



Research paper

Long-term wind speed interpolation using anisotropic regression kriging with regional heterogeneous terrain and solar insolation in the United States

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ABSTRACT

Wind speed is an important meteorological factor and is a parameter used to determine the air pollution assessment and the economic feasibility of wind energy as a renewable resource. In particular, the measurement of long-term average wind speed plays a role in the estimating of chronic exposure of air pollution and the siting of wind turbines; thus this study focuses on annual and monthly wind speed. However, due to spatially sparse and irregular meteorological stations, interpolation methods are used to predict unsampled areas. Therefore, the purpose of this study is to determine the optimal interpolation method among deterministic and geostatistical interpolation techniques. While most interpolation methods rely on spatial coverage and do not give an accurate characterization of small-area variations, cokriging and regression kriging (RK) can resolve the drawback by containing regional heterogeneity as auxiliary variables. In addition, this study applied isotropic and anisotropic approaches to geostatistical interpolations. This study showed that among the sampled methods, anisotropic RK with regional heterogeneous terrains and solar insolation was most likely to produce the best estimate for the highest accuracy for annual and monthly wind speeds with relatively unbiased spatial errors. In addition, while extreme wind speed decreases the accuracy of wind speed prediction, the number, range, and variance of observed wind speed significantly influence the accuracy of wind speed prediction.

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1. Introduction

Wind speed is an important meteorological factor, as a parameter for climatology, oceanography, renewable energy, aerosol and pollutant transport, urbanization, disaster management, and many others. In particular, average wind speed in the long term can be criteria to site wind turbine (Miller et al., 1997; Petković et al., 2013, 2017; Shamshirband et al., 2014) and plays an important role in the assessment of air pollution levels as the ventilation of air pollutants (Daniels, 2014). Air pollutants are concentrated or dispersed in the air, and concentrations of air pollutants vary dramatically in short distances (Ross et al., 2013). Therefore, as the meteorological information, wind speed plays an important role in determining ambient concentrations of air pollutants (Finzi et al., 1984; Kinney, 2008).

As an alternative to conventional fossil fuel, wind energy has a low environmental impact, has renewable characteristics (Nikolić et al., 2017; Petković et al., 2013, 2016), and is the world's fastest growing renewable energy source (Haymarket Media Group Ltd, 2018). In addition, compared with conventional power stations

using fossil fuels, the relatively low values of wind turbine-rated capacity owing to technological development has attracted a lot of attention (Petković et al., 2014a,b).

Wind speed is an important meteorological factor and a parameter for determining the feasibility of renewable energy use in a region. In particular, long-term average wind speed is a criterion for estimating energy produced by wind turbine (Miller et al., 1997). Electric energy produced by wind turbines relies on the kinetic energy of wind, including wind speed, the specific mass of air, and the air space where the wind is captured (Petković et al., 2014a,b). The design of wind turbines is dependent on the wind speed distribution at a given site (Petković et al., 2016). National Renewable Energy Laboratory (NREL) provides The Wind Integration National Dataset (WIND) Toolkit, which includes calculated wind turbine power for more than 126,000 sites in the continental United States for the years 2007–2013. However, wind speeds are currently measured at meteorological stations and are sampled from a portion of the land. It means that we rely on spatially sparse and irregular monitoring stations to measure wind speed. WIND uses the Weather Research and Forecasting (WRF) model to produce wind speed. WRF simulates wind speed with a relatively low spatial resolution in $2 \text{ km} \times 2 \text{ km}$ (Draxl

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et al., 2015). We may need a surface map of wind speed with high resolution due to the high variation of air pollution and wind speed over short distances. Spatial interpolation methods based on statistical techniques can create surface maps with high spatial resolution. Therefore, using spatial interpolation methods that wind speeds in unsampled regions are predicted based on sampled data, surface-level wind speeds and more accurate wind speed predictions for unsampled regions are required (Luo et al., 2008; Smith et al., 2005).

There are two types of spatial interpolation methods—deterministic and geostatistical. Most interpolation methods only rely on spatial coverage and are representative of the available monitoring stations, which are generally sparse; thus, they do not give an accurate characterization of small-area variations (Vienneau et al., 2009). While deterministic interpolations create surfaces from monitoring stations based on the extent of similarity or the degree of smoothing, geostatistical interpolations, as stochastic interpolation methods, estimate the relationship between measured points (Childs, 2004).

Among geostatistical interpolations methods, cokriging (Cok) and regression kriging (RK) apply spatial coverage as well as auxiliary variables, as regional conditions in small areas to each interpolation (Odeh et al., 1995). Previous studies (Friedland et al., 2017; Joyner et al., 2015; Luo et al., 2008) used only Cok, but not RK, to predict wind speed. While Cok has produced good interpolation results in the United Kingdom because of the relationship between wind speed and elevation (Luo et al., 2008), in some cases, Cok does not produce better results than other deterministic and geostatistical interpolation methods (Meng et al., 2013). RK can have superior performance compared to other interpolation methods that rely only on spatial coverage when the auxiliary variables in RK account for the variation of the variable of interest in a regression model, and residuals are spatially correlated (Eldeiry and Garcia, 2010).

As auxiliary variables used in Cok and RK, regional heterogeneous terrains (Bichet et al., 2012; Giovannini et al., 2014; He et al., 2013; Joyner et al., 2015; Petković et al., 2017) and solar irradiances (Bett and Thornton, 2016) have an effect on wind speed. Previous studies only considered elevation a predictive variable of wind speed (Luo et al., 2008; Sliz-Szkliniarz and Vogt, 2011) and regional heterogeneous terrains were only applied to the prediction of extreme wind speeds (Friedland et al., 2017; Joyner et al., 2015). In addition, wind speeds in particular locations are influenced by the ambient terrain as well as the terrain at the location. Therefore, the selection of the appropriate distance of influence in terrains near all monitoring stations is important for predicting wind speed. However, preexisting studies only considered the terrain at monitoring stations, not ambient terrains (Friedland et al., 2017; Joyner et al., 2015). In addition, solar irradiance has an inverse relationship with wind speed (Bett and Thornton, 2016); thus, this study adds solar insolation to the predictive variables of annual wind speed.

Meanwhile, geostatistical interpolation can be applied to the direction of wind speed. It separates into isotropy with uniform values in all directions, and anisotropy with different values in all directions. Generally, isotropy is used in the process of geostatistical interpolation when anisotropy is not applied. The anisotropic approach is more widely used for large-scale surface interpolation than the isotropic approach (Friedland et al., 2017; Luo et al., 2008). Each interpolation method yields a different result with the same data, so that the accuracy varies over the different methods (Willmott, 1984). In addition, depending on the measured sample characteristics, the accuracy may vary even though the same interpolation method is used.

The purpose of this study is to search for the optimal interpolation method which represents the reality of wind speed

data recorded across the continental United States (US) among deterministic and geostatistical interpolation methods. For deterministic interpolation, this study uses inverse distance weighting (IDW), radial basis function (RBF) including multiquadric (MQ) and thin plate spline (TPS), and local polynomial interpolation (LPI). As geostatistical interpolations, this study uses ordinary kriging (OK), universal kriging (UK), Cok, and RK. In this study, individual interpolation methods are used to predict annual and monthly wind speeds and are compared by interpolation surfaces, and the results of root mean square error (RMSE), mean absolute error (MAE), mean error (ME), and Pearson's correlation (Corr) between real and predicted values. In addition, this study compares the difference in prediction accuracy of wind speed depending on sample size, range, variance, extreme wind stations, etc., when the same interpolation is applied.

