Two-decades of GPM IMERG Early and Final Run Products Intercomparison: Similarity and Difference in Climatology, Rates, and Extremes

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Highlights:

- Twenty-year retrospective comprehensive cross-investigation of GPM IMERG Early Run product and Final Run product in terms of average, instantaneous rate, and extremes
- Climatology: Early Run estimated annual rainfall is systematically higher than Final Run worldwide
- Instantaneous Rates: Early Run and Final Run are closer in Europe and cold regions, while large differences are reported in Africa and (semi) arid regions
- Extreme: Early Run measures 33.0% higher extreme rainfall rates (at 99^{th} percentile) than Final Run

Abstract

Precipitation is an essential climate and forcing variable for modeling the global water cycle. Particularly, the recent Integrated Multi-satellite Retrievals for GPM (IMERG) product retrospectively provides an unprecedented two decades of high-resolution satellite precipitation estimates. The primary goal of this study is to examine the similarities and differences between the two latest and also arguably the most popular, GPM IMERG Early and Final Run (ER and FR) products across the globe. The results reveal that: (1) ER systematically estimates 12.0% higher annual rainfall than FR, particularly over land (16.7%); (2) ER and FR show significant differences in instantaneous rates (Root Mean Squared Difference: RMSD=2.38 mm h^{-1} and normalized RMSD: RMSD_norm=1.09), especially in Africa (RMSD=2.40 mm h^{-1}) and hot, arid regions (RMSD_norm=1.11), but less so in Europe (RMSD=2.16 mm h^{-1}) and cold areas (RMSD_norm=0.87); and (3) ER measures 33.0% higher extreme rainfall rates than FR over the globe. The exploration of their similarities and differences provides a first-order global assessment of various hydrological utilities: FR is designed to be more suitable for retrospective hydroclimatology and water resource applications, while the earliest available ER product, though not bias-corrected by rain gauges, still shows potential utility for operational modeling of rainfall-triggered hazards. The findings of this study can provide an assessment to product developers and broader data users and practitioners to address the inherent issues in hardware limitations, retrieval algorithms, and uncertainty quantification for research and applications.

Keywords: Climatology; Extremes; Early run; Final run; GPM IMERG; Satellite

1 Introduction

Satellite Precipitation Products (SPPs) are vital for providing global observations (Levizzani et al., 2020a,b), developing precipitation climatologies (Huffman et al., 2007; Sharifi et al., 2016; Tang et al., 2020; Yin et al., 2004), and hydrometeorological applications (Chen et al., 2020; Hong et al., 2004; Li et al., 2020a; Sorooshian et al., 2000; Tang et al., 2016a; Wang et al., 2017). Over the last two decades, the National Aeronautics and Space Administration (NASA) initiated two commissions in cooperation with the Japanese Aerospace Exploration Agency (JAXA) and many international agencies and universities. In 1997, the Tropical Rainfall Measuring Mission (TRMM) was launched with the precipitation radar (PR) and microwave imager (TMI) to enhance tropical precipitation measurement capabilities (Kummerow et al., 2000; Huffman et al., 2007). As TRMM was decommissioned in 2015, its successor, the Global Precipitation Measurement (GPM) Core Observatory (GPM CO), started operations to expand precipitation estimation over high latitudes (i.e., 65°N-S). With advances in the Dual-frequency Precipitation Radar (DPR) and the GPM Microwave Imager (GMI), GPM CO is capable of detecting light rain and falling snow from the mesoscale up to planetary-scale circulations (Hou et al., 2014; Skofronick-Jackson et al., 2017). To date, a number of quasi-global SPPs have been made available for open access to the public, e.g., TRMM Multi-satellite Precipitation Analysis (TMPA; Huffman et al., 2007), Climate prediction center MORPHing method (CMORPH; Joyce et al., 2004; Joyce & Xie, 2011), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks family (PERSIANN family; Hong et al., 2004; Nguyen et al., 2018; Sorooshian et al., 2000), Global Satellite Mapping of Precipitation (GSMaP; Kubota et al., 2007), and the latest NASA Integrated Multisatellite Retrievals for GPM (IMERG; Huffman et al., 2019a). In a nutshell, the IMERG algorithm is designed to intercalibrate, merge, and interpolate “all” satellite microwave precipitation estimates, together with microwave-calibrated infrared (IR) satellite estimates, precipitation gauge analyses, and potentially other precipitation estimators at fine time and space scales over the entire globe.

