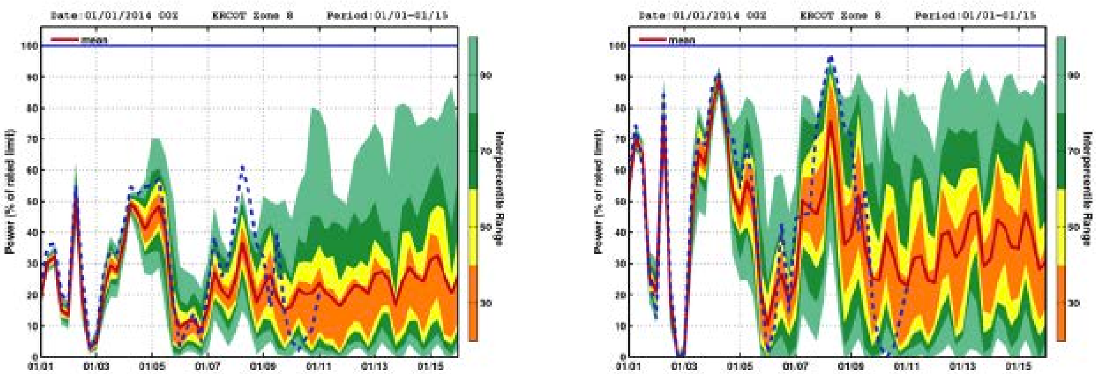

Figure II.10: Wind power prediction for ERCOT zone 8 initialized in 1/1/14. Left – original area averaging scheme; right – new upscaling scheme.

Bias and distributional correction

We have implemented a new bias correction based on weighted average mean bias, which has proven to be superior (particularly at longer lead-times) to the existing 14-day mean bias correction. The scheme is based on an adaptive (Kalman-type) algorithm to accumulate the decaying averaging bias. Basically, the bias $b_{ij}(t)$ is estimated for each forecast lead time and at each grid point (i, j):

$$b_{ij}(t) = f_{i,j}(t) - oa_{ij}(t)$$

where f represents quantile corrected ensemble mean the, and oa represents the operational analysis for that time interval. Next, the decaying average $B_{i,j}(t)$ will be updated based on the previous $B_{i,j}(t-1)$ and current bias $b_{i,j}(t)$ and using a decaying average with the weight coefficient w, as follows:

$$B_{i,j}(t) = (1 - w)*B_{i,j}(t-1) + w*b_{i,j}(t)$$

The corrected forecast is then represented by:

$$F\ corrected_{i,j}(t) = F\ q\text{-}to\text{-}q_{\ i,j}(t) - B_{i,j}(t)$$

The challenge is the selection of an appropriate weight (w) since w may vary regionally.

Currently, the ECMWF reforecasts are much more limited as they encompass the last 20 years and only feature a 5-member ensemble that is available once weekly. In May 2015, ECMWF will be making their reforecasts available twice weekly using an expanded ensemble size. However, there is a growing concern that the ECMWF historical reforecasts are diminishing in utility owing to the growing differences between the model version used for initializing the reforecasts and the current operational model.

Hence, we are continuing to rethink our calibration scheme, to reduce dependency on the reforecasts. In addition to these techniques we are also planning to evaluate approaches utilized in a recently completed precipitation forecast evaluation process. Here, we briefly summarize a few of the methods under consideration.

Logistic regression and recently extended logistic regression (Wilks 2009)[1] are a type of generalized linear model that uses a logistic function (Equation 1) to map a set of input variables, e.g., ensemble mean precipitation, ensemble standard deviation precipitation, total precipitable water, etc. to probability space (bounded between 0 and 1).

$$f(x) = \frac{1}{1+e^{-t}}, \text{where } t = \beta_0 + \beta_1 x^{\alpha} + \beta_2 x^{\alpha} \ (1)$$

Hamill et al. (2008)[2] uses a one-quarter power transformation factor (α = ¼), while other analyses where the ensemble standard deviation is not included often set the power-transformation factor slightly larger (α = 1/3 or α = ½). Generally, it is thought that for more-highly skewed distributions, a smaller exponent power transformation is needed. Unlike with temperature calibration where a small 30-day training set produces improved forecast skill, the Hamill et al. analysis clearly demonstrates the need for a large sample of reforecasts to improve precipitation forecast skill especially at higher precipitation thresholds and at longer lead times. Following this methodology we will investigate the optimal power transformation factors for wind speed and evaluate the use of logistic regression in adjusting the wind speed.

Another approach for probability calibration is known as the rank analog approach (Hamill et al. 2015)[3]. This approach is currently being used experimentally by NOAA ESRL for the GEFS Reforecast v2 here: http://www.esrl.noaa.gov/psd/forecasts/reforecast2/ccpa/index.html. The technique utilizes the reforecasts to identify historical analog events relative to the current forecast to compute probabilities of exceedances at varying forecast lead-times. The probabilities are then smoothed using a 2D Savitzky-Golay smoother. Verification of this approach clearly demonstrates improved forecast skill relative to the raw model but produces similar forecast gain to that seen with logistic regression and extended logistic regression.

Ensemble dispersion

A post-processing calibration of an under-dispersive ensemble forecast can have a negative impact on the forecast. It is more desirable to alleviate the under-dispersion by adding “good spread”, which is defined as an increase in ensemble variance that simultaneously improves statistical consistency (i.e., ensemble variance matches the MAE of ensemble mean), reliability, and resolution. For instance, adding noise does not create good spread since a decrease in resolution would result.

We judged our ensembles to be under-dispersive, especially for the first few days of the forecast. We improved the dispersion of our forecast ensembles by first computing an inverse normal cumulative distribution function (CDF) using the mean absolute error as the new sigma. This was then used as the

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1 Wilks, D. S., 2009: Extending logistic regression to provide full probability-distribution MOS forecasts. *Meteor. Appl.*, **16**, 361–368.

2 Hamill, T. M., R. Hagedorn, and J. S. Whitaker, 2008: Probabilistic forecast calibration using ECMWF and GFS ensemble reforecasts. Part II: precipitation. *Mon. Wea. Rev.*,**136**, 2620-2632.

3 Hamill, T. M., M. Scheuerer, and G. T. Bates, 2015, Analog probabilistic precipitation forecasts using GEFS Reforecasts and Climatology-Calibrated Precipitation, *Mon. Wea. Rev.*, accepted.

basis for redistributing ensemble members at each forecast time step.

To calibrate a zonal wind power forecasting scheme, historical estimates of the total wind power generation in each zone (Fig. II.1, top left) were first created by combining ERCOT-wide wind power generation data and zone-specific fuel-wide (coal, hydro, etc.) power generation data at 15 minute intervals. This produced zone-specific wind power data, an example of which is shown in Figure II.11 (black time series). These observational data were interpolated to 6-hour intervals and converted to a percentage of rated power in order to be compared to ensemble wind power forecasts. Due to sub-optimal initial perturbation-generation techniques and unattributed model errors, a common problem in operational probabilistic forecasting is under-dispersion of ensemble members (Wang and Bishop 2005), as is illustrated in Figure II.11 (left).

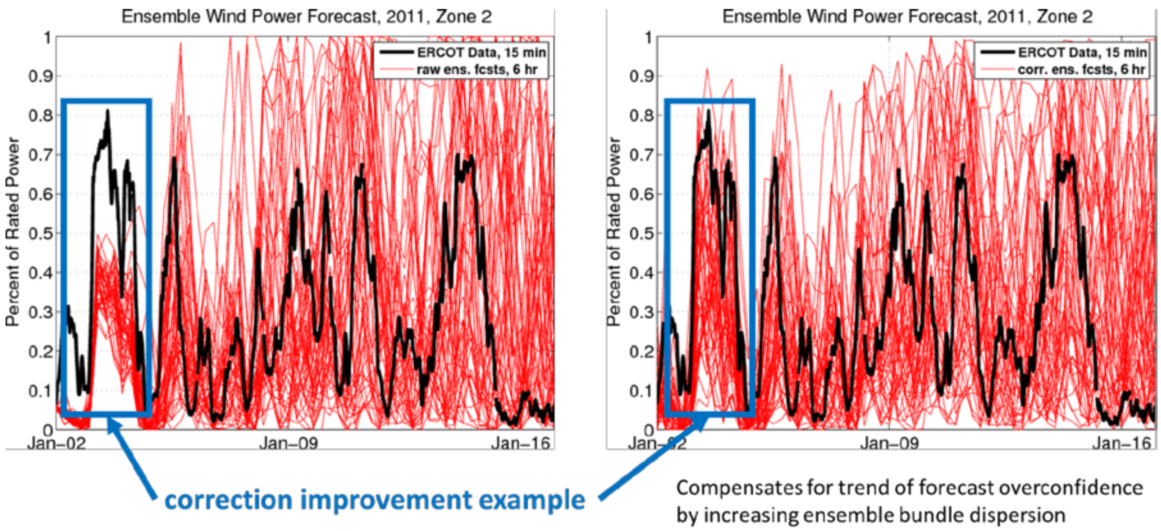

Figure II.11. In the left plot, the dispersion of ensembles (red time series) is insufficient to fully characterize the forecast uncertainty at shorter lead times. In the right plot, the forecast uncertainty is conditionally expanded via a lead-time dependent bias correction. The corrected forecast has greater spread at shorter lead times and encompasses the observation (black time series) in this example.

Ensemble clustering

When the ensembles show a wide spread, interpretation of the ensembles can be aided by clustering, which can increase the sharpness of the distributions and in the assessment of uncertainty. There are a variety of clustering methods that can be used, including self-clustering and regime clustering. CFAN has successfully implemented regime clustering in its seasonal forecasts, whereby ensemble members are clustered around values of the ENSO or the AO index.

CFAN has developed a new ‘Bayesian’ clustering approach that focuses on selecting a high-predictability cluster based upon initial verification of each ensemble member by subsequent observations or subsequently initialized forecasts. CFAN has successfully implemented the high-predictability clustering approach into our seasonal forecast products and also our daily hurricane forecasts by including the top five verifying cluster members into a high predictability cluster. The high-predictability clustering provides a basis for eliminating those ensemble members that are deviating towards an unlikely trajectory, thus providing for increased sharpness in the forecast. An example of ensemble clustering for the seasonal forecast is illustrated below, comparing the ensemble mean maps with maps determined from the high-predictability cluster.

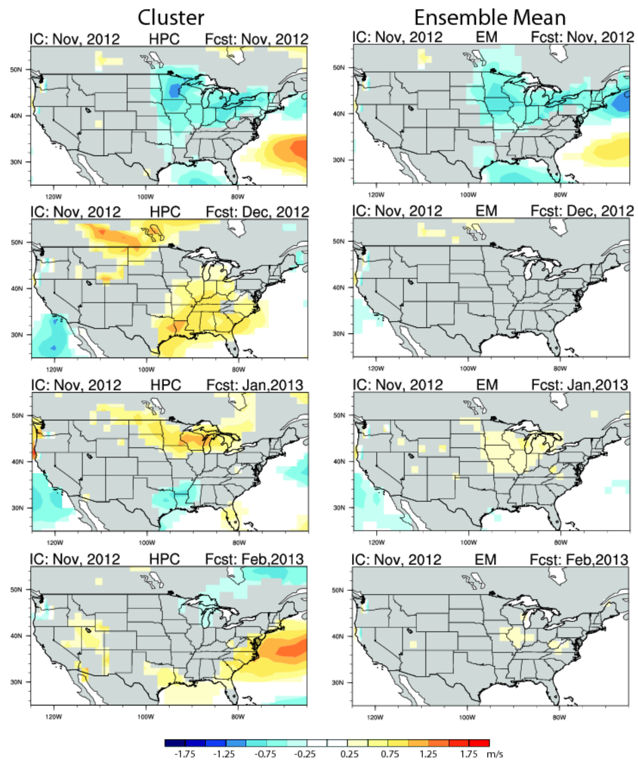

Figure II.12. Clustered forecast and ensemble mean forecast for 925 hPa wind anomalies. Forecast initialized 11/1/12; clustering based on monthly forecast initialized on 11/15/12.

