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RESEARCH ARTICLE - SPECIAL ISSUE

Assessing the variability of satellite and reanalysis rainfall products over a semiarid catchment in Tunisia

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Abstract

Precipitation is a key component in hydrologic processes. It plays an important role in hydrological modeling and water resource management. However, many regions suffer from limited and data scarcity due to the lack of ground-based rain gauge networks. The main objective of this study is to evaluate other source of rainfall data such as remote sensing data (three different satellite-based precipitation products (CHIRPS, PERSIANN, and GPM) and a reanalysis (ERA5) against ground-based data, which could provide complementary rainfall information in semiarid catchment of Tunisia (Haffouz catchment), for the period between September 2000 and August 2018. These remotely sensed-data are compared for the first time with observations in a semiarid catchment in Tunisia.

Twelve rain gauges and two different interpolation methods (inverse distance weight and ordinary kriging) were used to compute a set of interpolated precipitation reference fields. The evaluation was performed at daily, monthly, and yearly time scales and at different spatial scales, using several statistical metrics. The results showed that the two interpolation methods give similar precipitation estimates at the catchment scale. According to the different statistical metrics, CHIRPS showed the most satisfactory results followed by PERSIANN which performed well in terms of correlation but overestimated precipitations spatially over the catchment. GPM underestimates the precipitation considerably, but it gives a satisfactory performance temporally. ERA5 shows a very good performance at daily, monthly, and yearly timescale, but it is unable to represent the spatial variability distribution of precipitation for this catchment. This study concluded that satellite-based precipitation products or reanalysis data can be useful in semiarid regions and data-scarce catchments, and it may provide less costly alternatives for data-poor regions.

Keywords Precipitation · Satellite-based precipitation products · Spatial interpolation · Tunisia

Introduction

Precipitation is a key component in hydrologic processes (Jiang et al. 2012; Moges et al. 2022). It plays an important role in hydrological modeling, water balance, as well as in water resources management, and it provides potential support for decision-making Sustainable Development in Data-Poor Regions (Sheffield et al. 2018). Accurate, continuous rainfall observations represent an important contribution to hydrological research and practical applications (Moges et al. 2022). In addition, improved observations, models, and data assimilation systems will help to close the scientific gaps in the understanding of spatial–temporal variability regarding changes in climate variability and extreme events (Lahoz and De Lannoy 2014), and they will lead the way to improve hydrological predictions (Lettenmaier 2017).

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Precipitation information is generally derived from the ground-based rain gauges which are commonly used to measure precipitation directly at the Earth's surface, while meteorological radars, and satellite-based estimates precipitation at higher altitudes (Behrangi et al. 2011; Berg et al. 2016; Kidd 2001).

The progress in satellite technology allowed many countries to successfully develop a number of climate variable observations missions. In fact, precipitation products have been available worldwide for over four decades. The diffusion of satellite products recently provided more access to diverse climate data than ever before (Levizzani and Cattani 2019; Sun et al. 2018), and a series of satellite-based precipitation products produced high-resolution data with worldwide coverage (Li et al. 2015; Sun et al. 2018; Zhang et al. 2017).

The use of multiple sensors for the estimation and forecasting of precipitation indicated promising results recently. In this context, (Meydani et al. 2022) developed a weather forecast downscaling model for downscaling large-scale raw weather forecasts of ECMWF and NCEP to small-scale spatial resolutions using deterministic artificial intelligence techniques and a Bayesian Belief Network. The downscaled precipitation and temperature were fed to a hydrological rainfall-runoff model to optimize dam water allocation between agricultural and environmental demands in Urmia Lake basin in Iran.

In addition, (Brocca et al. 2019) showed that a global daily satellite precipitation data work relatively well in data-poor regions of the world, such as Africa and South America. Several recent studies have focused on the use of different precipitation datasets due to data scarcity and lack of follow-up in poorly gauged or ungauged catchments such as in Blue Nile River sub-basin in the Sudan (Abd Elhamid et al. 2020), in the north of Tunisia (Dhib et al. 2017), in Taiwan (Hsu et al. 2021), in Australia (Islam et al. 2020), in Andalusia in Spain (Moreno et al. 2022), in the Sio-Malaba-Malakisi river basin of East Africa (Omonge et al. 2022), and in the Mainland China (Yu et al. 2022).

Precipitation data are usually available at certain locations within a catchment. However, it is difficult and expensive to acquire continuous spatial data for most locations, especially for mountain and sea areas. Spatial interpolation methods represent a good alternative to generate distributed and accurate spatial information using available measurements on certain areas (Longo-Minnolo et al. 2022). Spatial interpolation techniques are therefore crucial for creating continuous area predictions based on sampled point values (Wang et al. 2014). To obtain better estimates of spatial precipitation, (Kumar et al. 2021) showed that gauge-interpolated analysis is recommended for precipitation trend and variability analysis. Despite the use of satellite rainfall estimates as a reference dataset, their interpolated estimates are rarely compared to interpolated observed rainfall estimates (Shi et al. 2022). There are different methods of interpolation, such as ordinary kriging (OK) and inverse distance weighting (IDW) (da Silva et al. 2019).

In many regions, arid and semiarid zones are characterized by official networks for hydrometric and meteorological monitoring (mostly, precipitation and discharges) which are not well distributed spatially and suffer from data gaps and often from poor-quality databases (Fehri et al. 2020). Thus, satellite data, gauge observation, and data reanalysis can help to better understand spatial characteristics of precipitation particularly in data-scarce region (Beck et al. 2017; Ning et al. 2017).

Although the satellite data provide valuable and important information for the weather process, drought, and hydrological monitoring, it is crucial and prerequisite to test their accuracy and performances for a correct use (Maggioni et al. 2016).

Several studies in different regions of the world have evaluated the performance of satellite products under different climatic conditions (Omar et al. 2023; Rachdane et al. 2022). In Tunisia, some studies used precipitation satellite products for different purposes: for example, for bias correction techniques (Dhib et al. 2021); for precipitation estimates and monitoring (Dhib et al. 2017); filling the gap in rainfall data for hydrological models (Guermazi et al. 2019; Medhioub et al. 2019); for drought monitoring and forecasting using machine learning in arid areas (Bouaziz et al. 2021); and as input of ERA5 to compare hydrological models performances for flood modeling (Cantoni et al. 2022). These studies were carried out without considering the spatial variability of rainfall within the basins. Given the characteristics of semiarid and steep relief regions with a high spatial and temporal variability of rainfall, the precipitation products may exhibit varying degrees of performance. Therefore, a study of the performances of these products at a reduced spatial scale (at the catchment scale) and in a semiarid climate is highly put forward in this paper. In this context, the remote sensing data used in the present study are compared for the first time with observations in semiarid area in Tunisia.

In this study, we use daily 12 rain gauges in and around Haffouz catchment (semiarid catchment in Tunisia), and three satellites data products and a reanalysis: (1) CHIRPS (Climate Hazards Group Infrared Precipitation with Stations (Rivera et al. 2018)), (2) PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (Eini et al. 2022)), (3) GPM (Global Precipitation Measurement (Smith et al. 2007)), and (4) ERA5 (Hersbach et al. 2020).

The objective of the present study is to assess performances of other source of rainfall data than the ground-based data, that do not necessarily represent the rainfall variability, and which could provide complementary rainfall information for Haffouz catchment. The specific objectives of this study include: (1) the assessment of the selected satellite data accuracy in terms of bias and temporal correlation using different evaluation metrics and (2) their spatial analysis related to the interpolated observed data.

The paper consists of five sections. In Section "Materials and methods," case study specifications including area of study, description of datasets are provided. Interpolation methods, evaluation metrics, and spatial evaluation are described in Section "Methodology." Section "Results and Discussion" outlines the results and discussion of findings. Finally, concluding remarks are presented in Section "Conclusion."

Materials and methods

Study area

The Haffouz catchment covers an area of 625 Km^2, is located in central of Tunisia, and has a semiarid climate (Fig. 1). It is a sub-basin of the Merguellil upstream catchment (1200 Km^2). It is under two climatic influences: a humid trend from the north (Tellien region, mountainous, cold, and rainy), and an arid trend from the south (a hot pre-desert region) (Chargui et al. 2013; Jebari et al. 2008). Climate is also influenced by the effect of latitude and relief (Slimani et al. 2007). Thus, the study area is characterized by high spatiotemporal variability in precipitation, according to a north–south gradient (Chargui et al. 2009), with annual values between 200 and 500 mm.

Datasets

Three different resolution satellites precipitation and reanalysis data are used with different grid size as shown in Fig. 2 which are CHIRPS, PERSIANN, GPM, and ERA5. Rain gauge observations in and around the watershed are shown in Fig. 1. Daily time series were used for all datasets. However, in this study, the analysis will be interpreted based on daily, monthly, and interannual scales.

The PERSIANN family contains three satellite-based precipitation products: (1) PERSIANN algorithm is relied

