MATHEMATICS/STATISTICS

Isotropic and Anisotropic Variogram Models for Interpolating Monthly Mean Wind speed Data of Six Selected Wind Stations in Nigeria

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Abstract

Mean Wind speeds often exhibit directionality in which they are increasing or decreasing across a surface; however, microclimatological effects sometimes produce high or low wind speed over a surface that can create confusion during kriging surface construction. The aim of this study was to investigate the appropriateness of anisotropic variogram models within ordinary kriging for interpolation of monthly mean wind speed data of six selected wind stations which include: Sokoto, Maiduguri, Ilorin, Ikeja, Port Harcourt and Enugu in Nigeria. Four types of isotropic and anisotropic variogram models were fitted: Linear, Spherical, Exponential, and Gaussian. Each model was described using the following parameters: the nugget variance, the sill, and the range. Three statistics to aid the interpretation of model output: the residual sum of square (RSS), R^2 and proportion $C/(C_0+C)$ were provided to give the best fitted model for each wind station. The study found that the six wind stations could be best fitted by linear, Gaussian and exponential anisotropic models. Sokoto wind speed showed the strongest spatial distribution (>7.8 m/s), Maiduguri and Enugu, Ikeja and Port Harcourt showed similar wind speed patterns (3.1-4.0) m/s and (2.1-3.0) m/s respectively whereas Ilorin showed a pattern of low wind speeds (<2.0m/s) . These results may assist in identifying wind stations that are suitable for exploitation of wind energy for electricity generation as well as in mitigating losses to structures due to excessive wind events.

Keywords: Anisotropic, geostatistics; semi variance, wind speeds, Nigeria,

1. Introduction

Wind is the horizontal motion of air that pass through a given point in a location and includes the direction from which the wind is coming from. Wind speed is the description of how fast the air is moving at certain point in a location. This is sometimes measured in meters per second. Wind speed, wind direction, air temperature, atmospheric pressure, humidity and solar radiation are important for monitoring and predicting weather patterns. Each of these parameters have numerous impact on the weather and quality of life. Almost every impact of climate variation involves wind speed either directly or indirectly (Abhishek *et al*, 2010; Tuller, 2004). For instance, one of the ways that air temperature variations affect objects and living organisms is through sensible heat flux density, which is a function of wind speed. According to Troccoli *et al*, (2012), accurate estimates of long-term linear trends of wind speed provide a useful indicator for circulation changes in the atmosphere and are invaluable for the planning and financing of wind energy.

Researches have showed that there have been comparisons of interpolation methods for temperature and precipitation, (Phillips *et al*., 1992; Collins and Bolstad, 1996; Goovaerts, 2000; Price *et al*., 2000; Jarvis and Stuart, 2001; Vicente-Serrano *et al*., 2003) few research efforts have been directed towards comparing the effectiveness of different spatial interpolators in predicting wind speed. Wind speed surface interpolation results suggest that deterministic methods should be avoided because they fail to account for spatial autocorrelation (Bentamy *et al*. 1996; Phillips *et al*. 1997; Sterk and Stein 1997; Venäläinen & Heikinheimo 2002; Oztopal 2006, Cellura *et al*. 2008; Luo *et al*. 2008; Zlatev *et al*. 2009; Akkala *et al*. 2010; Zlatev *et al*. 2010) and various forms of kriging have been shown to outperform other methods for interpolation of surface-level wind speeds (Lanza *et al*. 2001; Luo *et al*. 2008; Akkala *et al*. 2010; Zlatev *et al*. 2010). Although kriging has been shown to improve interpolation results, most previous studies that examined kriging focused on local- to regional-scale wind surfaces within a single country.

Kriging uses probability and spatial correlation to create a surface that is weighted by observed values through a distance and direction based semivariance function that can account for anisotropic spatial patterns and trends in wind behaviour (Luo *et al*. 2008). Isotropy (uniform values in all directions) is assumed during the kriging process unless anisotropy is specified. Consequently, comparisons between isotropic and anisotropic semivariogram-derived surfaces are not often made. Thus far, the use of anisotropy within kriging has been shown to be superfluous for local- and regional-scale modelling, although Luo *et al.* (2008) hypothesized that it may be more useful for meso- and macro-scale modelling.

In addition to issues of scale and anisotropy, the impact of heterogeneous terrain (or geographic diversity) on wind speed interpolations is also poorly understood. Etienne and Beniston (2012) examined extreme station data (i.e. top 10% of wind speeds) for wind storms in Europe using 'basic' kriging. The results found that topography greatly influences wind speeds and likely contributed to error effects not normally seen in interpolations of larger areas. Additionally, Zlatev *et al.* (2010) divided the United Kingdom into five areas of homogenous terrain to analyse wind speed interpolations and reduce the potential impact of over-smoothing and over fitting. Joyner *et al.* (2015) used cokriging to interpolate wind speeds for multiple European windstorms to account for errors associated with aspect, elevation, and land cover, further alluding to an impact of geographic diversity on wind speed interpolations.

The aim of this study was to investigate the appropriateness of anisotropic variogram models within ordinary kriging for interpolation of monthly mean wind speed data of six selected wind stations which include: Sokoto, Maiduguri, Ilorin, Ikeja, Port Harcourt and Enugu in Nigeria. Different theoretical models such as linear, spherical, exponential, and Gaussian were fitted to determine the best fitted model and finally, draw wind speed spatial distribution maps for each wind station.

2. Materials and Methods

2.1 Study Area and Data Used

Nigeria co-ordinates on latitude 10.00°N and longitude 8.00°E. The climate is tropical; humid in the south and semi-arid in the north. It comprises various ecotypes and climatic zones. There are two main seasons, namely, rainy and dry seasons. The rainy season lasts from March to November in the south and May to October in the north. During December to March, the Nigerian climate is entirely dominated by the north east trade winds, locally called "harmattan", which originate from Sub-Tropical Anticyclones (STA).This "harmattan" is associated with the occurrence of thick dust haze and early morning fog and mist as a result of radiation cooling at night under clear skies. The climate is dominated by the influence of Tropical Maritime (TM) air mass, the Tropical Continental (TC) air mass and the Equatorial Easterlies (EE) (Ojo, 1977) in (Abiodun *et al*, 2011).

