STATISTICAL MODELING TO SUPPORT POWER SYSTEM PLANNING

by

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A dissertation submitted to The Johns Hopkins University in conformity with the requirements for the degree of Doctor of Philosophy.

Baltimore, Maryland

December, 2015

Abstract

This dissertation focuses on data-analytic approaches that improve our understanding of power system applications to promote better decision-making. It tackles issues of risk analysis, uncertainty management, resource estimation, and the impacts of climate change. Tools of data mining and statistical modeling are used to bring new insight to a variety of complex problems facing todays power system. The overarching goal of this research is to improve the understanding of the power system risk environment for improved operation, investment, and planning decisions.

The first chapter introduces some challenges faced in planning for a sustainable power system. Chapter 2 analyzes the driving factors behind the disparity in wind energy investments among states with a goal of determining the impact that state-level policies have on incentivizing wind energy. Findings show that policy differences do not explain the disparities; physical and geographical factors are more important.

Chapter 3 extends conventional wind forecasting to a risk-based focus of predicting maximum wind speeds, which are dangerous for offshore operations. Statistical models are presented that issue probabilistic predictions for the highest wind speed

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expected in a three-hour interval. These models achieve a high degree of accuracy and their use can improve safety and reliability in practice. Chapter 4 examines the challenges of wind power estimation for onshore wind farms. Several methods for wind power resource assessment are compared, and the weaknesses of the Jensen model are demonstrated. For two onshore farms, statistical models outperform other methods, even when very little information is known about the wind farm.

Lastly, chapter 5 focuses on the power system more broadly in the context of the risks expected from tropical cyclones in a changing climate. Risks to U.S. power system infrastructure are simulated under different scenarios of tropical cyclone behavior that may result from climate change. The scenario-based approach allows me to address the deep uncertainty present by quantifying the range of impacts, identifying the most critical parameters, and assessing the sensitivity of local areas to a changing risk.

Overall, this body of work quantifies the uncertainties present in several operational and planning decisions for power system applications.

Readers:

Dr. Seth D. Guikema

Dr. Benjamin F. Hobbs

Dr. Charles Meneveau

Acknowledgments

The Ph.D. process is a true test of willpower, motivation, and confidence. It is an obstacle that cannot be tackled alone, and I owe the completion of this dissertation to the support of my advisor, mentors, family, and friends along the way. My advisor, Seth Guikema, has been unwavering in his enthusiastic encouragement of me and my work. Seth allowed me to pursue my research interests with his full support and was always ready to embrace a new project idea. His confidence in me was present when I lacked it myself, and for this I am especially grateful. Thanks also to Ben Hobbs whose curiosity and love of research are contagious. He has offered invaluable insight on my work, and conversations with him, on topics ranging from wind energy to travel destinations, are always educational.

Chapter 3 was a collaboration with Pierre Pinson at the Technical University of Denmark. I learned so much from Pierre during my time at DTU, and he has continued to serve as a valuable mentor. I am incredibly grateful that he agreed to host me as a visiting student on two separate occasions. My time spent in Copenhagen is a highlight of the PhD journey. Chapter 4 came about thanks to the assistance and advice of Claire VerHulst and Charles Meneveau, and I am especially thankful to Claire for providing the Jensen code and for helping me double check some of the early analysis.

My time at Hopkins was made infinitely better due to the fantastic students and postdocs that I had the pleasure of working with in DoGEE. Roshi, Sarah, Stefanie, Allison, and Laura taught me everything I needed to know about grad school and were the best lab mates, office mates, and friends that I could ask for. I am also thankful to the wonderful teammates and tribemates of Chesapeake Rugby and November Project for providing a great community in Baltimore and for helping to maintain my sanity through late night practices and early morning workouts.

It goes without saying that I could not have done this without my family. My parents have always been incredibly supportive of me, and their encouragement and understanding has kept me going through the good times and the bad. My sister Sarah has been my ultimate supporter and best friend, and I will always be incredibly grateful to her for everything that she has done and continues to do for me. While not quite family, I must also mention my dog Jasper. Getting a needy, energetic pup was not the smartest idea, but I am nonetheless grateful to him for managing to both drive me crazy and keep me sane over the past few years.

This work was funded by the Croft Fellowship, the Lee and Albert H. Halff Doctoral Student Award, the ARCS Foundation, and NSF PIRE Grant OISE 1243482.

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Chapter 1

Introduction

The purpose of the electric power system is to provide energy to customers when needed. At first glance, it seems like a simple task. In reality, there is a growing set of secondary goals that complicate the basic operations of a power system. Not only must the system provide power, this power must be reliable, it should be increasingly clean so as to minimize negative externalities, and it should be profitable for producers to provide. Meeting these secondary goals efficiently is challenging, and there is a large body of research focused on improving the methods used to meet these goals. Approximately six billion people have access to electricity around the world, and finding better solutions to meet any one of these goals is advantageous to all those invested in, and dependent on, the electric power system.[1] The research presented here tackles a small subset of the challenges that we are faced with in working towards a clean, reliable, and sustainable energy system.

1.1 Background

The electric power system is central to modern life in the developed world. We are dependent on it for our safety, productivity, financial security, comfort, and entertainment. It is also one of the most complex systems in operation today; it balances electricity generators, consumer demands, and transmission constraints, all in real-time. Broadly speaking, the power system seeks to minimize costs by planning ahead efficiently. This happens both on the local and regional scale and for short, medium, and long time horizons. Aside from cost, there are other considerations that are becoming increasingly important. Maintaining a high degree of reliability is essential, as many of our other critical infrastructure systems rely on electric power to operate, and failures in electric power can quickly cascade into other systems because of their high degree of dependence, and often times even interdependence.[2] Power losses or interruptions can result in billions of dollars worth of losses across sectors.[3] Therefore, it is important to evaluate and mitigate any risks to the power system that could result in inefficient operation, damage to the system, or a loss of power to consumers.

Efficient and reliable operations are the primary goal of the power system, but it is also important to consider the impact that this infrastructure has on other sectors. The adverse environmental impact of our electricity generation is an increasingly important consideration. Historically, we have relied heavily on fossil fuel-based sources for electricity generation, and these fuel sources produce large amounts of harmful pollutants when burned. There are significant detrimental health impacts from these pollutants in the short term, but there are also concerning long term effects that have only started to make their presence known.[4] Most notably, carbon dioxide is a byproduct of combustion and it is the main contributor to climate change on a global scale.[5] The effects of climate change will be widespread. Water resources, agriculture, coastal infrastructure, and human health will all face increased risk.[6] As a result, we now have stronger motivation than ever to pursue cleaner energy sources. We need to transition our electric power system towards generation sources that do not produce harmful emissions, both for short-term local health impacts and for long-term goals of climate change mitigation to lesson the forthcoming impacts.

Wind energy is one of the most promising sources of clean, renewable energy around the world. The estimated wind energy resource potential is more than 40 times greater than the world's current electricity demand.[7] Currently, only a small portion of this resource is being utilized, as we still rely heavily on fossil-fuel based sources of electricity generation. Globally, wind energy made up only 0.4% of our energy supply in 2013. However, it is one of the fastest growing sources with an average annual growth rate of 24.8%.[8] In 2014, the United States generated 4.4% of its electricity from wind energy. While still a small percentage, it was also the largest source of new generation installed that year.[9] The advantages of wind energy are significant. It is clean, renewable, and has no operational fuel costs. In addition, the resource is available locally (i.e., it does not have to be imported to generate power), and this fact turned out to be one of the main drivers of modern research into wind energy development. The U.S. invested heavily in wind energy following the 1973 oil crisis in an attempt to focus on domestic resources.[10] Wind turbines themselves have a relatively small footprint, and most of the land area of a wind farm remains usable for other purposes. This makes wind energy a particularly good partner for agricultural regions.[11] It is also highly scalable; turbines come in a wide range of capacities and wind farms can be built with any number of turbines. It is for these reasons that many countries have been quickly expanding their wind capacity and have implemented policies to promote wind energy development.[12,13]

Despite the advantages, wind energy also bring about significant challenges when integrating it into the larger power system. Wind is inherently intermittent and cannot simply be turned on or off when energy is needed. There have been continual advancements in the area of wind forecasting, but a perfect forecast is still impossible and some level of uncertainty in the variability of the wind will always remain. Wind farms can, in theory, be constructed in almost any location, but it is important to seek out areas with strong wind resources so that the resulting farm can generate enough electricity to remain profitable. As the technology has advanced, wind energy has become more and more cost-competitive with conventional generation. In 2014, average wind energy prices across the United States fell below the range for the nationwide wholesale price.[14] Whether or not a project is cost-competitive, however, depends on the strength of the wind resources present, and it is therefore critical to assess this accurately before investing in new wind development. The costs of poor resource assessment can be substantial. Large-scale wind development often requires significant investments in transmission capacity, as wind farms are typically located far from population centers where the electricity demands are high.[15] Poor planning can result in large inefficiencies if the wind farms do not produce at the expected levels or if the transmission lines are not sized properly.

Wind energy development can also be a contentious issue among local communities. The question of where a farm is built is dependent on more than just the strength of the wind resources. Public support at the local level can play a large role in the success or failure of a project, even if the benefits to society as a whole are substantial.[16–18] It is therefore important to understand the policies in place for incentivizing wind and to study the methods that have been successful previously.[19–21] Better policy design can lead to increased integration of wind energy.

Consideration of long-term climate impacts is also essential when planning for future power system investments and operation, as new investments will face a very different environment than what we know now. Many aspects of our power system will have to change in order to successfully adapt to a future with substantial climate change. The infrastructure involved will face new risks and new demands.[22] For example, increased summer temperatures could push peak demands over our current capacity limits, and changing weather patterns could bring more extreme storms to at-risk regions. We have already started to see changes, and infrastructure decisions made now will certainly have to account for this changing, but highly uncertain future.

Planning challenges today involve attempts to anticipate what this future will look like so that the decisions made today, in terms of investments, technology choice, and operating environments, will still stand up to the challenges of tomorrow.

Addressing these planning concerns is challenging for several reasons. There is a large amount of uncertainty present, and it exists at multiple scales, both spatially and temporally. Many clean and renewable energy sources (such as solar and wind power) are inherently uncertain, and they provide great examples of both spatial and temporal uncertainties. For example, one cannot say for certain where or when the wind will blow at a specific speed. These variable and intermittent resources need to be carefully understood before being incorporated into the power system so that the necessary measures can be used to manage the variability. If properly planned for, renewable sources of energy can play a large role in reducing the emissions of a region's electricity generation, as renewables have zero marginal cost and tend to displace dirtier forms of generation.[23] However, they often need a flexible mix of other generation units, intelligent operation strategies, or large amounts of storage to compensate for the variability. Planning for renewables must take into account both short- and long-term variability in the renewable resource (i.e., the wind forecast for tomorrow and the annual capacity factor) and the regional variability (i.e., sites with strong wind resources, correlation in wind production within a balancing area, or solar production among multiple states.) If we can better understand and characterize these inherent uncertainties, renewable generation can be incorporated into the power system more economically and in greater proportions of overall generation.

For conventional generation, there is still a large degree of uncertainty regarding the climate impacts of greenhouse gas emissions. This is even more difficult to characterize, as the eventual outcome in terms of climate change is dependent upon our actions and decisions made around the entire globe today. The realization of any change is dependent on many factors that themselves are unknown or highly uncertain.[5] The degree of global warming, for example, depends on the rate at which we continue to emit carbon dioxide, and this is closely linked to policy implementation, which adds yet another layer of uncertainty. If we act quickly to sharply curb our global emissions, the worst of the impacts may yet be avoided. On the other hand, our continued reliance on fossil fuels will speed up the warming process and the catastrophic impacts will be felt sooner rather than later. Aside from the temporal uncertainty (i.e., when the impacts will occur), there are also spatial and physical uncertainties that are equally important. Some regions of the world will be more heavily impacted than others, and certain areas may even stand to benefit economically from climate change.[24] The mechanisms of climate impacts are also subject to uncertainty, and this is a critical area of research. Without knowing how a warming climate will impact weather patterns, for example, it is nearly impossible to plan for the risks of extreme weather in an uncertain future. Both electricity generation and consumption depend on weather patterns to some extent (i.e., wind and solar depend directly on weather systems, cooling capacity of thermal generators depends on the ambient temperature, and electricity demand will also change with temperature.) Planning for a future in which these systems behave differently will require projections of these changes to the best of our abilities. Research into these potential changes needs to take place sooner rather than later, as many vulnerable systems cannot afford to wait. In the United States, for example, many of our infrastructure systems are long-lived projects. They are designed with 50+ year lifetimes, so investments made today will still be in operation in what could be a very different climate. Adapting to climate change requires investing in such long-lived infrastructure systems to operate effectively and meet the needs of both current and future customer demands. Decisions need to be made now based on the knowledge that we do have, including an understanding of the deep uncertainties present.

Fortunately, we are quickly improving our knowledge and understanding of these complex issues as well as the tools available to deal with planning and decision-making under uncertain conditions. The growing amount of available data and the increasing computational power of today's machines are allowing for new types of analyses to be performed. This dissertation makes use of some of this available data and uses it in new ways to bring insight to the challenges facing power system risk analysis, planning, and decision-making. I focus heavily on wind energy as a clean, renewable source of electricity generation and provide improved understanding of how best to take advantage of the benefits of wind despite the inherent uncertainty. The work presented here is motivated by climate change at its most basic level, both from a mitigation standpoint with a focus on cleaner energy sources and from an adaptation standpoint by assessing future climate hazards and the resulting impacts. I address a subset of the challenges mentioned previously, and this body of work contributes to solving the challenges facing wind energy development, presents new methods for reducing the operational risks present in offshore wind farms, provides a critical analysis of methods used to estimate wind farm power production, and quantifies the uncertain risks expected in future hurricane seasons.

1.2 Tools and Techniques

The growing availability of data is allowing for innovative analyses to be carried out on existing problems. In addition, computational resources are better able to handle large amounts of data in meaningful ways. Throughout this dissertation, I make use of statistical modeling techniques to learn from the available data in an attempt to capture the relationships among variables that can then be employed in a predictive capacity to provide greater insight into an unknown future.

The tools of statistical learning represent a wide-ranging suite of methods for understanding the relationships in data.[25] At a high level, these techniques can be split into two categories: supervised and unsupervised learning. In the supervised case, there is a target response variable that one seeks to estimate or predict. The relationships between and among the response variable and other variables, or covariates, are used to generate these predictions. In the unsupervised learning case, there is no response variable. Instead, the learning seeks to elucidate the relationships among the different variables in order to better understand any structure that may exist in the data.[26] The methods used throughout this dissertation are all examples of supervised learning. In each application, there is one particular variable of interest that is crucial to the problem at hand. I use the available data to find a function that maps the input, or covariates, to the output, or response variable. Various types of statistical models show up in the following chapters. In general, these models come from one of two families: parametric or nonparametric. Parametric models assign a specific function to the relationship between the covariates and response variable.[26] This functional form is chosen upfront, before feeding any data into the model. The modeling process then determines the parameters (hence the name *parametric* model) that best fit the available data. This process seeks to minimize the errors present in the fitted (or modeled) data. Nonparametric models do not require any assumption about the function relating the inputs to the output. The steps to fit such a model differ depending on the specific model type, but in general, they seek a function that comes closest to capturing the true data points as possible, subject to a possible smoothing function to avoid overfitting.[27]

There are tradeoffs between model types, and the choice of *best* model can depend on many factors, both intrinsic to the dataset itself and external considerations due to the nature of the problem, application, or end-user. Parametric models are often easier to interpret and do not require as many data points to provide a good fit. One downside, however, is that they require an assumption about the form of the model at the outset. If this assumption proves to be incorrect, the model will perform poorly. Nonparametric models do not require these assumptions, and they are good candidates for datasets about which little is known regarding the form of the relationships in the data. However, without a functional form to rely on, nonparametric models typically need a larger amount of data to produce an accurate model.[26] I use both parametric and nonparametric models in the following chapters, and in each instance, the final model choice was determined based on the specifics of the data and application. The models used throughout this dissertation are described in detail in the relevant chapters, and references are provided for an even deeper understanding of the specific algorithms used.

When using statistical models in practice, there is a very important distinction between fit and prediction. The fit of a model is measured by how well it can capture the relationships in the training data; that is, given a specific number of data points, how well does the model recreate the response values that it has already seen? Prediction, on the other hand, refers to a model's performance on a new, independent set of data points (often referred to as test data). This data has not been used to build (or train) the model, so by feeding it into a given model, one can create a true test of the model's ability to accurately capture the relationships among the variables and not just artifacts of the specific data used in training. The challenge of achieving both a strong fit and high predictive accuracy is captured in the bias-variance tradeoff. A model with high variance would give very different results if it were instead trained using a different set of data. Bias, on the other hand, measures a model's ability to capture the true problem well on average with something much simpler.[26] Both bias and variance are related to a model's flexibility. Models with high flexibility tend to overfit the available data. By trying to best capture each data point, we are left with high variance but very low bias. A less flexible model will not capture every data point, and this will result in low variance but much higher bias. By carefully selecting a model so as not to overfit the data (i.e., by finding the correct level of flexibility), both variance and bias can be controlled to produce high predictive accuracy in a test setting. This is the goal of any predictive modeling exercise. Predictive accuracy is often measured using mean squared error or root-mean squared error (other error metrics may be better suited depending on the dataset), and these metrics can then be used to compare different models and determine the best-performing ones.

Each chapter of this dissertation focuses on model prediction as a measure of performance. I am interested in understanding how the models will perform in a real-world setting, where the user is more interested in knowing what will happen tomorrow than what happened yesterday. It is therefore important to test each model using independent data so that the findings are not limited to the existing information that I have access to currently. A model with strong predictive accuracy can be used with confidence with new data going forward.

Cross validation is a powerful tool for evaluating models in a predictive capacity. At its simplest, it splits up a dataset into multiple parts so that a model can be evaluated for predictive accuracy independent of the training data.[27] Some portion of the data is held out of the training set and is then used for prediction as a test set. The holdout data is typically chosen randomly, and this process can be repeated a number of times to also assess the standard error (or amount of variation) of the test error. This is useful for model comparison to ensure that a particular model is robust across all holdouts and did not just outperform the others because of some discrepancy in the individual data chosen. If data is limited, various forms of cross-validation can be employed. Leave-one-out cross-validation allows for the largest training set possible while still maintaining an individual test set. In this approach, a model is trained on all but one observed data point and then used to predict for the single observation that was held out.[26] This is repeated until each data point has been held out for prediction exactly once. An extension of this is k-fold cross-validation. It follows the pattern of the leave-one-out method except that the data is divided into k partitions and each one is then held out in turn as the test set. These holdout methods allow for a model to be tested across multiple datasets, all while using the single dataset available.[27]

1.3 Wind Capacity Investment and U.S. State Policy

Wind energy has been a fast-growing source of generation in the United States over the past decade. On the state level, there are large disparities in the amount of capacity being built. There are also large disparities among the state policies designed to incentivize renewable energy development. The renewable portfolio standards (RPS), for example, are common mechanisms for states to reach renewable generation targets. State RPS's range from nonexistent targets in some states to 100% renewable generation in others. These policies may be contributing to the growth of wind energy in the states with large amounts of installed capacity, but there are other factors at work as well. Strong wind resources are sought after for wind development, and this also varies significantly by state. If these or other factors are the biggest drivers of wind investment currently, knowledge of what works in wind development can be used for improving policy development. If current policies are not driving wind investment, and if they were indeed designed to do so, they should be redesigned to account for what has been found to work well in other areas.

Data mining methods can be used to understand the driving factors behind wind energy investments, but there have been few attempts at doing so up until now. Much of the existing research into the differences in regional investment or the different success rates of renewable energy has been qualitative in nature. For example, see

Breukers and Wolsink.[28] The few attempts at quantitative modeling made use of a limited dataset or a region outside the United States.[20,29–31] In Chapter 2 I apply data mining techniques to a wide range of variables that could potentially influence wind energy investments in a state. This is an exploratory analysis to try to eek out the important relationships and understand which factors have strong predictive accuracy when it comes to determining whether or not a state is likely to have invested heavily in wind. The central issue is determining the extent to which state-based policies are strong predictors for wind capacity, and, if not, whether there are other factors that are proving to be more important.

1.4 Wind Forecasting and Risks in Offshore Environments

Wind farms face greater challenges in offshore environments than they do onshore. Weather is more extreme, maintenance is more expensive, and access can be limited. This is also true for other operations taking place offshore, such as oil platforms and shipping. Many of these offshore operations are dangerous to conduct during periods of very high winds. Predicting these high winds has many advantages. Wind turbine operations can be planned to avoid operating in potentially dangerous conditions, maintenance or construction can be delayed so as to avoid dangerously high winds, and workers can be kept out of severe danger. To date, there is a large and continually growing body of research focused on wind prediction.[32] For the most part, however, this research focuses on the mean value of a wind speed within a given time interval. This quantity is of critical importance for many power system planning and operation decisions, such as day-ahead bidding of a wind farm in an electricity market.

Mean-value wind predictions leave out a lot of information about the variability of the wind within a given time period. Different aspects of the variability matter in different contexts, but from a risk standpoint, the maximum wind speeds are the most critical for maintaining safe and reliable operations. Several studies have identified the importance of high-wind forecasting for purposes of informing decisions regarding grid operation and system safety.[33,34] With high-wind forecasts, a wind farm can be operated in such a way to minimize the transients during time periods with expected forays into wind speeds above the turbine threshold, for example. This is likely to extend a turbine's operating life. In Chapter 3 I focus on forecasting maximum wind speeds in offshore environments for short- and medium-range applications. I use statistical modeling techniques to predict both the expected value of maximum wind and the uncertainty associated with that prediction. By offering probabilistic forecasts, the user is able to better understand the situation at hand and makes better decisions by incorporating this additional knowledge of the uncertainty.

1.5 Assessing Wind Farm Power Production

Accurate estimates of wind farm production are needed in many contexts. For short time scales, this information is needed for power system operation. Knowledge of future wind production is used to determine how much a wind farm operator should bid in to the market or which power plants need to be turned on to meet demand. For longer time scales, wind production estimates drive planning decisions regarding if a farm should be built, where it should be built, and how it will be financed. In addition, transmission expansion decisions are often heavily dependent on future investments in new generation, and wind energy is quickly becoming one of the driving factors behind new transmission planning.[35] Many of these longer-scale planning decisions rely on coarse estimates of potential wind power production. If the eventual reality differs strongly from the initial estimates, inefficiencies and economic losses often result.

Turbine wake effects are a strong determinant of a farm's power production. With given input wind conditions, wake losses typically cause downstream turbines to produce significantly less power than upstream turbines. These losses have been modeled extensively and are well understood under certain conditions.[36–41] Most notably, validation of different model types has favored offshore farms. Models that capture the dynamics of offshore wind conditions do not necessarily perform equally as well for onshore wind farms. In Chapter 4 I analyze the capabilities of several different methods for estimating wind farm power production in onshore farms. I compare a simple wake decay model with a number of statistical models, with using no model at all, and with the estimates produced using meteorological downscaling techniques. I show that the complexities of some onshore farms result in wind conditions that are not accurately modeled by simple wake decay techniques and that alternatives methods have some strong advantages in practice.

1.6 Climate Change, Hurricanes, and the Impacts on Power Systems

Climate change is progressing quickly and impacts are unavoidable. We are now faced with challenges of adaptation in addition to the issues of mitigation that we have been dealing with for decades. A changing climate will impact many different sectors, and the impacts will be felt differently across the globe. One particular concern is the changing nature of extreme weather events. The damages from these extreme events has been steadily rising over the past few decades, and the potential impacts will only grow as economies also grow, placing more and more of our valuable assets at risk. The power system is especially vulnerable, and any negative impacts in this sector have the potential to cascade into other critical infrastructure systems. Historically, tropical cyclones in the United States have caused extensive damage to the power system. Widespread power outages are commonplace in the aftermath of a large storm. If climate change continues to progress, the effects will be seen in changing weather patterns, and this is likely to result in changes to tropical cyclone behavior in the North Atlantic basin. The nature of these changes, however, remains uncertain and traditional risk analysis is difficult in this context.

The large amount of uncertainty present is especially challenging to deal with; decisions must be made with very little information about future climate realizations. There are also multiple layers of uncertainty. For example, even if future climate projections are known with certainty, the exact relationship between climate and tropical cyclone strength, frequency, or location are still unknown. Fortunately, we do have a large amount of data that can be used to bring some light to the problems at hand. I use this available data, including data on the amount of uncertainty present, to assess the sensitivity of the U.S. power system to potential changes in tropical cyclone behavior. By employing this methodology, I can quantify the range of impacts expected and analyze the regional variability of future risks. This information is invaluable to decision-makers faced with difficult choices in the coming years. With proper planning, we can invest wisely so that our power system can withstand the risks faced in a changing climate.

1.7 Scope

The research presented here consists of four essays and they are organized in the following manner. Chapter 2 contains the first essay, and this project uses statistical models to gain insight into the reasons for the state-by-state disparities in wind capacity investment. This work is motivated by state policies and the effects that state-based policies have on wind energy growth. With better insight into the successes or failures of policies, we can work to improve them going forward to promote effective investments in clean energy. I present the data used in section 2.3, describe the models in section 2.4, and present the results of the analysis and a discussion of the research implications in section 2.5.

Chapter 3 contains the second essay and presents models developed to provide short- and medium-term predictions of the maximum wind speed in offshore environments. The motivation for this work is risk-based, as high winds cause safety and operational issues for both offshore wind farms and other offshore operations (i.e. exposed work on oil platforms.) The predictions are available for short- and medium-term planning and operational decisions, and the full distribution is given with each prediction to convey the uncertainty present. I introduce the problem and provide some background on other research in this area in section 3.1. I describe the methodology in section 3.2, including details of generating probabilistic predictions. Section 3.3 presents the case study and available data that the models were tested on, and section 3.4 provides the results for different training methods across lead times.

Chapter 4 contains the third essay, and this project evaluates several methods for wind power resource assessment and farm-level prediction. There are some standard benchmark models that are heavily validated in offshore wind farms, and I show that they are not necessarily appropriate for use in onshore farms with non-uniform turbine layouts. I provide statistical models as alternatives that can be used in this context instead, and I show that they perform well even with very little farm-specific data. I introduce the problem and provide background information on relevant research in this area in section 4.1. This essay focuses on two wind farms, and I present the data and a discussion of data quality issues in section 4.2. The implementation of the Jensen model is described in section 4.3, and the alternate methods tested are described in section 4.4. I present the results in terms of each method's predictive accuracy in section 4.5.

Chapter 5 contains the fourth and last essay. This work seeks to quantify some of the deep uncertainty facing the U.S. power system when it comes to future risks from tropical cyclones. I present a simulation that can be used to assess the changes in risk that would result from different scenarios of climate change in the future. I introduce the problem and offer some background information on the climate-tropical cyclone link in sections 5.1 and 5.2. The simulation structure and the models used within are described in section 5.3. The simulation results for the different scenarios are presented in section 5.4, and this includes a detailed look at metropolitan area impacts.

Chapter 2

Statistical Analysis of Installed Wind Capacity in the United States

2.1 Introduction

The United States had over 40,000 megawatts of installed wind power capacity at the end of 2010.[42] However, there is a great disparity among the states as to where this wind capacity exists. Many states use specific policies to encourage renewable energy development, or even wind energy development specifically. These policies can vary widely among states both in scope and implementation. Many states have chosen to implement renewable portfolio standards (RPS) in order to incentivize renewable energy. There is no federal goal for renewable energy, which allows the states to set targets at a level that they choose, even if it is none at all. While the RPS is one of the most popular forms of renewable energy policy, it does not always include requirements for specific sources of renewable energy.[43]

The effectiveness of these and other policies that have been put in place is not always reflected in the actual energy makeup of individual states. The installed wind capacity has been growing steadily over the past decade, as shown in Figure 2.1. This growth is not consistent across all states, and this chapter examines some of the possible reasons for this inconsistency. Wind development is heavily dependent on federal policies that incentivize renewable energy investment, but these apply to all states and do not account for the differences in wind power across states. For example, the Renewable Energy Production Tax Credit (PTC) has helped to make wind power much more cost effective. Under this policy, producers receive 2.2 cents per kilowatt-hour (adjusted for inflation) of qualified renewable energy that is produced and sold, including wind power.[44] However, the inconsistent history of the PTC is clearly represented in the amount of wind capacity that has been built. The PTC was initially instituted in 1992 and expired in 1999. It was then extended through the end of 2001, when it was allowed to expire. Another brief extension carried it through to the end of 2003, when it again expired and was not renewed until late in 2004. It has continued to be extended since 2005, but only for a couple of years at a time, which doesnt allow for financial long term planning.[45] Of particular note in Figure 2.1

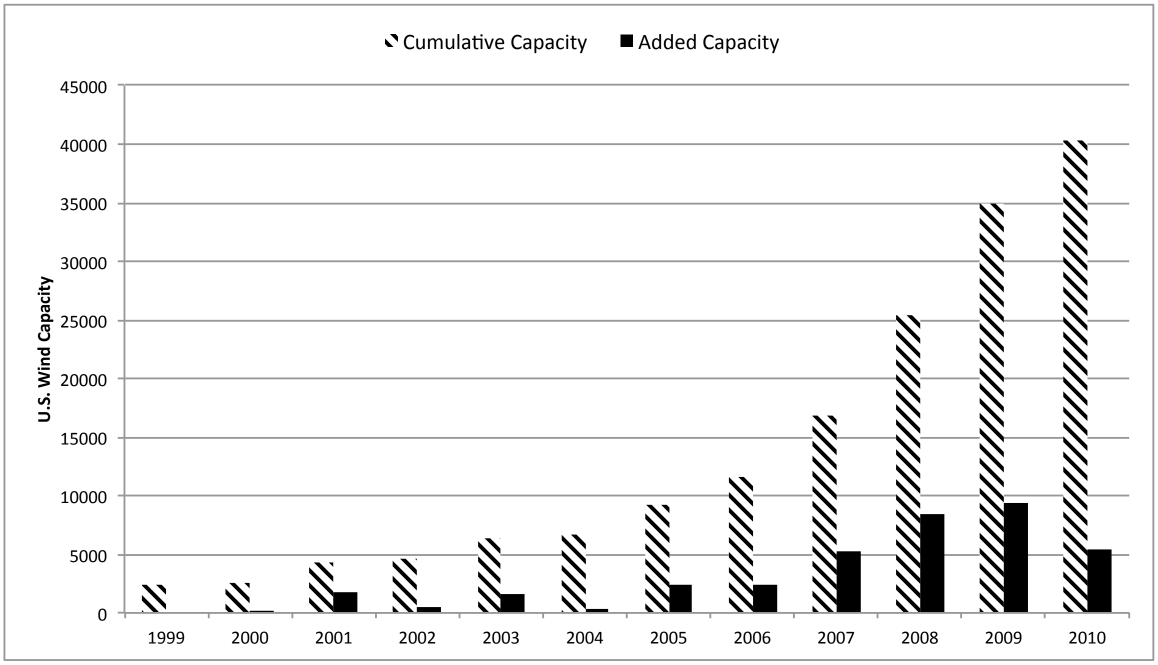


Figure 2.1: Installed wind power capacity in the United States, 1999-2010.

are the sharp drops in new capacity being built from 2001-2002 and from 2003-2004. These correspond to the years when the PTC was allowed to expire. This shows that federal policies can have significant effects on energy investment and development, and it is expected that state policies also influence these same decisions. The reasons behind decisions to build wind capacity are complicated and the results have proven difficult to model.

2.2 Background

There have not been many attempts made at using statistical methods to explain or predict differences in wind power (or any other renewable energy sources) across regions. Much of the research into the discrepancies between renewable investments among countries, regions, or states has been qualitative in nature, and the results present more of a discussion of the reasons behind any differences that were found. There have been a number of case studies that focused on European countries or regions, but there are also a few attempts at studying these issues in the United States as well.

Breukers and Wolsink[28] performed a case study to evaluate the large differences in wind power development in the Netherlands, England, and the German state of North Rhine Westphalia. They compare a number of parameters such as policies and policy stability, government involvement and ownership, public opinion and involvement, and institutional capacity building. Their results are discussion-based and do not include quantitative analysis of what worked or suggestions for future successes. Similarly, Toke et al.[20] compare the wind development in six European countries: Denmark, Spain, Germany, Scotland, the Netherlands, and England/Wales. They acknowledge that wind resources in a region are not always the driving factor, and they study other factors in addition to the wind potential of a country. They find that one of the most important factors is the level at which investment and siting decisions are made and who is involved in those decisions. They also find that most opposition to wind power is extremely localized, and supportive national policies are not always enough to overcome local opposition. Both of these studies were highly qualitative, and much of the data for their comparisons came from policy research and interviews with those involved in wind development.

In a related study, Toke uses regression analysis to look at local factors that influence the outcomes of wind power projects in England and Wales.[31] He focuses on all of the players at the local level, and looks at the influence that support of various groups has on the outcome of a project. Tokes findings show that developers can achieve much better outcomes by engaging local groups in the decision-making process. Economics also seem to play a big role, as local communities seek to benefit directly from wind development and are unsatisfied if policies arent laid out to do so. Tokes findings are insightful, but the studies were conducted on a small and local scale, as the analysis was conducted for individual wind projects in England and Wales. The data was focused on individual opinions of various local parish councils, planning officers, and environmental groups. Policies play a much smaller role here, as all of the sites in question fall under the same national policies and regulations of the United Kingdom.

It is useful to take note of what has worked for certain countries in Europe, but the politics, cultures, and economies of the United States differ substantially from Europe and many of the results of these case studies will not apply in the U.S. Bird et al.[46] studied this issue as applied to the United States, and they looked at the policies, financial incentives, gas price volatility, and market rules to see which were influential in driving wind development in specific states. They studied the states in which wind power has been successfully developed, and attempt to propose lessons learned that could be used to encourage wind projects in other states. They find that the two most important factors are state financial incentives and renewable portfolio standards (RPS) and that these work most effectively in states with high wind resources to begin with. They also find that high natural gas prices are a particularly strong driver for wind development, since it makes wind power much more cost-competitive. It should be noted that this paper was published in 2005, when gas prices were still rising quickly. The drastic drop in price in 2008 makes this finding much less relevant in todays markets.

Menz and Vachon[29] were the first to attempt regression analysis for factors affecting wind power in the United States. They used four different response variables with the same set of covariates. They looked at the fits of wind capacity in 2003, capacity growth from 2000-2003, capacity growth from 1998-2003, and the number of large projects using data that included wind energy potential and the following policy aspects: renewable portfolio standards, generation disclosure requirements, mandatory green power offering, public benefits funds, and retail choice. They also looked at the duration that these policies had been in effect in order to capture the time-dependence and lasting effects of certain policies. Their analysis was performed for only a subset of states. They left out states with little or no wind development or with poor quality wind resources available. After some initial regression analysis, they also chose to leave out California and Texas, with the reason being that these two states had significantly higher wind capacity than the other states being evaluated and they were throwing off the results. This left them with an analysis of 37 states, all with a moderate amount of wind capacity. This introduces a selection bias in the results, since the records were chosen to be fairly similar to each other and the very high and very low capacity states were purposely left out. In addition, since this paper was published in 2006, Texas has become even more of a wind power leader, and is more of an outlier today. California, on the other hand, has fallen to third in terms of wind capacity, having been passed by Iowa, with several other states following closely behind. Menz and Vachon only used linear models to fit their data, and they looked only at R-squared values of fit when forming their conclusions. They did not attempt to predict values based on their dataset. This makes it hard to judge whether the factors they analyzed are the true reasons behind a given states wind capacity, especially given the number of states that were left out of the analysis.

On a much more detailed scale, another analytical study was done by Mann et al.[30] for the state of Iowa. They divided the state up into one square kilometer blocks and used a logistic regression model to predict the locations where wind power developments have been built. The covariates in their analysis included wind energy density at two different heights, population density, cropland, and distance from power lines, highways, and airports. Their results show that analysis on an extremely small and local scale can result in fairly accurate predictions. Unfortunately, many of the covariates do not apply when looking at the state level, since there are significant differences in factors such as policies and economics across states.

2.3 Data

The data used in this analysis consists of variables that are thought to have a possible influence on the amount of wind power capacity built in each state in the United States. The response variable of interest is the built capacity, in megawatts, as of the end of the year 2010 in each of the fifty states. The data have been gathered from multiple sources in an attempt to collect information that can be used to describe the reasons behind the amount of wind capacity that has been built in this country. The data were chosen with the hope that these factors will be able to give a reasonably accurate picture of the causes that affect the vast differences in wind power capacity among the states and to inform decisions as to which factors are most effective in encouraging investments in wind power.

The variables that were used in this analysis cover a broad range of categories, and they include factors such as the political leaning of the individual states government and the level of the states renewable energy portfolio standard. The response variable is the amount of built wind power capacity in megawatts that each state had as of the end of 2010. Similarly, one of the covariates is the installed wind capacity for the year 2000, because it was thought that a states past energy decisions could have a potential impact on the installed capacity ten years later. This capacity information is from the U.S. Department of Energy.[42] Two of the covariates deal with the wind potential for each state, since small and highly developed states are less likely to be able to install widespread wind farms than large, rural states. For the dataset, I included the amount of land available for wind development (in square kilometers) and the percentage of each state that is available for wind development. Available land is defined as areas with a capacity factor of at least 30% at an 80-meter height, while accounting for excluded regions such as National Parks, wetlands, and urban areas. The National Renewable Energy Laboratory (NREL) performed the wind-potential analysis, and the data was accessed through the Department of Energy.[47] Next, I included a few demographic indices. One of these indices is the median income in each state averaged between 2008-2010 (in 2009 dollars), and this data came from the U.S. Census Bureau.[48] In addition, I included the percentage of the state legislature that identifies as Democrat in the year 2006, with the thinking that any wind project would take several years to be built, so a lag of several years was used. This information was obtained from the National Conference of State Legislatures.[49] I also chose to use the amount of cropland in each state (in acres) as a covariate. It has been suggested that agricultural landscapes and the people living there are more accepting of wind development, and by using it as a covariate, the analysis will show whether the data supports this claim (Sowers 2006). The crop data came from the US Department of Agricultures Economic Research Service.[50] Lastly, I included variables that are related to the electricity market and incentives in place for renewable energy. The first of these variables is the average price paid for electricity in each state, and the data were obtained from the U.S. Energy Information Administration.[51] Also included is the renewable portfolio standard data for each state, in terms of the target percentage of their energy that each state is aiming to get from renewables. This information comes from the Federal Energy Regulatory Commission.[52] The final pieces of information come in the form of any financial incentives for renewable energy that are in place in each state. These demonstrate which types of incentives each state has in place, and the incentive programs are broken down based on the form that the incentive takes such as tax, rebate, loan, or other. The tax incentives include personal tax, corporate tax, sales tax, and property tax incentives. The incentive programs that fall into the other category include things such as grants, bonds, and performance-based incentives. This information was available from the Database of State Incentives for Renewables and Efficiency that is funded through the U.S. Department of Energy.[53]

Table 2.1 shows the general characteristics of each variable. Many of the variables have relatively high standard deviations, which shows that there is very high variability among the states in many of these areas. This may be obvious to anyone who is familiar with the United States and renewable energy, but it a useful reminder as to the wide ranges that I dealt with when analyzing this dataset.

