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Modeling streamflow using multiple precipitation products in a topographically complex catchment

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Abstract

Precipitation is of primary importance in hydrological modeling and predicting streamflow. However, lack of gauged stations for long term precipitation data particularly in the data scarce Chitral River Basin (CRB) of Pakistan and other parts of developing world is a hindrance to understanding surface water hydrology. Therefore, this study aims to assess different sources of precipitation data for streamflow prediction in the CRB. A modified version of conceptual and semi-distributed hydrological model Hydrologiska Byråns Vattenbalansavdelning (HBV) known as HBV-light is used in this study to model streamflow by forcing it with precipitation inputs of different Precipitation Products (PPs). These PPs include, APHRODITE (V1101, V1801R1), CHIRPS V2.0, CPC-Global, ERA5, GPCC V.2018 (V2), GPCP-1DD V1.2, PERSIANN, PERSIANN CCS, PERSIANN CDR, and TRMM (3B42V7). The model was calibrated and validated for two periods (1995–2005 and 2007–2013, respectively), and showed good performance during both periods. Prior to assessing the performance of these PPs to simulate observed streamflow, they were assessed against gauged precipitation. Results of this study suggest that APHRODITE-based precipitation performed better than other precipitation products in the simulation of precipitation characteristics in the study region. Multiple efficiency evaluation metrics including KGE, NSE, and PBIAS were employed to assess streamflow prediction capability of different products. Results indicated that APHRODITE outperformed all other

precipitation products (KGE = 0.89) in terms of simulating observed streamflow in the CRB. The CPC Global precipitation product (KGE = 0.71) was found to be the least suitable product for hydrological modeling in the CRB. This study provides useful guidance for the selection and application of gridded precipitation products for long term continuous streamflow prediction in the Chitral River Basin.

Keywords: Streamflow prediction, Chitral River Basin., PCA, HBV-light, Gridded precipitation, Reanalysis, APHRODITE

Introduction

Understanding of hydrological implications of climatic variability is crucial for sustainable freshwater resources management (Ndehedehe et al. 2020), and hydrological modeling is widely used to improve understanding of hydrological processes (Beven 2011; Pakoksung and Takagi 2016; Belayneh et al. 2020; Kabood et al. 2020). Management of freshwater resources is also an integral part of food security and functioning of various ecosystems (e.g. aquatic biodiversity) (Agutu et al. 2019; Schroth et al. 2016; Cenacchi 2014; Tockner et al. 2010). One of the most important driving forces of a hydrological model and a component of the hydrological cycle is precipitation (Beck et al. 2017; Masih et al. 2010; Price et al. 2014). Characteristically, precipitation is highly variable, and its estimation is difficult, especially in regions with complex topography (Stephens et al. 2010; Herold et al. 2016; Prein and Gobiet 2017). It is also crucial for simulation of streamflow (Sun et al. 2018; Pena Arancibia et al. 2013) and better understanding of hydrometeorological processes (Hu et al. 2017; Ma et al. 2015).

Globally, there is a decline in gauged observations for precipitation due to lack of investment in gauge measurements (e.g., Ndehedehe 2019a). Even for regions with observational networks, their density falls below the World Meteorological Organization guidelines (Vorosmarty et al. 2001). Chitral River Basin (CRB) is in a geopolitical zone of Pakistan in the famous Hindukush-Karakoram-Himalayan (HKH) region and has shared transboundary water resources with Afghanistan. Both countries are emerging economies and depend on this shared natural resource (Biermann and Dingwerth 2004). These riparian countries not only face climate-induced adversities and variations in the hydrological cycle within their own boundaries but also across the borders, and this situation could lead to altercation and unrest on both sides (Wolf 2009). This calls

for a revision of the existing water related policies (which are inclined more towards national or sub-national frontiers) and transfer to new policies with a focus on transboundary menaces (Hashmi et al. 2019).

Recently, there have been some recommendations and guidelines in other regions of the world to address issues related to transboundary water resources and conflicts. And problems associated with transboundary water resources has resulted in water diplomacy and institutional framework that could be used to nurture the cooperation among different stakeholders (Akhmadiyeva and Abdullaev 2019; Atef et al. 2019; Ndehedehe et al. 2020). Water diplomacy is considered as one of the best choices in terms of relevant tools when it comes to the shared management of transnational water resources, engagement of political and institutional dialogues, and policies to keep up fruitful discussions related to different aspects of water sharing (e.g. legal) and to improve the functionality of transboundary water cooperation (Honkonen and Lipponen 2018, Grech-Madin et al. 2018; Schmeier and Shubber 2018).

To devise a policy that could account for the resolutions and better management of water resources, a good start would be the understanding of surface water hydrology and its relation key components of the water cycle (like precipitation). However, a key problem that arises is the lack of sufficient gauge data for hydrological applications, which creates a gap in knowledge, especially in understanding the complexity of natural processes and important drivers of surface water hydrology. As with other emerging economies, available ground precipitation data in Pakistan and specifically in the CRB are limited, which is a hurdle in detailed assessments of hydrological processes (Cogley 2009; Hewitt 2011; Adnan et al. 2017). Satellite and reanalysis based gridded precipitation products are among alternate sources of precipitation data. These observations have a high potential for freshwater resource management in the data-scarce regions and are becoming increasingly popular and widely used in surface water hydrology related studies (e.g. Li et al. 2018; Agutu et al. 2017**;** Ndehedehe et al. 2020). Recent studies in the African regions with limited gauging stations, for example, have successfully utilized different alternative precipitation products to understand the regional hydrology and the dynamics of freshwater resources (Skaskevych et al. 2019; Ndehedehe et al. 2018, 2019b).

