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THE EVOLUTION OF REMOTELY SENSED PRECIPITATION PRODUCTS FOR HYDROLOGICAL APPLICATIONS WITH A FOCUS ON THE TROPICAL RAINFALL MEASUREMENT MISSION (TRMM)

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This study examines the evolution of how remotely sensed precipitation products have impacted hydrologic modeling from six basins across the continental United States. Precipitation products include both ground-based (Multisensor Precipitation Estimator - MPE) and space-based products. Two space-based products are from the Tropical Rainfall Measurement Mission (TRMM) and include the real-time TRMM Multi-Satellite Precipitation Analysis (TMPA-RT) and TRMM 3B42 Research product. Precipitation products are compared between early (2004-2007) and late (2008-2010) periods. Additionally, version 6 and the new version 7 of these TRMM products are examined. Watersheds examined were moderately large (1233 to 8905 square kilometers) and include the San Pedro (Arizona), Cimarron (Oklahoma); Alapaha (Georgia), mid-Nueces (Texas), San Casimiro (Texas), and the mid-Rio Grande basins, which is a bi-national basin that spans the Texas-Mexico border. Precipitation products are used to drive streamflow simulations using the Soil Water Assessment Tool (SWAT). The main results of this study concludes that MPE is a mature remote sensing product that generally supports superior hydrologic simulations based on standard performance metrics such as mass balance error and Nash-Sutcliffe efficiency coefficient. Both versions of TRMM products generally support acceptable simulations. Improved performance during the late period for TMPA-RT is noted and this improvement is related to modification of TRMM in January 2009 with the addition of more satellite data and a climatologic bias correction, which greatly improves the real-time TMPA-RT product.

INTRODUCTION

Remotely sensed precipitation products have increasingly been used to support hydrologic modeling. A significant trend is that many of these products are merged based on multiple data sources. Products can be primarily ground-based or space-based precipitation data. In the continental United States (US), ground-based remote sensing of precipitation supports hydrological applications through several different suites of products (Quantitative Precipitation Estimator, QPE; Multisensor Precipitation Estimator, MPE; High Resolution Precipitation Estimator, HPE) that are derived from the extensive US Next Generation Weather Radar (NEXRAD) network (*e.g.* Fang et al. 2011; Kitzmiller et al, 2011; Lee et al. 2011). In these studies, NEXRAD based data generally supports acceptable hydrologic modeling. Specifically, MPE merges rainfall data from gauges, NEXRAD, and Geostationary Operational Environmental Satellite (GOES); but is based on Stage III NEXRAD data, which represents the area of a National Weather Service (NWS) River Forecast Center. MPE is a mature product that has estimated precipitation within the areas of a NWS River Forecast Centers (RFC) since 2005.

Space-based precipitation monitoring has the potential to record precipitation across the planet. Three of the more commonly used space-based precipitation product suites include the Remotely Sensed Information using Artificial Neural Network (PERSIANN; Hsu et al. 1997), National Aeronautic and Space Administration (NASA) Tropical Rainfall Measurement Mission (TRMM 3B42; Huffman et al. 2007, 2010), and the United States (US) National Oceanic and Atmospheric (NOAA) Climate Prediction Center's morphing technique (CMORPH, Joyce et al. 2004). Some studies that have used PERSIANN for hydrologic modeling include Hong et al. 2007 and Bitew and Gebremichael 2011. TRMM has been successfully utilized to support hydrologic simulations in numerous basins (e.g. Tobin and Bennett, 2009; Khan et al., 2011; Yu et al., 2011). Zeweldi et al. 2011 utilized CMORPH to model Goodwin Creek, which is a small watershed in Mississippi. Finally, there have been several studies that have systematically inter-compared streamflow simulations that have used all three of the above space-based precipitation products (Pan et al. 2010; Beighley et al. 2011). No satellite product is universally superior in terms of its ability to support hydrologic modeling and each product has advantages and disadvantages depending on climatic region and topography. This realization has prompted the developers of the core precipitation product to be associated with the soon to be launched Global Precipitation Measurement Mission (GPM) to produce the ultimate merged product based on the fusion of PERSIANN, TRMM, and CMORPH.

TRMM products have undergone a significant evolution over the last 16 years since the TRMM satellite was launched in 1997. The TRMM 3B42 series represents a fully merged estimate of precipitation based upon all available orbital platforms, which include both low orbit passive microwave (PW) and geostationary infrared (IR) sensors. As satellites are added (or fail) necessary modifications are needed to the core algorithm upon which rainfall retrievals for TRMM products are based. Additionally, orbital configurations change over time forcing modification of scanning footprints that can affect rainfall retrievals; the most notable example of this is the boost in the TRMM satellite orbit that occurred in 2001. For most of the last ten years the standard version of the TRMM product that has been available is version 6 (V6). Over the last decade two significant modifications have occurred to the TRMM 3B42 product (Huffman et al., 2010). Specifically, in February 2005 there was a doubling of the available microwave observations and in January 2009 there was an addition of more satellite data, which offset the failure of older satellites, and the addition of a climatologic bias correction; based on ground gauge data to the real-time version of the TRMM 3B42 product. Finally, in 2012 the newest version of the TRMM algorithm, version 7 (V7), has become available and has been applied retrospectively to existing TRMM products.

Previous Work and Objectives of Study

This study examines how the evolution of remotely sensed precipitation products have impacted hydrologic modeling from six basins across the continental US. Many of the basins have been previously examined (Tobin and Bennett, 2009, 2010a, 2010b, 2012, 2013). In brief, Tobin and Bennett (2009, 2010b) conducted a basic inter-comparison of how precipitation data affected modeled streamflow in three of the examined watersheds. Tobin and Bennett (2010a, 2012) developed and examined an adjustment method for TRMM data. Finally, Tobin and Bennett (2013) examined how model performance varied as a function of time scale between monthly and daily periods. This paper is distinct from these previous efforts in three important respects. (i) Previous studies focused on only V6 of the TRMM products while this effort examines both V6 and V7. (ii) To evaluate the evolution of TRMM products two time periods (early- 2005-2007; late- 2008-2010) were examined; whereas, previous studies focused on the early period. (iii) A new cross calibration approach was used to derive streamflow model results to help address the concern that parameter selection may control model results.