2.4 Statistical Models

Several different types of models were compared in order to find the best performer in terms of predictive accuracy. The most basic model used was a generalized linear

Table 2.1: Characteristics of the variables used in the wind capacity analysis. The response variable is the wind capacity in 2010, shown in bold.

Variable	Mean	Standard Deviation	Minimum	Maximum
2010 Wind Capacity (MW)	**805.34**	**1606.64**	**0**	**10089.43**
Available Land (sq km)	43827.65	76569.58	0	380305.9
Available Percentage of Land	18.2%	28.2%	0%	91.0%
RPS Mandate	15.35	11.6	0	50
Electricity Rate (cents/kwh)	10.04	3.55	6.2	25.12
Median Income (2009 $)	$50,647	$7,607	$36,850	$66,303
Democratic Portion of Gov't	0.50	0.15	0.19	0.87
Tax Incentives (binary)	0.94	0.24	0	1
Rebate Incentives (binary)	0.38	0.49	0	1
Loan Incentives (binary)	0.88	0.33	0	1
Other Incentives (binary)	0.74	0.44	0	1
2000 Wind Capacity (MW)	50.79	233.43	0	1615.99
Amount of Cropland (acres)	8,128,498	8,868,885	24,457	33,667,177

model, or GLM. This uses a linear function to model the relationship between the covariates and the response variable by assigning a coefficient to each covariate.[27] This type of model tends to work well when the relationship between the covariates and the response variable is linear, or close enough to be well approximated by a linear function. In addition to a GLM, a generalized additive model, or GAM, was also used in the analysis. In contrast to a linear model, a GAM does not assume a linear relationship between the response variable and the covariates. Instead, it uses a smooth, continuous function that can take on any form.[27] GAMs can work well when the data is highly nonlinear, but they can often over-fit the data due to their ability to pick up even slight fluctuations in the data. It is essential that GAMs be compared on their predictive accuracy and not their fit for this reason. A multivariate adaptive regression spline model, or MARS, was also tested on this dataset. This type of model uses piecewise-linear functions to build up an estimate of the relationship between the covariates and the response. These local linear approximations are added together to create the full basis function, after which individual terms are deleted in order to simplify the model and obtain better predictive accuracy.[54] It uses generalized cross validation to decrease the size of the model, thus avoiding the problem of over-fitting the data.

Lastly, a number of tree-based models were tested. Classification and Regression Trees (CART), bagged CART, Bayesian Additive Regression Trees (BART), and Random Forest models were applied to this dataset. The CART model grows a large tree by splitting the data recursively into smaller and smaller partitions and then prunes back the large tree into a smaller and simpler tree by penalizing complexity in the model.[55] The Bagged CART model is similar, but it applies bootstrap aggregation in order to improve predictive accuracy. The BART model uses Bayesian priors and builds a large number of very simple, weak learner trees, and then aggregates the predictions from each tree using a Markov chain Monte Carlo method to sample from the posterior distribution until convergence is reached.[56] This method allows for each relatively simple tree to be used to explain only a small portion of the response variable.

The last tree-based method that was applied to this dataset is random forest. This method again uses bootstrapping, but it grows a tree from each bootstrap sample. This results in relatively uncorrelated trees. By averaging predictions across a large number of these trees, the variance of the predictions is generally reduced.[57] The trees in random forest use a randomly selected subset of variables and choose optimal splitting points until a selected minimum node size is reached. These trees are not pruned, as they are in a CART model, for example. Instead, the minimum node size and random bootstrap samples usually keep the individual trees from being overly complex, and the averaging across all of the trees can often result in accurate predictions for a dataset.

2.4.1 Model Evaluation

In order to compare the predictive accuracy of these models, a holdout analysis cross-validation was performed. This method trains the models on a portion of the data, setting aside a test sample to be used later. For this analysis, I held out a randomly assigned 20% of the data for each of 100 holdout runs and compared the results of different model types for each run. I included two linear models, since they are relatively simple and a good point of comparison. One used variables based on some initial studies of GLM fit, and the second GLM used a step-based form of variable selection that allowed the model to choose the best variable combination within the cross-validation. I included one GAM for comparison as well, although some earlier attempts at using GAMs for this data did not produce very good results, and the GAM was not expected to perform well in the holdout analysis. I included a MARS model, even though this type of model is fairly similar to a GAM and is again not expected to predict well for this dataset. Lastly, I included the tree models discussed previously.

The variables in the dataset did not have high correlation factors, and the variable inflation factors were low for the linear models, so a principal component analysis transformation of the data was deemed to be unnecessary. The data was standardized before the models were trained. Many of the covariates are on different orders of magnitude and standardizing the data allows for a more intuitive comparison of variable influence. Many variable combinations were tried for the GLMs and GAMs. Although it is easy to evaluate for fit using methods such as the likelihood ratio test, assessing a models performance for prediction is only possible in the context of a holdout analysis. Even so, some of the variables could be removed from the models due to extremely high p-values. One of the linear models used in the holdout analysis contains a subset of the covariates based on the best fitting model. The other linear model allows for automatic variable selection by adding and subtracting covariates in order to end up with the best predictive model. Similarly, it is easy to choose variables for a GAM based on fit, but the GAM also allows for automatic variable elimination in order to end up at a simpler model.

2.5 Results and Discussion

The holdout analysis compared 8 different models in addition to the mean-only prediction, resulting in 9 total predictions to compare. The prediction error results are shown in Table 2.2. The random forest model has the lowest overall mean absolute error (MAE) at 514. It also had the lowest mean squared error (MSE.) In order to accurately compare the results of the 9 different models, a Bonferroni correction was applied to the results of t-tests between all of the model combinations. A Bonferroni correction accounts for the multiple, simultaneous hypothesis tests being conducted on the same data. It is necessary in this case since there are 9 models being compared. The corrected t-test values are shown in Table 2.3. The Random Forest model is significantly better than the mean-only model in terms of predictive accuracy. It also outperforms many of the other models tested, and I identified it as the best model for this dataset.

Table 2.2: Holdout analysis results: mean absolute error (MAE) and mean squared error (MSE)

	GLM1	GLM2	GAM	BART	CART	MARS	Bagged CART	Random Forest	Mean Only
MAE means	1,048	1,033	1,171	600	636	1,140	555	514	924
MAE std dev	882	949	1,339	290	388	965	322	299	286
MSE means	10,049,311	10,643,473	21,379,770	1,510,463	1,705,590	11,051,960	1,456,377	1,280,061	2,174,501
MSE std dev	36,187,916	43,562,519	82,762,292	2,439,893	2,415,892	43,083,895	2,474,729	2,277,692	2,993,220

Table 2.3: Corrected t-test values for model comparison using Bonferroni correction

Model	GLM1	GLM2	GAM	BART	CART	MARS	Bagged CART	Random Forest
GLM2	1.00							
GAM	1.00	1.00						
BART	0.00015	0.00098	0.00222					
CART	0.00129	0.00603	0.00729	1.00				
MARS	1.00	1.00	1.00	0.00002	0.00012			
Bagged CART	0.00002	0.00018	0.00067	1.00	1.00	0.00		
Random Forest	0.00	0.00003	0.00019	1.00	0.47602	0.00	1.00	
Mean	1.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00

The predictions for the random forest model are shown in Figure 2.2. As expected, the plot for random forest shows low variance in the predictions. The data points are closely grouped along a recognizable line, and the predictions match up well with the actual values. It had the lowest absolute errors overall, although it appears that it tends to underestimate capacity slightly across the board.

The random forest model does not assume linearity. Tree models in general are very flexible and can handle high variance in the data very well.[57] The wind data for these models is, for the most part, non-linear. This is one of the reasons that the random forest model outperforms some of the other models. Some of the other tree-based models also performed reasonably well, probably for the same reason of accounting well for non-linearity in the data. The GLM, GAM, and MARS models have errors that are higher than the mean-only model. It is likely that the GAM and MARS models tended to over-fit the data, which resulted in poor predictions. The GLM models may have been too simplistic to represent the relationships in the data.

2.5.1 Variable Importance

The importance of variables in a Random Forest model is determined by assessing the degree to which removing a variable from the model causes a reduction in the out-of-bag error. Removing the most important variables will account for the largest reductions in predictive accuracy, since the model is then left to use a subset of less influential variables. This importance measure, which can be interpreted as

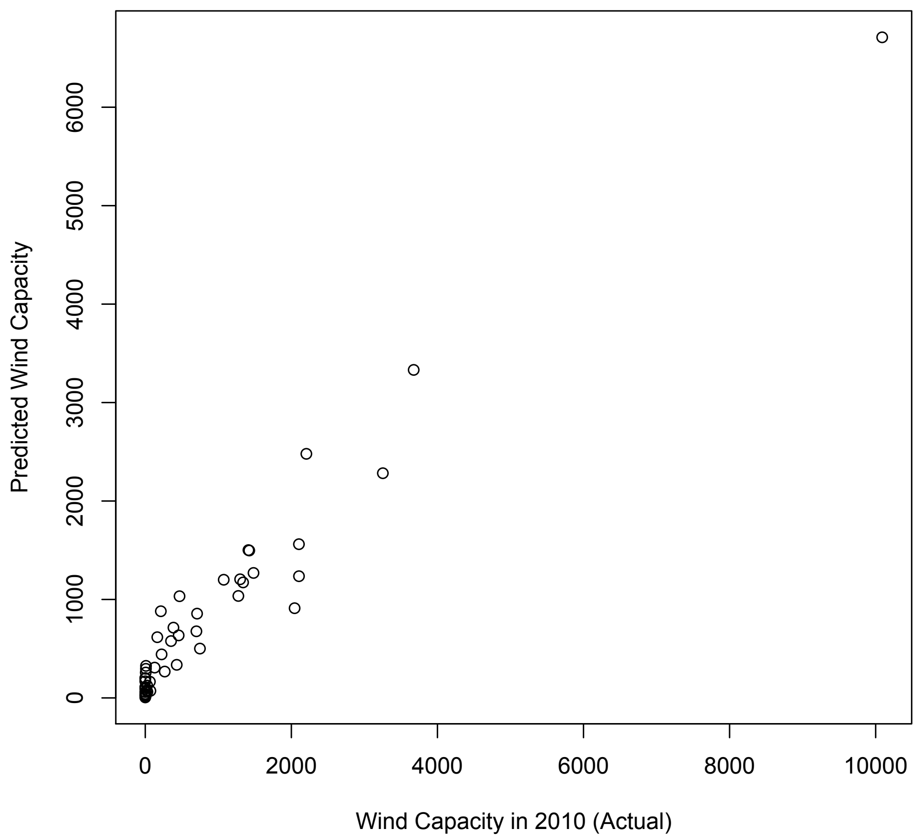


Figure 2.2: Random Forest predicted values vs. actual wind capacity

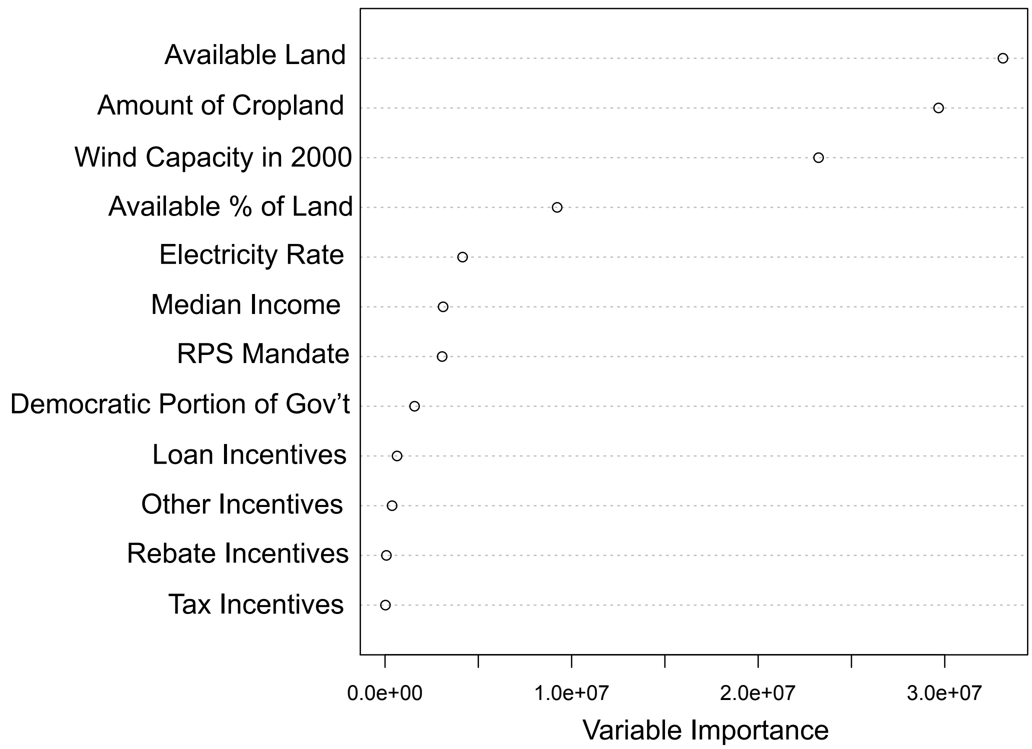


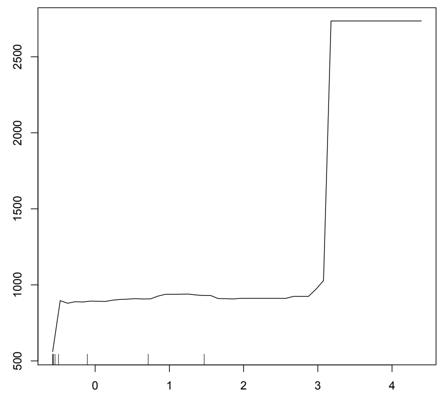
Figure 2.3: Variable importance plot for Random Forest model

the relative influence of the covariates, is shown in a Variable Importance Plot in Figure 2.3. The top four most influential variables are consistent with the most significant variables identified in many of the other models. The amount of available land is identified as the most important in terms of error reduction, followed by the amount of cropland, the built wind capacity in 2000, and the available percentage of land.

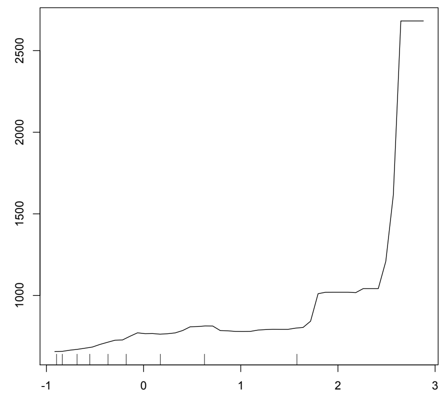
In order to visualize the level of influence of each of these variables, partial dependence plots are shown in Figure 2.4. Each plot shows the marginal influence that that particular variable has on the response. This is done by varying one variable at a time over its range and then evaluating how the response variable changes with respect to that variable alone. It should be noted that the ranges of each variable have been standardized for these plots, so a value of zero on the x-axis represents the mean value for each variable. These partial dependence plots are highly nonlinear for most of the variables of interest. This helps to explain why the Random Forest model generally outperforms many of the models that assume linear relationships between the covariates and the response, since it is able to deal with highly nonlinear data. The individual plots depict the nature of that variables influence on the response variable, which is the amount of installed wind capacity in the year 2010. The partial plot for the amount of available land for wind development shows a positive influence on the response, and there seems to be a threshold at which the response takes a big jump up, showing that the states with extremely high wind resources are more likely to invest in wind power. A similar relationship can be seen for the amount of cropland. It has a steadily increasing positive influence on the wind capacity in 2010, and the plot also jumps up towards the end for states with extremely large areas of cropland. The plot for the wind capacity in 2000 shows a positive influence, as expected, but it stays level after the initial jump. This seems to show that there is a barrier to a states initial investment in wind power, but after the first project, they are more likely to continue investing in wind. The available percentage of land in each state has a positive influence on the response variable for the most part, up until the higher values when it starts to drop off slightly. In addition to the top four variables, the partial plots for median income and RPS mandate are also included. The median income of a state seems to have a slight positive influence, but only up to the point of the initial jump, and the plot stays fairly steady from there on. The shape of the RPS mandate plot seems to be counterintuitive. Higher renewable portfolio standards would be likely to drive more investment in wind projects, but that doesnt necessarily seem to be the case. After the large initial spike and subsequent drop, the latter part of the plot levels out. The reason for the initial spike is unknown, but I hypothesize that it is greatly influenced by a few individual states, such as Texas and Iowa. Texas has, by far, the most installed wind capacity, but it also has one of the lowest RPS mandates. Similarly, Iowa has the second most wind capacity and a very low RPS mandate. These states show that the relationship between the RPS mandate and wind capacity is not as well defined as expected. It should be noted that the importance of these last few variables (available percentage, mandate, and income) are much lower than the top three mentioned previously. Looking again at Figure 3, there is a large gap between the importance of the capacity in 2000 and the rest of the variables below that.

2.6 Conclusion

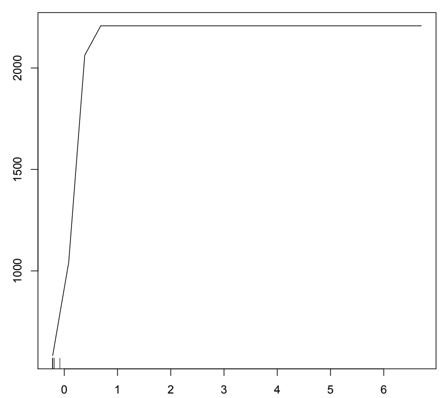
As expected, the amount of wind resources in a given state has a strong positive influence on the amount of built wind capacity in that state, and it proves to be



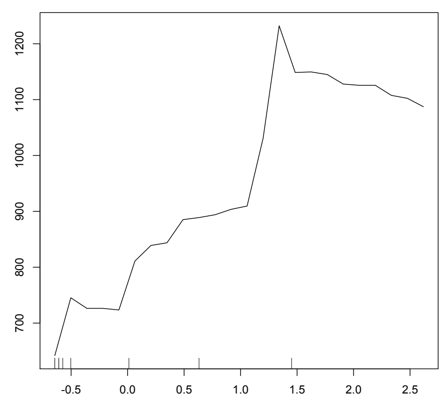
(a) Available Land



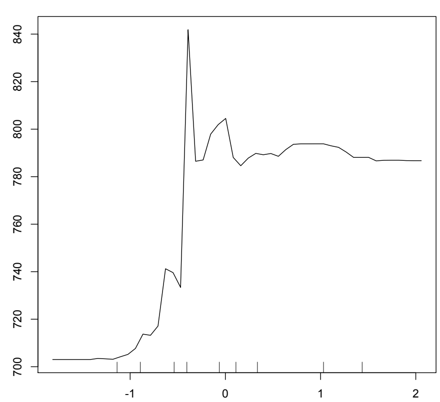
(b) Cropland



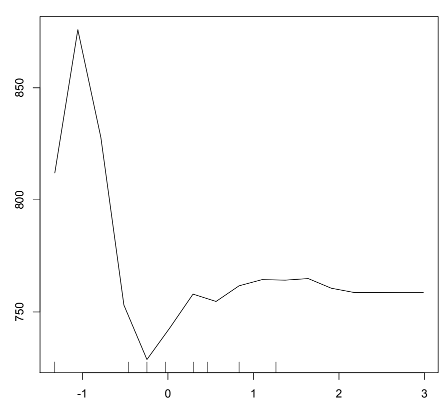
(c) Capacity in 2000



(d) Available Percentage of Land



(e) Median Income



(f) RPS Mandate

Figure 2.4: Partial dependence of selected variables in Random Forest model

the most influential parameter in making accurate predictions. This result is not surprising, nor is the finding that the amount of cropland also has a strong, positive influence. Previous studies have looked at the reasons for this and noted that agricultural areas are receptive to wind power. The results of our analysis support the idea proposed by Sowers that cropland would be a positive predictor for the amount of wind development.[11] The most surprising finding is that state policies seem to play a very small role in predicting wind power development. From the qualitative studies discussed earlier, policies should be very influential in driving state renewable energy investments. However, this turned out not to be the case in the models tested. Since these policies are specifically developed to incentivize investments in renewable energy (and sometimes even in wind energy explicitly,) they do not seem to be as effective as intended. A states renewable portfolio standard is designed to encourage investment and development of renewable energy sources, and yet it is only the fifth most important variable in the random forest model. Of course, the RPS is not specific to wind energy, and a state can meet its requirements by using any number of renewable sources. States that have a large solar resource, for example, would be more likely to meet the RPS using solar power as opposed to wind, and this flexibility could account for part of the reason behind the RPS not showing up as significant in the model. Our study also does not account for renewable energy contracts between states or the trading or renewable energy credits. Renewable energy credits (RECs) allow for states to meet their RPS mandates by purchasing credits for energy generated elsewhere. This leads to a complicated system of trading clean energy, which is not captured in the models presented. There were also financial incentives included in the dataset, and these did not show up as being significant at all. One reason for this could be that federal policies take precedence when deciding to invest in wind energy, and something like the production tax credit drives development far more than any local incentives that are put in place by individual states. The production tax credit has been shown to be very effective in encouraging wind energy development nationwide, but the state-based incentives do not seem to have much impact at all on wind power expansion in a given state.

It makes sense that the amount of wind resources available in a region would be important in terms of predicting the wind power development in that region. High quality wind resources will increase the likelihood that a project is profitable, since the farm will be producing more power than a farm located in an area of poor wind resources. The states that had previously made investments in wind power have been shown to be more likely to continue building their capacity. Although this study does not look into the reasons for the investment in wind prior to 2000, it is safe to assume that the same major factors, such as wind resource and cropland, were driving those decisions as well.

One of the drawbacks to this study is the small dataset. With only 50 states, it is difficult to deal with any outliers that may exist. States with extremely high or extremely low values of installed wind capacity can throw off the results of the trained model. Texas, for example, has almost three times more installed wind capacity than Iowa, which is second in capacity values. More accurate results could be possible by breaking the country up into smaller regions. Since state policies do not seem to have a strong influence on wind development, the geographic and demographic parameters could easily be captured on a smaller scale, and may prove to give even more accurate predictions for each region. This approach would be similar to the study conducted by Mann et al. discussed earlier.[30]

The interactions of policies and incentives for developing renewable energy in general, and wind power specifically, are complex. The decisions made by investors looking to build new wind farms are surely based on a number of considerations that are not captured in these models. Even so, this study has shown that there are some factors that are easy to measure and track, which can help to explain many of the differences in wind development among states. The policies currently in place do not provide enough of an incentive for significant investment in wind development. If individual states are looking to take advantage of wind power, the current policies need to be evaluated for effectiveness. If the United States is committed to developing renewable energy, it is likely that new policies will need to be instituted that will be more effective than the ones currently in place.

This research was originally published in *Energy Policy*.[58]

Chapter 3

Probabilistic Maximum-Value Wind Prediction for Offshore Environments

3.1 Introduction

Many offshore commercial activities are heavily reliant on weather forecasts for safe and efficient operations. Offshore wind farms are an obvious example; wind predictions are heavily relied upon for planning both farm and power grid operation schedules, but other offshore operations (i.e. oil platforms and shipping) are just as dependent on weather forecasts, and wind forecasts in particular. Knowledge of future wind speeds can improve the reliability, safety, and profitability of many operations. High wind speeds in particular can pose a significant risk to offshore structures and to workers exposed to high-wind conditions. A study of helicopter crashes related to oil and gas operations in the Gulf of Mexico, for example, found that 16% of accidents were due to adverse weather conditions that hinder work for offshore facilities, and almost a third of those cases were attributed to high winds.[59] With wind turbines specifically, they are designed to shut off when wind speeds reach a certain threshold, but even below this threshold, frequent operation at high wind speeds can cause significant damage to a turbine. Turbine reliability decreases with increasing exposure to high wind speeds or high accelerations.[60,61] Managing these risks can be done, in part, by integrating forecasts specifically for maximum wind speeds into the decision-making process when planning offshore operations, and these operations may extend to the fields of wind farm scheduling, wind turbine control, maintenance planning, offshore oil platforms, or shipping operations. In this chapter, I take a risk-based view of wind variability and focus on this one aspect of wind behavior: very high wind speeds for offshore applications. I demonstrate the capabilities of simple statistical models to forecast maximum wind speeds, and these predictions can be used to improve safety and operations for wind farms, offshore platforms, and shipping traffic.

3.1.1 Background and Existing Literature

There is a large body of work on wind speed prediction, and it has only continued to grow as the penetration of wind energy increases worldwide. The economic viability of wind is directly dependent on high quality wind forecasts, and this has led to great interest in improving wind-forecasting techniques. Wind is highly variable, and this can make accurate predictions difficult, especially when forecasting for very short time periods. It is usually more straightforward to forecast mean-value wind speeds for larger time scales, and much of the work in this field has focused on these mean-value forecasts and building better models with higher degrees of accuracy. An excellent overview, which details the various methods and techniques used in this field, can be found in a literature review by Giebel et al.[32] This chapter details the different forecasting approaches, including persistence models, numeric weather prediction, statistical models, and combinations of the aforementioned methods. For those interested in the use and application of wind forecasts, a report by Argonne National Laboratory gives a broader look at these issues.[62] This report covers the full spectrum of challenges present when integrating wind power: wind forecasting, subsequent power forecasting, estimating and presenting uncertainty, unit commitment of wind, and power grid operation with wind generation. Of the many proposed methods for wind prediction, strong examples include artificial neural networks, linear models, ensemble methods, and nonparametric approaches.[63–66]

Average-value forecasts are needed for planning, but they fail to capture the variability occurring within the associated time periods being evaluated, which are often one hour or more. The wind speeds within that period can deviate drastically from the mean-values forecasted.[67] Of this variability, maximum wind speeds are particularly important when assessing the risks to structures, workers, and ongoing activities. This risk is more of a concern in offshore environments because the wind speeds are often higher in general.

The field of offshore wind in particular would benefit strongly from maximum-wind forecasts, since farm operations are often scheduled a day in advance and turbines are susceptible to damage from extremely high winds. Power systems are already designed to deal with uncertainties and variability, historically in the realm of load forecasts.[33] Adding in the variability of wind is within the experience of system operators. However, as with load forecasts, wind forecasts are also needed to manage the uncertainty. An accurate knowledge of wind speeds is critical for efficient planning and operation of wind farms.[33,34,68] Electric grid operations are scheduled based on predicted mean wind speeds and subsequent power output estimates. Knowledge of the mean wind speed, however, does not give a full depiction of wind behavior, which can often vary greatly within very short time periods.[69] Therefore, in addition to mean value wind predictions, there is also a benefit to be gained from knowing what the maximum value winds will be in a certain time period. A careful operation scheme, where, for example, turbines are preventatively shut down when very high maximum wind speeds are predicted, could greatly increase turbine life and improve the current operating condition of the grid.

Several studies have identified the importance of high-wind forecasting for purposes of informing decisions regarding grid operation and system safety.[33,34] With the added high-wind forecasts, a wind farm can be operated in such a way to minimize the transients during time periods with expected forays into wind speeds above the turbine threshold, for example. In addition to farm operations, there are considerable safety concerns associated with high wind speeds. Wind farm construction and maintenance are all dependent on acceptable weather conditions, and the safety of the workers can be severely jeopardized if wind speeds pick up when they werent expected to. The same applies to offshore drilling platforms. Exposed maintenance operations, for example, should not be conducted if wind speeds rise above certain safety thresholds. Scheduled maintenance can be planned for periods with low predicted maximum wind speeds, thus reducing the exposure of the crew and equipment to high, and often dangerous, winds.

The body of work focusing on maximum winds, gust winds, or extreme value winds in short-term wind applications (i.e. on the order of several hours to a day) is much smaller than the work focused on mean-value winds. Gusts are usually defined as a three-second average above a threshold. Maximum winds are similar, but represent only the highest value recorded in a given time-period, without averaging and without a threshold. While the definitions of maximum wind speed and gust wind speed differ, the motivation for forecasting these high-speed wind events is similar. There are risks associated with both high maximum winds and strong gusts, and the literature looks at both.

Extreme-value theory is an often-used method for analyzing extremes of a parameter, but it is usually applied on long time scales, on the order of years.[70–72] Several studies have analyzed the annual maximum wind values using a generalized extreme value distribution.[73,74] This type of analysis is useful when deciding on design criteria to ensure that structures can withstand the fifty or one-hundred-year winds, but these values can often be underestimated.[75] In addition, these longer time scales are not useful for many planning operations, since decisions are made for time periods of hours or days ahead. This method has been successfully applied to daily wind speeds, however.[76] Research in the realm of gust predictions has been done by Brasseur using purely physical factors and by Ágústsson and Ólafsson using atmospheric models and highly localized terrain data, among others.[77,78] Thorarinsdottir and Johnson have developed a model to predict wind gusts using a gust factor and a probabilistic forecast for the maximum wind speed and appearance of gusts.[79] They use nonhomogeneous Gaussian regression to predict the distribution of daily wind speed and gust speed. The probabilistic nature of their models conveys a lot of information to the user, but the forecast is issued as the distribution for a given day in the future, and this time interval is often too long to be of great use when planning operations and maintenance. With a more risk-centric application, Petroliagis and Pinson evaluate the relationship between extreme wind events and medium-term (i.e. on the order of several days) warnings of extreme events.[80] The motivation for their work is similar to the research presented here; advance knowledge of high wind speeds can result in better decision-making regarding the safety of many operations, both onshore and offshore.

3.1.2 Chapter Objectives and Structure

In this chapter, I build upon the techniques used for predicting average-value wind speeds and instead focus on predicting, probabilistically, the maximum-value winds for a given location with forecast lead times reaching from zero hours out to five days (120 hours). I use simple statistical models and focus on maximum-winds that are not necessarily extreme, according to statistical properties. I compare several models and assess their predictive performance at various lead times using different training methods. The probabilistic predictions accurately capture the variability of the maximum wind speed and convey more useful information to the end user. I present the methodology in section 3.2. I apply these methods to a dataset of measured and modeled meteorological parameters for a chosen location in the North Sea, as discussed in section 3.3, and the results are shown in section 3.4.

3.2 Probabilistic Forecast Methodology

Our goal is to produce accurate probabilistic predictions, for both short- and medium-range forecast windows, for the maximum wind speed in a given time interval and a given location. For our purposes, I define maximum wind speed as the highest value sampled at a rate of 1 Hz during a ten-minute interval. By issuing probabilistic forecasts, I capture the variability of the maximum wind speeds and allow the user to factor in this uncertainty when making decisions about offshore operations, whether for a wind farm, offshore platform, or shipping activities. Although I am developing statistical models for the maximum-value wind speeds, our proposed method first determines the expected value, or mean, of the maximum wind speed and then determines the full probabilistic distribution around this mean (of the maximum) wind speed. The models used are trained to predict the expected value of the maximum wind speed. I assume that the maximum wind speed values are Gaussian of the form $\mathcal{N}(\mu, \sigma^2)$ with mean μ and variance σ^2. In order to build up the full distribution of wind speed, I estimate the mean and variance parameters separately. The models are developed to predict the mean value of the maximum speed, μ, and I use the parameters of the residual training errors to determine the variance, σ^2 (or standard deviation, σ.) The standard deviation of the residual training errors is used as the standard deviation of the new predicted distribution for each individual point forecast issued. The resulting predictions portray a normal distribution for the maximum wind speed in each time interval, so that any probabilistic prediction intervals can easily be calculated.

The model training and prediction process is conducted independently for each lead time. The full dataset is subset according to lead time. This subset is then split into two sequential groups; the first is used to train the models and the second is used to issue predictions. The models are trained on each training set for each lead time and then applied to predict new data points for the same lead time. The models, and therefore the model residuals, are specific to each lead time. The relationships among the covariates and the relative importance of the covariates in the models will likely differ for predictions issued at different lead times. Our method allows for the models to capture these changing interactions and variable importance.

3.2.1 Model Development

For preliminary model evaluation, I tried a large number of statistical model types and variable combinations. Based on the models that performed well in a few sample test cases, I was able to narrow down the field of feasible options. The model types initially tested included linear models, generalized additive models (GAM), random forests, multivariate adaptive regression splines (MARS), bagged classification and regression trees, and support vector machines.[27] For each of the models, variable selection was used to determine the best combination of parameters to be used; the combination of variables included differs for the different model types as a result. The models were compared based on their predictive errors: mean absolute error and root mean squared error. Based on the preliminary testing, three models were identified for further testing. A linear model, a GAM, and a MARS model all performed well. These three were then tested extensively for different forecast times, lead times, and training methods. The formulation of these three models is as follows. Given a vector of inputs, $\boldsymbol{X}_t^T = (X_{1t}, X_{2t}, \ldots, X_{p_t})$ and a response variable, Y_t for lead time t and the number of covariates p, the three model types discussed are given by the following formulations:

Linear Model Formulation:

$$Y_t = \beta_{0t} + \sum_{j=1}^{p} X_{j_t}\beta_{j_t} + \epsilon_t$$

where β_{0t} is the intercept term for lead time t, the β_{j_t}'s are the coefficients of each input variable for lead time t, and ϵ_t is the error term of the form $\mathcal{N}(0, \sigma_t^2)$, a normal distribution with zero mean and finite variance, σ_t^2. This assumes a purely linear relationship between each of the input variables and the response variable, maximum wind speed.

GAM Formulation:[81]

$$Y_t = \beta_{0t} + f_{1t}(X_{1t}) + f_{2t}(X_{2t}) + \cdots + f_{p_t}(X_{p_t}) + \epsilon_t$$

where β_{0t} is the intercept term, each $f_{it}(X_{it})$ specifies a function of each X_{it}, and ϵ_t is the error term of the form $\mathcal{N}(0, \sigma_t^2)$. The smoother functions take the form of cubic regression splines. The model is fitted by simultaneously estimating all p functions, allowing for nonlinear relationships between some or all of the input variables and the response.

MARS Formulation:[54]

$$Y_t = \beta_{0t} + \sum_{m=1}^{M} \beta_{mt} h_{mt}(\boldsymbol{X}_t) + \epsilon_t$$

where β_{0t} is the intercept term, the β_{mt}'s are the coefficients associated with each basis function, $h_{mt}(\boldsymbol{X}_t)$, M is the number of basis functions, and ϵ_t is the error term of the form $\mathcal{N}(0, \sigma_t^2)$. The basis functions can be formulated as hinge functions of the form $h(X_t) = (X_{j_t} - c)_+$ with c representing the location of the hinge, or as the product of two or more functions of the same form. These allow for nonlinearities of certain input variables or interactions between multiple input variables.

The models were trained using the R software environment, and the functions for linear models, GAMs, and MARS models can be found in the stats, mgcv, and earth packages, respectively.[82–84] The variable selection process is conducted separately for each model type. I initially assess variables using model fit as the guiding parameter, and well-performing variable combinations are then compared based on predictive accuracy.

3.2.2 Probabilistic Forecasts

Any prediction made is associated with a certain degree of uncertainty; this is inherent in the process. Predictions are often given as one deterministic value; for example, a typical weather forecast may predict that tomorrow will have a high temperature of 36 degrees. The uncertainty in this forecast is not passed along to the public. The uncertainty around a deterministic forecast is often as important as the forecast itself. For this reason, I focus on developing statistical models to provide probabilistic predictions of the maximum-value wind speeds instead of a single, deterministic value. There is a real benefit to be gained through the use of probabilistic weather forecasts, and this has been demonstrated frequently in the literature. Reliable, and even moderately reliable, probabilistic forecasts outperform standard forecasting practices, resulting in lower costs and higher value to the user.[85] When dealing specifically with wind forecasts, it has been shown that including the uncertainty in forecasts results in an increased market value for the forecast itself.[86] This increase in value is important, as it represents one of the three main measures of forecast goodness as described by Murphy.[87] The statistical models aim to produce accurate (i.e. high quality) and consistent forecasts, and the probabilistic aspect of the predictions only serves to increase the value to the user.

As stated earlier, I assume that the maximum wind values are Gaussian of the form $Y_t \sim \mathcal{N}(\mu, \sigma^2)$. The models presented here offer mean-value predictions, μ, for the maximum wind speed in a given time period. The predicted values represent the expected value of the probabilistic density function for the maximum wind speed in that time period. To estimate the distribution around this expected-value point prediction, I use the residuals to obtain the variance, σ^2 (and standard deviation, σ) in order to develop the prediction intervals around the expected value. I start by looking at the model residuals from the training set. The residuals are defined as $r_i = y_i - \hat{y}_i$ where y_i is the actual value and $\hat{y}_i$ is the predicted value for all i data points. I fit a normal distribution to the residuals, and determine the standard deviation based on the fitted curve. This standard deviation (of the residuals from each model) is then applied to each prediction made by the model to estimate the full distribution of the errors around the predicted expected value, μ. With the assumption of normality in the errors, the residual standard deviation, and the predicted expected value for the response, the distribution is fully defined for each future observation being predicted. The probabilistic predictions for a given data point can then be issued either as a full distribution or as defined quantiles of the distribution. This method was compared to the standard method for obtaining predictive intervals and found to be in good agreement. The method used here has the advantage of estimating the full distribution directly, and it can be used for any type of statistical model for which the residuals can be easily calculated.

The usual methods for assessing model predictive performance, such as mean absolute error or (root) mean squared error, cannot be used for probabilistic forecasts, since there is no single value of the distribution to compare. Instead, alternative metrics need to be used for evaluating probabilistic forecasts; here, I use the continuous ranked probability score, or CRPS, as our method of comparison. The CRPS compares the cumulative distribution function (CDF) of the prediction with that of the actual. In this case, the actual is simply an observation, but it can still be represented as a CDF. The CRPS is defined as follows:

$$CRPS(F, x) = \int_{-\infty}^{\infty} (F(y) - \mathbb{1}\{y \geq x\})^2 dy$$

where F is the CDF of the probabilistic forecast, x is the actual observation, and $\mathbb{1}\{y \geq x\}$ designates the function that takes a value of 1 if $y \geq x$ and 0 otherwise. The CRPS is exactly equivalent to the mean absolute error (MAE) in the case where the forecast is also deterministic.

3.3 Data and Application

In order to demonstrate the proposed models and assess the performance of the probabilistic predictions, I apply the methodology discussed in the previous section to a dataset of forecasted and measured wind and meteorological conditions for a location in the North Sea. I couple measured data from a meteorological tower with forecasts issued for the same location. The forecasted data is used to train and develop the models, and I assess the performance of the predictions against the actual measured data. Both the measured data and forecasted data were obtained for the time period starting in February 2010 and ending in May 2013. Wind data typically cycles on several different temporal scales. The most familiar cycles are daily and seasonal fluctuations. In addition to these, wind data sometimes has longer-scale cycles, lasting a year or more.[88] Having over three years worth of data allows for models that are not dependent on a single cycle, and this amount of data serves as a good representation of typical behavior in the designated area. The details of the data used for our application are discussed subsequently.

