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SCHOOL OF PHYSCIAL SCENCES
1ST BIENNIAL INTERNATIONAL CONFERENCE

PROCEEDINGS

Theme:
Science Technology and Innovation (STI): The Vision for Poverty Reduction and Sustainable Development

FEDERAL UNIVERSITY OF TECHNOLOGY MINNA, NIGER STATE, NIGERIA

PREFACE

This is the first international Conference organized by the school of Physical Sciences of the Federal University of Technology, Minna Nigeria the school is relatively new and consisting of the Departments of Physics, Chemistry, Mathematics, Statistics, Geology and Geography. It was exercised from the former school of Natural and Applied Sciences on the 6th of November 2014.

The school of Physical Sciences 1st Biennial International Conference is an interdisciplinary forum for the presentation of new ideas, recent developments and research findings in the field of Science and Technology. The Conference provides a platform to scholars, researchers in the academics and other establishments to meet, share and discuss how science and technology can help reduce poverty and bring about sustainable development. Submissions were received both nationally and internationally and severally reviewed by our international program committee. All contributions are neither published elsewhere nor submitted for publication as asserted by contributor.

We wish to express our gratitude to the school for challenging us to organize the first international conference. Special thanks to the Dean of the School Prof. A. S. Abubakar. Special thanks to all members of the organizing committee and sub-committee for their dedication, determination and sacrifice towards achieving a fruitful and successful conference.

The Local Organizing Committee Chairman
Kasim Uthman Isah (PhD).

Theme:

Science Technology and Innovation (STI): The Vision for Poverty Reduction and Sustainable Development

Sub-Themes

Scientific Research, Innovation and Entrepreneurship for Sustainable Development.

Scientific Research and Technological Development as tool for Poverty Reduction.

Scientific Research for Renewable Energy in Sustainable Energy Development.

Material Science, Nanoscience and Emerging Technologies in Sustainable Development.

Gender Issues in Quality Scientific Research Innovation and Sustainable Development.

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Prof. Kenneth Ozoemena

Prof. Kenneth Ozoemena obtained his PhD degree in Chemistry in 2003 at Rhodes University, after which he completed postgraduate qualifications in Management Development (MDP), as well as in Higher Education (PGCHE) at the University of Pretoria. He is an Extraordinary Professor at the University of the Western Cape and was a Principal Researcher and Research Group Leader of the Electrochemical Energy Technologies at the CSIR Materials Science and Manufacturing Division. He recently joined School of Chemistry of the University of the Witwatersrand as Professor of Materials for Energy & Electrochemistry,

His research is highly interdisciplinary, spanning several areas of Materials Science and Electrochemistry. By February 2014, he had published 125 articles in leading scientific journals (such as *ChemComm*, *J Mater Chem*, *Energy Environ Sci*, *PCCP, ACS Appl Mater Interfaces*, *Langmuir, Electrochem Commun*, and *Electrochim Acta*) as well as six book chapters. He has been cited 2 674 times and holds an H-index of 30 and i10-index of 74. Ozoemena is listed amongst the world's top 1% of chemists by the Thomson Reuters' Web of Knowledge. He is a Fellow of the Royal Society of Chemistry (FRSC) (UK) and a Chartered Chemist (CChem) of the Royal Society of Chemistry (UK). He is a member of the editorial board of several scientific journals, (including *Electrochemistry Communications*), as well as Associate Editor of *Materials Focus*, and served as Guest Editor of *Electrochemical Acta* and *Journal of Porphyrins and Phthalocyanine*s.

Professor Cheo, Emmanuel Suh

Professor Cheo, Emmanuel Suh was born on the first of July, 1969 in Mankanikong in the North West Region of Cameroon. He attended Obafemi Awolowo University, Ile Ife, Nigeria from 1987 – 1990 were he obtained a Bachelor of Science (B.Sc) first class degree in Geology. He also obtained a Master of Science (M.Sc) degree from the same University in 1992. Prof. Cheo Emmanuel Suh obtained his PhD degree in Applied Geology in 1997 at Abubakar Tafawa University, Buachi, Nigeria in collaboration with Technical University of Berlin, Germany. He also had post-doctoral fellowships in the following institutions:

1. 2001 – Royal Society at the University of Bristol, UK
2. 2002 – Alexander Von Humboldt Foundation, Technical University of Clausthal, Germany
3. 2004 – Smithsonian Institution, Museum of National History, Mineral Science Department, Washington DC, USA.

He has consulted as an economic geologist for gold, iron ore and uranium deposits for Legend Mining, Australia, African Aura Resources, UK, Cameroon Mining Company and Cameroon Mining Action. He attended the Mining Indaba in Cape Town in February, 2012 where the Iron Resources in Cameroon and Central African sub-region were discussed. In August of the same year, he also participated in a training workshop on Sustainable Mining in Africa at Brisbane, Australia. He has won many grants, attended many conferences and published many articles in both local and international journals. He is a scientific member of so many geological associations.

MODELLING MEAN SURFACE TEMPERATURE OF NIGERIA, USING GEOSTATISTICAL APPROACH

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Abstract

Understanding spatial variability of mean surface temperature (MST) of Nigeria is necessary for ecological restoration and national planning toward effects of unstable climate conditions. This study aimed to develop MST model derived from two geostatistical procedures and multiple linear regression (MLR) model using measurements of monthly MST in Nigeria. The geostatistical models includes ordinary kriging (OK) developed in two dimensions with isotropy and in three dimensional plane with anisotropy and regression kriging (RK) that employs both correlation with explanatory variables and spatial autocorrelation simultaneously. Six statistics were considered to evaluate the performance of the approaches used. The results revealed that in the fitted MLR model all the predictors are significant and the model explains 62% variability in the MST values. The one-leave-out cross-validation indicates that RK produced less errors compared to OK model with R^2 value of 78%. The OK with zonal anisotropic shows that the spatial continuity in the directions of north and north east are stronger than in the directions of east and south east at a distance of 930 kilometres and 460 kilometres respectively. The kriging weights for OK and RK were similar as shown in the maps.

Keywords: Geostatistical models, multiple linear regression, anisotropy and model performance.

1. Introduction

When we speak of temperature of an object, we often associate this concept with how hot or cool the object feels. Scientifically, temperature is a property of an object that decides the direction of flow of energy of the object when being encountered with another object. Temperature measurements were dated back to 1600 by Galileo and compatriot, Santario. Temperature measuring instruments varies, depending on the size, nature and the position of the body on the planet earth. According to National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies Scientists (2016)," *the average temperature for 2006 and 2009 tie with 2013, being the seventh warmest years since 1880".* (NASA) further emphasized that the weather pattern will cause drastic change in climate which resultant effect could bring about poor production and extinction of plants and animals. Therefore, it is necessary for a developing country like Nigeria to have a geostatistical model that is capable of predicting future temperature values at locations where surface temperature readings has not been measured, using data from the surrounding weather stations.

Surface temperature is an important site characteristic used in determining site suitability for agricultural and forest crops (Hudson and Wackernagel, 1994), and it is used in parameterizing the habitat of plant species (Rubio *et al.,* 2002) and in determining the patterns of vegetational zonation (Richardson *et al.,* 2004). Moreover, surface temperature is a factor related to plant productivity, as it is connected with the length of the vegetative period and evapotranspiration.

Different interpolation methods have been used to model the spatial distribution of surface temperature; the most widely used being the inverse distance interpolation weighting, Voronoi tessellation, regression analysis and more recently, geostatistical methods (Hengl, 2009). Lapen and Hayhoe (2003) compared inverse distance weighting to geostatistical methods ordinary kriging (OK) and cokriging, and ordinary kriging with kriging with external drift (OKED)) to spatially model the seasonal and annual temperature and total precipitation normals in the Great Lakes (Ontario, Canada); Hudson and Wackernagel (1994) mapped air temperature of Scotland using ordinary kriging with external drift; and Ishida and Kawashima (1993) used different kriging estimators, specially cokriging estimators, to evaluate the usefulness of these approaches in temperature modelling in Japan. Isah (2011) used multiple linear regression and cokriging procedure for joint modeling and prediction of wind speed and wind in Nigeria.

The main objective of this study is to develop MST model derived from geostatistical and multiple linear regression (MLR) models using four years of measurements of monthly MST in Nigeria.