STUDY AREAS

Figure 1 illustrates the location of the six examined basins in the United States (US). All basins are located in the southern United States below 40^{o} latitude, which is the upper limit for optimum data from Tropical Rainfall Measurement Mission (TRMM). Five basins are from the western US representing a dry climatic regime where TRMM has had historical difficulties with accurately detecting rainfall rates; strong positive biases have been detected especially during the warm season (e.g. Ebert et al. 2007; Tian et al. 2007). Western basins are from Arizona (San Pedro, 1971 km^2); Oklahoma (Cimarron, 3110 km^2); Texas (mid-Nueces, 7720 km^2; San Casimiro, 1233 km^2); and a bi-national basin that spans the Texas-Mexico border (mid-Rio Grande, 8905 km^2). Note that the San Casimiro watershed is a subbasin located within the larger mid-Nueces basin. The single eastern US basin is located in southern Georgia (Alapaha, 3596 km^2). These basins are defined based on the outlet location, which corresponds with the locations of streamflow gauges; both United States Geological Survey (USGS) and International Boundary and Water Commission (IBWC); for the mid-Rio Grande basin. Information regarding the location of basin inlets and outlets as well as basin size and land use characteristics is given in Table 1. Note that detailed descriptions of these basins have been previously provided in Tobin and Bennett (2009, 2010a, 2010b, 2012, 2013).

PRECIPITATION PRODUCTS

This paper examines three different precipitation products, which include the National Weather Service (NWS) Multisensor Precipitation Estimator (MPE) and from the Tropical Rainfall Measurement Mission (TRMM) products, which include the real-time TRMM Multi- Satellite Precipitation Analysis (TMPA-RT) and TRMM 3B42 Research Version (TRMM). TMPA-RT are both available with a minimal latency of a few hours; whereas the latency of the TRMM 3B42 Research product is two months.

MPE data were collected from four NWS RFC's (Southeast, Arkansas Red River, West Gulf, and Colorado Basin). MPE data from all but the Colorado Basin RFC (where the San Pedro basin

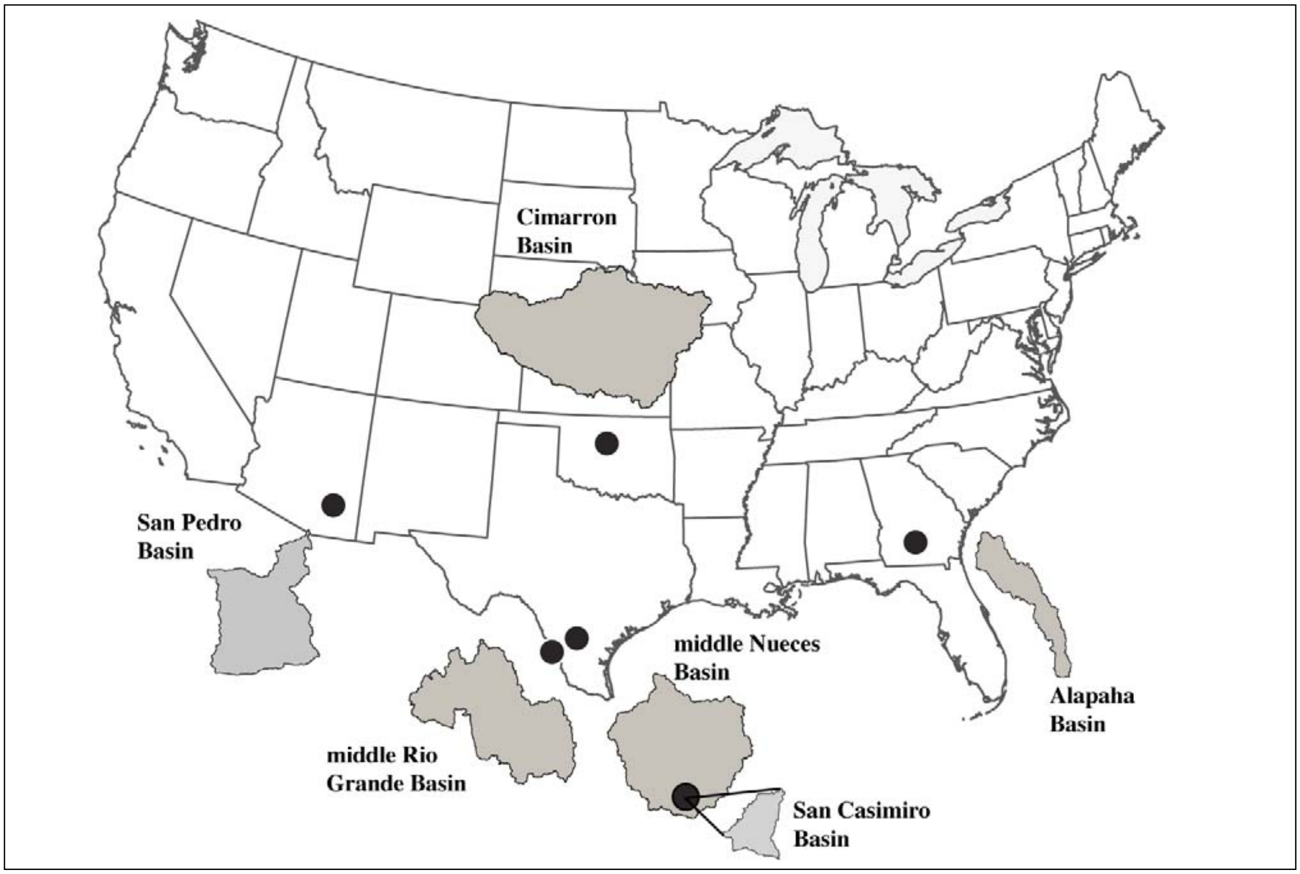

Figure 1. Map of CONUS illustrating the relative location of the six basins utilized in this study.

