Estimating Uncertainties in High-Resolution Satellite Precipitation Products: Systematic or Random Error?

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ABSTRACT

This study proposes a method to quantify systematic and random components of the error associated with satellite precipitation products. Specifically, the Precipitation Uncertainties for Satellite Hydrology (PUSH) model is expanded to provide an estimate of those components of the root-mean-square error. The framework is tested on the TRMM Multisatellite Precipitation Analysis (TMPA) 3B42, real time (3B42RT), and 3B42, version 7 (3B42V7), products over the contiguous United States, using the NOAA Climate Prediction Center (CPC) Unified gauge product as reference. Results show that 3B42V7 exhibits much smaller errors than the real-time product and that the major component of the error associated with both TMPA 3B42 products is random, as the systematic error is almost completely removed by the bias adjustment applied to the two products. A strong dependence of both systematic and random error components on satellite rain rates—with larger error components at larger rain rates—is observed for both satellite products, which suggests that future satellite bias adjustment procedures should account for this dependence. The resulting error estimates and their random and systematic components allow inferences about the accuracy of these datasets and will enhance their deployment in numerous applications, from hydrological modeling and hazard mitigation to climate change studies and water management policy.

1. Introduction

An accurate representation of the global hydrologic cycle is essential to the study and forecast of climate variations, extreme events mitigation, and agricultural planning (Hong et al. 2007; Hossain and Anagnostou 2004; Krajewski et al. 2000). Precipitation is the major driving force of the water cycle, and so it follows that characterizations of the hydrologic cycle are sensitive to errors in our estimates of precipitation, which are not always well described or defined. Satellite estimates of precipitation offer the best description of current and past global precipitation values, and the continued collection and innovation in these estimates through missions such as NASA’s Global Precipitation Measurement (GPM) offers advantages in the use of these estimates.

Given the importance of satellite precipitation data, their error estimates are of crucial importance in hydrological applications and climate studies, insofar as they allow inferences about the reliability of such products in their operational applications. However, evaluating satellite precipitation errors is a very challenging task because it relates to myriad factors, including the natural temporal and spatial variability of precipitation, measurement errors, and sampling uncertainties, especially at fine temporal and spatial resolutions. Uncertainty associated with satellite precipitation products includes both systematic and random errors. These errors depend on 1) the sensor observations; 2) the algorithms that produce the rain estimate from the observations; and 3) the sampling errors, since only a finite set of observations is sampled from the actual population of precipitation events. The random component mainly depends on the sensor sampling design, whereas biases arise from systematic problems such as the inclusion of gauge information that is only available over land (Huffman 1997). Because of the lack of high-quality
reference datasets to estimate these uncertainties, a complete removal of systematic and random errors is unlikely. However, this work provides an effort in that direction.

Many recent studies have evaluated the accuracy of global satellite precipitation products (e.g., Sapiano and Arkin 2009; Anagnostou et al. 2010; Arkin et al. 2005; Ebert et al. 2007; Tian et al. 2007; Hossain and Huffman 2008; Gebregiorgis and Hossain 2012), and a few studies have proposed a method to estimate satellite precipitation errors (Huffman 1997; Hong et al. 2006; Hossain and Anagnostou 2006; Bellerby and Sun 2005; Gebregiorgis and Hossain 2013). Moreover, AghaKouchak and Mehran (2013) provided the useful “Validation Toolbox,” a MATLAB source code to compute evaluation metrics and validation of gridded data like remotely sensed precipitation observations and model simulations. Nevertheless, error estimates with a strong theoretical background are not routinely provided for most publicly available products at fine spatial and temporal resolutions that are being used for research and real-time applications.