Predicting power ramps

We have implemented operational prediction of large-scale ramp events for ERCOT, which is illustrated in Figure II.13.

ERCOT Ramp Events

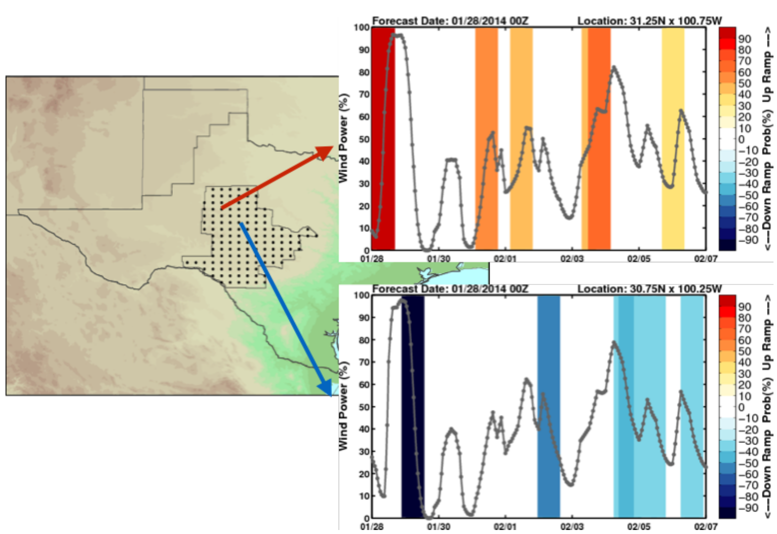

Figure II.13: Example of the power ramp forecast product for ERCOT Zone 7. Top right shows the ramp up probability as a function of forecast time while the bottom right graphic shows the ramp down probability. The gray line is the time series of the ECMWF ensemble mean wind power (%) with respect to total nominal power for a particular grid point.

The ramp event calculation follows the methodology outlined by Bossavy et al (2012)[4]. After calculating wind power for each grid point using the 100 m wind speed and the GE 1.5 power curve, a moving average linear filter is applied before computing the first-order finite differences for each grid point.

$$p_t^f = \frac{1}{n}\sum_{h=1}^{n} p_{t+h} - \frac{1}{n}\sum_{h=0}^{n-1} p_{t+h-n}$$

where p_t is the wind power time series and *n* is the order of the moving average filter and the time step of finite differences. For this analysis, we selected $n = 5$ hours based on the findings from Bossavy at identifying ramp events based on the ECMWF ensembles. The one major difference from Bossavy (2012) is we are calculating ramps with respective to differential, smoothed wind power anomalies. These anomalies are calculated after removing the ECMWF hindcast climatology power for each grid point. This approach removes systematic features (such as the diurnal cycle) and other biases (such as model drift), obviating the need for other statistical adjustments to the power time series.

A ramp is forecast to occur when the variation is high and steep enough and if the absolute value of p_t^f is higher than the variation threshold τ, which we define as 30% of the nominal wind power for a grid point. We classify ramps based on their support, timing, and intensity. The ramp support is defined as the duration in hours of the forecast ramp event $[t_s, t_e]$. The ramp timing is defined as the time when the absolute value of the filtered differential power signal p_t^f reaches its maximum amplitude, which also defines the ramp intensity.

We calculate ramp events for each ensemble member after applying an uncertainty prediction interval, $\delta = \{2, 5, 8\}$ hours about the ramp timing value. Using a maximum prediction interval of 8 hours, this value should account for most of the forecast wind error in phasing for the ensembles, while balancing the need of sharpness by end-users in the ramp forecasts. The resulting time series graphics display the probability of a ramp corresponding to each prediction interval and we calculate and display the ramp-up probabilities separate from the ramp-down probabilities. The probabilities are derived from the ECMWF ensembles. In the example in Figure II.13, the different width ranges of the probability bins illustrates how the methodology modifies the sharpness of the ECMWF forecasts at extended forecast lead-times. By displaying the probability for each ramp in its own color, a variety of end users with varying risk tolerances to false alarms may be able to use the same product. Furthermore, by providing the time series at each grid point for a given zone, an end-user may select the nearest grid point for their wind farm to find the most representative forecast for their location.

The 100 m wind speeds from the ECMWF operational analyses for each grid point in the ERCOT region are very well approximated by a Weibull distribution. We examined the ECMWF hindcasts for the period 12/5/2013 to 1/9/2014 for ERCOT, calculated the grid-point pdfs for ERCOT and conducted a one-sample Kolmogorov-Smirnov (K-S) test to evaluate the null hypothesis that the hindcast data comes from a standard normal distribution. For each lead-time that was evaluated -- 0, 24, 72, 120, 168, 240 hrs -- the K-S test rejected the null hypothesis, indicating the data are non-normal. Hence, the hindcasts maintain the appropriate pdf structure through 240 hrs lead-time (Figure II.14).

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[4] Bossavy, A., R. Girard, and G. Kariniotakis, 2012: Forecasting ramps of wind power production with numerical weather prediction ensembles. *Wind Energy*, **16**, 51-63.

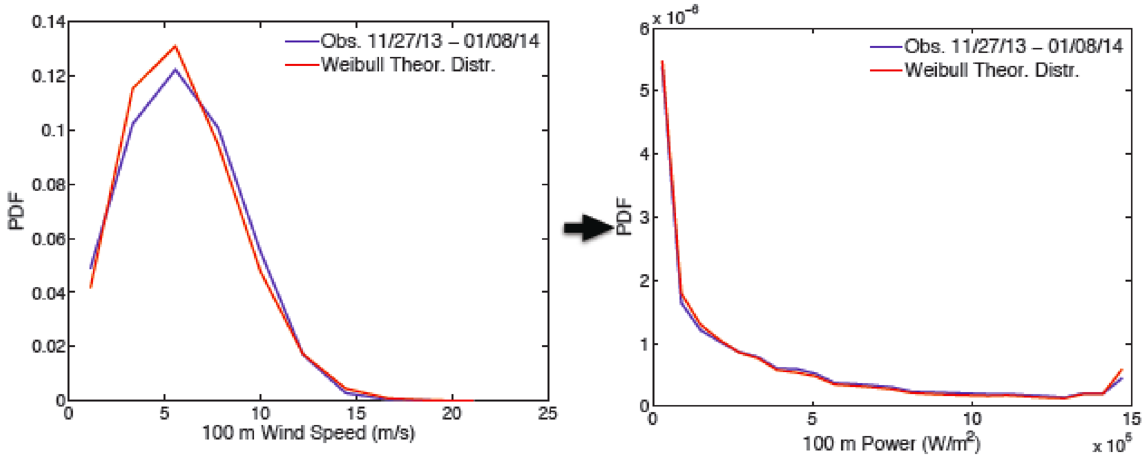

Figure II.14. (left) Probability distribution function of the ECMWF operational analyses 100 m wind speed for all grid points residing in ERCOT region (in blue) along with a theoretical fit to the observed PDF using a Weibull distribution (in red) for the period 11/27/2013 to 1/8/2014. Right similar to left, except shows the wind power for all grid points within ERCOT after applying the GE 1.5MW S power curve on the 100 m wind speeds from the ECMWF operational analyses (blue). Wind power for the 100 m wind speed Weibull distribution (in red) using same power curve is shown for comparison purposes.

3. Forecast evaluation and confidence assessment

Forecast evaluation is an integral part of the forecast product development. Our initial efforts were based on techniques utilized for our other product suites available in the market today. The closest approach was for those related to our temperature forecast products and more specifically the 15 day forecasts. We have also been investigating insightful evaluation measures for ramp likelihood forecasts.

15-day forecast evaluation

An evaluation of a variety of verification techniques traditionally used with meteorological variables was undertaken. This included items like Brier Score, Relative Operating Characteristics (ROC), and Root Mean Square Error (RMSE). The creation of useful verification outputs was complicated by three elements.

The first of these elements was the bounded nature of power forecasts. Traditionally RMSE is a very useful criteria used with temperature based product evaluations. Despite it being well received by end users, it requires the ability of free-floating values both above and below a forecast for effective use. As can be seen in Figure II.15, the RMSE values are impacted by the natural diurnal cycle seen in most wind farm locations. This creates an artificial fluctuation in the RMSE results that favor low wind situations.

However we were interested to evaluate the model’s capability of capturing longer time scales beyond the diurnal cycle. This led to shifting the evaluation to what we call bucket analysis. In this approach a forecast can be graded in a hit/miss capacity as well as degree of accuracy.

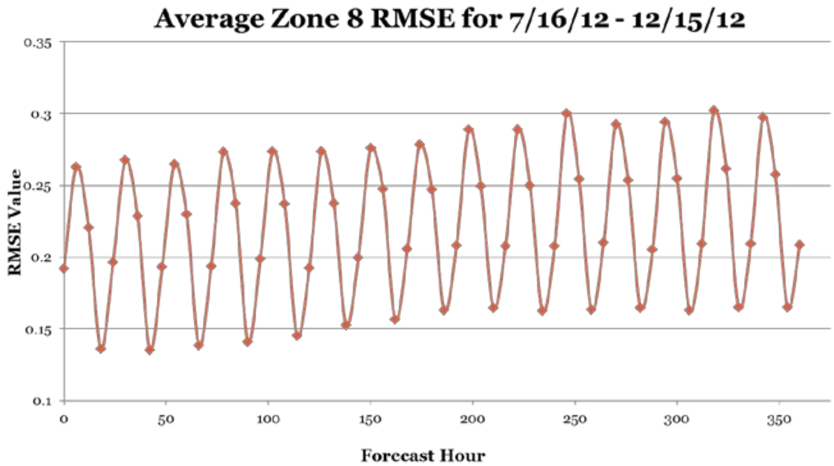

Figure II.15. Example of RMSE analysis for ERCOT Zone 8 over a six month period in 2012.

The bucket technique evaluates each forecast value at individual time steps for its proximity to the actual observation value at that time step. Each bucket consists of forecasts that fall into a range. For instance, all wind power forecasts between 10–20%, 20–30%, etc. Then the evaluation criteria are set for 'hits' and 'miss'. Typically some percentage around the forecast is given such as +/-5% around the bucket itself. As can be seen in Figure II.16, an evaluation is made for the same 6 month period as in RMSE analysis. In this case very stringent conditions were set for what was considered a hit with the requirement set to better understand the sensitivities for each of the buckets utilized.

% rated capacity (forecasts)	Total Forecasts	Miss High	Hit	Miss Low
0-10	2726	X	1122	1604
10-20	3922	938	803	2181
20-30	1761	507	229	1025
30-40	579	168	93	318
40-50	211	88	29	94
50-60	75	37	21	17
60-70	35	28	7	0
70-80	17	17	0	0
80-90	7	7	0	0
90-100	0	0	0	X

Figure II.16. Example of Bucket analysis for ERCOT region 8 over a six month period in 2012.

