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Observing and Simulating the Summertime Low-Level Jet in Central Iowa

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(Manuscript received 9 October 2014, in final form 19 February 2015)

ABSTRACT

In the U.S. state of Iowa, the increase in wind power production has motivated interest into the impacts of low-level jets on turbine performance. In this study, two commercial lidar systems were used to sample wind profiles in August 2013. Jets were systematically detected and assigned an intensity rating from 0 (weak) to 3 (strong). Many similarities were found between observed jets and the well-studied Great Plains low-level jet in summer, including average jet heights between 300 and 500 m above ground level, a preference for southerly wind directions, and a nighttime bias for stronger jets. Strong vertical wind shear and veer were observed, as well as veering over time associated with the LLJs. Speed, shear, and veer increases extended into the turbine-rotor layer during intense jets. Ramp events, in which winds rapidly increase or decrease in the rotor layer, were also commonly observed during jet formation periods. The lidar data were also used to evaluate various configurations of the Weather Research and Forecasting Model. Jet occurrence exhibited a stronger dependence on the choice of initial and boundary condition data, while reproduction of the strongest jets was influenced more strongly by the choice of planetary boundary layer scheme. A decomposition of mean model winds suggested that the main forcing mechanism for observed jets was the inertial oscillation. These results have implications for wind energy forecasting and site assessment in the Midwest.

1. Introduction

On many nights in the central United States, the weather is largely determined by the evolution of low-level winds near the top of the boundary layer. During the summer months, winds aloft accelerate after sunset with remarkable consistency in numerous regions throughout the central plains and Midwest states. These wind accelerations are known as low-level jets (LLJs), and their influence has been noted in many fields of study, such as clear-air turbulence (e.g., Banta et al. 2002), convective storm formation (e.g., Means 1952, 1954; Curtis and Panofsky 1958), forest fire propagation (e.g., Barad 1961), urban pollution transport (e.g., McNider et al. 1988; Banta et al. 1998; Hu et al. 2013), and turbulent transport (e.g., Prabha et al. 2007).

Low-level jets can also impact weather patterns at meso- and synoptic scales, as evidenced by research into the Great Plains low-level jet (GPLLJ), the broad nocturnal jet frequently observed over the central United States. While most of the United States experiences peak convective storm activity in the late afternoon, coinciding with maximum surface heating, the Midwest is often affected by storms during the overnight hours. Researchers have suggested links between the nocturnal GPLLJ and the nighttime maximum in storm formation in that region (Pitchford and London 1962; Rasmusson 1967; Maddox 1983; Astling et al. 1985; Zhong et al. 1996; Pu and Dickinson 2014).

Many studies have examined the preference for LLJ formation during the nighttime hours. One of the oldest and most robust explanations is the inertial oscillation theory proposed by Blackadar (1957), which identifies the nocturnal acceleration of air aloft as a consequence of the decoupling of boundary layer winds from the frictional drag of the surface. This process induces an inertial oscillation as the total-wind vector rotates around the geostrophic wind profile at the onset of the
oscillation, which occurs around sunset. Modifications have been made to this theory to produce more realistic wind profiles (e.g., Van de Wiel et al. 2010), but the underlying concept has withstood observational scrutiny.

Researchers have also attempted to explain the preponderance of nocturnal LLJ observations in the Great Plains region of the United States (Parish and Oolman 2010). The most common hypothesis suggests that differential heating and cooling rates over the regional slope from high elevations in the west to low elevations in the east produce temperature gradients (Bleeker and Andre 1951; Holton 1967). These temperature gradients beget pressure gradients, and the resulting baroclinicity drives accelerations of the winds above the plains and Midwest states. Other studies have hypothesized that these transient gradients in temperature and pressure can be enhanced by synoptic patterns associated with the subtropical high over the Atlantic (e.g., Wexler 1961; Jiang et al. 2007). Recent investigations have concluded that the G PLLJ is a product of both the inertial oscillation and baroclinic mechanisms, and neither one can solely reproduce the amplitude and phase of the phenomenon (Du and Rotunno 2014).

Despite the progress that has been made at understanding the theoretical basis behind the GPLLJ, most observational work has occurred within Oklahoma and Kansas, a region described as the spatial core of the jet (e.g., Lundquist and Mirocha 2008; Hu et al. 2013). The availability of a wide suite of instruments at the Atmospheric Boundary Layer Experiments (ABLE) facility in Kansas has engendered extensive study into jet properties at that location (e.g., Whiteman et al. 1997; Poulos et al. 2002; Banta et al. 2002; Song et al. 2005; Werth et al. 2011), though some recent work has focused on winds aloft north of the jet core (Walton et al. 2014). Observed jets most commonly reach maximum intensity within the first 500 m above ground level (AGL), occur on a majority of nights, are typically associated with southerly winds, and can serve as elevated sources of turbulence in the nocturnal boundary layer. However, global low-level jet climatologies have demonstrated that jet properties vary with location and GPLLLJ forcing mechanisms are not universal to all jets (e.g., Stensrud 1996; Rife et al. 2010). Additionally, questions remain pertaining to GPLLJ spatial extent, particularly in the Midwest, where strong LLJs are observed but the slope of the Great Plains is distant.

The growth of wind energy in the United States over the past couple of decades further motivates research to better understand and forecast the low-level jet. While LLJs often greatly increase the speed of the wind in the rotor layer of a turbine (40–120 m above the ground in this study), shear and veer place additional stresses on the structure that can increase the need for regular maintenance and the possibility of mechanical failure (Eggers et al. 2003; Kelley 2011). Correlation of wind speeds over large distances can also cause problems for balancing supply and demand on the energy grid if large amounts of wind-generated electricity dominate the system. Thus, large contiguous LLJs could complicate grid management. As a result, recent studies have investigated the effects of the jet on wind turbine inflow, and the ability of computational models to reproduce major jet features (e.g., Emeis et al. 2007; Storm et al. 2009; Nunalee and Basu 2014). However, most studies have sought to reproduce individual case study jets, often with only in situ tower measurements available to evaluate model performance.

