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ORIGINAL PAPER

Ranking of gridded precipitation datasets by merging compromise programming and global performance index: a case study of the Amu Darya basin

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Abstract
Accurate representation of precipitation over time and space is vital for hydro-climatic studies. Appropriate selection of gridded precipitation data (GPD) is important for regions where long-term in situ records are unavailable and gauging stations are sparse. This study was an attempt to identify the best GPD for the data-poor Amu Darya River basin, a major source of freshwater in Central Asia. The performance of seven GPDs and 55 precipitation gauge locations was assessed. A novel algorithm, based on the integration of a compromise programming index (CPI) and a global performance index (GPI) as part of a multi-criteria group decision-making (MCGDM) method, was employed to evaluate the performance of the GPDs. The CPI and GPI were estimated using six statistical indices representing the degree of similarity between in situ and GPD properties. The results indicated a great degree of variability and inconsistency in the performance of the different GPDs. The CPI ranked the Climate Prediction Center (CPC) precipitation as the best product for 20 out of 55 stations analysed, followed by the Princeton University Global Meteorological Forcing (PGF) and Climate Hazards Group Infrared Precipitation with Station (CHIRPS). Conversely, GPI ranked the CPC product the best product for 25 of the stations, followed by PGF and CHRIPS. Integration of CPI and GPI ranking through MCGDM revealed that the CPC was the best precipitation product for the Amu River basin. The performance of PGF was also closely aligned with that of CPC.

Keywords Compromise programming · Global performance indicator · Statistical metrics · Group decision making · Gridded data · Amu Darya River basin

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1 Introduction

Precipitation is one of the key components of the global hydrological cycle (Roca et al. 2019; Tapiador et al. 2017). Any variation in the amount of precipitation received in an area can result in significant changes to precipitation extremes, with severe consequences to water resources, agriculture and ecosystem services as well as an increase in hydrological hazards (Ahmed et al. 2016; Khan et al. 2019; Mukherjee et al. 2018; Wu et al. 2013). Precipitation is therefore regarded as one of the most important factors affecting the economic development of a region. Precipitation can generally be measured using in situ rain gauges, satellite sensors and weather radar (Shen and Xiong 2016; Sun et al. 2018). Gauge-based measurements are considered to be both the most important and the most reliable for collecting this data (Guo et al. 2020).

Long-term, consistent and accurate precipitation records are required for hydro-climatic studies and for other applications (Tan et al. 2020). Acquiring accurate and reliable gauge records can be a challenge, especially in areas of complex terrain and in developing nations (Jiang et al. 2016; Kidd et al. 2017; Li et al. 2018; Musie et al. 2019; Tan et al. 2020; Yang et al. 2020). As a consequence, long-term rainfall records from homogeneously distributed gauges are not available in most areas around the globe. Data availability issues, and the common issue of unsuitable spatial and temporal resolutions of any data which is available, significantly influence the outcome of hydrologic studies (Beven and Westerberg 2011). In many cases, gridded climatic data are used to fill this information gap. High spatiotemporal resolution gridded datasets have been developed, and these are widely used as a proxy to overcome any data availability issues (Bai et al. 2018; Duan et al. 2016; Guo et al. 2020; Liu et al. 2017; Rashid et al. 2019; Yang et al. 2020). Even though the use of GPDs is essential for hydro-climatic studies conducted in data-sparse regions, the appropriate selection of gridded products from the global climate data pool is also a challenging task (Nashwan and Shahid 2019; Salman et al. 2019). The selection of the most appropriate data products must consider the spatiotemporal resolution required for detailed hydro-climatic investigations (Gampe et al. 2019). A major drawback is the uncertainty associated with many gridded climate products so it is important to examine the performance and reliability of the chosen gridded products before use in any specific application. (Gampe and Ludwig 2017; Musie et al. 2019).

A number of studies have been undertaken to evaluate the performance of gridded precipitation products. Conventional statistical methods such as the use of the coefficient of determination (R^2), root mean square error (RMSE) and mean bias error are mostly employed. The selection of gridded precipitation datasets is primarily based on their ability to replicate extreme precipitation days and dry spells and to provide accurate precipitation density functions and other essential properties (Ahmed et al. 2017; Nashwan et al. 2019b). The selection of GPD has also been proposed based on run-off or flood simulation applications (Nashwan et al. 2019a; Try et al. 2020), and the association of gridded products with large-scale ocean-atmospheric phenomena (Erazo et al. 2018). Additionally, conventional statistical metrics and different similar measuring indices are also proposed for evaluating the performance of gridded data (Nashwan and Shahid 2019). A major challenge seen in many studies is the inconsistent results obtained when using differing metrics or precipitation properties. For example, a product may be good in replicating dry spell but may completely fail in reproducing extreme events (Muhammad et al. 2019). Precipitation products may show differing results when using alternative hydrological models to simulate run-off or flood events. To overcome this challenge multi-criteria decision-making tools are now used, with the results integrated to rank the gridded products (Salman et al. 2019). Machine learning algorithms such as random forest and symmetrical uncertainty are now used to assess the performance of gridded datasets (Nashwan and Shahid 2019). It should be noted, however, that the various machine learning algorithms available also produced differing rankings in regard to the gridded climate data. This again emphasizes the need for an MCGDM methodology as part of the decision-making process.

Compromise programming (CP) (Zeleny 1973) is a linear mathematical method used to analyse multi-objective problems. This has widely been used in recent years for decision-making and is based on the outcomes of different statistical metrics (Muhammad et al. 2019). The theory behind CP is based on choosing a solution closest to a set of ideal points determined by measuring the distance between a set of solutions. Salman et al. (2019) employed CP when selecting the best-gridded precipitation product for Iraq. Muhammad et al. (2019) applied a CP methodology for ranking evapotranspiration models. The method was also successfully used to rank global climate model (GCM) datasets (Raju et al. 2017). It has also been widely used in solving problems related to water resources and the environment (Brahim and Duckstein 2011; Samal and Kansal 2015; Zhang 2003).

The use of a global performance indicator (GPI) (Behar et al. (2015) is another robust approach used for solving a multi-objective problem. It combines different performance indicators to provide a single, unique solution (Behar et al. 2015). Researchers used GPI for the validation and ranking of solar radiation models (Despotovic et al. 2015; Fan et al. 2018; Jamil et al. 2020). Recently, Nashwan and Shahid (2020) used a GPI technique to rank GCMs by integrating six performance measures. The capability shown in efficiently solving multi-objective problems when selecting models indicates the potential of GPI use in the selection of GPD.