2. Study Area and Geostatistical methods

2.1 Study area and Data Used

Nigeria with an area of 909,890 square kilometres is situated between Latitude 4^0 and 14^0 North and between Longitude 3^0 and 14^0 East. The longest distance from East to West is about 767 kilometres and from North to South 1,605 kilometres NBS, (2009). Nigeria is also blessed with favourable and varied climatic conditions. NBS (2009) reported eleven climatic conditions in Nigeria of which this study covers four out of the eleven; namely; mean surface temperature, relative humidity, mean radiation and evaporation. Temperature in Nigeria vary according to the seasons of the year as with other lands found in the tropics. Nigeria's seasons are determined by rainfall with rainy season and dry season being the major seasons in Nigeria (http://www.nigeria-weather.com).

The study covers readings of average surface temperature by Meteorological and Hydrological service stations in Nigeria as contained in annual reports of National Bureau of Statistics (NBS), 2009. The data is used to model mean surface temperature as a function of mean relative humidity, mean radiation, elevation, evaporation, distance of state capitals of Nigeria to Lagos (nearby ocean/sea), longitude and latitude (position of each of the monitoring stations).

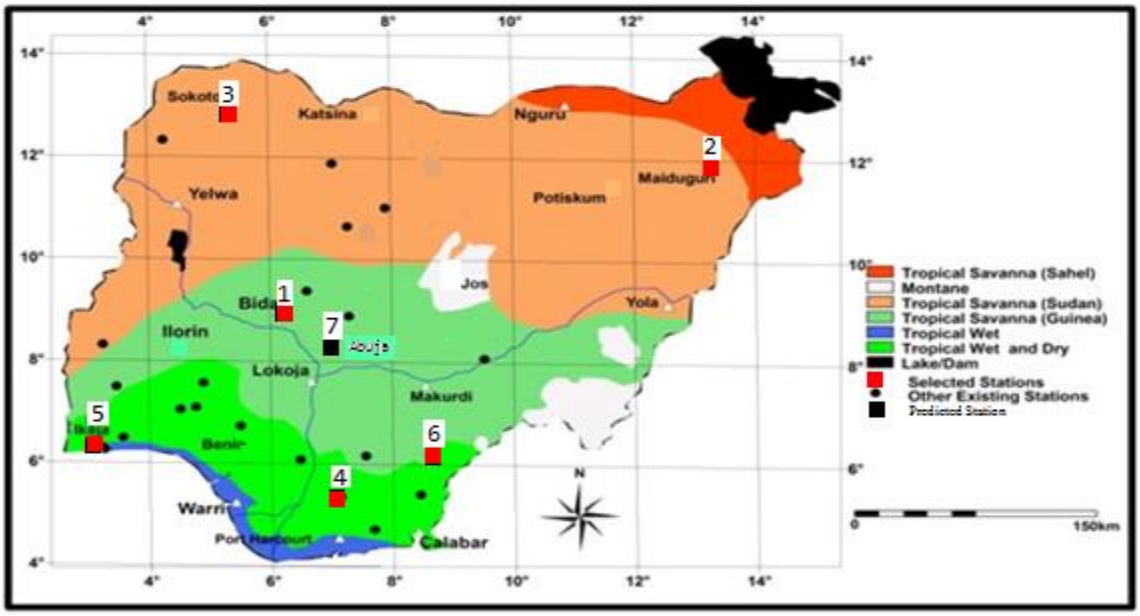


Figure 1: Map of Nigeria showing the locations of meteorological stations

2.2 Geostatistical Methods

Geostatistics is a valuable tool that can be used to characterize spatial, temporal or spatiotemporal phenomena. That is, each data value is associated with a location in space and there is at least an implied connection between the location and the data value. Location here could have two different meanings: One is simply a point in space which only exists in an abstract mathematical sense while the second is an area or volume in space (average value of an observed value).

2.2.1 Experimental Variogram

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 (Robinson and Metternicht, 2006):

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

where $N(h)$ is the number of data pairs with a given class of distance and direction.

If the values at $z(x_i)$ and $z(x_i+h)$ are auto-correlated, the result of equation (1) relative to an uncorrelated pair of point will be small. Using an analysis of the experimental variogram, a suitable model (Gaussian, linear, exponential or spherical) is fitted. This is made using weighted least square and relevant parameters of the covariance structure (range, nugget and sill) are then used in the kriging procedure.

Once the variogram model is estimated, it is used to derive semivariances at all locations and solve the kriging weights. The kriging weights are derived from a statistical model of spatial correlation expressed as semivariograms that characterized the spatial dependency and structure in the data. The OK weights are solved by multiplying the covariance:

$$\lambda_o=c^{-1}v_o\,;\ c(|h|=0)=c_o+c_1 \tag{2}$$

where c is the covariance matrix derived for $n\times n$ observations and v_o is the vector of covariance's at a new location (Hengl, 2009). The solution to the minimization, constrained by unbiasedness, gives the kriging equations (Hengl, 2009):

$$\Gamma^{-1}*\ell=\lambda \tag{3}$$

$$\begin{bmatrix} c(s_1,s_1) & \cdots & c(s_1,s_n) & 1 \\ \vdots & & & \vdots \\ c(s_n,s_1) & \cdots & c(s_n,s_n) & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix}^{-1} \begin{bmatrix} c(s_o,s_1) \\ \vdots \\ c(s_0,s_n) \\ 1 \end{bmatrix} = \begin{bmatrix} w_1(s_o) \\ \vdots \\ w_n(s_o) \\ \varphi \end{bmatrix} \tag{4}$$

where φ is the so-called Lagrange multiplier.

2.2.2 Ordinary Kriging (OK)

A standard version of kriging is called ordinary kriging (OK). Here the predictions are based on the model :

$$T(s)=\mu+\varepsilon(s) \tag{5}$$

where μ is the constant stationary function and $\varepsilon(s)$ is the spatially correlated stochastic part of variation.

The ordinary kriging prediction of $T(s)$ at location s_o is given by the following equation:

$$\hat{T}_{OK}(s_o) = \sum_{i=1}^{n} \lambda_i(s_o) T(s_i) \qquad (6)$$

where λ_i is an unknown weight for the measured value at the ith location, s_o is the prediction location so that the estimation of error variance in equation (7) is minimised, under the constraint of unbiasedness of the estimator equation (8).

$$\sigma_E^2 = Var[\hat{T}(s_o) - T(s_o)] \qquad (7)$$

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad (8)$$

2.2.3 Ordinary kriging with Zonal Anisotropy.

When observations are available at all directions and specified distances, the anisotropy may be modelled directly from the directional experimental variogram model (Hengl, 2009). When elevation is included in the kriging system the directional variograms show zonal anisotropy. Both directional variograms were modelled as the sum of an isotropic Gausian variogram and an Exponential variogram for the Z-axis, which constitutes a valid model:

$$\gamma(d) = \gamma_{Gausian}(X, Y, Z) + \gamma_{\text{Exponential}}(Z) \qquad (9)$$

Ordinary kriging is carried out calculating the sum variogram for each pair of observations for prediction point. All pairs of locations forming an angle with the horizontal greater than 3.29km were selected to calculate the directional variogram for the Z-axis, whereas those pairs of locations forming an angle with the horizontal smaller than 2.19km, and with elevation difference no greater than 840m, were selected to calculate the XY variogram. For each lag, the vertical component of the distance was averaged across all pairs of observations, both in the XY plane and in the Z direction variogram.

2.2.4 Regression Kriging (RK).

Matheron (1969) proposed that a value of a target variable at some location can be modelled as a sum of deterministic and stochastic components with the model below:

$$Z(s) = m(s) + \varepsilon(s) + \varepsilon' \qquad (10)$$

where $m(s)$ is deterministic part, $\varepsilon(s)$ is spatially correlated stochastic component and ε' is the error term, which he called the universal model of spatial variation, that both deterministic and stochastic components of spatial variation can be modelled separately.

Hengl (2009) proposed another approach in which he combined; OK and simple linear regression model (SLR) and called it RK with the predictor:

$$\hat{Z}(s_o) = b_o + b_1 q_1 + \sum_{i=1}^{n} \lambda_i (s_o) e(s_i) \tag{11}$$

where Z is the target variable at sampled location s_o, b_o is the estimated intercept, b_1 is the regression coefficient, q_1 is the explanatory variable, and $\lambda_i{}'s$ are the kriging weights determined by spatial dependence structure of the residual and $e(s_i)$ is the residual at location s_i.

