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Comparing Geostatistical and Non-geostatistical Techniques for the Estimation of Wind Potential in Un-sampled Area of Sindh, Pakistan

SAIF UR REHMAN
MUZAFFAR UDDIN QAZI
Department of Physics
Federal Urdu University of Arts, Science and Technology
Karachi, Pakistan
IMRAN SIDDIQUI
Department of Physics, University of Karachi
Karachi, Pakistan
SYED NASEEM HUSSAIN SHAH
Department of Physics
Federal Urdu University of Arts, Science and Technology
Karachi, Pakistan

Abstract:

To provide a uniform and continuous map of interested sites interpolation methods are used. The spatial interpolation is one of the techniques, to investigate un-sampled regions. This paper presents a comparative study of the Inverse distance weighting and residual kriging methods for estimation of the monthly mean wind potential in Sindh, Pakistan, with an objective to estimate the average wind speed of an un-sampled area. Moreover, the performance of these spatial interpolation methods is evaluated by cross-validation methods. Monthly average dataset includes 4 years (2002–2005) of data supplied by Pakistan Meteorology department. Using inverse distance weighting method, estimates obtained are RMSE ranging from 0.72 m/s in January (winter) to around 1.14 m/s in June (summer) and MAE ranges from 0.52 m/s to 0.89 m/s. In the residual Kriging procedure, topographical variables are used as external variable. Comparatively Residual Kriging technique gives better RMSE values ranging from 0.24 m/s in January (winter) to around 0.54 m/s in June (summer).

Values of R^2 for Residual Kriging, showing values above 0.8 the results indicates that, comparatively, residual Kriging performs better overall. It is quite clear from the results, that the proposed residual kriging method is the optimum spatial interpolation method for the monthly mean wind speed for the study area.

Key Words: inverse distance weighting, residual Kriging, Sindh, topographical variables, spatial interpolation

1. Introduction

Energy is the backbone of country's economy and plays a major role in the growth of a country. Considering limited fossil fuel resources, wind is one of the leading sources of renewable energy. The wind energy market is rapidly expanding worldwide [1]. Over the years the world's wind energy capacity has increased and is now 196630 Megawatt, with a growth rate of 23.6%[2].The availability of wind speed data for a specific location is one of the main component for estimating wind energy potential in that location. At un-sampled locations or at locations where wind parameters are not recorded, spatial interpolation techniques are used to obtained wind data.

Spatial interpolation is a technique by which wind speed data is estimated in an un-sampled location by using data of known, measured locations in the proximity. The main objective of this paper is to explore such interpolation techniques for generating wind speed data at un-sampled locations. Two different classes of interpolation are investigated, i.e., non-geostatistical (inverse distance weighting) and geostatistical (Residual Kriging techniques). Kriging techniques are one of the most widely used spatial interpolation techniques[2].The authors discussed various spatial interpolation techniques, and it is concluded that the optimum spatial interpolation technique of one climate factor cannot be used for the other climate factors in the same area or the same climate factor in different areas. The integration of GIS and environmental modeling is used for spatial interpolation [3, 4]. Tabios and Salas used various spatial interpolation for the analysis of precipitation and compared the methods [5]. Dodson and Marks used spatial interpolation techniques for daily maximum and minimum temperature [6]. For the sparse samples Goovaerts claimed that

Kriging has an advantage over simpler methods because Kriging incorporates the regional attributes [7]. Lahmer et al. used different types of Kriging for environmental problem modeling [8]. Ahmad investigated the groundwater to estimate TDS using Kriging method and showed the suitability and accuracy of this method [9]. Kriging is successfully used by Carr and Glassfor in the analysis of earthquake data [10]. The reliability of Kriging estimates may decline with the intricacy of the topography, or when the surface is not homogeneous. The estimates may also show low performance with land-sea discontinuities or with sparse data. For wind speed, particularly, these conditions present a challenge. Under these situations Kriging applies different techniques to enhance its performance. These techniques consider extra variables to perform the interpolation; it also bears for the deficiency of data and the inadequate sample size [11].These variables in the majority of the cases are associated to geographical or topographical distinctiveness. In residual Kriging these external variables are used in multiple linear regression fitted to the concerned variable and some exterior descriptive variables then; an ordinary Kriging technique is applied to the residuals of this multiple regression analysis [12]. In the last step, a map is acquired by combining together the multiple regression and the Kriging outcome. This method, although comparatively straightforward, is powerful, since it allows inclusion of outer information in the interpolation method, which may pay off for the small data size. Husain Alsamamra et al. applied the residual Kriging procedure over southern Spain for mapping global solar radiation [13]. Cellura et al. made a comparative study between inverse distance weighting and universal Kriging method for spatial interpolation of wind speed in Sicily[14].Chua and Bras used residual Kriging for the study of effect of elevation on rainfall amount [15]. Margaret and Holdaway applied Kriging and residual Kriging to the monthly temperature records of north central United States for partial interpolation [16]. Ustrnul and Czekierda applied residual Kriging for the study of temperature in Poland [17]. Prudhomme and Reed applied residual Kriging for the study of rainfall in Scoltland[18]. Jarvis and Stuartused inverse-distance weighting and Kriging to modeled daily temperatures over England and Wales [19]. Luo et al. used seven spatial interpolation methods for estimating daily mean wind speed across England and Wales. A comparative study revealed that there was an obvious difference among the performances of these interpolation techniques. Further, the study showed that the geostatistical methods were better than non-geostatistical methods [20]. Most of the groups estimated the wind potential for Sindh [21, 22]. Wind energy spatial interpolation has scarcely been used in Sindh (Pakistan).

