Bias Correction of Long-Term Satellite Monthly Precipitation Product (TRMM 3B43) over the Conterminous United States

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ABSTRACT

The Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) has provided a valuable precipitation dataset for hydrometeorological studies (1998–2015). However, TMPA shows some differences when compared to the ground-based estimates. In this study, a correction model is developed to improve the accuracy of the TRMM precipitation monthly product by reducing the bias compared to the ground-based estimates. The TRMM 3B43 precipitation product is compared with the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) and with gridded precipitation estimates acquired from the CPC Unified Precipitation Project, two ground-based precipitation estimates, in the conterminous United States. The bias between the satellite and ground-based estimates is compared with mean surface temperature and elevation, respectively. A weak linear relationship is observed between the bias and temperature but a moderate inverse linear relationship is observed between the bias and elevation. Based on these observations, a linear model is developed for the TRMM 3B43–PRISM bias and elevation. The developed model is calibrated and validated using Monte Carlo cross validation with 25% of the available data as a calibration set and the remaining 75% of the data as a validation set. The estimated model parameters are then used in a correction formula for the TRMM 3B43 dataset for elevations above 1500 m above mean sea level. The corrected TRMM 3B43 product is verified for the high-elevation regions over the entire United States as well as in two high-elevation local regions in the western United States. The results show a significant improvement in the accuracy of the monthly satellite product in the high elevations of the United States.

1. Introduction

Precipitation can be quantified using ground-based measurements or using remote sensing techniques. Ultimately, the choice of dataset depends on the application, catchment size, climate, and time period of study. In poorly gauged regions, the use of remotely sensed precipitation products is an absolute necessity. The Tropical Rainfall Measuring Mission (TRMM) and the TRMM Multisatellite Precipitation Analysis (TMPA) product (Huffman et al. 2007, 2010; Liu 2015;
Yong et al. (2015) have provided valuable precipitation datasets for hydrometeorological studies for nearly two decades (1998–2015).

Despite the areal coverage and advanced retrieval algorithm, numerous studies have shown that TMPA estimates of precipitation differ from ground-based estimates (e.g., Bitew and Gebremichael 2011; Duan and Bastiaanssen 2013; Hunink et al. 2014; Islam and Uyeda 2007; Javanmard et al. 2010; Nesbitt and Anders 2009; Ojo and Omotosho 2013; Tian et al. 2007). Precipitation at high elevations specifically in the winter months can be in solid form, and this complicates the retrievals from the TRMM multisatellite sensors. The TRMM multisatellite spaceborne sensors give an indirect measure of precipitation, based on passive sensors at multiple wavelengths (infrared and microwave) and radar. The passive microwave sensor precipitation retrieval on the TRMM multisatellite could misidentify the ice cover over the mountaintops as raining clouds (Dinku et al. 2010). The passive microwave is also not able to observe the orographic enhancement in the liquid phase over the complex terrain, leading to underestimation of the actual precipitation (over land, only scattering from solid hydrometeors is used; Shige et al. 2013). Since the microwave is used to calibrate the infrared, infrared thus inherits the same problem. Further, the TRMM satellite radar does not detect very low rainfall rates (<0.7 mm h$^{-1}$) and low to moderate levels of snowfall rate. In the events characterized by such low precipitation rates, TRMM underestimates the total monthly or yearly precipitation leading to a negative bias (Anders et al. 2006). As snow typically falls in high elevation and mountainous terrains, there is therefore a tendency for retrievals from the TRMM multisatellite to underestimate precipitation in such regions (Condom et al. 2011). The focus of this current study was to improve the accuracy of the TMPA product at high elevations and mountainous terrains by using ground-based estimates.

The issue in using a ground-based estimate to assess or improve the accuracy of any satellite product is the accuracy of the ground-based estimate. The first issue that arises is the spatial sampling, particularly where there is steep topography and mountainous terrain due to the orographic effect on precipitation rates. Several studies (e.g., Gervais et al. 2014; Nesbitt and Anders 2009; Roe 2005) have demonstrated that rain gauge data suffer from insufficient accuracy leading to negative or positive biases relative to the actual precipitation. The bias has been observed to be larger in the winter than in the summer, in particular at high latitudes, for example, in the northern United States (Groisman and Legates 1994; Yang et al. 2005). Gervais et al. (2014) showed that in mountainous regions of the western United States the low density of gauges leads to underestimation and negative bias. In mountainous regions, the high spatial variability of precipitation suggests that more gauges are needed to obtain accurate estimates of precipitation.

Bergeron (1961) found, over a small wooded hilly region (∼50 m high) of northern Sweden, rainfall differences of 20%–200% with an adjacent area at a distance of only a few kilometers. Accordingly, he stated that across the world, there is no official network of gauges dense enough to provide even a summary picture of the actual precipitation amount. Roe (2005) refers to Bergeron’s statement and points out that the density of the gauge network has not been improved much since 1961, with the problem being more severe in mountainous regions.

The second issue that arises is the wind-induced undercatch effect on gauge measurement (Koschmieder 1934; Legates 1987). Koschmieder (1934) stated that the gauge produces a disturbance of the air currents, and thereby this disturbance causes error in precipitation measurements by the gauge. Similarly, Yang et al. (2005) argue that the wind-induced undercatch is one of the largest errors in the ground-based precipitation measurement and suggest the correction factors of 10%–120% of the total measured precipitation for summer and winter months, respectively. In addition, the gauge record is a point precipitation measurement, which is not appropriate for hydrometeorological applications that require gridded precipitation data over a vast area. Regular spatial averaging of precipitation data from the existing gauge networks without accounting for the orographic and wind-induced undercatch effects on precipitation does not provide an accurate estimate of the mean areal precipitation, particularly over mountainous regions (Groisman and Legates 1994; Roe 2005). In this study, we used the ground-based gridded monthly precipitation dataset from the Climate Prediction Center (CPC) for comparison with the TRMM 3B43 satellite product.

