



# Potential long term water yield impacts from pine plantation management strategies in the southeastern United States

Kathryn L. Pisarello<sup>a,\*</sup>, Ge Sun<sup>b</sup>, Jason M. Evans<sup>c</sup>, Robert J. Fletcher Jr.<sup>d</sup>

<sup>a</sup> USDA-ARS, Southeast Watershed Research Laboratory, 2316 Rainwater Road, Tifton, GA 31793, USA

<sup>b</sup> Eastern Forest Environmental Threat Assessment Center, Southern Research Station, USDA Forest Service, Research Triangle Park, NC 27709, USA

<sup>c</sup> Institute for Water and Environmental Resilience, Stetson University, DeLand, FL 32723, USA

<sup>d</sup> Department of Wildlife Ecology and Conservation, University of Florida, Gainesville, FL 32611, USA

## ARTICLE INFO

### Keywords:

Pine plantations  
Water yield  
Multi-scale  
Statistical modeling  
Bioenergy  
Ecosystem services

## ABSTRACT

Changes in global bioenergy consumption have catalyzed the emergence of forest plantations as an important energy alternative. In the southeastern United States, land cover changes caused by increasing demands for pine trees as a bioenergy feedstock incite associated impacts on local ecosystem services (e.g., water yield). However, water yield impacts from pine plantation management strategies, such as thinning and short rotation, have yet to be simultaneously examined on multiple spatial scales. Here, we modeled the effects of thinning and clear-cut conditions on long term mean annual water yield across a 55-year time horizon at the watershed scale (watershed area ranging 696 – 7,374 km<sup>2</sup>) in northern Florida, southern Georgia, and southern Alabama. Additionally, we assessed the long term water yield effects of thinning, clear-cut, and short-rotation management at the pine plantation (i.e., plot) scale. We compared three plot-level evapotranspiration models as well as the watershed-level Water Supply Stress Index water balance model to simulate plot and watershed hydrologic responses from pine plantation management scenarios. Both methods showed that 10% thinning had the smallest increase in water yield (<6%), while clear-cut conditions imposed the greatest increase (up to 51% for plot scale and up to 25% for watershed scale simulations). Short-rotation management caused plot-level water yield increases ranging from 3% to 24%. Overall, greater water yield effects were seen in site simulations, rather than in watersheds, reinforcing the importance of scale when assessing water budget impacts given land cover changes. These results suggest that landowners have agency over the magnitude of water that is yielded from their plantations and that local water supply shortages can be mitigated by changing forestry biomass management strategies. The opportunity to supplement local water availability is especially valuable within the context of changing climate cycles that may bring about drier local conditions. The multi-scale approach presented here can support efforts from landowners and water managers to optimize profit as well as ecosystem service provision.

## 1. Introduction

The Intergovernmental Panel on Climate Change has identified biomass energy as a key pathway for mitigating global carbon emissions and consequent future climate change (Chum et al. 2011). Many governments throughout the world have instituted policies promoting biomass energy use, resulting in demand increases for biomass resources suitable for bioenergy production. In the southeastern United States, agricultural land use conversions for bioenergy production are expected to come mostly in the form of loblolly pine plantations (U.S. Department of Energy, 2016; Núñez-Regueiro et al., 2021; Perdue et al., 2017; USDA 2010). Pine plantation owners have responded to these changing energy

standards and have increased profits by overseeing a variety of factors ranging from fertilization rates to physical site characteristics (Trlica et al., 2021; Vance et al., 2010). As such, plantations are subject to various management practices for harvesting biomass for energy, as opposed to more traditional forest products (e.g., paper, board, and lumber). Practices for bioenergy harvesting include thinning, clear cut, and short rotation, where trees are typically harvested from younger stands (U.S. Department of Energy, 2016). Plantation management diversification can benefit the landowner economically and environmentally and can even yield benefits for local ecosystem services, like increased water availability. Such landscape alterations likely affect hydrological cycles across spatial scales with varying, nonlinear impacts

\* Corresponding author.

E-mail address: [katie.pisarello@usda.gov](mailto:katie.pisarello@usda.gov) (K.L. Pisarello).

<https://doi.org/10.1016/j.foreco.2022.120454>

Received 1 April 2022; Received in revised form 27 July 2022; Accepted 31 July 2022

Available online 14 August 2022

0378-1127/Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

(Boisier et al., 2014; Li et al., 2020; Miralles et al., 2011; Sanford & Selnick, 2013; Zhou et al., 2015).

Even in the “water rich” southeastern U.S., water shortages are not unprecedented and therefore are of concern. It is critical then to determine how water availability from forested lands will change under corresponding pine plantation management scenarios, given the socio-ecological reliance on high quality water from forests for purposes of agricultural, industrial, domestic, and ecological consumption (Sun et al., 2008; Liu et al., 2021). There is ample research on forest hydrology in the lower coastal plain of the southeastern U.S. (Riekerk, 1989; Sun et al., 1998 a,b; Sun et al., 2000; Jackson et al., 2004; Lockaby et al., 2013) as well as station-based studies on the hydrologic effects of specific climate and vegetative cover characteristics (Liu et al., 2018; Perrando et al., 2021; Sun et al., 2011a). With large biomass and deep roots that transpire soil water into the atmosphere, forests modify landscape hydrology largely through evapotranspiration (ET) (Miralles et al., 2011; Wei et al., 2017). It is widely accepted that a decrease in forest biomass decreases ET rates, which consequently increases water yield (Q) and groundwater recharge (Vache et al., 2021; McLaughlin et al., 2013; Sun et al., 2011a; Sun et al., 2015; Susaeta et al., 2017). Additionally, the structural changes to soil of deforested areas can facilitate increased flow rates by decreasing soil water retention capacity and infiltration (Peña-Arancibia et al., 2019).

Understanding of water yield impacts from bioenergy-based forestry management across a suite of management practices at multiple spatial scales is a known research gap (Evans and Cohen, 2009; Vose et al., 2014; Sun et al., 2017). It is unclear if forest thinning and clearing practices can help to mitigate the effects of drought, especially in watersheds that are heavily forested (Sun et al., 2015). Additional factors may dampen the expected ET decrease that occurs with clearing or thinning management conditions. For example, in energy-limited watersheds, water availability in the form of precipitation (P) can promote plant growth and allow the root system to recover such that longer-term ET rates can be sustained. Shallow groundwater tables in the vadose zone provide a means for roots to establish and grow a more extensive understory and canopy system, even after thinning has taken place (Liu et al., 2018). Moreover, research that addresses short rotation impacts on water yield is especially lacking (Griffiths et al., 2019; Vache et al., 2021).

Existing investigations on water yield (Q) responses to thinning in humid regions show variable results and suggest the importance of differing mechanistic drivers. Recent studies of loblolly pine plantations in the North Carolina, USA, coastal plain (Liu et al., 2018) and three Brazilian watersheds characterized by managed pine and natural forests (Perrando et al., 2021) indicated that thinning did not have a statistically significant impact on Q, as compared to baseline managed forest conditions. Instead, Q was mostly governed by P rates. However, Liu et al. (2018) determined leaf area index (LAI) was the next most important factor to P for governing ET and soil moisture when evaluating the conterminous U.S. A stronger hydrologic influence from land cover was found by McLaughlin et al. (2013), who reported that lower vegetative density of slash pine plantations in north Florida coastal plains yield higher Q rates. Susaeta et al. (2017) evaluated loblolly pine plantations in the coastal plains of South Carolina, Georgia, and Florida and similarly concluded Q increased with thinning and less dense tree planting. Additionally, it has been found that thinning loblolly pine stands in the coastal plain significantly increased flow (Grace et al., 2006). Lastly, Sun et al. (2015) applied the Water Supply Stress Index (WaSSI) model (Sun et al., 2011b) to test 18 scenarios at the 8-digit United States Geological Survey Hydrologic Unit Code scale (HUC8) across the conterminous United States and combined LAI reductions, a uniform increase in 10% in precipitation and temperature changes by 1–2 °C, and projected climate change scenarios. Sun et al. (2015) found that increased thinning yielded increased Q, but that precipitation changes of 10% had the biggest overall impact on Q rates.

