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Evaluation of Different Satellite Precipitation Data for Eastern Region of Nepal

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Abstract

A sound understanding of spatiotemporal variation of precipitation is crucial for hydrological and water resources assessment. Scarcity of ground-based rain gauge (GRG) station's data and their sparse distribution in widely varying topography, like in Nepal, is a challenge for developing hydrological model and utilize its potential for informed decision-making. Satellite precipitation products (SPPs) can potentially overcome the challenge posed by insufficient and inconsistent GRG measurements. This research aimed to evaluate the performance of four SPPs for eastern region of Nepal. Results revealed that PERSIANN-CDR SPP outperformed other SPPs in terms of Probability of Detection and Critical Success Index in the eastern region of Nepal. However, it consistently overestimated rainfall detection at all elevations and showed a significantly high negative PBIAS. CHIRPS SPP, on the other hand, exhibited fewer false alarms than other SPPs for all elevation ranges but always underestimated rainfall detection. Notably, TRMM and IMERG consistently showed higher false alarms for all elevation ranges. This study also observed that all the SPPs underestimated the daily rainfall amount with an increase in elevation range, showing a high negative percentage bias.

Keywords

magnitude-based index , performance-based index , SPPS

1. Introduction

Precipitation is a crucial component of the hydrological cycle and plays a significant role in sustaining human society and natural ecosystems. However, extreme or high-intensity precipitation can also trigger hydrological hazards such as floods, landslides, debris flows, and soil erosion [1]. To predict weather patterns and provide early indications of high-intensity extreme events, it is crucial to monitor precipitation patterns consistently and meticulously. The availability of observational precipitation data with high spatial and temporal resolutions is fundamental for the accuracy and reliability of such monitoring [1]. Dealing with the spatial and temporal variability of precipitation in mountainous regions poses a formidable challenge due to the complex topographic landscape, coupled with the intricate interplay of technological and economic limitations [2].

Satellite Precipitation Products (SPPs) present a promising avenue to address the constraints posed by the sparse distribution of ground-based rain gauge stations in remote and data-deficient areas like mountainous terrains [3]. These products furnish a unique vantage point through the maintenance of precipitation data on regular high-resolution grids. However, SPPs inherently harbor systematic and random biases that must be addressed before their seamless integration into hydrological models [4]. A rigorous performance evaluation becomes indispensable to gauge the accuracy of these satellite-derived estimates. The utilization of large-scale and spatially distributed hydrological models, propelled by widely accessible SPPs, emerges as a potent strategy to address the challenges of data scarcity in regions heavily reliant on water resources [5, 6].The availability of such granular data serves as an indispensable asset for water resource planning and management, particularly in regions where ground-based observational data are limited or not available at all. Overall, the incorporation of SPPs holds a promise as an avenue to enhance data collection, particularly in complex terrains. The adoption of large-scale models propelled by SPPs carries the potential to revolutionize water resource management in areas beset by data scarcity, ultimately facilitating informed and effective decision-making processes. [7]. Within the Indian subcontinent and the Himalayan region, including Nepal, earlier studies have found that SPPs have the potential to address data scarcity and complex terrain challenges [5]. Studies have shown that different SPPs perform differently based on their geographical location. Notably, TRMM, CHIRPS, MSWEP, and PERSIANN-CDR have been found to be consistent with ground-based precipitation measurements across different landscapes, including mountainous, Tibetan, and Himalayan regions [6]. One study highlighted the reasonable performance of PERSIANN-CDR over various regions of Nepal [8]. Another study (Khatakho et al., 2021)) highlighted the varying performance of IMERG and TRMM in different Nepalese river basins [9]. Similarly, another study highlighted IMERG and TMPA's capability of capturing precipitation patterns and drought events in an acceptable range and underestimation of mean annual precipitation in seven provinces [1]. These findings suggest that SPP performance is nuanced and location-dependent, emphasizing the need for careful consideration when selecting SPPs for particular regions. However, despite these promising findings, there is still a lack of comprehensive research into the performance of

SPPs within the intricate terrain and high-elevation regions of Nepal. The selection of suitable SPPs for specific river basins can significantly affect their effectiveness. This overall study signifies the importance of evaluation of SPPs before their application to various regions of Nepal.

