University of Tehran Press

Online Issn: 475-2345X

DESERT

Home page: https://jdesert.ut.ac.ir/

Evaluating the Accuracy of Precipitation Products Over Utah, United States Using the Google Earth Engine Platform

Hadi Shokati[1*], Mahmoud Mashal[1], Ali Akbar Noroozi[2], Saham Mirzaei[3]

[1] Department of Water Engineering, University of Tehran, Tehran, Iran. Email: hadi.shokati@ut.ac.ir
[2] Soil Conservation and Watershed Management Research Institute, Agricultural Research, Education and Extension Organization (AREEO), Tehran, Iran.
[3] Institute of Methodologies for Environmental Analysis (CNR-IMAA), Rome, Italy.

Article Info.	ABSTRACT

Article type:
Research Article

Article history:
Received: 26 Jan. 2023
Received in revised from: 07 May 2023
Accepted: 19 May 2023
Published online: 27 June 2023

Keywords:
CHIRPS,
ERA5,
Google Earth Engine,
GPM, PERSIANN-CDR,
TRMM.

Satellite-based precipitation missions can be used to estimate precipitation distribution, especially in areas where there are no rain gauging stations. Nevertheless, these products are still less used because of the lack of accuracy evaluation. This study evaluates the monthly rainfall values of five satellite precipitation products, including ERA5, GPM, CHIRPS, TRMM 3B43, and PERSIANN-CDR, at eight rain gauge networks over the Utah, United States using Google Earth Engine platform (GEE). For this purpose, different validating indices such as R^2, RMSE, and MAE were used to evaluate the accuracy of mentioned products from 2009 to 2019. The results showed that CHIRPS outperformed other rainfall products in this region with an R^2 value of 0.63. ERA5 ranked second with an R^2 of 0.6, and GPM, TRMM, and PERSIANN-CDR were in the subsequent ranks with R^2 values of 0.53, 0.52, and 0.32, respectively. The results also indicated that spatial resolution is directly related to the accuracy of the results. CHIRPS rainfall product had the highest spatial resolution (0.05°) among all studied products, which led to the most reliable results. On the other hand, the lowest spatial resolutions belonged to TRMM and PERSIANN-CDR (0.25°), which resulted in the weakest results. The results also revealed that the ERA5 precipitation product was more influenced by elevation, longitude, and rainfall factors than other products.

Cite this article: Shokati, H., Mashal, M., Noroozi, A.A., Mirzaei, S. (2023). Evaluating the Accuracy of Precipitation Products Over Utah, United States Using the Google Earth Engine Platform. DESERT, 28 (1), DOI:10.22059/jdesert.2023.93548

1. Introduction

Precipitation is a crucial parameter in the water cycle, which makes an important contribution to hydrological, meteorological, and ecological studies (Tang *et al.*, 2016; He *et al*., 2022). Therefore, factors such as soil moisture, vegetation distribution, and surface runoff are influenced by the spatial and temporal distribution of precipitation (Goodrich *et al*., 1995 and Li and Shao., 2010). Accurately estimating rainfall helps to better manage water resources and predict natural hazards such as droughts and floods (Arnaud *et al.*, 2002; Vischel and Lebel, 2007 and Tramblay *et al*., 2011). The amount of precipitation is recorded and presented by meteorological stations. But still many regions of the world are not equipped with these stations or the spatial distribution of these stations is low. On the other hand, data recorded by ground stations show only precipitation in the vicinity of the instruments (Collischonn *et al*., 2008; Bohnenstengel *et al*., 2011). However, the spatial distribution of precipitation is different. Therefore, interpolation of precipitation from ground stations, especially in poorly gauged areas, will not achieve the desired accuracy, and as a result hydrologic modelling may be unreliable.

With the advancement of remote sensing technology, various meteorological satellites have been made available for more accurate estimation of precipitation (Michaelides *et al.*, 2009). One of the advantages of satellite-based precipitation measurement is the ease of access to the data, which makes it possible to retrieve precipitation data on a large scale (Kidd and Levizzani., 2011). This accessibility, coupled with the efficient computational capabilities of Generalized Estimating Equations (GEE), enables researchers and practitioners to analyze time series data with remarkable efficiency. GEE offers significant time-saving advantages by swiftly handling the complex calculations involved in such analyses, ultimately resulting in reduced data processing time and enhanced productivity (Mansourmoghaddam *et al.*, 2022).

Some of the most commonly used precipitation products are the ECMWF[1] ERA5 reanalysis dataset (C3S[2], 2017), the Precipitation Estimation from Remotely-Sensed Information using Artificial Neural Networks-Climate Record (PERSIANN-CDR) (Hsu *et al.*, 1997), the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) (Funk *et al.*, 2015), the Tropical Rainfall Measuring Mission (TRMM) (Huffman *et al.*, 2007), and the Global Precipitation Mission (GPM) (Hou *et al.*, 2014). Several studies have been conducted to evaluate the accuracy of these precipitation products. Saeidzand *et al.* (2018) evaluated the performance of the monthly CHIRPS precipitation product using in situ data at different stations in Iran between 2005 and 2014. The results showed that the CHIRPS generally overestimated the amount of precipitation, although the correlation was reliable at the 0.01 significance level. However, this result varied by time and location. Kolios and Kalimeris (2020) evaluated the accuracy of the monthly TRMM rainfall product in estimating rainfall patterns in the central Mediterranean from 1998 to 2017. They concluded that the accuracy of TRMM depends on altitude and precipitation amount, so that it overestimates at higher altitudes and underestimates in regions with high precipitation. Cao *et al.* (2018) demonstrated the effects of land cover on the accuracy of TRMM 3B43. They showed that TRMM 3B43 had the best performance over cropland and urban areas and the lowest accuracy over forests and water bodies. Vega-Duran *et al* (2021) compared the accuracy of monthly MERRA2 and ERA5 reanalysis product in Colombia. They revealed that ERA5 generally produced more accurate results than MERRA2. However, both products consistently overestimate the average monthly precipitation at all times and throughout the study area. Ning *et al.* (2016) found that rainfall amount affects the accuracy of GPM IMERG, so it performed well in estimating the trend of heavy rainfall events. Some

[1] European Centre for Medium-Range Weather Forecast
[2] Copernicus Climate Change Service

researchers like Semire and Mohd-Mokhtar (2016), Tan *et al.* (2015) and Tan *et al.* (2017) have proven that monthly and annual precipitation measurements of satellite precipitation products generally outperform the daily precipitation measurements.

