Can the GPM IMERG Final Product Accurately Represent MCSs' Precipitation Characteristics over the Central and Eastern United States?

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ABSTRACT

Mesoscale convective systems (MCSs) play an important role in water and energy cycles as they produce heavy rainfall and modify the radiative profile in the tropics and midlatitudes. An accurate representation of MCSs' rainfall is therefore crucial in understanding their impact on the climate system. The V06B Integrated Multisatellite Retrievals from Global Precipitation Measurement (IMERG) half-hourly precipitation final product is a useful tool to study the precipitation characteristics of MCSs because of its global coverage and fine spatiotemporal resolutions. However, errors and uncertainties in IMERG should be quantified before applying it to hydrology and climate applications. This study evaluates IMERG performance on capturing and detecting MCSs' precipitation in the central and eastern United States during a 3-yr study period against the radar-based Stage IV product. The tracked MCSs are divided into four seasons and are analyzed separately for both datasets. IMERG shows a wet bias in total precipitation but a dry bias in hourly mean precipitation during all seasons due to the false classification of nonprecipitating pixels as precipitating. These false alarm events are possibly caused by evaporation under the cloud base or the misrepresentation of MCS cold anvil regions as precipitating clouds by the algorithm. IMERG agrees reasonably well with Stage IV in terms of the seasonal spatial distribution and diurnal cycle of MCSs precipitation. A relative humidity (RH)-based correction has been applied to the IMERG precipitation product, which helps reduce the number of false alarm pixels and improves the overall performance of IMERG with respect to Stage IV.

1. Introduction

Mesoscale convective systems (MCSs) develop from the upscale organization of individual thunderstorms into a single organized cloud system with a large anvil shield and contiguous precipitation (Houze 2004). MCSs play an important role in the hydrologic cycle as they produce abundant rainfall over an area on the order of hundreds of kilometers and last up to 24 h in both the tropics and warm midlatitudes (Houze 2004). For instance, MCSs account for 30%–70% of the warm season rainfall in the central United States (Fritsch et al. 1986; Nesbitt et al. 2006; Feng et al. 2016), and around 75% of the tropical rainfall (Roca et al. 2014) globally. MCSs also act as a key linkage between the mesoscale and large-scale circulations through the

vertical transport of momentum, water, and mass from the lower to upper troposphere (Fioleau and Roca 2013). MCSs are often associated with severe weather hazards, such as flash flooding, hail, severe winds, and tornados (Houze 2004; Schumacher and Johnson 2005). In the central and eastern United States, roughly 65%–74% of the warm season extreme rainfall events are caused by long-lasting MCSs (Schumacher and Johnson 2005, 2006). Studies (Cui et al. 2019; Parker and Johnson 2000; Schumacher and Johnson 2005) have found that MCSs with certain organization patterns have tendencies to produce heavier rainfall, which is directly related to the locations of stratiform and convective regions within the cloud systems. Accurate representations of MCSs' precipitation and their precipitation structure are thus crucial to determine their impact on the hydrologic cycle, and further, the global general circulation.

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MCSs have been extensively studied over the continental United States (CONUS) through the dense WSR-88D radar network because it can capture the large-scale continuous evolution and internal structure of MCSs at high temporal and spatial resolutions. In the past few decades, some milestone studies of MCS structure over the CONUS have been also established by using this network (Houze 2019). However, radar-based MCS studies are limited to over land, especially over the United States, Europe, and East Asia, while other regions may not be equipped with suitable radar coverage.

For the rest of the world, particularly over ocean, satellite measurements and retrievals serve as a crucial platform that allows analysis on MCSs to be performed (Houze 2019). Utilizing cloud-top temperature indicated by infrared (IR) imagers on satellites, the morphology of the cold cloud shield (CCS) of an MCS along its life cycle can be directly identified and investigated. For satellite-based precipitation estimation, passive microwave (PMW) and IR sensors are widely used. IR temperature is used to estimate rainfall based on the indirect relationship between cloud top temperature/height and surface precipitation (Joyce et al. 2004) that is rather ambiguous (Petković and Kummerow 2017). PMW sensors at different wavelengths (e.g., 19 and 85 GHz) retrieve rainfall by employing both absorption and scattering properties of hydrometeors to the observed radiances at the top of the atmosphere (Cui et al. 2016; Petković and Kummerow 2017). Nevertheless, precipitation studies related to mesoscale processes, particularly those associated with MCSs, have rarely been performed using the passive satellite-only precipitation products due to various issues including but not limited to coarse spatial and temporal resolutions, inconsistency in data availability, and errors in raw measurements. Progress has been made in incorporating satellite passive remote sensors with ground measurements (e.g., rain gauge) and even spaceborne active sensors.

One recent example of combining passive and active spaceborne sensors to retrieve precipitation is the Global Precipitation Measurement (GPM) satellite launched by National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) in 2014. As the successor to Tropical Rainfall Measuring Mission (TRMM; Huffman et al. 2007), GPM carries a Dual-Frequency Precipitation Radar (DPR) and a conical-scanning multichannel microwave imager on its *Core Observatory* on orbits between the equator and high midlatitudes ($\sim 65^\circ$; Hou et al. 2014). Taking advantage of the global coverage of GPM *Core Observatory* measurements, the latest GPM Integrated Multisatellite Retrievals (IMERG) product was developed