To our knowledge, the performance evaluation of different precipitation products for streamflow prediction, in the CRB has not been reported. This study therefore aims to evaluate efficiency of

different Precipitation Products (PPs) for streamflow prediction in the data-scarce region of CRB using hydrological modeling. The specific objectives of this study are to: (1) evaluate the performance of ten different precipitation products with respect to gauge precipitation in the CRB and (2) investigate the performance of these precipitation products for streamflow prediction.

Materials and Methods

Study area

The Chitral River is one of the most important rivers of the Hindukush ranges, in the Hindukush-Karakoram-Himalayan region. It covers an area of 11,396 km^2 and elevation in the CRB ranges from about a 1000 m to more than 7500 m above mean sea level (Fig. 1). It is one of the most topographically complex catchments and is in the humid region of Pakistan. Maximum precipitation is received in winter and spring (Hayat et al. 2019). CRB is bordered by Afghanistan in the west and river water is crucial for two nations to support their domestic activities and requirements, and for nurturing the socio-economic development of the region.

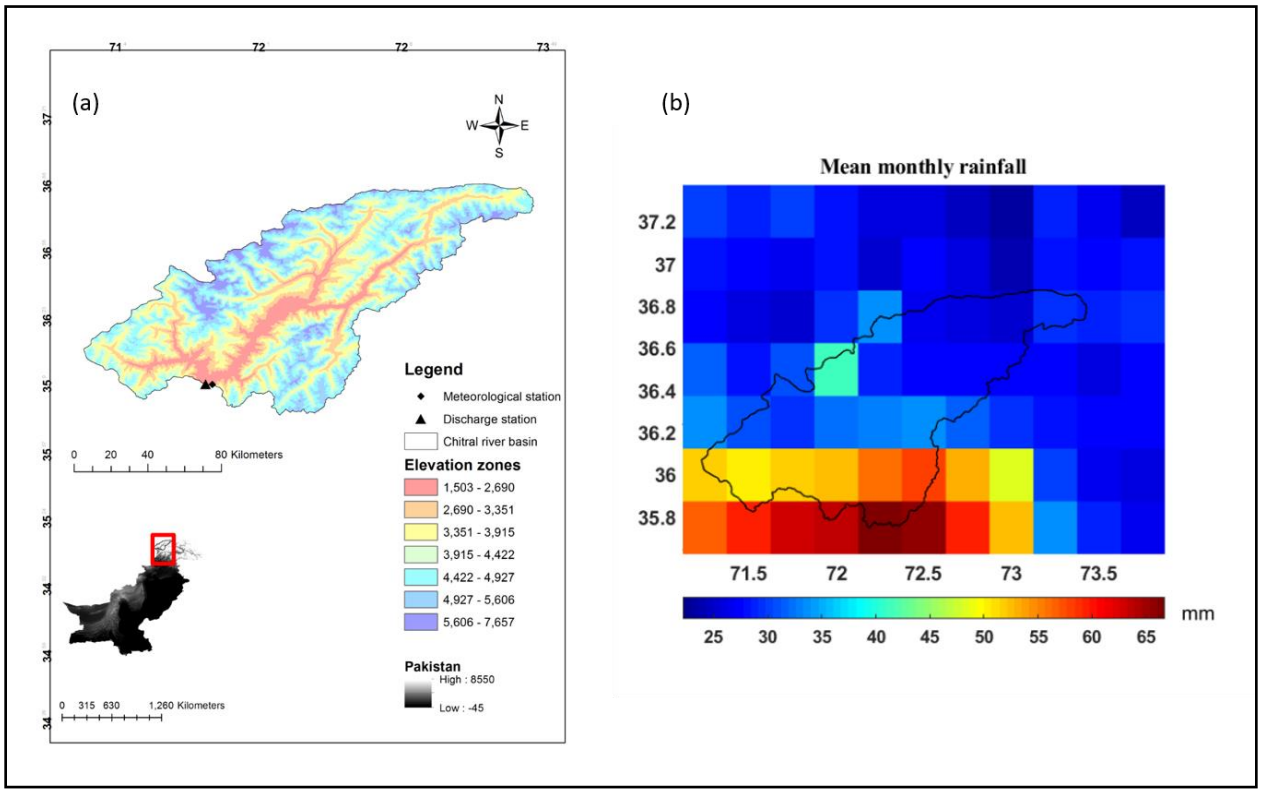

Fig. 1 (a) Physical characteristics and location map of the study area (b) mean monthly rainfall over the catchment

Hydrological model and input data

The Hydrological Bryans Vattenbalansavdelning HBV is a simple bucket type model (Bergström 1976; Lindström et al. 1997) used for streamflow simulation. In this study, a modified version of the model i.e. the HBV-light (Seibert and Vis 2012) is used, which has been extensively used worldwide (Vis et al. 2015; Hakala et al. 2018; Usman et al. in press). It is termed as a semi-distributed model, as spatial discretization of catchment (into different elevation and vegetation zones) is possible. Precipitation, air temperature, and estimated potential evapotranspiration data is used as input data in the HBV-light. Detailed description of the model can be found in (Siebert and Vis 2012; Bergström 1976; Lindström et al. 1997, Burhan et al. 2020). The Digital Elevation Model (DEM) was obtained from the Shuttle Radar Topographic Mission (SRTM) with a spatial resolution of approximately 90 m. Potential evapotranspiration was calculated using the method proposed by (Irmak et al. 2003).

