SWAT-Tb with improved LAI representation in the tropics highlights the role of forests in watershed regulation

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Abstract

Projecting the potential impacts of LULC (Land Use/Land Cover) change on watershed hydrological response is critical for water management decisions in a changing environment. An improved representation of vegetation dynamics is needed to improve the capability of several hydrological models to produce reliable projections of these impacts. Here we in troduce a modification in the plant growth module of SWAT (Soil Water Assessment Tool) to improve the representation of the bimodal seasonality of LAI (Leaf Area Index), which is particularly important for tropical watersheds with bimodal precipitation regimes. The new SWAT-Tb variant that we propose here reproduces not only observed streamflow, but also the bimodal seasonal pattern of LAI in a tropical mountain watershed of the Andes. In contrast, standard SWAT is inherently unable to reproduce this bimodality, although it can be calibrated to reproduce streamflow. Differences between models in the representation of LAI seasonality can lead to significantly different results about LULC change impacts on streamflow, and indicate that forests can play a crucial role in enhancing water availability during dry seasons. The seasonality of streamflow anomalies is switched due to forest-to-pasture conversion, implying that while forest expansion increases water availability in dry seasons, forest conversion into pasture decreases it. Due to its poor representation of LAI seasonality, standard SWAT largely underestimates this role of forest, which can be misleading for decision making about water security and forest conservation

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Key Points:

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13	•	New SWAT (Soil and Water Assessment Tool) model variant captures bimodal
14		tropical vegetation dynamics
15	•	Seasonality of streamflow anomalies is switched due to forest-to-pasture conver-
16		sion
17	•	Deforestation exacerbates low flows during dry season
18	•	Standard SWAT leads to misleading conclusion about deforestation impacts

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19 Abstract

Projecting the potential impacts of LULC (Land Use/Land Cover) change on watershed 20 hydrological response is critical for water management decisions in a changing environment. 21 An improved representation of vegetation dynamics is needed to improve the capability of 22 several hydrological models to produce reliable projections of these impacts. Here we in-23 troduce a modification in the plant growth module of SWAT (Soil Water Assessment Tool) 24 to improve the representation of the bimodal seasonality of LAI (Leaf Area Index), which 25 is particularly important for tropical watersheds with bimodal precipitation regimes. The 26 new SWAT-Tb variant that we propose here reproduces not only observed streamflow, but 27 also the bimodal seasonal pattern of LAI in a tropical mountain watershed of the Andes. In 28 contrast, standard SWAT is inherently unable to reproduce this bimodality, although it can 29 be calibrated to reproduce streamflow. Differences between models in the representation 30 of LAI seasonality can lead to significantly different results about LULC change impacts 31 on streamflow. SWAT-Tb results show that deforestation impacts on streamflow are more 32 pronounced for seasonal than for annual streamflow, and indicate that forests can play a 33 crucial role in enhancing water availability during dry seasons. The seasonality of streamflow 34 anomalies is switched due to forest-to-pasture conversion, implying that while forest expan-35 sion increases water availability in dry seasons, forest conversion into pasture decreases it. 36 Due to its poor representation of LAI seasonality, standard SWAT largely underestimates 37 this role of forest, which can be misleading for decision making about water security and 38 forest conservation. 30

40 **1** Introduction

Changes in Land Use/Land Cover (LULC henceforth) lead to some of the most concern-41 ing anthropogenic alterations of hydrological processes and concomitant environmental and 42 social phenomena (Foley et al., 2005; M. Zhang et al., 2017). In a watershed, the trans-43 formation of LULC affects multiple aspects and components of the surface water balance, 44 including soil permeability (Benavides et al., 2018), evapotranspiration (Ponette-González 45 et al., 2014), surface runoff (Roa-García et al., 2011), infiltration (Marín et al., 2019), base 46 flow, water yield (Ochoa-Tocachi et al., 2016), energy partitioning (Mercado-Bettín et al., 47 2019), and, ultimately, the watershed response via streamflow (Muñoz-Villers & McDonnell, 48 2013; Ramírez et al., 2017) and regulation capacity (e.g. the amplitude of the streamflow 49 regime) (Ochoa-Tocachi et al., 2016; Peña-Arancibia et al., 2019; J. F. Salazar et al., 2018). 50 Projecting the potential impacts of LULC change on watershed response and regulation is 51 critical for water management decisions in a changing environment (Montanari et al., 2013; 52 J. F. Salazar et al., 2018). 53

Deforestation is one of the most relevant forms of LULC change, especially in regions like 54 tropical South America with historically high deforestation rates that may be exacerbated by 55 climate change and complex social issues (Zemp et al., 2017; A. Salazar et al., 2018; Duque-56 Villegas et al., 2019). This is particularly problematic in the tropical Andes, where water and 57 related energy security rely largely on streamflow from mountain watersheds (Viviroli et al., 58 2007; Sáenz et al., 2014; Angarita et al., 2018; Immerzeel et al., 2020). Major LULC trends 59 in this region include the transformation of Andean forest and paramo vegetation to pastures 60 for cattle raising (García-Leoz et al., 2017), agricultural systems (Clerici et al., 2019), and 61 forest plantations (Bonnesoeur et al., 2019). Field observations show that forest conversion 62 into pasture or crops is associated with changes in the water balance components and related 63 surface properties such as soil permeability, surface runoff, and infiltration (Ramírez et al., 64 2017; Marín et al., 2019; Suescún et al., 2017). Therefore, understanding the potential 65 impacts of forest loss on streamflow is needed for the assessment of threats to sustainability, 66 especially in mountain watersheds that are becoming increasingly critical for water security 67 in lowland populations (Immerzeel et al., 2020; Viviroli et al., 2020). 68

The effects of LULC change on watershed response are largely assessed through hydro-69 logical models (e.g. M. Zhang et al., 2017; Dos Santos et al., 2018; Peña-Arancibia et al., 70 2019). Hydrological models are generally able to reproduce observed streamflow (Krysanova 71 et al., 2017). This is a result of, first, models being built upon physical principles, the main 72 of which is mass (water) conservation; and second, of models having numerous parameters 73 that can be tuned to reproduce observations (i.e. model calibration). However, the capa-74 bility of making reliable projections (e.g. for LULC scenarios) depends on the potential 75 of these models to reproduce the system's behavior for the right reasons (Kirchner, 2006). 76 When the performance of hydrological models is largely, or exclusively, evaluated by com-77 paring simulated and observed streamflow (e.g. Setegn et al., 2010; Villamizar et al., 2019). 78 there is a danger of ignoring unrealistic representations of other important water balance 79 components and related processes. 80

The Soil and Water Assessment Tool (SWAT) is among the most widely used hydro-81 logical models for investigating LULC change impacts on watershed response (Marin et al., 82 2020; Tan et al., 2020). One of the most critical model components for this task is the 83 vegetation dynamics module (Strauch & Volk, 2013; Alemayehu et al., 2017), since it directly affects the surface water and energy balances (Bonan, 2008). This module includes 85 a plant growth scheme that was originally developed for temperate regions (Neitsch et al., 86 2011) and, therefore, is not necessarily adequate for tropical regions (Strauch & Volk, 2013; 87 Alemayehu et al., 2017; Hoyos et al., 2019; H. Zhang et al., 2020). This limitation has been 88 partially addressed by using the Leaf Area Index (LAI) to represent vegetation dynamics 89 (Strauch & Volk, 2013; Alemayehu et al., 2017; Ma et al., 2019; Rajib et al., 2020). For in-90 stance, Alemayehu et al. (2017) developed a SWAT variant (named SWAT-T) that improves 91 the representation of LAI seasonality in tropical ecosystems, yet still fails to reproduce the 92 bimodal seasonality of LAI that is typical of many of them (Ye et al., 2021) and that is 93 related to the seasonal migration of the ITCZ (Urrea et al., 2019; Knoben et al., 2019). 94 An improved representation of vegetation dynamics is needed to improve the potential of 95 SWAT to produce reliable projections of LULC change impacts (Marin et al., 2020). 96

The goals of the present study were, first, to improve the representation of tropical veg-97 etation dynamics in SWAT, and then to use the improved model for studying the potential 98 impacts of LULC change on the response of a tropical watershed. More specifically, here we 99 introduce a modification in the plant growth module of SWAT to improve the representation 100 of LAI seasonality, which leads to a new variant that we refer to as SWAT-Tb. Then we 101 compare the performance of SWAT-Tb with other SWAT variants (i.e. standard or default 102 SWAT (Revision 627) and SWAT-T), and show that, in contrast to these other variants, 103 SWAT-Tb produces a realistic representation of not only streamflow but also LAI. Finally, 104 we use SWAT-Tb to study the potential effects of LULC change on streamflow, particularly 105 the expansion of either forest or pasture cover, in a tropical mountain watershed; and show 106 that using the standard SWAT can lead to misleading conclusions. 107

2 Revision of SWAT Model

The new variant of SWAT, namely SWAT-Tb, introduces a bimodal representation of vegetation dynamics into the SWAT-T model of Alemayehu et al. (2017). SWAT-Tb accounts for the bimodal seasonality of LAI that is typical of many watersheds in tropical (Hoyos et al., 2019; Knoben et al., 2019) and non-tropical (Alhamad et al., 2007; Yang et al., 2019) regions. In the following sections, we provide background on the SWAT model and explain the changes in the new variant.

