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# Impact of model complexity and precipitation data products on modeled streamflow

Kenneth J. Tobin and Marvin E. Bennett

## ABSTRACT

With the proliferation of remote sensing platforms as well as numerous ground products based on weather radar estimation, there are now multiple options for precipitation data beyond traditional rain gauges for which most hydrologic models were originally designed. This study evaluates four precipitation products as input for generating streamflow simulations using two hydrologic models that significantly vary in complexity. The four precipitation products include two ground products from the National Weather Service: the Multi-sensor Precipitation Estimator (MPE) and rain gauge data. The two satellite products come from NASA's Tropical Rainfall Measurement Mission (TRMM) and include the TRMM 3B42 Research Version 6, which has a built-in ground bias correction, and the real-time TRMM Multi-Satellite Precipitation Analysis. The two hydrologic models utilized include the Soil and Water Assessment Tool (SWAT) and Gridded Surface and Subsurface Hydrologic Analysis (GSSHA). Simulations were conducted in three, moderate- to large-sized basins across the southern United States, the San Casimiro (South Texas), Skuna (northern Mississippi), Alapaha (southern Georgia), and were run for over 2 years. This study affirms the realization that input precipitation is at least as important as the choice of hydrologic model.

**Key words** | GSSHA, MPE, remote sensing, streamflow, SWAT, TRMM

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## INTRODUCTION

Grayson & Bloschl (2001) indicate that model complexity and data availability control the predictive performance of a hydrologic model. In general, hydrologic models can be divided into three categories based on complexity: simple – entirely empirical, lumped models; complex – physically based, distributed models; and moderate – hybrid, semi-distributed models. Models selected for this study include the moderate in complexity Soil and Water Assessment Tool (SWAT; Arnold & Fohrer 2005; Gassman *et al*. 2007) and the complex Gridded Surface and Subsurface Hydrologic Analysis (GSSHA; Downer & Ogden 2006).

In terms of data availability, arguably the most important data type for driving a long-term hydrologic simulation is precipitation. With the proliferation of dozens of precipitation products over the last decade from diverse remote sensing platforms the issue of limited precipitation data availability can potentially become a moot point in the future. However, the accuracy and quality of remotely sensed precipitation products varies greatly. Historically, ground-based products, such as the National Weather Service (NWS) Multi-sensor Precipitation Estimator (MPE) outperform satellite platforms, such as products from the Tropical Rainfall Measurement Mission (TRMM; e.g., Gottschalck *et al*. 2005). The MPE product merges rainfall from rain gauges, NWS Next Generation Radar (NEXRAD), and Geostationary Operational Environmental Satellite and this merged product outperforms baseline NEXRAD data (e.g., Wang *et al*. 2008). However, TRMM has also undergone continuous improvement in the precipitation retrieval algorithm, with early 2009 defining the beginning of the latest era for this product, as a result of the addition of more satellite data than that which was previously available and the application of climatologic bias correction to the real-time TRMM Multi-Satellite

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Precipitation Analysis (TMPA-RT) product (Huffman *et al.* 2010).

With the near ubiquitous coverage of remotely sensed precipitation data, data availability is no longer a primary control on the performance of a hydrologic model. As remotely sensed precipitation becomes viable, hydrologic modelers need to begin to assess the quality of precipitation data as well as model complexity as a primary hydrologic model control. This study is an objective inter-comparison that evaluates how both precipitation type (MPE, rain gauge, TRMM) and model complexity (SWAT, GSSHA) influence the quality of streamflow simulations within three moderate-to-large basins from the southern United States.

## STUDY AREAS

This study focuses on three basins (Figure 1): the San Casimiro (south Texas; 1,233 km$^2$); Alapaha (south Georgia; 3,596 km$^2$); and Skuna (northern Mississippi; 661 km$^2$). Each of these basins has a United States Geological Survey (USGS) streamflow gauge present at the outlet of the watershed (San Casimiro, 08194200; Skuna, 07283000; Alapaha, 02317500). Note that these three basins are among the 1,861 candidate basins considered for the NOAA Model Parameter Estimation Project program (MOPEX); but were not selected within the final 431 basins because these watersheds lack a rain gauge station within their geographic confines. Tobin & Bennett (2012) previously examined the Alapaha basin, unlike the San Casimiro and Skuna basins.

However, the key characteristics of all three watersheds are given below.

