Evaluation of GSMaP Precipitation Estimates over the Contiguous United States

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ABSTRACT

Precipitation estimates from the Global Satellite Mapping of Precipitation (GSMaP) project are evaluated over the contiguous United States (CONUS) for the period of 2005–06. GSMaP combines precipitation retrievals from the Tropical Rainfall Measuring Mission satellite and other polar-orbiting satellites, and interpolates them with cloud motion vectors derived from infrared images from geostationary satellites, to produce a high-resolution dataset. Four other satellite-based datasets are also evaluated concurrently with GSMaP, to provide a better perspective. The new Climate Prediction Center (CPC) unified gauge analysis is used as the reference data. The evaluation shows that GSMaP does well in capturing the spatial patterns of precipitation, especially for summer, and that it has better estimation of precipitation amount over the eastern than over the western CONUS. Meanwhile, GSMaP shares many of the challenges common to other satellite-based products, including that it underestimates in winter and overestimates in summer. In winter, GSMaP has on average one-half less precipitation over the western region and one-third less over the eastern region, whereas in summer it has about three-quarters and one-quarter more estimated precipitation over the two respective regions, respectively. Most of the summer overestimates (winter underestimates) are from an excessive (insufficient) number of strong events (>20 mm day^{-1}). Overall, GSMaP's performance is comparable to other satellite-based products, with slightly better probability of detection during summer, and the different satellite-based estimates as a group have better agreement among themselves during summer than during winter.

1. Introduction

Precipitation estimates from satellite-based sensors have great potential for hydrological applications, especially as a result of their extensive spatial coverage and fine space and time resolutions. There have been many efforts in operational production of such high-resolution estimates, most notably since the launch of the Tropical Rainfall Measuring Mission (TRMM) in 1997. In addition, ongoing efforts to improve retrieval algorithms and estimation techniques from the community have resulted in newer products.

The Global Satellite Mapping of Precipitation (GSMaP; Okamoto et al. 2005; Kubota et al. 2007; Aonashi et al. 2009; Ushio et al. 2009) project is a recent addition to the repository of satellite-based high-resolution precipitation

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estimates. Supported by the Japan Science and Technology Agency (JST) and Japan Aerospace Exploration Agency (JAXA), GSMaP seeks to produce a high-precision, high-resolution precipitation map using satellite data. Currently, GSMaP incorporates extensive satellite input data streams from both passive microwave (PMW) and infrared (IR) sensors, and its global precipitation maps are appealing for a wide range of hydrological applications.

To facilitate GSMaP's application and assess the improvement from the newer algorithm, it is crucial to quantify and document its error characteristics. However, existing assessments are mostly confined over Japan (Ushio et al. 2009; Kubota et al. 2009). Detailed studies over other areas are lacking, especially on hydrology-relevant space and time scales. In this work, we evaluate GSMaP over the contiguous United States (CONUS). With the much larger spatial scale and accompanying variability in climate regimes, this study contributes to a more comprehensive understanding of GSMaP's error characteristics and their potential effects on hydrological applications.

To gain a better perspective, we evaluated GSMaP in parallel with a few other TRMM-era products, including TRMM Multisatellite Precipitation Analysis (TMPA) 3B42, Climate Prediction Center morphing technique (CMORPH), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and U.S. Naval Research Laboratory (NRL)-blended product (see section 2). These existing products have been extensively studied (e.g., Gottschalck et al. 2005; Ebert et al. 2007; Tian et al. 2007, 2009; Sapiano and Arkin 2009; Kubota et al. 2009), and their strengths and weaknesses are well understood. A simplified, near-real-time version of GSMaP (GSMaP_NRT), which uses less PMW input streams and a forward-only cloud advection scheme, has been routinely evaluated by the International Precipitation Working Group (Ebert et al. 2007; available on line at http://cics.umd.edu/~johnj/us_web.html). Building upon this existing knowledge, this study provides a better context and yields more insight into GSMaP's error characteristics.