to provide global rainfall information at fine scales (Huffman et al. 2019a). The horizontal and temporal resolutions have been improved from 0.25° to 0.1° , and from 3-hourly to half-hourly from the TRMM to the GPM era, which enables analyses focusing on the precipitation processes at small scales and of short duration. GPM also extends to higher latitudes, making possible to examine convective systems over the middle and high latitudes (Houze et al. 2019). IMERG is therefore a useful tool to study the MCS-related rainfall processes after its error and uncertainty are quantified. A number of studies have been conducted to determine the biases in IMERG products against surface measurements over different regions and at different temporal scales (Aslami et al. 2019; Asong et al. 2017; Beck et al. 2017; Chen and Li 2016; O et al. 2017; Gaona et al. 2016; Prakash et al. 2018; Sharifi et al. 2016; Tan et al. 2017; Tang et al. 2016; Wang et al. 2017; Xu et al. 2017). Some focus on determining the sources of errors in the dataset (Tan et al. 2016; Tian et al. 2018), but none of these studies looked at the precipitation specifically from MCSs. Prakash et al. (2016) investigated the capabilities of TRMM and IMERG in detecting and estimating heavy rainfall across India. IMERG showed notable improvements over TRMM in terms of the categorical and volumetric skill scores in capturing heavy rainfall events in their study, and the promising results of IMERG may help improve modeling of hydrological extremes. Mazzoglio et al. (2019) defined the IMERG accuracy in representing extreme rainfall events for varying time aggregation intervals at global scale and found poor performances for IMERG rainfall aggregation intervals lower than 12 h, with a probability of detection (POD) greater than 80% at a 24-h aggregation interval. O and Kirstetter (2018) evaluated the diurnal variation of summer precipitation derived from the GPM IMERG product over the CONUS. They found a significant difference in the timing of peak precipitation over the Great Plains with respect to the radar-derived precipitation, which results from the different sensitivities in satellite retrievals in estimating stratiform and convective types of precipitation associated with MCSs.

The main purpose of this paper is to evaluate and improve the half-hourly IMERG product in reproducing MCSs' rainfall over the central and eastern United States, where MCSs frequently occur during the warm season. The capabilities of IMERG in detecting and capturing MCSs' rainfall characteristics are examined in this study based on the radar-based quantitative precipitation estimates (QPE) Stage IV product over the central and eastern United States during the period 2014–16. Quantifying the errors in IMERG precipitation products is important for both hydrology and

climatology applications as these products may be widely used as a reference data over poorly instrumented or remote regions of the world, or used for regional and climate model evaluations. Through the comprehensive analyses on IMERG's ability to produce MCSs precipitation, we hope that the results in this paper would provide useful insights into the potential advantages and drawbacks of the dataset, especially those related to intense precipitation events associated with MCSs.

2. Datasets

a. Stage IV QPE product

The Hourly Stage IV QPE product from National Centers for Environment Prediction (NCEP) is used to analyze the precipitation properties of MCSs in this study. The hourly Stage IV product utilizes precipitation estimates computed with a $Z-R$ relationship from over 150 Doppler Next Generation Weather Radars (NEXRAD), and combines about 5500 hourly rain gauge measurements to produce precipitation analyses at 4-km resolution over the CONUS (Lin and Mitchell 2005). Each Stage IV precipitation estimate is initiated 35 min after each hourly gauge collection period, and then gauge-adjusted precipitation estimates are manually and automatically quality controlled (Lin and Mitchell 2005). Stage IV product has been used as a reference precipitation dataset in many satellite and model verification studies (AghaKouchak et al. 2011; Mehran and AghaKouchak 2014; Romine et al. 2013, 2014; Smalley et al. 2014).

b. IMERG product

The Level-3 half-hourly IMERG Final Run product (V06B) produced by NASA Goddard Space Flight Center (GSFC) is used in this study and evaluated against Stage IV product for MCS precipitation. IMERG provides surface precipitation at $0.1^\circ \times 0.1^\circ$ spatial resolution and covers 60°S – 60°N latitudes. The IMERG algorithm integrates several multisatellite retrievals from PMW and IR sensors which are then gridded, intercalibrated, and merged with the estimates from the GPM Core Observatory to form the final product (Huffman et al. 2019a). The precipitation gauge analyses are used in Final Run product to provide crucial regionalization and bias correction to the satellite estimates.

It should be noted that an overlap does exist in the gauge analysis used in the two datasets. But the effect of the overlapping in gauge analysis is considered insignificant because the calibration processes carried out in producing each dataset are significantly different

(Stage IV radar estimates are calibrated at each hourly time step, while IMERG uses the monthly gauge analysis to perform a weight adjustment to the half-hourly satellite estimates).

c. Observation datasets for identifying and tracking MCSs

The MCSs are identified using two observational datasets, one is the globally merged IR brightness temperature T_b data produced by NCEP/Climate Prediction Center (CPC), and the other is the mosaicked NEXRAD radar reflectivity from GridRad. The half-hourly globally merged IR dataset is constructed from five geostationary satellites from different institutions and different countries. The IR imageries from these satellites are forwarded to CPC and are quality controlled and merged onto a global grid (Janowiak et al. 2001). The IR data have a $4\text{ km} \times 4\text{ km}$ spatial resolution and are used to identify the deep convective clouds associated with MCSs. The GridRad radar reflectivity is used to obtain the 3D characteristics of MCSs. The hourly radar reflectivity data are produced by merging radar reflectivity data from 125 National Weather Service NEXRAD WSR-88D radars and rescaled onto a common grid (Homeyer and Bowman 2017). The GridRad data cover the CONUS and have $0.02^\circ \times 0.02^\circ$ horizontal and 1-km vertical resolutions.

d. RAP analysis

The relative humidity (RH) from the Rapid Refresh (RAP) hourly analysis at 13-km horizontal grid spacing is used to perform a correction on the IMERG precipitation estimates. The RAP is an hourly-updated assimilation/modeling system operational at NCEP and comprised primarily of a numerical forecast model and an analysis/assimilation system to initialize that model (Benjamin et al. 2016). The root-mean-square errors (RMSEs) of RH values from the 1-h forecast field are found to be less than 10% in the study of Benjamin et al. (2016) for pressure levels near the surface, and this value should be even smaller for the analysis field.

3. Methodology

The Flexible Object Tracker (FLEXTRKR) method introduced by Feng et al. (2018) is used in this study to identify and track the MCSs. The method first identifies and tracks large CCSs ($T_b < 241\text{ K}$) associated with deep convection using satellite T_b data, and subsequently identifies MCSs using radar defined convective features (Feng et al. 2018, 2019). A CCS will be defined as an MCS when the cold cloud shield area exceeds

FIG. 1. Time evolution of a tracked MCS during 0100–2100 UTC 13 Jul 2015. The snapshots are at 0100, 0600, 1100, 1700, and 2100 UTC for (a) satellite T_b temperature, (b) composite radar reflectivity, and hourly accumulated precipitation from (c) Stage IV and (d) IMERG.