2. Data and methods

2.1. Dataset

The variables of interest are the annual and monthly wind speed measurements in 2014. Annual and monthly wind speed data are derived from local climatological data from the National Centers for Environmental Information in the US (Memorial and Pabr, 2010). Wind speed is observed at the height of approximately 1.5 m above the surface from individual weather stations (National Centers For Environmental Information, 2021). The data are mapped into ArcGIS 10.5.1 through Geocoding. To remove seasonal or monthly bias, the data only include stations that estimate wind speed every day of every month from January to December. In addition, in this study, stations with standard scores (Z -score) exceeding +3.00 in observed annual and monthly wind speeds were defined as extreme wind speed stations. Z -score is given by

$$Z - \text{score} = \frac{X_i - u}{\sigma} \quad (1)$$

where X_i is the wind speed value at point i ; u is the average wind speed in observed stations; σ is standard deviation in observed stations. The differences in prediction accuracy when there are extreme wind speed stations will be explored.

As auxiliary variables used in RK and Cok, this study uses regional landscape heterogeneity such as green areas, elevation, slope, and solar insolation. All auxiliary variables are converted into a grid of 0.64 km² resolution using an aggregate tool in ArcGIS (version 10.5.1, Esri, US). The elevation is derived from the digital elevation data (0.008 km² resolution). The slope is determined from elevation data using the Spatial Analyst extension. Green areas are taken from the 2011 National Land Cover Database (NLCD) of the US Geological Survey (Homer et al., 2015), which is the most recent national land cover product for the US (0.0009 km² resolution). In terms of green areas, this study includes urban open spaces, deciduous forests, evergreen forests, mixed forests, woody wetlands, and emergent herbaceous wetlands that include trees. NASA Earth Observation provides daily solar insolation maps (160 km² resolution). The study calculates daily averaged solar insolation for annual and individual months for 2014 using the Raster Calculator tool in ArcGIS 10.5.1. This study explores the variation of wind speed in annual and individual months depending on the variations of solar insolation in annually averaged solar insolation and individual months, respectively.

2.2. Interpolation methods: Deterministic interpolation

2.2.1. Inverse Distance Weighting (IDW)

IDW is based on the extent of similarity and the power of adjacent samples depending on the distance. IDW predicts unsampled sites using a linear-weighting combination of sample points within a specific range (Bolstad, 2005; Nalder and Wein, 1998). IDW was used to predict temperature and precipitation (Serbin and Kucharik, 2009) and is appropriate for the rapid estimation of spatial interpolation (Mirás-Avalos et al., 2009). In IDW, the interpolation values are given by

$$\hat{Z}(S_0) = \left[\sum_{i=1}^N w(d_i) Z_i \right] / \left[\sum_{i=1}^N w(d_i) \right] \quad (2)$$

where $\hat{Z}(S_0)$ is the interpolation value at point S_0 , Z_i is data value at point i , and $w(d_i)$ is the weighting function where $w = d^{-a}$, d is the distance between stations. a is the exponent determining the weight (a value of 2 is often used as the default). The higher the value of a , the lower the weighting value by distance. The study applies the default value, 2, to IDW.

2.2.2. Radial Basis Function (RBF)

RBF is based on the degree of smoothing (Fasshauer, 1998). RBF minimizes the total curvature of the surface, using a method similar to fitting a rubber membrane through measured sample values. MQ and TPS are typical RBF interpolation methods. The basic RBF is defined as

$$\hat{Z}(S_0) = \sum_{i=1}^N w_i \varphi(r_i) + m \quad (3a)$$

where $\hat{Z}(S_0)$ is the interpolation value at point S_0 ; $\varphi(r_i)$ is the RBF selected by the MQ or TPS; r_i is the radial distance from point S_0 to point i ; w_i indicates the weights; and m represents the bias value as the Lagrangian value.

An MQ was used to create a wind field as a vector quantity that includes both wind speed and direction (Goodin et al., 1980). In MQ, a wind measurement is broken down into two Cartesian wind components (east–west and north–south). Individual components are interpolated through MQ, and the two components are combined by trigonometry. In RBF, MQ is defined as

$$\varphi(r) = \sqrt{r^2 + c^2} \quad (3b)$$

where r^2 is the square distance between two points; and c , which may be 0, determines the degree of smoothing. The $c \rightarrow 0$ is often to as the “flat” limit because $c = 0$ corresponds to a constant basis function (Mongillo, 2011).

In addition, TPS, a special class of spline, has been used for perceptible water vapor and humidity interpolations (Suparta and Rahman, 2016; Wahba and Wendelberger, 1980). TPS has a relatively straightforward formula. The values are given by

$$\varphi(r) = r^2 \ln(r) \quad (3c)$$

where r is the distance between two points.

2.2.3. Local Polynomial Interpolation (LPI)

LPI fits many polynomials, each within specified overlapping neighborhoods (ESRI, 2021). LPI is applicable when producing surfaces that capture the short-range variation (Wang et al., 2014).

2.3. Interpolation methods: Geostatistical methods

2.3.1. Ordinary Kriging (OK)

As the geostatistical method, Kriging (Krige, 1966) is a stochastic method that assesses the spatial correlation between measurement points using the semivariance as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(S_i) - Z(S_i + h)]^2 \quad (4)$$

where $N(h)$ is the number of pairs of measurement points with distance h . The semivariance function can be the function for distance using an isotropic spatial pattern or an anisotropic spatial pattern. The semivariance function is used to model different values that cannot be realistically measured (Cressie, 1985). OK is a typical geostatistical interpolation method and primarily uses a spherical model when a nugget effect is important, and there is an obvious range and sill effect (Burrough et al., 2015; Cressie, 2015). As a simple prediction tool, OK is considered flexible and relatively accurate (Smith et al., 2005).

2.3.2. Universal Kriging (UK)

UK is more appropriate than OK when a geographical trend matches the polynomial function that UK generally uses (Goovaerts, 1997). UK is used as a non-stationary stochastic model achieved by the superimposition of a stationary stochastic model on a global low-order polynomial-trend surface (Laslett and McBratney, 1990).

2.3.3. Cokriging (Cok)

Cok is a versatile statistical method when the interest and auxiliary variables are highly correlated (Eldeiry and Garcia, 2010). Cok is defined as

$$\hat{Z}(S_0) = \sum_{i=1}^N Z(S_i) A_j \quad (5a)$$

$$\sum_{i=1}^N A_j = I \quad (5b)$$

$$\sum_{j=1}^v \Gamma(S_i, S_j) + \Psi = \Gamma(S_i, S_0) \quad i = 1, \dots, n \quad (5c)$$

where $\hat{Z}(S_0)$ is the value at location S_0 to be interpolated; $Z(S_i)$ is the vector $Z_1(S_i) \dots Z_n(S_i)$; $\Gamma(S_i, S_j)$ and $\Gamma(S_i, S_0)$ are the cross-variograms; A_j is the weights associated with prediction; Ψ is the Lagrange multipliers for i from 1 to n ; and I is an identity matrix $= [1, 0, \dots, 0]^T$; T indicates a transpose.