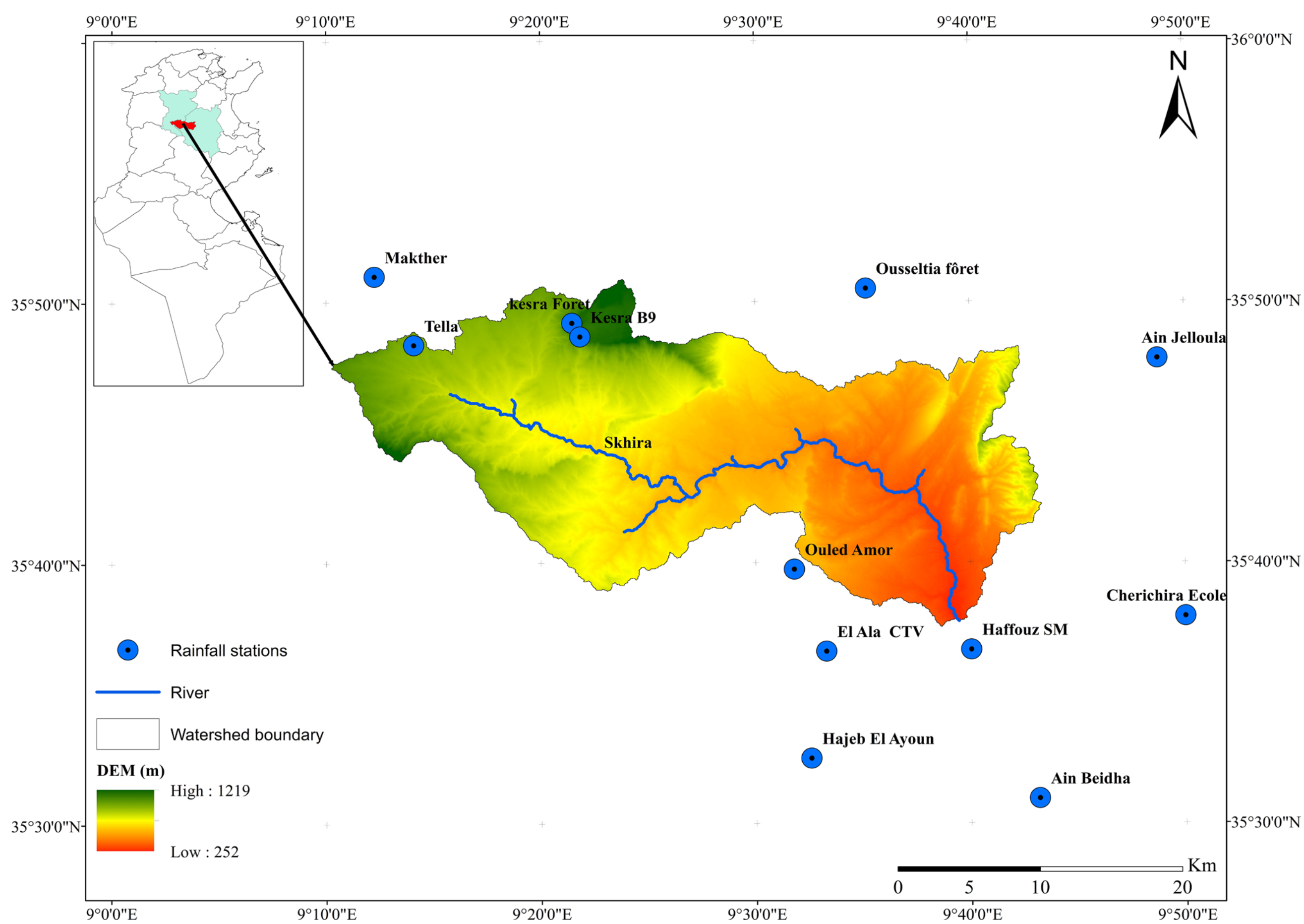


Fig. 1 Catchment location and rain gauge positions

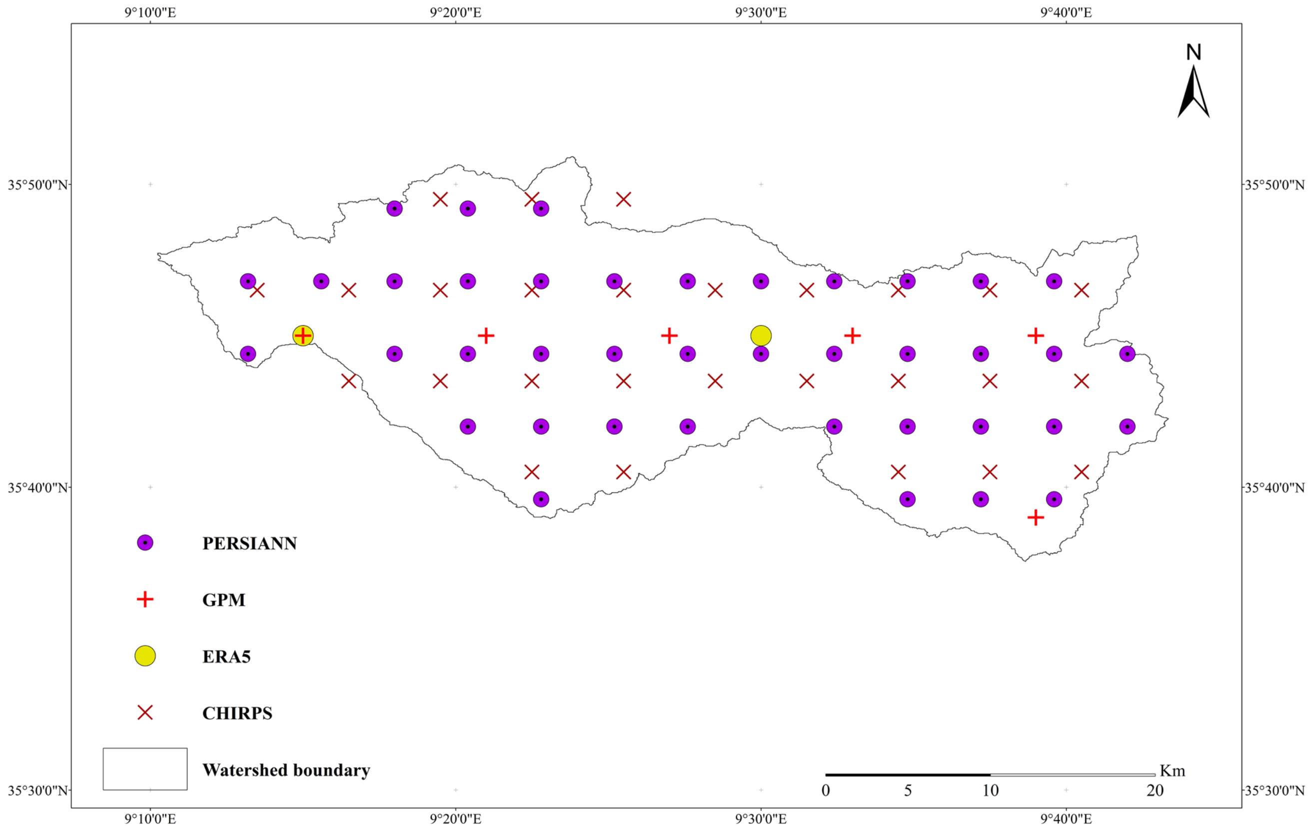


Fig. 2 Spatial distribution of satellite products grids on Haffouz catchment

on the synergy between sparsely sampled information from LEO satellites and high-frequency samples from GEO satellites. It computes rainfall rate estimates at each 0.25° × 0.25° pixel of the infrared brightness temperature images. (2) PERSIANN-CCS is an example of a cloud patch-based algorithm, using information from infrared cloud images that extracts features from cloud cover below a certain temperature threshold. (3) PERSIANN-CDR provides daily rainfall estimates at 0.25° for the latitude band 60N-60S over the period of 01/01/1983 to 12/31/2015 (delayed present). It is aimed at addressing the need for a consistent, long-term, high-resolution, and global precipitation dataset for studying the changes and trends in daily precipitation, especially extreme rainfall events, due to climate change and natural variability (Nguyen et al. 2018, 2019; Sorooshian et al. 2000).

The Global Precipitation Mission (GPM) is a program founded by a cooperation between two space agencies, the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA), launched in 2014. It is the immediate successor to the Tropical Rainfall Measurement Mission (TRMM) program that operated the first space-based precipitation radar. It brings two core observations, i.e., dual-frequency radar (DPR) and multi-channel GPM microwave imager (GMI). The DPR operates on two radar frequency bands, i.e., the Ka-band precipitation radar with a frequency of 35.5 GHz and the Ku-band precipitation radar at a frequency of 13.6 GHz. On the other hand, the GMI brings 13 channels of microwave signal sensors operating in the range of 10 to 183 GHz. The GPM delivers various global precipitation products. It does not record only the final synthesis product but also the intermediate data that contributed to its development, in order to keep track of the various processing procedures (Berges 2019; Ramadhan et al. 2022).

CHIRPS (The Climate Hazards Group Infrared Precipitation with Stations) is a semi-global rainfall product for monitoring drought and global environmental changes. It provides data with high spatial (around 5 km) and temporal resolutions (daily, pentadal, and monthly precipitation), starting from 1981 to near present. CHIRPS integrates satellite information in three ways: through satellite assets means to generate high-resolution precipitation, CCD fields to estimate monthly and pentadal precipitation anomalies, and satellite precipitation fields to estimate local distance decay functions guiding the interpolation process (Narulita et al. 2021). CHIRPS algorithm was used to quantify the hydrological effects of reduced precipitation and increased air temperature in the Greater Horn of Africa (Funk et al. 2015). Further, results showed good correlation between CHIRPS values and recorded precipitation over Mediterranean region (Katsanos et al. 2016).

ERA5, from the European Centre for Medium-Range Weather Forecasts (ECMWF), is the fifth generation of reanalysis global atmospheric datasets. It replaces the ERA-Interim reanalysis and is based on the Integrated Forecasting System (IFS). It covers the period from January 1950 to present. It provides a lot of variables such as atmospheric, land, and oceanic climate variables, with an hourly temporal resolution and a 31 km spatial resolution (Hersbach et al. 2020). (Lavers et al. 2022) showed that the use of precipitations detected and estimated by ERA5 is more reliable and recommended for climate monitoring activities in extratropical areas. However, the precipitation product estimated by ERA5 strongly depends on topography (Jiao et al. 2021).

In this study, the daily rainfall data were collected from Regional Agricultural Development Commission (CRDA) of Kairouan and Siliana for 12 rainfall stations in and around the study area, starting the year 2000. The gauges are installed at different elevations as given in Table 1.

Methodology

Interpolation methods

Spatial interpolation is the most traditional and known method for converting point precipitation to areal precipitation. Many spatial interpolation methods are tested and compared for their performance. The inverse distance weighting (IDW) and the ordinary kriging (OK) are the most frequently used methods (Li and Heap 2014). In this work, we use both interpolation methods (IDW and OK) to estimate precipitation.

Table 1 List of rain gauges in and around Haffouz catchment

ID	Name	Latitude	Longitude	Altitude (m)
1	Tella	35.80660	9.23470	863
2	Makther	35.85040	9.20410	919
3	Kesra Foret	35.82070	9.35782	1050
4	Kesra B9	35.81190	9.36400	956
5	Ain Beidha	35.51620	9.71969	297
6	Ain Jelloula	35.79710	9.81273	175
7	El Ala CTV	35.61070	9.55469	466
8	Ouled Amor	35.66320	9.52997	500
9	Cherichira Ecole	35.63240	9.83357	321
10	Hajeb El Ayoun	35.54230	9.54275	350
11	Haffouz SM	35.61150	9.66719	270
12	Ousseltia Foret	35.84230	9.58635	465

Inverse distance weighting (IDW) is a simple way of spatial interpolation, where observations are weighted based on their distance to a given point by a nonlinear relationship expressed by an exponent (typically equal to 2). IDW was first proposed by Shepard (1968), and widely used because of the simplicity and the applicability to rare and irregular datasets (Stisen and Tumbo 2015). The ordinary kriging (OK) is a geostatistical method based on statistical models involving autocorrelation. This is the most common method of kriging and it assumes a second-order stationary for the regionalized variable (Shi et al. 2022).

Spatial interpolation of precipitation can sometimes give unrealistic estimations due to a poor rain gauge network (Hussain et al. 2018; J. Li and Heap 2008; Scheel et al. 2011). That is why, a validation with the observed data is necessary. The validation approach used in this study is the "point-to-pixel." It is used in several research studies (Gebere et al. 2015; Jiang et al. 2016; Rachdane et al. 2022).

Further, to assess the efficiency of different satellite-based precipitation estimates, a comparison with the observed data as ground reference is necessary. The choice of ground reference is a very delicate and important step due to the spatial distribution of rain gauges which are characterized by a sparse network and the presence of missing data in the series of observations (Cudennec et al. 2005; Tramblay et al. 2016). So, the spatial interpolation of precipitation is important and used to generate rain fields in a grid of specific size (Teegavarapu et al. 2012) in order to compare observed data with satellite products.

