Ranking of the different gridded datasets for Satluj Basin using Compromise Programming and f-TOPSIS

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Abstract: The high degree of spatial variability of precipitation is a challenge to climate-resilient water resources planning. It gets enhanced in a physiographical diverse landscape like India. It is also exacerbated by the complex and variable interaction of the different weather determinants like monsoons, jet streams, etc. Another challenge that frequently presents itself in the study of water resources is the availability of unbroken and high-resolution data of climate inputs like precipitation. This challenge gets more complicated when physical access is constrained for a considerable portion of the study area by factors like local topography, transport networks, etc. It is often the case with Himalayan catchments in India, which are also highly vulnerable to medium and long term impacts of climate change along with land-use changes. In this context, it becomes essential to work with freely available global gridded data (precipitation) sets like APHRODITE, MERRA, etc. However, a pre-requisite to the use of such datasets is the analysis of their comparative accuracies with some reference data sets. In the backdrop of the limited data availability of the Himalayan region, the Himalayan basin of the river Satluj is chosen as the study area for the ranking of different gridded datasets given the observed precipitation data of eight stations. As a part of the ranking exercise, two approaches of multi-criterion decision-making, such as the Entropy-based Compromise Programming (deterministic approach) and Technique for Order Preference by Similarity to an Ideal Solution in Fuzzy field, f-TOPSIS (Stochastic approach) were used. The Compromise Programming has the advantage of being flexible in terms of its ability to accommodate any number of error indices according to the preference of the user, while for the f-TOPSIS, the relative importance of attributes is used by the fuzzy numbers is higher instead of precise numbers. In Compromise Programming, the error indices, namely, Correlation Coefficient (CC), Root Mean Square Error (RMSE), and distribution based Skill Score (SS), were used. The daily gridded data sets, namely APHRODITE, ERA-Interim, PFD, MERRA, CHIRP, IMD, and CFSR, were considered in this study for ranking purposes. The spatial resolution of these data sets was 0.25 degrees, while their temporal duration varied for different lengths. The result showed that the evaluation of weights of criteria and ratings of alternatives in f-TOPSIS by linguistic variables represented by fuzzy numbers overcome the deficiency in the deterministic approach. It was also observed that both the methods provided similar outcomes (Spearman rank correlation coefficient, R varies from 89 to 96%), which consequently increased the confidence of the ranking results. Furthermore, the present analysis also revealed that the APHRODITE consistently performed better in all the stations (CC, RMSE, and SS varies from 0.97-0.99, 0.44-0.56 and 0.87-0.96, respectively) followed by IMD (CC, RMSE, and SS ranges from 0.82-0.99, 0.44-0.62 and 0.89-0.99, respectively) and PFD (CC, RMSE, and SS ranges from 0.09-0.18, 1.00 and 0.95-0.98, respectively). Finally, the Group Decision Making methodology was used to aggregate the results over the entire study area, and it was found that APHRODITE was the best dataset for the whole study area. However, the study had

a limitation that all the observed data points were in the lower portion of the watershed. Although this limitation also opens up a scope of using interpolation techniques for the ungauged parts of the Satluj basin.

Keywords: Satluj Basin; Compromise Programming; f-TOPSIS; Spearman Rank Correlation Coefficient; Ranking

I. Introduction

Precipitation, one of the most crucial parameters of the hydrological cycle, which needs to be studied in space and time. However, it is essential to consider it's nature of distribution and variability of precipitation on local and regional scales (Venkatesh and Jose, 2007). The varied physiological features and altitudinal differences in India promote various types of climate range, which make precipitation as irregular and complex concerning time and space (Das et al. 2009). Hence, deviation in the precipitation pattern and the accuracy of a precipitation data set may significantly affect the outputs of land surface hydrological model studies (Salio et al., 2015; Hu et al., 2016). Therefore it is vital to obtain high-quality precipitation data sets with high spatial and temporal resolutions for these studies.