Precipitation Products (PPs)

Ten different precipitation products are evaluated in this study to predict streamflow, details of the products including spatial and temporal resolutions, available periods, and respective references are summarized in Table 1.

Table 1. Characteristics of precipitation datasets used in this study.

Datasets (short name)	Spatial resolution	Temporal resolution	Period (used in this study)	Reference
APHRODITE V1101, V1801R1	0.25˚	daily	1995-2013	(Yatagai et al. 2012),
CHIRPS V2.0	0.25˚	daily	1995-2013	(Funk et al. 2015)
CPC-Global	0.5˚	daily	1995-2013	(Xie et al. 2010)
ERA5	0.25˚	daily	1995-2013	Copernicus Climate Change Service (C3S) (2017)
GPCC V.2018 (V2)	1˚	daily	1995-2013	(Schamm et al. 2014)
GPCP-1DD V1.2	1˚	daily	October 1996-2013	(Huffman et al. 2001)
CHRS PERSIANN	0.25˚	daily	March 2000-2013	(Sorooshian et al. 2000)
CHRS CCS	0.25˚	daily	2003-2013	(Hong et al. 2004)
CHRS CDR	0.25˚	daily	2003-2013	(Ashouri et al. 2015)
TRMM 3B42 V7	0.25˚	daily	1998-2013	(Huffman et al. 2007)

Model calibration and validation

The HBV-light was calibrated with observed precipitation data as an input for a period of 1995-2005 with a spin up period of a year 1994, and validated for a period of 2007-2013 with a spin up period of a year 2006. Then the model was recalibrated for each satellite precipitation product. Model efficiency was evaluated using three different evaluation criteria i.e. Kling-Gupta Efficiency (KGE) (Gupta et al. 2009), Percent Bias (PBIAS), and the Lindström measure (Lm) (Lindström et al. 1997). Lm incorporates combined effects of two widely used metrics (Hakala et al. 2018) i.e. the Nash-Sutcliffe efficiency (NSE); (Nash and Sutcliffe 1970) and volume error. The Lindström measure is calculated as "NSE minus 0.1 multiplied by the relative volume error" (Hakala et al. 2018). KGE and Lm has a perfect value of 1, and PBIAS has a perfect value of 0, which shows the highest possible match between observed and modeled streamflow. Genetic algorithm and Powell optimization (GAP; Seibert 2000) method is an automatic calibration method, in which the selection of optimum parameters is done first, and then a fine tuning is done to further enhance the objective function. The HBV-light was calibrated using GAP and Powell optimization.

Statistical decomposition of precipitation

Single meteorological station is used in this study as this is the only station in the catchment with a relatively long-term data (i.e., greater than fifteen years). Some other important questions prior to our analysis are; what is the magnitude of spatial precipitation in that location where the gauge is located in comparison to other areas within the basin? How spatially variable is precipitation in the study area? So, the spatial and temporal patterns of precipitation in the whole catchment were analyzed to examine if this meteorological station captures the plenitude and magnitude of precipitation observed in the catchment. To this end, a statistical decomposition of precipitation grids into spatial and temporal patterns using the principal component analysis [PCA, (Jolliffe 2002)] was undertaken. The scree plot analysis was used to identify two significant modes of precipitation variability in the basin. No fixed criterion is established to define the number of substantial principal components (PCs) that are best reserved in a particular situation, however, the selection of truncation can differ from existing selection rules to more subjective picks (e.g., scree plot analysis) depending on the data and the purpose of the statistical rotation (see, e.g., Ndehedehe et al. 2020b; Wilks 2011; Martinez and Martinez 2005). In the statistical rotation of precipitation using the PCA method, a deseasonalized matrix of precipitation grids (i.e., after

removal of the mean) masked over the Chitral catchment would be given as equation 1 $\boldsymbol{C}_{precipitaion} = [z(\boldsymbol{u}_p, t)]$ where $\boldsymbol{u}_p$ is spatial locations; $p = 1, 2, \ldots, nz$, which depicts the number of spatial locations for $\boldsymbol{C}_{precipitaion}$, and t is the monthly time step from 2002 to 2018 i.e., temporal evolutions). As an illustrative example, the 0.25° monthly precipitation grids over the CRB for the period between 2002 and 2018, $\boldsymbol{C}_{j\times h}$ will have the size, $j = 183$ and $h = 96$ where j and h are the monthly time steps (2002 to 2018) and observations (precipitation grids over the Chitral catchment), respectively (Ndehedehe et al. 2020b). The statistical decomposition of precipitation grids into spatio-temporal patterns using this method is given as (Ndehedehe et al. 2019c),

$$\boldsymbol{C}_{precipitaion}(t) = \sum_{p=1}^{n} m_p \boldsymbol{u}_p \quad (1)$$

Where $m_p(t)$ are the temporal variations also known as expansion coefficients, which have been normalized using their standard deviation to make them unit free and $\boldsymbol{u}_p$ are the corresponding spatial maps (empirical orthogonal functions-EOF loadings). Usually the principal components (PCs) of these loadings are used to adjust (scale) them to their original units (millimeter), they provide the weights of the original variables employed in the PCs. This approach provides the knowledge of the distribution of precipitation in time and space over the CRB.

