Selection of the Most Suitable Gridded Precipitation and Temperature Datasets for the Kabul River Basin based on Statistical Indices - A Transboundary Basin between Pakistan and Afghanistan

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Abstract

Accurate and reliable long term meteorological data is very difficult to be obtained in developing countries especially in hard and mountainous regions. This paper focuses to select the most suitable and reliable gridded datasets for the two most important meteorological parameters i.e., precipitation and temperature in a sparsely gauged transboundary Kabul River Basin (KRB) between Pakistan and Afghanistan. Novelty of this study is that gridded datasets were evaluated for precipitation and temperature based on monthly, seasonal and annual timescales against the available observed stations data on both sides of the KRB. Based on the literature studies, the five most frequently used datasets namely; National Centers for Environmental Prediction, Climate Forecast System Reanalysis (NCEP-CFSR), Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation (APHRODITE v1101), Global Precipitation Climatology Centre (GPCC), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) and Climate Research Unit (CRU TS v4.02) with different spatial and temporal resolutions were selected and evaluated. Analyses were done using the four most widely used statistical indices i.e., Modified Index of Agreement (d_m), Pearson's Correlation Coefficient (r), Root Mean Square Error (RMSE), and Relative Bias (RB%). Results revealed that based on the statistical indices scores; APHRODITE (v1101) showed the best results followed by GPCC for precipitation while for temperature, CRU (TS v4.02) was found better compared to other datasets in the study basin. These findings can be used with confidence by the researchers for the future studies whose outcomes could be utilized by the water resource managers, planners and agriculturists.

Keywords: Evaluation, Gridded datasets, Statistical indices, Bilinear weighted interpolation technique, Kabul River Basin

1. Introduction

Error free and true precipitation data are necessary for the study of climate trends and variability, management of water resources, climate and hydrological predictions (Sun et al., 2018). In most of the developing and least developed countries, hydro meteorological study is difficult to undertake because of the sparsely distribution of monitoring stations particularly in the mountainous parts which hampers its use for climate simulation and many other climate related applications (Hassan et al., 2020; Ayoub et al., 2020). One of the challenging task especially in developing countries and distant parts of the world is the paucity of data where rain gauges are either sparse or not available due to the high cost of establishment and maintenance (Derin and

Yilmaz, 2014). To overcome these challenges, several global and regional based datasets have been prepared which the researchers now find a substitute input data for scientific, climatic and hydrological modeling studies (Darand and Khandu, 2020; Zandler et al., 2019; Ghulami et al., 2017).

Climate gridded datasets are prepared in three ways namely; Ground based observations datasets, Satellite based datasets, and Reanalysis based datasets (Hassan et al., 2020). Most of the times, reliability of these gridded datasets shows some disagreement between each other because observations are collected from different sources along with different methods of generation (Sun et al., 2018). The ground based datasets are considered more trusted but with few limitations. Data is collected from various parts of the globe, interpolated to grids using different interpolation techniques. The satellite based datasets use satellite technology which provides timely data over distant locations with precision and fine spatial resolution. The reanalysis datasets are developed by merging the irregular ground based observations with modeled outputs to give synthesized state of the system gridded datasets (Kanda et al., 2020). The global based gridded products have been generated at different spatial and temporal resolutions (Bai and Liu, 2018), which questions its suitability and direct application without evaluating its capability over a certain specific area for the planning and management of water resources (Hassan et al., 2020; Ghulami et al., 2017).

Several research studies have been carried out to evaluate the performance of the gridded datasets by comparing with the ground data. Islam et al. (2021) investigated the performance of APHRODITE precipitation dataset against rain gauge data in Bangladesh. Based on the statistical indices, the product tended to underestimate the observed rainfall data. Ayoub et al. (2020) evaluated the quality and reliability of the gridded precipitation satellite datasets namely; CHIRPS, TMPA 3B42v7 and PGFv3, and GSMaP RNL against the observed data in Malaysia. Results revealed TMPA 3B42v7 dataset performed the best while PGFv3 showed the poorest performance. Ahmed et al. (2019) investigated the performance of four gauge based gridded precipitation datasets which included APHRODITE, GPCC, UDel; and CRU products against the observed data of the arid, semi-arid, and hyper-arid regions of Balochistan (Pakistan). Based on the results, GPCC performed well in all the three regions of Balochistan. Anjum et al. (2018) validated the performance of the newly released IMERG of GPM mission, Real-time (3B42RT) and Posttime (3B42V7) TRMM/TMPA over northern regions of Pakistan. The datasets were evaluated on annual, seasonal, monthly and daily timescales using ground based data from April 2014 to December 2016 applying widely used statistical indices. Anjum et al. (2016) used the two successive versions v 6 and 7 of TRMM/TMPA and evaluated against rain gauge observations over a period of 1998-2014

in Swat watershed. Arshad et al. (2021) evaluated GPM-IMERG and TRMM-3B42 datasets against the observed data over Pakistan on daily, monthly, annual and seasonal timescales. Kanda et al. (2020) assessed the performance of seven datasets namely; APHRODITE, CRU-TS, ERA-I, GPCC, PGF, TRMM)/TMPA and UDel over North Western Himalava for three different climatic zones against the observed data of precipitation and temperature. Results concluded ERA-I, GPCC and TRMM datasets showed reliable for precipitation whereas for temperature, all the datasets performed quite well but CRU-TS and ERA-I were found more reliable. Miri et al., (2017) evaluated the performance of two gridded products namely; CRU TS3.23 on the basis of monthly precipitation and temperature and GPCC V 7 based on monthly precipitation against eighty-eight synoptic stations during 1985-2014 in Iran. Accuracy of GPCC for precipitation was found to be the best in all areas of Iran but for temperature, CRU performed well. Results also confirmed that precipitation data of GPCC and temperature data of CRU should be used in lack of data regions of Iran.

