Effects of spatial and temporal weather data resolutions on streamflow modeling of a semi-arid basin, Northeast Brazil

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Abstract: One major difficulty in the application of distributed hydrological models is the availability of data with sufficient quantity and quality to perform an adequate evaluation of a watershed and to capture its dynamics. The Soil & Water Assessment Tool (SWAT) was used in this study to analyze the hydrologic responses to different sources, spatial scales, and temporal resolutions of weather inputs for the semi-arid Jaguaribe watershed (73 000 km^2) in northeastern Brazil. Four different simulations were conducted, based on four groups of weather and precipitation inputs: Group 1- SWAT Weather Generator based on monthly data from four airport weather stations and daily data based on 124 local rain gauges; Group 2- daily local data from 14 weather stations and 124 precipitation gauges; Group 3- Daily values from a global coupled forecast model (NOAA's Climate Forecast System Reanalysis - CFSR); and Group 4- CFSR data with 124 local precipitation gauges. The four simulations were evaluated using multiple statistical efficiency metrics for four streamflow gauges, using: Nash-Sutcliffe coefficient (NSE), determination coefficient (R^2), the ratio of the root mean square to the standard deviation of the observed data (RSR), and the percent bias (PBIAS). The Group 4 simulation performed best overall (provided the best statistical values) with results ranked as "good" or "very good" on all four efficiency metrics suggesting that using CFSR data for weather parameters other than precipitation, coupled with precipitation data from local rain gauges, can provide reasonable hydrologic responses. The second best results were obtained with Group 1, which provided "good" results in three of four efficiency metrics. Group 2 performed worse overall than Groups 1 and 4, probably due to uncertainty related to daily measures and a large percentage of missing data. Groups 2 and 3 were "unsatisfactory" according to three or four of the efficiency metrics, indicating that the choice of weather data is very important.

Keywords: climate data resolution, hydrology, SWAT model, semi-arid basin, Brazil
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1 Introduction

Climate variability has substantial impact on hydrologic systems; including the availability and quality of water, as well as the frequency and severity of floods and droughts. Capturing climate variability and its hydrologic impacts is a major challenge in the development of a hydrological model.

Weather data are the most fundamental driving

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variables for hydrologic models; however, it is often difficult to acquire good-quality weather data, especially in developing countries. Weather stations are often inadequate in number, spatial distribution and periods of operation. In addition, data are often missing and instruments are sometimes poorly calibrated[1,2]. There is a serious limit on the application of hydrologic models when good quality measured weather data are not available, especially for large-scale watersheds[2,3].

Many models, such as the Soil and Water Assessment Tool (SWAT) water quantity and quality model[4,5],use the nearest weather station for each subbasin. However, if the station is far away or if it has poor quality data, the simulation quality will be adversely affected[1]. Daily data from an inadequately sited and maintained weather station network may represent well the dynamics needed for a good hydrologic simulation[3,6]. Numerical weather prediction models with greater resolution may provide an alternative data source for developing and testing large-scale hydrological models[2]. Inappropriate choices of data sources can have significant impacts on model estimates, introducing uncertainties. Quantification of errors and estimation of the uncertainty of meteorological input data can help to interpret the processes simulated[3]. It is even more important to evaluate the quality of input data and its effects on the reliability of model estimates when the results are used for decision support[3,7].

Many watersheds are poorly gauged or ungauged, and streamflow simulation in such basins is an ongoing problem[8]. A number of studies have investigated the impacts of different sources of climatic data on watershed modeling[8-18], including using rain gauge and Tropical Rainfall Measuring Mission (TRMM) data for SWAT modeling[8]; combining rain gauges, TRMM and Special Sensor Microwave Imager (SSM/I) datasets[9], and using both rain gauge with radar-based precipitation data[10]. These three studies[8-10] demonstrated that using more than one source of precipitation data can improve the efficiency of streamflow simulation.

Further testing has been conducted on how use of ground-based precipitation (Multisensor Precipitation Estimator - MPE) and space-based products (TRMM) affected hydrologic modeling results for six basins across the United States[11]. The MPE approach produced superior hydrologic simulations, although both versions of TRMM products resulted in acceptable hydrologic results. MPE (or Stage IV Next-Generation Radar) data were investigated regarding potential improved accuracy of stream flow simulations using SWAT[12,13]. It was suggested that modelling efforts in watersheds with poor rain gauge coverage can be improved with MPE radar data, especially at short time steps[12]. On the other hand, MPE Stage IV data was not adequate for simulation of a mountainous basin[13].

Climate Forecast System Reanalysis (CFSR) precipitation and temperature data have also been used to force SWAT for several different watersheds, resulting in stream flow simulations as good as or better than corresponding simulations based on traditional weather gauging stations[14]. Ensemble precipitation modeling has also been found to considerably increase the level of confidence in simulation results, particularly in data-poor regions[15].

Obtaining representative meteorological data for hydrological modeling can be difficult and time consuming[14], especially in regions that lack adequate weather station coverage. This points to a need to investigate different sources of climate data to discern which options can support hydrologic and water quality modeling studies. Thus the aim of this study is to analyze how hydrologic predictions respond to different weather inputs with different resolutions for the semi-arid Jaguaribe River watershed in northeastern Brazil. Specifically, the objectives of this research are to: (1) assess the sensitivity of the warm-up period durations and different evapotranspiration methods within the baseline SWAT streamflow calibration and validation process for the Jaguaribe River watershed, and (2) analyze the impacts of four different combinations of climate data sources on SWAT streamflow estimates for the Jaguaribe River watershed.

2 Materials and methods

2.1 Study area

The Jaguaribe Watershed is situated in the state of

Ceará in northeast Brazil (Figure 1), between latitude 4°30′ and 7º45′ south and longitude 37°30′ and 41°00′ west. The total length of the Jaguaribe River is about 610 km, which drains an area of approximately 73 000 km^2. The region's prevailing biome is the Brazilian Caatinga (Steppe Savanna) and the watershed is located in a zone with a predominantly semi-arid climate[20,21], which is characterized by strong seasonal precipitation and inter-annual variability, related to El Niño, that results in recurring droughts.

