Masters Program in **Geospatial Technologies**

A SPATIAL DECISION SUPPORT SYSTEM EVALUATING ENERGY AND RESOURCES FOR WIND TURBINE

The case study of Iowa, USA

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Dissertation submitted in partial fulfilment of the requirements for the Degree of *Master of Science in Geospatial Technologies*

NOVA IMS Information Management School

UNIVERSITAT JAUME•I

Westfälische Wilhelms-Universität Münster

A SPATIAL DECISION SUPPORT SYSTEM EVALUATING ENERGY AND RESOURCES FOR WIND TURBINE DEVELOPMENT

The case study of Iowa, USA

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February 2021

DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

This work has not been previously evaluated or submitted to NOVA Information Management School or elsewhere.

LISBOA, 26 FEBRUARY 2021

GABRIELLE PATRICIA MORRIS

ACKNOWLEDGEMENTS

I would like to thank my supervisors, Dr. Joel Dinis Silva and Dr. Marco Painho at Nova Information Management School, as well as Dr. Francisco Ramos at Jaume University I for their guidance and support, and the Erasmus Mundus programme for funding the thesis research. I would also like to acknowledge Dr. Ana Cristina Costa at Nova Information Management School and Dr. Michael Rossol with the National Renewable Energy Laboratory for their outside help.

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ABSTRACT

Energy goals have been set to address climate change and mitigate greenhouse gas emissions in accordance with the Paris climate agreement, a result of the United Nations Convention on Climate Change in 2015. Wind turbines have received a fast-growing interest since they do not produce carbon emissions when converting wind energy to power. It is expected that wind turbines will make up 20 percent of the United States electricity market by 2030 and 35 percent by 2050. A spatial decision support system (SDSS) was developed for a quantitative research study, evaluating wind energy and resources through mathematical modeling and geographic information systems (GIS). The SDSS proposed in the study is comprised of four steps: acquisition of data, resource forecasting, simulation and analysis, and ranking of alternative strategies. The SDSS was then applied to a case study in Iowa, United States for the year 2013. Wind turbine and resource datasets were extracted from the U.S. Wind Turbine Database and WIND Toolkit, respectively. Resources were forecasted using Ordinary Kriging spatial interpolation and Weibull distribution modeling. Weibull parameters were estimated using the power density method. Wind power density, turbine rotor swept area, and the power coefficient were used to simulate power output and capacity factors of presently located wind turbines. Finally, alternative strategies for wind turbine development were ranked based on the estimated energy yields of presently located wind turbines. The results found that most of Iowa exhibits Class III wind speeds, as defined by the International Electrotechnical Commission. Overall, it can be determined that Iowa's resources are economically suited for wind turbine development.

KEYWORDS

Spatial Decision Support System

Wind Energy

Weibull Distribution

Wind Power Density

Geographic Information Systems

ACRONYMS

AWEA	American Wind Energy Association
AWS	Amazon Web Services
CDF	Cumulative Distribution Function
CF	Capacity Factor
EC2	Elastic Compute
GIS	Geographic Information System
HSDS	Highly Scalable Data Service
IQR	Interquartile Range
LBNL	Lawrence Berkeley National Laboratory
NLCD	National Land Cover Database
NREL	National Renewable Energy Laboratory
OEDI	Open Energy Data Initiative
PDF	Probability Density Function
PDM	Power Density Method
S3	Scalable Storage Service
SDSS	Spatial Decision Support System
USDOE	U.S. Department of Energy
USGS	U.S. Geological Survey
USWTDB	U.S. Wind Turbine Dataset
WIND	Wind Integration National Dataset
WPD	Wind Power Density

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1. INTRODUCTION

Wind power is the one of fastest growing green technologies in the United States electricity market. In 2019, renewable energy made up 11 percent of the U.S. primary energy consumption, 24 percent of that renewable energy being derived from wind resources (U.S. Energy Information Administration, 2020). Ambitious goals were set to address global climate change and mitigate greenhouse gas emissions in accordance with the Paris climate agreement, a result of the United Nations Convention on Climate Change in 2015. The allure of wind turbines is that they do not produce CO_2 emissions when converting wind energy to power; therefore, they are not considered a contributor to climate change (Vagiona & Kamilakis, 2018).

With its vast amount of open land, coastal areas and resources, the United States has great opportunity for future wind facility development. According to a study by the U.S. Department of Energy in 2015, it was projected that wind power could make up 20 percent of the U.S. electricity market by 2030 and 35 percent by 2050. Generally, for a future wind site to be considered economically viable, average annual wind speeds of more than 6.5 m/s at 80-meters height or greater is preferred (Center for Sustainable Systems, University of Michigan, 2020). Wind turbines are engineered to match their site, so that wind power output is optimized. To match wind turbines to a site, wind resource variability must be evaluated.

Weibull parameter estimation and distribution modeling of wind speeds is the most widely investigated technique to evaluate wind resource variability. The Weibull model emulates the probability of wind speeds to occur at a site in the future (Azad et al., 2018). To estimate the probability of wind speeds and create a Weibull distribution, one must estimate its two parameters: the shape and scale factors (Rocha et al., 2012). In the Weibull probability density function (PDF) and cumulative distribution function (CDF), the shape factor (k) is dimensionless and determines the spread of the Weibull distribution curve, as the shape parameter is associated with slope. The scale factor (c) is measured in a unit equivalent to that of wind speed measurements, i.e., m/s. Once these two factors are determined, one can produce a Weibull distribution curve that shows the probability of observing certain wind speeds at a site (Azad, Rasul & Yusef, 2014). This methodology helps engineers match wind power technology to a site, in order to achieve optimal efficiency from turbines. The International Electrotechnical Commission (IEC) developed four wind classes, describing the wind conditions at a site. Depending on the wind class a site falls under will determine which type of turbine will be placed there. For example, if a site experiences Class III wind speeds, then a Class III wind turbine will be chosen for that site, which will best fit the conditions and take advantage of the resources available.

Higher wind speeds yield more wind power, and this is because the volume of air passing through a turbine rotor is proportional to the cube of the wind speed (Massachusetts Institute of Technology, 2010). Wind turbines can convert wind energy passing through its rotor to power at a theoretic maximum of 59 percent efficiency, according to Betz' Law. However, turbines typically operate at efficiencies much lower than that (Danish Wind Industry Association, 2003). To understand the capacity to which wind turbines operate, one can calculate its capacity factor (CF) which multiplies annual power output by installed capacity times the approximate number of hours in a year ($t = 8760$). Wind turbine power output data is often protected by the private sector due to its market-value. Nonetheless, turbine power output can be estimated by evaluating the turbine's rotor geometry and efficiency coefficient with the theoretical available power in the wind (Pishgar-Komleh, Keyhani & Sefeedpari, 2015).

The thesis aims (i) to develop a spatial decision support system (SDSS) for a quantitative research study that (ii) evaluates wind resource potential through mathematical modeling and geographic information systems, and (iii) estimates the power output of presently located wind turbines for a particular moment in time. The SDSS was applied to a case study in Iowa, United States.

2. LITERATURE REVIEW

Keenan and Jankowski (2019) stated that "spatial decision support systems combine spatial and non-spatial data, the analysis and visualization functions of Geographic Information Systems (GIS), and decision models in specific domains, to compute the characteristics of problem solutions, facilitate the evaluation of solution alternatives and the assessment of their trade-offs". The purpose of a SDSS is not the decision-making itself, but rather the development of data analysis and the presentation of processed information that assists the decision-maker (Crossland, 2008). According to an article by van Haaren & Fthenakis (2011), many criteria are involved in determining site suitability for wind farm development, many of which are spatially dependent. GIS are used to analyze and visualize site alternatives through thematic mapping, which aid decision-makers in assessing the tradeoffs of presented solutions (van Haaren & Fthenakis, 2011; Azizi & Malekmohammadi, 2014).

Many studies have evaluated several numerical methods that estimate shape and scale parameters for Weibull distribution modeling. For example, Rocha et al. (2012) compared seven Weibull parameter estimation methods for wind speed data in the northeast region of Brazil. The researchers found that the graphical method and the energy pattern factor method were the least effective for their case study location. In addition, they found that the equivalent energy method for determining k and c parameters was efficient for Weibull distribution modeling. In another study, Saxena and Rao (2015) tested four numerical Weibull parameter estimation methods using wind speed data for a desert region in India. The authors preferred the modified maximum likelihood (MML) method was best for Weibull parameter estimation when calculating annual CFs. Komleh and Sefeedpari (2015) performed a study and used the power density method, which uses wind power density to solve Weibull parameters.