In order to accommodate various requirements for latency and accuracy, three products are systematically generated (Tan et al., 2019a). The first two are Near-Real-Time (NRT) products denoted as IMERG Early Run (ER; ~4 hours latency) and Late Run (LR; ~14 hours latency); with more data available given the latency period, the final post-real-time (PRT) run uses monthly gauge data to create a research-quality Final Run product (FR; ~3.5 months latency). The algorithm-based differences between the three-staged products are summarized in Tan et al. (2019b). Despite IMERG being a state-of-the-art SPP, numerous users (e.g., research communities and operational agencies) oftentimes face many unanswered questions and lack clear guidance.

To the best of our knowledge, previous works of comparing the IMERG three-stage products are either temporally short or localized. O et al. (2017) evaluated the performance of the three products, referenced to two dense gauge networks in southeastern Austria, and found the accuracy is ranked as follows: FR>LR>ER. Wang et al. (2017) compared the three datasets with a hydrologic evaluation in a small Beijing River Basin in China, and they demonstrated that FR exhibits the best overall statistical performance with respect to ground rain gauges and streamflow gauges. Omranian & Sharif (2018b) similarly found that FR has better performance than ER and LR in the lower Colorado River Basin. Mahmoud et al. (2018) performed station-based event evaluation for the three products in Saudi Arabia and highlighted that FR performs best. In summary, FR generally outperforms ER and LR in terms of accuracy based on local case studies, mainly due to rain gauge adjustments. However, a comprehensive examination of the differences between ER and FR is still lacking from the perspectives of hydroclimatology, hydrometeorology, and hydrological extremes, especially in its full lifespan of data availability on a global basis. The overarching goal of this study is to systematically investigate the similarity and difference between the GPM IMERG Early and Final Run products over the globe for the last two decades. Their similarities and differences are revealed from three aspects: (1) precipitation climatology, (2) instantaneous precipitation rates, and (3) extreme precipitation events, which hopefully can provide valuable information for applications in the fields of hydroclimatology, hydrometeorology, and disaster monitoring and early warning. This study's findings and feedbacks will further motivate product developers to implement algorithmic corrections to address the inherent problems of IMERG Early Run, in order to maximize its joint advantages in both latency and accuracy. This paper is organized as follows: Section 2 introduces the statistics and datasets. Section 3 unveils the results at four levels. Section 4 discusses the limitations of this study. Section 5 concludes this study and provides some recommendations.

2 Material and methods

2.1 Study area

Precipitation is non-uniformly distributed over the globe, as over 95% is accounted for in the intertropical convergence zone (ITCZ), South Pacific convergence zone (SPCZ), and summer monsoon regions (Lau & Wu, 2011; Ricko et al., 2016). Different from previous versions, the IMERG V06 generates global precipitation (i.e., 90°N-S) at 0.1° spatial resolution at a half-hourly time interval. In the following sections, study areas include the globe as a whole and are further broken down into land vs. ocean surface. Over land, the areas are studied from the perspective of continents, elevations, and climate zones. It is worth noting that the characteristics of rainfall over land are more diverse than the ocean as land surfaces have more complicated terrain and influences on the generation of precipitation (Kim et al., 2017; Sharifi et al., 2016).

2.2 Dataset

2.2.1 IMERG

In this study, the latest IMERG Version 06B ER and FR are used for global precipitation assessment (https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGHH_06/summary?keywords=IMERG). ER is designed for warnings of natural hazards, including flash floods (Huang et al., 2019; Wang et al., 2017) and landslides (Hong et al., 2007a; Kirschbaum & Stanley, 2018). FR has been evaluated extensively for extreme weather conditions (Huang et al., 2019; Mazzoglio et al., 2019; Omranian et al., 2018a), production of climatologies (Sharifi et al., 2016; Tan et al., 2019a), and applications over complex terrain (Kim et al., 2017; Li et al., 2020b). LR is not considered in this analysis because it improves marginally over ER (Mazzoglio et al., 2019). The full-lifespan of data availability for ER and FR is depicted in Figure 1a and b, in which nearly 100% of data are available within 60°N-S. Outside of it, only partial data can be utilized due to the infrequent sampling and lack of IR measurements, and also the snowy/icy regions are completely masked out as described in the technical documentation (Huffman et al., 2019b; Tan et al., 2019b). A minimum of 40% of the total data length is set as a threshold to filter out regions mostly outside 60°N-S and to maintain consistent statistical significance of the results.

