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Comparison and Selection Criterion of Missing Imputation Methods and Quality Assessment of Monthly Rainfall in the Central Rift Valley Lakes Basin of Ethiopia

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Abstract

Missing data is a common problem in all scientific research and the availability of gap-free data is rare in most developing countries. Statistical and empirical methods are the most often used for approximation of missing data. The performance of eight missing estimation methods was evaluated using bias, RMSE, and NSE. The Multicriteria decision method of compromise programming approach was used to identify the best imputation method. Four homogeneity test methods were used to evaluate the homogeneity of the time series data. The Mann-Kendall trend test and Son's slope were used to locate the change and calculate the magnitude of the trend. Multiple Linear Regression and Multiple Imputation by chained equations were well performed over most stations. Alternatively, the modified version of IDWM based on spatial distance and elevation difference (IDWM_{E&D3}) was ranked as third at many stations. The inclusion of elevation differences between stations has improved the capability of the inverse distance weight method. However, the performance of all the missing estimation methods decreased as the percentage of missing increased. Radius influences have no significant impact on the performance of missing imputation methods. Only Butajera station exhibited nonhomogeneous. Dagaga, Iteya, Bui, and Butajera stations all exhibited decreasing trends. Kulumsa and Ejerese-lele stations presented an increasing trend in monthly rainfall. However, the rest station has shown no significant increasing or decreasing trends in monthly rainfall.

Key Words Missing data; Missing Imputation; Compromise Programming; Homogeneity test; Trend test; Central Rift Valley Lakes subbasin

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1. Introduction

Missing data is a common problem in all scientific research, project planning, and development of water resource infrastructures. It (i) reduces the power and precision of statistical analysis results (Piazza, 2011; Houari *et al.*, 2014; Schmitt *et al.*, 2015; Gao *et al.*, 2018); (ii) leads to a biased estimate and draws the wrong conclusion about the relationship between two or more variables (Pigott, 2001; Gao *et al.*, 2018; Ekeu-wei *et al.*, 2018; Gao *et al.*, 2018; Teegavarapu *et al.*, 2019). It is very common in hydrology and other related fields to estimate the missed values of a target station from the values of neighboring stations. There are various methods available to approximately calculate the missing value of the target station and they are grouped as empirical, statistical, and function fitting methods (Xia *et al.*, 1999; Sattari *et al.*, 2016). Unusually, deleting or substituting missing values by the arithmetic mean or median are used as alternative methods (Peugh and Enders, 2004). Modern approaches, including spatial interpolation techniques such as Inverse Distance Weighting Average (IDWA), Normal Ratio (NR), simple Arithmetic Average (AA), Kriging, and co-Kriging, are the most widely used techniques in different geographic locations (Hartkamp *et al.*, 1999; Ferrari and Ozak, 2014; El Kasri *et al.*, 2018; Barrios *et al.*, 2018). The statistical methods, including correlation coefficient weighting (CCW) and multiple linear regression (MLR), are used alternatively to compute the missing values of the target station (Xia *et al.*, 1999; Barrios *et al.*, 2018). Recently, the advance of big data analysis and the computing power of the computer have created an opportunity for the development of Multiple Imputation by Chained Equation (MICE) (Peugh and Enders, 2004; Schmitt *et al.*, 2015; Gao *et al.*, 2018).

Choosing any of the methods among the alternatives depends on the characteristics of the observed variables (Gao *et al.*, 2018), geographic location and spatial distance between the stations (Barrios *et al.*, 2018), percentage of missing data (Radi *et al.*, 2015) and characteristics of the missing mechanism (Rubin, 1976; El Kasri *et al.*, 2018). It is very common to use any of the imputation methods based on an individual's preferences, knowledge, or experience (Kashani and Dinpashoh, 2012). But, random use of any missing estimation method without evaluating its

performance will increase the error value and reduce the ability of the statistical results (Ismail and Ibrahim, 2017; Barrios et al., 2018; El Kasri et al., 2018).

Recently, research has started to evaluate the ability of missing imputation techniques using statistical metrics. As an example, Barrios et al., (2018) evaluated the capability of the five missing estimation methods and the impact of radius of influence on the complex topography of central South Chile and found the ANN, MLR, and IDW had produced the lowest errors and the best method for filling the gap of missed monthly rainfall. El Kasri et al., (2018) have evaluated the performance of five imputation methods in the southern Atlas of Morocco, and have recommended the Theisen polygon, normal ratio, inverse distance weighted, and multiple imputation, methods as the best methods for filling the gap of missed rainfall. Similarly, Ismail and Ibrahim, (2017) have recommended the inverse distance weighted and correlation coefficient methods to fill the data gap. The Normal Ratio (NR) and Multiple Imputation (MI) methods are considered as the most appropriate methods by Radi et al., (2015) at 5%, 10%, and 20% to represent various cases of missing data percentages.

All the above-mentioned studies have evaluated the ability of different missing imputation methods, and there are no significant studies reported to consider the problem from a multi-objective perspective and clear approach or criteria to select the best method from a wide range of alternatives for missing data management. This is more of a series in an area of complex topography, sparsely and unevenly located measuring stations, and specific climate conditions like the Central Rift Valley Lakes subbasin. For example, stations found at high altitude have received the highest amounts of rainfall compared to stations at lower altitude in the study region. Even so, stations located at similar altitude but in opposite directions, such as Leeward or Windward, have exhibited different agroecology and rainfall amounts. With this understanding, the proposed objectives of the study are: (i) identify performance metrics and evaluate the ability of eight missing imputation methods; (ii) application of a compromise programming method to rank and select the best imputation method; and (iii) assess the homogeneity and trend of the monthly precipitation dataset for each station.

2. Materials and Methods

2.4. Description of study area

The Great Rift of the Earth runs from Jordan southward through East Africa to Mozambique (Meshesha et al., 2012). The Ethiopian rift extends from the Kenya border up to the Red Sea and is divided into three subsystems: Chew Bahir (Lake Stephanie), the Central Rift Valley Lakes subbasin, “hereafter referred to as CRV Lakes subbasin” and the Afar triangle. The Katar and Meki watersheds are located in the CRV Lakes subbasin of Ethiopia’s Rift Valley Lakes Basin. Geographically, the Katar watershed extend between 38.880 to 39.410 E longitude, 7.36 to 8.180 N latitude eastward of Lake Ziway. The Meki watershed is extended between 38.220 to 39.000 E longitude and 7.830 to 8.460 N latitude westward of Lake Ziway. The altitudes are extended between 1630 to 4188 and 1624 to 3614 meters a.m.s.l. for the Katar and Meki watersheds, respectively (Figure 1).

