Assessing the efficacy of High-Resolution Satellite-based PERSIANN-CDR Precipitation Product in Simulating Streamflow

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**Abstract**

This study aims to investigate the performance of Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network – Climate Data Record (PERSIANN-CDR) in a rainfall-runoff modeling application over the past three decades. PERSIANN-CDR provides precipitation data at daily and 0.25° temporal and spatial resolutions from 1983 to present for 60S-N latitude band and 0-360 longitude. The study is conducted in two phases over three test basins from the Distributed Hydrologic Model Intercomparison Project - Phase 2 (DMIP2). In phase 1 a more recent period of time (2003 – 2010) when other high-resolution satellite-based precipitation products are available is chosen. Precipitation evaluation analysis, conducted against Stage IV gauge-adjusted radar data, shows that PERSIANN-CDR and TRMM Multi-satellite Precipitation Analysis (TMPA) have close performances with a higher correlation coefficient for TMPA (~0.8 vs. 0.75 for PERSIANN-CDR) and almost the same root mean square deviation (~6) for both products. TMPA and PERSIANN-CDR outperform PERSIANN, mainly due to the fact that, unlike PERSIANN, TMPA and PERSIANN-CDR are gauge-adjusted precipitation products. The National Weather Service (NWS) Office of Hydrologic Development (OHD) Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM) is then forced with PERSIANN, PERSIANN-CDR, TMPA, and Stage IV data. Quantitative analysis using five different statistical and model efficiency measures against USGS streamflow observation show that in general in all three DMIP2 basins the simulated hydrographs forced with PERSIANN-CDR and TMPA have close agreement. Given the promising results in the first phase, the simulation process is extended back to 1983 where only PERSIANN-CDR rainfall estimates are available. The results show that PERSIANN-CDR-derived streamflow simulations are comparable to USGS observations with correlation coefficients (~0.67-0.73), relatively low biases (~5-12%), and high index of agreement criterion (~0.68-0.83) between PERSIANN-CDR simulated daily streamflow and USGS daily observations. The results prove the capability of PERSIANN-CDR in hydrological rainfall-runoff modeling application, specially for long-term streamflow simulations over the past three decades.

1. Introduction

Streamflow is one of the most important components of the hydrological cycle. Many efforts have been made to develop different of models to emulate the hydrological cycle and simulate streamflow. Examples are statistical data-driven (e.g., Kim & Barros 2001; Sahoo et al. 2006; Piotrowski et al. 2006) or physically-based (Kobold & Brilly 2006; Borrell *et al.* 2006; Sirdas & Sen 2007) models in the forms of lumped (e.g. Sacramento Soil Moisture Accounting - SAC-SMA, Burnash et al. 1973; HBV, Bergstrom 1995), semi-lumped (e.g. VIC – Liang et al., 1994), and distributed (e.g. HL-RDHM – Koren et al. 2003, 2004, 2007). One of the most, if not the most, important criterion in all of these types of hydrological modeling schemes, but particularly in the distributed format, is the availability of high quality data with desirable spatial and temporal coverages. Satellite products with their global coverage are very well suited for this purpose. With the advancement in remote sensing science and technology, high resolution data and information about the Earth’s surface characteristics (e.g., topography, soil types, land uses) and hydrometeorological forcing (e.g., precipitation, temperature, and evapotranspiration) have been made available globally. Particularly, remote sensing of precipitation - as one of the key hydrometeorological variables in generating floods - has gained significant attention in the recent past. Numerous efforts have been made to produce satellite-based precipitation estimates at high spatiotemporal resolution in global scale. Examples are the CPC morphing technique (CMORPH; Joyce et al. 2004), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Hsu et al. 1997, 1999, Sorooshian et al. 2000), PERSIANN – Climate Data Record (PERSIANN-CDR; Ashouri et al. 2015), TRMM Multi-Satellite Precipitation Analysis (TMPA; Huffman et al. 2007), the NRL-Blend satellite rainfall estimates from the Naval Research Laboratory (NRL; Turk et al. 2010), and the Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG; Huffman et al. 2015). Such products are valuable sources of information and data for flood modeling in a distributed format.

Previous efforts have been made in evaluating the accuracy of different satellite-based precipitation products against gauge observation (e.g., Sorooshian et al. 2000, Hong et al. 2006, Ebert et al. 2007, Ashouri et al. 2016, among many), and utilizing such data in different applications, especially hydrological modeling (see Behrangi et al. 2011: Bajracharya et al. 2015; Maggioni et al. 2013; Nguyen et al. 2014, 2015a,b, Seyyedi et al. 2015). Feasibility of using satellite-based precipitation as input for hydrologic simulation has been demonstrated in the Mediterranean (Ciabatta et al. 2015) and for simulating high-flows in Africa (Thiemig et al., 2013). However, certain challenges and limitations with using satellite-based precipitation for rainfall-runoff modeling have been identified. Of reoccurring concern is bias in satellite-based precipitation estimates that carries over to hydrological simulations when used as model input (Guetter et al. 1996; Stisen and Sandholt 2010; Thiemig et al. 2013). Harris et al. (2007) also point to spatial resolution of coarse satellite-based precipitation products as a concern for use in hydrologic models, cautioning their use in an operational setting, and they recommend adjustments to the precipitation estimates even beyond simple bias adjustments.

