

Understanding Overland Satellite-Based Precipitation Errors in IMERG Products as a Function of Input Sources

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ABSTRACT

The multi-satellite precipitation product from the U.S. Global Precipitation Measurement (GPM) mission Science Team, the Integrated Multi-satellitE Retrievals for GPM (IMERG), is a widely used GPM product. It merges precipitation retrievals from passive microwave (PMW) and infrared (IR) sensors onboard a collection of satellites operated by several agencies around the globe. IMERG retrospectively provides over two decades' global precipitation data at fine temporospatial resolutions. This overland study evaluates the satellite-based precipitation statistics in the latest versions of IMERG (V06B and V07B) products over the Conterminous United States. High-resolution, ground-based radar precipitation estimates from a quality-controlled version of the Multi-Radar Multi-Sensor system—developed under the GPM Ground Validation effort—are used as the reference product. The relative performance of the two IMERG versions is evaluated using volumetric and categorical statistical metrics. The precipitation retrieval errors are further separated into three individual components: hit bias, missed-precipitation bias, and false-precipitation bias, and all traced back to the sensor-specific sources, as well as different levels of the IR input usage. The evaluation highlights the clear improvement in IMERG V07B precipitation product for all seasons, especially for winter, with reduced systematic bias and uncertainty, and increased precipitation detectability in comparison with V06B. The changes in V07B include use of input data processed with improved algorithms for both PMW and IR retrievals, the addition of PMW retrievals over frozen surfaces, and upgrades in the intercalibration that address sources of bias in V06B.

SIGNIFICANCE STATEMENT

This study conducts the first extensive evaluation of IMERG V07B against V06B at their native resolutions using ground-based radar data over CONUS, and traces errors in IMERG products back to specific sensors and the use of infrared data. The results indicate that the changes in V07B clearly improved the performance of IMERG estimates, with reduced systematic bias and uncertainty, and improved precipitation detection.

1. Introduction

Precipitation is one of most important elements in Earth system studies. The precise estimate of precipitation is essential to improving scientific understanding of the hydrologic cycle and risk management. Enormous success in satellite-based precipitation observation has

47 been achieved by NASA and JAXA with the successful Tropical Rainfall Measuring Mission
48 (TRMM; 1997–2015) (Simpson et al. 1996; Kummerow et al. 1998) and its successor, the
49 Global Precipitation Measurement mission (GPM; 2014–present) (Hou et al. 2014;
50 Skofronick-Jackson et al. 2017). GPM has been operating since 2014 with the launch of its
51 Core Observatory satellite and continuously delivering global precipitation estimates with
52 enhanced accuracy, expanded coverage, and finer temporospatial resolution. Its high-
53 resolution gridded algorithm, the Integrated Multi-satellitE Retrievals for GPM (IMERG) is a
54 next-generation precipitation product and has been the most used U.S. GPM product (Portier
55 et al. 2023). The IMERG algorithm combines precipitation estimates from different passive
56 microwave (PMW) sensors onboard the GPM constellation of low-Earth orbit satellites of
57 opportunity, and relatively low-quality precipitation estimates from infrared (IR)-based
58 sensors onboard the international collection of geosynchronous weather satellites. The
59 algorithm is calibrated and refined using data from the GPM Core Observatory, which carries
60 a dual-frequency precipitation radar (DPR) operating at Ku- and Ka-bands. This enables
61 higher-accuracy and more detailed three-dimensional precipitation measurements, including
62 improved detection of light rain and snow, better estimation of precipitation intensity, and
63 retrieval of drop size distributions. These capabilities mark a major advancement over the
64 single-frequency (Ku-band only) precipitation radar (PR) used in the TRMM mission. Given
65 the diversity of contributing sensors, the error in IMERG estimates results from a
66 combination of the errors coming from diverse contributing sensors' retrieval algorithms.

67 To continually improve the IMERG estimates, the product has been upgraded multiple
68 times, starting from the Version (V) 03 released in Jan 2015 to the latest V07 released in July
69 2023. Many upgrades have been applied in V07. Because of its advancements over all
70 previous versions, IMERG V07 has drawn considerable attention from the scientific and
71 applications communities since its release. An improved understanding of satellite-based
72 precipitation errors in IMERG products is of paramount importance for assessing suitability
73 in a wide range of scientific research, and especially for hydrometeorological applications.

74 Previous versions of IMERG products have been evaluated against each other, other
75 satellite-based products, gauges, and gauge-adjusted ground-radar data, globally and
76 regionally, over land and ocean. For instance, globally, Li et al. (2021) examined the
77 similarities and differences between V06 IMERG Early and Final Runs based on a 20-year
78 comparison, which provided a broad application overview for each product. Regionally,

Hamza et al. (2020) evaluated IMERG V06 and three other satellite-based products with the measurements from 24 gauges in the Hindu Kush Mountains of Pakistan. Bolvin et al. (2021) compared the monthly IMERG V06 Final Run precipitation estimates with gauge observations from 37 Pacific Ocean atolls; they found that IMERG underestimates light precipitation and overestimates heavy precipitation, which results in an overall slight overestimation bias of 0.67%. Wang et al. (2022) validated IMERG V05 and V06 precipitation products against oceanic observations from an S-band radar covering the waters surrounding Kwajalein in the central Pacific Ocean, and demonstrated that IMERG V06B outperforms V05B with reduced systematic bias and improved precipitation detectability. Derin et al. (2021, 2022) examined IMERG V06 performance over the coastal regions of the Conterminous United States (CONUS); they found better IMERG detection over ocean but with false alarms, and overestimation of the light rain rates and underestimation of high rain rates. It is worthwhile to mention that some early evaluations for IMERG V07 have been published. Wang et al. (2023) provided an early comparison of IMERG V07 against V06 over the globe and further compared V07 and V06 against rain gauges over China; the results showed noticeable differences between V07 and V06 precipitation estimates across scales. Aksu and Yaldiz (2025) validated the accuracy of IMERG V07 with gauge measurements and compared the V07 against V06 over Turkey; they found some notable improvements from V06 to V07 for all seasons, especially in winter. Zhu et al. (2024) quantified the enhancements of IMERG V07 against V06 over CONUS with emphasis on hydrologic applications. However, an assessment of IMERG V07 and its predecessor V06 with a focus on specific changes in the algorithm is still very limited to date, especially from different sensor-specific sources onboard various satellites.

This study investigates the satellite-based precipitation errors in the latest versions of IMERG (V06B and V07B) products over the CONUS across the GPM era in the period from June 2014 to August 2021. Note that V06B and V07B are the second retrospective processing for the respective algorithms after production issues were discovered. V06B corrected two issues in V06: 1) PMW precipitation estimates over frozen surfaces between 60°N-S were inadvertently retained, and 2) a damaged land/ocean map was employed in the Kalman filter module (Huffman et al. 2020). V07B removed very occasional, highly problematic sensor orbits in V07 (Huffman et al. 2024a).

The objective of this validation study is to further understand IMERG error characteristics over land, and to attribute these errors to specific inputs and methods within the IMERG algorithm. The error sources contributing to the IMERG precipitation estimate are identified at the 0.1° pixel and 0.5-h temporal resolution. High-resolution, ground-based radar precipitation estimates from a quality-controlled version of Multi-Radar Multi-Sensor system (MRMS)—developed under the GPM Ground Validation effort (GV-MRMS)—are utilized as the reference product. The volumetric and categorical statistical metrics are used to quantitatively evaluate the performance of the two satellite-based products. The precipitation errors are further traced back to the sensor-specific sources and different levels of the IR input utilization.

This study is presented in five sections. Section 2 provides information about the study region and introduces the satellite-based precipitation products and their contributing sources, as well as the ground-based reference products. Section 3 describes the study methodology and statistical metrics employed to evaluate the performance of IMERG products and the sources of error. Section 4 presents the results of the comparison between IMERG and GV-MRMS, and specifically discusses the contribution of errors from the individual sources. Finally, the main findings and discussions are provided in Section 5.

2. Study area and data sources

a. Study area

This study is carried out over the land area with latitude bounds of 25° and 50°N and longitude bounds of 125° and 65°W (Fig.1). This area is mainly CONUS along with parts of southern Canada and northern Mexico, which has a varied topography. Hills and relatively lower mountains are in the east, a vast plain is in the central interior, and high rugged mountain ranges are in the west. Due to CONUS' large size and wide range of geographic features, the precipitation systems differ substantially across the area and by season, including tropical and midlatitude cyclones, isolated thunderstorms, orographic precipitation, supercells, etc. Precipitation measurement and monitoring over CONUS have been greatly improved because of the deployment of the Next Generation Weather Radar network, along with a relatively dense and well-maintained network of rain gauges, which makes this area a prime region for evaluating overland satellite-based precipitation products. We restricted the study to land areas only due to the absence of rain gauges and radar coverage over the ocean.

A land/water mask (Fig. 1) with a 0.1° resolution is derived from the GPM Core Observatory's Microwave Imager (GMI) footprint surface type data. Here “water” is defined as oceans, gulfs, and the Great Lakes; all other surfaces are defined as “Land” and considered in this study. For IMERG satellite precipitation validations over oceans and land–coast–ocean continuum, the reader is referred to Wang et al. 2022, Watters et al. 2023, and Derin et al. 2021, 2022.