In this work, a comparative study of the residual Kriging and inverse distance weighting technique is presented for mapping monthly-averaged wind speed in Sindh (southern Pakistan). The aim of this work is to assess the potential worth of these methodologies and to assess the performance of the residual Kriging method for mapping the wind speed and wind potential resources in the region of Sindh (southern Pakistan). The region is characterized by a variety of topography and climate. One of the emphases is to find the topography-related external variables. Section two explains the study area, the data and the methodology, results are discussed in section three, while section four gives the conclusions.

2. Methodology

This part begins with the introduction of study area and the characteristics of data used in this research work. Then, the method used in this work is presented. The last part of this section explained models of evaluation procedures.

2.1. The Study Area & Data

Sindh, among the four provinces of Pakistan, is the second most populous province. Geographically, Sindh lies in the subtropical region, which is located on the western corner of South Asia and in the South-Eastern part of Pakistan (see Figure 1). Sindh lies between 23° 35ʿ and 28°30ʿ north latitude and 66°42ʿ and 71°1ʿ east longitude. Its geographical area is 140,914 Sq. km and contributes to 18% of Pakistan. Its length is about 579 km from north to south and its breadth is nearly 442 km, and has a 240 km long coastal belt. Temperatures frequently rise up to 46 ^{O}C during the period from May to

August, and the minimum average temperature recorded is 2 ^{O}C during the period from December to January. Annual average precipitation is 5 inches. In summer, Sindh becomes the lowest pressure area in the world. In winter, a high pressure develops over central Asia, which affects Sindh as well. Near the coast the wind speed is nearly 8 m/s during monsoon season. The prevailing wind is northerly and northwesterly in winter and southerly and south-westerly in summer. The process of wind generation begins when the air in Rajasthan and Thar Desert becomes hot and rises up and its replacement of cooler air comes from Arabian Sea. Topographically the region comprises dissimilar parts; the western part is an almost homogeneous flat area with coast and land interface whereas the eastern part contains some mountain ridges.

2.2 The Data

The investigations are performed on a dataset of 4 years (2002–2005) for monthly average wind speed, measured at 26 meteorological stations. The data is obtained from Pakistan Meteorological department. Wind speed distribution for Sindh shows a high wind energy belt between Katibandar, Karachi to Badin – Hyderabad [23]. Figure 1 shows the distribution of stations in the investigated region with geographical positions. Recorded data from 26 stations shows that, most of the stations are located in the southern zone and central parts of Sindh; in northern part of Sindh, the number of wind measuring stations is relatively small. The elevation of the wind stations ranged from 20m to 170 m, but the majority of them are below 40m.

Generally, the coastal areas have higher wind speeds. Range of average annual wind speed is 1.5 m/s to 5.6 m/s [24]. The value of wind speed is higher in southern region than northern region of Sindh. Before we proceed further it is important to know that measurement and recording errors are common in any experiment. Errors in climate data observations are also very common and can influence the interpolation. In the case of wind data, these errors lie in the range from 5% to 30% [25].

Data from nineteen monitoring stations are used for the evaluation of interpolation methods. Figure 2 shows a box-plot of the monthly average wind speed data for the investigated region. The extension of boxes is from the lesser to higher quartile values of the information; a line is drawn at the middle. The inter-quartile range is depicted by the extended whiskers; this extends away starting the envelope boundaries. The values outside the whisker limits circle represent outliers. In this region, June and July have high extreme values that are due to monsoon season. Additionally, it can be seen that January and July have the maximum relative unpredictability as it has both small and high data outlier.