2. Data

In this study, we used GSMaP's surface rainfall product currently known as "GSMaP_MVK+ version 4.8.4." Among the several GSMaP versions currently available, GSMaP_MVK+ uses the most satellite input streams. The estimates were obtained by the temporal interpolation of PMW retrievals using a PMW–IR-blended algorithm, with a two-way morphing technique from IR images (Joyce et al. 2004) and a Kalman filter (Ushio et al. 2009). The retrievals from the PMW sensors were computed from GSMaP's own algorithms using various attributes from TRMM data (Kubota et al. 2007; Aonashi et al. 2009). The rain/no-rain classification (RNC) scheme plays a key role in the PMW algorithms over land, with the RNC database derived from the TRMM precipitation radar (PR) for the TRMM Microwave Imager (TMI; Seto et al. 2005) and other imagers aboard the polar-orbit satellites (Seto et al. 2008). Rainfall estimates from the Advanced Microwave Sounding Unit-B (AMSU-B) were provided by the National Oceanic and Atmospheric Administration (NOAA; Ferraro et al. 2005). No ground-gauge correction is applied to this GSMaP product. The product's highest space and time resolutions are 0.1° and one hour, respectively. We chose a 2-yr period from 2005 to 2006 for this study, and all the datasets were evaluated at 0.25° resolution with daily accumulation.

For ground reference data, we used a newly available grid analysis of gauge dataset produced by the NOAA Climate Prediction Center (CPC), referred to as the CPC unified daily gauge dataset (CPC-UNI; Chen et al. 2008). This dataset employs an optimal interpolation (OI) technique to reproject gauge reports over CONUS to a 0.25° grid. The OI-based interpolation has been shown to have higher correlation with individual gauge measurements than other techniques (Chen et al. 2008). There are about 8000–10 000 gauge reports used daily in CPC-UNI for our study period.

To assess the uncertainties in the reference data, we intercompared CPC-UNI analysis with the NOAA CPC near-real-time daily precipitation analysis (Higgins et al. 2000) and the NOAA Next Generation Weather Radar (NEXRAD) stage IV data (Lin and Mitchell 2005). Over the eastern CONUS, the differences between the three datasets are small, because of the high density of the gauges and relatively flat terrain in this region. Therefore, we estimate the errors in CPC-UNI are one order of magnitude lower than those in the satellite data, and they will not qualitatively affect the evaluation of the satellite-based estimates. In the western CONUS, however, the uncertainties become much larger, especially in winter [December–February (DJF)]. Stage IV data severely underestimate relative to either gauge dataset, mainly because of the complex terrain. Meanwhile, Pan et al. (2003) show CPC near-real-time analysis also greatly underestimates by nearly 60%, an amplitude similar to those of the satellite-based datasets (see their Fig. 3). Consequently, over the western CONUS, negative biases in GSMaP could be severely underestimated, and positive biases overestimated, by roughly a factor of 2.

Four other TRMM-era datasets were used for parallel evaluation in this study. They are referred to as TMPA 3B42 (Huffman et al. 2007), CMORPH (Joyce et al.

2004; Janowiak et al. 2005), PERSIANN (Hsu et al. 1997, 1999; Sorooshian et al. 2000) and NRL blended, or NRL for short (Turk and Miller 2005). They are similar to GSMaP, as they all are produced from the combination of PMW and IR retrievals, although the combination techniques vary greatly. More details can be found in the references associated with each dataset, or in Table 1 of Tian et al. (2009). In fact, GSMaP is expected to be more similar to CMORPH, as it has inherited CMORPH's morphing algorithm (Joyce et al. 2004) to derive cloud motion vectors. However, there are some differences between them. GSMaP employs a new Kalman filter approach (Ushio et al. 2009) to assimilate IR-derived rain rates; although not as accurate as PMW retrievals, it can help to reduce the total errors with the Kalman filter. On the other hand, GSMaP has not implemented the normalization technique CMORPH uses to blend the various PMW retrievals. Thus, it would be interesting to see the effect of these trade-offs on the final product.

We also studied another TMPA product, 3B42RT (Huffman et al. 2009), which is a real-time version of 3B42 but without gauge correction. However, for the first half of our study period, the data were produced by an outdated algorithm and thus are considered obsolete; for the second half, its performance is not particularly different from other satellite-only products evaluated in this study. Therefore, the results with 3B42RT are not presented here.