Characterizing satellite precipitation errors and their random and systematic components is essential to develop bias reduction techniques, and thus to improve precipitation retrieval algorithms, and for many operational applications. Adjustments of overall and conditional biases have been proven to result in significant improvements in runoff predictions (Habib et al. 2008). For example, no hydrologic model was able to foresee the catastrophic flood that hit Colorado in September 2013; this failure was not in the model formulation, but rather in the input to the models (satellite precipitation) that underestimated the actual rainfall by one-third. Identification of such errors is particularly important in regions lacking sufficient in situ measurements, where satellite retrievals represent the only available precipitation estimate on which flood forecasting and water resources management can rely. Therefore, an estimate (and not a measurement) of errors associated with satellite precipitation product is extremely useful for real-time adjustments that would improve hydrological predictions.

This study presents a framework to better understand the systematic and random components of errors associated with fine-resolution satellite precipitation products. The framework is tested on the widely used Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42, real time (3B42RT), and 3B42, version 7 (3B42V7), products (Huffman et al. 2007, 2010) but can be applied over distinct regions of the globe and to different datasets. Specifically, the Precipitation Uncertainties for Satellite Hydrology (PUSH) model proposed by Maggioni et al. (2014) is here expanded to provide an estimate of the two components of the error associated with the satellite product at each time/location.

2. Datasets

The real-time (3B42RT) and the postanalysis version 7 (3B42V7) TMPA products developed by Huffman et al. (2007, 2010) were used in this study. The TMPA algorithm combines infrared (IR) information from geosynchronous satellites and several microwave (MW) precipitation estimates from active and passive microwave sensors. The 3B42V7 product is bias adjusted to the monthly Global Precipitation Climatology Centre (GPCC) gauge analyses (Schneider et al. 2008). On the other hand, the real-time product does not include any ground-based information, and it is calibrated by the passive microwave TRMM Combined Instrument (TCI) and the 3B43 algorithm. The TMPA products have a coverage of 50°N–50°S and are produced at the 3-h/0.25° temporal/spatial resolution. Since the two products use the same algorithm (i.e., TMPA), with the only difference being in the inclusion of gauge correction in the research product, they represent the ideal datasets for verifying the ability of the proposed framework to discern the systematic component from the random component of the error.

The reference dataset is the NOAA Climate Prediction Center (CPC) Unified gauge product (Higgins et al. 2000; Chen et al. 2008). CPC Unified uses an optimal interpolation objective analysis technique to produce daily/0.25° temporal/spatial scale across the conterminous United States (CONUS). Since CPC Unified precipitation is accumulated from 1200 UTC of the previous day to 1200 UTC of the current day, both TMPA products were also aggregated to the 1200–1200 UTC daily precipitation values to match this averaging as closely as possible. A map showing the average number of gauges that contributes to the daily estimate is shown in Fig. 1.

The GPCC gauge data used to correct the TMPA research product are adjusted for undercatch based on the Legates (1987) climatological corrections. The Legates climatological corrections fix for systematic errors in the gauge measurements due to wind, wetting on the gauge interior walls, and evaporation. Ancillary information, such as air temperature, wind speed, and vegetation coverage, is included in the Legates technique to correct interpolated rain gauge data. However, this correction is not applied to the CPC Unified dataset, and this difference in the two datasets could lead to known biases. Thus, the Legates (1987) corrections have
been applied to the CPC Unified product to remove these methodological differences.

Figure 1 shows the study region and the datasets used in this work. Specifically, precipitation averages are shown for the two satellite products (TMPA 3B42RT and 3B42V7) and the CPC Unified data during 2001–05 over CONUS (mm day$^{-1}$). A clear discrepancy is noted along the U.S. West Coast where TMPA 3B42RT cannot correctly estimate convective precipitation systems triggered by shallow orography. However, the research version (3B42V7), corrected with the GPCC gauge analysis, largely fixes the problem.

