Comparative analysis of interpolation methods for rainfall mapping in the Faria catchment, Palestine

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Received: (8/2/2021), Accepted: (28/12/2021)

Abstract:

The availability of rainfall data is essential for the prediction of extreme rainfall events, hydrological modeling, and the design of water resources systems. In Palestine, the limited available rain gauges and the available rainfall data are insufficient to precisely characterize the areal rainfall distribution over the entire area. Hence, it is essential to find proper methods to utilize the available rainfall data at the existing raingauges to predict rainfall values at certain locations where rainfall measurements are not available. This study aims at identifying the most suitable interpolation method that can be used to produce interpolated rainfall surfaces at the Faria catchment, Palestine. Faria catchment (320 km^2), located in the northeastern part of the West Bank, Palestine, is characterized by high temporal and spatial rainfall variations. Six, GIS-based, spatial interpolation methods have been tested by visual observation and cross-validation. These methods are: Inverse Distance Weighted, Spline completely Regularized, Spline with Tension, Ordinary Kriging, Universal Kriging, and Regression. Available seasonal rainfall data recorded at 16 locations for two rainy seasons; 2016/2017 and 2017/2018 were utilized. Results indicate that the Universal Kriging method has slightly a higher

correlation coefficient and lower mean relative error than the other methods for the two seasons that make the method the most optimal one for mapping rainfall distribution in the Faria catchment. Moreover, the spatial distribution of raingauges between the two seasons affects the performance of different interpolation methods in the catchment.

Keywords: Rainfall Distribution; Spatial Interpolation; Faria Catchment; Palestine.

Introduction

Reliable rainfall data is an essential input for hydrological modeling, extreme rainfall events (e.g. drought and flood) prediction, water resources quantity, and quality assessment (Keblouti, *et al*. 2012; Vicente-serrano, *et al*. 2014). In developing countries like Palestine, the limited available raingauges and available rainfall data are insufficient to precisely characterize the areal rainfall distribution over the entire area (Shadeed, 2008). Hence, it is essential to find proper methods to utilize the available rainfall data at existing raingauges to predict rainfall values at certain locations, where rainfall has not been measured.

Spatial interpolation is a commonly used method to produce a realistic surface (contours) between measurement points (Taylor *et al*. 2004). It can be used to predict rainfall values at certain points, given measured values at surrounding ones (Teegavarapu, *et al*. 2012). Despite the availability of several interpolation methods, it can be hard to judge which one best reproduces actual rainfall fields (Zhang, *et al*. 2016). The selection of one or the other depends on the aim of the study, as different aims can require different criteria for evaluation of the interpolation methods (Campling, *et al*. 2001). Also, it depends on the local characteristics of the study area (e.g. distribution of raingauges) (Renard & Comby, 2006).

Interpolation methods can be grouped into global, local (deterministic), and geostatistical methods. Global interpolation methods (e.g. multiple regression model) create dependence models between climatic (rainfall) data and other independent (geographic and topographic) variables (Vicente-serrano, *et al*. 2014). Thus, regression models have been able to predict the rainfall values at ungauged locations using the available values of the geographic and topographic variables (e.g. Tabios & Salas, 1985; Basist, *et al*. 1994; Daly, *et al*. 2002; Vicente-serrano, *et al*. 2014). A multiple regression model was developed to predict seasonal rainfall at unmeasured points in the Faria catchment. The rainfall prediction model was developed as a function of topography (ground surface elevations) and geography (x and y coordinates) of the existing measured points (Shadeed, 2008).

Local interpolation methods create surfaces from measured points based on either the similarity extent (e.g. Inverse Distance Weighted, IDW) or the smoothing degree (e.g. Spline) (Atkinson & Lloyd, 1998; Johnston, *et al*. 2001). IDW is the most often used interpolation method by GIS analysts. It predicts a value for any unmeasured points based on the measured values at the surrounding points weighted by an inverse function of the distance from the prediction point to the measured ones (Isaaks & Srivastava, 1989; Chang, 2010; Longley, *et al*. 2011, Ryu, *et al*. 2021). A spline is a form of interpolation function that employs a series of polynomials over adjacent intervals with continuous derivatives at the end-point of the intervals (Atkinson & Lloyd, 1998). It is also known as the basic minimum curvature interpolation as it depends on two main factors; the surface must pass exactly through the measured data points, and the interpolated surface must have minimum curvature (Naoum & Tsanis, 2004).