The second complication was brought on by user requirements. Feedback has suggested interval analysis is much more useful in support of decisions they make about products. With respect to meteorologically based systems, seasonally oriented analysis has proven most useful particularly given shifts in forecast performance based on changing seasonal regimes. Additionally, users tend to have different sensitivities with respect to forecast time scales. For instance forecasts in the 3-5 day range might be evaluated differently than those in 11-15 day window.

With this user feedback we adjusted the bucket analysis to incorporate both those criteria. Figure II.17 shows an example of the revised bucket analysis. In this example it can be seen that the proximity to zero was altered by using a range of 0-5%. Additionally the naming criteria were altered for easier user interpretation. A good forecast started with highly stringent grading requirements that eased in time as the forecast lead time extended out into the 15 day window. Additionally, the OK criteria level was provided for forecasts that were on the fringes of the 'Good' level and allows for more realistic evaluation of probability-based forecasts which would be hard to appraise otherwise with this approach.

Figure II.17 example demonstrates a quarterly time period and offline approach. The BETA user base indicated that verification analysis is something that is more often done offline as well as being better suited to a data format versus graphical where the inputs can be used in their own internal analysis.

Forecast: 0-5% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Days
Good	1047	1071	519	332
OK	170	168	109	68
Bad	239	176	49	20

Forecast: 25-35% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Da
Good	155	241	688	818
OK	170	277	863	1177
Bad	427	642	1092	1406

Forecast: 5-15% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Days
Good	981	1698	3069	2504
OK	389	514	744	580
Bad	751	865	1051	1163

Forecast: 35-45% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Da
Good	103	167	287	161
OK	84	153	326	174
Bad	303	409	676	513

Forecast: 15-25% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Days
Good	321	505	1542	1973
OK	327	485	1454	1961
Bad	595	714	1554	2110

Forecast: 45-55% Maximum Capacity

Grade	1-2 Days	2-5 Days	5-10 Days	10-15 Da
Good	50	114	142	28
OK	61	102	180	34
Bad	179	242	301	65

Figure II.17. Example of revised Bucket analysis.

The final complication relates to a need to have independent verification information on a much closer to real-time basis. While this becomes less critical for verification reports and data provided to the users for consideration when utilizing regular interval evaluations mentioned above, given the critical importance it plays in statistical correction this data remains critical in the support of statistical based forecast improvement. In trying to achieve this goal with forecasts there are essentially five approaches to be considered.

1. Utilize initial conditions from the forecasting model utilized to make the prediction
2. Utilize the reforecasts or reanalysis from a different model or proxy based data set
3. Utilize in situ measurements from an independent provider
4. Utilize in situ measurements from a wind farm(s) operator
5. Utilize proxy measurements developed with respect to wind power generation

The first approach mentioned would imply the use of ECMWF initial conditions as a basis for how the ECMWF forecasts performed. This is always a good first order tool and can provide useful insight and product development direction. This and model reforecasts can also be useful in helping forecast improvement. However, making a comparison between a model and itself does create a boxing limitation as it is impossible for a model to see beyond its own limitations. Techniques where this approach is most appropriate were covered in the statistical post processing section above.

The second approach is often used to validate general forecast model performance when it is known that another model or proxy is a strong performer. It can be particularly helpful in cases of grid based forecasts where a reasonable proxy of a large spatial area is required.

A key focus of our initial verification effort was the diurnal cycle. Our assessment focused on the locations and periods for which the WFIP SODAR data are available. We compared the closest grid point of the ECMWF operational analyses with the WFIP SODAR locations. Figure II-18 provides an example comparison of the forecast initialized 1 August 2011 at Cleburne, Texas, comparing the high frequency SODAR observations with the ensemble mean and the control member. There is a substantial amount of high frequency variability in SODAR observations that would not be captured by the coarse temporal resolution of the ECMWF forecasts.

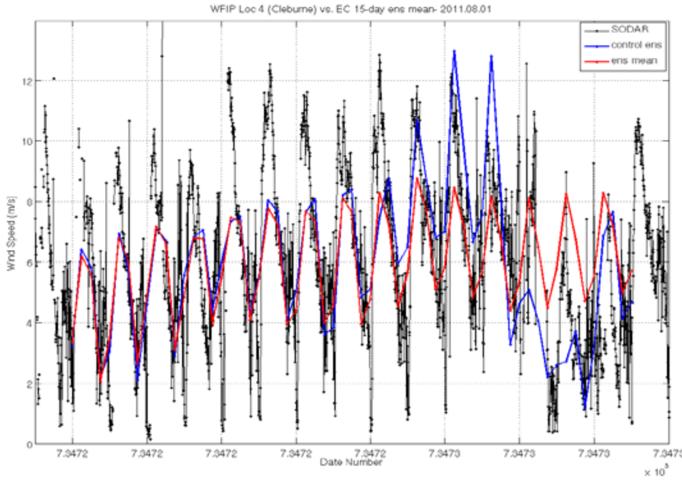

Figure II-18. Comparison of SODAR wind data at 100m for Cleburne with the ECMWF forecasts initialized 8/1/11.

In addition to the use of this data for point forecast such as the case above, it can also be utilized in a gridded format. Examples of data sets to leverage were covered in the Thrust I analysis. The MERRA data set for example provided a good proxy in comparison to the SODAR data above which conceptually made it useful although the delay in its availability makes it more viable for verification analysis versus real-time forecast enhancement.

Option three is potentially the most ideal for forecasts not geared to select end users, for example individual wind farms in this case. CFAN acquired data from Onsemble for this specific purpose as part of the project. This type of data delivers the benefit of in situ measurements that are hard to find for wind data at hub height. As can be seen in Figure II.19, the data can be used to adjust a raw model forecast for better performance. Additionally it has the obvious side benefit of being useful in providing an independent verification source. Wind speed measurements at the 17 stations were compared to the ECMWF 100m wind speed operational analyses (a gridded product at 6-hour intervals) in the closest single grid cell. Because the measurement stations produced data at 10 minute time steps, a number of temporal interpolation methods were applied to achieve the best fitting (Fig. II.19). Method 1 is an instantaneous sample, Method 2 is a 1-hr moving window, and Method 3 is a 3-hr moving window. The differentials showed that all three methods produced similar mean errors in 2013 (dashed lines).

These observational data and corresponding daily probabilistic wind speed forecasts from 2013 were used to train an ensemble dispersion correction. At each of the 17 locations, the lead-time dependent error characteristics of the ensemble mean versus Method 3 observational data were calculated. These historical error values were used to create a correction for gridded ECMWF wind speed forecasts. For each Texas ERCOT grid cell and each forecast time step, the raw 51-member ensemble distribution was transformed by computing the inverse of the normal cumulative distribution function (CDF). This was done using the mean of the raw data and the standard deviation of location-specific historical error values.

The challenge with this type of source is the lack of availability. During the course of this project the selected provider, Onsemble, shuttered its operation and the few others in the industry for the US have either ceased operations or have delayed roll-outs. In working with the Onsemble data, our team had substantial reservations about the data quality, as well as concerns about how true the representative point locations were to larger scale areas.

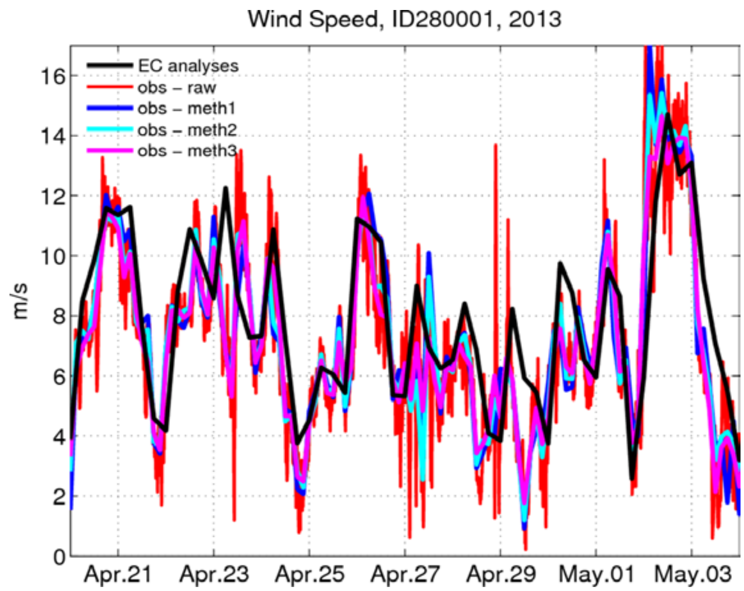

Figure II.19. Example of Onsemble in situ data utilized to enhance raw model forecasts.

The fourth approach is very similar to the third. The benefits though are generally limited to the wind farms supplying data. While the benefit could expand as more agreements are reached with wind farm operators such as our aforementioned project with the Southern Company, without large scale adoption it will be difficult to create zonal, regional, or gridded forecast enhancements with this type of product.

The final approach is one we undertook and achieved useful results. The regional grid operators such as ERCOT collect heavy amounts of data with respect to wind power generation. While not a direct measurement of wind at point locations, it does provide wind power information at zone/region levels. This provides an opportunity to verify and enhance forecasts on these scales as well as reverse engineer to a direct wind speed forecasts.

Figure II.20 shows a verification analysis for the 15 day forecast in Zone 2 of ERCOT utilizing ERCOT's wind power production data for the given zone. Note the substantial error reduction especially for the first 150 hours of forecast. Utilizing a reverse engineering technique, the wind power production data is turn into raw wind speed data. Based on this forecast error, the wind forecast is then adjusted before converted into power. This approach is essentially a reversed methodology compared to techniques where CFAN's wind speed forecasts are translated into wind power forecasts. For the example shown it can be seen how utilizing this technique allows for an overall wind speed forecast improvement particularly over the first 10 days. The overall potential benefits with wind forecast in the U.S. are high with this style of data sets. There are fewer organizations to work with across the U.S. in securing access to this type of data. While during the course of this project we used the data in a delayed fashion, ERCOT has worked with organizations like Xcel to provide data in a near real-time fashion.

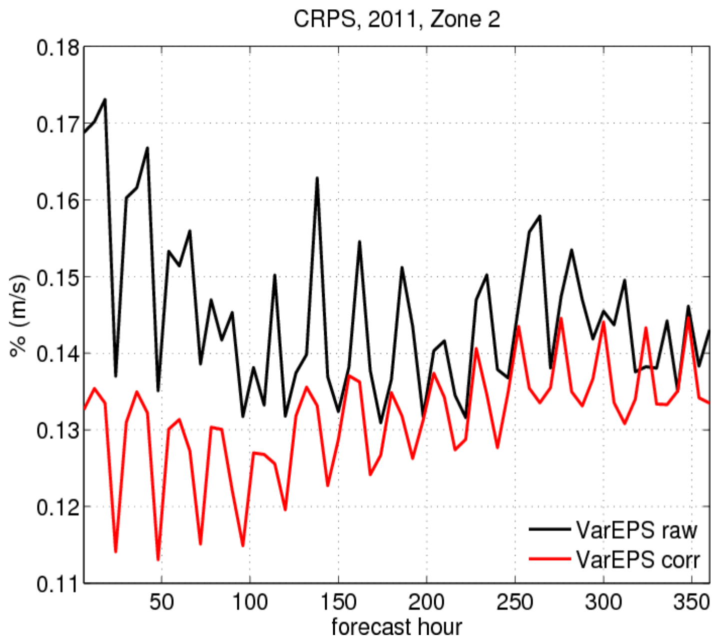

Figure II.20. Example of ERCOT power generation data used as both an enhancement to raw model forecasts as well as a source of forecast verification.