To produce the monthly post-real-time TMPA product (TRMM 3B43), the satellite and rain gauge data are merged to adjust the satellite product (Huffman et al. 2007). Incorporating the rain gauge data in the TRMM 3B43 precipitation algorithm is intended to increase the accuracy of the satellite product. However, the bias in the gauge data, due to low spatial sampling over the mountainous regions and the wind-induced undercatch effect, is reflected in the TRMM 3B43 product. It should be mentioned that TMPA applies a wind undercatch correction (averaging about 10%, but varying by season and location) to the data recorded by the TRMM multisatellite product as suggested by Legates (1987), which is not considered in the gauge measurement.
Studies have shown that the satellite products and rain gauge estimates of precipitation have a high dependence on the elevation of the land surface and topography. Several models of orographic precipitation have been developed to account for the effects on precipitation (e.g., Anders et al. 2006; Daly et al. 1994; Roe et al. 2002). In this study, we chose the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) as the other ground-based precipitation dataset to compare to the satellite product. PRISM was developed to interpolate climate variables in complex topographic landscapes (Daly et al. 1994, 2002, 2008). PRISM calculates a local climate–elevation relationship for each grid point and accounts for elevation, topographic features, and orographic effectiveness of the high-elevation terrain as the primary determinants of precipitation patterns. However, PRISM does not account for the climatological wind undercut effect. PRISM has full coverage of the entire conterminous United States (CONUS).

In this work, we compared the TRMM 3B43 precipitation product with the gridded precipitation dataset (CPC), based on rain gauges, and the PRISM precipitation estimate across the CONUS. The results showed a noticeable bias between the ground-based estimates of precipitation (considered as reference datasets) and the satellite equivalent in areas at elevations above 1500 m above mean sea level (MSL), many of which are mountainous. We developed a correction model, which was then applied to all satellite pixels at these high elevations. We calibrated and validated our correction model using 25% and 75% of the entire dataset. We presented the performance of the corrected TRMM 3B43 at the scale of the country and in two local areas at high elevations in the western United States. Comparison of the corrected satellite precipitation with ground-based estimates showed considerable improvement specifically in elevations above 1500 m MSL in the winter season. The correction formula contains time (in months) and elevation as variables and can be easily applied to the TRMM 3B43 product for use in hydrometeorological applications.

2. Datasets

a. Gridded precipitation dataset (GAUGE)

Gridded monthly precipitation for the entire CONUS was acquired from the CPC Unified Precipitation Project (Xie et al. 2007; Chen et al. 2008). The calculated gridded precipitation achieves a consistent and improved quality by combining all updated information sources available at CPC (monthly precipitation reports of ~6000 gauges across the globe) and using an optimal interpolation (OI) objective analysis technique (Gandin and Hardin 1965). The analyzed fields of daily precipitation climatology (defined from historical gauge observations) are collected at CPC. The gridded fields of the ratio between the daily precipitation and daily climatology are then calculated by interpolating the corresponding values at the gauge locations using the OI technique. Daily precipitation is then computed by multiplying the daily ratio and daily climatology values (Chen et al. 2008). For further details on this product, the reader may refer to Chen et al. (2008) and Xie et al. (2007).

There exist multiple CPC spatial resolution datasets depending on the number of available gauges. In the case of CONUS, CPC collects the daily precipitation data of ~8000 rain gauges from the combined daily gauge datasets collected at National Oceanic and Atmospheric Administration (NOAA)/CPC (Chen et al. 2008). In this study, we used the gridded total monthly precipitation based on the direct daily gauge measurement for the time period from January 1998 through January 2015 with spatial resolution of 0.25° latitude × 0.25° longitude (~25 km). With this spatial resolution, a 300 × 120 grid covers the entire CONUS. As this dataset is developed using the direct precipitation measurements at the gauges and a regular interpolation technique, we refer to it as the GAUGE precipitation dataset.

b. PRISM dataset

Elevation is one of the primary determinants of the precipitation pattern, and the relationship between precipitation and elevation varies according to the topography, namely, elevation, slope, and exposure, of the region. Precipitation typically increases with the elevation (e.g., Groisman and Legates 1994; Haiden and Pistotnik 2009; Jia et al. 2011; Konrad 1996). To this end, Daly et al. (1994) developed an algorithm (PRISM) that accounts for orographic features on Earth’s surface. PRISM calculates a local climate–elevation relationship for each grid point and each climate variable, for example, surface temperature and precipitation, at multiple temporal and spatial resolutions. PRISM uses the weather data from the closest station to populate the climate–elevation-dependent regression function. The function is developed from \( X, Y \) pairs of elevation and measured climate variables at the observation stations. A moving-window procedure is used to compute a unique climate–elevation regression function for each grid. The regression function is described as follows (Daly et al. 2008):

\[
Y = \beta_1 X + \beta_0, \tag{1}
\]
where \( Y \) is the predicted climate variable, \( X \) is the elevation data acquired from the digital elevation model (DEM) for the target pixel, and \( \beta_1 \) and \( \beta_0 \) are the regression slope and intercept, respectively.