In this study, we implement a newly developed precipitation climate data record, PERSIANN-CDR, into a long-term hydrological modeling framework to simulate historical streamflow and flood events. In other words, we seek to evaluate the performance of PERSIANN-CDR in a distributed rainfall-runoff modeling application and compare its performance with other high resolution precipitation products. For this purpose, the NWS Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM) model is used. This study is conducted in two phases. In the first phase, a period of time when PERSIANN-CDR, TMPA, and Stage IV gauge-adjusted radar data products are available is chosen and the hydrological modeling is performed for this period. The study period for this phase is selected from 2003 to 2010 when all the aforementioned precipitation products are available. The results of this phase reveal how PERSIANN-CDR performs compared with the well established TMPA data product as far as generating the streamflow in the study basin. In the second phase, the entire record of the 0.25° daily PERSIANN-CDR data is used to extend the modeling process back to 1983 allowing for long-term streamflow simulations conducted at a higher resolution than previously possible.

The paper is structured as follows: Section 2 describes the data used in this study; Section 3 provides detailed information about the methodology and modeling structure; Section 4 presents the results, and Section 5 concludes with a summary of the main findings.

1. Data

***TMPA***

The Tropical Rainfall Measuring Mission (TRMM), a joint mission between NASA and the Japan Aerospace Exploration Agency (JAXA), was launched in November 1997 with a design lifetime of 3 years. TRMM, however, produced more than 17 years of data to study tropical rainfall for weather and climate research. This mission officially came to an end on April 15, 2015. As one of the TRMM products, TRMM Multi-satellite Precipitation Analysis (TMPA; Huffman et al. 2007, 2010) contains near-global (50°S-N) precipitation data at 3-hourly temporal resolution and 0.25° x 0.25° grid cells. In this study version 7 of this product is used. TMPA has an established record in precipitation and hydrological modeling studies (For a complete list of TMPA citations refer to *ftp://precip.gsfc.nasa.gov/pub/trmmdocs/rt/TMPA\_citations.pdf*). From the hydrological modeling perspective, Su et al (2008) forced the Variable Infiltration Capacity (VIC) model with TMPA precipitation data over La Plata basin in South America. The study reported that the TMPA-driven simulations were able to capture the daily flooding events and to represent low flows, although upward biases were identified in peak flows. Another study over the Amazon basin (Collischonn et al 2008) showed that the TRMM-based simulated hydrographs depicted comparable performance to those calculated from rain gauge data. Given the findings of such studies, in order to compare the performance of PERSIANN-CDR with another high-resolution satellite-based precipitation product, TMPA 3B42 V7 (hereafter, TMPA) for the period of 2003-2010 is chosen.

***PERSIANN-CDR***

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network – Climate Data Record (PERSIANN-CDR; Ashouri et al. 2015) is a newly developed and released satellite-based precipitation product which covers more than 3 decades (01/01/1983 - 03/31/2015 to date) of daily precipitation estimations at 0.25° resolution for the 60°S–60°N latitude band. PERSIANN-CDR uses the archive of the Gridded Satellite Infrared Window (IR WIN) CDR (GridSat-B1; Knapp 2008a,b; Knapp et al. 2011) from the International Satellite Cloud Climatology Project (ISCCP; Rossow and Schiffer 1991; Rossow and Garder 1993) as the input to the trained PERSIANN model. The resulted rainfall estimates are then bias-corrected using the monthly Global Precipitation Climatology Project (GPCP v2.2) 2.5° product. The dataset has been released and made available for public access through NOAA National Centers for Environmental Information (NCEI; *http://www1.ncdc.noaa.gov/pub/data/sds/cdr/CDRs/PERSIANN/Overview.pdf*). PERSIANN-CDR has already shown its usefulness for a relatively wide range of different applications (Guo et al. 2015, Solmon et al. 2015, Ceccherini et al.2015, Yang et al. 2015, Yong 2015). Using different extreme precipitation indices Miao et al. (2015) evaluated the performance of PERSIANN-CDR in capturing the behavior of historical extreme precipitation events over China. Their results showed the capability of PERSIANN-CDR in reproducing similar spatial and temporal patterns of daily precipitation extremes as those depicted by the East Asia (EA) ground-based gridded daily precipitation dataset. In another study by Hagos et al (2016) which investigated changes in the frequency of landfalling atmospheric river and extreme precipitation in the simulation of the Community Earth System Model (CESM), PERSIANN-CDR was used as the the “observation” precipitation. Luchetti et al. (2016) used PERSIANN-CDR in a NOAA/NASA collaborative project for updating the ENSO-based rainfall climatology for regions in Hawaii and U.S.-Affiliated Pacific Islands. With respect to the applicability of PERSIANN-CDR, the paper concludes that their results “… solidified the ability of the high resolution PERSIANN-CDR to be more than adequate for use in long-term precipitation climatology studies.” With respect to hydrological application, Casse and Gosset (2015) used PERSIANN-CDR to study hydrological changes and flood increases in the Niger River and the city of Niamey (Niger) over the period of 1983 – 2013. The results showed that PERSIANN-CDR produces annual rainfall amounts comparable with those from gauge-adjusted satellite rainfall estimates and gauge data. The paper also concludes that “The PERSIANN-CDR based hydrological simulation presents a realistic inter-annual variability, and detects flooded years, but not the exact flooded period day by day.”