Table 1 Existing studies in Amu Darya basin and neighbouring regions using gridded data products

Author	Study area	Gridded data used	Major findings
White et al. (2014)	Amu Darya basin	CRU TS-2.1	CRU could not provide more suitable climatic inputs for water modelling
Törnqvist (2013)	Amu Darya basin	CRU temperature	Uncertainties associated with CRU usage. Increase in temperature by 2025 and 2100
Lutz et al. (2013)	Amu and Syr River basins	APHRODITE precipitation and PGMFD temperature	Used as a reference for climate projection
Savoskul and Shevnina (2015)	Syr Darya basin	CRU temperature	CRU upscaled to match with GCM
Shibuo et al. (2007)	Aral Sea catchment	CRU precipitation and temperature as input of models	Increase in evaporation due to irrigation and water diversion
(Malsy et al. 2015)	Ob river	CRU TS, GPCC, WFD, and APHRODITE precipitation	GPCC and APHRODITE are better hydrological modelling inputs
Haag et al. (2019)	Central Asia	CRU temperature and TRMM precipitation	CRU has good correlation with observed temperature
Khaydarov and Gerlitz (2019)	Uzbekistan	CHELSA precipitation and temperature	CHELSA agreed with observed temperatures and precipitation
Duethmann et al. (2015)	Tarim River	APHRODITE, GPCC, WRF, UDel and CRU precipitation	APHRODITE and GPCC are capable of providing spatial distribution data
Zandler et al. (2019)	The Pamir region of Tajikistan	CRU, GPCC, ERA-interim, ERA5, MERRA-2, MERRA-2 bias-corrected, PERSIANN-CDR precipitation	MERRA–2 bias-corrected and GPCC, indicated better performance

CRU climate research units, *TRMM* Tropical Rainfall Measuring Mission, *APHRODITE* Asian Precipitation-Highly-Resolved Observational Data Integration Toward Evaluation, *PGMFD* Princeton's Global Meteorological Forcing Data, *GPCC* Global Precipitation Climatology Centre, *WFD* Forcing Data, *CHELSA* Climatologies at high resolution for the earth's land surface areas, *WRF* Weather Research and Forecasting, *MERRA* Modern-Era Retrospective analysis for Research and Applications, *PERSIANN-CDR* The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record

The ranking and selection of a gridded precipitation product at a single gauge location is a relatively simple task. The challenge arises in deciding on the best GPDs to use based on the results obtained at different locations within a study area. A group decision-making approach is often taken to overcome this problem. Salman et al. (2018) proposed a multi-criteria group decision analysis (MCGDA) for selecting GCMs based on their performance at different locations in Iraq. In such an approach, each gridded precipitation product is provided with a weight based on the rank obtained by the product at different locations. Performance can then be measured based not only on the first rank but also on the ranks obtained in other areas.

This study is conducted in the Amu Darya River basin in Central Asia. The objective is to use two multi-objectives linear programming (MOLP) methods (CP and GPI) in the ranking of GPDs. In situ monthly precipitation data, recorded at 55 locations scattered throughout the basin area, were also used. The CP and GPI results obtained were integrated using an MCGDA and the best was then selected. The Amu Darya is the longest transboundary river in Central Asia, traversing the countries of Afghanistan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan (Froebrich and Kayumov 2004; Mergili et al. 2013). The river provides freshwater for multipurpose activities, such as drinking, irrigation and hydropower, and also supports the Aral Sea ecosystem (Kure et al. 2013; Lioubimtseva 2014). Despite the importance of the basin system, studies related to the hydro-climate is very limited, principally due to the nonavailability of longer period high-resolution precipitation data (Bobushev and Salnikov 2014; Immerzeel et al. 2012). It appears that few attempts have been made to source suitable gridded climate data for the Amu Darya basin and surrounding regions. A brief overview of existing studies is presented in Table 1; however, no comprehensive study has been conducted to assess the suitability of gridded precipitation products for the entire basin. The selection and ranking of GPDs would assist in reliably assessing hydro-climatic changes and impacts on water resources within the basin.

2 Study area and data

2.1 Study area

The Amu Darya river headwaters are located in the high glacier and snow-covered mountains of Tajikistan and Kyrgyzstan, then passing through the northern parts of the Hindu Kush, Whakhan in Afghanistan, the Kara-Kum and Kyzyl Kum deserts and the arid plains of Uzbekistan before discharging into the Aral Sea (Chevallier et al. 2012;

Ibrahimzada and Sharma 2012; Nezlin et al. 2004; White et al. 2014). (White et al. 2014; Ibrahimzada and Sharma 2012; Nezlin et al. 2004; Chevallier et al. 2012). The river is 2,540 km in length, with an annual average flow of about 75 billion m^3 (Ahmad and Wasiq 2004). The major tributaries of the Amu River consist of the Vahsh, Pandj and Zeravshan (Normatov and Normatov 2018). Figure 1 a shows the catchment area of the Amu Darya River basin. Most of the basin comprises steppe land. A typical continental climate dominates the region (Jalilov et al. 2013). The basin can be sub-divided into three unequal zones: (1) an upstream area characterized by high mountains with an average altitude of 7495 m; (2) a midstream section with several large irrigated oases; and (3) a downstream zone feeding the Aral Sea in the northwest (average elevation 200 m). The mean annual rainfall of the basin is 464 mm. The maximum precipitation of 2000 mm occurs upstream (in Eastern Pamir) and the minimum downstream (100 mm). Most rainfall occurs during winter (November to May) while the summer period (June to September) is relatively dry. The temperature in summer averages 35 °C, while in winter it falls to − 8 to − 20 °C (Gaybullaev and Chen 2013).

