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Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Improving the representation of forests in hydrological models

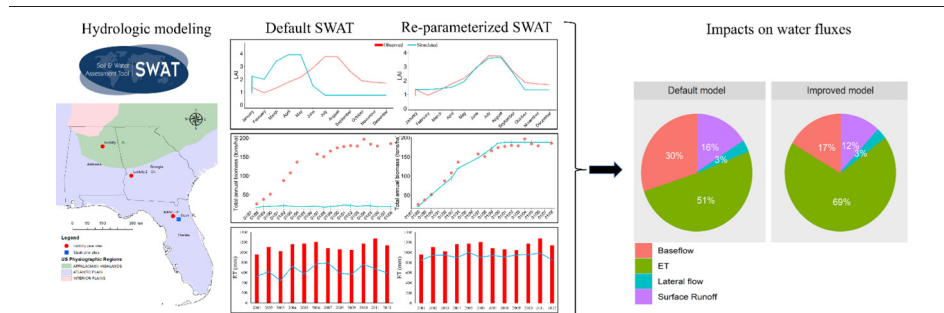
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HIGHLIGHTS

- SWAT generates inadequate biomass, leaf area index, and evapotranspiration (ET) in forestlands.
- A new method to improve the representation of forest dynamics in SWAT
- Re-parameterization of forest processes increases the simulation of ET and decreases water yield.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:

Received 23 August 2021

Received in revised form 21 October 2021

Accepted 31 October 2021

Available online xxxx

Editor: Fernando A.L. Pacheco

Keywords:

Leaf area index

Biomass

Evapotranspiration

SWAT

MODIS

Water balance

Southern pines

ABSTRACT

Forests play a critical role in the hydrologic cycle, impacting the surface and groundwater dynamics of watersheds through transpiration, interception, shading, and modification of the atmospheric boundary layer. It is therefore critical that forest dynamics are adequately represented in watershed models, such as the widely applied Soil and Water Assessment Tool (SWAT). SWAT's default parameterization generally produces unrealistic forest growth predictions, which we address here through an improved representation of forest dynamics using species-specific re-parameterizations. We applied this methodology to the two dominant pine species in the southeastern U.S., loblolly pine (*Pinus taeda* L.) and slash pine (*Pinus elliotti*). Specifically, we replaced unrealistic parameter values related to tree growth with physically meaningful parameters derived from publicly available remote-sensing products, field measurements, published literature, and expert knowledge. Outputs of the default and re-parameterized models were compared at four pine plantation sites across a range of management, soil, and climate conditions. Results were validated against MODIS-derived leaf area index (LAI) and evapotranspiration (ET), as well as field observations of total biomass. The re-parameterized model outperformed the default model in simulating LAI, biomass accumulation, and ET at all sites. The two parameterizations also resulted in substantially different mean annual water budgets for all sites, with reductions in water yield ranging from 13 to 45% under the new parameterization, highlighting the importance of properly

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parameterizing forest dynamics in watershed models. Importantly, our re-parameterization methodology does not require alteration to the SWAT code, allowing it to be readily adapted and applied in ongoing and future watershed modeling studies.

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1. Introduction

Forests play a critical role in the terrestrial water balance, greatly impacting both blue water (i.e., surface and groundwater that can be directly accessed and used for human needs) and green water (i.e., water stored in unsaturated soil layers and the plant canopy) (Falkenmark and Rockström, 2006; Naderi, 2020; Veetil and Mishra, 2016). Forests influence surface and groundwater dynamics by mediating transpiration (Bearup et al., 2014; Federer, 1973; Roberts, 1983), interception (Carlyle-Moses and Gash, 2011; Crockford and Richardson, 2000; Savenije, 2004), shading (Johnson and Wilby, 2015; Raz-Yaseef et al., 2010), and modification of the atmospheric boundary layer (De Kauwe et al., 2017; Leigh et al., 2017; Timouk et al., 2009). These processes are strongly coupled, making quantitative predictions about the hydrological impacts of forests and forest change a complex task, usually requiring a combination of field studies and modeling approaches (Golden et al., 2016).

Hydrologic models allow for the prediction of hydrologic responses of forested watersheds under different climates, land covers, or soil conditions than those experienced through field-scale measurements (Golden et al., 2016). Additionally, hydrologic models can be used to scale up results from field measurements to make predictions at the watershed or regional scale (Wattenbach et al., 2005). Conversely, field measurements can provide valuable information to improve the representation of fundamental forest dynamics in hydrological models, such as the temporal variability of forest leaf area index (LAI) and biomass (Guo et al., 2015). Overall, combining field measurements and process-based hydrological models enhance both approaches, and many authors have pursued data-model integration to investigate hydrological processes at the forest and watershed scales. For example, Saleh et al. (2004) modified the process-based Agricultural Policy/Environmental eXtender (APEX) model (Williams et al., 2008) to improve estimations of flow, sediment, and nutrient losses from silvicultural lands in Texas; Iames et al. (2018) applied the United States Department of Agriculture (USDA) Environmental Policy Integrated Climate (EPIC) model (Williams, 1990) to estimate LAI at four mixed-forest stands in Virginia and North Carolina; and Amatya and Skaggs (2001) applied the field-scale DRAINMOD (Skaggs, 1978) model to predict daily water table height in experimental watersheds located on a loblolly pine (*Pinus taeda* L.) plantation in North Carolina. Although based on physical principles and processes, hydrologic models such as APEX, EPIC, and DRAINMOD are appropriate only at plot or stand scale, since they are not designed to handle the landscape heterogeneities (e.g., varying soil properties, land-use/land-cover types, terrain topography) of larger areas such as watersheds and basins.

To evaluate forest hydrological processes at a larger scale (e.g., regional), watershed-scale hydrologic models are needed to account for the spatial variability in stand species, soil, and climate. One such watershed-scale model is the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998). SWAT is a popular semi-distributed process-based watershed model that has been used for a wide range of applications worldwide (Gassman et al., 2004) and is cited in over 4000 peer-reviewed journal articles as of December 31, 2021 (https://www.card.iastate.edu/swat_articles/). In particular, SWAT has been extensively applied for improving and evaluating crop yield simulation (Cibin et al., 2016; Karki et al., 2019; Mittelstet, 2015; Nair et al., 2011; Srinivasan et al., 2010; Trybula et al., 2015; Wang et al., 2015; Rath et al., 2021), as it is capable of simulating varying land-management practices such as fertilizer application, irrigation, biomass harvest, and crop rotation. With these capabilities, in principle, SWAT is suitable for

simulating both managed and unmanaged forests. However, the plant growth model within SWAT was developed primarily to simulate annual crop growth (Williams et al., 1989) and has not been sufficiently tested in forested ecosystems (Amatya and Jha, 2011; Yang et al., 2019). As a result, the default parameterization of forests in SWAT's plant database produces unrealistic dynamics (Yang and Zhang, 2016).

Given the expansive use of SWAT in the hydrological community, the known limitations of SWAT's default forest parameterization, and the integral role of forests in surface and groundwater dynamics of watersheds, there is a significant need for a methodology to re-parameterize the SWAT plant database so that hydrological impacts of forests and forest management are adequately represented. Since the tree species comprising forests around the world have a diverse array of biological and growth characteristics (Chisholm et al., 2014; Kattge et al., 2011; Reich, 2005), this re-parameterization methodology should be species-specific, focusing on the most important tree species within a given watershed. In this study, we developed a general re-parameterization methodology and applied it to the two dominant pine forest species in the Southeastern U.S. (SE-US): loblolly pine (*Pinus taeda* L.) and slash pine (*Pinus elliotii* Engelm.). Our methodology was validated against MODIS-estimated LAI and ET data and tree biomass accrual data from three forest research cooperatives across the SE-US.

2. Background

2.1. Limitations of current forest representation and parameterization in SWAT

SWAT (Arnold et al., 1998) was developed by the USDA Agricultural Research Service (ARS) and major model components include weather, hydrology, plant growth, water quality, and land management. SWAT was originally developed for the prediction of the long-term impact of rural and agricultural management practices on water, sediment, and nutrients in large, complex watersheds with varying soils, land use, and management conditions. SWAT delineates a watershed into multiple sub-basins based on drainage areas of tributaries. Within each subbasin, Hydrologic Response Units (HRUs) are created from unique combinations of land use, soil, and topography (Neitsch et al., 2011). HRU's are the smallest computational unit in SWAT and most of the land phase processes in SWAT, including vegetation growth, are simulated at this level.

SWAT simulates dynamics of the following forest structures and processes: canopy LAI, stand biomass, canopy height, leaf litter and residue production, and root mass distribution. Within SWAT, plant growth dynamics are modeled using a simplified version of EPIC (Williams, 1990), which is primarily governed by heat unit theory (Boswell, 1926; Magoon and Culpepper, 1932). As such, intra-annual forest dynamics are simulated based on daily accumulated heat units under optimal conditions (Neitsch et al., 2011). Inter-annual dynamics are additionally controlled by the age of the forest stand, where the maximum development in certain forest processes is limited to a fixed amount determined by forest maturity. Each of the forest growth processes within SWAT is interdependent with one or more other processes. This coupling leads to feedbacks between processes and nonlinear responses to changes in model parameters. Specific relationships and parameters describing the key forest processes simulated in SWAT are summarized in Section S1.1 of the supplementary materials (Appendix C).

Forests and hydrology are connected in SWAT through the processes of interception, shading of the soil surface, evapotranspiration, and

modification of the atmospheric boundary layer. Each of these processes depends on specific variables describing forest structural dynamics (e.g., tree height, LAI, belowground biomass). In some cases, these dependencies are very sensitive, meaning relatively small changes in forest structure induce large changes in hydrological dynamics. The specifics of the interdependencies and relevant parameters for all coupled forest/hydrological processes are summarized in Section S1.2 of the supplementary materials (Appendix C).

SWAT utilizes several parameters to control the many aspects of forest dynamics (see Section 1.1 in the Supplementary Materials under Appendix C), each of which must be assigned a specific value. Many of the default values of SWAT forest parameters were not defined using empirical data (Arnold et al., 2011), leading some to have unrealistic values (Yang and Zhang, 2016) that do not adequately reproduce the growth and dynamics of forests. A few specific examples (further detailed in Section S1.3 of the Supplementary Materials under Appendix C) include the following: 1) excessively high biomass converted annually to soil residue; 2) very generalized categorization of forest variation (limited to evergreen, deciduous, and mixed forests); and 3) poor representation of the growth and dynamics of juvenile trees. While these are just three (of many) examples of SWAT process limitations, they help illustrate how forest structure misrepresentation can lead to challenges in accurately simulating stand-scale and watershed hydrology.

2.2. Application case: loblolly and slash pine forests of the SE-US

We chose loblolly and slash pines of the SE-US as test case species for this re-parameterization because of their commercial relevance to both the U.S. and global wood supply (Susaeta et al., 2014), the large area over which they are planted (Barnett and Sheffield, 2004; Baker and Langdon, 2016), the data available for calibration and validation, and the empirical evidence that these two species can have substantial impacts on the hydrology of the catchments in which they grow (McLaughlin et al., 2013). Loblolly pine is considered to be the most important commercial tree species in the world (Will et al., 2015) and is the most commonly planted tree species in the U.S., covering approximately 13 million ha. This species is concentrated in the SE-US, comprising 84% of all seedlings planted in the region. Slash pine is the second most cultivated tree species in this region and has been planted on more than 4.2 million ha (Gonzalez-Benecke et al., 2014a). These two species are a large fraction of the SE-US wood product output, which accounts for approximately 60% of the total U.S. timber and about 18% of the global supply of industrial wood (Gonzalez-Benecke et al., 2014a).

Due to their commercial importance, the growth dynamics of slash and loblolly pine within the SE-US have been extensively studied. Therefore, there are a substantial amount of relatively long-term stand-scale data available for both species, which can be leveraged to re-parameterize SWAT. Increasingly, the hydrologic impacts of slash and loblolly pine plantations are being recognized and studied. For example, McLaughlin et al. (2013) found that cumulative water yield in pine stands managed for a low basal area can be up to 64% higher than in high-density timber stands over a 25-year rotation. This nexus of commercial importance, wide geographic extent, data availability, and known hydrological impacts make slash and loblolly pine ideal test case species for improving the representation of forest dynamics in hydrologic models. Additional details pertaining to the natural history of loblolly and slash pine, their use in commercial plantations, and their impacts on catchment hydrology can be found in Section S1.4 of the Supplementary Materials (Appendix C).

3. Methods and data

3.1. Re-parameterization and calibration strategies

Here we outline a method of implementing a re-calibration of important forest parameters for loblolly and slash pine in SWAT. While we only address these two species, the methodology applies to most

forest species and can be applied broadly. We start by adding two new plant types in SWAT's plant database: loblolly pine (LBPN) and slash pine (SLPN). The acronyms LBPN and SLPN were chosen by the authors for the sake of clarity, although it is worth highlighting that the USDA's standard codes for loblolly and slash pine are PITA and PIEL, respectively (<https://plants.usda.gov/home>). Initially, we parameterized these forest types with default values from SWAT evergreen forests (FRSE). Subsequent parameter modifications and calibration were conducted on the newly added LBPN and SLPN, leaving FRSE with its default values.

Next, we inventoried all user-defined forest parameters within SWAT related to processes that impact either forest dynamics or the interactions between forest and hydrological dynamics. These parameters were identified from SWAT theoretical and input/output documentation (Neitsch et al., 2011) and are related to one or more of the following forest structural properties or processes: canopy LAI, stand biomass, canopy height, leaf litter and residue production, root mass distribution, interception, shading of the soil surface, evapotranspiration, and modification of the atmospheric boundary layer. Parameter definitions and the primary processes they relate to are given in Table 1.