115 2.1 Model Description and Limitations

SWAT is a public domain, watershed-scale, process-based, hydrological model (Arnold et al.,
1998; Neitsch et al., 2011) that can simulate the response of watersheds (e.g. streamflow) to
a variety of forcings, including both climate and LULC change (Gassman et al., 2014; Tan

et al., 2020). It is a semi-distributed model wherein a watershed is divided into sub-basins that are further divided into Hydrologic Response Units (HRUs), which are characterized by uniform soil, slope, LULC, and management attributes. Hydrological processes simulated by SWAT include evapotranspiration, surface runoff, percolation, lateral flow, groundwater flow, transmission losses, and ponds (Arnold et al., 2012). The model also includes parameterizations for processes such as plant growth, erosion, nutrients cycling, and pesticides degradation (Neitsch et al., 2011).

The most common formulation for vegetation dynamics in SWAT uses a plant growth 126 127 module that simulates leaf area development, light interception, and conversion of intercepted light into biomass (Neitsch et al., 2011). This module is based on the Environmental 128 Policy Impact Climate (EPIC) model (Williams et al., 1989) that was developed for tem-129 perate regions and is not suitable for all tropical regions (Strauch & Volk, 2013; Alemayehu 130 et al., 2017). A key reason for this is that the EPIC-based module assumes that plant 131 growth, including leaf area development, is mainly controlled by variations in temperature 132 and daylength, which is especially relevant for temperate environments (Mwangi et al., 133 2016). For instance, this module assumes that plant growth is reduced as daylength ap-134 proaches that of the shortest day of the year (winter solstice) due to dormancy (Arnold et 135 al., 1998). However, tropical vegetation dynamics can be much less influenced by tempera-136 ture and daylenght-driven dormancy (Ma et al., 2019), and instead much more controlled by 137 precipitation through soil moisture (X. Zhang et al., 2006). Indeed, in our study watershed, 138 seasonal LAI is more related to precipitation than to temperature (see Section 4.1). This 139 model limitation and its implications for water balance have been highlighted in several 140 studies (Wagner et al., 2011; Strauch & Volk, 2013; Alemayehu et al., 2017; Hoyos et al., 141 2019; Ma et al., 2019; Rajib et al., 2020; H. Zhang et al., 2020; Marin et al., 2020). 142

Recognizing this limitation, previous studies have introduced novel representations of 143 vegetation dynamics into SWAT, which have produced satisfactory results for regions like 144 Central Brazil (Strauch & Volk, 2013), Kenya and Tanzania (Alemayehu et al., 2017), 145 southeast China (Ma et al., 2019), north central United States (Rajib et al., 2020), and 146 northern Australia (H. Zhang et al., 2020). For instance, Alemayehu et al. (2017) successfully 147 implemented their new SWAT-T variant in a tropical watershed in Kenya and Tanzania 148 after having modified the plant growth module. Many tropical watersheds, however, do 149 not conform to the unimodal cycle as prescribed in SWAT-T. In fact, Hoyos et al. (2019) 150 showed that although SWAT-T successfully reproduces streamflow in a watershed of the 151 tropical Andes and improves the representation of LAI dynamics as compared to SWAT, it 152 nevertheless fails in reproducing the observed bimodal seasonality of LAI. 153

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2.2 Changes in Plant Growth Module in SWAT-Tb

We built upon SWAT-T's vegetation module to develop SWAT-Tb. This enhanced module 155 has the capability of representing a bimodal LAI annual cycle. SWAT-T uses changes in the 156 Soil Moisture Index (SMI, computed as the ratio between 5-day aggregate precipitation (P) 157 and reference evapotranspiration (ET)) as a proxy for the dry to wet season transition in the 158 tropics, which then triggers a unimodal vegetation growth cycle (Alemayehu et al., 2017). 159 Unlike SWAT-T, SWAT-Tb uses precipitation as a proxy for seasonal variations in LAI. 160 This relation is based also on the assumption that the onset of the wet season triggers plant 161 growth (Liang et al., 2020), and agrees with observations of the annual cycles of precipitation 162 and LAI in the study watershed (see Section 4.1). Using precipitation (as in SWAT-Tb) 163 instead of SMI (as in SWAT-T) is also consistent with the fact that tropical environments 164 are not always water-limited (Gotsch et al., 2016), therefore there is not always a direct 165 relation between plant growth and soil moisture (Alemayehu et al., 2017). In the energy-166 limited environments that are common in the tropical Andes, precipitation is arguably a 167 better proxy of vegetation dynamics because it relates to both water and energy (e.g. peak 168 LAI comes after peak precipitation as shown in Section 4.1). Seasonal precipitation in the 169 tropical Andes is strongly controlled by the latitudinal migration of the ITCZ (Espinoza et 170

Data	Description	Source
DEM	Elevation data at a resolution of 1 arc-second (30 meters).	Jarvis et al. (2008)
Land cover	Land cover map for the Grande and Chico rivers wa- tersheds for the year 2015, scale 1:100,000.	CORANTIOQUIA and UNAL (2015)
Soil	Soil map for the the Grande and Chico rivers water- sheds, scale 1:50,000.	Machado et al. (2019)
Hydrometeorological	Precipitation, minimum and maximum temperature, relative humidity, evapotranspiration, and stream- flow for the period 1990–2016.	EPM^1 and $IDEAM^2$
LAI	MCD15A2Hv006 MODIS-LAI product for the period 2003–2016 with a spatial resolution of 0.5 km. Values are 8-days-composites.	Myneni et al. (2015)

Table 1.	Description	of data	used in	this	study.
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¹EPM: Public Utilities Company of Medellín, ²IDEAM: Colombian Institute of Hydrology, Meteorology and Environmental Studies.

al., 2020), which affects the surface energy balance, and therefore other vegetation-related variables such as photosynthetic rate, net productivity, and transpiration (Aparecido et al.,

¹⁷³ 2018). The SWAT-Tb executable and the associated changes with file examples (*.sub,

*.mgt and plant.dat) can be found in Supplementary Material S1.

3 Materials and Methods

3.1 Study Area

This study focuses on the Chico River (CR) watershed in the tropical Andes of Colombia 177 (Figure 1). The CR watershed is a tributary of the Grande River (GR) watershed, which is 178 strategic for water supply to local rural communities and more than 4 million people living in 179 the Metropolitan Area around Medellín, as well as for hydropower generation (the CR flows 180 into a reservoir, Figure 1d), agriculture, and dairy industry. The CR watershed covers a 181 drainage area of 169 km² with altitudes ranging between 2400 and 3260 m.a.s.l. (Figure 1e). 182 Mean annual precipitation is 1820 mm, and mean monthly temperature varies between 12°C 183 and 16° C with an average of 14° C. Precipitation seasonality is characterized by a bimodal 184 regime with two wet seasons: March-April-May (MAM) and September-October-November 185 (SON), and two dry seasons: December-January-February (DJF) and June-July-August 186 (JJA) (Poveda, 2004; García-Leoz et al., 2017). Land use in the watershed is dominated 187 by pastures (54.17%) of the area), followed by native forest (29.30%), shrubs (11.42%), and 188 paramo vegetation (4.89%) (Figure 1e). A considerable fraction of native vegetation (e.g. 189 native forest, shrubs, and paramo vegetation) has been converted into agro-pastoral uses in 190 the watershed (Berrouet et al., 2020). The dominant soil type is Andic Dystrudepts, which 191 makes up 62% of the watershed (Figure 1g). 192

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3.2 Input Datasets and Model Parameters

A summarized description of the data used in this study and their sources are presented in Table 1. Elevation data were used for the definition of sub-basins and HRUs. Based on previous studies for tropical Andean regions, the LULC map was reclassified to match the SWAT land use types (Supplementary Table S1; (Tapasco et al., 2015; Hoyos et al., 2019; Villamizar et al., 2019)), and the soil map was parameterized (Machado et al., 2019; Uribe et al., 2018, 2020). Processing of the above data yielded 7 sub-basins and 649 HRUs using the SWAT2012 extension (version 1.9) within QGIS 2.6.1 (Dile et al., 2019) software.



