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Sensitivity analysis and calibration of the SWAT model for a basin in northeastern Brazil using observed and reanalysis climatic data

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A B S T R A C T

The hydrological model SWAT is very widely used in Brazil, and calibration is needed to adjust results obtained through modeling to observed data. This article describes the spatial calibration of a SWAT model for the Goiana river basin in Pernambuco, using observed and reanalyzed climatic data. Nine rainfall stations were used, with the percentage of gaps in the simulation ranging from 0 to 14.19%. Nine stations of reanalysis climatic data obtained through the CFSR were used. The sensitivity and calibration analyses were performed in five subbasins. Use of observed data from local stations produced a greater number of satisfactorily calibrated stations. However, using both local stations and reanalysis climate data produced better statistics for subbasins with few rainfall stations that also had substantial missing data. The statistics obtained demonstrated the applicability of the model to monthly flow estimates. Even though model predictions for the driest area of the basin were unsatisfactory, the calibrated model provided good predictions for the main basin outlet.

Keywords: streamflow, hydrological modeling, SWAT, climatic data.

Introduction

As Medeiros and Silva (2014) described, mathematical models are widely used in climate studies, with their lower costs of implementation compensating for their uncertainties. Despite their uncertainties and probabilistic nature, hydrological models are capable of evaluating the processes at the river basin level and making projections of future conditions (Praskievicz and Chang, 2009). They are used for flood forecasting, water resources management, water quality assessment, estimation of erosion and sedimentation, assessment of the effects of land use and climate change, nutrient cycling and pesticide fate, among others (Devi, Ganasri and Dwarakish, 2015). For Engel et al. (2007) a model is a tool that can be used to analyze a particular hypothesis, not the hypothesis itself. Thus, its use is fundamental to testing and evaluating temporal and spatial changes due to hydrological phenomena (Pontes et al., 2016; Blainsk, Acosta and Nogueira, 2017).

Several models have been developed over time, including SWAT (Soil and Water Assessment Tool), MIKE SHE model (Systeme Hydrologique European), HBV model (Hydrologiska Byrans Vattenavdelning model), TOPMODEL, VIC model (Variable Infiltration Capacity model), and BASINS (Better Assessment Science Integrating Point & Non-point Sources) (Praskievicz and Chang, 2009; Devi, Ganasri and Dwarakish, 2015). A model that is being widely used in Brazil is SWAT (ARNOLD et al., 1998), which can be characterized as a semi-distributed hydrological model that performs daily calculations and is capable of predicting flow, surface runoff, sediment production, and water quality resulting from changes in land use and land cover at a watershed scale (Gassman et al., 2007; Arnold et al., 2012a).

According to Veith et al. (2010), since simulations with hydrological models give results that differ from observed data, it is often necessary to calibrate these models. Several studies have been carried out showing the applicability of the SWAT model. The use of manual or automatic calibration can achieve quite satisfactory results (Lelis et al., 2012; Pereira et al., 2014a; 2016; Santos et al., 2014; 2015; Bressiani et al., 2015; Fukunaga et al., 2015).

Sensitivity analysis is often performed prior to calibration, with the aim of identifying the parameters to which model outputs are most sensitive (Feyereisen et al., 2007; Lelis et al., 2012). These parameters are adjusted taking into account features of the basin and the processes involved, analyzing field measurements, and other data sources (Daggupati et al., 2015a; Brighenti, Bonumá e Chaffe, 2016). For Sarrazin et al. (2016) sensitivity analysis characterizes the effects of modifying input data on output data. According to Engel et al. (2007) and Nossent and Bauwens (2012) this analysis allows verification of the influence of certain parameters, as well as identification of which inputs are the most important. Nossent et al. (2011) highlights the importance of this analysis in verifying the effects of interactions among the parameters.

Most Brazilian studies have conducted sensitivity, calibration and validation analyses using data for only one watershed outlet, as can be seen in the works of Andrade, Mello and Beskow (2013), Pereira et al. (2014a, 2014b), Rodrigues et al. (2015); Brighenti, Bonuma and Chaffe (2016), and Franco and Bonumá (2017); however, some studies have used more detailed calibration and validation techniques, for example, Lelis et al. (2012), Bressiani et al. (2015), and Eduardo et al. (2016). Calibration using data from a single outlet, as indicated by Daggupati et al. (2015a) may be adequate for small basins with uniform features, but for larger basins the results can produce mean parameter values that are overestimated or underestimated at several points, and require spatially distributed calibration. Calibration results should still be analyzed carefully since, as Abbaspour (2005) points out, many solutions are produced by the calibration process, and the user must carefully analyze the conditions of the study area in order to choose the most appropriate set of parameter values.

Observed Brazilian weather data are often flawed, and alternative data sources are needed to better simulate hydrological processes. Problems related to weather data inputs were noted in the study of Bressiani et al. (2015) and Dile and Srinivasan (2014), and the authors used global Climate Forecast System Reanalysis (CFSR) data to analyze the effectiveness of using locally observed data that contained missing data as well as using CFSR data for river basins with poorly distributed weather stations or with stations with missing data.

Therefore, the main goal of this work was to perform spatially distributed calibration of a SWAT model for the Goiana river basin in Pernambuco, using both observed climatic data and CFSR data.

Material and methods

Characterization of the study area

The area of the Goiana River basin is 2,847.53 km^2, located between latitude 07º22'20" and 07º54'47" south and longitude between 34º49'06 " and 35º41'43" west, including parts of 26 municipalities of the Zona da Mata Norte, Agreste setentrional, and metropolitan areas (Figure 1).