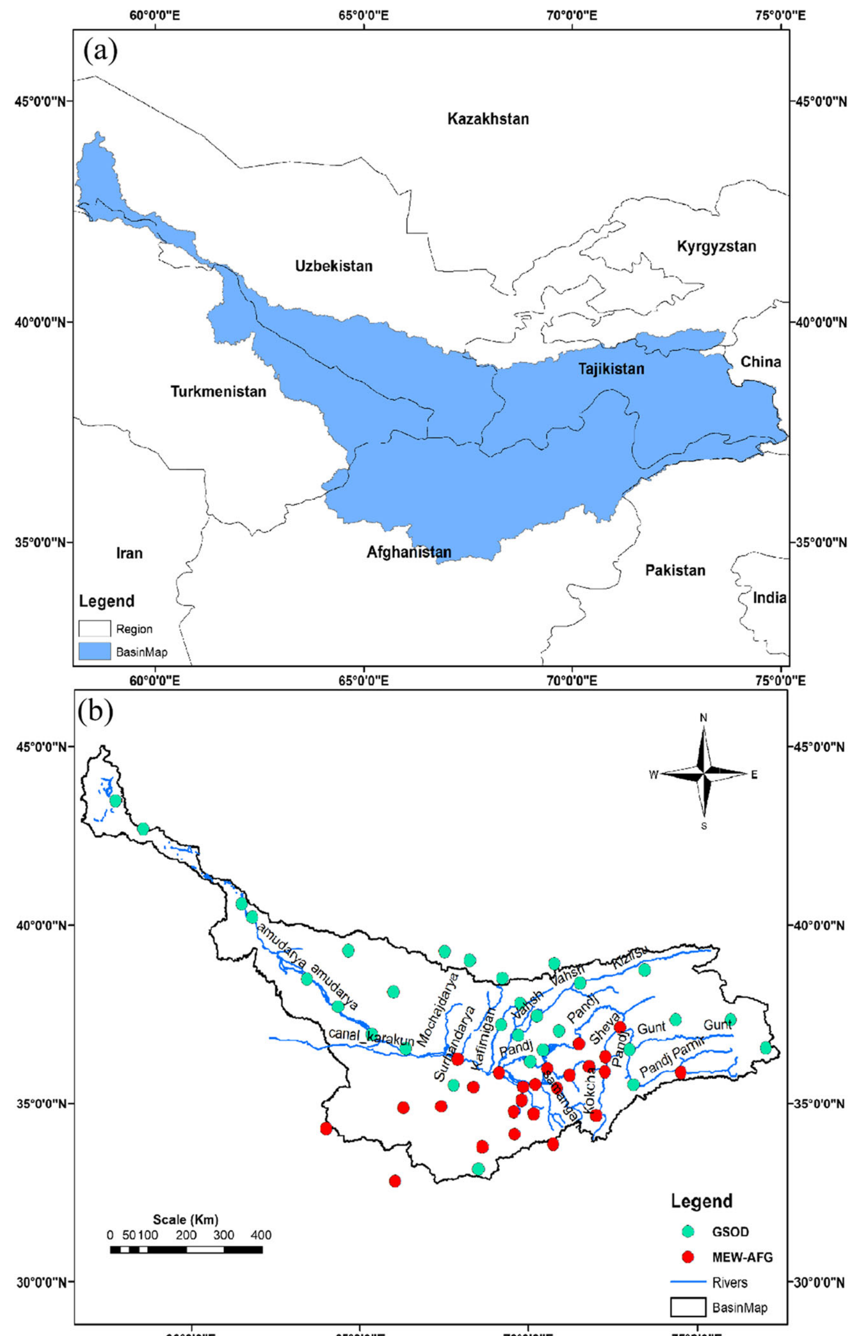

Fig. 1 **a** Location of the Amu Darya River basin in Central Asia. **b** Location of rain gauge stations used in this study. Coloured circles indicate data source

Most of the Central Asian countries are considered arid to semi-arid and are vulnerable to climatic changes (Yadav et al. 2019). Water derived from the Amu Darya river is considered to of prime importance for the economy and associated livelihoods of much of the Central Asia population (Unger-Shayesteh et al. 2013). This area is home to more than 50 million people (Babow and Meisen 2012). While the Amu River is predominantly fed by glacial meltwaters, the permafrost found within the soil profile also provides more than 40% of the river flow, especially during summer (Dodson et al. 2015; Novikov et al. 2009; Punkari et al. 2014).

2.2 Observed precipitation data

Observed daily precipitation data was collected from the Ministry of Energy and Water of Afghanistan (MEW-AFG) and the official website of Global Summary of the Day (GSOD): https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv=GSODandcountryabbv=andgeoregionabbv=. The differing data sources are marked with different coloured symbols in Fig. 1. The precipitation records of 55 stations for the 1979-2019 period were selected. A number of stations adjacent to the boundary of the basin were also selected due to the availability of longer period recorded data. Stations with missing or only short period records were discarded. The locations of stations within and adjacent to the river basin are shown in Fig. 1b. Most of these are centred within the east and southeast parts of the study area, with few located in the west and south-west. Fewer stations are located in the northwest so data from this area is scarce. In general, there is a good distribution of recording locations within the basin, though some spatial variability is evident.

2.3 Gridded precipitation data

Seven gridded precipitation datasets were evaluated. These include (1) Asian Precipitation-Highly-Resolved Observational Data Integration Toward Evaluation V1101 (APHRODITE), (2) Climate Hazards Group Infrared Precipitation with Station V2.0 (CHIRPS), (3) National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) global dataset, (4) University of East Anglia Climatic Research Unit TS V4.03 (CRU), (5) Global Precipitation Climatology Center (GPCC), (6) Princeton University Global meteorological forcing dataset for land surface modelling V3 (PGF), and (7) Centre for climatic research, University of Delaware V5.01 (Udel). Table 2 summarizes the type, resolution, frequency and period of the seven datasets. All the original data is formatted in Network Common Data Form (NetCDF). The statistical software programme *R* was used to extract the data in comma-separated values (.csv) format for the statistical analysis. The common period of GPDs is 1981-2015, so the performance of the datasets is compared with observed data from the 55 selected locations for the period 1981-2015.

Table 2 List of gridded precipitation datasets used in this study

Dataset	Type	Resolution	Frequency	Period
APHRODITE V1101	G	0.25°	Daily	1951–2015
CHIRPS V2.0	S	0.05°	Monthly	1981-2019
CPC	G	0.5°	Daily	1979-2019
CRU V4.03	G	0.5°	Monthly	1901–2018
GPCC	G	0.5°	Monthly	1891–2016
PGF	G	0.25°	Daily	1948-2016
Udel V5.01	G	0.5°	Monthly	1900-2017

G gauge-based data, *S* satellite-based data

The APHRODITE precipitation product is developed using gauge precipitation data obtained from the Global Telecommunication System (GTS) network, as well as in situ records (Yatagai et al. 2012). The product has been developed based on a new interpolation technique with accurate long-term gridded orographic precipitation for Asia (Kamiguchi et al. 2010). The data are available at http://aphrodite.st.hirosakiu.ac.jp/product/APHRO_V1101EX_R1/APHRO_MA/025deg_nc/.

CHIRPS is a quasi-global rainfall dataset, spanning all latitudes from 50° S to 50° N. This dataset has been developed by the Climate Hazard Group, combining the Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis version 7 (TMPA 3B42 v7), global cold cloud duration rainfall estimates and several other observed databases. The product is widely used in many fields, particularly for hydrologic simulations and modelling (Funk et al. 2015; Gao et al. 2018). The data can be downloaded from ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_monthly/bils/.

The CPC is an observation-based gridded precipitation product developed by the Climate Prediction Center, National Centers for Environmental Prediction (Tanarhte et al. 2012). The data are available at ftp://ftp.cdc.noaa.gov/Datasets/cpc_global_precip/. The CRU used an angular distance weighting interpolation method to grid monthly gauge data acquired from the World Meteorological Organization (WMO), NOAA and other national networks. These cover the entire global land surface apart from Antarctica (New et al. 2000). The data is available at https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/.

The GPCC was established in 1989 by Deutscher Wetterdienst as the German contribution to the World Climate Research Programme (WCRP) (Becker et al. 2012). The product was developed by combining data from the global telecommunication system (GTS), synoptic weather information, monthly climate monitoring reports and data from the national hydro-meteorological monitoring organizations of 190 countries around the world (Schneider et al. 2014), accessible via https://psl.noaa.gov/data/gridded/data.gpcc.html.