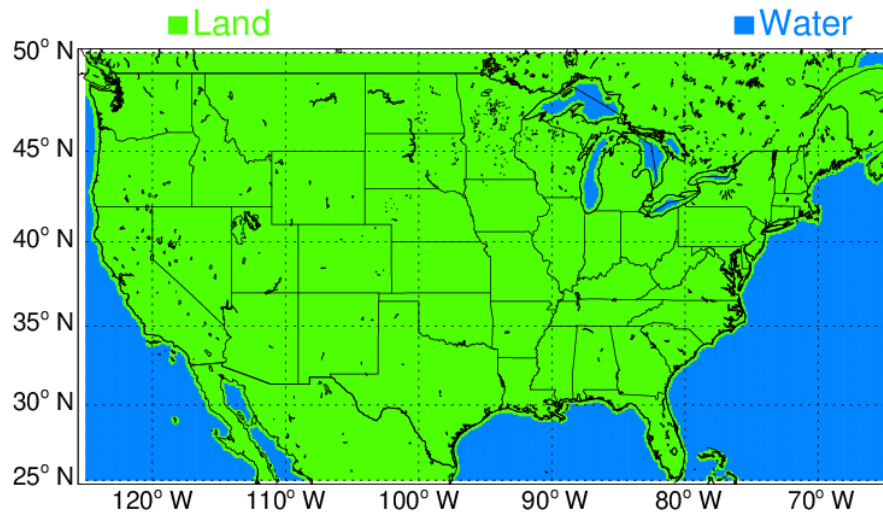


Fig. 1 Study area with the land/water mask at 0.1° resolution.

b. Monthly GPCC

To support long-term precipitation analyses and monitoring, the Global Precipitation Climatology Centre (GPCC) was established in 1989 at the request of the World Meteorological Organization (WMO), and is operated by Deutscher Wetterdienst (DWD), National Meteorological Service of Germany. GPCC generates suites of gridded precipitation analysis products from quality-controlled gauges worldwide via the WMO's Global Telecommunication System. In this study, the monthly GPCC Monitoring Product (GPCC_MP; Schneider et al. 2022a) at 1° resolution is used to assess the agreement between IMERG products and gauge-based precipitation estimates over land, as well as to evaluate GV-MRMS reliability at the monthly scale. GPCC_MP is one of the IMERG contributing data sources, providing monthly land-surface precipitation based on synoptic weather observation and monthly CLIMAT reports from 7,000 –9,000 gauges. The product is updated monthly, approximately three months after the observation month, and is often used for

calibration of satellite data. Other GPCC products (e.g. the Full Data monthly analysis [GPCC_FD; Schneider et al. 2022b]) suggested for hydrometeorological studies with a similar quality control and the same analysis scheme, may be of better accuracy and finer resolution compared to the GPCC_MP. However, they are not updated at regular time intervals due to their dependency on major data base improvements. As of this writing, the GPCC_FD is only available to 2020, which cannot fully cover our study period. Hence, the GPCC_MP is selected for this study. Table 1 lists all the products used in this study and their temporal and spatial resolutions.

Table 1. Specifications of data products used in this study.

Product	Spatial Resolution	Temporal Resolution
GPCC Monitoring Product	1°×1°	1 month
GV-MRMS	0.01°×0.01°	30 minutes
IMERG V06B	0.1°×0.1°	30 minutes
IMERG V07B	0.1°×0.1°	30 minutes

b. GV- MRMS

The MRMS system was originally developed by the National Severe Storms Laboratory (NSSL) to integrate data from ground radars and rain gauges in CONUS and southern Canada (Zhang et al. 2016). The MRMS products used in this study (GV-MRMS) undergo additional postprocessing specifically for the support of GPM Ground Validation (Kirstetter et al. 2012). The postprocessing includes gauge calibration of the radar product, resampling, and quality controls. The precipitation and radar quality index (RQI) products in GV-MRMS are at half-hourly and 0.01° resolutions. The RQI, generated for quality control, serves as an indicator of sampling and estimation uncertainty, depending on the radar beam sampling characteristics and the extent of beam blockage due to topography (Zhang et al. 2011). The RQI ranges from 0 (worst quality) to 100 (highest quality). The high-quality reference product is crucial for evaluating and understanding the error structure of satellite-based precipitation. The low-quality GV-MRMS data can be filtered out for specific temporal periods through comparisons with other precipitation products and for certain spatial areas by using the RQI.

A previous study for the comparisons among monthly precipitation rates over the CONUS from GPCC, GV-MRMS, TRMM 3B42 and GPM IMERG revealed that

precipitation from GV-MRMS during August 2017 to February 2018 are not reliable (Wang et al. 2021). Additionally, GV-MRMS data from January to May 2016 are missing because of several GV-MRMS system issues during the period (P. Kirstetter 2019, personal communication). Hence, these 12-month data (January - May 2016 and August 2017 - February 2018) are excluded from the study. From the commonly available 75-month datasets for both GV-MRMS and IMERG products, there are 5 winters (December 2014 to February 2015, December 2016 to February 2017, December 2018 to February 2019, December 2019 to February 2020, and December 2020 to February 2021) and 7 summers (June to August in 2014-2016, and 2018-2021) which will be analyzed.

Figure 2 shows the spatial distribution of GV-MRMS sampling frequencies with the best RQI (100). The sampling frequency is calculated at each 0.1° pixel and is defined as the percentage of the sample size for the best GV-MRMS data over the total sample size for all GV-MRMS data during the study period. High-quality samples appear most often in the central and eastern parts of the United States, with its maximum coverage in the southern part of the study region. In the Intermountain West, GV-MRMS's coverage is considerably spottier, and the quality is lower due to severe blockages by the complex terrain. The GV-MRMS data samples shrink to 38.64% for the entire study period when the RQI is set to 100.

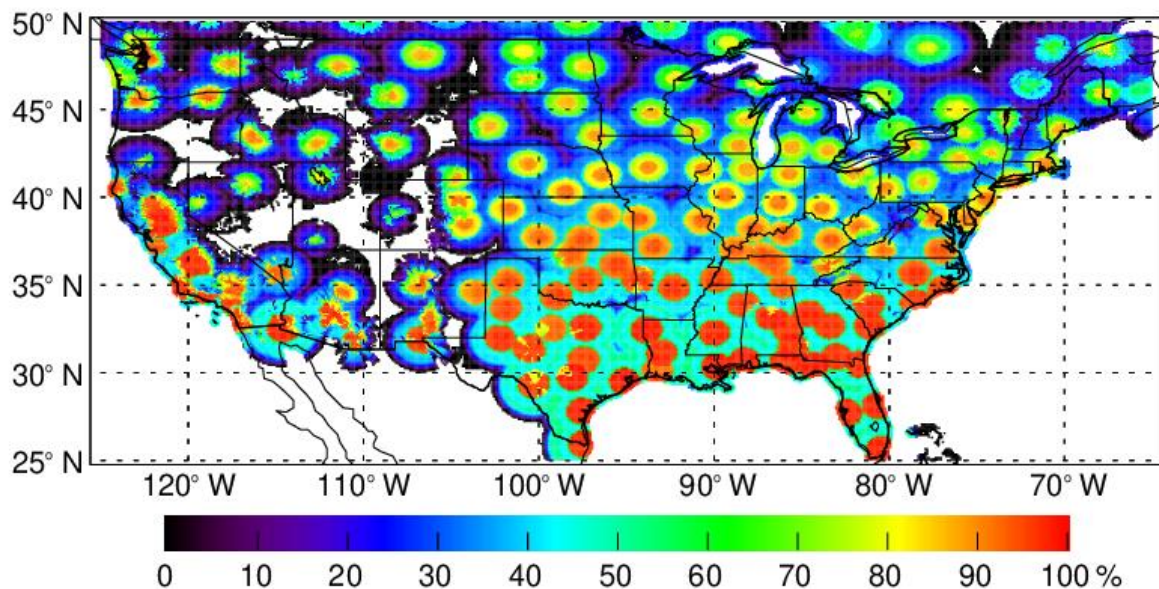


Fig. 2. Spatial distribution of GV-MRMS sampling frequencies. The frequency for each 0.1° pixel is defined as the percentage of the sample size of the GV-MRMS data with RQI of 100 over the total sample size for all GV-MRMS data.

d. *GPM IMERG products and their contributing sources*

IMERG is a gridded satellite-based precipitation product with global coverage at 0.1° every half-hour from June 2000 onwards and January 1998 onwards in V06B and V07B, respectively (Huffman et al. 2020, 2024a). The IMERG algorithm combines observations from the GPM constellation of low-orbiting satellites operated by multiple international partners including the USA, Japan, India and the European Union. Using the V07 Goddard Profiling Algorithm (GPROF; Kummerow et al. 2015; Pfreundschuh et al. 2024), the half-hourly precipitation estimates at 0.1° grids are retrieved individually from each PMW sensor onboard different satellite. The gridded PMW estimates are inter-calibrated to the Combined Radar-Radiometer Algorithm (CORRA; Grecu and Olson 2020, Olson 2018), which is based on coincident observations from the DPR and GMI on the GPM Core Observatory, as well as PR and TMI on the TRMM satellite. The calibrated estimates are then merged onto half-hourly $0.1^\circ \times 0.1^\circ$ maps. To fill temporal and spatial gaps between available PMW sensor swaths, quasi-Lagrangian time interpolation is applied to propagate the gridded PMW estimates forward and backward using displacement motion vectors (Tan et al. 2019). Meanwhile, an IMERG-specific adjustment using PMW precipitation estimates is applied to Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks–Dynamic Infrared Rain Rate (PDIR-Now; Nguyen et al. 2020) estimates of precipitation, which are based on an indirect relationship between the cloud top IR brightness temperature and the surface precipitation. Then, the forward- and backward-propagated PMW precipitation and the IR precipitation are merged via the Kalman filter-based morphing technique adapted from Joyce and Xie (2011). Thereafter, the Scheme for Histogram Adjustment with Ranked Precipitation Estimates in the Neighborhood (SHARPEN; Tan et al. 2021) is applied to the Kalman filter output to mitigate the averaging-induced distortion of the precipitation distribution (Rajagopal et al. 2021). Finally, the IMERG estimates over land are adjusted using the GPCC monthly gauge precipitation data to improve the accuracy after real time, and a seasonally varying climatological adjustment to GPCC in near-real time for V07B, but not V06B. To satisfy the various user needs and applications with different latency requirements, three IMERG products are generated, namely near-real time “Early” and “Late” Runs, and the post-real time “Final” Run with approximate latency of 4 h, 12 h, and 4 months, respectively. The IMERG development team continues to regularly upgrade and

refine the algorithm for the improvement of the global precipitation estimates. Currently, V07B is the latest version of IMERG.

Some noteworthy upgrades incorporated into the V07 algorithm include the following: PMW estimates are included over frozen surfaces, as an investigation suggested that PMW estimates may be useful over frozen surfaces (Huffman et al. 2024a); PMW intercalibration is improved to correct for biases; IR data quality control is automatically implemented, and the IR precipitation algorithm is updated to PDIR–NOW to replace the previous Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN-CCS; Hong et al. 2004); a 0.1° eastward offset in gridding of CORRA and GPROF in all previous versions is fixed (Watters et al. 2024); SHARPEN is implemented to mitigate the distortion of the precipitation distribution (Tan et al. 2021); SAPHIR is excluded from the PMW inputs in V07 due to its overall poor performance with the then-current algorithm (Wang et al. 2022; You et al. 2020; Sui et al. 2020); a joint Fuchs-Legates correction is implemented to mitigate the large under-catch by the Legates-Wilmott scheme in the GPCC gauge analysis over north of 45°N (Behrangi et al. 2018, 2019); and several variables within the half-hourly HDF5 file are renamed and re-organized to minimize misinterpretation. The full list of the changes from V06 to V07 can be found in Huffman et al. (2024a).

