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IMPROVING NDFD MODEL TEMPERATURE, DEW POINT, AND WIND SPEED FORECASTS BY USING AWS/WEATHERBUG OBSERVATIONAL DATA

Joby Hilliker, Department of Geology and Astronomy, West Chester University, West Chester, PA *
Girish Akasapu, Masters Student, Computer Science, West Chester University, West Chester, PA

1. INTRODUCTION

Weather forecasts using statistical equations derived from observational data are of utility to a variety of users. For example, traders at utility companies incorporate forecasts to decide whether to buy or sell electricity on the open market. Moreover, energy companies continually project the electricity usage, or "load," for their customer domain.

The natural question, then, is how best to obtain the most accurate short-term temperature forecasts? There are a few short-term forecasting products available. One product is the recently developed National Digital Forecast Database (NDFD). It is generated by the National Weather Service (NWS) and offers model forecasts every three hours for an array of grid boxes (NDFD 2004).

Although not forecasts, available from AWS Convergence Technologies, Inc. (AWS), a private corporation, are high-resolution observations for over 8000 sites across the country (AWS 2007).

This project's objective is to assess quantitatively the improvement of short-term NDFD model forecasts by incorporating AWS observations using statistical forecast equations via multiple linear regression.

Three variables pertinent to load forecasting are tested: temperature, dew point, and wind speed. Dew point is more relevant during the summer as it correlates to air-conditioning use, while wind speed is more relevant during the winter with respect to heating efficiency.

This study will also explore the magnitude of forecast improvement as a function of AWS observing location (i.e., siting). It is hypothesized that AWS observations would provide the greatest benefit to NDFD model forecasts for predictions at AWS weather stations located in higher elevations or next to water, as examples. This idea stems from the premise that numerical computer models do not have the spatial resolution to account for these local effects.

2. DATASETS AND THEIR ROBUSTNESS

Hourly AWS observations and NDFD forecasts were compiled for the 1-year period 15 April 2006 to 14 April 2007. Seventeen AWS stations, shown in Table 1, representing a variety of locations, climates, and elevations were tested.

Stations BRTTN, MTQCR, and MELBA were chosen because of their higher elevations, and RBBPH, WIVBT, and SEASF because they are in proximity to water sources. Stations PHLRH and KPEAE were chosen as controls because they lie in more homogenous terrain with no obvious local events.

AWS Identifier	Station Name	Station Location	Elevation (feet)
BRTTN	Bretton Woods Ski Resort	Bretton Woods, NH	1636
LRAY1	Shenandoah National Park	Big Meadows, VA	3450
PHLRH	Rohm and Haas	Spring House, PA	320
RBBPH	Boardwalk Plaza Hotel	Rehoboth Beach, DE	52
WIVBT	WIVB-TV	Buffalo, NY	655
RCHSC	Seton Catholic High School	Richmond, IN	935
CHC04	LaSalle Bank Building	Chicago, IL	592
CHINM	P. Notebaert Museum	Chicago, IL	587
CHCG5	De La Cruz School	Chicago, IL	594
CHC09	Hammond Elem School	Chicago, IL	594
CURIE	Curie Metro High School	Chicago, IL	600
BRRRD	Burr Ridge Middle School	Burr Ridge, IL	696
WNTRE	Wintergreen Mountain	Wintergreen, VA	3373
MTQCR	Crested Butte Mtn Report	Crested Butte, CO	9327
MELBA	Dans Ferry Service	Melba, ID	2799
SEASF	KING5 at SAFECO field	Seattle, WA	66
KPEAE	Peabody-Burns ES	Peabody, KS	1388

Table 1. Summary of AWS station identifiers with elevation data.

Corresponding author's address: Joby L. Hilliker, 223 Boucher Building, West Chester University, West Chester, PA 19382; e-mail: jhilliker@wcupa.edu

Because this system's success stems from the strength of statistical signals, it is critical that the number of cases with bad and/or missing data be minimized. AWS archives were generally of excellent quality, with the percentage of missing data <5% for the majority of stations.