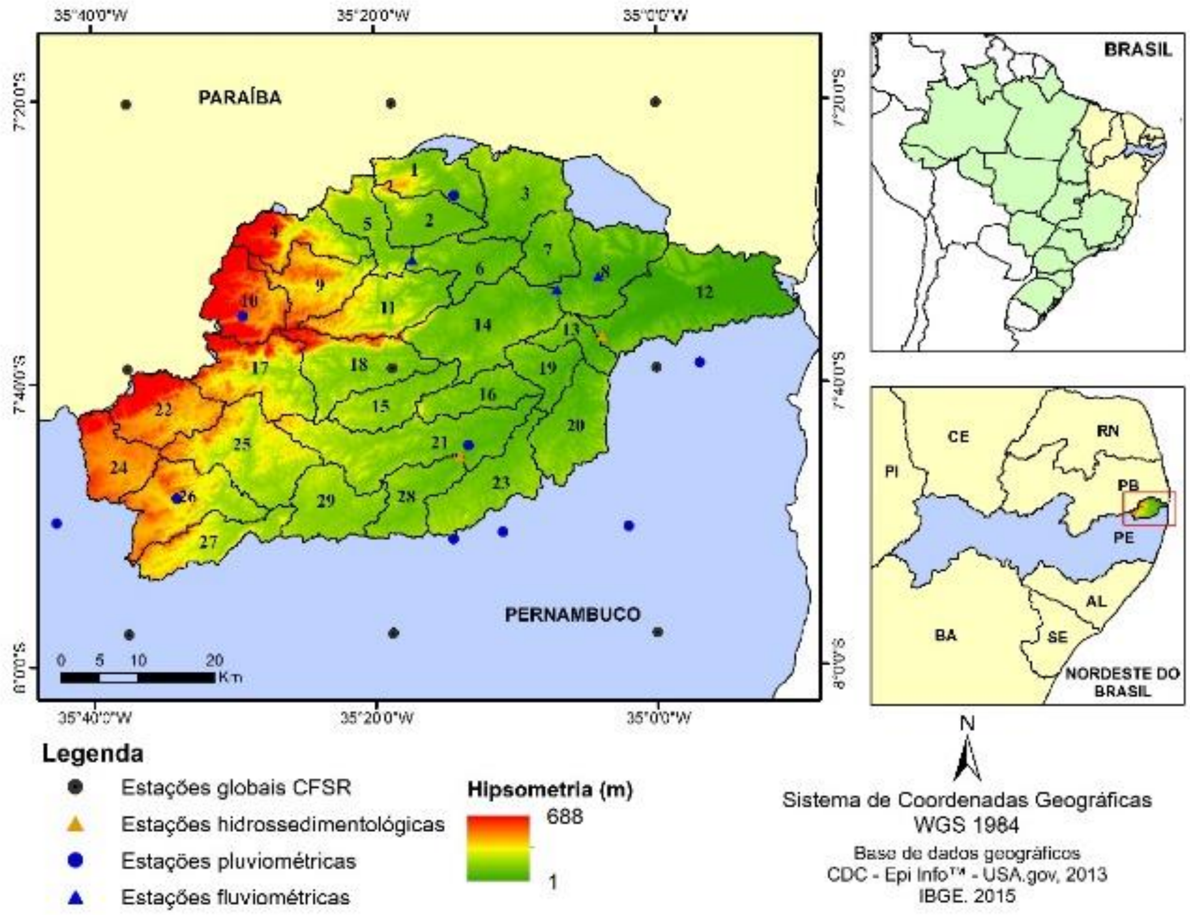

Figure 1. Location of the Goiana river basin in the Brazilian Northeast and hydroclimatic stations used.

The basin is composed of the subbasins of the river Capibaribe Mirim, Tracunhaém and the Goiana stricto sensu. The Goiana river basin is limited to the north within the state of Paraíba. In the south it is limited by the Capibaribe river basin and a group of small coastal river basins. In the east it reaches the Atlantic Ocean and to the west it reaches the state of Paraíba (APAC, 2016). The elevation of the basin varies from sea level to 688m at its highest point near the state of Paraíba. Outside the North Coast, most of the basin is located in the Crystalline Basin, and it depends on rainfall to supply its hydrographic network (CPRH, 2003).

The main uses of water in the region include shrimp farming and fishing, human consumption, public and industrial supplies, animal consumption, tourism, and recreation. The main factors impacting its water quality are: discharge of domestic, industrial and agroindustrial effluents, removal of sand from the river bed, construction of buildings in the vicinity of watercourses, unregulated withdrawal of river water, deforestation of riparian forests, and the dumping of garbage directly into the river (CONDEPE / FIDEM, 2005).

SWAT model

The model was developed by USDA Agricultural Research and Texas A & M University and has several components such as hydrology, climatic information, sedimentation, soil characterization, crop growth, nutrient and pesticide detailing, as well as agricultural crop management (Arnold et al. 2010). The SWAT model has two principal hydrologic components, consisting first of simulation of the hydrological cycle and second simulation of stream routing (Sarrazin et al., 2016).

The finest level of discretization used by the model is the Hydrologic Response Unit (HRU), as described by Arnold et al. (2010). HRUs are homogeneous areas of soil type, land use and land cover, topography, and management and are not spatially explicit (Gassman et al., 2007). The different variables that the model is able to estimate, as well as the characterization of the parameters and equations used for the model's operation are described in the theoretical documentation available online (NEITSCH et al., 2011). The model is based on the water balance equation:

$$SW_t=SW_0+\sum_{i=1}^{t} (R_{day}-Q_{surf}-E_a-w_{seep}-Q_{gw}) \quad (1)$$

Where SWt refers to the final soil water content (mm H_2O), SW0 is the initial soil water content on day i (mm H_2O), t is the time in days, Rday is the precipitation quantity on day i (mm H_2O), Qsurf is the amount of surface runoff at day i (mm H_2O), Ea is the evapotranspiration at day i (mm H_2O), Wseep is the amount of water entering the vadose zone from the soil profile on day i (mm), and Qgw is the quantitative return flow at day i (mm H_2O).

Among the methods available for estimation of potential evapotranspiration in the model (Neitsch et al., 2011), Penman-Monteith was the chosen because, according to Gassman et al. (2007), it should be used for climate change scenarios in relation to CO_2 levels. In order to predict rainfall runoff for different soil types and soil cover, the model uses the curve number method (CN; Arnold et al., 1998) as a function of soil moisture. This study used ArcSWAT version 2012 (revision 658) with the interface of ArcGIS 10.2.2 (ArcSWAT).

Data input and model setup

The SWAT model requires data for land use and cover, a digital elevation model (DEM) and daily weather data to perform a hydrosedimentological simulation (Figure 2). The resolution is important for the prediction of flow and sediment, with DEM being the most sensitive input (Cotter et al., 2003).

The subbasins of the Goiana basin were delineated using a digital terrain elevation model, and 29 subbasins were obtained, with areas varying from 36.94 to 218.07 km^2 and an average area of 98.85 km^2.

The digital terrain elevation model was obtained through EMBRAPA satellite monitoring (www.cnpm.embrapa.br), which provides images from the Shuttle Radar Topographic Mission (SRTM) with 90m resolution for the entire country.

Mapping of the soils of the region was performed through the Agroecological Zoning of Pernambuco (ZAPE) at a scale of 1: 100,000. Soil classification followed the Brazilian Soil Classification System (SiBCS, EMBRAPA, 2013). The physical and chemical characteristics of the soil layers were obtained through the Brazilian Soil Information System (SiSolos) of the Brazilian Agricultural Research Corporation (EMBRAPA) and included depth, texture and organic carbon. Other unmeasured parameters were estimated from pedotransfer equations. The hydrological classification of soils was performed according to the methods of Sartori, Lombardi Neto and Genovez (2005).

The land use and land cover map was obtained from the Brazilian Biological Diversity (Probio) Conservation and Sustainable Use Project coordinated by the Ministry of the Environment (MMA). This mapping was elaborated at a scale of 1: 250,000, with 2002 as the base year, using scenes from 1999 to 2005, concentrating most of the images in the years 2001-2003 and using scenes from the ETM + sensor of Landsat 7, SPOT4 and CCD/ CBERS (IESB, 2007).

Since SWAT does not yet have a detailed land cover classification for tropical areas, the classes of use and cover of Probio’s map were used, with parameters assigned considering those used in standard SWAT land use categories and Probio’s map.