Figure 1. (a-c) General location of the study area (South America, Colombia, and Antioquia, respectively). (d) Grande ("big") and Chico ("small") rivers watersheds including hydrometeorological gauges. (e) Digital Elevation Model (DEM), (f) land cover for the year 2015, and (g) soil types. Land cover and soil types codes are: RYEL: pasture, FRST: native Andean forest, RYEB: shrubs, BROM: paramo vegetation, RYEE: pasture with secondary growth, PINE: planted forest, URMD: urban, AD: Andic Dystrudepts, AH: Andic Humudepts, AU: Andic Udifluvents, LH: Lithic Hapludand, TD: Typic Dystrudepts, TH: Typic Hapludands, and TM: typic melanudands.

Daily hydrometeorological data (precipitation, maximum and minumum temperature, 201 relative humidity, evapotranspiration, and streamflow) from the available gauges (Figure 202 1d) were provided by the Colombian Institute of Hydrology, Meteorology and Environmen-203 tal Studies (IDEAM in Spanish) and the Public Utilities Company of Medellín (EPM in 204 Spanish). We used the Priestley-Taylor equation to calculate evapotranspiration as wind 205 data were not available from ground-based gauges, and global datasets (reanalyses) have a 206 limited capacity to represent wind over the complex terrain of the Andes (Posada-Marín et 207 al., 2019). The SWAT's internal WGENX weather generator (Neitsch et al., 2011) was used 208 to estimate daily solar radiation. Observed 8-day composites of LAI were obtained from 209 the MCD15A2H-MODIS product (Mvneni et al., 2015) for the 2003–2016 period at 0.5 km 210 spatial resolution. Further details on LAI data processing are given in Section S2 of the 211 Supplementary Material. 212

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3.3 Model Calibration, Validation and Uncertainty Estimation

The SWAT-Tb model is calibrated to simulate, first, monthly LAI, and then monthly 214 streamflow using both manual and automatized techniques. Parameters are initially se-215 lected based on a literature review (Arnold et al., 2012; Strauch & Volk, 2013; Abbaspour 216 et al., 2015; Alemayehu et al., 2017; H. Zhang et al., 2020) that includes previous studies 217 for Andean watersheds (Tapasco et al., 2015; Hasan & Wyseure, 2018; Hoyos et al., 2019; 218 Villamizar et al., 2019) (Supplementary Table S3). In order to obtain comparable results, 219 SWAT-T is also calibrated for LAI whereas SWAT is only calibrated for streamflow. Stream-220 flow and LAI calibration was conducted for 2003–2016, while validation was performed for 221 1993–2002. Three years are added at the beginning of each simulation as a spin-up period to 222 mitigate the influence of uncertain initial conditions, especially for soil moisture. Sensitivity 223 and uncertainty analyses, as well as automatized procedures for calibration and validation 224 are carried out in SWAT-CUP 2019 (version 5.2.1; Abbaspour, 2013) using the Sequential 225 Uncertainty Fitting (SUFI-2) algorithm (Abbaspour et al., 2004). 226

Calibration of LAI is performed for SWAT-Tb and SWAT-T through manual adjust-227 ment of parameters (Supplementary Table S2) while considering land cover types separately. 228 The Breaks for Additive Seasonal and Trend (BFAST) method (Verbesselt et al., 2010) was 229 implemented to exclude noise from the LAI time series. The Pearson correlation coefficient 230 (r), the percent bias (PBIAS), and the Kling–Gupta efficiency (KGE; Gupta et al., 2009) 231 are used to evaluate the agreement between simulated and observed LAI values. Since we 232 want to assess the effect of an inaccurate representation of vegetation dynamics, SWAT 233 is not calibrated for LAI, which is not an unusual practice (e.g. Villamizar et al., 2019; 234 Adhikari et al., 2020). Streamflow calibration is focused on the dominant land cover types 235 pasture (RYEL) and native Andean forest (FRST) that account for approximately 80% 236 of the watershed (Figure 1f)— and on the upper soil layers that are most directly affected 237 by vegetation change (Tobón et al., 2010; Marín et al., 2019). Parameters for the dominant 238 land cover types are calibrated independently, whereas parameters for all other land cover 239 types are grouped in order to reduce computational cost. 240

Sensitive parameters are identified with a sensitivity analysis based on 500 simulations. 241 This analysis starts with 33 parameters selected based on previous studies and literature 242 review (Supplementary Table S3), and yields 18 of them as the most sensitive (p-value 243 ≤ 0.05 , Supplementary Table S4). We also define an acceptable range of variability for each 244 sensitive parameter. Subsequently, we calibrate monthly streamflow with SUFI-2 using 1000 245 simulations per iteration (Latin hypercube sampling) for the selected parameter ranges. The 246 calibration goal is to obtain acceptable values for uncertainty statistics (p-value and r-value) 247 and the performance criteria proposed by Moriasi et al. (2007), which include Nash-Sutcliffe 248 Efficiency (NSE) as the objective function and other complementary statistics: percent 249 bias (PBIAS), determination coefficient, and RMSE-observations standard deviation ratio 250 (RSR). We also seek to obtain a reasonable representation of water balance components 251 by considering the following metrics: fraction of total runoff as baseflow, ratio between 252

total evapotranspiration and total precipitation, and ratio between surface runoff and total
streamflow. Model outputs for these metrics are compared with observation-based estimates
for Andean watersheds (Jaramillo-Robledo, 2003; García-Leoz et al., 2017; Suescún et al.,
2017; Bonnesoeur et al., 2019; Marín et al., 2019) (Supplementary Table S4).

257 **3.4 LULC Scenarios**

A control (CTL) scenario (i.e. LULC distribution for 2015 (CORANTIOQUIA & 258 UNAL, 2015), Figure 1f) and two extreme LULC scenarios are simulated: full watershed 259 forest loss (100% pasture, PAS) and forest cover (100% forest, FOR). These are not real-260 istic but "baseline"-type scenarios that are used to study the range of potential changes 261 in streamflow due to forest change in the watershed (e.g. Alvarenga et al., 2016; Tian et 262 al., 2017; Li et al., 2019; Peña-Arancibia et al., 2019). These scenarios not only represent 263 changes in the cover (e.g. LAI) but also in some soil properties based on parameteriza-264 tion of land cover types, to obtain a more realistic assessment of forest loss and intensive 265 pasture management impacts on water balance (Tobón et al., 2010; Marín et al., 2019; Peña-266 Arancibia et al., 2019). Each scenario is simulated for the period 1993–2016 (plus a spin-up 267 period of three years) using the best-fit parameter values from the calibration along with 268 1000 random combinations within the acceptable ranges. These simulations are performed 269 using the SUFI-2 algorithm (Abbaspour et al., 2004) and their output is used to assess the 270 effects of parameter variability and uncertainty on the results. Differences between scenarios 271 are analyzed using the non-parametric Wilcoxon rank-sum and signed-rank tests (Bauer, 272 1972). Since everything else is equal, these differences are entirely attributable to LULC 273 change. 274

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3.5 Comparison of SWAT variants

Three variants of the SWAT model that differ in their plant growth module are used: SWAT (default version, Arnold et al., 2012), SWAT-T (Alemayehu et al., 2017), and SWAT-Tb (present study). These variants are compared to evaluate their performance in reproducing the observed dynamics of plant growth, specifically LAI (see Section 4.1). As a proof-of-concept, we also compare SWAT calibrated for streamflow with SWAT-Tb calibrated for both LAI and streamflow.

²⁸² 4 Results

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4.1 LAI Calibration

The observed seasonality of precipitation and LAI for all vegetation types in the wa-284 tershed exhibits a marked bimodal regime (Figure 2). There are two wet seasons in MAM 285 and SON, and two "dry" (less rainy) seasons in DJF and JJA. The SMI follows this same 286 pattern. Relative to precipitation and SMI, LAI exhibits a pattern that can be described 287 as mirrored to precipitation with lower values around the wet seasons and higher values in 288 the dry seasons, which indicates energy-limited ecosystems. This suggests that during the 289 dry seasons plant growth is not as limited by reduced precipitation and moisture (SMI is 290 greater than 1 in all months but January) as it is enhanced by increased radiation resulting 291 from less cloud cover (Aparecido et al., 2018). These results confirm the role of precipita-292 tion (and cloudiness) in controlling vegetation seasonality, which according to our results 293 and previous observations appears to be greater than that exerted by temperature. This 294 contrasts the assumptions made in the EPIC model about the dominant role of temperature 295 in plant growth (Williams et al., 1989; Arnold et al., 2012). 296

²⁹⁷ Comparison between observed and simulated LAI using SWAT, SWAT-T, and SWAT-²⁹⁸ Tb for the dominant LULC types shows that SWAT fails to represent LAI seasonality, as ²⁹⁹ evinced by high biases (53% < |PBIAS| < 90%) and negative or low correlations (-0.51 < r < 0.13). Results for other LULC types are shown in Supplementary Figure S1. A default



Figure 2. Average seasonality of climate variables (1990–2016; gauging stations) and LAI (2003–2016; BFAST-MODIS; area weighted HRU mean) in the CR watershed. Land cover types as in Figure 1.