The main purpose of this study was to select the most representative long term datasets for precipitation and temperature for the Kabul River Basin which can be safely used for the future hydro-meteorological studies, drought analysis, crop modeling and climate change impacts on agriculture and other related applications.

2. Study Area

The Kabul River has a transboundary basin which is shared between Pakistan and Afghanistan. It is located at 65-75° E and 32.5-37.5° N with a total area of 91,297 km². Afghanistan and Pakistan, the two neighboring countries are both the upper and lower riparian respectively. The main sources of streamflow in Kabul River are the northern mountains capped with snow which are melted. Climatologically, the basin is dry and continental. Mountainous areas to the north receive the maximum precipitation of more than 1600 mm mostly in the form of snow which starts melting during the spring and summer seasons resulting in the increase of river flow (Masood et al., 2018). As many as 1600 glaciers are located in Kabul River Basin, out of which the highest and largest are present in the Kunar and Swat subbasins (Bokhari et al., 2018). Location map of the Kabul River Basin with different features is shown in Figure 1. This figure also shows maximum reduced level of about 7600 m above mean sea level (a.m.s.l) in the north-east of the basin, whereas minimum is 275 m (a.m.s.l) of Kabul River at Nowshera Hydrological Station.

Elevations of the meteorological stations vary from 327 m to 2114 m which cover lower part of the study area (Table 1), but in real terms, its elevation goes upto 7600 m as indicated in Figure 1. Figure 2 was developed on the basis of existing observed data as to show approximate climate of the basin on the existing elevations.

Based on the mean monthly precipitation of observed data (Figure 2), basin receives maximum precipitation during the month of February, March and April i.e., 100.9, 98.23 and 92.60 mm respectively. Months which receive minimum precipitation are June, October. November and December where precipitation is in the range of 28 to 33 mm. From Figure 2, it is also clear that maximum temperature occurs in the basin during the months of May, June, July and August where the temperature ranges between 31 to 35 °C. For mean monthly minimum temperature, the maximum temperature is recorded in the month of July (20.98 °C) whereas the minimum in the month of January (-0.72 °C).



Fig. 1 Location map of the Kabul River Basin showing its Digital Elevation Model (DEM), spatial distribution of the meteorological stations, Kabul River and its tributaries.



Fig. 2 Mean Monthly Precipitation, maximum temperature, and minimum temperature climograph based on the observed data for the Kabul River Basin (1993-2013)

3. Data and Methodology

3.1 Rain gauge data

Daily based observed meteorological data (precipitation, maximum and minimum temperature) of the six meteorological stations in the study basin was provided by Pakistan Meteorological Department (PMD) from 1993-2013 whereas limited data of precipitation of the four meteorological stations located in Afghanistan was provided by the Department of Agriculture, Afghanistan (Table 1).

3.2 Gridded precipitation and temperature datasets

Literature reveals gridded datasets are being frequently validated and then used for hydro-meteorological studies in place of observed data. Table 2 is prepared to show some of the basic information about the five gridded datasets used in this study. These include: spatial and temporal resolution, climate parameters, coverage and range of the data availability. These datasets are downloaded from their respective sources as explained below.

3.2.1 Station based datasets

APHRODITE (v1101): APHRODITE is a gauge based daily gridded fine resolution precipitation datasets developed at 0.5° and

 0.25° grid for whole Eurasian continent with domain 60° E - 150° E and 15° S - 55° N for the period from 1951 to 2007 (Yatagai et al., 2012). For the present study, APHRODITE (v1101) at spatial resolution of $0.25^{\circ} \ge 0.25^{\circ}$ daily timescale was used which could be downloaded from *https://www.chikyu.ac.jp/precip/english/downloads.html*.

CRU (TS v4.02): This dataset has been developed by the Climatic Research Unit, the University of East Anglia in the UK and consists of several climate variables including monthly precipitation on a $0.5^{\circ} \times 0.5^{\circ}$ global grid (Harris et al., 2020). CRU (TS v4.02, the latest version of the dataset, was used in this study. The precipitation and temperature data are available since 1901 to the most recent period and could be downloaded from *www.cru.uea.ac.uk*.

