Improvements in numerical prediction of low level winds

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Improvements in numerical prediction of low level winds

by

Adam Joshua Deppe

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Meteorology

Program of Study Committee:
William A. Gallus, Jr., Co-Major Professor
Eugene S. Takle, Co-Major Professor
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Iowa State University
Ames, Iowa
2011

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CHAPTER 1. GENERAL INTRODUCTION

1.1 Problem Statement

With fuel prices rising and concerns mounting about greenhouse gas emissions caused by the burning of fossil fuels, the U.S. Department of Energy developed a goal of having 20% of the nation’s electrical energy from wind by 2030 (Department of Energy 2008). However, as of 2009, wind energy accounted for only 1.9% of the total U.S. electrical production (Department of Energy 2010). Therefore, to reach the goal, a large amount of growth must occur in the wind energy sector.

Unlike other sources of energy, wind speeds vary greatly with time and space, causing production rates to fluctuate more strongly than other traditional fossil fuel sources. As a result, errors in the forecasted wind speed of only 1% for a 100-MW wind facility can lead to losses around $12,000,000 over that facility’s lifetime (Schreck et al. 2008). In order to optimize wind for power generation and create a reliable, clean energy source, more accurate forecasts are needed.

Meteorologists traditionally have focused wind forecasts at the 10 m level, a level where observations of wind speed and direction are abundant in the United States. However, with the increased growth in the wind energy sector, wind speed forecasts at turbine hub height (80 m) are now needed. Due to the lack of observations, validating forecasts at this height has been difficult and little attention has been paid to wind forecasts at 80 m in the meteorological community. The first study addresses this issue by comparing different planetary boundary layer (PBL) schemes in the Weather Research and Forecasting (WRF) model and evaluating model skill based on observations taken at
80 m from a wind farm in Iowa. With the potential for wind turbines to increase in height from 80 m to 120 m in the future, there is a greater chance that wind turbines will be affected by low-level jets (LLJ). Described as regions of moderately strong winds in the lower atmosphere, LLJs are an untapped resource for wind energy. Although a few studies have looked at validating model wind speeds during LLJ events, none have examined how different PBL schemes affect LLJ forecasts or addressed how LLJs would affect wind turbines at heights of 80 m and above. The second study addresses this issue by: a) comparing and evaluating the vertical wind speed profile produced by different PBL schemes during LLJ events, and b) comparing observed and modeled wind speeds at 96 m and 157 m during LLJs and non-LLJ events.

1.2 Thesis Organization

This thesis contains two papers to be submitted for publication. The first paper, *Creation of a WRF Ensemble for Improved Wind Forecasts at Turbine Height*, examines the model skill of six PBL schemes in WRF at predicting 80 m wind speed and ramp events over a 250 MW wind farm in Northwest Iowa. Different pre-run modifications and post-processing techniques were tested, and based on these results, a six member ensemble was developed. Statistical tests were done to determine whether the results were significant. I am the lead author on this paper, with my advisor Dr. Bill Gallus, Jr. and Dr. Gene Takle serving as coauthors. This paper will be submitted to *Weather and Forecasting*.

The second paper, *Simulation of Nocturnal LLJs with a WRF PBL Scheme Ensemble and Comparison to Observations from the ARM Project*, examines the model
skill of six PBL schemes in WRF at predicting LLJs over the Oklahoma ARM project site and how the results could affect wind energy production. I am the lead author on this paper with my advisor, Dr. Bill Gallus, Jr., serving as a coauthor, along with Kristy Carter, an undergraduate student at Iowa State University who worked on the project during her summer Research Experiences for Undergraduates (REU) internship at Iowa State. This paper will be submitted to Monthly Weather Review. This thesis is organized into four parts: General Introduction, A WRF Ensemble for Improved Wind Forecasts at Turbine Height, Simulation of Nocturnal LLJs with a WRF PBL Scheme Ensemble and Comparison to Observations from the ARM Project, and a General Conclusion.

1.3 References


CHAPTER 2. A WRF ENSEMBLE FOR IMPROVED WIND SPEED FORECASTS AT TURBINE HEIGHT

A paper to be submitted to Weather and Forecasting
Adam J. Deppe, William A. Gallus, Jr., and Eugene S. Takle

2.1 Abstract

The inherent variability of wind requires accurate forecasts to optimize wind power generation. The Weather Research and Forecasting (WRF) model with 10 km horizontal grid spacing was used to explore improvements in wind speed and ramp event forecasts at hub height (80 m). Results were validated using wind speed measurements at 80 m from a meteorological tower at the Pomeroy wind farm in northwest Iowa.

An ensemble consisting of WRF model simulations with different planetary boundary layer (PBL) schemes showed little spread among the individual ensemble members for forecasting wind speed. A second configuration using three random perturbations of the Global Forecast System model produced more spread in the wind speed forecasts, but the ensemble mean possessed less skill. A third ensemble with members having different initialization times showed model spread comparable to that from the perturbation results, but model skill was not compromised. In addition, we examined post-processing techniques such as bias correction of the diurnal cycle, training of the model for the day 2 forecast based on day 1 results, and bias correction based on observed wind direction. Evaluation suggests that, for the location and time period
studied, the ensemble mean of the first and third ensembles provides a more skillful wind forecast than any particular member, and further improvements occur when a bias correction of the diurnal cycle is applied to these forecasts.

To explore wind ramp forecasting, 138 wind ramp events were identified over 116 days for which a six-member WRF ensemble was run. An event was considered to be a ramp event if the change in wind power was 50% or more of total capacity in four hours or less. This was approximated using a typical wind turbine power curve such that any wind speed increase or decrease of more than 3 ms\(^{-1}\) within the 6-12 ms\(^{-1}\) window (where power production varies greatly) in four hours or less would be considered a ramp.

Model skill, climatology of ramp events, timing, and causes were examined. All PBL schemes examined predicted fewer ramp events compared to the observations, and forecasting skill for ramps in general was poor.

### 2.2 Introduction

In recent years, wind energy production has undergone rapid growth, and the U.S. Department of Energy goal of having 20% of the nation’s electrical energy from wind by 2030 will require continued growth (Department of Energy 2008). Wind, unlike other sources of energy, varies substantially over both space and time. Therefore, the production rates of wind energy fluctuate more strongly than those of other traditional fossil fuel sources of energy generation. To optimize wind for power generation, accurate forecasts are needed.

Unfortunately, there have been few evaluations of model forecasts of winds at 80 m, a height where the influence of friction from the earth’s surface can vary greatly
depending on the time of day, season, and vertical temperature stratification of the atmosphere. Meteorologists traditionally have focused wind forecasts at the 10 m level, a height at which official wind observations are taken, and a level at which winds are strongly influenced by surface friction. Prior wind forecasting research in the western United States has focused on flow in complex terrain (e.g. Wood 2000, Ayotte et al. 2001) and is therefore not applicable in Iowa where boundary layer stratification, low-level jets, and changing surface conditions are likely to be the dominant factors providing uncertainty in short-term forecasts at 80 m. Other modeling studies have taken a more statistical approach to predict wind speed at different levels (Huang et al. 1996); however, none have been reported for the state of Iowa, despite it being the state with the largest percentage of total power per capita coming from wind energy in 2010. Even fewer studies have examined the forecasting of ramp events, defined as rapid changes in wind speed that lead to extreme changes in wind power output. Large ramp events causing a 50% or greater change in the capacity of the wind speed were found to occur less than 7% of the time within 4 hours in a United Kingdom wind farm study (Greaves et al. 2009) and less than 4% of the time within 2 hours in a California wind farm study (Zack 2007). Although rare, ramp events occurring between the cut-in speed and the rated wind speed are extremely costly to energy companies because they may cause blackouts and overload the grid (Francis 2008) (Fig. 2.1). Along with being rare, ramp events are also difficult to forecast. It was found that ramp events were captured less than 36% of the time by a private forecast company forecasting for six wind farms in the United States (Greaves et al. 2009).

In the present study, the ability of version 3.1.1 of the Weather Research and
Forecasting (WRF) model to accurately reproduce 80 m wind speeds and ramp events was evaluated by comparing WRF simulations using six different planetary boundary layer (PBL) schemes to observations of 80 m wind speed gathered at the Pomeroy, Iowa wind farm site. The sensitivities of the two most widely used PBL schemes, the Yonsei University scheme (YSU), the Mellor-Yamada-Janji scheme (MYJ), along with the Quasi-Normal Scale Elimination PBL scheme (QNSE), the Mellor-Yamada Nakanishi and Niino level 2.5 PBL scheme (MYNN 2.5), the Mellor-Yamada Nakanishi and Niino level 3.0 PBL scheme (MYNN 3.0), and the Pleim PBL scheme (also called the asymmetric convective model [ACM2]) are examined. A brief review of the six different schemes can be found in the appendix.

2.2.1 Model Configuration and Data

For most of the simulations examined in the present study, a single domain with 10 km horizontal grid spacing was used, although some tests were performed embedding a nested 4 km grid spacing domain within the coarser domain (Fig. 2.2). Both domains had 47 vertical levels, with 16 levels in the lowest 1300m and an average vertical spacing of around 15 m in the lowest 100 m. The lowest sigma levels [heights] were 1.0 [surface], 0.999 [10 m], 0.997 [25 m], 0.995 [40 m], 0.993 [56 m], 0.991 [72 m], 0.989 [88 m], 0.987 [108 m], 0.983 [137 m], 0.978 [180 m], 0.970 [244 m], 0.954 [377 m], 0.934 [546 m], 0.909 [761 m], 0.880 [1016 m], and 0.849 [1300 m]. The physical schemes used include Ferrier microphysics (Ferrier et al. 2002), Rapid Radiation Transfer Model (RRTM) (Mlawer et al. 1997) for longwave radiation, and the Dudhia scheme (Dudhia 1989) for shortwave radiation. The Noah land surface scheme (Ek et al. 2003)
was used for all of the model runs except for the one using the ACM2 scheme which used the Pleim-Xiu scheme (Pleim and Xiu 1995; Xiu and Pleim 2001) since the Noah scheme is not applicable with the ACM2 PBL scheme. A cumulus scheme was not used for the 4 km runs while the 10 km runs used the Kain-Fritsch (Kain and Fritsch 1992). Six different PBL and surface layer schemes were evaluated in this study. The MYJ PBL scheme simulation used the Janjic Eta Monin-Obukhov surface layer scheme, the MYNN 2.5 and MYNN 3.0 PBL schemes used the MYNN surface layer scheme, the ACM2 PBL scheme used the Pleim-Xiu surface layer scheme, the QNSE PBL scheme used the QNSE surface layer scheme, and the YSU PBL scheme used the Monin-Obukhov (Hong and Pan 1996) surface layer scheme.

Fifty-four hour model runs were initiated at 18 UTC, 00 UTC, and 06 UTC using both the Global Forecast System (GFS) and North American Model (NAM) analyses for initial and lateral boundary conditions (ILBC). For each two-day period, twelve forecasts were made, one for each PBL scheme and each ILBC (Table 2.1). The first six hour period of each run was defined as model spin-up time and was not evaluated. A case study of instantaneous output compared to hourly averaged model output was done and results showed no significant differences, and therefore hourly model output was used in this study. Observed data for comparison with model results were taken from an 80 m meteorological tower on the southwest side of the Pomeroy, Iowa wind farm (Fig. 2.3) at 10 minute increments and averaged over one hour periods centered on each hour in attempt to measure the true sustained wind speed. Evaluation of 80 m wind speed was from June 2008 through September 2010, excluding periods during which missing data
were observed, while 58 cases spanning 116 days from June 2008 through June 2009 were validated in the wind ramp portion of this paper.

2.3 Methodology

Two forecast evaluations were performed. The first used mean absolute error (MAE) and bias to evaluate wind speed forecasts at 80 m elevation. For this examination, an operational ensemble was developed based on the skill of numerous member configurations examined in three sets of tests. The first set of tests, pre-run modification, explored different time initializations, grid spacing, and perturbations of the GFS ILBC. The second set of tests, post-processing, focused on three techniques, the neighborhood approach, training of the model, and bias correction. In the neighborhood approach, forecast values at grid points around the validation tower were averaged in lieu of using the grid point closest to the tower. The neighborhood approach has been successfully used to improve precipitation forecasting (Theis et al. 2005, Ebert 2009), although results have not been reported when applied to wind speed forecasting. Another technique examined training of the model based on model skill in the first 24 hour period. The three members with the highest skill during the first 24 hour period were used to form an ensemble to forecast the 24 to 48 hour period, referred to hereafter as day 2. The last technique focused on bias corrections based on (i) wind speed, (ii) wind direction, (iii) wind speed and direction, and (iv) the diurnal cycle. From the results of both pre-run and post-processing tests, a final ensemble was developed, hereafter known as final OP. The Wilcoxon signed-rank test was used to determine if the improvements in the final OP
ensemble were significant. The Wilcoxon signed-rank test was chosen as this test does not depend on the distribution of the data and is resistant to outliers (Wilks 1985).

