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Impacts of land use and climate changes on surface runoff in a tropical forest watershed (Brazil)

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Abstract

Surface runoff generation capacity can be modified by land use and climate changes. Annual runoff volumes have been evaluated in a small watershed of tropical forest (Brazil), using SWAT model. Firstly, the accuracy of SWAT in runoff predictions has been assessed by default input parameters and improved by automatic calibration, using 20-year observations. Then, the hydrological response under land uses (cropland, pasture and deforested soil) alternative to tropical forest, and climate change scenarios has been simulated. SWAT application has showed that, if forest was replaced by crops or pasture, the watershed's hydrological response would not significantly be affected. Conversely, a complete deforestation would slightly increase its runoff generation capacity. Under forecasted climate scenarios, the runoff generation capacity of the watershed will tend to decrease and will not be noticeably different among the representative concentration pathways. Pasture and bare soil will give the lowest and highest runoff coefficients, respectively.

Keywords: surface runoff; hydrological model; cropland; pasture; deforestation; Global Circulation Model.

1. Introduction

Tropical forests, the richest terrestrial ecosystems in biodiversity and structural complexity terms (Whitmore 1990), are essential for maintaining the ecological integrity of watersheds (Ataroff & Rada 2000; Neill et al. 2001). However, the negative effects of land use and climate changes threaten these delicate environments.

Land use is a critical issue that affects primarily the hydrological cycle and the water balance of an ecosystem (Sui 2005), since the land cover influences potential evapotranspiration, infiltration, surface runoff and sediment yield in a watershed (Durães et al. 2011). Land use is subject to changes at several spatial scales, which significantly affects ecological systems (Vitousek 1994; Piniewski et al. 2014). For instance, a heavy decrease in land cover of tropical areas, such as deforestation of upstream watersheds and urbanization pressure, generally leads to more intense stormflow and erosion events with higher impacts on the water balance (de Paulo Rodrigues da Silva et al. 2018). In tropical conditions the effects of changes in land use and cover on the hydrological response of a watershed is still controversial (dos R. Pereira et al. 2016a); regarding deforestation risk, researches are not unanimous on how the lack of tree cover due to human actions impacts hydrology in tropical watersheds (Baker and Miller 2013; Chandler 2006).

In addition, climate change, resulting from the increase in greenhouse gas emissions, determines modifications of the hydrologic response of a watershed, and these impacts on the water resources availability (Arnell 1999). Future climate trends on a planetary scale show a significant increase in the temperature and a reduction in annual rainfall (Estrela et al. 2012; Senent-Aparicio et al. 2017). The increase in global temperature, modifying the evapotranspiration rates (Paparrizos et al. 2016; Urrutia & Vuille 2009), will significantly change the frequency and magnitude of hydrological events (i.e., floods and droughts) and will heavily influence the hydrological processes at local and global scales.

In general, the hydrological impacts of climate change have been widely investigated using General Circulation Models (GCMs), which provide information about historical, current and future climate (Gonzalez et al. 2010; Jing et al. 2015). The impacts of change impacts on hydrology are commonly evaluated using a pre-processed output from one or several GCMs as climatic input to hydrological models (Piniewski et al. 2013). Future precipitation and temperature data forecasted by GCMs give insights on future potential changes in the hydrological response of a large-scale territory (Hoomehr et al. 2016). Different greenhouse gases emissions (GHGs) scenarios can be projected, following the so-called Representative Concentration Pathways (RCPs) of the Intergovernmental Panel on

85 Climate Change 5th Assessment Report (IPCC 2014; Almagro et al. 2017). According to the latest
86 IPCC report (IPCC 2014), the global mean surface temperature increased by 0.85 °C from 1880 to
87 2012.

88 The simulation of watershed hydrology is perhaps the most important tool for water
89 resource planning and management, since it helps to evaluate and predict by a quantitative approach
90 the hydrological processes that control water movement at various time scales (Spruill et al. 2000).
91 More specifically, watershed hydrology can be simulated to estimate freshwater availability and
92 distribution (Piniewski et al 2017), to predict stream flows, and to evaluate the hydrological
93 response due to changes in land use and cover (dos R. Pereira et al. 2016a), and also under
94 simultaneous scenarios of climate change. Computer models are essential for simulating hydrologic
95 processes and their responses to both natural and anthropogenic factors at watershed scale (Lironga
96 & Jianyuna 2012) and for developing water management strategies (de Paulo Rodrigues da Silva et
97 al. 2018). Hydrological computer models can be coupled to GCMs to produce potential scenarios of
98 climate change effects on water resources. By this combination, the effects of climate change can be
99 linked to the hydrological response of a watershed, estimating water runoff, sediment yield and
100 impacts on water quality (Ficklin et al. 2009).

101 A number of watershed-scale models able to simulate surface runoff, soil erosion and
102 sediment/pollutant transport have been developed in the last decades. These models vary in
103 complexity and data input requirements (Borah & Bera 2004). Among the available models, SWAT
104 is one of the most used to determine streamflow response to changes in land cover conditions,
105 agricultural operations, and natural rainfall trends. However, in spite of its great potential as
106 powerful tool for analyses about watershed hydrology, SWAT remains yet to be fully exploited for
107 hydrological and predictions in tropical regions (de Paulo Rodrigues da Silva et al. 2018).
108 Therefore, in order to consolidate its use in delicate and complex environments, SWAT still
109 requires implementation in watersheds with climate and soil typical of tropical conditions (dos R.
110 Pereira et al. 2016b). Previous applications in these environmental contexts have shown that, after
111 calibration and validation, SWAT provides satisfactory performances in simulating annual and
112 monthly stream flows (Dourado-Hernandes et al. 2018). These results make the model an effective
113 means for hydrological predictions of water yields at the watershed scale (Douglas-Mankin et al.
114 2010; Gassman et al. 2007).

115 However, although research has mainly focused on streamflow using the SWAT model for
116 temperate zones, less attention has been paid to evaluations of watershed hydrology under land
117 cover and climate change scenarios in Brazil (de Paulo Rodrigues da Silva et al. 2018). Only limited
118 applications of hydrological models to assess the effects of climate and land use changes on the

hydrological response of a tropical areas are available (e.g., dos R. Pereira et al. 2016a; Almagro et al. 2017; Dourado Hernandez et al. 2018; de Paulo Rodrigues da Silva et al. 2018). This is especially important in watersheds with low availability of environmental data (Fukunaga et al. 2015; Zema et al. 2018). These applications are instead important for a region where hydrology has a high level of complexity, sourcing from both natural variability and human influences (de Paulo Rodrigues da Silva et al. 2018). This is the case of the Atlantic forest, the most threatened biome in Brazil, where the hydrological functions in forest ecosystems have had little attention by researchers (Zema et al. 2018), also because of the scarcity of hydrological observations (De Mello et al. 2016; Marmontel et al. 2018). The basic hypothesis of this study is that the hydrological response of a tropical watershed, as modified by land use and climate changes at basin scale, can be simulated and predicted by the SWAT model. To address this hypothesis, this paper has evaluated the SWAT accuracy in simulating the surface runoff in a watershed of South-East Brazil, which is representative of the very small and numerous watersheds of Mata Atlantica tropical forest. A large temporal scale was adopted to evaluate the watershed's runoff generation capacity, simulated by the model at the daily scale, under changed climate and land use in successive dry and wet years. First, the applicability and reliability of SWAT have been verified using a 20-year (1993-2014) database of observations. Then, the model has been used at the annual scale to simulate the watershed hydrological response under land uses (cropland, pasture and deforested soil) alternative to tropical forest and climate change scenarios. These latter have been predicted using an ensemble of three GCMs (MIROC5, GISS-E2-H and MRI-CGCM3). By this modelling exercise, indications about the most sustainable land use for water resource protection in this delicate ecosystem on the long term and under climate change forecasts can be given to land planners.