Geostatistical interpolation methods (e.g. kriging) utilize statistical properties of the measured values to predict values at unobserved locations (Teegavarapu, *et al*. 2012). In geostatistical methods, the spatial configuration of the sample points is being estimated based on the spatial interpolation among measured points (Borga & Vizzaccaro 1997; Johnston *et al*. 2001; Keblouti *et al*. 2012; Campling *et al*. 2001; Vicente-serrano *et al*. 2003). Kriging is not deterministic but utilizes the closeness weighting approach of IDW which gives high weight to the closest measured points in the prediction of values for unknown points (Nalder & Wein 1998).

This study aims at identifying the most suitable interpolation method which can be used to produce interpolated rainfall surfaces at the Faria catchment, Palestine. Six, GIS-based, spatial interpolation methods were compared and evaluated to identify the proper one for estimating seasonal rainfall values in the Faria catchment. These methods are: Inverse Distance Weighted (IDW), Spline completely Regularized (SR), Spline with Tension (ST), Ordinary Kriging (OK), Universal Kriging (UK), and Regression (R). Available rainfall data recorded at 16 measured points (raingauges) for two rainy seasons; 2016/2017 and 2017/2018 were utilized.

The specific novel of this research is the simplified use of GIS in the mapping of different interpolation methods for the first-ever time in Palestine. Therefore, the results of this research are of high value to provide the required spatial rainfall information for hydrological modeling, drought analysis, and water resources management in Palestine as one of the data-scarce regions.

Materials and Methods

Study Area

The Faria catchment is one of the major arteries draining into the Jordan River. Geographically, it is located in the northeastern part of the West Bank, Palestine with a total area of about 320 km^2 accounting for 6% of the total West Bank area (see **Figure 1**). Ground surface elevations range from 350 m below to 900 m above sea level. The climate in the Faria catchment is arid to semi-arid climate, characterized by mild rainy winters and moderately dry, hot summers. The winter rainy season usually extends from October to April. Most of the annual rainfall (about 80%) occurs in winter (Shadeed, 2013). Faria catchment has low measurement rainfall network density. Historically, rainfall in the catchment is being measured by standard raingauges at five different locations (Nablus, Talluza, Tammun, Tubas, Beit Dajan).

For most of the locations, annual rainfall records are available for more than 50 years. Besides, some historical rainfall data (1960-1989) are available from a station that was located in the lower part of the catchment (at AL-Jiftlik). Rainfall in the catchment is characterized by high temporal and spatial variation. Overall, mean annual rainfall varies from about 660 mm in the upper parts of Nablus to about 150 mm in the lower parts in the proximity of the Jordan River (Shadeed, 2013).

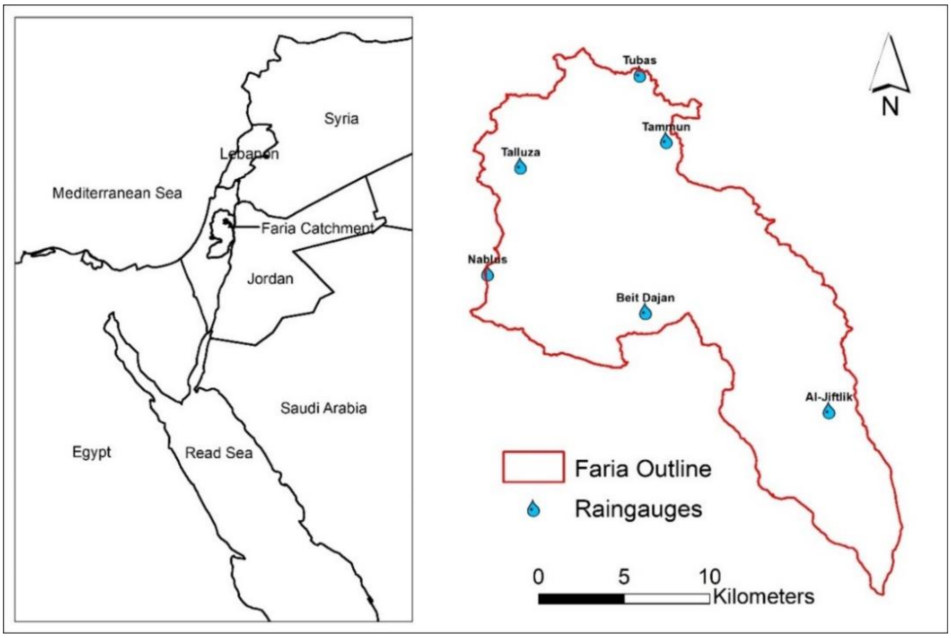


Figure (1): Regional location and historical raingauges of the Faria catchment.