In general, precipitation datasets are estimated from rain gauge observations, satellite observations, and various numerical or reanalysis models (Xie and Arkin, 1997). Among all the sources, rain gauge observations are typically used to measure precipitation directly at the Earth's surface (Kidd, 2001). However, gauge observations have some disadvantages, such as uneven areal coverage over most marine and sparsely populated areas (Kidd et al., 2017; Rana et al., 2015; Xie and Arkin, 1997; Salio et al., 2015). This challenge gets multiplied when physical access to hydrological data becomes constrained for a considerable portion of the study area by factors like local topography, transport networks, etc. Besides this, only a few studies have been conducted to investigate precipitation variations over the past century in Central Asia because of its limited data availability (Schiemann et al., 2008; Hu et al., 2016; Hu et al., 2017). However, they did not apply the original observations from meteorological stations in the area to evaluate the gridded precipitation data sets (Schiemann et al., 2008). Furthermore, scientific evaluations of those data sets will provide valuable guidance for users to select the most appropriate data sets for their particular applications like hydrological model studies (Hu et al., 2018). It is often the case with Himalayan catchments in India, which are also highly vulnerable to medium and long term impacts of climate change along with land-use changes. In this context, to overcome the deficiencies of gauge observations, it becomes essential to work with freely available global gridded datasets (viz. Satellite data sets and model-based datasets) due to its spatially homogeneous and temporally complete nature for vast area of the globe (Kidd & Levizzani, 2011; Xie et al., 2003). Although global gridded datasets also have a high level of uncertainties associated with satellite precipitation algorithms (Xie and Arkin, 1997) and input limitations (Sorooshian et al., 2011; Knutti and Sedlacek, 2013). Hence, before the data sets can be applied in these studies, their accuracies at local and regional scales should be first evaluated. In the backdrop of the limited data availability of the Himalayan region, the Himalayan basin of the river Satluj is chosen as the study area for the current study.

From the background mentioned above, the present study was taken up to provide a comprehensive evaluation of the accuracies of the seven gridded data sets, which will be helpful when selecting suitable data sets for future studies of long-term changes in precipitation over the Himalayan basin of the river Satluj. Therefore, to accomplish the objective of the study, the different gridded datasets (viz., APHRODITE, ERA-Interim, PFD, MERRA, CHIRP, IMD, and CFSR) were ranked over the Satluj basin of Himalayan Region with precipitation observations from meteorological stations. The article is organized as follows: at first the study area, data sets, and methodology are described in section II, which is followed by comprehensive evaluations and detailed discussion of the study in section III. In the last section, a conclusion is presented (section IV).

II. Study area / Materials and Methodology

The current section discusses the description of the study area, various data sets, and the employed method.

Study Area and Data

The Satluj River basin, upstream of the Bhakra Reservoir (Indian part), located in the western Himalayan region, was selected as a study area in the present study (Figure 1). The area of the study basin is about 22,275 km^2. The altitude of the basin varies widely from about 500 m to 7000 m. The Satluj River originates from the lakes of Mansarover and Rakastal in the Tibetan plateau at an elevation of more than 4500 m and forms a part of the Indus River system. Sutlej River is a perennial river. It receives water from glaciers and precipitation during summer and ground flow during winter (Singh et al., 2015). The study conducted by Singh and Kumar (1997) indicated that rainfall is concentrated mostly in the lower part of the basin. Hence, this river basin is characterized by diversified climatic patterns. Eight stations from Satluj Basin, India (Figure 1) were selected for this study: Bhakra RL 1700, Berthin, Deslehra, Kahu, Kasol, Kuddi, Rampur, and Suni. The details of these eight stations are given in Table 1. The station-based observed daily time series of precipitation were acquired from Bhakara Beas Management Board (BBMB), India. For this study, only those stations were included that are at least 95% complete within each year. Besides the observed station datasets, seven gridded datasets were used in this study. The details of different gridded datasets are given in Table 2.

Table 1: Details of meteorological stations

Name of station	Lat (N)	Long (E)	Duration of data (daily)
Bhakra RL 1700	31° 24' 56"	76° 26' 4.99"	1966-2010
Berthin	31° 25' 10.99"	76° 38' 54.99"	1962-2012
Daslehra	31° 24' 56"	76° 32' 56"	1965-2010
Kahu	31°13'	76°47'	1965-2007
Kasol	31° 21' 25"	76°52' 42"	1962-2012
Kuddi	31° 25' 27.99"	76° 49' 40"	1975-2007
Rampur	31° 26'	77°38'	1965-2012
Suni	31° 15'	77°7'	1970-2012

Lat., Long., N, E denote latitude, longitude, north, and east, respectively.

