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Comparative Analysis of Different Spatial Interpolation Methods for Estimating Distribution of Monthly Rainfall (Case of Genale Dawa River Basin, Ethiopia)

A Thesis In Hydraulic Engineering Stream

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A Thesis

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The undersigned have examined the thesis entitled **'Comparative Analysis of Different Spatial Interpolation Method for Estimating Distribution of Monthly Rainfall Data (Case of Genale Dawa River Basin, Ethiopia)**' presented by **Dereje Fituma Mamo**, a candidate for the degree of **Master of Science**, and hereby certify that it is worthy of Acceptance.

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ABSTRACT

For most hydrological modeling and water resources development plan studies, the distribution of rainfall data is a very important input parameter. The spatial distribution of rainfall is usually accessible from the limited number of rain gauge stations especially in developing countries; this limitation increases the necessity of using a suitable interpolation method to obtain the spatial distribution of rainfall. Spatial interpolation methods are used to predict the values of the unknown place using known location points. In this study, the main objective to select a suitable interpolation method for estimating the monthly distribution of rainfall data for the Genale Dawa River Basin. Using the frequently used methods for comparison of estimating the Rainfall value in the kinds of literature done before and passing spatial interpolation method selection criteria, by considering the sample size available and spatial variability on monthly rainfall data in the study area. As result, four spatial interpolation methods were selected for this study namely: Inverse Distance Weighting (IDW), Spline with Tension (ST) Ordinary Kriging (OK), and Universal Kriging (UK) methods. The historical mean monthly Rainfall records from a total of 23 rain gauge stations selected for this study in the river basin which covers the area of 172,889km,^{2}during 2000-2018 period used for the analysis were used to compare the interpolation methods. The performance evaluation of selected interpolation methods evaluated through a cross-validation test using the Geostatistical analyst tool. The spatial interpolation methods were compared with the (RMSE) Root Mean Square Error and Mean Absolute Error (MAE). The cross-validation result specifies that the Geostatistical spatial interpolation methods perform better than deterministic methods, particularly the OK interpolation method relatively has the lowest RMSE and MAE error metric at the River Basin level. Therefore, the OK is the suitable spatial interpolation method for estimating the mean monthly rainfall distribution for this study area. The UK, ST, and IDW methods are followed by in respectively. The Ordinary Kriging method similarly is the suitable method for estimating seasonal rainfall in the Belg and Kiremt seasons, whereas the UK is the suitable method for the Bega season. The suitable spatial interpolation method generating Map of areal mean rainfall distribution in each month, the monthly rainfall distribution decreased from northwest to southeast in the study area.

***Key Words**: Rainfall, Spatial Interpolation, Cross-validation, RMSE, MAE, Rain gauge station, Genale Dawa*

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ABBREVIATIONS

GIS: **G**eographic **I**nformation **S**ystem

Km: Kilometer

DEM: **D**igital **E**levation **M**odel

SNHT: **S**tandard **N**ormal **H**omogeneity **T**est

IDW: **I**nverse **D**istance **W**eighting

ST: **S**pline with **T**ension

OK: **O**rdinary **K**riging

UK: **U**niversal **K**riging

RBF: **R**adial **B**asis **F**unction

LOOCV: **L**eave **O**ne **O**ut **C**ross-**V**alidation

RMSE: **R**oot **M**ean **S**quare **E**rror

MAE: **M**ean **A**bsolute **E**rror

ME: **M**ean **E**rror

MSE: **M**ean **S**quare **E**rror

RMSSE: **R**oot **M**ean **S**quare **S**tandardized **E**rror

Q-Q: **Q**uantile- **Q**uantile

SD: **S**tandard **D**eviation

CV: **C**oefficient of **V**ariation

Max: Maximum

Min: Minimum

CHAPTER 1 INTRODUCTION

Ethiopia a country of great geographic diversity with high and rugged mountains; flat, topped plateau, deep gorge, river valley, and plains. This diversity ranks Ethiopia as the most district in terms of relief and elevation extremes in Northeast Africa (LAHMEYER and YESHI BER, 2007). The climate of a country is mostly governed by the seasonal movement of the Intertropical Converge Zone, which is influenced by the convergence of trade winds of the Northern and Southern hemispheres and the related atmospheric circulation (LAHMEYER and YESHI BER, 2007).

Rainfall was collected from either Rain gauge, radar or Remote sensed satellite. They have advantages and disadvantages. Rain gauge is relatively the true measurement of rainfall data. Radar and satellite rainfall collectors can cover a large area and good resolution .but lack accuracy, uncertainty (Berhanu *et al.*, 2016);(Hu *et al.*, 2019) .uncertainty in rain gauge estimate from instrumental errors and spatial sampling errors. Rainfall distribution is affected by the resolution type used, modification by wind, type of rainfall, temperature, mountain ridges, water body, and others (Mair and Fares, 2014);(Tao *et al.*, 2009).

Rainfall is the fundamental input of many hydrological models and streamflow analysis, the main components of the hydrological cycle (Berhanu *et al.*, 2016):(Tao *et al.*, 2009). Meteorological data cannot be measured at all points at the all-time, as the result, point rainfall data are generally accessible from the limited number of rain gauge station, these limitations increase the necessity of using suitable spatial interpolation method to obtain the spatial distribution of rainfall and generate a surface of areal rainfall map from point data value (Mair and Fares, 2014);(Tao *et al.*, 2009).

Rainfall is one of the most important climate elements which control agricultural activities and production throughout the world. Accurate estimation of the spatial distribution of rainfall very useful for agricultural activities in most African countries particularly, in Ethiopia where the rainfed agriculture system is practicing (Fitsum *et al.*, 2017).

The knowledge of spatial rainfall distribution is very important for numerous purposes like water resources management, hydrological modeling, flood forecasting, climate change studies, irrigation schedule, and others are greatly dependent on the correct estimation of rainfall distribution (Kumari *et al*., 2016). For those applications, the rainfall parameters is challenging due to inherent variability in space and time (Kumari *et al*., 2016);(Mair and Fares, 2014).

The ability to accurately description rainfall distribution requires a dense network of gauge, which is mostly not possible due to the involves prohibitive installation and maintenances cost (Mair and Fares, 2014). The solution extends by estimating point rainfall at the unrecording location from the measurement of the nearby recording station, resulting in continuous surface rainfall data. The generation of continuous rainfall surface was accomplished through different spatial interpolation methods (Mair and Fares, 2014);(Otieno *et al*., 2014).

GIS application is used for data processes such as; acquisition, organization, storage. Spatial query, analysis, and presentation. Is the key decision support system that provides great convince in the planning and management of water resources (Zhang and Srinivasan, 2009);(Nandi *et al*., 2016).

It is often challenging to differentiate the best interpolation methods to estimate the spatial distribution of rainfall for a particular study area. The reason that performance of Spatial interpolation methods depends on many factors such as sampling density, the spatial distribution of samples, surface type, data variance, grid size, and resolutions (Kumari *et al*., 2016);(Bhattacharjee *et al*.,2019). There was no consistent finding of how these factors affect the performance of spatial interpolation.

Therefore, a comparative study is usually conducted to find the best interpolation methods, Arc GIS is a good platform for making comparison interpolation methods (Goovaerts, 2000). A geostatistical analyst provides a powerful set and a varied range of tools exploring spatial data, data variation. And error estimation of modeling (Goovaerts, 2000).

(Boke, 2017), conducted a comparative study on five spatial interpolation methods (Nearest Neighbor, Inverse Distance Weighing Average, Modified Inverse Distance weighing Average, Kriging, Thine-Plate -Spline Methods)for predicting four Monthly Average metrological variables, namely rainfall, mean temperature, Wind speed, and a sunshine fraction over Ethiopia territory and found that Kriging and Thine-Plate Spline methods are not good methods, Nearest Neighbor, Inverse Distance Weighing Average, Modified Inverse Distance Average, are best the methods. Mean Error, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Relative Error are assessment statistics used.

A study was carried out by (Abdelaal, 2019), over Egypt to evaluate the performance of eight spatial interpolations (IDW, Spline, Kriging)for prediction, Mean monthly temperature, and rainfall distribution. Results found that optimal temperature mapping was obtained by Co-Kriging, Ordinary Kriging, and Spline with tension methods. Local Polynomial Interpolation and Co-Kriging methods are better than other methods for predicting surface rainfall distribution. Seven statistical accuracy assessment was done to select the best methods.

At a global scale (Mair and Fares, 2014), carried out a study over Mountainous Regions of a Tropical Island, used to compare rainfall interpolation methods(IDW, Thiessen Polygon, Linear Regression, Ordinary Kriging, Simple Kriging)found that Thiessen polygon produces the highest error and Ordinary Kriging produces the lowest error when rainfall variable has additional elevation, Ordinary Kriging methods produce more Accurate prediction. Root mean square error was the statistical accuracy assessment used.

(Res *et al.*, 2005), done a comparative analysis of five interpolation methods (IDW, Ordinary Kriging, Universal Kriging, Spline, Top to Raster) for predicted Monthly and annual Rainfall over Sri Lanka, from 300 Rain gauge stations, found that Kriging interpolation performs better estimation than other methods. The accuracy of each method is evaluated by Mean Absolute Error and Standardized Root Mean Square Error.

Another study (Basistha, *et al.*,2008), carried out over the Indian Himalayas of Uttarakhand Region using five interpolation methods(Simple Kriging with varying Local Means, Ordinary Co- Kriging, Regression Kriging, IDW, Ordinary Kriging)for annual rainfall data of 80 rain gauge station and found that Kriging with varying Local means Performs better than Ordinary Co-Kriging. Root Mean Square Error was used for statistical accuracy measurement of each method.

(Frazier *et al.*, 2016), conducted a comparing study on three Geostatistical interpolation methods (Ordinary Kriging, Ordinary Co-Kriging, Kriging with an External drift) for predicting monthly year rainfall data over the Hawaiian Islands, found that Ordinary Kriging produces the lowest Statistical error.

(Pellicone, 2018), Evaluate the performance of five spatial interpolation methods (Ordinary Kriging, Ordinary Cokriging and Kriging with External drift, Inverse Distance Weighting, and Radial Basis Function) for monthly rainfall in two catchments in Australia using 61 rain gauge station. Results found that Geostatistical interpolation outperforms the deterministic method, Ordinary Cokriging found the best interpolation method for both catchment areas. The performance assessment was done using statical error Root Mean Square, Mean Bias Error, and Coefficient of determination of I.

Several interpolation methods available in Arc GIS within a varying degree of complexity. This study intends to compare the commonly used spatial interpolation methods in the literature for comparison of estimating rainfall values (Boke, 2017); (Abdelaal, 2019); Res *et al.*, 2005); (Basistha, *et al.*,2008); (Pellicone, 2018), the methods were chosen on the bases of many studies done in the past for interpolated rainfall value, based on some criteria such as the sample size available in the study, smoothing and similarity of their features and methods found in Geostastical wizard options as a result of this, four spatial interpolation methods are selected namely: IDW, ST, OK, and the UK to evaluate the suitability of methods for estimation of monthly rainfall distribution over the study areas.

1.1 Statement of the problem

Metrological parameters patterns mostly Rainfall is very difficult to understand the spatial distribution in a region with complex topography. Measurement of the regular amount of metrological data may exhibit spatial variability due to meteorological and topographic conditions. By the form of; very irregular, lack of measurement in such region, uneven distribution rain gauges station, covering mainly valleys and low land areas (Ahmed *et al*., 2014).

Genale Dawa River Basin was known for variations of topographic features that have to affect rainfall distribution across the basin. As well as, rain gauge stations not spread out in the whole area, short and erratic records in operating stations. Incomplete and discontinuous measurement of rainfall records (LAHMEYER and YESHI BER, 2007);(Boke, 2017).

Spatial rainfall distribution requires a dense rain gauge network. However, the dense network station is constrained by economic, logistics services. As the result, point rainfall data from rain gauge stations may not occur in the target location .in this case, the spatial interpolation method has a great role in modeling the rainfall distribution in areas where no station is based on the observed value of the surrounding station.

In general, the integral effect above mentioned problems has an effect on rainfall distribution patterns over the Genale Dawa River Basin. Therefore, knowledge of the spatial distribution of rainfall over the river basin area is very vital in water resources management and planning future socio-economic activity. And it is necessary to have suitable interpolation methods in the study area for specific parameters for use intent purposes.

1.2 Research Questions

- ❖ Which spatial interpolation method is suitable for Estimating Monthly Rainfall distribution in the Genale Dawa River basin?
- ❖ Are there differences in spatial interpolation methods for estimating rainfall values at the monthly and Seasonal values?
- ❖ What are the most common error statistics to compare the performance of the interpolation methods?

1.3 Objective of The Study

1.3.1 General Objective

The primary objective of this research was to compare the performance of selected spatial interpolation methods for estimating Monthly spatial rainfall data distribution for the Genale Dawa River Basin.

1.3.2 Specific objective

The specific objective of the study:

- To find out the most suitable spatial interpolation method for estimating Monthly rainfall distribution over the river basin.
- Comparison of spatial interpolation methods for estimating seasonal rainfall value over the river basin.

1.4 Significance of the Study

This study is very important to identify the best data filling methods for a missed value of metrological data, especially the rainfall data, from the selected interpolation methods, the generated monthly areal rainfall distribution maps used to understand the rainfall profile of the river basin and seasonal values, which supports hydrological modeling, proper plan and design of any water resources projects in the river basin, the result obtained from this study can be used as input for further study on spatial rainfall distribution over the study area.

1.5 Scope of the Study

This study was done to select the suitable spatial interpolation method for estimating monthly rainfall distribution for the Genale Dawa River Basin. From a continuous record of mean monthly rainfall data during 2000-2018-year record from rain gauge network used for this purpose, using Arc-GIS and Microsoft excel. The study is limited only to analysis and comparison of selected spatial interpolation (IDW, ST, OK, and the UK) to estimating mean monthly and seasonal rainfall values. And generating areal rainfall distribution maps of the study area. In all to meet the above set specific objectives.

1.6 Organization of the Thesis

This research work was structured into five chapters: the introduction, statement of the problem, research objective, and significance of the study, which are discussed in chapter one. Chapter two discussed a review of different research works on GIS-based on the spatial interpolation method for rainfall data, type of interpolation method, features of the methods, accuracy metric for assessment of interpolation method, the method used for data quality control analysis.

Chapter three discussed the material and method part: description of the study area, topography, climate, metrological station. Data used, software tools used to do the study, and, the methodology used to carry out the study.

Chapter four, results and discussion part; the result of monthly rainfall distribution for the selected station, the result of selected spatial interpolation method monthly areal rainfall distribution in monthly and seasonal values, cross-validation test results, comparative criteria, result from RMSE and MAE error metric for interpolation methods, suitable spatial interpolation method. Finally, in Chapter Five, the conclusion and recommendation for the study, references. An appendix was presented.

CHAPTER 2 LITERATURE REVIEW

In this section GIS-based, some of the spatial interpolation methods are briefly presented in the form of; type of spatial interpolation method, the mathematical formula behind each interpolation method, the factor that affects interpolation methods, performance assessment, from different kinds of literature, criteria selections of spatial interpolation methods. Finally, methods of data quality control used for this thesis work were also presented.

In water resources studies and other fields, the modeling of metrological Parameters by Geographic Information Systems is growing. In developing countries where the lack of consistent metrological quality data and a spare network weather station the application of GIS is very important (Boke, 2017);(Dolui *et al*., 2013).

Mostly with aid of statistics and Geographic Information System, the spatial analysis can be done using different methods, several interpolation methods have been used for the spatial analysis, the biggest question among different researchers is to find out which is suitable for interpolating needed data values. Several researchers worked to find out the most suitable interpolation methods (Bhattacharjee *et al*.,2019);(Boke, 2017);(Mair and Fares, 2014).

2.1 Type of Interpolation method

The spatial interpolation method has different numbers and can broadly be divided into two major groups: the method of deterministic and geostatistical interpolation. For the formation of a surface grid from point data in Arc GIS. These methods are; Natural Neighbor, Inverse Distance Weighting, Spline, Top to Raster, Trend, and various from of Kriging methods (Bhattacharjee *et al*., 2019);(Ly *et al*., 2013).

The Spatial interpolation method estimation approach can be described by weighting the average of sample values, the general estimation equation of the spatial interpolation method is given as follows:

$$Z(x_o) = \sum_{i=1}^{N} w_i Z(x_i)$$ **Equation 2-1**

Where Z(x_o) represents the estimated value of the prediction parameter Z at an unsampled location x_o, $Z(x_i)$ is the actual interpolating point. xi, wi is the weighting interpolating point x_i and N is the number of points (Bhattacharjee *et al.*, 2019);(Ly *et al.*, 2013)

2.1.1 Deterministic Interpolation Method

The Inverse Distance Weighting, Natural Neighbor, Spline Trend, and Topo to raster method are categorized under deterministic interpolation methods. Those are assigned the value of location-based on the value measured around the predicted value and mathematical equation that determines the smoothness of the resulting surface (Bhattacharjee et al., 2019); (Adhikary *et al.*, 2017);(Scharifi *et al.*, 2019).

2.1.2 Inverse Distance Weighting Method

In this method estimation of the value of missing metrological variable at the point, of interest is done by a linear combination of the weighted mean of a measured variable at the surrounding station, it estimates the value of the unsampled point by the weighted average of observed data at a surrounding point as an inverse function of distance point of the interest from the surrounding station (Boke, 2017).

In the Inverse Distance Weighting method, the distance of the observation station is critical, closer observation point have more influence on the interpolation point, it is a most used by GIS Analyst, and easy to implement interpolation method point (Bhattacharjee *et al.*, 2019);(İçağa and Taş, 2018). The equation of IDW is as follows:

$$P = \frac{\sum_{i=1}^{n} \frac{1}{d^k} P_i}{\sum_{i=1}^{n} \frac{1}{d^k}}$$ **Equation 2-2**

Where P: Estimated value at interpolation point P_i: Observed value at the point i,

N: Number of samples points the specified power

d_i: Distance between the interpolation and observed point, k: is the power value.

2.1.3 Natural Neighbors

The method Natural Neighbors estimate the value of the missing attribute value based on the nearest sample location, by drawing perpendicular bisector between interpolating point, forming such as Theissen polygons (V_i, i=1,2…n) (Bhattacharjee *et al*., 2019);(Li, 2016). The weighting average is given in the equation below.

$$\Lambda_i = \begin{cases} 1 if, xi \in vi \\ 0, otherwise \end{cases}$$ **Equation 2-3**

2.1.4 Spline Method

The spline methods are categorized into the deterministic interpolation method and relate to the group of Radial Basis Function. The radial basis function involves a set of exact interpolation techniques, where the spatial estimation necessity goes whole with each sampled value. The spline method can predict the value above the maximum and below the minimum of the measured value (Borges *et al*.,2015).for the measurement of smooth spatial distribution from the number of the data point, the spline method usually used .when there are a significant shift in observational value within short a distance the techniques maybe not suitable (Taş, 2017). The prediction is a linear functional combination of:

$$\hat{Z}(s_o) = \sum_{i=1}^{n} \omega_i \varphi(\|S_i - S_o\|) + \omega_n + 1$$ **Equation 2-4**

$$\varphi I = \ln\left(\frac{\sigma . r}{2}\right) + K_o(\sigma . r) + C_{E'}$$ **Equation 2-5**

Where: φI is the radial basis function, $\|S_i - S_o\|$ is Euclidian distance between prediction location So and each data location S_i, ω_i are weight to be estimated. Σ is the smoothing parameter, K_o is the modified Bessel function, and C_E is the Euler constant (Borges et al., 2015).

Thin plate smoothing and regularized spline are two options of the spline interpolation method. The spline method uses a mathematical function that minimizes overall surface curvature, it is more convenient for a gently varying surface due to basic minimum techniques (Bhattacharjee et al., 2019).

2.1.5 Trend Method

The trend uses global polynomial interpolation that fits the flat surface defined by a mathematical function to the input sample point, there are two types of trend interpolation options, linear and logistic trend, the former used for continuous data, and then later for non-continuous data (Bhattacharjee et al., 2019).

2.1.6 Topo to Raster Method

It follows an iterative finite difference Interpolation technique that maximize the system of performance local interpolator without sacrificing surface. The interpolation methods explicitly designed to construct a surface that more closely represent a natural drainage surface continuity specifically designed to create a surface more closely represents natural drainage surface and better preserves both ridgelines and stream network from the input contour data (Bhattacharjee *et al.*, 2019).

2.2 Geostatistical Interpolation Method

The method of Geostatistical interpolation is based on the concept of a regionally variable and include a range of statistical methods for integrating the statistical dependency of measurement into data analysis (Li, 2016);(Borges *et al.*, 2015);(Goovaerts, 2000);(Adhikary *et al.*, 2017).

It is the generally chosen method because it allows one to account for spatial dependency between neighboring measurements to predict the value of ungauged location, additional benefit of Geostatistics interpolation is that comprehensive more densely sampled secondary features with lightly sampled observed of the primary feature (Mair and Fares, 2014).

Kriging is the well-known geostatistical interpolation method, provide unbiased estimation with minimum variance for spatial relation between input point data, the method of kriging state the spatial variance of any variable can be defined as that of the combination of three critical elements, in below (Kumari *et al.*, 2016);(Mair and Fares, 2014);(Borges *et al.*, 2015).

(a) A structural component with a constant average or trend.
(b) A random portion, yet spatial related and defined as the variation of regionalized variable, and
(c) A random noise or spatially uncorrelated

2.2.1 Semi variance and Variogram

Before the actual prediction, the spatial dependence of the data is evaluated by a variogram. Geostatistical uses the Semi variogram γ(**h**) as a measure of dissimilarity between observations, The experimental semi variogram γ(h) is calculated as half the average squared difference between the components data pairs, as in equation 2 .6 below (Mair and Fares, 2014).

$$\gamma^{\wedge}(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[z(u_i) - z(u_i + h)\right]^2$$ **Equation 2-6**

Where γ^(h) is experimental semi variogram, N(**h**) number of data location a vector **h** apart z(u_i) is the measured value of the parameter at a point i.and h distance between measured data.

A plot of γ^(h) versus h is referred to as the experimental Semi variogram, which shows three essential characteristics such as Nugget, Sill, and Range, the "Nugget" positive value of γ^(h) at h close to zero, which is the residual reflecting the variance of sample error. The "Range" is the distance value that is reached by the sill. Sill is the value of semi variance at range (Li, 2016);(Bhattacharjee *et al.*, 2019).

There is a great vary of semi variogram models such as Spherical, Circular, Exponential, Gaussian, and Linear, which in turn influence the prediction of unknown values. For this study the Spherical variogram model is adopted, it is characterized by linear behavior at the origin with a gradual curve towards the sill, the Spherical semi-variogram model is the most widely used because it usually provides the best fit in one, two, and three dimensions and the lowest estimation error (Mair and Fares, 2014);(Basistha *et al.*, 2008).

The Spherical Semi-variogram model written as :

$$\gamma^{\wedge}(h) = \theta_o + \theta_s.\left[1.5.\frac{h}{\theta_r} - 0.5.\left(\frac{h}{\theta_r}\right)^3\right] \textbf{ for } 0 \leq h \leq \theta_r$$ **Equation 2-7**

γ(h) $= \theta_s \ for \theta_r < h$, where h is the distance between two points, θ_o is the nugget, $\theta_s \geq 0$ is the spatial sill value, and θ_r is the range of the model (Borges *et al.*, 2015).

2.3 Type of Kriging

2.3.1 Simple Kriging

Simple kriging assumes that the mean is constant and known, it uses a local average. As a result, simple kriging is less precise than Ordinary Kriging. But it usually produces a result that is smoother and more beautifully (Xiao *et al.*, 2016).

2.3.2 Ordinary Kriging

This method is a type of univariate geostatistical interpolation method, in the Kriging family this technique is now the most frequently and widely used, the ordinary kriging method estimates the value of environment variables from the value at a given point at the neighboring station, and a variogram model for those parameters (Li, 2016).

$$Z^{*}_{OK}\left(x_o\right)=\sum_{i=1}^{n(xo)}\lambda^{ok}{}_{i} * z\left(x_i\right)$$ **Equation 2-8**

Where; $Z^{*}_{ok}\left(x_o\right)$ is the estimated parameter value, λ_i are the OK weight, $n\left(xo\right)$ is the number of data closest to the location xo, and $z(xi)$ is observed parameter value.