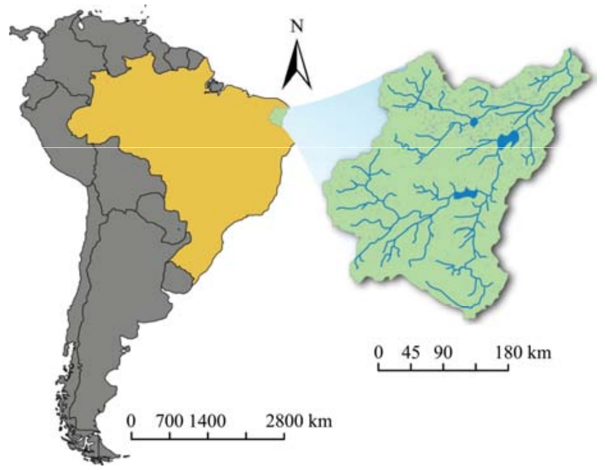


Figure 1 The location of the Jaguaribe watershed study area in northeast Brazil

Most of the rivers in the region are intermittent, so water management and the use of reservoirs are vital for both irrigated agriculture and municipal water supply, since the watershed also exports water to the metropolitan region of Fortaleza, with a population of approximately 8.5 million people[22-24].

2.2 SWAT model

SWAT has been applied in many studies around the world, especially in research related to water balance, land management, sediment, nutrient and pesticide transportation, water quality, and climate and land use changes[25-29]. It is a mathematically complex semi-distributed model, developed by the US Department of Agriculture, Agricultural Research Service (USDA-ARS). It is usually operated on a continuous daily time-step, and simulates water, sediment, nutrient and pesticide transportation at a watershed scale[30,31]. It is a process-based model that takes into account hydrologic, physical and chemical processes[32]. SWAT simulations are constructed by delineating a watershed into multiple subbasins, and then further subdividing each subbasin into hydrologic response units (HRUs) that consist of homogeneous landuse, soil, and landscape characteristics which are not spatially identified within the given subbasin; i.e., HRUs represent percentages of land areas within a subbasin. Flow and pollutant losses are initially estimated at the HRU level, then aggregated to the subbasin level and finally routed through the simulated stream system to the watershed outlet[25- 29].

SWAT requires the following daily weather data: precipitation, maximum and minimum temperature, solar radiation, wind speed and relative humidity. These weather data can be entered either from measured sources and/or generated internally in the model using SWAT's weather generator[19]. Long-term statistics are input into the weather generator to generate daily weather inputs. The weather generator is used to simulate data if the user specifies this option, or when measured data is missing. For example, for precipitation, the number of wet days is determined in the weather generator based on a first order Markov Chain model; skewed or exponential distributions are then used to estimate the rainfall amounts[1,19].

2.3 Model set up and data sets

The Jaguaribe SWAT model was constructed using freely available information. Most of the data were obtained via data collected through a World Bank program in partnerships with local government agencies[33]. The Digital Elevation Map (DEM) was built from the U.S. Geological Survey's (USGS) public domain Shuttle Radar Topography Mission (SRTM) DEM data[34], which consists of 3 arc-second, approximately 90 m resolution. The 1:600 000 soils map was vectorized by the Ceará State Water Resources and Meteorological Foundation (FUNCEME)[35]. The land use map used was also obtained from FUNCEME[33].

The Jaguaribe Watershed model setup was constructed using the ArcSWAT interface within the ArcGIS 10.0 platform[36]. The first step in constructing the SWAT simulations was to delineate the subbasins. This was performed in ArcSWAT by delineating the stream network, based on the SRTM DEM and setting the minimum drainage area for each subbasin to 250 km^2.

As a result, a total of 232 sub-basins were delineated in SWAT, with an average area of 315 km^2. Also 1,145 HRUs were generated, according to the watershed's land use, soil types, and slope characteristics.

The soil layer data required to define soil characteristics for the soils map were obtained from the ISRIC - World Soil Information world data base[37]. Previously developed Pedo Transfer Functions (PTF)[38] were used with ISRIC soil texture, organic matter and soil depth data to estimate the other soil parameters required for SWAT.

The initial land use map consisted of a limited set of broad categories. Data from the Municipal Agriculture Production for Ceará State from the Brazilian Institute of Geography and Statistics (IBGE)[39] were used to determine the planted area of different crops in the region. Major crops produced in the region include maize, dry beans, dry rice, cassava and cashew[23], and Ceará also produces 20 percent of the cowpeas in Brazil[40]. The traditional agriculture in the region[23] consists of (1) dryland systems dominated by short-cycle corn and bean production, and (2) sugarcane and cashew production[20,23] which are sometimes irrigated. Considering these different agricultural production characteristics of the region, the dryland crops simulated with SWAT simulations were corn and cowpea, potato (which was substituted for cassava because the SWAT crop parameter database does not have cassava parameters) while sugarcane and banana (substituted for cashew due to a lack of cashew crop parameters in the SWAT crop parameter database) were simulated as irrigated crops.

There are three large reservoirs in the watershed that were not included on the Jaguaribe SWAT model, because at the time no sufficient data was made available to perform and capture reservoir water balance dynamics through simulation. Regarding management operations, simplified approaches were used which included: (1) a single model-determined application of nitrogen fertilizer per year for each crop system, which was triggered when the stress factor of the plant declined below 0.75, and (2) a single auto-irrigation of sugarcane and banana, triggered when the plant water stress factor reached 0.75, with the maximum of 50 mm per irrigation. In addition, sugar-cane was simulated as a three year rotation consisting of a plant crop and two ratoons.