These reference datasets have been extensively studied (e.g., Gottschalck et al. 2005; Ebert et al. 2007; Tian et al. 2007, 2009; Sapiano and Arkin 2009), and each has its own unique strengths and weaknesses, resulting from the various enhancements and compromises in its construction. For instance, 3B42 incorporates global gauge data that help to dramatically reduce its biases, but it has long delays in availability due to the latency of the gauge data. As another example, CMORPH is more cautious in estimating precipitation over snow- and ice-covered land surfaces, resulting in less precipitation events over such surfaces. Therefore, the question, ''which dataset is the best,'' is often not easily defined. More importantly, they share many common challenges, which are largely a manifestation of some more fundamental limitations in the current precipitation remote sensing capability (Tian et al. 2009) and which partly motivate the upcoming Global Precipitation Measurement (GPM) mission.

3. Results

GSMaP performed reasonably well in capturing the spatial patterns of precipitation over CONUS, especially for summer [June–August (JJA)]. Figure 1 shows snapshots of precipitation patterns for two individual days selected as examples: a winter day (14 January 2006; Fig. 1a) and a summer day (28 July 2006; Fig. 1b). For both cases, GSMaP replicated the large-scale precipitation patterns over most parts of CONUS as well as the other multisensor products. For the winter day (Fig. 1a), there were two precipitation systems: one over the northwestern CONUS and the other over the eastern region. GSMaP, similar to the other datasets, captured the eastern system better then the one over the Northwest. In fact, the estimates for the system over the Northwest varied greatly among the five satellite-based datasets, with GSMaP being closest to CPC-UNI but still missing considerable fractions of the precipitating area. This may be related to the difficulty in capturing maritime or topographically driven low-level precipitation by PMW sensors. In addition, the satellite-based estimates tend to underestimate at higher latitudes (40°N and greater) for the eastern system. This underestimation may be caused by two factors: snow and ice cover on the ground and the lack of TRMM coverage over these latitudes.

For the summer day (Fig. 1b), GSMaP's estimates closely resemble the measurements by CPC-UNI of the southwest–northeast system across CONUS, and the five datasets have much better agreement for this summer day than for the winter day (Fig. 1a). Subtle differences exist between them, with GSMaP and PERSIANN having smoother rain patterns and each dataset having a different picture for the isolated storm over southern Nevada, for example, which may be related to PMW retrieval errors over arid areas.

Figure 2 shows the time series of daily area-averaged precipitation (Figs. 2a and 2b), probability of detection (POD; Figs. 2c and 2d), false-alarm rate (FAR; Figs. 2e and 2f), and equitable threat score (ETS; Figs. 2g and 2h) for the western and eastern CONUS (''the West'' and ''the East''), respectively. POD, FAR, and ETS were computed with a rain/no-rain threshold of 1 mm day^{-1} applied to each dataset. The two regions are delineated by the 100th meridian. For area-averaged precipitation amount, the western CONUS (Fig. 2a) sees much higher uncertainties among the satellite-based estimates than its eastern counterpart (Fig. 2b), with strong but disparate overestimates in summer and modest underestimates in winter (Fig. 2a), and GSMaP is fairly moderate in either season. In the East, the bias has the similar trend (overestimates in summer and underestimates in winter), but the amplitudes of these biases are relatively smaller than in the West, and the datasets, including GSMaP, have better agreement. In fact there is a tendency for the datasets to agree with one another better than their overall agreement to CPC-UNI, indicating systematic biases in