2. Study Area

Koshi, Madesh, and Bagmati provinces are three recently created provinces that make up Nepal's eastern area. Our study region included all 14 districts in the Koshi Province, as well as 5 of the 8 districts in the Madesh Province and 5 of the 13 districts in Bagmati province. Our study covered 42,064km^2, which is 28.57% of Nepal's total land area. This region includes the Koshi River basin, which is entirely located on Nepali soil. The region encompasses all of Nepal's physiographic divisions and the region's climate ranges from tropical in the Terai Plains and Low River Valleys to arctic on mountain summits. The region's diverse biodiversity is supported by the changing climatic conditions that occur as altitude rises [10]. Precipitation also varies greatly, ranging from 207 mm in the trans-Himalayan region to more than 3,000 mm in the Eastern mountains and mid-mountains [11].The map of study area is shown in figure 1.

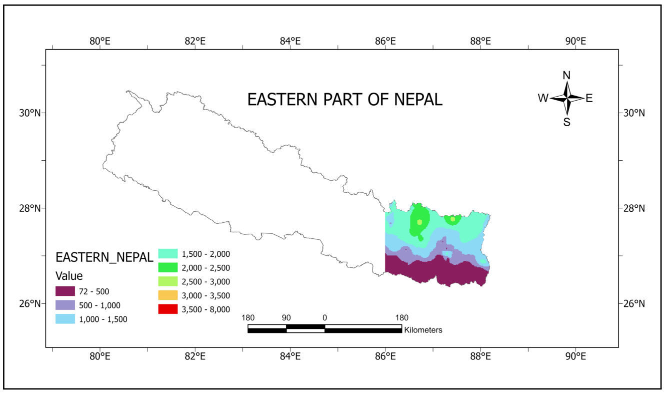

Figure 1: Location of Study Area in Nepal

The sparse distribution of meteorological stations in the study area and need of SPPs as an alternative of ground rain gauges can be visualized from the figure 2.

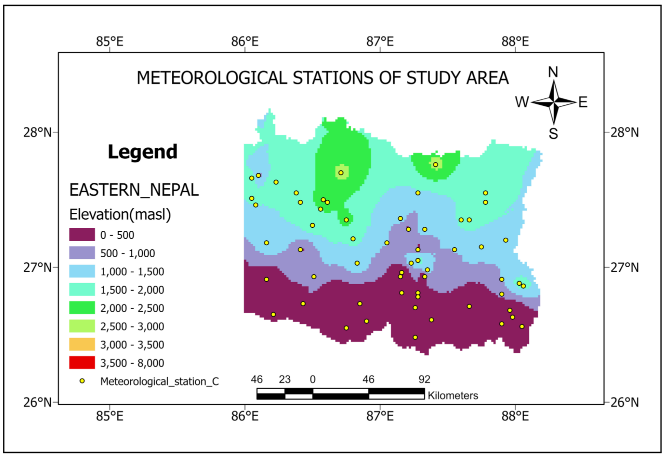

Figure 2: Study Area with Meteorological Stations

Figure 2 shows 59 stations in the Eastern part of Nepal for an area of 42,064 km2 which is quantitatively insufficient for effective management of water resources and poses a hindrance to proper research in that area.

3. Materials and Methods

3.1 Materials

Data preparation is a very important step for any study. The accuracy of its results relies heavily on the quality and completeness of the input data. Different types of data used for this study is shown in Table1

Data Type	Source	Spatial Resolution
CHIRPS	https://data.chc.ucsb.edu/products/CHIRPS-2.0/	$0.05° \times 0.05°$
PERSIANN	http://chrsdata.eng.uci.edu/	$0.025° \times 0.025°$
IMERG	https://gpm.nasa.gov/data/sources	$0.1° \times 0.1°$
TMPA	https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_7/summary	$0.025° \times 0.025°$

Table 1: Satellite Dataset

3.1.1 Observed data

Observed data refers to daily time series data from 2000 to 2015, of the meteorological stations in the study area and was collected from the data issued by The Department of Hydrology and Meteorology (DHM) in Nepal, which is responsible for collecting and providing climatic data for various regions in the country.