2.2.2 Earth surface data

In this study, Earth's surface is categorized as land, ocean, and coast to interpret the different signals from spaceborne measurements. Coastal regions are collected from Natural Earth Data (https://www.naturalearthdata.com/downloads/10m-physical-vectors/10m-coastline). The ocean coastline, which includes major islands resolved from a 10-meter resolution digital elevation model (DEM), is utilized to analyze IMERG measurements.

The DEM data to segregate the Earth surface regions are based on the NASA Earth observations (https://neo.sci.gsfc.nasa.gov/view.php?datasetId=SRTM_RAMP2_TOPO). This dataset is made from three sources: NASA's Space Shuttle, Canada's radarsat satellite, and topographic maps made by the U.S. Geological Survey. It comes with the same spatial resolution as IMERG data, namely 0.1°.

As a part of this study is to investigate the impact of climatologies on the differences between ER and FR, the modern climate Köppen-Geiger classification is adopted from (http://koeppen-geiger.vu-wien.ac.at/; Kottek et al., 2006), which has also been verified by the Global Prediction Climatology Center (GPCC) and applied to evaluate global climates and regionalization (Santini & di Paola, 2015; Yang et al., 2019). This classification is based on five main climate categories: equatorial, arid, warm temperate, snow, and polar. Furthermore, the sub-categories are based on atmospheric conditions according to the regional humidity and temperatures.

2.2.3 Auxiliary datasets

The GPCC product, used by IMERG FR to perform monthly gauge corrections at 1° spatial resolution, is retrieved from https://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html. The GPCC product provides the number of gauges inside each pixel at spatial resolutions of 0.5°, 1°, and 2.5°. In this study, the 0.5° one is selected as it is the closest to the spatial resolution of IMERG (i.e., 0.1°).

2.3 Computational Methods

Table 1 lists seven statistical metrics in which ER is considered as the estimate and FR as the reference. The first category consists of binary counts (i.e., POD, FAR, and CSI), aiming to examine rainfall detectability. The minimum rainfall rate is defined as 0.1 mm h^{-1} to avoid large uncertainties in light precipitation (Li et al., 2020; Tapiador et al., 2020). The second category evaluates the continuous differences, including the Relative Bias (RB), Mean Absolute Difference (MAD), Root Mean Squared Difference (RMSD), and the normalized RMSD (RMSD_norm). It should be noted that the evaluation shows the relative difference between ER and FR instead of the actual accuracy of ER because FR also contains uncertainties.

3 Results

3.1 Global Analysis

3.1.1 Rainy probabilities

Figure 1c and d illustrate the probability of rain for FR and the ER-FR difference, calculated from the 20-year datasets at 0.1° spatial resolution and half-hourly time scale. Globally, ER displays 5.84% of rainy probability on average, which is only 0.47% lower than FR (6.37%). However, 91.7% of the surface of the globe shows negative differences, meaning that ER detects less rainfall with respect to FR over a majority of the globe. The maximum rainy probabilities for both ER (35.8%) and FR (41.7%) occur in the ITCZ while the minima (nearly zero) are located in polar regions.

3.1.2 Global Annual Rainfall Average

The 20-year mean annual rainfall is shown in Figure 1 with FR (e) and ER-FR (f). The global annual rainfall average for ER (1201.8 mm $year^{-1}$) is 5.3% higher than FR (1141.6 mm $year^{-1}$), yet the maximum annual rainfall (8867.3 mm $year^{-1}$) of ER is 2.8% lower (9118.9 mm $year^{-1}$). Likewise, the maxima are located inside the ITCZ, which is comparable with the results revealed by Wang et al. (2018).

Over oceans, Figure 1e features the ITCZ that stretches across the Indian Ocean and the Pacific Ocean in the tropics. The tropical rainfall band across North America and Asian continents is obvious, associated with maxima in annual rainfall. In addition, another precipitation band extends from the subtropics to North America, denoted as mid-latitude storm tracks, which supplies a substantial amount of rainfall to higher latitudes. Some coastal regions with a significant amount of rainfall are also noticeable in tropical South America, Middle Africa, and South Asian islands. Over land, some striking features with remarkable rainfall amounts are observed in the equatorial African, South American, and Asian continental regions.