2.3 IDW (Inverse Distance Weight)

Inverse distance weight (IDW) is a deterministic estimation method whereby values at un-sampled points are determined by a linear combination of values at known sampled points. Weighting of nearby points is strictly a function of distance. The method is based on the concept that the correlation and the effect of neighbors varies with the distance and is proportional to the distance between them.

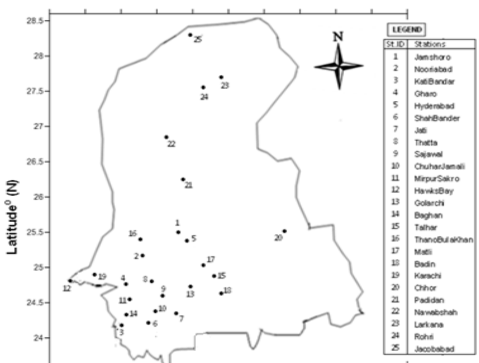


Figure 1 Map of study area with sampling points

It is called weight of a regionalized variable, which is expressed as a distance inverse function ($1/r$, $1/r^2$) of every point within the radius of influence. The radius of influence (local or global) and the power to the distance inverse function are considered the key factors in this method. In order to estimate an unknown value, there has to be enough sample points with a suitable spread. The value of predictor Z can be estimated as

$$Z_0 = \frac{\sum_{i=1}^{N} z_1 {d_1}^{-n}}{\sum_{i=1}^{N} {d_i}^{-n}} \tag{1}$$

Where
Z_0, estimated value of variable Z at point i.
Z_i, sample value at point i.
d_1, distance of sample point to estimated point, and lastly
n is a coefficient that determines weigh based on a distance.

One of the advantages of this method is its easy formulation but the drawback is that it does not take into account the regional effects in its formulation.

2.4. Residual Kriging

Kriging is a Geostatistical Interpolator. Kriging interpolation schemes are the fundamental tools in the field of spatial statistics developed by the founder of geostatistics, G. Matheron and named after D.G. Krige who proposed the technique for mining applications [26].

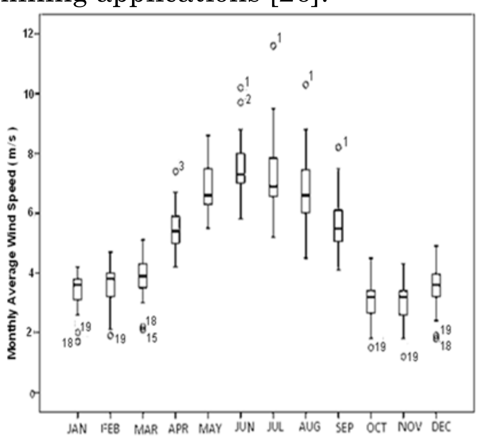


Figure 2 . Box-plot for whole Data set along the study region for each month average wind speed

A Krigingestimator needs a variogram for the spatial interpolation. A variogram is a measure of how quickly things change on the average. It is a graph which indicates the variance on y-axis against the value of distance (lag) on x-axis that is represented as h. Variogram is obtained using the expression,

$$\lambda(h) = \frac{1}{2(N-h)} \sum_{i=1}^{N-h} [z(x+h) - z(x)]^2 \qquad (2)$$

Mostly, Exponential, Spherical, Linear and Gaussian models are applicable models. Kriging uses a linear combination of weights at neighboring points to estimate values at other unknown points. The main difference between IDW and Kriging is that Kriging incorporates the basic concept of regionalization. It performs this with the help of semivariance estimator. Mathematically, the KRIGING function can be explained as to estimate a value of an unknown real-valued function, Z_v, at a point, (x, y), given the values of the function at some other points, $f(x1; y1); (x2; y2); (x3; y3)$ then Z_v, is estimated as follows

$$Z_V = \sum_{i=1}^{N} \lambda_i \, Zv_i \qquad (3)$$

λ_i is a dependent quantity weight of sample.
When there is a trend in the data, the ordinary kriging does not perform well, and sometimes produce results worse than those produced by deterministic methods. Two sorts of information are required for residual kriging. An estimate of trend as well as an estimate of the variogram. In residual kriging, the first step is, a multiple linear regression between $z(x)$ and some topographical variables $a_i(x)$, giving

$$Z(\boldsymbol{x}) = Z^*(\boldsymbol{x}) + E(\boldsymbol{x}) = \sum \alpha_i a_i(x) + E(x) \qquad (4)$$

