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A Comparative Analysis of Gridded Precipitation Data in the Himalayan Region of Bhutan

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Abstract - For hydrological modelling and weather forecasting, precise measurement of precipitation is crucial since rainfall is the main input to most hydrological systems. The distribution of the ground-based precipitation data is not homogeneous due to inconsistent results from the majority of stations situated close to the towns. Nevertheless, it has been demonstrated that these flaws may be corrected by using information gathered remotely. In this study, four gridded products—including the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis—are compared for their precipitation data. TMPA 3B42RT, Global Precipitation Measurement (GPM) IMERG V06, Asian Precipitation Highly Resolved Observation Data Integration towards Evaluation (APHRODITE), and Precipitation estimation from Remotely Sensed Information using Artificial Neural Network (PERSIANN) against 54 reliable ground-based observations recorded by National Centre for Hydrology and Meteorology (NCHM) over the entire region of Bhutan. A double Mass curve was utilized to examine the consistency of the gauge precipitation data and underperforming stations were not considered. To compare the gridded data to ground-based data using several conventional statistical indices and rainfall detection indices, the average of points to grid value was employed. The results show that the gridded products' correlation coefficient with respect to ground-based observations is negligible, with values often averaging between -0.05 and 0.5. Except for APHRODITE, which had a POD of 0.056, all samples had a probability of detection (POD) greater than 0.5. Additionally, it is shown that whereas APHRODITE and PERSIANN underestimate rainfall by 93% and 86% of the total grids, respectively, TRMM and GPM overestimate rainfall by 70% and 58%. Relative Root Mean Square Error (RMSER) exceeded 50% over the entire grid, indicating the non-reliability of the products. Additionally, the results of the investigation indicate that the gridded products need to have their biases corrected because they perform poorly in Bhutan's Himalayas.

Key Words: Precipitation, Tropical Rainfall Measuring Mission (TRMM), Global Precipitation Measurement (GPM), PERSIANN, APHRODITE.

1. INTRODUCTION

Variations in topography and altitude have a significant impact on the climate of the Himalayan region, including Bhutan. Most of the nation's precipitation is due to the Indian monsoon, which begins in early June and lasts until late October. Rainfall is a crucial component of the world's water and resource cycles (Tang et al. 2018). It also provides the foundational information for all hydrological initiatives. One of the simplest and most often used techniques for estimating rainfall is the use of rain gauges. Even if it provides precise point measurements, the lack of a spatial description of the distribution of rainfall events might be a serious drawback, especially in modelling applications (Adhikari et al. 2020). Moreover, it is challenging to operate rain gauges in isolated locations in a nation like Bhutan with its rugged topography. Finding additional data sources to enhance the current record is essential for scientific investigations in a nation like Bhutan with significant rainfall variability and little data.

Bhutan currently lacks a significant number of rain gauges, which are often located in conveniently accessible locations, primarily in and around human settlements, and generally close to a town. However, the World Meteorological Organization (WMO) has created a set of criteria on the density of hydrological stations in which it is explicitly stated that Bhutan requires at least 154 stations, or one station every 250 square kilometres (The International Bank for Reconstruction and Development 2018). If AWSs are excluded since they are found at some Class A sites, the gap is immense. While the stations need to be strengthened, the need for alternative sources of data is inevitable.

Any hydrological research in a country is difficult with insufficient datasets on the spatial and temporal fronts (Prakash et al. 2016). However, the development of remote sensing technology has made it possible to gather this dataset indirectly and utilize it for any hydrological investigations. Remote sensing in space provides coverage, making them an excellent supplement to but not a replacement for ground-based data (Plummer, Allsopp, and Lopez 2003)

These problems have been proven to be solved by the spatially integrated rainfall data from remote sensing which provides spatially dataset across a sizable extended region. Therefore, alternative sources of precipitation data include satellite rainfall estimates, remotely sensed data, data generated by applying cutting-edge technologies like artificial neural networks, and data gathered from various organizations such as the Global Telecommunication System (GTS) and the National Meteorological Services (NMS). Several gridded precipitation packages that include Bhutan have been made available over the last ten years. These include Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation (APHRODITE), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Global Precipitation Measurement (GPM) and Tropical Rainfall Measuring Mission (TRMM). TRMM and GPM are satellite-based products. Whereas Aphrodite is spatially interpolated data from existing 5000 to 12000 valid stations within Asia (Yatagai et al. 2012).