Each station is assigned a weight based on numerous factors, as shown in the equation below:

\[
W = W_c (F_d W_d^2 + F_z W_z^2)^{1/2} W_p W_l W_s W_e,
\]

where \( W_c, W_d, W_z, W_p, W_l, W_s, \) and \( W_e \) are the cluster, distance, elevation, vertical layer, topographic facet, vertical layer, topographic position, and effective terrain weights, respectively. Parameter \( F_d \) is a user-specified distance scalar, and \( F_z \) is an elevation weighting importance scalar (Daly et al. 2002). All weights and factors, individually and combined, are normalized to sum to unity (Daly et al. 2008). In the next step, some of the station data are downweighted in the case that they are distant from the target pixel. The distance–weight relation can be described as

\[
W_d = \begin{cases} 
1; & d - r_m \leq 0 \\
\left( \frac{d - r_m}{r_m} \right)^a; & d - r_m > 0 
\end{cases}
\]

where \( d \) is the horizontal distance between the station and the target pixel, \( a \) is the distance weighting exponent, and \( r_m \) is the minimum radius of influence. In the PRISM cluster weighting, Daly et al. (2008) populated the PRISM climate–elevation regression function with the climate variables collected from climatology stations encircling the target pixel that are within a given radius of influence. In the vertical distance, they determined the proximity of the elevation stations in order to be characterized as representing the same elevation using the cluster distance threshold. A station is downweighted when it is at a much different elevation than the target pixel [more details can be found in Daly et al. (2008)].

The ground-observed data used for producing the PRISM precipitation and temperature products are acquired from nearly 13,000 and 10,000 climate stations, respectively, across the CONUS and some stations near the northern border inside Canada. In addition to the ground-observed climate variable data, the regression-based PRISM uses DEM, other spatial datasets, and an encoded spatial climate knowledge base to generate estimates of climate variables with various spatial and temporal resolutions. The products are available at the annual, monthly, and daily basis and at spatial resolutions of 0.8 and 4 km (Daly et al. 2008). In this study, the total monthly precipitation and mean surface temperature with 4 km spatial resolution were used for the analysis.

c. TRMM 3B43 dataset

The TRMM was a joint project between the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) to observe precipitation between 40°N and 40°S latitude (more than two-thirds of Earth’s surface). The TRMM satellite was launched in late November 1997 and ended its mission in April 2015 (Huffman et al. 2007, 2010; Liu 2015).

Several versions of the TRMM data-processing algorithms have been released since the launch in 1997. The TMPA system produces estimates of quasi-glob al precipitation (50°N and 50°S latitude) that utilize multisatellite and gauge data for bias correction (Huffman et al. 2007, 2010). TMPA provides 3-hourly precipitation datasets of the global tropical and subtropical regions with a spatial resolution of 0.25° latitude × 0.25° longitude. The latest monthly multisatellite and gauge precipitation algorithm, 3B43 version 7, was released in mid-2011. The 3B43 merged precipitation product is based on a combination of microwave, infrared, and radar information from TRMM and other precipitation-relevant satellite sensors, infrared data from geostationary satellites (TRMM multisatellite), and ground-observed data merged in the Global Precipitation Climatology Centre (GPCC; Schneider et al. 2014). In this study, we used the TRMM 3B43 (monthly) precipitation product between January 1998 and January 2015 for comparison with GAUGE and PRISM datasets.

Figure 1 shows the average seasonal precipitation over a 17-yr time period (1998–2015) estimated by GAUGE, PRISM, and TRMM 3B43 covering the entire CONUS.

d. DEM dataset

The global 30 arc s elevation dataset (GTOPO30), which is a global DEM with a horizontal grid size of 30 arc s (~1 km), was used in this study to define the relationship between satellite precipitation bias (relative to ground-based estimates) and elevation. Using this spatial resolution, the elevation values covering the CONUS range from 0.0 to 4328 m MSL. We used the lowest DEM resolution dataset, as our objective was to resample the elevation data at the TRMM 3B43 grid size, which has a resolution of 0.25° × 0.25°.

3. Methodology

Spatial and temporal variability of precipitation are functions of surface temperature, latitude, elevation, distance from moisture sources, prevailing wind direction,
proximity to mountain ranges, and atmosphere-integrated water vapor. These factors influence precipitation patterns and may cause bias in the satellite products (Berg et al. 2002). In this study, we investigated the differences between satellite-based and ground-based precipitation estimates as functions of surface temperature and elevation. This allowed us to identify the variable(s) that have a substantial effect on the satellite product. Then, by using the bias–environmental factor relationship, we were able to remove the effect on the satellite product, thereby reducing bias and improving the accuracy.

a. Data processing

To carry out consistent comparisons between the different datasets, which we acquired from multiple databases, we resampled all datasets to the lowest spatial resolution and used that for the comparisons in this study. Accordingly, all datasets were resampled to the TRMM 3B43 grid size, which has a spatial resolution of 0.25° latitude × 0.25° longitude. For this, we simply averaged all grid values of the other datasets (GAUGE, PRISM, and DEM) that fall within a TRMM pixel and assigned that value to the new grid. The datasets used in this study are summarized in Table 1.

b. Statistical evaluation

To quantify the bias between the satellite data and the ground-based estimates, three statistical measures, the correlation coefficient $\rho$, mean absolute error (MAE), and relative bias $\delta B$, were used. Apart from the correlation, the measures were made on a pixel-by-pixel basis within the CONUS. We calculated these quantities

![Figure 1: Averaged seasonal precipitation (mm) map over the CONUS from three different data sources: (left) GAUGE, (center) PRISM gridded product, and (right) TRMM 3B43 satellite product. Seasons are defined as spring (March–May), summer (June–August), fall (September–November), and winter (December–February).](image-url)
using monthly averages over the study period from 1 January 1998 to 1 January 2015.