Thus, different evaluation metrics are used for satellite-based precipitation estimates to test their performance using observations as a reference. The network of rainfall stations is characterized by a poor spatial distribution and a long distance between stations on the one hand, and on the other hand, the series of observed data suffer from discontinuity at each time step, as well as gaps and anomalies. Thus, spatial interpolation seems to be a solution to fill these anomalies (Tramblay et al. 2016). To interpolate, a regular grid of points with a 2 km resolution within the catchment has been made. Then, precipitations are interpolated, by the two methods described before, and averaged at these points. In addition, the different satellite-based precipitation estimates data within Haffouz catchment are averaged at different time steps (daily, monthly, and yearly).

Evaluation metrics

Several statistical metrics were adopted in order to compare, better understand and evaluate the accuracy of the different satellite-based precipitation estimates (Table 2). Pearson correlation coefficient (CC) is used to measure the linear correlation between in situ gauge observations and satellite estimates.

Table 2 List of the statistical metrics used in this study

Statistic metrics	Equations	Range	Perfect value
Pearson correlation coefficient (CC)	$CC = \frac{\sum_{i=1}^{n}\left(G_i-\overline{G}\right)\left(S_i-\overline{S}\right)}{\sqrt{\sum_{i=1}^{n}\left(G_i-\overline{G}\right)^2}\sqrt{\sum_{i=1}^{n}\left(S_i-\overline{S}\right)^2}}$	−1 to 1	1
Relative bias (RBias)	$\text{RBias} = \frac{\sum_{i=1}^{n}(S_i-G_i)}{\sum_{i=1}^{n}G_i} \times 100\%$	$-\infty$ to $+\infty$	0
Root-mean-squared error (RMSE)	$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i-G_i)^2}{n}}$	0 to $+\infty$	0
Spearman's correlation coefficient (ρ)	$\rho_{rgS,rgG} = \frac{\text{cov}(rgS,rgG)}{\sigma_{rgS}\sigma_{rgG}}$	−1 to 1	1

Relative bias (RBias) describes the systematic biases of satellite-based precipitation estimates data and provides an average magnitude and sign of the differences between satellite estimates and in situ gauge observations. Root-mean-squared error (RMSE) represents the mean absolute deviation between the satellite estimate and the observed value and demonstrates the error characteristics of satellite estimates, which are sensitive to outliers. Spearman's correlation coefficient or Spearman's ρ (rho) is a nonparametric correlation between two variables. Spearman correlation is important when two statistical variables appear to be correlated without the relationship between the two variables being of an affine type.

where S_i are the satellite precipitation estimates, G_i is the observed rain gauge precipitation, $\overline{S}$ and $\overline{G}$ are the mean, n is the number of samples considered, cov(rgS, rgG) is the covariance of the rank variables, and σ_{rgS} *and* σ_{rgG} are the standard deviations of the rank variables.

Spatial evaluation

Spatial evaluation was first done by keeping the spatial resolution of each satellite product and the grid (2×2 Km^2) used in interpolation for observed data. Then, a spatial interpolation for each data was performed by a GIS tool. The mean daily pixel values were then extracted and aggregated to monthly and then annual sums for each product for the common period of 2000–2018. This was done to allow a fair comparison of the products since they have different spatial and temporal extents, but by keeping the same scale of values. The products were then mapped over the study area and compared based on mean monthly precipitation performances.

Results and Discussion

Evaluation and validation of interpolation methods

In this study, 12 precipitation gauges were used in the interpolation, these gauges were distributed at elevations from 252 to 1219 m, for a period from September 2000 to August 2018, with no gaps in the rainfall series. To ensure consistent comparisons between satellite precipitation and rain gauges, two spatial interpolation methods, the inverse distance weighting (IDW) and ordinary kriging (OK), were applied to estimate the spatial distribution of rainfall data, daily, monthly, and yearly, in Haffouz catchment. These methods seem to reproduce well the observed precipitation. However, it should be noted that the elevation was not considered. Thus, the application of a method in precipitation interpolation incorporating the altitude may give better estimations (Di Piazza et al. 2011). The performance of each spatial interpolation method was evaluated using the RMSE, RBias, CC, rho (ρ), and R^2 statistics to investigate their prediction accuracy.

To clearly and intuitively demonstrate that interpolated daily precipitation at the point scale, we compared the observed and interpolated daily precipitation from 1st September 2000 to 30th August 2018 at three observed stations which are Tella, Kesra B9, and Kesra Foret. The choice of these stations is due to the fact that they are in the same pixels of the grid and nearest to the pixel's centroid.

Figure 3 displays the values of the RMSE, RBias, CC, rho, and R^2 for the validation results. The CC was more than 0.9 at most stations at daily scale. The rho was higher than 0.6 for all stations. The RBias between all observed rain gauges with the two interpolation methods is low with a maximum value of the order of 0.14 and a margin of overestimation or underestimation of $\pm$1%. In terms of RMSE, it is low for the different stations with a maximum value of 3.7 mm/day. The two methods of interpolation show the same coefficient of determination about 0.9 between the interpolated values and the observed values for Tella and Kesra B9 stations. The IDW method tends to provide slightly better results than OK, except for Kesra foret station located at higher altitude.

Figure 4 shows the correlation between ordinary kriging interpolation and inverse distance weight for the different time steps. It gives a very good correlation between these two interpolation methods with a correlation coefficient of 0.98, 0.99, and 0.95 for the daily, monthly, and yearly time scales, respectively.

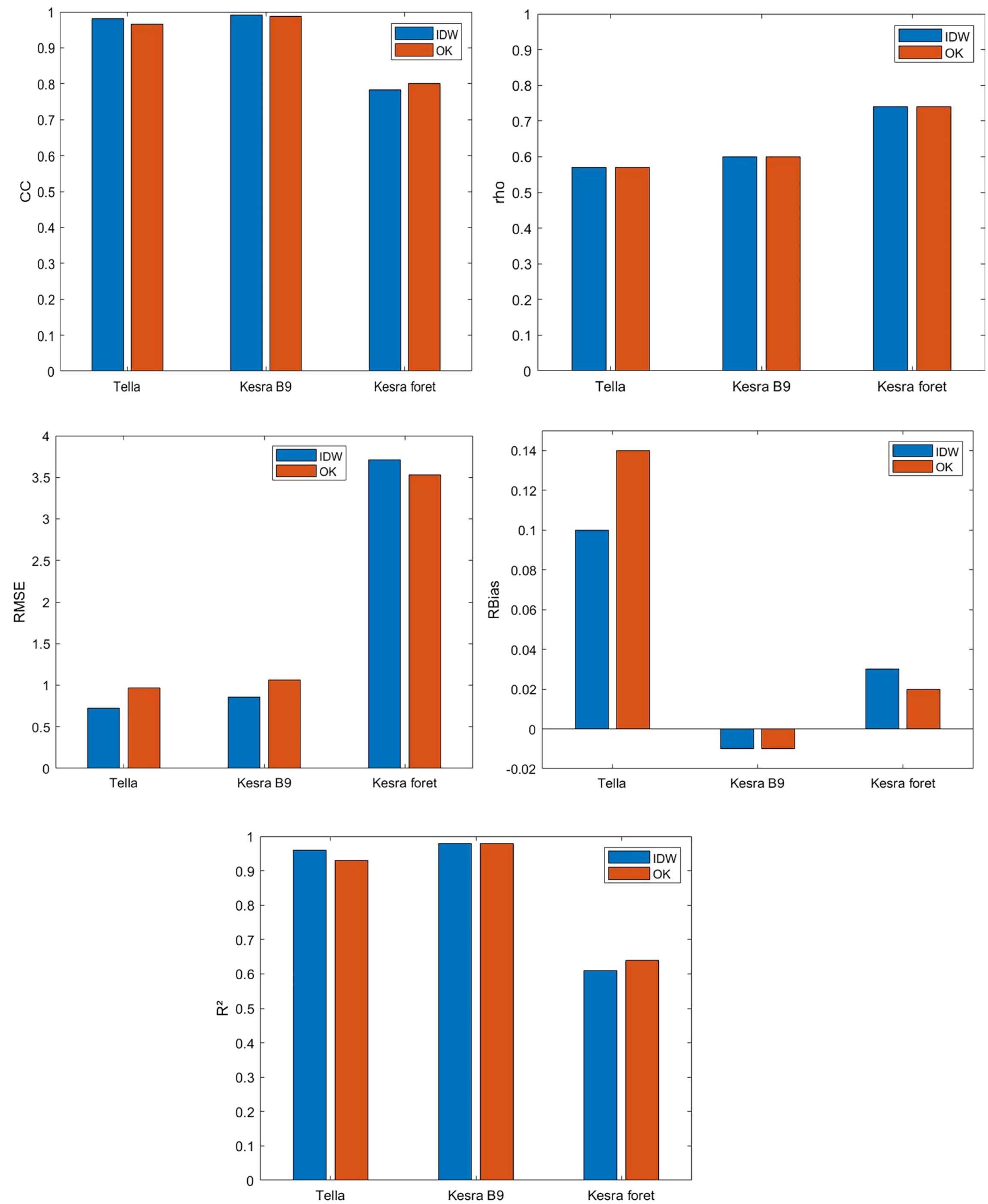


Fig. 3 Statistical metrics for result validation

Using the "point-to-pixel" approach, the results showed a strong correlation between interpolated values and observed data for three rain gauges (Kesra B9, Kesra foret, and Tella). So, the proposed interpolation method reproduced precipitation events well and was sufficiently accurate and provided very similar estimates.

