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Evaluation of Rain-gauge Network in Upper Teesta Basin Using Entropy

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ABSTRACT

The Upper Teesta River basin has been severely affected by excessive flash flood events due to vast rainfall in recent years. Evaluating existing networks is crucial for planning, designing, and adequately managing water resource projects. The network design helps lower project failure risk and minimize economic losses. The network should be reviewed and updated promptly until it reaches the optimal network so that it gives adequate information like rainfall. This paper uses the Shannon entropy theory to assess the existing precipitation network in the upper Teesta River basin using marginal entropy and trans-information index. The statistical parameters of nine rain gauge stations are determined. Daily rainfall records of TRMM, APHRODIRE and CFSR have been compared with ground-based observation records for the four different stations. Results show that satellite-based rainfall records are underestimated regarding ground-based observations at all rain gauge stations. The maximum information minimum redundancy concept is applied to the existing rain gauge network, and the result reveals that only nine rain gauge stations in the network are insufficient to capture the precipitation variability in the mountainous region as per WMO standards. These findings support the need to improve the existing network to understand flood modelling, prediction and water resource management.

Keywords: Marginal Entropy, Transinformation index, Redundancy, Conditional Entropy

INTRODUCTION

Rainfall is an essential parameter of hydrology and water resource research. Over the decade, climate change has significantly impacted the global hydrological cycle. Therefore, there is a need for a considerable amount of good quality data, both satellite as well as ground, based on studying the different components of the hydrological cycle. Good quality data can only be achieved with effective hydrometric network design. Over the decade, there has been a decline in hydrometric networks due to a lack of funding and socioeconomic complexities. (Sreeparvathy and Srinivas 2020; Ruhi et al. 2018; Keum et al. 2017; Mishra and Coulibaly 2009). As a result, a considerable amount of good quality data has been lost in both developed as well as developed countries. Efficient and effective rain gauge networks should assess the variability of precipitation on both temporal and spatial scales with a reduction in the cost of operation (Vivekanandan and Jagtap 2012). The evaluation of the precipitation network determines the optimum number of stations with the highest information and the lowest amount of duplicate information. (Li Chao 2012). The hydrometric network design of a rain gauge network still evolves in nature and reviewed periodically until it arrives at optimum networks. The different methods of hydrometric network design include statistical methods (Burn and Goulter 1991, Morin et al. 1979), user survey-based method (Davar and Brimley 1990, Singh et al. 1986), information theory-based method (Keum et al., 2017, Mishra and Colibaly 2010, Yang and Burn 1994, Husain 1989, Husain 1987), hybrid methods (Samuel et al., 2013, Markus et al., 2003,) and sampling strategies (Tsintikidis et al., 2002, Bras et al., 1988,). An entropy-based approach is a promising technique for hydrometric network design. Xu et al. (2018) propose a kriging amalgamated entropy-based method to determine the optimal rain gauge network in Shanghai with objective function minimum kriging standard error and maximization of net information. Chacon-Hurtado et al. (2017) determines several existing applications for senor network design concerning various criteria for maximization of information content. Prajapati et al. (2024) apply the principle of maximum entropy and monitoring value for precipitation monitoring networks in Bihar. Sreeparvathy and Srinivas (2020) propose an entropy approach with fuzzy techniques for the optimal design of hydrometric networks, calculating Entropy using various binning methods. Marginal Entropy and transformation are the tools (Krstanovic and Singh, 1992a; 1992b) used to measure the transmitted information among the random variables. Maximum Information and Minimum Redundancy (MIMR), particularly total correlation, has been widely applied in entropy-based hydrometric network design using various metaheuristic approaches (Alfonso et al., 2010a; 2010b). Samuel et al. (2013) introduced the Combined Regionalization and Dual Entropy-Multi-Objective Optimization (CRDEMO) framework to identify Pareto-optimal solutions that balance minimum redundant information with maximum information in the Canadian River basin.

The degree of randomness quantified by Entropy is the primary tool for rain gauge network design. The entropy-based precipitation network design significantly evaluates the existing network or expansion of the network to meet the WMO (2008) standard for minimum rain gauge networks in a particular terrain and captures the precipitation variability in both spatial and temporal resolution.

The first objective of this study is to compare the satellite-based rainfall records with ground-based data in Upper Teesta Basin. The second objective is to evaluate the existing rain gauge network in the Upper Teesta River Basin using the MIMR concept, particularly considering the severe impacts of extreme floods in recent years. The third objective is to prepare a rainfall distribution map spanning the past two decades to identify changes in precipitation patterns in the mountainous region. The rain gauge network design is a multi-objective problem with different Pareto optimal solutions. Most entropy-based rain gauge network designs focus on the plain areas of the temperate Mediterranean and tropical zones. Few studies have been done in India on mountainous regions due to poor-quality data and orographic precipitation variability. The structure of the paper is as follows: Section 2 introduces the concept of Entropy along with related theories and different evaluation criteria. Section 3 describes the study area along with different rainfall data. The results and discussion are presented in Section 4. Finally, Section 5 provides conclusions and limitations.