The second test of forecast skill focused on ramp events at 80 m. In this paper, an event was considered to be a ramp event if the change in wind power over four hours or less was 50% or more of total capacity (Greaves et al. 2009). This change was approximated using a typical wind turbine power curve such that any wind speed increase or decrease of more than 3 ms$^{-1}$ within the 6-12 ms$^{-1}$ window (where power production varies greatly) in four hours or less was considered a ramp (similar to Greaves et al. 2009). Defining the start and end of a ramp event was somewhat subjective. We defined start of a ramp as a sharp change in wind speed and its end as when the change in wind speed became minimal (Fig. 2.4). Ramps were classified into two categories: ramp-ups (increase in speed within four hours) and ramp-downs (decrease in speed within four hours), similar to the technique used by Freedman et al. (2008) for surface data in a west Texas study. Wind observations were put through extensive quality control, and cases were chosen from the subset of days when reliable data existed. The wind data archive contained wind speed values every 10 minutes, and observed ramps were determined using both the 10 minute data and top-of-the-hour data. The results to follow focus on the hourly data, since the large set of model output only had a temporal frequency of one hour. Model skill was evaluated in four areas: number of ramp events forecasted, amplitude of event, frequency of events, and model error. MAE, Probability of Detection (POD) (Equ. 1), False Alarm Rate (FAR) (Equ. 2), and Threat Score (TS) (Equ. 3) were calculated to determine model skill using the following equations:
2.4 Results

The evaluation of approaches toward forecasting of winds at 80 m is organized into two sections. The first, *Evaluation of 80 m Wind Forecasts*, is divided into two subsections, *Pre-run Modification*, which focuses on model improvement by adjusting parameters before the WRF run is completed and *Post-Processing*, which focuses on adjustments and bias corrections done after model runs were performed. The second section, *Evaluation of Ramp Event Forecasts*, focuses on each PBL scheme’s ability to predict magnitude, timing, and duration of ramp events.

### 2.4.1 Evaluation of 80 m Wind Forecasts

To compare the six different PBL schemes, 32 cases (eight from each season; winter, spring, summer, and fall) were chosen at random (using a random number generator) during periods having quality observed data. We created an ensemble from WRF model runs with different PBL schemes at the same initiation time, based on results of Harrison et al. (1999) and Stensrud et al. (2000) who found that varying the model physics was a powerful method to create a forecast ensemble. However, in our study changing the PBL schemes produced little ensemble member spread among all six PBL
schemes using the same initialization time (Table 1.2). Small spread is good if all model versions are predicting speeds correctly; however, more often it results in all models yielding incorrect forecasts, and it is generally desirable to have spread comparable to the skill (Houtekamer 1993, Whitaker and Loughe 1998). Therefore, three techniques were investigated to improve model scheme spread and skill over 10 cases during January 2010, for which GFS perturbation data were available.

2.4.1.1) Pre-run modification

The first attempt to improve model skill used different perturbations of the initial and lateral boundary conditions for the GFS model. As of 20 May 2006, GFS perturbations were developed using an ensemble transform (ET) technique (Wei et al. 2006). ET replaced the breeding method and eliminated paired perturbations, making all perturbations random to each other. Therefore, in this study we selected three perturbation members (2, 4, and 15) to compare against the three initialization times tested later. The perturbations picked were run for 10 cases in January 2010 using the YSU and MYNN 3.0 PBL schemes. The results of this trial increased model spread; however, model skill decreased from the six PBL schemes tested at 00Z in Table 2.2 (Table 2.3).

The second approach to improve model skill changed the grid spacing. A two member ensemble using the 10 km grid and the YSU and MYNN 3.0 PBL schemes was created and evaluated against a two member ensemble using a 4 km grid and the YSU and MYNN 3.0 PBL schemes over a 10-day period in January 2010. Both the YSU, MYNN 3.0, and the ensemble showed lower MAE with 10 km grid spacing as opposed to
the 4 km (Table 2.4), although results of the Wilcoxon signed rank test showed results were not highly significant. Another goal of this study was to design an ensemble that could be used by wind energy companies. With computing power limited in most private companies, running 10 km model runs are much more feasible than 4 km runs. Therefore, because the skill of the 4 km runs was not better than the 10 km runs, we focused the remainder of our study on 10 km grid spacing.

The third approach to improve model skill changed the time of initialization. The motivation to test different time initializations or time-lagged ensembles came from the success and usefulness achieved in many other previous short to medium range forecasting studies (Hoffman and Kalnay 1983, Dalcher et al. 1988, Walser et al. 2004, and Lu et al. 2007). In our study, WRF simulations using the YSU and MYNN 3.0 PBL schemes were initialized at 18 UTC, 00 UTC, and 06 UTC over a 10-day period in January. The 00 UTC and 18 UTC time initializations showed the best skill while the 06 UTC initialization, the initialization closest to the forecast period, showed the lowest model skill (Table 2.5), although these results were not highly significant. Compared to the perturbation ensemble, the time initialization ensemble showed higher model spread and better model skill with a highly significant lower MAE. Therefore, our final OP ensemble was designed to include both different PBL schemes and 00 UTC and 18 UTC time initializations.

2.4.1.2) Post-processing

We investigated three post-processing techniques which included training of the model, the neighborhood approach, and bias correction of the wind speed.
The first post-processing technique trained the model based on day 1 results. In this method, day 1 forecasts (hours 6-30) were analyzed and the three most accurate PBL schemes (lowest MAE) were chosen and a Selected ensemble was developed to forecast day 2 wind speeds. The three least accurate PBL schemes (highest MAE) were chosen as members of the Non-Selected ensemble (Table 2.6). We observed that the most accurate day 1 forecasts do not always give the most accurate day 2 forecasts. From the 15 cases studied, the Non-Selected ensemble showed the highest skill 4 out of the 15 times (27%), the Selected ensemble showed the highest skill 5 out of the 15 times (33%), and the ensemble, incorporating all six model members, showed the highest skill 6 out of the 15 times (40%). Therefore, the training approach was not a reliable method to predict wind speed as conditions change from day to day, a result similar to that found in Briggs and Ruppert (2004) and Hall et al. (2010).

The second post-processing technique used the neighborhood approach. Instead of basing a forecast for a location on the model grid point closest to that location, in the neighborhood approach, a set of grid points around the location of interest are averaged. The results of this test showed opposite results for different PBL schemes. The YSU scheme, a non-local and first order closure scheme, became more accurate when a large set of grid points around the location of interest were averaged while the MYNN 3.0 scheme, a local and second order closure scheme, became less accurate when a large set of grid points around the location of interest were averaged (Table 2.7). Ensemble results from this approach show better model skill when an average was taken from a box consisting of 17 by 17 grid points; ensemble skill did not improve when averaging over larger areas (Table 2.7). However, the improvement was very small and not statistically
significant. The improvement was also not as large as that resulting from the other methods tested.

The third post-processing technique used biases observed in the PBL schemes to adjust the forecasts. A bias in the model was computed by analyzing 30 random cases from all seasons between June 2008 and June 2009 (Figure 2.5). All PBL schemes except the YSU exhibited a diurnal cycle in the bias data. We observed a negative bias, or under-prediction of the wind speed, from hours 12 to 20 (0600 to 1400 LST), while a positive bias (over-prediction) occurred from hours 20 to 12 (1400 to 0600 LST). The same pattern existed in day 2 of the 54 hour forecast and was present in runs using both the GFS and NAM ILBC. The consistent diurnal trends in error allow for bias correction of the forecasts.

Four possible biases were examined; the diurnal cycle, wind speed along with direction, wind speed only, and wind direction only. Bias corrections computed from the 30 cases mentioned above were applied to each model based on its PBL scheme using a 00 UTC time initialization with GFS ILBC over a 32 day period from 11 October 2008 to 11 November 2008 (Table 2.8). From these results, forecasts using a wind speed bias correction showed the highest model skill. To determine the six members that would make up the final OP ensemble, a 15 day test period from 14-28 August 2009 was used to analyze the skill of runs adjusted by the wind speed bias correction for both the 00 UTC and 18 UTC time initializations and the GFS and NAM ILBC (Table 2.9). Again, the wind speed bias correction developed from the 30 cases spanning all seasons was applied to this 15 day period. From a possible 24 different combinations, a six member ensemble was created. The six members found to have the most skill after the wind speed bias
correction included 18 UTC Pleim GFS, 18 UTC Pleim NAM, 00 UTC Pleim GFS, 00 UTC YSU NAM, 00 UTC YSU GFS, and 00 UTC MYJ GFS (Table 2.10). All six members used 10 km grid spacing. From these six members, the final OP ensemble was created. Most of the time, simulations using GFS ILBC showed higher model skill than those using NAM, so that four out of the six members of final OP used the GFS ILBC. Five out of the six members that formed the ensemble used either the Pleim or YSU PBL scheme. As noted previously, the YSU and the Pleim PBL schemes use first order closure and non-local mixing, while the other four PBL schemes tested use TKE closures and involve local mixing. Therefore, from our results, it appears that non-local PBL schemes provide the highest model skill for 80 m wind speed forecasts in northwest Iowa.

To evaluate the final OP ensemble, a deterministic forecast (the 00 UTC YSU GFS; the PBL scheme that showed the best model skill) as well as four other six-member ensembles were compared. The standard deviation was also calculated to determine model spread and compared to the final OP ensemble. To test the final OP ensemble, 25 random cases from the summer and fall of 2010 were used. The six-member final OP ensemble model had the best model skill (lowest MAE) of any of the other six member ensembles tested, both before and after the wind speed bias correction (Table 2.11). Based on these results, significance testing was done using the Wilcoxon signed-rank test. When comparing the non-bias corrected final OP ensemble to the other non-bias corrected six member ensembles and the deterministic forecast, the improvement in MAE of the final OP ensemble was highly significant, with p-values all less than 0.08. This indicates that an ensemble consisting of different time initializations and the YSU, MYJ,
and Pleim PBL schemes was more skillful than an ensemble constructed of all six PBL schemes. Finally, comparing the bias corrected final OP ensemble model to the non-bias corrected six member ensembles and the deterministic forecast, the improvement in MAE of the bias corrected final OP ensemble was highly significant, with all p-values less than 0.004. This demonstrates that the final OP ensemble designed in this paper shows a high degree of improvement in wind speed forecasting. The standard deviation of the final OP ensemble was also larger than that of any of the other ensembles, indicating a larger spread in the final OP ensemble which should be helpful in capturing outlier events and identifying episodes of higher forecast uncertainty.

### 2.4.2) Evaluation of Ramp Event Forecasts

Because ramp events have a high level of impact on the wind energy industry, we examined in more detail the ability of the WRF model to forecast these events. Tables 2.12 and 2.13 show the number of ramp-up, ramp-down, and total ramp events for both the Day 1 (6-30 hours after model start up) and Day 2 (30-54 hours after model start up) periods. All the PBL schemes on Day 2 and all the PBL schemes except the MYNN 2.5 scheme on Day 1 forecasted a significantly lower number of ramp events than observed, according to the Wilcoxon signed rank test. This suggests that the forecast models may be showing more gradual transitions during events, such that the wind speed changes do not meet the definition of a ramp. During Days 1 and 2, the YSU scheme forecasted the fewest number of total ramp events, less than half of the number observed. This under-prediction of the model was echoed in a study by Bradford et al. 2010, in which a privatized version of the 3 km WRF model significantly underestimated the number of
surface ramp events over an area of northern Texas, western Oklahoma, and southern Kansas.

It was initially assumed that most ramp events would be associated with either frontal passage or the presence of thunderstorms, but these phenomena accounted for only 16% and 12%, respectively, of all ramps. Although some events did occur during these weather phenomena, 28% of the events happened without an obvious trigger being present. During 29% of all ramp events, a low-level jet existed, and it is possible that mechanical mixing brought stronger winds down during short periods. In other events, the only weather condition noted that seemed as though it could play a role was the presence of rather steep lapse rates near the surface, which could support propagating gravity waves of growing amplitude that become non-linear, break and create a high-wind episode at low levels. Fifteen percent of all ramp events occurred during the mid or late morning when one might expect wind to increase quickly near the ground as the PBL grows, and a few ramp-down events happened toward evening when the collapse of the PBL might explain the decrease. But these events that appeared to be linked to diurnal changes in the PBL did not dominate the sample.

From the 58 cases tested, amplitude was over-predicted by all six PBL schemes for ramp-up events during Day 1 and 2 (Table 2.14). This result suggests that on these occasions the PBL schemes are mixing higher momentum air downward too strongly, resulting in an over-prediction, although the subjective nature of defining a ramp event could influence the results. Ramp-up events were also predicted to have larger amplitudes than ramp-down events in all PBL schemes; however, no difference in amplitude between ramp-up and down events was seen in the observed data. No bias or
trend was associated with ramp-down events, although they showed a lower MAE compared to the ramp-up events.