2.3.1 Climate data inputs and climate scenarios

Different climate data sensitivity simulations were conducted with four groups of precipitation and other weather data inputs (Figure 2 and Table 1), holding all the other model inputs and configurations constant. These groups of data were chosen to test different spatial and temporal inputs and are described in detail as follows:

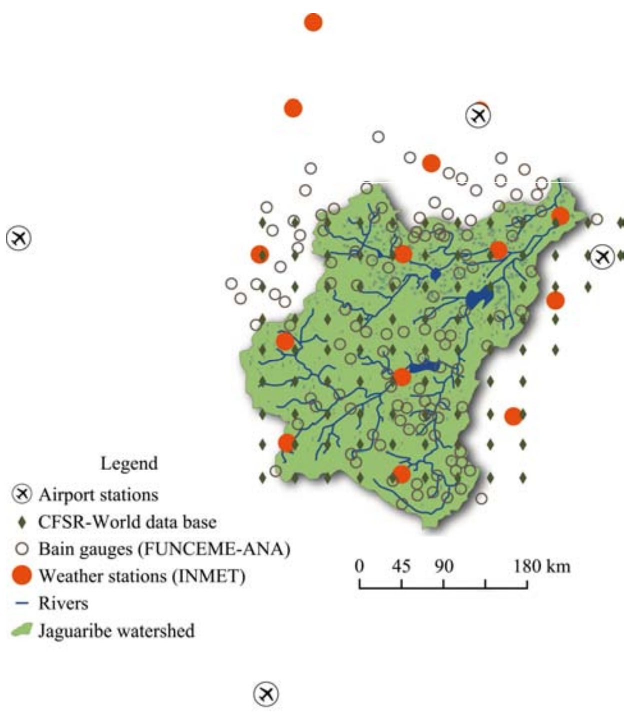


Figure 2 Location of weather and rain gauges that were used for the four groups of Precipitation and weather data

Table 1 Overview of the four weather and precipitation gauge groups

Group	Weather data scenario	Precipitation data source	Other daily weather data sources[a]	Weather generator data sources[b]
1	Airports and local rain gauges	Local Rain gauges (ANA+FUNCEME)	Generated internally in SWAT	Airports
2	Weather stations and local rain gauges	Local Rain gauges (ANA+FUNCEME)	Local Stations (INMET)	INMET
3	Global Database-CFSR	CFSR	CFSR	Airports
4	CFSR and local rain gauges	Local Rain gauges (ANA+FUNCEME)	CFSR	Airports

Note: [a] Includes maximum and minimum temperature, solar radiation, wind speed, and relative humidity climatic inputs.
[b] The SWAT weather generator was used to generate non-precipitation data for Group 1; the weather generator was also used to generate missing precipitation data for all four groups and any other missing data for Groups 2, 3 and 4.

Group 1: This consisted of a combination of monthly average climate data from the closest four airport stations (Figure 2), including those located outside of the study area, and local precipitation gauges. The precipitation data were based on 124 local rain gauges maintained by the Ceará State Water Resources and Meteorological Foundation (FUNCEME) and Brazilian National Water Association (ANA)[41], which are referred to as FUNCEME-ANA in Figure 2 and Table 1. The airport data are internet-accessible as provided by the National Climatic Data Center, National Oceanic and Atmospheric Administration (NOAA), USA[42]. Daily climate values were generated internally in SWAT from the monthly average values provided in the airport data, including precipitation data for missing days in the FUNCEME-ANA data.

Group 2: The daily precipitation data were from 124 FUNCEME-ANA rain gauges (Figure 2 and Table 1). The other daily climate data were input from the 14 INMET stations[43] (Figure 2 and Table 1), while missing data was generated in SWAT based on monthly statistics created from long-term measured data available from the 14 INMET stations. Solar radiation values available in the INMET local weather station network were estimated based on insolation[44-46].

Group 3: All of the daily climatic values were input from data obtained from NOAA's National Centers for Environmental Prediction Climate Forecast System Reanalysis (CFSR)[47], a global coupled atmosphere-ocean-land surface-sea ice system and forecast model. The CFSR data are available in SWAT input format on the SWAT website[48]. Missing data were generated internally in SWAT using the Airports weather generator data (Figure 2 and Table 1).

Group 4: This represented a combination of precipitation from the local rain gauges (FUNCEME-ANA) and CFSR daily climate values (Figure 2 and Table 1). Missing data were again generated internally in SWAT using the Airports weather generator data (Table 1).

2.4 SWAT calibration process

Appropriate SWAT streamflow - related parameters were changed from their default values in order to conduct a basic manual calibration for baseline streamflow conditions. The parameters identified to be changed were based on the most problematic aspects of the predicted hydrographs in comparison with the observed streamflow and evaluations based on Nash-Sutcliffe statistics[49,50]. Some variations in modified input parameters were tested for all four different groups of weather input simulations, based on the physical characteristics of the watershed. Ultimately, the same changes were performed for all four groups of simulations and for the entire watershed, based on the subset of input parameters that resulted in the most accurate streamflow results. The altered parameters and default values are presented in Table 2.

