How Accurately Can Satellite Products (TMPA and IMERG) Detect Precipitation Patterns, Extremities, and Drought Across the Nepalese Himalaya?

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Abstract This study aims to assess the accuracy of two satellite-based precipitation products (SBPPs), that is, Tropical Rainfall Measurement Mission (TRMM)-based Multi-satellite Precipitation Analysis (TMPA) and its upgraded version Integrated Multi-Satellite Retrievals for Global Precipitation Measurement (IMERG), in capturing spatial and temporal variation of precipitation and their application for extreme events (high-intensity precipitation and drought). They were evaluated against 142-gauge stations from Nepal during 2001–2018. The results show that, in general, both SBPPs show the overall characteristics of precipitation patterns, although underestimated the mean annual precipitation during the study period. It was also noted that IMERG product yields better performance to detect precipitation events (probability of detection) and no-precipitation events (false alarm ratio) than TMPA. Based on four different extreme precipitation indices: heavy precipitation events (R10mm), extreme precipitation events (R25mm), five consecutive dry days (CDD), and five consecutive wet days (CWD), it was observed that the SBPPs underestimated the frequency of R25mm and CDD spells while overestimated R10mm and CWD spells. Additionally, both SBPPs exhibited considerable capabilities in capturing the drought events during the study period. Overall, the drought event, bias, and frequency show that the IMERG product has slightly better capabilities to capture drought than the TMPA product. In general, IMERG was found to be superior at a daily timescale, while TMPA shows consistent performance on a monthly scale during the study period. Furthermore, there is still space for further improvement of IMERG rainfall retrieval algorithms.

1. Introduction

Precipitation is an indispensable component in the contemporary field of climatic and cryospheric studies. It plays a vital role in determining most of the environmental changes globally, altering the regional and global climate, water cycle, and water balance (McKee et al., 1993; Shrestha et al., 2000). The Himalayas are the large glaciated regions sustaining ecosystems and livelihoods downstream through glacier melt (Immerzeel et al., 2020). Precipitation in the form of snow is the source for glaciers, determining the mass balance, thus the fate of the Himalayan glaciers (Bolch et al., 2012). Moreover, excess or deficit precipitation is responsible for triggering floods, drought, avalanches, landslides, and soil erosion in the fragile Himalayas (Aryal et al., 2020; Chalise et al., 2019; Talchabhadel et al., 2020). Thus, precipitation is one of the essential and mandatory parameters for hydrometeorologists, glaciologists, engineers, and agriculturalists.

Precipitation highly varies in space and time due to large-scale atmospheric and oceanic circulation patterns (Hamal et al., 2020). Besides, the geography and topography of the region make it difficult to predict and estimate (Hu et al., 2016; Li et al., 2020). The sparsely distributed rain gauges do not provide reliable spatial representation and complete areal estimates, especially in the Himalayan country like Nepal (Sharma, Khadka, et al., 2020). Moreover, the rain gauges in Nepal are located in remote areas and valley bottoms, difficult for on-time data collection, continuous monitoring, and maintaining the stations (Barros et al., 2000; Duncan & Biggs, 2012; Kansakar et al., 2004). The station density in high mountain and the upper hill is...
The Tropical Rainfall Measuring Mission (TRMM) and its updated version, that is, Integrated Multi-Satellite Retrievals for Global Precipitation Measurement (IMERG), are the SBPPs jointly developed by National Aeronautics Space Agency (NASA) and Japan Aerospace Exploration Agency (JAXA) (Hou et al., 2014; Huffman et al., 2007, 2015). These products provide precipitation estimates in high spatial and temporal resolution globally (quasiglobal). TRMM and IMERG products are mainly based on passive microwave (PMW), calibrated infrared (IR), and PMW plus IR observations (Huffman et al., 2007, 2015). Additionally, the Global Precipitation Measurement Core Observatory (GPM-CO) was equipped with an advanced Dual-Frequency Precipitation Radar (DRP) and a multichannel GPM microwave imager (GMI), which can detect heavy to light rain and snow (Huffman et al., 2019). However, comprehensive evaluation of these precipitation products is an essential task for the performance improvement of these products and ultimately promotes their use for a variety of hydrometeorological applications (i.e., water resources management, flood forecasting, drought, and agricultural planning). Further, validation of SBPPs over different physiographic and climatic regions helps to identify their tendency and discrepancies, requiring attention and improve their accuracy under different circumstances.

Several previous studies evaluated the performance of SBPPs for different applications around the globe (Chen et al., 2013; Dembélé & Zwart, 2016; Hence & Houze, 2012; Jiang et al., 2012; Lu & Yong, 2018; Shrestha et al., 2012; Sungmin et al., 2017; Wang & Yong, 2020). The earlier studies have found that the IMERG is a good successor of TRMM and is promising for hydrometeorological applications (Chen & Li, 2016; He et al., 2017; Wang, Zhang, & Zhang, 2019). In contrast, some studies show that the TRMM product performed better than the IMERG product. For example, Yuan et al. (2019) evaluated the near-real-time IMERG, TRMM (3B42RT), GSMaP-NRT, GSMaP-MVK, and GSMaP-Gauge and found that IMERG and GSMaP product largely underestimated the total precipitation. Their study revealed 3B42RT to be superior among the evaluated near-real-time SBPPs. Similarly, studies conducted in Bolivian watersheds and Amazon wet region (Satgé et al., 2017) and northeastern Tibetan Plateau (Wang, Zhang, & Zhang, 2019) also found the better performance of TRMM (3B42V7) as compared to IMERG product. On the contrary, Fang et al. (2019) found that the IMERG product performed slightly better than TRMM because of the limited ability to detect extreme rainfall events in TRMM. However, both products were able to capture the spatial pattern of extreme precipitation over China. Compared with TRMM (3B42 V07), IMERG-V3 reduces the systematical bias and is more reasonable to capture the rainfall variability in southwestern China (Yang et al., 2020). Gebregiorgis et al. (2018) reported the improvement in new generation multisatellite precipitation (GPM IMERG) than TRMM-based Multi-satellite Precipitation Analysis (TMPA-RT) due to miss-rain and false-rain bias reduction. For the evaluation of drought in Xiang River Basin in China, IMERG Version 05 product achieved the best performance in SPI-1 (1 month SPI) estimations as compared to TRMM (3B42 V07) (Zhu et al., 2019). In Malaysia, although TRMM (3B43) performed better at capturing temporal drought events at shorter timescales, however, it was recommended to further algorithm improvement and bias correction for improving the accuracy (Tan et al., 2017).

