EXPLORING THE ROLE OF THE ATMOSPHERE ON WIND-ENERGY PRODUCTION: FROM TURBINE WAKES TO VARABILITY OF WIND SPEED

by

CHEUK YI JOSEPH LEE

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M.S., University of Colorado Boulder, 2015

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written by Cheuk Yi Joseph Lee

has been approved for the Department of Atmospheric and Oceanic Sciences

Dr. Caroline Draxl

Dr. Julie K. Lundquist

Date_____

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

ABSTRACT

Lee, Cheuk Yi Joseph (Ph.D., Atmospheric and Oceanic Sciences)

Exploring the Role of the Atmosphere on Wind-energy Production: From Turbine Wakes to Variability of Wind Speed

Thesis directed by Associate Professor Julie K. Lundquist

This dissertation explores the interactions between the atmosphere and wind turbines from numerous perspectives. The work presented here outlines three subjects: the characterization of wind-turbine wakes in the evening, the evaluation of simulated wind-power productions in a numerical weather prediction model, and the attempt to systematically quantify wind-speed (WS) variability over decades.

After introducing the background of wind-energy meteorology, the first part of this dissertation discusses the evolution of wind-turbine wakes during the evening transition. In observations as well as simulations from the Weather Research and Forecasting (WRF) model, turbine wakes, namely the in downwind WS reduction and turbulence enhancement, become more prominent in the evening. Hence, the power generations of downwind turbines decrease when the atmosphere changes from unstable to stable.

The second section of this dissertation focuses on validating the power-production predictions of the wind farm parameterization (WFP) scheme in the WRF model. Using the WFP with fine (~12 m) vertical grid resolution leads to the most accurate power simulations. Compared to the actual power generations, the WFP tends to underestimate power in stable

conditions with high winds and low turbulence. Overall, the accuracy of the WRF model in WS prediction dictates the skill of the WFP in simulating wind power.

The third topic of this dissertation explores optimal methods to assess the variability of WS and energy production. Among the 27 methods tested, the Robust Coefficient of Variation (RCoV), as a normalized, statistically robust and resistant spread metric, yields the strongest correlation in connecting the variations between monthly mean WS and monthly net energy generation. By comparison to a long data record from a reanalysis product, the RCoV also requires 6 years of WS data to effectively quantify the long-term variability of a location.

Finally, this dissertation ends with a remark on the importance of correctly using the WRF WFP and statistics. Future work includes improving the power curve and applying the variability metrics in evaluating financial risk.

DEDICATION

For my family (斐堅本忠), and for all that I have been through



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Tell me and I forget. Teach me and I remember. Involve me and I learn.

- Benjamin Franklin

"十年樹木,百年樹人" is a Chinese saying, and the direct translation reads "planting trees takes 10 years, nurturing people takes 100 years." Like agriculture, a successful education requires many elements pulled together.

First of all, I must thank my family who sowed the seed and established the foundation of my success. I have the perfect parents, Leung Kin and Linda Lee, and they have been giving me the ability as well as the opportunity to chase my dreams. My father is my role model who continues to inspire me my whole life, and my mother is the most caring person I will ever know. Choosing to send their only child abroad for almost a decade must be a difficult decision, and yet my parents still let me aim high and soar to this day. Their endless love is the reason I achieve and succeed. John and Lisa Lee, my terrific grandparents, taught me virtues and family values that define me. I am deeply privileged to be raised by the best parents and grandparents. I also have to thank the family of doctors: my uncle, aunt and cousins, Michael, Sophie, Matthew and Rachel Lee, for their faith in me. My family in Vancouver, the Yeung family, assist and encourage me often as well. Overall, I am beyond grateful to be a part of such an amazing family.

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ABBREVIATIONS

AEP	annual energy production
a.g.l.	above ground level
AMS	American Meteorological Society
ARW	Advanced Research WRF
ATOC	the Department of Atmospheric and Oceanic Sciences
AWEA	American Wind Energy Association
BAO	Boundary Atmospheric Observatory
CCAMS	Cornell Chapter of the American Meteorological Society
CONUS	Contiguous United States
CoV	Coefficient of Variation
CU Boulder	University of Colorado Boulder
CWEX	Crop Wind Energy eXperiment
D	rotor diameter
DBS	Doppler beam swinging
EIA	Energy Information Administration
ERA-I	ERA-Interim
ET	evening transition
EWP	explicit wake parameterization
GAD	generalized actuator disk
GE	General Electric
GFS	Global Forecast System
GW	Gigawatt
GWEC	Global Wind Energy Council
IAV	inter-annual variability
IGPPS	Geophysics, Planetary Physics and Signatures
IPCC	Intergovernmental Panel on Climate Change
IQR	interquartile range
ISU	Iowa State University
L	Obukhov length

LANL	Los Alamos National Laboratory
LCOE	levelized cost of energy
Lidar	Light Detection And Ranging
LES	large-eddy simulation
LLJ	low-level jet
LT	local time
MAD	median absolute deviation
МСР	measure-correlate-predict
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications, Version 2
MW	megawatt
MYNN	Mellor-Yamada-Nakanishi-Niino
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NREL	National Renewable Energy Laboratory
NSF	National Science Foundation
NWP	numerical weather prediction
OR	Oregon
P50	an estimate threshold of AEP of a wind farm that is expected to exceed 50%
	over its lifetime
PBL	planetary boundary layer
PSU	Pennsylvania State University
PTC	production tax credit
Q _H	surface sensible heat flux
r	Pearson's correlation coefficient
\mathbb{R}^2	coefficient of determination
RCoV	Robust Coefficient of Variation
RMSE	root-mean-squared error
r_s	Spearman's rho, or Spearman's rank correlation coefficient
SLE	super-long extended
σ	standard deviation
TI	turbulence intensity

TKE	turbulence kinetic energy
TX	Texas
τ	Kendall's tau, or Kendall's rank correlation coefficient
UTC	Coordinated Universal Time
WC	WINDCUBE
WD	wind direction
WFP	wind farm parameterization
WRA	wind resource assessment
WRF	Weather Research and Forecasting
WS	wind speed
XLE	extra-long extended
YKI	Yule-Kendall Index

This dissertation uses the International System of Units (SI).

Chapter 1

INTRODUCTION

We live in a society exquisitely dependent on science and technology, in which hardly anyone knows anything about science and technology.

- Carl Sagan

Wind energy, as a renewable energy source, is essential in a sustainable world. Most members of the scientific community agree that global warming is a prominent issue and is caused by humans (Cook et al., 2016). Renewable energy sources, including wind energy, play an indispensable role in mitigating climate change (IPCC 2014). Compared with other thermal power plants that use fossil fuels, wind turbines emit far fewer life-cycle greenhouse-gas emissions and air pollutants, and require less water in the cooling process (AWEA 2014; IPCC 2014). Wind energy contributes a remarkable share of our electricity generation, for 3.7% globally in 2015 (GWEC 2017), and for more than 5% in the U.S. in 2016 (EIA, 2017). By the end of 2017, the wind-power capacity in the U.S. was over 85 GW (AWEA, 2017).

Further reducing the cost of wind energy will anchor its predominance and its future in the energy business, regardless of the political environment. On one hand, even with government effort, such as the Paris Climate Accord or the Clean Power Plan proposed by the U.S. Environmental Protection Agency, the conversion from fossil-fuel energy to clean energy is still slow and is subjected to changes in administrations. On the other hand, through market forces, renewable energy technologies will continue to attract investments as long as their rates of return are higher than those of the non-renewables. Sometimes the renewable energy industry benefits from public policies. For example, the Renewable Electricity Production Tax Credit (PTC), first enacted in 1992, has fostered the development of the wind-energy industry in the U.S. by reducing the costs for project owners as well as the prices of electricity bills. Although the PTC constantly suffers from threats of shrinking or discontinuation, the unsubsidized cost of wind energy is already among the cheapest of all the non-renewable and renewable energy sources (Lazard, 2017). Hence, financially competitive clean energy sources can directly increase renewable energy penetration, and minimize the impacts from politics at the same time.

Research in wind-energy science and technology facilitates the reduction of its cost, as quantified by the levelized cost of energy (LCOE). The LCOE is defined as the total cost of installing and operating a project divided by the electricity generated over the life of the project, usually in \$ kWh⁻¹. According to the predictions by Dykes et al. (2017), continuing current wind research can cut the wind LCOE by half, and wind can become cheaper than natural gas by 2030. Atmospheric-science research and innovations serves a critical role to close the scientific knowledge gaps within the industry. Current research topics include improving wind-flow modeling, evaluating wind-energy production estimations, and reducing uncertainty in windenergy production.

Inherently, wind-energy generation is tightly coupled to the atmosphere and weather events. Nighttime mountain drainage flows act as a reliable yet inconsistent wind-energy source; wind turbines switch off during destructive winds from tropical storms for safety reasons; cold frontal passages create icing on turbine blades and halt power production. Among all meteorological variables, wind speed (WS) is the primary component in generating wind energy: the wind-turbine power curve illustrates the relationship between the pair. The wind-turbine power curve, usually provided by the manufacturers, describes the theoretical non-linear relationship between WS and turbine-power production (Figure 1.1): region I of the power curve applies to WS below the cut-in WS (in this example, 3.5 m s⁻¹), where the turbine blades remain at rest, hence the turbine produces zero power; region II is bounded by the cut-in speed and the rated speed (in this example, 14.5 m s⁻¹), and power production increases with WS non-linearly; region III represents the flat, maximum power production between the rated speed and the cut-out speed (in this case, 25 m s⁻¹); region IV illustrates no power production beyond the cut-out speed to avoid excessive loading. Region II is important in understanding the impacts of wake effects on wind-power productions in later chapters.



Figure 1.1: An example wind-turbine power curve, based on a model with nameplate capacity of 1.5 MW. The four regions represent the distinct relationships between WS and turbine-power production.

Besides the power curve, atmospheric science is also critical in other branches of wind energy. In operation, wind-farm operators can modify turbine yawing to steer wakes created by upwind turbines, so as to optimize power production (Frandsen et al., 2006; Fleming et al., 2017). In wind-power forecasting, forecast accuracy affects the wind-energy wholesale prices and the energy market (Bathurst et al., 2002; Jónsson et al., 2010). In grid integration, operators and utilities control, connect, and integrate power generations from single or multiple wind farms in various spatial regions with different wind-resource characteristics (Rodriguez-Amenedo et al., 2002). In wind resource assessment (WRA) before project construction, in situ meteorological measurements and long-term wind records are the key inputs in the measure-correlate-predict (MCP) process and the siting of turbines (Brower, 2012). In general, wind energy and atmospheric science are inseparable.

For instance, atmospheric stability affects turbine wakes and their dissipation. Figure 1.2 summarizes the wake behavior in different stability scenarios based on the literature (Magnusson and Smedman, 1994; Wu and Porté-Agel, 2011; Fleming et al., 2016; Vollmer et al., 2016). In an unstable case (Figure 1.2a), wakes diffuse and erode faster because of strong vertical mixing. In a stable environment (Figure 1.2c), wakes tend to be prominent, dissipate slower, and persist downwind. The role of atmospheric stability in wake evolution and power production is further discussed in later chapters.



Figure 1.2: A generic demonstration of wake effects in terms of downwind velocity deficit. The vertical cross-sections illustrate wakes in (a) an unstable, (b) a neutral and (c) a stable atmosphere downwind of a turbine.

Moreover, one of the major obstacles in expanding wind-energy penetration is its intermittency, causing challenges in maintaining a stable energy supply. Although connecting wind farms in different geographical regions can reduce the stress from variability on the grid, minimizing the losses and the uncertainties in power production of a particular wind farm remains a critical problem to solve. In wind energy, the gross energy production is the theoretical annual energy production (AEP) derived from the power curve. The net energy production is the actual AEP of a wind farm after accounting for all the losses, including the losses from curtailments, turbine unavailability, and wind-turbine wakes. The discrepancy between the gross and the net energy productions directly affects the profitability of a wind farm. Therefore, minimizing the losses relevant to atmospheric science is both interesting and valuable. The industry needs to understand how wind turbines interact with the atmosphere, and how to predict and anticipate those interactions. Exploring different uncertainties of power production that are

closely connected to the atmosphere, including wake losses and WS variations, reduces costs and facilitates further growth of the industry.

Primarily, the wake effect is the WS reduction caused by wind turbines, and undermines the power production of turbines located downwind. Typically, the intra-wind-farm wake effect contributes 6.4% of the production losses for North American onshore wind projects, and wakes can reduce 10% of energy generation (Table 1.1). Spatially, wakes span from turbine scale to wind-plant scale. Wake-induced turbulence enhancement and its evolutions, dependent on atmospheric stability, alter downwind power production (Magnusson and Smedman, 1994; Barthelmie et al., 2009; Barthelmie and Jensen, 2010; Mirocha et al., 2014). The literature has well documented wake behaviors in different atmospheric stability regimes (Magnusson and Smedman, 1994, 1999; Hansen et al., 2012; Aitken et al., 2014a; Abkar and Porté-Agel, 2015b), whereas the evolution of wakes in the evening, from unstable to stable condition, remains left untouched. Because the electricity demand usually spikes in the evening (Figure 1.3), the intrawind-farm wake propagation and its effects on power production are prime research subjects. Chapter 2 of this dissertation summarizes the investigation on evening wind-turbine wakes, and the findings are published in Boundary-Layer Meteorology, "Observing and Simulating Wind-Turbine Wakes During the Evening Transition" (Lee and Lundquist, 2017b).

Logg astagowy	Typical values in AWS	Ranges in Clifton	Examples of possible
Loss category	Truepower (2014)	et al. (2016)	mitigations
Availability	6.2%	2-5%	Long-term service agreement
Availability			with manufacturer
Cuntailmant	0%	0-4%	Negotiation and cooperation
Curtainnent			with local communities
Electrical	2.1%	0.5 - 3.5%	Optimizing layout
Environmental	2.7%	0-5%	Improved blade coatings and
Environmental			maintenance
Turbine	4.00/	1 20/	T 1
performance	4.0%	1 - 3%	Improved power curve
Wake effects	6.4%	0 - 10%	Improved wake models

Table 1.1: Different losses in percentage of energy production, adapted and modified from AWS Truepower (2014) and Clifton et al. (2016). The results from AWS Truepower (2014) are typical loss values for onshore projects in North America. The results from Clifton et al. (2016) are valid for projects designed and built from 2010 - 2015.



Figure 1.3: The electric load over 24 hours in New England averaged from 1 January 2017 to 31 December 2017, based on the data from the Independent System Operator New England.

Moreover, numerical models attract interest because of their widespread applications in the wind-energy industry and resulting broad implications on energy production. Inaccurate flow models incorrectly estimate wind resources, and the spatial variation of WS within a wind site can constitute over 10% of the overall uncertainty in complex terrain (Table 1.2). Modeling capabilities also relate to other uncertainties such as wake effect and historical wind resource, each contributing at most 35% and 6% of the total uncertainty in power production (Table 1.2). On average, wind-flow modeling causes 4% of uncertainty in energy production (AWS Truepower, 2014).

Accordingly, verifying and validating the accuracy of numerical models on wind and power simulations provides the legitimacy for model users. As a numerical weather prediction (NWP) model, the Weather Research and Forecasting (WRF) model is a commonly used tool in operational meteorology and academic atmospheric research. The wind farm parameterization (WFP) scheme of the mesoscale WRF model, released since the version 3.3 of the WRF model, accounts for wake effects and generates power output for each turbine-containing grid cell (Fitch et al., 2012). To quantify the minute- to day-long, wind-farm-scale power-production skill of the WFP, a case study using actual power-generation data over 4 days is conducted. The study aims to confirm the usefulness of the WFP and to provide directions for future model improvements. Chapter 3 of this dissertation appears in *Geoscientific Model Development*, "Evaluation of the wind farm parameterization in the Weather Research and Forecasting model (version 3.8.1) with meteorological and turbine power data" (Lee and Lundquist, 2017a).

Uncertainty	Typical ranges in AWS	Ranges in Clifton et	Examples of possible
category	Truepower (2014)	al. (2016)	mitigations
Historic wind resource	2.1 - 4.8%	1 – 6%	Use of reanalysis dataset
	3.2 - 4.8%	Electrical: 1 – 2%	
Dlont		Curtailment: 1 – 4%	Better inflow conditions,
Flain		Turbine	improved models, generation
performance		performance: $0 - 4\%$	management
		Wake: 13 – 35%	
Project lifetime variability	0.6 - 1.5%	1 - 10%	Improved quantification of variability
Site measurements	1.6 - 4.8%	0-2%	Better calibration
		Simple terrain:	
Spatial	2.4 - 8%	1 - 2%	Optimizing wind
variation		Complex terrain:	measurement locations
		> 10%	
Vertical	0-6.4%	0-6%	Deploying remote sensing
extrapolation			instruments

Table 1.2: Different uncertainties in percentage of energy production, adapted and modified from AWS Truepower (2014) and Clifton et al. (2016). The results from Clifton et al. (2016) are valid for projects designed and built from 2010 - 2015. The naming of the uncertainty categories between the two reports are different.

Another hurdle of wind energy due to meteorology is the variability of WS across temporal scales. Winds ramp up and down in seconds in the form of gusts; WS and wind direction (WD) fluctuate drastically for days during tropical storm landfalls and frontal passages; wind patterns change every year with climatic oscillations. The ever-changing wind resources create variable energy supply at a particular wind site. In contrast, electricity demand, although fluctuates over time, is perpetually continuous from 1 second to the next. Hence, a part of this dissertation is devoted to evaluating the uncertainty in the long-term AEP, namely the long-term variability of wind resources.

Our understanding on the long-term and inter-annual variability (IAV) of WS as a holistic subject, is weak and non-uniform, from its calculations to its representations. Therefore, this topic requires a thorough investigation. Long-term variations in WS affect the energy trading market, where the expectations on the wind-power volume affect the energy price and hedging. Moreover, wind variability accounts for 10% of total uncertainty at worst (Table 1.2), and one study found that the 10-year IAV of WS is 3.5% in general (AWS Truepower, 2014). However, various regions experience variability differently, and generalizing WS variability into one number across regions oversimplifies this uncertainty. What is worse, numerous methods are used to evaluate IAV, and the industry lacks a systematic way to quantify this critical parameter in WRA. Hence, Chapter 4 of this dissertation is dedicated to discussing the differences between various IAV quantification methods, using WS and energy-production data across hundreds of wind farms for over 2 decades. The contents in Chapter 4 will be submitted to *Wind Energy Science* in a manuscript titled "Assessing variability of wind speed: Comparison and validation of 27 methodologies".

Each chapter focuses on a specific topic on wind-energy meteorology, and they all follow the structure of scientific literature with abstract, introduction, methodology, results, discussion, conclusion, and acknowledgements, preceding by a chapter prologue. Figures and tables are numbered independently in the respective chapter. All references are assembled at the end of this dissertation. This dissertation spotlights several meaningful research topics with in-situ, highresolution data from modern instruments, outputs from the latest numerical models, contemporary data-analysis capabilities, and open-access data sharing. This dissertation summarizes my work of my Ph.D. journey at the University of Colorado Boulder (CU Boulder) and takes a deep dive to enhance our understanding of atmosphere-related uncertainties in wind energy. Enjoy.

Chapter 2

WIND-TURBINE WAKES DURING THE EVENING TRANSITION

When the sun has set, no candle can replace it.

– George R. R. Martin

In modern society, satisfying the household electricity peak demand in the evening is a daily challenge for utilities. At the same time, meteorologically, the evening transition (ET) begins when afternoon convection ceases and disappears at sunset. The atmosphere becomes less turbulent when the influence of the sun's heating on the planetary boundary layer (PBL) dissipates. In other words, the ET takes place when the daytime unstable atmosphere transforms into the nighttime stable regime. Because wind energy tightly connects with the atmosphere, this stability change influences the wind-turbine wake evolution and hence the wind-power production in the evening.

The wind-turbine wake effect is a well-established research topic. Researchers have used observations (S. Lissaman, 1979; Magnusson and Smedman, 1994; Whale et al., 1996; Barthelmie et al., 2003; Bingöl et al., 2009; Peña et al., 2009; Trujillo et al., 2011; Iungo et al., 2013; Rajewski et al., 2013), wind tunnel experiments (Massouh and Dobrev, 2007; Chamorro and Porté-Agel, 2009; España et al., 2011), statistical models (Marden et al., 2013) and numerical models (Ainslie, 1988; Sofrensen and Shen, 2002; Troldborg et al., 2010; Wu and Porté-Agel, 2011; Churchfield et al., 2012b; Meyers and Meneveau, 2012; Aitken et al., 2014a; Annoni et al., 2014; Mirocha et al., 2014) to analyze wake effects. Moreover, wake behavior has been studied in different stability conditions (Magnusson and Smedman, 1994, 1999; Aitken et al., 2014).

al., 2014a; Abkar and Porté-Agel, 2015b; Vollmer et al., 2016), yet wake evolution during a stability transition remains unanswered.

To reduce the loss and uncertainty caused by wind-turbine wakes, we first must understand how wakes behave in reality. Hence exploring and quantifying the intra- and interwind-farm wakes in the ET is an important step towards efficient wind-farm operations. Minimizing wake losses directly closes the gap between the gross and the net wind-energy productions of a wind farm.

This chapter discusses the turbine-scale and the wind-farm-scale evening evolutions of turbine wakes, using field observations and results from the Weather Research and Forecasting (WRF) model based on an evening case study. Understanding wake effects allows better flow management moving through a wind farm and thus improves wind-plant control and operational strategies, further maximizing energy production.

The following is reproduced and reformatted from:

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Julie Lundquist revised the manuscript and provided guidance of the research.

2.1 Abstract

Wind-turbine-wake evolution during the evening transition (ET) introduces variability to wind-farm power production at a time of day typically characterized by high electricity demand. During the ET, the atmosphere evolves from an unstable to a stable regime, and vertical stratification of the wind profile develops as the residual planetary boundary layer decouples from the surface layer. The evolution of wind-turbine wakes during the ET is examined from two perspectives: wake observations from single turbines, and simulations of multiple turbine wakes using the mesoscale Weather Research and Forecasting (WRF) model. Throughout the ET, the wake's wind-speed (WS) deficit and turbulence enhancement are confined within the rotor layer when the atmospheric stability changes from unstable to stable. The height variations of maximum upwind-downwind differences of WS and turbulence intensity gradually decrease during the ET. After verifying the WRF-model-simulated upwind WS, wind direction and turbulence kinetic energy profiles with observations, the wind-farm-scale wake evolution during the ET is investigated using the WRF-model wind farm parametrization scheme. As the evening progresses, due to the presence of the wind farm, the modelled hub-height WS deficit monotonically increases, the relative turbulence enhancement at hub height grows by 50%, and the downwind surface sensible heat flux increases, reducing surface cooling. Overall, the intensifying wakes from upwind turbines respond to the evolving atmospheric boundary layer during the ET, and undermine the power production of downwind turbines in the evening.

2.2 Introduction

2.2.1 Evening boundary layer and turbine wakes

Daily electricity demand typically increases in the early evening, making the balance of power supply and demand a challenge during this period (McLoughlin et al., 2013). Households require higher power demand in the evening, while solar-power generation is diminishing. The wind-power capacity of the world continues to grow, and providing stable electricity supply via wind power remains an ongoing challenge to power-grid operators due to the variability of wind-energy production. Therefore, it is important to understand utility-scale wind-turbine-wake behavior during the evening transition (ET) because wakes undermine downwind wind-power production. An enhanced understanding of wake evolution during the ET can also be helpful in other situations. For example, offshore wind farms often experience land and sea breezes such that coastal flow undergoes a similar transition to that of a continental ET (Angevine, 2007) and can affect wind-power production.

The unique characteristics of the ET have been explored in the past in terms of changes in temperature, turbulence, and surface fluxes (Deardorff, 1974a, 1974b; Mahrt, 1981; Nieuwstadt and Brost, 1986; Edwards et al., 2006). The ET is the period during which the daytime unstable atmosphere evolves into the nocturnal stable boundary layer, where a distinct transition is observed during conditions with quiescent synoptic forcing. Acevedo and Fitzjarrald (2001) identified the "early evening transition" as the period when the planetary boundary layer (PBL) is decoupled from the surface layer, and leads to a temperature decrease, a wind-speed (WS) reduction, and an increase in water vapor mixing ratio near the surface. Lothon et al. (2014) defined the ET as the period after the surface sensible heat flux (Q_H) reaches zero and before the establishment of the nocturnal stable layer. The ET can be further described by the temperature

profile evolution in the PBL, with the presence of a near-surface temperature inversion as an indication of a decoupled nocturnal boundary layer (Grimsdell and Angevine, 2002; Angevine, 2007). As a result, a temperature inversion near the surface forms at the start of the ET, usually at least 1 hour before sunset (Grimsdell and Angevine, 2002).