Ramp likelihood evaluation

Our ramp forecasts have initially been built around point locations. This implies that the various data sources we utilize elsewhere for forecast enhancement and improvement would possibly work well in the ramp verification process. As an example, the SODAR data was used in the verification of ramp forecasts. Figure II.21 shows the forecast verification of a ramp on 27 September 2012 for Zone 2, from a forecast initialized on 21 September. The diurnal amplitude is damped during frontal passages, and the predicted large-scale ramp compares very well with the SODAR data.

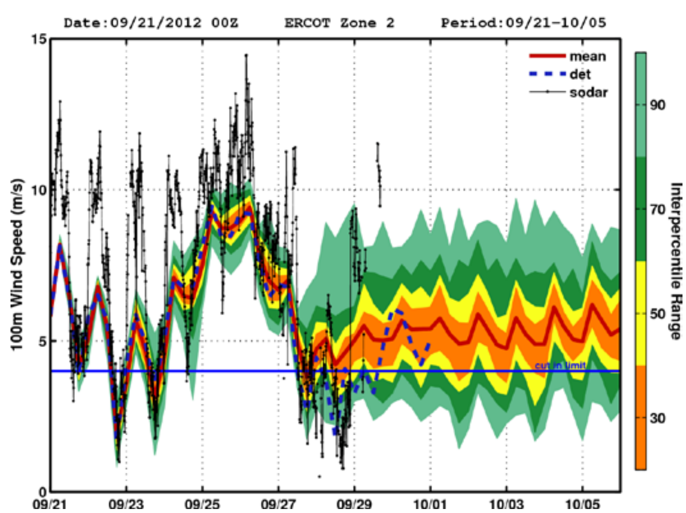

Figure II.21. Comparison of the forecast initialized on 9/21/12 for zone 2 with the SODAR observations at Cleburne.

For a given wind farm the optimal choice would of course be data from the given wind farm. Of course, the independent in situ sources would have also been ideal before their exit from the marketplace. When direct in situ measurements are not available, high resolution data sets such as the previously discussed MERRA are feasible.

Unlike the wind/power forecast which are probabilistic forecasts built around a mean or deterministic core, ramp likelihood comes from a reverse position. The goal is evaluate a probability while at the same time accounting for considerations such as timing shifts as the forecast lead time increases.

For the large area ramps, we assessed the raw model forecast capability for predicting the up ramps as a function of forecast lead-time (1-15 days). The following statistics are presented:

- Probability of Detection (POD): Ratio of correct forecasts to number of times it occurred (Perfect = 1)
- Probability of False Detection (POFD): Ratio of false alarms to the total number of nonoccurrences of the event (Perfect = 0)
- False Alarm Ratio (FAR): Fraction of yes forecasts that turn out to be wrong (Perfect = 0)
- Bias: Ratio of yes forecasts to the number of yes observations (unbiased = 1, overforecast > 1, underforecast < 1)

Eliminating the diurnal cycle, the probability of detection exceeds 60% at all lead times out to 7 days, whereas the probably of false detection is less than 20% for the first 6 days. The False Alarm Ratio is less than 0.3 for the first week. Overall, the ramps are over forecast, although the False Alarm Ratio would be reduced if the threshold cutoff for ramp amplitude was broadened.

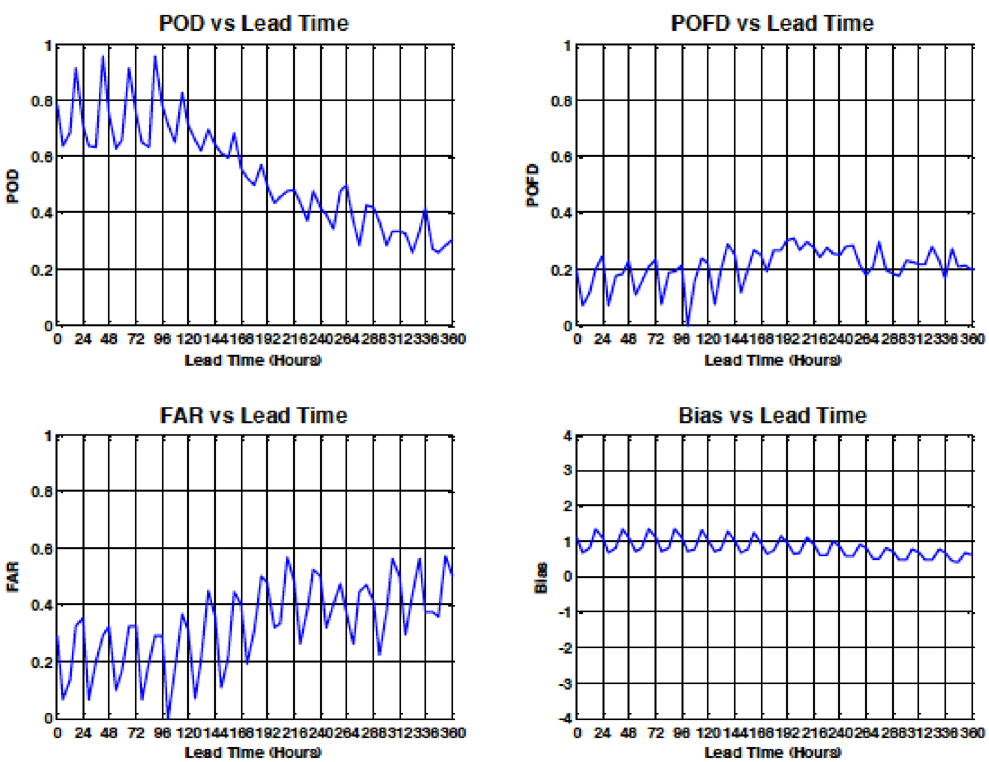

Figure II-22. Statistics of forecast versus observed large area up ramps as a function of lead time: POD, POFD, FAR, Bias.

Confidence assessment

There were two overall objectives of this task:

1. Determination of the lead time and averaging period for which there is useful prediction skill (statistics) for a particular variable, as a function of region, season, and weather regime.
2. Assessment of the confidence of individual subseasonal and season forecasts relative to the expected predictability, based on the ensemble spread, weather regime, historical predictability analysis, and recent forecast verification statistics.

Whereas it is relatively easy to make a prediction, it is much more difficult and arguably more important to objectively assess the confidence level for a specific prediction. Our research has shown that regional predictability is non-stationary and dependent on the background basic state. We have demonstrated that seasonal predictability is highest for high amplitude phases of ENSO.[5] We have further demonstrated that predictability is lowest during certain phases of the Madden Julian Oscillation (MJO). [6] [7]

CFAN has begun including an objective confidence assessment for its monthly and seasonal forecasts that are being provided to clients in the energy sector. An example of monthly forecast with confidence assessment is provided below:

CFAN US Monthly Temperature Outlook << (09/13/2012) >>						
Regions / Weeks 1-4	Northeast	Southeast	Midwest	South Central	Northwest	Southwest
Week 1 09/13 - 09/19	Moderate Confidence	Moderate Confidence	High Confidence	High Confidence	High Confidence	Moderate Confidence
Week 2 09/20 - 09/26	Moderate Confidence	High Confidence	High Confidence	Low Confidence	High Confidence	Low Confidence
Week 3 09/27 - 10/03	Moderate Confidence	Moderate Confidence	Moderate Confidence	Moderate Confidence	Moderate Confidence	Low Confidence
Week 4 10/04 - 10/10	Low Confidence	Low Confidence	Low Confidence	Moderate Confidence	Low Confidence	Low Confidence
	Temperature Anomaly Legend	≤ -8 ≤ -4 ≤ -2	> -2 & 2 <	≥ 2 ≥ 4 ≥ 8		

Figure II-23. Forecast table for weekly regional surface temperature, with confidence levels for each week/region. Forecast initialized 9/13/12.

[5] Kim, H. M., P. J. Webster and Judith A. Curry, 2012: Seasonal prediction skill of ECMWF System 4 and NCEP CFSv2 retrospective forecast for the Northern Hemisphere Winter, Clim. Dyn., DOI: 10.1007/s00382-012-1364-6 http://www.cfanclimate.com/Kim_Webster_Curry_2012_CD.pdf

[6] Kim, H. M., C. D. Hoyos, P. J. Webster and I. S. Kang, 2008: Sensitivity of MJO simulation and predictability to sea surface temperature variability. J. Climate, 21, 5304-5317. doi: 10.1175/2008JCLI2078.1 http://webster.eas.gatech.edu/Papers/Kim%20et%20al.%202012b_CD.pdf

[7] Agudelo, PA, CD Hoyos, PJ Webster, JA Curry, 2008: Application of a serial extended forecast experiment using the ECMWF model to interpret the predictive skill of tropical intraseasonal variability. Climate Dynamics. DOI 10.1007/s00382-008-0447-x http://webster.eas.gatech.edu/Papers/Webster2008d.pdf

Our proposed operational forecast confidence assessment included the following elements:

- Historical predictability analyses;
- Recent prediction verification statistics;
- Phase and amplitude of the Madden Julian Oscillation (MJO) and phase of ENSO;
- Spread of the forecast ensemble members and high prediction cluster;
- Relationship between ensemble spread and forecast error conditioned on teleconnection regimes.

During Phase I, we conducted predictability analyses for ENSO, NAO, AO and PNA (details are provided in the Phase I Final Technical Report). From an anomaly correlation plot derived between the model forecast and the reanalysis product (assumed to be the "truth") for the same period, one can readily see the degree of predictability and the periods of the year at which the correlations and forecast skill are largest. Such an analysis has been conducted for seasonal forecasts of the teleconnection regimes (ENSO, NAO, PNA, AO) and also regionally for U.S. surface temperatures and rainfall.

The utility of ensemble quantiles that are correct in a probabilistic sense depends on the ability to distinguish between situations with low and high uncertainty and on the sharpness of the distributions. We measure sharpness by the Interquantile Range (IQR), which represents the difference between the upper and lower quartiles. For the probabilistic forecast to be useful, it is essential that the IQR be smaller than the IQR obtained from historic data.

One of the traditional estimates of predictability is directly based on ensemble spread without considering ensemble intercorrelations. We have developed a new method for incorporating ensemble intercorrelations into the predictability analysis (although we have not yet implemented this scheme into our operational forecasts). Ensemble intercorrelations together with ensemble spread can be rendered in a phase-space diagram in which four different quadrants can be differentiated. Extremes in Quadrant I correspond to high intercorrelation and high spread. This case is typical of situations when the model is already set in a temporal pattern, i.e., there is low uncertainty in the evolution of the climate modes, but the magnitude of the response is susceptible to initial conditions or forcing variability. One example could be a seasonal forecast in the middle of an El Niño event, where the temporal evolution is well known as it tends to be locked to the annual cycle, but the magnitude of the event is not as predictable as its evolution. Extremes in Quadrant II reflect high intercorrelation and low spread, which correspond to the most predictable cases. Extremes in Quadrant III correspond to low intercorrelation and low spread. In this cases the magnitude of the forecasts are similar among the ensembles but the temporal evolution (troughs and ridges in the time series) are out of sync. This is the least likely of the cases and typically appears when forecasting normal or average periods. Finally, Quadrant IV corresponds to the least predictable scenario with low intercorrelation and high spread. A typical example of this situation is the seasonal forecasting of tropical pacific SSTs before the spring predictability barrier when not only the magnitude but also the temporal evolution of the SSTs are very sensitive to tropical and extratropical initial conditions and teleconnections.