Because NDFD forecasts are gridded (resolution .05°), NDFD forecasts were chosen to correspond to the grid box in which each AWS station lies. Also, in its current format, NDFD forecasts are valid every 3 hours, and updated in 3-hr intervals, starting at 00Z. Although forecasts are disseminated hourly, the following two hours' forecasts (those made at 01Z and 02Z, for example) are essentially a repeat of the original forecast (the 00Z forecast, to continue this example) until an update is made the subsequent hour (03Z, to complete the example). Table 2 summarizes the relationship between forecast hours and corresponding lead times tested.

FORECAST HOUR (Z)	LEAD TIME (HOURS)
00,03,06,09,12,15,18,21	3, 6, 9, 12
01,04,07,10,13,16,19,22	2, 5, 8, 11
02,05,08,11,14,17,20,23	1, 4, 7, 10

Table 2. Relationship between forecast hour and lead times.

The NDFD archive was also of excellent quality. Of the 8760 possible NDFD forecasts in the database, 581 (<7%) were missing.

3. STATISTICAL DESIGN

Hourly forecasts of temperature, dew point, and wind speed were made for 1-12 hours in the future for each AWS station, with the predictand simply the AWS observation at verification time.

Because all three parameters exhibit a diurnal pattern, statistical forecast equations were developed for each forecast hour. This strategy becomes imperative when one examines NDFD model bias. Figure 1 shows NDFD model bias for five selected AWS sites for temperature (top), dew point (middle), and wind speed (bottom).

The most significant NDFD bias is with temperature at two AWS mountain sites: BRTTN and MTQCR. Specifically, a significantly cold bias exists during the overnight hours (03-11Z), but markedly shifts to a warm bias during the afternoon. Also evident in Fig. 1a is a warm NDFD bias at CHC04 apparent only during the daytime. This pattern is perhaps attributable to the cooling afternoon lake breeze that the Chicagoan site may experience, particularly during the spring when the lake is relatively cold.

NDFD dew point bias is not as significant as temperature, but still exhibits a diurnal trend. A dry bias is apparent during the nighttime hours. Several intriguing observations can be made about the wind speed bias. First, a fast wind speed bias (of order 1 MPH) is evident for all sampled stations for all hours. The model's fast bias may be attributed to AWS siting. Unlike airports with few obstructions, most AWS sites are located atop buildings with surrounding structures and trees, which would retard the wind speed. Building heights may also be lower than the 10-m height that wind speeds are typically observed and forecast. Secondly, note there is a less marked diurnal trend in the model wind speed bias. It is likely NDFD is more successfully handling the diurnal component that naturally exists with this parameter.