Methodology to evaluate the efficiency of PPs in simulating observed precipitation and streamflow

Ten different PPs were evaluated against the gauge-based precipitation and then were used as forcing data to drive the HBV-light to simulate the observed streamflow. For comparison of precipitation of PPs and observed precipitation, all precipitation products were evaluated using correlation co-efficient R^2. As the major objective of this study was to analyze the performance of different precipitation products in predicting streamflow, other statistical criteria including KGE, NSE, and PBIAS were also used to evaluate the efficiency of the products in simulating observed streamflow. We evaluated performance of ten different PPs in their native resolution without any rescaling algorithms to avoid associated uncertainties (Hu et al. 2018). These precipitation products are often used to derive precipitation at a local scale without any added adjustments (Zandler et al. 2019), therefore, this approach was selected.

Results

Spatio-temporal variability of precipitation

A preliminary analysis of satellite precipitation over the catchment show that the first orthogonal mode of precipitation accounts for more than 88 % of observed total variability. The strongest loadings or spatial patterns are localized over the south where the gauged station is located as opposed to the dry northern section of the basin (EOF-1, Fig. 2). While this emphasizes the importance of assessing the hydrological processes of the south in terms of rainfall-runoff modeling, it justifies the use of this meteorological station in this study. This assumption holds given the observed magnitude of precipitation in the sub-grids of the vicinity where the station data used in the validation of precipitation products is located (Fig 1). The temporal patterns (PC-1, Fig. 2) associated with this leading mode of precipitation show considerable inter-annual fluctuations. The spatio-temporal variability of precipitation in the second mode (PC-2/EOF-2, Fig. 2) accounts for only 6.5 % and indicates short-term seasonal signals not relevant to the current analysis.

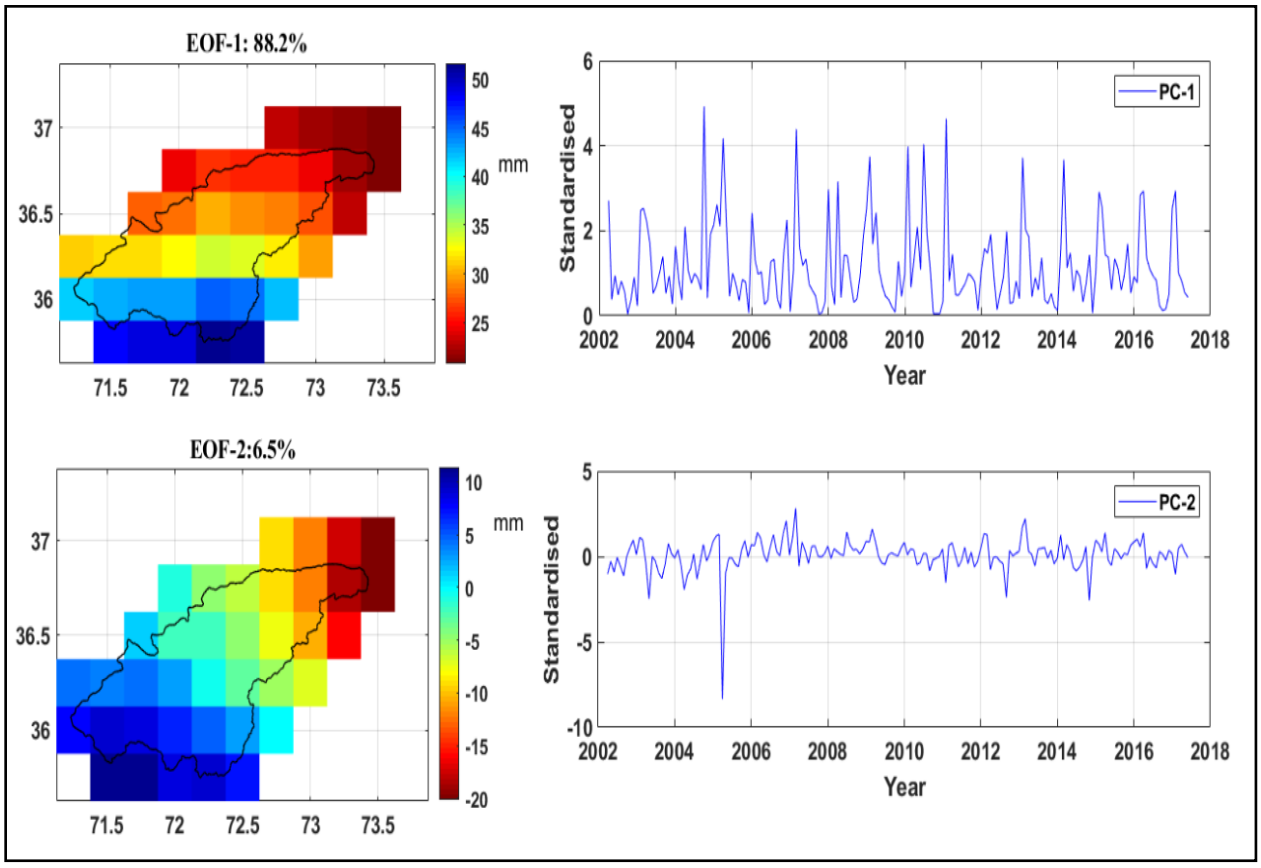

Fig. 2 Spatial and temporal analysis of precipitation over the CRB using TRMM-based precipitation (2002-2018). The EOFs (left) are the spatial patterns of rainfall associated with the temporal patterns on the right (principal components).