Fig. 1 Location of the study area, target station (red star) and neighboring stations (black star). The elevation data extracted from a 30 m resolution of Shuttle Radar Topographic Mission

2.5. Data accusation

2.5.1. Observed data

Monthly observed rainfall data for 22 meteorological stations was collected from National Meteorology Agency of Ethiopia (ENMA) for the time intervals of 1 January 1997 to 31 December 2017. Exploratory data analysis includes prescreening of negative values of precipitation, multiple dots between values, and computing the missing percentage and the outlier for each station. Additionally, the spatial distances between stations were calculated to determine the maximum radius of influence. Stations that were more than 40 kilometers away from any other station and had more than 25% missing values been excluded from the analysis. Sixteen meteorological stations were selected in this study for further analysis (Table 1).

Table 1 Geographic location of selected stations, average rainfall, and percentage of missed precipitation (1983-2005).

Basins	No	Name	Latitude	Longitude	Ele. (m)	μ RF	σ RF	%MD
Katar watershed	1	Arata	7.97 ⁰	39.05 ⁰	1765.00	766.46	98.37	10.14
	2	Asella	7.95 ⁰	39.13 ⁰	2413.00	1053.98	149.64	7.61
	3	Katar-genet	7.83 ⁰	39.10 ⁰	2400.00	801.38	202.77	22.1
	4	Kulumsa	8.00 ⁰	39.15 ⁰	2211.00	812.18	85.40	0.36
	5	Ogolcho	8.05 ⁰	39.00 ⁰	1682.00	710.68	150.05	8.7
	6	Sagure	7.75 ⁰	39.15 ⁰	2568.00	772.68	129.75	5.8
	7	Dagaga	7.43 ⁰	38.84 ⁰	2067.00	1049.89	135.74	
	8	Iteya	8.13 ⁰	39.33 ⁰	2129.00	1044.65	321.83	19.93
	9	Alem-tena	8.29 ⁰	38.91 ⁰	1656.00	840.14	106.74	

Meki watershed	10	Butajera	8.15 ⁰	38.37 ⁰	2000.00	1010.76	423.32	12.68
	11	Bui	8.33 ⁰	38.55 ⁰	2054.00	973.24	188.82	25.0
	12	Adami-tulu	7.86 ⁰	38.70 ⁰	1653.00	854.70	273.84	24.64
	13	Ziway	7.93 ⁰	38.70 ⁰	1640.00	743.92	136.43	3.62
	14	Ejersse-lele	8.24 ⁰	38.69 ⁰	1797.00	862.13	171.66	4.35
	15	Koshe	8.01 ⁰	38.53 ⁰	1878.00	760.19	209.16	4.71
	16	Meki	8.15 ⁰	38.82 ⁰	1662.00	742.82	98.54	14.13

Note: μ RF is mean annual rainfall; σ RF is the standard deviation of rainfall, % MD is the percent of missed data, Ele is the elevation in meters, lat. is latitude, Lon is longitude.

2.5.2. Reanalysis data

In Ethiopia, most stations are unevenly located on the main roads of cities and do not provide timely or sufficient data free of missing value. This is causing inhomogeneity, abrupt change, and trends in climate datasets. The reanalysis data has been extensively used as an alternative source of information for the study of climate variability (Dile and Srinivasan, 2013; Fuka et al., 2013; Funk et al., 2015; Alhamsry et al., 2020) and to evaluate the ability of regional climate model (RCMs) output (Bichet et al., 2020). In this study, the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) was downloaded from <http://climateserv.servirglobal.net/site> for the time span of 1983-2005 to assess the ability of missing imputation methods.

2.6. Approaches of the Evaluation

Four steps are followed to assess the performance of missing imputation methods. Monthly CHIRPS datasets of each grid point were extracted using a python script and interpolated into each meteorological station using four grid points around each observed station using IDWM (Table 1). Then, they deliberately and randomly assigned NA (Not Available) complete datasets of CHIRPS using R-program to represent different levels of missing percentage of 5%, 10%, 15%, 20%, and 25% of Table 1 using R software. Second, stations within a 20-and 40-kilometer radius of influence from the target station were considered as neighboring stations and recalculated the missed values of target stations using eight imputation methods. Third, the ability of the imputation method was evaluated using RMSE, PBIAS, and NSE. Fourth, multicriteria decision methods of compromise programming were applied to identify the best imputation method for each station, and finally, the quality of the data was studied for homogeneity and trend using the selected methods.

2.7. Methods of missing imputation Techniques

2.4.1. Spatial Imputation Method

A deterministic spatial interpolation technique such as the inverse distance weighting method is modified based on elevation difference, correlation coefficient (CC) and a combination of correlation coefficient or Euclidian distance as weighting factors to estimate missing values for the target station (Vieux, 2004; Barrios et al., 2018). The details of each method are given below.

a. Invers Distance Weighted Average (IDWA)

The Inverse distance weighting method is commonly used for approximately calculating missing data (Teegavarapu and Chandramouli, 2005). The missing value of the target station is determined from the observed values of neighboring stations using Eq. 1 (Vieux, 2004; Barrios et al., 2018).

$$P_{mi} = \frac{\sum_{i=1}^n d_{mi}^{-k} * q_{j(i)}}{\sum_{i=1}^n d_{mi}^{-k}} \quad 1$$

Where P_{mi} is the calculated missing value of the target station, n is the number of neighboring stations, d_{mi} is the Euclidian distance between the target and neighboring station i , and $q_{j(i)}$ is the observed value at station i . k is a coefficient and its value varies between 1 and 6, but the most commonly suggested value is 2 (Teegavarapu and Chandramouli, 2005). The negative sign of k implies that stations closer to the target stations are more important than those farther away (Vieux, 2004). The Euclidian distance between the target and neighboring stations is calculated using Eq. 2 (Barrios et al., 2018).

$$d_{m(i)} = \frac{\sqrt{(X_i - X_m)^2 + (Y_i - Y_m)^2}}{1000} \quad 2$$

Where X_i and Y_i are the projected coordinates of the neighboring stations, and X_m and Y_m are the projected coordinates of the target station.

b. Modified Inverse Distance Weighting (MIDW_{E&D}) based on Elevation

Elevation is one of the topographic factors that significantly affects the spatiotemporal distribution of precipitation and other climate variables (Golkhlatmi et al., 2012). As long as the elevation difference has an effect, the conventional inverse distance weighted method is modified by the inclusion of the elevation difference between the target and neighboring stations and missing values of the target station calculated using Eq. 3 (Barrios et al., 2018).

$$P_{mi} = \frac{\sum_{i=1}^n h_{mi}^{-a} * d_{mi}^{-k} * q_{j(i)}}{\sum_{i=1}^n h_{mi}^{-a} * d_{mi}^{-k}} \quad 3$$

Where h_{mi} is the elevation difference between the target and the neighboring station, and the exponent "a" is a power parameter and its value ranges from 1 to 3, with the most commonly used value being 1 (Barrios et al., 2018).

