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Statistical evaluation of satellite-based CHIRPS precipitation data averaged over the midland and highland regions of Kidangoor sub-catchment, Kerala

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सार – केरल की खड़ी स्थलाकृति, पूर्व में पश्चिमी घाट से लेकर पश्चिम में रेतीले समुद्र तटों तक फैली हुई है, जो जल विज्ञानिक और जल मौसम विज्ञानिक अध्ययनों की एक श्रृंखला के लिए अति सूक्ष्मल स्थानिक-कालिक विभेदन पर वर्षा डेटा के उपयोग की मांग करती है। राज्य के भौगोलिक प्रभागों में प्राप्त मॉनसून वर्षा में परिवर्तनशीलता का प्रतिनिधित्व करने में मौजूदा वर्षामापी नेटवर्क डेटा की सीमा को बेहतर विभेदन पर उपग्रह वर्षा डेटासेट का उपयोग करके दूर किया जा सकता है। इस शोध-पत्र में, किदंगूर उप-कैचमेंट के लिए उपग्रह से प्राप्त CHIRPS (क्लाइमेट हैज़र्ड्स ग्रुप इन्फ्रारेड प्रेसिपिटेशन विद स्टेशन) वर्षा डेटा का सांख्यिकीय मूल्यांकन स्टेशन वर्षा डेटा और आईएमडी ग्रिड डेटासेट के साथ तुलना करके किया गया। 95% विश्वासनीयता स्तर पर समरूपता परीक्षणों ने स्टेशन डेटा को 'उपयोगी' श्रेणी के अंतर्गत वर्गीकृत किया। इसके अतिरिक्त, सांख्यिकीय प्रदर्शन मैट्रिक्सट से पता चला कि CHIRPS डेटा ने प्रेक्षित स्टेशन वर्षा डेटा को थोड़ा कम करके आंका है। हालाँकि, मासिक श्रृंखला में निर्धारण गुणांक R^2 मान (0.95 - 0.97) और वार्षिक श्रृंखला में (0.37 - 0.64) ने डेटासेट के बीच एक सुदृढ़ से मध्यम सकारात्मक सहसंबंध प्रदर्शित किया। संक्षेप में, अध्ययन क्षेत्र में पहली बार मूल्यांकन किए गए मात्रात्मक सांख्यिकीय प्रदर्शन मैट्रिक्स ने प्रस्तावित किया कि CHIRPS वर्षा अनुमान जमीन-आधारित मासिक वर्षा डेटासेट को बहुत अच्छी तरह से पुन: पेश कर सकते हैं और आईएमडी ग्रिड डेटा के लिए एक अच्छे प्रतिस्थापन के रूप में भी काम कर सकते हैं।

ABSTRACT. The steep topographical setting of Kerala, traversing from Western Ghats in the east to the sandy beaches on the west, demands the use of precipitation data at a very fine spatio-temporal resolution for a range of hydrological and hydrometeorological studies. The limitation of the existing rain gauge network data in representing the variability in the monsoon showers received, across the physiographic divisions of the state, could be overcome using satellite rainfall dataset offered at a finer resolution. In this paper, a statistical evaluation of the satellite derived CHIRPS (Climate Hazards Group Infrared Precipitation with Stations) precipitation data for the Kidangoor sub-catchment was performed by comparing it with station rainfall data and IMD gridded data sets. The homogeneity test at 95 % confidence level classified the station data under 'useful' category. Additionally, the statistical performance matrices suggested that the CHIRPS data slightly underestimated the observed station rainfall data. However, the coefficient of determination R^2 values (0.95-0.97) in the monthly series and (0.37 - 0.64) in the annual series demonstrated a strong to moderate positive correlation between the datasets. To summarize, the quantitative statistical performance matrices, evaluated for the first time in the study area, proposed that the CHIRPS rainfall estimates could very well reproduce the ground-based monthly rainfall datasets and could also serve as a good replacement for IMD gridded data.

Key words – Box and whisker plots, CHIRPS, Homogeneity test, Statistical performance.

1. Introduction

Keen evaluation of hydrological and meteorological data is an 'a priori' and a vital input to every water resource, hydrological modelling and climate change studies (Ebert *et al*., 2007). The rainfall measurement using a hyetometer suffers from few inherent problems like missing rainfall records, sparse coverage of instruments, especially in remote and inaccessible areas (Essou *et al*., 2016). Rainfall received in tropics usually displays high spatial and temporal variability, the representation of which requires finely spaced observations which are not obtained from widely distributed rain gauge stations (Huffman, 2007). Due to recent growth in the field of remote sensing, high-resolution satellite-based rainfall products have emerged as an alternative to ground rainfall data (Huang *et al*., 2020). Based on data sources, the satellite rainfall products could be classified into satellite constructed, gauge interpolated and satellite reanalysis - based rainfall data (Chen *et al*., 2020). There are a multitude of satellite adjusted remote sensing precipitation data products available at varying degrees of spatial and temporal resolution. Gauge interpolated Tropical Rainfall Measuring Mission (TRMM) satellite dataset is a joint venture between NASA of United States and Japan Aerospace exploration Agency (JAXA) covering tropical and sub-tropical regions at 40° N and 40° S latitudes (Huffman, *et al*., 2007). Gauge interpolated data sets are generated by interpolating the station data into grids at varying spatial resolutions. Indian Meteorology Department (IMD) gridded rainfall data is a high resolution dataset at a spatial resolution of 0.25×0.25 degree is available for a period of 118 years from 1901 to 2018 across the Indian subcontinent (Pai *et al*., 2014). The NCEP/NCAR reanalysis based precipitation dataset presents the state of the earth's atmosphere as a globally gridded data set which is a joint venture product from National Centers for Environmental Prediction and National Center for Atmospheric Research (Kalnay, E. *et al*., 1996).