141

142 **2. Materials and methods**

143

144 **2.1 Study area**

145

146 The “A” micro-watershed (Figure 1) is located in the Parque Estadual da Serra do Mar (Cunha Municipality, Sao Paulo State, Brazil). It is a headwater, which is a tributary of the Paraibuna river, 147 which, in turn, flows into the main Paraíba do Sul river (East Atlantic region).The region is covered 148 with the Mata Atlantica rainforest, which is ecologically important for the conservation of 149 biodiversity and endemic species disappearance (Galindo-Leal and Câmara 2005).

150 The studied area consists of a mountain plateau at an altitude of 1000-1200 m. The 151 examined micro-watershed covers an area of 0.38 km², characterized by steep hillslopes (mean 152

slope of 22%). The main channel (whose mean slope is 12%) rises at 1171 metres a.s.l. and flows after 930 metres into the Paraibuna river (outlet coordinates 23°15'28"S, 45°2'26"W) at a height of 1062 m (Figure 1). According to Kirpich (1940), the concentration time of the watershed (that is, the time required by runoff to reach the closure section from the farthest hydraulically distant point, Chow et al., 1964) is estimated in 0.14 hours. The climate of the area is "Cwa", humid subtropical climate (Köppen classification). Precipitation is well distributed throughout the year (on the average 2200-2300 mm/year), and the maximum occurs in summer, while winters are dry. The average annual temperature is 19.1 °C, while the evapotranspiration is 682 mm/year (National Institute of Meteorology of Brazil, INMET). The latter is mainly due plant transpiration, since water evaporation from soil is quite negligible in Mata Atlantica (Fujieda et al. 1997).

Except on the case of very intense storms, the water course shows a constant hydrological regime, which is typical of tropical streams.

The area of the watershed is totally covered by tropical rain forest, an evergreen cover with a uniform canopy 20-m high, but some trees can reach 40 m (according to surveys by the Brazilian Institute of Geography and Statistics, IBGE) (Table 1). Since forest has been subjected to logging for more than 50 years, secondary vegetation is now recovering (Aguilar et al. 2001).

According to the taxonomic classification of the IBGE, the soil of the watershed is CX3 type (CX Tb Dystrophic + LVA Dystrophic), which corresponds to the Ferralic Cambisol and Rhodic Ferralsol classes of the FAO classification (Klam and Van Reeuwijk, 2000). Its texture is sandy loam (54% of sand, 16% of silt and 30% of clay, with 3.4% of organic matter) in the upper layer (350 mm) and clay (40% of sand, 7% of silt and 53% of clay, with 0.6% of organic matter) in the lower layer (350 to 1850 mm). The saturated hydraulic conductivity is 2 mm/h for both layers and the soil's hydrological group is "C" according the USDA-SCS classification (1986).

2.2 The hydrological database

Meteorological data were recorded by a weather station (Meteodata model) located at the watershed outlet. The station consisted of a rain gauge, a hygrothermograph, a pyranometer, a weather vane and an anemometer (Table 1).

Precipitation and runoff volumes were measured in 22 years (January 1993 to December 2014). Precipitation data was recorded at the daily scale, while discharge data were continuously measured at the watershed outlet by an ultrasonic flow meter (WR-11Z model, NAKAASA corporation, precision 0.5 cm) (Table 1). The measured flow depths were converted into water

186 discharge by a regression equation, as detailed in the studies of Cicco et al. (1987) and Zema et al.
187 (2018). Finally, the daily runoff volume was estimated from the discharge.

188 Observations of precipitation and runoff daily data simulated by SWAT were aggregated at
189 the annual scale for modelling purposes. The hydrological response of the watershed was quantified
190 by the annual runoff coefficient (hereinafter "RC"), equal to the ratio between the runoff volume
191 and the cumulative precipitation of the same year.

193 **2.3 Hydrological modelling**

195 *2.3.1 The SWAT model*

196
197 SWAT is a time-continuous, long-term, distributed-parameter, process-based hydrological model
198 that was developed to simulate surface and subsurface flow, soil erosion as well as sediment and
199 nutrient movement through a watershed (Arnold et al. 1998). Although SWAT has been mainly
200 used to study the hydrology of medium to large watershed (Piniewski et al. 2013), several
201 applications are found also in small watersheds (e.g., Meaurio et al. 2015; Qiu et al. 2012; Kang et
202 al. 2006; Licciardello et al. 2011).

203 In the SWAT model, a watershed is delineated into multiple sub-watersheds topologically
204 connected by stream networks (Strauch & Volk 2013). Each sub-watershed is further divided into
205 lumped hydrologic response units (HRUs). The HRUs are formed by overlaying maps of land use,
206 soil type, and topography (Neitsch et al. 2010), each one resulting of unique combination of these
207 features (De Mello et al. 2017).

208 The model simulates the hydrologic cycle separately for the "land phase" and "channel" or
209 "routing phase" processes (Strauch et al. 2013). The land phase, including water flow, nutrient
210 transport, and vegetation growth, is simulated at the HRU level (Strauch & Volk, 2013). Water,
211 sediments and nutrients are summed for all HRUs of a sub-watershed and the resulting flows are
212 then conveyed in the channel phase routing through channels, ponds, and reservoirs to the
213 watershed outlet (Ficklin et al. 2009). Therefore, land phase and channel processes are integrated by
214 SWAT at the sub-watershed level (Strauch & Volk, 2013).

215 In each HRU, SWAT estimates the components of the hydrological cycle (such as surface
216 runoff, baseflow, evapotranspiration, infiltration, and soil moisture change, Lironga & Jianyuna,
217 2012) using the following water balance equation (de Paulo Rodrigues da Silva et al. 2018):

218

$$SW_t = SW_0 + \sum_{t=1}^T (R - S_n - ET - W_a - R_f) \quad (1)$$

where:

SW_t = final soil water content on day t (mm)

SW_0 = initial soil water content on day i (mm)

T = time (days)

R = precipitation depth on day i (mm)

S_n = surface runoff volume on day i (mm)

ET = evapotranspiration depth on day i (mm)

W_a = amount of water entering the vadose zone from the soil profile on day i

R_f = amount of return flow on day i .

To estimate the components of the hydrological cycle, SWAT requires as input the daily data of precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed (de Paulo Rodrigues da Silva et al. 2018). Each hydrological component is estimated through SWAT sub-models related to climate, hydrology, erosion, land cover and plant growth, nutrients, pesticides, and land management (Neitsch et al. 2005). Surface runoff and infiltration volumes are simulated from daily precipitation using the Soil Conservation Service (SCS) Curve Number (CN) method (SCS, 1972).