Flow predictions were performed on a monthly base, and the simulation was carried out for a period of 10 years, starting in January 1996 with 3 years of warming up.

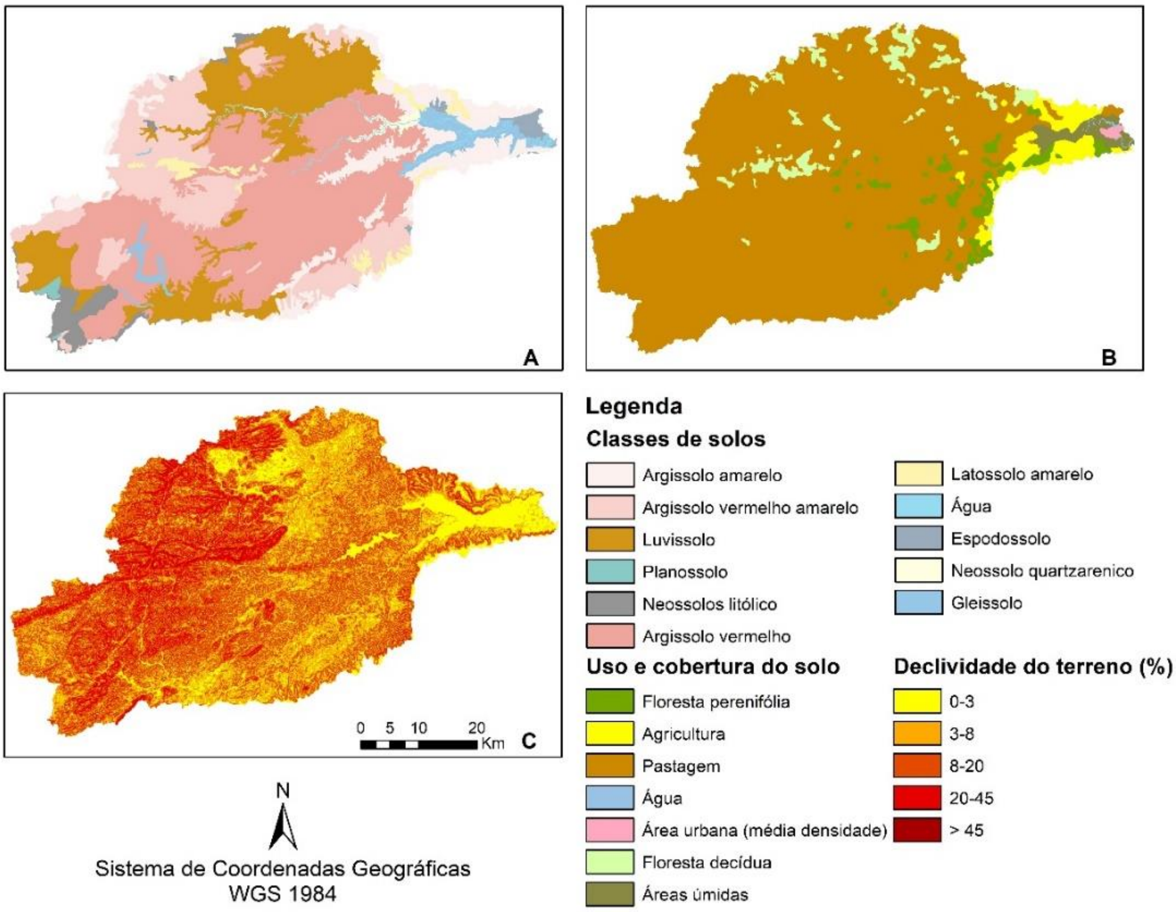

Figure 2. Maps of soil classes (A), land use and cover * (B) and slope of land (C) of the Goiana river basin. *Based on SWAT classes

Hydroclimatic Data

Three automatic stations of the National Institute of Meteorology (Inmet) for the Weather Generator (WGN) (Table 1) were used as input of monthly climatic data, for which we used data for about 50 years of precipitation, maximum and minimum air temperatures, humidity, solar radiation and wind speed.

Table 1. Stations used for the Weather generator from Inmet stations

Station Code	Name	Latitude	Longitude
82797	Surubim	-7.83	-35.71
82900	Recife	-8.05	-34.95
82798	JoãoPessoa	-7.1	-34.86

Rainfall stations with daily data available were obtained from INMET, the National Water Agency (ANA) and the Pernambuco Water and Climate Agency (APAC). The percentage of missing data for the period used in the simulation ranged from 0 to 14.19% (Table 2). The distribution of the stations was not homogeneous due to the difficulty of selecting stations with a satisfactory percentage of missing data (Figure 1).

The period with the lowest incidence of missing data was selected for the simulation (1999-2009), due to the availability of observed flow data for the same period.

Table 2. Rainfall stations used for hydrological simulation in the period from 1999 to 2009

Station Code	Station	Latitude	Longitude	Altitude	Percentage of gaps 1999 to 2009 (%)	Average annual rainfall 1999 to 2009 (mm)
28	Goiana (Itapirema)	-7.6442	-34.9489	87	6.82	2045.75
95	Carpina (est. exp. de Cana-de-açúcar)	-7.8511	-35.2408	183	0.15	1300.37
97	Nazaré da mata	-7.7408	-35.2228	82	7.07	1008.58
139	Bom jardim	-7.8017	-35.5678	340	0.32	784.82
269	Igarassu (Bar.catuca)	-7.8364	-35.0336	50	4.80	1347.98
271	São Vicente Ferrer	-7.5875	-35.4889	427	0.37	1084.79
457	Ferreiros	-7.4461	-35.2386	93	14.19	676.42
82797	Surubim	-7.83	-35.71	418	0.17	621.66
735157	Carpina	-7.8428	-35.1825	102	0.00	1456.24

Reanalysis data

Knowing that the distribution and availability of data is very important for hydrological modeling (El-Sadek et al., 2011), and after verifying that the available daily precipitation data from weather stations in the Goiana river basin were not satisfactorily distributed, CFSR data were used to complement weather station data. These were obtained through the Global Weather Data for SWAT (http://globalweather.tamu.edu/) available from Texas A & M University. Several studies had previously demonstrated the applicability of these data (Dile and Srinivasan, 2014; Fuka et al., 2014; Bressiani et al., 2015).

The daily CFSR data are complete for the period 1979 to 2014, having a resolution of 38km (0.3125 °) and global coverage. Information obtained from CFSR included daily precipitation, maximum and minimum air temperatures, humidity, solar radiation and wind speed. We used 9 areas within a latitude box -8.4669 to -7.0464 and longitude -35.777 to -34.585 (Table 3).