GPCC: GPCC are gauge based global gridded climate datasets for the land surface precipitation data available on monthly scale with spatial resolutions of $0.25^{\circ} \times 0.25^{\circ}$, $0.5^{\circ} \times 0.5^{\circ}$, $1^{\circ} \times 1^{\circ}$ and $2.5^{\circ} \times 2.5^{\circ}$ and temporal resolution from January 1891 to December 2018 (Schneider et al., 2018). For our study we downloaded data at spatial resolution of $2.5^{\circ} \times 2.5^{\circ}$ on monthly scale *https://climatedataguide. ucar.edu/climate-data/gpcc-global-precipitation-climatology-centre.*

3.2.2 Satellite based datasets

PERSIANN-CDR: Developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (UCL), PERSIANN-CDR provides satellite based quasi global (60° S -60° N) precipitation data on daily time step at a spatial resolution of 0.25° x 0.25° and temporal resolution from 1983-2019 (Sorooshian et al., 2014; Ashouri et al., 2015). The data can be accessed *http://chrsdata.eng.uci.edu/*.

3.2.3 Reanalysis based datasets

NCEP-CFSR: Produced by the National Centers for Environmental Prediction (NCEP), CFSR spreads over a period of 36 years from 1979 through 2014. The NCEP-CFSR is a global, high resolution, coupled atmosphere-ocean-land surface-sea ice system and provides best estimate of the state of these coupled domains over this period. NCEP-CFSR provides temperature (maximum and minimum) and precipitation data, daily based temporal resolution and 0.3125° x 0.3125° spatial resolution and covers global domain (Saha et al., 2010). The data can be accessed and downloaded from *https://globalweather.tamu.edu/.*

3.3 Site specific gridded data

In order to generate the site-specific gridded data, a number of techniques are available. Wei et al. (2017) reported that in situations where the satellite grid point and the ground station were close to each other, the comparison was carried out directly between the two data. But on the other hand where the ground station was lying between the four grid cells but not particularly close to any one, an average of the four grid point data was used as the base for comparison. Ud din et al. (2008) carried out a research study and applied technique of bilinear weighted interpolation to generate site specific precipitation data using TRMM 3B43 V6 data with a 0.25° grid. As the grid size is larger as compared to local interpretation, using the grid value for a specific location, or averaging of adjacent pixel values on 0.25° grid or else, it was postulated that technique of bilinear weighted interpolation

would be more realistic. Similar study was performed by Adjei et al. (2012) in Black Volta Basin in Ghana where he compared TRMM data with ground based data using technique of bilinear weighted interpolation to produce site specific TRMM 3B42 V6 data. In this study, we used bilinear weighted interpolation technique for those gridded datasets which didn't provide the required site specific gridded data.

3.4 Data preparation for precipitation and temperature (maximum and minimum)

The specific gridded data now available of the five gridded products namely; NCEP-CFSR, APHRODITE (v1101), GPCC, PERSIANN-CDR and CRU (TS v4.02) all having different spatial and temporal resolutions, were compared with ground based observations in a transboundary Kabul River Basin between Pakistan and Afghanistan, with varying land cover and elevation. To evaluate gridded datasets for precipitation, common data period from 1993-2013 was selected for all gridded dataset except APHRODITE whose data was limited up to 2007. For Afghanistan based stations, we evaluated precipitation for the same datasets on a limited observed data spanning over few years at few meteorological stations.

Further two gridded datasets namely; NCEP-CFSR and CRU (TS v4.02) were evaluated with the observed data for maximum and minimum temperature based on monthly, seasonal and annual scale only for Pakistan based stations, because temperature data of the Afghanistan based stations was not available. As stated before, the global gridded data products are developed at different temporal resolutions, the period from 1993-2013 was chosen based on the data accessibility. Monthly timeseries of all the datasets were prepared for each year which were further reduced to seasonal, *i.e.*, winter (December-February), spring (March-May), summer (June-August) and Autumn (September-November) and annual scales.

3.5 Method of Evaluation

To investigate the linear relationship between the observed and gridded datasets,

four widely used statistical indices namely; Modified Index of Agreement (d_m) which measures how modeled produced estimates (gridded dataset) simulate observed data (Pereira et al., 2018), Root Mean Square Error (RMSE) which calculates the differences between two datasets *i.e.*, gridded and observed and provides the average magnitude of error, Pearson's correlation coefficient (r) measures the degree of correlation between the gridded and the observed datasets, and the Relative Bias (RB) which calculates the tendency of the gridded dataset to over-estimate (Bias>0) or under-estimate (Bias<0) the observed data (Ayoub et al., 2020).

Four ranges of Pearson's correlation coefficients (r) are used while analyzing the

results, as reported by Iqbal and Athar (2018). These are: weak (r < 0.25), low ($0.25 \le r < 0.50$), moderate $(0.50 \le r \le 0.75)$ and strong (r > 0.75). To statistically analyze the results on the basis of RB (%), Wehbe et al. (2017) reported an evaluation criteria, there are three categories to check the performance of precipitation datasets; (a). under-estimation for RB < -10%, (b), over-estimation for RB>10%, and (c), acceptable range *i.e.*, -10% < RB < 10%. Similarly, Anjum et al. (2018) stated that the performance of satellite based precipitation products should be accepted if r value is greater than 0.7 and RB is between $\pm 10\%$. Ranges and perfect scores of the statistical indices used in this study are presented in Table 3.