Besides global studies, there are only a few studies that have evaluated the SBPPs over Nepal. For example, the TRMM precipitation product reasonably represented the observed spatial pattern over the mountainous

sparse with rain gauge coverage of ~7% and ~18%, respectively (Talchabhadel & Karki, 2019). The limited stations in high-elevation area with long-term precipitation data series expect a pyramid meteorological station at 5,050 m near Everest base camp, making it challenging for researchers to obtain the Himalayan climatology. Additionally, establishing and maintaining stations at high elevation is an expensive and challenging task. Reliable and precise precipitation records are vital for different studies as mentioned above, as well as for hydrological forecasting, irrigation, and hydropower. The rain gauges conventionally provide in situ measurements, although they have various limitations yet provide a real estimate at a point scale (Sun et al., 2018; Yamamoto et al., 2011). The use of gridded satellite-based precipitation products (SBPPs) overcomes such limitations rendered by the low spatial density of gauge stations (Derin et al., 2019; Ouyang et al., 2020; Wang & Yong, 2020). Various satellite missions provide remotely sensed real-time, nearly real-time, and posttime gridded estimates of precipitation (Sun et al., 2018). However, these SBPPs have uncertainties and discrepancies among them, along with their strength. Therefore, they are needed to be evaluated and validated before further applications; meanwhile, it will also assist in improving product quality and accuracy.
The superior performance of TRMM, CMORPH, and PERSIANN than GSMaP was found in representing the seasonal and diurnal variation of hourly gauge observed precipitation in the Khumbu region of Nepal (Yamamoto et al., 2011). Meanwhile, a study conducted by Duncan and Biggs (2012) found that TRMM product generally overestimated the precipitation values as compared to a gauge-based gridded product over Nepal. In contrast, TRMM precipitation product underestimated the gauge observation over the Himalayan region of the country. Tamrakar and Alfredsen (2013) evaluated TRMM (3B42) for hydrological application and found that TRMM product can be used for runoff simulations over Nepal. A study over multiple complex terrain regions found that GSMaP V07 was able to detect the orographic rainfall and the rainfall amounts and outperforms IMERG V06B in Nepal with evaluation against limited stations (Derin et al., 2019), whereas evaluation based on large-scale station network revealed that GSMaP-Gauge product was more consistent with reproducing spatial pattern while IMERG product was more reasonable to reproduce precipitation amount over the country (Sharma, Chen, et al., 2020). Similarly, Sunilkumar et al. (2019) found that IMERG product was reliable to estimate rainfall amounts as that in APHRODITE over Asian countries, including Nepal. However, most of the abovementioned global as well as regional studies suggested for continuous evaluation of SBPP for complex topography—still needed to further advance the product algorithms (Chen & Li, 2016; Lu & Yong, 2018; Saber & Yilmaz, 2018; Wang & Yong, 2020; Wang, Zhang, & Zhang, 2019). Moreover, many studies had considered limited stations and limited time periods for performance evaluation in Nepal. Additionally, so far, none of the studies have evaluated the improvement of IMERG against TRMM. Thus, in this study, we aim to evaluate TMPA (3B42 V07) and GPM-Era IMERG precipitation products over the entire Himalayan country, Nepal, for a long period of almost two recent decades. Their accuracy of detecting annual, seasonal, monthly, and daily precipitation was compared against 142 gauge stations during 2001–2018. Also, these products were used to appraise the spatial and temporal patterns of extreme precipitation events and drought episodes. Most importantly, verifications of SBPPs with available gauge stations data are most before any practical application. The result of this study will be useful for critical scientific references in selecting the appropriate SBPPs for future hydrometeorological research including extreme climate change and drought hazard assessment.
2. Materials and Methods

2.1. Study Areas

Nepal is a Himalayan country, extending about 885 km east-west and 140–250 km north-south with a total area of 147,516 km² (Figure 1). Within a relatively small width of the country, the elevation abruptly rises from lowlands in the south (60 m above sea level [asl]) to high mountains in the north (with an elevation of 8,848 m asl at Mt. Everest or the Sagarmatha in Nepal, the highest peak of the world), giving rise to five major distinct physiographical regions: Terai plains, Siwalik hills, middle hills, upper hills, and high mountains (Figure 1). Due to rapid change in the elevation from south to north, the country possesses several microclimates, varying from tropical to subtropical in the lowlands to polar and tundra in the high mountains (Karki et al., 2016). The impact of South Asian monsoon and westerly system brings different precipitation patterns, determining the four climatic seasons: premonsoon (March–May), monsoon (June–September), postmonsoon (October–November), and winter (December–February) (Kansakar et al., 2004; Nayava, 1980). Monsoon season is extensively wet, with about 80% of the total annual precipitation (Shrestha et al., 2000). Nepal receives winter precipitation in the form of snow in the high-elevation areas during the winter season. The country practices a traditional farming system, heavily relying on monsoon. The annual cycle of precipitation shows that July receives the highest precipitation followed by August, and combination of precipitation from these 2 months equals to half of the total annual precipitation (Talchabhadel et al., 2018).

