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Final Technical Report

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Recipient Organization:	WINData, LLC 104 second Street South, Suite 202 Great Falls, MT 59401
Project Title:	"Recovery Act: Use of real-time off-site observations as a methodology for increasing forecast skill in prediction of large wind power ramps one or more hours ahead of their impact on a wind plant."
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1 Executive Summary

In response to real world challenges at the Glacier Wind project in Northern Montana, WINData LLC, of Great Falls, MT (“WINData”), NaturEner USA, of San Francisco, CA (“NaturEner”) and OSIsoft Inc., of San Leandro, CA (“OSIsoft”) initiated work in Q4 of 2009 under funding from United States Department of Energy and the American Recovery and Reinvestment Act of 2009 to investigate the use of high fidelity, real-time off-site meteorological sensor data to improve short term wind forecasting and improve wind plant operations. The work was conducted to provide greater insight into the surrounding area’s meteorological characteristics and to help create increased situational awareness for the system operators, power forecasters/schedulers and the wind plant owner.

This research project involved the development, design, deployment and evaluation of improved observing sensor networks, new display tools and enhanced numerical weather forecasting techniques that aid utility operations for short-term (0-6 hour ahead) wind power integration, especially during periods of significant wind power ramping.

At the Glacier Wind site in Northern Montana, NaturEner operates its wind projects as merchant plants and acts as its own balancing authority. NaturEner has an obligation to deliver firm energy schedules 75 minutes ahead of the delivery hour. All energy must be delivered as scheduled in order to meet market and regulatory requirements. Once the power is scheduled, it is traded into the electricity market. Energy scheduled less than 75-minutes ahead of the delivery hour decreases the value of the product.

When the delivery is over the schedule (forecast), NaturEner is sometimes required to curtail or “cap” the windparks’ output. When the delivery is under the schedule (again forecast), NaturEner employs reserves to in order to meet the schedule. Due to current forecasting error in and around ramping events, this creates a fair amount of inefficiency in commercial operations. NaturEner has narrowed the initial efficiency gap, but needs substantial forecasting improvement to continue to improve the model.

While this revenue model is not optimal, it was believed to be the only option to bring additional wind generation to Montana. NaturEner believes strongly that their success, as evidenced by a working model with progressive changes, could stand as an example to larger, traditional balancing authorities. Continued forecasting improvement is crucial to efficient operations and to reducing the significant cost of wind integration.

Ramping events are the primary cause of disruptive forecast error in the operation of large wind power plants. Current wind power forecasts methods have not achieved the desired level of accuracy in predicting the magnitude and timing of ramping events, which leads to difficulty integrating wind power into the grid.

Improved temporal and spatial information on the local wind field, measured wind profiles at several carefully selected locations and the monitoring of the local atmospheric stability were hypothesized to potentially improve the detection and prediction of ramping events. To achieve this end, an array of advanced sensor technology was combined with state of the art data collection methods and integrated into newly developed advanced wind power ramp forecasting techniques. These new techniques were evaluated as to effectiveness in forecasting on an operational wind farm.

Substantial savings in annual system production costs can be achieved with improved wind forecasting accuracy, particularly if prediction of the magnitude and timing of ramp events in the 0 to 6 hour range can be improved. Accuracy of commercial wind energy forecasting services has been limited to a large degree by core meteorological and forecast products available from the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service, which to date has not focused on providing foundational meteorological information optimized for wind energy at or near hub-height. Improved techniques to provide economic and reliable operations for utilities will be required for unit commitment, transmission scheduling and generation control strategies as the amount of wind energy penetration increases.

The project work implemented and leveraged the significant power of the OSIsoft PI System which facilitated intelligent lay techniques and experiments conducted by WINData in parallel with the development of sophisticated modeling techniques by internationally known wind forecaster Garrad Hassan America, Inc. ("GH") to assimilate data from met masts and several surface pressure devices for adjusted sea level pressure, temperature, and wind speed into the WRF model. Performance evaluations were conducted internally by NaturEner and by 3TIER Inc. of Seattle, Washington ("3Tier").

The technical effectiveness of using real-time sensors and a PI system was demonstrated by WINData by detecting the onset of indicative regional patterns and weather conditions that subsequently predicted ramp events on a 1-3 hour advanced time horizon. GH also validated the fundamental hypothesis of the project: that offsite meteorological data has value in wind generation forecasts for sites in complicated terrain. It was demonstrated that forecasts which utilize strategically located offsite observations generally performed better than persistence of onsite generation measurements.

WINData collaborated with GH to devise and deploy a real-time pattern matching algorithm to rapidly augment the WRF forecasts for short-horizon ramp predictions. Improvements over persistence were seen in many of the traditional and ramp-tracking metrics over several horizons, independently in both the GH and NaturEner evaluations. It was concluded that these improvements would not have been possible without the use of the real-time data observations.

In using the offsite measurements, GH moved beyond traditional data assimilation (i.e. nudging of NWP) and used machine learning to train and inform a pattern matching algorithm to provide additional short term ramp information. GH acknowledges there are still drawbacks to this type of data utilization, but suggests that there are basic improvements that can be made simply by adding more strategic sensor locations. Many of the drawbacks in the techniques developed were manifested in, and masked by, the validation statistics which may obscure the true value of the offsite data during times when the impulses arrived from sectors in which observation systems were deployed. GH suggested several solutions to improve the accuracy, the most simple involving the installation of more data collection sources in high risk areas to add visibility of wind patterns in sectors sensitive to types of ramps towards which the algorithm was essentially blind.

The commercial value of the array and its efficacy in improving forecaster models was opined to be somewhat marginal by both NaturEner and their forecaster, 3Tier in its current state of development. NaturEner's evaluation suggested that although a significant improvement in ramp detections were observed, this improvement was marginalized by a companion increase in false ramp predictions. 3Tier likewise concluded that the inclusion of WINData observations into 3TIER's forecast system acts as an improvement in some periods and a degradation in others. In 3Tier's evaluation, the summary statistics show performance that is, at best, equivalent to the control forecasts. Further that there is a small increase in the probability of detection, but also a commensurate increase in the false alarm ratio which acts to negate the improved detection of true positives. Overall, the threat score for ramp event detection is about the same when the real-time observations are included.

3Tier concluded that the real-time observations, as they are currently sited, do not add significant benefits to their current forecast system. The 3TIER forecasts already incorporate the existing off-site meteorological data from tower "BR-1" and public weather stations in the region. 3Tier concluded that the real-time observations do not add enough new information that is independent of the data already sampled by 3Tier using the existing off-site sensors. 3Tier notes that this was not anticipated in advance, since there are relatively few observations in the region near the Glacier Wind facility; 3Tier had speculated that significant improvements were possible with deployment of just a few sensors in key areas.

The primary objective of the project was to demonstrate the value of well-located off-site real-time met sensors in reducing the uncertainty in the short-term forecasting of ramp events. The second objective was to demonstrate the advantages of leveraging OSIsoft PI System data infrastructure into next generation met data retrieval and its subsequent integration into power system operations centers. The third objective was to assess the amount of improvement in ramp forecasting skill that can be obtained through the use of this site specific off-site measurement network and to determine which forecast methods can extract the maximum value from this type of network.

Under this project, participants, a) developed a better understanding of next generation wind forecasting methodologies, requirements and possibilities in the hour-ahead and day-ahead time frames, b) developed a better understanding of operations planning requirements, and c) added to the ongoing dialog between the wind forecasting research, development, methodologies, applications and user communities.

The enhanced prediction methods developed under this research funding were presented in 2012 at both UVIG and at the OSIsoft User Conference and are being marketed as "WINDataNOW! ™ Technology". The system was also proposed to NOAA/DOE in response to the DE-FOA-0000343 RFP and was titled "Enhancing Short Term Wind Energy Forecasting for Improved Utility Operations".

2 Project Overview

The goal of the work was to seek improvement in the forecasting, scheduling and operational efficiency of the Glacier Wind project in Montana through the deployment of an array of off-site real-time met sensors feeding data into an OSIsoft PI System.

Available meteorological data and net power production information was aggregated, collected, and backfilled from the beginning of 2010 into WINData's central PI Server. All available met data, ASOS / METAR data from the surrounding region were collected and automatically fed into the central PI Server. The met data sets were reviewed for quality and accuracy and used to determine the primary sources of wind events and power production at the plant.

In the Figure below a map of the data sources in PI are shown in a Transpara KPI. These readings are taken at 15 minute intervals and are incorporated into the WINData PI System. In 2010 NaturEner purchased both an OSIsoft PI system and the Transpara KPI product.

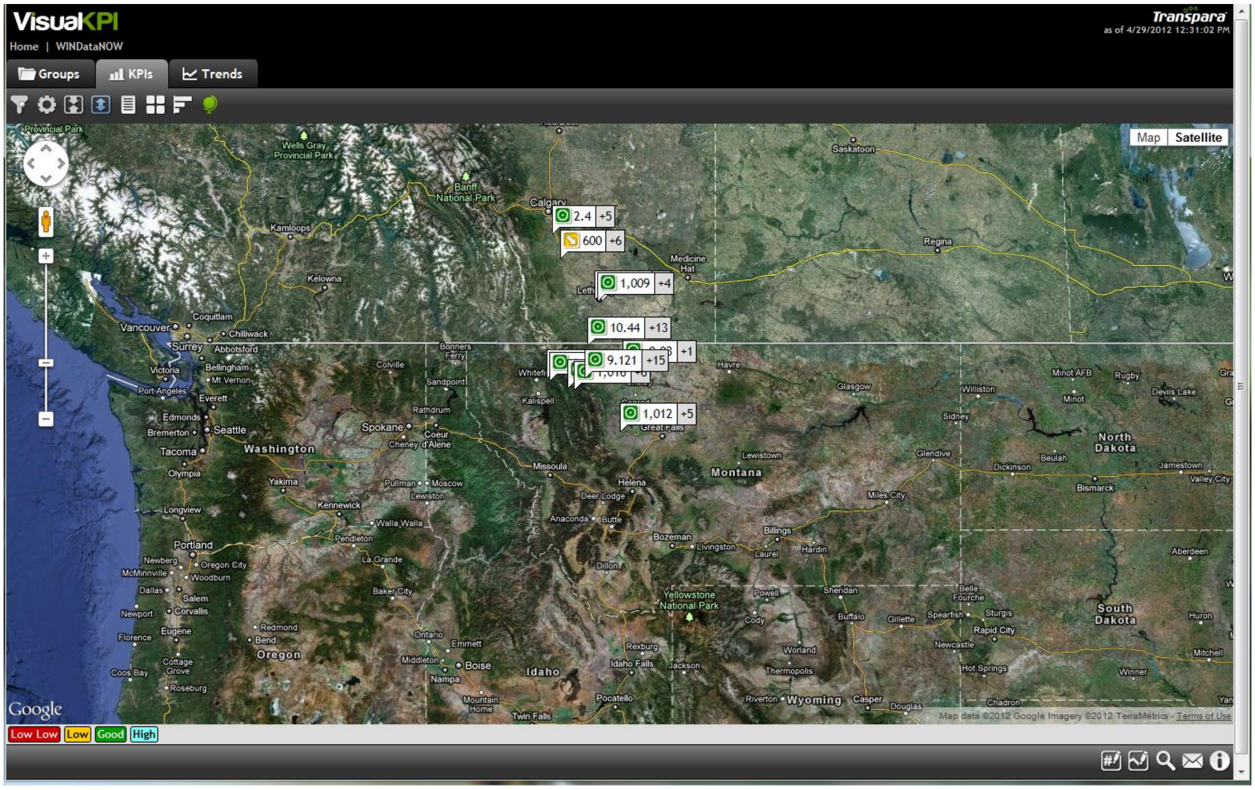


FIGURE 1 TRANSPARA KPI OF WINDATA SITES

2.1 Analysis of Regional Data to Determine Source of Ramping Events

Analysis of the initial data provided a preliminary regional climatology and a sense of the directionality of wind events at the Glacier Wind facility. Analysis of the data demonstrated that the wind at the plant is most frequently from the WSW (265°), but that the wind from both WSW and from the NNW may have significant influence on the variability of plant production. This phenomenon is shown in the wind rose from NaturEner site 4510 in Figures below.

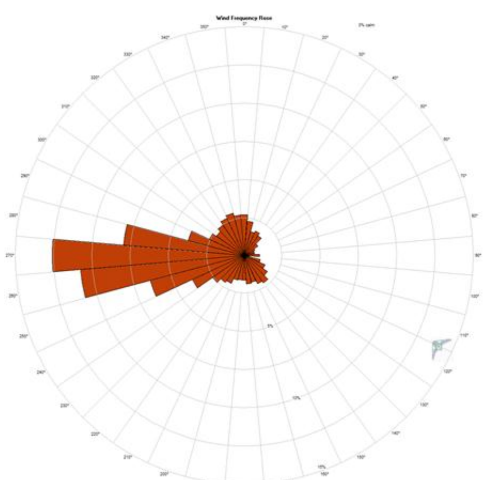


FIGURE 2 WIND FREQUENCY BY DIRECTION

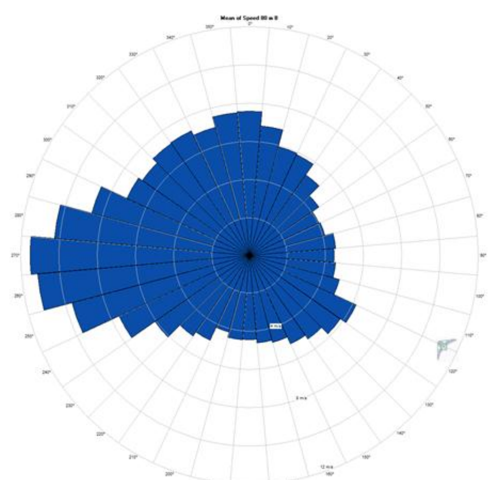


FIGURE 3 MEAN WIND SPEED BY DIRECTION

In the above figures it can be seen that the wind most frequently comes from the Marias pass at a heading of 265° from the plant and the majority of total energy production of the plant is from this direction. Infrequent but significant wind events also are seen to emanate from the NNW. A depiction of the Glacier Wind plant wind rose's indicating primary wind directions is shown in the Figure below.

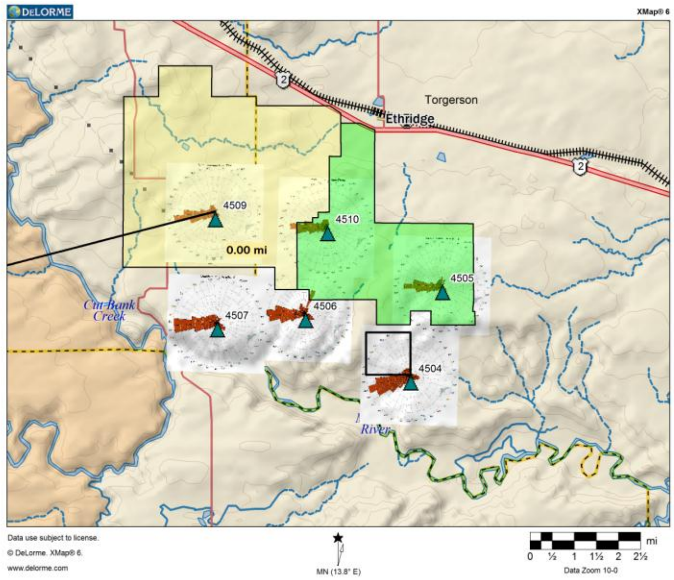


FIGURE 4 WIND ROSES AT SIX GLACIER WIND SITE WIND RESOURCE ASSESSMENT MET TOWERS

2.2 WINData Experiments Data Using OSIsoft PI Data Tools

2.2.1 Cardinal Directions

Examination of the regional met data and the enhanced data base on the PI Server assisted workers in identification of two cardinal directions that appear to interplay to create the variability and ramping events at the wind farm.

This analysis examined the pressure differentials between, a) Glacier Park (Kalispell) Airport ASOS and Havre ASOS and, b) Lethbridge Airport ASOS and Great Falls ASOS. The pressure gradients along these directions seem to drive the wind events and the change in dominance of one cardinal direction to the other seemed to coincide with the timing and propagation direction of significant ramp events.

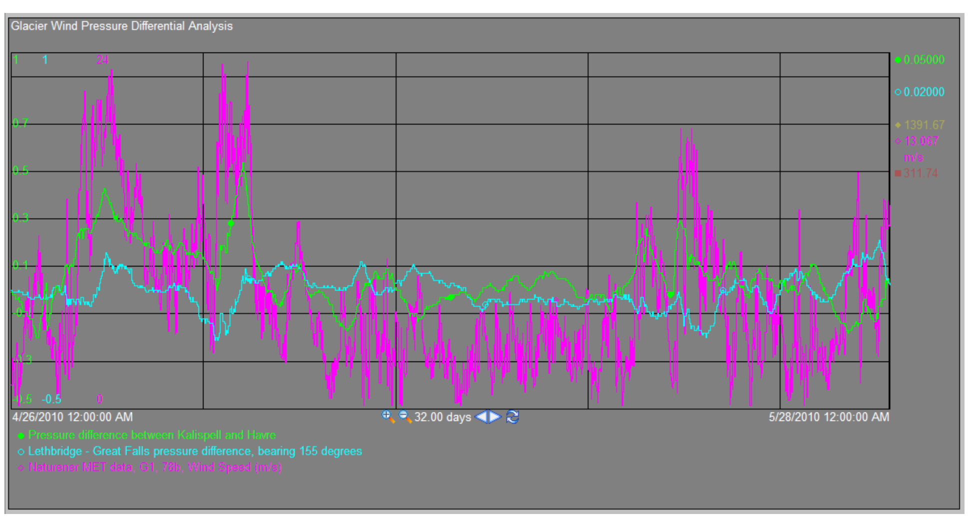


FIGURE 5 PRESSURE DIFFERENTIAL ANALYSIS FOR GRADIENTS CENTERED AROUND GLACIER WIND

Sixty miles to the west of the plant is the Marias pass, which is a good example of a Gap Wind type resource which occurs when a mountain barrier effectively separates two air masses of different densities. This results in a strong pressure gradient across the mountain barrier causing air to flow through the gaps in the terrain from high to low pressure, and since the terrain channels the winds, they are accelerated along the pressure gradient instead of becoming geostrophic.[1]

Winds from the North and Northwest seem to interrupt the otherwise predictable and stable westerly winds from the Marias Pass. The interruptions are infrequent but energetic and, although linear pressure gradients also seem to drive the NW winds, there is evidence of counterclockwise cyclonic cycling, which causes very unpredictable wind directions at the plant and in the region.

These cyclonic events may be associated with low pressure centers that move from the north in Canada, into the Glacier Wind plant area and then move off to the south east. Once the low pressure systems have moved off, the west wind from the pass is reestablished and more predictable power production resumes. In light of the identification of the cardinal directions of wind influence, sensor arrays were installed to augment existing instrumentation and capture additional data to describe this climatology.

Locations were determined to install two 60-meter off-site met towers, 1401 and 1402, for maximum positive impact. Wind speed, Wind direction, Pressure, temp and relative humidity data were gathered to provide the largest impact on forecast accuracy for the most significant ramp events.

FIGURE 6 WINDATA 60 METER MET TOWER WITH 3G REALTIME LOGGER - SITE 1401 EAST GLACIER, MT

2.2.2 Marias Pass

It was determined that regularly spaced pressure readings across the Marias pass could potentially provide a method of anticipating wind events at the 1401 met tower in East Glacier and, later, at the Glacier Wind plant. It was hypothesized that, if this sensor set could track the propagation of events

[1] Washington County High Winds, by Mark Struthwolf and Ed Carle, November 1997

through the pass to East Glacier, then this information could provide 1-3 hour advance warning of events emanating through the pass that later hit Glacier Wind It was also noted that the existing BR-1 met tower currently in use by forecasters missed the Marias Pass events and the disturbances from the NW.

As a means to gain access to sites and existing infrastructure across the remote and wild Marias Pass and to avoid siting challenges, it was decided that collocation could be accomplished using commercial sites, like bars and hotels, which had both internet (satellite in many cases) and a useful location in the pass that would provide suitable pressure readings.

WINData determined that the Davis Vantage Pro2 weather station would provide a zero footprint, near scientific quality method to collect NIST traceable data across the pass, and also in other non-critical directions to the south and east of the GW plant. Also, it was felt that the proprietors of these establishments would welcome the installation of a weather station and display for their local use.

Three stations were located west of the East Glacier 1401 site, at commercial establishments through the pass - WS200 was located at the Snow Slip Inn; 15 miles east of Essex, MT, WS300 at the Izaak Walton Inn, in Essex, MT, and WS400 at the Packers Roost Bar, in Coram, MT. Davis stations were installed on rooftops within wifi range of the internet router, at about 6M above ground. Pressure data were collected from these Davis devices via a wireless transmitter and fed to Weather Underground and imported into the WINData PI Server.

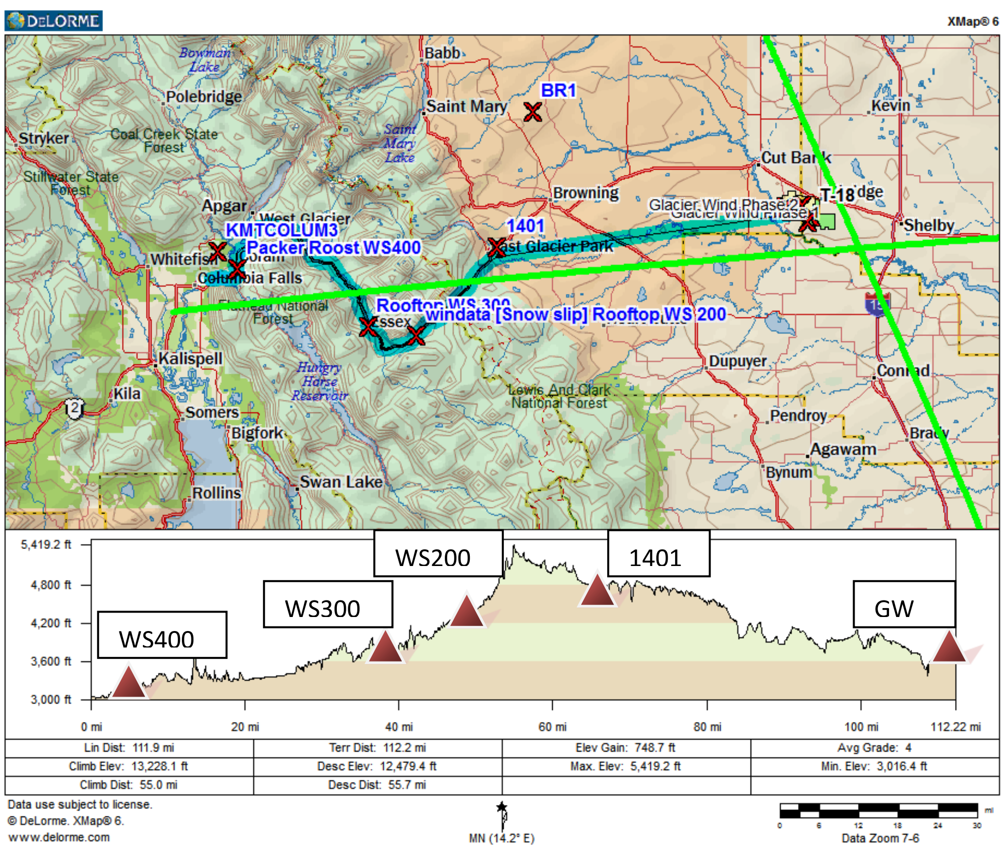


FIGURE 7 TOPOGRAPHY PROFILE SHOWING THE RELATIVE ELEVATIONS OF THE SENSOR SITE LOCATIONS ACROSS THE MARIAS PASS

The Davis weather display was mounted in a useful way for the proprietor's use, and was connected to the proprietor's router using a Davis weatherlink device. The data stations located across the pass are linked to the internet through Davis' weatherlink site which collects 15 minute data via IP protocol and then posts the data to weather underground[2]. From Weather Underground, the WINData PI Server can collect all data from a single interface. Data collected using this technique is seen in the following graphic.

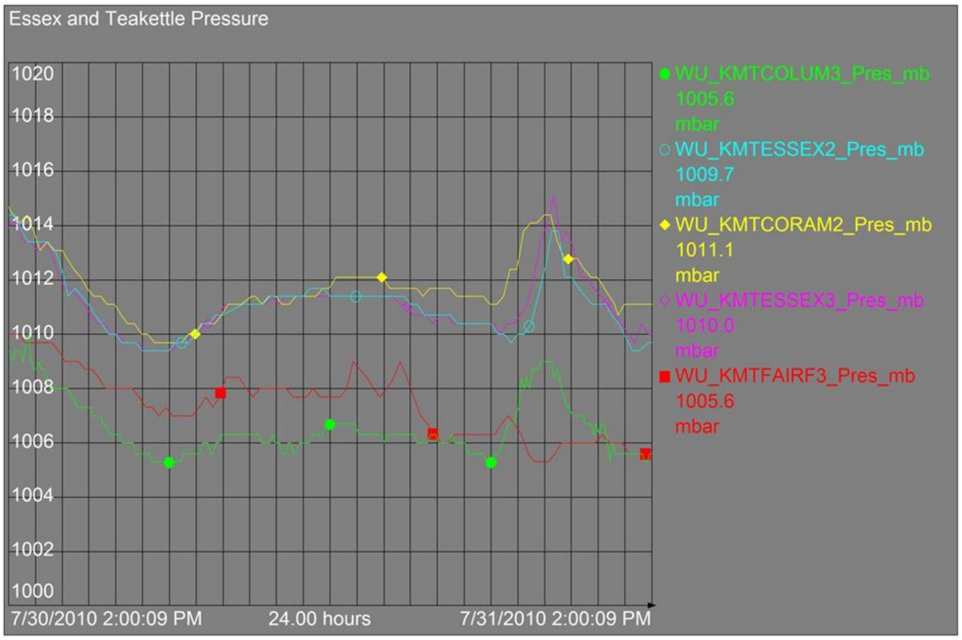


FIGURE 8 DAVIS PRESSURE READINGS COLLECTED IN PI DATA BASE

2.2.3 North South Flows

Site BR1 is an existing 60 meter tower that was also incorporated into the sensor array and the PI Server. In October of 2010 WINData finalized permitting and installed met tower 1402 as far to the north as possible whilst still remaining in the USA. Figure 9 below shows, the respective locations of the project sensors and the Glacier Wind plant - met towers 1401, 1402, and BR1 and the four Davis Weather Stations collecting pressure data across the Marias Pass.

An automated procedure was implemented to gather data the array data and data from regional ASOS / METAR stations into the WINData central PI Server. Additionally, meteorological observations were collected from NaturEner's Glacier 1 and Glacier 2 wind farms. This data was backfilled and incorporated into the PI Server. Data from all these sources was collected and updated on a regular basis.

Available data from existing data sources within NaturEner's meteorological systems and net-power-production information were aggregated, collected, and backfilled from the beginning of 2010 into WINData's central PI Server. New data from these sources is automatically gathered on an "as frequently-as-possible" periodic basis, down to a 1 Hz real-time standard.

[2] http://www.wunderground.com/wundermap/

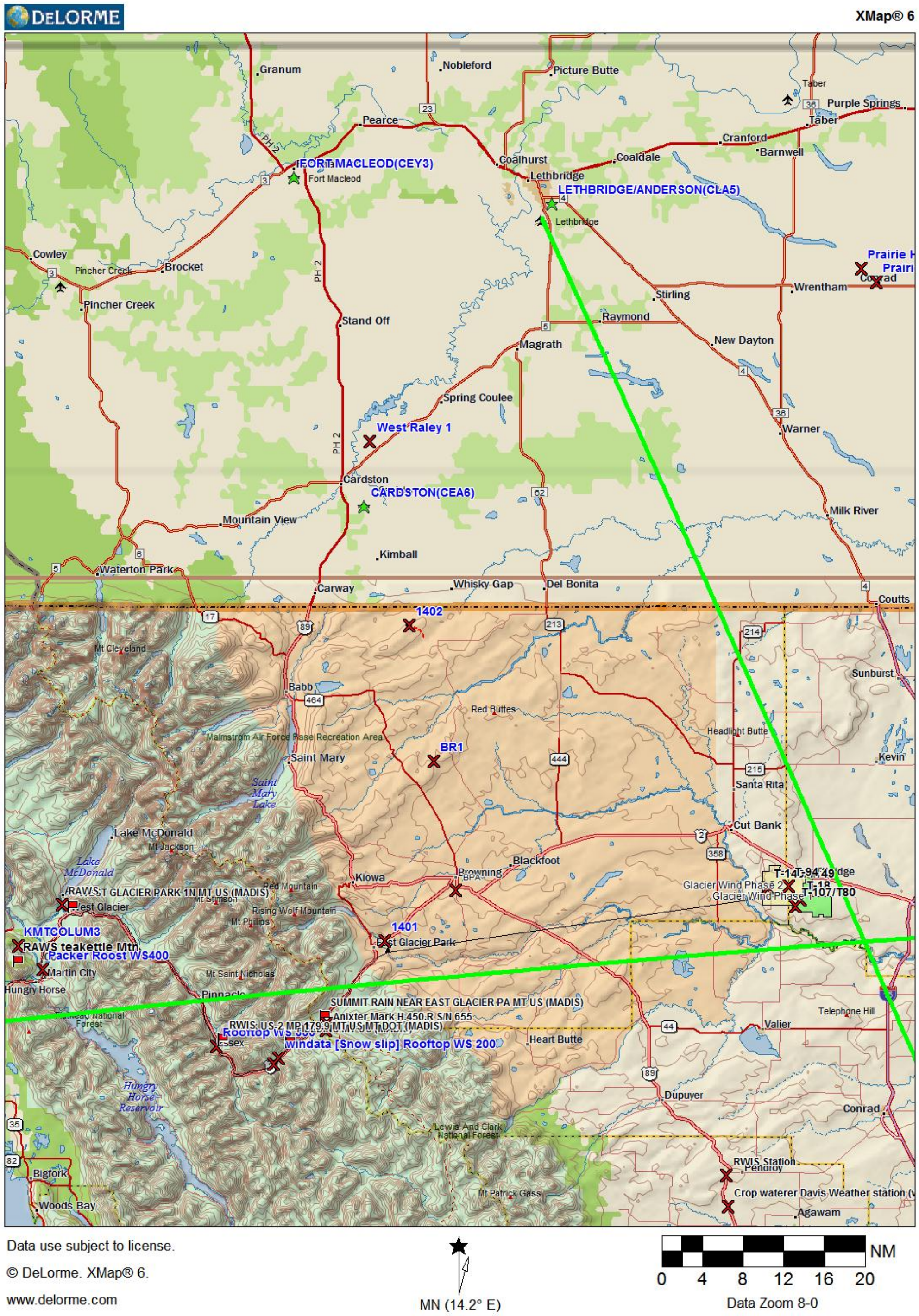


FIGURE 9 LOCATION MAP OF WINDATA MET TOWERS AND THE DAVIS WEATHER STATIONS WITH RESPECT TO GLACIER WIND

A screen shot of the WINData PI ProcessBook desktop for the project is shown in the Figure below.

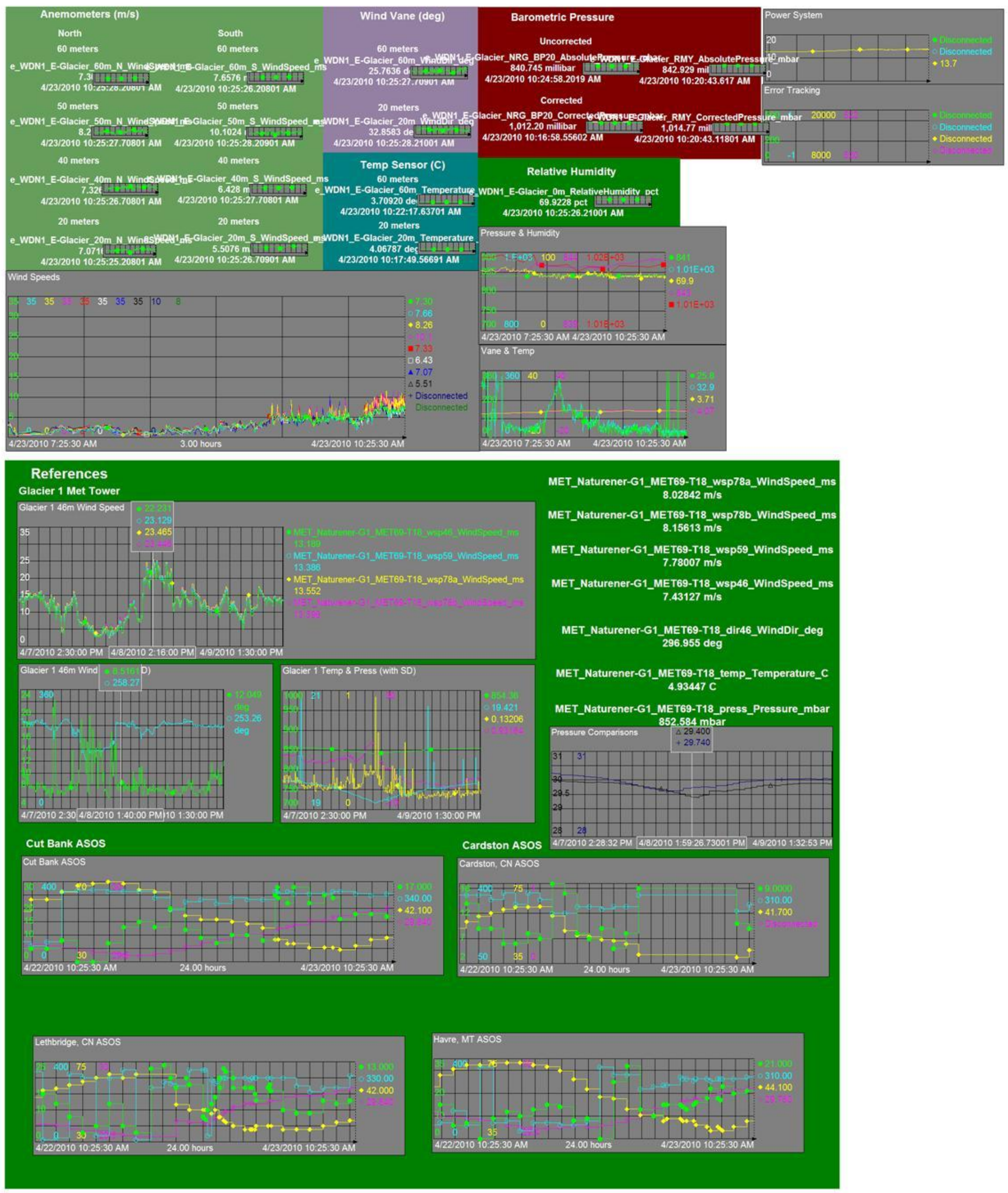


FIGURE 10 SCREEN SHOT OF WINDATA PI PROCESSBOOK DESKTOP DISPLAY

2.3 Ramp Prediction by WINData Using the PI System's Real-Time Data Tools

It was hypothesized that through collecting and reviewing a series of pressure measurements from geographically aligned sites and correlating the fluctuations in pressure readings with wind speed (and therefore power production), an "early warning" indicator could be developed to help forecasters and NaturEner better anticipate both timing and magnitude of future wind ramp events.

NaturEner provided a list of dates for ramp events that they regarded as "significant misses" in order to narrow the relevant dataset. This was used to narrow down the dates for back-casting analysis. The initial methodology consisted of observing how pressure disturbances in the Marias Pass manifest at the East Glacier 1401 met tower. Figure 11 shows that there can be a strong correlation between measured pressure events that propagate sequentially through the measurement stations along the Marias Pass and an eventual change in the wind speed at the East Glacier met tower.

In the figure, the traces displayed as Green, Cyan, and Yellow are geographically distributed from West to East along the Marias Pass. The White trace is the measured wind speed at 60 meters at the East Glacier 1401 met tower. It can be clearly seen that as the pressures at three upstream stations (presented in their geographic order from west to east) present a pressure gradient with a clear phase separation, which in turn drives a wind speed ramp event at the East Glacier met tower.

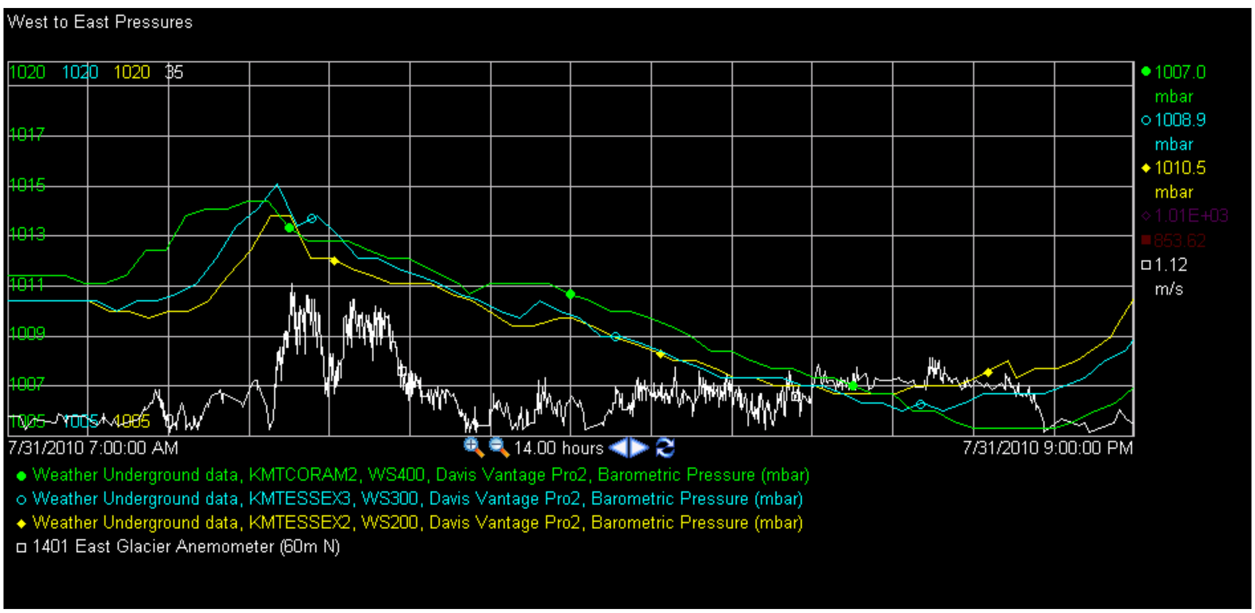


FIGURE 11 UPSTREAM PRESSURES IN MARIAS PASS' EFFECT ON EAST GLACIER MET TOWER WIND SPEED

It was also observed that the significance of the behavior at the met tower was governed by the pressure influence to the East of the met tower. If the pressure change in the Marias Pass was not significantly different than the pressure at the met tower, the effect of the pressure change was minimal.

Using the correlation developed from the data from these stations and the East Glacier met tower as a basis, analysis proceeded into how this behavior might manifest at the Glacier Wind plant. Because the point of interest was the actual wind plant and not necessarily the barometric pressure value at each site, it was determined that using the pressure measurements available at the Glacier Wind plant as a reference would create a data set that classified each offsite pressure measurement as a deviation from the current Glacier Wind plant's pressure, or a "driving force".

When the plant's barometric pressure was lower than the surrounding areas, the plant would act as a "well" and the directionality of a wind disturbance (or steady-state flow) would be determined by the measurement stations that reported higher pressures. What's more, measurement stations that were significantly further away from the plant that showed dramatic pressure variations with respect to other pressure observations closer to the plant might indicate impending climatological changes.

By creating calculations in the PI Server to continuously calculate "pressure differences" between the measurements at the various instrument sites and the Glacier Wind plant, variations in pressure along the West to East cardinal direction were easier to visually detect and flag for further analyze in Excel.

Figure 13 illustrates how the pressure differences along the West to East cardinal direction correspond subsequently to both a wind speed increase at the East Glacier met tower and a wind speed increase at the Glacier Wind plant.

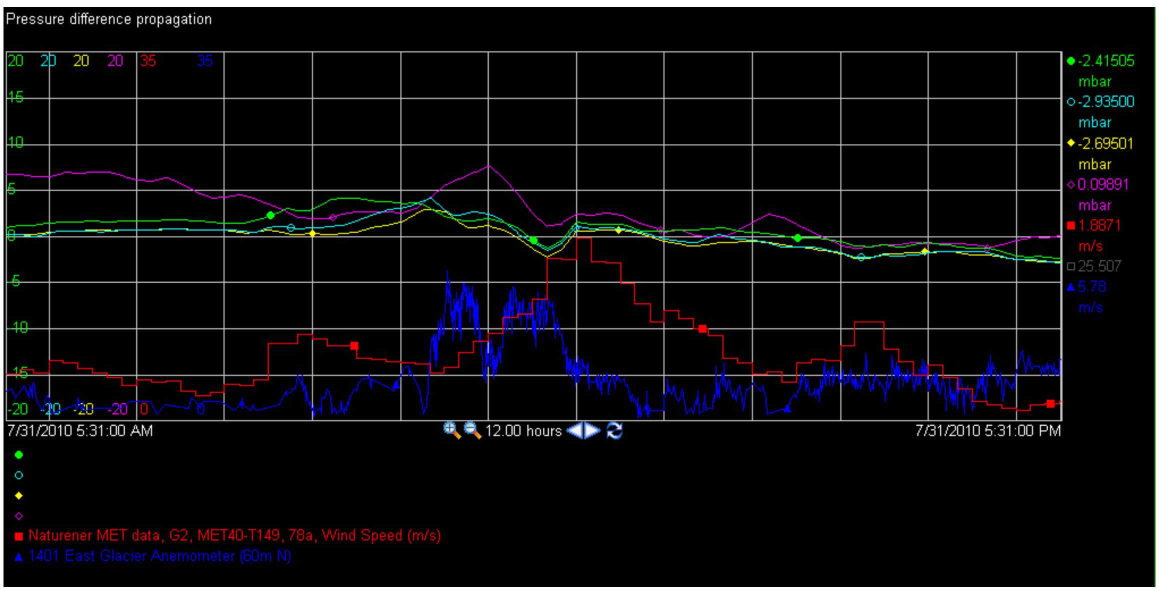


FIGURE 12 EXAMPLE PRESSURE WAVE PROPAGATION PRECEDING A RAMP EVENT

Note that the order of the traces from West to East is Green, Cyan, Yellow, and Magenta. The wind speed at the Glacier Wind Plant is designated in Red and the wind speed at the East Glacier met tower is designated in Blue. The pressure gradient traces above the center line of the trend are positive (i.e. pushing toward the Glacier Wind plant from West to East). The important point to note in this figure is the phase shift between the first observation of a pressure "wave" propagating through the Marias Pass and the eventual wind speed event at the Glacier Wind plant.