We used multiple methods, including empirical formulae and

ecohydrological models, to quantify water yield effects across three primary management strategies for pine plantations as bioenergy sources in the lower southeast coastal plain, USA. Multi-variate approaches can provide landowners with the framework necessary to evaluate the tradeoffs of production (i.e., profit) and ecosystem service provision (e.g., water yield, nutrient cycling, and biodiversity). With the consideration of multiple system objectives, one practice may benefit some but not all landowner-valued ecosystem services, although a preferable balance may be achieved across multiple services. For example, empirically driven biodiversity metrics for certain taxa are shown to be higher under thinning but lower under clear-cut conditions in bioenergy pine plantation systems (Gottlieb et al., 2017; Loy et al., 2020; Jones et al., 2022).

Our goal was to address knowledge gaps in forestry decision support for biomass energy systems by focusing on long term mean annual water yield effects given different levels of forest thinning, total forest clearing, and short rotation on plot and watershed scales. Specifically, we evaluated thinning and clear-cut conditions at the watershed scale and thinning, clear-cut, and short rotation management at the plot scale. We hypothesized: 1) the response of Q varies with magnitude of biomass removal; clear-cut would yield the greatest increase in Q, while short rotation scenarios would yield Q impacts that are similar to moderate thinning rates (around 50%), and 2) water budget effects are scale dependent; hydrologic response to forest cover change is greater at the plot scale than at the watershed level with mixed land uses. The combined methods and results presented here can improve our standing of how forest bioenergy management affect water use and water yield. Certain management practices could mitigate a lack of water availability and supplement landowners' water needs in drier conditions under a changing climate in the Southeast. Therefore, we inform better water management preparedness under changing forest production landscapes.

## 2. Methods

We applied two approaches to quantify hydrologic response to potential forest management scenarios. First, we conducted a regional watershed-scale analysis, which included an ecohydrological model (i.e., WaSSI) and a total of 48 HUC8 watersheds within the coastal plains of Alabama, Georgia, and Florida that contain the most productive pine plantation forests within the U.S. southeast (Perdue et al., 2017). Second, we evaluated hydrologic response at the plot scale using multiple analytical methods, including a process-based LAI model (Gonzalez-Benecke et al., 2011), a locally developed empirical LAI model (McLaughlin et al., 2013), and a series of locally developed empirical ET models (Cohen et al., 2018; Sun et al., 2011a). This multi-method approach was done to 1) reconcile the limitations of WaSSI, 2) form appropriate comparisons, and 3) provided uncertainty of hydrological response to biomass management. We detail each modeling approach below.

### 2.1. Study region and watersheds

The 48 watersheds in the coastal plains of Alabama, Georgia, and Florida (Figure S1) that we examined represent the study region of previous related work that investigated bioenergy effects on a variety of ecosystem services (Gottlieb et al., 2017; Jones et al., 2020; Loy et al., 2020; Ober et al., 2020; Jones et al., 2022). The watershed areas ranged from 696 to 7,374 km<sup>2</sup>, with a mean of 3,158 km<sup>2</sup>. Land cover, climate, and runoff data were retrieved from the online WaSSI modeling platform (<https://web.wassweb.fs.usda.gov/>), which were compiled at the United States Geological Survey HUC8 watershed scale. Climate and runoff timeseries data were based on FLUXNET eddy flux, PRISM, and USGS streamflow measurements, while land cover was established for the year 2011 (taken from Homer et al., 2015). Figure S1 shows watershed mean forest cover in 2011, as well as mean P and aridity

index (ratio of P to potential evapotranspiration, PET) conditions for 1961–2015. The 1961–2015 timeframe was chosen as the evaluation period to represent the long term mean annual water budget, and so that multiple short rotations could be simulated across a time horizon. Forest cover ranges from around 10% to 50% in the assessed watersheds, with most watersheds consisting of approximately 25–40% forest coverage. In this case, forest coverage was an aggregate of all forest types: deciduous forest, evergreen forest, and mixed forest. Watersheds in Florida generally experienced higher mean annual P and higher levels of humidity, as noted by the aridity index, than those in Alabama and Georgia.

## 2.2. Management scenarios

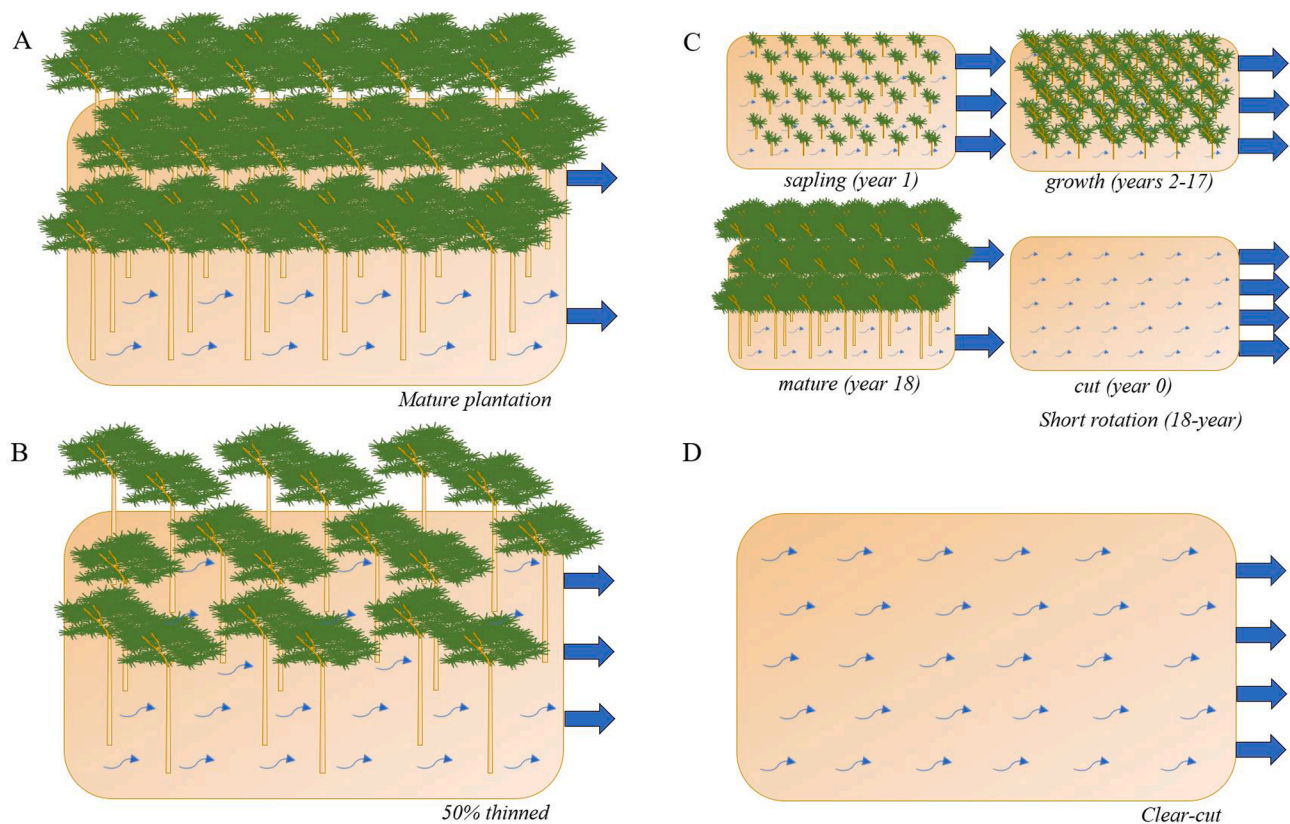
At the plot scale, we evaluated the impact on mean annual Q given three primary pine plantation management conditions: various degrees of thinning that correspond with the thinning levels of Sun et al., 2015 (10%, 20%, 50%, and 80% LAI reductions); short rotation (intensive 10-year and typical 18-year rotations); and clear-cut (100% reduction in LAI). Fig. 1 illustrates example changes in tree biomass and associated Q under each of the three primary management conditions as they compare to mature pine plantations. For these condition-based depictions, 50% thinning and 18-year short rotation scenarios are common thinning and short rotation conditions and are used to illustrate Q impacts under these respective practices. Compared to mature pine plantations, Q is expected to increase with clear-cut conditions. Short rotation Q rates vary over the course of the biomass growth cycle, which is dictated by tree growth stage (Fig. 1C). It should be noted that the same thinning and clear-cut conditions that were evaluated at the watershed scale would cause a similar hydrologic response to that described for plot-scale scenarios.