Table 2 Default and altered parameter values or methods for the SWAT simulations

SWAT Parameters	Parameters Description	SWAT Default	Altered
ESCO	Soil evaporation compensation coefficient	0.95	0.6
ICN	Curve number methods	0 (soil moisture)	1(ET)
CNCOEF	ET curve number coefficient	1	0.5
SHALLST/mm	Initial depth of water in the shallow aquifer	0.5	1000
GWQMIN/mm	Depth of water in shallow aquifer required for return flow	0	750
GW_REVAP	Groundwater revaporation	0.02	0.1
RCHRG_DP	Deep water percolation fraction	0.05	0.1
REVAPMN/mm	Depth of water in shallow aquifer for revaporation to occur	1	500
ALPHA_BF	Baseflow recession constant	0.048	0.0552

A key parameter used in many SWAT hydrologic calibrations is the soil evaporation compensation coefficient (ESCO)[26], which can be adjusted between 0.1 and 1.0 to affect the depth distribution that is used to meet soil evaporative demand; decreasing the ESCO value increases the ability of the model to extract evaporative demand from lower soil layers[51]. Migliaccio & Chaubey (2008)[52] performed a sensitivity analysis and concluded that most of the variance in the predicted flow in their study resulted from uncertainty in the ESCO parameter. Wu & Johnston (2007)[53] determined an ESCO value of 0.5 for average conditions, based on stream flow patterns and on minimizing stream flow deviation between measured and simulated data in southern Lousiana. Santhi et al. (2001)[54] adopted an ESCO value of 0.6 for a region in Texas. Due to the semi-arid and latitude characteristics of the Jaguaribe watershed, a range of ESCO values between 0.5 and 0.75 were tested by comparing the simulated streamflow performance with observed values based on hydrograph comparisons and calculation of Nash-Sutcliffe modeling efficiency (NSE) coefficients[49,50]; the resulting best ESCO parameter found was 0.6.

The three methods (Priestley Taylor, Penman-Monteith and Hargreaves)[51] available in SWAT to calculate the potential evapotranspiration were also tested (specific results are reported in the Results and Discussion section). The Penman-Monteith method was chosen because it performed slightly better according to the metrics established and because it is a more complex method that needs more meteorological data (in this sense evaluating the four sets of weather inputs). The two curve number methods available in SWAT[51], as a function of soil moisture (ICN=0) or as a function of plant evapotranspiration (ICN=1), were also tested. Overall, the daily curve number calculated as a function of plant evapotranspiration performed best, in conjunction with a value of 0.5 for the evapotranspiration curve number coefficient (CNCOEF). Groundwater parameters (Table 2) were also estimated to best fit the study area. The Jaguaribe watershed does not have large volumes of storage in aquifers, with most of the watershed located over crystalline rocks with low water storage potential[19].

2.5 Statistical evaluation criteria

Streamflow estimates for the four simulations were evaluated using multiple statistical criteria: NSE, coefficient of determination (R^2), the ratio of the root mean square to the standard deviation of the observed data (RSR) and the percent bias (PBIAS)[15,18,49,50,55,56], as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{1}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O}) \cdot (P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}} \right) \tag{2}$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right]} \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100\% \tag{4}$$

where, O_i corresponds to the observed data at the time step i; P_i to the modeled streamflow at the time step i; $\bar{O}$ and $\bar{P}$ are the mean values of observed and predicted streamflow (respectively) in the simulated time period, and n is the number of observations, being i=1, 2, 3,$\cdots$, n. The simulations were evaluatated on an aggregated monthly time step in which the SWAT daily streamflows were summed to monthly totals and compared with the corresponding observed monthly values.

Guidelines for model evaluation used in this study were based on performance ratings suggested by Moriasi et al. (2007)[49] for a monthly time step. Here a grading method was established to determine if the model performance was “Very good”, “Good”, “Satisfactory” or “Unsatisfactory”, by combining the three ranges of values of the statistical methods (NSE, RSR and PBIAS) evaluated by Moriasi et al. (2007)[49]. If one or more of the ranges of RSR, NSE and PBIAS indicated an “unsatisfactory” result, then the model performance was determined unsatisfactory. If no unsatisfactory results were indicated by the three statistical methods, then a grading system based on an overall summation as shown in Table 3 was used.

Table 3 Model Performance Ratings[49] and Classification used to evaluate the results of the different weather group (Table 1) simulations

Performance Rating	RSR	NSE	PBIAS/%	Grading for each	Classification - Sum
Very Good	0.00≤RSR≤0.50	0.75<NSE≤1.00	PBIAS<±10	3	7<E≤9
Good	0.50<RSR≤0.60	0.65<NSE≤0.75	±10≤PBIAS<±15	2	5<E≤7
Satisfactory	0.60<RSR≤0.70	0.50<NSE≤0.65	±15≤PBIAS<±25	1	3<E≤4
Unsatisfactory	RSR>0.70	NSE≤0.50	PBIAS≥±25	Unsatisfactory	Unsatisfactory

The SWAT model was used for the 4 proposed weather input scenarios, holding all the other model inputs and configurations constant. The simulations were evaluated based on the comparison among the discharges at four flow gauge stations. These four stations were chosen due to availability of data, and the spatial distribution of the flow gauges is shown in Figure 3.

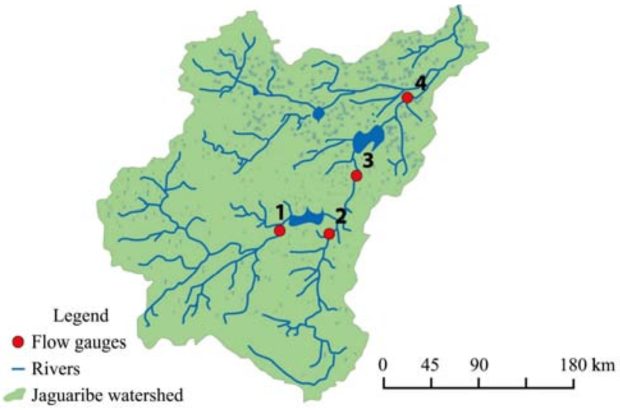


Figure 3 Location of streamflow gauge stations in the Jaguaribe watershed

Executing a warm-up or equilibration period is important to ensure that the hydrologic balance is accurately simulated in SWAT, although the use of such a warm-up period usually becomes less important as the simulation period increases[57]. In this study it could be hypothesized that a short warm-up period would be sufficient, because the simulation period of 20 years is relatively long. However, this may not be true due to the fact that, for example, the aquifers start empty in SWAT, as well as the soil moisture, etc. Thus both a 1-year and 5-year warm-up periods were tested. Therefore, the river discharge was simulated for the period of 01/01/1984 to 12/31/1999, with five years (1979-1983) as warm-up period, and for 01/01/1980 to 12/31/1999, with only one year of warm-up period (1979).