3.1.2 CHIRPS data

The CHIRPS dataset is created by combining satellite observations from TIR, atmospheric model rainfall fields from NOAA's Climate Forecast System, the Climate Hazards Precipitation Climatology (CHPClim), the TRMM 3B42 product from NASA, and rainfall observations from national and regional meteorological services. It is a high-resolution (0.05°) rainfall dataset developed by the Climate Hazards Group at the University of California, Santa Barbara and the US Geological Survey (USGS) [12].

3.1.3 IMERG data

It is a gridded precipitation product that is coupled with G.P.M. satellite observations. The GPM Core Observatory satellite, which has dual-frequency rainfall radar as well as a 13th-channel passive microwave imager, is IMERG's reference standard for the intercalibration and merging of precipitation estimates from individual passive microwave PMW satellites within a constellation. IMERG offers a high resolution of 0.1° every half-hour, spanning latitudes up to 60°. Three IMERG runs are offered, depending on the needs of the user. The Early Run, which is accessible at a 6-hour delay for real-time applications like hazard forecasting, is confined to rainfall morphing only forward in time. The late run, which has an 18-hour delay for purposes like crop forecasts, employs both forward and backward time evolution. The final run for research applications is delayed by 4 months. Early and late runs are climatologist adjusted, while the final run employs monthly calibration to reduce bias. Furthermore, because of the lag in data transfer, runs with longer delays will employ more PMW estimations [13].

3.1.4 PERSIANN-CDR data

It is a high-resolution (0.25°) rainfall dataset created by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine, and is available at https://chrsdata.eng.uci.edu/. It is a hybrid of Gridded Satellite Data (GridSat-B1) from the International Satellite Cloud Climatology Project (ISCCP) B1 Infrared Window (IRWIN) Channel and (2) Global Precipitation Climatology Project (GPCP) v2.2. The PERSIANN-CDR uses artificial neural network classification and approximation approaches to estimate daily rainfall based on infrared and daytime visible data from geostationary satellites [14].

3.1.5 TRMM data

It is the gridded precipitation product from the TRMM project. Just as with IMERG, TMPA uses the TRMM satellite to calibrate and combine PMW estimates from different platforms. Estimates derived from geosynchronous IR measurements calibrated against PMW estimates on a monthly basis are used to fill in the gaps in the PMW field. TMPA is available at a resolution of 0.25° every 3 h covering up to ±50° latitudes. Two different products of TMPA are available: the real-time product (with a 9-h delay) and the research product. This study uses the research product, which is available beginning in 1998. The research product utilizes the TRMM Precipitation Radar onboard the satellite for calibration and has the additional monthly gauge adjustment step [15].

3.2 Methodology

The overall methodology adopted in this study included downloading raw data of SPPs form google earth engine and evaluating the raw data compared to observed data based on performance and magnitude-based index. Figure 3 shows the overall methodological framework for our work.

3.2.1 Extraction of Raw SPPs

We have obtained data on various SPPs for 59 different meteorological station from Earth Engine, a platform that allows for the scientific analysis and visualization of geospatial datasets. This platform is available to academic, non-profit, business, and government users.

3.2.2 Evaluation of Raw SPPs

Evaluation of SPPs have been done based on six indices i.e., POD, CSI, FBI, FAR, RMSE and PBIAS. Among these six indices earlier four are performance-based indices and later two are