CHIRPS (Climate Hazards Group Infra-Red Precipitation Station), is a new rainfall product based on numerous data sources with high temporal and spatial precision. The CHIRPS product was developed at the University of California by the U.S. Geological Survey Earth Resources Observation and Science Center in collaboration with the Santa Barbara Climate Hazards Group (Paredes Trejo *et al*., 2016) (Paredes-Trejo *et al*., 2017). The two data products developed by the climate hazard group (CHG) are the CHIRP data and CHIRPS data (which is CHIRP data suitably blended with station rainfall data). CHIPRS, the station blended data based on several data sources, is much widely used due to its better spatio-temporal resolution (Ayehu *et al*., 2018) and is primarily used in drought monitoring studies (Funk *et al*., 2015). The calibrated Cold Cloud Duration (CCD) data, using the TRMM 3B42, is transformed to long term mean rainfall estimation using rain gauge station data from Food and Agriculture Organization (FAO) and the Global Historical Climatology Network-Monthly (GHCN) datasets to generate the CHIRPS dataset at a 5-day time scale. The daily CCD data is further used to disaggregate the 5 day CHIRPS data to daily rainfall data (Chen *et al*., 2020). Considerable number of literature refers to studies on comparative statistical and hydrological evaluation of the use of various satellite data products at different spatial and temporal resolutions for various applications (Islam, 2018) (Li *et al*., 2017) (Shrestha *et al*., 2017) (Xue *et al*., 2013). Several attempts to validate the CHIRPS rainfall data across the globe include the study done by (Paredes Trejo *et al*., 2016) to obtain better performance of CHIRPS rainfall dataset against station rainfall in Venezuela. Similar comparison studies conducted in Brazil (Nogueira *et al*., 2018), Cambodia (Phoeurn & Ly, 2018), Chile (Zambrano-Bigiarini *et al*., 2017) and China (Bai *et al*., 2018) validated the CHIRPS rainfall data sets and proved to be a good representation of ground station data. According to (Sharannya *et al*., 2020), the evaluation of the CHIRPS data product performed inferior compared to data from other satellite sensors like TRIMM in humid tropical catchments. The studies conducted by V. Tiwari (Tiwari *et al*., 2020), S. Prakash (Prakash, 2019), V. Gupta (Gupta *et al*., 2020) are a few among the very limited studies conducted so far to verify the potential of using CHIRPS data as a proxy to the station rainfall data in watersheds in Kerala and across the Indian sub catchments.

The ground station rainfall data may be in-homogeneous due to various non climatic reasons such as station relocations, changes in environment, changes in observational and computational techniques *etc*. However, its homogeneity is very crucial in many hydrological research (Bickici & Kahya, 2019) especially in studies related to flood. With the advancement of remote sensing technology, the satellite-based rainfall estimations, have become viable alternatives and better possibilities for bridging the gap. (Bickici & Kahya, 2019) performed the absolute homogeneity tests on monthly data using Petit test, Von Neuman Test, Bushand Range test and Standard normal homogeneity test on 160 meteorological stations for the period of 40 years from 1974 to 2014 and found that 44 out of 160 stations were inhomogeneous. Studies by (Ho, 2018) and (Al-lami *et al*., 2014) also scrutinized the homogeneity of the weather stations using the above mentioned 4 tests. The accuracy of the observed rainfall data is also questionable due to irregular spatial coverage and scanty distribution of rain gauge stations across a catchment (Hosseinzadeh *et al*., 2014). Where ground-based hydro-meteorological data is poor, satellite-based products are critical for addressing data issues and improving data quality, particularly in developing nations. Rain gauges do not offer continuous geographic measurements of rainfall, but satellite-based rainfall products do, and they are available over most marine and unpopulated land areas (Geleta & Deressa, 2021). However, for calibration, retrieval, error/bias correction, and validation, such products rely on ground observations. Drought and flood early warnings, food security monitoring, and hydrological analysis have benefited from continuous advancements in creating sophisticated rainfall products that make optimal use of both satellite and ground observations (Saeidizand *et al*., 2018).

The present study aims to evaluate the performance of satellite-derived-gauge blended CHIRPS rainfall estimates by comparing with available ground rain gauge station data using statistical performance indicators and graphical comparison tools. Lately, the watersheds of Kerala experiencing floods due to excess rainfalls during the monsoon season demands great consideration to conduct detailed hydrological studies for generating proper flood mitigations plans. The existing gaps in observed station data and non-availability of daily rainfall data for certain inaccessible regions of the state makes it cumbersome to execute accurate hydrological modelling. To the authors' best knowledge, this is the first attempt to justify the use of CHIRPS rainfall data product as a proxy to station rainfall data on a sub watershed in Kerala spread across the midland and highland regions of the state where station density is low.

2. Materials and methods

2.1. *Study area*

Towards the southwest coast of India is located Kidangoor sub-watershed of 592.3 sq km area covering 70% of Meenachil watershed in central Kerala, India. The catchment area is drained by the Meenachil river which originates from the Western Ghats in the east, takes a westerly course and empties itself into the Vemband Lake traversing through cities of Palai, Erattupetta, Ettumanur and Kottayam**.** The altitude of the Meenachil catchment ranges from 9m to 1185 m above mean sea level covering a total area of 836 sqkm (Deepa *et al*., 2022). The watershed experiences a tropical climate with an average annual rainfall varying from 2400 mm to 4500 mm. The

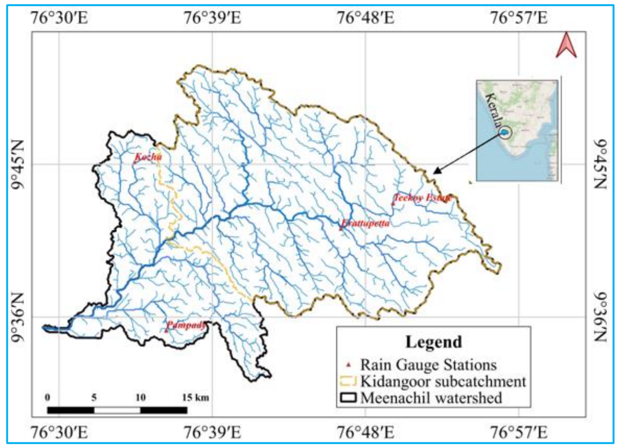

Fig. 1. Meenachil watershed with position of Rain gauge stations

major share of rainfall received by the watershed comes from the southwest monsoon (June to mid September).

