

Citação:

Manuel Esteban Lucas-Borja, Bruno Gianmarco Carrà, João Pedro Nunes, Léonard Bernard-Jannin, Demetrio Antonio Zema & Santo Marcello Zimbone (2020): Impacts of land-use and climate changes on surface runoff in a tropical forest watershed (Brazil), Hydrological Sciences Journal, DOI: 10.1080/02626667.2020.1787417

DOI: <https://doi.org/10.1080/02626667.2020.1787417>

1 **Impacts of land use and climate changes on surface runoff in a tropical forest** 2 **watershed (Brazil)**

3
4
5
6
7
8
9 4 Manuel Esteban Lucas-Borja⁽¹⁾, Bruno Gianmarco Carrà⁽²⁾, João Pedro Nunes⁽³⁾,
10 5 Léonard Bernard-Jannin^(4,5), Demetrio Antonio Zema^(2,*), Santo Marcello Zimbone⁽²⁾

11
12
13
14
15 7 *(1) Departamento de Ciencia y Tecnología Agroforestal y Genética, Universidad de Castilla La*
16 8 *Mancha, Campus Universitario s/n, C.P. 02071, Albacete (Spain)*

17
18 9 *(2) Department "Agraria", University "Mediterranea" of Reggio Calabria, Località Feo di Vito, I-*
19 10 *89122 Reggio Calabria (Italy)*

20
21 11 *(3) CE3C – Centre for Ecology, Evolution and Environmental Changes, Faculdade de Ciências,*
22 12 *Universidade de Lisboa, 1749-016 Lisboa (Portugal)*

23
24
25 13 *(4) Laboratoire d'Ecologie Fonctionnelle et Environnement (ECOLAB), UMR 5245 CNRS-UPS-*
26 14 *INPT Ecole Nationale Supérieure Agronomique de Toulouse (ENSAT), Avenue de l'Agrobiopole*
27 15 *BP 32607 Auzeville Tolosane (France)*

28
29
30 16 *(5) Institut des Sciences de la Terre d'Orléans (ISTO), UMR 7327 Université d'Orléans-CNRS-*
31 17 *BRGM, 1A rue de la Férellerie 45100 Orléans (France)*

32
33
34
35 19 (*) Demetrio Antonio Zema, corresponding author, dzema@unirc.it

36 37 38 39 21 Abstract

40 22 Surface runoff generation capacity can be modified by land use and climate changes. Annual
41 23 runoff volumes have been evaluated in a small watershed of tropical forest (Brazil), using
42 24 SWAT model. Firstly, the accuracy of SWAT in runoff predictions has been assessed by
43 25 default input parameters and improved by automatic calibration, using 20-year observations.
44 26 Then, the hydrological response under land uses (cropland, pasture and deforested soil)
45 27 alternative to tropical forest, and climate change scenarios has been simulated. SWAT
46 28 application has showed that, if forest was replaced by crops or pasture, the watershed's
47 29 hydrological response would not significantly be affected. Conversely, a complete
48 30 deforestation would slightly increase its runoff generation capacity. Under forecasted climate
49 31 scenarios, the runoff generation capacity of the watershed will tend to decrease and will not be
50 32 noticeably different among the representative concentration pathways. Pasture and bare soil
51 33 will give the lowest and highest runoff coefficients, respectively.

52
53
54
55
56 34 Keywords: surface runoff; hydrological model; cropland; pasture; deforestation; Global
57 35 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

1
2
3 70 Climate Change 5th Assessment Report (IPCC 2014; Almagro et al. 2017). According to the latest
4
5 71 IPCC report (IPCC 2014), the global mean surface temperature increased by 0.85 °C from 1880 to
6
7 72 2012.

8 73 The simulation of watershed hydrology is perhaps the most important tool for water
9
10 74 resource planning and management, since it helps to evaluate and predict by a quantitative approach
11
12 75 the hydrological processes that control water movement at various time scales (Spruill et al. 2000).
13
14 76 More specifically, watershed hydrology can be simulated to estimate freshwater availability and
15
16 77 distribution (Piniewski et al 2017), to predict stream flows, and to evaluate the hydrological
17
18 78 response due to changes in land use and cover (dos R. Pereira et al. 2016a), and also under
19
20 79 simultaneous scenarios of climate change. Computer models are essential for simulating hydrologic
21
22 80 processes and their responses to both natural and anthropogenic factors at watershed scale (Lironga
23
24 81 & Jianyuna 2012) and for developing water management strategies (de Paulo Rodrigues da Silva et
25
26 82 al. 2018). Hydrological computer models can be coupled to GCMs to produce potential scenarios of
27
28 83 climate change effects on water resources. By this combination, the effects of climate change can be
29
30 84 linked to the hydrological response of a watershed, estimating water runoff, sediment yield and
31
32 85 impacts on water quality (Ficklin et al. 2009).

31 86 A number of watershed-scale models able to simulate surface runoff, soil erosion and
32
33 87 sediment/pollutant transport have been developed in the last decades. These models vary in
34
35 88 complexity and data input requirements (Borah & Bera 2004). Among the available models, SWAT
36
37 89 is one of the most used to determine streamflow response to changes in land cover conditions,
38
39 90 agricultural operations, and natural rainfall trends. However, in spite of its great potential as
40
41 91 powerful tool for analyses about watershed hydrology, SWAT remains yet to be fully exploited for
42
43 92 hydrological and predictions in tropical regions (de Paulo Rodrigues da Silva et al. 2018).
44
45 93 Therefore, in order to consolidate its use in delicate and complex environments, SWAT still
46
47 94 requires implementation in watersheds with climate and soil typical of tropical conditions (dos R.
48
49 95 Pereira et al. 2016b). Previous applications in these environmental contexts have shown that, after
50
51 96 calibration and validation, SWAT provides satisfactory performances in simulating annual and
52
53 97 monthly stream flows (Dourado-Hernandes et al. 2018). These results make the model an effective
54
55 98 means for hydrological predictions of water yields at the watershed scale (Douglas-Mankin et al.
56
57 99 2010; Gassman et al. 2007).

55 100 However, although research has mainly focused on streamflow using the SWAT model for
56
57 101 temperate zones, less attention has been paid to evaluations of watershed hydrology under land
58
59 102 cover and climate change scenarios in Brazil (de Paulo Rodrigues da Silva et al. 2018). Only limited
60
61 103 applications of hydrological models to assess the effects of climate and land use changes on the

1
2
3 104 hydrological response of a tropical areas are available (e.g., dos R. Pereira et al. 2016a; Almagro et
4
5 105 al. 2017; Dourado Hernandez et al. 2018; de Paulo Rodrigues da Silva et al. 2018). This is
6
7 106 especially important in watersheds with low availability of environmental data (Fukunaga et al.
8
9 107 2015; Zema et al. 2018). These applications are instead important for a region where hydrology has
10 108 a high level of complexity, sourcing from both natural variability and human influences (de Paulo
11
12 109 Rodrigues da Silva et al. 2018). This is the case of the Atlantic forest, the most threatened biome in
13
14 110 Brazil, where the hydrological functions in forest ecosystems have had little attention by researchers
15 111 (Zema et al. 2018), also because of the scarcity of hydrological observations (De Mello et al. 2016;
16
17 112 Marmontel et al. 2018). The basic hypothesis of this study is that the hydrological response of a
18
19 113 tropical watershed, as modified by land use and climate changes at basin scale, can be simulated
20
21 114 and predicted by the SWAT model. To address this hypothesis, this paper has evaluated the SWAT
22 115 accuracy in simulating the surface runoff in a watershed of South-East Brazil, which is
23
24 116 representative of the very small and numerous watersheds of Mata Atlantica tropical forest. A large
25
26 117 temporal scale was adopted to evaluate the watershed's runoff generation capacity, simulated by the
27 118 model at the daily scale, under changed climate and land use in successive dry and wet years. First,
28
29 119 the applicability and reliability of SWAT have been verified using a 20-year (1993-2014) database
30
31 120 of observations. Then, the model has been used at the annual scale to simulate the watershed
32
33 121 hydrological response under land uses (cropland, pasture and deforested soil) alternative to tropical
34 122 forest and climate change scenarios. These latter have been predicted using an ensemble of three
35
36 123 GCMs (MIROC5, GISS-E2-H and MRI-CGCM3). By this modelling exercise, indications about
37
38 124 the most sustainable land use for water resource protection in this delicate ecosystem on the long
39
40 125 term and under climate change forecasts can be given to land planners.

41 126 42 43 127 **2. Materials and methods**

44 128 45 46 129 **2.1 Study area**

47
48 130
49
50 131 The “A” micro-watershed (Figure 1) is located in the Parque Estadual da Serra do Mar (Cunha
51 132 Municipality, Sao Paulo State, Brazil). It is a headwater, which is a tributary of the Paraibuna river,
52
53 133 which, in turn, flows into the main Paraíba do Sul river (East Atlantic region). The region is covered
54
55 134 with the Mata Atlantica rainforest, which is ecologically important for the conservation of
56
57 135 biodiversity and endemic species disappearance (Galindo-Leal and Câmara 2005).

58 136 The studied area consists of a mountain plateau at an altitude of 1000-1200 m. The
59
60 137 examined micro-watershed covers an area of 0.38 km², characterized by steep hillslopes (mean

1
2
3 138 slope of 22%). The main channel (whose mean slope is 12%) rises at 1171 metres a.s.l. and flows
4
5 139 after 930 metres into the Paraibuna river (outlet coordinates 23°15'28"S, 45°2'26"W) at a height of
6
7 140 1062 m (Figure 1). According to Kirpich (1940), the concentration time of the watershed (that is,
8
9 141 the time required by runoff to reach the closure section from the farthest hydraulically distant point,
10 142 Chow et al., 1964) is estimated in 0.14 hours. The climate of the area is "Cwa", humid subtropical
11
12 143 climate (Köppen classification). Precipitation is well distributed throughout the year (on the average
13
14 144 2200-2300 mm/year), and the maximum occurs in summer, while winters are dry. The average
15 145 annual temperature is 19.1 °C, while the evapotranspiration is 682 mm/year (National Institute of
16
17 146 Meteorology of Brazil, INMET). The latter is mainly due plant transpiration, since water
18
19 147 evaporation from soil is quite negligible in Mata Atlantica (Fujieda et al. 1997).

20 148 Except on the case of very intense storms, the water course shows a constant hydrological
21
22 149 regime, which is typical of tropical streams.