Table 3. CFSR climatic seasons for hydrological simulation from 1999 to 2009

Station Code	Latitude	Longitude	Average annual rainfall 1999 to 2009 (mm)
p-80-356	-7.96184	-35.625	879.43
p-76-356	-7.64961	-35.625	719.33
p-73-356	-7.33738	-35.625	898.61
p-80-353	-7.96184	-35.3125	1574.61
p-76-353	-7.64961	-35.3125	1158.81
p-73-353	-7.33738	-35.3125	1246.09
p-80-350	-7.96184	-35	2330.54
p-76-350	-7.64961	-35	1565.74
p-73-350	-7.33738	-35	1640.27

Analysis of sensitivity and calibration of the model

Sensitivity analysis was performed in the subbasins 28, 5, 13, 14 and 8 (Figure 3), delimiting 5 zones in the Goiana basin. These areas were established from fluviometric stations located within the basin, and the flow observed in these zones and used in this work corresponds to the observed value available at each indicated fluviometric station.

SWAT Calibration and Uncertainty Procedures (SWAT-CUP) software were used to identify the most sensitive parameters, which were then adjusted for greater consistency compared to the observed. SWAT-CUP has an interface that was developed for SWAT and is capable of performing sensitivity, uncertainty and calibration analysis (Abbaspour, 2015).

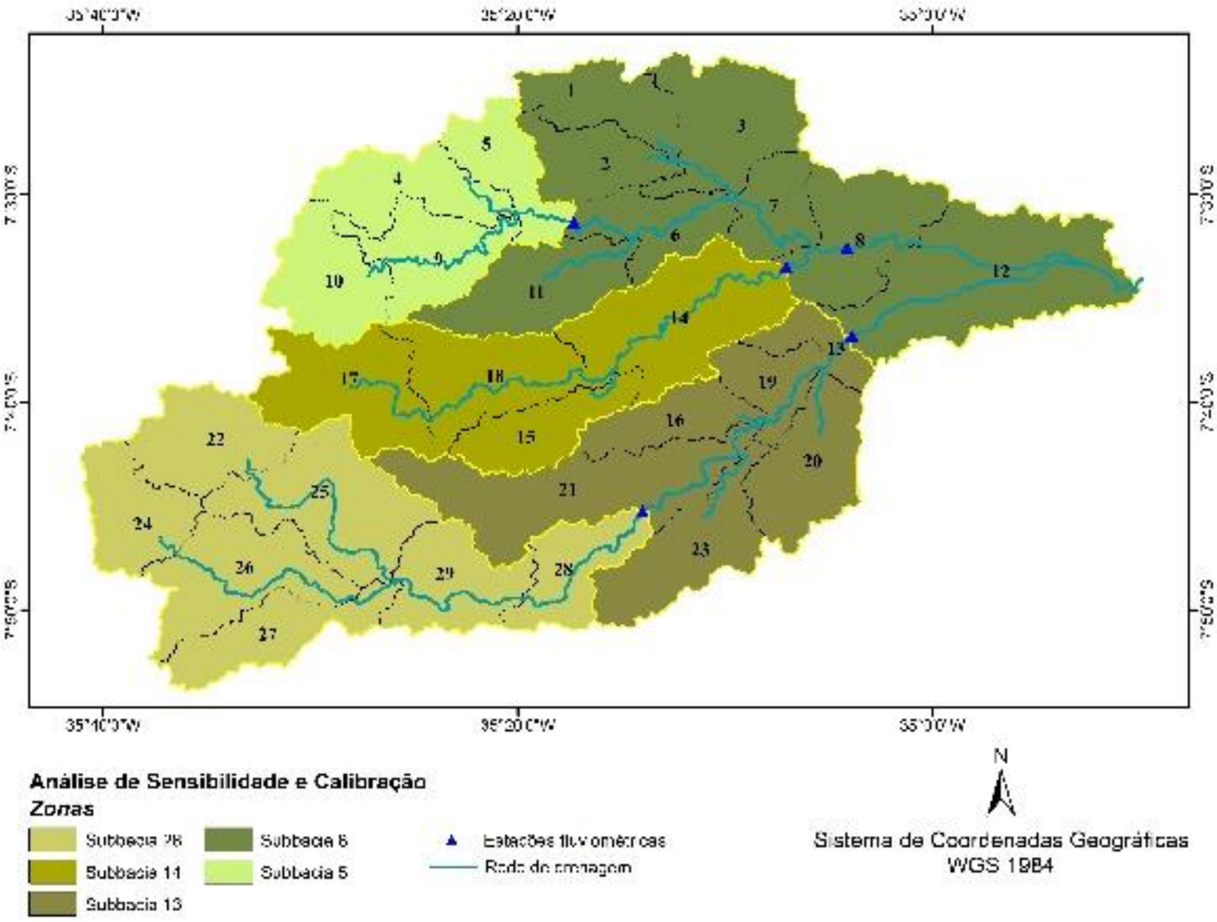

Figure 3. Zones used for sensitivity analysis and spatial calibration.

There are five different calibration methods in SWAT-CUP: SUFI-2, PSO, GLUE, ParaSol and MSMC. The SUFI-2 method was selected because of the good results found in several studies (DAGUPPATI et al., 2015a; FRANCO; BONUMÁ, 2017; PONTES et al., 2016) and its applicability in developed countries in several regions of Brazil. The chosen method includes an uncertainty analysis and can work with a large number of parameters (Abbaspour, 2005). The 95% prediction of uncertainty (95PPU) is calculated for each simulated variable (Schuol and Abbaspour, 2006).

Table 4 gives key parameters analyzed for their sensitivity and significance using t-stat and p-value. Andrade, Mello and Beskow (2013) used 21 parameters, and 19 were used in this work. Although some authors used a smaller interval for parameter calibration, Andrade, Mello and Beskow (2013) worked with a lower limit of -50% and an upper limit of + 50% for the parameters of CN2, SOL_Z, SOL_K and SOL_AWC. However, in this study we chose to use a lower range of variation, from -25 to + 25%, and for CN2 of only -10 and + 10% as verified in some studies.

The sampling of the parameters was done through the Latin hypercube (Mckay, Beckman and Conover, 2000). The sensitivity analysis was performed for subbasins 28, 13, 14, 8 and 5, using 500 iterations (Abbaspour, 2015; Santos, 2015). After identification of the most sensitive parameters, calibration was carried out with iterations until the best results of the statistics within the assigned ranges were obtained. The calibration and validation process recommendations of Engel et al (2007) and Daggupati et al. (2015b) were observed. A complex calibration process with multiple stations was used (Daggupati et al., 2015b), working from upstream to downstream (Arnold et al, 2012). The systematic calibration approach used a single-stage model with a single output variable, stream flow (Daggupati et al., 2015b). The best values were entered through manual calibration in Arcswat

.