Based on the given in-situ gauge station location, the data was extracted from the pixel encompassing the station. The analysis was performed by comparing the average rainfall of in-situ gauge stations lying in the same grid and the value of the pixel encompassing the stations.

This study focuses on three main objectives:

1. Obtain the relationship between rainfalls estimated by gridded products and gauged rainfall over Bhutan.
2. Perform an adequacy test of rainfall detected by gridded products.

Each in-situ gauge meteorological station underwent a consistency test utilizing the double mass curve and residual curve. It was specifically carried out by Adhikari et al. (2022) and the assessment used the outcome here. When comparing the gridded products to in-situ gauge rainfall data, the underperforming products were eliminated. Only the consistent data were used to evaluate the four gridded products TRMM (3B42RT Daily), PERSIAN, GPM (svc 3B-DAY-L.MS.MRG.3IMERG), and APHRODITE (APHRO MA V1101). Correlation, RMSE, RMSER, BIAS, and MBias were the evaluation indices that were utilized. Additionally, by creating a contingency table, detection indices such as the Critical Success Index, Probability of detection, and False Alarm Ratio are quantified.

2. Body of Paper

STUDY AREA

Bhutan confronts the Assam-Bengal plateau in southern India from its position in the easternmost part of the Himalayan range. Bhutan's topographic characteristics, as well as those of its surrounding areas, are intricate landforms. As a result, it is challenging to characterize the area's consistent climate trend. Although the monsoon has an impact on the weather and climate in the eastern Himalayan range, it varies widely from place to place in Bhutan's mountains. Meteorological Station locations are shown in Figure 1, together with the pixels of the corresponding grid products.

Bhutan may be roughly divided into three climatic regions: subtropical in the south, temperate in the centre, and subalpine in the north. Due to the country's rugged terrain, the precipitation patterns in these three areas varied significantly, with the subtropical zone seeing the most annual average precipitation and the subalpine zone experiencing the lowest. A total of 76 meteorological stations are located within these zones, with subtropical zones having 9 class A, 30 class C, and 3 Automated Weather Stations (AWS) while temperate zones have 7 class A and 20 class C stations (NCHM 2019). However, there are only six class C stations in the sub-alpine and one station in the alpine zone.

METHODOLOGY

The grided products are available in various spatial resolutions such as 0.25°x0.25° for TMPA-3B42RT, APHRO_MA-V1101 and PERSIANN and 0.1°x0.1° for IMERG_v06. The data extracted from the pixel compromising the gauge station was compared. At times, there was more than one gauge within a spatial domain of a pixel, in such cases, the average value of those stations was compared with the grided data. This approach is considered primarily to eliminate errors that would otherwise be introduced in an interpolated dataset. Moreover, to quantify the error distribution, it is critical to compare with the exact value and not with interpolated data. Further, the analysis was carried out separately for different seasons and months. Firstly, all twelve months were considered, next the analysis was performed seasonally (Autumn, Spring, Summer and Winter) and finally, only the wet season were analysed. This strategy adopted is in line with rainfall patterns over the region.

Two aspects were evaluated in this study; firstly the performance based on the amount of rainfall predicted by the grided data was evaluated and next using five different indices of error performance, namely coefficient of correlation, RMSE, RMSER, MBias and Bias. Furthermore, the adequacy of detection of rainfall by gridded products was analyzed by using a contingency table and detection indices such as Critical Success Index (CSI), probability of detection (POD) and False Alarm Ratio (FAR).