2.2. Data Sets

2.2.1. Gauge Observation

The meteorological station network of Nepal is maintained by the Department of Hydrology and Meteorology (DHM), Government of Nepal. This network of gauge stations is irregularly distributed, meaning denser on the southern lowlands (below 2,500 m elevation) and sparse over the complex terrain of the northern mountainous region (above 2,500 m elevation) (Figure 1). Such an irregular distribution of network creates an information gap, which ultimately hinders precipitation-related studies over the study region. Most of these data sets of gauge networks are manually collected and may subject to personnel and instrumental errors (Talchabhadel et al., 2017). Initially, data from 141 stations were collected from DHM, and an additional automatic weather station (AWS) pyramid station located near Everest base camp was also included in our study. Altogether a network of 142 rain gauge stations was selected to evaluate the SBPP from 2001 to 2018 (Figure 1). All the selected stations were further subjected to quality control (section 2.3). It is worth to mention that the Global Precipitation Climatology Centre (GPCC) product includes some of the DHM gauges (Becker et al., 2011), which was used to adjust satellite-only TRMM and IMERG precipitation totals. Therefore, a potential dependency problem may exist between selected DHM observation and gauge-corrected TRMM and IMERG product. Mean annual precipitation (mm/year) of 142 individual observed stations between 2001 and 2018 is illustrated in Figure 3a.

2.2.2. Satellite-Based Precipitation

TMPA is an SBPP developed by NASA in collaboration with JAXA and provides the precipitation estimation with a spatial resolution of 0.25° globally (50°N–50°S) (Huffman et al., 2010). The TMPA product is produced in different stages: First, TMPA combines several PMW data from multiple satellite (i.e., Advance Microwave Scanning Radiometer-EOS, Special Sensor Microwave/Imager, Microwave Humidity Sounder, TRMM Microwave Imager, and Advanced Microwave Sounding Unit-B) to estimate precipitation rates using the Goddard Profiling Algorithm (GPROF) (Huffman et al., 2007; Kummerow et al., 2015). Second, IR precipitation estimates are created using the merged PMW data. Finally, the GPCC-based gauge measurement is combined with PMW and IR (Huffman et al., 2010; Tan & Duan, 2017). Two different products are available based on different latency: near-real-time (TMPA-3B42RT) and post-real-time (TMPA-3B42V7), covering the period from 1998 to 2019. The 3B42RT product is developed based on PMW and IR estimation, while the post-real-time 3B42V7 is corrected by GPCC and the Climate Assessment and Monitoring System (CAMS) developed by the CPC. This study only focuses on the post-real-time 3B42V7 product. The daily data sets of TMPA-3B42V7 (hereafter TMPA) products from 2001 to 2018 were downloaded from the NASA’s website (https://gpm.nasa.gov/data-access/downloads/trmm).
IMERG is NASA Level 3 GPM-Era quasiglobal precipitation product, with a high spatial resolution (0.1°) (Huffman et al., 2015). IMERG product is based on both active and PMW sensors. Raw data are processed by the GPROF2017 algorithm (Randel et al., 2020). There are three different GPM products based on different algorithms and latency. Early Run (with a latency of 4 hr) only performs forward propagation of the microwave data, Late Run (with a latency of 12 hr) has both forward and backward propagations of the microwave data, while Final Run (with latency 2.5 months) uses the GPCC gauge-based precipitation data to calibrate the Late Run. Early Run and Late Run are near-real-time multisatellite precipitation products, while Final Run is gauge-adjusted multisatellite precipitation product and mostly recommended for research purpose. The half-hourly intercalibrated merged PMW (Final Run) estimates are adjusted by Morphing-Kalman filter (CMORPH-KF) Lagrangian time interpolation scheme and the PERSIANN-CCS recalibration scheme (Huffman et al., 2015, 2019). Therefore, daily data sets from a newer version of Final Run IMERG V6B (hereafter IMERG) between 2001 and 2018 were selected for this study. These daily accumulated precipitations were derived from the half-hourly GPM_3IMERGHH. The IMERG data were downloaded from the Precipitation Measurement Missions (PMW) website (https://pmm.nasa.gov/data-access/downloads/gpm).

2.3. Methodology

Rain gauge observation data were used as reference data sets to evaluate the accuracy of TMPA and IMERG precipitation products and their performances on detecting extreme precipitation events (high-intensity and drought). The complex topographic gradients and heterogeneous distribution of rain gauge station within the study region restrain the accurate rainfall interpolation (Monsieurs et al., 2018). Thus, the point-to-pixel method was adopted to compare rain gauge observation with grid-based satellite precipitation products (Bai & Liu, 2018; Liechti et al., 2012; Thiemig et al., 2012; Wang et al., 2017). Grid-based precipitation products were extracted to station location using the original resolution of TMPA and IMERG. The interpolation of observation was not performed to avoid additional errors by gridding the rain gauge observation (Feidas, 2010; Li et al., 2013; Wang, Ding, et al., 2019). Meanwhile, stations falling under the same grid were averaged for better representation of the pixel precipitation with station-based data sets. These satellite-based precipitation rates were first aggregated to the same period to match the measurement time windows (03UTC) as DHM gauge observation (Talchabhadel et al., 2017). The stations with the highest data records were considered for the study to maintain the quality control and data consistency through discarding the missing values of DHM data sets and simultaneously their corresponding values of TMPA and IMERG data. The stations featuring more than 84% of daily precipitation in a month (i.e., 25 days) were used to compute the monthly data; otherwise, a missing value was assigned to the precipitation in that month. Meanwhile, the same months were assigned a missing value for the satellite-based data for maintaining the consistency. The data availability of selected stations during the study period is presented in supporting information Table S1.

First, mean annual and seasonal precipitation (premonsoon, summer monsoon, postmonsoon, and winter season) of the observed and SBPPs were calculated for each station. Second, spatial consistency was performed by comparing the spatial distribution of mean annual and seasonal precipitation, while for temporal consistency, the annual cycle and monthly time series of precipitation in all data sets are analyzed. Furthermore, using different indices (sections 2.3.2 and 2.3.3), these data were used to assess the spatial and temporal accuracy of extreme precipitation events (high-intensity and drought).