Data Availability and Processing

In 2016, in the context of the project IMAP (Integrating Microwave Link Data for Analysis of Precipitation in Complex Terrain: Theoretical Aspects and Hydrometeorological Applications), 48 Tipping Bucket Raingauges (TBRs) were installed in 16 different locations (3 at each location) in the Faria catchment and for two rainy seasons; 2016-2017 and 2017-2018. As such, the TBRs were distributed to optimally capture the spatial rainfall extent over the entire catchment. Due to some reasons, the distribution (location) of the TBRs was slightly changed between 2016-2017 and 2017-2018 (see **Figure 2**). For instance, in the season 2016-2017, some TBRs were placed on the rooftop of private buildings that made it difficult to follow up and collect the rainfall data on time. This was because getting on the rooftops was not possible at any time as coordination was required. In the season 2017-2018, this was overcome by placing all of TBRs on the rooftop of public buildings (e.g. schools, municipalities, village councils).

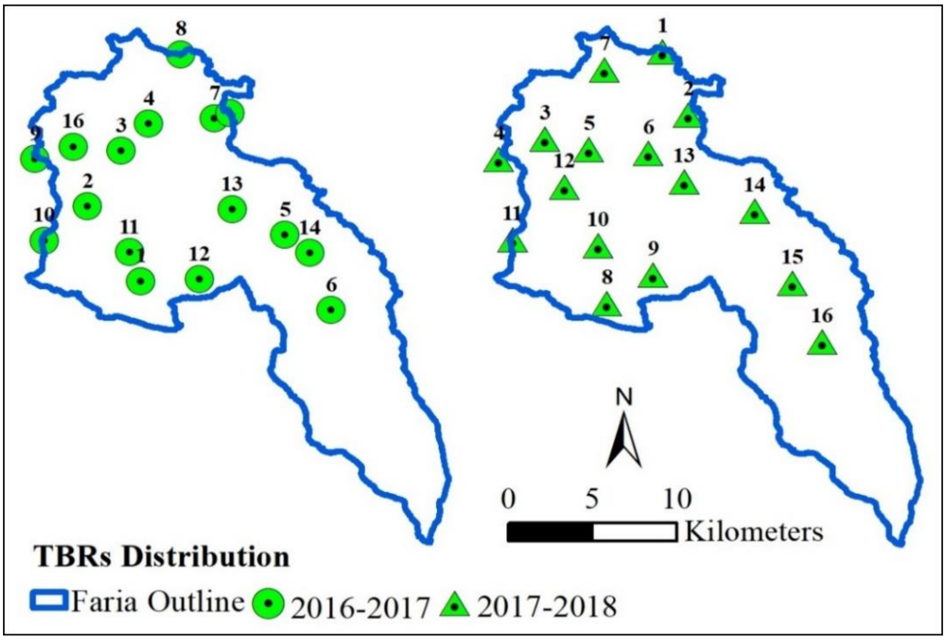


Figure (2): TBRs distribution for the two rainy seasons 2016-2017 and 2017-2018.

For each location, seasonal rainfall data obtained from the 3 TBRs were averaged. However, the data were firstly checked and unreasonable records in comparison to the other gauges at the same location were excluded. Accordingly, the seasonal rainfall sum for the 16 locations for the two rainy seasons 2016-2017 and 2017-2018 was calculated, as presented in **Table 1**. The data was then spatially processed by ArcMap 10.1 to assess the suitability of the 6 interpolation methods, mentioned earlier. The rainfall data presented in the table are accompanied by the location numbers shown in **Figure 2**. For example, location 8 in the season

2016-2017 was given number 1 in the season 2017-2018. Thus, comparing the rainfall recorded at the same number in the two seasons are not valid.

Table (1): Seasonal rainfall values for the two rainy seasons 2016-2017 and 2017-2018.