Calibration and validation of the HBV-light

For the calibration and validation of the model, values of different metrics that were achieved show a good performance of the model in capturing observed streamflow. For the calibration period, Lm value of 0.9 was achieved, and for the validation period, Lm value of 0.83 was achieved. Similarly, for the calibration period, a KGE value of 0.87 was achieved, and for the validation period a KGE value of 0.91 was achieved. PBIAS between the observed and modeled streamflow was 5.7 % during calibration period and 0.04 % during validation period. These results show that the HBV-light have performed remarkably well in the CRB. Comparison of observed and simulated streamflow in the CRB at daily and monthly time scales during calibration and validation periods is shown in (Fig. 3), which highlights the model's performance. Hydrological modeling approach was then used for assessing efficiency of different PPs.

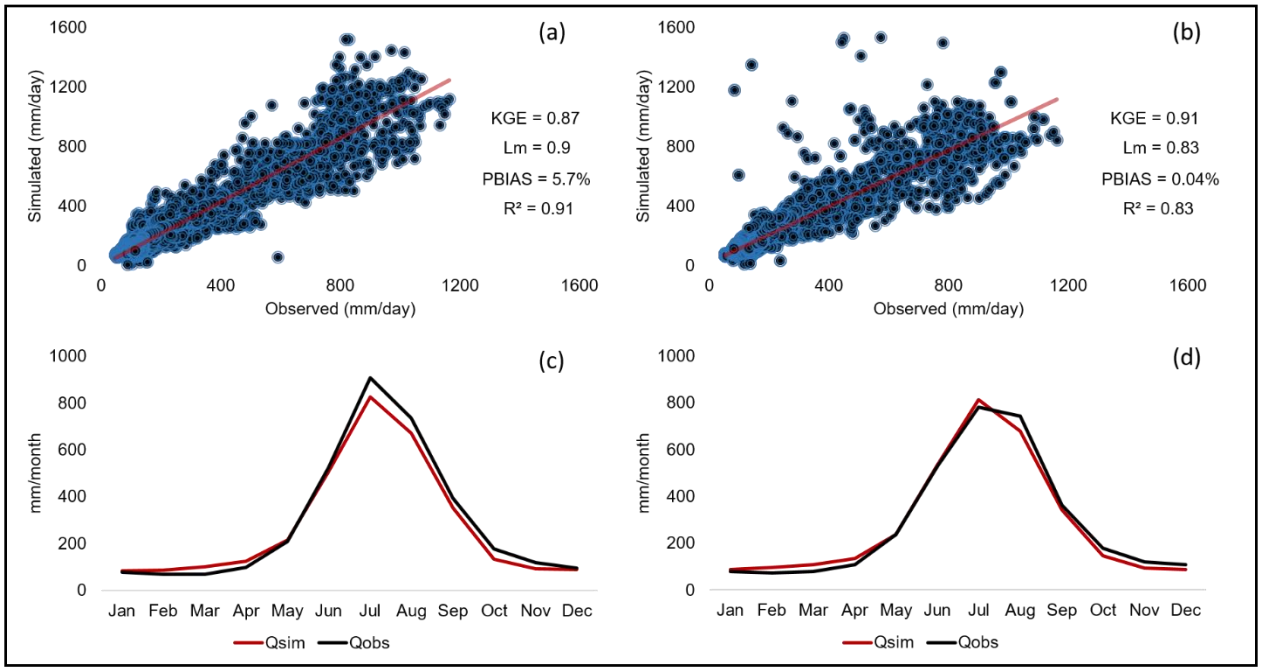

Fig. 3 Observed and simulated streamflow during calibration and validation periods. (a) Daily calibration 1995-2005 (b) daily validation 2007-2013 (d) monthly calibration 1995-2005 (d) monthly validation 2007-2013

Efficiency evaluation of different PPs in simulating observed precipitation

The classic statistical measure, i.e., the correlation coefficient ($R^{2)}$ between gauge-based and products-based daily precipitation is depicted in (Fig. 4). Range of R^2 for daily precipitation between observed and satellite-based products is from 0.001 to 0.574. Best representative of the

observed precipitation in terms of R^2 is the APHRODITE precipitation product and the least correlation with the observed precipitation is shown by TRMM 3B42 (Fig. 4).