Herein, we utilize measurements of the boundary layer taken in central Iowa during summer 2013 to examine the properties of low-level jets over the Midwest as well as our ability to simulate them. Iowa has experienced rapid, robust growth in wind farm construction over the past decade, and is currently ranked third among U.S. states for wind power capacity. Therefore, we analyze jets in this region with consideration toward wind energy concerns. We address three specific questions in this work:

1) What are the major characteristics of summertime low-level jets in Iowa, and are they similar to those observed in GPLLJ field campaigns?
2) How do observed jets affect inflow wind speed, shear, and variability in the turbine-rotor layer?
3) Can a modern mesoscale model accurately replicate observed LLJ evolution, and how can that information be useful for the wind industry?

In section 2, we detail the deployed instrumentation and the data processing required to detect LLJs. Section 3 describes observed jets and investigates the effect of the those jets on low-level wind properties. In section 4, we evaluate model simulations of observed LLJs and construct a simple ensemble to quantify spread. Finally, we conclude by discussing our results in the broader context of the wind industry and note potential implications of our findings.
field campaign involved the participation of Iowa State University, the University of Colorado Boulder, the National Center for Atmospheric Research, and the National Renewable Energy Laboratory (Lundquist et al. 2014a). The data site, located within an operating wind farm northeast of the city of Ames, features generally flat land and a patchwork vegetation surface of mostly corn and soybeans.

a. Instrumentation deployed during the CWEX 2013 campaign

In investigating observed low-level jets, we primarily focus on two of the many instruments deployed during the CWEX 2013 campaign: a profiling lidar and a scanning lidar. These commercially available platforms, referred to as the WINDCUBE V1 and 200S models, are both designed by Leosphere (note that the V1 model has been superseded by the V2 model of similar design). The two Doppler wind lidars were colocated for approximately 1 month, spanning 2 August–5 September. We focus on the period beginning 14 August, as no major data outages occurred after that date.

The V1 model is designed to measure vertical profiles of wind speed and direction at 1 Hz temporal resolution. The lidar uses a Doppler beam swinging (DBS) approach whereby radial wind measurements are taken along four cardinal directions at an inclination of 62.5° above the horizon. The lidar beam cycles through those four angles and after a full rotation uses the retrieved radial wind observations to calculate a vertical profile of wind vectors (Lundquist et al. 2014b). For this experiment, the lidar was configured to measure from 40 to 220 m AGL at 20-m increments, as in previous CWEX experiments (Rhodes and Lundquist 2013). In practice, the maximum height of the profile depends on the concentration of aerosols in the target flow (Aitken et al. 2012).

Unlike the V1, the 200S lidar can be set to any desired scanning pattern. In CWEX 2013, the 200S lidar was programmed to cycle through a varied suite of configurations, with the entire process taking approximately 30 min. One of the scanning strategies involved a 360° plan position indicator (PPI) scan, in which the lidar beam performs one full rotation across all azimuths at a set elevation angle (75° is used in this study). These data were used here to compute wind profiles; the process for profile derivation is described in the following section. One advantage of utilizing the 200S is the much greater vertical extent of wind measurements enabled by the stronger scanning beam. Range gates were set to span 100–5000 m along the radial line of sight at 50-m increments. Ultimately, this scanning range yielded profiles that almost always included the entire low-level jet.

Additionally, a network of seven surface flux stations was deployed throughout the wind farm by Iowa State University. We used wind and thermodynamic data from one of these stations to compute near-surface stability, with the Obukhov length L as our metric. We defined four stability classes: convective (−500 < L ≤ 0), neutral (L ≤ −500; L > 500), stable (75 < L ≤ 500), and very stable (0 < L ≤ 75). These classes were informed by the choices of Gryning et al. (2007) and Wharton and Lundquist (2012), with modifications based on observed boundary layer behavior during the present field campaign.

b. Computing wind profiles using data from the scanning lidar

To compute wind profiles from the 200S PPI scans, we utilized a common technique known as velocity azimuth display (VAD). The VAD retrieval process relies on the fact that radial wind observations across a 360° cone in roughly homogenous flow form a sinusoid as the azimuth angle progressively moves in and out of alignment with the horizontal wind direction. Least squares fitting was used to estimate parameters to the following sine-like function (Weitkamp 2005):

\[
v_r = a + b \cos(\theta - \theta_{\text{min}}),
\]

where \(v_r\) is the radial wind speed, \(\theta\) is the azimuthal angle, and the remaining variables are fit parameters. The horizontal wind speed and direction were then derived from the fit parameters using the following relations:

\[
u_{\text{hor}} = (u^2 + v^2)^{1/2} = h/cos\phi \quad \text{and} \quad (2a)
\]

\[WD = \theta_{\text{min}}, \quad (2b)
\]

where \(u_{\text{hor}}\) is the horizontal component of the wind, \(u\) and \(v\) are the zonal and meridional wind components, \(\phi\) is the beam inclination above the horizon, WD is the wind direction, and \(\theta_{\text{min}}\) is the azimuthal angle where the fit reaches a global minimum.

A number of steps were taken to filter out substandard radial wind retrievals, as the least squares fitting procedure is quite sensitive to anomalous values. First, a −27-dB carrier-to-noise ratio (CNR) threshold was imposed. The CNR represents the strength of the backscattered signal compared to background noise; values closer to 0 dB indicate a stronger signal relative to the noise. We found measurements with CNR less than −27 dB unreliable, as the lidar would report anomalously large radial wind speeds of 15 m s\(^{-1}\) and greater. The fitting procedure also requires continuous data coverage around the azimuth to produce a quality fit. Therefore,
following Holleman (2005), we required that no two neighboring 45° sectors of the azimuth contain less than 5 points of data achieving the CNR threshold. We also weighted the data used in fitting by the radial wind speed dispersion, a measure of the variance of the backscattered signal and therefore an indication of uncertainty about the value.