2.3.4. Regression Kriging (RK)

RK is the combination of linear regression and kriging. The simplest model applies a linear regression, such as ordinary least square (OLS), and then, OK is conducted with the residuals derived from the regression (Odeh et al., 1995). When the residuals are spatially correlated, RK is applicable (Eldeiry and Garcia, 2010). The difference between RK and Cok is that RK regresses the correlated combination between the variable of interest and auxiliary variables using OLS, and then OK interpolates the residuals of the OLS regression model to reduce the error values in the residuals; Cok takes advantage of the correlation between the variable of interest and auxiliary variables using OK (Eldeiry and Garcia, 2010). RK is defined by

$$\hat{Z}(S_0) = \sum_{k=0}^p \hat{\beta}_k \cdot q_k(S_0) + \sum_i^n w_i(S_0) \cdot e(S_i) \quad (6)$$

where $\hat{\beta}_k$ is the k th estimated regression coefficient; q_k is the k th external auxiliary variable at location S_0 ; p is the number of auxiliary variables; $w_i(S_0)$ is the weights; and $e(S_i)$ is the regression residuals.

2.4. Regional heterogeneous terrains and solar insolation

On a local scale, wind speed is affected by the local topography as landscape heterogeneity (Bichet et al., 2012; Giovannini et al., 2014; He et al., 2013; Joyner et al., 2015; Petković et al., 2017), including elevation and land friction. The difference between various elevations corresponds to a difference in air pressures. Air generally flows from higher pressure zones to lower pressure zones. In addition, higher altitudes and slopes over mountains can lead to significant variations in wind speed (Bowen and Lindley, 1977; Hertenstein and Kuettner, 2005; Petković et al., 2017). Another landscape heterogeneity, rough lands, including hills and trees, can slow wind speeds due to the friction of the land. There are two frictional factors—slope and green areas with grouped trees such as vegetation. The slope may negatively affect wind speed due to rough land friction; as the slope increases, wind speed decreases. The increase of green areas with grouped trees, as another frictional factor or roughness, reduced global wind speeds (Bichet et al., 2012). The locations of green areas come from NLCD.

This study identifies the appropriate neighborhood size of green areas, affecting that region's wind speed. To do so, this study uses A Distance Decay REgression Selection Strategy (AD-DRESS) (Su et al., 2009). In the prediction of air pollution, AD-DRESS was used to search for neighborhood size, which affects the air pollution level at that location. The stepwise multivariate regression technique (SMRT) is used to search for the highest correlation between wind speed and green areas for optimized neighborhood size. In this study, each buffer is set from the target region as 0.8 km. Green areas are estimated in each buffer, and the SMRT is used with other auxiliary variables.

In addition, as another local condition, solar insolation is represented by auxiliary variables. The amount of solar irradiance affects land temperature, so solar heating of the earth increases the turbulence and downward mixing of high speed air to the surface, so solar heating and wind speed are connected (Coker et al., 2013). Solar irradiance and wind speed are negatively correlated with the value of about -0.4 in Britain (Bett and Thornton, 2016).

Elevation, slope, green areas, and solar insolation are used in Cok and RK as auxiliary variables. Cok predicts annual wind speed with various combinations of auxiliary variables. In addition, this study transforms elevation, slope, and solar insolation to a square-root scale, so extreme prediction values are avoided, and OLS error terms can be normally distributed. OLS is a linear regression model, and high values in auxiliary variables can predict impractical wind speeds. Using OLS, this study employs an SMRT to establish the best model. First, the stepwise technique adds one variable that has the highest correlation with the variable of interest (i.e., measured wind speed in monitoring stations) to the model. Next, another variable that has the highest correlation with the residuals from the first model is added to the model fit, and this process repeats.

2.5. Assessment of interpolation methods

Cross-validation (CV) is used to estimate the performance of each interpolation method. This study uses the leave-one-out method as a CV method of, which is an exhaustive process where all possible ways to divide the original sample into a training set and a validation set are tested (Dudoit and Van Der Laan, 2005). This suggests that one observation is removed and is

then interpolated with the remaining observations. The actual and predicted values at the location of the removed point are compared. These processes are repeated for all observed points.

The ME is used to check the bias of predicted values. Ideally, the value is zero when the predicted values are perfectly unbiased. ME value is given by

$$ME = \frac{1}{N} \sum_{i=1}^N \hat{Z}(S_i) - Z(S_i) \quad (7)$$

where $\hat{Z}(S_i)$ is the predicted value, and $Z(S_i)$ is the observed value. Both MAE and RMSE are used to assess the interpolation accuracy by comparing observed and predicted values. The lower the values in MAE and RMSE, the higher the prediction accuracy. In RMSE, the errors are squared before they are averaged, which gives relatively higher weights to larger errors. RMSE is more useful when large errors are undesirable. MAE and RMSE are given by

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{Z}(S_i) - Z(S_i)| \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N [\hat{Z}(S_i) - Z(S_i)]^2}{N}} \quad (9)$$

where $\hat{Z}(S_i)$ is the predicted value, and $Z(S_i)$ is the observed value. Corr between the observed and predicted values from CV is used to check the similarity between the original and predicted images.

In addition, to explore the difference of ME and RMSE between individual months, ME and RMSE should be normalized. The normalized ME (NME) and normalized RMSE (NRMSE) are given by

$$NME = \frac{ME}{SD_{month}} \quad (10)$$

$$NRMSE = \frac{RMSE}{SD_{month}}, \quad (11)$$

where SD_{month} is the standard deviation of observed wind speed in each month.

3. Results and discussion

3.1. Monitoring data

As shown in Table 1, the number of monitoring stations ranges from 751 to 900. Though 751 stations estimated wind speed for 365 days, more stations estimated wind speed for each month. The average wind speed was higher in spring and winter than for the other seasons, except for December. The range in wind speed was lower from April to July than the others, and the variance in wind speed was the highest in January. The number of stations with extreme wind speed was the greatest in February. In addition, annual average wind speed seemed higher in great plains than in other regions and toward coastlines (Fig. 1).

3.2. Auxiliary variables

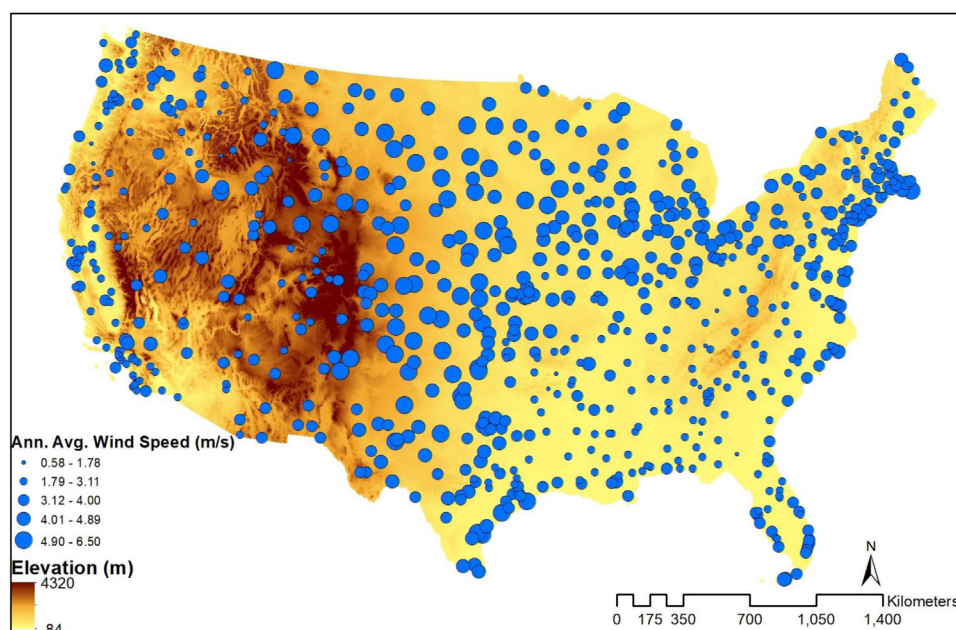
3.2.1. A Distance Decay REgression Selection Strategy (ADDRESS)