In observed value, the mean is constant and unknown is the principle behind the ordinary kriging method, its objective is to reduce the mean square prediction error, by generating a minimum variance estimate by considering: the distance between the estimated point, the distance data point itself, and the statistical structure of the variable (Bhattacharje *et al.*, 2019);(Mair and Fares, 2014).

2.3.3 Universal Kriging

This implies that the data has a dominant trend that can be modeled by deterministic function, mean that by a polynomial, this polynomial is subtracted from the original quantified point, and also the autocorrelation is modeled from random errors until the model matches the random error before making a prediction, the polynomial added to back the prediction to give meaningful result (Res *et al.*, 2004).

$$Z\left(x\right)=\mu\left(x\right)+\varepsilon\left(x\right)$$ **Equation 2-9**

$Z\left(x\right)$ the estimated value, $\mu\left(x\right)$ is trend function at location x, $\varepsilon\left(x\right)$ is value random error.

2.4 Spatial Interpolation Methods Features

2.4.1 Global Interpolation Versus Local Interpolation

The global methods take into account all the data available in the area of interest in the region and prediction is carried out with a general trend model for the whole region, on other hand, local methods operate the small range of search windows from the whole region of interest, and estimation is carried out considering the local trend model around the prediction points, such as IDW, Spline, Kriging method(Li, 2016);(Bhattacharjee *et al.*, 2019).

2.4.2 Exactness Versus Inexact

A Method that produces an estimation that is similar to the observed sample value at the sample point is known as the exact interpolation method. Otherwise inexact interpolation method (Bhattacharjee *et al.*, 2019);(Li, 2016).

2.4.3 Gradual Versus Abrupt

Depending on some criteria such as simple distance relation, minimization of variance, curvature, and the imposition of smoothness, the spatial interpolation method is categorized into gradual and abrupt. If the interpolation approach produces a discrete and abrupt surface it's called an abrupt interpolation. The method which produces a gradual and smooth surface is referred to as gradual interpolation(Bhattacharjee *et al.*, 2019).

2.4.4 Linear Versus Non-linear Interpolation

The linear interpolation method assumes that the sample are normally distributed, an example from kriging family SK, OK, UK, On the other hand, the non-linear method are carried over the transformed values of the observed data. Example Kriging method with external drift shows these features(Bhattacharjee *et al.*, 2019).

2.4.5 Univariate Versus Multivariate

The spatial interpolation method is known as the univariate method, which only uses a sample of primary variables in operating estimation. A method that also uses secondary variables is also known as the multivariate method, for example, other Kriging families (Bhattacharjee *et al.*, 2019).

2.5 Factors Affecting Performance of Spatial Interpolation Method

Spatial interpolation are applied in various disciplines, the performance of the spatial interpolation method is data specific and also dependent on the application type, many factors affecting the performance of the interpolation method (Bhattacharjee *et al*., 2019);(Li, 2016), are had reported in point presented as follows:

- Sample Size, density, and Sample Spatial Distribution.
- Distance from prediction point.
- Data variation and normality.
- Type of surface/terrain.
- Correlation between primary and secondary variables.
- Data quality.
- Grid size and resolution.
- Spatial autocorrelation approach.
- Interaction among factors.

2.6 Cross-Validation

Cross-validation was used to the comparison between the measured value with predicated value with feature attribute in the sample data set. And can help to select between a different method, in spatial interpolation, it is widely used to evaluate such a performance of different interpolation methods for a variety of intended purposes (Taş, 2017);(Basistha et al., 2008). There are two common validation method have been widely used to suggest for evaluating of the accuracy interpolation method, these are LOOCV (Leave-One-Out -Cross-Validation) and Split sample method.

Leave -One -Out -Cross Validation method includes temporarily removing the station data from the data set and estimating the value of some position using the remaining data (the witness observation station). This is then repeated until all the station in the data set is temporarily removed in turn calculated, it is embedded by Geostatistical wizard in ArcGIS Geostatistical Analyst extension to do (Li, 2016).

The inter data set is divided into two data sets in this method the entire raw data set, in the split sample method: training and test data set, the training data set is used to produce an interpolated surface. And the test data set is used for evaluating the performance of each interpolation method by comparing the difference between predicted and observed data value (Kumari *et al*., 2016);(Goovaerts, 2000).

2.7 Performance Evaluation of Spatial Interpolation Methods

The growing use in different disciplines of the application of spatial interpolation methods raises concerns about the accuracy and precision of the methods. The widely used error measurement method is Mean Error, Mean Absolute Error, Mean Squared Error, and Root Mean Square Error. Consequently, several scholars have reported and used a statistical indicator for error measurement to evaluate the performance of the spatial interpolation method. (Mair and Fares, 2014);(Otieno *et al*., 2014);(Bhattacharjee *et al*., 2019);(Basistha *et al*., 2008);(Goovaerts, 2000).

2.7.1 Mean **Error**

Mean Error shows the degree of bias between observed and predicted variables.it indicates the average direction of errors, an overestimation is indicated by positive bias, underestimation is indicated by negative bias. Its formula is as follows:(Bhattacharjee *et al*., 2019);(Ohmer *et al*., 2017).

$$ME= \frac{1}{n}\sum_{i=1}^{n}(P_i - P_o) \qquad \text{Equation 2-10}$$

where: n; number of data point(station) in consideration.

P_i: the predicted value of the variable at the base station.

P_o: the observed value of the variable at the base station.

2.7.2 Mean Absolute Error

Mean Absolute Error indicate the magnitude of the error which shows the accuracy of the method, and measure of how far is the predicted value from error regardless of sign (Bhattacharjee *et al*., 2019);(Ohmer *et al.*, 2017).

$$\textbf{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|P_i-P_o\right| \qquad \textbf{Equation 2-11}$$

where n is the number of a data point, P_i is the predicted value of a variable at the base station, P_o observed value of a variable at the base station.

2.7.3 Mean Square Error

The Mean Square Error determines the size of the error based on error squared, and it is very robust to outliers as it puts a large amount of weight on the big error (Bhattacharjee *et al.*, 2019).

$$\textbf{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(P_i-P_o\right)^2 \qquad \textbf{Equation 2-12}$$

where n is the number of the data point, P_i is the predicted value of a variable at a base station, P_o observed value of a variable at the base station.

2.7.4 Root Mean Square Error

Root Mean Square Error (RMSE) is the square root of MSE. It has similar property as MSE. And possess the same unit of the required value (Otieno *et al.*, 2014);(Li and Heap, 2008).

$$\textbf{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[P_{i-}P_o\right]^2} \qquad \textbf{Equation 2-13}$$

where n is a number of the data points, P_i is the predicted value of a variable at the base station, P_o observed value of a variable at a base station.

2.7.5 Root Mean Square Standardized Error

The RMSSE should be close to 1.an RMSSE greater than 1 means generally underestimation in the variability of prediction. An RMSSE smaller than 1 means generally overestimation of the variability (Li and Heap, 2008);(Ohmer *et al.*, 2017).

$$\text{RMSSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\frac{P_i - P_o}{\sigma_i}\right]^2}$$ **Equation 2-14**

where n is the number of the data point, P_i is the predicted value of a variable at a base station, P_o observed value of a variable at the base station. Σ_i is the standard deviation predicted value of a variable.

The performance evaluation for specified interpolation methods, selected from accuracy assessment RMSE. And MAE. Those error matric selected by considering error measurement generated in ArcGIS which are common for both these interpolators methods were compared. Accordingly, the selected spatial interpolation methods which have the lowest value of RMSE and MAE is the suitable method for estimating rainfall distribution in the seasonal and at Genale River basin level.

2.8 Spatial Interpolation Method selection

The selection of an appropriate spatial interpolation method for the data at hand is critical. The performance of spatial interpolation methods depends on many factors as mention in the above section as the variable under study, Sample size, data quality, and type of surface used are major ones. many factors should be considered in making appropriate method selection criteria (Bhattacharjee *et al*., 2019),(Li and Heap, 2008). The criteria may depend on the properties and assumption behind each method, nature, and spatial structure of the data for primary variables, sample density, and distributions (Bhattacharjee *et al*., 2019).

In the Genale Dawa River basin, the rainfall data collected from twenty-three rain gauge stations and has a sparse distribution rain gauge network, a monthly rainfall values shows variability, the data set used for interpolation was mean monthly rainfall observation from 2000 to 2018 year (will be discussed in chapter three), which need spatial interpolation method should suitability for sparse point, have quick processing speed, Univariate feature, weighted average method and require the model of spatial autocorrelation. **Table 2-1** below, shows the method found in the GIS software and the method selection criteria according to the nature of the method and availability of data for the study area. As a result, two methods from deterministic (IDW, ST) and Kriging family (OK, UK) methods were selected in this study for comparative analysis of estimating mean monthly rainfall value in the study area.

Table 2-1:Summary of Spatial interpolation method criteria selection

Methods	Type	Output data structure	Information from secondary variable	Sample requirement and assumption	Selection methods justifications
IDW	Deterministic	Grided surface	No	Sparse, regular data, smooth surface, and similarity of point	**Yes,** Exact, univariate, and Available in the Geostatistical wizard option for cross-validation tests
NN	Deterministic	Polygon	No,	Dense data, consider only the nearest data in the polygon	**No**, use a single sample point for estimation, produce the gradual or abrupt surface, not available in the Geostatistical wizard option for cross-validation test
Spline	Deterministic	Grided	No	Sparse data, local and exact, the fit surface was smooth	**Yes**, smooth, using nearby samples, available in the Geostatistical wizard option for cross-validation test as a group of radial basis function
Trend	Deterministic	Grided	No,	Dense data	**No**, it is global, needs the removal of the spatial trend in the data set, not available in the Geostatistical wizard option for cross-validation test.
Topo To Raster		Grided	Yes	Raster data	**No**, used for natural drainage surface, need the raster data, and not available in the geostatistical wizard option for cross-validation test
Kriging	Geostatistical	Continues Grided surface	No/yes	Well distribution and no discontinuity	**Yes**, local, stationarity, and an unbiased estimator, good for sparse data. utilizing addition to mathematical formula use statistic properties and available in Geostastical wizard option for cross-validation
GPI	Deterministic	Grided	Yes	Sample surface Vary from a point, have a global trend in the data set	**No**, use for examine trend surface analysis, it highly susceptible to the outlier, suitable for surface change slow or gradual, inexact method
LPI	Deterministic	Grided	Yes	Normal distribution	**No,** does not model the autocorrelation of data, use to identify long term range trend in the data set

2.9 Data Quality Control

2.9.1 Filling Missing Data

Typically, and mostly have incomplete observation data in the hydrology time series. There are several causes for missing rain gauge station records, such as the absence of an observer, missed record handling, natural phenomenon, instrumental failure (Subarmanya, 1984). Using a station near the station, the missing data can be filled out. there are various methods of filling data from missing time series: normal ratio, arithmetic mean. methods of regression, and method of inverse distance (Subarmanya, 1984);(scharifi et al., 2019). The normal ratio method for this study is selected to fill the missing rainfall data. It provides the monthly rainfall rain gauge stations considering a 10% percent of normal ratio of long term monthly average range in another normal long-term average of neighboring rain gauge station if the normal average is out of this percent the arithmetic method was used. The station correlation matric found in the basin was done and the more the involved rain gauge station used to fill for the missed one was correlated. The general formula of the normal ratio is given by:

$$P_x = \frac{N_x}{M}\left[\frac{P_1}{N_1} + \frac{P_2}{N_2} + \ldots \frac{P_n}{N_n}\right] \qquad \text{Equation 2-15}$$

Where: P_x =missing value of rainfall.

N_x = Average value of rainfall for required station

P_1, P_2, and P_n =Rainfall value of neighboring station during the missing period

N_1, N_2, and N_n = Average value of rainfall of neighboring station

M= Number of rain gauge station used

2.9.2 Test for Outlier

Time series data are often affected by outliers due to the influence of unusual and nonrepetitive events.in statistics, an outlier is a single observation that far away from the rest of the data can lead to an unrealistic conclusion (Adikaram *et al.*, 2015). It is recommended to test the outlier before analyzing the data. The Grubs and Becks(G-B) test was used for outlier detection (A.Ramachandara Rao, 2000).

$$X_H = \exp\left(Xmean + KN * \sigma\right)$$ **Equation 2-16**

$$X_L = \exp\left(Xmean - KN * \sigma\right)$$ **Equation 2-17**

$$KN = -3.62201 * N^{\frac{1}{2}} + 6.2844 * N^{\frac{1}{4}} - 2.4983 * N^{\frac{1}{2}} + 0.491436 * N^{\frac{3}{4}} - 0.0379 * N$$

Equation2-18

Where: N is the number of observed data, X_{mean} = mean of the natural logarithm of sample data. X_H =Highest data in time series, XL =Lowest data in time series, σ =standard deviation of the natural logarithm of sample data, KN= (G-B) constant function of an observed event.

2.9.3 Test for consistency of station data

During a recording period, the situation related to the recording of the rain gauge station undergoes a major shift, the inconsistency in the rainfall data of that station will occur. There are a range of causes of the inconsistency of the rainfall recording station, including the common one: moving the station to the new site, environment change due to calamities, and error of observation (Subramanya, 1984);(Adane *et al.*, 2020).

To verify the consistency of rainfall data, the double mass curve methods are used. The accumulated base rain gauge station is compared with the neighborhood station's corresponding group base station and plotted against the base station versus the total base station group (Subramanya, 1984). It should be changed if an alteration in the curve is detected using the equation below. The entire rain gauge station will not display a shift in the curve for this analysis.

$$P_a = \frac{b_a}{b_o} * p_o$$ **Equation 2-19**

Where: Pa adjusted rainfall, Po observed rainfall, ba slope of the graph to which records are adjusted and bo is the slope of the graph at which Po is observed (Adane *et al.*, 2020).

2.9.4 Homogeneity Test of station data

Homogeneity is an important issue in time series data. When time-series data is homogenous, it means that all the collected data belongs to the same statical population having a time-invariant mean, the test to check the homogeneity of data series is based on evaluating the significance of a change in the mean value (Deepesh and Madan, 2012).

There are different methods for detecting inhomogeneity in time series. For this study, the homogeneity of the annual rainfall of selected rain gauge stations in the river basin was done by statistical programming language R (version 2.14.2) Software, based on four methods of homogeneity test: von Neumann ratio Test, the Buishand range Test, Pettit Test, and Standard Normal Homogeneity Test.

According to (Wijngaard et al, 2003), the result of the homogeneity test done by the four methods above are classification made on the number of tests rejected the hypothesis into three class as below:

Class 1**: 'Useful'_**one or zero tests rejected the null hypothesis of a 5 % significant level considered. Under this class, the series is grouped as homogeneity and used for further analysis.

Class 2: **'Doubtful'_** two tests reject the null hypothesis of a 5% significant level. In this class, the series is having an inhomogeneous signal and should be critically inspected before further analysis.

Class 3: **'Suspect'_** three or four tests reject the null hypothesis of a 5% significant level. In this class, the series is ignored or deleted for further analysis.

2.9.5 Stationarity and Independence Test

The climatology time series is stationarity if it is free of the trend, shift, and periodicity. Thus, implies that the statical parameters of the series such as mean and variance constant through time (Machiwal and Jha, 2006). Static analysis of climatology time series was very essential before proceeding to model time series for different purposes.

There are different non-parametric method whose examine the stationarity of time series; t-test, stochastics model, Mann-Whitney test, Wald-Wolfowitz test, and other (Machiwal and Jha, 2006). For this study, the stationarity of the annual Rainfall data of the station was done by Wald -Wolfowitz test using the statistical programming language R Software.

The Wald-Wolfowitz test, comparing the value z with standard normal variety at 95% significance level .hypothesis of stationarity and independence was accepted only if the absolute value of z less than the tabulated u value equal to1.96 (A.Ramachandara Rao, 2000).

2.9.6 Normality Test

It is essential to assess the normality of the data set before applying the spatial interpolation methods. Geostatistical interpolation requires the normal distribution of the interpolated data values, normality assessed through graphical methods like histogram, Q-Q plots, and normal probability plot and also by analytical tests like Shapiro -Wilk, Anderson Darling, Lillierfors test, and Komogorov-Smirnow test (Ghasemi, 2014);(Mishra *et al.*, 2019).

CHAPTER 3 MATERIAL AND METHODS

3.1 Study Area

The Genale Dawa River Basin is Ethiopia's southernmost basin, covering part of the Oromia Region, a small part of the South Nation and Nationalities, and the Somali Region. Geographically located between latitudes 3º-30 'and 7º-20 North and 37º-05' and 43º-20 'East, the basin covers an area of 172,889km2. After Wabi Shebele, the Abay River basin is the third-largest river basin. The neighboring river basin Wabi Shebele River Basin to the North and East, and the West Rift Valley Basin (LAHMEYER and YESHI BER, 2007).

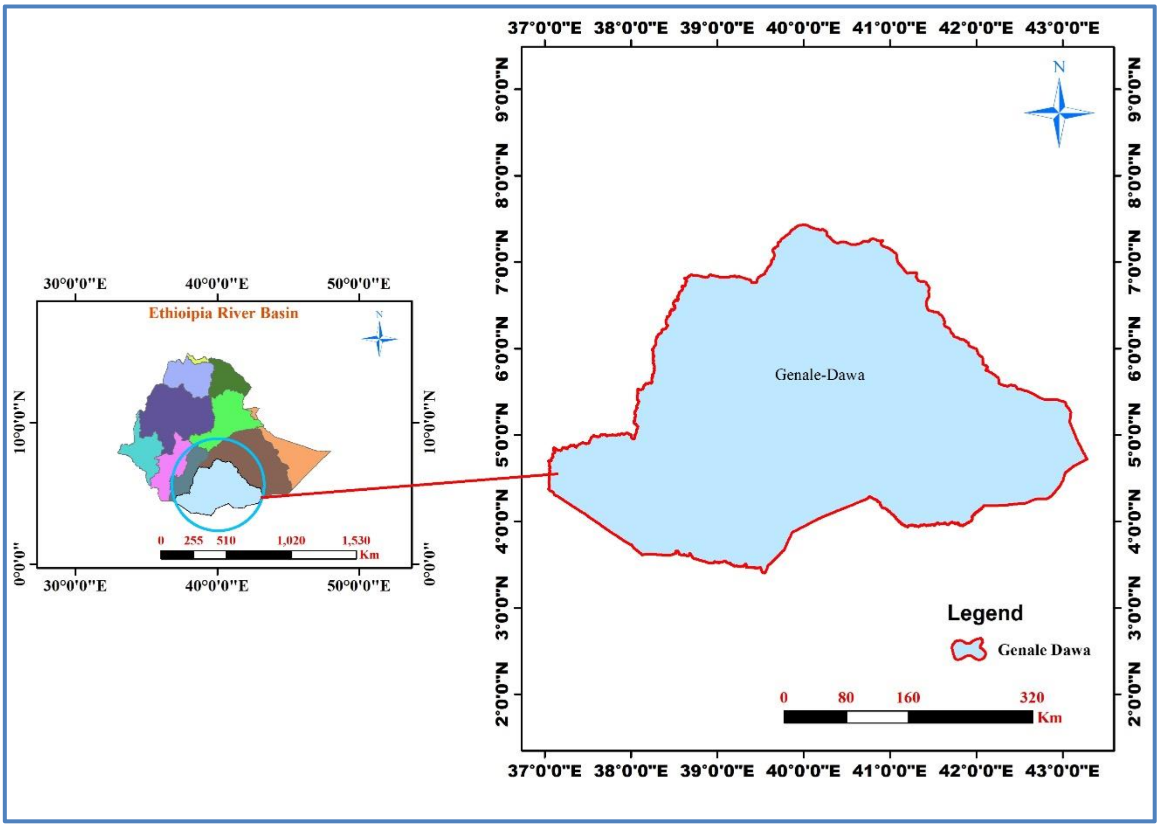


Figure 3-1:Map of Location of Study Area

3.1.1 Topography

The generally topographic feature of Genale Dawa River Basin has been grouped into four major landforms, namely: highland and plateau surrounded by a range an of the volcano, steep sloping escarpment, gently sloping lowland adjacent to the foot of the escarpment, and low land and flood plain basin, decrease in altitude from North to South and West to East, the basin has the lowest elevation of 171 m and highest elevation 4385 m, on the northern side of the basin Tulu Dimtu is the highest peak(4377m, above mean sea level) found in the Bale Mountains (LAHMEYER and YESHI BER, 2007).

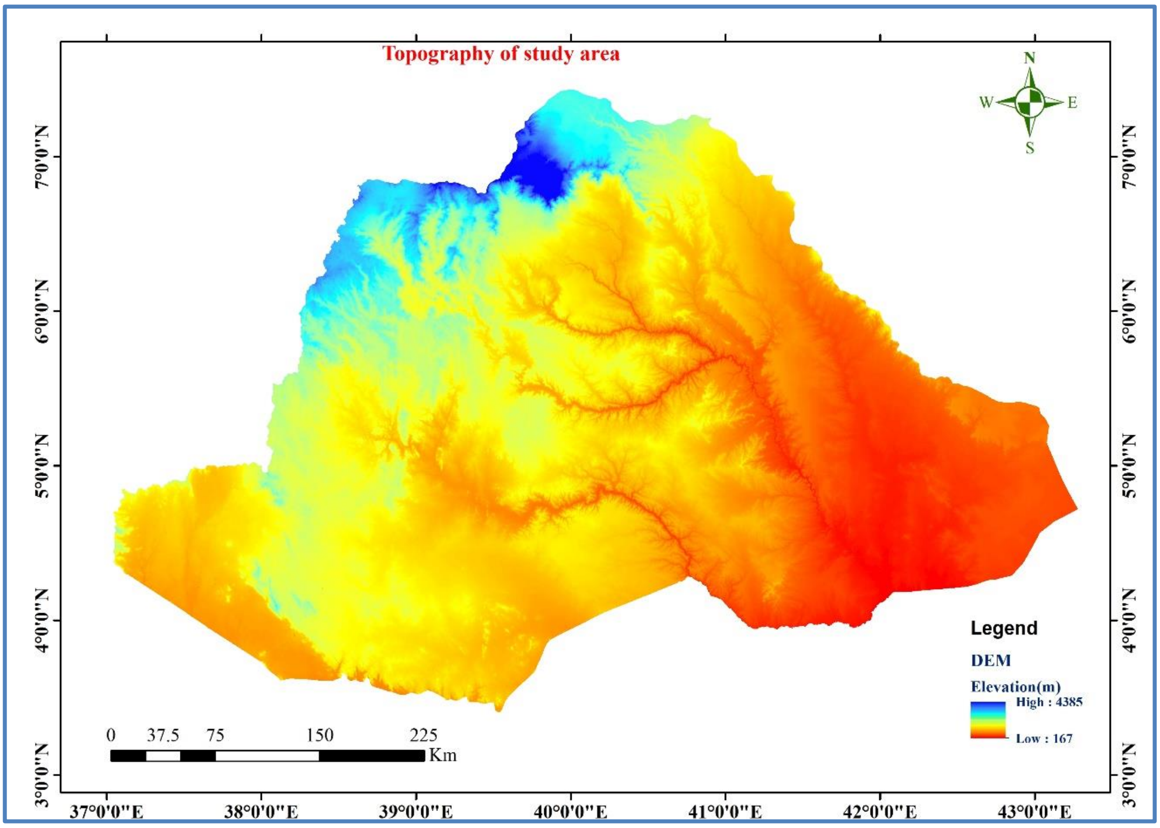


Figure 3-2: Map of Topography of study Area

3.1.2 Climate

A Genale Dawa River Basin weather system is usually governed by the location of the Inter-Tropical Convergence Zone, inform of intensity, position and direction. Its displacement enables the basin to have annual Bi-modal style rainfall distribution Rainfall and Temperature are correlated as rainfall increases the temperature and decreases with altitude (LAHMEYER and YESHI BER, 2007);(Bekele et al., 2017).

Traditional Ethiopian Climate classification based on altitude and mean temperature shows the presence of five main climate zone in the Genale Dawa River Basin.

- Wurch (Alpine)-cold climate at more than 3000m altitude and Mean Temperature below 11.5ºc.
- Dega (Temperate)-High Climate range above 2500m altitude and mean temperature in the range of 6-16ºc.
- Woina Dega (Subtropical)-warm between an altitude of 1500-2500m and within mean temperature in the range of 16-20ºc.
- Kola(tropical)-hot and arid type, less than 1500m altitudes and mean temperature range 20-28ºc.
- Bereha (Desert) -hot and hyper-arid climate, below 500m altitude and mean temperature above 28º c (LAHMEYER and YESHI BER, 2007).