2.3.2 Model implementation, calibration and validation

SWAT was implemented in the “A” micro-watershed, based on morphometry, climate, soil and land use input data, and evaluated across a period of 22 years (1993 to 2014).

A 30-m resolution Digital Elevation Model (produced by a Shuttle Radar Topography Mission) was used to generate the topography (Table 1). Thus, the watershed was discretised in SWAT into HRUs and its stream network was segmented into channels.

Climate data were provided by the meteorological station (Table 1) and input into the SWAT climate subroutines. Following Chow et al. (1964), surface runoff was separated from baseflow by the linear method applied to the observed streamflow records.

Soil parameters were derived from the Brazilian soil map prepared by IBGE in 2001 (Table 1). Two different soils (prevalently, sandy loam from surface to 350 mm, and clay from 350 mm to 1850 mm) were assumed. The land use was tropical rain forest.

The hydrological SWAT sub-model was run at the daily scale and its hydrological predictions evaluated at the annual scale by temporal aggregation. The default soil parameters were initially given to the model (Table 2). A default value of CN (equal to 70) of forest was first assumed, according to the standard procedure set by USDA (1972). The years of 1993 and 1994 were appended before the simulation period and used to warm up the model, in order to setup the soil's water content (Licciardello et al. 2007; von Stackelberg et al. 2007; Zhang et al. 2007; dos R. Pereira et al. 2016).

The model was calibrated and validated using the split-sample technique (Klemes 1986), applying the input parameters previously calibrated for a given period (calibration period, 1993-2004) to another period (validation period, 2005-2014) (dos R. Pereira et al. 2018). Prior to the calibration and validation process, the most sensitive parameters of the SWAT model for estimating surface runoff were identified by a sensitivity analysis, using SWAT-CUP (Calibration and Uncertainty Programs, Abbaspour 2007).

According the SWAT-CUP user's manual, the most sensitive parameters were identified using the "p-value" of a t-Student distribution, which tests the null hypothesis that each input parameter has not any effects on the model's output. A low p-value ($p = 0.05$ is the generally accepted threshold) indicates that this null hypothesis can be rejected. Therefore, if $p < 0.05$, the changes in the parameter are associated with changes in the surface runoff and that parameter is very sensitive.

SWAT-CUP was also used for the automated calibration of the model, adjusting the most influential parameters for streamflow simulation, as identified in the previous steps. More specifically, the automatic calibration was carried out (Fukunaga et al. 2015; Abbaspour 2007) as follows: (1) a threshold of the Nash & Sutcliffe coefficient (E, see below) higher than 0.4 was adopted as objective function; (2) physically meaningful absolute minimum and maximum ranges for the parameters being optimised were assumed using the values suggested in SWAT and SWAT-CUP guidelines; (3) one parameter at a time, all the parameters were varied between the minimum and maximum values until the highest value of E was achieved.

2.3.3 Evaluation of the runoff prediction capacity of the model in current conditions

Both for calibration and validation processes, the runoff prediction capability of SWAT was evaluated on the annual scale, due to the need of long-term (i.e., decadal) predictions required by this study.

SWAT performance was evaluated by (i) visually comparing the observed and simulated values of runoff volumes in scatterplots; and (ii) adopting a set of quantitative criteria, commonly used in hydrological modelling:

- the main statistics (i.e. the maximum, minimum, mean and standard deviation of both the observed and simulated values)
- the coefficient of determination (r^2)
- the coefficient of efficiency of Nash & Sutcliffe (1970, E)
- the Coefficient of Residual Mass (CRM, also reported as "percent bias", PBIAS).

The equations for their calculations are reported in the works of Moriasi et al. (2007), Zema et al. (2016), and Van Liew & Garbrecht (2003). The optimal values of these criteria are summarised as follows:

- the closer the statistics, the more accurate the model predictions;
- r^2 ranges from 0 (no agreement between model and data variance) to 1 (perfect agreement); values over 0.5 are acceptable (Santhi et al. 2001; Van Liew et al. 2003; Vieira et al. 2018);
- E, the most common measure of model accuracy, varies from $-\infty$ to 1; the model accuracy is "good" if $E \geq 0.75$, "satisfactory" if $0.36 \leq E \leq 0.75$ and "unsatisfactory" if $E \leq 0.36$ (Van Liew & Garbrecht 2003);
- CRM (or PBIAS), if positive, indicates model underestimation, whereas, if negative, overestimation (Gupta et al. 1999); an absolute value below 25% is considered fair (Moriasi et al. 2007).

2.3.4 Analysis of the watershed's hydrological response to land use and climate changes

Regarding land use changes, four scenarios were evaluated under the current weather conditions to assess the effect of land cover change on the hydrological response of the watershed. The differences of surface runoff generated by these scenarios in the period 1993-2014 were compared to the current landscape. In more detail, we simulated the hydrological effects of the replacement of native tropical forests (baseline scenario) with: (a) pasture (tropical herbaceous species); (b) crop cultivation (corn species); (3) bare soil (which is the effect of the total deforestation of the watershed) (Table 3). The choice of these scenarios is justified by the fact that areas previously covered by natural vegetation have been replaced by pasture or agriculture in most of the tropical semiarid regions of the world, resulting in a substantial increase in degraded or intensively cultivated areas. Hence, the scenarios analysed by the SWAT model can be helpful to identify conservation measures of natural resources and to recover degraded areas in Brazil and in tropical

319 regions (de Paulo Rodrigues da Silva et al. 2018). The hydrological effects of these land use
320 changes were input in SWAT by modifying the initial CNs. The values related to the land uses
321 alternative to forest were derived from the USDA-SCS guidelines for the soil hydrological group
322 "C".

323 Regarding the future weather projections, the climate changes forecasted for the next 80 years
324 were estimated by an ensemble of three Global Circulation Models (GCMs), which mathematically
325 represents the general circulation of a planetary atmosphere or ocean (Zhang et al. 2016). The GCM
326 numerical structure is based on integration of many equations describing fluid dynamics and
327 chemical processes (Krisanova et al. 2016). In this study, we used the following GCMs:

- 328 • MIROC5 (Atmosphere and Ocean Research Institute, University of Tokyo, National Institute
329 for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology,
330 Japan)
- 331 • GISS-E2-H (NASA Goddard Institute for Space Sciences, USA)
- 332 • MRI-CGCM3 (Meteorological Research Institute, Tsukuba, Japan).

333 Since GCMs usually provide global data at a rather coarse resolution (grid size about 100-200
334 km), GCM simulations were downscaled at a finer resolution suitable for regional or sub-regional
335 hydrological modelling (25-50 km). Following Zhang et al. (2016), the Statistical Downscaling
336 Method (SDSM), developed by Wilby et al. (2002), was applied to downscale the results for each
337 GCM in terms of regional climate forcing, i.e., the SWAT model input data over the watershed.
338 SDSM application consisted of five steps: 1) predictant (observed data) and predictor (large-scale
339 atmospheric variable) selection; 2) model calibration; 3) weather generator; 4) model validation;
340 and 5) future climate scenario generator.

341 Future monthly values were simulated and then transformed into daily values using the
342 weather generator of SWAT. The use of the internal weather generator of SWAT, instead of the
343 climate model outputs at the daily scale, allowed by-passing the not ease availability of data at the
344 lowest time scales of GCMs.