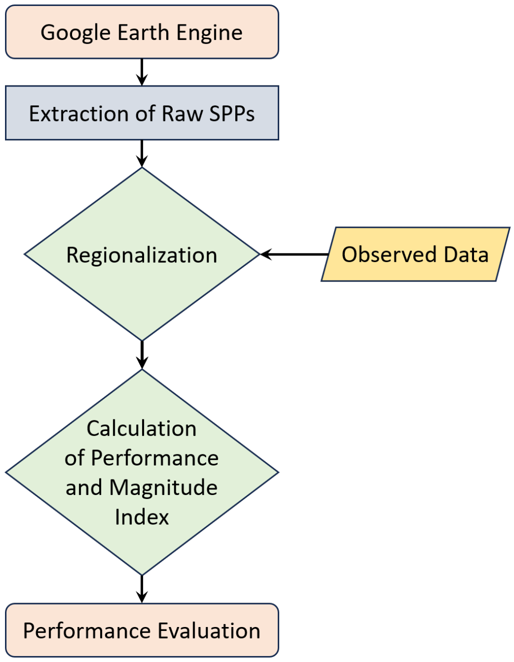

Figure 3: Methodological Framework

magnitude-based indices. POD shows the proportion of how well precipitation events are detected compared to that of total gauged based precipitation events. CSI shows the overall proportion of how well precipitation events are detected compared to that of total number of precipitation event detected either by gauge or satellite. The false alarm ratio for precipitation detection is the number of false precipitation detection per total number of precipitation detection FBI shows a biasness between gauge precipitation and satellite detected precipitation based on frequency. Regarding performance-related metrics, we have evaluated how Satellite Precipitation Products (SPPs) identify precipitation in comparison to various rain gauge measurements. The identification of intense precipitation is deemed:
"T" when both SPPs and rain gauge data indicate a daily rainfall $\geq 1mm$.
Conversely, it is classified as "F" when SPPs indicate rainfall on non-rainy days according to rain gauge data.
Similarly, the identification is labeled as a "M" when SPPs fail to detect rainy days based on rain gauge observations.
Detection is considered "I" when both SPPs and rain gauge data reflect a daily rainfall < 1 mm. Based on the total count of these detections, we calculated the probability of detection (POD), critical success index (CSI), false alarm ratio (FAR), and frequency bias index (FBI) as follows:

$$POD = \frac{T}{T+M} \tag{1}$$

$$CSI = \frac{T}{T+M+F} \tag{2}$$

$$FAR = \frac{F}{T+F} \tag{3}$$

$$FBI = \frac{T+F}{T+M} \tag{4}$$

The desirable values for both probability of detection (POD) and critical success index (CSI) are 1, while the desirable value for false alarm rate (FAR) is 0. Additionally, the preferred value for the false alarm bias index (FBI) is also 1. The value of FBI lesser than 1 signifies underestimation of precipitation detection and higher than 1 signifies overestimation of precipitation detection.

In case of magnitude-based indices, we have computed PBIAS and RMSE of selected SPPs with respect to gauged rain gauge observation. Percent bias (PBIAS): Percent bias (PBIAS): Percent bias (PBIAS) assesses the simulated data's average tendency to be greater or smaller than their observed equivalents [16]. PBIAS has an optimum value of 0, with low-magnitude values indicating accurate model simulation. Positive values indicate underestimation bias in the model, whereas negative values suggest overestimation bias in the model. PBIAS is calculated using the following equation:

$$PBIAS = \frac{\sum_{i=1}^{n} (SPP_i - \text{Gauge}_i) * 100}{\sum_{i=1}^{n} \text{Gauge}_i} \tag{5}$$

Root mean square error (RMSE): RMSE gives information regarding the performance of an SPPs by permitting a comparison of differences between the SPPs value and the gauge value. With a minimal and optimum value of RMSE of zero, a lower value of RMSE implies greater performance of SPPs data. Given its limitations, a few major errors in the total can result in a considerable increase in RMSE. The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (SPP_i - \text{Gauge}_i)^2}{n}} \tag{6}$$

3.2.3 Regionalization of Nepal

Here eastern part is considered as a part of Nepal having longitude greater than 86°. For evaluating the performance of SPPs for eastern part of Nepal, we have classified DHM stations of eastern Nepal on the basis of an elevation. We regionalize based on elevations as: < 500m, 500 – 1000m, 1000-1500 m, 1500 – 2000 m, 2000 – 2500 m, and > 2500 m.

