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Research papers

Understanding the effects of afforestation on water quantity and quality at watershed scale by considering the influences of tree species and local moisture recycling

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ABSTRACT

Forest restoration emerges as a sustainable practice to counteract biodiversity loss and enhance ecosystem services such as carbon sequestration and water quality improvement. However, more research is necessary on the hydrological effects of forest restoration under different strategies such as tree species options. In this study, we investigate how afforestation with longleaf pine (*Pinus palustris*) and loblolly pine (*Pinus taeda* L.) may affect the full hydrologic cycles including precipitation (P) and water quality across two large watersheds: the Alabama-Coosa-Tallapoosa (ACT) and Tombigbee-Black Warrior (TBW) river basins in the southeast United States. To capture the impacts of afforestation on precipitation, we leveraged the Soil and Water Assessment Tool (SWAT) model and a local moisture recycling ratio (LMR) dataset to establish a relationship between model-simulated evapotranspiration (ET) and LMR. Longleaf pine and loblolly pine have contrasting forest structure characteristics that affect model parameters and hydrological responses. Results showed that afforestation with longleaf pine increased mean annual ET by 3 % (25 mm/year) and 6 % (48 mm/year) across the ACT and TBW watersheds, respectively. As a result, mean annual streamflow decreased by 3.3 % (18 mm/year) and 1.6 % (11 mm/year) in the ACT and TBW watersheds, respectively. In contrast, afforestation with loblolly pine led to larger increases in mean annual ET of 17 % (131 mm/year) and 10 % (79 mm/year) in affected areas in the ACT and TBW watersheds, respectively. As a result, mean annual streamflow decreased by 5.2 % (29 mm/year) and 2.8 % (19 mm/year) at the watershed level in the ACT and TBW watersheds, respectively. Overall, the afforestation scenarios led to decreases in watershed-scale sediment and nutrient exports, especially under longleaf pine afforestation. Large-scale afforestation had negligible effects on precipitation via local moisture recycling at the watershed scale. Our study indicates that the choices of tree species and forest structure are important to water yield in the southeastern U.S. and that moisture recycling has minor influences on the local water cycle of the study region.

1. Introduction

The Earth's ecosystem is undergoing significant transformations due to changes in climate and human-induced disruptions such as land-use changes. Forest restoration (e.g., afforestation, reforestation) emerges as a sustainable and strategic practice to mitigate the loss of biodiversity and enhance the provision of ecosystem services such as carbon sequestration (Filoso et al., 2017; Jones et al., 2022; Verdone and Seidl, 2017). However, little is known about the effects of forest restoration on hydrological processes such as streamflow dynamics and water quality (Jones et al., 2022).

The effects of forest restoration on hydrological processes depend on factors such as tree species, antecedent land-use/cover, and scale (Ellison et al., 2012; Jones et al., 2022; Staal et al., 2024). Globally, there is an estimated 0.9 billion hectares of land that could be used for tree restoration (Bastin et al., 2019). In the southeast United States (SE-US), efforts are underway to increase the planted area of longleaf pine (*Pinus palustris*) ecosystems from 1.7 to 3.2 million hectares by 2025 (McIntyre et al., 2018). Longleaf pine trees were once the dominant forest species in the SE-US (Frost, 2006). However, extensive timber harvesting, fire suppression, and conversion to commercially valuable species like loblolly pine (*Pinus taeda* L.) led to longleaf pine ecosystems having today

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only 4 % of their original coverage (Noss et al., 2015; Younger et al., 2023). Loblolly pine trees are the dominant forest species in the SE-US and the most planted tree species in the country, covering approximately 13 million hectares of land (Bracho et al., 2018; Gonzalez-Benecke et al., 2011; Jokela et al., 2004). Highly valued for their rapid growth and timber production, loblolly pine is considered the most important commercial tree species in the world (Will et al., 2015) and managed loblolly pine plantations are expected to expand across the SE-US. Afforestation in the SE-US, either because of restoration efforts such as longleaf pine restoration, or driven by economic incentives to increase the planted area of loblolly pine, will likely induce hydrological changes in the region. Additionally, the impacts of afforestation with loblolly pine compared to longleaf pine will probably differ. For instance, longleaf pine forests have a more open canopy with low tree density. This may lead to longleaf pine areas having lower evapotranspiration (ET) rates and more streamflow compared to loblolly pine dominated regions (Brantley et al., 2018; Younger et al., 2023). Thus, afforestation efforts must be carefully considered and investigating the impacts of species-specific afforestation on water quantity and quality may provide key insights into water resources management.

Few studies have examined the hydrological implications of native forest restoration and compared the hydrology of native tree species with managed forest plantations (Jones et al., 2022). Traditionally, afforestation has been shown to decrease streamflow at local scales due to increased water uptake by trees and higher ET (Buechel et al., 2022; Herron et al., 2002; LV et al., 2019; Valente et al., 2021; Webb and Kathuria, 2012; Zhang et al., 2017). In contrast to small-scale watershed studies, large-scale modeling research suggests that afforestation might lead to an increase in river flow in certain areas such as downwind of reforestation areas because of atmospheric moisture recycling (Coe et al., 2009; Cui et al., 2022; Hoek van Dijke et al., 2022; Li et al., 2018; Stickler et al., 2013). Although extensive evidence can be found in the published literature that afforestation may increase rainfall and water yield at the global and regional scales through atmospheric moisture recycling (Coe et al., 2009; Hoek van Dijke et al., 2022; Li et al., 2018; Stickler et al., 2013), there is a notable lack of studies about the potential local (e.g., watershed-scale) implications of moisture recycling (Jones et al., 2022; Keys et al., 2012; te Wierik et al., 2021).

Hydrologic models can be valuable tools to study the potential effects of large-scale afforestation on hydrological responses. Semi-distributed watershed-scale hydrologic models (e.g., SWAT, VIC) can simulate water fluxes (e.g., surface runoff, groundwater, evapotranspiration, percolation), sediment yield, nutrient loadings, and plant growth at the terrestrial-aquatic interface. Watershed models have been applied from the field to the continental scales (Abbaspour et al., 2015; Arnold et al., 1999; Karki et al., 2020; Schuol et al., 2008) and can be particularly useful in predicting the impacts of land-use changes (e.g., afforestation) and management operations (e.g., replanting, irrigation, fertilization) on water quantity and quality at multiple levels. However, current watershed models treat precipitation as an exogenous variable, independent from and unaffected by land-use modifications such as forest restoration during the simulation period (Posada-Marín and Salazar, 2022; Wang-Erlandsson et al., 2018). Globally, over 50 % of the terrestrial evaporated water returns to the land as precipitation (Tuinenburg et al., 2020; Van der Ent and Savenije, 2010). Moreover, 40 % of terrestrial precipitation originates from terrestrial evaporation (Van der Ent, 2014) – 20 % of which originates from vegetation-fed moisture recycling (Keys et al., 2016). Thus, neglecting the effects of moisture recycling might limit the reliability of hydrologic models in investigating the effects of large-scale land-use changes such as forest restoration and afforestation.

Recent studies such as Link et al. (2020), Tuinenburg et al. (2020), and Theeuwen et al. (2023) have developed global databases of moisture recycling ratios using outputs from atmospheric moisture tracking models. Harnessing the power of watershed models and the availability of datasets in Earth system sciences may present a great opportunity to advance watershed modeling and create a more authentic representation of physical processes and real-world scenarios. In the context of forest-water interplays, leveraging readily available moisture recycling data to better inform hydrologic models in capturing land–atmosphere connections may enhance model reliability as a science-based tool to predict the impacts of afforestation on the hydrological cycle and in-stream water quality conditions.

In this study, we combine a watershed-scale hydrologic model and a global moisture recycling ratio database to study how large-scale afforestation with loblolly pine and longleaf pine might affect water quantity, quality, and precipitation at multiple scales. Our analysis is in the context of the Mobile Bay watershed-AL, a large and forested watershed draining to the Mobile Bay estuary in the northern Gulf of Mexico. More specifically, we explore three questions: (*i*) How does afforestation through increased longleaf and loblolly pine coverage affect water quantity and quality across the study domain? (*ii*) What is the importance of considering terrestrial moisture recycling in watershed-scale forest restoration studies? (*iii*) Can local moisture recycling offset the effects of afforestation on water quantity and quality?

By utilizing the Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998) and the local moisture recycling ratio (LMR) dataset (Theeuwen et al., 2023), we establish a quantitative relationship between model-simulated evapotranspiration (ET) and LMR data for current watershed conditions. This relationship is subsequently utilized to assess the potential effects of large-scale afforestation on precipitation, streamflow dynamics, and water quality loadings across the watershed domain. Our study is novel in realistically investigating the watershed responses of streamflow and water quality to restoring longleaf pine (*Pinus palustris*) ecosystems to their native range and in accounting for the potential effects of moisture recycling on rainfall and hydrological predictions. Such a level of detail about the local water cycle and depiction of real-world conditions could never be achieved by solely applying watershed models or simpler water balance models (e.g., Budyko frameworks).

2. Study area

The Mobile Bay watershed (MBW) (Fig. 1) is formed by the confluence of two large rivers: the Alabama and the Tombigbee rivers, which contribute 52 and 48 %, respectively, to the 1,758 m^3/s of discharge of the Mobile River (Johnson et al., 2002). The Mobile River flows approximately 30 miles downstream of its formation, where it splits into several distributaries that contribute approximately 95 % of the freshwater discharged to the Mobile Bay estuary in the northern Gulf of Mexico (GOM) (Johnson et al., 2002; Kemp et al., 2019). The MBW is mainly covered by forests (54 %), with loblolly pine being the dominant species. The average elevation above sea level ranges from sea level to 1,280 m, according to the 30-meter resolution National Elevation Dataset (NED). Annual average precipitation and temperature are 1,450 mm and 17 °C, respectively. The climate in the basin is mainly influenced by land-surface altitude and the distance from the GOM. Rainfall is the main form of precipitation, with evenly distributed amounts over the year, and snowfall is rare, averaging less than 25 mm per year.

The basin exerts great influence on the Mobile Bay estuary, which is the fourth largest estuary in the U.S. in terms of flow volume and has one of the most biodiverse aquatic fauna and flora in the country. The estuary is a nursery habitat for more than 300 species of fishes and birds, 68 species of reptiles, 57 species of mammals, and 40 species of amphibians (Barnes et al., 2008; MBNEP, 1997). During the summer months, when discharge from the upstream rivers is the lowest and water loss through evapotranspiration is the highest, the estuary experiences strong vertical stratification that prevents physical mixing and leads to hypoxic conditions (i.e., low dissolved oxygen concentration) in the bay. This, consequently, underlies a famous natural phenomenon in Mobile Bay: *Jubilee*, which essentially means large-scale fish kills. It is

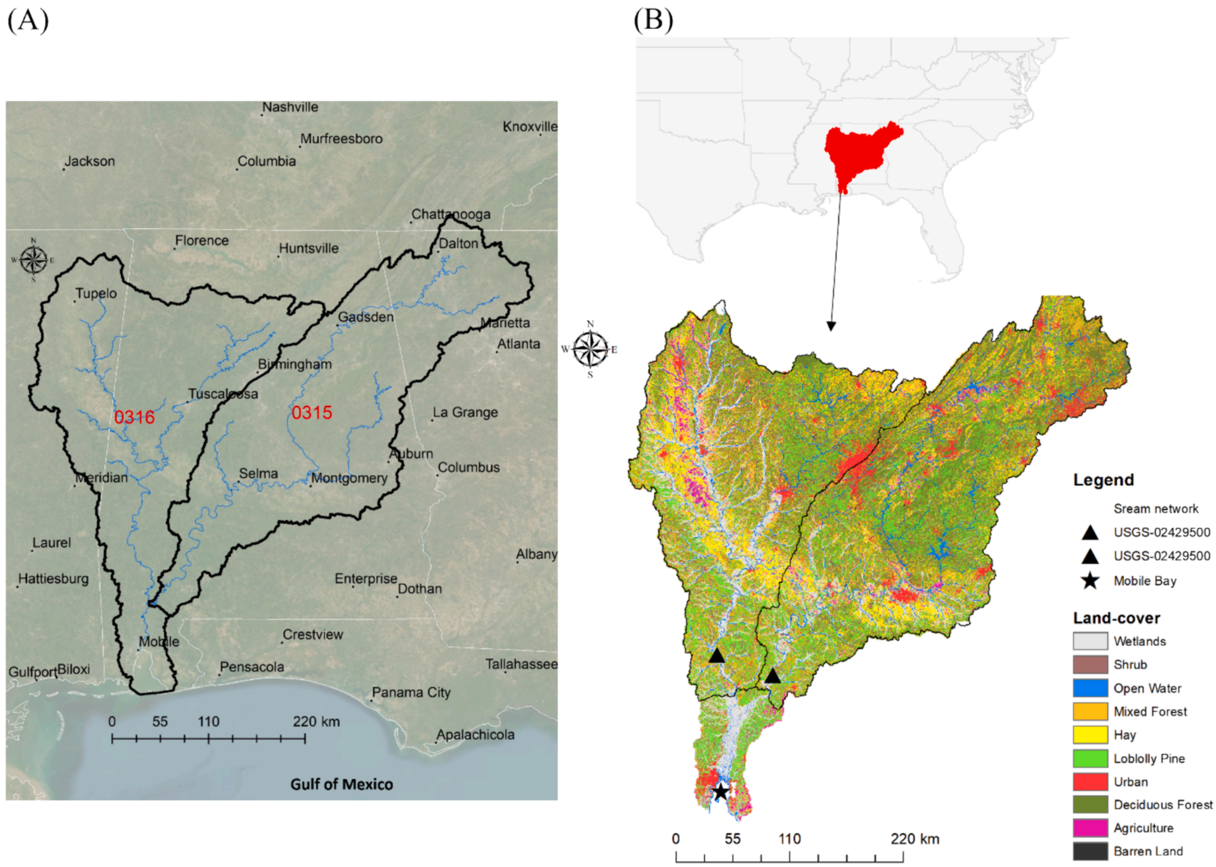

Fig. 1. Two HUC-4 watersheds used to delineate the TBW and ACT river basins (A), watershed domains for the ACT and TBW river basins (B).

believed that the Jubilee is becoming more frequent in the Mobile Bay and that this may be due to declining trends in freshwater discharge from the upstream rivers and water quality deterioration (Atkins et al., 2004; Harned et al., 2004; Johnson et al., 2002; McPherson et al., 2003; Montiel et al., 2019).