Where x belongs to the field where the observations a_i are accessible. The trend is calculated with the multiple regression models. The coefficients a_i are fitted using the ordinary least squares (OLS) procedure. When value of Z(x) is known, a residual inaccuracy r(x), can be defined as

$$r(x) = Z(\boldsymbol{x}) - Z^*(\boldsymbol{x}) \qquad (5)$$

The correlation between independent variables is selected with the stepwise regression procedure. After testing the MLR model it is made sure that the variable selection must be statistically and physically meaningful. The linear trend is subtracted from all data points, a Variogram of the residuals is formed without a trend, which is used in Kriging (residual kriging), and produces a map of $r^{\wedge}$ (***x*).** The final estimate Z ($\boldsymbol{x}$) is obtained by estimating $Z^*(\boldsymbol{x})$ and $r^{\wedge}$ ($\boldsymbol{x}$) separately on the kriging grid, and combining them:

$$\hat{z} = Z^*(\boldsymbol{x}) - r^{\wedge}(\boldsymbol{x}) \tag{6}$$

2.5 Evaluation procedure

The goal of this comparative effort is to determine which interpolator produces the most accurate depths in unmapped areas from the known datasets. Prediction Cross validation removes one data point from a sample and the remaining n–1 observation are applied to guess the missing data point [114]. A comparison is performed between the measured and the predicted value, this procedure is applied on the entire population. Cross validation is extremely effective when using randomly arranged, sparse datasets. Following scores were used

Mean error

$$ME = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]$$

Mean absolute error

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|z(x_i) - \hat{z}(x_i)|$$

Root mean square error

$$RMSE = [\frac{1}{N}\sum_{i=1}^{N}\left(z(x_i) - \hat{z}(x_i)\right)^2]^{1/2}$$

Normalized mean square error

$$NRMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left[\frac{z(x_i) - \hat{z}(x_i)}{\hat{\sigma}(x_i)}\right]^2\right]^{1/2}$$

Where “N” represents the number of stations used in the study. $Z(x_i)$ and $\hat{Z}(x_i)$ are the experimental and estimated values at point x_i and the Kriging variance for site x_i is $\sigma^2(x_i)$. The NRMSE would be one, if the model for the variogram is correct. Which means NMRSE is a gauge for the variogram model presentation.

3. Results and discussion

The residual Kriging methodology consists of two stages; in the first stage, the drift is removed from the observed wind speed values using explanatory variables. The drift or trend is estimated by a mathematical function. In the second step, the variogram of the residuals is computed in the typical way. The drift is added back to the computed residuals to generate the final result. The trend was calculated in terrain roughness and Latitude.

Table 1.Results of the multiple regression analysis for the Wind speed

Month	**Explained variance provided by the Terrain roughness(TR) alone and the Latitude(Lat) alone**		**linear regression parameters b1(TR), b2(Lat)**			**The explained variance of the model**
	R^2 (TR) %	R^2 (Lat.) %	b_1	b_2	c	R^2 %
January	68.7	2	-0.35	-0.36	11.9	0.72
February	74.7	2	-0.427	-0.397	13.8	0.78
March	64.7	1.2	-0.331	-0.4	13.4	0.677
April	77.4	5.6	-0.556	-0.255	11.07	0.79
May	74	2.2	-0.734	-0.089	10.86	0.74
June	76.1	3.5	-0.865	0.519	-6.41	0.783
July	51.6	6.7	-0.74	0.792	-13.2	0.556
August	73.3	2.1	-0.751	0.384	-3.5	0.743
September	76.1	4.9	-0.598	0.632	-10.7	0.796
October	73.6	3	-0.277	-0.149	6.3	0.742
November	56.1	2	-0.242	-0.245	6.7	0.582
December	50	3.4	-0.138	-0.173	8.4	0.508

3.2. Regression analysis

A multiple regression analysis was performed for all 12 months with the terrain roughness (TR) and Latitude (Lat) factor as independent explanatory variables. All stations were modeled. The model is represented by equation 7

$$Z = b_1 \text{ (TR)} + b_2 \text{ (Latitude)} + C \qquad (7)$$

Where Z is the predicted wind speed value, b_1 and b_2 are the multiple regression coefficients for every independent variable, and c the intercept. A step-wise process was used for the regression variable evaluation. A t-test was carried for the determination of model fitting significant at 5% level. The results of the multiple regression analysis for all stations dataset are shown in Table 1. The terrain roughness (TR) factor is found to be the strongest predictor, which is statistically important for all the months. This helpful variable, which is negatively correlated with the wind speed values, explains the variance from a minimum of 50% in December to a maximum of 77% in April. On the other hand, when Latitude (Lat) is also considered, the explained variance ranges from a minimum of 51% in December to a maximum value of 79.7% in April. Elevation was not found statistically significant.