Changes in turbulence also suggest the onset of the ET. An abrupt decay in turbulence kinetic energy (TKE), associated with the collapse of daytime turbulence, and the sign changes in Q_H , are indicators of the "early evening transition" (Nadeau et al., 2011). The delay between the time when Q_H becomes negative and the TKE decay has been quantified previously (Nieuwstadt and Brost, 1986; Sorbjan, 1997; Blay-Carreras et al., 2014). Sastre et al. (2015) also demonstrated that the WS reaches a minimum around the time of sunset, and the turbulence time scale decreases during the ET.

In this chapter, we define the ET as the time at which the near-surface atmospheric stability undergoes transition from convective to stable, and the value of Q_H changes sign. Though alternative approaches have been used previously, we find this definition the most appropriate. Using this approach, we can determine an unambiguous ET in the chosen case study as Q_H declines monotonically.

The ET presents a scientific challenge for wind-energy forecasting, since the flow becomes increasingly stratified during the ET, making the forecasting of wind-power production a challenge (Sanderse et al., 2011). While summer nocturnal low-level jets (LLJs) increase boundary-layer WSs (Bonin et al., 2015; Vanderwende et al., 2015), providing ample wind resources during the summer in the Great Plains, the power deficit, the reduction in power production of downwind turbines located within the wakes, increases with atmospheric stability (Hansen et al., 2012). New approaches to yawing upwind turbines in order to improve the power

production of downwind turbines (Fleming et al., 2015, 2016) require accurate wake prediction. The difficulties posed by uncertain flows, substantial wind resources, large power deficits and possible wake manipulation potentially affect wind-power production in the evening.

Wake features in different atmospheric stability regimes have been widely studied, but wake behavior during the ET remains unexplored. Early wake observations (Magnusson and Smedman, 1994) concluded that the WS deficit and the downwind turbulence generation are greatest in a stable atmosphere, as wakes erode minimally due to the lack of background turbulence. Wake behavior depends not only on thermal stability but also on the upwind wind profile, and wind-tunnel experiments have demonstrated that inhomogeneous upwind flow disturbs the vertical symmetry of the downwind WS deficit and turbulence (Chamorro and Porté-Agel, 2009). The WS deficit and the vortices in the wake also affect wake meandering and wake expansion from the turbine centerline (Howard et al., 2015).

2.2.2 Turbine-wake simulations

Comparisons of Light Detection And Ranging (LiDAR) measurements to large-eddy simulations (LESs) with a generalized actuator disk (GAD) model in the Weather Research and Forecasting (WRF) model are capable of representing wake-deficit characteristics qualitatively (Aitken et al., 2014a; Mirocha et al., 2014, 2015). GAD model results have indicated that turbine wakes expand more in the horizontal direction than vertically (Mirocha et al., 2014). At a downwind distance of 6.5 times the rotor diameter (D), the flow experiences up to 25% WS reduction in a weakly convective regime (Mirocha et al., 2014). LESs have also revealed that the WS deficit extends further downwind, the turbulence generation decreases and the overall wake recovers more slowly in the stable PBL than in the unstable PBL (Abkar and Porté-Agel, 2015b;
Bhaganagar and Debnath, 2015; Mirocha et al., 2015). However, modelled turbine wakes grow horizontally twice as rapidly, and the wake meanders from the wake centerline to a greater extent in convective than in stable conditions (Abkar and Porté-Agel, 2015b). Unfortunately, examining the wake behavior of a sizable wind farm using LES is computationally expensive (Churchfield et al., 2012a), and the simulation of wind-farm impacts using mesoscale meteorological models is more practical.

Various approaches of representing wind farms in mesoscale models have been explored. For example, surface roughness has been locally increased in climate models to represent the drag effects of wind turbines (Keith et al., 2004; Frandsen et al., 2009); however, this method ignores turbine impacts on flow phenomena such as below-rotor speed-up within the lowest few hundred meters above ground level (a.g.l.) (Fitch et al., 2012). Further, the use of the roughness approach generates turbine-induced daytime heating and nocturnal cooling (Fitch et al., 2013b) rather than the observed nocturnal heating (Zhou et al., 2012; Rajewski et al., 2013, 2014). Alternatively, the fact that the turbine rotor disk is elevated is considered by using flowdependent parameters to introduce the effects of turbines into the flow, resulting in turbineinduced elevated drag and an increase in turbulence intensity (TI). When the inflow speed increases, both the induced drag and the turbine-power production increase, according to the associated turbine-power curve (Blahak et al., 2010; Baidya Roy, 2011). In addition to the power curve, the use of the turbine thrust coefficient, which also varies with WS, provides a more accurate estimate of turbine drag and power loss (Fitch et al., 2012). This elevated-drag approach has been shown to reproduce correct nocturnal heating from wind farms (Fitch et al., 2013b).

Here, we use the mesoscale WRF model's wind farm parametrization (WFP) scheme (Fitch et al., 2012; Fitch, 2015) to simulate an actual wind farm. The WFP scheme is based on

(Blahak et al., 2010; Baidya Roy, 2011), and uses the turbine-thrust coefficients. In the WFP scheme, wind turbines are represented as a momentum sink and a source of turbulence at the altitudes at which turbine blades are located (Fitch et al., 2012; Fitch, 2015). The WFP scheme estimates local turbine drag based on the thrust coefficient, which is the total fraction of kinetic energy extracted from the atmosphere as a function of WS. The modelled generation of TKE varies with WS, and the momentum sink converts a fraction of kinetic energy into electricity generation (Fitch et al., 2012). Unlike LES, the WFP scheme does not account for wake meandering or the wake effects on turbines in the same grid cell (Fitch et al., 2012). The grid-averaged wake thus includes some uncertainty in characterizing wakes (Vanderwende et al., 2016). While the WFP scheme tends to underestimate the power deficit of downwind turbines, it is capable of qualitatively reproducing wind-farm impacts in different atmospheric stability conditions (Jiménez et al., 2015), and has been used to explore the impact of surface roughness on wind-farm production (Vanderwende and Lundquist, 2016).

Using the WFP scheme in the WRF model, wake evolution during the ET was briefly examined in (Fitch et al., 2013a), though without comparison to observations. In Fitch et al. (2013a), the background boundary-layer WS increased throughout the ET, leading to greater WS deficits and turbulence enhancement within the rotor layer and to heights up to 2D above the rotor layer. Even though the power production increased during the ET, downwind vertical mixing was inhibited within the growing stable layer, leading to strong and persistent wakes. However, Fitch et al. (2013a) did not include a comprehensive discussion on the response of wakes to atmospheric stability changes during the ET, the topic that we address herein.

Wake evolution during the evening stability change has not been addressed in previous work; therefore, we examine turbine-wake evolution during the transition using both measurements and simulations. The observations and the modelling approach are described in Sect. 2.3, and we discuss the observations of individual turbine wakes for one well-observed case study (Sect. 2.4.1). Then, we compare the upwind observed profiles to the simulated background atmosphere in the WRF model, so as to verify the modelled inflows (Sect. 2.4.2). Next, the aggregate wake evolution during the ET caused by multiple wind turbines is further explored using the WFP scheme (Sect. 2.4.3). The observations and model results demonstrate that, through the ET, increasingly persistent wakes develop, as quantified by downwind WS deficits and turbulence generation. The evolving atmosphere during the ET potentially poses challenges in the prediction of wind-power production.

2.3 Data and methods

2.3.1 Wake observations

Assessing the meteorological impacts of wind-turbine wakes and their subsequent impact on power production during the ET requires detailed atmospheric measurements of the upwind and downwind flow. To explore wake behavior, the Crop Wind Energy EXperiment 2011 (CWEX-11) collected wind observations in a 200-turbine wind farm in central Iowa from June to August 2011 (Rajewski et al., 2013, 2014; Rhodes and Lundquist, 2013). The hub height and the D of the 1.5-MW super-long extended (SLE) wind turbines manufactured by General Electric (GE) are 80 m and 77 m respectively, with the rotor layer extending from approximately 40 m to 120 m a.g.l. (Rajewski et al., 2013). The cut-in, rated and cut-out speeds of the turbines are 3.5, 14 and 25 m s⁻¹ respectively. High-resolution wind profiles upwind and downwind of a row of wind turbines were measured using two vertical profiling Doppler wind LiDARs and four surface-flux towers. Note that we present time as both local time (LT) and Coordinated Universal Time (UTC), where LT + 5 hours = UTC.

The WINDCUBE (WC) LiDARs measured velocity components at approximately 0.25 Hz from 40 to 220 m a.g.l., while the flux towers collected 20-Hz measurements of near-surface WS and wind direction (WD), Q_H , virtual temperature, and water vapor density at 4.5 m a.g.l. Since the prevailing WD at the site is southerly, the instruments were located directly north (250 m, about 3D) and south (164 m, about 2D) of a row of east-west oriented turbines (Figure 2.1). The two furthest downwind flux towers were positioned 664 m (about 8.6D) and 1036 m (about 13.5D) north of the row of turbines. As a result, turbine-wake impacts can be quantified via comparison of the upwind and downwind sites, including WS deficit, near-surface temperature change, TI and TKE enhancement. The TI can be calculated as

$$TI = \frac{\sqrt{\sigma_u^2 + \sigma_v^2}}{\overline{\upsilon}},\tag{2.1}$$

and the LiDAR-estimated TKE can be calculated as

$$TKE = \frac{1}{2}(\sigma_u^2 + \sigma_v^2 + \sigma_w^2),$$
(2.2)

where \overline{U} is the average horizontal WS, and σ^2 are the 2-minute averaged variances of the *u*, *v*, *w* velocity components (Stull, 1988).



Figure 2.1: Topography map of CWEX-11. Blue diamonds, red circles and yellow triangles represent the wind turbines (WT), the NCAR surface-flux stations (NCAR) and the WINDCUBE LiDARs (WC) respectively. The instrument locations were constant throughout the whole campaign. The contours represent the elevation above sea level in meters.

Pulsed LiDARs (WC1 and WC2) use the Doppler beam swinging (DBS) method to take wind measurements at all specified altitudes based on the same pulse, by comparing the backscattering arrival time at different heights to the pulse initialization time (Courtney et al., 2008). The method assumes flow homogeneity over a horizontal area so as to retrieve horizontal and vertical WSs. In CWEX-11, the wind components are averaged every 2 minutes to quantify the associated variability. However, the errors in cross-stream and vertical velocity components from near-wake LiDAR measurements at a distance 2D downwind can be significant in stable conditions (Lundquist et al., 2015). Besides, the WC LiDARs do not measure atmospheric turbulence precisely due to the spatial separation of the data points along the line-of-sight and in the conical section (Sathe et al., 2011). As a result, the observed 2-minute averaged turbulence parameters describe only the variances as observed by the LiDAR, rather than the evolution of small-scale turbulence. Nonetheless, the wake effects due to an individual turbine can still be described by contrasting the LiDAR-measured 2-minute averaged WS and LiDAR TKE, when the upwind flow is southerly and most of the wake overlaps the LiDAR scanning volume.

Wind outside of the downwind wake edges is occasionally measured when slight WD changes divert part of the wake outside of the LiDAR's sampling volume. At hub height, the cross-stream 1-Hz beams from the downwind LiDAR measure wind components beyond the wake edges when the inflow WD deviates by more than 3.19° on each side of the 180° WD. Downwind WS measurements derived from along-stream LiDAR beams are not affected by this caveat. However, the sampling beyond the wake edges introduces a source of uncertainty for downwind turbulence measurements, as the cross-stream observations are incorporated into such measurements.

The sonic anemometers and gas analyzers installed at the NCAR (National Center for Atmospheric Research) surface-flux stations provide 20-Hz measurements of wind velocity, virtual temperature and water vapor density at 4.5 m a.g.l. (Rajewski et al., 2013). The sonic wind vectors are rotated to correct for instrument tilt using the planar fit technique (Wilczak et al., 2001). The flux stations also record 2-m and 10-m air temperature, 2-m air pressure, and 2-m relative humidity at a rate of 1 Hz. In addition, located between the LiDARs and the NCAR flux stations, two upwind and downwind flux towers from Iowa State University (ISU) also provide 5-minute precipitation measurements. Since the locations of the NCAR flux towers are more

advantageous than the ISU tower locations in observing wakes in southerly flow, only highresolution data from the NCAR flux stations are analyzed herein.

2.3.2 Case study description

A case study for 9 July 2011 is chosen to illustrate the wake effects during the ET, based on several criteria. First, both LiDARs must report data without interruption between 1500 and 2200 LT; second, the WDs across the rotor layer, as measured by the LiDARs, must consistently record southerly inflow throughout the evening; third, the measured hub-height WSs must exceed the turbine cut-in speed; fourth, no major synoptic-scale system should influence the local weather in Iowa throughout the period. On this evening, WDs at the surface, 850-hPa level, and 500-hPa level were primarily southerly, south-westerly, and westerly, respectively. Throughout the campaign, southerly evening inflow was also recorded on two other evenings, 16 and 23 July 2011. However, the WC2 LiDAR did not record sufficient data during the evening of 16 July (Mirocha et al., 2015), and the ET on 23 July was ambiguous due to afternoon precipitation. Therefore, those two cases are not considered.

2.3.3 WRF model configurations

We use the Advanced Research WRF (ARW) model (version 3.6.1) (Skamarock and Klemp, 2008) to simulate the wake characteristics on a wind-farm scale during the ET. To ensure the mesoscale model depicts the upwind conditions correctly, simulation results are compared to the upwind observations before introducing the virtual wind farm. The simulations began at 0000 UTC on 9 July 2011 and ran for 30 h, and we focus on the model data during the ET, from 2000

UTC 9 July to 0300 UTC 10 July (1500 to 2200 LT 9 July). The Global Forecast System (GFS) reanalysis provides initial and boundary conditions for the one-way-nested three-domain simulations (Figure 2.2). We also tested other initial- and boundary-condition datasets, the ERA-Interim (ERA-I) dataset and the GFS 0.5-degree resolution dataset. The WRF-model results using the GFS reanalysis data with 1-degree resolution are selected because the wind field, turbulence and Q_H are more accurately modelled when forced with the GFS 1-degree resolution dataset (not shown). The finest domain, simulated with 571 × 511 points at 990-m horizontal resolution, covers the entire state of Iowa with an integration time step of 1 s. To capture the southerly surface flow and the westerly synoptic flow above the surface layer, the inner grids are located north-east of each coarser grid's center, thus ensuring adequate upwind coverage. To simulate high-resolution boundary-layer features, vertical levels are progressively stretched from the surface, with 70 levels in total. The vertical spacing below 200 m a.g.l. is about 22 m on average, allowing for four vertical levels in the rotor layer, approximately at 45, 67, 89, 112, 134, 156, 179 and 201 m a.g.l.



Figure 2.2: Map of the three domains simulated with the WRF model: largest grid as d01, intermediate grid as d02 (yellow) and finest grid as d03 (orange). The white cross marks the location of the CWEX-11wind farm.

The Mellor-Yamada-Nakanishi-Niino (MYNN) PBL scheme is currently required, for the WRF model to simulate the effects of wind farms via its WFP scheme (Fitch et al., 2012); the MYNN level-2.5 scheme predicts sub-grid TKE as a prognostic variable and produces local vertical mixing (Nakanishi and Niino, 2006). Based on the Mellor-Yamada-Janjić scheme, the MYNN scheme uses fundamental closure constants derived from LES, and includes stability effects on the mixing length and buoyancy effects on pressure covariance (Nakanishi and Niino, 2006). The MYNN surface layer and TKE advection in the PBL scheme are also applied. Microphysics is parametrized with the single-moment 3-class scheme (Hong et al., 2004) in the

model runs; longwave radiation is estimated with the Rapid Radiative Transfer Model (Mlawer et al., 1997); and the Dudhia scheme provides shortwave radiation (Dudhia, 1989). The simulations also use the unified Noah land-surface model, and for the cumulus parametrization, the Kain-Fritsch scheme (Kain, 2004) is enabled on the coarsest domain. The non-hydrostatic simulations allow simple diffusion with horizontal Smagorinsky first-order closure and an implicit gravity-wave damping layer.

Of the two sets of simulations, one actively employs the WFP scheme (the "WFP" run) and one has the WFP scheme inactive (the "control" run). In the simulations that included the wind-farm effects, virtual wind turbines are added to the finest domain via the WFP scheme. This scheme explicitly models the elevated drag and turbulent mixing of turbines by establishing an elevated momentum sink and a turbulence source (Fitch et al., 2012). We use the configurations of the 1.5-MW Pennsylvania State University (PSU) generic turbine (Schmitz, 2012), similar to the GE SLE turbine described above (80-m hub height and 77-m D). The standing thrust coefficient chosen is 0.041. The WFP run includes a 100-turbine wind farm, which comprised half of the turbines at the site of the CWEX-11 campaign to produce the utilityscale turbine-wake effects. Although the whole wind farm in this location consists of 200 turbines, here we focus on the southern half of the wind farm, the location of the meteorological measurements. Note that the size of a 100-turbine wind farm is representative of most wind farms in North America. Comparison between the control simulation and the WFP simulation indicates the progression of downwind horizontal WS deficits, TKE generation, Q_H sign changes and power production through the ET.

2.4 Results

2.4.1 Observations

2.4.1.1 Evening transition characterization

The near-surface region of the PBL undergoes a transition from convective to stable conditions at least 2 hours before sunset (at 2051 LT) on 9 July 2011 (0151 UTC 10 July), with the stability parameter, z L⁻¹ (where z is height and L is the Obukhov length) changing from negative to positive at 1830 LT (2330 UTC) (Figure 2.3a). The value of the Q_H changes sign at the same time (Figure 2.3b), while the latent heat flux decreases over time (Figure 2.3b). The abrupt collapse of the absolute temporal TKE change ($\left|\frac{d}{dt}TKE\right|$) at hub height (Figure 2.3c), which signifies the onset of the transition (Nadeau et al., 2011), coincides with the stability change. The above evidence suggests a distinct ET before sunset, consistent with the observations of Grimsdell and Angevine (2002). The differences of z L⁻¹ and heat fluxes between upwind and downwind sites are trivial, so the downwind stability observations are not presented here.



Figure 2.3: Time series of stability parameters from the upwind surface-flux station (NCAR1) and LiDAR (WC1) on 9 July: z L⁻¹ (a), 20-Hz surface sensible and latent heat fluxes (b), and the absolute temporal TKE change at turbine hub height of 80 m ($\left|\frac{d}{dt}TKE\right|$) (c). The purple vertical dash line indicates the ET at 1830 LT (2330 UTC). The green vertical dash line represents the time of sunset at 2051 LT (0151 UTC).

2.4.1.2 Wind-speed deficits and turbulence generation

The stability, heat flux, and temporal TKE changes affect the wake behavior in the evening, as illustrated in the upwind (Figure 2.4a) and downwind (Figure 2.4b) LiDAR wind profiles and the differences between them (Figure 2.4c). When the PBL undergoes transition from an unstable to a stable state, the wake WS deficit is less likely to extend above the height of the rotor top at 118.5 m (Figure 2.4c). Before the transition, convective vertical mixing, initiated by surface heating, leads to relatively uniform upwind WSs across the daytime boundary layer (Figure 2.4a). When the stable PBL begins to develop, stratification develops in the flow, with lower WSs near the surface and greater WSs aloft. Stable stratification is initiated at 1900 LT (0000 UTC 10 July), following the ET. As the stratification develops, the WS deficit becomes less intermittent over time and is mostly confined to the rotor layer (Figure 2.4c).



Figure 2.4: Time-height contours of 2-minute averaged LiDAR WS measurements on 9 July: upwind measurements from the WC1 LiDAR (a), downwind measurements from the WC2 LiDAR (b) and the difference of upwind minus downwind (c). The brown vertical dash line indicates the onset of the ET at 1830 LT (2330 UTC). The white horizontal dash line represents the top of the rotor layer, at 118.5 m a.g.l.

As with the WS deficit, the turbulence enhancement caused by the wind turbines becomes steady during the ET, as evidenced by the upwind TI value (Figure 2.5a), upwind TKE value (Figure 2.5b), downwind TI value (Figure 2.5c), downwind TKE value (Figure 2.5d), TI difference (Figure 2.5e), and TKE difference (Figure 2.5f). From Equations 2.1 and 2.2, TI represents the variations in horizontal velocities, while the TKE also accounts for vertical velocity deviations. In the case study, both the upwind TI and TKE values decrease dramatically when the PBL becomes stable (Figure 2.5c), although the increase in the TKE value persists above the rotor layer (Figure 2.5c), although the increase in the TKE value persists above the rotor layer (Figure 2.5c), while TI values have no substantial differences above the rotor top (Figure 2.5e). This contrast between TI and TKE values suggests that vertical velocity variations contribute most to the turbulence enhancement above the turbine rotor layer during the ET, consistent with previous wind-tunnel studies (Cal et al., 2010) and idealized LES results (Calaf et al., 2010), which emphasize the importance of the vertical flux stimulated by wakes.



Figure 2.5: Time-height contours of 2-minute averaged LiDAR-measured TI and TKE values on 9 July: upwind measurements from the WC1 LiDAR (a, b), downwind measurements from the WC2 LiDAR (c, d) and the difference of upwind minus downwind (e, f). The grey vertical dash line indicates the onset of the ET at 1830 LT (2330 UTC). The white horizontal dash line represents the top of the rotor layer, at 118.5 m a.g.l.

Within the rotor layer, the altitude of the maximum in downwind turbulence enhancement evolves throughout the transition. The height of maximum downwind turbineinduced turbulence generation varies within the rotor layer before 2000 LT (0100 UTC 10 July) and stabilizes at 60 m afterwards (Figure 2.5e). However, no distinct trends emerge regarding the changes in the height of the peak downwind TKE enhancement (Figure 2.5f).

Although upwind turbulence diminishes during the ET, the downwind turbulence enhancements within the rotor layer, due to the turbine, remain at the same order of magnitude throughout the ET. Our wake observations, recorded at a distance 3D downwind of turbines, differ from the conclusions of Magnusson and Smedman (1994), where the maximum values in turbulence enhancements diminish downwind more rapidly in unstable than in stable conditions. However, their observations, obtained at a distance 4.2D downwind, were only relevant to stable and unstable states and not to the transition period.

2.4.1.3 Wake evolution with heights and wind directions

Not surprisingly, wake features in the ET respond to subtle variations in the upwind wind profiles. The fluctuations of upwind variables decrease gradually during the transition, with the upwind hub-height WS oscillating around 8 m s⁻¹ and fluctuating less frequently after 1900 LT (0000 UTC 10 July) (Figure 2.6a). At the same time, the background TI and TKE values at hub height also begin to decline steadily (Figure 2.6b and c). As the inflow becomes steady after the ET, the wake signatures in WS, TI and TKE are only observed below the rotor top. In contrast, before the ET, these wake signatures appear occasionally above the rotor top (Figure 2.6d, e, and f). All three wake parameters vary collectively below hub height after 2030 LT (0130 UTC 10

July). Overall, the maximum wake effects steadily become more distinct within the rotor layer as the evening progresses.

This sensitivity of the height of the maximum downwind WS deficit to atmospheric stability has yet to be examined in the literature. Aitken et al. (2014b) summarized the discrepancy on the altitudes of peak WS deficit among previous investigations, although the role of atmospheric stability was not discussed, since stability was not always quantified in the historical observational studies. Using LESs, Bhaganagar and Debnath (2015) characterized WS deficit in two stable scenarios with different surface cooling rates. They concluded that in strongly stable atmospheric conditions, the maximum downwind deficit was found below hub height, while in weakly stable atmospheric conditions, the maximum downwind deficit stabilities was, nonetheless, not discussed. Abkar and Porté-Agel (2015b) hypothesized that the maximum WS deficit occurred at hub height regardless of atmospheric stability, though we have found different results in this case study: the height of maximum WS deficit changes over time as the atmosphere evolves from unstable to stable stratification.



Figure 2.6: Left column presents the time series of 2-minute averaged measurements from the WC1 LiDAR at 80 m a.g.l. on 9 July: WS in black (a), TI values in red (b) and TKE values in blue (c). Right column presents the altitude evolution of the absolute maximum differences between upwind and downwind LiDAR measurements in WS (d), TI (e) and TKE (f). The purple vertical dash line indicates the onset of the ET at 1830 LT (2330 UTC). The green horizontal dash line represents the top of the rotor layer, at 118.5 m a.g.l.