With a focus on the differences between ER and FR, the mean annual difference is about 60.1 mm year^{-1}, and 76.0% of the grid cells display positive differences globally. Specifically, most of the positive differences are situated in the copious rainfall regions in middle and low latitudes; however, negative differences tend to be prevalent in the high-latitude oceans and over complex terrain. The maximum annual difference of 3642.0 mm year^{-1} is found at Sarygamysh Lake (57.45°E, 41.85°N) in Uzbekistan (in the upper right subplot). There ER (FR) estimates the annual rainfall of 5310.9 (1668.9) mm year^{-1}, yet this region should not have such heavy rainfall (even 1668.9 mm year^{-1}) according to the regional climatology (https://www.climatestotravel.com/climate/turkmenistan). It could be ascribed to the GPROF algorithm that misrepresents the emissivity and temperature of water bodies on land, which in turn results in systematical overestimation (Tian and Peters-Lidard, 2007). It is worth noting that the gauge correction in Final markedly reduces systematic error, ensuring its appropriateness for water resources management applications.

3.1.3 Statistical analysis of two decades of hourly rainfall rates

Figure 2 provides global maps of the statistical metrics described in Table 1. The first three subplots (i.e., a, b, and c) show the global distribution of categorical indices (i.e., POD, FAR, CSI) for precipitation detection with respect to FR. Overall, ER is comparable with FR in rainfall detection (the mean POD=0.78, FAR=0.24, and CSI=0.63), especially in wet places (>1500 mm year^{-1}); however, ER deviates from FR markedly in dry places (<500 mm year^{-1}, e.g., cold oceanic regions, Sahara desert in North Africa, Tibetan Plateau, Middle East, and US Rocky Mountains), where POD is below 0.6 and FAR is above 0.5. Previous studies (e.g., Mahmoud et al., 2018) also showed relatively poor detection (below 0.6) of ER against ground observations in the Middle East. In these regions, ER possibly suffers from fractional coverage issues due to the lower availability of PMW estimates and their associated use in backward morphing. According to the morphing techniques described by Joyce et al. (2004), it is also likely that ER misses rainfall events, as it measures zero rainfall rate at the beginning (t=0 h), and then no rainfall value is propagated to the next half hour (t=0.5h) if only using forward morphing. However, it is possible that the subsequent overpass (t>0.5h) measures a nonzero value, and then the backward morphing will make up the value at t=0.5h. On the other hand, the estimated grid cell is unlikely to be reset to zero if the origin already has an initial rainfall value. Therefore, the morphing difference, forward morphing in ER compared to two-way morphing in FR, likely leads to more misses, which is reflected in the POD statistic.

For precipitation quantification with respect to FR, the overall RB (0.12) is significant on average over the globe, and ER measures slightly higher rainfall over 71.9% of the earth's surface (Figure 2d). Notably, the maximum RB (1264.1) is found in the Chugach Mountains (140.55°W, 60.15°N) near the Gulf of Alaska. Precipitation generally falls as snow here and also receives orographic enhancement, which are possible fundamental factors explaining the ER and FR discrepancies. In addition, the availability of PMW data is more limited in high latitudes because of masked snowy and icy surfaces, which challenges the morphing schemes as well.

The globally averaged MAD (and RMSD) is not negligible with values of 0.87 (1.82) mm h^{-1}, compared with the average rainfall rate of 2.61 mm h^{-1}. As these two metrics are highly correlated with the rainfall rate (Huffman, 1997), they are markedly scaled by large rainfall rates. Alternatively, the corresponding normalized RMSD (RMSD_norm) becomes useful for further investigation. The global mean value of RMSD_norm is 0.93, which is broken down as 1.09 over land surfaces and 0.84 over oceans. It suggests higher differences between ER and FR over land due to the use of gauge adjustments. Similar to the performance of categorical indices, large RMSD_norm (> 2) values are exhibited in arid regions (e.g., cold oceans and deserts).

