Systematic and random error components in satellite precipitation data sets

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[1] This study contributes to characterization of satellite precipitation error which is fundamental to develop uncertainty models and bias reduction algorithms. Systematic and random error components of several satellite precipitation products are investigated over different seasons, thresholds and temporal accumulations. The analyses show that the spatial distribution of systematic error has similar patterns for all precipitation products. However, the systematic (random) error of daily accumulations is significantly less (more) than that of high resolution 3-hr data. One should note that the systematic biases of satellite precipitation are distinctively different in the summer and winter. The systematic (random) error is remarkably higher (lower) during the winter. Furthermore, the systematic error seems to be proportional to the rain rate magnitude. The findings of this study highlight that bias removal methods should take into account the spatiotemporal characteristics of error as well as the proportionality of error to the magnitude of rain rate. **Citation:** AghaKouchak, A., A. Mehran, H. Norouzi, and A. Behrangi (2012), Systematic and random error components in satellite precipitation data sets, *Geophys. Res. Lett.*, *39*, L09406, doi:10.1029/2012GL051592.

1. Introduction

[2] Over the past three decades, development of satellite sensors have resulted in multiple sources of precipitation data sets. However, the quantification and understanding of uncertainties associated with remotely sensed satellite data remains a challenging research topic *Bellerby and Sun* [2005]. The uncertainties of satellite precipitation data arise from different factors including the sensor itself, retrieval error, and spatial and temporal sampling, among others [e.g., *Hong et al.*, 2006].

[3] Numerous studies have addressed validation, verification and uncertainty of satellite precipitation estimates against ground-based measurements [e.g., *Turk et al.*, 2008; *Ebert et al.*, 2007]. This study aims to go beyond the validation and inter-comparison of satellite products by analyzing error characteristics of precipitation algorithms. In this paper, systematic and random error components of several satellite precipitation products are investigated over different seasons, thresholds and temporal accumulations. Ideally, the systematic error is to be removed or minimized. In measurement theory, many algorithms have been developed to reduce systematic error with the aim of reducing the overall uncertainty *Taylor* [1999]. Evidently, understanding error properties including systematic and random components are fundamental for future improvements in precipitation retrieval algorithms, development of uncertainty models and bias adjustment techniques, and many other research studies and operational applications [*Sorooshian et al.*, 2011].

2. Data Resources

[4] The following satellite precipitation data sets are used for error analysis: (a) The CPC MORPHing (CMORPH) [*Joyce et al.*, 2004] algorithm; (b) The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) [*Sorooshian et al.*, 2000]; (c) The Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) real-time (hereafter, 3b42-RT) [*Huffman et al.*, 2007].

[5] The Stage IV radar-based gauge-adjusted precipitation data, available from the National Center for Environmental Prediction (NCEP), are used as the reference data set. The Stage IV data include merged operational radar data and rain gauge measurements in hourly accumulations and 4 km grids. The Stage IV observations are accumulated to 3-hourly and aggregated onto 0.25° grids to match with satellite data. The study area covers the entire conterminous United States (hereafter, CONUS). Three years of precipitation data (01/01/2005–12/31/2007) are used for the analysis. Hereafter, the difference between satellite estimates and Stage IV observations is termed as precipitation error.

3. Methodology and Results

[6] In this study, the Willmott decomposition technique is used for deriving the systematic and random components of error. *Willmott* [1981] suggested that the error in the numerical weather prediction models can be separated into systematic and random error components as:

$$\left(\sum_{i=1}^{n} \left(P_{sat} - P_{ref} \right)^2 \right) \Big/ n = \left(\sum_{i=1}^{n} \left(P_{sat}^* - P_{ref} \right)^2 \right) \Big/ n + \left(\sum_{i=1}^{n} \left(P_{sat} - P_{sat}^* \right)^2 \right) \Big/ n \qquad (1)$$

where: P_{sat} = satellite estimates
P_{ref} = reference measurements (here, Stage IV)