3.1.3 Rainfall

In general, Ethiopia has a rainfall regime, namely monomodal, modal type I, Bimodal type II, and diffused type. With most Bimodal type II and Bimodal type I categorizations for the Genale Dawa river basin. Bimodal type I is characterized by a quasi-double peak rainfall pattern with a small monthly peak, whereas Bimodal type II is characterized by a double peak rainfall pattern (LAHMEYER and YESHI BER, 2007).

(Berhanu *et al.*, 2016) The rainfall characterization in Ethiopia was similarly defined and found that the Genale Dawa River basin has Bi-modal type-I and Bi-modal type-II monthly rainfall distribution and is classified under high, moderate, intermediate, and low rainfall regimes.

3.1.4 Metrological Station

Our country Ethiopia have more than 1200 metrological station, among them, a total of 919 active metrological stations, station classified as class-1,class-2,class-3, and class -4.class -1 class-2 known by synoptic and principal station respectively have the observation of most climate elements, Class 3 or Ordinary station have rainfall and temperature, class -4 or rainfall recording station have to measure daily rainfall record (Berhanu *et al.,* 2016).

There are 70 metrological stations in the Genale Dawa River Basin, ranging from class -1 to class four, which are mostly synoptic stations. The distribution of the station network is sparse and most of them are inoperative in the lowlands of the basin (LAHMEYER and YESHI BER, 2007). the figure below shows the rainfall stations which are selected for the study.

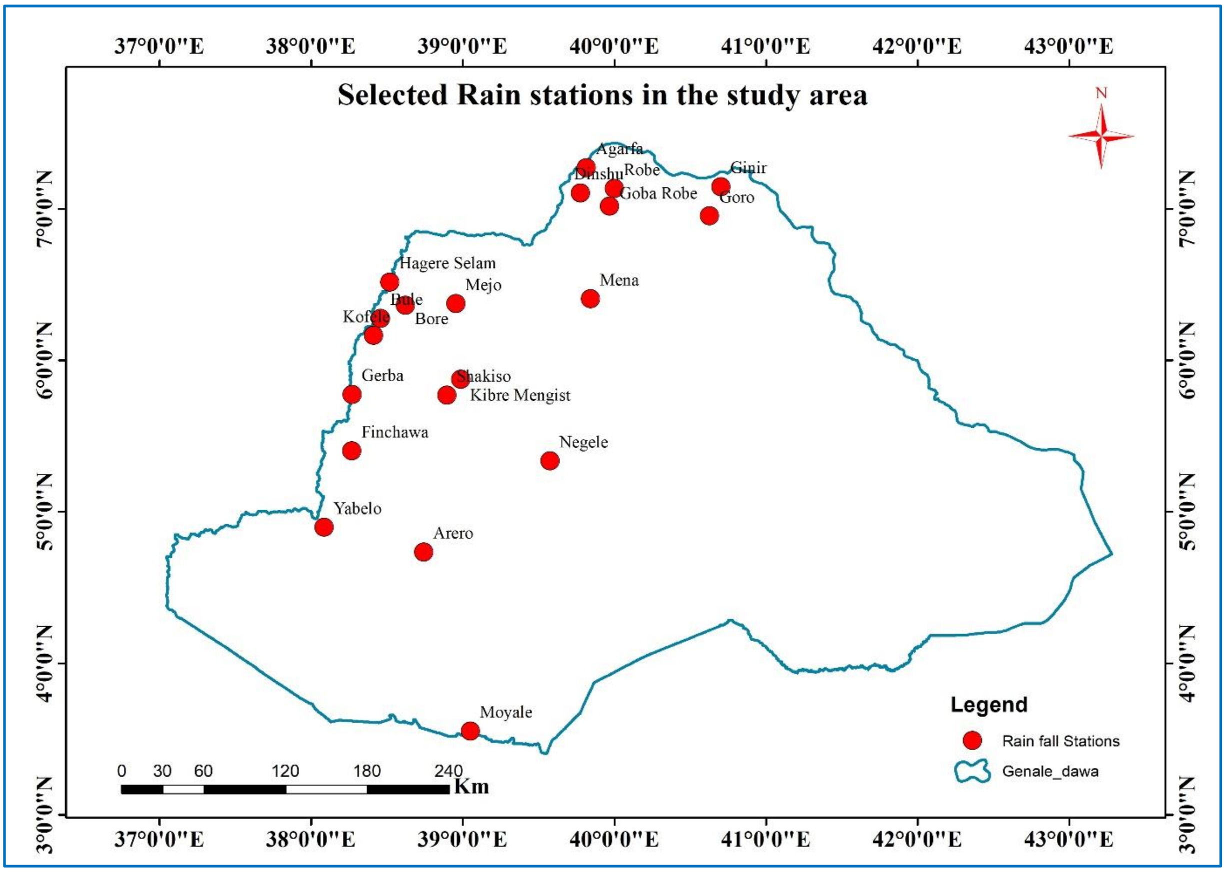


Figure 3-3: Map of Selected Rain gauge station in the study area

3.2 Software used for this Study

Table 3-1:Software used for this study

Name	Purpose	Sources
ArcGIS 10.4 version	• To prepare the study Area map. • To prepare areal monthly rainfall map • To perform Spatial analysis • To do spatial interpolation • To do Cross-validation using Geostatistical Wizard	http://www.esri.com
R-studio, Version 2.14.2	• To do a Homogeneity test • to do Stationarity test • to do a normality test	https://www.rstudio.com
Edraw -Max	• To draw frame work-study	https://www.edrawsoft.com
Mendeley Desktop	• To organize the referenced journals	https://www.mendeley.com

3.3 Data used and sources

Data used and sources for this study are summarized in Table 3-2 below.

Table 3-2:Data set used and their sources with their purpose

Type of data	Specific data name	Sources	Purposes
Metrological data	• Monthly time-scaled Rainfall	**National Metrological Agency**	• comparative analysis spatial interpolation methods
Topographic data	• Shapefile of the study area • Shapefile of the metrological station. • 90mx90 DEM	**Ethiopian Mapping Institute**	• For GIS application

3.4 Data Processing

3.4.1 Metrological Station processing

Genale Dawa has 70 rain gauge stations among them 38 rain gauge station monthly time-scaled rainfall data were collected from the period 1984 up to 2018.In this study, the rain gauge station which has an incomplete record, discontinuity measurement, and has more than 30% percentage of missing data been excluded from the analysis. Accordingly, 23 rain gauge stations have record lengths from 2000 up to 2018 used for the study. The selected rain gauge station used for this study is presented in **Table 3-3**.

Table 3-3:Selected Rain gauge station in the study area

S.no	Station Name	Long (°)	Lat(°)	Elevation (m)	Recorded length	Missing (%)
1	Argafa	39.883	7.21	2397	2000-2018	17.98
2	Arero	38.83	4.07	1785	2000-2015	22.91
3	Bore	40.02	7.01	2712	2000-2018	15.32
4	Bulle	39.9	7.13	2817	2003-2018	19.37
5	Delo Mena	39.83	6.41	1313	2000-2018	18.42
6	Dinsho	39.76	7.1	3072	2000-2018	19.29
7	Fincha wuha	38.26	5.39	1634	2000-2018	21.49
8	Gerba	39.19	11.15	1605	2003-2018	16.66
9	Gesera	39.93	7.13	2505	2000-2018	19.29
10	Ginir	40.7	7.13	1750	2000-2018	18.85
11	Goba	39.98	7.03	2614	2000-2017	19.74
12	Goro	40.46	7	4453	2000-2018	14
13	Hegere -Selam	38.4	5.16	2618	2000-2018	14.47
14	Hagere-Selam 2	38.52	5.49	2809	2000-2018	14
15	Kofale	38.48	7.07	2620	2000-2018	12.28
16	Mejo	38.55	5.45	1763	2000-2018	8.33
17	Moyale	39.03	3.55	1166	2000-2018	10.95
18	Negele	39.56	5.41	1544	2000-2017	17.12
19	Robe	40.03	7.13	2480	2000-2018	5
20	Robe -2	39.62	7.87	2441	2000-2018	18.33
21	Yabalo	38.1	4.48	1729	2000-2018	13.18
22	Dilla	38.3	6.39	1579	2000-2018	3.08
23	Kibre mengist	38.96	5.86	1680	2000-2018	9.64

3.5 METHODOLOGY

In this study, after data quality control was done, the historical mean monthly time-scaled rainfall data collected for a total of 23 rain gauge stations of the river basin during the 2000 - 2018 period was used for comparative analysis of spatial interpolation methods for estimating monthly rainfall value in the study area.

The mean monthly and Seasonal Rainfall input data set are exported in Arc GIS software in Geostastical analysis tools the Explore data using the Histogram, Normal QQ plot and Trend Analysis for particular months and seasonal values to examine there was normal distribution in data set in the form of skewness, Mean and median, trend analysis was to check observation of the global trend in data sets .When the data set was not normally distributed the natural logarithm transformed to into normal distribution and the first polynomial was used to remove the global trend in data set in Geostastical spatial interpolation methods. After input data was explored in the Geostatistical wizard option the cross-validation was done by setting in search Neighborhood type the standard, maximum, and minimum neighborhood fixed according to the number of the station used. Sector type was selected to reduce unbiased during the cross-validation test.

For this study, four interpolation methods which selected based on the input rainfall data quality, assumption methods, availability in Geostastical wizard option for cross-validation test, and frequently used method in the kind of works of literature in the comparison of estimation of rainfall value from kind of literature done before in the different area. Two are from the deterministic spatial interpolation method (IDW, ST), and the other two from Geostatistical spatial interpolation methods (OK, UK). To select the suitable interpolation method for estimating mean monthly rainfall distribution over the Ganale Dawa River Basin. and for seasonal rainfall values.

Geostatistical analyst tools used to do a cross-validation test between the observed and interpolated value, for performance evaluation of the interpolation methods, the RMSE and MAE error metrics are nominated from errors generated in cross-validation. Evaluation of the performance of interpolation methods was done based on these error metrics. The spatial interpolation method which has lower RMSE and MAE values from month to months in over the basin, and for seasonal value is the suitable method in the study. Areal rainfall mapping of monthly rainfall distribution was done by the suitable interpolation over the River Basin.

The methodological framework for this study is described in **Figure 3-5** below, the input data and results are presented in the form of Tables, Graphs, Maps, Figures.

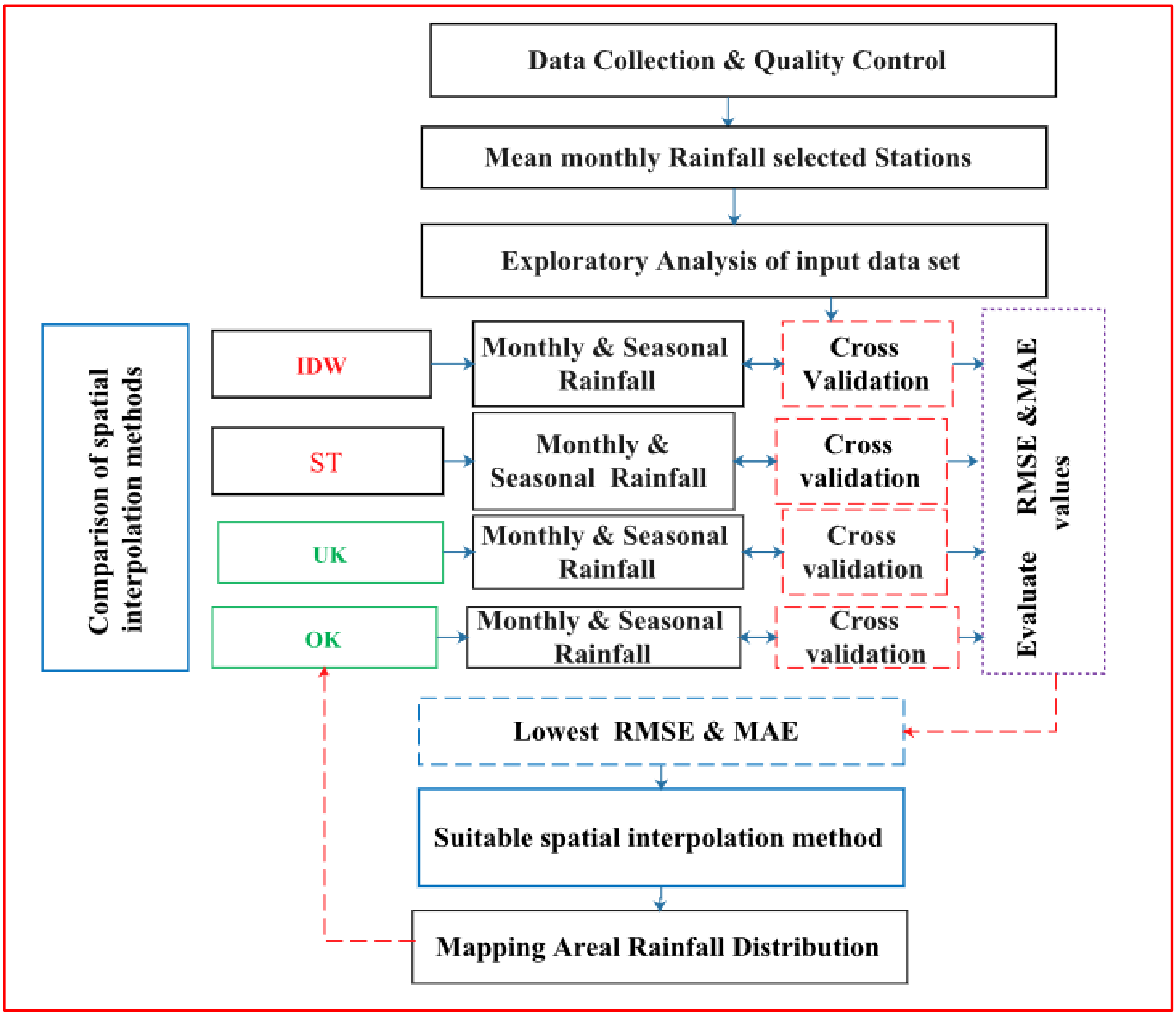


Figure 3-5: Methodological framework of the study

Chapter 4 Results and Discussions

4.1 Result Filling Missing Data

By the normal ratio method, the missed monthly time-scaled rainfall value used in stations for this study was filled. The normal ratio is used due to widely used filling missed rainfall value, ease to use, and efficiency. The station correlation was done to choose the nearby station, the station which has missed value-filled using stations with good correlation. The filled missed out rainfall value was attached in **Appendix A**.

4.2 Result of Outlier Test

The outlier test was done by Grubbs and Beck method, using equations 2-16,2-17 and 2-18 as described in the literature review section. The result of the test shows that there was no outlier detected for the used rain gauge station. **Table 4-1** presents a sample of the outlier test result for the Robe station.

Table 4-1:Sample of Outlier Test result for Robe Station

S.no	Year	Annual rainfall (mm)	Natural Log		
1	2000	920.99	2.964	Kn =	**2.360**
2	2001	881.7	2.945	N=	19
3	2002	902.01	2.955	Mean=	**2.964**
4	2003	946.06	2.976	XH=	**1290.92**
5	2004	780.3	2.892	XL=	**655.739**
6	2005	1030.1	3.013	Since from highest and lower data result, there is no outlier detected in Robe station	
7	2006	1129.8	3.053		
8	2007	1117.27	3.048		
9	2008	920.9	2.964		
10	2009	895.7	2.952		
11	2010	1012.27	3.005		
12	2011	863.5	2.936		
13	2012	749.5	2.875		
14	2013	1034.6	3.015		
15	2014	733.2	2.865		
16	2015	681.16	2.833		
17	2016	1054.7	3.023		
18	2017	947.3	2.976		
19	2018	1046.22	3.020		

4.3 Consistency check Result

Consistency cheeked by using a double mass curve. A result from the double mass curve for the entire stations shows that not display a shift in the curve for this analysis. And the correlation coefficient for stations are more of an approach to one since the correction does not need. The double mass curve of the Robe station was presented in the Figure below, the other station's double mass curve was attached in **Appendix B**.

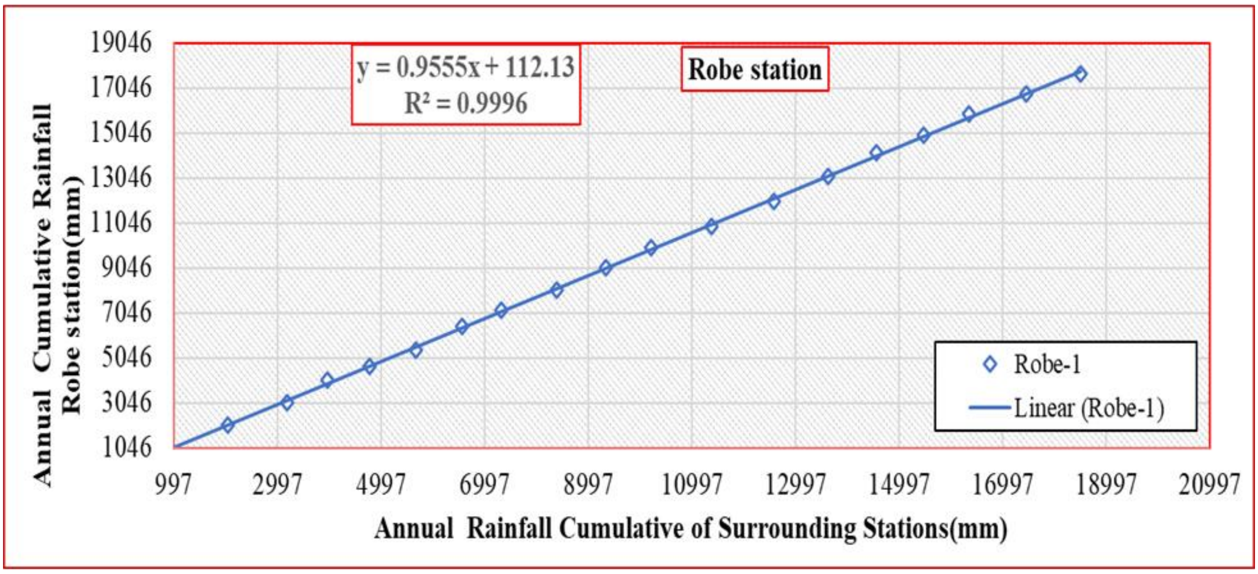


Figure 4-1:Sample of Consistency test for Robe station

4.4 Result of Homogeneity Test

The homogeneity test was done by R software in trend packages, using four methods as described in the data quality control section. The alpha and p-value were collected from R Software after the run of the tests, the p-value at a 5% significance level. If the value of p is greater than the critical p-value (0.05) the data is homogeneous otherwise inhomogeneity. The result of a total of 23 rain gauge stations selected for this study shows that two of them are classified under suspect class, the Ginir and Argafa station. Because of the low number of stations for this purpose the suspected station was used for further analysis. The summarized result homogeneity test is presented in **Table 4-2.**

Table 4-2:Homogeneity test result of the p-value for different methods

S.no	Station Name	Von Neumann test	Buishand Test	Pettitt-test	SNHT	Remark
1	Argafa	0.0061	0.0098	0.0098	0.0024	**Suspect**
2	Arero	0.3791	0.8229	0.904	0.5211	Useful
3	Bore	0.5836	0.6797	1	0.9556	Useful
4	Bulle	0.7436	0.8847	1	0.4399	Useful
5	Delo Mena	0.8649	0.9697	1	0.9901	Useful
6	Dilla	0.195	0.2602	0.1773	0.378	Useful
7	Dinsho	0.7376	0.9788	0.854	0.7944	Useful
8	Fincha wuha	0.2637	0.1225	0.05337	0.0731	Useful
9	Gesera	0.4315	0.1318	0.1222	0.1972	Useful
10	Ginir	0.02073	0.0321	0.01274	0.00568	**Suspect**
11	Goba	0.070	0.058	0.03446	0.05815	Useful
12	Gerba	0.6343	0.8716	0.4874	0.7115	Useful
13	Goro	0.8578	0.9995	1	0.9994	Useful
14	Hager Selam	0.1224	0.1717	0.1004	0.1085	Useful
15	Hager Selam2	0.3236	0.6822	0.4002	0.3644	Useful
16	Kibre Mengist	0.8082	0.6981	1	0.801	Useful
17	Kofale	0.2095	0.5282	0.2948	0.6696	Useful
18	Mejo	0.1192	0.3955	0.2948	0.1106	Useful
19	Negele	0.1729	0.3498	0.1773	0.1509	Useful
20	Moyale	0.4179	0.7461	0.2114	0.2616	Useful
21	Robe	0.3004	0.4551	0.9467	0.8927	Useful
22	Robe-2	0.1121	0.5823	0.400	0.006615	Useful
23	Yabalo	0.3663	0.1594	0.7653	0.1391	Useful

Critical p-value =0.05, when the value of p less than 0.05 hypothesis is rejected

4.5 Result of Stationarity and Independence Test

The stationarity and independence test were done by Wald -Wolfowitz test using R software in the trend package. From the Wald -Wolfowitz test by comparing the z value with standard normal variety at 95% significance level, the hypothesis of stationarity and independence was accepted only if the absolute value of z less than tabulated u value equal to 1.96. The test result shows that all selected station data sets have stationarity and independence. The summarized Wald Wolfowitz test is presented in **Table 4-3** below.

Table 4-3:Stationarity and independence test result for selected stations

S.no	Station Name	Z value	P-value	Remark
1	Argafa	1.8913	0.05858	Stationarity& Independence
2	Arero	0.43604	0.6628	Stationarity& Independence
3	Bore	0.56793	0.5701	Stationarity& Independence
4	Bulle	1.0846	0.2781	Stationarity& Independence
5	Delo Mena	0.91229	0.6164	Stationarity& Independence
6	Dinsho	0.8002	0.6164	Stationarity& Independence
7	Dilla	0.4997	0.6173	Stationarity& Independence
8	Gerba	0.32955	0.7417	Stationarity& Independence
9	Gesera	0.6817	0.4954	Stationarity& Independence
10	Goba	1.3078	0.191	Stationarity& Independence
11	Ginir	1.3888	0.1649	Stationarity& Independence
12	Goro	0.6747	0.4999	Stationarity& Independence
13	Hagere Selam	1.6869	0.0916	Stationarity& Independence
14	Hagere Selam-2	0.47504	0.6348	Stationarity& Independence
15	Kofale	0.6359	0.5248	Stationarity& Independence
16	Mejo	0.7375	0.4608	Stationarity& Independence
17	Negele	0.38561	0.6998	Stationarity& Independence
18	Robe	0.6376	0.5237	Stationarity& Independence
19	Robe_2	1.444	0.1486	Stationarity& Independent
20	Moyale	0.6497	0.5159	Stationarity& Independent
21	Yabalo	0.1763	0.86	Stationarity& Independent
22	Fincha Wuha	0.8421	0.8421	Stationarity& Independent
23	Kibre Mengist	0.7659	0.4437	Stationarity& Independent

Critical z value is 1.96

4.6 Result of Normality Test

The normality test was tested to observe the data set are normally distributed or not in analytical forms. For this study normality was done through an analytical method by Shapiro Wilk test using an R software from stast package. The Shapiro Wilk test results show that the statistic value of p is less than the critical value (0.05) at a 5% significance level for the first three months (January, February, and march) and July and august months in the basin area non normally distributed data set. The summarized the p-value was presented in the below table. Therefore, the transformation was done before using it for the variogram model and spatial interpolation for those months does not meet the normality requirement.

Table 4-4: Result of P-value for Normality test for monthly value

S.no	Months	P-value	Remark
1	January	1.562e-09	Not normality
2	February	1.789e-05	Not normality
3	March	0.00061	Not normality
4	April	0.2933	Normality
5	May	0.7479	Normality
6	June	0.0165	Normality
7	July	0.0076	Not normality
8	August	0.0126	Not normality
9	September	0.8566	Normality
10	October	0.6778	Normality
11	November	0.2598	Normality
12	December	0.2719	Normality

4.7 Result of Annual Rainfall Distribution

The mean annual rainfall of Genale Dawa River Basin for 23 stations rain gauge evaluated from the period 2000 up to 2018. Shows vary from 600mm in Moyale to 1564 in Bore station, the Maximum and minimum value annual rainfall for the selected station was 2781.1mm in Dilla and 374.4 mm in Yabalo station respectively. The coefficient of variation varies from 8 to 31 %, shows the rainfall variability in annual scale is in moderate scale.