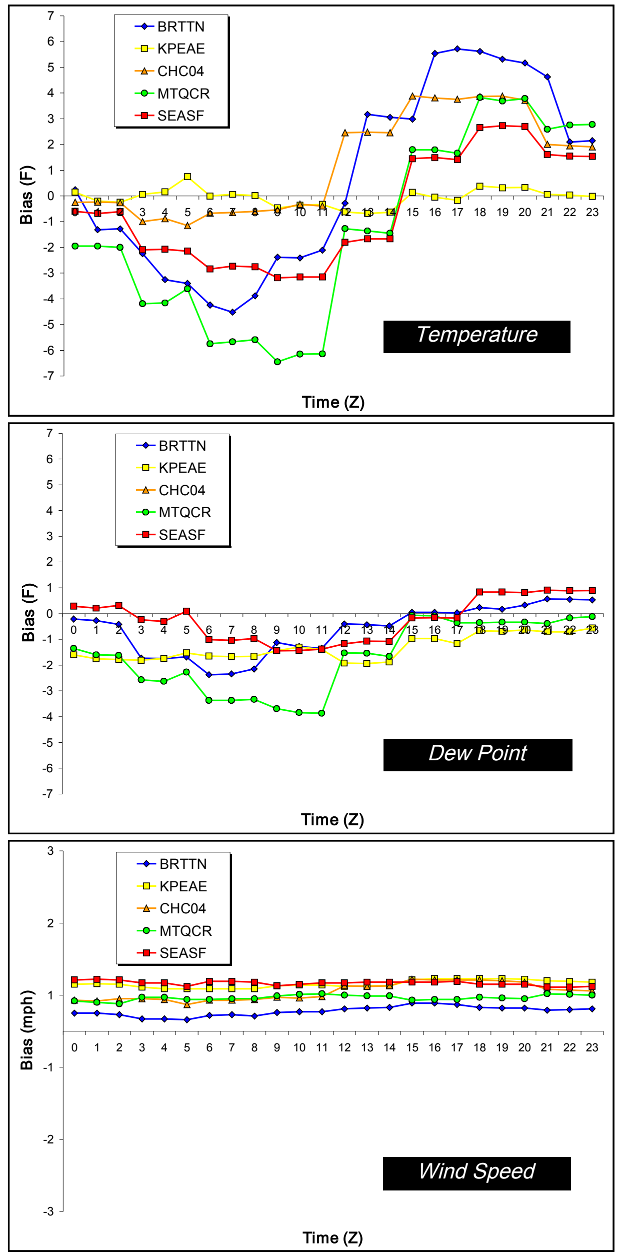

Fig. 1. Hourly bias of NDFD temperature, dew point, and wind speed forecasts for selected AWS stations.

Table 2 lists the candidate predictors considered in the system. The most obvious predictors to include were the most recent AWS observation and suite of NDFD forecasts of the particular parameter. Additional variables, such as the most recent relative humidity, precipitation, and past observations of the forecast parameter, were also considered.

PREDICTOR	NOTATION
Current Temperature	T_0
Temperature from 1 Hr Ago	T_{-1}
Temperature from 2 Hr Ago	T_{-2}
Current Relative Humidity	RH_0
Current Dew Point	TD_0
Current Wind Direction	DD_0
Current Wind Speed	FF_0
Current Precipitation (Yes/No Binary Predictor)	P_0
Current U-component of Wind	U_0
Current V-component of Wind	V_0
NDFD 1-3 Hr Forecast	$NDFD_{1\text{-}3}$
NDFD 4-6 Hr Forecast	$NDFD_{4\text{-}6}$
NDFD 7-9 Hr Forecast	$NDFD_{7\text{-}9}$
NDFD 10-12 Hr Forecast	$NDFD_{10\text{-}12}$

Table 2. Description of candidate predictors tested, and their notations.

Both the AWS and NDFD data archives were divided into two datasets. The first was a larger ("dependent") dataset from which the most powerful predictors for short-term temperature forecasting were derived, and then linked using multiple linear regression to form statistical forecast equations. The statistical software package *S-PLUS* was used to ascertain the most powerful predictors, with a forward stepwise regression ("efromyson") applied using an f-value threshold of 10.

Forecast equations were then applied to the smaller "independent" dataset to generate new temperature forecasts. These modified NDFD forecasts are referred to as NDFD+ forecasts, hereafter. The size ratio between the dependent and independent datasets is typically 3 to 1. Thus, days 1-23 of each month were dedicated to the dependent set, with the balance of the month committed to the independent data set.

4. RESULTS FROM DEPENDENT DATA

Table 3 shows a sampling of the final predictors -- temperature (top, for CHC04), dew point (middle, for CHINM), and wind speed (bottom, for CURIE) -- included in the forecast equations. Predictors are listed in order of benefit, with the first predictor the most highly correlated to AWS verification. The nature, order, and number of predictors (typically, 2-5) were consistent with other AWS stations.

It is intuitive that the majority of the chosen predictors are NDFD model output. The most beneficial NDFD forecasts are those that correspond to the forecast lead time (i.e., $NDFD_{7\text{-}9}$ for a 9-hr lead time), although there are exceptions (e.g., $NDFD_{4\text{-}6}$ for a 12-hr 00Z CHC04 temperature forecast).