3.3. Residual variograms

In this section, the semivariagrams for the residual kriging method is presented in Figure 3, for the months of January and June. The semivariagram is formed on the basis of residuals of the regression analysis. The linear trend model with topographical effect was deducted from all observations, and residuals were acquired. The residual were then utilized as input into the evaluation of the residual variogram. (i.e. the core variogram free of the trend). Monthly models and parameters for the residual variograms are specified in Table 2.

Table 2. Model and parameter for monthly residual Variogram after linear distending. Study area data is used. The results are used for Kriging (Residual Kriging) procedures.

Month	Model	Nugget (m^2 / S^2)	Range (Km)	Sill (m^2/S^2)
JANUARY	Spherical	0.028	70	0.128
FEBUARY	Spherical	0.04518	25	0.121
MARCH	exponentia	0.0131	30	0.3
APRIL	exponentia	0.0151	40	0.347
MAY	exponentia	0.0097	57	0.45
JUNE	Spherical	0.23	15	0.11
JULY	Spherical	0.0213	10	0.525
AUGUST	Spherical	0.027	35	0.45
SEPTEMBER	Spherical	0.0908	55	0.2
OCTOBER	Spherical	0.0497	12	0.0896
NOVEMBER	Spherical	0.0875	65	0.15
DECEMBER	Spherical	0.0411	50	0.06

3.4. Model evaluation

The monthly mean wind speed has been estimated using both the inverse distance weighting and the residual Kriging procedure. Model estimates are assessed in terms of the ME, MAE and RMSE. NRMSE is used only for RK method as the Kriging estimation errors.

3.5. Evaluation of Residual Kriging model

The evaluation of monthly wind speed for all 12 months is performed. Fig. 4.(A)- 4(B) show a comparison of the monthly measured and estimated wind speeds using Residual Kriging (RK) method for the months of January and June. Two months are selected for the study. Fig. 4(A) shows a comparison between observed and estimated wind speed for the month of January.

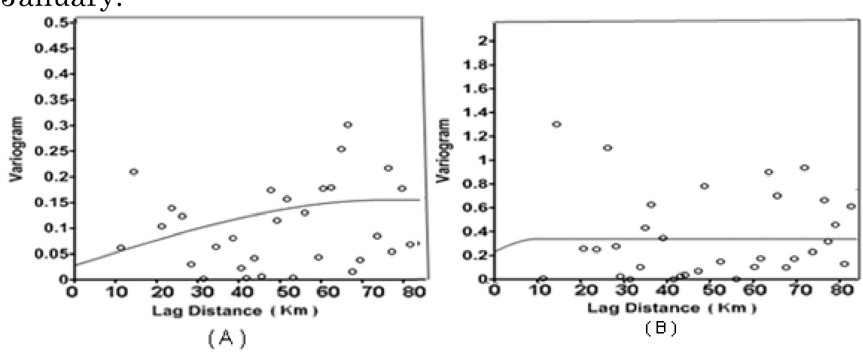


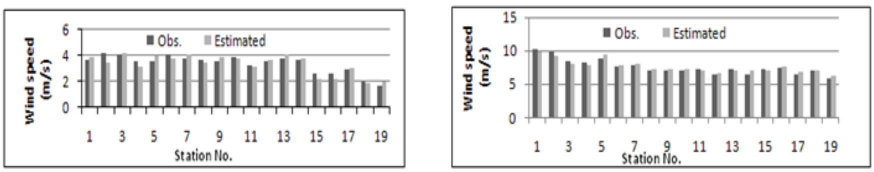
Figure 3. Variograms for the residuals data of the multiple regressions (a) January, (Spherical fitted model) (b) June (Spherical fitted model)

Overall the predicted values show good estimation; low values and higher values are predicted with small errors. Almost the same number of stations are over estimated, as the number of stations is under estimated. The data set used for the month of January has a minimum speed of 1.7 m/s and maximum wind speed of 4.2 m/s. The result obtained from this method shows that the minimum value is 1.8 m/s and maximum value of 4.25 m/s. The most under estimated station is Nooriabad (3.61m/s) and the most over estimated station is Golarchi (4.06m/s).

As illustrated in Fig.4 (B), the data set used for this method has a minimum speed of 5.8 m/s and maximum wind speed of 10.2 m/s. The result obtained from this method shows that the minimum value was 6.24 m/s and maximum value of 9.78 m/s. The most under estimated station was Talhar (6.48 m/s) and whereas the over-estimated station is Hyderabad (9.5 m/s). Although all stations are predicted with good agreement, but during summer season the accuracy is more compare to winter season. Table 3, shows the monthly validation results of the residual Kriging procedure. Negative ME indicates that forecasting has underestimated the observed values. Cross-validation gives up a minor bias error despite of the period. ME values shows an overall under estimation of wind speed values except for few months. The range of ME is noticeable. All the ME values are fairly low. MAE values range from 0.188 m/s in December to 0.426 m/s in July. The MAE value was approximately 5.5% for every months apart from November, when it raised to approximately 8.8%. The RMSE value ranges from 0.247 m/s in January to 0.549 m/s in July. The R^2 values show good results ranges from 90% to 67%. In current study, January, February and December show high values of NRMSE, the primary spatial variance of the random field was undervalued by the variogram and it was overestimated for the rest of months. Overall, NRMSE in the validation process shows values closer to one. This shows expectable accuracy of variogram.

