

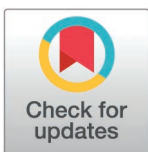
RESEARCH ARTICLE

Projected land use changes will cause water quality degradation at drinking water intakes across a regional watershed

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Abstract

Forest conversion to development threatens the ability of watersheds to provide stable and clean water supplies. Water managers are targeting forest conservation as a source water protection strategy to maintain healthy watershed function in developing areas, especially upstream of drinking water treatment facilities. Understanding the role of current forest cover in safeguarding these facilities is therefore crucial. We used the Soil and Water Assessment Tool (SWAT) to examine the relationship between upstream forest cover and downstream water resources under both current (2020) conditions and multiple projected land use scenarios for 2070 in the Middle Chattahoochee watershed, USA. We investigated the extent to which existing forest cover benefits water quality at 15 drinking water intake facilities within the watershed. Our analysis of four land use change scenarios revealed that forest conversion and increased development resulted in higher average annual concentrations of total suspended sediment (TSS) and total nitrogen (TN) at 13 out of 15 intake facilities, with potential increases of up to 318% for sediment and 220% for nitrogen. Conversely, concentrations decreased relative to the baseline when upstream agricultural land was converted to forest cover or new, low-intensity development, suggesting that certain types of development may improve water quality compared to maintaining agricultural land. Our results also indicated that extreme nitrogen and sediment concentration events – defined as days exceeding the highest 10th percentile of baseline concentrations – could become 3.6 to 6.6 times more frequent in the future, respectively. Notably, forest conversion to new development upstream of intakes with smaller subwatersheds could reduce water quality for utilities serving smaller towns and rural areas, which may have limited resources for managing this challenge. Our findings highlight vulnerable intake locations and underscore the benefit of forest conservation for source water protection under future land use change.

OPEN ACCESS

Citation: Gay ET, Martin KL, Caldwell PV (2025) Projected land use changes will cause water quality degradation at drinking water intakes across a regional watershed. PLOS Water 4(4): e0000313. <https://doi.org/10.1371/journal.pwat.0000313>

Editor: Ilunga Kamika, University of South Africa, SOUTH AFRICA

Received: September 25, 2024

Accepted: February 17, 2025

Published: April 23, 2025

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Data availability statement: Data used for SWAT model setup are included in the article and supplementary material. Data used to create the figures and tables are available in the Dryad repository at <https://doi.org/10.5061/dryad.3r2280gsm>.

Funding: This work was supported by the U.S. Department of Agriculture (USDA)

1. Introduction

As the world undergoes rapid urbanization, forests play an increasingly crucial role in safeguarding water resources [1]. Forested areas produce consistent, high-quality water yield relative to other land cover types [2,3]. This is due to their influence on watershed hydrology,

Forest Service Southern Research Station by agreement number 20-CS-11330180-053 to Dr. Katherine Martin at North Carolina State University. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

through processes such as high interception rates and enhanced infiltration capacity [4,5]. Forested areas improve water quality by filtering nutrients and contaminants, reducing overland flow and erosion, shading channel networks, lowering stream water temperatures, increasing water residence time, stabilizing stream banks against erosion, and providing physical roughness to slow down debris and sediment [6–8]. Therefore, when forests are converted to more intensive land uses like agriculture and development, these hydrological benefits are lost.

Agriculture and development land practices can elevate nutrient and sediment concentrations in a watershed, with agricultural practices sometimes contributing more to water quality degradation than urban areas [2]. On agricultural lands, fertilizer and manure applications are primary sources of riverine nitrogen pollution in the United States (US) [9], while crop cultivation can cause substantial erosion [10] and contribute towards elevated turbidity [11]. In urban areas, lawn fertilizer and pet waste are significant sources of nitrogen, particularly through stormwater runoff [12] while construction, extensive road networks, direct discharge points, and sewer systems can play a major role in both nutrient and sediment loading [13]. Elevated nutrient and sediment loadings from agricultural and developed land are of particular concern at downstream drinking water treatment facilities, where sediment and nitrogen remain principal pollutants [14].