c. Modified Inverse Distance Weighted (MIDWM_{D&C}) based on Correlation coefficient

For orographic and complex climate regions, the normal inverse distance weighted method is modified based on spatial distance and correlation coefficient between the target and the neighboring station (Romero et al., 1998). The missed value of the target station is estimated from the neighboring station by Eq. 4.

$$P_{mi} = \frac{\sum_{i=1}^n \alpha_{j(i)} * q_{j(i)}}{\sum_{i=1}^n \alpha_{j(i)}} \quad 4$$

$\alpha_{j(i)}$ is the weighting factor between the target station and the neighboring stations. The weighting factor is calculated by using the Euclidian distance and Pearson correlation target and neighboring stations by Eq. 5.

$$\alpha_{j(i)} = \frac{R_{j(i)}^2}{d_{j(i)}^2} \quad 5$$

Where, $R_{j(i)}^2$ is the correlation coefficient between the target station and the neighboring stations.

d. Coefficient of Correlation weighting method (CCWM)

In this version of the inverse distance weighting method, the weighting factors are substituted by the correlation coefficient (Teegavarapu and Chandramouli 2005; Teegavarapu 2009), and the missing value of the target station is given by Eq. 6.

$$P_{mi} = \frac{\sum_{i=1}^n R_{j(i)} * q_{j(i)}}{\sum_{i=1}^n R_{j(i)}} \quad 6$$

Where $R_{j(i)}$ is the coefficient of correlation, which is the ratio of covariance between the target and neighboring stations to the product of the standard deviation of the datasets. Its values are derived from available historical data.

2.4.2. Multiple Linear Regression (MLR)

Multiple linear regressions (MLR) are a statistical method used to estimate the relationship between one dependent and two or more independent variables. It is used to identify the best weighted combination of independent variables to predict the dependent variable (Sattari et al., 2017). Eischeid et al., (1995) emphasized the benefits of the multiple linear regression method for interpolating missed data using Eq. 7.

$$P_{mi} = a_{j(o)} + \sum_{i=1}^n a_{j(i)} q_{j(i)} \quad 7$$

Where $a_{j(i)}$ is the regression coefficient, and $a_{j(o)}$ is the intercept.

2.4.3. Multivariate Imputation by Chained Equation (MICE)

Multivariate imputation by chained equations is known as sequential regression imputation, which estimates several missing values systematically and generates distinct sets of complete datasets. In this method, the incomplete dataset can be copied several times and the missing values are imputed to each copied dataset differently. The imputed missed values are randomly estimated for each copied dataset and combined into the average value of the dataset (Ibrahim et al., 2005). The R package of Bayesian based MICE functions is available to compute missing values of the target station from the values of the neighboring stations. The default setting was used in the MICE function to generate

different imputed datasets using the predictive mean matching method (pmm) and five (m=5) number of imputations. Finally, the imputed values were averaged to represent the missed value of the target station.

2.5. Accuracy Assessment Methods

There are several model accuracy assessment metrics described in the literature (Moriassi et al., 2007). Root mean square error (RMSE), Nash-Sutcliffe (NSE), and percent of bias (PBIAS) are commonly used to assess the performance and predictive capability of missing estimation methods (Moriassi et al., 2007; Barrios et al., 2018). RMSE can measure the error between the observed and predictive values and give greater weight to any extreme outliers present in the prediction results (Plouffe et al., 2015). The optimal value varies between zeros, which means no residual variation and perfect model simulation, and a greater positive value (Moriassi et al., 2007) and calculated by Eq. 8.

$$RMSE = \left(\frac{(\sum_{i=1}^n (Y_{oi} - Y_{si})^2)}{(\sum_{i=1}^n (Y_{oi} - Y_{mi})^2)} \right)^{1/2} \quad 8$$

According to Moriassi et al., (2007) and Barrios et al., (2018), "Nash-Sutcliffe efficiency is a normalized statistic that determines the relative magnitude of the residual variance (noise) compared to the measured data variance (information)". It shows the degree of observed versus simulated aligned on the plot of the 1:1 line (Nash and Sutcliffe, 1970) and calculated by Eq. 9.

$$NSE = 1 - \left(\frac{(\sum_{i=1}^n (Y_o - Y_s)^2)}{(\sum_{i=1}^n (Y_o - Y_m)^2)} \right) \quad 9$$

Where Y_{oi} is the i^{th} observed value, Y_{si} is the i^{th} simulated value for Y_m is the mean of observed data, and n is the total number of observations. The NSE ranges between $-\infty$ and 1.0, with $NSE = 1$ being the ideal value and values between 0 and 1 being the range for acceptable levels of performance, while values <0.0 indicate unsatisfactory performance and the observed value is better predictor than the simulated (Moriassi et al., 2007).

Percent of bias (PBIAS) measures the average difference between the simulated and observed counterparts (Moriassi et al., 2007; Barrios et al., 2018) and is calculated by Eq. 10.

$$PBIAS = 100 * \left(\frac{\sum_{i=1}^n (Y_{oi} - Y_{si})}{\sum_{i=1}^n (Y_{oi})} \right) \quad 10$$

The optimal values of PBIAS vary between zero for perfect model simulation and a positive or negative value that shows model underestimation or over estimation of bias, respectively (Moriassi et al., 2007).

2.6. Multicriteria Decision Method (MCDM) of Compromise programming

There are several decision-making methods for different problems (Sabaei et al., 2015; Mardani et al., 2015; Majmder, 2015; Raju & Kumar, 2018). The multicriterion decision method of Compromise programming (CP) is used to measure the minimum distance between the ideal value and performance indicators to identify and rank the missed imputation by Eq. 11 (Raju et al., 2016).

$$L_{p(a)} = \left[\sum_{j=1}^J w_j^p (f_j^* - f_{j(a)})^p \right]^{\frac{1}{p}} \quad 11$$

Where indicators $j=1,2,\dots,J$, $L_{p(a)} = L_p$ metric for imputation method a for the chosen value of parameter p , $f_{j(a)} =$ Normalized value of indicator j , $w_j =$ weight of performance indicator j got from the entropy method, $p =$ parameter (1 for linear, 2 for Euclidean distance measure) and for this study we adopted the p value of 2. Based on the minimum value of the L_p metrics, the imputation methods were ranked accordingly and the best method was proposed for each station. To decide independently of the views of the decision maker, normalizing and weighting of the performance indicators is required. The Entropy method is used to normalize and estimate the weight of various criteria from the given payoff matrix (Pomerol and Romero, 2000; Raju & Kumar, 2014; Zhu et al., 2020). First, the performance indexes are standardized and the payoff matrix (P_{ij}) is calculated using Eq. 12 (Zhu et al., 2020).

$$P_{ij} = \frac{P_{ij}}{\sum P_{ij}} \quad 12$$

For a given normalized payoff matrix p_{ij} , an entropy E_i is calculated using Eq. 13 for a set of alternative criterion j .