Table 2: Details of gridded datasets

Data	Spatial Resolution	Temporal Resolution	Duration	Sources
CFSR	0.25	daily	1980-2010	Saha et al., 2010
MERRA	0.25	daily	1980-2010	Bosilovich et al., 2006
APHRODITE	0.25	daily	1962-2012	Yatagai et al., 2012
CHIRPS	0.25	daily	1981-2012	Funk et al., 2015

ERA-Interim	0.25	daily	1979-2012	Dee et al.2011
IMD	0.25	daily	1962-2012	Pai et al. 2014
PFD	0.25	daily	1962-2010	Sheffield et al., 2006

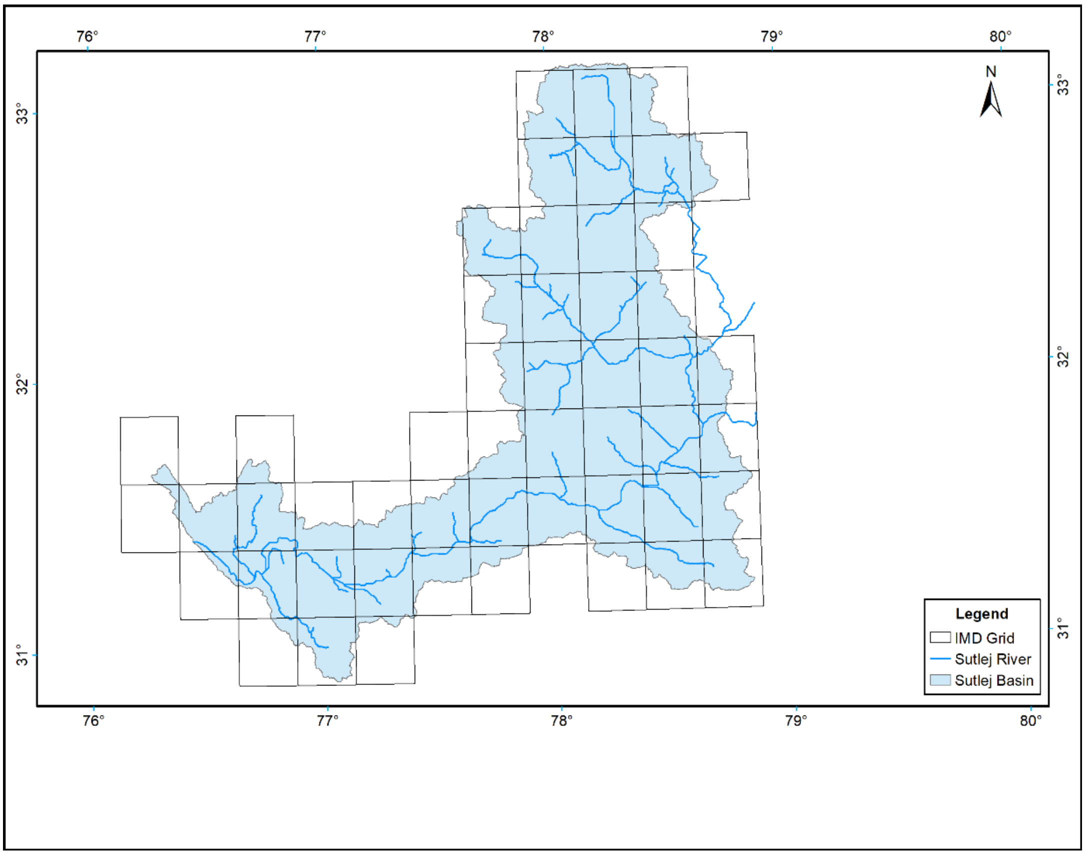

Fig. 1: Study area (Satluj Basin)

Performance indicator

Different researchers have suggested that meaningful but straightforward metrics should be used for evaluating a quantifiable measure to determine how different gridded datasets simulate the observed data (Preethi and Kripalani 2010; Schiemann et al., 2008; Hu et al., 2016; Hu et al., 2017). Three indicators, namely, root mean square error (RMSE), correlation coefficient (CC), and skill score (SS), were considered in this study among the numerous performance indicators available (Wilks 2011). The description of the performance indicators are given as follows:

Root mean square error (RMSE) is a measure of the difference between the observed station data and gridded dataset. The smaller the value of RMSE (preferably zero), the better is the performance of the model and expressed in Eq. 1,

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(G_t - O_t)^2}{n}} \qquad (1)$$

Where G_t represents the gridded data and O_t represents the observed data and *n* represents the total number of observations.