The regression coefficient b_1 can be estimated from the sample by using: either ordinary least squares (OLS) or Generalized Least Squares (GLS) (Cressie, 1993):

$$\hat{b}_{GLS} = (q^t c^{-1} q) q^t c^{-1} z \tag{12}$$

where $\hat{b}_{GLS}$ is the vector of estimated regression coefficients, c is the covariance matrix of residuals, q is the matrix of auxiliary variables at sampled locations and z is vectors of measured values of the target variable.

2.2.5 Multiple Linear Regression (MLR) Model

A common regression-based approach to spatial prediction is multiple linear regression (Draper and Smith, 1998; Kutner *et al*., 2004). Here, the predictions are obtained by weighted averaging:

$$\hat{Z}_{GLS}(s_o) = \hat{b}_o + \hat{b}_1 q_1(s_o) + \cdots + \hat{b}_p q_p(s_o) = \sum_{k=0}^{p} \hat{b}_k q_k(s_o) \tag{13}$$

where $q_k(s_o)$ are the values of the explanatory variables at the target location, p is the number of predictors or explanatory variables, and $\hat{b}_k$ are the regression coefficients solved using the

Ordinary Least Squares Hengl (2009):

$$\hat{b} = (q^t q)^{-1} q^t z \tag{14}$$

where q is the matrix of predictors $(n \times p + 1)$ and z is the vector of sampled observations.

3.1 Proposed Mean Surface Temperature (MST) Model

The proposed model is a combination of multiple linear regression (MLR) model as in equation (13) and the second part of RK model in equation (11). The predictors are given by:

$$\hat{T}\left(S_i\right)=\sum_{k=0}^{P} b_K q_K\left(S_i\right)+\sum_{i=1}^{n} \lambda_i (S_0) e\left(S_i\right) \tag{15}$$

where $q_K\left(S_i\right)$ are the values of explanatory variables at sampled locations, P is the number of explanatory variables, λ_i is the kriging weights, $e\left(S_i\right)$ is the residual at location S_i and b_K is the regression coefficients solved using generalised least squares (GLS) Cressie (1993).

$$\hat{b}_{GLS}=(q^t c^{-1} q) q^t c^{-1} z \tag{16}$$

The mean surface temperature (MST) at the unmonitored locations is given by equation (17)

$$\begin{aligned} MST\left(S_o\right)=b_o+b_1 MRH\left(S_o\right)+b_2 LAT\left(S_o\right)+b_3 DIST\left(S_o\right)+b_4 LONG\left(S_o\right) \\ +\ b_5 ELEV\left(S_o\right)+b_6 EVAP\left(S_o\right)+b_7 EMRAD\left(S_o\right)+\sum_{i=1}^{6}\lambda_i e\left(S_i\right) \end{aligned} \tag{17}$$

Where MRH mean relative humidity, ELEV denote elevation, MRAD denote mean solar radiation, EVAP denote evaporation and DIST denote distance to the nearby sea or ocean.

3.2 Relationship of Regression Kriging to Multiple Linear Regression

If the residuals show no spatial autocorrelation (pure nugget effect), the Regression Kriging converges to pure MLR equation (13) because the covariance matrix (C) becomes identity matrix (Hengl, 2009):

$$\begin{bmatrix} C_0+C_1 & \cdots & 0 \\ \vdots & C_0+C_1 & 0 \\ 0 & 0 & C_0+C_1 \end{bmatrix}=\left(C_0+C_1\right)\mathrm{I} \tag{18}$$

So the kriging weights in equation (2) at any location predict the mean residual zero. Similarly, the regression kriging variance (20) reduces to the MLR Variance.

$$\hat{\delta}_{RK}^2\left(S_0\right)=\left(C_0+C_1\right)-0+X_0^t\left(X^t\frac{1}{\left(C_0+C_1\right)}X\right)^{-1}X_0$$

$$\hat{\delta}^2_{RK}(S_0) = (C_0 + C_1) + (C_0 + C_1) X^t_0 (X^t X)^{-1} X_0 \quad (19)$$

And since $(C_0 + C_1)$ = $C(0)$ = MSE, the RK variance reduces to MLR variance (Hengl, 2009):

$$\hat{\delta}^2_{RK}(S_0) = \hat{\delta}^2_{OLS}(S_0) = MSE\left[1 + X^t_0 (X^t X)^{-1} X_0\right] \quad (20)$$

3.3 Relationship of Regression Kriging to Ordinary Kriging

If the target variable shows no correlation with the explanatory variables, the regression kriging model reduces to the ordinary kriging model because the deterministic part is equal to the global mean.

$$\hat{T}(S_0) = \mu_k = \frac{1}{n_k}\sum_{i=1}^{n_k} T(S_i) \quad (21)$$

Also from equations (6) and (11)

$$T_{RK}(S) = \mu + \mathrm{K}(S) = \mathrm{T}_{\mathrm{OK}}(S) \quad (22)$$

From the above, it implies that:

$$M(S) + e = \mu \quad (23)$$

3.4 Model Validation

The common validation method in climatological studies has been variously termed as cross validation (Nalder & Wein, 1998). Cross validation (leaving-one-out method) is based on removing one data point at a time and performing the interpolation for the location of the removed point using the remaining samples. At the final step of cross validation, the difference (residual) between observed and predicted values of the point are calculated. The leaving-one-out approach is repeated until every sample has been, in turn, removed (Davis, 1987) and estimates are calculated for each point. The overall performance of each kriging method is calculated using mean prediction error (MPE), mean standard prediction error (MSPE), average kriging standard error (AKSE), Root mean square prediction error (RMSPE), root mean square standardized prediction error (RMSSPE) and R^2:

$$MPE = \frac{1}{N}\sum_{k=1}^{n}(T_{OK} - T_{PK}) \quad (24)$$

$$MSPE = \frac{1}{N}\sum_{k=1}^{n}\frac{\left(T_{0K} - T_{PK}\right)}{\delta\left(K\right)} \qquad (25)$$

$$AKSE = \left[\frac{1}{N}\sum_{k=1}^{n}\delta(K)\right]^{\frac{1}{2}} \qquad (26)$$

$$RMSPE = \left[\frac{1}{N}\sum_{k=1}^{n}\left(T_{OK} - T_{PK}\right)^{2}\right]^{\frac{1}{2}} \qquad (27)$$

$$RMSSPE = \left[\frac{1}{N}\sum_{k=1}^{n}\frac{\left(T_{OK} - T_{PK}\right)^{2}}{\delta(k)}\right]^{\frac{1}{2}} \qquad (28)$$

$$R^2 = \frac{\sum\left(T_P - T_m\right)^2}{\sum\left(T_O - T_m\right)^2} \qquad (29)$$

where T_P is the predicted values of temperature, T_O is the observed values of temperature, T_m is the mean values of temperature, p is the total number of explanatory variables, n is the sample size, T_{OK} is the observed temperature at location K, T_{PK} is the predicted temperature at location K through ordinary kriging, N is the number of pairs of observed and predicted values and δ(K) is the prediction standard error at location K.

As an indicator of prediction error, the MPE and MSPE values reveal the degree of bias in model prediction and should be close to zero. Assessment of variability in prediction, the RMSPE and AKSE values show the precision of predictions and should be equal to one another. In other words, the RMSPE reveals the level of scatter that a model produces and provides a comparison of the absolute deviation between the predicted and the observed values. The lower the RMSPE values, the better a model is indicated to perform. Over estimation of variability occurs when AKSE > RMSPE and under estimation occurs when AKSE < RMSPE.

4. Results and Discussion

This study used observations from six different locations which was used to carry out all the analysis. The location seven (7) in the study was not monitored, however, the MST was predicted for location (7) using information from the other six (6) locations.

4.1 Preliminary Statistical Analysis

To develop mean surface temperature (MST) model using geostatistics procedures, the MST values were tested for normality by inspection of autocorrelation and histogram plots as in Figure 8. Looking at autocorrelation plot on MST values, it shows that the temperature values are spatially auto correlated and therefore possible to predict the value at one location based on the value sampled from a nearby location. Histogram plot with a normal density superimposed also shows that the MST distribution does not deviate too severely from normality.