3.3.1 Measured Data

Germany has installed three large offshore meteorological towers in order to collect data in designated areas where they are planning for large amounts of future offshore wind development. The three towers are referred to as FINO1, FINO2, and FINO3, and are all located in the waters north of Germany. For the purposes of this project, I chose to use the FINO1 data because of its long history of data collection and its location in a prime wind-development region. This tower is located in the North Sea waters off the coast of Germany, just north of the border between Germany and the Netherlands. The tower has been collecting data since 2003, and Germany is planning for projects adding up to almost two gigawatts of installed wind capacity in the area around the FINO1 tower in the near future.[89]

These towers are collecting a wide variety of data, including measures of wave height, wave direction, pressure, temperature, humidity, lightning events, sea currents, shipping traffic, and, of course, wind. The wind available data includes measures of wind speed and direction at 33, 40, 50, 60, 70, 80, 90, and 100-meter heights. The data is given as ten-minute averages, with the minimum speed, maximum speed, and variance also given for each ten-minute interval.[90] This additional information about the range and variability of the wind speeds give a more detailed picture of the actual wind behavior. With wind turbines increasing in both capacity and size, I chose to use the 100-meter data for our model development and predictions. This is expected to be the closest to turbine hub-height for the next generation of offshore wind turbines. This actual, measured data from the FINO1 tower is used to test and train models in tandem with the forecast data, which is discussed below. Missing values make up 3% of the measured data, but this is a very small percentage overall, and dropping the missing values in model development is not expected to have much of an effect.

3.3.2 Input Weather Forecast Data

In addition to the measured data discussed above, the models also use a number of parameters from weather forecasts issued by the European Center for Medium-Range Weather Forecasts (ECMWF).[91] These parameters are used as inputs to our models, and I use them to then issue our own predictions for maximum wind values.

ECMWF runs their global meteorological models to issue forecasts twice a day, at 00 and 12 UTC. This data can be downloaded for a specific location, with the earths surface divided into small grid cells of 16 kilometers for which the forecast data is determined through a bilinear interpolation from the four points located at the corners of the grid cell as output by the global model; in this case, the data is taken from the grid cell that contains the FINO1 tower. Each of these forecasts contains data looking out five days (120 hours) in three-hour increments. The data used includes the u and v components of wind speed at 10 meters and 100 meters, gust wind speed at 10 meters, temperature at 2 meters, mean sea-level pressure, convective available potential energy (CAPE), and Charnock. CAPE represents a measure of atmospheric instability based on the buoyancy of air over a vertical reference frame.[92] Charnock is a means of characterizing sea surface roughness in relation to wind stress, which, in a way, represents part of the relationship between wind and waves.[93] The data available from ECMWF has been shown to have generally high forecast skill scores and significant usefulness when performing further analysis and evaluation.[94]

3.4 Results

The models and methods described in section 3.2 were applied to the data described in detail in section 3.3. I identify the importance of the training approach when developing models using the meteorological parameters taken from the ECMWF forecasts. I tested both static and sliding training windows of various sizes, and the size and type of training window can make a big difference in model performance. I also assess the performance of the probabilistic predictions for the different lead times and training windows and identify the variables that are the most influential for each model across all lead times. The skill scores of our probabilistic predictions are compared to traditional baseline measures. Our models outperform these baselines and, as expected, offer a higher skill than a deterministic prediction alone. Our probabilistic forecasts are shown to be highly skilled in terms of accuracy. I also provide reliability diagrams for the probabilistic predictions.

All models were developed using the entire dataset encompassing three years and four months of forecasted and measured data. Predictions were statistically tested on a minimum of one year of data, with some model iterations tested on almost three years of data (in the case of the smallest training windows.) The large test sets used allow for high quality assessments of model accuracy and performance. Subsequently, an observation refers to one data point taken from a forecast issued at one point in time for one specific lead time. When training models for a given lead time and forecast time, only one observation per day is used. So, a model trained on 365 observations would be trained on one year of data from forecasts issued once each day for one specific lead time.

In terms of specific model formulation, the linear model is simplest; maximum wind speed is a function of the forecasted 10-meter gust speed, CAPE, and the u and v components of wind speed at both 10 and 100 meters. The GAM includes the same parameters listed for the linear model, with the addition of the Charnock parameter. The MARS model adds another two more variables to those included in the GAM: mean sea-level pressure and temperature at 2 meters. The addition of these other meteorological variables to the wind speed data gives the models more to work with when it comes to predicting high-value wind speeds.

3.4.1 Model Training

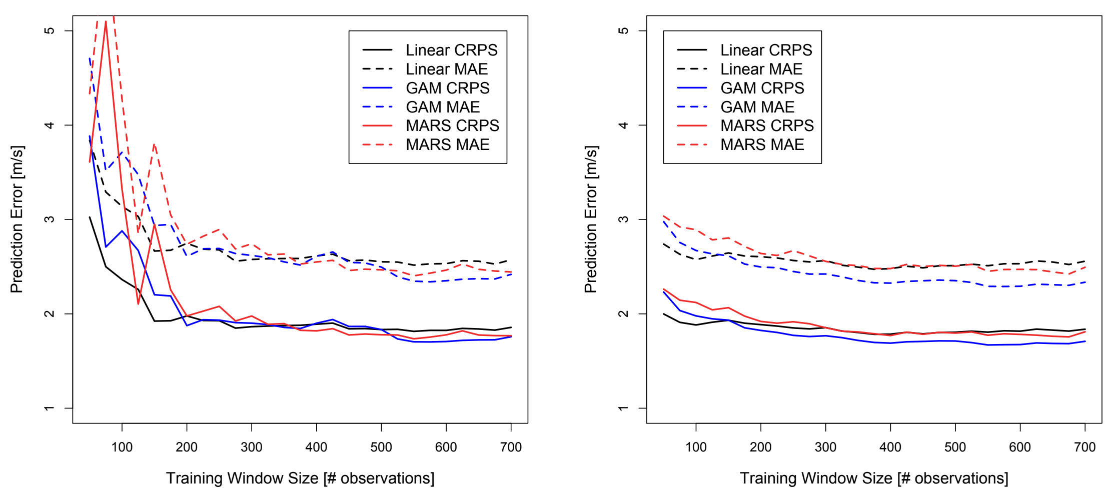
With any model development and prediction process, the choice of training data is critical. The training set should be large enough to capture enough information to accurately model any future data complexities that arise in the testing data; larger is generally better if sufficient data is available, but the marginal benefit may be minuscule after reaching a certain size. The size of the training set also depends on model complexity. As the model complexity increases, the model learns to capture even small perturbations in the training data, and the training error decreases. When using the same model to instead look at the test set error, or predictive error, errors tend to decrease only up to a certain point. Beyond that point, additional model complexity leads to an increase in predictive error—the classic bias-variance tradeoff problem.[27] The large dataset that I am working with, over three years worth of data, allows us to evaluate whether there is a significant performance improvement for very large training windows and to answer the question of what an optimal window size would be for this particular case of wind data. It should be noted, however, that even three years of data might not be enough to capture the very large time-scale variations that may exist for wind in certain regions.[88] Our models work by evaluating the relationships of the variables, and if these relationships were to change significantly due to large temporal fluctuations, the models may need to be retrained on more recent data in order to ensure optimal performance.

Here, I focus on test, or predictive, errors as a performance metric and analyze the predictive accuracy for the three models for a wide range of training window sizes under both static and sliding training conditions. Static training windows work by setting aside a subset of the data, training the model on that subset, and then using that model to predict the response variable for the remainder of the data. In the case of weather data, a static window tends to work best with large amounts of data spanning at least a year, since many climatological parameters cycle on a seasonal or annual time scale. Static windows are very simple to use, and the models never need to be retrained. Sliding training windows, on the other hand, use only the most recent data when predicting a given response data point. For a given training window size, n, a model is retrained for each individual data point (for a specific day and time) to be predicted, using only the n most recent observations (or days, in the case of the models presented here) for that point in the training set. This results in a custom model for each separate data point. Sliding windows tend to work well with meteorological data when the windows are small, since there is a tendency for the present weather to resemble the recent past weather. For issuing predictions on large amounts of data, the model has to be retrained for each individual data point. This is extremely time consuming, especially when the models become more complex and more computationally intensive to run.

Figure 3.1 shows the CRPS and MAE for the three models as a function of training window size for both static and sliding windows. Shown here are the plots for a 72-hour lead time. The behavior of the curves is similar for all other lead times, but the values differ as expected: lower errors for shorter lead times and higher errors for longer lead times. In the case of static training windows, the model errors do not settle into any sort of pattern until the training window reaches a size of 200 observations (corresponding to 200 days). After 200 observations, the model errors stay fairly stable for increasing window sizes. The plot of the sliding training windows has several distinct differences when compared to the static training plot. The models do not behave erratically for even very small training windows. The smallest window tested here is 25 observations—25 days using daily predictions for one specific lead-time—and the errors are relatively low and lack the erratic behavior seen in the small static training windows. The errors of the three models are grouped very closely, regardless of training window size, but there is a subtle minimum value for windows of around 600 observations (600 days). Although not all lead times are plotted here, the 600-observation minimum is consistent across lead times. For the dataset under evaluation, I show that a sliding training window of 600 days results in the smallest prediction errors on average. The relatively flat CRPS curve for these models demonstrates the extent to which these models are generalizable. With a sliding training window, the models can accurately predict maximum value wind speeds even in areas where data collection has only been ongoing for a couple of months. The predictive errors are less than 2 meters/second on average for predictions up to three days in the future and close to 1 meter/second on average for day-ahead predictions.

For all lead times, the dashed lines representing the MAE values lie above the solid lines representing the CRPS values. Issuing the predictions as probabilistic distributions, instead of deterministic point predictions, improves the overall value of the information provided in the prediction. The probabilistic predictions are able to convey more information regarding the uncertainty of each prediction, and this additional information results in lower overall errors and greater value when predicting the maximum-value wind speed.

I have identified three different models that all perform well for predicting maximum value wind speeds in time intervals stretching out to five days. The specific model performance depends on the training method and training window size, and the strength of this dependence depends on model type. In general, if large amounts of data are available, a training window of 600 days of observations will outperform other window sizes, both for static and sliding windows. The errors, as measured by the CRPS, are shown in Figure 3.2 for a training window of 600 observations (600



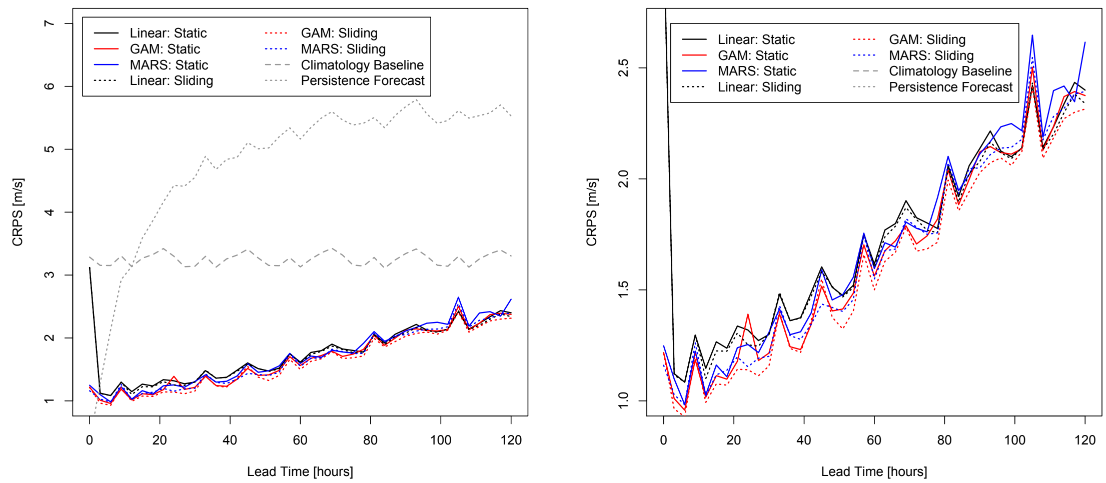
(a) static

(b) sliding

Figure 3.1: A comparison of maximum wind speed prediction errors for static 3.1(a) and sliding 3.1(b) training windows for the three models, shown with a lead time of 72 hours. The shape and behavior of the curves is consistent across lead times, but the values will differ. One observation equates to one day of training data, with one point per lead time per day.

days) for all models. It should be noted that the spike in the CRPS for the linear model with a lead time of zero is a result of a discrepancy in the dataset. The input forecast data does not include the 10-meter gust parameter for the zero-hour forecasts. This causes the higher-than-expected error, since the linear model would otherwise be heavily dependent on the gust parameter for issuing accurate predictions.

For both static and sliding training methods, the models outperform traditional baseline forecasting methods for large training windows (greater than 200 days.) The baselines used for comparison are climatology and persistence forecasts. Using climatology as a means of predicting the future is done by looking at the historical distribution of the parameter of interest, and making the assumption that the future will mirror the past. In our case, the climatology forecast, which is used as a baseline, requires the assumption that the distribution of maximum wind speed for each future time period being predicted will match that of the historical distribution of maximum wind speeds for our chosen location. This is an extremely simplistic means of prediction as it ignores any hourly, daily, or seasonal variation, but it does serves as a useful point of comparison because of its simplicity. The persistence forecast is another simple prediction tool that is often used as a baseline for comparison. A persistence forecast assumes that the conditions in the future will be the same as the conditions at the present moment, i.e. the maximum wind speed that is observed now is the prediction for the maximum wind speed in the next time period. Persistence forecasts are often very accurate in the very short term (a few hours or less), but the



(a) full view with baselines

(b) a closer look at the model errors

Figure 3.2: CRPS across all lead times of models trained with 600 observations (600 days) shown with baseline measures (climatology and persistence) in 3.2(a). Figure 3.2(b) gives a closer look at the individual model errors, again for all lead times and with a 600-observation (600 day) training window. Note the different y-axis values.

errors tend to become high when trying to predict values even one day in the future. For the case of comparison presented here, the persistence forecast is gathered for each separate five-day issued ECMWF forecast. I take the maximum wind speed observed at the time that the forecast is issued and use that value as the persistence prediction of the maximum wind speed for each time period during the following five days.

All three of the models presented here outperform the two baseline comparisons, climatology and persistence forecasting, for training windows of 600 observations (600 days). Not shown are plots for smaller training windows, but the models all outperform the baseline measures for training windows larger than 200 observations (200 days) for both static and sliding windows. The linear model, which is the most consistently behaved for the range of training window sizes, outperforms both baseline measures when using sliding training for all window sizes tested. Even with 50 observations (50 days) and 5-day lead times, the linear model trained with sliding windows results in a lower CRPS than both the climatology and persistence forecasts. In fact, a small sliding window outperforms the baseline measures for all three models. In the case of static windows, however, the training window size becomes significant. Small, static training windows (i.e. 100 days or less) are not reliable; errors are especially erratic for the GAM and MARS, and they are higher than the climatology forecast at certain lead times.

The simplicity of a linear model makes it much more resilient when it comes to changes in training methods or training window sizes. The GAM and MARS models are slightly more complex, and the higher degree of model complexity results in poor performance when the models are developed using very little data (100 days or less), and they end up being highly specific to the training data and not as generalizable as a simple linear model when applied to the unknown test data. For the most part, the sliding errors are lower than the static errors for each model. The GAM with a sliding window of 600 observations (600 days) has the lowest errors over the most lead times. For this reason, the GAM model will be used to demonstrate the predictive performance in the following section.

3.4.2 Prediction Performance

Two sample prediction plots are shown in Figures 3.3 and 3.4. Both have been plotted using the GAM with a sliding window of 600 observations (600 days), meaning that for each lead time, the previous 600 observations that came prior to the start of the period for which the prediction is being issued were used to train the models. It should be noted that in actuality, the training window size varies slightly due to occasional missing data in the dataset of measured values. Depending on the forecast period, training windows nominally set for 600 observations usually ended up containing between 545 and 595 observations. Figure 3.3 plots the probabilistic forecasts issued by the GAM for a randomly selected five-day period in April 2013. The shaded areas depict the 10-90% probabilistic predictions for each three-hour time interval. In this instance, the 10-90% prediction interval encapsulates all of the actual measured values for maximum wind speed. The spread of the 10-90% prediction interval varies over time, and the variance tends to increase as the lead-time of the prediction increases. Intuitively, this makes sense as predictions should be more accurate for smaller lead times, since the very near future is more likely to resemble most recent past data available than periods further out will.

Figure 3.4 shows another set of GAM predictions with a nominal 600-observation (600-day) sliding training window, but this prediction interval was chosen specifically because it includes the highest observed maximum wind speed value in the entire dataset that I am working with. This was done to test the predictive skill of our

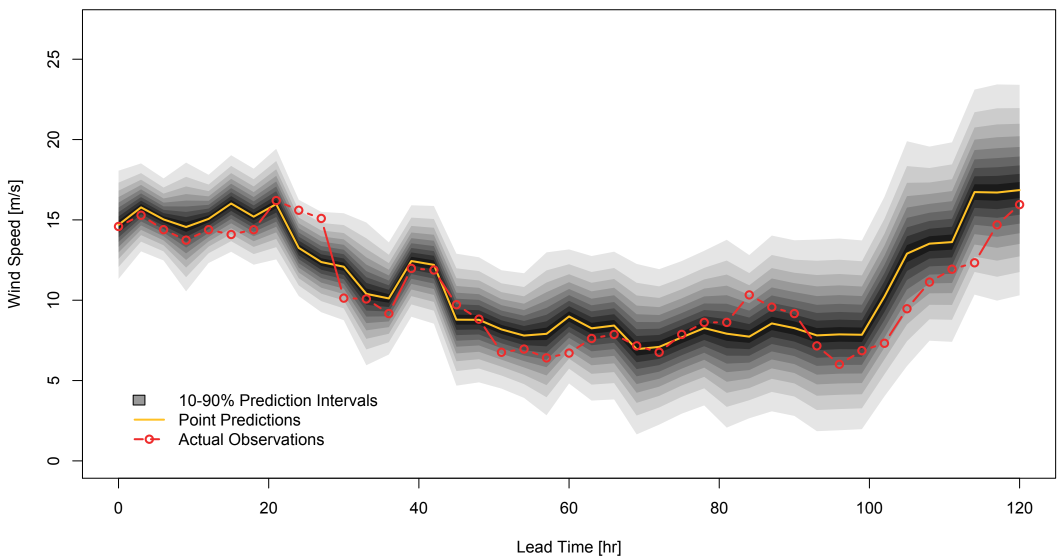


Figure 3.3: Probabilistic GAM predictions for the five-day period starting on 4 April, 2013 at 00 UTC. The shaded grey regions represent the 10–90% prediction intervals for each prediction. Also shown are the actual observations for both maximum and mean value winds for each time period.

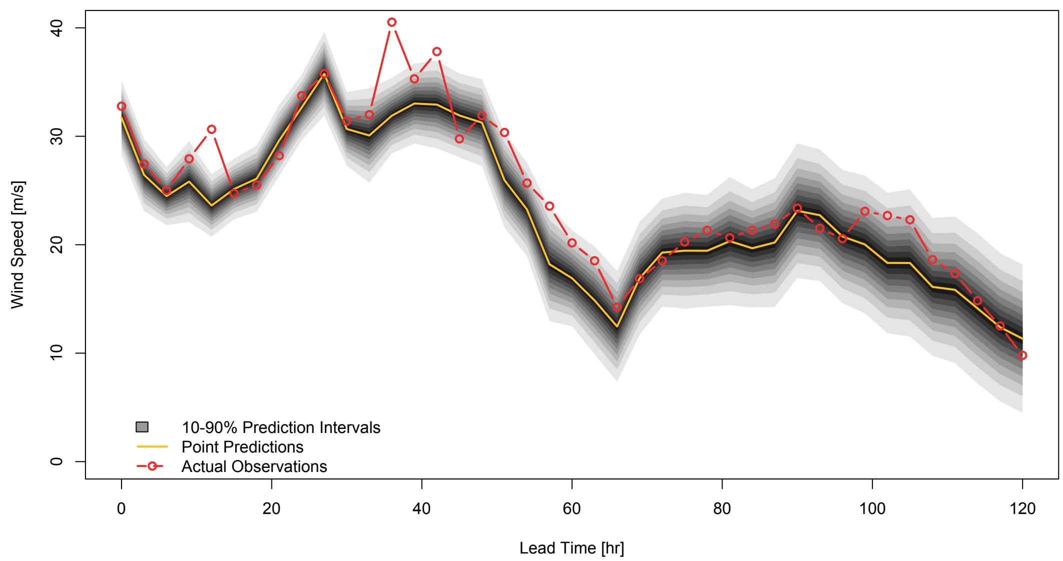
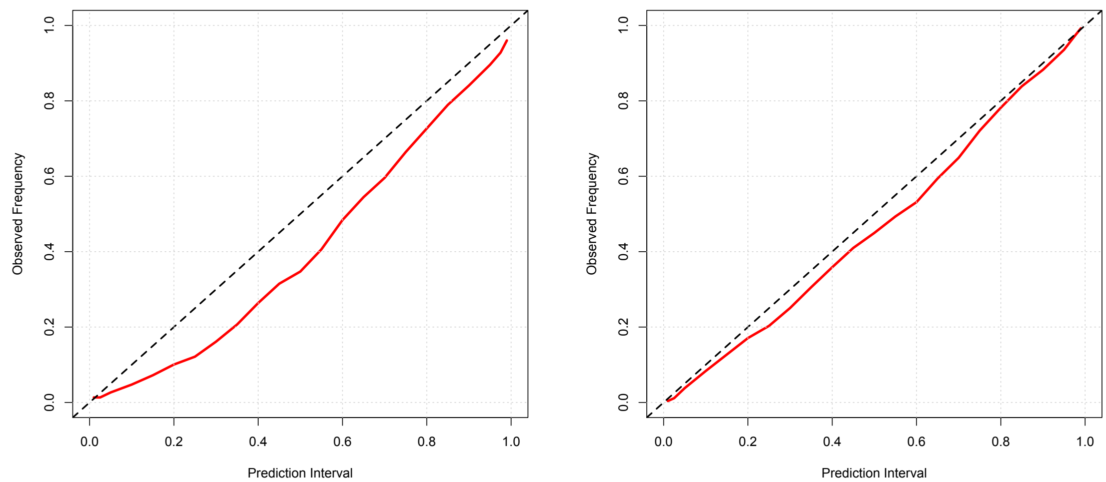


Figure 3.4: Probabilistic GAM predictions for the five-day period starting on 4 January, 2012 at 00 UTC. The shaded grey regions represent the 10–90% prediction intervals for each prediction. Also shown are the actual observations for both maximum and mean value winds for each time period. This interval contains the highest maximum wind speed observed in the available dataset.

models for the most extreme cases and to verify that they still maintained a reasonable level of accuracy far out into the tail of the distribution. For reference, the highest observed maximum-value wind speed is 40.52 meters per second, the median value for maximum wind is 12.61 meters per second, and the 99th percentile is 28.50 meters per second. For the extreme wind values in Figure 3.4, the 10-90% prediction interval misses only three of the peak values in the actual wind curve. The general shape of the predictions follows the curve of the actual data well, and only three data points, or 7.3% of the measured data, fall outside of the 10-90% prediction interval. Our models show that the prediction accuracy still holds for the most extreme wind values.

Instead of looking at individual five-day forecasts, I can assess the overall performance of the models by looking at their calibration, or reliability. Figure 3.5 shows a reliability diagram for the predictive performance of the GAM at two different lead times. With a large enough sample size, such as the one analyzed here, the reliability of the predictions can be estimated accurately. While most of the literature on reliability diagrams is applied to ensemble forecasts or binary events, the same principle can be applied here, where I have a parametric distribution for the predictions.[95,96] For the reliability diagrams in Figure 3.5, the x-axis represents probability intervals of the density distribution for the predicted values of maximum-wind. The y-axis measures the frequency with which the actual maximum-wind values fall below the associated predicted interval on the x-axis (i.e. what percentage of actual values correspond to the matching percentage of predictions). For perfect forecasts, the points lie along the diagonal, as shown by the dashed line.

There is a recognizable bias in the reliability plot for a 24-hour lead time. The prediction intervals capture a smaller portion of the true data than they ideally should. This bias likely stems from the parametric assumptions made throughout. The bias is significantly reduced for longer lead times, as seen in 3.5(b). The variance of the predicted distribution grows with increasing lead time, since there is more expected variability in predictions that are made further in advance. As shown, this results in a more reliable forecast for a lead time of 120 hours than for a lead time of 24 hours. The bias shown in the diagrams is present, but minimal for longer lead times.



(a) 24 hour lead time

(b) 120 hour lead time

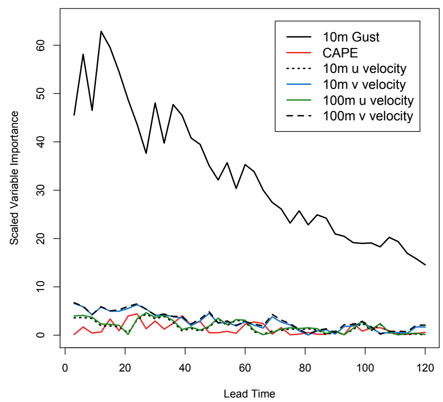
Figure 3.5: Reliability diagram of GAM predictions for 24-hour 3.5(a) and 120-hour 3.5(b) lead times. These plot the frequency with which the actual maximum wind values fall below a given prediction quantile.

The models capture the expected behavior of the maximum-wind speeds well, but the accuracy of the predictions varies with lead time.

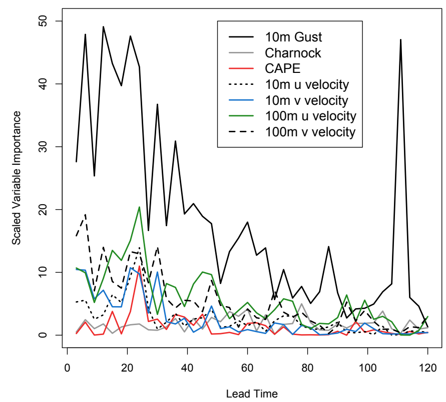
3.4.3 Variable Importance

The three models each include a set of covariates, made up of meteorological parameters, that were used in training the models and issuing predictions for new observations. The covariates in each model were chosen based on a variable selection process to minimize errors in model fit and predictive accuracy. The linear model makes use of the following forecasted values: wind velocities at 10 and 100 meter heights, the gust wind velocity at 10 meters, and CAPE. The gust speed is expected to be especially important here, since I am predicting maximum wind speeds, which are more similar to gust speeds than to the average wind speeds given by the other forecasted values. In addition, gust wind forecasts have been previously shown to be significant when predicting extreme weather events.[80] CAPE is a measure of atmospheric instability and can be useful in predicting severe weather. The GAM also includes the Charnock parameter. This is a rough equivalent to a measure of surface roughness specific to offshore conditions, and it is used to characterize the near-surface wind speeds over water. The inclusion of Charnock as a covariate can show the influence of roughness if it is present in the data.[97,98] Finally, the MARS model adds two more covariates: mean sea-level pressure and temperature at 2 meters. These standard meteorological measures give the MARS model more to work with. The model does not necessarily use all of the variables available; it performs variable selection during the fitting process in order to select the best combination of variables which result in the lowest GCV (generalized cross validation) score. This allows the model to use only those variables that help to improve the performance for each lead time, and the remaining variables are left out.

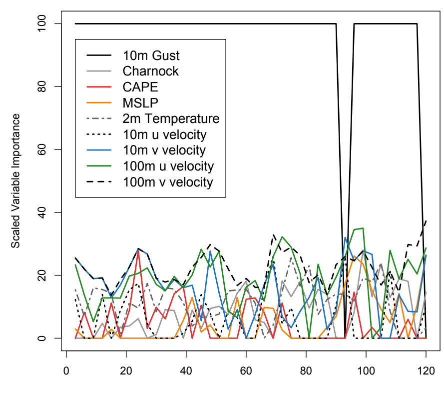
As discussed previously, the models are re-trained for each lead-time and training window. This results in different models with different levels of variable importance, and the importance is calculated differently based on model type. For the linear model, the importance is taken as the absolute value of the t-statistic for each variable. For the GAM, it is calculated using the log of the p-values. The MARS model



(a) Linear Model



(b) GAM



(c) MARS

Figure 3.6: Variable importance, as measured relative to other variables in each model, plotted against lead time for linear 3.6(a), GAM 3.6(b), and MARS 3.6(c) models.

calculates the total reduction in GCV error for each individual variable. Figure 3.6 shows the variable influence plotted against lead-times for each of the three models. The parameter plotted is the importance of each variable in model fit, not in prediction. There is a general decreasing pattern for the linear model and GAM as lead time increases. This is because predictions become less accurate at longer lead times, and the individual covariates do not contribute as much to error reduction. The MARS model calculates importance quite differently than the linear model or GAM, and the decreasing pattern does not show up for this reason. The MARS model can choose to exclude variables in each formulation, and Figure 3.6(c) shows that this exclusion occurs regularly for some variables, such as CAPE and MSLP. The 10-meter gust variable is the most important overall for all of the models, especially at shorter lead-times. Even with the MARS, the gust variable was of maximum importance in all but two lead times.

3.5 Conclusion

The need for high-wind forecasts in offshore environments is clear; turbine safety, worker safety, and efficient power grid operations all stand to benefit greatly from accurate short- and medium-range forecasts of maximum winds, in addition to the established practice of forecasting mean wind speeds. A probabilistic prediction of maximum winds will help to fill in a portion of the knowledge gap regarding the inherent variability and uncertainty of wind. I show that this can be done with a high degree of accuracy using relatively simple models. Three different types of models — a linear model, a GAM, and a MARS model — perform very well for predicting maximum wind speeds, and they are also able to convey the intrinsic variability of the predictions by describing the full parametric distribution around the expected value of maximum wind speed. The choice of the 'best' model depends greatly on the conditions used, available data, and the level of simplicity desired by the user. The CRPS (prediction errors) for the three models are low, but the values do depend on training method and lead-time. Our models achieve errors of less than 1 meter per second at lead times of six hours; even for lead times of five days, the errors are as low as 2.31 meters per second. For short-term planning of offshore operations, errors of this level are small enough to accurately inform decision-makers and to ensure operational safety of structures, components, and workers. Day-ahead predictions are essential for power system operation decisions, and predictions on the order of several days would be useful in the planning of maintenance or construction projects, whether for wind farms or other offshore operations.

I recognize the weakness of the prediction reliability for shorter lead times. The bias introduced is a function of the parametric assumptions made throughout the modeling process. Although the normal assumption is reasonable, it introduces biases. These biases could potentially be reduced by using a different distribution or by not assuming a parametric distribution at all and using non-parametric models. The lack of calibration would likely be improved, but the extent of improvement is not known. Even with this bias, however, the models have great value. They offer accurate predictions with an extremely high degree of simplicity. Our methods are highly skilled and cheap to implement, both in terms of complexity and computational cost. The simplicity presented here allows the methods to be adopted by a larger audience of users, and I leave the alternative modeling techniques as an interesting avenue for future work.

The model details associated with this finding are specific to the dataset used here, but the techniques and methodology are highly generalizable. The ECMWF forecasts provide high-quality data that allows us to accurately model the maximum wind speed, which is not represented in the forecasts. However, the success of these models, or any type of wind-forecast model, depends on the appropriate integration of the predictions into the decision-making process. The information should be communicated early enough and often enough so as to allow planned operations and any resulting dependencies to adapt. The cost savings realized by using such maximum-wind predictions could be calculated for the various industries mentioned that stand to benefit, but it is not assessed here. Such calculations would be interesting extensions and are left for future work.

This research was originally published in *Wind Energy*.[99]

Chapter 4

Assessing Power Output in Non-Uniform Onshore Wind Farms

4.1 Introduction

Wind energy is a fast-growing segment of the energy sector worldwide, and as wind starts to play a larger and larger role in our electricity systems, there is a growing research interest in using it efficiently. Wind power is not a dispatchable form of energy; it can not be turned on to a desired production level when needed, and managing its variability and intermittency is the biggest challenge faced when integrating it into the power system.[100] Reducing the uncertainty present in wind energy is highly beneficial. Knowledge of the amount of power that a wind farm will produce in a given hour, day, or year will improve the way that the farm is operated and financed. In reality, perfect knowledge of future wind power production is impossible. Recent research, however, has made great strides in estimating and predicting these quantities. Power estimation and prediction is important for multiple applications within the timeline of a wind energy project. In the initial planning stages of a farm, an important first step is to develop accurate estimates of what the wind conditions will be once the farm is built. This typically involves the installation of meteorological towers (or met towers) for data collection. Once enough data has been gathered, this information is used to determine the turbine layout and alignment within the farm that will best capture the available energy. These initial estimates of long-term expected wind conditions are used to then estimate the amount of power produced over time. This, in turn, is used to asses the financial viability of a wind farm, and small discrepancies can often make or break a new project. Thus, the decision of farm design and resource assessment is critical for questions of financing, as the return on investment is dependent on the ability of the wind farm to generate enough energy to recoup costs and remain profitable.

On a much different time scale, wind power production estimates are also needed for operational decisions, often looking at day-ahead production. These estimates are needed for efficient and profitable market operations. In a typical system, a wind farm operator will submit a bid for the energy they will provide in a given time period, and these quantities are chosen based on forecasts of future wind speeds. A mismatch between the forecasted wind and the actual wind can result in penalties, added costs, or lost revenue, as overproduction needs to be curtailed and underproduction requires another generator to make up the difference.

The benefits of accurate wind power estimates are clear. Research advancements have greatly improved these estimates for both time scales mentioned: long-term planning of annual farm production and short-term operational decisions in a market setting. The long-term planning analysis has spurred research into understanding the interactions among turbines in a large farm, as this can be used to optimize the placement and spacing of turbines within a farm. The wake from an operational wind turbine results in lower wind speeds behind the blades, since some of the energy has been extracted from the ambient flow. This will result in lower power production for any other turbines sitting behind the leading turbine in its wake. Our ability to model and characterize these wake effects can help when choosing a layout of turbines that will result in the highest amount of power produced.

For short-term (i.e., day-ahead, for example) decisions, the goal of accurate power estimates is the same, but the approach is typically different. Large-scale physical models are used to forecast the wind conditions across the globe. These are generally downscaled to provide a forecast for wind conditions at a much smaller regional or local level. Wind speed is certainly the greatest determinant of wind power, but, as noted above, turbine wake interactions complicate the simple translation of speed to power. For this, the same wake models can be used to calculate the winds seen throughout a farm given a certain known input condition, and this information can then be used to calculate the power produced by each turbine in the farm using the power curve and each turbine's unique input wind. Another approach involves the use of statistical models or data-mining techniques. If a farm has been operational long enough, there is, in theory, enough production data that can be used to train models so that overall farm production can be accurately predicted for specific input conditions.

Offshore wind farms have some strong advantages over onshore installations. The winds are generally stronger and more consistent offshore, the 'land' area does not typically have competing ownership, and offshore installations do not bother local communities. (These latter two points do not necessarily apply in every situation, and attempts at U.S. offshore wind development may tell the opposite story. In general though, offshore sites avoid conflicting interests more than many onshore installations.) In addition, turbine sizes and heights are increasing to capture more energy and higher altitude winds, and finding acceptable onshore sites for such large turbines is difficult due to constraints on proximity to communities and to other turbines themselves. For these reasons, the large wind farms in the near future will likely be built offshore, and much of the recent research has been focusing on offshore applications as a result.

Several factors are very likely to differ when analyzing a wind farm that is offshore instead of on. As noted, offshore sites see steadier wind. Onshore locations typically have higher turbulence that results in more mixing and less dramatic wake losses.[37]

Onshore farms also have the local geography to take into account. Complex terrain, or terrain of any sort, can strongly influence the wind flow in a region. In addition, offshore farms are often built with a uniform grid of turbines in evenly spaced rows and columns. This is not always the case onshore where there are significant constraints to turbine placement, such as roads, houses, hillsides, or protected lands. In theory, the models used to analyze wind farms can easily be modified to account for these factors. In practice, however, much of the research and model validation is done only on offshore (and occationally very near-shore) farms.[37,38,41,101] The model results do not always match up with reality in onshore farms and therefore should be used carefully so as not to promote false assumptions in the industry.

This chapter aims to take an analytical look at the performance of various model types used to analyze wind farm power production. In contrast to much of the existing research into wind farm wakes and turbine interactions, the models presented here are applied to onshore farms that are not aligned in a uniform grid. The findings show that validation done in offshore settings does not always maintain its accuracy when applied in these contexts. I focus on the performance of a simple wake model and compare it to other alternatives for estimating wind farm power production. This work presents a comparative analysis of several very different techniques for estimating wind farm power production. It is not meant to be a comprehensive study of all available methods; there are many different wake decay models that could be used in addition to or instead of the simple Jensen wake model employed here.[36] I chose to use the Jensen model because of its simplicity and accuracy. There are a number of studies that compare different types of wake models, and the Jensen model has been found to perform well in a variety of settings.[39,41] However, as mentioned previously, the comparisons are most frequently conducted in offshore settings. This research seeks to characterize the level of accuracy achieved for onshore wind farms instead.

4.1.1 Background

Estimates of wind farm power production are needed for many types of planning problems. Most power production estimates are used for short-term tasks such as load scheduling and dispatching, and these are usually conducted for an individual wind farm or a small group of farms within a region.[102,103] There is a sizable body of research on predicting power output for existing wind farms, and the methods are varied.[102,104] Generally, power forecasting models combine wind speed forecasts and farm-specific data, such as turbine characteristics, farm layout, and past generation data in order to generate power forecasts for that farm.

In practice, most of the work done on predictions for wind energy applications has been focused on generating accurate wind speed forecasts. As a result, there have been many advancements over the years in wind speed forecasting, both from a physical and statistical standpoint.[99,105,106] Many models focus on wind speed only, as this is obviously the most important factor in determining the amount of wind power that will be produced. Other models take a wind speed forecast as input and focus on improving the power estimate itself. See[32] for an overview. Even with a perfect wind speed forecast, translating from wind speed to wind power for an entire farm is not as straightforward as many would like.

Despite the growing focus on wind speed predictions, the subsequent conversion to wind power is often highly simplified. In fact, a lot of research does not distinguish between forecasts for wind speed and power, and this is generally acceptable for predictions regarding just one turbine.[107] The power curve of an individual turbine is well-understood and, for the most part, an accurate wind speed is the only piece of information needed to then determine the power output. However, the process is much more complex when dealing with an entire farm. Turbine wakes strongly affect the wind, and therefore power, of downstream turbines. The wake effects also depend on farm layout and wind direction.[108] Despite this, practitioners still often combine wind data with a single turbine power curve, that is then aggregated across the entire wind farm. The performance of an entire farm can differ greatly based on the wind conditions at a given time. The layout of the farm and the surrounding terrain determine the manner in which wind flows across each turbine. This changes with wind direction and wind speed, so the performance of a wind farm and the losses associated with turbulent wind also then depend on these factors. With reliable wind speed forecasts and detailed farm data, power estimates can be fairly accurate.[109]

In practice, the wind speeds seen by each individual turbine in a large wind farm are rarely known exactly. This is even more difficult when planning for a new farm that does not yet exist. Turbine wake interactions and complex terrain (for onshore farms) result in these differences in wind speeds seen at each turbine throughout a farm. There has thus been a strong focus on advancing the modeling techniques to better understand and represent the realities of fluid flow within a wind farm. Even with an accurate forecast for wind speed, conversions from wind speed to power are typically done by heuristics in practice, such as simply adding up the individual power curves of each turbine and applying a penalty to account for wakes.[110] Although these estimates are far from perfect, they are still useful for many large-scale planning decisions when simplicity is best. Farm power production estimates are also used for longer-term planning, integration, and optimization problems.[111,112] These often involve planning for future wind farms, understanding potential power grid impacts of additional wind, possible correlation among multiple farms, and transmission expansion to incorporate untapped wind potential. These integration studies need estimates of wind production for virtual wind farms, and these estimates use a lot of simplifying assumptions about actual farm behavior. Often the turbines are aggregated, despite the acknowledgement that deviations from the farm power curve are common and can be caused by a number of factors.[111] Therefore, accounting for some of these factors can increase the accuracy of the farm-wide power estimation.