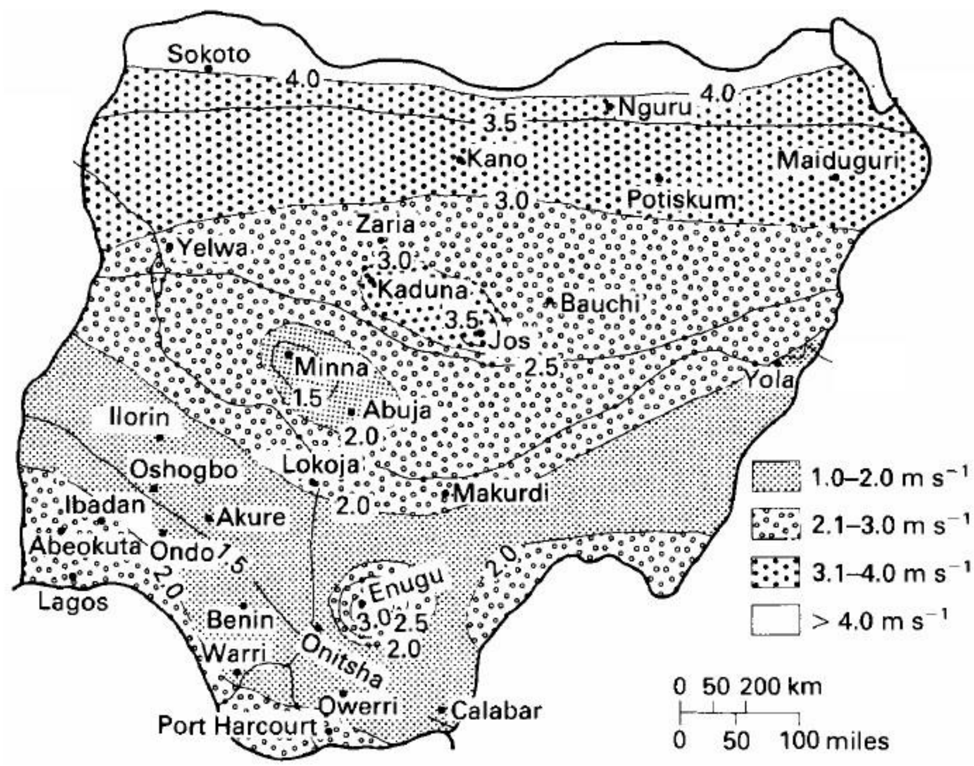


Figure 1**:** Nigeria annual average wind speeds distribution (isovents at 10 m height) showing four different wind speed regimes (Source: Ojosu and Salawu, 1990b)

The monthly mean wind speed data were obtained from archives of the Nigerian Meteorological Agency (NIMET) Oshodi, Lagos, Nigeria. The data obtained covered a period of twenty-six years (1990-2015) for six stations which include: Sokoto, Maiduguri, Ilorin, Ikeja, Port Harcourt and Enugu wind stations. Figure 1 is the map of Nigeria showing the anemometer stations used in the study Some missing entries were observed in the monthly wind speed data and were not replaced. Only one station got some missing observations. In geostatistics, data in the worksheet that are marked as missing are ignored during data builds and subsequent analyses. These values can be overridden by values specified. Permanent missing values appear as blank cells. The default missing value indicator (MVI) is the numeric value -99.0 but this can be changed in the user preferences window. Missing values appear in output files when a value cannot be interpolated because the location appears in an exclusive polygon or because numerical limitations disallow its computation (such as when a variogram model is inappropriately used during kriging). The examination of the monthly wind speed data indicated that they were not significantly different from a normal distribution (Figure 2).

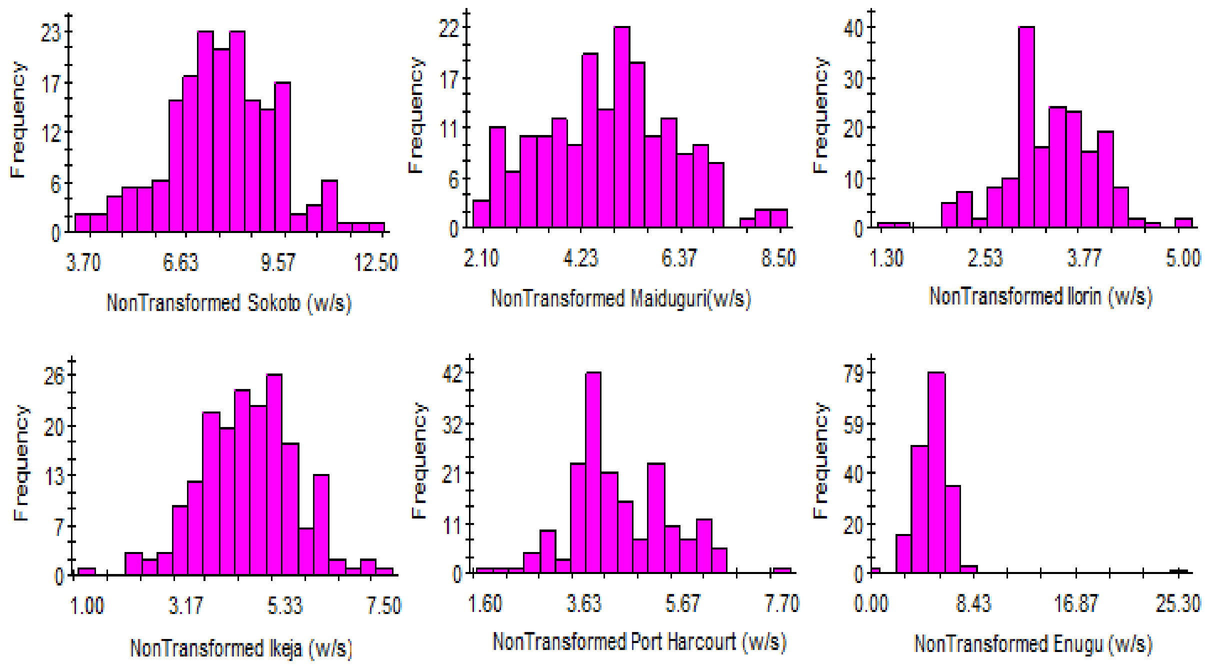


Figure 2: Non transformed frequency distribution for the six selected wind stations