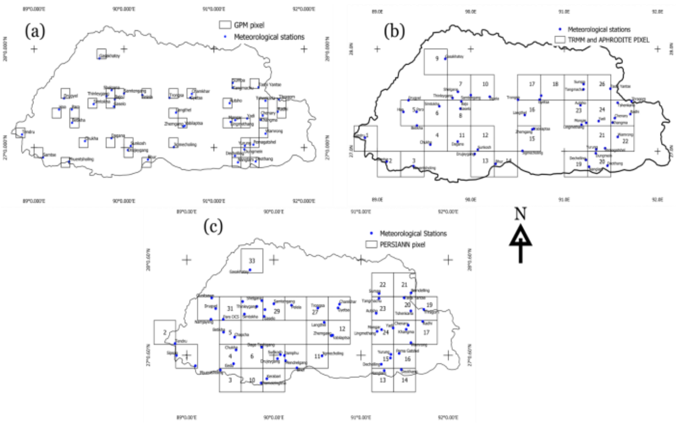

Figure 1: Number of meteorological stations and Pixel of each Product (a) GPM (b) TRMM and APHRODITE (c) PERSIANN.

Data

In-situ precipitation data

The National Centre for Hydrology and Meteorology (NCHM), an independent government organization under the Ministry of Economic Affairs, provided rainfall data on daily temporal frequency for the period of January 1996 to September 2019. For this research, stations with significant data gaps and stations displaying inconsistencies were excluded.

TRMM (TMPA-3B42RT)

The breakthrough Earth and Science initiative known as TRMM is devoted to studying tropical and subtropical rainfall. The mission was started by the Japan Aerospace Exploration Agency (JASA) and the National Aeronautics and Space Administration (NASA). With a geographical and temporal resolution of 0.250 x 0.250 at a 3-hour time scale, TRMM has been providing Real-Time inter-calibrated satellite precipitation data since December 1997. (Chen et al. 2011).

For the years 2000–2019, we used the 3B42RT Daily Product from GES DISC (disc.gsfc.nasa.gov). The rainfall data observed at 46 locations within 27-pixel grids were compared.

GPM (IMERG_v06)

After TRMM's success, a worldwide satellite network called Global Precipitation Measurement was created to give global observations of snow and rain. Additionally, GPM satellites include active radar scanning and multi-channel, dual-polarization PMW sensors. 1) The orbital inclination was extended to 650 degrees on GPM, and 2) the radar was enhanced with two frequencies, increasing its sensitivity to light precipitation. 3) 16.5 and 183.3 GHz high-frequency channels (Sharifi, Steinacker, and Saghafian 2016).

We used the daily IMERG v06 product for a 19-year period (2000-2019) for our investigation, which is available at GES DISC (disc.gsfc.nasa.gov). GPM product and observed rainfall data from 46 locations with 41-pixel grids were compared. It has 0.1 and 30 resolutions.

APHRODITE(APHRO_MA_V1101)

A dense network of regular rain gauge data from Asia, including the Himalayas, is included in the high-resolution grid precipitation product known as the Asian Precipitation Highly Resolved Observation Data Integration for Evaluation (APHRODITE). It offers information on 5000–12000 current stations dating back to 1951. The National Meteorological Services (NMS), Global Telecommunication Systems (GTS), and other organizations provide data from rain gauge monitoring networks (Yatagai et al. 2012).

For the years 1996 to 2007, APHRO MA 0.25deg V1101 was employed in the study. 46 sites with 27-pixel grids' observed rainfall data were compared.

PERSIANN

The Global Network for Water and Development Data for Arid Lands (G-WADI) program for UNESCO, NOAA, and the Center for Hydrometeorology at the University of California generate the PERSIANN bundle of precipitation products (Nguyen et al., 2018). Another gridded precipitation product, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network (PERSIANN), gives daily rainfall estimates at a spatial resolution of 0.25 x 0.25 degrees (Nguyen et al. 2018). Since it draws on a variety of data sources, it is dependable and offers long-term data sets with more than 30 years of data updated quarterly.

Validation Methods

Performance indices such as Coefficient of Correlation, Bias, Multiplicative Bias, Relative Root Mean Square Error, and Root Mean Square Error are for validation in this study. Contingency tables and detection indices such as Critical Success Index (CSI), Probability of Detection (POD) and False Alarm Ratio (FAR) have also been used to measure the adequacy of satellite products for their ability to detect rainfall.