4.2 Regression models

The relationship between MST and explanatory variables in the OLS regression models were fitted using equation (13) and the result presented n Table 1. The result shows that MRH and ELEV have negative contributions while, MRAD, EVAP and DIST have positive contributions to the MLR model. Although, the coefficients are significant and explained 62% of variability in the MLR model. A further question of interest is whether any of the observations greatly affect the estimates. The MLR fits to the full dataset and produce a set of four plots: residuals versus fitted values, a Q-Q plot of standardized residuals, a scale-location plot (square roots of standardized residuals versus fitted values, and a plot of residuals versus leverage that adds bands corresponding to Cook's distances figure 2. Cooks distance is a measure of how much the estimate changes as each observation is dropped. It was found that 62, 74 and 99 were outliers and after dropping the three outliers the MLR fitted is given in Table 1:

Table1: Result of Multiple Linear Regression (MLR) model of MST for the Selected Stations

Explanatory variables in MLR model	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	27.852	3.941	7.395	1.15e-11
Longitude (decimal degree)	0.114	0.076	-1.696	0.0022
Latitude (decimal degree)	0.033	0.059	-0.385	0.0015
MRH	-0.006	0.020	-0.322	0.0028
MRAD	0.204	0.164	1.684	3.43e-05
ELEV	-0.003	0.001	-4.280	0.0044
EVAP	0.564	0.480	1.175	6.030e-10
DIST	0.001	0.001	1.1917	0.0005

All the variables are significant at *p≤0.05*. *Adjusted* R-squared: 0.6213, Residual standard error = 1.811, F-statistic: 4.864 on 6 explanatory variables and *p-value*: 0.0001515.

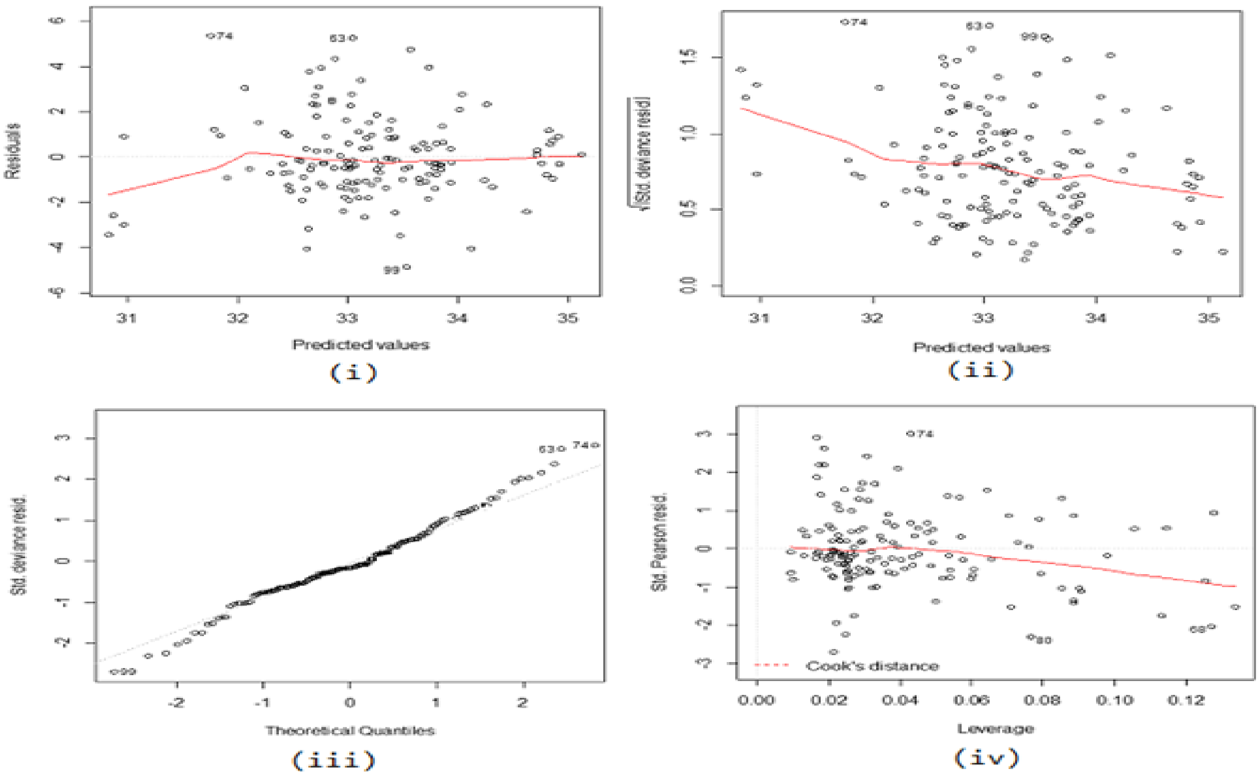


Figure 2: Residual scatter plot of the outliers (i) residuals versus fitted values, (ii) scale location plot (square roots of standardized residuals versus fitted values, (iii) Q-Q plot of standardized residuals, and (iv) plot of residuals versus leverage**.**

4.3 Results of Geostatistical Models

In order to fit the kriging model, it is sufficient to fit the variogram for the residuals. The parameters for the fitted theoretical variogram models are shown in Table 2. The Gaussian model explained the highest variability of (R^2 = 63%) of the fitted isotropic variogram model for MST; while exponential model explained the highest variability of 51% in the MST values of the fitted anisotropic variogram models. The Gaussian and exponential models were therefore chosen as the most reliable models for interpolating MST and used for the final map productions. The two models had the smallest residual sum of squares (RSS), which indicated a tight fit of the models to the MST distributed around 2.03 and 57.4 values respectively.

Table 2: Parameters for the fitted theoretical variogram models for MST

Isotropic Variogram						
Model Type	**Nugget Variance (C_0)**	**Structural Variance Sill(C_0+C)**	**Range (A)**	**Residual SS**	**R^2**	**Proportion (C/[(C_0+C)])**
Linear	0.827	1.906	6.355	3.950	0.277	0.556
Spherical	0.001	1.717	3.470	2.050	0.628	0.999

Exponential	0.001	1.749	4.020		2.260	0.608	0.999
Gaussian	0.062	1.676	2.355		2.030	0.629	0.963
Anisotropic Variogram							
Model Type	**Nugget Variance (C_0)**	**Structural Variance Sill(C_0+C)**	**Range Minor**	**Major**	**Residual SS**	**R^2**	**Proportion (C/[(C_0+C)])**
Linear	1.080	6.251	24.20	75.61	57.80	0.403	0.827
Spherical	0.936	6.106	31.28	72.21	58.40	0.204	0.847
Exponential	1.046	6.217	58.95	206.07	57.40	0.506	0.832
Gaussian	1.358	6.528	21.85	98.62	60.20	0.169	0.792

The fitted experimental variogram of isotropy using Gaussian model, and the four directional variograms in the XYZ plane of anisotropic using exponential model is presented in Table 3. The values of nugget, sill, range, residual sum of square and R^2 with isotropic variogram and with anisotropic variogram are shown in Figures 3 and 4 respectively.

Table 3: Directional variogram with isotropic and anisotropic models for MST

Isotropic Variogram						
Degree	**Nugget Variance (C_0)**	**Structural Variance Sill(C_0+C)**	**Range (A)**		**Residual SS**	**R^2**
	0.001	1.749	1.34		2.26	0.608
Anisotropic Variogram						
Degree	**Nugget Variance (C_0)**	**Structural Variance Sill(C_0+C)**	**Range Minor**	**Major**	**Residual SS**	**R^2**
0^0	1.168	6.338	15.35	15.38	63.60	0.072
45^0	1.245	6.416	11.28	29.80	58.10	0.073
90^0	1.358	6.529	13.77	56.94	60.21	0.069
135^0	0.788	5.959	10.00	10.01	72.90	0.076

In addition, the anisotropic variogram in Figure 4 shows that the spatial continuity in the directions of North with angle 0^0 and North-East with angle 45^0 are stronger than in the directions East with angle 90^0 and South East with angle 135^0. In the North and North East directions, the semivariogram levels off to the sill when it reached a distance of about 930 kilometres. While in the East and South East directions the spatial correlation for the semivariogram are similar except that it levels off earlier at about 460 kilometres.