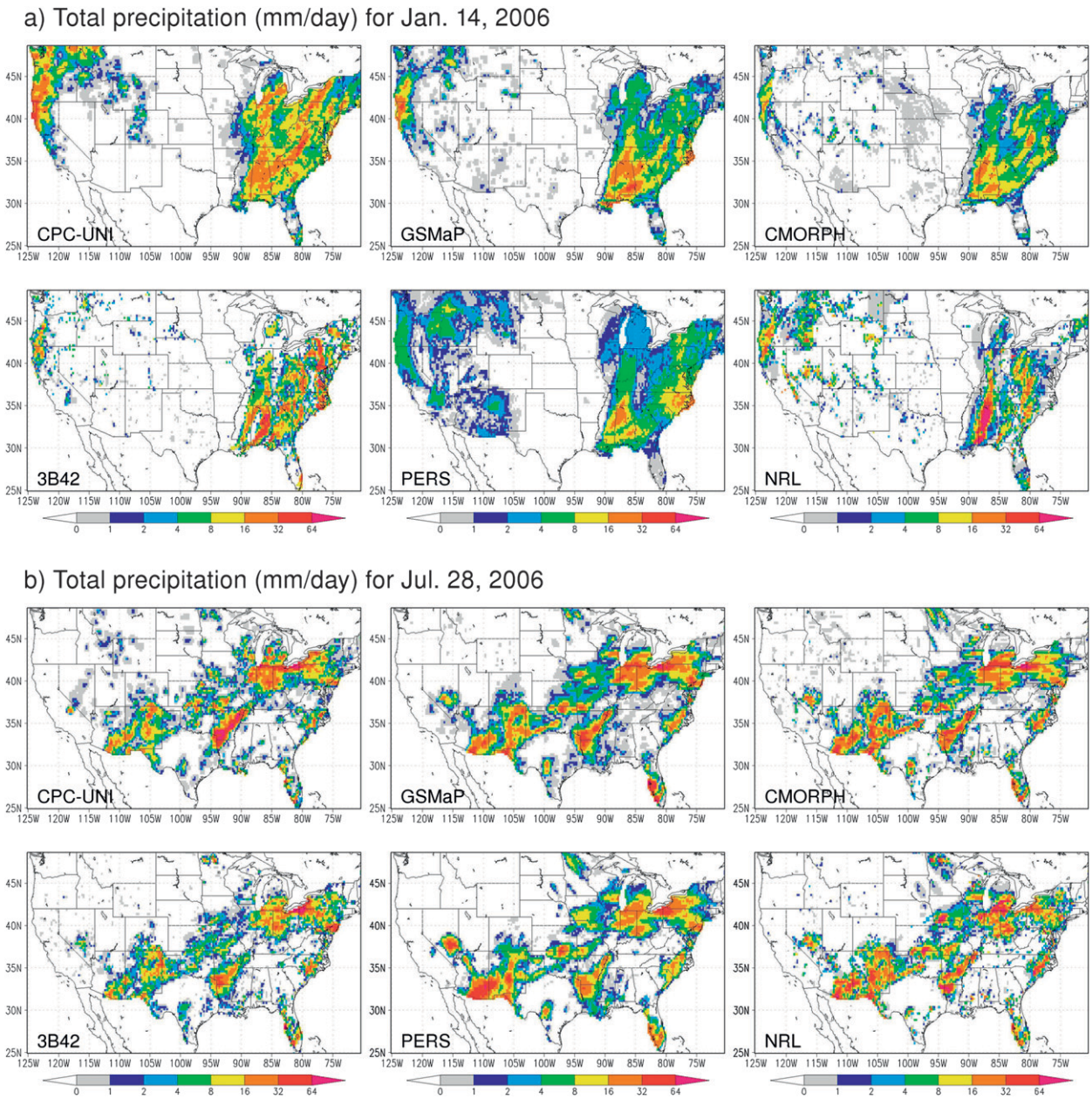

FIG. 1. Snapshots of daily precipitation pattern for (a) a winter day (14 Jan 2006) and (b) a summer day (28 Jul 2006) from each of the six datasets.

all the satellite-based datasets (except for TMPA 3B42). TMPA 3B42 has the lowest biases, as expected from its bias correction with gauge data. We speculate the higher uncertainties in the West are related to more topographically driven precipitation and fewer favorable land surface conditions (e.g., deserts, and snow and ice cover).

GSMaP has slightly better POD than other satellite-based datasets (Figs. 2c and 2d), especially during the second summer. Its highest POD reached nearly 80% (75%) in the East (West), and its FAR (Figs. 2e and 2f) is near the lower end of the group. In addition, its ETS is consistently the highest by itself in the western CONUS, and with CMORPH in the eastern CONUS. These favorable scores can be closely connected with the IR interpolation technique and the RNC scheme of the PMW algorithm. Kubota et al. (2009) demonstrated the effective application of the IR techniques for satellite-based daily averages using the ground-based radar analysis around Japan. Seto et al. (2005, 2008) showed better