The correlation coefficient (CC) provides information on the strength of the linear relationship between the observed station data and gridded dataset and expressed in Eq. 2,

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{(n-1)s_x s_y} \qquad (2)$$

Where r is the CC between observed data and gridded datasets x and y; x_i is the observed station data ; $\bar{x}$ is the mean of observed station data; y_i is the gridded dataset; $\bar{y}$ is the mean of the gridded dataset; s_x and s_y are the standard deviations of x and y, respectively, and n is the number of observations. CC values near 1 indicates good performance.

Skill Score (SS) (Perkins et al., 2007) provides a measure of similarity between two probability density functions (PDFs), which allows comparison across the entire PDF, and is expressed in Eq. 3,

$$SS = \sum_{i=1}^{nb} min(f_m f_0) \qquad (3)$$

Where nb is the number of bins used to calculate the PDF for a given region, $f_m$is the frequency of values in the given bin from the chosen gridded dataset, and f_0 is the frequency of values in the given bin from the observed station data. If a model simulates the observed conditions perfectly and poorly, the SS is 1 and close to zero, respectively.

Entropy Method

The entropy method allows the distribution of weights among the different error indices automatically (Raju and Kumar, 2014; Raju et al., 2017) using Eq. 4,

$$En_j = -\frac{1}{ln(T)}\sum_{a=1}^{T} k_{aj}\, ln(k_{aj}) \qquad for\ j=1,2,3\ldots\ldots J \qquad (4)$$

Where En_j represents entropy for each indicator j. T represents the number of indicators and k_{aj} represents the normalized error indices.

The degree of diversification and finally the weights of each index is then calculated by following Eq. 5 and 6 respectively,

$$Dd_j = 1 - En_j \qquad (5)$$

$$r_j = \frac{Dd_j}{\sum_{j=1}^{J} Dd_j} \qquad (6)$$

Where, Dd_j represents the degree of diversification and r_j represents the normalized weight of indicators.

Compromise Programming

The Compromise Programming is based on the methodology to construct a metric for each gridded datasets based on the minimum distance from an ideal dataset (observed datasets). The distance measure $L_p(a)$ (Raju et al., 2017) is calculated using the following Eq. 7

$$L_p(a) = \left[\sum_{j=1}^{J} w_j \left|f_j^* - f_j(a)\right|^p\right]^{\frac{1}{p}} \qquad (7)$$

Where, indicator $j=1,2,3.....J$; $L_p(a)$= L_p metric for $f_j(a)$ = Normalised value of indicator j for gridded dataset a; f_j^* = Normalised ideal value of indicator j; w_j = Weight of indicator j obtained from the entropy method. p = Parameter (1 for linear, 2 for squared Euclidean distance measure). In this case, p=2 was used.

F-TOPSIS

The Technique for Order Preference by Similarity to an Ideal Solution in Fuzzy field (f-TOPSIS), is based on the distance of each indicator for each gridded datasets from the ideal solution. In a deterministic approach (compromise programming), sometimes, it is very tough to assign a precise performance rating to an alternative for the attributes under consideration for a decision-maker. Hence, to overcome the problem of allocating the relative importance of attributes, the f-TOPSIS is developed using the fuzzy numbers instead of precise numbers (Yang and Hung, 2007). This method is particularly suitable for solving the group decision-making problem under fuzzy environment.

This technique was applied in this study by following few steps. At first, the fuzzy decision was determined considering the number of rainfall stations used, the different gridded datasets, and performance indicators evaluated in compromise programming. After that, to homogenize the evaluation supplied for all the criteria, their values were linearly normalized. Finally, the proximity coefficients (DS_Plus and DS_Minus) for each alternative were calculated by ideal and anti-ideal values selected for each indicator. This technique was designed to minimize the distance of a data object from the positive ideal solution (DS_Plus) and maximize the distance from the negative ideal solution (DS_Minus). The closeness coefficient (C) of each alternative was calculated as follows in Eq. 8

$$C = \frac{DS\_Minus}{DS_{Minus} + DS\_Plus} \qquad (8)$$

It was sufficient to sort them according to the decreasing values of their closeness coefficient to establish the ranking of gridded datasets. A clear example of a fuzzy approach to ranking climate models can be found in Raju and Kumar (2015). Equal weights were considered for each criterion, and ideal and anti-ideal values for all the indicators were chosen as (1, 1, 1) and (0, 0, 0).

