Insights on Satellite-Based IMERG Precipitation Estimates at Multiple Space and Time Scales for a Developing Urban Region in India

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ABSTRACT: Satellite-based rainfall estimates are a great resource for data-scarce regions, including urban regions, because of its finer resolution. Integrated Multi-satellite Retrievals for GPM (IMERG) is a widely used product and is evaluated at a city scale for the Hyderabad region using two different ground truths, i.e., India Meteorological Department (IMD) gridded rainfall and Telangana State Development Planning Society (TSDPS) automatic weather station (AWS) measured rainfall. The IMERG rainfall estimates are evaluated on multiple spatial and temporal scales as well as on a rainfall event scale. Both continuous and categorical verification metrics suggest good performance of IMERG on the daily scale; however, relatively decreased performance was observed on the hourly scale. Underestimated and overestimated IMERG estimates with respect to IMD gridded rainfall and AWS measured rainfall, respectively, suggest the performance depends on type of ground truth. Unlike categorical metrics, RMSE and PBIAS have a pattern implying a systematic error with respect to rainfall amount. Further, sample size, diurnal variations, and season are found to have a role in IMERG estimates’ performance. Temporal aggregation of hourly to daily time scales showed the improved IMERG performance; however, no spatial-scale dependence was observed among zonewise and Hyderabad region-wise rainfall estimates. Comparison of raw and bias-corrected IMERG rainfall-based intensity-duration-frequency (IDF) curves with corresponding hourly rain gauge IDF curves showcases the value addition via simple bias correction techniques. Overall, the study suggests the IMERG estimates can be used as an alternative data source, and it can be further improved by modifying the retrieval algorithm.

SIGNIFICANCE STATEMENT: Many urban regions are typically data sparse, which limits scientific understanding and reliable engineering designs of various urban hydrometeorology-relevant tasks, including climatological and extreme rainfall characterization, flood hazard assessment, and stormwater management systems. Satellite rainfall estimates come as a great resource and Integrated Multi-satellite Retrievals for GPM (IMERG) acts as a best alternative. The Hyderabad region, the sixth-largest metropolitan area in India, is selected to analyze the widely used satellite estimates, i.e., retrievals for GPM. The study observed inaccuracies in the IMERG estimates that varied with rainfall magnitudes and space and time scales; nonetheless, the estimates can be used as an alternative data source for decision-making such as whether rain exceeds a certain threshold or not.

KEYWORDS: Rainfall; Hydrometeorology; Automatic weather stations; Remote sensing; Satellite observations; Urban meteorology

1. Introduction

Floods are one of the principal hazards in urban areas owing to their potential ability to cause significant socioeconomic and environmental impacts. Large rainfall amounts, high rainfall intensities, and insufficient stormwater management systems (Rosenzweig et al. 2018) play an important role in flooding of urban areas. Reliable modeling and effective management of urban floods requires data of finer spatial and temporal resolution and models that mimic urban hydrological processes (Zevenbergen et al. 2010). Among all, rainfall is one of the key data inputs, and its high spatial and temporal variability, particularly in urban areas, underscores availability of rainfall data at finer scales. However, finer-resolution data are unavailable for most of the urban cities because of either a lack of funds for installation and maintenance of rain gauges or less appreciation of high-resolution rainfall measurements. In this context, gathering reliable and accurate rainfall measurements from a dense network of gauge stations is a challenging task, and the lack of data

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hinders monitoring, modeling, and management of floods in urbanized catchments.

Several methods and products are available for rainfall data acquisition, i.e., rain gauge networks, ground-based radars, re-analysis data products, and satellite estimates (G. Tang et al. 2020). Satellite-based rainfall estimates appear to be a viable option, especially in areas where the rain gauge network is absent or insufficient. The data's limitations, such as error in its estimates, do not limit its wide usage, but its near-global coverage and importantly its ease of access to the end users made it attractive. Various satellite rainfall products have been in use for the last two decades, e.g., TRMM Multisatellite Precipitation Analysis (TMPA; Huffman et al. 2007) at 0.25°/3 h (spatial and temporal resolution), Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN; Sorooshian et al. 2000) at 0.25°/6 h, PERSIANN–Cloud Classification System (PERSIANN-CCS; Hong et al. 2004) at 0.04°/1 h, Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004) at 8 km/30 min, Global Satellite Mapping of Precipitation (GSMap; Kubota et al. 2007) at 0.1°/1 h, and Integrated Multi-satellite E Retrievals for Global Precipitation Measurement (GPM) (IMERG; Huffman et al. 2015) at 0.1°/30 min. As can be seen, in recent years both the space and time resolution of satellite estimates became finer, e.g., IMERG estimates are of finer scale compared to the earlier products, and importantly the data latency has improved (Huffman 2019). Satellite rainfall products are made available with and without data processing; therefore, the final processed products take more time.

Preliminary studies on IMERG were performed on daily time scale for spatial scales ranging from a global scale to river basin scale, e.g., entire globe (60°S–60°N) (Libertino et al. 2016), China (Ning et al. 2016), Iran (Sharifi et al. 2016), Bangladesh (Islam 2018), Malaysia (Tan and Santo 2018), Brazil (Gadelha et al. 2019), Germany (Ramsauer et al. 2018), Canada (Asong et al. 2017), and river basins, namely, Ganjiang basin (Li et al. 2017), Upper Huaihe basin (Su et al. 2019), and Upper Mekong River basin (He et al. 2017) in China and the Mekong basin in Southeast Asia (Wang et al. 2017). These studies suggested a reasonable agreement between the IMERG estimates and ground truth data and good performance in capturing the heavy rainfall events.

Only a few studies evaluated the IMERG performance on hourly time scale, and these studies were performed on larger spatial scales across several regions, i.e., China (Chen et al. 2020; G. Tang et al. 2020; Xu et al. 2016); Netherlands (Gaona et al. 2016); Canada (Moazami and Najafi 2021); Tibetan Plateau (Ma et al. 2016); Ganjiang River basin (Li et al. 2016); Upper Blue Nile River basin, Ethiopia (Sahlu et al. 2016); and Lower Colorado River basin, Texas (Omranian and Sharif 2018). These studies suggested IMERG capabilities in detection of non-zero rainfall events at subdaily and hourly time scales and decreased performance in representing the rainfall depths in comparison to daily scale. A few studies have investigated the performance of IMERG Early, Late, and Final Run datasets and found that IMERG Final Run is the best product, which can be attributed to gauge adjustment (O et al. 2017; Wang et al. 2018; S. Tang et al. 2020; Li et al. 2021; Yu et al. 2021). In regard to the Indian subcontinent, studies analyzed the performance of various satellite rainfall products and observed the better performance of IMERG. However, the studies also suggested modification of retrieval algorithm to improve the performance further (Beria et al. 2017; Murali Krishna et al. 2017; Verma and Ghosh 2018; Singh et al. 2019; Reddy et al. 2019; Thakur et al. 2020). Limited studies are found on verification of IMERG rainfall estimates at hourly and daily time scales (Tan and Duan 2017; Mandapaka and Lo 2020) as well as on its usability for different applications (Sai Krishna et al. 2016; Varlas et al. 2019; Getirana et al. 2020; Kyaw et al. 2022; Li et al. 2022; Panda and Rath 2022; Guptha et al. 2021) for different cities across the world.