23
24 150 The area of the watershed is totally covered by tropical rain forest, an evergreen cover with
25
26 151 a uniform canopy 20-m high, but some trees can reach 40 m (according to surveys by the Brazilian
27
28 152 Institute of Geography and Statistics, IBGE) (Table 1). Since forest has been subjected to logging
29 153 for more than 50 years, secondary vegetation is now recovering (Aguiar et al. 2001).

30
31 154 According to the taxonomic classification of the IBGE, the soil of the watershed is CX3 type
32
33 155 (CX Tb Dystrophic + LVA Dystrophic), which corresponds to the Ferralic Cambisol and Rhodic
34
35 156 Ferralsol classes of the FAO classification (Klam and Van Reeuwijk, 2000). Its texture is sandy
36 157 loam (54% of sand, 16% of silt and 30% of clay, with 3.4% of organic matter) in the upper layer
37
38 158 (350 mm) and clay (40% of sand, 7% of silt and 53% of clay, with 0.6% of organic matter) in the
39
40 159 lower layer (350 to 1850 mm). The saturated hydraulic conductivity is 2 mm/h for both layers and
41 160 the soil's hydrological group is "C" according the USDA-SCS classification (1986).

42 43 161 44 45 162 **2.2 The hydrological database**

46 163
47
48 164 Meteorological data were recorded by a weather station (Metedata model) located at the watershed
49
50 165 outlet. The station consisted of a rain gauge, a hygrothermograph, a pyranometer, a weather vane
51
52 166 and an anemometer (Table 1).

53 167 Precipitation and runoff volumes were measured in 22 years (January 1993 to December
54
55 168 2014). Precipitation data was recorded at the daily scale, while discharge data were continuously
56
57 169 measured at the watershed outlet by an ultrasonic flow meter (WR-11Z model, NAKAASA
58
59 170 corporation, precision 0.5 cm) (Table 1). The measured flow depths were converted into water
60

1
2
3 171 discharge by a regression equation, as detailed in the studies of Cicco et al. (1987) and Zema et al.
4
5 172 (2018). Finally, the daily runoff volume was estimated from the discharge.

6
7 173 Observations of precipitation and runoff daily data simulated by SWAT were aggregated at
8
9 174 the annual scale for modelling purposes. The hydrological response of the watershed was quantified
10 175 by the annual runoff coefficient (hereinafter "RC"), equal to the ratio between the runoff volume
11
12 176 and the cumulative precipitation of the same year.

13 177 14 178 **2.3 Hydrological modelling**

15 179 16 180 *2.3.1 The SWAT model*

17 181
18
19 182 SWAT is a time-continuous, long-term, distributed-parameter, process-based hydrological model
20 183 that was developed to simulate surface and subsurface flow, soil erosion as well as sediment and
21 184 nutrient movement through a watershed (Arnold et al. 1998). Although SWAT has been mainly
22 185 used to study the hydrology of medium to large watershed (Piniewski et al. 2013), several
23 186 applications are found also in small watersheds (e.g., Meaurio et al. 2015; Qiu et al. 2012; Kang et
24 187 al. 2006; Licciardello et al. 2011).

25 188 In the SWAT model, a watershed is delineated into multiple sub-watersheds topologically
26 189 connected by stream networks (Strauch & Volk 2013). Each sub-watershed is further divided into
27 190 lumped hydrologic response units (HRUs). The HRUs are formed by overlaying maps of land use,
28 191 soil type, and topography (Neitsch et al. 2010), each one resulting of unique combination of these
29 192 features (De Mello et al. 2017).

30 193 The model simulates the hydrologic cycle separately for the "land phase" and "channel" or
31 194 "routing phase" processes (Strauch et al. 2013). The land phase, including water flow, nutrient
32 195 transport, and vegetation growth, is simulated at the HRU level (Strauch & Volk, 2013). Water,
33 196 sediments and nutrients are summed for all HRUs of a sub-watershed and the resulting flows are
34 197 then conveyed in the channel phase routing through channels, ponds, and reservoirs to the
35 198 watershed outlet (Ficklin et al. 2009). Therefore, land phase and channel processes are integrated by
36 199 SWAT at the sub-watershed level (Strauch & Volk, 2013).

37 200 In each HRU, SWAT estimates the components of the hydrological cycle (such as surface
38 201 runoff, baseflow, evapotranspiration, infiltration, and soil moisture change, Lironga & Jianyuna,
39 202 2012) using the following water balance equation (de Paulo Rodrigues da Silva et al. 2018):
40 203

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

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.

1
2
3 237 The hydrological SWAT sub-model was run at the daily scale and its hydrological
4
5 238 predictions evaluated at the annual scale by temporal aggregation. The default soil parameters were
6
7 239 initially given to the model (Table 2). A default value of CN (equal to 70) of forest was first
8
9 240 assumed, according to the standard procedure set by USDA (1972). The years of 1993 and 1994
10 241 were appended before the simulation period and used to warm up the model, in order to setup the
11
12 242 soil's water content (Licciardello et al. 2007; von Stackelberg et al. 2007; Zhang et al. 2007; dos R.
13
14 243 Pereira et al. 2016).

15 244 The model was calibrated and validated using the split-sample technique (Klemes 1986),
16
17 245 applying the input parameters previously calibrated for a given period (calibration period, 1993-
18
19 246 2004) to another period (validation period, 2005-2014) (dos R. Pereira et al. 2018). Prior to the
20
21 247 calibration and validation process, the most sensitive parameters of the SWAT model for estimating
22
23 248 surface runoff were identified by a sensitivity analysis, using SWAT-CUP (Calibration and
24 249 Uncertainty Programs, Abbaspour 2007).

25 250 According the SWAT-CUP user's manual, the most sensitive parameters were identified
26
27 251 using the "p-value" of a t-Student distribution, which tests the null hypothesis that each input
28
29 252 parameter has not any effects on the model's output. A low p-value ($p = 0.05$ is the generally
30
31 253 accepted threshold) indicates that this null hypothesis can be rejected. Therefore, if $p < 0.05$, the
32
33 254 changes in the parameter are associated with changes in the surface runoff and that parameter is
34
35 255 very sensitive.

36 256 SWAT-CUP was also used for the automated calibration of the model, adjusting the most
37
38 257 influential parameters for streamflow simulation, as identified in the previous steps. More
39
40 258 specifically, the automatic calibration was carried out (Fukunaga et al. 2015; Abbaspour 2007) as
41
42 259 follows: (1) a threshold of the Nash & Sutcliffe coefficient (E, see below) higher than 0.4 was
43
44 260 adopted as objective function; (2) physically meaningful absolute minimum and maximum ranges
45
46 261 for the parameters being optimised were assumed using the values suggested in SWAT and SWAT-
47
48 262 CUP guidelines; (3) one parameter at a time, all the parameters were varied between the minimum
49
50 263 and maximum values until the highest value of E was achieved.

51 265 *2.3.3 Evaluation of the runoff prediction capacity of the model in current conditions*

52 266

53 267 Both for calibration and validation processes, the runoff prediction capability of SWAT was
54
55 268 evaluated on the annual scale, due to the need of long-term (i.e., decadal) predictions required by
56
57 269 this study.
58
59
60

1

2

3 270

4

5 271

6

7 272

8

9 273

10 274

11

12 275

13

14 276

15 277

16 278

17 279

18

19 280

20

21 281

22 282

23 283

24 284

25 285

26 286

27 287

28 288

29 289

30 290

31 291

32 292

33 293

34 294

35 295

36 296

37 297

38 298

39 299

40 300

41 301

42 302

43 303

44

45

46

47

48

49

50

51

52

53

54

55

56

57

58

59

60

60

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

1
2
3 304 regions (de Paulo Rodrigues da Silva et al. 2018). The hydrological effects of these land use
4
5 305 changes were input in SWAT by modifying the initial CNs. The values related to the land uses
6
7 306 alternative to forest were derived from the USDA-SCS guidelines for the soil hydrological group
8
9 307 "C".

10 308 Regarding the future weather projections, the climate changes forecasted for the next 80 years
11
12 309 were estimated by an ensemble of three Global Circulation Models (GCMs), which mathematically
13
14 310 represents the general circulation of a planetary atmosphere or ocean (Zhang et al. 2016). The GCM
15
16 311 numerical structure is based on integration of many equations describing fluid dynamics and
17
18 312 chemical processes (Krisanova et al. 2016). In this study, we used the following GCMs:

- 19 313 • MIROC5 (Atmosphere and Ocean Research Institute, University of Tokyo, National Institute
20
21 314 for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology,
22
23 315 Japan)
- 24 316 • GISS-E2-H (NASA Goddard Institute for Space Sciences, USA)
- 25
26 317 • MRI-CGCM3 (Meteorological Research Institute, Tsukuba, Japan).

27 318 Since GCMs usually provide global data at a rather coarse resolution (grid size about 100-200
28
29 319 km), GCM simulations were downscaled at a finer resolution suitable for regional or sub-regional
30
31 320 hydrological modelling (25-50 km). Following Zhang et al. (2016), the Statistical Downscaling
32
33 321 Method (SDSM), developed by Wilby et al. (2002), was applied to downscale the results for each
34
35 322 GCM in terms of regional climate forcing, i.e., the SWAT model input data over the watershed.
36
37 323 SDSM application consisted of five steps: 1) predictant (observed data) and predictor (large-scale
38
39 324 atmospheric variable) selection; 2) model calibration; 3) weather generator; 4) model validation;
40
41 325 and 5) future climate scenario generator.

42 326 Future monthly values were simulated and then transformed into daily values using the
43
44 327 weather generator of SWAT. The use of the internal weather generator of SWAT, instead of the
45
46 328 climate model outputs at the daily scale, allowed by-passing the not ease availability of data at the
47
48 329 lowest time scales of GCMs.

49 330 GCMs are driven by atmospheric GHG concentrations. As GHG emission scenarios, the so-
50
51 331 called Representative Concentration Pathways (RCPs 2.6, 4.5, 6.0 and 8.5) were adopted (IPCC,
52
53 332 2013; Krisanova et al. 2016). The radiative forcing level in 2100 of RCP8.5 is the highest while that
54
55 333 of RCP2.6 is the lowest (Li and Fang, 2016).

56 334 From each GCM and RCP, the monthly precipitation and maximum and minimum
57
58 335 temperatures for four 20-year periods (2020-2039, 2040-2059, 2060-2079 and 2080-2099) were
59
60 336 forecasted, in order to simulate surface runoff for the experimental watershed under the current
337
338 tropical forest or the other simulated land uses (pasture, cropland and bare soil) (Table 3).