Using a three hour average of the midpoint of each ramp event, frequency of occurrence as a function of hour was examined for both ramp up and ramp down events (Figures 2.6 and 2.7). Model ramp-up events occurred most frequently between 22 UTC and 01 UTC (late afternoon) in all schemes except YSU, while observed ramp-up events occurred most frequently around 01 UTC. This sharp increase around 01 UTC in the observed data is believed to be associated with the decoupling of the surface layer as the ground begins to cool, an event that has been used to explain the formation of the Low Level Jet (LLJ). A secondary peak, occurring around 16 UTC can also be seen in the observed data. This ramp-up event may be due to the growth of the boundary layer in the morning hours, which would be a period when higher momentum air would begin mixing downward. If the hub height was located within the high friction surface layer in the early morning, then the growth of the PBL should allow for potentially rapid increases in wind speed. Only the YSU scheme showed this secondary peak at this time of day. No other scheme indicated a secondary maximum during this mid-late morning period. Thus, from a timing standpoint, the YSU scheme stands out as being substantially different from the other five schemes during ramp-up events.

For ramp-down events, a temporal trend in the observed data was less clear. A slight maximum in both the observations and in all the PBL schemes except the YSU was observed around 04 UTC and 13 UTC, although not as defined as the ramp-up maxima. Minima were observed around 07 UTC and 19 UTC. The MYNN 2.5 and MYNN 3.0 PBL schemes captured the 19 UTC minimum, but none captured the one occurring at 07
UTC. Once again, the YSU scheme behavior was distinctly different from the others with its peak at 01 UTC, a time when other schemes showed a distinct minimum.

To quantify timing error, MAE and bias were used to compare the different PBL schemes (Table 2.15). Bias values near zero with MAE values near zero indicate high model skill. In all cases, MAE was much larger than the bias, indicating that the PBL schemes were inconsistent with the timing of the ramp events. Ramp-up events had a higher MAE compared to ramp-down events in all PBL schemes, implying ramp-down events had better timing prediction than ramp-up events, although due to the subjective nature of defining the start of ramp events, caution must be used in interpreting these results.

Model error also was analyzed based on hits, misses, and false alarms. A hit was defined as a model ramp event occurring within +/- 6 hours of an observed ramp event of the same type (observed ramp-up to modeled ramp-up). Most ramp-up hits, false alarms, and ramp-up events forecasted were associated with the MYNN 2.5 PBL scheme. The high number of hits was due to the fact that this scheme forecasted the most events, and it was not associated with a high level of skill. For the ramp-down events, the QNSE scheme had the most forecasted ramp-down events, hits, and false alarms (tie), and again, the high number of hits was due to the high number of events forecasted and was not associated with high model skill.

Therefore, to further understand the skill of the various model runs, POD, FAR, and TS were calculated. Values of POD, FAR, and TS range from 0 to 1 with high model skill having a POD and TS near 1 and FAR near zero. For all PBL schemes except the YSU and Pleim, ramp-up events had higher POD scores, implying that models
exhibit more skill in the detection of ramp-up events compared to ramp-down events. The MYNN 2.5 PBL scheme showed the best POD, detecting ramp-up events nearly 50% of the time. As expected, Day 1 ramp events had higher PODs in all PBL schemes except the Pleim scheme, as forecast accuracy typically decreases with increasing lead time. Except for the YSU and Pleim schemes, a higher FAR was associated with ramp-down events compared to ramp-up events, implying models tend to forecast ramp-down events more often when observed ramp-down events are not present. The MYNN 2.5 PBL scheme showed the worst FAR, .50 or more on both days. Finally, in all schemes but the YSU and Pleim, the TS was higher for ramp-up events than ramp-down events, confirming better model skill in detecting ramp-up events than ramp-down events. The scheme with the best detection skill (highest TS) for ramp-up events was the MYNN 2.5 PBL scheme, while the Pleim PBL scheme had the best detection skill for ramp-down events.

2.5. Summary and Conclusions

Understanding the biases and strengths of different PBL schemes will help to improve wind speed forecasts at 80 m. In an examination of ensemble designs, it was found that perturbations of the GFS ILBC resulted in larger model spread than that achieved with use of six PBL schemes; however, the MAE was higher with the GFS perturbations. Simulations using the GFS ILBC also showed higher model skill than those using the NAM. Finally, ensembles using different time initializations gave larger spread and better model skill than the GFS perturbations tested.
The first post-processing technique examined, training the model based on day 1 results, was found to yield a forecast with low model skill as conditions apparently change too much from day to day. The second technique tested, the neighborhood approach, increased the accuracy of the models, although not significantly. The post-processing technique that was most successful was bias correction. Many different bias corrections were tested; however, the wind speed bias correction yielded the best results. From these results, a six member operational ensemble was developed that significantly outperformed other ensembles tested. Of the six members, the non-local mixing schemes of the Pleim and YSU formed five out of the six members, indicating, at least for this study, that non-local schemes outperform local schemes when predicting 80 m wind speed.

Many impediments preclude skillful forecasts of wind conditions at 80 m. We know at the surface winds decrease at night due to the decoupling of the surface layer, and increase during the day as the boundary layer grows and higher momentum air from above mixes down. However, with very few observations at 80 m, we have yet to develop a robust method for forecasting the time evolution of wind speed between the middle PBL and the surface. As a result, unforecasted ramp events, sharp increases or decreases in wind speed over a small time period, reduce the reliability of wind as a source of power.

For ramp events at 80 m, we found that all six PBL schemes tested underestimated the number of ramp-up and ramp-down events. Amplitude of modeled ramp-up events were over-predicted by all six PBL schemes, suggesting that the PBL schemes were mixing higher momentum air downward too strongly during these brief
periods. Regarding frequency of occurrence, modeled ramp-up events occurred most often between 22 UTC and 01 UTC, which closely matched observed ramp-up events (most frequent around 01 UTC). The sharp increase in observed ramp-up events around 01 UTC was associated with the decoupling of the surface layer as the ground began to cool, leading to the formation of the LLJ. In all ramp events, MAE was larger than the bias, indicating that the PBL schemes were inconsistent with the timing of the ramp events. In all PBL schemes except the YSU and Pleim, ramp-up events had higher POD, lower FAR, and higher TS, implying that models exhibit more skill in the detection of ramp-up events than ramp-down events. This prompts us to two conclusions: first, we need vastly more observations of wind and temperature in the lowest 500 m of the PBL under all conditions to establish a climatology for this region, and secondly, guided by these observations we need to re-examine the representations (local, non-local, turbulence order) of turbulent processes of PBL schemes used to represent mixing processes in this layer.

2.6. Acknowledgments

We would like to thank MidAmerican Energy Company for providing the 80 m observations. Partial funding was supplied by NSF grant BCS0618823, DOE grant #13-450-141201, Ames Laboratory Project 290-25-09-02-0031, and EPRC grant #400-60-12.
2.7 Appendix

Description of PBL schemes

PBL schemes were developed to help resolve the turbulent fluxes of heat, moisture, and momentum in the boundary layer. However, due to the complex nature of turbulence, closure has remained a problem. Two solutions to the problem of closure, local and non-local, will be discussed below. The first type, local closure, estimates unknown fluxes using known values and/or gradients at the same point. The second type, non-local closure, estimates unknown fluxes using known values and/or gradients at many points in space (Stull 1998, Bélair et al. 1999). Of the PBL schemes tested, the ACM2 and YSU schemes are non-local while the MYJ, QNSE, MYNN 2.5, and MYNN 3.0 are local closure schemes. A brief description of the six PBL schemes used in this study follows. Further details can be found in Janjic (1990), (1994) (MYJ), Hong et al. (2006) (YSU), Pleim (2007a), (2007b) (ACM2), Sukoriansky et al. (2005) (QNSE), and Nakanishi and Niino (2004) (MYNN).

The MYJ PBL scheme is one of four different local closure schemes evaluated in this study. The MYJ PBL scheme is a local turbulent kinetic energy (TKE), 1.5 order (2.5 level) closure scheme. Being a 1.5 order closure, it requires one additional prognostic equation to solve for the turbulent quantities (Janjic 1990, 1994, Shin and Hong 2011, Hu et al. 2010). The MYNN 2.5 and 3.0 PBL schemes are higher level schemes that were based on the MYJ scheme. The MYNN 2.5 scheme is a local TKE, 1.5 order (2.5 level) closure scheme while the MYNN 3.0 is a local TKE, 2.0 order (3.0 level) closure scheme. Both the MYJ and MYNN schemes apply the local mixing from the lowest to highest vertical level. The major difference between the MYJ and MYNN
2.5 and 3.0 schemes is the TKE equation, and more specifically, the master mixing length \( (l_m) \). The TKE equation is defined as:

\[
\frac{d\left(\frac{q^2}{2}\right)}{dt} - \frac{\partial}{\partial z} \left[ l_m q S_q \frac{\partial}{\partial z} \left( \frac{q^2}{2} \right) \right] = P_S + P_b + \varepsilon
\]

where the first term is the total derivative of \( q \), which is two times the TKE, the second term is the vertical redistribution of \( q \), \( P_S \) is the production of \( q \) by shear, \( P_b \) is the production of shear by buoyancy, and \( \varepsilon \) is the dissipation term. For the MYJ scheme, the master mixing length is defined as:

\[
l_m = l_o \frac{kz}{kz + l_o}
\]

where \( l_o \) is dependent on height and \( k \) is the von Karman constant. The master mixing length for the MYNN PBL schemes is a function of three independent length scales:

\[
\frac{1}{l_m} = \frac{1}{l_s} + \frac{1}{l_t} + \frac{1}{l_b}
\]

where \( l_s \) is the surface layer length, \( l_t \) is the turbulent layer length, and \( l_b \) is the buoyancy length (Olson and Brown 2009, Nakanishi and Niino 2004).

The QNSE scheme is a local TKE, 1.5 order (2.5 level) closure scheme that is similar to the MYJ scheme during neutral and unstable conditions. The QNSE scheme differs from the MYJ scheme during stable conditions, when spectral theory is used to develop eddy diffusivity profiles. This results in waves and turbulent eddies being treated as one entity. Like the MYJ and MYNN schemes, the QNSE scheme applies local mixing from the lowest to highest vertical level (Sukoriansky et al. 2005, Shin and Hong 2011).
The last two PBL schemes investigated in this study were the YSU and ACM2. These schemes are both first-order (requiring no additional prognostic equations), non-local schemes. The ACM2 scheme is a combination of a simple transient model (original Blackadar scheme) and an eddy diffusion model. The ACM2 scheme is able to switch between stable conditions (eddy diffusion) and unstable conditions (local and non-local transport). During stable or neutral conditions, the scheme uses local closure instead of non-local transport (Hu et al. 2010, Pleim 2007a, 2007b, Shin and Hong 2011). On the other hand, the YSU scheme is a bulk scheme that expresses non-local mixing by convective large eddies. Non-local mixing is achieved by adding a non-local gradient adjustment term (countergradient term) to the local gradient. At the top of the PBL, the YSU scheme uses explicit treatment of the entrainment layer, which is proportional to the surface layer flux (Hong et al. 2006, Shin and Hong 2011, Hu et al. 2010).

2.8. References


Bradford, K. T., R. L. Carpenter, and B. Shaw, 2010: Forecasting Southern Plains wind ramp events using the WRF model at 3km. *Ninth Annual Student Conference,*


<table>
<thead>
<tr>
<th>Member Number</th>
<th>PBL Scheme</th>
<th>Land Surface Scheme</th>
<th>Land Layer Scheme</th>
<th>Initial Boundary Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>YSU</td>
<td>Noah</td>
<td>Monin-Obukhov</td>
<td>GFS</td>
</tr>
<tr>
<td>2</td>
<td>MYJ</td>
<td>Noah</td>
<td>Janjic Eta Monin-Obukhov</td>
<td>GFS</td>
</tr>
<tr>
<td>3</td>
<td>QNSE</td>
<td>Noah</td>
<td>QNSE</td>
<td>GFS</td>
</tr>
<tr>
<td>4</td>
<td>MYNN 2.5</td>
<td>Noah</td>
<td>MYNN</td>
<td>GFS</td>
</tr>
<tr>
<td>5</td>
<td>MYNN 3.0</td>
<td>Noah</td>
<td>MYNN</td>
<td>GFS</td>
</tr>
<tr>
<td>6</td>
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<td>Pleim-Xiu</td>
<td>Pleim-Xiu</td>
<td>GFS</td>
</tr>
<tr>
<td>7</td>
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<td>Monin-Obukhov</td>
<td>NAM</td>
</tr>
<tr>
<td>8</td>
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<td>Noah</td>
<td>Janjic Eta Monin-Obukhov</td>
<td>NAM</td>
</tr>
<tr>
<td>9</td>
<td>QNSE</td>
<td>Noah</td>
<td>QNSE</td>
<td>NAM</td>
</tr>
<tr>
<td>10</td>
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<td>Noah</td>
<td>MYNN</td>
<td>NAM</td>
</tr>
<tr>
<td>11</td>
<td>MYNN 3.0</td>
<td>Noah</td>
<td>MYNN</td>
<td>NAM</td>
</tr>
<tr>
<td>12</td>
<td>ACM2</td>
<td>Pleim-Xiu</td>
<td>Pleim-Xiu</td>
<td>NAM</td>
</tr>
</tbody>
</table>

Table 2.1: Parameterization combinations used to create ensemble members.
Table 2.2: MAE associated with six PBL schemes using the 00 UTC time initialization and the GFS ILBC from 10 cases in January 2010. The six member ensemble average and the standard deviation (measure of model spread) are also listed.