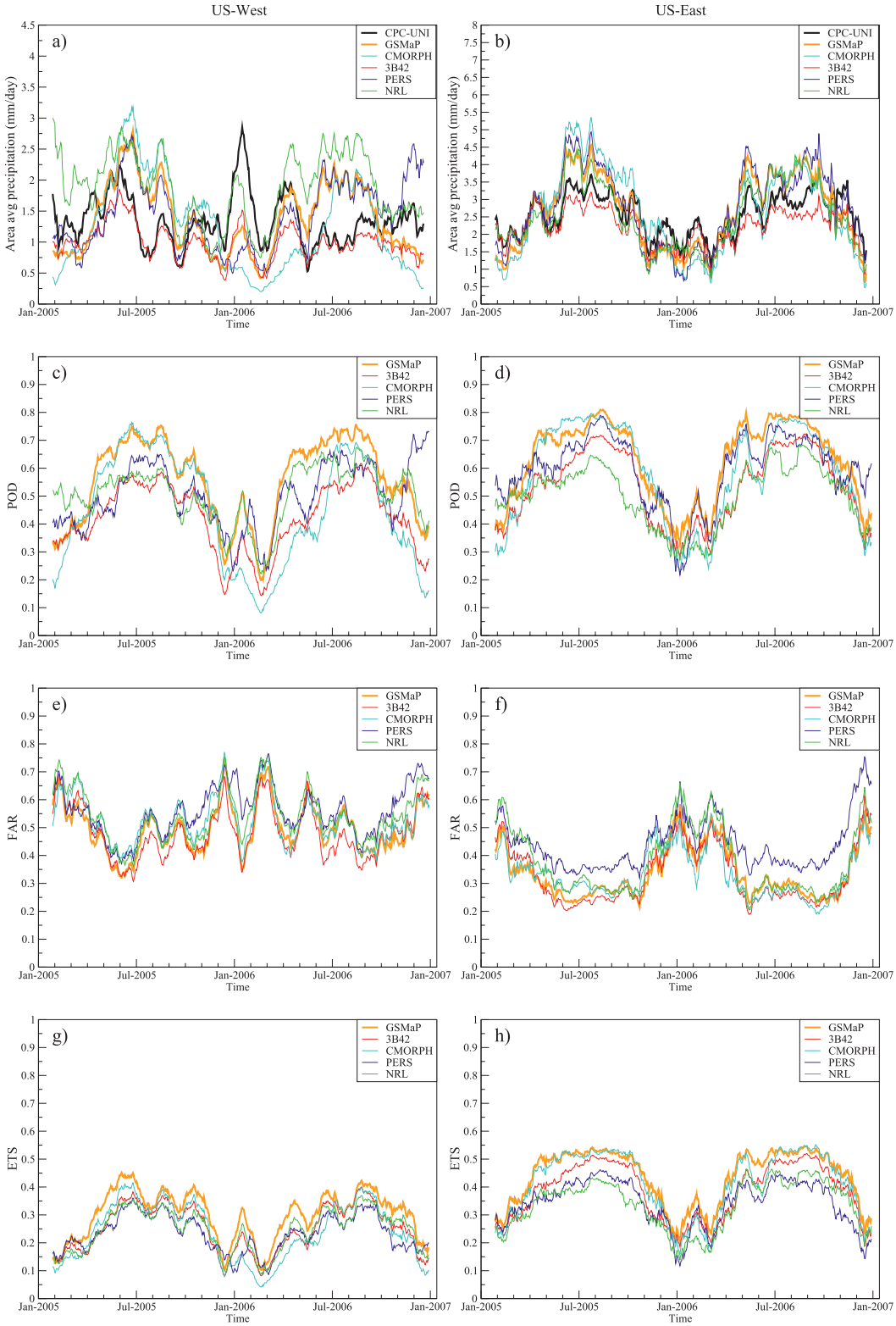

FIG. 2. Time series of (a),(b) area-averaged daily precipitation, (c),(d) POD, (e),(f) FAR, and (g),(h) ETS for (left) western and (right) eastern CONUS from each of the datasets. A 31-day running average was applied to each time series.