345 GCMs are driven by atmospheric GHG concentrations. As GHG emission scenarios, the so-
346 called Representative Concentration Pathways (RCPs 2.6, 4.5, 6.0 and 8.5) were adopted (IPCC,
347 2013; Krisanova et al. 2016). The radiative forcing level in 2100 of RCP8.5 is the highest while that
348 of RCP2.6 is the lowest (Li and Fang, 2016).

349 From each GCM and RCP, the monthly precipitation and maximum and minimum
350 temperatures for four 20-year periods (2020-2039, 2040-2059, 2060-2079 and 2080-2099) were
351 forecasted, in order to simulate surface runoff for the experimental watershed under the current
352 tropical forest or the other simulated land uses (pasture, cropland and bare soil) (Table 3).

353 Henceforth, these two conditions (actual precipitation, 1993-2014, and current land use, tropical
354 forest) will be indicated as "baseline" scenarios.

355 The baseline scenario (1993-2014) with the observed data may not agree with the same
356 period projected by the GCMs. If so, adjustments must be considered in the simulations of future
357 climate change scenarios, with data corrections to minimize the existing bias. These corrections are
358 based on the differences between observed and historical simulated values (Lenderink et al., 2007;
359 Santos et al., 2019). Therefore, the surface runoff was simulated by the calibrated SWAT model,
360 using the historical precipitation data of the three GCMs (available for the period 1993-2005).
361 These runoff simulations were finally compared to the corresponding values, simulated using the
362 historical data of observed precipitation for the same baseline period.

363

364 *2.3.4 Statistical analysis*

365

366 The statistical analysis was carried out using ANOVA. One-way ANOVA was applied to evaluate
367 the significance of differences: (i) in precipitation among the RCP scenarios of future climate
368 change; and (ii) in runoff volume and coefficient predicted by SWAT among the land uses. Then,
369 using two-way ANOVA and pairwise comparison by Tukey's test (at $p < 0.05$), we evaluated
370 whether the mean runoff volumes and coefficients (response variables) predicted by the model were
371 different among land use and climate change scenarios (independent factors). In order to satisfy the
372 assumptions of the statistical tests (equality of variance and normal distribution), the data were
373 subjected to normality test or were square root-transformed whenever necessary. All the statistical
374 tests were carried out by XLSTAT software.

375 3. Results

376

377 3.1 Evaluation of the runoff prediction capacity of SWAT model in current conditions

378

379 The values of the statistics and indexes used to assess the SWAT model performance in predicting
380 the surface runoff in the "A" micro-watershed are reported in Table 4. Although r^2 (equal to 0.82)
381 and CRM (0.15) were acceptable (> 0.50 and < 0.25 , respectively) when model run with default
382 input parameters, the E value was unsatisfactory ($= 0.35$, thus < 0.36). The positive CRM indicates
383 that the model tends to underestimate the observed annual runoff. Comparing the statistics of
384 predicted and observed runoff volumes, the errors were -15.4% and -35.5% for the average and
385 maximum values, respectively (Figure 2a).

386 The comparison of surface runoff values observed at the watershed outlet and predicted by
387 SWAT showed that, when the model run with default input parameters, its runoff prediction
388 capability was at the limit of acceptance. Using the SWAT-CUP procedure for SWAT calibration,
389 the model's performance noticeably improved. The good model performance given by the
390 calibration process was confirmed in the validation period. SWAT-CUP identified ten input
391 parameters, to which the model showed the highest sensitivity (Table 2 and Figure 3). After
392 calibration, the tendency to runoff underestimation was reduced, as shown by the CRM decreased to
393 a value close to zero). The changes in the input parameters let runoff predictions be closer to the
394 corresponding observations (Figures 2a and 4). More specifically, the mean, minimum and
395 maximum runoff volumes came very close to the corresponding observations and the differences
396 were lower than 3.5%. The E index (equal to 0.83) became good and the appreciable value of r^2 ,
397 achieved in model's runs with default parameters, increased to 0.86 (Table 4).

398 In the validation period, the degree of correlation between runoff observations and
399 predictions ($r^2 = 0.70$) decreased compared to the calibration period. The model's tendency to
400 underestimate the runoff in the calibration period turned to overestimation ($CRM < 0$) for the
401 validation period. The model efficiency, lower than in the calibration phase, remained however
402 satisfactory ($E = 0.70$). The predicted mean and maximum runoff volumes were practically equal to
403 the observations (differences of 1.7% and 2.8%, respectively). The prediction error increased only
404 for the minimum values (about 10%) (Table 4 and Figure 2b).

405 The difference between the precipitation, and runoff volume and coefficient simulated by
406 the SWAT model with the observed data and the corresponding simulations using the three GCMs
407 for the baseline period (1993-2005) was always lower than 1% and not statistically significant (at p

408 < 0.05) (Table 5). Therefore, no adjustments were considered in the simulations of future climate
409 change scenarios.

410

411 ***3.2 Evaluation of the watershed hydrological response to land use and climate changes***

412

413 ***3.2.1 Land use changes in the baseline period (1993-2014)***

414

415 Compared to the baseline value (1321 mm/yr, years 1993-2014), when the forest was the actual soil
416 cover, and under the same rainfall input (on the average 1847 mm/yr), land use change to pasture
417 would give the lowest surface runoff (on the average 1290 mm/yr, -2.32%), while the worst
418 hydrological response (that is, higher runoff) would be produced by a soil left bare due to total
419 deforestation (1437 mm/yr, +8.81%). Replacing the forest cover by agricultural activities, the
420 runoff would undergo a very slight change (1329 mm/yr, +0.63%) (Table 6).

421

422 ***3.2.2 Climate and land use changes in the future (2020-2099)***

423

424 Under the mean values of future climate projections, averaged among the adopted GCMs, and
425 assuming as baseline the actual land use (tropical forest, 1402 mm/yr of surface runoff), if the
426 hydrological variables are averaged among all the simulated climate change scenarios, crop cover
427 and soil left bare would increase of the surface runoff (1486 mm/yr, +6.0%, and 1562 mm/yr,
428 +11.4%), while pasture would slightly reduce runoff volume (1486 mm/yr, -1.6%) (Table 6).
429 Almagro et al. (2017) report that South-East Brazil (where the studied watershed is located) will be
430 one of the most greatly affected regions in terms of rainfall erosion, since a decrease (-5% to -41%,
431 depending on the GCM adopted) in mean rainfall erosivity is forecasted.

432 Referring to the different RCPs, RCP 4.5 is expected to give the highest precipitation
433 (averaging the three GCMs adopted, 1976 mm/yr, +7.0% compared the average value of the
434 baseline period, 1847 mm/yr, years 2003-2014), while RCP 8.5 will provide the lowest precipitation
435 input (1936 mm/yr, +4.8%). Under the other RCPs, the precipitation increase will be lower (1945,
436 RCP 2.6 and 1944, RCP 6.0, mm/yr) (Table 6 and Figures 5a to d). Compared to the baseline value
437 (on the average 1321 mm/yr), RCP 4.5 will presumably produce the highest runoff volumes in the
438 80-year period (on the average 1478 mm/yr, +11.9%). Conversely, the minimum surface runoff will
439 be achieved under RCP 2.6 and RCP 8.5 (1449 mm/yr, +9.7%, for both RCPs) (Table 6 and Figures
440 5a to d).