2.3.1. Statistical Metrics

Four different statistical metrics: correlation coefficient (CC), root-mean-square error (RMSE), mean error (ME), bias, and the Nash-Sutcliffe model efficiency coefficient (NSE), were applied for evaluation of SBPPs against the gauge observation. CC measures the degree of the linear relationship between SBPP and the observation (Equation 1). The RMSE depicts the mean and standard deviation of prediction from TMPA and IMERG products concerning observation (Equation 2). Here, ME estimates the positive and negative errors of the SBPP (Equation 3). The bias provides the average tendency of the SBPP to be larger or smaller than their corresponding observed data sets (Equation 4). Here, NSE is a normalized statistic, used to define the relative magnitude of the residual variance as compared to the variance of measured data, where the good and poor estimation ability is indicated by positive and negative values, respectively (Equation 5).
where $O$ is the observed data, $E$ is the estimated precipitation by TMPA and IMERG products, and $n$ is the sample size.

Additionally, a daily performance assessment was calculated for both TMPA and IMERG products based on categorical statistics to detect precipitation and no-precipitation events at each station. For the assessment, three categorical indices are considered in the study: the probability of detection (POD, Equation 6), which represents the SBP's ability to detect precipitation events correctly and ranges from 0 to 1 (with 1 is a perfect score); false alarm ratio (FAR, Equation 7), which provides the SBPP's capabilities to detect no-precipitation events (when there are no-precipitation events in gauge observed measurement) and ranges from 0 to 1 (with 0 is a perfect score); and accuracy (ACC, Equation 8), which is the fraction of all SBPP-based events that were correct. ACC ranges from 0 to 1, with 1 as a perfect score. All these daily categorical statistics are mainly based on two possible cases: a day with or without precipitation.

$$\text{POD} = \frac{A}{A + C}$$  \hspace{1cm} (6)

$$\text{FAR} = \frac{B}{A + B}$$  \hspace{1cm} (7)

$$\text{ACC} = \frac{A + D}{A + B + C + D}$$  \hspace{1cm} (8)

where $A$ and $D$ denote count of days when rainfall above 1 mm/day was recorded by both data sets (gauge observed and SBPPs). Meanwhile, $B$ and $C$ denote count of days when rainfall below 1 mm/day was recorded by gauges and SBPPs, respectively.

### 2.3.2. Extreme Precipitation Events

Precipitation intensity-related extreme events were calculated at each station using daily data sets, by selecting two indicators: R10mm and R25mm days. R10mm and R25mm days represent the total days of heavy ($\geq 10$ and $<25$ mm) and extreme precipitation ($\geq 25$ mm) events in the year, respectively. As these indices identify the intensive precipitation events, they often trigger flash floods and landslides. Consecutive dry days (CDD) and consecutive wet days (CWD) denote the five consecutive dry and wet days with $<1$ and $\geq 1$ mm rainfall, respectively. These duration indices indicate the wet and dry days, highlighting its importance in the field of agriculture (Casanueva et al., 2013). Both indices were illustrated for each selected station. These indices were adopted from the Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI), jointly developed by the World Meteorological Organization (WMO) and Commission for Climatology and the Research Programme on Climate Variability and Predictability. We introduce a slight modification to the selected indices.

### 2.3.3. Standardized Precipitation Index

Standardized Precipitation Index (SPI) uses precipitation as only one climatic variable to detect and monitor the drought (McKee et al., 1993). The easier calculation procedures and simple interpretation favor the application of this index to study the drought at different timescales (Guttman, 1998). This index has been widely...
accepted for the meteorological, agricultural, and hydrological study (Cancelliere et al., 2007; Seiler et al., 2002; Zhang et al., 2017). In this study, SPI-1 was taken for the study of the meteorological drought, which uses corresponding 1 month precipitation under calculation. The value of drought (dryness) and flood (wetness) conditions ranges from −1 to +1. The different categories of drought are given in Table 1.

The drought event is defined as a period in which SPI value is equal to or less than the threshold level of drought, that is, −1 (Tan et al., 2015). Once the event is determined, drought characteristics like duration, severity, and intensity are calculated. Drought frequency was used to assess the drought liability during a period of study. It is calculated through a cumulative frequency that shows the probability of the observations that fall below or above the particular threshold level (Equation 9).

\[
F(t) = \frac{1}{N} \sum_{i=1}^{N} 1(X_i < t)
\]

where \(N\) is the number of months in observations, \(X_i\) is the number of values less than the value \(t\), and \(t\) is the threshold value.

### 3. Results

#### 3.1. Annual Precipitation Cycle

The monthly precipitation cycle, as reflected by observed, TMPA, and IMERG products averaged over the study period, is shown in Figure 2. The precipitation in winter is primarily generated by the westerly wind system and is more prominent in the western region of the country (Hamal et al., 2020). In contrast, moisture transfer from the Bay of Bengal produces the widespread precipitation during the summer monsoon season over the country. The summer is the wettest season contributing 80% to the annual precipitation across the country, followed by premonsoon (13%), postmonsoon (4%), and winter (3%). The monthly precipitation cycle between 2001 and 2018 revealed that the precipitation sharply increased from April, with highest in July (~480 mm) due to control of the summer monsoon, while the lowest was observed in December (~10 mm). TMPA and IMERG precipitation products showed a very similar pattern to the observation.

![Figure 2. Monthly precipitation cycle in observed, TMPA, and IMERG products averaged over the study area during 2001–2018. Different colors represent the different seasons, and pie chart represents the amount of precipitation (%) for a different season.](image-url)

| SPI value | Drought category |
|-----------|------------------|
| −1.5 < SPI ≤ −1 | Moderate |
| −2 < SPI ≤ −1.5 | Severe |
| SPI ≤ −2 | Extreme |
although both data sets tend to underestimate the observed precipitation amount, especially during the monsoon season (Figure 2). Therefore, it can be concluded that the monthly variation of precipitation amount is well reflected by both of the SBPPs over the study region.