2.2. Geostatistical methods

2.2.1. Kriging

Kriging (Krige, 1966) is a stochastic technique similar to IDW, in that it uses a linear combination of weights at known points to estimate the value at an unknown point. Kriging weights are derived from a statistical model of spatial correlation expressed as semivariograms that characterize the spatial dependency and structure in the data. During surface construction, ordinary kriging was chosen to interpolate wind station data based on its superiority over other techniques (Luo *et al.* 2008; Akkala *et al.* 2010; Zlatev *et al.* 2010; Luo *et al.* 2011). Ordinary kriging is represented as

$$Z^*_{OK}(s_0) = \begin{cases} \sum_{i=1}^{n} \lambda_i Z(s_i) \\ \sum_{i=1}^{n} \lambda_i = 1 \end{cases} \tag{1}$$

where, $Z^*_{OK}(s_0)$ is the spatial location s_0; s_i is the location of measurement i; n is the number of observations to consider and λ_i is a real weight.

2.2.2. Semivariance Analysis of Wind Speed Interpolation

In contrast with deterministic methods, kriging provides a solution to the problem of estimation of the surface by taking account of the spatial correlation. The spatial correlation between the measurements points can be quantified by means of the semi-variance function: The experimental variogram measures the average degree of dissimilarity between un-sampled values and a nearby data value and consequently can depict autocorrelation at various distances. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half of the average squared difference between the value at $z(x_i)$ and the value at $z(x_i + h)$ (Robinson and Metternicht, 2006):

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \tag{2}$$

where $N(h)$ is the number of data pairs of measurement points with distance h apart. Using an analysis of experimental variogram model of ordinary kriging, a suitable four isotropic and anisotropic variogram models were fitted by different theoretical models such as spherical, exponential, linear, or Gaussian to determine three semivariogram parameters: the nugget (C_0), the sill (C_0 + C), and the range (A).

2.2.3 Accounting for Directional Influences— Anisotropic Variogram Models

There are two types of directional components that can affect the predictions in output surface: global trends and directional influences on the semivariogram or covariance (known as anisotropy). A global trend is an overriding process that affects all measurements in a deterministic manner. The global trend can be represented by a mathematical formula (e.g., a polynomial) and removed from the analysis of the measured points but added back in before predictions are made. This process is referred to as detrending

The shape of the semivariogram or covariance curve may also vary with direction (anisotropy) after the global trend is removed or if no trend exists. Anisotropy differs from the global trend because the global trend can be described by a physical process and modelled by a mathematical formula. The cause of the anisotropy (directional influence) in the semivariogram is not usually known, so it is modelled as random error. Even without knowing the cause, anisotropic influences can be quantified and accounted for.

Anisotropy is usually not a deterministic process that can be described by a single mathematical formula. It does not have a single source or influence that predictably affects all measured points. Anisotropy is a characteristic of a random process that shows higher autocorrelation in one direction than in another. For anisotropy, the shape of the semivariogram may vary with direction. Isotropy exists when the semivariogram does not vary according to direction. Isotropic variogram is a graph of semivariance against. separation distance. Where autocorrelation is present, semivariance is lower at smaller separation distances (autocorrelation is greater). This typically yields a curve such as that described in this analysis,

Anisotropic variogram models are similar to those for isotropic variograms but include directional information in the range parameter. Anisotropy refers to a direction-dependent trend in the data. The study used geometric anisotropy, i.e. anisotropy which is expressed as variograms with different ranges in different directions. The principal anisotropic axis (the major axis of the anisotropic model) is the direction with the longest range, i.e. the direction of major spatial continuity. The best way to evaluate anisotropy is to view the anisotropic semivariance surface (variogram map), and use the azimuth function to define and then set the principal anisotropic axis to the direction aligned with the lowest semivariance values (the direction of maximum spatial continuity, or major axis of the anisotropic variogram model). Anisotropic semivariograms were created during the interpolation procedure to account for directional dependence of wind speeds at varying distances, creating a spatial relationship for each direction that cannot be described by a single formula.

The principal axis is the direction of maximum spatial continuity, or base axis from which the offset angles for anisotropic analyses are calculated. Offset angles in this study are 0º, 45º, 90º, and 135º clockwise from the base axis; points aligned sufficiently close to one or another of these angles are included in the anisotropic analysis for that angle. The axis orientation should correspond to the axis of maximum spatial continuity, i.e. the major anisotropic axis. The default axis is 0º from the north-south (y) axis.

In anisotropic analyses, the offset tolerance determined how closely the alignment between any two points needs to be for those points to be included in the analysis for a given offset angle. Two points will be included in the analysis for a given offset angle if the angle between them is within the offset tolerance from the offset angle. For example, if the angle between two points is 59.3º and the offset tolerance is 15.0º, the points will be included only in the 45º angle class, which would include all angles between 30º and 60º. The default tolerance is 22.5º.

3.0 Results and Discussions

3.1 Descriptive Spatial Statistics

The descriptive spatial statistics of monthly wind speeds for six selected stations are given in Table 1. The calculated spatial statistic included mean centre, standard distance (S_D), minimum and maximum, relative distance (R_D), skewness and kurtosis. The relative distances (R_D) of 66.00%, 50.73% and 50.30% were stronger, which indicated high spatial variability of wind speed for Sokoto, Maiduguri and Enugu stations respectively. While Port Harcourt, Ikeja and Ilorin stations indicated low spatial variability with R_D of 44.95%, 40.52% and 37.70% respectively. Sokoto in the northwest indicated the windiest station with spectacular mean centre wind speeds of 7.02 m/s. Maiduguri and Enugu are in the same mean centre region between 3.44 to 3.56 m/s and Ikeja and Port Harcourt are in the same region between 3.32 to 3.37 m/s. The monthly mean of the wind speed are relatively low in the south west cities of Ilorn (2.34m/s). Studies on the wind speed pattern across Nigeria by Adekoya and Adewale (1992) based on wind data from 30 meteorological stations and Fagbenle and Karayiannis (1994) based on wind data for 18 stations and from 1979-1988 were consistent with current study. Fagbenle and Karayiannis (1994) specifically mentioned that average wind speeds in Nigeria range from about 2 m/s to about 4 m/s with highest average speeds of about 3.5 m/s and 7.5 m/s in the south and north areas, respectively.