We addressed Q impacts under various pine plantation management

strategies at both plot and watershed scales (Fig. 2). Thinning and clear-cut conditions were assessed at the watershed scale, and thinning, clear-cut, and short rotation management strategies were evaluated at the plot scale. It is important to note that relative changes in Q are scale-dependent, and so water availability impacts will be more pronounced at smaller spatial scales. Therefore, Fig. 2 shows a greater relative influence of clear-cut conditions on Q in the illustrated plot than it does for the illustrated watershed. Moreover, the proportion of original forested area in a watershed will determine management-induced Q changes, since logically less forested area equates to less potential management area and therefore lower watershed scale Q impacts.

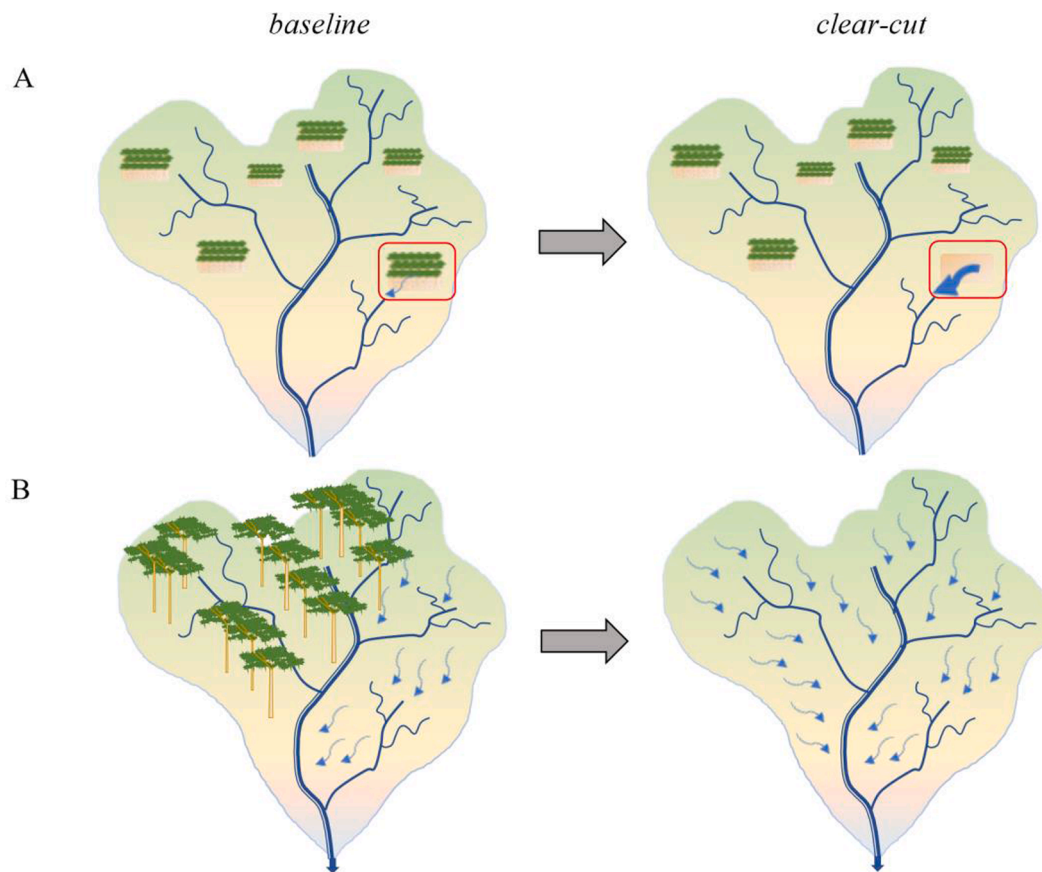
## 2.3. WaSSI watershed modeling

The WaSSI tool is an integrated monthly ecohydrological model used for quantifying water and carbon budget impacts from changes in anthropogenic (i.e., land use change and water demand) and climatic drivers at the HUC8 watershed scale (Sun et al., 2011b; Caldwell et al., 2015). Several components of the water budget can be estimated by this model, including ET, Q, and soil moisture storage. Specifically, changes in forest LAI (i.e., aggregated deciduous, evergreen, and mixed forest) and land cover conversions as well as changes in climatic conditions can be evaluated for their effects on monthly ET and Q. The WaSSI model was built by incorporating FLUXNET ET and carbon flux measurements, has been validated with gauged streamflow (Li et al., 2020), and has shown to yield comparable basin-scale results to Soil Water Assessment Tool (Caldwell et al., 2015). The model has been applied within large spatial scale assessments up to the national level to estimate water yield from various land cover types (Liu et al., 2021). Given this validation and that long term mean annual, larger spatial scale water budget assessments promote less variability than smaller spatiotemporal scale evaluations (e.g., interannual variability is muted), we assume that



**Fig. 1.** Pine plantation management scenarios assessed in this study: mature (A); thinned, where 50% is used here as an illustrative example (B); short rotation, where an 18-year rotation is used here as an illustrative example (C); and clear-cut (D). Expected water yield under each scenario is depicted by the number of blue arrows.





**Fig. 2.** Conceptual relationship of plot and watershed scales. (A) shows the comparative plot (encompassed by red rectangle) hydrologic effects within the watershed, while (B) shows hydrologic effects at the watershed scale. The example pine plantation management scenario illustrated here is clear-cut, and expected water yield is depicted by number and thickness of blue arrows.

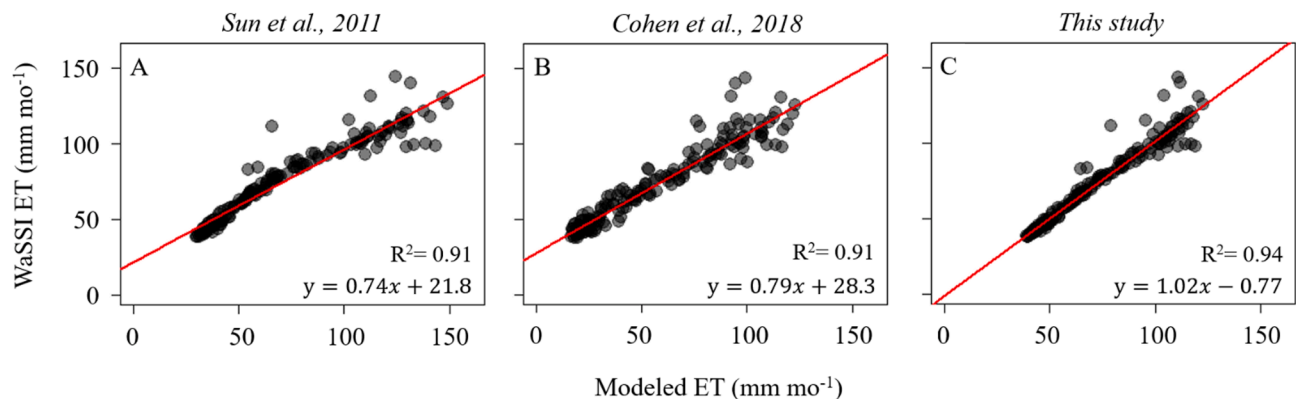
WaSSI sufficiently captures long term watershed ET dynamics, thus obviating a need to develop additional ET estimates.