This farm-level power estimation is difficult to do in a large wind farm or when planning for the production of a new wind farm. A site or a farm with met towers present can provide information on the wind at that particular location, but the resulting power production depends on the turbine layout. There are many tools available to help with choosing the layout of a wind farm. The goal of these tools is to model the farm as it would exist in an operational setting. It is therefore important to capture the wake effects of the turbines in the farm and the terrain effects of surrounding geography. Many of these models rely on computational fluid dynamics to model the fluid interactions with the turbines, but fast and simple analysis using the Jensen model, for example, can often be accurate enough.

The Jensen model is a basic wake decay model that has become the standard baseline in the research and industrial communities.[36] It is based on a simple, geometric calculation of the wake expansion behind a turbine and can be used to calculate the velocity deficit relative to the freestream at any point behind the turbine. It has been used as a point of comparison in countless experiments (sometimes referred to as the Park or Jensen/Park model). See[38–41] for a selection of examples where the Jensen/Park model is used. There have been many advancements in wake modeling that move beyond the Jensen model, especially as large eddy simulations of large turbine arrays have become computationally feasible. However, the Jensen wake model is still used with high degrees of accuracy in many cases.[41] There are some known weaknesses of the Jensen model due to its simplicity. The model focuses on individual wakes and, for very large farms, this can result in an under-prediction of the wake losses present.[37] However, these findings have been tested in offshore settings and there may be other factors that complicate the application to onshore farms. Still, the Jensen model serves as such a strong benchmark measure for comparison, and this model will be used for the analysis of the wind farms presented here in order to estimate the wake deficits, and therefore power production, within the farms.

4.2 Data

I have wind farm production data from two different onshore farms in the United States. The details of the farms must remain anonymous, and they will be referred to throughout as Farm 1 and Farm 2. Farm 1 is located in the south-central region of the country and is made up of 100 turbines with a rotor diameter of 77 meters and a hub height of 80 meters. The turbines have a cut-in wind speed of 3.5 m/s, a cut-out wind speed of 25 m/s, and a rated wind speed of 14 m/s. Farm 1 sits in a relatively flat geographical area in the midst of agricultural land. The turbine layout of Farm 1 can be seen in Figure 4.1. Farm 2 is located in the north-central region of the country and is made up of 140 turbines (of the same make and model as in Farm 1.) It also sits in a flat geographical area in the midst of agricultural land. The turbine layout of Farm 2 can be seen in Figure 4.2. Both farms have two met towers installed, the locations of which are also shown in Figures 4.1 and 4.2. Neither farm has a 'standard' layout, with turbines arranged in evenly spaced rows and columns, and the turbine spacing varies quite significantly both across the farm and with varying wind direction. For

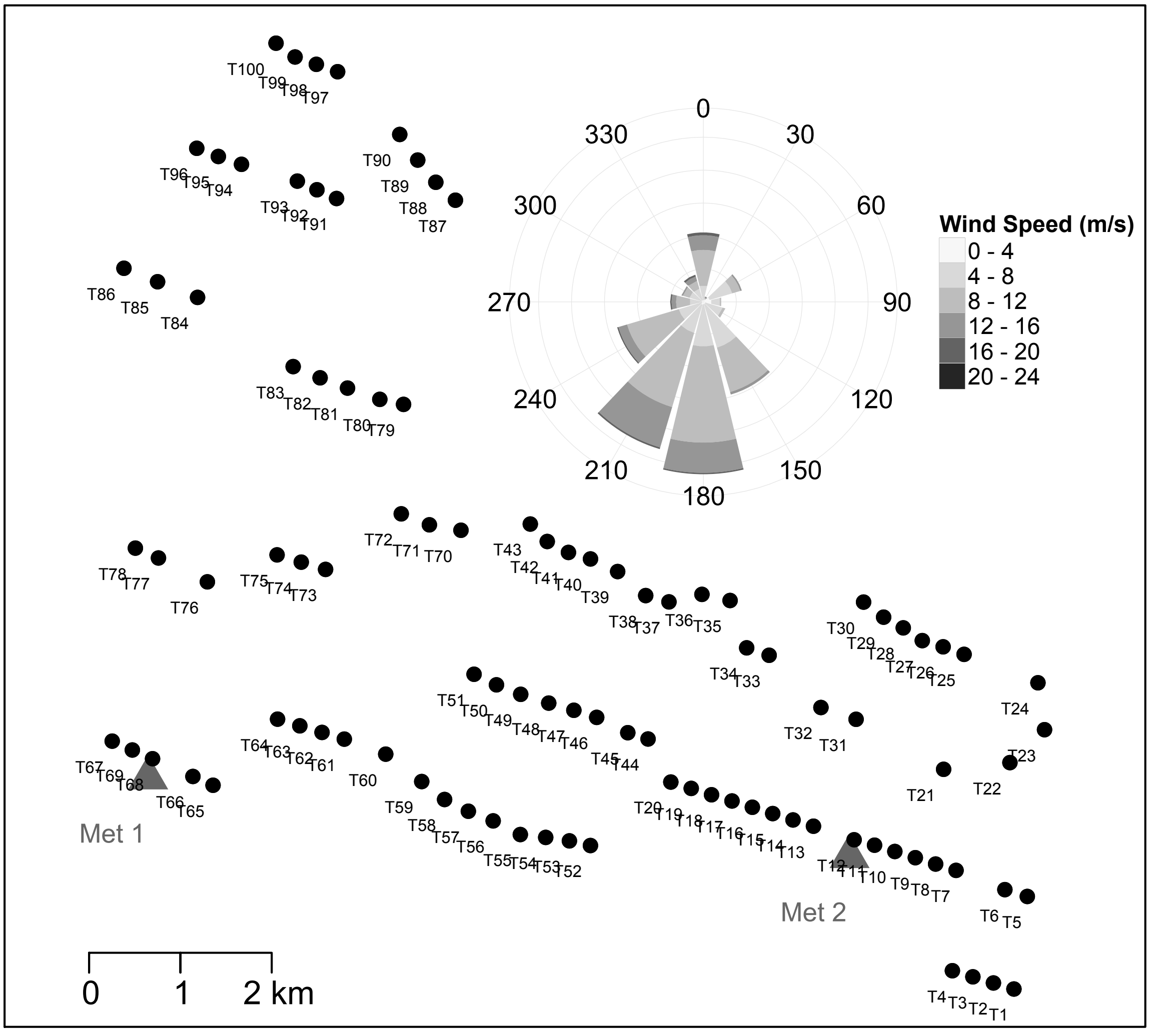


Figure 4.1: Turbine layout and meteorological tower locations for Farm 1.

Farm 1, the minimal turbine spacing is approximately 3 turbine diameters. In Farm 2, the minimal spacing is approximately 3.6 turbine diameters.

The available data from Farm 1 runs from November 2010 through October 2013, and the available data from Farm 2 runs from November 2010 through October 2014. For turbine data for both farms includes 10-minute averaged power production, wind speed (as measured on the nacelle), availability, and curtailment. The availability and

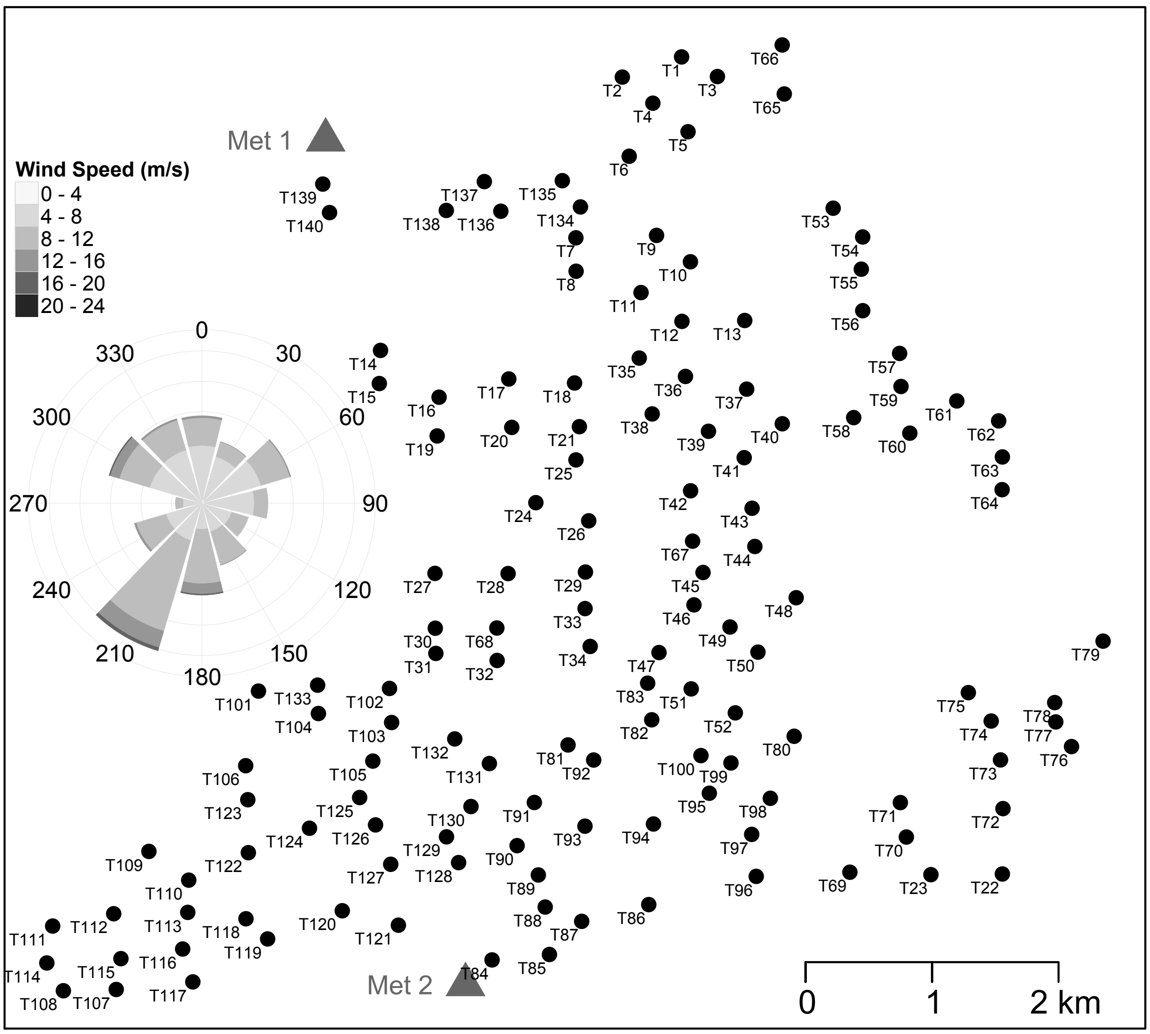


Figure 4.2: Turbine layout and meteorological tower locations for Farm 2.

curtailment data are 0-1 metrics representing the portion of the 10-minute period that a turbine was either available or curtailed, respectively. The met tower data consists of 10-minute averaged wind speed, wind direction, temperature, and, in the case of Farm 2 only, air pressure.

The supporting analysis for this work is specific to the data used. The findings represent these two wind farms only, although they are fairly representative of other large onshore wind farms in the United States. Ideally, all results would be corroborated with more wind farm cases, but it is often difficult to gain access to production data from wind farms and this is left as a future research area should more data become available. A more comprehensive analysis would include many more farms in a wide variety of sizes, locations, and layouts.

4.2.1 Data Quality

The data for both farms was cleaned and filtered based on several metrics. For Farm 2, the met tower data was filtered to remove extreme datapoints (i.e., where temperature or pressure values were outside of a normal range for the area) and datapoints with very large disagreement between the two temperature readings within the farm. In this case, the values were filtered according to historical measured data at a nearby airport. Deviations larger than 10°C were removed. Additional filtering was done based on the availability and curtailment data for both farms in order to have as complete of a dataset as possible for accurate comparison to wake models.

Ideally, only data in which availability equalled 1 and curtailment equaled 0 would be used so that every turbine would be fully operational, as is the case in the model runs. In reality, this limited the size of the dataset quite considerably and I instead chose more lenient thresholds for filtering. The remaining data used for analysis contains all of the data points in which all turbines have an availability value above 0.8 and a curtailment value below 0.2, meaning that every turbine was available at least 80% of the 10-minute interval and was curtailed no more than 20% of the interval. This limits the viable data considerably, resulting in approximately 11,400 observations for Farm 1 and 15,600 observations for Farm 2.

When working with real data, there is always the question of its accuracy. The results of any analysis using the data are only meaningful if the data itself is trusted. There are several possible sources of error in the available wind farm data. The met towers could be out of calibration, either in wind speed or direction. The turbines themselves could have sensors that are out of calibration, either for power or wind speed. The data provider assured us that the power measurements were accurate. This is, to the farm owner, the most important parameter and they have a strong interest in ensuring its validity. However, the power data can also be checked against the nacelle wind data, and vice versa. The wind data is measured behind the blades, so it is not identical to the incoming wind seen by the turbine. However, it is safe to assume that the drop in velocity through the blades remains consistent over time for different wind speeds and that is also similar across turbines. Thus, a plot of the

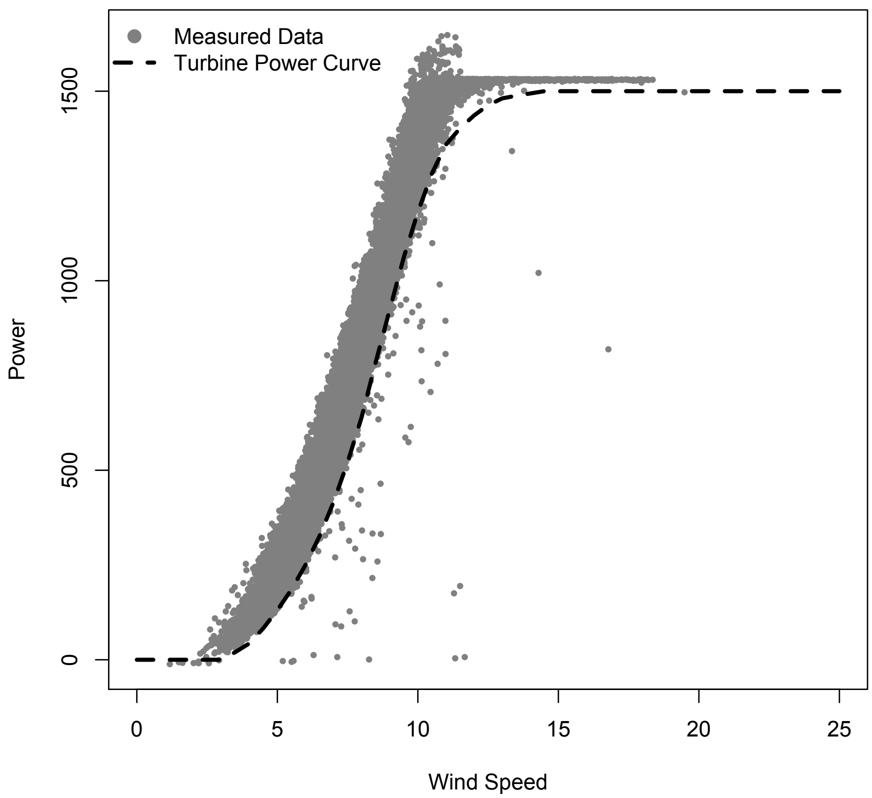


Figure 4.3: Turbine power is plotted as a function of the wind speed measured on the turbine nacelle behind the blades for Turbine 2 in Farm 2. The turbine power curve is overlaid.

individual turbine wind speed versus power should follow the manufacturer's power curve quite closely, but with a slight offset due to the wind measurement taken behind the blades, as opposed to in front. Figure 4.3 shows this plotted for a single turbine from Farm 2. The plots for all turbines in both farms are remarkably similar. It is safe to conclude that the turbine data (power and wind) are accurate.

The wind direction as measured at the met towers can be checked against expected farm performance metrics. For example, it is known that there will be reductions in power production for a turbine sitting directly behind another turbine when the wind is aligned with the turbines. This can be used to check the calibration of the measured wind direction. Figures 4.4 and 4.5 show the average power ratio of two adjacent turbines as a function of wind direction in Farm 1 and Farm 2, respectively. When the wind is aligned with an imaginary line connecting the two turbines, one would expect to see a drop in the power (or wind) ratio. This often has a shape similar to a bell curve as there is partial wake interaction as the wind direction moves away from direct alignment. This dip in relative power does not occur at the expected measured wind direction for either of the farms or either of the met tower measurements. For Farm 1, both met towers seem to have a direction offset error in the measurements. Further comparisons of turbines in Farm 1 confirm an offset at met tower 1 of +30°and at met tower 2 of +22°. For Farm 2, further comparisons confirm an offset at met tower 1 of -79°and at met tower 2 of -58°. The measured wind direction has been corrected by these values for subsequent comparisons across models.

4.3 Implementing the Jensen Model

The Jensen model takes as input two parameters: the wake decay coefficient and the thrust coefficient of the wind turbines. Use of the model when analyzing a real wind farm, however, requires that certain assumptions be made. The Jensen model can be used to calculate the velocity deficits in the turbine wakes, and this calculation is based on steady-state wind. For one constant wind direction, the deficits

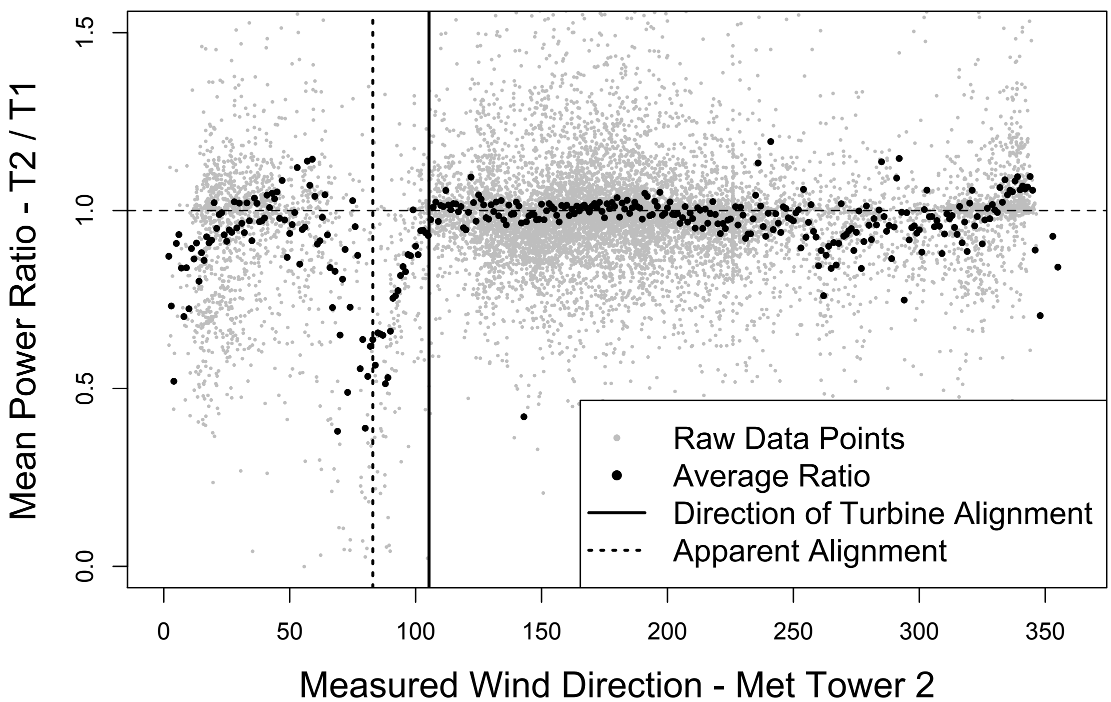


Figure 4.4: Relative power of turbine 2 compared to turbine 1 as a function of measured wind direction at met tower 2 in Farm 1. The turbines are aligned at an angle of 105°, and the expected drop in power should occur at this wind direction. In fact, we can see that the actual drop occurs at approximately 83°, so the direction measurement is too high by 22°for met tower 2.

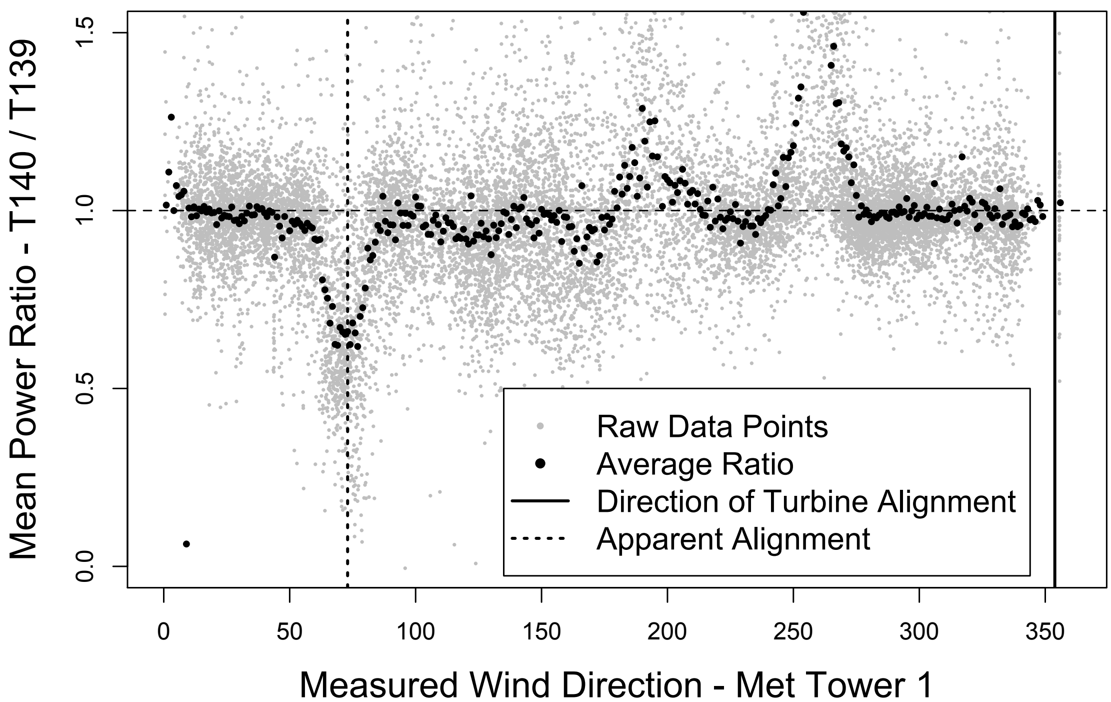


Figure 4.5: Relative power of turbine 140 compared to turbine 139 as a function of measured wind direction at met tower 1 in Farm 2. The turbines are aligned at an angle of 353°, and the expected drop in power should occur at this wind direction. In fact, we can see that the actual drop occurs at approximately 73°, so the direction measurement is too high by 281°(or too low by 79°) for met tower 1.

are calculated as a snapshot in time. Thus, the Jensen model is best suited for large scale resource assessment and is not the best option for evaluating real-time or rapidly changing wind power production. For the cases presented here, the data exists as 10-minute averages and, for some of the analysis, has been filtered to represent only conditions that are as close to steady-state as possible by using only the datapoints where both met towers in the farm agree in the measured wind direction. The Jensen model should work well under these limitations and can be used for farm power production estimates.

The Jensen model determines the effect that a turbine wake will have on a downstream turbine. The wake velocity deficit at a downstream turbine relative to the velocity seen by an upstream turbine is determined by

$$\delta V = \frac{1 - \sqrt{1 - C_T}}{(1 + 2kx)^2} \left(\frac{A_o}{A} \right)$$

where C_T is the turbine thrust coefficient, k is the wake decay coefficient, and x is the downstream distance at which the deficit is measured. For a turbine that sees only a partial wake from an upstream turbine, a correction is applied based on the fractional area of overlap, A_o and the swept rotor area A. For a large wind farm with multiple turbines, the deficit seen by any one turbine is a combination of all of the upstream wakes that interact with that turbine. This results in the following formulation that gives the overall velocity deficit as a result of the superposition of multiple upstream wakes as given by Katic *et al.*[113]

$$\frac{u}{u_0} = 1 - \sqrt{\sum_{j \in J} (\delta V_j)^2}$$

where J is the set of upstream turbines with wakes impacting a given downstream turbine. The choice of the parameter k determines the rate at which the wake decays behind a turbine, and it is dependent on the ambient turbulence, turbine-induced turbulence, and atmospheric stability. The choice of k should depend on the atmospheric stability, and this has been shown to have a strong influence on wake behavior.[101] Namely, stable conditions result in a slower wake recovery and therefore larger velocity deficits at downstream turbines. There is some consensus on a value of 0.075 for onshore applications and lower values (i.e., 0.04 or 0.05) for offshore applications to reflect the lower turbulence generally found offshore or near-shore.[114] The thrust coefficient, C_T, comes in the form of a turbine-specific curve that is a function of incoming wind velocity. A typical curve has the highest C_T value at low wind speeds (i.e., $C_T = 0.9$ for winds 5 m/s) and then drops off as wind speed increases (i.e., to a value of 0.2 above 20 m/s.)

With set values of k and C_T, the velocity deficits can be evaluated at each turbine in a farm for a given wind direction and compared to the actual data averaged over that same wind direction. The difference between the actual data and the Jensen deficit calculations for a wind direction of 180°are shown in Figures 4.6 and 4.7 for Farm 1 and Farm 2, respectively. The Jensen models used here were run with $k = 0.075$ and $C_T = 8/9$. These actuals are calculated using a subset of the farm data that should, in theory, most closely resemble the conditions used in the Jensen model. The farm data has been subset into only those datapoints with wind directions that fall between 180°±5°for *both* met towers. Since the two towers are spaced fairly far apart in both farms, agreement in the wind direction measurements indicates a relatively steady wind direction which should be consistent across all turbines in the farm. Even with the actual data reduced to the 'best' cases, there is a large discrepancy between the Jensen wind speeds and the actual data for both farms. The leading turbines in the Jensen plots all have a normalized velocity equal to 1, by definition. The turbines further back in the farm see lower velocities as the wakes from upstream turbines show their influence. In the actual farm data, however, the results deviate significantly from what is expected. Instead of seeing a trend toward lower wind speeds at the back of the farm in Farm 1, some of the rear turbines have much higher speeds than expected. Although most of the turbines have fairly small deficit errors, Farm 1 tends to have higher actuals than the Jensen model predicts while Farm 2 tend to have lower actuals.

There is not enough data to determine the exact cause of the mismatch between the Jensen-model predictions and the actual farm data. High turbulence or atmospheric instability are likely at play, although the extent of their influence is not known. The farms are quite large, spanning more than 6 kilometers in some directions. Two measurement points (i.e., the two met towers) may simply not be enough to provide information on the conditions present throughout the entire farm. The

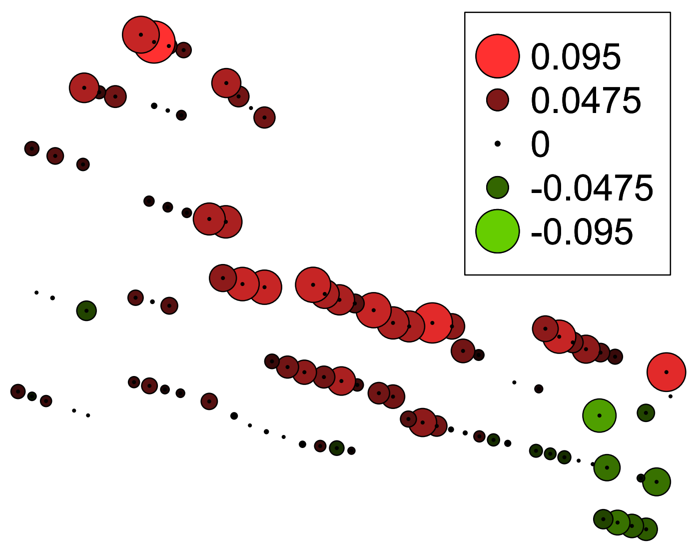


Figure 4.6: The difference between the actual data and the Jensen model estimates for wind velocity deficit relative to leading turbines for Farm 1. The wind direction is from the south (180°) and the wind speed deficit is relative to the leading turbines on the south side of the farm. The plot shows the actual data minus the Jensen estimates, so positive values are underestimates of the actual wind speeds whereas negative values are overestimates.

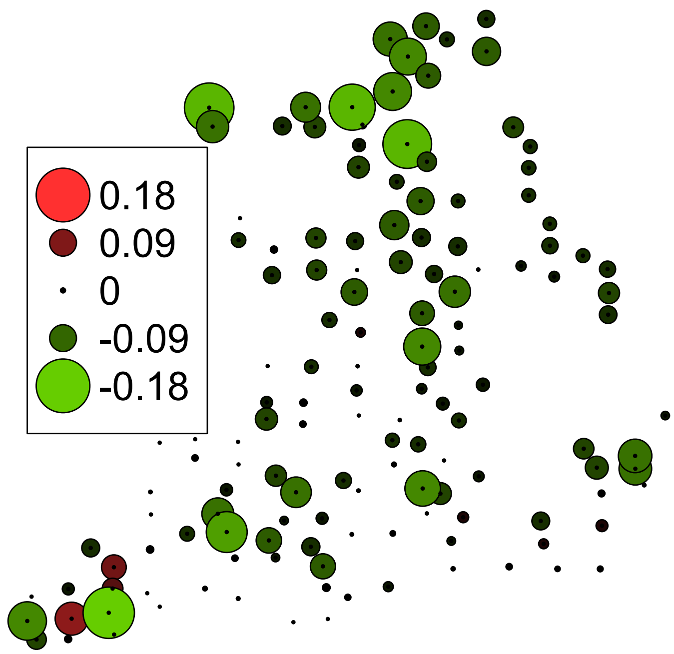


Figure 4.7: The difference between the actual data and the Jensen model estimates for wind velocity deficit relative to leading turbines for Farm 2. The wind direction is from the south (180°) and the wind speed deficit is relative to the leading turbines on the south side of the farm. The plot shows the actual data minus the Jensen estimates, so positive values are underestimates of the actual wind speeds whereas negative values are overestimates.

surrounding areas of both farms are flat and homogeneous by many standards, but small deviations could result in different conditions far from the met towers that would not show up in the available data. As given, the Jensen model does not capture the dynamics of these two farms and results in significant errors for production estimation using the given data.

This mismatch can be partially explained by the complex wake structure and propagation that is likely present in the farms. For the case of Farm 1, another study has measured these flow structures using Doppler radar, and the wake structures present are driven by short-term wind transients and terrain features.[115] This behavior has been shown to result in high momentum channels throughout the farm, and these channels could explain the discrepancies between the actual data observed and the expected behavior of the Jensen model. Turbines exposed to these higher-speed channels further back in the farm produce more power than otherwise would be expected, and in some cases they produce more than the leading turbines in the farm.[115] This phenomena is observed in the actual data from Farm 1.

The Jensen model can also be used to look at some standard benchmarking performance measures for wind farms. In a limited context, I can evaluate whether the Jensen model is capturing the localized effects expected in a wind farm. In closely-spaced lines of turbines, the wind speed typically drops off significantly after the leading turbine and may sustain smaller decreases in the downstream turbines.[37] This behavior is also predicted by the Jensen model and is expected to be seen in any

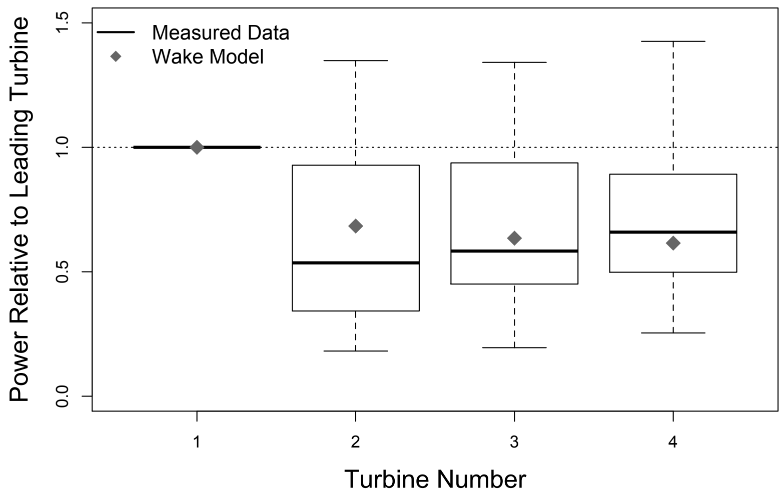


Figure 4.8: Comparison of wind velocity along a line of turbines. Shown here are the wind speeds (relative to Turbine 1) for Turbines 1-4 in Farm 1 when the wind is aligned with the line of turbines $\pm 2°$. The Jensen model shows the expected drop in wind speeds behind each turbine, and the actual farm data shows similar behavior on average, even if there is a large spread in the data. The standard errors for the relative power of turbines 2, 3, and 4 are 0.071, 0.084, and 0.084, respectively.

line of turbines subjected to oncoming winds parallel to the line. Figure 4.8 shows the comparison of the expected behavior of the Jensen model and the actual farm data. There are not many datapoints for this particular wind direction (105°), but there are enough to show that the wind farm does behave as expected in a limited setting with simple turbine interactions.

4.3.1 Relevance of Wake Models

Wake models such as the Jensen model are appropriate in cases where turbines in a farm are spaced closely enough so that the wakes from leading turbines do interact with downstream turbines. The exact distance at which a wake ceases to impact downstream turbines depends on the turbine size, the amount of turbulence in the surrounding flow, and any characteristics interfering with the flow, such as terrain features. At a minimum, it has been found that a wake can propagate for a distance of 8-10 rotor diameters, and this distance can be even longer if the turbulence is low.[116] Optimal turbine spacing, taking into account both wake effects and the economic cost of increased spacing, may be closer to 15-25 rotor diameters in some settings.[108] In the case of Farm 1, empirical evidence has shown wake effects propagating more than 15 diameters downstream under certain flow conditions.[115] Thus, it is reasonable to expect wake effects to be present in these two farms for spacings of 15 diameters, and the effects are expected to be substantial for spacings less than 10 diameters.

Figures 4.9 and 4.10 show the distribution of minimum spacing for the turbines in Farm 1 and 2, respectively. These plots incorporate the farm layout throughout the entire dataset, i.e., I have calculated the minimum upstream turbine distance for any turbines sitting within a 15°cone of potential influence. This upstream distance obviously varies with wind direction, but these figures capture the frequency for which any turbines see a certain level of upstream spacing in the dataset based on the actual observed wind directions. For each farm, a significant portion of upstream turbine spacing falls below 15 rotor diameters. For Farm 1, 26% of turbine datapoints have a minimum spacing of less than 15 diameters. For Farm 2, that number jumps to 60%, with almost 32% of datapoints at 10 diameters or less. These two wind farms should be good candidates for wake-effect models. The direction-dependent spacing in the

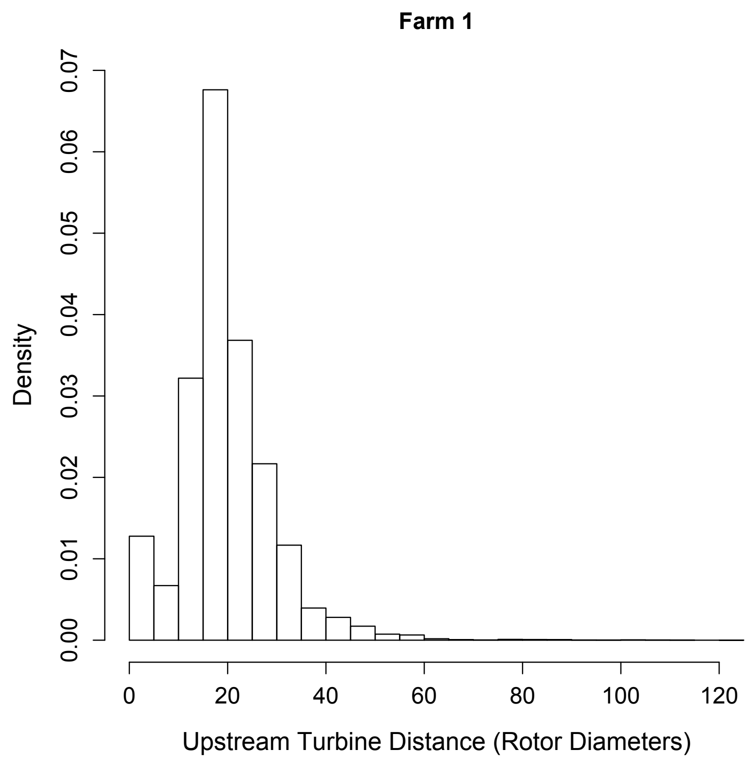


Figure 4.9: Minimum upstream turbine spacing for Farm 1

farms is low enough that significant wake effects are expected.

4.3.2 Choice of Wake Decay and Thrust Coefficients

There is no data on the levels of turbulence or atmospheric stability in either Farm 1 or Farm 2, and the best guess for the value of k, the wake decay coefficient for use in the Jensen model implementation, is therefore the industry-standard value for onshore farms of 0.075. The exact thrust coefficient curve is also unknown for these turbines,

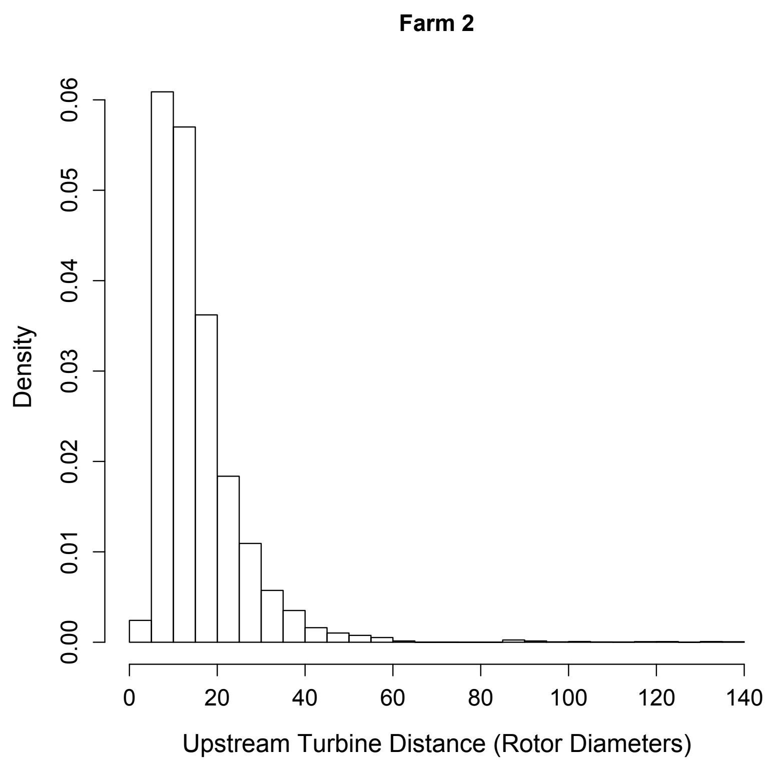


Figure 4.10: Minimum upstream turbine spacing for Farm 2

but again, an initial guess was used for the previous comparison. Initial tests of the Jensen model with these 'best-guess' parameter values led to poor representation of the actual farm behavior. Therefore, I decided to perform a sensitivity analysis on the choice of the k and C_T parameters.