All three basins are defined by a central valley surrounded by a dendritic drainage network and have a relatively modest elevational relief. Both the San Casimiro and Alapaha basins are elongated in a north–south direction, with water flowing to the north in the San Casimiro and south in the Alapaha basin. Conversely, the Skuna basin is elongated in an east–west direction with the basin outlet located in the west side of the watershed. The San Casimiro basin is exclusively rangeland and the Alapaha basin consists of a majority of forest with secondary agricultural land covers. The Skuna basin has a complex mixture of forest, rangeland, and agricultural land uses. The area of standing water within all basins is <1% with water confined to rivers and small ponds. Finally, the soils of the San

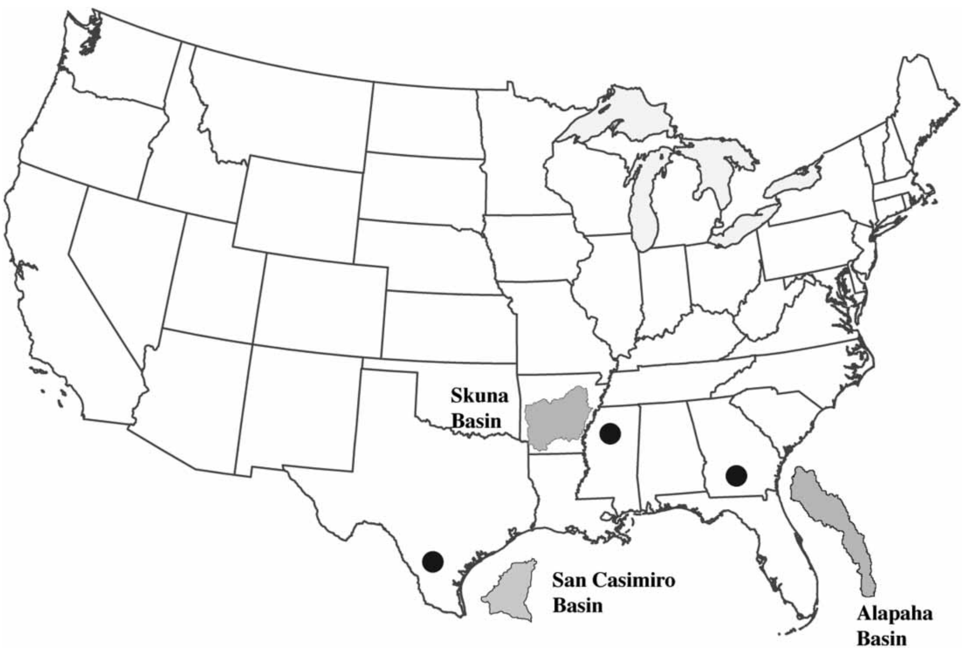


**Figure 1** | Map of CONUS illustrating relative location of three basins utilized in this study.

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Casimiro basin are dominated by clay (59%) with subdominant sandy clay loam (21%) and clay loam (20%). The Skuna basin consists of 79% silty loam and 20% loam. The Alapaha basin has sandy clay loam (72%) with minor sandy loam (20%), sand (6%), and miscellaneous soils (2%).

## PRECIPITATION PRODUCTS AND DATA

Four precipitation products are used as the fundamental input for the hydrologic models executed in this study. These products include two ground-based precipitation data types (rain gauge; MPE) and two satellite-based products (TMPA-RT, Version 6; TRMM 3B42, Research Version 6). NWS rain gauge data (hourly) were gathered from the NWS National Climate Data Center (http://www.ncdc.noaa.gov/oa/climate/stationlocator.html). MPE data were obtained from three NWS River Forecast Centers (Southeast, West Gulf, Lower Mississippi). Both of the TRMM-based products were gathered through the NASA Giovanni portal (http://disc2.nascom.nasa.gov/Giovani/tovas.shtml).

MPE is primarily based on the hourly NWS NEXRAD Stage III data that cover the area of a River Forecast Center; Wang *et al.* (2008) provide an overview of this product. Both of the TRMM products are based on precipitation estimations using passive microwave and infrared data from all available satellites. Therefore, both TMPA-RT and TRMM 3B42 are considered merged products taking advantage of all available orbital platforms (see Huffman *et al.* (2007) for a detailed description). TMPA-RT is a real-time product and is available with a nominal delay of a few hours whereas TRMM 3B42 has an up to 6-week latency before release. The delay associated with TRMM 3B42 is due to the application of monthly rain gauge data, which serve to correct for bias.

NWS rain gauge data are a point precipitation measurement, whereas MPE, TMPA-RT, and TRMM 3B42-V6 are grid-based. As indicated previously, there was no rain gauge with hourly data present in the examined watersheds and the closest gauge to the centroid of the watershed was selected (San Casimiro – Cotulla La Salle Co AP, 42 km; Skuna – Tupelo RGNL AP, 75 km; Alapaha – Dublin, 130 km). These rain gauges have a minimal number of missing dates and were selected only if a station had less than ten missing records within the examined period. Therefore, rainfall across the examined watersheds is based on a single rain gauge; although, in the SWAT model corrections are made for variations in elevation that are present within each watershed (Neitsch *et al.* 2002). The rationale for the use of limited rain gauge data is based on the premise that in the developing world, where satellite precipitation products will likely have the greatest utility, basins lacking rain gauges are a common occurrence (Pan *et al.* 2010). This study is configured in such a manner that its results can be transferred to data-poor settings.