To further develop these correlations, two specific cases were chosen from the plant "missed" ramp data where all measurements appeared to be valid and significant phenomena were captured. The first was during the time period of July 31st, 2010 and the second was September 4th, 2010.

2.3.1 July 31st, 2010 Ramp

On July 31st, 2010 a ramp-up event was detected at the plant, classified as a "miss" by NaturEner. Analysis of plotted sensor data against the Glacier Wind plant's normalized, reference "combined unit power production" during that time period provided insight into how this direction influences the plant's operation. By plotting the relative pressure driving forces from the Marias Pass against the wind speed at the East Glacier met tower (in orange) and the power production at the Glacier Wind plant (in cyan), it can be clearly seen that there is a correlation between upstream pressure observations and subsequent wind phenomena at the plant. This wind regime happened to be one of the "best possible" cases in that there were no northerly disruptive climatological effects present during this time period. This allowed for clear analysis of the West to East cardinal direction.

The first local maximum pressure anomaly was observed at around 9:30AM. The first wind speed local maximum at the East Glacier met tower was observed around 10:30AM. The first wind power local maximum anomaly at the Glacier Wind plant was observed at 12:00PM (noon). It is thought that with more analysis of cases such as this that an "early warning" trigger could be developed to both alert the plant of incoming disturbances and to assist forecasters in refining their near-term forecasts for the site.

Additionally, the subsequent subsidence of the ramp event appears to be illustrated by the upstream pressure differences as well. It has been observed frequently at the Glacier Wind plant that often a disturbance than originates from one cardinal direction may be disrupted by a disturbance originating from the orthogonal cardinal direction. WINData believes that installing upstream pressure measurements at greater distances to the North of the Glacier Wind plant would likewise assist in early detection of ramping conditions from the North.

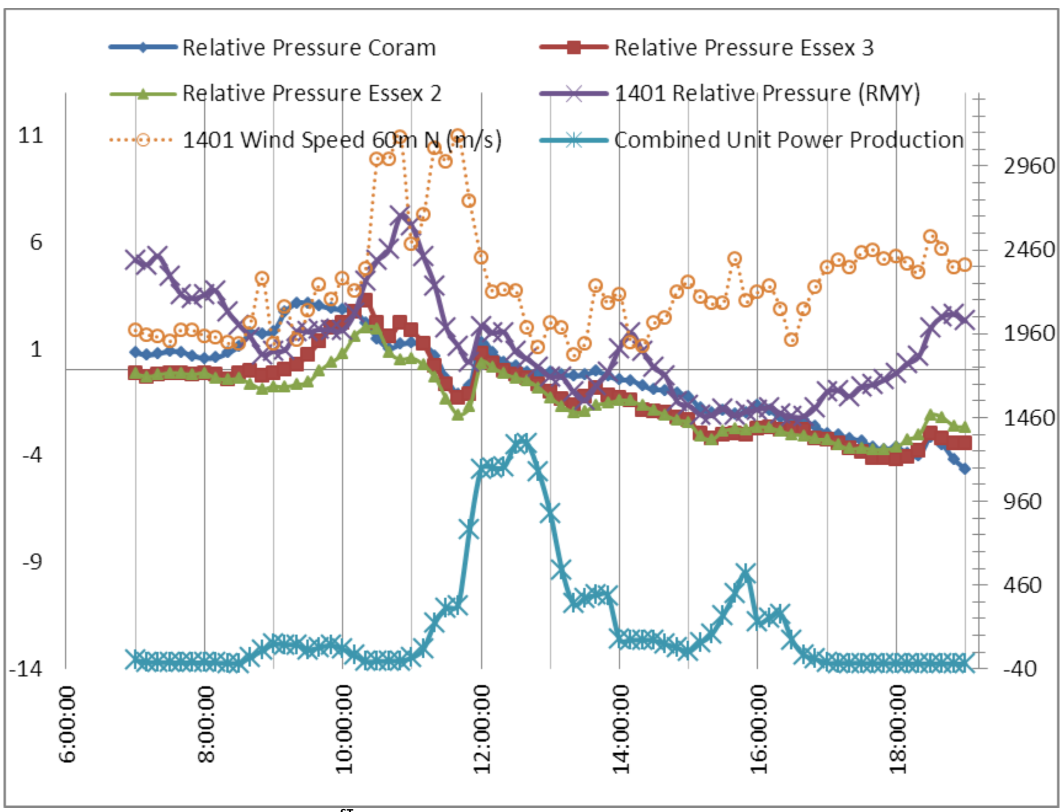


FIGURE 13 DETAILED EXCEL ANALYSIS OF JULY 31ST, 2010 RAMP EVENT

2.3.2 September 4th, 2010 Ramp

Another wind phenomena event that was captured by WINData using the PI tool illustrates how upstream pressure measurements can indicate the subsidence of the wind speed's driving force. As the Marias Pass is a fairly narrow "channel" through which wind passes, it has very few influences from the North and South. However, when the outlet of the pass (near the East Glacier 1401 met tower) comes under the influence of a pressure event from another direction, it can effectively "shunt" the driving force out of the Marias Pass and indicate that the wind out of the West to East cardinal direction will subside.

Figure 15 shows the time period from September 4th, 2010 where the upstream driving force in the Marias Pass was interrupted by pressure phenomena detected at East Glacier. This disruption (indicated by the green arrow) resulted in a wind speed subsidence at the East Glacier met tower and a subsequent power production loss at the Glacier Wind plant.

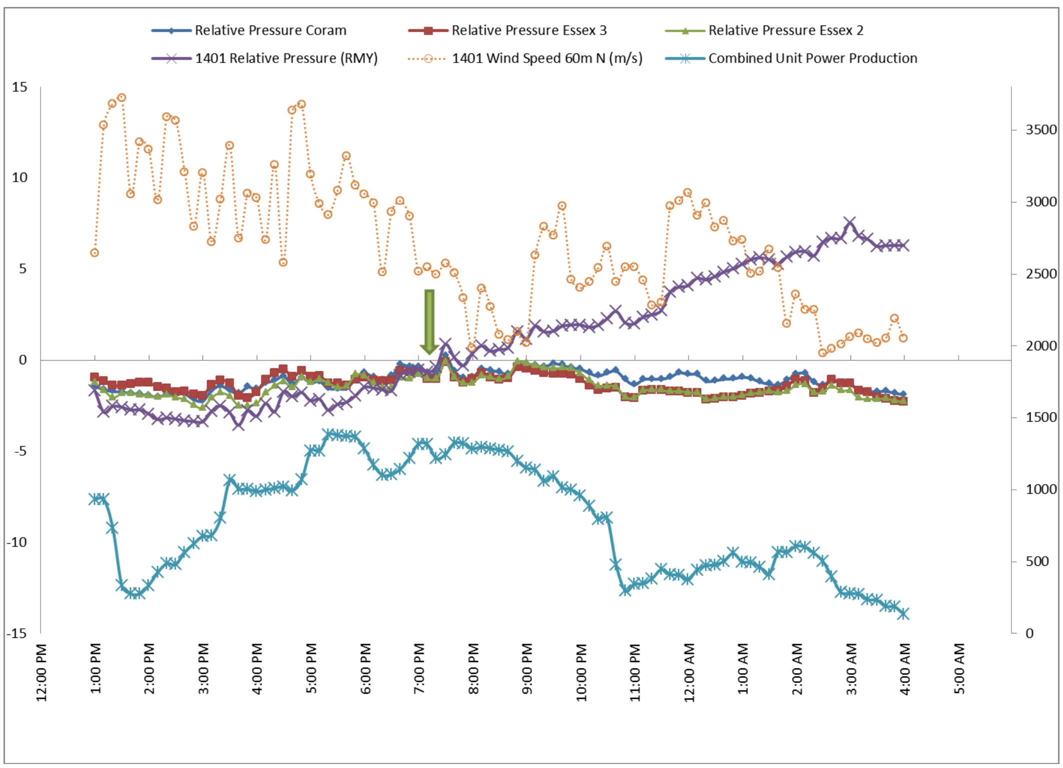


FIGURE 14 EAST GLACIER PRESSURE DRIVING FORCE EXCEEDING MARIAS PASS DRIVING FORCE INDICATING SUBSEQUENT WIND POWER EVENT AT GLACIER WIND PLANT

The pressure disruption detected at 1401 preceded the subsequent power drop-off (negative ramp event) at the Glacier Wind plant due to the fact that it originated from the South or South East.

Typically disruptions such as this originate from the Northwest and would be detected by instruments north of the Canada border. Because the East Glacier pressure driving force (with respect to the Marias Pass and with respect to Glacier Wind) rises ahead of the wind power production subsidence, it is possible that the point where the driving forces become equal (at the green arrow) could indicate an early warning of a pending down ramp event.

Further study of similar phenomena would be required to develop a better understanding of this behavior. Also, due to the fact that these types of disruptions originate predominantly from the Northwest, it is estimated that a better understanding will be developed using upstream instrumentation in that cardinal direction.

2.3.3 November 16th, 2010 Ramp

On November 16th, 2010 a significant ramp event originating from the Northwest direction was detected and recorded by all available measurement points. In order to better understand the correspondence between the propagation of disruptive Northerly wind phenomena, the data has been aligned, analyzed and is presented graphically below.

Figure 16 below shows a detailed analysis of this time period, specifically from the Northwesterly direction.

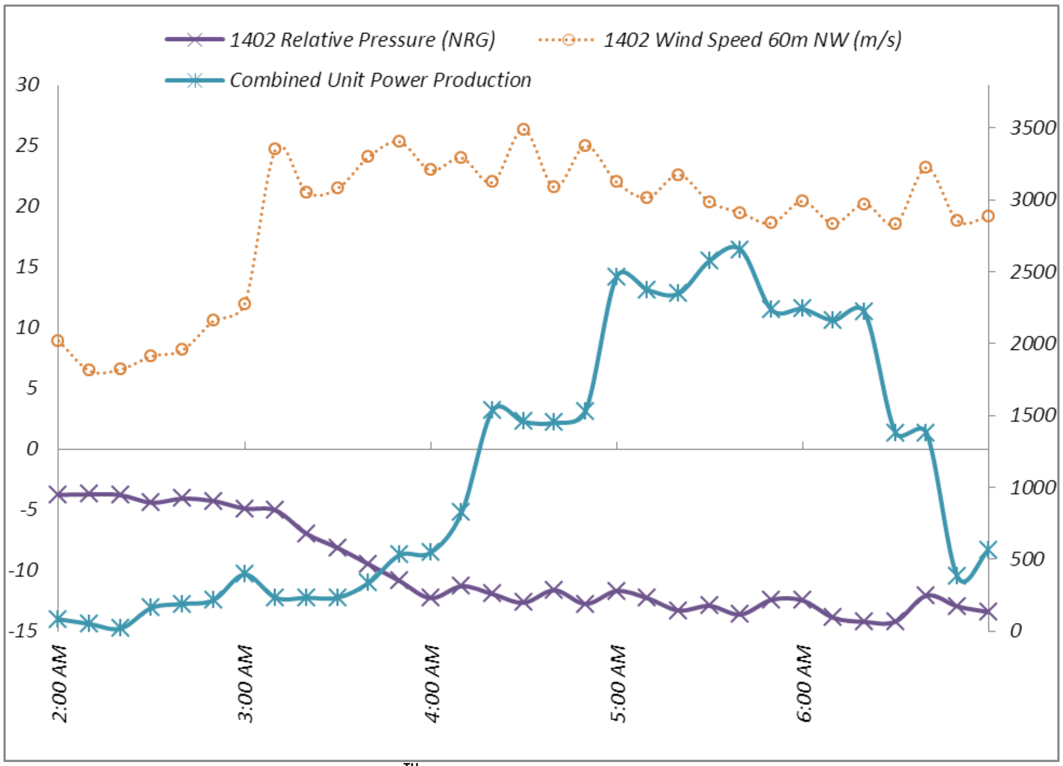


FIGURE 15 DETAILED EXCEL ANALYSIS OF NOVEMBER 16TH, 2010 RAMP EVENT

The relative pressure driving force between the upstream location and the Glacier Wind plant in millibar is illustrated as the purple trace - as the pressure "well" develops at the Glacier Wind plant, the wind speed at the upstream site increases. This indicates that a high pressure system has moved into the Northwest. The peak wind speed (yellow trace) and power production (cyan trace) shows that an early warning of this ramp event was possible. If upstream pressure measurements were available further to the North (i.e. in Canada), it is expected that a larger early warning time frame would be available as evidence of the pressure well would become apparent sooner.

Figure 17 shows the pressure driving force and the wind regime change in the West-to-East cardinal direction during the same time frame. Due to the fact that the measurement stations for this cardinal direction are essentially parallel to the Glacier Wind plant, the ramp detection time frame is significantly shorter compared to the measurements in the North-to-South cardinal direction.

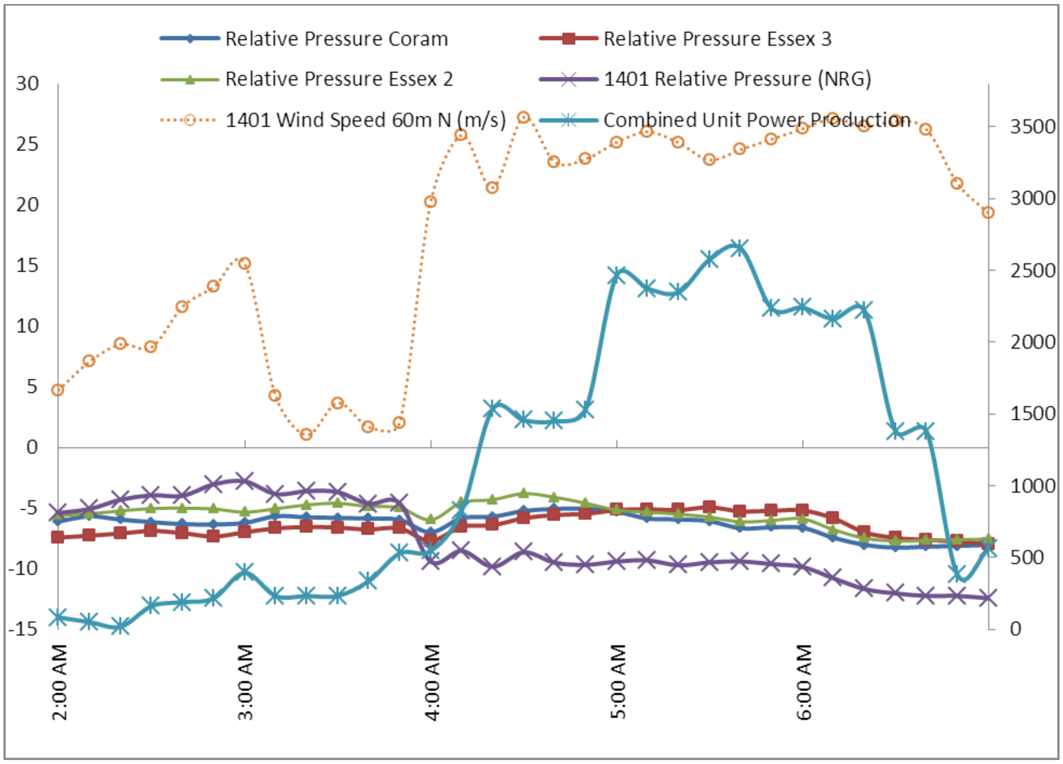


FIGURE 16 EAST GLACIER PRESSURE DRIVING FORCE THROUGH MARIAS PASS INDICATING SUBSEQUENT WIND POWER EVENT AT GLACIER WIND PLANT DURING NOVEMBER 16TH, 2010

The upstream pressure driving forces, as indicated in the Figure 17, illustrate a reversal of airflow through the Marias Pass. The spatial progression corresponds to the trace colors as follows: red, green, and finally dark blue. The flow reversal starts at the inflection point at 5AM.

A comparison of all the upstream measurement stations' wind speeds is illustrated in Figure 18.

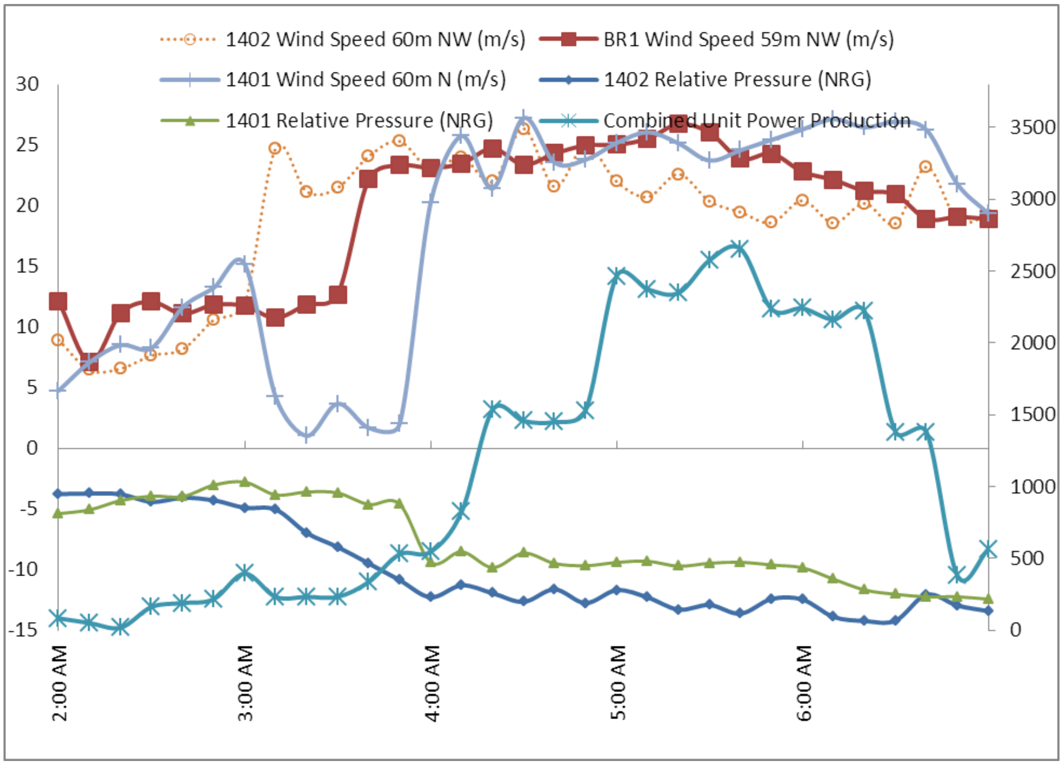


FIGURE 17 ILLUSTRATION OF ALL WIND SPEEDS, PRESSURE DRIVING FORCES, AND POWER PRODUCTION DURING NOVEMBER 16TH, 2010 RAMP EVENT

2.4 Development of Modeling Approach and Preliminary Models with Garrad Hassan

WINData contracted with Garrad Hassan America, Inc. (GH) under a Memorandum of Agreement setting forth the subcontract terms under which WINData and GH agreed to accomplish the goal of providing an enhanced accurate, one to two hour-ahead forecasts of substantial changes in wind speed and direction at the Glacier Wind Project.

During Q211, the WINData PI Server was successfully linked with the GH network for Mesoscale Model Integration of the data to facilitate the development of forecasting operations. Initially, due to computational and network limitations, only small subsets of data could be acquired at a time, necessitating staggered queries to the PI Server.

The numerical weather prediction model used by GH in this project is the Weather Research and Forecasting (WRF) model, developed at the National Center for Atmospheric Research (NCAR). The hypothesis that WRF nudged with observation should perform better than WRF without nudging was validated. GH ran WRF with and without nudging and compared the bias and mean absolute error (MAE), specifically at the first six horizon hours.

In the Figure below[3] it can be seen that, for 20-m winds at tower 1401, the nudged simulation (dashed) results in a reduced MAE for early look-ahead times with only negligible effect on bias, although the time series used is limited (we used only a week of concurrent model and quality observations). These

[3] Bias and Mean Absolute Error (MAE) between observed and modeled 20m wind speed by horizon hour for site 1401. Statistics were aggregated for the time period of July 1 to July 11, 2010. Aggregate statistics for nudged runs are shown in dashed lines while the statistics for non-nudged runs are in solid.

initial results confirm that the model is making use of the observational data to generate a unique solution, but work remains to optimize its use for further reduction of error and event detection.

When the observations are of high quality it is expected that the forecast accuracy can improve. As methodology using the offsite observations evolves and is further tested, validations will increasingly focus on the Glacier Wind plant site.

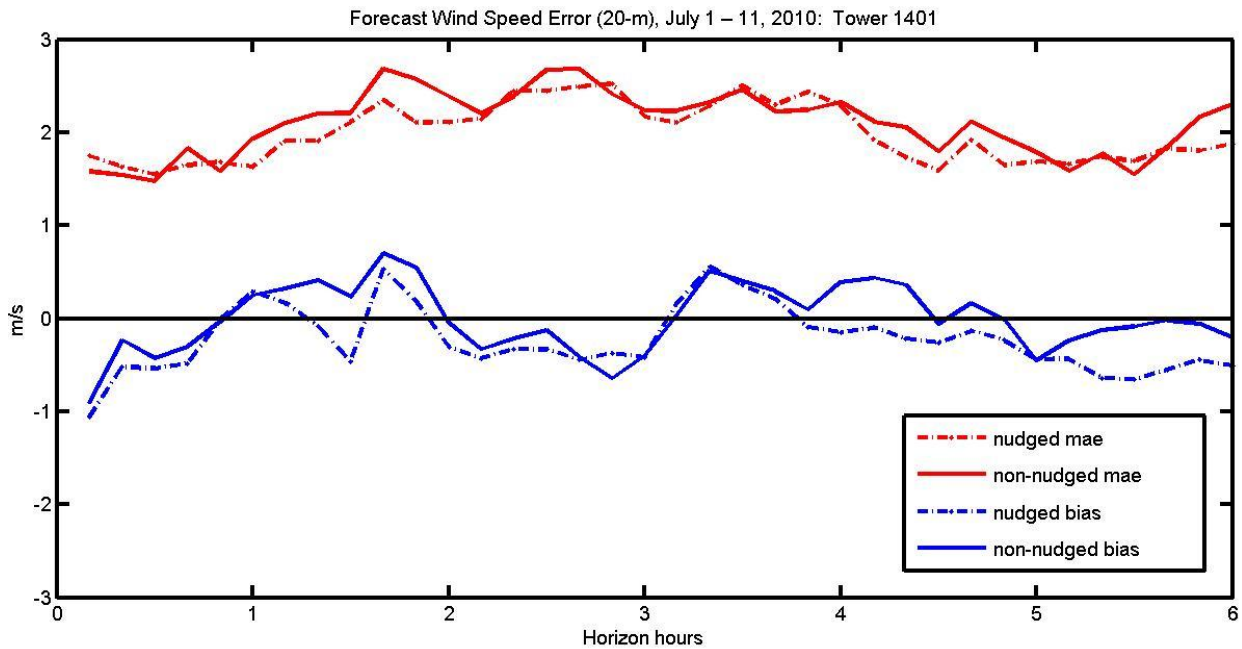


FIGURE 18 BIAS AND MEAN ABSOLUTE ERROR (MAE) BETWEEN OBSERVED AND MODELED 20M WIND SPEED BY HORIZON HOUR FOR SITE 1401

The above point validation confirms that efforts toward integrating the tower and station data with the numerical weather prediction model have been successful.

This also can be visualized in the flow differences between the nudged and un-nudged domains. The following Figure shows a difference map of the wind speed simulations for forecast 10-m wind on 2010-07-12 12:10 (Nudged WRF – non-nudged WRF). This visualization method demonstrates that the offsite data not only influence the collocated forecast but also perturb the flow surrounding the mast. We have highlighted the areas where we see the most change, which also correspond to areas closest to the Marias pass as well as the 1401 tower. If the flow though the pass can be better simulated with the aid of the 1401 tower, then there is benefit to the offsite towers at the downwind Glacier wind farm.

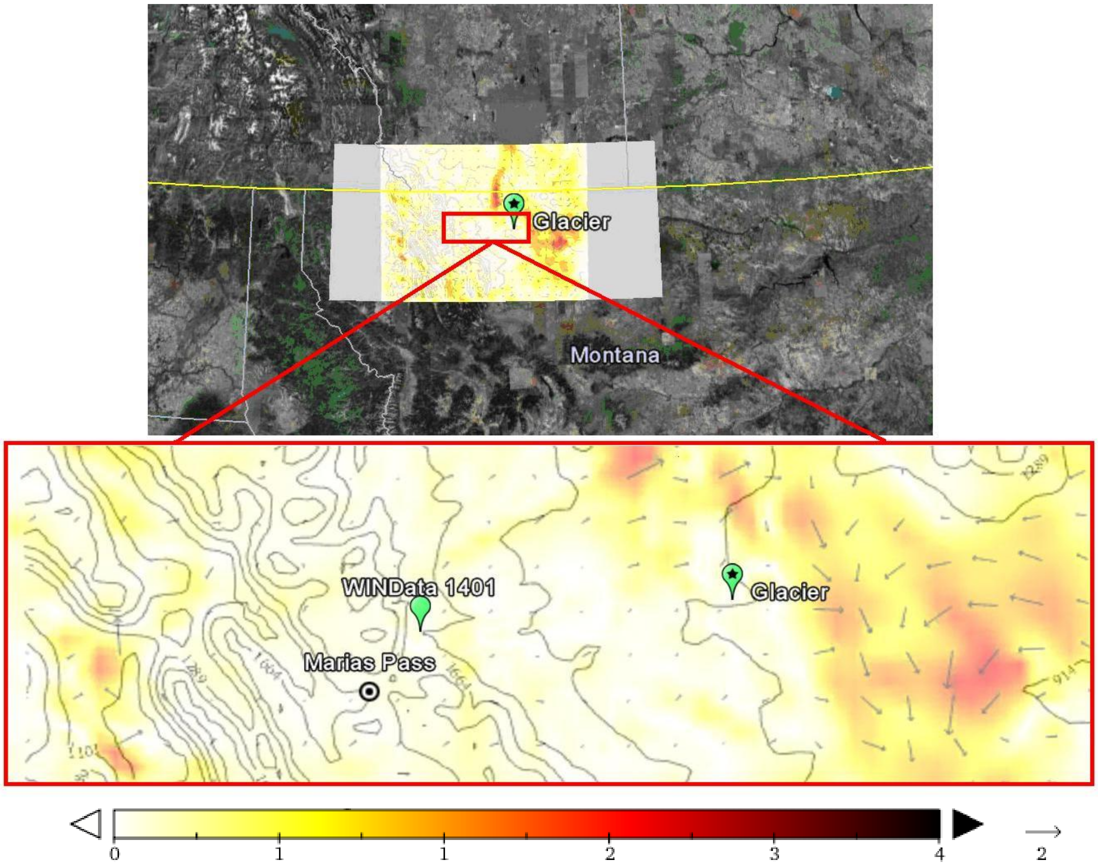


FIGURE 19 DIFFERENCE IN WIND SPEED AND WIND DIRECTION (INDICATED BY ARROWS) BETWEEN A NUDGED AND NON-NUDGED FORECAST FOR A SNAPSHOT OF 12:10 GMT FOR JULY 12, 2010.

This figure has been imported into Google Earth to show the location of the WINData tower, the NaturEner Glacier wind farm and their relation to the Marias Pass.

WINData/GH performed cluster and factor analysis using the offsite data. In this way, ensembles of observations were collected in categories that can serve as indicators to ramp events. This technique operates independently of data assimilation techniques by using leading indicators from the offsite measurements to alert and/or adjust the forecast for events.

The benefits of each technique will be measured against their computational costs. GH experimented with so-called Ward clustering and other hierarchical algorithms to intelligently organize the data into subgroups that share commonalities. The following figures are examples of such an exercise in data grouping.

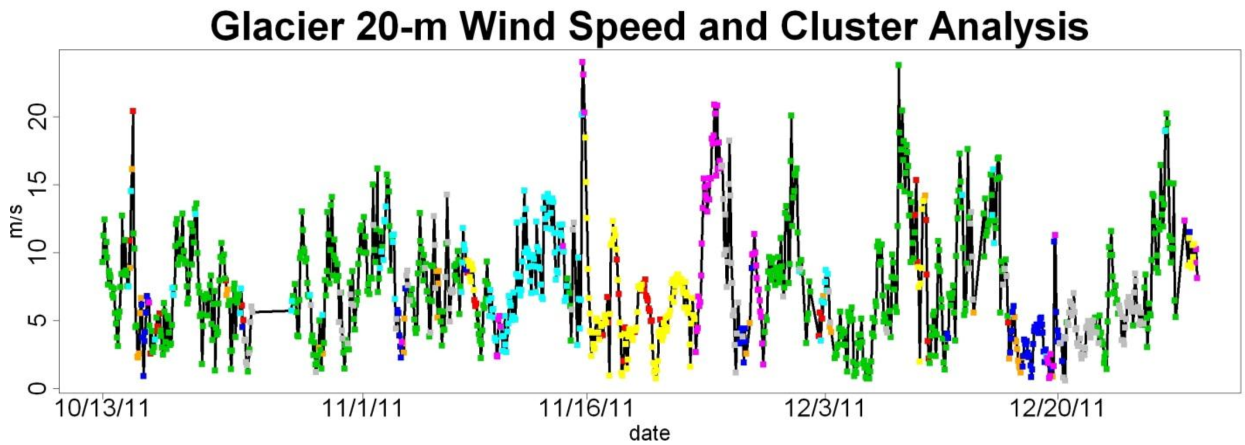


FIGURE 20 TIME SERIES OF WIND SPEED AT GLACIER WIND FARM (IN SOLID BLACK LINE), WITH COLORED POINTS OVERPLOTTED TO REPRESENT ONE OF 8 K-MEANS CLUSTERING CATEGORIES.

In the Figure above, each cluster has a characteristic center to its distribution whose mean variables are displayed by color in the Table below. In the Table, each row is a separate cluster, as indicated by the colors that correspond to the coded markers in the above plot. Each cluster has a unique mean value for each variable.

TABLE 1 THE MEANS OF MEASUREMENTS OF EACH CENTROID IN THE 8-MEMBER K-MEANS CLUSTERING.

	Glacier wind speed (m/s)	1401 pressure (mbar)	1401 wind speed (m/s)	1401 direction (deg)	1402 pressure (mbar)	1402 wind speed (m/s)	1402 direction (deg)
1	5.21	1025.8	4.99	253.9	1022.3	3.64	155.8
2	6.59	1024.2	4.14	218.4	1021.4	3.50	12.4
3	7.81	1019.9	9.64	228.1	1016.5	9.77	250.4
4	4.16	1023.4	2.11	109.0	1020.3	3.95	168.3
5	8.77	1024.4	8.38	235.3	1021.3	4.97	324.9
6	10.27	1025.5	3.01	21.5	1016.6	9.49	257.7
7	6.25	1027.5	3.27	44.3	1023.1	4.62	1.8
8	6.27	1016.7	7.22	219.6	1013.9	6.40	200.7

GH used the k-means algorithm to cluster into 8 unique groups. When plotted in time, we see several ramps in the time Glacier wind speed time series, many with a different colored cluster responsible for it. Cluster 6 (pink) has the highest average wind speed at Glacier. Interestingly, this cluster provides the strongest pressure gradient between 1401 and 1402: 1026 mbar – 1017 mbar = 9 mbar difference, with strong northerly flow at 1401.

The model can be trained to search for such a pattern within the forecast and/or the observational data. If this pattern is detected at East Glacier (1401) before the next forecast, we would adapt our forecast to expect a ramp ahead of time. Clusters 4 and 8 also appear to lead to ramps, and if their pressures and wind characteristics at the met masts were know prior to the forecast, we could adjust them accordingly. The choice of cluster number is arbitrary at the moment and requires formalization to make rigorous quality control logic in real time.

GH ran WRF with and without nudging and compared the bias and mean absolute error (MAE), specifically at the first six horizon hours. In Q311, GH tested this hypothesis at Glacier wind farm for hub-height power.

In the Figure below[4] it can be seen that for the site hub-height power, the nudged simulation (dashed) results in a reduced MAE for early look-ahead times with only negligible effect on bias, although the time series used is limited (GH used approximately 7 weeks of concurrent model and quality observations). These results confirmed that the model was making use of the observational data to generate a unique solution.

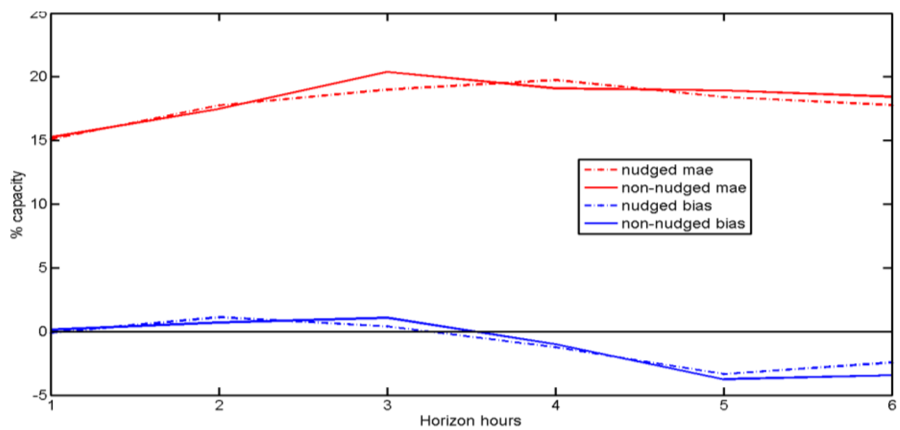


FIGURE 21 BIAS AND MEAN ABSOLUTE ERROR (MAE) BETWEEN OBSERVED AND MODELED HUB-HEIGHT POWER WIND SPEED BY HORIZON HOUR FOR THE GLACIER I WIND FARM.

Beyond error reduction, GH was also concerned with event detection and in Q311 focused their performance validation on metrics that track ramps. To do so, a ramp definition was established as a +/- 15% change in production relative to the farm capacity over the course of three hours. This is arbitrary but necessary to track ramps and their statistics, and also in accordance with industry definitions (e.g. NaturEner). Then binary flags are applied to the time series of both observations and modeled power output, to create a dichotomous contingency table. The four quadrants of this table are 'correct hits', 'correct misses', 'false negatives' and 'false positives'. These categories are then rearranged to give metrics such as Probability of Detection (POD), False Alarm Ratio (FAR) and Critical Success Index (CSI).

POD is mathematically defined as the number of correct hits (H) over the number of correct hits plus false negatives (FN). POD = H/(H + FN) It gives the fraction of occasions that a predicted ramp occurred relative to the amount of times any ramp was predicted. A POD value of 1 is ideal; a value of 0 is poor.

FAR is likewise defined as the number of false positives (FP) relative to the total amount of non-event correct misses (CM). FAR = FP/(FP + CM) It gives the frequency of forecasts that are wrong in predicting ramps when they actually do not occur. An FAR value of 0 is ideal; a value of 1 is poor.

[4] Bias and Mean Absolute Error (MAE) between observed and modeled 20m wind speed by horizon hour for site 1401. Statistics were aggregated for the time period of July 1 to July 11, 2010. Aggregate statistics for nudged runs are shown in dashed lines while the statistics for non-nudged runs are in solid.

CSI is defined as the number of hits over all events (N), such that it scores only correctly predicted ramps. CSI = H/N is the proportion of correct critical forecasts to all forecasts. The higher the CSI score, the better the forecast skill. The initial goal was set for scores in the 0.3 to 0.4 range.

GH used POD, FAR and CSI to assess how well the nudged NWP performs at ramp prediction at horizons outward. When the observations are of high quality it is expected that the forecast accuracy can improve. As methodology using the offsite observations evolves and is further tested, validations will increasingly focus on the Glacier Wind plant site.

To improve the forecast's performance in ramp detection metrics, GH proceeded with cluster and factor analysis using the offsite data. In this way, ensembles of observations were collected in categories that served as indicators to ramp events. This technique operated independently of numerical weather prediction data assimilation techniques by using leading indicators from the offsite measurements to alert and/or adjust the forecast for events.

Clustering requires a training period that aggregates the historic data into representative cluster and builds histograms of the types and magnitudes or ramps that occur between given cluster transitions. A sample training set and the histograms of ramps plotted on the power production times series is presented in the following figure.

As a set of observations arrives, is assigned to the cluster whose mean it most closely resembles. The GH algorithm assigns ramp forecasts by adding a range of possible ramp magnitude to the most recently reported power. The range of this magnitude is given by the ramp magnitude historically associated with the newly assigned cluster.   The last Figure portrays the subsequent forecast in real-time of the training data set parameters from the first Figure.

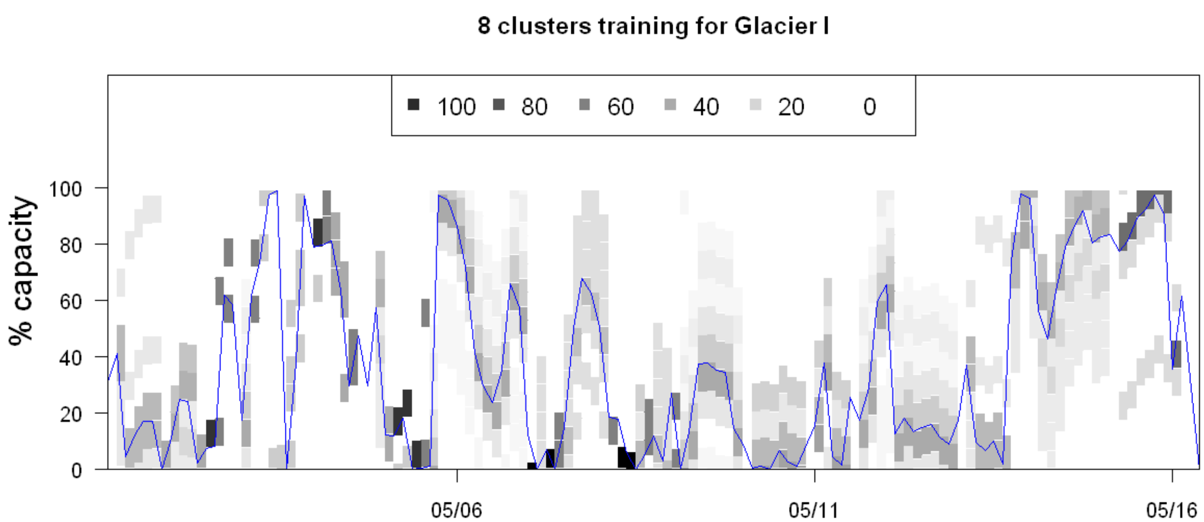


FIGURE 22 TRAINING PERIOD OF CLUSTER ALGORITHM.

Blue time series indicated plant power and grey shading corresponds to the probability in percent that the range of ramps occurred immediately afterwards. The legend indicates the magnitude of the shaded ramps.

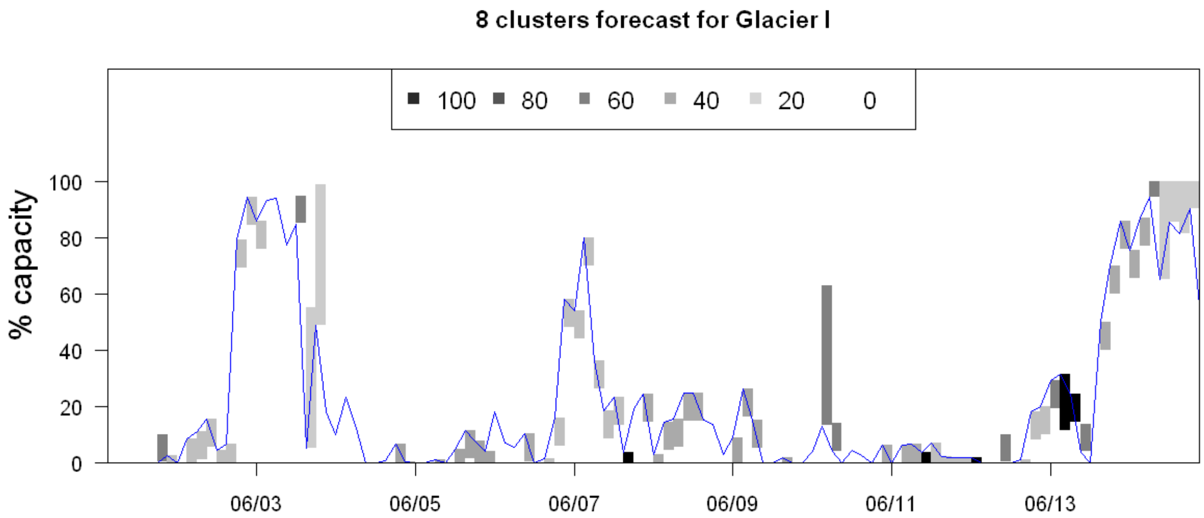


FIGURE 23 FORECASTS OPERATING IN REAL TIME ON THE CLUSTER ALGORITHM APPLIED FOR THE GLACIER WIND FARM

In the above Figure again, blue time series indicates power production and shaded boxes indicate ramps shaded by the likelihood given in the legend. Also worth considering is how many clusters are needed to characterize the regimes of the forecast of interest. If for instance only four types of weather states occur in the training, then only four clusters would ideally be needed to propagate the forecasts in real time. However, GH had no a priori knowledge of either how long or how many clusters stay 'fresh', and so performed a suite of experimental forecasts.

GH used the same training set length and period as the control, but varied the number of clusters and length of time the original solution was persisted as a parameter to the model. The intervals varied between 1 and 20 clusters and 1 to 8 weeks post-training window. In the graphic below GH combines the results in image plots to assess how the POD, FAR and CSI performed across "number of training cluster" experiments as seen below in the three Figures below, respectively.