6×10^4 km, contains a convective feature with radar reflectivity > 45 dBZ at any vertical level, and has a lifetime longer than 6 h (Feng et al. 2019). The precipitation associated with an MCS is then identified based on the CCS T_b mask. Due to radar beam blockage issues for west of the Rocky Mountains, only the MCSs over the central and eastern parts of the United States are examined in this study. Figure 1 shows an example of a tracked MCS on 13 July 2015. The MCS has a southeastward movement and consists of a leading convective line as illustrated from the radar reflectivity snapshots (Fig. 1b). The precipitating areas of the system from both datasets (Figs. 1c,d) are smaller than the T_b masked areas (Fig. 1a) because T_b contains the information from the nonprecipitating anvil region.

Half-hourly IMERG rain rate estimates are first processed to obtain the hourly accumulated rainfall. This step is simply done by taking the first (0–29 min) half-hourly rain rate (the unit is mm h^{-1}) plus the second (30–59 min) half-hourly rain rate then dividing by 2. Next, to match the grid spacing of IMERG product, the Stage IV and merged IR are interpolated using an areal conservative remapping method because the two datasets have much finer native resolutions (~ 2.5 times) than IMERG. RAP analyses are linearly interpolated to a $0.1^\circ \times 0.1^\circ$ grid. FLEXTRKR tracked MCS features are applied to both Stage IV

and IMERG products to identify precipitation associated with MCSs.

The precipitation properties of the tracked MCSs are then analyzed for four seasons: spring (MAM), summer (JJA), fall (SON), and winter (DJF). In the following analyses, the value of 0.05 mm h^{-1} is used as the threshold value to determine the rain/no-rain events because the IMERG product contains a significant amount of very small precipitation values ($< 0.01 \text{ mm h}^{-1}$) resulting from the morphing and calibration algorithms. This value is chosen because 0.05 mm h^{-1} is close to the minimum detectable value of original Stage IV data (0.04 mm h^{-1}). Also, this threshold is high enough to eliminate noise that might be introduced by the points with very small values, while at the same time is small enough that it will not affect the overall results.

4. Results

a. Overall precipitation from two datasets

Before examining the performance of IMERG in estimating precipitation from MCSs, the seasonal precipitation distributions and amounts from the two products are first illustrated and compared in Fig. 2. The difference between the two datasets is quantified using the relative difference percentage (RDP), which is calculated using the formula:

FIG. 2. Spatial distribution of accumulated precipitation for each season for the period 2014–16 from (a)–(d) Stage IV, (e)–(h) IMERG, and (i)–(l) their RDP.

$$\text{RDP} = (\text{IMERG} - \text{Stage IV}) / \text{Stage IV} \times 100\%. \quad (1)$$

The seasonal accumulated precipitation estimated by the two datasets is similar in spatial variation and rainfall amount, except the spatial transition of the rainfall amount is smoother in IMERG than Stage IV because of the coarser measurement resolution. The differences between the two datasets are relatively small for regions east of 100°W, where the RDP values are mostly varying between -25% and 25% throughout the year. RDP values greater than 80% in central Minnesota, west Montana and Wyoming, southern South Dakota, and southeast Texas found in winter, spring, and fall, occur in the regions with poor or no radar coverage that result in severe underestimations by Stage IV. For the farther western part of the study domain where RDP values exceed 100% , this is related to the larger uncertainties in Stage IV estimates over mountainous regions caused by radar beam blockage. Table 1 shows the seasonal mean of total (seasonal accumulated precipitation value including zero values) and hourly precipitation

(hourly precipitation value excluding the no-rain pixels) from Stage IV and IMERG (the pixels from each dataset for calculation are independent from the other dataset) over the study region. Except for winter, IMERG underestimates the precipitation intensity and the underestimation is the most severe during summer with an RDP value of $\sim 40\%$. This potentially implies that IMERG may have dry biases when estimating precipitation from convective systems. While opposite to the rainfall intensity, the seasonal rainfall amounts estimated by IMERG are higher than Stage IV for all seasons except summer. The differences in total amount are smaller than the mean intensity where RDP values are less than 10% during all seasons.

b. MCS precipitation seasonal characteristics

Figure 3 gives an overview of the occurrence number and spatial coverage of the tracked MCSs for each season during the study period. The value of each grid box shown in Figs. 3b–e represents the number of times MCSs have overpassed that grid box during that season.

TABLE 1. Seasonal hourly mean (mm; first row for each season, rain pixels only) and seasonal total precipitation (mm; second row for each season, accumulated precipitation from all pixels) values for IMERG and Stage IV and their RDP. The pixels used for calculating the hourly means from the two datasets are independent from each other.

	IMERG	Stage IV	RDP
DJF	1.02	0.99	3.0%
	179.68	163.71	9.8%
MAM	1.03	1.36	−24.3%
	279.41	276.69	0.9%
JJA	1.15	1.91	−39.8%
	296.28	307.01	−3.5%
SON	1.09	1.43	−23.8%
	206.31	201.81	2.2%

There are a total of 934 MCSs identified and investigated in this study. It is apparent that there is a seasonal variation, with the highest numbers (~ 170) occurring in summer and the lowest numbers (less than 50) occurring in winter. Similar results are reflected in the spatial distribution of the occurrence frequencies of MCSs. MCSs occur most frequently during spring and summer, with a peak occurrence number around 40 over the Great Plains. During winter, MCSs only occur east of 100°W and are most concentrated near Tennessee. The spatial distribution of MCSs occurrence during fall is less dense compared to the other three seasons, but the total number of MCSs occurrence is higher in the fall

than in the winter. These seasonal MCS distributions from the short 3-yr dataset are qualitatively consistent with the 13-yr records reported by Feng et al. (2019), suggesting the 3-yr dataset is representative of the MCS climatology in this region.