The two latest versions of IMERG (V06B and V07B) Final Run products are used in this study. Both IMERG V06B and V07B are reprocessed for the entire TRMM-GPM record, beginning June 2000 for V06B and January 1998 for V07B. The Final Run of IMERG is selected because it is at the best quality of all three runs due to the application of monthly gauge calibration, as well as the utilization of all available satellite data.

Various precipitation-relevant PMW sensors onboard different satellites contribute to IMERG precipitation estimates. The IMERG ancillary variable *MWprecipSource* in V07B or *HQprecipSource* in V06B provides the sensor information used in PMW precipitation estimates. Table 2 lists all these 7 sensors from 14 satellites contributing to IMERG over CONUS for this study period (June 2014-August 2021). Among these sensors, TMI, AMSR-2, SSMIS and GMI are conical-scanning imagers, whereas MHS, ATMS and SAPHIR are cross-track sounders. Note that SAPHIR was used in V06B but is excluded from V07B. The altitude of the GPM Core Observatory was raised from 407 km to 442 km after two orbit boost maneuvers on November 7 and 8, 2023.

Naturally, the errors from all the aforementioned sources and satellite-based precipitation products propagate into IMERG. To evaluate the effect of each IMERG contributing source, we categorize IMERG precipitation estimates (*precipitationUncal*) according to each of the 7 PMW sensors listed in Table 2 for their respective PMW overpass precipitation estimates. In addition, for IR and propagated (p) PMW estimates, we use the IR weights provided as a data variable in the IMERG files to categorize the IMERG estimates into three levels of IR use: propagated PMW only (PMW_p-only) if the weight is 0%; IR-only if the weight is 100%; and a mixture of PMW_p and IR (IR+PMW_p) if the weight is anything in between. Note that V07, unlike V06, includes a small addition of propagated PMW in its PMW overpass precipitation estimates, which will be further discussed in Section 4d.

Table 2. Satellite sensors contributing to IMERG for June 2014- August 2021. Note that SAPHIR was included in IMERG V06 but excluded from V07.

Sensor Acronym	Sensor Name	Sensor Type	Scan Pattern	Carrying Satellite	Altitude (km)	Swath (km)	Coverage
TMI	TRMM Microwave Imager	Imager	Conical	TRMM	402	878	38°N–38°S
AMS2	Advanced Microwave Scanning Radiometer Version 2	Imager	Conical	GCOM-W1	700	1,450	85°N-85°S
SSMIS	Special Sensor Microwave Imager/Sounder	Imager	Conical	DMSP-F16-19	833-850	1,707	85°N-85°S
GMI	GPM Microwave Imager	Imager	Conical	GPM Core	407-442	904	65°N-65°S
MHS	Microwave Humidity Sounder	Sounder	Cross-track	NOAA-18,19; MetOp-A, B	817-870	1,650-2,348	global
ATMS	Advanced Technology Microwave Sounder	Sounder	Cross-track	Suomi-NPP, NOAA-21	825	2,500	global
SAPHIR	Sounder for Atmospheric Profiling of Humidity in the Intertropics by Radiometry	Sounder	Cross-track	Megha-Tropiques	850-868	1,700	28°N-28°S

3. Methodology and Evaluation Metrics

IMERG, GV-MRMS and GPCC products are used in this study. First, GV-MRMS data reliability will be evaluated using GPCC, then IMERG will be evaluated against GV-MRMS.

GV-MRMS data are averaged from their native resolution of $0.01^\circ \times 0.01^\circ$ to IMERG-matched resolution of $0.1^\circ \times 0.1^\circ$ so that comparisons are collocated at the same nominal resolution. The two IMERG Versions (V06B and V07B) are evaluated using volumetric and categorical statistical metrics. The volumetric statistics, also called continuous statistics in some studies (e.g. Wu et. al 2018), are based on continuous precipitation volume. The volumetric statistics used in this study are Pearson correlation coefficient (CC), relative bias

(Bias), normalized mean absolute error (NMAE) and normalized root-mean-square error (NRMSE). CC quantifies the random error while Bias quantifies the systematic error; NMAE and NRMSE quantify the total error. Categorical statistics are based on precipitation occurrences within distinct categories (e. g. hit-or-miss), evaluating the detection ability for the satellite-based products. The probability of detection (POD), false-alarm ratio (FAR), and Heidke Skill Score (HSS) are used in this study.

To calculate categorical statistics, a simple 2×2 contingency table for a given precipitation or no precipitation threshold (0.1 mm h⁻¹) is constructed to divide pairs of precipitation rates from IMERG and GV-MRMS into hit (h), miss (m), false (f), and correct negative (c). For example, a hit occurs when a precipitation event is detected by both IMERG and GV-MRMS. POD, FAR and HSS can be calculated from h, m, f, and c. Both volumetric and categorical statistics are calculated at the 0.1° and 0.5 h resolutions using the equations listed in Table 3.

Table 3. A list of statistical metrics used in this study, where x_i and y_i are individual precipitation rates for reference (GV-MRMS) and satellite-based products (IMERG), respectively; $\bar{x}$ and $\bar{y}$ are their respective mean precipitation rates; n is sample size; h , m , f and c are the numbers of hits, misses, false alarms and correct negatives, respectively.

Metric	Formula	Range	Perfect Value
Correlation coefficient (CC)	$CC = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$	[-1, 1]	1
Relative bias (Bias)	$\text{Bias} = \frac{\bar{y} - \bar{x}}{\bar{x}} \times 100\%$	$(-\infty, \infty)$	0
Normalized mean absolute error (NMAE)	$\text{NMAE} = \frac{ \bar{y} - \bar{x} }{\bar{x}} \times 100\%$	$[0, \infty)$	0
Normalized root-mean-square error (NRMSE)	$\text{NRMSE} = \frac{\sqrt{\frac{1}{n} \sum_i (y_i - x_i)^2}}{\bar{x}} \times 100\%$	$[0, \infty)$	0
Probability of detection (POD)	$\text{POD} = \frac{h}{h + m}$	[0,1]	1
False alarm rate (FAR)	$\text{FAR} = \frac{f}{h + f}$	[0,1]	0

Heidke skill score (HSS)	$HSS = \frac{2(hc - fm)}{(h + m)(m + c) + (h + f)(f + c)}$	$(-\infty, 1)$	1
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In addition, a volumetric error decomposition approach (Tian et al. 2009) is utilized to decompose the total precipitation bias (T) into three independent components: (1) hit bias (H) where precipitation is detected by both IMERG and GV-MRMS, but IMERG either overestimates or underestimates precipitation relative to GV-MRMS; (2) bias due to missed precipitation (M) by IMERG; and (3) bias due to false precipitation detection (F) by IMERG. By definition, M is always negative whereas F is always positive. The three components sum up to the total precipitation bias: $T = H + M + F$.

4. Results and discussions

a. Spatial distribution of mean monthly precipitation

Figure 3 shows monthly precipitation maps for GPCC_MP, GV-MRMS ($RQI \geq 0$), and IMERG (V06B and V07B, Uncalibrated [Uncal] and gauge-Calibration [Cal]), from 75 months, 5 winters, and 7 summers, respectively, over the period of June 2014-August 2021. As mentioned in Section 2, the spatial resolution for IMERG and GV-MRMS is 0.1° whereas the resolution for the GPCC product used is 1° . The overall relative bias and spatial pattern correlation against GV-MRMS are included at the bottom right on the IMERG precipitation maps. IMERG V07B outperforms V06B in terms of both relative bias and pattern correlation except for summer when the V07B Cal bias is marginally larger in magnitude, and for 75 months when the V07B Uncal correlation is slightly smaller.

For the 75-mon average, all products exhibit a similar precipitation pattern with abundant precipitation in the Southeast and Pacific Northwest, and relatively lower precipitation in the western CONUS. However, noticeable differences exist among the four products. Some gaps of GV-MRMS coverages appear in western CONUS in winter. This is mainly because of snowfall and radar beam blockages caused by the complex terrain. The precipitation gradients in all IMERG products are smoother than in GV-MRMS, likely due to the challenges of satellite precipitation in capturing fine-scale spatial variability. Additionally, the precipitation gradient in IMERG Cal is smoother than in IMERG Uncal. This is a result of the smoothing effect from the GPCC gauge interpolation, which is carried over through the gauge adjustment. IMERG Cal best reproduces the precipitation pattern of GPCC as it is adjusted

337 using monthly GPCC gauge data. IMERG V06B severely overestimated wintertime
 338 precipitation (Huffman et al. 2024a) which is still evident even after the gauge adjustment.
 339 The overestimation for wintertime precipitation is reduced from 14.9% in V06B Cal to 8.1%
 340 in V07B Cal (Fig. 3).