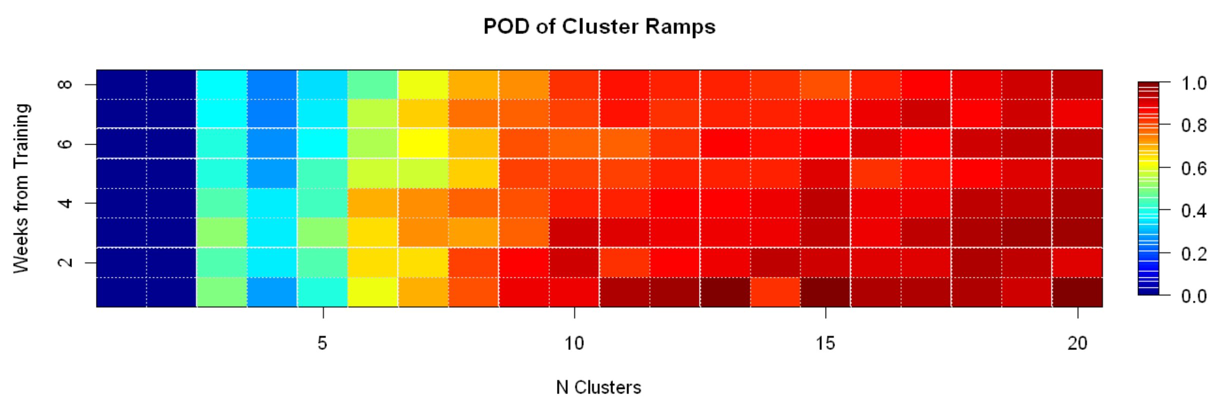


FIGURE 24 PROBABILITY OF DETECTION (FRACTION) AS A FUNCTION OF NUMBER OF TRAINING CLUSTERS AND NUMBER OF WEEKS SINCE TRAINING

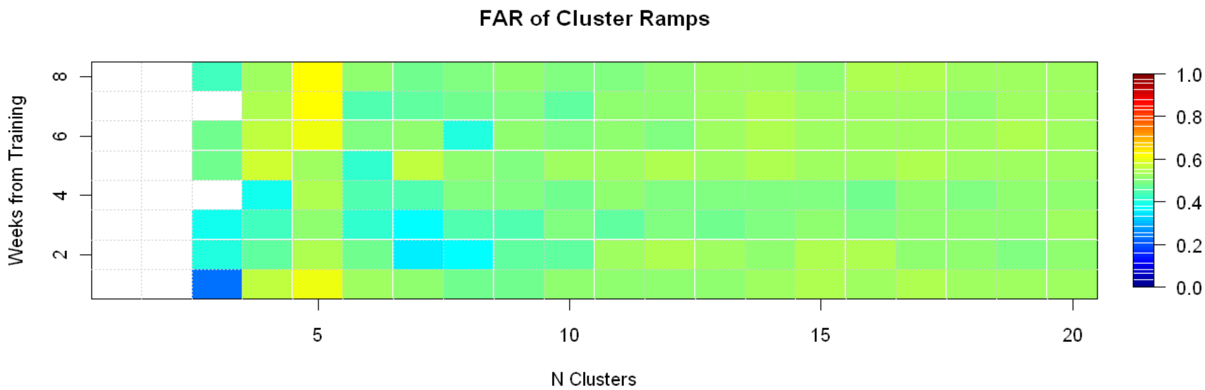


FIGURE 25 FALSE ALARM RATIO (FRACTION) AS A FUNCTION OF NUMBER OF TRAINING CLUSTERS AND NUMBER OF WEEKS SINCE TRAINING

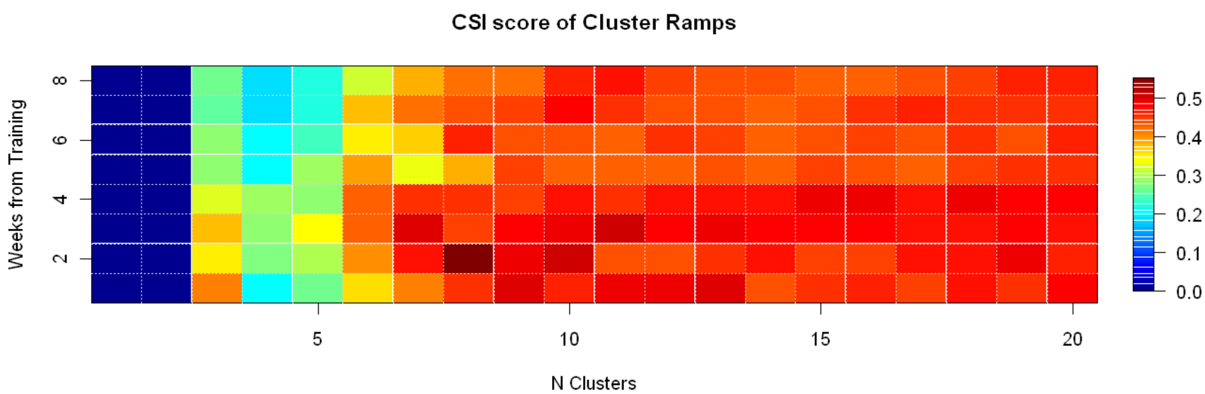


Figure 26 critical success index (csi) as a function of number of training clusters and number of weeks since training

In each figure, the x axis denotes the number of clusters used in the experiment, and the y-axis denotes the number of weeks elapsed since the end of the cluster training period (i.e., representing the "freshness" of the solution. From this experiment, it can be seen that maximizing CSI while minimizing FAR suggests that the ideal setup for best ramp tracking would be to require 4 to 8 clusters for training and to re-train the cluster algorithm every 2 to 4 weeks with additional data.

What remained as the ultimate goal was to take these two separate techniques and merge them into one single ramp forecast. GH formulated plans for augmenting NWP with the cluster-defined ramps and set-up a more robust method of providing this type of forecast in real time. GH commenced with the integration of the regional offsite data into the forecast model and compared standard and enhanced model outputs side by side.

Routine archive data review was performed on a daily and weekly basis in order to ensure the validity of the data set being recorded. Periodic investigations into data flow and communications outages were performed during the quarter. During the quarter, intermittent failures at 1401 led to replacement of the AppSrv CE through component procurement and provisioning of a mini PC running PI, as alternate collection means.

A replacement of the existing logger infrastructure at 1401 was configured and deployed for a short time at the site. It indicated a similar, unpredictable, intermittent failure pattern to that of 1402. This indicated a potential hardware defect from the manufacturer. Two alternate paths for collecting high resolution data were already in place. A second logger infrastructure was configured and deployed at 1401 based on a low-powered computer. Once all the data sources were in place, then the consumers were updated to use this new data infrastructure.

WINData prepared new data investigation queries for mesoscale modeling activities during this period as well. By using the PI System's OLEDB gateway (a SQL-based database connectivity standard) and creating a set of "linked tables" with "stored procedures" additional tables are now available to the mesoscale model on-demand, at an appropriate resolution. These data are structured in equally spaced intervals in SQL Server tables and can be processed using typical SQL language commands. Further, this setup allowed the data to be accessed securely, on a self-service approach without the use of text files and FTP sites – a significant objective of this grant.

After the success of linking the WINData PI Server with the GH network, rather than amassing a large historical data set, routines were written to query for only the most recent observations to couple with only the most recent NWP. All data required for the forecasting model including pressure, temperature, wind speed, and wind direction, were obtained from the PI Server in real-time and ingested into the forecast system.

New plant data connections to meteorological data were established in Q2 2011 from four turbine nacelle anemometer/wind vane sensors from distributed plant locations were tested and also then shared via similar SQL Server linked table methods as meteorological data from sites 1401 and 1402. These data also include power production data from the two production plants and the number of pieces of equipment in service.

2.5 Development of Enhanced Forecast Models Employing Real-Time Data

Trials were completed with the integration of the regional offsite data into the GH forecast model and preliminary results were assessed to compare standard NWP and enhanced model outputs side by side. Cluster forecast training was conducted on over a year of historical data to obtain a theoretical yield of the improvements that could be expected for a configuration in forecast mode. The improved metrics were compared to the baseline values that a stand-alone persistence model would achieve. The value of the offsite observations were thus measured in terms of percent improvement over persistence.

The forecast performance was evaluated through a comparison of the traditional metrics of bias and mean absolute error (MAE), but with a focus more on horizon specific values for the Critical Success Index (CSI), Probability of Detection (POD), overall event accuracy (ACC) and the False Alarm Rate (FAR)[5]. For bias, MAE, and FAR, a reduction at all horizons was sought, and for CSI, POD and ACC an increase relative to persistence at all horizons was sought.

GH conducted an internal statistical investigation of the forecast accuracy, in which it was sought to compare ongoing results against a null hypothesis of simple persistence model (simply applying the last measurement as the next forecast value). The results demonstrated improvement in all metrics, but not

[5] Metric parameters are used by NaturEner in evaluation of forecast performance and were contributed for evaluation of this work by Devon Yates at NaturEner.

at all horizons. The following figures summarize the results calculated over the forecast data delivered to date:

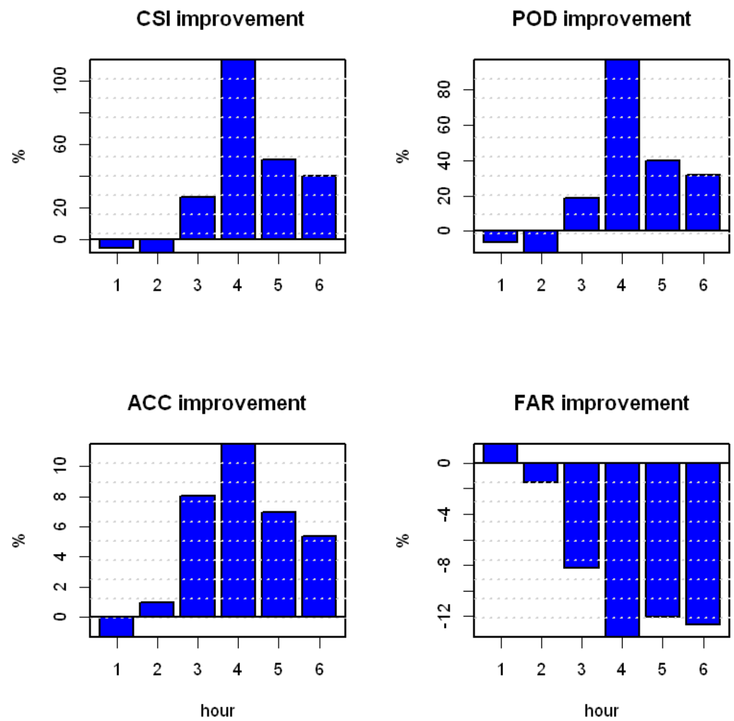


FIGURE 27 THE CHANGE IN THE GIVEN METRIC OF GH MODEL RELATIVE TO PERSISTENCE.

In the figure above, positive values of CSI imply that percentage increase over the same horizon's CSI as calculated for persistence. CSI improves rather dramatically for horizons 3 thru 6 as does probability of detection (POD) and accuracy (ACC). The false alarm ratio (FAR) was reduced, as indicated by the negative percentages, which is also what a superior forecast is supposed to produce in terms of deviation from a persistence model.

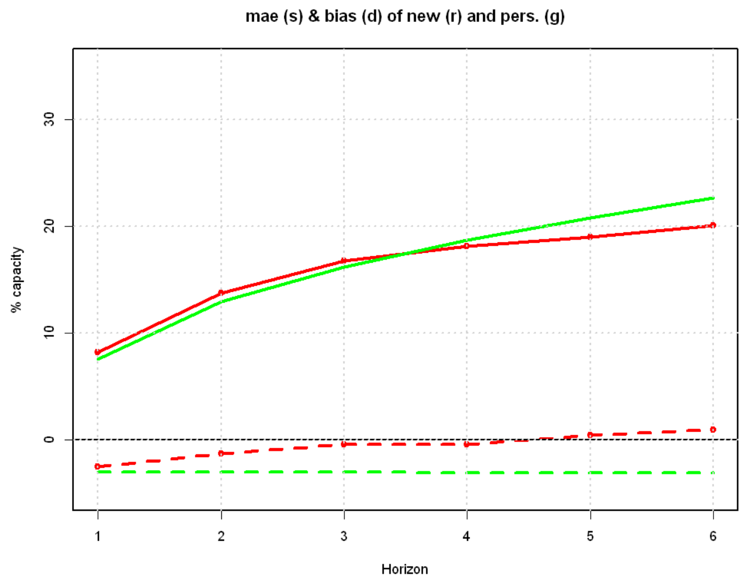


FIGURE 28 – GREEN SOLID LINE INDICATES MAE FOR PERSISTENCE, AND RED SOLID INDICATES MAE FOR OUR MODEL. APPLYING THE SAME COLORS, DASHED LINES INDICATE MEAN BIAS. BOTH MAE AND BIAS ARE CALCULATED RELATIVE TO CAPACITY OF GLACIER I WIND FARM.

The model was allowed to operate into additional seasons and weather regimes to test its applicability and effectiveness. The major finding of the operational results is that the offsite measurements can and do add value to short term ramp forecasts. For the length of the trial period in the internal analysis, the bias and MAE were better than or at least mimicked those scores of persistence at all horizons. Beyond horizon 4, the enhanced model outperformed simple persistence in MAE. The improvement in ramp metrics is not seen over all horizons, however, but we do see the most improvement beginning at hour 3 and onward to hour 6. It seems this particular configuration is limited at predicting ramps at 1 to 2 hours ahead better than persistence.

2.6 NaturEner Analysis and GH Commentary on trial model

After the initial trial period, the analysts of NaturEner provided valuable feedback in the form of a rigorous retrospective statistical analysis of the forecasts that were provided. The results of that analysis are included as an appendix to this final report. The key points will be presented and addressed herein.

Analysts from NaturEner were interested in a 90-minute-ahead forecast product, and as such computed statistics for this horizon value. The following table from the attached report compares the NaturEner persistence model with the WINData/GH forecasts at this horizon.

TABLE 2 SUMMARY OF RESULTS (FROM ATTACHED NATURENER APPENDIX)

	Persistence	WINData
Critical Success Index	20.1%	26.4%
False Alarm Ratio	26.2%	67.1%
Probability of Detection	20.5%	46.3%
Frequency Bias	27.7%	130.0%
MAE	11.2%	16.4%
Bias	-0.1%	-7.2%
HIT	45	94
MISS	175	109
CORRECT NEGATIVE	590	581
FALSE POSITIVE	16	192

This table illustrates several key elements of the model, both positive and negative. First, the CSI score was improved by an increment of 6.3% and the probability of detection improved by an increment of 25.8%. These two metrics are quite encouraging because they track ramp capturing ability, which is precisely what the pattern matching algorithm is supposed to improve. These are sizeable gains that would not be possible without the use of WINDataNOW! measurements.

The model more than doubled the amount of ramp 'hits' (94 hits compared to 45 persistence events, when the forecast captured an actual ramp event) and reduced the 'misses' (implying the model agreed more often than persistence did for non-ramp events) over the same time window. The model achieved comparable values for the amount of correct negatives as well.

This table also highlights where the model can be improved. For instance, the amount of 'false positives' is much higher than persistence (192 compared to 16), which is likely the cause of the higher MAE (16.4% compared to 11.2%) and a more negative bias. Additionally, the metric that tracks false positives (False Alarm Ratio) was too high (67.1% compared to 20.5% for persistence). This is a value that is considered as perfect when it is 0%.

The scores in which the enhanced forecast performed poorly reflect the configurations which were trained and tuned for more frequent 3-hour ramp events. This statistical analysis by NaturEner did not distinguish and separately assess the entire trial period into three distinct events, and the bulk statistics are likely skewed by Configuration I and II. Nevertheless, despite the propensity for predicting too many ramps, these results support our hypothesis that the performance statistics of a model using the offsite measurements would possess better skill at ramp prediction than would an onsite persistence model.

The model itself needs refinement at reducing false alarms that were likely the cause of insufficient coverage in sectors prone to calm air. Suggestions are made in later sections how to improve this model deficiency.

Another powerful graphic from the NaturEner analysis will benefit the forecasters in future model deployments. It portrays conditions when the model did well and likewise when it did poorly. It is also included in the appendix and copied here for the discussion.

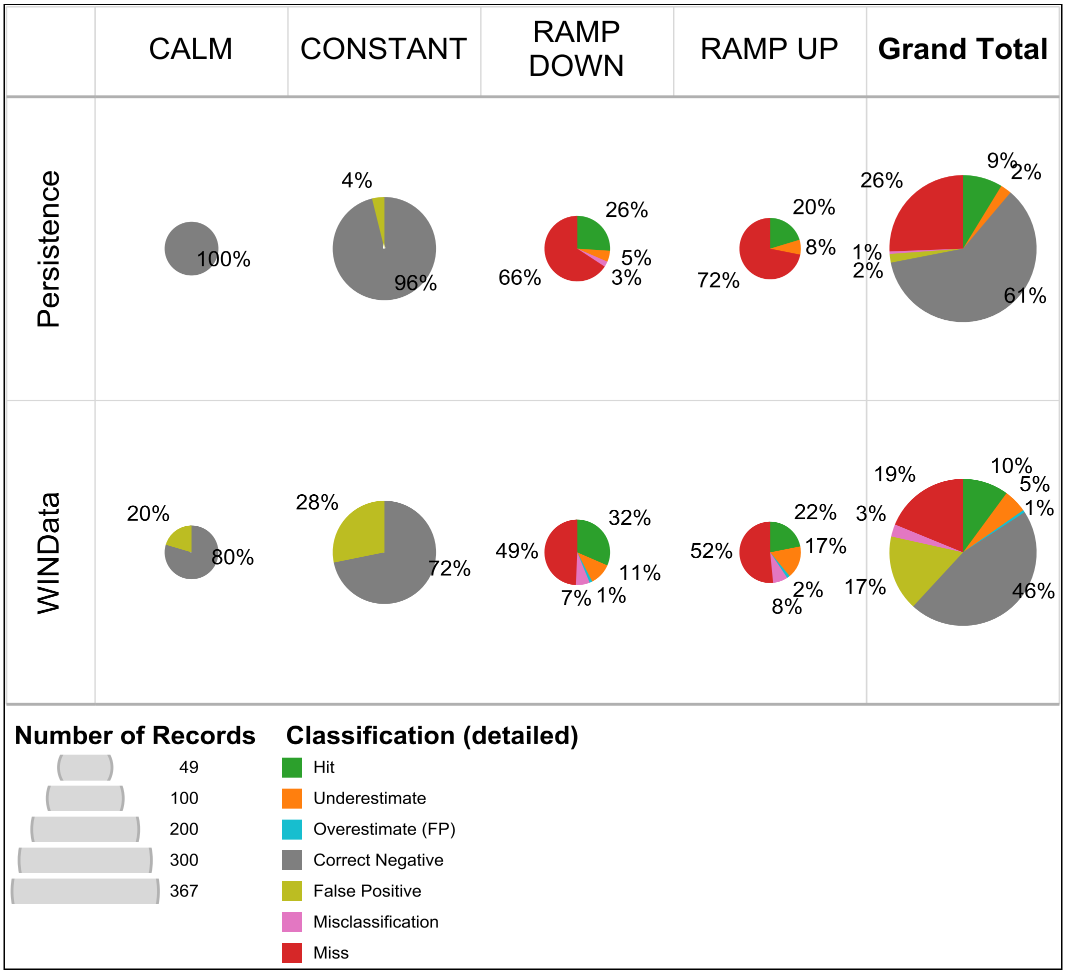


FIGURE 5: (COPY OF FIGURE 6 FROM APPENDIX 1) COMPARISON OF ACTUAL CATEGORY AGAINST FORECAST CATEGORY

This set of pie charts shows how the forecast system generates more false positive in 'calm' and 'constant' events than does persistence, demonstrated by the yellow wedges in columns one and two.

The majority of the performance issues with regards to false alarms can be explained by forecasts during these non-varying wind regimes. It is not surprising that persistence would perform quite well when the wind stayed constant for hours at a time or when winds were calm. The forecast system was trained to be especially sensitive to ramps; and this figure highlights that it may have been hyperactive. As expected, the forecast system demonstrated fewer missed ramps and more captured ramps than persistence.

It is evident that the number of hits for up and down ramps is increased with the model compared to persistence (green wedges in columns three and four), but overall (column 5) these relative improvements are overshadowed by the large number of false positives from columns one and two.

Clearly, the new forecast system performs well for ramp periods, highlighting the value of the offsite measurements, but the predictive components need to improve for calm periods or non-varying periods to be a reliable tool for operators. The suggestions that follow will address this shortcoming.

2.7 Finalized GH Enhanced Forecast Model

The finalized model consisted of three approaches that utilize offsite and onsite: persistence, data assimilation, and pattern matching. GH intelligently combined and blended the three techniques specific to each horizon of the 6-hour forecasts.

GH conducted comprehensive modeling system calibrations twice throughout the test period, which consisted of modifying the relative weights of the forecast sources to the final prediction, as well as adjusting the characteristics of the physical ramp pre-cursors on which the pattern recognition model relies. Accuracy can be assessed in three phases of the trial period, each preceded by a modeling system calibration. The following Figure shows the entire time series of the trial period, with boxes indicating the time periods of interest.

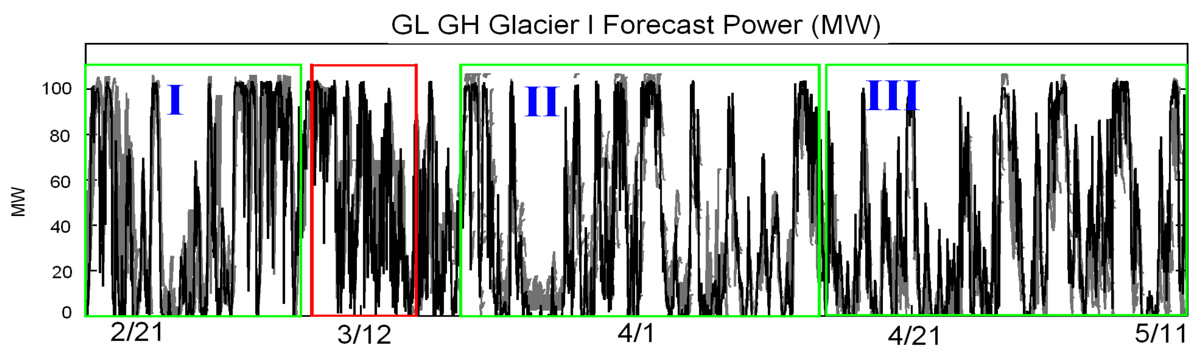


FIGURE 29 TIME SERIES OF FORECASTS (GREY) AND OBSERVATIONS OF GLACIER I GENERATION (BLACK). EACH GREY LINE INDICATES A 6 HOUR FORECAST. THE COLORED BOXES SEPARATE THE STUDY PERIOD INTO THE 3 TEST CONFIGURATIONS AND ABOUT 3 DAYS TO DISREGARD FOR A DST GLITCH.

2.7.1 Configuration I

The first trial period relied heavily on persistence as well as unsupervised training upon distinct meteorological patterns for ramp events. The offline training was performed on actual data with a variety of statistical and machine learning techniques. The designation of the training as 'unsupervised' implies that the algorithms were allowed to run freely and automatically without any *a priori* inputs. In later configurations, GH performed 'supervised' training in which analysts played more active roles in the initialization of the machine learning by supplying statistical criteria for the training to follow.

The particular training for Configuration I resulted in ramp patterns that favored matching on 6 hour ramps. This is seen most when we compare 3-hour and 6-hour Critical Success Index (CSI), a metric which quantifies the skill of forecast at a particular event. The event in question for this test is whether or not a ramp occurred over a given time period.

We define a ramp as a change in observed generation that is greater than 15% of capacity. We tracked both up and down ramps over the two durations. Configuration I demonstrated better skill for 6-hour duration ramps (6-hour CSI =0.39), than it did for 3-hour ramps (CSI = 0.14). This is consistent with the settings of Configuration I, which was trained without any *a priori* criteria to favor 3-hour ramps. Training based purely on automated machine learning favored patterns of 6-hour ramps.

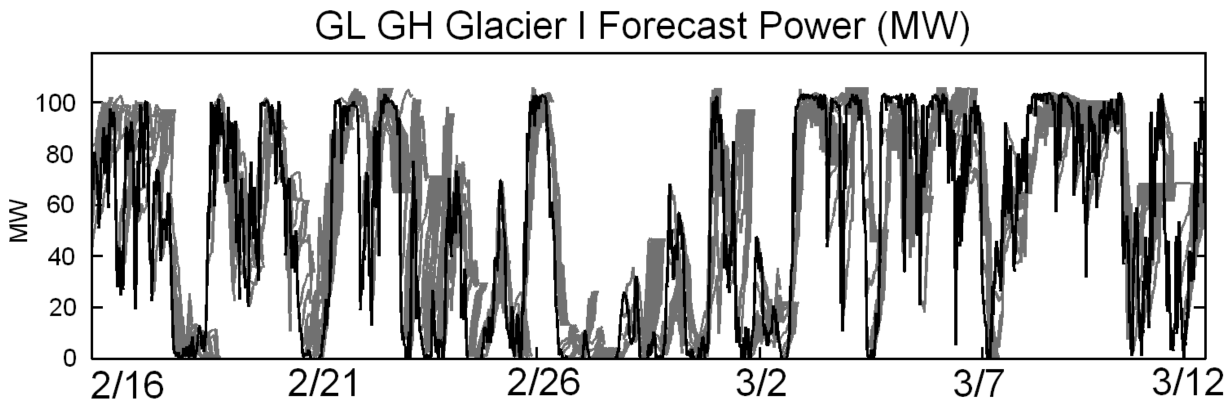


FIGURE 30 SUBSET OF TIME SERIES FOR CONFIGURATION I FROM FIGURE 31.

2.7.2 Configuration II

The second test period follows a forecast system calibration on March 14, 2012, in which supervised training was performed to provide patterns for real-time matching. In the Figure below, each individual forecast is plotted in grey out to 6 hours and the observations are shown in black. This type of visualization shows the evolution of forecasts at all horizons relative to the actual generation values.

Training of the pattern recognition for Configuration II was supervised, in that analysts seeded the model with specific criteria for 3-hour ramps. Examples of the criteria include changes in surface pressure among the stations in the Marias Pass, and changes in tower wind speed and concomitant wind direction that triggered specifically 3-hour ramps. This supervised pattern recognition resulted in improved skill at the 3-hour horizon (CSI = 0.17, compared to 0.14 from Configuration I). However, at the same time, Configuration II performed less favorably at the 6-hour horizon (CSI = 0.25, compared to 0.39 from Configuration I).

Additionally, there were a relatively larger number of false alarms at the 6-hour horizon seen in Configuration II than with Configuration I. This was due to the shift towards a pattern matching scheme more prone to predicting 3-hour ramps. Such tendency means 3-hour ramps often carried on their upward or downward trend out to 6 hours instead of leveling out. While the 3-hour ramps were captured better, the inadequate detail of the forecasts after 3-hours led to many false alarms.

Configuration II was also prone to predicting 'up' ramps, rather than 'down' ramps. While the training was focused on the meteorological triggers for 3-hour ramps in general, it was specifically tuned to recognize the surrounding meteorological that resulted in 3-hour 'up' ramps. In other words, the training was not tuned to recognize as much of the patterns in the meteorology for 'down' ramps. This configuration was more robust at capturing and translating downstream the impulses that led resulted in wind and power increases.

As later sections will explain, the events that led to decreases in wind occurred in sectors in which there were no observations. Therefore the training did a poor job at discriminating the type of conditions that led to sudden wind decreases, and the real-time model did a poor job at predicting power ramps for such conditions. Significant effort was focused on improvement of down ramp prediction in Configuration III.

Overall, due to the large number of false alarms, reduced fidelity with down ramps, and lower capture rate of 6-hour ramps, Configuration II performed the most poorly of the three distinct configurations.

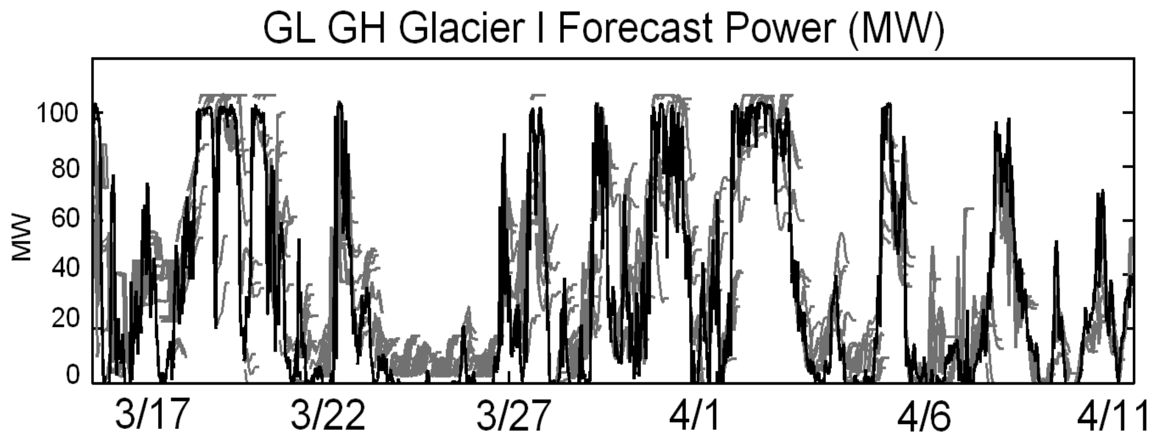


FIGURE 31 SUBSET OF TIME SERIES FOR CONFIGURATION II FROM FIGURE 1.

2.7.3 Configuration III

The final configuration GH tested is the most evolved. Not only does it incorporate all previous analysts' learning but also its pattern recognition is trained (supervised) on the largest time history which was obtained over the course of the trial period to date. The use of ramp patterns that were focused at 3-hour ramps of both directions was maintained.

In response to degraded forecasts at the longer horizons during Configuration II, there was a renewed focus on the 6-hour time frame. This was accomplished by the analysts' more thorough *a priori* input for the training, in which an equal amount of criteria were used to make a more balanced pattern matching on both 3- and 6-hour ramps. CSI scores improved for each duration window from the previous configurations (3-hour CSI = 0.27; 6-hour CSI = 0.31).

GH concluded that this was the best performing configuration of the experiment period, with the fewest false alarms and most captured ramps. The Figure below qualitatively shows fewer false alarms occurred than for the period in which Configuration II was active. Compared to the Figure for Configuration II, in which many more false up ramps were observed, the time series of Configuration III shows a better balance between up ramps and down ramps.

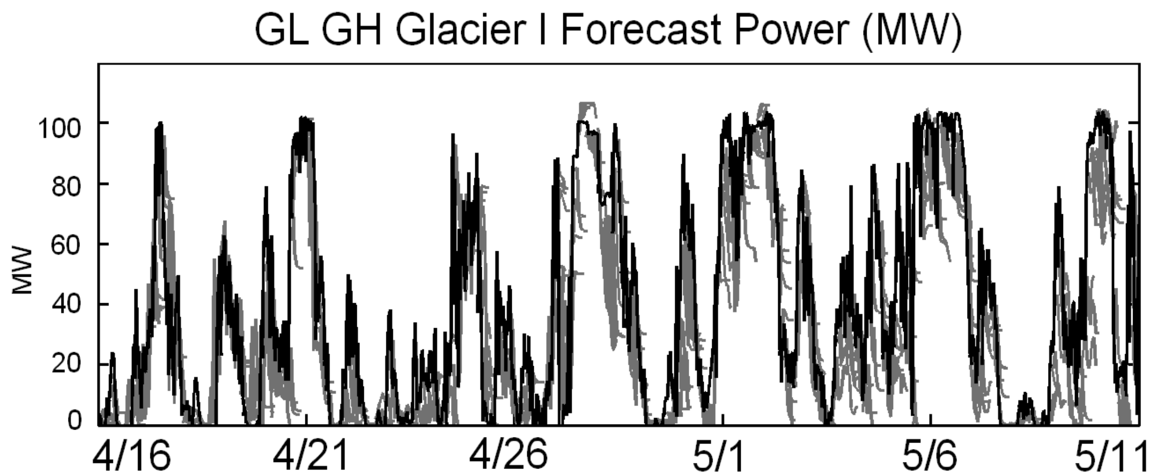


FIGURE 32 SUBSET OF TIME SERIES FOR CONFIGURATION III FROM FIGURE 1.

2.8 Problems and changes to Approach

In early 2010, Site 1401's data logger suffered several data communications losses due to Verizon's communication tower issues. These issues were resolved by the service provider. Power system issues at 1401 also impaired data collection for some period of time. It is thought that a manufacturing defect in the wind turbine used for power generation could not withstand temperatures below -20 C. The wind turbine's blades completely snapped off during a powerful wind storm that propagated through the Marias Pass.

Data from the 1401 and 1402 met towers have been high quality when the temperatures have remained above -20 C. At temperatures below -20 C, some of the wind vanes have a tendency to freeze in place. Other instruments remain unaffected.

Significant study and development was performed on the power system for the 1402 site installation. An entirely new charging and power generation system was created to ensure more reliable data logger and communications operations. Site 1401 was partially retrofitted with this new power system design.

In mid-2010, a 6 month freeze of funding resulting from the DOE audit Work was halted during this period. Accounting system changes were implemented to satisfy DOE. Technical work was halted while the funding was frozen, although troubleshooting and configuration support at site 1402 was performed remotely to ensure proper operation and data integrity since the location becomes permanently snowbound in winter

During Q1and Q2 of 2011 NEPA review of the met tower installations was conducted and finalized.

During Q4 2011, Verizon cut off communications to 1402 twice due to inaccurate "fraud alerts" on data transfers from the tower's modem. These significant delays in data transmissions caused gaps in the data which were partially recovered, but were not due to any mechanical failure on WINData's part. It was also discovered during these outages that Verizon was also allowing WINData's data plan to "roam" onto Canadian (international) data towers at a significantly higher data transfer price. WINData reconfigured its hardware to specifically disallow this behavior. During the transition to the new data delivery pathway, it was observed that a 50m anemometer at site 1401 had started to behave erratically. This is most likely due to the freezing temperatures or a wiring fault. This behavior was reported to all parties but will not impact the project as there is a redundant instrument already in place.

The project term was extended through Q312 to accommodate the final phases of the work, which included the forecasting tasks and evaluation of results.

3 Evaluation of Enhanced Forecast Using Offsite Data

3.1 Garrad Hassan Evaluation

WINData and GH were encouraged by the later horizon improvement and hypothesize as follows, after the fact, as to why a different configuration might improve at all horizons in the future. We believe the following improvements would result in even better performance in later iterations of the model:

(1) A higher density of upwind observations, both vertically and around the farm, to both nudge the model and also on which to perform pattern matching, that would include sectors previously unaccounted for and at distances closer to the site to capture shorter range ramps

(2) On-site wind speeds in order to convert the offsite patterns' signals into the on-site wind speed response. Currently the model uses the onsite power response, which is non-linearly related to wind speed and thus not a direct mapping of the local meteorological surroundings. The non-linear nature of the power curve model would best be suited to running wind speeds obtained from power matching than using power itself.

(3) To reduce seasonal dependence of training clusters, pattern matching would be performed untrained on the complete set of historic data. The algorithm to span the search space has proven to be rapid and accurate in offline tests, and if deployed in real time would eliminate biases created by using a smaller subset of generic meteorological conditions.

With the exception of a software glitch due to the change in day light savings time (DST) that occurred on March 13, 2012, the forecasts were otherwise delivered stable and routinely. The problem with the DST changeover resulted in the next few days following the change in time zones having stale NWP; the ramp forecasts were still unique, but the NWP was not spun-up correctly. This was corrected as soon as forecasters were aware of it, and the forecasts were produced correctly since.

3.2 3Tier Evaluation

The project was extended through September 30th, 2012 to allow 3Tier to conduct data analysis and determine whether the met towers and other sensors have an economic value to Glacier Wind in short term ramp forecasting. It was decided that depending on the outcome of 3Tiers' evaluation, either the sensor array would be turned over to NaturEner (or 3Tier) or signed over to and decommissioned by WINData.

The 3Tier write-up is provided below. 3Tier initially believe that the data quality was such that only a small amount of data could be used, they rechecked their QA/QC filtering and were able to make some revisions and included analysis using the 1401 E Glacier met tower.

Eric Grimit, Senior Scientist at 3Tier speaking –

"Thanks for your patience. As I alluded, our conclusions are no different - which is certainly disappointing. I know there is value here in this data as we have discussed. We will be running some data assimilation experiments soon and with your permission we would include the WINData observations. Please let me know if that is OK.

Eric"

"The following figures and tables summarize the forecasting experiments run by 3TIER for the Glacier Wind I wind project using the observation data supplied by WINData. WINData observations included two meteorological towers and four surface weather stations located in Montana. One of the met towers (1402 - Babb) was not used in this analysis to due its shorter length of record (available since August 2011) compared to the other met tower (1401 - East Glacier) and the four surface weather stations, at which consistent data was available as far back as August 2010.

For these experiments, only the wind speed and pressure observations were utilized. 3TIER ran the observational data through its standard quality control routines and discarded values that did not pass simple range, persistence, and step checks. These discarded values along with the missing observations that were not provided account for approximately 25% of the analyzed time period. The remaining 75% of the data was used for training and testing. The training period for all models was August 1, 2010 to December 31, 2011. The independent test period over which all results are summarized was January 1, 2012 - April 30, 2012.

3TIER trained two control forecasting models that mimic its operational forecasts provided to NaturEner in real-time for the Glacier Wind I facility. The first model is trained to minimize the mean-square-error (MSE) of standard power forecasts (3TIER, Control). The second model is trained to maximize the equitable threat score (ETS) for two-sided ramp events greater than 15% of installed capacity, within a tolerance of 15% (3TIER Ramp, Control). These thresholds for ramp classification were defined by NaturEner. Both of the control forecasts were developed from a predictor pool that consists of all NaturEner observations from on-site and the off-site met tower located near Browning, Montana, as well as all regularly reporting public weather stations in the region. Therefore, the control forecasts already include the use of off-site observations, which leads to large improvements over a persistence forecast benchmark.

Two additional models were trained with the WINData observations included in the predictor pool. The experimental model trained to minimize the power forecast MSE is denoted "3TIER, WINData Obs" and the model trained to maximize the ramp ETS is labeled "3TIER Ramp, WINData Obs".

All forecasts are evaluated for the 1-hour target period with a 75 minute lead starting from 45 minutes after each hour. The forecast horizon for this period is from 75 to 135 minutes into the future. It was assumed that all observations taken at, or prior to, 40 minutes after the hour would have been available for use. The performance of these experimental models compared to the control forecasts shows the incremental impact that the WINData observations supply to 3TIER's forecast system as it is currently configured.

The inclusion of WINData observations into 3TIER's forecast system acts as an improvement in some periods and a degradation in others. For both forecast types, the summary statistics show performance that is, at best, equivalent to the control forecasts. Rolling 30-day statistics, shown as time series for the February - April 2012 period illustrate the time periods of benefit and degradation. There is a small increase in the probability of detection, but also a commensurate increase in the false alarm ratio which acts to negate the improved detection of true positives. Overall, the threat score for ramp event detection is about the same when WINData observations are included.