$$E_j = \frac{1}{\ln(N)} \sum_{i=1}^N p_{ij} \ln(p_{ij}) \quad \text{for } j = 1, \dots, J \quad 13$$

Where N is the number of imputation techniques and j is the number of indicators. Degree of diversification of the information provided by the outcomes of criterion j calculated by Eq. 14.

$$D_j = 1 - E_j \quad \text{for } j = 1, \dots, J \quad 14$$

Then finally, the normalized weights of indicators calculated by Eq. 15.

$$w_j = \frac{D_j}{\sum_{j=1}^J D_j} \quad 15$$

2.7. Data Quality Check

2.7.1. Homogeneity test

In order to conduct reliable studies on climate variability, good quality and long-term datasets are required. Actually, many studies have confirmed that climate change analyses are not possible without a clear understanding of the homogeneity of data. There is an assumption that the climate record is considered homogeneous when its variations are caused only by changes in weather and climate (Caloiero et al., 2020; Kocsis et al., 2020; Patakamuri et al., 2020). However, there are non-climatic factors that make the magnitude of climate signals larger than the actual (Caloiero et al., 2020).

The following are the four test techniques that were chosen to assess the time series departure from homogeneity: The Standard Normal Homogeneity Test (SNHT), which is sensitive to detecting the breaks near the beginning and end of the data (Alexandersson, 1986), Buishand's Range Test (BRT) (Buishand, 1982), and the Pettitt Test (Pettitt, 1979), are sensitive to locating the breaks in the middle of the series, and the Von Neumann Range Test (VNRT) don't located the location of the break (Von Neumann, 1941). But, if there is a break in the data, the test statistics less than two and if not, the test statistics equal to two. Generally, the first three tests are able to locating the year of break that is likely to occur. The Pettitt test, unlike the SNHT and the Buishand's range test, does not assume that X_i values are regularly distributed. Since the Pettitt test is based on the rankings of the elements of a series rather than on the values themselves, such an assumption is not required. All tests are executed under the null hypothesis that annual values X_i of the testing variable X are independent and identically distributed. The alternative (H_a) hypothesis for NSHT, BRT, and PTT is a step-wise shift in the mean of the data. However, the alternative hypothesis for VNRT assumes that the time series data is not randomly distributed. All these were conducted using XLSTAT 2020. Then finally, the test results have been summarized by Wijngaard et al., (2003) as: useful (when the test has rejected none or one null hypothesis out of four tests), doubtful (when the test has rejected two null hypotheses out of four tests) and suspect (when the test has rejected three or all null hypotheses out of four tests).

2.7.2. Trend analysis

The Mann-Kendall Trend (MK) test is a non-parametric test which is used to determine the presence or absence of monotonic trends in time series data of a candidate station (Kocsis et al., 2020). The null hypothesis (H_0) of MK is that there is no trend, and the alternative hypothesis (H_a) is that the time series of a candidate station follows a monotonic trend over time. The Mann-Kendall test statistic is calculated by (Eq. 16).

$$S = \sum_{i=1}^{n-1} * \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad 16$$

Where X_i and X_j are the sequential data in the series and n is the size of the data series.

Where $j > i$ and $i = 1, 2, 3, \dots, n-1$ $k = 2, 3, 4, \dots, n$, and n is the number of data $\text{sign}(X_j - X_i)$ is calculated by (Eq. 17).

$$sign(X_j - X_i) = \begin{cases} +1 & \text{if } (X_j - X_i) > 0 \\ 0 & \text{if } (X_j - X_i) = 0 \\ -1 & \text{if } (X_j - X_i) < 0 \end{cases} \quad 17$$

The variance S is calculated by (Eq. 18).

$$var(S) = \frac{S(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5)}{18} \quad 18$$

Where

q is the number of tied groups in the dataset,

t_p is the number of data in the pth tied group,

n is the total number of data in the time series.

A positive value of S indicates that an increasing and negative value of S is decreasing trend of time series data of the candidate station.

The standardized Mann-Kendall test statistics is calculated by (Eq. 19).

$$Z = \begin{cases} \frac{S-1}{\sqrt{var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{var(S)}} & \text{if } S < 0 \end{cases} \quad 19$$

3. Results and Discussion

3.1. Comparison of Missing Estimation Method's

The ability of each missing estimation technique was evaluated using the statistical metrics of RSR, NSE, and PBIAS. Table 2 and Table 3 show the performances of each missing method at 20- and 40-kilometer radius of influence and different levels of missing percentage. The MLR and MICE methods gave the best results for all statistical performance measures over all stations. Alternatively, the Modified inverse distance method (IDWM_{E&D3}) presented lower values of RMSE, PBIAS and higher NSE.

The CCWM, normal IDWM and modified versions of IDWM such as IDWM_{C&D}, IDWM_{E&D1} and IDWM_{E&D2} presented higher biases in RMSE and PBIAS and lower NSE. As long as the percent of missing increases, the model performance tends to decrease for both radiuses of influence (a summary of the results is in Appendix A). Similar evaluation was observed in (Radi et al., 2015; El Kasri et al., 2018) to represent different cases of missing percentages of rainfall data and evaluate the performance of the missing estimation methods.

Table 2 Performance evaluation of missing estimation techniques at 40-kilometer radius of influence for Arata Stations (values in bold indicated the lowest value comparing to the others)

Percent of Missed and Evaluation Metrics															
METHODS	5%			10%			15%			20%			25%		
	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS
	Arata Station														
IDWM	6.75	-1.39	44.42	7.97	-2.33	69.91	13.69	-8.83	164.64	14.59	-10.17	190.46	16.68	-13.61	239.20
IDWM _{C&D}	7.14	-1.68	31.99	8.40	-2.70	42.44	14.44	-9.94	63.47	15.47	-11.56	66.88	17.69	-15.42	71.68
CCWM	7.03	-1.59	46.68	8.44	-2.74	75.62	14.35	-9.81	174.44	15.46	-11.54	203.68	17.48	-15.04	252.95
IDWM _{E&D1}	3.37	0.40	21.18	4.17	0.09	35.18	7.09	-1.64	82.81	6.92	-1.51	88.51	8.03	-2.38	114.92
IDWM _{E&D2}	1.66	0.85	8.44	2.44	0.69	16.23	3.85	0.22	38.10	2.92	0.55	32.61	3.91	0.20	46.95
IDWM _{E&D3}	1.33	0.91	5.34	2.16	0.75	11.62	3.23	0.45	27.23	2.11	0.77	18.97	3.27	0.44	30.40
MLR	0.48	0.99	2.60	0.66	0.98	-0.02	0.95	0.95	-0.97	0.94	0.95	1.81	0.80	0.97	3.76
MICE	0.62	0.98	1.98	0.72	0.97	0.84	1.45	0.89	3.08	1.31	0.91	-1.53	1.24	0.92	2.35

