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RESEARCH ARTICLE

Utilization of machine-learning algorithms for wind turbine site suitability modeling in Iowa, USA

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ABSTRACT

Because of the current shift away from fossil fuels and toward renewable energy sources, it is necessary to plan for the installation of new infrastructure to meet the demand for clean energy. Traditional methods for determining wind turbine site suitability suffer from the selection of arbitrary criteria and model parameters by experts, which may lead to a degree of uncertainty in the models produced. An alternative empirically based methodology for building a wind turbine siting model for the state of Iowa is presented in the study. We employ 'ecological niche' principles traditionally utilized to model species allocation to develop a new multicriteria, spatially explicit framework for wind turbine placement. Using information on suitability conditions at existing turbine locations, we incorporate seven variables (wind speed, elevation, slope, land cover, distance of infrastructure and settlements, and population density) into two machine-learning algorithms [maximum entropy method (Maxent) and Genetic Algorithm for Rule Set Prediction (GARP)] to model suitable areas for installation of wind turbines. The performance of this method is tested at the statewide level and a six-county region in western Iowa. Maxent and GARP identified areas in the Northwest and North Central regions of Iowa as the optimum location for new wind turbines. Information on variable contributions from Maxent illuminates the relative importance of environmental variables and its scale-dependent nature. It also allows validating existing assumptions about the relationship between variables and wind turbine suitability. The resultant models demonstrate high levels of accuracy and suggest that the presented approach is a possible methodology for developing wind turbine siting applications. Copyright © 2014 John Wiley & Sons, Ltd.

KEYWORDS
wind energy; turbine site suitability; machine-learning; multicriteria decision making; spatial modeling

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1. INTRODUCTION

1.1. Purpose and objectives

Because of the current shift away from fossil fuels and toward renewable energy resources, it is necessary to plan for the installation of new infrastructure to meet the demand for clean energy. Iowa is currently first in per capita and second in total production of wind energy in the USA. As of March 2012, the state had an installed capacity of 4,419 megawatts, a 20.2% increase from 2011.[1] The National Renewable Energy Laboratory estimates Iowa to have a wind energy potential of 570,714 MW of installed capacity, which is seventh in the nation in terms of wind energy potential.[2] Because of Iowa's tremendous wind energy resources, the state will continue to be a leader in the development of wind energy technology and the expansion of production capacity. These characteristics make Iowa an optimal study site to explore new methods of modeling turbine suitability.

There is a continuous need to identify suitable sites for wind turbine placement, which presents a number of challenges in terms of avoiding environmental, technical and societal constraints.[3,4] Traditional methods of farm-scale turbine site suitability modeling (or site screening) rely on the decisions of experts in selecting appropriate criteria and parameters that best define suitable locations for wind turbines. There are inherent problems with incorporating arbitrary criteria and artificial weights into suitability models. Errors and uncertainty may arise from the subjective judgments of planners, such as the failure to account for the interdependence of variables used to form the model. In response to the uncertainties of traditional siting applications, an alternative methodology for building a wind turbine siting model for the state of Iowa is introduced in this study. This method employs 'ecological niche' principles often utilized to model species distributions to develop data-driven models for determining wind turbine site suitability in Iowa.

Conventional ecological niche models (also known as species distribution models or habitat suitability models) relate known occurrences of species to environmental variables and use identified principles to predict geographic distribution of species in unsampled locations. In other words, the approach first applies statistical methods to determine key factors and optimal ecological parameters of species' spatial distribution (i.e. identifies its ecological niche). Then the method utilizes this knowledge to define probabilities of specie's presence at alternative sites based on their ecological properties.

Our approach provides an alternative method of modeling wind turbine suitability based on the current distribution of approximately 1850 wind turbines located in Iowa. This input is used to calibrate machine-learning algorithms, which are utilized to model suitability of prospective wind turbines sites in the rest of the state. This approach not only differs from traditional by the fact that it is based on known distribution of turbines, but it also helps validate what is known about the relationship between suitability and environmental variables.* Although presented modeling effort is primarily focused on wind turbine 'site screening' rather than individual turbine placement, the framework we propose can be used for both.

The objectives of this study are (i) to develop wind turbine suitability models for Iowa that employ ecological niche principles traditionally utilized to model species distributions; (ii) to test two machine-learning algorithms, maximum entropy method (Maxent) and Genetic Algorithm for Rule Set Prediction (GARP), for their performance in modeling wind turbine site suitability; (iii) to identify which environmental variables are most influential in generating the suitability distributions, as well as the relationships among the variables; (iv) to analyze the performance of the Maxent and GARP models at different spatial scales; and (v) to develop new knowledge that would assist in empirically validating traditional assumptions about the relative impact of environmental factors on wind turbine location.

An extensive review of previous literature on traditional methods of modeling wind turbine suitability was undertaken to determine the appropriate environmental, technical and societal criteria to be used to assess the suitability of wind turbines at a particular location. Wind turbine suitability models for Iowa are produced using the Maxent and the GARP, two machine-learning algorithms traditionally utilized for identifying ecological niches and predicting species distributions. As these by nature are 'presence-only' algorithms, the variable characteristics at the existing wind turbine locations are used in calibrating the models to create a prediction surface of wind turbine suitability. The models are validated and evaluated using accuracy assessment procedures. The performance of the Maxent model is tested at two scales: the statewide (macroscale) and a six-county region (mesoscale) in western Iowa. An examination of the variable contributions to suitability within each model helps to confirm previous assumptions about the role of specific variables toward determining wind turbine suitability. Comparing the predicted distribution of wind turbines and environmental variable contributions of the models at varying spatial scales provides insight as to how these methods can best be employed in future land-use suitability studies to overcome some of the limitations of traditional multicriteria analysis.