In addition to the changes in the altitude of the maximum wake WS deficit, the wake also becomes more sensitive to upwind WD during the ET, likely due to the smaller effect of ambient turbulence on the wake. Upwind WD influences the wake parameters across the rotor layer. Additionally, veering, or clockwise turning with height in the wind profile, commences during the ET; this veering affects the wake. Before the ET, southerly inflow ranges from directions 176° to 200° and produces the strongest normalized downwind WS deficit centered at 185° (Figure 2.7a), while the downwind turbulence enhancement is relatively weak in magnitude and thus indistinct (Figure 2.7c and e). After the ET, both the inflow and the wake start to veer with height. The WS deficit is greatest around 185°, especially below hub height (Figure 2.7b). In the same way, the normalized TI and TKE differences demonstrate intensifying wake effects, mainly at and below hub height (Figure 2.7d and f). In general, the turbulence enhancements veer with height, and have the greatest values around 185°. Note that Figure 2.7 only illustrates data up to 100 m a.g.l., as the downwind LiDAR might sample partial wakes beyond that height. Overall, the wakes veer and become more distinct during the ET of 9 July.



Figure 2.7: Contour plots of normalized differences between upwind and downwind LiDAR measurements in WS (a, b), TI (c, d) and TKE (e, f) as a function of upwind WD at heights across the rotor layer, from 40 to 100 m a.g.l. The left column (a, c, e) illustrates the normalized differences before the ET, from 1500 to 1830 LT (2000 to 2330 UTC). The right column (b, d, f) displays the wake effects after the ET, from 1830 to 2200 LT (2330 to 0300 UTC 10 July). The normalized differences are averaged in 2-degree WD bins.

2.4.2 Observation-simulation comparison

We first evaluate the skill of the WRF model in simulating the evolution of the upwind profiles of WS, WD, and TKE. Although the maximum absolute error of WS at hub height before, during and after the ET is 1.5 m s^{-1} , the model captures the temporal trend of the WS profile (Figure 2.8a). Even as the error of the WD profile grows over time, the simulation error in the 80-m WD is less than 10° throughout the ET. (Figure 2.8b). Moreover, the simulated TKE profile and its decline in magnitude during the transition generally agree with the observations (Figure 2.8c), with a hub-height maximum error in TKE of 0.18 m² s⁻². Note that the observed TKE is the LiDAR-measured, 2-minute averaged TKE. The WRF-calculated TKE is a mesoscale representation of atmospheric turbulence over the entire grid cell, and as such is not directly comparable to the observations, but is shown for reference in Figure 2.8c and Figure 2.9c.

Likewise, the comparison between modelled and observed time series further supports the claim that the WRF model is capable of simulating the upwind condition. The mean absolute errors between the simulated and observed time series of hub-height WS, hub-height WD, hubheight TKE and Q_H on 9 July are small, being 1.1 m s⁻¹, 7.7°, 0.17 m² s⁻² and 21 W m⁻², respectively (Figure 2.9). Nevertheless, the timing of the simulated atmospheric stability change is within 1 hour of the actual change: Q_H changed sign at 1755 LT (2255 UTC) in the WRF model, 35 minutes earlier than the observation. However, the simulated hub-height TKE experiences abrupt decay at the same time as that observed, 1900 LT (0000 UTC 10 July) (Figure 2.9c). Overall, the WRF model produces satisfactory background flows for this 9 July case study.



Figure 2.8: Vertical profiles from the WC1 LiDAR (abbreviated as Obs, dash lines) and the WRF-model simulations at the nearest grid point from the WC1 LiDAR (solid lines) of WS (a), WD (b), and TKE (c) at three different times, 1730 (red), 1830 (blue) and 1930 (black) LT on 9 July (2230, 2330 and 0030 UTC).



Figure 2.9: Time series from the WC1 LiDAR at 80 m a.g.l. (red) and the WRF-model simulations at the nearest grid point from the WC1 LiDAR (blue) on 9 July: 2-minute averaged hub-height WS (a), 2-minute averaged hub-height WD (b), 2-minute averaged hub-height TKE (c) and 1-minute averaged Q_H (d). The WRF-model variables plotted are interpolated to hub height. The purple vertical dash line indicates the onset of the ET at 1830 LT (2330 UTC).

2.4.3 Simulations with the WFP scheme

2.4.3.1 Downwind meteorological impacts

Via the WFP scheme, virtual wind turbines are introduced in the 9 July WRF model simulation to characterize the evolution of wake effects during the ET. The WS deficit, calculated by subtracting the horizontal WS of the "control" run with no virtual wind turbines from that of the "WFP" run with virtual turbines, is the primary method to quantify wind-farm wakes. The modelled WS deficits, produced by the 100-turbine wind farm, intensify at hub height over time, and extend further downwind after the ET at 1830 LT (2330 UTC) (Figure 2.10a to d). The WS deficits reach a maximum value within 5 km downwind from the northern edge of the virtual wind farm, and the WS deficits erode for distances further downwind. As the simulated WD shifts from south-westerly to southerly throughout the transition, the location of the wake WS deficits changes accordingly. Additionally, the hub-height WS of the control run varies between 8 and 11 m s⁻¹ during the 2 hours before and after the ET (Figure 2.9a). The wind-farm drag reduces the downwind WS by more than 1.2 m s⁻¹ throughout the transition; this wind-farm wake represents more than 10% of the inflow WS at the end of the transition (Figure 2.10d).

The simulated WS deficit within the rotor layer also becomes more intense during the ET. Throughout the ET, the WS deficit is greater below hub height than above (Figure 2.11). At the top of the rotor disk, the WS reduction is minimal before the ET, but doubles after the transition (Figure 2.11d and h). At all altitudes across the rotor disk, the WS deficits stretch further downwind after the transition than before the transition.



Figure 2.10: 1-hour averaged differences of simulated hub-height WS (a to d), hub-height TKE (e to h) and Q_H (i to l), subtracting the variables of the "control" run from those of the "WFP" run, over 4 hours from 1630 to 2030 LT (2130 to 0130 UTC) 9 July: 2130 to 2230 UTC (a, e, i), 2230 to 2330 UTC (b, f, j), 2330 to 0030 UTC (c, g, k), and 0030 to 0130 UTC (d, h, l). The black vectors represent the 1-hour averaged WD of the control run interpolated to hub height, and the vector lengths are proportional to the WS of the control run. The turbine locations are labelled as dots in cyan.



Figure 2.11: 2-hour averaged WRF-model WS difference, subtracting WS of the control run from WS of the WFP run from 1630 to 1830 LT 9 July (2130 to 2330 UTC) (a to d) and from 1830 to 2030 LT 9 July (2330 to 0130 UTC) (e to h) at 40 (a, e), 60 (b, f), 100 (c, g) and 120 (d, h) m a.g.l. As in Figure 2.10, the vectors represent the wind field of the control run and the cyan dots represent the wind-turbine locations.

Although the absolute changes in hub-height TKE difference decrease over time (Figure 2.10e to h), the virtual wind turbines increase the relative downwind TKE difference during the

ET. Since the background TKE diminishes as the evening progresses (Figure 2.9c), the TKE enhancement caused by the wind farm decreases in absolute terms but increases in relative terms. One hour before the ET, the turbines generate a maximum downwind TKE enhancement of more than $0.18 \text{ m}^2 \text{ s}^{-2}$ (Figure 2.10f), which is about 20% of the average ambient TKE value of the hour in the control run (Figure 2.9c). By the end of the transition, the downwind TKE enhancement is more than 50% of its base value (Figure 2.10h): the downwind TKE increases by 50% due to the existence of the wind farm.

Furthermore, the downwind TKE differences across the rotor layer display irregular variations, in contrast to the WS deficits. In general, the downwind TKE enhancement increases with height within the rotor layer throughout the ET (Figure 2.12). On one hand, particularly below hub height, the TKE enhancement induced by the virtual wind farm diminishes after the transition (Figure 2.12e and f). On the other hand, above hub height, the differences in TKE enhancement before and after the transition are subtler (Figure 2.12c, d, g, and h). Furthermore, in terms of horizontal extent, the downwind WS deficit at hub height persists for a distance of more than 15 km downwind after the ET (Figure 2.10c and d), but the downwind TKE enhancement dissipates after a distance of 10 km downwind (Figure 2.10g and h).

Besides, wind turbines also interrupt the evening reduction of the Q_H downwind, as well as the emergence of the near-surface stable layer. At the beginning of the ET, the virtual wind farm increases Q_H by less than 2 W m⁻² consistently (Figure 2.10i), which is less than 10% of the control value (Figure 2.9d). As the evening progresses, the wind farm enhances and expands the downwind flux increase by more than 6 W m⁻² at the end of the transition (Figure 2.10l), which is about 20% of the ambient value (Figure 2.9d). In contrast, Q_H in a typical environment should decrease and become negative in the evening. Therefore, the positive downwind heat-flux difference during the ET suggests the modelled wind turbines impede downwind surface cooling and hence the development of the nocturnal stable boundary layer.



Figure 2.12: As in Figure 2.11, the variable shown is 2-hour averaged TKE difference across the rotor layer.

2.4.3.2 Power production evolution

In the "WFP" simulations, turbine-power production can be calculated from the WS at hub height in a simulation cell. The power ratio (Figure 2.13) represents the ratio between the WFP-simulated power production and the calculated power production derived from the WSs of the same turbine-containing grid cells in the "control" run, based on the turbine power curve. As expected, waked grid cells produce less power. Because the WD shifts from south-south-westerly to southerly, the grid cells on the south-western half of the wind farm consistently yield higher power per turbine than those in the north-eastern half, which are usually waked. Note that the WFP scheme assumes that the virtual wind turbines are always oriented perpendicular to the flow (Fitch et al., 2012), and the power production of each grid cell is proportional to the number of turbines contained therein.

Because of the strengthening wakes during the 4-hour ET, the 1-hour averaged power ratio gradually decreases to 68%, from 82% (Figure 2.13). The reduction in the power ratio during the first 2 hours can be explained by the larger decline in the average WS of the WFP run compared to that of the control run (Figure 2.14). Meanwhile, the mean power ratio continues to decrease even when the WSs increase after 1900 LT (0000 UTC 10 July) (Figure 2.14), indicating a growing discrepancy between the potential and the WFP-simulated power productions throughout the ET. The continuous reduction in power ratio (Figure 2.13 and Figure 2.14) illustrates that the maturing wakes undermine the power production of downwind turbines.



Figure 2.13: 1-hour averaged power ratio in each grid cell over 4 hours from 1630 to 2030 LT (2130 to 0130 UTC) 9 July: 2130 to 2230 UTC (a), 2230 to 2330 UTC (b), 2330 to 0030 UTC (c), and 0030 to 0130 UTC (d). The black vectors represent the 1-hour averaged WSs of the WFP run, and vector lengths are proportional to the WS. The brown dots represent the turbine locations. The numbers following the time periods represent the 1-hour averaged power ratio of the 100 turbines.



Figure 2.14: Time series of the power ratio (yellow), the average control-run WS (black) and the average WS of the WFP run at hub height (red) among all turbine-containing grid cells, from 1600 to 2100 LT 9 July (2100 UTC to 0200 UTC 10 July). The purple vertical dashed line indicates the onset of the ET at 1830 LT (2330 UTC).

2.5 Discussion

Because daily electricity demand increases during the evening, efforts to provide reliable electricity generation from wind energy must include a characterization of wind-turbine-wake behavior during the ET. Here, we have investigated the evolution of wind-turbine wakes using both observations and model simulations of a case study when the lower PBL undergoes a transition from typical daytime convective to nocturnal stable conditions. Turbine wakes undermine power production of downwind turbines. Wake characteristics, such as downwind WS deficits and downwind turbulence generation, respond to the decoupling of the surface layer from the PBL during the ET. In the evening, the sign of Q_H becomes negative as the ground starts to cool, the atmospheric PBL develops stable stratification, and the background WD veers with height and undergoes transition into a laminar flow. During the ET, variable daytime turbine wakes coalesce and appear to be more persistent and more confined within the rotor disk altitudes.

The evolving upwind profile and the declining convective turbulence in the evening also determine the height of the strongest wakes within the rotor layer. In an unstable regime, the largest WS deficit is observed above hub height. After the ET, the maximum in the WS deficit is found below hub height (Figure 2.6a). The heights of the maximum WS deficit and turbulence production also coincide, especially after the ET, due to the strengthening atmospheric stratification (Figure 2.6). The wakes themselves begin to veer with height across the rotor layer after the ET (Figure 2.7). Previous studies (Aitken et al., 2014b; Abkar and Porté-Agel, 2015b; Bhaganagar and Debnath, 2015) did not examine the effects of atmospheric stratification on the height of the maximum WS deficit in the wake, and our study has demonstrated the strong influence of evolving stability on the height of the maximum wake. Empirical reduced-order wake models (Jensen, 1983; Katíc et al., 1986) could therefore be modified to account for evolving stability.

Introducing a virtual wind farm into the WRF-model simulations enables the exploration of wind-farm-wake behavior during the ET. The maximum hub-height WS deficit and turbulence enhancement take place within 5 km of the downwind edge of the wind farm (Figure 2.10a to h), which is consistent with the WRF-model simulations of Fitch et al. (2013a) and Jiménez et al. (2015). Moreover, after the ET, the hub-height WS deficit persists for more than 15 km downwind, while the turbulence enhancement vanishes beyond 10 km downwind. In contrast to LES studies with constant atmospheric stratification (Churchfield et al., 2012a; Mirocha et al., 2014, 2015; Abkar and Porté-Agel, 2015b; Vanderwende et al., 2016), the wake structure illustrated herein varies both temporally and spatially downwind of the wind farm. The turbine locations in these simulations, based on an actual wind farm, contribute to this variability. Furthermore, the left-hand-side downwind horizontal flow acceleration or turning during the ET found in Fitch et al. (2013a) does not emerge in the simulations presented herein. Nonetheless, we observe a strengthening of the downwind WS deficit throughout ET, similar to that of Fitch et al. (2013a). The validity of the power production from the WFP scheme awaits validation from observations.

The wake behavior in the individual wake observations is different from that in the windfarm wake simulations, and the results herein of wake evolution through the ET may serve as reference for improving the WFP scheme in the WRF model. Of course, differences between simulations and observations may be due to scale, as our observations are within one mesoscale model cell, and variability within the cell is not permitted using the current WFP scheme. Simulations suggest that after the ET, the modelled WS deficit strengthens more near hub height than at the top and bottom of the rotor layer (Figure 2.10c and d, and Figure 2.11), which agrees with the observations (Figure 2.7b). However, the WFP scheme underestimates the maximum WS deficit at and above hub height by about 1 m s⁻¹ (not shown). In addition, the observed maximum TKE enhancement within the rotor layer (Figure 2.5f) is also at least twice as large as the modelled downwind \bar{e} increase in the evening (Figure 2.10e to h, and Figure 2.12). Considering the WS deficit and TKE enhancement decrease with downwind distance, these observation-model differences may be due to the resolution of the mesoscale model as compared to the observations. After all, the observations are collected at a location about 240 m downwind, while the simulations are representative of a 1 km × 1 km grid cell. Moreover, the elevation of TKE enhancement also differs between measurements and simulations: after the ET, the simulated downwind TKE increase only occurs above hub height (Figure 2.12e to h), conversely, the observed TKE increase downwind across the rotor layer (Figure 2.5f and Figure 2.6f). Recognizing that the observations and the WFP scheme depict turbine wakes at different spatial scales, the parametrization still has difficulties describing evening wake evolution, particularly TKE enhancement below hub height. The observation-simulation disagreement in wake behavior is due to a combination of measurement errors, differences in observed and simulated upwind conditions, and the fundamental limitation of the WFP scheme in characterizing sub-grid features. In the CWEX-11 simulations, some grid cells contain multiple turbines, and the WFP scheme cannot model sub-grid scale phenomena, contributing to the observation-simulation differences.

During the ET, power production decreases in the wind-farm simulations, due both to strengthening wakes and the temporal and spatial variability of the inflow to the turbines. Accompanying the small fluctuations in the simulated hub-height WD of less than 20° (Figure 2.9b), the background WS oscillates between 8 to 11 m s⁻¹ and remains below rated speed during the ET (Figure 2.9a). The free-stream WS is in the Region II of the turbine power curve, where the power production is highly sensitive to WS variations. Before the ET, the temporal trend of power generation in the turbine-containing grid cells follows closely the upwind WS changes, which explains the rapid reduction of the power ratio during the ET (Figure 2.13 and Figure 2.14). After the ET, stronger wakes lead to a lower downwind power ratio, so the average power

production continues to plummet even as the WS rebounds. The modelled streaks of gusts or lower WSs across the whole wind farm also produce fluctuations in the overall power production. The stability transition near the surface modifies the wind-profile stratification; this progression can also lead to reductions in power output during the ET.

2.6 Conclusion

Herein, we present the evolution of both observed and simulated wind turbine wakes during the evening transition ET. Through the ET, the vertical extent of the wake WS deficit, produced by an individual turbine, gradually decreases and becomes confined within the rotor layer. After the upwind buoyancy-driven turbulence diminishes in the evening, the downwind turbulence generation rebounds and persists within the rotor layer. Transitioning surface inflow and strengthening wakes introduce temporal fluctuations in downwind power deficit.

The mesoscale WRF-model simulations using the WFP scheme also offer a basis for the prediction of power production when the daily electricity demand increases in the evening. As the ET progresses, the downwind turbines and the downwind atmosphere experience continuously strengthening wake effects. Compared to the control simulations with no wind-turbine effects, the virtual wind farm leads to an increase in hub-height WS deficit by more than 10%, a 50% increase of TKE at hub height, and a 20% increase in Q_H, which stalls surface cooling through the end of the ET. The power ratio, a measure of the simulated power generation to the potential power production given undisturbed inflow, decreases nearly 15% during the transition. Overall, turbine wakes respond to the evolving PBL during the ET, thereby affecting total wind-farm power production by reducing the productivity of downwind turbines. As wind-energy control research moves from a focus on manipulating individual turbines to optimizing
power production of larger plants (Fleming et al., 2014, 2016), these varying stability-driven wake characteristics should be incorporated into control schemes.

Having demonstrated that the WRF model has skill in simulating the ambient wind field for the selected ET case, we demonstrate that the WFP scheme is capable of modelling turbine wakes through changing atmospheric stability conditions. Thus, this study lays the groundwork for future investigations to compare the power output of the WFP scheme to the observed power production, which can be conducted with nacelle anemometer measurements (St. Martin et al., 2017). Since mesoscale modelling is crucial in predicting power production in wind farms (Marquis et al., 2011; Jiménez et al., 2015; Wilczak et al., 2015), comparisons of predicted and observed power output can help to identify areas for improvement in the WFP scheme in the WRF model. Moreover, accurate representation of wind farms in numerical weather prediction models is important for both simulating wind-energy production and planning for energy infrastructure (Jacobson et al., 2015; MacDonald et al., 2016).

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Chapter 3

EVALUATION OF THE WRF WIND FARM PARAMETERIZATION

Доверяй, но проверяй.

(Trust, but verify.)

- Russian Proverb

Fundamentally, meteorology boils down to understanding and forecasting the weather. Similarly, a branch of wind-energy meteorology focuses on wind-power forecasting. To a modern forecaster, numerical models are essential in forecasting the microscale, mesoscale, synoptic and global weather events that persist from minutes to seasons. For wind-energy purposes, the capability of a numerical weather prediction (NWP) model to accurately predict ambient WS dictates its ability to simulate wind-power production. For instance, the wind farm parameterization (WFP) scheme in the Weather Research and Forecasting (WRF) model, a widely used NWP approach, considers both the meteorological and the wind-turbine aspects of wind flow.

Since its first public release, research involving the WRF WFP scheme has been active at different locations, including the U.S. and Denmark (Jiménez et al., 2015; Vanderwende et al., 2015; Lundquist et al., 2016). Nonetheless, the simulated power productions of onshore wind farms have yet to be validated with real power generations, hence a question mark hangs over the validity of the skill of the WFP in estimating wind power. No model is perfect, therefore the research community demands a comprehensive validation of the WRF WFP.

This chapter takes the first step to quantify the performance of the WRF WFP and dissects when and why the WFP produces trustworthy results. Comparison between the recorded and the modelled power productions with a fixed WS in a neutral stability environment has been carried out in Jiménez et al. (2015). Building on the literature, the modeling community demands an assessment on the WFP using a range of WS and stability scenarios. Therefore, this chapter aims to examine the WFP performance thoroughly. This work illustrates the results from field data, observed turbine-power generations, and numerical model outputs on simple terrain with the layout of a real wind farm. From the meteorological standpoint, the case study chosen is interesting, considering the winds ramp up and down and the wind direction (WD) changes over time during the summer low-level jets (LLJs).

This chapter tests the ability of the WFP to simulate accurate power production of a wind farm with an irregular shape, which is common in reality. Improving accuracy in power predictions helps to advance wind-plant control and operational strategies. Ultimately, reducing the uncertainty from NWP models further decreases the levelized cost of energy (LCOE) of wind energy.

The following is reproduced and reformatted from:

Lee, Joseph C. Y., and Julie K. Lundquist. 2017. Evaluation of the wind farm parameterization in the Weather Research and Forecasting model (Version 3.8.1) with meteorological and turbine power data. *Geoscientific Model Development* 10 (11): 4229–44. doi: 10.5194/gmd-10-4229-2017.

Julie Lundquist revised the manuscript and provided guidance of the research.

3.1 Abstract

Forecasts of wind-power production are necessary to facilitate the integration of wind energy into power grids, and these forecasts should incorporate the impact of wind-turbine wakes. This chapter focuses on a case study of four diurnal cycles with significant power production, and assesses the skill of the wind farm parameterization (WFP) distributed with the Weather Research and Forecasting (WRF) model version 3.8.1, as well as its sensitivity to model configuration. After verifying the simulated ambient flow with observations, we quantify the value of the WFP as it accounts for wake impacts on power production of downwind turbines. We also illustrate that a vertical grid with approximately 12-m vertical resolution is necessary for reproducing the observed power production, with statistical significance. Further, the WFP overestimates the wake effects and hence underestimates downwind power production during high wind-speed (WS), highly stable and low turbulence conditions. We also find the WFP performance is independent of the number of wind turbines per model grid cell and the upwinddownwind position of turbines. Rather, the ability of the WFP to predict power production is most dependent on the skill of the WRF model in simulating the ambient WS.

3.2 Introduction

In recent years, numerical weather prediction (NWP) models have become an indispensable tool in the wind-energy industry, not only in day-to-day wind-energy production forecasts (Wilczak et al., 2015), but also to support wide-scale wind-power penetration (Marquis et al., 2011) and wind resource assessment (WRA). To forecast power production accurately at wind farms, the simulation tools should resolve all physical processes relevant to the wind field,

including possible impacts of the wind turbines themselves. Consequently, including the meteorological effects of wind farms in NWP models can improve power-production forecasts.

Researchers have developed various methods to numerically represent wind farms. Via large-eddy simulations (LESs), some investigators assess the meteorological impacts of wind turbines as well as power production (Jimenez et al., 2007; Calaf et al., 2010; Wu and Porté-Agel, 2011; Churchfield et al., 2012b; Aitken et al., 2014a; Mirocha et al., 2014; Abkar and Porté-Agel, 2015b; Na et al., 2016; Sharma et al., 2016). Simulating wind turbines and their effects in LESs is, while useful, computationally expensive, making wind-farm-scale simulations unreasonable in an operational setting.

At coarser spatial scales, suitable for global, synoptic or mesoscale models, numerically representing wind turbine effects may involve unrealistic assumptions. For example, researchers have used exaggerated surface roughness to represent the reduction of wind speed (WS) caused by wind farms in a global model (Keith et al., 2004; Frandsen et al., 2009; Barrie and Kirk-Davidoff, 2010). Similarly, the analytical wind park model of Emeis and Frandsen (1993) considers both the downward momentum flux and the momentum loss due to surface roughness. The revised model by Emeis (2010) accounts for the spatially averaged momentum-extraction coefficient by turbines, and the parameters become atmospheric-stability dependent. However, these models omit the consideration of turbine-scale interactions between the hub and the surface (Fitch et al., 2012, 2013b; Abkar and Porté-Agel, 2015a).