Thrust III. Decadal projections of the wind power environment

Our proposed overall strategy for developing regional scenarios of extreme weather events and climate variability on decadal time scales (out to 2040), included the following elements:

- Assess the historical prediction skill of the 10 year CMIP5 simulations. Infer the distributions of extreme wind and demand events using two complementary approaches: i) a Model Output

Statistics (MOS) approached (described in Thrust II) based upon the historical climate dynamics analysis; and ii) a 'weather typing' approach for developing regional statistics of extreme events (wind ramps and gusts; heat and cold events).

- Develop observationally-based scenarios based on phase-locked states and shifts in a synchronized network of climate indices. The historical climate dynamics analysis and 'weather typing' of extreme events is used in conjunction with scenarios of future shifts in these indices to develop the observationally-based scenarios.

During Phase II, we conducted a survey of the skill of the CMIP5 simulations. With regards to observationally based scenarios, the paper by Wyatt and Curry that provides the framework for this task has been published at *Climate Dynamics*. Curry has convened a UK-US Workshop on Climate Science Needed to Support Robust Adaptation Decisions that focuses specifically on developing regional climate scenarios for decadal time scales. A specific application of this methodology is being conducted for Florida Power and Light, to address interannual and decadal variability of hurricane landfall locations and extreme winds; one application of this analysis is siting of offshore wind generation. This thrust was allocated a reduced level of effort relative to the original proposal, owing to concerns about the utility of the climate models, the substantial uncertainty associated with predicting current modes of interannual and interdecadal variability, and the lack of interest from potential clients.

1. Develop scenarios from the CMIP5 decadal simulations

A key reason for the lack of utility of 21st climate model simulations on regional and decadal time scales has been the failure to simulate correctly the multi-decadal ocean oscillations. In an attempt to rectify this deficiency, the latest climate model simulations for the IPCC (CMIP5) coordinated decadal hindcast and prediction experiments with initialization from observations of both the atmosphere and ocean. It was anticipated that the CMIP5 decadal simulations would provide a valuable new resource for predicting regional climate variability and change on decadal time scales.

During year one, we downloaded and processed the results for the following models: CanCM4, CFSv2, CNRM-CM5, HadCM3, MIROC4h, MIROC5, and MRI-CGCM3. Given the volume of data, a script was developed for simultaneous synchronized downloading. The following monthly averaged gridded variables were downloaded: wind variables (surface and on the standard pressure levels), sea level pressure, surface temperature (mean, max and min) and precipitation. Three-hourly output is available only for the surface meteorological variables. We developed a NCL program to process model outputs and create results in output files in a unified format on the same spatial grid.

We have processed the results for most of the CMIP5 climate models in comparison to recent peer reviewed evaluations. Kim, Webster and Curry (2012)[8] assessed the CMIP5 decadal hindcast/forecast simulations of seven coupled ocean-atmosphere models: HadCM3 (UK), CanCM4 (Canada), CNRM-CM5 (France), MIROC4h (Japan), MIROC5 (Japan), MRI-CGCM3 (Japan), CFSv2 (US). Each decadal prediction consists of simulations over a 10-year period, initialized every five years from climate states of 1960/1961 to 2005/2006. Most of the models overestimate trends, whereby the models predict less warming or even cooling in the earlier decades compared to observations and too much warming in recent decades (Figure III.1).

[8] Kim, H.-M., P. J. Webster, and J. A. Curry (2012), Evaluation of short-term climate change prediction in multi-model CMIP5 decadal hindcasts, Geophys. Res. Lett., 39, L10701, doi:10.1029/2012GL051644.

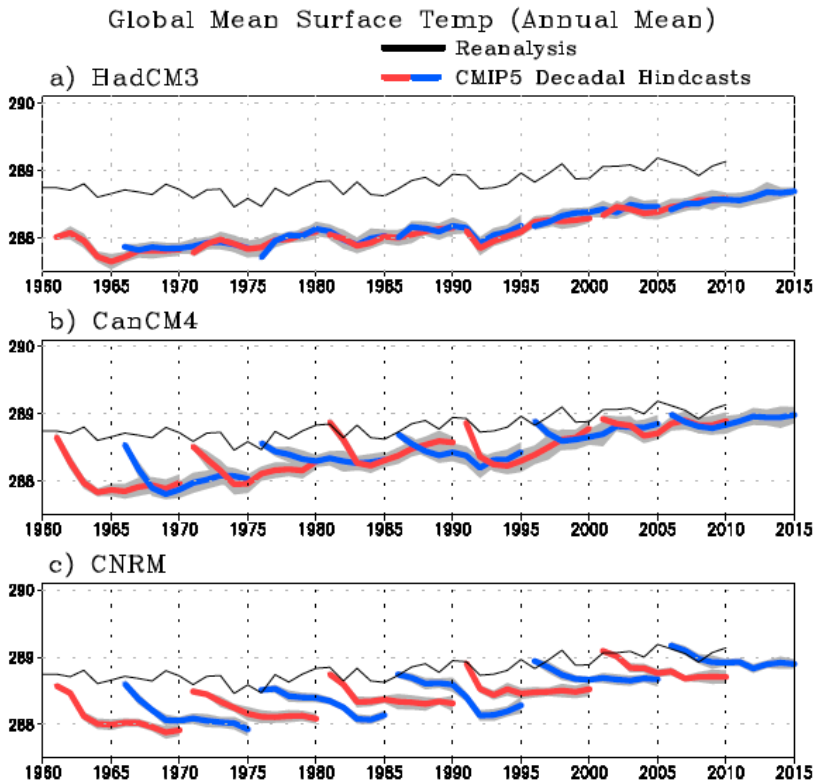

Figure III.1. Time series of globally averaged annual-mean surface temperature [K] for reanalysis (black) and the ensemble mean of the CMIP5 decadal hindcasts and forecasts (red and blue) for (a) HadCM3, (b) CanCM4, (c) CNRM, (d) MIROC4h, (e) MIROC5, (f) MRI and (g) CFSv2. Gray shades represent the ranges of one standard deviation of the ensembles in each hindcasts.

All models show high prediction skill for surface temperature over the Indian, North Atlantic and western Pacific Oceans, with low prediction skill found over the equatorial and North Pacific Ocean. As shown in Figure III.2, the AMO is predicted in most of the models with significant skill, while the PDO shows relatively low predictive skill. In fact, evaluation of the PDO forecasts showed that by far the best forecast was a simple persistence forecast. There is low prediction skill of North American surface weather including anticipated wind anomalies; what little prediction skill there is seems associated with the models' capability of simulating the AMO.

Of the models examined, MIROC4h and MIROC5 best meet the selection objectives of: horizontal resolution 100 m or less, at least 3 ensemble members, little drift following initialization, and relatively good performance over the U.S. and the North Atlantic. This analysis identified a key sensitivity of the simulations to the initialization strategy and to the initialization timing. Several models, notably CanCM4 and CNRM, which are initialized close to the observed state (full field initialization), drift towards the model climate over about a third of the integration period, with a drift magnitude that is substantially greater than the observed trend. Models that are initialized with anomaly assimilation (MIROC4h, MIROC5 and MRI) better represent the model's actual decadal variability.

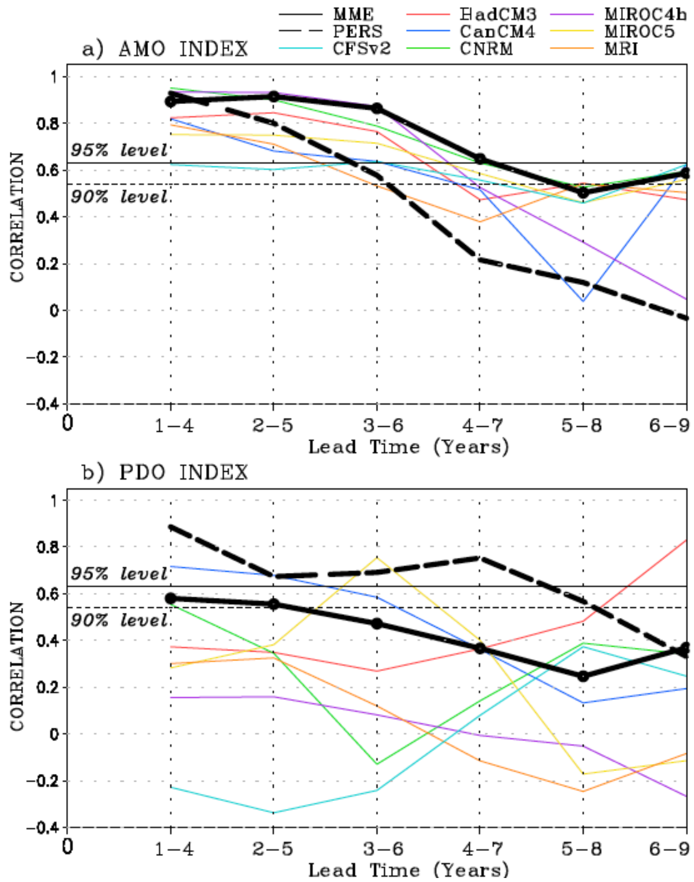

Figure III.2. Correlation coefficients for the (a) AMO and (b) PDO index predicted by MME, persistence (PERS) and ensemble mean of each CMIP5 decadal hindcasts as a function of lead time (years). Solid (dashed) horizontal line represents statistical significance of the correlation coefficients at 95% (90%) confidence level.

Based upon our experience with subseasonal and seasonal predictability, predictability is greatest when the model is initialized in a well-established climatic regime. For example, for subseasonal forecasts this depends particularly on where in the cycle of the Madden-Julian oscillation the model is initialized; and for seasonal forecasts, this depends on the magnitude of the ENSO signal at the time of initialization. Our preliminary analysis suggests that this same general principle holds for the decadal simulations. Hence, the year 2005 (when the 30 year simulation was initialized) is a good year to initialize in terms of the AMO, since 2005 was a peak (if not *the* peak) in the current warm phase of the AMO. This means that regional climate features that are sensitive to the AMO should be well represented. However, 2005 was not a good year for initialization in context of the PDO, since the PDO was in a flickering state during the middle of the previous decade.

Another result from Kim, Webster and Curry (2012) that provided useful guidance for this project is the evaluation of the multi-model ensemble (MME) relative to single models. Although the MME does not outperform all of the constituent models for every forecast skill metric, it has in general better forecast quality than the single models for global mean temperature, AMO, and PDO. This study partly supports the utility of the multi-model ensemble approach in overcoming the systematic model biases from individual models and in enhancing decadal predictability.