In addition, the seasonal statistical metrics are calculated and presented in Table 2. The TMPA product showed more consistent performance in terms of precipitation amount than IMERG product with smaller ME of $-2.53$, $-23.75$, and $-2.16$ mm/month during premonsoon, monsoon, and postmonsoon, respectively (Table 2). In contrast, IMERG appeared to perform better in the winter season with a smaller ME of $-0.9$ mm/month. In this season, minimum precipitation occurs, which is mostly in the form of snow especially in high-elevation areas of the county. In terms of RMSE, CC, and NSE, IMERG product performed better than TMPA, with a smaller degree of dispersion, smaller deviation, and strong ability to accurately capture actual precipitation patterns, although the difference is nominal. Both products evidently underestimated the precipitation amount in all season as indicated by negative bias values (Table 2). As similar to Figure 1, the seasonal performance also revealed that both products showed better performance (smaller ME and RMSE) in winter followed by postmonsoon, premonsoon, and monsoon seasons, respectively (Table 2). This indicates that when the precipitation is higher, the error is large and vice versa for the SBPPs.

### 3.2. Spatial Distribution of Annual Precipitation

The spatial distribution of mean annual precipitation (mm/year) in observation, TMPA, and IMERG during the study period is presented in Figure 3. The highest precipitation is in the midelevation areas of the central region with large spatial variations across the country. The maximum annual precipitation amount (>3,000 mm/year) was observed in the midelevation areas of the central region (Lumle), whereas the minimum amount (<500 mm/year) in the high-elevation areas of central and western Nepal (Figure 3a). The high and low precipitation areas are located within the same central region. This is because of the high mountains that remarkably block the atmospheric moisture from moving upward (northward) and considerably decreasing the precipitation in the leeward side, that is, trans-Himalayan areas (Manang and Mustang). TMPA and IMERG products moderately demonstrated a spatial pattern to that of the observation, with a noticeable decreasing pattern from the south to the north. Both SBPPs showed the maximum precipitation (~3,000 mm/year) in lower reaches of the eastern region, followed by low-elevation areas of the central region (~2,200 mm/year). The highest rainfall in SBPPs might be related with the monsoon trough and...
Figure 4. Spatial pattern of bias distribution for (a, b) premonsoon, (c, d) monsoon, (e, f) postmonsoon, and (g, h) winter season for TMPA and IMERG products during 2001–2018.
lows/depressions over the lower ranches in the eastern region of the country. Notably, both products are drier (<500 mm/year) in the high-elevation areas of central and western regions (Figures 3b and 3c). The SBPPs were also able to qualitatively capture the larger-scale patterns of the annual precipitation, that is, lower precipitation in the leeward side of north-central and northwestern regions and higher orographic precipitation in the windward side of the south-central region. The higher spatial resolution in IMERG (0.1°) product than TMPA (0.25°) might be the reason for the detailed spatial characteristics of precipitation in the IMERG product. Moreover, TMPA product generally estimates higher precipitation than IMERG product, although both products underestimated the observed mean annual precipitation across the country.

The spatial distribution of bias (mm/month) at each station for the different seasons in TMPA and IMERG products during the study period is illustrated in Figure 4. During the premonsoon and postmonsoon, both products underestimated the precipitation by <200 mm/month in midelevation areas (areas of high precipitation) of the central region (Figures 4a, 4b, 4e, and 4f). The spatial distribution of seasonal precipitation is generally concentrated in the summer monsoon accounting for about 80%; in this season, both products were less reliable (bias < −200 and >50 mm/month) to estimate the precipitation amount at most of the stations (Figures 4c and 4d). In contrast, both SBPPs showed very smaller bias distribution in the winter season (as seen small red and black points in Figures 4g and 4h). Notably, under the combined action of orographic uplift and low pressure, midelevation areas of the central region become very wet areas (Figures 4a–4f), making it difficult for SBPPs to retrieve precipitation amount. As similar to Table 2, Figure 4 also confirmed that the performance of SBPP also depends on the distribution of precipitation amount. Thus, spatial variations of the seasonal precipitation can significantly affect the performance of SBPPs in the study area. This may be primarily as a result of the higher amount and frequency of rain during the summer than the other three seasons. Besides, this result also could be associated with the evaporation loss before reaching the ground surface during the dry season.

Figure 5. Interannual variations of (a) mean daily precipitation averaged over Nepal from gauge observation, TMPA, and IMERG products, (b) bias in TMPA and IMERG products with respect to gauge observation, and (c) precipitation anomaly averaged over Nepal from 2001 to 2018.
3.3. Performance-Based on Daily Data Sets

The interannual variations of daily mean precipitation and bias in TMPA and IMERG as compared to gauge observation over the study region during the study period are shown in Figure 5. The interannual variation in IMERG product is almost similar to observed precipitation with a smaller magnitude of bias, whereas TMPA slightly overestimated before 2016 with a higher magnitude of bias than IMERG product. Both products showed a smaller bias in 2009, 2010, and 2012, while the larger magnitude of bias after 2016 (Figures 5a and 5b). TMPA and IMERG products use GPCC gauge-based data sets to calibrate on monthly value; meanwhile, better performance on daily timescale clearly showed that the IMERG algorithm was more capable than TMPA to estimate the daily precipitation amount. The interannual anomaly is calculated using their respective mean value during the study period (Figure 5c). The variability of precipitation anomaly also shows similar characteristics as interannual precipitation amounts.

The spatial distribution of POD, FAR, and ACC for both TMPA and IMERG products is shown in Figure 6. IMERG product showed a higher ability to detect the true precipitation events (detected the precipitation events in the same day as observation) in the range of >50%, which was <60% in TMPA product at most of the stations (Figure 6a). Notably, IMERG product achieved a lower FAR score in the range of <60%, while TMPA showed a higher FAR score of >60% at most of the stations, indicating that TMPA product shows higher false precipitation events (when gauges do not record precipitation events) as compared to IMERG product (Figure 6b). Slightly higher precipitation amount in TMPA product (in sections 3.1 and 3.2) might be related to a higher FAR score than the IMERG product. Moreover, both products are able to detect precipitation and no-precipitation events (ranges above 70%) over the study region (Figure 6c).