2.2. *Meteorological data*

To assess the CHIRPS data, derived from blending of satellite and gauge rainfall estimates, the station rainfall recorded by four rain gauge stations, located within the catchment were used. With daily, pentad, and monthly precipitation datasets from 1981 to present, the CHIRPS provides data at a horizontal resolution with 0.05 latitude-longitude precision and quasi-global coverage (50° N - 50° S, 180° W - 180° E) than existing operational datasets (Saeidizand *et al*., 2018). Further, the daily station rainfall data at Teekoy Estate, Erattupetah, Pampady and Kozha (Fig. 1) were obtained from the Kerala state Irrigation Design and Research Board (IDRB) for the years 1995 to 2019.

2.3. *Methodology*

The study aims to justify the use of CHIRPS rainfall dataset as a substitute to the station rainfall data in places where the station data is not available or sparse. In this context, the following methodology was proposed.

Step1 : *Checking for outliers*

The station data obtained from IDRB at the 4 stations were pre-processed to check for any missing data and existence of outliers. The Box and whisker plots were used for checking the outliers. This promotes better graphical visualization of large volumes of time series data to identify the outliers which otherwise will not be noticeable through classical statistical and mathematical analysis of raw data. The existence of outliers in the station rainfall data is not quite uncommon which could be due to instrument failures or extreme meteorological situation.

TABLE 1

Location of rain gauge stations and weighted area contribution by Theissen's polygon method

S. No.	Rain-Gauge Station	Location		Area Contribution (sq km)	Theissen's weights
		Latitude (°N)	Longitude (°E)		
1	Teekoy Estate	9.712	76.827	155.03	0.26
2	Erattupetta	9.687	76.776	273.67	0.46
3	Pampady	9.587	76.605	21.59	0.04
4	Kozha	9.752	76.574	141.88	0.24

Step 2 : *In-homogeneity detection in ground station rainfall data*

The pre-processed data was checked for its homogeneity using homogeneity tests, *viz*., SNHT, Buishand range test, Pettitt test and Von Neumann ratio test. Homogeneity tests play a very significant role in perceiving the variability of the rainfall data. Inhomogeneity can be detected using several methods classified under absolute methods and relative methods (Wijngaard *et al*., 2003). The absolute method approach was adopted in this study to check the consistency and homogeneity of the point rainfall data. The relative approach could not be used since the data from the adjoining stations, being imperative for the study, were not available for applying the method. The homogeneity tests were performed on monthly precipitation data to confirm the null hypothesis at 95% confidence level using XLSTAT software. Using the Monte Carlo approach, XLSTAT calculates the *p*-value and an interval around the *p*-value for each of the four tests (Khalil, 2021). The approach suggested by (Wijngaard *et al*., 2003) was used to condense and categorize the results into A or 'useful,' B or 'doubtful' and C or 'suspect,' based on whether the null hypothesis was rejected or accepted. When the data series satisfies the null hypothesis in at least three of the four homogeneity tests used in the study, it is classified as class A and more than two out of four tests, it is classified as class B. However, the data series is classified as class C when the null hypothesis rejects more than three tests or all the tests (Ahmed *et al*., 2021).

To detect a sudden change in the time series on a monthly scale or annual scale, Pettitt (Pettitt, 1979) suggested a non-parametric method, while Alexandersson, 1986 suggested the SNHT homogeneity test which is very frequently used in climate change studies. The null hypothesis in this test is satisfied if the critical values as specified in (Pettitt, 1979), (Alexandersson, 1986) is not exceeded. The Buishand test assuming a normal distribution data is sensitive to breaks in the middle of the data series (Wijngaard *et al*., 2003). If the test result

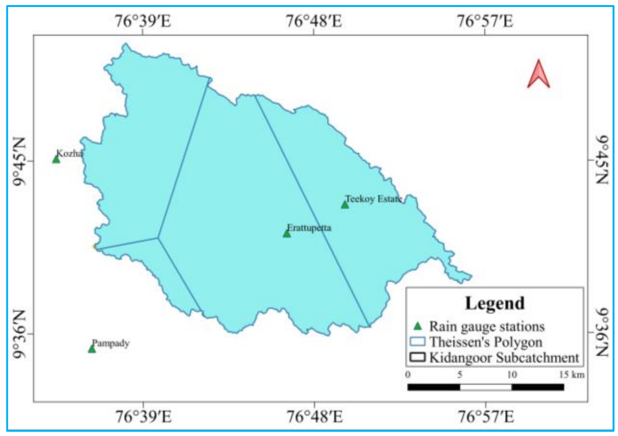

Fig. 2. Theissen's polygon weighted area contribution in Kidangoor sub catchment

values are less than the critical values specified by (Al-lami *et al*., 2014) and (Wijngaard *et al*., 2003), the null hypothesis is considered to be satisfied and the data is considered homogeneous as per Buishand test and Von-Neumann ratio test respectively.

Step 3: *Determination of mean station rainfall data*

The mean rainfall over the Kidangoor sub-catchment was determined using the Theissen's polygon method. A Theissen polygon was constructed in QGIS (Fig. 2), to determine the area contribution of the individual rain gauge stations and the theissen's weights (Table 1). The Theissen's weights so generated, were then applied to calculate the mean rainfall over the Kidangoor sub-catchment. The mean station rainfall will be denoted as 'G' and the CHIRPS rainfall as 'C', henceforth in the manuscript.

