UNIVERSITY OF CALIFORNIA,
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Assessment of the PERSIANN-CDR Products Bias-corrected with the GPCP Datasets Versions 2.2 & 2.3

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

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Thesis Committee:
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DEDICATION

To
kind, passionate, loving mom,
wonderful, supportive, kind dad,
beautiful, kind-hearted, inspiring brothers, Amir and Alireza,

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All this being said, ADVENTURE CONTIUNUES…

ABSTRACT OF THE THESIS

Assessment of the PERSIANN-CDR Products Bias-corrected with the GPCP Datasets Versions 2.2 & 2.3

By

Mojtaba Sadeghi

Master of Science in Civil Engineering

University of California, Irvine, 2018

Professor Soroosh Sorooshian, Chair

Accurate precipitation estimation at fine spatial and temporal scale is crucial for climatological studies. The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) is a well-known estimation product and is bias-corrected using the Global Precipitation Climatology Project (GPCP), which has been recently updated to version 2.3. In this study, we compare the PERSIANN-CDR dataset that is bias-corrected with GPCP V2.3 (called PERSIANN-CDR V2.3) with the previous version, which was bias-corrected by GPCP V2.2 (PERSIANN-CDR V2.2), at monthly and daily scales. First, we discuss the changes between the two versions of PERSIANN-CDR using Mean Absolute Difference (MAD) and Relative Mean Absolute Difference (MARD) at the monthly scales over the globe. The results show noticeable differences between PERSIANN-CDR V2.3 & V2.2 over the ocean for latitudes from 40 to 60 after 2003. The changes are also significant over the land area from 2009 onward. Second, we evaluate the improvements in the new version of PERSIANN-CDR (V2.3) with respect to a gauged-based reference, data from Climate Prediction Center (CPC), at monthly and daily scales over all globe land areas and again over CONUS. Over the globe, the estimation of PERSIANN-CDR V2.3 is more accurate than PERSIANN-CDR V2.2, especially over CONUS and Australia. Over CONUS, Root Mean Square Error (RMSE) has decreased

by 4.3% and Correlation Coefficient (CC) has improved by 3.8% compared to PERSIANN-CDR V2.2. The results emphasize that PERSIANN-CDR V2.3 has significantly improved in performance owing to refinement and input data from GPCP beginning in 2003.

Chapter 1

Introduction

Precipitation is the most important driver of the Earth's hydroclimatological cycle, playing a key role in hydro-meteorological and climatological studies. Providing long-term global precipitation records at high spatial and temporal resolutions is a great challenge for many hydrological applications, including flood forecasting and climate modeling (Miao et al. [2015]; Nguyen et al. [2016]; Beck et al. [2017]; Mallakpour and Villarini [2017]; Asanjan et al. [2018]; Mallakpour et al. [2018]). In other words, the ability of scientific communities to address hydrologic hazards and to manage water resources and extreme events is limited due to the lack of reasonably accurate global, long-term, high-resolution and comprehensive precipitation records (Katiraie-Boroujerdy et al. [2017b]).

Gauge, radar, and satellite instruments are the primary means for precipitation measurements. Direct precipitation measurements using ground-based rain gauges are the most frequent method; however, they are limited due to inadequate and sparse networks of stations over land, spatially remote areas, and lack of data over oceans (Maggioni et al. [2016]). Moreover, extending point observation to the gridded rainfall dataset is another drawback of rain gauges and a decisive source of uncertainty (Villarini et al. [2008]). Radar networks over most continents do not cover remote regions and it is an expensive technology both to establish and maintain (Guo et al. [2015]). Although radar networks provide continuous precipitation measurements with high temporal and spatial resolutions, they suffer from beam overshooting and beam blockage by mountains (Germann et al. [2006]). Due to the limitations of both ground-based rain gauges and radar measurements, satellite-based quantitative precipitation estimations are promising alternatives for providing homogeneous precipitation datasets over land and ocean. Passive microwave, visible and infrared data from Geosynchronous Earth orbit (GEO), and low Earth orbit (LEO) satellites have been frequently used for meteorological purposes and satellite-based precipitation retrieval algorithms. Information collected from different sensors are often combined in order to improve coverage and resolution of quantitative precipitation estimations (Sun et al. [2018]). Also, according to (Sorooshian et al. [2011]), utilizing any advanced methodology and new data sets related to rainfall information is the key to increasing the accuracy of satellite-based precipitation retrievals. Over recent decades, several satellite-based datasets have been developed with different spatial and temporal resolution, spatial coverage, temporal span, and data sources such as Climate Prediction Center (CPC) morphing technique (CMORPH) (Joyce et al. [2004]); Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) (Huffman et al. [2007]); PERSIANN (Hsu et al. [1997]); Global Satellite Mapping of Precipitation (GSMaP) (Ushio et al. [2009]); Self-Calibrating multivariate precipitation retrieval (SCaMPR) (Kuligowski [2010]).

Satellite-based precipitation estimation products have profound errors due to the deficiencies in algorithm and the indirect relationship between satellite observations and surface precipitation. Furthermore, as specified by World Meteorological Organization, more than 30 years of data is needed for global and regional climate studies. However, the satellite observations are limited to short-term records unlike gauge-based and reanalysis precipitation data. Many attempts have been made to integrate ground-based and satellite-based measurements to exploit the benefits of individual data sets and improve the accuracy of long-term global precipitation analyses(Xie et al. [2003]; Katiraie-Boroujerdy et al. [2017a]; Alharbi et al. [2018]). The CPC Merged Analysis of Precipitation (CMAP) (Xie and Arkin [1997]), Global Precipitation Climatology Project (GPCP) (Adler et al. [2003]), TRMM 3B43 (Huffman et al. [2007]) and Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al. [2017]) datasets combine rain gauges, multi-satellite observations, and atmospheric models to provide high quality precipitation data sources.

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) (Ashouri et al. [2015]) is one of the high-resolution precipitation datasets widely recognized for different applications requiring long-term data such as developing Intensity-Duration-Frequency (IDF) curves (Faridzad et al. [2018]; Ombadi et al. [2018]; Gado et al. [2017]), monitoring drought (Katiraie-Boroujerdy et al. [2017b]; Guo et al. [2016]), and simulating streamflow (Nguyen et al. [2015]; Liu et al. [2017]; Ashouri et al. [2016]; Zhu et al. [2016]; Ashouri et al. [2016]). This product relies on infrared imagery and comes up with $0.25°\times0.25°$daily precipitation estimates, from 1983 to present, using modified PERSIANN algorithm (Hsu et al. [1997]). The artificial neural network in PERSIANN-CDR model is trained with National Centers for Environmental Prediction (NCEP) stage IV hourly precipitation. Subsequently, PERSIANN-CDR estimates are adjusted by monthly GPCP precipitation data to diminution bias (Ashouri et al. [2015]).