Temporal analysis

The four statistical metrics results were used to assess the quality of the satellite data against observed data as displayed in Fig. 5. For CHIRPS, results showed that RBias had values between −0.05 and −0.07, RMSE between 3.9

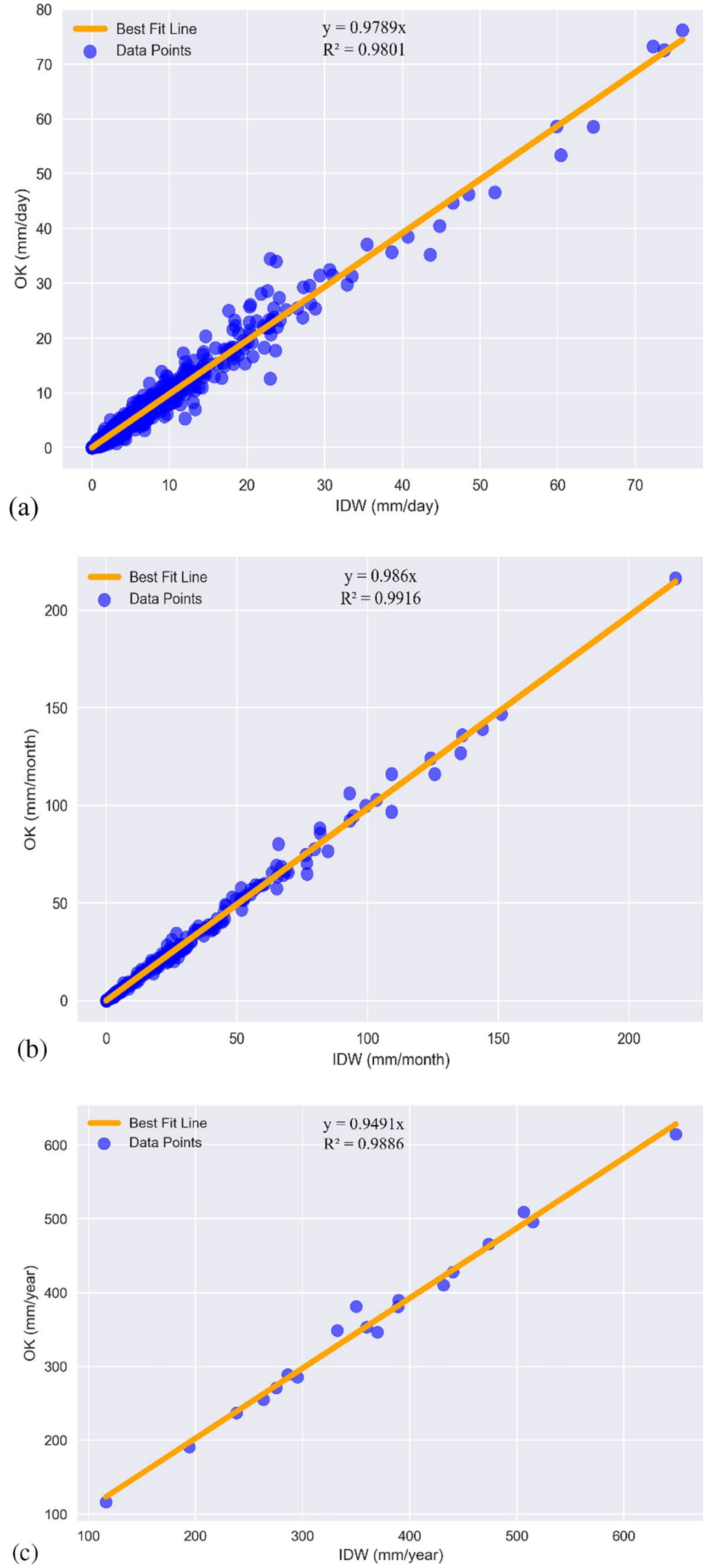
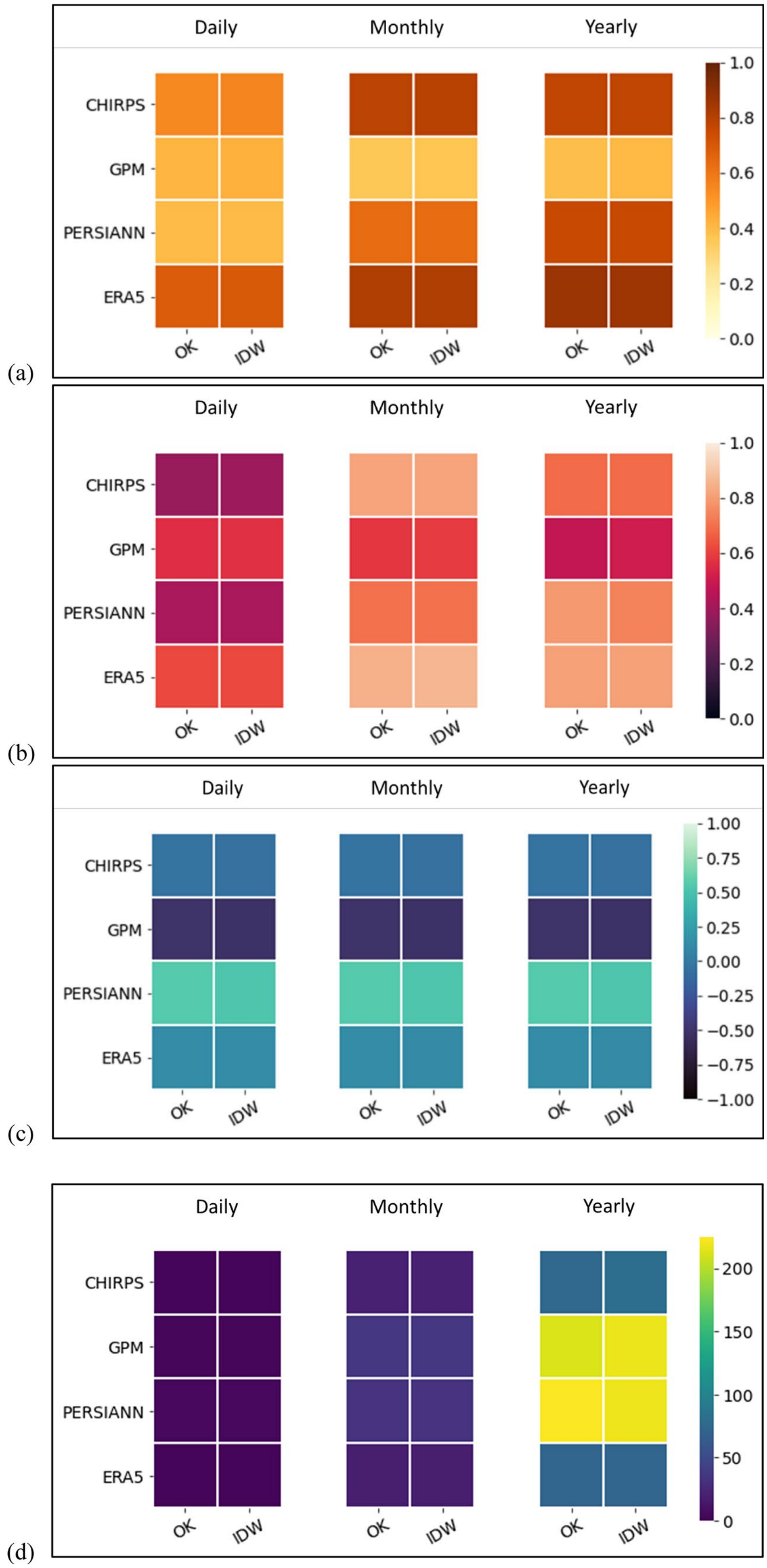


Fig. 4 Correlation between the ordinary kriging and the inverse distance weight at **a** daily, **b** monthly, and **c** yearly time scale

Fig. 5 Statistical metric between interpolated precipitation and satellite-based product precipitation **a** CC, **b** rho, **c** RBias, and **d** RMSE



and 80.23 mm, CC between 0.55 and 0.80, and rho between 0.38 and 0.82 for the different time steps, daily, monthly, and yearly (Fig. 5). The RBias gave minor underestimation with a value of approximately −0.07. The two methods of interpolation have positive correlation with CHIRPS with a CC larger than 0.6 for daily data and 0.8 for monthly and yearly time steps (Table 3). This indicates a very important correlation. Nonetheless, it should be noted that precipitation is not considered as a linear variable. For this reason, the correlation coefficient of Spearman (rho) at daily time step presents rather a low correlation with a value of around 0.39 for both interpolation methods. This value increases with the time step to achieve more than 0.8 at the monthly time step which is considered a strong correlation. The RMSE between CHIRPS and interpolated precipitation is around 3.29 mm, 20.5 mm, and 80.23, respectively, for daily, monthly, and yearly data (Table 3). Among the three satellite-based precipitation products (CHIRPS, PERSIANN, and GPM) and a reanalysis (ERA5), CHIRPS was, globally, the best product among the tested products. Indeed, it showed a good performance over the Haffouz catchment, especially at the monthly time step in terms of correlation coefficient (CC and rho) and RBias.

The GPM results presented CC values between 0.36 and 0.43, rho coefficients between 0.48 and 0.6, RBias around −0.5, and RMSE between 3.62 and 219 mm for daily, monthly, and yearly data. GPM data showed a large underestimation with RBias equal to −50% for each time steps (Table 3). The correlation between the GPM product and the observed data interpolated with the two methods of interpolations is low with a maximum correlation at daily time step equal to 0.43. However, the Spearman's coefficient shows a rather good correlation between GPM data and observed data with a rho coefficient larger than 0.59. RMSE results are comparable to CHIRPS for daily data and are slightly larger than CHIRPS for monthly analysis with a difference of around 10 mm/month. For yearly time steps, RMSE is double those for CHIRPS products (219 mm/year). In this study, the GPM product is not satisfactory for reproducing temporal rainfall patterns. However, several studies noted that its performance depends on several factors such as topography, semiarid climate and rainfall regime, rain gauge density, and the quality of the observed data (Chen et al. 2019; Chiaravalloti et al. 2018; Navarro et al. 2020; Saouabe et al. 2020).

For PERSIANN data, CC values are between 0.4 and 0.76, rho coefficient between 0.42 and 0.79, RBias around 0.56, and RMSE between 4.5 and around 223 mm for daily, monthly, and yearly data. PERSIANN did not present good performance in terms of correlation at daily time step (r and rho < 0.5). The linear and Spearman correlations are similar for the daily, monthly, and yearly time steps, respectively. These correlations are considered significant with a Spearman's coefficient larger than 0.79 for yearly time step (Table 3). However, PERSIANN data showed a severe overestimation with RBias larger than 50% for each time

Table 3 Summary of the results of the statistical parameters for the different time steps

Daily								
	CC		rho		RBias		RMSE	
Observed/sat. products	OK	IDW	OK	IDW	OK	IDW	OK	IDW
CHIRPS	0.55	0.56	0.38	0.39	−0.05	−0.07	3.29	3.29
GPM	0.42	0.43	0.56	0.57	−0.51	−0.52	3.62	3.64
PERSIANN	0.4	0.4	0.42	0.42	0.56	0.53	4.5	4.53
ERA5	0.69	0.7	0.62	0.62	0.12	0.12	2.87	2.85
Monthly								
	CC		rho		RBias		RMSE	
Observed/sat. products	OK	IDW	OK	IDW	OK	IDW	OK	IDW
CHIRPS	0.79	0.8	0.82	0.82	−0.05	−0.07	20.36	20.41
GPM	0.36	0.37	0.58	0.59	−0.51	−0.52	35.29	35.62
PERSIANN	0.64	0.64	0.7	0.7	0.56	0.53	32.89	32.83
ERA5	0.82	0.82	0.85	0.86	0.12	0.11	18.6	18.79
Yearly								
	CC		rho		RBias		RMSE	
Observed/sat. products	OK	IDW	OK	IDW	OK	IDW	OK	IDW
CHIRPS	0.78	0.78	0.69	0.69	−0.05	−0.07	75.26	80.23
GPM	0.39	0.41	0.48	0.51	−0.51	−0.52	212.13	218.52
PERSIANN	0.76	0.76	0.79	0.74	0.56	0.53	223.43	218.93
ERA5	0.87	0.86	0.81	0.81	0.12	0.11	72.20	72.75