1.2. Background: wind farm suitability analysis

Land-use suitability analysis involves identifying the optimum location of some feature based on a set of known criteria and preferences of ideal conditions.[5] The issue of wind farm siting is particularly complex, with a need to satisfy a number of conflicting interests. Environmental and technical constraints of a potential location must be avoided, while ensuring that there are sufficient wind resources to produce power. A number of spatial decision support systems, such as multicriteria decision making (MCDM), have been utilized to resolve issues of this complexity.[4,6] In general, MCDM methods are used to identify ideal, suitable and non-suitable locations to place wind turbines. To satisfy multiple objectives, data representing competing variables are collected and classified into layers based on their relationship to wind turbine suitability. Using the Boolean overlay techniques, the variable layers are then combined to generate composite suitability maps, which provide an assessment of potential locations for wind farms based on the criteria selected.[7–13]

With advances in geographic information systems (GIS), the process of siting wind turbines has become more automated.[14] Because of the improved efficiency that GIS provides through advanced geoprocessing and modeling capabilities, it has been effectively utilized in numerous wind farm siting studies. With the use of GIS, planners can process multiple models that incorporate raster and vector data, combine or isolate particular variables, and determine how environmental and technical factors affect land-use suitability.[15] For example, in a wind farm study on the Greek island of Lesvos, researchers used GIS to develop four case study models to examine how isolating certain criteria affected suitability

*In this paper, we use a broad definition of environmental variables, which refer to all physical and non-physical (e.g. human-related) factors affecting turbine placement (i.e. constituting the 'environment' in which turbine placement takes place).

conditions.[12] Weights are often applied to criterion layers using techniques such as the analytical hierarchy process to account for perceived levels of variable influence.[7,12,16]

Although MCDM techniques have been widely used to identify potential sites for wind turbines, there are some inherent problems with the methodology. Identifying the appropriate criteria and acquiring accurate input data can be challenging, especially if the data are collected at different measurement scales.[17,18] Malczewski[5] also criticized planners for ignoring the interdependence of some variables. This could cause some criteria to have an unjustified level of influence in the final suitability assessment. The process of assigning weights to different criteria is highly subjective, and relies on the experience of the decision makers involved in the study.[17–19] Selection bias of criteria and weights could lead to a noticeable degree of uncertainty in the models produced.

Alternative methods to suitability analysis utilize artificial intelligence techniques to mimic the capabilities of the human mind in making decisions.[5] These methods include artificial neural networks, generalized additive models, generalized linear models and genetic algorithms.[6,20] Malczewski[5] recommended a machine-learning approach for complex and poorly understood problems in which traditional methods of multicriteria analysis may be inadequate. To bypass some of the uncertainty that arises from traditional methods of turbine suitability analysis, such as in selecting adequate weights for criteria, two data-driven, machine-learning algorithms (Maxent and GARP) are used in this study to model wind turbine suitability. Zhou and Civco[18] contended that specific knowledge of experts is not necessarily needed for creating rules to determine site suitability. Instead, a well-trained genetic algorithm can closely estimate appropriate land-use suitability.

1.3. Criteria for wind farm siting

There is large variation among previous studies in terms of choosing and combining criteria to model wind farm suitability. Table I provides a summary of past wind turbine suitability studies and the criteria utilized in each. Some variability in criteria can be explained by the different geographic locations and environmental conditions specific to each study. However, the differences also stem from the complexity of wind farm siting and the subjective judgments made in respect to what constitutes suitable and unsuitable conditions. Some of the studies focused solely on the technical limitations of installing turbines.[3,9,16,21,22] In these studies, constraint maps were typically developed, indicating where turbines could not be installed. It was typical for this information to then be combined with data on wind speed or the cost of producing electricity. This allowed decision makers to gauge the most suitable locations for wind turbines based on the constraint-free land available. In our study, the consistent absence of turbines from certain locations, such as densely populated areas, causes those locations to be defined as likely unsuitable for wind turbine development.

The specific wind speed required for power generation varied among past studies, usually coinciding with the type and scale of wind turbines being installed. A few studies identified an average speed of $4\,\mathrm{m\,s^{-1}}$ as the minimum required for turbine installation.[8,12,23,24] Acker *et al.*[25] incorporated a classified wind scale into their study ranging from poor ($<5.5\,\mathrm{m\,s^{-1}}$), to marginal ($5.5–6.3\,\mathrm{m\,s^{-1}}$), to fair ($6.3–7.0\,\mathrm{m\,s^{-1}}$), to good ($7.0–7.5\,\mathrm{m\,s^{-1}}$), to excellent ($>7.5\,\mathrm{m\,s^{-1}}$). The vast majority of current wind turbines in Iowa are located in areas with an average annual wind speed above $7.0\,\mathrm{m\,s^{-1}}$.

A few studies, particularly in mountainous regions, identified elevation as a constraint. Bennui *et al.*[26] developed a wind farm study in Thailand in which only areas below 200 m would be considered for turbine placement. Other studies only considered areas below 1000 m to avoid high summits.[13,27] In a California study by Rodman and Meentemeyer,[28] elevation and wind speed data were combined into a single physical model layer. They identified areas high in elevation as well as wide, low valleys as being suitable for turbine development.

Slope is typically perceived as a constraint because of the difficulty of operating equipment necessary for turbine construction in high slope areas.[9] A maximum slope of 10% was commonly cited as being suitable for turbine placement.[9,21,29] Because of improved techniques in installing turbines, Tegou *et al.*[12] placed the maximum acceptable slope at 30%. Voivontas *et al.*[27] specified a maximum allowable slope of 60% for wind turbine placement.

The land cover of a region is important to incorporate into suitability studies to account for areas where constructing wind turbines would be highly controversial or prohibited. Most previous wind farm studies identified urban areas, forests, wetlands, rivers, lakes, reservations, parks and areas of historic significance as being unsuitable for development. A number of these studies placed a buffer around such protected areas, typically ranging from 200 to 2000 m.[3,9–12,22,24,26,27,29–32]

Many suitability studies have examined the visual impact of wind farms in an attempt to reduce issues of safety, visibility, noise, annoyance and economic impacts of turbines on local residents.[10,12,13,22,31,33,34] According to a study by Swofford and Slattery,[35] individuals living nearest to wind farms reported the strongest opposition to their development, while the opinions of residents living more than 10 km away from wind farms were mostly positive. Developing a framework for the visual impact of wind turbines is a difficult and largely subjective process, but population density can provide a rough estimate of the extent to which wind turbines will impact an area. Our study follows the approach of Janke,[7] who converted census block population data into a raster grid to create a population density layer for multicriteria analysis. He designated areas with a low population density as ideal for wind turbine development.

In some wind farm location studies, major roads were perceived as a constraint to be avoided because of safety issues.[11,22,24,26,30–32] Buffers ranging from 100 to 500 m were implemented to limit the distraction and risk to drivers.

Table I. Criteria used for wind farm siting in past suitability studies[a].