Table 3 Performance evaluation of missing estimation techniques at a 20-kilometer radius of influence for Arata stations (values in bold indicate the lowest value compared to the others)

Percent of Missed and Evaluation Metrics															
METHODS	5%			10%			15%			20%			25%		
	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS	RMSE	NSE	PBIAS
	Arata Station														
IDWM	6.64	-1.31	43.60	7.83	-2.22	68.53	13.46	-8.51	161.68	14.31	-9.75	186.67	16.38	-13.09	234.74
IDWM _{C&D}	7.05	-1.61	31.68	8.29	-2.60	42.06	14.25	-9.66	63.15	15.25	-11.20	66.53	17.45	-14.98	71.39
CCWM	7.22	-1.73	47.53	8.47	-2.77	74.28	14.58	-10.15	175.29	15.63	-11.82	203.89	17.89	-15.79	255.61
IDWM _{E&D1}	3.24	0.45	20.19	4.02	0.15	33.59	6.82	-1.44	79.27	6.59	-1.28	84.01	7.68	-2.09	109.59
IDWM _{E&D2}	1.62	0.86	8.07	2.41	0.70	15.63	3.77	0.26	36.77	2.81	0.59	30.92	3.82	0.24	44.95
IDWM _{E&D3}	1.32	0.91	5.24	2.16	0.76	11.46	3.21	0.46	26.89	2.09	0.77	18.53	3.26	0.44	29.89
MLR	0.43	0.99	2.25	0.73	0.97	-0.59	1.07	0.94	-1.60	0.88	0.96	0.54	0.91	0.96	2.24
MICE	0.55	0.98	2.05	0.94	0.95	-1.00	1.23	0.92	-2.08	1.25	0.92	-0.94	1.31	0.91	3.68

3.2. Impacts of Elevation difference, radius of influence and Exponent value “a”

The normal inverse distance weighted method (IDWM) is modified by the inclusion of the elevation difference between the target and neighboring stations and the exponent of value of "a", for distances which range from one to three. As the result is shown in Table 4, the inclusion of an elevation difference and gradually increasing the exponent values for distance, significantly lowered the error in terms of RMSE, PBIAS, and increased the NSE of the inverse distance weighted method. The inclusion of an elevation difference between the stations significantly increased the performance of normal IDWM. For example, the comparison between IDWM and the modified version IDWME&D1 has shown that the RMSE is reduced from 1.52 (IDWM) to 0.74 (IDWME&D1), PBIAS from 43.6 (IDWM) to 20.19 (IDWME&D1) and the NSE is increased from -1.31 (IDWM) to 0.45 (IDWME&D1) at 5% of missing percentage and a 20-kilo meter radius of influence for Arata station. This is also true for other stations that are considered in this study (Appendix B). A similar study was done on the impact of elevation on the performance of the missing estimation method (Barrios et al., 2018).

The other value added for IDWM is, the value of the exponent for the Euclidian distance between the target and neighboring stations. Gradually increasing the exponent value from 1 to 3 increases the performance of IDWM. For exponent values of $a=1$ and $a=3$, the performance of the models was significantly improved (see Table 4 as an example for Arata station and Appendix for all stations). Generally, accounting for the elevation difference and increasing the exponent value " $a=3$ " can increase the performance of the inverse distance weighted method by lowering the error of RSR and PBIAS and increasing the precision (NSE). However, as the assessment results have been shown in Table 4 and Appendix, both radiuses of influence have no significant difference on the IDWM and its version.

Table 4 Impact of the exponent value of "a" on the spatial distance of the Inverse Distance weighted method for Arata station

Performance evaluation based on Root Mean Square Error (RMSE)								
Missing percentage	IDWM		IDWM _{E&D} ^a for a=1		IDWM _{E&D} ^a for a=2		IDWM _{E&D} ^a for a=3	
	Radius of influence							
	20 Km	40Km	20 Km	40Km	20 km	40Km	20 Km	40Km
5	1.52	1.55	0.74	0.77	0.37	0.38	0.30	0.30
10	1.79	1.83	0.92	0.96	0.55	0.56	0.49	0.50
15	3.08	3.14	1.56	1.62	0.86	0.88	0.74	0.74
20	3.28	3.34	1.51	1.59	0.64	0.67	0.48	0.48
25	3.75	42.92	1.76	1.84	0.87	0.90	0.75	0.75
Nash Sutcliffe efficiency (NSE)								
5	-1.31	-1.39	0.45	0.40		0.85	0.91	0.91
10	-2.22	-2.33	0.15	0.09	0.70	0.69	0.76	0.75
15	-8.51	-8.83	-1.44	-1.64	0.26	0.22	0.46	0.45
20	-9.75	-10.17	-1.28	-1.51	0.59	0.55	0.77	0.77
25	-13.09	-13.61	-2.09	-2.38	0.24	0.20	0.44	0.44
Percent of Bias (PBIAS)								
5	43.60	44.42	20.19	21.18	8.07	8.44	5.24	5.34
10	68.53	69.91	33.59	35.18	15.63	16.23	11.46	11.62
15	161.68	164.64	79.27	82.81	36.77	38.10	26.89	27.23
20	186.67	190.46	84.01	88.51	30.92	32.61	18.53	18.97
25	234.74	239.20	109.59	114.92	44.95	46.95	29.89	30.40

3.3. Impact of Missing percentage

As shown in Table 3 and Table 4 for Arata station and in the Appendix for the rest of the stations, the performance of the missing estimation method has decreased as the missing percentage has increased over all stations. The MLR, MICE, and IDWM_{E&D3} performed very well for most stations at all levels of missing percentages compared to other missing estimation techniques. For example, the IDWM method presented the poorest performance for Arata station, which resulted in 16.68 RMSE, 239 PBIAS and -13 NSE. Similarly, for the rest stations, as long as the missing

percentages are increasing, the model performance tends to decrease to estimate accurately the missed values of the target station (Appendix). This is agreed with the studies by Program (2001) and El Kasri *et al.* (2018). The performance of the missing estimation methods was reduced as the missing values increased. Other studies have shown that the power and precision of statistical research methods can be affected as the missing percentages increase (Pigott, 201; Piazza, 2011; Houari *et al.*, 2014; Schmitt *et al.*, 2015; Gao *et al.*, 2018). This may result in uncertain flood estimates and imperfect flood management decisions and intervention mechanisms (Blackburn *et al.*, 2018).