Table 4. Parameters used for SWAT-CUP sensitivity analysis

Parameters	Description	Defined ranges
r__CN2.mgt	Curve number in condition 2 of moisture (dimensionless)	-0.1 to 0.1
v__ALPHA_BF.gw	Baseline flow recession factor (days)	0 to 1
a__GW_DELAY.gw	Underground flow delay time (days)	-30 to 90
a__GWQMN.gw	Minimum depth of surface aquifer for surface runoff (mmH2O)	-500 to 500
v__ESCO.hru	Soil evaporation compensation factor (dimensionless)	0 to 1
r__SOL_AWC().sol	Capacidade de água disponível (mm H_2O/ mm solo)	-0.25 to 0.25
r__SOL_Z().sol	Available water capacity (mm H2O / mm only)	-0.25 to 0.25
r__CH_K2.rte	Effective hydraulic conductivity in the main channel (mm / h)	-0.1 to 0.1
v__GW_REVAP.gw	Coefficient of underground flow (dimensionless)	0.02 to 0.2
v__REVAPMN.gw	Minimum water for surface runoff (mm)	0 to 1000
v__RCHRG_DP.gw	Percolation fraction for the deep aquifer (dimensionless)	0 to 1
r__SLSUBBSN.hru	Average slope length (m)	-0.25 to 0.25
r__SOL_K().sol	Hydraulic conductivity (mm h-1)	-0.25 to 0.25
r__USLE_P.mgt	Factor related to soil conservation practices	-0.25 to 0.25
r__SOL_ALB().sol	Soil Albedo (dimensionless)	-0.25 to 0.25
v__CH_N2.rte	Manning coefficient of the main channel (dimensionless)	-0.01 to 0.3
v__CANMX.hru	Maximum water storage in vegetative canopy (mm)	0 a 10
v__BIOMIX.mgt	Efficiency of biological (dimensionless)	0 to 1
v__EPCO.hru	Factor of water compensation by plants (dimensionless)	0 to 1
v__SURLAG.bsn	Coefficient of surface flow retardation (dimensionless)	0 to 24

Monthly flow data were used to make the first adjustments in the model, corresponding to the period from 1999 to 2009. The flow data used to calibrate the model were obtained from five fluviometric stations acquired through the Hydrological Information System (HIDROWEB) of ANA. The Nazaré da Mata, Engenho Itapessirica, Engenho Retiro, Engenho Volta, and Caricé stations were used to calibrate subbasins 28, 5, 13, 14 and 8, respectively.

In the period used for calibration, the streamflow stations had 9.8% missing data for sub-basin 28, 6.1% for sub-basin 13, 13.6% for sub-basin 14, 40.9% for sub-basin 5 and 9.8% for sub-basin 8.

The calibration was performed in the following order: subbasin 28, subbasin 13, subbasin 14, subbasin 5 and subbasin 8. After the best adjustments for each parameter were identified, the adjustments were made in the other sub-basins of each calibration zone.

Multiple criteria were used to compare model outputs to observed data (Klemes, 1986). Arnold et al. (2012a) and Gassman et al. (2007) indicate that different graphical and statistical methods can be applied. The most commonly used are R^2, NSE and PBIAS. In this study, the classification given by Moriasi et al. (2007) and the recommended statistics NSE, PBIAS and RSR can be represented by the following equations:

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

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100\% \quad (3)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}} \quad (4)$$

Where O_i refers to the observed data, P to the result after the modeling, $\bar{O}$ the average of the observed data and n is the number of observations.

Results and discussion

Sensitivity analysis

Due to the size and environmental variation within the five regions of Brazil, parameterization of SWAT may vary among Brazilian studies. Table 5 presents the results of the automatic sensitivity analysis performed by SWAT CUP. Some of the more sensitive parameters were also identified in other studies. Of the 20 parameters used in the analysis of flow, nine had the greatest sensitivities: CN2, GW_DELAY, ESCO, SOL_AWC, SOL_Z, RCHRG_DP, USLE_P, CANMX and EPCO. In comparison, Me, Abell and Hamilton (2015) identified 21 sensitive parameters for flow.

The most sensitive parameters in the present work refer to crop/vegetation management, soil, and groundwater. According to Schmalz and Fohrer (2009), the parameters of greatest influence in hydrological modeling are those related to groundwater and soil. Devi, Ganasri and Dwarakish (2015) further state that meteorological and soil parameters influence model performance due to their influence on simulation of vegetation, soil, groundwater and surface runoff.

Our sensitivity analysis was conducted independently for the different basins. We, like Aragão et al. (2013), found that sensitive processes vary among basins, and the same parameters should not necessarily be used for calibration of different basins. However, Lelis et al. (2012) found that the size of their subbasins did not influence the sensitivity of the parameters.

Arnold et al. (2012) reported that many papers use CN2, SOL_AWC, ESCO, GW_ALPHA and SURLAG in the calibration procedures, which indicates model sensitivity to these parameters. For Feyereisen et al. (2007), the parameters with the greatest relative sensitivities for water production, storm flow and base flow were related to soil surface conditions, such as CN2, SOL_AWC, ESCO and SOL_BD. Likewise, Schuol and Abbaspour (2006) found hydrologic outputs to be sensitive to CN2, SOL_AWC, ESCO, SURLAG, REVAPMN, RCHEG_DP, and MSK. Among these parameters, SURLAG did not show sensitivity in any of the Goiana subbasins, despite the sensitivity observed in other studies. This is due to the differences in the physical and climatic characteristics of the basins, which influenced the values of the parameters and thus, their sensitivity. In addition, the land use and land cover of each subbasin can influence the results, according to Lelis et al. (2012).

For Nossent, Elsen and Bauwens (2011) the most sensitive parameters were CN2, CH_N and GWQMN for stream flow calibration. Pereira et al. (2016) worked in the Pomba River basin in southeastern Brazil and identified SOL_K, APLHA_BF, ESCO, CN2, CH_N2, SOL_AWC and SOL_Z as sensitive parameters. For Andrade, Mello and Beskow (2013) the most sensitive parameters found for the Jaguara River Basin in the Rio Grande High region of Minas Gerais were CN2, ALPHA_BF, RCHRG_DP, ESCO, SOL_Z, SOL_K, SOL_AWC.

Fukunaga et al. (2015) found that the most sensitive parameters were those related to soil, land use and cover, groundwater and the transmission network, including CN2, GWQMN, ESCO, CANMIX, SOL_K, SOL_AWC, SOL_Z, ALPHA_BF, BLAI, CH_K2, CH_N2, GW_DELAY, SOL_ALB, EPCO, REVAPMN and SURLAG. However, the authors chose not to use all the parameters in their calibration.

ALPHA_BF has been reported to be a sensitive parameter in several works such as Wu and Johnston (2007), Andrade, Mello and Beskow (2013), Bressiani et al. (2015), and Fukunaga et al. (2015), however, it had one of the smallest influences and was not used in the calibration of the present study.

Daggupati et al. (2015b) mentioned that not all parameters considered sensitive need to be calibrated, this can be evaluated from experience in modeling or from results in the literature. This happened in the present work where EPCO, although found to be a sensitive parameter, was not used in the calibration. This is generally applicable when there is a large variation in soil uses in the basin.

