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Advanced Wind Resource Characterization and Stationarity Analysis for Improved Wind Farm Siting

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1. Introduction

A fundamental question of interest is "What are the geographic patterns of the renewable wind resources?" Knowledge of the location of local wind capacity remains vital to the industry, yet commercially viable renewable-related geospatial products that meet the needs of the wind and weather science industries are often suspect. There are three stages involved with wind power project planning and operations during which accurate characterization of the wind plays a critical role:

- Prospecting (Siting): uses historical data, retrospective forecasts, and statistical methods to identify potential sites for wind power projects;
- Site Assessment (Micrositing): determines the placement of a wind power project; and,
- Operations: uses wind forecasts to determine available power output for hour-ahead and day-ahead time frames.

The most critical of these is the first – identifying and characterizing the resource. This chapter will discuss this first stage in detail, outlining the state of the art in understanding the wind resource, and discussing the strengths and weaknesses of existing methods. For example, appropriate statistical and modeling methods to compute the wind speed probability density function (PDF) will be described and critically examined.

In addition, although there has been an increasing awareness of renewable energy as a viable energy supply source, there has not been a concomitant increase in the awareness of the impacts that any spatial and temporal trends in the resource (e.g., in the wind speeds themselves) may have on long-term production, use, and implementation of renewable energy and renewable energy policy. Thus, potential changes of the wind field under a changing climate will also be discussed. As will be described in more detail below, the main topics under examination in this paper are: 1) accurate portrayal of the resource; and 2) potential implications of climate change on the wind resource of the future. The overall result will be an improved understanding of how the siting process works.

2. Wind resource modeling

The first step in determining the amount of potential electrical generation is developing an accurate portrayal of the resource. Thus, for an accurate representation of the wind energy at a particular location, correct estimates of the wind speed are necessary. Figures 1 and 2 illustrate the types of products that are typically used by in determining the wind resource. Figure 1 represents the wind resource at 50 m over the contiguous United States (obtained from the US DoE Wind Powering America program; http://www.windpoweringamerica.gov/wind_maps_none.asp), and Figure 2 is a closer look at a particular state, in this case, the wind resource map for the state of Oklahoma (provided by the Oklahoma Wind Power Initiative; http:www.ocgi.okstae.edu/owpi). The fundamental core of these estimates of the resource is a model of the probability density function (PDF) of wind speed. This is increasingly used in the wind power industry where it is required for the assessment of power potential in different locations for wind farm and wind turbine siting (e.g., Hennessey 1977; Garcia-Bustamante et al. 2008; Li and Li 2005; Lackner et al. 2008). The wind power density is required for the estimation of power potential from wind turbines (Justus, 1978). Since it is a function of the wind speed probability density function, it is critical that the wind speed PDF be estimated accurately from the available data. The question then becomes how best to model the resource via fitting the wind speed or wind power density PDF. As stated by Manwell, et al. (2002): "In general, either of two probability distributions (or probability density functions) are used in wind analysis: (1) Rayleigh and (2) Weibull." (See also Conradsen, et al. (1984) for a description of the use of Weibull distribution for determination of wind speed statistics.)

Historically, the wind PDF is most often estimated using a parametric model. These models generally include the Weibull (Stevens and Smulder 1979), Rayleigh (Celik 2003b) and Lognormal functions (Zaharim et al., 2009). The two parameter Weibull function has generally been accepted, and is most often used in research and industry, as an adequate model for the wind speed PDF (Hennessey, 1977; Justus et al., 1979; Pavia and O'Brien, 1986; Ramirez and Carta, 2005; Monahan, 2006). However, as the Weibull distribution has become the industry standard, there have been many attempts to improve its overall applicability for modeling the wind speed PDF. For example, Justus and Mikhail (1976) developed an approach to adjust Weibull shape/scale parameters to a desired height. Stewart and Essenwanger (1978) developed a three-parameter Weibull distribution approach which shows a better fit than a traditional two-parameter Weibull; however, there are significant difficulties in estimating parameters, so its applicability has been limited.