Yaqoot et al. (2016) stated that there has been heavy opposition faced from urban planning agencies due to the lack of established protocol for renewable energy siting and failed projects that have resulted from poor resource availability. Research by Strupeit and Palm (2016) expressed the importance of using temporally rich data to support resource availability in the siting of renewable energy farms because once they are sited, the farm will be situated there for its entire lifetime. Site planning is the most important aspect in renewable energy expansion as it can strategically predict whether a project can succeed or not (Strupeit & Palm, 2016). To predict the future viability of a site, one can explore its wind resource variation and wind power potential through Weibull distribution modeling and geospatial visualization (Azad, Rasul & Yusef, 2014).

3. THEORETICAL FRAMEWORK

2.1 Wind Energy

Nearly 2 percent of the solar radiation warming the earth's surface is converted to wind energy (Center for Sustainable Systems, University of Michigan 2020). Due to the spherical shape of the earth, the distance that solar radiation travels to the earth's surface varies which causes temperature differences between the equator and the poles, driving the circulation of air. Cold air is heavier than hot air, and the equator is hotter than the poles. When the hot air rises above the cold air and reaches 10 kilometers altitude in the atmosphere, it then travels to the north and south poles causing the air to circulate.

Due to the rotation of the earth, the air movements of the northern hemisphere divert to the right and the southern hemisphere air movements bend to the left. The phenomenon described is known as the Coriolis force. When winds approach lower pressure areas, it has been observed that winds tend to rotate counterclockwise in the northern hemisphere and clockwise in the southern hemisphere. The atmospheric layer known as the troposphere is approximately 10-kilometers thick and surrounds the earth's surface. The directions of winds flowing in the troposphere is correlated with the latitudes and global trends have been observed.

"Geostrophic winds" is the term used to describe these observed global wind trends. Differences in temperature and air pressure are two variables that largely drive global winds and can be detected at approximately 1-kilometer above the ground. On the other hand, local winds are influenced by the characteristics of earth's surfaces up to 100-meters in altitude. Local winds nearer to the ground are slowed because of obstacles and surface roughness and their directions are slightly different those observed in the geostrophic realm due to the rotation of the earth. In addition, local climatic conditions may have an influence on local wind directions, however the observed wind direction of a particular location is a sum of both global and local wind influences.

The density of air, the rotor's swept area, and wind speed determine the amount of wind energy that the rotor blades can convert to power. However, it is impossible to capture all the wind energy using wind turbines due to Betz' Limit, or Betz' Law (see 2.2. Energy Output). A wind turbine can retrieve energy from the wind through its rotor blades by converting the wind's turning force on the rotor, or torque. Wind turbines are a device that capture the kinetic energy present in the wind by converting it to rotational energy, and as stated in the introduction, since the wind energy is captured through volumes of moving air, the amount of energy that a turbine can convert to power depends on the cube of the average wind speed (Danish Wind Industry Association, 2003).

2.3. Energy Output

The wind industry typically accounts for wind speed variation through Weibull distributions. Statistically, wind speeds are described using PDF distributions with its curve equal to one, and the probability that the wind will blow at some wind speed including 0 m/s should equal 100 percent. By multiplying each wind speed interval by the probability of that wind speed occurring and then take the sum, mean wind speed is derived. A Weibull distribution is calculated with two parameters called the shape and scale factors. The scale parameter (c) is used as an indicator of how windy a site is, and the shape parameter (k) describes how peaked the distribution is, i.e., if the wind speeds always tend to be very close to a certain value, the distribution will have a high k value, and will be very peaked as a result. A Weibull Rayleigh distribution is created when the shape parameter is set to 2.

Higher wind speeds yield more wind power, and this is because the volume of air passing through a turbine rotor is proportional to the cube of the wind speed (see Figure 1). For power calculations, one cannot simply use the average of wind speeds, but must weigh each wind speed probability with the wind power density. The more kinetic energy that is absorbed by the wind turbine rotor, the more the wind exiting the rotor will be slowed down. Ideally, a wind turbine should slow down the original speed of the wind by 2/3rds after exiting through the rotor. A fundamental physical law for wind turbine aerodynamics, called Betz' Law, states that wind turbines can convert 59 percent or less of the kinetic energy in the wind to mechanical energy, which was proven by Albert Betz in 1919.

Higher wind speeds have a richer energy content than lower wind speeds. The wind energy potential per second varies with the proportional density of the air and in proportion to the cube of the wind speed (see Figure 1). By multiplying each wind speed interval by the probability of wind speeds in the Weibull graph, the wind power density, or distribution of energy at different wind speeds is calculated. Wind speeds above the average wind speed of a site is where the bulk of wind energy is found.

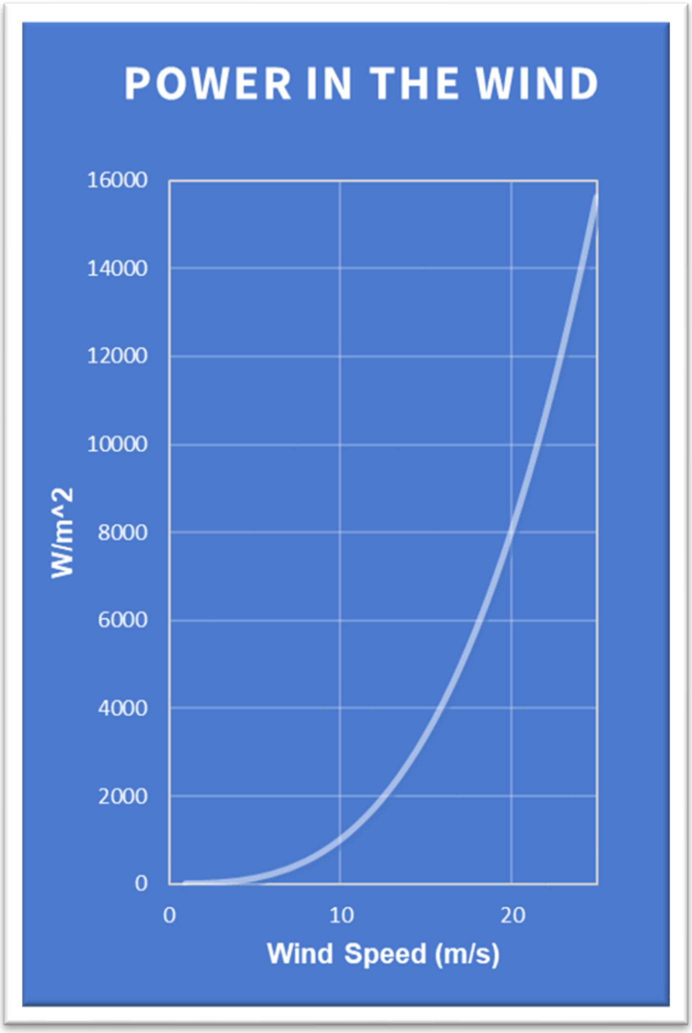

Figure 1. A figure illustrating the cube of the wind speed and theoretical available power in the wind.

Wind turbines are engineered to start running and stop running at certain wind speeds. These are called the cut-in and cut-out speeds. Wind turbines are designed to cut-in, or begin running, at wind speeds between 3 and 5 m/s. Moreover, turbines are programmed to cut-out, or stop running, at wind speeds above 25 m/s to avoid damage. Each turbine has a power curve, which is a plot that defines the electrical power output at different wind speeds. These power curves are derived from field measurements recorded by the manufacturer. This is done by placing an anemometer on the wind turbine or on a mast closely nearby. A pitfall of power curves is that they do not provide the power output of a wind turbine at an average wind speed.

To tell how efficiently a wind turbine is converting wind energy to electrical power, one must calculate the power coefficient. This value can be formulated by dividing the electrical power output by the wind energy input. Another way to calculate the power coefficient of a wind turbine is by dividing the power curve by the swept area of the rotor. When considering wind turbine efficiency, the optimal turbine keeps the cost per kilowatt hour to a minimum. Therefore, an optimal turbine does not always mean that it has the highest electrical power output per year.

To calculate the power output of wind turbines, first one must multiply the probability of each wind speed interval of 0.1 m/s using the Weibull curve with the wind turbine's power curve. Then, one must summate each of those multiplications to acquire the mean power output of the wind turbine in a particular location. In addition, one can evaluate the relationship between annual power output of a wind turbine and the average wind speed. It is important to note that wind turbine efficiency varies with wind speed, which is emulated by the power curve.