While studying rainfall variability on larger spatial scales, consideration of a single rainfall value for the entire region may dampen both intra- (within) and inter- (between) grid rainfall variability. Also, the variations in land use and land cover and topography within a grid smooth out, thereby achieving better performance of IMERG. However, as the spatial scale reduces to the level of urban locale, several processes that govern rainfall over the area as well as responsible for space–time variability in rainfall become more evident. The complexity of urban structure and the existence of the local climatic zones (Stewart and Oke 2012) in urban areas indicate the presence of numerous microclimatic patterns that modify rainfall over a region. In addition, the impact of urban heat island (UHI) alters the temporal distribution of rainfall, thereby leading to short-duration, intense rainfall extremes (Niyogi et al. 2017; Kishitawal et al. 2010; Niyogi et al. 2020). Note that the analysis at finer spatiotemporal scales requires the availability of finer ground truth data, which are unavailable for many of the urban regions. Keeping in view the aspect of data scarcity in conjunction with the challenges posed in understanding the urban climate, it is difficult to analyze the performance of the alternative sources of rainfall such as IMERG estimates. In this context this study puts an effort in understanding the performance of IMERG satellite estimates in representing the rainfall variability on both space and time scales as well as assessing its utility.

This study framed four objectives, i.e., (i) assess the IMERG’s performance at multiple space and time scales; (ii) analyze the IMERG’s ability in representing diurnal variations; (iii) evaluate the IMERG’s capability in capturing the 6-hourly rainfall events; and (iv) demonstrate the utility of IMERG via intensity–duration–frequency (IDF) curves. The proposed objectives will address the performance of IMERG in all possible spatiotemporal scales and also help in understanding the usability of IMERG rainfall in urban flood-prone regions.

2. Study area, datasets, and methodology

a. Study area

The Greater Hyderabad Municipal Corporation (GHMC) region houses the city of Hyderabad, which is the sixth-largest
metropolitan city in India and is chosen as the study area. The Hyderabad urban agglomeration, one of India’s fastest-growing metropolises, is densely populated (9.5 million people), and importantly a rapidly developing urban region that is on track to become a megacity (agglomerations with populations of more than 10 million people) by the next decade (UN DESA 2018). The region has a geographical area of 680 km² and is divided into five zones, i.e., north, south, east, west, and central zones based on administrative boundaries. The entire GHMC region and the five administrative zones together correspond to multiple space units. The region is in the tropics, i.e., 17.25°–17.60°N and 78.20°–78.75°E (Fig. 1a), and is characterized by semiarid climate (Peel et al. 2007). The topography slopes from west to east in general and the western region has isolated small hills. The southwest monsoon brings much of the region’s rainfall during the months of June–September, i.e., nearly 604 mm, an average value calculated over a period from 1971 to 2020; August is considered the wettest month with an average rainfall of 186 mm.

b. Datasets

Three precipitation datasets, i.e., the IMERG V06 Final Run data product, gridded rainfall estimates from the India Meteorological Department (IMD), and point rainfall of the 36 Automatic Weather Stations (AWS) from the Telangana State Development Planning Society (TSDPS), were used in this study. The three different precipitation sources differ in their period of the record, so a common period of record, i.e., 1 June 2013–31 May 2019, was chosen for this study. The AWS point rainfall data and IMD gridded data were considered as ground truths, and the performance of the IMERG rainfall is evaluated against these rainfall products. Details of these datasets are as follows.

1) IMERG V06 FINAL RUN PRODUCT

The Global Precipitation Mission (GPM) Core Observatory satellite is the result of the collaborative effort between the U.S. National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) (Huffman et al. 2015; Tan and Santo 2018; Sharifi et al. 2016), and the IMERG estimates are developed from the GPM. Although the mission was launched in 2014, the retrospective products of GPM-era IMERG are available from 2000 to present (Huffman et al. 2015). Based on the latency, the IMERG has three different products, i.e., the Early Run, which is a near-real-time product with a latency of 4 h; the Late Run, which is a postprocessed near-real-time product with a latency of 12 h; and the Final Run, which is a gauged-adjusted product using the GPCP Monitoring Product (version 4) and has a latency of about 3.5 months. This study used the latest version 06 release of IMERG, i.e., IMERG Final Run product (0.1°/30 min), and the
variable “precipitationCal” multisatellite precipitation estimate with gauge calibration, where the algorithm combines the early precipitation estimates collected during the operation of the TRMM satellite (2000–15) with the most recent precipitation estimates collected during operation of the GPM satellite (2014–present) (Huffman et al. 2020).

2) GROUND-BASED OBSERVATIONS

(i) IMD gridded rainfall data

The IMD provides gridded precipitation data with a spatial resolution of 0.25° gridded at a daily time scale (Pai et al., 2014), and this dataset is in wide use as ground truth (Dubey et al. 2021). The gridded rainfall estimates are developed by applying the inverse distance weighting (IDW) technique on station based rainfall data and available for the period 1901–2021. The IMD reports accumulated rainfall from 0830 IST (Indian standard time or 0300 UTC) of the current day to 0830 IST of the next day as daily rainfall for the next day. For this study, the gridded data are projected onto the study area and then mean areal rainfall for the study region is calculated.

(ii) IMD and AWS point rainfall data

TSDPS monitors the AWS network for the entire Telangana region and records four weather variables, i.e., rainfall, wind speed, humidity, and temperature, at every 1-h interval. The least count of the tipping-bucket rain gauge in these AWSs is 0.25 mm and has a maximum value of 600 mm h⁻¹ (Shoaib and Rasool 2015). This study used the data from the 37 AWSs, which have data for the period from 1 June 2013 to 31 May 2019. Further, IMD hourly rainfall data at its meteorological center in Hyderabad (78.46°E and 17.45°N) are used, and the data are available at every 1-h interval for around 20 years from 1 June 2000 to 31 December 2020.

c. Methodology

Accurate evaluation of IMERG rainfall estimates with ground-based measurements is quite challenging and involves a series of steps. Broadly, as part of the first step, the ground truth data are verified for quality control, which consists of removal of suspicious and repeated values before the calculation of mean areal rainfall. The following criteria were used to calculate the mean areal rainfall on hourly and daily time scales for two different spatial scales, i.e., the entire GHMC and zonewise region. To calculate the areal hourly GHMC region rainfall, at least 10 stations, i.e., more than quarter of the existing stations (37), should have the recorded rainfall data for one particular hour. To calculate the areal hourly rainfall for a zone, half of the existing stations in the zone should have no missing data. However, to calculate the areal daily rainfall at the GHMC or zone level, the hourly data should be available continuously for 24 h, i.e., 0900 local time of the current day to 0800 local time of the following day.