Step 4 : *Determination of IMD mean rainfall data*

The Theissen's polygon method was used to estimate the mean rainfall received in the catchment using the IMD gridded data. 9 grid points were identified in and around

TABLE 2

Location of IMD grid points and weighted area contribution: Theissen's polygon method

Grid Points	Location		Area Contribution (sq km)	Theissen's weights
	Latitude (°N)	Longitude (°E)		
2	9.5	76.75	33.37	0.06
4	9.75	76.5	26.03	0.04
5	9.75	76.75	509.78	0.86
6	9.75	77	23.18	0.04

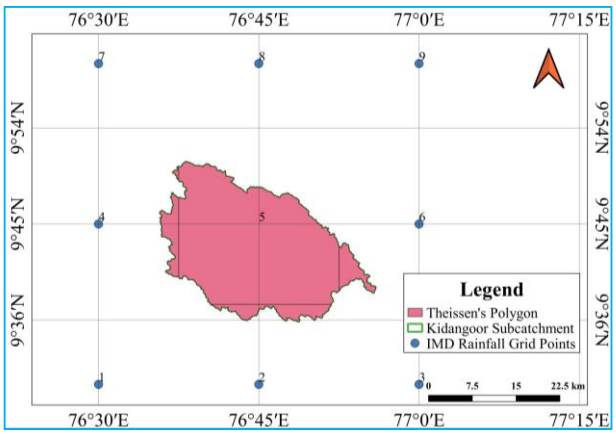

Fig. 3. Theissen's polygon weighted area contribution in Kidangoor sub catchment (IMD Grid Points)

the catchment. 1 out of 9 grid points were located outside the catchment boundary. The Theissen polygon constructed clearly reveals that only grid point no 5, located inside the catchment and grid points 2, 4 & 6, located outside the catchment could have an influence over the study area (Fig. 3). Hence the remaining grid points were neglected in calculating the mean rainfall received in the Kidangoor sub-catchment. The Theissen's weights and the contributing area of each grid point considered are presented in Table 2.The mean rainfall thus calculated over the Kidangoor sub catchment will be denoted as 'S' henceforth in the manuscript.

Step 5 : *Statistical evaluation of CHIRPS data*

Seven quantitative statistical metrics, *viz*., Pearson correlation coefficient (R), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Percent Bias (PBIAS), Nash Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970), Mean Error (ME), and Mean Absolute Error (MAE) (Table 3) were used to gauge the performance of the CHIRPS satellite rainfall data (C) with station rainfall data (G) & IMD Gridded Rainfall datasets (S).

The evaluation of the parameters R and R^2 was considered as a yardstick for performance assessment in many hydrological studies. A good agreement between the compared data sets is said to be obtained when the gradient of the regression line approaches 1 and intercept close to zero (Krause *et al*., 2005). Low values of parameters RMSE, MAE and ME, which expresses the difference between CHIRPS data and observed rainfall data in units of the variable (*i.e*., rainfall), can be considered as acceptable based on the published guidelines stating that the RMSE value must be less than half of the standard deviation of the observed (station rainfall) data (Singh *et al*., 2004). The parameter, PBIAS, measured the average tendency of the CHIRPS rainfall data to underestimate or overestimate the ground station rainfall data (Gupta, *et al*., 1999).

3. Results and discussion

3.1. *Box and whisker plots for checking presence of outliers*

The daily rainfall data at the four rain gauging stations, *viz*., Teekoy Estate (8 years), Erattupettah (25 years), Pampady (19 years) and Kozha (25 years) were organized into monthly and yearly series. The missing rainfall values at the Teekoy Estate station were estimated through linear interpolation from the IMD gridded datasets, which was validated and proved to be the best alternative to station data in humid tropics (Sharannya *et al*., 2020). The rainfall data were summarized into nine parameters, *viz*., minimum, first quartile (Q1), median, third quartile (Q3), maximum, mean, interquartile range (IQR), lower limit and upper limit (Doddy & Pranatha, 2018) (Adilah, *et al*., 2020) as presented in Table 4. The interquartile range (IQR) calculated as the difference between Quartile 3 and Quartile 1 values, was further used to obtain the lower limit values and the upper limit values for detecting outliers applying equation 1 and 2.

TABLE 3

Description and mathematical equations of statistical performance evaluation

Parameter	Acceptable range of values	Formula
R	−1 to 1, with 1 being the perfect score. Zero represents no linearity	$R=\frac{\sum_{i=1}^{n}\left(G_i-\overline{G_1}\right)\times\left(C_i-\overline{C_1}\right)}{\sqrt{\sum_{i=1}^{n}\left(G_i-\overline{G_1}\right)^2\times\sum_{i=1}^{n}\left(C_i-\overline{C_1}\right)^2}}$
R^2	0 to 1, higher values indicating lesser error variance	$R^2=\frac{\sum_{i=1}^{n}\left(C_i-\overline{G_1}\right)^2}{\sum_{i=1}^{n}\left(G_i-\overline{G_1}\right)^2}$
RMSE	The value of 0 represents the perfect fit	$RMSE=\sqrt{\frac{\sum_{I=1}^{N}\left(C_i-G_i\right)^2}{n}}$
PBIAS	Optimal value is 0. +ve for over estimation, -ve for underestimation	$PBIAS=\frac{\sum_{i=1}^{n}\left(C_i-G_i\right)\times 100}{\sum_{i=1}^{n}G_i}$
NSE	–∞ to 1 1 being the optimal value	$NSE=1-\frac{\sum_{i=1}^{n}\left(G_i-C_i\right)^2}{\sum_{i=1}^{n}\left(G_i-\bar{G}_i\right)^2}$
ME	It can take any negative or positive value and has a perfect score of 0	$ME=\frac{\sum_{i=1}^{n}\left(C_i-G_i\right)}{n}$
MAE	Only positive values Perfect score is 0	$MAE=\frac{\sum_{i=1}^{n}\left(\left|C_i-G_i\right|\right)}{n}$

Where: n refers to the number of samples, Gi : observed precipitation from rain gauge stations, Ci : precipitation estimates from the CHIRPS product, $\bar{G}$i: average observed precipitation from rain gauge stations, $\bar{C}$i: average precipitation estimates from the CHIRPS product.