The accuracy of satellite-based and reanalysis precipitation products has been extensively studied worldwide, revealing variations in accuracy across different locations. For instance, while IMERG demonstrates high accuracy on a daily scale in China (Tang *et al.*, 2016), it exhibits only moderate agreement with rain gauge data in the Blue Nile Basin (Sahlu *et al.*, 2016) and Iran (Sharifi *et al.*, 2016). Surprisingly, limited research has compared various precipitation products within a specific region and under diverse conditions, particularly in the United States. Consequently, conducting an initial assessment of these products becomes imperative to understand their performance within a specific area and to facilitate meaningful comparisons before their application. In light of this need, this paper aims to evaluate multiple satellite-based and reanalyzed precipitation products, including ERA5, GPM, CHIRPS, TRMM 3B43, and PERSIANN-CDR, on a monthly scale from June 2009 to June 2019 in the state of Utah, USA. By undertaking this evaluation, we aim to provide valuable insights into the capabilities and limitations of these precipitation products, thereby advancing our understanding of their suitability for various applications in the region.

2. Materials and methods

2.1. Study Area

In this study, the Utah state in the western United States was selected as the study area due to the good accessibility and availability of data (Figure 1). Utah state covers an area of 219,887 Km^2, while elevations in Utah vary widely, ranging from about 664 to 4123 meters (Gilbert *et al.*, 2016). The mountain ranges in the western United States have a significant impact on Utah's climate.

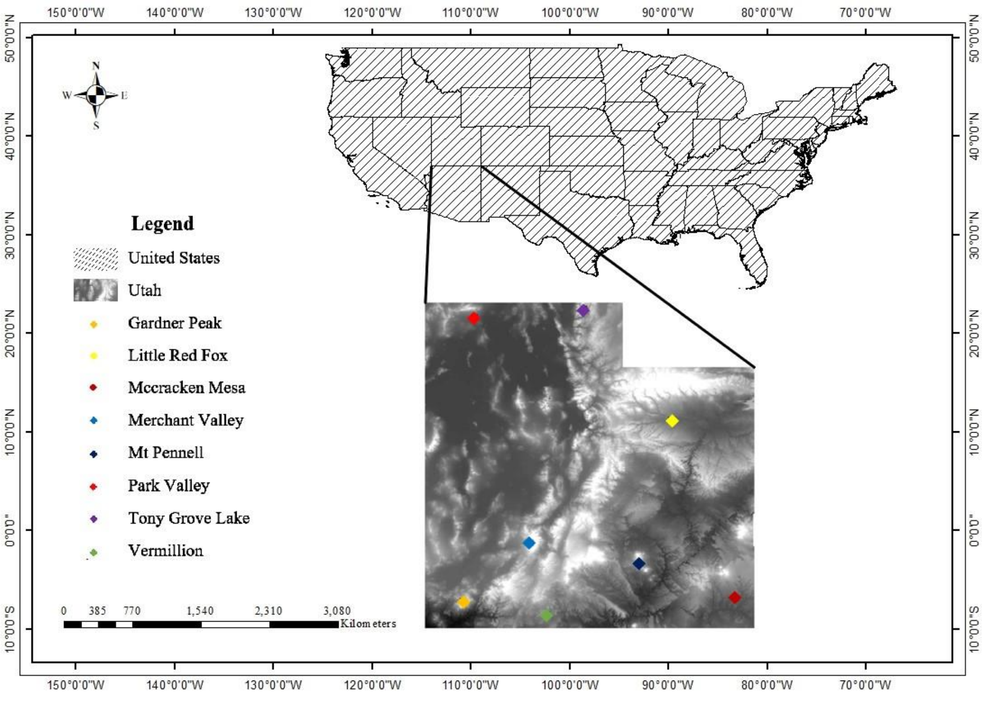

Figure 1. The study area and distribution of rain gauges

The usual air currents emanating from these mountains and reaching Utah are comparatively dry, resulting in light precipitation over most of Utah (Moller and Gillies, 2008). The average annual precipitation in Utah is 353.06 mm, according to Utah historical records from 1950 to 2017 (USDA reports).

2.2. Rain Gauges

Monthly precipitation from eight primary rain gauges from the United States Department of Agriculture (USDA) between June 2009 to June 2019 was selected for this study. We tried to choose rain gauges from different climate conditions across Utah State (see Figure 1 and Table 1). The monthly precipitation of some stations was not available in all the used periods, so we just used the available data of these stations. Figure 2 displays the monthly rainfall patterns for all used rain gauges.

Table 1. Characteristics of the eight rain gauge stations in Utah used for this study (USDA).

Network	Id	Name	Longitude	Latitude	Elevation (ft)	Average annual precipitation (mm)
SNOTEL	1066	Gardner Peak	-113.45988	37.40083	8322	662
SCAN	2155	Little Red Fox	-110.30464	40.17957	5395	224
SCAN	2140	Mccracken Mesa	-109.33776	37.44671	5315	220
SNOTEL	621	Merchant Valley	-112.43637	38.30285	8705	740
SNOTEL	1269	Mt Pennell	-110.79330	37.97793	9209	531
SCAN	2153	Park Valley	-113.28596	41.77318	5098	279
SNOTEL	823	Tony Grove Lake	-111.62957	41.89833	8474	1301
SCAN	2162	Vermillion	-112.19252	37.19061	6392	380

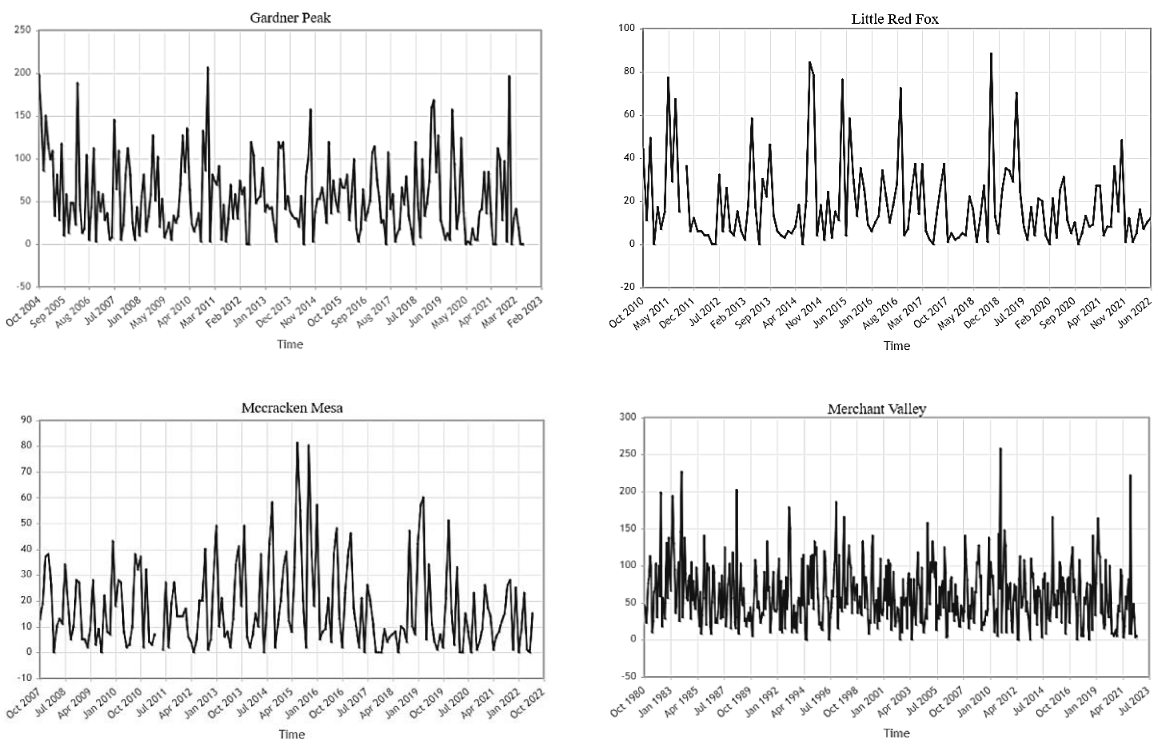

Figure 2. Monthly precipitation values for all used rain gauges (USDA).