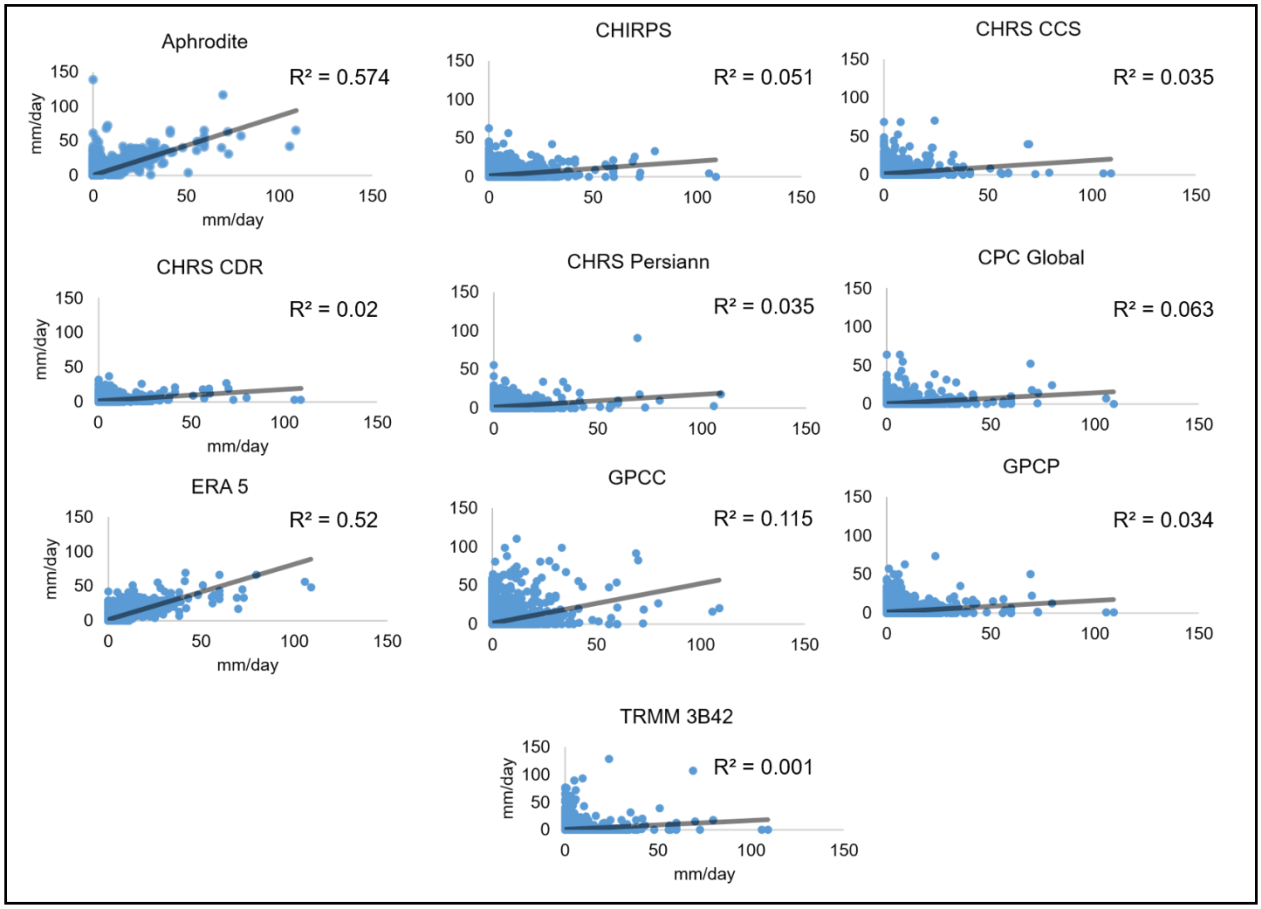

Fig. 4 Performance of different precipitation products in capturing observed precipitation.

Efficiency evaluation of the predicted streamflow using different PPs

The calibrated and validated model was forced with precipitation data of different PPs to simulate streamflow. KGE, NSE, and PBIAS have been selected to assess their performance. The performance indices include KGE ranging from 0.71 to 0.89, NSE from 0.78 to 0.87, and PBIAS ranging from -24 % to 17 % (Table 2). Results of the predicted streamflow indicated that APHRODITE outperformed all other products in simulating streamflow KGE = 0.89, NSE = 0.87, and PBIAS = 1 %. Some other products showed relatively better performance but not as optimum as APHRODITE.

Table 2. Evaluation metrics for assessing streamflow prediction.

Precipitation product	KGE	PBIAS (%)	NSE
APHRODITE	0.89	1	0.87
CHIRPS	0.85	-9	0.86
CHRS CCS	0.86	-4	0.85
CHRS CDR	0.87	-4	0.85
CHRS PERSIANN	0.79	-16	0.81
CPC	0.71	-24	0.78
ERA5	0.73	17	0.82
GPCC	0.84	7	0.86
GPCP	0.86	-8	0.86
TRMM	0.81	-14	0.84

Correlation between streamflow predicted by different precipitation products and observed precipitation is shown in (Fig. 5). Apparently, Aphrodite performed better overall compared to other products in simulating observed streamflow.

During dry period of the year, we note that streamflow is overestimated by ERA 5 followed by GPCC, APHRODITE, and CHRS CCS while it is underestimated by CPC Global followed by CHRS PERSIANN, TRMM 3B42, CHIRPS, GPCP, and CHRS CDR (Fig. 6) (mentioned in the order of maximum to minimum). However, in the wet period of the year, all the precipitation products have underestimated streamflow except the ERA 5 and GPCC, which overestimated the streamflow. Overall, the performance of APHRODITE is relatively better than other products throughout the year even with overestimation and underestimation in different periods.