Table 1: Descriptive Spatial Statistics for the Six Selected Wind Stations

Station	**Mean Center**	**S_D**	**Min**	**Max**	**R_D (%)**	**Skew**	**Kur**
Sokoto	7.021	4.634	3.70	12.50	66.002	0.000	0.180
Maiduguri	3.566	1.809	2.10	8.50	50.729	0.120	-0.490
Ilorin	2.341	0.906	1.30	5.00	37.701	-0.350	0.670
Ikeja	3.329	1.349	1.00	7.50	40.522	-0.130	0.430
Port Harcourt	3.373	1.516	1.60	7.70	44.945	0.290	0.190

Enugu	3.447	1.734	0.00	5.30	50.304.	-0.05	0.791

The variations of wind speed across the six stations are due to some roughness of the environment surrounding the stations, variations in the height and position of anemometers, and atmospheric forcing (atmospheric circulation) changes also produce substantial effects. Bichet *et al.* reported that increasing the vegetation roughness length caused by increasing vegetation decreases the land wind speed. Wind speed tend to be higher at well exposed sites than at stations in the vicinity of forests, hills, mountains and other intervening structures such as high rise buildings. The results observed here is expected since the north belongs to the arid and semi-arid ecotypes while the south is dominated by mangrove, swamp forests, tropical rainforests and guinea savanna tall grasslands Bichet *et al*, 2012.

Table 2: Best-fit Isotropic Variogram Models for the Six Selected Wind Stations

Station	**Best-fit Model**	**Nugget (C_0)**	**Sill (C_0+C)**	**Range A**	**RSS**	**R^2**	**C/(C_0+C)**
Sokoto	Spherical	0.1850	2.6860	0.1560	0.618	0.173	0.931
Maiduguri	Exponential	1.475	4.2880	18.0270	0.547	0.718	0.656
Ilorin	Exponential	0.0630	0.3910	0.1060	0.029	0.000	0.839
Ikeja	Spherical	0.0640	1.0940	0.1420	0.085	0.101	0.941
Port Harcourt	Linear	1.0175	1.0175	2.7480	0.059	0.000	0.000
Enugu	Spherical	0.0010	2.4550	0.2400	0.840	0.098	1.000

In order to fit the best isotropic and anisotropic variogram models, three statistics to aid the interpretation of model output was provided in Table 2 & 3: residual sums of squares (RSS)–provides an exact measure of how well the model fits the variogram data; the lower the reduced sums of squares, the better the model fits. When isotropic and anisotropic variogram models were fitted, RSS chooses parameters for each of the variogram models by determining a combination of parameter values that minimizes RSS for any given model. R^2–provides an indication of how well the model fits the variogram data; this value is not as sensitive or robust as the RSS value for best-fit calculations. And proportion $C/(C_0+C)$ -- this statistic provides a measure of the proportion of sample variance (C_0+C) that is explained by spatially structured variance C. This value will be 1.0 for a variogram with no nugget variance (e.g. Enugu was one indicating the nugget variance is zero where the curve passes through the origin); conversely, it will be 0 where there is no spatially dependent variation at the range specified, (e.g. Port Harcourt was zero indicating no spatially dependent variation where there is a pure nugget effect (Table 2).

Table3: Best-fit Anisotropic Variogram Models for the Six Selected Wind Stations

Station	**Best-fit Model**	**Nugget (C_0)**	**Sill (C_0+C)**	**Range A**		**RSS**	**R^2**	**C/(C_0+C)**
				Minor	**Major**			
Sokoto	Linear	2.6430	5.9878	11710.00	11711.00	10.50	0.171	0.559
Maiduguri	Gaussian	1.6520	8.3502	10.636	11.135	11.50	0.406	0.802
Ilorin	Exponential	0.3600	0.9560	29.910	92.640	0.217	0.134	0.623
Ikeja	Gaussian	1.0580	3.5710	16.731	24.872	2.710	0.150	0.704
Port Harcourt	Gaussian	0.9950	2.9240	10.895	21.806	1.980	0.243	0.660
Enugu	Gaussian	2.4230	11.209	911.578	911.578	1.450	0.059	0.784

The study used RSS to judge the effect of changes in model parameters. For isotropic models, spherical model was found to be the best fitted for Sokoto, Ikeja and Enugu with RSS values 0.618, 0.085 and 0.840 respectively; whereas spatial structures of Maiduguri and Ilorin were best fitted by the exponential model with RSS values 0.0.547 and 0.0.029 respectively and linear model was best fitted for Port Harcourt with RSS value 0.059 (Table 2). The corresponding isotropic variograms were given in figure 3 below.