***Stage IV Gauge-Adjusted Radar Data***

National Centers for Environmental Prediction (NCEP) Environmental Modeling Center (EMC) provides the Stage IV gauge-adjusted precipitation product (Fulton et al. 1998) from high-resolution Doppler Next Generation Radars (NEXRADs) and hourly rain gauge data over the contiguous United States. Stage IV radar data are available at hourly, 6-hourly, and 24-hourly scales at 4 km spatial resolution at Hydrologic Rainfall Analysis Project (HRAP) national grid system. Stage IV radar data are manually quality controlled at NWS River Forecast Centers (RFCs). More information about stage IV data can be obtained from *www.emc.ncep.noaa.gov/mmb/ylin/pcpanl /stage4/*. Stage IV precipitation data have been used in different studies (Ebert et al. 2007; Zeweldi and Gebremichael 2009; Anagnostou et al. 2010; Ashouri et al. 2015; among many). In this study, Stage IV data is first used as the reference data for evaluating satellite-based precipitation products. It is then used as a forcing data into the hydrological model to generate streamflow simulations.

In this study, all data products are first scaled to 0.25° and daily spatiotemporal resolution before use.

1. Methodology

As introduced earlier, the main goal of this study is to investigate the performance of the newly developed precipitation climate data record, PERSIANN-CDR, in a hydrological rainfall-runoff modeling application and compare its performance with other precipitation products. For this purpose, the NOAA’s National Weather Service (NWS) Office of Hydrologic Development (OHD) Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM; Koren et al. 2003, 2004, 2007) is used as the hydrological model to simulate the streamflow using the precipitation data products. HL-RDHM has been widely used for hydrologic studies (e.g., Smith et al. 2004, Moreda et al. 2006, Reed et al. 2007, Tang et al. 2007, Yilmaz et al. 2008, Wagener et al. 2009, Khakbaz et al. 2012, Smith et al. 2012a, and Smith et al. 2012b). The conceptually-based Sacramento Soil Moisture Accounting (SAC-SMA) provides the foundation of HL-RDHM. A schematic of SAC-SMA is shown in Figure 2. SAC-SMA features two conceptual layers, upper and lower zone storage, which each have two basic components, tension water and free water. An enhanced version of SAC-SMA known as the Sacramento Soil Moisture Accounting Heat Transfer (SAC-HT) includes the use of Noah Land Surface Model-based physics to estimate a physically meaningful soil moisture profile, allowing for the estimation of heat transfer within the column (Koren *et al.* 2007). The second HL-RDHM module that this study uses a routing scheme known as Rutpix9. This scheme consists of a hillslope component in which fast (overland flow) runoff is routed over a uniform conceptual hillslope and is combined with a slow (subsurface flow) component. Following hillslope runoff generation, a channel routing process moves water downstream using a topographically based, cell-to-cell method. In Rutpix9, the relationship between discharge and channel cross section is based on the rating curve method (NWS, 2011).

With respect to the calibration of the hydrological model, many studies have made a case for input-specific model calibration in order to compensate for possible pitfalls associated with a specific satellite precipitation product (Ciabatta et al. 2015; Qi et al. 2016; Stisen and Sandholt 2010; Thiemig et al. 2013, for example). While this technique allows for multiple satellite products to yield satisfactory hydrologic simulation performance despite discrepancies in precipitation estimates, it hinders efforts to improve the precipitation product as well as the model by allowing the two to compensate for one another’s deficiencies. For this reason, the work presented here relies on calibration of the model by experts who used precipitation estimates they deemed as the most dependable (radar-based in this case) for the particular model/study region. These parameters are held constant for evaluation across all precipitation products rather than performing product-specific calibration. This allows us to focus our evaluation solely on the performance of the precipitation products without their performance being altered by the potential improvements that product-specific calibration would bring. For HL-RDHM, the model has been expertly calibrated by NOAA NWS for the DMIP2 basins. *A priori* parameter sets have been derived from soil and land use data for HL-RDHM. Scalar multipliers of these parameter sets are used for calibration, assuming that the relationship of the individual pixels to one another is adequately characterized in the *a priori* sets. In this study, we rely on these expertly calibrated parameters by NWS experts for the calibration of the hydrological model. The calibrated parameters for SAC-HT and Rutpix9 provided by NWS are summarized as basin average values in Table 1. Detailed information about HL-RDHM can be found in its user manual (NWS, 2011, Koren and Barrett 1995).