The CF is defined as annual power output divided by the theoretical maximum of installed capacity and can be used to describe a project of turbines or individual turbines. Most wind turbines have a CF between 25 and 30 percent, and a larger CF does not always mean there is an economic advantage. The CF paradox states that turbines with a higher capacity factors tend to have a relatively stable power output while turbines with lower capacity factor tend to have a higher-power output and energy yield fluctuation (Danish Wind Industry Association, 2003).

4. METHODOLOGY

The primary research methods used in this study are parametric computation and analytical estimation of wind energy and resources. A case study is proposed on the state of Iowa, United States.

4.1. Data Acquisition

Two databases were used for the analyses presented in the thesis. First, data was extracted from the U.S. Wind Turbine Database (USWTDB), which was publicly released in collaboration by the U.S. Geological Survey (USGS), American Wind Energy Association (AWEA), and Lawrence Berkeley National Laboratory (LBNL) in April 2018. The turbine points were visually verified using high-resolution satellite imagery within 10-meters accuracy. The dataset includes attributes describing wind project and turbine characteristics, and other locational data.

Next, data was extracted from the Wind Integration National Dataset (WIND) Toolkit released by the National Renewable Energy Laboratory (NREL) as part of the Open Energy Data Initiative (OEDI) supported by the U.S. Department of Energy. The data was accessed through a cloud optimized tool, called the Highly Scalable Data Service (HSDS) developed by the HDF5 Group, and the h5pyd Python library using the Anaconda platform and Jupyter Notebook. The HSDS tool provides connection to the OEDI Data Lake which hosts 50-terrabytes worth of meteorological data stored using a combination of EC2 (Elastic Compute) and S3 Buckets (Scalable Storage Service) on Amazon Web Services (AWS). For the state of Iowa, temperature and wind speeds at 80-meters, as well as atmospheric pressure at 100-meters were extracted from the WIND Toolkit (WTK) using the methods described above. The meteorological data extracted provided monthly and annual means for meteorological conditions at a 2-km x 2-km spatial resolution for year 2013.

Additional datasets were used to examine spatial trends in respect to turbine placement in Iowa. The variables used for the information extraction include slope, erodibility factor, distance to grid, and land cover type. Each of these datasets are available in the ArcGIS Catalog Portal under ‘Living Atlas’. The datasets provided in the ‘Living Atlas’ are derived from authoritative sources.

4.2. Preprocessing

The USWTDB and WTK datasets were extracted from their respective sources in comma-separated value format with spatial coordinates listed for each recorded observation. The spatial data was preprocessed in ArcGIS Pro 2.7.1 and non-spatial data was preprocessed using Microsoft Excel Version 2101. The level of certainty was indicated for each turbine record in the USWTDB by ranking the record between one and three, three being most confident. Records with lower confidence ranking, equal to one, were removed from the dataset to ensure reliable results. In addition, only wind turbines ranging between 75- and 85-meters hub height, whose position fell within the state boundary of Iowa, and were constructed before 2013 were included in the study.

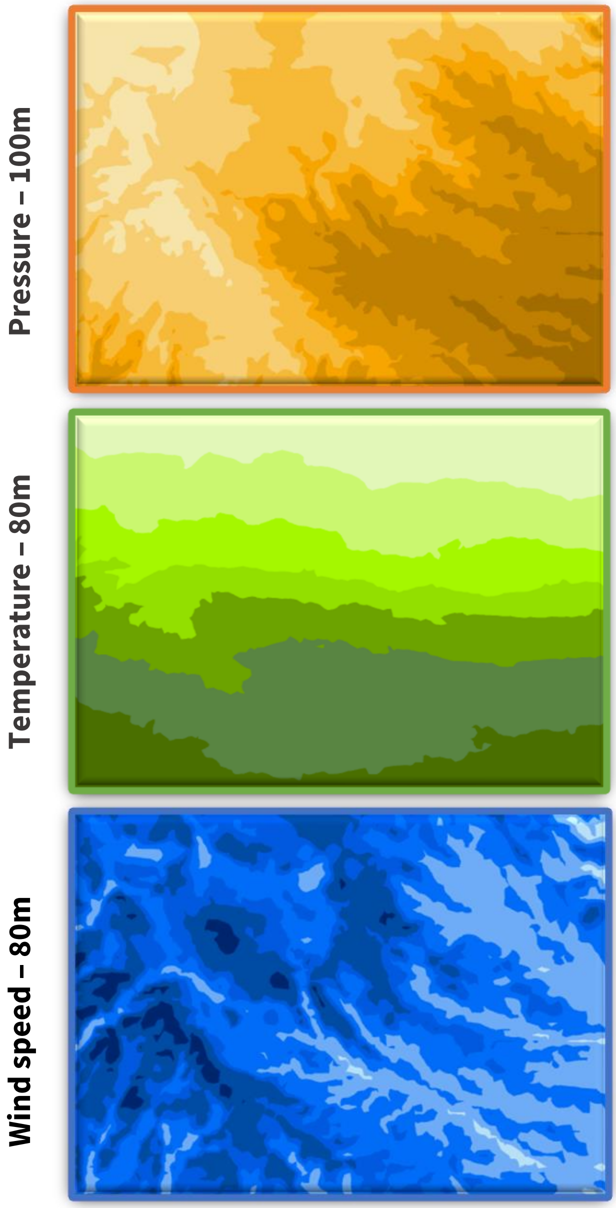

Figure 2. Predictive surfaces of the meteorological datasets extracted from the WIND Toolkit were interpolated by Ordinary Kriging using the Geostatistical Wizard in ArcGIS Pro 2.7.1.

Predictive surfaces of the meteorological datasets were interpolated by Ordinary Kriging using the Geostatistical Wizard in ArcGIS Pro (see Fig. 1). Each of the interpolated meteorological layers were rasterized and the surrounding values coincident with the wind turbines' spatial location were extracted into table format. The extracted values were used to estimate power output and capacity factor of the sampled turbines in Iowa.

4.3. Spatial Decision Support System

An SDSS has been developed to quantitatively evaluate energy and resources for an annual period at a specified site (see Fig. 2). The SDSS model explores the geographic relationship between meteorological conditions and wind turbine location and technical characteristics. The model developed for this study is based on the SDSS definition provided by Keenan & Jankowski in their 2019 review "Spatial Decision Support Systems: Three decades on", in which they state that:

> "spatial decision support systems combine spatial and non-spatial data, the analysis and visualization functions of Geographic Information Systems (GIS), and decision models in specific domains, to compute the characteristics of problem solutions, facilitate the evaluation of solution alternatives and the assessment of their trade-offs."

There are four steps to the SDSS proposed in this study. To begin, one must acquire meteorological observation datasets, including wind speed, temperature, and air pressure, at the desired hub-height with a monthly temporal resolution at minimum. In supplement, a wind turbine dataset that includes technical characteristics and locational data is required. Next, predicted surfaces of the meteorological datasets are interpolated in order to forecast resources across a specified area. The predicted resource values that are coincidental with the wind turbine location are used to estimate wind turbine power output, along with the turbine rotor swept area.

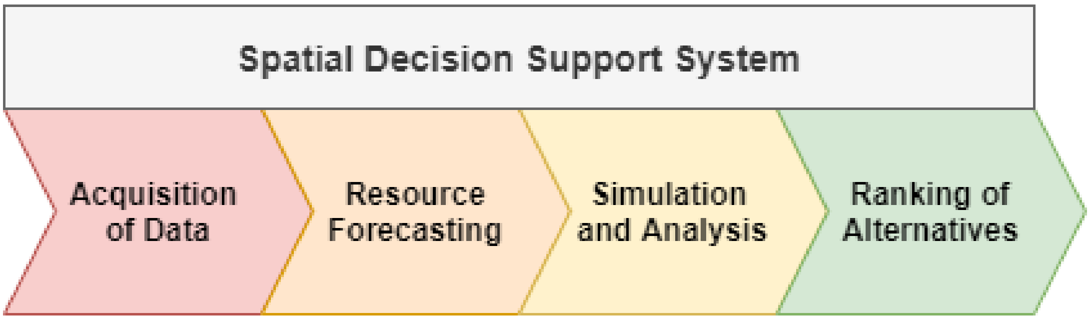

Figure 3. A spatial decision support system diagram for evaluating wind power potential for an annual period at a specified location using meteorological condition and wind turbine location and technical characteristic datasets.

Once the resource values are extracted, the power output and capacity factors of each wind turbine are simulated in a GIS. The top producing turbines and highest capacity turbines are then evaluated for their spatial trends, including wind power density, slope, aspect, and elevation, and distance from urban centers, transmission lines road and rail networks. A correlational study will compare each continuous variable with wind turbine power output, as well as capacity factor to determine the weight each variable will receive in the suitability analysis. Finally, two future wind project site suitability maps, based on estimated capacity factor and power output, will be developed to communicate alternative strategies, and evaluate trade-offs to decision-makers.