The datasets are available at multiple spatiotemporal scales, and for comparison purposes the data need to be brought to a common scale for the analysis, which is a second step broadly. This study employed the IDW (Shepard 1968) because of its wide usage to estimate mean areal rainfall values for the two spatial scales, i.e., entire GHMC and zonewise regions. Both for the AWS and IMERG, the region is divided into finer grids of 0.01° resolution and then rainfall for each of the finer grids is assigned employing the IDW technique. Average rainfall calculated from all finer grids corresponds to either the entire area or an administrative zone, which is the zonewise average rainfall. Note that the half-hourly data from the IMERG satellite estimates are accumulated to hourly and daily time scales and then used in the evaluation.

1) CONTINUOUS VERIFICATION METRICS

To evaluate the performances of the satellite rainfall data with ground truths, several widely used verification metrics are selected (Table 1). The metrics are root-mean-square error (RMSE), percent bias (PBIAS), and Pearson correlation coefficient (r) and are calculated using all the values including zero rainfall.

2) CATEGORICAL VERIFICATION METRICS

The categorical metrics help in understanding the ability of IMERG rainfall estimates in detecting an event in terms of its occurrence (ignoring volume), thereby differentiating a wet day/region and dry day/region. Four categorical metrics are as follows, i.e., probability of detection (POD), false alarm ratio (FAR), critical success index (CSI), and Heidke skill score (HSS) (Table 2). These metrics require calculation of number
of hits \((H)\), misses \((M)\), false alarms \((F)\), and negatives \((N)\) and are defined as follows: hits are the correctly detected rainfall events by both satellite and ground truth, misses are the rainfall events that detected by the ground truth but missed by satellite, false alarms are the rainfall events detected by satellite, and negatives are the rainfall events where no rainfall is recorded by both satellite and ground truth. POD measure evaluates the fraction of occurrences of rain that are correctly detected, FAR corresponds to the fraction of rain occurrences that are falsely detected, CSI is the proportion of correctly detected satellite rainfall occurrences to the overall ground data and false alarms by satellite, and HSS estimates the number of correctly identified hits or misses as a proportion of the total number of events including negatives. HSS is considered as an unbiased estimate as it accounts the matches of random chance (Wilks 2011). These metrics require definition of an event, and several events were defined in each section. Note that the nonzero rain event corresponds to the rainfall greater than 1 mm h\(^{-1}\) for hourly rainfall and 1 mm day\(^{-1}\) for daily rainfall.

3) GENERATION OF IDF CURVES

This study utilized the extreme value type (EVT) I distribution (Chow et al. 1953) for the construction of IDF curves by generating the annual maximum series of rainfall intensities from 1 to 24 h. This method calculates two parameters, i.e., mean (location) and standard deviation (scale) from the annual maximum rainfall intensity, and the third parameter, Gumbel frequency factor corresponds to the return period, is varied from 2 to 15 years. The IDF curves were developed for different rainfall intensities that are calculated from storms of different durations and for different return periods \((T_M)\):

\[
Z = \sigma K + \bar{Z}
\]

\[
K = -\frac{\sqrt{6}}{\pi} \left[\gamma + \log_{e} \left[\frac{\log_{e} T_M - \log_{e} (T_M - 1)}{\log_{e} T_M - \log_{e} (T_M - 1)}\right]\right]
\]

where \(Z\) is the return period rainfall intensity, \(\sigma\) is standard deviation, \(\bar{Z}\) is the mean, \(K\) is the frequency factor, \(\gamma = 0.5772\), and \(T_M\) is the recurrence interval.

3. Results and discussions

The major goal of this paper is to evaluate the performance of IMERG at multiple space and time scales in an urban region. Therefore, both continuous and categorical verifications metrics are calculated for the entire GHMC region and five different zones at hourly, daily, and monthly scales. Further, the IMERG rainfall estimates are evaluated with respect to diurnal variations, selected events, and IDF curves. Note that the both AWS and IMD grid-based rainfall estimates were used as ground truth.

a. GHMC region

The mean areal GHMC daily rainfall values from two different ground truths were compared, and a good association \((r = 0.9)\) is observed (Fig. 2a). Nonetheless, as compared to the AWS estimates, the IMD gridded estimates are typically
overestimated with PBIAS values of 26.7% and the bias appears to be present for all values of rainfall amounts. This might be because of integration of rainfall information from rain gauges other than or subset of TSDPS AWS network. The categorical verification metrics for nonzero rainfall amounts ($\geq 1$ mm) exhibited low FAR (0.19), medium CSI (0.7), and high POD (0.84) and HSS (0.8) values, indicating a strong agreement between the two ground truths.

The IMERG estimates exhibited a similar performance with respect to two ground truths (Figs. 2b,c). While a similar linear association, i.e., $r \approx 0.8$, is observed between IMERG and two ground truths, the IMERG estimates are overestimated as compared to the AWS (16.7%) and underestimated as compared to the IMD (−7.9%). Categorical verification metrics suggest a better discrimination of IMERG rainfall estimates for nonzero rainfall amounts with small FAR (0.28 and 0.27), medium CSI (0.6 and 0.6), high POD (0.79 and 0.77), and high HSS (0.68) values separately for the AWS and IMD gridded rainfall amounts, respectively. The study region falls in the southern peninsular region of India and the findings are in line with those of Prakash et al. (2018), who reported a good association between IMD and IMERG daily rainfall in terms of correlation coefficient, PBIAS, and RMSE values.

Further, the analysis is done with respect to a calendar month. For all 12 calendar months, scatterplots are presented in Fig. 3 and both continuous and categorical verification metrics are tabulated in Table 3. Season-based insights are as follows. The winter season comprising January and February experiences lesser rainfall in this region and is reflected in all three rainfall sources (Figs. 3a,b). The summer season, i.e., March–May, receives relatively higher and smaller rainfall amounts as compared to the winter, monsoon, and postmonsoon seasons (Figs. 3c–e). The categorical verification metrics calculated for nonzero rainfall events ($\geq 1$ mm) suggest a similar performance of IMERG estimates with both the ground truths in terms of smaller FAR values ($\sim 0.40$) and higher POD, CSI, and HSS values ($\sim 0.64$, $\sim 0.45$, $\sim 0.55$) (Table 3).