It has been shown, however, that wind speed does not always have a Weibull-like distribution (e.g., Tuller and Brett, 1984 , Jaramillo and Borja 2004; Yilmaz and Çelik 2008). The result is that for wind power density computations, large errors in the resource estimation will result from this imperfect Weibull approximation. This is especially true since wind power density is a function of the expected value of the cube of the wind speed (Petersen, et al., 1997). Therefore, there has been range of other approaches attempting to fit the wind speed (or wind power density) PDF. These include: Lognormal (Luna and Church, 1974); elliptical bivariate-normal (Koeppl, 1982, who describes the difficulty translating such an approach to univariate (speed-only) distributions); and inverse Gaussian (Bardsley, W.E., 1980, which is offered as an alternative to Weibull distribution, especially in cases with low frequencies near zero).

While much research has focused on parametric and related approaches to this critical estimation of the wind speed or wind power density PDF, when a robust, smooth histogram of the wind speed distribution can be determined from the available data, non-parametric techniques (e.g., Izenman, 1991; Silverman 1986) can also be used given their flexibility and the likelihood that the actual wind power density may not be adequately represented by one of the models listed above (Jaramillo and Borja, 2004). A commonly used non-parametric method in industry and for research is the kernel method (Silverman 1986, Juban et al., 2007). While the kernel method is becoming increasingly popular in industry, there are significant problems with this approach. For example, the PDF functional representation using the Kernel has a number of terms equal to the number of data points used in the fitting process. Thus, the kernel method is not an optimal method for estimating the wind speed PDF, since if a PDF estimator is to be used in further mathematical computations a tractable function with a limited number of terms is required (Hall 1980).