Correlation Coefficient (r)

A degree of association between two variables is defined as correlation (Asuero, Sayago, and González 2006). In this study, the correlation coefficient between in-situ precipitation data and gridded rainfall estimates is quantified to understand the performance of gridded produced. A higher value of r indicated a good performance of a gridded product.

$$r = \frac{\sum_{i=1}^{N}\left(Y_i - \overline{Y}\right)\left(Q_{i,0} - \overline{Q}\right)}{\sqrt{\sum_{i=1}^{N}\left(Y_i - \overline{Y}\right)^2}\sqrt{\sum_{i=1}^{N}\left(Q_{i,0} - \overline{Q}\right)^2}}$$

Here N is number of samples; represents gridded products rainfall estimates; y represents gauge observed precipitation; Q represents the time and i represent averaged rainfall estimates from gridded products and Q in-situ rain gauges respectively.

Bias, MBias, RMSE and RMSER

$$Bias = \frac{Y_i - Q_{i,0}}{Q_{i,0}}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i,0} - Q_{i,0}\right)^2}$$

$$MBias = \frac{\sum_{i=1}^{N} Y_{i,0}}{\sum_{i=1}^{N} Q_{i,0}}$$

$$RMSER = \frac{RMSE}{\frac{1}{N}\sum_{i=1}^{N} Q_{i,0}}$$

For the measurement of the magnitude of deviation of gridded rainfall from the in-situ precipitation data, these statistical metrics are used (Adhikari et al. 2020). Accordingly, Bias governs whether gridded products under or over-estimate the rainfall. RMSE indicates how accurately the model predicts the responses (HAMIS 2013). The Parameter RMSE can be used to evaluate the reliability of each data source (Franchito et al. 2009). According to Franchito et al., (2009) if the RMSE is less than 50% then the grid product is reliable

Rain Detection Adequacy Test

Precipitations estimated by the gridded products such as TRMM, GPM, APHRODITE and PERSIANN are discrete values; thus, categorical or descriptive methods supplements how good satellite estimates are. The contingency table which determines the frequency of "Yes" and "No" of the gridded products estimates was another assessing technique implemented. It is to test for the adequacy of satellite products for their ability to detect rainfall using certain indices. In the study, a threshold of 0.5 mm is employed to determine whether there has been rainfall. In other words, a station or satellite will reflect rain if it detects more than 0.5mm of precipitation.

Table 1: Contingency table

	Station "Rain"	**Station "No Rain"**
Satellite "Rain"	Hit (H)	False Alarm (FA)
Satellite "No Rain"	Miss (M)	Correct (CO)

This contingency table indicated as, "Yes, reflects an event had happened", or "No, if the event does not happen". Analysis of the table is determined by the set of following detection indices:

Probability of Detection (POD) is the ratio of the events correctly detected by the satellites. The ideal POD value is 1 (Tang et al. 2018).

$$POD = \frac{H}{H+M}$$

False Alarm Ratio (FAR) fraction of the events falsely reported by the satellites. The ideal FAR score is 0.

$$FAR = \frac{FA}{H+FA}$$

Critical Success Index (CSI) also called Threat Score (TS) is the function of POD and FAR and showcases a more balanced judgment of the gridded products. The ideal score for CSI is 1 (Tan et al. 2015).

$$CSI = \frac{H}{H+FA+M}$$

$Where; H = Hit, FA = FalseAlarm \wedge M = Miss$

RESULT AND DISCUSSION

Data Quality Control

A consistency test using a double mass curve was performed for a total of seventy-five ground-based gauge stations in the country. The results of the test were categorized into four groups (Best, Good, Satisfactory and Poor) based on the coefficient of determination, straightness of plot and minimum percentage of residual error. This categorization enhances the quick assessment of data without having to check the database. Stations in the Poor category do not necessarily mean they are inconsistent instead, indicate the quality of data having a relatively low coefficient of determination value.

Temporal and Spatial Variations of Evaluation Indices

The analysis revealed that all four products have a statistically insignificant relationship when evaluated against the rain gauge data. Considering a wet season for TRMM, GPM, PERSIANN and APHRODITE maximum average correlation was 0.14, 0.225, 0.06 and -0.01 with the BIAS of 0.3, 0.28, -1.75 and -60 respectively. Maximum correlation of 0.21, 0.9, 0.2 and 0.31 was found in October, November, December and January months for TRMM, GPM, PERSIANN and APHRODITE respectively. The Temporal and Spatial variation of evaluation indices for TRMM is shown in Figure 2 and Figure 3 respectively. The stations exhibiting the least correlation coefficient with maximum Bias are mostly owing to the localized action disturbing only the specific stations.