Table 1. Significant characteristics of examined basins.

Basin	Dominant Soil	Primary Landuse	Secondary Landuse	Basin Inlet/ USGS #	Basin Outlet/ USGS #
San Pedro AZ	Loam 95%	Rangeland 95%	Forest & Other 5%	Tombstone 09471550	Benson 09471800
Cimarron OK	Silty Loam 63%	Agricultural 85%	Rangeland & Other 15%	Dodge 07159100	Guthrie 07160000
mid-Rio Grande TX/Mexico	Sandy Loam 67%	Rangeland 93%	Agricultural & Other 7%	El Indio 08-4587 *	Laredo 08-4590 *
mid-Nueces TX	Clay-Clay Loam 57%	Rangeland 96%	Agricultural & Other 4%	Cotulla 08194000	Tilden 08914500
San Casimiro TX	Clay 81%	Rangeland 100%	None	None	San Casimiro 08194200
Alapaha GA	Loamy Sand 76%	Forest 53%	Agricultural & Other 47%	None	Statenville 02317500

is located) were used as the primary data source, which is based on hourly NWS NEXRAD Stage III data that covered the area of an RFC.

Additional information about the MPE product is given in Wang et al. (2008). In the Colorado Basin RFC the MPE product was based on the Parameter-elevation Regressions on Independent Slopes Model (PRISM) approach (Daly et al., 1994), which is an interpolation method based on rain gauge data and is adjusted for orography. MPE is based on a finer spatial resolution MPE (4 km^2) as opposed to TMPA-RT and TRMM 3B42 Research, which have a coarser resolution (625 km^2; 0.25^o). MPE data was spatially aggregated to 0.25^o grid that exactly corresponded with satellite data to facilitate inter-comparison. Temporal resolution varied with satellite products (3 hourly), and MPE (1 hourly; 6 hourly for Colorado Basin RFC); although, all data were temporally aggregated to a uniform daily time step.

Both versions 6 (V6) and 7 (V7) of the TMPA-RT and the TRMM 3B42 Research products were gathered using the NASA Giovanni portal (http://disc2.nascom.nasa.gov/Giovani/tovas.shtml). For TMPA-RT during the early period (2005-2007) only V6 was used whereas for the late period (2008-2010) only V7 was examined. The early period V6 product was obtained before application of the climatological calibration, which was retrospectively applied to TMPA-RT data early in 2009. For TRMM, both V6 and V7 were compared within both periods. V7 data examined was not the original release but was the reprocessed product (late 2012), which corrected for the omission of AMSU data that was accidentally left out of the original product. TRMM products were used at their native 0.25^o spatial resolution and were aggregated to a daily time step.

METHODOLOGY

Modeling Approach

The hydrologic model selected for this study was the Soil and Water Assessment Tool (SWAT), which is a physically based model with demonstrated global applications and has been validated at the watershed scale through the publication of hundreds of referred papers (see Gassman et al. 2007). This study seeks to compare simulated streamflow based on MPE, TMPA-RT, and TRMM 3B42 Research (TRMM) precipitation for two time periods (early; late). Additionally, versions 6 (V6) and 7 (V7) were examined for both TMPA-RT and TRMM. Simulated streamflow is compared with observed values to determine performance. There are a total of sixteen parameters in the SWAT model that can affect simulated streamflow. Of these sixteen parameters a total of 10 to 11 can be defined based on existing information from the literature or based on the characteristics of the watershed; referred to as defined parameters. The remaining 5 to 6 parameters are designed as unknown parameters.

The values for the defined parameters were determined through *a priori* knowledge and these values are given in Table 2. The initial runoff curve number (CN) was based on the unique combinations of HRU's within a watershed and was unchanged as were the main channel (Main_K) and tributary channel (Tributary_K), which were based on the permeability of the soils that underlie these landscape features. Additional soil parameters (Moist soil albedo - SOL_ALB; Soil Available Water Capacity - SOL_AWC) were not modified from default values. Manning values for overland, tributary, and main channel flow (n_Overland, n_Tributary, n_Main; respectively) were set based on observed landscape and channel characteristics. In most basins surface-groundwater interactions (ALPHA_BF) were determined by using a baseflow filter program developed for the SWAT model (Arnold et al., 1995; Arnold and Allen, 1999). Note that two values where used for ALPHA_BF based on the time periods examined (early - ALPHA_BF_E; late - ALPHA_BF_L), which are defined below. Peak flow timing (SURLAG) was determined through visual matching of simulated and observed streamflow hydrographs and in most cases best results for all precipitation types where obtained by using the minimum permissible value of 0.50. Finally, the selected maximum canopy interception (CANMX) value for three Texas basins (mid-Rio Grande, mid-Nueces, and San Casimiro) were consistent with the value derived for this parameter from a watershed in the nearby Texas Hill County (Afinowicz et al., 2005).

Table 2. Values of known hydrologic parameters in the SWAT Model.