With respect to the study area, three basins from the Oklahoma Test Basins from NOAA’s NWS Distributed Hydrologic Model Intercomparison Project - Phase 2 (DMIP2) are chosen (Figure 1). The two smaller study basins with outlets at Osage Creek near Elm Springs, AR (ELMSP) and Illinois River at Savoy, AR (SAVOY) have drainage areas of 337 km2 and 433 km2 and feed into the third study basin, which has an outlet located on the Illinois River south of Siloam Springs, AR (SLOA4) and a drainage area of 1489 km2 (Smith et al. 2012). The Illinois River Basin encompasses the three study basins and is characterized by an annual rainfall of ~ 1200 mm (Smith et al. 2004). It is noteworthy that the selection of these three test basins is based on the availability of the *A Priori* calibrated parameter sets from NWS, which were only available for these three basins at the time of this study.

Prior to setting up the hydrological modeling scheme, a preliminary evaluation on the accuracy of the utilized precipitation products against Stage IV gauge-adjusted radar data is conducted. After having the model structure in place, HR-RDHM is run in two phases. In the first phase, the time period of 2003 – 2010 when all products (PERSIANN, PERSIANN-CDR, TMPA, and Stage IV) are available is selected. The resulting hydrographs from HL-RDHM forced with the three precipitation products at the three study basins are compared with the USGS streamflow observations. The results of this phase depict how PERSIANN-CDR-simulated streamflow compares with other currently available precipitation products, i.e, TMPA and Stage IV data. Having proven the concept, in the second phase we extend the simulation process back to 1983 where only PERSIANN-CDR data is available.

In order to assess the closeness of the simulated streamflow to the USGS observations, the following statistical measures are calculated. In addition to correlation coefficient (CORR), centered root mean square error (RMSE), and percent volume bias (BIAS), the Nash-Sutcliffe coefficient and Index of Agreement is investigated. Nash-Sutcliffe (*E*, Nash and Sutcliffe 1970) is an efficiency criterion which is calculated as one minus the sum of the squared differences between observed and simulated values normalized by the variance of the observations.

where and are the observed and simulated values at time step *i,* respectively*.*  is the mean of the observation. *E* ranges from -∞ to 1 with 1 being the perfect fit and negative values indicating that the mean of the observation would be a better predictor than the model. The main drawback of the Nash-Sutcliffe criterion is that since the differences are squared this efficiency criterion is biased toward peak values and less sensitive during low flow periods (Legates and McCabe 1999). To overcome this problem, *E* is often calculated based on the logarithmic values of the observed and simulated data. In this study, we take the ln *E* approach.

The index of agreement *d* (Willmot 1984) is calculated as one minus the squared differences between the observed and simulated values normalized by the largest potential error. *d* is calculated using the following equation and ranges from 0 to 1, with 1 being the perfect fit.

The results of the two phases of the study are provided in the section below.

1. Results

Before conducting the hydrological modeling process, it is necessary to evaluate the accuracy of the precipitation products over the study region. A comparison of PERSIANN, PERSIANN-CDR, and TMPA precipitation products against Stage IV gauge-adjusted radar data as our reference dataset is conducted. Basic precipitation evaluation statistics, including Correlation Coefficient, Standard Deviation, and Root Mean Square Deviation are presented on Taylor Diagrams (Figure 3). The results show that in the three study basins TMPA and PERSIANN-CDR have close performances with slightly higher correlation coefficient for TMPA (~0.8 vs. 0.75 for PERSIANN-CDR) and similar RMSD (~6) for both products. TMPA shows a higher standard deviation (~10) than PERSIANN-CDR (~8). TMPA and PERSIANN-CDR both outperform PERSIANN,mainly due to the fact that, unlike PERSIANN, TMPA and PERSIANN-CDR are gauge-adjusted precipitation products.

Given the results of the previous section showing a reasonably accurate performance of PERSIANN-CDR and TMPA when compared to Stage IV radar data, we can reliably use these precipitation datasets as the forcing to the hydrological model. In the first phase, the simulation process is performed for 2003 - 2010 when all the four precipitation products are available. As mentioned in the methodology section, the NWS HL-RDHM model is used as our hydrological model. With respect to calibration, we relied on the calibrated *A Priori* parameter set(see Table 1)*,* calibrated by National Weather Service (NWS) experts for the basins we used. After setting up the model, HL-RDHM is forced with the PERSIANN, PERSIANN-CDR, TMPA, and Stage IV precipitation products to simulate streamflow at the outlet of the three study basins. The United States Geological Survey (USGS) Streamflow observations are used as the reference streamflow data. For a better visualization of the resulted hydrographs, specially for peak and low flows, we used the following transformation function proposed by Hogue et al. (2000) and used in different studies (Yilmaz et al. 2005; Khakbaz et al. 2009; Behrangi et al. 2011).