3.6. Surface wind speed maps using Residual Kriging model

Figure.5-A and Figure 5-B, show the maps for monthly average wind speeds acquired with the residual Kriging method. Overall, the pattern presents a comparable spatial pattern and regionalization throughout the study region.



(A) (B)

Fig. 4. Comparison of Observed and estimated wind speed of Sindh for the month of (A) Jan (B)June, using RK

Table 3. Results of Validation for residual Kriging. Scores are given in m/s except for NRMSE and R ^{2} which has no dimension.

Month	ME	RMSE	MAE	MAE %	NRMSE	R^2
January	0.0429	0.247	0.216	6.30%	1.5	0.885
February	-0.003	0.275	0.212	6.00%	1.4	0.852
March	-0.018	0.473	0.399	7.40%	1.38	0.677
April	-0.016	0.418	0.3539	6.40%	1.34	0.75
May	-0.003	0.479	0.399	5.80%	1.19	0.732
June	-0.014	0.421	0.32	4.20%	1.21	0.854
July	-0.028	0.549	0.426	5.70%	1.09	0.858
August	-0.026	0.488	0.375	5.50%	0.81	0.856
September	0.019	0.431	0.369	6.50%	1.3	0.826
October	-0.001	0.2708	0.208	6.90%	1.2	0.866
November	-0.007	0.327	0.256	8.80%	1.36	0.832
December	0.021	0.252	0.188	5.50%	1.85	0.901

The method captured the spatial and seasonality variability very well. The extension of some areas such as Gharo, Shah Bandar and Thatta with high value of wind speed is greater. There is no bull's eye and the biasness in estimation is shown in few areas such as Karachi, this being due to the fact that it is an urban area, and requires more parameters for further explanation. For the area around Hyderabad, where the stations are sparse and numbers of stations are few, some details are missing.

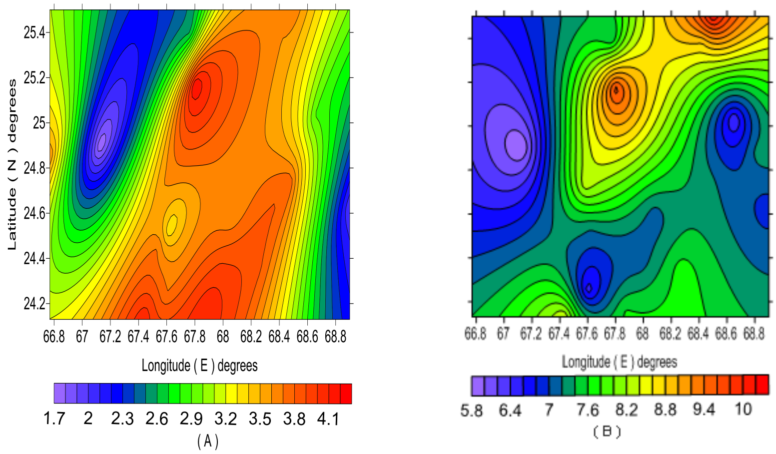


Figure 5.Wind speed (m/s) maps obtained by Residual Kriging procedure for (A) Jan(B) June

The noticeable thing about the map is that residual Kriging provides less homogeneous distribution, which means a higher spatial variability of wind speed, particularly in the central region of study area (Sindh). This indicates that residual Kriging has captured the regionalization more effectively. The regression Kriging model was able to capture a lot of variations in the field.

3.7. Inverse Distance Weighting (IDW) model evaluation

IDW is widely used to interpolate climatic data. The IDW parameters define in Surfer are the search radius, power selection, number of points and anisotropy. IDW was projected with powers of 1, 2, 3 and 4. The choice of the quantity of the closest samples used for estimation, also have an effect on the accuracy of IDW. Use of basic statistics for predetermination of interpolation methods and their parameters have many conflicting reports. [27] The report for high skewness (>2.5) power of four gives good estimates. Alternatively, Weber and Englund [28] reported that, with skewness coefficients in the range of four to six, IDW gives better estimates with a power of one. Similarly, a larger exponent formed better estimations when the data had low skewness. To find the best agreement among the measured data and the IDW results, Cross-validation procedure was used. The best weighting parameter was two. Power of 2 was set due to the sparse and irregularly spaced sampled locations. After further experimenting with different combinations of available options, the search radius and anisotropy was selected. Maximum numbers of points of 19 were used. IDW showed a regular but inadequate estimation for wind speed data. In this section, a comparison between observed and predicted monthly wind speeds for all twelve months is presented. Inverse Distance Weighting method is used for prediction. Figure 6.-A and Figure 6.-B show these comparisons.