Here, k is varied between 0.01 and 0.1, in increments of 0.01, and C_T is varied between 0.2 and 0.9 in increments of 0.1 to represent a wide range of plausible values for both parameters. The calculated velocity deficits were then used to predict the power output of each turbine, and the sum of turbine predictions was compared to the actual results for the farm power production. The predictions were also compared for different wind speed values to account for the variation of C_T with wind speed. Data was separated into three bins of either low (< 5 m/s), medium ($5 - 10$ m/s), or high (> 10 m/s) wind speed and prediction errors (in terms of mean absolute error and root-mean squared error) were calculated separately for each. The prediction error results from this sensitivity analysis can be seen in Figures 4.11 and 4.12 for Farm 1 and 2, respectively.

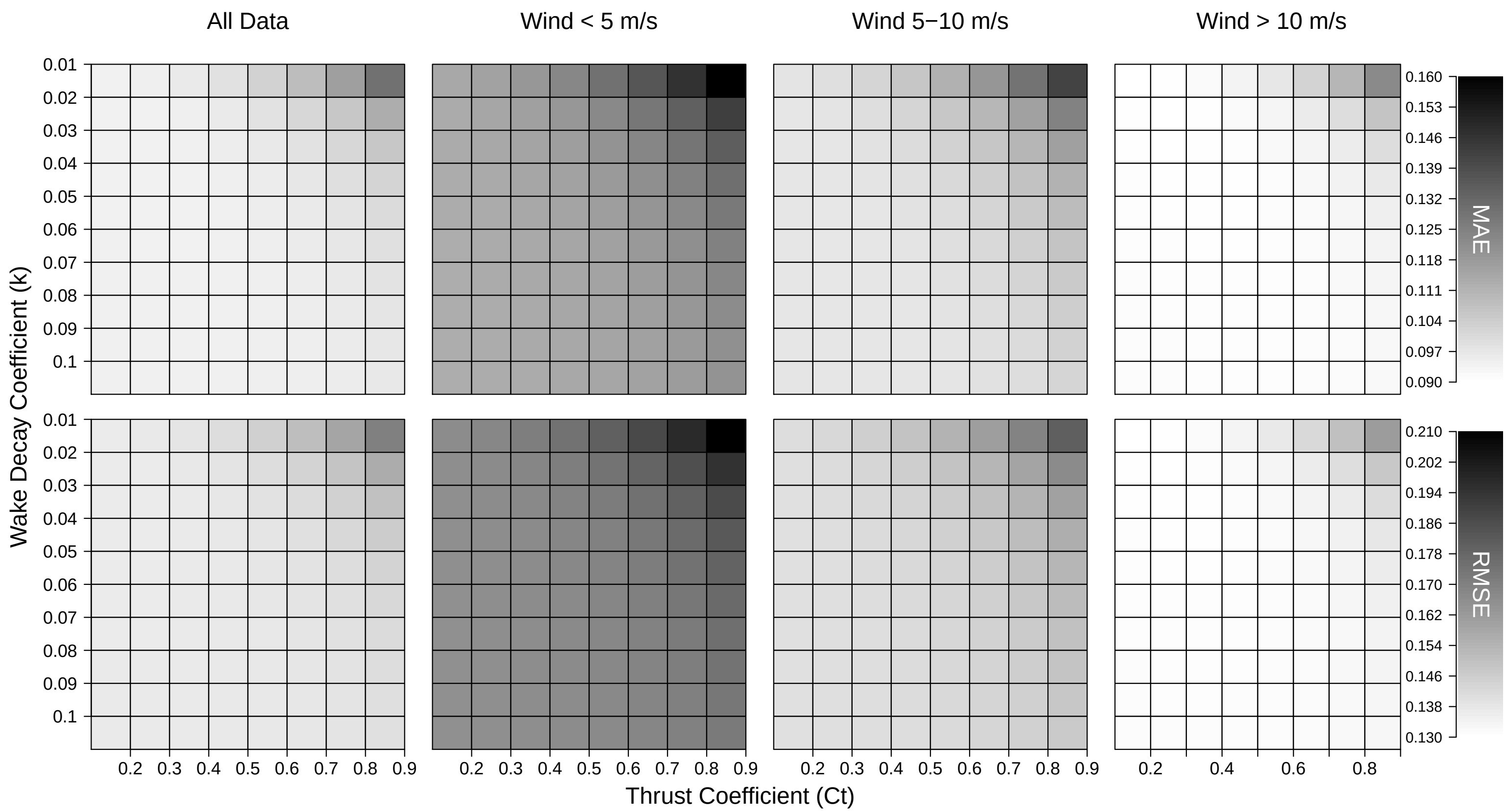


Figure 4.11: Mean absolute error (MAE) and root-mean squared error (RMSE) for Farm 1 power production as a function of k (y-axis) and C_T (x-axis) calculated using velocity data from met tower 1

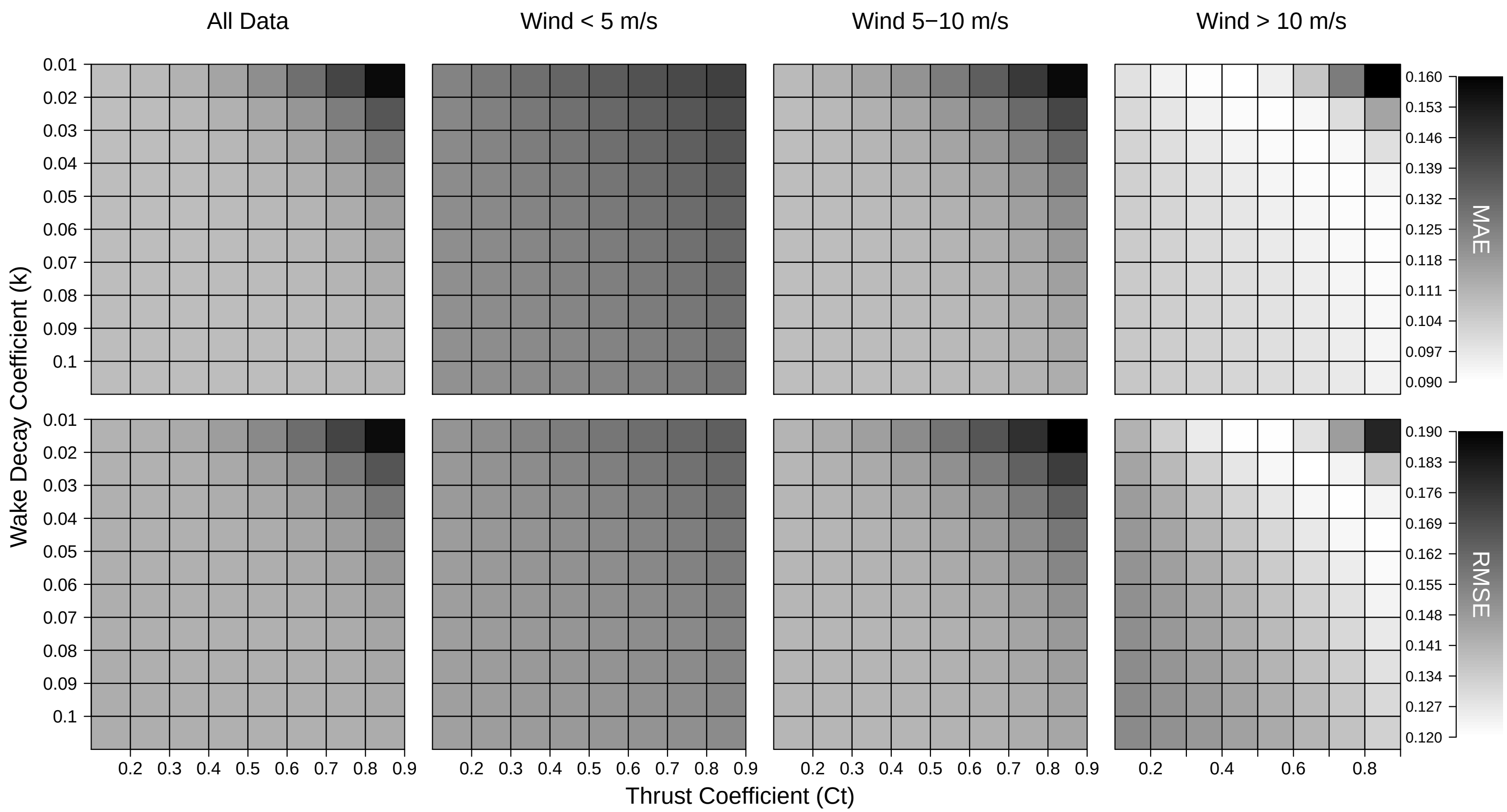


Figure 4.12: Mean absolute error (MAE) and root-mean squared error (RMSE) for Farm 2 power production as a function of k (y-axis) and C_T (x-axis) calculated using velocity data from met tower 1

The mismatch between the Jensen model and the actual data was high for the initial 'best-guess' values for k and C_T, and it intuitively follows that a reduction in prediction error would drive the values away from these initial guesses. The lowest errors occur on the extreme ends of the tested ranges, and these end values are at the very edge of what could reasonably be expected in a real wind farm. The Jensen model simply fails to capture the true wind dynamics present, even when accounting for the possibility of extreme turbulence or unrealistically low thrust coefficients. The one exception is the case of Farm 2 at high wind speeds. The lowest errors for this particular case occur across a band of low wake decay coefficients and mid-high thrust coefficients. High wind speeds are generally associated with increased atmospheric stability and therefore decreased turbulence, and the model may be capturing this relationship. However, thrust coefficient values are typically lower at high wind speeds, so the trend towards higher C_T values is counterintuitive.

Overall, the errors are lower for higher wind speeds. This in an artifact of the shape of a turbine power curve, since the steepest part of the curve lies in the medium-range wind speeds of $5 - 10$ m/s. Here, small errors in wind speed result in relatively large errors in power production. At higher wind speeds, where the power curve flattens out, the same small error in wind speed results in only a marginal error in power due to this flattened curve.

4.4 Alternative Methods for Power Prediction

The Jensen model fails to capture the true dynamics of either Farm 1 or Farm 2 when it comes to wind speed deficits and farm power production. It cannot be used as an accurate tool for either resource assessment or power prediction for the case studies presented here. There are alternatives to wake models for both resource assessment and power prediction, and I compare the accuracy of these other methods. Statistical models have been used for short-term wind power forecasting as well as wind farm production characterization (i.e., such as developing a farm-level power curve[109]). For resource assessment alone, the National Renewable Energy Laboratory (NREL) has developed a database of potential wind farm sites and offers virtual production data from each one. This data will also be used as a point of comparison for estimating power production from the two wind farms. Details of each of these methods are presented in the following sections.

4.4.1 Statistical Models

Statistical models have several advantages over wake-based modeling techniques. There is no need for explicit information about the physical details of the farm, atmosphere, surface roughness, or turbulence in a statistical model. If this information is not known outright, the relationships are intrinsically captured in the existing data when training the model. A model trained on Farm 1, for example, will have assumptions about the relationships in the data already built in, and they then are used when making predictions for Farm 1.

Initial testing was performed using a number of different statistical models. Generalized Linear Models (GLM), Generalized Additive Models (GAM), Random Forests, and Multivariate Adaptive Regression Splines (MARS) were initially tested for their predictive accuracy. For the wind farm datasets, the nonparametric models (Random Forest and MARS) resulted in much lower errors than the parametric models tested (GLM and GAM). From here, I further tested just these two model types, comparing their performance under different training conditions and testing across a varying number of trees in the case of the Random Forest model. While the two model types both performed well, the Random Forest model (implemented in R using the package RandomForest[57,117]) consistently outperformed the others. For each farm, several versions of a Random Forest model were created, both on the turbine level and the farm level. For the turbine level, a separate model was created for each individual turbine in the wind farm. This was done in one of two ways: 1) training the model using only data from the met towers or 2) using the met tower data along with turbine layout data. These are denoted T_{met} and T_{layout} respectively in Tables 4.2 and 4.3. The met tower data consisted of wind speed, direction, and temperature. The layout data for each turbine was made up of the streamwise distance and angle relative to any upstream turbines within a symmetric 30°cone pointing upstream. These

Table 4.1: Summary statistics for the statistical model input data

		Minimum	Median	Mean	Maximum
Farm 1	Wind Speed	0.8	9.0	9.0	21.1
	Wind Direction	0.0	191.1	187.2	360.0
	Temperature	-14.4	19.1	18.3	43.1
	Minimum Turbine Spacing	2.9	18.5	19.8	121.4
Farm 2	Wind Speed	1.7	7.8	8.1	21.4
	Wind Direction	0.0	196.1	185.3	360.0
	Temperature	-18.7	7	8.7	35.6
	Minimum Turbine Spacing	3.3	13.0	15.5	139.2

data values change with wind direction, and the resulting information is used in the statistical model as a proxy for possible wake interactions present at a given turbine. Models that incorporated seasonal and diurnal effects were also tested, but the resulting errors were higher in some cases and marginal at best in others, with changes in mean absolute error ranging from a 7% increase to a 0.4% decrease, and they are not presented here. Summary statistics for the data used in the statistical models is shown in Table 4.1. All upstream turbine distances were included, but only the minimum is shown here as it is the most critical distance parameter for wake effects.

The farm level models were also implemented in one of two ways: 1) training the model on Farm 1(2) using met tower data to predict Farm 1(2) power production or 2) training the model on Farm 1(2) using met tower data to predict Farm 2(1) power production. For the models trained using the same farm data, a holdout analysis was also performed to assess the consistency of the results. The training sample is drawn randomly in each case, using 70% of the available data to predict the remaining 30% of the observations. For the models used to predict the opposite farm, this was not done as the entire dataset was used for training in order to predict for the entire dataset of the alternate farm. The models trained on one farm and used to predict the other are expected to perform poorly compared to the other training methods. The intrinsic information that is captured when training the model does not necessarily (and in this case, is likely not to) apply to the other farm. Specific relationships between wind direction differences and farm power could imply a certain level of turbulence in one farm that affects power production. That may not be the case in the other farm, and farm-level power curves have been found to be specific to an individual farm.[109] Nevertheless, if such a model can provide a reasonable degree of accuracy, this technique can go a long way towards assessing wind production for farms that may not even exist yet.

4.4.2 NREL Wind Integration National Dataset

NREL provides an open-source database of potential wind sites that can be used for resource assessment, planning, and integration studies. The dataset consists of 112,471 onshore grid cells that contain up to 8 virtual turbines each. Each turbine is assumed to be a 2MW machine with a 100-meter hub-height. The power curve used in each grid cell is dependent on the assessed wind class, and each class power curve is made up of a number of representative manufacturer power curves for similar turbines.[110] The power production of each grid cell is estimated using the appropriate power curve and the wind speeds resulting from reanalysis of meteorological conditions using a Weather Research and Forecasting (WRF) model to provide 2km by 2km resolution on a 5-minute scale. Instead of explicitly modeling wake effects for the virtual farms, a correction is applied to reduce the wind speed in order to account for the presence of wakes. The power curve is then applied based on these new, corrected wind speeds. The correction is applied as follows

$$C_{wake} = 1 - \frac{1}{20}\left(\frac{n_{turbines} - 1}{7}\right)$$

where $n_{turbines}$ is the number of turbines in the grid cell. With a maximum number of 8, the wake reduction is no more than 5%. This correction, C_{wake}, is then multiplied by the met data wind speed to get the corrected grid cell wind speed for all turbines in the farm.

The dataset includes multiple grid cells within the areas of both Farm 1 and Farm 2. For the most accurate comparison between the actual data and the NREL dataset, I chose the individual grid cells located closest to the two met towers in each of the farms. The two sites in Farm 1 closest to met towers 1 and 2 contain 6 and 8 turbines, respectively, and use the power curve for class 1 winds. The two sites in Farm 2 closest to met towers 1 and 2 contain 8 turbines each and use the power curve for class 3 winds. The power data from these grid cells are normalized based on total grid capacity and then used as the 'predictions' for comparison to the actual farm data. The predictions are used individually from each met tower site and as an average of the two grid cells' production in each farm, so as to include wind conditions from locations spread across the area of the farms.

4.4.3 Aggregated Power Curves

If wakes are ignored, it can be assumed that the wind measured at one point in the farm is the same as that seen elsewhere in the farm. Therefore, a farm-wide power prediction can be made using no model at all, but by simply aggregating the individual power curves across the farm using met tower wind data. For these predictions, it was assumed that the wind seen by each turbine in the farm was the same as that measured at a given met tower. This wind speed was then translated into power using the turbine power curve and this power value is multiplied by the number of turbines to get the farm-level power. This was done using both met tower 1 and 2 data separately, and then using the mean value predicted from both. This aggregated method is the simplest to implement. There are no assumptions or corrections made about the wake effects in the farm. The farm layout does not matter at all; only the number of turbines. In theory, this method should result in an over-prediction of power production, since wake effects are ignored.

4.5 Prediction Errors

Predictions for the total farm power production were made using each of the methods previously mentioned. All predictions were normalized based on the installed farm capacity so that the errors can be compared across farms and across methods. The results of the model comparison for Farm 1 are shown in Table 4.2 and for Farm 2 in Table 4.3. The tables show the mean absolute error (MAE) and root mean squared error (RMSE) for statistical models, Jensen wake models, aggregated predictions (i.e., no model), and the NREL dataset predictions. All predictions have been normalized by total capacity, so the errors are in the units of normalized capacity as well. As mentioned previously, a holdout analysis was performed for some of the statistical model cases where applicable. For these, the errors reported in Tables 4.2 and 4.3 represent the mean value across all holdouts and the number shown in parenthesis is the standard error across all holdouts. There is very little variation across holdouts, showing that the models are robust in their predictive accuracy. For the statistical models, T refers to models created for each turbine individually and then aggregated and F refers to models trained on the farm as a whole. The subscripts *met* and *layout* refer to models trained using met data only and both met data and farm layout data, respectively. The subscripts *self* and *other* refer to models that were trained on Farm 1 to predict its own power and trained on Farm 2 to predict Farm 1's power, respectively. The mean values are the errors when the predictions from both met tower 1 and met tower 2 were averaged, and the average used as the prediction. For the first three error columns, the values shown are the result of a 20-replication holdout analysis with the mean of the 20 holdouts shown along with the standard deviation in parentheses.

The statistical model have the lowest errors overall, and they are significantly lower than the other methods tested. There is no advantage to be gained by including information about the layout of the farm; using the met data alone outperforms the model incorporating data on upstream turbines. A statistical model is able to intrinsically capture any critical turbine interactions present in the data, and nothing is gained by forcing it to explicitly include it. Most surprisingly, the errors stay quite low even when predicting for the *opposite* farm that the models were not trained on. A statistical model can still do a reasonably good job of estimating power production on an independent farm with no farm-specific data. The Jensen models have already been shown to disagree with the actual data, and this is reflected in the high error values. However, there is an advantage to be gained in terms of predictive accuracy by averaging the predictions from two different Jensen models applied using the data from the two met towers separately. In many cases there is poor agreement between the two met towers, and the errors therefore tend to cancel each other out, and this results in a lower combined error. The combined errors are still higher than the statistical model errors for Farm 2, but the mean Jensen predictions in Farm 1 actually fall below the level of the farm-level statistical model errors when predicting the opposite farm. In the third method tested, aggregating individual turbine power curves (and thus ignoring any wake effects) results in comparable, and in some cases, lower errors than the Jensen models. Again, the errors are reduced significantly by averaging the predictions from the two met towers, and these combined error measurements are similar to those obtained by the farm-level statistical model trained on the opposite farm. The NREL dataset predictions had the highest errors out of all the models tested and do not provide a strong estimate for farm power production at these locations. The individual site errors from the NREL data (from the two different met tower locations) were similar to that of the mean value, and they are not included in the tables.

Table 4.2: Normalized Farm 1 power prediction errors

	Statistical Models				Jensen Model			Aggregated Turbines			NREL
	T_{met}	T_{layout}	F_{self}	F_{other}	Met1	Met2	Mean	Met1	Met2	Mean	Mean
MAE	0.050 (0.0008)	0.053 (0.0008)	0.050 (0.0006)	0.082	0.095	0.101	0.079	0.095	0.095	0.080	0.156
RMSE	0.074 (0.0021)	0.077 (0.0021)	0.076 (0.0015)	0.110	0.140	0.144	0.114	0.139	0.139	0.113	0.217

Table 4.3: Normalized Farm 2 power prediction errors

	Statistical Models				Jensen Model			Aggregated Turbines			NREL
	T_{met}	T_{layout}	F_{self}	F_{other}	Met1	Met2	Mean	Met1	Met2	Mean	Mean
MAE	0.051 (0.0006)	0.051 (0.0006)	0.052 (0.0007)	0.087	0.127	0.111	0.099	0.116	0.116	0.085	0.227
RMSE	0.072 (0.0010)	0.070 (0.0009)	0.073 (0.0012)	0.114	0.160	0.147	0.128	0.148	0.148	0.112	0.295

The predictions derived from the NREL data have high errors compared to the other models used. This is largely due to the added layer of uncertainty present in this data. The wind speeds come from reanalysis data, and they are downscaled from larger weather models. They might be very accurate for capturing the dynamics of large weather patterns, but it is a lot more difficult to model weather at a very small spatial scale, and most reanalysis datasets in existence offer data at a much larger spatial resolution.[118] Wind speeds in particular are difficult to model for local areas, and this problem is worsened in areas of complex terrain.[119] To support this point, the correlation between the temperature values in the NREL dataset and the actual measured temperature at the met towers ranges from 0.97 to 0.98. The correlation for wind speeds, on the other hand, sits in a range of 0.66 to 0.69. This discrepancy in the local wind speeds carries over into discrepancies for farm power estimates.

4.6 Discussion

Statistical models achieve the lowest errors for estimating wind farm power production, and the errors stay reasonably low compared to the alternative methods even when the models are not trained on the same farm that they are predicting. The two farms are similar in that they are both situated in flat, agricultural areas, but they are in different regions of the country, have very different turbine layouts, and see different wind conditions. All of the existing literature suggests that the turbine layout is critical to characterizing farm power production because of the large effect that wakes have within a farm. The Jensen model was used to explicitly model the turbine wakes, but the complexities in these real farms are not captured by the Jensen model. There are a number of issues present when comparing wake models to actual measurements, including measurement errors, accounting for wake transport time, natural fluctuations of speed and direction, and time averaging, to name a few.[37,38] In addition, the actual wind conditions within an onshore wind farm with just minor terrain variation are more complex than the steady input flow used in the Jensen model. Because of the simplistic assumption of steady-state input flow to a wind farm, the Jensen model fails to capture these complex issues and therefore cannot provide accurate power predictions. The potential sources of error are plentiful, and I can speculate as to the sources, but a thorough investigation into the most critical parameters that result in these errors is left as an interesting avenue for future research. Data issues with the met towers are certainly one suspect (both in terms of calibration and location, if the met towers are not in freestream flow), but the natural variation of wind throughout such a large spatial area could also result in a significant mismatch between what the Jensen model predicts (based on what the met towers see) and the actual data.

The statistical models do not model the wakes at all, but they have the ability to intrinsically capture relationships between the turbines. If the farms presented here have unique but consistent wake behaviors, the statistical models will capture these relationships. It is especially surprising that the statistical models are still fairly accurate when predicting power production for another farm, since any unique wake behavior should not carry over to a different case study. Still, the results have important implications. It is likely that the geographical similarities are enough to result in accurate cross-farm statistical models even if substantial wake-effect differences exist. In addition, for rough estimates of farm power production, one can argue that no model is needed at all. The simplest approach is aggregating the power curves of a large number of turbines, and this method produces predictive accuracy on the same order of, or better than, the Jensen model. By using the aggregation method, however, no model of the farm nor data on the position of the turbines is needed. This method can be used for any farm estimates, even one that is not built or planned yet. Good estimates can be obtained with just a met tower installed.

Wake models are heavily tested on large offshore wind farms with uniform turbine alignment. The models have been continually improving and can capture the wake behavior in a number of case studies. Any user of these models, however, should be very careful when applying them to onshore sites. The two case studies presented here demonstrate the many ways that onshore farms do not follow the same well-behaved patterns seen in offshore farms, leading the models to break down.

Luckily, alternatives do exist and statistical models can be used for power prediction if training data exists for similar conditions to that which is to be predicted. For resource assessment when there is no training data available, it may be more advantageous to use a simple summation to aggregate the turbine power curves than to model the wakes explicitly. Obviously, the layout of the farm should be chosen carefully, but the real-world effects can result in drastically different behavior than what a model may predict, and the models should be used to inform but not determine a farm's design.

The results presented here also bring up practical questions about the value of wind forecasting. Accurate wind forecasts are highly sought after and are used to make operating decisions regarding wind integration in power systems. It has been shown, however, that even with a perfect forecast (i.e., the wind conditions are known exactly at the met towers in real time), the amount of power produced still contains uncertainty. The errors with statistical models are low but nonzero; errors in translating wind speed to power are present even with a perfect forecast. This is an interesting extension of this research and is left as future work.

Chapter 5

Simulation of Tropical Cyclone Impacts to the U.S. Power System Under Climate Change

5.1 Introduction

Tropical cyclones, and hurricanes in particular, have been the cause of extensive damage and financial loss in many regions of the United States. They rank among the most destructive natural hazards for coastal areas.[120–122] Hurricane Sandy, for example, left more than 8 million customers without power, resulting in estimated costs of $65 billion.[123] Power outages caused by tropical cyclones are one of the biggest concerns for affected communities; a lack of power can result in business interruptions, healthcare stresses, and cascading effects for dependent infrastructure systems, such as telecommunication or water networks.[124] While there have been strong developments in power-outage prediction models that have proven useful for local utility companies,[125–130] the focus has been on outage-forecasting in the days before a storm and not on long-term changes in risk. There is a need for infrastructure providers and emergency managers to plan for hurricanes on much longer time scales, i.e., on the order of decades. This planning must consider how future climate conditions may influence storm behavior.

The relationship between tropical cyclone hazard and climate change has been studied extensively, but there is still a great deal of uncertainty involved.[121,131–138] For example, the physics-based models developed by Knutson et al. suggest that the frequency of Atlantic hurricanes and tropical storms will likely be reduced in the future.[134] Results obtained by downscaling IPCC AR4 simulations also suggest a reduction in the global frequency of hurricanes in a warmer future climate scenario, with a potential increase in intensity in some locations.[131] Statistical models argue that the intensity and frequency of TCs will likely increase in a warmer future.[139,140] These examples from the literature highlight the deep uncertainty remaining; the direction of change (e.g., more storms vs. fewer storms) and, to a greater extent, the magnitudes of change remain uncertain.

Because many traditional risk and decision analysis methods struggle under such deep uncertainty, more robust planning tools are needed in this area.[141] One promising approach is to focus on actions that perform well under a range of scenarios that are within the realm of physical possibility as supported by the research literature. These scenarios can be modified over time as conditions change and new information comes to light.[142] Long-term planning for major infrastructure projects, such as updates to the electric grid, can leverage scenarios to assess the robustness of possible actions rather than as a basis for determining an optimal solution by assigning fixed probabilities to the scenarios. A key component of this is the ability to estimate the performance of infrastructure systems under future climate scenarios in a way that builds upon accurate models of system behavior and offers both broad-area insight and locally detailed performance estimates.

This chapter offers insight into one aspect of this long-term planning problem for areas along the Gulf and Atlantic coasts of the United States. It focuses on what tropical cyclone impacts might look like if climate change causes changes in storm behavior. I assess impacts for a wide range of future storm scenarios, including the status quo if the climate remains stable and tropical cyclone seasons remain within the observed historic variability. Here, the term scenario is used to represent potential realizations of climate-induced changes to tropical cyclone behavior in the North Atlantic basin. Using a simulation informed by the historical hurricane record, I compare baseline impacts to the outcomes under various scenarios for 23 states lying along the U.S. Gulf and Atlantic coasts. I create plausible scenarios of future tropical cyclone behavior based on the literature on the relationship between climate change and hurricanes. This literature offers a wide range of possible realizations. Regarding changes in intensity, for example, the general consensus is that storms will strengthen, although the degree of change varies.[133,143] There is less consensus on changes in storm frequency, with the literature showing both increases and decreases.[134,144] I vary storm intensity, storm frequency, and the distribution of landfall locations. For each scenario, the simulation results represent tropical cyclone impacts to the United States in terms of wind-induced power outages. The analysis is done at the census-tract level, resulting in localized projections of extreme wind speeds, the fraction of customers without power, and probabilities of power outages. In a field where much of the focus is global in scale, I provide more localized information for decision-makers that can aid in long-term planning for their specific area of concern.

The sensitivity to changes in tropical cyclone hazards can vary greatly among regions. This chapter provides insight into how power systems along the Gulf and Atlantic coasts of the United States may be affected by climate changes, which areas should be most concerned, and which areas are unlikely to see substantial changes under any tested scenario. The range of potential impact is a key component of informed planning models, since potential actions can be tested across this range to ensure robust and sustainable solutions.

5.2 Climate Change and Tropical Cyclone Activity

Depending on the model used, the projected climate change impact on North Atlantic tropical cyclones can vary significantly. Several studies suggest that the frequency of storms may decrease in the North Atlantic Basin, but the intensity may increase, perhaps substantially.[136] There is also concern that storm genesis location and track movement will be influenced by climate change, but there is not enough information to assess the nature of this impact with a reasonable degree of spatial precision.[145] There is potential for substantial changes in tropical cyclone hazard, but there also remains substantial unresolved uncertainty. Under such conditions, knowing the range of reasonable possible outcomes at a local level can result in more robust planning decisions. Scenario-driven planning can help local communities understand if they are particularly sensitive to climate-induced changes in tropical cyclone hazards or if they are in a relatively insensitive area. Plans can then be designed to perform adequately across this range of impacts, instead of optimizing for a single future or a small set of futures driven by highly uncertain insights into the climate-tropical cyclone relationship.[142]

I develop a range of plausible tropical cyclone scenarios and assess the impacts of these scenarios in terms of electric power outages and extreme wind speeds in the U.S. I simulate a large number of replicated tropical cyclone seasons in the United

States for 12 plausible tropical cyclone scenarios. A replicated tropical cyclone season represents one virtual year of tropical cyclone activity, in which the number of storms can vary from replication to replication. Virtual storms are independently generated and the resulting impacts are modeled through a power outage estimation model that was developed using the data of Han et al.[129,130] and Nateghi.[146]

I chose the scenario-based approach largely due to the high degree of uncertainty in future climate projections and the resulting impact on hurricanes. This approach gives great insight into the range of possible consequences and what different regions of the country may need to prepare for. The sensitivity analysis conducted here allows us to study which factors drive changes in impacts, how these impacts may vary over location, and which areas might be more or less sensitive to potential changes.

Catastrophe modeling is prevalent in industry, and it often focuses on financial losses for insurance companies. Companies such as AIR, RMS, and EQECAT all have their own versions of hurricane risk models for the U.S. Model details are not available publicly, but some models do attempt to characterize future risks as the climate changes. AIR, for example, has a version of their model that is conditioned on warm sea-surface temperatures.[147] RMS uses their model to assess short-term climate threats in the Risky Business report, but publicly available details are limited and the results focus only on changes in financial loss.[148] Validation is done on losses from past storms, so their ability to validate under climate change conditions is limited.[149] Our scenario-based approach focuses more on long-term future outcomes that deviate from the historical record, so there is no longer an applicable validation dataset to be used.

5.3 Simulation Methodology

The simulation uses historical hurricane and tropical storm data. The baseline runs take the historical data as input, and the alternative scenarios alter parameters from the historical data to simulate plausible climate-induced changes to storm behavior. For each replication in the baseline case, I first sample from a Poisson distribution, with a mean equal to the historical mean, to determine the number of storms making landfall in that replicated year. For each storm, I randomly sample a landfall location from a smoothed distribution that assigns a probability to each 50 km stretch of coastline from Texas through Maine on the basis of the historic landfall counts in each of the 50km coastal segments. I randomly sample a maximum wind speed at landfall from the historical record. Based on which section of the coastline the storm hits, I subset the historical tracks, keeping only those that made landfall in the same region. These tracks are then used to train a random forest model, which is a statistical model used to predict the storms movement in each six-hour time step. For each time step, the wind speed decays according to the hurricane decay models of Kaplan and Demaria[150] until the wind speeds fall below the tropical cyclone classification level. This relatively simple model was chosen because it uses wind speed as input (instead of pressure) and does not require a priori knowledge of storm size or movement. With the storm track and intensity determined, these parameters are fed into a wind field model based on the methods of Willoughby et al. and Holland to calculate the storm radius and wind distribution.[151,152] This model generates estimates for the maximum 3-second gust wind speed and the duration of wind speeds above 20 m/s for the centroid of each census tract.[120,129,130] This wind data is then passed to a statistical outage prediction model, which uses a random forest model that has been trained on past hurricanes in different areas of the U.S..[146,153] The outage prediction model is a simplified version of the work of Nateghi et al.[146] in that it uses only publicly available data and a reduced set of variables to estimate the number of customers without power as a result of a hurricane.

Using the baseline case as a point of comparison, I also simulate different climate-induced storm scenarios to examine the influence of climate-induced changes in tropical cyclone behavior in the North Atlantic Basin. The scenarios represent changes in intensity, frequency, and location. I vary intensity by taking the randomly sampled maximum wind speed for each storm and multiplying it by a factor. I simulate scenarios for intensity factors of 0.8, 1.2, and 1.4, meaning a decrease in strength of 20%, an increase of 20%, and an increase of 40%. These intensity changes are based on bounding the estimates of intensity changes in the climate literature. For scenarios of frequency, I adjust the mean of the Poisson distribution that is used to sample the number of storms in each replicated year. The baseline case has a mean of 2, and I simulate scenarios for means of 0.5, 1, 3, and 4, again based on bounding the frequency change estimates that I found in the climate literature.

The location scenarios are more subjective, and there is even more uncertainty about track changes than about frequency and intensity changes. I adjust the probability distributions while still retaining the general shape of the spatial probability distribution of landfall locations because it is based on actual geographical characteristics. For example, some land areas are more prone to hurricanes because they jut out into the path of oncoming storms. I created four modified distributions to assess the changing impacts as storm location changes. The first scenario shifts storms further up along the mid-Atlantic coast, the second shifts them further down into the Gulf of Mexico, the third spreads the distribution out more evenly to reduce the natural peak around Florida, and the fourth concentrates the peak around Florida, thereby reducing the probabilities in the Gulf and in the Northeast. All scenarios maintain the original shape of the smoothed distribution.

For each scenario, I ran the simulation for 1600 replications in order to reach convergence. The aggregated results from 1600 simulated years of tropical cyclone activity allow us to calculate expected return periods for the output values. I calculate the 100-year, 50-year, 25-year, and 4-year, and 2-year return periods for maximum wind speed, duration of winds above 20 m/s, and the fraction (and number) of customers without power for each census tract. I also calculate the probability of each census tract having at least 10% of customers without power in a given year. The aggregated results allow for many such calculations, but I chose these parameters to portray the potential climate change impacts on both a large and small spatial scale.

5.4 Results

The simulation results show the impact under both the status quo of the baseline case and the climate-change induced scenarios that were evaluated. The scenarios demonstrate the sensitivity of various areas of the country to potential changes in tropical cyclone behavior, and the results can be evaluated on a local level.

5.4.1 Baseline Impact

For an initial baseline, I simulate tropical cyclone impact assuming that the frequency, intensities, and locations of tropical cyclones follow the observed historical distributions as discussed above. For each storm, I forecast wind-induced power outages in each census tract within the range of the storm. I repeat this process for 1600 simulated years, yielding a probabilistic estimate of the impact of tropical cyclones on power systems in the United States at the census tract level using the power outage model of Guikema et al.[153] The key physical hazard input to the power outage model is the estimated spatial wind field of a given hurricane. The impacts of surge, rainfall, and inland flooding are incorporated only indirectly; outages due to these causes were included in the training data, but the differences in surge, rainfall, and inland flood-

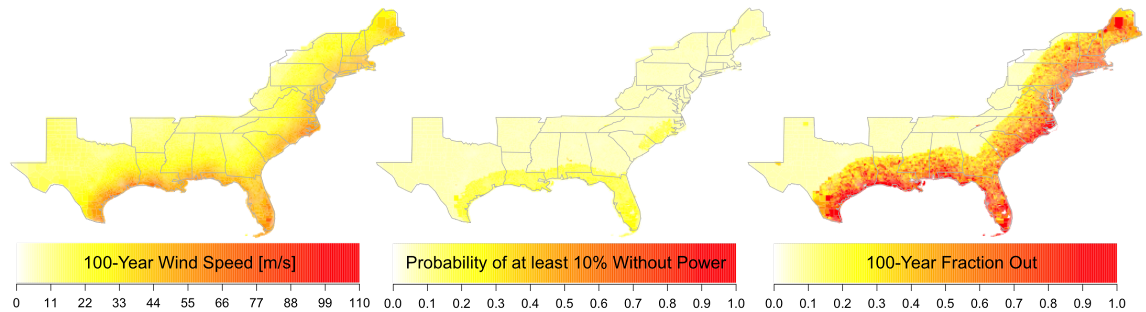


Figure 5.1: Baseline impacts of 100-year wind speed, annual probability of at least 10% of customers losing power, and 100-year fraction of utility customers without power plotted for each census tract.

ing between storms is not explicitly modeled. Other work has shown that excluding explicit modeling of surge impacts does not substantially impact the accuracy of the power outage predictions.[154]

Figure 5.1 shows the impact for 1600 replicated years with impact measures of (1) the 100-year wind speed (the wind speed with an annual probability of exceedance of 0.01), (2) the probability of at least 10% of customers losing power in a given year, and (3) the 100-year fraction of customers without power from a given storm, as assessed for each census tract individually.

These results show the estimated conditions under the historic state of tropical cyclone activity. I assume both a static population and a static power system (i.e. no upgrades or new technologies), so this level of impact represents the status quo. Some regions are expected to be more heavily impacted than others. The annual probability of at least 10% of the population being without power is 0.21 when averaged across the census tracts in the state of Florida. In contrast, when averaged over the entire region evaluated, this probability is 0.06. As expected, our simulation shows that the tropical-cyclone-induced 100-year wind speed drops off sharply as you move inland. The fraction of customers without power tells a slightly different story. This calculation depends not only on wind speed and duration of high winds, but also on the population of each census tract. Tracts with very low populations can appear as discrepancies among neighboring tracts. Information regarding the number of customers without power, instead of the fraction without power, is easily obtained as well and may be most useful for those planning storm responses, but it is more difficult to visually see impact trends due population variability among tracts.