Remotely sensed precipitation products (MPE, TMPA-RT, and TRMM 3B42-V6) provide a limited delineation of spatial trends within the examined basins. MPE data have a nominal spatial resolution of 4 km$^2$, whereas the two TRMM products are based on a 625 km$^2$ or $0.25^\circ \times 0.25^\circ$ grid. MPE data was spatially up-scaled to the $0.25^\circ$ resolution of the satellite products to facilitate inter-comparison of all remotely sensed products. A simple Theissen polygon approach was used to generate spatially distributed, remotely sensed precipitation data within the examined basins with polygons having a size of $0.25^\circ$. This method was chosen over more elaborate geostatistical interpolation approaches to facilitate inter-comparison of satellite precipitation products. The philosophy of this study was to not introduce artifacts associated with spatial interpolation, but rather to examine precipitation products at their nominal spatial resolution.

Temporal resolution between the four precipitation products differs (rain gauge – hourly, daily; MPE – hourly; satellite products – 3 hourly). Hourly precipitation data were used as input for the GSSHA model and the mean precipitation value for the satellite products during a 3-hourly period was used to generate three uniform hourly precipitation values for each hourly period. For the SWAT model daily precipitation was the primary input and MPE as well as satellite products were temporally aggregated to a daily time step.

Figure 2 summarizes the average annual precipitation for all precipitation products in the three examined basins. In the San Casimiro basin, for 2008–2010, all products are within 11% of each other and remotely sensed products (MPE, TRMM 3B42, TMPA-RT) have slightly lower rainfall

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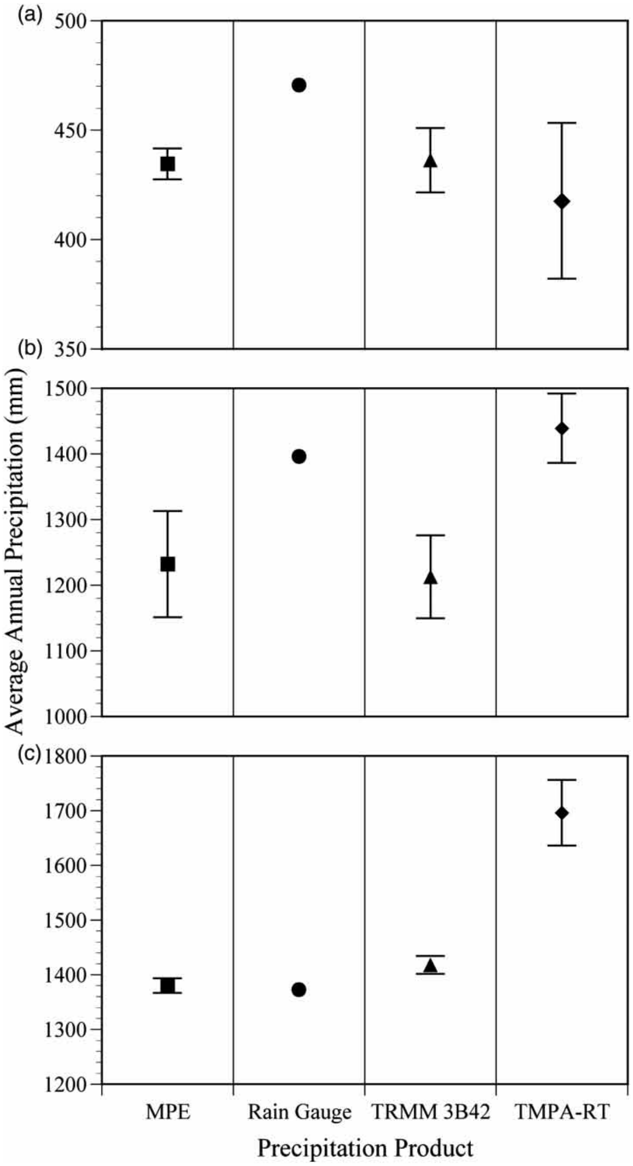


**Figure 2** | Annual average precipitation totals for examined basins: (a) San Casimiro; (b) Alapaha; (c) Skuna. Symbols are as follows: squares = MPE; circles = rain gauge; triangles = TRMM 3B42 Research; diamonds = TMPA-RT.

values. The Alapaha basin has an overall 16% difference between all precipitation products with lower values noted for MPE and TRMM 3B42 and higher values for rain gauge and TMPA-RT. Finally, the Skuna basin has a slightly greater divergence (24%) between examined precipitation products. Rain gauge, MPE, and TRMM 3B42 have a similar value, whereas TMPA-RT has a notable positive bias.