3. Methodology

A framework to estimate errors associated with satellite rainfall retrievals, namely the PUSH model, has been recently developed by Maggioni et al. (2014). This scheme provides estimates of errors for fine-resolution precipitation products by using a technique calibrated with high-quality validation data. Moreover, the PUSH framework evaluates several components of the satellite precipitation error, including 1) missed precipitation events (the satellite records a zero, but the reference detects precipitation), 2) false alarms (the satellite incorrectly detects precipitation, as the reference observes no rain), and 3) hit biases (both satellite and reference detect precipitation, but they disagree on the amount). The novelty of the PUSH methodology is that each single component is modeled differently but combined together into a unified procedure. Furthermore, unlike traditional multiplicative errors, it assigns an error even when the satellite estimate is zero. Results by Maggioni et al. (2014) show that PUSH adequately captures missed precipitation cases and false alarms, reproduces the spatial pattern of the error, and shows a good agreement between the probability density function (PDF) of the gauge analysis and the estimated PDF.

The PUSH parameters were calibrated based on the 2001–05 time series over CONUS for each single grid point through comparisons between the satellite product (3B42RT and 3B42V7) and the reference dataset, that is, CPC Unified. Parameters include probability of correct no-rain detection (probability of missed rain is the complement to 1); false alarm probability, which is modeled as exponential decrease as a function of satellite rainfall rate (the hit probability is the complement to 1); the gamma distribution parameters to describe the missed rainfall and the hit cases; and the parameters of the normal distribution that defines the false alarm
cases. We refer the reader to Maggioni et al. (2014) for further details about the precipitation error model.

Given the satellite observation \(x\), PUSH does not provide the error associated with it, but rather an estimate of the PDF of the reference precipitation \(y\) at each time step and grid point. This gives the user the flexibility to compute the error as difference or ratio between the satellite product \(x\) and the expected value of the estimated precipitation distribution \(E[y]\); hereinafter \(y\). The question to answer now is, what is the ratio of the systematic versus the random component of this error?

A methodology to discern the systematic and random components was developed by Willmott (1981) and was recently applied by AghaKouchak et al. (2012) to satellite precipitation products. Willmott (1981) suggested the following formulation for the systematic and random components of the mean-square error (MSE) in numerical weather prediction models:

\[
\text{MSE} = \text{MSE}_{\text{syst}} + \text{MSE}_{\text{rand}} \quad \text{and} \quad (1)
\]

\[
\frac{\sum_n (x - y)^2}{n} = \frac{\sum_n (\hat{x} - y)^2}{n} + \frac{\sum_n (x - \hat{x})^2}{n}, \quad (2)
\]

where \(x\) is the satellite precipitation, \(y\) is the reference precipitation (i.e., the expected value of the precipitation distribution estimated by PUSH), \(n\) is the number of time steps (here days), and \(\hat{x}\) is defined as

\[
\hat{x} = ay + b, \quad (3)
\]

where \(a\) and \(b\) are parameters (slope and intercept, respectively) to be calibrated. The systematic error is the part of the error to which a linear function can be fitted (Willmott 1981; Habib et al. 2009). This component represents systematic average deviations of satellite estimates with respect to the corresponding reference rainfall over the pixel size.

The two parameters \(a\) and \(b\) are calibrated independently for 3B42RT and 3B42V7 against the reference, that is, CPC Unified, for 2001–05 over CONUS. The percentage of systematic and random error at each location (i.e., pixel) is computed as

\[
\text{Syst} = \frac{\sum_n (\hat{x} - y)^2}{n}, \quad \text{Rand} = \frac{\sum_n (x - \hat{x})^2}{n}. \quad (4)
\]

Thus, systematic and random components of the estimated error (\(\text{Syst}\); \(\text{Rand}\)) are computed as a product of these calibrated error components (%) and the MSE between the satellite estimate and the PUSH output.