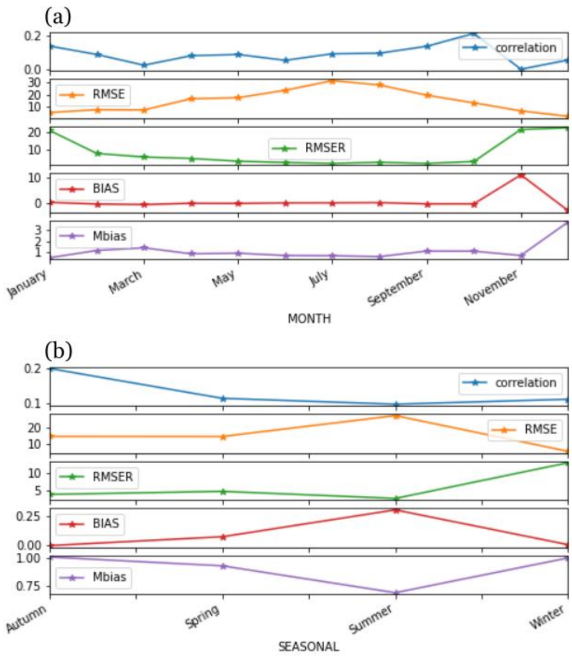

Figure 2: Temporal Variation of evaluation Indices for TRMM (a) Monthly (b) Seasonal

As reflected by BIAS value the TRMM and GPM Products overestimated the rainfall by 70% and 58% of the total grid respectively. Whereas APHRODITE and PERSIANN underestimated the rainfall by 93% and 86% of the total grid. TRMM makes use of a Passive TRMM Microwave Imager (TMI), Visible Infrared Sensor (VIS) and Precipitation Radar (PR) with a lightning detector for estimating the rainfall. However, the relationship with gauge daily rainfall data over Bhutan is poor. This could be due to the fact that TRMM is designed to estimate its daily variability on a monthly time scale (HAMIS, 2013). Interpolating the APHRODITE data from a limited number of gauge stations in the complex topography of Bhutan gives poor performance compared with other products.

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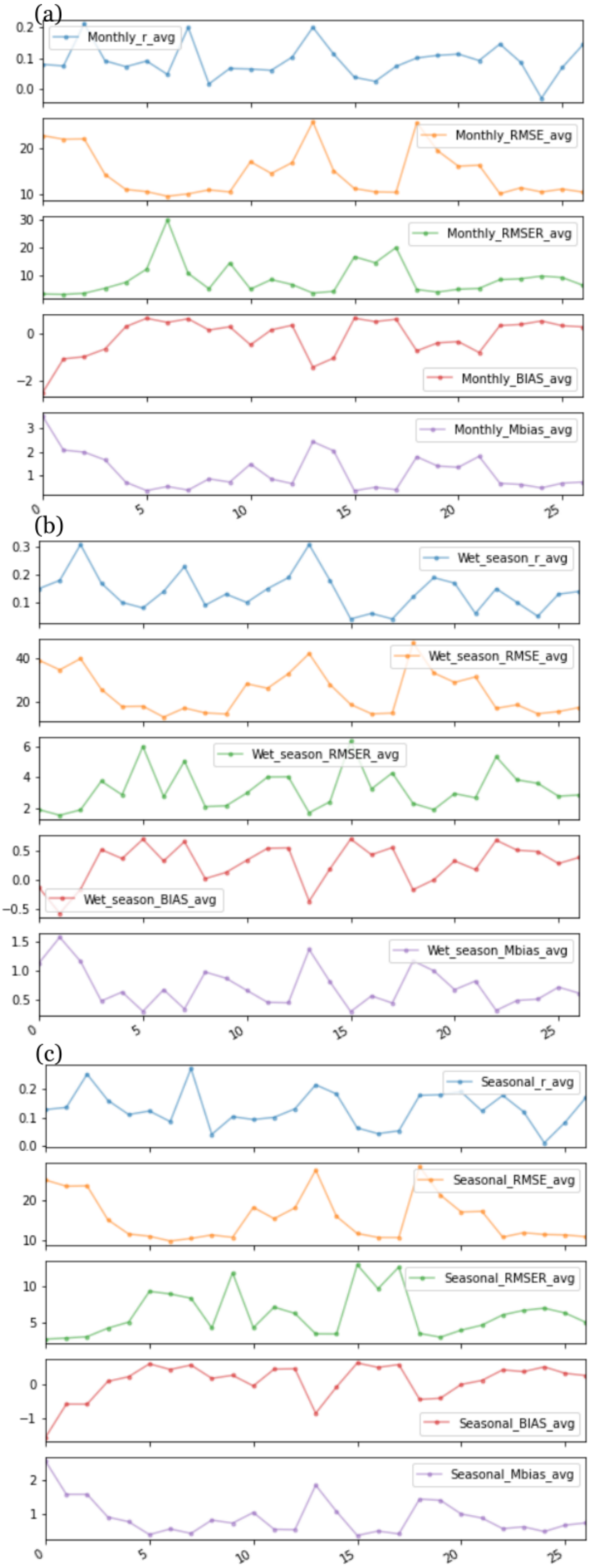