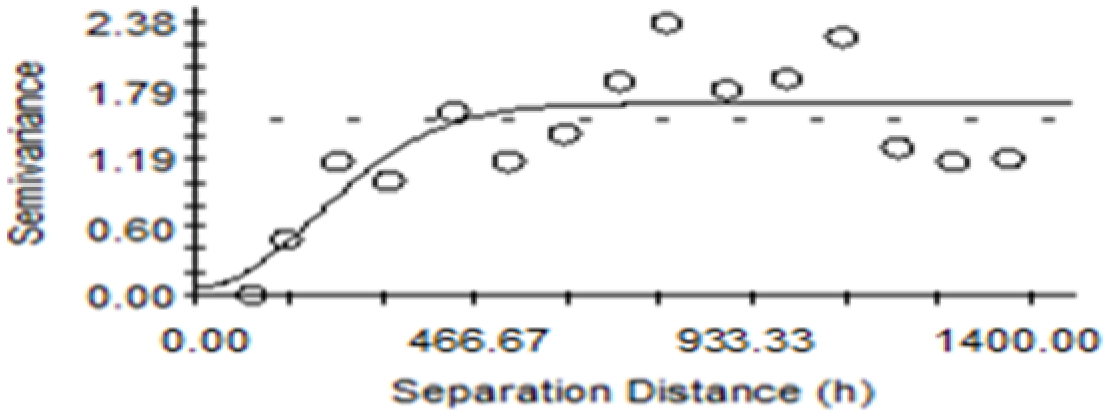


Figure 3: Variogram of fitted isotropic model for MST residuals

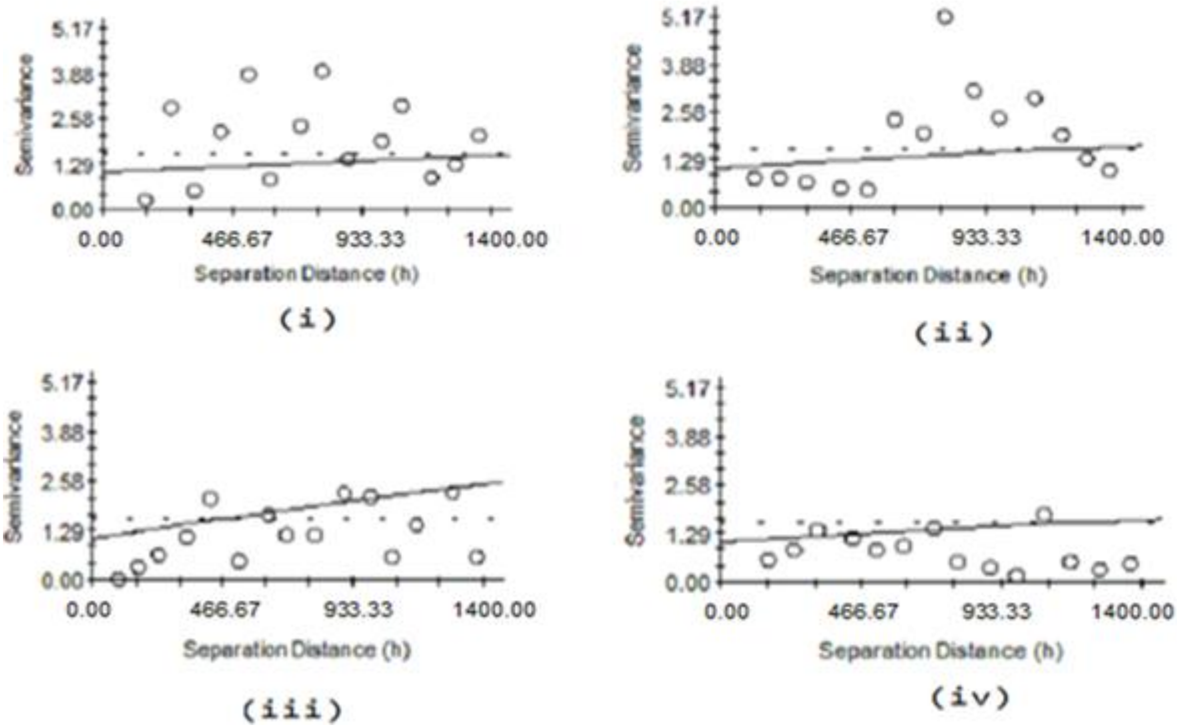


Figure 4: Variogram of fitted anisotropic models of (i) 0^0 (ii) 45^0 (iii) 90^0 and (iv) 135^0 for MST residuals.

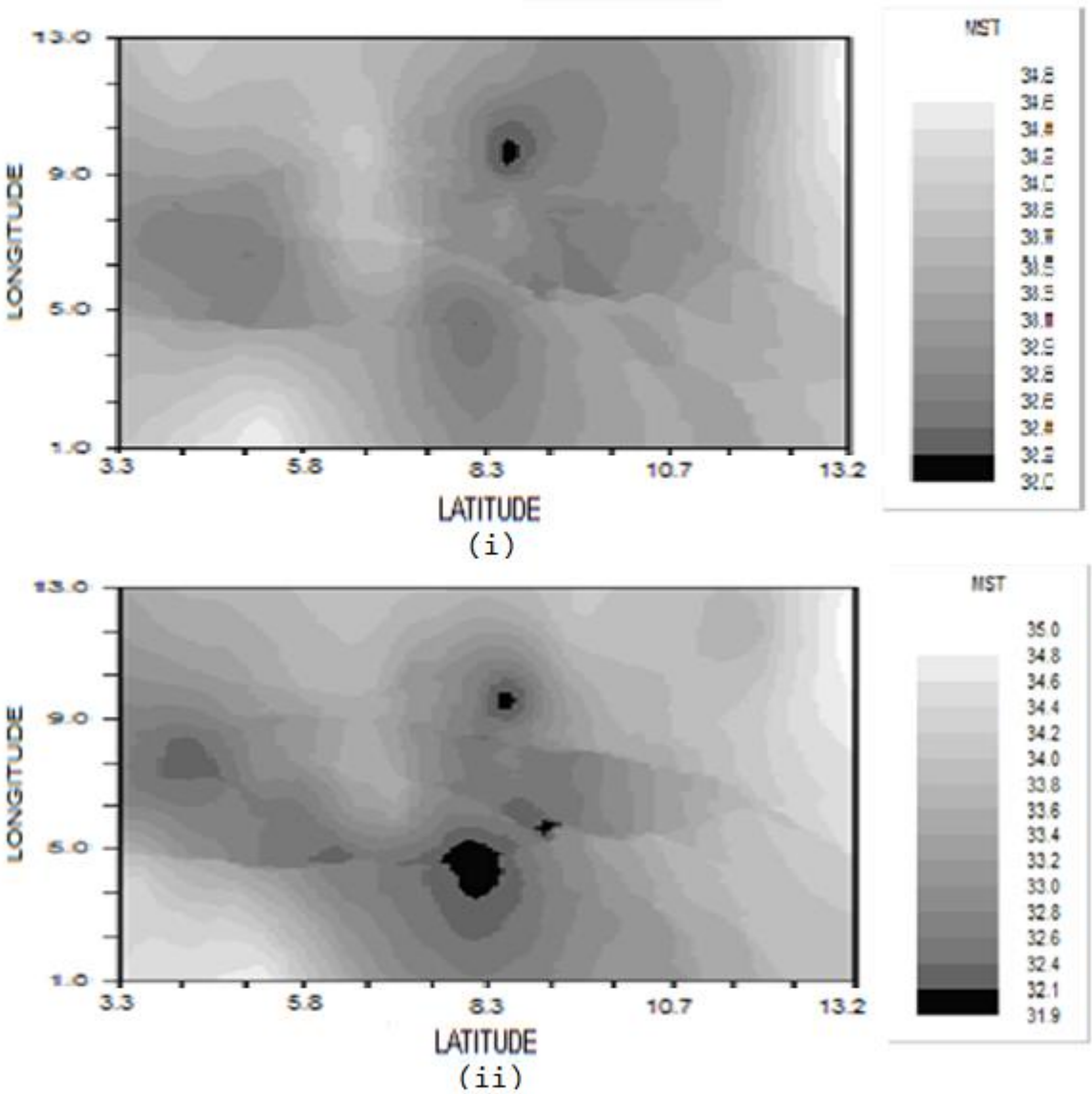


Figure 5: (i) OK and (ii) RK of isotropic variogram using Gaussian model: Spatial prediction of MST