METHDOLOGY

Entropy Concept

The information captured of a discrete random variable known as marginal entropy which mathematically expresses as

$$H(X_1) = -\sum_{x1} p(x_1) \log_2 p(x_1) \qquad (1)$$

The sum represents summation of all possible outcomes. It is a statistical tool calculated the randomness in a time series data.

Joint Entropy

Joint Entropy measured the overall information captured by multiple random variables. The joint entropy between two discrete random variables X_1 and X_2 known as Bivariate joint entropy and expressed as

$$H(X_1, X_2) = -\sum_{x1}\sum_{x2} p(x_1, x_2) \log_2\big(p(X_1, X_2)\big) \qquad (2)$$

The multivariate joint entropy is information captured by more than two random variables. The multivariate joint entropy defined as

$$H(X_1, X_2, \dots, X_n) = -\sum_{x1}\sum_{x2}\dots\sum_{xn} p(x_1, x_2, \dots, x_n) \log_2\big(p(X_1, X_2, \dots, X_n)\big) \qquad (3)$$

Transinformation, or mutual information, represents the shared information between random variables. Unlike Pearson's correlation coefficient, mutual information captures both linear and nonlinear dependencies, making it a more comprehensive measure. In contrast, Pearson's correlation is generally appropriate only for data with spherical

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or elliptical dependence structures. The bivariate Transinformation between two random variables X_1 and X_2 calculated as

$$T(X_1, X_2) = -\sum_{x1}\sum_{x2} p(x_1, x_2)\log_2 \frac{p(x_1, x_2)}{p(x_1)p(x_2)} \qquad (4)$$

Total Correlation

Total correlation is the measurement of the amount of duplicate information between the random variables (Watanabe, 1960). It is expressed as

$$C(X_1, X_2, \dots, X_n) = \sum_{i=1}^{n} H(X_i) - H(X_1, X_2, \dots, X_n) \qquad (5)$$

MIMR computation of Entropy Measures

The optimization of existing precipitation network has been done according to their information content. The process begins with the identification of a central station, selected based on the highest level of uncertainty—quantified by marginal entropy—in observed rainfall data. This central station reflects the greatest randomness among all monitoring locations. Subsequent stations are sequentially added to the network to reduce overall uncertainty and redundancy.

1. Consider a network of N precipitation stations. The rainfall series at each station is denoted as $X_i=\{X_{i1},X_{i2},\dots,X_{ij}\}$ where i represents the station index and j is the time step. The length of the rainfall series is assumed to be consistent across all stations.
2. The marginal entropy for each station is computed. The central station has highest amount of entropy as it exhibits the maximum level of uncertainty in observed rainfall data.
3. The central station is then paired with each of the remaining N−1 stations. For each pair, mutual information is computed. The station that, when coupled with the central station, yields the lowest transinformation is identified as the second priority station.
4. The pair is extended to include a third station from the remaining N−2 stations, and the triplet with the least transinformation is selected. This iterative process continues until all N stations are ranked in descending order of information contribution and minimum redundancy.
5. The process may be terminated prior to ranking all NNN stations by introducing a transinformation threshold, which defines the maximum allowable redundancy in the network. Once the calculated transinformation falls below this threshold, further station additions may be deemed unnecessary.

This approach effectively evaluates the performance of existing rain-gauge network. Locations for additional stations can also be done based on entropy measures, ensuring maximum information gain with minimal redundancy.

The correlation coefficient R can be estimated from transinformation T using the following expression:

Correlation Coefficient (R) = $(1 - e^{-2T})^{0.5}$

This relationship provides a direct link between information theory and traditional correlation analysis, allowing for a deeper understanding of spatial rainfall dependencies.

Evaluation Criteria

To evaluate the data quality of the gridded rainfall, four statistics i.e., bias, multiplicative bias (Mbias), root mean square error (RMSE) and correlation coefficient (CC) were used in this study. Bias represents the average difference between the gridded rainfall and gauge rainfall. Negative value of bias implies underestimation while its positive value indicates overestimation of observed rainfall. Mbias is the ratio of mean gridded rainfall estimation to mean ground observed rainfall. Mbias equals to 1 implies perfect match between mean gridded rainfall to mean ground observed rainfall. Mbias less and more than equal to 1 implies underestimation and overestimation of gridded rainfall. The root mean square error (RMSE) calculates weighted average error between gridded and observed

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rainfall. A lower value of RMSE implies less difference between gridded rainfall and observed rainfall. The correlation coefficient (CC) represents the relationship between the gridded rainfall estimate and observed rainfall. Value of CC ranges from -1 to 1 where its value equal to 1 implies perfect agreement between gridded rainfall estimate and observed rainfall whereas; -1 implies perfectly negative agreement between the two-rainfall data while 0 value of CC represents no relation between two rainfall data.