As one point of comparison, our estimated baseline 100-year wind speeds can be compared to standard design criteria wind speeds given by the American Society of Civil Engineers (ASCE) design manual, ASCE 7-10, that are based on historical data.[155] For hurricane-prone coastal areas, the simulation output matches well with the ASCE 7-10 100-year wind speeds. The 100-year wind speed for Houston, TX, for example, is only 1% lower in our simulation output than in the ASCE design standard. Similarly, our estimated 100-year wind speed for Orlando, FL is about 2% higher than in ASCE 7-10. Most areas of interest are within 10% of the ASCE wind speeds, although some inland areas have larger deviations. The simulation has some inherent variability. This, along with the choice of the smoothed landfall probability distribution and the wind decay model used may account for some of the larger differences. However, this generally close match to independent estimates of 100-year wind speeds gives confidence that I am estimating the long-term wind environment well, at least in the baseline situation.

5.4.2 Potential Climate Impacts

If climate were to impact tropical cyclone intensity, strength, or track, the resulting impact would not be felt equally across the country. The regional effects also vary depending on the measure of interest. To model the effects of varying intensity, I simulated an additional 1600 hurricane years but multiplied the intensity of each generated storm by an intensity factor, k. I repeated this for k = 0.8, 1.2, and 1.4, generating 1600 hurricane years for each k, to represent a reasonable range of changes in intensity as suggested by the literature. When looking at wind speeds, the effects of varying intensity are felt primarily in coastal areas. This can be seen in Figure 5.2, where the changes are seen primarily along the coasts. The biggest changes are in those areas that receive the most frequent hurricanes indicating that they are particularly sensitive to changes in hurricane intensity. The fraction of customers without power, however, depends both on wind speed and storm size. Stronger storms are generally larger, and our simulations show the effects of storm size as the reach of the stronger (or weaker) storms creates bands of increased (or decreased) impact. These are the areas on the margins of the impacted area and are areas of the country particularly sensitive to changes in hurricane intensity. Figure 5.3 shows this result, as, on average, the stronger storms impact areas further inland than in the baseline

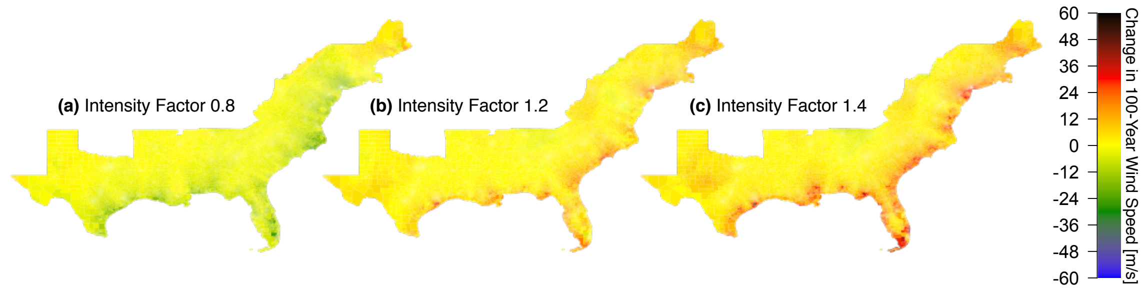


Figure 5.2: Changes in 100-year wind speeds for varying storm intensity away from baseline.

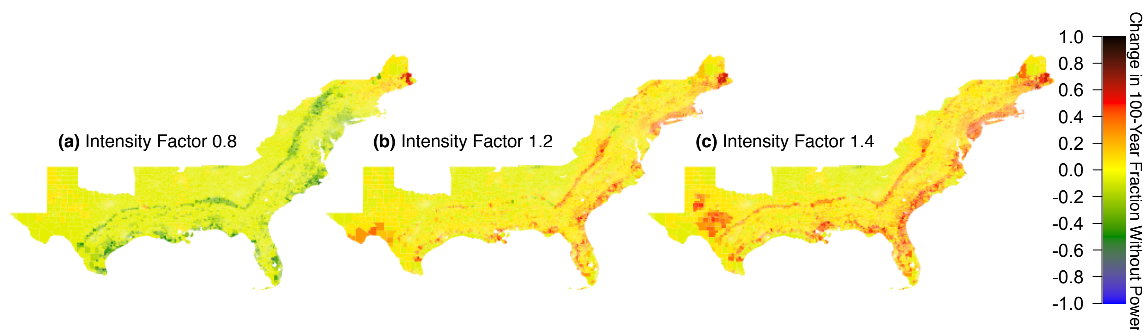


Figure 5.3: Changes in 100-year fraction of customers without power for varying storm intensity away from baseline.

case. The areas that fall on the edge of the impacted area see the largest changes when the average storm intensity varies. This is of particular interest because may of these areas are farther inland and do not have a strong history of experience with hurricanes. Additional consideration of hurricane preparation planning may be appropriate in such areas.

To examine the effects of varying hurricane frequency, I simulated an additional 1600 hurricane years but substituted in a different value for λ, the mean number of tropical cyclones making landfall per year. I repeated this for $\lambda = 0.5$, 1, 3, and 4, simulating 1600 hurricanes years for each, to represent a reasonable range of changes in frequency as suggested by the literature. A change in tropical cyclone frequency, as opposed to intensity, brings about changes of a different nature. The 100-year wind speeds change slightly, but not substantially. Extreme winds are driven by the strongest storms, not the frequency of more moderate storms. However, there is a more substantial impact on the annual probability of power outages, since more (or fewer) storms directly results in a larger (or smaller) probability of any given tract being impacted by a storm, and subsequently losing power. Figure 5.4 shows a comparison of these changes under different storm frequency conditions. The historical baseline is approximately 2 tropical cyclones making landfall in the U.S. per year ($\lambda = 2$). An average change of just one storm per year (more or less) can change the annual probability of at least 10% of the population without power by over 15% in some census tracts.

Although there is less evidence to support shifts in tropical cyclone location as a result of climate change, there is speculation that the locations of tropical cyclogenesis may shift in a warmer climate.[145] It is worth assessing how such changes may impact the U.S., but the scientific understanding is too weak to confidently support direct simulation of specific scenarios. Instead, I examined the sensitivity to changes in landfall location by adjusting the smoothed historical spatial probability distribution of landfall locations to shift storms further north and south, and also to spread out or concentrate the distribution (see Appendix D for details). As expected, the areas

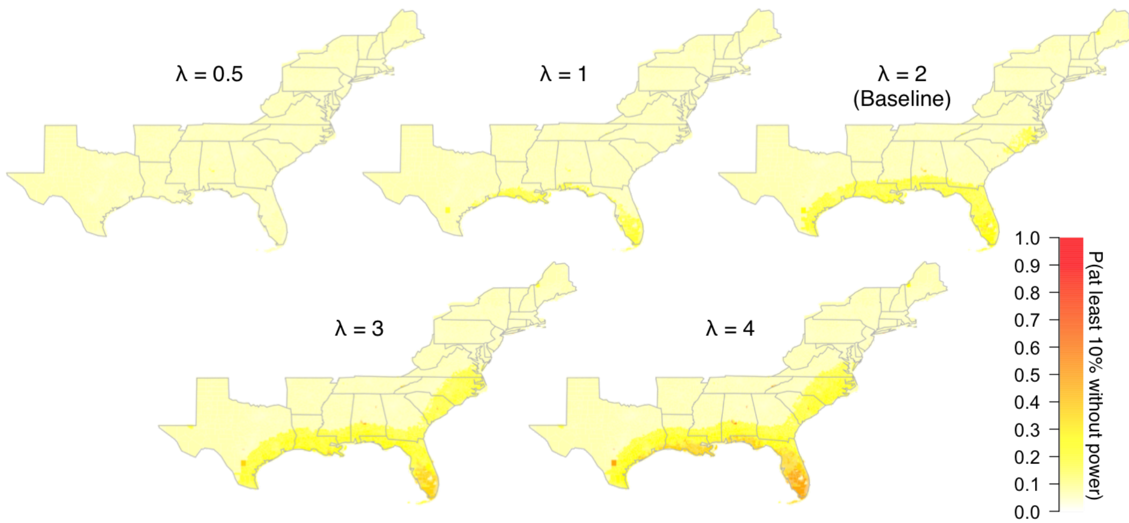


Figure 5.4: Changes in the probability of at least 10% of customers without power for varying storm frequencies.

hardest hit by tropical cyclones shift along with the shifting distributions, but our modified distributions are all based on the original distribution. This ensures that I still account for the geography of the coastline in determining landfall probabilities. Even with the modified distributions, some areas are still strongly impacted even when the probabilities of landfall are sharply reduced. For instance, Figure 5.5 shows the change in the probability of at least 10% of customers without power as the average landfall location distribution varies. I see that areas along both the Gulf Coast and southern Atlantic coast area particularly sensitive to changes in landfall locations, but in all scenarios I examined, the Florida peninsula continues to have a relatively high annual probability of at least 10% of the population losing power. The changes in maximum wind speeds and fraction of customers without power follow similar patterns, but there is more local variability.

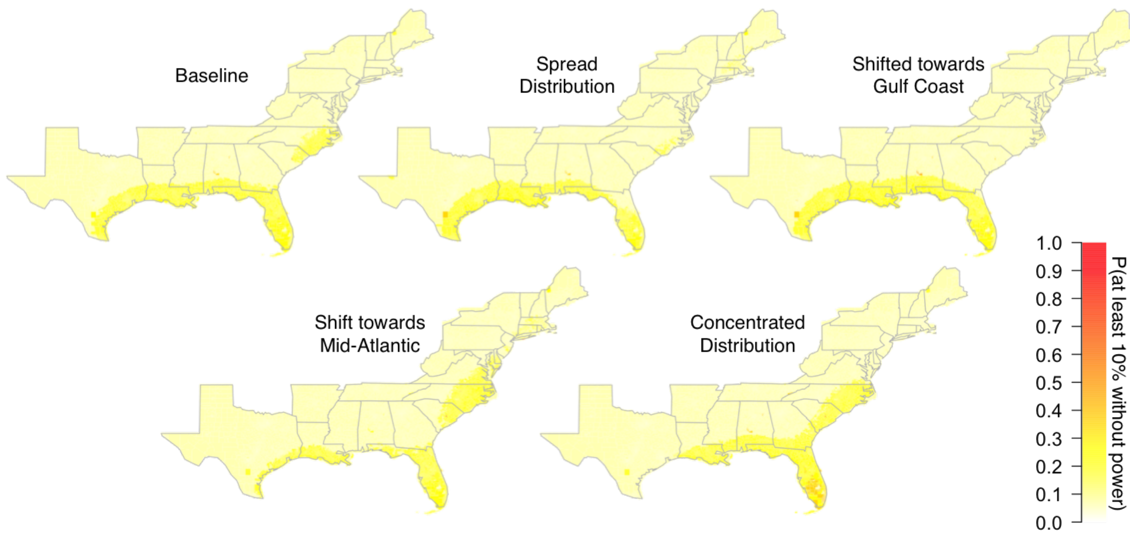


Figure 5.5: Changes in the probability of at least 10% of customers without power for varying landfall distributions.

I conducted additional analysis to compare the relative impacts of changes in frequency, intensity, and landfall location based on graphs of the empirical distribution of outages at the census tract level. The details of this process and the results are available in Appendix D. The overall conclusion is that changes in storm intensity have a greater potential impact on the U.S. power system than changes in frequency or landfall location. The impacts, both in terms of customers without power and maximum wind speeds, grow substantially worse as storms get stronger, on average. Changes in frequency or landfall, on the other hand, show relatively tightly grouped overall impacts, although the changes do depend strongly on location. When evaluating the entire United States as a whole, intensity largely dictates the severity of the outcome. Thus, characterizing the nature of future climate impacts on storm intensity should be an important focus of future work.

5.4.3 Metropolitan Area Impacts

Changes at the national level provide insight into the overall impact of potential future changes in tropical cyclone activity and are useful for federal agencies. Local decision-makers, however, are more concerned with smaller areas of potential impact, and the simulation results can also provide information at a much higher resolution. I demonstrate this by examining the impacts at the scale of several metropolitan areas: Houston (TX), New Orleans (LA), Miami (FL), Washington (DC), and New York (NY).

As expected, the results depend strongly on location because some areas of the country are more prone to tropical storms and others are more sensitive to climate changes affecting tropical cyclones. Figure 5.6 shows the return periods for the fraction of customers without power for the selected metropolitan areas under different hurricane intensities, together with the average return periods for the entire coastal area. The Houston, New Orleans, and Miami metropolitan areas are heavily impacted even for scenarios of lower intensity storms. These cities sit in already hurricane-prone areas, and strong storms only increase the already significant impacts. On the other hand, Washington and New York behave very differently. Both have relatively low impacts for low intensity storms, but New York sees sharp increases in the fraction of customers out as storm intensity increases, whereas Washington has a small range across all scenarios. New York is highly sensitive to changes in storm intensity, much more so than Washington. The Washington area is relatively protected from changes

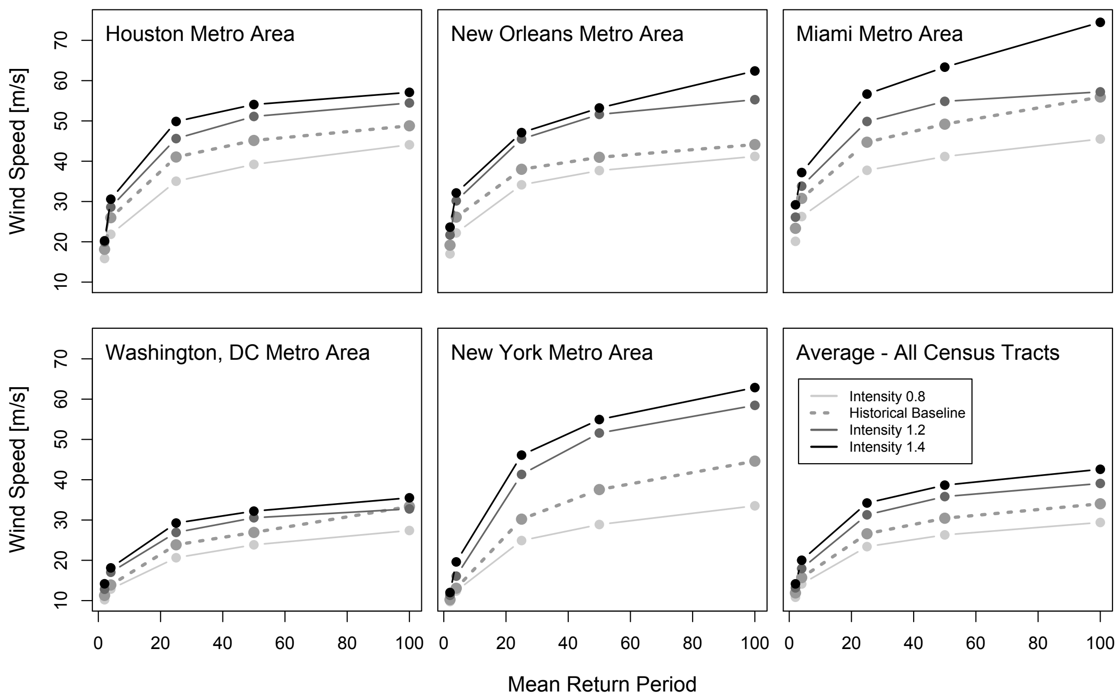


Figure 5.6: Mean return periods for the fraction of customers without power as intensity varies, plotting the average for five metropolitan areas and for all census tracts (bottom right) evaluated.

in intensity by virtue of its more inland location. The severe effects of higher wind speeds from stronger storms will be felt primarily along the coasts, as shown previously in Figure 5.2. The resulting power outages have the potential to be widespread in many regions of the country. In addition, the difference between the 100-year and 50-year storm impacts is minimal, and this has strong implications for design and mitigation to withstand tropical cyclones and the potential effects of climate change. New Orleans, Miami, and New York all see greater than 90% of customers without power for both the 50- and 100-year return periods.

I conducted additional analysis of the sensitivity of different regions to changes in frequency and landfall location, and I direct the reader to Appendix D for the details. I find that shifts in landfall location will have strong regional effects. Increases in storm frequency will worsen the impacts in already hurricane-prone areas. However, in general, the strongest changes in tropical cyclone hazard are seen in the scenarios of high storm intensity. For most regions of the country, increases in storm intensity will result in the most severe damages, but frequent, milder damages could occur if the frequency of tropical storms increases.

5.5 Conclusion

Planning for future climate change is a difficult task due to the high degree of uncertainty about potential changes in tropical cyclone frequency, intensity and track. This chapter examines a range of potential changes in tropical cyclone activity and quantifies how these changes could influence power outage risk. Tropical cyclones can cause substantial damage to power system infrastructure and can leave local utility companies and government agencies with high repair costs in the aftermath of a storm. Anticipating the nature of potential impacts allows for proactive mitigation against damage, reduced costs, and a more resilient power grid.

The scenarios assessed here were chosen to represent a range of plausible outcomes for a future affected by climate change and the resulting tropical cyclone impacts, but they are not tied to specific climate projections (i.e., they are not associated with a specific emissions scenario or GCM results). The range of results demonstrates the sensitivity of the U.S. power system to changes in storm behavior, and these impacts can be evaluated for small regional areas. Inland areas are generally more protected from the strongest impacts, but some areas may still see considerable changes in maximum wind speeds, power outage likelihood, and the number of customers losing power during a hurricane. A shift in landfall location could result in impacts to areas of the country with little experience in dealing with hurricanes. Coastal areas are particularly sensitive to increases in storm intensity. 100-year wind speeds are projected to increase by more than 50 percent in some areas with a 20% increase in storm intensity. The probability of customer power outages in a given area increases slightly, but the actual number of customers losing power would change more drastically as a result of stronger, and often larger, storms. A reduction in storm frequency, on the other hand, is projected to have a corresponding reduction in the likelihood of power outages. Future work remains, particularly in linking models such as this to specific climate scenarios, but the results presented here provide a starting point for improved climate adaptation, and the framework can be extended to explicitly link to specific climate scenarios.

This research was originally published in *Climatic Change*.[156]

Chapter 6

Conclusion

The four research projects presented here form a body of work tied together by the similarity in both the tools used and the overall application area. Each project makes use of statistical modeling and data analysis to broaden our understanding of power system planning. This dissertation sits at the intersection of the fields of power system modeling, risk analysis, uncertainty management, and decision support, and each project makes use of these areas to bring new insight to a variety of complex problems facing today's power system. Improved understanding of these problems and the required solutions will result in better operation, investment, and planning decisions.

6.1 Summary of Contributions

In this thesis, I have demonstrated the various ways that data analysis can be used to inform planning problems for power system applications. The four chapters tackle different problems, but they are tied together by their focus on improving decisions in the face of the many uncertainties facing our electric generation infrastructure. Each project makes use of statistical modeling in order to understand the relationships and influential factors present in the available data. With careful application, these data-analytic tools can increase our understanding of a problem, and this new information can then feed into the planning and decision-making process to improve the outcome. The projects all seek to provide value to decision-makers by offering knowledge or insight that did not exist previously.

Three of the four chapters focus on wind energy, and this research addresses a subset of the challenges faced in the industry. The analyses presented in Chapters 2, 3, and 4 provide advancements to our current understanding and methods for planning and operating wind farms for better integration into the greater power system. The findings in Chapter 2 can be used for improved policies regarding wind investment. The influence of state-based policies is dwarfed by geographical considerations. Renewable energy resources are highly location-dependent and policies should be designed to reflect that fact. A national renewable energy policy could take advantage of this fact more easily than the size-constrained states. The models and methodology presented in Chapter 3 address safety and reliability concerns associated with offshore wind farms in particular, but they are equally valuable for other offshore operations more generally. This work changes the traditional focus of wind forecasting away from mean-value forecasts for maximizing revenues and towards a risk-based view of wind farm operations. Frequent exposure to high wind speeds reduces turbine life, and high winds can also threaten worker safety while performing installation or maintenance work on a wind farm. I developed models that issue probabilistic forecasts of what the maximum wind speed will be in a given time interval. This information can then feed into decisions about farm operations, maintenance planning, or safety precautions. Chapter 4 addresses the difficulty of estimating wind farm power production. Turbine wake interactions complicate the flow through a wind farm. This is well-understood in some contexts—namely in uniformly aligned, offshore farms—but there are problems when applying this knowledge to other contexts. I provide a comparison of various methods for estimating onshore wind farm power production using two farms as case studies. I find that statistical models outperform other methods, including the Jensen model. This is not entirely surprising, but I also show that the same statistical models do not even need to incorporate knowledge of a particular wind farm to outperform some other methods, and this has strong implications for the way in which we plan for future wind farms and assess wind resources.

Moving away from strictly wind energy applications, Chapter 5 instead focuses on risks to the entire electric power distribution system from future tropical cyclones. In this work, I tackle the challenge of planning for long-lived infrastructure investments when faced with the deep uncertainty associated with climate change. I use wind speed and power outage estimates as proxies for the risks faced by the power system and demonstrate the range of impacts that can be expected under various climate change scenarios. By performing this sensitivity analysis, I quantify the impacts, compare them to baseline measures, and provide insight into the regional variability of the tropical cyclone hazard. I also offer localized results, which serve as valuable input for decision-makers faced with questions of building stronger infrastructure, relocating assets, or investing in protective measures.

6.2 Final Remarks and Research Limitations

The work presented throughout this dissertation represents a finite contribution to the infinite field of power system risk analysis and planning. In many cases, simplifications and assumptions must be made due to limited data, modeling capability, or simply because the benefits to be gained by using more advanced techniques are not worth the time or effort required to implement them. All research has limitations, and I will address some of the known areas for potential improvement in the projects presented here.

6.2.1 Statistical Analysis of Installed Wind Capacity in the United States

The findings in Chapter 2 can be used to inform policy development. The role of state policies are not as dominant as expected, but the mechanisms for incentivizing wind energy development are complex. Economic viability will always be the driving factor for new development, and thus, policies are designed to defray some financial burden when it makes sense to do so. For wind power, however, the economic viability of a project is highly location-specific. Wind resources, land rights, and construction costs can vary drastically from region to region, and these factors are likely to dominate small policy incentives. One particular weakness of this analysis is that it fails to capture some of these other considerations that may play an important role. Many of these factors are too complex to incorporate into a statistical model, and, in these cases, a mixture of quantitative and qualitative analysis is probably better suited. It is impossible to consider every variable, and I chose a set of variables that covered a wide range of influential categories in an attempt to identify any surprising relationships in the data. Other variables may well play an important role, and it may be useful to perform additional analysis with some other variables to determine whether or not there are other dynamics present that have not been captured by my analysis.

I performed the analysis on the state level to focus on the role that state-based policies play in incentivizing wind investment. By doing so, I limited the dataset to 50 observations. This relatively small number meant that the results are heavily influenced by outliers. There is high variability in the level of capacity present in each state, and the states with the most wind capacity are on a different order of magnitude from many of the other states. This may downplay the role that policies or other factors have in certain states if they do not follow the same trend of the dominant states.

I do not account for the trading of renewable energy credits (REC) in this analysis and focus instead on just the renewable portfolio standards (RPS) in each state. Since many states do trade REC's, renewable targets can often be met without actually having the capacity present in a given state. One could incorporate the allowable REC trading schemes and the utilization of REC trading among states to get a better idea of how much influence this has on where the actual capacity is built. This is left as a future research direction and would be important to consider for any potential policy changes going forward.

6.2.2 Probabilistic Maximum-Value Wind Prediction for Offshore Environments

The statistical models described in Chapter 3 can be used to modify farm operations or plan for maintenance operations to as to avoid periods of dangerously high wind speeds. This is done for short- and medium-term decisions, with forecasts being issued for lead times of 0–120 hours. This type of risk-based forecasting fills a gap in the field of wind forecasting by issuing a prediction for the maximum value only. This piece of information helps to improve our understanding of the inherent variability and uncertainty present in wind speeds, and it is of value for decisions made in offshore environments where people and equipment are typically exposed to higher wind speeds than land-based sites.

The model specifics are applicable for the dataset used here, which comes from a given location in the North Sea. The methods and model development process, however, are generalizable to any location where the same types of data are available. Use of these models does require high-quality meteorological forecast data. In this instance, I used data from ECMWF. If the available forecast data is of a lower quality or accuracy, the models will suffer and will likely have larger predictive errors. The choice of technique used to create the probabilistic forecasts relies on an assumption of normality in the residual errors. While this assumption did simplify the process somewhat, it came at a loss in accuracy for the residuals themselves. As the reliability diagrams show in Chapter 3, the normal distribution is a very good fit for long lead times, but it introduces a slight bias at shorter lead times. More work is needed to determine the best distribution to be used in this application, and this extension is left as an area for future research. A related extension of this work focuses on the choice of models for the maximum-wind predictions. Because the residuals were used to create the probabilistic distribution for each prediction, I chose to work with model types for which the residuals were fairly easy to calculate. Some other model formulations are very difficult to derive residuals from, but they may offer better overall prediction accuracy. Extending the techniques to other model types is again left as an interesting area for future research.

One last potential extension of this work would be a link between the predictions and the decisions to be made based on them. Currently, the models are designed to predict the highest wind speed observed in a three-hour time interval. It would be interesting to instead focus only on instances where that highest wind speed value is above a chosen threshold. Some improvements in model accuracy and in overall value as a risk-based decision support tool could be gained from focusing only on periods of concern and ignoring all those time periods with relatively low 'maximum' speeds.

6.2.3 Methods for Assessing Power Output in Non-Uniform Onshore Wind Farms

Planning for future wind farms requires a careful assessment of the available wind resource in a given location. Estimates of farm power production are critical to the financing decisions that determine a wind farm's success. These power production estimates are created using a number of different techniques depending on the nature of the application. For offshore farms, models that analyze the wake decay and subsequent turbine interactions have been shown to be accurate. The Jensen model, one of these wake decay models, performs poorly in the case of two onshore wind farms as demonstrated in Chapter 4. I compare a number of alternate methods to the Jensen model results and show that, surprisingly, statistical models do well even when no farm-specific data is used to train the models. This information can be used to generate greatly improved power production estimates for wind farms subject to a few limitations.

I only tested the models on two farms, and both were large farms located in relatively flat areas. More data would be required to generalize the results beyond this. It would be interesting to see these models applied to additional onshore farms with different layouts and also to offshore farms, where the Jensen model is expected to perform better. As for wake models, I tested only the Jensen model. While this is a popular benchmark model for good reason, it would be useful to compare some other types of wake models and even a full large eddy simulation model run. These extensions are left as suggestions for future research.

Complex terrain is known to induce unusual flow patterns in a wind farm. The farms tested here are both located on flat terrain, but, although flat, any small discrepancies can have large effects on the flow patterns and mixing throughout a farm. The impacts of terrain are somewhat incorporated into the Jensen model through the wake decay parameter, but the results of wake models could be improved by explicitly modeling these effects using a different modeling environment.

Finally, this project brings up a very important question: if the power produced by a wind farm is so difficult to predict when the wind conditions are known exactly, what then is the value of a perfect wind speed forecast? Improved accuracy in wind prediction may not matter at all when the power output predictions are driving the bulk of the error. Determining the value of a perfect forecast would be a fascinating extension of this research.

6.2.4 Simulation of Tropical Cyclone Impacts to the US Power System under Climate Change

It is difficult to tackle any long-term planning decisions in the face of climate change. Tropical cyclone behavior is expected to be strongly affected by a changing climate, but the exact nature of this effect is uncertain. The uncertainty is expansive; little is known regarding the timing of climate change and how long it will take for other weather patterns to become altered, and there is conflicting research on the exact mechanisms of change expected in storm behavior. The simulation presented in Chapter 5 addresses some of this uncertainty by evaluating the risks to the power system under a wide range of climate change scenarios. By looking at these *what-if* scenarios, we can start to understand which changes could potentially be the most harmful and which can safely be ignored or dealt with at a later time. There is a lot of regional variability when it comes to tropical cyclone risk, and the high level of spatial detail in the simulation model allows for better information to inform localized decisions.

The structure of the simulation makes several key assumptions that could be improved upon in future research. I assume that the power system is static, i.e., the power distribution system remains the same in each of the climate scenarios, and it responds to wind-induced stresses the same way as it did in the past based on the data for which the models were trained. This could be a problematic assumption when trying to assess risks far into the future. It is likely that investments will be made to improve the infrastructure over time, and perhaps this is especially true in regions that are expected to see more damages from tropical cyclones. Power system improvements could easily be incorporated into the simulation model in a simplistic way; a more rigorous approach would require significant changes to the internal model components and would be an interesting focus for further research. Another similar assumption is a static population level. Although I issue predictions in terms of the fraction of customers in a given area instead of simply a raw number, any major shifts in population or population density would affect the accuracy of the results. Population growth over time could be factored into the simulation, and this would have to be done in accordance with a time-dependent link to the climate scenarios. The best way to do this involves use of the database of climate projection data offered by the Intergovernmental Panel on Climate Change (IPCC). Additional analysis could be done to link the timeline of expected climate changes given by IPCC projections to a specified level of change in tropical cyclone behavior. Adding the temporal component to this analysis would improve the value for decision-makers. The timing of investments could be evaluated against the projected risk level in future years.

The models within the simulation could also be improved upon. The hurricane track model used is relatively simple. Although it produces reasonable results, there have been many advancements in hurricane track modeling. The tracks themselves can be linked to IPCC climate projection data to some extent as well, as there are some suggested links between hurricane movement and meteorological variables. The scenarios modeled are only a subset of possibilities. They represent a wide, but feasible, range of expected future climate outcomes. As our understanding improves in the area of tropical cyclones and climate, we can narrow down the scenario space and focus in on the most likely outcomes or the outcomes with the greatest potential for increased risk. These improvements are left as interesting extensions for future research.

Appendix A

Chapter 2 Supporting Material

The full dataset used for the analysis can be found in Table A.1. 2010 Capacity and 2000 Capacity refer to the installed wind capacity in MW in 2010 and 2000, respectively. Avail. Land (sq. km.) and Avail. Percent are the amounts available for potential wind development. RPS is the level of the renewable portfolio standard mandate. Electricity Rate is the average price paid for electricity in cents/kWh. Median Income is averaged between 2008 and 2010, in 2009 dollars. Portion Democrat is the portion of the state legislature that identifies as Democratic as of 2006. Tax, Rebate, Loan, and Other refer to types of incentive programs.

Table A.1: Dataset used for statistical analysis in Chapter 2

State	2010 Cap.	Avail. Land	Avail. Percent	RPS	Electricity Rate	Median Income	Portion Democrat	Tax	Rebate	Loan	Other	2000 Cap.	Cropland
Alabama	0	24	0%	0%	8.89	$42,218	63%	1	0	1	1	0	3,142,958
Alaska	9	98,941	7%	50%	14.76	$61,872	37%	1	0	1	1	1	86,238
Arizona	128	2,181	1%	15%	9.69	$47,093	37%	1	0	0	1	0	1,205,425
Arkansas	0	1,840	1%	0%	7.28	$38,600	73%	0	0	1	1	0	8,432,221
California	3253	6,822	2%	33%	13.01	$56,418	61%	1	1	1	1	1616	9,464,647
Colorado	1299	77,444	29%	30%	9.15	$59,669	53%	1	0	1	0	22	11,483,936
Connecticut	0	5	0%	23%	17.39	$65,958	66%	1	1	1	1	0	163,686
Delaware	2	2	0%	25%	11.97	$53,196	45%	0	1	1	1	0	432,773
Florida	0	0	0%	0%	10.58	$45,350	31%	1	0	1	0	0	2,953,340
Georgia	0	26	0%	0%	8.87	$44,992	43%	1	0	1	0	0	4,478,168
Hawaii	63	653	4%	40%	25.12	$59,125	80%	1	1	1	1	2	177,626
Idaho	353	3,615	2%	0%	6.54	$47,528	19%	1	0	1	1	0	5,918,899
Illinois	2045	49,976	34%	25%	9.13	$52,811	54%	1	1	1	1	0	23,707,699
Indiana	1339	29,646	32%	10%	7.67	$46,156	43%	1	0	0	0	0	12,716,037
Iowa	3675	114,143	78%	6%	7.66	$50,504	49%	1	0	1	0	242	26,316,332
Kansas	1074	190,474	89%	20%	8.35	$46,722	32%	1	0	1	1	2	28,216,064
Kentucky	0	12	0%	0%	6.73	$42,091	52%	1	1	1	1	0	7,278,098
Louisiana	0	82	0%	0%	7.8	$41,896	63%	1	1	1	0	0	4,691,344
Maine	266	2,250	3%	30%	12.84	$48,081	51%	1	1	1	1	0	529,253
Maryland	70	297	1%	20%	12.7	$64,596	70%	1	1	1	1	0	1,405,442
Massachusetts	18	206	1%	15%	14.26	$60,923	87%	1	1	1	1	0	187,406
Michigan	164	11,809	8%	10%	9.88	$47,871	45%	1	0	1	1	1	7,803,643
Minnesota	2205	97,854	45%	25%	8.41	$55,063	50%	1	0	1	1	291	21,948,603
Mississippi	0	-	0%	0%	8.59	$36,850	59%	0	0	1	1	0	5,530,825
Missouri	457	54,871	30%	15%	7.78	$47,460	39%	1	0	1	0	0	16,405,595
Montana	386	188,801	50%	15%	7.88	$42,005	51%	1	0	1	1	0	18,241,710
Nebraska	213	183,600	92%	10%	7.52	$51,504	35%	1	0	1	0	3	21,486,025
Nevada	0	1,449	1%	25%	9.73	$53,082	56%	1	1	1	1	0	753,718
New Hampshire	25	427	2%	23.8%	14.84	$66,303	37%	1	1	1	1	0	128,938

State	2010 Cap.	Avail. Land	Avail. Percent	RPS	Electricity Rate	Median Income	Portion Democrat	Tax	Rebate	Loan	Other	2000 Cap.	Cropland
New Jersey	8	26	0%	22.5%	14.68	$65,173	59%	1	1	1	1	0	488,697
New Mexico	700	98,417	31%	20%	8.4	$43,998	59%	1	0	1	1	1	2,334,018
New York	1274	5,156	4%	30%	16.41	$50,656	62%	1	1	1	1	18	4,314,954
North Carolina	0	162	0%	12.5%	8.67	$43,275	54%	1	0	1	1	0	4,895,204
North Dakota	1424	154,039	84%	10%	7.11	$50,847	30%	1	0	0	0	0	27,527,180
Ohio	10	10,984	10%	12.5%	9.14	$46,752	37%	1	0	1	1	0	10,832,772
Oklahoma	1482	103,364	57%	15%	7.59	$45,577	47%	1	0	1	1	0	13,007,625
Oregon	2104	5,420	2%	25%	7.56	$50,938	50%	1	1	1	1	25	5,010,408
Pennsylvania	748	661	1%	18%	10.31	$49,826	45%	1	1	1	1	11	4,870,287
Rhode Island	2	9	0%	16%	14.08	$52,771	82%	1	0	1	1	0	24,457
South Carolina	0	37	0%	0%	8.49	$42,059	41%	1	0	1	1	0	2,151,219
South Dakota	709	176,483	88%	10%	7.82	$48,168	28%	1	0	1	0	0	19,094,311
Tennessee	29	62	0%	0%	8.61	$40,026	52%	1	0	1	1	2	6,047,348
Texas	10089	380,306	56%	5%	9.34	$47,601	41%	1	0	1	1	184	33,667,177
Utah	223	2,621	1%	20%	6.94	$59,857	26%	1	0	0	1	0	1,837,904
Vermont	6	590	2%	20%	13.24	$53,490	60%	1	1	1	1	6	516,924
Virginia	0	359	0%	15%	8.69	$61,544	41%	1	1	1	1	0	3,274,137
Washington	2104	3,696	2%	15%	6.66	$58,330	55%	1	0	0	1	0	7,609,210
West Virginia	431	377	1%	25%	7.45	$40,824	66%	1	0	0	0	0	942,132
Wisconsin	469	20,751	14%	10%	9.78	$51,484	40%	1	1	1	0	23	10,116,279
Wyoming	1412	110,415	44%	0%	6.2	$53,236	23%	1	0	1	0	91	2,576,017

Appendix B

Chapter 3 Supporting Material

The input data used to develop the models in Chapter 3 came from two sources. Forecast data came from the European Center for Medium-Range Weather Forecasting (ECMWF), and actual measured data came from FINO1, a meteorological tower installed in the North Sea, off the coast of Germany. Summary statistics for the ECMWF forecast data are found in Table B.1, and statistics for the actual measured data at the FINO1 met tower are found in Table B.2.

Table B.1: Summary of ECMWF forecast data

Variable	Mean	Std. Deviation	Minimum	Maximum
u at 10m (m/s)	1.80	6.22	-17.67	25.44
v at 10m (m/s)	0.58	5.43	-18.71	21.53
u at 100m (m/s)	2.35	7.58	-21.70	34.39
v at 100m (m/s)	0.81	6.61	-23.57	27.76
Wind Direction at 10m (°)	202.0	96.2	0	360
Wind Direction at 100m (°)	203.8	96.0	0	360
Gust at 10m (m/s)	10.64	4.90	0.00	39.05
Temperature at 2m (K)	282.4	5.4	267.9	296.2
CAPE (J/kg)	9.5	51.4	0.0	2082.7
Charnock	0.020	0.011	0.006	0.111
Mean Sea Level Pressure (Pa)	101,417	983	95,478	104,783

Table B.2: Summary of FINO1 actual measured data

Variable	Mean	Std. Deviation	Minimum	Maximum
Wind Speed at 100m (m/s)	9.62	4.51	0.00	28.19
Minimum (m/s)	6.17	3.72	0.22	20.85
Maximum (m/s)	13.14	5.54	1.07	40.52

Appendix C

Chapter 4 Supporting Material

The prediction errors can be broken down based on the same wind speed categories used in the evaluation of the wake decay coefficient and the thrust coefficient. It is interesting to compare the different methods as a function of wind speed. Figures C and C show the mean absolute errors (MAE) for Farms 1 and 2, respectively, for the low, medium, and high wind speed bins. Figures C and C show the root mean squared errors (RMSE) for Farms 1 and 2, respectively, for the same wind speed bins. The statistical models consistently outperform the other methods for all wind speeds in both farms. Some of the other methods are particularly bad at certain wind speeds but not at others.