4.4. Wind Power Density

To estimate the kinetic energy available at a specified height above the ground, one can calculate its wind power density. First, we should calculate the variation and descriptive statistics of the wind speed data, which is denoted by calculating the mean wind speed for a time series (Eq. 1), quantifying how much the wind speed observations deviate from this mean value (Eq. 2), and the mean cube of the wind speed (Eq. 3). The mean and standard deviation of a wind speed dataset are defined by Akdag and Dinler (2019) as:

$$\bar{V} = \left(\frac{1}{n}\sum_{i=1}^{n} v_i\right) \tag{1}$$

$$\sigma = \left[\left(\frac{1}{n-1}\sum_{i=1}^{n}(v_i - \bar{V})\right)\right]^{0.5} \tag{2}$$

$$\overline{V^3} = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^3\right) \tag{3}$$

where n is the number of wind speed observations, v_i is the value of each individual wind speed observation in m/s, $\bar{V}$ is the average wind speed in m/s, and $\overline{V^3}$ is the average cube of the wind speed in m/s^3.

As previously mentioned, to estimate the kinetic energy available in the air at a site and specified height, one can calculate the wind power density by evaluating the air density and cube of the wind speed together (Eq. 5). The formula for air density is represented by the symbol ρ (rho) and is defined by Baseer et al. (2017) as:

$$\rho = \frac{\mathrm{P}}{R_{gas}T} \tag{4}$$

Where P is the pressure of the air in Pascals (Pa), R_{gas} is the specific gas constant (J/kg·K), and T is the recorded air temperature (ºK). The specific gas constant of dry air is used in this study, which is recorded to be 287.05 J/kg·K (Baseer et al. 2017). The wind power density of a wind speed time series is defined by Saxena and Rao (2015) as:

$$WPD = \frac{1}{2}\rho\left(\frac{1}{n}\sum_{i=1}^{n} v_i^3\right) \tag{5}$$

Defined by Akdag and Dinler (2019), this equation can also be written, as:

$$WPD = \frac{1}{2}\rho\overline{V^3} \tag{6}$$

where ρ is the air density in kg/m^3, and $\overline{V^3}$ is the average cube of the wind speed in m/s^3. These calculations will be applied to each of 12 monthly time series, in addition to the annual-averaged time series for year 2013 in Iowa, United States.

4.5. Weibull Distribution and Parameter Estimation

To assess wind speed variation at a specified site, Weibull distribution analysis is the most common approach (Eq. 7). The Weibull PDF and CDF used for plotting wind speed variation are defined by Masters (2004) as:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{7}$$

$$F(v) = 1 - exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{8}$$

where $f(v)$ is the probability of observing a wind speed, $F(v)$ is the probability of observing wind speeds less than or equal to the value of x, v is the wind speed bin midpoint, k is the dimensionless shape factor and c is the scale factor, measured in the same unit as the wind speed. The Weibull distribution's shape and scale factors were estimated using the Power Density Method (PDM) defined by Akdag and Dinler (2019) as:

$$PDM = \frac{1}{2}\rho\int_0^{\infty} v_i^3\, f(v)\, dv \tag{9}$$

where PDM is the WPD frequency at a wind speed bin midpoint, ρ is averaged air density for a time series, v_i is the wind speed bin midpoint, and $f(v)$ is the Weibull probability of observing a wind speed. For visualization, Rayleigh shape factor ($k = 2$) was used to normalize the shapes of the curves so that they could be compared to one another. The Solver Add-In in Excel was used to find the optimal c-factor value, by setting the sum of PDM to match the average WPD of the time series data.

To calculate the error attributed to the PDM method, three error processing methods were used including R-squared (Eq. 10), root-mean-square error (Eq. 11), and percent error (Eq.12). The formulas used to evaluate the associated error for c-factor estimation of each time series was calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{10}$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2\right]^{\frac{1}{2}} \tag{11}$$

$$\delta = \left|\frac{WPD - PDM}{PDM}\right| \tag{12}$$

where R^2 is R-squared, $RMSE$ is the root-mean-square error, δ is the percent error, N is the number of bins, y_i is the observed wind speed frequency distribution values, x_i is the Weibull frequency distribution value and $\bar{y}$ is the average of y_i values. The three error processing methods were applied to each wind speed time series.

4.6. Wind Turbine Power Output

Once the WPD is estimated to measure the kinetic energy available at a certain height above the ground, one can calculate wind turbine power output by multiplying the WPD by wind turbine rotor swept area (see Fig. 3) and the efficiency rate of the wind turbines (Wais 2017) (Eq. 14). The theoretical available wind energy (P_{avail}) in the stream of air entering through the wind turbine rotor swept area (A_R) at a constant velocity (v), is:

$$P_{avail} = \frac{1}{2}\rho v^3 A_R C_p \tag{14}$$

where ρ is the density of air in kg/m^3, p is the atmospheric pressure in Pa, $A_R = \pi r^2$ is the cross-sectional area of a wind turbine rotor in m^2, and C_p the power coefficient.

Betz' Limit states that wind turbines cannot have efficiencies higher than 59 percent. Although the efficiencies for different wind turbine models are not constant, due to the unavailability of this data, a constant power coefficient of 40 percent will be used. If power coefficients are known for turbine models, they should be used over the constant power coefficient defined in this study.

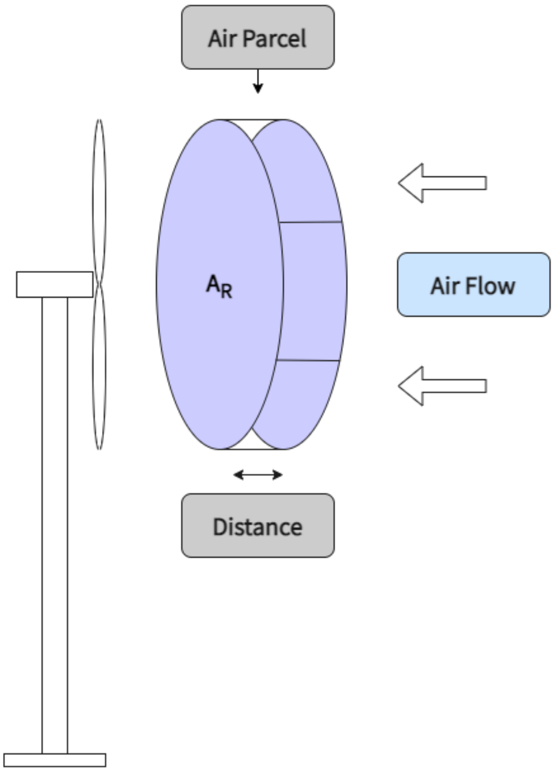

Figure 4. A diagram illustrating an air parcel traveling at some velocity, where the distance traveled equates to a 360 degree rotation of the wind turbine blades.

Wind turbine points were overlaid on the WPD interpolation map in a GIS (ArcGIS 2.7.1). The coincident values were extracted to the wind turbine shapefile and multiplied by the rotor swept area of each turbine and the constant-defined power coefficient to estimate the wind turbine power output.

The wind turbine capacity factors are obtained by dividing the annual energy output (E_{AO}) by the installed capacity (E_{IC}) multiplied by the number of hours in a year (Eq. 15). For displaying the spatial information, wind project centroids were determined, and the annual energy output and capacity factor means for each wind project were calculated. The capacity factor of wind turbines can be calculated as:

$$CF = \frac{E_{AO}}{E_{IC} \times 8760} \tag{15}$$

where E_{AO} is the annual energy output (kWh) and E_{IC} is the wind turbine installed capacity (kW).

5. RESULTS

5.1. Resource Forecasting

Line graphs were developed to illustrate monthly resource variation for air pressure at 100-meters, temperature at 80-meters and wind speed at 80-meters for year 2013 in Iowa (see Figure 5). In 2013, the distribution of air pressure in Iowa was approximately symmetrical, centered at about 96,600 Pa with most observations occurring between 96,000 and 97,200, a range of roughly 5,000, and no apparent outliers. Air pressure was highest in the winter months, November, December, and January, and was the lowest in the spring months, April, May, and June.