To conduct a robust calibration of the parameters in Table 1, we next identified the largest possible set of constraining information corresponding to each parameter. Ideally, this information would consist of high temporal and spatial resolution measurements of the forest and hydrological dynamics impacted by relevant parameters (e.g., canopy LAI, stand biomass, evapotranspiration, etc.). However, this type of data is often not available for all relevant parameters. In such cases, lower-resolution data, published literature, and expert knowledge can be used to constrain a calibration. In this study, constraining information consisted of stand-scale field measurements, remote-sensing data products, published literature values, and expert knowledge (summarized in Table 2). These constraints allowed us to define a plausible range of values that each relevant parameter could take for both loblolly and slash pine, which diverged substantially from the default values (Table 2). Parameter range selection is further detailed in Section S1.5 of the Supplementary Materials (Appendix C), and details about the specific datasets utilized are provided in Section 3.2 of the main text and Section S1.6 of the Supplementary Materials (Appendix C).

With relevant model parameters and relevant ranges selected, we then calibrated the model to the data summarized in Table 2. Based on our understanding of SWAT's plant growth module and how forest processes interact with hydrological computations in the model, we contend that LAI, biomass, and ET must be calibrated sequentially based on their specific interactions in SWAT. As an example, LAI on the first day of simulation is the minimum LAI in the plant database. LAI is then used directly in the computation of plant biomass increment, and along with rooting depth, partitions evapotranspiration between canopy evaporation and transpiration. Specifically, LAI-related parameters controlling the shape of the LAI curve and the length of the growing season were calibrated first and then held constant while biomass-related parameters were calibrated. Finally, both LAI- and biomass-related parameters were held constant while ET-related parameters were calibrated.

The calibration procedure was conducted using the automated Sequential Uncertainty Fitting – SUFI-2 calibration algorithm (Abbaspour et al., 2004) within SWAT Calibration and Uncertainty Program (SWAT-CUP 2019, version 5.2.1.) software (Abbaspour, 2015). We chose the SUFI-2 algorithm because it is the most frequently used method for SWAT applications (Malik et al., 2021) and has shown superior performance over other algorithms like GLUE and ParaSol (Shivhare et al., 2018). The plausible parameter ranges provided in Table 2 were used to define uniform sampling distributions for each parameter. For each sequential calibration, SUFI-2 drew 500 samples from the plausible parameter ranges and ran SWAT for each parameter combination. The resulting model outputs were used to perform a global sensitivity analysis to determine the relative importance of the inventoried parameters in simulating LAI, biomass, and ET. Parameter importance was quantified at a significance level of 0.05 (i.e., a p -value < 0.05 indicated a significant

Table 1

Inventory of identified user-defined forest parameters which impact watershed hydrological processes. Abbreviations: CL – canopy LAI, SB – stand biomass, CH – canopy height, LL – leaf litter and residue production, RD – root mass distribution, SS – shading of soil surface, ET – evapotranspiration, IN – interception, and AB – modification of atmospheric boundary layer.

SWAT parameter (units)	Parameter definition	Primary impacted forest processes	Primary impacted hydrological processes
FRGRW1	1st point on LAI development curve x-coordinate	CL	ET, IN
LAIMX1	1st point on LAI development curve y-coordinate	CL	ET, IN
FRGRW2	2nd point on LAI development curve x-coordinate	CL	ET, IN
LAIMX2	2nd point on LAI development curve y-coordinate	CL	ET, IN
DLAI	Fraction of growing season when LAI senescence begins	CL	ET, IN
HEAT_UNITS	Potential heat units to reach maturity in a growing season	CL	ET, IN
EPCO	Plant water uptake compensation factor	RD	ET
MAT_YRS (years)	Years to forest maturity	CL, SB, CH	ET, IN, SS, AB
CURYR_MAT (years)	Current age of forest	CL, SB, CH	ET, IN, SS, AB
ESCO	Soil evaporation compensation factor	–	ET
BIO_E ((kg/ha)/(MJ/m ²))	Radiation use efficiency	SB	SS, ET
RDMX (m)	Maximum rooting depth	RD	ET
T_OPT (Celsius)	Optimal growth temperature	CL, SB	ET, SS
T_BASE (Celsius)	Minimum temperature required for growth	CL, SB	ET, SS
GSI (m/s)	Maximum stomatal conductance	–	ET
VPDFR (kPa)	Determines slope of relationship between stomatal conductance and vapor pressure deficit	SB	ET
EXT_COEF	Light extinction coefficient	SB	SS, ET
CANMX (mm)	Maximum canopy storage	–	IN, ET
CHTMX (m)	Maximum canopy height of forest	CH	AB, ET
BIO_LEAF	Fraction of biomass	LL	SS, ET
BMX_TREES (tons/ha)	Maximum possible stand biomass	SB	SS, ET
BLAI (m ² /m ²)	Maximum possible canopy LAI	CL	ET, SS
ALAI_MIN (m ² /m ²)	Minimum possible canopy LAI	CL	ET, SS

parameter), and results are summarized in Tables S2–S5 in the Supplementary Materials (Appendix B).

3.2. Calibration datasets and study sites

Five primary datasets were used in our parameterization of loblolly and slash pine in SWAT. The first two datasets were long-term forest

stand measurements of above-ground biomass from productivity studies of loblolly pine (Gonzalez-Benecke et al., 2016) and slash pine (Gonzalez-Benecke et al., 2014b). The second two datasets were remotely sensed LAI and ET data products from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) mission. The final dataset consisted of root mass distribution data for loblolly and slash pine from the Managing Forests for Increased Regional Water Availability

Table 2

Constraining information and plausible value ranges for SWAT user-defined forest parameters which impact watershed hydrological processes.

Parameterization data source	Parameter (units)	Default value*	Plausible value/range – loblolly pine	Plausible value/range – slash pine	Reference
Remote sensing (MODIS MCD15A3H dataset)	FRGRW1	0.15	**	**	–
	LAIMX1	0.7	**	**	–
	FRGRW2	0.25	**	**	–
	LAIMX2	0.99	**	**	–
	DLAI	0.99	**	**	–
	HEAT_UNITS	1800	**	**	–
	BLAI (m ² /m ²)	5	**	**	–
	ALAI_MIN (m ² /m ²)	0.75	**	**	–
Expert knowledge***	MAT_YRS (years)	30	3–5	3–5	–
	CURYR_MAT (years)	–	1	1	–
	ESCO	0.95	0.8–1	0.8–1	–
	BIO_E ((kg/ha)/(MJ/m ²))	15	2.5–11.6	2.7–12.6	1,2,3,4
Literature review	RDMX (m)	3.5	1.5–3	1.6–3.3	5,6,7,8,9,20
	T_OPT (Celsius)	30	25	25	10,11
	T_BASE (Celsius)	0	4	5	10,11
	GSI (m/s)	0.002	0–0.0118	0–0.036	12,11,2,13,14,15,21
	VPDFR (kPa)	4	0.7–3.7	1–3.5	13,15,16,22
	EXT_COEF	0.65	0.41–0.69	0.46–0.715	1,11,17,18
	CANMX (mm, % of total rainfall)	0	0.5–1.8 mm, 14–28%	0.5–1.8 mm, 14–28%	19
	CHTMX (m)	10	7–18	8.5–19.8	5
	BIO_LEAF	0.3	0.02	0.02	23
	BMX_TREES (tons/ha)	1000	185–200	113–200	24, 25
Field observations	EPCO	1	0.48	0.38	26

References: 1: (Schultz, 1997); 2: (Roth, 2010); 3: (Pell, 2015); 4: (Allen et al., 2005); 5: (Martin and Jokela, 2004); 6: (Schenk and Jackson, 2002); 7: (Torreano and Morris, 1998); 8: (Qi et al., 2018); 9: (Albaugh et al., 2006); 10: (Gonzalez-Benecke et al., 2014b); 11: (Gonzalez-Benecke et al., 2016); 12: (Samuelson et al., 2012); 13: (Wightman et al., 2016); 14: (Aspinwall et al., 2011); 15: (Bartkowiak et al., 2015); 16: (Bracho et al., 2018); 17: (Sampson and Allen, 1998); 18: (White et al., 2000); 19: (Gavazzi et al., 2016); 20: (Rees and Comerford, 1986); 21: (Johnson et al., 1995); 22: (Teskey et al., 1994); 23: (Poorter et al., 2012); 24: (Bracho et al., 2012); 25: (Jokela and Martin, 2000); 26: (Cohen et al., 2018).

* The default parameter values refer to the forest type Evergreen Forests (FRSE) in SWAT's plant database.

** Plausible ranges of parameters governing the shape of the LAI curve are site-specific and depend on MODIS-derived data.

*** We spoke with William Harges, a former employee at the Southern Forest Nursery Management Cooperative, and Dr. Lisa Samuelson, a retired faculty at the School of Forestry & Wildlife Sciences at Auburn University, about reasonable values of MAT_YRS (the number of years required for a pine tree to transition from a seed to a sapling).

project (Cohen et al., 2018). Specific details for each of these datasets can be found in Section S1.6 of the supplementary materials (Appendix C). It is worth mentioning that there are uncertainties related to the MODIS ET (Mu et al., 2013) and LAI (Jensen et al., 2011) algorithms. Thus, the use of MODIS estimates as benchmark data must be interpreted with caution.

The remote-sensing and biomass accrual datasets described above were associated with pine plantation stands administered by three forestry cooperatives across the SE-US. Based on data availability, planted species, and spatial distribution, four sites were selected to test our methodology. Three of the sites consisted of loblolly pine plantations and are located in Alabama (AL) (Loblolly 1 - AL), Georgia (GA) (Loblolly 2 - GA), and Florida (FL) (Loblolly 3 - FL) (Fig. 1). The fourth site, a slash

pine plantation, is located in FL (Slash - FL), approximately 4 km from Loblolly 3 - FL. Characteristics of each site are summarized in Table 3, and detailed descriptions are presented in Section S1.7 of the Supplementary Materials (Appendix C).

3.3. Model setup and calibration

The information in Table 4 was used to develop and set up field-scale SWAT models representing each of the study sites using SWAT2012 (revision 664). Since the standard SWAT HRU definition provides no means for representing realistic field-scale management strategies (e.g., forest plots might spread across several HRUs), we employed the approach described by Marek et al. (2016) to delineate meaningful

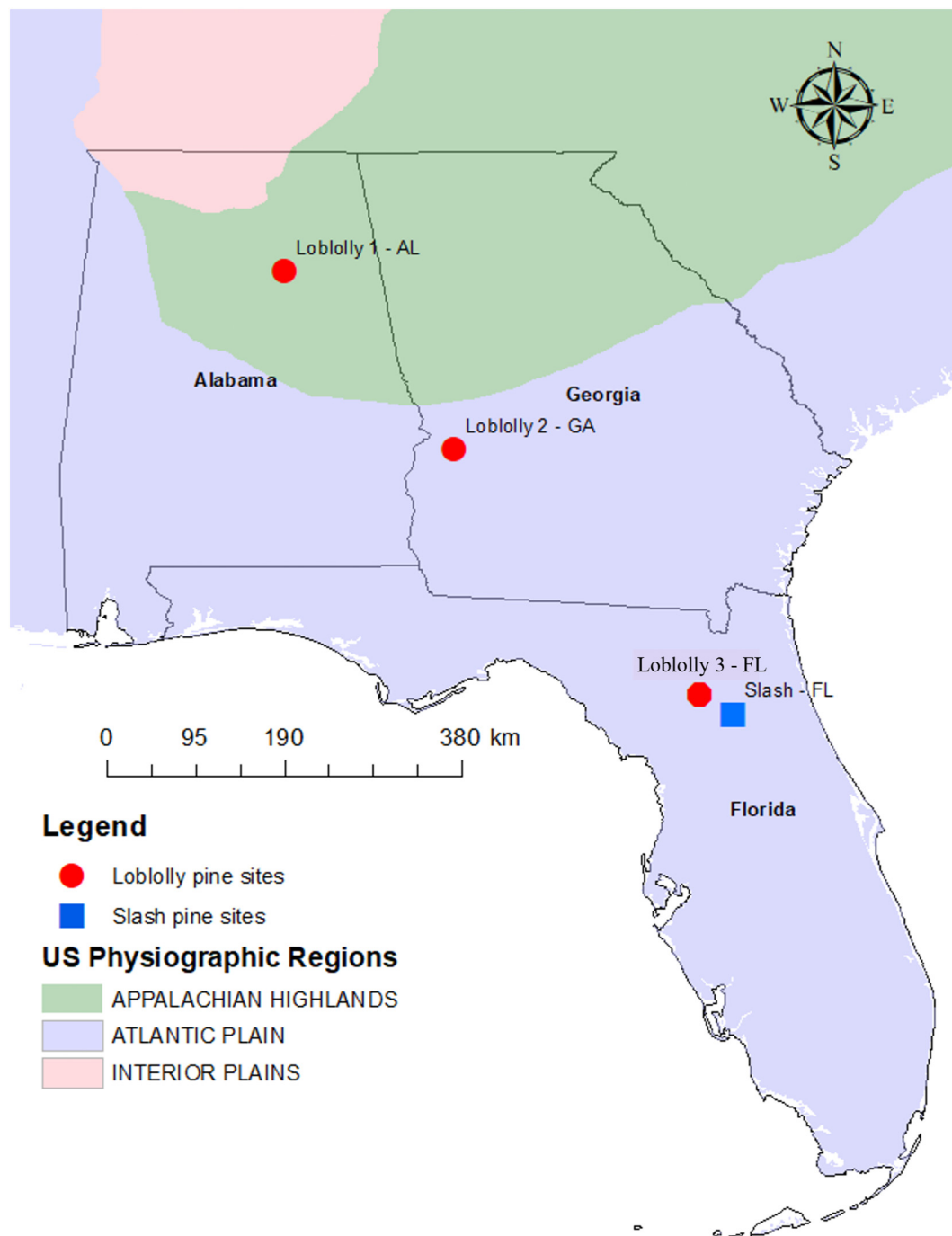


Fig. 1. Spatial distribution and location of the study sites comprised of four pine plantation fields located in Alabama, Georgia, and Florida. Red circles represent loblolly pine sites while the blue square represents the slash pine site. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Site and stand characteristics.