We conclude that the WINData observations, as they are currently sited, do not add significant benefits to 3TIER's current forecast system. The 3TIER forecasts already incorporate existing off-site meteorological data from both NaturEner's private sensors and public weather stations in the region. Evidently, the WINData observations do not add enough new information that is independent of the data already sampled by the existing off-site sensors. This was not anticipated in advance. Since there are relatively few observations in the region near the Glacier Wind facility, we had speculated that significant improvements were possible with deployment of just a few sensors in key areas."[6]

[6] Evaluation contributed by Eric Grimit, PhD, Senior Scientist, 3TIER Inc., 2001 6th Avenue, Suite 2100, Seattle, Washington 98121

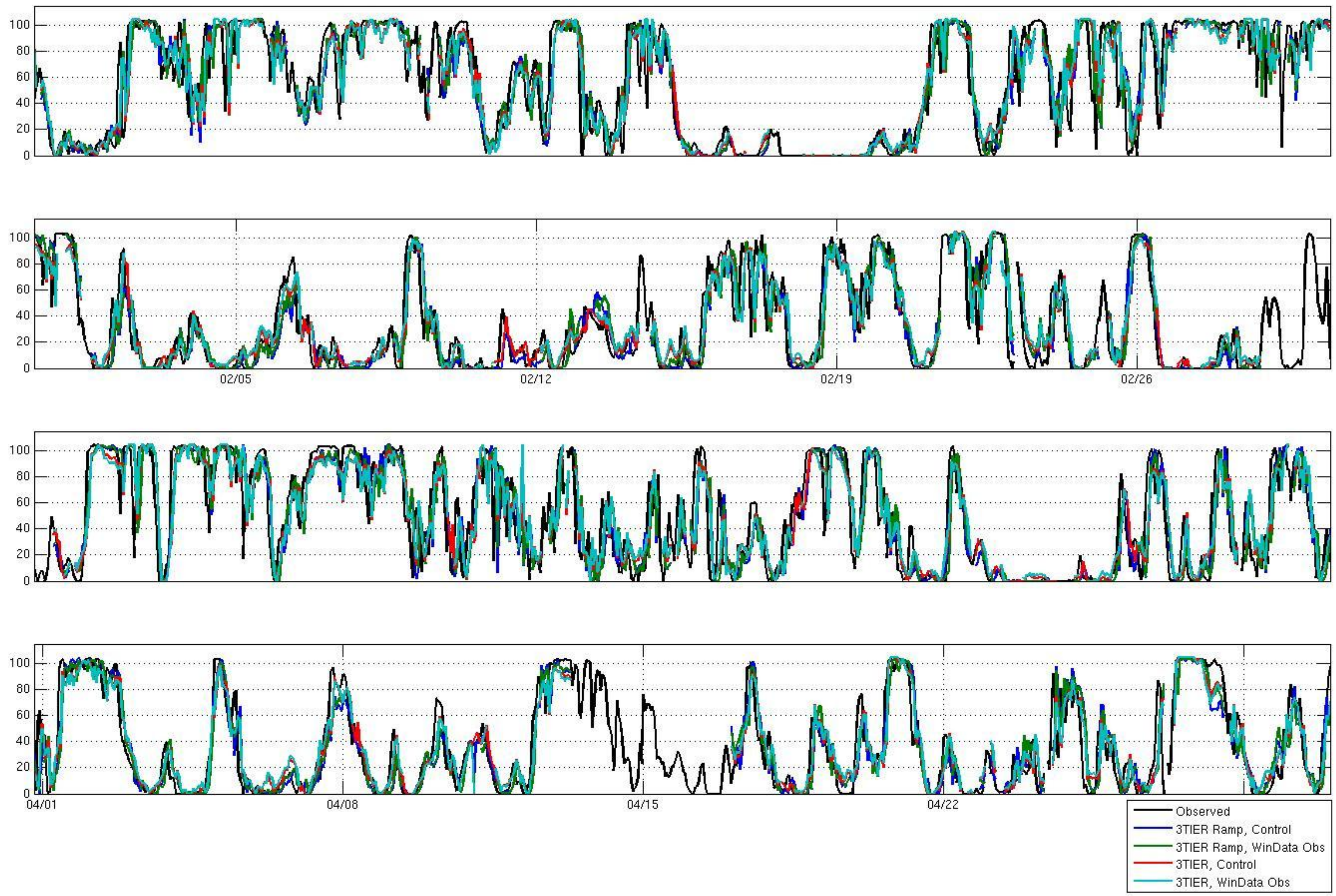


FIGURE 33 JANUARY - APRIL 2012 FORECAST TIME SERIES @ 75 MIN. LEAD

TABLE 3 JANUARY - APRIL 2012 SUMMARY METRICS BY MONTH

	3TIER Ramp, Control	3TIER Ramp, WINData Obs	3TIER , Control	3TIER, WINData Obs
Threat Score				
Jan	0.2509	0.244	0.2519	0.2692
Feb	0.3008	0.2863	0.2919	0.2857
March	0.3142	0.2902	0.2801	0.2897
April	0.3227	0.3206	0.3467	0.3255
Prob. Of Detection				
Jan	0.3273	0.3318	0.2955	0.3241
Feb	0.4229	0.4329	0.3446	0.3537
March	0.3993	0.37	0.3207	0.3394
April	0.4821	0.5153	0.4083	0.4157
False Alarm Ratio				
Jan	0.482	0.5203	0.3689	0.386
Feb	0.4897	0.5419	0.3441	0.4021
March	0.4041	0.4261	0.3111	0.3357
April	0.5061	0.541	0.303	0.4
MAE (MW)				
Jan	13.3123	13.8708	12.957	13.4252
Feb	11.2495	12.0193	10.7483	11.5177
March	15.1906	15.5746	14.8035	15.2945
April	11.2327	11.6886	10.5238	11.171
BIAS (MW)				
Jan	-0.5549	-0.0175	-0.3133	-0.3377
Feb	-1.25	-0.0047	0.8229	1.734
March	-1.4255	-1.1518	-0.5864	-0.2364
April	-1.0734	-1.0131	-0.0099	0.3994

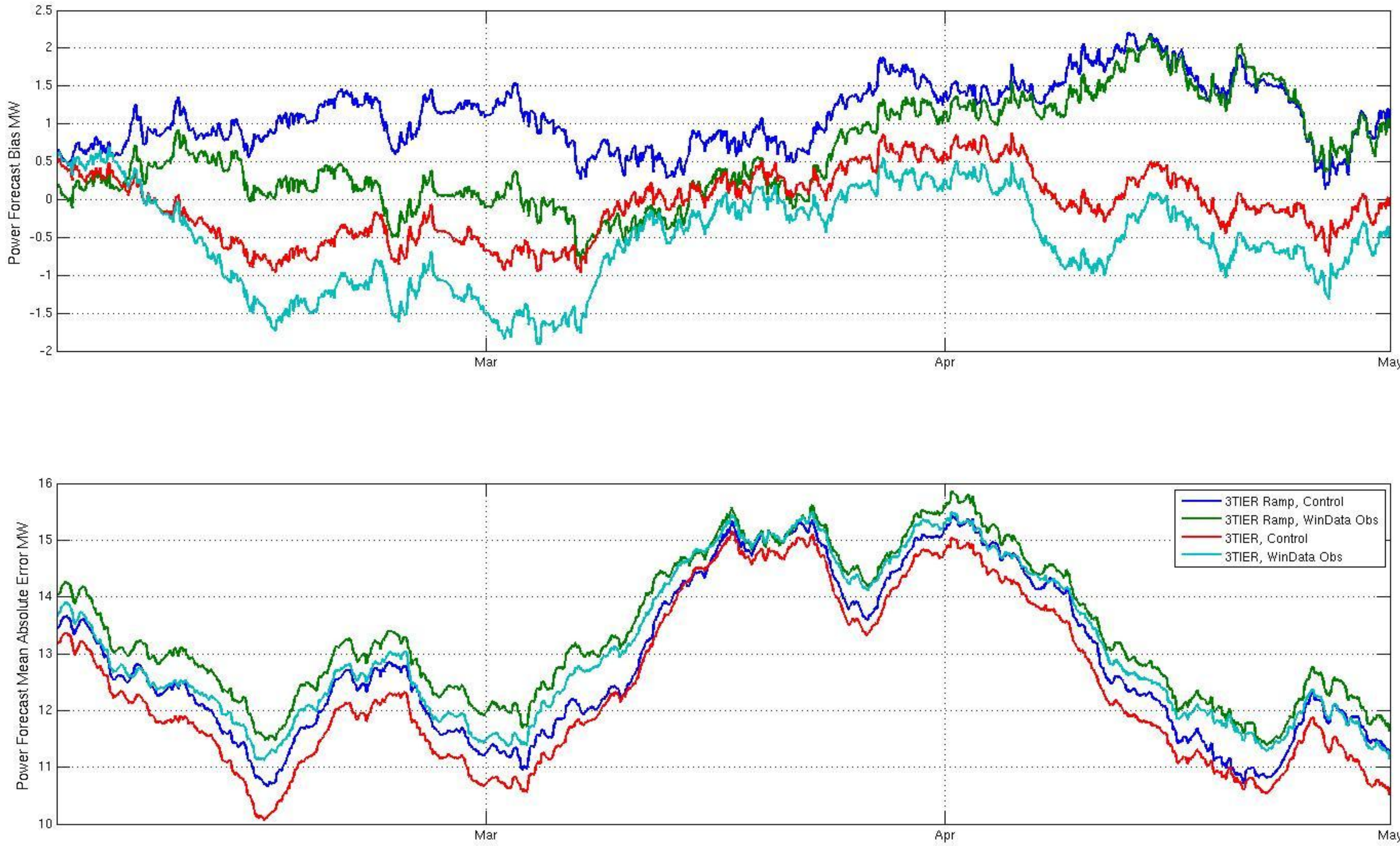


FIGURE 34 FEBRUARY - APRIL 2012 ROLLING (TRAILING) 30-DAY METRICS

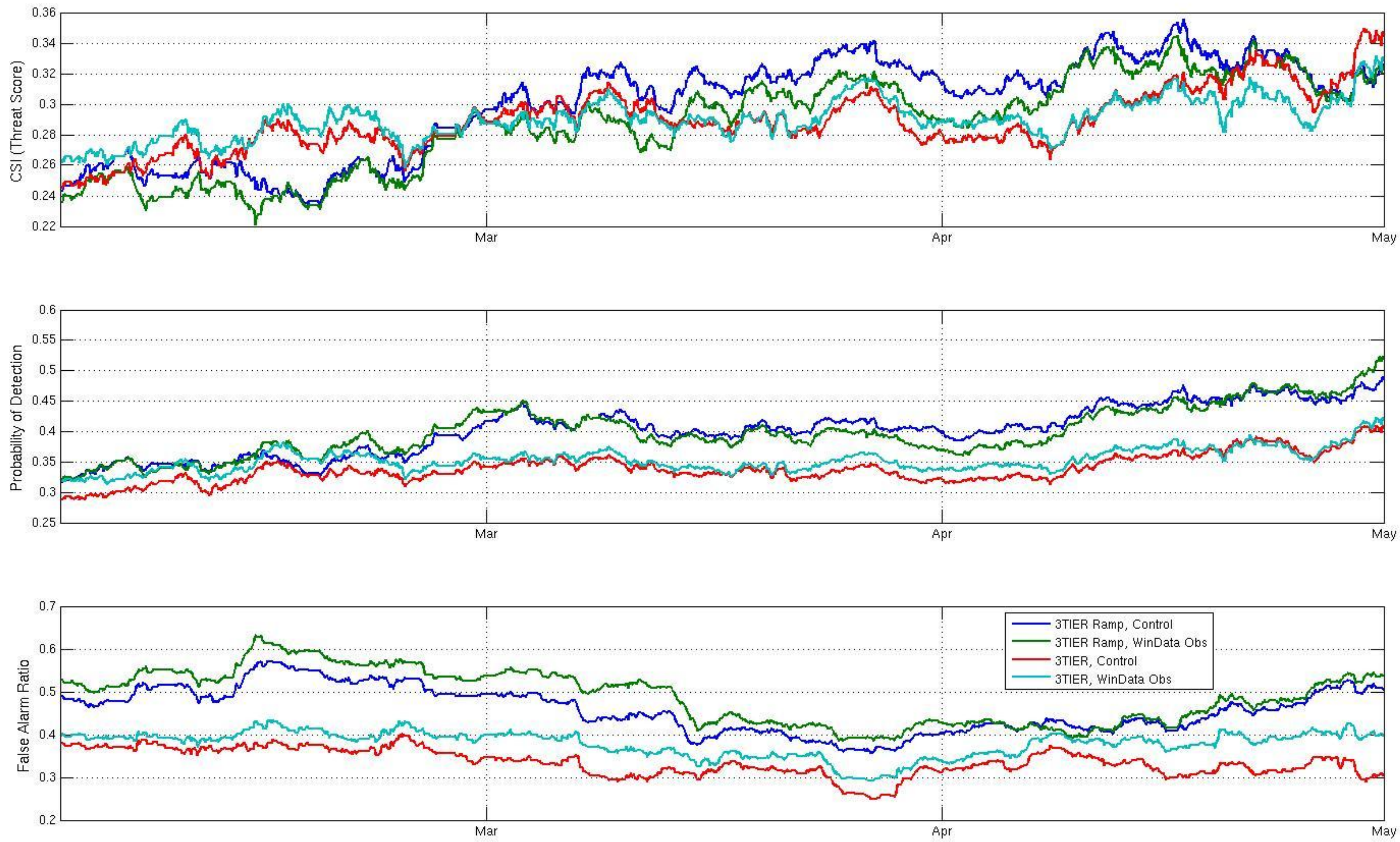


FIGURE 35 FEBRUARY - APRIL 2012 ROLLING (TRAILING) 30-DAY METRICS

4 Suggestions for Future Improvements to the Methodology

We are encouraged by much of the ramp detection improvement. However, there is room to grow the model to include fair weather, calm and constant predictions. We believe the following improvements would result in even better performance in later iterations of the model:

(1) A higher density of upwind observations, both vertically and around the farm, to nudge the model and on which to perform pattern matching, that would include sectors previously unaccounted for and at distances closer to the site to capture shorter range ramps. It is well established that use of offsite measurements can improve NWP – several agencies already perform this type of data assimilation, both in real-time operations and field campaigns. We know and have demonstrated that the WINData measurements do change the output our own internal NWP real-time runs. The difference between this study and the larger studies/operations is the strategic upwind location of the sensors relative to the Glacier wind farms. We know the placement of towers in the sensitive sectors of this unique wind regimes improved forecasts, but the improvement was confined to events when the wind was in those sectors. What we lacked was visibility to all sectors upwind and often missed down ramps that occurred from the south and east. A significant amount of events occur from these sectors, and our forecasts were inherently ignorant to these types of ramps. We hypothesize that future increased coverage would give more spatial awareness to the models and improve accuracy for more types of events.

(2) On-site wind speeds in order to convert the offsite patterns' signals into the on-site wind speed response. Currently the model uses the onsite power response, which is non-linearly related to wind speed and thus not a direct mapping of the local meteorological surroundings. The non-linear nature of the power curve model would best be suited to running wind speeds obtained from matching than using power itself. There is a subtle difference in this approach. For this project, we did not provide a superior wind forecast, *per se*, but rather attempted to provide a superior power forecast relative to on-site power. What we claim now is that the better approach is to first make a superior wind forecast, calculated against on-site wind speeds, and only then convert the wind speeds to power through a power model. Because curtailment, availability and other considerations that may mask biases in wind speed accuracy when validating with power exist, we should seek to make the best wind speed forecasts and compare against wind speed measurements. The ultimate goals remains to provide the best power forecast that are easily validated with onsite power measurements. At the time that delivery of the forecasts was required for the project timeline there were insufficient amounts of on-site wind speeds to use to this end. This new understanding will result in future versions of this type of forecast using this wind-to-power technique.

(3) To reduce seasonal dependence of training clusters, pattern matching could be performed untrained on the complete set of historic data. The algorithm to span the search space has proven to be as efficient and more accurate in offline tests, and if deployed in real time would eliminate biases created by using a smaller subset of generic meteorological conditions. Originally, the pattern matching was trained on the data that was available from the beginning of the project, which only accounted for about 3 months of overlapping

observations for all the sites and sensors. This limited our search space for ramp signatures to a single season. This became problematic as the seasons changed, and the signatures which we provided for the forecast pattern matching algorithm did not. One solution is to update the patterns every season. This would require seasonal calibration of the model by analysts. Another solution is to eliminate the simplification of creating generic subsets of ramp events for pattern matching, and instead allow the algorithm to search through any and all previous observations. This will provide much more unique matches and therefore much more unique forecasts. For example, if there are only 10 types of ramps to choose from (i.e. 5 up ramps and 5 down ramps), then a forecast can only produce 10 types of forecasts. Having hundreds or thousands of events to search through and choose from, on the other hand, means the algorithm can narrow down to specific events or even make an ensemble of the closest matches. Assuming the search space has over a year of data in it, the benefit of using the entire history should remove any seasonality biases from a subset of patterns. This new understanding will yield better pattern matching routines and also utilize much more meteorological for future forecast systems.

We did not test whether the observations could be used to improve physical weather model forecasts, which would also act to improve the statistical model predictions. Assimilation of the observation data directly into the NWP model initial state has been shown to dramatically improve 0-6 h physical model predictions of the local weather state. Testing the benefits that data assimilation could have was beyond the scope of what 3TIER has committed to under this project. We also speculate that human interpretation of the observations, especially by trained energy meteorologists, could have significant benefits well beyond what we have attempted in this objective statistical study and potentially at less cost than running an operational NWP data assimilation system.

5 Conclusions

In conclusion, WINData successfully completed the tasks that were outlined in the SOW. During the duration of the project, towers and sensors were installed and linked to provide real-time data to forecasters; the data was analyzed by the forecasters to train a machine learning algorithm and also to nudge real-time NWP; the forecasts were refined and routinely delivered to the wind farm operators and analysts; the owner-operator analysts performed a validation on several months of delivered forecasts.

WINData demonstrated that the OSIsoft PI system is a very powerful tool and is invaluable in effectively handling vast amounts of current and historical data and in setting up and conducting regional data experiments to determine the significant patterns of events and characteristics of the region around a wind plant.

WINData/GH validated the fundamental hypothesis of the project: that offsite meteorological data has value in wind generation forecasts for sites in complicated terrain and demonstrated that forecasts which utilize strategically located offsite observations generally performed better than persistence of onsite generation measurements. Modeling techniques were developed and verified to assimilate data from both met masts (1401 and 1402) and several surface pressure devices for adjusted sea level pressure, temperature, and wind speed into the WRF model. Furthermore, GH devised and deployed a real-time pattern matching algorithm to rapidly augment the WRF forecasts for short-horizon ramp predictions. The improvement over persistence was seen in many of the traditional and ramp-tracking metrics over several horizons, independently in both the GH and NaturEner assessments. These improvements would not have been possible without the use of the observations.

In using the offsite measurements, GH moved beyond traditional data assimilation (i.e. nudging of NWP) and used machine learning to train and inform a pattern matching algorithm to provide additional short term ramp information. GH acknowledges there are still drawbacks to this type of data utilization; however, they conclude there are basic improvements that can be made simply by adding more strategic locations.

Many of the drawbacks in the WINData/GH model are manifested in and masked by validation statistics, which can obscure the true value of the offsite data during times when the impulses arrived from sectors in which observation systems were deployed. GH suggested several solutions to improve the accuracy, the most simple involving the installation of more data collection sources in high risk areas to add visibility of wind patterns in sectors sensitive to types of ramps towards which the algorithm was essentially blind.

NaturEner and 3Tier evaluated forecasts which incorporated the sensor data and concluded that the commercial value of sensor array was not clearly demonstrated in this project.

Appendix 1 -Analysis of Jan-Feb forecast by NaturEner

Ramping Metrics

WINData– February-March 2011

Contingency Table

When evaluating a Dichotomous forecast, the source of the error statistics is a contingency table. For each category, there are 4 categories:

- Hit - The event was forecast, and then occurred
- Miss - The event occurred, but was not forecasted
    - Miss – A ramp occurred, but was not forecasted.
    - Misclassification – A ramp up was forecast, but a ramp down occurred, and vice versa.
    - Underestimate – The magnitude of the ramp was larger than was forecast
- False Positive - The event was forecast, but did not occur
    - False Positive – A ramp was forecast, but no ramp occurred.
    - Overestimate – The magnitude of the forecast was much larger than the actual ramp.
- Correct Negative - The event was not forecast, and did not occur

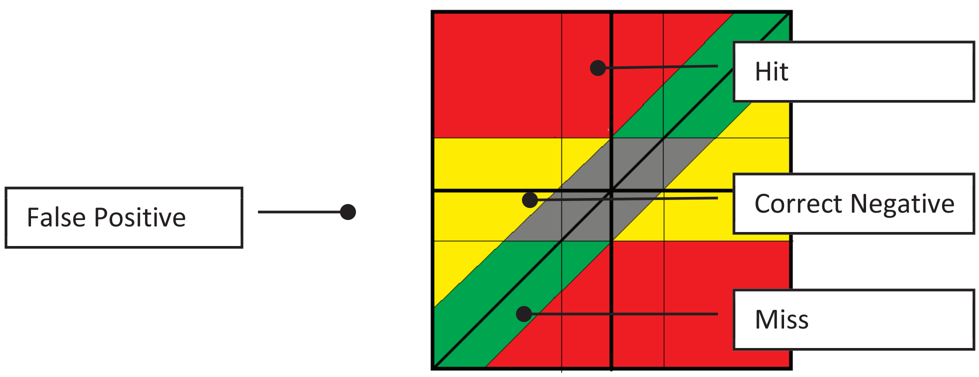


Figure 1: Forecast category sectors. The x-axis is the forecast ramp and the y-axis is the actual ramp.

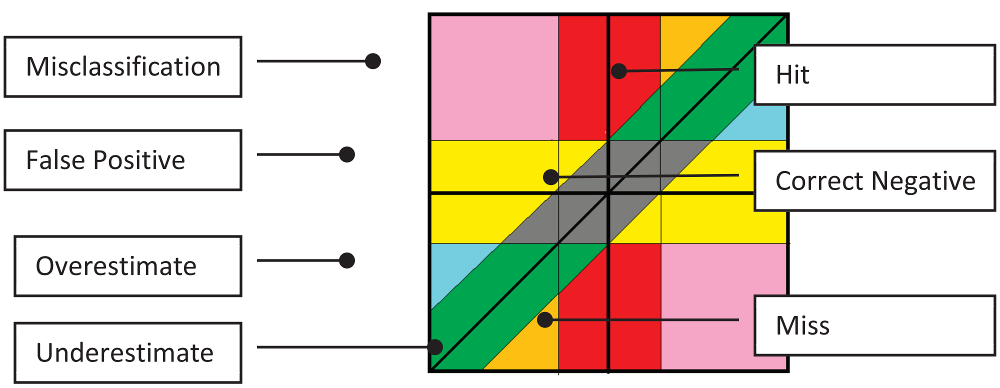


Figure 2: Forecast category sectors showing subcategories.

Table 1: Contingency Table

		Actual	
		Ramp	**No Ramp**
Forecast	**Ramp**	Hit	False Positive
	No Ramp	Miss)	Correct Negative

Metrics

The following table shows the most applicable metrics which can be calculated using this contingency table. The formula which can be used to calculate them is shown, along with a layman's description of what the metric means. This table borrows liberally from the document provided by for Australian Weather and climate research (http://www.cawcr.gov.au/projects/verification/).

Table 2: Dichotomous metrics

Accuracy	$Accuracy = \frac{hits + correct\ negatives}{total}$	What fraction of the forecasts was correct?
Frequency Bias	$BIAS = \frac{hits + false\ alarms}{hits + misses}$	How did the forecast frequency of "yes" events compare to the observed frequency of "yes" events?
Probability of Detection	$POD = \frac{hits}{hits + misses}$	What fraction of the observed "yes" events was correctly forecast?
False alarm Ratio	$FAR = \frac{false\ alarms}{hits + false\ alarms}$	What fraction of the predicted "yes" events actually did not occur (i.e., were false alarms)?
Threat Score (Critical Success Index)	$TS = CSI = \frac{hits}{hits + misses + false\ alarms}$	How well did the forecast "yes" events correspond to the observed "yes" events?
Equitable Threat Score (ETS)	$ETS = \frac{hits - hits_{random}}{hits + misses + false\ alarms - hits_{random}}$ Where, $hits_{random} = \frac{(hits + misses)(hits + false\ alarms)}{total}$	How well did the forecast "yes" events correspond to the observed "yes" events (accounting for hits due to chance)? Alternately, account for hits due to a basic forecast such as persistence.

Definition of a Ramp

The beginning of the ramp is the same for the target as it is for the forecast. The beginning of the ramp is defined as the hourly average potential generation for the hour preceding the forecast. For a forecast made at 6:45, this would represent the hourly average from 5:40 to 6:40. In this case we have rounded to the nearest 10 minute interval in deference to our data characteristics.

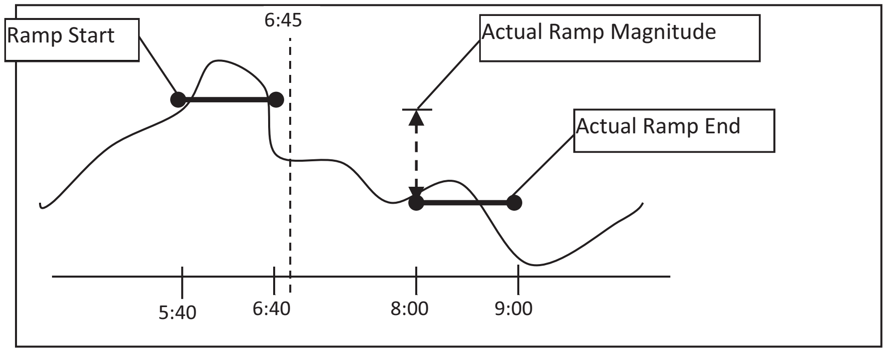


Figure 3: Definition of 75 minute ahead actual ramp specification

The end of the ramp is defined as the hourly average value within the hour of interest. For a T-75 forecast made at 6:45, this would be the hourly average value from 8:00 to 9:00. For the target value, this will be the hourly average measured value (adjusted for availability). For the forecast value, it will be the forecast for the generation in MWH, or the hourly average of the forecast power if sub hourly forecasts are used.

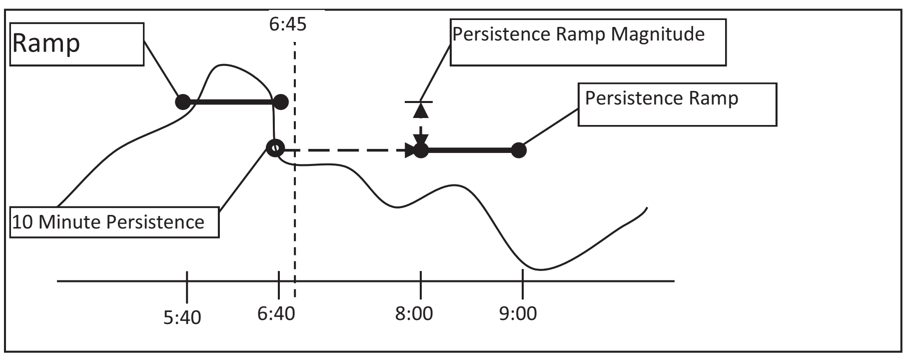


Figure 4: Definition of 75 minute ahead 10 minute persistence forecast ramp specification

In order to have a baseline forecast with which to compare the forecasts a persistent ramp forecast is generated. This persistent ramp is defined as the difference between the last 10 minute average measurement and the hourly average measurement at the time that the schedule is made. The persistent ramp hits are used as the “hits random” value for the ETS calculation.

We define a ramp as the difference between the hourly average values of the wind farm power generation, over the duration of approximately 3 hours. We would like to be able to predict ramps larger than 15% of installed capacity, 75 minutes ahead of the period start time.

Table 3: Ramp Definition

Time Averaging	1 Hour
Ramp Duration	3 Hours start to end (T-75 forecast)
Ramp Magnitude	15% of installed capacity

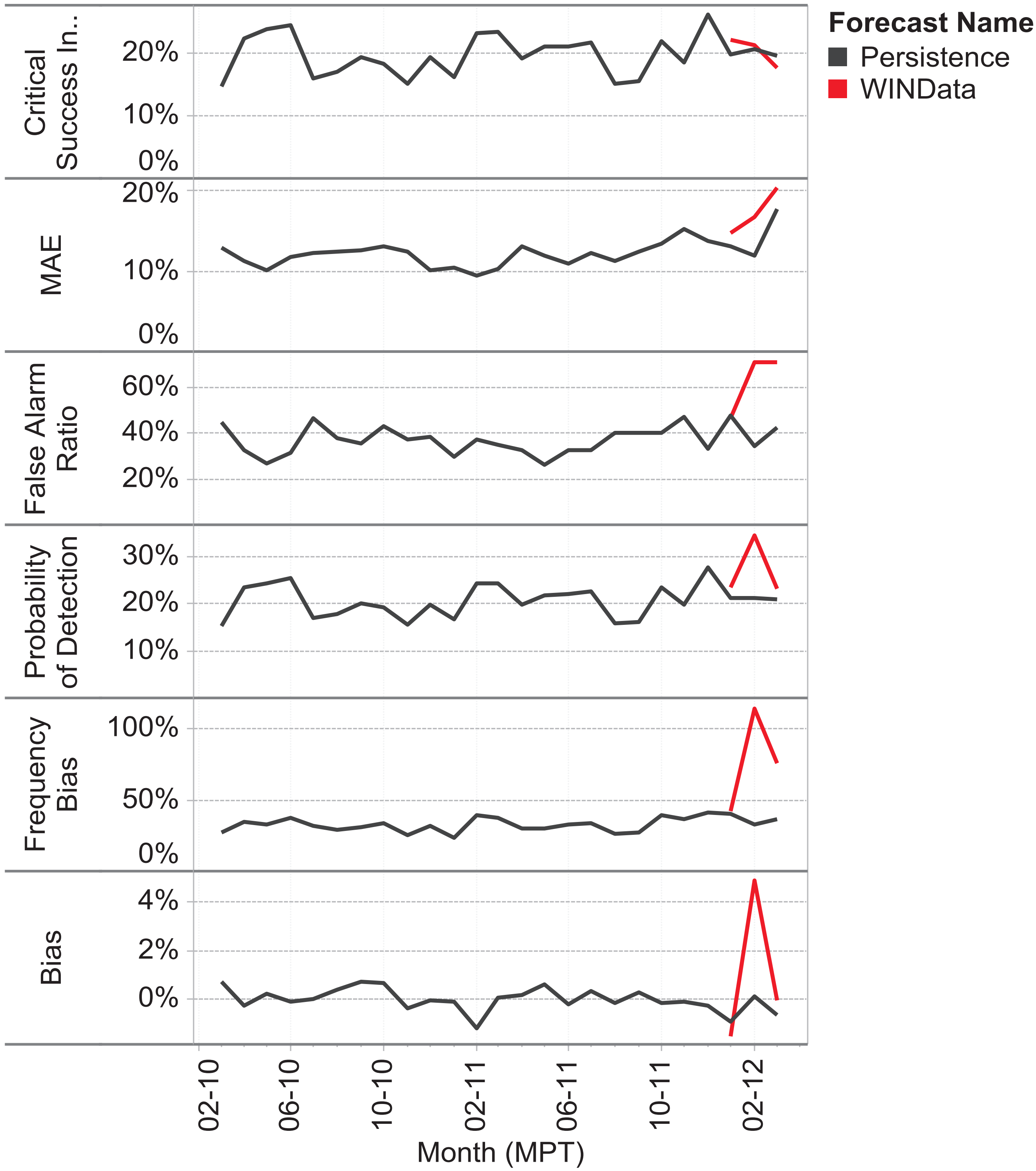


Figure 5: Year to Date Primary Metrics for Glacier Wind 1 75 minute ahead forecast

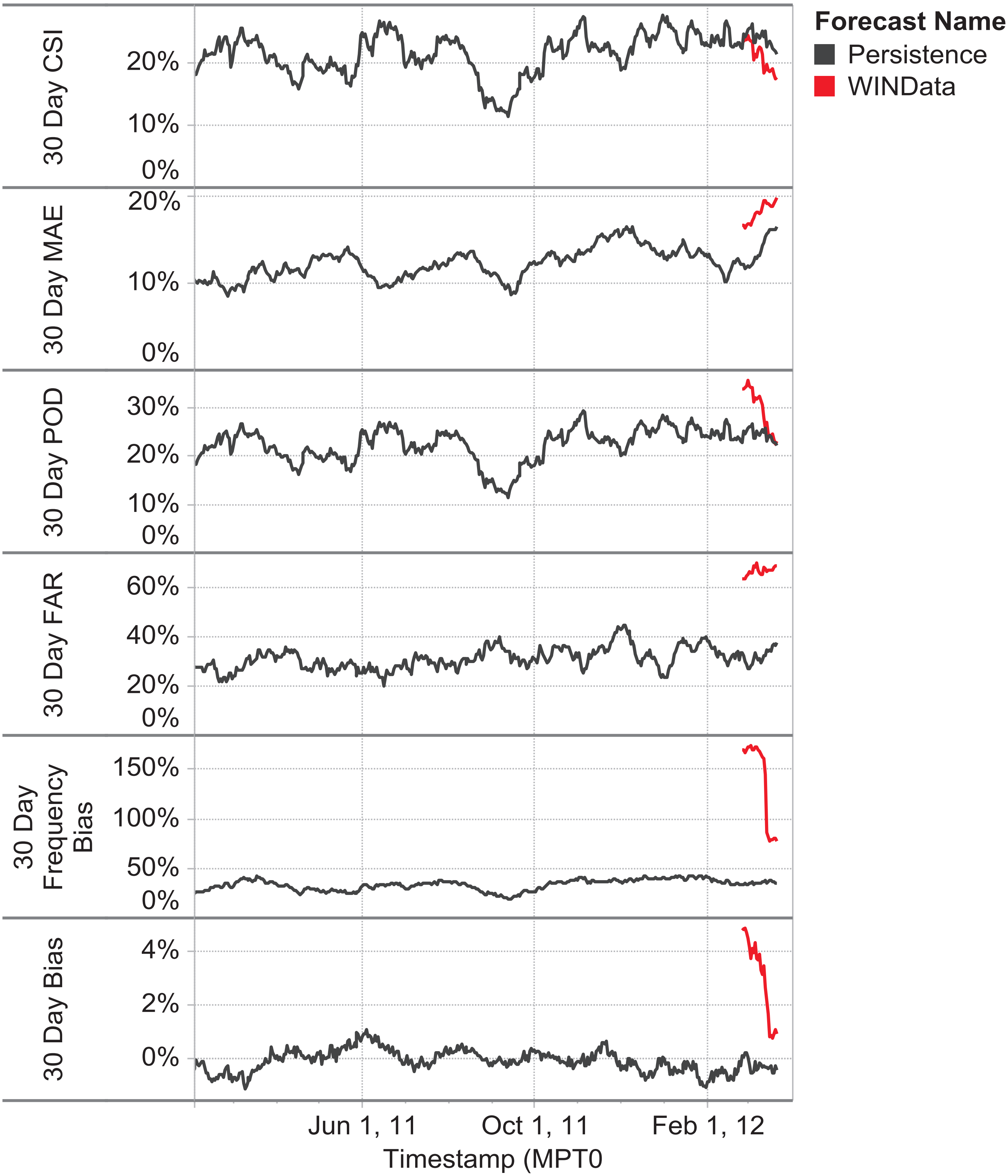
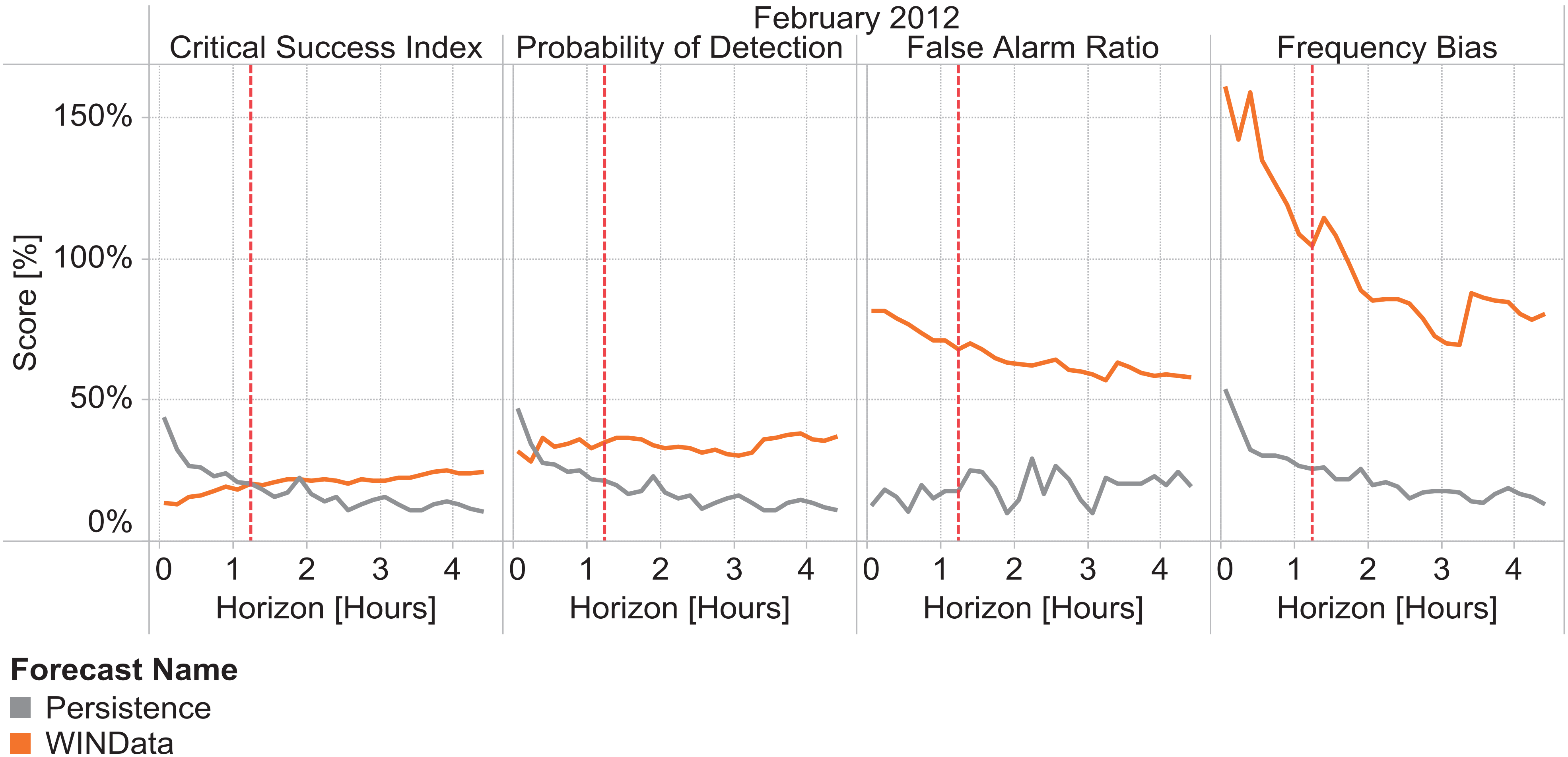
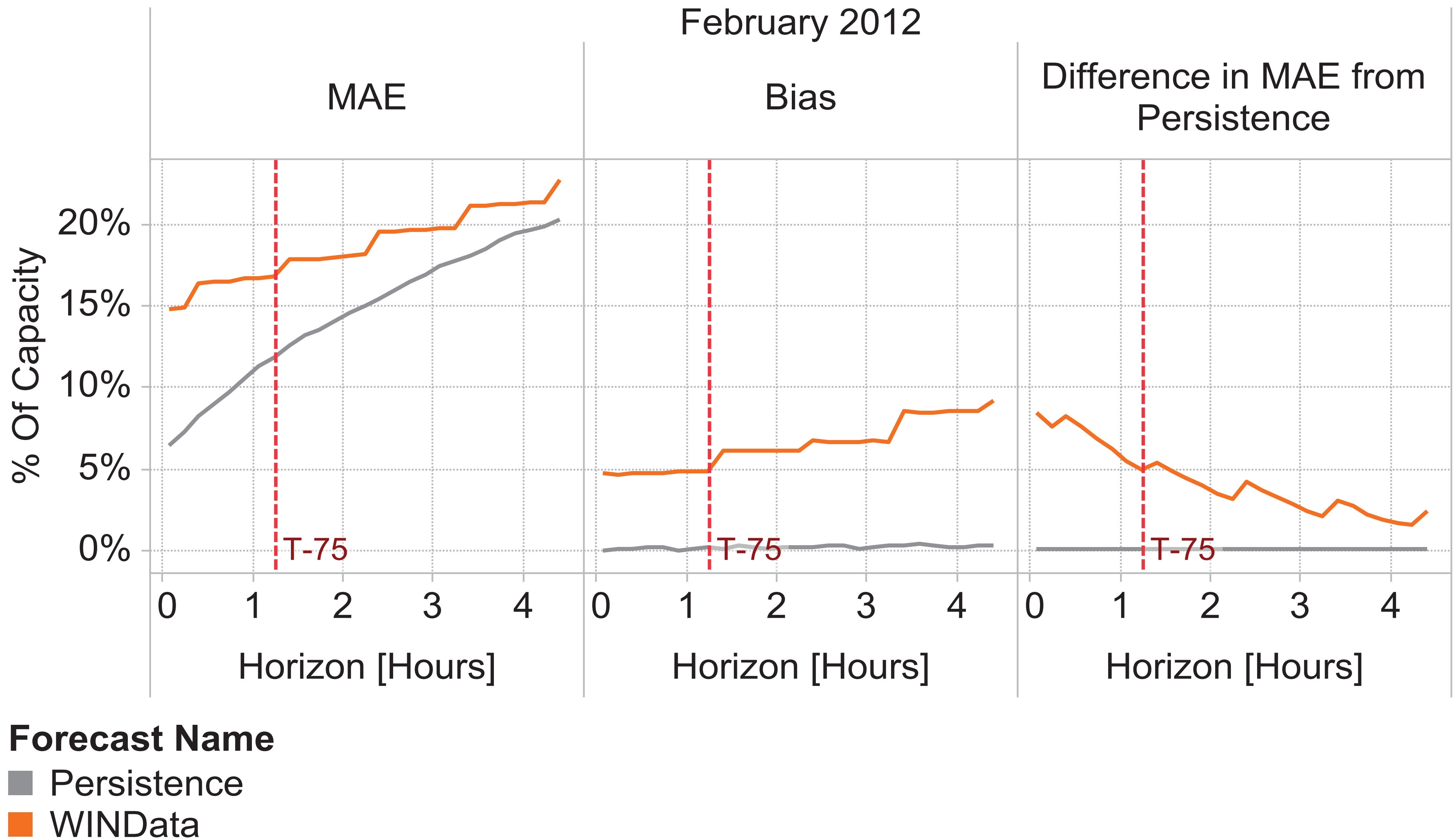


Figure 6: 30 day moving average metrics

Table 4: Summary of results

		Persistence	WINData
Critical Success Index	2012-02	20.5%	21.2%
	2012-03	19.5%	17.5%
False Alarm Ratio	2012-02	33.8%	70.7%
	2012-03	42.0%	70.2%
Probability of Detection	2012-02	21.2%	34.5%
	2012-03	20.7%	23.0%
Frequency Bias	2012-02	32.0%	114.3%
	2012-03	35.7%	75.3%
MAE	2012-02	11.8%	16.7%
	2012-03	17.7%	20.4%
Bias	2012-02	0.1%	4.8%
	2012-03	-0.7%	-0.1%
HIT	2012-02	43	68
	2012-03	47	51
MISS	2012-02	160	129
	2012-03	180	171
CORRECT NEGATIVE	2012-02	522	516
	2012-03	290	286
FALSE POSITIVE	2012-02	22	164
	2012-03	34	120


February 2012
Critical Success Index
Probability of Detection
False Alarm Ratio
Frequency Bias
Score [%]
150%
100%
50%
0%
0
1
2
3
4
Horizon [Hours]
Forecast Name
Persistence
WINData


February 2012
MAE
Bias
Difference in MAE from Persistence
% Of Capacity
20%
15%
10%
5%
0%
T-75
T-75
T-75
0
1
2
3
4
Horizon [Hours]
Horizon [Hours]
Horizon [Hours]
Forecast Name
Persistence
WINData