This study utilized the interactive online WaSSI platform through which mean annual Q impacts from thinning were assessed using a similar approach to Sun et al. (2015). For this study, WaSSI was used to assess HUC8 watershed sensitivity to four thinning levels (10%, 20%, 50%, and 80% LAI reductions) and clear-cut conditions (100% LAI reduction) (Figs. 4–5). To run these simulations, baseline climate data was set to historic for years 1961–2015, with appropriate LAI adjusted to reflect forest thinning and clearing for each scenario. Changes in long term mean annual Q for each watershed under the various scenario were compared to their corresponding baseline Q conditions across the

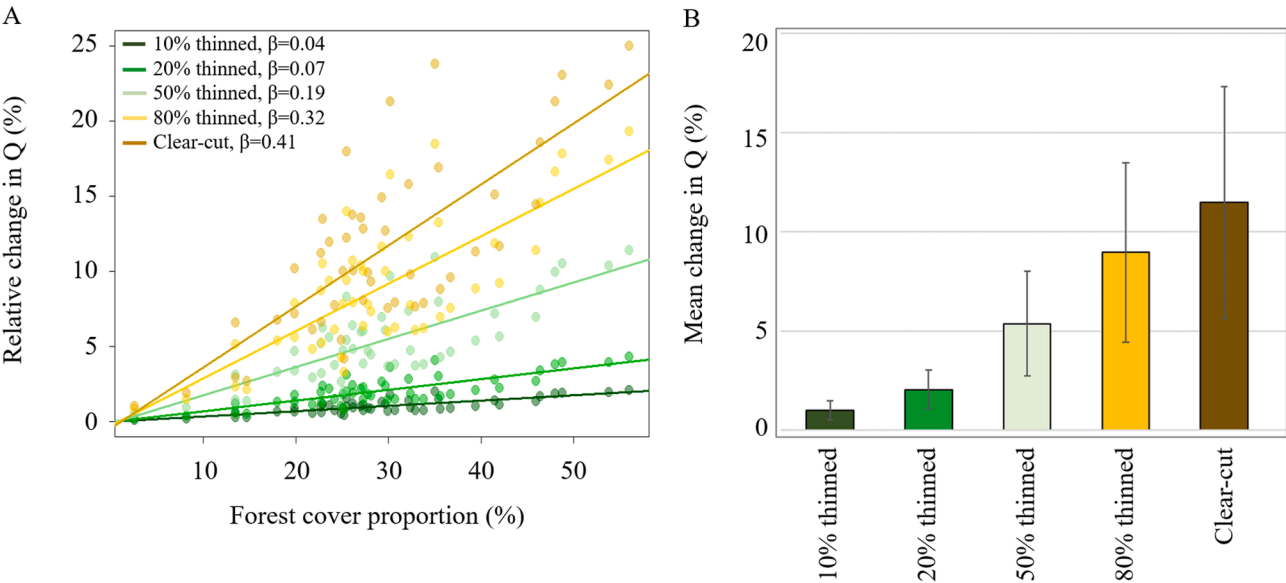
evaluated time period.

#### 2.4. Ensemble plot-scale simulations with ET models

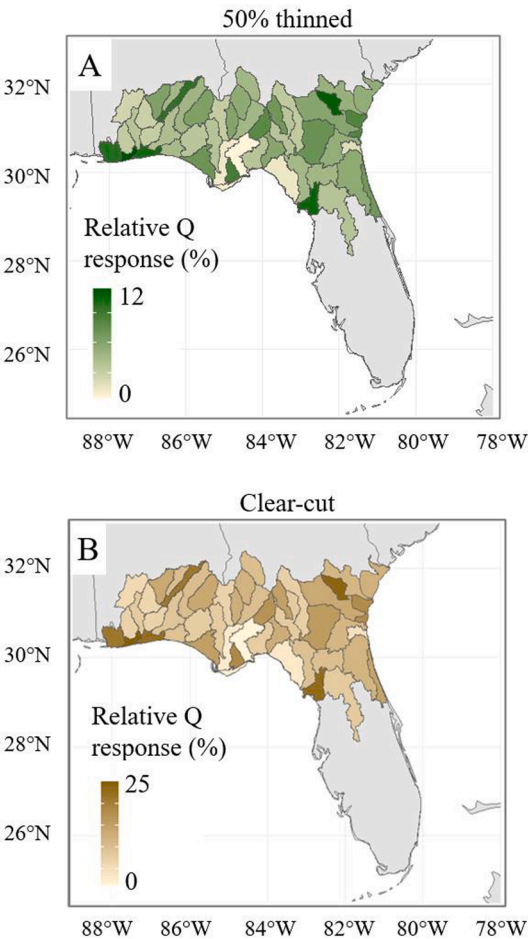
When short rotation strategies are implemented, pine stand biomass as represented by LAI increases over time as planted saplings grow and mature, clear cut harvesting events occur with corresponding LAI decreases, and saplings are planted to complete a full stand rotation. There is a temporal limitation of the online version of the WaSSI model in that dynamic changes in LAI across an assessed time horizon, such as those involved in short rotation scenarios, cannot be examined using this framework. Therefore, multiple empirical ET models (Table 1) were



**Fig. 3.** Modeled long term monthly ET as a function of long term monthly PET, P, and LAI<sub>p</sub> for 14 validation watersheds (n = 168 data points), following the methodology of Sun et al. (2011a) (A), Cohen et al. (2018) (B), and the model created in this study (C).



**Fig. 4.** Simulated relative change (%) of Q under thinning (10%, 20%, 50%, and 80% reductions in LAI) and clear-cut (100% LAI reduction) scenarios, as a function of forest cover proportion [.] for each watershed ( $n = 48$ ) (A), as well as mean scenario-based change in Q across watersheds for years 1961–2015 (B). All scenarios caused a Q impact that was significantly linearly related to forest cover proportion at  $p < 0.05$ . The corresponding regression slope,  $\beta$ , is provided for each simulation.



**Fig. 5.** WaSSI modeled spatial distribution of Q response (%) across watersheds under two land management scenarios, 50% forest LAI reduction (A) and clear-cut (B).

**Table 1**  
Six water budget calculation techniques that include two models for Leaf Area Index (LAI) and three methods for evapotranspiration (ET) estimation. Results of these six water budget estimation methods are shown in Fig. 6.

| Water budget estimation method | LAI method                                  | ET method                            |
|--------------------------------|---|--------------------------------------|
| 1                              | McLaughlin et al., 2013 (statistical)       | Sun et al., 2011a (statistical)      |
| 2                              | McLaughlin et al., 2013 (statistical)       | Cohen et al., 2018 (statistical)     |
| 3                              | McLaughlin et al., 2013 (statistical)       | This study (statistical)             |
| 4                              | Gonzalez-Benecke et al., 2011 (mechanistic) | ET (Sun et al., 2011a) (statistical) |
| 5                              | Gonzalez-Benecke et al., 2011 (mechanistic) | Cohen et al., 2018 (statistical)     |
| 6                              | Gonzalez-Benecke et al., 2011 (mechanistic) | This study (statistical)             |

employed to create an ensemble of simulations to form a reasonable estimate range of long term mean annual water budget impacts. This approach allowed for the examination of short rotation events with a dynamic LAI as well as the thinning and clear-cut practices that the WaSSI model evaluated. We employed multiple ET models to provide uncertainty of estimates of plot level water budgets under forest management scenarios (Table 1).

Here, 10- and 18-year stand rotations (SR10 and SR18, respectively) were assessed, where 10-year rotations represent more intensive systems that may be more financially attractive for bioenergy production (Trlica et al., 2021), and 18-year rotations represent more typical biological rotation ages (Gonzalez-Benecke et al., 2011). The same 55-year time horizon used in the watershed scale WaSSI analysis allowed for assessment of at least two full pine stand rotations.

Two different methods for estimating LAI growth (Gonzalez-Benecke et al., 2011; McLaughlin et al., 2013) and three different ET models (Equations 2–4) were used to assess pine management-induced Q impacts (Table 1). LAI is modeled as a function of stand age. It is important to note that LAI can be characterized in various ways, potentially confounding comparisons across measurements (Asner et al., 2003). The present analysis considered both statistically-determined LAI and mechanistically-determined LAI. McLaughlin et al. (2013) statistically

estimated plot scale total LAI,  $LAI_T$ , based on a variety of dominant species, through a change-point regression-based model shown as a function of southeastern pine stand age,  $x$ , in years by.

$$LAI_T = \begin{cases} 3, & x \leq 6 \\ 0.5x - 0.02, & 6 < x \leq 13 \\ 6.5, & x > 13 \end{cases} \quad (1)$$

These  $LAI_T$  values were converted to mean annual projected LAI,  $LAI_P$ , by applying the 2.68 conversion factor used by [McLaughlin et al. \(2013\)](#) for pine plantations in the southeastern U.S. (i.e.,  $LAI_P \times 2.68 = LAI_T$ ) ([Johnson, 1984](#); [Vose and Allen, 1988](#)).