3.2 Meridional Analysis

Figure 3 depicts the latitudinal distribution (grouped by every 10° latitudinal band) of rainy samples and annual rainfall amounts. In general, ER and FR perform similarly across latitudes. ER detects less rainy samples than FR systematically across all latitudes. The RB of rainy samples is almost symmetric, which peaks in the poles (-0.12) and then gradually improves to -0.04 in the 30°-60°N-S band, followed by another peak in the tropics (-0.06). As speculated previously, the difference is possibly ascribed to the morphing differences because the forward-only morphing ER possibly misses rainfall events. Regarding mean annual rainfall, ER (1025 mm year^{-1}) estimates 5.6% more annual rainfall than FR (982 mm year^{-1}), which is similar to the globally averaged difference (5.3%). Moreover, large discrepancies are found in low latitudes within the 30°N-S band, in which ER estimates mean annual rainfall amounts of 1429.9 mm year^{-1}, which is about 9% higher than FR (1326.7 mm year^{-1}). Within 60°N-S, the RB for rainfall amount increases to a peak at 30°N and 30°S (~0.1) and then decreases in the tropics (~0.05). Finally, outside of 60°N-S, the RB peaks for both rainy occurrences and rainfall amounts, which can be explained by the different numerical weather models used to provide cloud motion vectors and also the divergence between SPPs (Behrangi et al., 2016; Tan et al., 2019b).

3.3 Earth Surface-based Analysis

The performance of ER and FR with regard to three Earth surface types (i.e., land, ocean, and coast) are evaluated and intercompared at hourly time scale in Figure 4. In terms of systematic bias, the mode of RB for rainy samples is ranked in the order of inland (-6.88%), coast (-6.42%), and ocean (-5.31%) in Figure 4a. On average, the land surface exhibits higher bias (16.7%) compared to oceanic (5.21%) and coastal (7.05%) regions. This ranking still holds for the RB of rainfall amounts with land (5.49%), coast (2.14%), and ocean (0.05%) in Figure 4b. Concerning instantaneous discrepancies, even though the mode of RMSD in Figure 4c is ranked slightly differently with land (2.38 mm h^{-1}), ocean (2.18 mm h^{-1}), and coast (2.06 mm h^{-1}), the coast still yields the largest range (2.7 mm h^{-1}) compared to land (2.06 mm h^{-1}) and ocean (2.10 mm h^{-1}). The above results are somewhat anticipated because oceans have more homogenous surfaces while land areas have more diverse features in terms of topography, surface roughness, and land cover heterogeneity (Kim et al., 2017; Sharifi et al., 2016). These features complicate precipitation patterns and their retrievals, which ultimately magnifies the differences (see section 3.4.1).

The difference in coastal regions is described by the algorithmic transition between land and oceanic surfaces (Gruber et al., 2000; Tapiador et al., 2020). In addition, one can witness that the RMSD for both ocean and coast are bimodal with one mode inside the 30°N-S band (RMSD=1.7 mm h^{-1} for ocean and 1.5 mm h^{-1} for coast) and the other mode outside the 60°N-S band (RMSD=0.8 mm h^{-1} for ocean and 0.5 mm h^{-1} for coast). Within the 30°N-S band, the peak of RMSD is associated with increased precipitation (e.g., warm oceans); outside 60°N-S, the difference is again attributed to the different numerical weather models utilized as previously mentioned and potentially more PMW estimates in FR towards high latitudes.

3.4 Land-based Analysis

3.4.1 Elevation

The systematic bias of satellite precipitation products over high elevations is attributed to sensor limitations, precipitation type, retrieval algorithms, and temporal sampling (Hashemi et al., 2013, 2020). All these issues propagate to IMERG estimates. FR and ER adopt different approaches to derive cloud motion vectors from total precipitable water vapor (MERRA-2 for FR and GEOS-FP for ER; Tan et al., 2019b), and such differences in methodology are highly impacted by orography. In addition to that, ER potentially infuses more IR-based precipitation estimates than FR, which is hypothesized to condition differences on different elevations. Figure 5 shows the RB of rainy samples and precipitation amounts as functions of elevation. The general trend of RB for rainy samples decreases from nearly 0 to -0.2 with increasing elevation from 0 to 5500 meters. Overall, the rainy samples detected by ER is 11.2% lower than FR on average, and the RB (-0.21) peaks at the elevation range from 4500 to 5000 meters. Notably, above 2000 meters, each bin shows negative biases with more than 75% of the samples, suggesting a significant uncertainty of rainfall detection in high elevations.

For the annual precipitation amount, the mean RB is -0.06 overall, indicating that ER generally estimates less annual precipitation than FR. The RB gradually decreases from 0.2 to -0.3 going from 500 meters to 4500 meters, followed by a slight increase at the highest elevations (>4500 m). This behavior is similar to the study of Hashemi et al. (2020), in which a positive bias is found below 2000 meters, and then the bias transitions to a negative value above that.