The resulting streamflow simulations for SAVOY, ELMSP, and SLOA4 basins are shown in Figure 4, Figure 5, and Figure 6, respectively. The scatterplots of non-transformed flows against the USGS observations (black line) are shown on the right column of each figure. As shown in the scatterplots, in general, for all three DMIP 2 basins Stage IV radar data seems to outperform the other products. The simulated hydrographs results from PERSIANN-CDR and TMPA forcing generally show close agreement. For quantitative comparisons, different statistical measures including correlation coefficient, RMSE, BIAS, logarithmic Nash-Sutcliffe (*ln(E)*), and Index of Agreement (*d*) are calculated from the PERSIANN-, PERSIANN-CDR-, TMPA- and Stage IV-derived hydrographs when compared with USGS observation. As shown in the Tylor diagrams in Figure 7, Stage IV in general outperforms other products with higher correlation coefficient (~0.75-0.8), and lower RMSE and standard deviation in all three basins. TMPA and PERSIANN-CDR both perform well, with a higher correlation coefficient for TMPA at SAVOY and SLOA4 and a higher correlation coefficient for PERSIANN-CDR at ELM spring basin. PERSIANN-CDR shows lower standard deviation than TMPA in all three basins. PERSIANN shows a correlation coefficient of about 0.5-0.6. The high values of RMSE for PERSIANN are due to the nature of this product being a real-time product with no gauge correction. Table 2 summarizes all the statistics for the three study basins. The lower Bias in PERSIANN-CDR compared to PERSIANN shows the effectiveness of the bias-removal algorithm in reducing the bias in satellite estimates when compared to ground measurements. Possible reasons for large bias in the Stage IV radar data is discussed in the Discussion section.

In addition to the quantitative analysis over the entire record, an analysis on the long-term (2003-2010) annual cycle from daily USGS streamflow observation, as well as the Stage IV-, TMPA-, PERSIANN- and PERSIANN-CDR-derived hydrographs for the three study basins is conducted. As shown in Figure 8, PERSIANN-CDR and TMPA depict relatively similar performance for all seasons. PERSIANN’s performance degrades in the spring season. The improvements from PERSIANN to PERSIANN-CDR are also evident in Figure 8. Respective Daily-based statistical measures from Day-Of-Year long-term (2003-2010) annual cycle analysis are calculated against gauge observations and shown in Table 3. The reduction in the percentage volume bias from PERSIANN to PERSIANN-CDR is evident. At the SAVOY basin, TMPA shows the highest Index of Agreement (d) where this measure is the highest for PERSIANN-CDR. Stage IV shows the lowest RMSE in all the three catchments. PERSIANN-CDR shows a higher RMSE than TMPA at SAVOY but a lower RMSE at ELMSP basin. RMSEs from PERSIANN-CDR and TMPA are very close at the SLOA4 basin. With respect to the correlation coefficient, Stage IV radar data shows the best performance at SAVOY and ELMSP basins. PERSIANN-CDR shows a slightly higher correlation coefficient than TMPA at the ELMSP basin however TMPA outperforms PERSIANN-CDR in SAVOY and SLOA4 basins in this regard. The large negative bias in Stage IV radar data in ELMSP and SLOA4 is again observed in this analysis. The seasonal analysis (figures not presented) shows that the largest negative bias in Stage IV-derived streamflow happens in the summer and fall seasons.

Results of phase I analyses for the period when other high-resolution satellite-derived precipitation products are available show that the performance of PERSIANN-CDR has been close to other precipitation products. The findings of this phase reveal the high potential for PERSIANN-CDR data use in rainfall-runoff modeling applications, particularly long-term simulations of more than three decades, given the fact that PERSIANN-CDR rainfall data spans January 1, 1983 to present (delayed) time. Therefore, in phase II, HL-RDHM is forced with daily PERSIANN-CDR rainfall estimation for 1983 – 2012 to reconstruct historical streamflow at the three study basins. It is important to note that similar to phase I, we rely on the NWS *A Priori* parameter sets for the calibration of the model. The resulting hydrographs for SAVOY, ELMSP, and SLOA4 are shown in Figure 9 with the black line being the USGS observation and the blue line being the PERSIANN-CDR-derived hydrograph. As shown, an immediate result is that PERSIANN-CDR could reconstruct the full record of historical streamflow, specially for years prior to 1996 (except 1986 for SAVOY basin) when generally the USGS streamflow observations are not available for the three study basins. The scatterplots comparing the PERSIANN-CDR simulated streamflow against USGS observations for 1983- 2012 for the three study basins are shown in Figure 9. The summary of quantitative comparisons is presented in Table 4. The results depict high correlation coefficients (~0.67-0.73), relatively low biases (~5-12%), and high index of agreement criterion (~0.68-0.83) between PERSIANN-CDR simulated daily streamflow and USGS daily observations, demonstrating reasonable performance of PERSIANN-CDR despite the calibration of the hydrological model by a precipitation product other than PERSIANN-CDR. It is also noteworthy that the efficiency index of the logarithmic Nash-Sutcliffe coefficient derived in the second phase of the study is comparable, and even slightly better, than the same coefficient in the first phase of the study for other precipitation products.