TBRs ID *	Seasonal Rainfall (mm)	
	2016-2017 **	2017-2018 ***
1	322.5	336.1
2	428.5	256.0
3	260.6	460.6
4	295.4	414.0
5	152.8	365.5
6	135.9	269.8
7	235.8	282.6
8	273.4	350.0
9	491.2	308.5
10	428.2	335.8
11	340.3	430.3
12	255.8	406.4
13	219.2	206.9
14	156.4	200.4
15	206.8	214.1
16	414.6	175.1

*TBRs ID can be depicted from Figure 2 for the two rainy seasons
**Rainfall data recorded between November and April
***Rainfall data recorded between November and May

Validation

The obtained results of the tested interpolation methods have to be assessed by statistical tests that indicate the degree of matching between the interpolated (predicted) and measured rainfall values. The interpolation results were validated via cross-validation. Cross-validation, which was used by several researchers (e.g. Lloyd 2005; Wang, *et al*. 2011; Yang, *et al*. 2015; Zhang, *et al*. 2016), is being used in this study to compare measured values with interpolated values using only the information available in a measured data set. In this study, cross-validation was conducted to estimate the seasonal rainfall values based on the six interpolation methods for the 16 different locations and the two rainy seasons. The procedure followed can be summarized as:

- The measured value at a certain location was temporarily removed from the measured data set of the 16 locations;
- The value at the same location is then estimated using the remaining measurements at 15 locations; and
- The estimated value is then compared with the actual value which was initially removed from the measured data set.

To assess the goodness of fit between the measured and predicted rainfall values, the mean absolute error (MAE), and the mean relative error (MRE) were used (Vicente-Serrano, *et al*. 2003; Teegavarapu, 2012). The MAE summarizes the mean difference in the units of measured and predicted values, while the MRE represents the percentage of error between the measured and predicted values (Vicente-Serrano, *et al*. 2003). The MAE, and MRE, are defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Z_{oi} - Z_{ei}\right| \tag{1}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Z_{oi} - Z_{ei}}{Z_{oi}}\right| \tag{2}$$

Where Z_{oi} and Z_{ei} are the ith measured and predicted values, and n is the number of sample data set (rain gauges). Smaller values of MAE and MRE indicate that the predicted value is closer to the recorded one (Vicente-Serrano, *et al*. 2003; Wang, *et al*. 2011).

Results

The Accuracy of Different Interpolation Methods

Based on cross-validation, the accuracy of the obtained results for the two rainy seasons was indicated by MAE and MRE for the different interpolation methods as illustrated in **Figure 3**. The MAE and MRE values ranged from 22.0 mm to 43.5 mm and from 7.6% to 14.9%, respectively, across the six interpolation methods used for the two rainy seasons; 2016-2017 and 2017-2018. For the two rainy seasons, average values of MAE and MRE of the six interpolation methods amounted to 29.1 mm, 11%, and 37.6 mm, 12.9%, respectively.

For the rainy season 2016-2017, the MAE and MRE of IDW were close to the values of SR, and values of ST, OK, and R were also close to each other. Whereas, for the rainy season 2017-2018, the MAE and MRE values of ST, OK, and the UK were close to each other. For the two seasons, the average values of MAE (28.3 mm) and MRE (9.8%) were lower for the UK than the values obtained from the other interpolation methods.

Generally, it can be concluded that the performance of the six interpolation methods is better to map the spatial rainfall distribution in the Faria catchment in the season 2016-2017 in comparison to the results of MAE and MRE for the season 2017-2018. Further, the UK method is potentially the most accurate one to interpolate rainfall values in the catchment.