The Pearson correlation coefficient $\rho$ gives the degree of linear association between two variables, so it was used to define how well the TRMM 3B43 precipitation product corresponds to the GAUGE and PRISM estimates. This coefficient is defined as

$$
\rho = \frac{\sum_{i=1}^{n} (G_i S_i) - \left( \sum_{i=1}^{n} G_i \right) \left( \sum_{i=1}^{n} S_i \right)}{\sqrt{\left( \sum_{i=1}^{n} G_i^2 \right) - \left( \sum_{i=1}^{n} G_i \right)^2} \sqrt{\left( \sum_{i=1}^{n} S_i^2 \right) - \left( \sum_{i=1}^{n} S_i \right)^2}},
$$

(4)

where $G_i$ and $S_i$ are the ground-based and satellite-based precipitation estimates, respectively, at pixel $i$ and $n$ is the total number of pixels.

The root-mean-square error (RMSE) is one of the most common estimates of error. However, the RMSE is sensitive to the occasional large error, for example, in our study, extreme precipitation events, and was found to be heavily influenced by such events. As a result, RMSE does not reflect the bias properly. Instead, we used the MAE, which is less sensitive to extremes and provides a stable estimate of the differences in the temporal precipitation data. This is defined as follows

$$
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |S_i - G_i|.
$$

(5)

The relative bias $\delta B$ denotes the absolute bias divided by the precipitation and has the advantage that it is independent of the amount of precipitation. We defined the relative bias as

$$
\delta B_i = 2 \frac{S_i - G_i}{\epsilon + (S_i + G_i)},
$$

(6)

where the denominator $\epsilon$ contains a small number to regularize grids/pixels where very low values of precipitation can result in a very large relative bias. For example, if the estimates of precipitation by the satellite-based and the ground-based estimates are 0.1 and 1 mm month$^{-1}$, respectively, the relative error would be 160% without regularization, whereas for 100 and 100.9 mm month$^{-1}$, respectively, it would be 0.9%.

In our calculations, we used $\epsilon = 15$ (mm month$^{-1}$) corresponding to an average daily precipitation of about 0.5 mm, which then effectively reduces the large relative bias from low-precipitation events. Note that the relative bias is expressed as a fraction and can be multiplied by 100 to express a percentage of bias.

c. Correction model for satellite data

There are numerous bias correction techniques in which a transfer function, derived from the direct comparison between ground-based estimates and satellite-based products, is applied to the satellite data (e.g., Condou et al. 2011; Wanders et al. 2015; Yang et al. 2016). In these techniques, a correction model is developed based upon the historical data for a particular area and is then applied to the satellite data. These types of corrections are mostly site specific and hence cannot be applied to other regions. Further, the reasons for the bias in the satellite estimates are neither investigated nor considered in the bias correction formula. In this study, we took into account the environmental parameters (elevation and temperature), which, based on the previous studies (e.g., Dinku et al. 2010; Berg et al. 2006), are considered to be the primary factors causing bias in the satellite product. We then derived a correction model, which reduces bias in the satellite product taking into account the environmental parameters and a reference precipitation dataset. It is noted that the correction model was developed on a pixel-by-pixel basis over the high elevations of CONUS.

d. Calibration, validation, and verification

To assess the derived model, we used a Monte Carlo cross validation (MCCV) approach (Girard 1989; Haddad et al. 2013). The reason for choosing an MCCV scheme for validating the derived model was to minimize the influence of long-term effects such as periods of drought or excessive rainfall in the choice of calibration/validation years. The MCCV technique randomly selects a subset of cases for calibration in a dataset, estimates parameter values ($\alpha$ and $\beta$), and validates the model using the remaining cases. The procedure is iterated $N$ times, and for each iteration, MCCV retraining
the classifier from the starting point with the calibration set and then estimates the error $E_i$ using the current validation set. An actual error $E$ is then calculated as the average of the separate calculations $E_i$, as follows:

$$E = \frac{1}{n} \sum_{i=1}^{n} E_i. \quad (7)$$

In this study, we randomly split the entire satellite-based and ground-based precipitation datasets into calibration sets that included 4 years (monthly data), that is, 25%, of the dataset, and validation sets that included 13 years (monthly data), that is, 75% of the dataset. The random partitioning of the data was arbitrarily repeated 1000 times, deemed to be a sufficient level of sampling. After each calibration period the estimated coefficients were inserted in a correction model and used in the validation. The monthly average values of the computed coefficients were then employed in a correction model [see Eq. (9) below] to improve the accuracy of the satellite product.

To verify the performance of our approach with variability in space, we applied the correction model to all satellite grids/pixels covering the elevations above 1500 m MSL across the CONUS. In addition, we investigated the improvement at local scales in the western United States.