Known Parameters	**San Pedro**	**Cimarron**	**mid-Rio Grande**	**mid-Nueces**	**Alapaha**	**San Casimiro**
SURLAG	1.00	1.00	0.50	0.50	0.50	0.50
n Overland	0.600	0.090	0.600	0.600	0.100	0.600
n Tributary	0.100	0.050	0.100	0.100	0.050	0.100
n Main	0.050	0.014	0.014	0.050	0.050	0.040
Tributary K	40.00	1.20	100.00	20.00	18.00	20.00
Main K	3.30	150.00	1.00	0.27	0.81	0.27
ALPHA_BF_E	0.0001	0.0440	0.0206	Adjust	0.0533	0.0001
ALPHA_BF_L	0.0001	0.0117	0.0252	Adjust	0.0203	0.0001
CANMX	Unk	Unk	7.0	7.0	Unk	7.0
CN2	Varies based on Hydrologic Response Unit					
SOL_ALB	Varies based on Soil type					
SOL_AWC	Varies based on Soil type					

A sensitivity test based on the Latin Hypecube (LH) One-factor-At-a-Time (OAT) method (for details see Van Griensven and Meixner, 2003) determined the relative sensitivity (importance) of parameters in each basin. Unknown parameters include the soil evaporation compensation factor (ENCO), plant uptake compensation factor (EPCO), threshold depth in the shallow aquifer required for return flow to occur (GWQMN), the Groundwater "Reevap" coefficient (GW_REVAP), threshold depth in the shallow aquifer for percolation to the deep aquifer to occur (REEVAPMN), and CANMX in non-Texas basins. Finally, an acceptable simulation in the mid-Nueces was not achieved with using calculated ALPHA_BF values and this parameter was adjusted in an *ad hoc* fashion, treated as an unknown parameter, to drive acceptable streamflow simulations from this basin. Significant unknown parameters were identified based on having a relative sensitivity value that was greater than 1% of the total for all parameters. Default values were used for unknown parameters that have a relative sensitivity value that was less than 1%. Table 3 indicates the relative sensitivity of unknown parameters (on a % basis) for the two time periods examined.

The approach was to select values for significant unknown parameters that maximized goodness of fit between observed and simulated streamflow based on metrics described in the next section. Optimal parameter values for both periods examined are given in Tables 4 and 5. Additionally, a cross-calibration approach was taken where optimized unknown parameter values selected for the early (calibration-1) period were applied to the late (validation-1) period and optimized values for the late (calibration-2) period were used to drive early period (validation-2) simulations. For each simulation, a warm-up period of nine to twelve months was utilized to initialize the model. Two time periods were examined, which include an early (January 2005 to December 2007) and late (October 2008 to December 2010) period that were selected based on the availability of streamflow data. In the San Pedro Basin outlet streamflow data availability made it necessary to establish a slightly different early simulation period (October 2005 to September 2008). During both periods MPE and TRMM V6 and V7 were used to drive independent streamflow simulations. For the real-time TMPA-RT product V6 was used during the early period and V7 during the late period.

Table 3. Sensitivity of unknown SWAT Parameters (given in %).

Early Period

Unknown Parameters	San Pedro	Cimarron	mid-Rio Grande	mid-Nueces	Alapaha	San Casimiro
ENCO	2.73	7.83	14.94	13.77	3.85	13.77
GWQMN	0	0.16	0	0.33	3.35	0.33
CANMX	0.28	1.68	---	---	1.11	---
GW_REVAP	0	0	0	0	0.17	0
EPCO	0	0	0	0	0	0
REEVAPMN	0	0	0	0	0	0

Late Period

Unknown Parameters	San Pedro	Cimarron	mid-Rio Grande	mid-Nueces	Alapaha	San Casimiro
ENCO	2.53	8.77	5.47	13.65	3.69	13.65
GWQMN	0	0.02	0	0	3.12	0
CANMX	1.42	1.39	---	---	0.65	---
GW_REVAP	0	0	0	0	0.06	0
EPCO	0	0	0	0	0	0
REEVAPMN	0	0	0	0	0	0

Model Performance Quantification

This study used two standard performance metrics to compare simulated and observed streamflow including mass balance error (MBE) and Nash-Sutcliffe efficiency coefficients (NS).

$$MBE = \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})}{\sum_{i=1}^{n} Q_{obs,i}} \times 100\% \qquad (1)$$

$$NS = \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - Q_{obs,a})^2} \qquad (2)$$

where, $Q_{obs,a}$ is the average observed streamflow. Additionally, $Q_{sim,i}$ and $Q_{obs,i}$ are the simulated and observed surface runoff at the ith observation, respectively and n is the number of observations. The San Pedro Basin is evaluated for only the wet season (June-September).

Acceptable simulations, at both monthly and daily timescales, had surface runoff that was within 25% (mass balance error) of actual surface runoff values with NS values > 0.50 (Moriasi et al., 2007). Negative NS values indicated that simulated data performed poorer than if the average of the observed values were utilized when comparing the efficiency of observed and simulated values.

Table 4. Optimal unknown SWAT parameters selected during calibration - early period.

Basin	Precipitation Type	Parameter 1	Parameter 2	Parameter 3
mid-Rio Grande	All	ENCO=0.01	---	---
mid-Nueces	MPE	ENCO=0.20	ALAPHA=0.0285	---
mid-Nueces	TRMM-V6	ENCO=0.40	ALAPHA=0.0030	---
mid-Nueces	TRMM-V7	ENCO=0.01	ALAPHA=0.0050	---
mid-Nueces	TMPA-RT-V6	ENCO=0.01	ALAPHA=0.0001	---
San Casimiro	MPE	ENCO=0.82	---	---
San Casimiro	TRMM-V6	ENCO=0.76	---	---
San Casimiro	TRMM-V7	ENCO=0.60	---	---
San Casimiro	TMPA-RT-V6	ENCO=0.01	---	---
San Pedro	MPE	ENCO=0.50	---	---
San Pedro	TRMMV6/V7	ENCO=0.50	---	---
San Pedro	TMPA-RT-V6	ENCO=0.01	---	---
Cimarron	MPE	ENCO=0.50	Canmax=0	---
Cimarron	TRMM-V6	ENCO=0.50	Canmax=10	---
Cimarron	TRMM-V7	ENCO=0.50	Canmax=100	---
Cimarron	TMPA-RT-V6	ENCO=0.50	Canmax=100	---
Alapaha	MPE	ENCO=0.50	Canmax=0	GWQMN=100
Alapaha	TRMM-V6	ENCO=0.50	Canmax=100	GWQMN=400
Alapaha	TRMM-V7	ENCO=0.50	Canmax=100	GWQMN=500
Alapaha	TMPA-RT-V6	ENCO=0.50	Canmax=100	GWQMN=70