The spatial distribution of seasonal accumulated precipitation from MCSs is shown in Fig. 4. Stage IV and IMERG have similar spatial patterns of the MCS precipitation, where the locations of the highest precipitation amount correspond to the locations of peak MCS occurrence as seen in Fig. 3. The regions receiving the highest rainfall amounts are similar to those in Fig. 2, except the East Coast regions during summer where the majority rainfall is coming from tropical storms and hurricanes. During winter, a monotonic increase in MCS precipitation amounts is seen from west to southeast with a peak near Alabama. During the warm season, the Great Plains receive a large amount of MCS precipitation, at some locations exceeding 400 mm. A secondary peak in total precipitation over southern Louisiana during summer is captured by both datasets. The fall season MCS precipitation peaks over the southern Atlantic coast, and slightly higher precipitation amounts are observed in the central Mississippi basin. Western and northeastern parts of the study region receive the least MCS precipitation throughout the year. Overall, IMERG shows good agreement with Stage IV in terms of the spatial distribution of the MCS precipitation during each season, but large differences exist in the

FIG. 3. (a) The number of MCSs per season during the study period 2014–16. The spatial distribution of the occurrence number of MCSs during each season for 2014–16: (b) December–February (DJF), (c) March–May (MAM), (d) June–August (JJA), and (e) September–November (SON).

FIG. 4. As in Fig. 2, but for MCS precipitation.

estimated MCS precipitation amounts. IMERG generally overestimates the MCS accumulated precipitation, and the overestimation is more severe over the northern and eastern parts of the study domain with some regions having RDP values exceeding 200%. Still, the large differences in the western part of the study domain could be resultant from radar beam blockage and overshooting over complex terrain. Another possible factor contributing to the large RDP value is low precipitation values from Stage IV being used as the denominator in the calculation, which leads to a small signal-to-noise ratio.

Figure 5 illustrates the fraction of MCS precipitation to the total precipitation during each season. The fraction is computed on 0.1° grid scale using the IMERG/Stage IV estimated MCS precipitation divided by the IMERG/Stage IV total precipitation. MCSs contribute more precipitation during the warm season than the cold season. More than 70% of the total precipitation comes from MCSs over the Great Plains during spring and summer. During winter and fall, less than 30% of the total precipitation originates from

MCSs for most of the study region. IMERG tends to estimate more precipitation from MCSs than Stage IV, particularly over the Great Plains during the warm season where MCS precipitation fractions are $\sim 10\%$ – 20% more than Stage IV.

Table 2 summarizes the seasonal accumulated mean and hourly mean of MCSs' precipitation estimated by Stage IV and IMERG. The MCS precipitation intensities are almost twice as high as the values shown in Table 1 and account for 25%–30% of the seasonal total precipitation. The differences between the two datasets in MCS precipitation shows different behavior compared to the overall precipitation. During spring and summer, the accumulated precipitation amounts from MCSs are almost twice as much as those during fall and winter as estimated in both datasets. However, fall MCSs have the most intense precipitation (highest hourly mean precipitation), following by summer. Comparing the values from Stage IV and IMERG, although the total MCS precipitation amounts are higher in IMERG, the mean hourly precipitation values are lower than Stage IV during all seasons. The hourly precipitation in IMERG

FIG. 5. Spatial distribution of fraction of MCS to total accumulated precipitation for each season of the period 2014–16 from (a)–(d) Stage IV and (e)–(h) IMERG.

is roughly 20% less than Stage IV except during winter based on the RDP values. But regarding the seasonal total MCS precipitation, IMERG is higher than Stage IV and their difference is the largest in winter. The small difference in mean values but large difference in total precipitation amounts in winter could be a result of the difference in sample size and distribution, which is examined in the later analysis.

The diurnal cycles of the seasonal total MCS precipitation as a function of longitude (110°–80°W) from the two datasets are presented in Fig. 6 (first and second panels). The meridional mean of seasonal total precipitation from MCSs is computed for each longitude band. The regions east of 80°W are excluded from this analysis due to the limited land areas and MCS samples, and the errors associated with radar ground clutter because of the temperature and humidity inversions that often occur near coastal areas. These factors could produce large discrepancies between the two datasets. An eastward propagation of MCS precipitation is observed during all seasons. The diurnal variations of MCS precipitation are more obvious during spring and summer. Based on Stage IV estimates, the MCS precipitation initiates around 0000 UTC at 100°W, reaching a nocturnal maximum around 0600 UTC and then gradually weakening until 1800 UTC during the warm seasons (Figs. 6e,d,i,l). The diurnal cycles during fall resemble those in summer, except the total precipitation amounts at each hourly time step are much less than those during summer (Figs. 6l,p). Smaller variation in MCS precipitation

is found during winter, with the domain mean total precipitation varying from 250 to 300 mm throughout the day (Fig. 6d, red line). Even though IMERG shows overall good agreement with Stage IV in terms of the large-scale spatial pattern of diurnal variations in MCS precipitation (Figs. 6b,f,j,n), differences are observed between the two datasets regarding the amplitude and peak timings of the MCS diurnal precipitation. The differences between two datasets show inconsistencies throughout the day. During all seasons, the two datasets show similar total precipitation amounts at 1300 UTC, then IMERG shows higher precipitation amounts than Stage IV increasing from 1300 to 0500 UTC, then decreasing from 0600 to 1300 UTC. Also, an abrupt decrease in precipitation amount is found at 0600 UTC in IMERG, which does not follow the diurnal pattern of precipitation, resulting in the peak of precipitation occurring at 0400 UTC during spring, summer, and fall, which is 2 h earlier than the peak observed in Stage IV.

TABLE 2. As in Table 1, but for MCS precipitation.

	IMERG	Stage IV	RDP
DJF	2.49	2.52	−1.2%
	71.25	56.83	25.4%
MAM	2.32	3.10	−25.2%
	108.21	94.95	14.0%
JJA	2.57	3.47	−24.0%
	111.16	102.57	8.4%
SON	2.81	3.48	−19.3%
	56.98	50.79	12.2%

FIG. 6. Diurnal variations of MCS total precipitation as a function of longitude for each season of the period 2014–16 from (a),(e),(i),(m) Stage IV, (b),(f),(j),(n) IMERG, and (c),(g),(k),(o) their relative difference percentage. (d),(h),(l),(p) Line plots are the domain averaged total MCS precipitation for each hour.