The PGF datasets have been developed by Princeton University by combining several global station-based datasets with the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Duan et al. 2016). The PGF data are available at http://hydrology.princeton.edu/data/pgf/v3/0.25deg/daily/.

The UDel precipitation dataset has been developed by the University of Delaware. It is based mainly on the data of 22,000 globally distributed rain gauges. The product also uses Global Historical Climate Network data and data from the Legates and Willmott archive of station climatology (Matsuura and Willmott 2012). The data can be accessed via https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html.

3 Methodology

3.1 Procedure

The general procedure used in achieving the objectives of this study is as follows:

1. Daily observed rainfall records and gridded data (available only at the daily scale) were converted to monthly values to make them consistent in terms of frequency;
2. The ability to use the gridded precipitation in replicating observed precipitation at each station was examined via an array of statistical metrics;
3. The data values were standardized (range of 0 to 1) to remove the influence of the differing metrics;
4. CPI and GPI were employed to integrate the results;
5. The gridded precipitation products were then ranked using CPI and GPI for each station point;
6. Finally, the MCGDA technique was applied to merge the rankings of the precipitation product for the whole river basin.

The evaluation of the quality of gridded precipitation products is commonly performed by comparing gridded data with the data of the nearest rain gauge (Tan et al. 2020) or interpolation of gridded data at each gauge location (Ahmed et al. 2019). In this study, GPDs were interpolated at the station location using an inverse distance weighting method and then the interpolated precipitation was compared with the observed precipitation. Details of the statistical indices, MOLP methods and group decision-making methods used in the present study are described in the following sections.

3.2 Performance assessment

Six statistical metrics were used to evaluate the accuracy of the precipitation products. These included the coefficient of determination (R^2), normalized root mean square error (NRMSE), percentage of bias (PBIAS), Kling-Gupta efficiency (KGE), modified index of agreement (MD), and the ratio of standard deviation (rSD) These statistical methods are routinely used to evaluate the performance of the differing characteristics of observed precipitation, including the mean, variability and association. A description of the statistical indices is provided in Table 3. The range and optimum values of the indices are also shown in Table 3.

3.3 Multi-objective linear programming

Two MOLP methods (CPI and GPI) were used to integrate the results and to derive a single metric. The MOLPs are described below.

3.3.1 Compromise programming

The CP is a MOLP method. A Pareto-optimal solution of a multi-objective problem is obtained by estimating the minimum distance of a utopian solution (Raju et al. 2017; Zeleny 1973. It uses statistical metrics such as R^2, NRMSE, PBIAS, MD and other metrics in the calculation (Salman et al. 2019). CP uses 1 as the optimal value for R^2 and zero for other statistical indices. The CPI is expressed as:

$$CPI = \left[\sum_{1}^{n} \left| x_i^1 - x_i^* \right|^p \right]^{\frac{1}{p}} \tag{1}$$

where i is the statistical index; x_i^1 is normalized value of index i for gridded precipitation dataset 1; x_i^* is normalized ideal value of index i; and P is the parameter which is considered 1 for linear programming and more than 1 for non-linear programming. In this study, the P was considered 1. The CPI is always positive where a smaller value of CPI indicates better performance of a gridded data.

3.3.2 Global performance indicator

GPI (Despotovic et al. 2015) is a robust MOLP that can be used to overcome any disparities in the results derived from the different statistical metrics. It is estimated from the scaled values of the metrics by subtracting the value from the median value. The GPI of a gridded product, i can be defined as:

Table 3 Statistical indices used for evaluating the performance of precipitation products in estimating observed precipitation

Statistical indices	Range	Optimal value
$R^2 = \left(\sum_{n=1}^{n}(x_o - x_{-o})\frac{(x_g - x_{-g})}{\sqrt{\sum_{n=1}^{n}(x_o - x_{-o})}}{}^2\sum_{n=1}^{n}(x_g - x_{-g})^2\right)^2$	− 1 to 1	1
$NRMSE = \left[\left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_g - x_o)^2\right]^{1/2}\frac{}{sdv(x_o)}$	0 to ∞	0
$PBias = \left(\frac{\sum_{i=1}^{N}(x_o - x_g)}{\sum_{i=1}^{N}x_o}\right)$	− ∞ to ∞	0
$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$	− ∞ to 1	1
$\beta = \frac{\mu_g}{}\mu_o \quad and \quad \gamma = \frac{\sigma_g/\mu_g}{\sigma_o/\mu_o}$		
$MD = 1 - \sum_{i=1}^{n}(x_o - x_g)\frac{j}{\sum_{i=1}^{n}(\lvert x_g - x_{-o}\rvert} + \lvert x_o - x_{-g}\rvert)^j$	0 to 1	1
$rSD = \frac{sd(x_o)}{sd(x_g)}$	− ∞ to ∞	1

where, X_g and X_o are the gridded (g) and observed (o) precipitation, respectively; r is Pearson's correlation; μ and σ represent mean and standard deviation

$$GPI_i = \sum_{j=1}^{n} a_j\left(\widetilde{y}_j - y_{ij}\right), \quad where\ a_j = \begin{cases} -1\ for\ R \\ +1\ for\ all\ other\ errors \end{cases} \tag{2}$$

where $\widetilde{y}_j$ represents the median of the scaled values of indicator j; $y_{ij}$is scaled value of indicator j for ith gridded data and n is the number of statistical metrics. The higher value of GPI of a gridded data indicates a better performance.

3.4 Multi-criteria group decision-making

An MCGDA was employed to rank the GPDs for the whole Amu Darya River basin. In this proposed approach, each gridded product provided a weight based on the position achieved by the product at different stations to estimate an integrated index (I_x). The weight of a product was set as an inverse of the rank, meaning that if a product obtained first, second and third rank at a_1, a_2 and a_3 stations, I_x for the product was estimated to be:

$$I_x = a_1(1/1) + a_2(1/2) + a_3(1/3) \tag{3}$$

A gridded product ranked lower than three at a location was considered a poor performer at that location, and therefore assigned a zero weighting. The I_x value of different gridded products was used to provide a final ranking of the products in the basin.

4 Results

4.1 Spatial distribution of mean annual precipitation

The average annual precipitation between the observed and gridded data is presented in Fig. 2. This shows that the maximum precipitation was observed in the northeast of Afghanistan and south-east of Tajikistan while the minimum in the east of the basin. The gridded products also indicated maximum precipitation values in the northeast of Afghanistan and south-east of Tajikistan, and over a small part of Uzbekistan. Precipitation amounts decreased towards the west and northwest parts of the basin in Uzbekistan and Turkmenistan and over a wide area in the north of Afghanistan. The maximum mean annual precipitation in the north of the basin for each method was calculated as - UDel (1052 mm), CHIRPS (904.6 mm), APHRODITE (877.2 mm), GPCC (827.7 mm), PGF (728 mm), CRU (688 mm) and CPC (428 mm) The minimum values of annual average precipitation in the northwest were calculated as - CPC (53 mm), UDel (67 mm), CHIRPS (69 mm), GPCC (76.9 mm), PGF (98.72 mm), CRU (93 mm) and APHRODITE (84 mm).