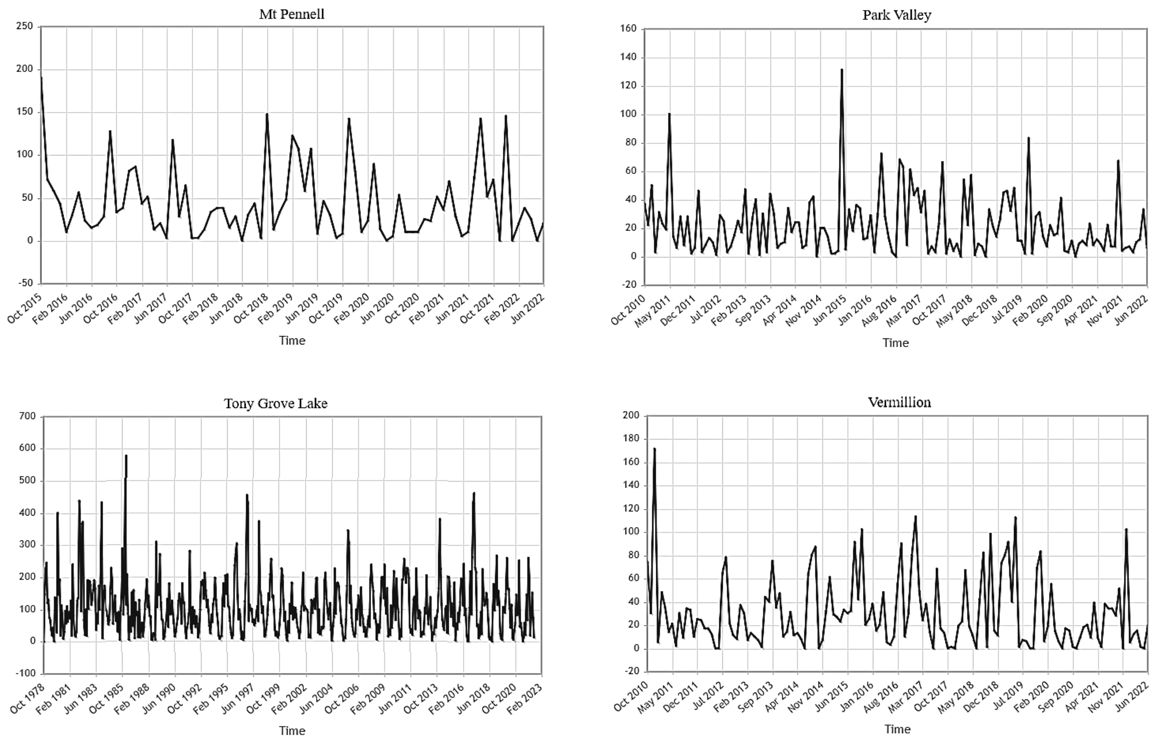

Figure 2. Continued

2.3. Precipitation products

In this paper, five high-resolution precipitation data including ERA5, GPM, CHIRPS, TRMM 3B43 and PERSIANN-CDR were called and evaluated in GEE. Table 2 provides basic spatial and temporal resolution information for all five precipitation products.

Table 2. Summary of used precipitation Products

Product	Spatial Resolution	Temporal Resolution
ERA5	0.25° x 0.25°	Monthly
GPM	0.1° x 0.1°	Monthly
CHIRPS	0.05° x 0.05°	Daily
TRMM 3B43	0.25° x 0.25°	Monthly
PERSIANN-CDR	0.25° x 0.25°	Daily

2.3.1. ERA5

ERA5, the fifth generation of ECMWF atmospheric reanalysis, serves as a comprehensive dataset for global climate analysis. Reanalysis, as a methodology, integrates model data and observations gathered worldwide to construct a dataset that is both globally comprehensive and internally consistent. In this regard, ERA5 supersedes its predecessor, the ERA-Interim reanalysis. ERA5 data encompasses the period from 1979 to the present, offering real-time values up to three months ahead. ERA5 monthly presents aggregated monthly values in 0.25°x0.25° spatial resolution (Noel *et al.*, 2021).

2.3.2. GPM

GPM is an international satellite mission aimed at delivering advanced observations of global precipitation patterns, encompassing both rain and snowfall. The Integrated Multi-satellite Retrievals for GPM (IMERG) serves as a unified algorithm that combines data from various passive-microwave instruments within the GPM Constellation, thereby providing comprehensive estimations of rainfall. In our study, we utilized the GPM IMERG Final Precipitation L3 1 V06 (GPM_3IMERGM) dataset with a spatial resolution of 0.1°x0.1°.

2.3.3. CHIRPS

CHIRPS represents a quasi-global rainfall dataset spanning a period of over 30 years. CHIRPS integrates satellite imagery with a resolution of 0.05° (Funk *et al.,* 2015), along with in-situ station data, to generate gridded time series of rainfall. This dataset is particularly suited for analyzing long-term trends and monitoring seasonal drought conditions. In our study, we employed the CHIRPS daily rainfall product, which we aggregated to obtain monthly values for our analysis.

2.3.4. TRMM 3B43

TRMM 3B43V7 presents 0.1°x 0.1° monthly precipitation data. TRMM 3B43 climatological calibrations remove topographic influences during the fitting process, so terrain elevations do not incredibly affect the TRMM 3B43 product (Bolvin and Huffman, 2015).

2.3.5. PERSIANN-CDR

PERSIANN-CDR is a remotely sensed precipitation product that uses artificial neural networks - climate dataset to represent daily rainfall at 0.25° x 0.25° spatial resolution (Hsu *et al*., 1997). In this paper, we aggregated PERSIANN-CDR daily rainfall product to monthly values on the GEE platform.