In addition to the spatial characteristics of MCS precipitation, the lifetime evolution of MCS precipitation properties are also investigated. The lifetime of each individual MCS is divided into 10 normalized life stages (by linearly interpolating the original values) following the method described in Bouniol et al. (2016), where 1 denotes the initiation and 10 represents the dissipation of a system. Next, the precipitation rate, precipitating area, areal total precipitation, skewness of precipitating pixels (pixels having hourly precipitation $> 0.05 \text{ mm h}^{-1}$),

and number of pixels having precipitation rate greater than 10 mm h^{-1} are computed for each normalized life stage for tracked MCSs and are shown in Fig. 7. The shaded area represents the standard deviation of the data at each life stage. The precipitation rate (Figs. 7a–d) of MCSs reaches its maximum at the early stages (stages 2–3) of system development, which is associated with the strong upscale growth of convection. The precipitation intensity is the strongest during fall, followed by summer, spring and winter. The time evolution of MCS

FIG. 7. Composite life cycles of MCSs for (a)–(d) hourly mean precipitation, (e)–(h) precipitating area, (i)–(l) areal total precipitation, (m)–(p) skewness of all precipitating pixels, and (q)–(t) the number of pixels having precipitation rate greater than 10 mm h^{-1} for each season from Stage IV (red) and IMERG (blue). The shaded area represents the one standard deviation. The x axis shows the normalized MCS life cycle, where 1 denotes convective initiation and 10 denotes dissipation.

precipitating area (Figs. 7e–h) is more symmetric compared to the precipitation rate. The precipitating area continues to increase until stage 5 or 6, then gradually decreases until the system dissipates. MCSs in winter have the largest precipitating area and as a result they produce more areal total precipitation (Fig. 7i) than the other seasons. A relatively small precipitating area is found in MCSs during summer. Comparing the time evolution of MCS precipitation properties estimated by

two datasets, IMERG shows systematic dry biases between 0.3 and 0.5 mm h^{-1} in terms of the precipitation rate except during winter. Opposite to the underestimations in precipitation rate, significant overestimations are found in IMERG estimated MCS precipitating area during all seasons. The overestimations are more severe during the mature stages of the system development. As a consequence, higher MCS areal total precipitation is observed in IMERG than Stage IV. The skewness values

FIG. 8. (a)–(d) The PDFs in percentage based on the Stage IV (red) and IMERG (blue) hourly estimates for MCS precipitation for four seasons; N represents the number of pixels that have a precipitation values greater than 0.05 mm in the two datasets. (e)–(h) The contribution of rainfall amount at each bin to the total precipitation from all bins in percentage for four seasons. The bin size used to construct the plots is 0.5 mm.

(Figs. 7m–p) of pixel level precipitation are higher in Stage IV than IMERG even during winter, indicating that the upper limits of hourly precipitation are always higher in Stage IV. Small variations in skewness values during the mature stage are observed by both datasets. Pixels with precipitation rates greater than 10 mm h^{-1} are usually considered convective pixels. The number of convective pixels as a function of MCS lifetime show the most distinct difference in winter, where the pixel number is almost doubled in IMERG with respect to Stage IV. During spring and fall, IMERG has ~ 20 convective pixels more than Stage IV, and two datasets are comparable during summer.

c. Comparisons of MCS precipitation detection and distribution

Pixel-level comparisons between IMERG and Stage IV are conducted to determine the factors that may lead to the differences in estimating MCS precipitation. The probability density functions (PDFs) of grid boxes with precipitation values greater than 0.05 mm from two datasets are first examined and shown in Figs. 8a–d. IMERG shows notably more pixels with precipitation values than Stage IV during all seasons. These additional pixels in IMERG are likely to have light precipitation values as the occurrence frequencies of hourly precipitation estimates less than 1 mm are significantly higher in IMERG than Stage IV. Excepting winter, the PDF differences for moderate precipitation between

1 and 3 mm are indistinguishable. However, for hourly precipitation values greater than 4 mm, the two PDFs start to deviate and their differences become larger with increasing hourly precipitation estimates. Even though IMERG is found to have more convective pixels in Fig. 7, the occurrence frequencies of IMERG are lower than those of Stage IV for intense precipitation ($>10 \text{ mm}$) for all seasons except for winter due to larger number of samples in IMERG (larger denominator, the differences in the number of pixels having hourly precipitation greater 10 mm between the two datasets is $\sim 2\%$). To quantitatively compare the two datasets, the contribution of precipitation amount at each bin to the total precipitation is presented in Figs. 8e–h. The contribution is simply computed by multiplying the count at each precipitation bin by the center bin value and dividing by the total precipitation added from all pixels. As expected, the light precipitation ($<3 \text{ mm}$ here) contributes more and intense precipitation ($>12 \text{ mm}$) contributes less in IMERG than Stage IV except winter, indicating that IMERG has many more pixels having light rain rate values.

Categorical scores, including POD, false alarm rate (FAR), critical success index (CSI), and skill score (HSS) are computed for the IMERG hourly precipitation estimates (Fig. 9), using Stage IV as a reference. POD is defined as the ratio of hits to the sum of misses and hits. Each hit represents an occurrence of a precipitation estimate greater than the threshold value in

FIG. 9. Probability of detection (POD), false alarm (FAR), critical success index (CSI), and Heidke skill score (HSS) as a function of hourly accumulated MCS precipitation (>0.05 mm) of IMERG estimates using Stage IV estimates as references for each season.

both Stage IV and IMERG datasets. A miss indicates the occurrence of an IMERG estimate that is lower than the threshold value when Stage IV estimate exceeds the threshold value. A false alarm represents an occurrence of an IMERG estimate greater than the threshold value when the Stage IV estimate is less than it. FAR is defined as the ratio of false alarms to the sum of false alarms and hits, and CSI is defined as the ratio of hits to the sum of hits, misses, and false alarms. HSS quantifies whether the IMERG estimate is worse or better than random chance relative to the Stage IV and the formula is defined in Heidke (1926).

