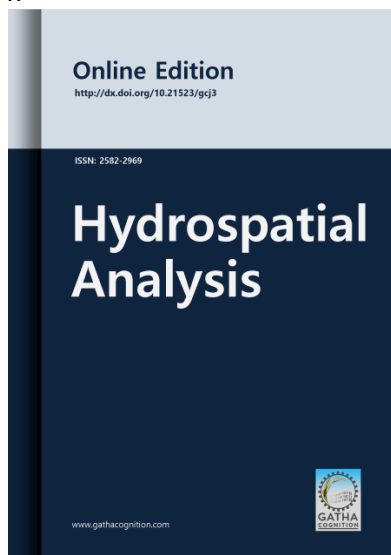


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Spatial Interpolations of Annual Rainfall in Ethiopia Using Simple and Universal Kriging Techniques

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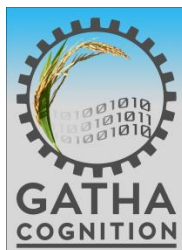
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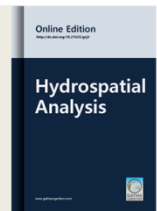
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Original Research Paper

Spatial Interpolations of Annual Rainfall in Ethiopia Using Simple and Universal Kriging Techniques



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Abstract

The study of spatial distribution of precipitation is an important aspect of water-related research like, hydrological modeling, disaster prediction and watershed management. But, spatial interpolations of annual average rainfall in Ethiopia using Simple and Universal Kriging type through different models has not yet investigated. This study was focused on to select the best fit semivarogram model for annual rainfall interpolation and to map the spatial distribution of rainfall of Ethiopia. In this study, long term mean annual rainfall which was collected from 931 meteorological stations were interpolated using different mathematical variogram models of Kriging to select the best fit variogram model useful to predict continuous surface values of annual average rainfall in Ethiopia. Spherical model was found to be the best fitted variogram model and most accurate model for interpolation using both Simple and Universal Kriging with the value of ME (0.005), RMSE (1.21) and MSDR (121.32) and ME (0.001), RMSE (0.88) and MSDR (144.11), respectively. Since the kriging results of spherical model indicate good model efficacy for this study, it may be useful to map spatial pattern of annual rainfall in Basin level in Ethiopia.

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Keywords

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1 INTRODUCTION

Rainfall trends are often cited as one of the most important factors in explaining various socio-economic problems, such as food insecurity, in the country whose economy is heavily dependent on low productivity rainfed agriculture (Cheung *et al.*, 2008). The study of spatial distribution of precipitation is an important aspect of water-related research like, hydrological modeling, disaster prediction and watershed management (Chen *et al.*, 2017). Geostatistical methods are widely applied in spatial interpolation from point measurement to continuous surfaces (Ly *et al.*, 2011).

Kriging/cokriging, areal interpolation and Baysian kriging are geostatistical approaches in estimating spatial distribution of environmental variables through geostatistical wizard in Arc GIS environment. Kriging/cokriging consist several

methods, including ordinary, simple, universal, indicator, probability and disjunctive, which are commonly applied for estimating spatial distribution of variables in the environment (Dindaroğlu, 2014; Gyamfi *et al.*, 2016).

In Ethiopia, Najnin and Sahalu (2019) has analyzed the spatial pattern of precipitation in the north-western part of Ethiopia (Gojjam) using spatial interpolation (Inverse Distance Weighting) and different geostatistical interpolation methods, like, ordinary kriging, simple kriging and universal kriging. Taye *et al.* (2018) also, analysis the spatial patterns of rainfall across the agro-climatic zones of Jema watershed in the northwestern highlands of Ethiopia using the Ordinary Kriging (OK), Simple Kriging (SK), Universal Kriging (UK), Disjunctive Kriging (DK), Ordinary Cokriging (OCK), Inverse Distance

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Weighting (IDW), Global Polynomial Interpolation (GPI), Local Polynomial Interpolation (LPI) and Radial Basis Function (RBF) interpolation models.

Spatial interpolations of annual average rainfall in Ethiopia using Simple and Universal Kriging types by different models like stable, spherical, gaussian and RQ has not yet investigated. Therefore, the present study was conducted to select the best fit semivariogram model for annual rainfall interpolation in Ethiopia using simple and universal kriging and to map the spatial distribution map of the average annual rainfall of Ethiopia. The study may have advantages to understand spatial variations in rainfall in a given area and useful in the field of irrigation for water management, water resource planning and management for different organization in Ethiopia.