Figure 3. Observed (MODIS) and simulated (SWAT, SWAT-T, and SWAT-Tb) seasonality of LAI in the CR watershed for native Andean forest (top) and pasture (bottom). Time series (a, d), average annual cycle (b, e), and the corresponding box-plots and performance statistics (c, f).

assumption of the SWAT model is that LAI is zero at the beginning of each simulation year, 301 which is unrealistic for tropical vegetation. This assumption is kept for the proof-of-concept, 302 and because it is behind an important limitation of SWAT for tropical watersheds (Strauch 303 & Volk, 2013; Mwangi et al., 2016; Alemayehu et al., 2017; Hoyos et al., 2019; H. Zhang et 304 al., 2020). Regardless of whether this assumption is changed, SWAT does not reproduce LAI 305 bimodality. Calibrated SWAT-T realistically reproduces the range of variability of LAI but 306 fails to represent LAI bimodality because it has a prescribed unimodal regime with a single 307 vegetation growth cycle per year (Alemayehu et al., 2017; Hoyos et al., 2019). Calibrated 308 SWAT-Tb outperforms both SWAT and SWAT-T in reproducing the observed bimodality 309 of LAI, as indicated by the correlation values. 310

4.2 Streamflow Calibration and Validation

SWAT-Tb is calibrated for streamflow by varying the most sensitive parameters (Sup-312 plementary Table S3). The best-fit parameter values and acceptable ranges (i.e. range 313 of parameter values for which simulations are acceptably realistic) are presented in Table 314 2. Simulated and observed monthly streamflow are shown in Figure 4 for the calibration 315 (2003–2016) and validation (1993–2002) periods. Based on multiple criteria (NSE, RSR, 316 and PBIAS), the model performance can be considered as "very good" and "good" for 317 calibration and validation, respectively (Moriasi et al., 2007). Furthermore, water balance 318 components are realistic as compared to the reference values (Supplementary Table S4). 319

Likewise, using the best-fit parameter values in Table 2, the performance of standard SWAT in reproducing observed streamflow varies between "very good" (for calibration) and "good" (for validation) (Moriasi et al., 2007, Supplementary Figure S2). This illustrates how standard SWAT can show high performance to reproduce streamflow despite having a low capability to simulate dynamics of LAI (Figure 3 and Supplementary Figure S1).

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4.3 Forest versus Pasture Impacts on Streamflow

SWAT-Tb results show that the potential impact of forest cover change on the watershed response is much more pronounced in monthly (Figure 5c) than in annual streamflow (Figure 5f). The results based on annual streamflow would misleadingly indicate that there are small differences between the FOR and PAS scenarios. In contrast, forest change leads to

Danamatanl	Description	Scaling	Range		Rost fit value	
rarameter	Description	$type^2$	min	max	- Dest-iit value	
CN2.mgt_RYEL	Runoff curve number for moisture condition II.	r	-0.22	-0.20	-0.20	
ESCO.hru_RYEL	Soil evaporation compensation factor.	v	0.35	0.50	0.42	
ESCO.hru_FRST	Soil evaporation compensation factor.	v	0.25	0.40	0.27	
ALPHA_BF.gw	Baseflow alpha factor $(1/days)$.	v	0.030	0.045	0.030	
CN2.mgt_FRST	Runoff curve number for moisture condition II.	r	-0.20	-0.18	-0.19	
SOL_K(1).sol_RYEL	Saturated hydraulic conductivity (mm/hr).	r	-0.35	-0.2	-0.23	
GWQMN.gw_FRST	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H ₂ O).	v	1500	2000	1988.25	
CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/hr).	v	25	75	52.63	
GWQMN.gw_RYEL	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H ₂ O).	v	2000	2500	2490.25	
ESCO.hru_BPRR	Soil evaporation compensation factor.	v	0.15	0.30	0.29	
SOL_K(1).sol_FRST	Saturated hydraulic conductivity (mm/hr).	r	-0.20	-0.10	-0.16	
SOL_BD(1).sol_BPRR	Moist bulk density (g/cm^3) .	r	-0.15	0.0	-0.039	
CN2.mgt_BPRR	Runoff curve number for moisture con- dition II.	r	-0.18	-0.15	-0.17	
SOL_AWC(1).sol_FRST	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil).	r	-0.30	-0.15	-0.25	
SOL_BD(1).sol_RYEL	Moist bulk density (g/cm^3) .	r	0.15	0.25	0.24	
GWQMN.gw_BPRR	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O).	v	1800	2200	1866.20	
SOL_K(1).sol_BPRR	Saturated hydraulic conductivity (mm/hr).	r	-0.15	0.0	-0.08	
SOL_AWC(1).sol_RYEL	Available water capacity of the soil layer (mm H_2O/mm soil).	r	0.35	0.50	0.37	

Table 2. Best-fit values for parameters and their acceptable range for the calibrated SWAT-Tbmodel.

¹Numbers (1, 2) refer to the soil layer number. FRST: native Andean forest, RYEL: pasture, and BPRR: paramo vegetation, planted forest, shrubs, and pasture with secondary growth. ²Scaling type: v (absolute) indicates that the parameter is replaced by the given value, r (relative) indicates that the parameter is multiplied by [1 + (given value)], which preserves spatial variability.



Figure 4. Calibration (2003–2016) and validation (1993–2002) of SWAT-Tb for monthly streamflow. Vertical bars show monthly rainfall from SWAT output, calculated from records in climate stations. NSE: Nash-Sutcliffe coefficient, PBIAS: percent bias, R^2 : coefficient of determination, and RSR: RMSE-observations standard deviation ratio. 95PPU: the 95% prediction uncertainty. Model performances based on the criteria of Moriasi et al. (2007): ^{*a*} Good (0.65<NSE≤0.75, 0.50<RSR≤0.60, ±10%<BIAS< ±15%) and ^{*b*} Very Good (0.75<NSE≤1.00, 0.00<RSR≤0.50, BIAS≤±10%).

significant differences in monthly streamflow seasonality, which are particularly pronounced 330 during the dry seasons (DJF and JJA). The occurrence of 100% forest cover in the watershed 331 leads to increased streamflow during the dry seasons (e.g. average streamflow in January 332 is about 10% greater in the FOR than in the CTL scenario), whereas its absence causes 333 a streamflow reduction (e.g. average streamflow in January is about 6% lower in the PAS 334 than in the CTL scenario). During the wet seasons, the most significant difference is found 335 in April when streamflow is reduced in the FOR scenario, while it is increased in the PAS 336 scenario. Differences between scenarios are smaller in the SON wet season. These results 337 remain valid when considering 1000 combinations of parameters values within the acceptable 338 ranges (Supplementary Figure S3). 339

Differences between scenarios seem small when looking at box-plots for the annual cycle 340 (Figure 5b) and annual average (Figure 5e). This is because these box-plots do not show 341 the year-to-year variability of monthly streamflow. Figures 5c and 5f clarify this by showing 342 the distribution (box-plots) of monthly differences computed as the difference of stream-343 flow between scenarios for the same month and year. This is important to guarantee that 344 the comparison is done between LULC scenarios under the same climate forcing (precipi-345 tation and temperature). For instance, PAS scenario streamflow under La Niña conditions 346 (above-normal precipitation) is not comparable to FOR scenario streamflow under El Niño 347 conditions (below-normal precipitation). 348

Despite their comparable ability to reproduce observed streamflow, SWAT and SWAT-349 Tb results do not support the same conclusions. For instance, streamflow increase in the 350 FOR scenario during the dry seasons is largely underestimated (in DJF) or even reversed (in 351 July and August) (Figure 5c) in SWAT output. The median percent increase of streamflow 352 from SWAT can be less than half the corresponding increase in SWAT-Tb (e.g. $\sim 4\%$ versus 353 $\sim 10\%$ in January). Further, SWAT results indicate that the median annual streamflow 354 would barely change due to extensive modification of LULC in the FOR and PAS scenarios 355 (Figure 5d). In contrast, SWAT-Tb output show a greater change in the median annual 356 streamflow. The statistical significance of this change will be discussed below. 357



Figure 5. Comparison of monthly (left) and annual (right) streamflow between scenarios and models. Input precipitation (blue bars) is the same for all scenarios and models (a,d). Average annual cycle (b) and annual streamflow (e) in all scenarios for 1993–2016. Percent differences between monthly (c) and annual (f) streamflow in the control (CTL) and LULC (FOR and PAS) scenarios for 1993–2016 as simulated by SWAT-Tb and SWAT using best fit parameters. Positive (negative) values indicate that streamflow is increased (decreased) in the LULC change scenario. Boxes (dark green and yellow) show variability of monthly differences in SWAT-Tb output, whereas lines with dots (light green and orange) show the corresponding median from SWAT output. Asterisks identify months for which the difference between medians in the FOR and PAS scenarios is statistically significant (n=24, p < 0.05) for SWAT-Tb output.