All monsoon months, i.e., June–September, showed a good correlation with the IMERG estimates; the lowest and highest correlation values, 0.65 and 0.86, respectively, were observed for August and September (Table 3). The rise in RMSE values from summer to monsoon is primarily attributable to the higher rainfall amounts (Table 3 and Figs. 3f–i). Better performance is seen in categorical metrics with decreased FAR values (0.27) and increased POD (0.78), CSI (0.6), and HSS (0.65) values as compared to summer. Out of the three postmonsoon months, i.e., October–December, the month of October, being a monsoon withdrawal month, usually receives higher rainfall amounts (Figs. 3j–l). October IMERG rainfall is underestimated with PBIAS values of 10% (−20%) for AWS (IMD); nevertheless, a good association is observed between IMERG and ground truths with a correlation coefficient of $\sim 0.9$. This implies the better ability of IMERG in capturing October rainfall (Fig. 3j and Table 3). The November and December months usually record very small amounts of rainfall; however, rainfall estimates corresponding to 13 November 2014 are noticeable and underestimated by IMERG rainfall estimates, i.e., $\sim 13$ mm (Fig. 3k). In addition to November and December, both January and February do not receive much rainfall; therefore, there are relatively a lot of zero values, and consequently sample size appears small (Figs. 3a,b,k,l) and the metrics vary significantly (see Table 3).

The results imply a distinct performance signature among the seasons, and the region’s hydroclimate mechanism explains it to
TABLE 3. Continuous and categorical verification metrics calculated for the IMERG daily rainfall with AWS and IMD gridded daily rainfall at the monthly scale; the values are presented for all calendar months. Full forms of the metrics are found in Tables 1 and 2.

<table>
<thead>
<tr>
<th>Month</th>
<th>POD AWS</th>
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<th>POD IMERG</th>
<th>POD MERG</th>
<th>RMSE AWS</th>
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<td>December</td>
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an extent. The region’s summer season is characterized by rainfall events of short periods and higher intensities that occur across small spatial scales, and the satellite’s inability to capture small-scale rainfall heterogeneities may explain IMERG’s relatively lower performance in summer season. Contrarily, the monsoon season and October exhibited better performance, which might be because of the rainfall that in general is of longer duration and widespread in nature.

b. Rainfall thresholds

The mean areal GHMC daily rainfall is classified into nine categories based on AWS rainfall amounts and its percentiles, and corresponding rainfall from IMD and IMERG is obtained. The nine categories are no rain (0–1 mm, 75th percentile), light rain (1–3 mm, 87th percentile), moderate rain (3–7.5 mm, 93rd percentile), heavy rain (7.5–12 mm, 95th percentile), very heavy rain (12–21 mm, 98th percentile), extreme rain (31–37 mm, 99.5th percentile), rare extremes (37–77 mm), all rain (>1 mm), and alert rain (>7.5 mm). In the context of flooding, rain from the three categories, i.e., no rain, light rain, and moderate rain, has an insignificant role and less information content. In this regard, rain from the remaining categories is combined and formed as a new category, i.e., alert rain. Further, rain from all categories except from the no rain category is combined and formed all rain.

Scatterplots showing the IMERG rainfall estimates’ association with two ground truths in terms of scatter and correlation coefficient are developed for all the categories (Fig. 4). In addition, both continuous and categorical verification metrics are calculated for all the nine categories for IMERG rainfall with respect to both ground truths, i.e., AWS and IMD areal rainfall values (Table 4). The scatter and small correlation coefficients for no rain, light rain, and moderate rain can be attributed to the absence of information in the satellite estimates and decreased variability in the sample (Figs. 4a–c), and this is reflected in the large error, i.e., higher or closer to the maximum. Rainfall of a specific category, and high PBIAS values (Table 4). Positive bias, i.e., overestimation of the satellite rainfall estimates, is an artifact and is attributed to a few large rainfall estimates, for example, the no rain category (Fig. 4a). A decrease in the PBIAS is observed with the increase in rainfall amount until rainfall amounts that are categorized as very heavy rain. Then, underestimated rainfall is observed for large rainfall amounts, i.e., rainfall of extreme and rare extreme categories. However, the rainfall estimates with reference to the IME grid rainfall exhibited a slightly different pattern, i.e., underestimated, but relatively of small bias for the first three categories, and then underestimated rainfall, but relatively of large magnitude for the rainfall amounts of heavy rain and higher amounts. Nonetheless, the RMSE values with respect to both ground truths are of similar magnitude with slightly higher values for the IMD rainfall and increased with rainfall amounts (Table 4). It implies a similar and decreasing accuracy of the IMERG rainfall estimates with increasing rainfall amounts. The fact that the RMSE is smaller than the minimum rainfall value.
of a specific category suggests overall better performance of rainfall estimates and associated value with it. Note that the relatively higher and negative PBIAS values for rainfall categories exceeding 12 mm (Table 4) with reference to the IMD rainfall are due to a combination of relatively larger errors and difference of IMD and AWS rainfall amounts (Fig. 4). However, in terms of other aspects, i.e., scatter and linear association, IMERG estimates exhibited better performance with IMD rainfall, particularly for categories of large rainfall amounts (Figs. 4d–f), except for the category rare extreme rain (Fig. 4g), which has a small sample (Table 4). For example, for the extreme rain category, the continuous verification metrics suggest better performance of rainfall estimates with the AWS rainfall (Table 4, row corresponding to extreme rain and first two columns); however, per the scatterplot, the estimates are better aligned with IMD rainfall (Fig. 4f). The possibility of using the same station data in both IMD and IMERG rainfall estimates needs to be explored.

For the no rain category, the IMERG exhibited good performance with both AWS and IMD with high POD (0.92), high CSI (0.87), high HSS (0.7), and lower FAR (0.06) values (Table 4). In the remaining categories, i.e., from light to rare extreme rainfall, lower PODs (~0.3), CSIs (0.15), and HSSs (0.2) and higher FARs (~0.7) were observed with both ground truths indicating poor performance of IMERG in detecting a particular rainfall event. However, the all rain and alert rain categories depicted higher PODs (~0.75), good CSIs (~0.55), good HSSs (~0.65), and lower FARs (~0.35), which highlights the ability of IMERG in detecting the rainfall in wider rainfall ranges.

All verification metrics and scatterplots suggested a better performance when rainfall amounts exceeding a threshold are pooled, i.e., all rain and alert rain, as compared to the rainfall amounts of individual categories (Figs. 4h,i). Also, no significant difference in performance of rainfall estimates with respect to both ground truths was observed. These imply the
TABLE 4. Continuous and categorical verification metrics calculated for IMERG with AWS and IMD at various rainfall thresholds; n corresponds to sample size.