As illustrated in the Figure 6.A, overall the predicted values are typically not closer to the measured values. The data set used for this month has a minimum speed of 1.7 m/s and maximum wind speed of 4.2 m/s. The results obtained from this method show that the minimum estimated value was 2.84 m/s and the maximum value - 3.78 m/s. The most under-estimated station was Nooriabad (3.09 m/s), while Karachi station was most over-estimated (3.59 m/s). The distribution of residuals is not normal, with a mean value of 0.05.

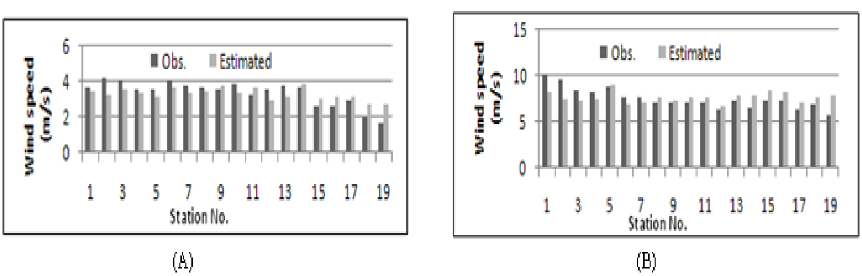


Figure 6. Comparison of Observed and estimated wind speed of Sindh for the month of (A) January (B) June, using IDW.

Table 4. Evaluation results of the IDW procedure. Units are all in m/s except the R^2 coefficient

Month	ME	RMSE	MAE	R^2
January	-0.047	0.723	0.529	0.02
February	-0.018	0.75	0.564	0.001
March	-0.00137	0.871	0.685	0.015
April	0.025	0.97	0.783	0.121
May	-0.021	1.05	0.8	0.017
June	-0.21	0.95	0.743	0.15
July	-0.057	1.14	0.899	0.153
August	-0.074	1.08	0.864	0.063
Septembe	-0.041	0.816	0.613	0.258
October	-0.0177	0.76	0.578	0.1
Novembe	-0.038	0.813	0.597	0.002
Decembe	-0.055	0.705	0.52	0.107

As illustrated in the figure 6(B), overall the predicted values are showing better performance as compared to previous months. Although low values and higher values are not predicted very well, this still shows reasonable values. The data set used for this month has a minimum speed of 5.8 m/s and maximum wind speed of 10.2m/s. The results obtained from this method show that the minimum value is 6.95 m/s. while the maximum value is 9.22 m/s. The most under-estimated station was Katibander (7.41 m/s) and Karachi station was most over-estimated (6.03 m/s).

Table 4 shows the results of error analysis. This shows that IDW underestimates overall, the wind speed, except April. ME ranges from -0.0013 m/s in March to 0.025 m/s in April. Additionally, the estimates show strong bias, regarding the RMSE, values ranging from 0.705 m/s in December to 1.14 m/s in July. The coefficient of determination R^2 is very low.

3.8 Surface wind speed maps using Inverse Distance Weighting

Figure 7 A and Figure 7 B show the estimated monthly average wind speeds maps based on the IDW procedure; they shows variability, associated within sparse areas, isolated points applying a weight in every direction which lessens consistency and leads to typical 'bull's eye' patterns in the projected wind surface. The monthly variation is clear in the maps with highest values in July and lowest values in January.

3.9 Comparative study of IDW and RK interpolation methods

A comparative study is carried out by estimation Errors (ME, MAE, RMSE) and the Correlation coefficient R^2. Both methods under estimate almost all stations, which is reflected by ME values. Residual Kriging shows lowest values of MAE over the whole year (0.188 m/s to 0.426 m/s) as compared to IDW (0.52 m/s to 0.899 m/s). The performance of RMSE shows approximately more than 60% relative improvement. The Residual Kriging method showed clear superiority over other method, which is evident in RMSE values. A similar comparison reveals that the Kriging method also supersedes the other method, in RMSE with 0.247 m/s to 0.549 m/s (with more than 71% improvement). The unmatched improvement is found in R^2. Generally, for the southern part of Sindh, the Kriging standard deviations were lesser than compared to the northern part. This was due to comparatively few of meteorological stations in this part. The standard Deviations for RK were the smallest, where numbers of stations are good, and largest for the area with the smallest number of stations. It was also large in some areas close to the urban coastal regions, such as Karachi and for the summer season (June, July and August).