3.4. Extreme Precipitation Events

The higher precipitation amounts are related to natural disasters, as it triggers floods and landslides. The spatial distribution of extreme precipitation events in observed, TMPA, and IMERG products during the study period is presented in Figure 7. The higher number (>500) of heavy precipitation events (R10mm) is observed in mid-elevation areas of the central and eastern region. The stations located in southern lowland areas show <400 R10mm events, while a relatively small number (<200) of events are observed in...
high-elevation areas (Figure 7a). The spatial distribution of extreme precipitation events (R25mm) is very similar to heavy precipitation events and being more intense in mid-elevation areas of the central region than low- and high-elevation areas (Figures 7a and 7b). Both TMPA and IMERG products overestimated the number of heavy precipitation events, especially in lowland areas. In contrast, both products underestimated the extreme precipitation events in mid-elevation areas. However, both products show a consistent performance at a higher elevation with a smaller number (<100) of total R25mm events. Overall, the IMERG product is more reliable to estimate the total frequency of R10mm events, while TMPA precipitation product is more consistent with reproducing R25mm events with observation as
indicated by smaller bias and RMSE. It is worth to note that, in the eastern reaches, a higher number of both events (R10mm and R25mm) are captured by both SBPPs, which is quite similar to the distribution of annual precipitation (section 3.2).

The total frequency of five CDD and CWD at each station for 18 year period (2001–2018) is presented in Figure 8. As consistent with precipitation distribution (section 3.2), high-elevation areas experience relatively higher CDD spell compared to low-elevation and midelevation areas (Figure 8a, upper panel).

![Spatial distribution of (a) five consecutive dry days (CDD) and (b) five consecutive wet days (CWD) in TMPA and IMERG at each station during 2001–2018 over the country.](image)

Figure 8. Spatial distribution of (a) five consecutive dry days (CDD) and (b) five consecutive wet days (CWD) in TMPA and IMERG at each station during 2001–2018 over the country.

indicated by smaller bias and RMSE. It is worth to note that, in the eastern reaches, a higher number of both events (R10mm and R25mm) are captured by both SBPPs, which is quite similar to the distribution of annual precipitation (section 3.2).
Meanwhile, higher CWD spells are observed at midelevation areas of the central and eastern regions as compared to low- and high-elevation areas (Figure 8b, upper panel). Both TMPA and IMERG products showed a very similar distribution and underestimated the total frequency of CDD spells and overestimated the CWD spells as indicated by negative and positive bias, respectively (Figures 8a and 8b).

We further compared the TMPA and IMERG’s abilities in reproducing an interannual variability of extreme events over the study region (Figure 9). The temporal distribution showed the years 2003, 2007, 2013, and 2018 with a higher number of extreme events, while the years 2005, 2009, 2012, and 2015 with a lower number of extreme events (Figures 9a and 9b). It is worth noting that the five CDD (CWD) are much higher (lower) in the years, whereas extreme events (R10mm and R25mm) are lower (Figures 9b and 9c). Both TMPA and IMERG products showed a similar variation with observation; however, they overestimated the total frequency of five CWD and R10mm and underestimated the CWD and R10mm and five CDD and R25mm during the study period (Figure 9). TMPA product generally showed a higher frequency of R25mm and five CWD spells than IMERG product; in contrast, IMERG product showed a higher frequency of R10mm and five CDD spells than TMPA product.

### 3.5. Drought Scenarios

The temporal variation of SPI-1 over Nepal is calculated using observed, TMPA, and IMERG data sets during the study period (Figure 10). Based on the definition of SPI for different timescales, the 1 month precipitation series is used to calculate SPI-1, which represents the meteorological drought. The observed fluctuating frequency of alternating positive and negative values of SPI indicates the corresponding wet and dry conditions in the study region (Figure 10a). IMERG product showed a similar temporal variation (Figure 10a) and also able to capture drought events as that of observed data in the years December 2001, November 2005, July–August 2006, February 2008, September 2009 and 2013, and December 2015 (Figure 10d). However, the drought bias (<−0.5) was observed in the years March 2004, November 2011, November–December 2016, and July–August 2017 (Figure S1). Compared with IMERG, TMPA is less reliable for drought monitoring over Nepal, because of the disparities in drought captured in the years July 2008, August 2012, July 2014, January 2016, and November 2017 (Figure 10c). Furthermore, the drought bias is relatively higher in TMPA during 2012–2018 (Figure S1). In general, TMPA overestimated the drought events and their...
severity over Nepal. Besides, the drought occurrence in the different months is identified (Figures 10b–10d), which is not uniform during the study period. Drought events mainly appeared during January–August before 2010, however, after 2010, obvious tendency of drying and increased drought severity during June–December (Figure 10b). Among SBPPs, this pattern is well reproduced by IMERG (Figure 10d), while TMPA showed larger disparities along with the time (Figures 10a and S1).

In the overall study period, the cumulative occurrence of SPI-1 drought in observed, TMPA, and IMERG was 17.6%, 16.2%, and 17.1%, respectively (Figure 11a). Moreover, the occurrence frequency ration in IMERG and TMPA was 0.97 and 0.92, respectively, indicating that IMERG was more capable of representing the drought frequency. The total number of drought events (SPI ≤ −1) at a 1 month timescale during the study period reported by observed, TMPA, and IMERG was 32, 28, and 30, respectively (Figure 11b). This implies

Figure 10. (a) Temporal time series of SPI-1 calculated from observed, TMPA, and IMERG data sets. The dotted black line represents the threshold (SPI ≤ −1) of drought. The monthly contour of SPI-1 obtained from (b) observed, (c) TMPA, and (d) IMERG over Nepal during 2001–2018. The positive and negative values in the color bar represent the wetness and dryness, respectively.
that IMERG has a better capability for monitoring drought frequency and drought events over Nepal than that of TMPA.