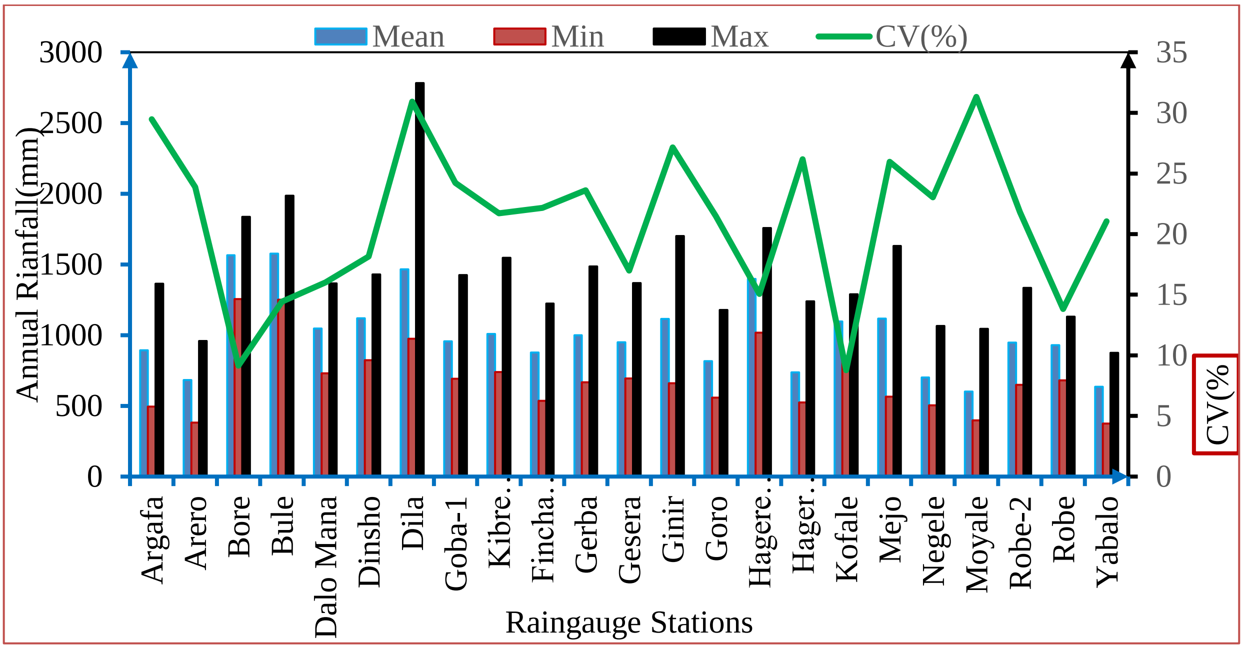


Figure 4-2: Annual rainfall distribution in the Genale Dawa River Basin for the selected station

4.8 Result of Monthly Rainfall Distribution

The mean monthly rainfall of Genale Dawa River basin for selected 23 rain gauge stations, monthly rainfall data investigated, from a period of 2000 to 2018, the Descriptive statistics of the monthly rainfall data for the study presented in **Figure 4-3 and Table 4-5.**

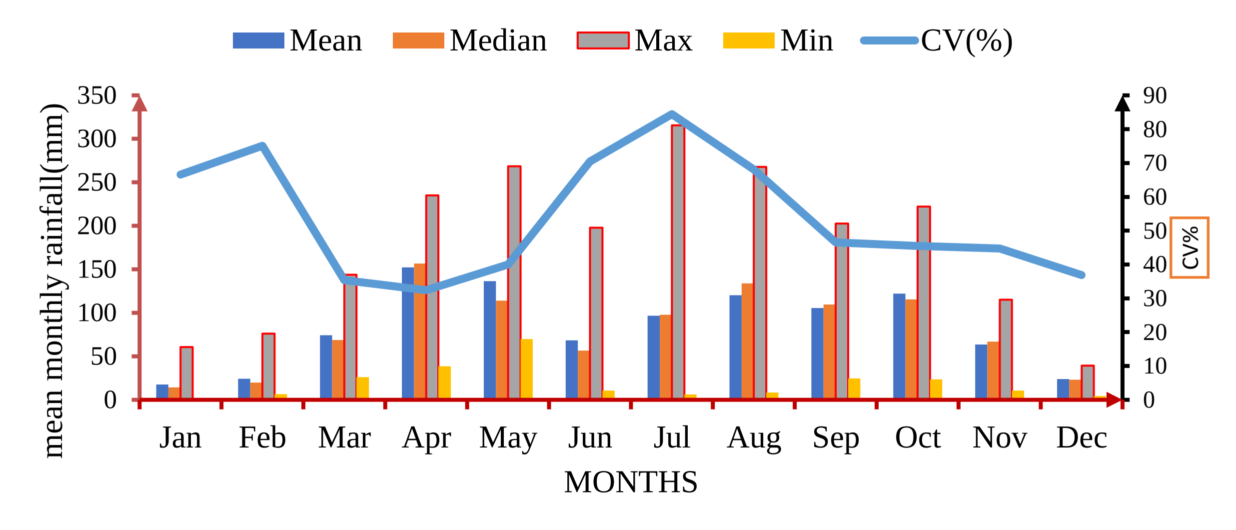


Figure 4-3: Monthly Rainfall Distribution of Genale Dawa for selected rain gauge stations

Table 4-5: Result of Descriptive statistics of the monthly rainfall data (mm) for 23 stations.

Month	Mean	Median	Max	Min	SD	CV (%)	SK	KU
January	17.65	14.16	60.47	1.48	11.49	66.55	2.36	7.58
February	24.11	19.65	76.14	6.42	18.11	75.09	1.81	3.16
March	74.28	68.57	143.75	26.01	26.24	35.32	1.18	1.84
April	152.29	156.78	235.13	38.41	49.35	32.41	-0.50	-0.26
May	136.58	114.04	268.48	69.76	54.67	40.04	0.83	-0.21
June	68.49	56.48	197.72	10.62	48.26	70.46	1.06	0.99
July	96.78	97.95	315.53	6.06	81.72	84.44	0.9	0.78
August	120.19	133.80	267.88	8.47	81.79	68.05	0.03	-1.25
September	105.48	109.57	202.72	24.78	49.11	46.57	-0.004	-0.45
October	122.08	115.64	222.23	23.42	35.51	45.47	0.11	-0.86
November	63.70	66.90	114.91	10.53	28.50	44.74	-0.03	-1.02
December	23.76	23.06	39.23	4.24	8.75	36.83	-0.4	0.22

SD= Standard deviation: CV=coefficient of variation: SK=skewness: KU=kurtosis

The result of the statistical analysis in **Table 4-5** shows that the mean monthly rainfall in the Genale Dawa river basin varied from 152.29 mm in April to 17.65 mm in January. The maximum monthly value was detected in July (315.13 mm) while the minimum was identified in January (1.48).

The coefficient of variation given by the ratio between Standard deviation and the Mean monthly rainfall ranges between 32.4 and 84.44%. This high dispersion of monthly rainfall in the Genale Dawa river basin.

The mean and median values from **Table 4-5** are generally related and the Kurtosis value is almost far from three, the general value of kurtosis. And skewness values are an approach to zero as were observed, thus shows the monthly value of rainfall in the study area have a non-normal statistical distribution of data series. For this reason, the transformation of data required for each month in Geostatistical analysis before doing the cross-validation may obtain the normally distributed data.

4.9 Result of Data Explore and Variogram model

4.9.1 Data Explore

Geostatistical analyst options were graphical explored data inform of; histogram, normal Q-Q plot, trend analysis, and semi variogram/covariances cloud before proceeded to cross-validation. Trend analysis and semi variogram/ covariance cloud were done for geostatistical interpolation in this study. The log transformation is used to make a normal distribution for the not fit a normality requirement, the histograms show the Skewness and Kurtosis of the data set for each month.

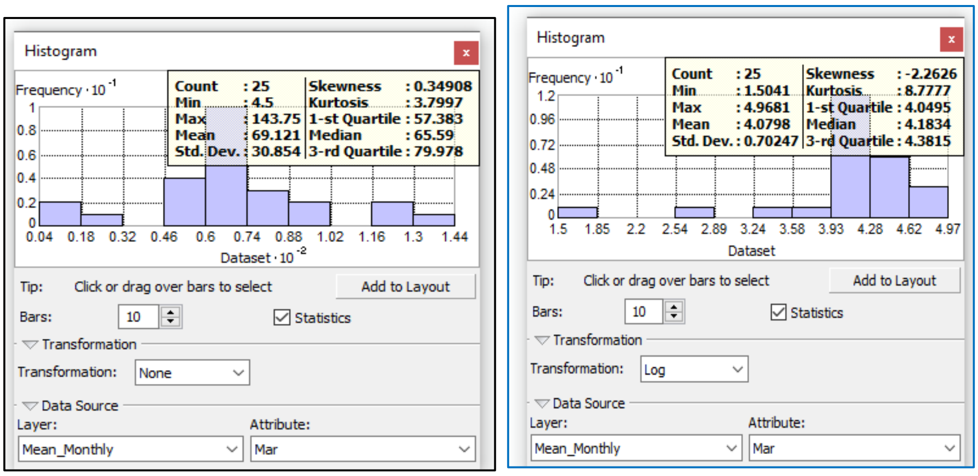


Figure 4-4: Example of a sample of histogram before and after transformation for March month

From **Figure 4-4**, the ante transformation of data distribution shows the non-normal distribution, whereas the post-transformation of rainfall histograms data is close to normal distribution. The normal Q-Q plot checks the normality of the data set, results of all month's rainfall data set distribution analyzed by normal Q-Q plot for all datasets in each month. The data series are followed normal distribution after transformation by Q-Q plot as to see in figure the data point approach to a straight line.

Trend analysis and semi variogram /covariances cloud, in trend analysis looking at the global trend for individual monthly rainfall data set, is important to make an appropriate model to smooth continuous surfaces. For geostatistical interpolations, the data sets are checked whether have a global trend or not, by observing the curve through a projected point is flat for non-trend, if the projected point is not flat there is a global trend in the data. Therefore, global trend removal was done by order of polynomial function that fit the model before modeling the variogram.

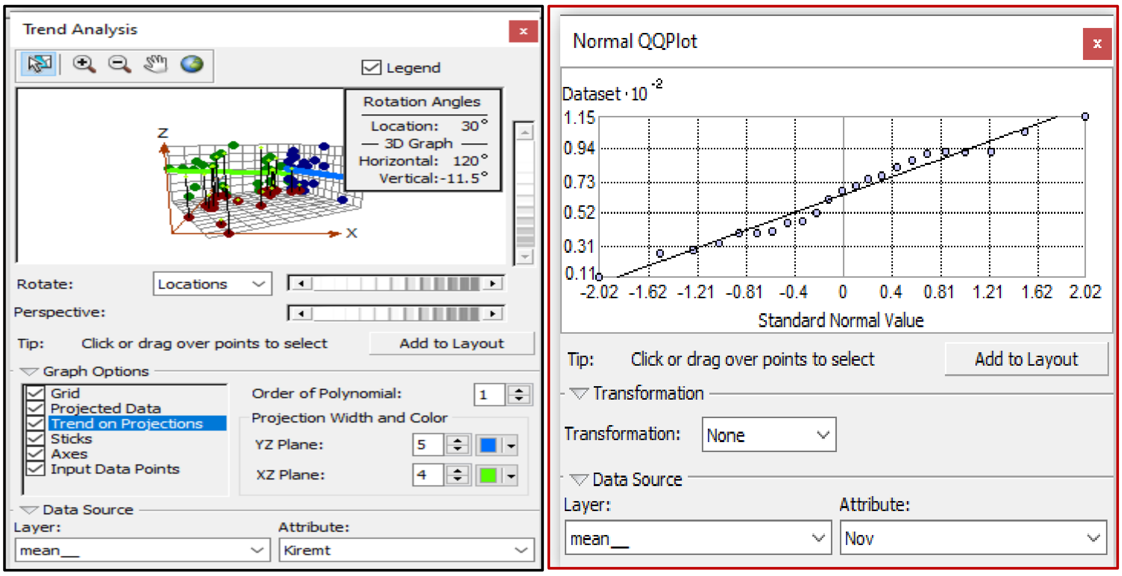


Figure 4-5:Sample of Trend analysis for Kiremt seasons and normal QQ plot for November month

4.9.2 Result of Variogram Model for Geostatistical Interpolation Method

Geostatistical interpolation requires the estimation of a direct variogram model for rainfall data, for this study the spherical variogram model is selected. because of its characteristic linear behavior at the origin. An anisotropy experimental variogram was not estimated for this study assuming that the site of rain gauge stations free from wind effects and low rain gauges in the study area. The semi variogram of the spherical model, done under transformation type by log transformation, the order of trend removal by the first polynomial, in the first polynomial the used rainfall data set not shows a global trend. Kernel function, the optimal set of weights to be used with the sampling point, the Gaussian kernel function was selected. As the result, the semi variogram model developed shows that the pairs of points in the semi variogram produce in some months a horizontal straight line, which means that there may be no spatial correlation in the used data set.

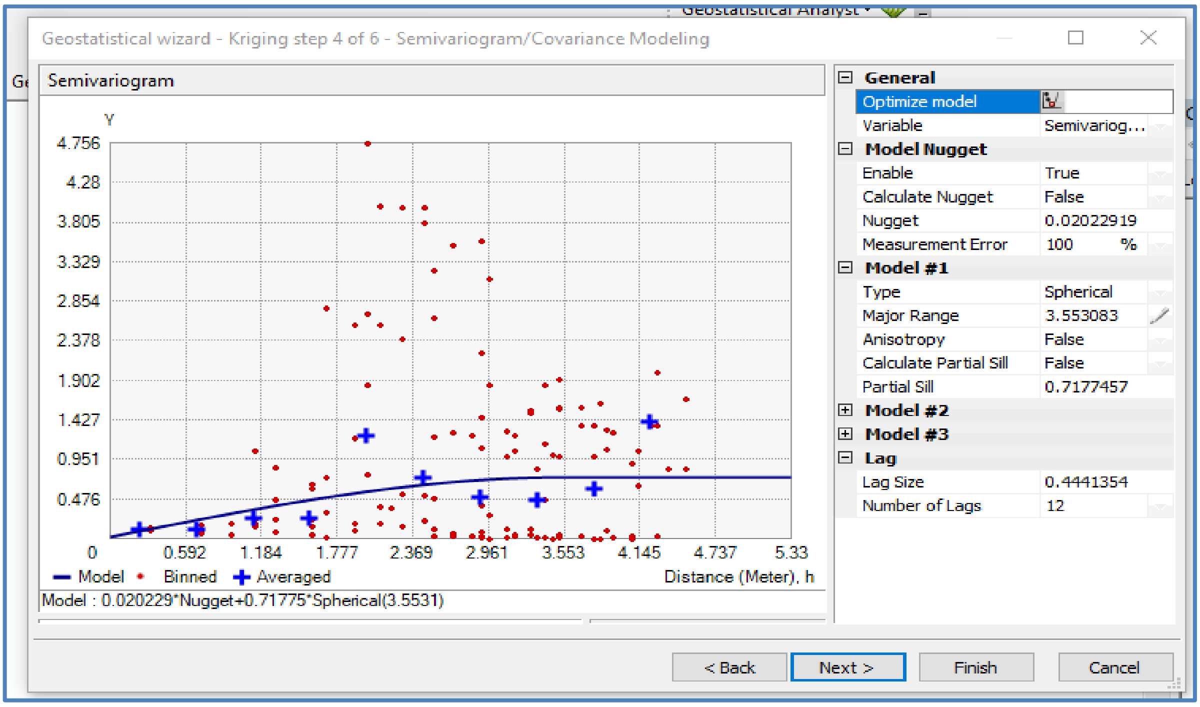


Figure 4-6: Example of a sample experimental variogram model

4.10 Cross-Validation Result for selected Interpolation Methods

Cross-validation was done to evaluate the performance of the selected interpolation method, based on the error metric unit RMSE and MAE values. The cross-validation result of the selected interpolation method at basin level, seasonal level for study are presented in this section.

Cross-validation is done in the Geostatistical analyst tools option by the Geostatistical wizard tool. For deterministic methods (IDW, Radial basis function), cross-validation is done under general properties; the power of 2 is adopted for IDW, Kernel function spline with tension in Spline interpolation. For the searching neighborhood type, the shape of the data set circle shape was considered for analysis due to no direction influence on data sets.

The standard option was selected for both of them for searching the neighborhood stations, Maximum neighborhood station, and minimum neighborhood station was adjusted by considering the interpolation concept of, things that are close to one another more like than those further away. The sector used to avoid bias in a particular direction to have an equal number of points to be selected, based on this type four sector was selected to carry out cross-validation. **Figure 4-7** shows the general properties of cross-validation for samples.

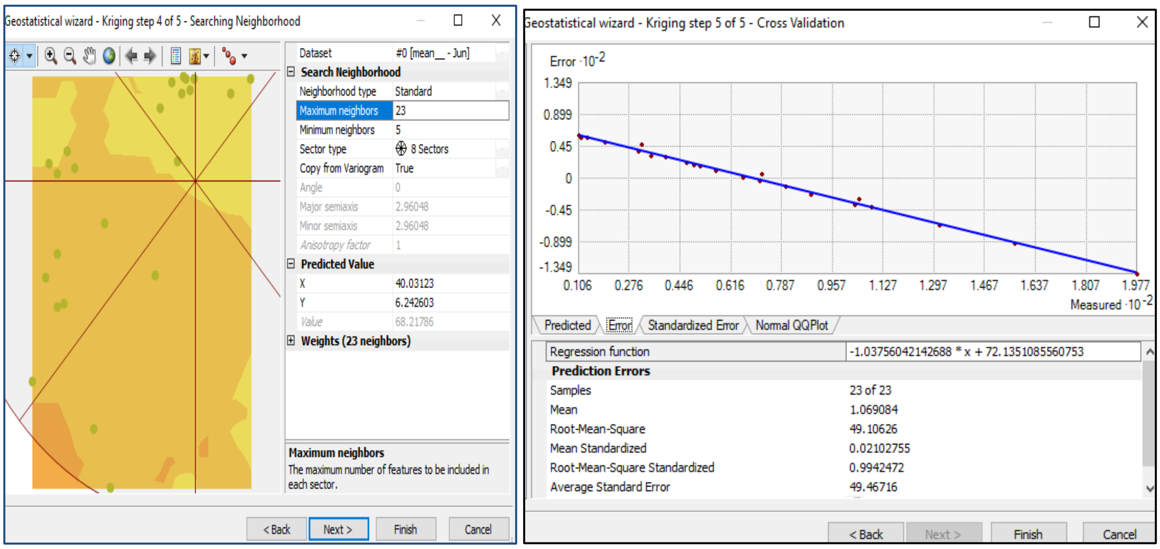


Figure 4-7:sample of Cross-validation result for OK interpolation for June month

Under Geostatistical methods (Ordinary Kriging, Universal Kriging), cross-validation was done for the general properties; transformation type by log transformation, an order to trend removal by the first-order polynomial, search neighborhood standard was selected. The maximum and minimum neighborhood station was adjusted according to the number of stations used in the study area, Kernel function for Universal kriging, the Gaussian was selected. Sector’s type 4,8 sectors were selected to performs cross-validation.

Table 4-6, present the number of neighborhood station used for the prediction and validation process in form of maximum, and minimum station in geostatistical analyst. And the number of sectors used to include neighborhood stations to reduce bias error while cross-validation.in the search neighborhood station, the standard option was adopted. Four types with 45-degree offset and eight sector types were used for performance evaluation in both spatial interpolation methods to validate the result in the over river basins.

Table 4-6:Result of number of the neighborhood stations; maximum, minimum stations, and number of sectors used for validation in Seasonal value and over the river basin

Seasonal				Over River Basin			
Seasons	Max	Min	Sector	Month	Max	Min	Sector
Belg (ONDJ)	23	5	8	Jan	23	5	8
Bega (FMAM)	23	5	8	Feb	23	5	8
Kiremt (JJAS)	23	5	8	Mar	23	5	8
				Apr	23	5	8
				May	23	5	8
				Jun	23	5	8
				July	23	5	8
				Aug	23	5	8
				Sept	23	5	8
				Oct	23	5	8
				Nov	23	5	8
				Dec	23	5	8

Mont=months, Jan= January= February, Mar=March, Jun= June, Oct = October

4.10.1 Result of RMSE and MAE values at River Basin level

In this study, the primary objective is to select the suitable interpolation method over the Genale Dawa river basin for estimating monthly rainfall distribution .as result, twenty-three rain gauge stations were selected for comparative analysis in the study area, the value of comparison criteria was collected after the cross-validation done presented in the table below.

Table 4-7:RMSE and MAE over the River basin based on cross-validation test

	RMSE (mm)				MAE (mm)			
	Spatial Interpolation methods				Spatial Interpolation methods			
Months	**IDW**	**ST**	**OK**	**UK**	**IDW**	**ST**	**OK**	**UK**
January	13.47	12.72	12.14	13.30	0.17	0.03	0.88	0.04
February	21.03	19.46	18.54	19.38	0.52	0.21	0.01	0.59
March	33.54	29.23	27.46	29.73	0.15	0.28	0.006	0.88
April	59.76	55.43	48.71	49.14	6.34	1.98	0.89	3.46
May	63.90	57.50	55.56	54.19	0.51	0.48	1.03	5.28
June	46.88	42.03	46.36	41.44	11.05	2.41	1.08	0.87
July	79.41	75.60	76.15	76.03	16.20	4.33	3.07	1.65
August	71.57	66.62	69.14	62.95	20.02	5.94	3.93	3.59
September	46.13	43.15	44.96	44.01	10.64	1.80	1.87	1.71
October	68.50	62.85	56.92	58.35	6.06	1.43	1.62	3.17
November	32.76	30.62	28.25	27.86	4.39	1.44	0.51	0.51
December	10.86	11.37	9.09	10.44	0.35	0.24	0.31	0.64

4.10.2 Results of RMSE and MAE values for seasonal rainfall

The study area has a Bimodal rainfall characterization, Bimodal type I, and Type II rainfall regime. Three seasonal rainfall patterns are named ***Belg*** (February -March), ***Kiremt*** (June-August), and ***Bega*** (October-January) found in seasonal rainfall distribution over the basin area. *Belg* and *Kiremt* seasons are known to have a more rainfall value and April and July months are the peak rainfall value in the seasons. The *Bega* is the driest seasonal rainfall in the study area. The River basin has seasonal variability of rainfall value, based on this the comparison spatial of the interpolation method for estimating seasonal rainfall value was done to identify the suitable interpolation method for estimating seasonal rainfall for each season in the study area. The table below presented the RMSE and MAE values generated from the cross-validation test for each season during the period used for the analysis of selected rain gauge stations in the study area.

Table 4-8:RMSE and MAE based on cross-validation test for seasonal rainfall value

	RMSE (mm)				**MAE (mm)**			
	Spatial Interpolation methods				Spatial Interpolation methods			
Seasons	**IDW**	**ST**	**OK**	**UK**	**IDW**	**ST**	**OK**	**UK**
Belg	148.43	136.87	127.01	130.14	6.41	2.97	0.11	2.21
Kiremt	206.85	190.56	199.64	179.92	57.93	15.96	7.97	4.17
Bega	111.43	103.41	93.02	95.75	9.78	2.93	1.55	1.49

4.11 Comparison of Selected Interpolation Methods

Before evaluating the performances of selected spatial interpolation methods using error measuring statistics, it is very important to compare the descriptive statistics of the observed rainfall data, with the descriptive statistics of interpolated rainfall values. The comparison of descriptive statistics of mean monthly Rainfall data obtained from twenty-three rain gauge stations during the period used for analysis with the extracted rainfall value from maps of selected spatial interpolation methods.

Referencing **Table 4-9**, the maximum, minimum, and mean rainfall value is near estimated to observed value by the IDW interpolation method in most months, except the June, July overestimated the maximum value and underestimated the mean value. Standard deviation was underestimated in all months by IDW Method.

Spline with Tension (ST) interpolation, interpolate the maximum and minimum rainfall value overestimated to observed value in most months, the mean monthly rainfall value near estimated to observed value in February, January, and April months by ST method, in May, September, and October months the mean rainfall value overestimated by ST method. Standard deviation is overestimated each month.