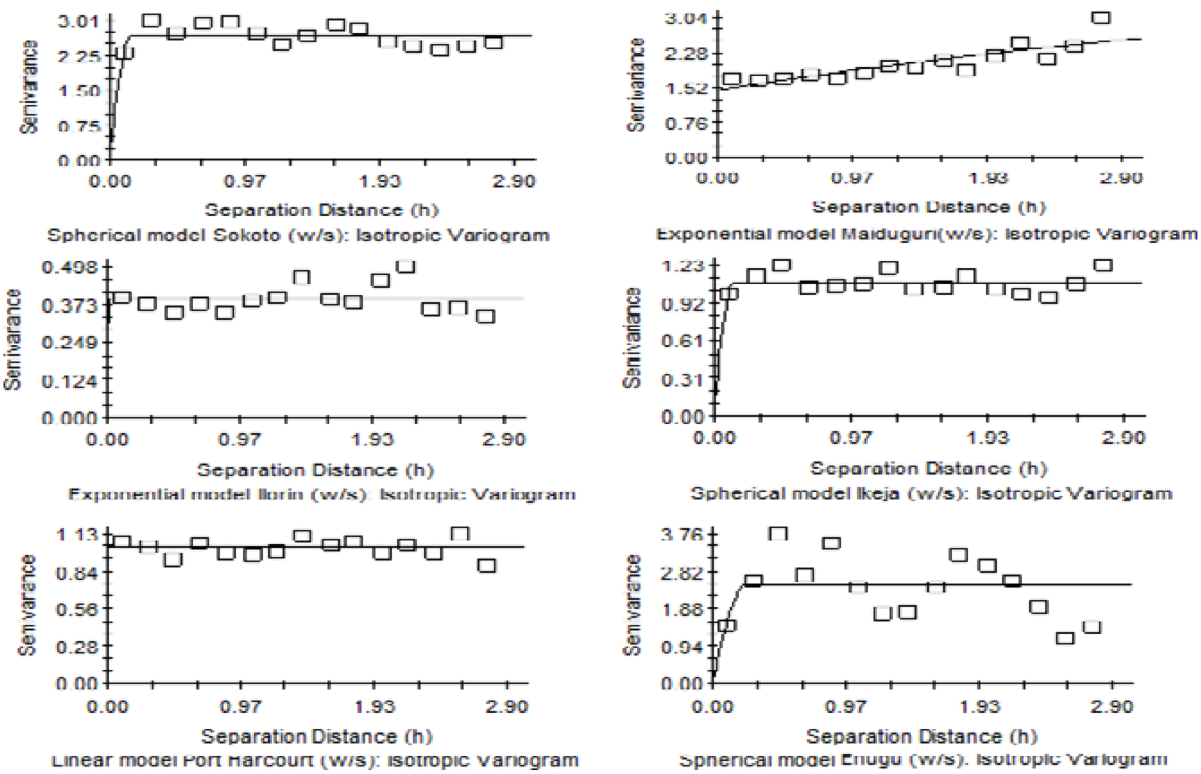
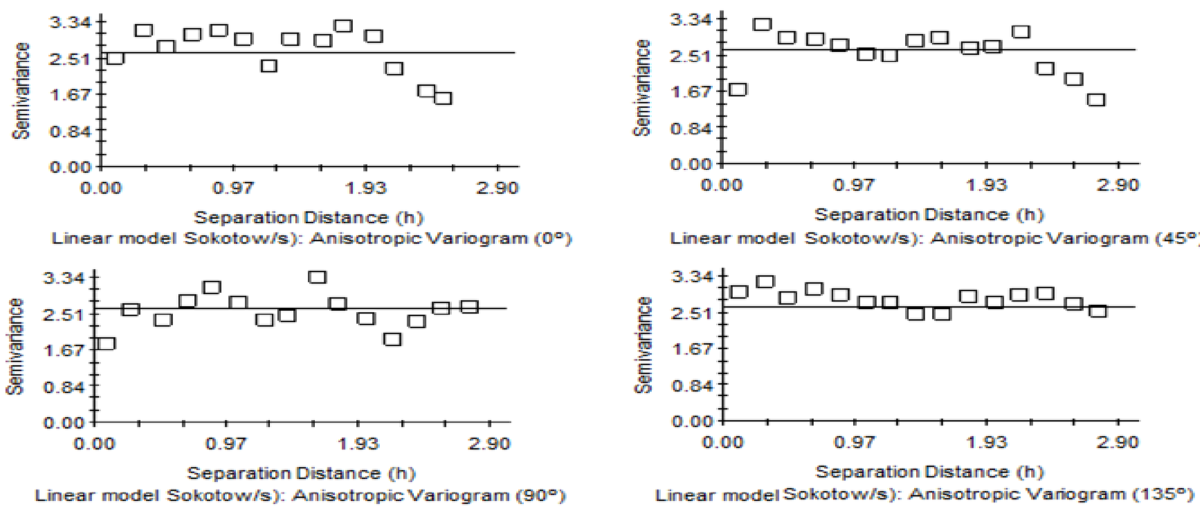
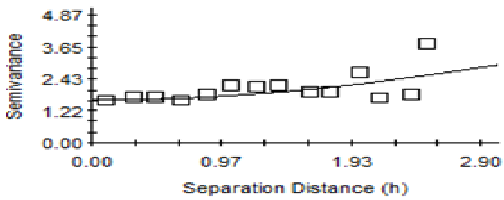


Figure 3: Best fitted Isotropic Variograms for the Six Selected Wind Stations

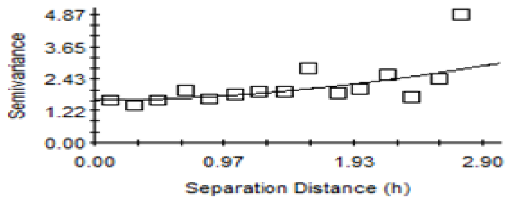
In other hand, for anisotropic models, linear model was found to be the best fitted for Sokoto, with RSS value 10.50; whereas spatial structures of Maiduguri, Ikeja, Port Harcourt and Enugu were best fitted by the Gaussian model with RSS values 11.50, 2.710, 1.980 and 1.450 respectively and exponential model was best fitted for Ilorin with RSS value 0.217 (Table 3).

The anisotropic variograms were fitted in four different directions. For consistency, the angles in the semivariances are between 0º and 180º, so that a value greater than 180º will appear as that value less 180º (e.g. 225º will be opposite of 90º in the semivariance). The nugget variance is the semivariance intercept of the model and can never be greater than the sill. The best-fitted isotropic and anisotropic models have low nugget variances (Figure 3 & 4). The range is the separation distance over which spatial dependence is apparent and cannot be less than 0. All values of range were greater than or equal to 0.1060m for isotropic variogram models (Table 2) and greater than or equal to range value from 10.636m to 11.135m for anisotropic variogram models (Table 3). Therefore, all the six selected wind stations had a range value greater than zero indicating existence of a spatial structure for them (Figure 3 & 4). In addition, the ordinary kriging with anisotropic produced an outline map of each wind speed within the larger interpolation grid area. Based on the Nigeria wind speeds classification, winds are classified into four different regimes: very low wind speeds (1.0-2.0 m/s), low wind speeds (2.1- 3.0 m/s), high wind speeds (3.1-4.0 m/s) and very high wind speeds (> 4.1 m/s). High wind speeds appeared in yellow and low wind speeds appeared in blue (Figure 4). The spatial distributions of Sokoto wind speed is stronger (>7.8m/s), Maiduguri and Enugu showed similar wind speed patterns (3.1-4.0m/s) and the spatial distribution of Ikeja and Port Harcourt is between (2.1-3.0m/s) whereas Ilorin showed a pattern of low wind speeds (<2.0m/s).