Study	Year	Wind speed	Elevation	Slope	LU–LC: forests	LU–LC: protected areas	Urban areas	Population	Highways	Airports	Power grid
Ouammi *et al.*	2011			<10%		Constraint	1000 m buffer		Within 1500 m	2500 m buffer	Within 1000 m
Janke	2010	Weighted			Weighted	Weighted	Weighted	Weighted	Weighted		Weighted
Mari *et al.*	2010	$4\,m\,s^{-1}$			Constraint	Constraint					
Sliz-Szkliniarz and Vogt	2010	$5\,m\,s^{-1}$			200 m buffer	500 m buffer	500 m buffer		100 m buffer	3000 m buffer	200 m buffer
Tegou *et al.*	2010	$4\,m\,s^{-1}$		<30%		500 m buffer	1000 m buffer		Within 10,000 m	Constraint	
Van Hoesan and Letendre	2010	Weighted	600–1050 m	<60°	Weighted						
Aydin *et al.*	2009					250–1000 m buffer	2000 m buffer			2500 m buffer	
Simao *et al.*	2009				Weighted	Weighted	Weighted		Weighted		
Yue and Yang	2009	$5\,m\,s^{-1}$			250 m buffer	250 m buffer	500 m buffer		Constraint		
Dutra and Szklo	2008	$6\,m\,s^{-1}$				Constraint					
Lejeune and Feltz	2008				200 m buffer	100–2000 m buffer	Constraint		Weighted	5000 m buffer	150 m buffer
Bennui *et al.*	2007	Weighted	<200 m	<15%		2000 m buffer	2500 m buffer		500 m buffer	3000 m buffer	
Bravo *et al.*	2007			<10%	Constraint	Constraint	Constraint				
Byrne *et al.*	2007	$4\,m\,s^{-1}$									
Ramierez-Rosado *et al.*	2007	Weighted	Weighted	Weighted	500 m buffer	500 m buffer	500 m buffer		Weighted	Constraint	Weighted
Acker *et al.*	2006	Weighted		<20%	50% constraint	Constraint	Constraint			3000 m buffer	within 10 mi
Nguyen	2006	Weighted	Weighted		500 m buffer	500 m buffer	2000 m buffer	Weighted	100 m buffer	2500 m buffer	
Hansen	2005	Weighted			300 m buffer	300 m buffer	500 m buffer		150 m buffer	500 m buffer	200 m buffer
Rodman and Meentemeyer	2005	$4.5\,m\,s^{-1}$	Weighted	<40°	Constraint	Constraint	Constraint				
Ramachandra and Shruthi	2004	Weighted									
Krewitt and Nitsch	2003	$4\,m\,s^{-1}$			500 m buffer	500 m buffer	500 m buffer		500 m buffer		
Baban and Parry	2001	$5\,m\,s^{-1}$	Constraint	<10%	500 m buffer	1000 m buffer	2000 m buffer		within 10,000 m		within 10,000 m
Hillring and Krieg	1998	Weighted			Constraint	Constraint	Constraint				
Voivontas *et al.*	1998	$6\,m\,s^{-1}$	<1000 m	<60%	Constraint	2000 m buffer	1000 m buffer			2500 m buffer	
Criteria usage in studies		79%	29%	42%	67%	88%	83%	8%	54%	46%	33%

[a]Values indicate the constraints for wind turbine placement. The term weighted indicates if the study used a custom scale to weight criterion layers in the suitability study.

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Other studies viewed locations near major highways as ideal in order to improve access for construction and maintenance.[7,9,10,12,16,29] For example, Baban and Parry[29] and Tegou *et al.*[12] considered areas more than 10 km away from major highways as unsuitable for wind turbines.

A summary of criteria utilized in past wind turbine suitability studies assisted the development of the models tested in this paper. Only the most relevant criteria related to wind turbine placement were incorporated into our models. In the previous studies examined, land cover/land use and wind speed were the most frequently used criteria selected for siting wind turbines (Table I). Proximity of urban areas, transportation infrastructure and slope were also frequently incorporated in past suitability analyses. A recent review of wind farms in China indicates the practice of placing wind turbines in sparsely vegetated and populated areas, as well as on land with low slopes.[36] Mann *et al.*[37] conducted a study in which they developed a logistic regression model that attempted to explain location of wind turbines in Iowa. This analysis provided empirical evidence that wind speeds, infrastructure location, land use and population play important roles in wind turbine placement. Although data availability was a limitation, most of the criteria utilized in previous studies were incorporated into the models developed in this study. Given that the primary task was to test the applicability of machine-learning algorithms to wind turbine siting, we limited our analysis to only a few key variables. Other place-specific factors and constraints, such as protected lands and endangered habitats, could be added to this modeling framework in its future applications.

2. METHODS

2.1. Algorithms and software

Maxent (version 3.3.2) is an open source software program from openModeller. In its traditional use, Maxent estimates a species distribution based on known occurrence locations of a species and landscape variables over the entire study area.[38] The average value of each environmental variable at the occurrence locations serves as the target value for the probability distribution. A number of distributions matching the desired target values are produced, but only the distribution of maximum entropy is chosen. Maximum entropy refers to the most uniform distribution (subject to constraints), which maximizes uncertainty by assuming nothing about incomplete information. In this manner, the distribution modeled is an unbiased reflection of only what is known about the data.[38] This data-driven approach produces a natural distribution of phenomena. The distribution computed by Maxent is characterized by maximum entropy among those satisfying the constraints with the expectation of each environmental variable matching empirical average.[39] Maxent uses an exponential model and empirically derived functions of environmental variables that are subjected to the sequential-update algorithm that adjusts coefficients in order to achieve desired distribution. The algorithm is deterministic, and is guaranteed to converge to the maximum entropy probability distribution.[38] Maxent's output is a surface that indicates predicted probability that conditions in a given point are suitable.[†]

The advantage of the Maxent algorithm is that it is able to predict the probability that conditions are suitable for locating an object using presence-only data, i.e. known locations of existing objects (e.g. animals or wind turbines). This is critical because in many cases binary (presence or absence) data are not available, and creating surrogate absences may be problematic.[38,40] Therefore, for the type of data at hand in this study, Maxent has considerable edge compared with other modeling options, including generalized linear models, generalized additive models, regression trees and multivariate adaptive regression splines, which are based on logistic regression and require binary training data.[40]

Maxent has traditionally been used to model species distributions and has also been utilized to model abiotic phenomena. Benito and Peñas de Giles[41] used Maxent to create suitability maps for greenhouses in Spain. In another study, Parisien and Moritz[42] used Maxent to rate locations most at risk for wildfires in California. In our study, current locations of wind turbines serve as the 'species' for which an ecological niche will be defined and projected across the state of Iowa. Maxent has a number of advanced capabilities, including the ability to work with both categorical and continuous data, account for interactions between environmental variables and identify how each variable relates to suitability.[43] A key assumption of this type of modeling is that current turbines have been largely built in the desired (suitable) locations. This is important because the suitability distribution for future wind turbines is based on these locations. Dudik *et al.*[44] noted how the averages of the environmental variables at the presence locations will approach, but will not equal, the true values constituting its ecological niche.