		-			*	-
S. No.	Meteorological Station	Latitude	Longitude	Elevation (a.m.s.l)	Data period of Precipitation	Data period of Maximum and Minimum Temperature
1	Chitral	35.85°	71.83°	1498 m	1993-2013	1993-2013
2	Dir	35.20°	71.85°	1375 m	1993-2013	1993-2013
3	Drosh	35.56°	71.78°	1464 m	1993-2013	1993-2013
4	Parachinar	33.90°	70.06°	1775 m	1993-2013	1993-2013
5	Peshawar	34.16°	71.56°	327 m	1993-2013	1993-2013
6	Saidu Sharif	34.73°	72.35°	961 m	1993-2013	1993-2013
7	Paghman	34.58°	68.98°	2114 m	2006-2013	N.A*
8	Sarobi	34.53°	69.68°	1396 m	2006-2013	N.A
9	Kariz Mir	34.63°	69.05°	1905 m	2006-2011	N.A
10	Qargha	34.55°	69.28°	2007 m	2006-2013	N.A

Table 1. Details of the Meteorological Stations with data period used for study in Kabul River Basin

Note: Stations from S. No. 1 to 6 lie in Pakistan and the remaining stations lie in Afghanistan * means Not Available

Table 2. Details of the observed and gridded data sets

S. No	Name	Spatial/Temporal Resolution	Climatic Parameter	Spatial Coverage	Temporal coverage	Reference
1	OBSERVED DATA	Point data/daily	Precipitation, Maximum and Minimum Temperature	Study area	1993-2013*	PMD
2	NCEP-CFSR	0.312° x 0.312°/daily	Precipitation, Maximum and Minimum Temperature	Global	1979-2014	Saha et al. (2010)
3	APHRODITE V1101	0.25° x 0.25°/daily	Precipitation	Asia	1951-2007	Yatagai et al. (2012)
4	GPCC	2.5° x 2.5°/monthly	Precipitation	Global	1891-2018	Schneider et al. (2018)
5	PERSIANN- CDR	0.25° x 0.25°/daily	Precipitation	Quasi global (60° S-60° N)	1983-2019	Sorooshain et al. (2014)
6	CRU (TS v.4.02)	0.5° x 0.5°/monthly	Precipitation, Maximum and Minimum Temperature	Global	1901-2017	Harris et al. (2020)

Note: PMD stands for Pakistan Meteorological Department *Observed data provided by PMD for use in this study

S. No.	Name of the statistical index	Range	Perfect Score	References
1.	Pearson's Correlation Coefficient, r	-1 to +1	+1	Benesty et al. (2009)
2.	Modified Index of Agreement, d _m	0 to +1	+1	Willmott (1981)
3.	Root Mean Square Error, RMSE	0 to $+\infty$	0	Fox (1981)
4.	Relative Bias (%)	$-\infty$ to $+\infty$	0	Kanda et al. (2020)

Table 3. Statistical indices with their ranges and scores

Source: Rizwan et al. (2019)

Results were computed for each of the gridded dataset on the basis of Equations (1) - (4) which are presented in Tables 4-9 for the study area.

 $d_{m} = 1 - \left[\sum_{i=1}^{n} |Pi - Oi| / \sum_{i=1}^{n} (|Pi - \overline{O}| + |Oi - \overline{O}|)\right] (1)$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Oi - Pi)^{2}}{n}}$$
(2)
$$r = \frac{\sum_{i=1}^{n} (Oi - \overline{O})(Pi - \overline{P})}{\sqrt{\sum_{i=1}^{n} (Oi - \overline{O})^{2} \sum_{i=1}^{n} (Pi - \overline{P})^{2}}}$$
(3)

RB (%) =
$$\frac{\sum_{i=1}^{n} (Pi - Oi)}{\sum_{i=1}^{n} Oi} \ge 100$$
 (4)

Where O_i represents observed data, P_i represents predicted/gridded data, \overline{O} and \overline{P} are the respective average values of observed and gridded data, and "n" is the total number of data points.

4. Results and Discussion

4.1 Precipitation

Figures 3-5 (Boxplots) show the maximum and minimum values of d_m , RMSE and r of the gridded precipitation datasets at all meteorological stations in the study area on monthly, seasonal and annual scales.

Figure 3 presents visual comparison (Boxplots) of the gridded datasets performance based on d_m in the study area. Boxplot of each dataset shows the maximum and minimum values of d_m in the study area. Based on d_m results, APHRODITE was found to be the best in the study area where its values ranged from 0.65-0.72, 0.67-0.89, 0.64-0.82, 0.37-0.80 and 0.32-0.79 on monthly, winter, spring, autumn and annual scale respectively. For summer, NCEP-CFSR showed good results where its values ranged from 0.28-0.71.

For RMSE (Figure 4), compared to other datasets, APHRODITE performed well for having smaller range (maximum and minimum values) of RMSE's in the study area on monthly, winter, spring, summer, autumn and annual basis and its values varied from 17.10-39.21 (mm), 24.16-104.71 (mm), 24.11-109.84 (mm), 39.11-93.31 (mm), 22.24-72.90 (mm) and 74.58-330.64 (mm) respectively.