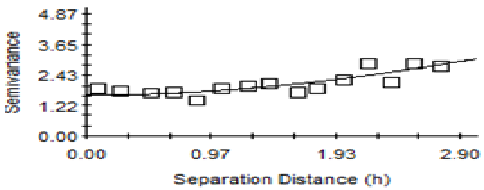




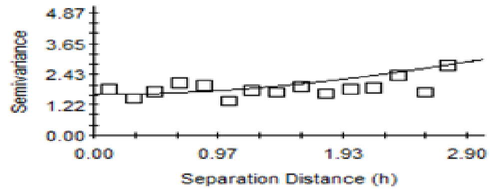
Gaussian model Maiduguri(w/s): Anisotropic Variogram (0°)



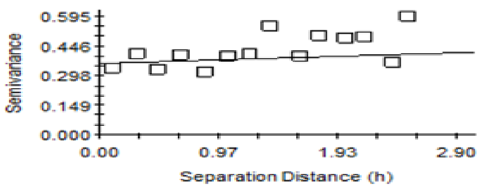
Gaussian model Maiduguri(w/s): Anisotropic Variogram (45°)



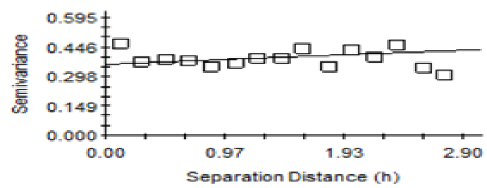
Gaussian model Maiduguri(w/s): Anisotropic Variogram (90°)



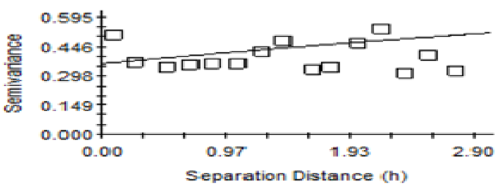
Gaussian model Maiduguri(w/s): Anisotropic Variogram (135°)



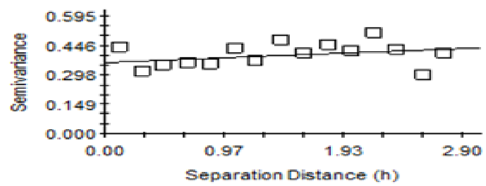
Exponential model Ilorin (w/s): Anisotropic Variogram (0°)



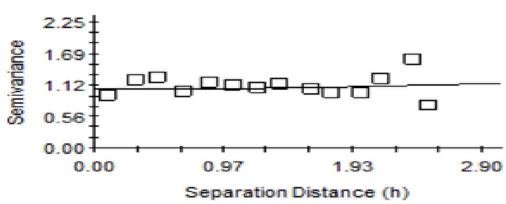
Exponential model Ilorin (w/s): Anisotropic Variogram (45°)



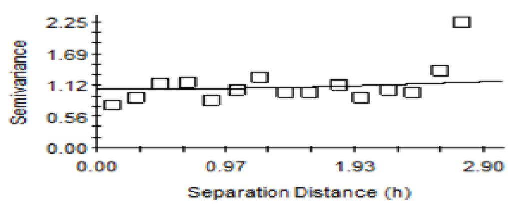
Exponential model Ilorin (w/s): Anisotropic Variogram (90°)



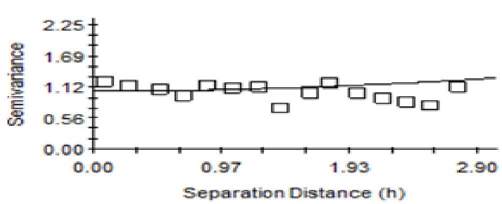
Exponential model Ilorin (w/s): Anisotropic Variogram (135°)



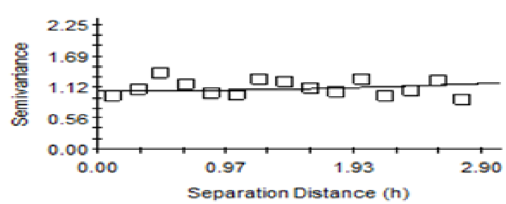
Gaussian model Ikeja (w/s): Anisotropic Variogram (0°)



Gaussian model Ikeja (w/s): Anisotropic Variogram (45°)



Gaussian model Ikeja (w/s): Anisotropic Variogram (90°)



Gaussian model Ikeja (w/s): Anisotropic Variogram (135°)