2 STUDY AREA

The geographic locations of meteorological stations are shown on the map (Figure 1). Ethiopia has various climate zones that oscillating from semi-arid desert in the lowlands to humid and warm (temperate) in the southwest of the country. According to [Berhanu *et al.* \(2014\)](#), the mean annual rainfall in Ethiopia ranges from 141 mm in the arid region of the country's eastern

borders to 2275mm in the southwest highland. The mean annual temperature also varies widely based on the altitude difference from 15°C on the highlands to 25°C on the lowlands ([Regassa *et al.*, 2010](#)).

3 METHODOLOGY

3.1 Rainfall Data

In this particular study long term mean annual rainfall which was collected from 931 meteorological station of Ethiopia (Figure 1) distributed randomly throughout the Ethiopia. The data was collected from the Ethiopia meteorological agency.

3.2 Geostatistical Methods

Geostatistical method is an application of the theory of random functions to spatially distributed data ([Wackernagel, 2004](#)). A continuous surface values can be predicted between the known locations from a scattered set of known points through a geostatistical methods like Kriging or Cokriging ([Belkhiri *et al.*, 2020](#)). From a scattered set of annual average rainfall data recorded at meteorological station, continuous surface values of the rainfall were forecasted among the known locations using Kriging or Cokriging (ordinary, simple, universal, indicator, probability and disjunctive).

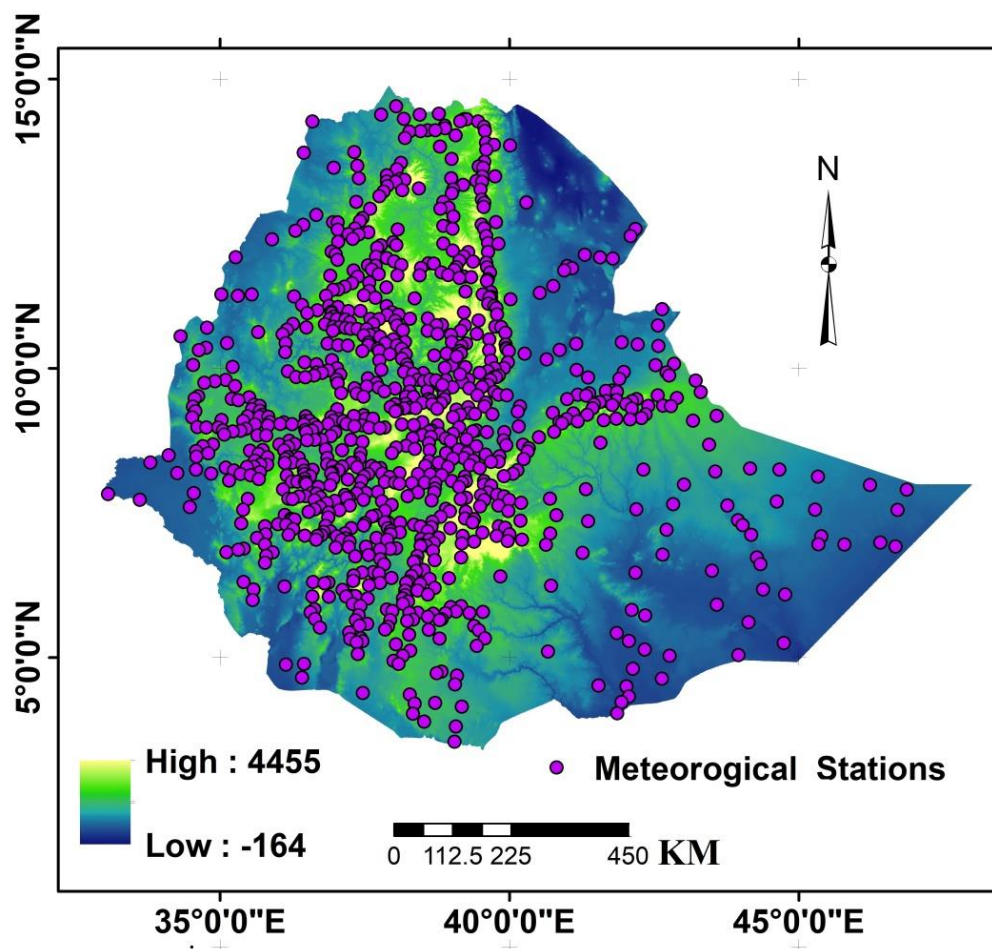


Figure 1. The study area with meteorological stations in Ethiopia

Simple and Universal kriging interpolation techniques were used to estimate continuous surface maps of the annual rainfall in Ethiopia. The change in semivariance between metrological stations displayed through semivariogram as the distance between them increases. At a given lag (h), the semivariance function $\gamma(h)$ is calculated using the following formula (Trangmar et al., 1986):