Figure 9 shows POD, FAR, CSI, and HSS as functions of hourly accumulated precipitation (starting from 0.05 mm) for IMERG estimates. When the threshold value equals 0.05 mm, IMERG captures the majority of the precipitating events in Stage IV as POD values are near 0.9 during all four seasons. PODs decline with the increase of hourly rainfall, and the values decline faster in warm seasons than cold seasons. CSIs exhibit similar patterns as those in PODs. FARs around 0.33–0.4 are found for the 0.05-mm threshold, indicating that IMERG has roughly 40% more precipitating pixels than Stage IV. Regarding HSSs, IMERG shows poor performance for light rainfall less than 1 mm; HSSs reach a maximum around 2 mm then decline with the increase of the threshold value during all four seasons, indicating IMERG captures the light to moderate (~ 1 –2 mm) precipitation more efficiently. HSSs are relatively low in summer for hourly rainfall less than 10 mm, and IMERG shows basically no ability to detect hourly rainfall that is greater than 20 mm at the exact same locations (at ~ 10 -km scale) as those detected by Stage IV.

The errors in IMERG precipitation estimates are separated into three independent components, hit bias E_{hit} , missed precipitation E_{miss} , and false precipitation E_{false} following the method of Tian et al. (2009). The total difference (IMERG – Stage IV) is first calculated for each component, and then normalized by dividing by the total precipitation of Stage IV. The total error E_{tot} can be computed in relation to the three components

as: $E_{\text{tot}} = E_{\text{hit}} - E_{\text{miss}} + E_{\text{false}}$. The mean errors, mean categorical scores, and RMSEs of IMERG are summarized in Table 3 (values in first row of each season). The RMSE value is the largest during summer and the smallest during winter. A higher RMSE value during summer is expected because RMSE scales with precipitation magnitude in general, and precipitation is generally more intense during summertime. POD values ~ 0.9 as well as very small E_{miss} values ~ 0.1 are found for all seasons. Higher FAR and E_{false} values are found during warm seasons when the MCS activity is the most frequent. The E_{hit} value is the highest in winter; the large discrepancies between two datasets are expected because both Stage IV and IMERG could have difficulties in estimating winter precipitation, especially for events associated with snow.

5. Discussion

Based on the results of analyses above, the error in IMERG is dominated by false alarms for MCS rain detection. IMERG retrieves the rainfall based on the PMW and IR measurements of MCS ice-cloud information from the mid- to upper troposphere. Therefore, a significant number of false alarms could occur when the hydrometeors evaporate before they reach the ground in dry regions (Kuligowski et al. 2016). Moreover, MCSs are characterized by large nonprecipitating anvil regions consisting of ice particles. Anvil regions have cold cloud tops and, with the absence of PMW measurements, the IR algorithm may falsely assign precipitation to pixels with cold T_b values. Another possible factor contributing to the overestimation of precipitating area could be related to the morphing scheme used in IMERG. The scheme performs Lagrangian interpolation of precipitation between successive PMW overpasses within 90 min of the PMW measurement time, which is reported to have introduced a higher fractional precipitation coverage than the actual PMW overpasses (Huffman et al. 2019b). As illustrated in Fig. 1, the pixels with T_b values less than ~ 225 K are identified as

TABLE 3. The RMSE (mm), categorical scores and composite errors of IMERG (first row in each season category) and RH-corrected IMERG (second row in each season category) hourly estimates for four seasons. The threshold value used for performing categorical and composite error analyses is 0.05 mm. The RDP for hourly and seasonal total precipitation, and correlation coefficient (CC) between IMERG, RH-corrected IMERG, and Stage IV are also included.

		RDP (hourly)	RDP (total)	CC	RMSE	POD	FAR	CSI	E_{hit}	E_{miss}	E_{false}	E_{tot}
DJF	IMERG	−1.2%	25.4%	0.365	3.936	0.846	0.343	0.587	−0.155	−0.071	0.187	−0.038
	IMERG-RH	−2.0%	−13.1%	0.380	3.861	0.876	0.320	0.621	−0.096	−0.035	0.112	−0.019
MAM	IMERG	−25.2%	14.0%	0.323	5.061	0.892	0.415	0.546	0.058	−0.048	0.246	0.257
	IMERG-RH	−14.8%	−2.1%	0.325	5.011	0.830	0.354	0.571	0.063	−0.067	0.177	0.174
JJA	IMERG	−24.0%	8.4%	0.269	5.670	0.891	0.393	0.565	0.117	−0.050	0.253	0.319
	IMERG-RH	−17.9%	−4.6%	0.273	5.642	0.813	0.316	0.585	0.120	−0.087	0.188	0.220
SON	IMERG	−19.3%	12.2%	0.339	5.263	0.919	0.339	0.624	0.024	−0.035	0.186	0.175
	IMERG-RH	−11.8%	−3.3%	0.350	5.144	0.906	0.302	0.650	0.021	0.030	0.133	0.124

precipitating pixels in IMERG. Through the MCS lifetime (Fig. 6), the difference in the precipitating area between Stage IV and IMERG is the maximum at the mature stage when the CCS area reaches its maximum (Feng et al. 2019) when the system contains the largest anvil region. It is also shown in Fig. 4 that the fraction of MCS precipitation to total precipitation is higher in IMERG than Stage IV, as a consequence of the CCSs associated with MCSs often being larger than CCSs associated with non-MCSs. IMERG overestimates the total seasonal MCS precipitation but underestimates the hourly mean precipitation, indicating that the false alarm pixels are mostly consisting of small precipitation values produced either by the misclassification of the precipitation events or from the morphing algorithm.