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

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

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

349 *2.3.4 Statistical analysis*

350
351 The statistical analysis was carried out using ANOVA. One-way ANOVA was applied to evaluate
352 the significance of differences: (i) in precipitation among the RCP scenarios of future climate
353 change; and (ii) in runoff volume and coefficient predicted by SWAT among the land uses. Then,
354 using two-way ANOVA and pairwise comparison by Tukey's test (at $p < 0.05$), we evaluated
355 whether the mean runoff volumes and coefficients (response variables) predicted by the model were
356 different among land use and climate change scenarios (independent factors). In order to satisfy the
357 assumptions of the statistical tests (equality of variance and normal distribution), the data were
358 subjected to normality test or were square root-transformed whenever necessary. All the statistical
359 tests were carried out by XLSTAT software.

3. Results

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

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

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

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

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

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

394 < 0.05) (Table 5). Therefore, no adjustments were considered in the simulations of future climate
395 change scenarios.

397 ***3.2 Evaluation of the watershed hydrological response to land use and climate changes***

398 *3.2.1 Land use changes in the baseline period (1993-2014)*

400
401 Compared to the baseline value (1321 mm/yr, years 1993-2014), when the forest was the actual soil
402 cover, and under the same rainfall input (on the average 1847 mm/yr), land use change to pasture
403 would give the lowest surface runoff (on the average 1290 mm/yr, -2.32%), while the worst
404 hydrological response (that is, higher runoff) would be produced by a soil left bare due to total
405 deforestation (1437 mm/yr, +8.81%). Replacing the forest cover by agricultural activities, the
406 runoff would undergo a very slight change (1329 mm/yr, +0.63%) (Table 6).

407 *3.2.2 Climate and land use changes in the future (2020-2099)*

408
409 Under the mean values of future climate projections, averaged among the adopted GCMs, and
410 assuming as baseline the actual land use (tropical forest, 1402 mm/yr of surface runoff), if the
411 hydrological variables are averaged among all the simulated climate change scenarios, crop cover
412 and soil left bare would increase of the surface runoff (1486 mm/yr, +6.0%, and 1562 mm/yr,
413 +11.4%), while pasture would slightly reduce runoff volume (1486 mm/yr, -1.6%) (Table 6).
414 Almagro et al. (2017) report that South-East Brazil (where the studied watershed is located) will be
415 one of the most greatly affected regions in terms of rainfall erosion, since a decrease (-5% to -41%,
416 depending on the GCM adopted) in mean rainfall erosivity is forecasted.

417 Referring to the different RCPs, RCP 4.5 is expected to give the highest precipitation
418 (averaging the three GCMs adopted, 1976 mm/yr, +7.0% compared the average value of the
419 baseline period, 1847 mm/yr, years 2003-2014), while RCP 8.5 will provide the lowest precipitation
420 input (1936 mm/yr, +4.8%). Under the other RCPs, the precipitation increase will be lower (1945,
421 RCP 2.6 and 1944, RCP 6.0, mm/yr) (Table 6 and Figures 5a to d). Compared to the baseline value
422 (on the average 1321 mm/yr), RCP 4.5 will presumably produce the highest runoff volumes in the
423 80-year period (on the average 1478 mm/yr, +11.9%). Conversely, the minimum surface runoff will
424 be achieved under RCP 2.6 and RCP 8.5 (1449 mm/yr, +9.7%, for both RCPs) (Table 6 and Figures
425 5a to d).

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"),

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

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

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

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

1
2
3 495 Almost all the previous evaluations of SWAT model in the same climatic and
4
5 496 geomorphological conditions were carried out by comparing the observed and predicted daily and
6
7 497 monthly stream flows rather than the annual values as in this study. SWAT prediction capacity of
8
9 498 runoff at the daily scale, beyond the aims of this study, was not satisfactory in the experimental
10 499 watershed, as highlighted by the large difference in the majority of the evaluation criteria (mean, E
11
12 500 and CRM, data not shown) adopted for model's performance evaluations (under the acceptance
13
14 501 limits suggested by literature). The values of the Nash and Sutcliffe coefficient were in the range
15 502 0.41 (Strauch et al. 2013) to 0.82 (Dourado-Hernandes et al. 2018), while the maximum absolute
16
17 503 value of PBIAS (5.9) was found by Strauch & Volk (2013). All the authors reported that SWAT
18
19 504 model predicted high stream flows better than low flow conditions (de Paulo Rodrigues da Silva et
20
21 505 al. 2018). Regarding the only model's application at the annual scale at the authors' knowledge, De
22 506 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
23
24 507 of 0.76, E of 0.37 and PBIAS of -16.7 in the validation period in SWAT implementation in Sarapuá
25
26 508 River watershed (southeast Brazil) for water quality predictions.

27 509 28 29 510 **4.2 Evaluation of the watershed hydrological response to land use and climate changes**

30
31 511
32 512 The hydrological response of the watershed to land use and climate changes were quantified in this
33
34 513 study by adopting the annual runoff coefficients of each land use and climate scenario. This allows
35
36 514 the assessment of the water resource dynamics, which is governed by the succession of wet and dry
37
38 515 years, in the natural and delicate ecosystem of the studied watershed. The analysis of a multidecadal
39
40 516 scale is in accordance to Krysanova et al. (2016), who suggests comparisons of outputs of
41 517 hydrological models, driven by climate model data, for the reference and future scenario periods,
42
43 518 using 30-year average annual and monthly outputs.

44 519 45 46 520 **4.2.1 Land use changes in the baseline period (1993-2014)**

47 521
48
49 522 The actual forest cover of the watershed determined a runoff coefficient, averaged in the period
50
51 523 1993-2014, of 0.71. This value is about 9% lower (and significant at $p < 0.05$) than for bare soil
52
53 524 (RC = 0.78), which simulates a complete deforestation of the watershed. This increase shows the
54
55 525 role of vegetation cover in the influence of the hydrological balance of the watershed. As a matter
56
57 526 of fact, the presence of tropical forest increases water losses, providing greater water infiltration and
58
59 527 storage in soil, replenishing groundwater and improving flow regularity (Zema et al. 2018). More
60 528 generally, forests increase canopy interception, transpiration of plant tissues, evaporation from soil

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

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

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

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

1
2
3 562 The increase of runoff generation capacity in a deforested area suggested by SWAT in the
4
5 563 studied micro-watershed agrees with the results of dos Reis Pereira et al. (2014; 2016b). These
6
7 564 authors studied the impacts of deforestation on a watershed on the Brazilian east coast and found an
8
9 565 increased water flow in the analysed river due to decreased evapotranspiration.
10 566

11 567 *4.2.2 Climate and land use changes in the future (2020-2099)*

12 568

15 569 Under the future climate projections, a decadal variability of runoff coefficients was forecasted as
16
17 570 watershed responds to variations of input precipitation in time windows of 20 years. More
18
19 571 specifically, while an almost constant runoff coefficient may be expected throughout the 80-year
20
21 572 period, the related values fluctuate for all the studied land uses with a similar shape. In spite of these
22
23 573 fluctuations, the negative slope of the regression lines of RCs indicates that across the forecast
24
25 574 period the runoff generation capacity of the experimental watershed will slightly decrease (Figures
26
27 575 6a to 6d). Among the different RCPs, the hydrological response of the watershed soil will be more
28
29 576 intense under RCP 4.5 for all the investigated land uses, except for the pasture cover (Figures 6 and
30
31 577 7). The differences in precipitation and runoff coefficient were not significant at $p < 0.05$ among the
32
33 578 RCP scenarios, while runoff was significantly different among some RCPs. Moreover, while the
34
35 579 runoff was significantly different between forest and pasture on one side, and cropland and bare soil
36
37 580 on the other side, all the evaluated land uses gave significantly different runoff coefficients (Table
38
39 581 6).

38 582 If the runoff coefficients of the observation period (1993-2014) are assumed as reference, a
39
40 583 combined analysis of the effects of climate and land use changes on the future hydrological
41
42 584 response of the watershed can be made.

43 585 Firstly, the mean runoff generation capacity of the experimental watershed is expected to
44
45 586 slightly decrease in pasture for all the RCPs analysed (on the average by -0.9%), while an increase
46
47 587 can be forecasted under forest (+0.8%), except for RCP 2.6, and crop (+6.8%) covers. If the soil
48
49 588 will be bare (e.g., for a deforested watershed), this increase will be the highest (+12.4%) among the
50
51 589 analysed land uses (Figure 7a). This indicates that, compared to tropical forest or cropland,
52
53 590 pastureland is more efficient to govern the hydrological response of the watershed.

53 591 Secondly, the maximum runoff coefficients will increase (positive variations compared the
54
55 592 baseline, on the average +23.3%) under all the land use and climate change scenarios. Since the
56
57 593 highest RCs can be expected in occasion of years with floods (that is, when the soil is saturated and
58
59 594 the runoff capacity generation gets its maximum value) and is linked to soil erosion, this means that
60
595 in the future the climate change will determine an aggravation of the flood and soil erosion risks in

1

2

3 596 this tropical watershed. However, although flooding is one of the problems of the studied
4 watershed, the flood risk is not the most critical. While it is obvious that over bare soil this increase
5 597 will be the highest (+33.3%), less expected is the fact that agricultural activities and forest cover
6 598 will induce higher RCs (+25.8% and +18.3%, respectively) compared to pasture (+15.9%) (Figure
7 599 7b).

10 600

11

12 601 Thirdly, it is well known that a minimum runoff generation is vital for surface water body
13 602 recharge and thus to feed potable water to population and irrigation resources to crops, when
14 603 groundwater is not exploited. Small watersheds of tropical forests must have an adequate water
15 604 supply to compensate the high evapotranspiration rates of forest throughout the year (Zema et al.
16 605 2018). If the availability of surface water is related to the minimum values of runoff coefficients,
17 606 from the future predictions of surface runoff provided by SWAT model it is evident that a pasture
18 607 cover will produce the highest reduction of surface runoff (on the average -2.8%). Conversely, the
19 608 minimum runoff generation capacity will remain constant under tropical forest (-0.84%), while it
20 609 will increase in cropland (+3.7%) and in particular in bare soil (+9.6%) (Figure 7c).