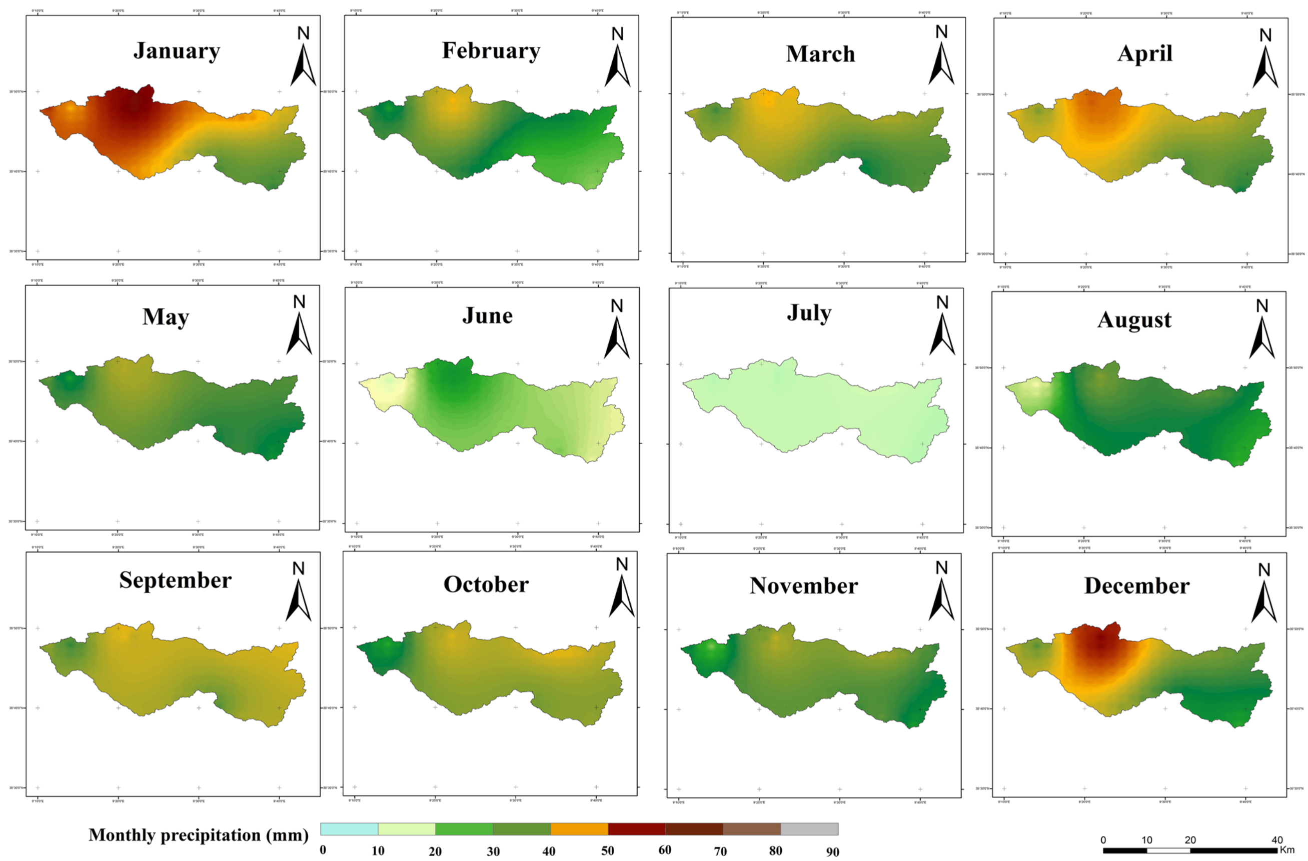


Fig. 6 Spatial distributions of the interpolated monthly precipitation with IDW method for the period of 2000–2018 in the Haffouz catchment

steps. This overestimation is confirmed by a high RMSE of 223 mm/year.

For ERA5 data, CC values are between 0.70 and 0.87, the rho coefficient between 0.62 and 0.86, RBias around 0.12, and RMSE between 2.85 and 73 mm for daily, monthly, and yearly data. ERA5 data show a very significant correlation for the two methods of interpolation with CC and rho coefficients, respectively, around 0.87 and 0.81 for yearly data. The RBias shows an overestimation, which have a value of approximately + 12%. The RMSE between ERA5 data and interpolated precipitation is 2.87 mm, larger than 18 mm, and 72.75 mm for, respectively, daily, monthly, and yearly data (Table 3). However, this study area is characterized by rare and intense precipitation events (Slimani et al. 2007). Indeed, precipitation is very sensitive variable especially spatially in Tunisia (Aouissi et al. 2018). So, this product is unable to reproduce precipitation spatially in this region.

The lowest CC was obtained for PERSIANN daily data, and for GPM monthly and yearly data. Based on the rho coefficient, performance of CHIRPS product was not satisfactory with around 0.38 for daily data with the ordinary kriging method. However, CHIRPS data show the best rho correlation at monthly time step. For the RBias, CHIRPS provided the best results with a slight underestimation of 5%, followed by ERA5 with an overestimation of 12% for each time step. In terms of RMSE, PERSIANN has the highest RMSE, followed by GPM, CHIRPS, and ERA5, for daily and yearly data. However, for monthly data, GPM shows the highest RMSE with a value equal to 36 mm/month. Both CHIRPS and ERA5 show a similar RMSE. Due to this similarity in performance, no product could be selected as superior based on the RMSE values alone. It shows that the CHIRPS and ERA5 results are significantly better than the other datasets, and PERSIANN is the least performer at different time steps, in terms of CC and rho for this case study.

This case study has been conducted to determine whether high resolution could be used to reliably estimate for rainfall. The twelve rain gauge stations in the study region had recorded rainfall between September 2000 and August 2018, so the study compared the recorded with three satellite-based precipitation products and a reanalysis, in order to provide further insight into the capability of these products to assist in rainfall modeling. The analysis reveals that ERA5

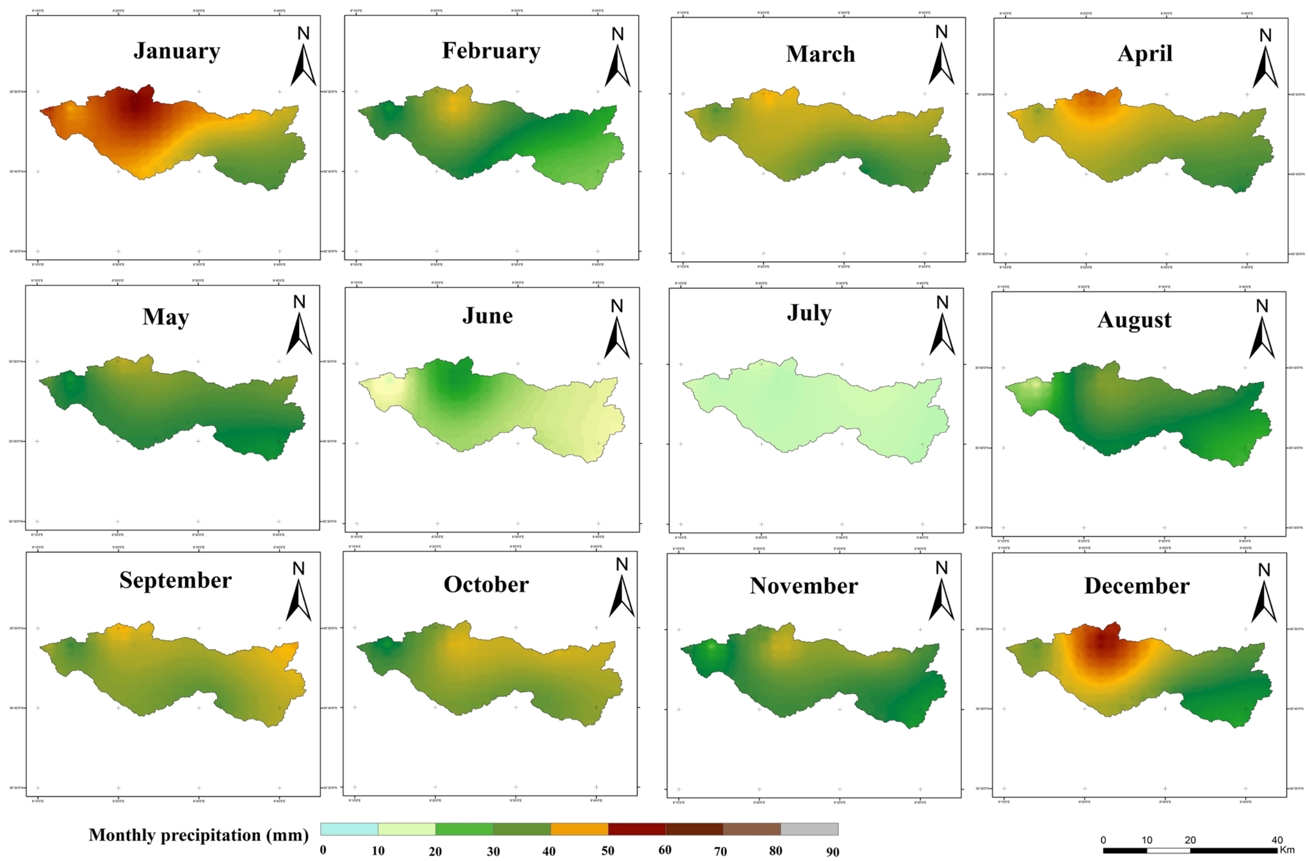


Fig. 7 Spatial distributions of the interpolated monthly precipitation with OK method for the period of 2000–2018 in the Haffouz catchment

appears best at temporal scale for the three time steps daily, monthly, and yearly, while CHIRPS products showed good performance in terms of RBias. All precipitation products seem to either underestimate or overestimate the rainfall, during this period.

Spatial analysis

The spatial distribution of precipitation is vital for understanding the precipitation spreading within the catchment. Figures 6, 7, 8, 9 illustrate the monthly precipitation distribution for a grid with spatial resolution 2*2 km^2, with 162 pixels to represent the areal mean monthly precipitation over Haffouz catchment from 2000 to 2018. Both interpolation methods of observed precipitation indicated similar spatial distribution with a difference of about 1 mm/month (Figs. 6 and 7). Results show that the spatial precipitation pattern for wet months (months of December to March) is correlated with the topography as rainfall is more abundant in the northeast characterized by the highest altitude. It is also explained by the sub-humid climate in the northeastern part. Further, there is an overall decreasing gradient from northeast to southwest. The rainiest months are January, April, and December with a precipitation higher than 57 mm/month. The driest months are July and June.

The CHIRPS product has 27 pixels over the entire Haffouz basin. Monthly CHIRPS precipitations for each pixel are similar as interpolated observed precipitation with a slight difference of 10 mm/month (Fig. 8). The rainfall follows an upstream–downstream gradient, in this context, (Kingumbi 1997) showed that precipitation in the Merguellil watershed (with Haffouz as a sub-basin) follows a rainfall gradient of 20 mm per 100 m of altitude.

