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From TRMM to GPM: How well can heavy rainfall be detected from space?

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ABSTRACT

In this study, we investigate the capabilities of the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) and the recently released Integrated Multi-satellitE Retrievals for GPM (IMERG) in detecting and estimating heavy rainfall across India. First, the study analyzes TMPA data products over a 17-year period (1998–2014). While TMPA and reference gauge-based observations show similar mean monthly variations of conditional heavy rainfall events, the multi-satellite product systematically overestimates its inter-annual variations. Categorical as well as volumetric skill scores reveal that TMPA over-detects heavy rainfall events (above 75th percentile of reference data), but it shows reasonable performance in capturing the volume of heavy rain across the country. An initial assessment of the GPM-based multi-satellite IMERG precipitation estimates for the southwest monsoon season shows notable improvements over TMPA in capturing heavy rainfall over India. The recently released IMERG shows promising results to help improve modeling of hydrological extremes (e.g., floods and landslides) using satellite observations.

1. Introduction

Accurate estimation and prediction of heavy precipitation are crucial for many applications such as water resources management, flood forecasting and early warning, and disaster management and mitigation. Flash floods caused by the extreme precipitation events lead to substantial socio-economic losses [9,21,34,36]. Given the availability of Earth-observing satellite measurements, it is now possible to track and monitor heavy precipitation systems. However, there are still unquantified and often large uncertainties in satellite-derived precipitation products, especially for heavy precipitation events [4,16–18,31,35]. These uncertainties limit their use in practical applications [1,5,20,25].

India, a unique country in terms of geography and topography, receives most of its annual precipitation during the southwest (northern hemisphere summer) monsoon season and experiences a considerable number of heavy precipitation events that can cause devastating flash floods in flood-prone regions. Reliable estimation and detection of heavy rainfall events are formidable challenges for a wide range of applications [32]. In recent decades, heavy rainfall events over India have increased in frequency with substantial spatial variations [7,8,23]. Similar to other parts of the globe, the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) is more reliable than other contemporary multi-satellite rainfall products over India in the representation of mean monsoon rainfall and its variability [25–29]. We have now more than 17 years of retrospective processed version 7 (V7) of TMPA data sets. Motivated by the splendid success of the TRMM satellite, the Global Precipitation Measurement (GPM) Core Observatory launched in early 2014 to explore global precipitation characteristics in a more detailed and advanced way [10,17]. A high resolution and advanced Integrated Multi-satellitE Retrievals for GPM (IMERG) data set was recently released that considers the global and regional error characteristics in TMPA estimates as a benchmark [14,35]. The released data set also integrates advantages of other multi-satellite precipitation products, including Climate Prediction Center Morphing (CMORPH; [15]) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; [11,30]). In this study, we first evaluate the conditional heavy precipitation estimation from the current version (V7) of TMPA across India using an appreciably dense network of rain gauge observations at a daily timescale for a 17-year period (January 1998–December 2014). We use several traditional as well as recently proposed performance metrics and volumetric skill scores specific to the extreme precipitation verification for assessment. We also examine the capability of IMERG

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estimates in detection of heavy rain events over India using the limited data available, as a preliminary assessment.

2. Data and methods

We have used the 3-hourly 0.25° × 0.25° TMPA-3B42 research-quality product (Version 7, hereafter V7) that combines observations from a wide variety of contemporary microwave and infrared satellite-based sensors to gauge analysis over the land [12,13]. The reference data set used is a daily gridded rainfall product available at 0.25° latitude × 0.25° longitude resolution developed by the India Meteorological Department (IMD) from a reasonably good network of rain gauge observations spread across the country [22]. This gauge-based gridded rainfall data set reproduces the sharp gradient of orographic rainfall more realistically than other existing gauge-based rainfall data sets, while still representing finer scale monsoon rainfall features. Seventeen years of records (January 1998–December 2014) for both the data sets are used for analysis in this study. It is noted that TMPA data set from October to December 2014 has a slightly different calibration due to unavailability of precipitation radar data post October 2014. We also used a post-real-time version 03D IMERG research product [14], released in January 2015, for the 2014 southwest monsoon season (June–September, JJAS) to analyze heavy precipitation.