26 609

27 610

28 Comparisons of our results with other literature experiments are quite hard, due to the lack
29 611 of similar studies analysing the effects of climate change in tropical watersheds. Regarding other
30 612 SWAT applications in other environmental contexts, we should consider modelling experiences in
31 613 USA, Spain, China, Malaysia and India. The study of Ficklin et al. (2009), carried out in an
32 614 agricultural watershed of California, showed its high sensitivity to the climate change, indicating
33 615 that not only temperature and precipitation have significant effects on all hydrological components
34 616 of the water cycle, but also that these effects are complicated by the activities of irrigated
35 617 agriculture. In the headwater of the Segura River basin (South-eastern Spain), Senent-Aparicio et al.
36 618 (2017) showed that, compared the baseline period (1971-2000), the negative and positive trends of
37 619 precipitation and temperature, respectively, will lead to a decrease in the availability of water
38 620 resources by between 2 and 5% in this important water supplying basin. Raneesh & Thampi
39 621 Santosh (2011) implemented SWAT in an Indian watershed (humid tropics) with forest and
40 622 agricultural land uses and predicted that stream flow will undergo a declining trend under future
41 623 climate change scenarios. However, the effect will not adversely affect agricultural production in
42 624 the watershed, because the future temperature increase will be compensated by an expected storm
43 625 intensity increase in the summer and pre-monsoon periods. A mountainous large watershed of
44 626 China was monitored and modelled using SWAT by Zhang et al. (2016), who noticed relatively
45 627 slight changes in stream flows in both RCP 2.6 and RCP 4.5, but increases under RCP 8.5.
46 628 However, these authors suggested that future projections given by GCM emission scenarios must be
47 629 considered with caution. As a matter of fact, GCMs generally cannot fully capture the interactions

60 629

1
2
3 630 between atmospheric and hydrological processes and thus the effects of future climate changes on
4
5 631 stream flows are largely uncertain (Knutti & Sedláček 2013). Tan et al. (2017) got to the same
6
7 632 conclusions (that is, larger surface runoff changes under the RCP 8.5 compared to the RCP 2.6 and
8
9 633 RCP 4.5, and large uncertainties in GCMs and RCPs), applying SWAT to a large watershed
10 634 dominated by tropical rainforest and rubber and oil palm plantations in Malaysia.

11
12 635 From a social approach, the evaluation of land use and climate impacts on future
13
14 636 management of water resources at the watershed scale indicates that deforestation must be avoided.
15 637 Leaving the soil bare would increase the flood risk in urban areas (with possible loss of lives and
16
17 638 infrastructure damages) and this would be a very large impact under the forecasted climate change.
18
19 639 Moreover, although the SWAT simulations have demonstrated that a land use change from forest to
20
21 640 pasture or cropland would have a moderate impact on the runoff generation capacity, this
22 641 conversion would determine a significant lost of biodiversity in highly natural watersheds of the
23
24 642 tropical environment; society should not accept that this hazard may happen in one of the most
25
26 643 delicate ecosystems in the world. Finally, the risk of water resource reduction in tropical rivers can
27 644 be expected in some of the simulated climate scenarios, and this could lead to the reduction of clear
28
29 645 water availability for potable uses.

30
31 646 Overall, since the study has shown that SWAT is able to delineate the hydrological response
32
33 647 of tropical watersheds to natural (e.g., climate change) or anthropogenic (e.g., land use
34 648 modification) forcing, this model represents a useful tool for land planners and, more in general,
35
36 649 socio-economic stakeholders, in order to adopt the most suitable measures for water resource and
37
38 650 soil protection.

39 651 40 41 652 **5. Conclusions**

42
43 653
44 654 Once the applicability and reliability of SWAT model in predicting surface runoff have been
45
46 655 verified at the annual scale and improved by calibration in a tropical forest watershed, its
47
48 656 hydrological response under four alternative land uses (forest, cropland, pasture and bare soil) and
49
50 657 forecasted climate changes has been simulated. The results of model application showed that the
51
52 658 tropical watershed under investigation does not show a high sensitivity to land use, regardless of the
53
54 659 type of the change introduced, provided that the soil is not left bare. If forest was replaced by crops
55 660 or pasture, slight increases or decreases of the runoff coefficients would be expected, but the
56
57 661 watershed's hydrological response would not significantly been affected. Conversely, a complete
58
59 662 deforestation, leaving the soil bare, would increase the runoff generation capacity of the watershed.
60

1

2

3 663

4

5 664

6 665

7 666

8 667

9 668

10 669

11 670

12 671

13 672

14 673

15 674

16 675

17 676

18 677

19 678

20 679

21 680

22 681

23 682

24 683

25 684

26 685

27 686

28 687

29 688

30 689

31 690

32 691

33 692

34 693

35 694

36 695

37 696

38

39

40

41

42

43

44

45

46

47

48

49

50

51

52

53

54

55

56

57

58

59

60

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

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

References

- Abbaspour, K.C., 2007. User Manual for SWAT-CUP, SWAT Calibration and Uncertainty Analysis Programs. Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, Switzerland.
- Aguiar, O.T., Pastore, J.A, Rocha, F.T., Baitello, J.B., 2001. Flora fanerogamic a stretch of Secondary Dense Forest in the Serra do Mar State Park - Core Cunha/Indaiá (SP). *Journal of Forestry Institute- São Paulo*, 13(1), 1-18.
- Almagro, A., Oliveira, P. T. S., Nearing, M. A., & Hagemann, S., 2017. Projected climate change impacts in rainfall erosivity over Brazil. *Scientific reports*, 7(1), 8130.
- Almeida, A.C., Soares, J.V., Landsberg, J.J., Rezende, G.D., 2007. Growth and water balance of Eucalyptus grandis hybrid plantations in Brazil during a rotation for pulp production. *For. Ecol. Manag.*, 251, 10–21.
- Arnell, N.W., 1999. Climate change and global water resources. *Glob. Environ. Chang.*, 9, 31–49.

1

2

3 697 Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling
4 and assessment. Part I: model development. *J. Am. Water Resour. Assoc.*, 34, 73–89.

5 698

6 699 Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi,
7 C., Harmel, R.D., van Griensven, A., van Liew, M.W., Kannan, N., Jha, M.K., 2012.

8 700

9 SWAT: model use, calibration, and validation. *Trans. ASABE*, 55, 1491–1508.

10 701

11 702 Ataroff, V., Rada, F., 2000. Deforestation impact on water dynamics in a Venezuelan Andean cloud
12 forest. *Ambio*, 29, 440–444.

13 703

14 704 Baker, T.J., and Miller, S.N., 2013. Using the Soil and Water Assessment Tool (SWAT) to assess
15 land use impact on water resources in an East African watershed. *J. Hydrol.*, 486, 100–111.

16 705

17 706 Borah, D.K., and Bera, M., 2004. Watershed-scale hydrologic and nonpoint-source pollution
18 models: Review of applications. *Transactions of the ASAE*, 47(3), 789-803.

19 707

20 708 Brauman, K.A., Freyberg, D.L., Daily, G.C., 2012. Potential evapotranspiration from forest and
21 pasture in the tropics: A case study in Kona, Hawai ‘i. *Journal of Hydrology*, 440, 52-61.

22 709

23 710 Chandler, D.G., 2006. Reversibility of forest conversion impacts on water budgets in tropical karst
24 terrain. *For. Ecol. Manag.*, 224, 95–103.

25 711

26 712 Chow, V.T., 1964. Handbook of Applied Hydrology. McGraw-Hill, New York, USA.

27 713

28 714 Cicco, V., Emmerich, W., Fujieda, M., 1987. Determinacao da curva-chave do vertedouro da bacia
29 hidrografica experimental ‘D’ no parque estadual da Serra do Mar. Nucleo Cunha, SP. Bol.
30 Tec. IF. Sao Paulo 41, 79-96 (in Portuguese with English abstract).

31 715

32 716 da Silva, V.D.P.R., Silva, M.T., Singh, V.P., de Souza, E.P., Braga, C.C., de Holanda, R.M., Braga,
33 A.C.R., 2018. Simulation of stream flow and hydrological response to land-cover changes in
34 a tropical river basin. *Catena*, 162, 166-176.

35 717

36 718 de Mello, C.R., Norton, L.D., Pinto, L.C., Beskow, S., Curi, N., 2016. Agricultural watershed
37 modeling: a review for hydrology and soil erosion processes. *Ciência e*
38 *Agrotecnologia*, 40(1), 7-25.

39 719

40 720 Pereira, D.D.R., Almeida, A.Q.D., Martinez, M.A., Rosa, D.R.Q. , 2014. Impacts of deforestation
41 on water balance components of a watershed on the Brazilian East Coast. *Revista Brasileira*
42 *de Ciência do Solo*, 38(4), 1350-1358.

43 721

44 722 Douglas-Mankin, K.R., Srinivasan, R., Arnold, J.G., 2010. Soil and Water Assessment Tool
45 (SWAT) model: Current developments and applications. *Transactions of the ASABE*, 53(5),
46 1423-1431.

47 723

48 724 Dourado-Hernandes, T.A., Scarpore, F.V., Seabra, J.E.A., 2018. Assessment of impacts on basin
49 stream flow derived from medium-term sugarcane expansion scenarios in
50 Brazil. *Agriculture, Ecosystems & Environment*, 259, 11-18.