Site characteristic	Loblolly 1 - AL	Loblolly 2 - GA	Loblolly 3 - FL	Slash - FL
Latitude	33.8434° N	32.1241° N	29.7603° N	29.7548° N
Longitude	−86.2993° W	−84.6552° W	−82.2906° W	−82.1633° W
Annual average precipitation (mm)	1500	1282	1300	1256
Annual average temperature (°C)	16	18	20.5	20.5
Annual average solar radiation (MJ/m ²)	16.87	17.67	17.7	17.9
Dominant Hydrologic Soil Group	D	C	A	B
Elevation range (m)	177–192	176–189	50–57	38–50
Average stand biomass (tons/ha)	56	82	133	73
Average maximum MODIS LAI (m ² /m ²)	3.8	3.1	2.2	5.1
Stand age in the first year of measured data (years)	4	6	4	3
Observation period	2002–2010	1999–2010	1987–2008	2001–2012

field-boundaries based on an area of interest (AOI), producing four “watershed” SWAT models (one for each study site), each having one sub-basin and one HRU representing the pine plantation field. Further details of this process are provided in Section S1.8 of the Supplementary Materials (Appendix C).

The automated model calibration software SWAT-CUP was used to individually perform model calibration at each study site. In the first step of the calibration, only LAI development curve parameters were calibrated at monthly time-step to accurately represent intra-annual LAI behavior. To do so, we used remotely sensed MODIS LAI time series data for a single year from each site, targeting years with relatively smoothly varying LAI estimates. We opted for this calibration rationale to (1) circumvent SWAT-CUP's inability to generate averaged outputs for the entire simulation period, and (2) avoid years having excessively noisy MODIS estimates. Next, parameters controlling the magnitude of simulated maximum and minimum LAI and total biomass were calibrated simultaneously using annual maximum and minimum MODIS LAI values and field measured annual stand biomass as constraints, respectively, for all simulated years. Maximum and minimum inter-annual LAI and total biomass were calibrated simultaneously so that the model performance with respect to LAI did not degrade its performance relative to biomass. We used the Kling-Gupta Efficiency (KGE) metric (Gupta et al., 2009) as the objective function and assigned equal weights to LAI and biomass. As highlighted by Althoff and Rodrigues (2021), equal weights are conventionally assigned to all variables when using KGE. The specific period used for inter-annual LAI and biomass calibrations varied across the study sites according to available data: 2002–2010 (biomass) and 2003–2010 (LAI) for Loblolly 1 – AL; 1999–2010 (biomass) and 2003–2010 (LAI) for Loblolly 2 – GA; 1987–2008 (biomass) and 2003–2008 (LAI) for Loblolly 3 – FL; and 2001–2012 (biomass) and 2003–2012 (LAI) for Slash – FL. Each model was run with a 3-yr warm-up period to initialize conditions such as

antecedent soil moisture; trees were planted as seedlings during this period to avoid bare soil conditions.

Next, ET-related parameters were calibrated for each site using MODIS 8-day ET estimates aggregated to a monthly time step. For ET calibration, we used the percentage bias (PBIAS) as the objective function rather than the KGE to avoid excessive model over or underestimation. KGE is sensitive to data “peaks” (Pool et al., 2018), and MODIS ET estimates are very noisy, often showing multiple peaks during the year. The specific calibration periods were 2002–2018 at Loblolly 1 – AL and Loblolly 2 – GA, 2002–2008 at Loblolly 3 – FL, and 2002–2012 at Slash – FL. For LAI and ET, model performance was assessed using the coefficient of determination (R^2), PBIAS, and Root Mean Square Error (RMSE). For total biomass, we opted for the Nash-Sutcliffe Efficiency (NSE) coefficient instead of R^2 since the observed total biomass data presents less variability than monthly LAI and ET and facilitates the use of NSE as goodness of fit metric. Since we only had annual observations of total biomass, model calibration for biomass was carried out at annual basis. These statistical metrics are commonly used to evaluate model performance in simulating variables such as LAI, biomass, and ET (Alemayehu et al., 2017; Strauch and Volk, 2013; Yang et al., 2018; Yang and Zhang, 2016). For further details about these statistical rating metrics, the reader is referred to Althoff and Rodrigues (2021) and Moriasi et al. (2007).

3.4. Quantifying the effects of improved forest parameterization on water fluxes

Changes to each site's hydrology from the improved forest parameterization were assessed by comparing the mean annual water budgets of default and improved model simulations. The mean annual water balance was chosen since it is heavily driven by mean annual ET, which is often the largest outflowing

Table 4
Description of input data and sources.

	Data	Description	Source
Model input data	Topography	National Elevation Dataset at 10 m resolution	United States Department of Agriculture (USDA) Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/)
	Land use	2008 Cropland Data Layer	United States Department of Agriculture (USDA) Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/)
	Soil	Gridded Soil Survey Geographic (gSSURGO)	United States Department of Agriculture (USDA) Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/)
	Climate	Daily precipitation, maximum/minimum temperature, solar radiation, wind speed	PRISM climate group (http://www.prism.oregonstate.edu/), National Land Data Assimilation Systems (NLDAS) phase 2 (https://ldas.gsfc.nasa.gov/nldas/NLDAS2model_download.php), National Solar Radiation Database (https://nsrdb.nrel.gov/)
Model calibration	Atmospheric deposition	Wet and dry deposition of nitrate and ammonia	National Atmospheric Deposition Program (NADP) (http://nadp.slh.wisc.edu/)
	Seasonal LAI	4 days composite dataset at 500 m pixel resolution	Moderate Resolution Imaging Spectroradiometer (MODIS) (https://lpdaac.usgs.gov/products/mcd15a3hvv006/)
	ET	8 days composite dataset at 500 m pixel resolution	Moderate Resolution Imaging Spectroradiometer (MODIS) (https://lpdaac.usgs.gov/products/mod16a2v006/)
	Biomass	Field-measured annual total trees biomass	Long-term field studies conducted FMRC, FBRC, and PMRC in Georgia, Florida and Alabama, respectively
	Annual LAI	Field-measured annual LAI	Long-term field studies conducted FMRC, FBRC, and PMRC in Georgia, Florida and Alabama, respectively

catchment water flux and can be substantially impacted by SWAT forest parameterization.

4. Results

4.1. Re-parameterization effects on simulated forest structure

4.1.1. Leaf area index

The improved pine forest parameterizations applied here yielded tremendously improved agreement between simulated and observed intra-annual LAI compared to default models (Fig. 2), with mean R^2 values across sites increasing from 0.14 to 0.76. Marked differences between default and improved parameterizations included improvements in predicting the start and end of the growing season. While the default parameterization had unreasonably early annual LAI peaks (February–April), the improved parameterization and MODIS LAI benchmark data (Fig. 2) were well matched, generally peaking between June and August. Additionally, the default parameterization predicted the start of senescence between April and May, while the improved parameterization and MODIS LAI data showed LAI decline starting between July and August and were closely aligned (Fig. 2).

The new parameterization also improved predictions of inter-annual LAI at all sites (Fig. 3), with R^2 increasing from the range 0.00–0.20 with the default model to 0.11–0.57 with the new parameterization across the study sites. The default parameterization strongly overestimated LAI for loblolly pine (mean $PBIAS$ = −43%) and underestimated LAI for slash pine ($PBIAS$ = 17.3%). The improved parameterization reduced model over/underestimation by 88%, 94%, and 76% for Loblolly 2 – GA, Loblolly 3 – FL, and Slash – FL, respectively, but increased $PBIAS$ from −7.5% to +20% for Loblolly 1 – AL. The enhanced accuracy of the improved parameterization was also reflected in a reduction of mean RMSE from 2.27 to 0.75, a 67% decline (Fig. 3).

4.1.2. Forest biomass

With improved parameterization, modeled annual total biomass ($BIO_{tot,yr}$) was much better matched with observations across all sites (Fig. 4). Indeed, SWAT-simulated biomass using the default parameterization yielded an unrealistic and unrepresentative pattern with little, if any, biomass accumulation over time. As a result, the default models underestimated biomass by more than 70% at all sites, while simulations with improved parameters had a mean absolute $PBIAS$ of 12.2%. The new parameterization also led to significant improvements in temporal estimates at all sites, with mean NSE^2 values across sites increasing from −4.8 to 0.97. Mean RMSE was also reduced from 82.8 to 16.0, an 81% decline.

4.2. Re-parameterization effects on simulated water fluxes

4.2.1. Evapotranspiration

SWAT was able to capture the inter-annual and seasonal variability of ET reasonably well at all sites with both the default and improved parameterizations (Fig. 5). However, with the default parameterization, SWAT substantially underestimated ET compared to MODIS estimates (mean $PBIAS$ = 22.5%), while the new parameterization reduced model underestimation at Loblolly 3 – FL and Slash – FL (mean $PBIAS$ = 14%) and yielded small model overestimation for Loblolly 1 – AL and Loblolly 2 – GA (mean $PBIAS$ = −10.5%). The improved parameterization also led to substantially improved R^2 values for all sites (except Slash – FL, which declined only slightly), with an overall increase in mean R^2 from 0.22 to 0.54 across the four sites. RMSE was similarly improved at all sites (except Loblolly 2 – GA, which increased slightly), with an overall decrease in mean RMSE from 32.8 to 27.0 when using the new parameterization, an 18% reduction.

4.2.2. Water budget partitioning

Beyond improvements in ET estimation, the more realistic forest processes simulated using improved model parameters also translated into

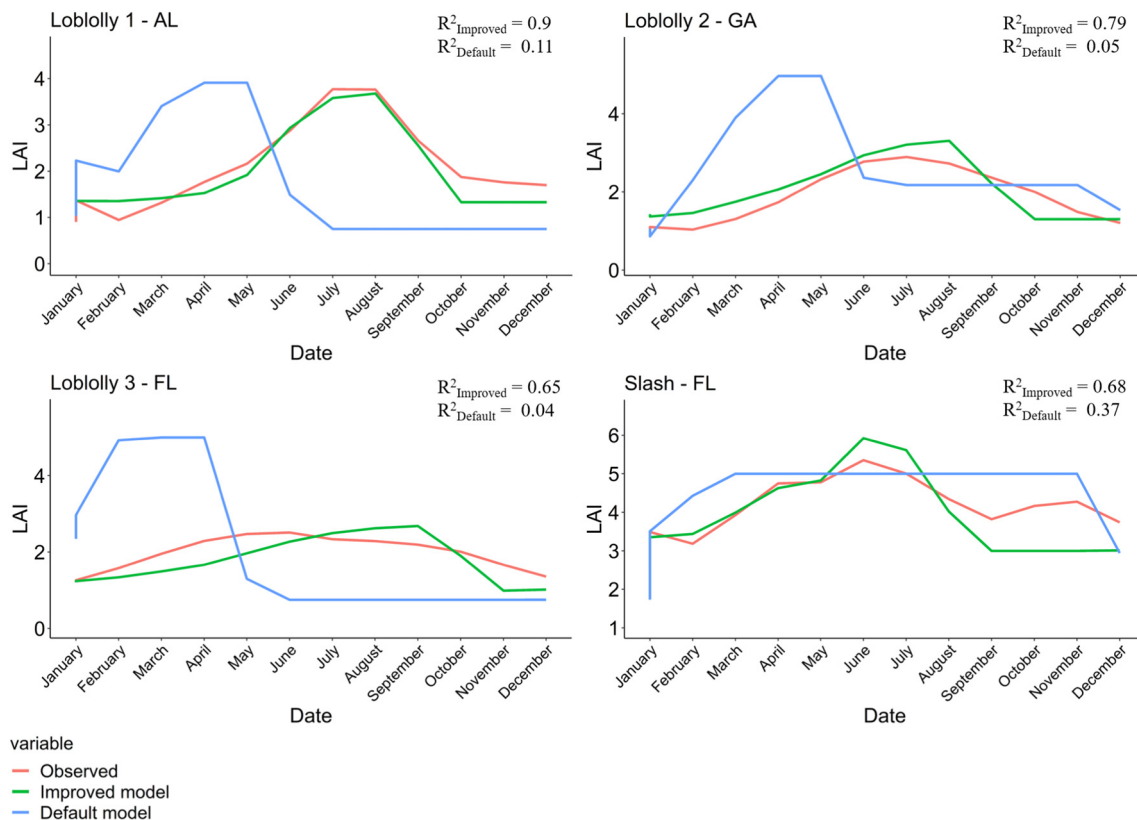


Fig. 2. SWAT simulation results of intra-annual LAI under default and improved forest parameterizations compared to MODIS estimates at all study sites. The displayed results referred to a single year.