The remaining predictors come from AWS observations, confirming the benefit of an observations-based forecast system. There is also the trend for the most recent AWS observation to be weighted more heavily for shorter lead times, with NDFD output emphasized for longer lead times.

A notable exception, however, are the most powerful variables for forecasting wind speed. For a 3-hr lead time, the most recent wind speed observation, in general, is not the top predictor. In fact, there is virtually no presence of supplemental AWS observations beyond 6 hrs. This result provides the first insight into the limited ability of short-term wind speed forecasting using an obs-based system. This is not surprising, however, given the higher variability of this parameter as compared to temperature or dew point.

One additional observation is the frequent presence of U_0, the east-west component of the wind, as a beneficial predictor for forecasting dew point for CHINM, a site located 12 km from Lake Michigan. This result is encouraging in that the forecast system is confirming a relationship between wind direction and moisture content of this Chicago site.

TEMPERATURE – CHC04				
Forecast Hour (Z)	3-hr Lead Time	6-hr Lead Time	9-hr Lead Time	12-hr Lead Time
00	T_0, $NDFD_{10\text{-}12}$	T_0, $NDFD_{10\text{-}12}$, FF_0	$NDFD_{4\text{-}6}$, T_0, TD_0	$NDFD_{4\text{-}6}$, RH_0

DEW POINT – CHINM				
Forecast Hour (Z)	3-hr Lead Time	6-hr Lead Time	9-hr Lead Time	12-hr Lead Time
12	TD_0, $NDFD_{4\text{-}6}$	$NDFD_{4\text{-}6}$, TD_0, U_0	$NDFD_{7\text{-}9}$, U_0, TD_0	$NDFD_{10\text{-}12}$, U_0, T_0

WIND SPEED – CURIE				
Forecast Hour (Z)	3-hr Lead Time	6-hr Lead Time	9-hr Lead Time	12-hr Lead Time
00	$NDFD_{1\text{-}3}$, FF_0, V_0, $NDFD_{7\text{-}9}$	$NDFD_{7\text{-}9}$, FF_0, V_0	$NDFD_{7\text{-}9}$, U_0	$NDFD_{10\text{-}12}$, $NDFD_{7\text{-}9}$

Table 3. A sampling of the most powerful predictors as a function of forecast hour and lead time for temperature, dew point, and wind speed forecasting for CHC04, CHINM, and CURIE, respectively. Predictors are listed in order of decreasing power. Predictor notation is referenced in Table 2.

5. RESULTS FROM INDEPENDENT DATA

Forecast equations containing the above final predictors were applied to generate modified NDFD (NDFD+, hereafter) forecasts. To assess forecast improvement, the mean absolute error (MAE) between the NDFD+ forecasts and verification (i.e., the actual AWS observation) were calculated. This methodology was repeated for each of the three parameters.

Figure 2 shows the mean absolute temperature and wind speed error for CURIE as a function of lead time, averaged over the eight forecast hours from Table 1.

The average NDFD+ temperature error is 1.1°F at 1 hr and increases logarithmically to 3.1°F by 12 hrs. For reference, the MAE of the original NDFD forecasts, 3.2° F regardless of lead time, is also depicted. Results for dew point at CURIE (not shown) are similar to temperature in both magnitudes and pattern.

For wind speed, the mean NDFD forecast error was 2.2 MPH. By incorporating AWS observations, the MAE dropped to 1.7 MPH at the 1-hr lead time to trivial improvements beyond 6 hr.