Using ADDRESS, this study identified the buffer size of green areas that affect wind speed using the SMRT (Table 2). The buffer size was different in each month and year. Except for August, the buffer size seemed higher for higher average wind speeds. In each month and year, buffer sizes derived from the SMRT were also added to Cok.

Table 1

Summary statistics of stations for annual and monthly wind speed based on the estimation of stations.

Month	Number of stations	Average wind speed (m/s)	Min. wind speed (m/s)	Max. wind speed (m/s)	Wind speed range (m/s)	Wind speed variance (m/s) ²	The number of stations with extreme wind speed ($Z \geq 3$)
Jan	844	3.749	0.248	9.891	9.643	1.451	3
Feb	847	3.573	0.484	9.468	8.984	1.123	7
Mar	847	3.969	0.564	10.410	9.847	1.145	3
Apr	860	4.159	0.699	7.689	6.990	1.191	0
May	885	3.590	0.736	6.925	6.189	1.069	3
Jun	858	3.428	0.650	7.978	7.328	1.227	4
Jul	862	3.036	0.573	7.322	6.748	0.963	1
Aug	876	2.736	0.420	9.507	9.087	0.918	3
Sep	888	2.870	0.538	12.729	12.191	1.010	2
Oct	900	3.147	0.437	15.612	15.174	1.106	4
Nov	873	3.720	0.560	9.756	9.196	1.270	2
Dec	887	3.223	0.462	9.586	9.124	1.042	3
Annual	751	3.425	0.585	6.474	5.889	0.990	2

**Fig. 1.** Annually averaged wind speed in 2014 at weather stations and elevation across the continental United States.

3.2.2. Ordinary least square regression for regression-kriging

Before the prediction of wind speed, OLS regression was conducted for RK. For monthly and annual wind speed prediction in 2014, an OLS regression model using a stepwise multivariate technique was established (Table 2). All variables were statistically significant with $p < 0.05$, which means there was no coefficient with a zero value. The variance inflation factors (VIFs) were less than 1.5, which means that there is little to no multicollinearity between variables.

Green areas, solar insolation, and slope are negatively associated with monthly and annual wind speed, but the elevation is positively associated with monthly and annual wind speed. This is consistent with the theory that heterogeneous terrains with fraction and higher solar insolation decrease wind speed, and higher altitude increases wind speed. However, for the OLS regression model in August, solar insolation was positively associated with monthly wind speed, which was inconsistent with the theory. For annual wind speed prediction, green areas, solar insolation, and slope are each first, second, fourth most correlated variables, respectively, with annual wind speed with a negative trend. Based on the OLS coefficients displayed in Table 2, an increase of 1 km² in green areas, 1 W/m² of solar insolation, 1° in slope, reduced each 2.350×10^{-6} , $(0.495)^2 \approx 0.245$, and $(0.698)^2 \approx 0.487$,

respectively, in annual wind speed (m/s). The elevation is the third most correlated variable to annual wind speed and has a positive association with it. When elevation increased by 1 m, the annual wind speed increased by $(0.021)^2 \approx 0.0004$ m/s.

3.3. Interpolation surface and validation for annual wind speed

For annual wind speed predictions, IDW was inappropriate where monitoring stations are uneven or for sparsely distributed observation points (Fig. 2(a)). Across the US, the isolated observation points predicted discontinuous patterns like bullseyes, in which the values are either much higher or much lower than surrounding values. Two RBF methods represented abrupt changes over small distances, particularly in the Southwest Mountains and the Great Plains (Fig. 2(b)(c)). LPI applied more continuous results than other deterministic interpolation methods when predicting wind speed (Fig. 2(d)).

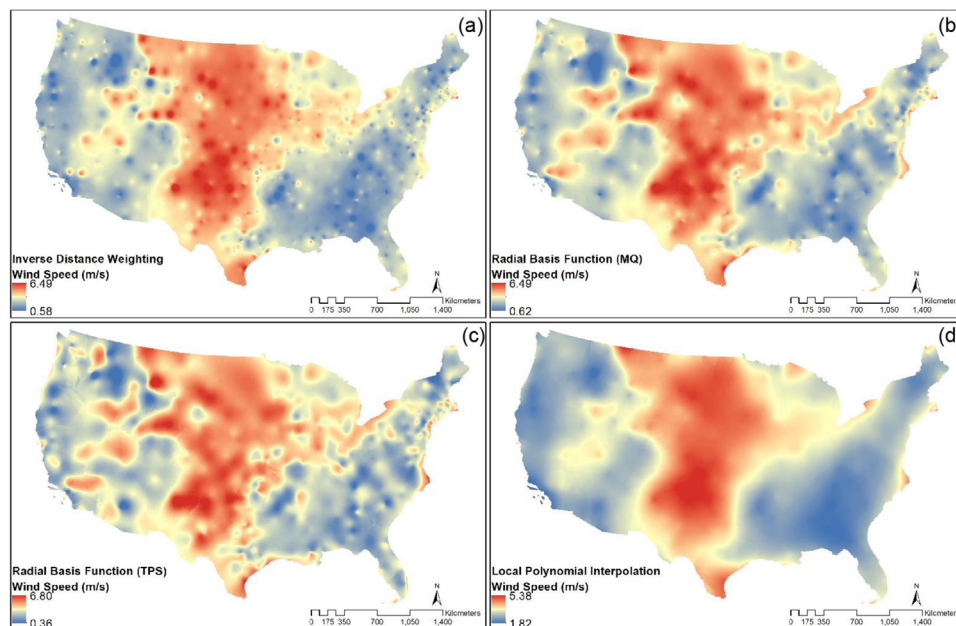
For annual wind speed prediction, anisotropic OK, UK, and Cok depicted higher wind speed in the Great Plains region, consistent with observed values, showing smoother wind speed than deterministic interpolations in annual wind speed prediction (Fig. 3(a)(c)(e)). In addition, as shown in Fig. 3(b), (d), and (f), the prediction standard error estimated the uncertainty over the entire

Table 2

The ordinary least square (OLS) regression results between averaged annual wind speed, local topographies, solar insolation, and buffer size of green areas.