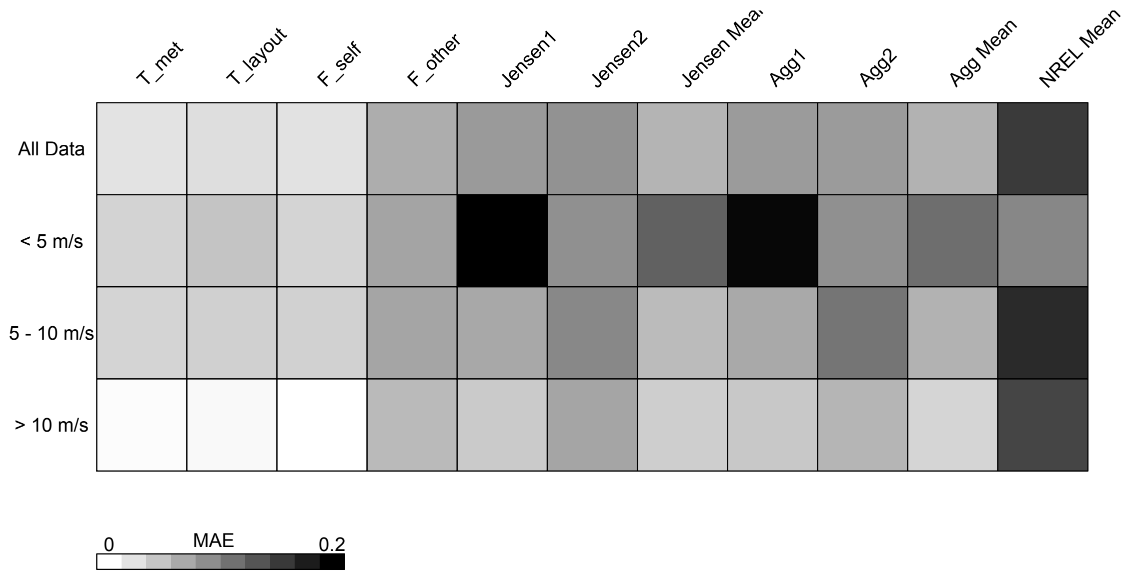


Figure C.1: MAE for Farm 1 showing each method's accuracy overall and as a function of wind speed

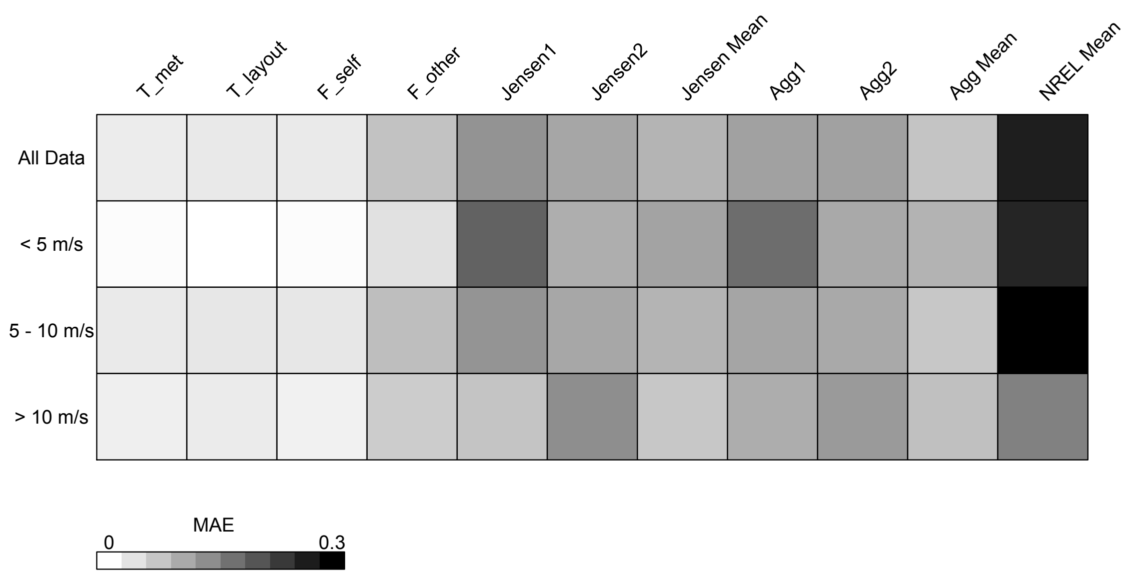


Figure C.2: MAE for Farm 2 showing each method's accuracy overall and as a function of wind speed

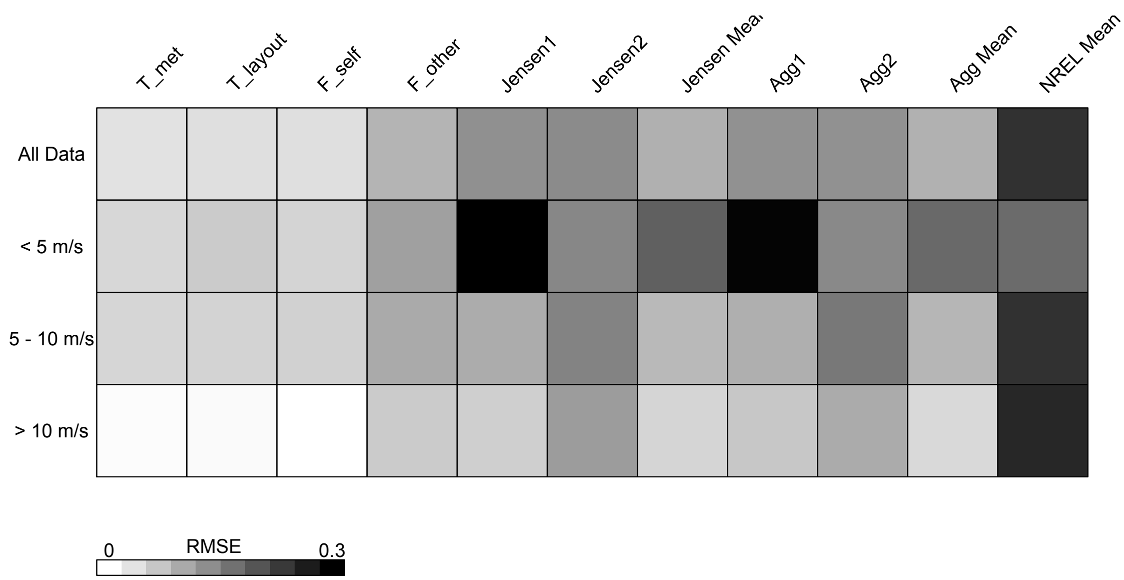


Figure C.3: RMSE for Farm 1 showing each method's accuracy overall and as a function of wind speed

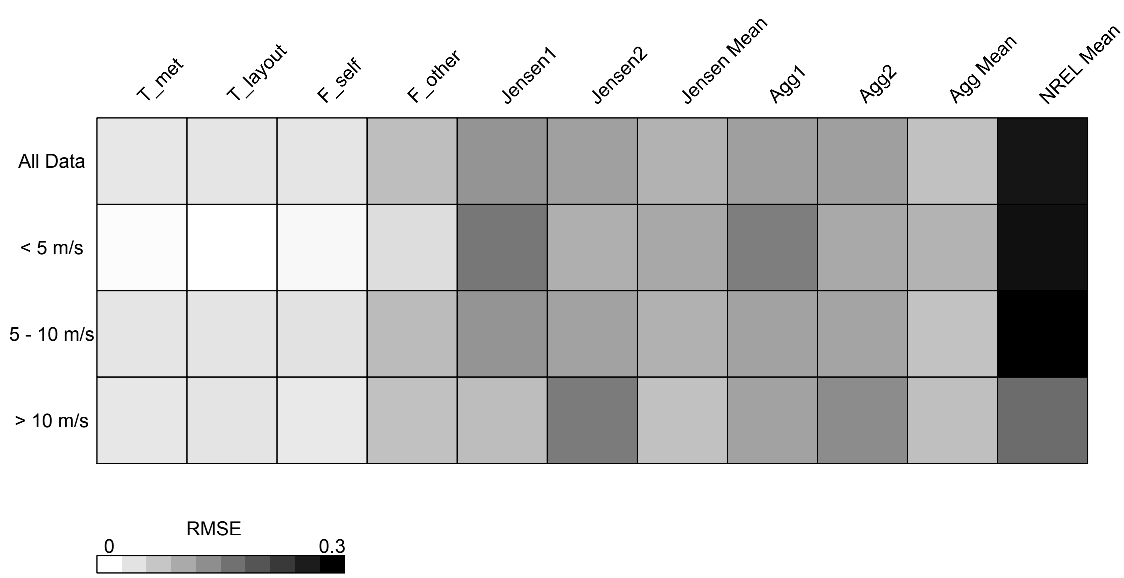


Figure C.4: RMSE for Farm 2 showing each method's accuracy overall and as a function of wind speed

Appendix D

Chapter 5 Supporting Material

The scenarios of varying storm intensity and frequency are straightforward. The landfall scenarios are less obvious, and are better understood through visualization. To create the landfall scenarios, I first divided the entire coastline into 50-kilometer segments. These segments are labeled from 1 to 98, starting at the Texas-Mexico border and ending at the Maine-Canada border. Each storm in the historical record was binned according to these segments. I then created a smoothed distribution based on the probability that a storm makes landfall in a given segment of coastline. This is the baseline distribution, from which the simulation sampled from to get the landfall location of each simulated storm. Each of the alternative scenarios is a modification of the baseline. The shape of the distribution is tied to the geographical characteristics of the coastline, so I tried to maintain the shape as much as possible while still creating enough variety among the alternative scenarios. The alternate scenarios are

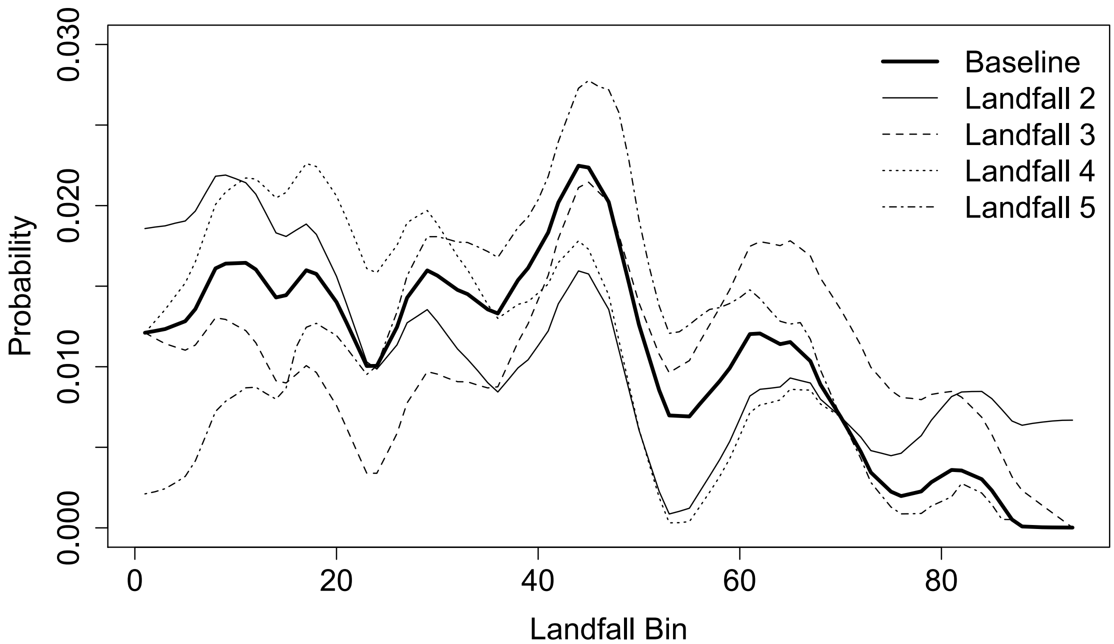


Figure D.1: Landfall scenario distributions: Landfall 2 spreads the distribution out more, Landfall 3 focuses more on the Gulf of Mexico, Landfall 4 shifts the distribution towards the mid-Atlantic and Northeast, Landfall 5 concentrates more on the Florida peninsula.

not designed to represent actual realizations informed by climate models; instead, they are designed to assess the sensitivity of various coastal regions to changes in storm location. The scenario distributions are shown in Figure D.

The variation in landfall distribution is more clearly seen when plotted on a map showing the actual changes for each location. Figure D plots the color-coded probabilities for each segment of the coastline under each landfall scenario.

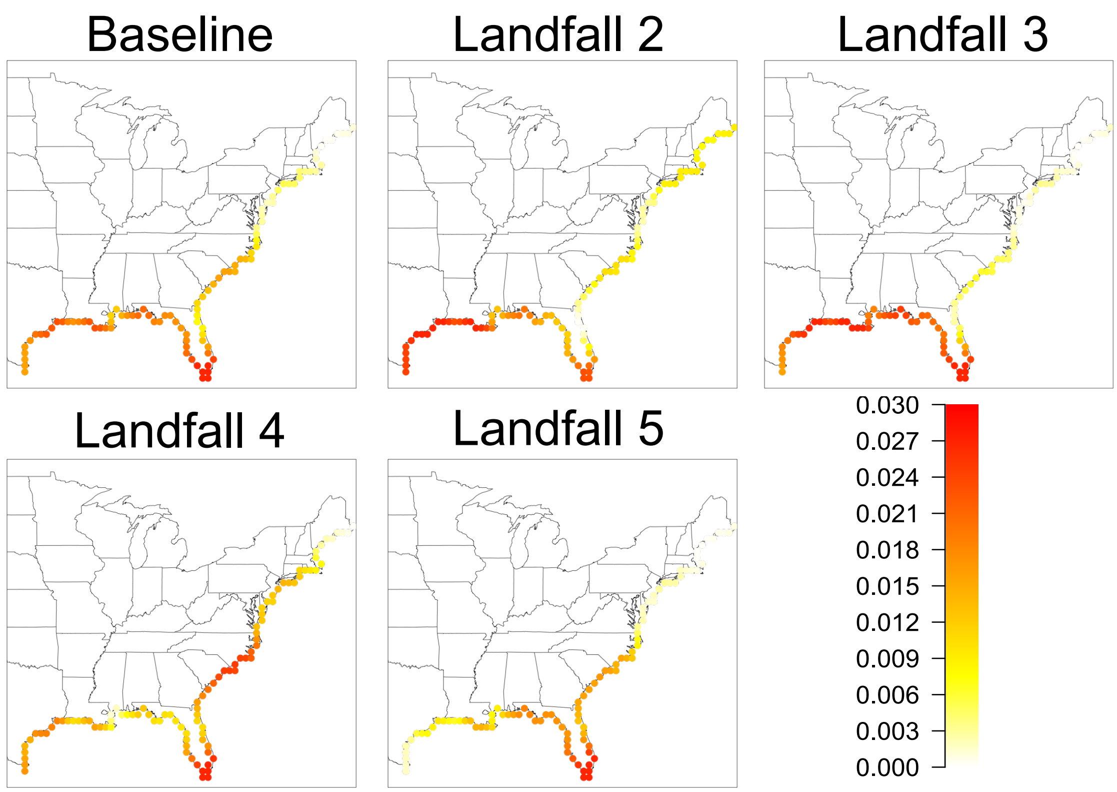


Figure D.2: Mapped landfall scenarios, with the darker color showing the highest probabilities of a virtual storm making landfall in that stretch of coastline. Value represent annual probability of landfall in each segment.

D.1 Detailed Results

The impacts of tropical cyclones in the U.S. are not felt equally in all areas. Some areas are more prone to damage than others, and, while the level of impact may change, the spatial trends remain consistent in the scenarios of varying storm intensity and frequency. Scenarios of varying intensity, as expected, strongly impact the maximum wind speeds and fraction of customers without power. In contrast, scenarios of varying frequency do not result in large changes in 100-year wind speed or fraction out, but they do have large impacts on the probability of outages. Scenarios of varying landfall distributions, in contrast to intensity and frequency, result in changes to the location of impacts. The changes in wind speed and fraction out are subtle, but the probability of outages shifts noticeably as the landfall probability distribution shifts.

For the five metropolitan areas presented in Chapter 5, the changes are not felt equally. Coastal areas in hurricane-prone areas are sensitive to changes in storm intensity and frequency. Inland areas and regions not typically prone to hurricanes are less sensitive to these changes, and the range of impact is not as high. The worst impacts in terms of both wind speeds and fraction of customers without power occurs for the scenarios with a 40% increase in storm intensity (the highest intensity evaluated). The annual probability of power outages, however, sees the greatest increase as storm frequency increases. For changes in landfall, the resulting impacts depend on the landfall scenario and the area of interest. Washington DC, for example, sees shifts in impacts as the probability of landfall in that region shifts. The outage probability changes significantly, but the changes in wind speed and fraction of customers out are still dominated by the storm intensity.

D.2 Overall Impacts

I also examine the parameters that are most important when assessing the overall expected impact on the entire U.S., regardless of the local changes. Figures 6 and 7 plot the empirical cumulative distributions for both the 100-year wind speed and the 100-year fraction of customers without power. These are not strictly probability distributions. Rather, they are an exceedance plot the fraction of census tracts that exceed a given wind speed or fraction without power. The estimated density is shown in the inset of each plot. These plots show how much the impacts change as I vary storm intensity, frequency, and landfall location. In the case of both 100-year wind speed and 100-year fraction of customers without power, changes in intensity cause the largest shifts in the empirical distributions. For wind speed in Figure 6(a), the distribution shifts to the right as storm intensity increases. This results in larger probabilities of seeing higher wind speeds. The shifts are significant; for example, the percentage of census tracts with the 100-year wind speed falling below 60 m/s is almost 100% in the baseline case. When the intensity is increased to a factor of 1.4, that percentage drops to 70%. The changes in frequency (lambda) and landfall

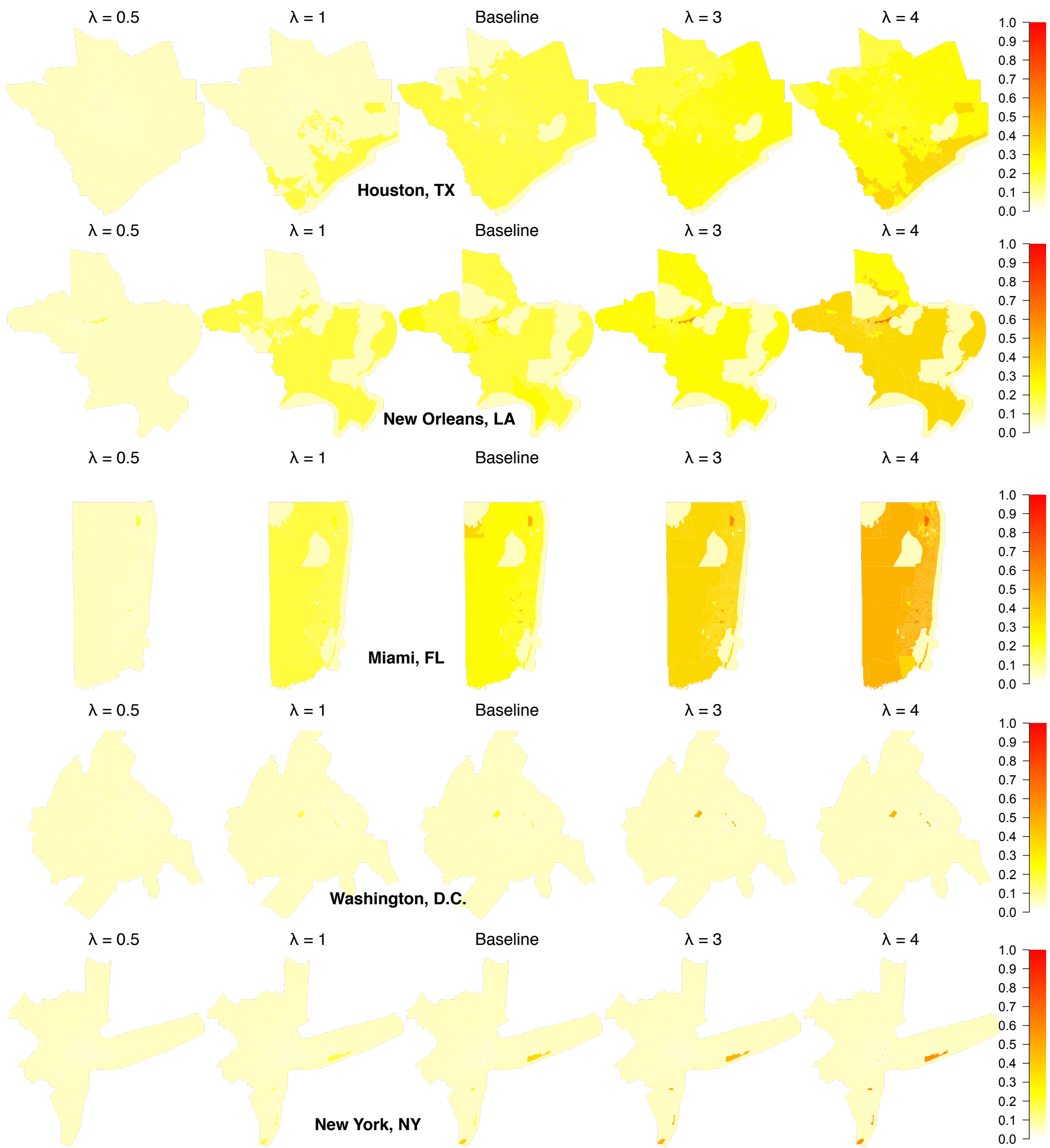


Figure D.3: Annual probability of at least 10% of customers without power for metropolitan areas for scenarios of varying storm frequency

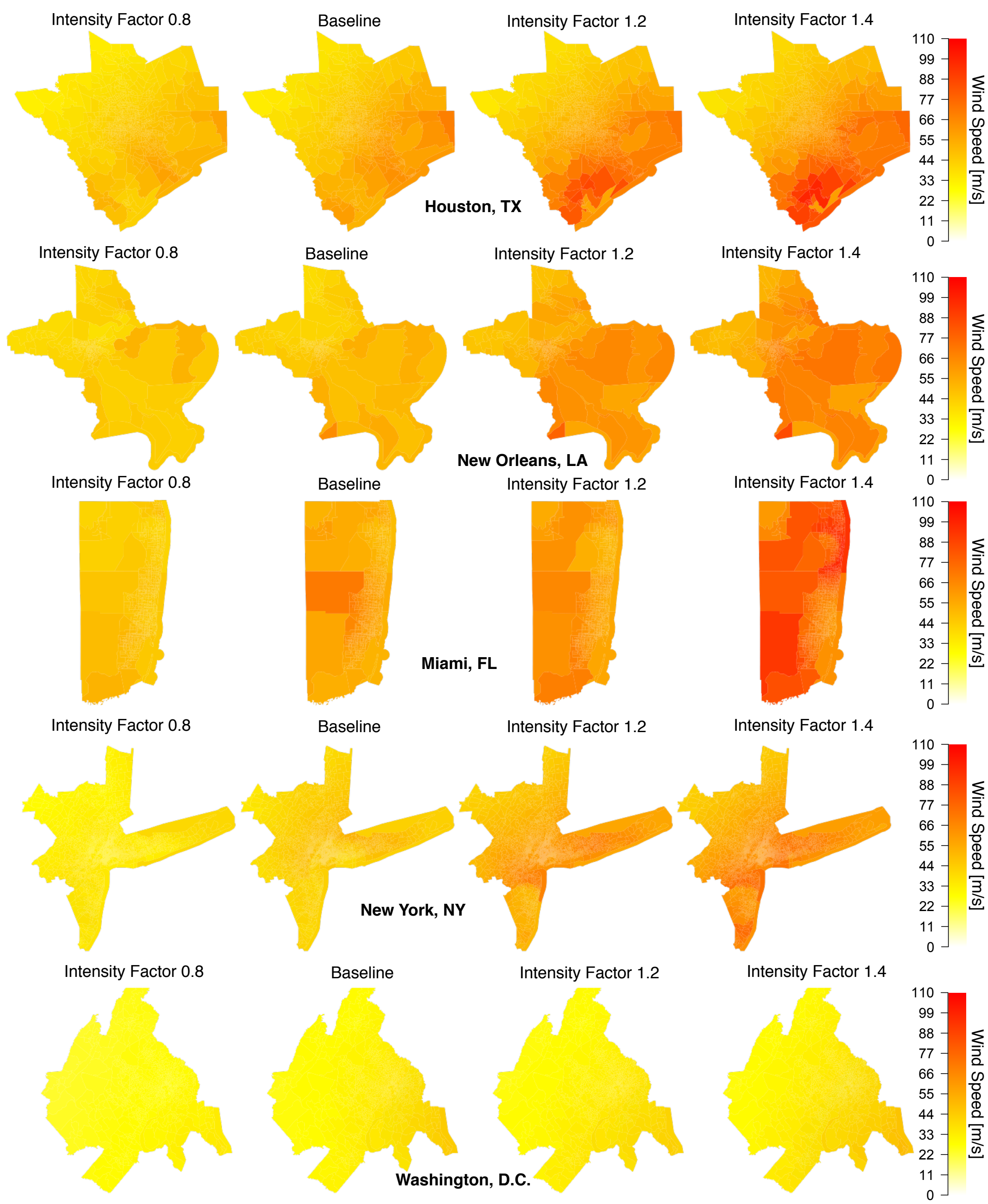


Figure D.4: The 100-year wind speed plotted for metropolitan areas for scenarios of varying storm intensity

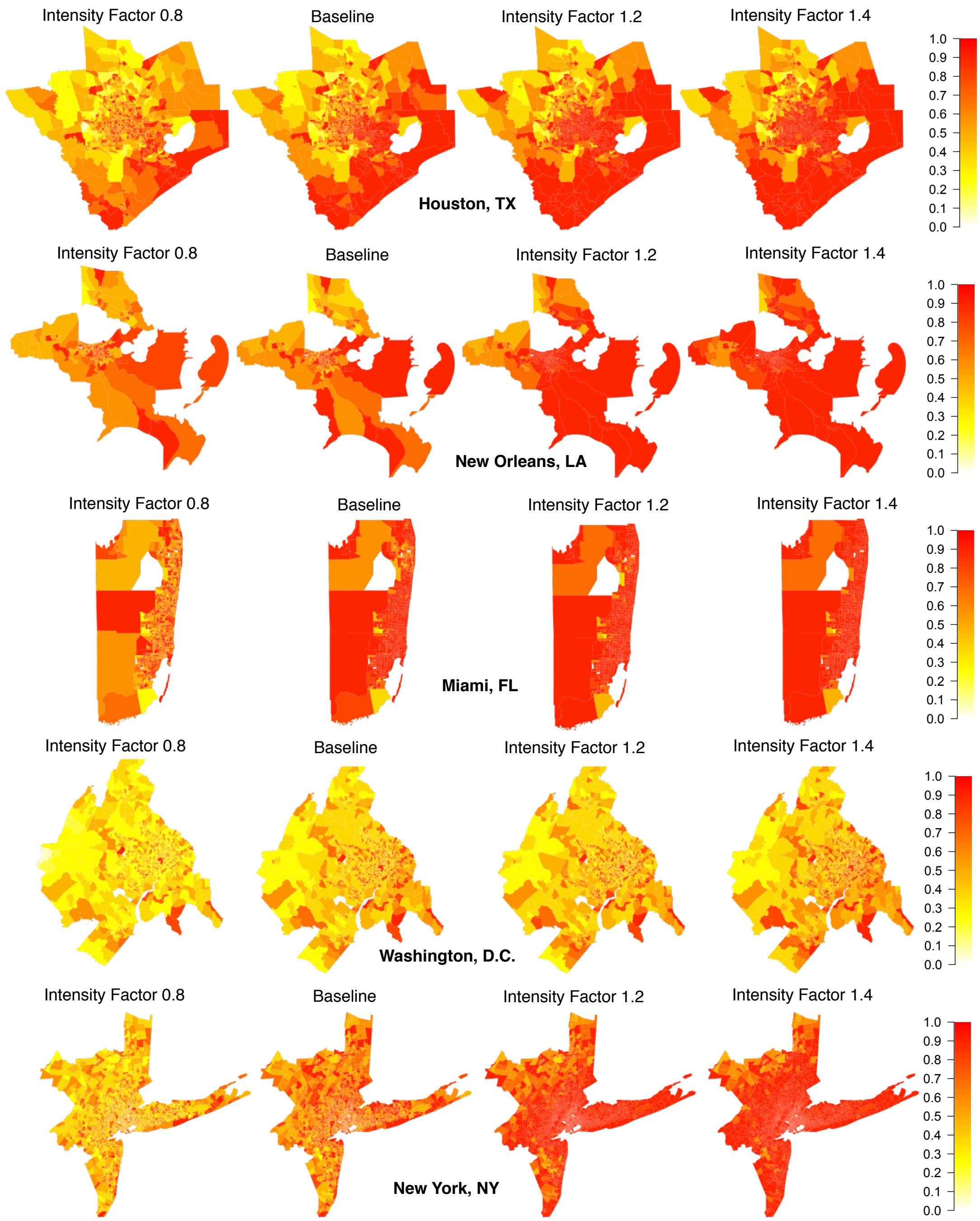


Figure D.5: The 100-year fractions of customers without power for metropolitan areas for scenarios of varying storm intensity do not result in such drastic shifts in the distributions; all scenarios are fairly tightly grouped, with only small deviations. Varying frequency and landfall location can result in large changes to some local areas, but the overall impact is not as large as it is for changes in intensity.

Similar results appear in the plots of 100-year fraction of customers without power, shown in Figure 7. Again, changes in intensity result in substantial shifts in the distributions. Looking at the inset density plot in Figure 7(a), for example, the increasing intensity results in the appearance of an increasingly large spike for 100% of customers without power. This shows that for the 100-year storm, the probability of a given census tract losing power completely rises sharply as storm intensity increases. The empirical CDFs show that for the baseline case, the percentage of census tracts with a fraction out of less than 0.6 is about 70%. This goes down to just under 50% when the intensity factor is increased to 1.4. The likelihood of having a large fraction of customers without power rises substantially as the storm intensity increases.

D.3 Sensitivity to Changes

I also focus on the sensitivity of coastal metropolitan areas to changes in tropical cyclone behavior. While the simulation is run for the the entire coastline, I selected several smaller areas to better compare regional differences. I singled out the metropolitan areas of San Antonio, TX; Dallas, TX; Houston, TX; Austin, TX; New

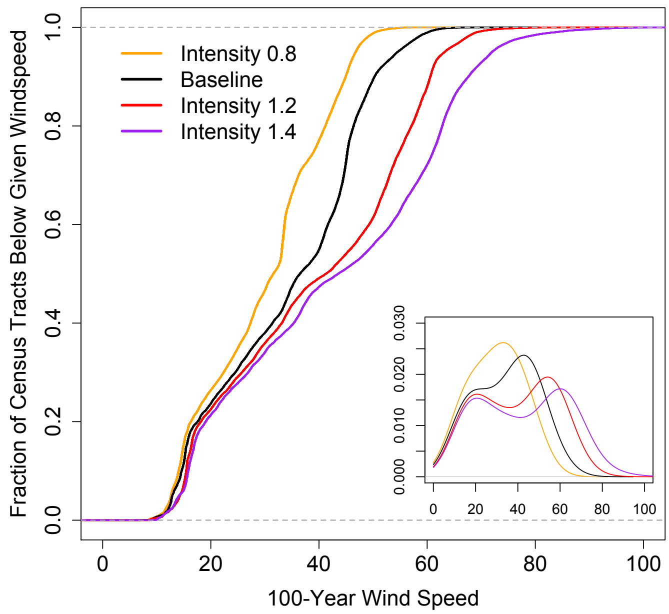


Figure D.6: Empirical CDF and inset density plot for the 100-year wind speed for changes in storm intensity

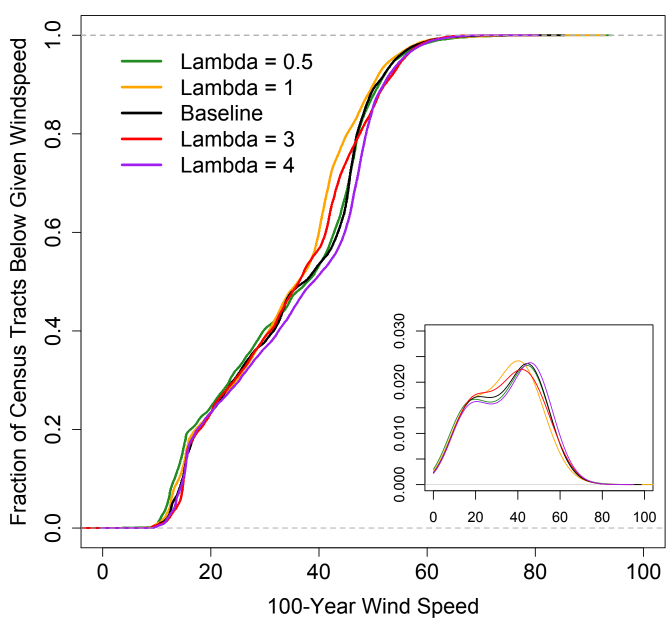


Figure D.7: Empirical CDF and inset density plot for the 100-year wind speed for changes in storm frequency

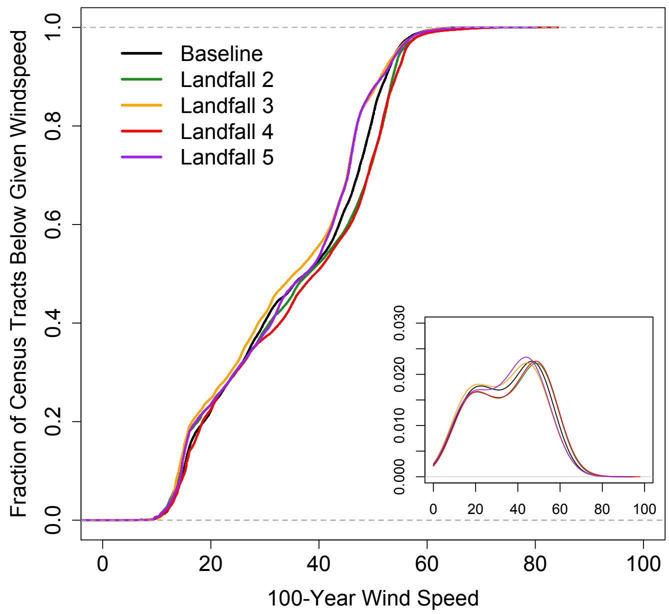


Figure D.8: Empirical CDF and inset density plot for the 100-year wind speed for changes in storm landfall location

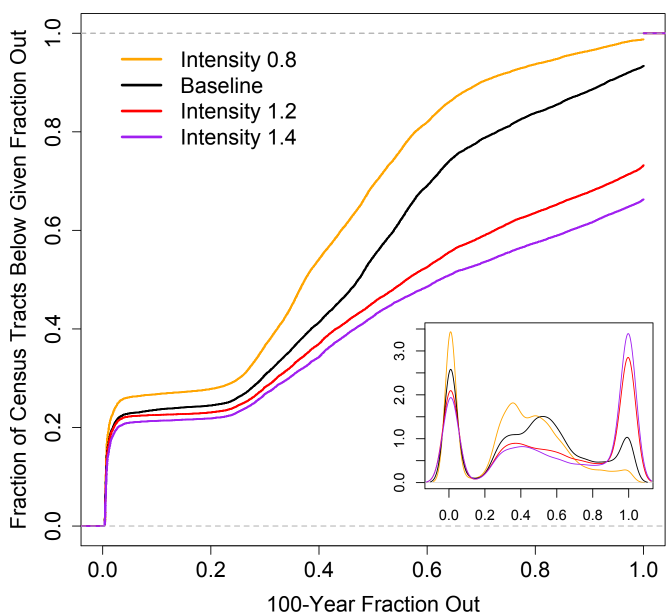


Figure D.9: Empirical CDF and inset density plot for the 100-year fraction of customers without power for changes in storm intensity

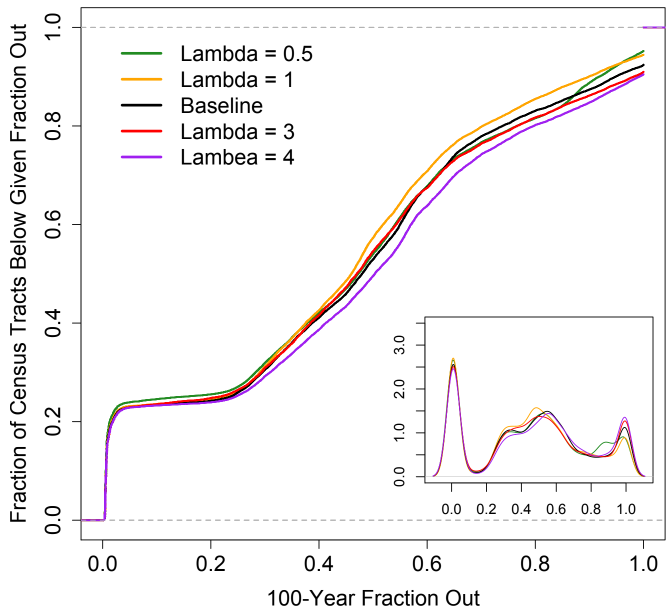


Figure D.10: Empirical CDF and inset density plot for the 100-year fraction of customers without power for changes in storm frequency

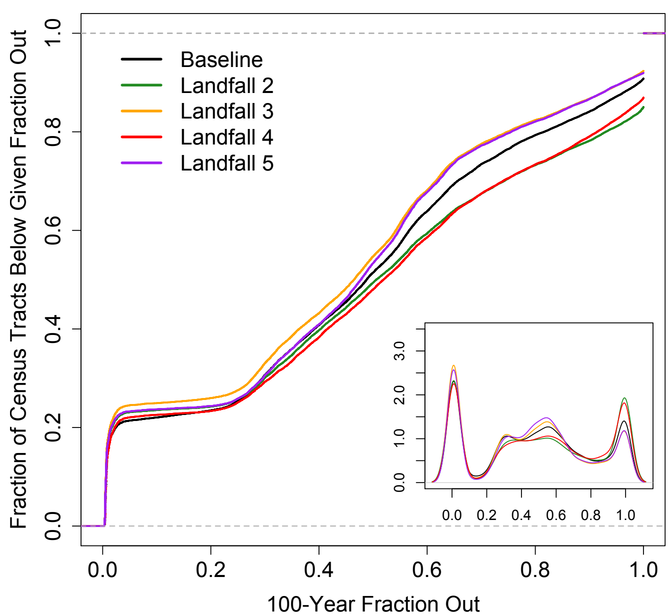


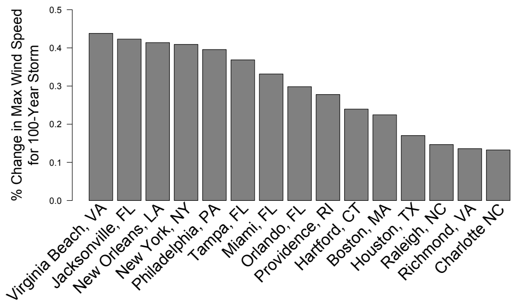
Figure D.11: Empirical CDF and inset density plot for the 100-year fraction of customers without power for changes in storm landfall location

Orleans, LA; Birmingham, AL; Atlanta, GA; Miami, FL; Tampa, FL; Orlando, FL; Jacksonville, FL; Charlotte, NC; Raleigh, NC; Virginia Beach, VA; Richmond, VA; Washington, DC; Baltimore, MD; Philadelphia, PA; New York, NY; Hartford, CT; Providence, RI; and Boston, MA. For each of these 22 metropolitan areas, I assessed the changes in risk level that would be expected under each scenario. This shows which areas are the most sensitive to changes in climate. The results are not consistent across the board. The selection of most sensitive metropolitan area depends heavily on both which variable of climate change I am assessing and which measure of risk (or impact) I am using to determine sensitivity. For example, the top ranked metropolitan areas in Figure D.12 change positions depending on the metric used. When assessing the change in the wind speed with a 1% exceedance probability for the highest intensity scenario, Virginia Beach, VA is in the top position with a 44% increase when compared to the baseline case. However, if we instead look at the sensitivity of the fraction of customers expected to be without power that one would expect to exceed once, on average, every 100 years, the top-ranked metropolitan area is Philadelphia, PA, with an increase of almost 57%. Virginia Beach moves down to the sixth position in this ranking. These results are calculated for the highest intensity scenario as compared to the baseline case in the left-hand column, and for the highest frequency scenario as compared to the baseline case in the right-hand column. The wind speed and fraction of customers out both represent the impacts that are expected to be exceeded, on average, once every 100 years.