441

4. Discussions

4.1 Evaluation of the runoff prediction capacity of SWAT model

The automated calibration procedure has demonstrated the importance of the tree canopy interception ("CANMX.hru" parameter) in tropical forests, whose value was increased during calibration. Shares of tree canopy interception close to 15-20% has been quantified by several studies in tropical forests (e.g., Franken et al. 1982a; 1982b; Zema et al. 2018). Also Strauch et al. (2012, in Brazil) as well as Zhang et al. (2016, in China) and Raneesh & Thampi Santosh (2011, in India) found that SWAT is strongly sensitive to this input parameter.

Also water infiltration in the soil was modified, decreasing the available water capacity of the soil ("SOL_AWC().sol") and increasing the fraction of the infiltrating water into the deep aquifer percolation fraction ("RCHRG_DP.gw") as well as the soil evaporation compensation factor ("ESCO.hru") (Table 2). The increase of the latter parameter allowed the model to reduce the evaporative demand from lower soil levels, when it accounts for the effect of the capillary action, crusting and cracks. "SOL_AWC().sol" and "ESCO.hru" were among the most sensitive parameters in SWAT model applications in the same environmental contexts (Strauch et al. 2012; De Mello et al. 2016) and in other climate conditions (e.g., Tan et al. 2017, in Malaysia; Zhang et al. 2016, in China; Raneesh et al. 2011, in India; Senent-Aparicio et al. 2017, in Spain). The initial CN for antecedent moisture condition II ("CN2.mgt"), a basic parameter for accurate surface runoff prediction for almost all the prediction models using the SCS-CN hydrological component (Licciardello et al. 2007; Strauch et al. 2013; Zema et al. 2017), was increased from the default value of 70 to 77.3. This change increased the soil's aptitude to produce surface runoff and thus reduced the model's tendency to its underestimation (Table 4). A similar increase was needed in the study of Strauch & Volk (2013), in order to reach a better fit to peak flows observed in a watershed under the same environmental conditions (Cerrado bioma, Brazil). Conversely, Strauch et al. (2012; 2013) reported the need to decrease CN2 parameter in Brazilian basins, since the soil physical properties and practices (such as the infiltration capacity and management activities) were not properly reflected in initial CN2 and the initially assumed reference values were too high (Fukunaga et al. 2015). Also De Mello et al. (2016) and Strauch et al. (2012) found a high sensitivity of SWAT model to "CN2.mgt" parameter under the same environmental conditions as those of this study.

Other minor changes needed by SWAT-CUP to improve runoff prediction capacity of SWAT were applied to the moist bulk density ("SOL_BD().sol"), effective hydraulic conductivity in tributary channel alluvium ("CH_K1.sub"), lateral flow travel time ("LAT_TTIME.hru"),

476 Manning's coefficient "n" value for overland flow ("OV_N.hru") and saturated hydraulic
477 conductivity ("SOL_K().sol"). All these parameters were noticeably increased, since under default
478 simulations many of these were assumed as null (Table 2). It is interesting to highlight that the
479 calibrated value of the saturated hydraulic conductivity set by SWAT-CUP may be unrealistic, but
480 it must be also noted that: (i) the model's sensitivity to this input parameter was quite limited; and
481 (ii) the calibrated value came from a mathematical optimisation rather than a physically-based
482 optimisation.

483 It should be also evidenced that other input parameters that were identified by SWAT-CUP
484 as the most influential in SWAT applications of other studies (for instance, "ALPHA_BF" =
485 Baseflow recession constant, "GW_DELAY" = Groundwater delay time, "GWQMN" = Water
486 depth in shallow aquifer for return flow, "CH_N2" = Manning's "n" value for the main channel,
487 "RCHRG_DP" = Deep aquifer percolation fraction) (De Mello et al. 2016; Strauch et al. 2012; Tan
488 et al. 2017; Zhang et al. 2016; Raneesh et al. 2011; Senent-Aparicio et al. 2017) were not
489 considered as sensitive parameters in this study (Figure 3). The low sensitivity of SWAT to these
490 parameters is quite surprising, since the hydrological processes which many of these factors govern
491 (for instance, deep percolation, sub-surface flow, filtration in deeper layers of soil) have a large
492 importance in the hydrological cycle of small forest watersheds under tropical conditions (Fujieda
493 et al. 1997; Zema et al. 2018). This indicates that autocalibration should be done within relatively
494 strict parameter ranges set after manual calibration or using additional hydrological observations
495 such as evapotranspiration or soil moisture. Moreover, this confirms again that SWAT-CUP
496 calibration often lacks realistic links to the physical processes.

497 Overall, the evaluation over the entire period of more than 20 years (1993-2014) showed
498 that, provided that the model is calibrated: (i) SWAT slightly underestimates the observed runoff
499 volumes (CRM = 0.01); (ii) the model is able to give very accurate annual predictions of surface
500 runoff, as shown by r^2 and E, both close to 0.82; (iii) the differences between the observed and
501 predicted means are negligible (lower than 2-3%) (Table 4). As the results of calibration and
502 validation procedures have demonstrated, the predicted runoff volumes on the annual scale were
503 very close to the observations, approaching to the identity line of the scatter plot, with very few
504 exceptions (Figure 4). Model performance was more satisfactory in the calibration period than for
505 validation, as shown by the higher values of the evaluation criteria adopted in this study. This is due
506 to the fact that the parameter values are specifically optimised for the calibration period and thus the
507 validation period may have different conditions that cause the calibrated parameters to be less than
508 optimal (Fukunaga et al. 2015).

509 Almost all the previous evaluations of SWAT model in the same climatic and
510 geomorphological conditions were carried out by comparing the observed and predicted daily and
511 monthly stream flows rather than the annual values as in this study. SWAT prediction capacity of
512 runoff at the daily scale, beyond the aims of this study, was not satisfactory in the experimental
513 watershed, as highlighted by the large difference in the majority of the evaluation criteria (mean, E
514 and CRM, data not shown) adopted for model's performance evaluations (under the acceptance
515 limits suggested by literature). The values of the Nash and Sutcliffe coefficient were in the range
516 0.41 (Strauch et al. 2013) to 0.82 (Dourado-Hernandes et al. 2018), while the maximum absolute
517 value of PBIAS (5.9) was found by Strauch & Volk (2013). All the authors reported that SWAT
518 model predicted high stream flows better than low flow conditions (de Paulo Rodrigues da Silva et
519 al. 2018). Regarding the only model's application at the annual scale at the authors' knowledge, De
520 Mello et al. (2017) found r^2 of 0.82, E of 0.71 and PBIAS of -12.1 in the calibration period, and r^2
521 of 0.76, E of 0.37 and PBIAS of -16.7 in the validation period in SWAT implementation in Sarapuá
522 River watershed (southeast Brazil) for water quality predictions.

523

524 ***4.2 Evaluation of the watershed hydrological response to land use and climate changes***

525

526 The hydrological response of the watershed to land use and climate changes were quantified in this
527 study by adopting the annual runoff coefficients of each land use and climate scenario. This allows
528 the assessment of the water resource dynamics, which is governed by the succession of wet and dry
529 years, in the natural and delicate ecosystem of the studied watershed. The analysis of a multidecadal
530 scale is in accordance to Krysanova et al. (2016), who suggests comparisons of outputs of
531 hydrological models, driven by climate model data, for the reference and future scenario periods,
532 using 30-year average annual and monthly outputs.