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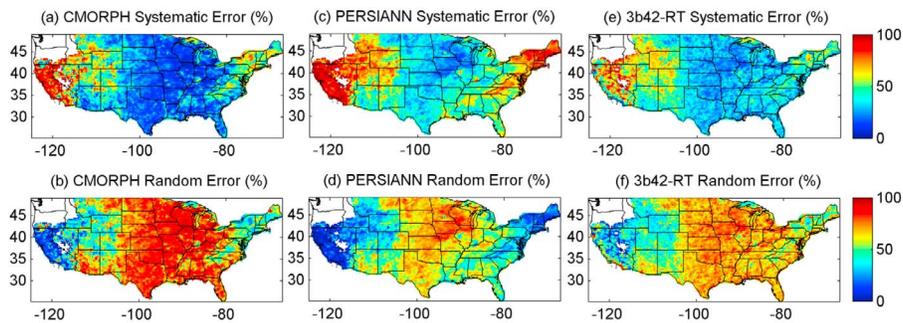
Figure 1. (a–f) Systematic and random error components (%) for 3-hr satellite precipitation data (2005–2007).

$$P^*_{sat} = a \times P_{ref} + b$$
$$a = \text{Slope}$$
$$b = \text{Intercept}$$

[7] This approach decomposes the total mean squared error (MSE) into two components: (a) systematic error (MSE_s, first term in equation (1)); and (b) random error (MSE_r, second term in equation (1)). The systematic error is defined as the part of error to which a linear function can be fitted (see *Willmott* [1981] and *Habib et al.* [2009] for more details). This methodology is adopted to explore random and systematic error of satellite precipitation data across the CONUS. Figures 1 and 2 display systematic ($MSE_s/MSE \times 100$) and random ($MSE_r/MSE \times 100$) components of error (% of total error) for 3-hr and daily precipitation data, respectively. Figure 1 indicates that CMORPH leads to the least systematic error as opposed to PERSIANN and 3b42-RT. As the data is accumulated to daily (lower temporal scale), all three products tend to behave similarly in terms of random and systematic error. One can see that the systematic error of daily data is much less than 3-hr (higher temporal scale) data. This behavior expected as the effect of temporal sampling reduces as the temporal accumulation increases. Overall, both figures indicate that all satellite products exhibit less systematic error (relative to total error) across the central CONUS compared to the western and northeastern CONUS. This is consistent with larger uncertainty and relatively high negative bias of satellite data over the western CONUS, especially in the winter, reported in *Tian et al.* [2009]. Furthermore, *Tian et al.* [2009] revealed heavy underestimations of precipitation over the northeastern CONUS which coincides with high systematic error in Figures 1 and 2.

[8] Previous studies show that satellite precipitation algorithms exhibit different biases, probability of detection and miss rainfall ratio in the summer and winter [e.g., see *AghaKouchak et al.*, 2011; *Tian et al.*, 2009]. The analyses of error components reveal that satellite precipitation data lead to remarkably different levels of systematic and random error in the summer (JJA) and winter (DJF). Figure 3 demonstrates the systematic error components in the summer (upper row) and winter (lower row) for 3-hr satellite data, whereas Figure 4 displays the empirical CDF of the summer (thin lines) and winter (thick lines) precipitation total error. As shown, the systematic error and total error distributions are substantially different during the winter and summer. Daily accumulations also exhibit a similar difference in the summer and winter systematic error components (not shown here).

[9] Proportionality of error of remotely sensed precipitation data to the magnitude of rain rate has been discussed in several studies [e.g., *Habib et al.*, 2009; *AghaKouchak et al.*, 2010; *Behrangi et al.*, 2011]. In a recent work, *AghaKouchak et al.* [2011] highlighted the discrepancies between satellite estimates and ground-based measurements at high thresholds of rain rates (75, 90 and 95 percentiles). In the following, the systematic error and its proportionality to the magnitude of rain rate is investigated. Figure 5 displays the systematic error components of CMORPH (upper row), PERSIANN (middle row) and 3b42-RT (lower row) for different thresholds of reference precipitation rates: <5 mm/hr, 5–10 mm/hr, and >10 mm/hr. Pixels with less than 100 samples of satellite and Stage IV data are not included. One can see that the systematic error (relative to total error) increases significantly as the magnitude of rain rate increases. This indicates that future bias adjustment algorithms should take
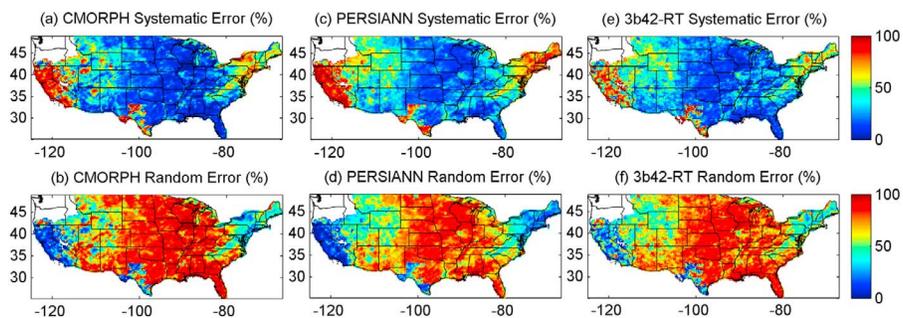