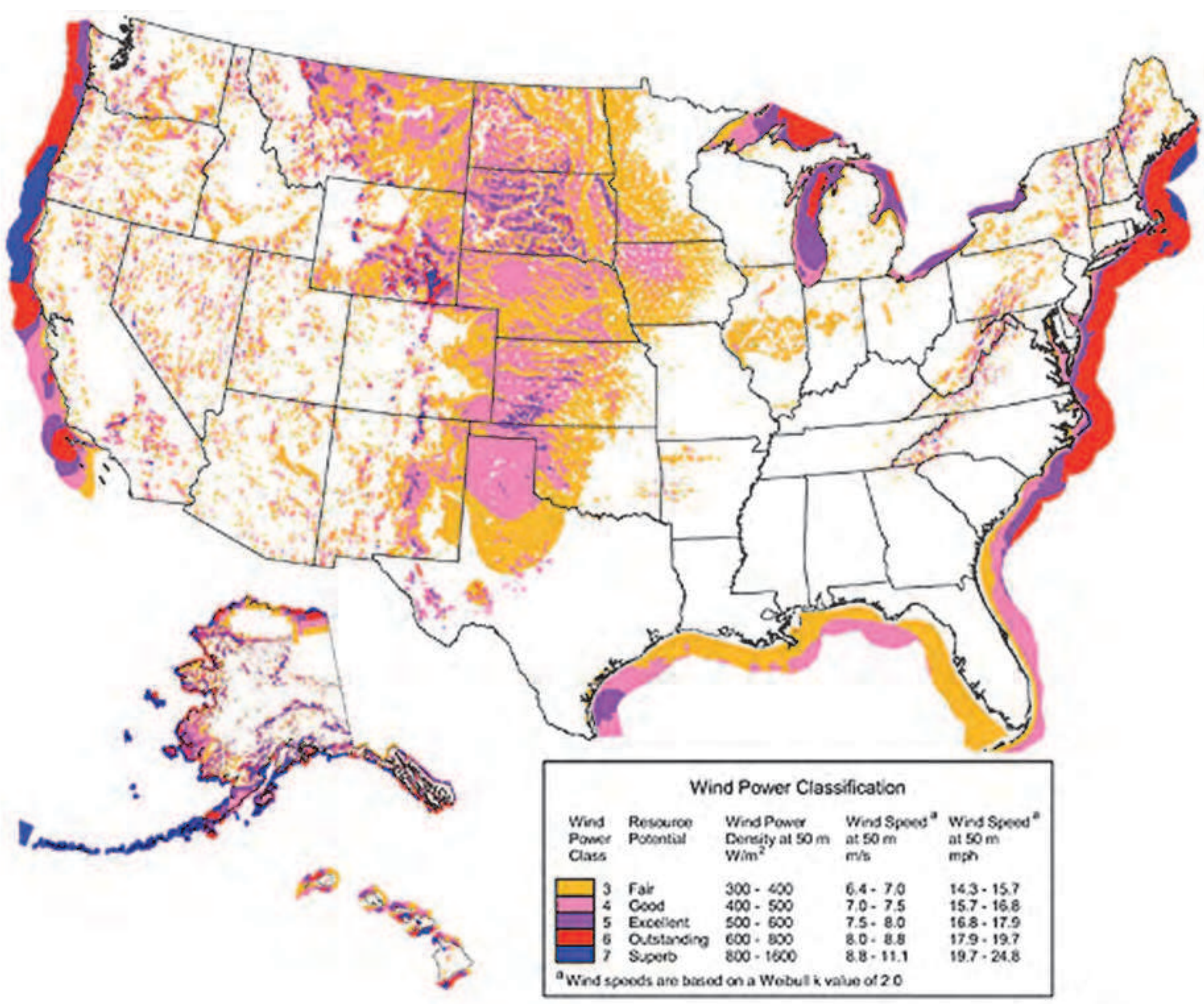

Fig. 1. U.S. Wind Resource Map US wind resource map provided by the Wind Powering America Program (http://www.windpoweringamerica.gov/wind_maps_none.asp

There has also been recent research to utilize concepts from the field of geostatistics to develop a transform function of the wind speed PDF as a function of scale (Morrissey, et al., 2010a, 2010b). If knowledge of the variance of the wind speed at a given scale is known (or can be estimated) then the probability density function representing the required scale may be estimated. In simple terms, the PDF from the higher resolution estimates can be 'upscaled' to match that from the lower resolution estimates. Thus, the PDFs can be scale-corrected, and the problems associated with the Weibull or other approaches can be overcome. This innovative approach uses the theoretical basis of orthogonal series estimators, or more specifically, Hermite polynomials (Schwartz (1967), Hall (1980) and Liebscher (1990)).