## BRIEF MODEL DESCRIPTION

The SWAT model is a semi-distributed model in which water balance calculations occur within each subbasin present within a watershed (Arnold & Fohrer 2005; Gassman *et al.* 2007). The number of subbasins in a watershed is determined based on the size of the land area that is upstream of each tributary stream reach. Within each subbasin fundamental computational sub-units are defined, which are referred to as hydrologic response units (HRU). A HRU is a unique combination of soil and land use type. Water balance calculations within each subbasin are determined based on an area-weighted average of the curve number (CN) values defined based on the HRUs present in each subbasin. Note that the spatial location of the HRUs within each subbasin is not considered, and therefore, SWAT is not a fully distributed model. Additionally, SWAT has the ability to compensate for antecedent moisture conditions and can adjust CN formulation as moisture status changes within the watershed. Excessive runoff is initially routed as overland flow within a subbasin until this water intersects a channel. Channel flow is routed downstream to an adjacent subbasin until water exits the watershed at its outlet using the variable storage method (Williams 1969). Another element of the SWAT model that enhances its complexity is its ability to calculate daily potential evapotranspiration values using the Priestly–Taylor method (Neitsch *et al.* 2002) allowing for more accurate delineation of the water balance within each SWAT subbasin.

GSSHA is a physical, fully distributed model in which water balance calculations occur within a regular grid framework and are based more on a physics-based as opposed to empirical approach (Downer & Odgen 2004). GSSHA is a comprehensive model that is capable of simulating a wide range of hydrologic phenomena. Infiltration within each grid was determined using the Green and Ampt method (Green & Ampt 1911), which is a more physics-based approach to determine infiltration compared with the CN method. Overland flow is routed, in two dimensions, using the alternating direction explicit method (Downer *et al.* 2002). Channel routing, which is one-dimensional, is facilitated using the diffusive wave-form of the St-Venant equations (Ogden & Julien 2002). Evapotranspiration is determined using a modification of the Penman–Monteith

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method to account for seasonal changes in canopy resistance. Stream–groundwater interactions, in two dimensions, are simulated using Darcy's law.

## SPATIAL DATA DESCRIPTION

The land use layer for SWAT and GSSHA models was obtained from the GIRAS Land Use dataset available from the US Department of Agriculture (USDA 1986) and is 1:250,000 in spatial resolution. The hydrography layer used in the SWAT model was obtained from the National Hydrography Dataset (United States Geological Survey (USGS 1999)) at a resolution of 1:100,000. The State Soil Geographic Data base (STATSGO) soil data (1:250,000) was utilized (USDA 1994). Finally, high resolution (10 m) digital elevation models (DEMs) from the National Elevation Dataset (NED; Gesch *et al.* 2002; Gesch 2007) were used for GSSHA and SWAT (Skuna) modeling. A coarser resolution USGS 90 Meter Resolution, 1-arc second DEM supports SWAT modeling in the Alapaha and San Casimiro basins (USGS 1995).

## MODEL SET-UP DETAILS

For the San Casimiro and Skuna basins streamflow simulations were executed from October 1, 2008 to December 31, 2010. For the Alapaha basin, the model was only completed to December 31, 2009. The somewhat limited periods examined were the result of the computationally intensive nature of the GSSHA model, which requires extensive time (days) to execute even the relatively short time series examined in this study. The period selected corresponds with improvements made to the TRMM products (Huffman *et al.* 2010). For the SWAT model simulations began January 1, 2008 and the initial nine months were used as a warm-up period to initialize the model.

### SWAT model set-up

The SWAT model has 17 parameters that effect modeled streamflow, which can be divided into known and unknown parameters. Known parameters are not adjusted and have specific values in each watershed, which are defined by the physical characteristics of a basin. The initial runoff CN is based on the unique combinations of HRUs within a watershed and is unchanged from default values defined in the SWAT model. Soil parameters (Moist soil albedo – *SOL_ALB*; Soil Available Water Capacity – *SOL_AWC*) were not modified from default values as defined in the STATSGO soil database. The hydraulic conductivity of main channel (*Main_K*) and tributary channel (*Tributary_K*) sediment was based on the permeability of the soils from the STATSGO database, that underlies these landscape features (Table 1). Additionally, 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 within the examined watersheds (Table 1). Surface–groundwater interactions (*ALPHA_BF*) were determined by using a baseflow filter program developed for the SWAT model (Arnold *et al.* 1995; Arnold & Allen 1999; Table 1). Finally, the selected maximum canopy interception (*CANMX*) value for the San Casimiro basin was consistent with the value derived for this parameter from a watershed in the nearby Texas Hill County (Afinowicz *et al.* 2005; Table 1).