3. Data and methods

3.1. The SWAT model

The Soil and Water Assessment Tool (SWAT) (Arnold et al., 1999) hydrological model was used in the current study to calibrate and validate historical water quantity and quality and investigate the effects of forest restoration on basin-wide hydrology and water quality. SWAT is one of the most widely used hydrological models worldwide and a well-established tool capable of simulating various water fluxes (e.g., surface runoff, lateral flow, groundwater contribution) and plant growth. Additional model components include weather, transport of sediment, and nutrients. The model discretizes a watershed into sub-watersheds, which are further discretized into unique combinations of land use, soils, and slope called hydrological response units (HRU's) (Neitsch et al., 2011).

In SWAT, the minimum meteorological data required to drive the hydrologic cycle comprises of time-series of precipitation, and minimum/maximum temperature (Neitsch et al., 2011). These time-series data are provided by the user and are not coupled with land processes. The water balance calculation for each HRU considers five storages: snow, canopy storage, the soil profile with up to ten layers, a shallow aquifer, and a deep aquifer. The water balance is calculated using the following:

$$\Delta S = \sum_{t=1}^{t} (P - Q_{total} - ET - w_{seep}) \tag{1}$$

where, ΔS is the change in water storage, P, Q_{total}, ET, and w_{seep} are the daily amount of precipitation, total water yield, evapotranspiration, and the total amount of water exiting the bottom of the soil profile on a given day, respectively. The value of w_{seep} is a sum of the amount of water percolating out of the lowest soil layer and the amount of water flowing past the lowest boundary of the soil profile due to bypass flow. The total water yield (Q_{total}) represents an aggregated sum of surface runoff, lateral flow, and the base flow contribution to streamflow.

In this research, surface runoff was computed using the Soil Conservation Service (SCS) Curve Number (CN) method based on daily rainfall observations, and the Penman-Monteith (Monteith, 1965) method was selected for estimating potential evapotranspiration (PET). The Muskingum method (Cunge, 1969) was used to route runoff volume from the subbasins to the main channel.

3.2. Model setup and input data

Two individual SWAT projects were built to model water quantity and quality across the MBW. Two HUC-4 (Fig. 2), namely 0316 and 0315, draining to the Mobile Bay were selected as upstream drainage basins and further discretized into subbasins and HRU's in ArcSWAT. Hereafter, HUCs 0316 and 0315 are referred to as the Tombigbee-Black-Warrior (TBW) and the Alabama-Coosa-Tallapoosa (ACT) river basins, respectively. The drainage areas of the TBW and ACT river basins are 51,367 and 57,775 km^2, respectively.

The input datasets used for constructing and calibrating/validating the SWAT models for the historical and current watershed conditions, as well as their sources, are summarized in Table 1. A detailed description

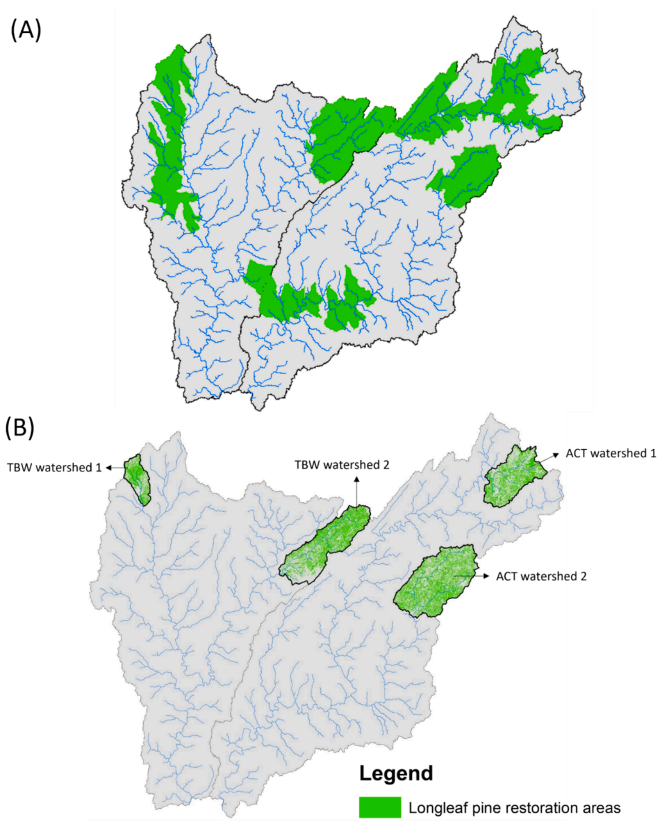

Fig. 2. Areas with high tree-restoration potential according to Bastin et al. (2019) that were selected for LLPR across the entire ACT and TBW river basin domains (A), and selected watershed to assess the local effects of forest restoration (B). The spatial distribution of tree restoration potential according to the data of Bastin et al. (2019) is shown in Fig. S22 in the Supplementary Materials.

of the data can be found in the supplementary material file (section B). Based on the described data, SWAT2012 (revision 664) through the ArcSWAT interface with a 10 %-10 %-0% (land-use, soils, slope) threshold generated 268 subbasins and 3819 HRU's for TBW, whereas 320 subbasins and 4758 HRU's were generated for the ACT. The models were run from 1979 to 2020, using 3 years (1979–1981) of initialization as model warm-up period.

3.3. Model calibration and performance evaluation

Automated calibration of streamflow and water quality for the models described in section 3.2 was carried out at the watershed's outlet. To accomplish this, the SWAT-CUP (Abbaspour, 2015) software through the Sequential Uncertainty Fitting (SUFI-2) algorithm (Abbaspour et al., 2004) was employed. Streamflow calibration was performed from 1982 to 2010 against daily observations for the USGS stations 02,428,400 and 02469761, which are the most downstream monitoring stations in the ACT and TBW basins, respectively. The period 2011–2020 was used for model validation. Water quality was calibrated and validated for the 1982–2015 and 2016–2020 periods, respectively, for the following variables: total suspended solids (TSS), nitrate (NO_3^-), phosphate (PO_4^+), and total organic carbon (TOC). Observed water quality concentration data was downloaded using the *Data Retrieval* package (De Cicco et al., 2018) in the statistical software RStudio for the period 1982–2020. The Weighted Regressions on Time, Discharge, and Season (WRTDS) (Hirsch et al., 2010) method through the R-package EGRET (Exploration and Graphics for RivEr Trends) (Hirsch and De Cicco, 2015) was used to generate continuous monthly time-series of water quality variables from infrequent (e.g., bimonthly) observations. Water quality observations were derived from the USGS-02429500 and USGS-02469762 stations in the ACT and TBW river basins, respectively. Actual evapotranspiration (ET) was manually calibrated using remote-sensing estimates from MODIS (Moderate Resolution Imaging Spectroradiometer) MOD16A2 (Mu et al., 2013) algorithm as the benchmark. Watershed averaged MODIS ET data at the 500-m spatial and 8-day temporal resolution was retrieved through the Google Earth Engine (GEE) (Gorelick et al., 2017) platform and aggregated to monthly basis. Model simulations of monthly ET were compared against remote-sensing estimates during the period 2002–2020 and sensitive parameters (Haas et al., 2022) were adjusted until a reasonable agreement was found.

The model performance during the calibration and validation periods was assessed using the following statistical rating metrics: coefficient of determination (R^2), Nash-Sutcliffe model efficiency coefficient (NSE), and model percent bias (PBIAS). For a detailed description of these evaluation criteria, the reader is referred to Moriasi et al. (2007), Moriasi et al. (2015), and Althoff and Rodrigues (2021). Model calibration results for the ACT and TBW river basins can be found in the Supplementary Materials file (Appendix C).

Table 1
Description of data and their sources. Model input data refers to datasets utilized to construct the watershed models and calibrate streamflow and water quality.

	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	2016 NLCD	United States Department of Agriculture (USDA) Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/)
	Forest types	National Forest Type Dataset at 250 m resolution	USDA Forest Service (https://data.fs.usda.gov/geodata/rastergateway/forest_type/)
	Soil	State Soil Geographic (STATSGO)	United States Department of Agriculture (USDA) Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/)
	Climate	Daily precipitation, maximum/minimum temperature, solar radiation, and wind speed from 1979 to 2020.	GridMet (https://www.climatologylab.org/gridmet.html)
	Atmospheric deposition	Average annual wet and dry deposition of nitrate and ammonia from 1982 to 2020.	National Atmospheric Deposition Program (NADP) (https://nadp.slh.wisc.edu/)
	Point sources	Monthly discharge and loading from wastewater treatment plants from 2007 to 2020.	EPA's ECHO Portal (https://echo.epa.gov/trends/loading-tool/get-data/monitoring-data-download)
Model calibration/ validation	Water quality	Instantaneous concentrations of TSS, NO3–, PO4+, and TOC, and WT for 1982–2020 period.	Water Quality Portal (https://www.waterqualitydata.us/)
	Streamflow	Daily discharge from USGS gage stations 02,428,400 and 02,469,761 for the 1982–2020 period.	USGS Water data (https://waterdata.usgs.gov/nwis)
	Actual evapotranspiration	500-m and 8-d resolution ET data from MODIS MOD16A2	USGS Earth Data (https://lpdaac.usgs.gov/products/mod16a2v061/)

3.4. Longleaf pine and loblolly pine parameterization

Longleaf pine restoration (LLPR) is an important land management objective in the SE-US and can have significant implications for hydrology and water availability, particularly when compared to species like loblolly pine (Appendix A.2. – Supplementary Material file). To assess the effects of LLPR on basin-level water quantity/quality using watershed models, reliable modeling tools, scenarios, and representation of physical processes are necessary. Here we build upon the effort of Haas et al. (2022) and propose a longleaf pine (*Pinus palustris*) parameterization for the SWAT model based on remote-sensing data, field observations, and published literature to accurately represent the ecophysiology of longleaf pine trees. To accomplish this, we inventoried used-defined parameters in SWAT that were related to forest processes such as leaf area index (LAI) development, canopy interception, transpiration, soil evaporation, actual evapotranspiration, and aboveground biomass accumulation. Next, we searched the literature to find studies carried out on longleaf pine plantations across the SE-US from which we could derive species-specific remote-sensing ET and LAI information. Notably, we selected relevant studies from Samuelson et al. (2019) and Samuelson et al. (2014) in Georgia, and the AmeriFlux site US-DPP (Disney Wilderness Preserve Pine Flatwoods) located in Florida (https://ameriflux.lbl.gov/sites/siteinfo/US-DPP). Aerial imagery was employed to verify that these sites predominantly featured forests as the primary landscape cover during the 2002–2020 period so that remote-sensing estimates of LAI and ET could be retrieved. We used MODIS algorithms MCD15A3H and MOD16A2 to derive LAI and ET data, respectively, for the selected longleaf pine sites. A field-scale SWAT model was built for the site described in Samuelson et al. (2019) and calibrated against remote-sensing LAI and ET estimates in order to find reasonable values for parameters governing LAI development and ET rates.

The parameters inventoried to develop the longleaf pine parameterization, along with their calibrated values, are provided in Table 2. Time-series of simulated versus remote-sensing LAI and ET, as well as performance rating metrics, are shown in the Supplementary Material file (Appendix C, Table S5, and Table S19). For a detailed step-by-step account of the parameterization process, we direct readers to Haas et al. (2022).