Since the IMD gauge-based data set accumulates rainfall ending at 0300 UTC, daily rainfall is computed from three-hourly TMPA data and half-hourly IMERG data ending at the same time. Only rainfall over the Indian landmass is considered. IMD defines a rainy day if daily rainfall exceeds 2.5 mm and a heavy rain event if daily rainfall exceeds 64.5 mm [8,23]. Heavy rain events are not frequent across the country, so this definition of heavy rainfall is used for long-term analysis (only for Fig. 1 in this study) and we define an additional heavy rainfall threshold corresponding to the 75th percentile of precipitation (for Figs. 2 and 3) from reference data over India as a whole [19]. Additionally, conditional heavy rainfall is computed with respect to rainy days because heavy rainfall events constitute a small fraction of the total number of days in the study period. The frequency of conditional heavy rain events is computed with respect to total number of rainy days using the following equation:

$$\text{Frequency of heavy rain events} = \frac{\text{Number of heavy rain events}}{\text{Number of rainy days}} \times 100\% \quad (1)$$

In order to verify the capability of the TMPA research-quality product in capturing conditional heavy rain events, two recently developed categorical skill indices—extremal dependence index (EDI) and symmetrical EDI (SEDI) are computed. These indices are supposed to be non-degenerating, base-rate dependent, asymptotically equitable and appropriate for rare events verification [6]:

$$EDI = \frac{\log F - \log H}{\log F + \log H} \quad (2)$$

$$SEDI = \frac{\log F - \log H - \log(1-F) + \log(1-H)}{\log F + \log H + \log(1-F) + \log(1-H)} \quad (3)$$

where, F and H are false alarm rate and hit rate, respectively. Both EDI and SEDI range from −1 to 1 with a perfect score of 1.

Several traditional categorical skill metrics, such as probability of detection (POD), false alarm ratio (FAR), miss rate (MR), frequency bias index (FBI), and critical success index (CSI) based on a 2 × 2 contingency table [33], are computed to examine the capability of TMPA and IMERG data in detection of heavy rainfall. Moreover, four volumetric skill scores—volumetric hit index (VHI), volumetric false alarm ratio (VFAR), volumetric miss index (VMI), and volumetric critical success index (VCSI) introduced in AghaKouchak and Mehran [2] are used to assess the volumetric performance of TMPA and IMERG in estimating heavy rainfall across India. POD, FAR, MR, CSI, VHI, VFAR, VMI, and VCSI range from 0 to 1, with 1 being the perfect score for POD, CSI, VHI, and VCSI, and 0 being the perfect score for FAR, MR, VFAR, and VMI. The total volumetric error (bias) in the satellite-derived precipitation estimates can be decomposed in terms of VHI, VFAR, and VMI [2].

3. Results

Fig. 1(a) shows the percentage contributions of each month to annual rainy days and conditional heavy rain events (≥ 64.5 mm day^{-1}), separately derived from IMD gauge-based and TMPA-3B42 data sets averaged over India for the study period. Both gauge- and satellite-based rainfall estimates show similar variability in rainy days as well as conditional heavy rain events. India receives the largest rainy days in the peak monsoon months of July and August (about 20% each month). The most heavy rain events occur in July, about 30%, and about 23% occur in August. India receives considerable heavy rain events primarily from May to October, and about 82% of heavy rain events occur during the southwest monsoon season from June to September. This period is also responsible for about 68% of all rainy days across the country. The inter-annual variation of heavy rain event frequency with respect to rainy days from IMD gauge-based and TMPA-3B42 data sets (Fig. 1b) shows a systematic overestimation by the multi-satellite data set. On an average, about 3.31% of rainy days over India is heavy-rain producing, as inferred from the gauge-based data, whereas the satellite-derived estimates put this average at about 4.43%. It is to be noted that there is no bias correction applied to the TMPA data set for further analysis here.