Precipitation is more abundant during January and February, respectively. In addition, it is noted that precipitation increases with altitude but does not reproduce the same spatial distribution patterns on the highest altitudes. Thus, an underestimation is noted in the northeast part. In this regard, several researchers in different regions of the world have tested the CHIRPS product under similar climatic conditions. This research showed that the performance of CHIRPS can differ from one region to another, while also showing its capability to be a tool for monitoring and assessing dry and wet conditions (Eltazarov et al. 2021; Paredes-Trejo et al. 2017; Rivera et al. 2019).

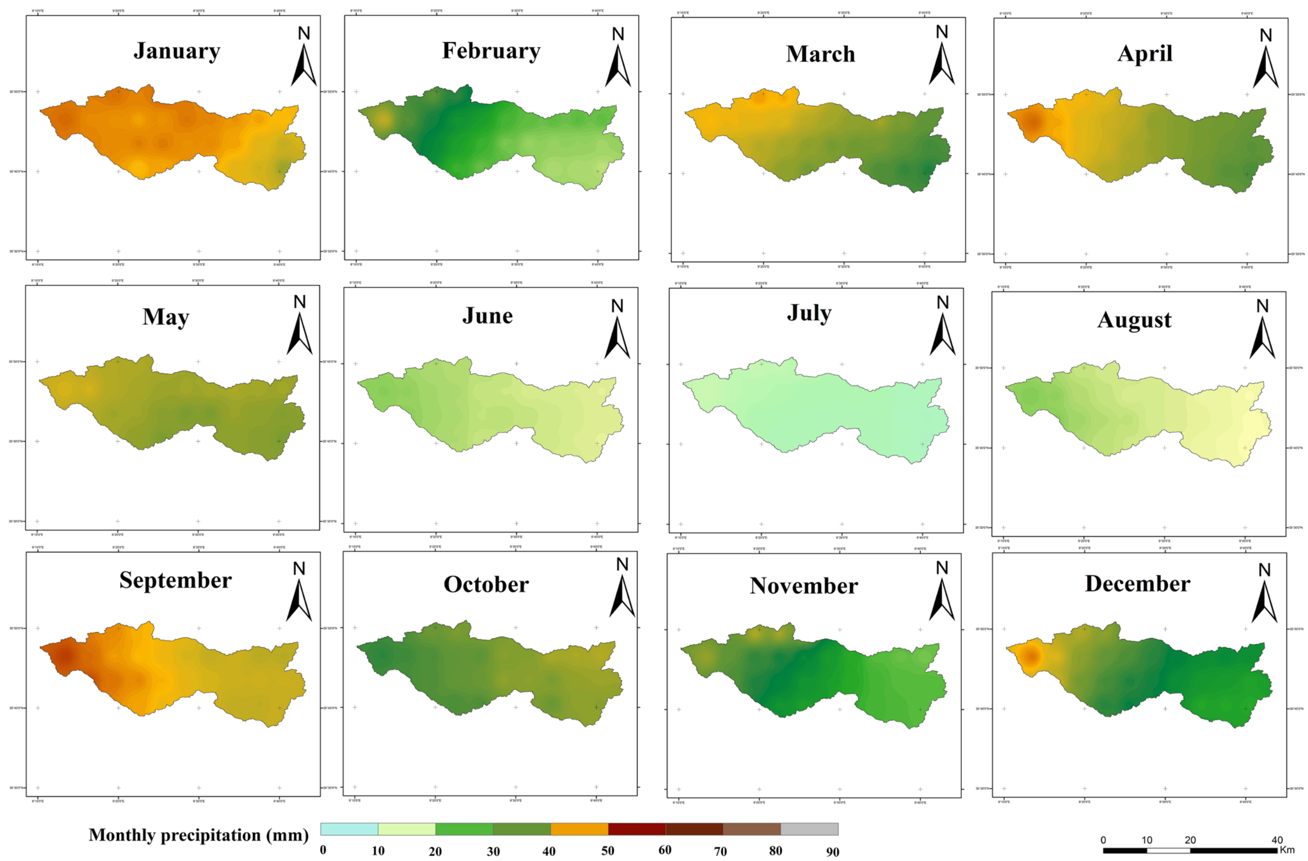


Fig. 8 Spatial distributions of CHIRPS precipitation for the period of 2000–2018 in the Haffouz catchment

PERSIANN has a higher spatial resolution with 40 pixels compared to CHIRPS. The spatial pattern going from the northeast to southwest of the basin is still represented but with lesser contrast. An overestimation is observed for all months with a maximum difference of 46 mm in September in the northern part of the catchment (Fig. 9). For the wet months, there is a strong overestimation in the downstream region and the south part ranging from 25 to 40 mm depending on the month. During the summer months June to August, there is an overestimation over the entire basin with a maximum of 25 mm in August. The spatial distribution over the catchment was not representative and indicated an overall overestimation. Similar studies using PERSIANN reported that its performance is rather poor over the regions with high elevation (de Brito et al. 2022; Singh et al. 2022; Suliman et al. 2020).

Conclusion

In this study, we compared and evaluated three satellite precipitation products and a reanalysis with a high spatiotemporal resolution which are CHIRPS, PERSIANN, ERA5, and GPM. These products were assessed using observed data from 12 rain gauging stations located in semiarid region in central Tunisia for the period from September 2000 to August 2018. These products have been evaluated for temporal scale, at daily, monthly, and yearly scales and for spatial scale. Before the comparison of the satellite-based precipitation estimations, two methods of interpolation inverse distance weighting (IDW) and ordinary kriging (OK) were used to calculate the ground-reference areal precipitation over the watershed. Both methods reproduced similar precipitations for Haffouz catchment based on validation with three observed rain gauges with different altitude locations. The abilities of the three different satellite precipitation products and a reanalysis to replicate the observed precipitations are very different. CHIRPS showed the most satisfactory results for all time steps and for both spatial scales, followed by PERSIANN at the monthly and yearly scales, and by GPM product at the daily and monthly scales. ERA5 showed a very good performance temporally, but in this case, it cannot be evaluated due to its low spatial resolution in the catchment. GPM performed poorly with a high underestimation over the entire catchment at monthly time scale. Although

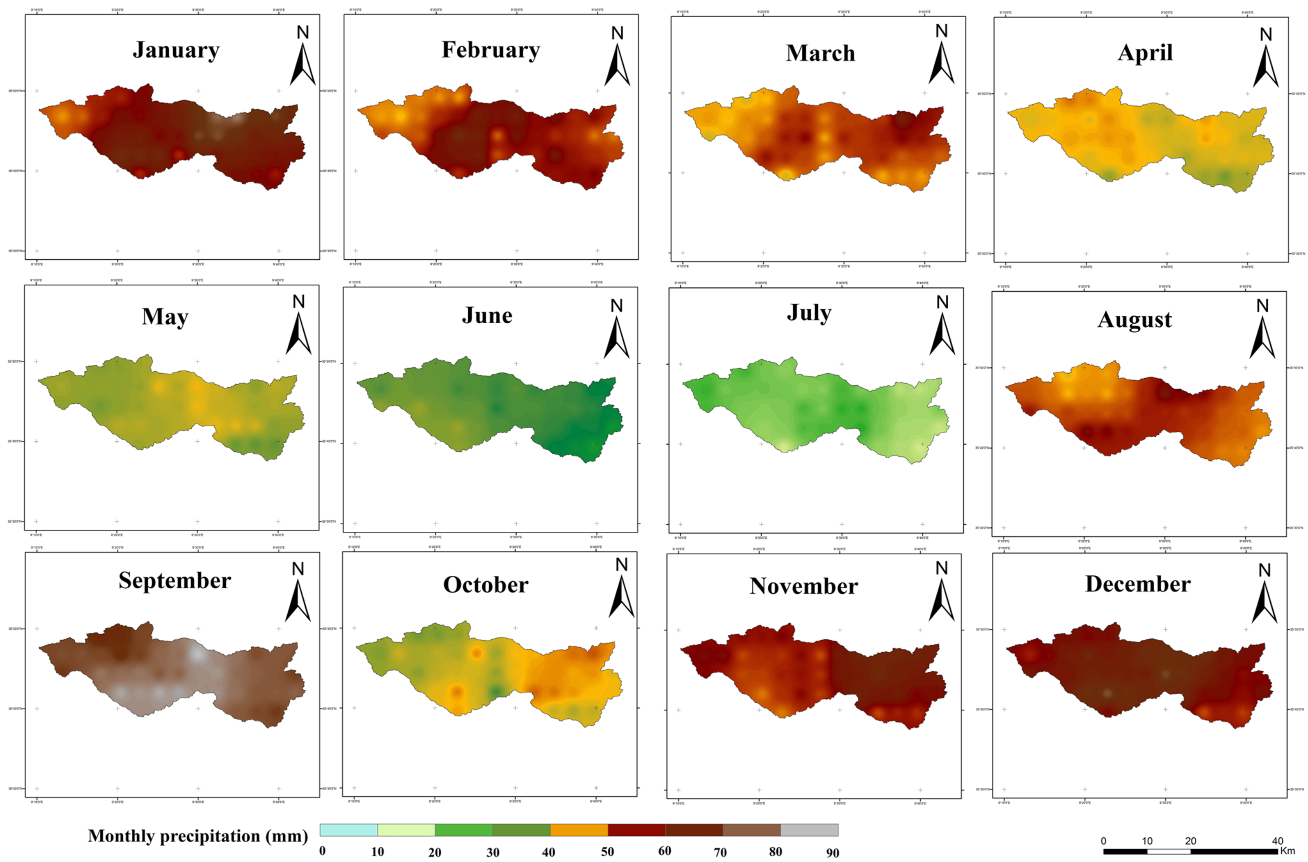


Fig. 9 Spatial distributions of PERSIANN precipitation for the period of 2000–2018 in the Haffouz catchment

some satellite products have a high spatial resolution, they cannot reproduce precipitation well, such as PERSIANN which showed a poorer spatial distribution compared to other products. But, others like ERA5 showed a better performance even with two grids only over the entire watershed. Thus, the performance of precipitation reproduction is not necessarily related to the spatial resolution of the product. The performances of satellite precipitation products are affected by rain gauge network, topography, and the climate. It should be noted that arid and semiarid regions are characterized by short rainfall events that may impact the satellite precipitation products.

The obtained results may provide insights into the performance of different satellite-based precipitation products in ungauged arid and semiarid areas. These products are of high importance for hydrological modeling and water resource management in these regions of the world.