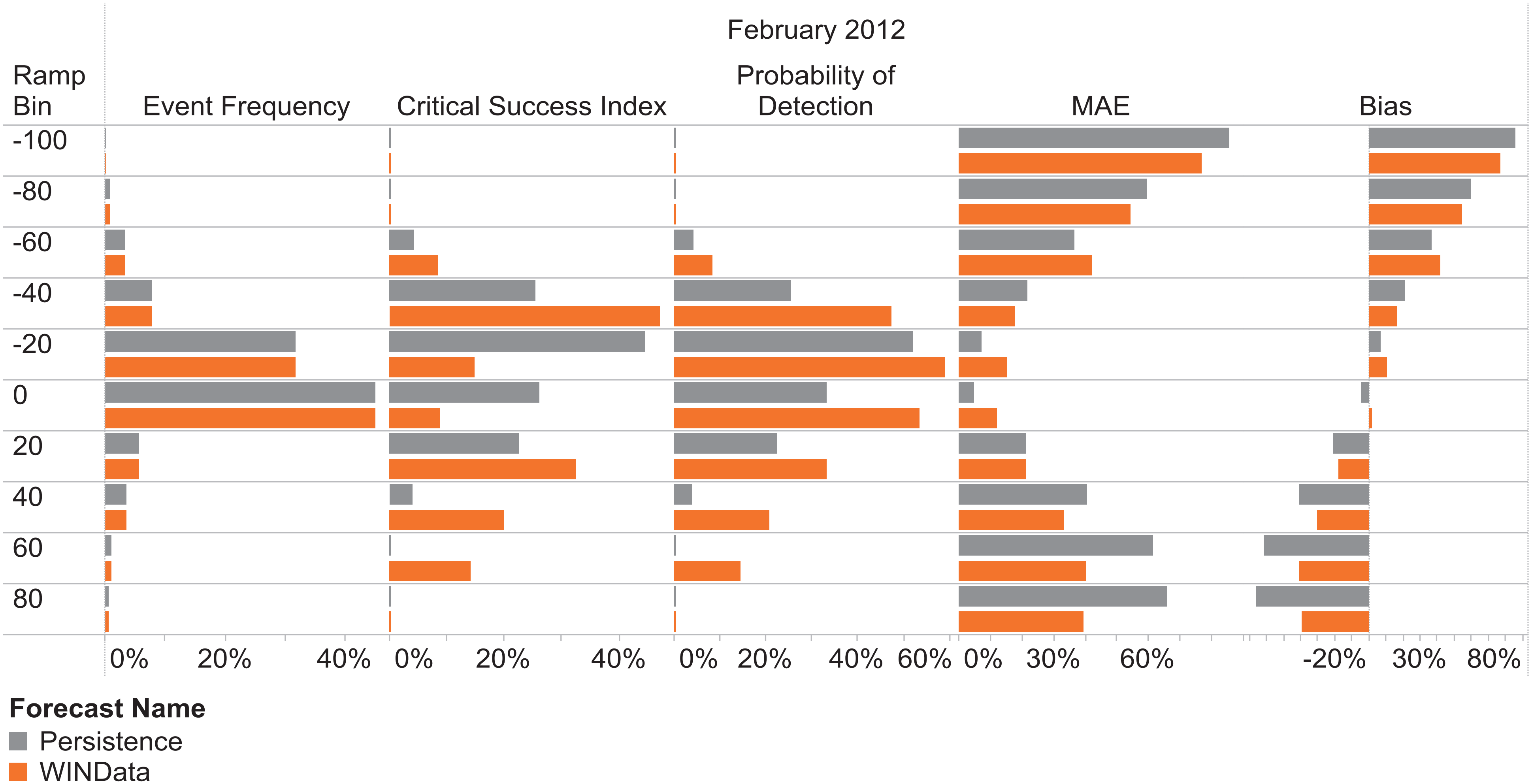
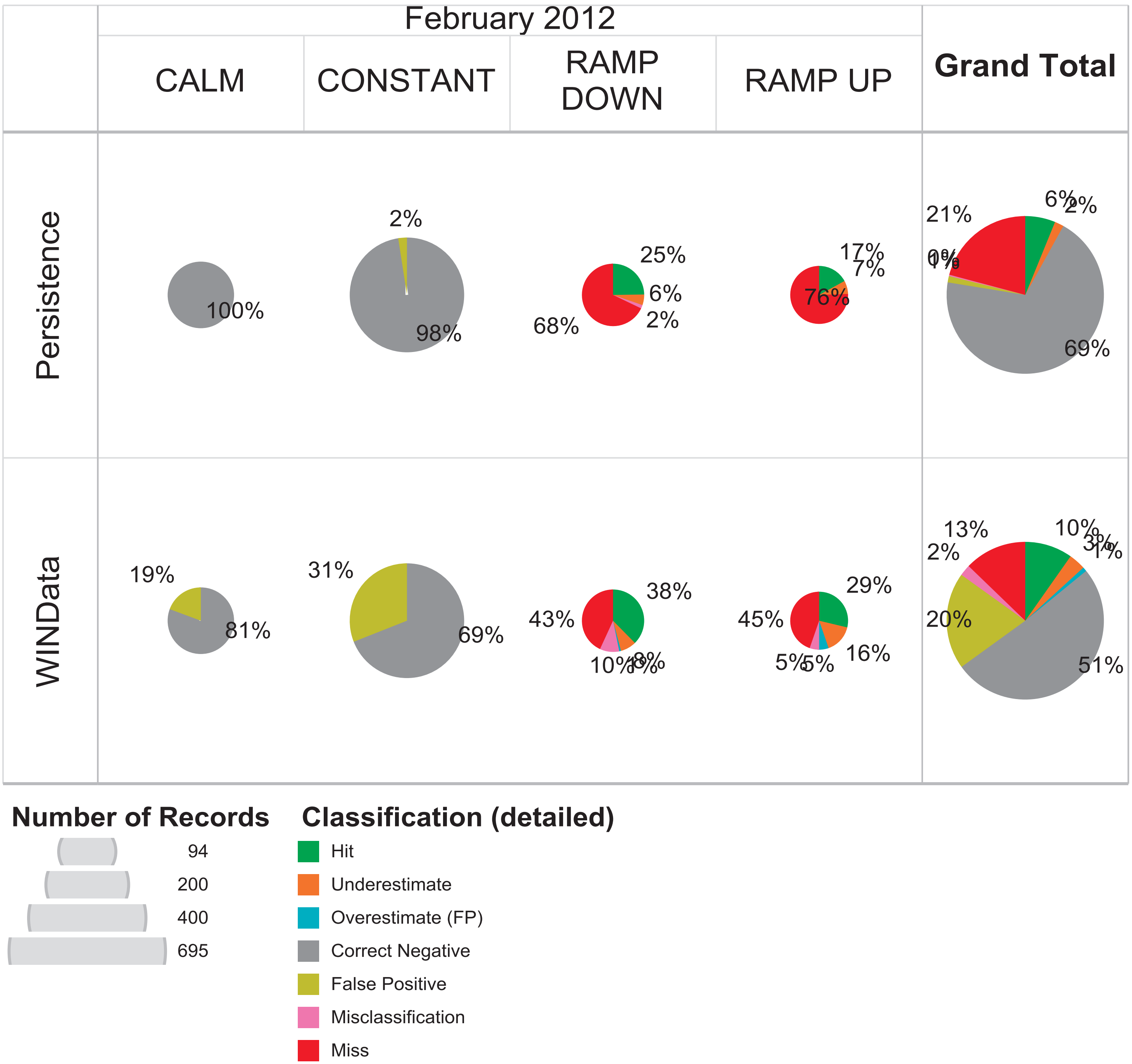


Figure 7: Comparison of MAE and Bias for forecast error and ramping error by actual ramp size and ramp length



February 2012
CALM
CONSTANT
RAMP DOWN
RAMP UP
Grand Total
Persistence
WINData
100%
2%
98%
25%
6%
2%
68%
17%
7%
76%
21%
6%
2%
0%
1%
69%
19%
81%
31%
69%
38%
43%
10%
8%
29%
45%
5%
5%
16%
13%
10%
3%
1%
2%
20%
51%
Number of Records
94
200
400
695
Classification (detailed)
Hit
Underestimate
Overestimate (FP)
Correct Negative
False Positive
Misclassification
Miss

Figure 8: Comparison of Actual Category against Forecast Category

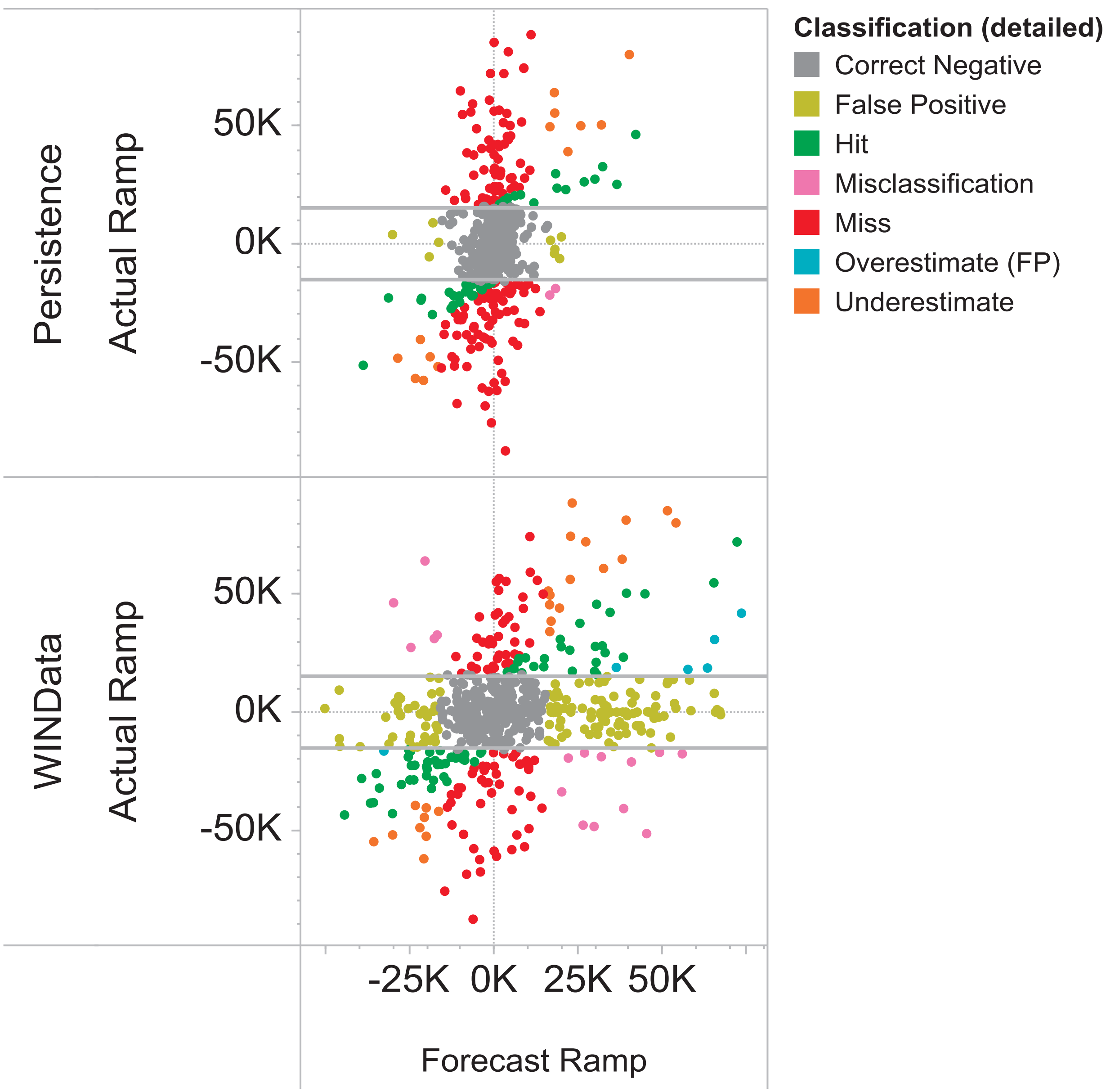


Figure 9: T-75 Scatter plot with classification detail

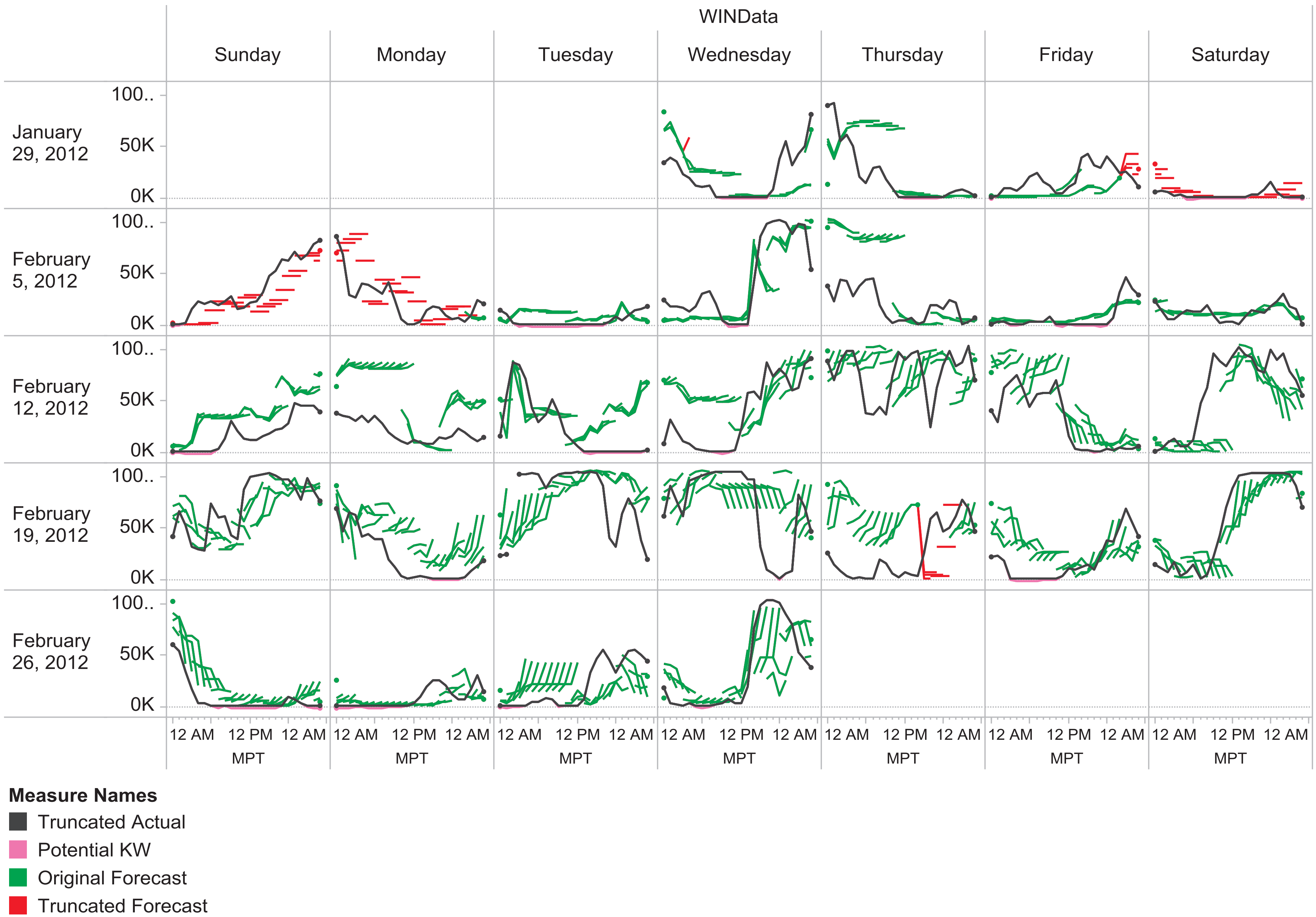
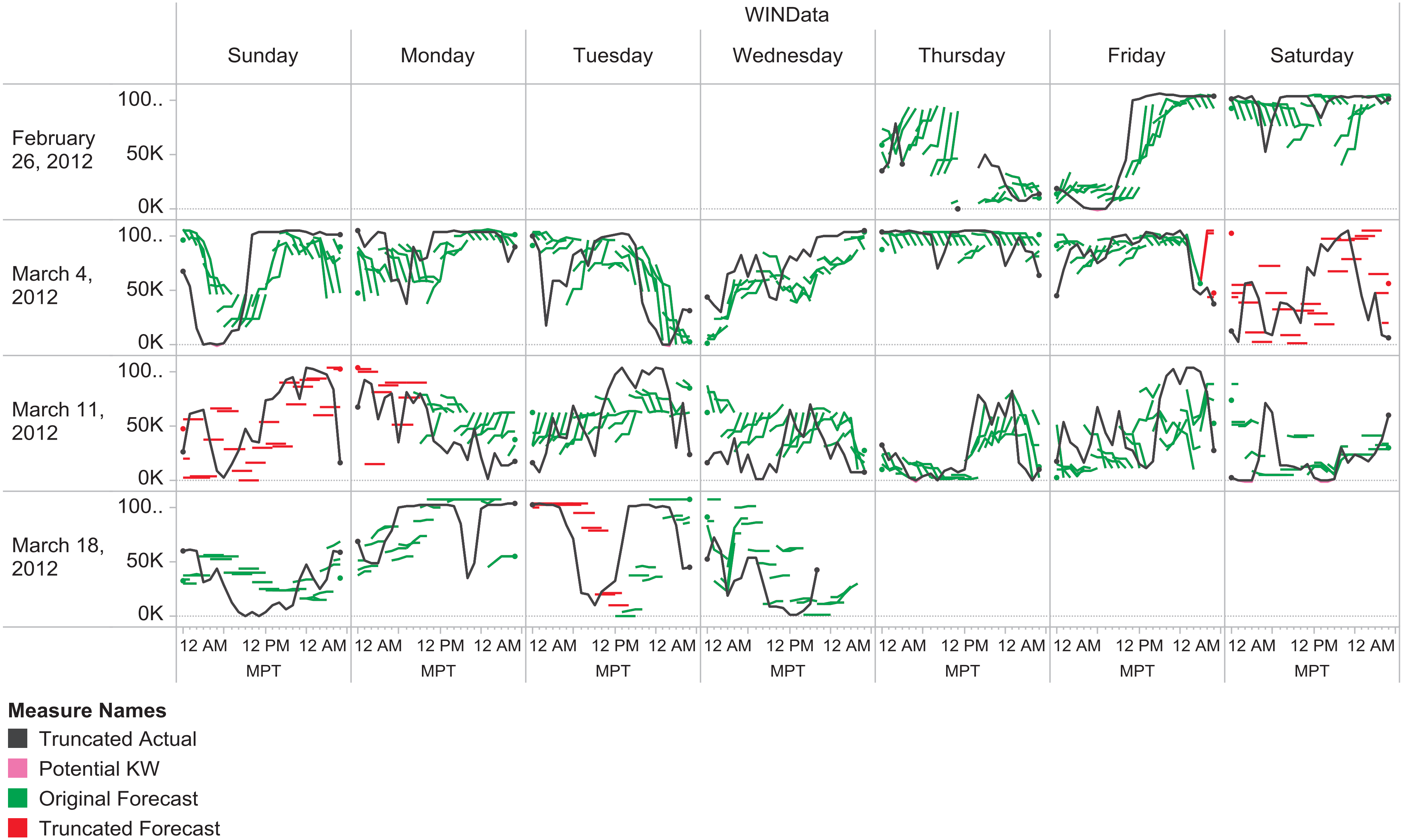
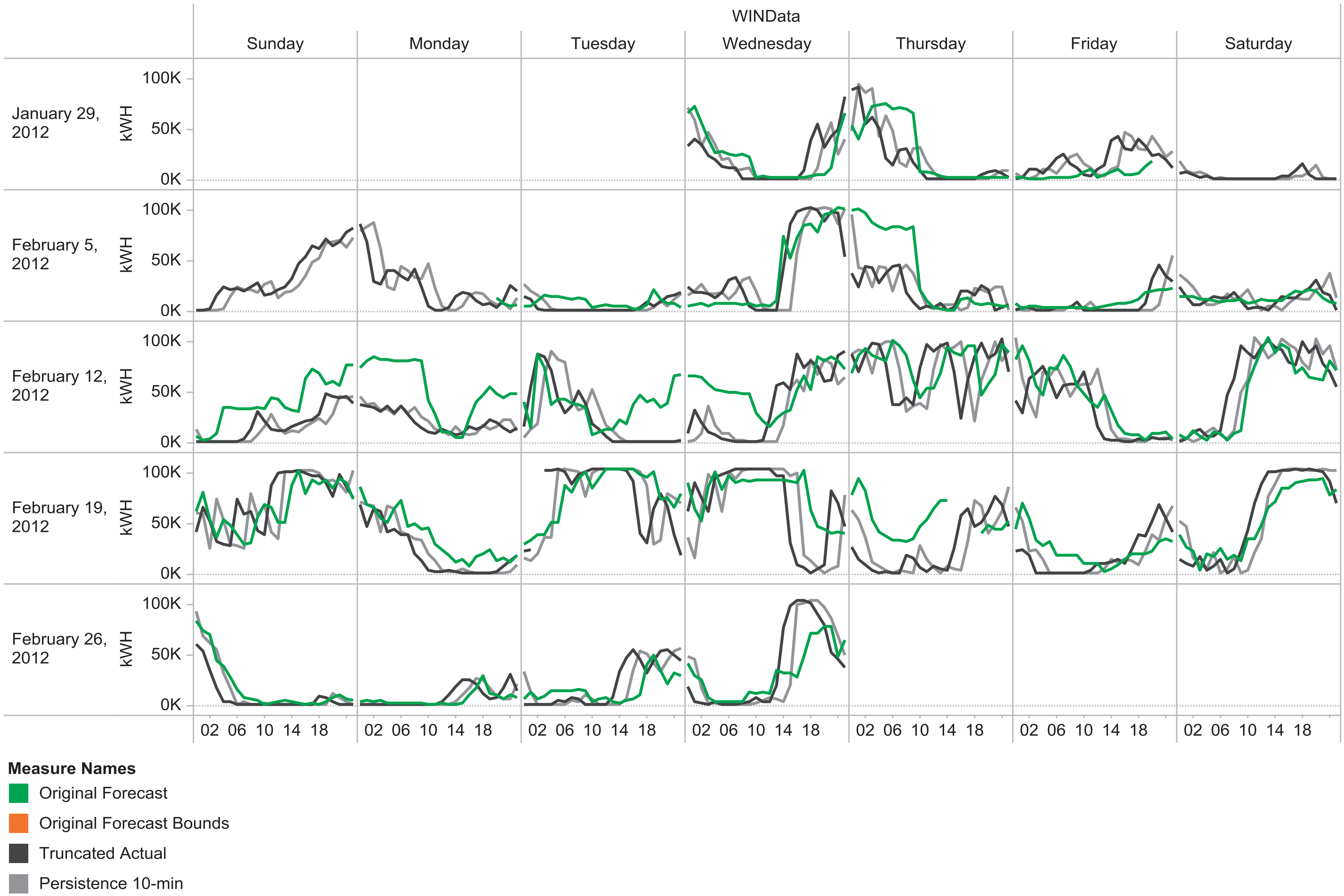
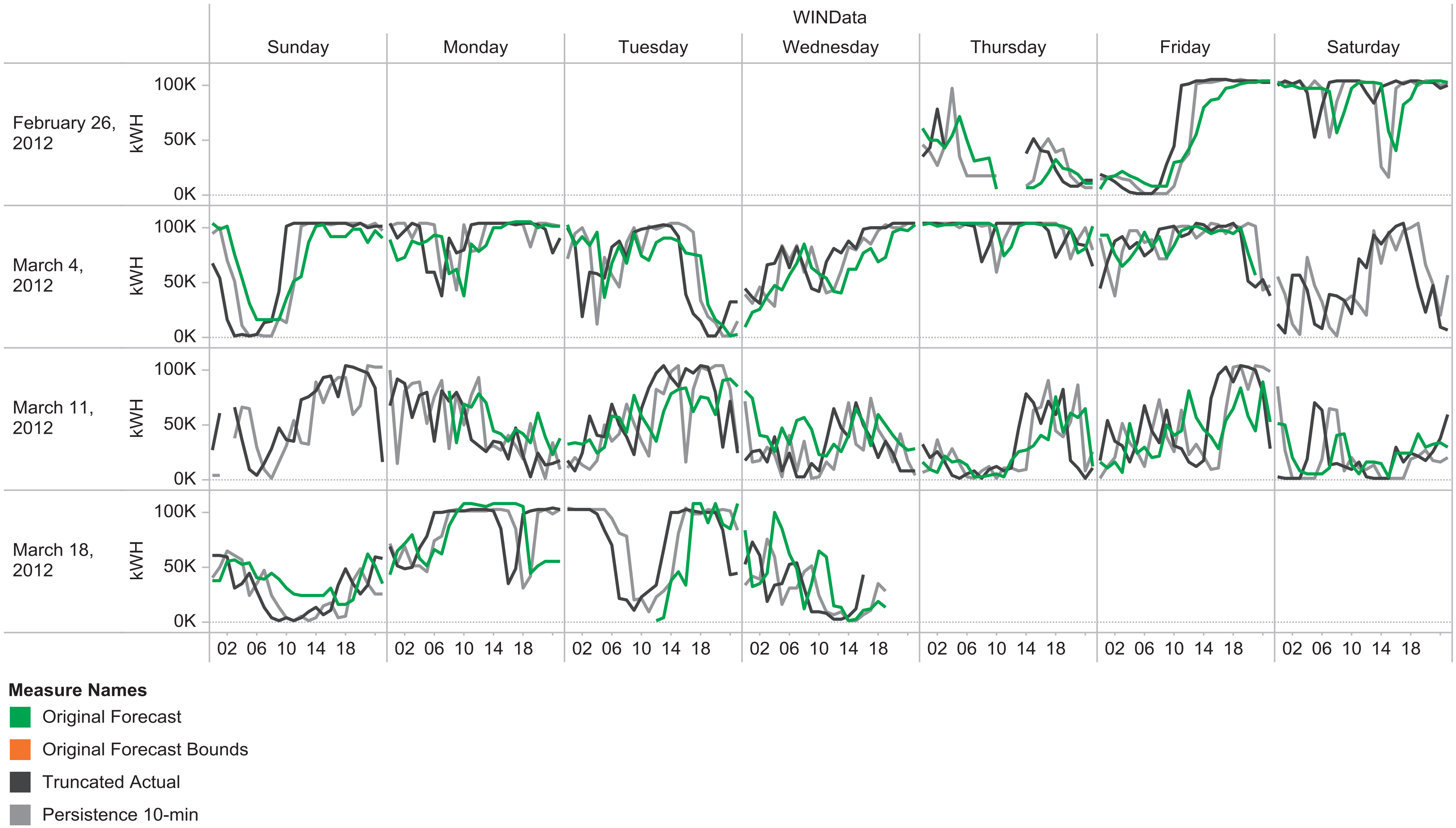


Figure 10: Forecast Time Series




WINData
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
January 29, 2012
February 5, 2012
February 12, 2012
February 19, 2012
February 26, 2012
kWH
100K
50K
0K
02 06 10 14 18
Measure Names
Original Forecast
Original Forecast Bounds
Truncated Actual
Persistence 10-min


WINData
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
February 26, 2012
March 4, 2012
March 11, 2012
March 18, 2012
kWH
100K
50K
0K
02 06 10 14 18
Measure Names
Original Forecast
Original Forecast Bounds
Truncated Actual
Persistence 10-min

Appendix 2 - UWIG 2012 Tucson – WINDataNOW! Presentation

Short-term Forecasting for Glacier Wind Plant

Marty Wilde
WINDataNOW Technology
marty.wilde@windata-inc.com

Patrick Shaw
GL Garrad Hassan
Patrick.Shaw@gl-garradhassan.com

Department of Energy Project

RECOVERY.GOV
TRACK THE MONEY

Funding secured in 2009 by WINData LLC with cost sharing by NaturEner and OSIsoft, LLC

Objectives:

1. Demonstrate value of well-located off-site met sensors in reducing uncertainty in short-term ramp forecasting.
2. Demonstrate use of OSIsoft PI System data infrastructure in next generation met data retrieval.
3. Assess improvement in ramp forecasting skill and determine which forecast methods extract maximum value from the sensor network.

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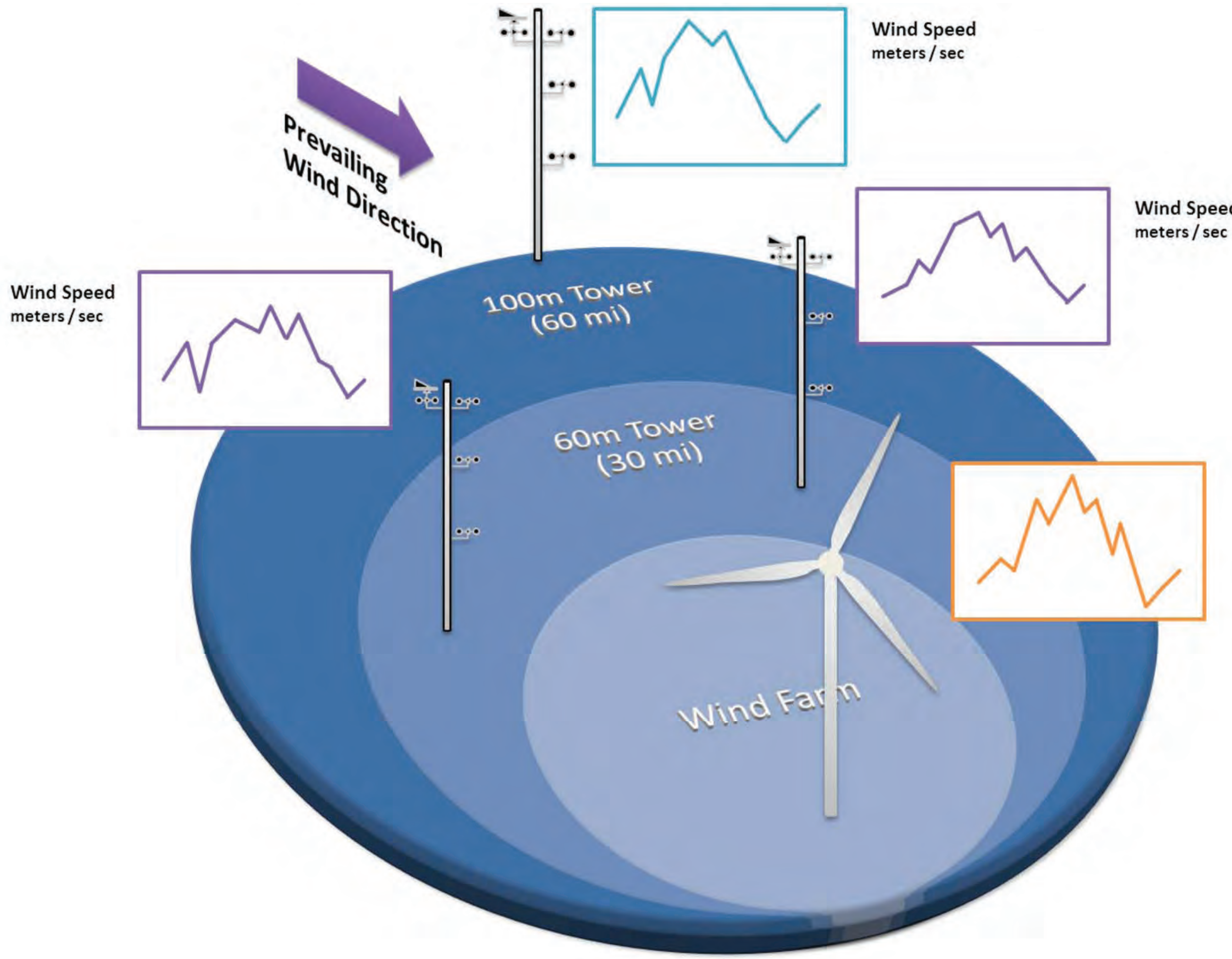
Situational awareness



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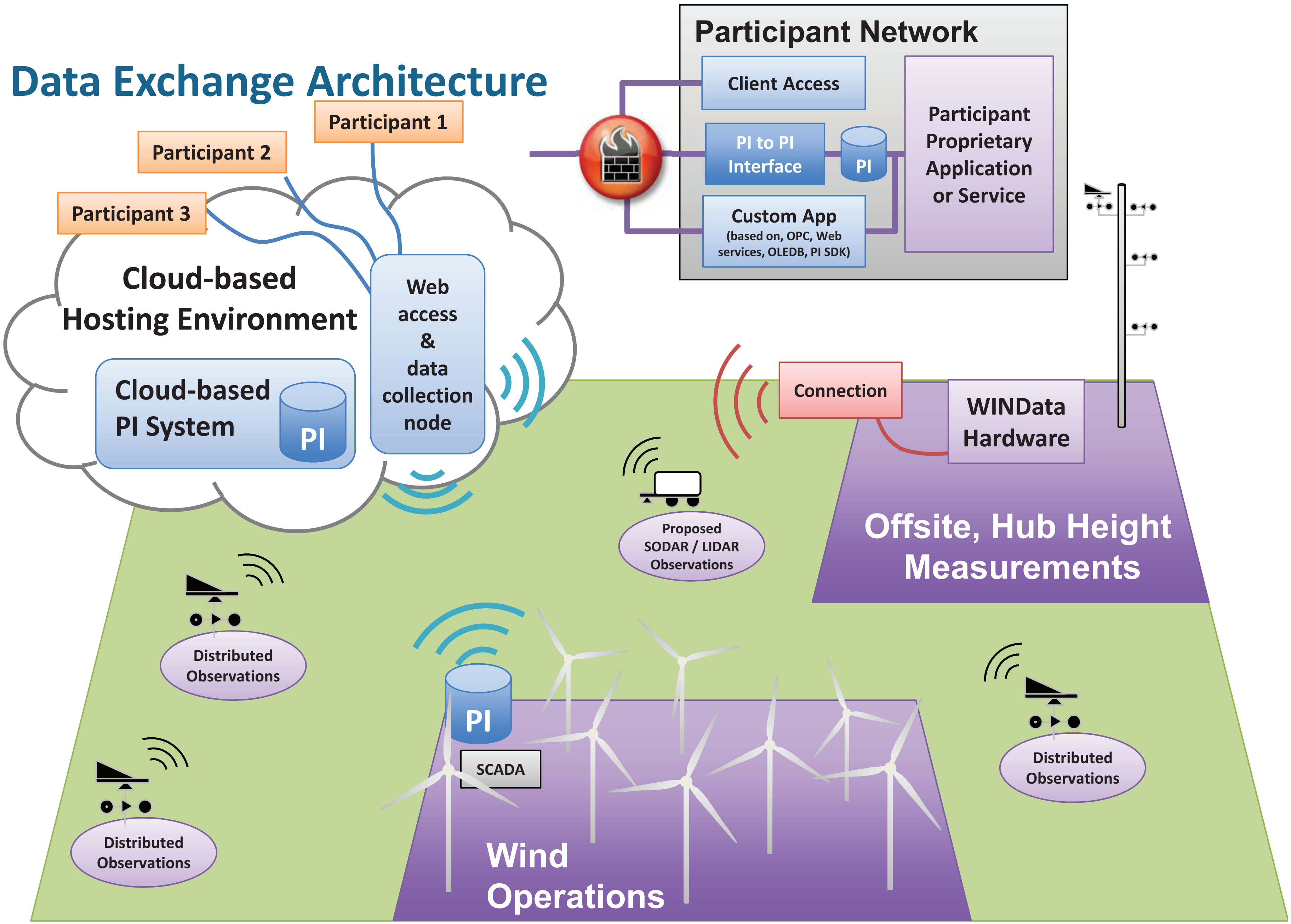

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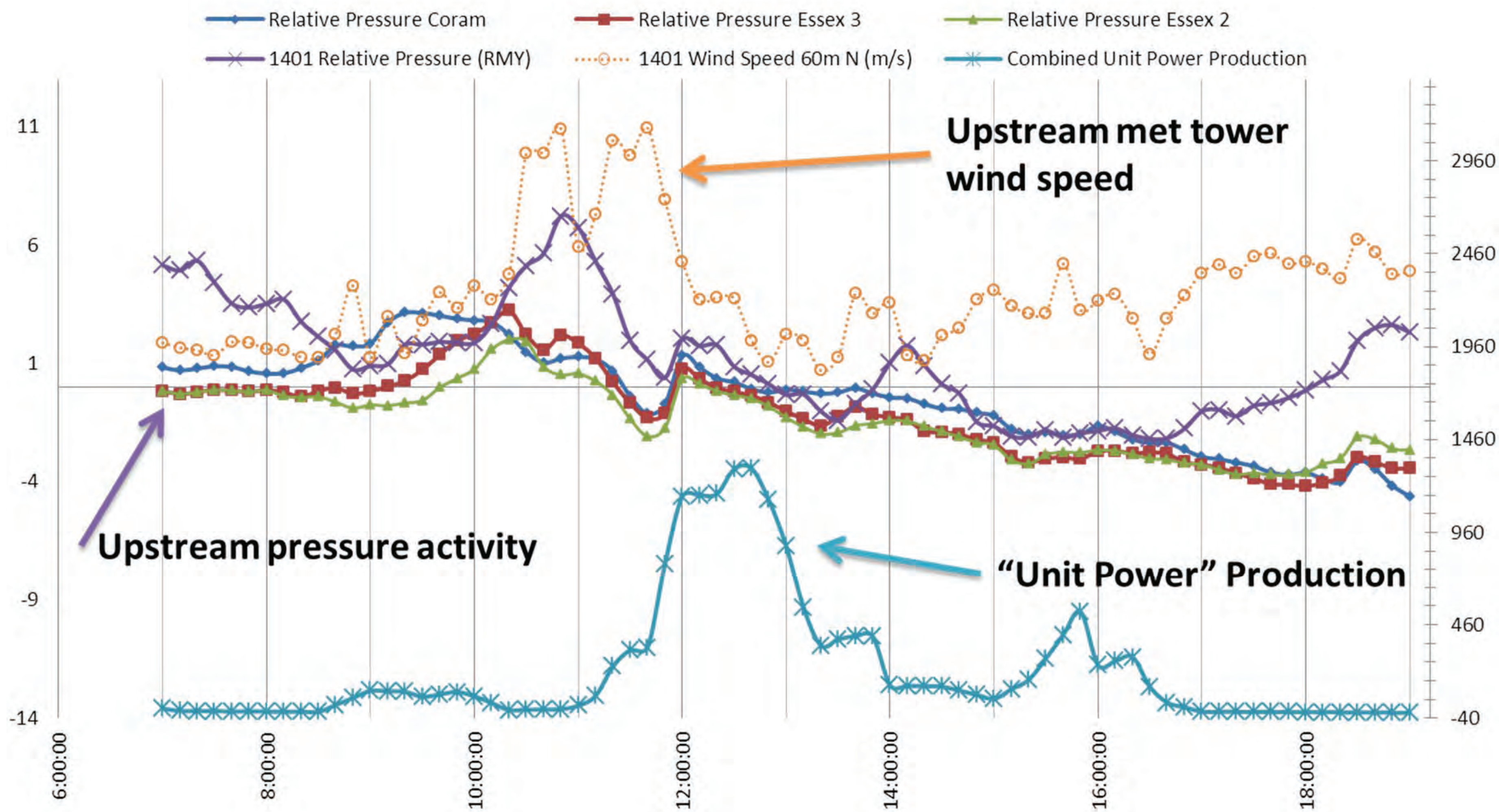
Offsite data predicting power production



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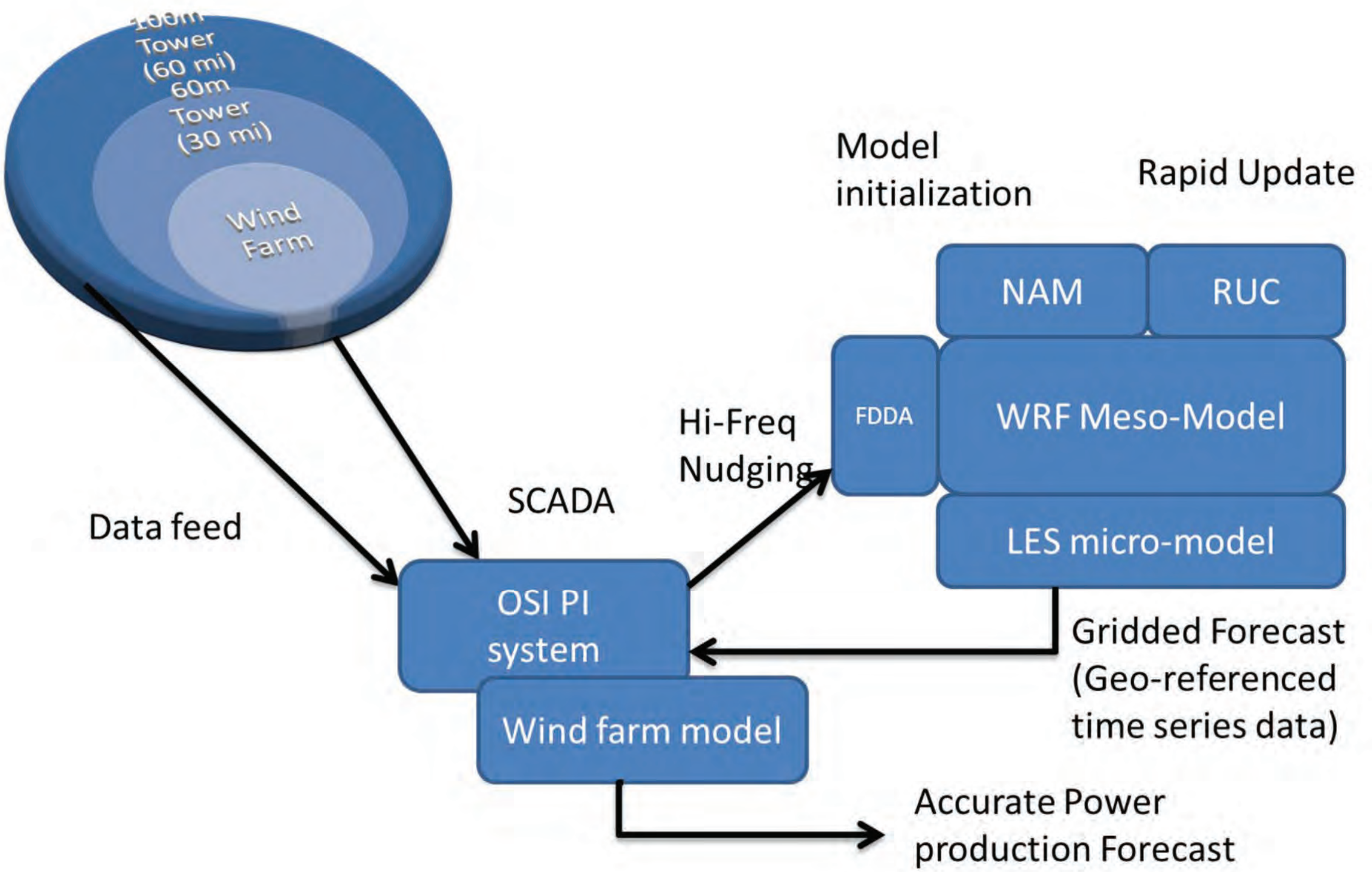
Integration of data network into advanced forecasting models