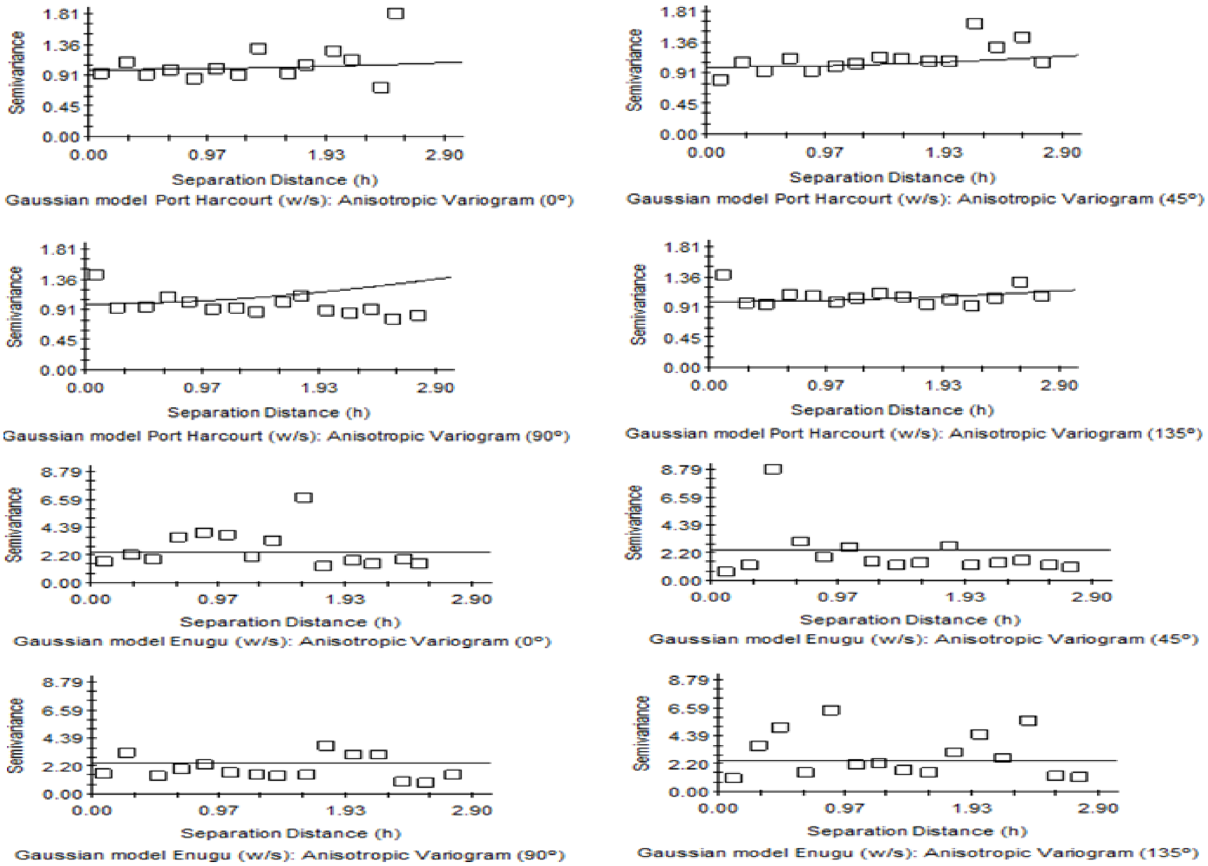
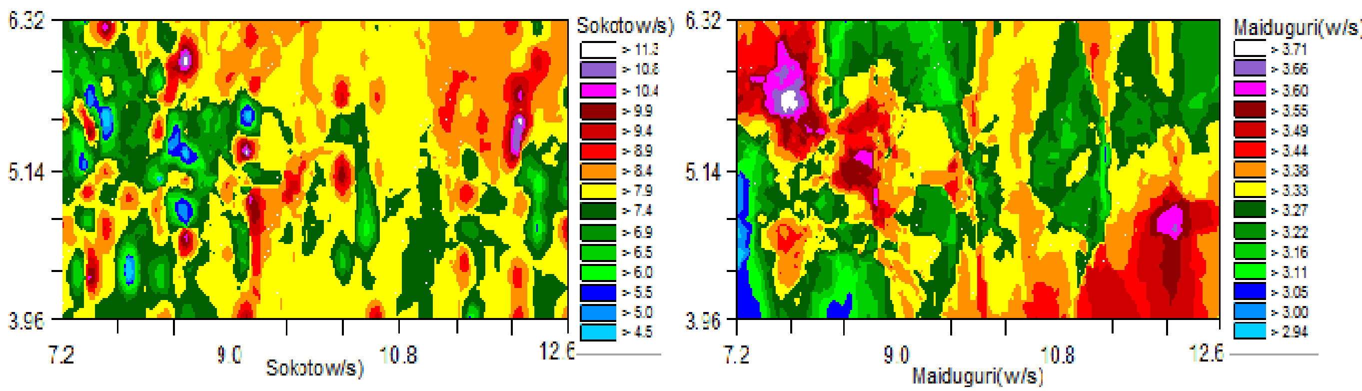
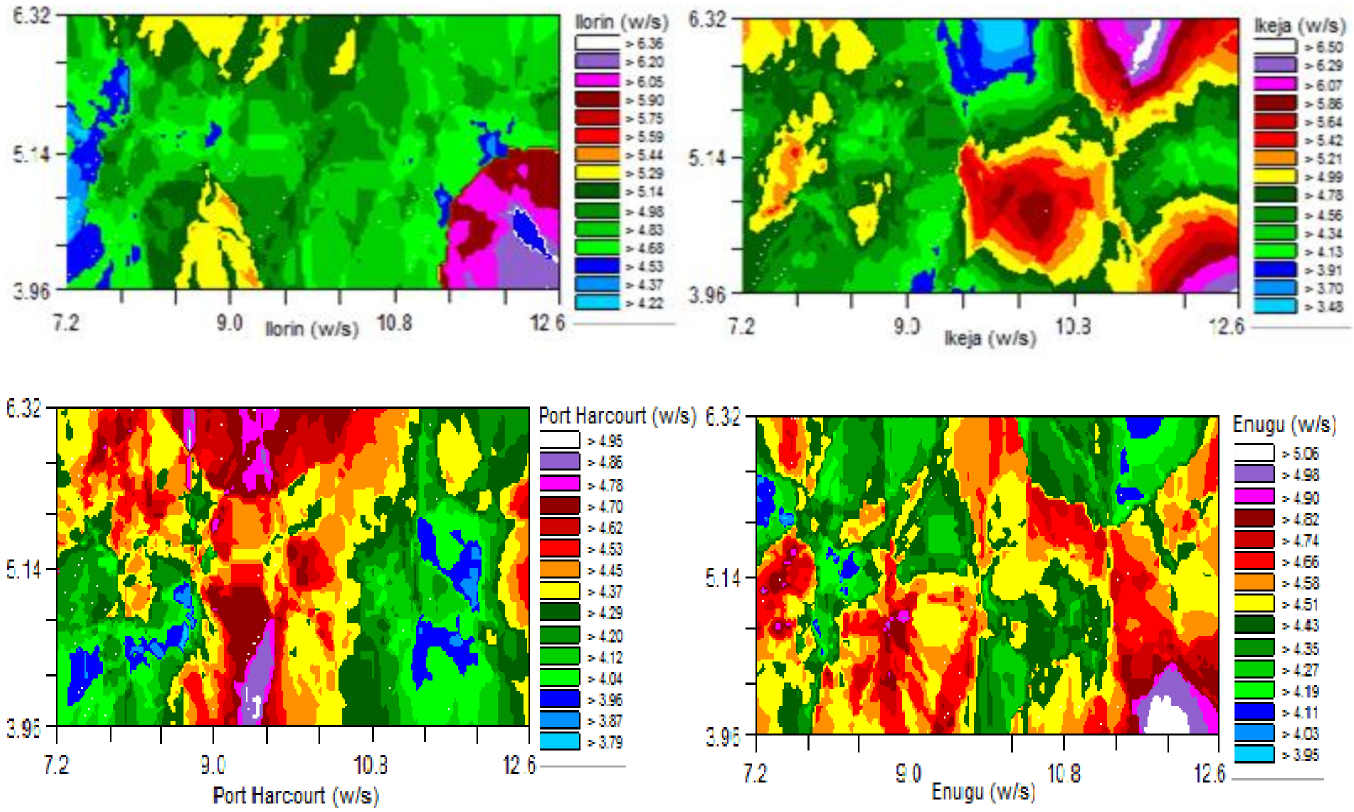