In addition to Maxent, the GARP is used in a similar fashion to generate a predictive distribution for wind turbines. GARP is used extensively for modeling diseases, invasive species and ecological niches.[45] The specific algorithm used in this study was GARP version 3.0.2, DesktopGARP implementation. Like Maxent, GARP uses a set of known occurrence locations combined with environmental layers to form a predictive distribution. The algorithm combines sets of positive and negative rules of particular environmental conditions, as compared between occurrence locations and a

[†]A detailed technical review of the Maxent algorithm is available in the papers of Phillips *et al.*,[38] Dudik[40] and Dudik *et al.*[44]

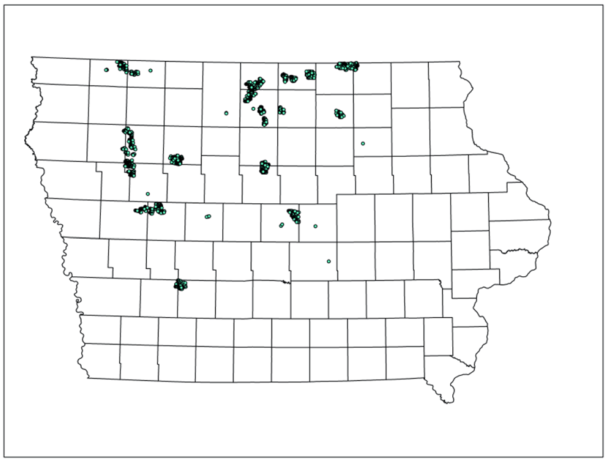

Figure 1. Wind turbine locations in Iowa used in analysis.

random sample.[45,46] Together, these rules create a prediction surface that represents an ecological niche. The rules are identified, tested and incorporated (or rejected) during the iterative model-fitting process. Rules may be combined and evolve in a manner that mimics DNA evolution to achieve maximum predictive accuracy.[‡] We used GARP to compare with Maxent in terms of predictive modeling performance.

According to Ortega-Huerta and Peterson,[43] GARP and Maxent performed well among a test of six genetic algorithms in terms of the significance of the predictions and validation statistics. However, in another test of species prediction methods, Maxent outperformed not only GARP but also several other modeling techniques.[47,48] In a different study, where Maxent and GARP were compared directly, both algorithms were shown to produce a good estimate of the species' distribution, but Maxent proved to be the superior method after examining statistical test results.[38] Both methods are compared in this study to evaluate their performance in predicting wind turbine suitability.

2.2. Data

Present locations of wind turbines are required for Maxent and GARP to generate suitability distributions. A vector layer of 1852 wind turbines in Iowa (Figure 1) was obtained from the Iowa Department of Natural Resources. One of the challenges of biological species distribution modeling is the limited number of known occurrence locations of a particular species. This leads to a degree of uncertainty in determining the ecological niche of a species.[44] In this study, all current locations of wind turbines are known, reducing the uncertainty that the optimum conditions for wind farm development will be identified. However, because the full potential of wind turbine development in Iowa has not been realized, some uncertainty remains in determining the true extent of the 'ecological niche' of wind turbines. According to Phillips *et al.*,[38] the larger number of observations there are, the more accurate the distribution produced by Maxent will be. It is believed that Iowa has a sufficient number of wind turbines in place to generate an adequate estimate of the optimal conditions for future wind turbine development.

Both algorithms require environmental variables to produce a suitability distribution. Based on the literature review, seven variables were chosen to incorporate into the suitability models: wind speed, elevation, slope, land cover, distance to highways, distance to settlements and population density. Wind speed data were obtained from the Iowa Energy Center, which provides annual average wind speeds in Iowa at the 50 m level. Average annual wind speeds for the state ranged from 5.5 to 8.0 m s^{-1}. A 30 m digital elevation model was obtained from the DNR. A continuous slope layer was derived from this elevation dataset using spatial analysis tools in ArcGIS. A DNR land cover shapefile for 2000 was obtained, which classifies land cover by type. This layer was then reclassified to the categories: water, forest, agriculture and grassland, urban and other. In Iowa, agricultural land and grassland cover about 90% of the state, which is advantageous for wind farm development in terms of the reduced technical constraints of erecting turbines. To account for the visual impact of turbines, Iowa census block population density data from the 2010 Census were acquired, and then converted to a raster for incorporation in the suitability models. In addition to the population density layer, a distance to settlements raster was produced from a populated places vector layer obtained from the Iowa DNR. This layer helps to account for both large and small, rural communities in Iowa that may be negatively impacted by wind turbine development. A raster surface was produced from a vector layer of major highways in Iowa based on distance to highways.

[‡]A detailed review of the GARP algorithm is available in the paper of Stockwell and Peters.[45]

2.3. Procedure

The seven environmental layers were prepared as ASCII rasters, as required by Maxent and GARP. The modeling requires a common cell size and extent for all layers. Each layer was resampled to a 200 m cell size to increase model processing speed and to account for the needed spacing between wind turbines on the ground. Each cell on the output distribution therefore represents a potential site for a single turbine. Each layer was then masked to the geographic border of Iowa to produce a macroscale distribution of wind turbine suitability. Lastly, all of the environmental rasters were converted to ASCII raster grids. The current wind turbine location data were converted to a comma separated value file containing a turbine ID and the latitudinal and longitudinal coordinates of each wind turbine.