The Geostatistical interpolation method, the Ordinary Kriging method estimates the mean rainfall near to the observed value in most months, in some month like June, August and September underestimated the mean value by OK method, the maximum rainfall value underestimating for most months, only near estimated to observed value for February and August month. The minimum rainfall value overestimating in most months by the OK method, in August and September months it estimates to near the observed value. And the standard deviation underestimated by an OK method in all months.

The UK method estimates the mean, maximum, and minimum monthly rainfall value underestimated in most months. In April month the mean, Maximum, and minimum rainfall value is estimated near to the observed value. While the standard deviation estimated near observed value in January and February months, in other month underestimated by UK method.

Table 4-9:The Descriptive statistics of observed monthly Rainfall value and estimated value from the spatial Interpolation methods in the study area

Months	Comparison Factors	Observed Rainfall(mm)	Interpolated Rainfall (mm)			
			IDW	**ST**	**OK**	**UK**
January	Mean	**17.65**	16	13.50	17.79	7.3
	Max	**60.46**	60	64.23	47.56	29
	Min	**1.48**	1.5	25.66	6.98	20
	SD	**11.74**	2.7	6.56	1.10	11
February	Mean	**24.11**	21.87	26	24.22	6.2
	Max	**76.14**	76.08	83	74.75	38
	Min	**6.41**	6.42	30	5.86	36
	SD	**18.10**	5.24	19	2.52	18
March	Mean	**74.27**	73	76	74	74.21
	Max	**143.75**	140	180	84	84.19
	Min	**26.0**	26	41	66	65.75
	SD	**26.23**	6.6	18	0.068	0.06
April	Mean	**152.28**	160	240	152.28	180
	Max	**235.12**	230	520	168.63	250
	Min	**38.41**	38	58	103.50	130
	SD	**49.35**	13	110	0.24	27
May	Mean	**136.54**	136.95	200	140.38	108.38
	Max	**268.48**	267.03	420	213.96	171.23
	Min	**69.75**	69.78	4.4	92.25	32.19
	SD	**54.66**	16.96	99	11.39	31.51
June	Mean	**68.49**	59	3	48	7.67
	Max	**191.71**	200	230	140	139.49
	Min	**10.62**	11	96	20	195.78
	SD	**48.26**	18	55	18	77.66
July	Mean	**96.77**	80	76	97	4.3
	Max	**315.52**	320	330	150	170
	Min	**6.05**	6.01	400	62	220
	SD	**81.01**	29	170	0.45	92
August	Mean	**120.18**	99	75	84.23	0.53
	Max	**267.88**	270	320	265.39	209.98
	Min	**8.47**	8.5	440	9.28	253.49
	SD	**81.78**	33	180	29.12	107.29
September	Mean	**105.45**	95.00	500	76	0.53
	Max	**202.72**	202.08	2600	150	210
	Min	**24.77**	24.79	330	33	250
	SD	**49.10**	22.67	740	24	110
October	Mean	**122.07**	130	226.45	129.3	130
	Max	**222.23**	220	519.32	180.9	150
	Min	**23.42**	23	78.15	69.03	110
	SD	**55.51**	14	131.11	8.88	8.6

4.11.1 Comparison over the River Basin

Based on **Table 4-7** and **Figure 4-8**, a Comparison of the selected spatial interpolation methods in terms of RMSE value for estimating mean monthly rainfall value over the river basin area, the Geostatistical spatial interpolation methods, particularly the OK method has lower RMSE in most months, while in May, June, August, December months the UK method has a lower RMSE value. From the deterministic methods, the Spline with Tension method has a lower RMSE value in July and September months, the IDW method has a higher RMSE value than other methods value in all Months.in October month. The UK method also has high RMSE value than other methods. Evaluation of the performance of each interpolation method in terms of MAE values, the OK method has lower MAE in most of the months. While the UK method has a lower MAE value in June, July, August, and September months. In the January, May, October, and December months the Spline with Tension method has a lower MAE value. IDW method has a high MAE value in June, July, August, and September month. The Universal Kriging Method has higher MAE values for estimating mean monthly rainfall value in March, May, October, and December months. The IDW method has higher MAE values than other methods in all months. therefore, considering the lower error matric in Estimating mean monthly Rainfall value from this selected spatial interpolation method the Ordinary Kriging was the suitable method, the UK, ST and IDW followed by respectively

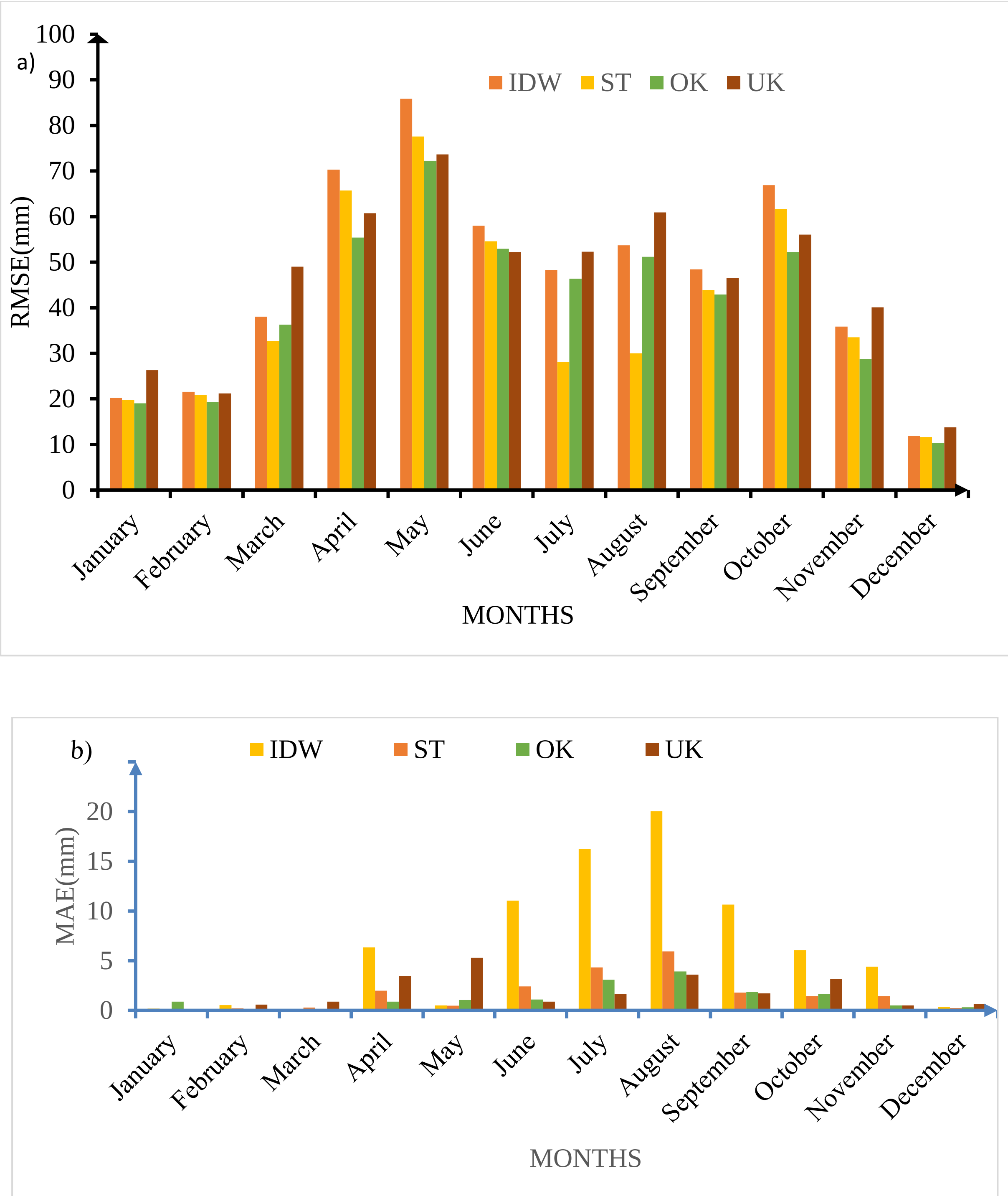


Figure 4-8: RMSE(a) and MAE (b)value for the selected interpolation method at the river basin level

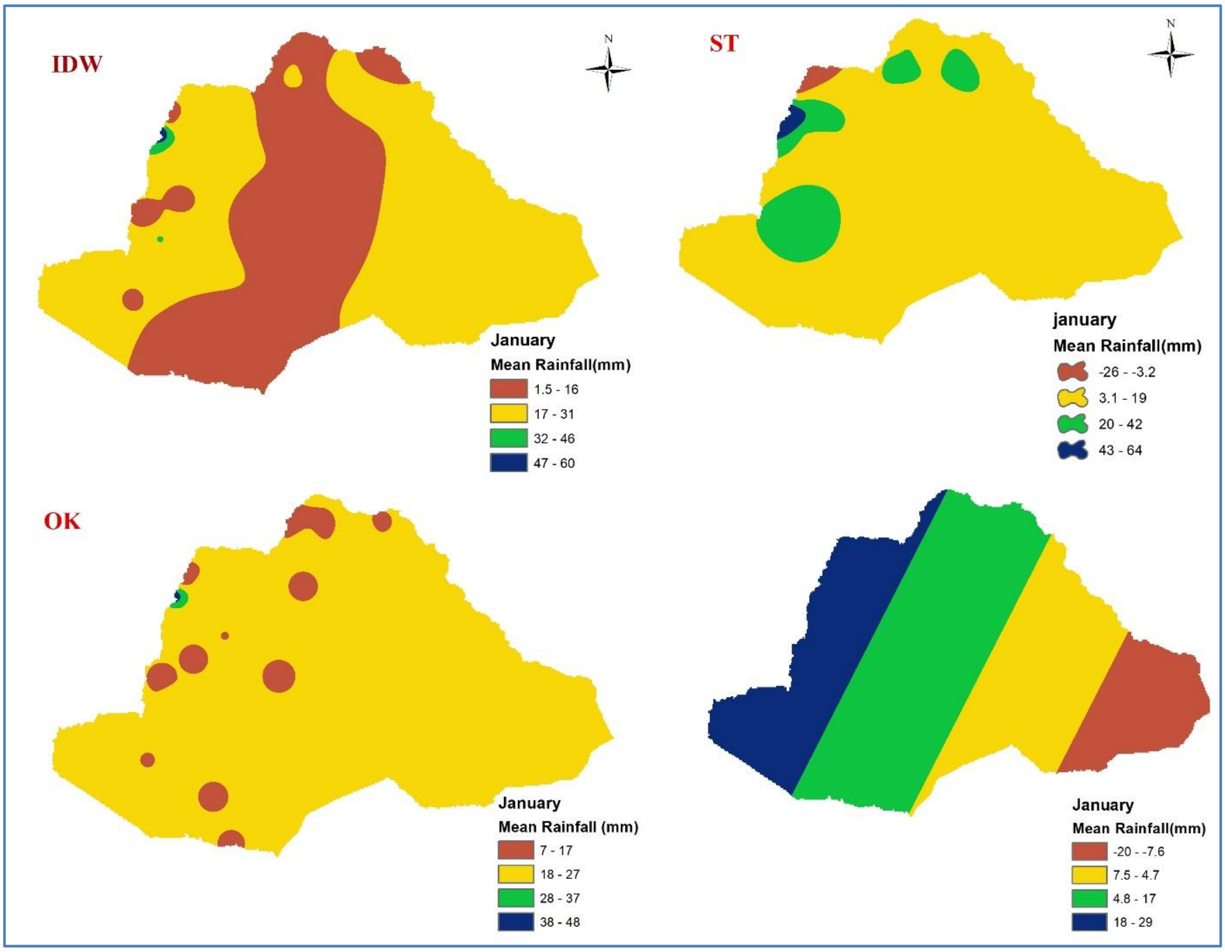


Figure 4-9: Areal rainfall map in interpolation methods over the study area for February Month

The average RMSE values over River Basin for months by IDW, ST, OK, and UK methods are 45.65mm,42.21 mm,41.10mm, and 40.50mm. respectively, whereas the average MAE values for months by IDW, ST, OK, and UK methods are 6.36mm,1.71mm, 1.26mm, and 1.86 mm, respectively.

4.11.2 Comparison of Estimating Seasonal Rainfall values

Based on **Table 4-8** and **Figure 4-10,** evaluation of the performance of the selected spatial interpolation methods for estimating the seasonal rainfall value using the comparison criteria of the RMSE and MAE. The Geostatistical spatial methods have a lower RMSE and MAE value in Belg and Kermit Rainfall Seasons, while the deterministic methods have higher RMSE and MAE value in all the seasonal, particularly the IDW method, Spline with Tension method has lower RMSE values in Bega seasons. The Ordinary Kriging method has a lower error metric in *Belg* and *Kermit seasons*.

In the *Kiremt* season, the UK method has a lower MAE value than other methods. For estimating seasonal rainfall values. The OK method is suitable for the *Belg* and *Kermit* season, the Universal Kriging method is a suitable method for estimating rainfall in *Bega season*.

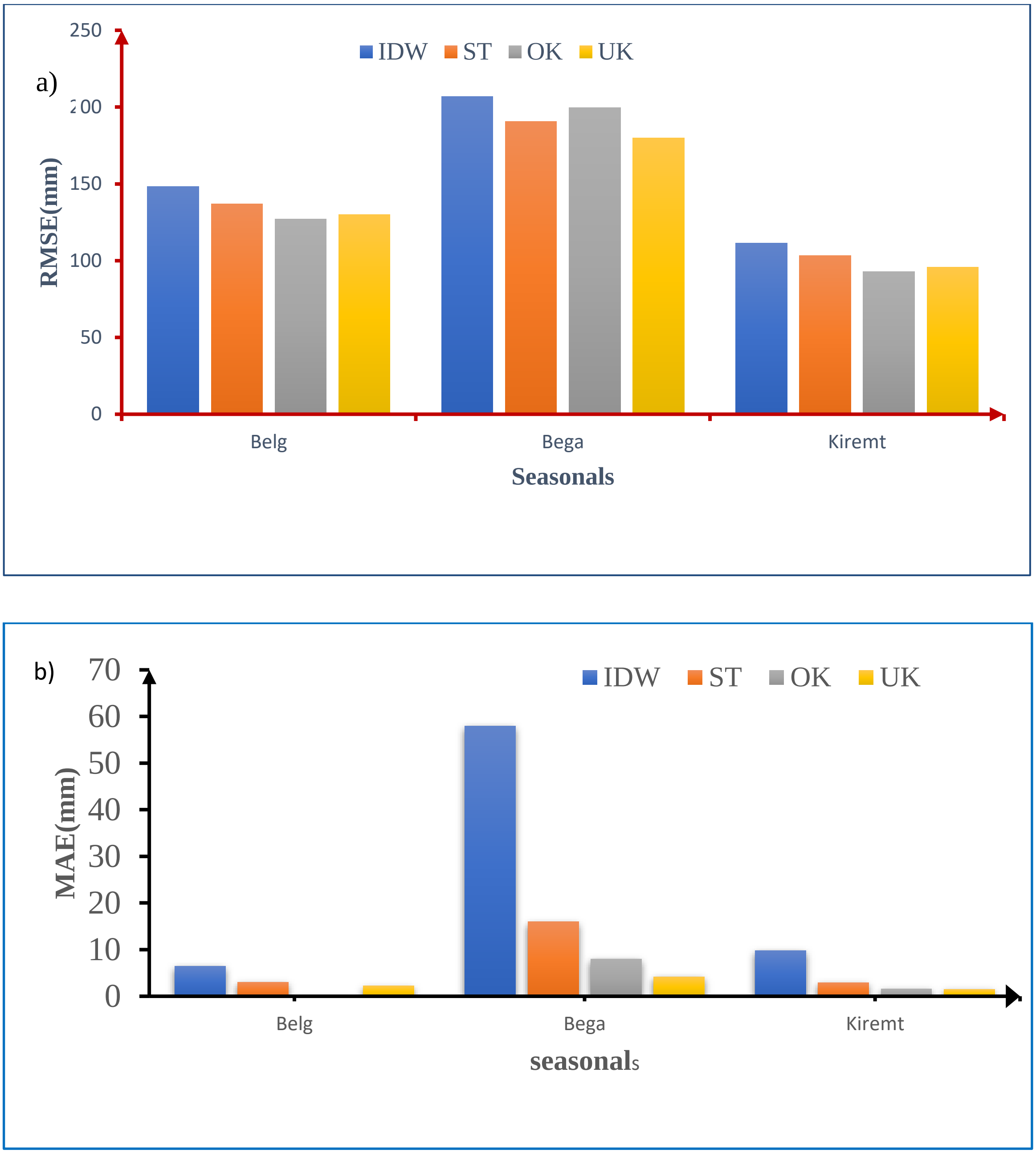


Figure 4-10:RMSE(a) and MEA(b) values of selected spatial interpolation method at seasonal level

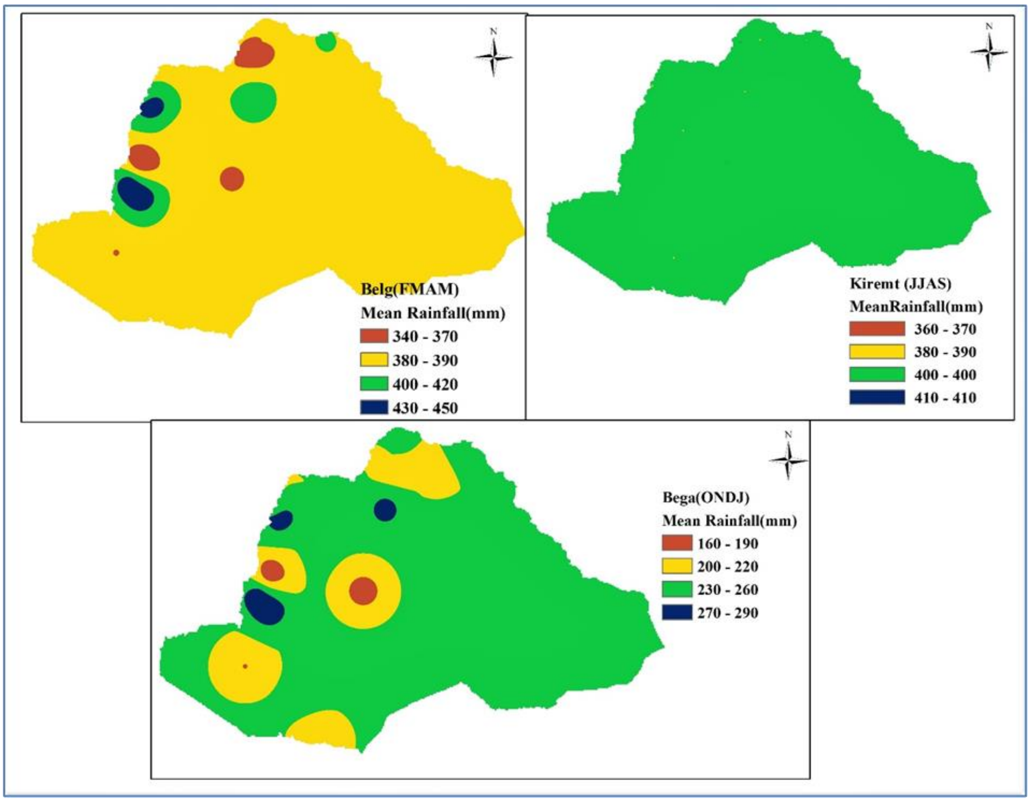


Figure 4-11: Map of Spatial Distribution of Seasonal Rainfall values for the study area using Ordinary Kriging method

4.12 Mapping Monthly Areal Rainfall Distribution

On analyzing the rainfall distribution for the suitable interpolation method, depending on the maps of the areal rainfall distribution prepared in the study area, it is found that the mean monthly spatial rainfall distribution decreased from the Northwest to Southeast in the study area.

4.12.1 Areal Rainfall Distribution Over River Basin

Visual analysis of the areal map of monthly time-scaled rainfall distribution over the Genale Dawa River Basin from **Figure 4-12**, generated by the suitable Spatial interpolation of the ordinary kriging method, using mean monthly rainfall values. It creates the smooths surface maps of areal rainfall distribution. Because it takes into account the spatial dependence of rainfall data.

Bimodal type II seasonal rainfall type, observed in the Belg and Kermit seasons, the having double Rainfall seasons, April and August months are the two-peak rainfall in the Genale Dawa River Basin. Spatial Mean Monthly Rainfall distribution in Belg Season; February, March, April, and May months have high rainfall value. Spatial Rainfall distribution in the Kiremt season; June, July, August, and September months have moderate rainfall value and the Bega Season; October, November, December, and January months have relatively low rainfall value than the other two seasons.

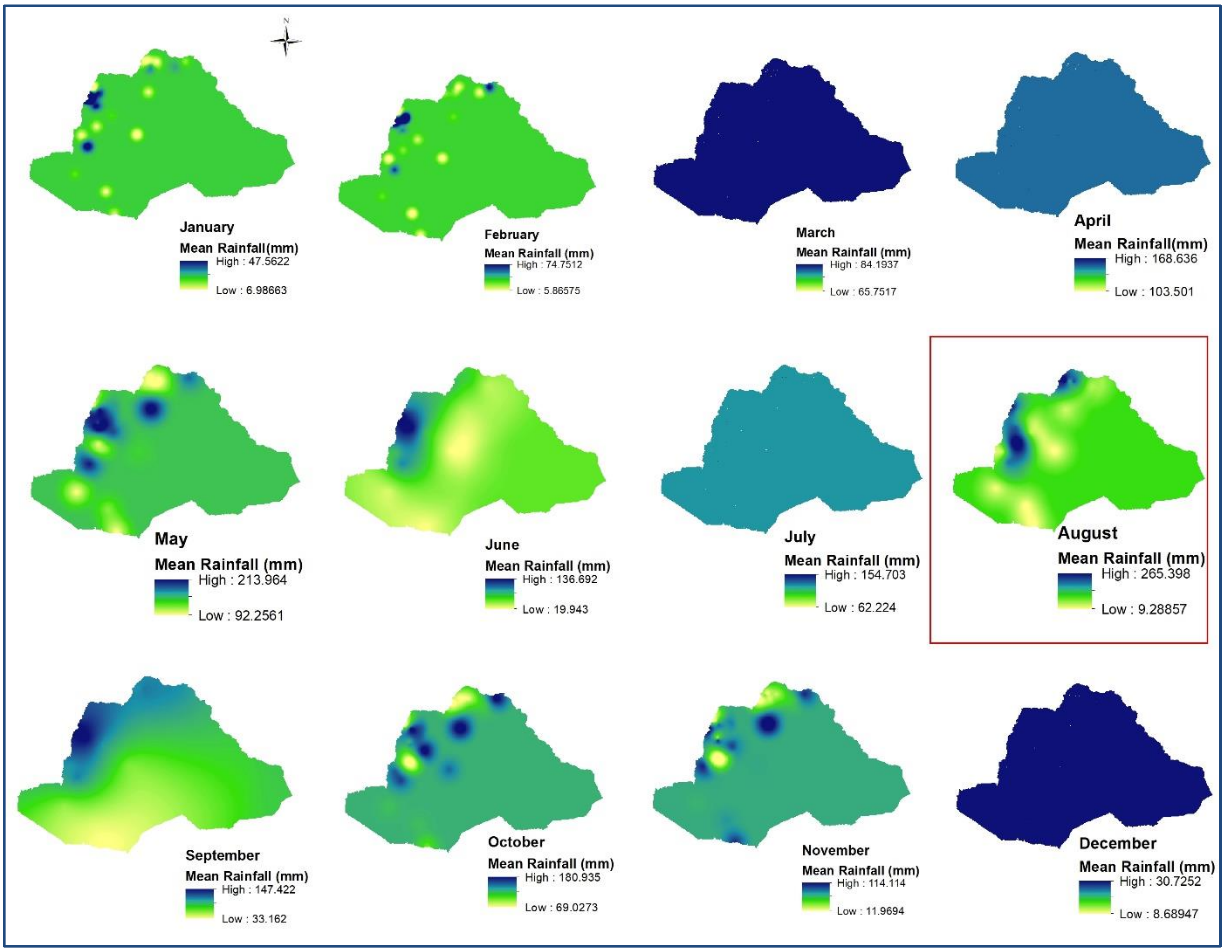


Figure 4-12: Map of Spatial Distribution of Mean Monthly Rainfall over the River Basin Using Ordinary Kriging method

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSION

Rainfall is one of the most important climate elements, which inputs for hydrologic study, irrigation, agriculture activities. Accurate estimation of the spatial distribution of rainfall patterns needed for numerous water resources studies.