Figure 6. Annual cycle and percent differences between monthly (a) actual evapotranspiration (ET), (b) surface runoff (SURQ), (c) lateral flow (LATQ), (d) percolation (PERC), (e) groundwater contribution to streamflow (GWQ), and (f) water yield (WYLD) in the control (CTL) and LULC (FOR and PAS) scenarios for 1993–2016 as simulated by SWAT-Tb at the watershed scale. Variables are HRU area-weighted means for each month. Positive (negative) values indicate that the variable is increased (decreased) in the LULC change scenario. Vertical bars show mean monthly precipitation (PCP).

4.4 Water Balance Components

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Differences in streamflow between scenarios are caused by differences in the watershed's 359 water balance components (Figure 6). The largest differences between the CTL and LULC 360 scenarios are found for surface runoff (Figure 6b), lateral flow (Figure 6c), percolation (Fig-361 ure 6d), and groundwater contribution (i.e. baseflow) to streamflow (Figure 6e). The sum of 362 these differences leads to differences in water yield (Figure 6f). By comparison, differences 363 in evapotranspiration are much less pronounced (Figure 6a; note that their magnitudes 364 never exceed 6%). All these differences consider the year-to-year variability as explained 365 previously for Figure 5. 366

In our simulations, differences between output from SWAT-Tb and SWAT are entirely 367 caused by differences in the simulated LAI values (Figure 7a). The resulting differences in 368 water balance components are more pronounced for the PAS than for the FOR scenario 369 (Figure 7b–g). As compared to SWAT-Tb, in the PAS scenario SWAT overestimates water 370 yield throughout the year (Figure 7g), with larger values during JJA and SON, i.e. during 371 the second dry and wet seasons of the year in the actual bimodal regime. This overestima-372 tion in JJA–SON results from greater production of surface runoff (Figure 7c), lateral flow 373 (Figure 7d), and base flow (Figure 7f), as well as from reduced evapotranspiration (Figure 374 7b). In DJF–MAM, there are mixed patterns in the water balance components that lead 375 to a smaller overestimation of water yield. In the FOR scenario, SWAT underestimates 376 LAI throughout the year, mostly in DJF, which leads to mixed results in water balance 377 components. In both scenarios, differences of surface runoff between models (Figure 7c) are 378 minimal ($< \pm 0.5$ mm), hence the effects on streamflow result mainly from variations in 379 evapotranspiration and groundwater flows (i.e. lateral flow, percolation, and base flow). 380



Figure 7. Differences between SWAT and SWAT-Tb in the monthly median of (a) Leaf Area Index (LAI), (b) total biomass (BIOM, i.e. above-ground and roots at the end of the period reported as dry weight), (c) actual evapotranspiration (ET), (d) surface runoff (SURQ), (e) lateral flow (LATQ), (f) percolation (PERC), (g) groundwater contribution (GWQ), and (h) water yield (WYLD) for each LULC scenario (PAS and FOR) at the watershed scale (area-weighted HRU mean for each month).

381 5 Discussion

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5.1 Advantages of SWAT-Tb over SWAT

There is no noticeable difference between SWAT-Tb and SWAT in representing monthly streamflow (Figures 5b and S2). However, there are visible differences in their capability to reproduce vegetation dynamics through LAI (Figure 3), as well as in their results regarding the potential impact of forest conversion on streamflow (Figure 5c) and the underlying changes in the water balance components (Figure 7).

Our proof-of-concept illustrates how SWAT can be calibrated to realistically simulate 388 streamflow despite being intrinsically unable to reproduce the observed dynamics of LAI, 389 which has multiple effects on the water balance components including evapotranspiration, 390 canopy interception, and surface runoff (Neitsch et al., 2011; Strauch & Volk, 2013; Ale-391 mayehu et al., 2017). Hence, there is a danger of getting the right results (e.g. the model 392 reproduces observed streamflow) for the wrong reasons (Kirchner, 2006), which strongly 393 limits the capability of models (i.e. SWAT in the present case) to produce reliable results 394 for informing decisions. 395

We argue that SWAT results (Figures 5 and 7), and perhaps also the results of studies 396 using the approach of calibrating and validating SWAT for streamflow but not for LAI 397 (e.g. Villamizar et al., 2019; Adhikari et al., 2020), may be misleading about the impacts 398 of tropical forest change on streamflow. In contrast, SWAT-Tb provides better insight 399 by reproducing not only the observed streamflow but also the bimodal dynamics of LAI 400 that are typical of many tropical watersheds. This is particularly important for assessing 401 water balance components that affect water security in the tropical Andes threatened by 402 undergoing deforestation (A. Salazar et al., 2018; Viviroli et al., 2020). 403

5.2 Forest Impact on the Watershed's Regulation Capacity and Water Availability

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Results of previous studies about forest change impacts on streamflow are diverse 406 (M. Zhang et al., 2017; Ochoa-Tocachi et al., 2016; Jones et al., 2020), which suggests that 407 conclusions about this are hardly generalizable. However, a number of previous studies have 408 concluded that increased forest cover in a watershed leads to decreased annual streamflow, 409 mainly as a consequence of increased evapotranspiration (Ellison et al., 2012; Muñoz-Villers 410 & McDonnell, 2013; Ogden et al., 2013; M. Zhang et al., 2017). In our results, differences 411 412 in annual streamflow between scenarios are not statistically significant (p > 0.05; Figure 5f and Supplementary Figure S3f), which does not necessarily imply that these differences are 413 negligible or physically meaningless (Amrhein et al., 2019). Given this, and in addition to 414 the significant differences in the annual cycle, our results indicate that annual streamflow is 415 almost always greater in the FOR than in the CTL and PAS scenarios, which is opposite to 416 the aforementioned conclusion. 417

There are statistically significant differences in monthly streamflow between scenarios 418 (p < 0.05; Figure 5c and Supplementary Figure S3c), particularly in dry seasons (DJF and 419 JJA). This is relevant from the perspective of regulation, defined here as the capacity of 420 watersheds to reduce streamflow variability and attenuating extreme streamflows (Ochoa-421 Tocachi et al., 2016; J. F. Salazar et al., 2018; Rodríguez et al., 2018). This regulation 422 implies a contrasting capacity of watersheds to increase low streamflows while reducing 423 floods (J. F. Salazar et al., 2018; Rodríguez et al., 2018). The CR watershed's regulation capacity is increased in the FOR scenario, as revealed by higher streamflow during the dry 425 season while little change during the wet season, relative to the CTL scenario. 426

Increased forest cover leads to reduced direct runoff and lateral flow, as well as to 427 increased percolation and groundwater contribution to streamflow (i.e. base flow), as com-428 pared to the effect of increased pasture cover (Figure 6), which is consistent with field 429 observations in the region of the CR watershed by García-Leoz et al. (2017); Suescún et al. 430 (2017). Although these effects of forest change are the same throughout the year (Figure 431 6), their impact on streamflow is not the same because it depends on the relative contribu-432 tion of each water balance component to streamflow. In dry seasons, streamflow depends 433 more on base flow than on direct runoff and lateral flow. In contrast, during wet seasons 434 precipitation may contribute more to streamflow via direct runoff and lateral flow than base 435 flow. As a result, the impacts on streamflow of reduced direct runoff and lateral flow, and increased percolation and base flow, vary across seasons. The increased presence of forest 437 can increase low streamflow during dry seasons mainly through increased base flow, while 438 it can reduce streamflow during the wet season mainly through reduced direct runoff and 439 lateral flow. 440

441 These results are consistent with some theoretical hypothesis and previous observational studies. The infiltration trade-off hypothesis for tropical environments (Bruijnzeel, 1989, 442 2004) proposes that reduced forest cover in a watershed can lead to reduced low streamflow 443 in dry seasons as a result of reductions in infiltration and water storage in soils during wet 444 seasons, which are not compensated by water gains due to reduced evapotranspiration. The 445 forest reservoir hypothesis (J. F. Salazar et al., 2018) proposes that tropical forests enhance 446 the capacity of watersheds to regulate streamflow, mainly through their role in mediating 447 land-atmosphere interactions. Ellison et al. (2012) divide the forest water debate into two 448 schools of thought: the "demand-side" and the "supply-side" schools. While the former 449 sees trees and forests as consumers of available water and competitors for other downstream 450 water uses, the latter supports the beneficial impact of forest cover on the hydrological cycle, 451 452 emphasizing that increasing forest cover raises water yield. Our results lend support to the "supply-side" perspective. 453

454 Observational and modeling studies have shown that forest conversion into pasture or 455 croplands in tropical watersheds can result in decreased low streamflows and increased floods (Roa-García et al., 2011; Ogden et al., 2013; Ochoa-Tocachi et al., 2016; Ramírez et al.,
2017; Krishnaswamy et al., 2018; Peña-Arancibia et al., 2019; López-Ramírez et al., 2020).
Our results indicate that forest cover gain (i.e. FOR scenario) leads to increased infiltration
and groundwater recharge (Figures 6c-e) and little changes in evapotranspiration (Figures
6a). Field observations in the region of the CR watershed have indicated that the difference
between evapotranspiration of native Andean forest (FRST) and pasture (RYEL) is small
(García-Leoz et al., 2017), as it is in our results.