1. Discussion

There are few points what we would like to clarify via the explanations below. Firstly, we would like to point out that the main reason for including the real-time PERSIANN product in our analysis was to investigate the progress that the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine has made over time in improving its precipitation products. Regarding this, the improvements are evident from both the precipitation and simulated streamflow point of views. Having that said, there are certain facts that should be considered here since a blind comparison of real time precipitation products (e.g., PERSIANN or TMPA-RT (3B42RT)) with gauge-adjusted products (e.g., TMPA, PERSIANN-CDR) may not be a fair comparison in general. In the case of PERSIANN and PERSIANN-CDR, the latter one is indirectly gauge corrected based on the gauge information from the Global Precipitation Climatology Centre (GPCC; Schneider et al. 2008) used in the GPCP monthly precipitation product (see <ftp://precip.gsfc.nasa.gov/pub/gpcp-v2.2/doc/V2.2_doc.pdf)>, whereas PERSIANN is a real-time product without any gauge-adjusting component. Real time PERSIANN data is useful for real time applications such as global flood monitoring while the long-term (+30 years), daily PERSIANN-CDR rainfall data makes it useful for long-term hydrological and climatological studies and applications. As is the case with other satellite-based products, the choice of PERSIANN or PERSIANN-CDR depends on the type of application, period of the study, and the constraints of the problem.

The second point refers to the relatively high % bias observed in the Stage IV streamflow simulations for ELMSP and SLOA4 basins compared to PERSIANN-CDR and TMPA. There could be couple of reasons for that. Firstly, the validation period in this study is not the same as the calibration period for which the *A Priori* parameters are estimated, so there is no guarantee that Stage IV is always better than the other products in the discharge simulations. More importantly, calibration performed by the NWS (see Kuzmin et al. 2008) is based on a multi-time scale form of RMSE and does not include bias in the objective function. In Table 2, Stage IV simulation has the lowest RMSE which is consistent with the calibration methods. It is noteworthy that the correlations of Stage IV simulations in all cases are better than the others.

The third point is about the low Nash-Sutcliff efficiency values obtained from the simulated streamflow time series. The key point here is the calibration of the hydrological model. As explained in the Introduction and Methodology sections, instead of conducting product-specific calibration we relied on the NWS expertly calibrated *A Priori* parameter sets for the calibration of the HL-RDHM for the study basins. These parameters are kept fixed for all the precipitation products allowing us to focus our evaluation solely on the performance of the precipitation products, rather than mixing it with the improvements that product-specific calibrations of the hydrological model can, and do, introduce in the final simulations. It is obvious that by conducting product-specific calibration, one would achieve higher efficiency results.

The fourth point is about the performance of PERSIANN-CDR in reproducing the observed peak flows during the 1983 – 2012 period (Figure 9), when observations are available. Part of the mismatch is due to the fact our hydrological model was not specifically calibrated with PERSIANN-CDR data. In addition to that, it could be partly due to the fault of the forcing precipitation, the fault of the model, or even the fault of the precipitation product used for calibration (or a combination of all).

1. Conclusion

The main goal of this study was to evaluate the performance of the newly developed precipitation climate data record, PERSIANN-CDR, in a rainfall-runoff modeling scheme and compare its performance with other high-resolution precipitation products. In examining the accuracy of the precipitation products, PERSIANN-CDR and TMPA showed close performances compared to Stage IV gauge-adjusted radar data product. Focusing only on the PERSIANN products, it is found that PERSIANN-CDR outperforms PERSIANN real-time product depicting better statistical measures. This is mainly due to the fact that PERSIANN-CDR is gauge-corrected whereas PERSIANN is a real-time product with no gauge-correction component.

For the purpose of evaluating PERSIANN-CDR's application in hydrological modeling, two phases of study were designed. In the first phase, the main goal was to test how PERSIANN-CDR’s performance compares with the performance of other precipitation products. In order to have all the products available, the time period of 2003 – 2010 was selected. The NWS HL-RDHM model was run separately for each of these precipitation data products to simulate streamflow hydrographs at the outlets of three DMIP2 study basins where NWS *A Priori* parameters are available. The simulations at SAVOY, ELMSP, and SLOA4 basins were compared with USGS observations. The results show that PERSIANN-CDR- and TMPA-derived simulations have close performances with higher correlation coefficients and better RMSEs for TMPA and lower Biases for PERSIANN-CDR. Annual cycle analysis of simulated hydrographs also depicts close performance between TMPA and PERSIANN-CDR. Phase 1 of this study serves as the proof of concept regarding the applicability of PERSIANN-CDR in rainfall-runoff modeling. Given this result and the fact that PERSIANN-CDR precipitation data spans from 1983 to present time, we could extend the simulation process back to 1983 to reconstruct the historical record of streamflow. This is particularly important when even USGS streamflow observations are not available prior to year 1996 for the three study basins. In this phase of the study, only PERSIANN-CDR precipitation data were available as the forcing to the model. The resulting PERSIANN-CDR-derived hydrographs were compared with USGS observations depicting high correlation coefficients, relatively low biases, and high index of agreement criterion.