In addition, three categorical statistical indices which include the probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) were also used to compare the rain detection capabilities of gridded rainfall products. POD represents the ratio of number of times rainfall is correctly identified by gridded data product to the number of rainfall occurrences observed by reference data; FAR denotes the proportion of cases in which the gridded product records rainfall when the rain gauges do not; and CSI shows the overall proportion of rainfall events correctly diagnosed by the gridded rainfall product. POD, FAR, and CSI range from 0 to 1, with 1 being a perfect POD and CSI and 0 being a perfect FAR.

STUDY AREA AND DATA USED

Study Region and Data used

The focus research area is the upper Teesta River basin, covering the entire state of Sikkim, with a total area of approximately 7,096 km². Figure 1 illustrates the geographical location of the study area, which lies between longitudes 80°00′E to 80°55′E and latitudes 26°55′N to 28°08′N. The Teesta River originates from the Pauhunri massif at an elevation of 7,127 meters, with its mountain section stretching over a length of 182 km (Wiejaczka et al., 2014). The basin is bordered by China to the east and north, Nepal to the west, and the Indian state of West Bengal to the south. During the monsoon season, from June to September, average rainfall ranges between 4,000 and 6,000 mm (Starkel et al., 2017). The upper Teesta River basin is characterized by a high discharge capacity, attributed to its notable relief ratio (ranging from 88.16 to 14.78), and features a steep structural ridge sloping south westward (Chaubey et al., 2021).

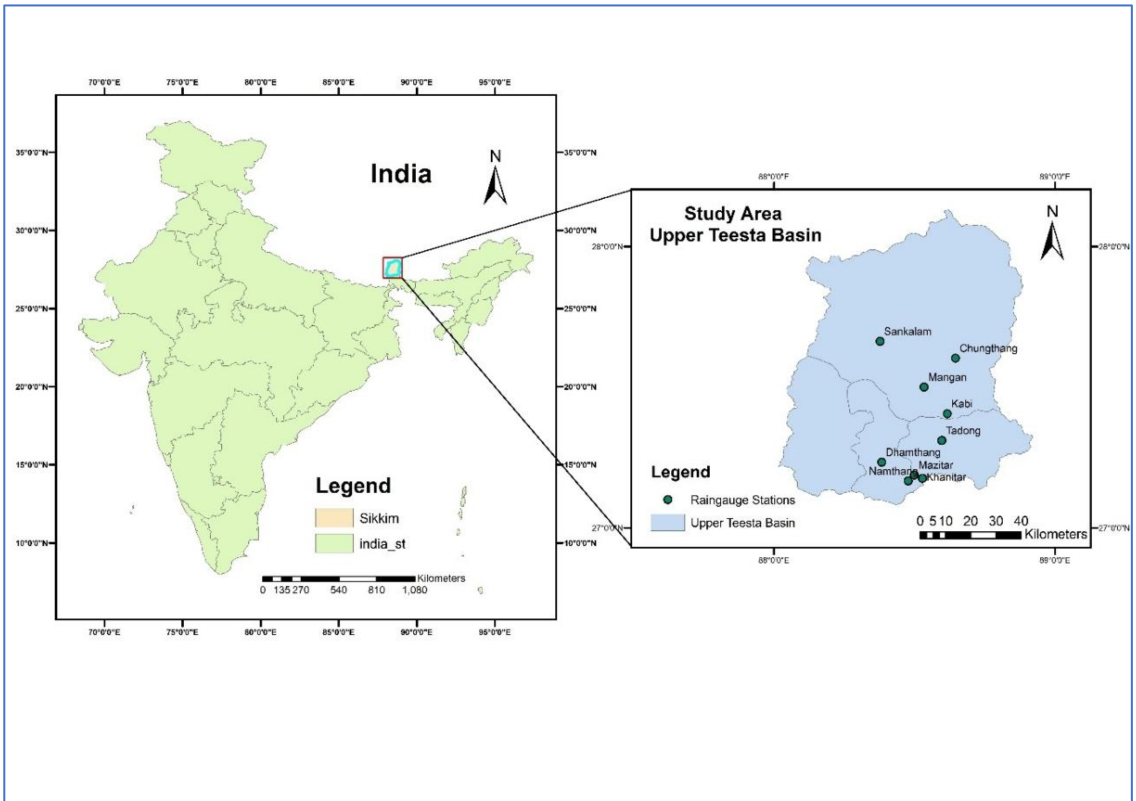

Fig1: Location of Rain gauge Stations in Upper Teesta River Basin

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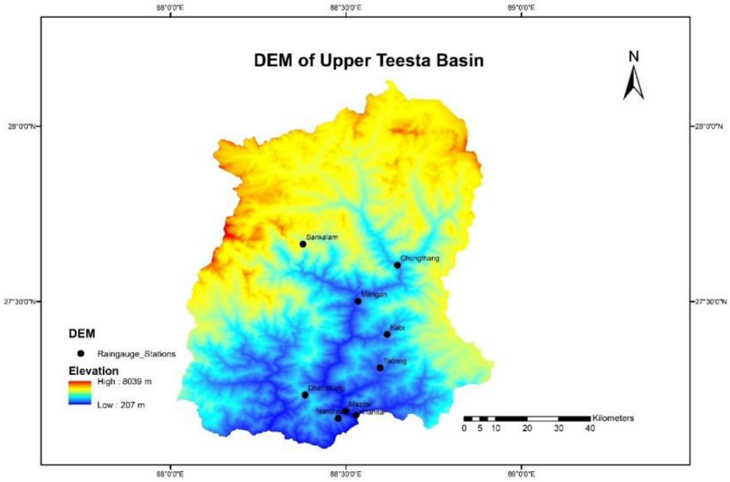