In the US, advancements in monitoring and water treatment technology at intake facilities have led to improved finished drinking water quality over time [15]. However, this progress has occasionally shifted attention away from the importance of protecting source water supplies [16]. As population and subsequent development have risen alongside these technological improvements, upstream forest cover has decreased. Consequently, raw water entering treatment facilities is increasingly originating from agricultural, residential, and industrial lands [17], with corresponding decreases in source water quality [18]. In response, water resource managers are prioritizing source water protection strategies to mitigate the compounded effects of increased water demand and degraded water quality [16,19]. In 2024, for the first time, source water protection was ranked the top issue among more than 2,400 water professionals in the US [20].

Multiple studies have investigated the relationship between land use and water resources from site-specific to broad watershed scales. However, fewer studies explicitly examine how changes in land use impact water quality at water treatment facilities. The Soil and Water Assessment Tool (SWAT) has been commonly used internationally to examine the effects of land use change on the water balance at the watershed scale [21–23], on nitrogen pollution within an urban area [24], and on sediment yield in river systems [25]. While SWAT has been used to evaluate extreme flood events [26] and nutrient export [27,28] in drinking water supply reservoirs, its use to examine how land use change affects water quality at drinking water treatment facilities remains limited. Studying land cover change at these facilities is particularly critical now, as upstream forest cover has been linked to better water quality [2] and reduced treatment costs [29–31] in source water areas. Therefore, this study addresses this critical gap by directly studying how upstream land use change affects downstream water quality at drinking water treatment facilities in a rapidly urbanizing watershed, deepening insights into the benefit of current forest cover relative to predicted future losses.

This study uses a novel methodology to advance our understanding of how forest cover contributes to source water protection by assessing the impacts of projected future land use change on drinking water quality in the Middle Chattahoochee watershed in the US Southeast (SE). Using SWAT, we examined the relationship between upstream forest cover and downstream water quality under both current (2020) conditions and multiple projected land use scenarios for 2070. Our investigation specifically focused on the benefits that existing forest

cover provides to 15 drinking water intake facilities within the watershed. Using model outputs, we assessed the importance of current forest cover for source water protection and identified intake locations where water quality is projected to decline in response to upstream land use change. These findings can help land managers develop strategies to strengthen drinking water supply resiliency in a developing watershed.

2. Methods

2.1. Study watershed

Our study area is the Middle Chattahoochee (MC) watershed, situated within the larger Apalachicola-Chattahoochee-Flint (ACF) River Basin in the US SE (Fig 1). The Chattahoochee River originates in northern Georgia (GA) and forms the headwaters of the ACF. It connects the physiographic regions of the Blue Ridge, Piedmont, and Coastal Plain and crosses the states of Georgia, Alabama, and Florida. The Chattahoochee River eventually converges with the Flint River at the Georgia-Florida border, forming the Apalachicola River, which ultimately drains into the Apalachicola Bay.

The MC watershed, spanning 11,132 km² and identified with the United States Geological Survey (USGS) HUC-8 #03130002, originates downstream of the Upper Chattahoochee Watershed (HUC-8 #03130001) near Atlanta, GA and extends to the area near Columbus, GA. Consequently, both its headwaters and outlet are located near large cities. We focused on the MC portion of the larger Chattahoochee watershed due to its substantial forest cover that is highly vulnerable to development [33]. As of 2019, the MC was approximately 60% forested, 15% developed, 10% agriculture, 10% barren/grassland, and 5% wetlands [34]. The topography ranges from elevations of 51 m to 547 m and primarily consists of ultisol soils [35]. There are several hydropower facilities on the Chattahoochee River and the largest, West Point Lake Reservoir, is located within the MC. There are 15 surface water drinking intakes managed by 13 Public Water Systems within the MC watershed, supplying water to over 690,000 individuals [32]. The MC faces significant water quality challenges stemming from rapid development, wastewater discharges, agricultural land cover, and nonpoint source pollution. Recent incidents, such as harmful algal blooms at Lake Harding [36], and elevated *E. coli* levels from wastewater spillage [37], have necessitated temporary closures of portions of the Chattahoochee River to the public.