4.2 Statistical performance of gridded precipitation datasets

The ability of the gridded precipitation products to replicate the differing properties of the observed data at all stations was evaluated using six statistical indices. Results for the different datasets at all stations are presented in Fig. 3. The upper, middle and lower lines of the box

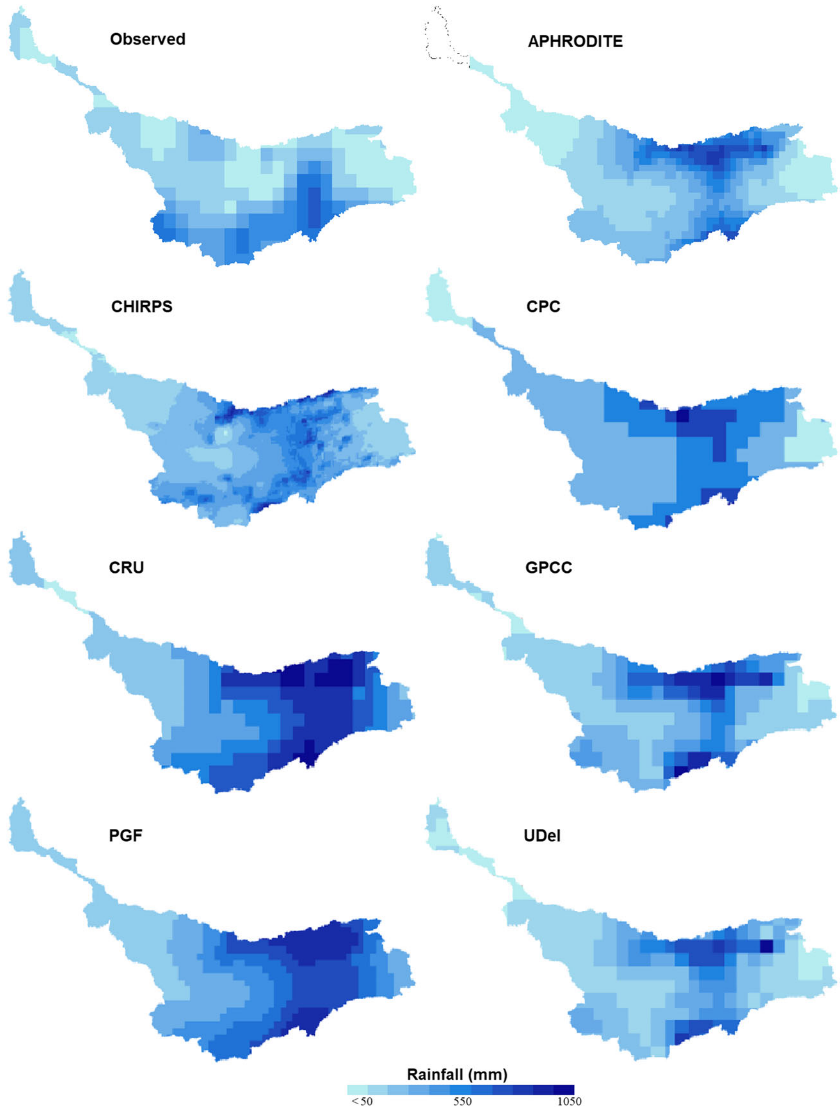

Fig. 2 Spatial distribution of mean annual precipitation, observed and gridded products over Amu Darya basin

represent the 75th, 50th (median) and 25th percentile values, where values of a product are closer to the optimum value of a metric (Table 3) than the product can be considered superior. Figure 3 also shows that the median of R^2 for CPC was closest to 1 (optimum value) followed by PGF, CHIRPS and APHRODITE. The median of KGE was close to 1 only for PGF and CPC, while it was more or less the same for the other products. The CPC showed good agreement in terms of median of rSD, followed by CRU and GPCC. The value closest to zero PBIAS (optimum) was observed for CPC, while the performance of other products was found to be similar in terms of PBIAS. The lowest NRMSE was obtained for APHRODITE, CPC, PGF and CHIRPS.

Table 4 provides a summary of stations showing the performance of the various gridded precipitation products (representing the number of stations at which a product ranked first in terms of particular metrics). APHRODITE was found to be the best at 11, 8, 1, 6 and 8 stations in terms of R^2, KGE, MD, rSD, PBIAS and NRMSE respectively. Likewise, CHIRPS was found best at 15, 12, 16, 8, 6 and 13 stations in terms of R^2, KGE, MD, rSD, PBIAS and NRMSE respectively. At some locations, more than one product had the same R^2, and therefore, they were given the same rank. To illustrate this, it can be seen that a high R^2 value (0.65) was obtained for both APHRODITE and CPC at a station located in the northwest. Both were therefore ranked 1st in that specific location. For this reason, the total number of locations at which different products obtained a first rank rating is greater than the total number of stations (55) studied.

The analysis indicates that CPC was the best performer for the majority of the stations (stations 19, 22, 26, 16, 23