Fig 2: DEM of Upper Teesta River Basin with Rain gauge Stations

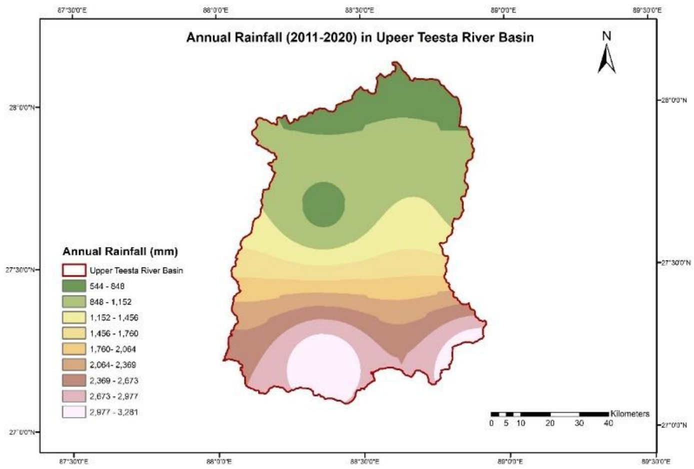

Fig 3: Annual Rainfall Map of Upper Teesta River Basin 2011-2020

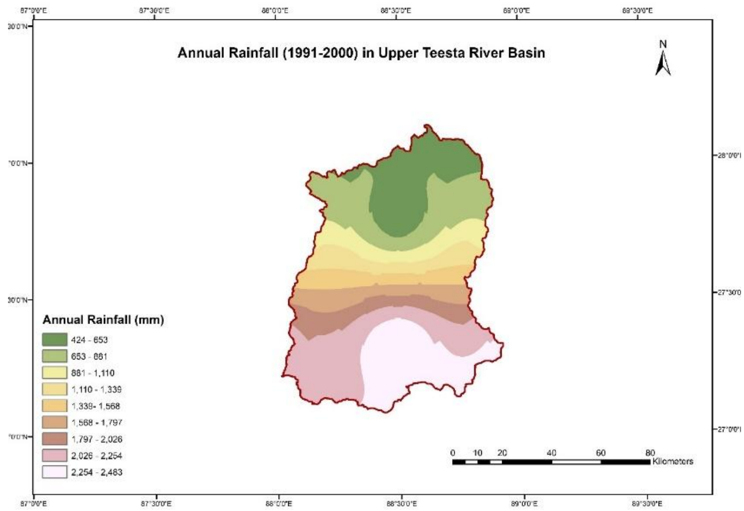

Fig 4: Annual Rainfall Map of Upper Teesta River Basin 1991-2000

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The Teesta River Basin is characterized by steep mountainous terrain and altitudinal variation from low foothills to high Himalayan peaks, and it experiences intense orographic rainfall with high spatial and temporal variability. So, there is a need for a well-distributed rain gauge network to capture the variability in precipitation. The Teesta River is the main contributor to the river Brahmaputra. The rainfall data is crucial for water management studies in this region. This region is very vulnerable to extreme hydrological events like GLOF, Flash floods, etc. Reliable rainfall records are very crucial for rainfed agricultural production. Properly designing and regularly monitoring the precipitation network is essential for regional hydrological modelling, climate change studies, and glacial hydraulics.

The daily gridded rainfall data from the APHRODITE (V1003R1 dataset), with a spatial resolution of 0.25° × 0.25° (approximately 25 km), was utilized to compare in this study. This dataset, available at http://www.chikyu.ac.jp/precip/, is developed by the Research Institute for Humanity and Nature, Japan; it is based on observations from 5,000 to 12,000 rain gauge stations and currently represents the only long-term, high-resolution daily precipitation dataset available at the continental scale for Asia. The daily rainfall data from CFSR, available from 1979 to the present, with a spatial resolution of 0.31° × 0.31° (approximately 31 km), was obtained from https://globalweather.tamu.edu/#pubs. This dataset was developed as a global, high-resolution, fully coupled atmosphere-ocean–land–surface–seep ice system aimed at providing the most accurate representation of the state of these interconnected components over the specified period. The TRMM 3B42V7 daily rainfall data, available from 1998 onward, was downloaded from https://mirador.gsfc.nasa.gov/. This dataset offers average daily rainfall measurements on a 0.25° × 0.25° grid derived from thermal infrared and microwave sensor observations.