2.4. Accuracy evaluation

In this study, we used ERA5, GPM and TRMM 3B43 monthly products along with CHIRPS and PERSIANN-CDR daily products. In the next step, CHIRPS and PERSIANN-CDR daily products were aggregated to monthly values using GEE platform. For the evaluation, the pixels where the rain gauges were located were identified and the monthly rainfall values of all products for these pixels were extracted and compared with the in situ monthly rainfall values. We used three evaluation indices including Root Mean Square Error (RMSE), Coefficient of Determination (R^2) and Mean Absolute Error (MAE) to assess the performance of precipitation products (Shi *et al,* 2015 and Chen *et al,* 2019).

$$R^2 = \frac{\sum_{i=1}^{n}[(P_i-\bar{P})(O_i-\bar{O})]}{\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}} \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \quad (2)$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}|P_i-O_i|}{n} \quad (3)$$

Where P is the precipitation product value and O is the observed precipitation value in the rain gauge. R^2 is used to assess the accuracy of the precipitation product (Zhang *et al,* 2018) and its values range from zero to one. Higher R^2 values indicate high product accuracy. RMSE is used to calculate the deviation between observed and predicted values and MAE is used as a bias index. In general, the products with a higher R^2 and a lower MAE and RMSE are the most accurate.

3. Results and Discussion

In this study, we first assessed the performance of precipitation products in the studied stations (Figures 3 to 7) to choose the best one for every station. In the next step, we evaluated the accuracy of precipitation products to select the most accurate product every month (Table 3). The results are as follows:

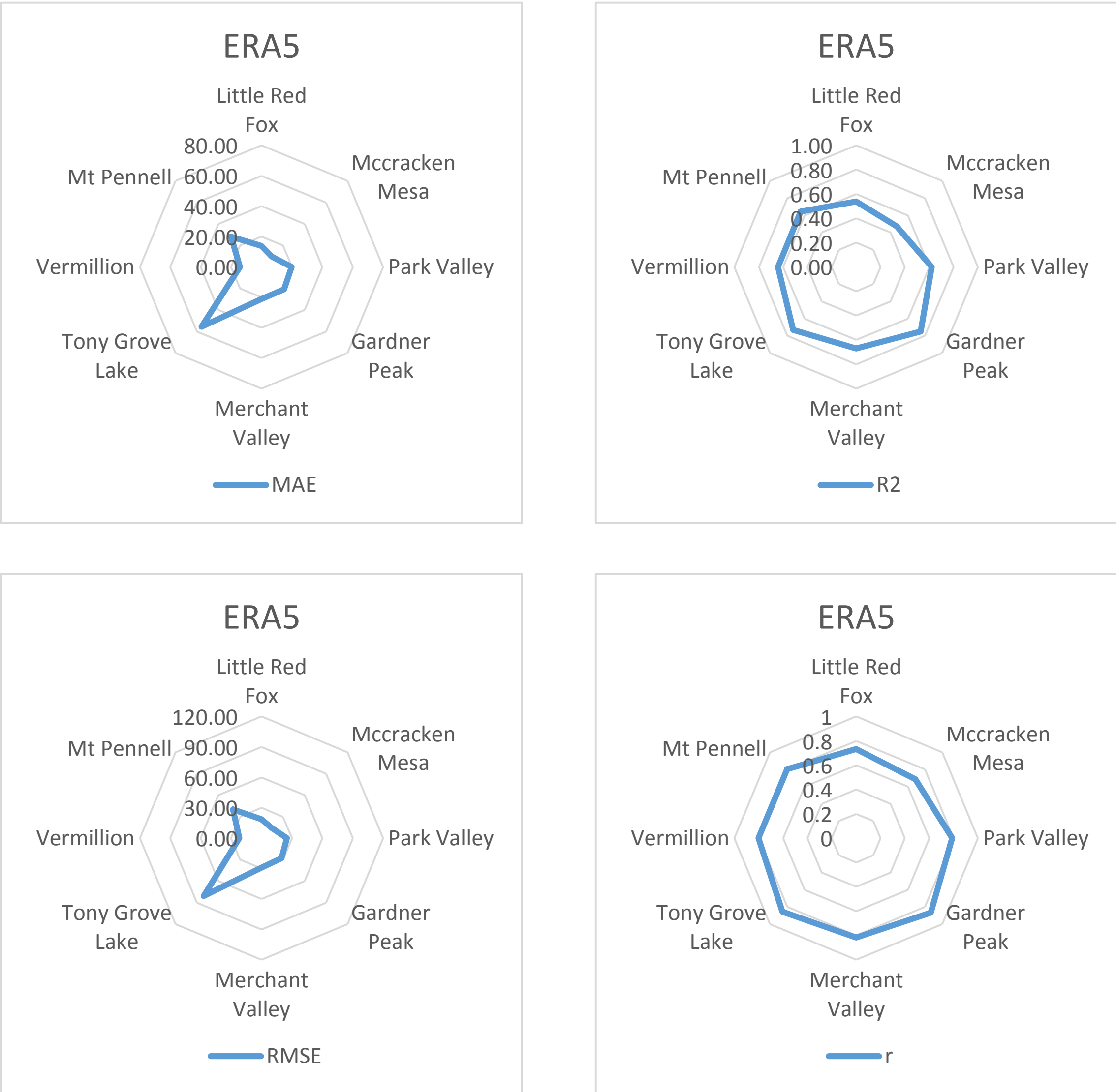

Figure 3. Evaluation of monthly ERA5 data compared to in situ observations over Utah for the period 2009-2019.

3.1. The results of the stations

3.1.1. Evaluation of ERA5

The accuracy of all precipitation products was evaluated using the statistical metrics of R^2, RMSE, and MAE. The results are given in Figures 3 to 7. The results showed that ERA5 was most accurate at the Gardner Peak station (R^2 = 0.75). However, RMSE and MAE values in Gardner Peak station were high due to the relatively high precipitation in this station. Also, ERA5 had the worst performance in Mccracken Mesa with an R^2 value of 0.47.

3.1.2. Evaluation of GPM

As given in Figure 4, GPM rainfall values had the best correlation with ground-based data at Mt Pannell station with R^2 equal to 0.87. It should be noted that this value for R^2 was the highest among all the stations and products used in this paper. For GPM, the lowest amount of R^2 and the highest amount of RMSE and MAE belonged to Tony Grove Lake station. The mentioned station had the most average rainfall among all the stations.