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

where, $\gamma(h)$ = semi-variance, Z = regionalized variable (i.e. annual mean rainfall), $z(x_i)$ = measured sample at point x_i , $z(x_i + h)$ = measured sample at point $(x_i + h)$, $N(k)$ = number of pairs separated by distance.

The estimation of unknown true value $Z(x_o)$ through kriging can be stated as:

$$Z(x_o) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (2)$$

where, $Z(x_o)$ = estimate of unknown true value, λ_i = weighted coefficient, n = number of neighboring observation used in kriging.

Information about the arrangement of the spatial variation as well as the input parameters for kriging can deliver through mathematical models (Belkhir et al., 2020). In this study, four mathematical models were fitted to the long year average annual rainfall variables in the entire area of Ethiopia. In its effective ranges, the year average annual rainfall data of the country had a spatial autocorrelation. Stable, spherical, gaussian and rational quadratic models were used to fit the variogram of average annual rainfall data through simple and universal kriging.

3.2.1 Simple Kriging

Estimating values of continuous random spatial variables from the given data set without bias and with minimum variance is possible using simple kriging technique (Webster and McBratney, 1987). According to Cressie (1991) and Radhakrishna and Helge (1995), It is the simplest case of geostatistical prediction and can be introduced as heterogeneously linear predictor in the form of:

$$\hat{Z}(s_0) = p(Z, s_0) = \lambda_0 \lambda^T Z(s) \quad (3)$$

3.2.2 Universal Kriging

Universal kriging is an estimation procedure within the context of the regionalized variable theory (Olea, 1974). It is a type of interpolation method for producing contour maps from irregularly spaced sample points, taking into account the trend which is of known form through assuming a known covariance model to express correlation of points at a short distance apart (Warnes, 1986). Based on the universal kriging theory, the relationship of the predicted value $\hat{U}(s_0)$ and measured values $U(s_i)$ on n locations can be expressed as a linear combination of the following formula (Kastelec and Košmelj, 2002):

$$\hat{U}(s_0) = \sum_{i=1}^n \lambda_i U(s_i) \quad (4)$$

where, λ_i = linear coefficients, $\hat{U}(s_0)$ = predicted annual rainfall value, $U(s_i)$ = measured annual values

3.2.3 Model Validation and Error Assessments

The validation and uncertainty of models of the two kriging techniques (simple and universal kriging) of this study were estimated by the difference between the observations and the predictions at the validation sites and were calculated by the following terms and equation.

1. The mean error (ME): It is used to determine the degree of bias during estimation and expressed as in the form of:

$$ME = \frac{\sum_{i=1}^n [\hat{Z}(s_i) - Z(s_i)]}{n} \quad (5)$$

2. The root mean square error (RMSE): This gives an estimate value of the standard deviation of the residuals (prediction errors) and calculated by the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n [\hat{Z}(s_i) - Z(s_i)]^2}{n}} \quad (6)$$

3. The mean squared deviation ratio (MSDR): It is the mean of the ratio of the squared prediction errors to the kriging variance and expressed as follows:

$$MSDR = \frac{1}{n} \sum_{i=1}^n \frac{[\hat{Z}(s_i) - Z(s_i)]^2}{\sigma^2(s_i)} \quad (7)$$

According to Tziachris et al. (2017), in order to say best fit model the ME should be close to zero for unbiased predictions, the MSDR should be close to one for a good model, and a low RMSE is associated with greater predictive accuracy of the model.