In Figure 5, variation of the r values for each gridded dataset in the KRB at all timescales has been shown with the help of boxplots separately. This figure depicts that APHRODITE showed good results on monthly, spring, and summer where its values ranged from 0.8-0.93, 0.71-0.99 and 0.60-0.97, respectively. For winter and autumn, the best performance was indicated by GPCC, and its values ranged from 0.77-0.97 and 0.52-0.96, respectively. This figure also shows that NCEP-CFSR showed good performance on annual scale, where its values varied between 0.39-0.88.

Figure 6 (a) illustrates comparison between the observed and gridded precipitation datasets on mean monthly scale. The comparison can be described in many steps. As can be seen from the figure, all the considered gridded datasets followed the observed data pattern very closely from January to February. From February to May, CRU was found to closely follow the observed data pattern whereas from May to September, the two datasets i.e., GPCC and PERSIANN-CDR captured the observed data pattern. Similarly, from September to December, three datasets namely; GPCC, PERSIANN-CDR and CRU datasets very closely matched the observed data pattern. This figure summarizes that on mean monthly scale, no single gridded dataset followed the observed data pattern completely.



Fig. 3 Comparison between the performance of the gridded datasets against the observed data based on d_m on monthly, seasonal and annual scale for precipitation in the study area



Fig. 4 Comparison between the performance of the gridded datasets against the observed data based on RMSE on monthly, seasonal and annual scale for precipitation in the study area



Fig. 5 Comparison between the performance of the gridded datasets against the observed data based on r on monthly, seasonal and annual scale for precipitation in the study area



Fig. 6 Comparison of the gridded datasets against observed data on mean monthly basis for precipitation, maximum temperature and minimum temperature in the study area

Table 4 explains the monthly, seasonal and annual correlations between the gridded precipitation datasets and observed data on different statistical measures. Correlation coefficient tested at 5% significant level and index of agreement were used to measure the general agreement between the gridded datasets and observed data. The root mean square error (RMSE) and the relative bias (BIAS) were used to describe the errors and biases. On monthly comparison for the whole of the basin, APHRODITE (v1101) was found to be the best with r as 0.85 followed by GPCC as 0.72, both of which have been tested for statistical significance at 5% probability level. Other datasets also showed moderate results with r > 0.50 included PERSIANN-CDR, CRU (TS v4.02) and NCEP-CFSR with r values as 0.67, 0.62 and 0.61, all of which are statistically significant at 5% level, respectively. Based on the RB evaluation criteria as reported by Wehbe et al. (2017) and Anjum et al. (2018), on monthly basis, all the datasets either overestimated or underestimated the observed data. The overestimation was found in order of: CRU (TS v4.02) (94.65%), GPCC (79.58%), PERSAAINN-CDR (31.14%) and APHRODTE (v1101) (11.85%). Amongst all the considered datasets, NCEP-CFSR underestimated the observed data with RB as -24.24%.

On the basis of seasonal and annual scales using r, APHRODITE (v1101) outperformed in spring, summer and annual with r values as 0.86, 0.86 and 0.61 ($\alpha = 5\%$ significant level) respectively, whereas GPCC was found to be the best in winter and autumn with r values as 0.89 and 0.79 respectively. Based on d_m , APHRODITE (v1101) had values for winter (wet season), spring, summer (dry season), autumn and annual as 0.79, 0.72, 0.38, 0.60 and 0.51 respectively. Based on RMSE, all the datasets showed poor results as it provided very high RMSEs for all timescales. Looking at the results, it can also be concluded that wet season is better than dry season in terms of all statistical scores. Based on RB (%), all the datasets either overestimated or underestimated precipitation on seasonal and annual timescales. In general, for precipitation, most of the considered datasets showed good agreements with the observed data on the basis

of r and d_m but for the same datasets, poor results were obtained for RMSEs and RB (%) in the study area.

4.2 Maximum and minimum temperature

Figures 6 (b) and (c) present comparisons between the gridded and observed datasets on mean monthly scales for maximum and minimum temperature. From these figures, it can be seen that CRU dataset follows closely the observed data pattern as compared to CFSR basin wise.

Tables 5-7 show the maximum and minimum values of d_m, RMSE and r of the two gridded datasets i.e., NCEP-CFSR and CRU (TS v4.02). These datasets were evaluated against the observed data for maximum and minimum temperature in the study area. Table 5 for maximum temperature shows the ranges of d_m whose values varied between 0.18-0.74 and 0.12-0.77 for winter and spring seasons respectively for CRU (TS v4.02) while for rest of the timescales, it showed poor ranges. For minimum temperature in the same table, CRU (TS v4.02) dataset, d_m values ranged between 0.03-0.58 for winter while for rest of the timescales, it showed poor variations. Looking at the table, it can be revealed that NCEP-CFSR dataset didn't show good results for both the maximum and minimum temperature.

The maximum and minimum values of RMSE in the study area are shown in Table 6. For maximum temperature and CRU (TS v4.02) dataset, the RMSE values on monthly, winter, spring, summer, autumn and annual timescales varied between 1.37-11.56, 0.95-10.41, 0.75-11.88, 0.65-12.66, 1.11-10.86 and 0.55-11.50 respectively. These ranges of RMSE for CRU (TS v4.02) are relatively good as compared to NCEP-CFSR dataset. Similarly for minimum temperature in the same table, variation of the RMSEs can be seen for both the datasets *i.e.*, CRU (TS v4.02) and NCEP-CFSR at all timescales.