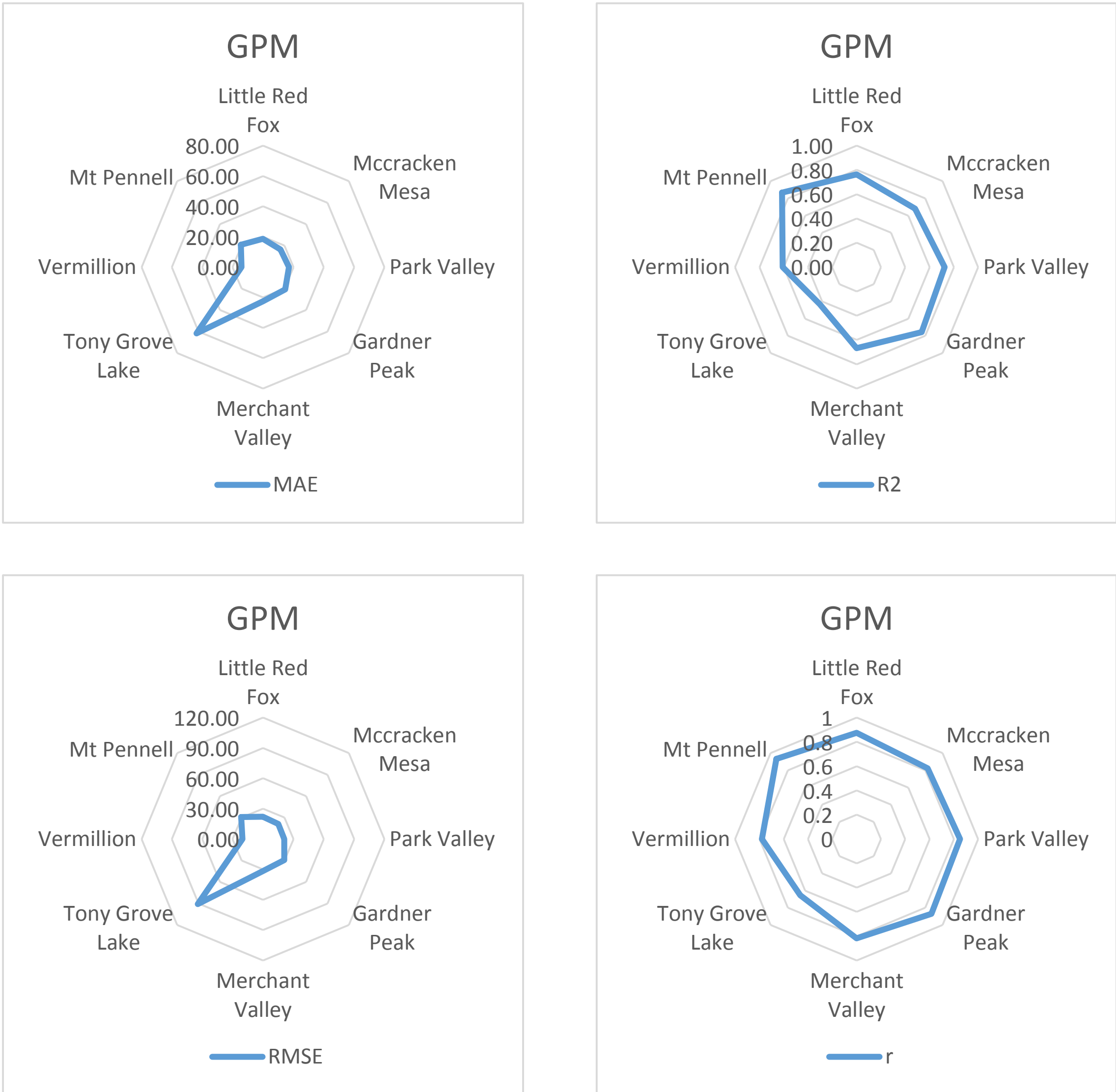

Figure 4. Evaluation of monthly GPM data compared to in situ observations over Utah for the period 2009-2019.

3.1.3. Evaluation of CHIRPS

The spatial resolution of the CHIRPS product was higher than all the used products. The results indicated that the highest correlation of CHIRPS data with rain gauge data happened at Little

Red Fox station (R^2 = 0.81). Also, its lowest correlation is at the Mt Pannell station with an R^2 value of 0.49 (Figure 5).

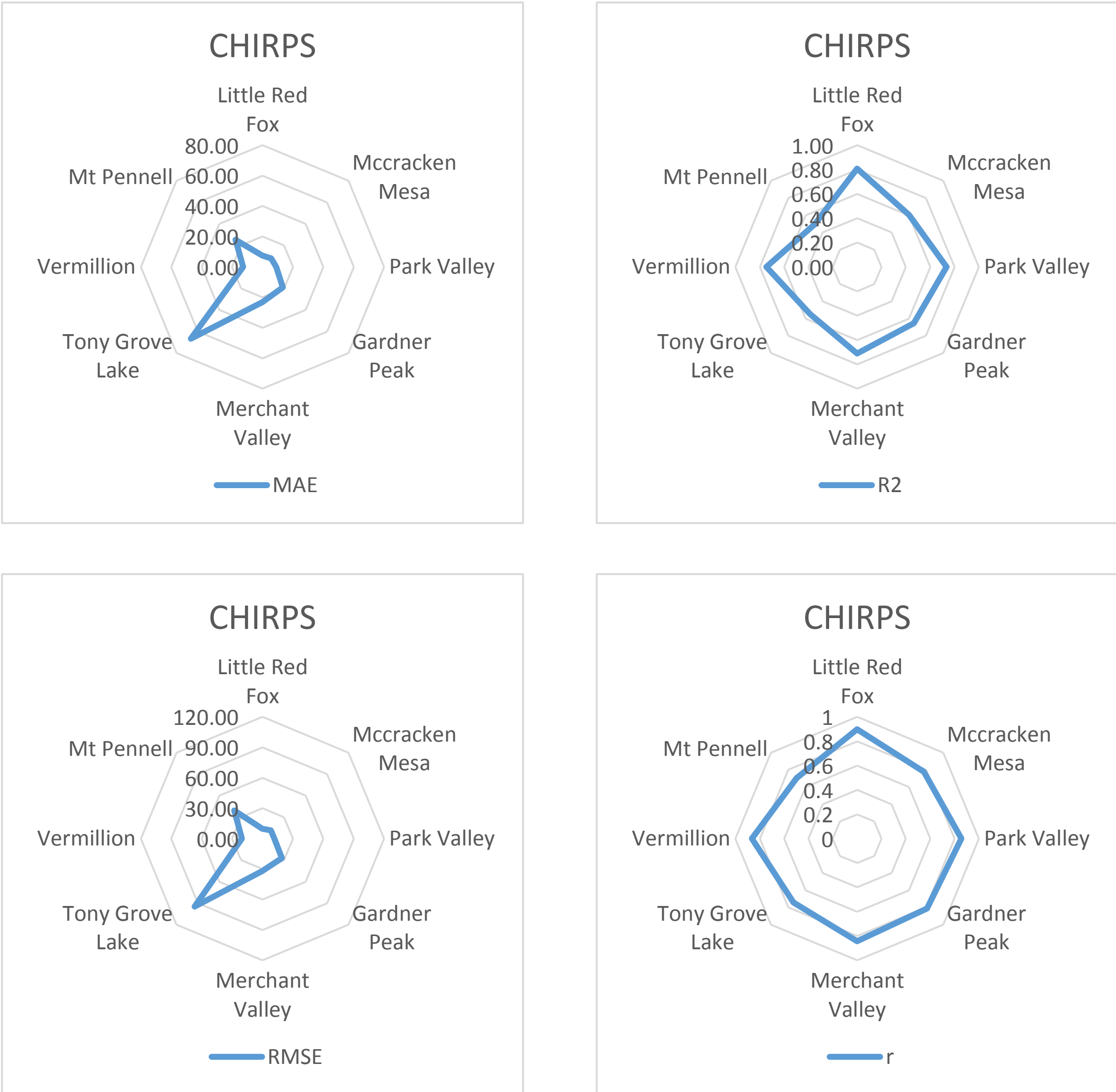

Figure 5. Evaluation of monthly CHIRPS data compared to in situ observations over Utah for the period 2009-2019.