The parameter values shown in Haas et al. (2022) were used to describe the growth and dynamics of loblolly pine trees in the current study. Maximum and minimum LAI values were changed to 3.7 and 1.2 m^2/m^2, respectively, based on MODIS estimates for the study watersheds.

Table 2
Calibrated values of parameters representing longleaf pine processes of LAI development, ET, and aboveground biomass accumulation.

Parameter (units)	Meaning	Data source	Reference	Calibrated value
BIO_E.dat ((kg/ha/ MJ/m^2))	Radiation use efficiency	Literature	Gonzalez-Benecke et al. (2014)	8
MAT_YRS.dat (years)	Number of years to reach maturity		Sampson et al. (2006)	100
RDMX.dat (m)	Rooting depth	ET calibration	Mendonca et al. (2023)	3.7
T_OPT.dat (Celsius)	Optimum temperature		Bryars et al. (2013)	25
T_BASE.dat (Celsius)	Base temperature		Bryars et al. (2013)	4
GSI.dat (m/s)	Stomatal conductance		Samuelson et al. (2019), Gonzalez-Benecke et al. (2016)	0.0075
CHTMX.dat (m)	Canopy height			24
EPCO.hru	Soil evaporation compensation factor			0.75
ESCO.hru	Plant water uptake compensation factor			0.98
CANMX.hru	Maximum canopy storage			0.39
HEAT_UNITS.mgt	Heat units	LAI calibration		5000
DLAI.dat	LAI senescence factor			0.91
FRGRW2.dat	LAI shape coefficient			0.36
FRGRW1.dat	LAI shape coefficient			0.15
LAIMX1.dat	LAI shape coefficient			0.34
LAIMX2.dat	LAI shape coefficient			0.71
LAIMX.dat	Maximum LAI			2.25
ALAIMIN.dat	Minimum LAI			0.7

3.5. Realistic afforestation scenarios

The forest parameterization described in section 3.4 was utilized to develop two afforestation scenarios:

1. Increased loblolly pine coverage (LOBR): this scenario represents an economically feasible situation where wood production is prioritized.
2. Increased longleaf pine coverage (LLPR): this scenario represents a conservation effort where the restoration of native ecosystems is prioritized.

We utilized the global tree-restoration potential map developed by Bastin et al. (2019) to guide the development of realistic forest restoration and conversion scenarios. Instead of arbitrarily converting a fixed percentage of the watershed area to longleaf pine at random locations, we overlaid the boundaries of the ACT and TBW river basins with the tree restoration potential dataset, identifying areas with high tree restoration potential (see Fig. S22 in the Supplementary Material file). To accomplish this, we used the Forest Restoration Potential web interface (https://crowtherlab.com/maps/#/ (accessed on 09/09/2023)) from the study of Bastin et al. (2019). According to this data-driven approach, 30 % of the ACT and TBW river basins can potentially be converted into forests. Although we have no reason to doubt the study of Bastin et al. (2019), we believe that this estimate might be too high since the study watersheds are already highly forested. Thus, we interpret this 30 % potential as an upper limit. It is important to note that the data of Bastin et al. (2019) consists of a global dataset, which has inherent uncertainties and might be biased for local analyses. To mitigate this, we have also used guidelines from a regional business plan for longleaf pine conservation to critically assess the outputs of the dataset of Bastin et al. (2019). According to this regional report (https://www.nfwf.org/sites/default/files/longleaf/Documents/longleaf-forests-rivers-business-plan.pdf (accessed on 09/09/2023; Fig. 1)), a large portion of the MBW is considered a focal area for longleaf pine restoration across the southeast United States. Our efforts primarily focused on clustered areas with the highest tree restoration potential. Next, we used NLCD16 to identify the main land cover classes that could be restored into forests according to the data of Bastin et al. (2019). Notably, we found range (RNGB), hay (HAY), and deciduous forests (FRSD) as the predominant land cover classes in the ACT river basin. Similarly, the same classes plus agricultural lands (AGRL) were found for the TBW river basin. This rationale resulted in 15 and 17 % of the entire ACT and TBW river basins, respectively, being converted to longleaf pine (Fig. 2A).

We also assessed the effects of forest restoration at local scales (<5,000 km^2). To accomplish this, we selected watersheds witnessing more than 30 % afforestation (according to the data-driven approach outlined above) across the ACT and TBW river basins (Fig. 2B). These afforestation rates are expected to have significant impacts on hydrological responses. The drainage areas of these watersheds are in the range of 800–3,800 km^2 and the percentage of forest restoration ranges from 33 to 75 %.

The steps below describe how the LLPR was implemented in the model:

We utilized the subbasin vector file generated by ArcSWAT's watershed delineation process to identify the subbasin IDs overlapping with the clustered tree-restoration areas from Bastin et al. (2019).
The HRU files (*.hru*) of the marked subbasins (step 1), which included RNGB, HAY, FRSD, and AGRL as land-cover classes, were modified according to the longleaf pine parameterization outlined in Table 2 for the*.hru* parameters.
The plant database file (*.dat*) was updated to include a new land-use class named 'PITA,' representing longleaf pine ecosystems, with parameter values as described in Table 2 for the*.dat* parameters.
The previously calibrated model was rerun with the longleaf pine parameterization.

Additionally, we designed a forest conversion scenario involving the conversion of existing loblolly pine forests to longleaf pine stands. This scenario aimed to test the hypothesis that longleaf pine ecosystems exhibit lower evapotranspiration (ET) and higher water yield compared to loblolly pine (Amatya et al., 2022; Qi et al., 2021; Trettin et al., 2018; Younger et al., 2023). Results of the conversion scenario are presented in section G of the Supplementary Material file. Our focus for the remainder of this study is on the restoration scenario since this scenario represents an increase in ET and a potential increase in precipitation via local moisture recycling. Testing the hypothesis that decreased ET leads to decreased precipitation is beyond the scope of the current study and must be addressed in a future endeavor.

3.6. Coupling hydrologic modeling and local moisture recycling

We used global local moisture recycling ratios (LMR) obtained from Theeuwen et al. (2023) to consider the effects of terrestrial moisture recycling resulting from the afforestation scenarios described in section 3.5. Research indicates that large-scale afforestation can increase rainfall both locally and regionally through moisture recycling mechanisms, indicating a close relationship between evaporation and moisture recycling that affects water availability (Costa and Foley, 1997; Cui et al., 2022; Hoek van Dijke et al., 2022; Keys et al., 2016; Li et al., 2007; Stickler et al., 2013; Wang-Erlandsson et al., 2018; Yosef et al., 2018). To include LMR in the modeling framework, we developed a relationship between SWAT-simulated ET and the LMR estimates from Theeuwen et al. (2023) for the ACT and TBW river basins (Figs. S23 and S26 of the Supplementary Materials) using the baseline models representing historical and current watershed conditions. Our rationale is rooted in the recycling of moisture through ET mechanism (Savenije, 1995; Spracklen et al., 2012) and assumes a strong and positive relationship between ET and LMR, supported by both global data (Theeuwen et al., 2023) and our analysis (Figs. S23–S28 in the Supplementary Materials). Our approach draws from methodologies employed in previous studies, such as those by Wang-Erlandsson et al. (2018) and Hoek van Dijke et al. (2022), which utilized simulated ET and moisture recycling data to predict rainfall changes under afforestation conditions. We adopt a similar assumption to that of Hoek van Dijke et al. (2022), suggesting that afforestation would intensify the current ET-moisture recycling dynamics presented in the LMR dataset of Tuinenburg et al. (2020). Under our approach, LMR is explained by a single independent variable (i.e., ET), which allows us to estimate LMR after forest restoration. The methodology includes the following steps:

Establish a relationship between simulated ET (ET_{curr}) and LMR data (LMR_{curr});
Run the SWAT model under the LLPR and LOBR scenarios;
Recalculate LMR (LMR_{new}) from the ET simulated in (2) (ET_{new}) using the relationship developed in (1);
Determine the amount of ET returning to the land as precipitation (P_{LMR}=LMR_{new} x (ET_{new} – ET_{curr}));
Update present-day precipitation (P_{curr}) with the values determined in (4);
Rerun (2) with $P_{curr} + P_{LMR}$.

To carry out steps (4) and (5), we calculated the average seasonal ET for each watershed in order to capture the higher ET rates in the summer and encompass seasonality in our analysis. Additionally, P_{LMR} was only added to P_{curr} on rainy days (i.e., when $P_{curr} > 0$ mm).

3.7. Experimental design and changes in hydrology and water quality

Modeling experiments were conducted to assess the effects of LLPR and LOBR on streamflow dynamics, soil erosion, and nutrient exports at multiple scales with and without local moisture recycling. The modeling experiments were as follows:

1. **Baseline model (M_0)**: SWAT2012 Rev. 664 was set up and calibrated according to current precipitation and land-cover conditions;
2. **Afforestation (M_{LLPR} and M_{LOBR})**: the model was run with LLPR and LOBR land-cover conditions without moisture recycling (P_{curr});
3. **Afforestation with local moisture recycling ($M_{LLPR+LMR}$ and $M_{LOBR+LMR}$)**: the model was run with LLPR and LOBR land-cover conditions and with local moisture recycling effects ($P_{curr} + P_{LMR}$);

Changes in streamflow and water quality loadings stemming from restoration without and with LMR were calculated according to equations (4) and (5), respectively:

$$\%\Delta withoutLMR = \frac{M_{aff} - M_0}{M_0} \tag{4}$$

$$\%\Delta withLMR = \frac{M_{aff+LMR} - M_0}{M_0} \tag{5}$$

where M_{aff} is the model run with present-day precipitation and either M_{LLPR} or M_{LOBR} land-cover conditions, M_0 is the model calibrated with present-day precipitation and land-cover conditions, and $M_{aff+LMR}$ is the model run with moisture recycling and either M_{LLPR} or M_{LOBR}.

4. Results

4.1. Annual water balance

Table 3 summarizes how the afforestation of 15 and 17 % of the ACT and TBW watershed areas, respectively, impacted mean annual ET and rainfall. Under the M_{LLPR} scenario, watershed averaged mean annual ET increased by 3.3 % (or 25 mm) and 6.3 % (or 48 mm) in the ACT and TBW river basins, respectively, in the period 1982–2020. During the same period, M_{LOBR} led to increases in mean annual ET of 17 % (131 mm) and 10 % (79 mm).

Considering only the afforested areas (Fig. 2), 2.9 % (20 mm) and 16.2 % (116 mm) increases in average annual ET with M_{LLPR} were found in the ACT and TBW basins, respectively; while M_{LOBR} led to much larger increases of 35.4 % (242 mm) and 38.1 % (272 mm).

The inclusion of local moisture recycling in the model led to very small changes in rainfall. $M_{LLPR+LMR}$ increased mean annual rainfall by

Table 3
Changes in mean annual precipitation (P), evapotranspiration (ET), surface runoff (SQ), lateral flow (LQ), and baseflow (GW) for the period 1982–2020 stemming from afforestation without moisture recycling and with moisture recycling. The "LUC" notation refers to the areas witnessing afforestation (shown in Fig. 2).

	Water balance component	M_0 (mm)	LLPR (mm)	LLPR+LMR (mm)	LOBR (mm)	LOBR+LMR (mm)
ACT	P – Basin averaged	1404.2	1404.2	1404.6	1404.2	1406.7
	ET – Basin averaged	755	780	780	887	888
	ET – Afforested areas	684	704	704	926	927
TBW	P – Basin averaged	1476.6	1476.6	1477.4	1476.6	1478.1
	ET – Basin averaged	761	809	809	839	839.8
	ET – Afforested areas	714	830	830	986	986.8

0.4 and 0.8 mm in the ACT and TBW basins, respectively, while $M_{LOBR+LMR}$ resulted in slightly higher increases of 2.5 and 1.5 mm/year. The basin averaged LMRs for the M_{LLPR} scenario were 1.76 % and 1.56 % in the ACT and TBW basins, respectively, with slightly higher ratios in the Spring and Summer months. For the M_{LOBR} model, LMRs were slightly higher, with 1.8 % of the increased ET returning to the land as rainfall via moisture recycling.

4.2. Effects of longleaf pine and loblolly pine afforestation on streamflow

4.2.1. Basin-wide effects

Fig. 3 summarizes the effects of longleaf pine afforestation on streamflow dynamics with and without local moisture recycling across the entire ACT and TBW basins in the period 1982–2020. In the absence of moisture recycling, longleaf pine restoration caused a 3.3 % (or 18 mm) and 1.6 % (or 11 mm) reduction in average annual streamflow across the ACT and TBW river basins, respectively. In the ACT basin, spring flows were particularly affected, experiencing a reduction of 4.3 %, while summer and autumn flows were reduced by 2.9 and 2.3 %, respectively. In the TBW basin, spring and summer flows were impacted the most, witnessing reductions of 2.2 and 3.2 %, respectively, while autumn flows were reduced by only 1 %. Minimum and maximum flows of daily (1-day) and seasonal (90-day) durations were also reduced in both watersheds. In the ACT river basin, minimum flows decreased within the range of 2.2–3.8 %, while maximum flows witnessed reductions in the range 2.6–3.5 %. In the TBW basin, minimum flows had reductions ranging from 1.9 to 4.7 %. Maximum flows of seasonal duration had very small reductions (1.1 %), while maximum flows of daily duration increased by 0.1 % compared to the reference scenario.