The seven ASCII rasters and the wind turbine locations *.csv file were uploaded to the Maxent user interface. All of the environmental layers were specified as continuous except for the categorical land cover layer. For training the data set, we used 80% of the turbine presence records (1482 turbines). Using Maxent's built-in validation mechanism, we randomly selected 20% of the records (370 turbines) to verify the accuracy of the predictive distributions. The default regularization values were used as follows: linear quadratic product (0.050), categorical (0.250), threshold (1.00) and hinge (0.500). These regularization techniques are used to avoid overfitting, or the creation overly complex models, by forcing Maxent to focus on the most important features of the model.[38] Models were run no fewer than 10 times to ensure robustness.

Preparing for GARP using openModeller was similar to Maxent, which again required loading the same presence records file and environmental layers prior to initiating a run. The model was prepared using the following parameters: training proportion (50%), total runs (20), hard omission threshold (100%), models under omission threshold (20), commission threshold (50%), commission sample size (10,000), maximum generations (400), maximum number of threads (1), convergence limit (0.01), population size (50) and resamples (2500). A number of models are produced during processing, but the best-subsets procedure selects those which have optimum omission (false negative) and commission (false positive) error characteristics.[45] The resultant model was displayed on a floating point ASCII raster grid, which was then masked to the geographic extent of Iowa.

The important objective of this study was to compare the results of predictive modeling of wind turbines at different geographic scales. Specifically, we analyzed the contribution of environmental variables to the models at both the statewide level (macroscale) and a sub-state scale (mesoscale). A turbine-abundant six-county region in west-central Iowa consisting of Cherokee, Buena Vista, Pocahontas, Ida, Sac and Calhoun counties was chosen for this analysis. Maxent was utilized for the mesoscale model because of its advantages in providing variable contribution data, a high-resolution continuous distribution and its generally higher rated performance compared with GARP.[45] The same parameters and environmental variables utilized in the macroscale model were used here. Only the geographic extent and the number of turbine location records (441) were different; 110 of the locations were used for model validation.

3. RESULTS

3.1. Model outputs

The statewide (macroscale) distribution for wind turbine suitability produced by Maxent is displayed in Figure 2. A continuous probability distribution is shown with a range of values from 0 to 1, corresponding with the predicted probability

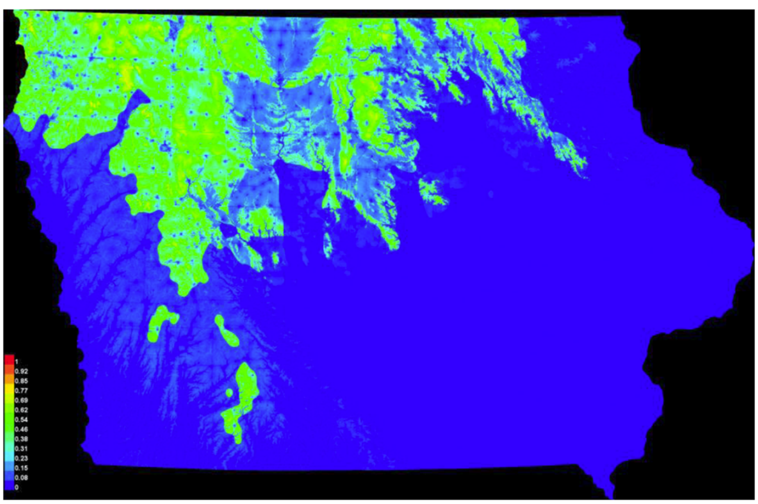

Figure 2. Map of the suitability of wind turbines produced by Maxent at the macroscale. Green and yellow areas indicate higher predicted suitability for placement.

that conditions are suitable for turbine placement. A continuous display is beneficial for making fine distinctions of suitability at particular sites, and is one of the benefits of using Maxent over GARP.[44]The green and yellow regions of the map can be interpreted as areas satisfying the 'ecological niche' for wind turbines, and thus indicate a higher probability that conditions are suitable for wind turbine development. Closer examination of the distribution shows that Maxent identified highways, densely populated areas and settlements as unsuitable for wind turbine development, as indicated in blue. Much of the suitable area for wind turbine development is located in the Northwest and North Central regions of the state, corresponding with areas of high wind speed and relatively high elevation, a result supported in our studies.[37]

Figure 3 shows the suitability distribution produced by GARP, with red areas indicating a high probability for wind turbine development. The distribution produced by the GARP algorithm is generally similar to Maxent, as areas in the Northwest and North Central regions of Iowa are predominantly deemed suitable for wind turbines. Making fine distinctions between locations is difficult because of the discrete output of GARP. As compared with Maxent, a much broader area of the state is displayed as having a high suitability for wind turbines. This could be the result of commission error, or overprediction, in which the model falsely identifies unsuitable areas as suitable.[48] The distribution produced, however, may more closely match the true potential extent of wind turbines, as high probability areas unique to the GARP distribution are generally associated with high wind speeds necessary for turbine development.

The six-county mesoscale distribution produced by Maxent is shown in Figure 4. Almost the entire region is shown in blue, corresponding with a low probability for wind turbine development. Surprisingly, a very limited area is deemed suitable, despite the presence of 441 turbines in the area, most of which, however, are located in high suitability areas.

3.2. Variable contributions

In addition to producing a suitability map for wind turbine development, it is also important to reveal which environmental variables had the greatest influence in forming the model. While Maxent is running, the effect of variables on the model is recorded.[38] Table II shows the relative contribution of each of the seven environmental layers. The values provide a rough estimate of the importance of specific layers in formulating the model. At the macroscale, wind speed had a 57.3% contribution, followed by elevation with 36.7%, indicating the high level of importance for these two factors. These values should be interpreted with caution. However, if certain variables are highly correlated with each other, the effects of one could overshadow the other. At the mesoscale, elevation was the dominant factor, with a 78.3% contribution to the suitability distribution.

Jackknifing was used to provide an additional analysis of relative variable importance. The jackknife method shows the training gain of each variable if the model was run in isolation, compared with all variables combined. This is useful to identify which variables contribute the most individually.[39] The test confirmed that elevation and wind speed are the two most important variables: they registered the highest Maxent model gain when used in isolation. The environmental variables that decreased the gain the most when omitted were (again) elevation and wind speed, which therefore appear to have the most information that is not present in the other variables.