The remaining parameters are essentially unconstrained by prior information and 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*), potential

**Table 1** | Parameter values for the SWAT model established by prior knowledge

| Parameters | San Casimiro | Alapaha | Skuna |
|---|---|---|---|
| *n Overland* | 0.600 | 0.100 | 0.150 |
| *n Tributary* | 0.100 | 0.050 | 0.050 |
| *n Main* | 0.050 | 0.050 | 0.050 |
| *Tributary K* | 20.00 | 18.00 | 0.34 |
| *Main K* | 0.27 | 0.81 | 0.34 |
| *ALPHA_BF* | 0.0352 | 0.0606 | 0.0969 |
| *CANMX* | 7.0 | – | – |

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maximum leaf area index for plants (*Blai*), peak flow timing (*SURLAG*), and *CANMX* in the Skuna and Alapaha basins. To determine the importance of the above unknown parameters a sensitivity test based on the Latin Hypercube (LH) One-factor-At-a-Time method was executed (for details see Van Grinesven & Meixner 2003). Sensitive unknown parameters that were adjusted in this study have a relative sensitivity value that is greater than 1% of the total for all parameters. In the San Casimiro basin, the only sensitive parameter is *ENSO* and an optimal value for each precipitation type was determined through iterative model runs (Table 2). In the Alapaha basin, *ENSO*, *GWQMN*, and *SURLAG* were deemed sensitive and iterative model runs were used to determine best model performance for each precipitation type by adjusting the above three parameters (Table 2). Finally, in the Skuna watershed, there were five sensitive parameters (*ENSO*, *GWQMN*, *REVAPMN*, *CANMAX*, *Blai*). Our approach for the Skuna was modified from procedure outlined by Kannan *et al.* (2007) where an ensemble of stochastic simulations was executed based on the lowest, mid-point, and highest values of the five sensitive parameters. The ensemble consisted of every combination of parameter values resulting in 243 model runs from which the best model results, generally simulations with the least mass balance error (MBE) (described below), were determined from each precipitation product (Table 2). Model results reflect only surface water flow; baseflow was calculated using the baseflow filter program developed for the SWAT model (Arnold *et al.* 1995; Arnold & Allen 1999) and was separated from surface quickflow.

## GSSHA model set-up

As much as possible, the selection of GSSHA model parameters was based on the default values published in the GSSHA user manual (Downer & Ogden 2006). Below are highlighted key model set-up details for GSSHA as well as parameter adjustments that deviate from default values. Previous studies executed GSSHA with a grid size ranging from 10 to 250 m, although grid sizes as big as 1,000 m are supported (Downer & Ogden 2006). The Skuna basin, which is the smallest basin, is still larger than the recommended size (100 km$^2$) for complex process-based models such as GSSHA (Shen & Phanikumar 2010). Considering that the models executed were long-term simulations requiring extensive computational time, a grid size of 250 m was selected for the San Casimiro and Skuna basins. Since the Alapaha watershed is well over

**Table 2** | Optimal sensitive parameter values for the SWAT model

| Basin | Precipitation product | *ENSO* | | | | |
|---|---|---|---|---|---|---|
| San Casimiro | MPE | 0.67 | | | | |
| San Casimiro | Rain gauge | 0.10 | | | | |
| San Casimiro | TRMM 3B42 | 0.76 | | | | |
| San Casimiro | TMPA-RT | 0.67 | | | | |
| **Basin** | **Precipitation product** | ***ENSO*** | ***GWQMN*** | ***SURLAG*** | | |
| Alapaha | MPE | 0.50 | 30 | 0.5 | | |
| Alapaha | Rain gauge | 0.50 | 40 | 10 | | |
| Alapaha | TRMM 3B42 | 0 | 100 | 0.5 | | |
| Alapaha | TMPA-RT | 0 | 400 | 0.5 | | |
| **Basin** | **Precipitation product** | ***ENSO*** | ***GWQMN*** | ***REVAPMN*** | ***CANMX*** | ***Blai*** |
| Skuna | MPE | 1.00 | 500 | 0 | 0 | 3.0 |
| Skuna | Rain gauge | 1.00 | 0 | 0 | 100 | 0.5 |
| Skuna | TRMM 3B42 | 0 | 500 | 500 | 10 | 3.0 |
| Skuna | TMPA-RT | 0.50 | 0 | 0 | 10 | 0.5 |

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an order of magnitude greater than the recommended maximum size for GSSHA, a coarse grid size of 1,000 m was selected. Additionally, to test the sensitivity of grid size on model performance, a MPE-based model run at 1,000 m was executed in the Skuna basin. Typical standard practice when modeling large basins with GSSHA is to split the basin into a number of computational distinct sub-basins. However, this procedure was not possible for the Alapaha basin due to the lack of interior stream gauge data within the basin. Additionally, we did not want to lose the fully distributed character of our GSSHA model runs, which could be compared with semi-distributed SWAT results.