Fig. 1(c) and (d) shows the spatial distributions of the frequency of conditional heavy rain events (≥ 64.5 mm day^{-1}) from IMD gauge-based and TMPA-3B42 data sets across India. Two regions of the country are prone to heavy rain events primarily: (a) the west coast including Gujarat state; and (b) the western parts of northeast India including Sikkim, Meghalaya states. The west coast of India, the windward side of the Western Ghats, receives higher rainfall during the southwest monsoon season associated with the low-level monsoon jet, whereas the leeward side gets much less rainfall known as a rain-shadow region. Central India, the east coast and the Himalayan foothills get 3–5% of conditional heavy rainfall events as seen by the reference IMD gauge-based data. In general, TMPA shows a larger frequency of conditional heavy rainfall events across India. Additionally, TMPA shows relatively larger areas receiving conditional heavy rainfall as compared to gauge-based observations.

The spatial distributions of FBI, EDI, and SEDI from TMPA-3B42 in detecting conditional heavy rainfall events for the study period are also shown in Figures 1(e-g) with respect to the reference gauge-based data set across the country. Regions getting insignificant heavy rainfall during the study period are not considered for the skill score computation. FBI shows over-detection of conditional heavy rain events by TMPA as compared to gauge-based observations during most parts of the heavy rain regimes. Along the east coast of India and over some pockets of the monsoon trough, TMPA under-detects conditional heavy rainfall events. EDI and SEDI are two recently proposed metrics for verification of rare events that take both hits and false alarms into account. Even though EDI and SEDI share the same properties, EDI is neither transpose symmetric nor complement symmetric, whereas SEDI is complement symmetric [6]. EDI and SEDI show that TMPA performs reasonably well in the detection of heavy rain events across the country, except over the northern Gujarat state and some parts of northeast India (see ., Fig. 1 (f and g)). This shows substantial improvement in detected extremes compared to previous version of TMPA (e.g., Version 6) in different locations of the globe [e.g., [3,24,26]]. Over the monsoon trough region and along the east coast of India, TMPA shows notably higher EDI and SEDI scores of the order of 0.6 to 0.8 as compared to gauge-based data.