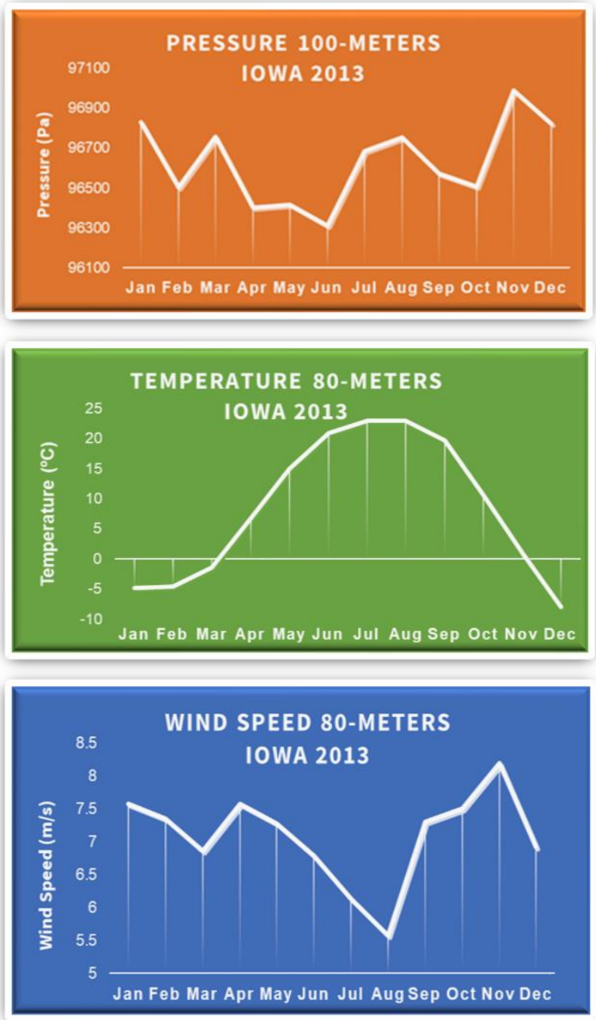

Figure 5. Descriptive charts showing resource variation in Iowa for 2013.

The distribution of temperature was approximately symmetrical, centered at around 9 degrees Celsius with most temperatures being between -3 and 20 degrees, a range of 36 degrees, and no apparent outliers. Temperature was the highest in the summer months, June, July, and August, and the lowest in the winter months, December, January, and February.

The distribution of wind speeds was slightly skewed to the left, centered at about 7.1 m/s with most wind speeds occurring between 6.6 and 7.6 m/s, a range of 5.8 m/s, and no apparent outliers. Wind speeds were the highest in November, January, and April and the lowest in July and August.

The annual mean wind speed for the year 2013 in Iowa was 7.08 m/s with a standard deviation of 0.37 and a mean cube of the wind speed at 357.93 m/s^3 (see Table 1). August had the lowest mean wind speed at 5.57 m/s and November had the highest mean wind speed at 8.20 m/s in 2013. Of the all the months, April had the least variation in wind speeds with a standard deviation of 0.34 and September experienced the most variation with a standard deviation of 0.48. Regarding the cube of the wind speed, the volume of wind was highest in the month of November at 555.63 m/s^3 and lowest in August at 175.82 m/s^3.

The annual mean air density for Iowa in 2013 was 1.20 kg/m^3. The highest air density was observed in the month of December and the lowest air density was observed in a tie between June, July and August at 1.14 kg/m^3. The annual mean WPD for Iowa in 2013 was 213.93 W/m^2. The month with the highest WPD was November at 342.47 W/m^2 and the lowest mean WPD occurred in August at 100.07 W/m^2 (see Table 1).

For Weibull distribution modeling and shape-factor (k) equaling 2, the outcome of scale-factor (c) ranged between 5.10 m/s and 7.48 m/s with the highest probable wind speeds happening in November and the lowest in August (see Figure 6). The annual probable wind speed occurring at 6.46 m/s in Iowa for 2013. The resulting c-factors followed the same variation as wind speed with predicted values slightly lower than the observed monthly wind speed means.

The error calculated based on the results of the PDM Weibull parameter estimation, show R-squared values closer to 0, with an annual error of 8.2684% and a monthly

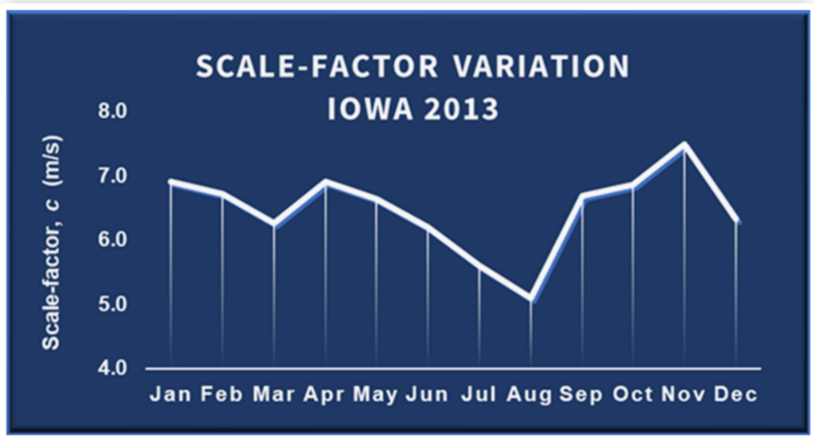

Figure 6. A line graph illustrating the monthly scale-factor (m/s) variation for Iowa in 2013.

	$\overline{V}$ (m/s)	σ	$\overline{V^3}$ (m/s^3)	ρ (kg/m^3)	$\overline{WPD}$ (W/m^2)	k	c (m/s)	R^2	$RMSE$	δ
Annual	**7.08**	**0.37**	**357.93**	**1.20**	**213.93**	**2**	**6.46**	**8.2684%**	**1.6672%**	**0.0020%**
January	7.57	0.40	438.23	1.26	275.52	2	6.91	8.1573%	1.5909%	0.0002%
February	7.35	0.39	400.71	1.25	250.87	2	6.71	8.2885%	1.6160%	0.0010%
March	6.86	0.40	325.56	1.24	201.96	2	6.26	9.6392%	1.5720%	0.0015%
April	7.57	0.34	436.64	1.20	261.91	2	6.90	7.1980%	1.7029%	0.0005%
May	7.27	0.38	388.06	1.17	226.22	2	664	8.3162%	1.6269%	0.0021%
June	6.78	0.46	316.65	1.14	180.68	2	6.20	11.5002%	1.4362%	0.0005%
July	6.13	0.37	233.19	1.14	132.64	2	5.60	10.0939%	1.6649%	0.0030%
August	5.57	0.42	175.82	1.14	100.07	2	5.10	13.8120%	1.4938%	0.0030%
September	7.31	0.48	395.06	1.15	226.93	2	6.68	10.6101%	1.4178%	0.0018%
October	7.50	0.44	426.57	1.18	252.66	2	6.85	9.1363%	1.5073%	0.0019%
November	8.20	0.42	555.63	1.23	342.47	2	7.48	7.4429%	1.5630%	0.0012%
December	6.93	0.43	336.10	1.27	213.72	2	6.33	10.3055%	1.5031%	0.0015%

Table 1. A table showing monthly and annual calculations for mean wind speed, standard deviation, mean cubed wind speed, mean air density, mean wind power density, and Weibull parameter estimation and error, shape-factor, scale-factor, R-squared, root-mean-square-error and percent-error, respectively.

range between 7.1980% and 13.8120% (see Table 1). The highest values of variation occurred in August and the lowest occurred in April. The RMSE of annual predicted values was calculated to be 1.6672% and percent error was 0.0020%. Regarding the monthly RMSE and percent error, highest values were recorded at 1.7029% in April and 0.0030% in July and August, and lowest values at 1.4178% in September and 0.0002% in January, respectively.

The probability of wind speeds occurring in Iowa followed seasonal trends (see Figure 7). The seasons for Iowa are as follows: spring makes up March, April and May, summer makes up June, July, and August, autumn makes up September, October, November, and winter makes up December, January, February. In the summer months, the probability of lower wind speeds occurring is higher. In the winter and spring months, the probability of wind speeds occurring was close to the annual probability of wind speeds occurring. The winter and spring months have a wider spread than the summer probability distribution and a narrower spread than the autumn months.