A final filter was applied to the data after the fitting procedure. We determined from visual inspection that fits with coefficient of determination values of less than 0.7 were not well constrained by the data. Therefore, only fits with $R^2$ values above 0.7 were used when analyzing profiles. Three sample fits with excellent quality, acceptable quality, and unacceptable quality ($R^2 < 0.7$) respectively are shown in Fig. 1. Raw radial wind speed data are presented along with the least squares fit. In addition, the offset and phase shift are shown with horizontal and vertical dashed lines for each fit.

c. Instrument performance and homogeneity assumptions

The profiles obtained from the two lidar platforms feature overlapping data coverage at the 200-m-AGL level, which enabled us to investigate the relative performance of the two instruments and profile computation techniques. To minimize differences between the lidar measurements, we used 3-min averages of V1 data, as that is the time required for a complete 200S VAD scan. We found excellent agreement between the lidars for horizontal wind speeds, with a simple linear regression producing an $R^2$ of 0.97. Figure 2 illustrates the scatter among the lidars for each aforementioned stability class and the line of best fit for all conditions. The vast majority of variability between the two instruments occurred during convective conditions, a result of strong turbulent motions in the scanning volume.

The strong horizontal wind agreement between the two lidars existed despite differing measurement volumes at the 200-m comparison height. Because each lidar beam was inclined from the horizon at different angles, the size of the measurement cone at matching heights differed between the instruments. At 200 m AGL, the V1 lidar, with its 62.5° inclination, scanned over a circle of 208-m diameter, while the 200S lidar, with its 75° inclination, scanned over a circle with a 107-m diameter. Each retrieval method relies on an assumption of horizontal homogeneity over the scanning volume (Weitkamp 2005). The validity of that assumption depends on nature of the flow and size of the volume. It should be noted that this volume became very large at high heights. At 2000 m AGL, the 200S wind retrieval assumes horizontal homogeneity over a circle with a 1072-m diameter. Fortunately, atmospheric flow tends to become more uniform with height as the turbulent influence of the surface wanes.

d. Detecting LLJs systematically from lidar profiles

Given the large number of wind profiles available, we sought an objective method for detecting LLJs. Multiple approaches exist in the literature, but most involve analyzing gradients of wind speed around the nose of the jet. Since we seek to examine both weak and strong LLJs, we adopted the identification criteria first developed by Bonner (1968) and later modified by Whiteman et al. (1997) and Song et al. (2005). The
detection technique will subsequently be referred to as the BWS method.

A profile must meet two criteria to be classified as a jet profile. First, the profile must contain a maximum wind speed (i.e., the speed at the jet maximum) above a certain threshold, and this speed must occur below a certain height. Song et al. impose a maximum height of 2 km because of the availability of data at their site. While we often observed valid data up to 2.5 and even 3 km using the 200S lidar, we also used the 2-km restriction to maximize data coverage across utilized height levels. All observed jets were contained within the bottom 2 km of the atmosphere, further justifying the chosen height restriction.

The second criterion that a profile must meet involves the reduction in wind speed above the jet maximum. Again, this shear value must exceed a certain threshold for a positive jet identification. Four jet intensities were specified, with higher intensity jets requiring larger wind speeds at and shear above the jet maximum. These classes will be referred to as LLJ-0 through LLJ-3, with 0 being the weakest and 3 the strongest, following the convention established by Whitman et al. (1997). The specific criteria required for each class are listed in Table 1.

3. Characteristics of observed LLJs and their impact on low-level winds

Low-level jets of all intensity classes were observed throughout the period spanning 14 August–5 September, as summarized in Table 1. Approximately half of all LLJs occurred during very stable near-surface conditions, with an even higher proportion of strong LLJ-2 and LLJ-3 following the same pattern. These results illustrate the strong dependence summertime jets in the region have on surface conditions.

Southwesterly winds were most commonly observed at the height of the jet maximum (sometimes referred to as the nose of the jet), as illustrated in Fig. 3. Each data point represents one 200S lidar profile (available once every 30 min), color coded by near-surface stability. The distance from the origin indicates the maximum speed of the jet observation. Jets were much less frequently observed for winds in the other three quadrants, and jets that did form with those wind directions were typically weak. The prevalence of southwest winds during jet events follows from common synoptic patterns over the central and eastern United States during late summer. The subtropical high over the North Atlantic Ocean typically migrates westward during the summer (Davis et al. 1997). Weak westerlies are forced northward over the plains states by this persistent weather feature, yielding southerly jets in that region (Song et al. 2005; Lundquist and Mirocha 2008). Farther north, in the Midwest states, the flow again begins rotating toward the east around the high. As a result, southwest winds

![FIG. 2. The relationship between 200-m winds (m s\(^{-1}\)) from the V1 profiling lidar and 200S scanning lidar for various stability classes. V1 data are averaged for 3 min to match the scanning time of the 200S. An equation for a line of best fit encompassing all data is provided.](image)

### Table 1. Number of observed low-level jets for each strength and near-surface stability category from the 200S lidar data.

<table>
<thead>
<tr>
<th>Jet category</th>
<th>Max speed criterion (m s(^{-1}))</th>
<th>Upper shear criterion (m s(^{-1}))</th>
<th>Convective (L &gt; 500), (L \leq 500), Stable (L &gt; 75), Very stable (L &gt; 0),</th>
<th>No. of jets by near-surface stability</th>
</tr>
</thead>
<tbody>
<tr>
<td>LLJ-0</td>
<td>≥10</td>
<td>≥5</td>
<td>Convective (L &gt; 500)</td>
<td>26</td>
</tr>
<tr>
<td>LLJ-1</td>
<td>≥12</td>
<td>≥6</td>
<td>Neutral (L \leq 500)</td>
<td>34</td>
</tr>
<tr>
<td>LLJ-2</td>
<td>≥16</td>
<td>≥8</td>
<td>Stable (L &gt; 75)</td>
<td>11</td>
</tr>
<tr>
<td>LLJ-3</td>
<td>≥20</td>
<td>≥10</td>
<td>Very stable (L &gt; 0)</td>
<td>11</td>
</tr>
<tr>
<td>Total</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>82</td>
</tr>
</tbody>
</table>

In the table, the columns represent the number of jets observed for each category under different stability conditions, with the rows indicating the jet intensities.
are common in Iowa during late summer, as shown by the 382-m wind rose in Fig. 4. The strongest winds originated from the southwest; many of these strong wind observations were the result of jet development and intensification.