For the local investigations, we selected a TRMM 3B43 pixel together with the surrounding eight pixels to create a verification area. The correction models were then applied to the original TRMM 3B43 precipitation product, and the results were compared with ground-based estimates of precipitation. For the comparison, the precipitation value of all pixels that fell inside each region (nine pixels) were averaged and compared with the average precipitation value of the corresponding ground-based data. The two selected regions are located at latitude 37.25°–38.0°N and longitude 104.75°–105.50°W, which corresponds to the southeastern Rocky Mountains (southern Colorado; region A), and latitude 44.00°–44.75°N and longitude 114.50°–115.25°W, which corresponds to northwestern Rocky Mountains (the central region of Idaho; region B). The average elevations of these two areas were 2315 and 2221 m MSL for regions A and B, respectively. We applied the developed model including computed coefficients, which is based on the averaged monthly values (12 correction models) of the calibration dataset (each coefficient is averaged over the calibration datasets for particular months, for example, January, February, etc.), to the TRMM 3B43 precipitation time series during the study period (204 months during 17 years). This was done to test the performance of the correction model with variability in time.

4. Results and discussion

We present the results based on the three precipitation datasets (one satellite-based and two ground-based) and two environmental parameters (mean surface temperature and elevation). The analyses consist of statistical measures, bias calculation, bias correction, and error analysis. We defined the relationship between satellite-based and the two ground-based precipitation estimates. We also calculated bias between the satellite and ground-based precipitation estimates and investigated its relationship with environmental parameters using seasonal data. The seasonal analysis (spring, summer, fall, and winter) presents the impact of surface temperature and elevation on the bias between the satellite (TRMM 3B43) and the two ground-based estimates (PRISM and GAUGE). Next, a more thorough analysis is presented using estimates of monthly accumulated precipitation using TRMM 3B43 and PRISM, where the correction model for the retrievals from the TRMM multisatellite is investigated over the CONUS as well as at the local scale. It is also noted that for simplicity in the analysis and also because a significant portion of the high elevations of the CONUS (>1500 m MSL) is occupied by the complex terrain in the western region of the country, we therefore used high elevation merely as a surrogate for the high mountainous terrain.

a. Bias calculation and analysis

The relative bias between the satellite product and the two ground-based datasets was calculated at the pixel level. Figure 2 shows the relative bias calculated between TRMM 3B43 and PRISM as well as mean surface temperature, both averaged on a seasonal basis, in comparison with the elevation map (DEM) over the CONUS. The corresponding correlation between the relative bias and mean surface temperature shows a very weak linear relationship ($\rho \approx 0.1$). However, a moderate inverse linear relationship was observed ($\rho \approx -0.4$) between the relative bias and elevation over the CONUS. To define that the relationship between the elevation and bias is statistically significant, we applied a null hypothesis test. According to the test, the $p$ value is equal to 0, which is less than the chosen significance level (set to 0.01), implying that it is acceptable to have a 1% probability of incorrectly rejecting the null hypothesis. So, the calculated correlation is statistically significant. In the remainder of the paper we therefore focus solely on the effect of elevation on the bias.

In Fig. 3 the corresponding scatterplots of the relative bias in Fig. 2 are shown as a function of elevation. As seen in Figs. 2 and 3, in the high-elevation terrain of the western United States, TRMM 3B43 generally
FIG. 2. Relative bias, mean surface temperature, and elevation over the CONUS. Relative bias, calculated based on TRMM 3B43 and PRISM precipitation datasets, and surface temperature are averaged over each season.
underestimates the ground-based precipitation estimates leading to negative bias. The bias is slightly greater than zero at the low elevations (<1500 m MSL). Although the mean surface temperature in the northern parts of the country (near the border with Canada) in the winter is below or close to zero, the bias is still positive. It appears that this is because TRMM 3B43 applies a wind-induced undercatch correction (explained earlier) to the recorded data by the TRMM multisatellite. Hence, the TRMM 3B43 precipitation data average is higher than those produced by PRISM, which does not account for climatological undercatch effect, in the low elevations.

The linear dependence of bias on elevation seems to be stronger during the wet and cold seasons defined as spring, fall, and winter. In particular, the negative bias in the satellite data could be due to the high spatial variability of the precipitation or more snowfall occurrences at high elevations (above 1500 m MSL) in the wet and cold seasons.

Based on the results shown in Figs. 2 and 3, we note that the TRMM 3B43 precipitation estimate is in general lower than that estimated precipitation by the PRISM at high elevations. Importantly, this underestimation is present at all seasons while there is no dependence (or very weak correlation) on surface temperature. The pattern of underestimation corresponds well with the regions at higher elevations. Moreover, although TMPA applies the wind undercatch correction, we still see TRMM 3B43 underestimates the ground-based estimates over the high elevations. It, to some extent, means that high complex topography and orographic enhancement (which is accounted for in PRISM product) have a greater effect on the precipitation estimated by the satellite rather than wind-induced undercatch impact. These findings are in

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**Fig. 3.** Scatterplots illustrating relative seasonal bias between TRMM 3B43 and PRISM against elevation. The dashed line shows the mean relative bias at each elevation, and the bold lines show linear fits of the data below and above 1500 m MSL, respectively.
agreement with the study by Nesbitt and Anders (2009), who observed a clear precipitation–topography relationship in South Asia and northwest South America.

The demonstrated discrepancies between the satellite data and the ground-based estimates (in the high elevations) in Figs. 2 and 3 could possibly be influenced by poor sampling of the ground measurements of precipitation in high mountainous regions. Figure 4 shows the rain gauge density (number of rain gauges per unit area) at seven elevation ranges across the CONUS. There are about 13,000 rain gauges within the CONUS operated by various agencies such as the National Weather Service Cooperative Observer Program (COOP) and Weather Bureau Army Navy (WBAN) stations. Details of the climatology stations can be found in Daly et al. (2008). Note that the highest elevation located inside the CONUS is 4,328 m MSL, but as we resampled the DEM data into the TRMM 3B43 grid size (of 0.25°), the elevation data above 3,500 m were reduced to between 3,000 and 3,500 m MSL. As can be seen in the figure, there is an almost uniform density of rain gauges at each elevation range across the country. An increased sampling could possibly improve the ground measurements in the high mountainous regions (Groisman and Legates 1994). However, we feel that the relatively high density of rain gauges at high elevation, particularly in mountainous terrains, and the quality of the PRISM precipitation product, where care has been taken to account for these effects, makes it improbable that poor sampling alone can explain the results shown in Figs. 2 and 3.