<table>
<thead>
<tr>
<th>PBL Scheme</th>
<th>MAE (ms(^{-1}))</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYJ ((\text{ms}^{-1}))</td>
<td>1.38</td>
<td>---</td>
</tr>
<tr>
<td>MYNN 2.5 ((\text{ms}^{-1}))</td>
<td>1.43</td>
<td>---</td>
</tr>
<tr>
<td>MYNN 3.0 ((\text{ms}^{-1}))</td>
<td>1.38</td>
<td>---</td>
</tr>
<tr>
<td>Pleim ((\text{ms}^{-1}))</td>
<td>1.29</td>
<td>---</td>
</tr>
<tr>
<td>QNSE ((\text{ms}^{-1}))</td>
<td>1.39</td>
<td>---</td>
</tr>
<tr>
<td>YSU ((\text{ms}^{-1}))</td>
<td>1.31</td>
<td>---</td>
</tr>
<tr>
<td>Ensemble ((\text{ms}^{-1}))</td>
<td>1.26</td>
<td>0.66</td>
</tr>
</tbody>
</table>
Table 2.3: MAE associated with three different GFS perturbations using the YSU and MYNN3.0 PBL schemes from 10 cases in January 2010. The two member ensemble average and the standard deviation (measure of model spread) are also listed.

<table>
<thead>
<tr>
<th>Perturbation Number</th>
<th>2</th>
<th>4</th>
<th>15</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYNN 3.0 MAE (ms⁻¹)</td>
<td>1.88</td>
<td>1.73</td>
<td>1.80</td>
<td>---</td>
</tr>
<tr>
<td>YSU MAE (ms⁻¹)</td>
<td>1.60</td>
<td>1.59</td>
<td>1.72</td>
<td>---</td>
</tr>
<tr>
<td>Ensemble MAE (ms⁻¹)</td>
<td>1.58</td>
<td>1.53</td>
<td>1.62</td>
<td>0.98</td>
</tr>
</tbody>
</table>
Table 2.4: MAE associated with the wind speed at 80 m from two different grid spacings (4 km and 10 km) from 10 cases in January 2010. The two member ensemble average is also listed.

<table>
<thead>
<tr>
<th>Grid Spacing</th>
<th>MYNN 3.0 MAE (ms⁻¹)</th>
<th>YSU MAE (ms⁻¹)</th>
<th>Ensemble MAE (ms⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 km</td>
<td>1.37</td>
<td>1.29</td>
<td>1.18</td>
</tr>
<tr>
<td>4 km</td>
<td>1.70</td>
<td>1.33</td>
<td>1.27</td>
</tr>
</tbody>
</table>

Table 2.4: MAE associated with the wind speed at 80 m from two different grid spacings (4 km and 10 km) from 10 cases in January 2010. The two member ensemble average is also listed.
Table 2.5: MAE associated with the wind speed at 80 m from three different initialization times from 10 cases in January 2010. The two member ensemble average and the standard deviation (measure of model spread) are also listed.

<table>
<thead>
<tr>
<th>Time Initialization</th>
<th>18 UTC</th>
<th>00 UTC</th>
<th>06 UTC</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYNN 3.0 MAE (ms⁻¹)</td>
<td>1.42</td>
<td>1.37</td>
<td>1.38</td>
<td>---</td>
</tr>
<tr>
<td>YSU MAE (ms⁻¹)</td>
<td>1.32</td>
<td>1.29</td>
<td>1.61</td>
<td>---</td>
</tr>
<tr>
<td>Ensemble MAE (ms⁻¹)</td>
<td>1.23</td>
<td>1.18</td>
<td>1.28</td>
<td>1.09</td>
</tr>
<tr>
<td>Model Number</td>
<td>Day 1 MAE (ms⁻¹)</td>
<td>Times Selected</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------</td>
<td>------------------</td>
<td>----------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00 UTC MYJ GFS with a 10 km grid spacing</td>
<td>2.51</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00 UTC MYJ NAM with a 10 km grid spacing</td>
<td>2.61</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00 UTC Pleim NAM with a 10 km grid spacing</td>
<td>2.58</td>
<td>4</td>
<td></td>
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<tr>
<td>00 UTC Pleim GFS with a 10 km grid spacing</td>
<td>2.36</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00 UTC YSU NAM with a 10 km grid spacing</td>
<td>2.32</td>
<td>11</td>
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<tr>
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<tr>
<td>Ensemble Mean</td>
<td>1.97</td>
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</table>

<table>
<thead>
<tr>
<th>Day 2 Selected ensemble best MAE</th>
<th>Day 2 Non-Selected ensemble best MAE</th>
<th>Day 2 All Member Ensemble best MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>5/15</td>
<td>4/15</td>
<td>6/15</td>
</tr>
</tbody>
</table>

Table 2.6: MAE calculated for the first 24 hour period. The three PBL schemes with the greatest skill were chosen, making up the Day 2 Selected ensemble. Times Selected indicated the number of times a model was chosen as a member of the Day 2 Selected ensemble. The Non-Selected ensemble incorporated the least accurate models for the first 24 hour period. Day 2 All Member Ensemble incorporated all six model members.
Table 2.7: MAE for wind speed at 80 m associated with the neighborhood approach.

<table>
<thead>
<tr>
<th>Grid Averaging</th>
<th>MYNN 3.0 MAE (ms(^{-1}))</th>
<th>YSU MAE (ms(^{-1}))</th>
<th>Ensemble MAE (ms(^{-1}))</th>
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</thead>
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<tr>
<td>Point</td>
<td>1.37</td>
<td>1.29</td>
<td>1.18</td>
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<tr>
<td>3x3</td>
<td>1.36</td>
<td>1.28</td>
<td>1.17</td>
</tr>
<tr>
<td>5x5</td>
<td>1.36</td>
<td>1.25</td>
<td>1.16</td>
</tr>
<tr>
<td>11x11</td>
<td>1.38</td>
<td>1.18</td>
<td>1.14</td>
</tr>
<tr>
<td>17x17</td>
<td>1.39</td>
<td>1.16</td>
<td>1.13</td>
</tr>
<tr>
<td>21x21</td>
<td>1.40</td>
<td>1.17</td>
<td>1.14</td>
</tr>
<tr>
<td>Bias Corrections</td>
<td>MYJ  (ms$^{-1}$)</td>
<td>MYNN 2.5 (ms$^{-1}$)</td>
<td>MYNN 3.0 (ms$^{-1}$)</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>------------------</td>
<td>----------------------</td>
<td>----------------------</td>
</tr>
<tr>
<td>No Bias</td>
<td>2.34</td>
<td>2.49</td>
<td>2.41</td>
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<td>2.33</td>
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<tr>
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<td>2.26</td>
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<td>2.14</td>
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<td>2.01</td>
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<td>Best Improvement</td>
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<td>0.45 ms$^{-1}$</td>
<td>0.40 ms$^{-1}$</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>% of Improvement</td>
<td>14.1%</td>
<td>22.1%</td>
<td>20.0%</td>
</tr>
</tbody>
</table>

Table 2.8: MAE associated with different bias corrections developed for each PBL scheme for the 00 UTC GFS ILBC. This case study was done from 11 October 2008 to 11 November 2008.
Table 2.9: MAE associated with different PBL schemes using the wind speed bias correction. The best PBL skill was produced by the YSU and Pleim schemes. The case study was done during 14-28 August 2009.
<table>
<thead>
<tr>
<th>Member Number</th>
<th>PBL Scheme</th>
<th>Time Initialization</th>
<th>Land Surface Scheme</th>
<th>Land Layer Scheme</th>
<th>Initial Boundary Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ACM2</td>
<td>18 UTC</td>
<td>Pleim-Xiu</td>
<td>Pleim-Xiu</td>
<td>GFS</td>
</tr>
<tr>
<td>2</td>
<td>ACM2</td>
<td>18 UTC</td>
<td>Pleim-Xiu</td>
<td>Pleim-Xiu</td>
<td>NAM</td>
</tr>
<tr>
<td>3</td>
<td>ACM2</td>
<td>00 UTC</td>
<td>Pleim-Xiu</td>
<td>Pleim-Xiu</td>
<td>GFS</td>
</tr>
<tr>
<td>4</td>
<td>YSU</td>
<td>00 UTC</td>
<td>Noah</td>
<td>Monin-Obukhov</td>
<td>NAM</td>
</tr>
<tr>
<td>5</td>
<td>YSU</td>
<td>00 UTC</td>
<td>Noah</td>
<td>Monin-Obukhov</td>
<td>GFS</td>
</tr>
<tr>
<td>6</td>
<td>MYJ</td>
<td>00 UTC</td>
<td>Noah</td>
<td>JanjicEta Monin-Obukhov</td>
<td>GFS</td>
</tr>
</tbody>
</table>

Table 2.10: Parameterization combinations used in the final OP ensemble to forecast wind speed at 80 m.
Table 2.11: MAE of final OP ensemble after wind speed bias correction compared to other six member ensembles tested for 25 cases during the summer and fall of 2010. The deterministic forecast is the best individual model found from the period studied. Standard deviation (measure of model spread) for each ensemble is also calculated. The bold value indicates a high level of statistical improvement from the non-bias corrected six member ensembles/deterministic forecast to the non-bias corrected final OP ensemble, with p-values less than .08 determined from a Wilcoxon signed-rank test. The italics value indicates a high level of statistical improvement from the non-bias corrected six member ensembles/deterministic forecast to the bias corrected final OP ensemble, with p-values less than .01 determined from a Wilcoxon signed-rank test.

<table>
<thead>
<tr>
<th>Ensemble</th>
<th>MAE after Bias Correction (ms⁻¹)</th>
<th>MAE Prior to Bias Correction (ms⁻¹)</th>
<th>Standard Deviation after Correction (ms⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS 00 UTC</td>
<td>1.67</td>
<td>1.99</td>
<td>0.74</td>
</tr>
<tr>
<td>GFS 18 UTC</td>
<td>1.66</td>
<td>2.05</td>
<td>0.80</td>
</tr>
<tr>
<td>NAM 00 UTC</td>
<td>1.68</td>
<td>1.91</td>
<td>0.67</td>
</tr>
<tr>
<td>NAM 18 UTC</td>
<td>1.70</td>
<td>1.93</td>
<td>0.73</td>
</tr>
<tr>
<td>Deterministic Forecast</td>
<td>1.70</td>
<td>1.77</td>
<td>- - -</td>
</tr>
<tr>
<td>Final OP Ensemble</td>
<td>1.52</td>
<td>1.67</td>
<td>0.98</td>
</tr>
</tbody>
</table>
### Table 2.12: Number of ramp events during Day 1 (06-30 hours after model start up).

Bold values indicate PBL schemes which were found to have a significantly lower number of Day 1 ramp events than the observations, with p-values less than 0.1 determined from a Wilcoxon signed-rank test.

<table>
<thead>
<tr>
<th>PBL Scheme</th>
<th>MYJ</th>
<th>MYNN 2.5</th>
<th>MYNN 3.0</th>
<th>Pleim</th>
<th>QNSE</th>
<th>YSU</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ramp-up</td>
<td>23</td>
<td>29</td>
<td>27</td>
<td>19</td>
<td>26</td>
<td>16</td>
<td>35</td>
</tr>
<tr>
<td>Ramp-down</td>
<td>23</td>
<td>28</td>
<td>21</td>
<td>14</td>
<td>28</td>
<td>13</td>
<td>31</td>
</tr>
<tr>
<td>Total Ramp Events</td>
<td><strong>46</strong></td>
<td><strong>57</strong></td>
<td><strong>48</strong></td>
<td><strong>33</strong></td>
<td><strong>54</strong></td>
<td><strong>29</strong></td>
<td><strong>66</strong></td>
</tr>
</tbody>
</table>
Table 2.13: Number of ramp events during Day 2 (30-54 hours after model start up). Bold values indicate PBL schemes which were found to have a significantly lower number of Day 2 ramp events than the observations, with p-values less than 0.1 determined from a Wilcoxon signed-rank test.