To illustrate the effect that LLJs have on wind shear and veer in the boundary layer, median profiles of each BWS jet class along with the median profile for time periods with no jet are provided in Fig. 5. The shaded regions represent one median absolute deviation, a robust measure of dispersion, about the median profile. Note the increasingly prominent maximum in the wind speed profile as jet intensity increases in Fig. 5a. Strong shear below the jet maximum was apparent, with more gradual shear above the nose. The shear spanned a deeper layer for more intense jets. Past modeling studies suggest that the strongest jets may also be associated with upward vertical motion conducive to nocturnal convective precipitation events (e.g., Astling et al. 1985). Unfortunately, such broad gentle motion is outside of the capability of the 200S lidar to accurately capture.

Wind direction shifts with height (veer) were also larger for more intense jets, as illustrated in Fig. 5b. The median wind direction is shown relative to the lowest observation height (approximately 100 m) for each jet category, so additional veer may occur between the surface and 100 m, as observed by Rhodes and Lundquist (2013) and Walton et al. (2014). Vertical veer profiles of weaker jets (LLJ-0/1) were almost indistinguishable from periods with no jet present. Interestingly, above the upper extent of the jet wind acceleration there appeared to be less vertical wind veer during moderate to strong jet cases than in cases with weak or no jets.

a. Prolonged periods with powerful jets

The bulk of LLJ observations throughout the campaign originated in a series of prolonged, often intense jets. This disposition toward temporally contiguous features is immediately apparent in Fig. 6, a summary of all jet observations for each day of the field campaign. The time of day is presented in both UTC and local standard (LST = UTC − 6 h) formats for convenience. Persistent jets (labeled throughout as LLJ-P), those jets observed for at least three consecutive hours, are indicated by bold gray outlines. The majority of these persistent jets formed in the evening hours, and expired in the late morning to early afternoon period. Persistent jets were mostly found within two time frames: 20–22 August and 24–28 August. These two periods featured large high pressure systems to the southeast and east of the Midwest, respectively. Indeed, this synoptic pattern appears to be very conducive for strong, persistent jets in Iowa.
The wind speed, height, and wind direction of most persistent jets followed common patterns, as shown in Figs. 7a–c, respectively. The most variability among the jets was seen in the wind speed at the jet maximum. Four of the jets rapidly intensified into class 2–3 strength within 3 h after formation, while the remainder either slowly intensified or maintained approximately constant strength. The decline in wind speed as the jets dissipated was less orderly than intensification. This result intuitively follows from the decay of the nocturnal jet during the morning transition, where the atmosphere rapidly shifts from stable to neutral to convective conditions. By the time daytime convection is firmly established near the surface, only a weak residual jet remains. Two weak jets formed in the early morning hours; these jets were likely the remnant signature of the strong jets that preceded them. The strongest jets were nocturnal, having occurred primarily between 2200 and 0900 LST, and peak speeds were usually reached by 0400 LST. Such timing means that the wind power generated by the jets will be anticorrelated with periods of maximum electricity demand, which in the summer occur during the middle to late afternoon.

The height of the jet maximum also evolved with time of day, as seen in Fig. 7b. For the most part, the observed jets persisted within a relatively narrow height range similar to that of the GPLLJ. The height of the strongest jets was particularly consistent, as they were typically found between 250 and 500 m AGL. In general, jet heights varied more for weaker intensities and during the evening transition. In the morning and early afternoon, weakening jets appeared to rise rapidly above their nocturnal heights. In most cases, the height of the nose was increasing because of convective erosion of the jet from below, and not from upward translation by vertical winds. Because the nocturnal LLJ is often colocated with the top of the stable boundary layer (Means 1952), the upward trend of the jet during the morning...
hours can suggest insight into the growth rate of the mixed layer in the absence of direct thermal profile measurements. The height of the jet can also determine the impact on rotor-layer shear, as lower jets will generally modify turbine inflow more dramatically than higher jets given similar intensity.

Wind directions of persistent jets tended to veer throughout the night, as seen in the temporal evolution of the jet maximum wind direction, shown in Fig. 7c. For the majority of the jets, the wind direction rotated from approximately 200° to 240° over 13 h, yielding a rate of about 3° h⁻¹. The rate of veering was extremely consistent throughout, and falls within the range of values reported in prior studies of the GPLLJ (Bonner 1968; Zhong et al. 1996; Banta et al. 2002; Song et al. 2005). Veering ceased at around 0800 LST, as near-surface conditions became convective and the jets began to weaken, indicating the end of the ageostrophic inertial forcing. The similarity in wind directions for most of the persistent jets was a consequence of the typical eastward position of the aforementioned synoptic high pressure systems.

b. The impact of observed jets on rotor-layer winds

While the 2005 results heretofore described yield impressively strong and persistent jets, they do not give us insight into winds in a typical wind-turbine-rotor layer (many modern turbines span 40–120 m AGL). As most of the jets occurred during stable conditions, it is uncertain whether LLJ impacts will extend low enough to be of concern for wind energy producers. Fortunately, the V1 lidar is designed precisely to measure winds in this layer. Therefore, we can quantify the impact that such jets have on turbine inflow.