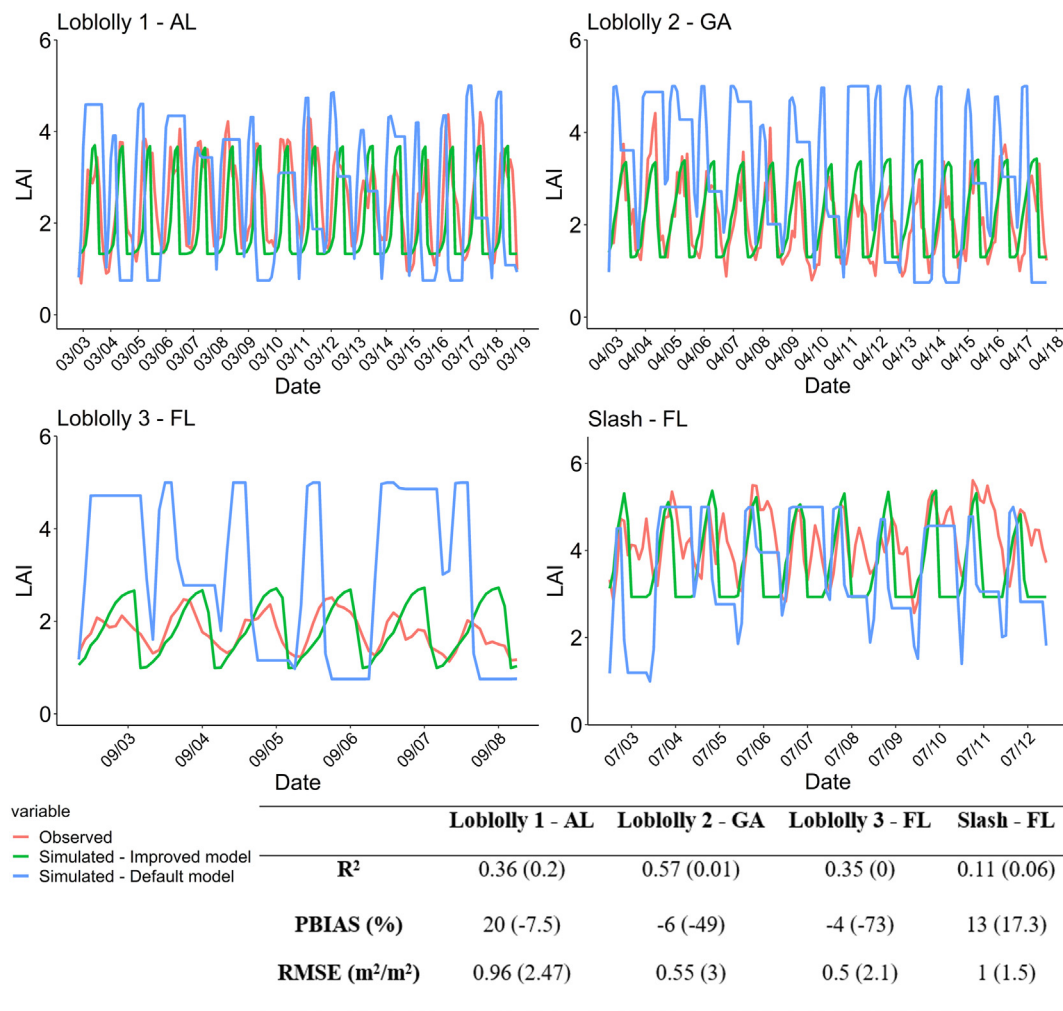


Fig. 3. Simulated versus MODIS LAI under default and improved model parameterizations. The bottom table shows the model performance for predicting monthly LAI under default and improved parameterizations. Values in parenthesis refer to the default model performance.

marked differences across all elements of water balance partitioning (Fig. 6). Overall, ET dominated the water budget at all sites and was also the component that changed the most under the new model parameterization. For example, at the Loblolly 1 – AL site, ET accounted for 43% of outgoing water fluxes in the default model (616 mm), followed by 31% via groundwater outflow (GW_Q; 446 mm), and 26% via surface water outflow (SURQ; 385 mm). Under the new SWAT parameterization, the proportion of outflow from ET increased to 53% (772 mm), with groundwater and surface water fluxes of 25% and 22%, respectively (358 and 316 mm). The relatively high surface runoff rates simulated for this site may be explained by soils, which belong to hydrological soil group (HSG) D. At the Loblolly 2 site, as a result of 27% increase in ET with the improved parameterization, GW_Q was reduced from 368 mm (or 30% of the water balance) to 204 mm (or 17% of the water balance), while SURQ decreased from 200 mm/year (16% of the water balance) to 148 mm/year (12% of the water balance) (Fig. 6). Similar trends were found at the Loblolly 3 site, but with the main difference observed in sub-surface fluxes. With default SWAT forest parameterization, ET represented 56% of the water budget (670 mm), while GW_Q and lateral flow (LATQ) represented 43% (516 mm) and 1% (12 mm), respectively. Under the improved forest parameterization, ET:P increased to 60% (ET = 729 mm), while GW_Q:P dropped to 38% (462 mm) and LATQ:P remained unchanged. SURQ was insignificant at this site, most likely because of the site's HSG being A and soil texture being 95% of sand.

Surface flows were minor at the Slash – FL site due to soils in HSG B, but this site saw the most dramatic effect of improved forest parameterization

on water balance partitioning. In the default simulation, 54% of annual precipitation was lost as ET (637 mm), 39% contributed to groundwater outflow (456 mm), and only 6% contributed to surface water outflow (74 mm). Using the improved model parameterization, these proportions substantially changed, with 77% of annual rainfall lost to ET (919 mm), 17% going to groundwater (209 mm), and 5% contributing to surface water (Fig. 6).

4.3. Sensitivity analysis and model re-parameterization

The improved values for the SWAT parameters associated with LAI, biomass, and ET are given in Table 5. Notably, the improved values largely differed from the default values displayed in Table 2. Marked differences were found for parameters such as *BIO_E*, *VPDFR*, *T_BASE*, *T_OPT*, *GSI*, *CANMX*, *BIO_LEAF*, *CHTMX*, denoting the discrepancies between the default's SWAT forest parameterization and physically meaningful values. Results showed that the calibrated parameter values varied not only across the studied species but also across locations for the same species. This is especially true for parameters governing the intra-annual LAI dynamics. Other parameters such as *BIO_E*, *EXT_COEF*, *BLAI*, *VPDFR*, *CANMX*, *GSI*, *CHTMX* also presented large variations in their calibrated values according to the site's location.

The sensitivity analysis results displayed in Tables S2–S5 of the Supplementary Materials section (Appendix B) showed that, overall, five out of eight parameters were sensitive at the 95% confidence interval to biomass simulation, namely *BIO_E*, *RDMX*, *EXT_COEF*, *BLAI*, *MAT_YRS*.

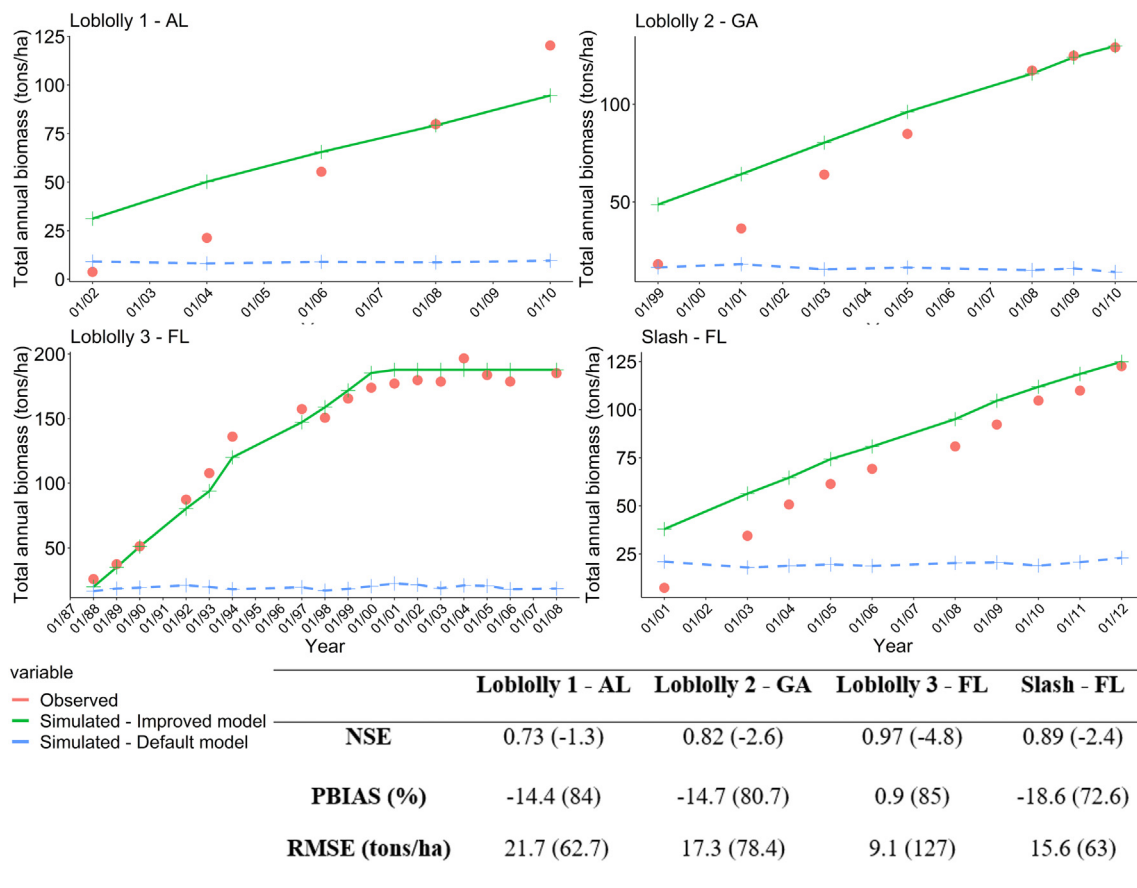


Fig. 4. Simulated versus field measured total annual biomass under default and improved model parameterizations. The bottom table shows the model performance for predicting annual biomass under default and improved parameterizations. Values in parenthesis refer to the default model performance.

Except for the slash pine site, all selected parameters were sensitive to monthly LAI prediction. Similarly, results indicate that all selected parameters were sensitive to seasonal ET simulation. Overall, *BIO_E* and *MAT_YRS* showed the highest sensitivity to biomass, while *GSI* and *CHTMX* were the most sensitives to ET.

5. Discussion

Given the widespread application of SWAT as a hydrologic simulator, its simplistic plant database for modeling forest dynamics, and the importance that forests play in driving hydrological processes, we contend that forests in SWAT's plant database should be re-parameterized for species-specific trees before conducting hydrological and water quality assessments.

Here we present a methodology to re-parameterize SWAT's plant database using publicly available remote-sensing data, published literature, and field measurements to derive physically meaningful parameter values underlying key forest processes in SWAT. Our improved parameterization aimed to enable SWAT to reasonably simulate the growth and dynamics of two widely cultivated tree species in the SE-US and serve as a starting point for future modeling studies in this region and open new avenues for SWAT re-parameterization of other tree species worldwide. Our results highlight the benefits of re-parameterization for modeling forest processes such as LAI development and biomass accumulation and their subsequent effects on hydrologic processes such as ET, demonstrating the magnitude of water balance changes brought about by improving SWAT's skills in simulating forest processes. We believe the re-calibration approach and results presented in this work are important for advancing scientifically based and

data-driven parameterization of hydrologic models and increasing the reliability of such models as decision-making tools.

5.1. Re-parameterization effects on simulated forest structure

5.1.1. Leaf area index

LAI controls canopy evaporation and strongly influences plant transpiration and needs to be accurately represented in hydrologic models in order to estimate the amount of water being lost as ET (Sampson et al., 2011).

The intra/inter-annual LAI predicted by all re-parameterized models showed good agreement with MODIS estimates and findings from forestry studies. For instance, Wightman et al. (2016) found that loblolly pine LAI peaked at the end of July in northern Florida. The authors also reported peak values of LAI ranging from 2 to 3.6 m²/m² in 2012–2013, similar to the MODIS estimates and model predictions presented here (Fig. 3), although simulated LAI peaks usually occurred in August. The divergent timing of maximum LAI may be due to natural variability, site management conditions, or annual variation associated with climatic variability between our study site and that of Wightman et al. (2016). Another reason could be the uncertainties associated with MODIS LAI estimates, which might have delayed the LAI peak during the parameterization stage. Notably, Samuelson et al. (2017) reported peak LAI of 2 to 3.2 m²/m² in late August or early September for loblolly pine stands in GA, which is in good agreement with the results presented here for Loblolly 3 – GA.

Despite some uncertainties in the MODIS-derived LAI algorithm (Jensen et al., 2011), these data proved useful for deriving species-specific phenological patterns and stand characteristics and generally improved SWAT's skills in predicting inter-annual LAI. However, there

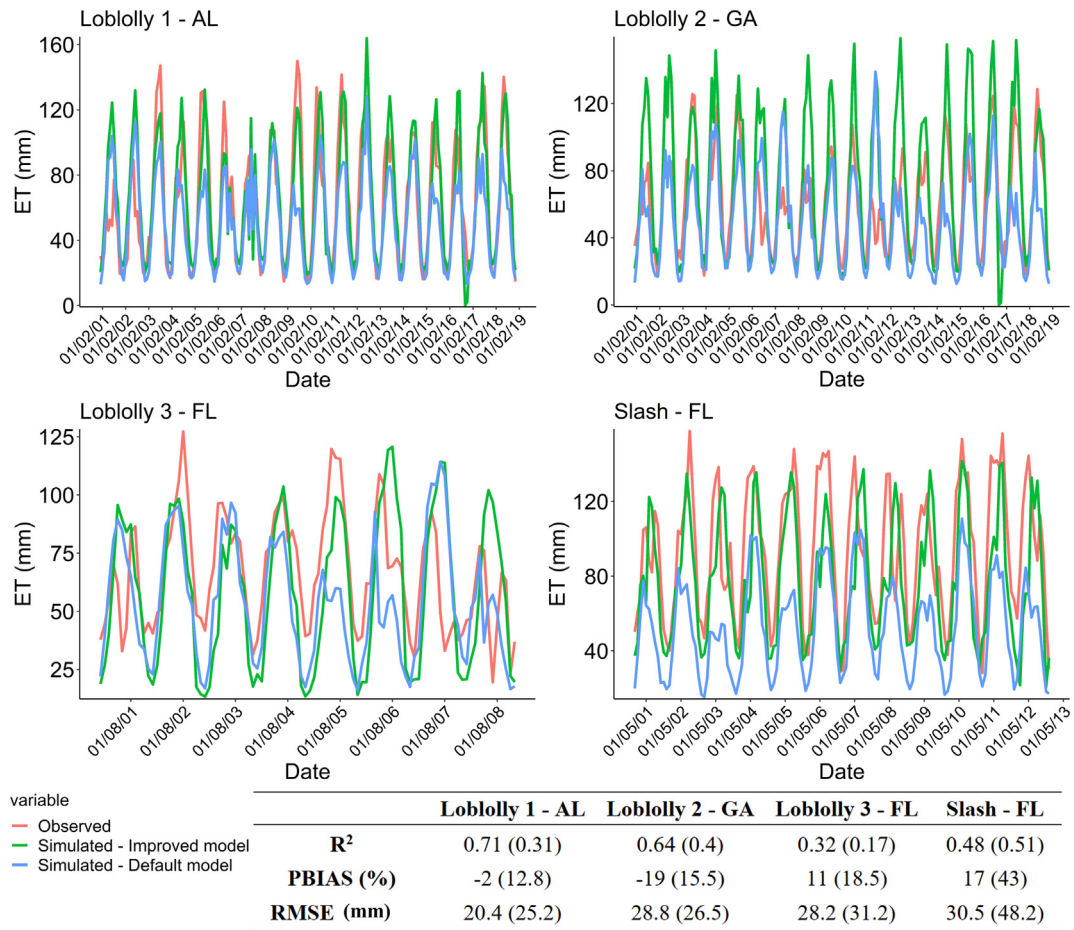


Fig. 5. Simulated versus MODIS ET under default and improved model parameterizations. The bottom table shows the SWAT model performance for predicting monthly ET under default and improved parameterizations. Values in parenthesis refer to the default model performance.