51 725

52 726
53 727
54 728
55 729
56 730
57
58
59
60

- 1
2
3 731 Durães, F., Mello, C.R., Naghettini, M., 2011. Applicability of the SWATmodel for hydrologic
4 simulation in Paraopeba river basin, MG. *Cerne*, 17, 481–488.
- 5 732
6 733 Estrela, T., Pérez-Martín, M.A., Vargas, E. 2012. Impacts of climate change on water resources in
7 Spain. *Hydrol. Sci. J.*, 57, 1154–1167.
- 8 734
9
10 735 Ficklin, D.L., Luo, Y., Luedeling, E., Zhang, M., 2009. Climate change sensitivity assessment of a
11 highly agricultural watershed using SWAT. *Journal of Hydrology*, 374(1-2), 16-29.
- 12 736
13 737 Franken, W., Leopoldo, P.R., Matsui, E., Ribeirrom, N.G., 1982a. Estudo de interceptacao da agua
14 de chuva em cobertua florestal amazonica do tipo terra firme. *Acta Amazonica*, 12, 327–331
15 738 (in Portuguese with English summary).
- 16 739
17 740 Franken, W., Leopoldo, P.R., Matsui, E., Ribeirrom, N.G., 1982b. Interceptacao das precipitacoes
18 em floresta amazonica de terra firme. *Acta Amazonica*, 12, 15-22 (in Portuguese with
19 741 English summary).
- 20 742
21 743 Fujieda, M., Kudoha, T., de Cicco, V., de Calvarcho, J.L., 1997. Hydrological processes at two
22 subtropical forest catchments: the Serra do Mar, Sao Paulo, Brazil. *Journal of Hydrology*,
23 196, 26–46.
- 24 744
25 745
26 746 Fukunaga, D.C., Cecílio, R.A., Zanetti, S.S., Oliveira, L.T., Caiado, M.A.C., 2015. Application of
27 the SWAT hydrologic model to a tropical watershed at Brazil. *Catena*, 125, 206-213.
- 28 747
29 748 Galindo-Leal, C., Câmara, I.G., 2005. Status do hot spot Atlantic: a synthesis. In: C. Galindo-Leal
30 & I.G. Hall (eds.). *Atlantic Forest biodiversity, threats and prospects*. Sao Paulo: Fundação
31 SOS Mata Atlântica - Belo Horizonte, Brazil.
- 32 749
33 750
34 751 Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The Soil and Water Assessment
35 Tool: historical development, applications, and future research directions. *Trans. ASABE*, 50,
36 1211–1250.
- 37 752
38 753
39 754 Gonzalez, P., Neilson, R.P., Lenihan, J.M., Drapek, R.J., 2010. Global patterns in the vulnerability
40 of ecosystems to vegetation shifts due to climate change. *Glob. Ecol. Biogeogr.*, 19 (6),
41 755–768.
- 42 756
43 757 Gupta, H.V., Sorooshian, S., Yapo, P.O., 1999. Status of automatic calibration for hydrologic
44 models: comparison with multilevel expert calibration. *J. Hydrol. Eng.*, 4 (2), 135–143.
- 45 758
46 759 Hoomehr, S., Schwartz, J.S., Yoder, D.C., 2016. Potential changes in rainfall erosivity under GCM
47 climate change scenarios for the southern Appalachian region, USA. *Catena*, 136, 141–151.
- 48 760
49 761 Intergovernmental Panel on Climate Change (IPCC), 2013. In *climate change 2013: the physical
50 science basic contribution of Working Group 1 to the Fifth Assessment Report of the
51 Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge,
52 United Kingdom and New York, USA.
- 53 762
54 763
55 764
56
57
58
59
60

- 1
2
3 765 Jing, Z., Dan, H., Xie, Y., Yong, L., Yang, Y., Hu, S., Guo, H., Lei, Z., Rui, Z., 2015. Integrated
4
5 766 SWAT model and statistical downscaling for estimating streamflow response to climate
6
7 767 change in the Lake Dianchi watershed, China. *Stoch. Env. Res. Risk A.*, 29 (4), 1193–1210.
- 8
9 768 Kang, M.S., Park, S.W., Lee, J.J., Yoo, K.H., 2006. Applying SWAT for TMDL programs to a
10 769 small watershed containing rice paddy fields. *Agricultural Water Management*, 79(1), 72-
11
12 770 92.
- 13
14 771 Kirpich, Z.P., 1940. Time of concentration of small agricultural watersheds. *Civil Engineering*,
15 772 10(6), 362.
- 16
17 773 Klamt, E., and Van Reeuwijk, L.P., 2000. Evaluation of morphological, physical and chemical
18
19 774 characteristics of ferralsols and related soils. *Revista Brasileira de Ciência do Solo* 24(3),
20 775 573-587.
- 21
22 776 Knutti, R., and Sedláček, J., 2013. Robustness and uncertainties in the new CMIP5 climate model
23
24 777 projections. *Nat. Clim. Chang.*, 3 (4), 369–373.
- 25
26 778 Krause, P., Boyle, D.P., Base, F., 2005. Comparison of different efficiency criteria for hydrological
27 779 model assessment. *Advances in Geosciences*, 5, 89-97.
- 28
29 780 Krysanova, V., Kundzewicz, Z.W., Piniewski, M., 2016, Assessment of climate change impacts on
30
31 781 water resources. In: V.P. Singh (Ed.), *Handbook of applied hydrology*, McGraw-Hill Education,
32
33 782 New York, USA, 148.1-148.12.
- 34
35 783 Legates, D.R., and McCabe, G.J., 1999. Evaluating the use of “goodness of fit” measures in
36 784 hydrologic and hydroclimatic model validation. *Water Resources Research*, 35, 233-241.
- 37
38 785 Lenderink, G., Buishand, A., Deursen, W., 2007. Estimative of future discharges of the river Rhine
39 786 using two scenario methodologies: Direct versus delta approach. *Hydrol. Earth Syst. Sci.*,
40
41 787 11, 1145–1159.
- 42
43 788 Li, Z., and Fang, H., 2016. Impacts of climate change on water erosion: A review. *Earth-Science*
44
45 789 *Reviews*, 163, 94-117.
- 46
47 790 Licciardello, F., Rossi, C. G., Srinivasan, R., Zimbone, S.M., Barbagallo, S., 2011. Hydrologic
48 791 evaluation of a Mediterranean watershed using the SWAT model with multiple PET
49
50 792 estimation methods. *Transactions of the ASABE*, 54(5), 1615-1625.
- 51
52 793 Lironga, S., and Jianyuna, Z., 2012. Hydrological response to climate change in Beijiang River
53 794 Basin based on the SWAT model. *Procedia Eng.*, 28, 241–245.
- 54
55 795 Loague, K., and Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport
56
57 796 models: Overview and application. *Journal of Contaminant Hydrology*, 7, 51-73.
- 58
59
60

- 1
2
3 797 Marengo, J.A., Jones, R., Alves, L.M., Valverde, M.C., 2009. Future change of temperature and
4 precipitation extremes in South America as derived from the PRECIS regional climate
5 798 modeling system. *International Journal of Climatology*, 29, 2241–2255.
6 799
8 800 Marmontel, C.V.F., Lucas-Borja, M.E., Rodrigues, V.A., Zema, D.A. 2018. Effects of land use and
9 sampling distance on water quality in tropical headwater springs (Pimenta creek, São Paulo
10 801 State, Brazil). *Science of The Total Environment*, 622: 690-701.
11 802
12 803 Meaurio, M., Zabaleta, A., Uriarte, J. A., Srinivasan, R., Antigüedad, I., 2015. Evaluation of SWAT
13 804 models performance to simulate streamflow spatial origin. The case of a small forested
14 watershed. *Journal of Hydrology*, 525, 326-334.
15 805
16 806 Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T. L., 2007.
17 807 Model evaluation guidelines for systematic quantification of accuracy in watershed
18 808 simulations. *Transactions of the ASABE*, 50(3), 885-900.
19 809
20 810 Nash, J.E., and Sutcliffe, J.V., 1970. River flow forecasting through conceptual models: Part I. A
21 discussion of principles. *Journal of Hydrology*, 10, 282-290.
22 811
23 812 Neill, C., Deegan, L.A., Thomas, S.M., Cerri, C.C., 2001. Deforestation for pasture alters nitrogen
24 and phosphorus in small Amazonian streams. *Ecol. Appl.*, 11, 1817–1828.
25 813
26 814 Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2005. Soil and Water Assessment Tool –
27 Theoretical Documentation, Version 2005. Texas, USA.
28 815
29 816 Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Srinivasan, R., Williams, J., 2010. Soil and
30 Water Assessment Tool Input/Output File Documentation Version 2009. Texas Water
31 Resources Institute Technical Report No. 365, College Station, TX, pp. 604.
32 817
33 818 Paparrizos, S., Maris, F., Matzarakis, A., 2016. Integrated analysis of present and future responses
34 of precipitation over selected Greek areas with different climate conditions. *Atmos. Res.*, 169
35 (Part A), 199–208.
36 819
37 820 Pereira, D.D.R., Martinez, M.A., da Silva, D.D., Pruski, F.F., 2016a. Hydrological simulation in a
38 basin of typical tropical climate and soil using the SWAT Model Part II: Simulation of
39 hydrological variables and soil use scenarios. *Journal of Hydrology: Regional Studies*, 5,
40 149-163.
41 821
42 822 Pereira, D.D.R., Martinez, M.A., Pruski, F.F., da Silva, D.D., 2016b. Hydrological simulation in a
43 basin of typical tropical climate and soil using the SWAT model part I: Calibration and
44 validation tests. *Journal of Hydrology: Regional Studies*, 7, 14-37.
45 823
46 824 Piniewski, M., Okruszko, T., Acreman, M.C., 2014. Environmental water quantity projections
47 under market-driven and sustainability-driven future scenarios in the Narew basin,
48 Poland. *Hydrological Sciences Journal*, 59(3-4), 916-934.
49 825
50 826
51 827
52 828
53 829
54 830

- 1
2
3 831 Piniewski, M., Szcześniak, M., Kardel, I., Berezowski, T., Okruszko, T., Srinivasan, R.,
4
5 832 Kundzewicz, Z.W., 2017. Hydrological modelling of the Vistula and Odra river basins using
6
7 833 SWAT. *Hydrological Sciences Journal*, 62(8), 1266-1289.
- 8
9 834 Piniewski, M., Voss, F., Bärlund, I., Okruszko, T., Kundzewicz, Z.W., 2013. Effect of modelling
10 835 scale on the assessment of climate change impact on river runoff. *Hydrological sciences*
11
12 836 journal, 58(4), 737-754. Qiu, L.J., Zheng, F.L., Yin, R.S., 2012. SWAT-based runoff and
13
14 837 sediment simulation in a small watershed, the loessial hilly-gullied region of China:
15 838 capabilities and challenges. *International Journal of Sediment Research*, 27(2), 226-234.
- 16
17 839 Raneesh, K.Y., and Thampi Santosh, G., 2011. A study on the impact of climate change on
18
19 840 streamflow at the watershed scale in the humid tropics. *Hydrological Sciences*
20
21 841 *Journal*, 56(6), 946-965.
- 22 842 Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R., Hauck, L.M., 2001.
23
24 843 Validation of the SWAT model on a large river basin with point and nonpoint sources. *J.*
25
26 844 *Am. Water Resour. Assoc.*, 37 (5), 1169–1188.
- 27 845 Santos, C.A., Rocha, F., Ramos, T.B., Alves, L.M., Mateus, M., Oliveira, R.P.D., Neves, R., 2019.
28
29 846 Using a hydrologic model to assess the performance of regional climate models in a semi-
30
31 847 arid watershed in Brazil. *Water* 11(1), 170.
- 32
33 848 Santos, W.L.D., and Augustin, C.H.R.R., 2015. Water and sediment loss through runoff in areas of
34
35 849 forest and pasture cover in southwestern Amazonia–Acre–Brazil. *Zeitschrift für*
36 850 *Geomorphologie*, Supplementary Issues, 59(2), 23-39.
- 37
38 851 Senent-Aparicio, J., Pérez-Sánchez, J., Carrillo-García, J., Soto, J., 2017. Using SWAT and Fuzzy
39
40 852 TOPSIS to assess the impact of climate change in the headwaters of the Segura River Basin
41
42 853 (SE Spain). *Water*, 9(2), 149.
- 43 854 Spruill, C.A., Workman, S.R., Taraba, J.L., 2000. Simulation of daily and monthly stream discharge
44
45 855 from small watersheds using the SWAT model. *Trans.ASAE*, 43, 1431–1439.
- 46 856 Strauch, M., Bernhofer, C., Koide, S., Volk, M., Lorz, C., Makeschin, F., 2012. Using precipitation
47
48 857 data ensemble for uncertainty analysis in SWAT streamflow simulation. *J. Hydrol.*, 414,
49
50 858 413–424.
- 51 859 Strauch, M., Lima, J.E., Volk, M., Lorz, C., Makeschin, F., 2013. The impact of Best Management
52
53 860 Practices on simulated streamflow and sediment load in a Central Brazilian catchment. *J.*
54
55 861 *Environ. Manag.*, 127, S24–S36.
- 56
57 862 Strauch, M., and Volk, M., 2013. SWAT plant growth modification for improved modeling of
58
59 863 perennial vegetation in the tropics. *Ecological Modelling*, 269, 98-112.
- 60