As mentioned, PERSIANN-CDR has been widely used as a long-term satellite-based precipitation estimation dataset period. This is vital to continuously improve and evaluate the quality of this product. Recently, GPCP has been updated to version 2.3. PERSIANN-CDR bias-corrected with GPCP V2.3, called PERSIANN-CDR V2.3, is compared and evaluated with the previous version of PERSIANN-CDR (V2.2). For comparison, the differences between PERSIANN-CDR V2.3 and previous version (PERSIANN-CDR V2.2) and also the two latest versions of GPCP (V2.2 & V2.3) at monthly scale are determined. For evaluation, estimation accuracy of the two versions of PERSIANN-CDR with respect to CPC gauge-based precipitation dataset, as a reference, is compared at monthly and daily scales over CONUS and the globe. This article is organized as follows. Section 2 explains the detailed structure of data sets. In Section 3, a description of methodology is provided. The results, along with statistical and visual analysis, are discussed in Section 4. The paper concludes with Section 5 which highlights the main findings and evaluations.

Chapter 2

Data

2.1 Global Precipitation Climatology Project (GPCP) Monthly product

The Global Precipitation Climatology Project (GPCP) is a part of the Global Energy and Water Cycle Exchanges (GEWEX) activity under the World Climate Research Program (WCRP). The GPCP monthly 2.5°×2.5°precipiataion product provides consistant global data by merging different satellite-based estimations (passive microwave/infrared) over the land and ocean along with precipitation gauge information from Global Precipitation Climatology Centre (GPCC) over the land. In 1997, the first version of GPCP monthly dataset was released (Huffman et al. [1997]). During the past years, updates to the primary product were reported and the second version of this product was described by Adler et al. [2003]. Recently the current version of GPCP (Version 2.3) was reported by Adler et al. [2018] in terms of changes in cross-calibration procedures of rainfall estimates from different satellite sensors (TOVS to AIRS from January 2003 and from SSMI to SSMIS after the year 2009) and updates in gauge analysis (CPCC V7 full analysis for the period of 1979 to 2013 and GPCC

Monitoring products for 2014 and beyond). The GPCP dataset is available via the Earth System Science Interdisciplinary Center (ESSIC) and Cooperative Institute for Climate and Satellites (CICS), University of Maryland College Park (http://gpcp.umd.edu).

2.2 PERSIANN-Climate Data Record

PERSIANN-CDR product was developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (UCI). This dataset is available as an operational climate data record via NOAA National Centers for Environmental Information (NCEI) Program (https://www.ncdc.noaa.gov/cdr) and CHRS Data Portal (http://chrsdata.eng.uci.edu/). This near-global (60°S - 60°N, high-resolution (0.25 °×0.25 °), long record (from 1983 to present) precipitation product has daily, monthly, and yearly temporal resolution. PERSIANN-CDR algorithm utilizes GridSat-B1 infrared information as input and NCEP stage IV hourly precipitation data to update the model parameters. In order to reduce the bias, this product is bias-adjusted by GPCP monthly precipitation records. Additional details about PERSIANN-CDR algorithm can be found in Ashouri et al. [2015].

2.3 CPC Global Unified Gauge-Based Analysis of Daily Precipitation

The CPC Global Unified Gauge-Based Analysis of Daily Precipitation dataset is a National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (CPC) product. The spatial coverage of this product is 89.75SN-89.75SN, 0.25E-359.75E and it has a spatial resolution of 0.5°×0.5°. This daily precipitation dataset is devoted to combining information from ground-based networks with 30,000 stations. This dataset includes measurement from 1979 to present. In this study, CPC data is considered as a reference for evaluation and the dataset is available for public use (ftp://ftp.cdc.noaa.gov/Datasets). A comprehensive description of CPC interpolation algorithm can be found in Chen et al. [2008] and Xie et al. [2010].

Chapter 3

Methodology

In the first part of this study, we will determine the amount of changes between two versions of both PERSIANN-CDR and GPCP at monthly scales for the period from 1983 to 2013. Both versions of PERSIANN-CDR at daily scale are aggregated to monthly time scale. In this study, all the analyses and comparisons are done for the period from 1983 to 2013 since PERSIANN-CDR provides precipitation estimations beginning from 1983. We limit the assessment to 2013 as the impact of continuing use of the GPCC Monitoring product after 2013 on GPCP is under investigation. (Adler et al. [2018]). According to the data section above, changes in the new version of GPCP are mainly due to modifications in satellite data inputs in the years 2003 and 2009. As PERSIANN-CDR is bias adjusted with GPCP dataset, these modifications change the PERSIANN-CDR dataset at monthly and daily scales. Therefore, we determine the difference indices at monthly scale to track the changes in three periods: i) 1983-2013 (whole period of study) ii) 2003-2009 iii) 2009-2013. In order to track the amount of changes each year, we plot a time series of mean precipitation at monthly scale. For further analysis, these time series are plotted over land and ocean separately to determine in which parts of the globe, these changes are more significant. To determine the amount of changes between the two latest versions of PERSIANN-CDR and also GPCP over the globe, we used Mean Absolute Difference (MAD) (Equation 1). Mean Relative Absolute Difference (MRAD) is also computed to display in which areas the percentage of the changes is more significant. (Equation 2)

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|V2.3 - V2.2| \tag{3.1}$$

$$MRAD = \frac{\frac{1}{n}\sum_{i=1}^{n}|V2.3 - V2.2|}{\sum_{i=1}^{n}V2.3} \tag{3.2}$$

In the second part, we evaluate the performance of PERSIANN-CDR V2.3 and V2.2 with respect to CPC data at monthly and daily scales over all globe land and again over CONUS. For this matter, we re-project PERSIANN-CDR V2.2 and V2.3 into 0.5 $\times$0.5 resolutions to be the same with CPC dataset. Then two commonly-used statistical matrices, including Correlation Coefficient (CC) and Root Mean Square Error (RMSE) (Equation 3 & 4), are used for the evaluations, as shown in Table 2. CC is employed to measure the agreement between two versions of PERSIANN-CDR, as satellites datasets, and CPC, as an in situ measurement. On the other hand, the RMSE is widely used to measure the error in estimation of satellite datasets compared with observed dataset.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\Big(S_i - G_i\Big)^2} \tag{3.3}$$

$$CC = \frac{\frac{1}{n}\sum_{i=1}^{n}(S_i - \overline{S_i})(G_i - \overline{G_i})}{\sigma_S \sigma_G} \tag{3.4}$$

Chapter 4

Results and Discussion

4.1 Monthly assessment

4.1.1 Changes in the PERSIANN-CDR and GPCP Monthly Analysis from V2.2 to V2.3

In this section, we discuss the changes in Mean Absolute Difference (MAD) and Mean Relative Absolute Difference (MRAD) between the two latest versions of PERSIANN-CDR (V2.3 and V2.2) and GPCP (V2.3 and V2.2) at monthly scale. The changes in MAD and MRAD are presented and discussed at spatial and temporal scales. **Comparison at spatial scale**