2.2. Hydrologic modeling approach

2.2.1. SWAT model description. We utilized the Soil and Water Assessment Tool (SWAT) ArcSWAT 2012 interface (version 10.7.1) to model streamflow, total suspended sediment (TSS), and total nitrogen (TN) in the MC watershed under multiple land use scenarios. SWAT is a semi-distributed hydrologic model that uses spatial and tabular inputs to simulate water, sediment, and nutrient outputs [38]. Watershed delineation requires a pre-processed digital elevation model (DEM) to define the stream network and discretize the watershed into subbasins. Users can add a watershed inlet, create subbasin outlets, and add reservoir locations. These subbasins are further divided into hydrologic response units (HRUs) based on land use, soil data, and slope classifications. SWAT first computes land and water routing within each HRU before aggregating to the subbasin level. Weather data inputs include daily averages of precipitation, solar radiation, wind speed, relative humidity, and minimum and maximum temperature. SWAT can run for daily, monthly, or yearly simulation periods and can output various water balance and water quality parameters [39].

2.2.2. SWAT model inputs and set-up. We used a 30 m DEM from the USGS National Map [40] and a 3,000 ha drainage area threshold to define the stream network. To provide

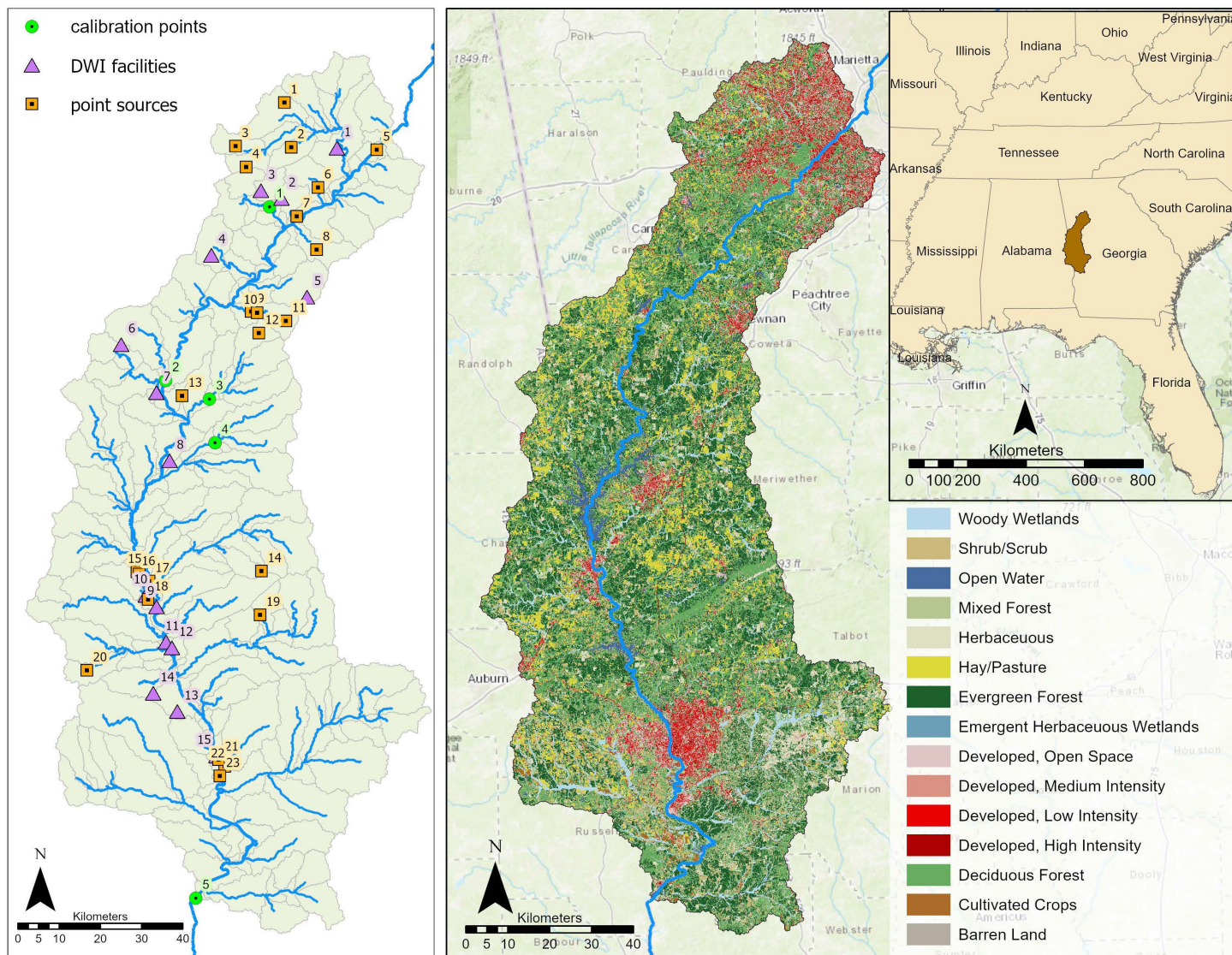


Fig 1. Middle Chattahoochee study area with the 2011 NLCD showing point source, calibration gage, and drinking water intake facility locations. Facility location data were derived from the US Environmental Protection Agency Safe Drinking Water Information System [32]. Service layer credits: Esri, HERE, Garmin, FAO, USGS, NGA, EPA, NPS, NLCD.

<https://doi.org/10.1371/journal.pwat.0000313.g001>

sediment and nutrient inputs from the Upper Chattahoochee watershed, the MC upstream extent was delineated using a water quality monitoring site (RV_12_3891) from the Georgia Environmental Monitoring and Assessment System (GOMAS) portal [41]. A downstream USGS flow gage (02336490) provided upstream flow inputs to the MC, with flow values scaled by drainage area (1%) to approximate flow at the water quality monitoring site. The final inlet input file contained daily records for streamflow (m^3/day), TSS (metric tons/day), and TN (kg/day) that were held constant for all land use scenarios.