Spearman Rank Correlation

The Spearman rank correlation (R) is useful to determine the measure of association between the ranks achieved in two different methods, i.e., here, the correlation between the results of the Entropy-based compromise programming and the f-TOPSIS. If U and V denote the ranks achieved by the above methods(s) for the same gridded datasets, then R is defined as (Gibbons, 1971) in Eq. 9

$$R = 1 - \frac{6\sum_{a=1}^{N} D_a^2}{N(N^2-1)} \qquad (9)$$

Where D_a is the difference between ranks U and V achieved by the same gridded datasets, and N is the number of the gridded datasets. R values vary between −1 and +1.

Group Decision Making Approach

The values of the Lp metric are useful for ranking of the gridded datasets for individual stations. However, to aggregate the rankings of each station into a single rank over the study area, Group Decision Making methodology (Raju et al., 2017) was employed which is explained below.

The descending order of rankings of gridded datasets in each station was divided into upper and lower portions: X = n/2 where n is the number of gridded datasets. The gridded datasets with rankings from 1 to X constitute the upper portion.

Strength of each gridded datasets, e.g., ST_a is given in Eq. 10

$$ST_a = \sum_{k=1}^{m} \sum_{z}^{x} (x - z + 1) q_{az}^{k} \forall a, k \forall z = 1, \dots . x \tag{10}$$

Where, q_{az}^{k}=1 if gridded datasets a is at position z for the station k, otherwise 0. Here, a corresponds to the gridded datasets in the upper portion; z is the position in the upper portion ranging from the 1st position to the xth position (z =1st, …xth), and k represents a station (k =1, 2,..8).

The weakness of the gridded datasets a, WE_a is given in Eq. 11

$$WE_a = \sum_{k=1}^{m} \sum_{z=y}^{n} (z - y + 1) q_{az}^{k} \forall a, k \forall z = y, \dots . n \tag{11}$$

Where, q_{az}^{k}=1 if gridded datasets a is in position z for the station k, otherwise 0. Here, a corresponds to the gridded datasets in the lower portion; z is the position in the lower portion ranging from the 1st position to the lower portion (yth) up to the last ranking in the lower portion.

Net strength of each gridded datasets a is computed by Eq. 12

$$NS_a = ST_a - WE_a \tag{12}$$

The net strength, $NS_a$is used to rank the gridded datasets.

III. **Results**

Station wise (various latitude and longitude combinations resulting in eight stations) values of precipitation were analyzed to assess how the individual gridded datasets can be ranked concerning the three performance indicators (RMSE, CC, and SS) using the Entropy-based compromise programming. The ranking exercise was also analyzed by using the f-TOPSIS method under the fuzzy payoff matrix of performance indicators (RMSE, CC, and SS). The employed methodology was demonstrated for the individual stations and later extended for the whole selected basin by using the group decision-making approach. The group decision-making approach was employed to aggregate the ranking patterns for the whole selected basin covering eight observed stations. Related results are presented in the following sections.

The results of the three indicators (RMSE, CC, and SS) for the eight observed stations are presented in Table 3. Minimum or zero error is desirable in the case of RMSE, whereas an ideal value of 1 is desirable for CC and SS. Table 3 shows that in the case of CC, APHRODITE data was correlated well with the observed data with a value of 0.97 to 0.99, whereas a minimum RMSE was observed with a value of 0.44-0.56. Hence, APHRODITE data showed the lowest RMSE and highest CC value among the other gridded datasets. Similar trends were also found for SS. In this case, APHRODITE showed 87-95% similarity with the observed PDFs, whereas CHIRPS showed a 100% similarity for every observed station. Though CHIRPS datasets showed very high value for SS for every station, other performance indicators depicted less importance than the other stations. Among the three indicators, CC was given the high importance (0.97 to 0.99 and 0.82 to 0.99 for APHRODITE and IMD datasets respectively) which means that its effect on ranking of gridded datasets is very significant followed by RMSE (0.44-0.56 and 0.46- 0.62 for APHRODITE and IMD datasets respectively) and skill score (0.87-0.95 and 0.89-0.99 for APHRODITE and IMD datasets respectively) for the observed rainfall stations of Satluj Basin. The above analysis indicated that each indicator responded differently for various gridded datasets. It was observed from the Entropy method that weights of performance indicators were varying (instead of assuming equal or some other proportion) for each observed station and expected to affect the ranking pattern of gridded datasets. Table 3 also presents the values of Lp metric from Compromise programming for each gridded datasets for the observed rainfall stations of the Satluj Basin. A minimum amount of the Lp metric was considered to be suitable, and the ranking pattern is obtained accordingly for all gridded datasets. It was observed that the Lp metric was varying between 0.07-0.14 (first rank) and 0.21-0.27 (last rank) over seven ranks. APHRODITE and IMD were occupying the first two ranks with Lp metric values of 0.07-0.23 and 0.08-0.22, respectively, for every station except Kasol and Rampur. It is worth noting that the ERA-Interim, CFSR, and MERRA with Lp matric values of 0.16-0.26; 0.21-0.25 and 0.21-0.27, respectively occupied fifth, sixth, and seventh positions always for individual stations except Rampur stations.