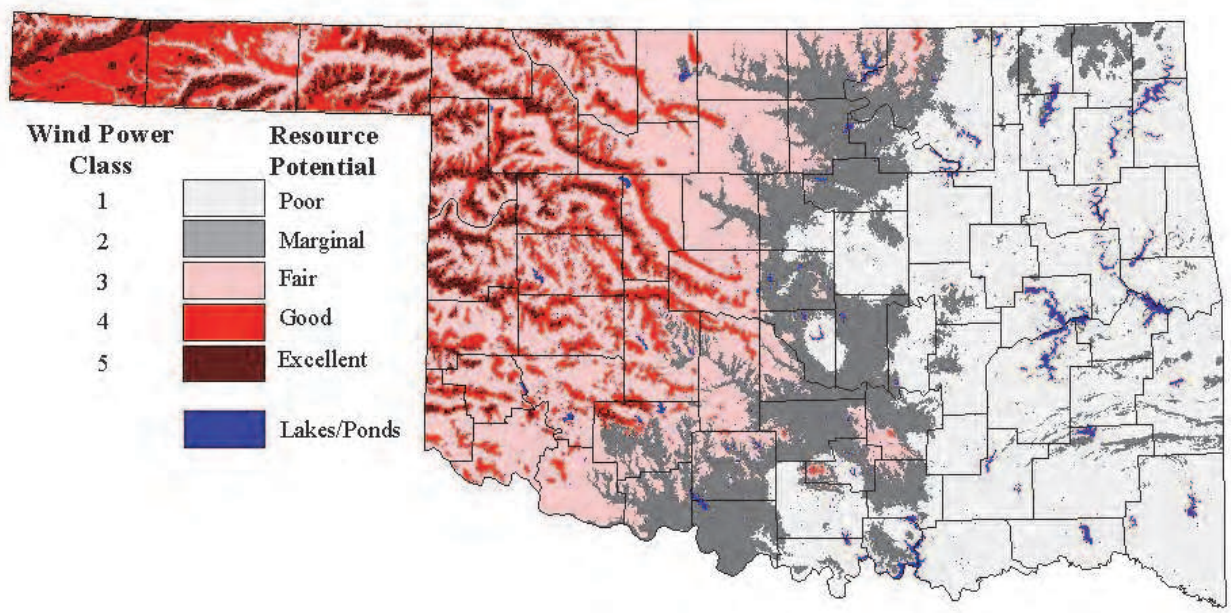

Fig. 2. Oklahoma Wind Resource Map Modeled wind resource provided by the Oklahoma Wind Power Initiative, http://www.ocgi.okstate.edu/owpi. Classes are defined as above with Figure 1.

To illustrate this new approach, a series of data fits were applied to a dataset of 10m windspeeds at five-minute intervals from Boise City, Oklahoma, which is part of the Oklahoma Mesonetwork (Brock, et al., 1995). The results are shown in Figure 3. The y-axis in Figure 3 is a representation of wind power density. The value is normalized wind power density per unit speed. The units are watts/square meter/meter per second divided by air density. This value is used so that the when the integral of the curve is computed, the units reflect a measure of the actual wind power density. Although not commonly used in previous research, this is how the wind PDF values should be developed, as it is a more representative value of the variable in interest (e.g., actual electrical production).

A standard Weibull fit is compared to a kernel estimator and to a new approach using a Gauss-Hermite polynomial expansion (see Morrissey, et al., 2010a for details on the Gauss-Hermite approach). While there is a noticeable variation in the middle of the distribution, this is less significant in terms of the computation of the overall wind power. The Weibull distribution performs poorly where it matters the most – at the higher wind speeds. As might be expected, both non-parametric methods provide a better fit to the histogram than does the Weibull. The mean squared error for the Weibull distribution is approximately 10 times higher than the value for the other model approaches. Since the upper end of the wind speed distribution is the most significant when attempting to determine potential energy, this illustrates that the Weibull approach is not the best approach to fit the wind power PDF. For this location, the Gauss-Hermite and Kernel approaches have approximately the same error. However, since the kernel estimates are produced using parameters which are computed over the whole range, there is a tendancy and risk that the kernel approach will be too weighted toward the lower (e.g., less significant, from an electrical production standpoint) end of the spectrum, and therefore the Gauss-Hermite approach will yield results which more accurately model the wind power density and the electrical production potential.