Periods with jets did yield significant differences in rotor-layer wind characteristics. Four measures of rotor-layer wind impacts—80-m wind speed and variability and 40–120-m wind shear and veer—are presented in Figs. 8a–d, respectively. Median values are provided for the four jet intensity classes as well as periods with no jet, and periods with no jet and stable to very stable near-surface conditions. Comparison with stable conditions should indicate whether the jet itself is impacting winds or if differences are merely an artifact of diurnal stability trends. Jets of all intensities increased both 80-m wind speeds and 40–120-m wind shears above the range of typical variability for periods with no jet. Veer was also elevated during strong jet periods, though such values were consistent with nonjet stable periods. The high rotor-layer shear (~3.5 m s⁻¹) and veer (~7°) values present during strong jet episodes produce forces on turbine structures that can impact long-term mechanical reliability (Kelley 2011). While the V1 lidar cannot directly measure turbulence, we can estimate wind variability by taking the standard deviation of 1-Hz measurements for each 3-min averaging period. Here we find that variability was elevated for all jet classes above values typically seen during stable nighttime conditions. Such rapid wind variability can also put added stresses on the turbine structure and gearbox over extended periods of time (e.g., Thomsen and Sørensen...
Finally, rapid increases or decreases of wind speeds in the rotor-layer have been connected to low-level jets in modeling studies (Deppe et al. 2013). These events, known as ramps, can complicate the integration of variable wind farm power output into the electricity grid (Bossavy et al. 2013; Yang et al. 2013). The combined abilities of the V1 and 200S lidar allow us to observe jets and ramp events simultaneously. Here, we followed the convention of Deppe et al. (2013), who define a ramp as a 3 m s$^{-1}$ change in wind speed within a 2-h time window. This wind speed change must occur within a range of 6–12 m s$^{-1}$, as that combination yields the largest power output change in modern utility-scale turbines (ramp events near the cutout wind speed of a turbine, where winds are so strong the turbine shuts down, would produce a larger change; however, these events are not present in our dataset). Ramp periods are visually indicated in Fig. 6, with red circles indicating an increase in winds and blue circles a decrease. It is beyond the scope of this paper to examine individual cases; however, note that jet formation periods were fertile times for ramp events. Throughout the observational period, 54% of upward ramps and 38% of downward ramps occurred concurrently with a low-level jet.

4. Simulating observed jets using the WRF Model

As the results in the prior section illustrate, low-level jets in Iowa have a large impact on rotor-layer winds. Accurate model forecasts of low-level jet periods are essential to manage variable wind power output within the electricity system at large. Therefore, we ran simulations using version 3.4.1 of the Weather Research and Forecasting (WRF) Model to evaluate its ability to reproduce observed LLJs. The WRF Model is a popular community-driven, fully compressible, nonhydrostatic, Reynolds-averaged Navier–Stokes system (Skamarock et al. 2008).

We performed a suite of simulations wherein we evaluated model sensitivity to various initial and boundary condition (IBC) datasets and PBL schemes. All simulations shared the same grid, which featured
three nested domains with two-way information exchange that range from 31.25- to 1.25-km resolution in the horizontal. The 60-level vertical grid was stretched so that spacing between levels was smallest in the boundary layer (approximately 6 m at the surface) and grew as one approached model top, using a hyperbolic tangent function to set the growth rate. The RRTM longwave and Dudhia shortwave radiation schemes and the WRF single-moment 6-class microphysics scheme were also common to all model runs. All but one simulation used the Noah land surface model (LSM), with the exception having used the Pleim–Xiu LSM, designed to work with the Asymmetric Convective Model version 2 (ACM2) boundary layer scheme. The Grell 3D cumulus parameterization simulated convection on the two coarser grids.

An IBC dataset provides both initial conditions at the start of the simulation and boundary conditions for the outermost domain throughout the integration period. Therefore, the selection of particular input data can have a large impact on the accuracy of the model solution at both local and region scales relevant to the LLJ. Five reanalyses were utilized as IBC data: the Interim European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA-Interim; Dee et al. 2011), National Centers for Environmental Prediction Climate Forecast System Reanalysis (CFSR; Saha et al. 2010), North American Regional Reanalysis (NARR; NCEP 2014a), Global Forecast System FNL observational analysis (GFS-FNL; NCEP 2014b), and National Aeronautics and Space Administration (NASA) Modern-Era Retrospective Analysis for Research and Applications (MERRA; Rienecker et al. 2011). Specific details about each dataset are listed in Table 2.

Realistic surface fluxes and turbulent mixing processes are also influential when modeling the LLJ, as they are responsible for maintaining diurnal cycles in boundary layer stability. In WRF, these physics are determined by the selection of the coupled PBL and surface layer schemes. Again, five options were evaluated: the Mellor–Yamada–Janjić (MYJ; Janjić 1994), Mellor–Yamada–Nakanishi–Niino level 2.5 (MYNN2; Nakanishi and Niino 2006), quasi-normal-scale elimination (QNSE; Sukoriansky et al. 2005), Yonsei University (YSU; Hong et al. 2006), and ACM2 (Pleim 2007) schemes. The MYJ, MYNN2, and QNSE schemes are classified as 1.5-order closure schemes, which require an additional prognostic equation for TKE, and utilize local mixing formulations. The YSU and ACM2

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Source</th>
<th>Temporal (h)</th>
<th>Horizontal</th>
<th>Vertical</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERA-Interim</td>
<td>ECMWF</td>
<td>6</td>
<td>~0.7°</td>
<td>38 levels</td>
</tr>
<tr>
<td>GFS-FNL</td>
<td>NCEP</td>
<td>6</td>
<td>1°</td>
<td>27 levels</td>
</tr>
<tr>
<td>NARR</td>
<td>NCEP</td>
<td>3</td>
<td>32 km</td>
<td>30 levels</td>
</tr>
<tr>
<td>CFSR</td>
<td>NCEP</td>
<td>6</td>
<td>~1/2°</td>
<td>38 levels</td>
</tr>
<tr>
<td>MERRA</td>
<td>NASA</td>
<td>6</td>
<td>1/2–2/3°</td>
<td>32 levels</td>
</tr>
</tbody>
</table>

Fig. 8. Median values of (a) 80-m wind speed (m s$^{-1}$), (b) 80-m wind variability (m s$^{-1}$), (c) 40–120-m wind shear (m s$^{-1}$), and (d) 40–120-m wind veer (°) observed by the V1 lidar. The whiskers represent the median deviation about the median, while the violet circles indicate the mean value. Results are provided for each jet class, all times with no jet, and periods with no jet and stable conditions near the surface.

TABLE 2. A summary of the initial and boundary condition datasets used in our model evaluation.
schemes are both first-order closure schemes, meaning they require no additional prognostic equations. They parameterize local mixing using $K$ theory while also representing the effects of nonlocal mixing by large convective eddies. The details of each PBL scheme are summarized in Table 3.