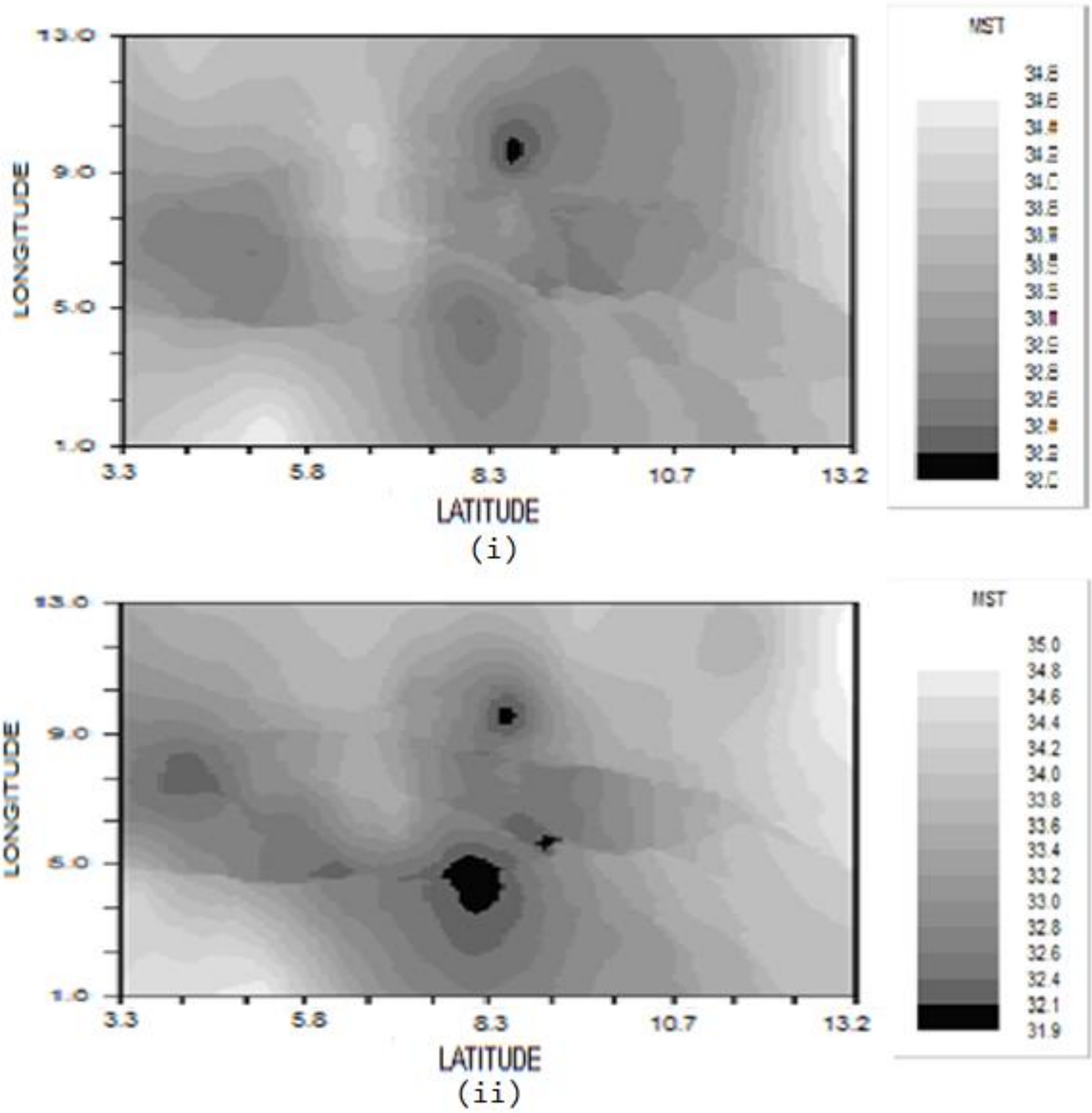


Figure 6: (i) OK and (ii) RK of anisotropic variogram using exponential model: Spatial prediction of MST

For a comparison, the predictions at all locations of OK and RK were compared side-by-side in figures 5 and 6. Visually, there are clear differences in the two maps. It could be observed that low MST predictions occur in the North Central region in OK maps in the model with isotropy and anisotropy as compared to RK models . Since visual comparison may not be enough, the study also used the leave-one-out cross validation method as in (Pebesma, 2004).

4.4 The Semivariogram

To compute the values for the Γ matrix in equation (3), we examined the structure of the data by creating the semivariogram. In a semivariogram, half the difference squared between the pairs of locations of longitude is plotted relative to the distance that separates them:

Table 4: Semivariance of Pairs of Locations

S/N	Pairs of Sampled Locations (MST Value)	Distance	Difference^2	Semivariance
1	L(1, 2) = 57	1055	1	0.5
2	L(1, 3) = 58	537	4	2
3	L(1, 4) = 54	729	4	2
4	L(1, 5) = 54	743	4	2
5	L(1, 6) = 55	1275	1	0.5
6	L(2, 3) = 59	1204	1	0.5
7	L(2, 4) = 55	1331	9	4.5
8	L(2, 5) = 55	820	9	4.5
9	L(2, 6) = 56	891	4	2
10	L(3, 4) = 56	1257	16	8
11	L(3, 5) =56	1050	16	8
12	L(3, 6) = 57	849	9	4.5
13	L(4, 5) = 52	652	0	0
14	L(4, 6) = 53	131	1	0.5
15	L(5, 6) = 53	1110	1	0.5

With larger dataset the number of pairs of locations will increase rapidly and will quickly become unmanageable. Therefore, pairs of locations are grouped, which is referred to as binning. A bin is a specified range of distances. That is, all points that are within 100 to 300 kilometres apart are grouped into the first bin, those that are within 300 to 500 kilometres apart are grouped into the second bin, and so forth.

The average semivariance of all pairs of points is obtained after grouping the observations into bins and result is presented in Table 5.

The semivariance for any distance can be determined by semivariance = 0.907*h.

Table 5: Binning the Semivariance

Lag Distance	Paired Distance	Average Distance	Paired Semivariance	Average Semivar.
100 - 300	131	131	0.5	0.5
300 - 500	0	0	0	0
500 - 700	537, 652	594.5	2, 0	1
700 - 900	727, 743, 820, 849, 891	806	2, 2, 4.5, 4.5, 2,	3
900 -1100	1050, 1055	1052.5	8, 0.5	4.25
1100 - 1300	1110, 1204, 1257, 1275, 1331	1235.4	0.5, 0.5, 8, 0.5, 4.5	2.8

Distance is the distance between pairs of locations and is symbolized as *h*. The semivariance for any distance is determined by:

Γ Matrix (Gamma)

$$\begin{array}{cc} & \begin{array}{ccccccc} 1 & 2 & 3 & 4 & 5 & 6 & \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \ \end{array} & \begin{bmatrix} 0 & & & & & & \\ 118.817 & 0 & & & & & \\ 487.059 & 591.364 & 0 & & & & \\ 659.389 & 673.901 & 743.740 & 0 & & & \\ 952.350 & 956.885 & 956.885 & 952.350 & 0 & & \\ 100.677 & 1092.028 & 1140.099 & 1156.425 & 1207.217 & 0 & \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Now the Γ gamma matrix and its inverse are used to obtain weights (λ_i) to assign to the measured values surrounding the prediction location. Thus, the inverse of Γ^{-1} is obtained.

Γ^{-1} Matrix

$$\begin{array}{cc} & \begin{array}{ccccccc} 1 & 2 & 3 & 4 & 5 & 6 & \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \ \end{array} & \begin{bmatrix} 0.0025 & & & & & & \\ -0.0016 & -0.0002 & & & & & \\ -0.0001 & 0.0006 & -0.0011 & & & & \\ 0.0003 & 0.0002 & 0.0003 & -0.0010 & & & \\ 0.0004 & -0.0001 & 0.0002 & 0.0003 & -0.0007 & & \\ -0.0015 & 0.0011 & 0.0002 & -0.0002 & -0.0001 & 0.0003 & \\ 0.8128 & -0.4088 & 0.1136 & 0.2505 & 0.3957 & -0.1638 & -532.346 \end{bmatrix} \end{array}$$

Next, the ℓ vector was created for the unsampled location that we wish to predict. For example, to use location 7 (Abuja), the distance from Abuja to each of the sampled locations could be determined using the formula Semivariance = 0.907* h, which was derived earlier. The ℓ vector for Abuja is given in table 6.