Similarly, Table 7 shows the maximum and minimum values of r for CRU (TS v4.02) and NCEP-CFSR for maximum and minimum temperature at all timescales in the study area. For maximum temperature, results of both the datasets for all timescales were found

	Indices	Monthly	Winter	Spring	Summer	Autumn	Annual
	$d_{\rm m}$	0.59	09.0	0.52	0.44	0.47	0.45
	RMSE (mm)	40.93	75.01	104.60	119.16	76.80	285.08
NUEF-UF3K	C.C (r)	0.61^{*}	*9 2 . 0	0.61*	0.58^{*}	0.56*	* <i>L</i> S· 0
	RB (%)	-24.24	4.84	-12.48	-44.67	-44.92	-17.38
	d_m	0.69	62.0	0.72	0.38	09.0	0.51
	RMSE (mm)	25.81	48.53	65.05	69.20	52.09	171.72
APHKUDILE (VI101)	C.C (r)	0.85*	*78.0	0.86*	0.86^{*}	*69.0	0.61 *
	RB (%)	11.85	-4.03	-5.52	38.72	4.36	-2.21
	d_m	0.50	0.62	0.43	0.28	0.46	0.35
	RMSE (mm)	44.25	87.72	141.64	134.53	80.53	361.10
Uruc	C.C (r)	0.72*	*68.0	0.66*	0.65*	*67.0	*65.0
	RB (%)	79.58	4.51	0.55	182.43	49.02	21.58
	$d_{\rm m}$	0.53	0.64	0.47	0.35	0.52	0.41
	RMSE (mm)	38.63	81.91	117.45	97.14	60.17	257.84
FERDIAININ-CUK	C.C (r)	•.67*	0.83 *	0.60*	0.49*	*69.0	* <i>L</i> S· 0
	RB (%)	31.14	-5.33	-10.97	87.71	16.44	3.20
	$d_{\rm m}$	0.51	0.63	0.51	0.30	0.46	0.34
	RMSE (mm)	42.52	78.86	112.22	129.89	69.51	315.97
CKU (13 V4.UZ)	C.C (r)	0.62*	0.84*	0.66*	0.44^{*}	0.65*	0.57*
	RB (%)	94.65	15.37	25.05	217.50	43.98	38.58

Table 4. Evaluation Results of the Basin Averaged Precipitation on monthly, seasonal and annual basis for NCEP-CFSR, APHRODITE

Note: Best values of the indices among NCEP-CFSR, APHRODITE, GPCC, PERSIANN-CDR CRU are shown in bold font *Refers to statistical significance at $\alpha = 5\%$

satisfactory at 5% significant level based under the lists of maximum values in the table. Similarly, for minimum temperature, only CRU (TS v4.02) provided satisfactory results on the basis of the maximum values in the study area. Comparing reliability of both the datasets on the basis of r (Table 7), NCEP-CFSR dataset showed a number of negative values of r compared to CRU (TS v4.02) for both maximum and minimum temperature. This showed that CRU (TS v4.02) dataset performed well compared to NCEP-CFSR.

Table 8 presents the statistical summary of the evaluation of gridded datasets for maximum temperature. Using evaluation criteria of r>0.70 by Anjum et al. (2018), and considering r for evaluation, CRU (TS v4.02) performed very well in winter (r = 0.77) and spring (0.85) seasons at 5% significant level but didn't give satisfactory results for rest of the timescales. Based on RMSE, CRU (TS v4.02) showed good results for all timescales compared to NCEP-CFSR. Based on the RB evaluation criteria, both the datasets underestimated the observed data on monthly, seasonal and annual timescales.

For minimum temperature, Table 9 shows results of d_m , r, RMSE and RB for the two datasets *i.e.*, NCEP-CFSR and CRU (TS v4.02). Using the same evaluation criteria (Anjum et al., 2018) for r>0.70, both the datasets showed poor agreements (r<0.7) with the observed data. But on the basis of RMSE, CRU (TS v4.02) showed good agreements at all timescales. On the basis of d_m , both the datasets failed to show good results. On the basis of RB, both the datasets underestimated the observed data in the study area with highest underestimation for winter season.

4.3 Discussion

Kabul River Basin which is a transboundary basin between Pakistan and Afghanistan in which 39% lies in Pakistan while rest in Afghanistan. The area has been given less attention by the research community in terms of research, though it carries its own importance. Before such study, Ghulami et al. (2017) had carried out similar work in the recent past by evaluating various gridded precipitation datasets including APHRODITE (v1101). The missing part in their study was that they covered only part of the basin on Afghanistan side with limited data, few stations were evaluated only for precipitation. They concluded that APHRODITE (v1101) performed better than other datasets.