Additionally,  $LAI_P$  was mechanistically estimated by the Growth Yield and Carbon Balance (GYCB) Model for planted loblolly pines under short rotation conditions, version 1.32 ([Gonzalez-Benecke et al., 2011](#)). Like Equation (1), this excel-based model is not spatially explicit but is based on equations specifically calibrated for loblolly pine plantations in the coastal plains and piedmont regions of the southeastern U.S. The GYCB Model has been validated against data reported in the literature for carbon accumulation and net ecosystem production for loblolly pine plantations. Therefore, we used this model to compare hypothetical thinning and short rotation impacts on general  $Q$  rates at the plot scale. These modeled  $LAI_P$  were simulated from establishment (planting).

The relationship between LAI and ET rates were then statistically determined to assess short rotation, thinning, and clear-cut impacts on long term mean annual  $Q$  via the long-term water budget. Thinning and clear-cut scenarios were simulated by reducing modeled LAI from baseline conditions, which were assumed to be pine plantations at mature stand age ( $\geq 14$  years old). This age was chosen because it is the growth stage at which LAI no longer increases for both [McLaughlin et al. \(2013\)](#) and GYCB LAI frameworks. An illustrative example of LAI dynamics as they relate to ET under short rotation conditions over time can be seen in [Figure S2](#), which illustrates [McLaughlin et al. \(2013\)](#) LAI and ET calculated by the [Sun et al. \(2011a\)](#) model (Equation (2)).

Over the 55-year time horizon, ET was estimated through three regression models as a function of long term mean annual  $P$ , ET, LAI, and PET. [Sun et al. \(2011a\)](#) derived an ET model from eddy flux and sapflow measurements at 13 sites across a gradient of biomes in the southeastern U.S., eastern Australia, and northern China. The authors described monthly,  $m$ , ET as a function of monthly PET, monthly  $P$ , and monthly averaged  $LAI_P$  as.

$$ET_m = 11.94 + 4.76LAI_P + PET_m(0.032LAI_P + 0.0026P_m + 0.15) \quad (2)$$

[Cohen et al. \(2018\)](#) provides an update to the ET regression equation from [McLaughlin et al. \(2013\)](#) (see Equation S1), and statistically assesses ET as a function of PET and  $LAI_P$  at six sites across Florida, representing a gradient of forest conditions. [Cohen et al. \(2018\)](#) describe long term mean monthly ET as.

$$ET_m = (0.11LAI_P + 0.38)PET_m \quad (3)$$

To compare with previously existing models, we also created a new statistical model for the present study to describe monthly ET as linearly related to monthly  $P$ , PET, and  $LAI_P$ . The regression was created using a random sample of approximately 70% of the basins, resulting in 34 basins for calibration and 14 basins for validation. We used watershed  $P$ , PET, ET, and  $LAI_P$  WaSSI data for model calibration from the 2000–2012 time frame. Therefore, monthly ET is expressed as.

$$ET_m = 6.118 + 5.915LAI_{P_m} + 0.147P_m + 0.426PET_m \quad (4)$$

All three statistical methods (Equations 2–4) were compared against WaSSI modeled long term monthly ET for the validation subset of the original 48 watersheds ([Fig. 3](#)). Long term mean monthly  $P$ , PET, and  $LAI_P$  provided by WaSSI for each watershed for 2000–2012 was used, since this was the range of temporal availability for empirical  $LAI_P$ . The WaSSI framework supplies a mean monthly (2000–2012)  $LAI_P$  sourced from MODIS remote sensing ([Zhao et al., 2005](#)) for each land use type (crop, deciduous forest, evergreen forest, mixed forest, grassland,

shrubland, wetland, water, urban, and barren) across HUC8 watersheds, although when simulating  $Q$  changes, only forest LAI (the aggregate of deciduous, evergreen, and mixed forest) can be modified. Note that the WaSSI  $LAI_P$  data provided here were only used to validate the previously established ET regression models ([Sun et al., 2011a](#) and [Cohen et al., 2018](#)) as well as calibrate and validate the model developed in this study.

Equations (2) and (4) were therefore used to simulate management-induced changes on the monthly water budget, which were aggregated to the annual scale. Long term mean monthly values for  $P$  and PET across the 48 WaSSI watersheds were found by spatially averaging the values across the 55-year time horizon (1965–2015) to represent the general climate of the assessed region. These long term monthly PET and  $P$  values were held constant in each simulation to isolate the effect of management scenarios on the water budget. Simulated monthly ET values for each scenario were then compared to baseline LAI conditions in which stand age ( $\geq 14$  years old) and were aggregated to the annual scale, at which Equation (3) operates. Long-term mean annual  $Q$  was ultimately estimated via the long-term water budget,  $Q = P - ET$ .

### 3. Results

#### 3.1. ET model validations

[Fig. 3](#) illustrates the performance of the statistical models used to investigate water budget dynamics under the various management scenarios. All three ET models from [Sun et al. \(2011a\)](#), [Cohen et al. \(2018\)](#), and this study's model performed well with significant fits at  $p$ -value  $< 0.001$ . The [Sun et al. \(2011a\)](#) and [Cohen et al. \(2018\)](#) models produced similar slopes and intercepts, and both had an  $R^2 = 0.91$ , which is notable since [Sun et al. \(2011a\)](#) calibrated their model using data from different sites around the world, and [Cohen et al. \(2018\)](#) used data from sites in Florida. This study performed the best overall, with the highest  $R^2$  value and intercept value closest to zero at  $-0.77$ . This makes sense that the model in this study would perform best, given it was both calibrated and validated using WaSSI data, albeit different data subsets for each.

#### 3.2. Management impacts on $Q$ at the watershed scale

The WaSSI  $Q$  simulations included thinning (10%, 20%, 50%, 80% LAI reductions) and clear-cut (100% LAI reduction) conditions. [Fig. 4A](#) shows relative pine management scenario-based  $Q$  impacts (%) for each watershed arranged by increasing forest cover, where there was a positive linear relationship between pine management-induced  $Q$  increases and forest coverage. The positive relationship between  $Q$  response and forest cover proportion was generally the strongest for the clear-cut scenario (slope,  $\beta = 0.41$ ) and the weakest under 10% thinning ( $\beta = 0.04$ ), which is reasonable since a total clearing of a more forested watershed would sensibly yield a stronger  $Q$  response than one that is less forested. Lastly, linear predictive power decreased with LAI reduction, with  $R^2$  ranging from 0.64 for 10% thinning to 0.57 for clear-cut ([Table S1](#)). Full results for the linear models, including standard errors for parameter estimates, are provided in [Table S1](#).

Results showed that clear-cut yielded the greatest overall increase in mean annual  $Q$  across the 48 examined watersheds ([Fig. 4B](#)). [Fig. 2C](#) reveals that the variability in  $Q$  response across watersheds was greatest for the clear-cut scenario and least for 10% thinning. This is reasonable, since the 10% thinning scenario imposes the smallest overall effect on the water budget of all evaluated management and climate scenarios.

The  $Q$  response to each management scenario varied spatially but did not show coherent spatial grouping or adjacency patterns ([Fig. 5](#)). There also were no notable differences in the  $Q$  responses between coastal and inland watersheds. Climatic characteristics like  $P$  and aridity index also did not show to have any effect on management-induced  $Q$  impacts. Instead, underlying biophysical mechanisms that characterized the

watersheds influenced Q response. The watersheds that were more forested (Figure S1A) experienced a greater Q response under 50% thinning, which is a relationship also supported by Fig. 4A.