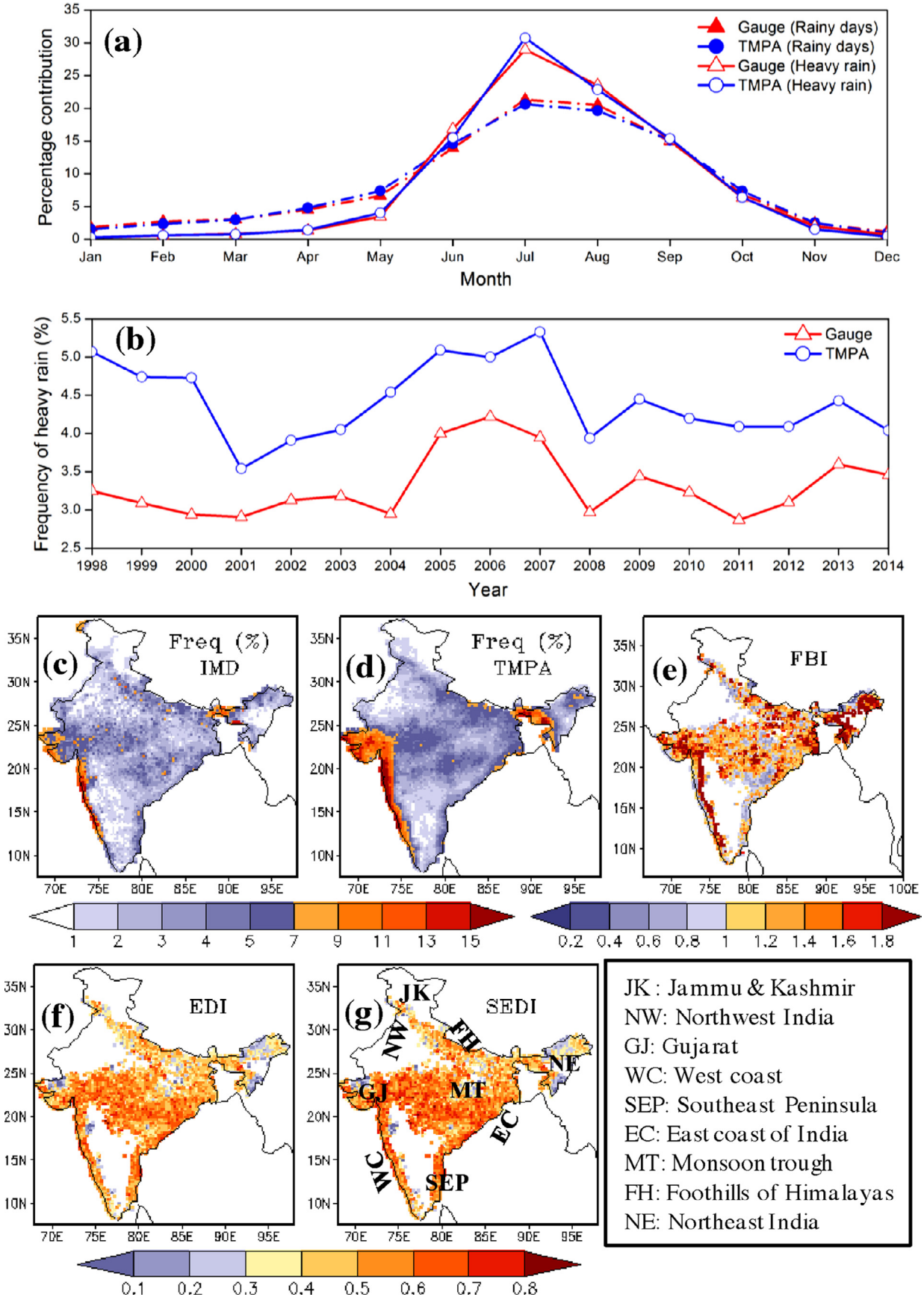

Fig. 1. (a) Monthly variations of rainy days and conditional heavy rainfall events over India from daily IMD gauge-based and TMPA-3B42 data sets. Percentage contributions of monthly rainy days and conditional heavy rainfall events are computed against their respective annual mean (Jan 1998–Dec 2014). (b) Inter-annual variations of frequency of conditional heavy rainfall events over India from IMD gauge-based and TMPA-3B42 data sets. Frequency of conditional heavy rainfall events over India derived from daily. (c) IMD gauge-based and (d) TMPA-3B42 data sets. (e) Frequency bias index (FBI). (f) Extremal dependence index (EDI), and (g) symmetrical EDI (SEDI) of TMPA-3B42 product, as compared to IMD gauge-based data, in detection of heavy rainfall events are also shown.