Fig. 4 illustrates the effects of loblolly pine afforestation on streamflow dynamics in the ACT and TBW basins. In the absence of LMR, loblolly pine afforestation caused a 5.2 % (29 mm) and 2.8 % (19 mm) reduction in average annual streamflow in the ACT and TBW river basins, respectively. Spring flows in the ACT basin saw the most significant reductions (7 %), while in the TBW basin, summer flows were most affected, with reductions of 4.8 %. Minimum (maximum) flows of daily and seasonal durations were also reduced in both basins, ranging from 5.7 % to 9.3 % (1.6 % to 4.5 %) in the ACT basin and 3.2 % to 7.1 % (0.7 % to 2.2 %) in the TBW basin.

Local moisture recycling had minimal effects on streamflow responses at both watersheds. Loblolly pine afforestation in the ACT watershed (Fig. 4A) yielded the largest LMRs, which resonated in a 0.2 % increase in mean annual streamflow. Summer flows and minimum flows of 1-day duration had marginally higher increases of 0.4 % when local moisture recycling was considered.

4.2.2. Local effects

The effects of afforestation on streamflow were bigger at the local scale. Fig. 5 summarizes the effects of afforestation with longleaf and loblolly pine on mean annual streamflow with and without local moisture recycling across the selected watersheds (Fig. 2B).

In the absence of moisture recycling, longleaf pine restoration caused a 6 % (or 47 mm) and 15 % (or 76 mm) reduction in average annual streamflow across the watersheds ACT 1 and ACT 2, respectively, during the period 1982–2020. The watersheds TBW 1 and TBW 2 witnessed 11 % (or 68 mm) and 12 % (or 83 mm) reductions in mean annual streamflow under the longleaf pine restoration scenario.

Loblolly pine restoration led to a 9.4 % (or 79 mm) and 23.8 % (or 123 mm) decrease in average annual streamflow in watersheds ACT 1 and ACT 2, respectively, from 1982 to 2020. Similarly, watersheds TBW 1 and TBW 2 experienced reductions of 18 % (or 111 mm) and 15.8 % (or 113 mm) in mean annual streamflow due to afforestation with

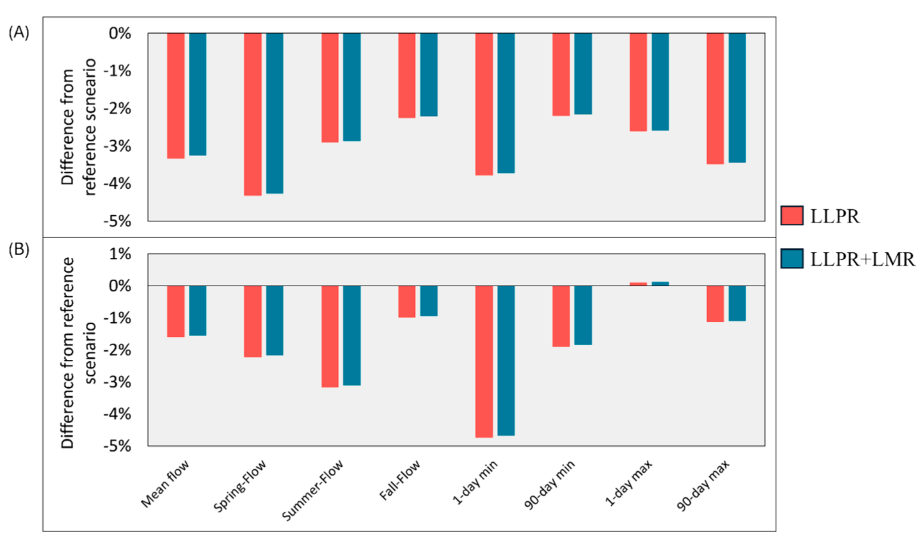

Fig. 3. Changes in mean annual streamflow, seasonal flows, minimum, and maximum flows for the period 1982–2020 stemming from longleaf pine afforestation with and without moisture. The top row (A) refers to the Alabama-Coosa-Tallapoosa river watershed river basin, while the bottom row (B) refers to the Tombigbee-Black-Warrior river watershed.

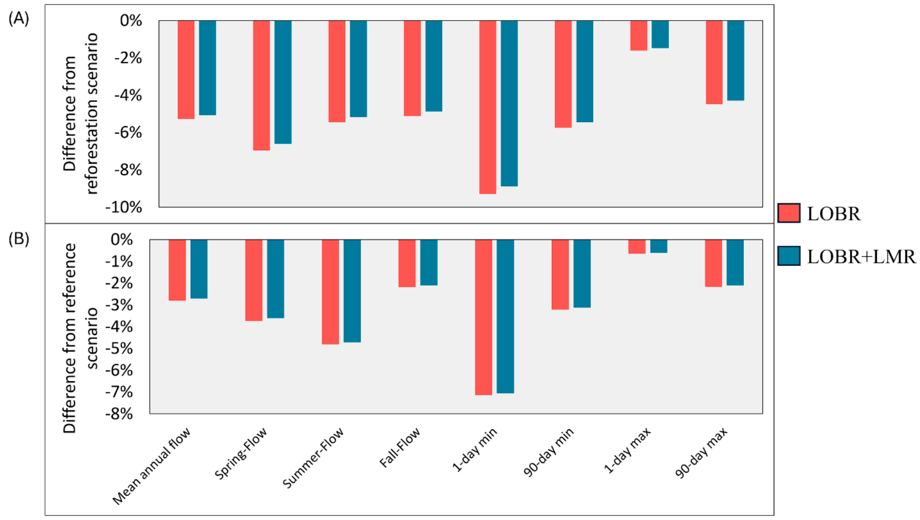

Fig. 4. Changes in mean annual streamflow, seasonal flows, minimum, and maximum flows for the period 1982–2020 stemming from loblolly pine afforestation with and without moisture recycling. The top row (A) refers to the Alabama-Coosa-Tallapoosa river watershed river basin, while the bottom row (B) refers to the Tombigbee-Black-Warrior river watershed.

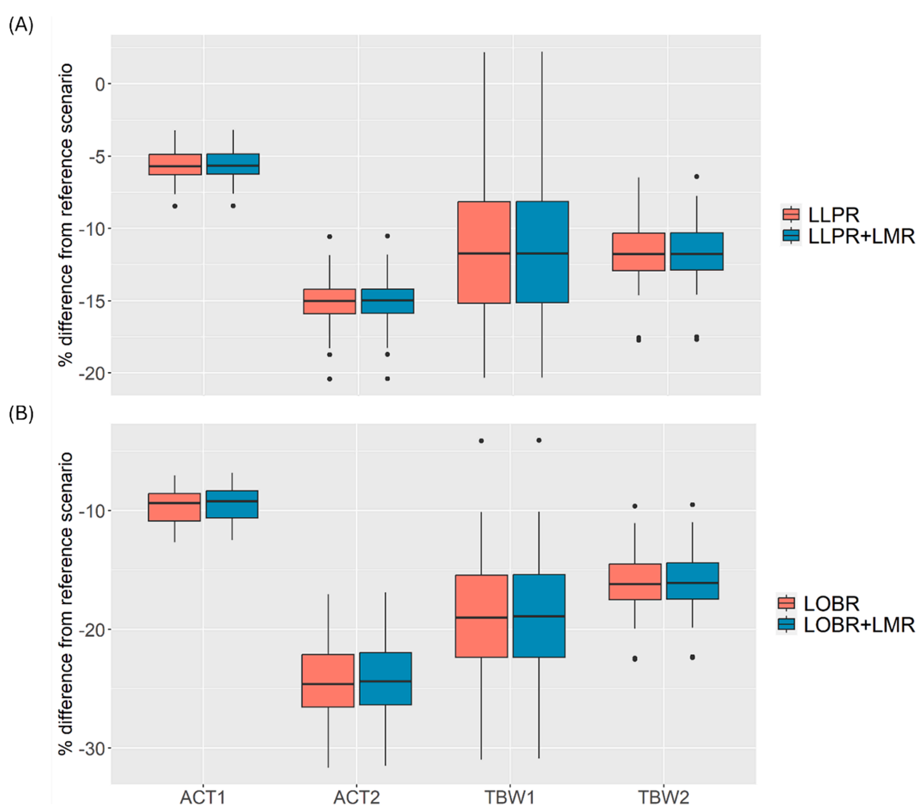

Fig. 5. Percent changes in simulated annual average streamflow for the period 1982–2020 under (A) longleaf pine afforestation and (B) loblolly pine afforestation with and without local moisture recycling across the selected local watersheds.

loblolly pine.

Local moisture recycling had negligible impacts on streamflow responses at the selected local watersheds, generating increases in streamflow ranging from 0.1 to 1.42 mm/year, compared to the afforestation scenarios not considering moisture recycling.

4.3. Effects of longleaf pine and loblolly pine afforestation on water quality

4.3.1. Basin-wide effects

Fig. 6 illustrates the effects of afforestation on annual water quality loadings for the period 1980–2020. Without moisture recycling, longleaf pine afforestation led to mean reductions in sediment, organic nitrogen, nitrate, and phosphate loadings of 5.3 %, 16.1 %, 6.3 %, and 14.7 %, respectively, in the ACT basin. In the TBW basin, sediment loading was

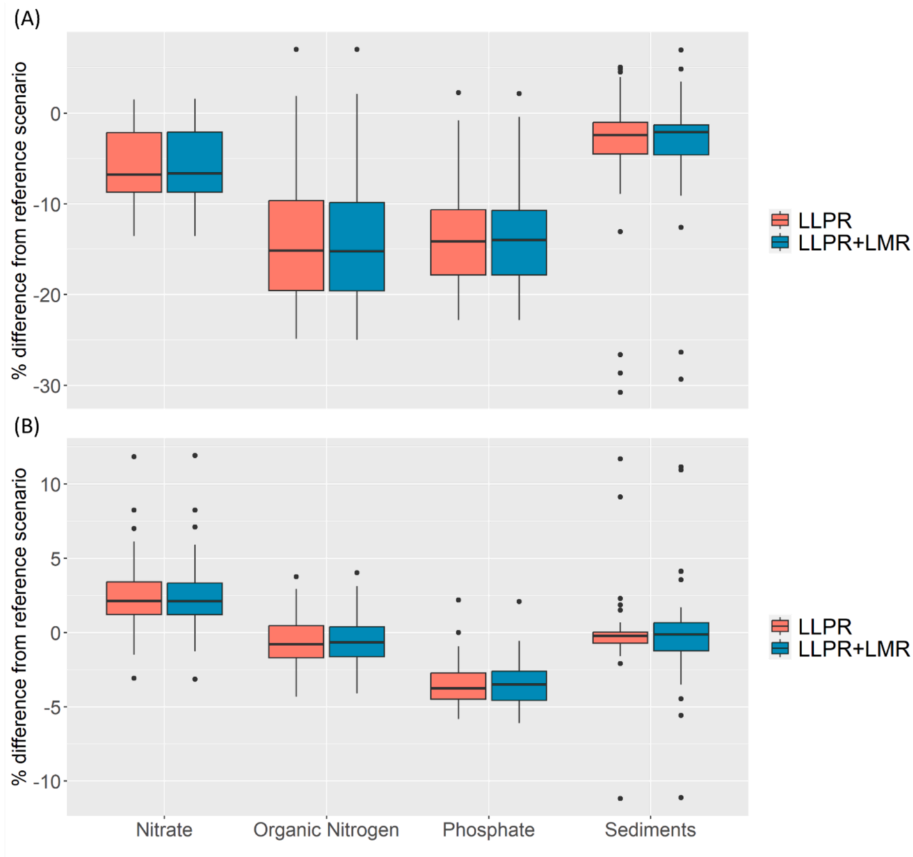

Fig. 6. Percent changes in simulated water quality loadings for the period 1982–2020 under longleaf pine afforestation in the (A) Alabama-Coosa-Tallapoosa river watershed, and (B) Tombigbee-Black-Warrior river watershed with and without local moisture recycling.

unaffected by longleaf pine restoration, whilst organic nitrogen and phosphate loadings were reduced by 0.35 % and 3.4 %, respectively, and nitrate loading was increased by 2.6 %.

Loblolly pine afforestation (Fig. 7) resulted in mean reductions in sediment, organic nitrogen, and nitrate loadings of 5.1 %, 0.1 %, 8.6 %, and 14.7 %, respectively, in the ACT basin. Phosphate loading had a 0.1 % increase compared to the reference scenario. In the TBW basin, sediment, organic nitrogen, nitrate, and phosphate loadings decreased by 3 %, 1.3 %, 2.2 %, and 3.2 %, respectively, as a result of loblolly pine afforestation.