In this study, four GIS-based spatial interpolation methods these commonly used in the kind of works of literature done before to evaluate the performance spatial interpolation methods for estimating Rainfall values in different areas .and the methods appropriate to the sample available, mean monthly rainfall data quality of the study area .Based on this two from deterministic (IDW, ST) and the other two Geostatistical (OK, UK) methods, are selected to analyze the suitable interpolation method for estimating monthly rainfall distribution at the River Basin level and seasonal Rainfall values. Historically mean monthly scaled point rainfall data recorded from 23 rain gauge stations during 2000 up to 2018 periods used for performance evaluation. In GIS the Geostatistical analyst tool is used to explore the statistical data set and modeling the optimum variogram parameters, before proceeding to cross-validation. Cross-validation used to compare and evaluate the performance of the selected interpolation method, using the most common comparison criteria in the interpolation method; the RMSE, and MAE values. The method which has the lowest value of RMSE and MAE from month to month in River Basin level, and has a lower error in seasonal value is the suitable spatial interpolation method for estimating rainfall values.

The result of the cross-validation test shows that the Geostatistical method was better estimation than the deterministic one, particularly the OK is the suitable interpolation method for estimating each monthly rainfall in the River Basin level. and the suitable method for estimating rainfall for Belg and Kiremt Seasons, while the Universal Kriging is a suitable method for estimating Bega rainfall Season. In general, deterministic methods suitable for estimating maximum and minimum rainfall value, but the ST method was overshot above and below the observed rainfall value. the IDW method is shown to have the highest error than other methods for estimating the mean monthly rainfall value for the study area.

5.2 RECOMMENDATIONS

Depend on the final result of this study, the following points recommended for the further advancement of the study:

- For other parameters, like temperature and relative humidity, when the spatial interpolation method can be compared. It will improve the result of the interpolation method at an annual scale.
- The study does not consider anisotropy in the data analysis, station-to-station distance, and used defined variogram model, and having to consider these may improve the interpolation method result.
- The rain gauge station network is sparse in the study area, which can improve the accuracy of the interpolation method if optimizing the observation station.
- Other results may be obtained for further advancement of this study by applying multivariate variables to spatial interpolation methods and including other methods.
- Since the study area has a sparse and unevenly distributed rain gauge network, the distribution of surface rainfall may improve if the comparison is done with satellite product rainfall.

REFERENCES

A.Ramachandara Rao, K. H. H. (2000) *FLOOD FREQUENCY ANALYSIS*, *CRC Press*. Edited by P. U. W.F.CHEN. New York, London: CRC Press LLC. Available at: https://www.m-culture.go.th/mculture_th/download/king9/Glossary_about_HM_King_Bhumibol_Adulyadej's_Funeral.pdf.

Abdelaal, M. M. (2019) 'An evaluation of Spatial Interpolation Methods for Estimating rainfall and air temperature in Egypt', (August).

Adane, G. B. *et al.* (2020) 'Spatial and Temporal Analysis of Dry and Wet Spells in Upper Awash River Basin, Ethiopia', *Water*. MDPI, 12(11), p. 3051. doi: 10.3390/w12113051.

Adhikary, S. K., Muttil, N. and Yilmaz, A. G. (2017) 'Cokriging for enhanced spatial interpolation of rainfall in two Australian catchments', *Hydrological Processes*, 31(12), pp. 2143–2161. doi: 10.1002/hyp.11163.

Adikaram, K. K. L. B. *et al.* (2015) 'Data transformation technique to improve the outlier detection power of grubbs' test for data expected to follow linear relation', *Journal of Applied Mathematics*, 2015. doi: 10.1155/2015/708948.

Ahmed, K. and Shahid, S. (2014) 'Spatial interpolation of climatic variables in a predominantly arid region with complex topography', pp. 555–563. doi: 10.1007/s10669-014-9519-0.

Basistha, A., Arya, D. S. and Goel, N. K. (2008) 'Spatial Distribution of Rainfall in Indian Himalayas – A Case Study of Uttarakhand Region', pp. 1325–1346. DOI: 10.1007/s11269-007-9228-2.

Bekele, F., Mosisa, N. and Terefe, D. (2017) 'Analysis of current rainfall variability and trends over Bale-Zone, South Eastern highland of EthiopiaClimate Change', *Climate Change*. Discovery Publication, 3(12).

Berhanu, B. *et al.* (2016) 'Bias correction and characterization of climate forecast system re-analysis daily precipitation in Ethiopia using fuzzy overlay', *METEOROLOGICAL APPLICATIONS*. Royal Meteorological Society, 243(March), pp. 230–243. DOI: 10.1002/met.1549.

Bhattacharjee, S., Ghosh, S. K. and Chen, J. (2019) *Semantic Kriging for Spatio-temporal Prediction*. Edited by 1. Singapore: Springer. DOI: doi.org/10.1007/978-981-13-8664-0.

Boke, A. S. (2017) 'Comparative Evaluation of Spatial Interpolation Methods for Estimation of Missing Meteorological Variables over Ethiopia', *Journal of Water Resource and Protection*. Scientific Research Publishing Inc, pp. 945–959. doi: 10.4236/jwarp.2017.98063.

Borges, P. D. A., Franke, J., and Bernhofer, C. (2015) 'Comparison of spatial interpolation methods for the estimation of precipitation distribution in Distrito Federal , Brazil', 2012. doi: 10.1007/s00704-014-1359-9.

Childs, B. C. and Services, E. E. (no date) 'Interpolating Surfaces in ArcGIS Spatial Analyst'.

Dolui, G. *et al.* (2013) 'A COMPARATIVE STUDY OF DIFFERENT INTERPOLATION METHODS FOR RAINFALL DISTRIBUTION MAPPING USING REMOTE SENSING AND GIS TECHNOLOGIES IN PURULIA', *International Journal of Remote Sensing & Geoscience*. IJRSG, 2(6), pp. 8–18.

Frazier, A. G. *et al.* (2016) 'Comparison of geostatistical approaches to spatially interpolate month-year rainfall for the Hawaiian Islands', *NTERNATIONAL JOURNAL OF CLIMATOLOGY*. Royal Meteorological Society, 1470(August 2015), pp. 1459–1470. doi: 10.1002/joc.4437.

Ghasemi, A. (2014) 'Metabolism', *Endocrinol Metab*, 10(December 2012), p. 5. doi: 10.5812/ijem.3505.

Goovaerts, P. (2000) 'Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall', *Hdrology*. Elsevier B.V, 228, pp. 113–129.

Hu, Q. *et al.* (2019) 'Rainfall spatial estimations: A review from spatial interpolation to multi-source data merging', *Water (Switzerland)*. MDPI, 11(3), pp. 1–30. doi: 10.3390/w11030579.

İçağa, Y. and Taş, E. (2018) 'Comparative Analysis of Different Interpolation Methods in Modeling Spatial Distribution of Monthly Precipitation Comparative Analysis of Different Interpolation Methods in Modeling Spatial Distribution of Monthly Precipitation A ylık Yağışın Konumsal Dağ', *Journal of Natural Hazards and Environment Araştırma*. Artvin Çoruh University, 2(May). doi: 10.21324/dacd.387061.

Kumari, M. *et al.* (2016) 'Comparison of Spatial Interpolation Methods for Mapping Rainfall in Indian Himalayas of Uttarakhand Region', pp. 159–168. doi: 10.1007/978-3-319-18663-4.

LAHMEYER and YESHI BER (2007) *The Federal Democratic Republic of Ethiopia Ministry of Water Resources Genale-Dawa River Basin Integrated Resources Development Master Plan Study Final Report A . Hydrology and Climate*. Addis Ababa.

Li, J. (2016) 'A Review of Spatial Interpolation Methods for Environmental Scientists', (March).

Li, J. and Heap, A. D. (2008) 'A Review of Spatial Interpolation Methods for Environmental Scientists', *Australian Geological Survey Organisation*. 2008th edn. Geoscience Australia, GeoCat# 68(2008/23), p. 154. doi: http://www.ga.gov.au/image_cache/GA12526.pdf.

Ly, S., Charles, C. and Degré, A. (2013) 'Different methods for spatial interpolation of rainfall data for operational hydrology and hydrological modeling at watershed scale . A review', 17(2), pp. 392–406.

Machiwal, D. and Jha, M. K. (2006) ‘Time series analysis of hydrologic data for water resources planning and management: a review’, *Journal of Hydrology and Hydromechanics*, 54(3), pp. 237–257. Available at: https://www.researchgate.net/publication/47737331_Time_Series_Analysis_of_Hydrologic_Data_for_Water_Resources_Planning_and_Management_A_Review.

Machiwal, D. and Jha, M. K. (2012) *Hydrologic Time Series Analysis:Theory and Practice*. Heidelberg, Germany. In: Springer.

Mair, A. and Fares, A. (2014) ‘Comparison of Rainfall Interpolation Methods in a Mountainous Region of a Tropical Island’, *JOURNAL OF HYDROLOGIC ENGINEERIN*, (April 2011). doi: 10.1061/(ASCE)HE.1943-5584.0000330.

Mishra, P. *et al.* (2019) ‘Descriptive statistics and normality tests for statistical data’, *Annals of Cardiac Anaesthesia*. Wolters Kluwer-Medknow, 22(1), pp. 67–72. doi: 10.4103/aca.ACA_157_18.

Nandi, S. *et al.* (2016) ‘Geographical Information System (GIS) in Water Resources Engineering’, *International Journal of Engineering Research*, 6890(5), pp. 210–214. doi: doi : 10.17950/ijer/v5i1/050.

Ohmer, M. *et al.* (2017) ‘On the optimal selection of interpolation methods for groundwater contouring: An example of propagation of uncertainty regarding inter-aquifer exchange’, *Advances in Water Resources*. Elsevier Ltd, 109, pp. 121–132. doi: 10.1016/j.advwatres.2017.08.016.

Otieno, H. *et al.* (2014) ‘Influence of Rain Gauge Density on Interpolation Method Selection’, *Hydrol. Eng*. American Society of Civil Engineers, 19(1998), pp. 1–8. doi: 10.1061/(ASCE)HE.1943-5584.0000964.

Pellicone, G. (2018) 'Application of several spatial interpolation techniques to monthly rainfall data in the Calabria region (southern Italy)', *International Journal of Climatology*. Royal Meteorological Society, (April), pp. 3651–3666. doi: 10.1002/joc.5525.

Res, C. *et al.* (2004) 'Spatial interpolation techniques for climate data in the GAP region in Turkey', 28(1911), pp. 31–40.

Res, C. *et al.* (2005) 'Spatial interpolation of weekly rainfall depth in the dry zone of Sri Lanka', *Climate Research*, 29, pp. 223–231.

Scharifi, E. *et al.* (2019) 'Influence of plastic deformation gradients at room temperature on precipitation kinetics and mechanical properties of high- strength aluminum alloys', *Journal of Engineering Research and Application*, 9(1), pp. 24–29. doi: 10.9790/9622.

Subramanya, K. (1984) *Engineering Hydrology*. third. Kanpur: McGraw.Hill. doi: 10.1016/0022-1694(75)90105-5.

Tao, T. *et al.* (2009) 'Uncertainty Analysis of Interpolation Methods in Rainfall Spatial Distribution – A Case of Small Catchment in Lyon', *J. Water Resource and Protection,*. Scientific Research, 2009(August), pp. 136–144. doi: 10.4236/jwarp.2009.12018.

Taş, E. (2017) 'Comparison of Areal Precipitation Estimation Methods in Akarcay Basin, Turkey', *International Symposium on GIS Applications in Georgraphy and Geosciences (ISGGG)*, (December). Available at: https://www.researchgate.net/publication/321746427_Comparison_of_Areal_Precipitation_Estimation_Methods_in_Akarcay_Basin_Turkey.

Wijngaard, J. B., Klein Tank, A. M. G. and Können, G. P. (2003) 'Homogeneity of 20th century European daily temperature and precipitation series', *International Journal of Climatology*. Wiley InterScienc, 23(6), pp. 679–692. doi: 10.1002/joc.906.

Xiao, Y. *et al.* (2016) 'Geostatistical interpolation model selection based on ArcGIS and spatio-temporal variability analysis of groundwater level in piedmont plains, northwest China', *SpringerPlus*. Springer International Publishing, 5(1). doi: 10.1186/s40064-016-2073-0.

Zhang, X. and Srinivasan, R. (2009) 'Gis-Based Spatial Precipitation Estimation ':, *JAWRA Journal of the American Water Resources Association*, 45(4), pp. 894–906. doi: 10.1111/ j.1752-1688.2009.00335.x.

APPENDICES

APPENDICES A: RAINFALL DATA USED AFTER MISSING FILLED

Argafa Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	58.3	133.8	206.9	47.4	107	308	174.6	237.1	18	72.4
2001	0	**24.66**	168.8	143.7	172.5	100.5	137.3	269.5	131.3	131.4	50.7	22.2
2002	41.6	0	105.3	212.2	91.8	71.8	78.8	108.5	164.8	117.4	0	228.5
2003	2.2	0	17.2	194.3	61.2	72.4	156.9	89.9	88.8	46.7	26.1	50.6
2004	53.3	0	23.1	205.8	28.5	57.1	128.1	110.8	264.9	80	30.7	22.2
2005	98.9	3.2	94.7	157.7	176.9	31.6	141.5	86.2	113.3	99.9	40.5	0
2006	4.3	53.5	44.8	135.6	90.4	37.1	81.1	97.1	**128**	**140**	36.7	45.7
2007	**25.02**	55.2	55	152.2	58.7	98.8	184	254.3	133	59.1	57.8	0
2008	**14.58**	**14.81**	**9.14**	**80.77**	**96.07**	**99.80**	56	**155.9**	74.4	**86.76**	44.7	89.9
2009	139.4	98.7	190.1	201.5	150	39.4	107.4	139.4	55.1	45.9	1.80	0
2010	0	0	3.5	49.6	137.1	**49.13**	80.1	69.1	73.5	43.3	70.5	0
2011	0	0	37.6	133	67.2	23.4	71.3	145.1	**99.3**	60.2	11.4	10
2012	10.9	0.8	200.6	73.7	20.4	18.7	122.5	245.3	83.4	59.4	59.1	0
2013	0	**11.16**	22	18.8	53.5	45.5	54.9	97	80.1	127.3	41.9	3.50
2014	0	0	25.1	49	75.1	65.4	48.8	67.4	70.4	49.6	43.8	0.3
2015	29.4	10.2	31.6	**73.79**	105.6	49.2	44.8	148.6	**113.4**	80.4	78.8	0
2016	**0**	**9.15**	**14.1**	**37.65**	**52.7**	5.2	49.4	208.2	105.4	**97.37**	**32.2**	**52.30**
2017	0	18.3	28.8	75.3	105.4	8.1	**122.3**	**179.3**	**169.7**	**65.78**	**42.2**	**17.6**
2018	**16.14**	**28.16**	**57.18**	**77.72**	**73.74**	**51.88**	**88.51**	**147.7**	63.5	61.7	**44.5**	**15.57**

Bore Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	14.9	0.1	14.1	89.3	270.1	294.5	117.9	166.7	152.9	467.6	88.1	25.2
2001	23.8	22.7	**88.9**	155	381.6	139	148.1	164.2	168.6	195.5	90.4	6.6
2002	26.5	8	104.8	149.5	257.7	149.4	218.9	157.8	129.2	151.9	42.1	81.6
2003	26.8	12.2	49.5	208.8	136.1	359	74.3	182.3	149.5	92.8	41.8	77.3
2004	**46.65**	54	86.5	195.9	272.9	151.9	74.2	219.2	167	124.5	202.7	50.9
2005	**22.30**	**4.90**	100.9	134.3	420.5	170.9	64.5	**189.55**	**198.4**	**198.2**	**35.93**	4.5
2006	4	**3.99**	60.3	267.9	202.2	269.2	69.5	258.9	94.7	254.9	96.2	14.2
2007	46.2	39.1	**40.23**	142.5	307.6	**225.9**	141.7	154.3	237	174.5	126.7	0
2008	5.3	0	30.2	194.2	217.5	268.7	**154.8**	195.2	**204.5**	189.5	64.7	18.4
2009	53.6	26.3	46.8	94.9	266	104.3	109.8	176.1	136.2	151.9	31.8	58.4
2010	30.7	163.	130.6	273.5	331.4	174.2	67.7	161.8	238.5	**73.53**	12.6	20.6
2011	4.2	33.6	42.9	109.1	341.5	**214.1**	239.8	148.7	218.9	108.3	166	**10.7**
2012	**7.4**	6	44.5	251.8	233.7	216.4	**201.1**	**194.26**	335.2	**71.22**	96..4	12.6
2013	19.2	5.7	280	**228.8**	**190.7**	**160.1**	158.8	158.5	397.9	118.6	**117.6**	**0.2**
2014	24	**6.29**	0	97.1	234.5	166.8	153.5	149.1	260.2	269.2	113.4	20.9
2015	2.4	22.8	57.4	300.1	287.7	188.6	128.8	149.3	**128.7**	**72.42**	**133.4**	**47.2**
2016	**15.75**	30.2	38.3	281	**173.4**	112.5	144.6	94.1	180.2	185.1	71.7	**7.79**
2017	5.7	21.8	67.15	97.7	289.6	232.8	154.6	172.8	310.6	260.8	116.6	**8.43**
2018	0	49.4	44.67	264.7	292.4	158.2	60	177.2	143.4	124.5	102.2	25.3

Delo Mana Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	6.8	0	6.8	173.6	370.6	10.5	3.5	6.9	**39.13**	226.8	36.8	41.2
2001	0.4	21.4	64.6	232.6	249.8	30.1	4.7	42.8	132.3	270.1	136.6	5.7
2002	49.8	0	115	145.1	121	11.5	15.2	0.5	132.5	249.1	28.5	72
2003	10.5	0	46	325.7	247.3	38.1	21.2	26.9	80.1	78.1	104.6	84.1
2004	32	4.5	7.5	162	64.1	28.6	22.3	46.7	111.6	126	174.4	27.8
2005	15	**23.78**	86.9	252	507.8	**20.12**	**19.57**	**21.72**	**67.94**	**210.06**	**135.20**	0
2006	5.2	44.4	94.7	254.2	147.8	64.7	10.9	69.5	86.8	250	148.1	22.7
2007	2.3	6.4	138	145.5	172.2	106.5	21.3	38.6	151.5	182.8	**58.22**	0
2008	2.5	0	0.8	128.5	236.1	39.3	18.3	32.3	68.6	214.3	181	0
2009	56.3	**143.9**	20	174.9	185.7	12.3	0.6	11.9	158.2	168.4	47.2	79.4
2010	**3.63**	115.9	**209**	91.7	397.3	7.3	34.3	64.8	109.7	101.4	57	0
2011	0	**2.17**	0	29.1	169.6	34.8	**24.2**	**24.0**	**68.9**	**196.7**	180.3	0
2012	0	0	17.2	350.5	181.5	2.3	8.1	27.8	89.7	157.2	154.6	15.7
2013	32.6	0	252	303.7	169.5	24.5	**71.18**	48.2	**72.19**	191.4	199.8	0
2014	0	6	166	167.8	0	0	14	36.1	**78.8**	**341.7**	**139.5**	**3.1**
2015	**3.63**	**0**	**50.3**	159.7	244.7	63.3	17.76	29.61	57.2	338.8	**89.59**	6.6
2016	1.1	**6.97**	15.2	366.2	260.7	38.6	14	63	22.5	291	66.6	16.6
2017	0	**5.5**	20	187.7	181.6	21	25.9	41.2	181.4	203.3	124.2	0
2018	0	**23.8**	**78.4**	**207.5**	**205.5**	**29.3**	**20.8**	38.7	74.2	113.7	**121.10**	**20.3**

Dinsho Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	**8.45**	0	45.1	174.4	73.2	47.1	184.1	228	94.6	169.4	18.5	48.7
2001	0	32.7	101.2	103.4	147	**134.9**	314	88.7	58.8	105.4	34	9.8
2002	0	2.8	156.6	117.3	**55**	44.9	88.5	89.7	71.5	99.4	6.3	164
2003	8.4	0	14.9	167.3	37.8	86.9	150.4	145.6	132.1	44.7	36.6	50.8
2004	27.9	20.9	23.7	196.6	61	55.4	142.1	**238.71**	106.5	67	59.8	39.1
2005	53.9	19	81	**218.1**	147.4	57.5	96.8	131.9	93.1	153.4	65	2
2006	6	58.3	43.4	219.9	77.4	39.8	174.1	**375.25**	98.4	141.1	100.1	49.9
2007	2	**35.30**	**75.02**	251	66.2	86.2	170.1	**362.01**	**159.1**	**128.8**	**56.58**	**0**
2008	**6.33**	22.2	0	0	95.8	109.1	**225.6**	188.1	116.2	89.9	57.5	0
2009	76.5	**15.09**	29.5	126.1	97.2	16.7	106.4	**177.72**	69.6	78.7	43.9	66.5
2010	3.6	137.8	222.1	195	118.3	47.7	308.3	**207.63**	89.1	77	20	2.5
2011	0	0	0	9.5	144	**182.3**	116.1	**167.84**	72.9	57.1	73	0
2012	0	0	45.8	234.4	96.5	52.4	248.9	158.8	150.1	135.8	56.6	26.5
2013	**12.9**	33.5	**69.18**	204.9	**150.5**	53	142.9	**295.9**	116	110.8	80.8	2.4
2014	0	16	123.2	126	121.8	91.7	117.5	208.1	98.8	131.5	37.8	2.5
2015	0	0	59	72.7	109	140.5	72.3	114.7	154.3	76.1	77.8	**21.5**
2016	0	22.6	20	194.3	**170.4**	**145.4**	**140.6**	**257.4**	76.2	210.5	42.4	121
2017	0	21.8	25.3	58.9	170.4	39.3	140.6	257.4	203.1	73.1	**59.29**	**28.9**
2018	**2.86**	**31.64**	**61.94**	**142.4**	**120.4**	**251.5**	**168.7**	**233.4**	**121.1**	**111.8**	**60.11**	**23.8**

Dilla Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	20.4	190.1	312.9	19.7	98.7	113.3	144.6	162.8	69.8	13.1
2001	**15.7**	25.2	105.6	226.7	194.8	144.4	72.4	145.3	157.4	197.4	52.4	28.8
2002	35.6	18.7	208	86.6	137.9	104.8	69.6	109	88.2	57.4	69.9	115.7
2003	56.7	4	76.1	146.9	100.3	102.9	55.5	118.7	67.3	128	95.4	22.2
2004	87.3	32.1	63.3	275.5	113	40.2	73.7	63.4	136	70	112.2	45.4
2005	44.6	9.3	77	273.2	246.2	63.7	76.9	95.9	144.8	183.4	58.6	4
2006	15.5	51.4	151.1	206.2	158.4	151.4	53.7	159.5	130.3	292.1	82	39.4
2007	81.3	10.5	95.2	149.8	340.2	164.5	83.2	276	212.2	193.3	54.5	0
2008	10.5	4.5	983.2	198.5	213.9	85.1	143.8	89	161.7	815.7	74.6	0.6
2009	52.6	40.8	39.5	207.2	134.6	72	25.9	46	177.3	156.5	15.9	127.1
2010	45.4	141	203.9	217	313.7	139.8	80.5	147.5	126.6	238.7	7.3	8.2
2011	11	894	39.5	135.6	276.4	110.5	99.2	180.3	190	223.6	198.7	11.5
2012	14.8	12.6	29.2	136.4	198.9	113.7	114.6	**117.5**	175.9	181.2	54.1	**90.91**
2013	16.9	12.4	**210.6**	175.5	231.5	93.8	151.5	233.6	217.1	206.5	111.3	0.6
2014	8.8	23.6	122.6	134.5	368.5	74.9	96.7	104.9	140.4	312.8	108.8	12.6
2015	6.3	0.3	72.1	145.3	162.9	159	81.2	60.7	140	151.7	95.5	52
2016	31.5	31.9	56	201.2	233.3	126.6	69.8	155.6	66.9	175.6	65.2	23
2017	1.5	36.4	45.7	140.3	237.3	89.4	77.3	206	269.2	255	59.6	0
2018	1.6	97.7	132.3	225.8	179.8	210	8.6	120	171.2	220.7	180.2	38.3