- 1
2
3 864 Sui, J., 2005. Estimation of design flood hydrograph for an ungauged watershed. *Water Resources*
4
5 865 *Management*, Oxford, v. 19, p. 813-830.
- 6
7 866 Tan, M.L., Yusop, Z., Chua, V.P., Chan, N.W., 2017. Climate change impacts under CMIP5 RCP
8
9 867 scenarios on water resources of the Kelantan River Basin, Malaysia. *Atmospheric*
10 868 *Research*, 189, 1-10.
- 11
12 869 Urrutia, R., and Vuille, M., 2009. Climate change projections for the tropical Andes using a
13
14 870 regional climate model: temperature and precipitation simulations for the end of the 21st
15 871 century. *J. Geophys. Res.-Atmos.*, 114, 1–15.
- 16
17 872 USDA, 1972. National Engineering Handbook. Section 4: Hydrology.
- 18
19 873 Van Liew, M.W., and Garbrecht, J., 2003. Hydrologic simulation of the Little Washita River
20
21 874 experimental watershed using SWAT. *Journal of the American Water Resources*
22 875 *Association*, 39: 413-426.
- 23
24 876 Van Liew, M.W., Arnold, J.G., Garbrecht, J.D., 2003. Hydrologic simulation on agricultural
25
26 877 watersheds: choosing between two models. *Trans. ASAE*, 46 (6), 1539–1551.
- 27
28 878 Vieira, D.C.S., Serpa, D., Nunes, J.P.C., Prats, S.A., Neves, R., Keizer, J.J., 2018. Predicting the
29 879 effectiveness of different mulching techniques in reducing post-fire runoff and erosion at
30
31 880 plot scale with the RUSLE, MMF and PESERA models. *Environmental Research*, 165, 365-
32
33 881 378.
- 34 882 Vitousek, P.M., 1994. Beyond global warming: ecology and global change. *Ecology*, 75 (7), 1861–
35
36 883 1876.
- 37
38 884 von Stackelberg, N.O., Chescheir, G.M., Skaggs, R.W., Amatya, D.M., 2007. Simulation of the
39
40 885 hydrologic effects of afforestation in the Tacuarembó River Basin, Uruguay. *Trans. ASABE*,
41 886 50, 455–468.
- 42
43 887 Whitmore, T.C., 1990. *An Introduction to Tropical Rain Forests*. Clarendon Press, Oxford, UK.
- 44
45 888 Wilby, R.L., Dawson, C.W., Barrow, E.M., 2002. SDSM — a decision support tool for the
46 889 assessment of regional climate change impacts. *Environ. Model. Softw.*, 17 (2), 147–159
- 47
48 890 Willmott, C.J., 1982. Some comments on the evaluation of model performance. *Bulletin of*
49
50 891 *American Meteorological Society*, 63(11), 1309-1313.
- 51
52 892 Wolf, S., Eugster, W., Majorek, S., Buchmann, N., 2011. Afforestation of tropical pasture only
53 893 marginally affects ecosystem-scale evapotranspiration. *Ecosystems*, 14(8), 1264-1275.
- 54
55 894 Zema, D.A., Lucas-Borja, M.E., Carrà, B.G., Denisi, P., Rodrigues, V.A., Ranzini, M., Zimbone,
56
57 895 S.M., 2018. Simulating the hydrological response of a small tropical forest watershed (Mata
58 896 Atlantica, Brazil) by the AnnAGNPS model. *Science of the Total Environment*, 636, 737-
59
60 897 750.

- 1
2
3 898 Zema, D.A., Bingner, R.L., Denisi, P., Govers, G., Licciardello, F., Zimbone, S.M., 2012.
4
5 899 Evaluation of runoff, peak flow and sediment yield for events simulated by the AnnAGNPS
6
7 900 model in a Belgian agricultural watershed. *Land Degrad. Dev.*, 23, 205–215.
- 8
9 901 Zema, D.A., Denisi P., Taguas Ruiz, E.V., Gómez, J.A., Bombino, G., Fortugno, D., 2016.
10 902 Evaluation of surface runoff prediction by AnnAGNPS model in a large Mediterranean
11
12 903 watershed covered by olive groves. *Land Degrad. Develop.*, 27(3), 811-822.
- 13
14 904 Zema, D.A., Labate, A., Martino, D., Zimbone, S.M., 2017. Comparing Different Infiltration
15
16 905 Methods of the HEC - HMS Model: The Case Study of the Mésima Torrent (Southern
17
18 906 Italy). *Land Degrad. Develop.*, 28(1), 294-308.
- 19 907 Zhang, H.G., Fu, S.H., Fang, W.H., Imura, H., Zhang, X.C., 2007. Potential effects of climate
20
21 908 change on runoff in the Yellow River Basin of China. *Trans. ASABE*, 50, 911–918.
- 22
23 909 Zhang, Y., You, Q., Chen, C., Ge, J., 2016. Impacts of climate change on streamflows under RCP
24
25 910 scenarios: A case study in Xin River Basin, China. *Atmospheric Research*, 178, 521-534.
- 26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 911 **TABLES**
4
5 912

6 913 Table 1. Values and source of the input data for implementation of the SWAT model at "A" micro-
7
8 914 watershed (Brazil).
9

10 915

<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)	

46
47 916
48
49
50
51
52
53
54
55
56
57
58
59
60

917 Table 2. Input parameters with default values and calibrated by SWAT-CUP procedure in SWAT model implementation at the "A" micro-watershed
 918 (Brazil).
 919

Parameter		SWAT acronym	Measuring		Value	
Name	unit		default	calibrated		
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	

1	Maximum canopy storage	CANMX.hru	mm H ₂ O	0	0.15
2	Surface runoff lag coefficient	SURLAG.bsn	(-)	2	21.4
3	Average slope length	SLSUBBSN.hru	m	15.2	130
4	Lateral flow travel time	LAT_TTIME.hru	days	0	18.8
5	Initial groundwater height	GWHT.gw	m	1	21.5
6	Effective hydraulic conductivity in tributary channel alluvium	CH_K1.sub	mm/hr	0	69.8
7	Manning's coefficient "n" value for the tributary channels	CH_N1.sub	(-)	0.01	18.9
8					
9					
10					
11					
12					
13					
14					
15					
16					
17					
18					
19					
20					
21					
22					
23					
24					
25					
26					
27					
28					
29					
30					
31					
32					
33					
34					
35					
36					
37					
38					
39					
40					
41					
42					
43					
44					
45					
46					

921 Table 3. Scheme of the land use and climate change Representative Concentration Pathways (RCPs) adopted for evaluation the hydrological
 922 response of the "A" micro-watershed (Brazil) by the SWAT model.
 923

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

924 Note: RCP = Representative Concentration Pathways.

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

Surface runoff	Model input parameters	Mean	Std. Dev.	Min	Max	r^2	E	CRM (PBIAS)
		(mm/yr)						
<i>Calibration (1993-2003)</i>								
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
<i>Validation (2004-2014)</i>								
Observed	-	1347	271	912	1843	-	-	-
Predicted	Validated	1370	251	1002	1895	0.71	0.70	-0.02
<i>Whole period (1993-2014)</i>								
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

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

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

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

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

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	-	

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 (at $p < 0.05$).