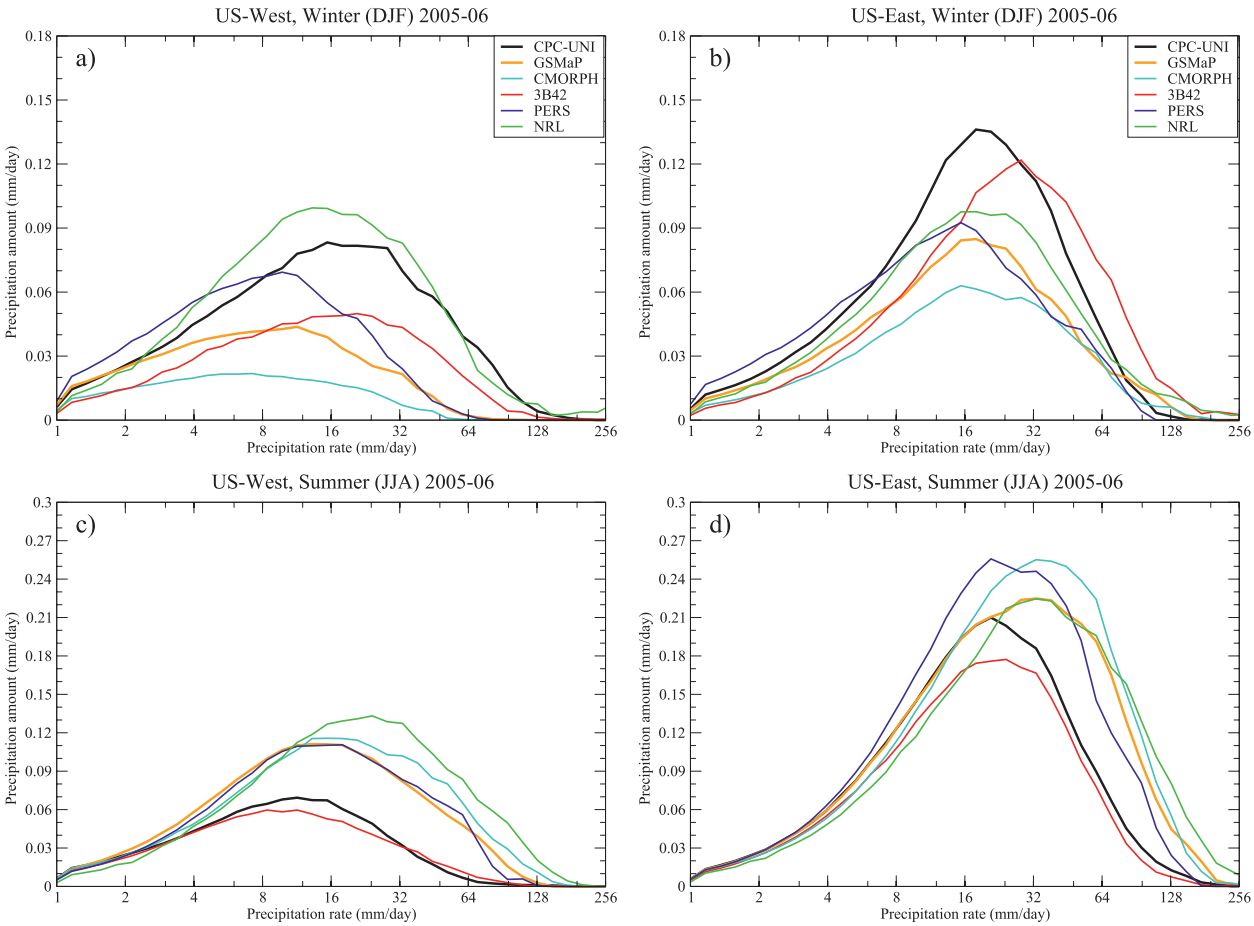

FIG. 3. Intensity distribution of precipitation amount for (a),(b) winter and (c),(d) summer over (left) western and (right) eastern CONUS from each of the six datasets.

performance of the RNC scheme than the Goddard Profiling algorithm (Kummerow et al. 2001) when evaluated against the TRMM PR data. Overall, all the satellite-based estimates share the tendency that their PODs (FARs) are higher (lower) in summer or over the East than in winter or over the West. Therefore, GSMaP, as well as the other datasets, has the best (worst) detection of precipitation in summer over the East (in winter over the West).

Finally, we show the intensity (or rain rate) distributions of daily precipitation amount in Fig. 3 and the daily number of precipitation events in Fig. 4. The intensity distributions of daily precipitation amount provide unique insights into the error dependence on rain rate and also the potential impact of the errors on hydrological applications. This is because most hydrological processes, such as surface runoff, are highly sensitive to the intensity distributions as well as the total precipitation amount. For winter, most datasets, including GSMaP, largely underestimate over a wide range of rain rates, except NRL in the West (Fig. 3a) and 3B42 in the East (Fig. 3b). Over the West, GSMaP, as well as CMORPH and PERSIANN, missed most precipitation with rain rate higher than 40 mm day^{-1}, whereas over the East, most misses are in the intermediate range (~8–40 mm day^{-1}). In summer, except for 3B42, all the estimates considerably overestimate over either the West (Fig. 3c) or the East (Fig. 3d), mostly over the stronger end of rain rates (>20 mm day^{-1}). Again, GSMaP is fairly moderate in these aspects, and for summer, the differences between the satellite-based datasets (except for 3B42) are smaller than their difference as a whole from CPC-UNI, suggesting systematic biases in the common input date streams used by these products.