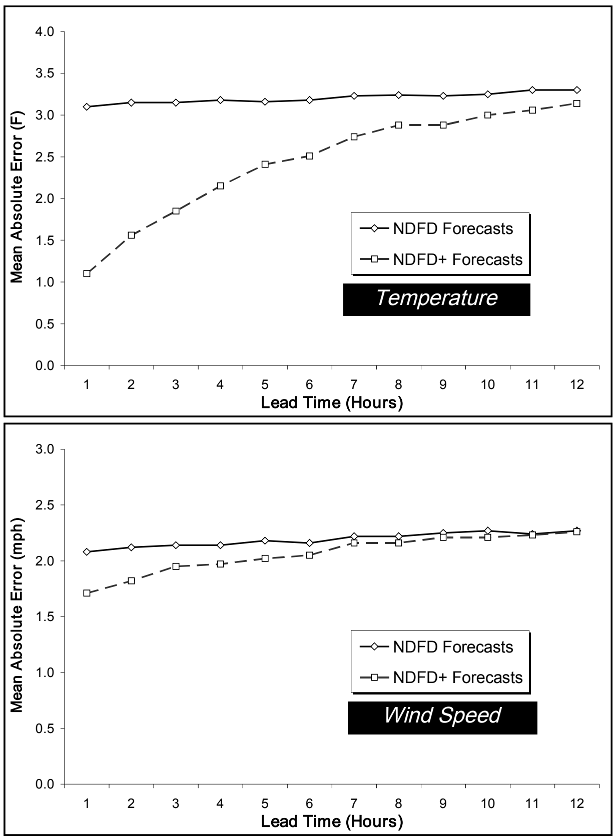

Fig. 2. Mean absolute temperature and wind speed error between verification and: a) NDFD+ forecasts (dashed line), and b) original NDFD forecasts (solid line) as a function of lead time for CURIE.

Alternatively, the percent improvements of NDFD+ forecasts over those of the original NDFD can be shown. Figure 3 shows these percent improvements as a function of lead time for all tested AWS stations. The black solid line in each figure represents an average over all sites.

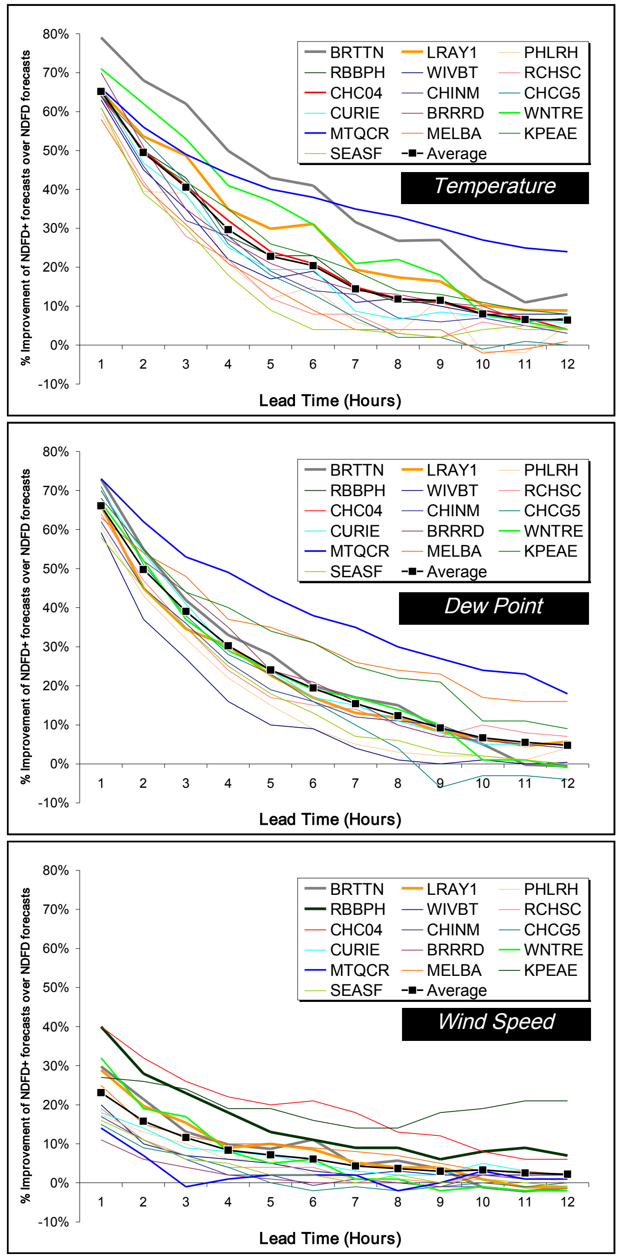

Fig. 3. Percent improvements of NDFD+ forecasts over original NDFD forecasts for temperature, dew point, and wind speed as a function of lead time for each AWS station. The black, solid line in each figure is an average over all tested AWS stations.