533

534 ***4.2.1 Land use changes in the baseline period (1993-2014)***

535

536 The actual forest cover of the watershed determined a runoff coefficient, averaged in the period
537 1993-2014, of 0.71. This value is about 9% lower (and significant at $p < 0.05$) than for bare soil
538 (RC = 0.78), which simulates a complete deforestation of the watershed. This increase shows the
539 role of vegetation cover in the influence of the hydrological balance of the watershed. As a matter
540 of fact, the presence of tropical forest increases water losses, providing greater water infiltration and
541 storage in soil, replenishing groundwater and improving flow regularity (Zema et al. 2018). More
542 generally, forests increase canopy interception, transpiration of plant tissues, evaporation from soil

543 and water infiltration; thus, the share of precipitation that turns to surface runoff is reduced.
544 Furthermore, forest vegetation and in particular riparian complexes play positive effects for
545 conservation of water quality in tropical headwater watersheds, where, instead, agriculture and
546 pasture may represent a threat against natural resource preservation (Marmontel et al. 2018).

547 A conversion of the current land use (forest) to cropland or pasture would determine a slight
548 increase ($RC = 0.72$, $+0.63\%$) or decrease ($RC = 0.70$, -2.32%), respectively, of the runoff
549 coefficients; these variations were not significant at $p < 0.05$. This means that the experimental
550 tropical watershed does not show a so high sensitivity to land use, regardless of the type of the
551 change introduced. In other words, a slight decrease of water losses, expected under pasture and
552 agricultural activities, would not significantly affect the water balance of the watershed.

553 The lower runoff generation capacity of pasture compared to the other land uses is in
554 accordance with findings of de Paulo Rodrigues da Silva et al. (2018), who applied SWAT in a
555 tropical river basin of Eastern Brazil. These authors showed that: (i) the smallest runoff was
556 generated in areas with pasture cover; (ii) its replacement by maize cultivation increased the surface
557 volume drained to the regions; and (iii) the runoff increased by 70% in areas with bare soil. These
558 results indicated an increasing trend in runoff from pasture to cropland and areas without vegetation
559 cover. Conversely, Dourado-Hernandes et al. (2018) found that a limited expansion of cropland
560 (namely sugarcane) should have no effect on stream flows generated in a watershed of Cerrado
561 biome (same tropical conditions), also under climate change scenarios (until 2030). The slightly
562 higher runoff generation capacity simulated by SWAT in tropical forest in comparison with pasture
563 cover may be quite surprising and however would deserve deeper investigations. A possible
564 explanation has been found here by an analysis of the different components of the hydrological
565 cycle simulated by SWAT. It emerged that pasture supports a higher evapotranspiration compared
566 to forest (on the average 483 against 460 mm/yr, respectively). The more intense evapotranspiration
567 rate of pasture may be supported by both the higher re-evaporation from the shallow aquifer (97
568 against 92 mm/yr) to the root zone and the lower percolation (80 against 72 mm/yr) into
569 groundwater, presumably due to the denser basal area of the pasture cover of the root zone. This is
570 accordance to Wolf et al. (2011), who report that in tropical environments the fraction of
571 evaporation from the soil is higher in the pasture than at the forest sites. Furthermore, in tropical
572 regions, grassland has the potential to transport as much or more water vapour to the atmosphere
573 than forest does (Brauman et al. 2015). Santos et al. (2015) report that, compared to forest, higher
574 levels of compaction may have favoured greater water loss in pasture areas of tropical areas
575 (Southwestern Amazonia).

576 The increase of runoff generation capacity in a deforested area suggested by SWAT in the
577 studied micro-watershed agrees with the results of dos Reis Pereira et al. (2014; 2016b). These
578 authors studied the impacts of deforestation on a watershed on the Brazilian east coast and found an
579 increased water flow in the analysed river due to decreased evapotranspiration.

580

581 4.2.2 Climate and land use changes in the future (2020-2099)

582

583 Under the future climate projections, a decadal variability of runoff coefficients was forecasted as
584 watershed responds to variations of input precipitation in time windows of 20 years. More
585 specifically, while an almost constant runoff coefficient may be expected throughout the 80-year
586 period, the related values fluctuate for all the studied land uses with a similar shape. In spite of these
587 fluctuations, the negative slope of the regression lines of RCs indicates that across the forecast
588 period the runoff generation capacity of the experimental watershed will slightly decrease (Figures
589 6a to 6d). Among the different RCPs, the hydrological response of the watershed soil will be more
590 intense under RCP 4.5 for all the investigated land uses, except for the pasture cover (Figures 6 and
591 7). The differences in precipitation and runoff coefficient were not significant at $p < 0.05$ among the
592 RCP scenarios, while runoff was significantly different among some RCPs. Moreover, while the
593 runoff was significantly different between forest and pasture on one side, and cropland and bare soil
594 on the other side, all the evaluated land uses gave significantly different runoff coefficients (Table
595 6).

596 If the runoff coefficients of the observation period (1993-2014) are assumed as reference, a
597 combined analysis of the effects of climate and land use changes on the future hydrological
598 response of the watershed can be made.

599 Firstly, the mean runoff generation capacity of the experimental watershed is expected to
600 slightly decrease in pasture for all the RCPs analysed (on the average by -0.9%), while an increase
601 can be forecasted under forest (+0.8%), except for RCP 2.6, and crop (+6.8%) covers. If the soil
602 will be bare (e.g., for a deforested watershed), this increase will be the highest (+12.4%) among the
603 analysed land uses (Figure 7a). This indicates that, compared to tropical forest or cropland,
604 pastureland is more efficient to govern the hydrological response of the watershed.

605 Secondly, the maximum runoff coefficients will increase (positive variations compared the
606 baseline, on the average +23.3%) under all the land use and climate change scenarios. Since the
607 highest RCs can be expected in occasion of years with floods (that is, when the soil is saturated and
608 the runoff capacity generation gets its maximum value) and is linked to soil erosion, this means that
609 in the future the climate change will determine an aggravation of the flood and soil erosion risks in

610 this tropical watershed. However, although flooding is one of the problems of the studied
611 watershed, the flood risk is not the most critical. While it is obvious that over bare soil this increase
612 will be the highest (+33.3%), less expected is the fact that agricultural activities and forest cover
613 will induce higher RCs (+25.8% and +18.3%, respectively) compared to pasture (+15.9%) (Figure
614 7b).

615 Thirdly, it is well known that a minimum runoff generation is vital for surface water body
616 recharge and thus to feed potable water to population and irrigation resources to crops, when
617 groundwater is not exploited. Small watersheds of tropical forests must have an adequate water
618 supply to compensate the high evapotranspiration rates of forest throughout the year (Zema et al.
619 2018). If the availability of surface water is related to the minimum values of runoff coefficients,
620 from the future predictions of surface runoff provided by SWAT model it is evident that a pasture
621 cover will produce the highest reduction of surface runoff (on the average -2.8%). Conversely, the
622 minimum runoff generation capacity will remain constant under tropical forest (-0.84%), while it
623 will increase in cropland (+3.7%) and in particular in bare soil (+9.6%) (Figure 7c).