4. Results and discussion

4.1 Evaluation of Raw SPPs

Evaluation on the basis of performance and magnitude-based index was done for each classified region of eastern Nepal. The result of evaluation of raw and bias corrected SPPs for each classified region is discussed below:

4.1.1 For elevation <500m

For this region, PERSIANN-CDR performed well in terms of POD and CSI while CHIRPS but showed well performance in terms of FBI and FAR than other SPPs. Mean value less than 1 of FBI for CHIRPS suggests the underestimation of the rainfall detections. TRMM and IMERG showed lower CSI and POD and higher value of FAR. Both overestimated the rainfall event detection having FBI value higher than 1. The plot of performance-based index for this elevation range is sghown in figure 4.

Similarly figure 5 shows, the plot of magnitude index for this elevation range. RMSE mean value is in similar range for all SPPS. PERSIANN showed higher mean PBIAS. Higher value for mean PBIAS(-ve) of PERSIANN suggests it highly underestimate the rainfall amount than any other SPPs. PBIAS value for other SPPs were near to zero, which shows good estimation of rainfall amounts.

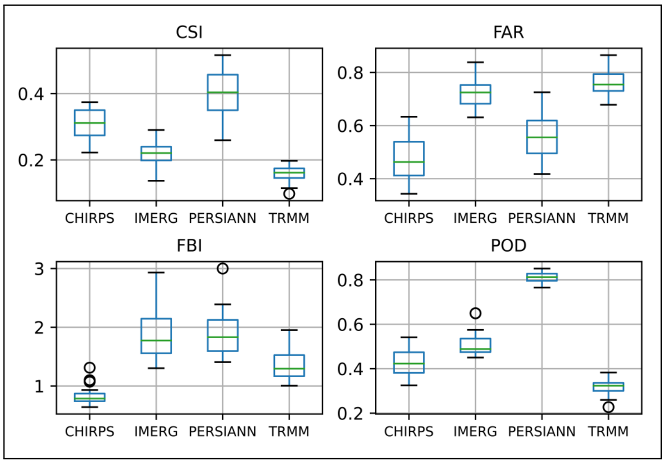

Figure 4: Performance Index for elevation < 500m

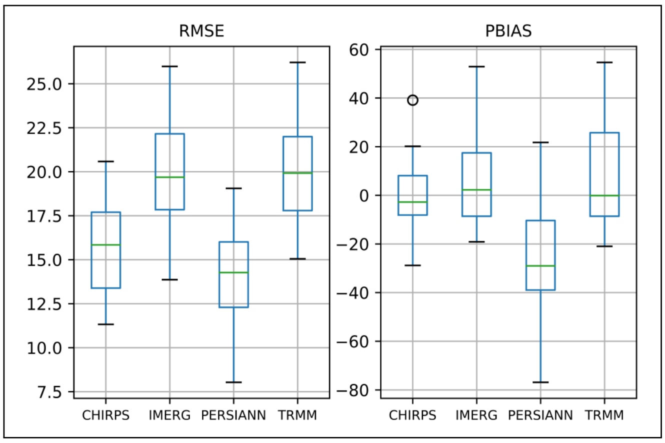

Figure 5: Magnitude Index for elevation < 500m

4.2 For elevation 500-1000m

This elevation region consisted only one station among the considered 59 stations. For this region PERSIANN-CDR showed better performance in terms of CSI and POD. FBI value greater than 1 and grater than of all other SPPs of PERSIANN-CDR suggests overestimation of rainfall events. CHIRPS showed lesser false alarms where as TRMM has highest false alarms. CHIRPS only underestimated the rainfall detection among other SPPs. PERSIANN-CDR showed lesser RMSE and higher PBIAS than any other SPPs. IMERG has slightly lesser RMSE than that of PERSIANN-CDR and shows good estimation of rainfall amount compared to observed data. CHIRPS and TRMM values were comparable in terms of RMSE and PBIAS.

4.3 For elevation 1000-1500m

For this region PERSIANN-CDR showed better performance in terms of CSI and POD. FBI values were greater than 1 for all the product except CHIRPS indicating overestimation of rainfall events. CHIRPS showed lesser false alarms whereas TRMM has highest false alarms. The plot of performance index for this elevation range is shown in figure 6.