Figure 1 displays the precipitation pattern between MAD of the two latest versions of both GPCP (V2.3 & V2.2) and PERSIANN-CDR (V2.3 & V2.2) at monthly scale for three time periods. The same precipitation patterns between MAD of the two versions of both products can be observed for all of those periods. This observation is executed since PERSIANN-CDR at monthly scale is bias-adjusted using GPCP dataset. Secondly, MAD between two versions of GPCP and PERSIANN-CDR at monthly scale is only noticeable over the oceans in the higher latitude (40-60) and over the equator for each of the three periods. The changes exceed 0.1 mm/day in those regions for periods of 2003 to 2008 and 0.25 mm/day for 2009 and afterward. The largest amount of these changes in MAD is detectable at 60 degrees South latitude and over Indonesia. On average, from 2003 to 2008, the MAD between two versions of GPCP and therefore also PERSIANN-CDR (at monthly scale) in latitude bands of 60 °S to 60 °N is approximately 0.04 mm/day and this amount increases by 0.07 mm/day from 2009 onward. These findings are in line with Adler et al. [2018] as they showed that corrections in the new version of GPCP create more increases over the oceans in the latitude band 40 to 60 after 2003. They show that increases are higher (up to 0.04 mm/day) from January 2009 onward due to improved cross-calibration in SSMIS with respect to the previous version. Note that we calculate MAD instead of difference, which Adler et al. calculated to show the amount of increase.

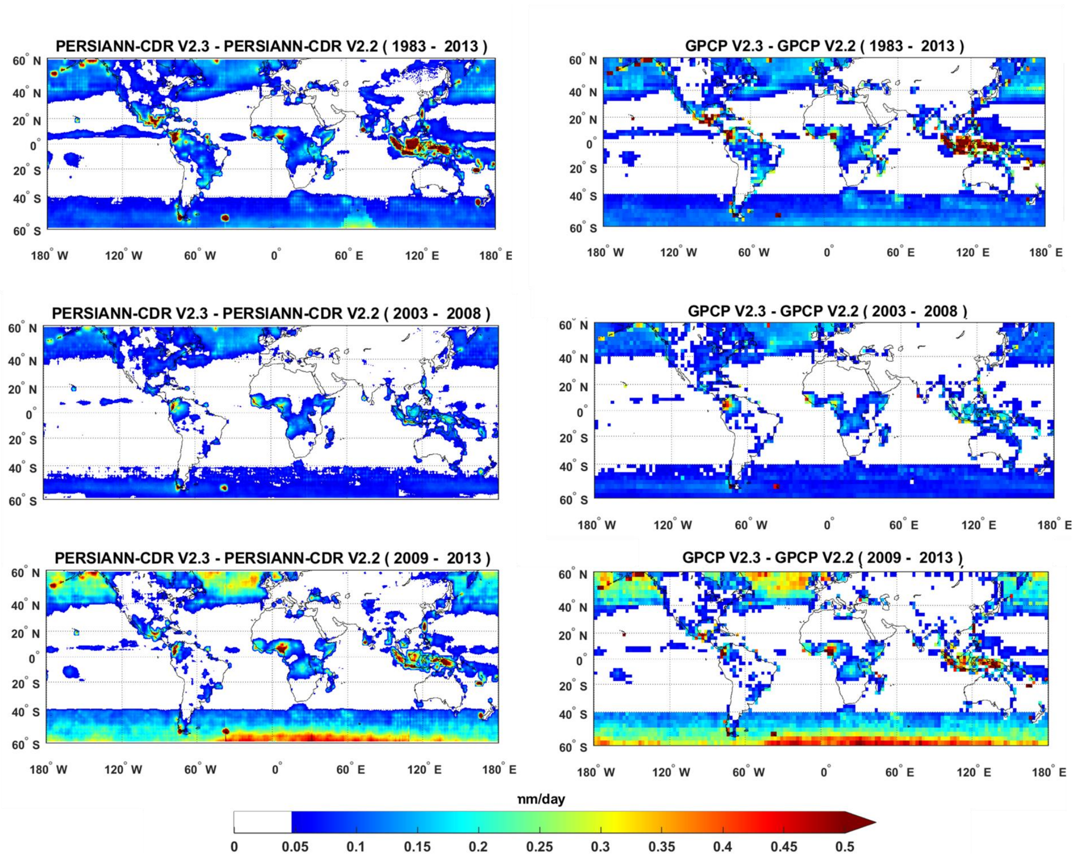

Figure 4.1: MAD (mm/day) between the two versions of PERSIANN-CDR (V2.3 - V2.2) and GPCP(V2.3 - V2.2) at monthly scale for three time periods.

However, due to unequal global precipitation, MAD between the new version of PERSIANN-CDR and the previous one (Fig 2.a) cannot represent all the information regarding the changes between them. For having more information, MRAD between the two versions of PERSIANN-CDR can also be useful (Fig 2.b). This index determines in which regions the percentage of change in MAD are more significant. The results display that although more MAD can be observed around equator and oceans between 40 to 60 degrees Northern and Southern hemisphere, MRAD between two versions of PERSIANN-CDR is more noticeable over North Africa, Australia, north China, Mongolia, and southeastern Russia. In these regions the mean annual precipitation is less than in the other parts of the globe; therefore, a small change in the new versions of GPCP and also PERSIANN-CDR could create significant variations in MRAD.