3 Results and discussion

3.1 Initial testing of warm-up period duration and ET method

The statistical results (NSE values) of testing the four different groups of weather inputs (Table 1) with either a one- or five-year warm-up period at the four streamflow gauge stations (Figure 3) are shown in Figure 4. It is clear from the plots in Figure 4 that the use of 5 years as warm-up period provided better results for all of the gauge stations and weather groups combinations (except for Group 3 on gauge station 4), especially for the Group 2 performance. This difference in results shows the importance of using adequate warm-up periods to better establish the watershed initial conditions, and also implies that the length of needed warm-up period can vary between different conditions. The better performance of Group 2 with the five-year warm-up period than with the one-year warm-up period is probably due to poorer weather data for the first few years of the time-series and/or the greater sensitivity of this group of weather inputs to the initial conditions of the model.

The results of testing the three previously described ET methods at streamflow gauge station 3 (Figure 3) are presented in Table 4 in terms of PBIAS, NSE and RSR statistics as a further assessment of SWAT simulation performance. Gauge station 3 was chosen for this phase of testing because it is located in the middle of the watershed, upstream of a major reservoir (Figure 3) that was not included in the SWAT model simulation. No absolutely clear pattern was established between the three ET methods. However, Hargreaves (HG) method resulted in the most overall unsatisfactory evaluations, while Penman-Monteith (PM) method had the strongest overall performance (with one satisfactory and one very good evaluation). Thus, the PM method was selected for the remaining weather group testing based on its performance and because it was the most complex method that uses a full suite of weather inputs. It should also be noted that while several of the combinations of ET methods and gauge station 3 resulted in unsatisfactory results, stronger overall results were obtained for two of the climate groups as discussed in section 3.5.

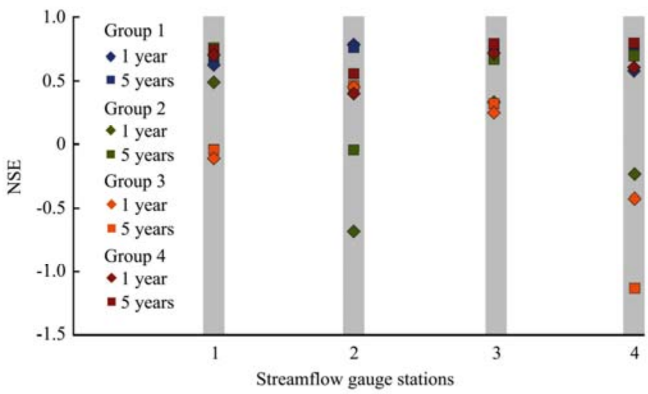


Figure 4 Comparison of Nash-Sutcliffe (NSE) values at gauge stations 1-4 (Figure 2) for the SWAT simulations (Groups 1-4; Table 1) with warm-up periods of 1 or 5 years

Table 4 Performance metrics for simulations conducted with different ET methods at gauge station 3 (Figure 3)

Group	NSE			PBIAS			RSR			Evaluation		
	PM*	PT*	HG*	PM	PT	HG	PM	PT	HG	PM	PT	HG
1	0.76	0.78	0.69	17.33	11.75	-41.10	0.49	0.47	0.49	Satisfactory	Good	Unsatisfactory
2	0.69	0.71	0.77	-51.39	-58.21	-38.68	0.56	0.54	0.48	Unsatisfactory	Unsatisfactory	Unsatisfactory
3	0.32	0.34	0.37	-27.14	-46.09	-33.07	0.82	0.81	0.79	Unsatisfactory	Unsatisfactory	Unsatisfactory
4	0.79	0.78	0.77	-6.75	-24.69	-15.19	0.46	0.46	0.48	Very Good	Satisfactory	Satisfactory

Note: *PM = Penman-Monteith; PT = Preistley-Taylor; HG = Hargreaves.

3.2 Graphical comparisons of simulated and observed streamflow

Simulated and observed monthly flows at gauge station 1 (Figure 3) are presented for 01/1984 to 12/1999 in Figure 5, to visually evaluate the performance of the proposed simulations. Overall there is a general agreement among the hygrographs; the SWAT simulation performed with Group 3 (Table 1) overestimated the peaks more than the others.

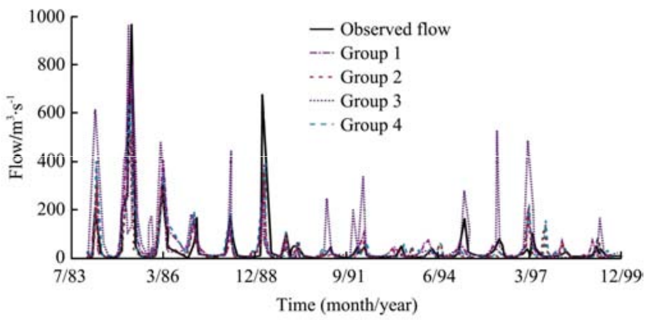


Figure 5 Observed and simulated monthly flows from 01/1984 to 12/1999 at Gauge 1

In Figure 6 the average monthly flows for the entire period are presented for the simulated scenarios and observed data, for all four gauge station locations (Figure 3). The Group 3 SWAT simulation (Table 1) overestimated the streamflows more than the other sources of weather data for gauge sites 1 and 4. In comparison, the Group 2 SWAT simulation (Table 1) overestimated streamflows the most at gauge station 2 and was similar to the estimated Group 3 streamflow at gauge station 3.