Table 3: Rank of the different gridded dataset for each station from Compromise programming along with its parameter (Lp) and performance indicator payoff matrix (RMSE, CC, and SS)

	Root Mean Square Error (RMSE)						
	CFSR	**MERRA**	**APHRODITE**	**CHIRPS**	**ERA-Interim**	**IMD**	**PFD**
Bhakra RL 1700	0.81	0.78	0.56	0.84	0.79	0.59	1.00
Berthin	0.75	0.73	0.50	0.89	0.72	0.54	1.00
Daslehra	0.79	0.76	0.54	0.88	0.77	0.58	1.00
Kahu	0.80	0.77	0.55	0.86	0.77	0.62	1.00
Kasol	0.78	0.75	0.54	0.90	0.73	0.53	1.00
Kuddi	0.80	0.78	0.56	0.89	0.77	0.59	1.00
Rampur	0.67	0.61	0.49	0.81	0.57	0.46	1.00
Suni	0.72	0.69	0.44	0.89	0.67	0.49	1.00
	Correlation Coefficient (CC)						
Bhakra RL 1700	0.01	0.07	0.99	0.38	0.46	0.91	0.14
Berthin	0.00	0.05	0.99	0.33	0.44	0.93	0.15
Daslehra	0.01	0.06	0.99	0.37	0.44	0.92	0.18
Kahu	0.02	0.04	0.99	0.34	0.40	0.82	0.14
Kasol	0.02	0.02	0.97	0.33	0.46	0.99	0.15
Kuddi	0.02	0.04	0.99	0.36	0.44	0.91	0.14
Rampur	0.01	0.01	0.98	0.17	0.40	0.99	0.09
Suni	0.01	0.02	0.99	0.24	0.38	0.91	0.12
	Skill Score (SS)						
Bhakra RL 1700	0.92	0.95	0.95	1.00	0.86	0.96	0.98
Berthin	0.90	0.94	0.93	1.00	0.84	0.93	0.96
Daslehra	0.90	0.94	0.93	1.00	0.84	0.96	0.96

Kahu	0.91	0.95	0.92	1.00	0.84	0.99	0.96
Kasol	0.90	0.96	0.93	1.00	0.84	0.94	0.95
Kuddi	0.89	0.95	0.96	1.00	0.83	0.98	0.95
Rampur	0.91	0.99	0.89	1.00	0.83	0.92	0.97
Suni	0.90	0.96	0.87	1.00	0.82	0.89	0.97
	Lp						
Bhakra RL 1700	0.22	0.22	0.09	0.13	0.18	0.10	0.14
Berthin	0.21	0.21	0.07	0.15	0.17	0.08	0.14
Daslehra	0.21	0.21	0.07	0.13	0.17	0.09	0.14
Kahu	0.22	0.23	0.08	0.15	0.19	0.12	0.15
Kasol	0.21	0.21	0.09	0.13	0.16	**0.09**	0.15
Kuddi	0.21	0.21	0.07	0.14	0.16	0.08	0.16
Rampur	0.25	0.27	0.23	0.18	0.26	0.22	**0.14**
Suni	0.23	0.23	0.10	0.15	0.19	0.11	0.16
	Rank from Compromise programming						
Bhakra RL 1700	6	7	1	4	5	2	3
Berthin	6	7	1	3	5	2	4
Daslehra	6	7	1	3	5	2	4
Kahu	6	7	1	4	5	2	3
Kasol	6	7	2	3	5	1	4
Kuddi	6	7	1	3	5	2	4
Rampur	5	7	4	2	6	3	1
Suni	6	7	1	3	5	2	4

Table 4: Rank of the different gridded dataset for each station from f-TOPSIS along with its parameters (DS_Plus, DS_Minus, and C)