Figure 2. Systematic and random error components (%) for daily satellite precipitation data (2005–2007).
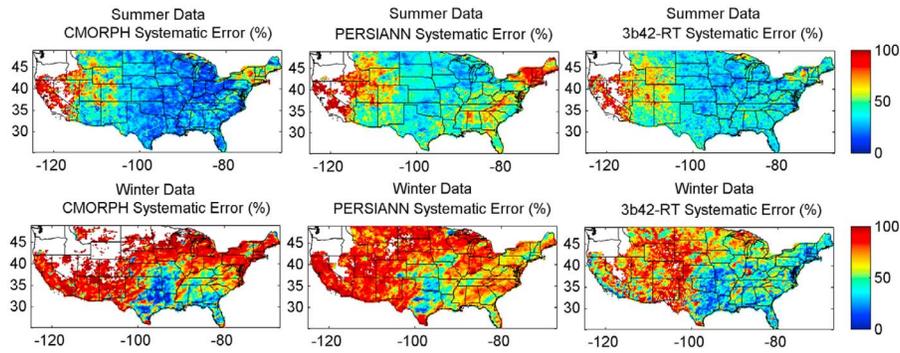
Figure 3. Systematic error (3-hr data; 2005–2007): (top) summer and (bottom) winter.

into account the proportionality of error to the magnitude of rain rate.

4. Conclusions and Final Remarks

[10] The spatial coverage of current in-situ and ground-based precipitation measurement networks is inadequate for monitoring precipitation globally. In recent years, remote sensing of precipitation has emerged as a major source of information. Currently, several satellite-based precipitation products are available in near real-time and on a quasi-global scale. However, uncertainties in satellite precipitation products is the main limitation in utilizing them in operational applications. In a recent review, *Sorooshian et al.* [2011] emphasized the importance of developing more sophisticated bias adjustment techniques and uncertainty models for satellite precipitation data. This study contributes to the ongoing research on characterization of satellite precipitation error which is fundamental to the development of uncertainty models and bias reduction algorithms.

[11] The results indicated that in daily accumulations, the systematic bias was significantly less than the random error component for all precipitation products (see Figure 2). However, in a higher temporal resolution (i.e., 3-hourly) the systematic error component was relatively higher. The analyses showed that the spatial distribution of the systematic error across the CONUS had similar patterns for all precipitation products. This could be due to performance of input satellite precipitation products over different climate conditions, and geographical locations, some of which were highlighted in *Tian et al.* [2009] (e.g., higher uncertainties in the western CONUS, higher error and missed precipitation in the winter).

[12] One should note that the systematic biases of satellite precipitation were distinctively different in the summer and winter. The results revealed that the systematic error was remarkably higher during the winter. The main reasons behind this increase may be problems with high latitude precipitation detection and winter precipitation estimation [see *Sorooshian et al.*, 2011]. Given the changes in characteristics of error in space and time, one can conclude that future bias adjustment algorithms should account not only for the spatiotemporal variability of error but also its distribution (see Figure 4). In addition to variability of error in space and time, systematic error is proportional to the magnitude of rain rate (see Figure 5). The results showed that the systematic error increases as the rain rate increases. This

finding is consistent with studies that reported the proportionality of the magnitude of total error to rain rate [e.g., *Habib et al.*, 2009].