	Adjusted R ²	Coefficient					Buffer size (km)
		Constant	Green areas	Solar insolation on square root scale	Elevation on square root scale	Slope on square root scale	
Jan	0.243	7.571	-3.383×10^{-4} (0.000)	−0.388 (0.000)	0.019 (0.000)	−0.705 (0.000)	74.4
Feb	0.294	6.600	-8.921×10^{-4} (0.000)	−0.289 (0.000)	0.022 (0.000)	−0.454 (0.000)	43.2
Mar	0.326	7.583	-3.944×10^{-4} (0.000)	−0.293 (0.000)	0.024 (0.000)	−0.383 (0.000)	72.8
Apr	0.489	10.839	-3.357×10^{-4} (0.000)	−0.505 (0.000)	0.028 (0.000)	−0.520 (0.000)	92.0
May	0.514	6.515	-2.042×10^{-4} (0.000)	−0.155 (0.000)	0.019 (0.000)	−0.444 (0.000)	115.2
Jun	0.503	5.696	-5.917×10^{-4} (0.000)	−0.114 (0.000)	0.029 (0.000)	−0.306 (0.000)	68.8
Jul	0.440	5.687	-1.133×10^{-3} (0.000)	−0.157 (0.004)	0.012 (0.000)	–	44.8
Aug	0.405	1.932	-0.814×10^{-4} (0.000)	0.125 (0.003)	0.019 (0.000)	–	160.0
Sep	0.408	7.672	-4.074×10^{-4} (0.000)	−0.395 (0.000)	0.020 (0.000)	–	75.2
Oct	0.296	6.923	-3.298×10^{-4} (0.000)	−0.351 (0.000)	0.015 (0.000)	–	75.2
Nov	0.313	7.128	-1.567×10^{-4} (0.000)	−0.335 (0.000)	0.015 (0.000)	−0.409 (0.000)	117.6
Dec	0.275	5.815	-3.480×10^{-4} (0.000)	−0.275 (0.016)	0.007 (0.000)	−0.304 (0.000)	72.0
Annual	0.494	9.448	-2.350×10^{-6} (0.000)	−0.495 (0.000)	0.021 (0.000)	−0.698 (0.000)	79.2

Green areas (km²), Solar: monthly and annual average solar insolation (W/m²) on square root function, Elevation: Elevation (m) on square root function, Slope: Slope (degree) on square root function, (): probability (p) values.

**Fig. 2.** Surface map of annually averaged wind speed for deterministic interpolations: (a) IDW, (b) RBF MQ, (c) RBF TPS, (d) LPI.

surface. Kriging yields the standard error maps with the standard errors of interpolated values. The standard error maps are assessed by the minimized RMSE that makes kriging optimal (Krivoruchko, 2011). The estimated rule is that the actual surface value will be within the interval formed by the predicted value ± 2 times the prediction standard errors approximately 95% of the time if data are normally distributed (Johnston et al., 2001). For example, when the predicted wind speed is 4 m/s and one standard error is 1, the actual value is between 3 and 5 m/s in

68% confidence and between 2 and 6 m/s in 95% confidence. It suggests that the higher the standard error value, the higher the uncertainty of the predicted value. The standard errors represent abrupt changes over small distances (Fig. 3(b), (d), and (f)), as standard deviations were suddenly much higher in regions in which monitoring stations are sparse. Using independent regional conditions such as heterogeneous terrains and solar insolation, anisotropic RK depicted more variable and detailed wind speed (Fig. 3(g)). RK represented higher wind speed in the Great Plains

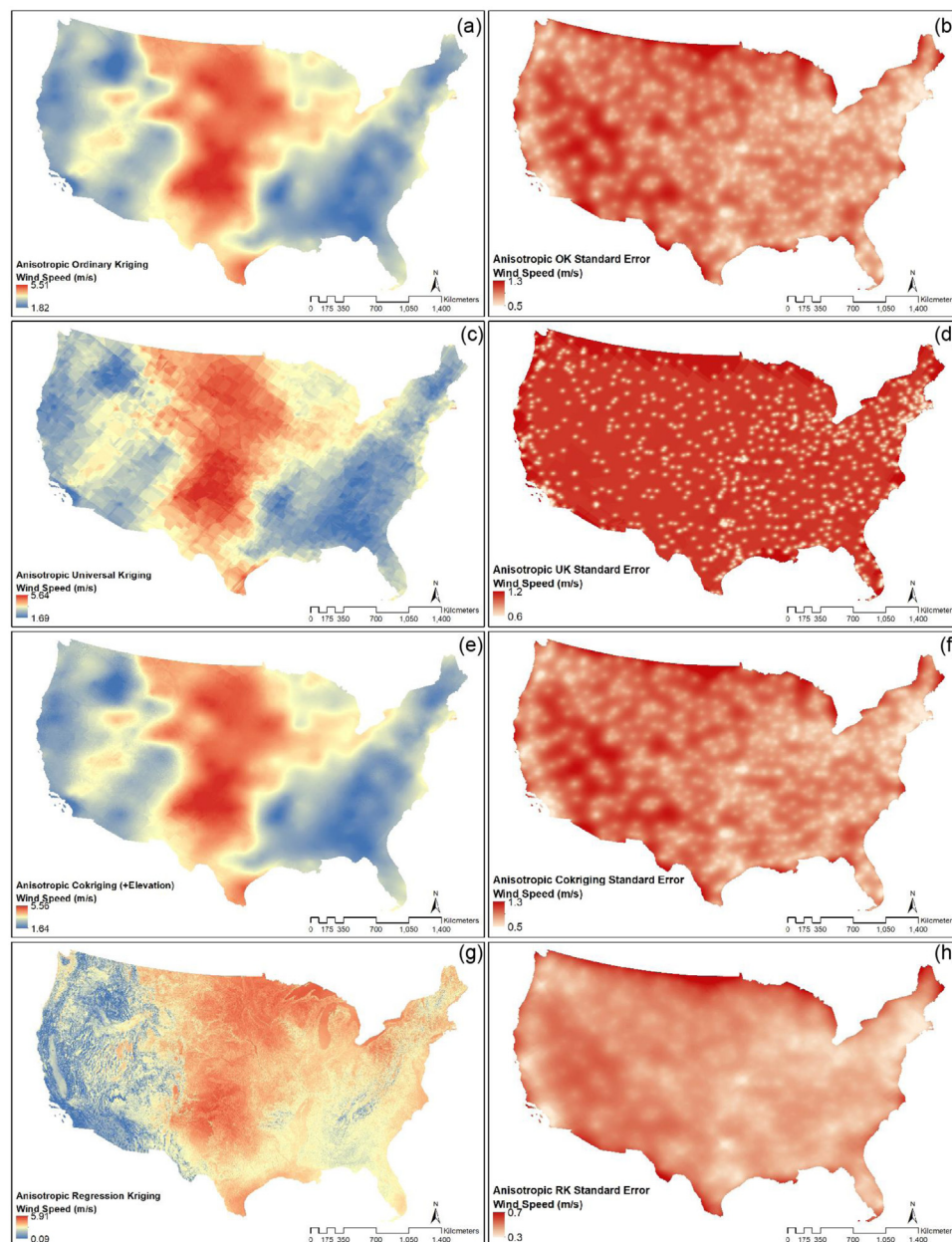


Fig. 3. The annually averaged wind speed and standard deviation of wind speed surfaces for geostatistical interpolations; anisotropic OK (a), (b); anisotropic UK (c), (d); anisotropic Cok (e), (f); anisotropic RK (g), (h).

region, consistent with observed data. In addition, the standard deviation in RK represented a relatively smoother change, and the values are lower than other kriging methods (Fig. 3(h)).