In addition to the inlet site, the watershed outlet and four co-located flow and water quality monitoring sites were delineated in the SWAT subbasin network (S1 Table; Fig 1). These gage locations provide observed records of streamflow, TSS, and TN used during calibration and validation to evaluate model performance. The overall outlet for the watershed was defined

Table 1. Drinking water intake facilities in the Middle Chattahoochee Watershed SWAT model. Facility locations were added as outlets of subbasins. Facility location data were derived from the *US Environmental Protection Agency Safe Drinking Water Information System* [32]. Population served is at the Public Water System level, thus for Public Water Systems with more than one intake facility, the population served is the total served across all facilities in the Public Water System and are not additive.

<i>ID</i>	<i>Public Water System</i>	<i>Population Served</i>	<i>Facility Name</i>
1	East Point	33712	Sweetwater Creek
2	Douglasville-Douglas County Water and Sewer Authority	109694	Bear Creek
3	Douglasville-Douglas County Water and Sewer Authority	109694	Dog River
4	Carroll County	45380	Snake Creek
5	Coweta Water and Sewer Authority	68803	BT Brown Reservoir
6	Heard Water and Sewer Authority	8172	Centralhatchee Creek
7	Heard Water and Sewer Authority	8172	Hillabahatchee Creek
8	Lagrange Water and Sewer Authority	41852	West Point Lake
9	West Point Lake	3929	Chattahoochee River
10	Chattahoochee Valley Water Supply District	32	Chattahoochee River
11	Opelika Utilities	38943	R.A. Betts Intake
12	Harris County Water System	20062	Bartlett's Ferry Reservoir
13	Smiths Water and Sewer Authority	29859	Lake Oliver
14	Columbus Water	229000	Lake Oliver
15	Phenix City Utilities	35358	Chattahoochee River

<https://doi.org/10.1371/journal.pwat.0000313.t001>

at USGS gage 02342881 Chattahoochee River at Spur 39, near Omaha, GA. The watershed contains 23 point sources across 20 subbasins (S2 Table), with locations and load summaries obtained from the *Point-Source Nutrient Loads to Streams of the Conterminous United States* dataset [42]. Mean monthly loadings for point source flow and TN were kept constant throughout all land use scenarios (S2 Table). We included the locations of 15 drinking water intake (DWI) facilities (Table 1) derived from the *US Environmental Protection Agency (USEPA) Safe Drinking Water Information System* [32], which includes the population served by each Public Water System, enabling us to quantify the population affected by land use changes. The final MC model encompasses 11,132 km², partitioned into 206 subbasins with a 1,632 km long stream network.