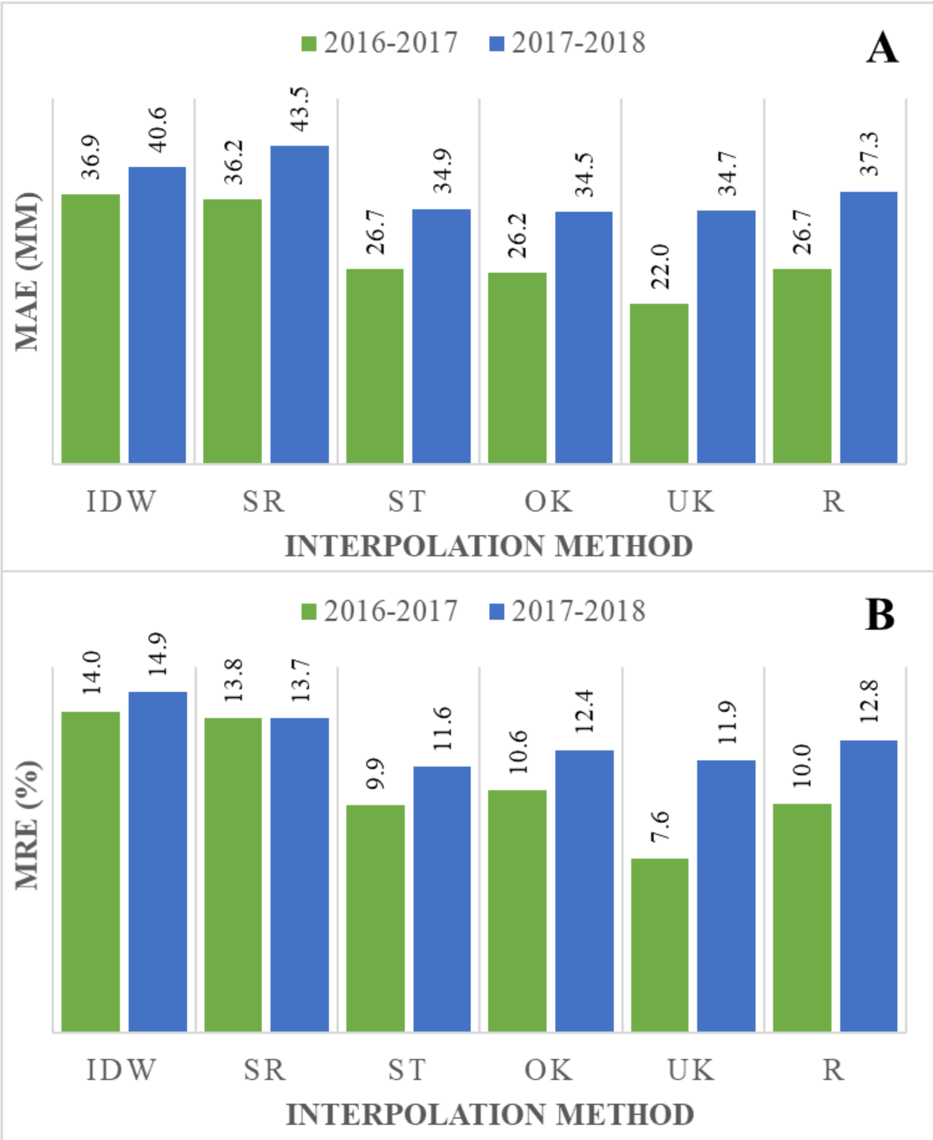


Figure (2): MAE (A) and MRE (B) for the six interpolation methods for the two rainy seasons; 2016-2017 and 2017-2018.

The Relationship between Observed and Interpolated Data

The spatial distribution of the Faria catchment rainfall was developed based on the six interpolation methods as shown in **Figure 4**. Depending on which of the six interpolation methods was used, different rainfall spatial distribution patterns were obtained. Generally, and for the two rainy seasons, a northwest-southeast rainfall gradient exists in all the maps. High rainfall in the northwest (more than 400 mm) and low rainfall in the southeast (less than 150 mm) of the Faria catchment. This is compatible with the previous study of Shadeed, 2013 which concluded that rainfall averages in the Faria catchment decrease from north to south and west to east.

ST, SR, UK, and R interpolation were generally consistent with one another, producing similar rainfall gradients. However, for the IDW and OK methods, there exist some spatial heterogeneity between the rainfall gradients in the middle and lower parts of the catchment. This is because the IDW and OK methods are utilizing the closeness weighting approach which gives high weight to the closest measured points in the prediction of values for unmeasured points (Nalder & Wein, 1998).

Rainfall interpolated values at the lower parts, in the vicinity of the catchment outlet, which is a bit higher than those at the middle parts. This can be attributed to the lack of measuring points (raingauges) therein and the localized effects of the existing measuring points.