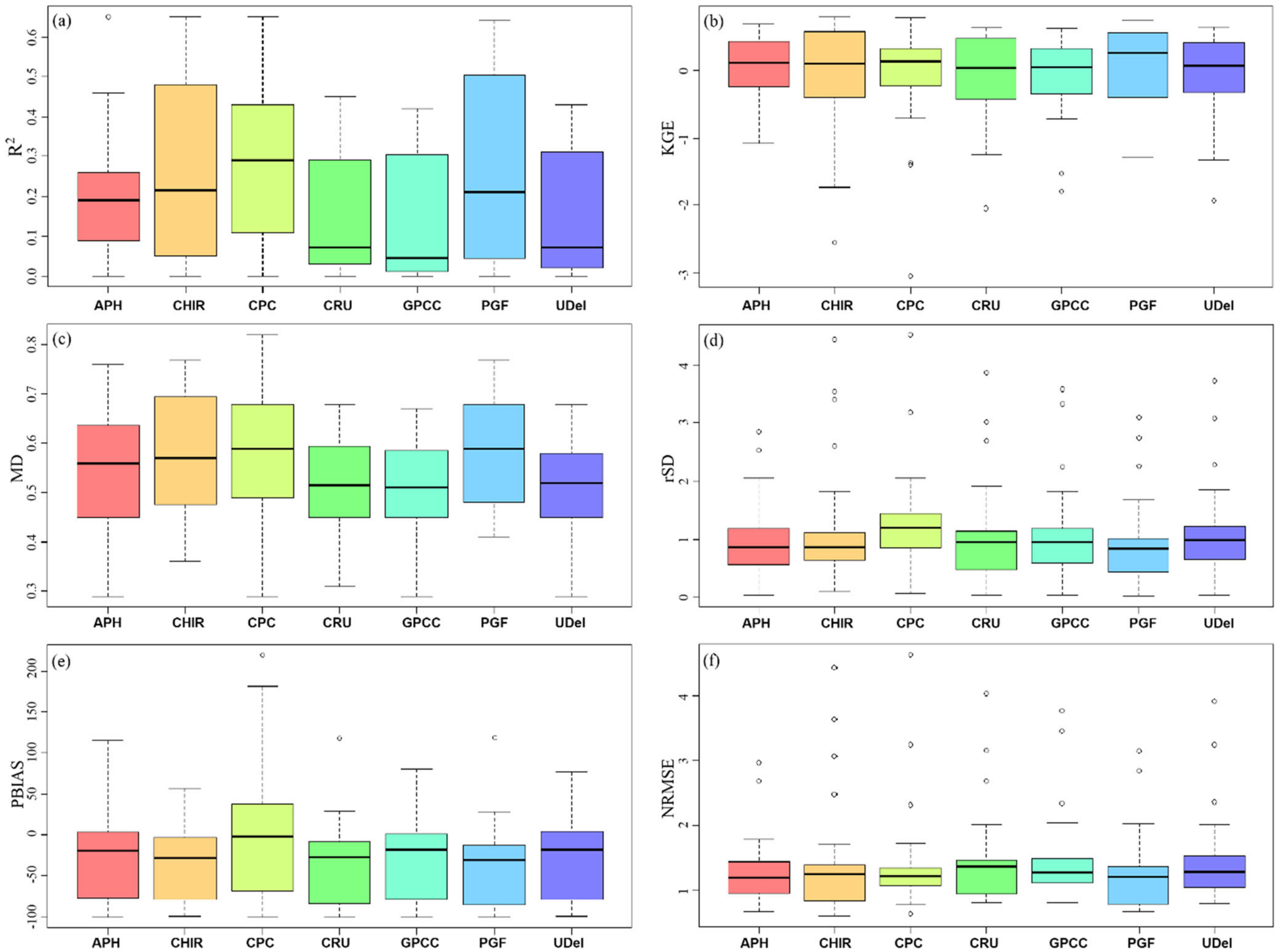

Fig. 3 Box and Whisker plots of R^2, KGE, MD, rSD, PBIAS and NRMSE, obtained by different gridded precipitation products at 55 observed locations in Amu Darya River basin (*APH* APHRODITE, *CHIR* CHIRPS)

and 18 in terms of R^2, KGE, MD, rSD, PBIAS and NRMSE, respectively). It was not possible, however, to conclusively determine performance ability due to the statistical indices exhibiting dissimilar results when compared with the observed data. Station elevation may also affect product suitability. As a result, CPI and GPI were estimated for all products at each location based on their performance.

4.3 Ranking of gridded precipitation datasets using compromise programming

The CPI of each gridded precipitation product was estimated from the statistical metrics at each different location. CPI values at all the 55 stations, for all seven gridded precipitation products, are presented in Fig. 4. The values are presented using a colour ramp where green indicates a

Table 4 Number of stations at which different gridded datasets were ranked top in terms of various statistical measures

Statistical indices		Gridded precipitation data					
	APHRODITE	CHIRPS	CPC	CRU	GPCC	PGF	UDel
R^2	11	15	19	0	0	16	0
KGE	8	12	22	0	1	15	1
MD	1	16	26	0	1	15	1
rSD	6	8	16	8	7	7	7
PBIAS	6	6	23	6	4	5	7
NRMSE	8	13	18	0	0	16	1

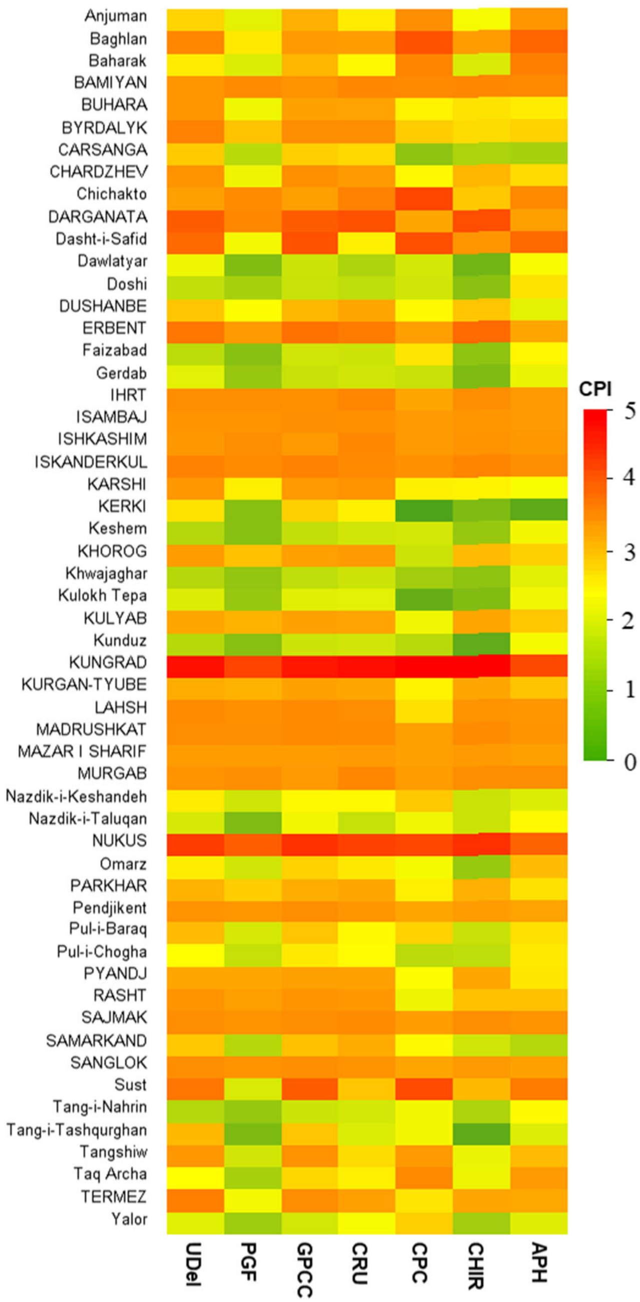

Fig. 4 The heat map showing the CPI values estimated for different gridded precipitation datasets at all the observed locations in the study area