Each simulation spanned an 8-day period from 20 to 28 August. This subset of the CWEX 2013 field campaign was chosen for its excellent lidar data coverage, favorable synoptic pattern (only one frontal passage), lack of precipitation at the field site, and recurring incidence of strong LLJs. To limit the number of test simulations required, all IBC model runs shared the same PBL scheme (MYNN2), and all PBL runs shared the same IBC dataset (ERA-Interim).

a. Sensitivity of WRF simulations to IBC and PBL choice

In general, WRF accurately represented the broad patterns in jet evolution throughout the period. A time series summary of model LLJ results is shown in Fig. 9. Data are split into two categories: one suite differentiated by the choice of IBC data and another differentiated by the choice of PBL scheme. Lidar results are also shown for qualitative evaluation. Note that the model runs labeled ERA-Interim and MYNN2 are in actuality the same run sharing IBC and PBL settings. The run is displayed twice to facilitate comparison with each respective run suite. The two time frames that featured regular, persistent nocturnal jet growth, spanning 20–22 August and 24–28 August, were well simulated. A time–height cross section of winds during the latter period is shown in Fig. 10 for both lidar observations and the ensemble mean of the WRF runs (the ensemble is discussed in more detail in the next section). Jet initiation and termination times occurred within a few hours of those observed.

The model had more difficulty in simulating the 22–24 August pattern, which featured a synoptic frontal passage. This time frame was more challenging to reproduce because the passage of the cold front disrupts the regular diurnal cycle of stability. Therefore, small errors in the timing of the frontal passage could yield large stability differences for a given period. However, despite the lower forecast skill, WRF produced weaker jets during this time, and it seems that the intensity of the inertial oscillation was reduced.

We considered a number of quantitative metrics for model LLJ performance and eventually settled on the Heidke skill score (HSS) as the most appropriate benchmark for our purpose. As it is a feature-based metric, we can use the HSS to judge model skill based on jet intensity. The BWS classification scheme utilizes the whole boundary layer-wind profile; therefore, we can consider a large amount of data within a single parameter, including the implications on rotor-layer winds described by Fig. 8. In computing the score, the performance of a particular model run, relative to the 200S lidar observations, was compared to a hypothetical simulation in which

<table>
<thead>
<tr>
<th>PBL scheme</th>
<th>Type</th>
<th>Closure order</th>
<th>Surface layer scheme</th>
<th>Land surface scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYJ</td>
<td>Local</td>
<td>1.5</td>
<td>Eta similarity</td>
<td>Noah</td>
</tr>
<tr>
<td>MYNN2</td>
<td>Local</td>
<td>1.5</td>
<td>MYNN</td>
<td>Noah</td>
</tr>
<tr>
<td>QNSE</td>
<td>Local</td>
<td>1.5</td>
<td>QNSE</td>
<td>Noah</td>
</tr>
<tr>
<td>ACM2</td>
<td>Hybrid</td>
<td>1</td>
<td>Pleim–Xiu</td>
<td>Pleim–Xiu</td>
</tr>
<tr>
<td>YSU</td>
<td>Nonlocal</td>
<td>1</td>
<td>MM5 similarity</td>
<td>Noah</td>
</tr>
</tbody>
</table>
there exists a random chance the feature will be present (Warner 2010). Positive skill scores represent value added over this random simulation. More details on the HSS computation are available in the appendix.

In general, the ability of the WRF Model to correctly simulate any jet was more dependent on the choice of IBC, as summarized by the “any” category in Fig. 11. Results are organized in a fashion similar to Fig. 9, with each configuration suite displayed separately. We also evaluated performance for each jet category as well as persistent jets. Model runs that performed well at simulating intense (weak) jets often exhibited poor performance for weak (intense) jets, indicative of difficulty in representing jet evolution. Again, small timing errors in the diurnal cycle of stability or spurious convective cells can drastically disrupt LLJ formation and persistence. Among IBC selections, the ERA-Interim run yielded the highest skill scores on average for this time period, though the GFS-FNL run was the best performer during intense LLJ-3 jet periods. Overall jet accuracy was less sensitive to PBL scheme. However, the run using the QNSE parameterization was the most proficient at simulating moderate to intense LLJs, as well as persistent jets.

The standard deviation in skill score for each model configuration suite is shown for all jet categories in Table 4. The choice of input data was more important for accurate simulation of jet presence, as indicated by the IBC skill score deviation (0.074) being over 3 times larger than the PBL deviation (0.022) for the generation of jets of any intensity. A large contribution of IBC skill score variance likely originated with the position and timing of the synoptic front, which in general will be more sensitive to input data than PBL scheme. Overall, skill score deviation increased with jet intensity, indicating that accurately representing stronger jets depended more on model configuration than weak jets. For weak to moderate LLJs, the choice of IBC data and PBL scheme had approximately equal impact. However, for LLJ-3 jets, the choice PBL scheme more strongly determined the quality of the simulation. There appeared to be a performance discrepancy between the local and nonlocal PBL schemes here, with the local schemes providing better performance in general for intense jets.

A similar investigation into WRF sensitivity to IBC and PBL choice was conducted for low-level wind shear by Storm and Basu (2010). Their study examined wind profiles from a period with strong, recurring, nocturnal LLJs in the southern Great Plains. They discovered that the choice of PBL scheme strongly impacted the shear profile below modeled jets, a result that echoes our findings for strong LLJs. In their simulations, WRF produced insufficient wind shear below the jet, which they attributed to the overly diffusive nature of the chosen PBL schemes.
They used WRF-ARW version 3.1.1, however, and many of the PBL parameterizations have since received significant modification, particularly the YSU scheme in version 3.4.1 [as examined in Hu et al. (2013)].

b. Using an ensemble to analyze jet wind evolution and uncertainty

The use of ensembles is common in simulation and forecasting, as they provide an indication of the model uncertainty and can increase skill over single deterministic forecasts when evaluated over long periods (Warner 2010). Here, we combined the IBC and PBL suites to create a nine member ensemble, which was then used to estimate LLJ probability. Mean and median wind profiles were computed, and the BWS method was applied to derive the ensemble mean and median jet simulations (we also calculated an ensemble mean weighted by HSS, which yielded no significant improvement in performance). The ensemble mode was computed by taking the most common jet class simulated by the nine members. If there was a tie, the higher class was used. The skill scores of the deterministic ensemble mean, median, and mode are shown in Fig. 11. All three parameters performed within the range of skill scores produced by the ensemble members. This result is broadly consistent with the work of Deppe et al. (2013), who found that an ensemble constructed by varying PBL schemes in WRF did not demonstrate significant skill increases when forecasting 80-m wind speeds.