Several points can be gleaned from Fig. 3. It is stressed, however, that the improvements above will not be as great (exceptions being the 3-, 6-, 9-, and 12-hr lead times) once NDFD forecasts are updated hourly.

Percentage improvements for temperature and dew point, when averaged over all stations, are comparable in magnitude. Improvements are greatest at the 1-hr lead time at 60-70%, decrease exponentially to 15-25% at the 6-hr lead time, and are trivially skillful by 12 hrs.

A more careful analysis, though, reveals differences in improvements with respect to location. The skill in forecasting temperature is greatest for MTQCR, BRTTN, LRAY1, and WNTRE. Table 1 reveals these four sites are a subset of the five highest elevation sites tested. This result furthers the suggestion that an obs-based system is of greatest utility when adjusting NDFD temp forecasts in rugged or higher-altitude locations.

Spread in skill among stations is also evident with dew point, but with individual stations behaving differently. There continues to be a correlation -- albeit weaker with dew point -- between NDFD+ performance and altitude as two (MTQCR, MELBA) of the three most skillful sites are located > 2500 ft.

An exponential decrease in skill is also evident with wind speed; however, overall NDFD+ forecast improvements are markedly lowest of the three parameters. Improvements average 20% at the 1-hr lead time and fall below 10% by 4 hr. In fact, some wind speed predictions were worsened by the inclusion of AWS observations – a testament of the high variability, and thus low predictability, of wind speed.

A notable amount of spread in skill among stations is also evident with wind speed, with the obs-based system showing forecast skill for longer lead times for a few (KPEAE, CHC04, RBBPH) of the tested stations. One commonality with these sites is their proximity to water. Local effects (e.g., lake breeze) are likely influencing the wind speed, allowing an obs-based system to again demonstrate its strength.

6. CONCLUSIONS

The results from this grant provided several encouraging results in determining the utility of AWS observations in improving short-term NDFD model temperature, dew point, and wind speed forecasts. For the first experiment, a sample of 17 AWS sites was chosen located in varying terrain and proximity to water to test the influence of AWS physical location on forecast improvement. For the second experiment, observations from nearby AWS sites were included in the pool of candidate predictors to determine if additional NDFD+ forecast improvement can be generated.

The main conclusions from this study are:

- The incorporation of AWS observations decreased the MAE of original NDFD forecasts by 60-70% at the 1-hr lead time, dropping exponentially to ~20% at 6 hrs, and are only trivially superior by 12 hr.

- Higher altitude stations, where local effects dominate and whose locations may not be well modeled, generally exhibited the highest forecast skill for temperature and dew point.

- Dew point results were similar to temperature in both final predictor type (i.e., the most recent dew point observation the top predictor for short lead times) and magnitudes of improvement.

- Thus, it is expected NDFD+ forecasts of heat index will have comparable percent improvements to temperature and dew point.

- NDFD forecasts have a fast bias with wind speed, likely the result of AWS siting.

- Because of wind speed's higher variability, NDFD+ improvements were significantly lower than temperature or dew point: 20% improvement for a 1-hr lead time, and trivial superior in as little as 4 hrs.

- Stations located next to water, where again local effects dominate, generally showed the highest wind speed forecast skill.

- NDFD+ forecasts of wind chill will likely have skill inferior to temperature or heat index because of the inherent limitations in predicting wind speed.

This study provides additional support for which future projects involving energy and utility companies are possible. One logical extension would be to construct a prototype forecast system that outputs short-term temperature, dew point, and heat index forecasts similar to the NDFD+ forecasts generated here. Locations with pronounced local effects (e.g., higher altitude, proximity to water) are ideal for applying an AWS observations-based system to improve original NDFD forecasts.

7. REFERENCES

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