<table>
<thead>
<tr>
<th>Rainfall category</th>
<th>No rain (0–1 mm)</th>
<th>Light rain (1–3 mm)</th>
<th>Moderate rain (3–7.5 mm)</th>
<th>Heavy rain (7.5–12 mm)</th>
<th>Very heavy rain (12–21 mm)</th>
<th>Extreme rain (21–37.5 mm)</th>
<th>All rain (&gt;1 mm)</th>
<th>Alert rain (≥3.5 mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>1602</td>
<td>149</td>
<td>136</td>
<td>125</td>
<td>120</td>
<td>110</td>
<td>418</td>
<td>146</td>
</tr>
<tr>
<td>PBIAS (%)</td>
<td>0.9</td>
<td>1.1</td>
<td>0.4</td>
<td>0.6</td>
<td>0.9</td>
<td>0.8</td>
<td>0.9</td>
<td>0.4</td>
</tr>
<tr>
<td>POD</td>
<td>23.5</td>
<td>4.4</td>
<td>7.1</td>
<td>7.7</td>
<td>8.8</td>
<td>3.5</td>
<td>8.9</td>
<td>7.2</td>
</tr>
<tr>
<td>FAR</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
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<tr>
<td>CSI</td>
<td>0.92</td>
<td>0.79</td>
<td>0.71</td>
<td>0.71</td>
<td>0.64</td>
<td>0.75</td>
<td>0.76</td>
<td>0.75</td>
</tr>
<tr>
<td>HSS</td>
<td>0.92</td>
<td>0.91</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>RMSE (mm day⁻¹)</td>
<td>1.1</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
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</tr>
</tbody>
</table>

The 37 AWSs are distributed across the five zones as mentioned here: 12 AWSs in the north zone (103 km²), 10 AWSs in the central zone (101 km²), 6 AWSs in the south zone (101 km²), 5 AWSs in the west zone (154 km²) and 4 in the east zone (125 km²). As it is seen, the three zones, i.e., north, central, and south, have approximately similar areas and are smaller than the two other zones. Thus, the zones differ in their AWS density, urbanization, urban heat islands (Sannigrahi et al. 2017), flood vulnerability, rainfall, and period of record. Coarser resolution of IMD’s gridded rainfall does not allow the evaluation at zonal scale; therefore, only AWS based data are used for the zonewise rainfall evaluation. The mean area zonewise AWS and IMERG rainfall estimates were calculated and compared at hourly and daily time scales via scatterplots and verification metrics (Fig. 5). Further, the entire GHMC region corresponding plots were added to draw interpretations with respect to spatial scale.

The range of correlation coefficients from 0.41 to 0.52 suggests a modest linear association among AWS and IMERG hourly rainfall estimates for all five zones. However, the scatterplots imply no association for the larger portion of the data except underestimated IMERG rainfall estimates corresponding to large AWS estimates (Figs. 5a,c,e,g,i). Similar observations were made for the entire GHMC that consists of all five zones (Figs. 5k,l). A similar error (RMSE) is observed for all five zones as well as for the entire GHMC; however, note that the maximum rainfall and period of the record, i.e., sample size differ among zones—these facts explain having three different PBIAS values, i.e., 6%, 13%, and 17%. The IMERG rainfall estimates exhibited low to medium performance in discrimination of nonzero rainfall amounts (≥1 mm), i.e., ~0.45 HSS, ~0.35 CSI, ~0.5 FAR, and ~0.55 POD values. While the verification metrics, particularly an error of 0.6 mm h⁻¹, give a positive picture in the flood context, the scatter implies no significant association between IMERG and AWS hourly rainfall estimates. However, similar PBIAS values (~14%) with increased better linear association (~0.7) and improved performance in discrimination of nonzero rainfall amounts (≥1 mm) (relatively low FARs and high CSI and HSS values as compared to hourly estimates) were observed on daily time scale (Figs. 5b,d,f,h,j,l). Importantly, no significant difference is observed between the entire GHMC and zonewise rainfall estimates of both hourly and daily time scales. In conclusion, aggregation of hourly rainfall estimates onto a daily time scale either reduced or removed time lag errors, which consequently enhanced skill in multiple aspects and is shown in values of multiple verification metrics. Thus, the results suggest improved performance via temporal aggregation but apparently role of range of pooled rainfall values, consequently the role of sample size; note that both categories have relatively large sample as compared to other categories (Table 4). As the alert category contains rainfall events that potentially leads to floods, the good performance of IMERG estimates in this category implies usability of the rainfall estimates in flood-relevant tasks and decision-making.

c. Zonewise distribution of rainfall in the GHMC region

The 37 AWSs are distributed across the five zones as mentioned here: 12 AWSs in the north zone (103 km²), 10 AWSs in the central zone (101 km²), 6 AWSs in the south zone (101 km²), 5 AWSs in the west zone (154 km²) and 4 in the east zone (125 km²). As it is seen, the three zones, i.e., north, central, and south, have approximately similar areas and are smaller than the two other zones. Thus, the zones differ in their AWS density, urbanization, urban heat islands (Sannigrahi et al. 2017), flood vulnerability, rainfall, and period of record. Coarser resolution of IMD’s gridded rainfall does not allow the evaluation at zonal scale; therefore, only AWS based data are used for the zonewise rainfall evaluation. The mean area zonewise AWS and IMERG rainfall estimates were calculated and compared at hourly and daily time scales via scatterplots and verification metrics (Fig. 5). Further, the entire GHMC region corresponding plots were added to draw interpretations with respect to spatial scale.

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no positive role of spatial aggregation, i.e., zonal level to the entire study area.

Factors such as wrong reporting of time intervals (O et al. 2017) and integration of upper-atmospheric and urban hydroclimate variables, such as weather radar data, rain gauge data from a dense network, and humidity, are suggested to be explored to improve the performance at hourly intervals.

d. Diurnal variations of rainfall

The diurnal variation corresponds to the accumulated hourly distribution of rainfall amounts, and analysis of it provides insights on subdaily rainfall variations and the hours, if any, that typically receive large rainfall amounts (e.g., Deshpande et al. 2012). This diurnal variability is studied in two parts. First, the ability of the IMERG estimates in capturing the diurnal variation for all four seasons is analyzed (Fig. 6). Second, a calendar day is split into eight segments, each segment is 3 h, and then the association between the two rainfall sources at hourly scale is examined (Fig. 7). As the IMD gridded rainfall data are not available at the subdaily scale, only AWS areal rainfall data are used.

Accumulated rainfall magnitudes in the winter season are of small values, i.e., 1 cm, therefore, no insights were drawn (Fig. 6a). Contrarily, the summer season rainfall amounts are relatively higher, and the AWS rainfall exhibited two peaks at 0400 and 1600 local solar time (LST). The IMERG estimates captured the two peaks including subdaily variations; however, the values are underestimated (Fig. 6b).