Several recent papers have analyzed the CMIP5 circulation regimes and surface meteorological variables. A recent paper by Schoof and Pryor (2014)[9] assessed the fidelity of CMIP5 climate models in simulating modes of variability in the atmospheric circulation regimes (ENSO, PNA, AO) and their relation to near surface wind speeds. Spatial patterns and temporal indices for ENSO, AO, and PNA derived from daily output of 10 CMIP5 models indicate that all models reproduced some aspects of these modes, both in the spatial and temporal domains. The models are capable of reproducing at least some fraction of the wind climate variability that arises due to variations in the AO and PNA, but are less skillful in reproducing the influence of the ENSO, and particularly La Niña, on flow over the contiguous US. Sheffield et al. (2013)[10] found that no model stands out as being particularly unskillful, bolstering the argument to consider all models irrespective of performance to encompass the uncertainties.

2. Develop observationally-based scenarios

The objective of this task was to develop and evaluate strategies for empirical data-based scenarios for the next two decades of statistics of the variability of the wind power and demand environment.

The simplest observationally-based climate scenario is a 'physics free' forecast that assumes that the climate for the next two decades is the same as that for the previous 30 years, which is referred to as the 'climatology' scenario. The climatology scenario provides a quantitative 'zero skill' target for evaluation of forecasts based on more complicated models. The key issue that discriminates a persistence forecast from a climatology forecast is that a shorter period is used as the basis for the persistence forecast, and that there is a physical rationale for selecting the particular period. Here we use the period since 2002, based upon the identification by Tsonis et al.[11] and Swanson et al.[12] of a global climate shift occurring 2001/2002 that included a major shift in the circulation of the Pacific Ocean and encompasses a shift to the cool phase of the Pacific Decadal Oscillation (PDO). This new regime is characterized by more frequent La Nina events and a break in the global mean temperature trend. More frequent La Nina events are associated with higher surface wind speeds.

More sophisticated empirically-based models for a non-stationary climate are being developed using a dynamic climatology approach using networks of climate teleconnection indices and analysis of the synchronization among the indices. Tsonis et al.[11] showed that that when these indices of climate variability (ENSO, PDO, NAO, NPO) are synchronized, and the coupling between those modes increases, then the climate system becomes unstable and is thrown into a new state that is marked by a change in the character of ENSO variability and the global mean temperature trend.

Subsequent analyses that includes larger numbers of indices found additional shifts of relevance to the interpretation of regional climate variability and change. Wyatt and Curry (2014)[13] framed multidecadally varying climate-related phenomena within the context of a signal propagating throughout a network of synchronized chaotic quasi-oscillators, effectively compressing individual circulations into nodes of an interconnected network, with each node representing, or related to, a subset of processes. The sequence

[9] Schoof, JT and SC Pryor 2014: Assessing the fidelity of AOGCM-simulated relationships between large-scale modes of climate variability and wind speeds. J. Geophys. Res., 119, 9719–9734, doi:10.1002/ 2014JD021601

[10] Sheffield JT et al. 2013: North American Climate in CMIP5 Experiments. Part II: Evaluation of Historical Simulations of Intraseasonal to Decadal Variability. Journal of Climate, DOI: 10.1175/JCLI-D-12-00593.1

[11] Tsonis, AA, K. Swanson, S. Kratsov, 2007: A new dynamical mechanism for major climate shifts. Geophys. Res. Lett., 34, L12705. https://pantherfile.uwm.edu/aatsonis/www/2007GL030288.pdf

[12] Swanson, K.L., AA Tsonis, 2009: Has the climate recently shifted? Geophys. Res. Lett, 26, DOI: 10.1029/ https://pantherfile.uwm.edu/kswanson/www/publications/2008GL037022_all.pdf

[13] Wyatt MG and JA Curry 2014: Role for Eurasian Arctic shelf sea ice in a secularly varying hemispheric climate signal during the 20th century. *Climate Dynamics* http://link.springer.com/article/10.1007%2Fs00382-013-1950-2#page-1

below indicates the order of the signal's propagation through the network of eight climate indices. The years in parentheses indicate the mean phase shifts (lag times) between indices:

> -NHT → (4y) → -AMO → (7y) → +AT → (2y) → +NAO → (5y)→ +NINO → (3y) → +NPO/+PDO → (3y) → +ALPI → (8y) → +NHT → (4y) → +AMO → (7y) → -AT → (2y) → -NAO → (5y)→ -NINO → (3y)→ -NPO/-PDO → (3y) → -ALPI → (8y) → -NHT .

where NHT is Northern Hemisphere Mean Temperature, AMO is the Atlantic Multidecadal Oscillation, AT is the Atmospheric Mass Transfer Anomaly, NAO is the North Atlantic Oscillation, NINO is the NINO 3.4 Index, NPO is the North Pacific Oscillation, PDO, is the Pacific Decadal Oscillation, and ALPI is the Aleutian Low Pressure Index.

The sequence depicted above, referred to as the 'stadium wave', indicates the propagation of a climate signal through a collection of atmospheric and oceanic teleconnections. The secular-scale duration of this hemispheric propagation was estimated to be ~ 64 years during the 20th century. Wyatt's Ph.D. thesis[14] shows that the observed 20th century signal-propagation has existed for the past 300 years. The key finding is that that there appears to be a statistically significant succession of indices carrying this climate signal, where expression of the signal in one index is expected to follow in all other indices in successive lagged order. A simplified version of the stadium wave is illustrated in the diagram below.

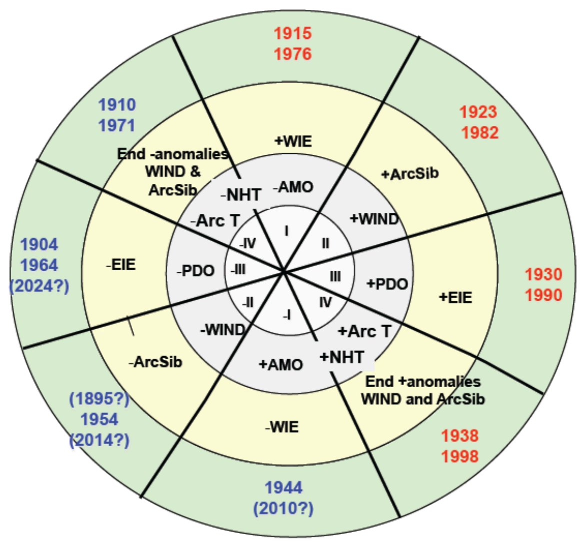

Figure III.3. Illustration of the progression of the stadium wave. The stadium-wave 'wheel' is divided into segments (from center to perimeter): the light gray ring identifies the segment number; the dark gray ring indicates key hemispheric indices; sea ice indices are in the yellow ring; and the outer green ring provides peak dates for the segment. Segment I begins with a cold North Atlantic (-AMO), maximum sea ice extent in the European Arctic shelf seas (+WIE). Segments II through IV show evolution of the climate signal initiated in the cold Atlantic. As sea ice growth increases eastward into the Siberian Arctic (+ArcSib), strong winds develop that convert an initially cold ocean-ice signal into a warming atmospheric one (Segment II). Events proceed, carrying the signal across Eurasia and into the Pacific (+PDO; Segment III), ultimately culminating in maximum Arctic and NH surface temperatures in Segment IV. Segment –I follows with maximum warmth in the North Atlantic and minimal sea ice in the European Arctic shelf seas. This marks a shift whereby trends of AMO and WIE decrease and increase, respectively. An initial warm signal converts to a cooling one until reaching Segment –IV, where temperatures dip to their minima, followed soon after by shift to a warming regime (I). (adapted from Wyatt and Curry, 2014).

[14] Wyatt, MG 2012: A multidecadal climate signal propagating across the Northern Hemisphere through indices of a synchronized network. Ph.D. thesis, Department of Geology, University of Colorado-Boulder.

The stadium wave is used to develop scenarios of regional climate variability on decadal time scales that accounts for uncertainty in timing of the most recent transitions and the uncertainty in the length of the individual regimes. Regional expressions of the stadium wave analysis are accomplished through linking the climate regimes to the statistics of weather regimes and regional meteorological variables (mean values as well as extreme event statistics).

The elements are now in place to apply this methodology to developing scenarios of future wind power. This allows CFAN to work with individual prospects to develop plausible scenarios for a given development project and the potential risk exposure for project success. A particular benefit of this method is ability to evaluate a ranking of plausible scenarios to better capture the true uncertainty associated with a given location and time scale in consideration.

3. Applications

In February 2014, Curry organized an international Workshop on Climate Science Needed to Support Robust Adaptation Decisions[15] that focuses specifically on developing regional climate scenarios for decadal time scales and using them to support robust decision making. The title of Curry's talk was *Generating possibility distributions of scenarios for regional climate change.*[16] The findings of the Workshop were reported in a series of 5 blog posts:

- UK-US Workshop on Climate Science to Support Robust Adaptation Decisions[17]
- Perspectives from the private sector in climate adaptation[18]
- Strategies for robust decision making for climate adaptation[19]
- Limits of climate models for adaptation decision making[20]
- Broadening the portfolio of climate information[21]

The Workshop brought together atmospheric scientists/climate researchers with social scientists and decision makers in both the public and private sectors who are engaged in adaptation to climate change. The Workshop provided an opportunity to integrate some of the research funded under this project into a broader range of climate adaptation applications; at the same time, the Workshop provided insights for this project in terms of the challenges of applying decadal-scale climate information to decision making.

Of particular interest at the workshop was renewable energy and its role in meeting supply not just in national level grids but also at local levels especially in developing countries. As large companies and NGOs look to increase involvement in different areas of the globe, a particular deficiency identified is appropriate infrastructure including power supply. Workshop participants explored ways that both the CMIP simulations and Stadium Wave approaches can help provide insight on appropriate large-scale investments including self-funded power supply options such as wind and solar.

Application for Florida Power and Light

One of the proposed applications for decadal scenarios is for the siting of offshore wind farms, where a key issue of concern is vulnerability oddly enough to winds from hurricanes on the Atlantic and Gulf coasts as these large scale weather events are potentially the most destructive to infrastructure including

[15] http://www.eas.gatech.edu/event/climate-workshop-feb-6-7
[16] http://www.eas.gatech.edu/sites/default/files/UK-US%20JC%20talk.pptx
[17] http://judithcurry.com/2014/02/10/uk-us-workshop-on-climate-science-needed-to-support-robust-adaptation-decisions/
[18] http://judithcurry.com/2014/02/12/uk-us-workshop-part-ii-perspectives-from-the-private-sector-on-climate-adaptation/
[19] http://judithcurry.com/2014/02/14/uk-us-workshop-part-iii-strategies-for-robust-decision-making-for-climate-adaptation/
[20] http://judithcurry.com/2014/02/18/uk-us-workshop-part-iv-limits-of-climate-models-for-adaptation-decision-making/
[21] http://judithcurry.com/2014/03/19/uk-us-workshop-part-v-broadening-the-portfolio-of-climate-information/

offshore assets. CFAN has a client, Florida Power and Light (FPL), who has expressed interest in decadal projection of hurricanes (out to 20 years) in the area around Florida, to help support their decision making including mitigation techniques (both looking at how the infrastructure can be made more resilient and how long-term energy choices affect the ability to withstand tropical cyclones), and how climate change may affect the severity and frequency of tropical cyclones.

A preliminary analysis was done to assess the impact of the AMO and PDO on Florida landfalling tropical cyclones as well as the broader Gulf of Mexico and Coastal Atlantic regions. The analysis took into account the CMIP findings that the most credible low frequency features include the AMO and PDO. It is seen in Figure III.4 that there are more Florida landfalls during the warm phase of the AMO (yellow and green), with the phase of the PDO having less of a meaningful impact although the analysis shows it is a more likely indicator of whether tropical cyclones will track toward the Atlantic coast versus being pushed into the Gulf of Mexico.