Table 5. Sensitivity analysis of the parameters for flow

Parameters	SB 28	SB 13	SB 14	SB 5	SB 8
r__CN2.mgt	1	14	1	1	8
v__ALPHA_BF.gw	18	19	17	15	20
a__GW_DELAY.gw	6	7	6	4	3
a__GWQMN.gw	16	18	14	6	18
v__ESCO.hru	2	2	2	5	2
r__SOL_AWC().sol	4	3	7	3	5
r__SOL_Z().sol	5	6	10	7	6
r__CH_K2.rte	19	17	20	17	15
v__GW_REVAP.gw	17	5	5	13	13
v__REVAPMN.gw	14	12	12	14	11
v__RCHRG_DP.gw	3	1	3	18	1
r__SLSUBBSN.hru	10	15	15	10	17
r__SOL_K().sol	9	11	13	11	14
r__USLE_P.mgt	12	9	11	9	9
r__SOL_ALB().sol	11	13	16	8	12
v__CH_N2.rte	13	10	8	12	10
v__CANMX.hru	7	8	9	6	7
v__BIOMIX.mgt	15	16	19	19	19
V__SURLAG.bsn	20	20	18	20	16
v__EPCO.hru	8	4	4	2	4

Calibration of the model

Based on the parameters obtained in the sensitivity analysis, the most sensitive for each of the subbasins were adjusted during the flow calibration process. For each of the subbasins, the calibrated values found were different, even though we worked with the same parameters in all subbasins, as can be seen in Table 6.

Table 6. Parameters used in the calibration

Parameters SB28	Calibrated Value	Parameters SB13	Calibrated Value	Parameters SB14	Calibrated Value
CN2	-0.08519	RCHRG_DP	0.381004	CN2	-0.07262
RCHRG_DP	0.471794	ESCO	0.276827	ESCO	0.438359
ESCO	0.303912	SOL_AWC	0.248508	RCHRG_DP	0.455415
SOL_AWC	0.248123	GW_REVAP	0.087755	GW_REVAP	0.130872
SOL_Z	0.199801	SOL_Z	0.095000	GW_DELAY	-27.52166
GW_DELAY	-24.1585	GW_DELAY	-29.9764	SOL_AWC	0.104324
CANMX	19.26619	CANMX	4.608878	CH_N2	0.277646
SOL_K	-0.14453	USLE_P	-0.06060	CANMX	9.532859
SLSUBBSN	0.014511	-	-	SOL_Z	0.031403

Table 6. (Continuation) Parameters used in the calibration

Parameters SB5	**Calibrated Value**	**Parameters SB8**	**Calibrated Value**
CN2	-0.09295	CN2	-0.00789
SOL_AWC	0.208182	GW_DELAY	-7.28545
GW_DELAY	53.05331	ESCO	0.501378
ESCO	0.672376	SOL_AWC	0.092922
GWQMN	990.3423	SOL_Z	0.254504
SOL_ALB	0.231693	REVAPMN	596.7773
USLE_P	0.071065	RCHRG_DP	0.021149
SLSUBBSN	-0.21433	USLE_P	-0.00640
SOL_K	0.213173	CH_N2	0.170758
		CANMX	8.472565

For the different subbasins calibrated in this study, the final values of the parameters obtained (Table 9) were compared to values used by other Brazilian and international studies, analyzing the climatic characteristics of the sites. For ESCO, Wu and Johnston (2007) indicated that for average climatic conditions the value is 0.5 and for drier conditions 0.8. For the present study, the parameter was sensitive for all subbasins used in the calibration process, and the highest and lowest values for subbasins 5 and 13 were respectively 0.67 and 0.28.

The calibrated value for ESCO found by Pereira et al. (2016) was 0.3 for a basin in southeastern Brazil that has an annual average precipitation of 1400 mm. This value is similar to the one calibrated for subbasin 28. Bressiani et al. (2015) found the best value to be 0.6 for the Jaguaribe basin located in a semi-arid area of northeastern Brazil. This value approaches the value found for subbasin 5, whose annual rainfall is lower than the other subbasins. Castro et al. (2013) obtained 0.1 for the Alto Jardim experimental basin located in the Brazilian cerrado in the Federal District. A similar value was also obtained by Kim and Kang (2016) for a basin located in South Korea. Shuol and Abbaspour (2006) presented a final calibration interval ranging from 0.12 to 0.50 for a rugged basin in West Africa that includes the Niger River Basin, Volta and Senegal. Fukunaga et al. (2015) found a calibration value of 0.566 for a basin located in Espírito Santo. Andrade, Mello and Beskow (2013) found a lower value for this parameter (0.043) for an area with an average annual temperature of 19ºC and annual rainfall of 1500mm in the Alto Rio Grande region of Minas Gerais.

For the parameter referring to the fraction of percolation in the deep aquifer, RCHRG_DP, calibrated values include 0.1 for Bressiani et al. (2015) and 0.484 for Andrade, Mello and Beskow (2013). Shuol and Abbaspour (2006) found that calibrated values ranged from 0.56 to 0.70. In this work, this parameter was sensitive for the subbasins 28, 13, 14 and 8, with calibrated values of 0.47, 0.38, 0.45 and 0.02, respectively. The different values for this parameter are related to soil type, land use and land cover, and climate of the subbasins. Areas containing fragments of Atlantic Forest are important for groundwater recharge, as noted in the work of Alvarenga et al. (2012).

The available water capacity (SOL_AWC) is the capacity of a soil to store and release water to the plant's root (Silva et al., 2014). It has been found to be a sensitive parameter in some studies. For example, Shuol and Abbaspour (2006) found calibrated values ranging from 0.145 to 0.175. This parameter was considered sensitive for all the subbasins analyzed and calibration resulted in increasing the values of the variable by 0.25, 0.21, 0.25, 0.10 and 0.09 respectively for basins 28, 5, 13, 14 and 8. Variation among the values was related to the different types of soil and the conditions modeled for each of the subbasins. Care must be taken not to increase values beyond those measured under natural conditions in order to improve calibration statistics. Fukunaga et al. (2015) added 41.8% to this parameter in the calibration process, though in this work it was limited to 25%.

Rainfall can be intercepted by the vegetation and reach the soil later, influencing infiltration of water into the soil and runoff; therefore, it can be important in hydrological studies (Xiau et al., 2000). The amount of intercepted water (CANMIX) varies by vegetation type, and Fukunaga et al. (2015), used a calibrated value of 11.3 mm for a watershed with coffee plantations, eucalyptus woodlands, pasture, native forest, secondary forest, urban areas and stony lands. Pereira et al. (2014a) simulated an area of

Atlantic Forest, but didn't change the parameter CANMIX, modifying other SWAT vegetation parameters such as BLAI, GSI, RDMX and OV_N. In our work the values of CANMIX were changed to 19.27, 4.60, 9.53 and 8.47 mm respectively for subbasins 28, 13, 14 and 8.