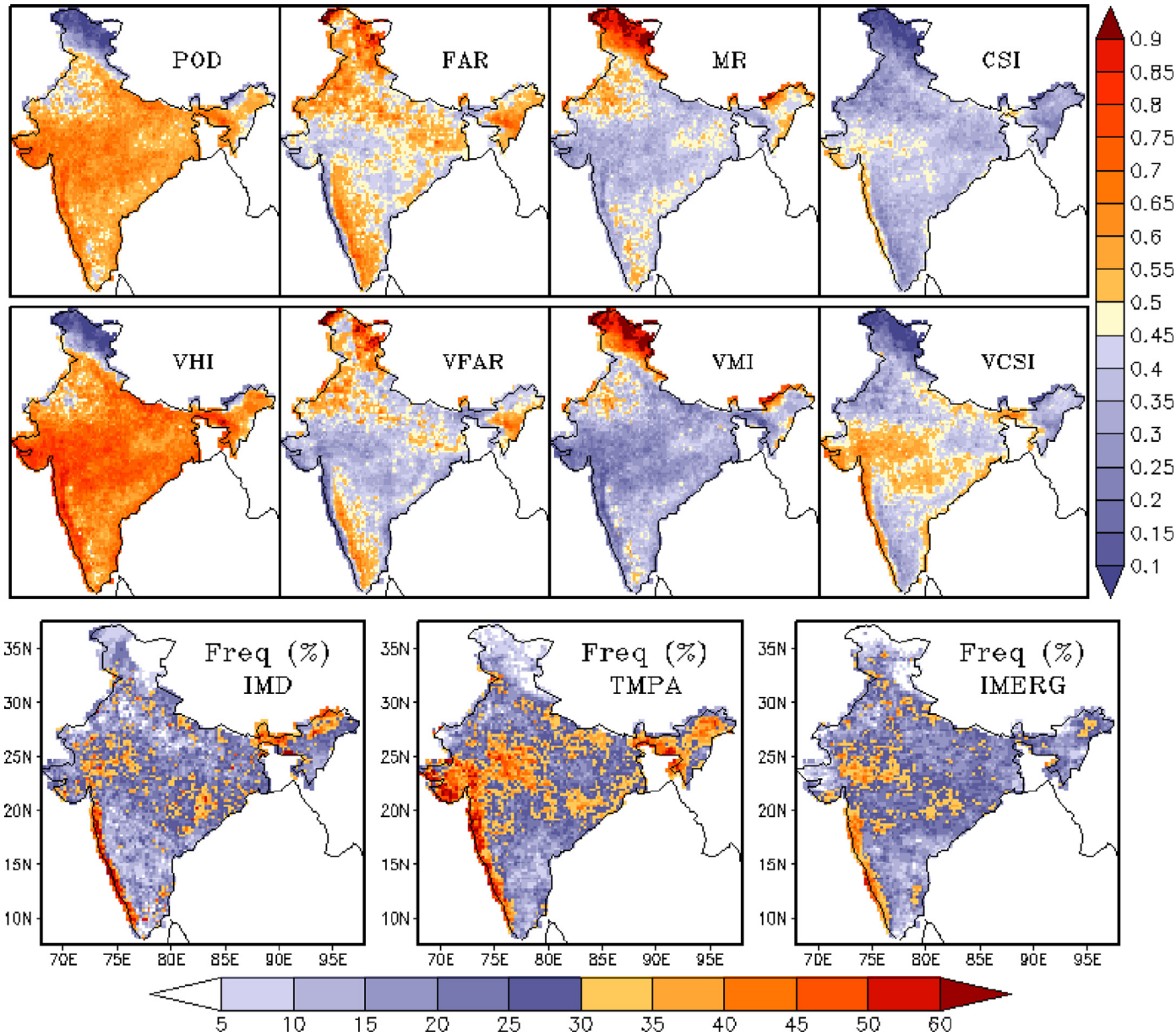

Fig. 2. (Top and middle panels) Probability of detection (POD), false alarm ratio (FAR), missing rate (MR), critical success index (CSI), volumetric hit index (VHI), volumetric FAR (VFAR), volumetric missing index (VMI), and volumetric CSI (VCSI) of daily TMPA-3B42 product, as compared to IMD gauge-based data, in detection and estimation of rainfall events above 75th percentile over India for the period of Jan 1998–Dec 2014. (Bottom panels) Frequency of rainfall events above 75th percentile over India for the southwest monsoon season (JJAS) of 2014 from daily IMD gauge-based, TMPA-3B42, and IMERG data sets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