TABLE 4

The box and whisker plot parameters generated using annual rainfall data (in mm) at the four rain gauge stations

S. No.	Parameters	Rain Gauge Station			
		Teekoy Estate	Erattupettah	Pampady	Kozha
1	Minimum	2825	2272.3	1380.4	1787.6
2	Q1	3267.1	3358.5	2581.7	2592.9
3	Median	4379.2	3825.3	2802.2	3166.5
4	Q3	4658.8	4315.9	3356	3647
5	Maximum	4972	4630.4	4657	4004.1
6	Mean	4100.2	3765.5	2871.3	3115.6
7	IQR	1391.7	957.4	774.3	1054.1
8	Lower Limit	1179.5	1922.4	1420.3	1011.7
9	Upper Limit	6746.4	5752	4517.5	5228.1

TABLE 5

The *p*-values from the statistical tests

Station Name	Test	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Teekoy	PT	0.60	0.53	0.98	0.98	0.61	0.64	0.61	0.62	0.14	0.62	0.62	0.55
	BRT	0.24	0.37	0.56	0.27	0.74	0.73	0.88	0.75	0.97	0.60	0.97	0.60
	VNT	0.10	0.19	0.57	0.40	0.73	0.94	0.49	0.25	0.98	0.41	0.75	0.80
	SNHT	**<0.0001**	0.07	0.74	0.21	0.83	0.80	0.92	0.44	0.89	0.80	0.71	0.52
Erattupettah	PT	0.34	0.70	0.26	0.73	0.24	0.71	0.57	0.43	0.88	0.42	0.33	0.87
	BRT	0.92	0.16	0.23	0.37	0.95	0.64	0.74	0.40	0.71	0.76	0.18	0.73
	VNT	0.44	0.07	0.51	0.28	0.58	0.49	0.39	0.64	0.52	0.34	0.21	0.66
	SNHT	0.88	0.28	0.32	0.26	0.57	0.57	0.52	0.66	0.82	0.66	0.39	0.83
Pampadi	PT	0.34	0.33	0.17	0.49	0.21	0.21	0.71	0.55	0.16	0.29	0.65	0.71
	BRT	0.94	0.86	0.90	0.39	0.57	0.52	0.67	0.47	0.90	0.18	0.36	0.54
	VNT	0.68	0.18	0.80	0.80	0.92	0.93	0.58	0.21	0.65	0.49	0.10	0.39
	SNHT	0.79	0.16	0.79	0.59	0.72	0.79	0.64	0.60	0.90	0.37	0.59	0.78
Kozha	PT	0.05	0.80	0.47	0.67	0.12	0.96	0.68	0.62	0.53	0.50	0.09	0.11
	BRT	0.73	0.98	0.91	0.78	0.65	0.32	0.46	0.87	0.54	0.22	0.95	0.61
	VNT	0.80	0.83	0.87	0.70	0.97	0.97	0.27	0.69	0.68	0.50	0.44	0.14
	SNHT	0.40	0.98	0.96	0.81	0.87	0.45	0.25	0.49	0.43	0.22	0.25	0.38

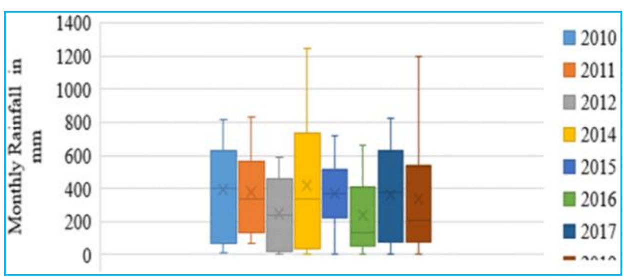

Fig. 4. Box and Whisker plot of monthly rainfall data at Teekoy Estate (from year 2010 to 2019)

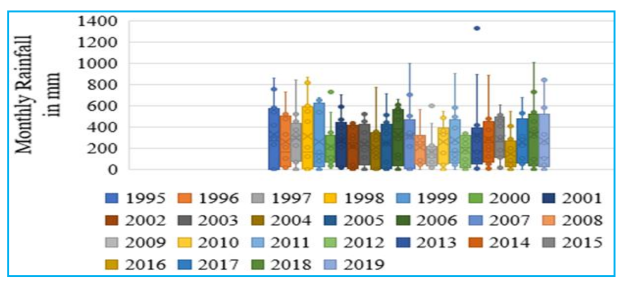

Fig. 6. Box and Whisker plot of monthly rainfall data at Kozha (from year 1995 to 2019)

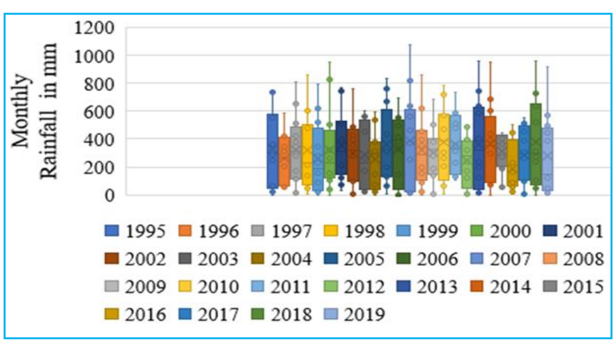

Fig. 5. Box and Whisker plot of monthly rainfall data at Erattupettah (from year 1995 to 2019)