If poor sampling in high mountainous terrains could explain the dependence of bias on elevation, there should also be a noticeable difference between the relative bias calculated between retrievals from the TRMM multisatellite and PRISM (which is elevation corrected) and relative bias calculated between retrievals from the TRMM multisatellite and GAUGE (which is not elevation corrected). In Figs. 5a and 5b the relative biases averaged over seasons for TRMM 3B43–GAUGE and TRMM 3B43–PRISM are plotted against elevation. In both comparisons, the mean relative bias in the elevation ranges between 0.0 and 1500 m MSL is positive but close to zero, implying that the precipitation estimates from TRMM 3B43, GAUGE, and PRISM agree well at low elevation for the years between 1998 and 2015. As a result, we conclude that the ground-based precipitation estimates (GAUGE and PRISM) are accurately represented by TRMM 3B43, and the slightly higher precipitation estimated by TRMM 3B43 is mainly due to the climatological undercatch adjustment, which is accounted for by only TRMM 3B43 at elevations lower than 1500 m MSL.

Above 1500 m MSL, TRMM 3B43 tends to underestimate the precipitation estimated by both GAUGE and PRISM. The average relative bias is larger in the wet and cold seasons (spring, fall, and winter) than in the summer season, with the greatest relative bias occurring for the highest elevation band (3000–3500 m MSL) for the winter season (Figs. 5a, b). We also found that the average relative bias is larger for TRMM 3B43–PRISM than for TRMM 3B43–GAUGE. This discrepancy could be explained by the fact that retrievals from the TRMM multisatellite and GAUGE both underestimate the actual precipitation at high elevations leading to a relative bias between TRMM 3B43 and GAUGE that is less than the corresponding relative bias between TRMM 3B43 and PRISM. Given that PRISM is an elevation-corrected precipitation estimate, the lower observed bias between GAUGE and retrievals from the TRMM multisatellite at higher elevations can be explained by both of them underestimating the actual precipitation.

The correlation coefficient \( r \) derived from the linear regression model at the 99% significance level between mean monthly precipitation for TRMM 3B43–PRISM and TRMM 3B43–GAUGE comparisons is 0.98 and 0.96, respectively. Accordingly, 96% and 92% (corresponding to correlation squared) of the monthly precipitation variation estimated by PRISM and GAUGE are accounted for by retrievals from the TRMM multisatellite.

We chose PRISM as our reference ground-based dataset to which we will compare the TRMM precipitation retrievals. The reason for the choice of
PRISM as the suitable ground-based estimate is that it corrects for elevation biases in the spatial interpolation of rainfall from rain gauge observations.

### b. Correction model, calibration, and validation

To formulate the best correction model that is able to effectively reduce bias in the satellite product, multiple relative bias equations were tested [including Eq. (6)]. Ultimately, Eq. (8) was chosen as a basis for developing the correction model. Assuming a linear dependence between the relative bias and elevation above 1500 m MSL, we proposed the following model for the relative bias \( \Delta B_i \) at pixel \( i \):

\[
\Delta B_i = \frac{G_i}{S_i + 1} - 1 = \alpha E_i + \beta,
\]

where \( G_i \) denotes the ground-based estimate, \( S_i \) denotes the satellite product, \( E_i \) denotes the elevation above mean sea level, and \( \alpha \) and \( \beta \) are two unknown coefficients. This suggests that a corrected satellite precipitation \( S_{ic} \) at pixel \( i \) may be written as

\[
S_{ic} = S_i (\alpha E_i + \beta + 1).
\]

The two unknown coefficients (\( \alpha \) and \( \beta \)) were estimated using simple linear regression [Eq. (8)] using the MCCV approach. As observed in Fig. 6, the computed coefficients are at a minimum in the summer months (defined as May–October) and tend to increase in the wet and cold months (defined as November–April), which is due to the observed larger differences between the PRISM and the satellite product during those seasons (Fig. 5). The computed coefficients do not deviate significantly from the mean in each month, with larger deviations in the winter than in the summer months. This also reflects the stronger bias in the satellite data during the wet and cold months (as explained above). Table 2 contains the average values of the acquired coefficients.

To quantify that the improvement in the satellite product resulted from using of the correction model, the average MAE for the validation period (the remaining 13 years, which corresponds to about 75% of the data) was calculated in the MCCV scheme in each iteration. Figure 7 and Table 3 show the average MAE between TRMM 3B43 and PRISM before and after the correction made, using the coefficients acquired through calibration, during the validation period for each month. As expected, the improvement in MAE is at a minimum during the summer months (June–August), as the MAE is lowest in summer to start with and reaches a maximum in the wet and cold months (Fig. 7, Table 3). We see that the correction model behaves well during the validation period, applying more of a correction in the months where there was larger bias in the satellite product.