It is worth noting that the RB of precipitation amounts and rainy samples covary positively with elevation, suggesting that the systematic bias is possibly due to the missed events caused by forward-only morphing in ER. Given the context of this study, we focus mainly on the intercomparison of similarity and difference exposed in merged products. As for the impact of IR estimates, one can analyse it by isolating IR-only precipitation from the merged products. Also other root causes are worth exploring for an independent research topic.

3.4.2 Continents

Since FR bears less uncertainty in places with rain gauges (i.e., the gauge density in the GPCC), it is worth exploring the differences between ER and FR with respect to available gauges. The RMSD field of the IMERG product is aggregated to 0.5° to match the GPCC resolution. Figure 6a shows the spatial distribution of the GPCC gauges. It is visually discernable that Europe has the densest gauge networks of all continents, with as many as 40 gauges inside one grid box. On the other hand, Africa and South America exhibit more sparsely distributed gauge networks. Figure 6b illustrates the RMSD as a function of gauge numbers within each grid box. Compared to pixels with no gauges, pixels containing at least one gauge exhibit higher differences, highlighting the effect of the gauge-based correction that was applied. Also notably, increasing the number of gauges in each pixel reduces the interquartile range (IQR) of the RMSD. The exception to this result is the bin with more than 20 gauges per pixel, but the sample size is much smaller. Therefore, higher gauge numbers in a pixel tend to reduce the uncertainty and stabilize the bias correction.

Figure 7 exhibits the RMSD grouped by continents. Figure 7a shows the spatial distributions of RMSD, and Figure 7b reveals the gauge density in each continent obtained from GPCC (standardized by the maximum). The standardized gauge density in each continent is ranked in the following order: Europe, Asia, North America, Australia, Africa, and South America. For the RMSD, the instantaneous differences between ER and FR are ranked as follows: Africa (2.82 mm h^{-1}), Australia (2.76 mm h^{-1}), South America (2.42 mm h^{-}

$^{-1}$), Asia (2.42 mm h^{-1}), North America (2.40 mm h^{-1}), and Europe (2.16 mm h^{-1}). Moreover, the IQR for RMSD shows that North America has the smallest uncertainties while Australia has the largest ones. The IQRs in other continents are relatively similar. Combining the RMSD and gauge density as in a Taylor plot (Figure 7b), Europe stands out to be the top continent to be able to take advantage of ER products for research and operations. Beyond that, the Americas and Asia could also be suitable continents for applying such ER products. Unfortunately, the continent of Africa that needs satellite data the most for flood alerting and water resource management suffers the most from large discrepancies and low gauge densities. Even though it does not imply ER is not suitable in these regions, further attentions should be drawn when using ER for applications.

3.4.3 Climates

Figure 8 depicts the normalized instantaneous hourly difference (RMSD_norm) for different climates according to the Köppen-Geiger classifications. Figure 8a shows the distribution of RMSD_norm, and Figure 8b complements it with standardized gauge densities. The mean RMSD_norms are ranked according to the following climates: arid (1.86), warm climate (1.21), equatorial (1.16) and snow (1.16), and polar (0.91). As a result, arid regions like North Africa and the Middle East have the largest instantaneous differences. When considering temperatures, the RMSD_norms are then ranked in the following order: hot arid (1.90), cold arid (1.79), extremely continental (1.67), hot summer (1.11), cold summer (1.07), and polar (0.87). Therefore, in general, arid regions with higher temperatures (i.e., hot arid regions) exhibit the highest instantaneous differences. This is likely due to the effect of sub-cloud evaporation causing large discrepancies between the remote-sensing estimates and in-situ observations, which lowers FR estimates from the initial ER values. Additionally, the forward-only morphing in ER may miss the short-duration rainfall events common in arid environments. Since most of the gauge networks are located in warm temperate regions, hot arid and cold snow regions remain the most problematic regimes for the GPM era.