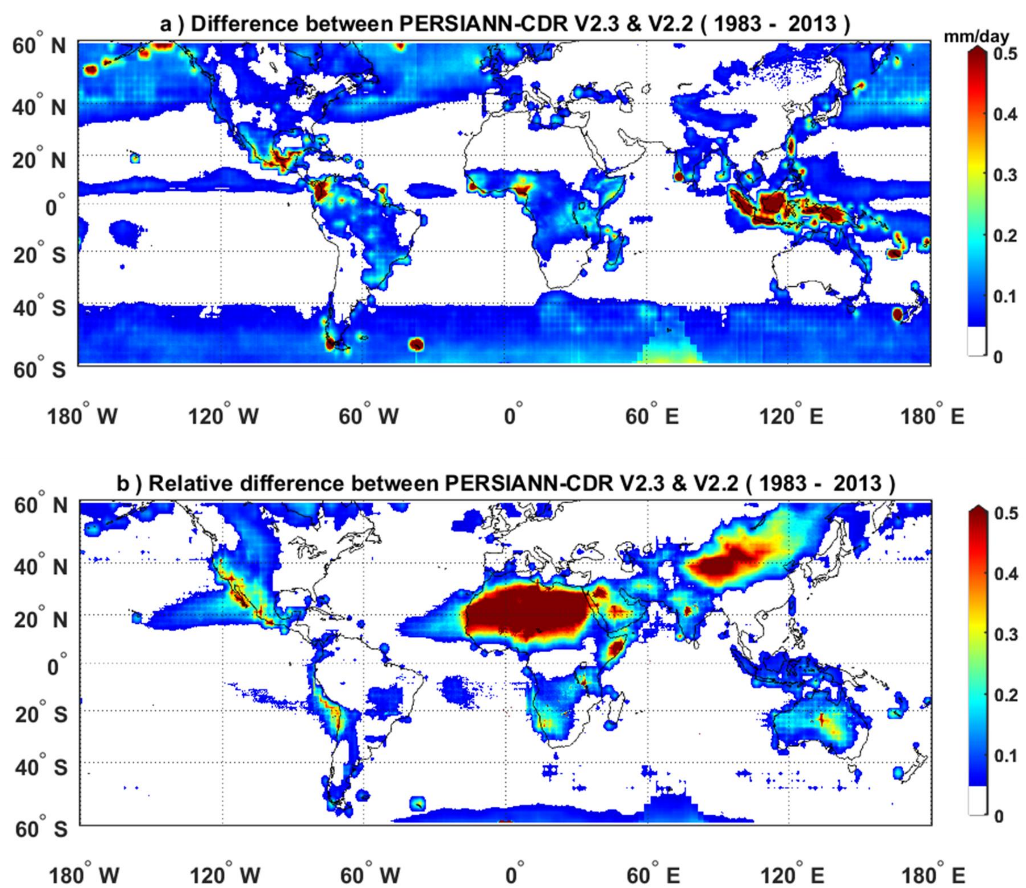

Figure 4.2: a) MAD b) MRAD between PERSIANN-CDR V2.3 and V2.2 at a monthly scale for the years of 1983-2013.

Comparison at the temporal scale

Figure 3 shows the time series of mean precipitation between latitude bands 60°S to 60°N for the two versions of PERSIANN-CDR (Fig 3.a) and GPCP (Fig3.b) at monthly scale. This figure indicates that the changes between two versions of PERSIANN-CDR and GPCP are subtle but important corrections for many applications, especially for 2003 and beyond. These changes include the updates to the gauges analysis that effect the land precipitation and corrections to cross-calibration of satellite data, which have effects on both land and ocean precipitation estimation. In order to determine how these changes effect the amount of precipitation over land and ocean, we plot the time series of their mean precipitation separately.

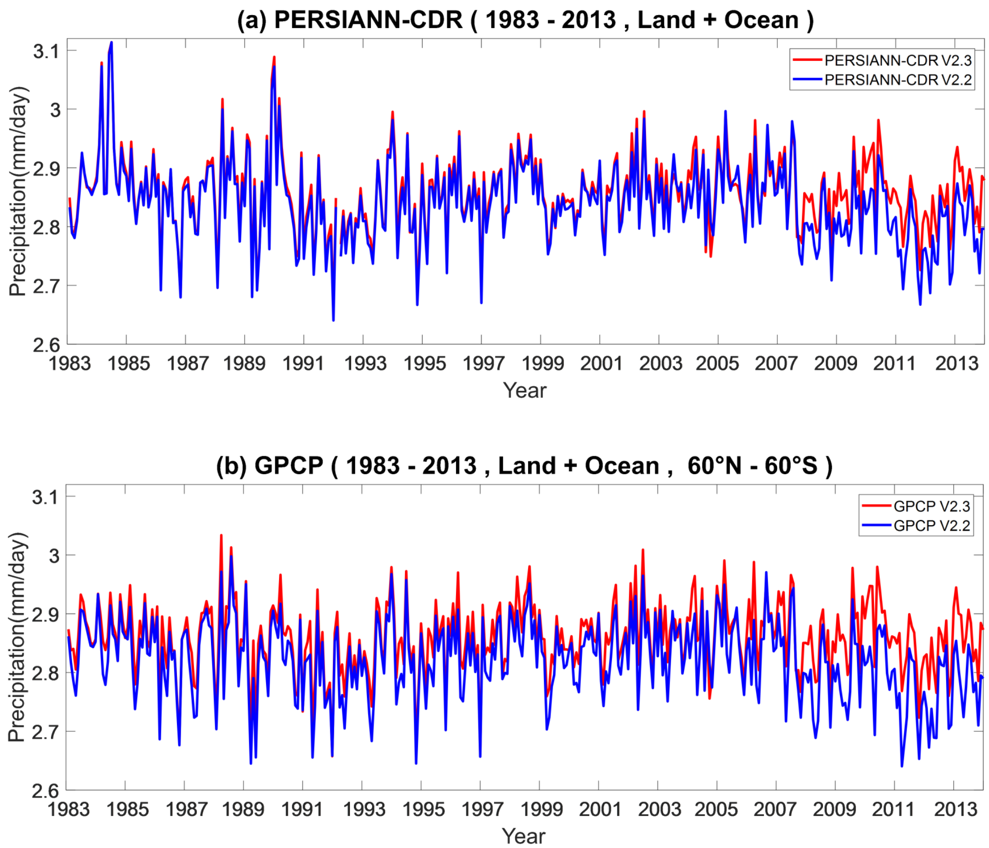

Figure 4.3: Time series of a) PERSIANN-CDR V2.3 (red) and V2.2 (blue) b) GPCP V2.3 (red) and V2.2 (blue) daily mean precipitation over the globe between 60°N - 60°S

Figure 4 indicates the time series of mean precipitation over all ocean regions within the latitude band 60°S to 60°N for the two latest versions of PERSIANN-CDR (Fig 4.a) and GPCP (Fig 4.b). The corrections in version 2.3 of both GPCP and consequently PERISANN-CDR affect ocean precipitation in two ways. From January 2003 onward, the daily precipitation increases due to the improved cross-calibration of precipitation estimation from TIROS Operational Vertical Sounder (TOVS) to Atmospheric Infrared Sounder (AIRS). From January 2009 onward, precipitation increases over the oceans because of the improvment in cross-calibration from Special Sensor Microwave Imager/Sounder (SSMIS) from the previous precipitation estimation of SSMI (Adler et al. [2018]). These replacements produce an approximately 0.02 mm/day increase in precipitation estimation over oceans within the latitude band 60°S to 60°N from 2003-2008 and around 0.05 mm/day increases starting from 2009 over those regions.