3.4. Statistical assessment

3.4.1. Annual wind speed

The analysis in this study checked the range and bias of predicted values (ME), the accuracy (MAE and RMSE), and the similarity between observed and predicted wind speed (Corr) in each interpolation method for the prediction of annual wind speed in 2014 (Table 3). In the range from minimum to maximum in annual wind speed, the range in IDW was the closest to the real measurement since IDW's characteristics are interpolated within the range of real measurements. Except for IDW, isotropic and anisotropic RK interpolations were closer to the original measurements than other interpolations.

Values for ME, MAE, and RMSE were relatively higher in deterministic interpolations than in geostatistical interpolations, and values in Corr were relatively higher in geostatistical interpolations than in deterministic interpolations, although some values in geostatistical interpolation had different results. As a bias check of predicted values, ME values in all interpolation methods were low. It means that predicted values in all interpolation methods did not seem biased. MAE and RMSE were the lowest in anisotropic RK at 1.058 and 1.3821, respectively. In other words, the prediction error values for annual wind speed were the lowest in anisotropic RK. Finally, Corr was the highest in anisotropic RK with a value of 0.7852. This suggests that for annual wind speed, the predicted image for anisotropic RK was the most similar to the real image.

For anisotropic RK, this study used the spherical model of OK as kriging with the residuals after establishing an OLS regression model. From the spherical model, the semivariogram of annual

Table 3
Validation of individual interpolation methods.

Interpolation methods			Min	Max	ME	MAE	RMSE	Corr
Deterministic interpolation		IDW	0.582	6.471	−0.011	0.528	0.688	0.7226
		RBF_TPS	0.356	6.813	0.020	0.626	0.817	0.6536
		RBF_MQ	0.600	6.467	0.005	0.540	0.702	0.7188
		LPI	1.831	5.387	0.020	0.510	0.665	0.7417
Geostatistical interpolation	Ordinary Kriging	Isotropy	1.813	5.480	−0.007	0.503	0.656	0.7490
		Anisotropy	1.804	5.493	−0.006	0.502	0.655	0.7497
	Universal Kriging	Isotropy	1.591	5.649	−0.004	0.509	0.664	0.7419
		Anisotropy	1.689	5.640	−0.004	0.508	0.661	0.7451
	Cokriging	Isotropy (+Elevation)	1.844	5.409	−0.002	0.504	0.655	0.7487
		Anisotropy (+Elevation)	1.640	5.538	−0.008	0.501	0.653	0.7470
		Isotropy (+Solar insolation)	1.924	5.400	−0.005	0.507	0.660	0.7452
		Anisotropy (+Solar insolation)	2.058	5.409	−0.004	0.508	0.659	0.7460
		Isotropy (+Green areas)	1.831	5.431	−0.002	0.504	0.657	0.7479
		Anisotropy (+Green areas)	1.844	5.413	−0.004	0.503	0.657	0.7480
		Isotropy (+Slope)	1.898	5.404	−0.002	0.504	0.657	0.7474
		Anisotropy (+Slope)	1.916	5.396	−0.004	0.504	0.657	0.7479
		Isotropy (+Elevation+Solar insolation)	1.898	5.400	−0.003	0.504	0.657	0.7477
		Anisotropy (+Elevation+Solar insolation)	1.907	5.387	−0.004	0.504	0.657	0.7478
		Isotropy (+Elevation+Slope)	2.049	5.364	−0.003	0.505	0.658	0.7470
		Anisotropy (+Elevation+Slope)	2.004	5.378	−0.004	0.504	0.658	0.7473
		Isotropy (+Elevation+Green areas)	1.840	5.413	−0.002	0.504	0.657	0.7484
		Anisotropy (+Elevation+Green areas)	1.862	5.400	−0.003	0.504	0.657	0.7484
		Isotropy (+Solar insolation+Slope)	1.978	5.378	−0.003	0.506	0.659	0.7466
		Anisotropy (+Solar insolation+Slope)	2.067	5.378	−0.002	0.507	0.658	0.7474
		Isotropy (+Solar insolation+Green areas)	1.876	5.413	−0.002	0.504	0.657	0.7479
		Anisotropy (+Solar insolation+Green areas)	1.849	5.418	−0.003	0.503	0.657	0.7481
		Isotropy (+Slope+Green areas)	1.858	5.422	−0.002	0.504	0.657	0.7479
		Anisotropy (+Slope+Green areas)	1.871	5.409	−0.003	0.504	0.657	0.7481
		Isotropy (+Elevation+Solar insolation+Slope)	2.062	5.364	−0.003	0.506	0.659	0.7466
		Anisotropy (+Elevation+Solar insolation+Slope)	2.036	5.378	−0.004	0.506	0.658	0.7468
		Isotropy (+Elevation+Solar insolation+Green areas)	1.858	5.409	−0.002	0.504	0.657	0.7482
		Anisotropy (+Elevation+Solar insolation+Green areas)	1.822	5.422	−0.003	0.503	0.656	0.7484
		Isotropy (+Elevation+Slope+Green areas)	1.831	5.422	−0.002	0.504	0.657	0.7483
		Anisotropy (+Elevation+Slope+Green areas)	1.853	5.409	−0.003	0.503	0.656	0.7486
		Isotropy (+Solar insolation+Slope+Green areas)	1.876	5.413	−0.002	0.504	0.657	0.7478
		Anisotropy (+Solar insolation+Slope+Green areas)	1.844	5.418	−0.003	0.503	0.657	0.7481
	Regression Kriging	Isotropy	0.093	5.822	0.002	0.470	0.615	0.7847
		Anisotropy	0.102	5.924	0.002	0.470	0.614	0.7853

Min: minimum value of predicted wind speed; Max: maximum value of predicted wind speed; ME: checking bias of error values; MAE and RMSE: assessing the accuracy of interpolation methods; Corr: checking the similarity between the original and predicted images.

wind speed was fitted to two different directions: 10° and 100° (Fig. 4). The NW-SE direction at 100° was more continuous than the NE-SW direction at 10°. For the NW-SE direction, the semivariogram value was off to the sill when it reached a range of 922 mi. For the NE-SW direction, the range was 751 mi. Therefore, the difference in the ranges of the two directions increased the predictive precision in the corresponding spherical models. In addition, the scatter plot for CV estimates and observed values using anisotropic RK is shown in Fig. 5; estimated values that fitted to observed values have an R^2 of 0.82.

3.4.2. Monthly wind speed

In each month, this study compared NRMSE and NME between four typical interpolations which represented the highest accuracy with ME, RMSE, and Corr in deterministic and geostatistical interpolations such as LPI, anisotropic OK, Cok with elevation, and RK for the prediction of annual wind speeds (Figs. 6 and 7). NRMSE and NME are used rather than RMSE and ME because the variance of wind speed is different each month, so it is not valid to compare the performance of each method in different months with RMSE ME. NRMSE was the lowest in anisotropic RK each month. NME was relatively lower in the kriging methods than in LPI. In particular, anisotropic RK was also the lowest in each month except for February.