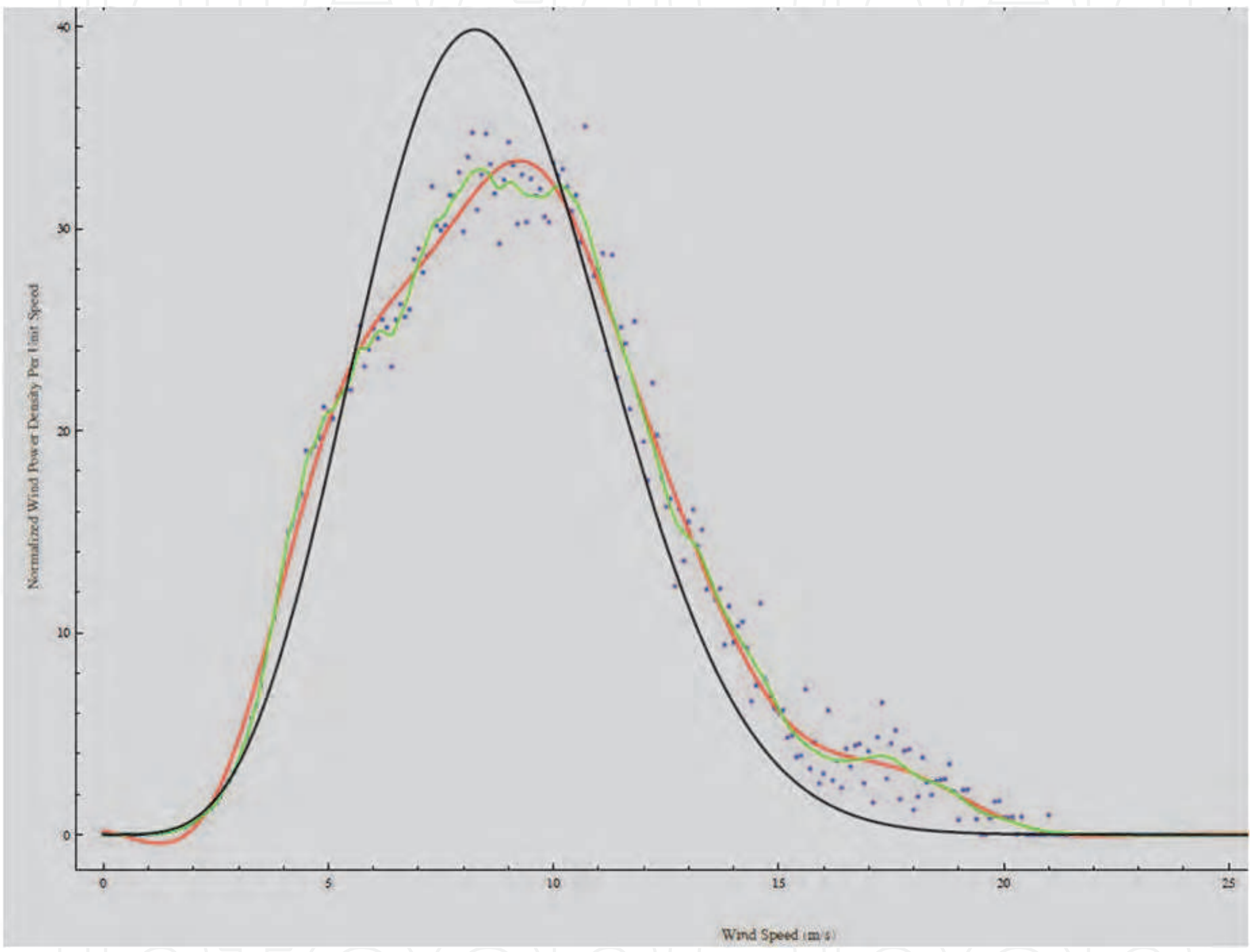

Fig. 3. Actual and Modeled Wind Power Density at Boise City, Oklahoma. Values represent model estimates of scaled wind power density. The Black curve Weibull distribution fit; the Green curve is a Kernel estimator, and the Red curve is a Gauss-Hermite expansion fit.

3. Non-stationarities and impact of climate change

It is well-known that climate change can influence the radiation balance and therefore wind patterns. Recent findings from the Intergovernmental Panel on Climate Change (IPCC, 2007) have shown that greenhouse gas-induced climate change is likely to significantly alter climate patterns in the future. One wind-industry relevant example is that climate change global warming is expected to affect synoptic and regional weather patterns, which would result in changes in wind speed and variability. Therefore, there is a need to examine climate change scenarios to determine potential changes in wind speed, and thus wind power. Wind power facilities typically operate on the scale of decades, so understanding any potential vulnerabilities related to climate variability is critical for siting such facilities. An exhaustive review of the existing research on the projected impacts of climate change on the wind industry can be found in Greene, et al. (2010). The purpose of this section is not to reproduce that work, but to illustrate what the potential impacts might look like.