The scatterplot of the SPI-1 value of observed versus TMPA and IMERG products during the study period is presented in Figure 12. The CC, RMSE, and NSE were applied to evaluate the performance of the TMPA and IMERG precipitation products on drought monitoring with gauge observation (Figure 12). Similar to the results of the cumulative frequency of drought estimates, IMERG showed the best performance in SPI-1 estimations, with the highest CC (0.95), lowest RMSE (0.32), and NSE (0.90) and outperformed TMPA (Figure 12).

4. Discussion

In recent decades, SBPPs emerge as reliable alternatives for gauge observations. The accuracy of these products depends on various sources such as rainfall retrieval algorithms, sensors used in these satellites, quality, and spatial distribution of assimilated gauge observation. The complex topography, combined with heterogeneous precipitation distribution, makes it challenging to estimate precipitation for SBPPs. Thus, the wide range of uncertainties is associated with SBPPs and gauge observations and may have influenced the above results.

The new generation GPM IMERG product features advanced precipitation retrieval algorithms and more onboard satellite sensors (i.e., DPR radar) than its predecessor TMPA product. However, both products

![Figure 12. Comparison of SPI-1 calculated from the (a) TMPA and (b) IMERG with observed data sets between 2001 and 2018.](image-url)
showed a similar spatial distribution and moderately captured the general characteristics of observed spatial pattern, where rainfall occurrence is strongly associated with the southeastern monsoon activities and large topographic relief. As mentioned in earlier studies, the complex topographic nature of the study region significantly influences the performance of the SBPP (Cattani et al., 2016; Dinku et al., 2007; Wang, Liu, et al., 2019). Meanwhile, large-scale local climatic variation might be another factor to characterize the uncertainty in SBPPs (Gebregiorgis & Hossain, 2013). Notably, even with the higher spatial resolution, IMERG product performed as similar to TMPA.

It is a fact that rain gauge stations are very limited over the mountainous region of the country and mostly located at the valley bottom (Barros et al., 2000; Sharma, Chen, et al., 2020), which may not represent the actual precipitation distribution over the Himalayas. The overestimation of observed precipitation by these SBPPs is evident in earlier studies (Duncan & Biggs, 2012), and this overestimation might be related to the insufficient spatial coverage of the gauge station. The monsoon precipitation might have a significant influence on the performance of SBPPs over the country. Both TMPA and IMERG products are less reliable (large ME and bias) during the monsoon season than that of other seasons (Figure 2 and Table 2). The seasonal comparison also indicates that TMPA tends to estimate precipitation more reliably (lower bias) during premonsoon, monsoon, and postmonsoon, while IMERG seems more consistent with precipitation amount during the winter season. Equipped DPR in GPM IMERG improved the capability in detecting light rain especially in the winter season (precipitation generally occurs in the form of snow), while TRMM product has difficulty in detecting light rainfall and snow (Retalis et al., 2018). Generally, IMERG product shows better overall performance with lower RMSE and higher CC (Table 1 and Figure 4) values for all seasons than TMPA product, indicating a higher ability to capture the seasonal rainfall variability over the study region. Since the terrain varies significantly over the midelevation and high-elevation areas, the complex topographic nature and distribution of seasonal rainfall amount could be associated with the spatial distributions of seasonal bias values in IMERG and TMPA products. Moreover, as mentioned in previous study, IMERG product slightly outperforms TMPA, which might be attributed to the satellite overpasses and sensor capability (Chen & Li, 2016; Gebregiorgis et al., 2018; Yang et al., 2020).

The frequent overestimation of rainfall occurrence produced by the weighted average-based disaggregation/aggregation procedures, TMPA product, tends to estimate more false precipitation events as compared to IMERG product. As mentioned in the earlier study, SBPP algorithms simulate that heavy rainfall is linked with high echo-top height (Shige & Kummerow, 2016), which can lead to prominent underestimation especially in the areas with heavy orographic precipitation (midelevation areas of central region). The different heating patterns of air between the southern lowlands and adjacent northern mountainous areas (central Nepal) in conjunction with high wind speed at mountainous area jointly drive and control the orographic convection and may have influenced the performance of SBPPs (Kubota et al., 2009). IMERG product is found superior in terms of detecting true precipitation. In addition, the IMERG product showed comparatively reduced false events. Overall, increased detection and reduced false alarm hint superior applicability of IMERG to TMPA. Meanwhile, higher false events in TMPA product significantly influence the estimated rainfall amount (as seen slightly higher precipitation than IMERG product in Figure 2). This result also confirms the finding of Gebregiorgis et al. (2018). The total frequency of extreme precipitation events (R25mm) in TMPA product was much higher than the IMERG product; in contrast, IMERG product showed a higher frequency of R10mm and five CDD spells. This pattern showed that TMPA and IMERG products were more consistent with observation to detect higher-intensity (>25 mm/day) and lower-intensity (<25 mm/day) precipitation events. An important thing to highlight is that even though both products overestimated the heavy precipitation events (Figure 9a), they both underestimated the precipitation amount significantly (not shown). An overestimation of heavy precipitation events followed by an underestimation of precipitation amount during the extreme precipitation events is very crucial, particularly in the application of SBPPs in a flash flood, landslide prediction. A precise analysis of the appraisal of the correction factor of SBPPs on a subdaily scale (half-hourly to hourly) is necessary to mimic the extreme precipitation intensity. Overall, both products underestimated the extreme precipitation events and five CDD spells while overestimated the heavy precipitation events and five CDD spells over the country; this could be associated to overestimation of low precipitation values and underestimation the higher precipitation values over the country as similar to the study conducted in China (He et al., 2017; Wu et al., 2018) and India (Prakash et al., 2016).
Notably, IMERG product captured major drought events in 2005, 2006, 2007, 2008, and 2015 due to below-normal precipitation (Hamal et al., 2020; Wang et al., 2013) and demonstrated comparable drought monitoring capabilities to observation and even presented higher accuracy than TMPA in detecting drought frequency. The temporal distribution of SPI-1 bias in TMPA and IMERG products shows that TMPA has a larger magnitude of bias than IMERG product (Figure S1). Additionally, SPI-4, SPI-6, and SPI-12 are calculated for TMPA and IMERG products (Figure 13), further to verify the temporal variation of drought at different timescale. Precipitation of past 3, 5, and 11 months including the corresponding month was used for calculation of SPI-4, SPI-6, and SPI-12 representing short- to long-term drought, respectively. The fluctuation between dry and wet conditions with timescale is relatively slower than SPI-1, which is related to the number of months used in the calculation. Similar to the results of SPI-1, IMERG product performs better than TMPA at all timescales, indicating that IMERG product is also more reasonable to represent short- to long-term drought monitoring. TMPA product shows a larger bias in 2005, 2006, 2009, 2013, and after 2016, while IMERG shows more consistent performance throughout the study period (Figure S1). Higher capabilities in detecting five CDD spells could be another reason for better reflection of major drought episodes in IMERG product during the study period.