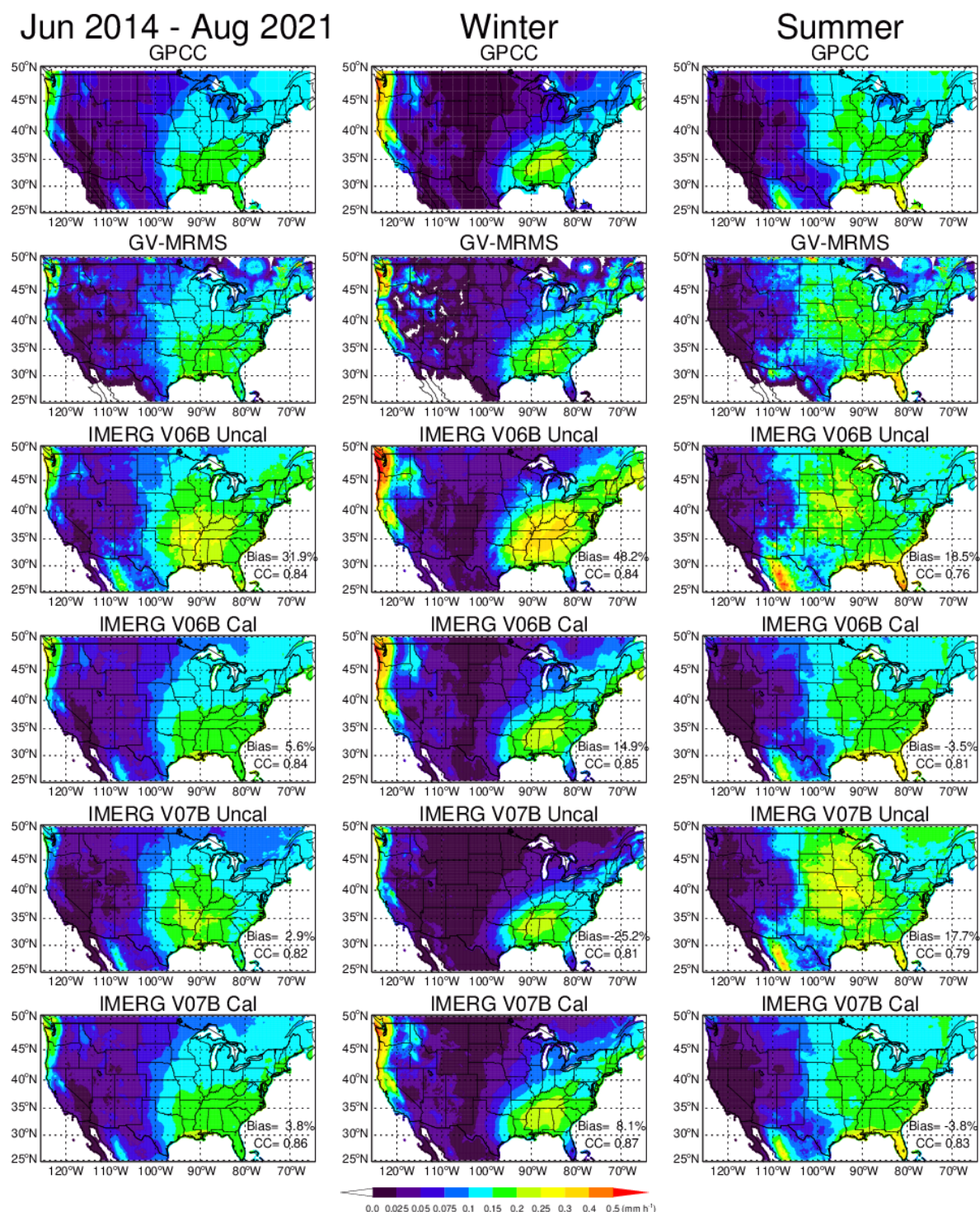
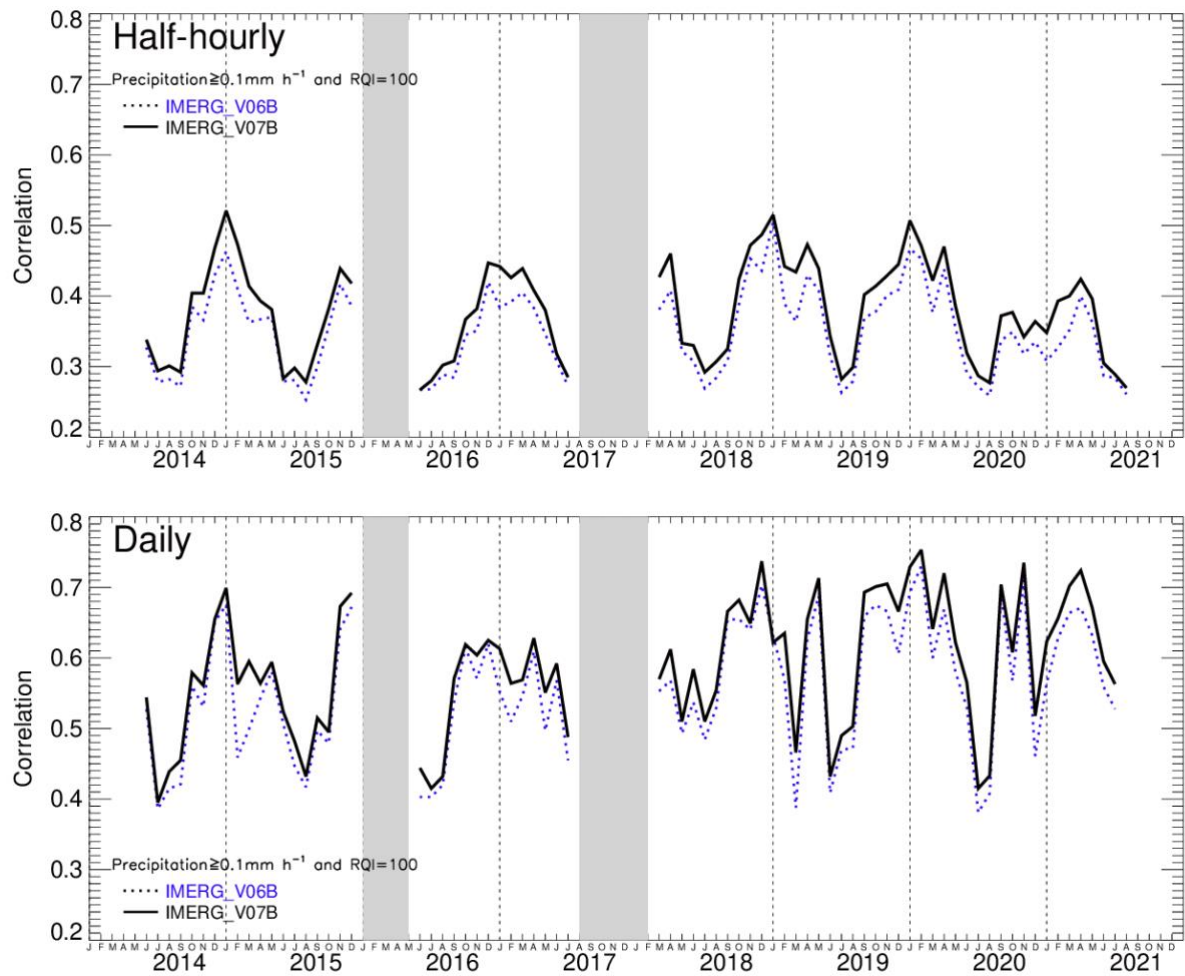


Fig. 3. Monthly precipitation maps for GPCC_MP, GV-MRMS(RQI $\geq$ 0), IMERG V06B Uncal, V06B Cal, V07B Uncal and V07B Cal from (left) 75 months, (middle) 5 winters, and (right) 7 summers, respectively, over the period of June 2014-August 2021. The spatial resolution for IMERG and GV-MRMS is 0.1° whereas the resolution for GPCC is 1°.

b. Temporal distribution of monthly correlation coefficients

Figure 4 shows the time series of monthly correlation coefficients between IMERG and GV-MRMS precipitation rates. Two sets of correlations are computed using precipitation data from 0.1° pixels: one based on half-hourly data (upper panel) and the other on daily data (lower panel). To increase confidence in the analysis, the data are filtered with two conditions: 1) RQI=100 for GV-MRMS and 2) precipitation at least 0.1 mm h⁻¹ for both IMERG and GV-MRMS data. Figure 4 clearly demonstrates that IMERG V07B constantly outperforms V06B throughout the study period. The correlation coefficients range from 0.25 to 0.52 for half-hourly precipitation and from 0.38 to 0.75 for daily precipitation, with generally higher correlations observed during winter months compared to summer. The clear contrast between the two panels highlights the impact of temporal resolution: daily correlations are markedly higher, reflecting reduced noise and temporal mismatches relative to half-hourly estimates. While the focus of this study is on evaluating IMERG at its native half-hourly resolution, the inclusion of daily correlations here provides important context by illustrating the inherent challenges and increased uncertainty involved in validating satellite

361 precipitation products at high temporal resolution.



362

363 *Fig. 4. Time series of correlation coefficients between IMERG (V06B and V07B) and GV-*
 364 *MRMS, calculated from half-hourly (upper panel) and daily (lower panel) precipitation at*
 365 *0.1° resolution for each month. Only pixels associated with GV-MRMS RQI value of 100 and*
 366 *precipitation at least 0.1 mm h⁻¹ for both IMERG and GV-MRMS are used. The grey bars*
 367 *indicate the periods excluded from this study.*

368 *c. Distribution of sampling frequencies for each IMERG source*

369 The error sources contributing to the IMERG precipitation estimate are identified for 0.1°
 370 pixels and 0.5-h intervals. Knowledge of the temporal-spatial coverages of IMERG sources is
 371 important in understanding the uncertainty in the satellite-based precipitation. Figure 5 shows
 372 the spatial distribution of the sampling frequencies for each of the ten IMERG sources,
 373 including four imagers (TMI, GMI, AMSR-2, SSMIS), three sounders (MHS, ATMS and
 374 SAPHIR), and three levels of IR use (IR-only, PMW_p-only and IR + PMW_p). The time
 375 series of monthly sample sizes for each IMERG V06B source are shown in Fig. 6. The
 376 sampling frequency at each 0.1° pixel is defined as the percentage of the sample size for each

source over the total sample size for all sources during the study period. Here, ‘sources’ include both the PMW sensor types identified by the ancillary variable *MWprecipSource* in V07B (or *HQprecipSource* in V06B), and the three levels of IR use indicated by the variable *IRinfluence* in V07B (or *IRkalmanFilterWeight* in V06B), as described in Section 2d.

PMW_p and IR+PMW_p together contribute 61.08% of the total samples (Fig. 5). The weighting in the IMERG algorithm ends up emphasizing PMW sensors, and then propagated PMW data, with PMW-calibrated IR data to fill the PMW gaps. The IR contribution to IMERG depends on the latitude and season. In general, the IR contributes less over the southern region of CONUS in warm seasons and more over northern regions in cold seasons (Figs. 5 and 6). In V06B and earlier versions, IR precipitation was used instead of PMW precipitation over frozen surface, which has widespread coverage during the winter. However, in V07B, this longstanding policy of masking out PMW retrievals over frozen surfaces was removed as noted earlier. Therefore, PMW retrievals over frozen surfaces are used in V07B (Huffman et al. 2024a). As a result, IR-only samples in V07B during the GPM era are much rarer, occurring only when there is a gap between the forward propagated and the backward propagated fields. These samples were more frequent earlier in the record, when the PMW constellation was sparser.