Aside from indirectly representing wind turbines via exaggerated roughness, another common approach is to use the turbine power curve to deduce elevated drag and turbulence production of wind turbines. A power curve illustrates the relationship between inflow WS at hub height and power production of a particular turbine model. This method can model meteorological impacts of wind turbines and the impact of turbine drag force (Blahak et al., 2010; Baidya Roy, 2011). Based on this technique, Fitch et al. (2012) added the consideration of the turbine thrust coefficient to simulate both turbine drag and power loss.

In the wind farm parameterization (WFP) of the Weather Research and Forecasting (WRF) model, wind turbines in each model grid cell are collectively represented as a turbulence source and a momentum sink within the vertical levels of the turbine rotor disk (Fitch et al., 2012). A fraction of the kinetic energy extracted by the virtual wind turbines is converted to power, and the turbulence generation is derived from the difference between the thrust and power coefficients. In the WFP scheme, the use of the WS-dependent thrust coefficients accounts for the effects of local wind drag on wind-energy extraction as well as on power estimation. The WRF WFP offers flexibility, where users can modify the parameters of a turbine model, such as its hub height, rotor diameter (D), power curve, and thrust coefficients, and does not require other empirically-derived parameters. By simulating wind farms in a mesoscale weather model, WRF users can simulate aggregated effects of wind-turbine wakes and thus the effects of power production of downwind turbines.

An approach similar to the WRF WFP proposed by Abkar and Porté-Agel (2015a) relies on an extra parameter, which is the ratio of the free-stream velocity to the horizontally averaged hub-height velocity of a turbine-containing grid cell. This ratio depends on various factors such as the wind-farm density and layout, and requires preliminary simulation results (Abkar and Porté-Agel, 2015a). Therefore, the publicly available WFP in the WRF model is chosen in this project for observed power comparison. Several approaches are available to incorporate impacts of wind farms into mesoscale simulations. The explicit wake parameterization (EWP) recently designed by Volker et al. (2015) uses classical wake theory to describe the unresolved wake expansion. Both the WRF WFP and the EWP average the drag force within grid cells. Nevertheless, users of the EWP need to adjust the length scales that determine wake expansion in the EWP for different situations.

In this chapter, we evaluate the WFP in the WRF model via comparison to actual powerproduction data. The WRF WFP has been widely used to assess the impacts of onshore and offshore wind farms at different spatial scales and in different stability regimes (Fitch et al., 2013a, 2013b; Vautard et al., 2014; Eriksson et al., 2015; Jiménez et al., 2015; Miller et al., 2015; Vanderwende and Lundquist, 2016; Vanderwende et al., 2016; Lee and Lundquist, 2017b). Whereas WFP predictions have been compared to power production of offshore wind farms for a limited set of WSs (Jiménez et al., 2015), here we explore a range of WSs, wind direction (WD), turbulence, and atmospheric stability conditions. The large range of wind conditions induces spatially and temporally diverse power production, thereby providing a basis for a comprehensive evaluation of the WFP. The uniqueness of this project lies in the in-depth assessment of the WRF WFP performance in forecasting and simulating wind energy of a sizable onshore wind farm, using observed power-production data.

We describe the observation data and the model design in Section 3.3. In Section 3.4, we evaluate the simulations by comparing the meteorological and power-generation data with a statistical examination. We close with a proposal of improvements on the WRF WFP in Section 3.5.

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3.3 Data and methods

3.3.1 Observations

The 2013 Crop Wind Energy eXperiment (CWEX-13) took place in central Iowa at a 200-turbine wind farm to quantify far-wake impacts of multiple rows of turbines (Lundquist et al., 2014). In CWEX-13, measurements from seven surface flux stations, a radiometer, three profiling LiDARs (or Light Detection And Ranging) and a scanning LiDAR were collected. This campaign was a component of the larger CWEX project, which explored the interactions of wind turbines with crops, surface fluxes and near-surface flows in different atmospheric stability regimes in flat terrain (Rajewski et al., 2013). Research facilitated by the CWEX projects include: diurnal changes in observed turbine wakes (Rhodes and Lundquist, 2013), turbine interactions with moisture and carbon dioxide fluxes (Rajewski et al., 2014), LES modelling of turbine wakes in changing stability regimes (Mirocha et al., 2015), nocturnal low-level jet (LLJ) occurrences (Vanderwende et al., 2015), diurnal changes of the microclimate near wind turbines (Rajewski et al., 2016), multiple-wake interactions (Bodini et al., 2017), the evolution of turbine wakes during the evening transition (Lee and Lundquist, 2017b) and coupled mesoscale-microscale modelling (Muñoz-Esparza et al., 2017).

This wind farm consists of 200 wind turbines, represented by the red dots in Figure 3.1. Half of the wind turbines in the wind farm are General Electric (GE) 1.5-MW super-long extended (SLE) model, and the other half are GE 1.5-MW extra-long extended (XLE) model (Rajewski et al., 2013). The cut-in and cut-out speeds of the SLE model are 3.5 and 25 m s⁻¹ respectively, and the rated speed is 14 m s⁻¹. With the same cut-in speed, the XLE model has lower rated and cut-out WSs at 11.5 and 20 m s⁻¹. The hub height of both models is 80 m; the Ds of the SLE and the XLE model are 77 and 82.5 m respectively. For simplicity, references to the D herein refer to the 77-m D. Power generated by each turbine is recorded by the Supervisory Control and Data Acquisition, also known as SCADA, system every 10 minutes, and we sum up the power production of all turbines for wind-farm production for each 10-minute period.

Observations of the wind profile are collected by a profiling LiDAR and a scanning LiDAR. The WINDCUBE (WC) v1 profiling LiDAR (yellow square in Figure 3.1) is located 528 m, or 6.3 D, south of the nearest turbine. The WC LiDAR measures winds at about 0.25 Hz from 40 to 220 m above ground level (a.g.l.) every 20 m via the Doppler beam swinging (DBS) method. The WC LiDAR derives wind components by measuring radial velocities using DBS at an azimuth angle of 28°. Note that the WC-observed turbulence parameters, namely the turbulence kinetic energy (TKE) and the turbulence intensity (TI), are derived from the variances of the three wind components in 2-minute intervals, and hence do not represent small-scale turbulence. The turbulence parameters, TI and TKE, are defined in Equations 3.1 and 3.2. In CWEX-11, wind-turbine wake measurements at a different location in this wind farm were collected with these instruments (Rhodes and Lundquist 2013), and the errors in the WC LiDAR measurements due to inhomogeneous flow were explored by Bingöl et al. (2009) and Lundquist et al. (2015).



Figure 3.1: Map of the three domains (d01, d02 and d03) in the WRF simulations (a), with the white x representing the CWEX-13 wind farm. Zoom-in map of the wind farm (b), with the black horizontal and vertical lines outlining the WRF grid cells, the red dots as the actual locations of wind turbines, the blue numbers as the number of wind turbines per WRF grid cell, the yellow square as the WC LiDAR, the green square as the 200S LiDAR and the purple square as the surface flux station. Other instruments were deployed in CWEX-13, and only the instruments used herein are shown.

The WINDCUBE 200S scanning LiDAR (green square in Figure 3.1) is positioned 437 m, or 5.7 D, north of the nearest turbine row. In CWEX-13, the 200S LiDAR scanning strategy included velocity azimuth display (also known as VAD) scans that measures winds from ~100 to

~4800 m a.g.l. approximately every 50 m for every 3 minutes. In this chapter, we use the 200S 75° elevation scans (Vanderwende et al., 2015) to estimate horizontal winds every 30 minutes to validate the simulated winds in the boundary layer. In the case study chosen, the dominant WD is south-easterly to south-westerly (Vanderwende et al., 2015), and thus some of the 200S measurements below the rotor top (about 120 m a.g.l.) could be influenced by turbine wakes during conditions when the wakes persist longer than 5 D downwind from the turbine (Bodini et al., 2017). However, the WC measurements are largely unaffected by turbine wakes except when WD is east of 150°. The closest upwind turbine during this simulation period was located over 2.7 km (33 D) to the south-east.

The measurements from the surface flux station can also quantify model skill. The surface flux station of interest (purple square in Figure 3.1) is located 681 m, or 8.8 D, south of the closest turbine. At 8 m a.g.l., the station measures 20-Hz winds via a CSAT3 sonic anemometer, as well as virtual temperature and water-vapor density via a HMP45C probe. After tilt correction (Wilczak et al., 2001), we calculate surface sensible heat flux (Q_H) using a 30-minute averaging time period. We use the Obukhov length (*L*) to categorize atmospheric stability conditions:

$$L = -\frac{\overline{T_{\nu}}u_*^3}{kg(\overline{w'T_{\nu'}})_s},\tag{3.1}$$

where $\overline{T_v}$ is the mean virtual temperature, u_* is the frictional velocity, k is the von Karman constant, g is the gravity acceleration, and $(\overline{w'T_v'})_s$ is the surface virtual temperature flux calculated from the 20-Hz measurements (Stull, 1988). A positive Q_H and Obukhov length ratio $(z L^{-1})$, where z is 8 m, indicates a stable atmosphere, whereas a negative ratio represents unstable conditions.

From 24-27 August 2013, nocturnal LLJs were observed (Vanderwende et al., 2015). No major synoptic events affected the area during this period. Moreover, when the near-surface flows are southerly, the WC and the surface flux station measure winds unaffected by wind turbines (Muñoz-Esparza et al., 2017). Additionally, no curtailment of wind turbines occurred, and the instruments operated normally during the period, making these 4 days ideal for model validation.

3.3.2 Modelling

To establish direct comparison with the observations, we simulate winds with and without the WFP using the Advanced Research WRF (ARW) model (version 3.8.1) (Skamarock and Klemp, 2008). We simulate the winds on each day separately, from 0000 Coordinated Universal Time (UTC) to 0000 UTC, after 12 hours of spin-up time. The ERA-Interim (ERA-I) (Dee et al., 2011) and the 0.5° Global Forecast System (GFS) reanalysis datasets provide boundary conditions for two different sets of model runs. We set three domains in our simulations with horizontal resolutions of 9, 3 and 1 km respectively, where the finest domain covers the state of Iowa (Figure 3.1). To capture the westerly synoptic flow and the southerly near-surface winds, we position the inner grids north-east of the centers of the coarser grids.

The WFP scheme simulates wind farms and their meteorological influences on the atmosphere. We provide a brief summary here, and the details are discussed in Fitch et al. (2012). Wind turbines slow down ambient wind flow and convert a part of the kinetic energy of wind into electrical energy. The WFP represents this wind-turbine drag force as the kinetic energy harvested by the turbine from the atmosphere:

$$\boldsymbol{F}_{drag} = \frac{1}{2} C_T(|\boldsymbol{V}|) \rho |\boldsymbol{V}| A \boldsymbol{V}, \tag{3.2}$$

where C_T is the turbine-specific thrust coefficient (discussed in detail in Fitch, 2015), V is the horizontal velocity vector, ρ is air density, $A = \frac{\pi}{4}D^2$ is the cross-sectional rotor area, and D is the rotor diameter. This kinetic-energy extraction also causes changes in the atmosphere, namely the kinetic energy loss in the grid cell, which is described by the momentum tendency:

$$\frac{\partial |V|_{ijk}}{\partial t} = \frac{N_t^{ij} C_T(|V|_{ijk}) |V|_{ijk}^2 A_{ijk}}{2(z_{k+1} - z_k)},\tag{3.3}$$

where *i*, *j*, and *k* represent the zonal, meridional, and vertical grid indices, N_t^{ij} is the number of wind turbines per square metre, and z_k is the height at model level *k*. Of the kinetic energy extracted by the turbines, the WFP accounts for the electricity generation with the following:

$$\frac{\partial P_{ijk}}{\partial t} = \frac{N_t^{ij} C_P(|V|_{ijk}) |V|_{ijk}^3 A_{ijk}}{2(z_{k+1} - z_k)},\tag{3.4}$$

where P_{ijk} is the power output in the grid cell in watts, and C_P is the power coefficient. Assuming negligible mechanical and electrical losses, the rest of the kinetic energy harvested turns into TKE:

$$\frac{\partial TKE_{ijk}}{\partial t} = \frac{N_t^{ij} C_{TKE}(|V|_{ijk}) |V|_{ijk}^3 A_{ijk}}{2(z_{k+1} - z_k)},$$
(3.5)

where TKE_{ijk} is the TKE in the grid cell, and C_{TKE} is the difference between C_T and C_P .

In this chapter, we employ two resolutions of vertical grids: approximately 12-m and 22-m resolution below 400 m a.g.l., with 80 and 70 total levels respectively (Figure 3.2). Three and six vertical levels intersect the atmosphere below and within the rotor layer in the finer vertical grid, while the 22-m grid only allows one full level below and four levels within the rotor layer

(Figure 3.2). The vertical levels are further stretched beyond the boundary layer. In past research involving the WRF WFP scheme, the selections of vertical resolution within the rotor layer include 9 to 18 m in Vanderwende et al. (2016), about 10 to 16 m in Volker et al. (2015), about 15 m in Fitch et al. (2012), Fitch et al. (2013a), Fitch et al. (2013b) and Vanderwende and Lundquist (2016), about 20 m in Miller et al. (2015) and Vautard et al. (2014), about 22 m in Lee and Lundquist (2017), and about 40 m in Eriksson et al. (2015) and Jiménez et al. (2015).



Figure 3.2: Illustration of the two vertical grids chosen: the 12-m grid on the left in blue and the 22-m grid on the right in purple. Both grids shown use the ERA-I as the boundary conditions. The simulations initiated with the 0.5° GFS have similar vertical grids.

Moreover, the Mellor-Yamada-Nakanishi-Niino (MYNN) level 2.5 planetary boundary layer (PBL) scheme is required for the WFP in the WRF model version 3.8.1 (Fitch et al., 2012). Note that substantial upgrades were made on the MYNN PBL schemes in WRF version 3.8 (WRF-ARW, 2016). The MYNN PBL scheme supports TKE advection, active coupling to radiation, cloud mixing from Ito et al. (2015), and mixing of scalar fields. The MYNN scheme also uses the cloud probability density function from Chaboureau and Bechtold (2002), and here we keep the mass-flux scheme deactivated. We summarize the other model configuration details in Table 3.1.

Parameterization Scheme		Reference	
Cumulus	Kain-Fritsch	Kain (2004)	
Land surface	NOAH LSM	Ek et al. (2003)	
Land surface roughness	Thermal roughness length	Chen and Zhang (2009)	
Microphysics	Thompson aerosol-aware	Thompson and Eidhammer (2014)	
PBL	MYNN Level 2.5	Nakanishi and Niino (2006)	
Radiation	RRTMG	Iacono et al. (2008)	

Table 3.1: The WRF model configuration.

After validating the background flow simulated by the WRF model (first four rows in Table 3.2), virtual turbines are added via the WFP (last four rows in Table 3.2). We simulate all the turbines using the 1.5-MW Pennsylvania State University (PSU) generic turbine model (Schmitz, 2012), in which its specifications are based on the GE 1.5-MW SLE model installed at the wind farm. The turbines within the WRF grid cells are located using the latitudes and longitudes provided by the wind-farm owner-operator. The model grid cells within the wind farm,

containing 1 to 4 wind turbines per cell, are labelled as blue numbers in Figure 3.1. With the WFP activated, the model simulates the total power production at each time step in each turbinecontaining grid cell, regardless of the number of turbines per cell. To match the 10-minute average power data from the turbines, we sample 10-minute power from the WFP output.

Run name	Boundary condition	Vertical resolution	WFP
ERA12	ERA-I	12 m	No
ERA22	ERA-I	22 m	No
GFS12	0.5° GFS	12 m	No
GFS22	0.5° GFS	22 m	No
ERA12WF	ERA-I	12 m	Yes
ERA22WF	ERA-I	22 m	Yes
GFS12WF	0.5° GFS	12 m	Yes
GFS22WF	0.5° GFS	22 m	Yes

Table 3.2: List of WRF simulations and their features.

We also estimate the power generation of the WRF simulations without using the WFP. Based on the ambient WS of the turbine-containing grid cells in the control WRF runs, we use the turbine power curve to obtain an assessment of the power every 10 minutes. We then multiply the power with the number of turbines per cell to calculate power in each grid cell, as would be done in wind-energy forecasting without a wake parameterization. This method of power estimation omits the wake effects, in contrast to the WFP.

3.4 Results

3.4.1 Ambient flow evaluation

The WRF-model simulations without the WFP simulate accurate ambient winds compared to the LiDAR measurements. Qualitatively, the ERA12 simulation (see Table 3.2 for a listing of all the simulations) has skill in simulating WS and WD during the 4-day period, including the occurrence, the strength and the elevation of the nocturnal LLJs (Figure 3.3). The 200S records the vertical shear caused by LLJs above 100 m (Figure 3.3a), and the WC measures the near-surface winds with high temporal resolution (Figure 3.3b). In the observations and the simulations of WS (Figure 3.3c), the night-time WS profile is stratified whereas the daytime atmosphere is well-mixed. The WD simulations also match well with the measurements, where in the evening the winds veer, or turn clockwise with height (Figure 3.4), while the WD remains relatively constant with height during daytime. Except for the last hours on 24 August, the ERA12 captures the general temporal and vertical fluctuations in WS and WD, when the winds change from south-easterly to south-westerly (Figure 3.3 and Figure 3.4). The 200S measurements above the rotor layer (120 m) are unaffected by turbine wakes (Figure 3.3a and Figure 3.4a); the LLJs observed above the rotor layer resemble those from the ERA12, confirming the skill of the simulations. To evaluate the effects of boundary conditions and vertical resolutions on simulating winds, we compare the four no-WFP runs: ERA12, ERA22, GFS12 and GFS22.



Figure 3.3: Time-height contour of WS from the 200S (a), the WC (b) and the ERA12 at the closest grid point to the 200S (c).



Figure 3.4: As in Figure 3.3, but for WD.

Quantitatively, simulations using finer vertical resolution have more skill in simulating winds than those with coarser resolution (Table 3.3). In comparison to the 200S and WC observations, the mean absolute errors in WS and WD of the 12-m runs are lower than those of

the 22-m runs over the 4-day period, by 0.3 m s⁻¹ and 0.8° on average. Particularly in the ERA12, the errors in WS decrease by at least 19% relative to the ERA22. Although the GFS22 yields smaller WS errors than the ERA22, refining the vertical grid of the simulations using either boundary condition dataset improves the WS-prediction skill of the WRF model more than changing the boundary conditions (Table 3.3). The errors in simulating WD remain similar regardless of the choice of boundary condition or vertical grid. Of all our control runs, the ERA12 simulates the most accurate inflow.

	ERA12	ERA22	GFS12	GFS22
200S 120 m WS	1.49	1.84	1.35	1.54
WC 120 m WS	1.21	1.63	1.34	1.48
WC 80 m WS	1.24	1.64	1.36	1.55
WC 40 m WS	1.47	1.90	1.53	1.86
200S 120 m WD	14.99	15.98	14.68	14.99
WC 120 m WD	12.66	13.86	13.07	13.47
WC 80 m WD	13.23	14.55	13.85	14.24
WC 40 m WD	14.19	15.58	14.83	15.15

Table 3.3: Average absolute error in WS (m s⁻¹) and WD (°) of different no-WFP runs. The smallest errors across different WRF settings are highlighted in bold.

3.4.2 Power simulations

The simulation omitting the WFP ignores the wake effects on power production of downwind turbines, and therefore overestimates total power. For each 10-minute time step, we compare the spatial distribution of power production as well as the total power between the ERA12, the ERA12WF, and the observations; Figure 3.5 represents one 10-minute time step in

the 4-day period. As mentioned above, we calculate the power estimates of ERA12 using the ambient WS, the number of turbines in each grid cell, and the power curve (Figure 3.5a). The WRF WFP generates power predictions (Figure 3.5b), and we sum up the actual power production in each grid cell (Figure 3.5c). We present the total 10-minute simulated and observed power of the whole wind farm at the bottom of each panel in Figure 3.5, and the total power production of the WFP run matches the observed. We then assemble the 576 10-minute total power values over the 4-day period and compare the simulations to the observations (Figure 3.6). We also calculate an error and a bias of modelled total power for each 10-minute interval, summarizing as the daily root-mean-squared errors (RMSEs) and average biases in Table 3.4 and Table 3.5. The large average biases in Table 3.5 highlight the consistent power overestimation of the no-WFP runs.



Figure 3.5: The power production for one 10-minute period from the ERA12 estimates (a), the ERA12WF outputs (b) and the observation (abbreviated as OBS) (c). The total power in each grid cell is presented regardless of the number of turbines in each cell, and the wind-farm totals are summarized at the bottom. The vectors indicate the simulated winds, and their lengths correspond to the horizontal velocity magnitude.



Figure 3.6: Scatterplots comparing the 10-minute average observed total wind-farm power over the 4-day period against the calculated total power from the ERA12 (a) and the ERA22 (b), and the simulated total power from the ERA12WF (c) and the ERA22WF (d). The dots represent the total power productions on 24 August (purple), 25 August (blue), 26 August (green) and 27 August (yellow).

	24 Aug	25 Aug	26 Aug	27 Aug	4-day mean
ERA12	73.6	73.5	35.4	22.6	51.3
ERA22	79.5	72.8	48.5	41.0	60.5
GFS12	62.0	76.5	58.3	40.9	59.4
GFS22	73.9	89.6	65.3	51.9	70.2
ERA12WF	42.2	49.4	31.1	46.5	42.3
ERA22WF	61.7	61.2	50.9	71.6	61.4
GFS12WF	46.2	54.6	34.1	36.1	42.8
GFS22WF	40.0	60.0	32.6	37.3	42.5

Table 3.4: RMSE of 10-minute total power (in MW) of different model runs each day.

	24 Aug	25 Aug	26 Aug	27 Aug	4-day mean
ERA12	68.3	62.6	26.8	8.1	41.5
ERA22	58.3	52.1	28.0	6.2	36.2
GFS12	49.4	65.0	51.8	29.0	48.8
GFS22	65.5	80.7	60.3	35.8	60.6
ERA12WF	17.5	16.6	-12.2	-41.6	-4.9
ERA22WF	10.4	0.6	-17.6	-53.6	-15.1
GFS12WF	3.8	22.2	9.6	-18.6	4.3
GFS22WF	2.9	29.7	10.9	-12.3	7.8

Table 3.5: Average bias of 10-minute total power (in MW) of different model runs each day. The RMSEs and biases closest to zero across different days are highlighted in bold.

Over the 4-day period, the WFP produces total power of the whole wind farm that generally agrees with observation (Figure 3.6c). Although the RMSEs between the no-WFP and WFP runs are comparable (Table 3.4), the average biases are smaller in the WFP simulations

(Table 3.5). For instance, the ERA12WF slightly under-predicts total power by -4.9 MW on average (Figure 3.6c and Table 3.5). The ERA12, by contrast, consistently over-predicts power production by 41.5 MW (Figure 3.6a and Table 3.5). The daily positive biases of the ERA12 in the first 2 days are nearly 20% of maximum wind farm production (Table 3.5). The average positive power bias of 36.2 MW in the ERA22 is also remarkably larger than the mild negative bias of -15.1 MW in the ERA22WF (Figure 3.6b and d, and Table 3.5). Furthermore, the ERA12 and the GFS12 generally outperform the ERA22 and the GFS22 in power predictions, particularly in RMSE (Figure 3.6 and Table 3.5). However, on the last day, with more southwesterly flow, the ERA12 and the ERA22 outperform the ERA12WF and the ERA22WF, while the GFS12WF and the GFS22WF yield smaller errors and biases (Table 3.4 and Table 3.5). Nonetheless, in aggregate, the simulations using the WFP predict wind-farm power production with more skill than simulations without the WFP.

As demonstrated by the average absolute errors (Table 3.3), the WFP power simulations improve when using 12-m rather than 22-m vertical resolution (Figure 3.6). Changing the vertical grid improves the predictions more than changing boundary conditions (Table 3.4 and Table 3.5). In particular, in the ERA-I simulations, the RMSE each day decreases by 19% to 39% when switching from ERA22WF to ERA12WF (Table 3.4; Figure 3.6c and d). Since the power-prediction skill of the ERA-I-initiated runs and the GFS-initiated runs are comparable, the rest of the chapter will focus on the WFP runs using the ERA-I as initial and boundary conditions.