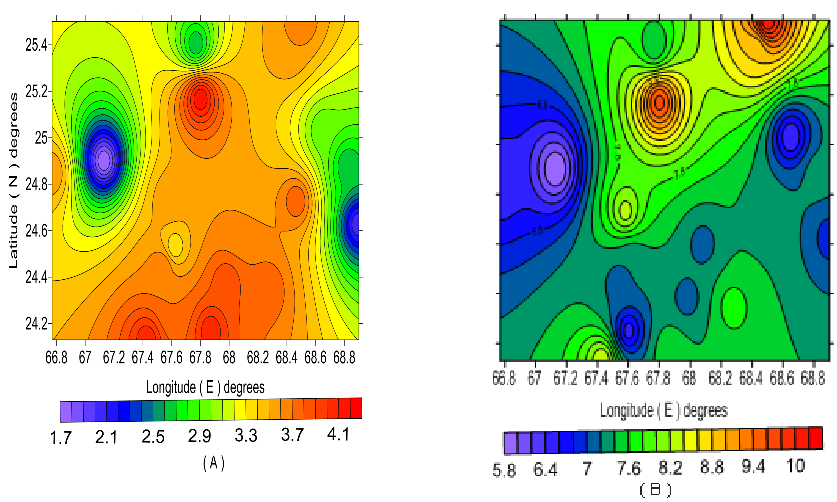
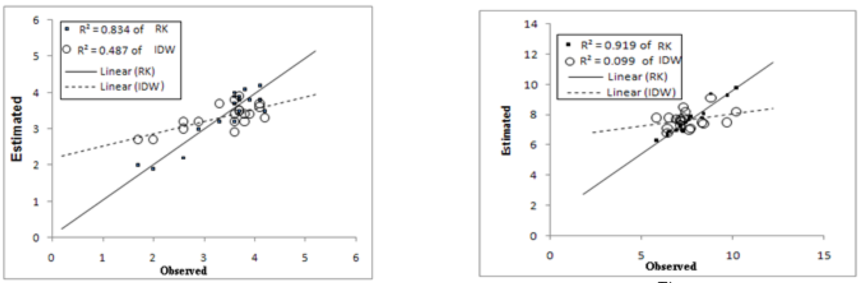


Figure 7. Wind speed (m/s) maps obtained by Inverse Distance Weighting procedure for (A) Jan and (B) June

Scatter plots of the observed against predicted wind speed values, using both the Residual kriging (RK) and Inverse distance weighting (IDW) methods are shown in Figure 8, for January.



(A) (B)

Fig. 8. Scatter plots of the observed and predicted wind speed, using both the Residual kriging (RK) and Inverse distance weighting (IDW) methods, (A) for January (B) for June.

The residual kriging wind speed estimate fits fairly fine with the observed values; as compared to IDW method (Fig. 8) the residual kriging provides better estimates.

4. Conclusion

Two different procedures have been evaluated, residual Kriging and IDW. Two techniques have shown diversity in predicting the wind speed values in the study region, of Sindh (Pakistan). This study reveals that residual Kriging interpolation technique is far better than inverse distance weighting technique for producing continuous wind speed surface. IDW is a precise interpolator, so high unpredictability in the contributed data accordingly generate a rougher surface, which may lead to unrealistically sharp gradients in regions with fewer station exposure. Both methods comparatively showed better performance for winter months than for the summer months. Also the estimations are better for lower values of the wind speed. In general, the Residual Kriging technique is able to offer good estimation of the wind speed in Sindh (one of the province of Pakistan), with RMSE ranges from 0.72m/s in January (winter) to around 1.14 m/s in July (summer) and MAE rages from 0.52 m/s to 0.89 m/s. By incorporating external information in the interpolation procedure, estimations of the residual Kriging give lesser errors than the IDW, with all month showing R2 values above 0.7. The error analysis depicts that the RK method is a more sophisticated interpolation technique than IDW. The kriging maps demonstrated more details than IDW maps. However, due to a lack of meteorological stations, interpolated results underestimate or overestimate larger wind speed. Additional research is recommended to investigation, whether other parameters, could produce a better estimation of wind speed for the study region. Overall, Rk has proven to be very useful for mapping wind speed. To conclude, all estimation measures consistently recognized Residual Kriging (RK) as the most excellent method for interpolating surfaces. The main utility of the wind speed estimation techniques is in the field of environmental study and renewable energy applications.

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