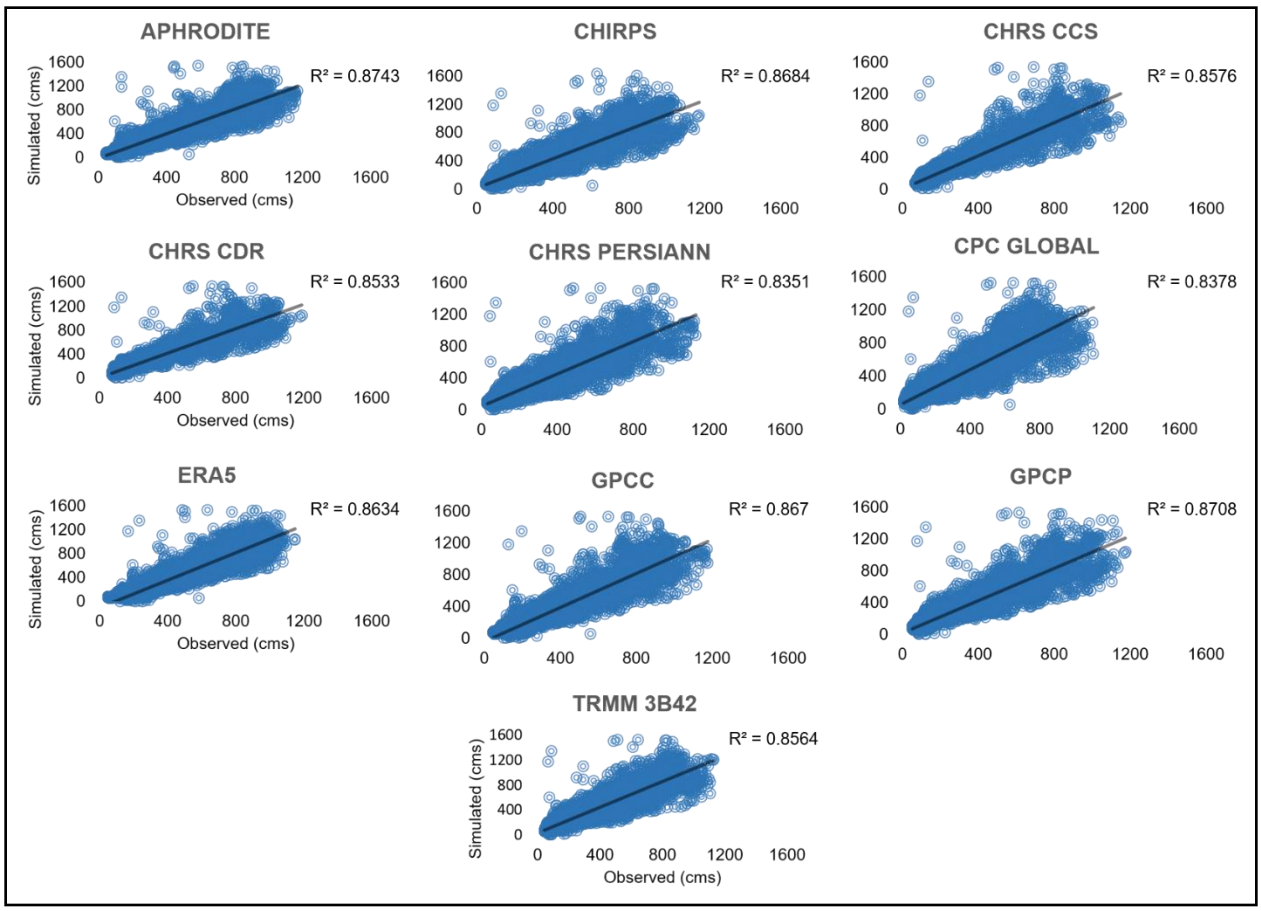

Fig. 5 Predicted streamflow by different precipitation products with respect to daily observed streamflow.

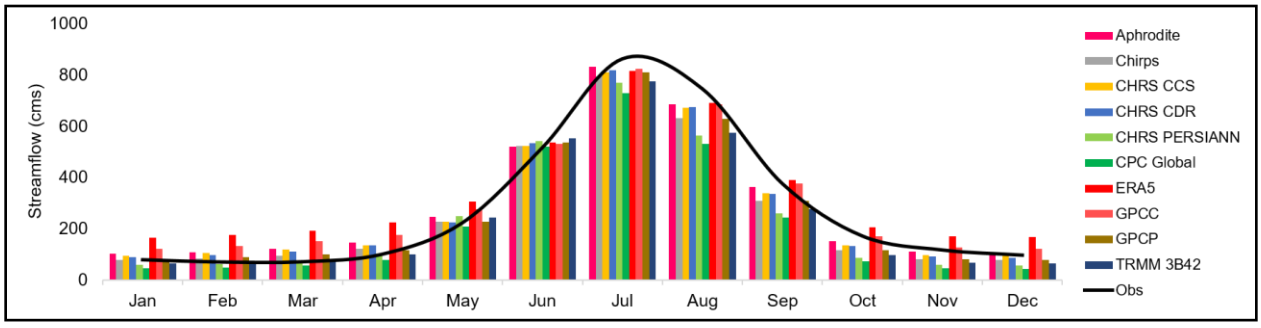

Fig. 6 Observed and simulated (using different precipitation products) monthly streamflow.

KGE is considered as the most important metrics for streamflow simulation (Brocca et al. 2020) and has been given a significant weight in overall assessment of streamflow prediction ability of different precipitation products. APHRODITE with maximum KGE, NSE, and minimum Percent

bias (negligible overestimation) was found to be the most appropriate precipitation product that could be used for hydrological modeling in the CRB.

Different products seem appropriate for the purpose of streamflow prediction in the CRB. However, their suitability is season dependent, that is, if their performance is better in one half of the year it is worse in other half. For instance, CHRS CDR has a KGE = 0.87, NSE = 0.85, and PBIAS of only -4 %, and it predicted the streamflow very efficiently during the dry period of the year with an average monthly streamflow of 100 m^3/s compared to the observed average streamflow of 101 m^3/s. However, when it comes to streamflow prediction in wet period of the year, it appears to underestimate streamflow significantly (453 m^3/s as compared to 470 m^3/s which is observed streamflow).

The other product that performed well was CHRS CCS, indicating a KGE = 0.86, NSE = 0.85, and PBIAS of only -4 %. It predicted streamflow more efficiently in the dry period of the year with an average monthly streamflow of 107 m^3/s compared to the observed average streamflow of 101 m^3/s. However, when it comes to streamflow prediction during wet period, it underestimates streamflow (451 m^3/s as compared to 470 m^3/s, which is observed streamflow).