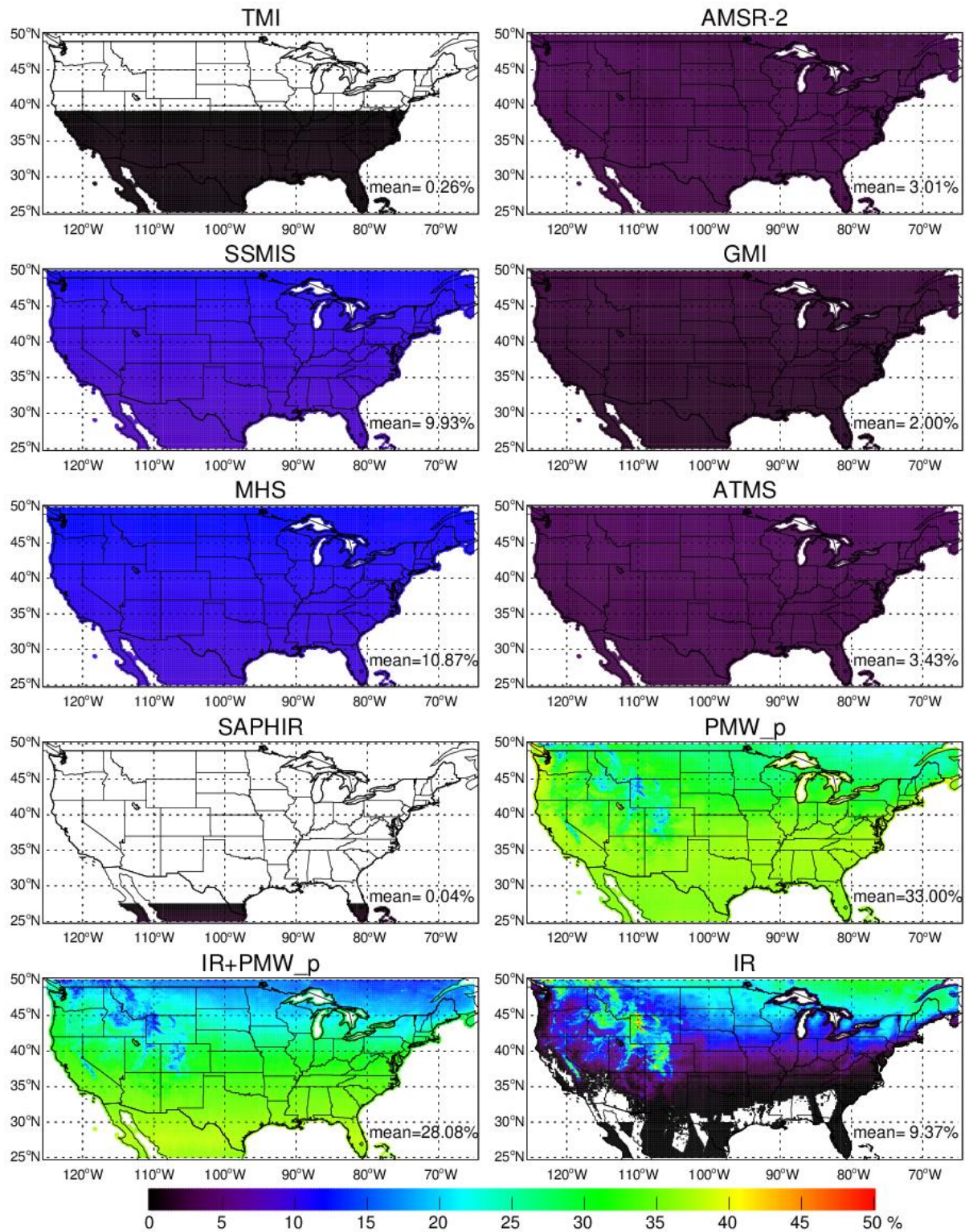
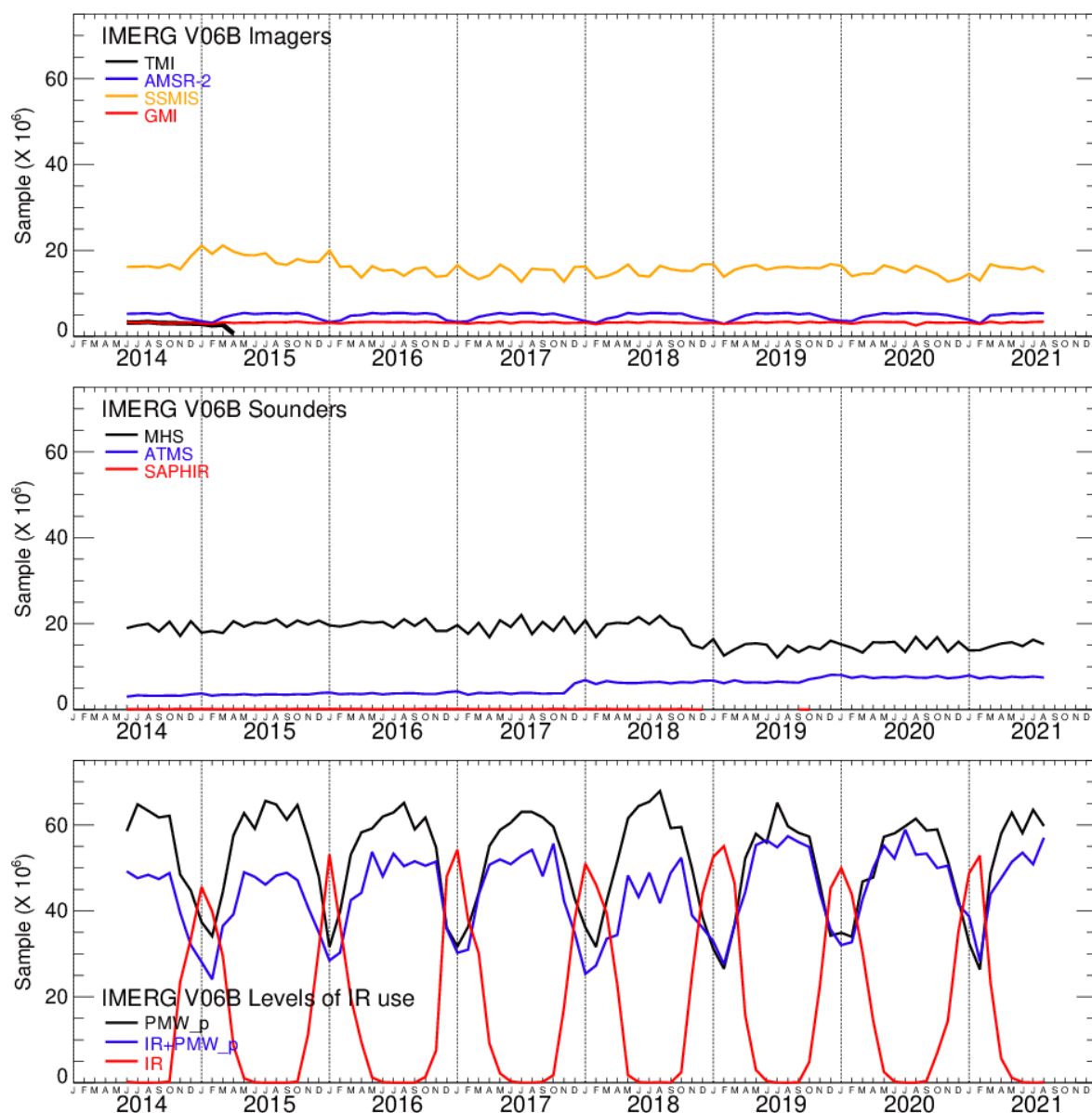


Fig. 5. Spatial distributions of the sampling frequencies for each of the ten IMERG V06B sources including four imagers (TMI, GMI, AMSR-2, SSMIS), three sounders (MHS, ATMS and SAPHIR), and three levels of IR use (IR-only, PMW_p-only and IR + PMW_p). The sampling frequency at each 0.1° pixel is defined as the percentage of the sample size for each IMERG source over the total sample size for all sources during the study period. The mean

400 *sampling frequency averaged over all land pixels – including those with and without*
 401 *sampling - is shown at the bottom right of each panel.*



402
 403 *Fig. 6. Time series of monthly sample sizes for each source of IMERG V06B. Upper:*
 404 *imagers (TMI, AMSR-2, SSMIS, GMI); middle: sounders (MHS, ATMS, SAPHIR); bottom:*
 405 *levels of IR use (IR, PMW_p, IR+PMW_p).*

406 MHS (on board the NOAA and MetOp series satellites) and SSMIS (on board the DMSP-
 407 F16-19 satellites) have wider swaths (Table 3), so they provide better spatial coverage (Figs.
 408 5 and 7) and thus contribute higher sampling (Figs. 6 and 8) relative to other sensors.
 409 Although having a comparable swath width with MHS and SSMIS, ATMS sounder
 410 contributes relatively fewer samples because the IMERG algorithm prioritizes SSMIS and

411 MHS over ATMS as the former two generally perform better than the latter (You et al. 2020;
412 Wang et al. 2022).

413 The sampling frequency for TMI is very low because TMI only covered latitudes up to
414 38°N and ceased scientific operations in April 2015 when the TRMM spacecraft was
415 deorbited.

416 SAPHIR onboard the French-Indian Megha-Tropiques Mission was included in V06B
417 (Figs. 5 and 6) for the purpose of enhancing the precipitation sampling in lower latitudes but
418 was excluded from V07B (Figs. 7 and 8). It is anticipated that SAPHIR will again be used in
419 IMERG V08 after the retrieval algorithm is revised. In V06B, SAPHIR contributed only
420 1.0% of total samples with an average of 0.1×10^6 samples per sampled month. It provided
421 data from June 2014 to December 2018, and then intermittently from September to October
422 2019 (Fig. 6), although the mission continued until March 2023. As such, we show SAPHIR
423 graphics for completeness, but do not further discuss it.