	DS_Plus						
	CFSR	**MERRA**	**APHRODITE**	**CHIRPS**	**ERA-interim**	**IMD**	**PFD**
Bhakra RL 1700	3.96	3.94	3.45	3.77	3.80	3.51	3.61
Berthin	3.95	3.98	3.49	3.69	3.84	3.54	3.61
Daslehra	3.96	3.95	3.47	3.68	3.83	3.52	3.59
Kahu	3.95	3.99	3.44	3.74	3.83	3.57	3.60
Kasol	3.94	3.97	3.53	3.69	3.81	3.52	3.59
Kuddi	3.94	3.97	3.46	3.69	3.83	3.52	3.64
Rampur	3.91	3.96	3.67	3.71	3.86	3.64	3.51
Suni	3.94	3.98	3.52	3.69	3.83	3.58	3.61
	DS_Minus						
Bhakra RL 1700	0.10	0.07	0.55	0.23	0.20	0.49	0.40
Berthin	0.11	0.07	0.51	0.31	0.17	0.46	0.40
Daslehra	0.09	0.06	0.53	0.32	0.17	0.48	0.41
Kahu	0.12	0.08	0.56	0.26	0.17	0.43	0.41
Kasol	0.12	0.08	0.47	0.31	0.19	0.48	0.41
Kuddi	0.12	0.09	0.54	0.31	0.17	0.48	0.37

Rampur	0.14	0.09	0.33	0.29	0.14	0.36	0.50
Suni	0.11	0.08	0.48	0.31	0.17	0.42	0.40
	C						
Bhakra RL 1700	0.02	0.02	0.14	0.06	0.05	0.12	0.10
Berthin	0.03	0.02	0.13	0.08	0.04	0.11	0.10
Daslehra	0.02	0.02	0.13	0.08	0.04	0.12	0.10
Kahu	0.03	0.02	0.14	0.06	0.04	0.11	0.10
Kasol	0.03	0.02	0.12	0.08	0.05	0.12	0.10
Kuddi	0.03	0.02	0.13	0.08	0.04	0.12	0.09
Rampur	0.03	0.02	0.08	0.07	0.03	0.09	0.13
Suni	0.03	0.02	0.12	0.08	0.04	0.11	0.10
	Rank form f-TOPSIS						
Bhakra RL 1700	6	7	1	4	5	2	3
Berthin	6	7	1	4	5	2	3
Daslehra	6	7	1	4	5	2	3
Kahu	6	7	1	4	5	2	3
Kasol	6	7	2	4	5	1	3
Kuddi	6	7	1	4	5	2	3
Rampur	5	7	3	4	6	2	1
Suni	6	7	1	4	5	2	3

Similarly, the three indicators named RMSE, CC, and SS were calculated under the fuzzy field in the f-TOPSIS method for the eight observed stations. Table 4 presents DS_Plus, DS_Minus, and C values for every rainfall station used. In the f-TOPSIS, the top three ranks were always occupied by APHRODITE, IMD, and PFD for every station, with the relative closeness of 0.08-0.14; 0.09-0.12 and 0.09-0.13, respectively, except Kasol and Rampur. It is interesting to note that the fourth, fifth, sixth, and seventh positions were always occupied by CHIRPS, ERA-Interim, CFSR, and MERRA respectively for every station, with the relative closeness of 0.06-0.08; 0.03-0.05; 0.02-0.03 and 0.02, respectively except Rampur stations. Ranks obtained for the different gridded datasets using the Entropy-based compromise programming and f-TOPSIS are shown in Table 3 and Table 4, and the corresponding Spearman rank correlation (R) for both the methods varies from 89 to 96%.