The monsoon season rainfall amounts are in general of high values and exhibited a clear cyclic pattern with increasing rainfall amounts from 1500 to 0600 LST of the following day (Fig. 6c). The maximum rainfall amount is observed between 2000 and 0200 LST and is consistent with the findings of Sen Roy and Balling (2007), who observed that the Deccan Plateau (where the study region lies) receives maximum rainfall before a few hours of midnight. Although the IMERG replicated the pattern of the monsoon diurnal variation, it systematically overestimated the rainfall amounts with the exception of underestimated values at 1800 LST. Similar to the monsoon, the postmonsoon season has a cyclic pattern with decreased rainfall amounts and long durations for low rainfall amounts (Fig. 6d). The higher rainfall amounts observed approximately for 10 h, i.e., from 1700 to 0300 LST of the following day. The IMERG rainfall estimates captured low rainfall amounts but underestimated the maximum rainfall amounts, yet still mimicked the diurnal variability. Overall, underestimated rainfall amounts were observed in summer and postmonsoon seasons and systematic overestimated values were seen in the monsoon season.

According to Sen Roy (2009) and Deshpande et al. (2012), occurrence of extreme rainfall amounts in short durations, i.e., 1, 3, 6, and 12 h are on the rise. In this study, 3-h durations were considered wherein the 24-h period is divided into eight sets of 3-h periods, and then the hourly rainfall values in each of the 3-h duration were compared (Fig. 7). The naming system is as follows: 0000–0200 LST is late night, 0300–0500 LST is early morning, 0600–0800 LST is morning, 0900–1100 LST is late morning, 1200–1400 LST is early afternoon, 1500–1700 LST is late afternoon, 1800–2000 LST is evening, and 2100–2300 LST is night (Singh and Nakamura 2009). Scatterplots and
moderate correlation coefficients (~0.6–0.73) imply a similar IMERG performance for all the 3-h segments (Fig. 7). The higher RMSE values (~1–1.3 mm) were observed during the segments of large rainfall amounts, i.e., late night, early morning, morning, evening and night (Figs. 7a–c.g.h), whereas the lower RMSE (~0.7 mm) is observed during late morning and early afternoon, which typically receive relatively smaller rainfall amounts (Figs. 7d.e); a similar observation in terms of time of day and rainfall amount can be made from Fig. 6. Positive PBIAS values, which imply overestimation of IMERG were observed for all the segments except for the late afternoon (Fig. 7f). The convection driven by the surface solar heating is one of the causative mechanisms leading to the rainfall maximums in the late afternoon and evening, which were also reported for several other regions in India during monsoon (Sen Roy and Balling 2007; Murali Krishna et al. 2017) and postmonsoon (Rajeevan et al. 2012). Note that the IMERG exhibited better performance on the average in the
segments of relatively large rainfall amounts from late afternoon to night.

Figure 8 corresponds to a radar plot that has the four categorical metrics calculated for the eight aforementioned segments and for six different rainfall amounts exceeding a certain threshold, i.e., nonzero hourly rainfall, $\geq 0.1$, $\geq 1$, $\geq 2$, $\geq 3$, $\geq 4$, and $\geq 5$ mm. As the rainfall event threshold is increased, a decline in POD, CSI, and HSS values and rise in FAR values are observed for all eight segments except for late morning, which consists of lesser rainfall amounts (Figs. 6 and 7) and small sample size (Fig. 8). Furthermore, relatively higher and increasing (decreasing) POD, CSI, and HSS (FAR) values were observed for evening, night, late night, early morning, and morning segments. These segments were found to have higher rainfall amounts and relatively higher number of rainy instances of which one consequence is larger sample size (Figs. 8a–f).

This highlights the IMERG’s ability in detecting rainfall during those segments where significant rainfall amounts were observed in the ground truth, i.e., rainfall from the AWSs. The morning segment has higher POD values, but note that the sample size is small, which means the number of nonzero rainfall events are less in number. Thus, overall, diurnal variations, consequently sample size imply information content and play a key role in influencing the verification metrics.

e. Subdaily events

A rainfall event implicitly corresponds to a certain rainfall amount in a particular period, therefore its identification, which depends on rainfall amount and duration, is subjective. In this study, events are defined as those that have accumulated rainfall amounts greater than 10 mm in a 6-h period (Mohammed et al. 2022) with an interevent time of 4 h. Accumulated rainfall for all possible 6 h is calculated from which the 6-h event that has maximum rainfall is chosen as the event rainfall. The 6-h period is selected as it is found to be within the range of climatological event duration (Mohammed et al. 2022) and importantly increasing trends were observed at 99% confidence level (Agilan and Umamahesh 2017). The interevent time of 4 h is chosen as the serial correlation of mean areal hourly rainfall dropped below the significant value. This criterion resulted in 69 events (Table S1 in the online supplemental material) with the highest number of events, i.e., 46 in the monsoon season (Fig. 9).

The IMERG rainfall estimates for summer events are underestimated and exhibited a poor performance in terms of high PBIAS, 63.6%, no linear association (correlation coefficient; 0.0) and high miss ratio, 0.75 (Fig. 9a); although no clear pattern is seen, small sample size inhibits in making robust conclusions. However, the IMERG estimates exhibited a better
performance for the postmonsoon events, i.e., a correlation coefficient of 0.72 and relatively low PBIAS, ~37%, and high hit ratio, 0.53 (Fig. 9b). The rainfall estimates for the monsoon events appeared to be performing better in terms of high hit ratio, 0.61, but exhibited poor performance as compared to the postmonsoon season, i.e., low correlation coefficient (Fig. 9c). Note that the monsoon events have the lowest PBIAS values and highest error, however the error is low as compared to the magnitude of the rainfall events that the monsoon has. A careful analysis of the plot suggests that the poor performance can be attributed to seven largely underestimated events (labeled in Fig. 9c). The labeled first four of the seven events form a cluster and have mean areal AWS based daily rainfall greater than 40 mm, whereas the other three events, labeled as five, six, and seven, clustered into a group with values ranging from 25 to 30 mm. Removal of these seven points visibly increased the performance in terms of verification metrics, i.e., correlation coefficient increased from 0.38 to 0.71, RMSE decreased from 14.7 to 8.3 mm, and PBIAS decreased from ~31% to ~13%. Thus, the new verification metrics suggest the better performance of monsoon rainfall events and is on par or better compared to the postmonsoon season.