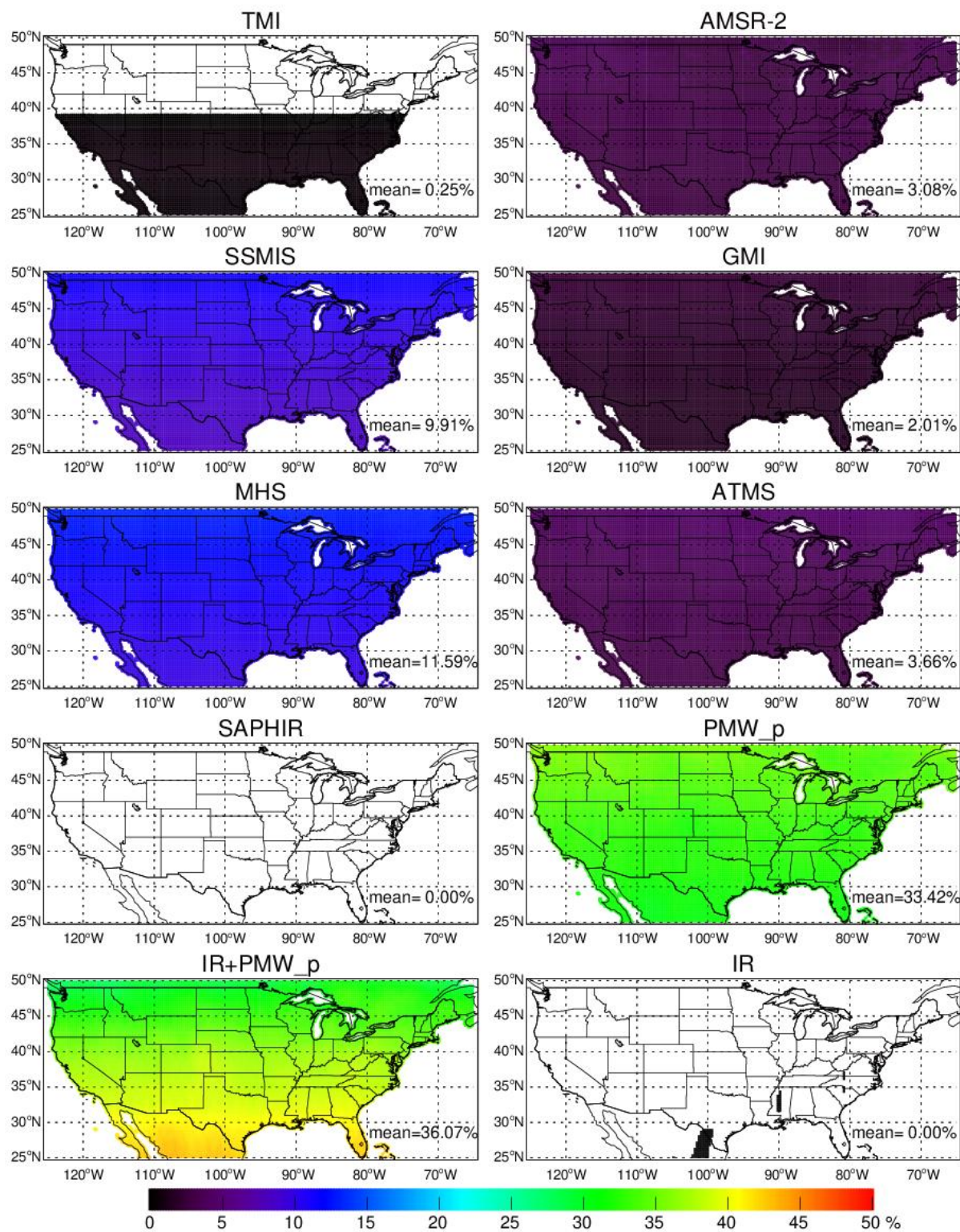


Fig. 7. Same as Fig. 5 except for IMERG V07B.

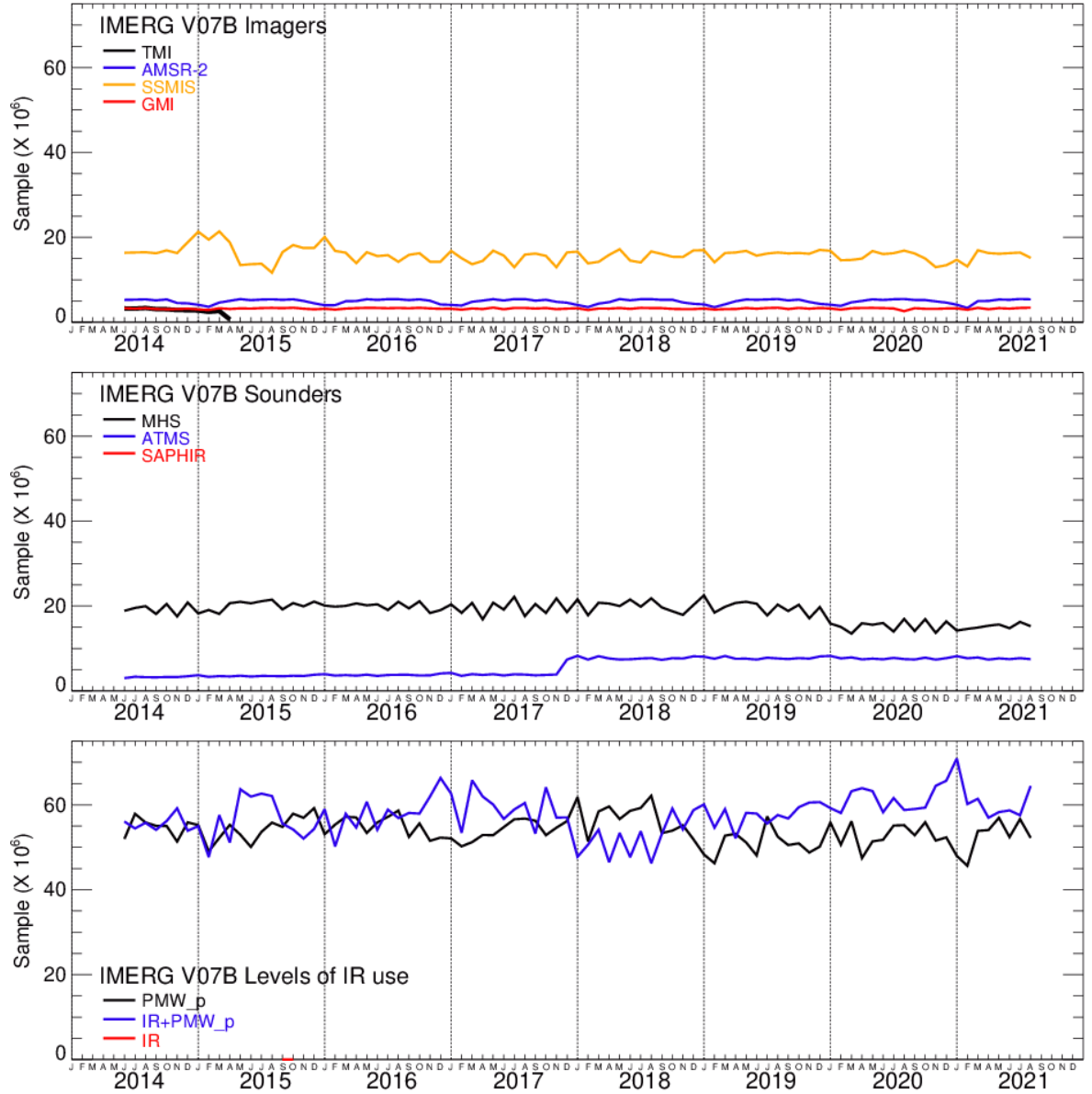


Fig. 8. Same as Fig. 6 except for IMERG V07B.

d. Statistical metric

The IMERG Final Run satellite-only data variable, *precipitationUncal* (prior to gauge calibration), instead of *precipitation* (after gauge calibration), is utilized in this analysis because the gauge-calibration step affects the contribution from each IMERG source and hence makes the analysis difficult. It is worth noting that for *precipitationUncal* in V07 (but not in V06), the PMW precipitation estimate combines instantaneous PMW-only precipitation with a small addition of propagated precipitation, as instantaneous PMW estimates are integrated into the Kalman filter (Huffman et al. 2024a). A purely PMW

assessment would require the use of *MWprecipitation* (instantaneous PMW-only precipitation estimate); however, the difference between the PMW precipitation estimates in *MWprecipitation* and *precipitationUncal* is minimal (see Supplementary Figs. S1 and S2), which aligns with expectations during IMERG V07 development. To incorporate all IMERG sources in the comparisons, including all PMW sensors and the three levels of IR usage, *precipitationUncal* is used in Figs. 9–14.

Figure 9 presents statistical metrics evaluating the performance of IMERG V06B as a whole and its individual sources, relative to GV-MRMS with an RQI of 100 for all 75 months. The sample size in the upper right of Fig. 9 is the number of matched 0.1 ° pixels for IMERG (or each IMERG source) and GV-MRMS with condition of precipitation rates at least 0.1 mm h⁻¹. The total sample size for all IMERG sources is 159,153,282. The sample sizes for different sources are very different, ranging from 20,244 (0.01%) for SAPHIR to 60,907,454 (38.27%) for propagated PMW (PMW_p). About 28.68% of the total samples are directly from PMW overpasses in the half hour, whereas 71.32% are from PMW_p, IR-only and IR+PMW_p mixture. The IMERG source with larger sample size certainly has more impact to the overall IMERG performance.

Imagers (TMI, AMSR-2, SSMIS, GMI) generally perform slightly better than sounders (MHS and ATMS for both V06B and V07B, and SAPHIR for V06B only) in terms of most metrics. Among four imagers, TMI and GMI are the best overall. However, TMI only accounts for 0.4% of the total samples for IMERG V06B or V07B.

Among sounders, MHS is the best in both V06B and V07B, and SAPHIR in V06B is the worst. SAPHIR is excluded from PMW inputs in V07B because of its overall poor performance as noted above.

Considering the classes of IR use, PMW_p-only is better than the IR+PMW_p mixture as PMW_p-only draws on pixels close to satellite overpass times, whereas the IR+PMW_p mixture is for pixels far from the overpasses. As expected, IR-only is the worst in V06B for correlation, BIAS, NMAE, NRMSE, POD, FAR and HSS. IR-only is rarely used in V07B over CONUS because of the implementation of automated IR quality control and inclusion of PMW retrievals over frozen surfaces, as discussed in Sections 2d and 4c.