It is noteworthy that for the three DMIP2 study basins there were periods of time, mostly before 1996, where time series of daily data were not available. Using PERSIANN-CDR and HL-RDHM we could simulate the streamflow for those periods and fill the gaps. This is particularly important for long-term trend studies where full data coverage over a long period of time, at least 30 years according to the World Meteorological Organization (WMO) report (Burroughs 2003), is needed. To conclude, PERSIANN-CDR could prove its usefulness for long-term hydrological rainfall-runoff modeling and streamflow simulation. It can be particularly helpful for simulating streamflow in ungauged basins.

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Table 1. HL-RDHM parameter descriptions and their basin average values (Koren et al. 2004)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Parameter** | **Description** | **SLOA4** | **ELMSP** | **SAVOY** |
| *SAC-HT* |  |  |  |  |
| sac\_UZTWM (mm) | Upper zone tension water capacity | 68.46 | 74.74 | 51.41 |
| sac\_UZFWM (mm) | Upper zone free water capacity | 20.52 | 21.17 | 18.11 |
| sac\_UZK (day-1) | Fractional daily upper zone free | 0.2978 | 0.2775 | 0.3427 |
| sac\_ZPERC (DL) | Maximum percolation rate | 117.9 | 125.9 | 100.5 |
| sac\_REXP (DL) | Exponent for the percolation equation | 2.026 | 2.065 | 1.943 |
| sac\_LZTWM (mm) | Lower zone tension water capacity |  |  |  |
| sac\_LZFSM (mm) | Lower zone supplemental free water capacity | 173 | 177.1 | 163.2 |
| sac\_LZFPM (mm) | Lower zone primary free water capacity | 83.57 | 74.87 | 101.6 |
| sac\_LZSK (day-1) | Fractional daily supplemental withdrawal rate | 0.1140 | 0.1074 | 0.1285 |
| sac\_LZPK (day-1) | Fractional daily primary withdrawal rate | 0.01704 | 0.01754 | 0.01513 |
| sac\_PFREE | Percent/100 of percolated water which always goes directly to lower zone free water storages | 0.3591 | 0.3743 | 0.3304 |
|  |  |  |  |  |
| *rutpix9* |  |  |  |  |
| rutpix\_Q0CHN | Specific channel discharge per unit channel cross-section area | 0.3281 | 0.3389 | 0.3377 |
| rutpix\_QMCHN (DL) | Power value in relationship between discharge and cross-section | 1.288 | 1.288 | 1.288 |
| sac\_PCTIM (fraction) | Minimum impervious area | 0.001 | 0.001 | 0.001 |
| sac\_ADIMP (fraction) | Additional impervious area | 0 | 0 | 0 |
| sac\_RIVA (fraction) | Riparian vegetation area | 0.035 | 0.035 | 0.035 |
| sac\_SIDE (fraction) | Ratio of non-channel baseflow to channel baseflow | 0 | 0 | 0 |
| sac\_RSERV | Percent/100 of lower zone free water which cannot be transferred to lower zone tension water | 0.3 | 0.3 | 0.3 |
| sac\_EFC (fraction) | Effective forest cover | 0 | 0 | 0 |

Table 2. Mean, Standard Deviation (SD), centered Root Mean Square Error (RMSE), Correlation Coefficient (CORR), logarithmic Nash-Sutcliffe (ln(E)), Percent Volume Bias (Bias), and Index of Agreement (d) for simulated streamflow (2003-2010) from PERSIANN, PERSIANN-CDR, Stage IV, and TMPA compared to USGS streamflow observations.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Basin | Product | Mean | SD | RMSE | CORR. | Ln(E) | Bias (%) | d |
| SAVOY | PERSIANN | 7.79 | 21.69 | 17.44 | 0.604 | -0.203 | 61.2 | 0.725 |
| PERSIANN-CDR | 5.54 | 8.17 | 11.46 | 0.686 | 0.274 | 14.6 | 0.728 |
| Stage IV | 4.2 | 7.58 | 10.3 | 0.808 | 0.536 | -13.0 | 0.781 |
| TMPA | 5.86 | 11.2 | 10.2 | 0.750 | 0.254 | 21.2 | 0.833 |
| ELMSP | PERSIANN | 5.83 | 17.15 | 14.73 | 0.52 | -2.47 | 26.6 | 0.567 |
| PERSIANN-CDR | 4.14 | 7.1 | 6.36 | 0.648 | -1.88 | -10.1 | 0.781 |
| Stage IV | 2.72 | 4.56 | 5.54 | 0.721 | -4.72 | -41.05 | 0.756 |
| TMPA | 3.83 | 8.37 | 7.07 | 0.622 | -2.19 | -16.84 | 0.767 |
| SLOA4 | PERSIANN | 25.45 | 64.68 | 53.24 | 0.572 | -0.662 | 55.1 | 0.631 |
| PERSIANN-CDR | 18.04 | 26.05 | 24.35 | 0.677 | 0.166 | 9.91 | 0.798 |
| Stage IV | 12.1 | 17.16 | 23.2 | 0.733 | -0.113 | -26.34 | 0.75 |
| TMPA | 17.74 | 31.33 | 23.8 | 0.724 | 0.156 | 8.08 | 0.841 |