Response curves for each environmental factor are generated by Maxent to indicate how the prediction is affected by a change in the variable. As the value of each variable (horizontal axis) increases, a corresponding change in the predicted suitability (vertical axis) occurs. Figure 5 displays response curves at the macroscale level for the state of Iowa. In general,

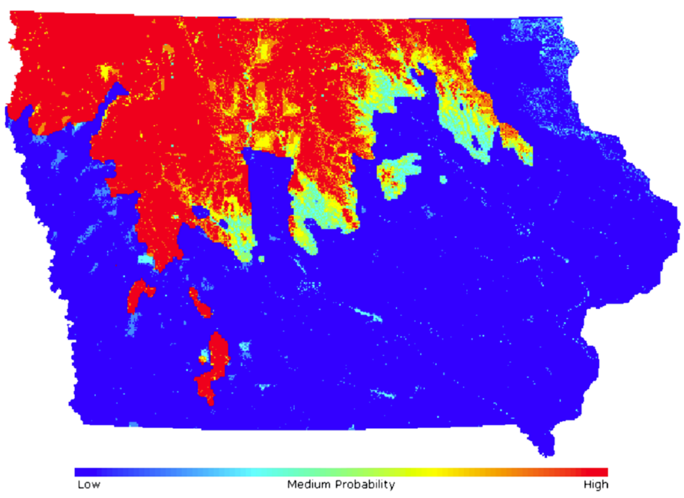

Figure 3. Map of probability distribution of wind turbines produced by GARP at the macroscale. Red and yellow areas indicate higher predicted suitability for placement.

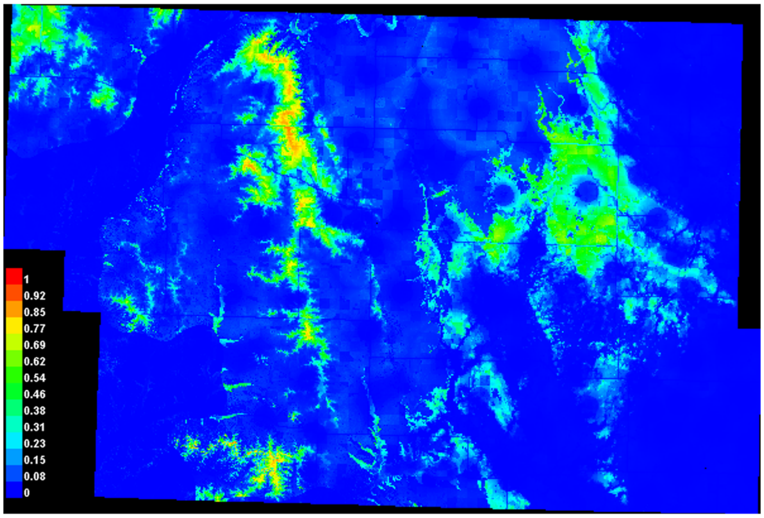

Figure 4. Map of the suitability of wind turbines produced by Maxent at the mesoscale. Green and yellow areas indicate higher predicted suitability for placement.

Table II. Variable contributions in the Maxent models at the macroscale and the mesoscale.

Variable	Macroscale variable contributions, %	Mesoscale variable contributions, %
Wind speed	57.3	9.8
Elevation	36.7	78.3
Population density	1.9	2.7
Distance from city	2.0	7.6
Slope	0.8	1.0
Distance to major road	1.0	0.6
Land cover	0.3	0.1

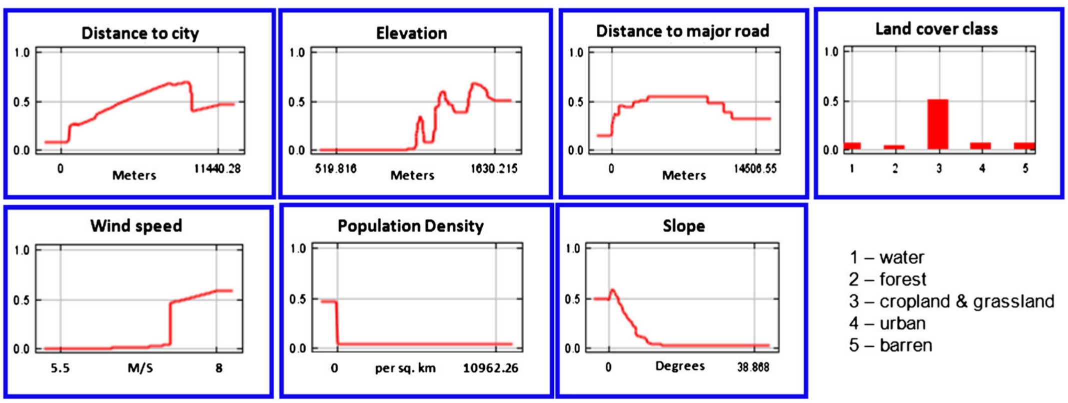

Figure 5. Response curves of environmental variables for Maxent at the macroscale.

the curves indicate a positive relationship between the increase of the suitability of wind turbines and increase of wind speed, elevation and distance from cities. Availability of grassland and cropland is also a positive factor. As population, slope and distance from highways increase, suitability estimates decline. These results generally correspond to the logistic regression model developed by Mann *et al.*,[37] although relationships observed here are more complex. Figure 5, for example, illustrates that suitability of a cell for wind turbine development is higher when it is located not too close but not too far from a road or a settlement. Also the suitability seems to rapidly increase in locations with wind speeds exceeding $6.5\,\mathrm{m\,s^{-1}}$.

Figure 6 displays the response curves for the mesoscale region. The response curves here indicate generally the same relationships among environmental variables and the suitability for siting wind turbines as detected at the macroscale. Elevation is the variable that shows a strong positive correlation with suitability. This, in addition to Table II, suggests that terrain characteristics and changes in elevation are more critical for siting wind turbines at this scale. Annual average wind speeds vary little over the span of this study area with most existing turbines installed in high wind speed locations; therefore, it may not be an ideal predictor for identifying the optimum locations for wind turbines. Characteristics such as distance to major roads and cities showed high variation within the study area, making it difficult for Maxent to identify any clear trends among those variables and suitability.