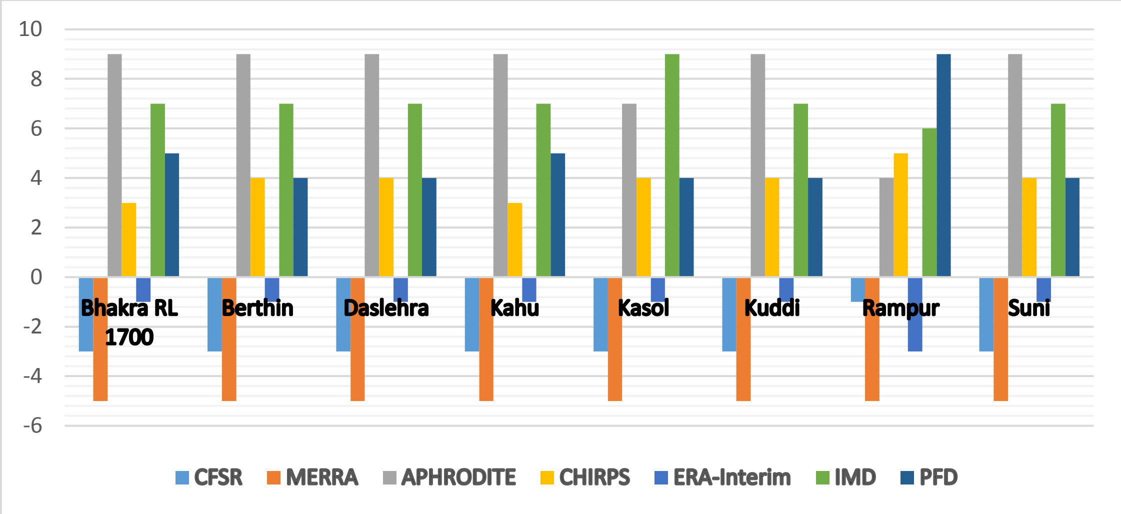

Fig. 3: Net strength of gridded dataset in group decision making for varying weight scenario for individual stations

An effort is also made to rank the gridded datasets for the whole Staluj basin (considering every observed station) using the group decision-making approach explained in Section III. It is observed from Fig. 3 that first three ranked gridded datasets, i.e., APHRODITE, IMD, and PFD, have a net strength (on an average) of 8, 7, and 5, respectively, whereas CHIRPS, ERA-Interim, CFSR, and MERRA (fourth, fifth, sixth, and seventh ranks) have a net strength (on an average) of 4, -1, -3 and -5 respectively. Hence, gridded datasets occupied by sixth and seventh ranks were not considered for the Satluj basin due to a difference between the net strengths of these gridded datasets compared to the first three for every station, which also supports the conclusion made from the values of performance indicator (Table 3). In summary, the current study shows that APHRODITE is a better data set than the other gridded datasets in the Himalayan basin of the river Satluj. The rainfall characteristics may have caused the large underestimations for the gridded data sets over mountainous areas, local topography of the mountainous region, and limited stations used in their approaches (Willmott and Matsuura, 2012; Harris et al., 2014; Schneider et al., 2014). Therefore, APHRODITE should be the more reasonable data set to detect long-term precipitation variations over the Himalayan basin of the river Satluj.

IV. Conclusions

The accuracies of gridded precipitation data sets are essential for regional climate studies and hydrological models (Hu et al., 2018). In this paper, the Entropy-based Compromise Programming and the Technique for Order Preference by Similarity to an Ideal Solution in Fuzzy field, f-TOPSIS were applied to understand the effectiveness of both algorithms in deriving the best dataset as a part of the ranking exercise. This was illustrated through its application to precipitation data in the Himalayan basin of the river Satluj, India. For the Entropy-based Compromise Programming, the minimum distance (Lp matric) of a gridded dataset from an ideal in the available set (observed dataset) were determined by using three performance indicators, namely Correlation Coefficient (CC), Root Mean Square Error (RMSE) and distribution based Skill Score (SS) on eight stations with seven gridded datasets (8x7 matrix). It was found from the Entropy-based Compromise Programming that APHRODITE and IMD were occupying the first two ranks with Lp metric values of 0.07-0.23

and 0.08-0.22, respectively, for every station except Kasol and Rampur. f-TOPSIS was also applied with two different distances such as the shortest distance from the ideal solution and the farthest distance from the negative ideal solution and approximations was tackled through fuzzy logic. In f-TOPSIS, the top three ranks were always occupied by APHRODITE, IMD, and PFD for every station, with the relative closeness of 0.08-0.14; 0.09-0.12 and 0.09-0.13, respectively except Kasol and Rampur**.** When the performances of the Entropy-based compromise programming and f-TOPSIS methods were compared, it was observed that both the methods provided similar outcomes (R varies from 89 to 96%), which consequently increased the confidence of the ranking results. Furthermore, our analysis also revealed that APHRODITE had the highest correlation and lowest bias (RMSE) compared with other gridded datasets when against the observed station rainfall datasets. In this context, Hu et al., 2018 reported that the discrepancies in the performances between the gridded data sets were primarily induced by their different interpolation methods and the numbers of available meteorological stations used in the interpolation. Besides, the limited observed meteorological stations (all stations are located in the lower portion of the Satluj Basin) also impact the performance of those methods, but this limitation also created the scope of using interpolation techniques for the ungauged parts of the Satluj basin. Finally, the Group Decision Making methodology was used to aggregate the results over the entire study area, and it was found that APHRODITE was the best dataset for the whole study area.

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