In the upper Teesta River basin, nine rain gauge stations are distributed across the basin, as depicted in Figure 1. Daily rainfall data from these stations were obtained from the Indian Meteorological Department (IMD) for a 27-year period (1990–2020). IMD data are widely acknowledged for their reliability and are commonly used in meteorological research across India, with strict quality control procedures ensuring data accuracy. Figure 2 presents the Digital Elevation Model of the study area, illustrating a distinct rise in elevation from approximately 200 meters in the south to 8,375 meters in the north. Figure 3 and Figure 4 display the spatial distribution of annual rainfall across the upper Teesta River basin for the period 2011 to 2020. Detailed information regarding the rain gauge stations including their geographic coordinates (latitude and longitude), altitude, and annual average rainfall is provided in Table 1. These data are vital for monitoring change in weather pattern and climatic variability within the basin.

Table 1: Precipitation stations located in Upper Teesta Basin

Sl. No.	Rain gauge Station	Latitude	Longitude	Annual Rainfall (mm/year)	Height (m)
01	Tadong	27.3106 N	88.5976 E	3604	1322
02	Khanitar	27.1761 N	88.5287 E	2204.8	321
03	Chungthang	27.6034 N	88.6465 E	2589.2	1790
04	Sankalam	27.6635 N	88.3778 E	1932.5	833
05	Mangan	27.5005 N	88.5346 E	3303.9	956
06	Namthang	27.1668 N	88.4779 E	2565.3	1246
07	Dhamthang	27.2333 N	88.3834 E	2864.5	1852
08	Kabi	27.4058 N	88.6174 E	2934.7	1799
09	Mazitar	27.1876 N	88.4997 E	1731.9	334

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RESULT AND DISCUSSION

The discrepancy in the average monthly rainfall derived from APHRODITE, CFSR, and TRMM alongside the IMD and CWC rain gauge data for the years 1998-2007 is illustrated in Figure 5. Most gridded datasets depict similar patterns with observed rainfall throughout the year; peak rainfall seems to occur in July, while the lowest happens during winter months (December to February). Apart from Tadong, all the gridded product datasets underestimate observed data at other rain gauge stations, without the Tadong station, where the APHRODITE dataset does overestimate rainfall during monsoons (June–September). The geographical location of the rainfall gauging stations (IMD and CWC used in the present case) is such that all the stations are free from snowfall except Lachung, where rainfall occurs in the valley. Snowfall occurs in the high mountains surrounding the valley. Rainfall variation at the observed stations shows that annual rainfall at Lachung is comparatively less than at other stations. Overall, the quality of the APHRODITE data is better than that of other gridded datasets at all the stations, except at Lachung, where APHRODITE data fails to represent the observed monthly rainfall amount. The poor performance of APHRODITE at Lachung is attributed to the lack of rainfall observation stations maintained by IMD in the upstream region of the Teesta basin above Tadong.