3.3. Accuracy assessment

Accuracy assessment was performed using set-aside subsets of randomly selected turbine locations, and Maxent and GARP built-in validation mechanisms. All models exhibited relatively high accuracy, although Maxent performed better than GARP. The receiver operating characteristic (ROC) curve can be used to interpret the accuracy of each model. The performance of a model whose output is based on varying parameters is displayed by the ROC curve.[37] The area under the ROC curve (AUC) value determined from each curve can be used as a measure of accuracy. The AUC describes the probability that the model correctly identifies a random negative example from a random positive example.[37] An AUC value of 1 would indicate perfect prediction, and a random prediction would have an AUC value of 0.5. Therefore, the value should be as close to 1 as possible. Figures 7 and 8 display the ROC curves produced for the Maxent models. The macroscale Maxent model had an AUC value of 0.877 for the training data and 0.901 for the test data. The mesoscale Maxent model had an AUC value of 0.931 for the training data and 0.926 for the test data. The GARP model had an overall AUC value of 0.870. While it is a notable difference, it was expected for Maxent to produce higher AUC values because continuous distributions generally score higher than discrete distributions.[37]

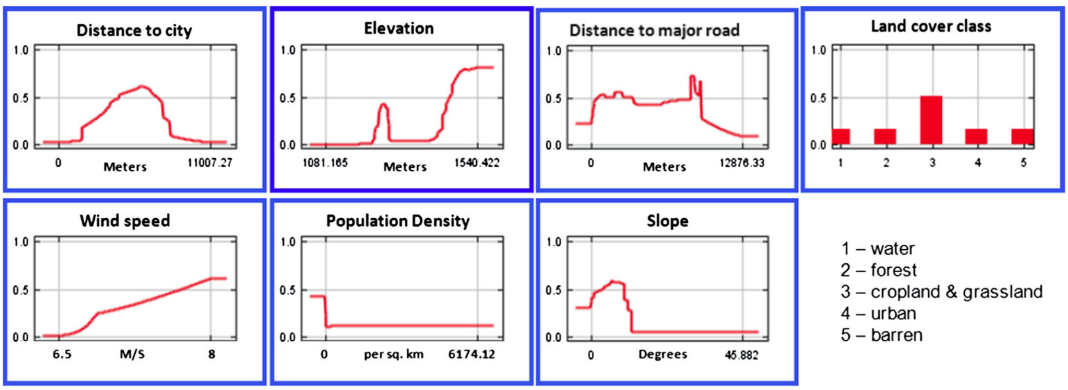

Figure 6. Response curves of environmental variables for Maxent at the mesoscale.

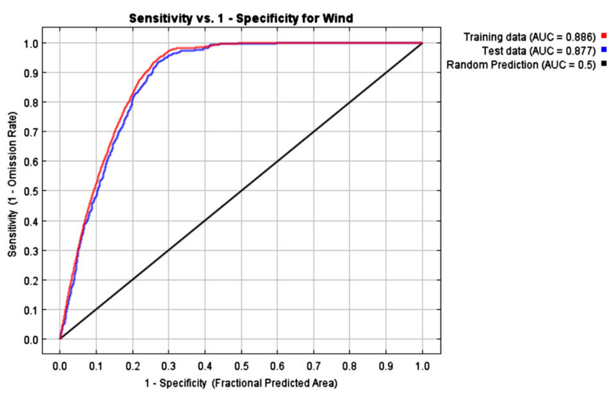

Figure 7. ROC curve for Maxent at the macroscale.

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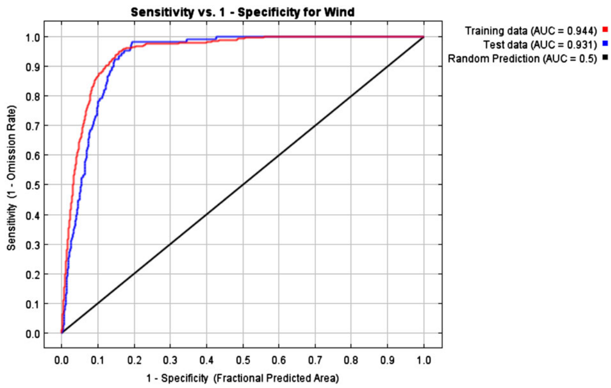

Figure 8. ROC curve for Maxent at the mesoscale.

4. DISCUSSION

4.1. Models and variable contributions

The resultant models demonstrated high levels of accuracy, and suggest an 'ecological niche' approach using machine-learning algorithms tested as a possible methodology to develop wind turbine siting applications. Areas in the Northwest and North Central regions of the state are shown to have conditions most suitable for wind turbine development. Based on the variable contribution results, wind and elevation appear to be the greatest predictors of identifying suitable locations for wind turbines. In Iowa, there is a strong correlation between wind speed and elevation across the state, in which higher elevations in the Northwest coincidently have the greatest wind resources. This is not to suggest that an increase in elevation always produces an increase in wind speed; other environmental and climatic factors likely are the cause for higher wind speeds in the Northwest. Rodman and Meentemeyer[28] noted how low valleys can also serve as a channel for increasing wind speeds. Variables such as land cover, slope and distance to highways and cities scored considerably lower in terms of influencing the final suitability distribution. It is likely that current turbines cover areas with a broad range of values for these variables, so none of these variables alone are a good predictor of turbine suitability.

A closer examination of the variable response curves (Figures 5 and 6) reveals how the relationships among environmental variables and turbine suitability described by Maxent support previous research on the desired landscape characteristics for placing turbines. The wind speed response curve indicates a sharp rise in suitability with an average annual wind speed of 6.5 $m\,s^{-1}$. Few of Iowa's current wind turbines are located in areas with lower average annual wind speeds. The distance to city variable indicates a very low probability for placing near settlements but steadily increases as distance from the city increases. The distance to highway variable shows good suitability for placing turbines near highways but not in their immediate vicinity. The curves indicate how sparsely populated areas and agricultural land have the greatest probability for siting future wind turbines. The elevation and slope response curves display uneven relationships with suitability. The general trend, however, of favoring high elevations and flat land for turbine placement is supported by this model. These observations help to validate traditional assumptions about wind turbines siting factor behaviors, since response curves are empirically derived by Maxent without any preconceived knowledge of the relationship among the variables and suitability.

4.2. Maxent and GARP comparison

Both Maxent and GARP were used in this study to examine how two related machine-learning algorithms would predict the extent of wind turbine suitability in Iowa using identical input variables. Based on the accuracy assessment results, Maxent demonstrated better performance than GARP. Maxent also has the benefit of providing information on the influence of individual variable to the model. Although this is not present in GARP, it can be surmised that wind speed was the dominant variable in forming the GARP distribution (Figure 3). The boundary between unsuitable and suitable locations closely corresponds with the 7 $m\,s^{-1}$ annual average wind speed threshold. Although Maxent also heavily relied on wind speed at the macroscale (Table II), the model also identified elevation as having a strong influence. This is indicated not only by the variable contribution table but also by the gap in suitability in North Central Iowa (Figure 2), which is an area of lower elevation at which few turbines in Iowa are currently located.