Similar to the streamflow responses, the inclusion of local moisture recycling had very small effects on water quality loadings. The largest implications were found for the loblolly pine afforestation scenario in the ACT watershed, where local moisture recycling led to increases in water quality loadings in the range 0.06–0.32 % compared to the afforestation scenario without moisture recycling.

4.3.2. *Local effects*

At the local level, the effects of afforestation on simulated water quality loadings were substantially bigger than those of watershed averaged. Without the moisture recycling effects, watersheds ACT 1 (ACT 2) witnessed reductions in sediment, organic nitrogen, nitrate, and phosphate loadings of 5 % (39 %), 41 % (55 %), 16 % (17 %), and 32 % (51 %), respectively, as a result of afforestation with longleaf pine (Fig. 8). At the TBW 1 watershed, sediment and phosphate loadings were reduced by 4 % and 7 %, respectively. Organic nitrogen was not affected by longleaf pine afforestation and nitrate was increased by 11 %. At the TBW 2 watershed, sediment, organic nitrogen, and nitrate loadings had increases of 13 %, 4 %, and 7 %, respectively. Conversely, phosphate loadings showed 6 % reductions.

Fig. 9 illustrates the effects of afforestation with loblolly pine on water quality. In the watersheds ACT 1 and ACT 2, water quality responses to afforestation with loblolly pine and longleaf pine were similar, although loblolly pine yielded smaller reductions of mean annual loadings than longleaf pine compared to the reference scenario. In watersheds TBW 1 and TBW 2, more contrasting effects were found. Phosphate and nitrate loadings had reductions of 6 and 24 %, respectively, in the TBW 1 watershed, while organic nitrogen and sediments loadings increased by 1.2 and 6.3 %, respectively. In the TBW 2 watershed, phosphate, nitrate, and organic nitrogen loadings were reduced by 10, 4.2, and 5 %, respectively, while sediments loadings increased by 3.6 %.

Local moisture recycling slightly impacted water quality simulations. The largest effects were found in the ACT 2 watershed, where the inclusion of local moisture recycling in the model led to increases in water quality loadings in the range 0.17–0.55 %, compared to the afforestation scenario not considering moisture recirculation. In some cases, such as for nitrate in the ACT 1 and TBW 1 watersheds, the inclusion of local moisture recycling maximized the reductions in nitrate loadings by 0.34 and 0.12 %, respectively.

5. Discussion

5.1. *Effects of afforestation on water quantity and quality*

In the current study, we converted 15 and 17 % of non-forested lands of the Alabama-Coosa-Tallapoosa (ACT) and Tombigbee-Black-Warrior (TBW) river basins, respectively, to longleaf pine and loblolly pine forests. The afforestation scenario resulted in increased ET and decreased streamflow. This is not surprising since tall vegetation like trees are

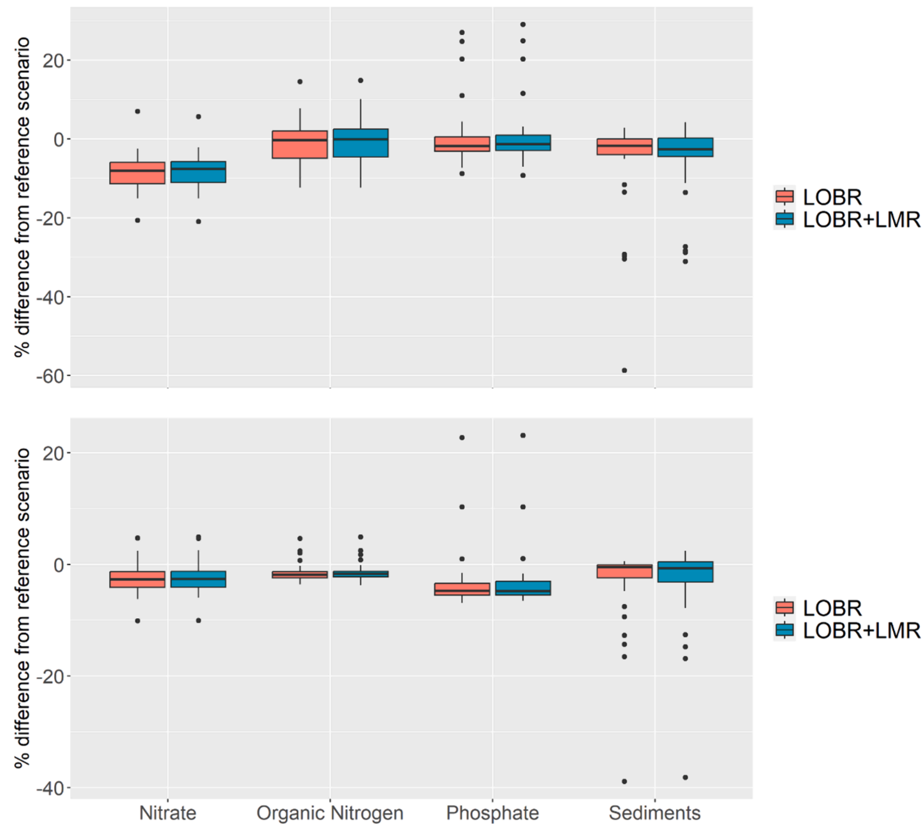

Fig. 7. Percent changes in simulated water quality loadings for the period 1982–2020 under longleaf pine afforestation in the (A) Alabama-Coosa-Tallapoosa river watershed, and (B) Tombigbee-Black-Warrior river watershed with and without local moisture recycling.

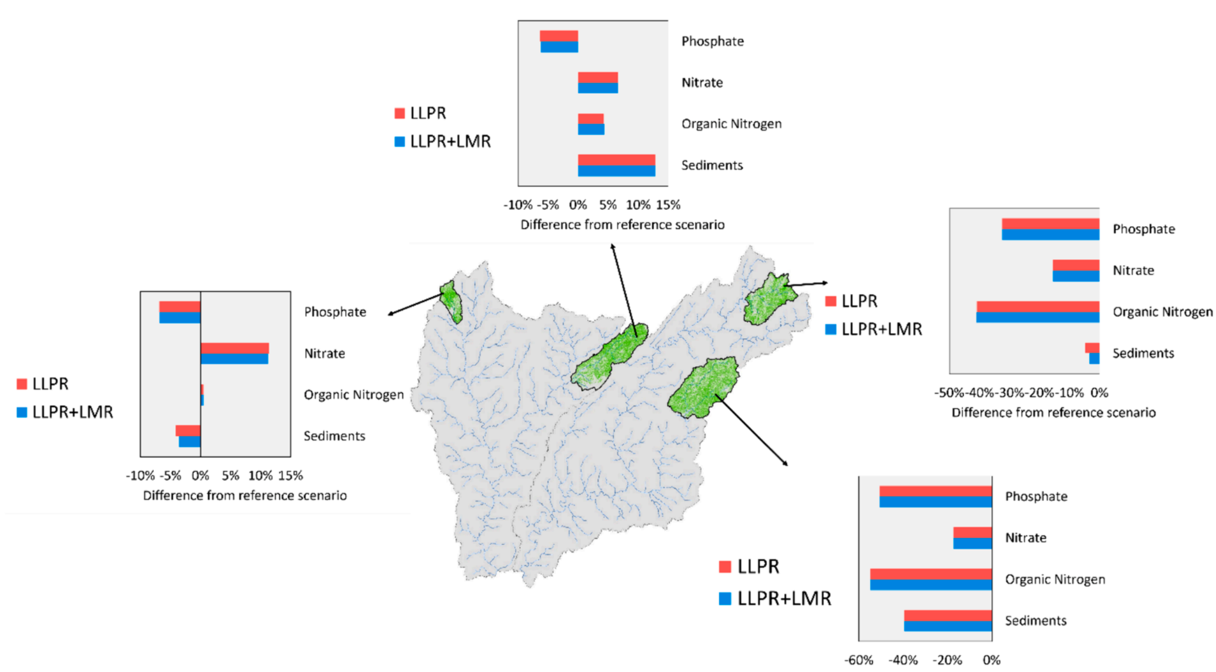

Fig. 8. Percent changes in simulated water quality loadings for the period 1982–2020 under longleaf pine afforestation across the selected local watersheds.

usually associated with higher ET rates compared to shorter vegetation. This is due to factors such as aerodynamic conductance, which is substantially higher in trees (Muzylo et al., 2009). Under the longleaf pine restoration scenario, watershed averaged ET increased by 25 and 48 mm/year in the ACT and TBW basins, respectively. Consequently, basin-wide streamflow decreased by 3.5 % (18 mm/year) in the ACT basin, while a 1.5 % (11 mm/year) decrease was found in the TBW basin. Increases in ET were substantially higher under the loblolly pine afforestation scenario, increasing by 131 and 78 mm/year in the ACT and TBW river basins, respectively, compared to the reference scenario. As a

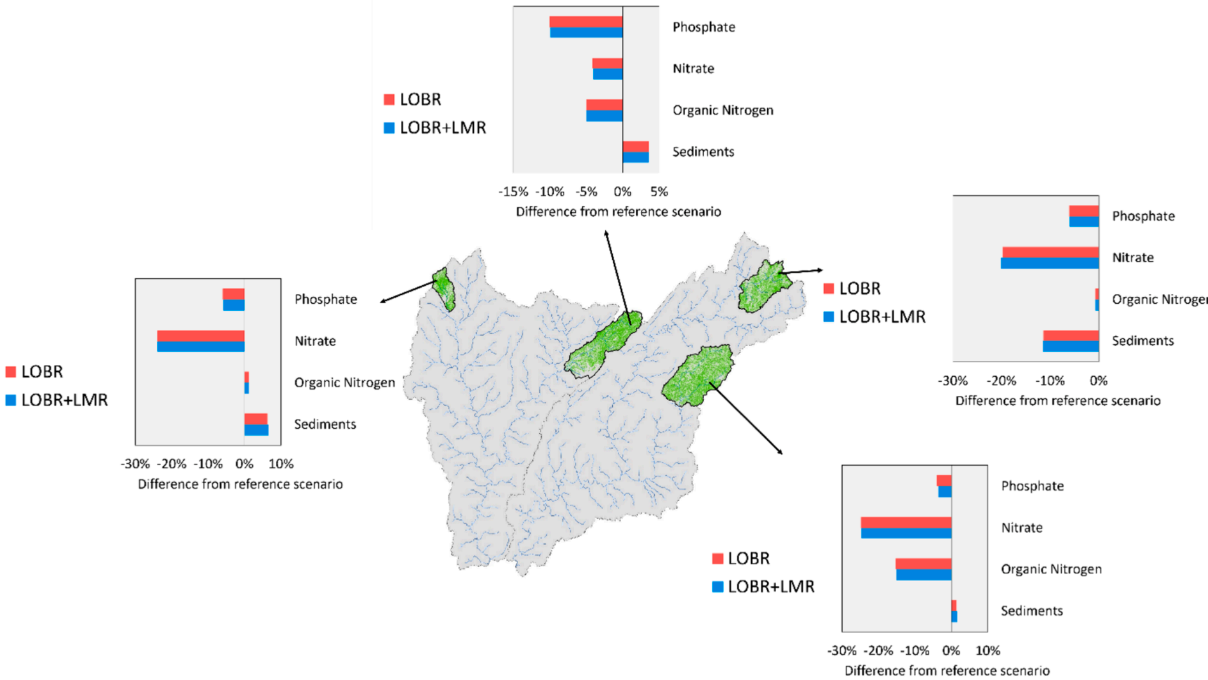

Fig. 9. Percent changes in simulated water quality loadings for the period 1982–2020 under loblolly pine afforestation across the selected local watersheds.

result, mean annual streamflow decreased by 5.3 % (29 mm/year) and 2.8 % (19 mm/year). Different hydrological responses to afforestation might be attributed to varying physical watershed characteristics such as climate, topography, and soils. The predominant hydrologic soil groups (HSGs) in the ACT basin are *B* and *C*, whilst in the TBW basin HSGs *C* and *D* are prevalent. Moreover, mean annual precipitation amounts to 1,404 and 1,477 mm in the ACT and TBW basins, respectively. HSGs *C* and *D* are associated with higher potential runoff rates, which combined with higher mean annual precipitation in the TBW may help to explain the higher streamflow simulated in this watershed. Studies such as Zhang et al. (2004) and Zhou et al. (2015) have demonstrated that water-limited watersheds (PET/P>1) are more sensitive to afforestation than energy-limited watersheds (PET/P<1). Considering that the PET is 1,360 and 1,332 mm in the ACT and TBW basins, respectively, both watersheds are energy-limited, which may help to explain the somewhat small basin-wide effects of afforestation on streamflow found in the current study.