A number of other categorical and volumetric indicators are also used for further evaluation of heavy precipitation rates. To ensure a large sample size, we use the 75th percentile of reference precipitation [19] for rainy days (rainfall larger than 1 mm day^{-1}) as the heavy precipitation threshold. Fig. 2 shows the spatial distributions of traditional categorical skill metrics and their corresponding volumetric indices across the country from TMPA-3B42 as compared to IMD gauge-based observations above the 75th percentile. TMPA shows rather higher POD over most parts of the country except over northern India (e.g., Jammu and Kashmir state). Although TMPA can detect heavy rainfall along the windward side of the Western Ghats, it has rather large FAR along the leeward side (e.g., southeast peninsular India), a rain-shadow region. Comparing FAR and VFAR, results indicate that while the FAR is large over some regions, the volume of rain, corresponding to those false estimates, is relatively small (i.e., more blue areas in VFAR compared to FAR). Lower POD and CSI with higher FAR and MR over the northern and northwest India suggest that TMPA has a problem detecting heavy rainfall primarily over these regions. The spatial distributions of volumetric skill metrics (Fig 2) are similar to categorical skill metrics, however their magnitude is different. VHI indicates that TMPA captures most of the rainfall volume in the detected rainy days. TMPA shows reasonable performance in estimation of heavy rainfall over most parts of the country, except over the northern, northeast, and southeast peninsular India. We also note that the gauge density is not sufficient over the Jammu and Kashmir regions for a valid comparison [22]. Hence, the results over these regions have more uncertainty.

For the available IMERG record during summer monsoon (JJAS-2014), we performed similar validation and verification as most of the heavy rainfall events occur during this season across the country