Table 3. Same as Table 2 but for Day-Of-Year long-term (2003-2010) annual cycle analysis

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Basin | Product | Mean | SD | RMSE | CORR. | Ln(E) | Bias (%) | d |
| SAVOY | PERSIANN | 7.86 | 8.7 | 7.24 | 0.56 | -0.388 | 62.7 | 0.664 |
| PERSIANN-CDR | 5.56 | 3.39 | 4.16 | 0.673 | 0.313 | 15.2 | 0.754 |
| Stage IV | 4.21 | 2.99 | 3.66 | 0.804 | 0.601 | -12.7 | 0.802 |
| TMPA | 5.88 | 4.24 | 3.6 | 0.767 | 0.330 | 21.78 | 0.843 |
| ELMSP | PERSIANN | 5.83 | 7.01 | 5.83 | 0.588 | -1.325 | 26.61 | 0.580 |
| PERSIANN-CDR | 4.14 | 3.03 | 2.38 | 0.666 | -0.451 | -10.09 | 0.802 |
| Stage IV | 2.72 | 1.95 | 2.02 | 0.685 | -2.541 | -41.05 | 0.694 |
| TMPA | 3.83 | 3.39 | 2.63 | 0.653 | -1.074 | -16.85 | 0.776 |
| SLOA4 | PERSIANN | 26.13 | 28.23 | 23.76 | 0.557 | -0.827 | 59.52 | 0.560 |
| PERSIANN-CDR | 18.46 | 11.9 | 9.99 | 0.649 | 0.306 | 12.71 | 0.792 |
| Stage IV | 12.47 | 8.16 | 8.96 | 0.660 | 0.118 | -23.89 | 0.749 |
| TMPA | 18.13 | 13.44 | 9.83 | 0.706 | 0.355 | 10.67 | 0.826 |

Table 4. Bias, Correlation Coefficient, and RMSE statistics for simulated streamflow from PERSIANN-CDR against USGS observed streamflow for 1983-2012.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Product | Basin | Mean | SD | RMSE | CORR. | Ln(E) | Bias (%) | d |
|  | SAVOY | 5.65 | 8.1 | 13.4 | 0.6719 | 0.265 | 12.24 | 0.681 |
| PERSIANN-CDR | ELMSP | 4.04 | 7.23 | 6.49 | 0.7342 | -1.81 | -10.9 | 0.83 |
|  | SLOA4 | 18.2 | 28.3 | 29.4 | 0.7344 | 0.236 | 5.26 | 0.81 |

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1. Figure

|  |
| --- |
| Figure 1. The three study basins (SAVOY, ELMSP, and SLOA4) (modified from Smith et al. 2012) |

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| Figure 2. Schematic of the SAC-SMA (Burnash et al. 1973, Image source: http://ldas.gsfc.nasa.gov/nldas/images/SAC\_schematic.jpg |

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| Figure 3. Precipitation comparison plots for SAVOY (top), ELMSP (middle), and SLOA4 (bottom) basins for 2003-2010. |

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| Figure 4. Simulated and observed streamflow hydrographs and respective scatterplots at the outlet of SAVOY basin using Stage IV, TMPA, PERSIANN, and PERSIANN-CDR (bottom) precipitation products. The solid black line shows the USGS observations. |

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| Figure 5. Simulated and observed streamflow hydrographs and respective scatterplots at the outlet of ELMSP basin using Stage IV, TMPA, PERSIANN, and PERSIANN-CDR (bottom) precipitation products. The solid black line shows the USGS observations. |

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| Figure 6. Simulated and observed streamflow hydrographs and respective scatterplots at the outlet of SLOA4 basin using Stage IV, TMPA, PERSIANN, and PERSIANN-CDR (bottom) precipitation products. The solid black line shows the USGS observations. |

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| Figure 7. Tylor diagram showing the correlation coefficient, standard deviation, and root mean square deviation from the PERSIANN-, PERSIANN-CDR-, TMPA- and Stage IV-derived hydrographs for SAVOY (top), ELMSP (middle), and SLOA4 (bottom) basins for 2003-2010. |

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| Figure 8. Long-term (2003-2010) annual cycle from USGS observation and Stage IV-, TMPA-, PERSIANN- and PERSIANN-CDR-derived hydrographs for SAVOY (top), ELMSP (middle), and SLOA4 (bottom) basins. Daily statistics (from top to bottom: Correlation Coefficient, RMSE, Percent Volume Bias, Nash-Sutcliffe (E), and Index of Agreement (d) for Savoy (left), ELMSP (middle) and SLOA4 (right) basins based on the streamflow simulation derived from Stage IV, TMPA, PERSIANN, and PERSIANN-CDR precipitation data products. |

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| Figure 9. Long-term (1983-2012) simulated streamflow from PERSIANN-CDR daily precipitation data (blue) versus USGS streamflow observations (black) for SAVOY (top), ELMSP (middle), and SLOA4 (bottom) basins, plus the respective scatterplots on the right column. |

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