Our results show that longleaf pine forests have over 15 % lower annual ET compared to loblolly pine. Average annual simulated ET of loblolly and longleaf pine stands were 960 and 811 mm, respectively, across the study watersheds. Our results are in line with studies such as McLaughlin et al. (2013) and Whelan et al. (2015), which reported ET rates of loblolly and longleaf pine stands in the range 938–1,087 and 489–816 mm/year, respectively, across the SE-US. This indicates the robustness of our longleaf pine parameterization in realistically representing the ecophysiology of longleaf pine forests (Table 2). For instance, the maximum LAI of longleaf pine was parameterized as 2.25 m^2/m^2 and showed a good match with remote-sensing information (Figs. S5 and S19). Comparatively, the maximum LAI of loblolly pine was 3.7 m^2/m^2 in the current study, and was based on a loblolly pine parameterization previously developed for the SWAT model (Haas et al., 2022). Moreover, the parameter *canmx*, which controls the maximum canopy storage, was 0.39 mm for longleaf pine and 0.6 mm for loblolly pine. Similarly, longleaf pine forests had smaller stomatal conductance than loblolly pine. This was represented through the parameter *gsi* in SWAT. These factors may have led to lower rates of interception and evaporation, increasing the amount of water reaching the forest floor and potentially impacting streamflow.

When we isolated the areas that had undergone forest restoration (Fig. 2A), larger impacts on hydrology and water quality predictions were found. Local watersheds witnessing afforestation with longleaf pine had 20 and 116 mm/year more water lost as ET compared to the reference scenario in the ACT and TBW basins, respectively. Mean annual streamflow decreased 47 and 76 mm in the subwatersheds ACT 1 and ACT 2, respectively. The former watershed witnessed 33 % forest restoration in a drainage area of 2,200 km^2, while the latter saw 50 % forest restoration across its drainage area of 3,800 km^2. Similarly, subwatersheds TBW 1 (800 km^2) and TBW 2 (3,000 km^2), which had forest restoration rates of 75 and 60 %, respectively, witnessed reductions in mean annual streamflow of 68 and 83 mm. When the same areas were converted to loblolly pine, mean annual ET increased by 242 mm/year and 272 mm/year in the ACT and TBW watersheds, respectively. As expected, loblolly pine afforestation led to larger decreases in mean annual streamflow because of larger increases in ET. In the ACT 1 and ACT 2 watersheds, reduction in mean annual streamflow of 9.4 % (79 mm/year) and 23.8 % (123 mm/year) were found. Similarly, in the TBW 1 and TBW 2 watersheds, mean annual streamflow decreased by 18 % (111 mm/year) and 16 % (113 mm/year) because of afforestation with loblolly pine. These results indicate that basin-wide afforestation can greatly increase (decrease) ET (streamflow) at local scales, despite smaller impacts on the most downstream basin outlets.

Although other studies have investigated the potential effects of longleaf pine restoration on watershed-scale water budget, our study is the first to realistically simulate longleaf pine restoration at the regional level. For instance, while studies such as Qi et al. (2021) arbitrarily converted certain portions of the land to longleaf pine, we used a data-driven approach to guide our analysis. Additionally, we developed a physically meaningful representation of longleaf pine ecophysiology in the model and investigated potential water quality impacts. Our results indicate that converting land classes such as hay, range, crops, and deciduous forests to either longleaf pine or loblolly pine forests might reduce sediment and nutrient loadings and thus improve water quality conditions. Afforestation with longleaf pine was more efficient in reducing water quality loadings compared to loblolly pine, especially at the basin level. Reductions in sediment and nutrient loadings compared to the reference scenario might be related to the conversion of deciduous forests to pine stands. Deciduous forests across the Mobile Bay watershed area are mostly comprised of red oaks, which have larger aboveground biomass compared to low-density forests such as longleaf pine. Deciduous forests lose their leaves during the dormant season and a portion of the aboveground biomass is converted to soil residue. This residue contributes to the fresh organic nitrogen pool in SWAT and is eventually mineralized into ammonium which is converted into nitrate through nitrification (Neitsch et al., 2011). Additionally, the Modified Universal Soil Loss Equation (MUSLE) used in SWAT to calculate sediment yield is affected by plant biomass through the cover and management factor. Thus, increased (decreased) plant biomass may result in increased (decreased) sediment loadings in SWAT. Consequently, the conversion of denser deciduous forests to low-density evergreen forests most likely reduced the amount of residue on the ground and resonated in decreased sediment and nutrient loadings being transported to the stream channel. This may also help to explain the greater reductions in sediment and nutrient exports found with the longleaf pine restoration scenario. Longleaf pine and loblolly pine stands were parameterized with an initial aboveground biomass of 47 and 90 tons/ha, respectively, based on gridded forest biomass estimates (Blackard et al., 2008) Also, reduced runoff resulting from afforestation most likely contributed for reducing water quality loadings.

5.2. What is the importance of considering local moisture recycling in watershed modeling?

There is a growing body of literature showing the importance of considering moisture recycling when assessing the hydrological implications of large-scale forest restoration, especially in the tropics (e.g., Amazon) and Sahel regions (Bagley et al., 2014; Meier et al., 2021; Oguntunde et al., 2014; Spracklen and Garcia-Carreras, 2015; Swann et al., 2015; Wang-Erlandsson et al., 2018). These studies indicate that rainfall can be greatly affected by changes in ET stemming from regional or global afforestation efforts. However, as highlighted by te Wierik et al. (2021), there is still a lack of studies assessing the importance of moisture recycling at smaller scales such as watersheds. The local moisture recycling ratio database developed by Theeuwen et al. (2023) presents a great opportunity for researchers to better investigate this. As highlighted by Theeuwen et al. (2023), the authors expect that the LMR can be useful in studying the impacts of land-use/cover changes such as afforestation on the local water cycle. Our study helps to fill this knowledge gap and our findings reveal that local moisture recycling has very small impacts on precipitation, streamflow, and water quality across our study domain. For instance, in the ACT river basin, afforestation of longleaf pine increased mean annual precipitation by 0.44 mm/year in comparison to the reference scenario. In the TBW river basin, mean annual precipitation increased by 0.8 mm/year due to local moisture recycling. The impacts of local moisture recycling on basin averaged rainfall were slightly bigger when afforestation with loblolly pine was implemented. For instance, mean annual rainfall increased by 2.4 and 1.4 mm/year in the ACT and TBW watersheds, respectively. The local moisture recycling ratios (LMR) across the ACT and TBW basins ranged from 1.4 to 2 % of the ET (Fig. S32) for the climatological period 2008–2017. Our results agree with those of Theeuwen et al. (2023) showing that, on average, 1.7 % of global ET returns locally to the land as rainfall. This small fraction of evaporated water raining out over the land explains the small effects of considering local moisture recycling in our model. Past research has also shown small vegetation-climate feedbacks across the SE-US (Jackson et al., 2005). This might be due to several climatic and geographic variables controlling atmospheric moisture circulation and addressing them is beyond the scope of our study. Here, we simply leverage the LMR estimates of Theeuwen et al. (2023) to assess the importance of considering moisture recycling in watershed scale forest restoration scenarios. Overall, our findings reveal that terrestrial moisture recycling stemming from large-scale afforestation efforts is not likely to play an important role for streamflow, water quality, and rainfall dynamics within the Mobile Bay watershed area. As demonstrated by Theeuwen et al. (2023), LMR is also driven by factors such as latitude, wind speed, and energy balance and peak LMR are found in elevated and wet regions such as the Ethiopian Highlands, the Congo Basin, and Southeast Asia. Evaporation seems to be particularly relevant in areas situated between 15 and 30°of latitude and we expect that our study can open avenues for the incorporation of local moisture recycling in modeling studies carried out in these locations. Our results concur with those of Hoek van Dijke et al. (2022) in illustrating that despite the effects of terrestrial moisture recycling, afforestation still leads to streamflow reductions because of increased ET. In our study, since terrestrial moisture recycling was restricted to a 50 km radius of its source, the impacts were even smaller and led to negligeable offsets of streamflow and water quality reductions.

5.3. Limitations and broader implications

Even though our results are consistent with the current understanding of the effects of moisture recycling on precipitation and hydrology, several potential caveats should be highlighted. First, our whole rationale is rooted in the hypothesis that ET can explain local moisture recycling. Although our analysis shows a strong-positive and statistically significant (*p-value* < 0.05) relationship between simulated ET and LMR, we acknowledge that there are several other factors influencing moisture recycling. For instance, midlatitude westerlies, land surface warming, wind speed, cloud cover, and albedo changes resulting from forest restoration can impact moisture recycling patterns (Portmann et al., 2022). However, here we simply utilize the data from Theeuwen et al. (2023) to establish a correlation between present-day ET and LMR in order to capture the potential indirect effects of moisture recycling on precipitation in future afforestation scenarios. As with any modeling product, the LMR data has uncertainties. Similarly, SWAT-simulated ET also has uncertainties. Although we have calibrated ET against remote-sensing estimates, our simulated mean annual ET was slightly higher than MODIS-estimated ET. Furthermore, our model-data integration approach consists of loose coupling. In other words, land-use change does not automatically interact with precipitation in the model unlike earth system models, and this process requires user intervention. Although our methodology is simple and relies on readily available data, this may hinder the inclusion of moisture recycling in watershed models. It is important to highlight that the relationships established in the current study between ET and LMR were solely to estimate the potential impacts of afforestation on rainfall and water resources across our study areas. These relationships should not be interpreted as physically based models or generalized to other study areas. As discussed in Theeuwen et al. (2023), land-use/cover changes such as afforestation would change other factors (e.g., energy balance) influencing moisture recycling, and, thus, LMR. This warrants the necessity of estimating how LMR would respond to land-use/cover changes.

Despite the limitations, our study has valuable findings and presents a novel and simple approach to capturing land–atmosphere interactions in watershed modeling. Moreover, our study is novel in accounting for the effects of terrestrial moisture recycling locally using a semi-distributed watershed-scale hydrologic model. This approach advances beyond past research employing Budyko models (Hoek van Dijke et al., 2022) or simpler hydrologic models (Wang-Erlandsson et al., 2018), as SWAT enables the simulation of in-stream water fluxes, nutrient and sediment loadings in the channel, and species-specific plant growth and dynamics. Additionally, we were able to simulate ecologically relevant flow metrics such as minimum and maximum flows of daily (1-day) and seasonal (90-day) durations. These metrics are crucial for ecohydrology studies and the management of aquatic species, as they provide insights into low-flow conditions that can impact habitat availability, water quality, and ecosystem health (Dosdogru et al., 2020; Poff and Zimmerman, 2010). Such a level of detail could only be achieved by a semi-distributed process-based hydrologic model, highlighting the importance of our approach in advancing the understanding of forest-water interactions at the watershed scale.

Current watershed models do not consider land–atmosphere feedback. This may be related to a lack of data and the scale of the issue since terrestrial moisture recycling is tightly related to global atmospheric circulation. The recently published LMR dataset presents a great opportunity for modelers to incorporate moisture recycling into watershed models in assessing local and regional effects of land-use changes. Our methodology relies on freely available data and can be applied to other watershed systems around the world. Additionally, we introduce a physically meaningful longleaf pine parameterization for the SWAT model, which can greatly benefit ecohydrological modelers, particularly in the SE-US. As highlighted by Ellison et al. (2012), forest type impacts the local water balance. Our study confirms this and reveals differing hydrological and water quality responses to afforestation with longleaf pine and loblolly pine trees in the Mobile Bay watershed area. This can be important for regional stakeholders and decision makers such as The Longleaf Alliance, America's Longleaf, and the Mobile Bay National Estuary Program, which are collaborative efforts between public and private sector partners to guide longleaf pine restoration/conservation and protect estuaries of national significance like the Mobile Bay. Amid ongoing global climate variability and declining trends of streamflow and water quality deterioration being reported across the SE-US (Dai, 2016; Engström et al., 2021; Lins and Slack, 2005; Rice et al., 2015; Rodgers et al., 2020; Tamaddun et al., 2016), our findings suggest that forest conversion and/or restoration may be a sustainable practice to alleviate such impacts.

6. Summary and conclusions

The effects of longleaf pine and loblolly pine afforestation on streamflow dynamics, water quality, and precipitation were assessed at the basin (>50,000 km^2) and watershed (<5,000 km^2) scales using data-driven forest restoration scenarios. Model predictions were evaluated with and without the inclusion of local moisture recycling to test the importance of vegetation-atmosphere feedback in watershed modeling. The following summarizes the key findings of our study:

- Conversion of non-forested lands to loblolly pine and longleaf pine led to increased (decreased) ET (streamflow) across the Mobile Bay watershed area;
- Loblolly pine forests had approximately 15 % higher mean annual ET compared to longleaf pine trees;
- Overall, afforestation with longleaf pine and loblolly pine led to reduced sediment, nitrate, organic nitrogen, and phosphate loadings;
- The incorporation of local moisture recycling in the model had very small effects in offsetting the reductions in streamflow and water quality loadings stemming from afforestation;

CRediT authorship contribution statement

Henrique Haas: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Latif Kalin:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Ge Sun:** Writing – review & editing, Validation, Supervision, Methodology. **Sanjiv Kumar:** Writing – review & editing, Supervision, Methodology, Formal analysis.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.131739.