### 3.3. Management impacts on Q at the plot scale

We employed two different plot-scale LAI estimates in this study, one statistical (McLaughlin et al., 2013) and one based on mechanistic processes (GYCB). Using these two LAI estimates as inputs, the three statistical water budget estimates yielded varying long term mean annual Q responses under thinning, short-rotation, and clear-cut management scenarios for each LAI estimate (Fig. 6). Like in the WaSSI simulations (Fig. 4), clear-cut provided the greatest increase in Q when compared to baseline conditions for both LAI estimates, followed by the next largest thinning scenarios (80% and 50%, respectively). Under short rotation conditions, the number of years in rotation (i.e., 10 versus 18 years) had a greater Q effect when McLaughlin et al. (2013) LAI was used when compared to GYCB LAI. Also, the Q response under each management scenario was overall greater for McLaughlin et al. (2013) LAI compared to GYCB LAI, because GYCB LAI is estimated as lower than that of McLaughlin et al. (2013). For both LAI methods, long term mean annual Q response under 50% thinning was larger than both short rotation scenarios, although GYCB LAI yielded a Q response that was smaller than 20% thinning under SR18. Consistently, the two statistical ET models, Sun et al. (2011a) and Cohen et al. (2018), produced the highest Q response for each scenario, while the statistical model derived in the current study produced the lowest Q response.

## 4. Discussion

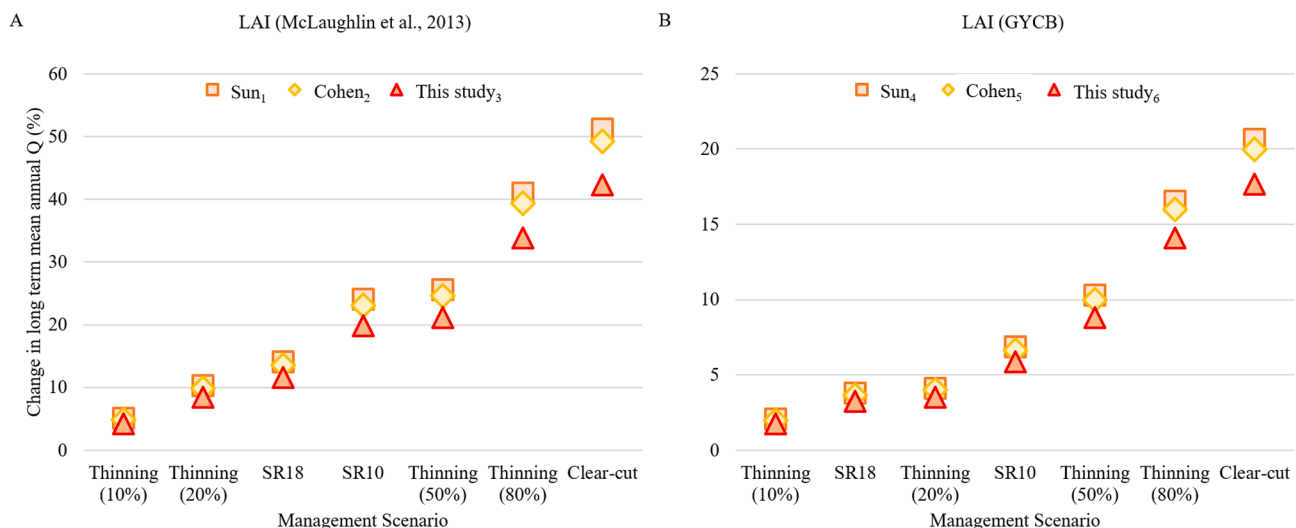
We hypothesized that clear-cut conditions would yield the greatest Q increase, short rotation scenarios would yield a Q increase close to 50% thinning conditions, and management-induced Q effects are scale dependent, with Q response being greater at the plot rather than watershed scale. Both the WaSSI watershed and pine plantation plot simulations mostly supported our hypotheses. Clear-cut yielded the greatest Q increase, and SR10 with LAI derived from McLaughlin et al. (2013) was close to the Q impact of 50% thinning (Fig. 6A). This suggests that more intensive short-rotation management practices could have a similar water budget impact to 50% thinning on the plot scale, although GYCB LAI yielded a Q effect that was smaller under SR10 and SR18. Also, there were discrepancies in hydrologic impact between the

two modeled spatial scales, where plot-scale analyses showed on average a larger Q impact with each management scenario. Overall, our results support the notion that landowners can mitigate local water supply shortages via biomass management practices, especially since they are operating at the plot-scale where hydrologic impacts can be more responsive to management strategies than at the watershed scale.

Sun et al. (2011a) calibrated their ET model using sites that comprised multiple ecosystem characteristics and encompassed three continents. Despite the physical site disparities, the model performed as well as for the 14 validation watersheds in the southeast as did the Cohen et al. (2018) model that was calibrated on pine plantations in the southeast. This study's ET model performed only slightly better ( $R^2 = 0.94$  compared to 0.91), which was calibrated on the watersheds in the assessed southeastern region. This could be a reason for why this study's model showed lower Q impact than both Sun et al. (2011a) and Cohen et al. (2018). The high performance of Cohen et al. (2018) could be in part because the authors do not include P as a variable in their model, and the assessed region has a relatively low P variability across validation watersheds, with a range of 1,130 mm yr<sup>-1</sup> to 1,563 mm yr<sup>-1</sup> and a coefficient of variation equal to 0.09. Therefore, Cohen et al., 2018 may more easily capture the overall mean evaporative behavior of a system with comparatively spatially consistent P rates.

Aridity and P can theoretically play a role in resilience against management-induced land cover perturbations and their effect on the water budget. Liu et al. (2018) found that more energy-limited (i.e., humid) systems are less vulnerable to Q changes given thinning conditions. Figure S1 illustrates that P is generally higher and aridity is generally lower in the evaluated Florida watersheds than those in Georgia and Alabama. However, our results showed there was no difference in Q impact from management scenarios in watersheds that were humid versus those that were less humid, nor in watersheds with comparatively higher P. These results could be because the range of humidity is relatively small (1.03–1.41) for this region.

At the watershed scale, the distribution of the WaSSI modeled relative impacts on Q from various management scenarios was related to watershed biophysical characteristics. We found a positive linear relationship between management-induced Q changes and forest cover proportion based on WaSSI (Fig. 4A). This is physically reasonable, since it would be expected that a more forested watershed would yield a more detectable hydrologic impact due to a uniform change in forest cover (i.e., there is more forest to be deforested). Although our results indicated an increasingly positive relationship between Q impacts and forest



**Fig. 6.** Changes in long term mean annual Q (%) at the plantation (i.e., plot) scale. Two differentiated LAI estimates were used, McLaughlin et al., 2013 (A) and GYCB (B) models, which were inputs into three statistical ET models to assess water budget impacts under thinning and short rotation scenarios. Subscripts 1–6 correspond to the water budget evaluation method described in Table 1.



coverage, predictive power as denoted by  $R^2$  decreased (Table S1). These results suggest that there is an increasingly variable hydrologic response under more extreme management conditions (i.e., greater decreases in LAI). Since these management scenarios were simulated as being uniformly applied on forests across the watershed, it is evident that other varying biophysical factors apart from forest coverage (such as the spatial distribution of forest LAI) are involved in mitigating Q response to land cover changes at the watershed scale. Some watersheds may therefore be more resilient to certain changes in drivers that impact Q rates.

Relative changes in Q due to management practices were different between the WaSSI watershed analyses and the statistical site-based approaches, with an average larger impact on Q under thinning and clear-cut conditions at the site rather than watershed scale. The plot-scale management-induced Q increases were variable across the two LAI methods and three ET methods, ranging from about 2%–51%. This range is corroborated by McLaughlin et al. (2013) and Susaeta et al. (2017). However, Liu et al. (2018) assessed only one pine plantation over a smaller time frame (2006–2015) and found a comparatively smaller Q increase when pine biomass decreased. For our WaSSI watershed simulations, the range of Q impacts was 0%–25%, where the smallest values represented the management scenario of smallest impact (i.e., 10% thinning) in watersheds that had the lowest forest cover. The WaSSI results presented here are consistent with the national-scale WaSSI-based study by Sun et al. (2015), in which they showed that increased LAI reductions yielded increased Q rates of around 10–30% for the same evaluated region.