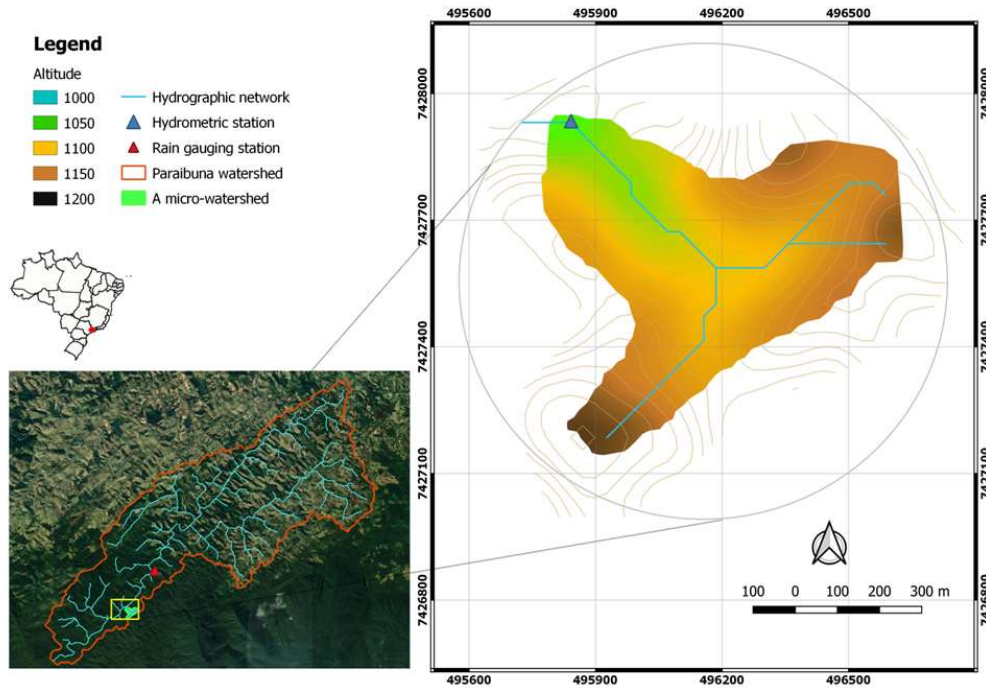
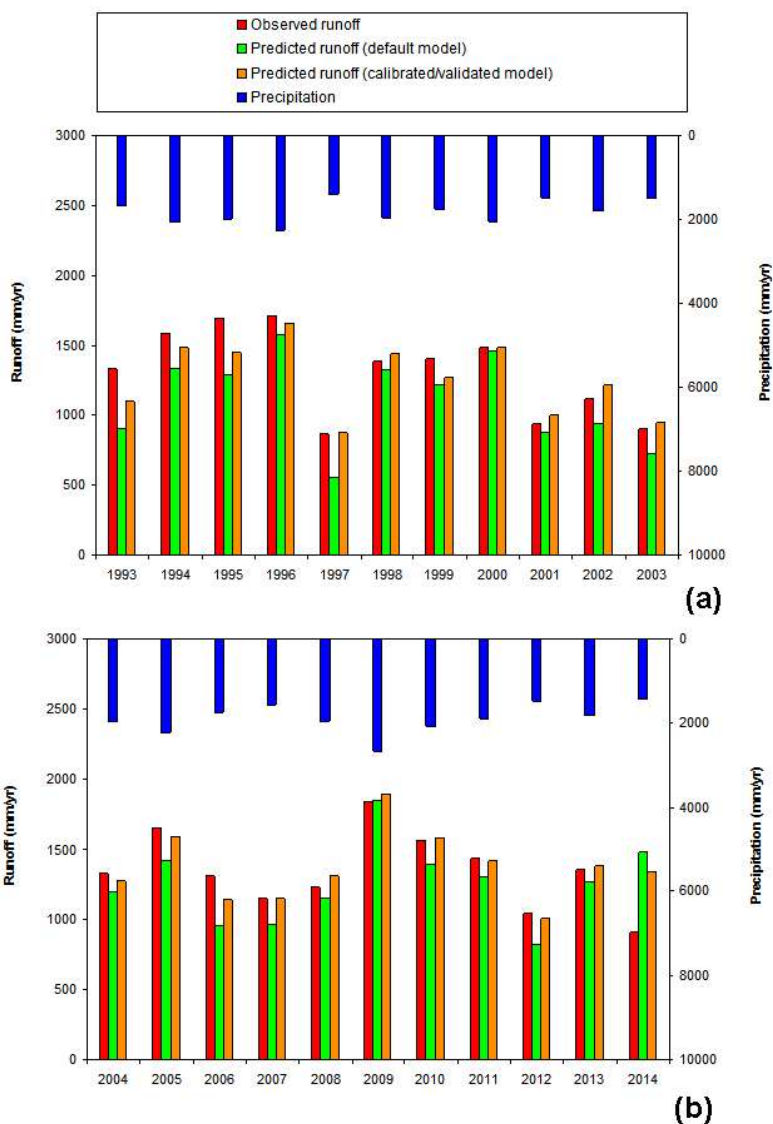


Figure 1. Geographical location (a) and land use map (b) of the "A" micro-watershed (Brazil).

254x190mm (96 x 96 DPI)



Figures 2a, b. Annual precipitation and surface runoff volumes observed at the outlet and simulated by the SWAT model (run with the default and calibrated input parameters) in the "A" micro-watershed (Brazil) - (a) calibration period, 1993-2003; (b) validation period (2004-2014).

190x254mm (96 x 96 DPI)

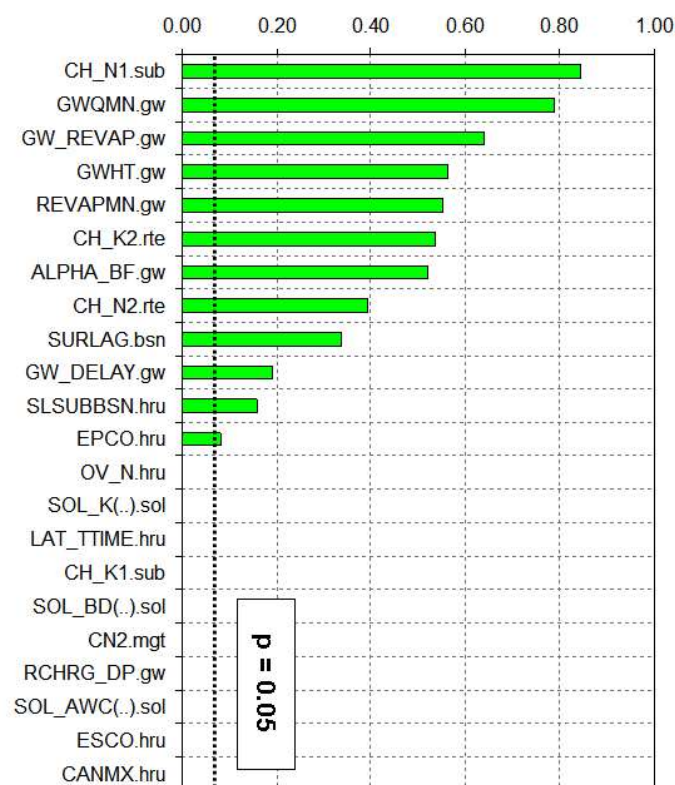


Figure 3. p-values of the input parameters of the SWAT model given by SWAT-CUP procedure applied to simulate surface runoff in the "A" micro-watershed (Brazil) - the most sensitive input parameters correspond to a p-values < 0.05.

190x254mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

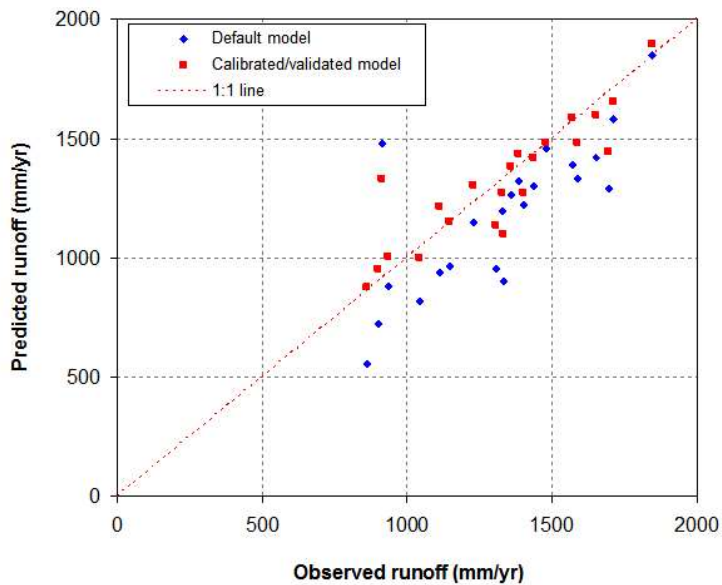
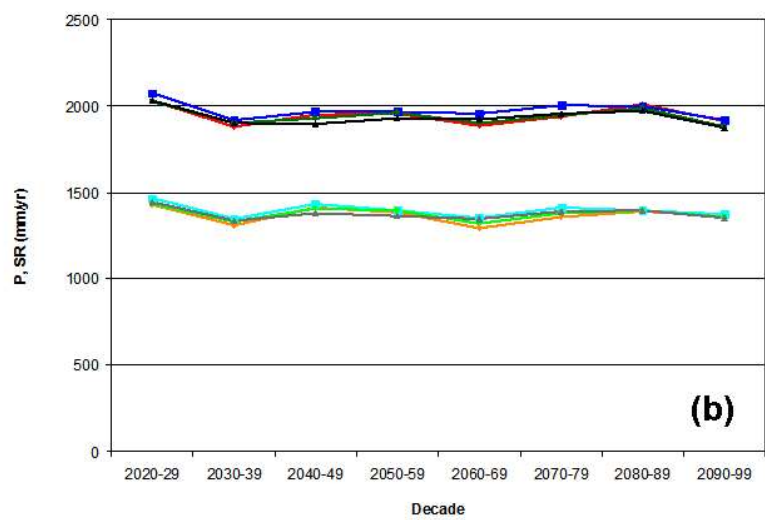
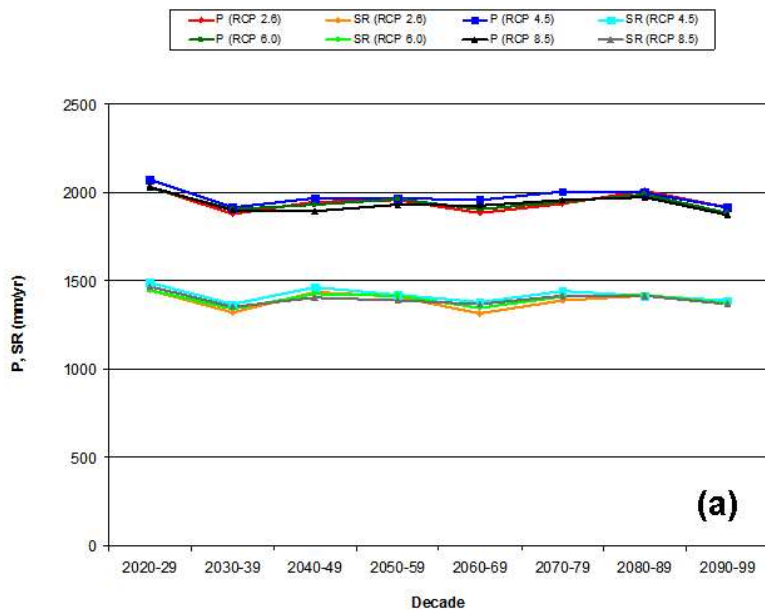