Similarly figure 7 shows, the plot of magnitude index for this elevation range. PERSIANN-CDR showed lesser RMSE and higher PBIAS than any other SPPs. CHIRPS having mean value of PBIAS near to zero shows good estimation of rainfall amount than other SPPs. IMERG and TRMM values were comparable in terms of RMSE and PBIAS.

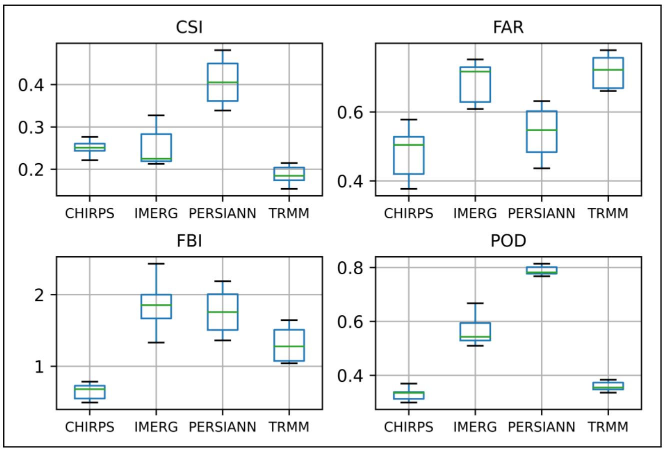

Figure 6: Performance Index for elevation 1000-1500 m

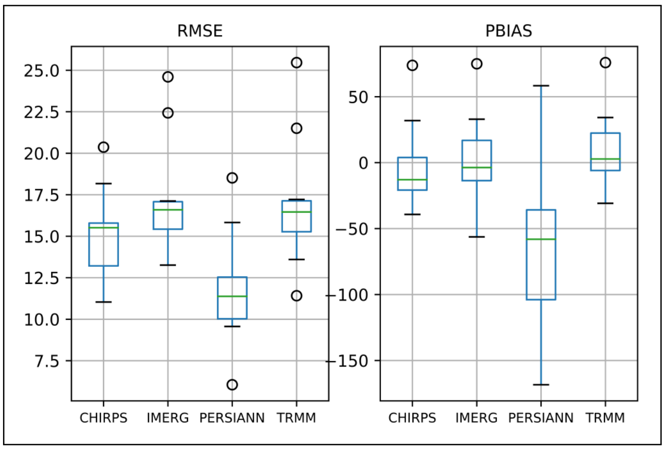

Figure 7: Magnitude Index for elevation 1000-1500m

4.4 For elevation 1500-2000m

For this region PERSIANN-CDR showed better performance in terms of CSI and POD. FBI values were greater than 1 for all the product except CHIRPS indicating overestimation of rainfall events. CHIRPS showed lesser false alarms whereas TRMM has highest false alarms. The plot of performance index for this elevation range is shown in figure 8.

Similarly, Figure 9 shows, the plot of magnitude index for this eleavtion range.PERSIANN-CDR showed lesser RMSE and higher PBIAS than any other SPPs. CHIRPS, IMERG and TRMM had mean value of PBIAS near to zero showing good estimation of rainfall amount.