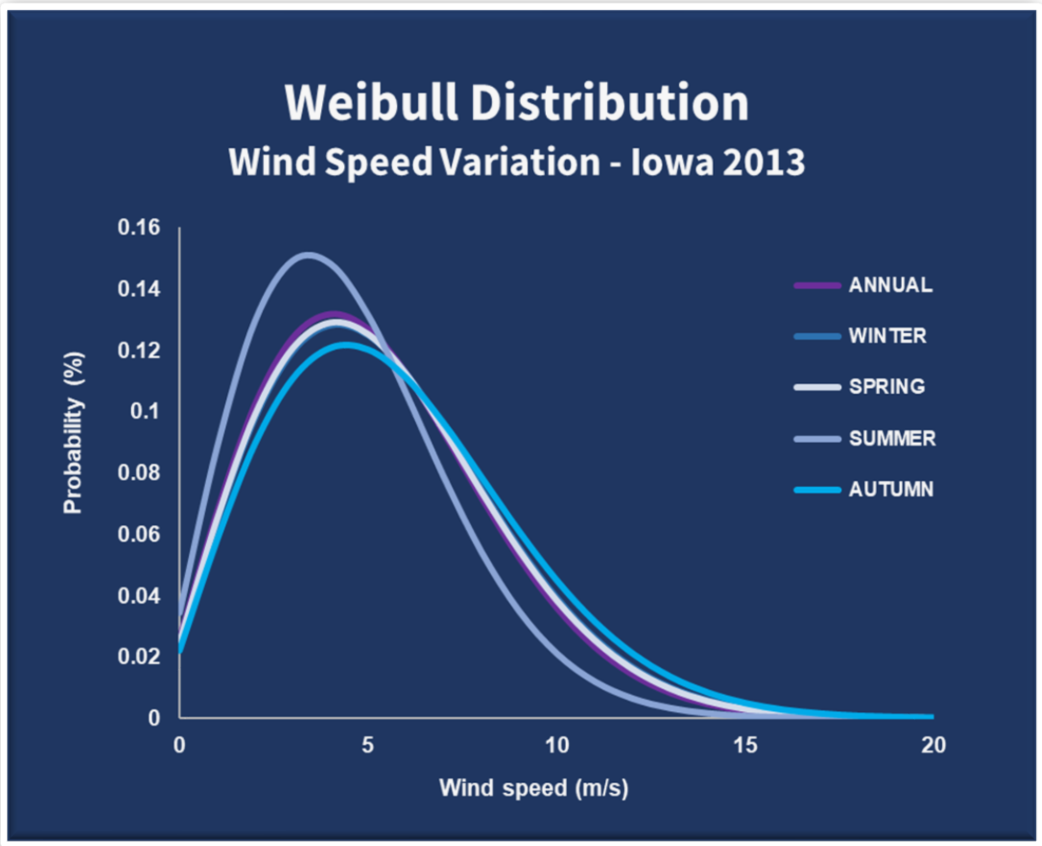

Figure 7. A Weibull distribution model showing the probability of wind speeds to occur in Iowa based on seasonal and annual averages in 2013.

Finally, the autumn months predicted probability for higher wind speeds to occur more steadily than other seasons.

5.2. Simulation and Analysis

After the USWTDB dataset was preprocessed, a total of (n = 2276) wind turbines and (N = 67) wind projects remained. The mean centers of each wind turbine project were used to display the results, and the average turbine productivity and capacity factors were calculated by wind project. The sampled turbines were constructed between 2003 and 2012.

Each project has an average of around 33 turbines with a standard deviation of approximately 42 turbines, a mode of 1 turbine and a range of 192 turbines. The annual WPD extracted for each turbine point was interpolated using nearest neighbor estimation. Most of the wind turbines produced wind energy in areas with WPD values between 240 and 265 W/m^2. The mean wind power density available at turbine locations is about 252 W/m^2 in Iowa for 2013 with a standard deviation of 19.73 W/m^2 and a range around 175 W/m^2 (see Table 2). The mean wind energy that turbines produced was approximately 668 kW with a standard deviation of 176.59 kW and a range of 986 kW.

About 78.6 percent of wind turbines fell within land cover class '82 – Cultivated Crops' and 12.4 percent fell within '21 – Developed, Open Space', as defined by NLCD. Wind turbines were placed in locations with soil erodibility factors up to 52

	WPD (W/m^2)	$Energy$ (kW)	CF (%)
Mean	252.61	668.22	0.36
Median	254.11	650.62	0.35
Standard Deviation	19.73	176.59	0.06
Sample Variance	389.18	31184.36	0.00
Range	175.59	985.55	0.33
Minimum	125.22	176.78	0.17
Maximum	300.82	1162.33	0.49

Table 2. A table showing the forecasted resource and simulated wind energy captured by wind turbines in Iowa in year 2013.

percent, with most turbines being placed in areas between 31 and 43 percent erodibility and a range of about 47 percent. Around 95.5 percent of wind turbines were placed in area with a slope ranging between 0 and 10 degrees, with a median slope of 2 degrees and a range of about 87 degrees overall. The average distance wind turbines were placed from the electricity grid is 3.7 kilometers, with most turbines being placed between 1.2 and 5.2 kilometers away and an overall range of 23.9 kilometers.

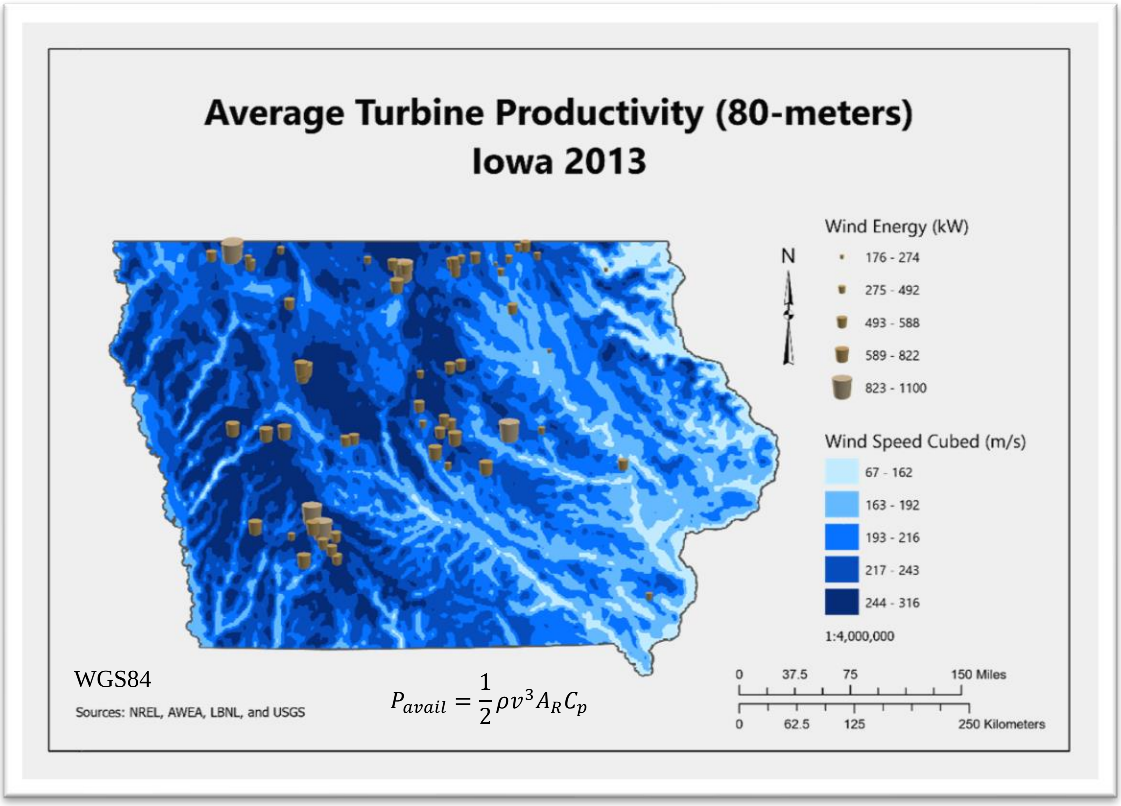

Figure 8. A map showing the mean power output of wind turbines by project, measured in kilowatts. The basemap illustrates wind speed cubed for the state of Iowa at 80-meters. The sampled turbines include all that fell within the state of Iowa, was constructed before 2013, and have a hub height between 75- and 85-meters.

The productivity of wind turbines was averaged by their corresponding project and illustrated using a GIS (see Figure 8). Around 99.99 percent of sampled wind turbines fell within an area that experienced annual wind speeds above the 6.5 m/s threshold to be considered an economically viable location. The size of the symbology displayed on the average turbine productivity map are based on the wind power density of the area, turbine rotor swept area and power coefficient. Larger cylindrical symbols mean a project has higher average wind energy production and smaller cylindrical symbols indicate lower average wind energy production, relatively.