Moreover, to statistically differentiate the power productions from various model runs, we apply the two-sample Student's t-test. The null hypothesis of a two-sample t-test is that the two population means are the same, assuming the underlying distributions are Gaussian (Wilks, 2011). Hence, if the resultant p-value is equal to or below 0.05, the two distributions are statistically significantly different at the 95% confidence level. For example, the difference between the 4-day power-production averages from the ERA12 and from the ERA12WF is -46.8 MW, and the respective p-value is 0 (Table 3.6). Thus, the difference between the means is statistically significant. In other words, the ERA12 and the ERA12WF yield different power-production distributions at any confidence level. Similarly, the GFS12 and the GFS12WF lead to statistically different power outputs as the p-value from t-test is 0 as well (Table 3.7). We also use the two-sample t test to contrast the actual and the modelled power distributions. For instance, all the p-values between the no-WFP runs and the observation are 0, implying those simulations yield power-generation distributions significantly different from the reality (Table 3.8).

		ERA12	ERA12WF	ERA22WF
	4-day mean	41.8	-4.9	-15.1
ERA12	41.8		-46.7; 0	
ERA22	36.1	5.7; 0.03		-51.2; 0
ERA12WF	-4.9			
ERA22WF	-15.1		10.2; 9.6×10 ⁻⁴	

Table 3.6: Differences of the 4-day means (first value) and p-values (second value) from twosample t-tests of simulated power from different ERA-I runs.

		GFS12	GFS12WF	GFS22WF
	4-day mean	48.6	4.2	7.8
GFS12	48.6		-44.4; 0	
GFS22	60.5	-11.9; 1.1×10 ⁻⁷		-52.7; 0
GFS12WF	4.2			
GFS22WF	7.8		-3.6; 0.16	

Table 3.7: As in Table 3.6, but for GFS runs.

	Simulated 4-day	Observed 4-day	Difference of	n volvo	
	mean	mean	means	p-value	
ERA12	212.7		41.8	0	
ERA22	207.0		36.1	0	
GFS12	219.5	170.0	48.6	0	
GFS22	231.4		60.5	0	
ERA12WF	166.0	170.9	-4.9	0.106	
ERA22WF	155.8		-15.1	6.5×10 ⁻⁶	
GFS12WF	175.1		4.2	0.167	
GFS22WF	178.7		7.8	0.014	

Table 3.8: The p-values from 2-sample t-tests of the 10-minute observed power and the 10-minute simulated power from different model runs.

Given the utility of the WFP, assessing the interactions between atmospheric forcing and power production is an important step to further examine the performance of the WFP. As with the ERA12, the ERA12WF adequately simulates the evolution of the meteorological variables over the 4-day period (Figure 3.7a to d). Both the ERA12 and the ERA12WF capture the overall trends of hub-height ambient WS and WD measured by the WC (Figure 3.7a and b), corresponding to Figure 3.3 and Figure 3.4. Nonetheless, although the simulations suggest stronger TKE diurnal cycles than the observations, especially in the first 36 h, the simulated values follow the trends of the WC-measured TKE (Figure 3.7c). Although the magnitudes of the Q_H of the surface flux station and the simulations differ, their signs change at similar times, particularly in the last 3 days (Figure 3.7d). Hence the WRF model is capable of representing diurnal atmospheric stability changes. Note that in Figure 3.7c, the LiDAR derives TKE using 2-minute variances, which is intrinsically different from the modelled TKE, as discussed in Kumer et al. (2016) and Rhodes and Lundquist (2013). Hence, readers should focus on the general trends of the TKE time series, rather than their absolute values.

The observed WS fluctuates more than the mesoscale-simulated WS during daytime (Figure 3.7a). The ramp events, when the WS changes rapidly in a short period (Potter et al., 2009; Kamath, 2010), induce considerable swings in power production (Figure 3.7e). The five distinct ramp events with sudden WS increases are from 0000 to 0100 UTC on 24 August, from 1800 to 1900 UTC 24 August, from 0000 to 0100 UTC 25 August, from 0000 to 0200 UTC 26 August, and from 0000 to 0200 UTC 27 August. Most of the ramp events are related to the LLJs (Figure 3.3), and the simulated WS usually lags behind that observed (Figure 3.7a). Therefore, the WFP under-predicts total power in nearly all the ramp events (Figure 3.7e). Note that the measured WS ranges between the cut-in and rated speed of the wind turbine, when power production is highly sensitive to WS. The strong linkage between the temporal fluctuations of WS and power emphasizes the importance of accurate WS predictions.



Figure 3.7: Time series of hub-height WS (a), hub-height WD (b), hub-height TKE (c), surface sensible heat flux (Q_H) (d), and total wind-farm power (e) from the simulations (ERA12, in blue; ERA12WF, in black) and the measurements (in light blue). The simulated values are interpolated to hub height in the grid cell closest to the WC. In (b), the grey horizontal dash line marks the WD of 180°. In (d), the grey horizontal dash line marks the heat flux of 0 W m⁻².

Along the same line, the WFP power performance changes in different meteorological conditions. To quantify WFP's skill, we use the bias in total power as a benchmark, calculated by subtracting the observed power from the WFP simulated power every 10 minutes (Figure 3.8). Particularly, in conditions of strong winds and weak turbulence, the WFP overestimates the wake effects and thus underestimates power. However, for calm conditions with moderate or strong turbulence, the WFP tends to underestimate the wake effects and thereby over-predicts power (Figure 3.8a and c). Besides, the Pearson's correlation coefficient (r) between total power bias and WC-observed TKE is 0.48 (not shown).

On the contrary, WD and atmospheric stability have weaker influence on the skill of the WFP in general. The winds gradually rotate from south-easterly to south-westerly over this 4-day period while maintaining similar magnitudes of WS. During this direction shift, the WFP demonstrates a weakly positive power bias when the WD is strictly southerly, while the biases skew negative when the winds have more easterly or westerly component (Figure 3.8b). Similarly, the WFP power bias is generally unresponsive to stability changes, although biases tend to be small in strongly stable conditions (Figure 3.8d). Moreover, strongly stable conditions tend to have stronger and more distinct wakes (Magnusson and Smedman, 1994; Rhodes and Lundquist, 2013; Abkar and Porté-Agel, 2015b; Lee and Lundquist, 2017b).



Figure 3.8: Scatterplots of the bias of the ERA12WF 10-minute total power and the WCobserved hub-height WS (a), hub-height WD (b), hub-height TI (c) and stability parameter z L^{-1} measured at the surface flux station (d). The *r* represents the Pearson's correlation coefficient. Similar to Figure 3.6, different colored dots represent biases on different days. The horizontal black dash lines mark the zero-power bias. In (d), the vertical black dash line at zero z L^{-1} differentiates the two stability regimes.

To isolate the WFP errors in power predictions from the WRF model errors in simulating ambient winds, we analyze a subset of data where the winds are simulated accurately. When the absolute error in WS is smaller than 1 m s⁻¹ and the absolute error in WD is smaller than 5°, the relationships between power bias and WS, WD and TI (Figure 3.9a to c) remain similar to the general trends shown in Figure 3.8a to c. The WS-power-bias and TI-power-bias correlations become stronger in this subset (Figure 3.9a and c), compared to the correlations using all the data in the 4-day period (Figure 3.8a and c). Moreover, when considering only cases of accurate wind predictions, the correlation between power bias and stability increases from -0.06 (Figure 3.8d) to -0.42 (Figure 3.9d). In the few (27 10-minute time steps) unstable conditions with accurate WS predictions, the power bias is generally positive, given moderate WS and high TI (Figure 3.9a, c and d). In the stable regime, the WFP tends to underestimate power, regardless of WD (Figure 3.9b and d): 106 of the 125 stable data points are negatively biased. If the few strongest stability points (z L⁻¹ larger than 0.55) are removed from the subset shown in Figure 3.9d, a weakly negative correlation between power bias and stability emerges as r becomes -0.61. Additionally, generally south to south-westerly flows yield stronger negative power biases (Figure 3.9).



Figure 3.9: As in Figure 3.8, and only including data when the winds are accurately simulated in the ERA12WF run: the modelled-observed absolute error in WS smaller than 1 m s⁻¹ and the absolute error in WD smaller than 5°. Different colors represent different WD bins: 150° to 170° in blue, 170° to 190° in cyan, 190° to 210° in orange, 210° to 230° in red, and 230° and beyond in maroon. The n values illustrate the sample size in each WD bin. Solid circles represent unstable conditions (z L⁻¹ smaller than 0) and hollow circles represent stable conditions (z L⁻¹ smaller than 0).

As expected, when the model properly simulates ambient WS, the WFP performs better. When the ERA12WF predicts larger WS than observed, the simulation over-predicts the total power. The positive WFP power bias corresponds to WS overestimation, and the negative bias is associated with WS underestimation (Figure 3.10). Interestingly, when the error in simulated total power lies between ± 30 MW, the error of the simulated WS is mostly within ± 2 m s⁻¹ (Figure 3.10). Nevertheless, the power bias does not seem to be related to WD or to ambient TKE: the correlation between the power bias and the simulated WD (TKE) bias is low, at 0.3 (0.22) (not shown). Although the simulated WD and TKE generally match the WC observations (Figure 3.7b and c), and the model's skill in simulating WD and TKE does not strongly influence the WFP's power performance.



Figure 3.10: Scatterplot between the bias of the ERA12WF 10-minute total power compared to observation, and its bias of the simulated hub-height WS in the closest grid cell to the WC. The r represents the Pearson's correlation coefficient.

Although the WFP omits sub-grid-scale wake interactions between the wakes of multiple turbines within a cell, this omission does not affect the accuracy of the ERA12WF in power prediction: the performance of the WFP is insensitive to the number of turbines per model grid cell. The turbine-normalized bias demonstrates no dependence on the number of turbines within the model grid cell (Figure 3.11). Each whisker in Figure 3.11 marks the maximum, the upper quartile, the median, the lower quartile, and the minimum of the average bias. Despite the large positive biases of the maxima, more than half of the average biases fall between ± 1.5 MW, regardless of the numbers of turbines per cell (Figure 3.11). Simulating one or four turbines in a grid cell (Figure 3.1) does not influence the WFP's overall power-prediction performance in the cases shown here.



Figure 3.11: Boxplot of the average bias of the ERA12WF simulated power across different numbers of wind turbine per WRF grid cell (Figure 3.1) every 10 minutes during the 4-day period.
Furthermore, the WFP performance remains consistent between upwind and downwind turbines, based on their positions against the ambient winds (Figure 3.12). Given the square shape of grid cells, we determine the sequential rows of turbines during strictly southerly flows, with WD between 175° and 185° (Figure 3.12a). The bulk of the normalized power biases fall within 0 to 0.4 MW, regardless of the upwind-downwind positions of turbines (Figure 3.12b). Additionally, the power bias is independent of the mean distance between the actual turbine locations and the center points of their respective grid cells (not shown).



Figure 3.12: Map of the wind farm where the blue numbers represent the row number from the upwind row during southerly winds (a). The upwind row number is reset to 1 when the next two downwind grid boxes to the north contain no turbines. Boxplot of the average ERA12WF power bias normalized over different number of wind turbine rows, when the hub-height WD in the grid cell closest to the WC is between 175° and 185° (b).

3.5 Discussion

Herein, we compare WRF model simulations with different choices of vertical resolutions and boundary conditions. The evidence suggests that, at least for this onshore case with a strong diurnal cycle, the vertical resolution is more crucial than the choice of boundary conditions in simulating accurate winds and wind-power production. Shin et al. (2011) have explored the impacts of the lowest model level on the performance of various PBL schemes in the WRF model, suggesting that increasing the number of model layers can simulate more accurate surface layer in different stability regimes. In this study, we further illustrate that establishing more vertical levels in the boundary layer as well as the rotor layer improves the skill of the WRF model in simulating ambient WS, ambient WD and wind power (Table 3.3, Table 3.4 and Table 3.5). Furthermore, Carvalho et al. (2014) discussed the effects of different reanalysis datasets on wind-energy production estimates, and found the ERA-I presents the most precise initial and boundary conditions, followed by the GFS. Herein, we test the ERA-I and the 0.5° GFS, and both datasets produce simulations that resemble observed winds and power generations. Since the simulated power is sensitive to the resolution of the model vertical grid, particularly near the surface, future WRF WFP users should select vertical levels with care.

Additionally, the outcomes from the statistical tests among the model runs further validate the importance of using the WFP as well as using a fine vertical grid. From the Student's t-test, the p-values of all the no-WFP and WFP pairs are 0 (Table 3.6 and Table 3.7), demonstrating that the differences between the power-generation distributions of the no-WFP runs and the WFP runs are statistically significant at any confidence level. Therefore, to accurately simulate power production, applying the WFP is better than not using it, regardless of the choice of vertical resolution and boundary condition, and the corresponding improvements in

Table 3.4 and Table 3.5 are statistically significant. Although the distinction between the GFS12WF and GFS22WF is not statistically significant at the 90% confidence level (Table 3.7), switching from ERA22WF to ERA12WF improves power simulations significantly at 99% confidence (Table 3.6). In particular, the RMSE drops by 19.1 MW and the bias reduces by 10.2 MW on average in the ERA12WF (Table 3.4 and Table 3.5), and these are proven statistically significant.

Similarly, results from the statistical tests between the distributions of power from simulations and observations support the value of the WFP applied in a fine vertical grid. The p-values of the ERA12WF-observed pair and the GFS12WF-observed pair are 0.106 and 0.167 respectively (Table 3.8). The high p-values illustrate that the distinctions between the distribution of observed power and the distributions of simulated power from the 12-m WFP simulations are not statistically significant, at the 90% confidence level. Among all the simulations analyzed above, running the WFP over the 12-m vertical grid is the only combination that is not statistically different from observations (Table 3.8). In other words, the 12-m WFP simulations provide the closest approximations to the actual power production, regardless of the boundary-condition dataset.

One of the objectives of this study is to propose general directions for improvements on the WFP. First of all, as the key determinant of wind-power production, WS plays a critical role. Ramp events pose a challenge to the WRF model in simulating WS as well as to the WFP in predicting power (Figure 3.7a and e). However, windy conditions of WS exceeding 10 m s⁻¹, although below the rated speed, lead to WFP power underestimation (Figure 3.8a). Furthermore, the WFP performance depends more on the horizontal winds and turbulence, rather than their vertical components, since the power bias correlates more strongly with TI than TKE (Figure 3.8c). Reducing turbulence diffusion in the WRF model could potentially yield more accurately simulated winds in stable conditions, including LLJs (Sandu et al., 2013); active research in modifying mixing lengths (Jahn et al., 2017) also suggests promising model improvements. More importantly, sharpening the skill of the WRF model in simulating WS can improve the WFP power performance (Figure 3.10). Future versions of the WRF model and the WFP should aim to better account for instantaneous horizontal WS variations and the subsequent sub-grid wake interactions.

Besides necessary improvements in simulating ambient WS, the WFP scheme itself also requires refinements. When background winds are accurately predicted, the power-bias dependence on WS and TI remains strong (Figure 3.9a and c). Moreover, the correlation between the WFP performance and atmospheric stability becomes weakly negative without the strongly stable data (Figure 3.9d). Therefore, even when the simulated winds are close to observations, the WFP tends to underestimate power during high WS, low TI and stable conditions. In contrast, the WFP tends to over-predict power in calm, unstable, and turbulent conditions, with the caveat that a small number of unstable cases are considered here. The WFP scheme appears to overestimate wake loss within a grid cell in stable and windy conditions, and underestimate the wake effects in an unstable and well-mixed atmosphere. Certainly, the interactions between WD and wind-farm layout affect the power-bias relationships, and further sensitivity tests can provide more insight into the WFP performance, particularly in intra-cell WS reduction. We demonstrate that inter-cell wake effects are not the critical factor to power error (Figure 3.12b); hence the inability of the WFP to simulate intra-cell wake effects can explain the biases when many of the turbines experience accurately simulated ambient flow.

In contrast, WD has no clear influence on the WFP skill (Figure 3.8b) in this case, although the irregular shape of the wind farm adds uncertainty to this relationship. Similarly, the skill of the WFP for this case is insensitive to the number of virtual turbines per cell, and the downwind position of turbines against inflow (Figure 3.11 and Figure 3.12). Compared to the power overestimation of downwind turbines in the idealized cases described in Vanderwende et al. (2016), both the upwind and downwind turbine-containing cells presented in this study have consistent positive biases on power production (Figure 3.12). Our findings suggest that the WFP is skillful in simulating power of aggregate wind turbines and can represent the impact of intercell wakes on power. In the end, the primary limitation of the WFP is rooted in the ambient simulated WS in the WRF model.

3.6 Conclusion

The WFP scheme in the WRF model (version 3.8.1) provides a convenient way to represent wind farms and their meteorological impacts in the NWP models. However, its power predictions have not been validated for onshore wind farms or in a range of WS conditions. Herein, we evaluate the performance of the WFP in various atmospheric conditions to guide users of the WFP and to suggest future WFP advancements.

Using data from the CWEX-13 campaign, we select a 4-day period, from 24 to 27 August 2013, for our case study, due to the consistent nocturnal LLJ occurrences. We use measurements from a profiling LiDAR, a scanning LiDAR and a surface flux station to validate the ambient flows simulated by the WRF model. The wind farm of interest, located in central Iowa, consists of 200 1.5 MW wind turbines.

We explore the role of vertical resolution in the operation of the WRF WFP. We evaluate two vertical grids with 12-m and 22-m resolution near the surface. We find that the finer vertical resolution produces simulations that agree better with observed WS, WD and power than the simulations with coarser vertical resolution. Further, because the WFP accounts for the wake effects on power production of downwind turbines, the use of the WFP enables more accurate power prediction, whereas simulations without the WFP generally over-predict power production. Statistically, the WFP simulations with a fine vertical grid, regardless of the boundary conditions, are the most skillful in simulating power.

The skill of the WFP varies with meteorological conditions. When the model simulates WS close to the observations, the WFP predicts power properly, making WS the critical factor in improving the WFP. Rapid temporal fluctuations in WS introduce errors in power simulations, especially during ramp events. Further, in windy, stable and less turbulent conditions, the WFP tends to overestimate the wake effects and thus underestimates power production. However, the WFP performance demonstrates no clear dependence on the number of turbines per model grid cell or the downwind distance of turbines with respect to the upwind ones.

In conclusion, we demonstrate the value of the WRF WFP and the importance of using a fine vertical grid. Since WS greatly affects the skill of the WFP, subsequent research could include evaluating the WFP for an even larger range of WSs, especially at WS beyond the turbine cut-out speed (which would be 25 m s⁻¹ in this case; no such high WSs were observed during the CWEX-13 campaign). Evaluating the performance of other wind-farm layouts in locations with complex terrain is also needed. Modifications in the inflow WS considered by the WFP, for example, considering the rotor equivalent WS (Wagner et al., 2009), may bring promising improvements. More accurate power forecasts will help shape a more competitive

wind-energy industry, and further facilitate grid integration of wind energy (MacDonald et al., 2016).

3.7 Data availability

The code of the WRF-ARW model (doi:10.5065/D6MK6B4K) is publicly available at http://www2.mmm.ucar.edu/wrf/users/download/get_source.html. This work uses the WRF-ARW model and the WRF Preprocessing System (WPS) version 3.8.1 (released on 12 August 2016), and the WFP is distributed therein. The PSU generic 1.5 MW turbine (Schmitz, 2012) is available at doi:10.13140/RG.2.2.22492.18567. The user input required to run the WRF WFP is available at doi:10.5281/zenodo.847780.

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Chapter 4

LONG-TERM VARIABILITY OF WIND SPEED

I can live with doubt, and uncertainty, and not knowing. I think it's much more interesting to live not knowing than to have answers which might be wrong.

– Richard Feynman

Assessing and extracting wind energy, an intermittent energy source, inevitably entails uncertainty. Inter-annual variability (IAV) of wind resources is a key component in the overall uncertainty for wind projects. Particularly, uncertainty is defined as the variability of the differences between predictions and measurements of both wind speed (WS) and energy production.

Because wind turbines cost no fuel to operate, a large part of the cost for wind-farm owners is fixed or paid upfront. Once built, relocating wind turbines is also nearly impossible with current technologies. Therefore wind-farm developers need to select a site productive for decades. One of the goals of the wind resource assessment (WRA) process attempts to quantify the uncertainties that are not caused by turbine operations, in opposite to mechanical failure. One example is the uncertainty from wind fluctuations, because turbines produce no power at low WSs below their cut-in speeds as well as at high WSs beyond their cut-out speeds. From the WRA and system planning perspective, IAV remains a critical topic.

A common practice in the industry is to represent IAV as a percentage, which is the standard deviation (a spread metric) around the mean (an average metric) based on a Gaussian distribution of WS. The Gaussian assumption simplifies statistical analyses, yet it is rarely

applicable. Hence, the industry should reconsider the Gaussian approach, and evaluate using alternative parametric or non-parametric distributions. Reviewing different methods of evaluating variability and exposing their shortcomings is a first step to start the discussion.

Building on the contents in previous chapters, this chapter expands the spatial and temporal scale of the analysis to the contiguous United States (CONUS) across multiple decades. This chapter presents results from a fusion of atmospheric science, statistics, and wind energy. Understanding the long-term variability of WS consolidates our confidence in assessing uncertainties in wind energy, further facilitates electric grid integration, and improves the performance of existing and future wind farms.

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Jason Fields and Julie Lundquist revised the manuscript and provided guidance of the research. Readers are advised to seek out the final version of the journal article.

4.1 Abstract

Because wind resources vary from year to year, the long-term and inter-annual variability (IAV) of wind speed (WS) is a key component of the overall uncertainty in the wind resource assessment process and causes challenges to wind-farm operators and owners. We present a critical assessment of several common approaches for calculating variability by applying each of the methods to the same 37-year monthly mean WS and energy-production time series to highlight their differences. We then assess the accuracy of the variability calculations by correlating the WS variability estimates to the variabilities of actual wind-farm energy production. We recommend the Robust Coefficient of Variation (RCoV) for systematically estimating variability, and we underscore the advantages as well as the importance of using a statistically robust and resistant method. Using normalized spread metrics, including RCoV, high variability of monthly mean WSs at a location effectively denotes strong fluctuations of monthly total energy generations, and vice versa. Meanwhile, the WS IAVs computed with annual-mean data do not adequately represent energy-production IAVs of wind farms. Finally, based on this analysis, we suggest quantification of WS variability via RCoV and derivation of energygeneration variability with 10 ± 3 years of monthly mean WS records, resulting in 90% statistical confidence. Spatially, wind-energy development should focus on regions with strong WSs and low RCoVs.

4.2 Introduction

The P50, a widely used parameter in the wind energy industry, is an estimate of the threshold of annual energy production (AEP) of a wind farm that is expected to exceed 50% of the time (Clifton et al., 2016). The P50 is usually determined over the lifetime of a wind farm,

typically 20 years. To estimate P50 in the wind resource assessment (WRA) process, a single percentage value is usually assigned to represent the uncertainty for the desired certain time period at a wind site (Brower, 2012). The inter-annual variability (IAV) of wind resources, along with site measurements and wind plant performance, is an important component in the overall uncertainty in power production (Klink, 2002; Pryor et al., 2006; Lackner et al., 2008; Clifton et al., 2016). The IAV also plays a critical role in the measure-correlate-predict (MCP) process (Lackner et al., 2008), which usually considers wind measurements spanning less than 2 years.

Analysts and researchers use numerous metrics to quantify wind-speed (WS) variability, and the most common method is standard deviation (σ). For instance, the variability in historical or future wind resources is often represented as the σ from the annual-mean WS of a certain location (Brower, 2012). As wind-turbine power generation is a function of WS, the variability of wind resources has important implications on resultant long-term energy production. Financially, when wind resources in some regions, for example the United Kingdom, is projected to fluctuate more from year to year (Hdidouan and Staffell, 2017), the levelized cost of wind energy increases as well.

Because the profitability of wind farms depends on wind variability, past research has explored the implications of inter-annual and long-term variability in wind energy. Pryor et al. (2009) analyze trends of annual-mean WS and IAV, without explicitly quantifying IAV values. Archer and Jacobson (2013) evaluate the seasonal variability of wind-energy capacity factor. Lee et al. (2018) assess the spatial discrepancies between WS variabilities of different temporal scales, from hourly mean to annual-mean data. Bett et al. (2013) use σ and Weibull parameters to assess the wind variability in Europe. Extreme event analysis also offers another perspective to assess variability. For example, Cannon et al. (2015) examine extreme wind-energy generation events via reanalysis data and discuss the associated seasonal and inter-annual variability qualitatively. Leahy and McKeogh (2013) also quantify the return periods of multi-week wind droughts.