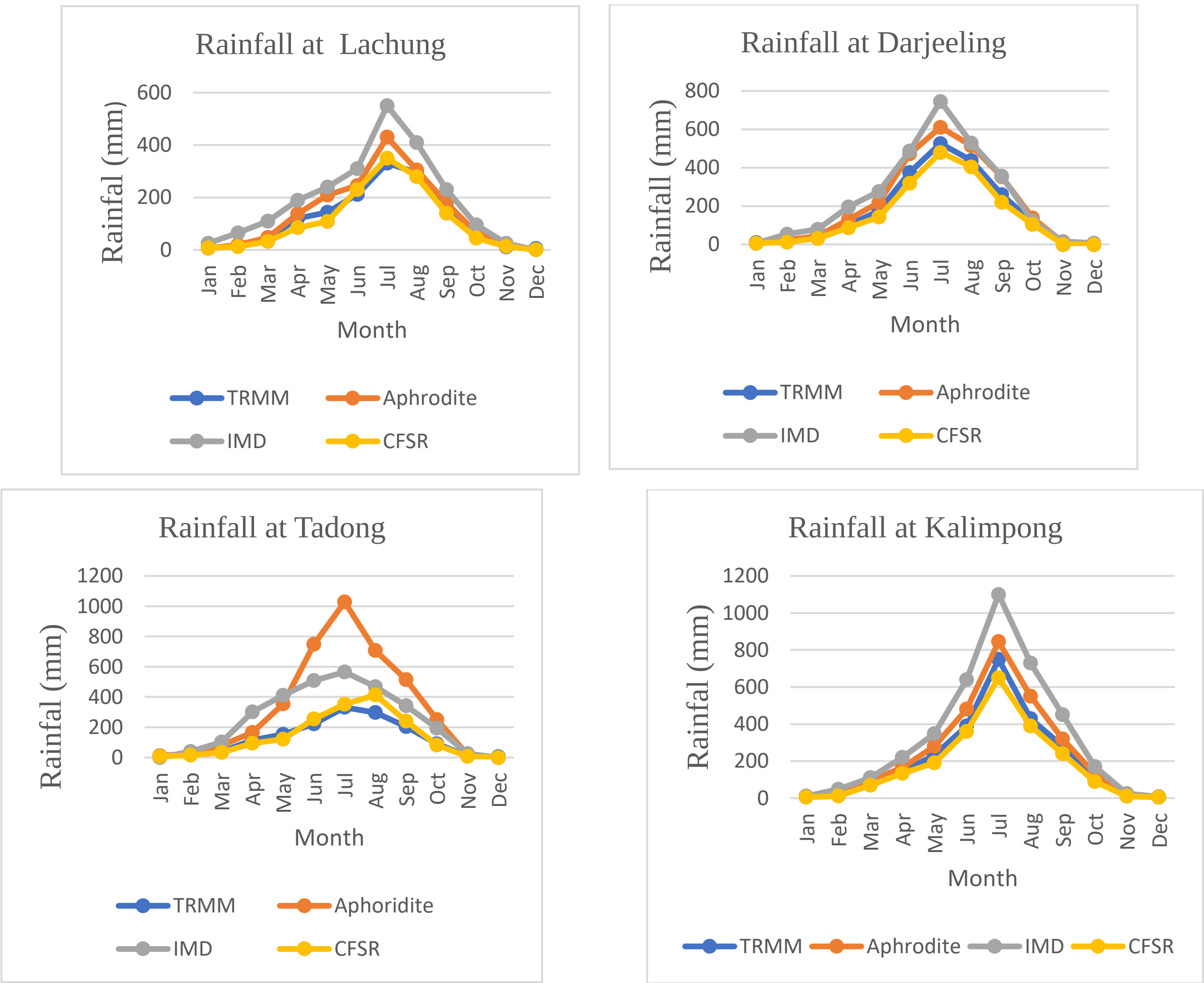

Fig 5: Comparison of Satellite Based Rainfall Records with Ground Based Rainfall Records

The statistical values using this study to compare gridded rainfall with observed rainfall are presented in Table 2.

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Table 2: Statistical value of gridded and Observed Rainfall Data

	Bias	Mbais	RMSE	CC	POD	FAR	CSI
Aphrodite							
Lachung	-3.69	0.41	8.39	0.32	0.86	0.12	0.75
Darjeeling	-3.04	0.62	14.29	0.53	0.93	0.18	0.79
Tadong	2.01	1.15	23.16	0.37	0.85	0.15	0.73
Kalimpong	-3.06	0.75	19.25	0.52	0.82	0.22	0.72
CFSR							
Lachung	-2.16	0.65	12.63	0.28	0.89	0.12	0.73
Darjeeling	-4.51	0.47	17.38	0.41	0.77	0.11	0.74
Tadong	-4.62	0.43	18.46	0.27	0.83	0.22	0.69
Kalimpong	-8.53	0.21	23.54	0.29	0.61	0.1	0.57
TRMM							
Lachung	-2.88	0.57	12.76	0.35	0.68	0.18	0.56
Darjeeling	-1.81	0.77	16.43	0.44	0.67	0.15	0.63
Tadong	-4.32	0.48	17.82	0.26	0.63	0.27	0.51
Kalimpong	-2.85	0.57	11.37	0.33	0.66	0.19	0.59

Values of -3.69, -3.04- and 3.06 mm day-1 for Bias and 0.41,0.62 and 0.75 for Mbais at Lachung, Darjeeling, and Kalimpong imply underestimation and values of 2.01 day-1 for Bias and 1.15 for Mbias shows an overestimation of Aphrodite data. The highest RMSE value observed at Tadong was 23.16, which shows the high difference between the observed and Aphrodite data sets. The lowest RMSE value at Lachung, 8.39, is attributed to its lower annual rainfall than other rain gauge locations. A moderate positive correlation (CC) is observed between the observed and APHRODITE rainfall at Darjeeling and Kalimpong, while a weak positive relationship is observed at Tadong and Lachung.

Gridded CFSR rainfall describes the underestimation of observed rainfall at all gauging stations, particularly at Kalimpong. The highest bias value of -8.53 mm day^{-1} and bias 0.21 indicates a significant deviation from ground-based rainfall records. A weak positive relationship is observed between the observed and CFSR daily rainfall at all stations.

In Kalimpong and Tadong the TRMM gridded rainfall data shows an underestimation. The High negarive bias -4.32 mm day^{-1} at Tadong, along with Mbias 0.48 describes a clear underestimation. The RMSE value of 17.82 mm day^{-1} at Tadong highlight a significant change between TRMM and observed daily rainfall.

The difference of POD, FAR, and CSI values at gauging stations for gridded rainfall data indicates that APHRODITE is the best at all but two of the stations, with the maximum POD and CSI and minimum FAR, in comparison to CFSR and TRMM. At Lachung, CFSR indicates maximum POD and CSI and minimum FAR. The better performance of APHRODITE at all other places except Lachung is due to its dependence on IMD rain gauge data from which it originated. For designing a rain gauge network, ground-based rainfall records are considered.