Figure 4: Best fitted anisotropic variograms in the directions N 0° E, N 45° E, N 90° E, and N 135° E with angular tolerance of 22.5 for the Six Selected Wind Stations





.Figure 5: Anisotropic kriging wind speed interpolation for six selected wind stations

The comparison between estimated and actual values of monthly wind speed for each sample station is given in figure 6. The regression coefficient described at the right corner of the graph represents a measure of the goodness of fit for the least-squares model describing the linear regression equation. A perfect 1:1 fit would have a regression coefficient (slope) of 1.00 and the best-fit line (the solid line in the graph above) would coincide with the dotted 45-degree line on the graph. The standard error refers to the standard error of the regression coefficient; the r^2 value is the proportion of variation explained by the best-fit line; and the y-intercept of the best-fit line is also provided. The SE Prediction term is defined as $SDx(1 - r^2)^{0.5}$, where SD is standard deviation of the actual data (the data graphed on the y-axis).

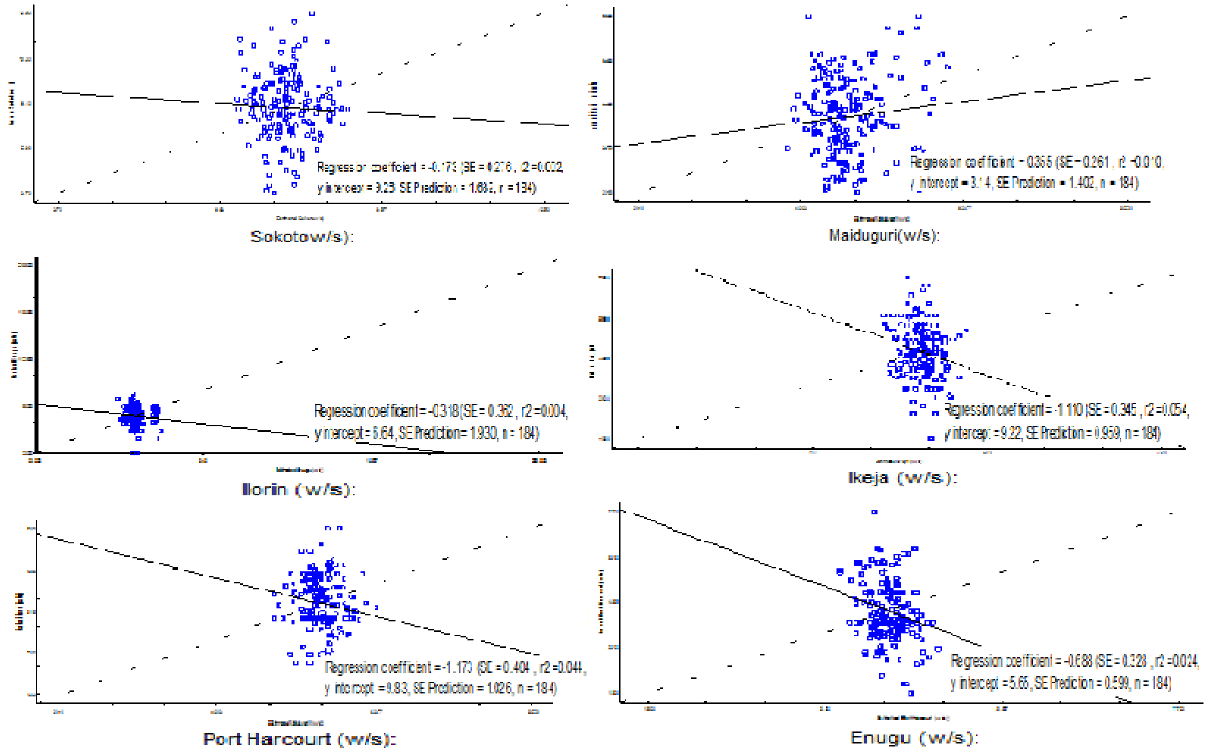


Figure 6: Comparison between actual and estimated wind speed via kriging

4. Conclusions

This study extended previous findings (e.g. Luo *et al.* 2008; Zlatev *et al.* 2009, Carol *et al.* 2016) about the appropriateness of kriging for the interpolation of wind data by analysing isotropic and anisotropic semivariogram-derived kriging surfaces and evaluating a large surface across geographically diverse terrain. A geostatistical approach was applied to investigate the appropriateness of anisotropic variogram models within ordinary kriging on monthly mean wind speed data of six selected wind stations which include: Sokoto, Maiduguri, Ilorin, Ikeja, Port Harcourt and Enugu in Nigeria. The calculated relative distances (R_D) of 66.00%, 50.73% and 50.30% were stronger, which indicated high spatial variability of wind speed for Sokoto, Maiduguri and Enugu stations respectively, whereas Port Harcourt, Ikeja and Ilorin stations indicated low spatial variability with R_D of 44.95%, 40.52% and 37.70% respectively. Sokoto in the northwest indicated the windiest station with spectacular mean centre wind speeds of 7.02 m/s. Maiduguri and Enugu are in the same mean centre region between

3.44 m/s to 3.56 m/s and Ikeja and Port Harcourt are in the same region between 3.32 m/s to 3.37 m/s. The monthly mean of the wind speed are relatively low in the south west cities of Ilorn (2.34m/s). The empirical semivariograms of the six wind stations could be best fitted by linear, Gaussian and exponential anisotropic models.

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