Table 6: ℓ vector for un-sample location

Pairs of Un sampled Location with Sampled Locations	**Distance**	**ℓ vector for Abuja**
L(7, 1) = 56	117	106.12
L(7, 2) = 57	918	832.63
L(7, 3) = 58	793	719.25
L(7, 4) = 54	498	451.69
L(7, 5) = 54	467	423.57
L(7, 6) = 55	857	777.30

The kriging equation becomes:

$$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ \\ \end{array} \begin{array}{c} \begin{array}{ccccccc} 1 & 2 & 3 & 4 & 5 & 6 & \end{array} \\ \left[\begin{array}{ccccccc} 0.0025 & & & & & & \\ -0.0016 & -0.0002 & & & & & \\ -0.0001 & 0.0006 & -0.0011 & & & & \\ 0.0003 & 0.0002 & 0.0003 & -0.0010 & & & \\ 0.0004 & -0.0001 & 0.0002 & 0.0003 & -0.0007 & & \\ -0.0015 & 0.0011 & 0.0002 & -0.0002 & -0.0001 & 0.0003 & \\ 0.8128 & -0.4088 & 0.1136 & 0.2505 & 0.3957 & -0.1638 & -532.346 \end{array}\right] \end{array} \left[\begin{array}{c} 106.119 \\ 832.626 \\ 719.251 \\ 451.686 \\ 423.569 \\ 777.299 \\ 1 \end{array}\right] = \left[\begin{array}{c} -1.2068 \\ 0.5937 \\ 0.1461 \\ 0.3112 \\ 0.2281 \\ 0.9277 \\ -551.376 \end{array}\right]$$

4.5 Making a Prediction

Table 7 is on kriging predictor for the six locations on which measurements were taken.

Table 7: Prediction of kriging predictor

Location	**Weights (λ)**	**MST Values**	**Weights (λ)*MST Values**
1	-1.2068	28	-33.7904
2	0.5937	29	17.2173
3	0.1461	30	4.3830
4	0.3112	26	8.0912
5	0.2281	26	5.9306
6	0.9277	27	25.0479

			kriging predictor =26.8796

Kriging variance

According to Webster and Oliver, (2001) the kriging variance of the prediction error is defined as the weighted average of the covariances from the new location (S_0) to all calibration points $\left(X_1,\ldots,X_n\right)$ and the Lagrange multiplier. The square root of the kriging variance is called the kriging standard error.

Table 8: Kriging variance

Location	Weights (λ)	ℓ vector	Weights (λ)* ℓ vector
1	-1.2068	106.119	-128.0644
2	0.5937	832.626	494.3301
3	0.1461	719.251	105.0826
4	0.3112	451.686	140.5646
5	0.2281	423.569	96.6161
6	0.9277	777.299	721.1003
	-551.376	1	-551376
			Kriging Variance = 878.2533

In this case, the Kriging Standard Error (KSE) is 29.6353. If it is assumed that the errors are normally distributed, with 95 percent prediction interval using: Kriging Predictor $\pm$ 1.96*KSE

The value 1.96 comes from the standard normal distribution where 95 percent of the probability within the interval -1.96 to 1.96. This means that if predictions are made again and again from the same model, in the long run 95 percent of the time the prediction interval will contain the value at the prediction location. In this problem the prediction interval ranges from 31.21 to 84.96.

The proposed mean surface temperature (MST) prediction derived by RK is:

$$\hat{T}\left(S_0\right)=\sum_{k=0}^{6} b_K q_K\left(S_0\right)+\sum_{i=1}^{6}\lambda_i e\left(S_i\right)$$

$$\hat{T}(s_0) = 27.852 + 0.114LONG(s_0) + 0.033LAT(s_0) - 0.006MRH(s_0) + 0.204MRAD(s_0)$$

$$-0.003ELEV(s_0) + 0.564EVAP(s_0) + 0.001DIST(s_0) - 1.2068e(s_1) + 0.5937e(s_2) + 0.1461e(s_3)$$

$$+0.3112e(s_4) + 0.2281e(s_5) + 0.9277e(s_6)$$

4.6 Validation and Kriging Error Distribution

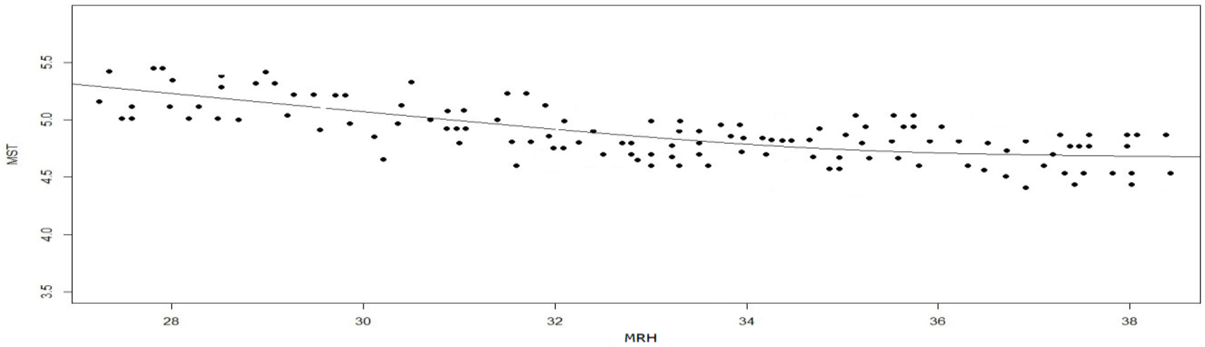
Using cross-validation, the study compared six error statistics summaries. To estimate how much of variation has been explained by OK and RK models, it shows that OK is not much worse than RK. Although RK is a better predictor, the difference is only about 12%. This is possibly because variables ELEV, EVAP and DIST are also spatially continuous, and because the samples are equally spread in geographic space. Indeed, Figures 5 and 6 again, shows that the two maps do not differ much. Furthermore, the amount of variation explained by RK is about 78%, which is satisfactory.