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Data availability All data used in the study are available upon request from the first author.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

References

Abd Elhamid AMI, Eltahan AMH, Mohamed LME, Hamouda IA (2020) Assessment of the two satellite-based precipitation products TRMM and RFE rainfall records using ground based measurements. Alex Eng J 59(2):1049–1058. https://doi.org/10.1016/j.aej.2020.03.035

Aouissi J, Benabdallah S, Lili Chabaâne Z, Cudennec C (2018) Valuing scarce observation of rainfall variability with flexible semi-distributed hydrological modelling – Mountainous Mediterranean context. Sci Total Environ 643:346–356. https://doi.org/10.1016/j.scitotenv.2018.06.086

Beck HE, van Dijk AIJM, Levizzani V, Schellekens J, Miralles DG, Martens B, de Roo A (2017) MSWEP: 3-hourly 0.25 global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. Hydrol Earth Syst Sci 21(1):589–615. https://doi.org/10.5194/hess-21-589-2017

Behrangi A, Khakbaz B, Jaw TC, AghaKouchak A, Hsu K, Sorooshian S (2011) Hydrologic evaluation of satellite precipitation products over a mid-size basin. J Hydrol 397(3–4):225–237. https://doi.org/10.1016/j.jhydrol.2010.11.043

Berg P, Norin L, Olsson J (2016) Creation of a high resolution precipitation data set by merging gridded gauge data and radar observations for Sweden. J Hydrol 541:6–13. https://doi.org/10.1016/j.jhydrol.2015.11.031

Berges J-C (2019) GPM, le programme *Global Precipitation Measurement* (NASA/JAXA)—fondements théoriques et accès à la base de données. Climatologie 16:23–51. https://doi.org/10.4267/climatologie.1374

Bouaziz M, Medhioub E, Csaplovisc E (2021) A machine learning model for drought tracking and forecasting using remote precipitation data and a standardized precipitation index from arid regions. J Arid Environ 189:104478. https://doi.org/10.1016/j.jaridenv.2021.104478

Brocca L, Filippucci P, Hahn S, Ciabatta L, Massari C, Camici S, Schüller L, Bojkov B, Wagner W (2019) SM2RAIN–ASCAT (2007–2018): global daily satellite rainfall data from ASCAT soil moisture observations. Earth Syst Sci Data 11(4):1583–1601. https://doi.org/10.5194/essd-11-1583-2019

Cantoni E, Tramblay Y, Grimaldi S, Salamon P, Dakhlaoui H, Dezetter A, Thiemig V (2022) Hydrological performance of the ERA5 reanalysis for flood modeling in Tunisia with the LISFLOOD and GR4J models. J Hydrol Reg Stud 42:101169. https://doi.org/10.1016/j.ejrh.2022.101169

Chargui S, Cudennec C, Slimani M, Pouget JC, Aouissi J (2009) Robust and flexible hydroinformatics to account for rainfall space–time variability in a data-sparse region. In: Proc. of Symposium HS.2 at the Joint IAHS & IAH Convention, Hyderabad, India, September 2009. IAHS Publ. 333, pp 295–299

Chargui S, Slimani M, Cudennec C (2013) Statistical distribution of rainy events characteristics and instantaneous hyetographs generation (Merguellil watershed in central Tunisia). Arab J Geosci 6(5):1581–1590. https://doi.org/10.1007/s12517-011-0440-2

Chen H, Yong B, Gourley JJ, Liu J, Ren L, Wang W, Hong Y, Zhang J (2019) Impact of the crucial geographic and climatic factors on the input source errors of GPM-based global satellite precipitation estimates. J Hydrol 575:1–16. https://doi.org/10.1016/j.jhydrol.2019.05.020

Chiaravalloti F, Brocca L, Procopio A, Massari C, Gabriele S (2018) Assessment of GPM and SM2RAIN-ASCAT rainfall products over complex terrain in southern Italy. Atmos Res 206:64–74. https://doi.org/10.1016/j.atmosres.2018.02.019

Cudennec C, Slimani M, le Goulven P (2005) Accounting for sparsely observed rainfall space—time variability in a rainfall—runoff model of a semiarid Tunisian basin/Prise en compte d'observations peu denses de la variabilité spatiotemporelle de la pluie dans une modélisation pluie—débit d'un bassin semi-aride Tunissien. Hydrol Sci J 50(4):4. https://doi.org/10.1623/hysj.2005.50.4.617

da Silva ASA, Stosic B, Menezes RSC, Singh VP (2019) Comparison of interpolation methods for spatial distribution of monthly precipitation in the state of pernambuco. Brazil J Hydrol Eng 24(3):04018068. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001743

de Brito CS, da Silva RM, Santos CAG, Brasil Neto RM, Coelho VHR (2022) Long-term basin-scale comparison of two high-resolution satellite-based remote sensing datasets for assessing rainfall and erosivity in a basin in the Brazilian semiarid region. Theoret Appl Climatol 147(3–4):1049–1064. https://doi.org/10.1007/s00704-021-03857-w

Dhib S, Mannaerts CM, Bargaoui Z, Retsios V, Maathuis BHP (2017) Evaluating the MSG satellite Multi-sensor precipitation estimate for extreme rainfall monitoring over northern Tunisia. Weather Clim Extremes 16:14–22. https://doi.org/10.1016/j.wace.2017.03.002

Dhib S, Chaney N, Mannaerts CM, Bargaoui Z (2021) Comparison of two bias correction methods for TRMM 3B42 satellite daily rainfall estimates over northern TUNISIA. Arab J Geosci 14(7):626. https://doi.org/10.1007/s12517-021-06916-8

Di Piazza A, Conti FL, Noto LV, Viola F, La Loggia G (2011) Comparative analysis of different techniques for spatial interpolation of rainfall data to create a serially complete monthly time series of precipitation for SICILY, Italy. Int J Appl Earth Obs Geoinf 13(3):396–408. https://doi.org/10.1016/j.jag.2011.01.005

Eini MR, Rahmati A, Piniewski M (2022) Hydrological application and accuracy evaluation of PERSIANN satellite-based precipitation estimates over a humid continental climate catchment. J Hydrol Reg Stud 41:101109. https://doi.org/10.1016/j.ejrh.2022.101109

Eltazarov S, Bobojonov I, Kuhn L, Glauben T (2021) Mapping weather risk—a multi-indicator analysis of satellite-based weather data for agricultural index insurance development in semi-arid and arid zones of central Asia. Clim Serv 23:100251. https://doi.org/10.1016/j.cliser.2021.100251

Fehri R, Khlifi S, Vanclooster M (2020) Testing a citizen science water monitoring approach in Tunisia. Environ Sci Policy 104:67–72. https://doi.org/10.1016/j.envsci.2019.11.009

Funk C, Peterson P, Landsfeld M, Pedreros D, Verdin J, Shukla S, Husak G, Rowland J, Harrison L, Hoell A, Michaelsen J (2015) The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data 2(1):150066. https://doi.org/10.1038/sdata.2015.66

Gebere S, Alamirew T, Merkel B, Melesse A (2015) Performance of high resolution satellite rainfall products over data scarce parts of eastern Ethiopia. Remote Sens 7(9):11639–11663. https://doi.org/10.3390/rs70911639

Guermazi E, Milano M, Reynard E (2019) Performance evaluation of satellite-based rainfall products on hydrological modeling for a transboundary catchment in northwest Africa. Theoret Appl Climatol 138(3–4):1695–1713. https://doi.org/10.1007/s00704-019-02928-3

Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, Nicolas J, Peubey C, Radu R, Schepers D, Simmons A, Soci C, Abdalla S, Abellan X, Balsamo G, Bechtold P, Biavati G, Bidlot J, Bonavita M, Thépaut J (2020) The ERA5 global reanalysis. Q J R Meteorol Soc 146(730):1999–2049. https://doi.org/10.1002/qj.3803

Hsu J, Huang W-R, Liu P-Y (2021) Performance assessment of GPM-based near-real-time satellite products in depicting diurnal precipitation variation over Taiwan. J Hydrol Reg Stud 38:100957. https://doi.org/10.1016/j.ejrh.2021.100957

Hussain Y, Satgé F, Hussain MB, Martinez-Carvajal H, Bonnet M-P, Cárdenas-Soto M, Roig HL, Akhter G (2018) Performance of CMORPH, TMPA, and PERSIANN rainfall datasets over plain, mountainous, and glacial regions of Pakistan. Theoret Appl Climatol 131(3–4):1119–1132. https://doi.org/10.1007/s00704-016-2027-z

Islam MdA, Yu B, Cartwright N (2020) Assessment and comparison of five satellite precipitation products in Australia. J Hydrol 590:125474. https://doi.org/10.1016/j.jhydrol.2020.125474

Jebari S, Berndtsson R, Bahri A, Boufaroua M (2008) Exceptional rainfall characteristics related to erosion risk in semiarid Tunisia. Open Hydrol J 2(1):25–33. https://doi.org/10.2174/1874378100802010025

Jiang S, Ren L, Hong Y, Yong B, Yang X, Yuan F, Ma M (2012) Comprehensive evaluation of multi-satellite precipitation products with a dense rain gauge network and optimally merging their simulated hydrological flows using the Bayesian model averaging method. J

Hydrol 452–453:213–225. https://doi.org/10.1016/j.jhydrol.2012.05.055

Jiang S, Zhou M, Ren L, Cheng X, Zhang P (2016) Evaluation of latest TMPA and CMORPH satellite precipitation products over yellow river basin. Water Sci Eng 9(2):87–96. https://doi.org/10.1016/j.wse.2016.06.002

Jiao D, Xu N, Yang F, Xu K (2021) Evaluation of spatial-temporal variation performance of ERA5 precipitation data in China. Sci Rep 11(1):17956. https://doi.org/10.1038/s41598-021-97432-y

Katsanos D, Retalis A, Michaelides S (2016) Validation of a high-resolution precipitation database (CHIRPS) over Cyprus for a 30-year period. Atmos Res 169:459–464. https://doi.org/10.1016/j.atmosres.2015.05.015

Kidd C (2001) Satellite rainfall climatology: a review. Int J Climatol 21(9):1041–1066. https://doi.org/10.1002/joc.635

Kingumbi A (1997) Caractérisation morphométrique du bassin versant du Merguellil : application à la simulation des écoulements de surface et à l'érosion. Thesis, Tunis National School of Engineering, p 96

Kumar M, Hodnebrog Ø, Sophie Daloz A, Sen S, Badiger S, Krishnaswamy J (2021) Measuring precipitation in Eastern Himalaya: ground validation of eleven satellite, model and gauge interpolated gridded products. J Hydrol 599:126252. https://doi.org/10.1016/j.jhydrol.2021.126252

Lahoz WA, De Lannoy GJM (2014) Closing the gaps in Our knowledge of the hydrological cycle over land: conceptual problems. Surv Geophys 35(3):623–660. https://doi.org/10.1007/s10712-013-9221-7

Lavers DA, Simmons A, Vamborg F, Rodwell MJ (2022) An evaluation of ERA5 precipitation for climate monitoring. Q J R Meteorol Soc 148(748):3152–3165. https://doi.org/10.1002/qj.4351

Lettenmaier DP (2017) Observational breakthroughs lead the way to improved hydrological predictions: observational breakthroughs in hydrology. Water Resour Res 53(4):2591–2597. https://doi.org/10.1002/2017WR020896

Levizzani V, Cattani E (2019) Satellite remote sensing of precipitation and the terrestrial water cycle in a changing climate. Remote Sens 11(19):2301. https://doi.org/10.3390/rs11192301