NRMSE was higher in October than in July (Fig. 6). However, it should also be noted that compared to July and October, the mean value was similar, but the range was wider in October

than in July and variance was also higher in October than in July (Table 1). This means that in similar mean wind speed, the wider the range and the higher the variance, the lower the prediction accuracy. Compared to February and November, a smaller sample size might make the prediction accuracy lower, despite the similarities of the mean, range, and variance of monthly wind speed. Luo et al. (2008) highlighted that large sample size could increase the prediction accuracy, where particularly wind speed is relatively high. January, June, and November showed relatively low NRMSE compared to other months due to high variance. It suggests that as shown in Eq. (11), when the differences in RMSE are marginal and SD_{month} (i.e., square root variance) in the three months are relatively high, the NRMSE in the three months get high.

3.4.3. Comparison of isotropic and anisotropic regression kriging with and without extreme wind speed

This study compared NRMSE, as the accuracy test, in monthly wind speed prediction between isotropic and anisotropic RK interpolations (Fig. 8). In addition, there are stations that measured extreme wind speed with $Z \geq 3$ (Table 1). To explore how RK predicts extreme wind speed, this study estimated NRMSE of RK with and without stations with extreme wind speed in each month (Fig. 8). NRMSE values were lower in anisotropic RK than isotropic RK each month. NRMSE values in both RK with stations with extreme wind speed were much higher than those with those without extreme wind speed.

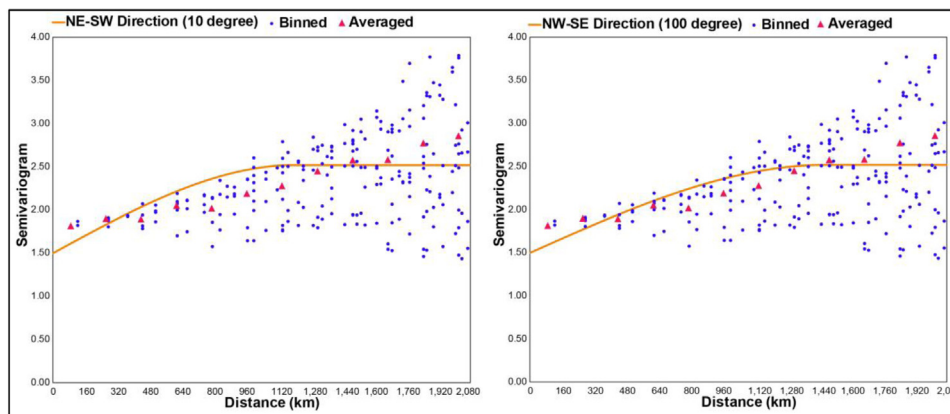


Fig. 4. Semi-variogram values in NE-SW (10 degree) and NW-SE (100 degree) directions. Points: difference in wind speed between stations by distance; triangle: averaged difference in wind speed between stations by distance; continuous line: theoretical spherical semi-variogram.

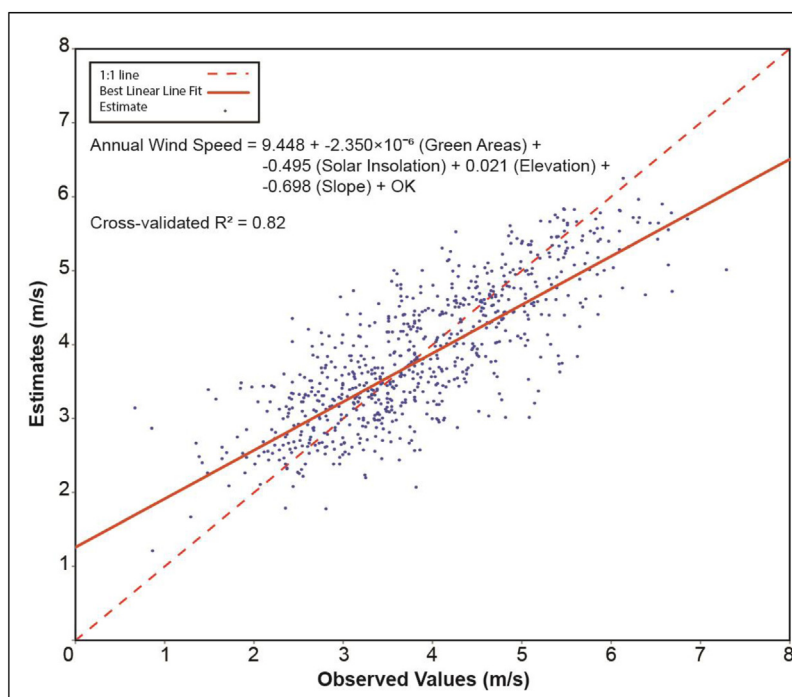


Fig. 5. Scatter plots between cross-validated prediction values and observed values using anisotropic RK for annual wind speed.

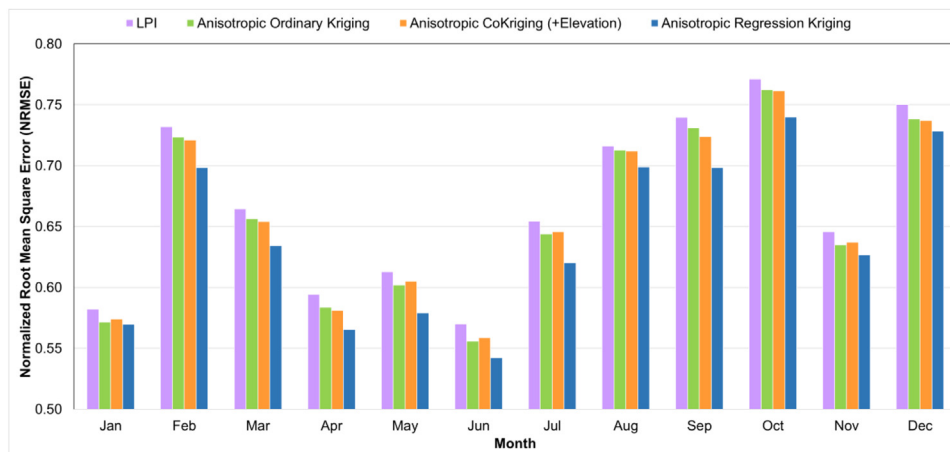


Fig. 6. NRMSE each month between four interpolation methods: LPI, anisotropic OK, anisotropic Cok (+Elevation), and anisotropic RK.

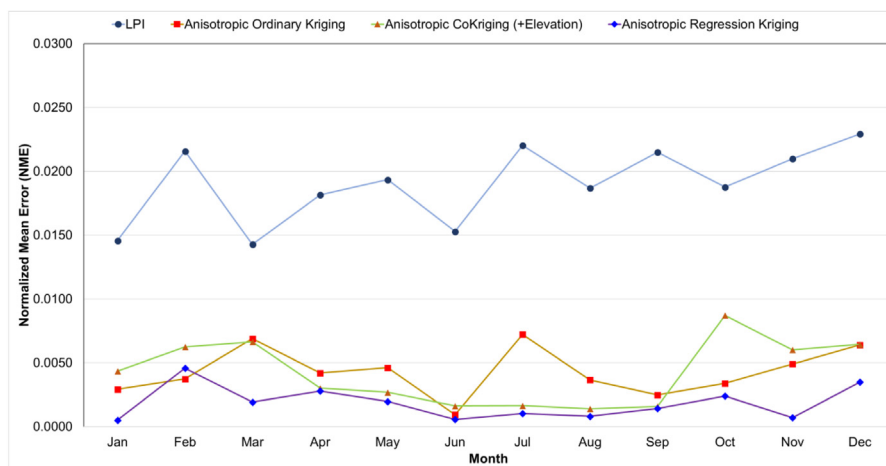


Fig. 7. NME each month between four interpolation methods: LPI, anisotropic OK, anisotropic Cok (+Elevation), and anisotropic RK.