Finally, since the SWAT model tends to perform less robustly during extremely dry periods (Van Liew et al., 2005, 2007; Feyereisen et al., 2007) overprediction of simulation streamflow during dry periods is expected and for the dry San Pedro Basin months with zero observed streamflow were omitted from analysis.

RESULTS

Precipitation Data

Average annual precipitation values for both early and late periods from all basins are presented in Figure 2 with the nearest rain gauge to each watershed plotted for comparison . The early period represents a significantly wetter interval compared to the late period for all watersheds except Alapaha (Figures 2a-e). In the Texas watersheds, during the early period all precipitation products had a positive bias compared with MPE (TRMM Research V6 = 5 to 8%; TRMM Research V7 = 16 to 21%; TMPA-RT V6 = 57 to 69%; Figures 2a-c). During the late period in the Texas basins all products exhibited less bias when compared with MPE (TRMM Research V6 = -2 to 4%; TRMM Research V7 = 9 to 15%; TMPA-RT V6 = 13 to 22%; Figures 2a-c). In the San Pedro Basin, comparison was made against the TRMM V6 product. MPE in the western US is based on the Mountain Mapper, which has known accuracy issues. Bias associated with TRMM Research V7

Table 5. Optimal unknown SWAT parameters selected during calibration - late period.

Basin	Precipitation	Parameter 1	Parameter 2
mid-Rio Grande	All	ENCO=0.01	---
mid-Nueces	MPE	ENCO=0.20	ALAPHA=0.0010
mid-Nueces	TRMM-V6	ENCO=0.40	ALAPHA=0.0040
mid-Nueces	TRMM-V7		
mid-Nueces	TMPA-RT-V6	ENCO=0.01	ALAPHA=0.0001
San Casimiro	MPE	ENCO=0.67	---
San Casimiro	TRMM-V6	ENCO=0.76	---
San Casimiro	TRMM-V7	ENCO=0.63	---
San Casimiro	TMPA-RT-V6	ENCO=0.01	---
San Pedro	MPE	ENCO=0.50	Canmax=10
San Pedro	TRMMV6/V7	ENCO=0.50	Canmax=100
San Pedro	TMPA-RT-V6	ENCO=0.01	Canmax=100
Cimarron	MPE	ENCO=0.50	Canmax=100
Cimarron	TRMM-V6	ENCO=0.50	Canmax=100
Cimarron	TRMM-V7	ENCO=0.50	Canmax=100
Cimarron	TMPA-RT-V6	ENCO=0.50	Canmax=100
Alapaha	MPE	ENCO=0.50	GWQMN=40
Alapaha	TRMM-V6	ENCO=0.50	GWQMN=0
Alapaha	TRMM-V7	ENCO=0.50	GWQMN=200
Alapaha	TMPA-RT-V6	ENCO=0.50	GWQMN=200

increased from early to late periods (-10% and 34%; respectively); whereas, TMPA-RT bias markedly decreased between early to late periods (107% and 2%;respectively; Figure 2d). In the Cimarron Basin, TRMM Research V6 exhibited minimal bias compared to MPE during both periods (-1 to -2%; Figure 2e); whereas, TRMM Research V7 had greater bias (15 to 21%). TMPA-RT had a strong bias during the early period(50%) with significantly less bias during the late period (19%) comparable to TMPA-RT values noted from the Texas watersheds (Figure 2e). Finally, in the Alapaha basin TMPA-RT did not exhibit a strong positive bias and all precipitation products clustered within a relatively tight range during both periods (Figure 2f).

Streamflow Data

Streamflow performance metrics (MBE, Monthly NS, Daily NS) are presented in Figures 3 and 4 with the three Texas basins (mid-Rio Grande, mid-Nueces, San Casimiro; Figure3) and other basins (San Pedro, Cimarron, Alapaha; Figure 4). In the three Texas basins, during the early period, models derived from both MPE and TRMM (V6/V7) greatly outperform those associated with TMPA-RT-V6, which had a strong positive bias in precipitation that produced poor simulated streamflow results with negative NS values (Figure 3). During the late period, TMPA-RT-V7 supported simulations that were comparable to those based on the other precipitation Conversely, in the San Casimiro watershed while TMPA-RT-V7 based model results were improved during the