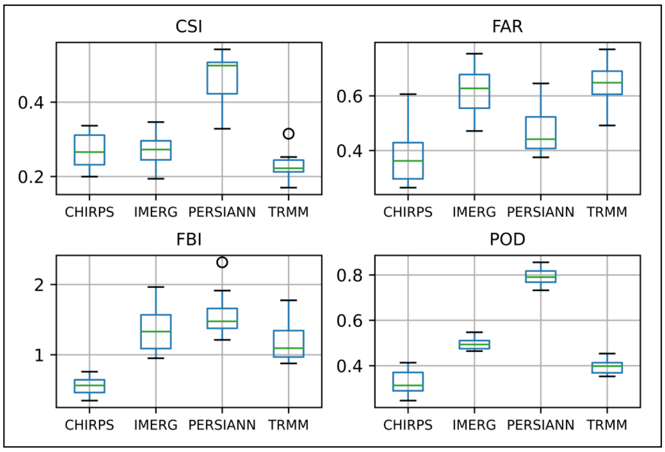

Figure 8: Performance Index for elevation 1000-1500 m

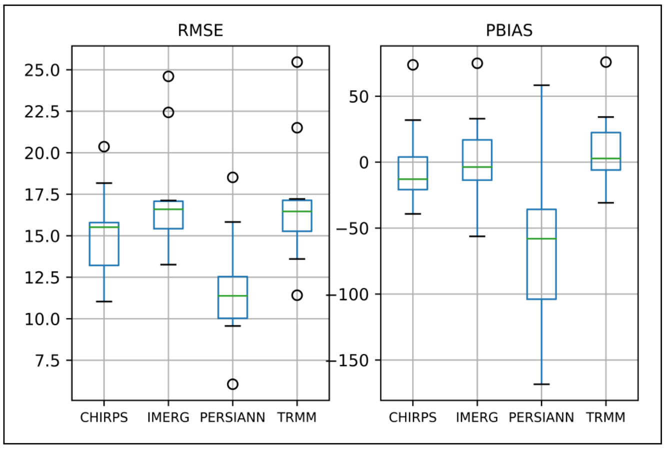

Figure 9: Magnitude Index for elevation 1500-2000 m

4.5 For elevation 2000-2500m

For this region PERSIANN-CDR showed better performance in terms of CSI and POD. FBI values were greater than 1 for all the product except CHIRPS, indicating overestimation of rainfall events. Overall TRMM had a good estimation of rainfall detection than other SPPs. CHIRPS showed lesser FAR value indicating lesser false alarm whereas TRMM showed more false alarms.The plot of perfromance index for this elevation range is shown in Figure10.

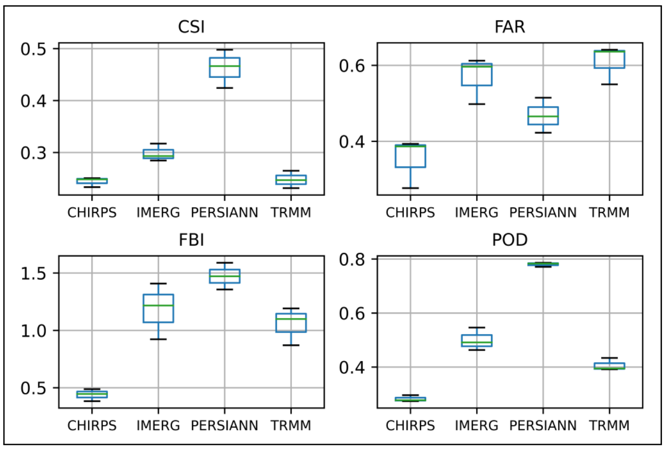

Figure 10: Performance Index for elevation 2000-2500 m

Similarly, Figure 11 show, the plot of magnitude based index of this elevation range. PERSIANN-CDR showed lesser RMSE and higher PBIAS than any other SPPs. CHIRPS, IMERG and TRMM had comparable mean value of PBIAS. All other except PERSIANN-CDR overestimated the rainfall amount, while PERSIANN-CDR highly underestimated precipitation amount.

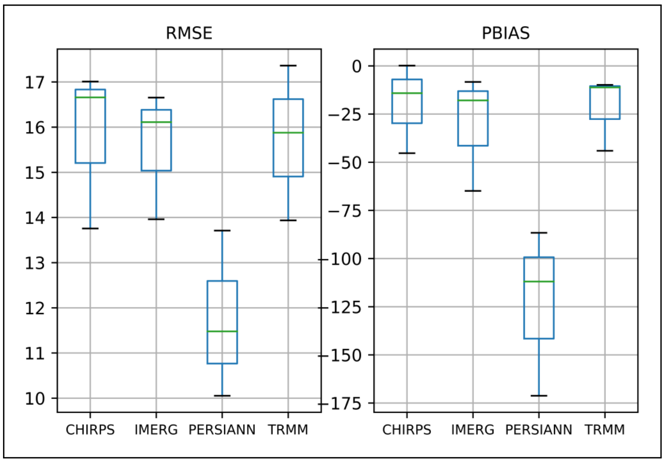

Figure 11: Magnitude Index for elevation 2000-2500 m

4.6 For elevation >2500m

For this region PERSIANN-CDR showed better performance in terms of CSI and POD. Mean FBI values were greater than 1 for all the product except CHIRPS indicating overestimation of rainfall events. Overall TRMM and IMERG had a good estimation of rainfall detection than other SPPs. CHIRPS showed lesser FAR value indicating lesser false alarm whereas TRMM showed more false alarms. The plot of performance Index for this elevation range is shown in Figure 12