Thus, as an example of the specific impacts of climate change on a particular location, future summer wind speed estimates at 10m were computed for Chicago, Illinois. The data used represents estimates of daily wind speed. The dates of the model outputs were: 1990-1999, and for the decades of the 2020s, 2040s, and 2090s This was accomplished by using the Parallel Climate Model (PCM) model, and then downscaling the data. The PCM was developed at the National Center for Atmospheric Research (NCAR), and is a coupled model that provides state-of-the-art simulations of the Earth's past, present, and future climate states (see Hayoe, et al., 2008a, 2008b). The projections for the future using the AOGCM are based on the IPCC Special Report on Emission Scenarios (SRES, Nakićenović et al., 2000) higher (A1FI) and lower (B1) emissions scenarios. These scenarios set the future atmospheric carbon equivalent amounts based upon estimates of a range of variables that could impact carbon emissions. These include estimates of future changes in population, demographics, and technology, among others. The B1 scenario values are considered a proxy for stabilizing atmospheric CO_2 concentrations at or above 550 ppm by 2100, and atmospheric CO_2 equivalent concentrations for the higher A1FI scenario are approximately 1000 ppm (Nakićenović et al. 2000). These estimates do not explicitly model carbon reduction policies, but are considered an approximate surrogates for carbon policy (B1), or a "business as usual" option (A1F1).

The results shown in Figure 4 illustrate the changes in average wind speed throughout the spring and summer months (April – August), for the different decades listed above. Results show a decrease for April -June of approximately 3-5% by the end of the century. There is a slight increase for July and August. Overall for the summer, the total values are approximately equal (decreases of 0-1%), but the changes in the seasonal patterns illustrate the need for a more complete analysis in computing the climate change impact on wind speed and wind power density. Also, potential carbon management policy implications need to be considered. Figure 4 shows that there is a significant difference for the 2090s between the policy and no-policy estimates. For example, the May values show a decrease of 5% for the no policy option, and increase of over 4% for the climate policy estimates. This difference illustrates that for this location, a carbon management public policy would dramatically increase the wind, and therefore the potential for increased electrical production.

4. Summary and conclusions

This chapter has provided an overview of some key points associated with improved understanding of wind farm siting. Specifically, the focus has been on two areas of importance in this topic: 1) accurate wind resource assessment; and 2) potential implications of climate change on the wind resource of the future.

For the first topic, there has been much research into the best way to model the wind speed probability density function, as this is the core basis for estimation of the resource. Traditionally, the industry standard has been to model the PDF using either a Weibull or Rayleigh distribution. It has been pointed out that both of these approaches suffer severe limitations that call into question their effectiveness, and other approaches have been suggested by a range of different authors. A review of the trends and current state of the wind PDF modeling has been provided, illustrating a several new and potentially useful approaches. However, many of these approaches have the same inherent flaws, in that the efforts have been spent on modeling the wind speed PDF, when what the industry (e.g., utilities and electrical providers) are really interested in is an estimate of the amount of electrical production. Thus, this analysis of the existing research has illuminated two areas of potential improvement. First, continued improvements in the wind PDF modeling, including, for example, adopting approaches from other disciplines, such as the Gauss-Hermite approach illustrated above, are necessary to develop more accurate portrayals of the resource. Second, geographers and climatological researchers need to more effectively link their efforts to industry needs on trying to model, reproduce, and understand the resource of interest to utilities (e.g., potential electrical production) rather than the more simple and straightforward approach of analyzing the climatological variables (e.g., the wind speed).