To quantify variability, the normalized standard deviation or the Coefficient of Variation (CoV), the σ divided by the mean of a time series, is a commonly used tool. Justus et al. (1979) calculated and compared the CoVs of monthly and yearly mean WSs at different sites across the United States. Baker et al. (1990) quantified inter-annual and inter-seasonal variations of both WS and energy production at three locations in the Pacific Northwest. They found the annual CoVs ranged from 4% to 10%, matching the conclusions from Justus et al. (1979). Recently, Li et al. (2010) calculate hub-height WS variance and σ of 30 years to spatially evaluate seasonal and inter-annual variability in the Great Lakes region. Bodini et al. (2016) estimate the IAV of wind resources with a modified version of CoV, using observed meteorological data in Canada. As the sample period increases, the IAVs of most sites gradually increase, averaging 5 to 6% among the chosen sites (Bodini et al., 2016). Krakauer and Cohan (2017) correlate the CoVs of monthly mean WSs with different climate oscillation indices, and find the global mean CoV at 8%. Other than characterizing WS, the metric is also used to evaluate the benefits of grid integration. For example, Rose and Apt (2015) conclude the inter-annual CoV of aggregate wind-energy generation in the central U.S. at $3 \pm 0.1\%$, much smaller than that of individual wind plants between 5.4% and 12%, $\pm 4.2\%$.

Aside from CoV, other metrics representing the spread of data have also been chosen to estimate variability in the literature. For example, the Robust Coefficient of Variation (RCoV), dividing the median absolute deviation (MAD) by the median, is a substitute to CoV. Gunturu and Schlosser (2012) quantify the spatial RCoV of wind-power density in the U.S. and demonstrate that the regions east of the Rockies, especially the Plains, generally have weaker variability and higher availability of wind resources. Seasonality index, originally used in Walsh and Lawler (1981) for precipitation purpose, is another measure to express variability. Chen et al. (2013) use the seasonality index to assess the inter-annual trend and the variability of WS in China, and they relate WS IAVs to climate oscillations.

Alternative variability metrics emphasize the long-term trends via contrasting WSs of different periods. The "wind index", used in Pryor et al. (2006) and Pryor and Barthelmie (2010), is a ratio of WSs of a reference period and an analysis period. An entirely different wind index evaluated in Watson et al. (2015) is a ratio of spatially-averaged WSs during two different periods.

Despite the importance of long-term variability, the wind-energy industry lacks a systematic method to quantify this uncertainty. As various metrics to assess variability exist, a comprehensive comparison of measures is necessary. Therefore, the goal of this study is to evaluate various methods of estimating long-term and inter-annual variability in a reliable way using a comprehensive long-term database. Specifically, our objective is to determine the optimal metric in relating WS variability and energy-production variability. We describe the WS and energy-generation data, the methodology and the chosen variability metrics in Section 4.3. We evaluate different variability measures via two case studies in Section 4.4. We also contrast the results computed from monthly mean and annual-mean data, and we illustrate the spatial distribution of WS variability in Section 4.4. We then recommend the best practice in using the ideal method in Section 4.5. After all, we focus on the applicability of imposing such metrics to quantify the variabilities of WSs and wind-energy productions.

4.3 Data and methodology

4.3.1 Wind and energy data

In this study, we use a 37-year time series of monthly mean WS and monthly total windenergy production in the Contiguous United States (CONUS) to calculate their variabilities. For WS, we use hourly horizontal wind components in the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) reanalysis dataset (Global Modeling and Assimilation Office (GMAO), 2015; Gelaro et al., 2017) by the National Aeronautics and Space Administration (NASA) from 1980 to 2016. We then derive the monthly mean WS at 80 m above the surface, to represent hub height in this chapter, via the power law (4.1) and the hypsometric equation (4.2):

$$\frac{u(z_2)}{u(z_1)} = \left(\frac{z_2}{z_1}\right)^{\alpha},\tag{4.1}$$

$$z_2 - z_1 = R_d \bar{T} ln\left(\frac{p_2}{p_1}\right),$$
(4.2)

In (4.1), $u(z_1)$ and $u(z_2)$ are the horizontal WSs at heights z_1 and z_2 , α is the shear exponent; in (4.2), R_d is the dry air gas constant, \overline{T} is the average temperature between levels z_1 and z_2 , p_1 and p_2 are atmospheric pressures at z_1 and z_2 . In most grid cells, we use the MERRA-2 meteorological output at 10 and 50 m above surface. In mountainous regions, sometimes the heights at 850 hPa, or 500 hPa are closer to 80 m than 10 m above surface, hence we use data at the next available level of 850 hPa or 500 hPa.

The horizontal resolution of the MERRA-2 is 0.5° in latitude (about 56 km) and 0.625° in longitude (about 53 km). The MERRA-2 reanalysis interpolates the data and the metadata at the exact output latitude and longitude, hence the WS, air density and elevation refer to the grid

points with the particular sets of latitude and longitude (Bosilovich et al., 2016). Hence, the longest distance between a wind farm and the its closest MERRA-2 grid-cell center is about 39 km.

For energy-production data, we use the net monthly energy production of wind farms in megawatt-hours (MWh) from the Energy Information Administration (EIA) between 2003 and 2016. Each of the wind farm has a unique EIA identification number. After we neglect about 300 wind sites with incomplete or substantial zero production data, a total of 607 wind farms in the CONUS are selected in this analysis. For simplicity, the CONUS in this analysis is defined as the area bounded by 127°W, 65°W, 24°N and 50°N, and geographically includes the 48 states in CONUS and Washington, D.C. (Figure 4.1).

4.3.2 Methodology

4.3.2.1 Linear regression and data post-processing

We focus on the direct relationship between WS and energy production to investigate approaches of calculating long-term variability. Therefore, we must minimize the influence from other determinants of energy production, such as curtailment and maintenance. First, we eliminate data with zero monthly energy productions, which is typical in the first months of a new wind farm. Next, we linearly regress the monthly total energy production on the monthly mean MERRA-2 80-m WS at the closest grid point to each wind farm from 2003 to 2016. In other words, each wind site is assigned with its own regression equation. We then remove any production data below the 90% confidence interval to exclude under-productions for reasons other than low WSs, and omit the data above the 99% confidence interval, or potentially erroneous over-productions. Hence, we focus on presenting the results from the linear fit in this study.

After regressing the outlier-free energy data on WS, we then filter the wind farms based on the coefficient of determination (R^2), which indicates the confidence of the linear regression. We select the R^2 threshold of 0.75, and 349 of the original 607 wind farms pass this filter. Considering some farms lack years of complete generation data, we extend the monthly total energy production to 37 years using the same site-specific linear models with the monthly mean MERRA-2 WS. In other words, we compute the predicted energy-production data from 1980 to 2016 based on the linear fit.

We then further apply a second filter using the Pearson's correlation coefficient (r) between the predicted and actual monthly total energy productions, and only choose the 195 wind farms with r larger than 0.8. As a result, of the r-filtered wind sites, we ensure WS is the primary driver of wind-power production, and we confirm the energy predictions match well with those observed.

The non-filtered, R^2 -filtered and *r*-filtered wind farms carpet most of the popular windfarm regions across the CONUS (Figure 4.1), even with the high *r* threshold at 0.8. Thus, the *r*filtered samples provide a sufficient representation of the wind farms across the United States. To illustrate our analysis with examples, we select one site in Oregon (OR) and another site in Texas (TX) that demonstrate distinct WS distributions. We choose the two sites to contrast the results of different variability metrics throughout the chapter, and both pass the *r* filter (Figure 4.1).



Figure 4.1: Wind-farm locations in the CONUS: non-filtered 607 sites in dark red, R^2 -filtered 349 sites in orange, and *r*-filtered 195 sites in yellow. The yellow square represents the OR site and the yellow star indicates the TX site (Table 4.2). The grey box illustrates the boundary of the CONUS used in this study.

Recognizing that the horizontal resolution of the MERRA-2 data could be perceived as undermining the linear regressions, we explore any possible role of the distance between the closest MERRA-2 gird point and the actual wind farm, but we find no reason for concern. In particular, horizontal and vertical discrepancies between the model and the observations do not affect the resultant R^2 in the linear regressions. More than half of the 607 wind farms pass the R^2 filter, and more than half of those pass the *r* filter (Figure 4.2a). The distribution shapes of the horizontal distances and the elevation differences between the closest MERRA-2 gird point and the actual wind farm remain similar with the two filters applied (Figure 4.2b and c). In other words, the horizontal and vertical model-actual distances have no apparent impact on the representativeness of the wind farms in the linear regression. Hence, the model-actual horizontal spatial range and the ability of MERRA-2 to represent terrain complexity are not the major determinants in the WS-energy relationships.



Figure 4.2: (a) Histogram of R^2 of all non-filtered sites (dark red), R^2 -filtered sites (orange) and *r*-filtered sites (yellow); (b) Histogram of horizontal distances between the closest MERRA-2 grid cell and the actual locations of the sites; (c) Histogram of absolute elevation differences between the closest MERRA-2 grid cell and the actual locations of the sites.

Additionally, we analyze the uncertainty of the linear regression method. We first test the influence of the error term in the regression, to account for the uncertainty associated with the input data. Specifically, after a wind farm passes the R^2 threshold of 0.75, we add a random value within one standard error to the predicted energy production of each month. This random error term introduces uncertainty to the regression process but does not affect the R^2 of the site-specific regression. Furthermore, we also test the sensitivity of the R^2 and r thresholds by analysing the results after modifying those limits. Particularly. We loosen the R^2 and r thresholds to 0.6 and 0.7, and we tighten the R^2 and r thresholds to 0.85 and 0.9.

We also consider the hub-height air density extrapolated from MERRA-2 as another regressor in the regressions. However, air density is a statistically insignificant predictor and thus is not discussed in the rest of this chapter. We further perform the regression based on the WS anomalies after removing the long-term means and the impacts of annual cycles, but the R² results are unsatisfying. Moreover, we perform the same analysis with the ERA-Interim (ERA-I) reanalysis dataset (Dee et al., 2011). The results of the key variability parameters such as σ , CoV and RCoV resemble the findings using MERRA-2, hence we focus on the MERRA-2 findings in this chapter.

Our analysis, although comprehensive, is constrained by the quality of our data. On one hand, reanalysis datasets have errors and biases in WS predictions from complexities in elevation and surface roughness (Rose and Apt, 2016). Reanalysis datasets also demonstrate long-term trends of surface WSs as well (Torralba et al., 2017). The MERRA-2 dataset can also depict different meteorological environments than those at the wind-farm locations, especially in complex terrain. Thus, regressing actual energy production on reanalysis WS adds uncertainty to our analysis. On the other hand, constrained by the monthly total energy-production data from

the EIA, our analysis ignores the signals finer than monthly cycles. The quality of the EIA data also varies across wind sites, therefore the filtering process via linear regression is necessary.

4.3.2.2 Variability metrics relating wind speed and energy production

To evaluate the variabilities of both the WSs and the predicted energy generations from the filtered wind farms, we investigate a total of 27 combinations and variations of existing methods describing the spread of data. We categorize different variability metrics according to statistical robustness (insensitivity to assumptions about the data, for instance, Gaussian distribution) and statistical resistance (insensitivity to outliers) (Wilks, 2011). Of the 27 variability methods tested, we select four representative measures to inter-compare and discuss in detail, according to their robustness, resistance, and the nature of normalization by an average metric:

- RCoV, defined as the MAD divided by the median (Gunturu and Schlosser, 2012; Watson, 2014), is a spread metric divided by an average metric, and is both statistically robust and resistant;
- Range (maximum subtract minimum) divided by trimean (weighted average among quartiles) is a spread metric divided by an average metric, and the numerator is not resistant;
- CoV (Justus et al., 1979; Baker et al., 1990; Wan, 2004; Rose and Apt, 2015; Bodini et al., 2016; Hdidouan and Staffell, 2017; Krakauer and Cohan, 2017), defined as the σ divided by the mean, is a spread metric divided by an average metric, and both the denominator and the numerator are not robust or resistant;
- σ is simply a spread metric that is not robust or resistant.

Among the four measures, only RCoV is completely statistically robust and resistant, and the first three methods are all normalized spread metrics. We further describe all the tested variability methods comprehensively in Table 4.3, and they are easy to implement via basic Python packages such as NumPy and SciPy with no more than a few lines of code. In addition, based on the exponential scaling relationship between power and WS developed by Bandi and Apt (2016), we also analyze the results from the exponential CoV and the exponential RCoV in this chapter (Table 4.3).

In addition to calculating variabilities with the spread measures, we evaluate other diagnostics that describe distribution characteristics. These diagnostics include averaging metrics such as the arithmetic mean (not resistant) and median (the 50th percentile, which is resistant), symmetry metrics such as skewness (involving the third moment, not robust or resistant) and Yule-Kendall Index (YKI, robust and resistant), a tailedness metric, namely kurtosis (involving the fourth moment, not robust or resistant), the Weibull scale and shape parameters (not robust), and the autocorrelation with 1-year lag to dissect the inter-annual cycles. We summarize the diagnostics evaluated in this analysis in Table 4.4. Along with the regression results, results from the four representative variability metrics and other distribution diagnostics demonstrate differences between the two selected sites (Table 4.2).

Herein, we quantify the variabilities of the 37-year extended time series of WS and energy production via different methods, using a range of time frames: 1 year, 2 years, and up to 37 years for each wind farm. A metric is considered useful when the resultant WS variability correlates well with the resultant energy-production variability across wind farms, even when random errors are implemented and the thresholds R^2 and r are changed. In this analysis, we inter-compare results with three correlation metrics: Pearson's r, Spearman's rank correlation coefficient (r_s) and Kendall's rank correlation coefficient (τ) (Table 4.1).

	D - 1	
	KODUST	
Correlation metrics	and	Description
	resistant	
Pearson correlation	No	Calculate the covariance of x and y, divided by the
coefficient (r)	INO	product of standard deviations of x and y.
Spearman's rho, or Spearman rank correlation coefficient (r_s)	Yes	Transform x and y values into ranks within x and y themselves, then calculate the covariance of ranks in x and y, divided by the product of standard deviations of ranks in x and y.
Kendall's tau, or Kendall's rank correlation coefficient (τ)	Yes	Match all data pairs between x and y, with $\frac{n(n-1)}{2}$ matches possible with sample size of <i>n</i> . Define concordant pair as both x ₁ larger than x ₂ and y ₁ larger than y ₂ , or both x ₁ smaller than x ₂ and y ₁ smaller than y ₂ . Define discordant pair as either x ₁ larger than x ₂ and y ₁ smaller than y ₂ , or x ₁ smaller than x ₂ and y ₁ larger than y ₂ . Calculate $\tau = \frac{2(Concordant pairs - Discordant pairs)}{n(n-1)}$.

Table 4.1: Details of the three correlation metrics applied, adapted from Wilks (2011). All three metrics yield values between -1 and 1.

To assess the applicable time frames of various variability metrics, we evaluate the asymptote period of correlations for each method. In most cases, the correlation coefficients asymptote to the 37-year value after a certain analysis time frame. Using RCoV as an example, the Pearson's r's of shorter analysis periods (1-year, 2-year, etc.) gradually concenter to the 37-year value at 0.856 as the RCoV-calculation time frame expands (Figure 4.5a). Hence, for each metric, assuming the 37-year correlation coefficient represents the long-term correlation, we

calculate the normalized differences between the correlation coefficients and the 37-year value in each time frame, starting from 1-year. When the absolute mean of the normalized differences drops below 0.05 in a particular year, we determine that year as the length of data required for reliable results via that variability method. In other words, the asymptote year of a certain metric illustrates that the error of the resultant correlation between WS and energy-production variability via that data length is under 5% from the long-term value. For example, the asymptote period of RCoV correlations is 3 years according to Pearson's r (Table 4.5).

To relate the IAVs between WS and energy production, we also perform the same analysis for annual-mean data. Strictly speaking, calculating the variabilities using monthly mean data yield inter-monthly variabilities, because the results account for monthly, seasonal and annual signals. To isolate the signals from inter-annual variations, we also examine the metrics and their correlations between the annual-means of hub-height WSs and energy productions, after linear regressing and filtering via monthly means. However, the sample of each site are then limited to 37 data points of annual-mean WS and annual-total energy production. Besides, selecting de-trend data from long-term means to calculate variabilities and their correlations leads to trivial results because of the small sample sizes, and hence is omitted in this chapter.

4.3.2.3 Investigation on wind-speed RCoV

After we demonstrate RCoV is the most systematic approach in linking WS and energygeneration variabilities in Section 3.2, we further examine the details of using RCoV, specifically determining the minimum length of WS data necessary to quantify variability effectively. We use 37 years of WS in every MERRA-2 grid cell in the CONUS (a total of 5049 grid points), and we calculate the RCoVs with 1 to 37 years of data for each grid cell. Because the RCoVs calculated using data between 1980 to 2016 are only samples of the true long-term WS variability and hence the results involve uncertainty, we select a confidence interval approach.

We assume that the distribution of RCoV is Gaussian with infinite years of WS. Hence, we use a chi-square (χ^2) distribution to set bounds for the σ 's from samples of RCoV. In other words, because the derived RCoVs differ with years of WSs sampled, we use the χ^2 distribution to quantify the confidence intervals of RCoV for each sample size. To determine the minimum data required for RCoV calculation, we use the following criterion (Montgomery and Runger, 2014):

$$\sigma_{37} \ge |\sqrt{\frac{(n_i - 1)\sigma_i^2}{\chi^2_{\alpha/2, n_i^{-1}}}}|, \qquad (4.3)$$

where σ_{37} is the per-determined 37-year σ of RCoV, n_i is the sample size of n years in year i which is between 1 to 36 years, σ_i^2 is the variance of the sample of RCoVs in year i, and $\chi^2_{\alpha/2,n_i-1}$ is the percentage point of the χ^2 distribution given the confidence level of α and the degrees of freedom of $n_i - 1$. We select a pair of α levels, 90% and 95%, hence we use four percentage points of the χ^2 distribution at 0.025, 0.05, 0.95 and 0.975 to construct the respective confidence intervals. Because the 37-year RCoV is an estimate of the truth, which is the WS RCoV of infinite years, its singular value does not yield any variance or possess any distribution shape. Thus, to construct the confidence interval of the standard deviation of the truth, we set the pre-determined σ_{37} as a fraction of the 37-year RCoV. Particularly, the σ_{37} are 10% and 5% of 37-year RCoV for the 90% and 95% confidence levels respectively.

In summary, for each grid point, we first determine an uncertainty bound based on the 37-year WS RCoV of the location and assign a 37-year σ dependent on the confidence level,

which is either 5% or 10% of the 37-year RCoV. For each year i, from 1 to 37 years, we calculate the pairs of χ^2 -derived σ 's of year i, which represent the lower and upper bounds of the confidence interval. When both of the χ^2 -derived σ 's become smaller than the per-determined 37-year σ , year i becomes the minimum length of data required to calculate RCoV effectively at the specific confidence level. We analyze the WS RCoV via both monthly mean and annual-mean WSs. We label the resultant minimum length of WS data based on the χ^2 method as convergence year, in contrast to the asymptote period which determines the asymptote year of correlation coefficients.

4.4 Results

4.4.1 Case studies: OR and TX sites

We select two sites from two different geographical regions with considerable windenergy deployment, the southern Plains and the Pacific Northwest in the United States, to contrast the results of various variability metrics. Based on the site-specific regressions, we extend the monthly total energy-production time series to 37 years (Figure 4.3a and b) for the two sites. Both sites pass the R²-filter at 0.75 and the *r*-filter at 0.8. Although the OR site is farther from the closest MERRA-2 grid point in a region with more complex terrain, the resultant R² (0.87) and predicted-actual energy Pearson's *r* (0.91) are larger than those of the TX site (0.79 and 0.81 respectively) (Table 4.2). The 37-year-average WS of about 7.6 m s⁻¹ at the TX site is larger than that of the OR site at about 6.8 m s⁻¹ (Table 4.2). Additionally, the 12-monthlag autocorrelations demonstrate that the annual cycle of monthly mean WSs of the TX site is stronger than that of the OR site, yet the autocorrelations of the sites, 0.53 and 0.32, are still lower than the CONUS median of 0.58 (Table 4.2). None of the monthly and yearly mean WS distributions of the sites are not perfectly Gaussian. According to the kurtosis, skewness and YKI values of the monthly mean WSs (Table 4.2), the monthly mean WS distribution at the OR site skews towards lower WSs with more and stronger extremes (Figure 4.3c). The skewed distribution at the OR site leads to 71.2% of the monthly mean WSs locating within 1 σ from the mean, compared to the classic Gaussian of 68.3%. Nevertheless, although the TX site monthly mean WS distribution is very close to symmetric with fewer outliers (Figure 4.3d), which is supported by near-zero skewness and YKI (Table 4.2), only 64.6% of monthly mean data fall within 1 σ from its mean. For annual-mean WSs, the averaging with a 12-month time span at both sites reduces the ranges, and thus leads to kurtosis close to -1 (Table 4.2). Although the skewness and YKI are close to 0 (Table 4.2), only 59.5% and 56.8% of the annual-mean WSs locate within 1 σ from the means of the OR and TX sites respectively.

The four selected variability methods yield similar resultant monthly variabilities that are close to the respective CONUS medians based on the 37-year monthly mean data. On one hand, for variabilities of monthly mean WSs, the differences between the two sites are ambiguous because the comparison among the results of the four metrics is inconclusive (Table 4.2). Even though, the monthly variabilities are not far from the national medians (Table 4.2). On the other hand, results from the normalized spread metrics (RCoVs, range divided by trimean, and CoV) using the 37-year and the observed energy production illustrate that the OR site generates more variable wind power than the TX site (Table 4.2). The magnitudes of the variabilities between the 37-year and the actual monthly total energy productions are also comparable, except for the RCoVs at the TX site. The TX site only records 9 years of monthly total energy production, leading to a larger MAD, a smaller median, and thus a larger RCoV than the simulated energy

time series. Nonetheless, the predicted and the observed monthly total energy productions of the two sites demonstrate resembling variability characteristics overall.



Figure 4.3: (a) Time series of MERRA-2 monthly mean 80-m WS (black), actual monthly net EIA energy production (lime), and extended monthly total energy production from 1980 to 2016 (green) at the OR site; (b) Time series at the TX site with the same annotations as in (a); (c) Histograms of MERRA-2 monthly mean WS distribution (black) and yearly-mean WS distribution (grey) at the OR site from 1980 to 2016. The blue curve indicates the Gaussian fit of the monthly mean WSs via the mean and the σ , and the cyan curve represents the Gaussian fit of the annual-mean data; (d) Histograms and curves of Gaussian fit of WS distributions at the TX site with the same annotations as in (c).

					CONUS	
Site specifics	OR site		TX s	TX site		
Site specifies	UK OK	OK SIL				
					mean)	
Location, region and state	Condon,	Condon, Columbia		Bryson, north-west		
	Gorg	Gorge, OR		of Fort Worth, TX		
Nominal capacity (MW)	24.6		120			
Elevation at closest MERRA-2 grid	-501.4		-67.4			
point - elevation of actual wind						
farm (m)						
Horizontal distance between	33.07		21.22			
MERRA-2 location and actual						
$D^{2} = f(x) + \frac{1}{2}$	0.0	0.070		0.704		
R ² of final linear regression	0.8	0.868		0.794		
RMSE (root-mean-squared error)	114	0.5	4185	4185.0		
Of final linear regression (MWR)						
Pearson's <i>r</i> between predicted and	0.906		0.809			
actual energy	Monthly	Annual	Monthly	Annual		
Variability metrics	mean	maan	Monuny	maan		
37 year WS PCoV	0.082	0.020		0.023	0.102	
37-year energy-production RCoV	0.082	0.029	0.094	0.023	0.102	
Actual energy-production RCoV	0.220	0.057	0.100	0.0+1 0.055	/	
27 year WS range	0.233	0.007	0.212	0.000	2.066	
37-year w S trimean range	0.893	0.129	0.596	0.122	2.066	
37-year energy-production $\frac{range}{trimean}$	2.050	0.288	1.059	0.218	/	
Actual energy-production $\frac{range}{trimogn}$	1.768	0.307	1.303	0.305	/	
37-year WS CoV	0.134	0.036	0.127	0.031	0.143	
37-year Energy-production CoV	0.333	0.081	0.225	0.055	/	
Actual energy-production CoV	0.341	0.088	0.279	0.089	/	
37-year WS σ	0.909	0.242	0.964	0.234	0.895	
37-year energy production σ	2.599	0.632	5.828	1.421	/	
Actual energy-production σ	2.663	0.687	6.964	2.228	/	
	Monthly	Annual	Monthly	Annual		
57-year w 5 diagnostics	mean	mean	Mean	mean		
mean (m s^{-1})	6.79	6.79	7.59	7.59	6.45	
median (m s^{-1})	6.64	6.79	7.63	7.57	6.51	
kurtosis	0.886	-0.962	-0.663	-0.872	-0.482	
skewness	0.811	-0.129	-0.074	0.172	0.045	
YKI	0.153	0.101	-0.072	0.041	-0.024	
12-month-lag autocorrelation	0.324	0.039	0.525	-0.052	0.578	

Table 4.2: Site details, monthly means, and annual-means of various metrics at the two selected sites based on 37 years of monthly and yearly mean WSs, 37 years of predicted energy

productions, and actual energy productions; and the CONUS medians of WS metrics using 37 years of monthly mean data.