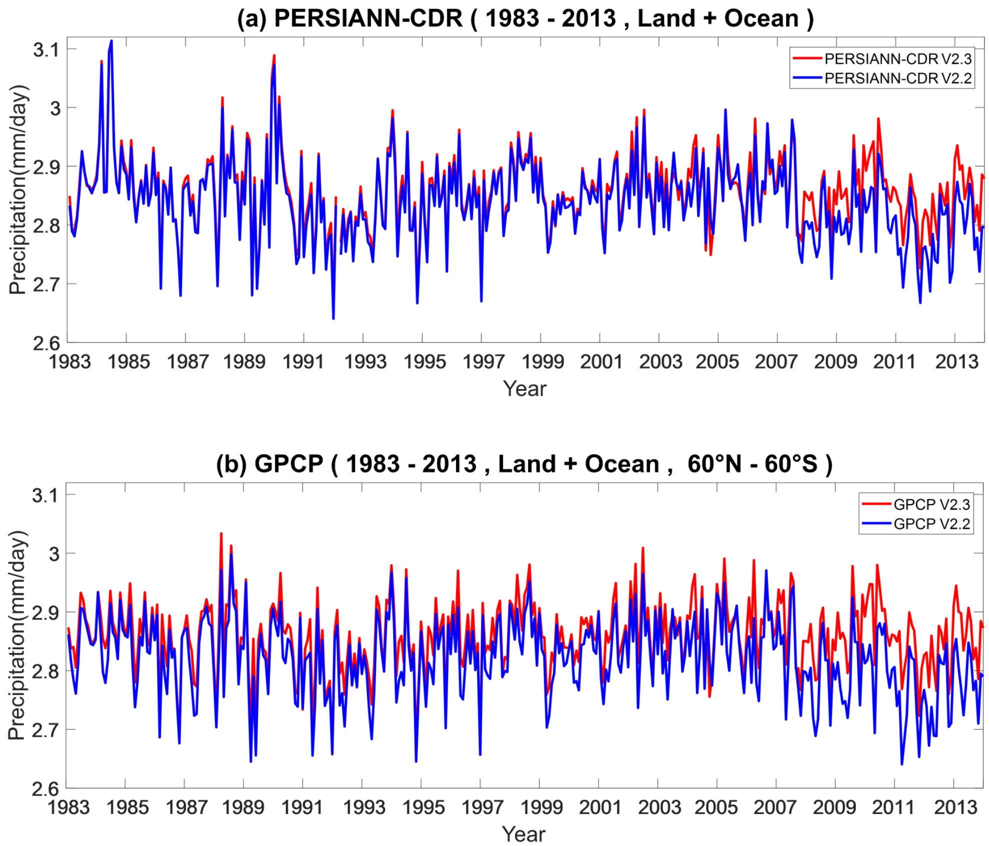

Figure 4.4: Time series of a) PERSIANN-CDR V2.3 (red) and V2.2 (blue) b) GPCP V2.3 (red) and V2.2 (blue) daily mean precipitation over the oceans between 60°N - 60°S

Figure 5 shows the time series of mean daily precipitation over the land between 60 °S to 60 °N for two versions of PERSIANN-CDR (Fig 5.a) and GPCP (Fig5.b). Changes in precipitation over the land is noticeable after 2009. This observation is primarily due to increases in gauge sampling and replacement of GPCC Monitoring to the Full products after 2009 (Adler et al. [2018]). This improvement increases the precipitation over the land in latitude band 60°S to 60°N by approximately 0.04 mm/day after 2009.

Tables 1 and 2 respectively display the differences between the two versions of PERSIANN-

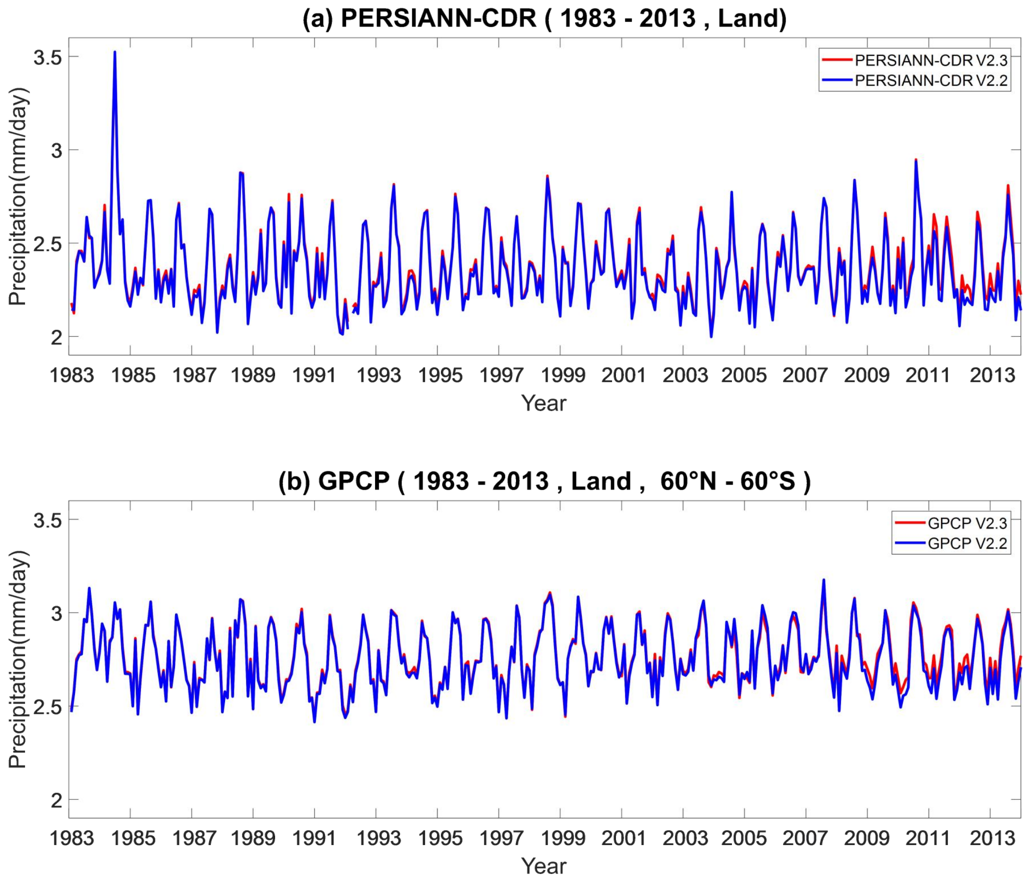

Figure 4.5: Time series of a) PERSIANN-CDR V2.3 (red) and V2.2 (blue) b) GPCP V2.3 (red) and V2.2 (blue) daily mean precipitation over the land between 60°N - 60°S

CDR and GPCP over the globe, lands and oceans within 60°S to 60°N. The changes in GPCP and PERSIANN-CDR are all less than 1% between 1983 to 2013 and less than 2% between 2003 to 2013. However, these amounts of change are important for many applications of satellite precipitation estimation products, especially for tracking global precipitation trends. Comparing tables 1 and 2 also indicates that changes in the new version of GPCP create nearly the same amount of changes in the new version of PERSIANN-CDR at monthly scale.