3.4. Identifying of the Best Method

To identify the best infilling technique, the multicriteria decision with compromise programming (CP) method was used. Here the result for Arata station has been shown for demonstration. Among the three performance indicators, PBIAS (0.498) has a significant weight on the ranking of the missing estimation methods, followed by RMSE (0.421) and NS_E (0.08). Equations 11-15 were coded in Excel 2016 and the entropy, degree of diversification, normalized weight and payoff matrix (P_{ij}), L_p metrics were calculated subsequently. Then, based on the minimum values of L_p metrics, each missing estimation method was ranked. As the results in Table 5 and 6 showed for Arata station, the MLR, MICE, and IDWME&D3 were ranked as 1st, 2nd, and 3rd best methods respectively. The normal IDWM and CCWM are ranked 7th and 8th. Similarly, for the rest stations, the results of the best of three methods are summarized in Appendix A. A similar study has been conducted by Radi *et al.*, (2015) on the performance of missing estimation methods, and the analysis of variance (anova) was used to identify the best method. Raju *et al.*, (2016), applied the compromise programming method to select the best global climate models for India.

Table 5 Multi-criteria decision method for Arata Station compromise programming within a 40-kilometer radius of influence

Compromise programming result										
	5%		10%		15%		20%		25%	
Methods	Lp	Rank	Lp	Rank	Lp	Rank	Lp	Rank	Lp	Rank
IDWM	7.837	7	23.997	7	150.309	7	287.062	7	388.279	7
IDWMC&D	4.034	6	9.056	6	26.040	5	41.189	5	45.846	5
CCWM	9.382	8	28.187	8	175.437	8	340.488	8	456.425	8
IDWME&D1	1.522	5	5.830	5	42.451	6	67.395	6	103.858	6
IDWME&D2	0.186	4	1.345	4	15.869	4	18.820	4	38.646	4
IDWME&D3	0.065	3	0.783	3	12.362	3	13.843	3	31.082	3
MLR	0.007	1	0.152	1	8.449	1	11.090	1	25.211	1
MICE	0.009	2	0.155	2	8.463	2	11.122	2	25.280	2

Table 6 Multi-criteria decision method for Arata Station compromise programming within a 20-kilometer radius of influence

Compromise programming result										
	5%		10%		15%		20%		25%	
Methods	Lp	Rank	Lp	Rank	Lp	Rank	Lp	Rank	Lp	Rank
IDWM	5.998	7	20.759	7	115.223	7	207.711	7	301.108	7
IDWMC&D	3.039	6	7.701	6	17.467	5	25.707	5	27.658	5
CCWM	6.650	8	24.281	8	129.482	8	237.888	8	329.490	8
IDWME&D1	1.245	5	5.267	5	28.727	6	43.936	6	66.303	6
IDWME&D2	0.150	4	1.130	4	5.927	4	5.623	4	10.479	4
IDWME&D3	0.046	3	0.585	3	2.974	3	1.777	3	4.197	3
MLR	0.001	1	0.001	1	0.003	1	0.001	1	0.015	1
MICE	0.002	2	0.005	2	0.027	2	0.005	2	0.022	2

3.5. Quality Assessment for Precipitation Data

3.5.1. Statistical Characteristics of Precipitation

The long-term mean and maximum monthly observed rainfall in the Katar subbasin varied from 58.24 mm to 87 mm and 230.6 mm to 581 mm, and for the Meki subbasin varied from 60 mm to 85.63 mm and 292.3 mm to 489.3 mm respectively. The standard deviation (SD) varied from 57 to 94.33 and the coefficient of variation (CV) varied from 84.69% to 108.42% for the Katar subbasin. Similarly, for the Meki subbasin, SD and CV varied from 62 to 86.23 and 97.32% to 119.01%, respectively. This presented that there was a great temporal variability of monthly rainfall during 1997-2017 in both subbasins. The highest variations were observed at Adami-tulu and Iteya stations (Table 7).

Table 7 Monthly rainfall statistics for 16 stations from 1983 to 2017 after missing data have been filled

Stations	Minimum (mm)	Maximum(mm)	Average(mm)	SD	CV (%)
Adami-tulu	0.00	435.60	68.02	80.94	119.01
Alem-tena	0.00	392.50	70.26	78.68	111.99
Bui	0.00	353.90	81.64	82.44	100.99
Butajera	0.00	438.00	85.63	86.23	100.71
Ejersa-lele	0.00	348.30	72.02	79.01	109.70
Koshe	0.00	292.30	63.74	62.03	97.32
Meki	0.00	489.30	61.43	65.23	106.19
Ziway	0.00	292.30	59.99	62.26	103.77
Arata	0.00	230.60	63.21	57.03	90.22
Asella	0.00	318.20	88.23	74.72	84.69
Dagaga	0.00	269.70	85.07	73.72	86.66
Iteya	0.00	581.00	87.00	94.33	108.42
Katar-genet	0.00	368.90	63.90	65.11	101.90
Kulumsa	0.00	272.10	65.49	57.41	87.66
Ogolcho	0.00	322.90	58.24	57.74	99.15
Sagure	0.00	406.00	62.59	58.71	93.80

SD is standard deviation and CV is coefficient of variation

3.5.2. Homogeneity Tests

An absolute homogeneity test was applied using SNHT, Buishand's, Pettit, and Von Neumann tests to check whether the long-term climatological data belongs to the same population with no temporal variation. If any change in the time series was only attributed to a natural occurrence. Based on the hypothesis test for homogeneity, the empirical calculated p-value is at 95% of the significant level summarized in Table 8 for the Katar and Meki watersheds. Based on the test results, seven stations were homogeneous in the Katar watershed based on the above four tests. However, one (Iteya) station was nonhomogeneous only by the Buishand's test. Similarly, for stations in the Meki watershed, the homogeneity tests were conducted. Except for Butajera station, all stations were homogeneous based on the test results of SNHT, Buishand's, Pettit and Von Neumann tests at 95% of significant level (Table 9). An extensive examination was carried out on the meta-data and archive information concerning the history of the measurements for both stations. No apparent explanation could be found for the causes of the changes. Based on [Wijngaard et al., \(2003\)](#) classification for homogeneity, 15 stations were classified as useful and only Butajera stations were suspected. [Schönwiese and Rapp \(1997\)](#) and [Patakamuri et al. \(2020\)](#) found similar classification.