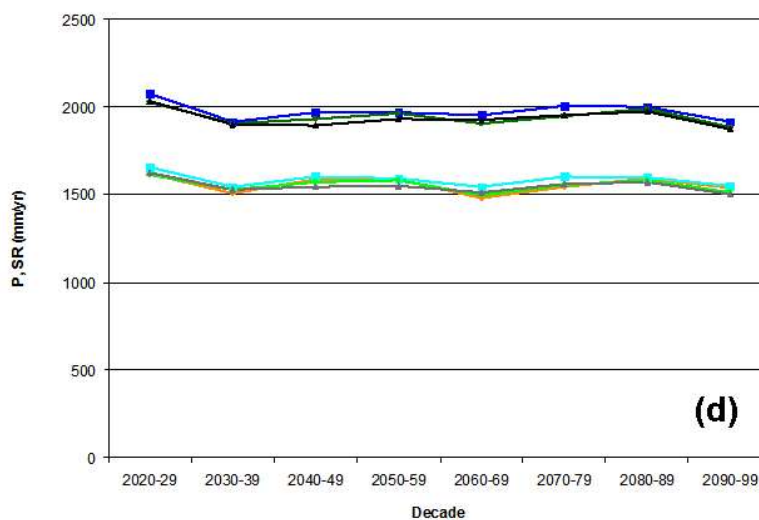
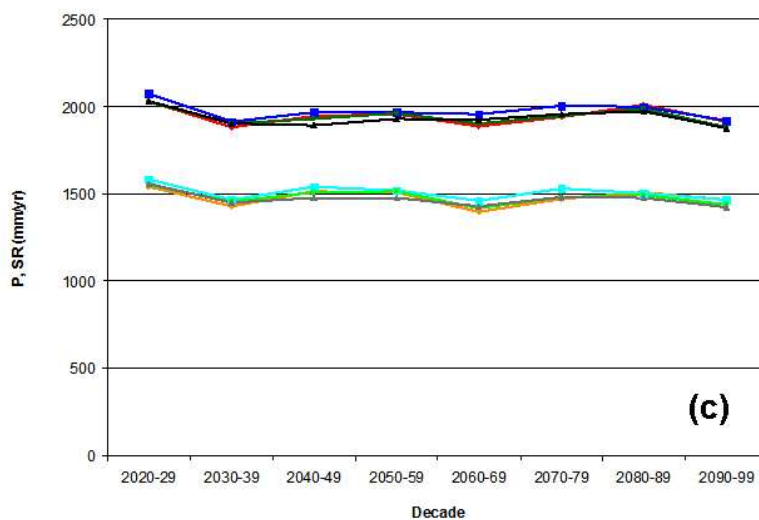
Figure 4. Scatter plots of annual runoff volumes observed at the outlet and predicted by the SWAT model in the "A" micro-watershed (Brazil).

190x254mm (96 x 96 DPI)



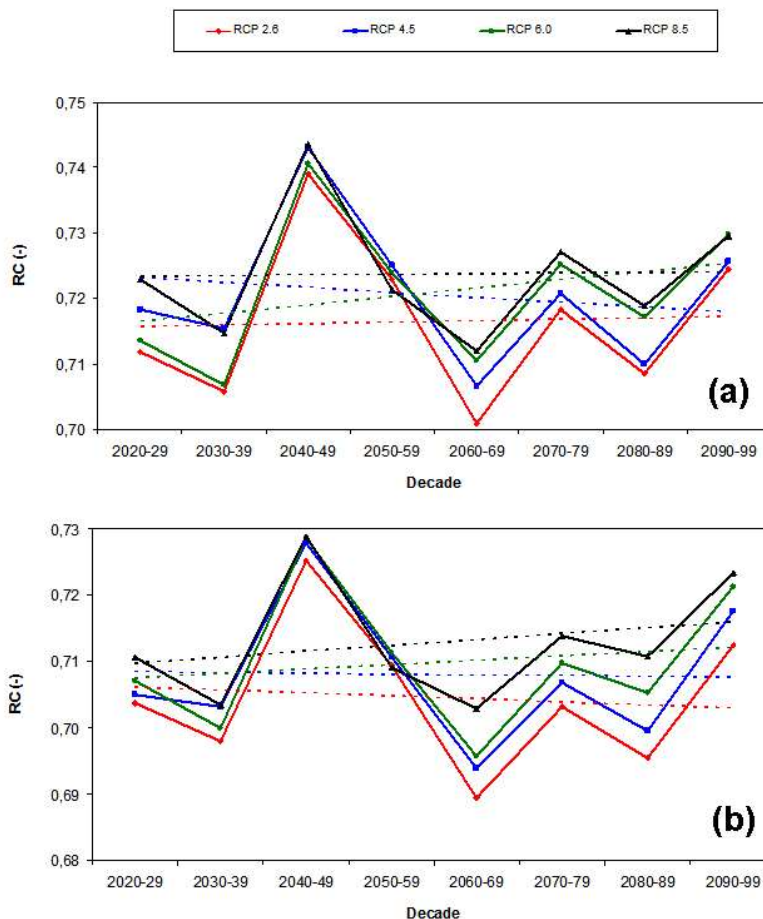
190x254mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60



Figures 5a, b, c and d - Annual precipitation (P) and surface runoff (SR) volumes simulated by the calibrated SWAT model under climate (four RCPs) and land use change scenarios in the "A" micro-watershed (Brazil) - (a) forestland; (b) pasture; (c) cropland; (d) bare soil (standard deviations among the evaluated GCMs are not shown due to the small scale).

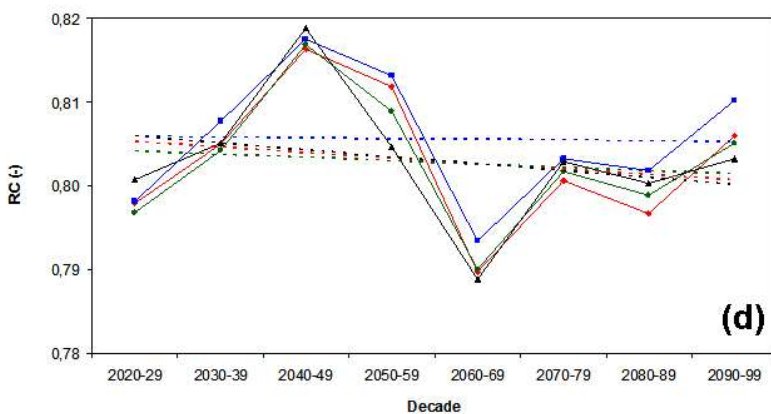
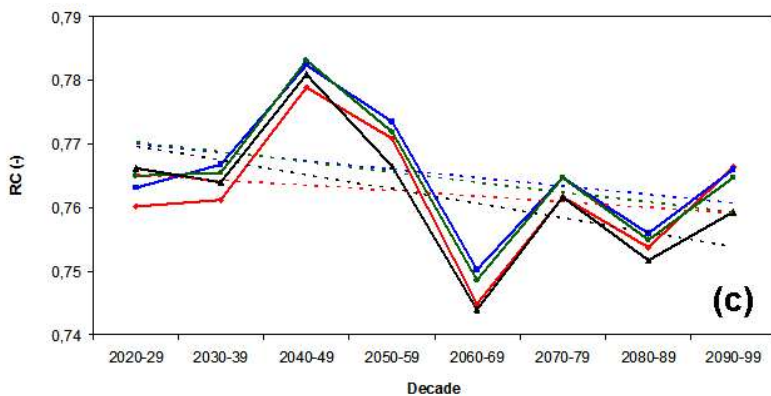
190x254mm (96 x 96 DPI)



Figures 6a, b, c and d - Runoff coefficients (RC) at the annual scale simulated by the calibrated SWAT model under climate (RCP) and land use change scenarios in the "A" micro-watershed (Brazil) - (a) forestland; (b) pasture; (c) cropland; (d) bare soil. The dashed line is the linear regression model.

190x254mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60



Figures 6a, b, c and d - Runoff coefficients (RC) at the annual scale simulated by the calibrated SWAT model under climate (RCP) and land use change scenarios in the "A" micro-watershed (Brazil) - (a) forestland; (b) pasture; (c) cropland; (d) bare soil. The dashed line is the linear regression model.

190x254mm (96 x 96 DPI)

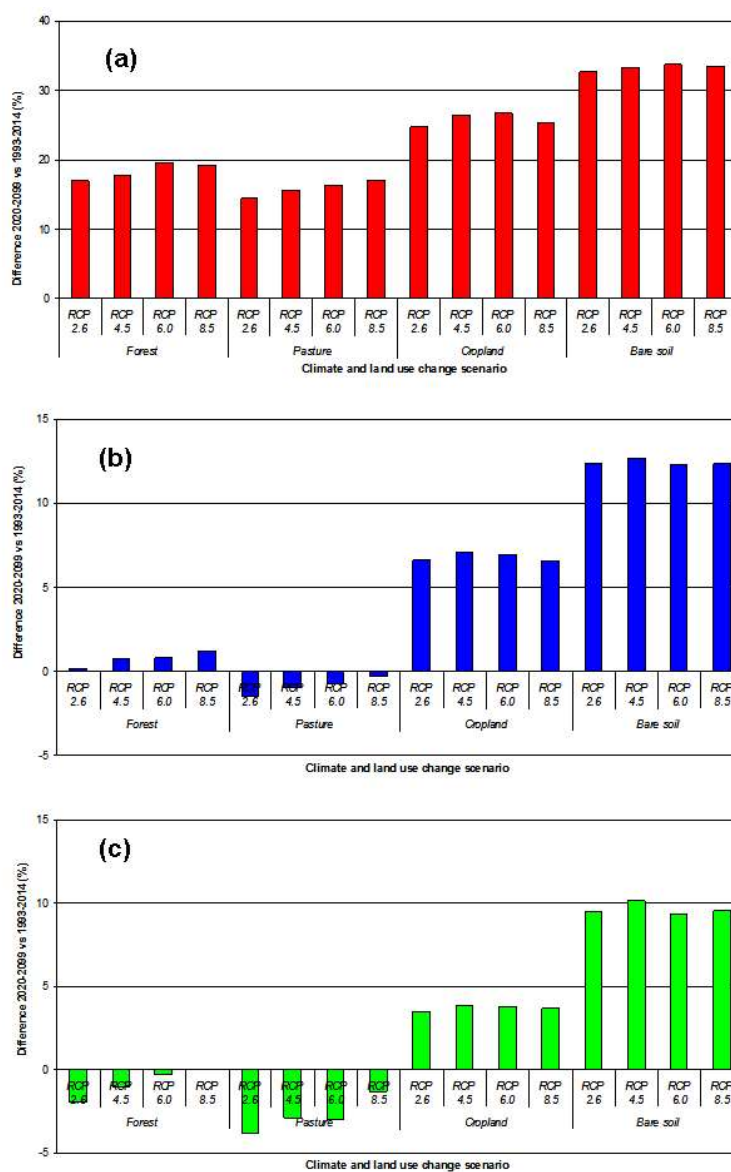


Figure 7a, b and c - Difference between the mean (a), maximum (b) and minimum (c) runoff coefficients at the annual scale observed in the period 1993-2014 and simulated by the calibrated SWAT model under climate (RCP) and land use change scenarios in the "A" micro-watershed (Brazil).

190x254mm (96 x 96 DPI)