<table>
<thead>
<tr>
<th>PBL Scheme</th>
<th>MYJ</th>
<th>MYNN 2.5</th>
<th>MYNN 3.0</th>
<th>Pleim</th>
<th>QNSE</th>
<th>YSU</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ramp-up</td>
<td>17</td>
<td>25</td>
<td>24</td>
<td>17</td>
<td>26</td>
<td>11</td>
<td>37</td>
</tr>
<tr>
<td>Ramp-down</td>
<td>19</td>
<td>22</td>
<td>16</td>
<td>20</td>
<td>23</td>
<td>11</td>
<td>35</td>
</tr>
<tr>
<td>Total Ramp Events</td>
<td><strong>36</strong></td>
<td><strong>47</strong></td>
<td><strong>40</strong></td>
<td><strong>37</strong></td>
<td><strong>49</strong></td>
<td><strong>22</strong></td>
<td><strong>72</strong></td>
</tr>
<tr>
<td>PBL Scheme</td>
<td>MYJ (ms(^{-1}))</td>
<td>MYNN 2.5 (ms(^{-1}))</td>
<td>MYNN 3.0 (ms(^{-1}))</td>
<td>Pleim (ms(^{-1}))</td>
<td>QNSE (ms(^{-1}))</td>
<td>YSU (ms(^{-1}))</td>
<td>Obs (ms(^{-1}))</td>
</tr>
<tr>
<td>------------------</td>
<td>-------------------</td>
<td>------------------------</td>
<td>------------------------</td>
<td>-------------------</td>
<td>-------------------</td>
<td>-------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Ramp-up (Day 1)</td>
<td>4.50</td>
<td>4.62</td>
<td>4.75</td>
<td>4.85</td>
<td>4.60</td>
<td>4.67</td>
<td>4.53</td>
</tr>
<tr>
<td>Ramp-up (Day 2)</td>
<td>4.54</td>
<td>5.16</td>
<td>5.2</td>
<td>4.56</td>
<td>4.69</td>
<td>4.73</td>
<td>4.01</td>
</tr>
<tr>
<td>Ramp-down (Day 1)</td>
<td>3.74</td>
<td>4.62</td>
<td>4.20</td>
<td>4.60</td>
<td>4.31</td>
<td>4.17</td>
<td>4.34</td>
</tr>
<tr>
<td>Ramp-down (Day 2)</td>
<td>3.83</td>
<td>4.28</td>
<td>4.46</td>
<td>4.27</td>
<td>4.59</td>
<td>4.43</td>
<td>4.21</td>
</tr>
</tbody>
</table>

Table 2.14: Average amplitude of ramp events divided into ramp-up/down events on Day 1 and Day 2.
Table 2.15: Model error associated with ramp events for each PBL scheme. Probability of Detection (POD), False Alarm Rate (FAR) and Threat Score were calculated. The Bias and MAE show the timing error associated with each PBL scheme. A hit means the model correctly predicted the ramp event within +/- 6 hours.
Figure 2.1: Power curve for the 1.5 MW wind turbines used at the Pomeroy, Iowa Wind farm. Cut-in speed is around 3.5 ms$^{-1}$ while the rated wind speed is around 12 ms$^{-1}$ (General Electric Company 2005).
Figure 2.2: The 10 km and 4 km model domains used in this study. The black dot is the location of the Pomeroy, Iowa Wind Farm.
Figure 2.3: (Left) The 10 km domain with outline of Pomeroy wind farm (right) where the individual wind turbines are the black dots and the 80 m meteorological tower (observed data location) is the red dot.
Figure 2.4: Example of a ramp-up event. Start is assumed to be at 01 UTC when sharp change in wind speed begins and ends when the change in wind speed becomes minimal at 04 UTC.
Figure 2.5: Composites of PBL biases by hour. Each line represents a different PBL scheme; MYJ (Black), MYNN 2.5 (Red), MYNN 3.0 (Blue), Pleim or ACM2 (Green), QNSE (Turco), and YSU (Magenta).
Figure 2.6: Three hour averaged diurnal cycle of ramp-up events using the midpoint of the ramp event. Black line is observed ramp-up events.
Figure 2.7: Three hour averaged diurnal cycle of ramp-down events using the midpoint of the ramp event. Black line is observed ramp-down events.
Chapter 3. Simulation of Nocturnal Low Level Jets with WRF PBL Schemes and Comparison to Observations from the ARM Project

A paper to be submitted to Monthly Weather Review

Adam J. Deppe, William A. Gallus, Jr., Kristy C. Carter

3.1 Abstract

Low Level Jets (LLJ), regions of moderately strong winds in the lower troposphere commonly found over the Great Plains, have become important in the study of wind power as turbine heights gradually increase. To improve understanding of these events, thirty LLJ cases were selected and simulated using the Weather Research and Forecasting (WRF) model with six different planetary boundary layer (PBL) schemes and 10 km grid spacing. The Lamont, OK, wind profiler site, within the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) project, was used to validate the ensemble because of its high vertical resolution and data availability at elevations below 500 m. The thirty cases examined were selected based on the presence of a nocturnal LLJ at the site between June 2008 and May 2010. All PBL schemes were found to under-predict the maximum LLJ wind speed, with the Yonsei University scheme (YSU) PBL scheme exhibiting the largest under-prediction. The height of the LLJ maximum was under-predicted by over 125 m in all PBL schemes except the YSU scheme, which under-predicted the maximum height by only 15 m. These differences between the YSU
scheme and the other PBL schemes are likely the result of enhanced mixing in the YSU scheme.

3.2 Introduction

Low Level Jets (LLJs), first described in the late 1930’s by Goualt (1938) and Farquharson (1939), significantly influence many aspects of weather including mesoscale convective complexes (MCC) (Maddox 1980, 1983) and wind power production over the Midwest. Although the most well-known and documented LLJs occur over the Great Plains of the United States, LLJs can be found around the world including Europe, Africa, and Australia (Stensrud 1996). As areas of relatively fast-moving winds in the lower atmosphere, LLJs were first studied because of their roll in transporting warm, moist air from the Gulf of Mexico into the Great Plains, strongly influencing nocturnal convective events (Means 1952, Lettau 1954, Blackadar 1955, Stensrud 1996). On average, maximum winds during nocturnal LLJ events over the Great Plains are between 10 m/s and 30 m/s, and they occur most often during the summer months (Whiteman et al. 1997). LLJ characteristics are, however, highly variable depending on time, season, and intensity (Stull 1988, Whiteman et al. 1997). With the potential for wind turbine hub heights to increase from 80 m to 120 m or higher, LLJ interaction with wind turbines could affect substantially the power performance of wind farms (Schwartz and Elliot, 2005).

Over the years, several physical mechanisms have been established to explain LLJ occurrence, including the inertial oscillation (Blackadar 1957), isallobaric forcing
(Uccellini and Johnson 1979, 1980), and terrain effects (Wexler 1961). Of these, the first (Blackadar 1957) is the most widely accepted theory on nocturnal LLJ formation over the Great Plains. Blackadar (1957) proposed that the formation of LLJs originates from frictional decoupling of the surface leading to inertial oscillations in the early evening. During this process, a temperature inversion develops, which inhibits mixing, and causes the wind speed aloft to be unaffected by friction at the surface. This loss of surface friction results in an acceleration of the wind speed and the development of a LLJ.

Bonner (1968) established a criteria for the classification of LLJs based on wind speed and intensity during the event. Following Bonner (1968), Whiteman (1997) classified two years of LLJs in northern Oklahoma and discovered that LLJs occur 47% of the time during the warm season and 45% of the time during the cold season. Whiteman (1997) also noted that approximately 50% of the maximum wind speeds during LLJ events occurred less than 500 m above the surface. This low elevation of the jet’s maximum wind presents a potential problem as the best method at present to observe LLJs is through the National Oceanic and Atmospheric Association (NOAA) Wind Profiler Network 404-MHz radar profilers, which measure wind speeds only between 500 m and 19 km (Arritt et al. 1997).

While a thorough classification of observed LLJs exists, few studies have examined the performance of forecasting models such as the WRF during these events, or the sensitivity of simulations of LLJs to PBL or surface layer schemes. As a result, current numerical weather prediction models do not accurately predict LLJ magnitude or location (Banta et al. 2002). Of the studies that have been completed on LLJs, most have examined the forcing mechanisms (McCorcle 1988; Zhong et al. 1996; Wu and Raman
1997) or effects of LLJs on precipitation or convection (Arritt et al. 1997, Monaghan et al. 2010). A case study by Storm et al. (2009) analyzed LLJ winds as simulated using two PBL schemes, the YSU and the Mellor-Yamada-Janjic scheme (MYJ), but only two LLJ events were studied. In summary, the behavior of PBL schemes and how they affect modeled LLJs has not been studied in great detail.

In this study, the ability of the WRF model to accurately reproduce vertical wind structure during LLJ events is evaluated by comparing WRF simulations using six different planetary boundary layer (PBL) schemes to observations from the Lamont, OK wind profiler site. The sensitivities of the two most-widely used PBL schemes, the YSU and MYJ, along with the Quasi-Normal Scale Elimination PBL scheme (QNSE), the Mellor-Yamada Nakanishi and Niino level 2.5 PBL scheme (MYNN 2.5), the Mellor-Yamada Nakanishi and Niino level 3.0 PBL scheme (MYNN 3.0), and the Pleim PBL scheme (also called the asymmetric convective model (ACM2)) are examined. More information on the six different schemes can be found in the appendix.

3.3 Data and Methodology

The WRF version 3.1.1 simulations examined in the present study used a single domain with 10 km horizontal grid spacing (Figure 3.1). The domain had 47 vertical levels, with 16 levels in the lowest 1300 m. The lowest sigma levels [heights] were 1.0 [surface], 0.999 [10 m], 0.997 [25 m], 0.995 [40 m], 0.993 [56 m], 0.991 [72 m], 0.989 [88 m], 0.987 [108 m], 0.983 [137 m], 0.978 [180 m], 0.970 [244 m], 0.954 [377 m], 0.934 [546 m], 0.909 [761 m], 0.880 [1016 m], and 0.849 [1300 m]. The vertical distribution of levels was chosen to provide largest refinement near the surface for wind
energy forecasting; it can be seen that vertical resolution was rapidly coarsening near or just above the level where LLJs typically are strongest. The relatively coarser resolution in this region likely has some effect on simulated LLJ characteristics, although it should be noted that the resolution in the present study is roughly similar to that used operationally. The physical schemes used include Ferrier microphysics (Ferrier et al. 2002), Rapid Radiation Transfer Model (RRTM) (Mlawer et al. 1997) for longwave radiation, Kain-Fritsch (Kain and Fritsch 1992) for the cumulus parameterization, and the Dudhia scheme (Dudhia 1989) for shortwave radiation. The Noah land surface scheme (Ek et al. 2003) was used for all of the model runs except for the one using the ACM2 scheme which used the Pleim-Xiu scheme (Pleim and Xiu 1995; Xiu and Pleim 2001) since the Noah scheme is not applicable with the ACM2 PBL scheme. Six different PBL and surface layer schemes were evaluated. The MYJ PBL scheme simulation used the Janjic Eta Monin-Obukhov surface layer scheme, the MYNN 2.5 and MYNN 3.0 PBL schemes used the MYNN surface layer scheme, the ACM2 PBL scheme used the Pleim-Xiu surface layer scheme, the QNSE PBL scheme used the QNSE surface layer scheme, and the YSU PBL scheme used the Monin-Obukhov (Hong and Pan 1996) surface layer scheme.

Fifty-four hour model runs were initialized at 00 UTC, approximately 24-30 hours prior to the start of each LLJ event. For each two-day period, six forecasts were made, one for each PBL scheme using GFS ILBC. The first six hours of each run were defined as model spin-up time and output was not evaluated. Otherwise, model output was evaluated hourly during LLJ events. Observed data was obtained from a U. S. Department of Energy ARM project wind profiler located at the Lamont, OK. The
Lamont, OK site (Figure 3.1) is located just southeast of the city of Lamont on 160 acres of cattle pastures and wheat fields. Equipped with a 915-MHz wind profiler, the Lamont, OK site can measure wind speeds below 500 m, unlike the NOAA 404-MHz profilers. Observed wind speed data ranged from 96 m above the surface to 2462 m above the surface, with a vertical resolution of 60 m. For this study, 30 LLJ cases were chosen between June 2008 and May 2010. Dates were selected for inclusion based on the presence of both strong and weak nocturnal LLJs at the site. For comparison, 30 non-LLJ events were also found during the same data period. The periods from 14 November 2008 to 7 December 2008 and 10 April 2009 to 13 August 2009 were omitted because of erroneous or missing data. The dates selected for both LLJ and non-LLJ events are shown in Table 3.1.

Model skill was assessed based on analyses of maximum wind speed, height of the LLJ maximum wind speed, duration of the LLJ event, Bonner classification, and occurrence of the LLJ maximum. As a control, wind speeds at 460 m during non-LLJ events were also analyzed and compared to LLJ events. The height of 460 m was chosen as it is the closest model level to the average observed height of the LLJ maximum found in the present study. The Wilcoxon signed-rank test (Wilks 1985) was used to determine if the maximum LLJ wind speed and height predicted by the YSU PBL scheme was significantly different than the other schemes. Although many studies of LLJs mention duration, there is no formal definition documented in the literature (Piety 2005). Some studies restrict the time analyzed to be between 02 UTC and 12 UTC (Song et al. 2005) or between 02 UTC and 11 UTC (Whiteman 1997). In this study, the duration of the LLJ was defined as the length of time the wind speed was greater than 50% of the LLJ
maximum wind speed, a method that worked well to confine LLJ events to the night time
hours. LLJ maximum wind speed, height of the LLJ maximum, and duration were also
broken down and analyzed according to the Bonner classification system as follows
(Bonner 1968):

- Criteria 1 – Maximum wind speed must equal or exceed 12 m s\(^{-1}\) and must
decrease by at least 6 m s\(^{-1}\) by 3 km
- Criteria 2 – Maximum wind speed must equal or exceed 16 m s\(^{-1}\) and must
decrease by at least 8 m s\(^{-1}\) by 3 km
- Criteria 3 – Maximum wind speed must equal or exceed 20 m s\(^{-1}\) and must
decrease by at least 10 m s\(^{-1}\) by 3 km.