The spatial dependence of the average annual rainfall in Ethiopia was determined by semivariance analysis: the average annual rainfall in each metrological station were modeled with stable, spherical, gaussian, exponential and rational quadratic semivariograms with a nugget effect and it's spatial dependency was evaluated in terms of the ratio of nugget (C_0) to sill ($C_0 + C$) in percentage. The spatial continuity of average annual rainfall data at close distances can be expressed using an indicator of nugget effect (Paz-Gonzalez et al., 2000). The semivariogram with lower nugget effect was selected as the best semivariogram model for the study and the kriging value of this model was then used to map the spatial pattern of annual rainfall in Ethiopia.

According to Belkhir et al. (2020) the environmental variable is considered as a strong spatial dependence when the value of nugget (C_0) to sill ($C_0 + C$) ratio is less than 25%, a moderate spatial dependence when this value is between 25% and 75%, and a weak spatial dependence when the value is greater than 75%.

4 RESULTS AND DISCUSSION

The average annual rainfall of Ethiopia from 931 meteorological stations in the country was interpolated through simple and universal kriging in different mathematical models of stable, spherical, gaussian and rational quadratic to predict the continuous surface annual average rainfall values from scatter pointed rainfall data. The graph of predicted average annual rainfall from the different models and the measured values indicate positive correlation (Figure 2). This is an indicator that different models of kriging can interpolate the continuous surface data of amount rainfall in good manner for the whole area of Ethiopia from pointed measured meteorological rainfall data.

4.1 Best Fitted Variogram Models

In this study, the average annual rainfall spatial dependence was determined by semivariance analysis using different mathematical models. The result of these models indicated that the amount of average annual rainfall which was modeled with different semivariogram models with a nugget effect in good conditions. The Mean Error (ME), Root Mean Square Error (RMSE) and Mean Square Deviation Ratio (MSDR) provided precise measure of how well the model suitable with the variogram data.

The different fitted models, parameter values of this study are presented in Table 1. The results of the

study indicated that, spherical model was the best fitted variogram model and most accurate model for average annual rainfall interpolation of Ethiopia in both simple and universal Kriging with the value of ME (0.005), RMSE (121.32) and MSDR (1.021) and ME (0.001), RMSE (144.112) and MSDR (0.876), respectively (Table 1).

Spatial dependency of the average annual rainfall of Ethiopia was assessed in terms of the ratio of nugget (C_0) to sill ($C_0 + C$) and indicates a strong spatial dependence values for all models. Because, as indicated in Table 2 the value of nugget (C_0) to sill ($C_0 + C$) ratio is less than 25%, for all models of this study. Table 2, clearly indicates that the spatial dependence of average annual rainfall for the best fitted semivariogram of spherical model is strong with a nugget (C_0) to sill ($C_0 + C$) ratio of 1.23% and 1.66% for simple and universal kriging, respectively.

This strong spatial dependence values of annual rainfall in Ethiopia found in line with the research result of climatic variability and drought characterization in Ethiopia over three decades by Suryabhagavan and extremes (2017), spatial and temporal trends and variability of rainfall using long-term satellite product over the Upper Blue Nile Basin in Ethiopia by Ayehu et al. (2021) and Spatio-temporal rainfall variability and trend analysis in the Tekeze-Atbara river basin, northwestern Ethiopia by Abebe et al. (2022).

Table 1. Evaluation value for different models of simple and universal kriging

Models	Kriging Types					
	Simple			Universal		
	ME	MSDR	RMSE	ME	MSDR	RMSE
Stable	-0.024	0.875	169.667	-0.005	0.819	164.668
Spherical	0.005	1.021	121.322	0.001	0.876	144.112
Gaussian	-0.04	0.86	183.352	-0.023	0.705	229.876
RQ	0.017	1.233	111.961	-0.026	0.829	191.336

Table 2. Best fitted semivariogram and models parameters for average annual rainfall

Models	Kriging Types							
	Simple				Universal			
	Range	Nugget (C_0)	P-sill (C)	Nugget-Sill ratio (%)	Range	Nugget (C_0)	P-sill (C)	Nugget-Sill ratio (%)
Stable	4.74	24820.23	206888.7	10.71	17.63	18955.52	550800.29	3.33
Spherical	4.74	2593.07	208222.3	1.23	14.75	9040.61	535553.7	1.66
Gaussian	4.49	30875.9	199849.3	13.38	7.99	49537.46	340775.8	12.7
RQ	4.74	7920.96	180279.6	4.21	17.63	33777.98	408316.8	7.64