Table 4.1: Mean daily precipitation for PERSIANN-CDR V2.3 and V2.2 from 1983-2013

Product	Land+Ocean	Land	Ocean
PERSIANN-CDR V2.3	2.86	2.37	3.03
PERSIANN-CDR V2.2	2.84	2.36	3.01
Difference (mm)	0.02	0.01	0.02
Relative difference	0.70%	0.42%	0.67%

Table 4.2: Mean daily precipitation between 60°N to 60°S for GPCP V2.3 and V2.2 from 1983-2013

Product	Land+Ocean	Land	Ocean
GPCP V2.3	2.84	2.76	2.95
GPCP V2.2	2.82	2.75	2.93
Difference (mm)	0.02	0.01	0.02
Relative difference	0.70%	0.36%	0.68%

4.1.2 Monthly evaluation of two versions of PERSIANN-CDR with CPC over the CONUS and globe

In this section, the performance of the two versions of PERSIANN-CDR will be evaluated, using CPC as a gauge-based observation dataset, over global land areas and CONUS. Figure 6 shows the RMSE and CC time series for PERSIANN-CDR V2.3 (red) and V2.2 (blue) over CONUS. The differences between the two versions of PERSIANN-CDR at monthly scale based on RMSE and CC indices are not noticeable before 2009. This result is reasonable as the change from GPCC monitoring to Full product, which is the main reason for changes in land precipitation, was done after 2009. The mean CC between PERSIANN-CDR V2.2 and CPC at monthly scale over CONUS for 2003-2013 is 0.79 (Table 3). This amount increases by approximately 4 percent in the new version.The mean RMSE of PERSIANN-CDR V2.2, with respect to CPC dataset, is 0.97 mm/day and decreases to 0.93 mm/day in version

2.3. Furthermore, the highest correlation and the least RMSE happen during the month of February, June, and July, when rainfall is less compared to the other months of the year for both versions of PERSIANN-CDR.

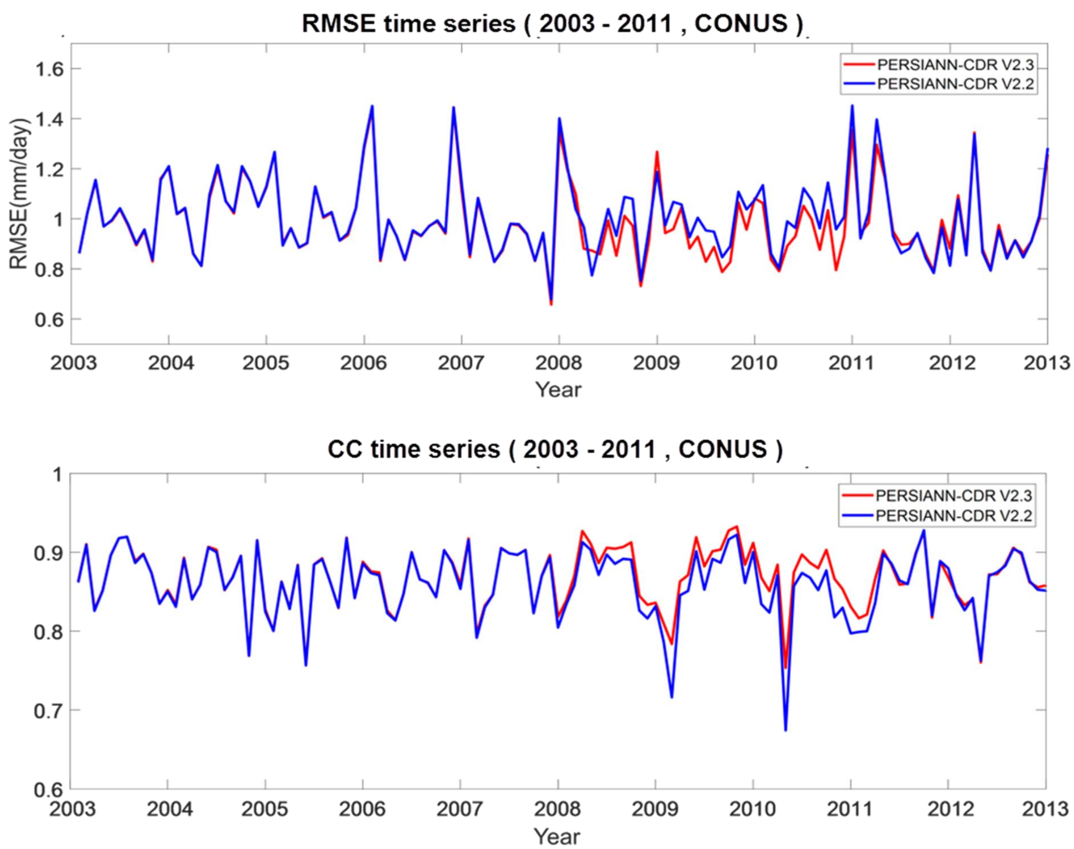

Figure 4.6: RMSE and correlation coefficient time series of PERSIANN-CDR V2.3 (red) and V2.2 (blue) against CPC for 2003-2013 over CONUS

Table 3 shows that on average the performance of the new version of PERSIANN-CDR is better than the previous one over CONUS. However, it would be useful to show in which areas the accuracy of the new version is most improved. Figure 8 indicates the spatial correlation and root mean square error (mm/day) between the two versions of PERSIANN-CDR and CPC and their difference over CONUS from 2009 to 2013. Locations with higher values in Figure 7.c (CC) and 8.c (CC) show where PERSIANN-CDR V2.3 has improved the correlation with CPC, with respect to PERSIANN-CDR V2.2; locations with lower values in Figure 7.c (RMSE) and 8.c (RMSE) show where PERSIANN-CDR V2.3 have a reduced RMSE with CPC, when comparing with PERSIANN-CDR V2.2. Figure 7 displays that the performance of PERSIANN-CDR V2.3 increases noticeably over the western and northeastern United States. The highest improvement can be detected over Virgina, New York, Pennsylvania, and Oregon, where the correlation has improved by approximately 0.08 and RMSE has decreased by 0.15 mm/day.