Fincha ’a Wuha

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	5.9	138.4	274.1	4	0	30	10.5	206.3	78	16.4
2001	16.6	0	54.1	206.7	81.1	36.6	3.5	43.5	75.3	48.8	99.6	0
2002	12.8	5.4	94	125	121.2	40.3	9.2	0	36.1	110.6	10.7	96.4
2003	22.4	5.7	76.7	350.9	242.3	0	0	37	23	63.1	51.4	79.5
2004	72.7	9.5	33.1	141	89.3	8.9	16.2	11.6	58.4	71.9	227.4	5.4
2005	21.6	9.5	78.3	158.9	364.6	17	9.5	17.1	31.1	162.5	41.1	0
2006	0	20.6	55.2	303	48.7	12.9	5.1	26.9	45.2	318.3	126.1	50.7
2007	5.3	**6.51**	24.3	208.9	69.6	83	**27.99**	58.9	145.2	78.3	26.2	0
2008	2.6	**0.31**	59	127.9	42.1	30.2	22.5	14.1	109.8	176.2	109.5	0
2009	30.2	0	66	87.3	149.8	18.9	18	0	13.7	72.6	**37.36**	**41.06**
2010	12	41.5	89.6	382.8	187.5	202	51	52.6	25.5	115.1	2	1.3
2011	0	12.5	3.9	150.2	136.4	33.6	12.2	122.6	81.4	123.4	249.1	0
2012	0	0	72.6	111.5	106.1	38.4	61.8	70.7	98.7	**132.12**	**54.62**	**29.00**
2013	**3.37**	**0.88**	**184.9**	**262.2**	**196**	7.3	24.7	46.7	**83.47**	145.57	**150.7**	**4.49**
2014	**0.16**	**12.3**	**93.01**	198.6	**106.6**	27.7	18.95	55.70	29.6	**307.53**	112.5	**4.7**
2015	0	0	20.2	262.9	190.7	**34.6**	7.5	0	76.6	182.21	**80.65**	**9.60**
2016	**1.03**	**2.32**	24.9	318.1	**299.3**	**47.3**	**19.95**	**36.40**	**50.50**	**225.0**	**74.15**	**25.80**
2017	0	0	0	102	179	0	38.5	62.8	126.0	175.9	119.5	0
2018	0	22.7	132.1	438.1	**125.9**	**16.5**	**10.4**	**20.5**	**106.3**	**223.9**	**105.5**	**22.32**

Arero

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	4	30	229.6	6.8	10.2	3.9	4.8	92.5	84.7	32.9
2001	14.6	1.8	60.8	178.4	10.6	15.7	6	35.3	24.1	79.1	57.1	0
2002	4	2.6	78.2	177	171	7.6	15.1	1.88	57.2	**188**	79	176.6
2003	31.6	0	**56.05**	334.1	133.2	13.9	8.6	0	0	27.7	38.4	27.7
2004	**62.7**	41.4	**20.7**	186.5	26.6	**9.2**	0	2.7	15.7	163	193.3	13.5
2005	17.9	0	97.9	247.8	211.3	42.8	44.2	13.4	8.8	74.2	89.2	0
2006	**0**	22.5	42.1	198.1	56.1	1.3	0	2.5	9.9	86.8	66.3	46.4
2007	0	4.2	32.1	131.9	132.9	117	2.2	11.1	91.1	96.6	51.4	0
2008	1.3	0	72.7	38	58.3	80.3	91.6	0	21.6	303	70.3	0
2009	3.2	0	**62.4**	142.3	312.6	14.8	2.4	0	40.5	63.2	5.6	0
2010	0	10.7	96.2	308.6	0	21.1	0	0	5.9	116	45.1	0
2011	0	3.2	0	61.9	**115.46**	5.4	5.9	0	10.6	46.9	123.5	**9.3**
2012	**0**	0	**76.2**	**192.8**	**68.5**	**30.5**	**27.1**	**59.9**	**137.2**	**132.9**	**38.6**	**41.9**
2013	**36.34**	**3.22**	**80.4**	**220.1**	**136.5**	**48.0**	**24.9**	**22.0**	**59.0**	**164.7**	**106.6**	**8.3**
2014	**5.9**	**19.9**	**58.6**	**161.6**	**121.5**	**48.7**	**27.9**	**44.0**	**30.8**	**217.6**	**88.0**	**4.9**
2015	0	0	46.2	273.2	21.6	**45.0**	**18.7**	**5.0**	**35.70**	**100.4**	**49.63**	**7.38**

Bulle Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	**103.3**	**110.5**	**150.1**	164.5	112	189.3	145.3	143.5	139.5	71.8	71.5	39.1
2004	122	53.9	26.2	375.1	126.6	220.1	220.1	256.9	206.1	139.2	95.9	86.2
2005	26.6	15.5	**241.7**	156.2	342.4	155.2	49.2	134.3	276.6	**131.4**	**92.4**	0
2006	13	133.1	91.4	275.9	185.5	135.4	82.7	153.5	75.1	202.4	57.2	115
2007	51	31.3	49.7	186.9	167.7	426.7	101.5	159.9	171.3	149.5	125	19.3
2008	4.8	11.7	58.2	104.6	183.7	177.3	102.8	168.3	111	131.3	107	69.9
2009	76.1	66.3	85.9	223.8	154.3	102	42.1	133.2	178.3	146.5	82.5	87.7
2010	40.8	162	213.1	205.1	336.8	106.2	155	179.8	240.6	256.7	12	14.6
2011	33	38	33.6	118	292.6	74.3	195	181.4	207.2	114.9	145	37.8
2012	5.5	3	**112.5**	161.4	**172.6**	**144.5**	129	103.8	154.8	201.8	125	48.2
2013	**134**	**9.48**	**234.6**	223.7	264.6	81.9	168.7	197.1	232.5	200.8	91.1	0
2014	**71.9**	**110.8**	**205.0**	97.4	**123.5**	152	**175.5**	**212.4**	119.6	**114.5**	112	**0.55**
2015	8.2	55.6	133.2	213.9	**189.7**	164	45.7	96.6	158.9	186.3	148	**19.3**
2016	18.6	63.1	55.9	167.1	152	**122.1**	**319.6**	108.3	**209.4**	**41.8**	**262**	**4.83**
2017	26.5	27.9	**86.6**	122.3	168.1	106.6	63.9	201.1	277.3	285	38.5	**0.0**
2018	232	207.9	134.9	173.2	**186.8**	153.5	281.6	304.4	**104.2**	**80.7**	119	**7.87**

Goba Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	15.9	0	14.5	140.1	117.7	39.5	120	188.9	119.4	119.7	31.6	30.7
2001	0	5.9	146.5	147.7	118.6	93.5	104.7	209.1	186	152.8	55.4	10.4
2002	42.2	0	104.2	102.3	47.6	36.1	85.7	117	61.4	105	6.7	93.3
2003	0	0	55.6	105.6	80.7	62.8	175.9	175.3	91.6	43.5	45.9	84.4
2004	40.7	14	22.2	142.8	19.7	66.7	162	168.4	176.3	69.2	23.4	68.5
2005	**38.15**	**9.0**	29.2	181	74.9	54.1	55	82.4	116.7	186.5	55.5	2.5
2006	24.6	93.1	88.2	189.3	**104.30**	25.9	142.6	274.5	159.3	211.4	39.7	61.2
2007	**36.18**	15.5	**117.1**	145.6	136.3	111.3	129	188.3	139.1	116	80.1	0
2008	10.7	**6.71**	**23.2**	180.1	96.6	34.2	106.7	123.2	151	106.6	66.6	2.4
2009	43.4	**7.17**	20.6	100.9	67.3	33.4	32.4	**202.0**	112.3	45.4	29.5	46.6
2010	11.3	113	71.2	175.2	77.4	32.2	63.4	90.2	139.2	25.8	3.8	**24.0**
2011	0	**1.6**	**1.5**	11.5	52.4	121.3	69.1	69.6	94.4	148.8	**153**	**0**
2012	0	0	16.6	116.4	59.9	28.5	74	162.6	90.3	92.5	47.5	2.5
2013	4.3	0	4.3	**162.7**	125.3	36.5	**101.7**	126.7	76.3	107.4	129	0
2014	0	**33.0**	48.2	**174.1**	74.9	25.5	80.8	80.8	109.1	134.9	**31.7**	**1.0**
2015	**2.88**	0	39	**76.4**	81.2	26.5	50.7	102.1	**115.5**	**65.0**	**44.9**	**117**
2016	**181.6**	**33.3**	**42.6**	**226.6**	**148.2**	**50.8**	**161.9**	**191.8**	**128.1**	**105.9**	**117**	**36.4**
2017	0	25	**72.2**	**118.3**	174.6	80	125.7	167.9	190.3	125.8	58.8	0

Goro Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	29.3	217.2	88.8	22.6	28.1	40.4	71.2	**94.4**	**60.1**	**40.1**
2001	**71.6**	**5.2**	**121.0**	**105.4**	110.8	55.5	12.2	75	220.8	105.9	59.4	29.6
2002	30.6	0	151.2	147.2	56.2	0	19.1	0	151.6	333.2	2.2	85
2003	0	0	3.5	191.2	98.1	4	37.5	12.7	32.6	52.8	35.6	89.8
2004	187.8	0	38	203.7	83.8	11.3	13.9	30.5	30.5	22.2	59.8	28.8
2005	10.6	18.9	201.1	54.6	199.3	20.2	29.4	6.9	72	134.8	70.8	10.6
2006	0	31	118.3	249.7	158.7	59.3	0	125.9	181.2	214.2	36.8	2
2007	**24.9**	0	94.3	77.9	127.1	**20.9**	39.6	45.4	131.9	129	114.9	0
2008	0	0	**68.5**	116.8	101.8	3	**35.8**	42.7	**33.**	102.9	92.6	0
2009	18.8	**0**	35.6	147.7	127.3	12.4	2	0	147.3	106	45.4	26.5
2010	0	105.9	148.4	275.5	204.8	21.4	**53.7**	69.8	171.1	**17.3**	33.7	0
2011	0	0	0	61.4	322.3	32.5	**50.5**	80.4	63.4	137	92.1	10.7
2012	0	**0**	7.3	175.4	38	0	0	42.4	**213.0**	97.1	0	14.5
2013	45.7	0	319.8	200	54.2	27.9	46.3	107.7	85.1	**56.2**	48.7	0
2014	0	0	35.8	83.4	91.2	0	19.1	64.5	154.9	138.2	56.1	1.5
2015	0	0	**59.3**	82.1	272.3	4	17.8	0	88.7	183.9	158.7	22.6
2016	**1.4**	12.3	3.5	238.5	227.9	51.5	33.9	25.6	94.4	**13.2**	82.4	48.5
2017	0	**7.65**	6	159.4	139.2	0	35.3	77.1	79.8	144.5	98.9	0
2018	**0**	**57.0**	**140.5**	**191.6**	**193.0**	**22.5**	**43.9**	28.1	62.7	114.2	**13.8**	**16.5**

Hager Selam Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	**11.49**	139	161	84.1	41.1	190.1	240	442.4	61.6	30
2001	74.2	45.3	122.8	193.7	161.5	86	75.2	209.5	155	179.3	60.2	7.7
2002	33.7	43.1	132.8	106.9	163.5	85.1	130.7	39.1	115.1	172.9	13	133.3
2003	69.6	11.7	74.7	94.7	74.4	185.3	77.1	117.5	198	36.6	41.6	36.4
2004	80.6	41.5	25.2	184.3	182.3	64.8	104.7	169.2	14.7	150.4	102.4	35.9
2005	**40.5**	29.5	82.5	123.3	324.3	104.3	87.5	142.9	145.1	253.2	64.9	0
2006	**21.0**	76.4	56.5	161.1	131.8	136.8	112.7	133.1	**202.2**	177.5	86.8	60.7
2007	84.2	51.7	53.3	209.5	196.2	256.7	117.2	278.5	**184.6**	84.7	**64.9**	2
2008	0	23.3	47.4	109.4	159.7	168.5	90	158	212.3	143.6	114.4	5
2009	91.9	36.3	30.6	126.6	179.6	69.9	46.6	249.2	72.9	142.8	29.6	77.3
2010	25.9	181	200.7	263.1	329.9	111.1	96.3	130.6	193.2	214.5	3.6	6.1
2011	2.4	2.1	24.5	264.7	368.4	150.2	143.3	154.5	150.2	199.4	259.7	**2.87**
2012	2.4	2.1	24.5	264.7	**259.5**	**149.3**	**315.0**	78.8	**235.**	145.1	39.2	34.5
2013	5.9	8	**125.6**	322.4	**72.2**	116.9	**247.8**	**207.8**	**130.0**	**139.4**	119.2	0
2014	**0.0**	**21.6**	**116.5**	**82.0**	**72.1**	262.3	**177.9**	**217.1**	245.2	**77.8**	110.6	**0**
2015	30	22.6	**55.5**	244.1	244.9	113.8	58.5	135.8	122.1	116.4	**73.4**	**15.2**
2016	29.5	10.5	75.3	199.8	283	179.6	133.5	182.2	159.6	176.8	47.8	**7.9**
2017	1	5.2	50.4	71.6	**191.9**	**56.**	218.8	206	365.1	**105.3**	**55.7**	**34.9**
2018	**4.6**	109	137.7	476.7	172.4	118.6	106	112.2	167.3	185.8	112.8	34.9

Gerba Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	9	43	59.9	78.7	0.4	52.4	274.3	289.3	99.1	0	0	50.4
2004	10.6	34.2	36.2	213	**96.5**	32.7	193.7	**223.7**	**65.8**	**124.7**	**67.4**	**19.6**
2005	**13.2**	**23.7**	**163.0**	**136.4**	**259.8**	**152.4**	**204.0**	**225.8**	**144.3**	**133.9**	**28.0**	**0**
2006	16.9	14.6	178	84.3	30.3	8.5	216.2	303.2	53	39.9	84.3	12
2007	24.7	**47.6**	25.9	107	16	23.1	305.4	125.6	97.6	38.5	1.9	0
2008	21.5	0	0	48.3	70.4	55.8	220.4	176	132.6	126.7	4.1	0
2009	23.4	46.8	67.8	24.7	**96.1**	214.7	229.7	206.2	24.9	**178.6**	14.6	80
2010	0	73.5	117.7	67.2	43.1	18.2	374.8	326.3	29.2	9.2	26.4	0.8
2011	7.6	0	39.2	34	156.5	16.8	193.3	270.5	26.1	6.5	**129.8**	0
2012	0	0	29.5	86.6	22.6	40.7	341.2	276.7	6.7	4.9	0	0
2013	22.6	0	90.6	55	42.1	5.8	350.1	252.1	47.2	66.6	0	0
2014	**8.65**	12.5	59.6	41.5	149.4	0	258.3	284.3	89.5	108.2	4	0
2015	0	3.8	26	0	155.3	15	35	203.6	125.7	0	53.1	**49.49**
2016	6.3	**21.6**	**46.7**	**229.2**	80.6	52.2	258.4	423.7	**118.2**	**146.4**	**39.6**	**62.9**
2017	0	46.4	86.3	78.7	49.2	0	181.8	245.8	73.4	35.8	0	0
2018	0	23.5	23	81.6	35.8	58.8	188.9	185.9	94.3	44.2	69.7	**17.4**

Hager Selam 2

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	**11.4**	139	161	84.1	41.1	190.1	240	442.4	61.6	30
2001	74.2	45.3	122.8	193.7	161.5	86	75.2	209.5	155	179.3	60.2	7.7
2002	33.7	43.1	132.8	106.9	163.5	85.1	130.7	39.1	115.1	172.9	13	133.3
2003	69.6	11.7	74.7	94.7	74.4	185.3	77.1	117.5	198	36.6	41.6	36.4
2004	80.6	41.5	25.2	184.3	182.3	64.8	104.7	169.2	14.7	150.4	102.4	35.9
2005	**40.5**	29.5	82.5	123.3	324.3	104.3	87.5	142.9	145.1	253.2	64.9	0
2006	**21.0**	76.4	56.5	161.1	131.8	136.8	112.7	133.1	**202.2**	177.5	86.8	60.7
2007	84.2	51.7	53.3	209.5	196.2	256.7	117.2	278.5	**184.6**	84.7	**64.9**	2
2008	0	23.3	47.4	109.4	159.7	168.5	90	158	212.3	143.6	114.4	5
2009	91.9	36.3	30.6	126.6	179.6	69.9	46.6	249.2	72.9	142.8	29.6	77.3
2010	25.9	181.6	200.7	263.1	329.9	111.1	96.3	130.6	193.2	214.5	3.6	6.1
2011	2.4	2.1	24.5	264.7	368.4	150.2	143.3	154.5	150.2	199.4	259.7	**2.8**
2012	2.4	2.1	24.5	264.7	**259.5**	**149.3**	**315.0**	78.8	**235.0**	145.1	39.2	34.5
2013	5.9	8	**125.6**	322.4	**72.2**	116.9	**247.8**	**207.8**	**130.0**	**139.4**	119.2	0
2014	**0.0**	**21.6**	**116.5**	**82.0**	**72.1**	262.3	**177.9**	**217.1**	245.2	**77.8**	110.6	**0**
2015	30	22.6	**55.5**	244.1	244.9	113.8	58.5	135.8	122.1	116.4	**73.4**	**15.2**
2016	29.5	10.5	75.3	199.8	283	179.6	133.5	182.2	159.6	176.8	47.8	**7.9**
2017	1	5.2	50.4	71.6	**191.9**	**56.0**	218.8	206	365.1	**105.3**	**55.7**	**34.9**
2018	4.6	110	137.7	476.7	172.4	118.6	106	112.2	167.3	185.8	112.8	34.9

Kofale Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	**12.3**	**0.0**	**49.8**	**136.**	**110.4**	**66.8**	102.7	116.4	232.2	95.1	40.8	48.9
2001	8.6	50.3	198.2	**75.6**	161.4	122	92.7	111.7	101.7	158.9	22.2	24.4
2003	63.6	41.2	194	79.6	105.2	101	116.3	167.1	118.3	**71.6**	**3.1**	57.4
2004	36.8	26.6	206.2	**154.8**	37.9	189	124.6	130.7	213	86.7	28.7	53.7
2005	61.3	15	129.7	234.1	86.3	105.9	114.3	145.4	114.5	**56.25**	54.6	29.7
2006	**36.7**	75.6	213.3	120.1	**88.1**	**64.8**	158.3	121.6	129.3	89	10.9	28.2
2007	48.2	87.6	179.7	165.5	142.1	79.6	95.4	144	138	48.3	12.5	1
2008	5	14.2	40.7	45.8	238.2	152.7	91.3	131.1	143.1	129.9	77.4	0.7
2009	79.2	28.7	76.5	62.8	47	97.5	93.3	173.5	127.2	108.9	11.3	196
2010	58.6	87.6	98.8	144.6	142.2	95	94.7	97	140.3	45	30.1	44.1
2011	25.6	3.6	102.1	45.3	157.9	92.8	177.1	166.8	135.1	34.2	68.2	0
2012	0	2.2	73.7	129	74.3	117	61.4	131.3	165.7	32.3	39	21
2013	46	9.3	186.6	113.8	138.7	94.7	89	169.8	125.4	78.3	26.9	0
2014	19.7	58.3	182.7	141.3	186	53.8	90.3	167.6	161.9	131.8	54	1.1
2015	3.8	12.2	102.1	66.2	113.3	110.7	107	199.2	163.6	41	20.4	38.7
2016	24.3	**11.1**	74.6	105.2	186.2	60.3	107.6	137.6	153.9	**122.8**	121.5	10.2
2017	1.2	66.5	55.1	67.6	126.3	131.4	**101.87**	173.1	189	103	33.4	0
2018	**1.43**	**34.7**	**128.1**	**116.1**	**128.0**	**166.5**	**159.**	126.3	135.1	**91.7**	**43.6**	16.6

Mejo

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	12	10.1	33.2	128	285.9	230.8	114.1	12.6	25.4	0
2001	0	28.5	79.4	22.5	111	131.5	184.7	175.6	54.9	0	0	0
2002	0	0	8.9	13.7	6.5	62.4	193.5	169.2	95.2	0	0	14.9
2003	40.6	55.9	74.9	84.3	23.2	129	393.2	148.6	96.1	0	0	14.3
2004	15.5	0	99.3	114.6	9.8	**77.2**	393.8	201.2	116.9	99.1	32.4	**19.4**
2005	**40.8**	**15.7**	160.5	149.6	195.4	200.5	320.6	308.7	143.5	14.6	10.9	0
2006	1.6	38.5	90.5	61.6	19.2	109	344.4	362.7	131.8	24.9	2.6	12.3
2007	54.1	23.7	83.8	49.6	111	129.7	222.8	227.9	91.4	7.6	0	0
2008	1.5	0	0	61.9	76.7	137	431	404.4	188.7	89.4	50.8	0
2009	39.2	6	26.3	62.9	12.7	95.3	213.8	330.3	66.2	214.5	6.5	34.6
2010	0	85.2	7.7	151.9	119.5	73.4	254.2	170.4	246.7	0	1.4	0
2011	0	0	47.4	54.9	122	54.6	193	175.6	**140.4**	0	0	0
2012	0	0	37.8	43	**163.5**	**94.1**	524.4	419.7	147	0	0	0
2013	0	0	85.8	32.9	121.3	98.5	420	232.3	69.2	36.4	0	0
2014	0	16.8	51.9	2.9	7.6	27.4	260.7	257.2	154.3	96.3	0	0
2015	**15**	0	0	0	186.3	117.6	156.9	275.2	93.9	8.5	21	0
2016	12.1	32.7	18.2	258.7	83.6	117.7	531.6	**361.7**	76.8	**105.9**	31.5	0
2017	**0.5**	**10.4**	57.4	17.8	155.2	44.1	319.1	**340.4**	**278.4**	0	0	**17.4**
2018	**2.3**	**65.0**	**101.6**	**283.2**	**137.7**	133.4	351.4	297.8	43.2	0	17.5	0

Negele Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0.8	0	0	105.1	134.8	0.3	2.2	6	4.5	169.4	66.1	23.1
2001	0	9.7	76.4	213.3	94.2	2.9	3.2	5.4	49.7	112.3	37.6	2.2
2002	4.9	0	119.7	67.9	93.5	0.9	1.7	2.5	68.2	206.4	6.2	119.6
2003	9.7	0	25.3	242.3	192.9	2.1	2.9	17.9	7.1	50.5	21.2	43.5
2004	49.8	9.5	27.4	225.7	56	5.1	0	0.3	19.3	138.1	127	5.2
2005	33.9	7.5	**102.4**	225.3	339.7	4.6	5.8	1	2.7	100.2	54.6	0
2006	0	25.2	119	301.8	102.6	1.3	3.3	23.6	5.1	149.2	45.4	15.9
2007	0	0	27.1	198.7	85.8	3.6	6.9	2.7	43.9	309.2	98.8	0
2008	14.4	**54.4**	31.8	127.2	131.6	**29.2**	1.1	0	46	129	35.1	12.9
2009	3.2	24.9	121.2	116.5	41.3	0.8	3.7	7.7	30.6	128	25.2	0
2010	0	1.2	0.5	62	148.9	2.2	5.5	1.1	19.8	120.9	257.9	19.6
2011	0	0	0	206.9	62.3	1	2.4	5.2	52.8	128.4	**72.64**	4.6
2012	1.5	**0.3**	**219.8**	174.1	**216.6**	39.9	1.2	**38.0**	44.9	155.5	116.1	0
2013	0	5.9	**171.6**	167	81.5	8.4	39.1	32.9	24.9	159.5	**5.7**	**7.1**
2014	**7.0**	0	24	191.8	144	11	0	**16.6**	**54.7**	**225.1**	**75**	1.1
2015	**19.1**	**6.1**	**99.2**	**262.5**	**156.8**	**47.3**	**61.7**	7	**50.5**	**255.00**	**74.15**	**25.80**
2016	**0**	**10.6**	**23.0**	**145.8**	**191.6**	**13.2**	2	10.3	32.8	**175.9**	**119.5**	**0**
2017	0	0	27.1	198.7	85.8	3.6	6.9	2.7	43.9	309.2	98.8	0
2018	14.4	**54.4**	31.8	127.2	131.6	**29.2**	1.1	0	46	129	35.1	12.9