The greatest difference in SWAT streamflow results was predicted at gauge station 4, the furthest downstream gauge station (Figure 3). This gauge station is also downstream of a large reservoir, which was not included in the SWAT simulations; therefore, differences between simulated and measured flows would be expected. However, the predicted Group 3 streamflow is much higher than streamflows from the other three simulations and the observed flow. This could be due to problems with the CFSR world weather data for this region due to its proximity to the ocean.

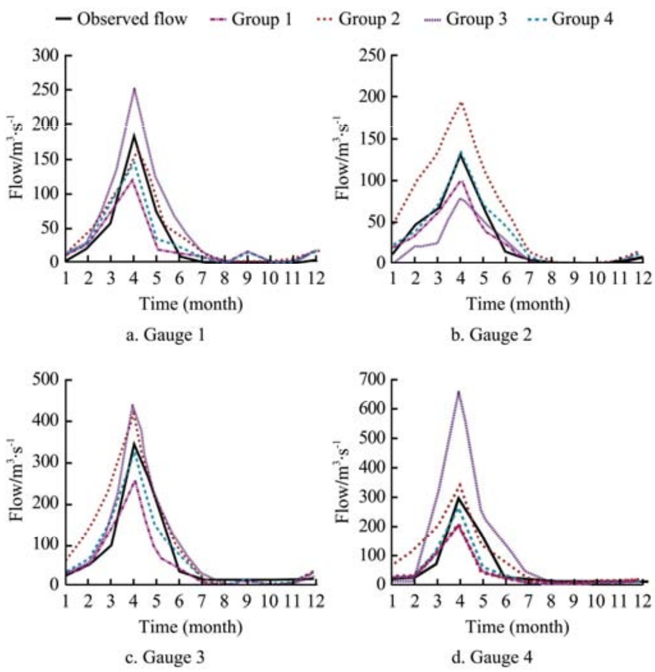


Figure 6 Observed and simulated average monthly flows for 1984-1999 at Gauge 1 (Figure 5a), 2 (b), 3(c), and 4(d)

Streamflow for gauge 2 (Figure 3) is overestimated by Group 2 (Table 1) but is underestimated by Group 3 (Table 1). In contrast, for the other three gauge stations, Group 3 overestimated streamflow. Gauge station 2 is the farthest upper stream site (Figure 3), so this may be an effect of the smaller drainage scale of gauge station 2 and/or be a problem related to the data of a local INMET station close to that area. There is also a small reservoir upstream of gauge 2, which was not incorporated in the SWAT simulations and may have influenced the results. The SWAT simulations with Groups 1 and 4 (Table 1) performed better than Groups 2 and 3 at all four sites. Both Groups 1 and 4 consistently under estimated observed streamflows, with Group 1 under estimating observed flows more than Group 4 at all four gauges.

3.3 The influence of the SWAT weather generator

The simulations made with Groups 1, 2 and 4 have the same precipitation input data series (Table 1), but SWAT's weather generator had an important role because the percentage of missing data is high (about 32% for the ANA+FUNCEME rain gauges, due especially to scarce precipitation data after 1992). The Group 2 generated weather is based on local weather stations (INMET; Table 1) while the Groups 1 and 4 generated weather are based on the airport stations (Table 1). This difference had an influence on the simulated precipitation data for the missing values of each group and also on the other weather components, leading to different results. Group 3 relied on the same weather generator data as Groups 1 and 4 (Table 1), but there are very few missing precipitation data for Group 3 (<0.2%) so the weather generator influence on the Group 3 results was minor.

The resulting differences related to groups 1 and 4 versus group 2, especially in precipitation, can be attributed to the different weather generator variables. At the same time the three groups have different weather inputs (other than precipitation) that have direct effect on evapotranspiration, which in this region accounts for about 80% of precipitation. Therefore, relatively small differences on weather input can have a large impact on the different hydrological components.

Weather generator variables for both weather generators used (Table 1) and the relative difference between them are presented on Table 5. The variables are weighted averages by station coverage area. A clear difference between the precipitation input variables for example can be seen: 3% for the total long term average annual precipitation, over 64% for the probabilities of being a wet day followed by a wet day and nearly 24% for a wet day followed by a dry day. Other large differences can also be seen between some of the other weather input variables (Table 5), including the monthly average dew point and the monthly average of daily minimum temperature standard deviation.

3.4 Overall water balance results

The average values and components of the water balance over the 16-year simulation period (1984 to 1999) are presented for the entire watershed for the four different weather input scenarios (Table 6). The average annual precipitation for Group 3 is about 6% greater than the precipitation for Groups 1, 2 and 4, which was a combination of local ANA+FUNCEME precipitation gauges in combination with generated precipitation data. The Group 2 simulation (Table 1) generated more water yield than the other climate groups and also resulted in the smallest generation of sediment. In contrast, the Group 1 simulation (Table 1) resulted in the highest potential evapotranspiration, which is 45% higher than the other three simulations. This is probably due to the airport stations having a tendency to measure high temperatures because of both local effects such as black surface and radiation, and also due to the fact that two of the weather stations were close to the coast and thus were impacted by high wind speed and relative humidity.

Table 5 Variables for the weather generators used for the different climate groups described in Table 1