Regarding groundwater parameters, Fukunaga et al. (2015) changed GW_DELAY to 287 days, GW_REPVAP to 0.188, and GWQMN to 3907mm. The parameter GW_DELAY relates to the time required for water to leave the soil profile and reach the aquifer. It is affected by the hydraulic properties of the geological formations in the areas (Arnold et al., 2012b) and therefore can vary among locations in the basin. In the present study, GW_DELAY values were reduced in subbasins 28 by -24.16 days, subbasin 13 by -29.98 days, subbasin 14 by -27.52 days and subbasin 8 by -7.29 days. For subbasin 5, the driest subbasin, the value of of GW_DELAY was increased by 53.05 days. In addition, other hydrogeological conditions also contribute to the flow of groundwater, such as transmissivity and storage coefficient indicated in the work of Tirogo et al. (2016) in Burkina Faso in West Africa.

The statistics found (Table 7) show that calibration improved simulated results, except in subbasin 5. The results indicate that the use of observed (local) stations combined with CFSR data gave more satisfactory results for some areas of the Goiana basin, probably due to a better distribution of simulated precipitation within the basin. However, for subbasin 8, calibration slightly reduced accuracy of the simulation, and in subbasin 14 calibration produced unsatisfactory results. This result was probably due to introduction of weather data that were unrepresentative of the actual weather in the subbasin.

Table 7. Comparison of simulations before and after calibration for local and global stations.

Subbasin	**Local Stations**			**Local+Global Stations**		
	NSE	**PBIAS**	**RSR**	**NSE**	**PBIAS**	**RSR**
28I	0.47	-82.58	0.73	0.56	-75.74	0.66
28II	0.79	-10.69	0.46	0.80	-6.76	0.44
13I	-0.19	-116.0	1.01	-0.09	-112.3	1.04
13II	0.80	-21.53	0.44	0.87	-17.00	0.36
14I	-0.23	-67.08	1.11	0.05	-39.27	0.98
14II	0.62	4.43	0.62	0.34	30.08	0.80
5I	0.08	-18.08	0.71	0.08	-18.08	0.71
5II	0.43	17.99	0.56	0.43	17.99	0.56
8I	0.46	-61.69	0.73	0.58	-41.43	0.65
8II	0.82	-9.70	0.42	0.80	11.62	0.44

I – Before Calibration; II – After Calibration[1]

The subbasins in which simulated results were closest to those observed were subbasin 8 with NSE of 0.82, PBIAS -9.70 and RSR 0.42 and subbasin 28 with NSE 0.79, PBIAS - 10.69 and RSR 0.46 for simulations using only local weather station data. For simulations from local + global CFSR stations (L+G), the same stations had the best results. Subbasin 8 produced the following values: NSE of 0.80, PBIAS 11.62 and RSR 0.44 and subbasin 28 with NSE 0.80, PBIAS -6.76 and RSR 0.44.

On the other hand, subbasin 5 presented unsatisfactory results for both simulations, possibly because in this area of the basin, weather data are scarcer and less well distributed. Also, this area of the basin has a slightly drier climate than some of the other areas, and has the lowest observed flows recorded in the basin. (Figure 4).

[1] After the calibration procedure, using the local climatic data the performance achieved using the classification of Moriasi et al. (2007) was: sub28 - good; sub13 - satisfactory; sub14 - satisfactory; sub5 - unsatisfactory; and sub8 - very good. For local climatic data combined with global data: sub28 - very good; sub13 - satisfactory; sub14 - unsatisfactory; sub5 - unsatisfactory; sub8 - good.

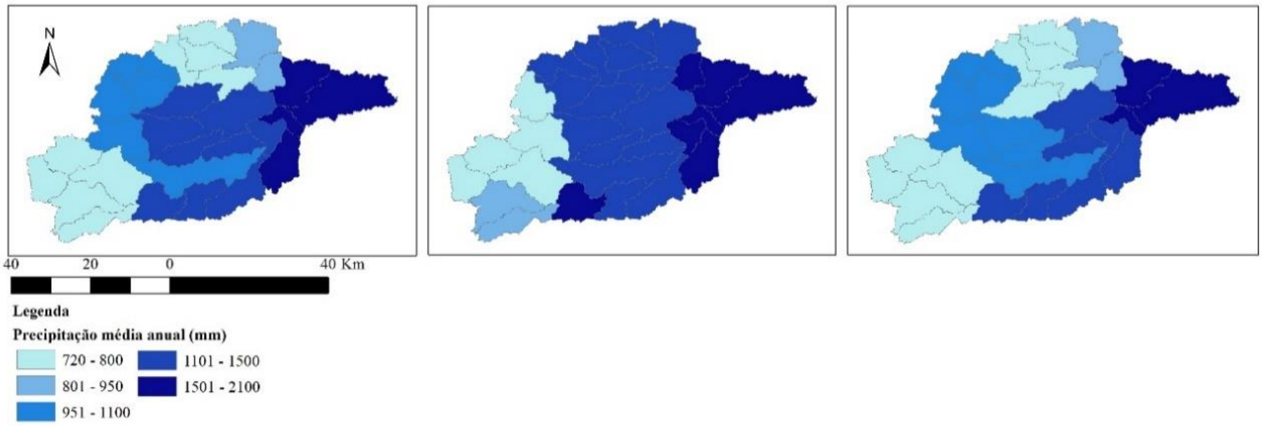

Figure 4. Average annual precipitation of the basin from 1999 to 2009 using local observed (a), (b) global reanalysis data and (c) both.

Despite the satisfactory results of using local and global climate data, the unsatisfactory result found in subbasin 14 points to the importance of performing tests with CFSR data to verify if the climatic characteristics of these data represent the local reality.

In other Brazilian studies using the SWAT, similar statistics were found. For example, Brighenti et al. (2016) found values of 0.70 and 0.73 for different calibration periods and 0.63 and 0.55 for validation of monthly flows in the Rio Negrinho basin in Santa Catarina with an approximate area of 200 km^2. For simulation of daily flow, Pereira et al. (2016) found suitable values of NSE for the calibration and validation of 0.76 and PBIAS of 4.6 and 5.1, respectively, for a basin of 8600 km^2 in southeastern Brazil. The results found by Andrade, Mello and Beskow (2013) were also satisfactory, obtaining NSE values of 0.66 and 0.87, and PBIAS values of 4.33 and -1.59 for the calibration and validation stages of the model in a 32km^2 basin. Pereira et al. (2014a) found NSE values of 0.65 and 0.70 for the periods of calibration and validation of daily flow data in the Córrego do Galo basin in Espírito Santo as part of a study of the effects of different scenarios of environmental preservation and degradation. Castro et al. (2013) found a value of NSE of 0.66 for daily flows in a Brazilian cerrado basin. Fukunaga et al. (2014) also found satisfactory values for calibration of daily stream flows, obtaining values of NSE of 0.75, PBIAS of 11 and RSR of 0.50. During the validation the values obtained were 0.67, 22 and 0.57, respectively.

Although some subbasins of the present work have presented very good or good results, according to the classification of Moriasi et al. (2007), we found that peak flows were underestimated in some months (Figure 5). However, it is important to note that subbasins with better statistics have a more accurate estimates of flows. The results of subbasin 5 has differences between peak flows and delays in simulated flows. During drier periods, when the flow rate is lower, variation can also be observed between the simulated and observed values.