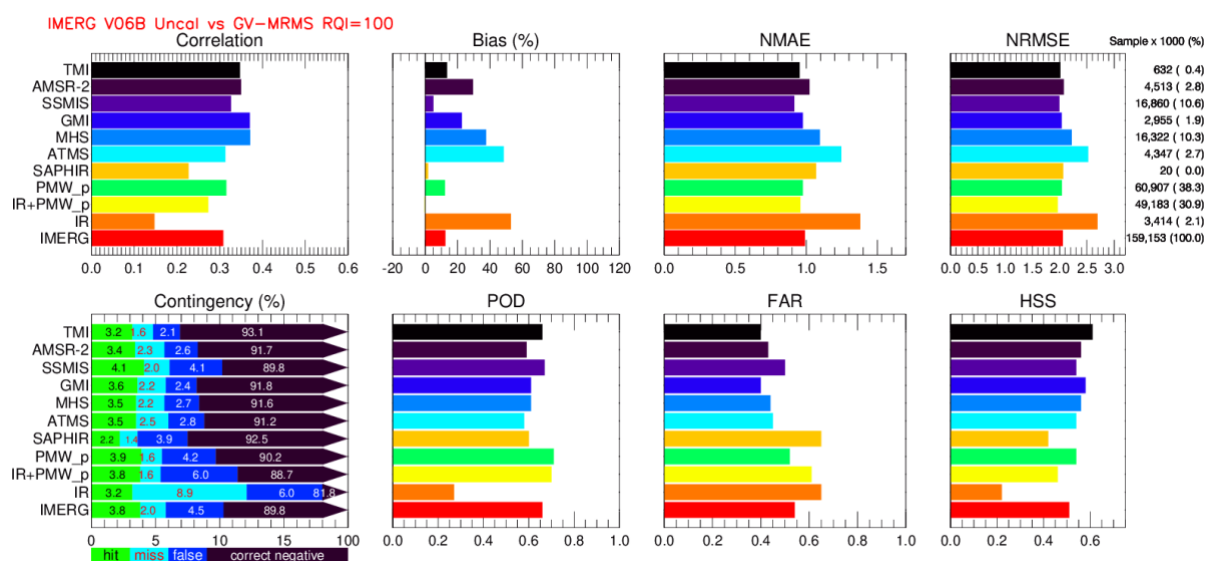
The statistical metrics for IMERG V07B are depicted in Fig. 10. Comparing Figs. 9 and 10, one sees distinct improvements in IMERG performance from V06B to V07B in terms of

the precipitation detection, systematic bias, and random bias. The improvement is clearer for winter (Figs. 11 and 12). Each source in V07B has a better HSS score than the same source in V06B for winter (Figs. 11 and 12) and all year regardless of season (Figs. 9 and 10). The random bias is also greatly reduced as indicated by increased correlation and decreased NRMSE from V06B to V07B for winter (Figs. 11 and 12) and all year (Figs. 9 and 10). A striking feature in the comparison between V06B (Fig. 11) and V07B (Fig. 12) is that a very large positive relative bias (from 33.1% to 112.0%) from each source in V06B is dramatically reduced to a small negative bias (all better than -10%) in V07B for winter.

The improvement from IMERG V06B to V07B is also noticeable for summer, though less pronounced than for winter. While the relative bias for summer remains negative in both versions, its magnitude is reduced in V07B compared to V06B. This will be explored further in the next section.

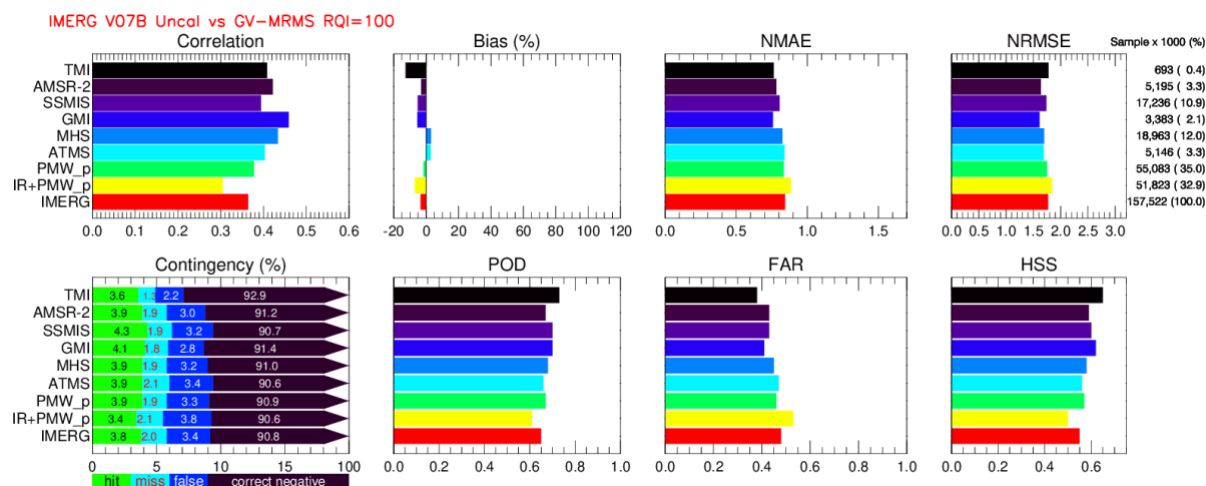
IMERG V07B substantially reduced the overestimation observed in V06B, particularly during winter, through several key algorithmic changes (Huffman et al. 2024a). First, a major source of bias in V06B—the GPCP-based adjustment applied to CORRA over land—was removed in V07B, eliminating an artificial inflation of precipitation rates. Second, V07B implemented improved PMW retrievals over frozen surfaces, incorporating updated surface classification and retrieval algorithms, which reduced errors in snow-covered and cold land regions. Lastly, the intercalibration procedure was refined to improve consistency among sensors, resulting in more accurate and harmonized precipitation estimates. Although these changes did not alter the instrument measurements themselves, they substantially improved the overall quality of precipitation retrievals and contributed to the observed reduction in

490 bias.



491

492 *Fig. 9. Statistical metrics for IMERG V06B without gauge-calibration and its sources*
 493 *relative to GV-MRMS. (Top row): Pearson correlation coefficient (correlation), relative bias*
 494 *(Bias), normalized mean absolute error (NMAE), and normalized root mean square error*
 495 *(NRMSE). (Bottom row): contingency table with hit (green), miss (aqua), false alarm (blue),*
 496 *and correct negative (black). Probability of detection (POD), False alarm ratio (FAR) and*
 497 *Heike skill score (HSS) are also displayed. The numbers at the right in the top row are*
 498 *matched sample sizes and their percentages of the total sample size conditional on*
 499 *precipitation rates from both IMERG (or each IMERG source) and GV-MRMS at least 0.1*
 500 *mm h⁻¹.*



501

502 *Fig. 10. Same as Fig. 9 except for IMERG V07B.*

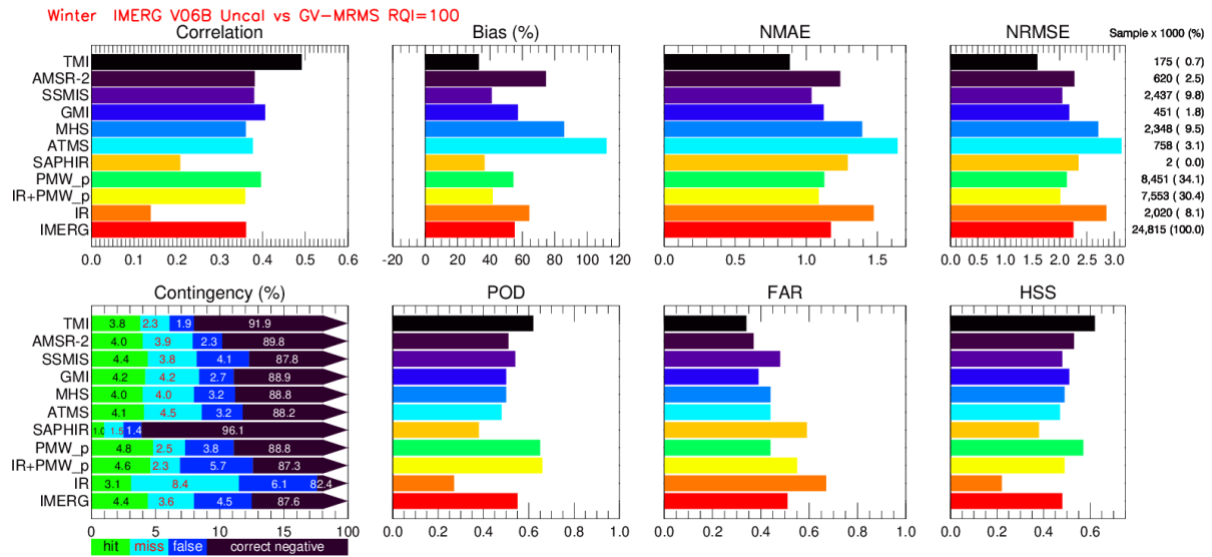


Fig. 11. Same as Fig. 9 except for winter.

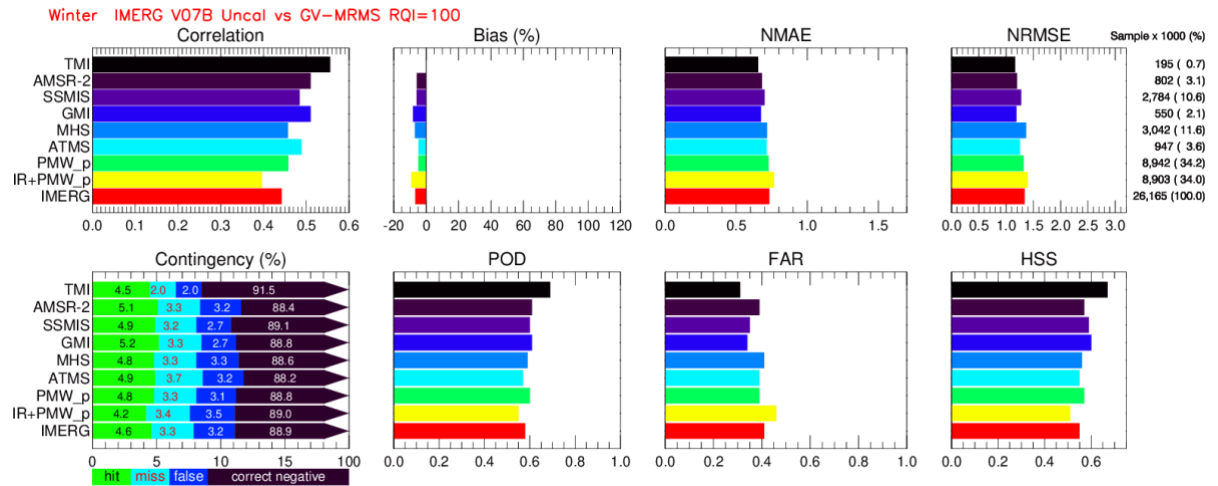


Fig. 12. Same as Fig. 11 except for IMERG V07B.

e. Error decomposition

Using the Tian et al. (2009) error decomposition approach, the total bias (T) can be further decomposed into hit (H), missed-precipitation (M), and false-precipitation (F) biases for IMERG V06B and V07B, at 0.1° and 0.5-h resolutions for the entire study period. Figure 13 shows obvious improvements from V06B to V07B for each IMERG source and IMERG regardless of its sources. For IMERG regardless of seasons (Fig. 13), the large positive total bias in V06B is reduced to a much smaller bias in V07B. The improvement is more pronounced for winter (Fig. 14) compared to the entire year (Fig. 13) and summer (Fig. 15). A similar result is reported in research over Turkey (Aksu and Yaldiz 2024). For most

IMERG sources, the magnitudes of hit, missed-precipitation, and false-precipitation biases are all reduced from V06B to V07B. The most prominent feature in Figs. 13-15 is that IR has the worst negative missed-precipitation bias and very large positive false-precipitation bias in comparison with other sources in V06B.