Table 4.3: Summary of comparison metrics for two versions of PERSIANN-CDR against CPC for the period of 2009 to 2013 over the CONUS

Product	RMSE(mm/day)	CC
PERSIANN-CDR V2.3	0.93	0.81
PERSIANN-CDR V2.2	0.97	0.78
Difference (mm)	- 0.04	0.03
Relative difference	- 4.3 %	3.8%

The performance of PERSIANN-CDR V2.2 and V2.3 at monthly scale is also evaluated over the globe. Figure 8 displays that estimation accuracy of PERSIANN-CDR V2.3 is improved mostly over CONUS and Australia due to increases in correlation and decreases in RMSE with respect to CPC. PERSIANN-CDR V2.2 shows higher correlation with CPC over Africa than the new version. However, due to the poor quality of the CPC dataset over tropical Africa, the higher correlation cannot prove that the previous version of PERSIANN-CDR

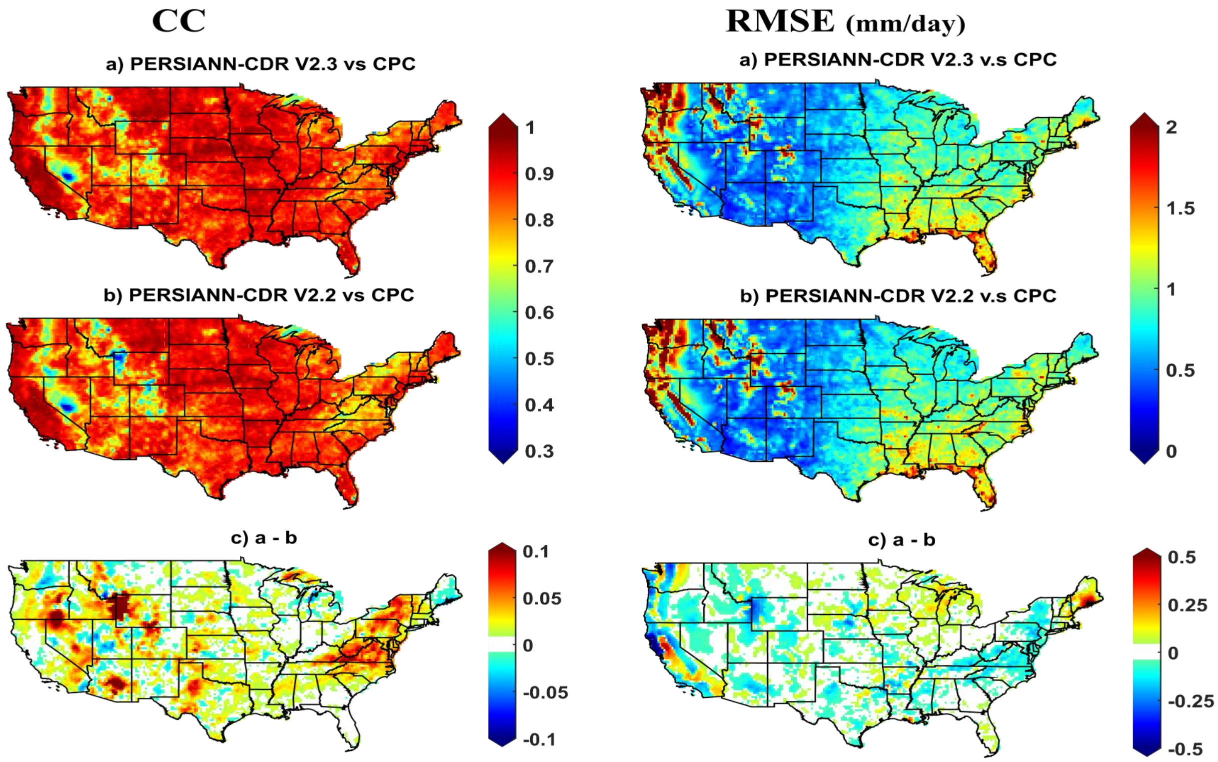

Figure 4.7: Spatial comparison metrics for PERSIAN-CDR V2.2 and PERSIANN-CDR V2.3 against CPC for the period of 2009-2013 over the CONUS

estimates precipitation more accurately.

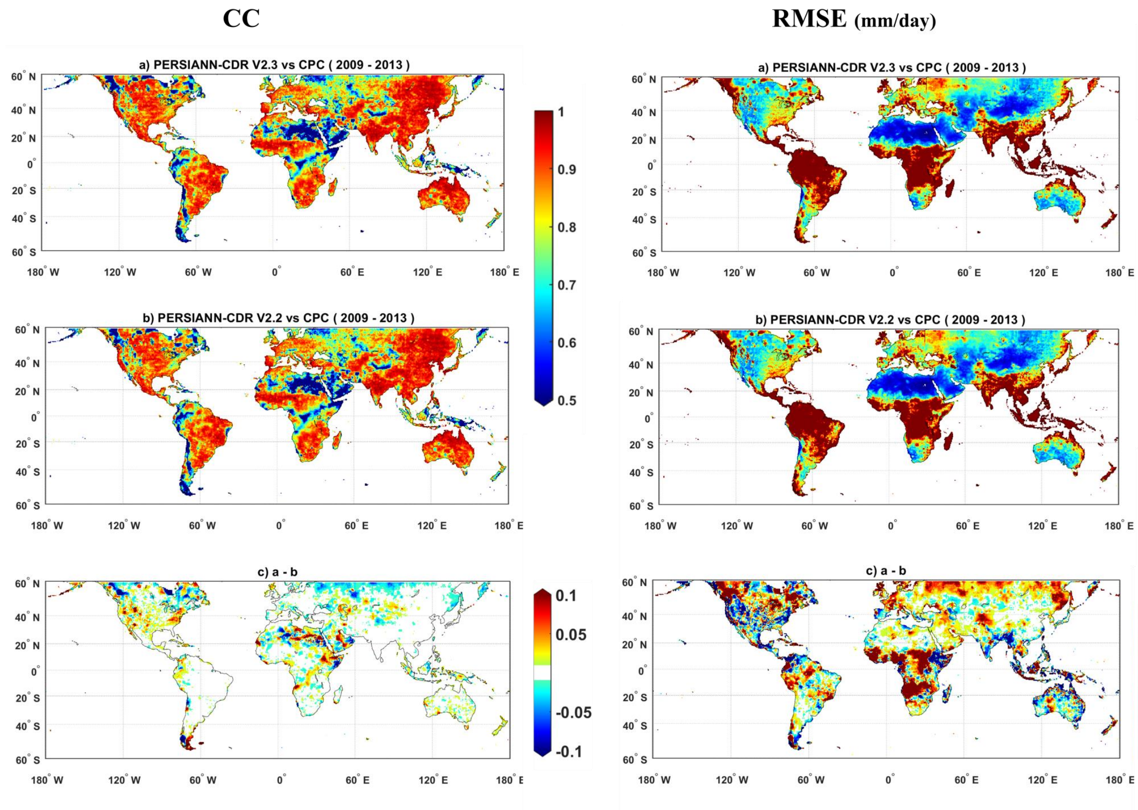

Figure 4.8: Spatial comparison metrics for PERSIAN-CDR V2.2 and PERSIANN-CDR V2.3 against CPC at a monthly scale from 2009-2013

4.2 Daily assessment

PERSIANN-CDR has daily temporal resolution; therefore, it is important to evaluate the performance of the new version of PERSIANN-CDR with respect to the previous version at daily scale. Figure 9 displays that for most parts of the globe, the new version of PERSIANN-CDR predicts precipitation more accurately with respect to correlation and RMSE indices over the global land areas within the latitude band 60°S - 60°N. This improvement in precipitation estimation accuracy is higher over CONUS, especially the western states and Australia.