GSSHA has a unique feature in that initial soil moisture values can be specified eliminating the need for a warm-up period, which is important due to the excessive computational time (days) required for a single simulation. Initial soil moisture value was selected based on examination of precipitation events several months before the start date (October 1, 2008) for the GSSHA model runs. For the San Casimiro basin, dry conditions preceded the model period and therefore wilting point moisture values were selected. Alapaha and Skuna basins were set at field capacity. The sensitivity of initial moisture was examined and streamflow values generally converged within 1–2 weeks no matter what initial moisture was selected. Therefore, the impact of the selected initial moisture was deemed minimal on the long-term simulations executed in this study.

Selected parameters were adjusted based on conditions within the examined watershed. In the San Casimiro basin, the major modification to the GSSHA model was associated with upward adjustment of overland roughness parameters for rangeland land covers (0.6). This high value was identical to that recommended in the SWAT User Manual (Neitsch *et al*. 2002). In the Alapaha basin, to better account for more complex channel routing scheme utilized by GSSHA, two Manning roughness factors were selected (*main channel* = 0.05; *tributary* = 0.10), which was unlike SWAT in which a roughness value of 0.05 was used for all streams. The main GSSHA parameter adjusted was hydraulic conductivity of soils, which was optimized to produce the best model results for each precipitation product as indicated in Table 3. As with SWAT results only surface runoff was evaluated.

**Table 3** | Optimal hydraulic conductivity values (cm/hr) for major soil types used in the GSSHA model with area of soils (%)

| Basin | Precipitation product | Sandy clay loam (21%) | Clay loam (20%) | Clay (59%) |
|---|---|---|---|---|
| San Casimiro | MPE | 2.70 | 0.80 | 0.18 |
| San Casimiro | Rain gauge | 2.70 | 0.80 | 0.18 |
| San Casimiro | TRMM 3B42 | 2.70 | 0.80 | 0.10 |
| San Casimiro | TMPA-RT | 2.70 | 0.80 | 0.08 |
| **Basin** | **Precipitation product** | **Sand (6%)** | **Sandy clay loam (72%)** | **Sandy loam (18%)** |
| Alapaha | MPE | 11.78 | 0.06 | 1.09 |
| Alapaha | Rain gauge | 11.78 | 0.06 | 1.09 |
| Alapaha | TRMM 3B42 | 11.78 | 0.05 | 1.09 |
| Alapaha | TMPA-RT | 11.78 | 0.06 | 1.09 |
| **Basin** | **Precipitation product** | **Loam (20%)** | **Silt loam (79%)** | |
| Skuna | MPE | 0.50 | 0.33 | |
| Skuna | Rain gauge | 0.33 | 0.20 | |
| Skuna | TRMM 3B42 | 0.15 | 0.08 | |
| Skuna | TMPA-RT | 0.30 | 0.15 | |

## SURFACE STREAMFLOW PERFORMANCE EVALUATION

Two primary measures of simulated surface streamflow (or quickflow) performance compared to observed values were used in this study. Metrics include relative MBE and Nash–Sutcliffe efficiency coefficients (NS), which are defined below:

$$\mathrm{MBE} = \left(\frac{\sum_{i=1}^{n}\left(Q_{\mathrm{obs},i} - Q_{\mathrm{sim},i}\right)}{\sum_{i=1}^{n}\left(Q_{\mathrm{obs},i}\right)}\right) * 100\% \tag{1}$$

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

where $N$ is the number of observations. $Q_{\mathrm{obs},a}$ is the average observed streamflow and $Q_{\mathrm{sim},i}$ and $Q_{\mathrm{obs},i}$ are the simulated

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**Table 4** | Performance metrics used to evaluate streamflow performance

| Description | NS | Absolute *MBE* |
|---|---|---|
| Perfect | 1.00 | 0% |
| Very good | 0.75 | 10% |
| Good | 0.65 | 15% |
| Satisfactory | 0.50 | 25% |
| Unacceptable | <0.50 | >25% |

and observed surface runoff at the *i*th observation. Criteria for evaluating streamflow simulations have been developed by Moriasi *et al.* (2007) and are indicated in Table 4. Moriasi *et al.* (2007) indicate that an acceptable streamflow simulation has an absolute MBE within 25% and NS values >0.50 for both a monthly and daily timescale. Note that for a simulation to be acceptable both MBE and NS values have to be within the above-specified values.

## STREAMFLOW RESULTS

In the San Casimiro basin, both MPE and TRMM 3B42 yielded acceptable streamflow values with GSSHA and SWAT at a monthly time scale (Table 5). Interestingly, the MPE-based GSSHA simulation does not exhibit a large drop-off in performance even at a daily time scale (Table 5). Both rain gauge and TMPA-RT data do not support acceptable simulations with any model (Table 5). In the Alapaha basin, all precipitation products yielded acceptable streamflow simulations at the monthly time scale (Table 6). No acceptable simulations were generated at a daily time scale (Table 6). GSSHA supports acceptable simulations based on all precipitation products, whereas only MPE and TMPA-RT SWAT-based simulations are marginally acceptable (Table 6). Finally, in the Skuna basin the opposite trend is noted between GSSHA and SWAT where SWAT generally exhibits superior performance over GSSHA (Table 7). Both MPE and TRMM 3B42 yielded acceptable streamflow values with GSSHA and SWAT at a monthly time scale (Table 7). The rain gauge simulation was unique in that acceptable streamflow simulations were obtained with the SWAT model at a monthly time scale but not with GSSHA (Table 7). Finally, TMPA-RT data do not support acceptable simulations with any model in this basin (Table 7).