Moyale

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	23	0	0	48.5	105.9	2.5	10.2	11.6	16.9	81.8	71.6	64.8
2001	53.1	5.3	99.7	103.1	12.3	2.3	11.3	17.9	15.6	74.6	**62.3**	**11.2**
2002	19.2	0	35.6	148.3	**82.3**	16.3	0.1	2.4	24.9	117.3	34.6	90.9
2003	17	4.9	**43.5**	93.5	52.8	13.1	0.8	13.1	2.2	4	159.5	23.8
2004	38.5	16.5	26.7	199.6	15	10.5	3.1	0.7	12.6	122.4	98.3	19.9
2005	8.4	4.6	22.6	138.8	158.3	20.9	9.8	3.1	2.6	21.9	36.9	0
2006	0.5	2.9	26.7	333.5	78.2	5	2.2	10.2	68.9	328.7	158.7	28.2
2007	**6.2**	29.6	**34.7**	**236.0**	**88.5**	18.1	38.1	17.2	47	69.4	54.8	**5.28**
2008	4.9	0	28.7	79.1	65.6	49.7	8.5	6.4	10.6	170.2	24.7	0
2009	52.4	1.9	22.9	81.4	83	9.2	0	2.5	**119.4**	78.1	86.7	38
2010	17.7	78.6	311.1	255	15	8.5	19.5	4	23.9	34.5	17.5	2.4
2011	2.7	18.6	0.8	33.4	62.9	16.1	17.6	0.5	17.1	146.5	198	1.4
2012	0	0	16.3	174.1	99	2.7	1.2	21.1	38	94.4	95.5	33.5
2013	0	0	250	206.7	99	6.8	11.2	14.9	1.4	**119.4**	83	**56.5**
2014	0	3.6	58.3	108.8	135.5	1.2	0	4.3	5.8	110.2	**146.6**	**4.9**
2015	0	0	31.6	92.2	106.9	8.3	26	4.3	0	121.2	133.2	58.6
2016	0	0	6.9	221.7	71.3	3.5	0	0	2.7	1.8	**62.1**	**28.0**
2017	0	0.8	42.1	47.2	203.9	1.8	6	15.8	30.5	41.1	**106.5**	**25.6**
2018	0	66.1	119	**353.2**	128.2	18	20.7	11	30.6	107.3	**102.1**	**40.1**

Robe Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	15.1	0	13.9	71.9	132.6	**86.0**	44.1	249.3	83	97.4	28.4	9.5
2001	22.2	10.9	118.1	63.6	72.5	77.4	118.7	111.2	123.8	66.8	26.7	7.2
2002	29.6	2.3	89.8	46.4	54.3	35.7	67.6	69.9	120.2	45.7	3.5	83.9
2003	7.7	0	55.6	163	68.2	103.5	98.6	152.2	92	49.2	37.2	64.2
2004	55.5	11.2	44.5	110.7	22.7	69	124.8	**233.7**	**72.7**	60.7	14.5	13.8
2005	16.1	12.5	**162.8**	155.3	**162.**	**100.8**	**203.8**	**241.2**	**97.5**	**41.4**	**33.3**	0
2006	6.4	33.1	**75.7**	**164.2**	**61.1**	54.1	**246.5**	**322.**	**108.0**	**74.0**	**35.8**	**13.7**
2007	0	**16.56**	**69.3**	**153.8**	**63.2**	**80.9**	**204.9**	**250.5**	**101.1**	**34.0**	64.9	0
2008	5.1	0	41	105.8	77.4	71.7	78.2	179.5	80	82.7	106.3	0
2009	30.1	8.3	31.6	107.4	53.1	35.4	66.4	134.9	106.5	100.2	36.2	38.3
2010	4.4	136.8	193.9	136.3	101	70.1	108.8	160	**132.6**	71.2	0	0.2
2011	0	0.2	20	70.9	126.7	37.9	133.5	133	152.9	36.9	57.2	0
2012	0	0	8.8	158.6	59.4	34.1	150.6	222.9	136.7	68.7	3.2	12.3
2013	12.4	0	115.2	81.7	104.4	79.5	153.7	183	60.7	102.5	116.4	0
2014	0	7	33.4	73.7	**91.4**	37.5	**177.**	87.8	97.2	105	**22.2**	**0.2**
2015	1.7	0	39.7	52	196.4	64.4	60.5	153.9	**80.19**	55.6	48.2	2.6
2016	**7.2**	**18.5**	**55.1**	**171.0**	**122.5**	**110.0**	**314.9**	**266.1**	**101.5**	**90.5**	**37.1**	**40.4**
2017	**0.16**	15.2	**72.1**	**113.4**	**174.4**	**66.3**	**213.3**	197.6	269.7	76.6	**43.0**	**17.3**
2018	**11.0**	**53.8**	**69.2**	**162.0**	**87.4**	**154.9**	**227.5**	168.1	64.1	71.7	**41.2**	**7.9**

Robe 2

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	1	0	3.5	124.4	**106.7**	48.5	113	177.1	89.6	136.6	12.3	108.2
2001	0.8	41.6	93.1	69.8	120.5	89.1	138.3	189.8	64.7	52.5	11.4	10.1
2002	65	2.5	135.9	152.4	32.2	34.4	76.3	122.8	152.8	43.9	0	83.9
2003	12.3	0	44.1	142.4	26.1	90.3	195.5	262.8	83.7	32.1	9.1	48.2
2004	26.7	29.1	57.4	115	35.6	89.6	135.9	141	93.2	46.1	7.7	3
2005	41.1	2	58.7	136.1	174.9	132.1	136.5	139.5	125.2	42.1	39.7	2.2
2006	23.5	28.5	80	185.1	60.9	60.1	231.5	210.5	125.1	68.9	10.7	45
2007	**0.9**	38.5	54.5	87.9	169.7	135.4	130	239.4	177.1	58.8	25	0
1008	0.6	1.4	5.7	62.2	95.8	155.9	194.7	156.6	91.6	64.8	83.1	8.5
2009	82.3	0	12.8	58.8	57.2	40.6	106.1	230.5	101.8	140.2	17.5	47.9
2010	10.6	139.4	108	59	137.6	67.5	**208.7**	198.6	73.8	5.5	0	3.9
2011	0	17.2	27.2	67.7	144.2	81.6	172.5	133.7	130.6	4.2	84.6	0
2012	0	0	31	108.4	67.5	39	135.1	141.3	192.1	28.5	1.6	5
2013	21.6	0	150.1	113.4	85.6	119.8	169.3	203.6	68.3	70	32.9	0
2014	0	7.7	71.1	68.8	85.3	21.4	118.6	185.4	78.4	91.4	5.1	0
2015	**16.3**	**18.7**	6.2	**104.1**	104	86.1	96.8	110.1	67.4	22.8	45.5	3.1
2016	23.4	0	10.5	218.6	110.2	41.2	216.2	246	102.3	35.1	27.4	23.8
2017	0	15.6	89.3	25.9	222.9	28.6	151.4	162.7	191.7	32.7	26.5	0
2018	0	**32.7**	**64.4**	**150.5**	**102.2**	**157.3**	**166.0**	175.3	62.6	71.7	**46.4**	**17.3**

Yabalo

Year	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
2000	4.5	0	11.3	109.7	69	**2.26**	0	15.8	12.6	85.1	48.7	15.4
2001	53.1	5.3	99.7	103.1	12.3	2.3	11.3	17.9	15.6	74.6	**66.51**	**5.3**
2002	22.5	4.1	161	118.5	115.5	10.7	6.3	0.2	45.7	110	35.4	125.5
2003	15.7	4.2	72.7	188.1	166.2	0.1	1	33.5	2.2	24.7	64.4	31.4
2004	59.4	39.4	38.2	298.1	126.9	0	3.8	0	56.7	89.8	158.9	2.6
2005	19.4	22.8	58.1	175.5	142.4	16.3	9.9	0.8	4.6	108.6	54	0
2006	1.5	50	47.6	**215.0**	12.2	2.6	1.8	31.9	4.2	213.9	48.5	55
2007	0	14.2	44.3	158	85.8	16.3	**25.8**	**35.2**	**70.3**	**81.9**	**27.6**	**5.6**
2008	9.2	0	72.9	**135.2**	**64.5**	26.3	**12.6**	17.2	0.7	**220.9**	189.6	**0**
2009	30.8	0	72.2	123.8	147.8	1.8	1.8	2	44.5	295	24.3	58
2010	**47.8**	**120.6**	**173.9**	125.5	158.1	3.6	6.7	29.1	**26.7**	**92.5**	**14.9**	**1.2**
2011	**0.9**	29.9	18.6	75.6	82.7	**26.1**	**11.7**	**41.4**	12.1	91.3	145.2	12.8
2012	**0**	0	**35.3**	**164.1**	**89.1**	17.9	1.1	1.6	29.1	122.5	30.3	5.9
2013	32.1	**1.2**	**218.2**	142.9	19.4	14.5	5.8	10.1	78.6	125.9	**116.3**	**20.3**
2014	0.4	0	87.4	54.9	72.8	5.8	0.4	121.4	6.8	144.2	30.7	1.1
2015	0	4.1	50.9	123.5	79.3	52.4	0	5.9	6.7	112.7	80.1	50.1
2016	2.8	46	20	304.5	57.3	50.5	0	0	12.2	24.6	**70.1**	**41.7**
2017	1.2	14.5	54.4	18.3	82.2	0	14.8	31.3	**63.1**	215.7	37.8	**8.5**
2018	0	48	162	227.2	101	5.4	0.1	2.5	6.7	64.9	27.6	33.1

Kibre Mengist Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	0	0	15.4	197.9	264.4	15.9	7.4	56.9	28.1	210.9	71.3	11.4
2001	10	12.8	66.8	308.5	193.9	49.5	17.8	53.6	91.5	191	73	4.3
2002	15.2	0	115	87.4	167	5.4	11.7	3.1	83.2	247.8	27.1	108.6
2003	43.6	0	67.5	246.3	276.2	52	27.4	53.7	13.8	66.3	30.4	52.2
2004	65.7	16.9	48.5	174.6	11.8	13.6	21.1	11.6	101.6	117.6	252.5	17.9
2005	100.8	31.7	142.2	320.8	358.3	24	28.5	29.2	92	281.1	137.3	0
2006	0	30.3	107.9	152.1	111.1	43.6	2.5	94.2	28.4	279.2	64.3	33.7
2007	7.3	18.4	85.5	252.3	125.4	124.2	57	59.7	128.8	156.8	19.3	**12.9**
2008	**3.73**	1.7	0	101	132.9	147.3	18	63	49.6	160	155.1	42
2009	**36.5**	**19.5**	**49.0**	**232.2**	**166.4**	56.5	18.3	62.6	27	**165.7**	**55.3**	**43.7**
2010	5.6	79.5	194	289	269.6	1.7	12.8	82.3	30.3	120.6	51.8	0
2011	**0.8**	**1.7**	**35.1**	45.6	61.1	28.1	**27.4**	**39.0**	**96.7**	**216.9**	**204.0**	**18.3**
2012	0	0.5	287.8	260	10.9	37.3	43.3	103.7	260.1	106.3	3.2	**24.5**
2013	21.3	0	222.2	283.8	283.8	96.8	48.7	19.3	61	192.8	107.2	0
2014	0	37	76.6	119.3	198.5	110	20.5	66.4	38	363.3	53.4	0
2015	0	0	26.3	200.9	185.3	50.1	37.5	20.4	30.5	154.6	56.2	6.4
2016	2	0	41.5	465.6	338	56.1	25.9	9.8	78.5	219	81.7	35
2017	0	26.5	49.2	147.9	214.2	18.7	15.6	50.8	70.6	148.5	114.8	0
2018	0	19	56.6	25.9	45.1	3.8	0	2.3	138.5	334.1	**89.4**	**24.2**

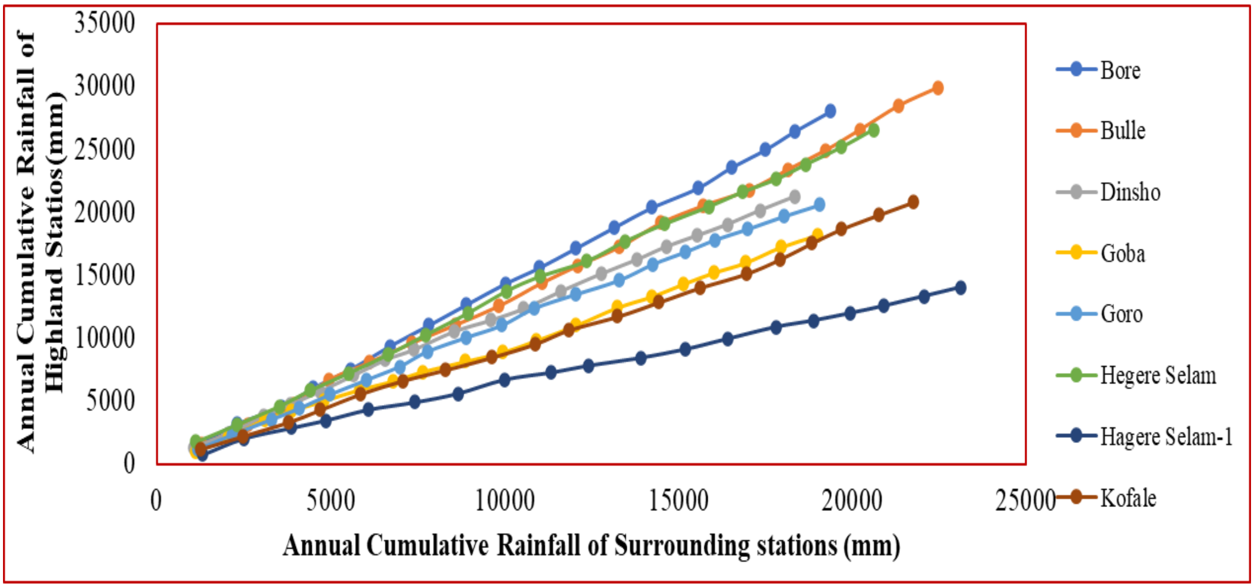
Gesera Station

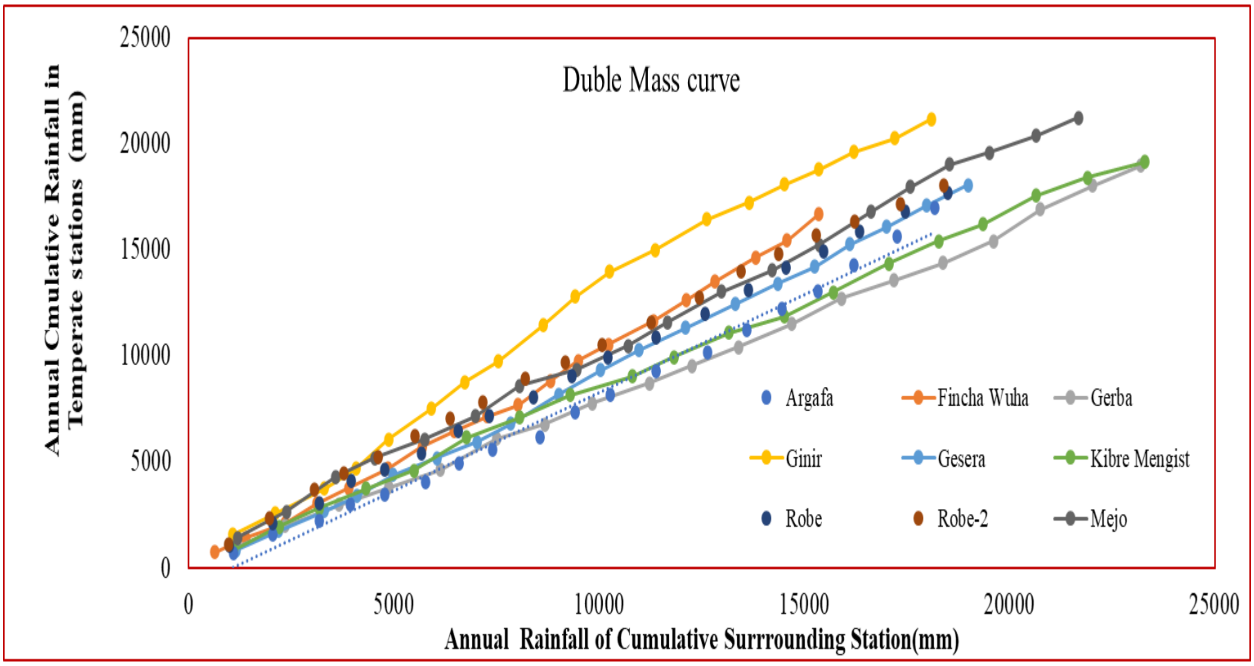
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	1.7	0	26.7	180.1	**137.8**	54.3	99.4	177.1	119.6	117.3	42.5	8.1
2001	0	31.8	91.7	116.4	179.7	104.2	63.8	160.7	129.5	81.6	25.7	26.3
2002	24.3	0	116.2	145.1	65.2	60.1	79.8	31.7	113.3	92.4	0	83.6
2003	14.5	0	105.4	136	86.8	176.5	**185.7**	131.3	107	30.2	42.8	53.3
2004	41.4	0	55	167.4	8.3	70.9	20.1	76.7	175.9	117.8	19.4	26.1
2004	**25.7**	14.6	89	174.7	148.3	52.3	151.1	71.8	115	101.2	42.4	0
2005	0	32.8	48.5	188.3	129.4	47.4	135.1	157.6	150.8	166	29.8	20.7
2006	0	11.7	58.6	142.1	86.7	97.2	123.1	199.2	113.5	117.6	106.9	0
2007	28.5	0	**33.7**	195.5	106.1	68	151.7	155.6	52.1	66.7	73.6	0
2008	**62.8**	**15.8**	**21.7**	**196.3**	**82.3**	**32.7**	51	**131.4**	465	30.9	20.7	**47.2**
2009	2.5	73.6	227.9	454.8	227.3	58	123.7	68.7	62.8	68.7	0	0
2010	0	2.3	44.1	**73.4**	**110.8**	**87.2**	**113.3**	**103.4**	**167.9**	**51.8**	**100.6**	**3.9**
2011	1.7	0	26.7	180.1	**137.8**	54.3	99.4	177.1	119.6	117.3	42.5	8.1
2012	0	0	7.3	256.3	53.2	**30.8**	109.2	169.4	56.9	65.5	15.9	11.2
2013	13.5	0	13.5	**56.7**	110.4	34.6	129.2	174.2	112.8	55.6	87.1	0
2014	0	0	99	107	188.6	**24.3**	**99.7**	**145.9**	**200.5**	**113.5**	**30.6**	**0**
2015	**0**	0	15.5	50.1	54.8	90.9	43.2	117.6	114.8	111.8	81.8	13.2
2016	16.3	**11.6**	0	269.2	106	49.3	51.9	100.1	**174.6**	79.9	79.2	0
2017	**17.4**	11.6	60.9	79.6	176.5	45.5	48.5	82.5	274	73.8	**26.5**	0
2018	**16.7**	**12.5**	**72.9**	**147**	**108.7**	**65.3**	**101.6**	**118.2**	75.3	77.2	**37.9**	**19.6**

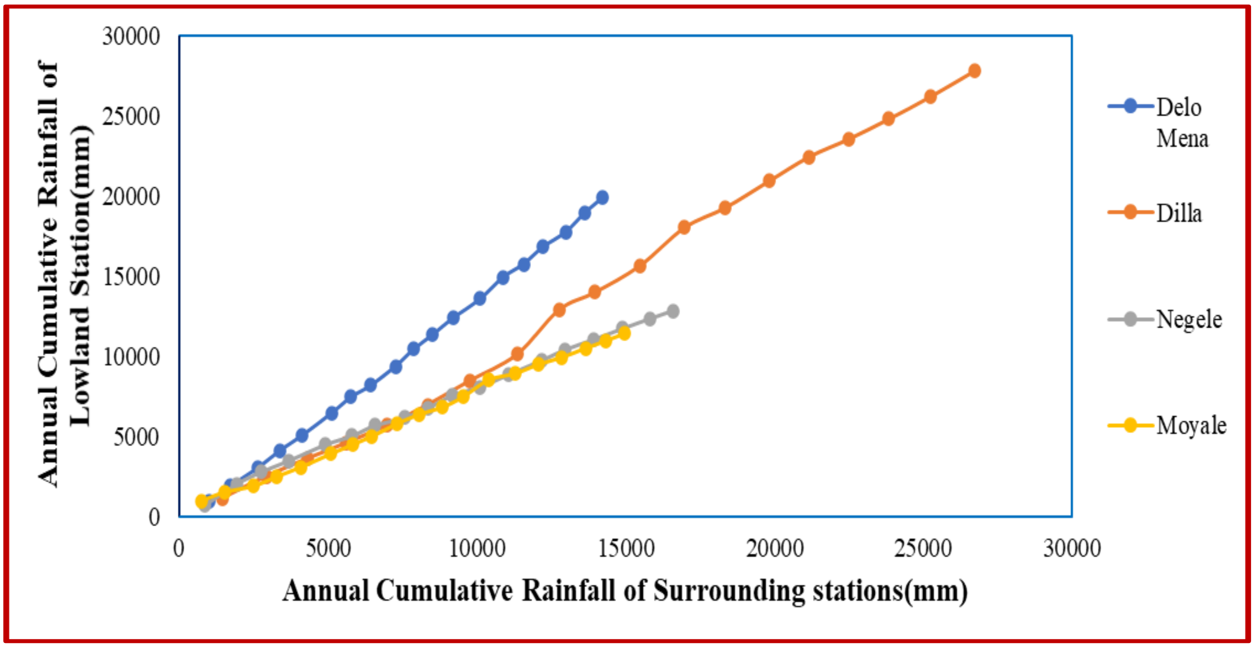
Ginir Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	19.01	0.00	22	**143.8**	**254.8**	29.7	0	55	85.7	229	40.8	23.5
2001	0	0	60.9	66.1	101.3	36.6	1.1	57.3	114.5	182.6	17	22.5
2002	44.5	0	127.5	133.1	43.5	24.6	6.3	0	122	242.9	26	41.1
2003	1.1	0	10.3	159.8	105.5	53.9	17.1	68.6	32.4	103.3	68.5	93.1
2004	85.8	0	3.9	218.9	79.5	2.7	0	18.1	93.7	183.9	78.1	76
2005	6.4	0	57.5	200.2	190.7	**50.9**	**24.9**	**19.5**	**51.1**	**125.2**	**84.6**	0
2006	5.2	31.8	81.1	346.8	139.6	77.6	3.2	16.7	126.8	404.3	82.2	102
2007	**7.2**	0.3	45.1	263.1	107.5	56.2	21.9	**77.9**	**247.9**	**147.7**	**62.8**	**10.6**
2008	8.7	0	0	220.7	**199.4**	**86.9**	40.5	**54.4**	**90.5**	**250.5**	206.8	0
2009	38.9	406	19.1	245.9	113.1	22.2	5.4	2.7	225.2	159.8	83.4	39
2010	0	108.8	312	315.2	547.8	25	50.2	15	105.8	181.3	39.5	0
2011	3	2	**0.62**	109.1	214.6	79.9	39.7	63.3	**114.6**	145.3	173.9	35.3
2012	0	**0**	5.6	150.8	219.9	34	2.9	232.2	284.3	157.3	110.5	46
2013	56	0	238.5	385	219	3.5	94.2	49.1	45.4	93.2	157.6	108.6
2014	0	0	155.7	**356.8**	**91.1**	5.5	14	127.9	125.8	318.2	180.7	0
2015	0	0	100.6	114.8	164.8	74.5	14.7	2.5	105.6	287.6	81.1	5.7
2016	6.5	13.4	14.5	**561.9**	141.8	52	12.5	41	72.3	**147.7**	65.4	33
2017	0.6	**8.7**	**99.7**	**208.2**	**222.4**	**18.0**	**20.3**	44.5	75.8	156.2	93.5	**51.2**
2018	**0.00**	**278.1**	**350.2**	**268.3**	**182.9**	**23.5**	23.5	8.5	91.5	197.5	**99.1**	**57.9**

APPENDICES B: Double Mass Curve for selected Stations






Annual Cumulative Rainfall of Lowland Station(mm)
30000
25000
20000
15000
10000
5000
0
0
5000
10000
15000
20000
25000
30000
Annual Cumulative Rainfall of Surrounding stations(mm)
Delo Mena
Dilla
Negele
Moyale