For HRU definition in the baseline model, we used soil data from the NRCS SSURGO and STATSGO2 datasets [43] and land cover/land use data from the 2011 National Land Cover Dataset (NLCD) [34]. Land use data for future scenarios are described below. Historical climate data was acquired from Daymet [44] and gridMET [45] datasets, processed through Google Earth Engine and R statistical software [46]. Daymet provided observed precipitation and temperature data, while gridMET supplied wind speed, relative humidity, and solar radiation necessary for the Penman-Monteith Potential Evapotranspiration calculations [47]. GridMET data also supplemented the Daymet dataset by providing information for leap years not included in Daymet. Daymet and GridMET data were downloaded from Google Earth Engine using centroids of the 206 subbasins. The spatial resolutions for Daymet and gridMET are 1 km and 4.6 km, respectively, and the average MC subbasin size is 54 km². These climate data were held constant for all land use change scenarios. Gridded climate datasets like Daymet and gridMET have inherent uncertainty, mainly from spatial interpolation methods and lack of weather station density [48]. Sparse station and gauge coverage increases uncertainty, especially in regions with high spatial variability in precipitation [49]. Both datasets aim to reduce interpolation bias through cross-validation and comparison with observed data [44,45]. While these methods can enhance accuracy, they will not fully eliminate errors, especially in regions with complex terrain or limited monitoring. However, the less-complex terrain and dense

monitoring network of the Middle Chattahoochee make Daymet and GRIDMET suitable models to use in hydrologic analysis in this region [50].

We also included annual atmospheric nitrogen deposition data for ammonia and nitrate from the National Atmospheric Deposition Program National Trends Network site GA41 (nadp.slh.wisc.edu/) for the ATMO.ATM file in SWAT (S3 Table). SWAT default land use-specific fertilizer applications were held constant from baseline to future scenarios.

2.2.3. Model calibration and validation. We used sediment and nutrient concentration observations from five USGS stream gages and co-located water quality monitoring sites within the SWAT model to create continuous daily load records for model calibration and validation. We used the Weighted Regressions on Time, Discharge, and Season (WRTDS) model, part of the EGRET package [51] for R [46], to derive loads from concentration data and fill in missing records.

The baseline model operated on a daily time-step from January 1, 2010, to December 31, 2020, with a 3-year warm-up period beginning on January 1, 2007. Daily calibration occurred from 2010–2016 and validation from 2017–2020 for streamflow, TSS, and TN loads. We used the SWAT-CUP (Calibration and Uncertainty Program) [52] Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm to perform stochastic calibration. SUFI-2 aims to encompass the majority of observed records within the 95% prediction uncertainty (95PPU), derived from simulated outputs. Parameter uncertainties, sampled using Latin hypercube sampling, define this distribution. The goal of SUFI-2 calibration is to capture the majority of observed data within the 95PPU. We adjusted parameters within realistic ranges based on empirical and literature values to optimize the Nash Sutcliffe efficiency (NSE) [53] and percent bias (PBIAS) for streamflow, TSS, and TN. Daily calibration was performed at the watershed outlet (USGS 02342881), with daily goodness-of-fit evaluated at other gauges in the watershed using Python version 3.11.7 [54] and R statistical software [46].

Calibration was accomplished in multiple steps. First, we jointly calibrated streamflow and TSS with 1,000 simulations, evaluating daily NSE and PBIAS across the watershed and adjusting parameter ranges based on significance and trends. We used the best-fit parameter set to replace default values in the uncalibrated ArcSWAT model. Subsequently, the model was rerun, and the calibrated streamflow and TSS scenario was used for nutrient calibration. The TN calibration used nutrient-specific parameters to run another 1,000 simulations, each assessed for fit at the outlet, while continually refining parameter ranges for optimal performance, and checking the fit across the watershed. The final parameter set most effectively optimized NSE and PBIAS throughout the watershed (S4 Table).