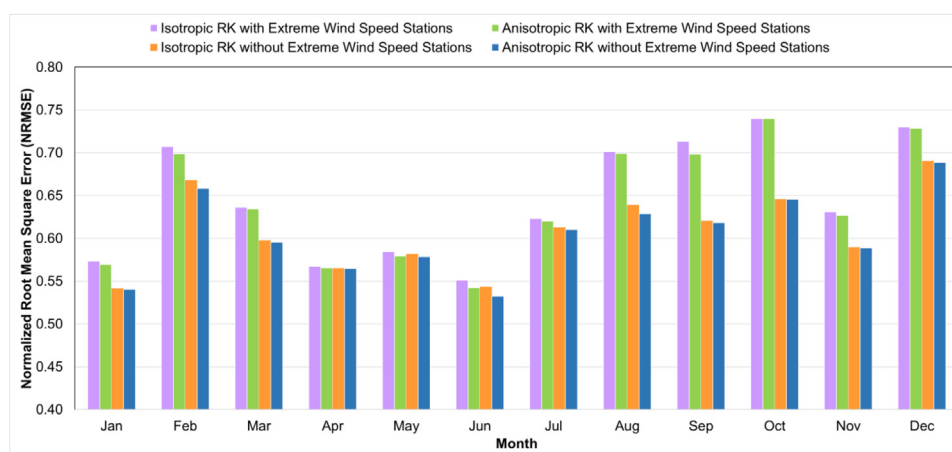


Fig. 8. NRMSE each month between isotropic and anisotropic RK with extreme wind and without extreme wind ($Z \geq 3.00$).

3.5. Discussion

Though this study used existing interpolation methods, it has some differences. First, this study used RK to predict long-term wind speed. No study has used RK to predict long-term wind speed, though RK was often used in other fields. In addition, this study showed that RK was superior to other deterministic and geostatistical interpolations in terms of model performance, including CV and surface maps predicted. Second, using ADDRESS, this study identified the appropriate distance of influence at all monitoring stations. Preexisting studies only used terrain types at the monitoring station (Friedland et al., 2017; Joyner et al., 2015), but the wind speed was influenced by surrounding terrains (He et al., 2013) and the distance of influence was different annually and monthly. Third, this study added solar insolation to another predictive variable, and it had predictable power for long-term wind speed. Windy days often tend to be cloudy, though there was a weak anticorrelation between wind speed and solar insolation (Bett and Thornton, 2016). However, most studies only considered regional heterogeneous terrains predictive variables of interest (Friedland et al., 2017; He et al., 2013; Joyner et al., 2015; Nikolić et al., 2017).

This study predicted annual and monthly wind speeds in 2014 with deterministic and geostatistical interpolation methods, making subsequent comparisons. IDW was the most similar to the range of observed data in wind speed, but was not available where observed data were sparsely or unevenly distributed

(Fig. 2(a)). Two RBF interpolations with MQ and TPS represented abrupt changes in wind speed and were significantly higher in MAE and RMSE, and lower in Corr. In LPI, the wind speed was more smoothly predicted than other deterministic interpolations methods, but compared to the observed data, the range of estimated wind speed was too narrow to produce representative results.

On the other hand, geostatistical interpolations were superior to deterministic interpolations. These methods depicted smooth wind speed surface, with results that produced relatively higher accuracy readings than did deterministic interpolations in MAE, RMSE, and Corr. In OK, UK, and Cok, for the difference in the range of wind speed prediction, for ME, RMSE, and Corr, the standard error is very small, but the UK depicted the most abrupt change in the standard error, particularly the distance from the monitoring stations. Cok, with its combination of regional heterogeneous terrains and solar insolation, did not provide better results than OK and UK, despite Cok's time-consuming interpolation technique. RK with regional heterogeneous terrains and solar insolation provided relatively higher accuracy and smoother distribution of standard error than other kriging methods. The reason that RK gave better results than other kriging methods is that the wind speed changed locally and was affected by heterogeneous spatial terrain and solar insolation, which can be modeled with RK. In addition, while both Cok and RK require a high correlation between the interest and auxiliary variables, the residuals derived from the OLS regression in RK captured the variation in wind speed.

Furthermore, in most kriging methods, anisotropic approaches represented more accurate predictions than isotropic approaches, although the difference is tiny. It suggests that at the macro-scale, the anisotropic approach was well-suited (Friedland et al., 2017). In particular, anisotropic RK depicted the most unbiased and accurate prediction values. However, the accuracy of RK for stations with extreme wind speeds was significantly lowering. In addition, the sample size, range, and variance of monthly wind speed affected prediction accuracy. Specifically, a higher sample size, a narrower range, and lower variance of wind speed improved the prediction accuracy.

4. Conclusions

The results of this study indicate that anisotropic RK with regional heterogeneous terrain and solar insolation was superior to other deterministic and geostatistical interpolation methods for predicting wind speeds in the US, based on annual and monthly wind speed interpolation. The major findings include:

- (1) Overall, anisotropic RK depicted more detailed and smoother wind speed surfaces and lower and smoother error surfaces than other kriging methods.
- (2) Whereas previous studies found Cok with regional land cover and elevation as a covariate improved interpolated wind surfaces, RK with regional heterogeneous and solar insolation results in the greatest reduction of MAE and RMSE and in the greatest increase of Corr.
- (3) The anisotropic approach also improved accuracy in the prediction of annual and monthly wind speed, although the reduction in RMSE is slight.
- (4) Both isotropic and anisotropic RK with extreme speed stations reduced the accuracy for the wind speed prediction.
- (5) Range, variance, and sample size in observed data are important attributes to consider when selecting a spatial interpolation method.

However, this study has some limitations, and directions for future studies are suggested. First, if there are local conditions explaining the differences in air pressure that indicate that winds flow from higher to lower pressure zones, more predictable interpolation results using RK can be established. Second, in study areas consisting of wide areas along longitudes, such as the US, China, and Brazil, the Earth's rotational velocity may be considered in the wind speed interpolation. Third, this study only considered different spatial differences, but did not include time series. The same wind speed series can show different circumstances over time (Nikolić et al., 2017); thus, future studies need to consider the time series predictive variables of wind speed. Fourth, the study estimated surface wind speed, but did not consider the wind speed in height more than 100 m from the surface where wind turbines are generally located. When getting the wind speed information in height more than 100 m from meteorological stations, anisotropic RK can be utilized to estimate the wind speed over the continental US. Fifth, this study does not include wind speed information over water areas, so although the study created wind speed over the water areas, the study did not validate the estimation of wind speed over the water areas.

CRedit authorship contribution statement

Changyeon Lee: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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