On the other hand, the intensity distributions of the daily number of precipitation events, or histograms (Fig. 4), enable one to see better the errors at low rain rate. In winter, both the West and East show large disagreements between the datasets. GSMaP has about 20%–50% fewer events than CPC-UNI across the range of 2–32 mm day^{-1} (Figs. 4a and 4b). In comparison,

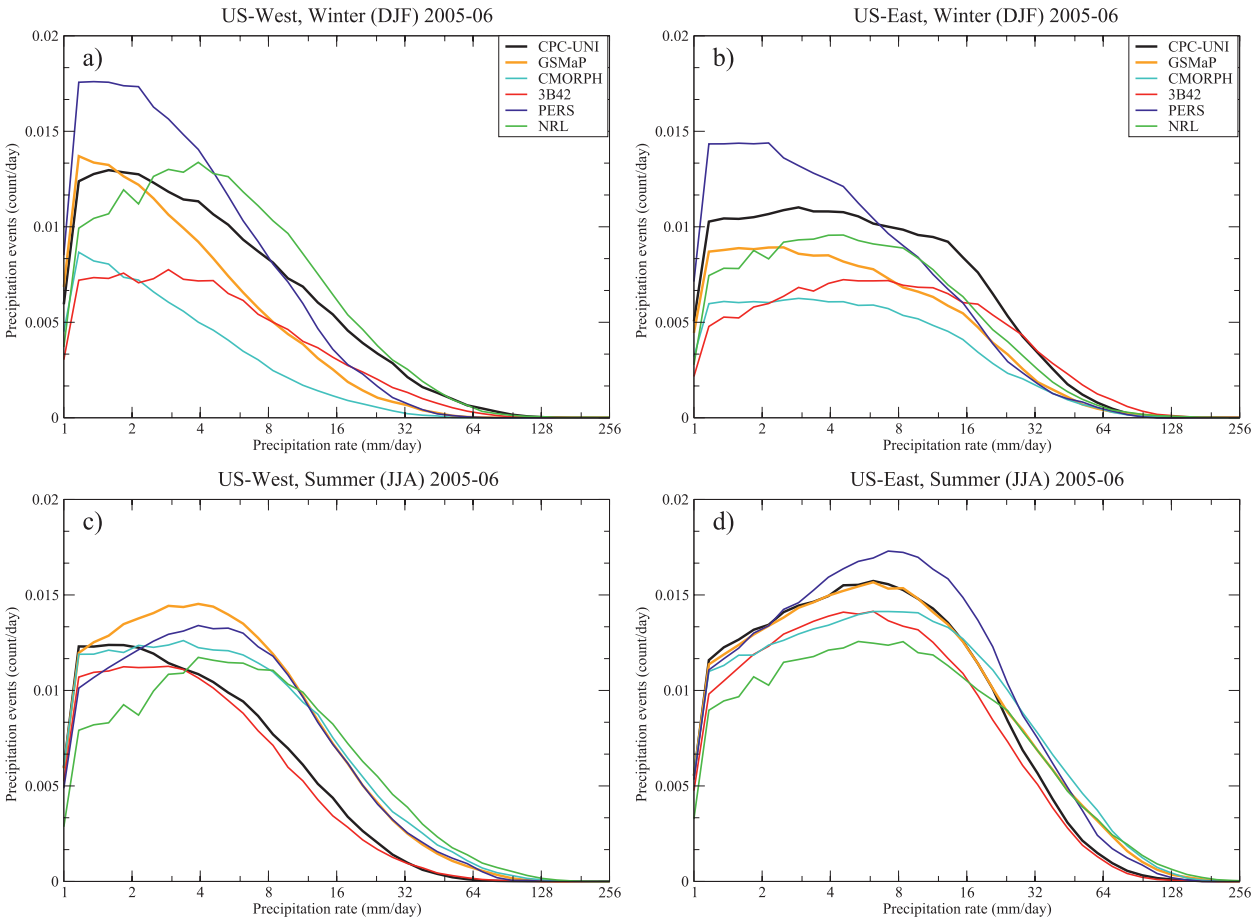

FIG. 4. Same as Fig. 3 but for precipitation event count.