## DISCUSSION AND SUMMARY

A primary insight realized in this study is that poor, non-representative precipitation data produce unsatisfactory simulated streamflow independent of model complexity. Additionally, hydrologic model complexity or model parameterization is not a panacea for poor quality or non-representative precipitation data. These insights support the primacy of precipitation data over model set-up or complexity in supporting quality streamflow simulations. The old adage seems correct in that even complex models are vulnerable to the paradigm where 'garbage in' produces 'garbage out'.

**Table 5** | Streamflow performance for San Casimiro basin

| Model | Precipitation type | Resolution | *MBE* | Monthly NS | 3-day NS | Daily NS |
|---|---|---|---|---|---|---|
| GSSHA | MPE | 250 m | – 4.56% | 0.83 | 0.84 | 0.73 |
| SWAT | MPE | 10 m | 1.79% | 0.90 | 0.76 | 0.09 |
| SWAT | MPE | 90 m | – 4.47% | 0.75 | 0.11 | 0.09 |
| GSSHA | Rain gauge | 250 m | 3.64% | – 0.35 | – 0.33 | – 0.73 |
| SWAT | Rain gauge | 90 m | 24.33% | – 0.14 | – 0.05 | – 0.03 |
| GSSHA | TRMM 3B42 | 250 m | 5.39% | 0.81 | 0.77 | 0.32 |
| SWAT | TRMM 3B42 | 90 m | – 2.34% | 0.69 | 0.09 | 0.07 |
| GSSHA | TMPA-RT | 250 m | – 4.36% | – 0.07 | 0.04 | – 0.05 |
| SWAT | TMPA-RT | 90 m | 0.38% | – 0.08 | – 0.03 | – 0.02 |

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**Table 6** | Streamflow performance for Alapaha basin

| Model | Precipitation type | Resolution | *MBE* | Monthly NS | Daily NS |
|---|---|---|---|---|---|
| GSSHA | MPE | 1,000 m | – 2.21% | 0.76 | – 0.28 |
| SWAT | MPE | 90 m | 1.59% | 0.55 | 0.25 |
| GSSHA | Rain gauge | 1,000 m | 2.84% | 0.72 | 0.03 |
| SWAT | Rain gauge | 90 m | – 8.72% | 0.34 | – 0.60 |
| GSSHA | TRMM 3B42 | 1,000 m | – 16.54% | 0.73 | 0.10 |
| SWAT | TRMM 3B42 | 90 m | 11.69% | 0.45 | 0.22 |
| GSSHA | TMPA-RT | 1,000 m | – 6.76% | 0.62 | – 0.05 |
| SWAT | TMPA-RT | 90 m | 6.10% | 0.74 | 0.31 |

**Table 7** | Streamflow performance for Skuna basin

| Model | Precipitation type | Resolution | *MBE* | Monthly NS | Daily *NS* |
|---|---|---|---|---|---|
| GSSHA | MPE | 250 m | 6.86% | 0.53 | 0.15 |
| GSSHA | MPE | 1,000 m | 8.01% | 0.54 | 0.16 |
| SWAT | MPE | 10 m | 0.29% | 0.72 | 0.48 |
| GSSHA | Rain gauge | 250 m | 0.23% | 0.37 | – 0.61 |
| SWAT | Rain gauge | 10 m | 0.67% | 0.84 | 0.00 |
| GSSHA | TRMM 3B42 | 250 m | 14.24% | 0.61 | – 0.23 |
| SWAT | TRMM 3B42 | 10 m | 0.74% | 0.66 | – 0.26 |
| GSSHA | TMPA-RT | 250 m | 10.69% | 0.03 | – 0.59 |
| SWAT | TMPA-RT | 10 m | 16.98% | 0.22 | – 0.73 |

Comparison of performance of precipitation products across the three examined watersheds was insightful (Tables 5–7). Both MPE and TRMM 3B42 supported acceptable simulations in all three basins, whereas rain gauge produced satisfactory results in two basins and TMPA-RT in only one watershed (Alapaha). These results indicate that the spatially distributed nature of MPE data confer an advantage over point precipitation measurements when watersheds are moderate to large in size (100 s to 1,000 s km$^2$); however, the fact that rain gauges are located outside the boundaries may also explain the relatively poor performance of this type of precipitation data. The unacceptable rain gauge model set from the San Casimiro basin obviously represented spatially non-representative precipitation data where one gauge was located outside this watershed. The semi-arid climatic regime characterizes the San Casimiro watershed and precipitation is commonly associated with highly localized and short-lived convective systems (Hollinger *et al.* 2002), unlike the other basins where synoptic-scale cyclonic systems have a greater impact (Diem 2006). Obviously, using geostatistical methods to interpolate spatially representative rainfall across the region could produce more representative precipitation values from gauge data.