Figure 3: Spatial Variation of evaluation Indices for TRMM (a) Monthly (b) Wet Season (c) Seasonal

The poor relationship of APHRODITE with high BIAS and RMSER when compared with Bhutan's ground observed daily data is due to the fact that the APHRODITE gridded data depends upon the density of rain gauge available, which for Bhutan varies significantly in space and time. The variation of evaluation indices considering wet season for TRMM, GPM, PERSIANN and AHPRODITE are shown in Figure 4.

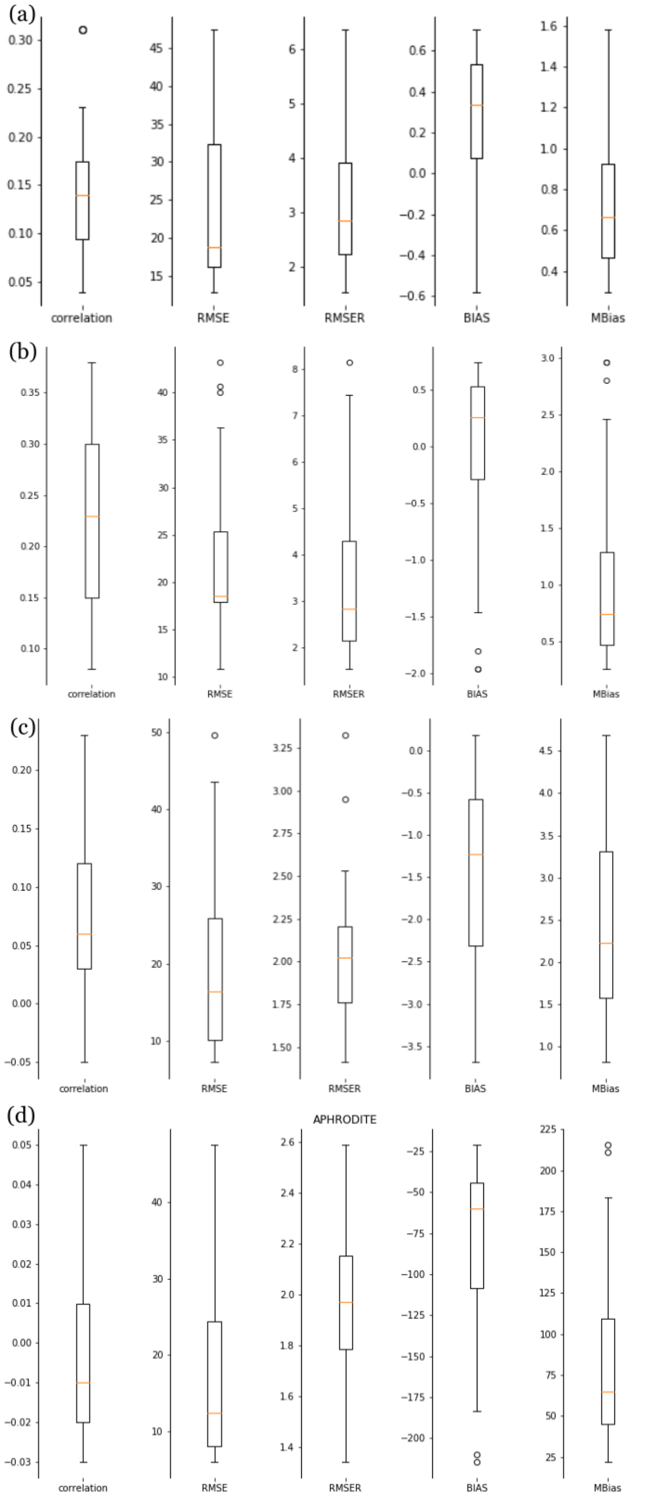

Figure 4: Variation of statistical parameters considering Wet Season (a) TRMM (b) GPM (c) PERSIANN (d) APHRODITE

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The reliability of the gridded products for TRMM, GPM, APHRODITE and PERSIANN was assessed using relative RMSE (RMSER). These products are considered reliable only when their RMSER value comes less than 0.5 (<50%). Among all grids (27, 41, 27 and 33 grid evaluated for TRMM, GPM, APHRODITE and PERSIANN respectively) no grid had RMSER less than 50%, indicating the unreliability of the products over the Himalayas of Bhutan.

Table 2: Mean Evaluation Indices Correlation Coefficient, Root Mean Square Error, Relative Root Mean Square Error, BIAS and MBias for (a)Monthly (b)Wet Season (c)Seasonal

(a) Considering all seasons

Evaluation Matrix	TRMM	GPM	Aphrodite	PERSIAN N
Correlation	0.0913	0.1156	0.0033	0.1588
RMSE	14.7334	13.5796	10.868	42.3877