For the two rainy seasons, correlation relationships between observed and simulated (predicted) rainfall data for the six interpolation methods are presented in **Figure 5**. The straight 45° line indicates absolute coincidence between observed and simulated rainfall data for the different interpolation methods (Vicente-Serrano *et al*. 2003). The accuracy of the six methods is tested using the coefficient of determination (r^2) between observed and simulated rainfall data. Generally, there are little differences between them for each of the rainy seasons (r^2 = 0.9 to 0.96 for 2016/2017, and r^2 = 0.8 to 0.88, for 2017-2018). However, a slightly higher correlation coefficient was obtained for the UK interpolation method for both seasons; where r^2 = 0.95 for 2016-2017 and r^2 = 0.88 for 2017-2018. Moreover, r^2 for the

IDW method was 0.9 and 0.85 for the two seasons, respectively. This, in turn, indicates the effect of the spatial distribution of raingauges in the performance of different interpolation methods to reproduce the spatial rainfall distribution in the Faria catchment.

Therefore, even the differences between observed and simulated rainfall data are similar in most of the methods, the UK interpolation method is the optimal method for interpolating seasonal rainfall in the Faria catchment based on its higher values of r^2 and lower values of MRE for the two rainy seasons.

The slightly better results of the UK (a geostatistical interpolation) method is because the method utilizes both the statistical properties of the observed values to predict values at unobserved locations (Teegavarapu, *et al*. 2012) and the closeness weighting approach which gives high weight to the closest observed points in the prediction of values for unobserved locations (Nalder & Wein, 1998), which were not considered in the other methods at the same time.