PERSIANN catches more events than CPC-UNI in the range of 1–8 mm day^{-1}, whereas CMORPH has the fewest events among all the datasets, probably as a result of its more conservative estimate of raining area in the presence of snow cover. In summer, GSMaP and other datasets overestimate the number of precipitation events for rain rates higher than 4 mm day^{-1} in the West, except 3B42, which has a histogram very close to CPC-UNI (Fig. 4c). In the East, GSMaP has excellent agreement with CPC-UNI in the range of 1–20 mm day^{-1} but overestimates events above this range. In fact, all the datasets overestimate the number of stronger rainfall events, except 3B42 (Fig. 4d). Again, all the satellite-based datasets tend to have better agreement among them in summer than in winter.

4. Summary

GSMaP (Version MVK+) provides a new high-resolution precipitation product based on merging the most available PMW and IR satellite retrievals. It is attractive to a wide range of hydrological applications, but it has not been evaluated extensively over continental-scale land surfaces. In this study, we studied the error characteristics of GSMaP over CONUS, in parallel with four existing satellite-based datasets: 3B42, CMORPH, PERSIANN, and NRL. The findings of this study include:

1) GSMaP compares favorably with the other existing satellite-based datasets in capturing the spatial patterns of precipitation, especially in summer. Along with CMORPH, it has the highest probability of detection and equitable threat scores among all the datasets in summer (Figs. 2c–2h), but it has 10%–30% lower biases than CMORPH (Table 1).
2) GSMaP, similar to the other multisensor products, consistently underestimates precipitation in winter and overestimates in summer, and it performed better over the East than the West. The amplitudes of GSMaP's errors are not outstandingly higher or lower than the other datasets. Table 1 summarizes the biases of all the datasets. GSMaP's winter bias is −50% (−32%) over the West (East), whereas the

TABLE 1. Spatially averaged daily precipitation (mm), and relative biases (in parentheses, %) to CPC-UNI gauge data, for the period of 2005–06.

Season	Region	CPC-UNI	GSMaP	CMORPH	3B42	PERS	NRL
Winter	West	1.56 (0)	0.78 (−50)	0.40 (−75)	0.92 (−41)	1.14 (−27)	1.78 (14)
	East	1.99 (0)	1.35 (−32)	1.04 (−48)	1.83 (−8)	1.54 (−23)	1.64 (−18)
Summer	West	1.11 (0)	1.97 (77)	2.08 (88)	1.02 (−8)	1.91 (72)	2.32 (109)
	East	3.15 (0)	3.93 (25)	4.17 (32)	2.74 (−13)	4.04 (28)	3.83 (22)

biases of the other four datasets range from −75% to 14% over the West (from −48 to −8% over the East; −48%). For summer, GSMaP has 77% (25%) biases over the West (East), whereas the other datasets range from −8% to 109% over the West (from −13% to 32% over the East).

3) The overestimates in GSMaP for summer result from an excessive number of strong (>20 mm day^{-1}) precipitation events (Figs. 3c, 3d, 4c, and 4d); GSMaP misses a significant number of such events for winter, particularly over the West (Figs. 3a and 4a), leading to substantial underestimates.

These error characteristics will have significant hydrological implications. They will lead to considerable underestimation in streamflow and snowpack accumulation in the western CONUS in winter, for example (Pan et al. 2003), and their excessive amount of strong events in summer will overpredict surface runoff and generate false flood alerts in the eastern CONUS.

Overall, GSMaP and the other multisensor precipitation products without gauge correction produce precipitation estimates that are closer to each other than to the CPC-UNI. The gauge-corrected 3B42 is more similar to the gauge-based CPC-UNI by design. This highlights the systematic errors in the common input streams used by these purely satellite-based products (e.g., McCollum et al. 2002), and it suggests that all satellite-only products could benefit from gauge-based bias corrections similar to 3B42. Similarly, improvements made to one product in reducing detection or false-alarm errors could possibly be applied to other products as well. More fundamentally, more efforts should be devoted to reducing the errors in the upstream of the input data, by measures including better calibration, algorithm improvement, and increased spatial and temporal coverage of PMW retrievals to be offered by the upcoming GPM mission.

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