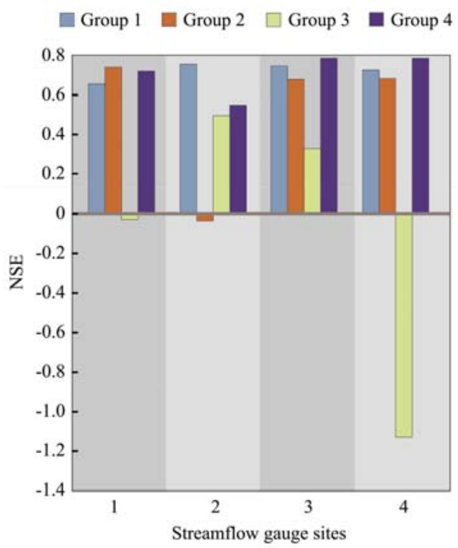
Variables in the weather generator	INMET	Airports	Difference/%
Annual average precipitation/mm	551.54	535.51	3.0
Average monthly probability of a wet day to follow a dry day	0.17	0.10	64.4
Average monthly probability of a wet day to follow a wet day	0.39	0.51	-23.7
Monthly average of number of days of precipitation	4.85	4.39	10.6
Monthly average solar radiation/($MJ\cdot m^{-2}\cdot d^{-1}$)	20.84	26.94	-22.6
Monthly average dew point/℃	30.83	21.30	44.7
Monthly average wind speed/($m\cdot s^{-1}$)	3.03	3.66	-17.3
Monthly average of minimum daily temperature/℃	32.91	32.58	1.0
Monthly average of maximum daily temperature/°C	22.06	24.18	-8.8
Monthly average of daily maximum temperature standard deviation	1.68	1.80	-7.0
Monthly average of daily minimum temperature standard deviation	1.26	1.79	-29.8

Table 6 Average annual water balance components for the entire watershed and 16-year simulation period for the four climate input groups described in Table 1

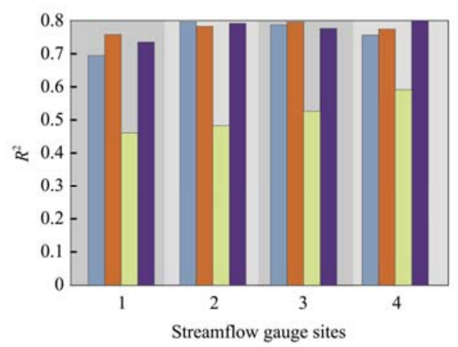
Water balance component	Group 1	Group 2	Group 3	Group 4
Precipitation/mm	682	690	721	682
Water Yield/mm	52	81	76	74
Runoff/mm	36	39	39	41
Percolation/mm	104	146	143	131
Evapotranspiration/mm	597	535	574	542
Potential Evapotranspiration/mm	2724	1872	1775	1775
Sediment Loading/($t\cdot hm^{-2}$)	13	4	11	16

3.5 Statistical evaluation of the streamflow impacts of the four climate groups

NSE and R^2 values are shown in Figure 7, which represent comparisons between monthly aggregated observed and simulated flows for the four simulated weather groups and four streamflow gauge stations, for the 16-year simulated period (1984 to 1999). The NSE values for Group 3 are negative for gauge stations 1 and 4, and are less than 0.5 for the other two gauge stations. For Group 2, there is also one negative NSE value at gauge station 2, which is the worst NSE value determined for this gauge station. The Group 1 and 4 simulations resulted in satisfactory or better NSE values (>0.55 for Group 4 and >0.65 for Group 1). The monthly R^2 values for Group 3 are the smallest for all gauge stations; the other three group simulations have overall good results, with all R^2 values equal to or greater than 0.69.



a



b

Figure 7 Nash-Sutcliffe (NSE) values (a) and R^2 values (b) between observed and simulated and monthly flows for the four climate groups (Table 1) and the four gaugestations (Figure 3) over the 16-year simulation period (1984 to 1999)

The Group 1 simulation (Table 1) resulted in good NSE values for all four gauge stations. The Group 4 simulation (Table 1) also performed well for all four gauge stations while Group 2 (Table 1) resulted in good NSE values for gauges 1, 3 and 4, but an unsatisfactory value for Gauge 2. This suggests that daily measured weather data from the fourteen local INMET gauge stations are actually providing worse estimates than the monthly mean from the four airports that are outside the study area (Group 1) and the global database for weather data with local rain gauges data (Group 4), for the flow gauges where the flow was compared. This is due to the uncertainty related to the daily weather measurements and that the stations had a great deal of missing data during the simulation period (an average of 36% for the INMET stations). According to Schuol & Abbaspour (2006)[1] the quality of daily weather data is not always very reliable in some regions and there are also often large amounts of missing data. The authors compared SWAT discharge outputs for climatic inputs across the northwest Africa subcontinent from local weather stations versus the Climatic Research Unit (CRU) coupled with a weather generator (dGen-CRU), which was based on a Markov Chain approach (similar to SWAT's weather generator). The authors concluded that weather data from the local stations may not be the best available climatic input and that the dGen-CRU data produced significant better estimations of flow than the simulation with the local weather measured data. Similar results were found in this study, where Group 1 and Group 4 performed better than daily weather data from Group 2.

The absolute bias percentage values (PBIAS) and the ratio of the root mean square to the standard deviation of the observed data (RSR) between the simulated scenarios in SWAT and the observed flows for monthly time steps for the four flow gauge stations are presented in Figure 8. The Group 1 and 4 simulations (Table 1) performed better overall. Group 4 was the only Group to have satisfactory[49] PBIAS values for all four streamflow gauge stations per the previously described criteria in Table 3.

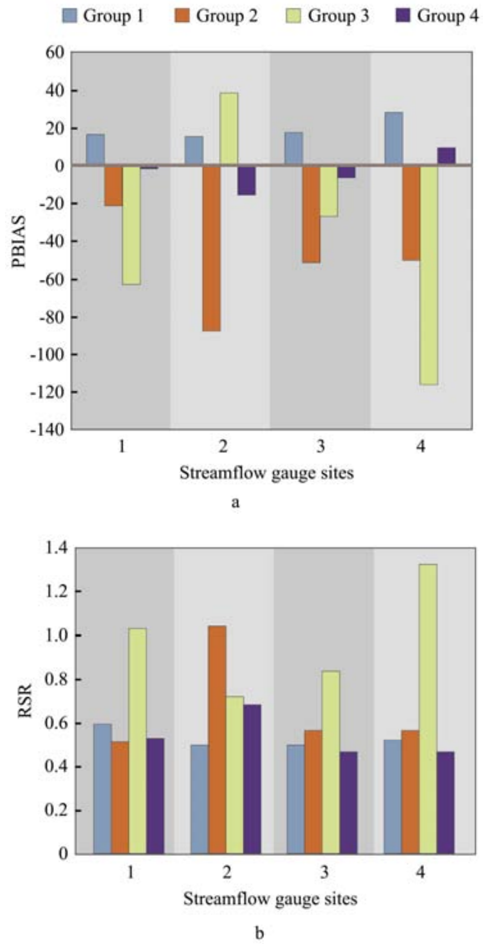


Figure 8 Bias Percentages (PBIAS) (a) and RSR (b) values between observed and simulated monthly flows