6 Conclusions

Bimodal seasonal patterns of vegetation dynamics are common to many watersheds, 464 especially (although not exclusively) in tropical regions under the influence of the ITCZ. 465 The new SWAT-Tb variant reproduces not only observed streamflow, but also the bimodal 466 seasonal pattern of LAI in a tropical mountain watershed. In contrast, standard SWAT 467 is inherently unable to reproduce this bimodality in vegetation dynamics, although it can 468 be calibrated to reproduce streamflow. These variations in the representation of LAI sea-469 sonality can lead to significantly different results when assessing LULC change impacts on 470 streamflow. 471

Regarding the effect of forest change on streamflow, our results show that impacts 472 can be much more pronounced for seasonal than for annual streamflow, and indicate that 473 forests can play a crucial role in enhancing water availability during dry seasons. We found 474 that the seasonality of streamflow anomalies is largely switched due to forest-to-pasture 475 conversion, implying that while forest expansion increases water availability in dry seasons, 476 deforestation (e.g. forest conversion into pasture) can strongly decrease it. Due to its poor 477 representation of LAI seasonality, standard SWAT largely underestimates this role of forest, 478 which can be misleading for decision making about water security and forest conservation. 479

480 Data availability

The SWAT-Tb executable and code will be available through SWATshare (https:// 481 mygeohub.org/groups/water-hub/swatshare_landing), which is a cyberinfrastructure for 482 sharing, simulation, and visualization of SWAT models. For review purposes, the data 483 are available online at https://bit.ly/2XT8uxs. After publication, we may change the 484 link to keep the files permanently available in SWATshare. Emails requesting necessary 485 technical support can be directed to the corresponding author. The data used in this 486 study are publicly available. Sources to access these data, including any other infor-487 mation to replicate the results, are provided in the references, tables, and supporting 488 information. Also, they are accessible through links provided below: Digital Elevation 489 Model was from http://srtm.csi.cgiar.org/. MODIS-LAI data was obtained from 490 https://lpdaac.usgs.gov/products/mcd15a2hv006/. IDEAM from 491

http://dhime.ideam.gov.co/atencionciudadano/. Land cover and soil types maps is
available through CORANTIOQUIA and UNAL (2015) and Machado et al. (2019), respectively.

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Supporting Information for "SWAT-Tb with improved LAI representation in the tropics highlights

- ² improved LAI representation in the tropics high
- the role of forests in watershed regulation"

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⁹ Contents

- ¹⁰ 1. Supplementary Material S1: SWAT-Tb implementation
- 2. Supplementary material S2: Leaf Area Index (LAI) data and calibration
- ¹² 3. Figures S1 to S3
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- ¹⁴ 5. References

Supplementary Material S1: SWAT-Tb implementation

- ¹⁵ Alemayehu, Griensven, Woldegiorgis, and Bauwens (2017) modified SWAT by adding
- $_{16}$ two parameters (based on Strauch and Volk (2013)) that represent the end of the dry

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season (SOS1) and the beginning of the wet season (SOS2). In SWAT-Tb, we added three 17 new parameters (SOS3, SOS4, and SOS5) to represent the seasonality of precipitation 18 characterized by a bimodal regime with two wet and dry seasons. In this case, SOS1 19 and SOS2 represent the months of the end and beginning of the first dry-wet season 20 transition, respectively. SOS3 represents the end of the first wet season and the beginning 21 of the second dry season (i.e. a new growth cycle), whereas SOS4 and SOS5 indicate, 22 respectively, the first and last month of the second dry-wet season transition. In SWAT-23 T, SOS1 and SOS2 parameters are estimated using the seasonal pattern of SMI based on 24 precipitation and a reference evapotranspiration ratio (Figure 2; Alemayehu et al., 2017). 25 The SOS(1,2,3,4,5) parameters are defined using mean monthly precipitation and LAI 26 seasonality for each land cover category in the CR watershed. 27

Implementation of SWAT-Tb requires the user to add the lines shown below to the *allocate_parm.f, getallo.f, grow.f, modparm.f, readsub.f,* and *zero.f* subroutines from SWAT-T (Alemayehu et al., 2017). New lines are annotated as [svalencia]. The SWAT-Tb executable as well as the *.sub, *.mgt, and subroutines files, which must be adapted, are available online at https://bit.ly/2XT8uxs. This link is intended only to allow detailed revision of the manuscript. After publication, we may change the link to keep the files permanently available.

$allocate_parm.f$

- ³⁵ ! allocate tropical plant growth variables [talemayehu]
- ³⁶ allocate (iseason(mhru))
- ³⁷ allocate (sos1(msub))
- $_{38}$ allocate (sos2(msub))

- ³⁹ allocate (sos3(msub)) !! Added by [svalencia]
- ⁴⁰ allocate (sos4(msub)) !! Added by [svalencia]
- allocate (sos5(msub)) !! Added by [svalencia]

getallo.f

- $_{42}$ read (27,6100) subfile
- 43 call caps(subfile)
- ⁴⁴ open (25,file=subfile)
- ⁴⁵ do j = 1, 57 !! changed (54) [svalencia]
- $_{46}$ read (25,6000) titldum
- 47 end do

grow.f

- 48 !! INCOMING VARIABLES
- ⁴⁹ !! sos1(:) |month |starting month of transition to first wet season added by [talemayehu]
- ⁵⁰ !! sos2(:) |month |ending month of transition to first wet season added by [talemayehu]
- ⁵¹ !! added by [svalencia]
- ⁵² !! sos3(:) |month |ending of the first wet season and the starting of the second dry season
- ⁵³ !! sos4(:) |month |starting month of transition to second wet season
- ⁵⁴ !! sos5(:) |month |ending month of transition to second wet season
- 55
- 56
- $_{57}$ if (smi_tr <=0.0) smi_tr = 0.5
- $_{58}$ idp = idplt(j)

```
X - 4
```

```
<sup>59</sup> if (Abs(sub_lat(hru_sub(j))) < 20. AND.
```

:

```
_{60} iseason(j) == 0 .AND.
```

- $_{\mbox{\tiny 61}}$ & i_mo >= sos1(hru_sub(j)) . AND.
- $_{62}$ & i_mo <= sos2(hru_sub(j))) then
- 63 smi=0.
- 64

```
_{65} if (count_D(j)>0) then
```

- $_{66}$ do kk = 1, w_size-1
- ⁶⁷ pet_subA(w_size-kk+1,(j)) = pet_subA(w_size-kk,(j))
- 68 end do
- $_{^{69}} \quad \mathrm{pet_subA}(1,\!(j)) = \mathrm{pet_sub}((j))$
- 70 else
- $_{^{71}} \ \mathrm{pet_subA}(1,(j)) = \mathrm{pet_sub}((j))$
- 72 end if
- $_{^{73}}\;\; {\rm if}\; ({\rm count_D}(j)>0) \; {\rm then}\;$
- ⁷⁴ do kk = 1, w_size-1
- $_{^{75}}$ sub_pcpA(w_size-kk+1,(j)) =
- ⁷⁶ & sub_pcpA(w_size-kk,(j))
- 77
- 78 end do
- $_{^{79}} \ \mathrm{sub_pcpA}(1,\!(j)) = \mathrm{sub_pcp}(\mathrm{hru_sub}(j))$
- 80 else
- ${}_{^{81}} \ {\rm sub_pcpA}(1,hru_sub(j)) = {\rm sub_pcp}(hru_sub(j))$

```
_{82} end if
```

- $_{s_3}$ count_D(j) = count_D(j) +1
- $_{84}$ if(count_D(j) > w_size) count_D(j) = w_size
- $_{s_5}$ if(count_D(j) == w_size) then
- smi = sum(sub_pcpA(:,(j)))/sum(pet_subA(:,(j)))

:

- $_{87}$ if (smi >= smi_tr) then
- ⁸⁸ call changeseason
- ⁸⁹ count_D(j) = 0

```
90 end if
```

```
91
```

```
92 end if
```

- $_{93}$ if(count_D(j) < w_size) then
- $_{94}$ smi = 0.0
- 95 end if
- $_{96}$ else if $(Abs(sub_lat(hru_sub(j))) < 20$. AND.
- ⁹⁷ & iseason(j) == 0 .AND. i_mo > $sos2(hru_sub(j))$
- .AND. i_mo $\leq sos3(hru_sub(j))$ then !! Added by [svalencia]
- ⁹⁹ call changeseason

```
100 \operatorname{count}_D(j) = 0
```