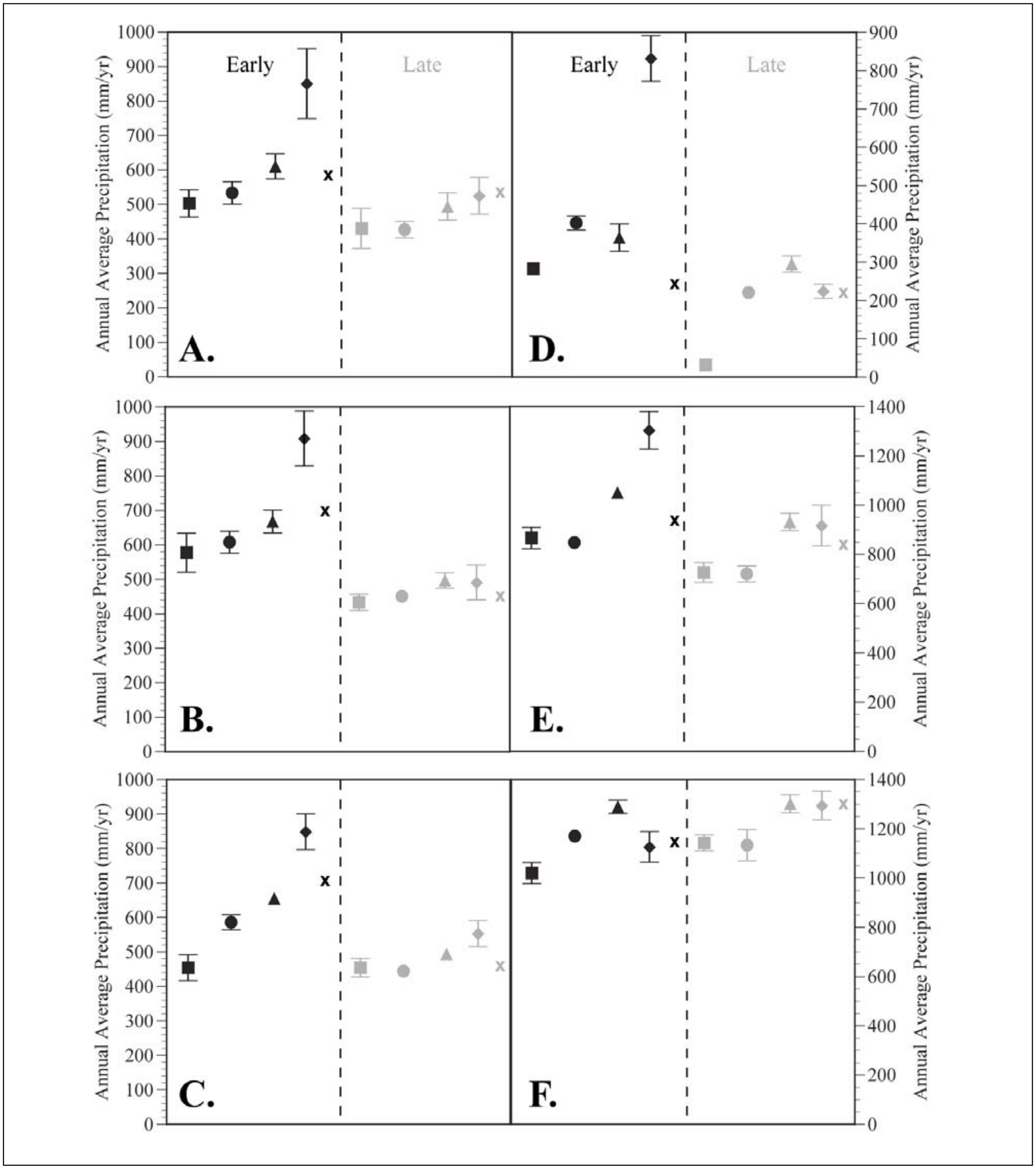

Figure 2. Average annual precipitation for the six examined watereds (a) middle Rio Grande Basin, (b) middle Nueces Basin, (c) San Casimiro Basin, (d) San Pedro Basin, (e) Cimarron Basin, and (f) Alapaha Basin. Symbols include MPE (squares), TRMM V6 (circles, TRMM V7 (triangles), TMPA-RT (diamonds), nearest rain gauge (x). Early period is black whaeras the late period is gray.

late period with acceptable NS values through there is still an excessive positive bias in simulated streamflow (Figure 3c). Additionally, there were some differences in simulations based on TRMM V6 and V7 from the Texas basins. In the mid-Rio Grande Basin, during the early period, there was a drop-off in model performance at a daily time scale noted for simulations based on TRMM V7. Conversely, in the San Casimiro basin during the early period, TRMM V7 based models