An additional aspect of this study looked at LLJ impacts on wind energy. For this
study, observed non-LLJ and LLJ events were compared and analyzed based on the wind
speed at 96 m and 157 m only. The 96 m and 157 m heights were chosen for this study
as these levels correspond to the two lowest levels at the Lamont, OK wind profiler site.
Along with observational analysis at 96 m and 157 m, model skill was also analyzed. For
this examination, mean absolute error (MAE), bias, and the Wilcoxon signed-rank test
were used to evaluate wind speed forecasts during LLJ and non-LLJ events at 96 m and
157 m for six different PBL schemes. As the largest wind turbine currently manufactured
has a hub height of 135 m and reaches a total height of 198 m (Enercon 2010),
understanding model behavior at 157 m is becoming just as important as at 96 m or 80 m
(the standard hub height) to the wind energy sector.
3.4 Results

The evaluation of model skill during LLJ events is organized into two sections. The first, *Evaluation of LLJ Structure*, focuses on PBL scheme evaluation of maximum wind speed, height of LLJ maximum, duration, and occurrence of the LLJ maximum. The second, *Influences on Wind Energy*, focuses on LLJ impacts on wind speed and model skill at 96 m and 157 m.

3.4.1 Evaluation of LLJ Structure

A comparison of maximum LLJ wind speeds (Table 3.2) showed that during the 30 LLJ cases, all six PBL schemes under-predicted the observed maximum wind speed. On average, the QNSE scheme predicted the strongest maximum LLJ wind speed at 19.1 ms$^{-1}$, although, compared to observations, resulted in an average under-prediction of 3.6 ms$^{-1}$. The YSU scheme predicted the weakest maximum LLJ wind speed of any scheme at 16.3 ms$^{-1}$, underestimating the maximum speed on average by 6.4 ms$^{-1}$. Comparing the YSU PBL scheme to the other PBL schemes using the Wilcoxon signed-rank test, the under-prediction of the wind speed in the YSU PBL scheme was found to be highly significant compared to the other schemes, with all p-values less than 0.0002.

Because all PBL schemes led to an underestimate in wind speed, two sensitivity tests were performed to gain insight into the role that grid spacing and lateral boundary conditions might be having on the predicted wind speed. With some fields like precipitation, much larger amounts often occur with finer grid spacing because of the large gradients occasionally present. A test case from March 24, 2009 showed little
change, less than 1.0 m\(s^{-1}\), between the wind speed predicted with 4 km grid spacing and that occurring with 10 km grid spacing, implying the underestimates are not due to inadequate horizontal grid spacing. It also must be noted that the Lamont, OK site is not at the center of our model domain due to other forecast needs, and the southern boundary is only a few hundred kilometers away. Therefore, a sensitivity test was done to make sure that the lateral boundary conditions were not primarily responsible for the weak wind speeds. Again, little change in wind speed magnitude (less than 1.0 m\(s^{-1}\)) was observed between a model run centered over the Lamont, OK test site and the present model domain.

As a control, the wind speed at 460 m during 30 non-LLJ events also was analyzed. For these non-LLJ events, all schemes but the QNSE under-predicted the wind speed (Table 1.3). However, in four out of the six PBL schemes, the predictions were within +/- 0.5 m\(s^{-1}\) of the average non-LLJ wind speed at 460 m. The YSU scheme again predicted the weakest wind speeds during non-LLJ events, underestimating the wind speed by 1.34 m\(s^{-1}\). This is much less than the 6.4 m\(s^{-1}\) value for LLJ events noted previously. In a relative sense, the underestimate is less than 15% of the observed average speed, compared with a nearly 30% underestimate for LLJ events. Significance testing was done comparing the YSU PBL scheme to the other PBL schemes using the Wilcoxon signed-rank test, and the under-prediction of the wind speed in the YSU PBL scheme was found to be highly significant compared to the other schemes, with all p-values less than 0.03.

Regarding the height of the LLJ maximum (Table 3.4), all six PBL schemes under-predicted the observed height. On average, the YSU scheme predicted the highest
height of the LLJ maximum at 538.3 m, an average under-prediction of only 14.7 m. However, the other PBL schemes all under-predicted the height by over 125 m. The MYNN 3.0 PBL scheme predicted the lowest height of the LLJ maximum at 340.4 m, underestimating the maximum height, on average, by 212.7 m. Comparing the YSU PBL scheme to the other PBL schemes using the Wilcoxon signed-rank test, the higher height predicted by the YSU PBL scheme was found to be highly significant compared to the other schemes, with all p-values less than 0.002.

As noted in the analysis of the maximum LLJ wind speed and height, the YSU scheme behaved significantly different than the other PBL schemes tested. One possible reason for this difference was discovered by Shin and Hong in 2011. They found that the eddy viscosity (K_m) value was much larger in the YSU scheme during stable conditions than in any other PBL scheme. To determine if strong amounts of mixing (large K_m) were a contributing factor to the behavior of the YSU scheme during LLJ events in the present study, the LLJ event on 24 March 2009 was examined in more detail. Wind speed (Figure 3.2), potential temperature (Figure 3.3), and eddy viscosity (Figure 3.3) are shown at the time of the maximum intensity of the LLJ. Analyzing the wind speed profile, the YSU scheme (Figure 3.2) showed little or no LLJ, while the other five PBL schemes had a distinctive LLJ feature present. The potential temperature profile (Figure 3.3) indicated a stable regime in all PBL schemes, although the YSU scheme appeared to be slightly more neutral in the lowest 1000m, however the profiles were similar above that height. Finally, the K_m profile (Figure 3.4) showed that the YSU scheme had an eddy viscosity value five times larger than any other scheme. With a larger eddy viscosity, more mixing and turbulence occurred and resulted in the YSU scheme
predicting a substantially weaker LLJ with a higher elevation of the maximum than the other PBL schemes. As a result, higher speeds occurred above and below the jet core, with higher momentum air being mixed closer to the surface. Although only one case was examined in detail in the present study, findings were consistent with that found in Shin and Hong 2010.

Regarding the duration of simulated LLJ events for all PBL schemes, the average duration was around 10.5 hours (Table 1.5), a value matching observations, albeit with a slight under-prediction. The YSU scheme showed the shortest duration at 10.3 hours while the local PBL schemes (MYJ, QNSE, MYNN 2.5, MYNN 3.0) showed the longest duration at 10.6 hours. Again, unlike previous studies, we objectively defined LLJ duration. Therefore, direct comparisons to other studies are not possible, although it is of note that the average duration found in this study compared quite well to the time period studied (02Z to 12Z) in Song et al. (2005) and (02Z to 11Z) in Whiteman et al. (1997).

Analyses of these LLJ parameters were also performed using the Bonner classification criteria shown earlier. For Bonner Criteria 1, all schemes except the YSU over-predicted the average maximum LLJ wind speed, while all schemes except the MYJ over-predicted the average height of the LLJ maximum (Table 3.6). The average duration was under-predicted by all PBL schemes for this criterion and by as much as 6 hours for the Pleim scheme. Throughout Bonner Criteria 2 cases (Table 3.7), the schemes performed opposite to that of Bonner Criteria 1, under-predicting the average maximum LLJ wind speed and average height of the LLJ maximum. The YSU scheme again showed the lowest LLJ maximum wind speed, under-predicting by 4 ms$^{-1}$, while showing the highest predicted LLJ maximum height at 538 m, 124 m higher than any other
scheme. During Bonner Criteria 3 cases (Table 3.8), all PBL schemes under-predicted the average maximum LLJ wind speed, average height of the LLJ maximum, and average duration. Maximum wind speeds were underestimated by around 6 ms\(^{-1}\) for all PBL schemes during Bonner Criteria 3 cases except the YSU scheme, which underestimated the maximum wind speed by 9.1 ms\(^{-1}\). Heights of the LLJ maximum during Bonner Criteria 3 were again underestimated by over 125 m in all schemes except the YSU, which underestimated the height of the LLJ maximum by 27 m.

For analysis of the timing of the LLJ maximum, all six PBL schemes showed the maximum LLJ wind speed occurring near or just after midnight (Figure 3.5), with a peak occurring around 08 UTC (2 am LST) for the MYJ, YSU, Pleim, and QNSE schemes and a peak around 06 UTC (midnight LST) for the MYNN 2.5 and MYNN 3.0 schemes. Observed maximum LLJ wind speeds occurred later, with dual peaks at 08 UTC and 10 UTC (4 am LST). Overall, the PBL schemes appeared to predict the timing of the peak LLJ occurrence reasonably well with perhaps a small early bias.

### 3.4.2 Influences on Wind Energy

To quantify the effect of LLJs on wind energy at higher hub heights, observed wind speed and speed shear differences during nocturnal LLJ cases and cases without nocturnal LLJs were investigated. To compare LLJs and non-LLJ events, 30 cases of each, as mentioned previously, were examined. During non-LLJ events, nocturnal wind speed was analyzed from 04 UTC to 14 UTC, as this corresponded to the average start and end time of the LLJs seen in our study. The average wind speed at 96 m was 6.2 ms\(^{-1}\) during LLJ events and 5.8 ms\(^{-1}\) during non-LLJ events (Table 3.9). At 157 m, the average wind speed was 10.3 ms\(^{-1}\) during LLJ events while
7.3 ms$^{-1}$ during non-LLJ events (Table 3.9). With this 3.0 ms$^{-1}$ increase in wind speed at 157 m occurring in the most sensitive part of the power curve (6 ms$^{-1}$ to 12 ms$^{-1}$), substantially more power will be generated during LLJ events. However, as the results indicate the potential for improved performance at higher heights, wind turbines must also be designed with improved durability as the speed shear, the wind speed difference between 157 m and 96 m, is over twice as large during LLJ events compared to non-LLJ events (Table 3.9).

Model skill was evaluated based on the behavior of the six different PBL schemes at 96 m and 157 m during LLJ and non-LLJ events. At 96 m, all six PBL schemes over-predicted the wind speed during LLJ events, as seen with the positive bias and large MAE (Table 3.10). It should be noted this is opposite to what the schemes did for peak LLJ winds. The YSU scheme showed the lowest MAE at 96 m, while the highest MAE was observed with the MYNN 2.5 and MYNN 3.0 schemes. Based on these results, significance testing was done using the Wilcoxon signed-rank test. When comparing the YSU PBL scheme to the other PBL schemes at 96 m, the reduction in MAE of the YSU PBL scheme during LLJ events was highly significant, with $p$-values less than 0.01. This result indicates that during LLJ events, the YSU PBL scheme was significantly more skillful at forecasting 96 m winds than any other PBL scheme. During non-LLJ events at 96 m, all PBL schemes over-predicted the wind speed as seen with the positive bias and MAE, however, the bias and MAE were much smaller during non-LLJ events compared to LLJ events (Table 3.11). The MYNN 2.5 and MYNN 3.0 schemes both showed MAE values over 3.0 ms$^{-1}$ larger during LLJ events compared to non-LLJ events at 96 m. The YSU scheme again showed the lowest MAE at 96 m during non-LLJ events, while the highest MAE was observed with the MYNN 2.5 scheme. Significance testing was done comparing the YSU PBL
scheme to the other PBL schemes at 96 m, and the reduction in MAE of the YSU PBL scheme during non-LLJ events was highly significant, with p-values less than 0.01.

At 157 m, again all six PBL schemes over-predicted the wind speed during LLJ events, as indicated by the positive bias in Table 3.12. Similar to 96 m, the YSU scheme showed the lowest MAE at 157 m during LLJs, while the highest MAE was observed in the MYNN 2.5 PBL scheme. Comparing the YSU PBL scheme to the other PBL schemes at 157 m, the reduction in MAE of the YSU PBL scheme during LLJ events was highly significant (p-values less than 0.01) in all cases except when compared against the Pleim scheme (p-value 0.24). This demonstrates that during LLJ events, the YSU PBL scheme was significantly more skillful at forecasting 157 m winds than any other PBL scheme, except the Pleim. During non-LLJ events at 157 m, all PBL schemes except the YSU over-predicted the wind speed (Table 3.13). The largest bias at 157 m during non-LLJ events was 1.19 ms\(^{-1}\) and occurred in the MYNN 2.5 PBL scheme. As observed at 96 m, the MAE was much smaller during non-LLJ events compared to LLJ events at 157 m. Again, the lowest MAE was associated with the YSU scheme during 157 m non-LLJ events, while the highest MAE was observed in the MYNN 2.5 scheme. When comparing the YSU PBL scheme to the other PBL schemes at 96 m, the reduction in MAE of the YSU PBL scheme during 157 m non-LLJ events was highly significant, with p-values less than 0.05. It is thus interesting to note that the YSU scheme has the lowest underestimate of maximum LLJ wind speeds, but yet the best forecasts at these two levels close to the ground.
3.5 Summary and Conclusions

A comparison of six different configurations of the WRF model to observations from the Lamont, OK wind profiler shows that LLJ maximum wind speeds are under-predicted by all PBL schemes, with the largest under-prediction occurring with the YSU scheme. Of potentially more importance to wind energy interests, all the PBL schemes except the YSU scheme under-predicted the height of the LLJ maximum by more than 125 m. In the YSU scheme, the likely cause of the under-predicted LLJ maximum wind speed and higher jet elevation than the other schemes tested appears to be a result of the strong eddy viscosity occurring during stable conditions. With increased mixing, LLJs in the YSU scheme were substantially under-predicted and momentum was spread out over a deeper layer of the atmosphere. These findings suggest that numerical weather prediction schemes need further development to increase forecast accuracy of maximum LLJ wind speeds and the height of the LLJ maximum. However, the duration of modeled LLJ events agreed rather well with observed data.