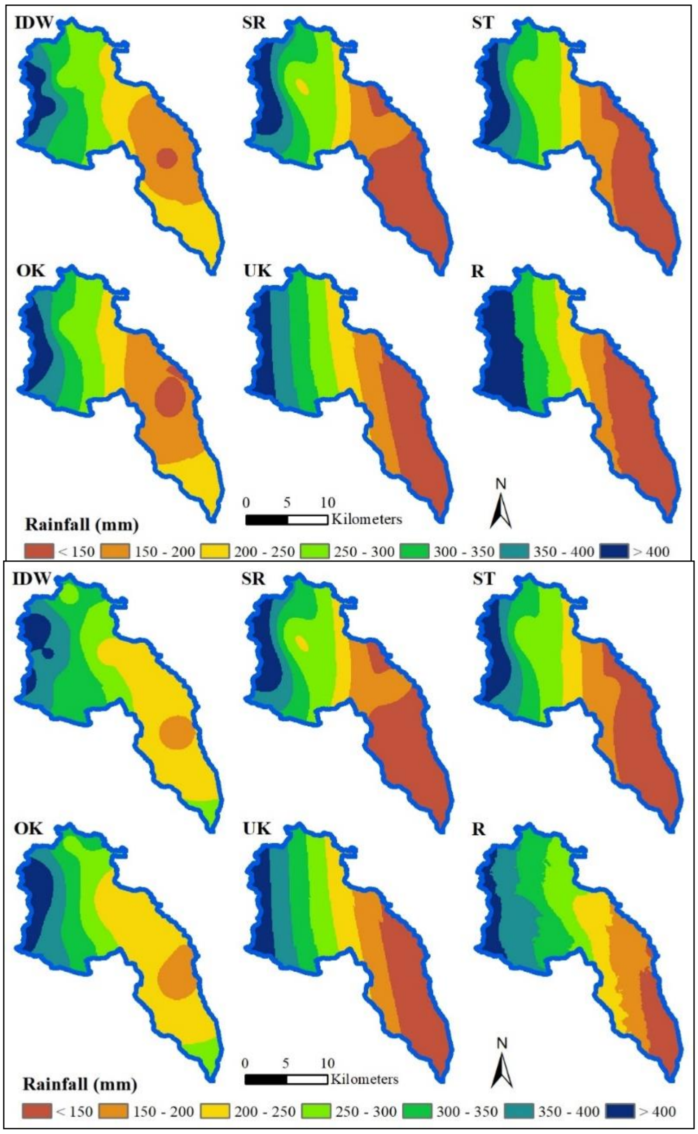
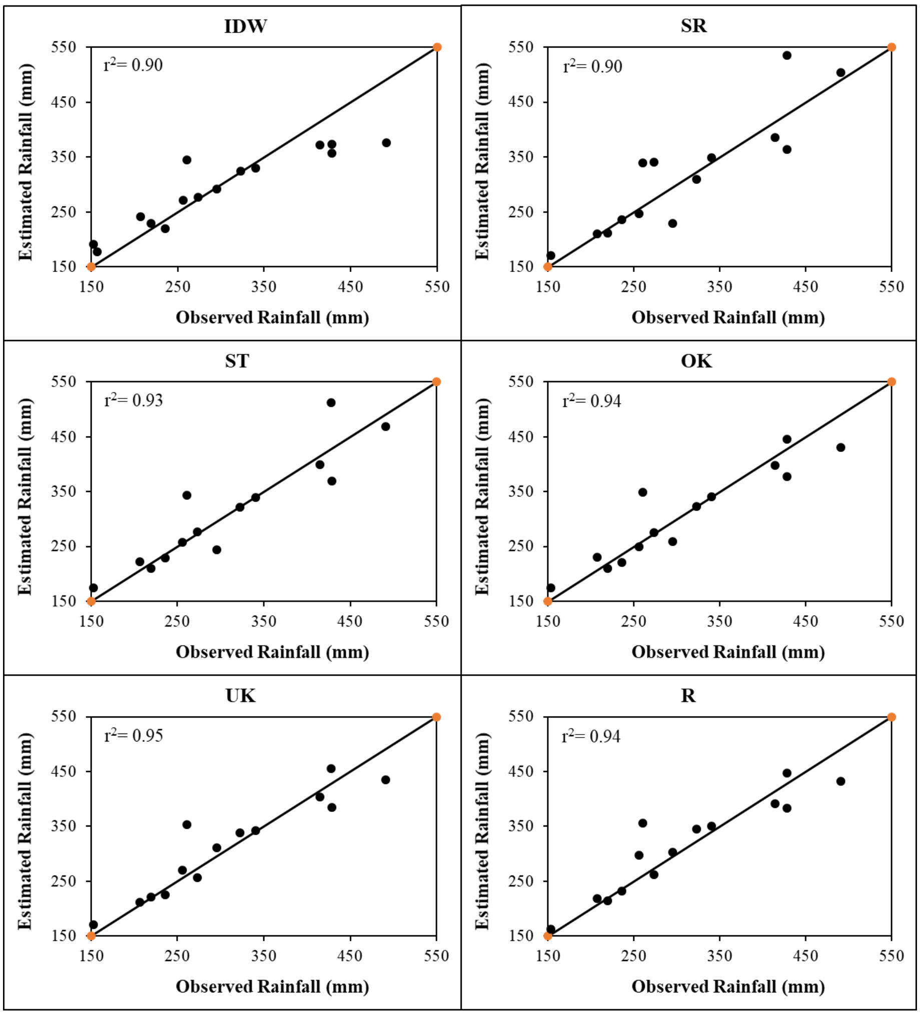


Figure (4): Rainfall distribution in the Faria catchment by different interpolation methods; the season 2016-2017 (left) and the season 2017-2018 (right).


IDW
r^2= 0.90
SR
r^2= 0.90
ST
r^2= 0.93
OK
r^2= 0.94
UK
r^2= 0.95
R
r^2= 0.94
Estimated Rainfall (mm)
Observed Rainfall (mm)
150
250
350
450
550