The differences between the watershed and plot-scale simulations are likely due to spatial discrepancies, in which plot-level pine LAI has a larger effect on ET dynamics than the WaSSI watershed-level forest LAI effects on ET. It is widely accepted that the impacts of land cover on water budget do not linearly scale up (Lawrence and Vandecar, 2015; Li et al., 2020; Zhang et al., 2017), in that plot-level perturbations could yield different relative impacts on Q than watershed or regional scale land cover perturbations. It is also worth noting that the ET models from Sun et al. (2011a) and Cohen et al. (2018) were calibrated at the plot scale, while this study's ET model was calibrated using the WaSSI watershed data and applied to the plot scale. Moreover, for the WaSSI watershed analyses, the magnitude of Q change is influenced by the actual amount of forest coverage present in the watershed, since this is based on empirical data, whereas the plot simulations assume a system of uniform forest coverage. Lastly, the WaSSI algorithms are different than those of the statistical plot simulations and include multiple land cover types and other spatially varying biophysical attributes that impact hydrology. It is then feasible that over larger areas, relative land cover-induced changes on the water budget are less extreme, and instead hydrologic dynamics are governed mostly by climate at bigger spatial scales (Boisier et al., 2014; Zhang et al., 2017).

This study has a few limitations. First, it would be ideal to compare the interannual variability of Q response under each management scenario instead of simply considering long term mean annual water availability. A future analysis may evaluate long term monthly Q responses from pine plantation management practices and therefore better characterize seasonal dynamics that can be compared with drier seasons that result in lower surface water availability. It additionally might be useful to assess Q responses under both climate and management practices in order to explore compounded effects on the water budget. Second, short-rotation management could not be applied in the WaSSI watershed analysis via the online platform, but a complementary study may consider the WaSSI model's governing equations to assess the relationship between Q and LAI changes over time. Third, long term Q data availability under a variety of pine management scenarios at multiple spatial scales is lacking, therefore complicating true model validation. Despite these limitations, this work provides a solid baseline to assess a suite of management possibilities and their impacts on water availability at both plot and watershed scales. The results presented here

are meaningful for landowners who seek to assess the product yield and hydrologic tradeoffs of different management practices.

## 5. Conclusions

Our results suggest that forest biomass is a major control of ET and water yield in the southeastern U.S. Evapotranspiration models developed for local conditions with limited forest structure information beyond LAI are sufficient for quantifying hydrologic response to forest bioenergy management. We considered multiple approaches that include process-based physical models as well as empirically-based statistical methods to capture ecohydrological dynamics at both the pine plantation plot and watershed scales in the southeastern U.S. The methods used here can serve as a foundation for integrating multiple techniques for assessing multi-scale water budget changes under a variety of management conditions.

Here we conclude water yield is highest under clear-cut conditions but still increases correspondingly with thinning intensity. Forest thinning therefore can yield optimized values for both biodiversity and water yield, despite not fully maximizing both ecosystem services. Ultimately, the increase in water yield under certain imposed management strategies can allow for increased local resilience to climate variability where water availability may be unpredictable, like in periods of drought. Landowners' increased knowledge of the tradeoffs associated with practices within their local system provides for greater power of choice when deciding which potential strategies are most concurrent with their economic and ecological objectives.

## 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.

## Acknowledgements

This research was supported in part by USDA-NIFA Initiative Grant No 2017-67019-26291, the University of Florida, and by the Southern Research Station, US Forest Service, United States.

## Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.foreco.2022.120454>.

## References

- Asner, G.P., Scurlock, J.M., Hicke, A., J., 2003. Global synthesis of leaf area index observations: implications for ecological and remote sensing studies. *Glob. Ecol. Biogeogr.* 12 (3), 191–205.
- Boisier, J.P., de Noblet-Ducoudré, N., Ciais, P., 2014. Historical land-use-induced evapotranspiration changes estimated from present-day observations and reconstructed land-cover maps. *Hydrol. Earth Syst. Sci.* 18 (9), 3571–3590.
- Caldwell, P.V., Kennen, J.G., Sun, G., Kiang, J.E., Butcher, J.B., Eddy, M.C., Hay, L.E., LaFontaine, J.H., Hain, E.F., Nelson, S.A.C., McNulty, S.G., 2015. A comparison of hydrologic models for ecological flows and water availability. *Ecohydrology* 8 (8), 1525–1546.
- Chum, H., Faaij, A., Moreira, J., Berndes, G., Dhamija, P., Dong, H., Gabriella, B., Goss Eng, A., Lucht, W., Mapako, M., Masero Cerutti, O., McIntyre, T., Minowa, T., Pingoud, K. (2011). Bioenergy. In: O. Edenhofer, R. Pichs-Madruga, Y. Sokona, D. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickenmeier, G. Hansen, S. Schlomer, C. von Stechow (Eds.), *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*. Cambridge, UK: Cambridge University Press. <http://www.ipcc.ch/site/assets/uploads/2018/03/Chapter-2-Bioenergy-1.pdf>.
- Cohen, M., McLaughlin, D., Kaplan, D., 2018. *Managing Forests for Increased Regional Water Availability* (20834). Retrieved from Florida Dept Agriculture and Consumer Services website.
- Evans, J., Cohen, M., 2009. Regional water resource implications of bioethanol production in the Southeastern United States. *Glob. Change Biol.* 15 (9), 2261–2273.
- 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 (3), 749–776.