Further detailed analysis of these events suggested that the events occurred in different years and a significant amount of rainfall happened in either 2 or 3 h (Table A1 in the appendix). However, as these events happened in the monsoon, they exhibited less spatial variation (Fig. A1). The climate mechanism for all the events can be attributed to low pressure systems that are typically seen in the region (Fig. A2). Thus, the driving mechanism of the selected events is not very different. It is interesting to note that the IMERG rainfall estimates significantly underestimated the rainfall amounts, but the IMERG estimates were able to mimic zero and nonzero rainfall amounts and corresponding hours (Fig. A3). All these facts imply that the source for the inaccurate estimation of these events is satellite relevant, which could be either sensor aspects or retrieval algorithm. As the IMERG estimates are a product that resulted from the constellation of the satellites, detailed analysis of these events with respect to the satellites that recorded these events and corresponding algorithm might provide additional information.

f. IDF curves

The IDF curves have a key role in flood relevant designs and studies. Both the IMD hourly gauge rainfall data and the IMERG grid (that has the IMD gauging station) rainfall estimates were considered to construct the IDF curves; because of the small sample size, the AWS data are not used. As a first check, the IMD and IMERG hourly rainfall were compared (Fig. 10a). The RMSE and PBIAS values suggest an overall small error; however, the small correlation coefficient suggests a poor association and is clearly seen in the scatterplot. Further, conditional bias, i.e., large error for high rainfall amounts is clearly observed—it highlights the necessity of bias correction of the IMERG rainfall estimates. Among various bias correction methods, the linear scaling bias correction technique (Teutschbein and Seibert 2012; Fang et al. 2015), which is simple and widely used, is chosen.

The linear scaling bias correction technique is calibrated on 3-h rainfall segments, which is then applied on hourly rainfall amounts. The 3-h rainfall segment was chosen because (i) the IMERG data prior to 2014 are originally available on a 3-h scale which is then disaggregated into half-hourly values (Huffman et al. 2015, 2020; Huffman 2019), and (ii) a clear diurnal variation at the 3-h resolution is observed (Fig. 7). Further, the current temporal resolution on which the bias correction has been operating, i.e., month, is inefficient in representing the fast-changing weather patterns particularly in cities (Huffman et al. 2015, 2020; Huffman 2019), and (ii) a clear diurnal variation at the 3-h resolution is observed (Fig. 7). Further, the current temporal resolution on which the bias correction has been operating, i.e., month, is inefficient in representing the fast-changing weather patterns particularly in cities (Huffman et al. 2015, 2020). Therefore, a finer temporal resolution is chosen for the study region. The IMERG bias-corrected rainfall is obtained by calculating the ratio of the mean areal 3-h IMD based rainfall to the corresponding IMERG rainfall estimates and then multiplying it with the individual hourly rainfall value of the same segment of the same day; the equation as follows, i.e.,

\[
\text{IMERG}_{\text{bias-corrected, hourly, data (i,j,k)}} = \text{IMERG}_{\text{hourly, data (i,j,k)}} \times \frac{\mu [\text{IMERG}_ {i,j,k}]}{\mu \overline{[\text{IMERG}_ {i,j,k}]}},
\]

where \( i \) corresponds to an hour and \( j \) corresponds to 3-h segment of the \( k \) day.
The bias-corrected IMERG hourly mean areal rainfall estimates exhibited a relatively better association with the corresponding AWS rainfall estimates, and it is seen in terms of structured scatter, increased correlation coefficient, and decreased RMSE (Fig. 10b). The PBIAS values were high but only when all the data were considered. Values of the conditional verification metrics suggest better performance of the bias-corrected IMERG rainfall estimates as compared to the raw IMERG rainfall estimates as well as the employed bias correction method (Table A2). To examine the utility of IMERG estimates, the IDF curves were constructed using the rainfall from all three rainfall sources, i.e., IMD gauge, IMERG, and bias-corrected IMERG hourly rainfall (Fig. 10). The annual maximum rainfall intensity series corresponding to storm duration ranging from 1 to 24 h were generated, and then the EVT I method based IDF curves developed for the return periods ranging from 2 to 15 years.

The IDF curves of all the three different rainfall sources for the return periods $T = 2, 10,$ and 15 years were plotted (Fig. 11), and all curves suggested a decrease in rainfall intensity for increased event duration, which is a well-known fact. Further, the plots suggest low rainfall intensities for the raw IMERG rainfall estimates as compared to the two other sources of rainfall. No significant difference in rainfall intensities is observed among the values calculated from bias-corrected IMERG rainfall estimates and IMD hourly rainfall data. And the difference in estimates decreased with the increase in rainfall event duration, i.e., only a small difference is observed among the rainfall intensities corresponding to 24 h. While the IDF plots suggest the use of IMERG rainfall estimates without bias correction on a daily time scale, the fact that the IMERG estimates are available at finer spatial and temporal resolution encourages the use of finer-resolution data.

The IDF curves of the IMD hourly data, IMERG hourly data, and IMERG bias-corrected hourly data for 2-, 10-, and 15-yr return periods.
4. Summary and conclusions

This study evaluated the performance of IMERG rainfall estimates over the GHMC region for the period of 1 June 2013–31 May 2019. The rainfall estimates compared with two ground truths, i.e., the automatic weather station (AWS) data and IMD gridded data at different temporal and spatial scales. Further, the role of bias in IMERG rainfall estimates is assessed in terms of IDF curves. The key conclusions are as follows.

1) The IMERG daily rainfall estimates exhibited a strong linear association with both ground truths; however, the rainfall values were overestimated with respect to the AWS-based data and underestimated with respect to the IMD gridded data.

Fig. A1. The spatially interpolated AWS rainfall of the GHMC region for the seven monsoon events that are largely underestimated.

Fig. A2. Geopotential height at 500 hPa for seven monsoon events that are largely underestimated.
The difference in performance with respect to the two ground truths is seen more clearly as part of the conditional verification, i.e., rainfall evaluation with respect to rainfall amount.

2) The RMSE of IMERG estimates increased with increase in rainfall threshold; however, no significant change is observed in terms of categorical verification metrics for rainfall amounts of large values. Decreased error and increased performance were observed for the rainfall amounts of greater range with a large sample.

3) The IMERG estimates exhibited diurnal variations as well as its dependence with season, i.e., overestimated rainfall amounts were observed in the monsoon season, whereas underestimated rainfall observed in the winter, summer, and postmonsoon season. Also, the event-based evaluation suggested better performance of the IMERG estimates in monsoon and postmonsoon seasons.

4) The IMERG estimates showed the improved performance with temporal aggregation, i.e., from hourly to daily. Contrarily, no spatial scale dependence is observed, i.e., a similar performance is observed in the zonewise and the entire GHMC rainfall estimates.

5) The bias-corrected hourly IMERG estimates displayed improved performance across different ranges of rainfall amounts and matched with hourly observed rainfall based IDF curves.