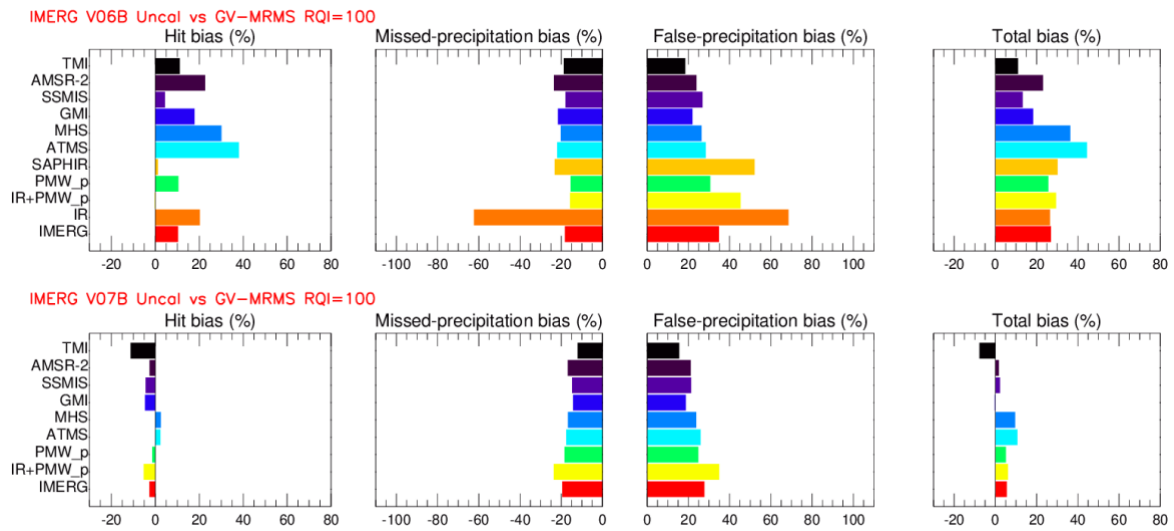


Fig. 13. Error components for IMERG (V06B and V07B) and their sources relative to GV-MRMS with RQI of 100 at 0.5 h and 0.1° resolutions.

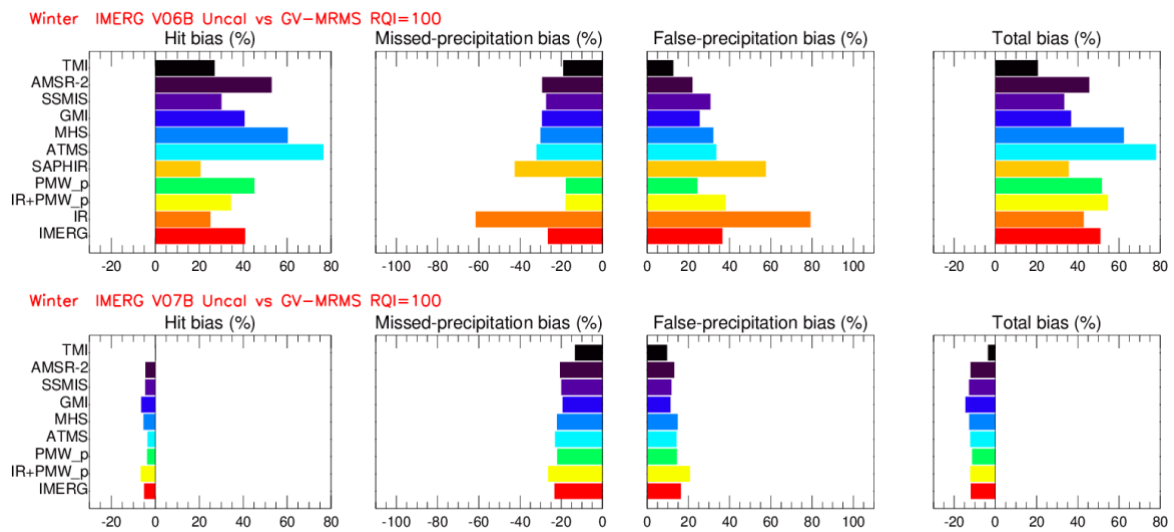


Fig. 14. Same as Fig. 13 except for winter.

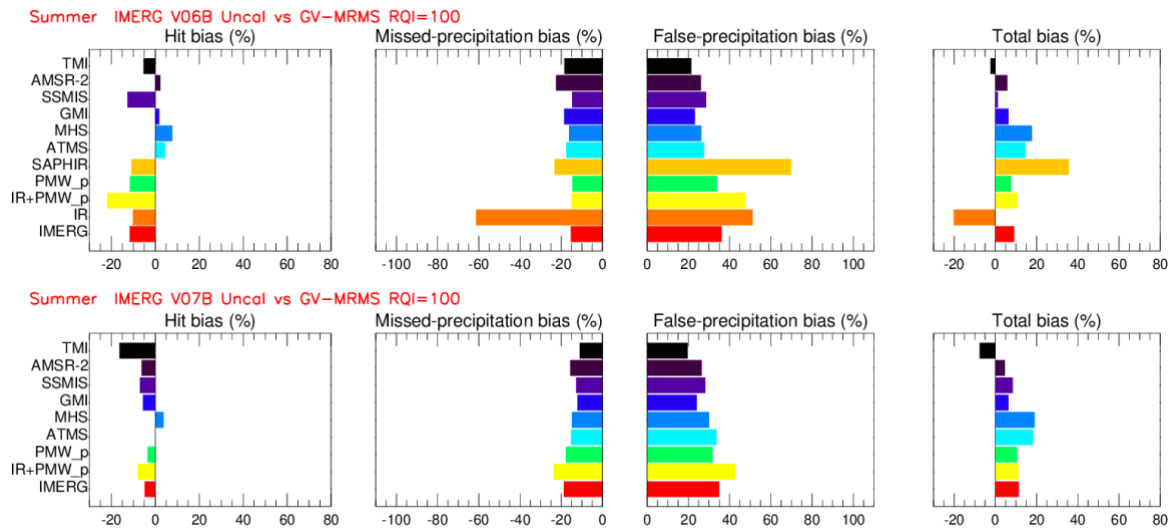


Fig. 15. Same as Fig. 13 except for summer.

5. Conclusions and discussions

In this study, the relative performance of the two satellite-based products IMERG V06B and V07B has been evaluated against the ground radar-based product GV-MRMS over CONUS across the GPM era in the period of June 2014–August 2021 using volumetric and categorical statistical metrics. Ten types of sources contributed to errors in IMERG estimates, including four imagers (TMI, GMI, AMSR-2, SSMIS), three sounders (MHS, ATMS and SAPHIR), and three levels of IR use (IR-only, PMW_p-only and IR + PMW_p) have been identified and investigated in depth. To further examine the error sources, a volumetric error decomposition approach has been applied to decompose the total bias of precipitation volume into hit bias, missed-precipitation bias and false-precipitation bias. The major findings can be summarized as follows.

IMERG V06B and V07B display precipitation features that match those shown by GV-MRMS and GPCC, namely abundant precipitation in the Southeast and Pacific Northwest, and relatively lower precipitation in the western CONUS. The precipitation gradients in all IMERG products appear smoother than in GV-MRMS, likely due to the challenges of satellite precipitation in capturing fine-scale spatial variability.

Considering IMERG estimates before gauge adjustment, V07B shows a clear improvement with reduced systematic bias and uncertainty, and increased precipitation detectability in comparison with V06B. The improvement is more pronounced for winter. IMERG V07B substantially reduced the overestimation of wintertime precipitation in V06B

547 primarily due to the removal of the GPCP adjustment to CORRA over land, replacement of
548 most IR with PMW retrievals over frozen surfaces, and other changes in the intercalibration
549 to correct biases.

550 Among IMERG sensors, imagers are slightly better than sounders in terms of most
551 metrics despite the fact that the imagers' low-frequency channels are not quantitatively useful
552 over land primarily because of surface emissivity variability. Among imagers, TMI and GMI
553 are the overall best. Among sounders, MHS is the best. Among levels of IR use, PMW_p-
554 only is better than IR+PMW_p, and IR-only is the worst in V06B. IR is the major error
555 contributor, especially for the winter.

556 It should be noted that the GV-MRMS dataset utilized as a reference in this study does
557 not actually provide the absolute ground truth (Kirstetter et al. 2020, among many others),
558 especially over complex topography and in snowfall (Fig. 2). GV-MRMS is a precipitation
559 product from ground radars and calibrated with ground rain gauges. As with all other ground
560 radar precipitation estimates, GV-MRMS data quality is subject to innate uncertainties caused
561 by radar hardware calibration and stability, signal attenuation, nonuniform beam filling, and
562 retrieval of surface precipitation from elevated scans (Cifelli et al. 2011), as well as some
563 operational issues which might result in inferior and/or missing data. The gauge data used in
564 GV-MRMS also introduce uncertainties. Fortunately, GV-MRMS data can be quality-
565 controlled using the RQI variable it provides. This study selects only the best RQI (100) to
566 ensure the highest possible reference quality, although at the expense of introducing regional
567 and seasonal sampling biases. The findings of this study provide valuable insights for
568 IMERG product development by demonstrating the benefits of recent V07B updates—
569 particularly the removal of GPCP-based climatological adjustments over land—which have
570 substantially reduced the wintertime overestimation observed in V06B. The analysis also
571 highlights persistent limitations in IR-based retrievals during winter, suggesting that reducing
572 dependence on IR observations or enhancing IR retrieval algorithms could further improve
573 IMERG accuracy. Moreover, the evaluation of different sensor types reveals the relatively
574 varied performance across sensors and associated algorithms, offering guidance for sensor
575 prioritization when multiple sensor overpasses occur within the same time window. These
576 findings not only support improvements in sensor selection, intercalibration, and bias
577 correction strategies for the upcoming V08 algorithm but also benefit the broad community

of product users for understanding the inherent issues in sensor-specific retrieval challenges and uncertainty quantification.

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Data Availability Statement.

V06B and V07B IMERG Final Run products are publicly available at Huffman et al. (2019, 2024b), respectively. GPCC Monitoring Product can be accessed from https://opendata.dwd.de/climate_environment/GPCC/html/gpcc_monitoring_v2022_doi_download.html. The quality-controlled GV-MRMS data are open for the NASA Precipitation Measurement Missions Science Team; contact jianxin.wang@nasa.gov for GV-MRMS data request.

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