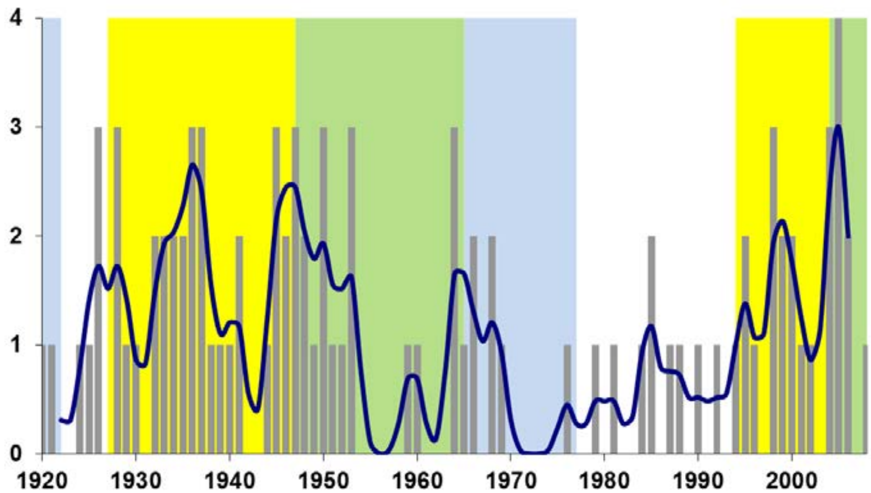

Figure III.4 Statistics of landfalling tropical cyclones striking the Florida coast. Yellow corresponds to the warm phase of the AMO, green to the warm phase of the AMO and cool phase of the PDO, blue to the cold phases of both the PDO. This analysis was done utilizing data from the National Oceanic and Atmospheric Administration Hurricane Database (HURDAT), which has been post-processed by CFAN to ensure physical consistency between the best-track data and the location and intensity of landfall.

This type of analysis can help FPL in making decisions about siting offshore wind farms, particularly when evaluating considerations about risk related to each coastal region. In turn that can lead to more targeted return period risk exposure as well as climate regime analysis for which FPL is exposed to with its placement in the transition region between tropical and mid-latitude climates.

IV. Decision support tool

The delivery of successful web-based decision support tools is a key aspect of CFAN's success. Our ability to effectively match critical user criteria with influential meteorological and climatological variables in a framework that enhances and streamlines the decision making process is essential basis of these successful tools. Our objective for Thrust IV of the project was to apply these techniques around quality forecast elements related to wind energy decision making in hopes of delivering a solution of superior quality and novel elements to the diverse set of users. The cycle employed for this objective encourages constant interaction with alpha and beta users, and in turn translating their inputs and suggestions into viable dashboard based tools. Our beta users included energy market users and regional power providers.

1. *Identification of user preference and needs*

Preference and need information focused on continued interaction with alpha and beta phase users. They have provided useful and thoughtful feedback on what they like and changes they think could enhance the offering.

Obtaining user feedback

Simple and quick emails have proven the most effective approach to provide feedback. To encourage this behavior we made it easy to email us directly from the Dashboard when the users have ideas they wish to convey in real-time. While this information is very useful we still wanted to obtain some more quantitative type information, particularly as it relates to forecast quality. Accordingly, we also provided a feedback form that permitted users to submit responses to targeted questions as well as in a generalized structure. The creator could also choose to submit the data anonymously.

We also took to direct interaction with users to solicit feedback and obtain both product type and delivery advice. This type of solicitation and dialog uncovered a need multiple users had with obtaining forecast outputs in a data structure for further use by the end user. This allowed us to modify both production and delivery components to create a streamline method through which users could obtain data inputs to utilize with their internal modeling and risk management tools which often use core meteorological inputs.

In addition to interaction with current product users, we continue to also acquire inputs from the broader wind power community. Our team is engaged with this community through industry meetings, associations and business development efforts. The feedback obtained through this approach is often in the context of competitive products and what those users like or dislike about tools they currently use.

Over the course of the project we engaged Dawnbreaker to undertake a competitive landscape analysis as well as explore avenues for our offerings particularly with organizations with which we not had previous interaction or limited interaction. The year one feedback continued to shape our development efforts to help CFAN strike the best balance in providing both required product elements as well as bringing novel tools and approaches to the marketplace. Year two dug deeper into organizations related to the wind industry, particularly some of the grid operators. The contacts identified by Dawnbreaker provide new avenues for potential feedback from the user type most directly engaged with both suppliers and consumers of wind energy. Dawnbreaker also clearly identified areas where they still see current wind forecasts falling short of their needs as well as those of the market as a whole.

Feedback and response

The nature of our development process allowed us to consider feedback continually during the Phase II process and to incorporate useful feedback into our product interface. Generally, feedback could be categorized as related to either functionality or content. The following examples introduce not only some of the feedback received but the product evolution accordingly integrated by CFAN:

- *Provide varied scales of forecasts both in time and geography* – Our initial dashboard design provided a focus on small regional forecasts covering days 1-32. Working with a wind farm operator it was clear they wanted more point and long range elements. Accordingly we developed point ramp forecasts and seasonal anomaly outlooks.
- *Providing delineated text and/or csv outputs* – We have experience providing data based outputs with clients for other forecasting solutions, but it was unclear initially if users would have this need for the wind forecast products. Working with an energy trading company we developed

outputs that could be ingested directly into their internal proprietary forecasting system that helps market traders project pricing impacts. This is achieved via direct web link without the user having to locate and retrieve the data via a web browser.

- *Showing elements that impact power consumption besides wind* – This need was brought to us by different user types but all had a necessity to understand additional drivers to wind generation impacts and overall power needs. CFAN developed a US wide view that is subdivided into grid based regions showing population weighted temperature information that provides a first degree power consumption perspective that can then be combined with projected wind power anomalies over 6 hour increments. This allows the various user types to ingest these two most primary and critical inputs into large scale response behaviors.
- *More mobile friendly components* – This topic is obviously very hot in today's environment and CFAN has adjusted various outputs to be well displayed on mobile devices, however the ever changing mobile landscape and functionality requires a patiently evolving approach. Our future updates are likely to include scalable vector graphics and location driven content to continue the enhancements that can benefit not only mobile but regular users alike.

2. Dashboard design and implementation

Evolution of the visual dashboard was focused within the first year of the project, while the second year included increased content and delivery such as mobile and data. As of the end of Phase II, all planned elements have been delivered along with additional content, features and functions not originally planned in the initial project plan. Forecasts are being delivered across all key wind generation regions across the US. As of now the product is considered live and fully supported by our operational team.

Working toward a full BETA version release

The primary objective of the design work during year 1 was reaching the goal of having a full BETA release available by the end of the year. From a design standpoint this was accomplished with most of the visible aspects solidified before entering year two of the project. During alpha and Phase I development the project was generally segmented to elements that often were built independently and with their own layout and structure. While it was convenient for the researchers, forecasters and designers, it minimized the amount of useful feedback that ultimate product users could provide as access was not always available for all content nor could they get a sense of what the finished solution may look like.

Figure IV.1 shows visually the transition that has taken place between the initial BETA release early in the project and the finalized BETA dashboard release. While the core elements from the first release remain visible, both layout and content changes are immediately visible. Most of the visible alterations were driven based on user inputs during the design phase. This finalized dashboard will serve as version 1 of the released product. As with all quality products, the dashboard will evolve over time, but the goal with this release is to have created a solution with an effective balance of elements and interaction for the array of user types likely to engage with the product.

Enhancements and incorporation of user feedback

As mentioned previously, we received a wide array of feedback regarding suggested changes to the initial and subsequent dashboard layouts. Whether the addition of 'quick maps' that users now have access to by simply hovering their mouse over the word 'map' or adjusting layout positioning of elements into combinations not previously used, CFAN continued to enhance the planned final offering to maximize its potential usefulness to the widest possible user base. We took very seriously the feedback provided by users and highlight in more detail here how we translated that feedback into viable solution elements.

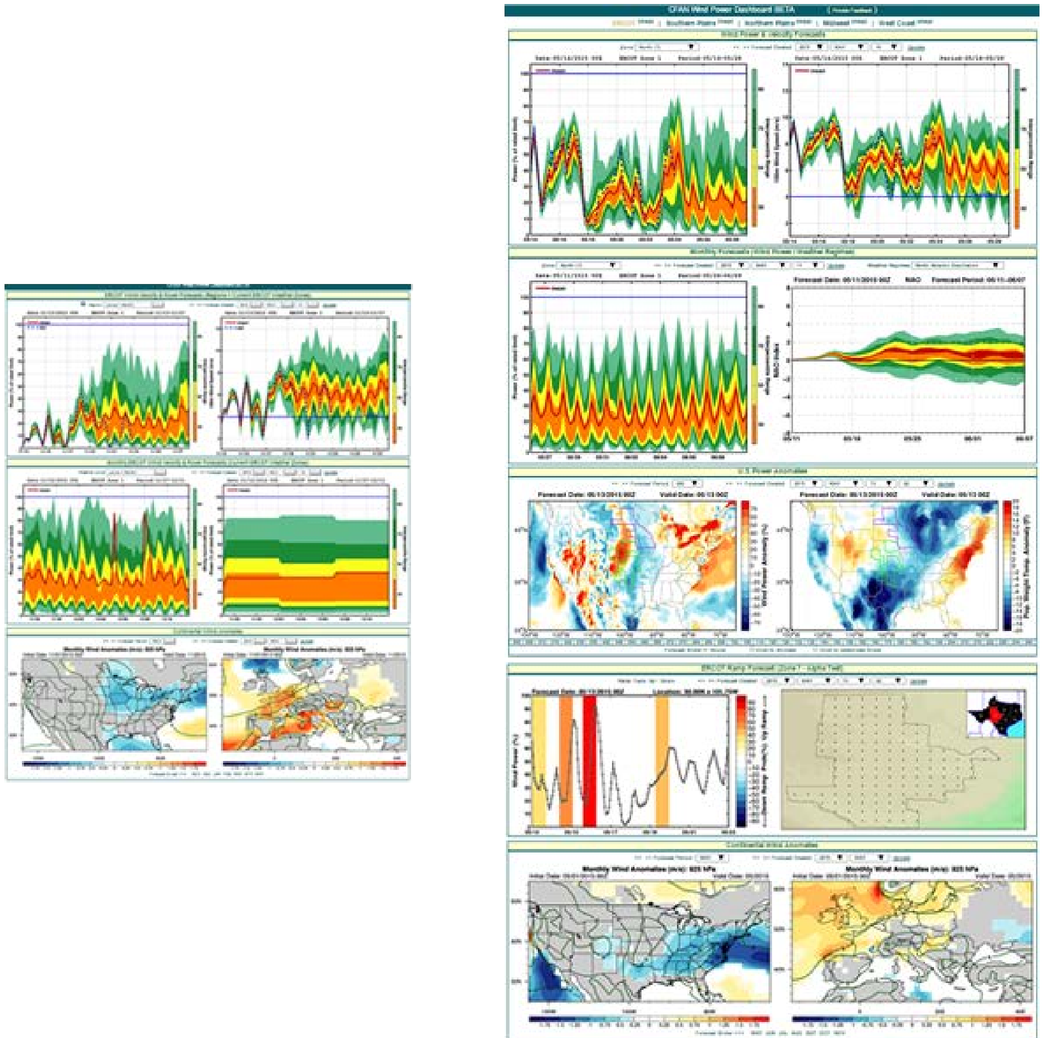

Figure IV.1. Comparison of initial beta wind dashboard (left) with the fully developed wind power forecast dashboard (right).