Figure 6 shows the monthly variation of ground-based rainfall at different stations used in this study. All the station receives maximum rainfall during the monsoon period.

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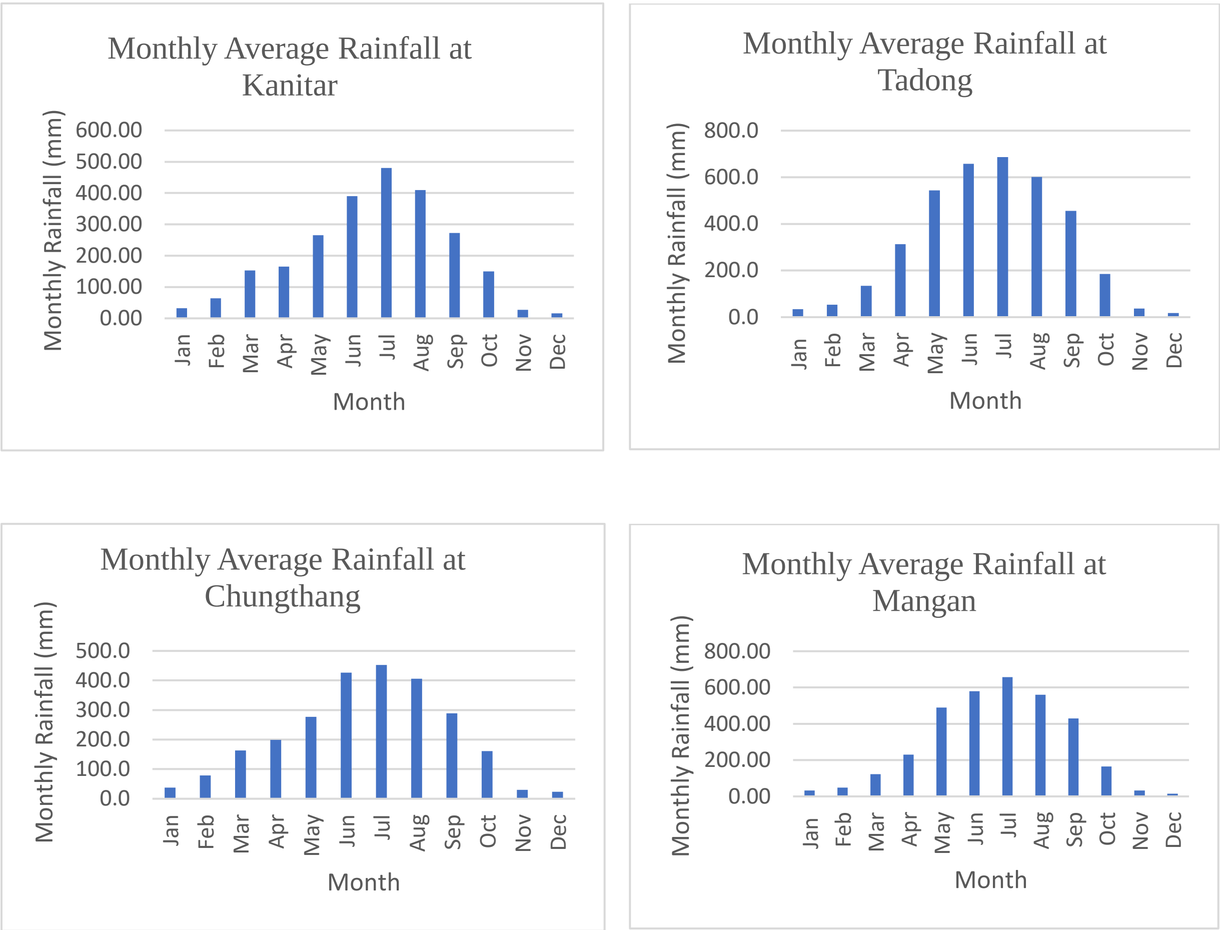

Fig 6: Monthly Average Rainfall at Khanitar, Tadong, Chungthang and Mangan

The Maximum information minimum redundancy methodology applied to Upper Teesta River Basin to evaluate the rain gauge network by using a computer programming. The program calculates the KS statistics and evaluates the central station based on marginal entropy and arranges the subsequent rain gauge stations based on Transinformation index. The statistical parameters are presented in Table 3 showing the mean, standard deviation, coefficient of variation and KS statistics in each rain gauge station in upper Teesta River basin.