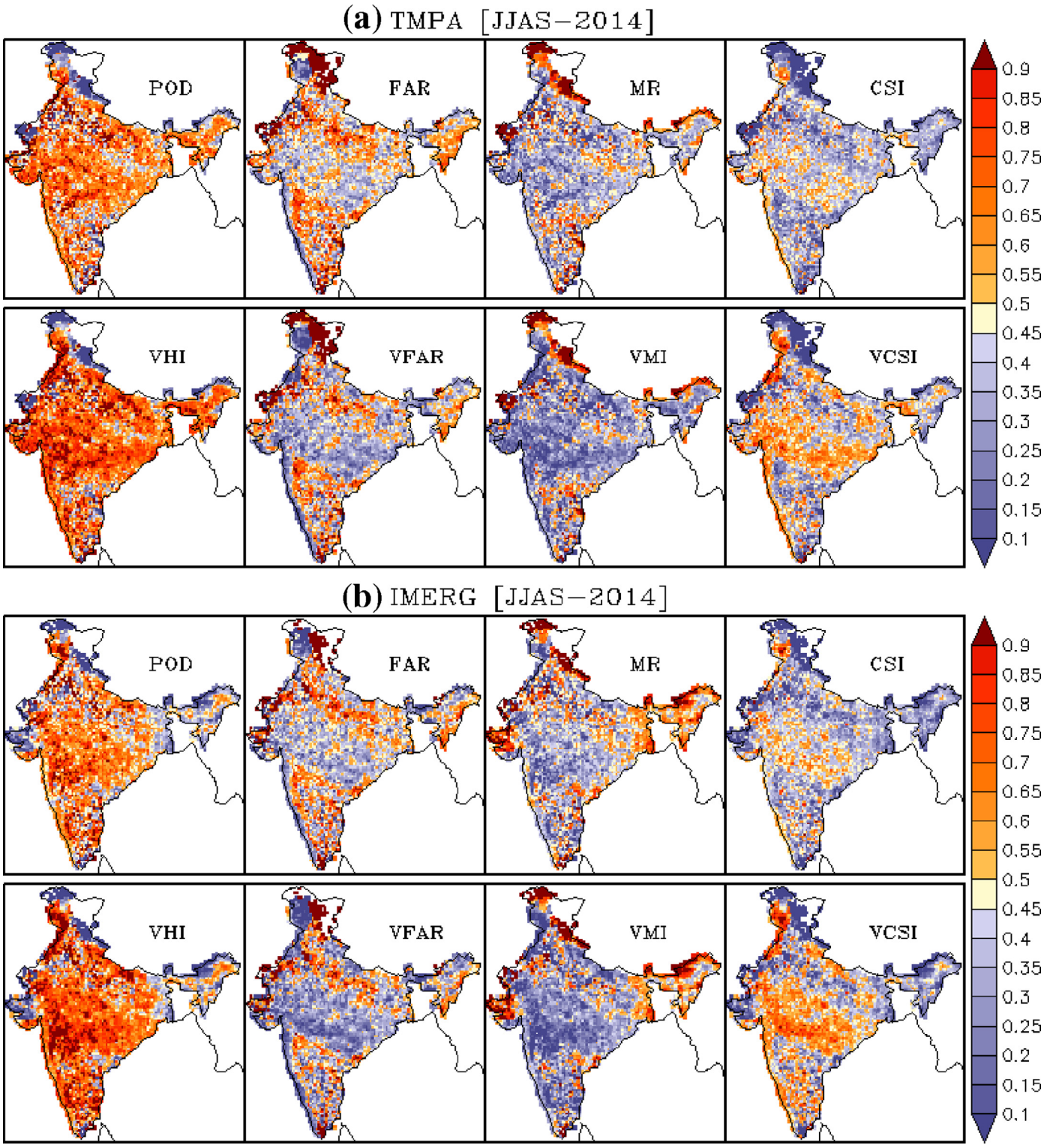

Fig. 3. Categorical and volumetric skill metrics (same as those defined in Fig. 2) of daily (a) TMPA-3B42 and (b) IMERG research-quality data sets, as compared to IMD gauge-based observations, in detection and estimation of rainfall events above 75th percentile over India for the period of JJAS-2014.

(e. g., Fig. 1a). Fig. 2 (bottom panels) shows the frequency of daily rainfall events above the 75th percentile with respect to rainy days from IMD gauge-based, TMPA-3B42, and IMERG data sets. TMPA shows a larger part of the country has a higher frequency of heavy rainfall, which is notably improved in the IMERG estimates as compared to gauge-based observations. IMERG is more consistent with the ground-based observations. IMERG shows a clear improvement over TMPA in detecting heavy rainfall events along the Himalayan foothills and over northwest India, especially over Gujarat state. For instance, TMPA shows a heavy rainfall frequency of about 36% averaged over the northwest region bounded by 20° N to 27° N and 68° E to 77° E, whereas IMERG and IMD gauge-based data show 25% and 26%, respectively. TMPA shows a wider area of the west coast receiving noticeable heavy rainfall events, which is reduced in IMERG, and

is in better agreement with the reference gauge-based observations. However, IMERG underestimates the frequency of heavy rainfall over parts of the northeast India (Fig. 2 bottom panels). FAR and VFAR are slightly reduced in IMERG relative to TMPA, while VHI values in the western central India are slightly larger in IMERG compared to TMPA (Fig. 3). Overall, the volumetric indicators, presented in Fig. 3, show that IMERG performs similar to TMPA in terms of the volume of hit, missed and false precipitation.

4. Conclusion

Capabilities of the TMPA research-quality product (V7) and GPM-based IMERG are assessed against IMD gauge-based observations across India. The monthly variations of mean rainy days and heavy rain events showed good agreement between TMPA and IMD gauge-based data. But, TMPA systematically overestimates the inter-annual variations of mean heavy rainfall events. Even though TMPA showed larger POD and smaller MR in heavy rain (above the 75th percentile) detection over most parts of the country, it showed large FAR and relatively small CSI. Furthermore, TMPA showed reasonable performance in estimation of heavy rainfall based on volumetric skill metrics over most parts of the country. While there are limitations in the detected number of heavy rainfall events, the VHI results showed that TMPA captures most of the heavy rainfall events' volume. However, TMPA has problems in detecting and estimating heavy rainfall over northern India and southeast peninsular India.

An initial assessment of the IMERG research-quality product for detecting heavy rainfall event frequency across India at a daily time scale during the southwest monsoon season showed a notable improvement over TMPA as compared to gauge-based observations, especially along the Himalayan foothills and over northwest India. However, IMERG performs very similar to TMPA with respect to the volume of hit, missed and false precipitation. The results promise improved modeling of hydrological extremes using satellite precipitation products. Longer IMERG records are needed for a more comprehensive assessment of heavy precipitation events. We expect these IMERG estimates to be released in 2016 using retrospective processing of TMPA data since 1998, and plan to continue this work with a comprehensive analysis using that long-period of data.

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