Moreover, using the four selected methods based on the annual-mean data, the results represent IAV exactly. For both variables, WS and energy generation, nearly all metrics illustrate that the OR site has stronger IAV than the TX site, except for using σ to quantify energy-production IAV (Table 4.2). Echoing the results of the monthly mean data above, using normalized metrics suggest the energy production at the OR site varies more than that at the TX site, inter-monthly and inter-annually. Note that all the IAVs are smaller than the variabilities calculated using monthly means (Table 4.2), because the annual averaging collapses variations in the data.

Additionally, the magnitudes of energy variabilities and IAVs are also nearly or more than twice as large as those of WS (Table 4.2). The reason is the nature of the power curve: wind-power generation is a function of WS to the third power. Therefore, small WS variations propagate into large energy-production fluctuations that are discernible in monthly and yearly mean data.

4.4.2 Variability metrics comparisons

Matching the WS and energy variabilities over 37 years at each r-filtered site, RCoV, as a statistically robust and resistant metric, yields the highest Pearson's r (0.86) among the four highlighted methods as well as all the variability metrics evaluated (Figure 4.4 and Table 4.3). A perfect variability measure would link WS and wind-power variations closely together with a correlation of unity, and herein RCoV is the best of all. On one hand, a strong correlation between the WS RCoV and the energy-production RCoV implies that the high WS variability at a wind farm translates to high energy-generation variability, and vice versa (Figure 4.4a). For instance, the moderate 37-year WS RCoVs of the OR and TX sites indicate modest fluctuations in energy productions between months (Figure 4.4a). On the other hand, a non-resistant method, range divided by trimean, leads to a lower r (0.64) and labels the OR site of having comparatively variable WS and energy production (Figure 4.4b). For the other two non-robust and non-resistant methods, the CoV results in a modest r (0.70) with a similar scatter as the RCoV (Figure 4.4c); the σ , not normalized by an average metric, does not relate WS and energy variabilities effectively (Figure 4.4d). The positions of the two wind farms relative to the rest of the sites in Figure 4.4 illustrate that the TX site experience average variabilities in wind resource and energy production, whereas the OR site has above-average energy-generation variability. The four methods lead to different representations of energy variability at the OR site, signifying their differences in robustness and resistance.



Figure 4.4: Scatterplots of 37-year WS variability and energy variability via four metrics: (a) RCoV, (b) $\frac{range}{trimean}$, (c) CoV and (d) σ , based on monthly mean data from the 195 *r*-filtered wind sites. Each black dot represents each filtered site, and the *r* value at the corner of each panel indicates the Pearson's *r* between each pair of WS and energy spread metrics. The yellow square and the yellow star denote the OR and the TX sites respectively.

Spread metrics	37-year r	Robust and resistant	Why not robust and resistant
Interquartile range $(IQR) = q_{0.75} - q_{0.25}$	0.214	Yes	/
$\frac{IQR}{median}$	0.845	Yes	/
IQR trimean	0.834	Yes	/
Median deviation from median = $median[x - median(x)]$	-0.048	Yes	/
Median Absolute Deviation (MAD) = $median x - median(x) $	0.196	Yes	/
Robust Coefficient of Variation (RCoV) $= \frac{MAD}{median}$	0.856	Yes	/
Exponential $RCoV = \frac{\ln(MAD)}{\ln(median)}$	0.595	Yes	/
MAD trimean	0.848	Yes	/
Standard deviation $(\sigma) = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$	0.184	No	Reason I
<i>Variance</i> $(\sigma^2) = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2$	0.136	No	Reason I
$Coefficient of Variation (CoV) = \frac{\sigma}{mean}$	0.704	No	Reason I
Exponential CoV = $\frac{\ln(\sigma)}{\ln(mean)}$	0.466	No	Reason I
Mean deviation from mean = $\overline{(x - \overline{x})}$	-0.043	No	Reason I
Mean Absolute Deviation = $\overline{ x - \overline{x} }$	0.187	No	Reason I
Trimmed standard deviation (Trimmed σ)			
= standard deviation without values below Q1			
$= \sqrt{\frac{1}{n-2k}\sum_{i=k+1}^{n-k} (x_{(i)} - \bar{x}_a)^2}$, k as the nearest integration of the second s	0.206	No	Reason I
$\times n$			
Trimmed σ	0.775	No	Reason I
$ar{x}$ Range	0.177	No	Reason II

$\frac{Range}{\overline{x}}$	0.609	No	Reason I
Seasonality Index = $\frac{\sum x - \bar{x} }{n \times \bar{x}}$ (modified from Walsh and Lawler (1981))	0.744	No	Reason I
$\frac{\sigma}{median}$	0.743	Partially	Reason III
$\frac{\sigma}{trimean}$	0.728	Partially	Reason III
$\frac{IQR}{\bar{x}}$	0.818	Partially	Reason IV
$\frac{\overset{\sim}{MAD}}{\bar{x}}$	0.834	Partially	Reason IV
$\frac{Trimmed \sigma}{median}$	0.806	Partially	Reason III
$\frac{Trimmed \sigma}{trimean}$	0.794	Partially	Reason III
Range median	0.650	Partially	Reason V
Range trimean	0.635	Partially	Reason V

Table 4.3: Description of the 27 spread metrics tested, adapted from Wilks (2011), and the 37year *r*'s from the *r*-filtered monthly mean data. $q_{0.25}$ is the 25th percentile (first quartile), $q_{0.5}$ is the 50th percentile (median), and $q_{0.75}$ is the 75th percentile (third quartile). *Trimean* = $\frac{1}{4}(q_{0.25} + 2 \times q_{0.5} + q_{0.75})$, $range(x) = \max(x) - \min(x)$, and an overbar (\bar{x}) indicates the arithmetic mean. Reason I: the metric is not robust because the metric possesses distribution constraints which is usually Gaussian, and the metric is not resistant because outliers influence it; Reason II: the metric is not resistant as outliers influence it; Reason III: the numerator of the metric is not robust or resistant; Reason IV: the denominator of the metric is not robust or resistant; Reason V: the numerator of the metric is not resistant.

			Robust	Why not
Distribution diagnostics	Meaning	37-year <i>r</i>	and	robust and
			resistant	resistant
$Kurtosis (Tailedness)$ $= \frac{\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})^4}{(\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})^2)^2}$	Positive value means the distribution is tail-heavy with more and more extreme outliers compared to Gaussian; vice versa	0.936	No	Reason I
Skewness = $\frac{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2)^{\frac{3}{2}}}$	Positive value means long right tails, or right- skewed; vice versa	0.943	No	Reason I
Yule - Kendall Index (YKI) = $\frac{q_{0.25} - 2 \times q_{0.5} + q_{0.75}}{IQR}$	Positive value means long right tails, or right- skewed; vice versa	0.778	Yes	/
Weibull scale parameter	Determine the peak and the stretch	0.379	No	Reason II
Weibull shape parameter	Determine the average, the symmetry and the shape	0.721	No	Reason II
Autocorrelation	Pearson's <i>r</i> with its own past and future values	Not applicable	Not applicable	/

Table 4.4: Description of the distribution diagnostics tested, adapted from (Wilks, 2011) and the 37-year r's from the r-filtered monthly mean data. Reason I: the metric is not robust because the metric possesses distribution constraints which is usually Gaussian, and the metric is not resistant because outliers influence it; Reason II: the metric is not robust because it assumes Weibull distribution.

By increasing the years included in the variability calculations using monthly means, the resultant correlations of most metrics vary less, the correlations gradually concenter to their 37-year values, and their asymptote periods vary. The 37-year Pearson's r values from the four selected metrics between WS and energy-production variabilities in Figure 4.4 transform into the 37-year marks in Figure 4.5, and we use a 5% threshold of normalized deviation to determine the

asymptote periods. Particularly, the *r*'s from RCoV and CoV (Figure 4.5a and c) reach their respective asymptotes steadily with longer length of data, whereas the *r*'s from range divided by trimean does not (Figure 4.5b). The 37-year correlation using σ is weak and thus the method is not as useful after all, even though the *r*'s approach to the 37-year value (Figure 4.5d). Pairing with a high long-term *r*, the asymptote period of a metric indicates the appropriate time span of WS data required to represent the variability of wind-energy production. For example, the resultant *r*'s using RCoV asymptote after 3 years, meaning one needs 3 years of WS data to estimate the WS variability so as to adequately infer the energy-production variability of a certain or potential wind farm via RCoV.



Figure 4.5: Boxplots of Pearson's *r* between WS variability and energy variability for differet analysis time frames, from 1 year to 37 years: (a) RCoV, (b) $\frac{range}{trimean}$, (c) CoV and (d) σ , based on the monthly mean data from the 195 *r*-filtered wind sites. The 37-year correlations equal to the *r* values listed in Figure 4.4.
The three correlation coefficients yield consistent results among all variability metrics tested, hence we primarily present the results using Pearson's r herein. Table 4.5 summarizes the 37-year correlations (r, r_s and τ), between the WS variabilities and the energy-production variabilities using the r-filtered data, and the respective asymptote periods of the methods. The r and τ of RCoV are the largest (0.86 and 0.67 respectively) among all variability metrics, and the associate asymptote periods are also relatively short (2 to 3 years) (Table 4.5). Another normalized, robust, and resistant spread metric, interquartile range (IQR) divided by median, results in the highest r_s , and the r_s of RCoV is the second largest (Table 4.5). More importantly, the asymptote periods of RCoV are the smallest of all, regardless of the choice of correlation coefficient. In other words, fewer years of data are necessary to calculate RCoV to effectively connect WS and energy variabilities than any other metric. Overall, when a spread metric yields strong correlations between variabilities of WS and energy generation, the correlation metrics agree with each other (Table 4.5). Therefore, the results in this chapter focus on Pearson's r, which is a commonly used correlation coefficient.

Spread metrics	37- year <i>r</i>	Asymptote years from r	37- year r _s	Asymptote years from r_s	37- year τ	Asymptote years from τ
CoV	0.704	5	0.754	4	0.565	9
$\frac{\sigma}{median}$	0.743	4	0.781	3	0.595	4
$\frac{\sigma}{trimean}$	0.728	4	0.770	3	0.583	6
IQR mean	0.818	4	0.821	3	0.636	6
IQR median	0.845	3	0.843	3	0.662	6
IQR trimean	0.834	3	0.834	3	0.650	6
RCoV	0.856	3	0.836	2	0.663	3
MAD mean	0.834	3	0.822	3	0.648	5
MAD trimean	0.848	3	0.832	3	0.660	5
Range mean	0.609	30	0.711	28	0.516	31
$\frac{Trimmed \sigma}{median}$	0.806	3	0.807	3	0.631	5
$\frac{Trimmed \sigma}{trimean}$	0.794	4	0.801	4	0.622	6
Seasonality Index, modified from Walsh and Lawler (1981)	0.744	5	0.766	4	0.584	7
Distribution diagnostics						
Kurtosis	0.936	1	0.934	14	0.785	24
Skewness	0.943	1	0.938	1	0.798	18
YKI	0.778	23	0.712	33	0.538	34
Weibull shape parameter	0.721	4	0.741	5	0.559	7

Table 4.5: Correlations and the associated asymptote periods of WS variability and energy variability using various methods, diagnosites with different correlation metrics, based on the monthly mean data of the 195 r-filtered wind sites.

In addition to the spread metrics, other distribution diagnostics also yield strong correlations between the 37-year monthly mean WS and energy production. For example, kurtosis and skewness result in r and r_s above 0.9. Since we determine the asymptote periods based on normalized deviations, when the 37-year correlation benchmark of a metric is high, the respective asymptote period tends to be shorter. Therefore, only 1 year of monthly mean data is required to compute kurtosis and skewness adequately, except for using r_s in kurtosis, where those r_s 's of smaller number of years are low. (Table 4.5). Moreover, the symmetry and the shape of energy-production distribution can be characterized using WS data, given the moderately strong correlations of YKI and Weibull shape parameter (Table 4.5).

Additionally, we also perform the same correlation and asymptote analyses on the data from changing the R^2 and r filter thresholds as well as the data with random error, and RCoV again yields the strongest correlations and the shortest asymptote periods among all methods. We adjust the R^2 and r requirements in the linear-regression process, thus changing the filtered sample sizes. On one hand, reducing the R^2 threshold to 0.6 and r threshold to 0.7 increases the respective sample sizes to 461 and 306 wind farms, but weakens the correlations between WS and energy variabilities for all methods (Table 4.6). On the other hand, increasing R^2 threshold to 0.85 and r threshold to 0.9 strengthens the WS-energy correlations of all the metrics, and shrinks the sample sizes to 212 and 83 wind farms respectively (Table 4.6). Modifying the filtering thresholds leads to different r's yet similar asymptote periods among all metrics. Moreover, we also test the vigorousness of our findings by introducing an error term, randomized based on the standard error, in predicting the 37-year energy productions. The error term adds uncertainty to resemble the reality of noisy WS and power-production data. We introduce the error term to the predicted energy productions for each of the 349 wind farms that pass the original R^2 -threshold

of 0.75. This approach weakens the correlations and lengthens the asymptote periods for most metrics (Table 4.6). Overall, according to the results from the R^2 -r-threshold and the random error tests, RCoV yields the highest *r*'s among all methods, and its asymptote periods remain reasonably short.

	$R^2 = 0.6$		$R^2 = 0.85$		Dan dama arman		
	r = 0.7		r = 0.9		Random error		
Spread metrics	37-	Asymptote	37-	Asymptote	37-	Asymptote	
	year <i>r</i>	years	year <i>r</i>	years	year <i>r</i>	years	
CoV	0.650	6	0.787	3	0.675	6	
$\frac{\sigma}{median}$	0.682	5	0.820	2	0.708	4	
$\frac{\sigma}{trimean}$	0.671	5	0.804	3	0.695	5	
IQR mean	0.786	4	0.837	3	0.774	7	
<u>IQR</u> median	0.811	3	0.865	2	0.799	6	
IQR trimean	0.801	4	0.851	3	0.789	7	
RCoV	0.815	3	0.879	2	0.808	6	
$\frac{MAD}{mean}$	0.793	3	0.859	3	0.786	7	
MAD trimean	0.807	3	0.870	3	0.800	6	
Range mean	0.524	31	0.767	26	0.567	29	
$\frac{Trimmed \sigma}{median}$	0.736	5	0.816	3	0.741	6	
$\frac{Trimmed \sigma}{trimean}$	0.753	4	0.831	3	0.758	5	
Seasonality Index, modified from Walsh and Lawler (1981)	0.695	5	0.804	3	0.710	5	
Distribution diagnostics							
Kurtosis	0.896	5	0.927	1	0.886	14	

Skewness	0.931	1	0.951	1	0.918	8
YKI	0.756	23	0.833	19	0.669	25
Weibull shape parameter	0.656	5	0.802	3	0.706	4

Table 4.6: As in Table 4.5, but calculated metrics, the associated correlations and asymptote periods using different R^2 and r filters and adding random standard error to predicted monthly total energy productions. The sample sizes of the 0.7-r threshold test, the 0.9-r threshold test and the random error tests are 306, 83, and 195 wind farms respectively.

Besides, normalized and simple spread metrics yield different relative WS variabilities between wind sites. On one hand, the correlations coefficients between 37-year monthly mean WS RCoV and CoV, two spread metrics that are normalized by average metrics, are nearly unity (Figure 4.6a). The comparison between two simple spread metrics, MAD and σ , result in correlation coefficients close to 1 too (Figure 4.6d). The relative positions of OR site highlight the differences between Figure 4.6a and Figure 4.6d: compared to other wind farms, the OR site has moderate WS RCoV and CoV, but small MAD and σ . Compared to Figure 4.6a, the lower r_s and τ in Figure 4.6d illustrate that MAD and σ can misrepresent the relative WS variabilities of a wind site. On the other hand, the results between a normalized spread metric (RCoV and CoV) and the respective simple spread metric (MAD and σ), which is also the numerator of the normalized spread metric, lead to weaker correlations (Figure 4.6b and c). The r, r_s and τ between 37-year monthly WS RCoV and σ are 0.684, 0.738, and 0.579 respectively (not shown). The wind sites with slower average WSs and thus disproportionately larger normalize spread results cause the deviations from perfect correlations in Figure 4.6b and c. Therefore, normalized spread metrics, which account for the differences in WS magnitude, become advantageous over simple spread metrics in comparing variabilities of wind sites. Note that we demonstrate similar comparisons between WS spread metrics via annual-mean data in Figure 4.7.



Figure 4.6: Similar to Figure 4.4, but for scatterplots to compare 37-year WS variability metrics: (a) RCoV and CoV, (b) RCoV and MAD, (c) σ and CoV, and (d) σ and MAD, based on monthly mean data from the 195 *r*-filtered wind sites. Each black dot represents each filtered site, and the *r*, r_s and τ at the corner of each panel indicate the Pearson's *r*, the Spearman's rank correlation coefficient and the Kendall's rank correlation coefficient between each pair of WS spread metrics. The yellow square and the yellow star denote the OR and the TX sites respectively.



Figure 4.7: As in Figure 4.6, but the metrics are calculated using yearly mean WS.

Meanwhile, using annual-mean data to compute IAVs can lead to misleading interpretations. Scatterplots of the 37-year WS and energy IAVs similar to Figure 4.4 are illustrated in Figure 4.8. The correlations via yearly averages are generally weaker except for a few metrics, including range divided by mean which yields the largest r of all (Table 4.7). However, the 37-year correlations do not adequately represent the long-term values (Table 4.7), so even the resultant asymptote periods are longer than those using monthly mean data, the asymptote analysis method is unsuitable for annual-mean data. Moreover, using annual averages

greatly limits the sample size at each site even with 37 years of hourly mean WS data. Statistically, a smaller sample leads to a smaller spread of that distribution. Accordingly, with few years of data, small spreads in annual-mean WSs result in a tight cluster of IAVs among all the wind farms. Therefore, the compact collection of WS and energy-production IAVs causes strong correlations, solely because of the small number of annual averages used in the IAV calculation. Thus, the correlations via annual means demonstrate a downward trend with increasing length of data, regardless of the variability metrics chosen (Figure 4.9). Although the correlations asymptote to the 37-year values, the weakening correlations with more years included in the IAV calculations imply that using less data is preferred in connecting the two IAVs. Note that the spread cannot be computed with one data point and hence the correlations between WS IAVs and energy IAVs do not exist with a single year of data (Figure 4.9). Overall, the asymptote analysis causes deceiving results, and given the nature of the annual means, we cannot determine the sufficient length of data to effectively link the IAVs of WS and energy production. In other words, relating WS IAV and energy-generation IAV with annual-mean data is flawed.



Figure 4.8: As in Figure 4.4, but the metrics are calculated using annual-mean WS and energy production.



Figure 4.9: As in Figure 4.5, but for annual-mean data.

IAV metrics	37-year <i>r</i>	Asymptote years
CoV	0.573	27
$\frac{\sigma}{median}$	0.567	27
<u>σ</u> trimean	0.569	27
IQR mean	0.699	24
IQR median	0.697	24
IQR trimean	0.699	24
RCoV	0.668	27
MAD	0.670	25
MAD trimogn	0.670	25
Range	0.723	27
$\frac{Trimmed \sigma}{median}$	0.567	27
$\frac{Trimmed \sigma}{trimean}$	0.569	27
Seasonality Index, modified from Walsh and Lawler (1981)	0.547	29
Distribution diagnostics		
Kurtosis	0.985	5
Skewness	0.980	4
YKI	0.853	12
Weibull shape parameter	0.649	28

Table 4.7: As in Table 4.5, but calculated metrics, the associated correlations and asymptote periods using different R^2 and r filters and adding random standard error to predicted monthly total energy productions. The sample sizes of the 0.7-r threshold test, the 0.9-r threshold test and the random error tests are 306, 83, and 195 wind farms respectively.

4.4.3 Wind-speed RCoV calculation and spatial distribution

Considering RCoV is a powerful tool in relating WS and energy-generation variations, we then assess the required length of data to sufficiently calculate the RCoV of WS. We compute the site-specific RCoVs using different spans of monthly mean WSs, including the OR and the TX sites (Figure 4.10). The variations of RCoVs decrease with more years included in the calculations, and for each location we use the 37-year WS RCoV as the long-term benchmark. For example, the 37-year WS RCoV of 0.082 at the OR site means that the median among the absolute deviations from the median is 8.2% of the median monthly mean WS (Figure 4.10a and Table 4.2). We determine the 37-year σ 's as 10% and 5% of the 37-year RCoV, and we apply the χ^2 approach at 90% and 95% confidence levels respectively to derive the convergence years, or the minimum length of WS data required to calculate RCoV effectively. The convergence years of the OR and TX sites are 12 and 25 years with 90% confidence, and 20 and 31 years with 95% confidence respectively (Table 4.8). In other words, for the OR site, one needs 12 years of monthly mean WSs to compute RCoV with 90% confidence that the resultant RCoV is within 10% deviation from the 37-year RCoV.



Figure 4.10: Boxplots of WS RCoV using monthly MERRA-2 data for different time frames from 1 year to 37 years at (a) the OR site and (b) the TX site.

Monthly mean WS	RCoV		CoV		σ	
Confidence level		95%	90%	95%	90%	95%
37-year sample size (of 5049 grid points)	5049	4923	5049	5039	5049	5048
Convergence years - CONUS median	10	20	4	12	4	12
Convergence years - CONUS MAD	3	4	2	5	2	5
Convergence years - OR site	12	20	6	15	6	15
Convergence years – TX site	25	31	7	24	5	24
Yearly mean WS	RCoV		CoV		σ	
Confidence level	90%	95%	90%	95%	90%	95%
37-year sample size (of 5049 grid points)	4414	2565	5034	4292	5034	4301
Convergence years - CONUS median	27	33	20	28	19	28
Convergence years – CONUS MAD	4	2	4.5	3	4	3

Table 4.8: Convergence years based on the χ^2 approach of WS RCoV (as in Figure 4.10 and Figure 4.11), WS CoV, and WS σ , using monthly and yearly mean WSs. The calculations of median and MAD exclude the data with convergence years beyond 37 years in the CONUS.

To quantify the long-term variability of WS at a wind farm, RCoV requires 10 years of monthly mean WS record with 90% confidence. In general, the σ 's of WS RCoVs across the CONUS decrease with more years included in the RCoV calculation (Figure 4.11a). For each grid point, the sample size of RCoV also becomes smaller, from 37 RCoVs of 1 year of data to 1 RCoV of 37 years of data, and hence the σ of RCoV decreases with the length of WS records (Figure 4.11a). With the σ 's of RCoVs across 37 years, we determine the convergence years via the χ^2 method. For a certain confidence level, the cumulative fraction of the CONUS grid cells exceeding the associated threshold of χ^2 -derived confidence intervals increases with the length of data (Figure 4.11b). Among all of the MERRA-2 grid cells in the CONUS, the median convergence year is 10 years and the associated MAD is 3 years at 90% confidence level (Figure 4.11b and Table 4.8). In other words, to assess the WS variability via RCoV with a maximum of 10% error from the long-term value and 90% confidence, one needs 10 ± 3 years of monthly mean WS records.

Moreover, raising the confidence level extends the minimum length of WS data to compute RCoV. At 95% confidence level, the median convergence years is 20 years, and 2.5% of grid points in the CONUS require more than 37 years of monthly mean data to calculate RCoV (Figure 4.11b and Table 4.8). Additionally, using yearly mean WSs to calculate RCoV leads to longer convergence years. At 95% confidence, 33 years of annual-mean data is the average required length, and half of the CONUS grid points have convergence years over 37 years (Figure 4.11b and Table 4.8). We also perform the same analysis on CoV and σ of WSs (Table 4.8). Although CoV and σ result in shorter convergence years, these non-robust and non-resistant methods yield worse correlations between WS and energy-production variabilities than RCoV, and hence we focus on demonstrating the RCoV results.