[13] Quantification of systematic and random error components of precipitation may lead to a major advancement in the development of next-generation bias removal algorithms. Currently, most adjustment algorithms are based on correcting the volume of rain rate over a certain period of time (e.g., monthly). While this approach adjusts the total volume of rainfall, it may result in an underestimation or overestimation of precipitation peaks. The findings of this study highlight that future bias removal methods should take into account the proportionality of error to the magnitude of rain rate.

[14] It is worthwhile to point out that satellite retrieval algorithms do not use spatially homogeneous data sets and thus do not have homogeneous error characteristics, including systematic errors. For example, PERSIANN is mainly based on one input data set (Infrared (IR) brightness temperature calibrated with microwave observations). Thus PERSIANN is expected to have more homogeneous errors than 3b42-RT TMPA which combines multiple microwave sensors with gaps filled with IR-based estimates. On the other hand, CMORPH is based on a Lagrangian interpolation technique that morphs microwave data sets. Hence the error patterns may be expected to vary both spatially and temporally according to the time from the nearest microwave overpass, resulting in significantly more spatial and temporal
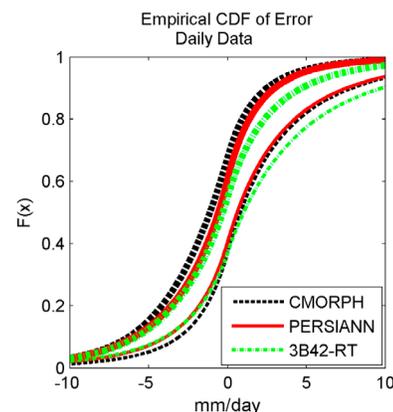

Figure 4. Empirical CDF of total error (2005–2007): winter data (thick lines); summer data (thin lines).
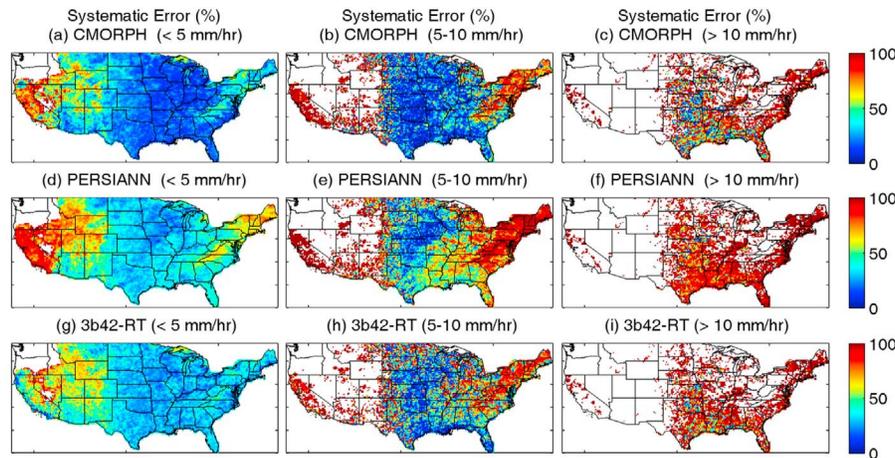
Figure 5. Systematic error components of (top) CMORPH, (middle) PERSIANN and (bottom) 3b42-RT for different thresholds of reference precipitation rates: <5 mm/hr, 5–10 mm/hr, and >10 mm/hr (2005–2007).

variation in error characteristics than the other two data sets. This issue will affect the interpretation of the systematic and random error decomposition results. For this reason, this approach may not be suitable for the intercomparison of satellite algorithms. Instead, we propose this type of error decomposition for understanding error characteristics (e.g., the dependence on magnitude of rain, temporal variability of error) to improve the retrieval algorithms.

[15] Finally, systematic and random error decomposition is not limited to method presented in this paper, and neither do we claim that the presented approach is sufficient to capture all systematic patterns. Defining reliable and meaningful methods of error decomposition requires extensive research (e.g., using nonlinear systematic error functions). Currently, efforts are underway by the authors to develop other methods of systematic and random error decomposition. We strongly believe that in near future more effort should be devoted to improve bias removal algorithms. Hopefully, future advancements in error analysis and characterization as well as bias removal techniques will lead to more reliable and accurate precipitation data sets.

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