Satellite precipitation products (TRMM 3B42, TMPA-RT) generally performed more poorly compared to simulations based on MPE data (Tables 5–7). However, TRMM 3B42 data support acceptable simulations in all of the basins examined primarily based on the monthly gauge bias correction that transforms this product from raw, real-time data (Huffman *et al.* 2010). Other researchers have obtained acceptable simulations using satellite precipitation data from various watersheds around the world (Behrangi *et al.* 2011; Yu *et al.* 2011; Zeweldi *et al.* 2011; Bitew *et al.* 2012). The acceptable values produced by TMPA-RT in the Alapaha basin were consistent with the superior results of this product noted from non-coastal regions of the southeast United States by Tian *et al.* (2007). Positive bias was associated with TMPA-RT throughout central and western CONUS, especially during the warm season (Ebert *et al.* 2007; Tian *et al.* 2007). This may explain the poor results associated with TMPA-RT from the Skuna basin (Figure 2(c)). The main conclusion relating to precipitation type is that MPE yields slightly superior results compared to TRMM 3B42, whereas TMPA-RT has not matured to consistently support hydrologic modeling.

A surprising insight was that there is not a clear choice in terms of whether GSSHA or SWAT was superior for the basins examined. In results from the San Casimiro and Alapaha basins, GSSHA seem to support better model results (Tables 5 and 6), whereas in the Skuna basin (Table 7) SWAT seems to be superior. Additionally, no clear trends resulted when examining different combinations of precipitation and model type in terms of the MBE of simulated streamflow. Most simulations had a MBE within ±10%, which is consistent with the similar precipitation values

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present in all basins with the above-noted exception of TMPA-RT data from the Skuna basin (Figure 2).

Details associated with model set-up such as grid size can affect performance. To determine the impact of grid size on GSSHA model results, two different grid sizes (250, 1,000 m) were selected for the Skuna GSSHA model runs (MPE) and which yielded nearly identical results (Table 7). Therefore, it becomes tempting to assert that semi-distributed models can perform as well as fully distributed models given the superior performance of SWAT in the Skuna basin.

Considering that coarser resolution DEMs were used for the SWAT modeling of the San Casimiro and Alapaha basins (90 m) as compared with the Skuna basin (10 m), it is perhaps not surprising that GSSHA outperforms SWAT in these basins. To test the effect of DEM resolution, a high-resolution (10 m) SWAT model (MPE) was executed for the San Casimiro basin yielding better monthly NS values than the comparable GSSHA simulation from this basin; however, poorer performance is noted at finer time scales (Table 5). Based on the above results, higher resolution DEMs can support better SWAT model performance, at least at coarse time scales, with an ideal resolution of $\leq$10 m. However, the impact of model resolution within GSSHA is not manifest, requiring consideration of another factor (basin size).

SWAT can support the modeling of small to very large watersheds in excess of 1,000,000 km$^2$ (Gassman *et al.* 2007), whereas GSSHA is designed for smaller basins (Shen & Phanikumar 2010). Simply stated, all basins examined are greatly in excess of the recommended upper limit (100 km$^2$) for the size of a watershed that can be directly modeled by GSSHA. Consequently, the application of GSSHA in this study is perhaps fundamentally disadvantaged compared with SWAT. However, despite the identified limitations associated with GSSHA in this study an MPE-based simulation from the San Casimiro basin supported daily simulations unlike SWAT, which yielded acceptable simulations only at coarser time scales (Table 5). Additionally, San Casimiro TRMM 3B42 simulation based on GSSHA yielded acceptable results when an objective evaluation of simulated streamflow was made over a 3-day period (NS $=$ 0.77; Table 5) and only sharply fell to unacceptable levels at a daily timescale (NS $=$ 0.32; Table 5). Conversely, SWAT simulations based on TRMM 3B42 were only acceptable at a monthly timescale (Table 5). These results suggest that even under less than ideal modeling conditions, the model complexity associated with a fully distributed model can confer an improvement in performance at finer time scales over semi-distributed models. Admittedly, this conclusion is based on modeling results from only one basin and additional research is clearly needed to determine whether this conclusion can be extended to other watersheds. These insights are useful if one wants to use GSSHA, or other distributed models, with satellite precipitation products whose level of development at this point is only sufficient to support modeling in moderate to large sized basins. SWAT certainly can support modeling using satellite precipitation data; however, this study suggests that model performance, at especially finer time scales, will not be as potentially robust as simulations based on distributed models like GSSHA.

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