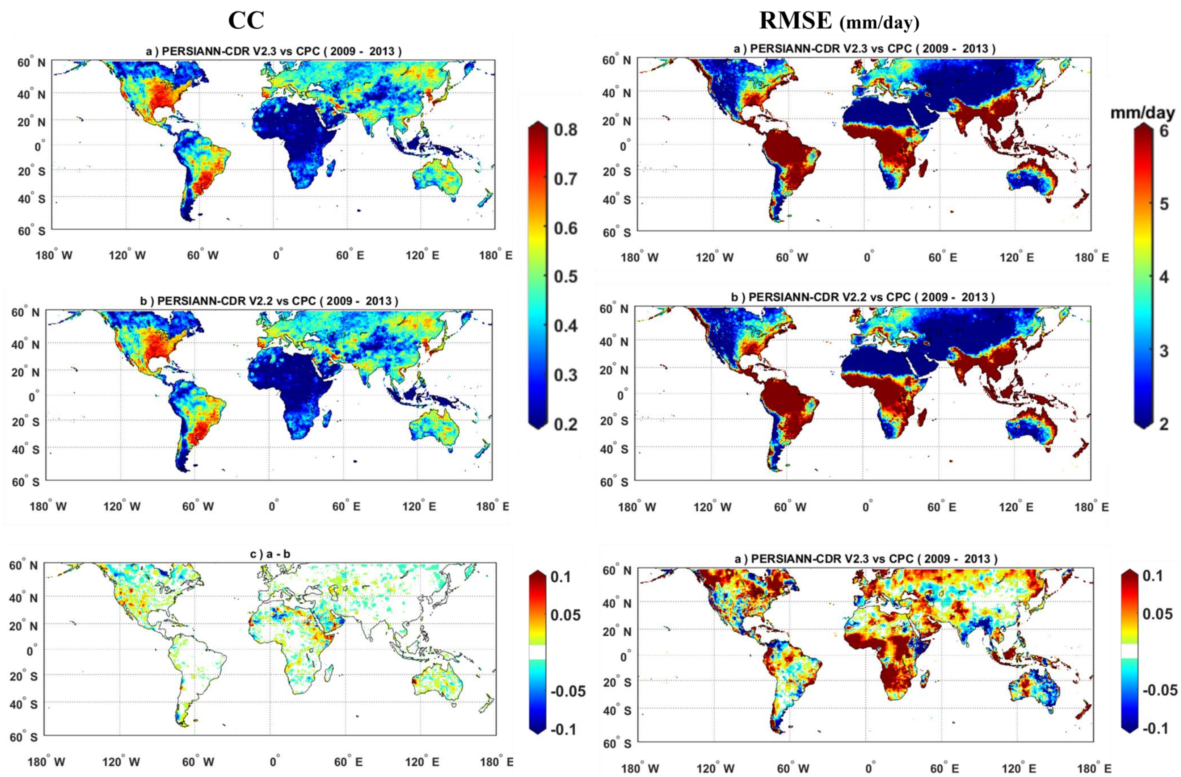

Figure 4.9: Spatial comparison metrics for PERSIAN-CDR V2.3 and PERSIANN-CDR V2.2 against CPC at a daily scale from 2009 to 2013

Chapter 5

Conclusion

Historical precipitation estimates from the PERSIANN-CDR product have been widely used for climatological studies over the globe. Accurate precipitation information from PERSIANN-CDR could contribute to meteorological, hydrological, and water resources management applications. Recently, GPCP has been updated to version 2.3 by applying the adjustments in cross-calibration of satellite data inputs and updating the gauge analysis. In this study, we compare PERSIANN-CDR V2.3, with the previous version of PERSIANN-CDR (V2.2). First, the differences between the two recent versions of PERSIANN-CDR (V2.3 & V2.2) and GPCP (V2.3 & V2.2) are described. We utilize Mean Absolute Difference (MAD) and Mean Relative Absolute Difference (MRAD) for tracking the changes between the latest two versions of PERSIANN-CDR and GPCP. Then, we evaluate the accuracy of the latest version of PERSIANN-CDR (V2.3) and the previous version (V2.2) using the CPC Unified dataset, at monthly and daily scales for land areas over the globe.

Comparing the two versions of PERSIANN-CDR over ocean areas at a monthly scale indicates that the changes in MAD are more than 0.1 mm/day at latitude bands between 40 to 60 after 2003. The changes have increased by an amount of 0.25 mm/day from 2009 onwards. The step-wise increase in the changes in PERSIANN-CDR is mainly due to the adjustments implemented on the GPCP V2.2 dataset. These adjustments include improvement in cross-calibration of precipitation from TOVS to AIRS since January 2003 and from SSMI to SSMIS after 2009. However, over land areas, changes in MAD are more significant from 2009, especially over the equator. In contrast, the highest percentage of changes (MRAD) are detectable in other regions of the globe which include North Africa, Australia, North China, Mongolia, and Southeastern of Russia. The main reasons for these changes in MAD and MRAD over the global land areas are i) increasing the gauge samples over the entire period of the record, and, ii) updating from the GPCC Monitoring product to the GPCC Full product.

The two versions of PERSIANN-CDR are evaluated over CONUS and over the global land areas using the CPC dataset as a reference. Over CONUS, results display that on average the performance of the latest version of PERSIANN-CDR (V2.3) has improved in terms of RMSE and correlation coefficient. Between 2009 and 2013, RMSE has decreased by 4.3% and the correlation has increased by 3.8% compared to PERSIANN-CDR V2.2. Improvements in terms of RMSE and correlation are evident over various states (e.g., Virginia, New York, Pennsylvania, and Oregon). Over global land areas, results indicate that the performance of PERSIANN-CDR V2.3 at monthly scale is better than the previous version, especially over CONUS and Australia. Nevertheless, due to the poor quality of the CPC dataset, comparisons between the two versions of PERSIANN-CDR over some regions (e.g., Africa) are not reliable. Furthermore, at the daily scale the comparison between the two versions of PERSIANN-CDR demonstrates that the PERSIANN-CDR V2.3 provides more accurate precipitation estimates according to the CPC product. Overall, the changes and improvements in the latest version of PERISANN-CDR and GPCP are significant from 2003 onward. These corrections are crucial when applied to large areas, particularly over oceans and for some regions, where the changes and improvements in accuracy of the latest dataset are significant.

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