References

Abbaspour, K.C., 2015. SWAT Calibration and Uncertainty Programs. Eawag aquatic research. Eawag: Swiss Federal Institute of Aquatic Science and Technology 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., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J. Hydrol. 524, 733–752. https://doi.org/10.1016/j.jhydrol.2015.03.027.

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., Ssegane, H., Hamidi, M.D., Trettin, C.C., 2022. Evaluating watershed-scale effects of longleaf pine restoration on water yield using a paired watershed and modeling approaches. In: Willis, John L.; Self, Andrew B.; Siegert, Courtney M., eds. Proceedings of the 21st Biennial Southern Silvicultural Research Conference. Gen. Tech. Rep. SRS-268. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station: 268, 39.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development1. JAWRA Journal of the American Water Resources Association 34, 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Allen, P.M., 1999. Continental scale simulation of the hydrologic balance. J. Am. Water Resour. Assoc.

Atkins, J.B., Zappia, H., Robinson, J.L., McPherson, A.K., Moreland, R.S., Harned, D.A., Johnston, B.F., Harvill, J.S., 2004. Water quality in the Mobile River Basin, Alabama, Georgia, Mississippi, and Tennessee, 1999-2001 (USGS Numbered Series No. 1231), Water quality in the Mobile River Basin, Alabama, Georgia, Mississippi, and Tennessee, 1999-2001, Circular. U.S. Geological Survey. https://doi.org/10.3133/cir1231.

Bagley, J.E., Desai, A.R., Harding, K.J., Snyder, P.K., Foley, J.A., 2014. Drought and deforestation: has land cover change influenced recent precipitation extremes in the Amazon? J. Clim. 27, 345–361. https://doi.org/10.1175/JCLI-D-12-00369.1.

Barnes, H.H., Callaway, C., Davis, H.R., Kraft, B., Griggs, M.J., King, M.T., Perry, M.S., Swann, D.L., Wright, D.R., Bender, D., Crozier, D.G., Quackenbush, D.S., Fogarty, M. B., Hinesley, M.P., Mahoney, M.S., Struthers, M.E., Valentine, D.J., 2008. State of Mobile Bay: A status report on Alabama's Coastline from the Delta to Our Coastal Waters, MBNEP Executive Committee.

Bastin, J.-F., Finegold, Y., Garcia, C., Mollicone, D., Rezende, M., Routh, D., Zohner, C. M., Crowther, T.W., 2019. The global tree restoration potential. Science 365, 76–79. https://doi.org/10.1126/science.aax0848.

Blackard, J.A., Finco, M.V., Helmer, E.H., Holden, G.R., Hoppus, M.L., Jacobs, D.M., Lister, A.J., Moisen, G.G., Nelson, M.D., Riemann, R., Ruefenacht, B., Salajanu, D., Weyermann, D.L., Winterberger, K.C., Brandeis, T.J., Czaplewski, R.L., McRoberts, R.E., Patterson, P.L., Tymcio, R.P., 2008. Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. Remote Sensing of Environment, Remote Sensing Data Assimilation Special Issue 112, 1658–1677. https://doi.org/10.1016/j.rse.2007.08.021.

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., Laviner, 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. Manage. 424, 39–52. https://doi.org/10.1016/j.foreco.2018.04.029.

Brantley, S., Vose, J., Wear, D., Band, L., 2018. Potential of longleaf pine restoration to mitigate water scarcity and sustain carbon sequestration: Planning for an uncertain future.

Bryars, C., Maier, C., Zhao, D., Kane, M., Borders, B., Will, R., Teskey, R., 2013. Fixed physiological parameters in the 3-PG model produced accurate estimates of loblolly pine growth on sites in different geographic regions. For. Ecol. Manage. 289 https://doi.org/10.1016/j.foreco.2012.09.031.

Buechel, M., Slater, L., Dadson, S., 2022. Hydrological impact of widespread afforestation in Great Britain using a large ensemble of modelled scenarios. Commun Earth Environ 3, 1–10. https://doi.org/10.1038/s43247-021-00334-0.
Coe, M.T., Costa, M.H., Soares-Filho, B.S., 2009. The influence of historical and potential future deforestation on the stream flow of the Amazon River – land surface processes and atmospheric feedbacks. J. Hydrol. 369, 165–174. https://doi.org/10.1016/j.jhydrol.2009.02.043.
Costa, M.H., Foley, J.A., 1997. Water balance of the Amazon Basin: dependence on vegetation cover and canopy conductance. J. Geophys. Res. Atmos. 102, 23973–23989. https://doi.org/10.1029/97JD01865.
Cui, J., Lian, X., Huntingford, C., Gimeno, L., Wang, T., Ding, J., He, M., Xu, H., Chen, A., Gentine, P., Piao, S., 2022. Global water availability boosted by vegetation-driven changes in atmospheric moisture transport. Nat. Geosci. 15, 982–988. https://doi.org/10.1038/s41561-022-01061-7.
Cunge, J.A., 1969. On the subject of a flood propagation computation method (Musklngum Method). J. Hydraul. Res. 7, 205–230. https://doi.org/10.1080/00221686909500264.
Dai, A., 2016. Historical and Future Changes in Streamflow and Continental Runoff. In: Terrestrial Water Cycle and Climate Change. American Geophysical Union (AGU), pp. 17–37. https://doi.org/10.1002/9781118971772.ch2.
De Cicco, L.A., Hirsch, R.M., Lorenz, D., Watkins, D., 2018. dataRetrieval. https://doi.org/10.5066/P9X4L3GE.
Dosdogru, F., Kalin, L., Wang, R., Yen, H., 2020. Potential impacts of land use/cover and climate changes on ecologically relevant flows. J. Hydrol. 584, 124654 https://doi.org/10.1016/j.jhydrol.2020.124654.
Ellison, D., Futter, N., Bishop, K., 2012. On the forest cover–water yield debate: from demand- to supply-side thinking. Glob. Chang. Biol. 18, 806–820. https://doi.org/10.1111/j.1365-2486.2011.02589.x.
Engström, J., Praskievicz, S., Bearden, B., Moradkhani, H., 2021. Decreasing water resources in Southeastern U.S. as observed by the GRACE satellites. Water Policy 23, 1017–1029. https://doi.org/10.2166/wp.2021.039.
Filoso, S., Bezerra, M.O., Weiss, K.C.B., Palmer, M.A., 2017. Impacts of forest restoration on water yield: a systematic review. PLoS One 12. https://doi.org/10.1371/journal.pone.0183210.
Frost, C., 2006. History and Future of the Longleaf Pine Ecosystem. In: Jose, S., Jokela, E. J., Miller, D.L. (Eds.), The Longleaf Pine Ecosystem: Ecology, Silviculture, and Restoration, Springer Series on Environmental Management. Springer, New York, NY, pp. 9–48. https://doi.org/10.1007/978-0-387-30687-2_2.
Gonzalez-Benecke, C.A., Gezan, S.A., Martin, T.A., Jr..Cropper, W.P., Samuelson, L.J., Leduc, D.J., 2014. Individual tree diameter, height, and volume functions for longleaf pine. Forest Science 60(1): 43-56 60, 43. https://doi.org/10.5849/forsci.12-074.
Gonzalez-Benecke, C.A., Martin, T.A., Jokela, E.J., Torre, R.D.L., 2011. A flexible hybrid model of life cycle carbon balance for loblolly pine (Pinus taeda L.) management systems. Forests 2, 749–776. https://doi.org/10.3390/f2030749.
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. Manage. 361, 237–256. https://doi.org/10.1016/j.foreco.2015.11.025.
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, Big Remotely Sensed Data: Tools, Applications and Experiences 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.
Haas, H., Reaver, N.G.F., Karki, R., Kalin, L., Srivastava, P., Kaplan, D.A., Gonzalez-Benecke, C., 2022. Improving the representation of forests in hydrological models. Sci. Total Environ. 812, 151425 https://doi.org/10.1016/j.scitotenv.2021.151425.
Harned, D.A., Atkins, J.B., Harvill, J.S., 2004. Nutrient mass balance and trends, mobile River Basin, Alabama, Georgia, and Mississippi1. JAWRA Journal of the American Water Resources Association 40, 765–793. https://doi.org/10.1111/j.1752-1688.2004.tb04458.x.
Herron, N., Davis, R., Jones, R., 2002. The effects of large-scale afforestation and climate change on water allocation in the Macquarie River catchment, NSW, Australia. J. Environ. Manage. 65, 369–381. https://doi.org/10.1006/jema.2002.0562.
Hirsch, R.M., De Cicco, L.A., 2015. User guide to Exploration and Graphics for RivEr Trends (EGRET) and dataRetrieval: R packages for hydrologic data, book, 4. ed. U.S, Geological Survey Techniques and Methods.
Hirsch, R.M., Moyer, D.L., Archfield, S.A., 2010. Weighted regressions on time, discharge, and season (WRTDS), with an application to Chesapeake Bay River. JAWRA Journal of the American Water Resources Association 46, 857–880. https://doi.org/10.1111/j.1752-1688.2010.00482.x.
Hoek van Dijke, A.J., Herold, M., Mallick, K., Benedict, I., Machwitz, M., Schlerf, M., Pranindita, A., Theeuwen, J.J.E., Bastin, J.-F., Teuling, A.J., 2022. Shifts in regional water availability due to global tree restoration. Nat. Geosci. 15, 363–368. https://doi.org/10.1038/s41561-022-00935-0.
Jackson, R.B., Jobbagy, E.G., Avissar, R., Roy, S.B., Barrett, D.J., Cook, C.W., Farley, K. A., McCarl, B.A., Murray, B.C., 2005. Trading Water for Carbon with Biological Carbon Sequestration 310, 5.
Johnson, G.C., Kidd, R.E., Journey, C.A., Zappia, H., Atkins, J.B., 2002. Environmental setting and water-quality issues of the Mobile River Basin, Alabama, Georgia, Mississippi, and Tennessee (USGS Numbered Series No. 2002–4162), Environmental setting and water-quality issues of the Mobile River Basin, Alabama, Georgia, Mississippi, and Tennessee, Water-Resources Investigations Report. https://doi.org/10.3133/wri024162.
Jokela, E.J., Dougherty, P.M., Martin, T.A., 2004. Production dynamics of intensively managed loblolly pine stands in the southern United States: a synthesis of seven long-term experiments. Forest Ecology and Management, Long-Term Production Dynamics of Loblolly Pine Stands in the Southern United States 192, 117–130. https://doi.org/10.1016/j.foreco.2004.01.007.
Jones, J., Ellison, D., Ferraz, S., Lara, A., Wei, X., Zhang, Z., 2022. Forest restoration and hydrology. For. Ecol. Manage. 520, 120342 https://doi.org/10.1016/j.foreco.2022.120342.
Karki, R., Srivastava, P., Veith, T.L., 2020. Application of the soil and water assessment tool (SWAT) at field scale: categorizing methods and review of applications. Trans. ASABE 63, 513–522. https://doi.org/10.13031/trans.13545.
Kemp, C.M., DeVries, D.R., Wright, R.A., 2019. Freshwater predators on the edge: assessing the temporal and spatial variation in diet of largemouth bass in mobile bay estuary, Alabama, USA. Marine and Coastal Fisheries 11, 162–176. https://doi.org/10.1002/mcf2.10067.
Keys, P.W., van der Ent, R.J., Gordon, L.J., Hoff, H., Nikoli, R., Savenije, H.H.G., 2012. Analyzing precipitationsheds to understand the vulnerability of rainfall dependent regions. Biogeosciences 9, 733–746. https://doi.org/10.5194/bg-9-733-2012.
Keys, P.W., Wang-Erlandsson, L., Gordon, L.J., 2016. Revealing invisible water: moisture recycling as an ecosystem service. PLoS One 11, e0151993.
Li, K.Y., Coe, M.T., Ramankutty, N., Jong, R.D., 2007. Modeling the hydrological impact of land-use change in West Africa. J. Hydrol. 337, 258–268. https://doi.org/10.1016/j.jhydrol.2007.01.038.
Li, Y., Piao, S., Li, L.Z.X., Chen, A., Wang, X., Ciais, P., Huang, L., Lian, X., Peng, S., Zeng, Z., Wang, K., Zhou, L., 2018. Divergent hydrological response to large-scale afforestation and vegetation greening in China. Sci. Adv. 4, eaar4182. https://doi.org/10.1126/sciadv.aar4182.
Link, A., van der Ent, R., Berger, M., Eisner, S., Finkbeiner, M., 2020. The fate of land evaporation – a global dataset. Earth Syst. Sci. Data 12, 1897–1912. https://doi.org/10.5194/essd-12-1897-2020.
Lins, H.F., Slack, J.R., 2005. Seasonal and regional characteristics of U.S. streamflow trends in the United States from 1940 to 1999. Phys. Geogr. 26, 489–501. https://doi.org/10.2747/0272-3646.26.6.489.
Lv, M., Ma, Z., Peng, S., 2019. Responses of terrestrial water cycle components to afforestation within and around the Yellow River basin. Atmos. Oceanic Sci. Lett. 12, 116–123. https://doi.org/10.1080/16742834.2019.1569456.
MBNEP, 1997. Mobile Bay National Estuary Program: First Year Annaul Workplan.
McIntyre, R.K., Guldin, J.M., Ettel, T., Ware, C., Jones, K., 2018. Restoration of longleaf pine in the southern United States: a status report. In: Kirschman, Julia E., comp. Proceedings of the 19th biennial southern silvicultural research conference; 2017 March 14-16; Blacksburg, VA. e-Gen. Tech. Rep. SRS-234. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station 2018, 297–302.
McLaughlin, D.L., Kaplan, D.A., Cohen, M.J., 2013. Managing forests for increased regional water yield in the Southeastern U.S. Coastal Plain. JAWRA Journal of the American Water Resources Association 49, 953–965. https://doi.org/10.1111/jawr.12073.
McPherson, A., Moreland, R.S., Atkins, J.B., 2003. Occurrence and distribution of nutrients, suspended sediment, and pesticides in the Mobile River Basin, Alabama, Georgia, Mississippi, and Tennessee, 1999-2001. https://doi.org/10.3133/wri034203.
Meier, R., Schwaab, J., Seneviratne, S.I., Sprenger, M., Lewis, E., Davin, E.L., 2021. Empirical estimate of forestation-induced precipitation changes in Europe. Nat. Geosci. 14, 473–478. https://doi.org/10.1038/s41561-021-00773-6.
Mendonca, C.C., Samuelson, L.J., Stokes, T.A., Ramirez, M.R., Gonzalez-Benecke, C., Aspinwall, M.J., 2023. Soil moisture and vapor pressure deficit controls of longleaf pine physiology: results from a throughfall reduction study. Trees 37, 1249–1265. https://doi.org/10.1007/s00468-023-02423-3.
Monteith, J.L., 1965. Evaporation and environment. Symp. Soc. Exp. Biol. 19, 205–234.
Montiel, D., Lamore, A., Stewart, J., Dimova, N., 2019. Is submarine groundwater discharge (SGD) important for the historical fish kills and harmful algal bloom events of Mobile Bay? Estuar. Coasts 42, 470–493. https://doi.org/10.1007/s12237-018-0485-5.
Moriasi, 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.
Moriasi, D.N., Gitau, M.W., Pai, N., Daggupati, P., 2015. Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria.
Mu, Q., Zhao, M., Running, S.W., 2013. MODIS global terrestrial evapotranspiration (ET) product (NASE MOD16A2/A3). Algorithm Theoretical Basis Document, Collectio 5, 600.
Muzylo, A., Llorens, P., Valente, F., Keizer, J.J., Domingo, F., Gash, J.H.C., 2009. A review of rainfall interception modelling. J. Hydrol. 370, 191–206. https://doi.org/10.1016/j.jhydrol.2009.02.058.
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.
Noss, R.F., Platt, W.J., Sorrie, B.A., Weakley, A.S., Means, D.B., Costanza, J., Peet, R.K., 2015. How global biodiversity hotspots may go unrecognized: lessons from the North American Coastal Plain. Divers. Distrib. 21, 236–244. https://doi.org/10.1111/ddi.12278.
Oguntunde, P.G., Abiodun, B.J., Lischeid, G., Merz, C., 2014. Modelling the impacts of reforestation on the projected hydroclimatology of Niger River Basin, West Africa. Ecohydrology 7, 163–176. https://doi.org/10.1002/eco.1343.
Poff, N.L., Zimmerman, J.K.H., 2010. Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. Freshw. Biol. 55, 194–205. https://doi.org/10.1111/j.1365-2427.2009.02272.x.
Portmann, R., Beyerle, U., Davin, E., Fischer, E.M., De Hertog, S., Schemm, S., 2022. Global forestation and deforestation affect remote climate via adjusted atmosphere