3.1.4. Evaluation of TRMM 3B43

As shown in Figure 6, the TRMM product yielded the best performance at Mt Pennell station whose R^2 value was equal to 0.76. However, the lowest R^2 belonged to Merchant Valley station (R^2 = 0.4).

3.1.5. Evaluation of PERSIANN-CDR

In general, the accuracy of the PERSIANN-CDR product was unacceptable at all the stations, so its best performance was at McCracken Mesa station (R^2 = 0.35), and its lowest correlation with ground data occurred at Mt Pennell station with R^2 equal to 0.11 (Figure 7).

3.1.6. Comparing products

In four out of eight studied stations (Little Red Fox, Merchant Valley, Park Valley, and Vermillion), the CHIRPS rainfall product showed better results than others. Also, in three stations (Gardner Peak, Mccracken Mesa, Mt Pennell), GPM performed best. At one station (Tony Grove Lake), the ERA5 rainfall product resulted in a better correlation with rain gauge data. At all stations, the PERSIANN-CDR precipitation product had the least accuracy, and its results were unreliable, which is in line with Tan and Santo (2018), who evaluated the performance of TMPA 3B42 and 3B42RT, GPM IMERG, and PERSIANN-CDR products over Malaysia. Their results indicated that PERSIANN-CDR performed the worst in estimating all precipitation classes and significantly underestimated the values.

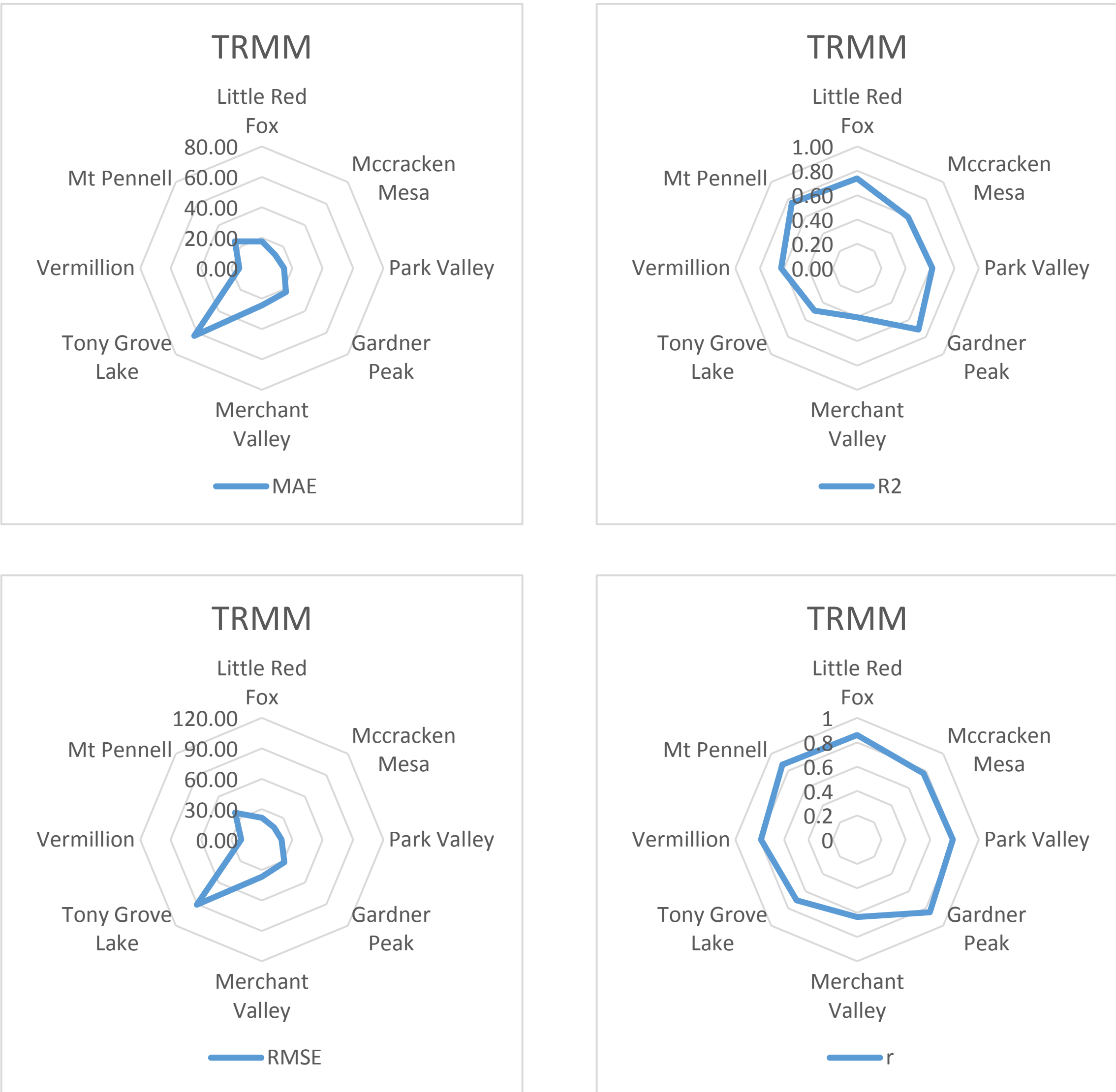

Figure 6. Evaluation of monthly TRMM data compared to in situ observations over Utah for the period 2009-2019.

Figure 7. Evaluation of monthly PERSIANN-CDR data compared to in situ observations over Utah for the period 2009-2019.

3.2. Monthly performance results

Performance results for different months of the studied period are shown in Table 3. The results revealed that the ERA5 rainfall product had the best performance from December to March among all the products. The highest accuracy of ERA5 was related to June ($R^2 = 0.78$), and the least RMSE and MAE values also resulted in this month. However, the lowest accuracy was in August ($R^2 = 0.24$).

GPM had its best performance in June, where R^2 was maximum (0.85), and RMSE and MAE were the least (14.52 and 9.74, respectively). GPM also outperformed other products this month. In January, GPM showed the worst performance, where R^2 was equal to 0.29. In September, the GPM rainfall product estimated the amount of precipitation as weaker than the other products.

Considering R^2 values, in seven out of 12 months of the year (April, May, July, August, September, October, and November), the rainfall data of Chirps was superior to other products.

In April and May, Chirps did better than in other months (In both months, R^2 is equal to 0.79). The lowest relationship between CHIRPS rainfall product and ground data occurred in the first three months of the year, where R^2 was equal to 0.46. Our results are consistent with the findings of Saeidizand *et al.* (2018), who revealed that the precipitation product of CHIRPS has the highest and lowest correlation with rain gauge data in May and January, respectively.