Figure 2 shows a summary of the methodology framework. First, the systematic and random components are calibrated through comparison between satellite estimate \((x)\) and the reference, that is, CPC Unified, following the Willmott–AghaKouchak method. Second, the satellite retrieval \((x)\) is used as input to PUSH to obtain the expected value of the estimated precipitation distribution \((y)\) and the estimated root-mean-square error (RMSE) is computed between \(x\) and \(y\). This procedure is introduced to be applied to future realizations of satellite precipitation and for real-time adjustments. Finally, the Willmott–AghaKouchak method.

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**Fig. 2.** Schematic of the methodology framework to discern the systematic and random components of the satellite precipitation error. Step 1 shows the calibration procedure and step 2 shows the estimation process to be applied to future realizations of satellite retrievals.
is applied to discern the systematic and random components of that estimated RMSE.

PUSH is a hybrid model, defined as a combination of additive and multiplicative approaches, that estimates the overall error characteristics of precipitation, including missed precipitation and false alarms (Maggioni et al. 2014). Specifically, the multiplicative error model was chosen to model the hits, as it was shown to produce superior prediction of error characteristics for these cases (Tian et al. 2013). However, a purely multiplicative error model is unable to produce a nonzero estimate for cases when the satellite detects no rain—such as missed rainfall—and is therefore not suitable to describe the full range of satellite precipitation uncertainties. Even though a hybrid methodology for the subdivision of the error into its components would be desirable, the simple Willmott–AghaKouchak technique, based upon an additive model, is investigated here and applied to the PUSH hybrid model.

4. Results

The systematic and random components are estimated based on a calibration performed over CONUS during 2001–05 (Fig. 3) for both 3B42RT and 3B42V7. As expected, the systematic component assumes lower values in 3B42V7 when compared to 3B42RT because of the rain gauge adjustment performed in the research. The systematic and random components are estimated based on a calibration performed over CONUS during 2001–05 (Fig. 3) for both 3B42RT and 3B42V7.

![Fig. 3](image-url)

**Fig. 3.** (left) Systematic and (right) random components (%) over CONUS during 2001–05 for (a),(b) 3B42RT and (c),(d) 3B42V7 daily precipitation products.

### Table 1. Correlation coefficients between estimated RMSE and observed RMSE and between estimated and observed systematic/random component. Mean values and ranges (defined as means plus/minus twice the standard deviation) are also shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>3B42RT</th>
<th>3B42V7</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>Systematic</td>
<td>Random</td>
</tr>
<tr>
<td>2001</td>
<td>0.78</td>
<td>0.59</td>
</tr>
<tr>
<td>2002</td>
<td>0.81</td>
<td>0.72</td>
</tr>
<tr>
<td>2003</td>
<td>0.8</td>
<td>0.67</td>
</tr>
<tr>
<td>2004</td>
<td>0.89</td>
<td>0.55</td>
</tr>
<tr>
<td>2005</td>
<td>0.78</td>
<td>0.71</td>
</tr>
<tr>
<td>2006</td>
<td>0.84</td>
<td>0.75</td>
</tr>
<tr>
<td>Mean</td>
<td>0.79</td>
<td>0.7</td>
</tr>
<tr>
<td>Range</td>
<td>0.74–0.84</td>
<td>0.57–0.83</td>
</tr>
<tr>
<td>3B42V7</td>
<td>0.83–0.92</td>
<td>0.49–0.66</td>
</tr>
</tbody>
</table>
product. In addition to the rain gauge data correction, in 3B42V7, the IR calibration period is the calendar month in which the observation time falls, rather than the trailing 30-day accumulation in 3B42RT, and the TCI product (2B31) is used as the calibrating standard in 3B42V7, which gives better estimates than the TRMM Microwave Imager (TMI) by itself (Huffman and Bolvin 2015; Huffman et al. 2007, 2010). Even though some systematic error is introduced in the west continental region, Fig. 3 shows how the majority of the systematic error is almost completely removed along the West Coast and in the eastern United States thanks to the

FIG. 4. Dependence of the two error components on the sample size for (a) 3B42RT and (b) 3B42V7.