Regarding the errors from hit pixels, during winter, a more significant wet bias ($\sim 20\%$) is found, while relatively small dry biases $\sim 10\%$ are found during the other three seasons. The occurrence frequency of heavier precipitation (>10 mm) during winter in IMERG is also higher than Stage IV as shown in Fig. 7a. The hit errors most likely come from the pixels located in the northern part of the country where the surface is usually covered by snow during the wintertime. Overestimation occurs because of an increase in the amount of scattering at the surface as seen by PMW sensors using high-frequency channels (Adler et al. 2018; Cui et al. 2016). The other problems might come from the Global Precipitation Climatology Centre (GPCC) gauge analysis (Schneider et al. 2014) used in IMERG to calibrate the satellite estimates. An undercatch-corrected adjustment is applied to the GPCC gauge analysis to reduce the wind effects on drizzle and snowflakes (Huffman et al. 2019b), so it is possible that the correction is systematically high (Chen and Li 2016). However, the underlying issues associated with radar overshooting and Z – R relationships that could result in dry bias in winter precipitation estimates should not be neglected (Cui et al. 2016).

In addition to the composite errors, discontinuities are also found in IMERG estimates when examining the diurnal variations of MCS precipitation (Fig. 6). IMERG estimates are composed of different satellite measurements, thus the inconsistencies in total precipitation amounts could stem from the incorrect calibration among different PMW sensors (one sensor overestimates while another sensor underestimates) or the inherent differences in IR and PMW precipitation estimates. To verify this assumption, the contribution of PMW sensors to the precipitation estimates over the study domain have been examined based on the HQprecipSource variable provided in the IMERG product, which is shown in Fig. 10. The value of each pixel in the plot represents the ratio of the total number of PMW measurements from the specific sensor to the total number of PMW measurements from all sensors during the entire study period. Over the study domain, the PMW estimated precipitation values are primarily from Advanced Microwave Scanning Radiometer 2 (AMSR-2), Special Sensor Microwave Image/Sounder (SSMIS), Microwave Humidity Sounder (MHS), and Advanced Technology Microwave Sounder (ATMS) but the measurement availability varies throughout the day. As an abrupt decrease in IMERG precipitation amounts is found at 0600 UTC (Fig. 6), which corresponds to the least frequent availability of PMW measurements. Therefore, the IMERG precipitation estimates at 0600 UTC over the study domain are mainly from the morphing scheme or filled by the IR estimates, which leads to a jump in the diurnal precipitation amount. The diurnal variation in the differences between the two datasets is also related to the availability of the PMW measurement from the specific sensor. During the hours with adequate PMW measurements from SSMI (1200–1400 UTC), the wet biases in IMERG total precipitation tend to be smaller than the other hours.

Limited by the spatial resolution and the fact that PWM sensors infer surface precipitation from just the

FIG. 10. Source of microwave estimates as a function of time. Color coded value represents the number of estimates from that source to the total number of estimates from all PMW sources. Index values are 1, TMI; 3, AMSR2; 5, SSMIS; 7, MHS; 9, GMI; and 11, ATMS. The full list of PMW precipitation estimate sources can be found in [Huffman et al. \(2019b\)](#).

ice-scattering signal, the precipitation structure of an MCS presented in IMERG is thus less reliable than radar. Particularly, as MCSs consist of both stratiform and convective components, significant uncertainties could arise when these two parts are not reasonably represented. IMERG utilizes the latest GPROF algorithm ([Kummerow et al. 2015](#)), which does not separate the retrievals based on morphology (stratiform versus convective). O et al. (2018) found that the performance of IMERG is dependent on the precipitation morphology because their respective ice-scattering signatures are seen differently by PMW sensors. They found that IMERG performs better in detecting convective precipitation than in observing coexisting stratiform precipitation within the MCS, given that the area of large ice particles lifted by strong updrafts in convective cores leads to lower brightness temperatures for the satellite PMW retrievals. This leads to a time lag in the stratiform maximum behind the convective maximum on the order of a few hours (O et al. 2018). Therefore, the errors in IMERG may be exaggerated when estimating MCS precipitation, as an MCS commonly consist of both stratiform and convective regions through its life cycle. Also, based on results from [Fig. 8](#) it is seen that IMERG has a lower occurrence frequency for heavier precipitation greater than 10 mm with respect to Stage IV, which can lead to underestimations in IMERG for intense rainfall. The underestimation in intense precipitation events in IMERG is also found in [Tan et al. \(2016\)](#) and [Kidd et al. \(2016\)](#). Because MCSs are often associated with severe weather hazards including flash flooding, the accuracy of flash flood prediction is largely affected by the location and the duration of the heavy precipitation. If using IMERG estimates as input into

hydrologic models, the misrepresentation of stratiform and convective precipitation, the underestimation in intense precipitation events, along with the too-large spatial extent of precipitating area, could lead to significant uncertainties in the model outputs. Therefore, the IMERG should be used with caution when analyzing and performing model studies on extreme rainfall events.

6. Error correction

As the dominant error source in IMERG is from false alarm pixels, this section will focus on eliminating those pixels by investigating the relationship between rainfall and environmental variables. First the precipitation estimates of false alarm and hit pixels are plotted as a function of T_b shown in [Fig. 11](#). As expected, most of the false alarms are concentrated in a range of T_b from 220 to 240 K with hourly precipitation less than 0.3 mm. However, the false alarm errors resulting from IR algorithms falsely assigning precipitation values to non-precipitating anvil pixels might be difficult to correct here, as a significant numbers of hit pixels also fall into the same T_b and precipitation ranges as the false alarm pixels in both datasets ([Figs. 10b,c](#)). Thus, the reduction of false alarms is more focused on the rainfall in dry regions.