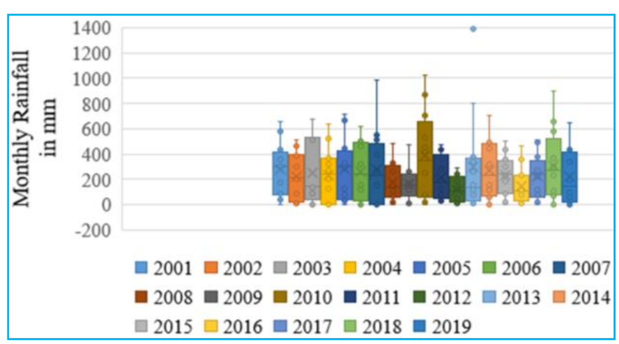

Fig. 7. Box and Whisker plot of monthly rainfall data at Pampady (from year 2001 to 2019)

TABLE 6

Qualitative interpretation of the statistical results

Station Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Teekoy	A	A	A	A	A	A	A	A	A	A	A	A
Erattupettah	A	A	A	A	A	A	A	A	A	A	A	A
Pampadi	A	A	A	A	A	A	A	A	A	A	A	A
Kozha	A	A	A	A	A	A	A	A	A	A	A	A

TABLE 7

***p* values for the monthly precipitation series**

Station Name	Pettitt	SNHT test	Buishand	von Neumann	Class
Teekoy	0.931	0.415	0.583	<0.0001	A
Erattupettah	0.252	0.284	0.86	<0.0001	A
Pampadi	0.713	0.355	0.643	<0.0001	A
Kozha	0.2	0.05	0.651	<0.0001	A

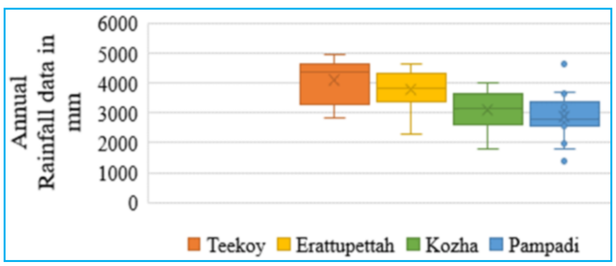

Fig. 8. Box and Whisker plot of annual rainfall data at the four rain gauge stations

$$\text{Lower limit value for outliers} = Q1 - (1.5*IQR) \quad (1)$$

$$\text{Upper limit value for outliers} = Q3 + (1.5*IQR) \quad (2)$$

The graphical plot of the monthly rainfall data presented in Figs. 4&5 for Teekoy Estate & Erattupettah respectively displays no outliers. However, Kozha (Fig. 6) and Pampady (Fig. 7) displays an upper limit outlier in the year 2013. This could indicate the occurrence of above average rainfall events which probably could have led to floods in the year 2013 in the adjoining waterbody and land further downstream of the catchment area. A similar occurrence of an extreme event, likely to have happened in the year 2000 and 2009 are also marked as outliers in the Kozha station. The graphical plot of the yearly values of the station Pampadi, exhibiting upper limit and lower limit outliers as presented in Fig. 8, were suggestive of the region experiencing excess rainfall and deficient rainfall in the respective year.

3.2. *Inhomogeneity detection in monthly rainfall data series*

To detect the inhomogeneity, the daily rainfall series of four stations were grouped into monthly data. The SNHT, Pettitt test (PT), Buishand range test (BRT) and Von-Neumann test (VNT) were applied to grouped monthly rainfall data at every station. The tests were applied to confirm the null hypothesis that the data is homogeneous at 95% confidence level. The *p* values derived from the statistical tests is shown in Table 5.

The In-homogeneity in the time series is indicated by any *p*-value less than the significance level of 5% (Khalil, 2021). All the stations were found to be homogenous and confirms the null hypothesis for all the months except in the month of January at the Teekoy station for the SNHT test. The qualitative interpretation of the results obtained from the four statistical tests (Table 6) classified the rainfall data into class A (useful) for all the months. None of the data fell into class B (doubtful) or class C (suspect) category in any month.

The cumulative monthly rainfall series of all the stations were then subjected to absolute homogeneity tests from 1995 to 2019. Table 7 illustrates the findings of the

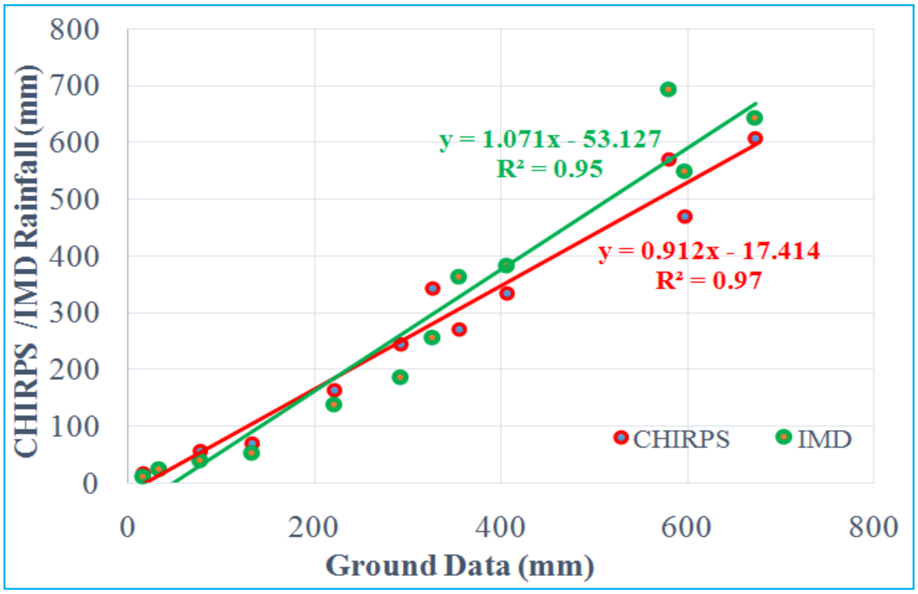

Fig. 9. Scatter plot between monthly CHIRPS rainfall dataset against ground station/IMD data