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Developing advanced forecast models

Data mining provides:

- characteristic atmospheric means and trends
- unique off-site meteorological signatures for certain events
- associated ramp behavior at site

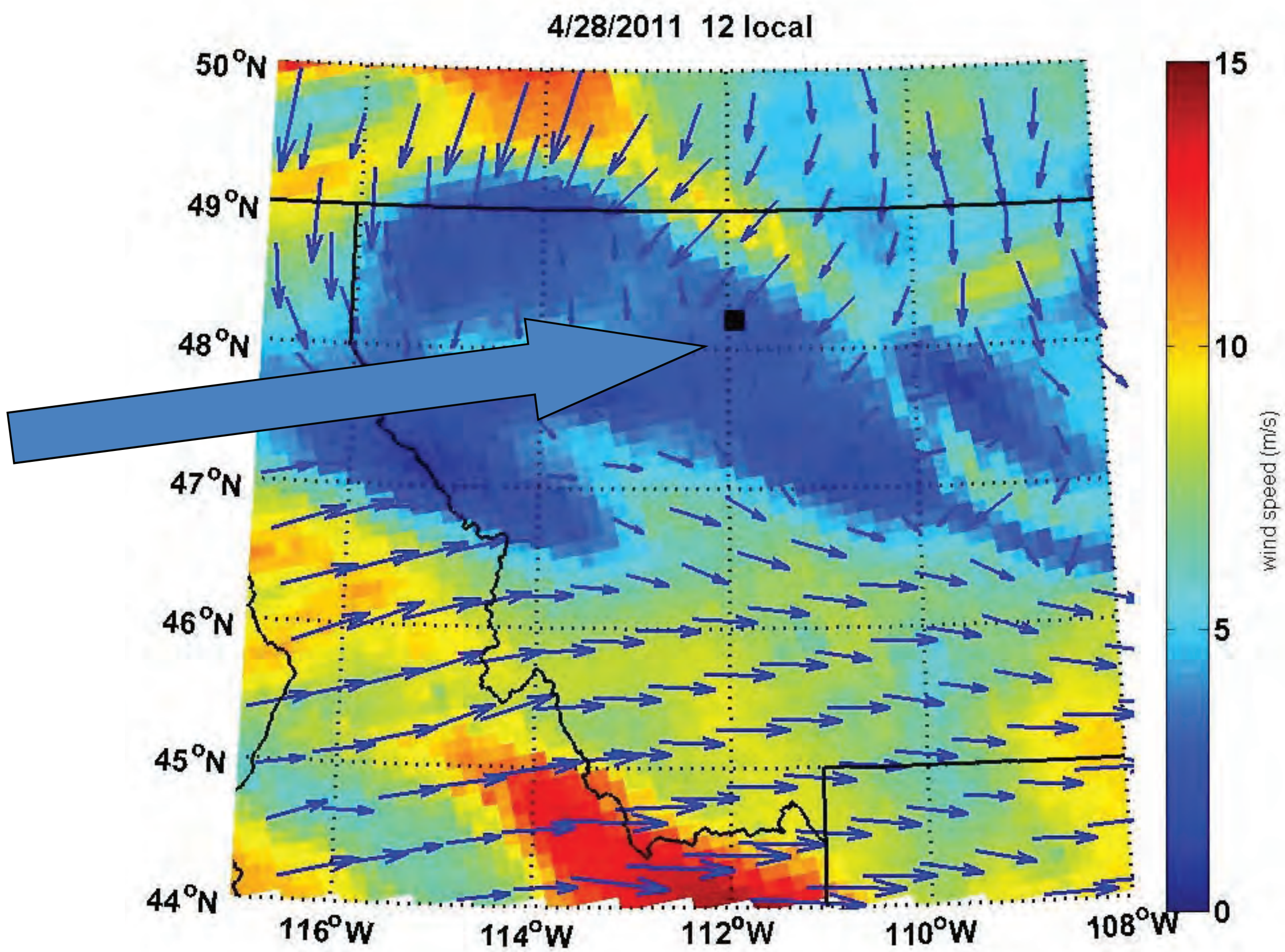
Customized forecast relies on:

- training on historical observations
- most recent off-site observations
- reduction of original data set
- real-time rapid pattern matching

Observations provide three types of forecasts:

- Nudged NWP
- Pattern matching of historical data
- Persistence of on-site data

NWP for Captured Ramp



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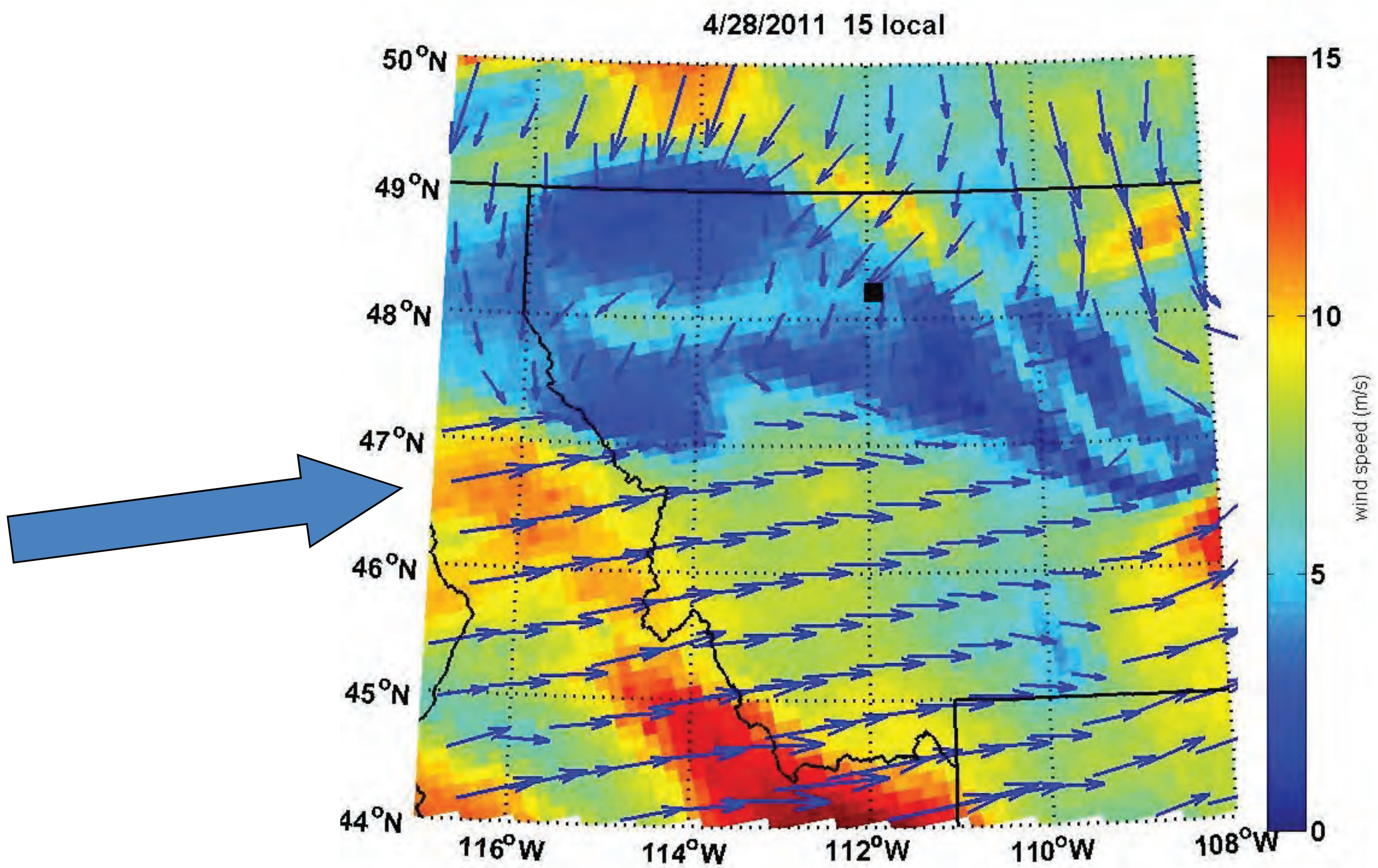
NWP for Captured Ramp



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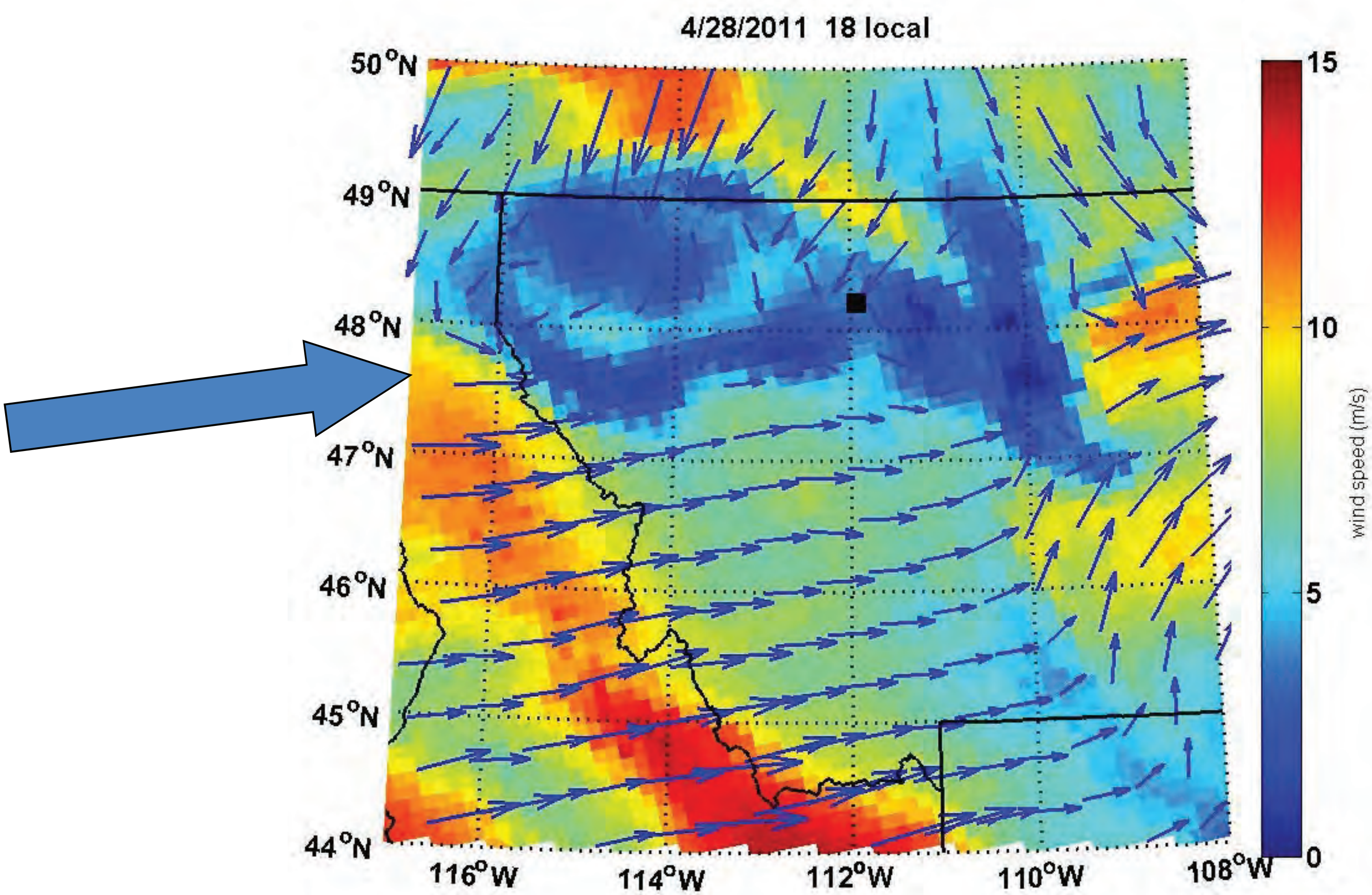
NWP for Captured Ramp



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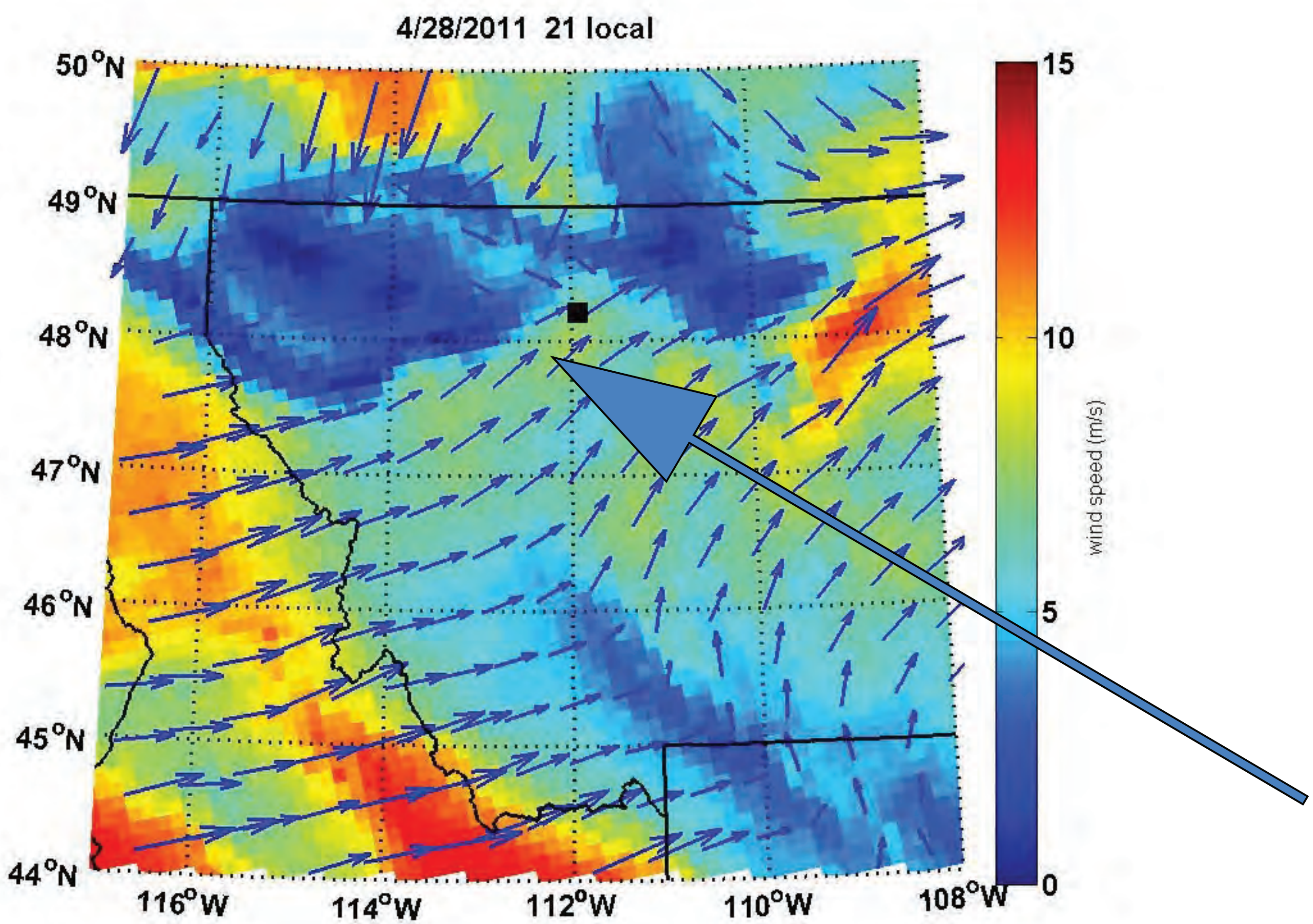
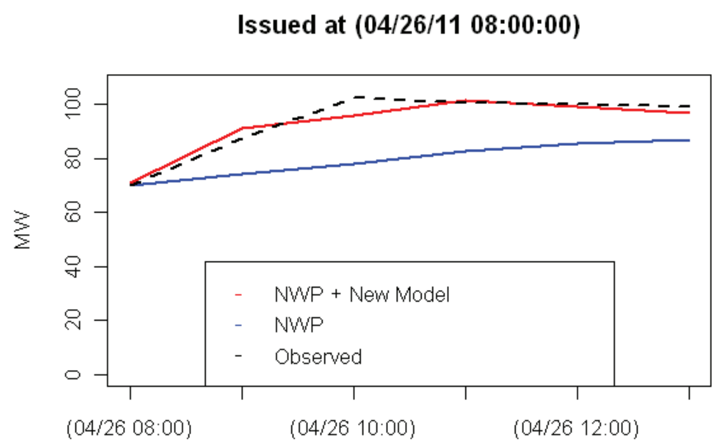
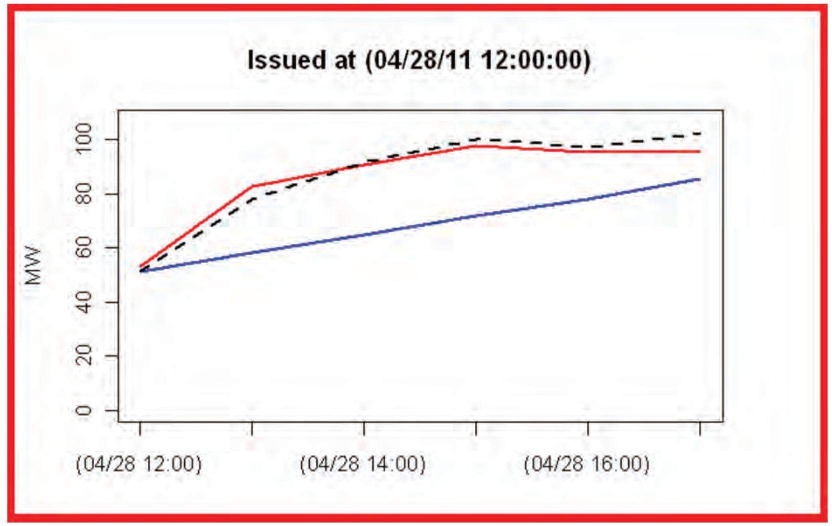
NWP for Captured Ramp

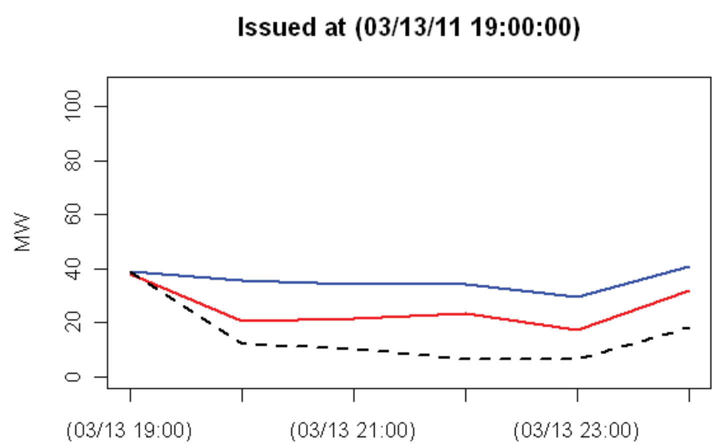


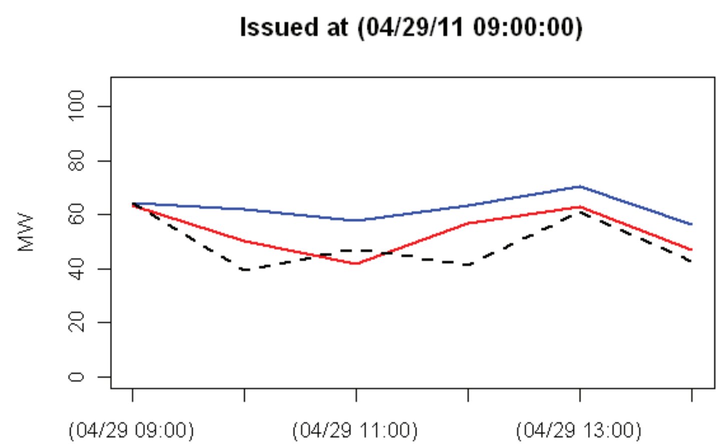
Captured Ramps

Ramp Definition: +/- 15% change in production over previous 3 hours, and forecast within 15% of capacity to observation









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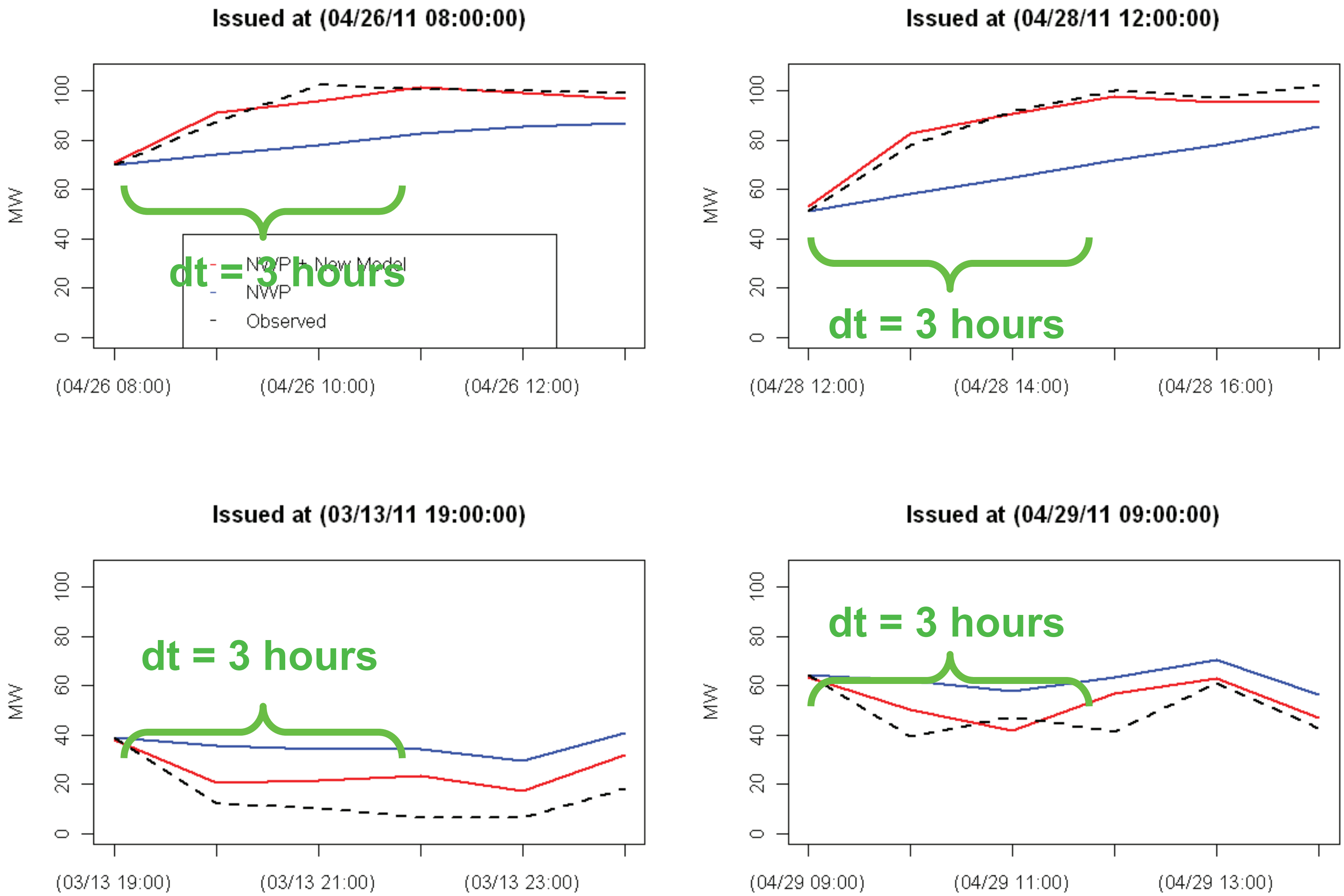
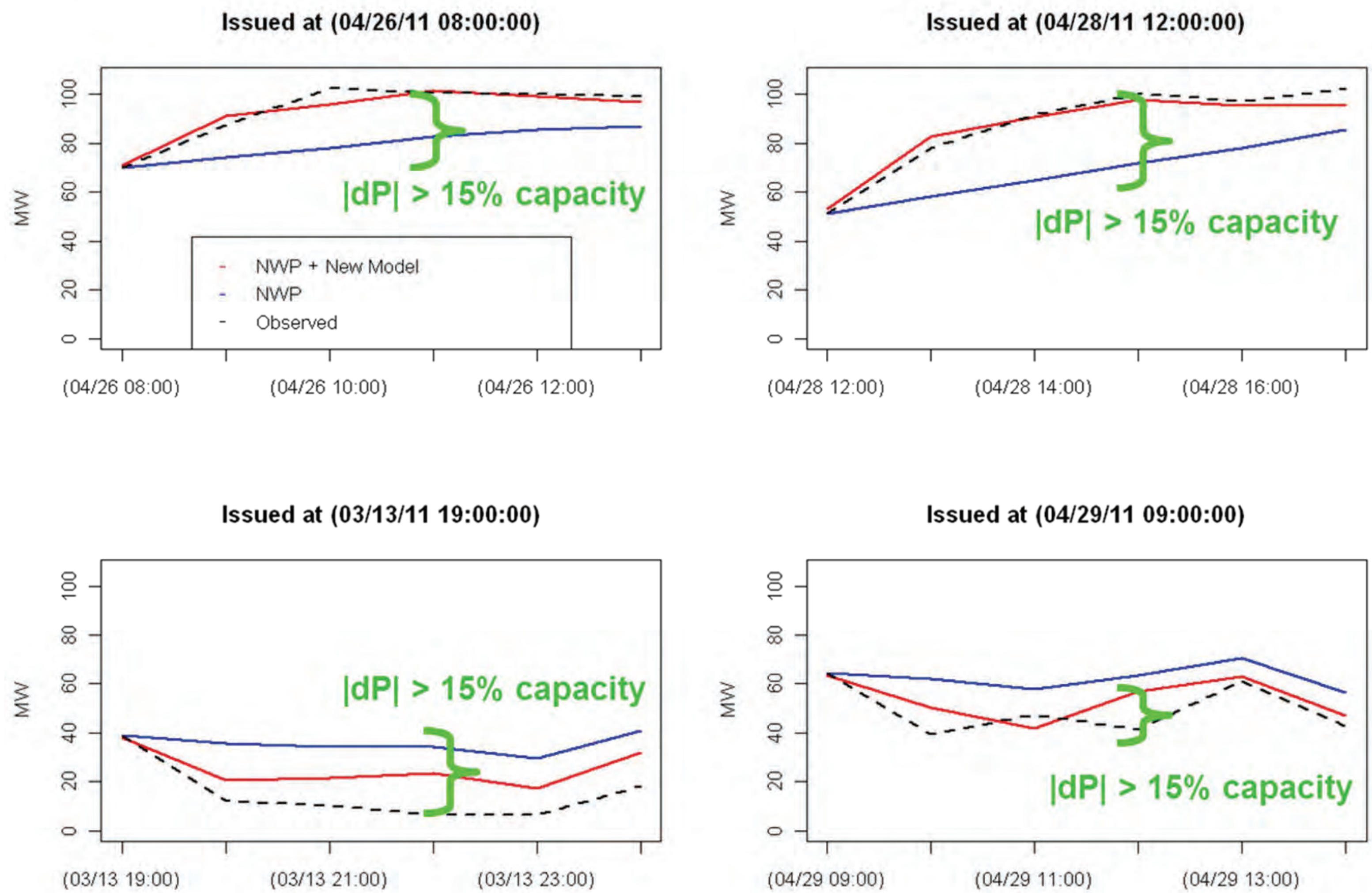
GL

Captured Ramps



Captured Ramps



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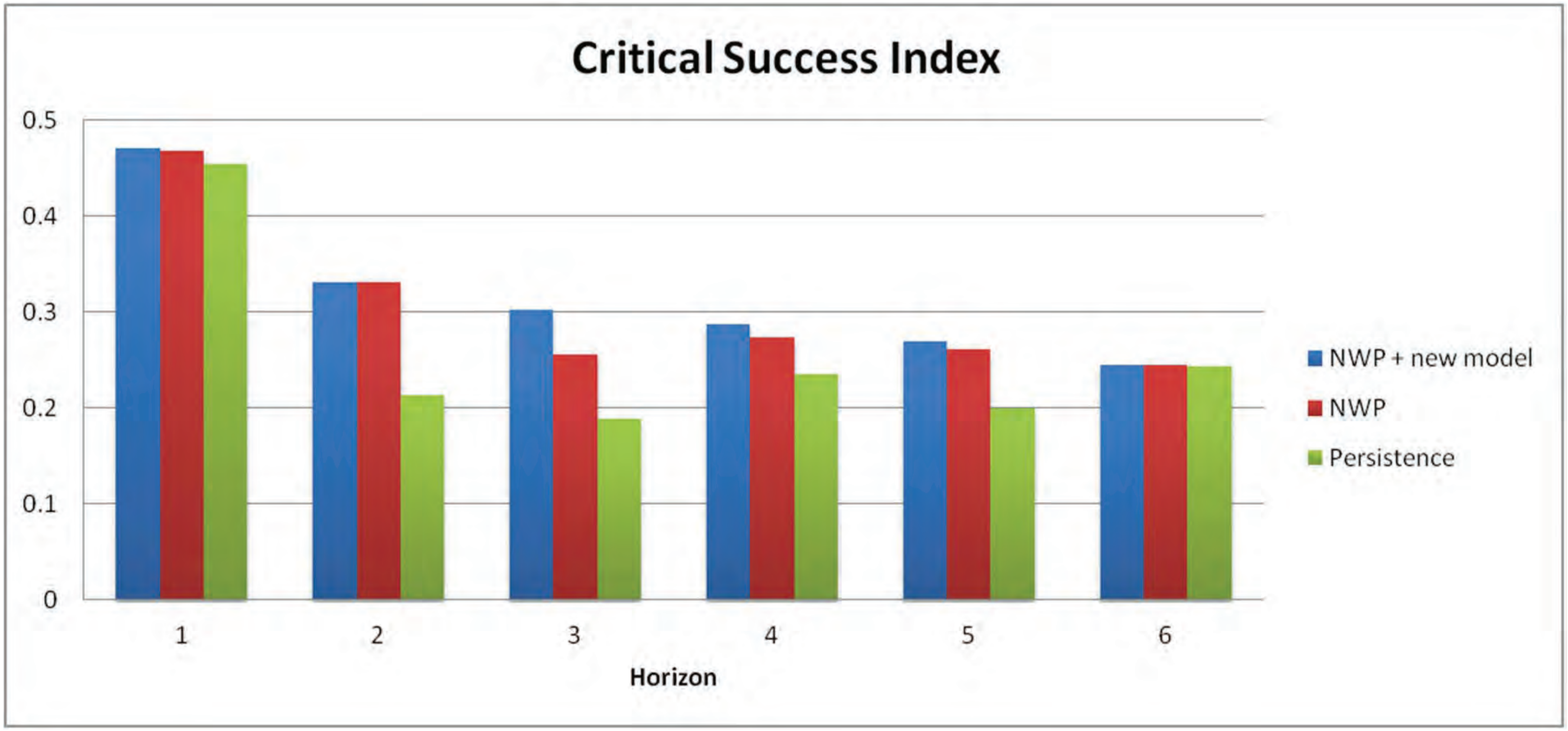
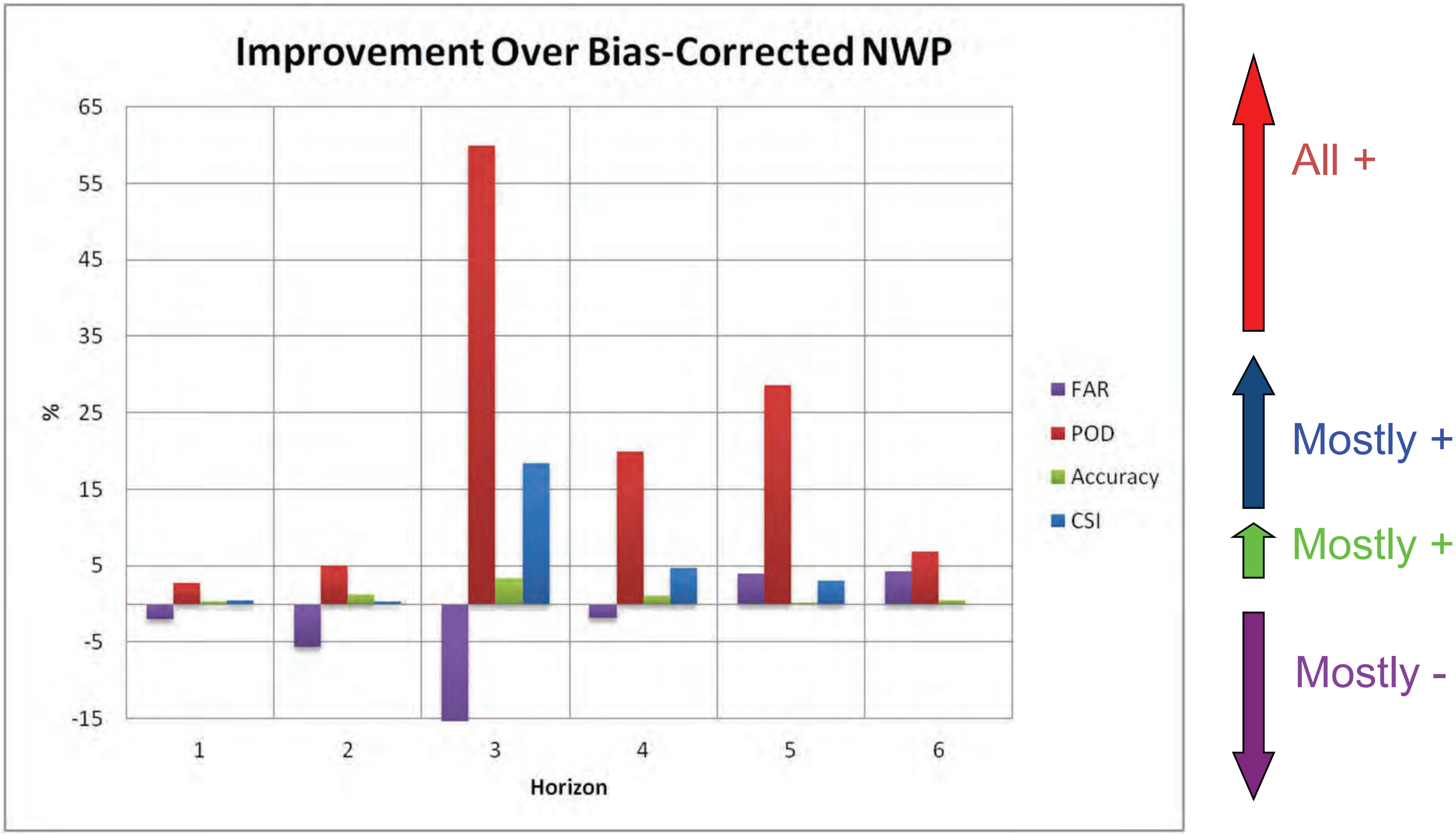
Results: CSI

Metrics show improvement over persistence and bias-corrected NWP with addition of pattern matching and nudging



Results: other metrics

Other metrics show improvement over bias-corrected NWP with addition of NWP nudging and pattern matching augmentation



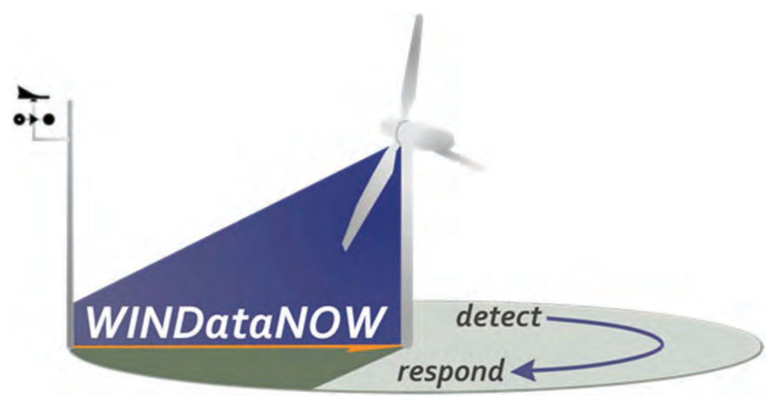
Conclusions and next steps

Conclusions:

- Offsite measurements can add value to bias-corrected NWP and persistence

Coming attractions:

- Automation of this technology in operational settings for expanded set of seasons and conditions
- Use of additional off-site data sets and improved NWP configurations
- Deployment at different sites and geographic settings



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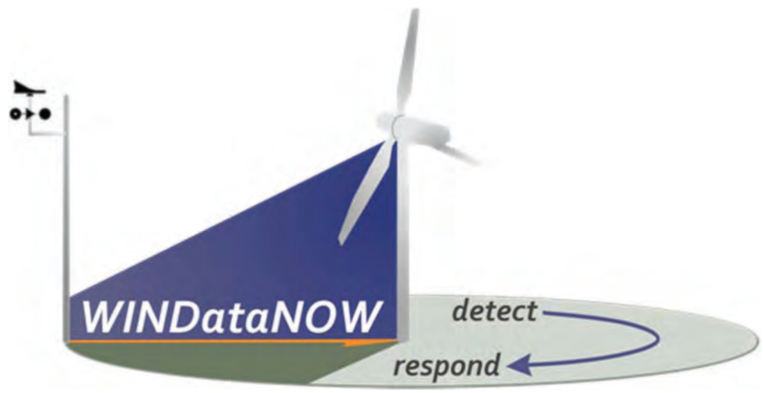
Bonus Material



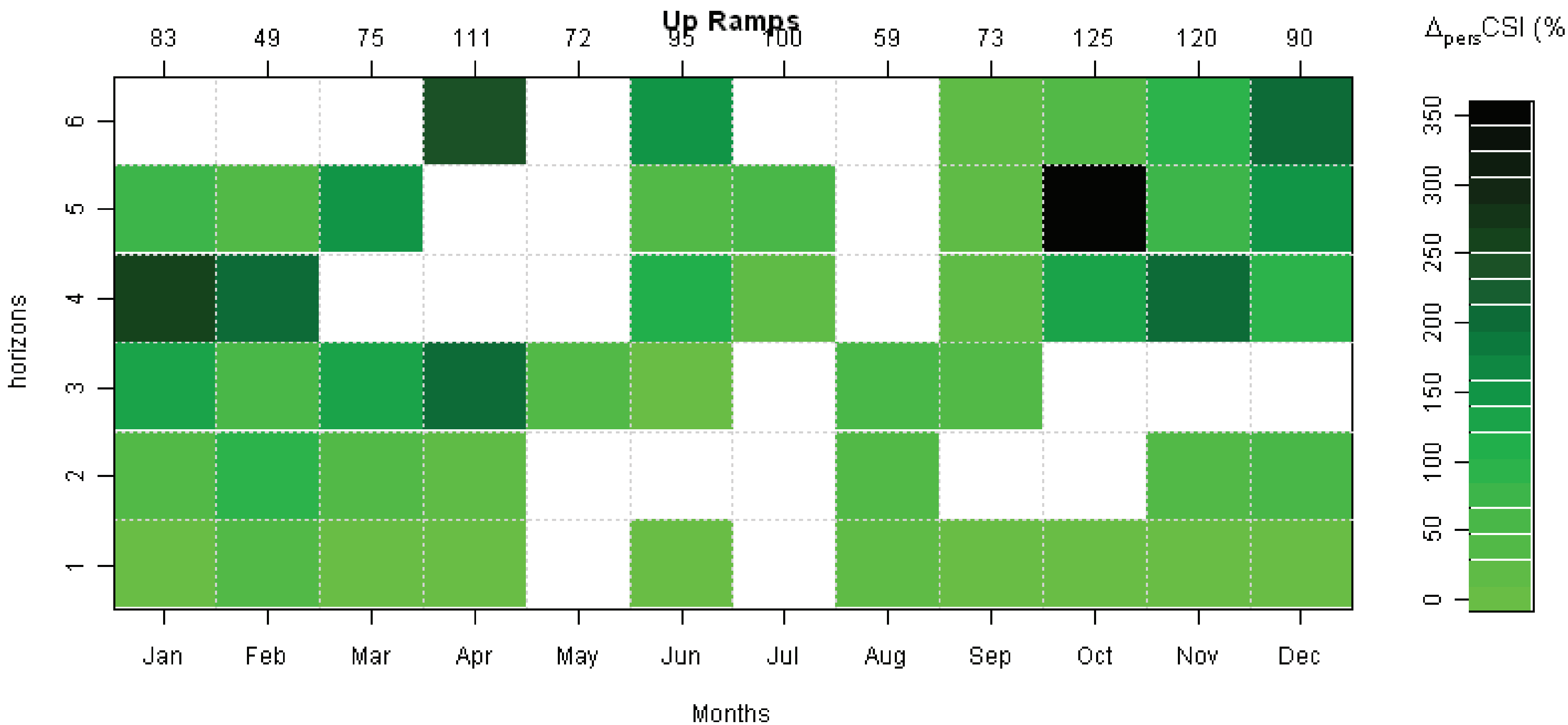
Bonus Material: Hind-casting results

Impact of observations for a given metric:

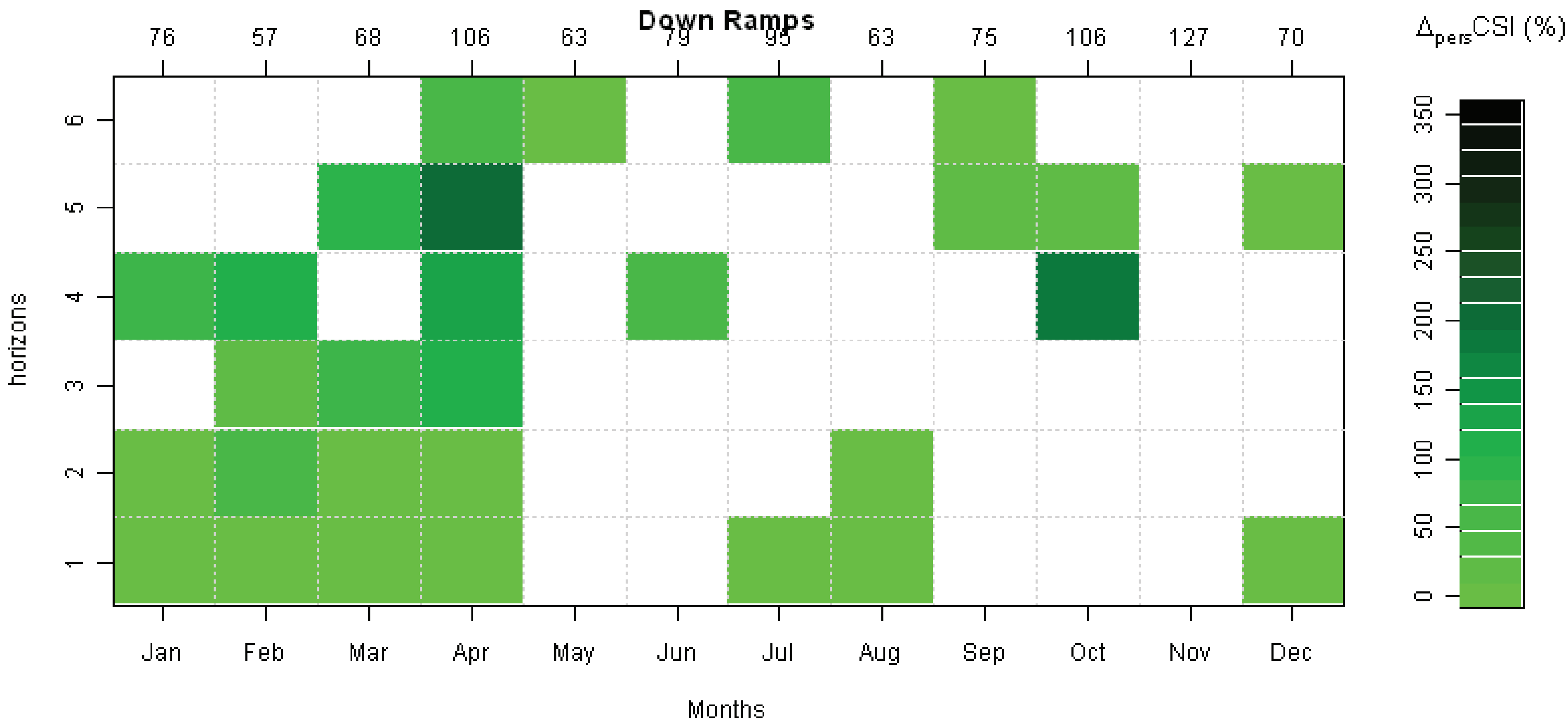
$$\Delta_{pers}(\%) = (\text{New Model} - \text{Persistence})/\text{Persistence}$$

$$\Delta_{raw}(\%) = (\text{New Model} - \text{Raw NWP})/\text{Raw NWP}$$

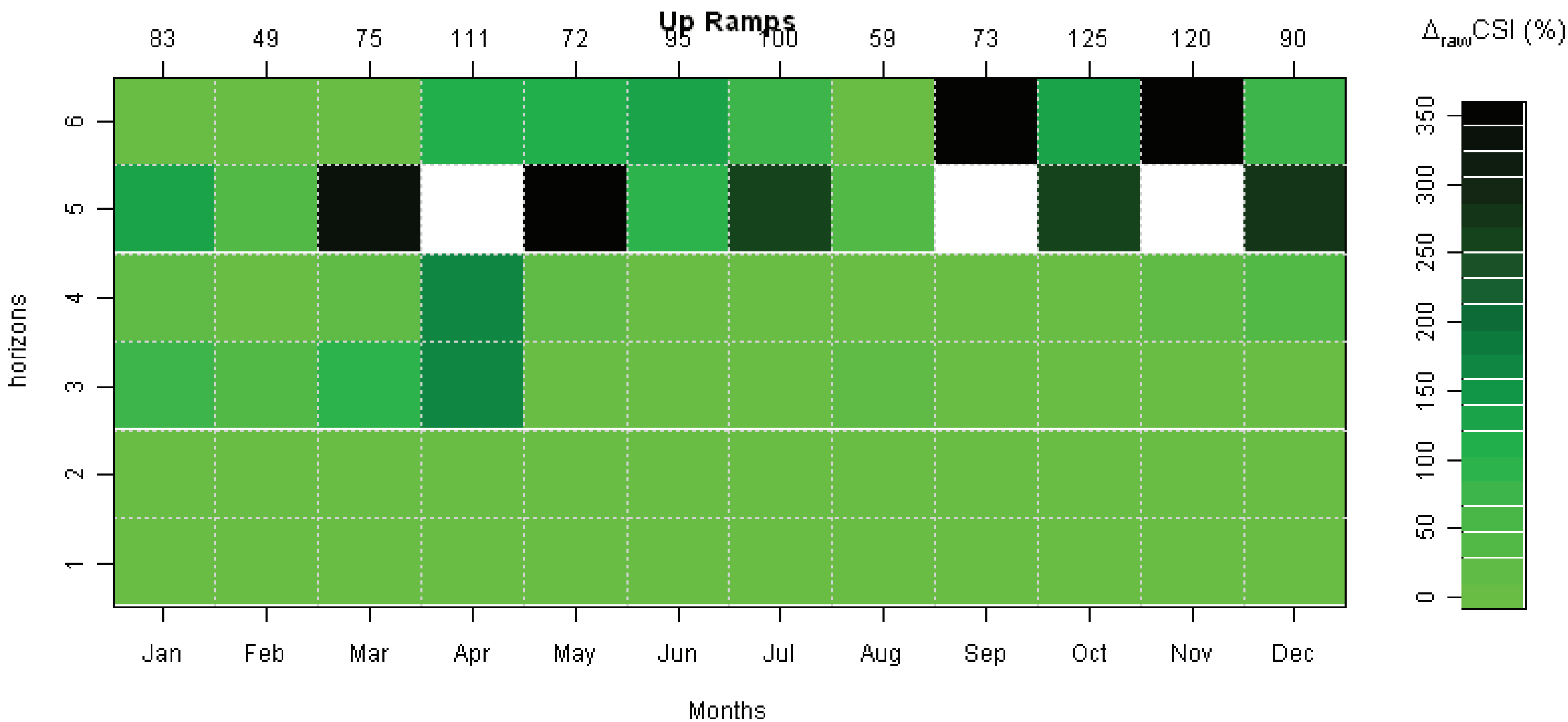
Bonus Material: Improvement in up ramp CSI over persistence



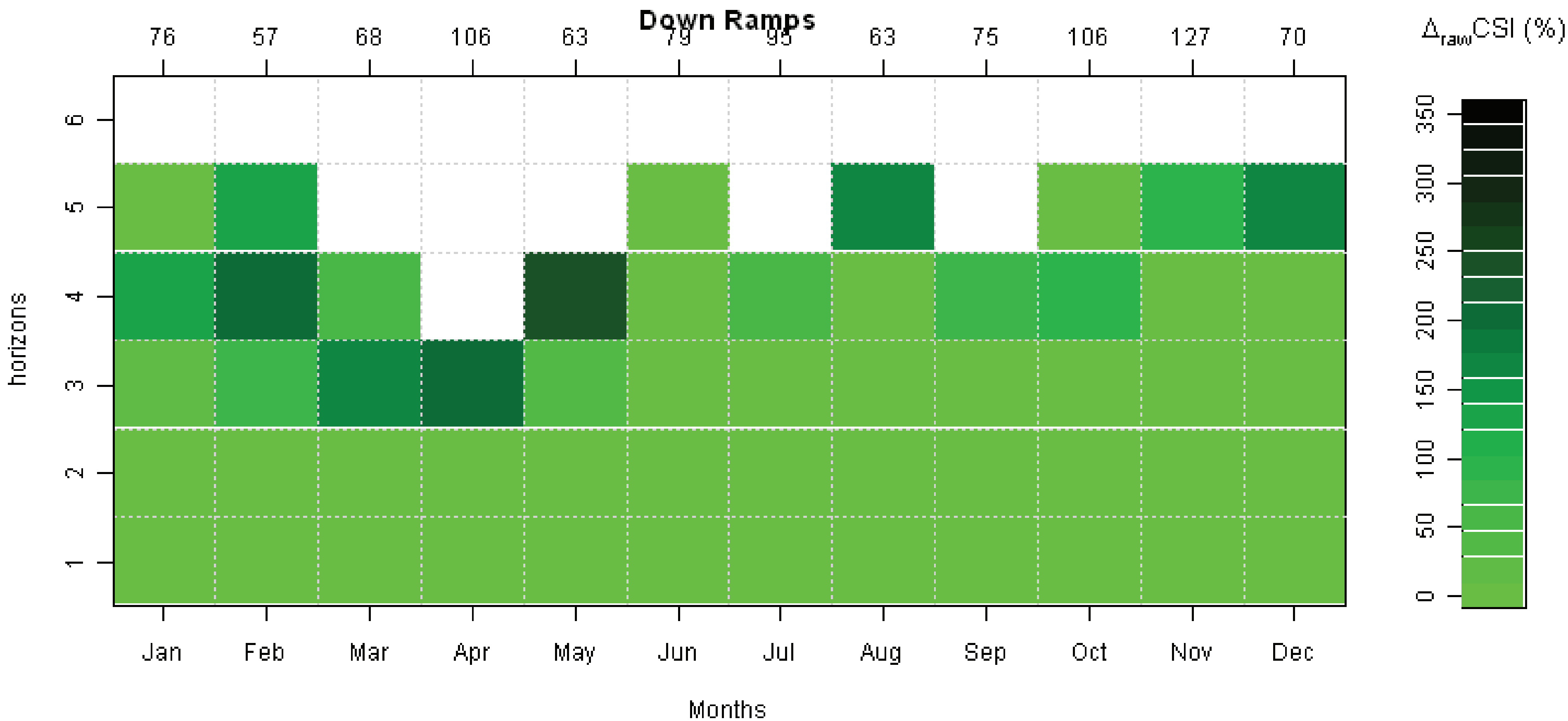
Bonus Material: Improvement in down ramp CSI over persistence



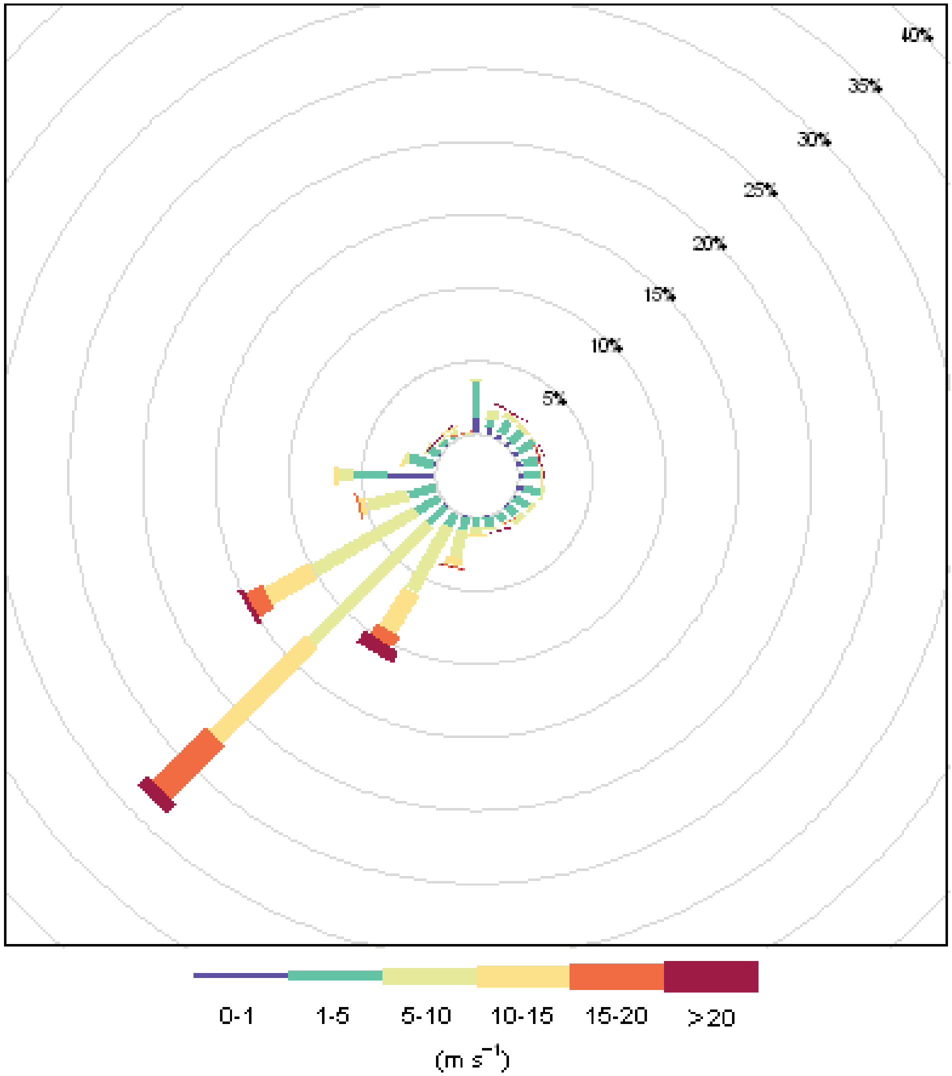
Bonus Material: Improvement in up ramp CSI over bias-corrected NWP



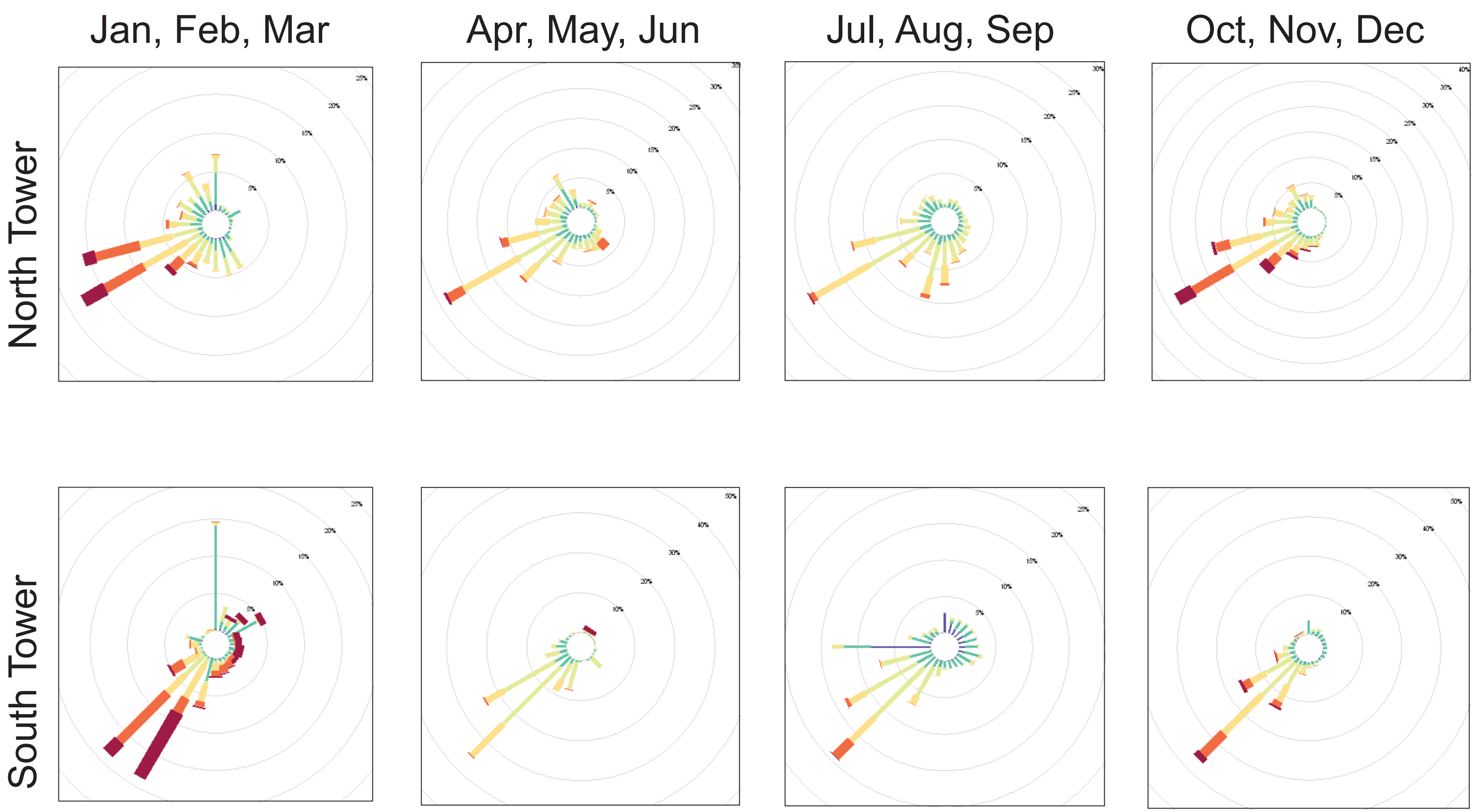
Bonus Material: Improvement in down ramp CSI over bias-corrected NWP



Bonus Material: Annual Wind Rose (South Tower)



Bonus Material: Sensitivity to Direction



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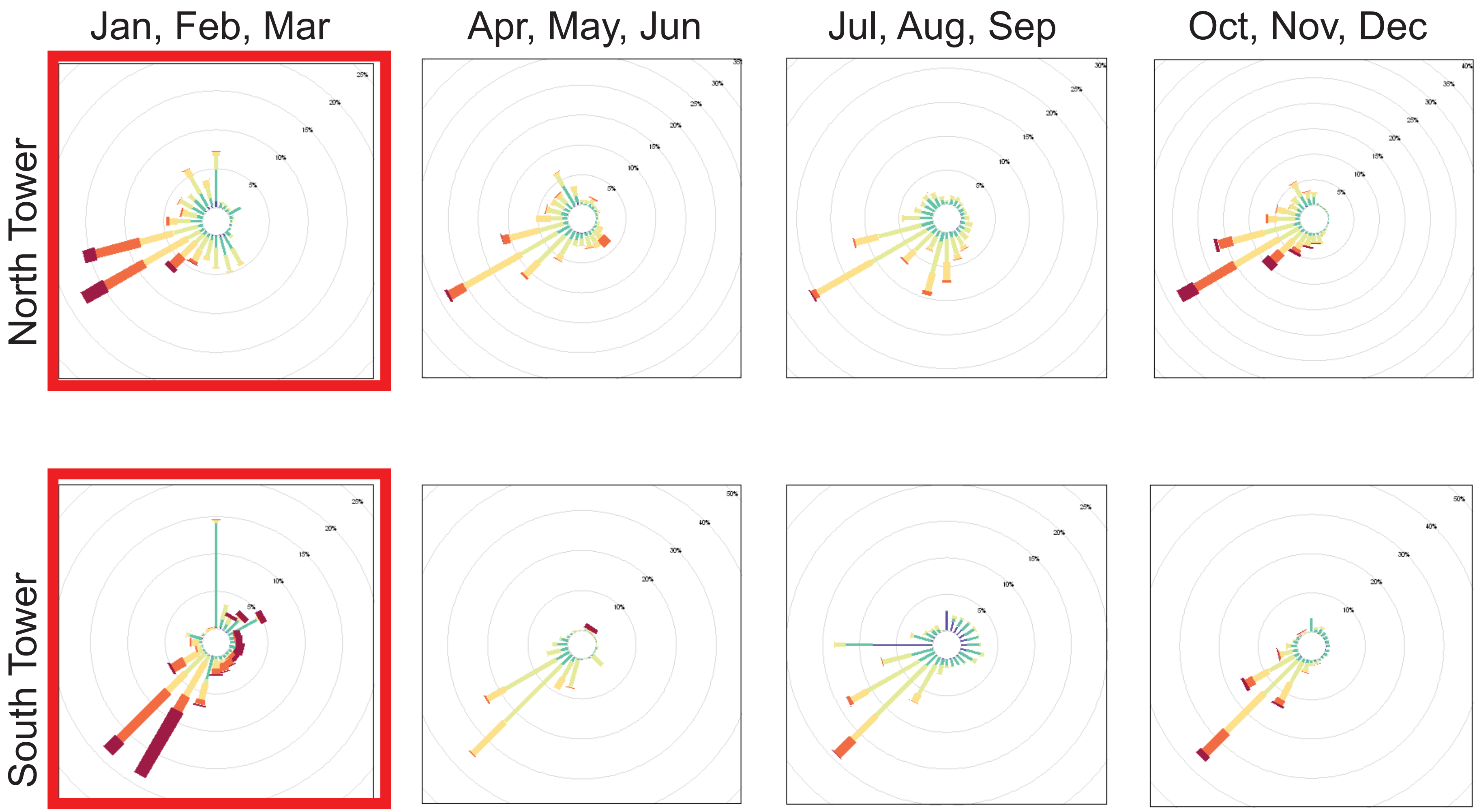
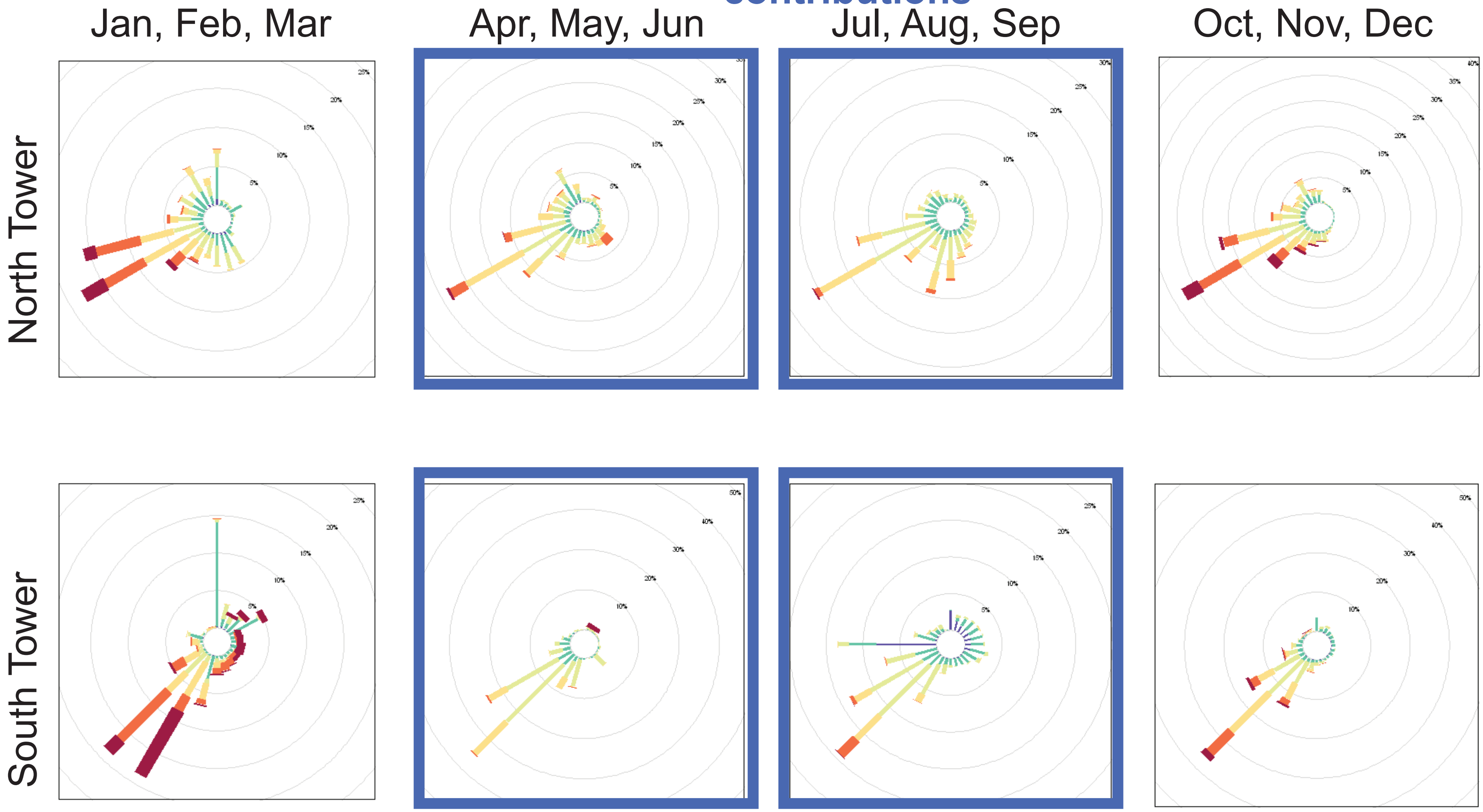
Bonus Material: Sensitivity to Direction

Most Improvement in ramps at early horizons → stronger winds, northerly contribution



Bonus Material: Sensitivity to Direction

Little improvement as early horizons → weaker winds, little northerly components, more easterly contributions



Appendix 3 –OSIsoft User Conference 2012 WINDataNOW! Presentation

OSIsoft.

USERS CONFERENCE 2012

The Power of Data

Marty and Gregg's Big "Montana-Wind" Adventure

(using the PI System to help with anticipating ramp events at the Glacier Wind Plant)

Presented by

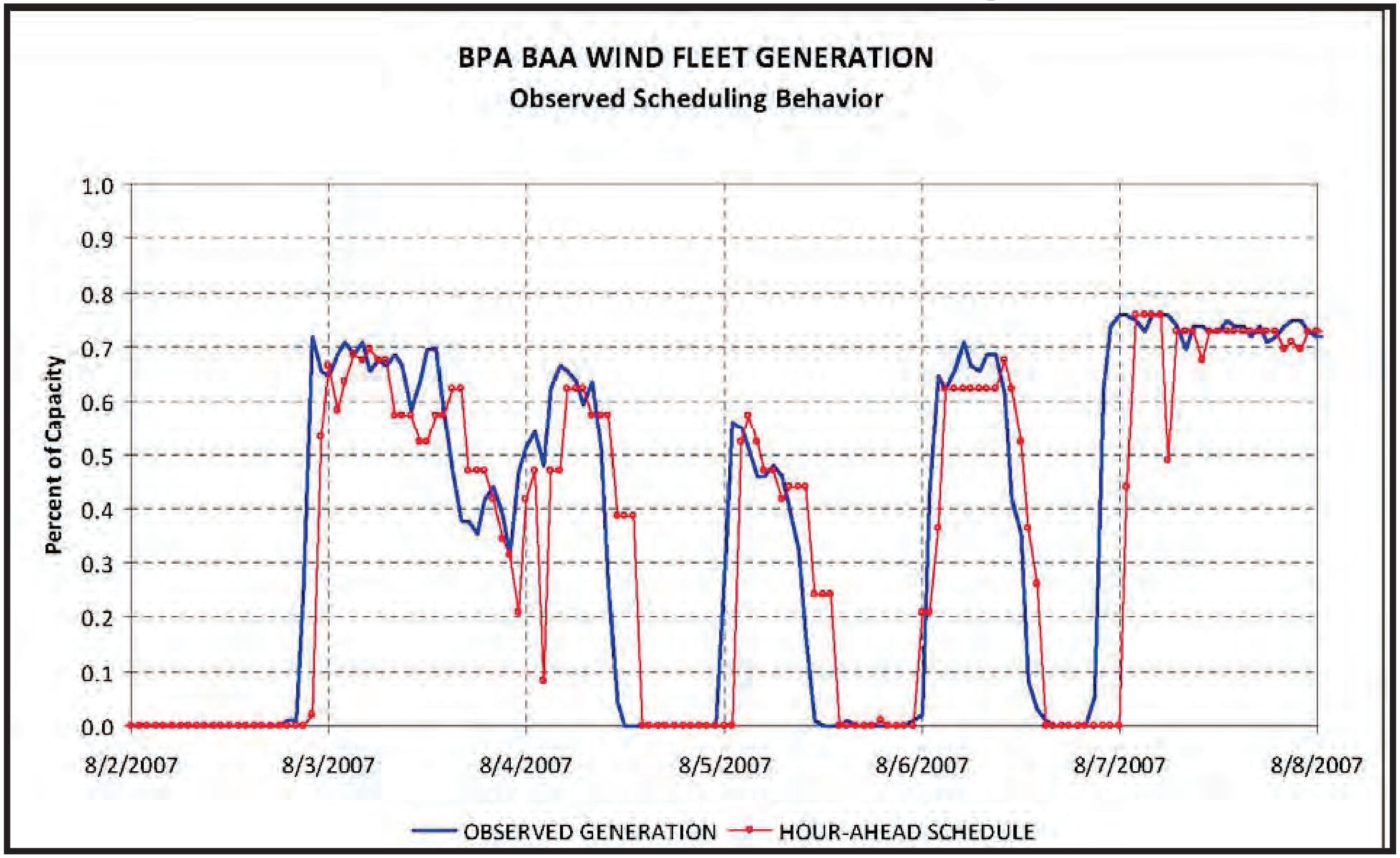
Marty Wilde and
Gregg Le Blanc
WINDataNOW Technologies LLC

The Problem

Forecast Uncertainty at Glacier Wind Plant

Glacier Wind Plant – “Climate”

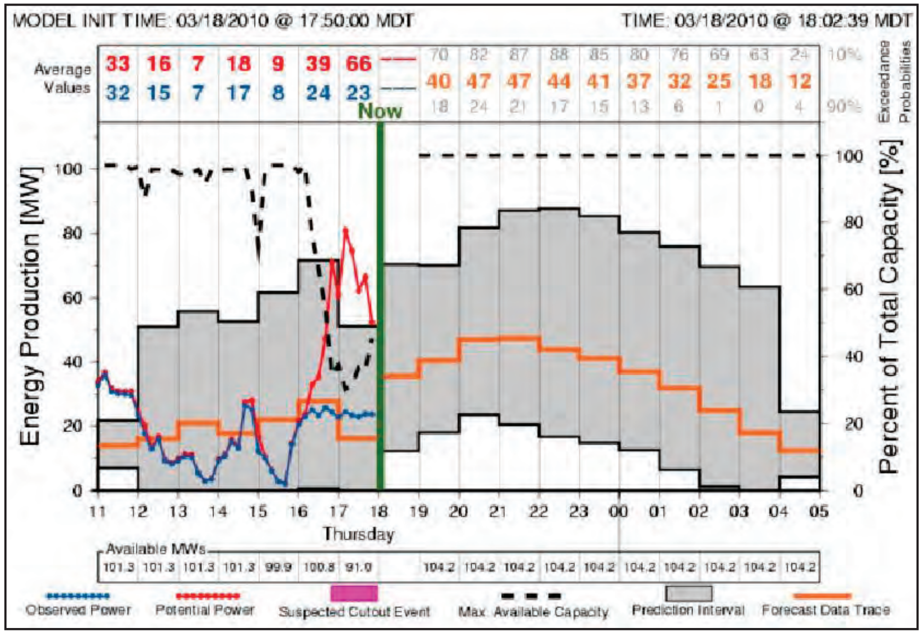
Variable Generation Scheduling

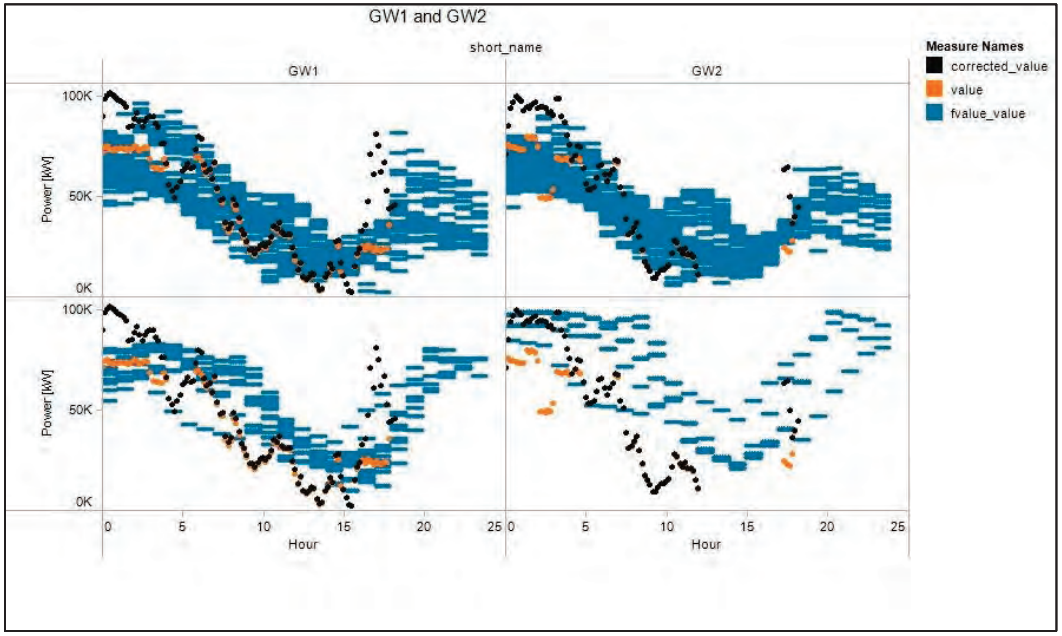


Wind Forecasting Challenge

- GW schedules output 70-min ahead of the production hour.
- Economic benefits from accuracy improvement in forecasting large, rapid changes in generation – **"Ramps".**
- Better forecast facilitates more energy integration into power system.