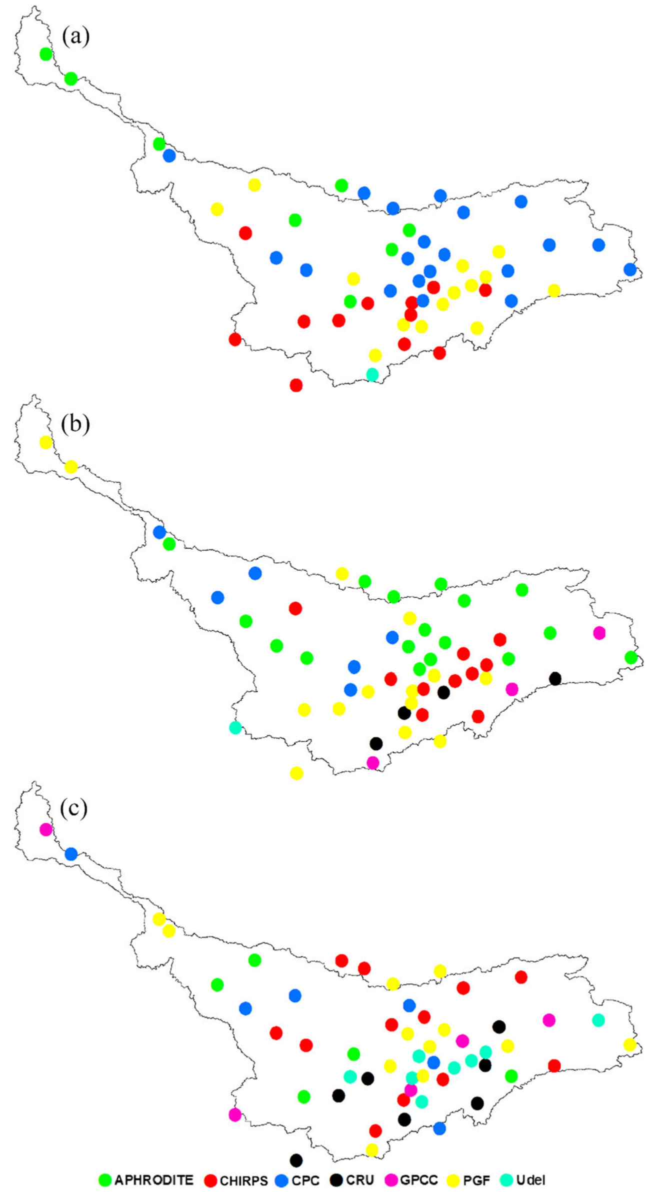

Fig. 5 Ranking of gridded precipitation products based on CPI for all stations over the study area ((a) is 1st position, (b) is 2nd position and (c) is 3rd position)

high value of CPI, red indicates a low value of CPI and yellow indicates a performance result near to the median value of CPI. Results revealed a superior performance for PGF and CHIRPS at many of the stations. These results indicate that, PGF and CHIRPS performed best at many stations when they were ranked using CPI, while CPC performed best at many stations in terms of different statistics.

Further evaluation of CPI performance was undertaken. The spatial distribution of the stations where a product achieved 1st, 2nd and 3rd rank is shown in Fig. 5. Figure 5

Table 5 Overall rank of the gridded precipitation products for the study area

Products	Rank based on CPI			Rank based on GPI			MCGDM
	1st	2nd	3rd	1st	2nd	3rd	
APH	8	17	5	2	22	5	5.47
Chrips	12	10	12	10	12	12	6.83
CPC	20	6	6	25	7	3	9.08
CRU	0	4	7	0	3	7	1.36
GPCC	0	3	5	1	2	5	1.14
PGF	14	14	12	16	8	13	8.22
Udel	1	1	8	1	1	10	1.5

a shows that CPC was the best-gridded product observed, with most locations aligned with the observed values. CHIRPS was also found to be a good performer at many stations, particularly those located in the south. PGF gave superior results in the central region, while APHRODITE was best at a number of locations in the northwest. Figure 5 b shows APHRODITE as the second-best product in the central and northern region of the Amu Darya basin. The PGF and CHIRPS were ranked second at many locations where they were not ranked the best. A large heterogeneity was noticed in the 3rd ranked gridded product. Overall, CHIRPS and PGF were ranked third at most of the locations where they were not ranked 1st or 2nd.

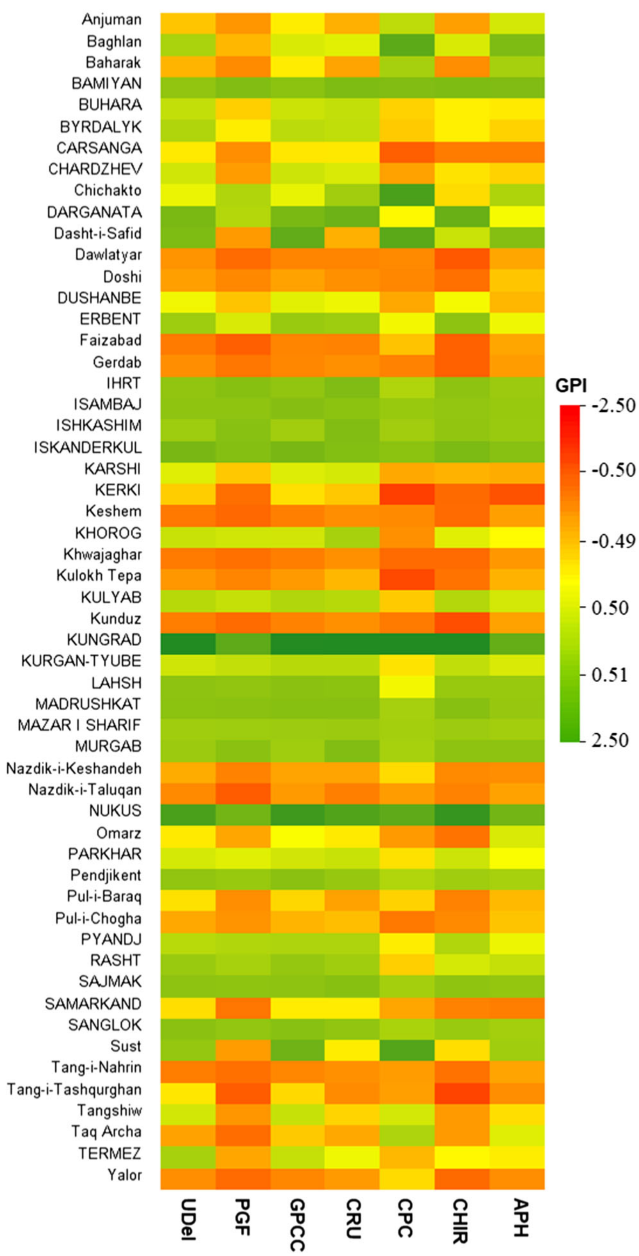

Fig. 6 Heat map showing GPI values estimated for different gridded precipitation datasets at observed precipitation stations in the study area