Table 3: Statistical Parameter of Annual Rainfall in Upper Teesta River Basin

Sl. No	Rain Gauge Station	Statistical Parameter			Computed value of KS Statistics	Marginal Entropy
		Mean	SD	CV (%)		
01	Tadong	3604	455.6	12.6	0.132	8.137
02	Khanitar	2204.8	492.5	22.3	0.096	7.892
03	Chungthang	2589.2	903.6	34.9	0.173	7.832
04	Sankalam	1932.5	711.8	36.8	0.085	7.045
05	Mangan	3303.9	732.4	22.2	0.138	6.732
06	Namthang	2565.3	637.5	24.8	0.124	6.546

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07	Dhamthang	2864.5	563.4	19.6	0.083	7.489
08	Kabi	2934.7	588.7	20.1	0.156	7.254
09	Mazitar	1731.9	386.5	22.3	0.118	6.789

From Table 3, Tadong station gathers the highest average annual rainfall of about 3604 mm. The coefficient of variation values varies between 12.6-36.8%. Based on goodness of fit test results the computed KS statistics all 9 rain gauge stations with normal distribution less than critical value 0.218 at 5% significance level. Table 4 represents the Transinformation index matrix for the different stations in the upper Teesta River basin. Table 5 presents details on the redundant information transmitted by each station, as measured by the transinformation index. It also includes the corresponding correlation coefficient values. It is important to note that Mazitar station provides complete (100%) information, as reflected by its transinformation index value. The nine rain gauge station in upper Teesta River basin with area 7096 Km² is not satisfies the WMO minimum criteria 600-900 Km² per station in mountainous and hilly area. As the hilly area the rainfall is predominant by orographic effect, the nine rain gauge station unable to capture the variability in precipitation. So, there is a need to improve the existing rain gauge network with addition of other stations by Value of monitoring concept in the adjacent station group Prajapati et al. (2024). The findings are anticipated to aid stakeholders in making informed decisions regarding RGN optimization in the Upper Teesta River Basin.

Table 4: Transinformation matrix based on Shanon Marginal Entropy

Station Name	Marginal Entropy	Transinformation index							
		S2	S3	S4	S5	S6	S7	S8	S9
Dhamthang	7.489	0.3898	0.6074	0.8383	0.981	1.063	1.1323		
Kabi	7.254	0.3473	0.6256	0.848	0.9671	1.1681	1.2058	1.2542	
Mazitar	6.789	0.42	0.6192	0.9766	1.0812	1.191	1.244	1.295	1.362
Namthang	6.546	0.3681	0.6095	0.7993	0.9619	1.033			
Chungthang	7.832	0.3667	0.547						
Sankalam	7.045	0.3581	0.5617	0.7446					
Mangan	6.732	0.352	0.6453	0.8524	0.9554				
Tadong	8.137								
Khanitar	7.892	0.3024							

Table 5: Details of redundant information with corelation coefficient

Rain gauge station	Transinformation Index	Optimum Redundant Information	Corelation Coefficient
Khanitar	0.3024	22.1912	0.6736
Chungthang	0.547	40.1409	0.8155
Sankalam	0.7466	54.788	0.8805
Mangan	0.9554	70.1108	0.9230

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Namthang	1.033	75.8274	0.9345
Dhamthang	1.1323	83.0924	0.9466
Kabi	1.2542	92.0378	0.9584
Mazitar	1.3627	100	0.9666

CONCLUSION AND LIMITATION

In this study, daily rainfall estimates of TRMM, APHRODITE, and CFSR was compared with observed data for the period 1998-2007 in four rain gauge locations at Darjeeling, Kalimpong, Tadong and Lachung. Results showed rainfall was underestimated by all the gridded product data with respect to observed data at all rain gauge stations except at Tadong at which APHRODITE rainfall showed overestimation during monsoon season (June-September). APHRODITE rainfall outperformed CFSR and TRMM at locations (Darjeeling, Kalimpong, and Tadong) where IMD rain gauges are present and in areas near to snow-covered area where no IMD rain gauge is present, CFSR results in better evaluation statistics than APHRODITE and TRMM. Hence, CFSR rainfall data can be used for various purposes such as hydrological modeling in ungauged areas of upper Teesta basin. This paper also evaluates the existing precipitation network in Upper Teesta Basin through MIMR criteria. The evaluation based on marginal entropy and transinformation index. The average annual rainfall varies between 1731.9-3604 mm and coefficient of variation based on average annual rainfall ranges between 36.8-12.6%. The result produces that the Tadong station is the central station as it has the maximum amount of marginal entropy and Mazitar station shows 100 % redundant information for computation of duplicate information to compare the other stations in the network. The amount of duplicate information giving by Mangan, Namthang, Dhanthang and Kabi are about 70, 75, 83 and 93 percent respectively. The only nine stations in the Upper Teesta Basin are not sufficient to capture the variability of orographic precipitation as per WMO guidelines for minimum station in the mountainous region. There are few limitations in this study area. The long-term data availability from this basin is very difficult. Around 30% area of this basin is snow covered but still date no gauge present in the area. With minimum number of rain gauge station, it is very difficult to monitor the climatic variation in this study area So, there is a need of restructuring the existing precipitation network. The results assist the decision maker to improve the gauging network in Upper Teesta Basin.

CONFLICT OF INTEREST

The authors declare no conflict of interest

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