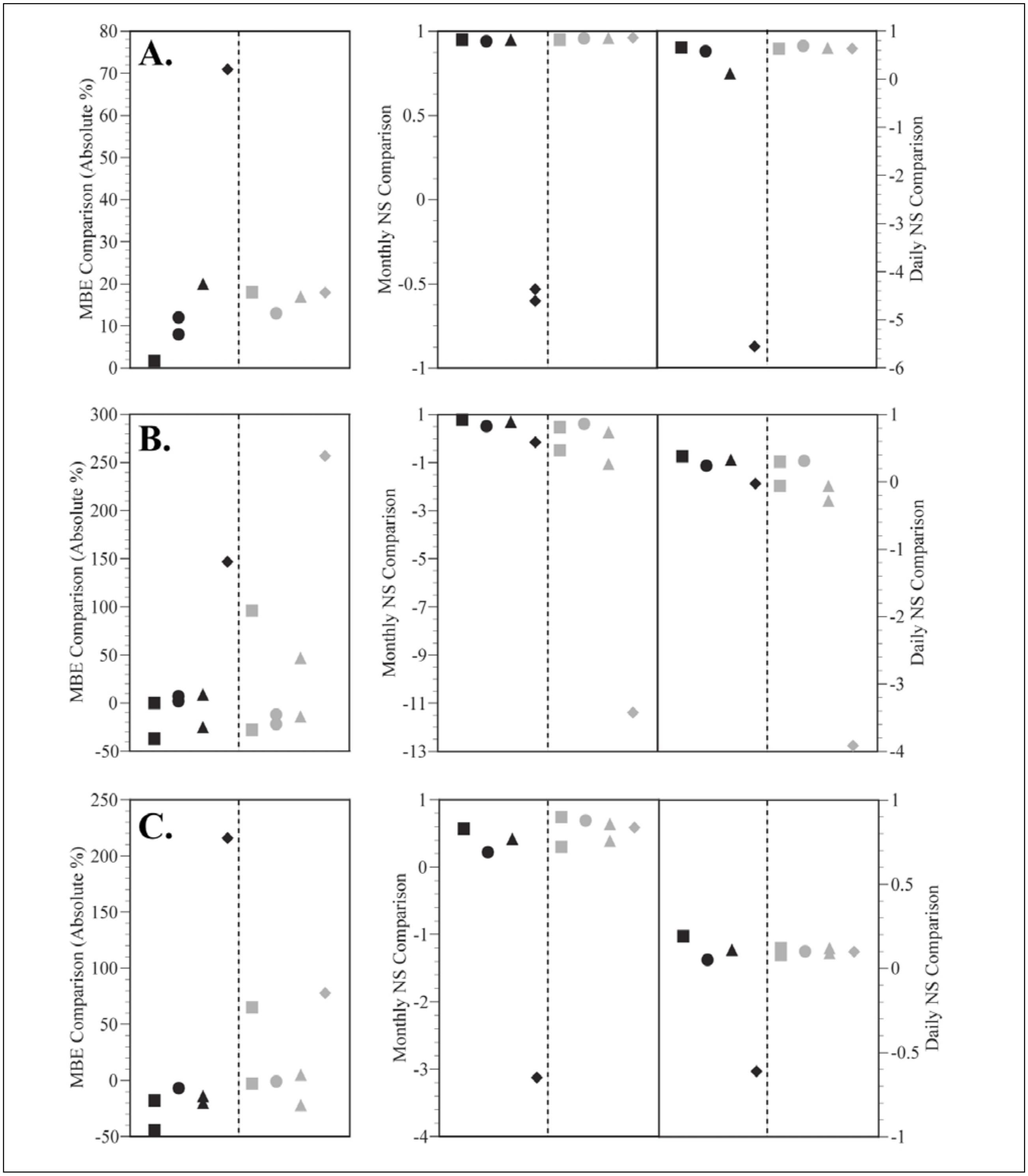

Figure 3. Streamflow performance based on MBE, Monthly NS, and Daily NS values from (a) San Pedro Basin, (b) Cimarron Basin, (c) Alapaha Basin. Symbols as in Figure 2. Each set of symbols for a basin/precipitation type/ time period reflects divergent results based on cross-calibration approach described in the text.

slightly outperformed those based on TRMM V6; although both simulation sets did not yield acceptable results (Figure 3c). Interestingly, in the mid-Nueces basin extremely poor performance during the late period was noted for models based on TRMM V7; however, during the early period TRMM V7 simulations outperformed TRMM V6 (Figure 3b).