The highest and lowest accuracy of the TRMM product in estimating rainfall was in June and January, respectively. Also, the TRMM product in May predicted rainfall values worse than other products.

Among all the studied products, the PERSIANN-CDR rainfall product in all months of the year except May, August, and September had the weakest correlation with the rain gauge data. The highest and lowest R^2 values of the PERSIANN-CDR product were in September and June, respectively. The results showed a poor agreement between PERSIANN-CDR product and rain gauge data, especially in June and July (equal to 0.01 and 0.02, respectively).

Taking into account the values of average monthly precipitation in general, CHIRPS outperforms other precipitation products in the study area. This finding is in line with those found in a previous study by Duan *et al.* (2016) in Italy. They revealed that CHIRPS showed better performance than other products including TRMM 3B42, GSMaP_MVK, PGF, and three products from CMORPH. We achieved an average R^2 value of 0.63 for the CHIRPS product in the entire study area. ERA5 ranked second with average R^2 equal to 0.6, and GPM, TRMM, and PERSIANN-CDR were in the subsequent ranks (average R^2 values were equal to 0.53, 0.52 and 0.32, respectively). Our follow-up study shows that spatial resolution is directly related to the accuracy of the results. Because CHIRPS rainfall product had the highest spatial resolution (0.05°), which led to the most reliable results, on the other hand, the lowest spatial resolutions belonged to TRMM and PERSIANN-CDR (0.25°), leading to the weakest results. One possible reason for this is that satellite missions represent precipitation in terms of area on a raster scale (pixels), whereas rain gages take point measurements. This means that the conversion from point to area precipitation via the satellite grid could affect these data comparisons. This finding is consistent with Takara *et al.* (2010).

It should be emphasized that all precipitation products studied were developed using multiple datasets and techniques to blend, combine, and correct for bias. Consequently, poor matches between the assessed products and rain gauge data are influenced by a number of factors, including errors in the algorithms used to estimate rainfall from individual platforms (rain gauge analysis, weather prediction model, satellite), errors in satellite sampling, and errors in the algorithms used to blend or combine individual estimates (Shen *et al.*, 2010).

As shown in Table 3, all the studied products had poor agreements with rain gauge data in cold months (December to February), which was more valid for GPM, CHIRPS, and TRMM products. The weakest performance of these products happened in cold months. In addition, all products apart from PERSIANN-CDR had a strong relationship with rain gauge data in June.

Of all the elements affecting the accuracy of satellite-based missions, the weak performance in the cold months can be attributed to two factors: (i) The reason for most of the precipitation during the cold months in Utah is non-convective currents, which is difficult to detect by satellites (Tian *et al.* 2007, Ebert *et al.* 2007 and Mei *et al.* 2014). On the other hand, satellite algorithms are more accurate in detecting rainfall patterns derived from convection currents that occur during hot months. (ii) The land surface is covered with a large amount of ice and snow during the cold months, which weakens the performance of microwave-based satellites in estimating precipitation.

This is because they produce robust interference signals similar to those produced by ice particles in the atmosphere (Ebert *et al.* 2007 and Tian *et al.* 2014).

Table 3. Performance results of the tested precipitation products on the monthly scale in Utah State from June 2009 to June 2019.

Dataset	static	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ERA5	RMSE	54.15	61.02	41.98	33.25	25.02	13.50	31.88	30.79	22.39	33.81	36.57	44.77
	R^2	0.53	0.62	0.66	0.67	0.72	0.78	0.24	0.24	0.71	0.70	0.68	0.62
	MAE	30.15	30.93	27.49	23.82	17.03	8.19	22.67	22.43	15.86	21.12	22.04	30.96
GPM	RMSE	63.18	68.69	47.67	39.82	23.00	14.52	23.80	22.26	25.77	30.53	40.21	55.62
	R^2	0.29	0.39	0.46	0.48	0.76	0.85	0.48	0.52	0.52	0.70	0.46	0.45
	MAE	35.35	37.34	33.11	27.72	17.94	9.74	17.72	16.36	18.18	20.50	25.78	36.57
CHIRPS	RMSE	59.41	67.24	49.18	38.24	26.10	16.72	27.74	21.96	21.51	39.14	38.28	52.16
	R^2	0.46	0.46	0.46	0.79	0.79	0.71	0.50	0.62	0.77	0.76	0.73	0.54
	MAE	28.36	29.46	27.05	23.49	17.54	9.54	17.55	15.52	15.92	23.49	20.79	30.37
TRMM	RMSE	62.45	67.76	46.47	38.75	33.11	14.04	23.05	21.03	23.37	34.29	41.66	57.38
	R^2	0.35	0.45	0.44	0.42	0.61	0.74	0.50	0.54	0.59	0.60	0.42	0.55
	MAE	36.54	36.13	30.46	26.40	21.41	9.60	17.13	15.64	17.07	20.42	25.30	37.73
PERSIANN-CDR	RMSE	70.84	80.91	57.34	50.43	34.44	55.37	46.19	26.48	26.56	45.80	49.88	65.82
	R^2	0.09	0.06	0.32	0.34	0.65	0.01	0.02	0.45	0.62	0.56	0.28	0.41
	MAE	40.51	44.78	38.03	34.45	23.46	26.14	26.77	18.36	18.42	28.95	30.49	40.54

Figure 8 indicates the spatial distribution of monthly precipitation for October 2018 estimated from ERA5, GPM, CHIRPS, TRMM, and PERSIANN-CDR.

3.3. Effects of coordinates on the accuracy of products

The correlation coefficient (r) of the tested rainfall products with latitude and longitude was calculated (Table 4). The results showed that latitude had no significant effect on any of the products. Longitude, on the other hand, had a significant effect only on ERA5. In general, the correlation of ERA5 data with rain gauge data decreased as one moved from the west to the east of the state of Utah. The highest performance was observed at the westernmost station (Gardner Peak) with an R^2 value of 0.75, and the lowest performance was at the easternmost station tested (Mccracken Mesa) with an R^2 value of 0.47.

3.4. Effects of elevation on the accuracy of products

The results of correlation coefficients of rainfall products with elevation are shown in Table 4. The results showed that GPM and TRMM precipitation products were not affected by terrain elevation, which is consistent with Bolvin and Huffman (2015) who stated that terrain elevations do not incredibly affect the TRMM 3B43 product due to their climatological calibrations. However, elevation had a slight negative correlation with the CHIRPS and PERSIANN-CDR products. This means that as elevation increases, precipitation estimation accuracy decreases for these products. However, the ERA5 product has a positive correlation with elevation and estimates the rainfall more accurately in high elevation regions.