The average capacity factor, or efficiency that turbines performed within a project, is 36 percent with a standard deviation of 6 percent and a range of 33 percent. The average rotor swept area of the sampled turbines was 6600 m^2, with most turbines having a rotor swept area between 5281 and 8012 m^2 and an overall range of about 8278 m^2. The size of the symbology displayed on the project capacity factor map are based on the annual productivity of wind turbines and the installed capacity multiplied by the number of hours in a year (see Figure 9). Larger spherical symbols indicate a higher project capacity factor and smaller spherical symbols indicate a lower project capacity factor, relatively.

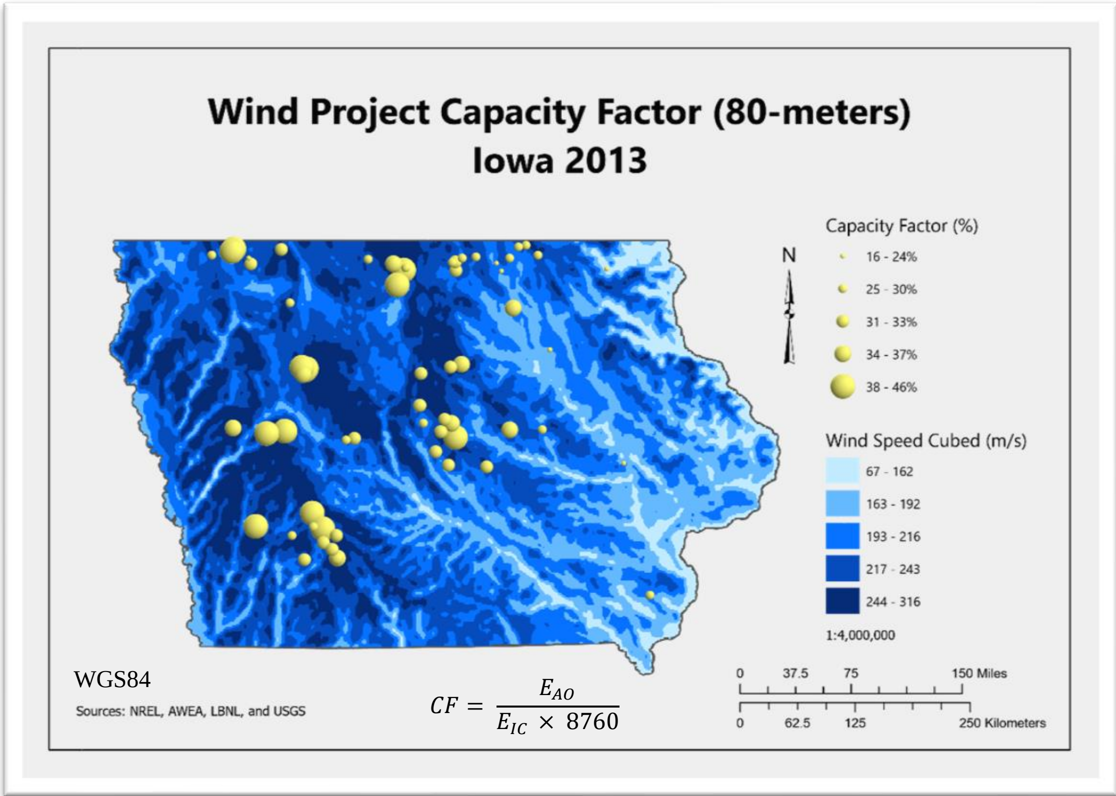

Figure 9. A map showing the mean capacity factor of wind turbines by project, measured in kilowatts. The basemap illustrates wind speed cubed for the state of Iowa at 80-meters. The sampled turbines include all that fell within the state of Iowa, was constructed before 2013, and have a hub height between 75- and 85-meters.

5.3. Ranking of Alternative Strategies

Iowa has sufficient WPD to host wind turbines throughout the state. The IEC designates specific wind classes that are based on annual average wind speeds. The state of Iowa experienced three of four wind classes defined by the IEC in 2013: Class

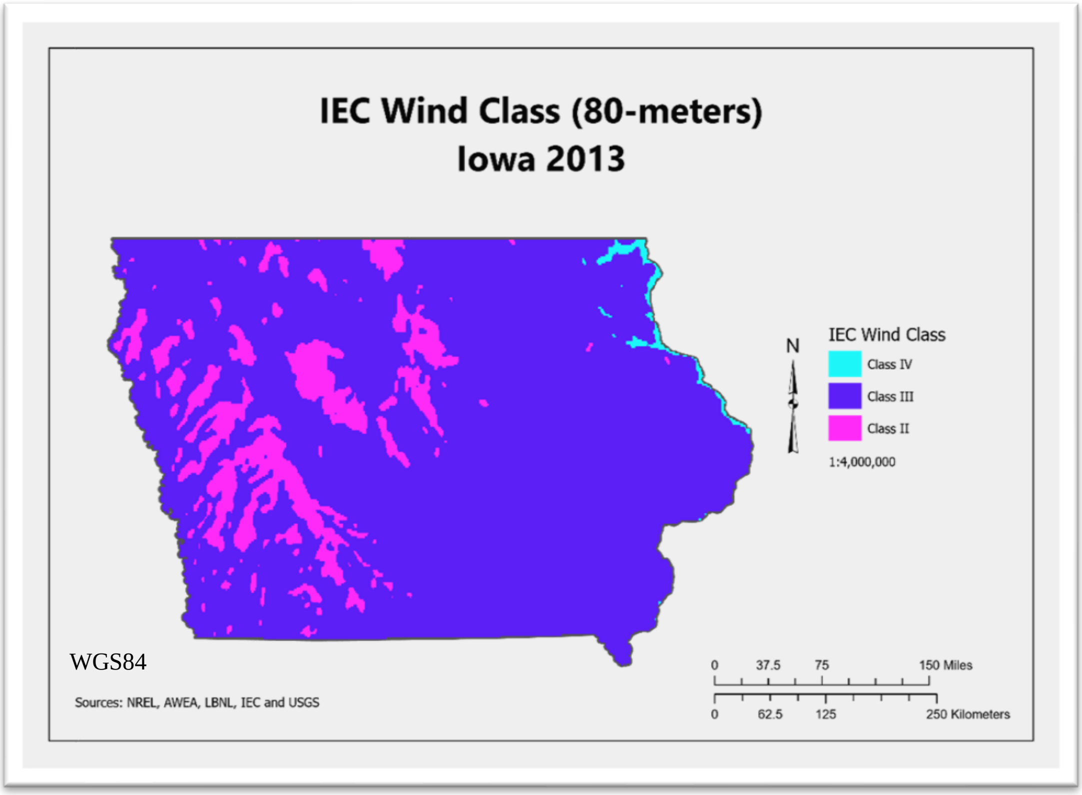

Figure 10. A map showing IEC Wind Classes for the year 2013. The state of Iowa mostly experienced Class III wind speeds, Class II wind speeds in the western portion of the state and Class II wind speeds in the northeastern corner.

II, III and IV (see Figure 10). Most of Iowa would support class III wind turbine technology, with class II turbine opportunity located throughout the western portion of the state. In the northeastern edge of the state, a very small section of land could host class IV turbines. Four of five classes have WPD values above 163 W/m^2 (see Figure 11), which is around of the minimum threshold for hosting an economically viable wind project. The area with the most wind power density can be observed in the western portion of the state with the far eastern portion exhibiting less economic value.