Moreover, we found that GPCP has also performs well in terms of statistical criteria evaluation with KGE, NSE, and PBIAS of 0.86, 0.86, and -8 % respectively. However, it underestimates the streamflow in dry period and even more in the wet period of the year. Average predicted streamflow in dry period by GPCP is 90 m^3/s compared to 101 m^3/s observed streamflow and average predicted streamflow in wet period (437 m^3/s) compared to 470 m^3/s (observed streamflow).

APHRODITE was the only precipitation product that outperformed other products in terms of the statistical evaluation metrics used in this study (KGE, NSE, R^2, PBIAS), and streamflow prediction both in dry and wet period of the year. Average predicted streamflow in dry period by the APHRODITE-based precipitation is 116 m^3/s compared to 101 m^3/s (observed streamflow) and average predicted streamflow in wet period is 465 m^3/s unlike observed streamflow which is 470 m^3/s.

Discussion

Modeling streamflow using a hydrological model is one of the widely used method to assess the suitability of different precipitation products for streamflow prediction. In this study, gauged based streamflow data were used for performance assessment of ten different Precipitation Products (PPs). As shown in this study, the hydrological model HBV-light performed considerably well both during calibration and validation periods. The results of this calibrated model indicate a high correlation between observed streamflow (monitored at the gauge) and the streamflow simulated by the model. This correlation (KGE = 0.87 and 0.91 during calibration and validation respectively) is an indication of minimal errors of model structure, parameters and atmospheric forcings (Hakala et al. 2010). After the model setup, the next step was to assess the performance of ten different PPs, each of which have their own characteristics. The performance evaluation was carried out in two phases. In the first phase, efficiency of the precipitation products in replicating gauged-based precipitation was assessed, and in the second phase, the performance of these products in predicting observed streamflow was evaluated. Prior to conducting this two-phase analysis, an important preliminary aspect of this study was to assess whether the gauged precipitation data (consisting of one meteorological station) was good enough to capture the patterns of spatial and temporal variability within the whole basin or not. To this end, the Principal Component Analysis (PCA) technique was employed to decompose satellite-based rainfall into leading modes of variability. We found that more than 88 % of the changes in precipitation within the basin occurred around the point where the gauge is located. After this, the two-phase analysis of performance evaluation was then undertaken.

PPs used in this study among others have been evaluated in different regions of the world for understanding of hydrometeorological processes. Results of several such studies are location-specific, which implies that a dataset that has performed better in one region, might depict good or poor performance in another region. For instance, Guo et al. (2015) found out that TRMM performed better while CHRS PERSIANN could not achieve good correlation coefficients in the Central Asia region. On the contrary, in our study (which is in South Asia) CHRS PERSIANN performed better than TRMM. On the other hand there are instances, where a particular SPP was found to be perform well in different parts of the world, e.g. results of this study indicated that APHRODITE has better performance in terms of simulating observed precipitation over a complex terrain catchment in Pakistan. Tan et al. (2015) also reported that APHRODITE performed best over Malaysia, which suggests that a precipitation product that performs better over Malaysia also

has a good performance over Pakistan (even though different regions in both countries have different climatic characteristics). Results from our study are also consistent with those of Thom et al. (2017) and Ji et al. (2020) who argued that the APHRODITE datasets indicated good performance as input data to a hydrological model, performing well over Asia.

Furthermore, results in this study are align with the findings of Ménégoz et al. (2013), who suggested that the APHRODITE dataset was one of the most accurate precipitation products for Asia. Lauri et al. (2014) and Chen et al. (2017) also found out that APHRODITE was the best performing precipitation product for runoff simulations. Moreover, Li et al. (2018) showed that APHRODITE was a better choice for hydrological studies in Western Himalayas, which is also one of the most topographically complex regions in Asia. Vu et al. (2011) also reported that APHRODITE performed better for streamflow simulation in a study conducted over a river basin in Vietnam. The use of APHRODITE in hydro-ecological applications and modeling of water resources thus offer opportunities to fill gaps in gauged measurements in this data-deficient region.

Conclusions

The importance of consistent and long-term streamflow records to understand surface hydrology is well recognized. This is particularly true for different regions of developing world where long term data is scarce because of limited gauging stations. This study investigated the potential of ten different Precipitation Products (PPs), namely APHRODITE (V1101, V1801R1), CHIRPS V2.0, CPC-Global, ERA5, GPCC V.2018 (V2), GPCP-1DD V1.2, PERSIANN, PERSIANN CCS, PERSIANN CDR, and TRMM (3B42V7) using a hydrological modeling to predict streamflow in one of the most topographically complex catchments of the high mountain Asia i.e. the Chitral River Basin (CRB). A key aspect of assessing PPs performance to predict streamflow is to improve the modeling of streamflow using a hydrological model. In this study we used the hydrological model HBV-light to simulate streamflow in the CRB. Key findings of this study are summarized as follows.

- The Hydrological model's performance was good in modeling observed streamflow evidenced in the calibration (1995-2005) and validation (2007-2013) periods.
- APHRODITE was the most efficient precipitation product that captured gauged precipitation in comparison to other products in simulating observed precipitation.

- Different PPs including, CHRS CDR, CHRS CCS, and GPCP showed a good potential to be used for streamflow prediction. However, their good performance was season dependent, i.e., the performance was good in the dry period of the year but poor during the wet half of the year.
- The APHRODITE-based precipitation showed a better performance for streamflow prediction throughout the year unlike other PPs in this topographically complex terrain and catchment of the Chitral River Basin.

These results are promising and could be helpful for understanding of the hydrological processes in the region as well as sustainable management of freshwater resources.

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Conflict of Interest:

Authors declare no conflict of interest.

Data availability:

Data is available from authors upon reasonable request.

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