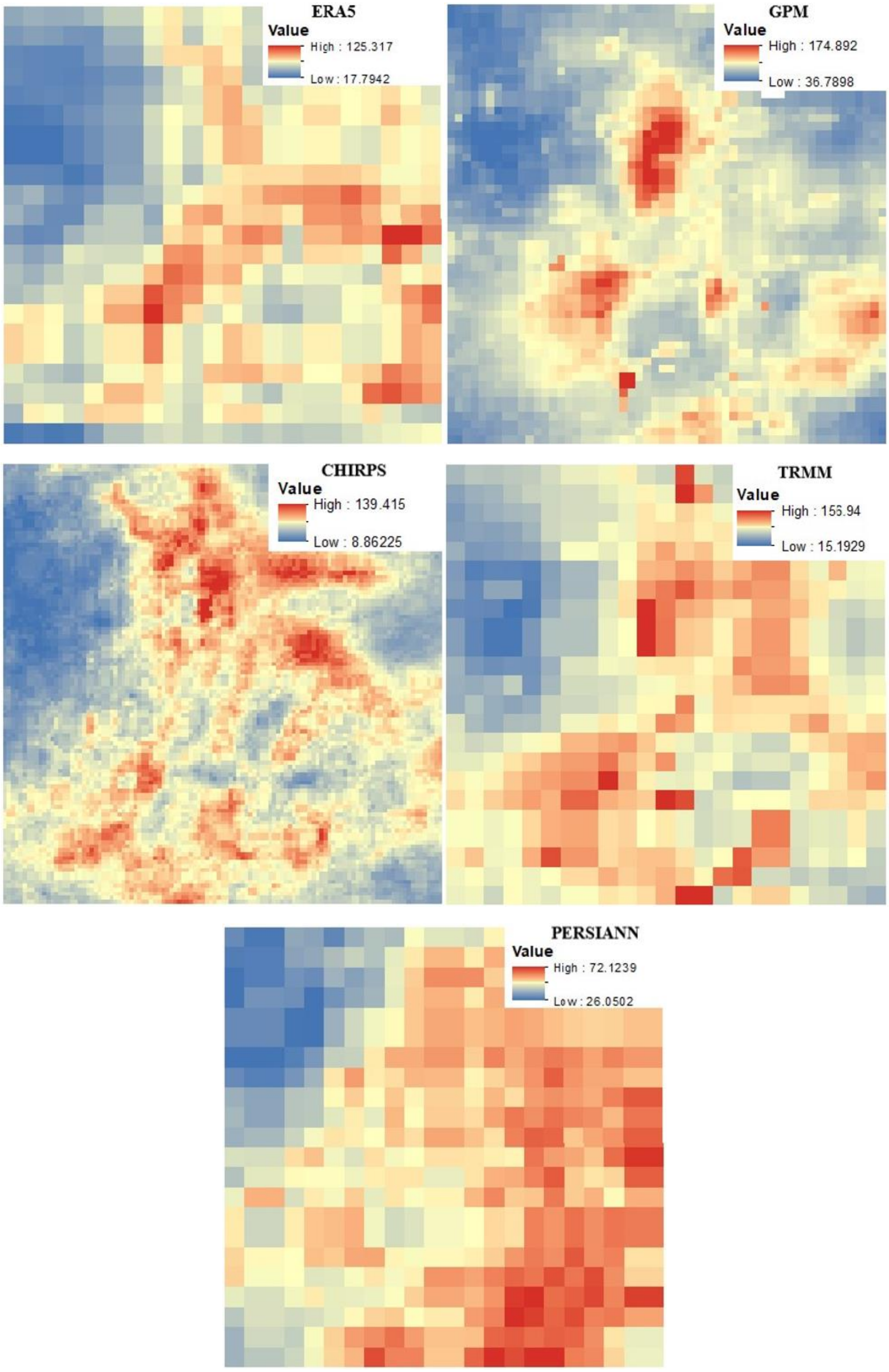

Fig. 8. Spatial distribution of monthly precipitation for October 2018 estimated from ERA5, GPM, CHIRPS, TRMM, and PERSIANN-CDR

3.5. Effects of precipitation on the accuracy of products.

As shown in Table 4, the accuracy of precipitation estimation of all the tested products, except the PERSIANN-CDR product, is influenced by the amount of precipitation. The accuracy of rainfall prediction of GPM, CHIRPS, and TRMM rainfall products decreases with the increase in rainfall. However, the ERA5 product has a positive correlation with the rainfall amount, so that it performs better in rainy areas.

Table 4. The correlation coefficient values between precipitation products and different factors

Dataset	Longitude	Latitude	Elevation	Precipitation
ERA5	- 0.76	0.10	0.73	0.76
GPM	0.10	- 0.40	0.00	- 0.63
CHIRPS	- 0.26	0.10	- 0.59	- 0.48
TRMM	0.17	- 0.17	- 0.17	- 0.49
PERSIANN-CDR	0.22	- 0.32	- 0.39	- 0.10

4. Conclusions

In this study, the accuracy of five precipitation products, including ERA5, GPM, CHIRPS, TRMM 3B43, and PERSIANN-CDR was assessed from June 2009 to June 2019 in Utah. In four out of eight studied stations (Little Red Fox, Merchant Valley, Park Valley, and Vermillion), the CHIRPS rainfall product showed better results than others. Also, in three stations (Gardner Peak, Mccracken Mesa, Mt Pennell), GPM performed best. At one station (Tony Grove Lake), the ERA5 rainfall product resulted in a better correlation with rain gauge data. At all stations, the PERSIANN-CDR precipitation product had the least accuracy, and its results were unreliable. The results also showed that CHIRPS outperformed other rainfall products in the study area with an average R^2 value of 0.63. CHIRPS rainfall product had the highest spatial resolution (0.05°) among all tested products, which led to the most reliable results. On the other hand, the lowest spatial resolutions belonged to TRMM and PERSIANN-CDR (0.25°), which resulted in the weakest results. The results also revealed that the ERA5 precipitation product was more influenced by elevation, longitude, and rainfall factors than other products. Latitude and longitude did not have a significant effect on any of the products, except for the ERA5. Generally, moving from the west to the east of the state of Utah, the correlation of ERA5 data with rain gauge data decreased. GPM and TRMM precipitation products were not affected by terrain increment. However, elevation had a slight negative correlation with CHIRPS and PERSIANN-CDR products. But the ERA5 product had a direct relationship with the elevation and estimated the rainfall more accurately in high-elevation regions. The accuracy of precipitation estimation of all the tested products, except the PERSIANN-CDR product, was influenced by the amount of precipitation. The accuracy of rainfall prediction of GPM, CHIRPS, and TRMM rainfall products decreased with the increase in rainfall. However, the ERA5 product had a direct relationship with the amount of precipitation, and the accuracy of this product was higher in rainy areas.

In summary, we have shown that all studied precipitation products except PERSIANN-CDR, have acceptable potential for estimating rainfall patterns in Utah. The performance of satellite precipitation products depends on several factors, including longitude, latitude, elevation, precipitation amount, and spatial and temporal resolution of the product. Therefore, the results may not be readily applicable to other areas. Since the accuracy of the products depends on the spatial and temporal resolution of the product, future extensions of this work can include the evaluation of downscaled precipitation products. In addition, the effects of different land-uses on the accuracy of the products can also be investigated.

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