FIG. 5. Case study over Texas during 2006 for 3B42RT: (a) average CPC Unified, (b) average 3B42RT, (c) PUSH-estimated RMSE, and (d) PUSH-estimated MRE.
adjustments added in the research product (i.e., 3B42V7). The bias introduced over the Rocky Mountains is due to the low amount of gauges available in the region, which translates into an additional bias in 3B42V7. This has been observed in several parts of the world with scarce gauge coverage (e.g., Habib et al. 2012). Nevertheless, the major component of the error associated with both TMPA 3B42 products is random, whereas the systematic component is almost completely removed by the bias adjustment applied to the two products: the climatological correction by the TCI and 3B43 in the case of 3B42RT and the rain gauge correction in the case of 3B42V7.

To assess the viability of applying the PUSH-estimated RMSE to any future realization, we performed a cross validation. The calibration time series, which spans from 2001 to 2006, is divided into subsets by removing one year each time. The PUSH parameters are calibrated for each subset and applied to the year that was removed by the original time series, which represents an independent validation dataset. Table 1 shows correlation coefficients between estimated RMSE and actual RMSE, between estimated and actual systematic components, and between estimated and actual random components for the six cross-validation experiments. All metrics show little variability across the six samples, with the minimum and the maximum values falling within the average plus or minus twice the standard deviation. The correlation values range between 0.5 and 0.9, demonstrating a strong relationship between the estimated and actual error components and overall RMSE. The 3B42RT shows correlations of ~0.7 for both components, which shows that the proposed methodology performs equally well in estimating the systematic and random errors. In the case of 3B42V7, higher correlations are observed between estimated and actual random components (~0.8) when compared to the systematic ones (~0.6). This exhibits a slightly poorer performance of the proposed technique in estimating the systematic component, when this component represents a minor component of the total RMSE.

Additional analysis has been conducted to assess the size of the sample needed for convergence of the systematic and random components, estimated with the Willmott–AghaKouchak method. Results demonstrate that the two error components converge if the sample size is larger than 350 days for both 3B42RT and 3B42V7.
3B42V7 (Fig. 4). Therefore, one year of data would be enough to calibrate the systematic and random components of the error. However, to avoid biases in the calibration datasets (e.g., particularly dry or wet years), 5 years of data (2001–05) are used for estimating the error components with the Willmott–AghaKouchak method. This demonstrates that the training dataset is sufficient and the calibrated model is stable enough to apply those parameters to future realization of 3B42 to estimate the error components.

A case study is shown for Texas during 2006, an independent period that is not included in the calibration dataset, in Figs. 5 and 7 for 3B42RT and in Figs. 6 and 8 for 3B42V7. Texas was chosen for its diversity in terms of topography, rainfall regimes, and vegetation coverage. Figures 5 (top) and 6 (top) show average daily precipitation maps of the reference CPC Unified (Figs. 5a, 6a) and the TMPA product (Figs. 5b, 6b). Figures 5 (bottom) and 6 (bottom) show the RMSE (Figs. 5c, 6c) and the mean relative error (MRE) estimated using the PUSH model (Figs. 5d, 6d). The two precipitation maps show a strong precipitation gradient with a dry region in the western part and a wetter region in the eastern part.

As expected, 3B42V7 presents lower errors both in terms of RMSE and MRE because of the bias adjustment inherent to the product. By looking at the spatial pattern of the RMSE for both TMPA products, the western region of Texas is characterized by errors smaller than 5 mm day$^{-1}$, whereas higher RMSEs are observed along the Gulf of Mexico coast and in the eastern part of the study area. While 3B42RT exhibits RMSE values larger than 20 mm day$^{-1}$ in these regions, the RMSE in 3B42V7 reaches maxima of 15 mm day$^{-1}$. On the other hand, the MRE shows an overestimation in the western part of the region and slight underestimation in the central region, with the area affected by the overestimation being larger in the research product than the real-time version.