To reduce the false alarm error primarily due to the evaporation below the cloud base, an additive RH adjustment method developed in [Kuligowski et al. \(2016\)](#) is used. The RH from the RAP model analysis is used in this study. The difference between each paired Stage IV and IMERG hourly estimates is calculated. The precipitation difference values are sorted in order of

FIG. 11. Scatter density plot of brightness temperature T_b and hourly precipitation rate for (a) false alarm pixels in IMERG, (b) hit pixels in IMERG, and (c) hit pixels in Stage IV; N indicates the total sample number for each category.

the matched RH value at surface and then divided into bins of equal sample size (Kuligowski et al. 2016). The mean RH and precipitation differences in each bin are computed and a linear regression is applied to fit the resulting mean values. Thus, an additive humidity adjustment of rainfall is derived:

$$RR_{\text{add}} = RR + 0.039\,505\,5[\max(RH, 55)] - 3.683\,30, \quad (2)$$

where RR is the original value of IMERG estimate and RR_{add} is the value after RH adjustment. RH is in percentage, and zero is assigned to any negative RR_{add} value. For the RH values below 55%, only the most intense cloud-level rainfalls are assumed to reach the surface because the correction removes the precipitation that is not sufficiently intense (Kuligowski et al. 2016). Which means for drier areas, the RR needs to be larger than 1.51 mm h^{-1} to be kept. The additive adjustment method is also found to eliminate too many IMERG pixels with low precipitation rates but corresponding to a high RH . To improve the skill of the RR_{add} , the original IMERG value is assigned to the grid point that has RH greater than 85% but with RR_{add} being equal to zero. The RH threshold of 85% was selected by maximizing the CSI value in this study.

Figure 12 shows an example of the successive hourly precipitation images from an MCS on 6 July 2015. The three rows from top to bottom represent precipitation estimates from Stage IV, IMERG, and RH corrected

IMERG, respectively. At each time step, the RH adjusted IMERG shows less precipitating area compared to the original IMERG, and the shape of the system agrees better to Stage IV. The correction method removes the pixels at the edge of the system and is the most effective in drier regions where RH values are below 50% (Figs. 11d,e), but at the same time slightly diminishes the precipitation intensity.

The use of the RH correction further improved performance of IMERG statistically, as shown in Table 3 (values in second row of each season). After the RH adjustment, the RPD values for hourly estimates have reduced to half of their original values, and for seasonal total precipitation, RDP values become negative and are less than $\sim 5\%$ except winter. The RH correction does not help increase CC (increase roughly by 0.01) since it is more related to the location mismatch, and the improvement of RMSE is also insignificant. Regarding the categorical scores and error components, the FAR decreases and CSI increases, along with a significant decrease in false alarm bias by $\sim 30\%$. The overall error is also found to be lower than original IMERG by $\sim 30\%$.

The impacts of RH correction on changing precipitation distribution and improving HSS are shown in Fig. 13. A reduction in occurrence frequency can be seen for hourly precipitation estimates falling between 0.5 and 1.2 mm. This is likely to be the range where most of the false alarm pixels fall into. The PDFs of the calibrated IMERG become closer to those of the Stage IV for moderate precipitation between 3 and 10 mm, but

FIG. 12. Three time snapshots of hourly precipitation for the MCS that occurred at 0300, 0700, and 1100 UTC 6 Jul 2015 estimated by (a)–(c) Stage IV, (d)–(f) IMERG, and (g)–(i) RH-corrected IMERG. Color contours are the relative humidity from RAP analysis at each time step.

a large difference is still found for heavier precipitation. Similarly, basically no improvement is found in HSS for precipitation greater than 8 mm, but HSS has increased ~ 0.2 for very light precipitation less than 0.5 mm.

7. Summary

This study assesses the performance of the satellite-based GPM IMERG product in estimating MCS precipitation against the radar-based QPE Stage IV product in the central and eastern United States, from April 2014 to November 2016. The analyses are performed for the spatial distribution, diurnal cycle, and time evolution of MCS precipitation during all four seasons. To quantify the bias in IMERG estimates, a composite error analysis is performed to determine the source of errors. Finally, a RH correction method is applied to improve the current IMERG estimates. The main findings are summarized below:

- 1) The spatial distribution of seasonal total MCS precipitation in IMERG resembles Stage IV, but large regional discrepancies exist. Wet biases are found in IMERG for most of the study region in terms of the total precipitation. However, systematic dry biases are found in IMERG hourly mean precipitation.
- 2) The overestimation in total precipitation and underestimation in hourly mean precipitation in IMERG is related to the evaporation of light rain under the cloud base or the misclassification of anvil regions as precipitating pixels or the additional precipitation coverage created by the morphing scheme. These false alarm pixels are the dominant error source in IMERG estimates for MCS precipitation.
- 3) Regarding the diurnal cycle of MCS precipitation, discontinuities are found in IMERG. An abrupt decrease in total precipitation is observed roughly at 0600 UTC, which is linked to the least availability of PMW measurements.

FIG. 13. (a) PDF in percentage as a function of hourly accumulated precipitation for Stage IV, IMERG, and RH-corrected IMERG estimates. (b) HSS of IMERG and RH-corrected IMERG estimates as a function of hourly accumulated precipitation (>0.05 mm) using Stage IV estimates as reference. Only the precipitation estimates with matched RAP RH estimates are used for calculation.

- 4) False alarm rates are reduced in IMERG after applying a correction for evaporation below the cloud base based on RAP model RH analyses, although additional errors from miss events are introduced. The overall performance of IMERG is improved regarding the bias, and CSI values.

The other underlying issues of satellite-derived precipitation such as the wet bias in estimating winter rainfall, the dry bias in heavier precipitation, and the misrepresentation of stratiform and convective rainfall should be taken into consideration when using the dataset. Particularly the two latter issues, along with the problem of IMERG in producing too large of precipitating area, would bring significant uncertainties if using IMERG as an input into hydrological models for simulating MCS and extreme events, or flash flood forecasting. Reducing the false alarm rate and improving the estimation of intense precipitation would be critical in improving the MCS precipitation estimation.

It should be noted that the results presented in this paper may only be valid over the central and eastern United States. Errors related to topographic and oceanic precipitation are not examined. Besides, additional uncertainties could be brought to IMERG due to the inconsistency in satellite measurements as found in this study and Tan et al. (2016).

Under the same situation, the RH correction method adopted from Kuligowski et al. (2016) used in this study is only applied to the central and eastern United States. Whether this correction is suitable for other regions is not determined. For areas without dense

radar or gauge networks (e.g., ocean), the rainfall information from DPR on board GPM *Core Observatory* would be helpful in performing the correction. Even so, a reliable RH product is needed to perform the correction.

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