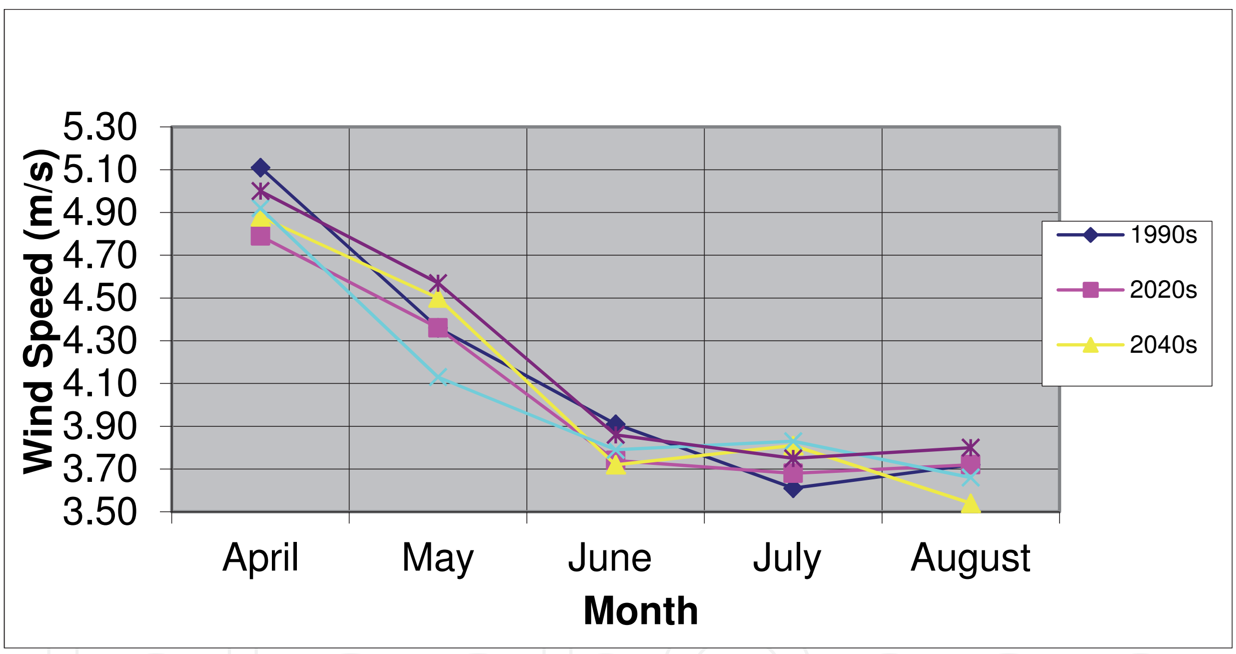

Fig. 4. Estimated Future Wind Speeds, Chicago. Values represent GCM-estimated wind speeds.

Finally, previous research has shown a projected slight decrease in wind speeds in the future, which would result in serious implications for wind farm siting. As shown in the analysis performed here, in the United States, particularly for the wintertime, this is theorized to be associated with a poleward shift of the mean thermal gradient as the earth warms and results in a northward shift of the associated storm track patterns. It is suggested that there will be pronounced regional and seasonal variability in the changes that are currently underway. The wind industry has been growing exponentially over the last decade, and is projected to expand and continue to play an ever-increasing role in electrical production around the world. Improved understanding of the resource, and in any inherent non-stationarities in the wind will help with transition to a sustainable energy future.

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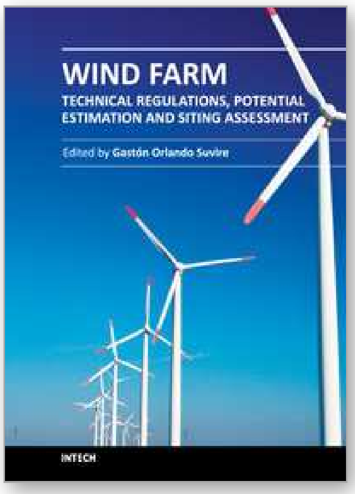

Wind Farm - Technical Regulations, Potential Estimation and Siting Assessment
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The evolution of wind power generation is being produced with a very high growth rate at world level (around 30%). This growth, together with the foreseeable installation of many wind farms in a near future, forces the utilities to evaluate diverse aspects of the integration of wind power generation in the power systems. This book addresses a wide variety of issues regarding the integration of wind farms in power systems. It contains 10 chapters divided into three parts. The first part outlines aspects related to technical regulations and costs of wind farms. In the second part, the potential estimation and the impact on the environment of wind energy project are presented. Finally, the third part covers issues of the siting assessment of wind farms.

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