Li J, Heap AD (2008) A review of spatial interpolation methods for environmental scientists. Geoscience Australia, Record 2008/23, p 137

Li J, Heap AD (2014) Spatial interpolation methods applied in the environmental sciences: a review. Environ Model Softw 53:173–189. https://doi.org/10.1016/j.envsoft.2013.12.008

Li Z, Yang D, Gao B, Jiao Y, Hong Y, Xu T (2015) Multiscale Hydrologic applications of the latest satellite precipitation products in the yangtze river basin using a distributed hydrologic model. J Hydrometeorol 16(1):407–426. https://doi.org/10.1175/JHM-D-14-0105.1

Longo-Minnolo G, Vanella D, Consoli S, Pappalardo S, Ramírez-Cuesta JM (2022) Assessing the use of ERA5-Land reanalysis and spatial interpolation methods for retrieving precipitation estimates at basin scale. Atmos Res 271:106131. https://doi.org/10.1016/j.atmosres.2022.106131

Maggioni V, Meyers PC, Robinson MD (2016) A review of merged high-resolution satellite precipitation product accuracy during the tropical rainfall measuring mission (TRMM) era. J Hydrometeorol 17(4):1101–1117. https://doi.org/10.1175/JHM-D-15-0190.1

Medhioub E, Bouaziz M, Achour H, Bouaziz S (2019) Monthly assessment of TRMM 3B43 rainfall data with high-density gauge stations over Tunisia. Arab J Geosci 12(2):15. https://doi.org/10.1007/s12517-018-4155-5

Meydani A, Dehghanipour A, Schoups G, Tajrishy M (2022) Daily reservoir inflow forecasting using weather forecast downscaling and rainfall-runoff modeling : application to Urmia Lake basin. Iran J Hydrol Reg Stud 44:101228. https://doi.org/10.1016/j.ejrh.2022.101228

Moges DM, Kmoch A, Uuemaa E (2022) Application of satellite and reanalysis precipitation products for hydrological modeling in the data-scarce Porijõgi catchment. Estonia J Hydrol Reg Stud 41:101070. https://doi.org/10.1016/j.ejrh.2022.101070

Moreno M, Bertolín C, Ortiz P, Ortiz R (2022) Satellite product to map drought and extreme precipitation trend in Andalusia, Spain: a novel method to assess heritage landscapes at risk. Int J Appl Earth Obs Geoinf 110:102810. https://doi.org/10.1016/j.jag.2022.102810

Narulita I, Fajary FR, Mulyono A, Kusratmoko E, Djuwansah MR (2021) Application of climate hazards group infrared precipitation with station (chirps) satellite data for drought mitigation in bintan island, Indonesia. IOP Conf Ser Earth Environ Sci 789(1):012052. https://doi.org/10.1088/1755-1315/789/1/012052

Navarro A, García-Ortega E, Merino A, Sánchez JL, Tapiador FJ (2020) Orographic biases in IMERG precipitation estimates in the Ebro River basin (Spain): the effects of rain gauge density and altitude. Atmos Res 244:105068. https://doi.org/10.1016/j.atmosres.2020.105068

Nguyen P, Ombadi M, Sorooshian S, Hsu K, AghaKouchak A, Braithwaite D, Ashouri H, Thorstensen AR (2018) The PERSIANN family of global satellite precipitation data: a review and evaluation of products. Hydrol Earth Syst Sci 22(11):5801–5816. https://doi.org/10.5194/hess-22-5801-2018

Nguyen P, Shearer EJ, Tran H, Ombadi M, Hayatbini N, Palacios T, Huynh P, Braithwaite D, Updegraff G, Hsu K, Kuligowski B, Logan WS, Sorooshian S (2019) The CHRS data portal, an easily accessible public repository for PERSIANN global satellite precipitation data. Scientific Data 6(1):180296. https://doi.org/10.1038/sdata.2018.296

Ning S, Song F, Udmale P, Jin J, Thapa BR, Ishidaira H (2017) Error analysis and evaluation of the latest GSMap and IMERG precipitation products over eastern china. Adv Meteorol 2017:1–16. https://doi.org/10.1155/2017/1803492

Omar GM, Paturel J-E, Salles C, Mahé G, Jalludin M, Satgé F, Nour MI (2023) Evaluation of rainfall products in semi-arid areas: application to the southeast of the republic of Djibouti and a focus on the ambouli catchment. Water 15(12):2168. https://doi.org/10.3390/w15122168

Omonge P, Feigl M, Olang L, Schulz K, Herrnegger M (2022) Evaluation of satellite precipitation products for water allocation studies in the Sio-Malaba-Malakisi river basin of East Africa. J Hydrol Reg Stud 39:100983. https://doi.org/10.1016/j.ejrh.2021.100983

Paredes-Trejo FJ, Barbosa HA, Lakshmi Kumar TV (2017) Validating CHIRPS-based satellite precipitation estimates in Northeast Brazil. J Arid Environ 139:26–40. https://doi.org/10.1016/j.jaridenv.2016.12.009

Rachdane M, Khalki EME, Saidi ME, Nehmadou M, Ahbari A, Tramblay Y (2022) Comparison of high-resolution satellite precipitation products in sub-saharan morocco. Water 14(20):3336. https://doi.org/10.3390/w14203336

Ramadhan R, Marzuki M, Yusnaini H, Muharsyah R, Suryanto W, Sholihun S, Vonnisa M, Battaglia A, Hashiguchi H (2022) Capability of GPM IMERG products for extreme precipitation analysis over the Indonesian maritime continent. Remote Sens 14(2):412. https://doi.org/10.3390/rs14020412

Rivera JA, Marianetti G, Hinrichs S (2018) Validation of CHIRPS precipitation dataset along the central Andes of Argentina. Atmos Res 213:437–449. https://doi.org/10.1016/j.atmosres.2018.06.023

Rivera JA, Hinrichs S, Marianetti G (2019) Using CHIRPS dataset to assess wet and dry conditions along the semiarid central-western Argentina. Advances in Meteorology 2019:1–18. https://doi.org/10.1155/2019/8413964

Saouabe T, El Khalki EM, Saidi MEM, Najmi A, Hadri A, Rachidi S, Jadoud M, Tramblay Y (2020) Evaluation of the GPM-IMERG precipitation product for flood modeling in a semi-arid mountainous basin in morocco. Water 12(9):2516. https://doi.org/10.3390/w12092516

Scheel MLM, Rohrer M, Huggel Ch, Santos Villar D, Silvestre E, Huffman GJ (2011) Evaluation of TRMM Multi-satellite precipitation analysis (TMPA) performance in the central Andes region and its dependency on spatial and temporal resolution. Hydrol Earth Syst Sci 15(8):2649–2663. https://doi.org/10.5194/hess-15-2649-2011

Sheffield J, Wood EF, Pan M, Beck H, Coccia G, Serrat-Capdevila A, Verbist K (2018) Satellite remote sensing for water resources management: potential for supporting sustainable development in data-poor regions. Water Resour Res 54(12):9724–9758. https://doi.org/10.1029/2017WR022437

Shi J, Bao Z, Zhang J, Liu C, Jin J, Liu Y, Wang G (2022) Comparison of the performance of IMERG products and interpolation-based precipitation estimates in the middle reaches of yellow river basin. Water 14(9):1503. https://doi.org/10.3390/w14091503

Singh VG, Singh SK, Kumar N, Kumar P, Gupta PK, Singh PK, Gašparović M, Ray RL, Saito O (2022) Water accounting using satellite products and water accounting plus framework in a semi-arid betwa river basin. India Water 14(21):3473. https://doi.org/10.3390/w14213473

Slimani M, Cudennec C, Feki H (2007) Structure du gradient pluviométrique de la transition Méditerranée-Sahara en Tunisie : déterminants géographiques et saisonnalité/*structure of the rainfall gradient in the Mediterranean-Sahara transition in Tunisia: geographical determinants and seasonality*. Hydrol Sci J 52(6):1088–1102. https://doi.org/10.1623/hysj.52.6.1088

Smith EA, Asrar G, Furuhama Y, Ginati A, Mugnai A, Nakamura K, Adler RF, Chou MD, Desbois M, Durning JF, Entin JK, Einaudi F, Ferraro RR, Guzzi R, Houser PR, Hwang PH, Iguchi T, Joe P, Kakar R, Zhang W (2007) International Global Precipitation Measurement (GPM) Program and Mission: An Overview. In Levizzani V, Bauer P, Turk FJ (Éds.), *Measuring Precipitation From Space* (p. 611-653). Springer, Netherlands. https://doi.org/10.1007/978-1-4020-5835-6_48

Sorooshian S, Hsu K-L, Gao X, Gupta HV, Imam B, Braithwaite D (2000) Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. Bull Am Meteor Soc 81(9):2035–2046. https://doi.org/10.1175/1520-0477(2000)081%3c2035:EOPSSE%3e2.3.CO;2

Stisen S, Tumbo M (2015) Interpolation of daily raingauge data for hydrological modelling in data sparse regions using pattern information from satellite data. Hydrol Sci J. https://doi.org/10.1080/02626667.2014.992789

Suliman AHA, Awchi TA, Al-Mola M, Shahid S (2020) Evaluation of remotely sensed precipitation sources for drought assessment in Semi-Arid Iraq. Atmos Res 242:105007. https://doi.org/10.1016/j.atmosres.2020.105007

Sun Q, Miao C, Duan Q, Ashouri H, Sorooshian S, Hsu K (2018) A Review of global precipitation data sets: data sources, estimation, and intercomparisons. Rev Geophys 56(1):79–107. https://doi.org/10.1002/2017RG000574

Teegavarapu RSV, Meskele T, Pathak CS (2012) Geo-spatial grid-based transformations of precipitation estimates using spatial interpolation methods. Comput Geosci 40:28–39. https://doi.org/10.1016/j.cageo.2011.07.004

Tramblay Y, Thiemig V, Dezetter A, Hanich L (2016) Evaluation of satellite-based rainfall products for hydrological modelling in Morocco. Hydrol Sci J 61(14):2509–2519. https://doi.org/10.1080/02626667.2016.1154149

Wang S, Huang GH, Lin QG, Li Z, Zhang H, Fan YR (2014) Comparison of interpolation methods for estimating spatial distribution of precipitation in Ontario, Canada: comparison of interpolation methods for precipitation distribution. Int J Climatol 34(14):3745–3751. https://doi.org/10.1002/joc.3941

Yu L, Leng G, Python A (2022) A comprehensive validation for GPM IMERG precipitation products to detect extremes and drought over mainland China. Weather Clim Extremes 36:100458. https://doi.org/10.1016/j.wace.2022.100458

Zhang Q, Shi P, Singh VP, Fan K, Huang J (2017) Spatial downscaling of TRMM-based precipitation data using vegetative response in Xinjiang, China: spatial downscaling of TRMM-based precipitation data. Int J Climatol 37(10):3895–3909. https://doi.org/10.1002/joc.4964