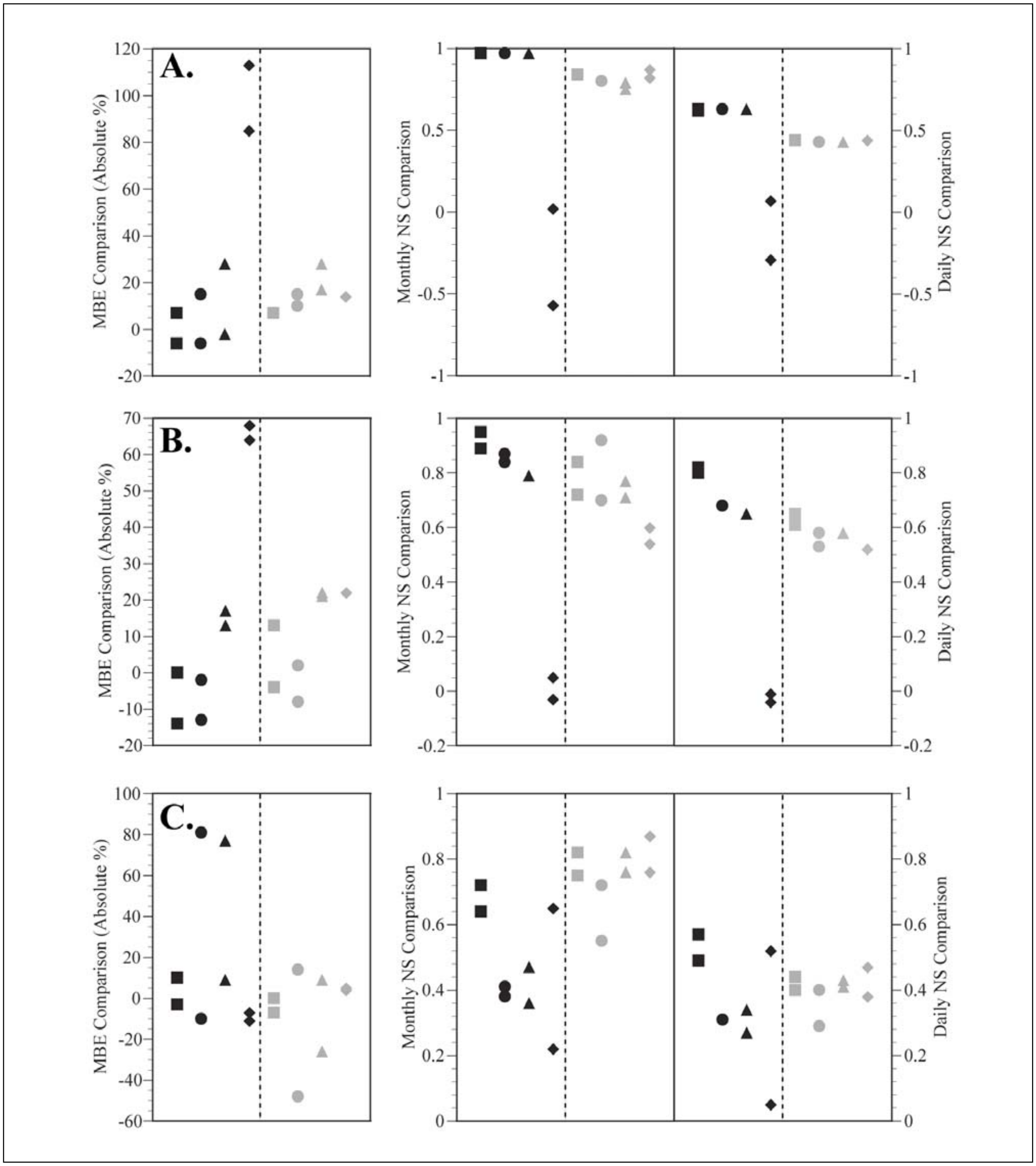

Figure 4. Streamflow performance based on MBE, Monthly NS, and Daily NS values from (a) San Pedro Basin, (b) Cimarron Basin, (c) Alapaha Basin. Symbols are as in Figure 2. Each set of symbols for a basin/ precipitation type/ time period reflects divergent results based on cross-calibration approach described in the text.

From the non-Texas basins there was consistency in results from the semi-arid San Pedro and Cimarron basins in which both MPE and TRMM (V6/V7) supported acceptable simulations during both time periods (Figures 4a, b). Additionally, during the early period TMPA-RT-V6 based models had a strong positive bias like those noted from the Texas basins; whereas, during the late period, TMPA-RT-V7 supported simulations comparable to those derived from the other precipitation products (Figures 4 a, b). Conversely, in the Alapaha basin, period TMPA-RT-V6 actually outperformed models based on TRMM V6/V7 during the early period (Figure 4c); but, during the late period all precipitation products yielded similar acceptable results.

DISCUSSION AND SUMMARY

MPE generally supported superior hydrologic simulations. Of the twelve-streamflow model sets presented in this study (six early, six late) only one simulation (late, mid-Nueces) yielded unacceptable results based on the MPE product. In the mid-Nueces basin *ad hoc* adjustments to model parameters were needed to achieve calibration. The difference in NS values between late and early periods for five basins (omitting mid-Nueces) ranged from -0.13 to 0.17 (average = -model performance. In essence, MPE has reached a plateau (Figures 3, 4) and reflects a highly developed product that is used for operational river streamflow forecasting at each of the NWS RFC's across the US. The success of the NWS MPE product is largely based on input regarding landscape characteristics and precipitation anomalies from numerous NWS offices across the US global product where there is a limited capacity to adjust rainfall retrievals based on local conditions. Additionally, the spatial and temporal resolution for MPE is much finer than that of TRMM. Conversely, TRMM is nearly a global product where there is a limited capacity to adjust rainfall retrievals based on local conditions. Therefore, it is not realistic to expect TRMM to support the same level performance as MPE. As we approach the era of the GPM (launch expected in 2014) it becomes critical for us to understand where both the research and real-time versions of TRMM stand in their evolutionary development, as GPM will be built off of the legacy of TRMM.

The research version of TRMM supported acceptable simulations in the majority of the basins examined primarily based on the monthly gauge bias correction that transformed this product from the raw real-time product. During the early period, both versions of TRMM (V6/V7) supported acceptable simulations in four out of the six basin; unacceptable models were produced in the San Casimiro and Alapaha basins (Figures 3, 4). During the late period, acceptable models were obtained in all basins except the mid-Nueces where TRMM V7, which yielded anomalous unacceptable results (negative NS values; Figure 3b). Additionally, the difference in NS values between late and early periods for five basins (without Nueces) ranged from -0.16 to 0.47 (average = 0.15; standard deviation = 0.25) for TRMM V6 and -0.18 to 0.45 (average = 0.10; standard deviation = 0.24) for TRMM V7. While improvement in model performance between late and early periods was discernable it was not statistically significantly different at the 95% confidence level from MPE. This level of limited improvement between early and later periods is consistent with results obtained from other studies that have used TRMM to support watershed scale hydrologic modeling (*e.g.* Yong *et al.* 2012). An additionally noteworthy observation is that hydrologic model performance is essentially unchanged between V6 and V7 algorithms. During the early period the difference in NS values between V7 and V6 range, in the five basins (omitting Nueces), from -0.07 to 0.20 (average = 0.03; standard deviation = 0.10) and during the late period NS differences vary from -0.15 to 0.10 (average = -0.03; standard deviation = 0.09). Perhaps the TRMM research product is approaching a plateau in performance similar to MPE, which is noteworthy given the impeding launch of GPM.

Finally, during the early period (before 2009), the real-time version of TRMM that was then available during that era is TMPA-RT-V6, which only supports acceptable simulations in one watershed (Alapaha). This basin is from the southeastern United States; a region where TRMM has been noted to exhibit superior performance (Tain *et al.* 2007). During the late period, TMPA-RT-V7 supported improvement in modeled streamflow in five out of the six watersheds examined where the only exception was again the mid-Nueces Basin. The difference in TMPA-RT NS values between late (V7) and early (V6) periods for five basins (without Nueces) range from 0.11 to 3.71 (average = 1.48; standard deviation = 1.38) and was statistically significantly different at the 95% confidence level from MPE. These results underscore the importance of the introduction of the climatologic bias correction to the real-time version of TRMM in early 2009 in terms of generating a useable precipitation product. However, model performance was still not quite at the level achieved when simulations were based on either MPE or TRMM in the mid-Nueces, San Casimiro, and Cimarron basins (Figures 3b,c, 4c) indicating that additional refinements to either precipitation retrievals and/or bias correction routines are required in at least in some geographical regions. These basins are located in a semi-arid climatic regime, which is a region where there is still difficulty in obtaining accurate precipitation retrievals (Tain *et al*., 2007).

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