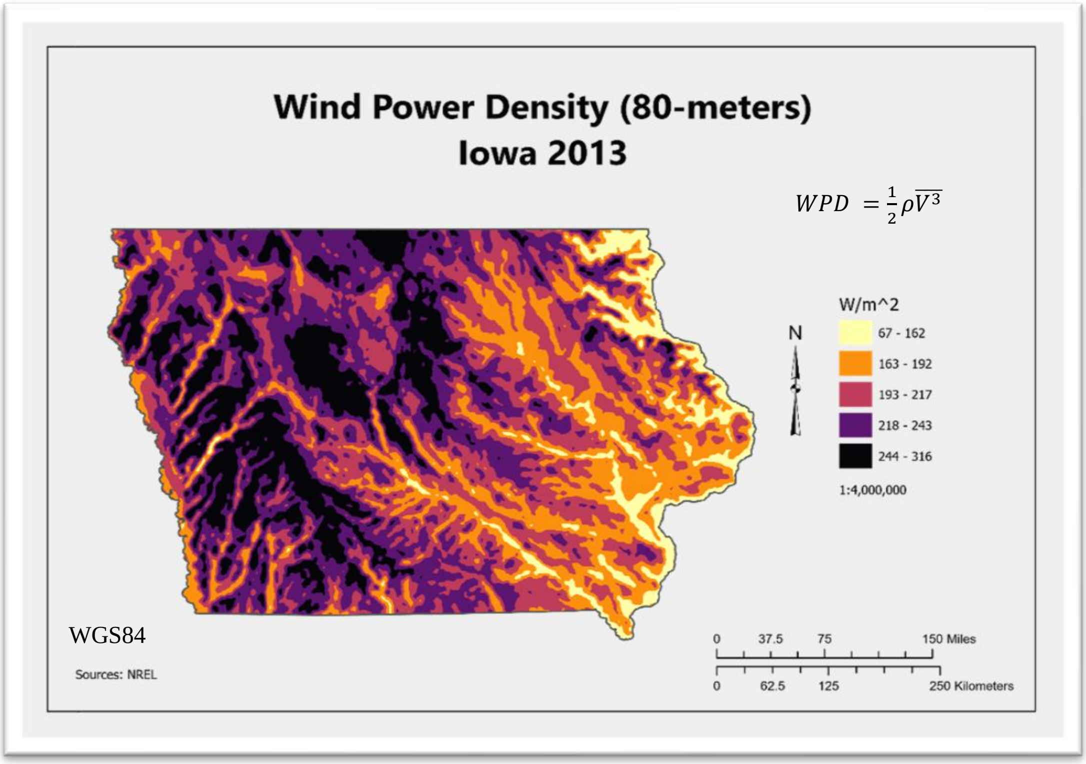

Figure 11. A map showing annual wind power density of Iowa in 2013. Darker areas indicate higher wind power density and lighter areas indicate lower wind power density.

6. DISCUSSION

A decision model was developed for evaluating energy and resources for wind farm development. The SDSS combined spatial and nonspatial data, extracted from databases online and using a Python cloud optimized tool. The information was communicated graphically and with a GIS through mapmaking using Microsoft Excel and ArcGIS Pro software. The four stages the SDSS proposes include acquisition of data, resource forecasting, simulation and analysis, and ranking of alternative strategies. The SDSS was applied to a case study in Iowa, United States.

The first stage of the SDSS, acquisition of data, consisted of downloading datasets from the USWTDB and WIND Toolkit. The USWTDB dataset is a collection of "onshore [and] offshore wind turbine locations in the United States, corresponding facility information, and turbine technical specifications" (Hoen et al. 2021). Meteorological datasets, including temperature, wind speed and air pressure were downloaded through NREL's Wind Toolkit. The HSDS cloud optimized tool (Draxl et al., 2015) required more computational resources that initially planned. Servers at NREL were accessed to process the large datasets into comma-separated value format. The resource datasets extracted were preprocessed from a point shapefile to an interpolated geostatistical layer in ArcGIS 2.7.1. Tobler (1970) invoked "the first law of geography: everything is related to everything else, but near things are more related than distant things". Based on this, one can assume that the pairs of locations surrounding an observed point in space are related. The assumption that 'near things are more related' becomes the foundation to the study.

The second stage of the SDSS, resource forecasting, explored the meteorological variation of Iowa in 2013. Seasonal variations were evident in Iowa that year, spanning winter, spring, summer, and autumn. Cold air is more dense than warm air, and the heavier the air, the more kinetic energy a turbine blade can absorb (Danish Wind Association, 2003). A Rayleigh shape-factor of ($k = 2$) was used to fit the Weibull probability curves. The PDM (Pishgar-Komleh, Keyhani, & Sefeedpari, 2015; Akdag and Dinler, 2019) was applied to each step in the time series using the Excel Solver Add-In, which effectively optimized the monthly and annual scale-factors (c). Although estimated scale-factor (c) closely mimicked the monthly variation observed in the wind speed dataset (see Figures 5 and 6), the parameter predicted lower wind speeds and less variation than the observed values.

Based on the Weibull probability model (see Figure 7), the summer months of Iowa had higher chances of lower wind speeds, and the most variability in time series. Autumn had a steadier probability of higher wind speeds and the least variability of the seasons. The winter, spring and annual average Weibull probability curves were similar in scale, exhibiting less variability and favoring a wider spread like the Weibull curve of autumn. It can be concluded that resource variation in Iowa was the lowest in the autumn months, with slightly less variation occurring in the winter and spring months. The most resource variation in year 2013 was predicted for the summer months, where temperature increased, and air density plummeted.

The third stage of the SDSS, simulation and analysis, measured the average turbine productivity and capacity factor of wind projects. The average WPD available at wind turbine locations was 252 W/m^2. The productivity of wind turbines depends on the wind power density of the site, the rotor swept area and power coefficient. The power coefficient differs by turbine type and the value is not constant (Danish Wind Association, 2003). Due to unavailability of information regarding turbine power coefficients, a constant power coefficient of 40 percent was used. Thus, the average turbine productivity and capacity factor of wind projects are subjected to bias.

Overall, wind turbines present in Iowa with hub heights between 75- and 85-meters produced 1.52 GW of wind energy in the year 2013. The mean capacity factor of wind projects, which measures the efficiency between annual energy output and installed capacity, was calculated around 36 percent (see Table 2). Paradoxically, a higher capacity factor does not always mean more energy output (Danish Wind Association, 2003). In other words, a wind turbine may have a high-capacity factor and a steady annual productivity, while another turbine may have a low-capacity factor where resource variation is extreme and annual energy output is high. The wind project simulations emulate the importance of matching turbine technical specifications to the resources available at the site. Wind turbine power output and efficiency are directly affected by technology and site characteristics.

The fourth stage of the SDSS, ranking of alternative strategies, involved extracting supplementary information about wind turbine locations and illustrating different development solutions and their tradeoffs. Resource information coincident with wind turbine locations, such as slope, distance to electricity grid, soil erodibility factor, and land cover type, unveil past spatial decision-making trends for the state of Iowa up until 2013. Most of Iowa falls within IEC Wind Class III (see Figure 10), which supports decisions on the kind of wind turbine technology to be chosen for a site. Very dense pockets of wind energy are sporadically located in the Western half the state (see Figure 11). The areas of highest WPD could potentially host Class II turbines, and Class IV turbines in areas along the northern eastern edge.

Spatial decision-making trends were found regarding turbine placement in Iowa up until 2013. About 78.6 percent of wind turbines were in cultivated cropland and 12.4 percent in developed open space. In addition, 95.5 percent of wind turbines were placed in areas with slope less than 10 degrees and were an average of 3.7 kilometers distance from the electricity grid. Finally, most wind turbines were placed in areas with soil erodibility factor between 31 and 43 percent. Overall, the state of Iowa is suitable for wind turbine development, with some locations presenting more advantage in terms of power yield than the alternatives. The efficiency performance of wind turbines is directly affected by how well the technology matches the site. Finally, spatial decision-making trends are apparent, particularly in respect to land cover and slope.

The WIND Toolkit and USWTDB datasets are available for every state in the United States, and the methods proposed in the study are reproducible on other case studies. Modeling resource variation with Weibull distributions found that Iowa had steadier variation in the winter and spring months, with the least variation in the autumn months and most variation in the summer months. Most of Iowa experiences IEC Class III wind speeds; therefore, Class III turbines should be selected to match the characteristics of the site. Last, nearly 96 percent of wind turbines erected in Iowa prior to 2013 were placed on a slope of no more than 10 degrees and 91 percent were placed in land cover classes: cultivated cropland or developed, open space.

7. CONCLUSIONS

The WIND Toolkit and USWTDB are effective datasets for evaluating energy and resources, wind turbine productivity and efficiency. The SDSS proposed can be replicated on other states of the United States using the same data sources and methodologies. Overall, seasonal variations of energy and resources were evident for Iowa in 2013. Wind speed monthly means vary between 5.5 and 8.2 m/s with August having the lowest wind speeds and November experiencing the highest. Higher temperatures and lower air density were experienced in the summer months, while lower temperatures and higher air density was experienced in the winter months. Weibull scale-factor (c) predicted lower and less variable wind speeds than the observed monthly wind speed means. Wind turbines constructed before 2013 were in areas with higher WPD, so future wind farm development should take this information into account. WPD is denser in the western half of Iowa and future wind turbine development should aim to locate infrastructure within those resource rich areas. Iowa hosts three wind classes: IV, III and II. Most of Iowa falls within IEC Wind Class III, meaning Class III-engineered wind turbines should be selected to match these areas. For future research, the SDSS can be coupled with a suitability analysis, evaluating other variables of importance, such as soil characteristics, surface roughness, slope, wind direction and distance to grid. In addition, replicators are encouraged to substitute the one-year resource analysis with a multi-year observational analysis, which will improve the accuracy of the model.

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