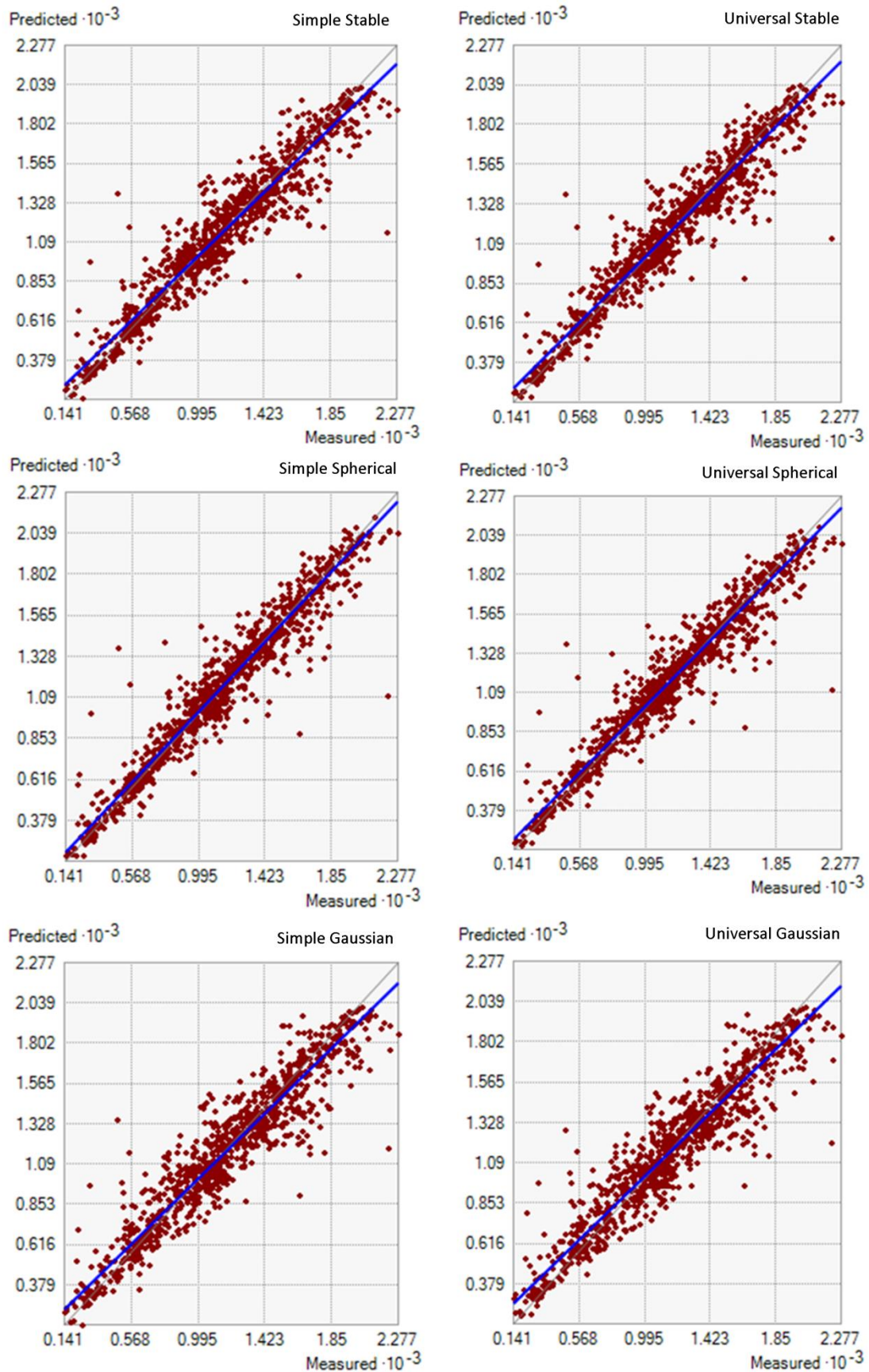


Figure 2a. Predicted and measured values

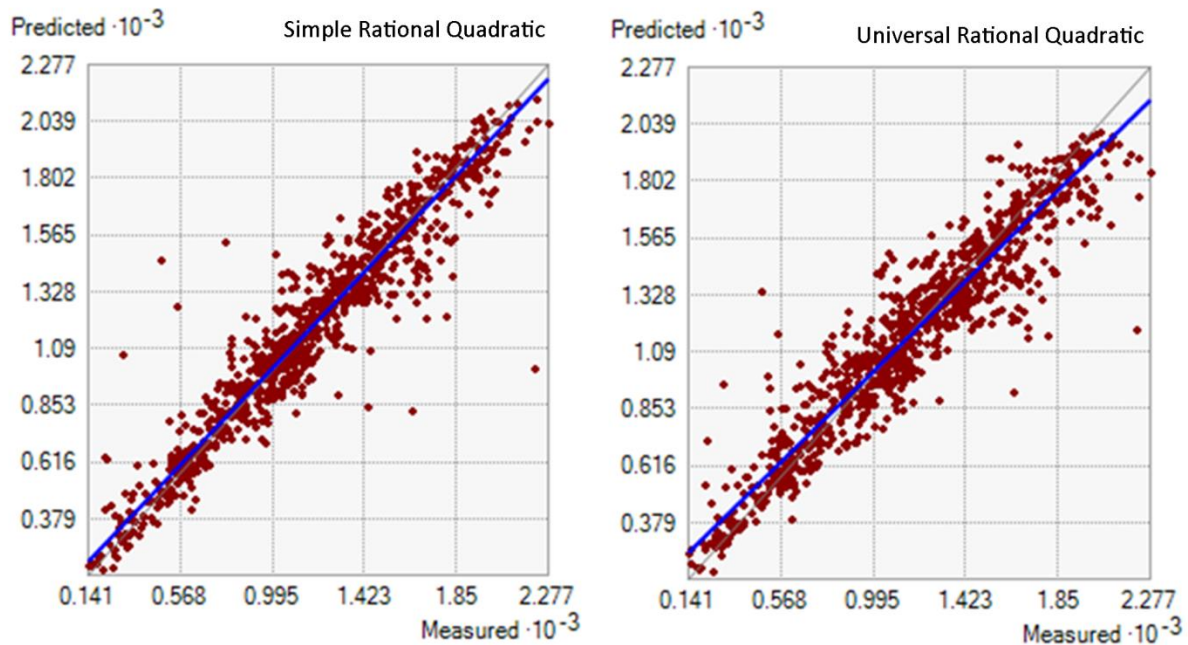


Figure 2b. Predicted and measured values

4.2 Spatial Distribution of Average Annual Rainfall

The spatial patterns of annual average rainfall of Ethiopia are investigated for selected models using universal and simple kriging. The spatial maps of universal and simple kriging for the models of stable, gaussian, exponential, spherical and rational quadratic are shown in figure 4. The map of stable and gaussian models for both simple and universal kriging and universal rational quadratic are smooth.

All models of this study indicated that the higher value of annual average rainfall is found in the central and western high land of the country. The southeastern (Somali Region and low land area of Oromia and SNNP) and northeastern (Afar and some part of Amhara) part of the country get lowest value average annual rainfall. According to Mera (2018), this part of the country (southeastern and northeastern) get less than 600mm annual average rainfall and severe drought has 30% chance of occurrence in each year. The medium range of average annual rainfall is found in the northern and eastern high lands of the country.

5 CONCLUSION

Kriging/cokriging consist several methods, including ordinary, simple, universal, indicator, probability and disjunctive, which commonly applied in estimating spatial distribution of variables in the environment. In this study different mathematical variogram models of

Simple and Universal Kriging were conducted to select the best fit variogram model to predict continuous surface values of annual average rainfall of Ethiopia between the known locations.

An exact measure of how well the model fit with the data in variogram may be expressed using the Mean Error (ME), Root Mean Square Error (RMSE) and Mean Square Deviation Ratio (MSDR). This was measured with the value of ME close to zero, the MSDR close to one, and a low RMSE value. Based on these points, spherical model was the best fitted variogram model and most accurate model for average annual rainfall interpolation of Ethiopia in both Simple and Universal Kriging.

In this study, the spatial dependence of the average annual rainfall in Ethiopia was expressed by ratio of nugget (C_0) to sill ($C_0 + C$) of variogram model also indicate that spherical model as the best semivariogram model. Based on this study in Ethiopia higher value of annual average rainfall is found in the central and western high land of the country and the southeastern (Somali Region and low land area of Oromia and SNNP) and northeastern (Afar and some part of Amhara) part of the country get lowest value average annual rainfall. This is a clear indicator that the spatial dependence of rainfall. As a recommendation, since the kriging result of spherical model indicate good model efficacy for this study, it may use to map spatial pattern of annual rainfall at Basin level in Ethiopia.