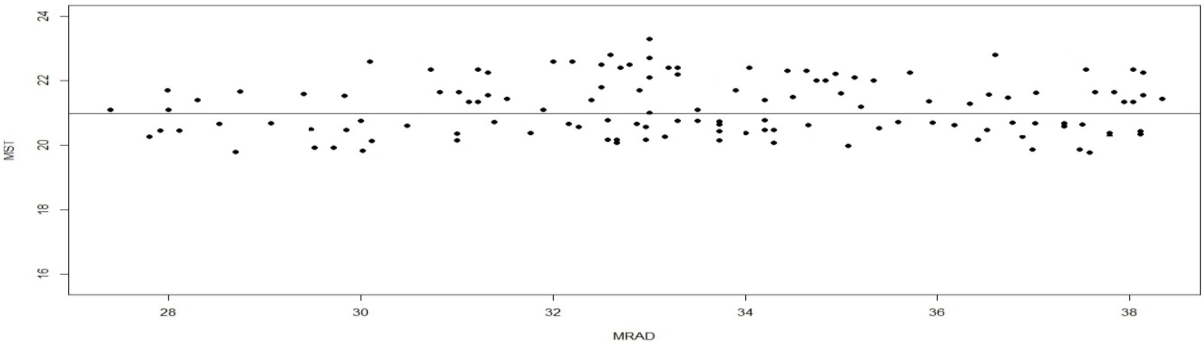
Table9 : Comparison of RK to MLR and OK

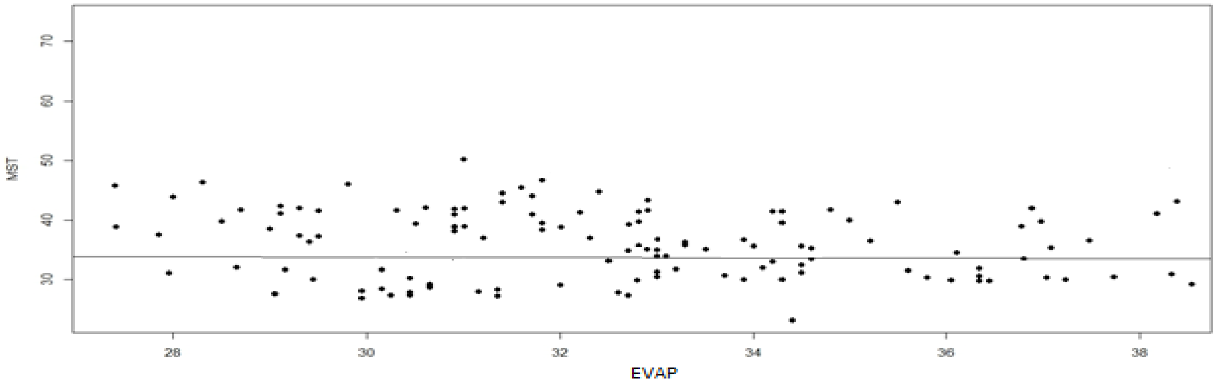
Method	MPE	RMSPE	AKSE	MSPE	RMSSPE	R^2
OK	-0.014	1.06	2.50	0.221	0.76	0.66
RK	-0.017	1.02	2.06	0.203	0.85	0.78
MLR						0.62

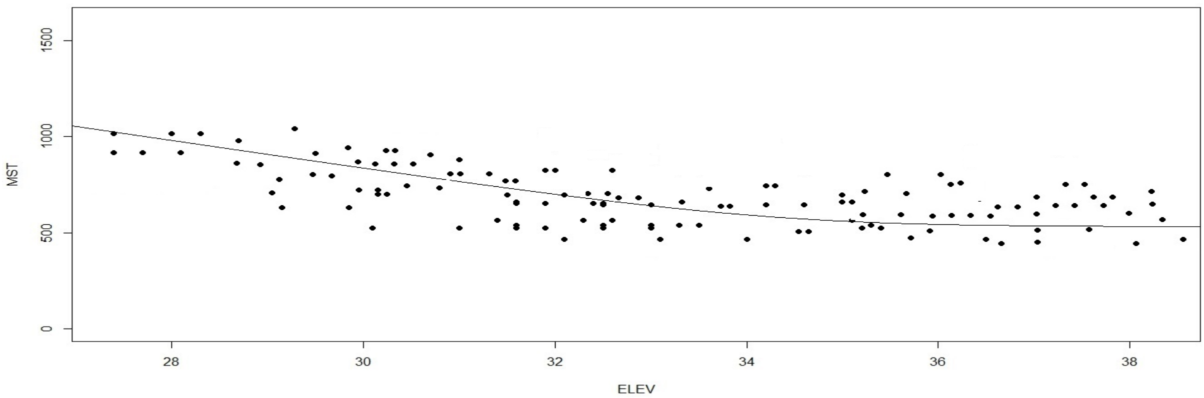
4.7 Relationship between the MST, MRH, MRAD, ELEV, EVAP and DIST

Figure 7 is the individual relationship between MST, MRH, MRAD, ELEV, EVAP and DIST. It shows that MST drops with MRH, ELEV and DIST whereby MRAD and EVAP have linear trend and scatter around the regression lines. Nevertheless, figure 7 also shows that there is a significant scatter around the regression lines, which means that the residuals are significant.




MST
24
22
20
18
16
28
30
32
34
36
38
MRAD


MST
70
60
50
40
30
28
30
32
34
36
38
EVAP


MST
1500
1000
500
0
28
30
32
34
36
38
ELEV

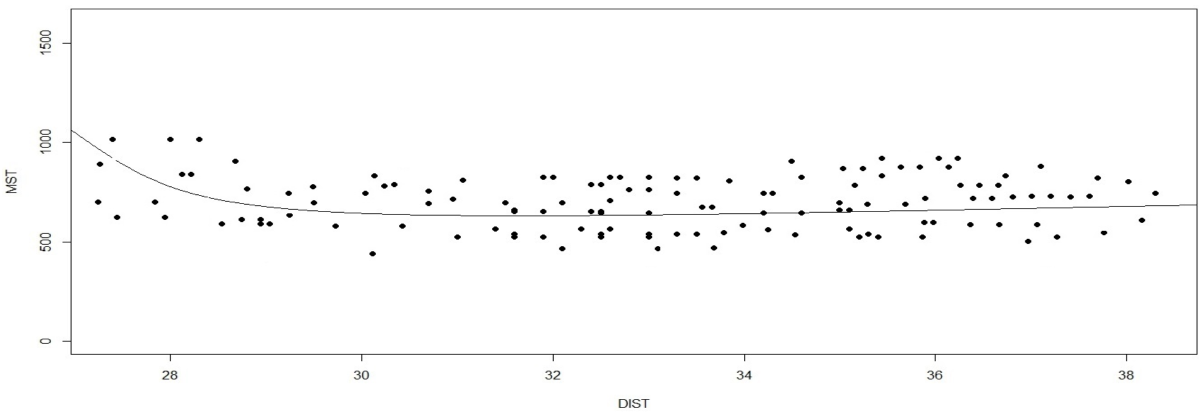

MST
1500
1000
500
0
28
30
32
34
36
38
DIST

Fig. 7: Scatter plots showing the general relationship between mean surface temperature (MST) against mean relative humidity (MRH), mean radiation (MRAD), evaporation (EVAP), elevation (ELEV) and distance (DIST).

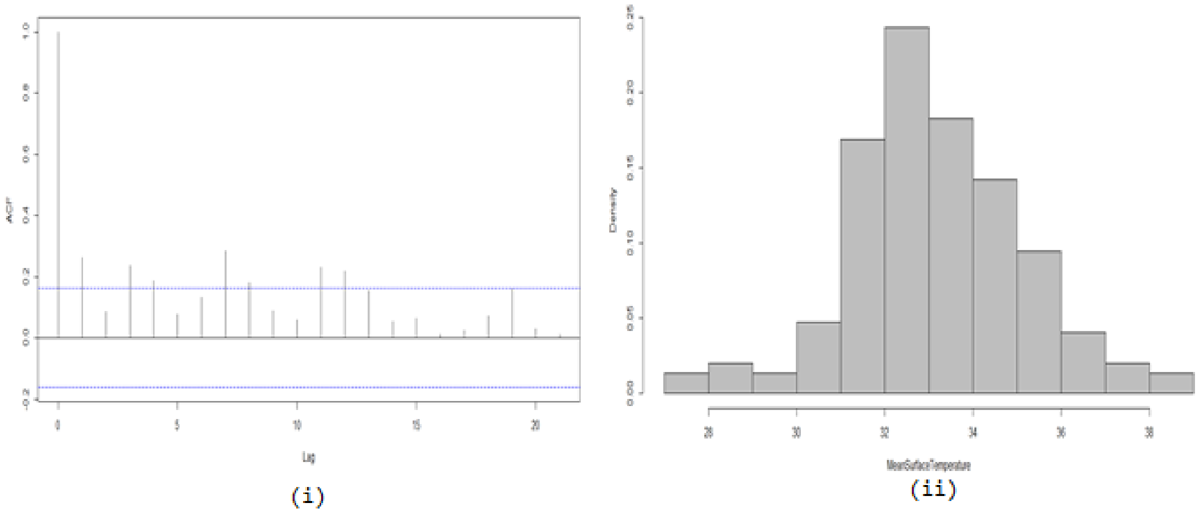


Figure.8: (i) Auto correlation function (acf) of MST (ii) A histogram of MST

5. Conclusion

The study has developed MST model using geostatistical technique with mean relative humidity, mean radiation, elevation, evaporation, distances of monitoring station Lagos (ocean/sea), longitude and latitude (position of each of the state capitals) as explanatory variables. The relationships between MST and the predictors in OLS and MLR models were positive and significant at 0.05 level. The experimental variogram is isotropic with Gaussian model, and the four directional variogram in the XYZ plane is anisotropic with exponential model as the best for the OK model. The OK XYZ with zonal anisotropic in the Z direction shows that the spatial continuity is in the North-East direction. The result also shows that predictions of estimates and kriging variances for OK and RK were similar as shown in the maps. The predictions are reasonable with RK model performing best.

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