Moreover, the accuracy of SBPPs also depends on the quality and quantity of assimilated gauge-based precipitation records. To minimize the bias, satellite-only estimates of TMPA and IMERG products are calibrated using gauge-based GPCC data sets (Becker et al., 2011). However, these data sets are not effectively calibrated for those areas where rain gauge data are not available. Hence, performances of the TMPA and IMERG products were also influenced by the quality and temporal range of the adjusted gauge-based GPCC product, respectively. Although the gauge density is very small in midelevation and high-elevation areas, both SBPPs perform fairly well in representing the monthly and seasonal precipitation patterns.
Additionally, a scatterplot is plotted, and statistical matrices are given to compare the daily and monthly performance of IMERG and TMPA products (Figure 14). It is evident that IMERG product outperformed TMPA in the daily timescale as indicated by smaller RMSE (4.30 mm/day), ME (−0.08 mm/day), and higher CC (0.77) (Figure 14b); meanwhile, TMPA showed better performance for monthly estimates (Figure 14c). The monthly precipitation accumulation ratio of TMPA and IMERG products is calibrated using GPCC, while a noticeable improvement on daily performance is a reflection of improved precipitation retrieval algorithms of the IMERG product. Furthermore, overlaps may lead to dependency on the evaluation of monthly-based comparison, and the mutual station between TMPA, IMERG, and observation was not identified due to lack of information. Therefore, depending on temporal resolution (daily, monthly, or seasonal), one could prioritize the use of these SBPPs. For a water balance and intervention analyses on a monthly to seasonal scale, the use of TMPA might be a better option, whereas if the interest is on a daily scale, the use of IMERG would be a wise decision. This study will be helpful to water resources/climate practitioners and decision makers in selecting the appropriate data sets for their future study.

5. Conclusions

In this study, the spatiotemporal accuracy of the TMPA and IMERG SBPPs was evaluated against 142-gauge stations, including an AWS station near Everest base camp (Figure 1) from Nepal during 2001–2018. Furthermore, their application on extreme precipitation events (both high-intensity and drought) were also accessed based on daily and monthly timescale.

Precipitation varies across the country during different season and locations. TMPA and IMERG products are able to capture the monthly precipitation cycle ($R = >0.80$) as revealed by the observation. TMPA
algorithms tend to produce higher precipitation than IMREG does, although both products underestimated the monthly cycle of precipitation.

Both SBPPs moderately captured the spatial distribution of rainfall over Nepal. The TMPA product produced systematically lower ME and bias values for seasonal rainfall estimates during premonsoon, monsoon, and postmonsoon season, while IMERG product produced lower ME and bias during the winter season. In terms of ME, RMSE, CC, and NSE, IMERG product outperforms the TMPA product in capturing the seasonal precipitation variabilities across the country.

The result based on daily precipitation values, IMERG product, shows the improved ability to detect the true precipitation events (>80%) and smaller error to detect no-precipitation events (<60%) as compared to TMPA product. However, both products accurately captured the precipitation and no-precipitation events (>70%) over the country.

IMERG product is more capable of detecting the frequency of heavy precipitation events (R10mm) with smaller bias, while TMPA product is more consistent to capture extreme precipitation events (R25mm) events across the country. For capturing CDD and CWD spells, IMERG product outperforms the TMPA product during the study period. It is worth noting that both products overestimated the frequency of CWD and R10mm events, meanwhile underestimated the CDD and R25mm events. Moreover, both TMPA and IMERG products captured the overall spatial and temporal pattern of extreme precipitation events over the country.

Among the two SBPPs, IMERG has detected a nearly equal number of drought events as that of observed, indicating that IMERG has better capability to monitor the drought frequency and drought events than that of TMPA. In general, IMERG products can be used to evaluate future extreme events and drought episode in all timescales.

Moreover, the evaluation of TMPA and IMERG products in the Himalayan country, Nepal, reveals that even after the various updated sensor and improved rainfall retrieval algorithms, IMERG product only shows slight improvement to older generation TMPA products. In general, this study suggests that the IMERG product can be suggested as a potential alternative to gauge stations for evaluating the future extreme precipitation events and monitoring drought. Additionally, this study will assist in the selection of appropriate SBPPs in the future hydrometeorological application.

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**Conflict of Interest**

The authors declare that there are no conflicts of interest.

**Data Availability Statement**

The Integrated Multi-Satellite Retrievals for Global Precipitation Measurement Version 6 (IMERG V6) and TRMM Multi-satellite Precipitation Analysis (TMPA) Version 7 (3B42 V7) data sets used in this study were produced with the Giovanni online data system and developed and maintained by the NASA GES DISC. The daily data sets for all the stations used in this study can be purchased from DHM, Government of Nepal (http://www.dhm.gov.np/). Pyramid station data are provided by EvK2-CNR Committee upon request (http://www.evk2cnr.org/cms/en/research/integrated_programs/share). The GPM Level 3 IMERG V6, daily (GPM_3IMERGDF) data used in this study can be freely accessed from NASA GES DISC (https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_06/summary?keywords=IMERG), and the daily TMPA (3B42 V7) data can be freely obtained at the NASA GES DISC (https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary?keywords=3b42%20daily).
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