Table 8 Calculated P-values for homogeneity testes at alpha (α) = 0.05 for Katar sub basin and decision made based on (Wijngaard et al., 2003)

No	Station's	Pettit	SNHT	Buishand's	Von Neumann	α -value	Decision
1	Arata	0.463	0.720	0.861	< 0.0001	0.05	Useful
2	Asella	0.203	0.647	0.949	< 0.0001	0.05	Useful
3	Dagaga	0.759	0.653	0.668	< 0.0001	0.05	Useful
4	Iteya	0.148	0.092	0.017	< 0.0001	0.05	Useful
5	Katar-genet	0.489	0.788	0.381	< 0.0001	0.05	Useful
6	Kulumsa	0.146	0.651	0.991	< 0.0001	0.05	Useful
7	Ogolcho	0.635	0.782	0.897	< 0.0001	0.05	Useful
8	Sagure	0.673	0.113	0.712	< 0.0001	0.05	Useful

Table 9 Calculated P-values for homogeneity tested methods at alpha (α) = 0.05 for Meki sub basin and decision made based on (Wijngaard et al., 2003)

No	Station's	Pettit	SNHT	Buishand's	Von Neumann	α -value	Decision
1	Adami-tulu	0.130	0.094	0.136	<0.0001	0.05	Useful
2	Alem-tena	0.184	0.895	0.976	<0.0001	0.05	Useful
3	Bui	0.345	0.520	0.235	<0.0001	0.05	Useful
4	Butajera	0.000	0.001	0.001	<0.0001	0.05	Suspect
5	Ejerse-lele	0.444	0.879	0.941	<0.0001	0.05	Useful
6	Koshe	0.738	0.847	0.496	<0.0001	0.05	Useful
7	Meki	0.174	0.997	0.992	<0.0001	0.05	Useful
8	Ziway	0.927	0.906	0.596	<0.0001	0.05	Useful

3.6. Trend Analysis

Each chosen station has 17 series (12 months, four seasons, and an annual series), for a total of 255 time series data from 15 meteorological stations. Monthly, seasonal and annual monotonic upward or downward trends in rainfall were assessed for each station independently using the Mann-Kendall trend test, and the magnitude of the trend was estimated using the Sone's slope for the time series data of 1997-2017.

3.6.1. Monthly trend analysis

As shown in Table 10, the rainfall had a combination of increasing and decreasing trends at all stations. There was a statistically significant decreasing trend for Dagag station for the month of January with a magnitude of 1.52mm/month. For Iteya station, the rainfall amount shows a decreasing trend for the months of June, August, and October with a magnitude of 2.15, 5.05, and 3.06 mm, respectively. At Kulumsa station, there was a significant increasing trend in rainfall for the months of May and September, with a magnitude of 4.38 and 3.13 mm, respectively. Similarly, Bui station showed a statistically significant decreasing trend with a magnitude of 0.83 mm. At Butajera station for the months of March, April, August and October, there was a significant decreasing trend with a magnitude of 6.82, 4.54, 5.7 and 4.07 mm, respectively. For Ejerese-lele station, there was a significant increase in monthly rainfall during September with a magnitude of 2.63 mm. However, the rest station has shown no statistically significant increasing or decreasing trends in monthly rainfall.

3.6.2. Seasonal and Annual Trend Analysis

Seasonal trend analysis was performed and considered the sum of three consecutive months, such as for spring (March, April, and May), summer (June, July, and August), and autumn (September, October, and November) and for winter (December, January, and February). Annual trend analysis was performed for a time series of rainfall data from 1983-2017. As a trend, analysis results are stated in Table 11, both increasing (positive) and decreasing (negative) in the seasonal and annual rainfall. A decreasing trend in seasonal rainfall was observed for Iteya station during summer (10.65 mm) and autumn (11.48 mm). Dagaga station had a statistically significant decrease in seasonal rainfall during autumn (6.41 mm). Similarly, Butajera showed a significant decreasing trend during spring (14.75 mm) and autumn (9.9 mm). The annual based trend analysis resulted in increasing and decreasing trends in the annual rainfall series. Iteya and Butajera stations have shown statistically significant decreasing trends with a magnitude of 34.84 mm/year and 40.36 mm/year respectively.

113 **Table 10** Monthly based trend analysis for meteorological stations in Katar and Meki watersheds at alpha ($\alpha = 0.05$)

Stations	Tests	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Arata	Z-Value	-0.65	-0.88	-0.57	-0.97	0.63	-0.33	1.09	0.75	-0.09	-1.27	-1.32	-0.14
	Sen's slope	0.00	-0.28	-0.85	-1.49	1.05	-0.66	2.51	1.35	-0.05	-0.84	-0.39	0.00
Asella	Z-Value	-0.65	-0.27	-0.09	-1.00	1.60	-1.66	0.03	0.27	1.66	-1.24	-0.24	-1.28
	slope	0.00	-0.36	-0.38	-2.62	4.89	-2.35	-0.03	0.71	2.32	-2.82	-0.11	-0.03
Dagaga	Z-Value	-2.52*	0.76	-1.66	-0.51	1.45	-0.75	-0.15	-0.45	-0.88	-1.81	-0.45	-1.34
	Sen's slope	-1.52	0.17	-2.99	-1.09	2.92	-1.58	-0.42	-0.67	-1.32	-2.99	-0.15	-0.19
Iteya	Z-Value	-2.30*	0.09	-1.57	-1.78	1.36	-1.84	-1.12	-1.96*	-2.08	-1.42*	0.00	-0.38
	Sen's slope	-2.15	0.00	-2.77	-2.56	1.51	-2.65	-2.37	-5.03	-5.88	-3.06	0.00	0.00
Ketar-genet	Z-Value	-1.22	1.00	0.42	-0.15	-0.12	-0.51	0.18	1.72	1.12	-0.73	0.60	0.71
	Sen's slope	-0.11	0.18	0.59	-0.17	-0.28	-1.02	0.26	4.57	1.49	-0.87	0.00	0.00
Kulumsa	Z-Value	-1.48	0.36	-0.73	-0.51	2.33*	-1.48	0.82	-0.91	2.57*	-1.15	0.03	-0.43
	Sen's slope	-0.46	0.07	-1.31	-1.04	4.38	-2.02	1.97	-1.50	3.13	-2.29	0.00	0.00
Ogolcho	Z-Value	-1.28	0.34	-0.60	-0.15	1.36	-0.45	-0.39	0.15	0.63	-0.91	0.16	-0.29
	Sen's slope	0.00	0.00	-1.21	-0.16	2.00	-0.42	-0.60	0.22	0.88	-0.94	0.00	0.00
Sagure	Z-Value	-1.55	0.57	-2.00	-0.39	-0.94	-1.42	-1.18	0.70	1.91	0.73	1.54	-2.22*
	Sen's slope	-0.37	0.17	-2.70	-0.49	-1.25	-2.24	-1.03	0.46	1.24	0.45	0.31	-0.53
Adami-tulu	Z-Value	-1.11	0.66	-0.36	-1.21	0.79	0.27	1.24	-0.45	-0.12	-0.82	1.26	-0.61
	Sen's slope	0.00	0.00	-0.26	-2.69	1.70	0.70	2.87	-1.54	-0.37	-1.41	0.00	0.00
Alem-tena	Z-Value	-1.42	-0.45	-0.30	-1.90	2.87*	0.39	0.45	0.03	1.30	-1.65	0.67	-0.10
	slope	-0.10	0.00	-0.62	-4.27	6.91*	0.68	2.11	0.09	2.86	-1.37	0.00	0.00
Bui	Z-Value	-2.18*	-0.47	-0.21	-0.12	0.88	-1.18	-1.30	0.06	0.51	-1.61	-0.34	-1.01
	Sen's slope	-0.83	0.00	-0.56	-0.21	1.70	-2.07	-3.25	0.16	0.88	-2.24	0.00	0.00
Butajera	Z-Value	-0.61	0.00	-2.78*	-2.02*	-0.82	-1.90	-0.39	-2.02*	-1.72	-3.14*	-0.68	-0.10
	Sen's slope	-0.29	0.03	-6.82	-4.54	-1.58	-5.88	-1.12	-5.70	-4.23	-4.07	-0.04	0.00
Ejerse-lele	Z-Value	-2.03*	-0.03	-0.27	-0.88	1.81	-0.45	-0.76	-0.67	2.63*	-1.28	-0.46	0.45
	Sen's slope	-0.48	0.00	-0.62	-1.73	2.70	-0.56	-2.06	-1.21	3.34	-0.62	0.00	0.00
Koshe	Z-Value	0.10	-0.73	-1.18	0.70	-1.36	0.15	-1.24	-0.03	-0.94	1.38	1.24	-0.63
	Sen's slope	0.00	-1.17	-1.51	2.21	-2.97	0.31	-2.87	-0.26	-1.72	0.00	0.00	-7.26
Meki	Z-Value	-1.05	-0.90	-0.57	-1.54	1.72	0.48	0.27	-1.30	1.42	-0.66	0.98	0.64
	Sen's slope	0.00	-0.09	-0.84	-2.50	2.39	0.85	0.63	-3.24	1.54	0.00	0.00	0.00
Ziway	Z-Value	-0.77	0.25	-1.66	-1.18	1.15	-0.45	0.51	-0.63	-0.39	-0.70	0.94	0.83