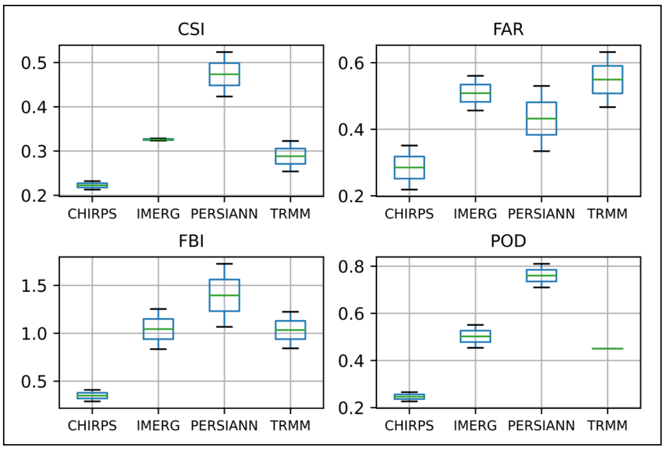

Figure 12: Performance Index for elevation >2500 m

Similarly, Figure13 shows the magnitude index for this elevation range. PERSIANN-CDR showed lesser RMSE and higher PBIAS than any other SPPs. All product underestimated the rainfall amount. TRMM showed good results in terms of PBIAS and RMSE.

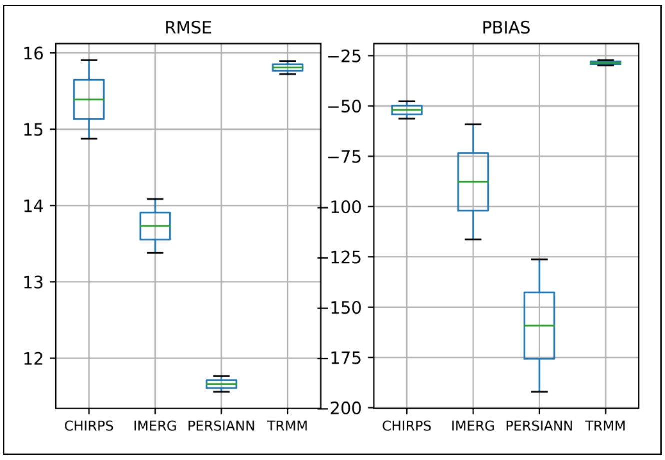

Figure 13: Magnitude Index for elevation > 2500 m

5. Conclusions

The study conducted in Nepal's eastern region assessed several SPPs based on their performance and magnitude-based index. PERSIANN-CDR showed better performance in terms of POD and CSI compared to other SPPs in the eastern region of Nepal. However, it consistently overestimated rainfall detection at all elevations and showed a significantly high negative PBIAS. On the other hand, CHIRPS displayed fewer false alarms than other SPPs for all elevation ranges but always underestimated rainfall detection. TRMM and IMERG exhibited consistently higher false alarms for all elevation ranges. It is worth noting that with an increase in elevation range, all the SPPs underestimated the daily rainfall amount, showing a high negative PBIAS. The underestimation of precipitation events by CHIRPS and a decline in performance of SPPs with rise in altitude was also highlighted by (Prajapati et al., 2022) [17]. The result of this study suggests that SPPs needs proper corrections method before using it for hydrological applications in eastern Nepal. This information is crucial for professionals in the field of water resource management, including designers, planners, and policymakers, as they can utilize these findings to develop sustainable approaches towards water resource management.

Acknowledgments

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