624 Comparisons of our results with other literature experiments are quite hard, due to the lack
625 of similar studies analysing the effects of climate change in tropical watersheds. Regarding other
626 SWAT applications in other environmental contexts, we should consider modelling experiences in
627 USA, Spain, China, Malaysia and India. The study of Ficklin et al. (2009), carried out in an
628 agricultural watershed of California, showed its high sensitivity to the climate change, indicating
629 that not only temperature and precipitation have significant effects on all hydrological components
630 of the water cycle, but also that these effects are complicated by the activities of irrigated
631 agriculture. In the headwater of the Segura River basin (South-eastern Spain), Senent-Aparicio et al.
632 (2017) showed that, compared the baseline period (1971-2000), the negative and positive trends of
633 precipitation and temperature, respectively, will lead to a decrease in the availability of water
634 resources by between 2 and 5% in this important water supplying basin. Raneesh & Thampi
635 Santosh (2011) implemented SWAT in an Indian watershed (humid tropics) with forest and
636 agricultural land uses and predicted that stream flow will undergo a declining trend under future
637 climate change scenarios. However, the effect will not adversely affect agricultural production in
638 the watershed, because the future temperature increase will be compensated by an expected storm
639 intensity increase in the summer and pre-monsoon periods. A mountainous large watershed of
640 China was monitored and modelled using SWAT by Zhang et al. (2016), who noticed relatively
641 slight changes in stream flows in both RCP 2.6 and RCP 4.5, but increases under RCP 8.5.
642 However, these authors suggested that future projections given by GCM emission scenarios must be
643 considered with caution. As a matter of fact, GCMs generally cannot fully capture the interactions

644 between atmospheric and hydrological processes and thus the effects of future climate changes on
645 stream flows are largely uncertain (Knutti & Sedláček 2013). Tan et al. (2017) got to the same
646 conclusions (that is, larger surface runoff changes under the RCP 8.5 compared to the RCP 2.6 and
647 RCP 4.5, and large uncertainties in GCMs and RCPs), applying SWAT to a large watershed
648 dominated by tropical rainforest and rubber and oil palm plantations in Malaysia.

649 From a social approach, the evaluation of land use and climate impacts on future
650 management of water resources at the watershed scale indicates that deforestation must be avoided.
651 Leaving the soil bare would increase the flood risk in urban areas (with possible loss of lives and
652 infrastructure damages) and this would be a very large impact under the forecasted climate change.
653 Moreover, although the SWAT simulations have demonstrated that a land use change from forest to
654 pasture or cropland would have a moderate impact on the runoff generation capacity, this
655 conversion would determine a significant loss of biodiversity in highly natural watersheds of the
656 tropical environment; society should not accept that this hazard may happen in one of the most
657 delicate ecosystems in the world. Finally, the risk of water resource reduction in tropical rivers can
658 be expected in some of the simulated climate scenarios, and this could lead to the reduction of clear
659 water availability for potable uses.

660 Overall, since the study has shown that SWAT is able to delineate the hydrological response
661 of tropical watersheds to natural (e.g., climate change) or anthropogenic (e.g., land use
662 modification) forcing, this model represents a useful tool for land planners and, more in general,
663 socio-economic stakeholders, in order to adopt the most suitable measures for water resource and
664 soil protection.

666 5. Conclusions

667
668 Once the applicability and reliability of SWAT model in predicting surface runoff have been
669 verified at the annual scale and improved by calibration in a tropical forest watershed, its
670 hydrological response under four alternative land uses (forest, cropland, pasture and bare soil) and
671 forecasted climate changes has been simulated. The results of model application showed that the
672 tropical watershed under investigation does not show a high sensitivity to land use, regardless of the
673 type of the change introduced, provided that the soil is not left bare. If forest was replaced by crops
674 or pasture, slight increases or decreases of the runoff coefficients would be expected, but the
675 watershed's hydrological response would not significantly been affected. Conversely, a complete
676 deforestation, leaving the soil bare, would increase the runoff generation capacity of the watershed.

677 Despite the uncertainty of future weather projections, under forecasted climate change
 678 scenarios, the most conservative and sustainable land use on the long term basically will depend on
 679 water management purposes established by land planners. More specifically, the runoff generation
 680 capacity of the watershed will tend to decrease and will not be noticeably different among the four
 681 climate change scenarios simulated throughout the next 80-year period. In the RCP 4.5, which will
 682 produce the most intense hydrological response in the watershed, pasture and bare soil have been
 683 found to give the lowest and highest runoff coefficients, respectively. To protect the watershed from
 684 floods and soil erosion, the most "hydrologically" efficient land use is pasture, since the conversion
 685 from forest to a natural herbaceous cover (as pasture is) will allow a decrease of the maximum
 686 values of the runoff coefficient. Finally, since the minimum runoff generation capacity will remain
 687 basically constant under tropical forest, the presence of the current tree cover will be suitable to
 688 assure surface water body recharge and thus to feed potable water to population and irrigation
 689 resources to crops. The societal implications of the forecasted changes in tropical forest watersheds
 690 go from the aggravation of the flood risk to the reduction of water resource availability for potable
 691 uses.

692 Overall, the study has confirmed the good accuracy in runoff predictions of the SWAT
 693 model, and provided useful indications about the sustainability of water resource management in
 694 tropical watersheds under climate and land use change scenarios. The model can support land
 695 planners' strategies in view of the conservation of the delicate ecosystems of tropical forests.

696

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698

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925 **TABLES**

926

927 Table 1. Values and source of the input data for implementation of the SWAT model at "A" micro-
928 watershed (Brazil).

929

<i>Input data</i>	<i>Source</i>	<i>Notes</i>
<i>Topography</i>	Topodata project of the National Institute of Spatial Investigation (INPE) of Brazil, based on data from the Shuttle Radar Topography Mission (SRTM)	Spatial resolution of 30 metres
<i>Soil</i>	Soil map of 2001, prepared by the Brazilian Institute of Geography and Statistics (IBGE)	Ferralic Cambisol Rhodic Ferralsol
<i>Land use</i>	Land use map of 2014, prepared by the Brazilian Institute of Geography and Statistics (IBGE)	Tropical rain forest
<i>Weather</i>	Meteorological station installed in the watershed	Hygrothermograph Pyranometer Weather vane Anemometer
<i>Hydrology</i>	Precipitation measured using a rain gauging station (W11-00-60 model, NAKAASA Instruments Company Ltd., Japan)	Precision 0.5 mm
	Water flow depth measured by ultrasonic flow meter (WR-11Z model, NAKAASA Instruments Company Ltd., Japan)	

930

931 Table 2. Input parameters with default values and calibrated by SWAT-CUP procedure in SWAT model implementation at the "A" micro-watershed
932 (Brazil).
933