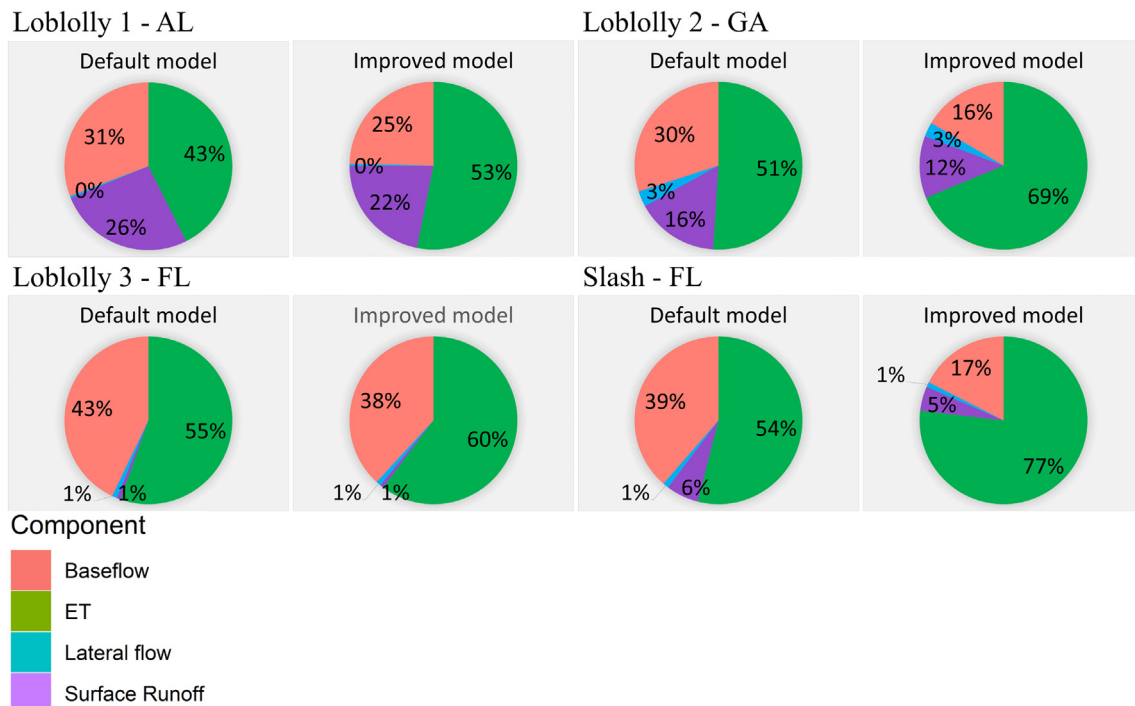


Fig. 6. Mean annual water budget under default and improved model parameterization across all sites.

Table 5

Calibrated values of parameters used for LAI, biomass, and ET calibration.

	Parameter	Loblolly 1 - AL	Loblolly 2 - GA	Loblolly - 3 - FL	Slash - FL	Default value
LAI shape	v__HEAT_UNITS([1],1).mgt	5912.39	4485	5518.84	5551	1800
	v__DLAI{128}.plant.dat	0.89	0.91	0.95	0.5	0.99
	v__FRGRW1{128}.plant.dat	0.31	0.15	0.21	0.45	0.15
	v__FRGRW2{128}.plant.dat	0.45	0.36	0.49	0.85	0.25
	v__LAIMX1{128}.plant.dat	0.52	0.34	0.35	0.43	0.7
	v__LAIMX2{128}.plant.dat	0.69	0.71	0.69	0.73	0.99
LAI + biomass	v__EXT_COEF{128}.plant.dat	0.41	0.56	0.42	0.59	0.65
	v__BMX_TREES{128}.plant.dat	139	187	187	141	1000
	v__BIO_LEAF{128}.plant.dat	0.02	0.02	0.02	0.02	0.3
	v__BIO_E{128}.plant.dat	8	7	11	3	15
	v__T_BASE{128}.plant.dat	4	4	4	5	0
	v__T_OPT{128}.plant.dat	24	25	25	25	30
	v__BLAI{128}.plant.dat	3.7	3.4	2.8	5.4	5
	v__ALAI_MIN{128}.plant.dat	1.3	1.3	1.3	2.9	0.75
	v__MAT_YRS{128}.plant.dat	5	4	1	4	30
	v__CURYR_MAT([1],1).mgt	1	1	1	1	–
	v__RDMX{128}.plant.dat	2.9	2	2	2	3.5
	v__VPDFR{128}.plant.dat	1.2	2.9	1.8	2.3	4
	v__CANMX.hru	1.59	0.6	0.93	0.95	0
	v__ESCO.hru	0.84	0.85	0.84	0.74	0.95
ET	v__GSI{128}.plant.dat	0.01	0.008	0.005	0.02	0.002
	v__CHTMX{128}.plant.dat	7.14	20	7	14	10
	v__EPCO.hru	0.48	0.48	0.48	0.38	1

were several specific times and locations where even the improved model diverged from remotely sensed LAI estimates. For example, at the Loblolly 1 – AL site, the re-parameterized SWAT model often failed to capture LAI dynamics at the beginning of the growing season, leading to a substantial underestimation of LAI (Fig. 3). Specifically, MODIS-estimated LAI began to increase around February, potentially related to understory greening (Biudes et al., 2014; Jensen et al., 2011), while SWAT-simulated LAI remained low and constant until beginning to increase in April. Additionally, while the re-parameterized model for Slash – FL was improved ($R^2 = 0.11$) over the default model ($R^2 = 0.06$), the model did not match well with the observed inter-annual LAI pattern (Fig. 3). The model's relatively poor performance at this site may be related to the high seasonal variability in MODIS LAI at this site, including multiple annual LAI peaks, which can challenge model calibration. The second LAI peak observed in MODIS estimates (Fig. 3) at the slash pine site is likely related to understory growing, which cannot be captured by SWAT. This mismatch between simulated and MODIS LAI values resulting from understory greening led to a substantial model underestimation of monthly LAI. However, the re-parameterized model showed good skills in replicating the first LAI peak, which we content denotes a good model performance in simulating the monthly LAI dynamics of slash pine.

5.1.2. Total stand biomass

Our re-parameterization substantially improved biomass simulations. The main reason for SWAT's poor performance in simulating tree biomass with the default parameterization was an unrealistically high value for the parameter *BIO_LEAF*. This parameter controls the fraction of total biomass converted to residue during dormancy annually; the default value is 30%, impeding reasonable biomass accumulation (Fig. 4), an issue also reported by Yang and Zhang (2016). Using field measurements of aboveground biomass and foliage biomass, we determined a more realistic value for *BIO_LEAF* across sites (Tables 2 and 5). We note that unrealistically high conversion of biomass to residue can also substantially affect SWAT's water quality algorithms. For instance, SWAT considers three organic nitrogen pools to model the soil nitrogen (N) cycle (Neitsch et al., 2011). The fresh N pool is associated with plant residue and is a direct source of nitrate (NO_3^-) via mineralization. Consequently, the overestimation of residue has the potential to unrealistically increase NO_3^- transport to downstream water bodies. Indeed, we found higher residue levels under the default model parameterization compared to

the improved parameterization (Tables S6–S9), which were associated with greatly increased mineralization of fresh organic N (not shown). While beyond the scope of this study to calibrate parameters related to mineralization and nitrification, this should be addressed in future efforts to better constrain forest soil nutrient cycling in hydrological models.

Beyond its contribution to soil nutrients, the amount of residue on the soil surface also affects sediment yield in SWAT since the Universal Soil Loss Equation (USLE) (Williams, 1975) cover and management factors are computed as a function of plant residue (Neitsch et al., 2011). Finally, biomass is important because it directly affects soil evaporation (Eqs. (S15) and (S16)). With potential impacts on both hydrology and water quality, getting plant biomass is critical for hydrological modeling applications, especially in forested ecosystems. Our findings point to a strong need to revise model parameters related to forest growth and dynamics of dominant species when applying SWAT in forestlands and highlight the benefits of our improved model parameterization over the default.

5.2. Re-parameterization effects on simulated water fluxes

5.2.1. Evapotranspiration

Model re-parameterization substantially increased the proportion of precipitation lost as ET at all study sites and led to better agreement between SWAT-simulated and MODIS-estimated ET. These findings concur with Yang et al. (2018), who also found the default SWAT model to greatly underestimate ET in forested ecosystems. Although biomass and LAI both affect ET estimates in SWAT (Eqs. (S17) and (S19)), we had to calibrate several additional ET-related parameters to account for variations among tree species and climate conditions (Table 5). Overall, the maximum stomatal conductance (*GSI*) was the most sensitive parameter for ET across all sites (Tables S1–S4 in the supplementary materials under Appendix B). The calibrated values of *GSI* ranged from 0.005 to 0.02 m/s, substantially higher than the default value of 0.002 m/s, which could be a primary reason why SWAT underestimates ET when using the default *FRSE* forest type. Studies such as Samuelson et al. (2012) and the ones shown in Table 2 point to higher stomatal conductance associated with slash pine trees compared to loblolly pine. This is in line with Gonzalez-Benecke et al. (2016) and Gonzalez-Benecke et al. (2014b), who derived canopy conductance for loblolly and slash pine stands based on data from long-term eddy covariance sites in North Carolina and meteorological measurements.

The simulated average annual ET was highest for the Slash – FL site (930 ± 45 mm), which was expected given that site's higher (simulated) LAI compared to the three loblolly pine sites. However, even after re-parameterization, the model underestimated monthly ET by 17% at this site. This under-prediction could be related to unrealistically low soil evaporation resulting from biomass overestimation (Fig. 4). As shown in Eqs. (S15) and (S16), higher aboveground biomass reduces the maximum soil evaporation in SWAT (due to shading). While the model underestimation was high, average annual ET values for the Slash – FL site was in good accordance with McLaughlin et al. (2013), who compiled studies investigating ET in the Southeastern Coastal Plain and found an ET range of 754–1168 mm/year at slash pine plantations in Florida. Additionally, our results are in line with the findings of Gonzalez-Benecke et al. (2014b), who reported ~900–1200 mm/year of rainfall lost as ET on slash pine plantations in the SE-US. Although the climatic conditions at the Loblolly 2 – GA and Loblolly 3 – FL sites are similar (Table 3), ET was higher in GA (857 ± 66) than FL (700 ± 64 mm), respectively. This difference is probably due to higher LAI at the GA site, which increases the interception rates and consequently the amount of water readily available for evaporation. Even though Loblolly 1 – AL receives more annual precipitation, on average, than Loblolly 2 – GA, and the mean annual LAI values are similar, simulated annual ET was lower (772 ± 69 mm) in AL. This is most likely related to the site's soil type (HSG D), which generates high surface runoff, leaving less water to infiltrate the soil profile for potential evapotranspiration.

Although the default SWAT models reconstructed the seasonal pattern of ET fairly well, marked underestimations were found. Beyond leading to better predictions of LAI and biomass, our re-parameterization further improved SWAT ET simulations and reduced the underestimation of ET.

5.2.2. Water budget partitioning

Our forest re-parameterization modified the simulated water balance across all study sites towards increased ET and decreased surface, subsurface, and groundwater fluxes. The fraction of precipitation lost as ET changed the most, from 43 to 56% under the default parameterization to 53–77% after re-parameterization. These proportions are in line with the findings of Lu et al. (2003) and McLaughlin et al. (2013), who reported an average ET:P ratio ranging from 50 to 95% and 70%, respectively, in the SE-US. ET is often the main outflow component of the water budget, with fractions as high as 90% of rainfall in densely forested ecosystems like pine plantations (McLaughlin et al., 2013). Consequently, small changes in ET can lead to major impacts on other water balance components, and forest dynamics must be well represented in hydrological modeling studies for forested regions. For example, land use/land cover change studies considering the impacts of afforestation and/or deforestation must be shown to accurately simulate forest dynamics before drawing conclusions about the water resource impacts of different scenarios. In this context, our study holds the promise to contribute to and improve future hydrological modeling studies in forested watersheds.