Application of the Bonner classifications revealed some differences in behavior based on the strength of the LLJ events. In summary, maximum LLJ wind speeds were most accurately predicted during Bonner Criteria 1 cases while the duration was substantially underestimated in all PBL schemes. Compared to other schemes, the YSU scheme predicted the highest heights of the LLJ maximum and the weakest LLJ wind speeds during all Bonner Criteria. During Bonner Criteria 3 events, the PBL schemes under-predicted both average height of the LLJ maximum and average duration, a result similar to that found during Bonner Criteria 2 events. Lastly, examining the temporal trends of the LLJ maximum, we found the models had wind speed maxima occurring
near or just after midnight (06-08 UTC), typically a few hours before observed LLJs (08-10 UTC).

Finally, analysis of LLJ impacts at 96 m and 157 m showed increased wind speeds and speed shear during LLJ events compared to non-LLJ events. This implies that wind production would increase during LLJ events; however, wind turbine durability would need to be improved to accommodate the increased shear. To analyze forecast skill at 96 m and 157 m during LLJ and non-LLJ events, six different PBL schemes were tested. At both 96 m and 157 m, larger biases and higher MAEs were observed during LLJ events compared to non-LLJ events. During both LLJ and non-LLJ events at both 96 m and 157 m, the YSU scheme consistently showed the lowest MAE, implying that the YSU PBL scheme is the most skillful scheme of the six tested at forecasting nighttime low level wind speeds.

Overall, the results suggest substantial differences exist in the simulation of LLJs depending on which PBL scheme is used. While the YSU PBL scheme excelled at forecasting 96 m and 157 m wind speed during LLJ and non-LLJ events, the scheme struggled to predict maximum LLJ wind speed. As a result, no one scheme performed considerably better than any other throughout the lower troposphere during LLJ events and all showed room for improvement.

3.6 Acknowledgments

The ARM data was acquired from the Atmospheric Radiation Measurement (ARM) project, in conjunction with the U.S. department of Energy and Biological and
3.7 Appendix

Description of PBL schemes

PBL schemes were developed to help resolve the turbulent fluxes of heat, moisture, and momentum in the boundary layer. However, due to the complex nature of turbulence, closure has remained a problem. Two solutions to the problem of closure, local and non-local, will be discussed below. The first type, local closure, estimates unknown fluxes using known values and/or gradients at the same point. The second type, non-local closure, estimates unknown fluxes using known values and/or gradients at many points in space (Stull 1998, Bélair et al. 1999). Of the PBL schemes tested, the ACM2 and YSU schemes are non-local while the MYJ, QNSE, MYNN 2.5, and MYNN 3.0 are local closure schemes. A brief description of the six PBL schemes used in this study follows. Further details can be found in Janjic (1990), (1994) (MYJ), Hong et al. (2006) (YSU), Pleim (2007a), (2007b) (ACM2), Sukoriansky et al. (2005) (QNSE), and Nakanishi and Niino (2004) (MYNN).

The MYJ PBL scheme is one of four different local closure schemes evaluated in this study. The MYJ PBL scheme is a local turbulent kinetic energy (TKE), 1.5 order (2.5 level) closure scheme. Being a 1.5 order closure, it requires one additional prognostic equation to solve for the turbulent quantities (Janjic 1990, 1994, Shin and Hong 2011, Hu et al. 2010). The MYNN 2.5 and 3.0 PBL schemes are higher level
schemes that were based on the MYJ scheme. The MYNN 2.5 scheme is a local TKE, 1.5 order (2.5 level) closure scheme while the MYNN 3.0 is a local TKE, 2.0 order (3.0 level) closure scheme. Both the MYJ and MYNN schemes apply the local mixing from the lowest to highest vertical level. The major difference between the MYJ and MYNN 2.5 and 3.0 schemes is the TKE equation, and more specifically, the master mixing length \((l_m)\). The TKE equation is defined as:

\[
\frac{d(q^2/2)}{dt} - \frac{\partial}{\partial z} \left[ l_m q S_q \frac{\partial}{\partial z} \left( \frac{q^2}{2} \right) \right] = P_s + P_b + \varepsilon
\]

where the first term is the total derivative of \(q\), which is two times the TKE, the second term is the vertical redistribution of \(q\), \(P_s\) is the production of \(q\) by shear, \(P_b\) is the production of shear by buoyancy, and \(\varepsilon\) is the dissipation term. For the MYJ scheme, the master mixing length is defined as:

\[
l_m = l_o \frac{kz}{kz + l_o}
\]

where \(l_o\) is dependent on height and \(k\) is the von Karman constant. The master mixing length for the MYNN PBL schemes is a function of three independent length scales:

\[
\frac{1}{l_m} = \frac{1}{l_s} + \frac{1}{l_t} + \frac{1}{l_b}
\]

where \(l_s\) is the surface layer length, \(l_t\) is the turbulent layer length, and \(l_b\) is the buoyancy length (Olson and Brown 2009, Nakanishi and Niino 2004).

The QNSE scheme is a local TKE, 1.5 order (2.5 level) closure scheme that is similar to the MYJ scheme during neutral and unstable conditions. The QNSE scheme differs from the MYJ scheme during stable conditions, when spectral theory is used to develop eddy diffusivity profiles. This results in waves and turbulent eddies being
treated as one entity. Like the MYJ and MYNN schemes, the QNSE scheme applies local mixing from the lowest to highest vertical level (Sukoriansky et al. 2005, Shin and Hong 2011).

The last two PBL schemes investigated in this study were the YSU and ACM2. These schemes are both first-order (requiring no additional prognostic equations), non-local schemes. The ACM2 scheme is a combination of a simple transient model (original Blackadar scheme) and an eddy diffusion model. The ACM2 scheme is able to switch between stable conditions (eddy diffusion) and unstable conditions (local and non-local transport). During stable or neutral conditions, the scheme uses local closure instead of non-local transport (Hu et al. 2010, Pleim 2007a, 2007b, Shin and Hong 2011). On the other hand, the YSU scheme is a bulk scheme that expresses non-local mixing by convective large eddies. Non-local mixing is achieved by adding a non-local gradient adjustment term (countergradient term) to the local gradient. At the top of the PBL, the YSU scheme uses explicit treatment of the entrainment layer, which is proportional to the surface layer flux (Hong et al. 2006, Shin and Hong 2011, Hu et al. 2010).

3.8 References


Lettau, H., 1954: “Graphs and Illustrations of Diverse Atmospheric States and Processes observed during the seventh test period of the Great Plains Turbulence Field
Program, Occasional Report No. 1, Atmospheric Analysis Laboratory, Air Force Cambridge Research Center.


Table 3.1: LLJ and Non-LLJ events examined in this study.

<table>
<thead>
<tr>
<th></th>
<th>LLJ Event Dates</th>
<th>Non-LLJ Event Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>June 2008</td>
<td>26</td>
<td>16, 21, 22</td>
</tr>
<tr>
<td>July 2008</td>
<td>13</td>
<td>8, 9</td>
</tr>
<tr>
<td>August 2008</td>
<td>4</td>
<td>20, 21</td>
</tr>
<tr>
<td>September 2008</td>
<td>2, 3, 8, 30</td>
<td>-----</td>
</tr>
<tr>
<td>October 2008</td>
<td>5, 19, 21</td>
<td>16, 17, 18, 25, 28</td>
</tr>
<tr>
<td>November 2008</td>
<td>-----</td>
<td>2, 7, 8, 9</td>
</tr>
<tr>
<td>December 2008</td>
<td>14, 26</td>
<td>26</td>
</tr>
<tr>
<td>January 2009</td>
<td>-----</td>
<td>13, 18</td>
</tr>
<tr>
<td>February 2009</td>
<td>7, 27</td>
<td>25</td>
</tr>
<tr>
<td>March 2009</td>
<td>5, 6, 19, 24, 27</td>
<td>21, 25</td>
</tr>
<tr>
<td>April 2009</td>
<td>-----</td>
<td>3, 5, 9</td>
</tr>
<tr>
<td>August 2009</td>
<td>26, 28</td>
<td>17, 19, 21, 23</td>
</tr>
<tr>
<td>November 2009</td>
<td>6, 7, 8, 9, 13, 14</td>
<td>-----</td>
</tr>
<tr>
<td>January 2010</td>
<td>-----</td>
<td>02</td>
</tr>
<tr>
<td>April 2010</td>
<td>10, 22</td>
<td>-----</td>
</tr>
<tr>
<td>May 2010</td>
<td>6</td>
<td>-----</td>
</tr>
<tr>
<td>Maximum LLJ Wind Speed</td>
<td>MYJ (ms(^{-1}))</td>
<td>Pleim (ms(^{-1}))</td>
</tr>
<tr>
<td>------------------------</td>
<td>----------------</td>
<td>----------------</td>
</tr>
<tr>
<td>19.0</td>
<td>18.2</td>
<td><strong>16.3</strong></td>
</tr>
</tbody>
</table>

Table 3.2: Average maximum LLJ wind speed (ms\(^{-1}\)) for each PBL scheme and the observed data from the 30 LLJ cases. The under-prediction of the maximum LLJ wind speed in the YSU PBL scheme was found to be highly significant compared to the other schemes (bold value indicates p-values less than 0.01 in a Wilcoxon signed-rank test).
Table 3.3: Average 460 m non-LLJ wind speed (ms\(^{-1}\)) for each PBL scheme and the observed data from the 30 non-LLJ cases. The under-prediction of the 460 m non-LLJ wind speed in the YSU PBL scheme was found to be highly significant compared to the other schemes (bold value indicates p-values less than 0.03 in a Wilcoxon signed-rank test).

<table>
<thead>
<tr>
<th>460 m Non-LLJ Wind Speed</th>
<th>MYJ (ms(^{-1}))</th>
<th>Pleim (ms(^{-1}))</th>
<th>YSU (ms(^{-1}))</th>
<th>QNSE (ms(^{-1}))</th>
<th>MYNN 2.5 (ms(^{-1}))</th>
<th>MYNN 3.0 (ms(^{-1}))</th>
<th>OBS (ms(^{-1}))</th>
</tr>
</thead>
</table>
Table 3.4: Average height of low level jet maximum (m) for each PBL scheme and the observed data from the 30 LLJ cases. The higher height of the LLJ maximum predicted in the YSU PBL scheme was found to be highly significant compared to the other schemes (bold value indicates p-values less than 0.01 in a Wilcoxon signed-rank test).
<table>
<thead>
<tr>
<th>Duration of LLJ Event</th>
<th>MYJ (hr)</th>
<th>Pleim (hr)</th>
<th>YSU (hr)</th>
<th>QNSE (hr)</th>
<th>MYNN 2.5 (hr)</th>
<th>MYNN 3.0 (hr)</th>
<th>OBS (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10.6</td>
<td>10.4</td>
<td>10.3</td>
<td>10.6</td>
<td>10.6</td>
<td>10.6</td>
<td>11.1</td>
</tr>
</tbody>
</table>

Table 3.5: Average duration of the LLJ event (hr) for each PBL scheme and the observed data from the 30 LLJ cases.
<table>
<thead>
<tr>
<th></th>
<th>Avg Max Wind Spd (ms(^{-1}))</th>
<th>Avg Height of LLJ Max (m)</th>
<th>Avg Duration (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYJ</td>
<td>15.2</td>
<td>270.0</td>
<td>7.7</td>
</tr>
<tr>
<td>Pleim</td>
<td>14.5</td>
<td>490.0</td>
<td>5.3</td>
</tr>
<tr>
<td>YSU</td>
<td>13.7</td>
<td>583.3</td>
<td>5.7</td>
</tr>
<tr>
<td>QNSE</td>
<td>15.8</td>
<td>463.3</td>
<td>8.0</td>
</tr>
<tr>
<td>MYNN2.5</td>
<td>15.1</td>
<td>436.7</td>
<td>8.0</td>
</tr>
<tr>
<td>MYNN3.0</td>
<td>14.3</td>
<td>403.3</td>
<td>8.0</td>
</tr>
<tr>
<td>OBS</td>
<td>13.9</td>
<td>366.7</td>
<td>11.3</td>
</tr>
</tbody>
</table>