114 *Represents significant at 95% confidence level with the corresponding critical value of 1.96

115 **Table 11** Seasonal and annual rainfall trend analysis for the Katar and Meki watersheds

	Annual		Spring		Summer		Autumn		Winter	
Stations	MK	SS	MK	SS	MK	SS	MK	SS	MK	SS
Arata	-0.69	-3.10	0.03	-0.12	1.06	2.97	-1.75	-4.93	-0.85	-0.75
Asella	-0.09	-0.61	0.15	1.11	0.03	0.01	-0.63	-2.69	-0.75	-1.61
Kulumsa	0.27	1.17	0.27	1.04	-0.69	-1.23	0.03	-0.14	-0.33	-0.37
Ogolcho	0.03	0.26	0.45	1.27	-0.15	-0.52	-0.09	-0.33	-0.52	-0.16
Sagure	-1.15	-6.09	-1.63	-4.14	-1.12	-2.43	1.72	2.43	-0.94	-0.81
Dagaga	-1.78	-10.45	-0.03	-0.23	-0.21	-0.97	-2.39*	-6.41	-1.48	-1.65
Katar-genet	0.33	2.41	-0.27	-0.79	0.57	4.31	0.03	0.16	0.48	0.12
Iteya	-2.81*	-34.84	-0.63	-2.22	-2.08*	-10.7	-3.05*	-11.5	-1.60	-2.57
Adami-tulu	0.21	3.81	-0.63	-1.57	0.03	-0.10	-0.82	-2.81	-0.21	-0.29
Alem-tena	1.06	4.50	0.88	2.91	0.33	1.62	0.69	1.11	-0.42	-0.28
Bui	-1.00	-9.84	0.94	3.84	-1.18	-7.25	-1.66	-2.85	-1.69	-2.43
Butajera	-2.20*	-40.4	-2.99*	-14.8	-0.94	-8.73	-3.05*	-9.90	-1.66	-4.07
Ejersse-lele	-0.45	-2.67	0.21	1.37	-0.33	-1.31	0.82	2.09	-1.13	-1.79
Koshe	-0.63	-7.26	-0.39	-1.07	-0.45	-2.49	-0.69	-1.79	-0.06	-0.34
Meki	0.21	2.37	-0.27	-0.57	0.03	0.45	0.09	0.31	-0.85	-0.82
Ziway	-0.51	-3.42	-0.94	-3.04	0.03	0.03	-0.45	-1.72	0.30	0.54

116 *Represents significant at 95% confidence level with the corresponding critical value of 1.96.

117 **4. Conclusion**

118 In this study, the performance of eight missing estimation methods has been evaluated using three statistical metrics:
119 RMSE, NSE, and PBIAS. Specifically, we purposely assigned missing (NA) for the CHRIPS dataset at 5%, 10%,
120 15%, 20%, and 25% and examined two radiuses of influence (20 and 40 kilo meter) between the target and neighboring
121 stations. The Multicriteria decision method (MCDM) of compromise programming (CP) was used to identify the best
122 missing imputation technique for each station. MLR and MICE methods were selected as the best approach for missing
123 infilling for the most stations. And an alternative, modified version of IDWM based on spatial distance and elevation
124 difference (IDWME&D3) preferred as the third option.

125 The ability of IDWM was significantly improved by the inclusion of the elevation difference and gradually increasing
126 exponent value for "a = 3" for the distance between the target and neighboring stations. The study results showed that
127 the performance of all missing estimation techniques was significantly decreased as the percentage of missing data
128 increased. A study for a homogeneity test for time series data has shown that, except for one station, the majority of
129 stations are homogeneous and they are useful. Monthly, seasonal, and annual trends have been observed in decreasing
130 Dagaga and Iteya and an increasing trend in Kulumsa stations of the Katar subbasin. In the same way, Bui and Butajera
131 have shown a significant decreasing trend in monthly rainfall and Ejersse-lele station has shown a significant increase
132 in monthly rainfall in the Meki subbasin. However, the rest stations have shown no significant increasing or decreasing
133 trends in rainfall.

134 **5. Statements & Declarations**

135 **Conflict of interest:** The authors declare that they have no competing interests regarding this article.

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141 Amare Bantider. All authors have read and approved the final manuscript.

142 **Availability of data:** All datasets, raw or preprocessed, are available upon request from the corresponding author.
143 However, permission is required for observed data collected from National Meteorology Agency of Ethiopia.

Declarations (ethics)

- **Consent to participation:** Not applicable' for that specific section
- **Consent to publish:** Not applicable' for that specific section

Ethical Approval: Hereby, I Mr. Sisay Kebede Balcha certainly assure that the manuscript entitled “Comparison and Selection Criterion of Missing Imputation Methods and Quality Assessment of Monthly Rainfall in the Central Refit Valley Lakes Basin of Ethiopia” the following is fulfilled:

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5. All sources used in this research paper are properly cited and those who supported this research financially, by provision of data properly and training were properly acknowledged.
6. We, authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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