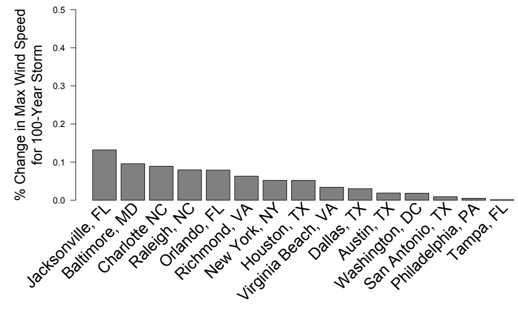
In addition, one can see that changes in intensity drive the worsening impacts more so than changes in storm frequency. The impacts that are expected to be exceeded once every 100 years, both in terms of maximum wind speed and customers without power, are significantly higher for the scenario of a 40% increase in hurricane intensity than they are for the scenario of a 100% increase in the average hurricane frequency. Having twice as many storms, on average, still does not drive the worst of the impacts on the power system.

It is particularly interesting to compare the top-ranked cities in terms of sensitivity to maximum wind speed and the fraction of customers without power for the highest intensity scenarios (see Figures 5.2 and 5.3. The three highest increases in wind speed occur in what are thought to be hurricane-prone areas: Virginia Beach, VA; Jacksonville, FL; and New Orleans, LA. It is intuitive that places that have historical experience with strong storms will see even stronger storms in the future, should this scenario play out. On the other hand, the three highest increases in fraction of customers without power are Philadelphia, PA; Atlanta, GA; and New York, NY. These are not typically places associated with extreme hurricane risk. The assessment of power outages depends also on the power distribution system, as opposed to hurricane characteristics alone, as in the case of maximum wind speed values. Strong storms cause more power outages, but *proportionally* fewer in regions that already see a lot of strong storms. Therefore, the *change* in impact is not as large in some of the most hurricane-prone areas. Instead, places with relatively low baseline risks see the largest potential increases; they are the most sensitive to an increase in hurricane intensity.

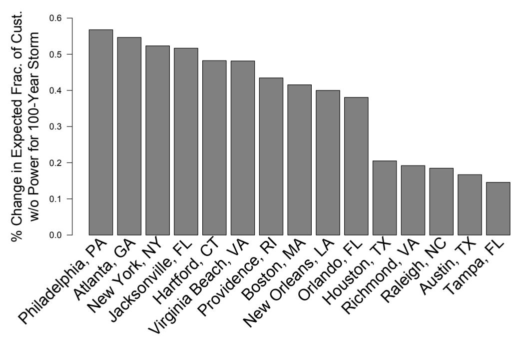
The scenarios of varying storm location are more subjective than those for either intensity of frequency. It is difficult to compare the baseline case to the worst alternative scenario in this case, since the alternatives that may be worst for some areas will be much better for others. In this case, instead of simply comparing two scenarios, I show the standard deviation of the impacts across all of the five scenarios. This allows us to assess which areas have the largest spread based on where storms make landfall. Of course, this is somewhat dependent on our choice of alternative landfall probability distributions to use as our scenarios. I show the results of these impacts in Figure D.13.



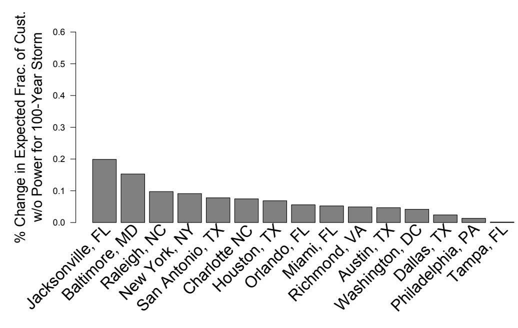
(a) Maximum Wind - Sensitivity to Intensity



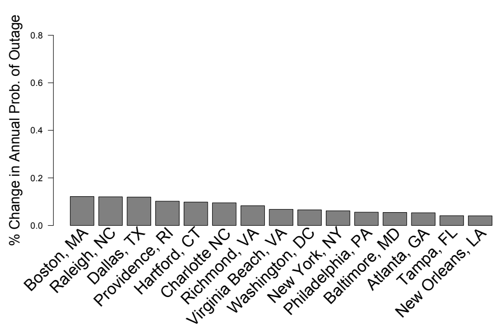
(b) Maximum Wind - Sensitivity to Frequency



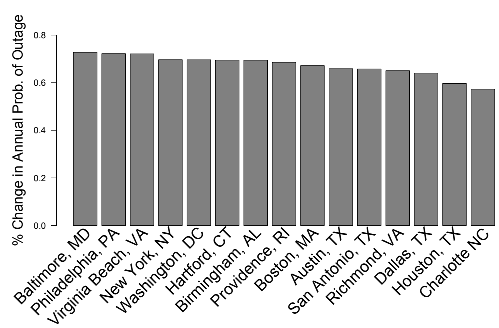
(c) Fraction without Power - Sensitivity to Intensity



(d) Fraction without Power - Sensitivity to Frequency

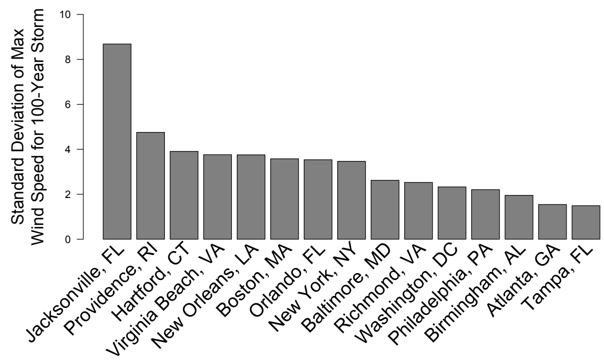


(e) Annual Probability of Outage - Sensitivity to Intensity

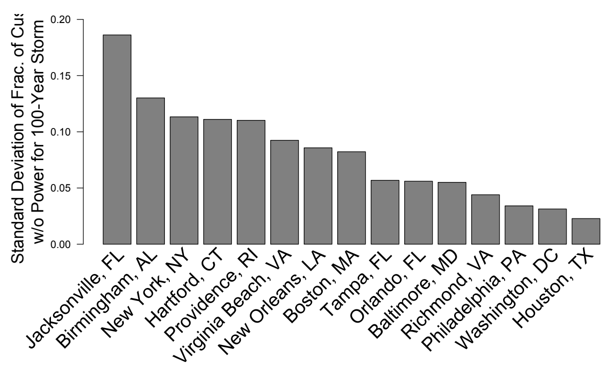


(f) Annual Probability of Outage - Sensitivity to Frequency

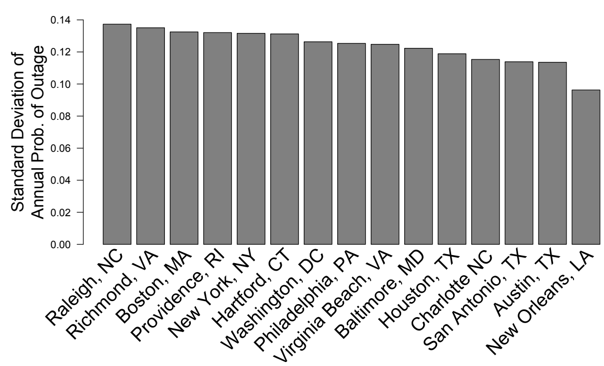
Figure D.12: Top 15 metropolitan areas ranked by sensitivity to changes in storm intensity and frequency. These values represent the percentage change in the maximum wind speed (D.12(a) & D.12(b)), the fraction of customers expected to be without power D.12(c) & D.12(d)), and the annual probability of a power outage (D.12(e) & D.12(f)).



(a) Maximum Wind - Sensitivity to Location



(b) Fraction without Power - Sensitivity to Location



(c) Probability of Outage - Sensitivity to Location

Figure D.13: Top 15 metropolitan areas ranked by sensitivity to changes in storm landfall location. These values represent the standard deviation of impacts across all scenarios for the maximum wind speed D.13(a), the fraction of customers expected to be without power D.13(b), and the annual probability of a power outage D.13(c).

Bibliography

[1] International Energy Agency, "Energy access database," 2014. [Online]. Available: http://www.worldenergyoutlook.org/resources/energydevelopment/energyaccessdatabase/

[2] E. E. Lee, J. E. Mitchell, and W. Wallace, "Assessing vulnerability of proposed designs for interdependent infrastructure systems," in *System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on.* IEEE, 2004, p. 8 pp.

[3] K. H. LaCommare and J. H. Eto, "Cost of power interruptions to electricity consumers in the United States (US)," *Energy*, vol. 31, no. 12, pp. 1845–1855, 2006.

[4] M. Kampa and E. Castanas, "Human health effects of air pollution," *Environmental pollution*, vol. 151, no. 2, pp. 362–367, 2008.

[5] M. Collins, R. Knutti, J. Arblaster, J. Dufresne, T. Fichefet, P. Friedlingstein, X. Gao, W. Gutowski, T. Johns, and G. Krinner, "Climate change 2013: the

physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," *Long-term Climate Change: Projections, Commitments and Irreversibility, Cambridge Univ.Press, Cambridge, UK, and New York*, 2013.

[6] T. R. Karl, *Global climate change impacts in the United States.* Cambridge University Press, 2009.

[7] X. Lu, M. B. McElroy, and J. Kiviluoma, "Global potential for wind-generated electricity," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 106, no. 27, pp. 10 933–10 938, Jul 7 2009.

[8] International Energy Agency, "Renewables information," IEA, Tech. Rep., 2015.

[9] American Wind Energy Association, "Wind was largest source of new electricity in 2014, congress still must provide long-term policy certainty," 2015. [Online]. Available: http://www.awea.org/MediaCenter/pressrelease.aspx?ItemNumber=7294

[10] R. L. Thomas and W. H. Robbins, "Large wind-turbine projects in the united states wind energy program," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 5, no. 3, pp. 323–335, 1980.

[11] J. Sowers, “Fields of opportunity: wind machines return to the plains,” *Great Plains Quarterly*, p. 131, 2006.

[12] R. Saidur, M. Islam, N. Rahim, and K. Solangi, “A review on global wind energy policy,” *Renewable and Sustainable Energy Reviews*, vol. 14, no. 7, pp. 1744–1762, 2010.

[13] J. K. Kaldellis and D. Zafirakis, “The wind energy (r)evolution: A short review of a long history,” *Renewable Energy*, vol. 36, no. 7, pp. 1887–1901, 2011.

[14] R. Wiser and M. Bolinger, “2014 wind technologies market report,” 2015.

[15] A. D. Mills, “The cost of transmission for wind energy: A review of transmission planning studies,” *Lawrence Berkeley National Laboratory*, 2009.

[16] E. Devlin, “Factors affecting public acceptance of wind turbines in Sweden,” *Wind Engineering*, vol. 29, no. 6, pp. 503–511, 2005.

[17] A. Jobert, P. Laborgne, and S. Mimler, “Local acceptance of wind energy: Factors of success identified in French and German case studies,” *Energy Policy*, vol. 35, no. 5, pp. 2751–2760, 2007.

[18] J. Firestone, W. Kempton, and A. Krueger, “Public acceptance of offshore wind power projects in the USA,” *Wind Energy*, vol. 12, no. 2, pp. 183–202, 2009.

[19] A. Mulder, “Do economic instruments matter? wind turbine investments in the eu (15),” *Energy Economics*, vol. 30, no. 6, pp. 2980–2991, 2008.

[20] D. Toke, S. Breukers, and M. Wolsink, "Wind power deployment outcomes: How can we account for the differences?" *Renewable and sustainable energy reviews*, vol. 12, no. 4, pp. 1129–1147, 2008.

[21] M. Munday, G. Bristow, and R. Cowell, "Wind farms in rural areas: How far do community benefits from wind farms represent a local economic development opportunity?" *Journal of Rural Studies*, vol. 27, no. 1, pp. 1–12, 2011.

[22] N. Stern, *The economics of climate change: the Stern review.* Cambridge University Press, 2007.

[23] K. Siler-Evans, I. L. Azevedo, M. G. Morgan, and J. Apt, "Regional variations in the health, environmental, and climate benefits of wind and solar generation," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 110, no. 29, pp. 11 768–11 773, Jul 16 2013.

[24] C. B. Field and M. V. Aalst, *Climate change 2014: impacts, adaptation, and vulnerability.* IPCC, 2014, vol. 1.

[25] L. Getoor, *Introduction to statistical relational learning.* MIT press, 2007.

[26] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning.* Springer, 2013.

[27] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning.* Springer, 2009, vol. 2, no. 1.

[28] S. Breukers and M. Wolsink, "Wind power implementation in changing institutional landscapes: an international comparison," *Energy Policy*, vol. 35, no. 5, pp. 2737–2750, 2007.

[29] F. C. Menz and S. Vachon, "The effectiveness of different policy regimes for promoting wind power: Experiences from the states," *Energy Policy*, vol. 34, no. 14, pp. 1786–1796, 2006.

[30] D. Mann, C. Lant, and J. Schoof, "Using map algebra to explain and project spatial patterns of wind energy development in Iowa," *Applied Geography*, vol. 34, pp. 219–229, 2012.

[31] D. Toke, "Explaining wind power planning outcomes: some findings from a study in england and wales," *Energy Policy*, vol. 33, no. 12, pp. 1527–1539, 2005.

[32] G. Giebel, R. Brownsword, G. Kariniotakis, M. Denhard, and C. Draxl, "The state-of-the-art in short-term prediction of wind power: A literature overview," *ANEMOS. plus*, 2011.

[33] L. Jones, R. Zavadil, and W. Grant, "The future of wind forecasting and utility operations," *Power and Energy Magazine, IEEE*, vol. 3, no. 6, pp. 57–64, 2005.

[34] J. C. Smith, M. R. Milligan, E. A. DeMeo, and B. Parsons, "Utility wind in-

tegration and operating impact state of the art," *Power Systems, IEEE Transactions on*, vol. 22, no. 3, pp. 900–908, 2007.

[35] Y. Gu, J. D. McCalley, and M. Ni, "Coordinating large-scale wind integration and transmission planning," *Sustainable Energy, IEEE Transactions on*, vol. 3, no. 4, pp. 652–659, 2012.

[36] N. O. Jensen, *A note on wind generator interaction.* Risø National Laboratory, 1983.

[37] R. J. Barthelmie, K. Hansen, S. T. Frandsen, O. Rathmann, J. Schepers, W. Schlez, J. Phillips, K. Rados, A. Zervos, and E. Politis, "Modelling and measuring flow and wind turbine wakes in large wind farms offshore," *Wind Energy*, vol. 12, no. 5, pp. 431–444, 2009.

[38] M. Gaumond, P.-E. Réthoré, S. Ott, A. Peña, A. Bechmann, and K. S. Hansen, "Evaluation of the wind direction uncertainty and its impact on wake modeling at the Horns Rev offshore wind farm," *Wind Energy*, vol. 17, no. 8, pp. 1169–1178, 2014.

[39] P. Beaucage, M. Brower, N. Robinson, and C. Alonge, "Overview of six commercial and research wake models for large offshore wind farms," *Proceedings of the European Wind Energy Associate (EWEA)*, 2012.

[40] R. J. Stevens, D. F. Gayme, and C. Meneveau, "Coupled wake boundary layer

model of wind-farms," *Journal of renewable and sustainable energy*, vol. 7, no. 2, p. 023115, 2015.

[41] A. Peña, P.-E. Réthoré, and M. P. Laan, "On the application of the Jensen wake model using a turbulence-dependent wake decay coefficient: the Sexbierum case," *Wind Energy*, 2015.

[42] U.S. Department of Energy, "Energy efficiency & renewable energy: Wind powering america," http://www.windpoweringamerica.gov/wind_installed_capacity.asp, 2011.

[43] T. Berry and M. Jaccard, "The renewable portfolio standard: Design considerations and an implementation survey," *Energy Policy*, vol. 29, no. 4, pp. 263–277, 2001.

[44] Internal Revenue Service, "Form 8835. Renewable Electricity, Refined Coal, and Indian Coal Production Credit," 2011.

[45] U.S. Department of Energy, "Database of state incentives for renewables and efficiency," http://dsireusa.org/incentives/incentive.cfm?Incentive_Code=US13F, 2012.

[46] L. Bird, M. Bolinger, T. Gagliano, R. Wiser, M. Brown, and B. Parsons, "Policies and market factors driving wind power development in the United States," *Energy Policy*, vol. 33, no. 11, pp. 1397–1407, 2005.

[47] National Renewable Energy Laboratory, "Wind resource potential," http://www.windpoweringamerica.gov/windmaps/resource_potential.asp, 2012.

[48] U.S. Census Bureau, "Current population survey, 2009 to 2011 annual social and economic supplements. three-year-average median household income by state: 2008-2010," http://www.census.gov/hhes/www/income/data/statemedian/, 2011.

[49] National Conference of State Legislatures, "State legislatures composition," 2011. [Online]. Available: http://www.ncsl.org/

[50] U.S. Department of Agriculture, "Economic research service," 2012. [Online]. Available: http://www.ers.usda.gov/StateFacts/

[51] U.S. Energy Information Administration, "Average price by provider," http://205.254.135.7/state/state-energy-profiles-more-prices.cfm, 2011.

[52] Federal Energy Regulatory Commission, "Renewable power & energy efficiency: Energy efficiency resource standards (eers) and goals," http://www.ferc.gov/market-oversight/othr-mkts/renew/othr-rnw-eers.pdf, 2011.

[53] U.S. Department of Energy, "Database of state incentives for renewables and efficiency." http://www.dsireusa.org/summarytables/finre.cfm, 2010.

[54] J. H. Friedman, "Multivariate adaptive regression splines," *The annals of statistics*, pp. 1–67, 1991.

[55] L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen, *Classification and regression trees.* CRC press, 1984.

[56] H. A. Chipman, E. I. George, and R. E. McCulloch, "BART: Bayesian additive regression trees," *The Annals of Applied Statistics*, vol. 4, no. 1, pp. 266–298, 2010.

[57] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[58] A. Staid and S. D. Guikema, "Statistical analysis of installed wind capacity in the United States," *Energy Policy*, vol. 60, pp. 378–385, 2013.

[59] S. P. Baker, D. F. Shanahan, W. Haaland, J. E. Brady, and G. Li, "Helicopter crashes related to oil and gas operations in the Gulf of Mexico," *Aviation, Space, and Environmental Medicine*, vol. 82, no. 9, pp. 885–889, 2011.

[60] P. Tavner, C. Edwards, A. Brinkman, and F. Spinato, "Influence of wind speed on wind turbine reliability," *Wind Engineering*, vol. 30, no. 1, pp. 55–72, 2006.

[61] L. Dueñas-Osorio and B. Basu, "Unavailability of wind turbines due to wind-induced accelerations," *Engineering Structures*, vol. 30, no. 4, pp. 885–893, 2008.

[62] C. Monteiro, R. Bessa, V. Miranda, A. Botterud, J. Wang, and G. Conzelmann,

"Wind power forecasting: state-of-the-art 2009," Argonne National Laboratory (ANL), Tech. Rep. ANL/DIS-10-1, 2009.

[63] M. Alexiadis, P. Dokopoulos, H. Sahsamanoglou, and I. Manousaridis, "Short-term forecasting of wind speed and related electrical power," *Solar Energy*, vol. 63, no. 1, pp. 61–68, 1998.

[64] G. Riahy and M. Abedi, "Short term wind speed forecasting for wind turbine applications using linear prediction method," *Renewable Energy*, vol. 33, no. 1, pp. 35–41, 2008.

[65] P. Pinson, H. Nielsen, H. Madsen, and G. Kariniotakis, "Skill forecasting from ensemble predictions of wind power," *Applied Energy*, vol. 86, no. 7, pp. 1326–1334, 2009.

[66] P. Pinson, H. A. Nielsen, J. K. Møller, H. Madsen, and G. N. Kariniotakis, "Non-parametric probabilistic forecasts of wind power: required properties and evaluation," *Wind Energy*, vol. 10, no. 6, pp. 497–516, 2007.

[67] P.-J. Trombe, P. Pinson, C. Vincent, T. Bøvita, N. A. Cutululis, C. Draxl, G. Giebel, A. N. Hahmann, N. E. Jensen, B. P. Jensen, N. F. Le, H. Madsen, L. B. Pedersen, and A. Sommer, "Weather radars – the new eyes for offshore wind farms?" *Wind Energy*, 2013.

[68] M. R. Milligan, A. H. Miller, and F. Chapman, "Estimating the economic value of wind forecasting to utilities," *National Renewable Energy Laboratory*, 1995.

[69] C. L. Vincent, P. Pinson, and G. Giebel, "Wind fluctuations over the North Sea," *International Journal of Climatology*, vol. 31, no. 11, pp. 1584–1595, 2011.

[70] D. Cooley, D. Nychka, and P. Naveau, "Bayesian spatial modeling of extreme precipitation return levels," *Journal of the American Statistical Association*, vol. 102, no. 479, pp. 824–840, 2007.

[71] E. Towler, B. Rajagopalan, E. Gilleland, R. S. Summers, D. Yates, and R. W. Katz, "Modeling hydrologic and water quality extremes in a changing climate: A statistical approach based on extreme value theory," *Water Resources Research*, vol. 46, no. 11, 2010.

[72] E. Gilleland, B. G. Brown, and C. M. Ammann, "Spatial extreme value analysis to project extremes of large-scale indicators for severe weather," *Environmetrics*, vol. 24, no. 6, pp. 418–432, 2013.

[73] B. Brabson and J. Palutikof, "Tests of the generalized Pareto distribution for predicting extreme wind speeds," *Journal of Applied Meteorology*, vol. 39, no. 9, pp. 1627–1640, 2000.

[74] J. Holmes and W. Moriarty, "Application of the generalized Pareto distribution

to extreme value analysis in wind engineering," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 83, no. 1, pp. 1–10, 1999.

[75] X. G. Larsén and J. Mann, "The effects of disjunct sampling and averaging time on maximum mean wind speeds," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 94, no. 8, pp. 581–602, 2006.

[76] P. Friederichs and T. L. Thorarinsdottir, "Forecast verification for extreme value distributions with an application to probabilistic peak wind prediction," *Environmetrics*, vol. 23, no. 7, pp. 579–594, 2012.

[77] O. Brasseur, "Development and application of a physical approach to estimating wind gusts," *Monthly Weather Review*, vol. 129, no. 1, pp. 5–25, 2001.

[78] H. Ágústsson and H. Ólafsson, "Forecasting wind gusts in complex terrain," *Meteorology and Atmospheric Physics*, vol. 103, no. 1-4, pp. 173–185, 2009.

[79] T. L. Thorarinsdottir and M. S. Johnson, "Probabilistic wind gust forecasting using nonhomogeneous Gaussian regression," *Monthly Weather Review*, vol. 140, no. 3, pp. 889–897, 2012.

[80] T. I. Petroliagis and P. Pinson, "Early warnings of extreme winds using the ECMWF extreme forecast index," *Meteorological Applications*, 2012.

[81] T. Hastie and R. Tibshirani, "Generalized additive models," *Statistical science*, pp. 297–310, 1986.

[82] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2012, ISBN 3-900051-07-0. [Online]. Available: http://www.R-project.org/

[83] S. Wood, *Generalized additive models: an introduction with R.* CRC Press, 2006.

[84] Stephen Milborrow. Derived from mda:mars by Trevor Hastie and Rob Tibshirani, *earth: Multivariate Adaptive Regression Spline Models*, 2012, r package version 3.2-3. [Online]. Available: http://CRAN.R-project.org/package=earth

[85] A. H. Murphy, "The value of climatological, categorical and probabilistic forecasts in the cost-loss ratio situation," *Monthly Weather Review*, vol. 105, no. 7, pp. 803–816, 1977.

[86] P. Pinson, C. Chevallier, and G. N. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *Power Systems, IEEE Transactions on*, vol. 22, no. 3, pp. 1148–1156, 2007.

[87] A. H. Murphy, "What is a good forecast? An essay on the nature of goodness in weather forecasting," *Weather and forecasting*, vol. 8, no. 2, pp. 281–293, 1993.

[88] G. Sinden, "Characteristics of the UK wind resource: Long-term patterns and

relationship to electricity demand," *Energy Policy*, vol. 35, no. 1, pp. 112–127, 2007.

[89] FINO, "Forschungsplattformen in Nord- und Ostsee Nr. 1,2,3," http://www.fino-offshore.de/en/, September 2013.

[90] German Maritime and Hydrographic Agency, "FINO1 database information," http://www.bsh.de/en/Marine_data/Observations/MARNET_monitoring_network/FINO_1/index.jsp, September 2013.

[91] ECMWF, "European Centre for Medium-Range Weather Forecasts," http://www.ecmwf.int/, September 2013.

[92] M. Moncrieff and M. Miller, "The dynamics and simulation of tropical cumulonimbus and squall lines," *Quarterly Journal of the Royal Meteorological Society*, vol. 102, no. 432, pp. 373–394, 1976.

[93] H. Charnock, "Wind stress on a water surface," *Quarterly Journal of the Royal Meteorological Society*, vol. 81, no. 350, pp. 639–640, 1955.

[94] P. Pinson and R. Hagedorn, "Verification of the ECMWF ensemble forecasts of wind speed against analyses and observations," *Meteorological Applications*, vol. 19, no. 4, pp. 484–500, 2012.

[95] F. Atger, "Estimation of the reliability of ensemble-based probabilistic fore-

casts," *Quarterly Journal of the Royal Meteorological Society*, vol. 130, no. 597, pp. 627–646, 2004.

[96] T. M. Hamill, "Reliability diagrams for multicategory probabilistic forecasts," *Weather and forecasting*, vol. 12, no. 4, pp. 736–741, 1997.

[97] H. Hersbach, "Sea surface roughness and drag coefficient as functions of neutral wind speed." *Journal of Physical Oceanography*, vol. 41, no. 1, 2011.

[98] O. M. Phillips, "On the generation of waves by turbulent wind," *Journal of Fluid Mechanics*, vol. 2, no. 05, pp. 417–445, 1957.

[99] A. Staid, P. Pinson, S. D., and Guikema, "Probabilistic maximum-value wind prediction for offshore environments," *Wind Energy*, 2014.

[100] J. DeCesaro, K. Porter, and M. Milligan, "Wind energy and power system operations: A review of wind integration studies to date," *The Electricity Journal*, vol. 22, no. 10, pp. 34–43, 2009.

[101] K. S. Hansen, R. J. Barthelmie, L. E. Jensen, and A. Sommer, "The impact of turbulence intensity and atmospheric stability on power deficits due to wind turbine wakes at Horns Rev wind farm," *Wind Energy*, vol. 15, no. 1, pp. 183–196, 2012.

[102] L. Landberg, G. Giebel, H. A. Nielsen, T. Nielsen, and H. Madsen, "Short-term prediction—an overview," *Wind Energy*, vol. 6, no. 3, pp. 273–280, 2003.

[103] J. Pease, "Challenges with the integration of large scale wind by a regional utility," Bonneville Power Administration, Tech. Rep., 2006. [Online]. Available: https://www.bpa.gov/Power/PGC/wind/Challenges_of_large_scale_wind_integration_paper.pdf

[104] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa, "A review on the young history of the wind power short-term prediction," *Renewable and Sustainable Energy Reviews*, vol. 12, no. 6, pp. 1725–1744, 8 2008.

[105] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renewable Energy*, vol. 34, no. 5, pp. 1388–1393, 2009.

[106] J. M. Sloughter, T. Gneiting, and A. E. Raftery, "Probabilistic wind speed forecasting using ensembles and Bayesian model averaging," *Journal of the american statistical association*, vol. 105, no. 489, pp. 25–35, 2010.

[107] R. J. Barthelmie, F. Murray, and S. C. Pryor, "The economic benefit of short-term forecasting for wind energy in the UK electricity market," *Energy Policy*, vol. 36, no. 5, pp. 1687–1696, 5 2008.

[108] J. Meyers and C. Meneveau, "Optimal turbine spacing in fully developed wind farm boundary layers," *Wind Energy*, vol. 15, no. 2, pp. 305–317, 2012.

[109] Y.-H. Wan, E. Ela, and K. Orwig, "Development of an equivalent wind plant power curve," *NREL, Golden, CO, Tech.Rep.NREL/CP-550-48146*, 2010.

[110] J. King, A. Clifton, B.-M. Hodge, and L. RePPAE, *Validation of Power Output for the WIND Toolkit*. National Renewable Energy Laboratory, 2014.

[111] C. W. Potter, H. A. Gil, and J. McCaa, "Wind power data for grid integration studies," in *Power Engineering Society General Meeting, 2007. IEEE*. IEEE, 2007, pp. 1–6.

[112] C. W. Potter, D. Lew, J. McCaa, S. Cheng, S. Eichelberger, and E. Grimit, "Creating the dataset for the western wind and solar integration study (USA)," *Wind Engineering*, vol. 32, no. 4, pp. 325–338, 2008.

[113] I. Katić, J. Hjstrup, and N. Jensen, "A simple model for cluster efficiency," in *European Wind Energy Association Conference and Exhibition*, 1986, pp. 407–410.

[114] H. S. Jacobsen, "Wasp wake effect model," 2015. [Online]. Available: http://www.wasp.dk/wasp#details__wakeeffectmodel

[115] B. D. Hirth, J. L. Schroeder, W. S. Gunter, and J. G. Guynes, "Coupling Doppler radar-derived wind maps with operational turbine data to document wind farm complex flows," *Wind Energy*, vol. 18, no. 3, pp. 529–540, 2015.

[116] J. F. Manwell, J. G. McGowan, and A. L. Rogers, *Wind energy explained: theory, design and application*. John Wiley & Sons, 2010.

[117] A. Liaw and M. Wiener, "Classification and Regression by randomForest,"

R News, vol. 2, no. 3, pp. 18–22, 2002. [Online]. Available: http://CRAN.R-project.org/doc/Rnews/

[118] D. Dee, J. Fasullo, D. Shea, and J. Walsh, "The climate data guide: Atmospheric reanalysis: Overview & comparison tables," *National Center for Atmospheric Research*, 2015. [Online]. Available: https://climatedataguide.ucar.edu/climate-data/atmospheric-reanalysis-overview-comparison-tables

[119] M. N. Schwartz and R. L. George, "On the use of reanalysis data for wind resource assessment," in *11th Applied Climatology Conference*. National Renewable Energy Laboratory, 1998.

[120] Z. Huang, D. Rosowsky, and P. Sparks, "Hurricane simulation techniques for the evaluation of wind-speeds and expected insurance losses," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 89, no. 7, pp. 605–617, 2001.

[121] R. A. P. Jr, C. Landsea, M. Mayfield, J. Laver, and R. Pasch, "Hurricanes and global warming," *Bulletin of the American Meteorological Society*, vol. 86, no. 11, pp. 1571–1575, 2005.

[122] P. J. Vickery, F. J. Masters, M. D. Powell, and D. Wadhera, "Hurricane hazard modeling: The past, present, and future," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 97, no. 7, pp. 392–405, 2009.

[123] C. Zamuda, B. Mignone, D. Bilello, K. Hallett, C. Lee, J. Macknick,

R. Newmark, and D. Steinberg, "US Energy Sector Vulnerabilities to Climate Change and Extreme Weather," U.S. Department of Energy, Tech. Rep. DOE/PI-0013, 2013. [Online]. Available: http://energy.gov/sites/prod/files/2013/07/f2/20130716-Energy%20Sector%20Vulnerabilities%20Report.pdf

[124] R. Zimmerman and C. E. Restrepo, "Analyzing cascading effects within infrastructure sectors for consequence reduction," in *IEEE Conference on Technologies for Homeland Security.* IEEE, 2009, pp. 165–170.

[125] H. Liu, R. A. Davidson, D. V. Rosowsky, and J. R. Stedinger, "Negative binomial regression of electric power outages in hurricanes," *Journal of Infrastructure Systems*, vol. 11, no. 4, pp. 258–267, 2005.

[126] H. Liu, R. A. Davidson, and T. Apanasovich, "Statistical forecasting of electric power restoration times in hurricanes and ice storms," *Power Systems, IEEE Transactions on*, vol. 22, no. 4, pp. 2270–2279, 2007.

[127] R. Nateghi, S. D. Guikema, and S. M. Quiring, "Comparison and validation of statistical methods for predicting power outage durations in the event of hurricanes," *Risk Analysis*, vol. 31, no. 12, pp. 1897–1906, 2011.

[128] J. Winkler, L. Duenas-Osorio, R. Stein, and D. Subramanian, "Performance assessment of topologically diverse power systems subjected to hurricane events," *Reliability Engineering & System Safety*, vol. 95, no. 4, pp. 323–336, 2010.

[129] S.-R. Han, S. D. Guikema, and S. M. Quiring, "Improving the predictive accuracy of hurricane power outage forecasts using generalized additive models," *Risk Analysis*, vol. 29, no. 10, pp. 1443–1453, 2009.

[130] S.-R. Han, S. D. Guikema, S. M. Quiring, K.-H. Lee, D. Rosowsky, and R. A. Davidson, "Estimating the spatial distribution of power outages during hurricanes in the gulf coast region," *Reliability Engineering & System Safety*, vol. 94, no. 2, pp. 199–210, 2009.

[131] K. Emanuel, R. Sundararajan, and J. Williams, "Hurricanes and global warming: Results from downscaling IPCC AR4 simulations," *Bulletin of the American Meteorological Society*, vol. 89, no. 3, pp. 347–367, 2008.

[132] A. Henderson-Sellers, H. Zhang, G. Berz, K. Emanuel, W. Gray, C. Landsea, G. Holland, J. Lighthill, S.-L. Shieh, and P. Webster, "Tropical cyclones and global climate change: A post-IPCC assessment," *Bulletin of the American Meteorological Society*, vol. 79, no. 1, pp. 19–38, 1998.

[133] T. R. Knutson, J. L. McBride, J. Chan, K. Emanuel, G. Holland, C. Landsea, I. Held, J. P. Kossin, A. Srivastava, and M. Sugi, "Tropical cyclones and climate change," *Nature Geoscience*, vol. 3, no. 3, pp. 157–163, 2010.

[134] T. R. Knutson, J. J. Sirutis, S. T. Garner, G. A. Vecchi, and I. M. Held, "Simulated reduction in Atlantic hurricane frequency under twenty-first-century warming conditions," *Nature Geoscience*, vol. 1, no. 6, pp. 359–364, 2008.

[135] M. E. Mann and K. A. Emanuel, "Atlantic hurricane trends linked to climate change," *EOS, Transactions American Geophysical Union*, vol. 87, no. 24, p. 233, 2006.

[136] R. Mendelsohn, K. Emanuel, S. Chonabayashi, and L. Bakkensen, "The impact of climate change on global tropical cyclone damage," *Nature Climate Change*, vol. 2, no. 3, pp. 205–209, 2012.

[137] T. Yonetani and H. B. Gordon, "Simulated changes in the frequency of extremes and regional features of seasonal/annual temperature and precipitation when atmospheric CO2 is doubled," *Journal of Climate*, vol. 14, no. 8, pp. 1765–1779, 2001.

[138] L. Mudd, Y. Wang, C. Letchford, and D. Rosowsky, "Assessing climate change impact on the US east coast hurricane hazard: Temperature, frequency, and track," *Natural Hazards Review*, 2014.

[139] K. Emanuel, "Increasing destructiveness of tropical cyclones over the past 30 years," *Nature*, vol. 436, no. 7051, pp. 686–688, 2005.

[140] M. A. Saunders and A. S. Lea, "Large contribution of sea surface warming to recent increase in Atlantic hurricane activity," *Nature*, vol. 451, no. 7178, pp. 557–560, 2008.

[141] N. Ranger, T. Reeder, and J. Lowe, "Addressing 'deep' uncertainty over long-

term climate in major infrastructure projects: four innovations of the Thames Estuary 2100 Project," *EURO Journal on Decision Processes*, vol. 1, no. 3-4, pp. 233–262, 2013.

[142] W. E. Walker, M. Haasnoot, and J. H. Kwakkel, "Adapt or perish: a review of planning approaches for adaptation under deep uncertainty," *Sustainability*, vol. 5, no. 3, pp. 955–979, 2013.

[143] R. A. P. Jr, "Future economic damage from tropical cyclones: sensitivities to societal and climate changes," *Philosophical transactions.Series A, Mathematical, physical, and engineering sciences*, vol. 365, no. 1860, pp. 2717–2729, Nov 15 2007.

[144] P. J. Webster, G. J. Holland, J. A. Curry, and H.-R. Chang, "Changes in tropical cyclone number, duration, and intensity in a warming environment," *Science*, vol. 309, no. 5742, pp. 1844–1846, 2005.

[145] P. S. Dailey, G. Ljung, G. Zuba, and J. Guin, *Probability of Hurricane Intensification and United States Hurricane Landfall under Conditions of Elevated Atlantic Sea Surface Temperatures*, ser. Hurricanes and Climate Change. Springer, 2009, pp. 121–138.

[146] R. Nateghi, S. Guikema, and S. M. Quiring, "Power outage estimation for tropical cyclones: Improved accuracy with simpler models," *Risk analysis*, 2013.

[147] AIR Worldwide, "Assessing U.S. Hurricane Risk: Do the Models Make Sense?" AIR Worldwide, Tech. Rep., 2012. [Online]. Available: http://www.air-worldwide.com/publications/white-papers/documents/assessing-u-s--hurricane-risk--do-the-models-make-sense-

[148] Risky Business Project, "Risky Business: The Economic Risks of Climate Change in the United States," Risky Business, Tech. Rep., June, 2014. [Online]. Available: http://riskybusiness.org/uploads/files/RiskyBusiness_Report_WEB_7_22_14.pdf

[149] Risk Management Solutions, Inc., "Principles of Model Validation: United States Hurricane Model," Risk Management Solutions, Inc., Tech. Rep., 2012. [Online]. Available: rmsplatform.org/Publications/PrinciplesOfModelValidation.pdf

[150] J. Kaplan and M. DeMaria, "A simple empirical model for predicting the decay of tropical cyclone winds after landfall," *Journal of Applied Meteorology*, vol. 34, no. 11, pp. 2499–2512, 1995.

[151] H. Willoughby, R. Darling, and M. Rahn, "Parametric representation of the primary hurricane vortex. Part II: A new family of sectionally continuous profiles," *Monthly Weather Review*, vol. 134, no. 4, pp. 1102–1120, 2006.

[152] G. Holland, "A revised hurricane pressure-wind model," *Monthly Weather Review*, vol. 136, no. 9, pp. 3432–3445, 2008.

[153] S. D. Guikema, R. Nateghi, S. Quiring, A. Staid, A. Reilly, and M. Gao, "Predicting hurricane power outages to support storm response planning," *IEEE Access*, 2014.

[154] S. D. Guikema, I. Udoh, J. Irish, and R. Nateghi, "The effects of hurricane surge in power system outage risk models," *Proceedings, Probabilistic Safety Assessment and Management 11/ESREL 12, Helsinki, Finland*, June 2012.

[155] ASCE 7-10, "ASCE 7-10 Wind Speeds," 2014. [Online]. Available: http://windspeed.atcouncil.org/

[156] A. Staid, S. D. Guikema, R. Nateghi, S. M. Quiring, and M. Z. Gao, "Simulation of tropical cyclone impacts to the u.s. power system under climate change scenarios," *Climatic Change*, 2014.

Vita

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