The Willmott–AghaKouchak method is then used to separate the estimated error into its systematic and random components. Figures 7 and 8 show these components in millimeters per day [Figs. 7 (top) and 8 (top)] and as normalized values to the total RMSE [Figs. 7 (bottom) and 8 (bottom)].
The random error is the predominant component in both satellite precipitation products, which is consistent with the rest of CONUS and with the fact that the product algorithms include an adjustment to reduce the systematic error. Specifically, the normalized systematic component varies between 0.1 (0.1) and 0.7 (0.6) in 3B42RT (3B42V7) with an average of 0.4 (0.3), while the random component does not drop below 0.6 (0.7) in any pixel across the study region and has an areal mean of 0.9 (0.9) for 3B42RT (3B42V7). Figures 7 and 8 also show how larger RMSEs correspond to a larger magnitude of rain rates for both satellite products, which corroborates results from several other studies (e.g., Habib et al. 2009; AghaKouchak et al. 2010; Behrangi et al. 2011; Tian et al. 2009). In the 3B42 algorithm, the adjustment procedure is based on correcting monthly precipitation, which may result in underestimating or overestimating precipitation peaks. Future bias adjustment methods should take into account the dependence of error on the magnitude of rain rate.

A further analysis presents the dependency of the systematic and random components as a function of satellite precipitation rate. Figure 9 clearly shows how the error components increase as precipitation rate increases for both TMPA products. This corroborates and supplements what was demonstrated by Mehran et al. (2014), who observed a strong dependence of false alarms and detection capabilities on the amount of rainfall measured by the satellite. Moreover, the systematic and random error components exhibited by 3B42V7 are much smaller (over a third) than the ones associated with the real-time product. Specifically, the systematic error is almost completely removed by the bias adjustment applied to 3B42V7, whereas the random error is still present, even if largely reduced.

5. Conclusions

Uncertainties in satellite precipitation still represent the main limitation in utilizing these products in operational applications. This work contributes to the ongoing research on the estimation of satellite precipitation errors, which is fundamental to the development of precipitation error models as well as the improvement of satellite precipitation product algorithms.
This study presents a framework to quantify systematic and random components of the error associated with satellite precipitation products. Specifically, the RMSE is estimated with the PUSH model (Maggioni et al. 2014), and subsequently decomposed into its systematic and random components, using a methodology developed by Willmott (1981) and applied to satellite precipitation products by AghaKouchak et al. (2012). The resulting error estimates and their random and systematic components could be attached to the standard products for the scientific community to use.

The major conclusions drawn from this study are as follows:

- The error and its systematic and random components associated with 3B42RT are larger than the ones exhibited by the latest TMPA research product (i.e., 3B42V7). The systematic error is largely reduced in 3B42V7, even though some bias is added over the Rocky Mountains, where the density of rain gauges, on which the adjustment in the 3B42V7 algorithm is based, is scarce.

- The random error is the major component for both 3B42 products because of the bias corrections performed in the algorithm (a climatological correction for 3B42RT and a rain gauge correction for 3B42V7).

- A sample size larger than 350 days is recommended to calibrate the Willmott–AghaKouchak method for estimating the two components of the error.

- Larger error components correspond to a larger magnitude of rain rates for both satellite products. Therefore, future bias adjustment algorithm should take into account this dependence of the error on the rain rate.

As pointed out by AghaKouchak et al. (2012), the 3B42 retrieval algorithm does not use spatially homogeneous datasets and therefore 3B42 products do not have homogeneous error characteristics, including systematic errors. For this reason, the proposed method needs a local quantification of the systematic and error components. This means that in order to apply this methodology to other regions of the world, a reference dataset would be needed to estimate those components. The TRMM Precipitation Radar (PR) and the Dual-Frequency Precipitation Radar (DPR) on board the GPM core observatory could provide accurate benchmark datasets to expand this study to regions of the world where ground observations are sparse or absent altogether.

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