The relative percent changes of surface and subsurface water fluxes from the default to the improved forest parameterization varied substantially across the study sites, with the highest changes at sites with the greatest increases in ET, namely Loblolly 2 – GA and Slash – FL. Across sites, reductions in water yield with the new forest parameterization are not surprising given substantial increases in the ET:P ratio. Overall, groundwater was most sensitive to increases in ET. Our results suggest that relying on SWAT's default forest parameterization may lead to overestimation of groundwater fluxes and aquifer storage, which can potentially lead to flawed conclusions were the model to be used to support decision-making. The simulated rates of lateral flow were relatively low across all sites, varying from 0 to 3% of the water balance. This is due to a combination of site slope and saturated hydraulic conductivity values, since in SWAT, lateral flow is computed as a function of the water content in a saturated soil layer, the saturated

hydraulic conductivity, and slope. The study site showing the highest lateral flow, Loblolly 2 – GA, has a moderate saturated hydraulic conductivity (108 mm/h) but is located in a relatively flat area. The site Loblolly 1 – AL, for instance, while being located in the highlands, has a low hydraulic conductivity (32 mm/h). The sites located in Florida have the lowest slope among all study sites. This combination of factors leads to small lateral flow being simulated in our models. Future work should assess whether improved forest parameterization also improves watershed-scale fluxes such as surface runoff, lateral flow, and baseflow, observed data that were not available for this study.

5.3. SWAT forest re-parameterization and broader implications

The SWAT model has found wide applications for various purposes worldwide and is considered to be the most widely used hydrological model in the world (Abbaspour et al., 2019), but it has not been sufficiently tested in forested ecosystems (Amatya and Jha, 2011; Yang et al., 2019). As highlighted by Gassman et al. (2007), SWAT's plant database is limited and needs to be expanded to support a larger variety of plant species. Notably, the plant database was originally parameterized based on observations from annual crops, and the model is generally robust and straightforward for simulating crop biomass (Nair et al., 2011; Wang et al., 2015; Yang et al., 2018). However, growth rates, plant size, water and nutrient demands, biomass accumulation, and energy exchange can differ greatly between crops and trees, representing a shortcoming for tree growth modeling in SWAT. Parameters such as *BIO_E*, *T_BASE*, *T_OPT*, *GSI*, *CANMX*, *BIO_LEAF*, and *CHTMX*, for example, represent physical processes that can be usually measured via field experiments and for which values are many times documented in the published literature. The marked differences between SWAT's default values of such parameters and the values found during the re-parameterization stage illustrate the limitations of SWAT in accurately representing forest processes. Particularly, we identified unrealistic values of *T_BASE*, *T_OPT*, *BIO_LEAF*, *BLAI*, and *GSI* for representing loblolly and slash pine in SWAT. As shown by Eqs. (S1)–(S2), *T_BASE* and *T_OPT* directly influence the total number of heat units required for a forest to complete a growing season and consequently impact the intra-annual LAI dynamics. Our findings are in line with Yang and Zhang (2016), who have also identified low *T_BASE*, high *T_OPT*, and high *BIO_LEAF* in SWAT's default forest parameterization. As shown by Eq. (S12), *BLAI* impacts the maximum canopy storage with underlying effects on simulated ET. We identified excessively high *BLAI* values in SWAT's plant database for simulating loblolly pine, which is in accordance with the findings of Iames et al. (2018). On the other hand, SWAT's default *BLAI* is low for representing slash pine. Overly low *GSI* leads to underestimation of ET with the default forest parameterization, as illustrated by Eqs. (S17)–(S18).

As expected, substantial differences in model parameterization were found between loblolly and slash pine, as demonstrated by the improved values of parameters such as *BLAI*, *ALAI_MIN*, *RDMX*, *VPDFR*, and *GSI* (Table 5). The variation in their calibrated values should not come as a surprise given the physiological differences existing between loblolly and slash pine species (Dalla-Tea and Jokela, 1991; Jokela and Martin, 2000; Roth et al., 2007; Samuelson et al., 2012). Further, our findings show variations in improved parameter values across the loblolly pine sites, which suggests the existence of site-specific characteristics influencing the simulation of forest processes in SWAT. For instance, differences in intra/inter-annual LAI and biomass-related parameters can be interpreted based on the benchmark data used to calibrate the models. On the other hand, differences in parameters such as *HEAT_UNITS*, and *BIO_E* are most likely related to climate characteristics such as temperature and solar radiation. Phenological characteristics such as LAI may have influenced the values of parameters like *EXT_COEF* and *GSI*, while soil properties may help to understand the differences in *RDMX* across the loblolly pine sites. Differences in loblolly pine productivity and physiology have been reported across sites and largely

attributed to nutrient deficiencies (i.e., nitrogen and phosphorus) in the SE-US (Ducey and Allen, 2001; Green et al., 1994; Gregoire and Fisher, 2004; Will et al., 2015). It is worth highlighting that our study sites present varying physical characteristics such as mean annual temperature and solar radiation, total precipitation, and soil properties, which favors the application of our re-parameterization to a broad geographical range across the SE-US.

Sensitivity analysis was performed on 18 parameters related to the simulation of plant growth and dynamics in SWAT. Not all inventoried parameters were included in the sensitivity analysis since parameters such as *BIO_LEAF*, *T_BASE*, *T_OPT*, *EPCO*, and *CURYR_MAT* were assigned fixed values rather than optimized within a certain range. Considering that parameters usually represent processes in SWAT, identifying sensitive parameters may help to understand the processes influencing the prediction of variables such as LAI, biomass, and ET and interpret the relative importance of different parameters in simulating such variables. Our findings show the importance of parameters regulating the shape of the LAI curve in predicting intra-annual LAI and indicate that they should be optimized to adequately simulate LAI development in SWAT. Moreover, parameters such as *GSI* and *CHTMX* were highly sensitive to ET simulation and demonstrate the importance of processes such as stomatal conductance and system states such as maximum canopy height in predicting ET. This should not come as a surprise given the role played by stomatal conductance and canopy height in the PM formulation (Eqs. (S17)–(S20)). Additionally, *CANMX* was shown to be highly sensitive to ET, which indicates the importance of canopy interception in simulating ET in SWAT. Although the parameters sensitivity to inter-annual LAI and biomass simulation varied substantially across the study sites, the results presented here highlight the importance of *BIO_E* and *MAT_YRS*. As illustrated by Eqs. (S5)–(S6), *BIO_E* represents the efficiency of the tree in converting the intercepted photosynthetically active radiation into biomass and can be interpreted as the representation of photosynthesis in SWAT. The importance of *MAT_YRS* comes from the fact that this parameter influences the maximum amount of biomass that can be accumulated by the stand in a single year (Eq. (S12)) and highlights the necessity of adjusting the number of years required by a certain species to reach maturity when predicting stand biomass in SWAT. In the current study, trees were planted in the warmup period and *MAT_YRS* should be interpreted here as the number of years required by the trees to transition from a seedling to a sapling. If the default *MAT_YRS* value of 30 years had not been changed, the biomass accumulation would have been excessively low with underlying effects on soil evaporation (Eqs. (S15)–(S16)) and simulated water fluxes. Although our re-parameterization was not validated against independent datasets such as accrual measurements of LAI and ET, due to the lack of available data, the nowadays large availability of remote-sensing data facilitates the validation of our methodology at the watershed-scale in the SE-US. We acknowledge that some of the parameters calibrated here are highly site-specific (e.g., *BMX_TREES*) and may not be directly applicable for other modeling studies. However, given the wide geographical and climatological range of sites considered in this study, the loblolly and slash pine parameterization presented here should be broadly useful.

6. Conclusions

Here we introduced a novel methodology to enhance the representation of forest processes in the widely used SWAT model and showed its benefits over the default parameterization at four pine plantation stands across the SE-US. Our results showed that under the default forest parameterization, SWAT was unable to accurately represent forest dynamics due to unrealistic parameter values in the model's plant database, leading to inadequate LAI predictions, large underestimations of annual biomass, and monthly ET across all study sites. Our proposed re-parameterization, validated using field and remotely sensed data, improved the representation of forest structures and processes such as LAI, biomass, and ET.

Re-parameterization translated into changes in the simulated water budget, with large impacts on ET, surface, and subsurface fluxes. Overall, the new parameterization increased ET and decreased surface runoff, lateral flow, and baseflow at all sites. The extent to which the improved forest parameterization affected hydrological processes in SWAT suggests that forest dynamics should be considered before conducting any model application in forested ecosystems. Inventorying physically meaningful values of important parameters impacting interception, soil evaporation, transpiration, canopy height, LAI, biomass accumulation, and modification of the atmospheric boundary layer are a step forward to adequately representing the effects of forest dynamics on hydrological processes in SWAT and can be applied in other settings. Overall, these findings provide valuable information for improving the representation of forest processes in SWAT and can strengthen the application of watershed models in forested ecosystems worldwide.

CRedit authorship contribution statement

Henrique Haas: Conceptualization, Methodology, Writing - original draft. **Nathan G. F. Reaver:** Writing, Methodology. **Ritesh Karki:** Methodology. **Latif Kalin:** Supervision, funding, writing - review & editing. **Puneet Srivastava:** Supervision, funding, writing - review & editing. **David A. Kaplan:** Writing - review & editing. **Carlos A. Gonzalez-Benecke:** Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We would like to thank USDA-NIFA (AFRI Water for Agriculture Challenge Area Grant 2017-68007-26319) for providing funding for this research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2021.151425>.

References

- Abbaspour, K.C., 2015. SWAT Calibration and Uncertainty Programs. Eawag Aquatic Research. Eawag: Swiss Federal Institute of Aquatic Science and Technology, p. 100.
- Abbaspour, K.C., Johnson, C.A., van Genuchten, M.T., 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone J.* 3, 1340–1352. <https://doi.org/10.2113/3.4.1340>.
- Abbaspour, K.C., Vaghefi, S.A., Yang, H., Srinivasan, R., 2019. Global soil, landuse, evapotranspiration, historical and future weather databases for SWAT applications. *Sci. Data* 6, 263. <https://doi.org/10.1038/s41597-019-0282-4>.
- Albaugh, T.J., Allen, H.L., Kress, L.W., 2006. Root and stem partitioning of *Pinus taeda*. *Trees* 20, 176–185.
- Alemayehu, T., van Griensven, A., Woldegiorgis, B.T., Bauwens, W., 2017. An improved SWAT vegetation growth module and its evaluation for four tropical ecosystems. *Hydrol. Earth Syst. Sci.* 21, 4449–4467. <https://doi.org/10.5194/hess-21-4449-2017>.
- Allen, C.B., Will, R.E., Jacobson, M.A., 2005. Production efficiency and radiation use efficiency of four tree species receiving irrigation and fertilization. *For. Sci.* 51, 556–569. <https://doi.org/10.1093/forestscience/51.6.556>.
- Althoff, D., Rodrigues, L.N., 2021. Goodness-of-fit criteria for hydrological models: model calibration and performance assessment. *J. Hydrol.* 600, 126674. <https://doi.org/10.1016/j.jhydrol.2021.126674>.
- Amatya, D.M., Jha, M.K., 2011. Evaluating the SWAT model for a low-gradient forested watershed in coastal South Carolina. *Am. Soc. Agric. Biol. Eng.* 54 (6), 2151–2163.
- Amatya, D.M., Skaggs, R.W., 2001. Hydrologic modeling of a drained pine plantation on poorly drained soils. *For. Sci.* 47, 103–114. <https://doi.org/10.1093/forestscience/47.1.103>.
- Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. *J. Am. Water Resour. Assoc.* 34, 73–89. <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>.