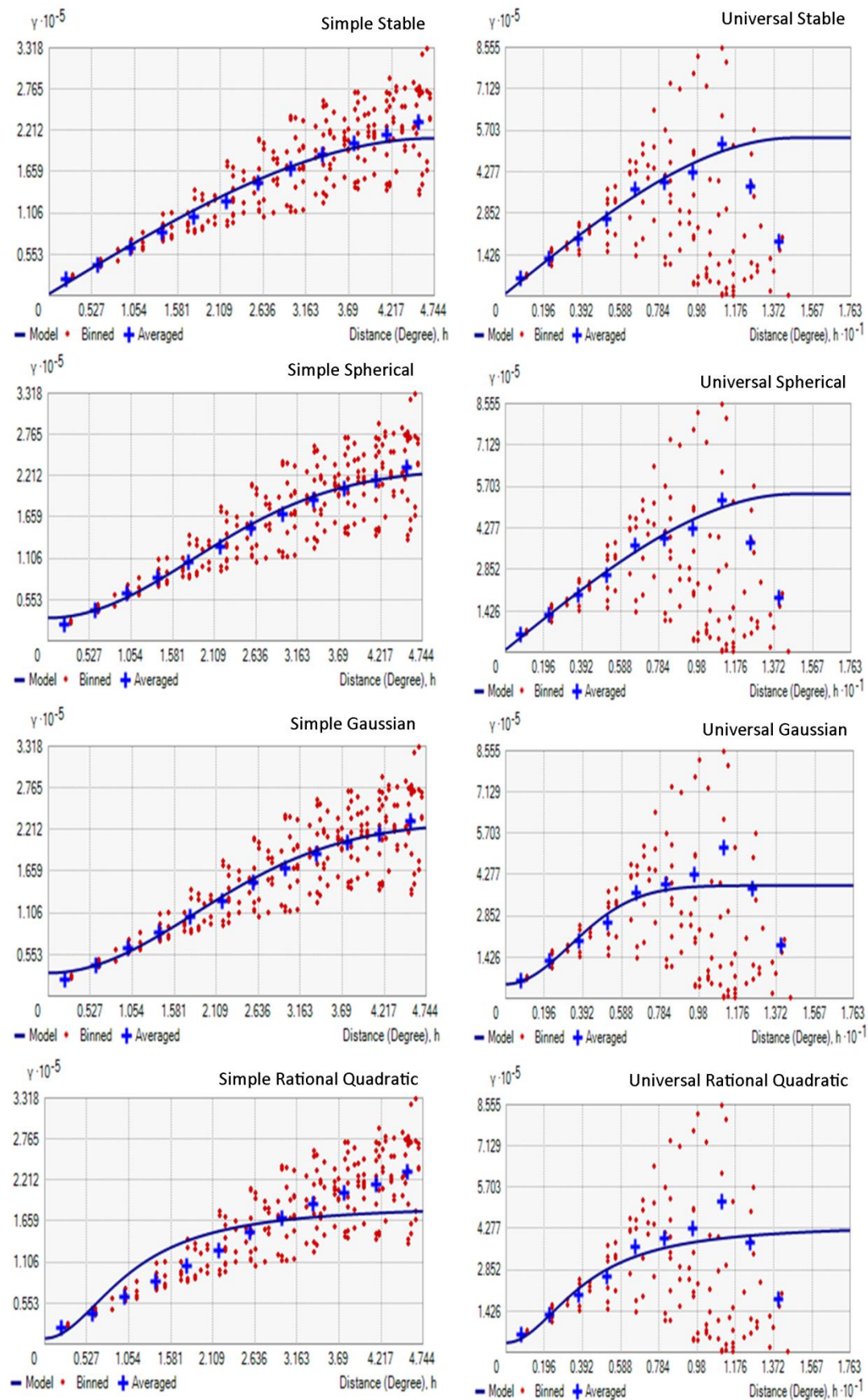


Figure 3. Simvarogram of different models

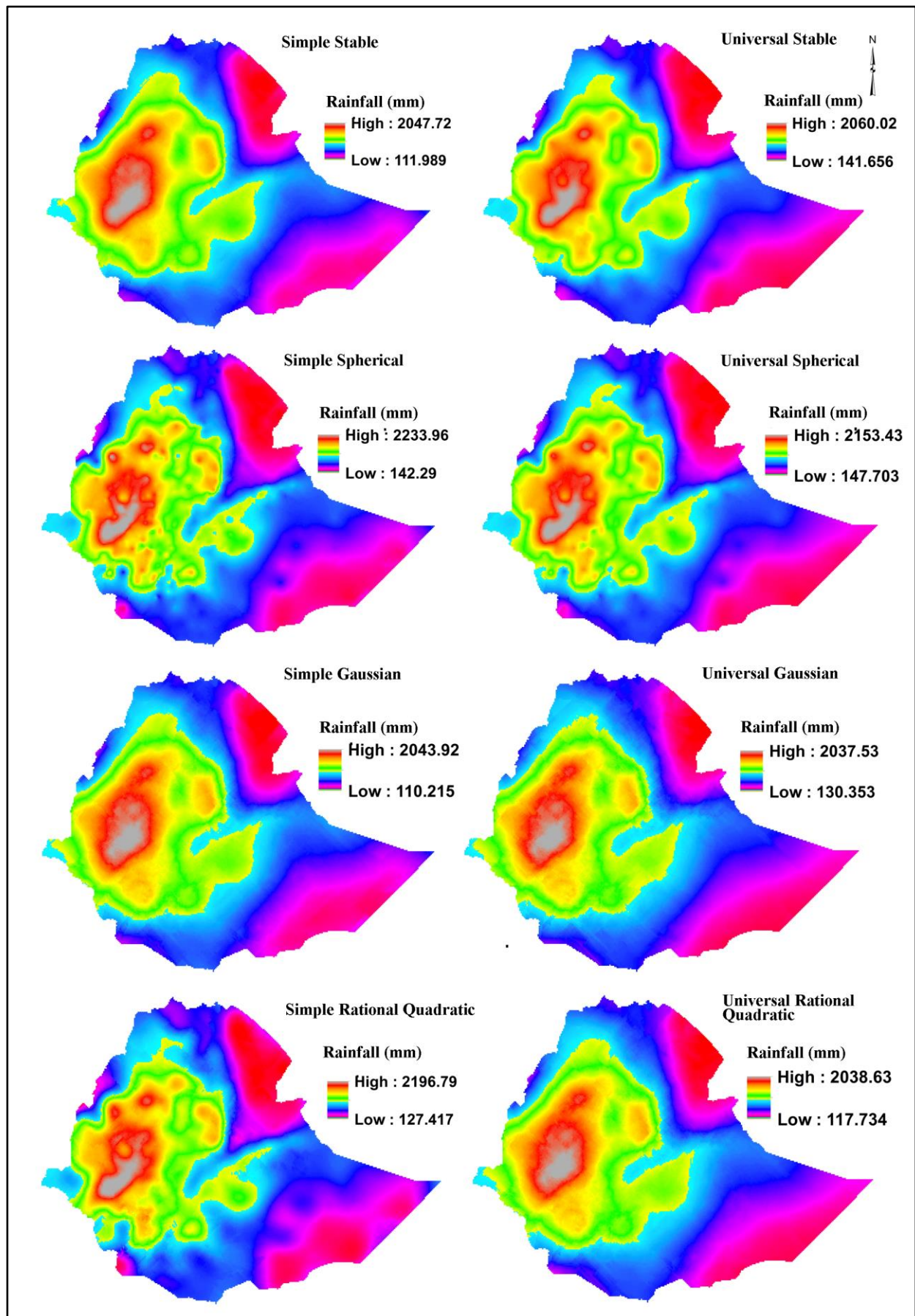


Figure 4. Estimated average annual rainfall using different models

CONFLICT OF INTEREST

No conflict of interest exists to publish the article.

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ABBREVIATIONS

DK: Disjunctive Kriging; **GPI:** Global Polynomial Interpolation; **IDW:** Inverse Distance Weighting; **LPI:** Local Polynomial Interpolation; **ME:** Mean Error; **MSDR:** Mean Square Deviation Ratio; **OCK:** Ordinary Cokriging; **OK:** Ordinary Kriging; **RBF:** Radial Basis Function; **RMSE:** Root Mean Square Error; **SK:** Simple Kriging; **UK:** Universal Kriging.

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