RMSER	8.6752	6.2011	5.3116	29.4926
BIAS	0.7437	-0.6168	-713.12	-4.171
MBias	1.151	1.6168	714.12	12.1684

(b) Considering only the wet-seasons

Evaluation Matrix	TRMM	GPM	Aphrodite	PERSIAN N
Correlation	0.1393	0.2254	-0.003	0.0793
RMSE	24.6418	22.6839	18.6506	19.8469
RMSER	3.2258	3.4039	1.9567	2.0444
BIAS	0.2762	-0.0751	-81.716	-1.4769
MBias	0.7238	9.9199	83.812	2.4769

(c) Considering only the dry-seasons

Evaluatio n Matrix	TRMM	GPM	Aphrodit e	PERSIA NN
Correlation	0.1294	0.1435	-0.0103	0.1295
RMSE	15.6454	14.8655	11.82	13.2233
RMSER	6.1485	5.44	3.343	4.4222
BIAS	0.0942	-0.2122	-69.533	-1.5639
MBias	0.9058	1.2114	70.5056	2.1566

Rain Detection Adequacy Test

The four products used in the study did not perform well with the GPM IMERGE_v06 exhibiting the highest POD value of 0.724, then TRMM TMPA 3B42RT (POD=0.618), PERSIANN (POD=0.546) and APHRO_MA V1101 (POD=0.056). APHRODITE showed poor performance, because of the additional error while interpolating the rainfall observations from the limited number of rain gauges from the complex topography of Bhutan. The spatial variation of POD for 46 stations in TRMM, GPM, APHRODITE and 54 stations in PERSIANN is shown in Figure 5. The evaluation indices showed that the gridded products are not reliable and are not performing well in Bhutan. However, the Probability of detection for GPM, TRMM and PERSIANN was found greater than 50 %, indicating that the rainfall detection was done more or less well.