- 101
- ¹⁰² <u>!!</u> Added by [svalencia]
- else if $(Abs(sub_lat(hru_sub(j))) < 20.$
- AND. iseason(j) == 1 AND.





modparm.f

- ¹⁴⁶ !! added for plant growth modification for tropics added by [talemayehu]
- ¹⁴⁷ integer, dimension (:), allocatable :: iseason, sos1, sos2, sos3, sos4, sos5 !! last three added by [svalencia]

:

readsub.f

- read (101,*) sos1(i) !! added by [talemayehu]
- read (101,*) sos2(i) !! added by [talemayehu]
- read (101,*) sos3(i) !! added by [svalencia]
- read (101,*) sos4(i) !! added by [svalencia]
- read (101,*) sos5(i) !! added by [svalencia]

zero0.f

- ¹⁵³ !!initialize tropical plant growth variables added by [talemayehu]
- 154 iseason = 0
- 155 sos1 = 0
- 156 sos2 = 0
- $_{157}$ sos3 = 0 !! added by [svalencia]
- $_{158}$ sos4 = 0 !! added by [svalencia]
- $_{159}$ sos 5 = 0 !! added by [svalencia]

160 $smi_tr = 0.$

¹⁶¹ Supplementary material S2: Leaf Area Index (LAI) data and calibration

LAI data were obtained from the MCD15A2H-MODIS product (Myneni et al., 2015) for the GR watershed with a spatial and temporal resolution of 0.5 km and 8-days (composites), respectively. Only pixels with a corresponding "best quality" flag (LAI_QC=0) were kept for the analysis. We processed LAI data following methods used in Alemayehu et al. (2017) and Hoyos et al. (2019). For most land cover types, LAI values were extracted as follows: (i) polygons with an area at of least 5 km² within the CR watershed are selected for each land cover, (ii) LAI values are associated to each land cover type only

¹⁶⁹ in pixels where such land cover type covers at least 60% of the area. For shrubs (RYEB) ¹⁷⁰ and planted forest (PINE), which cover less than 12% of the CR watershed, polygons ¹⁷¹ are smaller than 5 km². Therefore, the corresponding LAI values were extracted from ¹⁷² polygons in the vicinity of the CR watershed, within the GR watershed. Median LAI ¹⁷³ values for each land cover type and period (8-day composites) were calculated from the ¹⁷⁴ aforementioned polygons as suggested by Strauch and Volk (2013) and Alemayehu et al. ¹⁷⁵ (2017).

For the LAI calibration, the initial values of parameters such as the initial (LAI_INIT), 176 minimum (ALAI_MIN) and maximum (BLAI) LAI values for each land cover type were set 177 based on the long-term MODIS-LAI time series (Figure 3 and Supplementary Figure S1). 178 Initial values of Plant Heat Units (PHU) were calculated using the long-term daily mean 179 temperature, as suggested by Strauch and Volk (2013). Other initial parameters were 180 defined based on literature (e.g., T_BASE, T_OPT, CHTMX, and CANMX; see Table 181 S2) and default values (e.g., FRGW1, FRGW2, LAIMX1, LAIMX2, and DLAI). These 182 parameters were calibrated by a trial-and-error process to ensure that the LAI values 183 simulated by SWAT-T and SWAT-Tb mimicked the smoothed MODIS-LAI. The Pearson 184 correlation coefficient (r), the percent of bias (PBIAS), and the Kling–Gupta efficiency 185 (KGE) (Gupta et al., 2009) were used to evaluate the agreement between simulated and 186 observation-based estimates (MODIS) of LAI. 187

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Table S1. Reclassification of land cover types in the CR watershed according to SWAT

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categories.

Land cover type	SWAT cate- gory	Description	Area (%)
Pasture	RYEL	Pasture dominated by <i>Pennisetum clandestinum</i> <i>Hochst, ex Chiow (Poaceae)</i> , used for cattle dairy	51.24
Native Andean forest	FRST	Forest dominated by mature Andean Oak (<i>Quercus humboldtii</i> Bonpl. Fagaceae)	29.30
Shrubs	RYEB	Secondary succession with little to no human in- tervention	11.42
Paramo vegeta- tion	BROM	High altitude native grasslands with sparse vege- tation cover and ocasional presence of shrubs	4.89
Pasture with secondary growth	RYEE	Unmanaged grasslands with occurrence of sparse secondary vegetation	2.93
Planted forest	PINE	Forest dominated by <i>Pinus patula</i> Schltdl. Cham	0.09

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Parameter Description					FDST	O	alibrated	values (in	nitial value	s)	DINE
calibrated values in the SWAT-Tb model.											
Table S2.	LAI-ralated	parameters	for	each	land	cover	type	and	their	initial	and

	F	FRST	RYEL	RYEB	RYEE	BROM	PINE
LAI_INIT ¹	Initial leaf area index (m^2/m^2)	4.20* (4.17)	1.80* (1.90)	3.50* (3.74)	2.30 (-)	3.10* (3.16)	3.60* (3.80)
BIO_INIT	Initial dry weight biomass (kg/ha)	50000^2 (-)	20000 ³ (-)	20000 (-)	20000 (-)	200004 (-)	50000 (-)
PHU_PLT ⁵	Total number of heat units or growing degree days needed to bring plant to maturity	3000* (1700)	3000* (1700)	1700 (-)	1800* (1700)	2000 (-)	5000 (-)
BLAI ¹	Maximum potential leaf area index (m^2/m^2)	4.40* (3.79)	1.95^{*} (1.68)	4.50* (3.22)	2.80^{*} (2.0)	3.20* (2.62)	3.90* (3.50)
ALAI_MIN ¹	Minimum leaf area index (m^2/m^2)	2.60* (3.38)	1.25^{*} (1.35)	1.85^{*} (1.44)	1.45* (1.41)	2.0^{*} (1.19)	2.0^{*} (2.70)
FRGRW1	Fraction of PHU corresponding to the 1^{st} point on the leaf area development curve	0.15^{*} (0.05)	0.10^{*} (0.20)	0.07^{*} (0.20)	0.07^{*} (0.20)	0.07^{*} (0.45)	$0.10^{*} (0.15)$
FRGRW2	Fraction of PHU corresponding to the 2^{nd} point on the leaf area development curve	0.38* (0.40)	0.40^{*} (0.45)	0.20^{*} (0.45)	0.40^{*} (0.45)	0.20^{*} (0.80)	0.38^{*} (0.25)
LAIMX1	Fraction of BLAI corresponding to the 1^{st} point on the optimal leaf area development curve	0.70^{*} (0.05)	0.10^{*} (0.32)	0.15^{*} (0.32)	0.10^{*} (0.32)	0.15^{*} (0.02)	0.40^{*} (0.70)
LAIMX2	Fraction of BLAI corresponding to the 2^{nd} point on the optimal leaf area development curve	0.90^{*} (0.95)	0.99^{*} (0.95)	$0.99^{*} (0.95)$	$0.99^{*} (0.95)$	0.99^{*} (0.95)	$0.90^{*} (0.99)$
DLAI	Fraction of PHU when LAI beings to decline	0.20^{*} (0.99)	0.99^{*} (0.50)	0.5** (-)	0.99^{*} (0.50)	0.85** (-)	0.99* (-)
T_BASE	Minimum temperature for plant growth (oC)	9.30^{6} (-)	0^{*} (7.0 ⁷)	9.30 ⁷ (-)	9.30 ⁷ (-)	7.0^{*} (4.0 ⁸)	0^{*} (10.0 ⁷)
T_OPT	Optimal temperature for plant growth (oC)	18.60 ⁶ (-)	18.0 ⁷ (-)	18.6 ⁶ (-)	18.60^{6} (-)	$18.0^{*} (10.0^{8})$	14.0 ⁷ (-)
BIO_E	Radiation use efficiency $((kg/ha)/(MJ/m^2))$	18.0^{*} (15.0)	10.0* (30.0)	10.0* (30.0)	$10.0^{*} (30.0)$	15.0* (35.0)	10.0^{*} (15.0)
CHTMX	Maximum canopy height (m)	25.0 ⁹ (-)	$0.30^{3,10}$ (-)	1.20^{10} (-)	1.20^{10} (-)	0.50^8 (-)	25.0 ⁹ (-)
CANMX	Maximum canopy storage (mm H ₂ O)	$0.30^{11,12}(-)$	$0.05^{10}(-)$	$0.20^{10,12}(-)$	$0.05^{10,12}(-)$	$0.15^{13}(-)$	0.10(-)
BMDIEOFF	Biomass die-off fraction	0.1 ** (-)	0.05^{**} (0.1)	0.1** (-)	0.1**(-)	$0.1^{*}(-)$	0.1*(-)
SOS1 ¹⁴	First month of the 1^{st} dry-wet season transition			3	(-)		
$SOS2^{14}$	Last month of the 1^{st} dry-wet season transition			4	(-)		
$SOS3^{14}$	End of first wet season and the beginning of second dry season			6	(7)		
$SOS4^{14}$	First month of the 2^{nd} dry-wet season transition			10	(9)		
$SOS5^{14}$	Last month of the 2^{nd} dry-wet season transition			11	(10)		