TABLE 8

***p* values for the annual precipitation series**

Station Name	Pettitt Test	SNHT test	Buishand Range Test	Von Neumann	Class
Teekoy	0.618	0.981	0.869	0.583	A
Erattupetah	0.817	0.812	0.83	0.705	A
Pampadi	0.087	0.973	0.85	0.856	A
Kozha	0.369	0.681	0.735	0.691	A

TABLE 9

Summary of the statistical performance metrics on a monthly scale

Data Sets Used	R	R^2	RMSE (mm/month)	PBIAS (%)	NSE	ME (mm/month)	MAE (mm/month)
CHIRPS Vs Station Data	0.983	0.966	59.52	-14.42	0.92	-44.67	47.47
CHIRPS Vs IMD Data	0.976	0.952	61.64	-4.86	0.932	-13.54	49.23
IMD Vs Ground	0.97	0.950	63.139	-10.05	0.91	-31.13	51.35

four tests. Although, in the Von Neumann test, all the stations failed to accept the null hypothesis, the results reveals all the stations' data (Teekoy, Erattupettah, Pampadi, and Teekoy) could be classified into class A (useful).

3.3. *Inhomogeneity detection in annual rainfall data series*

To check for inhomogeneity in the precipitation data on an annual scale, the yearly rainfall for all stations during the period from 1995 to 2019 was used. The outcome of the four tests tabulated in Table 8, found that all the stations were classified into class A (useful) as these stations executed all four tests satisfying the null hypothesis at 95 % confidence level.

3.4. *Quantitative statistical evaluation of CHIRPS rainfall against station rainfall & IMD rainfall*

The statistical performance matrices evaluated on monthly scale for the CHIRPS data against the station

TABLE 10

Summary of the statistical performance metrics on an annual scale

Data Sets Used	R	R^2	RMSE (mm/month)	PBIAS (%)	NSE	ME (mm/month)	MAE (mm/month)
CHIRPS Vs Station Data	0.8	0.64	576.75	-10.31	0.39	-369.47	422.28
CHIRPS Vs IMD Data	0.6	0.37	634.05	5.98	0.23	181.62	534.88
IMD Vs Ground	0.9	0.81	638.49	-15.37	0.24	-551.09	551.09

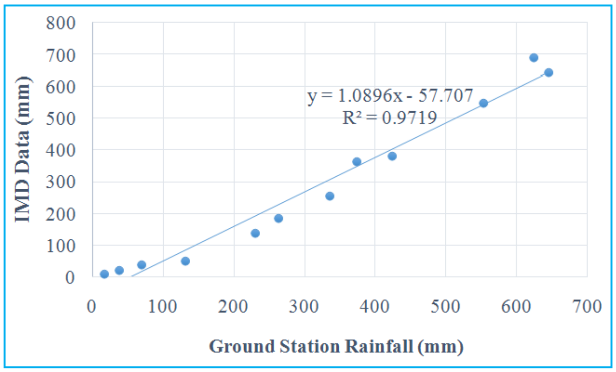

Fig. 10. Scatter plot between IMD rainfall dataset against Ground station data

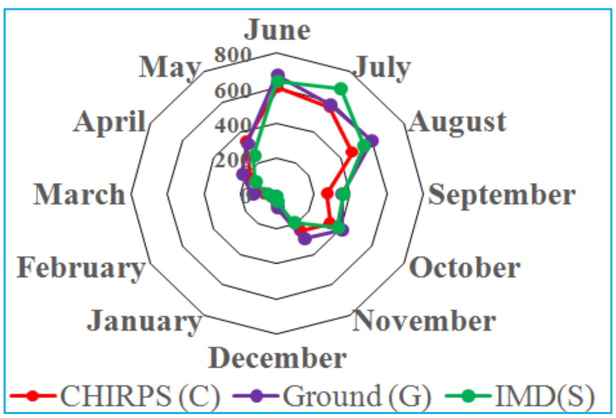

Fig. 11. Mean monthly CHIRPS satellite-based rainfall, IMD data sets and ground station rainfall dataset

rainfall and IMD gridded data, are summarized and tabulated in Table 9. The high R and R^2 values demonstrate a strong positive linear relationship between the data sets. The least square regression line was also fitted to the scatter plot of the monthly CHIRPS, station rainfall data sets and IMD data sets to compare and observe their deviation from 45° line (Fig. 9). The R and R^2 value approaching unity demonstrates that the monthly datasets are in good correlation with each other. Additionally, the NSE value, close to 1 implies less noise (residual variance) of CHIRPS satellite-based rainfall. The greatest disadvantage in determining NSE is that it results in overestimation of excess rainfall values and underestimation of lower values eventually getting ignored since, the difference between the CHIRPS and station rainfall data was calculated as squared values (Legates & McCabe, 1999). The RMSE and MAE values were also in the acceptable range as they were approximately less than half of the standard deviation of the observed rainfall data.

The plot of IMD data sets against the Ground station data sets also demonstrated a very strong positive correlation (Fig 10) with high R^2 values. The negative value of PBIAS and ME, obtained in the comparison of data sets, indicates that the CHIRPS/IMD product tends to slightly underestimate the observed monthly precipitation. As illustrated in Fig. 11, although the data sets record the maximum and minimum values of rainfall in the respective months of June and January, the CHIRPS/IMD data was found to slightly underestimating the observed rainfall data. However, it can be assumed that, the observed, IMD data sets and CHIRPS rainfall values are in good agreement with each other.

Table 10 summarizes the results of statistical performance metrics tabulated on a yearly scale. The R and the R^2 value demonstrate that two datasets have a good positive linear relationship though not very strong. However, the low NSE value indicates an increase in the residual variance of yearly CHIRPS rainfall estimates. On the other hand, the RMSE and MAE values were found to be too high compared to the ideal value indicating a significant error between the satellite and the rain gauge data.