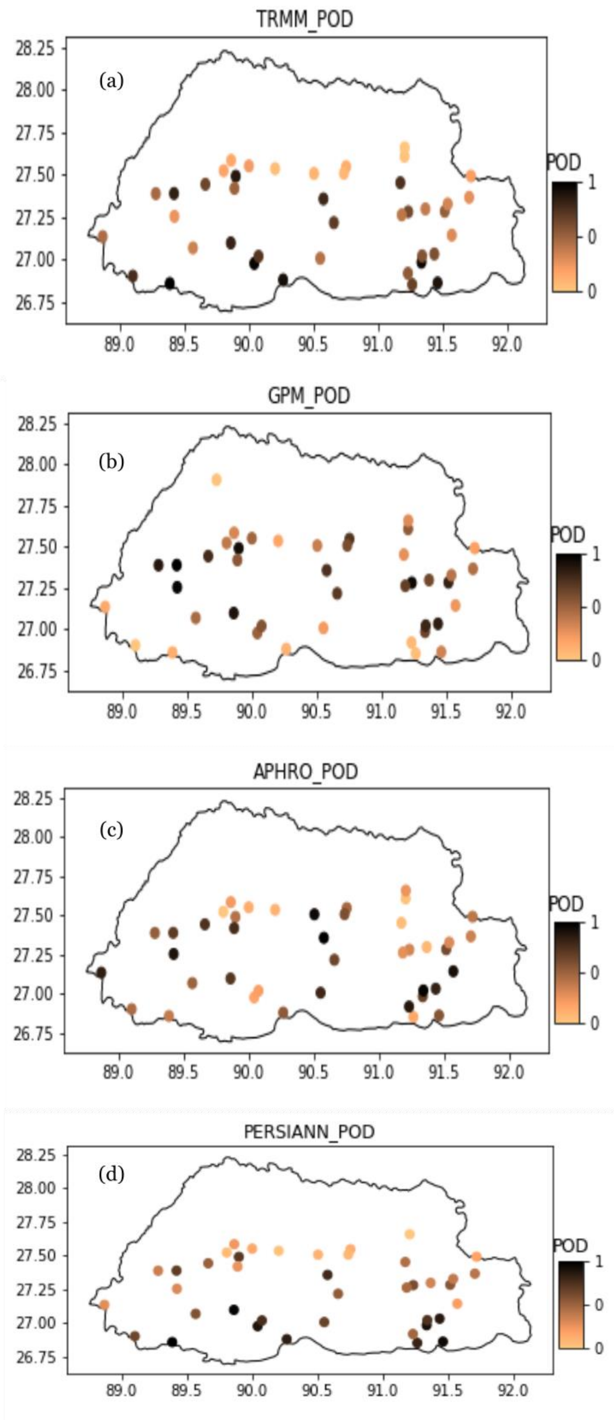

Figure 5: Spatial Variation of Probability of Detection (a) TRMM (b) GPM (c) APHRODITE (d) PERSIANN

3. CONCLUSIONS

An evaluation of TRMM, GPM, APHRODITE and PERSIANN with the existing gauge data was performed over the Himalayas of Bhutan to assess its performances for the wet season, seasonal and monthly periods. The evaluation is to weigh whether these gridded products can be used in concurrence with ground data for hydrological needs.

Five different standard statistical error performance indices such as Correlation Coefficient, RMSE, RMSER, Bias, and MBias, were used for the performance validation.

Further, detection indices namely; Probability of Detection (POD); False Alarm Ratio (FAR) and Critical Success Index (CSI) are three indices used to test the adequacy of gridded products.

Therefore, the following are the key findings of this study:

1. It is found that TRMM and GPM overestimate the rainfall of 70% and 58% of the total grids respectively whereas; APHRODITE and PERSIANN underestimate the rainfall of 93.1% and 86.08% respectively.
2. Karl Pearson's correlation coefficient (r) between the gridded products and ground data is insignificant and negatively correlated with APHRODITE.
3. RMSER of all four products was more than 0.5 (>50 percent) in all the stations signifying that the products are unreliable.
4. This analysis suggests that the gridded products cannot be used in concurrence with gauge data without modifications.

In our study area, the sampling errors for gridded products get intensified as the estimated precipitation data over the grids could significantly differ. Grid value, however, reflects the mean rainfall over the region, either overestimating or underestimating when compared against the average of ground data falling in the same grid. With a grid having a greater number of stations, the average values of these stations are taken to evaluate against the gridded products..

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