Table 3 illustrates about 5.4% correction in average MAE for all months whereas the improvement is more.
significant for wet and cold months (7.5%) relative to summer season (with almost zero improvement). These results demonstrate the ability of the correction model to reduce the bias between the retrievals from the TRMM multisatellite and the ground-based estimate by taking the elevation into account.

c. Verification

This section presents the verification of the corrected TRMM 3B43 at high elevations over the entire country as well as in two high mountainous regions of the western United States during the years between 1998 and 2015.

The developed correction model [Eq. (9)] was used together with the mean values of the estimated coefficients ($\alpha$ and $\beta$) retrieved using the MCCV scheme described above. The model was applied to monthly estimates of precipitation given by the TRMM 3B43 product and compared with PRISM. Figure 8 shows the total monthly precipitation amount estimated by PRISM, TRMM 3B43, and corrected TRMM 3B43 at high elevation (>1500 m MSL) for the CONUS during the whole study period. As can be seen in the figure, the ground-based total monthly precipitation (PRISM) is underestimated by TRMM 3B43 with maximum differences in the spring, fall, and winter months and minimum differences in the summer months. However, we significantly reduced the differences between the PRISM and TRMM 3B43 estimates after the correction of the satellite product, particularly in the spring and fall months. This result shows that the correction model reduces bias in the original monthly retrievals from the TRMM multisatellite at high elevations in the United States. As can be seen in Fig. 8, the highest bias before correction is $0.3 \times 10^6$ and $0.37 \times 10^6$ mm in March and December, respectively, and this reduces to $0.05 \times 10^6$ mm, proving the efficacy of the correction model.

In typical hydrometeorological applications, however, the precipitation data are used on a local level. The map in Fig. 9 depicts two selected regions A and B where we investigated the improvement at a local level. The bar diagrams present the mean monthly precipitation estimated by PRISM, TRMM 3B43, and corrected TRMM
3B43 over regions A and B during the study period. The time series show the comparison of these monthly precipitation estimates. In region A, the bar diagram shows that the difference between the average monthly PRISM and corrected TRMM 3B43 is significantly reduced. As a result, 95.6% of the precipitation underestimated by the TRMM 3B43 product is now accounted for in the corrected TRMM 3B43. This improvement shows that the developed bias-correction model has substantially improved the TRMM 3B43 precipitation product in this region. The time series analysis for region A indicates minor discrepancies between PRISM and the corrected satellite-based time series in a few major precipitation events, for example, years 2006, 2010, and 2012. All of these major differences occurred in the wet and cold months (November–April) when there are usually thunderstorms, and possibly frozen precipitation, taking place at the higher elevations and most likely at low temperatures. According to the NOHRSC snow record, area B received over 500 mm of snow in November 2006 and March 2010 and 2011.

d. TRMM 3B43 bias correction over the CONUS

The primary objective of this study was to make a correction to the entire satellite product for the high-elevation regions (>1500 m MSL) of the CONUS. A single linear regression model was developed including coefficients $a$ and $b$ [from Eqs. (8) and (9)] to describe the bias above 1500 m MSL. The coefficients were computed during the calibration period and validated through an MCCV approach. Then, we applied our correction model [Eq. (9)], by taking into account the elevation parameter, to the average monthly precipitation values from the TRMM 3B43 product to reduce bias in the satellite data.

Figure 10 shows scatterplots of the average relative bias between TRMM 3B43 and PRISM for 12 months (taking into account the entire study period 1998–2015) versus elevation. As observed in the figure, the relative bias below 1500 m MSL is almost zero or close to zero;
however, in the wet and cold months (November–April), the deviation around the mean relative bias is higher than during the dry and warm months (May–October). This is most likely related to high-intensity precipitation (thunderstorm activity) as well as the larger quantity of precipitation during the wet and cold months.

Above 1500 m MSL, the relative bias tends to decrease to below zero (TRMM 3B43 underestimates the PRISM estimate), particularly in the winter months. In the summer months, TRMM 3B43 still tends to underestimate the precipitation for which the underestimation is minimum or close to zero during the driest months—for example, June. The calculated relative bias shows that TRMM 3B43 can underestimate the PRISM estimate by as much as 80% at the highest elevations (>3000 m MSL) during the winter months (December–February). In the summer months (June–August), TRMM 3B43 can underestimate the PRISM estimate by up to 30%.

Figure 11 shows scatterplots of the average relative bias between the corrected TRMM 3B43 [using Eq. (9) together with the acquired coefficients in Table 2] and PRISM for 12 months versus elevation. The correction model was applied to the monthly average values of the entire satellite product for the areas above 1500 m MSL. The average relative biases between TRMM 3B43 and PRISM at high elevation for winter and summer months were reduced from 80% (Fig. 10) to almost 10% (Fig. 11) and from 30% to nearly 0.0%, respectively (Figs. 10, 11). The results indicate the efficacy of the correction model and computed coefficients in reducing bias in the satellite product at the high elevations of the CONUS. Based on the results presented in Table 2 and Fig. 11 and taking into account Eq. (9), we propose the

![Figure 9](image-url)
correction of TRMM 3B43 for hydrology and atmospheric application at the high elevation (>1500 m MSL) of the CONUS.

5. Summary

The long-term comparison between the satellite-based and ground-based precipitation estimates reveals a bias in the satellite product. We found a general bias in the satellite product in the high-elevation regions of the western United States where TRMM 3B43 significantly underestimates the ground-based estimates in the wet and cold months. Based on our findings, it appears that the bias is essentially related to the nature of TRMM multisatellite temporal and spatial resolutions and sensor technology.