The scatter plot of CHIRPS and ground rainfall estimates fitting the linear regression equation (Fig. 12) also determines a low R^2 value which indicates lesser collinearity between the two rainfall estimates, however it appears to be greater for IMD data with respect to station rainfall data (Table 10). The negative value of PBIAS and ME implies that the underestimation of the observed data

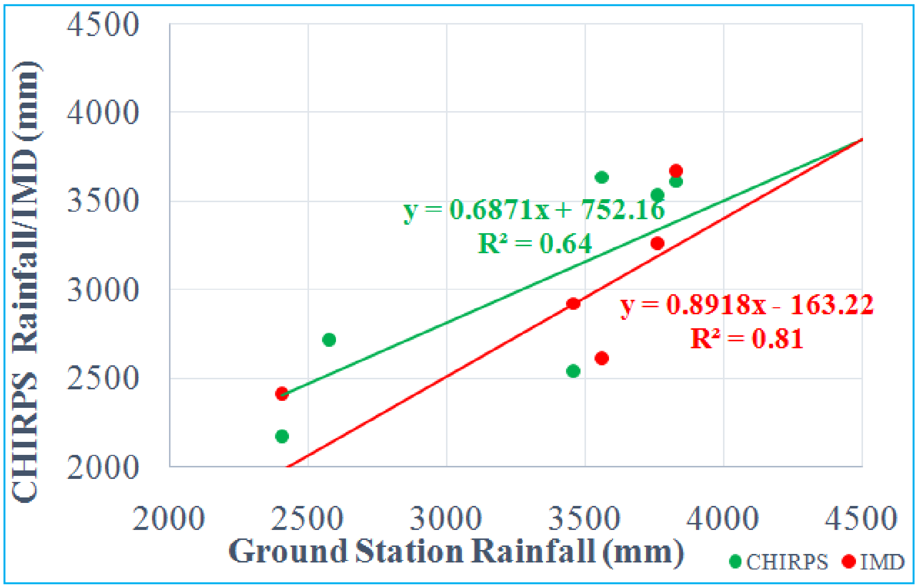

Fig. 12. Scatter plot between CHIRPS rainfall dataset and annual ground station rainfall dataset/IMD

not only applies to monthly, but it also follows on the yearly values. The RMSE and MAE values were found to be slightly higher than the ideal value (393.23 mm) for the annual time series indicating a minor error between the CHIRPS satellite data and the rain gauge data. Therefore, on an annual scale, CHIRPS product does not show good agreement with the station annual rainfall as compared to IMD data sets.

4. Conclusion

The present work focused primarily on realizing if CHIRPS rainfall data could be a suitable alternative for the station rainfall datasets. The use of CHIRPS data could prove to be a beneficial alternative in steep watersheds where the rain gauge stations are either inaccessible or scanty. The IMD gridded data sets, though has proved to be a very good source of data for many hydrometeorological studies (*viz*., Saikrishna *et al*., 2022), the Kidangoor sub-watershed captured data only from one IMD grid point located inside the watershed. A minimum of 2 to 3 grid point data is required to carry out a reasonably accurate analysis. Hence the use of other alternatives to IMD data sets gains priority over IMD data for carrying out analysis on smaller watersheds where data is required at a much finer spatial resolution. Thus, better conclusions could be derived from the analysis using CHIRPS data sets (available at a finer spatial resolution) the accuracy of which is tested for the Indian subcontinent by Saicharan and Rangaswamy, 2023.

The initial pre-processing of the available ground station data was required for suitable benchmarking. The graphical Box and the Whisker plots observed a few outliers in the datasets of Pampady and Kozha stations while the Teekoy Estate and the Erattupettah datasets were free from outliers. The anomalous rainfall values obtained in the years 2000, 2009 and 2013 at Pampady and Kozha highlights its departure from normal average rainfall. Occurrences of extreme rainfall events over the state of Kerala in the recent past could be attributed to the above mentioned departures. The monthly and the annual datasets at the all the stations, further checked for homogeneity, using the four statistical tests at a 5% significance level confirmed that all the station data were homogeneous at 95% confidence level and could be classified under class A (useful) category.

Seven statistical parameters were used for comparing the monthly and the annual CHIRPS rainfall estimates with the station rainfall data and IMD datasets. The coefficient of correlation and coefficient of determination demonstrated very good correlation between the CHIRPS rainfall data and the ground station data/IMD (R^2 varied from 0.95 to 0.97). The calculated high NSE value of 0.92-0.93 for monthly data sets thus suggests strong fit between CHIRPS and ground station datasets as compared to the NSE value of 0.24-0.385 obtained for corresponding yearly data values indicating weaker fit between the datasets. Although it was also observed that for datasets analyzed on an annual scale, RMSE, PBIAS, ME, and MAE values were slightly deviating from the perfect fit values, there seemed to be a better performance relationship on a monthly scale. Thus, based on the analysis, the CHIRPS rainfall estimates displayed good performance and agreed well with ground rainfall data on a monthly scale but slightly deviated away on a yearly scale. This could be owing to probable lumping errors while calculating the accumulated annual rainfall. Also, since there is an inherent uncertainty in measured hydrological parameter, although minor, could be magnified when grouped. It is worth mentioning that, although the CHIRPS data sets were slightly underestimating the ground station dataset, it was quite justifiable since only limited years of station data were available for calculating the mean station rainfall over the sub catchment. Hence, it can be concluded that the CHIRPS satellite data can produce reliable results and hence could be recommended to be used in hydrological studies. The CHIRPS rainfall data could be a very good alternative in places where sufficient number of IMD grid points are not available within the study area and where reliable ground station data is not obtainable(Prakash, 2019), particularly in places where rain gauge stations are irregular and sparse. It can be employed for hydro-climatological investigations such as drought monitoring and flood forecasting after considering the performance indicators described in this study. However, it is recommended to perform further relevant application-based appraisal, using updated versions of the CHIRPS data set, before integrating them into hydrological models.

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