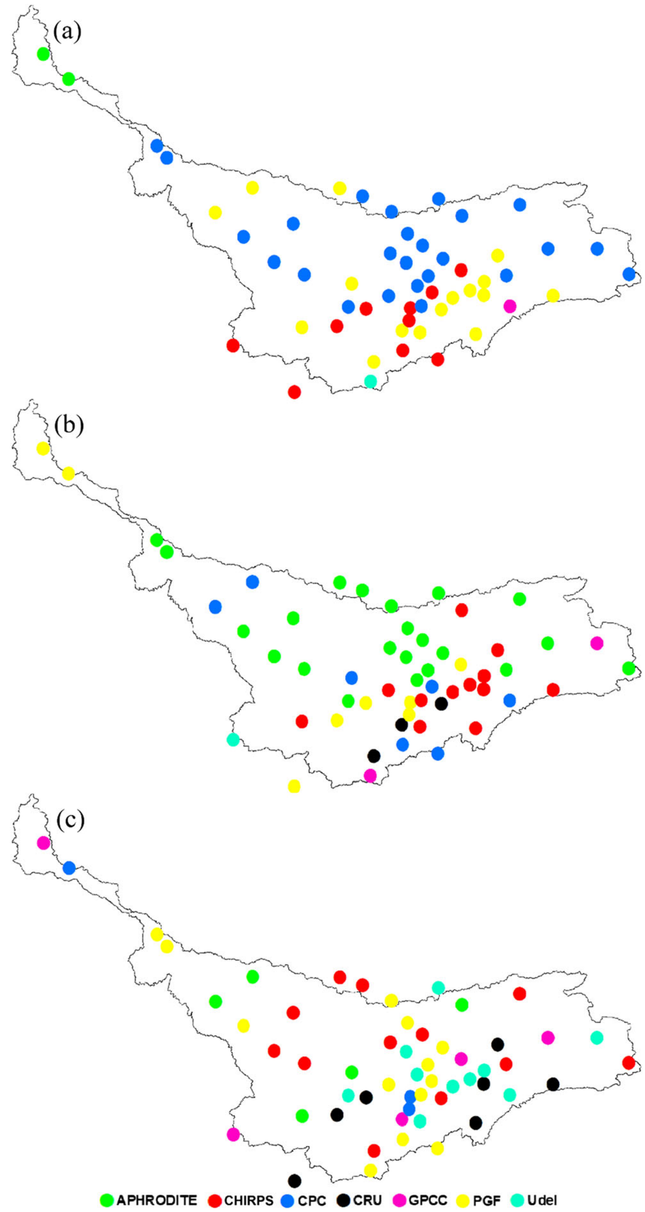

Fig. 7 Ranking of gridded precipitation products based on GPI at all stations over the basin

A summary of stations at which different products achieved 1st, 2nd and 3rd rank based on CPI are given in Table 5. The results show that CPC ranked top in terms of CPI at most of the stations (20). This was followed by PGF (14), CHIRPS (12) and APHRODITE (8). The CRU and GPCC did not rank well at any location, while Udel ranked top only at a station located on the border of the basin in the south-central part of the study area. APHRODITE ranked 2nd at most of the stations (17) followed by PGF (14) and CHIRPS (10). PGC and CHIRPS were also ranked 3rd at most of the stations (12). CPC ranked best at 20 stations and was second or third best for only six stations.

4.4 Ranking of gridded precipitation datasets using GPI

Colour-coded GPI for all the products at all stations is presented in Fig. 6. The minimum absolute value of GPI indicates the best performance of a product.

The CPC for most of the stations indicated a performance result near the median value. Both PGF and CHIRPS also recorded GPI values near zero for many stations. Stations where a product achieved 1st, 2nd and 3rd rank based on GPI are shown in Fig. 7. The spatial pattern of the results obtained using GPI was found to be very similar to those obtained using CPI. CPC was the best-gridded precipitation product, with most of the locations aligned with estimated values (Fig. 7a). CHIRPS was found best as some locations in the south and PGF was better at stations mostly located in the central region. APHRODITE was the second best gridded precipitation product at most of the locations (Fig. 7b). PGF and CHIRPS were also ranked the 2nd best product at many locations. PGF and CHIRPS ranked 3rd at most of the stations (Fig. 7c).

Table 5 shows a summary of the results obtained by GPI. This shows CPC is the best product in terms of GPI at 25 locations, followed by PGF (16) and GHIRPS (10). Other products were only found to be best at between zero and two locations. APHRODITE ranked 2nd at most of the stations (22) followed by CHIRPS (12) and PGF (8). PGF and CHIRPS were also found to achieve a 3rd rank at most of the stations (13 and 12 stations, respectively), followed by Udel at 10 stations and CRU at 7 stations. CPC was best at many stations; however, it was not good at most locations where it was not ranked best.

4.5 Group decision-making process

MCGDA was used to select the best gridded dataset as the results obtained from CPI and GPI were too disparate. The results are presented in Table 5. The GPD products were first weighted according to the number of stations achieving 1st, 2nd and 3rd ranks, with the results then used to derive an integrated index (last column, Table 5) using Eq. (3). Higher values indicate a better performance for a particular product. Table 5 shows the highest value for CPC (followed by PGF and CHIPS) suggesting that CPC is the best product for representing precipitation in the Amu Darya River basin. The integrated index for CPC and PGF were very close; it should be noted, however, that the spatial resolution of PGF (0.25°) is higher than CPC (0.5°). For this reason, PGF is ideal for hydro-climatic studies where higher resolution precipitation data is essential.

5 Conclusion

Seven gridded precipitation datasets for the Amu Darya River basin were evaluated. The results of six statistical indices were merged using two MOLP algorithms. These were subsequently integrated using an MCGMA approach to rank the GPDs products. The results indicate that CPC appears to be the most suitable product for studying the spatiotemporal hydro-climate characteristics of the basin. PGF also provided results that were very close to the CPC values. The use of both MOLP and MCGMA has provided an ability to select and use reliable gridded precipitation products. CPC can be recommended as an ideal technique to use in hydro-climatic studies. PGF can also be used, particularly where high spatial resolution is required. The selection of an accurate and reliable gridded climate product for a particular geographic region can be a challenging task as some compromise is usually required in regard to the ability of the product to simulate different precipitation properties. The methodology proposed in this study for selecting the best gridded climate product can be employed in any region. It should be noted, however, that only precipitation products with long recording timeframes and higher spatial resolutions (~ 0.5°) were considered. A large number of reliable, satellite-based precipitation products are now available, albeit for shorter time spans, and the performance of those products needs to be evaluated in the future to determine suitability for use. Other multi-objective linear and non-linear methods, as well as group decision methods, can also be employed and should be investigated.

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Code availability The codes used for the processing of data can be provided on request to the corresponding author.

Author contribution All the authors contributed to the conceptualization and design phases of the study. The data were gathered by Obaidullah Salehie and Kamal Ahmed; the programming code was written by Shamsuddin Shahid and Md Asaduzzaman; an initial draft of the paper was prepared by Obaidullah Salehie and S Adarsh; individual revisions and the final version were provided by Tarmizi bin Ismail and Ashraf Dewan.

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Data availability All the data are available in the public domain at the links provided in the texts.

Declarations

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Consent to participate Not Applicable

Consent for publication All the authors consented to publish the paper.

Conflict of interest The authors declare no competing interests.

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