Our research study is a novel study because it considered all the available observed stations data in the two countries, covering whole of the basin and were evaluated for precipitation, maximum and minimum temperature. Results indicated that APHRODITE (v1101) followed by GPCC performed well for precipitation and CRU (TS v4.02) for maximum and minimum temperature. Interestingly, APHRODITE (v1101) was found to perform better for precipitation in both the studies. As stated before no immediate comparative study is available for temperature in Kabul River Basin but in a very recent study performed by Kanda et al., (2020) which assessed the performance of 5 gridded datasets for temperature in Northwestern Himalaya (NWH). Results revealed that CRU-TS and ERA-I produced more true estimates which confirms our findings.

In the recent past, several research studies have been conducted in the bordering areas of Kabul River Basin. These include: Krakauer et al. (2019), Iqbal et al. (2019), Anjum et al. (2016) and Islam et al. (2021). Krakauer et al. (2019) found APHRODITE (v1101) performed well followed by GPCC in the Indus Basin on seasonal basis using Nash-Sutcliffe efficiency (NSE) as statistical measure. Study conducted by Iqbal et al. (2019) over Gilgat Baltistan concluded that APHRODITE performed well in terms of precipitation. Some other researchers including Anjum et al. (2016) assessed TMPA-v6 and v7 for Swat watershed of Kabul River Basin and found that TMPA-v7 did better as compared to other datasets. Anjum et al. (2018) conducted research over northern high lands of Pakistan and found that IMERG performed better than TRMM 3B42V7 and 3B42RT. Islam et al., (2021) in their study reported that APHRODITE data has been frequently used for validation of the satellite rainfall products, analysis of climate change, investigating changes in winter precipitation over China, evaluation of TMPA 3B42-V6 rainfall estimates over Nepal and validation of

		Maximum 7	Maximum Temperature			Minimum J	Minimum Temperature	
Timescale	NCEP	NCEP-CFSR	CRU (TS v4.02)	S v4.02)	NCEP	NCEP-CFSR	CRU (T	CRU (TS v4.02)
	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value
Monthly	0.42	0.07	0.55	0.12	0.35	0.16	0.41	0.07
Winter	0.48	0.12	0.74	0.18	0.44	0.08	0.58	0.03
Spring	0.55	0.07	0.77	0.12	0.38	0.1	0.45	0.05
Summer	0.33	0.03	0.45	0.04	0.28	0.07	0.32	0.07
Autumn	0.42	0.03	0.32	0.06	0.28	0.16	0.39	0.07
Annual	0.33	0.03	0.5	0.05	0.23	0.09	0.42	0.04
able 6. Rar	nge of RMSEs for	Table 6. Range of RMSEs for Maximum and Minimum		Temperature in the study area	1			
		Maximum	Maximum Temperature			Minimum	Minimum Temperature	
Timescale	NCE	NCEP-CFSR	CRU (1	CRU (TS v4.02)	NCE	NCEP-CFSR	CRU (CRU (TS v4.02)
	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value
Monthly	19.56	2.27	11.56	1.37	16.24	1.6	6.83	2.41
Winter	17.03	3.47	10.41	0.95	19.26	1.04	7.29	1.75
Spring	20.79	1.93	11.88	0.75	16.48	1.38	6.92	2.27
Summer	19.81	1.73	12.66	0.65	15.03	1.02	7.78	1.82
Autumn	20.04	1.46	10.86	1.11	13.51	1.15	6.23	2.18
Annual	19.49	1.59	11.5	0.55	16.15	1.02	6.74	1.95
able 7 Ran	ige of Pearson's Co	orrelation Coefficie	Table 7 Range of Pearson's Correlation Coefficient (r) values for Maximum and Minimum Temperature in the study area	aximum and Mini	imum Temperature	e in the study area		
		Maximum T	Maximum Temperature			T minimum	Minimum Temperature	
Timescale	NCEP	NCEP-CFSR	CRU (TS v4.02)	5 v4.02)	NCEP	NCEP-CFSR	CRU (T	CRU (TS v4.02)
	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value
Monthly	0.72*	0.39	0.70*	0.42	0.42	0	0.74*	0.26
Winter	0.96*	-0.55*	0.96*	0.12	0.83*	-0.03	0.91^{*}	0.15

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		Maximum	Maximum Temperature			Minimum T	Minimum Temperature	
Timescale		NCEP-CFSR	CRU (T	CRU (TS v4.02)	NCEP	NCEP-CFSR	CRU (T	CRU (TS v4.02)
	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value
Monthly	0.72*	0.39	0.70^{*}	0.42	0.42	0	0.74^{*}	0.26
Winter	0.96*	-0.55*	0.96*	0.12	0.83*	-0.03	0.91^{*}	0.15
Spring	0.84*	0.61^{*}	0.95*	0.59*	0.60*	-0.19	0.92*	0.44
Summer	0.56*	-0.12	0.68*	0.27	0.37	-0.39	0.46*	-0.01
Autumn	0.53*	0.18	0.56*	0.09	0.42	-0.59*	0.62^{*}	-0.04
Annual	0.79*	0.28	0.81^{*}	0.17	0.46^{*}	-0.44*	0.78*	-0.04
*	*D of our to statistical significances at a = 50/	i contraction of a	- 50/					