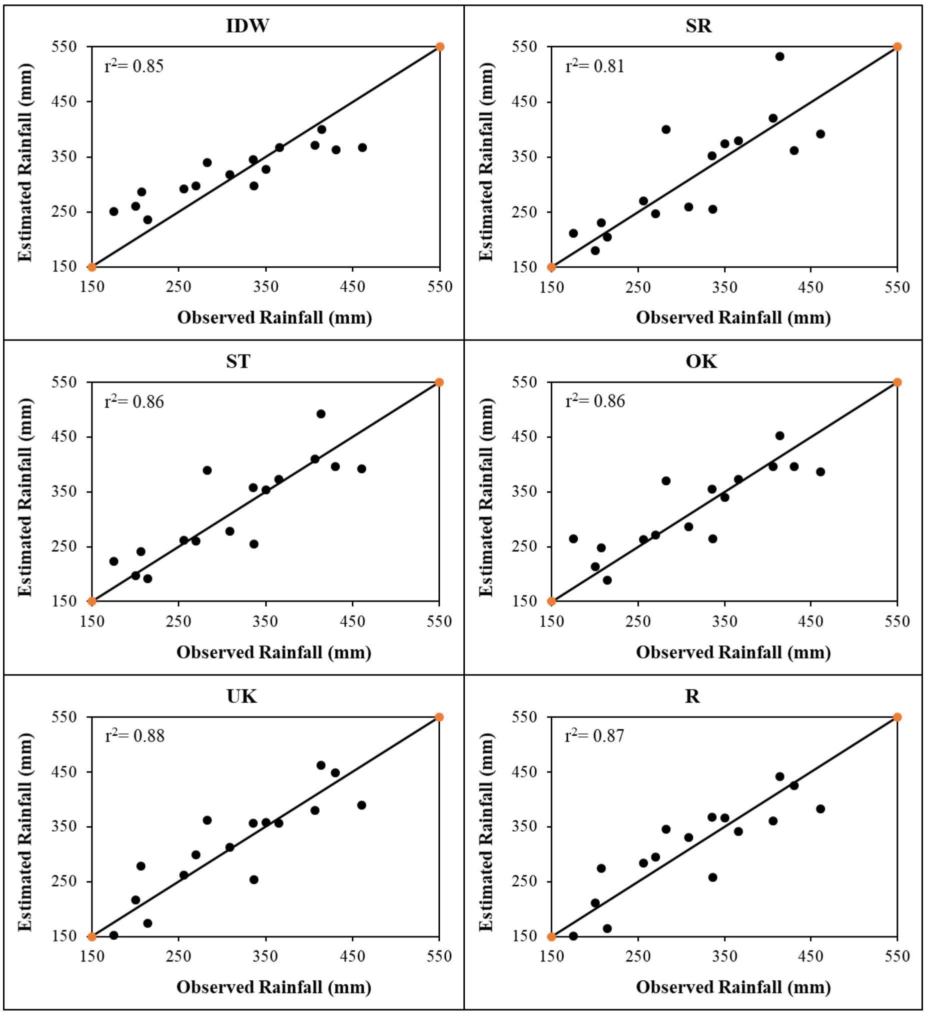


Figure (5): Differences between observed and estimated rainfall values (mm) in different interpolation methods; the season 2016-2017 (left) and the season 2017-2018 (right).

Concluding Remarks

In this study, the spatial interpolation of seasonal rainfall of the two rainy seasons (2016/2017 and 2017/2018) of a different raingauges distribution was studied using six interpolation methods; IDW, SR, ST, OK, UK, and R. The spatial distribution of raingauges affects the performance of different interpolation methods to reproduce the spatial rainfall distribution in the Faria catchment. Depending on which of the six interpolation methods was used, various spatial rainfall patterns were obtained. In general, a northwest-southeast rainfall gradient exists in all of the developed rainfall maps. Based on the mean the absolute error (MAE), the mean relative error (MRE), and correlation coefficient (r^2), results indicate that most of the six methods are good to predict rainfall values but, the UK is the most optimal (higher r^2 and lower MAE) interpolation method to mapping rainfall in the Faria catchment for the two rainy seasons. The general conclusions are summarized as follows:

1. Based on the six interpolation methods and for the two rainy seasons (2016/2017 and 2017/2018), high rainfall detected in the northwest (more than 400 mm) and low rainfall were estimated in the southeast (less than 150 mm) of the catchment which is compatible with actual rainfall trend in the catchment;

2. ST, SR, UK, and R interpolation were generally consistent with one another, producing similar rainfall gradients;

3. For the IDW and OK methods, there exists some spatial heterogeneity between the rainfall gradients in the middle and lower parts of the catchment. This is because the IDW and OK methods are utilizing the closeness weighting approach which gives high weight to the closest measured points in the prediction of values for unmeasured points; and

4. For the two rainy seasons, the r^2 and MRE values of the UK interpolation method were slightly better than the values for other methods that indicating the UK interpolation method is potentially the most accurate one to interpolate rainfall values in the Faria catchment.

Acknowledgments

This work was performed within the project IMAP (Integrating Microwave Link Data for Analysis of Precipitation in Complex Terrain: Theoretical Aspects and Hydrometeorological Applications), funded by the DFG. The financial support is gratefully acknowledged.

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