An example of an update we made specifically based on user feedback is the inclusion of wind power activity within the context of broader elements that could impact power demand. Through the discussion it was determined that the most influential element on demand was likely to be temperature anomalies. Additionally it was determined that understanding this in the context of the larger U.S. power market would be useful. Accordingly we developed an area of the dashboard that focuses on the both the large scale and regional power anomaly behavior. As can be seen in Figure IV.2, this section of the dashboard displays this information in a U.S. map form broken down into 6 hour values. There is also provided an opportunity to utilize forecast slider and animation elements that are more common in our other products but had not been a particular fit for the wind power dashboard.

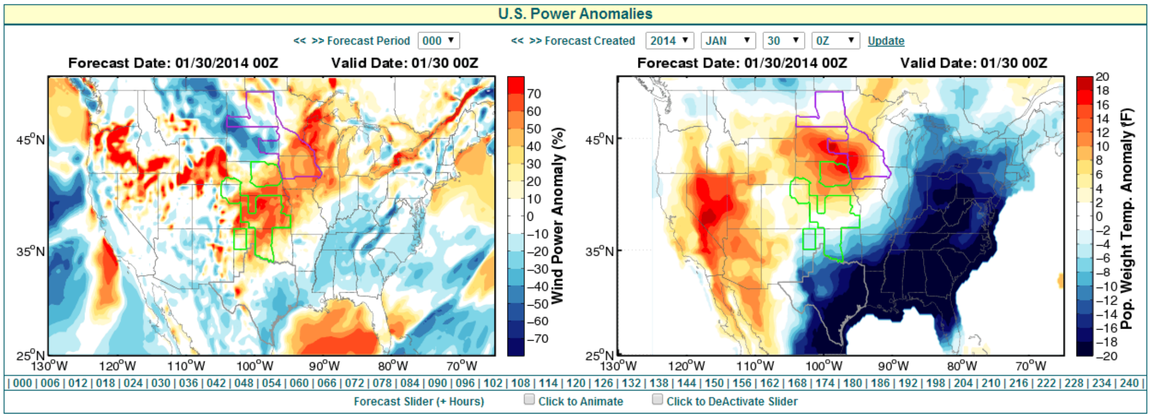

Figure IV.2. Close up of the 'Power Anomaly' section of the dashboard. Left is 6 hour interval wind power anomaly projection for the continental and offshore areas of the U.S. Right is a corresponding population weighted temperature anomaly forecast for land areas of the U.S.

Another challenge that has been unique to the wind power solution is providing data that is oriented to tight spatial variability. While CFAN has worked to develop point based solutions such as those associated with our city MOS temperature solutions, understanding the timing variance behavior in very close range has not been of particular need for our clients. Also, since our focus for this solution is not on forecasts in the very near term, high-resolution tools have not been required. However, in developing tools around wind ramps it became clear that being able to visualize behavior at a wind farm level would be particularly useful. Figure IV.3 shows this final section added to the dashboard that allows users to mouse over different grid points which display latitude and longitude information until they find the one most useful for them. They can then select that point to see updated ramp behavior forecasts for both up and down events. Utilizing the accompanying map, they can also select nearby locations that will provide additional understanding with respect to timing and location sensitivities.

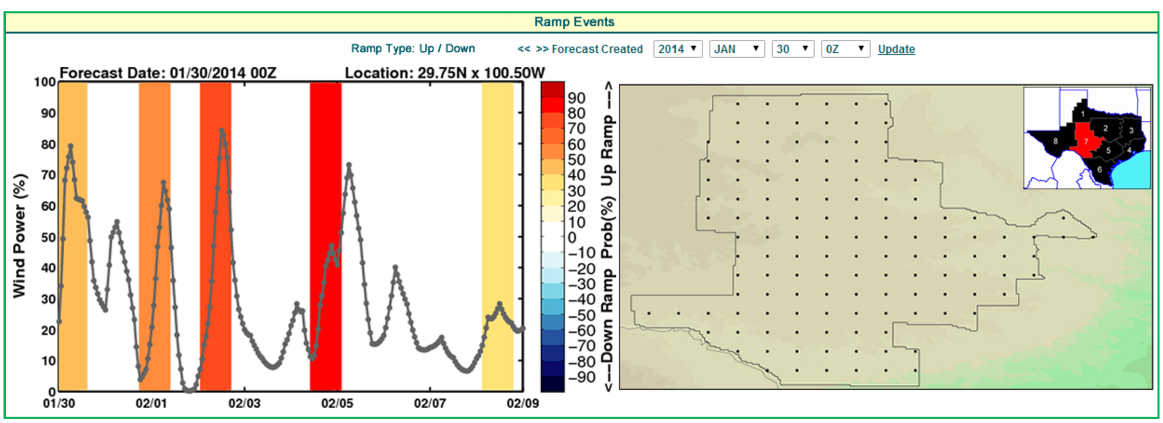

Figure IV.3. Close up of the new 'Ramp Event' section of the dashboard.

A final consideration CFAN made was the potential of having unique user or even client type dashboards. While at this stage we have found that the user mix generally seems happy with the available components, there remains expectations that this could change over time especially when mobile elements are considered. That said, our coding and design have been structured in such a way were a 'pick and choose elements' methodology can be adapted if necessary with minimal time and cost.

Ultimately all the choices we have made in design and implementation have been focused on maximizing the user benefits and broadening the user base potential in an effort to reach as large of a prospective market as possible.

Going live and into operational mode

The final step in Phase II was to take the last release of the Dashboard and migrate it into CFAN's operational environment. This included not only the visible web components but also the data delivery elements mentioned earlier as well as all the forecast creation elements. The current processing routine utilizes approximately 6 hours of server processing on a normal day and an additional 2 hours on days when monthly outlooks are generated. Should future demand warrant, the system could be shifted to a twice daily product, although that would essentially require a dedicated processing server and dedicated data array.

The web based Dashboard is part of our multi-server redundancy cached environment. This allows for minimal slowness and virtually eliminates outages no matter where across the globe a visitor may access the site. The web site does not currently utilize encryption in delivery mode to ensure the fastest retrieval times possible, although an encrypted version is possible in the future should any client data be ingested by CFAN servers in the production of outputs.

All these forecast creation routines, outputs and servers are as of the end of Phase II fully supported by our operational staff that provides 24x7x365 support for this product. This transition required a stringent debugging check and development of full product documentation. Accordingly, our support team can now handle any issues that may arise or inquiries from the user community.

6. Identify products developed under the award and technology transfer activities

a. Publications: Relevant publications authored by team members, including those initiated under separate funding, that were influenced by the needs of this project (including Phase I):

Kim, HM, PJ Webster, JA Curry, 2012: Seasonal prediction skill of ECMWF System 4 and NCEP CFSv2 retrospective forecast for the Northern Hemisphere winter. *Climate Dynamics*, DOI 10.1007/s00382-012-1364-6 http://www.cfanclimate.com/Kim_Webster_Curry_2012_CD.pdf

Kim, HM, PJ Webster, JA Curry, 2012: Asian summer monsoon prediction in ECMWF System 4 and NCEP CFSv2 retrospective forecasts. *Climate Dynamics*, DOI 10.1007/s00382-012-1470-5. http://webster.eas.gatech.edu/Papers/Kim%20et%20al.%202012b_CD.pdf

Kim, HM, PJ Webster, JA Curry 2012: Multi-model decadal predictions in CMIP5 decadal hindcast experiment. *Geophys. Res. Lett.,* 39, Article Number: L10701 http://curryja.files.wordpress.com/2012/05/kim-et-al-2012_grl.pdf

Wyatt, MG and JA Curry 2014: Northern hemispheric climate variability: dynamics of climate signal hemispheric propagation. *Climate Dynamics*, Volume 42, Issue 9-10, pp 2763-2782 https://curryja.files.wordpress.com/2013/10/stadium-wave1.pdf

Kravtsov, S., M. G. Wyatt, J. A. Curry, and A. A. Tsonis, 2014: Two contrasting views of multidecadal climate variability in the twentieth century. *Geophys. Res.*, DOI: 10.1002/2014GL061416 http://www.wyattonearth.net/images/KWCT2014_main_FINAL.pdf

Toma, V., PJ Webster and JA Curry: Re-evaluating the ENSO predictability barrier and its interannual variability. To be submitted to *Climate Dynamics*

Belanger, JI, JA Curry, K Shrestha and M Jelinek: Extended-range predictability of wind power for ERCOT. To be submitted to *Journal of Applied Meteorology and Climatology*

Relevant conference presentations:

Curry JA: Generating possibility distributions of scenarios for regional climate change. UK-US Workshop on Climate Science Needed to Suppport Robust Adaptation Decisions. Atlanta, GA, Feb 7, 2014. - http://www.eas.gatech.edu/sites/default/files/UK-US JC talk.pptx

Kim, HM and PJ Webster: ENSO and ENSO teleconnections. ECMWF Seminar, Reading, UK 3-7 Sept. 2012. http://www.ecmwf.int/newsevents/meetings/annual_seminar/2012/presentations/Kim.pdf

Curry, JA: Climate models: fit for what purpose? Presented at the Royal Society Workshop on Uncertainty in Weather and Climate Prediction, With Application to Health, Agronomy, Hydrology, Energy and Economics. Chicheley Hall, UK, 4-5 October 2012. http://curryja.files.wordpress.com/2012/10/rs-uncertainty-12.pdf

Toma, V: Seasonal Weather Predictability and Prediction. 7th Annual Earth Networks Energy Weather Seminar Winter Outlook 2012-2013. New York City, 18 October 2012.

Annual Meeting of the American Meteorological Society, January 2013, Austin TX:

Shrestha, KY, JA Curry, JI Belanger, J. Mittelman, J Freedman, J. Zack, P. Beaucage: Medium-Range Wind Power Ensemble Forecasting for Texas. https://curryja.files.wordpress.com/2015/05/wind-ams-15-final.ppt

Mittelman, J, JA Curry, KY Shrestha, JI Belanger: Subseasonal predictability of regional wind power generation. https://curryja.files.wordpress.com/2015/05/monthly-ams.pptx

Curry, JA, JI Belanger, M Jelinek, V Toma, PJ Webster: A seamless system for medium range, subseasonal and seasonal probabilistic forecasts of energy demand. https://curryja.files.wordpress.com/2015/05/omnicast-ams.ppt

b. Web site or other Internet sites that reflect the results of this project

<< Confidential information
Site: http://cfan.eas.gatech.edu/BETA/wd.php
User: DOE
Pass: Phase!!2015
ends here >>

c. Networks or collaborations fostered

We have developed new collaborations with:

- AWS TruePower
- WSI
- Southern Company

This project has also extended existing collaborations with:

- Shell
- Calpine

d. Technologies/Techniques

Forecast product technologies and techniques are described in the research Thrusts in section 5 above

e. Inventions/Patent Applications, licensing agreements

- MOU with AWS TruePower
- MOU with Southern Company
- License agreement with WSI

f. Other products

N/A

7. For projects involving computer modeling, provide the following information with the final report:

N/A