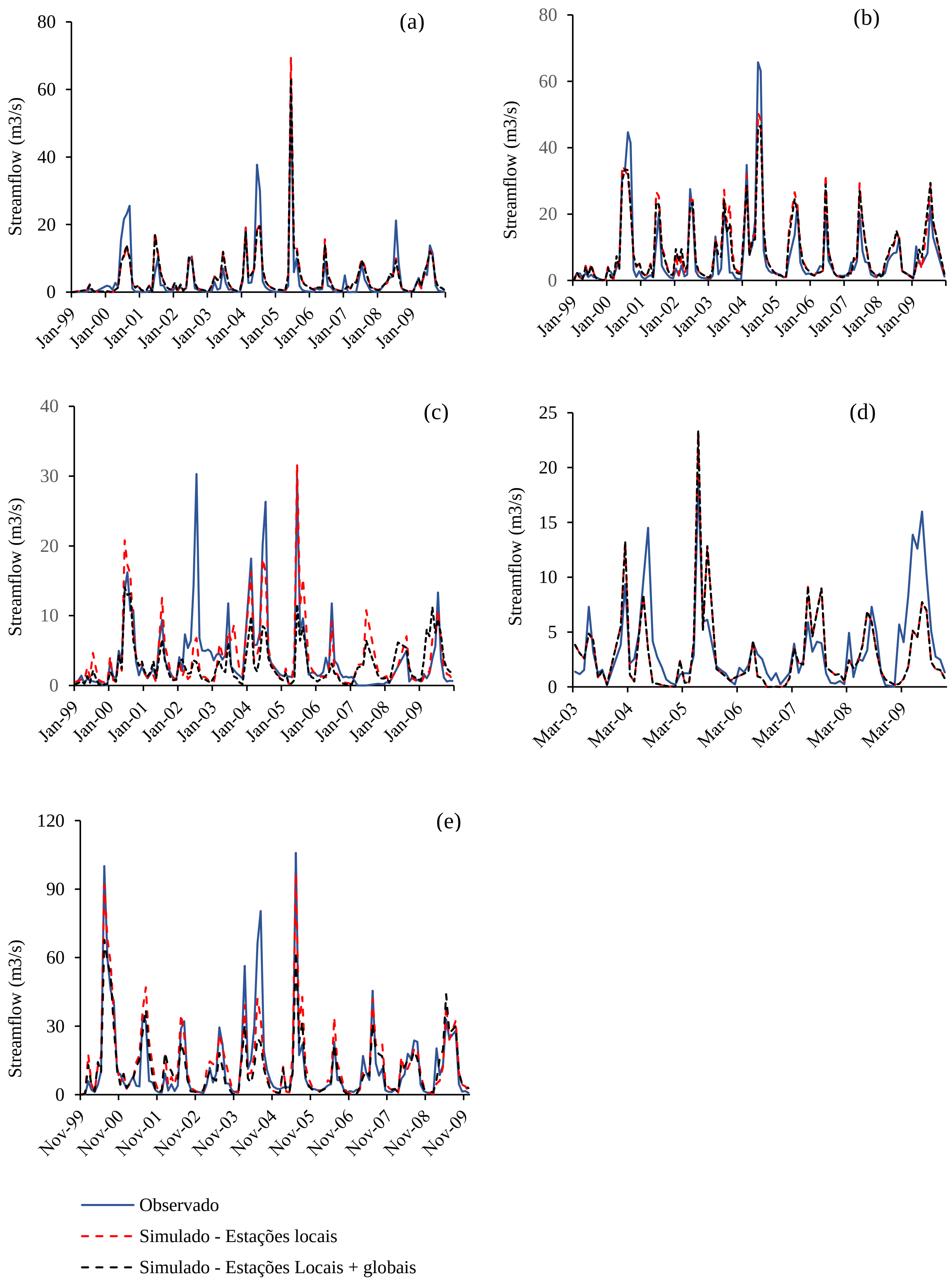

Figure 5. Comparison of the calibrations performed in subbasin 28 (a), subbasin 13 (b), subbasin 14 (c), subbasin 5 (d) and subbasin 8 (e) for the period from 1999 to 2009 using local and global climate data.

Issues related to rainy and dry periods were discussed by Feyereisen et al. (2007) who found that the model of the Little River experimental basin in southwest Georgia produced better results for wet years than for dry years. Subbasin 5, besides having a drier climate than the other areas of the basin, produced lower flows throughout the analyzed period, with minimum values of zero and maximum values close to $25m^3$/ s.

Feyereisen et al. (2007) found an NSE of 0.89 for water production in the monthly outputs and 0.55 for daily outputs in the wet years. On the other hand, in dry years they obtained 0.59 for monthly simulations and 0.22 for daily simulation. For stream flow simulations, the results were similar. For the wet years: a daily NSE was 0.62 and for the dry years the daily NSE was -0.80. In the modeling of subbasin 5 for monthly flows, after the calibration the results were: NSE 0.43 and PBIAS 17.99.

This was also found by Van Liew et al. (2007), who tested the performance of SWAT in five USDA ARS experimental basins in the United States and verified better performance for areas with moist climates than desert or semi-desert areas. Brighenti et al. (2016) performed individual calibration for each year between 2003 and 2012 and verified that calibration and validation were more efficient in wet years than in dry years. In contrast, Govender and Everson (2005) verified that the performance of the model was better in dry years than wet years in an experimental basin in South Africa.

For this work, the basins with greater rainfall gave superior results, both statistically and graphically, than the basins with lesser rainfall.

Conclusions

The sensitivity analysis performed through SWATCUP identified sensitive parameters and calibrated these parameters. The parameters used in this analysis that gave the greatest sensitivities were the CN2, GW_DELAY, ESCO, SOL_AWC, SOL_Z, RCHRG_DP, USLE_P, CANMX and EPCO.

In spite of being a single medium-size basin, because it contained different land uses and regions with different climatic characteristics, the sensitivity parameters varied among subbasins, and the calibrated parameter values varied among subbasins, indicating that calibration of individual subbasins can be beneficial.

The use of observed data from local stations produced more satisfactorily calibrated stations than using data from a combination of local stations and CFSR data. However, using CFSR and local station data improved the statistics for subbasins with few rainfall stations that also had substantial missing data.

The results show the possibility of using observed weather station data and CFSR reanalysis data together where there is lack of weather data or stations with a large fraction of missing data; however, it should be noted that simulations may be unsatisfactory in dry areas with erratic, poorly distributed rainfall.

The statistics obtained in the SWAT modeling show the applicability of the model to simulation of monthly stream flows. This showed good and very good predictions for sub-basin 8, the station closest to the river mouth of the basin, which receives flow from the zone in which sub-basin 5 is located and the area where sub-basin 14 is located.; however, simulations of the driest areas of the basin, sub-basin 5, were unsatisfactory.

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