- Arnold, J.G., Kiniry, J.R., Srinivasan, R., Williams, J.R., Haney, E.B., Neitsch, S.L., 2011. Soil and Water Assessment Tool Input/Output File Documentation Version 2009. Grassland, Soil and Water Research Laboratory - Agricultural Research Service Blackland Research Center - Texas AgriLife Research.
- Aspinwall, M.J., King, J.S., McKeand, S.E., Domec, J.-C., 2011. Leaf-level gas-exchange uniformity and photosynthetic capacity among loblolly pine (*Pinus taeda* L.) genotypes of contrasting inherent genetic variation. *Tree Physiol.* 31, 78–91. <https://doi.org/10.1093/treephys/tpq107>.
- Baker, J.B., Langdon, O.G., 2016. Loblolly pine. In: Burns, R.M. (Ed.), *Silvicultural Systems for the Major Forest Types of the United States*, pp. 148–152.
- Barnett, J.P., Sheffield, R.M., 2004. Slash pine: characteristics, history, status, and trends. In: Dickens, E.D., Barnett, J.P., Hubbard, W.G., Jokela, E.L. (Eds.), *Slash Pine: Still Growing and Growing! Proceedings of the Slash Pine Composium*.
- Bartkowiak, S.M., Samuelson, L.J., McGuire, M.A., Teskey, R.O., 2015. Fertilization increases sensitivity of canopy stomatal conductance and transpiration to throughfall reduction in an 8-year-old loblolly pine plantation. *For. Ecol. Manag.* 354, 87–96. <https://doi.org/10.1016/j.foreco.2015.06.033>.
- Beaup, L.A., Maxwell, R.M., Clow, D.W., McCray, J.E., 2014. Hydrological effects of forest transpiration loss in bark beetle-impacted watersheds. *Nat. Clim. Chang.* 4, 481–486. <https://doi.org/10.1038/nclimate2198>.
- Biudes, M.S., Machado, N.G., Danelichen, V.H. de M., Souza, M.C., Vourlitis, G.L., Nogueira, J. de S., 2014. Ground and remote sensing-based measurements of leaf area index in a transitional forest and seasonal flooded forest in Brazil. *Int. J. Biometeorol.* 58, 1181–1193. <https://doi.org/10.1007/s00484-013-0713-4>.
- Boswell, V.R., 1926. The influence of temperature upon the growth and yield of garden peas. *Proc. Am. Soc. Hortic. Sci.* 23, 162–168.
- Bracho, R., Starr, G., Gholz, H.L., Martin, T.A., Cropper, W.P., Loesch, H.W., 2012. Controls on carbon dynamics by ecosystem structure and climate for southeastern U.S. Slash pine plantations. *Ecol. Monogr.* 82, 101–128. <https://doi.org/10.1890/11-0587.1>.
- Bracho, R., Vogel, J.G., Will, R.E., Noormets, A., Samuelson, L.J., Jokela, E.J., Gonzalez-Benecke, C.A., Gezan, S.A., Markewitz, D., Seiler, J.R., Strahm, B.D., Teskey, R.O., Fox, T.R., Kane, M.B., Lavinier, M.A., McElligot, K.M., Yang, J., Lin, W., Meek, C.R., Cucinella, J., Akers, M.K., Martin, T.A., 2018. Carbon accumulation in loblolly pine plantations is increased by fertilization across a soil moisture availability gradient. *For. Ecol. Manag.* 424, 39–52. <https://doi.org/10.1016/j.foreco.2018.04.029>.
- Carlyle-Moses, D.E., Gash, J.H.C., 2011. Rainfall interception loss by Forest Canopies. In: Levita, D.F., Carlyle-Moses, D., Tanaka, T. (Eds.), *Forest Hydrology and Biogeochemistry: Synthesis of Past Research and Future Directions*. Springer Netherlands, Dordrecht, pp. 407–423. https://doi.org/10.1007/978-94-007-1363-5_20.
- Chisholm, R.A., Condit, R., Rahman, K.A., Baker, P.J., Bunyavejchewin, S., Chen, Y.-Y., Chuyong, G., Dattaraja, H.S., Davies, S., Ewango, C.E.N., Gunatilleke, C.V.S., Gunatilleke, I.A.U.N., Hubbell, S., Kenfack, D., Kiratiprayoon, S., Lin, Y., Makana, J.-R., Pongpattananurak, N., Pulla, S., Punchi-Manage, R., Sukumar, R., Su, S.-H., Sun, I.-F., Suresh, H.S., Tan, S., Thomas, D., Yap, S., 2014. Temporal variability of forest communities: empirical estimates of population change in 4000 tree species. *Ecol. Lett.* 17, 855–865. <https://doi.org/10.1111/ele.12296>.
- Cibin, R., Trybula, E., Chaubey, I., Brouder, S.M., Volenc, J.J., 2016. Watershed-scale impacts of bioenergy crops on hydrology and water quality using improved SWAT model. *GCB Bioenergy* 8, 837–848. <https://doi.org/10.1111/gcb.12307>.
- Cohen, M., McLaughlin, D., Kaplan, D.A., Archarya, S., 2018. Managing Forests for Increased Regional Water Availability. Report on Task 7: Year 3 Annual Report Final. FDACS Contract No. 20834. https://www.fdacs.gov/content/download/76293/file/20834_D_e7.pdf 86.
- Crockford, R.H., Richardson, D.P., 2000. Partitioning of rainfall into throughfall, stemflow and interception: effect of forest type, ground cover and climate. *Hydrol. Process.* 14, 2903–2920. [https://doi.org/10.1002/1099-1085\(200011/12\)14:16/17<2903::AID-HYP126>3.0.CO;2-6](https://doi.org/10.1002/1099-1085(200011/12)14:16/17<2903::AID-HYP126>3.0.CO;2-6).
- Dalla-Tea, F., Jokela, E.J., 1991. Needlefall, canopy light interception, and productivity of young intensively managed slash and loblolly pine stands. *For. Sci.* 37, 1298–1313. <https://doi.org/10.1093/forestscience/37.5.1298>.
- De Kauwe, M.G., Medlyn, B.E., Knauer, J., Williams, C.A., 2017. Ideas and perspectives: how coupled is the vegetation to the boundary layer? *Biogeosciences* 14, 4435–4453. <https://doi.org/10.5194/bg-14-4435-2017>.
- Ducey, M., Allen, H.L., 2001. Nutrient supply and fertilization efficiency in midrotation loblolly pine plantations: a modeling analysis. *For. Sci.* 47, 96–102. <https://doi.org/10.1093/forestscience/47.1.96>.
- Falkenmark, M., Rockström, J., 2006. The new blue and green water paradigm: breaking new ground for water resources planning and management. *J. Water Resour. Plan. Manag.* 132, 129–132. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2006\)132:3\(129\)](https://doi.org/10.1061/(ASCE)0733-9496(2006)132:3(129)).
- Federer, C.A., 1973. Forest transpiration greatly speeds streamflow recession. *Water Resour. Res.* 9, 1599–1604. <https://doi.org/10.1029/WR009i006p01599>.
- Gassman, P.W., Williams, J.R., Benson, V.W., Izaurralde, R.C., Hauck, L.M., Jones, C.A., Atwood, J.D., Kiniry, J.R., Flowers, J.D., 2004. Historical Development and Applications of the EPIC and APEX Models. <https://doi.org/10.13031/2013.17074>.
- Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. *Trans. ASABE* 50, 1211–1250. <https://doi.org/10.13031/2013.23637>.
- Gavazzi, M.J., Sun, G., McNulty, S.G., Treasure, E.A., Wightman, M.G., 2016. Canopy rainfall interception measured over ten years in a coastal plain loblolly pine (*Pinus taeda* L.) plantation. *Trans. ASABE* 59, 601–610. <https://doi.org/10.13031/trans.59.11101>.
- Golden, H.E., Evenson, G.R., Tian, S., Amatya, D.M., Sun, G., 2016. Hydrological modelling in forested systems. In: Amatya, D.M., Williams, T.M., Bren, L., Jong, C. de (Eds.), *Forest Hydrology: Processes, Management and Assessment*. CAB International, pp. 141–161. <https://doi.org/10.1079/9781780646602.0141>.
- Gonzalez-Benecke, C.A., Gezan, S.A., Albaugh, T.J., Allen, H.L., Burkhart, H.E., Fox, T.R., Jokela, E.J., Maier, C.A., Martin, T.A., Rubilar, R.A., Samuelson, L.J., 2014a. Local and general above-stump biomass functions for loblolly pine and slash pine trees. *For. Ecol. Manag.* 334, 254–276. <https://doi.org/10.1016/j.foreco.2014.09.002>.
- Gonzalez-Benecke, C.A., Jokela, E.J., Cropper, W.P., Bracho, R., Leduc, D.J., 2014b. Parameterization of the 3-PG model for *Pinus elliotii* stands using alternative methods to estimate fertility rating, biomass partitioning and canopy closure. *For. Ecol. Manag.* 327, 55–75. <https://doi.org/10.1016/j.foreco.2014.04.030>.
- Gonzalez-Benecke, C.A., Teskey, R.O., Martin, T.A., Jokela, E.J., Fox, T.R., Kane, M.B., Noormets, A., 2016. Regional validation and improved parameterization of the 3-PG model for *Pinus taeda* stands. *For. Ecol. Manag.* 361, 237–256. <https://doi.org/10.1016/j.foreco.2015.11.025>.
- Green, T.H., Mitchell, R.J., Gjerstad, D.H., 1994. Effects of nitrogen on the response of loblolly pine to drought. *New Phytol.* 128, 145–152. <https://doi.org/10.1111/j.1469-8137.1994.tb03997.x>.
- Gregoire, N., Fisher, R.F., 2004. Nutritional diagnoses in loblolly pine (*Pinus taeda* L.) established stands using three different approaches. *For. Ecol. Manag.* 203, 195–208. <https://doi.org/10.1016/j.foreco.2004.07.049>.
- Guo, T., Engel, B.A., Shao, G., Arnold, J.G., Srinivasan, R., Kiniry, J.R., 2015. Functional approach to simulating short-rotation woody crops in process-based models. *Bioenergy Res.* 8, 1598–1613. <https://doi.org/10.1007/s12155-015-9615-0> 54, 2151–2163.
- Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. *J. Hydrol.* 377, 80–91. <https://doi.org/10.1016/j.jhydrol.2009.08.003>.
- Iames, J.S., Cooter, E., Schwede, D., Williams, J., 2018. A comparison of simulated and field-derived leaf area index (LAI) and canopy height values from four Forest complexes in the southeastern USA. *Forests* 9, 26. <https://doi.org/10.3390/f9010026>.
- Jensen, J.L.R., Humes, K.S., Hudak, A.T., Vierling, L.A., Delmelle, E., 2011. Evaluation of the MODIS LAI product using independent lidar-derived LAI: a case study in mixed conifer forest. *Remote Sens. Environ.* 115 (3625–3639), 3625–3639. <https://doi.org/10.1016/j.rse.2011.08.023>.
- Johnson, M.F., Wilby, R.L., 2015. Seeing the landscape for the trees: metrics to guide riparian shade management in river catchments. *Water Resour. Res.* 51, 3754–3769. <https://doi.org/10.1002/2014WR016802>.
- Johnson, J.D., Byres, D.P., Dean, T.J., 1995. Diurnal water relations and gas exchange of two slash pine (*Pinus elliotii*) families exposed to chronic ozone levels and acidic rain *. *New Phytol.* 131, 381–392. <https://doi.org/10.1111/j.1469-8137.1995.tb03075.x>.
- Jokela, E.J., Martin, T.A., 2000. Effects of ontogeny and soil nutrient supply on production, allocation, and leaf area efficiency in loblolly and slash pine stands. *Can. J. For. Res.* 30, 1511–1524. <https://doi.org/10.1139/x00-082>.
- Karki, R., Srivastava, P., Kalin, L., Lamba, J., Bosch, D.D., 2019. Multi-variable Sensitivity Analysis, Calibration, and Validation of a Field-scale SWAT Model: Building Stakeholder Trust in Hydrologic/Water Quality Modeling. In: 2019 Boston, Massachusetts July 7–July 10, 2019. Presented at the 2019 Boston, Massachusetts July 7–July 10, 2019. American Society of Agricultural and Biological Engineers <https://doi.org/10.13031/aim.201901362>.
- Kattge, J., Díaz, S., Lavorel, S., Prentice, I.C., Leadley, P., Bönsch, G., Garnier, E., Westoby, M., Reich, P.B., Wright, I.J., Cornelissen, J.H.C., Violle, C., Harrison, S.P., Bodegom, P.M.V., Reichstein, M., Enquist, B.J., Soudzilovskaia, N.A., Ackerly, D.D., Anand, M., Atkin, O., Bahn, M., Baker, T.R., Baldocchi, D., Bekker, R., Blanco, C.C., Blonder, B., Bond, W.J., Bradstock, R., Bunker, D.E., Casanoves, F., Cavender-Bares, J., Chambers, J.Q., Iii, F.S.C., Chave, J., Coomes, D., Cornwell, W.K., Craine, J.M., Dobrin, B.H., Duarte, L., Durka, W., Elser, J., Esser, G., Estiarte, M., Fagan, W.F., Fang, J., Fernández-Méndez, F., Fidelis, A., Finegan, B., Flores, O., Ford, H., Frank, D., Freschet, G.T., Fyllas, N.M., Gallagher, R.V., Green, W.A., Gutierrez, A.G., Hickler, T., Higgins, S.L., Hodgson, J.G., Jalili, A., Jansen, S., Joly, C.A., Kerkhoff, A.J., Kirkup, D., Kitajima, K., Kleyer, M., Klotz, S., Knops, J.M.H., Kramer, K., Kühn, I., Kurokawa, H., Laughlin, D., Lee, T.D., Leishman, M., Lens, F., Lenz, T., Lewis, S.L., Lloyd, J., Llusià, J., Louault, F., Ma, S., Mahecha, M.D., Manning, P., Massad, T., Medlyn, B.E., Messier, J., Moles, A.T., Müller, S.C., Nadrowski, K., Naeem, S., Niinemets, Ü., Nöllert, S., Nüske, A., Ogaya, R., Oleksyn, J., Onipchenko, V.G., Onoda, Y., Ordoñez, J., Overbeck, G., Ozinga, W.A., Patiño, S., Paula, S., Pausas, J.G., Peñuelas, J., Phillips, O.L., Pillar, V., Poorter, H., Poorter, L., Poschlod, P., Prinzing, A., Proulx, R., Rammig, A., Reinsch, S., Reu, B., Sack, L., Salgado-Negret, B., Sardans, J., Shiodera, S., Shipley, B., Siefert, A., Sosinski, E., Soussana, J.-F., Swaine, E., Swenson, N., Thompson, K., Thornton, P., Waldram, M., Weiher, E., White, M., White, S., Wright, S.J., Yguel, B., Zaehle, S., Zanne, A.E., Wirth, C., 2011. TRY – a global database of plant traits. *Glob. Chang. Biol.* 17, 2905–2935. <https://doi.org/10.1111/j.1365-2486.2011.02451.x>.
- Leigh, A., Savanto, S., Close, J.D., Nicotra, A.B., 2017. The influence of leaf size and shape on leaf thermal dynamics: does theory hold up under natural conditions? *Plant Cell Environ.* 40, 237–248. <https://doi.org/10.1111/pce.12857>.
- Lu, J., Sun, G., McNulty, S.G., Amatya, D.M., 2003. Modeling actual evapotranspiration from forested watersheds across the southeastern United States. *J. Am. Water Resour. Assoc.* 39 (4), 887–896.
- Magoon, C.A., Culpepper, C.W., 1932. Response of Sweet Corn to Varying Temperatures from Time of Planting to Canning Maturity. United States Department of Agriculture, Technical Bulletin No. 312 Washington, D. C. pp. 1–40.
- Malik, M.A., Dar, A.Q., Jain, M.K., 2021. Modelling streamflow using the SWAT model and multi-site calibration utilizing SUF-2 of SWAT-CUP model for high altitude catchments, NW Himalaya's. *Model. Earth Syst. Environ.* <https://doi.org/10.1007/s40808-021-01145-0>.
- Marek, G.W., Gowda, P.H., Evett, S.R., Baumhardt, R.L., Brauer, D.A., Howell, T., Marek, T.H., Srinivasan, R., 2016. Calibration and Validation of the SWAT Model for Predicting Daily ET Over Irrigated Crops in the Texas High Plains Using Lysimetric Data. <https://doi.org/10.13031/trans.59.10926>.
- Martin, T.A., Jokela, E.J., 2004. Developmental patterns and nutrition impact radiation use efficiency components in southern pine stands. *Ecol. Appl.* 14, 1839–1854. <https://doi.org/10.1890/03-5262>.