FRST: native Andean forest, RYEL: pasture, RYEB: shrubs, RYEE: pasture with secondary growth, BROM: paramo vegetation, PINE: planted forest.¹BFAST-MODIS LAI time series; *Manual adjustment during calibration process; **Default values in SWAT; ²Spracklen and Righelato (2016); ³Peters, Franco, Schmidt, and Hincapié Carvajal (2011); ⁴Hofstede, Castillo, and Osorio (1995); ⁵Initial values estimated from local temperature records following Strauch and Volk (2013) and other studies (Hoyos et al., 2019); ⁶González-Orozco¹, Jarvis, and Palacio (2011); ⁷Cook et al. (2005); ⁸Cárdenas Agudelo et al. (2016); ⁹Orwa et al. (2009); ¹⁰García-Leoz et al. (2017); ¹¹Veneklaas and Van Ek (1990);¹²Jaramillo-Robledo (2003); ¹³Leguizamon and Marín (2017); ¹⁴ Parameters determined using LAI filtered data, precipitation seasonality, and manual LAI calibration.

Table S3. Global sensitivity analysis in the SWAT-Tb model. Sensitivity is indicated by a high t-statistic value (in absolute terms) and a low p-value. Parameters are listed from high to low sensitivity.

:

Parameter ¹	Description		Ra	nge	t statistic	n valuo	
1 ai ainetei				Max	-statistic	c p-value	
CN2.mgt_RYEL	Runoff curve number for moisture condition II	r	-0.25	0.25	-16.989	0.000	
ESCO.hru_RYEL	Soil evaporation compensation factor	v	0.01	1	-9.989	0.000	
ESCO.hru_FRST	Soil evaporation compensation factor	v	0.01	1	-8.197	0.000	
ALPHA_BF.gw	Baseflow alpha factor (1/days)	v	0.01	1	-7.299	0.000	
CN2.mgt_FRST	Runoff curve number for moisture condition II	r	-0.25	0.25	-6.280	0.000	
SOL_K(1).sol_RYEL	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-4.802	0.000	
GWQMN.gw_FRST	Threshold depth of water in the shallow aquifer required for return flow to occur (mm $\mathrm{H_2O})$	v	0	5000	4.669	0.000	
CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/hr)	v	0	150	4.428	0.000	
GWQMN.gw_RYEL	Threshold depth of water in the shallow aquifer required for return flow to occur (mm $\rm H_2O)$	v	0	5000	3.996	0.000	
ESCO.hru_BPRR	Soil evaporation compensation factor	v	0.01	1	-3.314	0.001	
SOL_K(1).sol_FRST	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-3.158	0.002	
SOL_BD(1).sol_BPRR	Moist bulk density (g/cm ³)	r	-0.20	0.20	-2.902	0.004	
CN2.mgt_BPRR	Runoff curve number for moisture condition II	r	-0.25	0.25	-2.774	0.006	
SOL_AWC(1).sol_FRST	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	-2.599	0.009	
SOL_BD(1).sol_RYEL	Moist bulk density (g/cm ³)	r	-0.20	0.20	-2.468	0.014	
GWQMN.gw_BPRR	Threshold depth of water in the shallow aquifer required for return flow to occur (mm $\rm H_2O)$	v	0	5000	-2.399	0.017	
SOL_K(1).sol_BPRR	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-2.238	0.026	
SOL_AWC(1).sol_RYEL	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	-1.950	0.050	
SOL_K(2).sol_RYEL	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-1.867	0.062	
SOL_BD(2).sol_BPRR	Moist bulk density (g/cm^3)	r	-0.20	0.20	-1.770	0.077	
SOL_BD(1).sol_FRST	Moist bulk density (g/cm ³)	r	-0.20	0.20	-1.607	0.109	
SOL_K(2).sol_BPRR	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-1.541	0.124	
RCHRG_DP.gw	Deep aquifer percolation fraction	v	0	1	-1.527	0.128	
SOL_AWC(2).sol_FRST	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	-1.186	0.236	
SOL_AWC(2).sol_RYEL	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	-1.175	0.241	
SOL_K(2).sol_FRST	Saturated hydraulic conductivity (mm/hr)	r	-0.50	0.50	-1.010	0.313	
GW_DELAY.gw_RYEL	Groundwater delay times (days)	v	0.01	500	0.406	0.685	
GW_DELAY.gw_FRST	Groundwater delay times (days)	v	0.01	500	-0.379	0.705	
SOL_AWC(1).sol_BPRR	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	0.354	0.723	
GW_DELAY.gw_BPRR	Groundwater delay times (days)	v	0.01	500	0.309	0.758	
SOL_AWC(2).sol_BPRR	Available water capacity of the soil layer (mm $\rm H_2O/mm$ soil)	r	-0.50	0.50	-0.170	0.865	
SOL_BD(2).sol_FRST	Moist bulk density (g/cm ³)	r	-0.20	0.20	0.115	0.908	
SOL_BD(2).sol_RYEL	Moist bulk density (g/cm ³)	r	-0.20	0.20	0.027	0.978	

¹Numbers (1, 2) refer to the soil layer number. Land cover types are native Andean forest (FRST), pasture (RYEL) and BPRR (paramo vegetation, planted forest, shrubs, and pasture with secondary growth). ²Scaling type: v (absolute) indicates that the parameter is replaced by the given value, r (relative) indicates that the parameter is multiplied by [1 + (given value)].

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Model	SWAT average water flux components 1 (mm/yr)								Ratios		
	PREC	SURQ	LATQ	GWQ	PET	ET	REVAP	WYLD	Baseflow ratio (GWQ/ WYLD)	Runoff ratio (SURQ/ WYLD)	ET ratio [(ET+R EVAP)/ PREC]
SWAT-T	1841.43	114.36	60.67	590.47	862.68	358.19	17.25	1464.77	0.40	0.07	0.20
SWAT-Tb (LAI calibration)	1841.43	96.52	46.28	401.03	862.68	747.19	17.25	1074.82	0.37	0.09	0.42
SWAT-Tb (LAI + streamflow calibration)	1841.43	16.72	49.88	319.97	862.68	838.80	17.25	954.23	0.33	0.02	0.46
Reference value									$0.4-0.5^2$	$0.04 - 0.16^3$	0.5-0.64

calibration with reference values.

Calibration period from 2003 to 2016.¹ PREC = precipitation, SURQ = surface runoff contribution to streamflow, LATQ = lateral flow contribution to streamflow, GWQ = grundwater contribution to streamflow, PET = potential evapotranspiration, ET = actual evapotranspiration, REVAP = amount of water moving from shallow aquifer to plants/soil profile, and WYLD = water yield. Reference values from: ² baseflow filter (https://engineering.purdue.edu/mapserve/WHAT/), ³ Jaramillo-Robledo (2003), and ⁴ García-Leoz et al. (2017).



Figure S1. Observed (MODIS) and simulated (SWAT, SWAT-T, and SWAT-Tb) seasonality of LAI in the CR watershed for for (a-c) shrubs (RYEB), (d-f) paramo vegetation (BROM), (g-i) pasture with secondary growth (RYEE), and (j-k) planted forest (PINE). Time series (a,d,g,j), average annual cycle (b,e,h,k), and the (c,f,i,l) corresponding boxplots and performance statistics.



Figure S2. Calibration (2003–2016) and validation (1993–2002) of SWAT for monthly streamflow. Vertical bars show monthly rainfall from SWAT outputs, calculated from records in climate stations. Model performances based on the criteria of Moriasi et al. (2007): ^{*a*} Good (0.65<NSE \leq 0.75, 0.50<RSR \leq 0.60, \pm 10%<BIAS< \pm 15%) and ^{*b*} Very Good (0.75<NSE \leq 1.00, 0.00<RSR \leq 0.50, BIAS \leq \pm 10%).



Figure S3. Comparison of monthly (left) and annual (right) streamflow between scenarios using 1000 simulations with parameters ranges as we did for the model calibration. Input precipitation (blue bars) is the same for all scenarios and models (a,d). Average seasonal cycle (b) and annual streamflow (e) in all scenarios for 1993–2016. Percent differences between monthly (c) and annual (f) streamflow in the control (CTL) and LULC (FOR and PAS) scenarios for 1993–2016 as simulated by SWAT-Tb and SWAT using best fit parameters. Positive (negative) values indicate that streamflow is increased (decreased) in the LULC change scenario. Asterisks identify months for which the difference between medians in the FOR and PAS scenarios is statistically significant (n=24000, p < 0.05) for SWAT-Tb output.