Table 3.6: Maximum LLJ wind speed, height of the LLJ Maximum, and duration for all cases classified as Bonner Criteria 1.
<table>
<thead>
<tr>
<th></th>
<th>Avg Max Wind Spd (ms⁻¹)</th>
<th>Avg Height of LLJ Max (m)</th>
<th>Avg Duration (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYJ</td>
<td>19.4</td>
<td>365.0</td>
<td>12.0</td>
</tr>
<tr>
<td>Pleim</td>
<td>18.1</td>
<td>414.0</td>
<td>11.9</td>
</tr>
<tr>
<td>YSU</td>
<td>17.7</td>
<td>538.0</td>
<td>11.6</td>
</tr>
<tr>
<td>QNSE</td>
<td>19.0</td>
<td>352.0</td>
<td>12.0</td>
</tr>
<tr>
<td>MYNN2.5</td>
<td>18.3</td>
<td>373.0</td>
<td>12.0</td>
</tr>
<tr>
<td>MYNN3.0</td>
<td>17.8</td>
<td>373.0</td>
<td>11.9</td>
</tr>
<tr>
<td>OBS</td>
<td>21.7</td>
<td>592.0</td>
<td>10.2</td>
</tr>
</tbody>
</table>

Table 3.7: As in Table 3.6 except for Bonner Criteria 2.
<table>
<thead>
<tr>
<th>Method</th>
<th>Avg Max Wind Spd (ms$^{-1}$)</th>
<th>Avg Height of LLJ Max (m)</th>
<th>Avg Duration (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYJ</td>
<td>20.2</td>
<td>410.9</td>
<td>10.5</td>
</tr>
<tr>
<td>Pleim</td>
<td>19.7</td>
<td>441.3</td>
<td>10.4</td>
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<tr>
<td>YSU</td>
<td>16.7</td>
<td>548.1</td>
<td>10.4</td>
</tr>
<tr>
<td>QNSE</td>
<td>20.5</td>
<td>369.1</td>
<td>10.4</td>
</tr>
<tr>
<td>MYNN2.5</td>
<td>19.7</td>
<td>400.0</td>
<td>10.5</td>
</tr>
<tr>
<td>MYNN3.0</td>
<td>19.3</td>
<td>358.1</td>
<td>10.5</td>
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<tr>
<td>OBS</td>
<td>25.8</td>
<td>575.0</td>
<td>12.0</td>
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</table>

Table 3.8: As in Table 3.6 except for Bonner Criteria 3.
<table>
<thead>
<tr>
<th></th>
<th>LLJ (ms⁻¹)</th>
<th>Non-LLJ (ms⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>96 m Wind Speed</td>
<td>6.2</td>
<td>5.8</td>
</tr>
<tr>
<td>157 m Wind Speed</td>
<td>10.3</td>
<td>7.3</td>
</tr>
<tr>
<td>Speed Shear</td>
<td>5.9</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Table 3.9: Wind speed at 96 m and 157 m, and speed shear during the 30 LLJ events and 30 non-LLJ events. The speed shear is the difference between 157 m and 96 m.
<table>
<thead>
<tr>
<th>LLJ 96 m</th>
<th>MYJ (ms⁻¹)</th>
<th>MYNN 2.5 (ms⁻¹)</th>
<th>MYNN 3.0 (ms⁻¹)</th>
<th>Pleim (ms⁻¹)</th>
<th>QNSE (ms⁻¹)</th>
<th>YSU (ms⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Speed Bias</td>
<td>5.61</td>
<td>6.70</td>
<td>6.48</td>
<td>5.10</td>
<td>6.22</td>
<td>3.91</td>
</tr>
<tr>
<td>Wind Speed MAE</td>
<td>5.99</td>
<td>6.98</td>
<td>6.79</td>
<td>5.59</td>
<td>5.91</td>
<td>4.77</td>
</tr>
</tbody>
</table>

Table 3.10: The bias and MAE associated with 96 m wind speed forecasts for six different PBL schemes during LLJ events. The reduction in MAE of the YSU PBL scheme during LLJ events at 96 m was highly significant compared to the other PBL schemes (bold value indicates p-values less than 0.01 in a Wilcoxon signed-rank test).
Table 3.11: The bias and MAE associated with 96 m wind speed forecasts for six different PBL schemes during non-LLJ events. The reduction in MAE of the YSU PBL scheme during non-LLJ events at 96 m was highly significant compared to the other PBL schemes (bold value indicates p-values less than 0.01 in a Wilcoxon signed-rank test).

<table>
<thead>
<tr>
<th>Non-LLJ 96 m</th>
<th>MYJ (ms(^{-1}))</th>
<th>MYNN 2.5 (ms(^{-1}))</th>
<th>MYNN 3.0 (ms(^{-1}))</th>
<th>Pleim (ms(^{-1}))</th>
<th>QNSE (ms(^{-1}))</th>
<th>YSU (ms(^{-1}))</th>
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<tbody>
<tr>
<td>Wind Speed Bias</td>
<td>1.37</td>
<td>1.76</td>
<td>1.69</td>
<td>0.65</td>
<td>1.64</td>
<td>0.09</td>
</tr>
<tr>
<td>Wind Speed MAE</td>
<td>2.78</td>
<td>3.11</td>
<td>2.99</td>
<td>2.42</td>
<td>2.98</td>
<td><strong>2.09</strong></td>
</tr>
</tbody>
</table>
Table 3.12: The bias and MAE associated with 157 m wind speed forecasts for six different PBL schemes during LLJ events. The reduction in MAE of the YSU PBL scheme during LLJ events at 157 m was highly significant compared to all the PBL schemes except the Pleim scheme (bold value indicates p-values less than 0.01 for all PBL schemes except Pleim (p-value of 0.24) in a Wilcoxon signed-rank test).

<table>
<thead>
<tr>
<th>LLJ 157 m</th>
<th>MYJ (ms$^{-1}$)</th>
<th>MYNN 2.5 (ms$^{-1}$)</th>
<th>MYNN 3.0 (ms$^{-1}$)</th>
<th>Pleim (ms$^{-1}$)</th>
<th>QNSE (ms$^{-1}$)</th>
<th>YSU (ms$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Speed Bias</td>
<td>3.79</td>
<td>4.34</td>
<td>4.08</td>
<td>2.75</td>
<td>3.92</td>
<td>0.55</td>
</tr>
<tr>
<td>Wind Speed MAE</td>
<td>3.70</td>
<td>4.11</td>
<td>3.89</td>
<td>3.02</td>
<td>3.76</td>
<td><strong>2.29</strong></td>
</tr>
<tr>
<td>Non-LLJ 157 m</td>
<td>MYJ (ms(^{-1}))</td>
<td>MYNN 2.5 (ms(^{-1}))</td>
<td>MYNN 3.0 (ms(^{-1}))</td>
<td>Pleim (ms(^{-1}))</td>
<td>QNSE (ms(^{-1}))</td>
<td>YSU (ms(^{-1}))</td>
</tr>
<tr>
<td>--------------</td>
<td>------------------</td>
<td>------------------------</td>
<td>------------------------</td>
<td>-------------------</td>
<td>-------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>Wind Speed Bias</td>
<td>0.94</td>
<td>1.19</td>
<td>1.12</td>
<td>0.14</td>
<td>1.15</td>
<td>-0.32</td>
</tr>
<tr>
<td>Wind Speed MAE</td>
<td>2.09</td>
<td>3.16</td>
<td>2.99</td>
<td>2.37</td>
<td>3.10</td>
<td>1.97</td>
</tr>
</tbody>
</table>

Table 3.13: The bias and MAE associated with 157 m wind speed forecasts for six different PBL schemes during non-LLJ events. The reduction in MAE of the YSU PBL scheme during non-LLJ events at 157 m was highly significant compared to the other PBL schemes (bold value indicates p-values less than 0.05 in a Wilcoxon signed-rank test).
Figure 3.1: The 10 km model domains used in this study and the location of the Lamont, OK 915-mHZ wind profiler site (black dot).
Figure 3.2: Wind speed as a function of height during the LLJ peak on March 24, 2009 at 10pm LST. Black dots represent observations from the 915-mHz wind profiler while each line represents a different PBL scheme; MYJ (Black), MYNN 2.5 (Turquoise), MYNN 3.0 (Magenta), Pleim or ACM2 (Red), QNSE (Blue), and YSU (Green).
Figure 3.3: Potential temperature as a function of height during the LLJ peak on March 24, 2009 at 10pm LST. Each line represents a different PBL scheme; MYJ (Black), MYNN 2.5 (Turquoise), MYNN 3.0 (Magenta), Pleim or ACM2 (Red), QNSE (Blue), and YSU (Green).
Figure 3.4: Eddy viscosity as a function of height during the LLJ peak on March 24, 2009 at 10pm LST. Each line represents a different PBL scheme; MYJ (Black), MYNN 2.5 (Turquoise), MYNN 3.0 (Magenta), Pleim or ACM2 (Red), QNSE (Blue), and YSU (Green).
Fig. 3.5: Hourly occurrence at which the maximum wind speed occurred for both simulations and observed data. Observations are given with the black line while each bar represents a different PBL scheme; MYJ (Gray), MYNN 2.5 (Turquoise), MYNN 3.0 (Magenta), Pleim or ACM2 (Red), QNSE (Blue), and YSU (Green).
CHAPTER 4. GENERAL CONCLUSIONS

4.1 Summary of Results

The two studies in this thesis use different PBL schemes to investigate wind speed behavior and improve wind speed forecasts at turbine hub height. In the first study, significant improvement was made in wind speed forecasts at hub height by investigating both pre-run modification and post-processing techniques. During pre-run modification, time initialization, grid spacing, and GFS perturbations were tested. Results from the tests showed that an ensemble consisting of different time initializations produced more model spread and higher model skill than any other pre-run modification. During post-processing, techniques including training of the model, the neighborhood approach, and bias corrections of the wind were investigated. Training of the model proved to be an inconsistent method and the neighborhood approach only improved results slightly, however, the development of a wind speed bias correction provided the highest model skill of any post-processing technique. Although, the best model skill was achieved when pre-run modifications and post-processing techniques were combine together to create an operational ensemble. Of the six members that made up the operational ensemble, five members used either the YSU or Pleim PBL scheme, both of which are non-local closure schemes. Ramp event skill was also addressed in this study. From the results, it appears forecasts were more skillful in detecting ramp-up events, albeit with larger errors in the amplitude, than ramp-down events. As seen in previous studies, all PBL schemes showed significant errors in ramp forecasting and much improvement is needed.
The second study in this thesis examined PBL scheme behavior during LLJ and non-LLJ events and analyzed model skill at possible future hub heights (96 m and 157 m). Throughout the 30 LLJ events, wind speed during the LLJ peak was under-predicted by all PBL schemes, although the largest under-prediction (6.4 m s\(^{-1}\)) occurred with the YSU scheme. The height of the LLJ maximum was also under-predicted by over 150 m in all PBL schemes except the YSU scheme, which under-predicted by only 14.7 m. The likely cause of the YSU scheme under-predicting the LLJ peak wind speed and having a more accurate LLJ maximum height than any other scheme appears to be a result of strong eddy viscosity occurring during LLJ events. With an eddy viscosity value five times larger than any other scheme, strong mixing is occurring in the YSU scheme, resulting in substantially under-predicted LLJs. In this second study, model skill at 96 m and 157 m during LLJ and non-LLJ events was also analyzed. The best model skill at 96 m and 157 m during both LLJ and non-LLJ events was observed in the YSU and Pleim PBL schemes, identical to the result seen in the first paper at 80 m. However, the MAE at 96 m and 157 m during LLJ events was much larger than during non-LLJ events. Thus, it appears substantial improvements are still needed in numerical weather prediction schemes to improve accuracy during LLJ events.

4.2 Recommendations for Future Work

To expand on the work of the first study, many research avenues are possible. First, simulations of more events throughout the year would be desired. Although many cases were studied, analysis of observed wind speed data at 80 m indicated that during the winter months, little to no diurnal signal was present in the observed data, while a
pronounced diurnal signal was observed in the summer months. As a result, seasonal bias corrections may improve wind speed forecasts even more. Secondly, to improve wind power forecasts, wind speed forecasts for individual turbines would be desired. As found in a study by Mechali et al. 2006, wind turbines downstream produce 20% less power than upstream wind turbines experiencing no wake effects from other turbines. To analyze the wake effect, nacelle data (the wind anemometer and wind vane that are located on each wind turbine) would need to be obtained and studied. Modeling with grid spacing on the order of 500 m or less would also be desired to replicate the wake effect from individual wind turbines.

In continuing work on the second study, many more cases would be preferred to evaluate model behavior. In studies by Whiteman (1997) and Song et al. (2005), over two years of events had been observed and analyzed while just 30 events had been analyzed in our study. In addition, observed data from 915-MHz wind profilers in other locations would be desired to determine how results found at the Lamont, OK site compare to other locations. Finally, LLJs have been most frequently studied because of their role in transporting warm, moist air from the Gulf of Mexico into the Great Plains, leading to convection. In our study, we found that all PBL schemes under-predicted the peak LLJ wind speed and height of the LLJ maximum. We also noticed that the YSU scheme behaved significantly different than the other schemes tested. Thus, modeled output from these six different PBL schemes would be desired to determine their effect on precipitation and moisture fields over the Great Palins.
4.3 References


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