The high temporal variability of precipitation over the high mountainous terrain (Bergeron 1961) as well as
time gaps in the recorded data by TRMM multisatellite (every 3 h) results in less accuracy in the satellite product due to the inability to capture some of the high-intensity precipitation events (typical for the high mountainous terrain). For instance, if a short-term thunderstorm occurs during the gap between revisits of the TRMM multisatellite to a particular spot, the event will not be observed. If the satellite captures such events, the probability of the observation coinciding with the precipitation peak is small, resulting in underestimation of high-intensity rainfall. Furthermore, assuming that the spatial resolution of retrievals from the TRMM multisatellite is $0.25^\circ \times 0.25^\circ$, it implies that the precipitation estimate is averaged over a vast area, thereby smoothing precipitation peaks. This smoothing results in underestimation of the actual precipitation in the regions under the influence of the orographic precipitation, for example, high mountainous terrain. We also found that, as TRMM 3B43 is a post-real-time gauge-corrected product, any potential error in the rain gauge data could
also be reflected in the satellite product. On the other hand, the estimated precipitation by TRMM 3B43 in low elevation (<1500 m MSL) is slightly higher than the ground-based estimate. Yet, only TRMM 3B43 takes into account the climatological undercatch effect, and hence, TRMM 3B43 appears to be more accurate than the ground-based estimates over the low elevations.

We would also like to point out the inability of TRMM multisatellite sensors in accurately capturing frozen precipitation, as explained earlier. However, all the multisatellite sensors, temporal resolution, and the algorithms informed by the Global Precipitation Measurement (GPM) mission are improved. The GPM Core Observatory was launched in February 2014 with highly advanced sensors to capture frozen precipitation. The Integrated Multisatellite Retrievals for GPM (IMERG) product is available at a spatial resolution of 0.1° latitude × 0.1° longitude (~10 km at the equator).

### 6. Conclusions

This study is one of the first to map and analyze the TRMM 3B43 monthly precipitation data using the entire period (1998–2015) of the monthly satellite product over the CONUS. The primary objective of this study was to reduce satellite monthly precipitation bias relative to the ground-based estimates by applying a linear regression model as a correction. We compared the bias between the satellite precipitation product and ground-based estimates with surface temperature and elevation and found no correlation between bias and surface temperature, but a moderate correlation between bias and elevation. The analysis of bias with respect to elevation indicated a strong bias–elevation relationship associated with two distinct elevation ranges, below and above 1500 m MSL, with significant negative bias at the high elevations. It is noted that the high elevations across the CONUS are largely mountainous terrain in the western part. The examination of the satellite bias also showed two distinct seasons, wet and cold and dry, with the bias being larger in the wet and cold seasons.

We developed a model to correct the TRMM 3B43 product under the assumption that the bias is related to retrievals from the TRMM multisatellite as well as merging the ground-based estimate with TRMM multisatellite estimates, and in particular, is dependent on elevation. Because of the time-dependent nature of the satellite bias (Berg et al. 2006) as well as regionally defined characteristics (elevation above 1500 m MSL), we used monthly accumulated values of precipitation in our evaluation. The analysis of the monthly data shows that the bias is larger in the months of November–February and smaller in May–August. The satellite product, however, shows high consistency with the ground-based estimates at low elevation particularly, in the summer months.

It is evident that the rain gauge estimate suffers from insufficient accuracy in high mountainous terrain leading to underestimation of actual precipitation. We found, however, that retrievals from the TRMM multisatellite underestimate the precipitation as estimated with elevation-corrected ground-based estimates (PRISM) as well as with ground-based measurements where no correction for elevation has been made (GAUGE). We chose the elevation-corrected ground-based estimate (PRISM) as a reference dataset to make a correction to the TRMM 3B43 precipitation product over high elevations (>1500 m MSL) of the CONUS. We calibrated the model for 4 years (randomly taken from the whole dataset) and validated the model for the rest of the available TRMM 3B43 dataset (13 years) using an MCCV technique. We then verified the results at large and local scales.

At the large scale, we compared the satellite product with the ground-based estimate at high elevation over the entire country. The results showed a significant improvement of the monthly satellite precipitation product when compared with the ground-based precipitation estimate over high-elevation terrain. At the local scale, we selected two areas in the high mountainous terrain of the western United States with identical areas of about 5625 km² and with nine TRMM 3B43 pixels falling inside each area. We directly compared the monthly precipitation of the ground-based, satellite-based, and corrected satellite-based datasets. The results also showed major improvement in the satellite product, more than 95% and 56% for the regions A and B, respectively, after applying our bias correction algorithm with the exception of some major precipitation events. As a result, we propose this methodology for correction of the TRMM 3B43 product at the high elevations of the CONUS for use in the hydrometeorology applications. We have provided a correction model [Eq. (9)] with monthly correction coefficients (Table 2), which could be used in the future applications.

To conclude, our approach demonstrates significant improvement of the satellite product for typical precipitation events, but with less improvement in major rainfall and snowfall events. The correction model works effectively to reduce bias in the wet and cold as well as dry and warm months. Although other high-accuracy precipitation products over the CONUS exist, for example, PRISM, we believe that each product has its own strength and weakness. For instance, our new product, corrected 3B43, has an advantage of wind
undercatch correction, which is not accounted for in, for example, PRISM and CPC. We are continuing our efforts to extend the work by applying a similar methodology to all TMPA products by considering various temporal resolutions and spatial coverage. Given the current GPM multisatellite constellation mission, we hope that our work in correcting the past 17 years of TRMM 3B43 precipitation product will be a valuable contribution to the current and future satellite precipitation products for hydrometeorological studies over the CONUS.

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