While deterministic ensemble products allow us to quickly analyze skill, one of the main benefits of ensembles is their use in probabilistic forecasting. The probability of a particular intensity jet occurring, according to the ensemble simulation, is summarized in Fig. 12. This plot is but one of many ways one can represent probability and ensemble spread. In this visualization, we can quickly get a sense of both the most likely jet intensity (from the most common solution, or mode) as well as the spread of the ensemble members.

Such information can be particularly useful for decision makers. For example, while many members of the ensemble sporadically showed jets forming on 22–23 August, the ensemble spread indicated that there is a 15% chance of no jet for a majority of both nights. This probability is significant, given the potential impacts the jet can have on rotor-layer winds and the possibility of ramp events (which did occur on 22 August but not 23 August). While rotor-layer weather can be simulated directly, LLJs are regular features in many high-wind locations (Rife et al. 2010). Therefore, the inherent predictability of the jets can increase confidence in a particular wind forecast in the rotor layer, if the connection between the jet and low-level winds is understood.

c. Insights into jet forcing from model wind decomposition

The large-scale spatial variance of winds is an area of active research in the wind energy community. Ideally, if

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**Table 4.** The standard deviation among model run Heidke skill scores within the initial and boundary condition data and planetary boundary layer scheme configuration suites for each jet category. These values are calculated using the scores summarized in Fig. 11.

<table>
<thead>
<tr>
<th>Jet category</th>
<th>IBC suite</th>
<th>PBL suite</th>
<th>All runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>LLJ-0</td>
<td>0.042</td>
<td>0.041</td>
<td>0.064</td>
</tr>
<tr>
<td>LLJ-1</td>
<td>0.051</td>
<td>0.043</td>
<td>0.078</td>
</tr>
<tr>
<td>LLJ-2</td>
<td>0.055</td>
<td>0.054</td>
<td>0.094</td>
</tr>
<tr>
<td>LLJ-3</td>
<td>0.080</td>
<td>0.127</td>
<td>0.102</td>
</tr>
<tr>
<td>LLJ-P</td>
<td>0.075</td>
<td>0.063</td>
<td>0.079</td>
</tr>
<tr>
<td>Any jet</td>
<td>0.074</td>
<td>0.022</td>
<td>0.074</td>
</tr>
</tbody>
</table>

---

**Fig. 11.** Heidke skill scores for all WRF Model runs as well as the ensemble mean, median, and mode. Scores are displayed for each jet class, persistent jets, and model representations of any jet, regardless of intensity. Note that the model runs labeled ERA-I and MYNN2 are identical and are shown twice for the sake of comparison with other input data and PBL choices.
the wind decreases within a particular wind farm, another farm on the same electric grid will be anti-correlated and make up for the shortfall. As the Midwest and Great Plains are both areas with high-wind resources and frequent nocturnal jets, it is important to understand the mechanisms driving those jets. As mentioned in the introduction, the GPLLLJ is primarily driven by both the inertial oscillation and sloping terrain baroclinicity. The former is more of a local phenomenon, driven by local stability, while the latter is driven by large-scale variability in the diurnal cycle of density. If the jets in Iowa are at least partially forced by terrain baroclinicity, the correlation between the Iowa jets and the GPLLLJ should be higher.

To investigate the forcing mechanisms, we used the 8-day WRF ensemble mean to estimate the 382-m geostrophic wind vector over our data site. The zonal and meridional gradients of pressure at that height were approximated using finite differencing across the innermost domain (spanning 270 and 210 km in each respective direction). Pressure values from five grid cells were averaged at each end of the finite difference to minimize the influence of small-scale features. The meridional and zonal geostrophic wind components were then computed from these differences. The geostrophic wind vector was subtracted from the total-wind vector, yielding the ageostrophic contribution.

The inertial oscillation should contribute to the ageostrophic vector, while the baroclinic forcing should be contained with the geostrophic vector. This dynamical separation was justified by the spatial extent (on the order of 100 km) of the estimated pressure gradients. Such scales should capture any regional pressure perturbations caused by the gradual downward slope of the plains to the west (along with the impact of anticyclone pressure fields), with the remaining wind contribution comprised of local effects such as the nocturnal decoupling of surface friction.

To elucidate the impact of the geostrophic and ageostrophic contributions at respective time scales, we performed a fast Fourier transform on the total, \(u\)-component, and \(v\)-component time series to generate spectra of variance values for a range of frequencies [in cycles per day (cpd)]. These spectra are shown in Fig. 13, with the total wind in black, the geostrophic contribution in violet, and the ageostrophic contribution in green.

Two variance peaks are evident from the data: the first at frequencies below 0.4 cpd and the second centered at 1 cpd. The former low-frequency peak was caused by wind direction changes associated with the motions of large high pressure systems that were advected from west to east by global wind patterns. In the summer months, these anticyclones are the dominant weather feature in the region at synoptic scales. The variance in the wind components dwarfs the variance of the wind speed magnitude, as the passage of high pressure systems and associated gentle gradients in pressure and
temperature mainly affects the wind direction. Meanwhile, the variance peak at 1 cpd was directly attributable to the regular wind cycle associated with the low-level jet. This peak manifested in both the wind components and the speed magnitude, as the jet both accelerated the wind and caused veering with time. Other diurnal phenomena such as drainage flows and solenoidal circulations (e.g., sea/land breezes) should not be present over central Iowa at 382 m AGL.