The Group 2 simulation (Table 1) resulted in large absolute PBIAS values, especially for site 2. The high PBIAS values for Group 2 can be attributed to a few rainfall events that the model did not capture during the later years of the simulation period, due to missing precipitation data (after 1992 the precipitation data are scarce). This is a problem, especially in low rainfall, semi-arid regions, where the spatial distribution of rainfall may not be captured by a network of rain gauges. The Group 3 simulation also resulted in high absolute PBIAS values, all of which are considered unsatisfactory.

The composite simulation results based on the Table 3 grading system are presented on Table 7. Overall, Group 4 (Table 1) performed best, showing good results for the two upstream gauges and very good metrics for the downstream gauges. These results show the importance of good quality weather data that are well distributed spatially. Our results are consistent with those of others[8-10] indicating that that good spatially distributed weather data can improve the accuracy of streamflow simulation.

The Group 1 simulation resulted in good metrics (Table 7) for the streamflow comparisons at gauge stations 1-3 (Figure 3) but unsatisfactory streamflow estimate for gauge station 4, which is located below a large reservoir. The Group 1 streamflow prediction at gauge station 4 did result in good metrics for NSE and RSR (Figures 7 and 8), but the PBIAS value slightly exceeded the defined threshold classification value[49], thus producing anoverall unsatisfactory result per the criteria of Table 3. The Group 2 (Table 1) simulation resulted in an acceptable performance for gauge station 1 but an unsatisfactory outcome for the other three gauge stations (Table 7), due to the high absolute values of PBIAS. The Group 3 (Table 1) simulations were unsatisfactory for all four gauges (Table7), leading to the worst SWAT predictions.

Table 7 Model Performance Evaluation based on Efficiency Metrics and the grading system from Table 3

Stations groups	Streamflow Gauge			
	1	2	3	4
1	Good	Good	Good	Unsatisfactory
2	Good	Unsatisfactory	Unsatisfactory	Unsatisfactory
3	Unsatisfactory	Unsatisfactory	Unsatisfactory	Unsatisfactory
4	Good	Good	Very good	Very good

Fuka et al. (2013)[14] demonstrated that CFSR data could be reliably applied to watershed modelling across a variety of hydroclimate regimes and watersheds and that it produced as good as or better streamflow predictions than local rain gauges. However, for the Jaguaribe watershed the streamflow results simulated in this study with CFSR data for weather and precipitation data were unsatisfactory, performing worse than the other three groups. Group 4 (CFSR and local rain gauges, Table 1) simulation provided good results, suggesting that the use of CFSR data for weather parameters other than precipitation (which are usually less reliable in quantity, quality and spatial distribution), coupled with precipitation data from local rain gauges, can provide reasonable simulations of hydrologic response.

This can be of advantage, especially in developing countries like Brazil, since it is usually easier to obtain adequate precipitation data than data for other weather parameters. Another advantage of using CFSR data is that it can be obtained from the SWAT web site in SWAT input format (on text files ready to be used on the model), reducing the effort needed to reformat data other than precipitation from many weather stations.

4 Conclusions

In this study we demonstrated the importance of using adequate warm-up periods to better establish the watershed model initial conditions and the high sensitivity to the difference in warm-up periods used (1 and 5 years), in which the longer warm-up period had an overall better simulation response, especially for one group of weather inputs (Group 2). No absolutely clear pattern was found to establish which ET method worked best for the different weather input groups, based on tests of the three different ET methods available in SWAT in combination with the different weather groups. However, it was clear that the model was very sensitive in response to the different ET methods and that there is a need for testing and comparing the ET methods for specific study regions and weather input data.

In this study we demonstrate that large uncertainties in hydrologic simulation result from weather input data, and that the choice of the weather data is very important. The simulation with the world daily data base from NOAA's CFSR coupled model, but with precipitation from the local precipitation gauges (Group 4) performed best overall, providing good predictions at all four stream gauge stations. The simulation that used daily local precipitation with monthly data from the airport stations and SWAT's weather generator (Group 1) provided good results for three of the four gauge stations. This suggests that using spatialized global quality CFSR data for weather parameters other than precipitation, coupled with precipitation data from local rain gauges, can provide reasonable simulations of hydrologic response in this semi-arid region. This can be an advantage, since it is usually difficult to have quality data from a dense weather station network for all the weather data needed for SWAT, but it is easier to have a denser network of precipitation stations with longer periods of data.

The daily measured weather data from the 14 local gauge stations of INMET (Group 2) (which are a more dense network) actually provided worse estimates than those generated with SWAT's weather generator from monthly mean data from the 4 airports that are outside the study area, for the flow gauges where the flow was compared. This is probably due to the uncertainty related to daily measures and to the fact that over one-third of the data from these stations were missing.

The Group 3 simulation with the Climate Forecast System Reanalysis (CFSR) data had high PBIAS values and the smallest values of R^2, and the simulation was considered unsatisfactory for all of the streamflow gauges. Although it has performed well previously[14], it was not a good precipitation source for the Jaguaribe watershed region. This difference may have occurred because of the region's semi-arid climate with strong seasonal and inter-annual variability in precipitation, which could have resulted in the CFSR precipitation data being poorly calibrated with local weather stations. Better calibration of the CFSR precipitation data in the future could greatly reduce the problems we encountered using this data source.

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