Parameter		Measuring <i>unit</i>	Value	
<i>Name</i>	<i>SWAT acronym</i>		<i>default</i>	<i>calibrated</i>
Initial SCS runoff curve number for moisture condition II	CN2.mgt	(-)	70	77.3
Baseflow alpha factor	ALPHA_BF.gw	1/days	0.91	0.93
Groundwater delay time	GW_DELAY.gw	days	31	367
Threshold depth of water in the shallow aquifer required for return flow to occur	GWQMN.gw	mm H ₂ O	1000	1725
Groundwater "revap" coefficient	GW_REVAP.gw	(-)	0.02	0.19
Soil evaporation compensation factor	ESCO.hru	(-)	0.95	0.99
Plant uptake compensation factor	EPCO.hru	(-)	1	0.73
Manning's coefficient "n" value for the main channels	CH_N2.rte	(-)	0.014	0.251
Effective hydraulic conductivity in main channel alluvium	CH_K2.rte	mm/hr	0	498
Available water capacity of the soil layer	SOL_AWC().sol	mm H ₂ O/mm soil	0.06	0.03
Moist bulk density	SOL_BD().sol	g/cm ³	1.40	2.34
Saturated hydraulic conductivity	SOL_K().sol	mm/hr	2	1152
Threshold depth of water in the shallow aquifer required for "revap" or percolation to the deep aquifer to occur	REVAPMN.gw	mm H ₂ O	750	96
Manning's coefficient "n" value for overland flow	OV_N.hru	(-)	0.60	13.6
Deep aquifer percolation fraction	RCHRG_DP.gw	(-)	0.05	0.23

Maximum canopy storage	CANMX.hru	mm H ₂ O	0	0.15
Surface runoff lag coefficient	SURLAG.bsn	(-)	2	21.4
Average slope length	SLSUBBSN.hru	m	15.2	130
Lateral flow travel time	LAT_TTIME.hru	days	0	18.8
Initial groundwater height	GWHT.gw	m	1	21.5
Effective hydraulic conductivity in tributary channel alluvium	CH_K1.sub	mm/hr	0	69.8
Manning's coefficient "n" value for the tributary channels	CH_N1.sub	(-)	0.01	18.9

934 Table 3. Scheme of the land use and climate change Representative Concentration Pathways (RCPs) adopted for evaluation the hydrological
 935 response of the "A" micro-watershed (Brazil) by the SWAT model.

936

		Land use scenarios			
		<i>Forest (baseline)</i>	<i>Cropland</i>	<i>Pasture</i>	<i>Bare soil</i>
Climate change scenarios	<i>Baseline (1993-2014)</i>	X	X	X	X
	<i>RCP 2.6 (2020-2099)</i>	X	X	X	X
	<i>RCP 4.5 (2020-2099)</i>	X	X	X	X
	<i>RCP 6.0 (2020-2099)</i>	X	X	X	X
	<i>RCP 8.5 (2020-2099)</i>	X	X	X	X

937 Note: RCP = Representative Concentration Pathways.

938 Table 4. Statistics and model evaluation criteria for the surface runoff observations and predictions
 939 by the SWAT model at the "A" micro-watershed outlet (Brazil).
 940

Surface runoff	Model input parameters	Mean	Std. Dev.	Min	Max	r ²	E	CRM (PBIAS)
		(mm/yr)						
Calibration (1993-2003)								
Observed	-	1309	312	862	1712	-	-	-
Predicted	Default	1108	326	556	1583	0.82	0.35	0.15
	Calibrated	1265	257	874	1657	0.86	0.83	0.03
Validation (2004-2014)								
Observed	-	1347	271	912	1843	-	-	-
Predicted	Validated	1370	251	1002	1895	0.71	0.70	-0.02
Whole period (1993-2014)								
Observed	-	1328	286	862	1843	-	-	-
Predicted	Default	1180	309	566	1848	0.62	0.25	0.11
	Calibrated/ validated	1321	253	875	1881	0.78	0.78	0.01

941

942 Table 5. Difference (%) between the hydrological data simulated by the SWAT model with
 943 observed and projected precipitation (provided by three GCMs) for the baseline period (1993-2005)
 944 at the "A" micro-watershed outlet (Brazil).
 945

Statistics	Global Circulation Model								
	MIROC5			GISS-E2-H			MRI-CGM3		
	Rainfall	Runoff	Runoff coeff.	Rainfall	Runoff	Runoff coeff.	Rainfall	Runoff	Runoff coeff.
Mean	0.05	-0.56	0.03	-0.61	-0.95	0.30	-0.13	0.20	0.99
Minimum	-0.98	-0.84	0.14	-0.98	-0.66	0.32	-0.62	0.38	1.00
Maximum	0.71	0.89	-0.12	0.95	0.41	-0.83	0.82	0.90	-0.22
Standard deviation	0.31	0.64	-0.27	1.02	-0.54	0.52	0.67	0.64	0.52

946 Note: all differences are not statistically significant after one-way ANOVA (at $p < 0.05$).

947

948 Table 6. Statistics (mean $\pm$ std. dev. among GCM models) of the surface runoff predictions by the SWAT model under climate and land use change

949 Representative Concentration Pathways (RCPs) at the "A" micro-watershed outlet (Brazil).

950

Climate scenario		Precipitation (mm)	Surface runoff (mm)					Runoff coefficient				
			Land use scenario					Land use scenario				
			Forest (baseline)	Cropland	Pasture	Bare soil	Mean	Forest (baseline)	Cropland	Pasture	Bare soil	Mean
1993-2014 (baseline)		1847	1321 a	1329 a	1290 a	1437 a	1344	0.71 a	0.72 a	0.70 a	0.78 b	0.73
2020-2099	RCP 2.6	1945 $\pm$ 27 A	1391 $\pm$ 18	1480 $\pm$ 16	1368 $\pm$ 16	1557 $\pm$ 17	1449 $\pm$ 17 A	0.72 $\pm$ 0.004	0.76 $\pm$ 0.006	0.70 $\pm$ 0.004	0.80 $\pm$ 0.006	0.75 $\pm$ 0.005 A
	RCP 4.5	1976 $\pm$ 30 A	1421 $\pm$ 21	1509 $\pm$ 18	1397 $\pm$ 18	1587 $\pm$ 30	1478 $\pm$ 22 B	0.72 $\pm$ 0.004	0.77 $\pm$ 0.005	0.71 $\pm$ 0.005	0.81 $\pm$ 0.006	0.75 $\pm$ 0.005 A
	RCP 6.0	1944 $\pm$ 22 A	1398 $\pm$ 15	1483 $\pm$ 14	1377 $\pm$ 14	1555 $\pm$ 14	1453 $\pm$ 14 AB	0.72 $\pm$ 0.004	0.76 $\pm$ 0.006	0.71 $\pm$ 0.004	0.80 $\pm$ 0.006	0.75 $\pm$ 0.005 A
	RCP 8.5	1936 $\pm$ 42 A	1398 $\pm$ 28	1471 $\pm$ 26	1377 $\pm$ 26	1550 $\pm$ 28	1449 $\pm$ 27 A	0.72 $\pm$ 0.0005	0.76 $\pm$ 0.006	0.71 $\pm$ 0.005	0.80 $\pm$ 0.007	0.75 $\pm$ 0.006 A
	Mean	1950 $\pm$ 30	1402 $\pm$ 20 a	1486 $\pm$ 19 b	1380 $\pm$ 18 a	1562 $\pm$ 22 c	-	0.72 $\pm$ 0.004 a	0.76 $\pm$ 0.006 b	0.71 $\pm$ 0.005 c	0.80 $\pm$ 0.006 d	-

951 Note: Different lowercase and capital letters indicate significant differences among land use and climate change scenarios, respectively, after two-way ANOVA and Tukey's test

952 (at $p < 0.05$).

953