and ocean circulation. Nat. Commun. 13, 5569. https://doi.org/10.1038/s41467-022-33279-9.
Posada-Marín, J.A., Salazar, J.F., 2022. River flow response to deforestation: contrasting results from different models. Water Security 15, 100115. https://doi.org/10.1016/j.wasec.2022.100115.
Qi, J., Brantley, S.T., Golladay, S.W., 2021. Simulated longleaf pine (Pinus palustris Mill.) restoration increased streamflow—a case study in the Lower Flint River Basin. Ecohydrology N/a e2365. https://doi.org/10.1002/eco.2365.
Rice, J.S., Emanuel, R.E., Vose, J.M., Nelson, S.A.C., 2015. Continental U.S. streamflow trends from 1940 to 2009 and their relationships with watershed spatial characteristics. Water Resour. Res. 51, 6262–6275. https://doi.org/10.1002/2014WR016367.
Rodgers, K., Roland, V., Hoos, A., Crowley-Ornelas, E., Knight, R., 2020. An analysis of streamflow trends in the southern and Southeastern US from 1950–2015. Water 12, 3345. https://doi.org/10.3390/w12123345.
Sampson, D., Waring, R., Maier, C., Gough, C., Ducey, M., Johnsen, K., 2006. Fertilization effects on forest carbon storage and exchange, and net primary production: a new hybrid process model for stand management. For. Ecol. Manage. 221, 91–109. https://doi.org/10.1016/j.foreco.2005.09.010.
Samuelson, L.J., Stokes, T.A., Butnor, J.R., Johnsen, K.H., Gonzalez-Benecke, C.A., Anderson, P., Jackson, J., Ferrari, L., Martin, T.A., Cropper, W.P., 2014. Ecosystem carbon stocks in Pinus palustris forests. Can. J. for. Res. 44, 476–486. https://doi.org/10.1139/cjfr-2013-0446.
Samuelson, L.J., Stokes, T.A., Ramirez, M.R., Mendonca, C.C., 2019. Drought tolerance of a Pinus palustris plantation. For. Ecol. Manage. 451, 117557 https://doi.org/10.1016/j.foreco.2019.117557.
Savenije, H.H.G., 1995. New definitions for moisture recycling and the relationship with land-use changes in the Sahel. J. Hydrol. 167, 57–78. https://doi.org/10.1016/0022-1694(94)02632-L.
Schuol, J., Abbaspour, K.C., Yang, H., Srinivasan, R., Zehnder, A.J.B., 2008. Modeling blue and green water availability in Africa. Water Resour. Res. 44 https://doi.org/10.1029/2007WR006609.
Spracklen, D.V., Arnold, S.R., Taylor, C.M., 2012. Observations of increased tropical rainfall preceded by air passage over forests. Nature 489, 282–285. https://doi.org/10.1038/nature11390.
Spracklen, D.V., Garcia-Carreras, L., 2015. The impact of Amazonian deforestation on Amazon basin rainfall. Geophys. Res. Lett. 42, 9546–9552. https://doi.org/10.1002/2015GL066063.
Staal, A., Theeuwen, J.J.E., Wang-Erlandsson, L., Wunderling, N., Dekker, S.C., 2024. Targeted rainfall enhancement as an objective of forestation. Glob. Chang. Biol. 30, e17096.
Stickler, C.M., Coe, M.T., Costa, M.H., Nepstad, D.C., McGrath, D.G., Dias, L.C.P., Rodrigues, H.O., Soares-Filho, B.S., 2013. Dependence of hydropower energy generation on forests in the Amazon Basin at local and regional scales. Proceedings of the National Academy of Sciences 110, 9601–9606. https://doi.org/10.1073/pnas.1215331110.
Swann, A.L.S., Longo, M., Knox, R.G., Lee, E., Moorcroft, P.R., 2015. Future deforestation in the Amazon and consequences for South American climate. Agric. For. Meteorol. 214–215, 12–24. https://doi.org/10.1016/j.agrformet.2015.07.006.
Tamaddun, K., Kalra, A., Ahmad, S., 2016. Identification of streamflow changes across the continental united states using variable record lengths. Hydrology 3, 24. https://doi.org/10.3390/hydrology3020024.
te Wierik, S.A., Cammeraat, E.L.H., Gupta, J., Artzy-Randrup, Y.A., 2021. Reviewing the impact of land use and land-use change on moisture recycling and precipitation patterns. Water Resour. Res. 57, e2020WR029234 https://doi.org/10.1029/2020WR029234.
Theeuwen, J.J.E., Staal, A., Tuinenburg, O.A., Hamelers, B.V.M., Dekker, S.C., 2023. Local moisture recycling across the globe. Hydrol. Earth Syst. Sci. 27, 1457–1476. https://doi.org/10.5194/hess-27-1457-2023.
Trettin, C.C., Amatya, D.M., Gaskins, A.H., Miniat, C.F., Chow, A., Callahan, T., 2018. Watershed response to longleaf pine restoration–application of paired watersheds on the Santee Experimental Forest. Proceedings of the 6th Interagency Conference on Research in Watershed 2018, 194.
Tuinenburg, O.A., Theeuwen, J.J.E., Staal, A., 2020. High-resolution global atmospheric moisture connections from evaporation to precipitation. Earth Syst. Sci. Data 12, 3177–3188. https://doi.org/10.5194/essd-12-3177-2020.
Valente, M.L., Reichert, J.M., Cavalcante, R.B.L., Minella, J.P.G., Evrard, O., Srinivasan, R., 2021. Afforestation of degraded grasslands reduces sediment transport and may contribute to streamflow regulation in small catchments in the short-run. Catena 204, 105371. https://doi.org/10.1016/j.catena.2021.105371.
Van der Ent, R.J., 2014. A new view on the hydrological cycle over continents. Delft University of Technology. Ph.D Thesis,.
Van der Ent, R., Savenije, H., 2010. Length and time scales of atmospheric moisture recycling. Atmos. Chem. Phys. Discuss. 11 https://doi.org/10.5194/acpd-10-21867-2010.
Verdone, M., Seidl, A., 2017. Time, space, place, and the Bonn Challenge global forest restoration target. Restor. Ecol. 25, 903–911. https://doi.org/10.1111/rec.12512.
Wang-Erlandsson, L., Fetzer, I., Keys, P.W., van der Ent, R.J., Savenije, H.H.G., Gordon, L.J., 2018. Remote land use impacts on river flows through atmospheric teleconnections. Hydrol. Earth Syst. Sci. 22, 4311–4328. https://doi.org/10.5194/hess-22-4311-2018.
Webb, A.A., Kathuria, A., 2012. Response of streamflow to afforestation and thinning at Red Hill, Murray Darling Basin, Australia. Journal of Hydrology, Hydrology Conference 2010 (412–413), 133–140. https://doi.org/10.1016/j.jhydrol.2011.05.033.
Whelan, A., Starr, G., Staudhammer, C.L., Loescher, H.W., Mitchell, R.J., 2015. Effects of drought and prescribed fire on energy exchange in longleaf pine ecosystems. Ecosphere 6, art128. https://doi.org/10.1890/ES15-00111.1.
Will, R.E., Fox, T., Akers, M., Domec, J.-C., González-Benecke, C., Jokela, E.J., Kane, M., Laviner, 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.
Yosef, G., Walko, R., Avisar, R., Tatarinov, F., Rotenberg, E., Yakir, D., 2018. Large-scale semi-arid afforestation can enhance precipitation and carbon sequestration potential. Sci. Rep. 8, 996. https://doi.org/10.1038/s41598-018-19265-6.
Younger, S.E., Cannon, J.B., Brantley, S.T., 2023. Impacts of longleaf pine (Pinus palustris Mill.) on long-term hydrology at the watershed scale. Sci. Total Environ. 902, 165999 https://doi.org/10.1016/j.scitotenv.2023.165999.
Zhang, L., Hickel, K., Dawes, W.R., Chiew, F.H.S., Western, A.W., Briggs, P.R., 2004. A rational function approach for estimating mean annual evapotranspiration. Water Resour. Res. 40 https://doi.org/10.1029/2003WR002710.
Zhang, M., Liu, N., Harper, R., Li, Q., Liu, K., Wei, X., Ning, D., Hou, Y., Liu, S., 2017. A global review on hydrological responses to forest change across multiple spatial scales: importance of scale, climate, forest type and hydrological regime. J. Hydrol. 546, 44–59. https://doi.org/10.1016/j.jhydrol.2016.12.040.
Zhou, G., Wei, X., Chen, X., Zhou, P., Liu, X., Xiao, Y., Sun, G., Scott, D.F., Zhou, S., Han, L., Su, Y., 2015. Global pattern for the effect of climate and land cover on water yield. Nat. Commun. 6, 5918. https://doi.org/10.1038/ncomms6918.