For the LLJ (diurnal) variance peak, we found that the elevated variability at that scale was entirely contained within the ageostrophic wind. This result suggests that the inertial oscillation was the dominant contributing forcing mechanism for the simulated jets. The baroclinic forcing described by Holton (1967) was not evident in our decomposed winds, probably because Iowa is well east of the largest Great Plains slope angles. This result suggests that the inertial oscillation is the dominant contributor to low-level jets in the region [as suggested by Parish et al. (1988), Zhong et al. (1996), and others].

5. Discussion and conclusions

Data collected during a summer 2013 field campaign in central Iowa have been used to detect and examine low-level jets in a region with strong wind industry presence. Two commercial grade lidars sampled boundary layer winds from 40 to 2000 m above the surface. After the performance of the systems was validated, data from the scanning lidar, featuring a more extensive vertical coverage of the boundary layer, were used to detect and classify LLJs over a period spanning 14 August–5 September. Jets were classified according to the system devised by Bonner (1968) and modified by Whiteman et al. (1997) and Song et al. (2005).

Jets were found matching all intensity criteria, with weak to moderate jets common during all stability regimes and intense jets mostly relegated to very stable conditions. Strong, persistent jets were almost exclusively observed during the night. The winds at the jet core were typically from the southwest, a result of summertime general circulation patterns around the subtropical high. Nighttime jets exhibited veering with time, on the order of 3° h⁻¹. Observed LLJs had a number of effects on rotor-layer winds, including increased wind speed, shear, veer, and variability. Ramp events, in which wind speeds rapidly increase or decrease, were commonly observed during jet formation times.

We used the Weather Research and Forecasting Model to simulate an 8-day period from the field campaign spanning 20–28 August. Five initial and boundary condition datasets and five planetary boundary layer schemes were tested to determine the sensitivity of the model solution to those configurations. Overall WRF representation of jet presence and timing was good, as indicated by positive Heidke skill score values, consistent with the results of WRF simulations farther south (Hu et al. 2013). Model performance was more consistent in simulating observed LLJs than a frontal passage that also occurred during the simulation period. Jet existence was most sensitive to the choice of input data, while intensity depended on both the IBC dataset and the PBL scheme. An ensemble was computed using all of the simulations. The ensemble provides added information about jet probability that cannot be represented from single simulations. Finally, a decomposition of the winds into geostrophic and ageostrophic contributions suggested that the inertial oscillation was the dominant LLJ forcing mechanism at our field site.

The jets observed during this field campaign share many characteristics with the aforementioned GPLLJ. Average jet maximum heights were at or below 500 m AGL, and jet wind directions exhibited a dominant southerly component. The strongest observed jets were recurring, nocturnal phenomena, like those commonly observed over Oklahoma, Kansas, and Nebraska (as seen in, e.g., Whiteman et al. 1997; Banta et al. 2002; Song et al. 2005). Indeed, while we do not have sufficient observations to confirm the connection, it is probable that many nocturnal LLJs in Iowa coincide with GPLLJ episodes, despite the lack of baroclinic forcing in Iowa. This conclusion is supported by Bonner’s (1968) analysis of radiosonde data. Future investigations could further examine the connection among jets in the central United States to improve understanding of spatial variability across a region with burgeoning wind power capacity.

The importance of the inertial oscillation to the generation and evolution of modeled jets in this region implies that accurate representation of near-surface stability is crucial to correctly representing these LLJs. That said, our model analysis demonstrates the skill already displayed by modern mesoscale codes in simulating observed low-level jets. Our results are significant for any wind energy developer who wishes to build a wind farm in a location where low-level jets are common. The enhanced wind shear and veer extending from just above the surface to the jet maximum has implications for both power generation and turbine wear. The success of the WRF Model in predicting the onset and decay of jets demonstrates the utility of mesoscale modeling for the wind industry, both for forecasting and for site assessment. An important potential future extension of the present work would involve analysis of the
impact on simulation performance of various land surface data and model selections.

Finally, the data presented in this study highlight the abilities of a new generation of commercial Doppler lidars that are now available to industry and the research community. The profiling and particularly the scanning lidars are able to provide significant insight into boundary layer wind patterns. We anticipate such instruments will facilitate greatly increased data coverage in the boundary layer.

Acknowledgments. This work was supported by the U.S. Department of Energy under Contract DE-AC36-08GO28308 with the National Renewable Energy Laboratory. CWEX is supported in part by the National Science Foundation under the State of Iowa EPSCoR Grant 1101284. We are grateful for the hard work of the CWEX 2013 field team, particularly Mr. Russ Doorenbos, without whom this study would not have been possible. We thank Leosphere, Inc., for the provision of the Windcube 200S lidar used in the field campaign. We appreciate the collaboration of Dr. Rod Linn and the Institutional Computing Program at the Los Alamos National Laboratory, who arranged for the computer time necessary to run our simulations. Finally, we thank our reviewers, whose insightful comments provided clarity and focus to this work.

APPENDIX

Computing the Heidke Skill Score

The Heidke skill score (HSS) is a feature-based metric commonly used to assess meteorological model output. It succinctly evaluates the added skill provided by a particular model over a random chance forecast. Four possible outcomes are compared. These outcomes are typically summarized in a contingency table. An example for low-level jets is given in Table A1. Using such a contingency table, the HSS can be calculated as follows:

\[
HSS = \frac{2(ad - bc)}{[(a + c)(c + d) + (a + b)(b + d)]},
\]  

(A1)

where \(a\) represents “hits,” \(b\) represents “false alarms,” \(c\) represents “misses,” and \(d\) represents “correct negatives.” The best possible forecast consists of only hits and correct negatives and will yield a score of unity. A forecast with no skill will have an equal proportion correct and incorrect and yield a score of zero. A negative score implies that the simulation or forecast has less skill than a random forecast.

<table>
<thead>
<tr>
<th>Event forecast</th>
<th>Event observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Yes</td>
<td>b</td>
</tr>
<tr>
<td>No</td>
<td>d</td>
</tr>
<tr>
<td>Total</td>
<td>a + c</td>
</tr>
<tr>
<td></td>
<td>b + d</td>
</tr>
</tbody>
</table>

Table A1. A sample contingency table used in the calculation of the Heidke skill score. Four outcomes are possible, based on simulated and realized outcomes.

REFERENCES