The results imply good performance and thus usability of IMERG rainfall estimates across the entire GHMC and its five administrative zones at daily scale; however, relatively decreased performance on the hourly scale and the performance dependence on various factors, e.g., time of day, time of year, type of ground truth, rainfall amount, sample size, and temporal resolution, may limit its usage. As simple bias correction shows the utility of rainfall estimates in the construction of IDF curves, modification or postprocessing of rainfall estimates via integration of the above information may further improve the reliability and accuracy of the rainfall estimation. Noting that the Final Run product is not a near-real-time product, it cannot be utilized for real-time forecasting but its availability on hourly and finer spatial scales encourages its wide usage including development of IDF curves (Kyaw et al. 2022; Venkatesh et al. 2022) and monitoring of natural hazards (Getirana et al. 2020). Also, as it is seen, the value addition of the IMERG estimates is obvious in certain aspects, e.g., whether rain exceeds a threshold or not. However, noting that the performance is region specific, a detailed region-specific evaluation is must as it is done in this study. The pursued

![Table A1](image)

<table>
<thead>
<tr>
<th>Event</th>
<th>AWS rainfall (mm)</th>
<th>IMERG rainfall (mm)</th>
<th>No. of hours with 80% of rainfall</th>
</tr>
</thead>
<tbody>
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<td>2000 IST 25 Aug 2017</td>
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<td>17.6</td>
<td>3</td>
</tr>
<tr>
<td>0800 IST 31 Aug 2016</td>
<td>56.7</td>
<td>25.9</td>
<td>2</td>
</tr>
<tr>
<td>0400 IST 8 Jun 2017</td>
<td>54.3</td>
<td>19.4</td>
<td>3</td>
</tr>
<tr>
<td>1800 IST 11 Jul 2013</td>
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<td>8.5</td>
<td>3</td>
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<td>2100 IST 27 Aug 2016</td>
<td>29.4</td>
<td>2.6</td>
<td>2</td>
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<td>2.9</td>
<td>2</td>
</tr>
<tr>
<td>1900 IST 9 Aug 2018</td>
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<td>3.1</td>
<td>3</td>
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</tbody>
</table>

**Fig. A3.** AWS and IMERG rainfall for seven monsoon events that are largely underestimated. The 6-h rainfall period along with 3 h before and after the event are shown.
research diurnal variation of rainfall, conditional verification metrics, city-, zone-, and eventwise rainfall verification and utility of bias-corrected rainfall estimates via IDF curves together corresponds to a holistic approach of verification, and the insights from the evaluation assist in revision of retrieval of the algorithm. Thus, improved rainfall estimates will have an important role to play for cities that lack rainfall of finer resolution but get floods more frequently because of rapid urbanization and climate change. Integration of the regional factors in rainfall estimates with projected better rainfall estimates derived from satellites with increased number of passive microwave sensors of finer resolution and more frequency channels is a way forward for the effective utility of rainfall estimates.

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Data availability statement. The IMERG Final Run V06 precipitation estimates are available in the website https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGHH_06/summary?keywords=imerg and can be freely accessed. The India Meteorological Department (IMD) gridded daily dataset is also freely available at https://www.imd.gov.in/Climate_Pred_LRF_New/Grided_Data_Download.html. Due to Memorandum of Understanding (MoU), the hourly data from automatic weather station network of TSDPS and IMD gauge hourly data will not be freely available to the readers.

<table>
<thead>
<tr>
<th>Rainfall threshold</th>
<th>$r$ [IMD and IMERG (raw)]</th>
<th>$r$ [IMD and IMERG (bias corrected)]</th>
<th>RMSE [IMD and IMERG (raw)]</th>
<th>RMSE [IMD and IMERG (bias corrected)]</th>
<th>PBIAS [IMD and IMERG (raw)]</th>
<th>PBIAS [IMD and IMERG (bias corrected)]</th>
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<tbody>
<tr>
<td>≥0.1 mm</td>
<td>0.24</td>
<td>0.58</td>
<td>4.9</td>
<td>4.2</td>
<td>−39.4</td>
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<tr>
<td>≥1 mm</td>
<td>0.16</td>
<td>0.53</td>
<td>7.5</td>
<td>6.4</td>
<td>−58.4</td>
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<td>≥2.5 mm</td>
<td>0.12</td>
<td>0.48</td>
<td>10.1</td>
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<td>−69.2</td>
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<tr>
<td>≥5 mm</td>
<td>0.16</td>
<td>0.44</td>
<td>13.6</td>
<td>11.1</td>
<td>−79.2</td>
<td>−44.1</td>
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<tr>
<td>≥7.5 mm</td>
<td>0.2</td>
<td>0.39</td>
<td>16.6</td>
<td>13.3</td>
<td>−83.5</td>
<td>−46.5</td>
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<tr>
<td>≥10 mm</td>
<td>0.18</td>
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<td>18.6</td>
<td>14.9</td>
<td>−84.2</td>
<td>−46.4</td>
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<td>≥15 mm</td>
<td>0.15</td>
<td>0.26</td>
<td>23.4</td>
<td>17.8</td>
<td>−85.8</td>
<td>−48.2</td>
</tr>
</tbody>
</table>

APPENDIX

Characteristics of Seven Rainfall Events That Are Largely Underestimated by IMERG

The three figures in the appendix provide additional information on characteristics of seven monsoon events that are largely underestimated by the IMERG.

Figure A1 is developed to understand the spatial distribution of rainfall for the selected events. Plotted spatial rainfall estimates correspond to interpolated AWS rainfall data. The plots suggest no significant spatial rainfall variability specific to an event indicating widespread rainfall, which is typically observed in the monsoon, however, rainfall amounts corresponding to an event differ.

Figure A2 is developed to understand atmospheric mechanism that drives these selected events. The ERA5 data is used to plot the geopotential heights at 500 hPa. The plots suggest that the major driving mechanisms for these events are low pressure systems.

Figure A3 is developed to understand the rainfall variations before, during, and after the event. The plots show the IMERG’s ability in capturing rainfall peaks in terms of rainfall amount and peak time. It is observed that IMERG is able to capture the corresponding hours of zero and nonzero rainfall, but is unable to represent the rainfall amounts.

Table A1 provides the event details for which AWS and IMERG differ significantly and the number of hours in which a significant fraction of the rainfall (~80%) occurred. It is observed that the majority of rainfall occurred in a duration of 2–3 h.

Table A2 illustrates the performance of IMERG raw and bias-corrected hourly rainfall values with respect to the IMD hourly rainfall for various thresholds. The calculated continuous verification metrics highlight the higher correlation coefficients, lower RMSE, and lower PBIAS values for the bias-corrected IMERG estimates. The values suggest a good association with IMD rainfall when rainfall amounts of a large range are considered, i.e., relatively higher correlation coefficient and low error values are observed for the category of rainfall with threshold of ≥0.1, ≥1, and ≥2.5 mm.

REFERENCES


Mohammed, A., S. K. Regonda, and N. R. Kopparthi, 2022: Climatological features of high temporal resolution rainfall over