Ramp Forecasts used for Power Scheduling



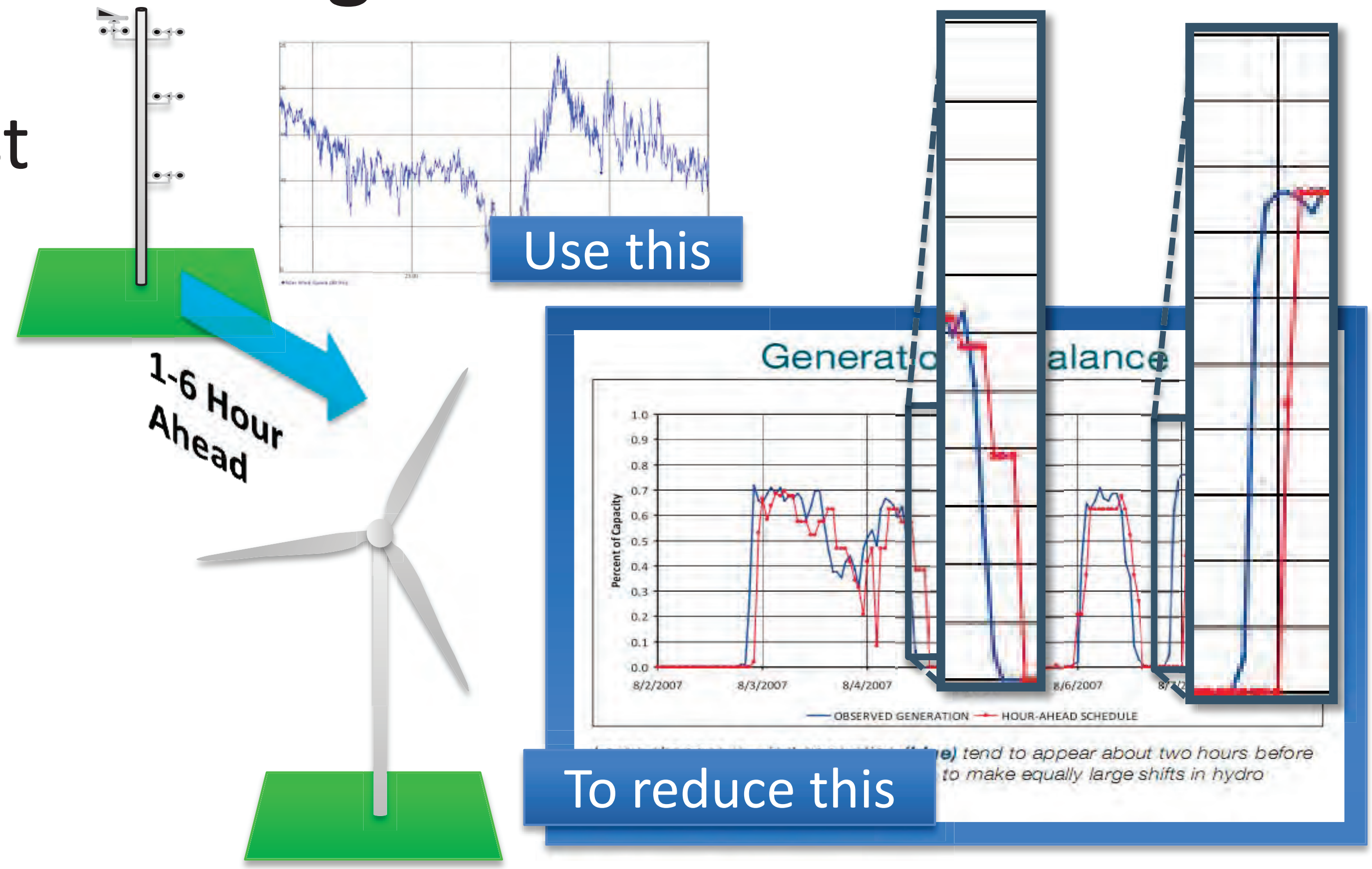


The Idea

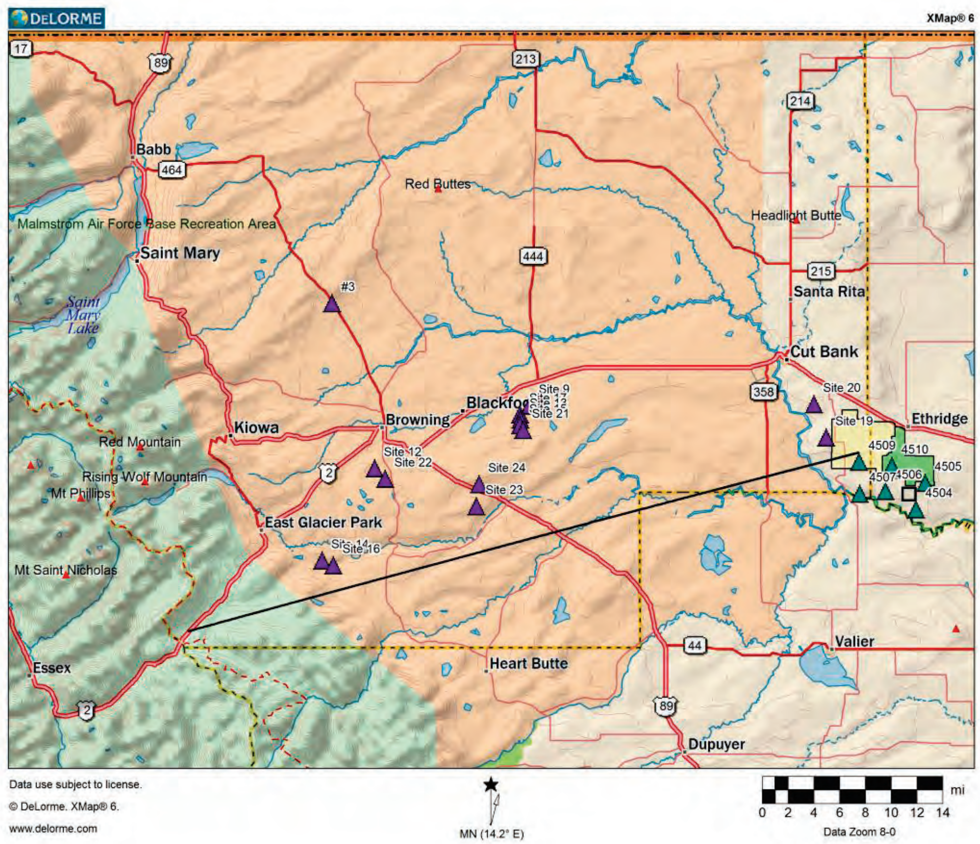
Better Data from Strategic Locations

Better Data from Strategic Locations

- Decrease forecast error around ramp events
- Operate less conservatively

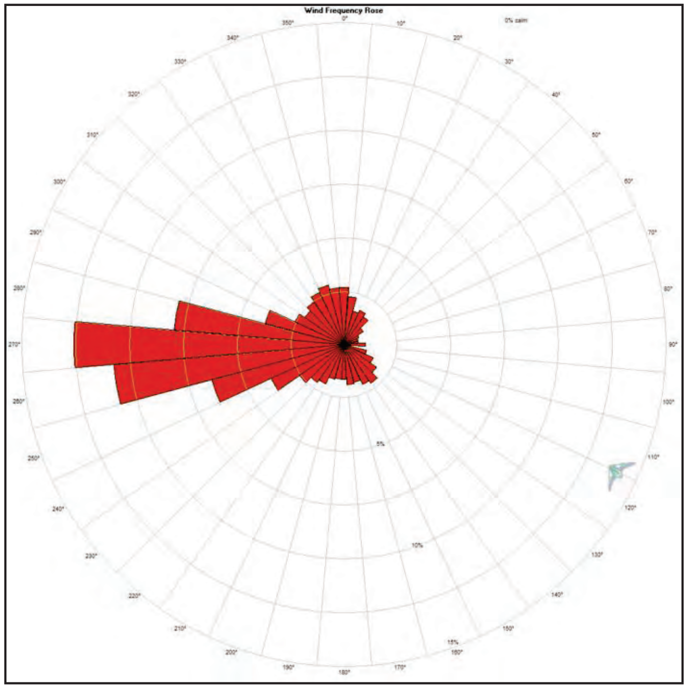


Historical Met data Locations

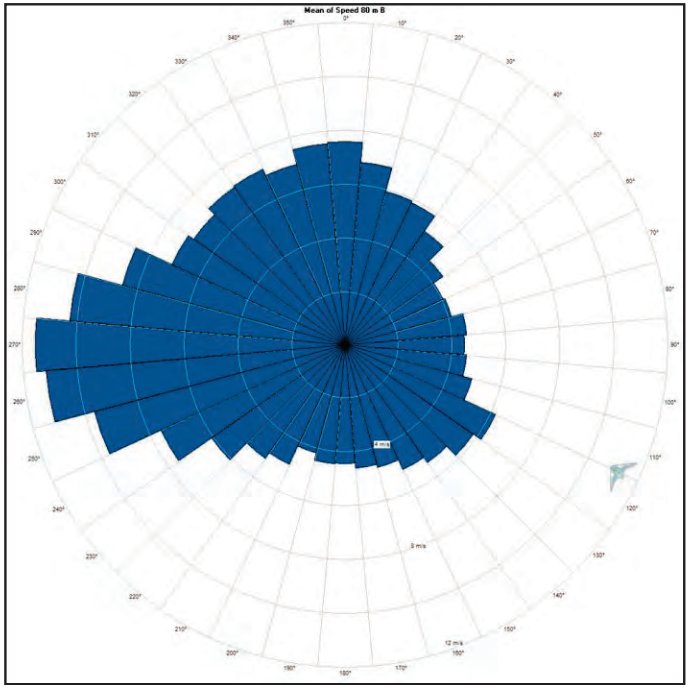


Met Data From Region

Wind **Frequency** by Direction



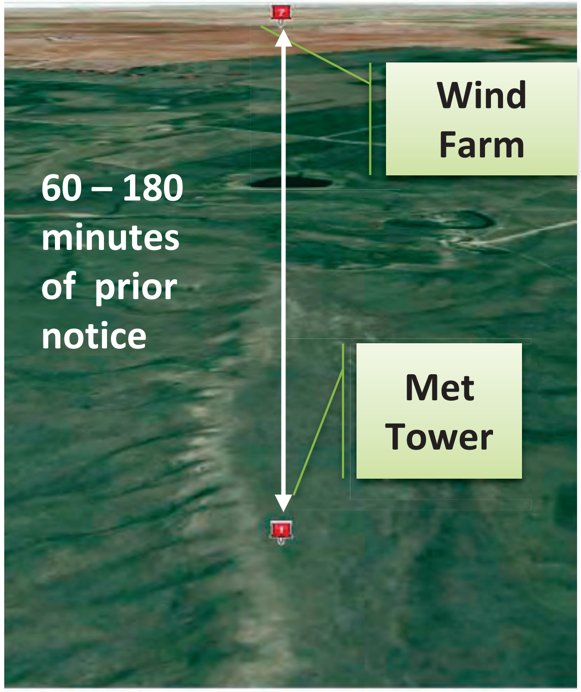
Mean Wind **Speed** by Direction



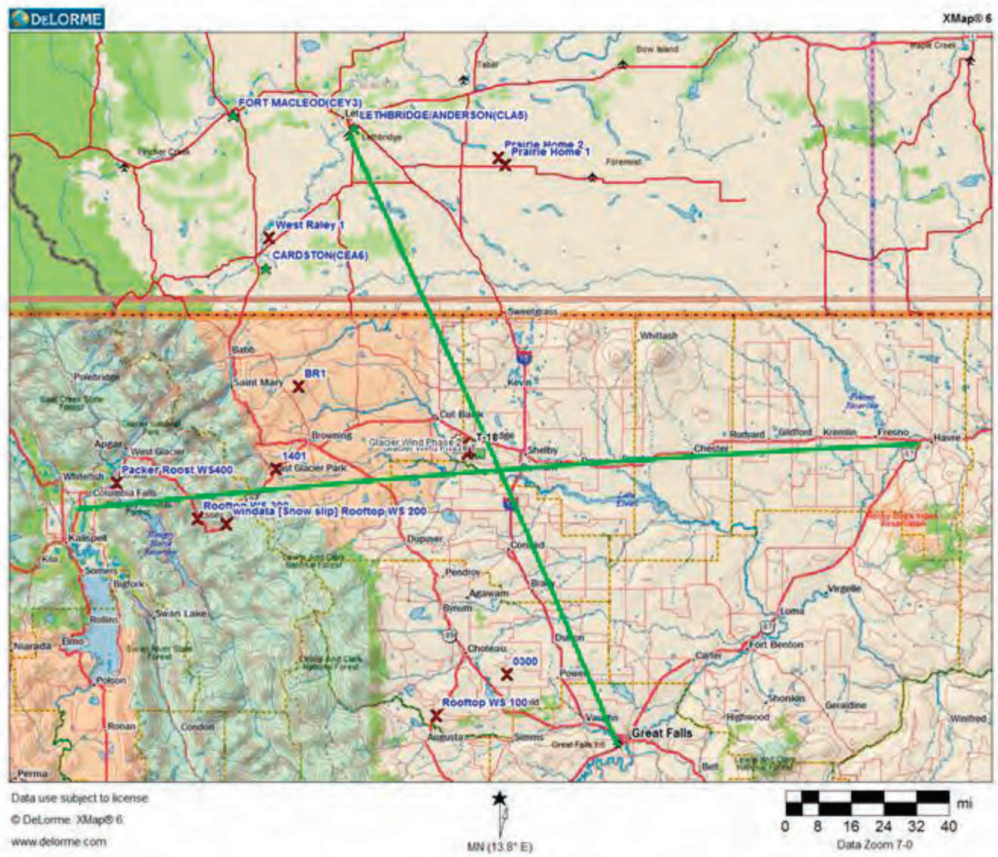
Theory and Methodology

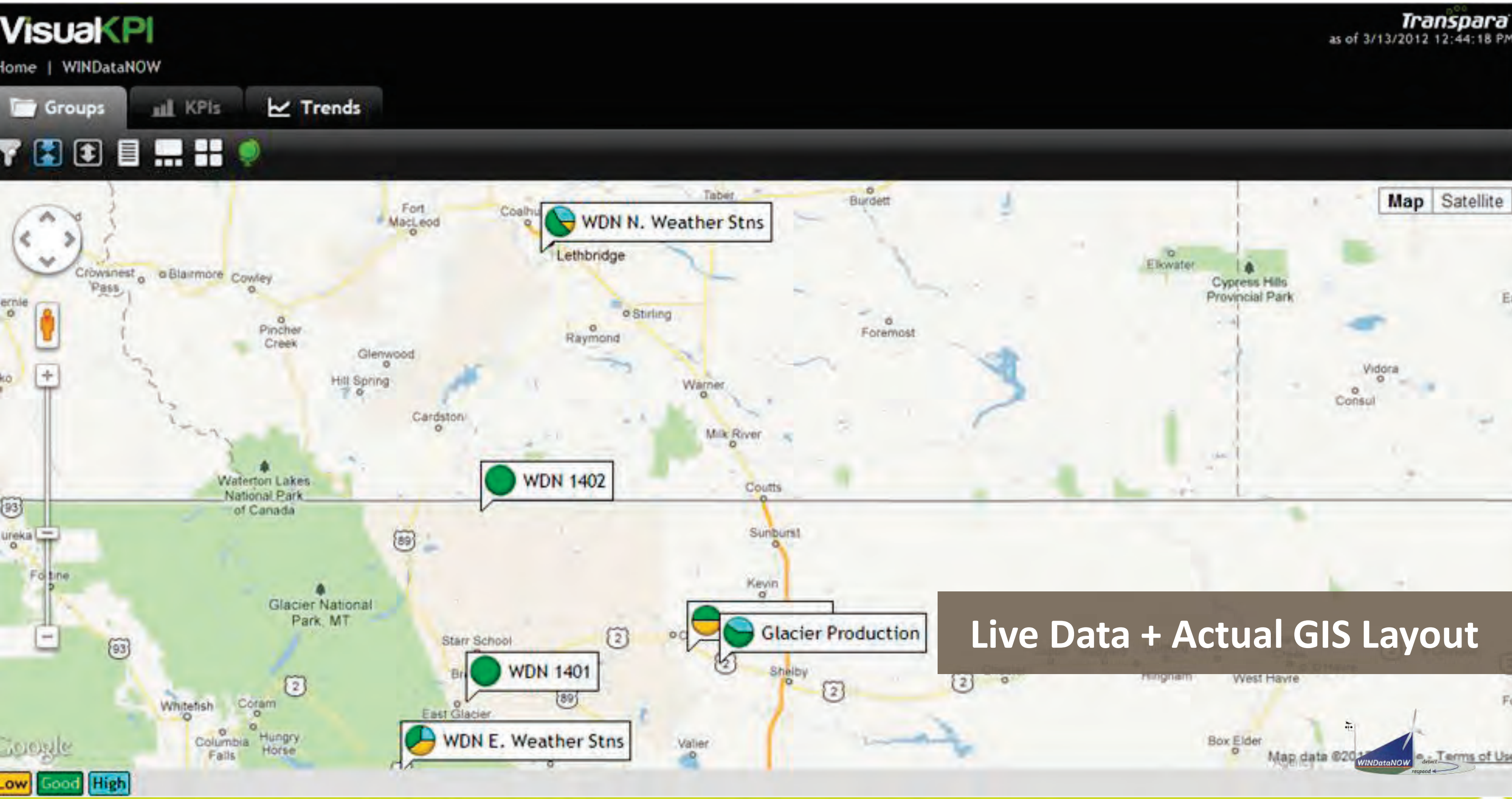
- **Sensors located strategically**
- **Deploy new logger technology**
- **High fidelity data near real-time**
- **Use data to detect anomalies for better situational awareness and study of patterns**

"Offsite" Locations



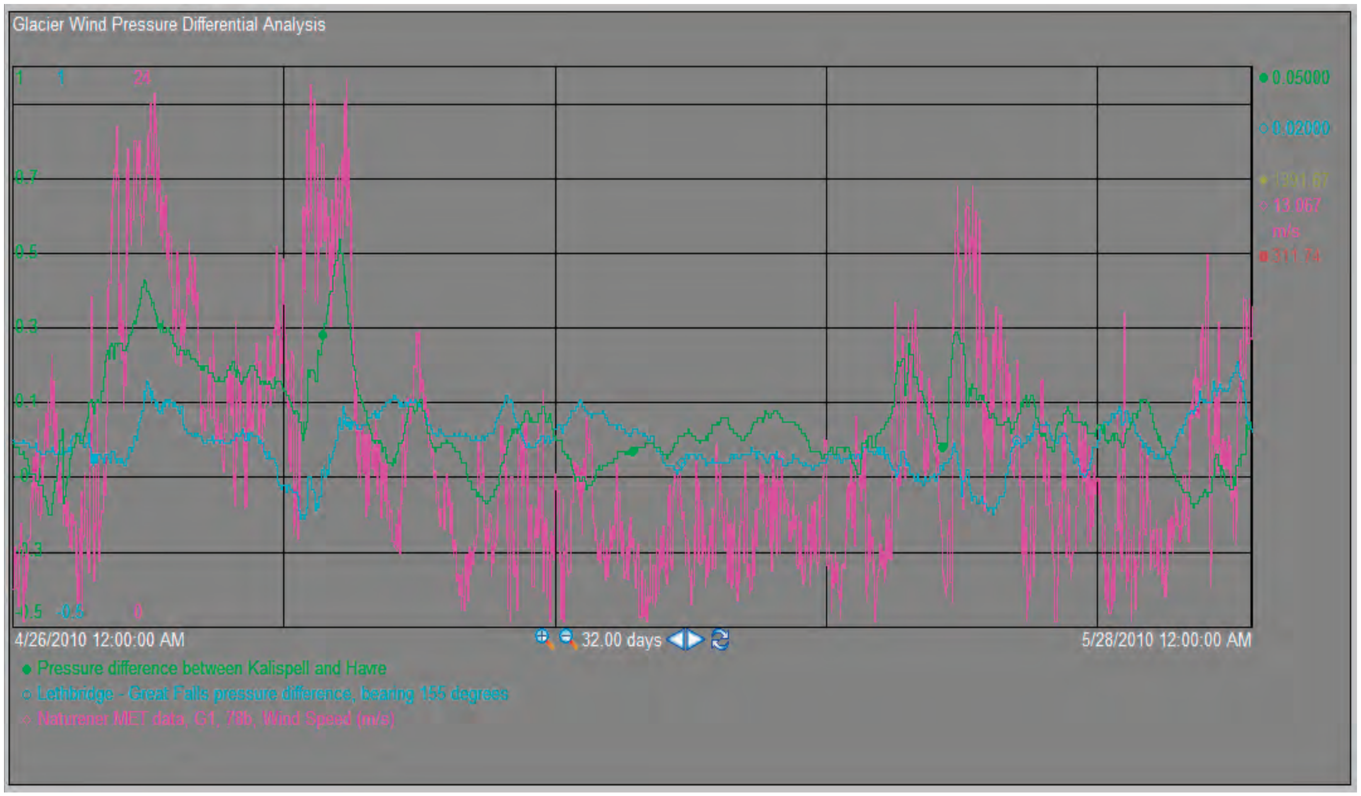
Cardinal Directions for event tracking





Live Data + Actual GIS Layout

Pressure Differential Analysis Around Plant



The Cool Experiment

Use PI to determine cause and predict Ramps

Marty / Gregg - WFU

(Wind Forensics Unit)

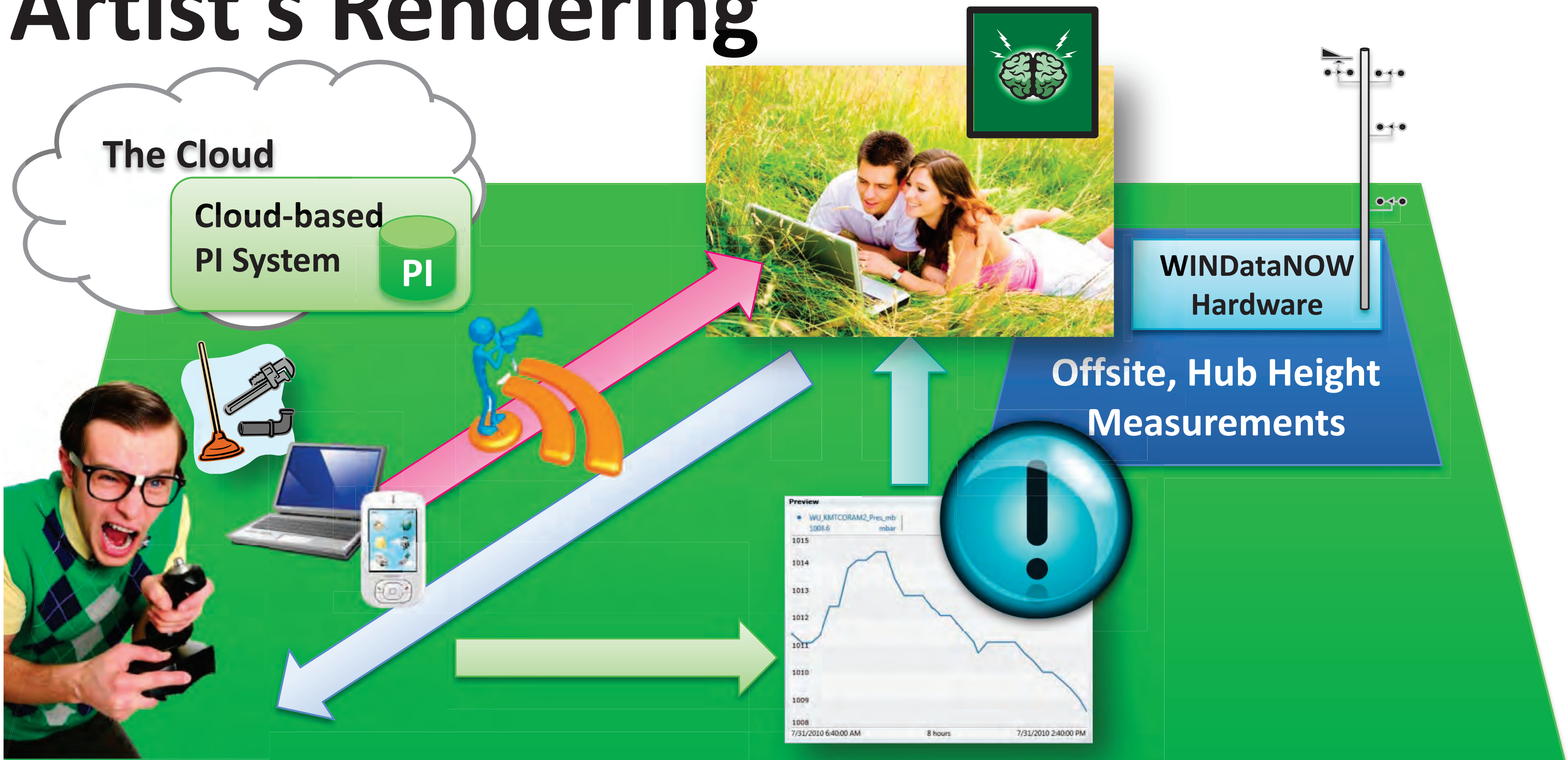
Marty in Montana

Gregg in Oakland

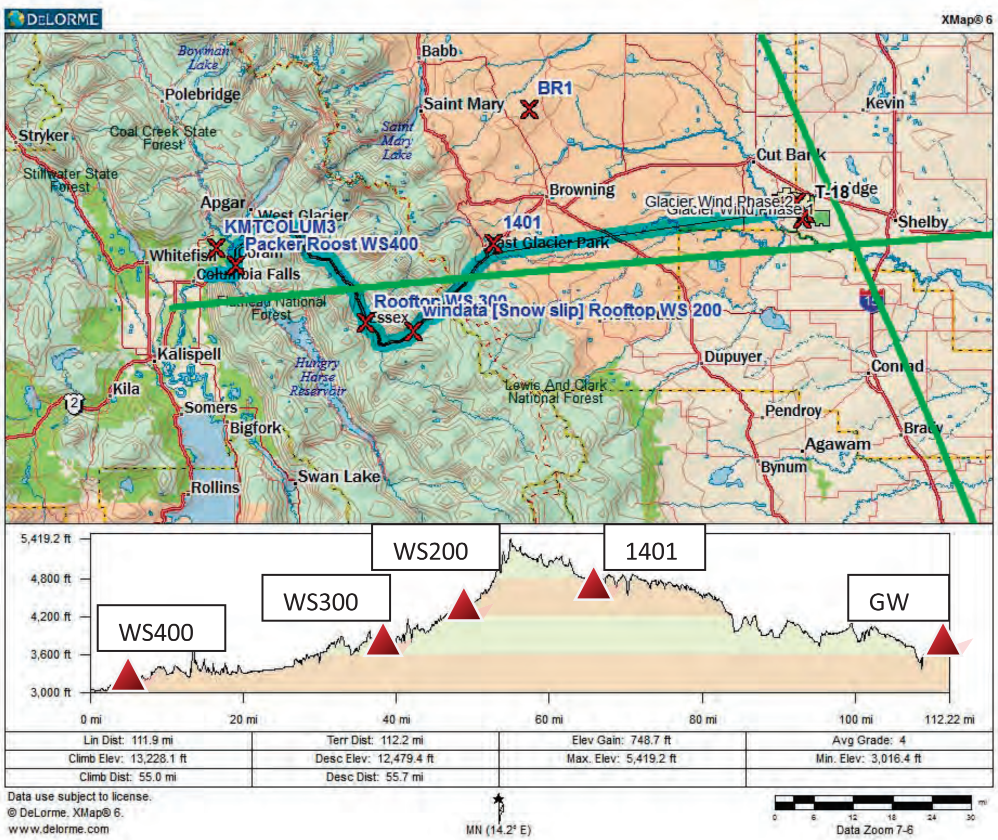
or

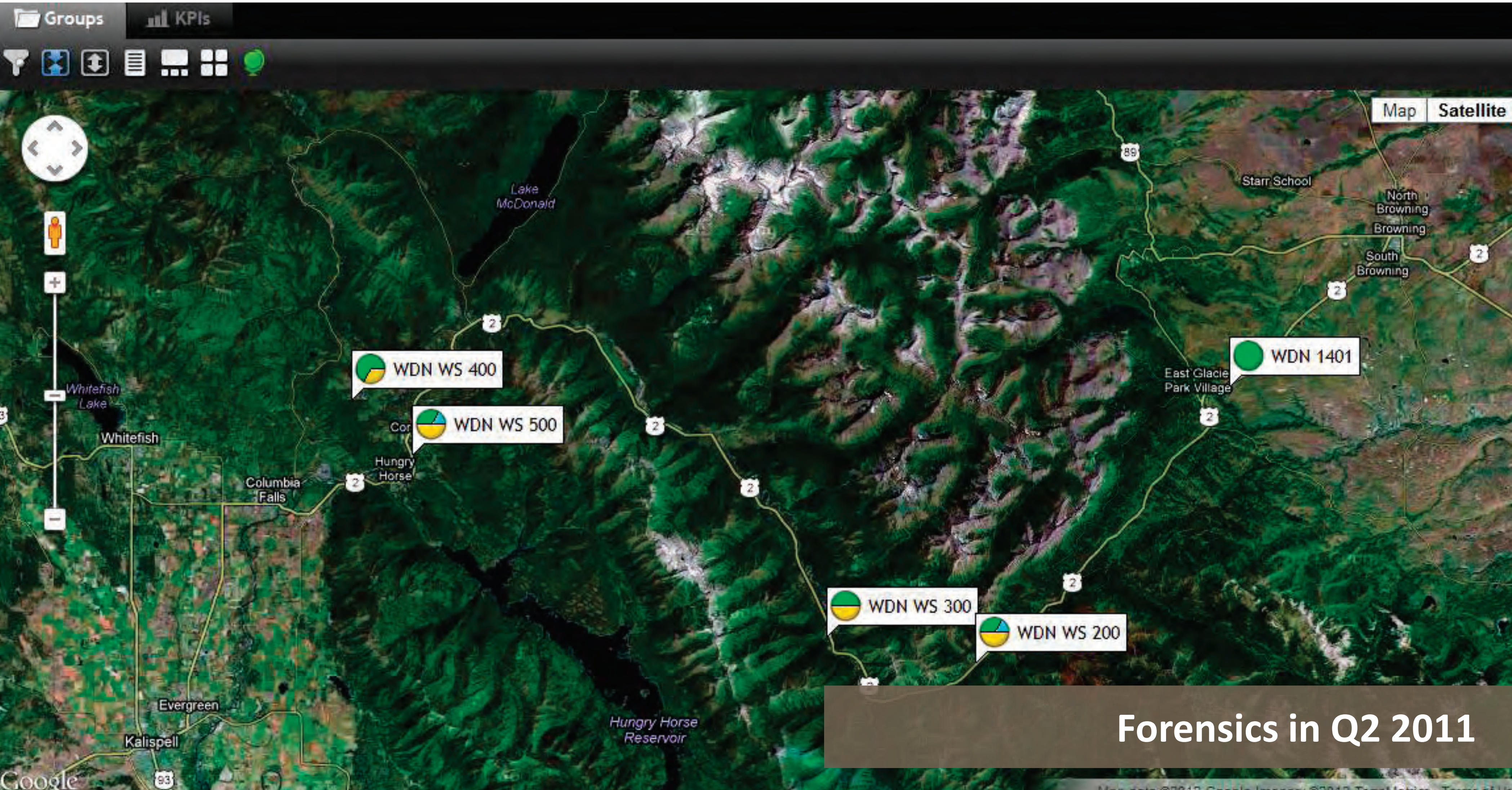
Gregg in New York

Artist's Rendering

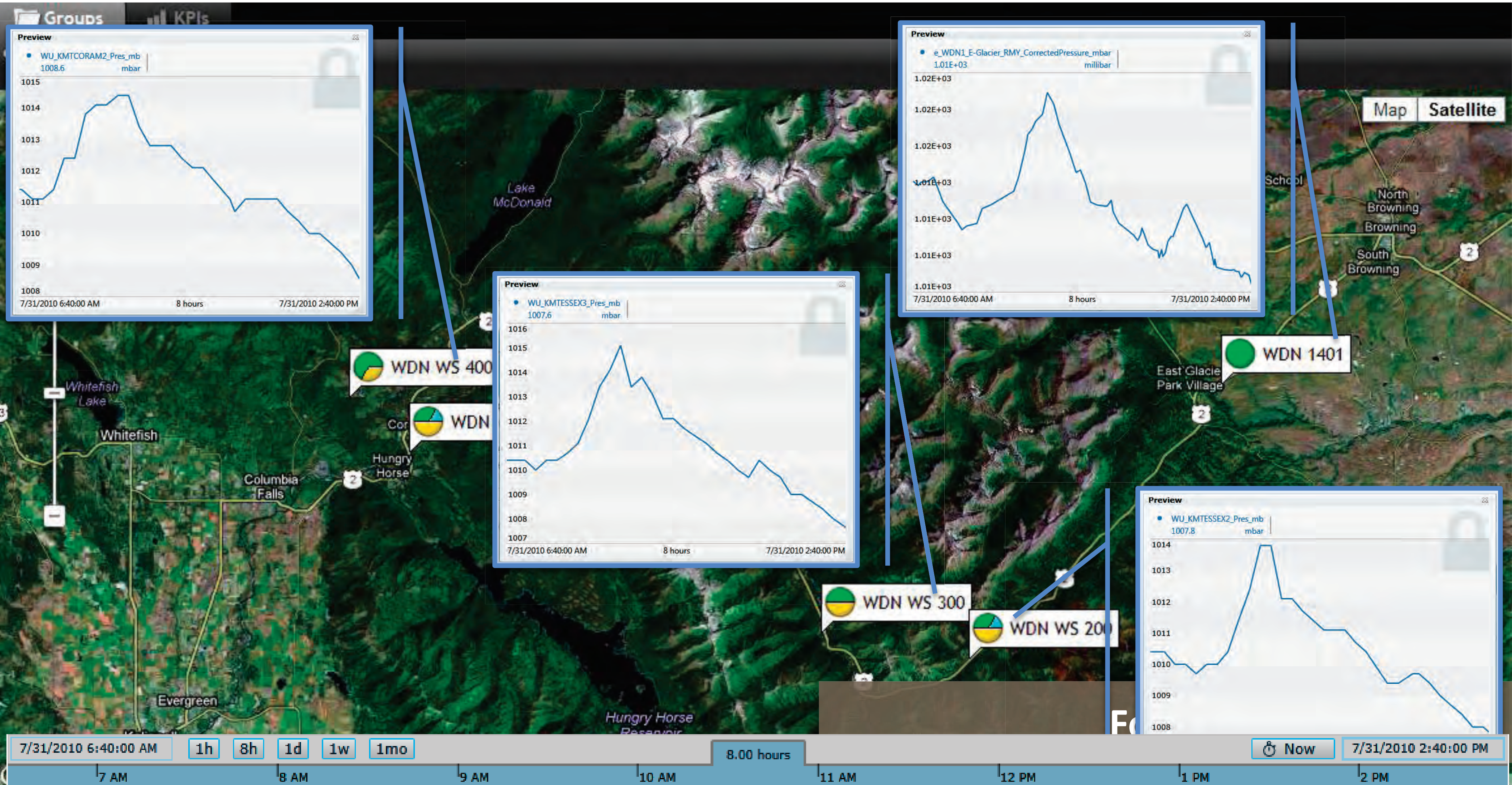


West to East event tracking

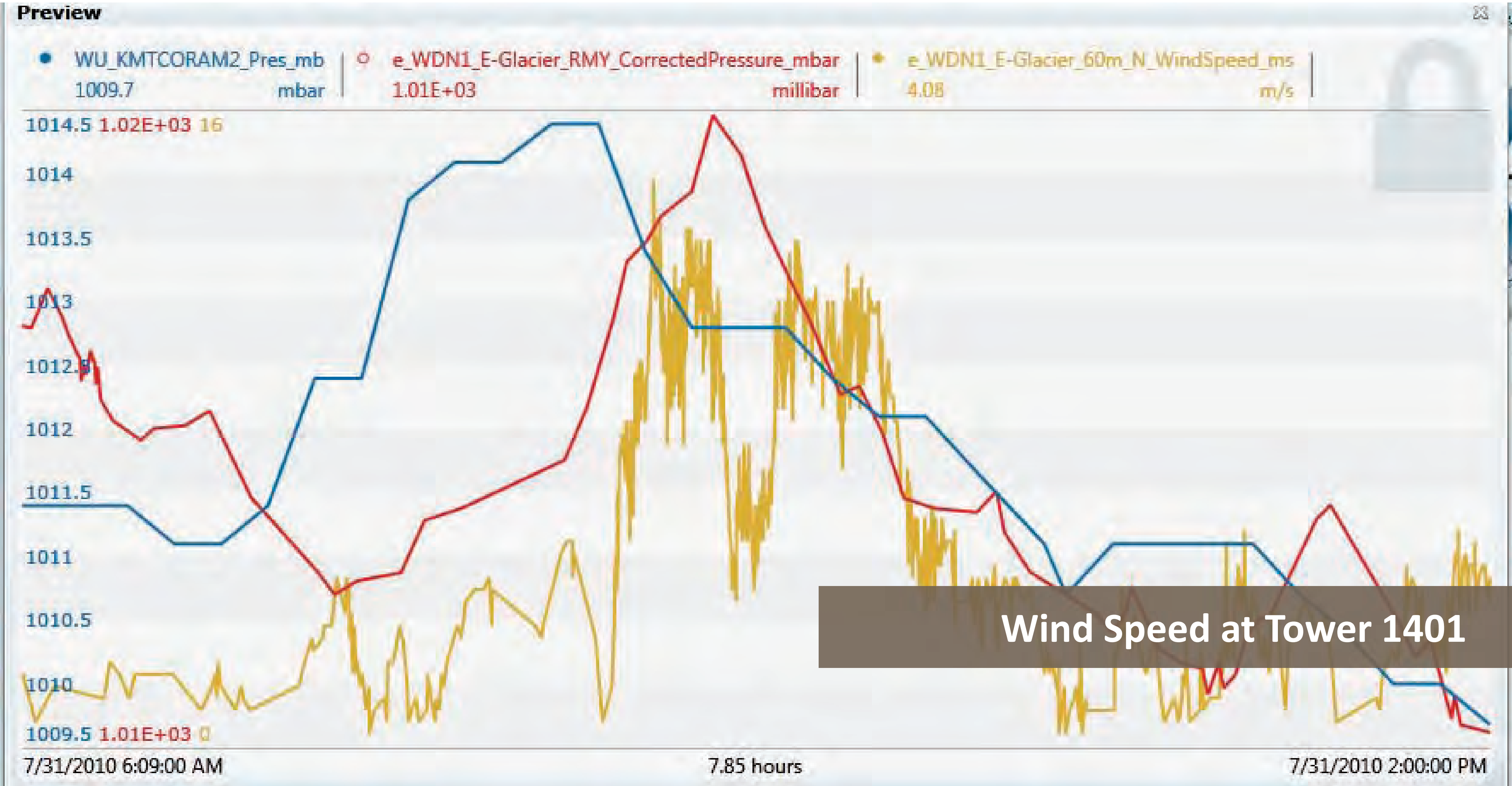


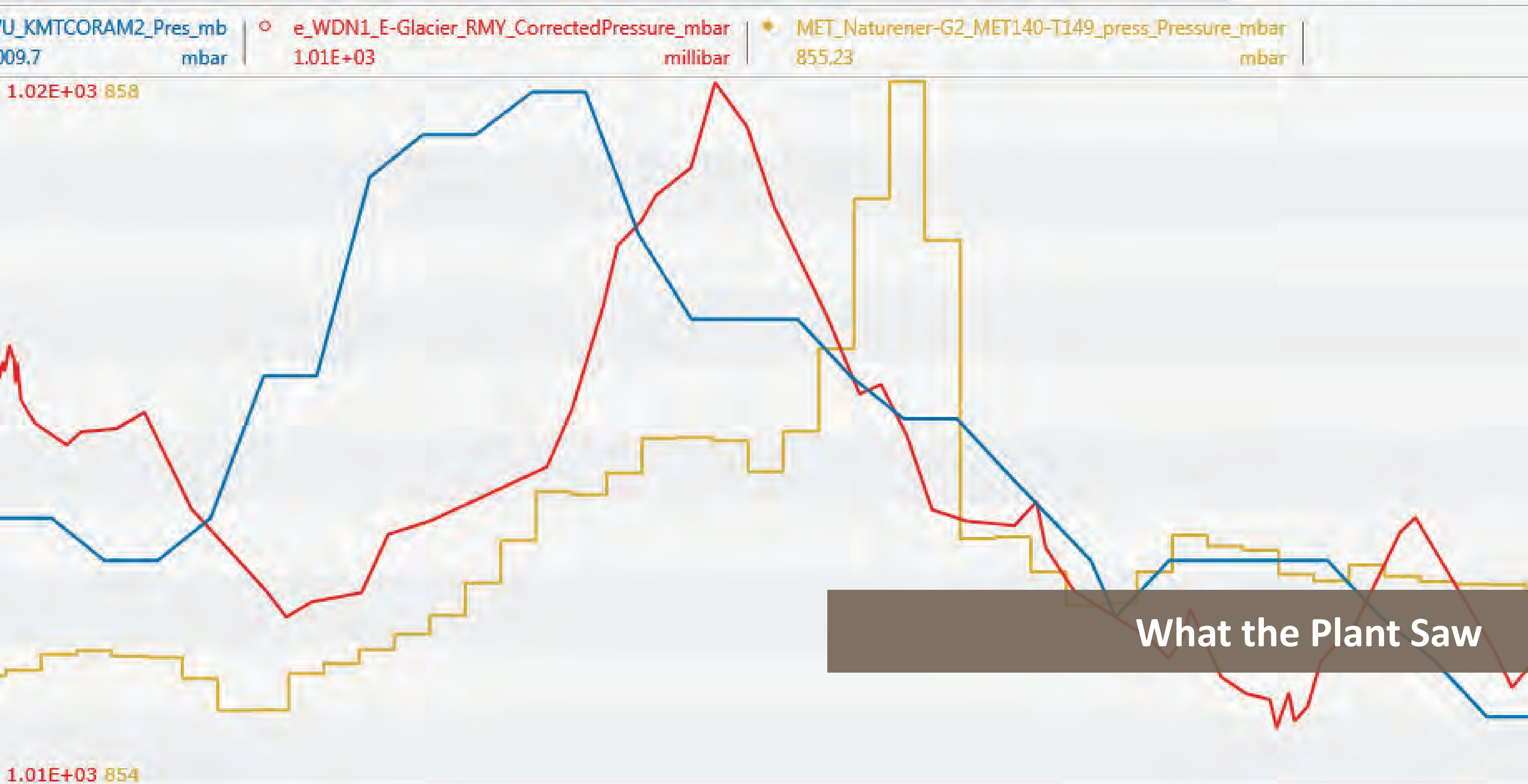


Forensics in Q2 2011


Groups
KPIs
Preview
WU_KMTCORAM2_Pres_mb
1008.6 mbar
7/31/2010 6:40:00 AM 8 hours 7/31/2010 2:40:00 PM
Preview
e_WDN1_E-Glacier_RMY_CorrectedPressure_mbar
1.01E+03 millibar
7/31/2010 6:40:00 AM 8 hours 7/31/2010 2:40:00 PM
Preview
WU_KMTESSEX3_Pres_mb
1007.6 mbar
7/31/2010 6:40:00 AM 8 hours 7/31/2010 2:40:00 PM
Preview
WU_KMTESSEX2_Pres_mb
1007.8 mbar
WDN WS 400
WDN 1401
WDN WS 300
WDN WS 200
Map
Satellite
Lake McDonald
Whitefish Lake
Whitefish
Columbia Falls
Hungry Horse
Evergreen
East Glacier Park Village
North Browning
Browning
South Browning
Hungry Horse Reservoir
7/31/2010 6:40:00 AM
1h 8h 1d 1w 1mo
8.00 hours
Now
7/31/2010 2:40:00 PM
7 AM 8 AM 9 AM 10 AM 11 AM 12 PM 1 PM 2 PM

Cascading pressures

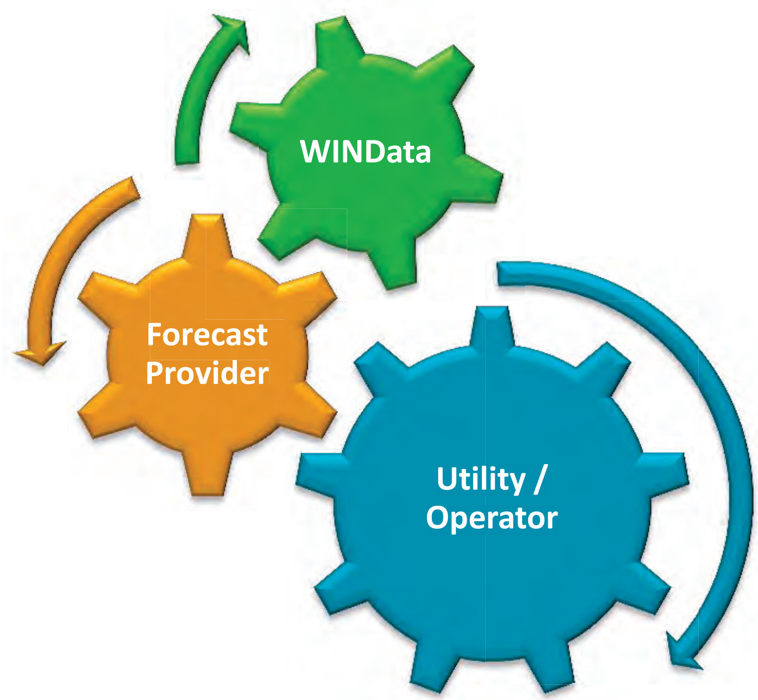

Preview
WU_KMTCORAM2_Pres_mb 1009.7 mbar
e_WDN1_E-Glacier_RMY_CorrectedPressure_mbar 1.01E+03 millibar
e_WDN1_E-Glacier_60m_N_WindSpeed_ms 4.08 m/s
1014.5 1.02E+03 16
1014
1013.5
1013
1012.5
1012
1011.5
1011
1010.5
1010
1009.5 1.01E+03 0
7/31/2010 6:09:00 AM
7.85 hours
7/31/2010 2:00:00 PM
Wind Speed at Tower 1401



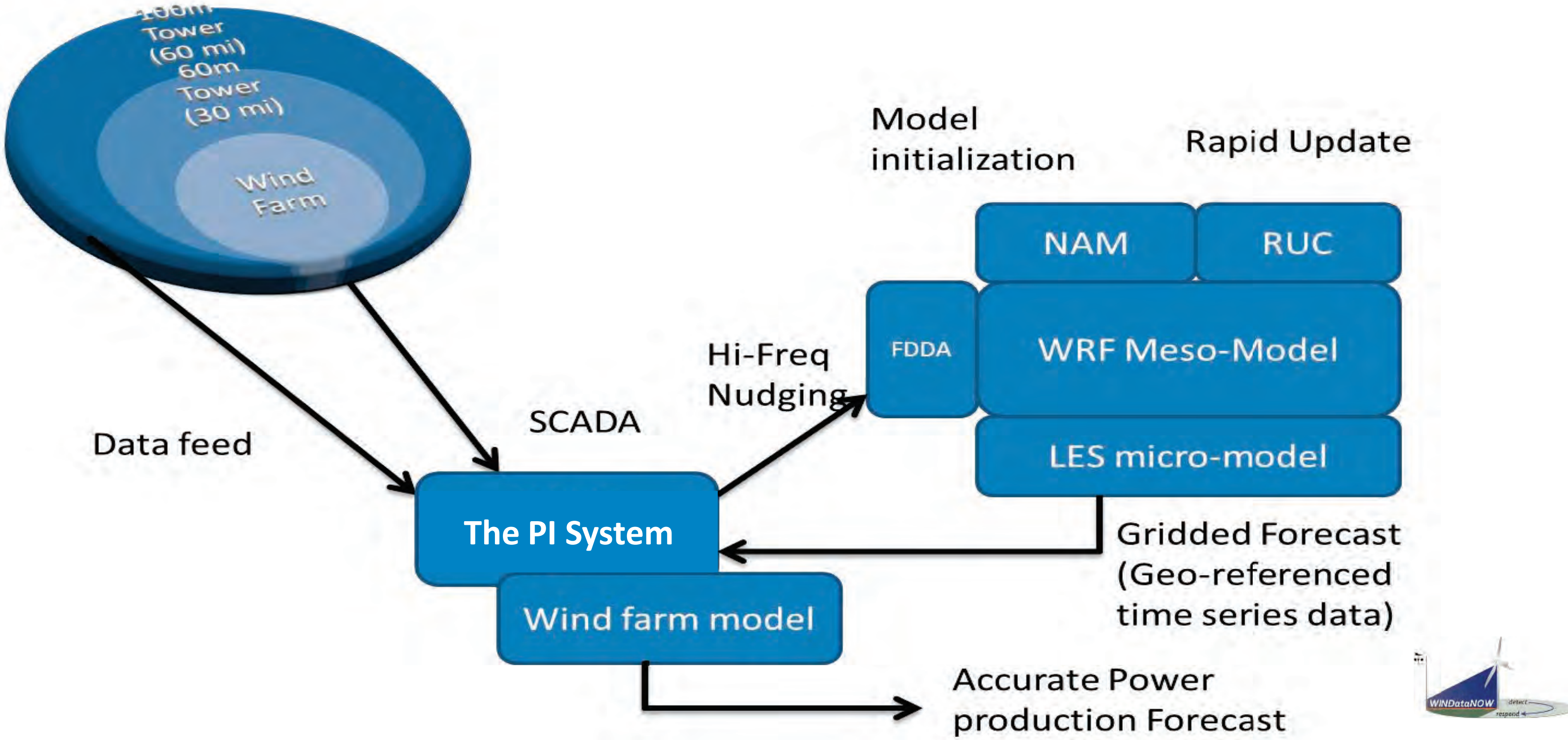
U_KMTCORAM2_Pres_mb
009.7 mbar
e_WDN1_E-Glacier_RMY_CorrectedPressure_mbar
1.01E+03 millibar
MET_Naturener-G2_MET140-T149_press_Pressure_mbar
855.23 mbar
1.02E+03 858
1.01E+03 854
What the Plant Saw

Working together to improve forecasts

- Goal: Design a program that results in better forecasts
  - Operator
  - WINDataNOW
  - Forecast Vendor
- Team up to improve wind energy integration



Integrating Sensor network with Forecasting System



THANK YOU

Gregg LeBlanc
gregg.leblanc@windata-inc.com
Marty Wilde
marty.wilde@windata-inc.com

WINDataNOW detect respond

Brought to you by OSIsoft.