4.3. Scale comparison

The relative influence of environmental factors varied between the Maxent models at the macroscale and mesoscale. At the macroscale, wind speed is the dominant variable in determining turbine suitability. Elevation becomes the dominant indicator of suitability at the mesoscale. A possible explanation of this variation could be the resolution of the wind speed data available. Annual average wind speeds vary little in a statewide dataset at the local scale where other variables, such as land cover and terrain characteristics, can have significant effects on local wind speed variability.[10] The fine resolution of the elevation dataset is more applicable to the mesoscale, in which small changes in topography are a better predictor of turbine suitability than the average annual wind speeds across the study area. According to Rodman and Meetenmeyer,[28] high ground and ridge crests are preferred for turbine siting as compared with low-lying areas. This relationship is confirmed in this study, as most turbines within the six-county region are located at high elevations.

From visual examination, Maxent appeared to perform better at the macroscale than at the mesoscale. Although over 400 wind turbines were located within the mesoscale study region, the remaining surrounding landscape was not indicated as being suitable for wind turbines. Previous studies have acknowledged the issue of small sample sizes being used to generate probability distributions.[37,38,44] They contend that more accurate distributions can be achieved with more presence records. Here, the problem may be an overabundance of environmental variables. This has the effect of overfitting the model, in which the desired characteristics of wind turbine suitability are too specific, leading to a relatively narrow range for siting further wind turbines in the surrounding landscape. This is an obvious issue when implementing these models at mesoscale, as it could hardly be contended that a location a few miles away from a current wind farm would be regarded as unsuitable for wind turbines. It appears that a more appropriate use of Maxent is for larger regions, in which there is a broader range of values among the environmental variables. This allows the algorithm to better discern which characteristics are most influential, and identify patterns that can generate clearer suitability distributions.

4.4. Limitations of the modeling frameworks and future directions

The tested machine-learning algorithms have a number of limitations, which complicate their use for wind turbine modeling. One of them is the need for high quality data. With the availability of higher-resolution wind speed data covering a range of altitudes, more accurate predictive distributions of wind turbine suitability could be made, especially at the mesoscale. Even at the macroscale, however, the coarse nature of the wind speed data used resulted in Maxent and GARP producing sharp boundaries between suitable and unsuitable locations for siting wind turbines. Further environmental variables could be utilized in future studies, including distance to airports and the power grid, agricultural land quality, a visibility index and aspect of slope. However, it is important not to incorporate too many environmental parameters into Maxent, as this could increase the risk of overfitting.[38] Warren and Seifert[49] examined how well Maxent represents biological truth in modeling species distributions. They noted how overly complex or simple models may cause biases in the parameters, leading to model uncertainty. Developing a model with the correct level of complexity is a difficult task, considering the discrepancies within the literature of exactly which factors are necessary in determining proper turbine location.

Further knowledge of the models used in this study, and genetic algorithms in general, is needed to better understand how the predictive distributions are produced and what can be learned from the variable contributions and response curves. Preliminary analysis of the model outputs suggests Maxent may overfit, or generates too specific, suitability distributions, while GARP overpredicts, or produces too general distributions. A better understanding of the models and how to control their respective statistical parameters is necessary to cope with issues such as commission and omission errors. There is still some debate as to whether the precision of genetic algorithm outputs is adequate, so it is recommended that artificial intelligence approaches such as Maxent and GARP are used in conjunction with traditional methods of suitability analysis.[5]

The potential for Maxent and GARP to be utilized in future abiotic suitability studies extends to only those phenomena for which there are a sufficient number of occurrence locations for the algorithms to learn from. In wind turbine siting applications, the models can only be reliably employed in areas with turbines already in place. A related issue is inherent sampling biases due to turbine concentrations in particular areas as a result of selective decision making. The characteristics that define prime locations for wind turbines in Iowa may not be applicable in other regions. The variable contributions provide some information of the relative importance of each variable but should not be interpreted as the amount of weight given to a particular variable in other suitability studies. Complications such as closely related variables or the clustering of current phenomena could lead to an unjustified level of variable influence in the models produced. Maxent and GARP are likely better used as supplements to other methodologies in making land-use decisions. Benito and Peñas de Giles[41] showed that the use of Maxent enhanced the performance of other land-use change simulators, therefore producing better suitability maps. For overly complex decision-making processes, Maxent and GARP are practical applications for assisting and improving land-use decisions.

5. CONCLUSION

The methodology presented in this study represents a novel approach to modeling wind turbine site suitability. Limitations of traditional studies on wind turbine siting, such as bias in determining factor weights, have prompted the search for new empirically driven modeling frameworks of wind turbine siting and suitability analysis. Two machine-learning software algorithms, Maxent and GARP, were used to produce suitability distributions for wind turbines in Iowa by analyzing the locations of 1852 wind turbines and seven environmental variables: wind speed, elevation, slope, land cover, population, and distance to cities and highways. In addition, Maxent was used to create a suitability distribution for wind turbines at the mesoscale consisting of a six-county region in west-central Iowa. The accuracy assessments revealed that Maxent generally performed better than GARP. Visual examination of the suitability maps suggests that Maxent may underestimate wind turbine potential in Iowa, whereas the GARP appears to suffer from overprediction by identifying some unsuitable locations as suitable.

The Maxent models provide information on the relative influence of environmental variables on forming the models, and showed wind speed and elevation to be the dominant variables in predicting turbine location. Variable response curves generated by Maxent reveal relationships between environmental variables and turbine suitability that are consistent with past studies and generally validate traditional assumptions about wind turbine suitability criteria. The presence-only nature of Maxent and GARP algorithms, and their well-documented advantages for producing highly accurate geographic distributions of suitability make these methods highly attractive for potential use in wind turbine siting analysis at different scales. Successful in producing suitability distributions, Maxent and GARP are also likely to be exceptionally useful as supplements to traditional spatial decision making processes. The alternative modeling framework provided by these models can add a new block to the continuing development and refinement of wind turbine siting applications.

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