Figure 4.11: (a) Boxplots of σ 's of WS RCoVs, where the RCoVs are calculated using monthly mean MERRA-2 data of 1 to 37 years. For each year, each box summarizes the σ from each MERRA-2 grid cells in the CONUS; (b) The fraction of grid cells in the CONUS that the pair of the χ^2 -derived σ 's from each of those grid cells become smaller than the 37-year σ . The solid black, dash black, solid orange, and dash orange lines respectively indicate the minimum length of data: when the WS RCoV using monthly mean data yield 10% deviation at maximum from the 37-year value at 90% confidence level; when the WS RCoV using monthly mean data yield 5% deviation at maximum from the 37-year value at 95% confidence level; when the WS RCoV using yearly mean data yield 10% deviation at maximum from the 37-year value at 90% confidence level; and when the WS RCoV using yearly mean data yield 5% deviation at maximum from the 37-year value at 95% confidence level.

Spatial distributions of WS RCoVs across the CONUS identify locations with reliable wind resources. Based on the site-specific convergence years at 90% confidence level (Figure 4.12a), we calculate the RCoVs with monthly mean WSs of the particular time spans at each grid point and normalize with the CONUS median (Figure 4.12b). Regions requiring long WS records irregularly scatter across the continent, such as the Northeast, the Dakotas, and Texas; whereas the pattern of WS RCoV displays geographical arrangements, and the mountainous states generally illustrate high RCoVs, including the Appalachians and the Rockies. Given the strong correlations between the WS RCoV and energy-production RCoV, Figure 4.12b offers a realistic estimation of the general spatial pattern of the variability in wind-energy production as well. Note that qualitatively, Figure 4.12b is similar to the maps of WS variability in Figure 13a of Gunturu and Schlosser (2012) and in Figure 3 in Hamlington et al. (2015), which also illustrate the variability of wind resources in the CONUS. In addition, using a fixed length of WS data of 10 years for all CONUS grid points to compute RCoV results in a nearly identical spatial distribution to the pattern in Figure 4.12b.

Further, an ideal location for wind farms should exhibit ample WSs with low variability. We combine the spatial variations of the normalized RCoV and the long-term wind resource (Figure 4.12b and c), and we differentiate regions according to the CONUS median RCoV and WS (Figure 4.12d). Favorable candidates for wind-farm developments have above-average WSs and below-average variabilities, such as the Plains, parts of the Upper Midwest, spots in the Columbia River region and the Carolinas; poor places for wind power with weak winds and strong variabilities include the Appalachians and most of the Northeast.

The convergence years in some CONUS grid points are beyond 37 years when we increase the confidence level from 90% to 95% (Figure 4.11b and Table 4.8), and those grid

points do not demonstrate any geographical pattern as in Figure 4.12a. Additionally, using RCoV to represent IAV, the spatial patterns of required data lengths and the resultant normalized RCoVs are notably different from the monthly mean results, and geographical features seem to be irrelevant (Figure 4.13). Furthermore, the categorical features of CoV demonstrates very similar to those of RCoV for onshore wind resources in the CONUS, whereas using σ results in notably distinct classifications of CONUS wind resources (Figure 4.12d and Figure 4.14).



Figure 4.12: (a) Map of the convergence years, or years of monthly mean WS data required to derive a maximum of 10% deviation from the 37-year RCoV at each grid point, at 90% confidence level. The CONUS median is 10 years with the MAD of 3 years; (b) Map of RCoV of monthly mean WS using the grid-cell-specific convergence years in (a), normalized using the CONUS RCoV median at 0.100. The RCoVs illustrated are averaged over (37-convengence year+1) available year blocks. The MAD of the normalized RCoV in the CONUS is 0.224; (c) Map of the mean monthly WS at 80 m of 37 years from 1980 to 2016. The CONUS median is 6.45 m s⁻¹ with the MAD of 1.03 m s⁻¹; (d) Map of wind resource and its variability, by summarizing (b) and (c) into four categories: regions with below-median WS and above-median RCoV (grey), regions with below-median RCoV (orange red), and regions with above-median WS and below-median RCoV.



Figure 4.13: As in Figure 4.12, but the data plotted are annual-mean WSs: (a) Map of the convergence years, or years of WS data required to derive a maximum of 10% deviation from the 37-year RCoV at each grid point, at 90% confidence level. Because 12.6% of the CONUS grid points yield convergence years beyond 37 years using annual-mean data (solid orange line in Figure 4.11 and first column in Table 4.8), we assign 37 years as the convergence years for those grid points. After excluding the non-numeric values, the CONUS median is 27 years and the MAD is 4 years; (b) Map of RCoV of annual-mean WS using the grid-cell-specific convergence years in (a), normalized using the CONUS RCoV median at 0.020. The RCoVs illustrated are averaged over (37-convergence year+1) available year blocks. The MAD of the normalized RCoV in the CONUS is 0.205.



Figure 4.14: As in Figure 4.12d, but the spread metrics are (a) σ and (b) CoV, calculated using monthly mean WSs of 37 years.

4.5 Discussion

When using statistically robust and resistant variability metrics, stronger correlations between variabilities of WS and energy production emerge. Statistically, robust methods do not assume or require any underlying WS distributions, and resistant methods are insensitive to WS extremes. Of all methods, three robust and resistant metrics, RCoV, MAD divided by trimean and IQR divided by median, result in the largest three r's in Table 4.3 and Table 4.5, suggesting them as the most useful metrics to quantify long-term variability. Depending on the meteorological-data availability, WS characteristics, and terrain complexity, different methods are appropriate in different conditions. Nevertheless, robust and resistant methods are the most applicable to connect WS variability with energy-generation variability, and RCoV is the best one among all.

Overall, of all methods, RCoV consistently yields the strongest correlations in WS and energy variabilities with reasonable asymptote periods (Table 4.3 and Table 4.5), even after accounting for random standard errors and modifying the R^2 and r thresholds (Table 4.6). In addition, assessing WS RCoV with 90% statistical confidence requires 10 ±3 years of monthly WS means (Figure 4.11 and Table 4.8), which exceeds the asymptote periods of 2 to 6 years to yield strong WS and energy-production correlations (Table 4.5). Even though different locations require various spans of data (Figure 4.12a), the average of the resultant RCoVs using 10 years of WSs leads to nearly identical spatial distributions (Figure 4.12b). Therefore, to effectively quantify WS variability and thus to adequately derive energy-generation variability, we recommend using the RCoV with 10 years of monthly mean WSs.

Annual-mean data are inadequate in relating WS and energy-production IAVs as well as in representing WS IAVs. We cannot determine the minimum years of data to sufficiently relate WS and energy IAVs because their correlations decline with the length of data available (Figure 4.9). Moreover, the coarse time resolution of annual averages smooths out fluctuations of smaller time scales. In other words, generalizing a year of WS records with one number omits the signals from microscale gusts to synoptic-scale fronts, resulting in smaller magnitude of spread metric results (Figure 4.8 and Table 4.2). Yearly mean WSs also possess different distribution characteristics, such as skewness and kurtosis, compared to those of finer temporal resolutions (Lee et al., 2018). Decades of WS data is also necessary to compute RCoV and represent IAV (Figure 4.13a), and the resultant features of IAV (Figure 4.13b) differ from those calculated via monthly mean WSs (Figure 4.12b). For instance, the low IAVs in the Appalachians (Figure 4.13b) contradict with the pattern of high monthly mean WS RCoVs in mountainous areas (Figure 4.12b) as well as the findings in past research (Gunturu and Schlosser, 2012; Hamlington et al., 2015). Moreover, some of the grid points require more than 37 years of yearly mean data to calculate WS RCoV with statistical confidence (Figure 4.11 and Table 4.8). Although RCoV

does not yield the strongest 37-year r in relating WS and energy IAVs, readers should be cautious when using a limited length of annual-mean WS records to derive IAVs. In short, to effectively assess the long-term variability of wind-farm productivity, one should use WSs finer than yearly mean data.

Regions with ample wind resources and low variability favor and rationalize wind-energy developments, coinciding the locations of many existing wind farms in the CONUS (Figure 4.12d). Wind farms in the Plains and parts of the upper Midwest benefit from the above-average WSs and the below-average WS RCoVs. Other regions, such as segments in the Columbia River region and the Carolinas, also have strong, consistent winds in the long run. The Northeast and the Appalachians is relatively unfavorable for supplying stable onshore wind energy, whereas the area east of Cape Cod in Massachusetts and sections along the West Coast exhibit promising offshore wind resource. Wind-farm developers should account for wind resource as well as its long-term variability in repowering existing turbines and building new wind farms.

Furthermore, mathematically, a normalized spread metric, namely a spread statistic divided by an average metric, is more useful than solely a spread metric in assessing variability. Moreover, a normalized spread metric should always be presented with the corresponding averaging metric. For example, RCoV and CoV between WS and energy production yield larger r's than MAD and σ (Table 4.3 and Table 4.5), and the r's between WS RCoV and WS CoV are also higher than the same WS comparisons involving MAD and σ (Figure 4.6). For σ , which is the root-mean-square of the deviation from the mean, is not statistically robust or resistant, and 1 σ represents that the uncertainty is 18.3% from the mean. Hence, CoV, or the σ divided by the mean, is the respective normalized uncertainty metric to σ . For instance, the WS CoVs of both the OR and TX sites are about 0.13 (Table 4.2), implying the σ is 13% from the mean. In

contrast, using RCoV, or the MAD divided by the median, is a robust and outlier-resistant metric of normalized uncertainty. For example, the WS RCoVs of the OR and TX sites are 0.08 and 0.09 respectively (Table 4.2), indicating the MADs are 8% and 9% from their median WSs. Even though RCoV is not as commonly used and is not as intuitive as σ or CoV, RCoV is unrestricted by any assumptions of the underlying distribution of WS. Overall, to correctly and effectively use the normalized spread metrics, both the normalized spread metric and the average value need to be stated clearly in pairs. In other words, a statement of "variability is 2%" oversimplifies the statistics of uncertainty quantification. Therefore, we recommend presenting both the RCoV and the median of a time series together in estimating variability.

Distribution diagnostics, on top of the variability metrics, are also effective in identifying the characteristics of wind-energy production at a location. We examine a few distribution parameters that result in strong WS-energy correlations, including kurtosis and YKI (Table 4.4 and Table 4.5). Both metrics assess the degree of deviations from a Gaussian distribution. For instance, we confirm the monthly and yearly mean WS distributions of the OR and TX sites are not perfectly Gaussian because of their non-zero kurtosis and skewness values (Table 4.2), as well as their portions of data within 1 σ . Moreover, a multi-modal or an asymmetrical WS distribution (Figure 4.3c and d) also implies a non-Gaussian energy-production distribution. Generally, Gaussian distribution is invalid for WSs across averaging time scales (Lee et al., 2018). Hence, understanding the underlying distribution of wind resources can validate the applications and the legitimacy of Gaussian statistics, especially in quantifying the P50, and the associated losses and uncertainties in wind energy.

4.6 Conclusion

Because WS variability is a crucial component in assessing overall uncertainty of P50, this chapter highlights the importance of using rigorous methods to estimate inter-annual and long-term variability. To search for the suitable ways to quantify this uncertainty under different conditions, we investigate 27 combinations of spread metrics over hundreds of wind farms in the US, with closer examination of two geographically-distinct sites. We evaluate the methods for statistical robustness to non-Gaussian distributions and statistical resistance to extreme values, in contrast to the common practice of using only σ . We calculate variabilities using the monthly mean WSs from the MERRA-2 reanalysis dataset and the wind-farm monthly net energy productions from the EIA. We find that within the CONUS, statistically robust and resistant methods predict variabilities more accurately, in which the WS variabilities and energy-production variabilities produce strong correlations.

We recommend RCoV to quantify variabilities of wind resource and energy production. RCoV, defined as the median of absolute deviation from median divided by the median, is a statistically robust and resistant spread metric. This metric yields strong correlations consistently in various sensitivity tests via different correlation coefficients. In other words, using RCoV, a wind farm with high WS fluctuations also possesses high variations in wind-energy generations and vice versa, whereas other metrics do not translate that relationship as effectively. Contrary to the custom of displaying uncertainty in one percentage value, we advise users to assess both the RCoV and the median in estimating the variability. Moreover, depending on the location, on average 10 ± 3 years of monthly mean WS data is necessary to compute WS RCoV with 90% statistical confidence, where the resultant RCoV deviates within 10% of the long-term RCoV. RCoV, as a normalized spread metric, also leads to a more accurate depiction of WS variabilities than σ , a simple spread metric.

Additionally, we can characterize the distributions of wind resources and wind-energy productions adequately via RCoV and other distribution diagnostics. The relatively low monthly mean WS RCoVs in the central U.S. indicate stable long-term wind resources, and its overall spatial distribution in the CONUS agrees with the findings from past research. Other distribution diagnostics, such as kurtosis and skewness, also result in high correlations between monthly mean WS and energy generation, and thus they are considered useful in representing energy-production characteristics.

Furthermore, readers should avoid calculating IAVs using annual-mean data because the long-term correlations between the WS and energy-production IAVs are weak. Hence, we cannot determine the minimum length of annual-mean data required for satisfactory results. Although the concept of IAV has been essential in determining the AEP in the WRA process, annual-mean WSs mask the signals of finer temporal scales and thus lead to unreliable representations of long-term variability.

Future work includes expanding the current analysis using high-resolution WS and energy-production data to assess finer-scale variations. With data of different temporal scales, the autocorrelation of wind resources and its relationship with long-term energy-production variations can also be quantified. We can also assess the influence of climatic cycles and seasonal monsoon patterns of WS on energy production as well. Furthermore, applying the concept of RCoV to quantify the uncertainty of P50 and assist financial decisions will be beneficial to the industry.

4.7 Data availability

The MERRA-2 data and the EIA data used in this chapter are publicly available at disc.sci.gsfc.nasa.gov/ and www.eia.gov/renewable.

4.8 Acknowledgements

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Chapter 5

CONCLUSION

欲窮千里目,更上一層樓。

(Advance to another level to see a thousand miles further.)

- 王之渙

This dissertation covers three different topics on wind-energy meteorology. Specifically, the previous chapters include the exploration on the evening evolution of wind-turbine wakes and their interactions with power production, the validation of the power-production predictions of the Weather Research and Forecasting (WRF) model with observations, and the assessment of a statistically robust process to evaluate the long-term variability of wind resources.

First, I characterize the evening transition of wakes caused by a single turbine and a wind farm using observations and the wind farm parameterization (WFP) scheme in the WRF model. When the evening atmosphere changes from unstable to stable, the turbine-induced wind-speed (WS) deficit and turbulence enhancement become more prominent after sunset. The wake also primarily locates within the rotor layer during and after the evening transition (ET). Therefore, the overall wind-power production decreases in the case study. Wind-farm operators should account for and incorporate these wake changes in the evening into the optimization control processes to maximize power production.

Next, I evaluate the skill of the WRF WFP scheme on power production in range of WSs, wind directions (WDs), and stability conditions during a period of summertime low-level jets

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(LLJs). Performing simulations on wind and power generation with a fine vertical grid of about 12 m is recommended. Even though the WFP overstates wake losses and thus underestimates power production in a windy, non-turbulent, and stable atmosphere, predicting power via the WFP is far more accurate than that without it. Ultimately, improving the WFP performance requires better predictions of ambient winds.

Finally, I search for the best approach to represent the long-term variability of wind resource and energy production. The Robust Coefficient of Variation (RCoV), as a statistically robust and resistant metric, is the optimal method to assess WS variability as well as to relate WS and wind-energy-production variabilities. Future wind-energy developments should focus on regions with strong winds and low WS RCoVs, such as the Plains and the Upper Midwest in the U.S. In contrast to the common practices in the industry, evaluating the inter-annual variabilities (IAVs) of wind resources with annual-mean values oversimplifies the small-scale WS fluctuations and hence is inferior.

After all, in accordance to the nature of research in combining "re" and "search", this work triggers more and deeper explorations. In addition to enhancing our understanding of atmosphere-related uncertainties in wind energy, this dissertation aims to bring positive influence on the community and push the industry forward. For example, the WRF modeling work mentioned above helps to promote and publicize the use of the mesoscale numerical weather prediction (NWP) model in the wind-energy sector. The applications of the WRF WFP span from wind resource assessment (WRA) to operational forecasting. Proving the value of the WFP suggests that such numerical parameterization for other weather-dependent renewable technologies such as utility scale solar farms can also be feasible and useful. After all, the WFP

validation paves a foundation for further tests of the WFP onto complex terrain, during extreme weather conditions, or in wind farms of irregular shapes.

Moreover, determining the best approach to quantify the financial risk of the P50 is a logical next step. The RCoV is ideal to assess WS variability, yet whether the metric works as well to estimate the spread between P50, P90 and P99 (the estimate thresholds of AEP of a wind farm that are expected to exceed 50%, 90%, and 99% over its lifetime) in dollar terms remains uncertain. In contrast to the direct relationship between WS and wind energy, more independent variables affect the variabilities of energy productions and energy prices: energy prices fluctuate according to market changes; wind farms have customized power purchase agreements with utilities; curtailment compensations are complex and case-specific. Nonetheless, the industry needs to improve beyond using standard deviations (σ 's) to represent uncertainties, and extending the application of statistically robust and resistant metrics to the financial side will be meaningful.

Additionally, the wind-energy industry should consider other energy sources as complements than competitors. In the end, the wind community is competing with itself. Given decades of wind, power and other operational data, we should aim to bring the current renewable energy production to the next level: lower the pre-construction cost, simplify the WRA process, reduce the wholesale price, optimize wind-farm layout, maximize the annual energy production (AEP), reduce the need of maintenance, and minimize production uncertainty. Since wind energy is a keystone in our sustainable future, the industry needs to make the most out of academic research when moving forward and making innovations.

Take the power curve as an example. From WRA to operations, the industry uses the power curves (Figure 1.1) provided by the manufacturers and assumes little uncertainty about

them. Even the WRF WFP derives power outputs using theoretical power curves as inputs. The power curve undoubtedly serves as a basis for most wind-energy research. In reality, wind-power production does not increase linearly with WS, and in operation the WS-power data scatter all around. In other words, wind turbines often under- and over-perform. The industry needs to understand how meteorological factors other than WS, such as turbulence and atmospheric stability, correlate with power production. Thus, constructing a multi-variate relationship between meteorological variables and power generation is extremely impactful.

The incompetence of presuming a smooth and simple power curve in wind-energy research leads to another question: the role of uncertainty propagation. For example, according to Lorenz's Chaos Theory, researchers should assess the impacts of input uncertainties when they use numerical models. For example, the uncertainty in the boundary conditions of the WRF model magnifies the uncertainty in the output WSs. Furthermore, evaluating and validating our analyses becomes necessary for bookkeeping in the age of reproducible research. However, the industry seems to underestimate the magnification of input uncertainties. Therefore, we should also grow from a deterministic approach to a probabilistic mindset.

Along the same line, statistics and data science continue to reshape the industry gradually when we collect more data every day. Not only should researchers not abuse statistics, the industry should also beware the weaknesses of the Gaussian distribution. The Central Limit Theorem requires a large sample size to validate a Gaussian distribution, and hence making the Gaussian assumption inadequate at times. Additionally, the knowledge about past events actually limits our ability in quantifying variabilities, especially those in the future, and blindsides analysts during extreme events. For example, forecasting the intensity of ramp events or predicting the wind resource months ahead of time remains challenging. Improved models definitely continue to assist us, and understanding their limitations is equally important.

One future exploration should focus on the repowering of existing wind turbines. With the enormous number of aging turbines around the world, repowering gains growing attention and momentum. Topics about repowering include revising the WRA, extending the agreements between stakeholders, updating the wind-farm optimization with new turbines, recycling of old turbines, etc. We can always improve from the past, and repowering offers the best chance to apply what we have learned. Given the ocean of operational data the industry has collected, owner-operators should harvest the maximum amount of energy by installing more reliable and powerful turbines. The whole industry can learn the lessons and take actions better than the first attempts. Moreover, the repowering process extends the production cycle and proves that the wind-energy industry can stay dynamic and innovative. After all, repowering inevitably determines the future directions of the maturing wind-energy industry.

EPILOGUE

Education is what remains after one has forgotten what one has learned in school.

- Albert Einstein

Oh, "Ph.D.", such a fancy title.

Honestly, I cannot care less about this new title. Looking back, the primary reason I chose to enter graduate school was: to deepen my understanding of atmospheric science. I was madly in love with the subject, and I still proudly am.

Inevitably, graduate school is a long, lonely journey. In late August 2013, I started with being a student (taking classes and studying for the written comprehensive exam) and a teacher (teaching assistant for a weather laboratory class) at the same time. Then in May 2014, I began my research endeavor with calculating ogive functions using the Crop Wind Energy EXperiment 2011 (CWEX-11) data. In the meantime, I served as the Lead Graduate Teacher of the Graduate Teaching Program for the Department of Atmospheric and Oceanic Sciences (ATOC) in 2014 and 2015. Thanks to my collaborators at the Los Alamos National Laboratory (LANL), my first project changed from contrasting three case studies to focus on one case study in ET in the spring of 2015. In the fall of 2015, I used my ET study to complete my research comprehensive exam. In early 2016, I finally submitted the ET paper and experienced the bittersweet taste of publishing in a journal for the first time. My second project had fewer twists, while learning to use the WRF model and the WFP scheme was tough. Working on the WFP paper when interning at General Electric (GE) led to a productive summer in 2016. Starting from 2017, I transitioned

from mainly conducting independent research to collaborating with team members on the Performance, Risk, Uncertainty, and Finance, or PRUF, project at the National Renewable Energy Laboratory (NREL). And here I am, crafting the last chapter of my thesis in a cubicle of a national lab.

Meaningful adventures take time. Over the years, I transitioned from MATrix LABoratory (also known as MATLAB), to Interactive Data Language (also known as IDL), to NCAR Command Language (also known as NCL), to Python, and I learned the pros and cons of each of them. I also participated in various campaign planning meetings, and the campaigns themselves, including the eXperimental Planetary boundary layer Instrumentation Assessment, or XPIA, at the Boundary Atmospheric Observatory (BAO) and the Wind Forecast Improvement Project 2, or WFIP2, in the Pacific Northwest, both through the Atmosphere to Electrons, or A2e, initiative of the Department of Energy. I learned how to inflate weather balloons and launch radiosondes by myself in the dark, and even set up and operate profiling LiDARs (Light Detection And Ranging), radiometers, surface flux stations, and tethered lifting system in suboptimal weather conditions. I was also privileged to present my work at numerous conferences, including a couple of American Meteorological Society (AMS) annual meetings, the AMS Symposium on Boundary Layers and Turbulence, the American Wind Energy Association (AWEA) Wind Resource & Project Energy Assessment Conference, the International Conference on Energy & Meteorology, the International Conference on Future Technologies in Wind Energy, LANL, and switchCU~. And of course, not all my efforts were fruitful and sweet. My analysis for the Lidar Uncertainty Measurement Experiment, or LUMEX, was never published. The BAO was closed and took down in 2017, and part of the Columbia Gorge was on fire earlier that year.

Overall, my graduate study was composed of infinite items on the to-do list, countless curses, thousands of emails, a lot of late nights, many (pushed-back) deadlines, some frustration, a few breakdowns, a handful of stress-free vacations, and a constant self-doubt: why am I doing this?

As a wind-energy enthusiast, I must quote Bob Dylan: the answer, my friend, is blowing in the wind. Besides, the hottest fire makes the hardest steel. At the end of the day, I love atmospheric science, with all my heart.

I am completely grateful to have such an amazing combination of family, friends, mentors and colleagues. I would not have survived otherwise. This long journey certainly contained no blood and no tears, and was full of laughter, experience, knowledge, insights, wisdom, and memories. I state the following with full confidence: my graduate study humbled me, and I have become a better person.

A Ph.D. is simply a license to learn, and nothing else. In the ever-learning journey of life, at least I tried to prove my open mind, my eagerness to learn, and my persistence. An end is another beginning.

Benjamin Franklin once said, "if you would not be forgotten, as soon as you are dead and rotten, either write things worth reading, or do things worth the writing." I sincerely hope I did something worth writing, and I wrote something worth reading.

Joseph C. Y. Lee 12 April 2018 Boulder, CO

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