- McLaughlin, D.L., Kaplan, D.A., Cohen, M.J., 2013. Managing forests for increased regional water yield in the southeastern U.S. Coastal plain. *J. Am. Water Resour. Assoc.* 49, 953–965. <https://doi.org/10.1111/jawr.12073>.
- Mittelstet, A.R., 2015. Using SWAT to simulate crop yields and salinity levels in the north Fork River basin, USA. *Int. J. Agric. Biol. Eng.* 8, 16.
- Moriassi, D.N., Arnold, J.G., Liew, M.W.V., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations.
- Mu, Q., Zhao, M., Running, S.W., 2013. MODIS Global Terrestrial Evapotranspiration (ET) Product (NASE MOD16A2/A3). Algorithm Theoretical Basis Document, Collectio. 5, p. 600.
- Naderi, M., 2020. Assessment of water security under climate change for the large watershed of dorudzan dam in southern Iran. *Hydrogeol. J.* <https://doi.org/10.1007/s10040-020-02159-1>.
- Nair, S.S., King, K.W., Witter, J.D., Sohngen, B.L., Fausey, N.R., 2011. Importance of crop yield in calibrating watershed water quality simulation Tools1. *J. Am. Water Resour. Assoc.* 47, 1285–1297. <https://doi.org/10.1111/j.1752-1688.2011.00570.x>.
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and water assessment tool theoretical documentation: version 2009. Texas Water Resources Institute Technical Report No. 406. Texas Water Resources Institute, USA.
- Pell, C., 2015. The Effects of Fertilization and Four Years of Throughfall Reduction on Leaf Physiology of Loblolly Pine (*Pinus taeda* L.).
- Pool, S., Vis, M., Seibert, J., 2018. Evaluating model performance: towards a non-parametric variant of the kling-gupta efficiency. *Hydrol. Sci. J.* 63, 1941–1953. <https://doi.org/10.1080/02626667.2018.1552002>.
- Poorter, H., Niklas, K.J., Reich, P.B., Oleksyn, J., Poot, P., Mommer, L., 2012. Biomass allocation to leaves, stems and roots: meta-analyses of interspecific variation and environmental control. *New Phytol.* 193, 30–50. <https://doi.org/10.1111/j.1469-8137.2011.03952.x>.
- Qi, J., Markewitz, D., Radcliffe, D., 2018. Modelling the effect of changing precipitation inputs on deep soil water utilization. *Hydrol. Process.* 32, 672–686. <https://doi.org/10.1002/hyp.11452>.
- Rath, S., Zamora-Re, M., Graham, W., Dukes, M., Kaplan, D., 2021. Quantifying nitrate leaching to groundwater from a corn-peanut rotation under a variety of irrigation and nutrient management practices in the Suwannee River Basin, Florida. *Agric. Water Manag.* 246, 106634. <https://doi.org/10.1016/j.agwat.2020.106634>.
- Raz-Yaseef, N., Rotenberg, E., Yakir, D., 2010. Effects of spatial variations in soil evaporation caused by tree shading on water flux partitioning in a semi-arid pine forest. *Agric. For. Meteorol.* 150, 454–462. <https://doi.org/10.1016/j.agrformet.2010.01.010>.
- Rees, K.C.J.V., Comerford, N.B., 1986. Vertical root distribution and strontium uptake of a slash pine stand on a Florida spodosol. *Soil Sci. Soc. Am. J.* 50, 1042–1046. <https://doi.org/10.2136/sssaj1986.03615995005000040041x>.
- Reich, P.B., 2005. Global biogeography of plant chemistry: filling in the blanks. *New Phytol.* 168, 263–266. <https://doi.org/10.1111/j.1469-8137.2005.01562.x>.
- Roberts, J., 1983. Forest transpiration: a conservative hydrological process? *J. Hydrol.* 66, 133–141. [https://doi.org/10.1016/0022-1694\(83\)90181-6](https://doi.org/10.1016/0022-1694(83)90181-6).
- Roth, B., 2010. Genotype x Environment Interactions in Selected Loblolly (*Pinus taeda* L.) and Slash Pine (*P. elliottii* Engelm. var. *elliottii*) Plantations in the Southeastern United States. <https://doi.org/10.13140/rg.2.1.4418.5041>.
- Roth, B.E., Jokela, E.J., Martin, T.A., Huber, D.A., White, T.L., 2007. Genotype×environment interactions in selected loblolly and slash pine plantations in the southeastern United States. *For. Ecol. Manag.* 238, 175–188. <https://doi.org/10.1016/j.foreco.2006.10.010>.
- Saleh, A., Williams, J.R., Wood, J.C., Hauck, L.M., Blackburn, W.H., 2004. Application of apex for forestry. *Trans. ASAE* 47, 751–765. <https://doi.org/10.13031/2013.16107>.
- Sampson, D.A., Allen, H.L., 1998. Light attenuation in a 14-year-old loblolly pine stand as influenced by fertilization and irrigation. *Trees* 13, 80–87. <https://doi.org/10.1007/s004680050190>.
- Sampson, D.A., Amatya, D.M., Lawson, C.D.B., Skaggs, R.W., 2011. Leaf area index (LAI) of loblolly pine and emergent vegetation following a harvest. *Trans. ASABE* 54, 2057–2066. <https://doi.org/10.13031/2013.40664>.
- Samuelson, L.J., Stokes, T.A., Johnsen, K.H., 2012. Ecophysiological comparison of 50-year-old longleaf pine, slash pine and loblolly pine. *For. Ecol. Manag.* 274, 108–115. <https://doi.org/10.1016/j.foreco.2012.02.017>.
- Samuelson, L.J., Kane, M.B., Markewitz, D., Teskey, R.O., Akers, M.K., Stokes, T.A., Pell, C.J., Qi, J., 2017. Fertilization increased leaf water use efficiency and growth of *Pinus taeda* subjected to five years of throughfall reduction. *Can. J. For. Res.* 48, 227–236. <https://doi.org/10.1139/cjfr-2017-0357>.
- Savenije, H.H.G., 2004. The importance of interception and why we should delete the term evapotranspiration from our vocabulary. *Hydrol. Process.* 18, 1507–1511. <https://doi.org/10.1002/hyp.5563>.
- Schenk, H.J., Jackson, R.B., 2002. Rooting depths, lateral root spreads and below-ground/above-ground allometries of plants in water-limited ecosystems. *J. Ecol.* 90, 480–494. <https://doi.org/10.1046/j.1365-2745.2002.00682.x>.
- Schultz, R.P., 1997. Loblolly pine: the ecology and culture of loblolly pine (*Pinus taeda* L.). *Agriculture Handbook* 713. U.S. Department of Agriculture, Forest Service, Washington, D.C. 493 p.
- Shivhare, N., Dikshit, P.K.S., Dwivedi, S.B., 2018. A comparison of SWAT model calibration techniques for hydrological modeling in the Ganga River watershed. *Engineering* 4, 643–652. <https://doi.org/10.1016/j.eng.2018.08.012>.
- Skaggs, R.W., 1978. A water management model for shallow water table soils [WWW document]. *Environ. Sci. Report No. 134* (Water Resources Research Institute of the University of North Carolina). University of North Carolina, North Carolina, pp. 1–178. URL <https://www.semanticscholar.org/paper/A-water-management-model-for-shallow-water-table-Skaggs/ca09421c349952eae28717d2c6ebbfcdab6654a6>. (Accessed 5 September 2020).
- Srinivasan, R., Zhang, X., Arnold, J., 2010. SWAT ungauged: hydrological budget and crop yield predictions in the upper Mississippi River basin. *Trans. ASABE* 53, 1533–1546. <https://doi.org/10.13031/2013.34903>.
- Strauch, M., Volk, M., 2013. SWAT plant growth modification for improved modeling of perennial vegetation in the tropics. *Ecol. Model.* 269, 98–112. <https://doi.org/10.1016/j.ecolmodel.2013.08.013>.
- Suseta, A., Carter, D.R., Adams, D.C., 2014. Sustainability of forest management under changing climatic conditions in the southern United States: adaptation strategies, economic rents and carbon sequestration. *J. Environ. Manag.* 139, 80–87. <https://doi.org/10.1016/j.jenvman.2014.02.033>.
- Teskey, R.O., Gholz, H.L., Cropper, W.P., 1994. Influence of climate and fertilization on net photosynthesis of mature slash pine. *Tree Physiol.* 14, 1215–1227. <https://doi.org/10.1093/treephys/14.11.1215>.
- Timouk, F., Kergoat, L., Mougin, E., Lloyd, C.R., Ceschia, E., Cohard, J.-M., Rosnay, P.de, Hiernaux, P., Demarez, V., Taylor, C.M., 2009. Response of surface energy balance to water regime and vegetation development in a Sahelian landscape. *J. Hydrol.* 375, 178–189. <https://doi.org/10.1016/j.jhydrol.2009.04.022>.
- Surface processes and water cycle in West Africa, studied from the AMMA-CATCH observing system.
- Torreano, S.J., Morris, L.A., 1998. Loblolly Pine Root Growth and Distribution Under Water Stress.
- Trybala, E.M., Cibin, R., Burks, J.L., Chaubey, I., Brouder, S.M., Volenc, J.J., 2015. Perennial rhizomatous grasses as bioenergy feedstock in SWAT: parameter development and model improvement. *GCB Bioenergy* 7, 1185–1202. <https://doi.org/10.1111/gcbb.12210>.
- Veettil, A.V., Mishra, A.K., 2016. Water security assessment using blue and green water footprint concepts. *J. Hydrol.* 542, 589–602. <https://doi.org/10.1016/j.jhydrol.2016.09.032>.
- Wang, R., Bowling, L.C., Cherkauer, K.A., 2015. Estimation of the effects of climate variability on crop yield in the Midwest USA | elsevier enhanced reader [WWW document]. *Agric. For. Meteorol.* <https://doi.org/10.1016/j.agrformet.2015.10.001>.
- Wattenbach, M., Hattermann, F., Weng, R., Wechsung, F., Krysanova, V., Badeck, F., 2005. A simplified approach to implement forest eco-hydrological properties in regional hydrological modelling. *Ecol. Model.* 187, 40–59. <https://doi.org/10.1016/j.ecolmodel.2005.01.026>.
- Special Issue on Advances in Sustainable River Basin Management.
- White, M.A., Thornton, P.E., Running, S.W., Nemani, R.R., 2000. Parameterization and sensitivity analysis of the BIOME-BGC terrestrial ecosystem model: net primary production controls. *Earth Interact.* 4, 1–85. [https://doi.org/10.1175/1087-3562\(2000\)004<0003:PASAO7>2.0.CO;2](https://doi.org/10.1175/1087-3562(2000)004<0003:PASAO7>2.0.CO;2).
- Wightman, M.G., Martin, T.A., Gonzalez-Benecke, C.A., Jokela, E.J., Cropper, J., Ward, E.J., 2016. Loblolly pine productivity and water relations in response to throughfall reduction and fertilizer application on a poorly drained site in northern Florida. *Forests*, 7 <https://doi.org/10.3390/f7100214>.
- Will, R.E., Fox, T., Akers, M., Domec, J.-C., González-Benecke, C., Jokela, E.J., Kane, M., Lavinier, M.A., Lokuta, G., Markewitz, D., McGuire, M.A., Meek, C., Noormets, A., Samuelson, L., Seiler, J., Strahm, B., Teskey, R., Vogel, J., Ward, E., West, J., Wilson, D., Martin, T.A., 2015. A range-wide experiment to investigate nutrient and soil moisture interactions in loblolly pine plantations. *Forests* 6, 2014–2028. <https://doi.org/10.3390/f6062014>.
- Williams, J.R., 1990. The erosion-productivity impact calculator (EPIC) model: a case history. *Phil. Trans. R. Soc. Lond. B* 329, 421–428. <https://doi.org/10.1098/rstb.1990.0184>.
- Williams, J.R., 1975. Sediment-yield Prediction with Universal Soil Loss Equation Using Runoff Energy Factor. Present and Prospective Technology for Predicting Sediment Yield and Sources. Agricultural Research Service, US Department of Agriculture, Washington, D.C., USA, pp. 244–252.
- Williams, J.R., Jones, C.A., Kiniry, J.R., Spaul, D.A., 1989. The EPIC crop growth model. *Trans. ASAE* 32, 0497–0511. <https://doi.org/10.13031/2013.31032>.
- Williams, J.W., Izaurralde, R.C., Steglich, E.M., 2008. Theoretical Documentation 131.
- Yang, Q., Zhang, X., 2016. Improving SWAT for simulating water and carbon fluxes of forest ecosystems. *Sci. Total Environ.* 569–570, 1478–1488. <https://doi.org/10.1016/j.scitotenv.2016.06.238>.
- Yang, Q., Almendinger, J.E., Zhang, X., Huang, M., Chen, X., Leng, G., Zhou, Y., Zhao, K., Asrar, G.R., Srinivasan, R., Li, X., 2018. Enhancing SWAT simulation of forest ecosystems for water resource assessment: a case study in the St. Croix River basin. *Ecol. Eng.* 120, 422–431. <https://doi.org/10.1016/j.ecoleng.2018.06.020>.
- Yang, Q., Zhang, X., Almendinger, J.E., Huang, M., Leng, G., Zhou, Y., Zhao, K., Asrar, G.R., Li, X., Qiu, J., 2019. Improving the SWAT forest module for enhancing water resource projections: a case study in the St. Croix River basin. *Hydrol. Process.* 33, 864–875. <https://doi.org/10.1002/hyp.13370>.