- Gottlieb, I.G., Fletcher Jr, R.J., Nuñez-Regueiro, M.M., Ober, H., Smith, L., Brosi, B.J., 2017. Alternative biomass strategies for bioenergy: implications for bird communities across the southeastern United States. *GCB Bioenergy* 9 (11), 1606–1617.
- Grace III, J.M., Skaggs, R.W., Chescheir, G.M., 2006. Hydrologic and water quality effects of thinning loblolly pine. *Trans. ASABE* 49 (3), 645–654.
- Griffiths, N.A., Rau, B.M., Vaché, K.B., Starr, G., Bitew, M.M., Aubrey, D.P., Martin, J.A., Benton, E., Jackson, C.R., 2019. Environmental effects of short-rotation woody crops for bioenergy: what is and isn't known. *GCB Bioenergy* 11 (4), 554–572.
- Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Megown, K., 2015. Completion of the 2011 national land cover database for the conterminous united states—representing a decade of land cover change information. *Photogramm. Eng. Remote Sens.* 81 (5), 345–354.
- Jackson, C. R., Sun, G., Amatya, D., Swank, W. T., Riedel, M., Patric, J., & Ice, G. G. (2004). Fifty years of forest hydrology in the Southeast. In: Ice, GG; Stednick, JD A century of forested and wildland watershed lessons. Bethesda, MD: The Society of American Foresters. 33-112. Chapter 3.
- Johnson, J.D., 1984. A rapid technique for estimating total surface area of pine needles. *Forest Sci.* 30 (4), 913–921.
- Jones, G.M., Brosi, B., Evans, J.M., Gottlieb, I.G.W., Loy, X., Núñez-Regueiro, M.M., Ober, H.K., Pienaar, E., Pillay, R., Pisarello, K., Smith, L.L., Fletcher, R.J., 2022. Conserving alpha and beta diversity in wood-production landscapes. *Conserv. Biol.* 36 (3) <https://doi.org/10.1111/cobi.v36.310.1111/cobi.13872>.
- Jones, G.M., Smith, L., Gottlieb, I.G.W., Ober, H.K., Brosi, B., Fletcher, R.J., 2020. Herpetofaunal responses to intensification of woody bioenergy production in a global biodiversity hotspot. *For. Ecol. Manage.* 477, 118493. <https://doi.org/10.1016/j.foreco.2020.118493>.
- Lawrence, D., Vandekar, K., 2015. Effects of tropical deforestation on climate and agriculture. *Nat. Clim. Change* 5 (1), 27–36.
- Li, C., Sun, G.e., Caldwell, P.V., Cohen, E., Fang, Y., Zhang, Y., Oudin, L., Sanchez, G.M., Meentemeyer, R.K., 2020. Impacts of urbanization on watershed water balances across the conterminous United States. *Water Resour. Res.* 56 (7) <https://doi.org/10.1029/2019WR026574>.
- Liu, N., Caldwell, P.V., Dobbs, G.R., Miniati, C.F., Bolstad, P.V., Nelson, S.A.C., Sun, G.e., 2021. Forested lands dominate drinking water supply in the conterminous United States. *Environ. Res. Lett.* 16 (8), 084008. <https://doi.org/10.1088/1748-9326/ac09b0>.
- Liu, X., Sun, G.e., Mitra, B., Noormets, A., Gavazzi, M.J., Domec, J.-C., Hallema, D.W., Li, J., Fang, Y., King, J.S., McNulty, S.G., 2018. Drought and thinning have limited impacts on evapotranspiration in a managed pine plantation on the southeastern United States coastal plain. *Agric. For. Meteorol.* 262, 14–23.
- Lockaby, G., Nagy, C., Vose, J. M., Ford, C. R., Sun, G., McNulty, S., et al. (2013). Forests and water. In: *Wear, David N.; Greis, John G., Eds. 2013. The Southern Forest Futures Project: Technical Report. Gen. Tech. Rep. SRS-GTR-178. Asheville, NC: USDA-Forest Service, Southern Research Station. 309-339., 178, 309–339.*
- Loy, X., Gruenewald, D., Gottlieb, I.G., Dobbs, E.K., Miljanic, A.S., Botsch, J., Brosi, B.J., 2020. The impacts of bioenergy pine plantation management practices on bee communities. *J. Appl. Ecol.* 57 (5), 952–962.
- McLaughlin, D.L., Kaplan, D.A., Cohen, M.J., 2013. Managing forests for increased regional water yield in the southeastern US Coastal Plain. *JAWRA J. Am. Water Res. Association* 49 (4), 953–965.
- Miralles, D.G., De Jeu, R.A.M., Gash, J.H., Holmes, T.R.H., Dolman, A.J., 2011. An application of GLEAM to estimating global evaporation. *Hydrol. Earth Syst. Sci. Discuss.* 8 (1).
- Núñez-Regueiro, M.M., Siddiqui, S.F., Fletcher Jr, R.J., 2021. Effects of bioenergy on biodiversity arising from land use change and crop type. *Conserv. Biol.* 35 (1), 77–87.
- Ober, H.K., Jones, G.M., Gottlieb, I.G., Johnson, S.A., Smith, L., Brosi, B.J., Fletcher Jr, R. J., 2020. Bat community response to intensification of biomass production for bioenergy across the southeastern United States. *Ecol. Appl.* 30 (7), e02155.
- Peña-Arancibia, J.L., Bruijnzeel, L.A., Mulligan, M., Van Dijk, A.I., 2019. Forests as 'sponges' and 'pumps': assessing the impact of deforestation on dry-season flows across the tropics. *J. Hydrol.* 574, 946–963.
- Perdue, J.H., Stanturf, J.A., Young, T.M., Huang, X., Dougherty, D., Pigott, M., Guo, Z., 2017. Profitability potential for Pinus taeda L. (loblolly pine) short-rotation bioenergy plantings in the southern USA. *Forest Policy and Economics* 83, 146–155.
- Perrando, E.R., Breunig, F.M., Galvão, L.S., Bostelmann, S.L., Martarello, V., Straube, J., De Marco, R., 2021. Evaluation of the effects of Pine management on the water yield and quality in southern Brazil. *J. Sustainable For.* 40 (3), 217–233.
- Riekerk, H., 1989. Influence of silvicultural practices on the hydrology of pine flatwoods in Florida. *Water Resour. Res.* 25 (4), 713–719.
- Sanford, W.E., Selnick, D.L., 2013. Estimation of evapotranspiration across the conterminous united states using a regression with climate and land-cover data 1. *JAWRA J. Am. Water Res. Association* 49 (1), 217–230.
- Sun, G., Amatya, D.M., McNulty, S.G., Skaggs, R.W., Hughes, J.H., 2000. Climate change impacts on the hydrology and productivity of a pine plantation 1. *JAWRA J. Am. Water Res. Association* 36 (2), 367–374.
- Sun, G., Alstad, K., Chen, J., Chen, S., Ford, C.R., Lin, G., et al., 2011a. A general predictive model for estimating monthly ecosystem evapotranspiration. *Ecohydrology* 4 (2), 245–255.
- Sun, G., Caldwell, P.V., McNulty, S.G., 2015. Modelling the potential role of forest thinning in maintaining water supplies under a changing climate across the conterminous United States. *Hydrol. Process.* 29 (24), 5016–5030.
- Sun, G., Caldwell, P., Noormets, A., McNulty, S.G., Cohen, E., et al., 2011b. Upscaling key ecosystem functions across the conterminous United States by a water-centric ecosystem model. *J. Geophys. Res.* 116, G00J05.
- Sun, G., McNulty, S.G., Moore Myers, J.A., Cohen, E.C., 2008. Impacts of multiple stresses on water demand and supply across the Southeastern United States 1. *JAWRA J. Am. Water Res. Association* 44 (6), 1441–1457.
- Sun, Ge.;Zhang, Liangxia;Duan, Kai;Rau, Benjamin 2017. Impacts of forest biomass removal on water yield across the United States. In: R. A. Efraymon, M. H. Langholtz, K.E. Johnson, and B. J. Stokes (Eds.), 2016 Billion-Ton Report: Advancing Domestic Resources for a Thriving Bioeconomy, Volume 2: Environmental Sustainability Effects of Select Scenarios from Volume 1. ORNL/TM-2016/727. Oak Ridge National Laboratory, Oak Ridge, TN. 640p. doi 10.2172/1338837.
- Sun, G., Riekerk, H., Comerford, N.B., 1998a. Modeling the forest hydrology of wetland-upland ecosystems in Florida. *JAWRA J. Am. Water Resour. Assoc.* 34 (4), 827–841.
- Sun, G., Riekerk, H., Comerford, N.B., 1998b. Modeling the hydrologic impacts of forest harvesting on Florida flatwoods. *JAWRA J. Am. Water Resour. Assoc.* 34 (4), 843–854.
- Susaeta, A., Adams, D.C., Gonzalez-Benecke, C., Soto, J.R., 2017. Economic feasibility of managing loblolly pine forests for water production under climate change in the southeastern United States. *Forests* 8 (3), 83.
- Trlica, A., Cook, R.L., Albaugh, T.J., Parajuli, R., Carter, D.R., Rubilar, R.A., 2021. Financial Returns for Biomass on Short-Rotation Loblolly Pine Plantations in the Southeastern United States. *Forest Sci.* 20, 1–12.
- Usda, 2010. A USDA regional roadmap to meeting the biofuels goals of the renewable fuels standard by 2022. *Biofuels Strategic Production Report*, USDA, Washington, D. C., USA.
- U.S. Department of Energy. 2016. *2016 Billion-Ton Report: Advancing Domestic Resources for a Thriving Bioeconomy, Volume 1: Economic Availability of Feedstocks*. M. H. Langholtz, B. J. Stokes, and L. M. Eaton (Leads), ORNL/TM-2016/160. Oak Ridge National Laboratory, Oak Ridge, TN. 448p.
- Vache, K., Meles, M.B., Griffiths, N.A., Jackson, C.R., 2021. Ensemble modeling of watershed-scale hydrologic effects of short-rotation woody crop production. *Biofuels, Bioproducts and Biorefining*.
- Vance, E.D., Maguire, D.A., Zalesny Jr, R.S., 2010. Research strategies for increasing productivity of intensively managed forest plantations. *J. Forest.* 108 (4), 183–192.
- Vose, J.M., Allen, H.L., 1988. Leaf area, stemwood growth, and nutrition relationships in loblolly pine. *Forest Sci.* 34 (3), 547–563.
- Vose, J.M., Miniati, C.F., Sun, G.e., Caldwell, P.V., 2014. Potential implications for expansion of freeze-tolerant eucalyptus plantations on water resources in the southern United States. *Forest Sci.* 13, p.
- Wei, Z., Yoshimura, K., Wang, L., Miralles, D.G., Jasechko, S., Lee, X., 2017. Revisiting the contribution of transpiration to global terrestrial evapotranspiration. *Geophys. Res. Lett.* 44 (6), 2792–2801.
- Zhang, M., Liu, N., Harper, R., Li, Q., Liu, K., Wei, X., 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.
- Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W., 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sens. Environ.* 95 (2), 164–176.
- Zhou, G., Wei, X., Chen, X., Zhou, P., Liu, X., Xiao, Y., Sun, G., Scott, D., Zhou, S., Han, L., Su, Y., 2015. Global pattern for the effect of climate and land cover on water yield. *Nat. Commun.* 6, 5918.