*Refers to statistical significance at $\alpha = 5\%$

	Indices	Monthly	Winter	Spring	Summer	Autumn	Annual
	dm	0.23	0.27	0.25	0.18	0.17	0.16
	RMSE (°C)	9.54	9.46	9.75	8.35	9.40	8.98
NCEP-CF3K	C.C (r)	0.58*	0.39	0.74*	0.32	0.33	0.52*
	RB (%)	-44.18	-76.72	-40.20	-21.12	-34.27	-36.67
	$d_{\rm m}$	0.28	0.42	0.32	0.19	0.19	0.22
	RMSE (°C)	5.75	5.03	5.58	5.83	5.29	5.27
CKU (15 V4.02)	C.C (r)	0.62*	0.77*	0.85*	0.48*	0.33	0.52*
	RB (%)	-20.50	-32.87	-19.16	-14.60	-14.44	-17.98

Table 8. Evaluation Results of the Basin Averaged Maximum Temperature on monthly, seasonal and annual basis for NCEP-CFSR, and CRU (TS v4.02) in the study area

Best values of the indices among NCEP-CFSR and CRU are shown in bold font Note:

*Refers to statistical significance at $\alpha = 5\%$

Table 9. Evaluation Results of the Basin Averaged Minimum Temperature on monthly, seasonal and annual basis for NCEP-CFSR, and CRU(TS v4.02) in the study area

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Name of dataset	Indices	Monthly	Winter	Spring	Summer	Autumn	Annual
RMSE (°C) 6.67 6.73 6.50 C.C (r) 0.28 0.48* 0.30 RB (%) -246.58 -22207.79 -65.67 dm 0.25 0.28 0.21 dm 0.25 0.28 0.21 RMSE (°C) 4.22 3.67 4.25 RMSE (°C) 0.47* 0.57* 0.62* RN (%) -179.77 -8451.39 -18.36		$d_{\rm m}$	0.28	0.33	0.27	0.19	0.23	0.22
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		RMSE (°C)	6.67	6.73	6.50	6.67	5.67	6.17
RB (%) -246.58 -22207.79 -65.67 dm 0.25 0.28 0.21 RMSE (°C) 4.22 3.67 4.25 C.C (r) 0.47* 0.57* 0.62* RB (%) -179.77 -8451.39 -18.36	NCEP1-CFOK	C.C (r)	0.28	0.48*	0.30	-0.07	0.05	0.12
dm 0.25 0.28 0.21 RMSE (°C) 4.22 3.67 4.25 C.C (r) 0.47* 0.57* 0.62* RB (%) -13977 -845139 -1836		RB (%)	-246.58	-22207.79	-65.67	-31.65	-54.34	-60.77
RMSE (°C) 4.22 3.67 4.25 C.C (r) 0.47* 0.57* 0.62* RB (%) -179 77 -8451 39 -18 36		d_m	0.25	0.28	0.21	0.17	0.21	0.15
C.C (r) 0.47* 0.57* 0.62* RB (%) -129 72 -8451 39 -18 36		RMSE (°C)	4.22	3.67	4.25	4.58	3.86	4.02
-129 72 -8451 39 -18 36	CKU (13 V4.UZ)	C.C (r)	0.47*	0.57*	0.62*	0.06	0.29	0.30
		RB (%)	-129.72	-8451.39	-18.36	-12.08	-13.29	-17.85

Best values of the indices among NCEP-CFSK and CKU are shown in bold font Note:

*Refers to statistical significance at $\alpha = 5\%$

PERSIANN Satellite precipitation products over Iran; which in other words certify the reliability and potentiality of APHRODITE data in this region.

5. Conclusions and Recommendations

5.1 Conclusions

For precipitation, APHRODITE (v1101) and GPCC datasets showed high degree of correlations on the basis of r and d_m on monthly, seasonal and annual basis for precipitation whereas for temperature, CRU (TS v4.02) showed significant agreement with the observed data in the study area. This research study concludes that APHRODITE (v1101) and GPCC precipitation datasets and CRU (TS v4.02) temperatures datasets, can be safely used as alternate sources of data for the studies like climate change and drought analysis, hydro-meteorological and agriculture related studies in the study area.

5.2 Recommendations

In the present study, we evaluated five gridded datasets for precipitation and two for temperature in Kabul River Basin. Kabul River has a transboundary basin between Pakistan and Afghanistan where representative observed data is a major challenge to assess the true climate of the basin. Limited observed stations at lower elevations in the river valley are present on Pakistan side while on Afghanistan side, the data has either been lost or not available due to war. For the present study, observed meteorological data was collected from the concerned departments of both the countries. PMD provided data of precipitation and temperature of all the meteorological stations in the basin whereas limited data of precipitation only (few years) was provided by the Ministry of Agriculture, Afghanistan. Analyses were made based on this data and conclusions were drawn as elaborated in the "Results and Discussion" section of this paper. Now it is highly recommended that in future, complete evaluation may be carried out to reach out to some more realistic conclusions subject to the availability of complete observed data of meteorological stations of the part of KRB in Afghanistan.

Author's Contribution

Mahmood Alam Khan conducted this research work as part of his Ph.D dissertation. As a first author, he proposed the main concept, collected and analyzed the data and did the write up. Muhammad Shahzad Khattak performed technical review and proof read of the manuscript before its submission. Amjad Khan was involved in preparation and formatting the tables, illustrations and figures.

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