3.5 Precipitation Extremes

Extreme precipitation is defined here as rainfall rates in the 99th percentile during the twenty-year time period at each grid cell (Liu and Zipser, 2015). Notably, IMERG precipitation rates are capped to a maximum of 120 mm h^{-1} in the current 06B version, which is likely to impact this extreme event analysis (Skofronick-Jackson et al., 2017). Due to the aforementioned fact that FR is heavily dependent on the gauge densities, the extreme precipitation rates captured by FR may not be homogenous. Figure 9a depicts the extreme rainfall rate analysis for ER and FR with the corresponding conditional differences. ER estimates a globally averaged extreme rainfall rate of 12.1 mm h^{-1}, which is 33.0% higher than FR (9.1 mm h^{-1}). While in contrast to previous results that the location with maximum annual rainfall occurs at the same place for ER and FR, the maximum extreme rainfall rates are more distant. The maximum for ER (60.0 mm h^{-1}) occurs in the Arabian Sea (57.4°E, 10.5°N) while FR (52.1 mm h^{-1}) is near Mount Hubbard (138.3°W, 59.9°N). In fact, the location of the maximum extreme rainfall rate estimated by FR is adjacent to the location with the maximum RB of annual rainfall in the Gulf of Alaska.

Instead of overestimation (RB>0) of ER in terms of annual rainfall average worldwide, the conditional RB (RB_cond) in extreme events is trivial (-0.08), though with 80% of the grid cells showing negative RB_cond. This indicates the comparable performance of ER and FR in capturing the extreme rainfall rates. The maximum RB_cond (30.3) is obtained in Egypt (30.5°N, 26.0°E), surrounded by deserts. This finding aligns well with previous results (i.e., climate zone analysis) of large differences in arid regimes. Moreover, the conditioned RMSD (RMSD_cond) over the globe is 4.87 mm h^{-1}, while the maximum (24.7 mm h^{-1})

observed at (84.7°E, 27.8°N) is in a mountainous region. This is again likely caused by the misrepresentation of orographic precipitation as discussed in Section 3.4.1.

4 Conclusions

This study presents a 20-yr intercomparison of GPM IMERG early run (ER), and final run (FR) precipitation products. These products are compared globally and regionally with a focus on the following three aspects: (1) precipitation climatology for water resource management, (2) instantaneous rainfall rate differences for general hydrometeorology, and (3) hydrological extremes for flood hazards.

Regarding precipitation climatology, the similarities and differences of rain detection and mean annual rainfall amount are evaluated. First, ER detects less rainy samples than FR over 79.6% of the grid cells, leading to an overall 8.4% under-detection in relation to FR. However, ER has higher mean annual rainfall amounts in 71.9% of the grid cells, yielding an average 12.0% higher amount. Over land, the relative bias (16.7%) is slightly exacerbated due to the diverse terrain that impacts precipitation dynamics and the emitted brightness temperatures.

The instantaneous rainfall rate differences between ER and FR are higher over land with RMSD and RMSD_norm (2.38 mm $h^{-1}$and 1.09) than ocean surfaces (2.18 mm $h^{-1}$and 0.84). This is again likely due to the heterogeneity of the land cover and terrain. When examining differences over continents, ER exhibits the most similarities with FR in Europe with the lowest RMSD (2.16 mm h^{-1}) where the rain gauge densities are highest. Meanwhile, over Africa, a continent in need of satellite data for its flood alert and water resources management systems suffers from the largest RMSD (2.82 mm h^{-1}). Regarding climate zones, hot arid regions (RMSD_norm=1.86) and cold snow regions (RMSD_norm=1.16) remain the most problematic places for the GPM-era algorithms. We also found in this study that grid boxes containing gauges have higher differences than those grid cells containing no gauges, highlighting the effect of the gauge-based correction that was applied.

For extreme precipitation (i.e., the top 1%), the globally averaged rainfall rate for ER (12.1 mm h^{-1}) is 33.0% higher than with FR (9.1 mm h^{-1}). In contrast to mean rainfall estimates, the RB conditioned on extreme events shows that ER slightly measures less intense rainfall over the globe.

The similarities and differences revealed in this study can provide a broad overview of the circumstances for using ER. First, in long-range simulations (i.e., decadal/annual scale), ER is biased, and some statistical bias correction methods should be applied prior to use. Second, for mid-range simulations (i.e., monthly/weekly scale), ER can be conditionally applied in regions that have acceptable instantaneous differences (e.g., Europe/cold regions). Lastly, for short-range simulations (daily/hourly scale), ER is appropriate for hydrometeorological applications such as the early warning or alerting of precipitation-induced hazards. Future events-based studies aided by hydrologic modeling are necessary to examine the flood prediction capabilities of ER versus FR.

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