2.3. Land use sensitivity scenarios

To gauge the sensitivity of water quality and quantity to land use change and to verify that our land use projection methodology was robust, we ran two initial hypothetical land use scenarios: fully forested and fully developed. The first scenario transformed all terrestrial land in the 2011 NLCD to mixed forest cover (NLCD class 43; SWAT class FRST) and the second scenario changed all terrestrial land to medium-intensity development (NLCD class 23; SWAT class URHD). Open water, woody wetlands, and emergent herbaceous wetlands were held constant. The sediment, nutrient, and water balance results from these hypothetical scenarios were compared with those of a 2020 land use described below.

2.4. Projected land use modeling

We evaluated four projected land use change scenarios in SWAT that were sourced from the USDA Forest Service Resources Planning Act Assessment (RPA) [55]. The RPA projected

decadal land use across the conterminous US from 2020 to 2070 using multiple combinations of Global Climate Models (GCM) and Shared Socioeconomic Pathways (SSP). SSPs, developed by the Intergovernmental Panel on Climate Change (IPCC), offer socioeconomic narratives utilized alongside GCMs to anticipate future conditions [56]. The RPA assesses the status and projected trends of US natural resources under four SSPs (SSP1, SSP2, SSP3, and SSP5). We utilized two SSPs that encapsulate a broad range of socioeconomic outcomes in the US and globally: SSP3 depicting regional rivalry and lower growth and SSP5 depicting rapid development and high economic growth [57].

The RPA projected land use at the county scale [58,59] and then downscaled to a 90 m grid as described in Brooks et al. [60]. We used 2070 projections from [60] for spatial realization case 10, representing a realization in which the landscape pattern, i.e., forest fragmentation, was centered between the most extreme (case 20) and the least extreme (case 1). We disaggregated the broad land use classes in the RPA assessment (water, developed, forest, other natural, pasture, and crop) into the narrower NLCD classes used in SWAT by overlaying the 2016 NLCD on the 2020 RPA basemap (derived from the 2016 NLCD), and assigning NLCD land cover classes to each 2020 RPA basemap pixel based on that overlay. These disaggregated land cover classes were retained for the future projections where no land use change was projected to occur. Future land use changes were mapped to NLCD classes: new development to NLCD class 22 (developed, low intensity), new forest to NLCD class 43 (mixed forest), new pasture to NLCD class 81 (pasture/hay), and new crop to NLCD class 82 (cultivated crop).

We employed land use projections based on two GCMs: HadGEM2-ES [61] described as “hot” in the RPA and MRI-CGCM3 [62] described as “least warm”. For each GCM, SSP3 represented lower growth and SSP5 indicated higher growth under constraints of the corresponding GCM. The 2020 RPA basemap raster served as the baseline for the future scenarios. We configured five scenario simulations within ArcSWAT: the baseline scenario, (BASE20), which represents conditions up to 2020, and four future projected scenarios using constraints from the HadGEM2-ES and MRI-CGCM3 GCMs paired with SSP3 and SSP5. We only simulated land use change under these GCMs and did not change climate. We will refer to the future scenarios as follows: LG-1 (low growth; HadGEM2-ES and SSP3), HG-1 (high growth; HadGEM2-ES and SSP5), LG-2 (low growth; MRI-CGCM3 and SSP3), and HG-2 (high growth; MRI-CGCM3 and SSP5). We used a land use change methodology detailed below to transfer the calibrated parameter values to the scenario models. We held climate constant at 2010–2020 levels to isolate the effect of land use change on water quality.

2.5. Running land use scenarios

To run land use change scenarios in ArcSWAT, we updated the HRUs from the baseline model using the new land use rasters. The HRU definition phase occurs after watershed delineation, so all scenarios had the same delineation, stream network, subbasins, and outlets. During HRU definition, we only updated the land use raster, keeping soil data, slope classifications, and HRU thresholds constant. We also kept point sources, atmospheric deposition, and weather parameters constant across all scenarios to isolate the effects of land use change. When ArcSWAT creates new HRUs, it resets all parameters to default values. Therefore, we transferred calibrated values to the scenarios. To update parameter values, we used the *Manual Calibration Helper* and *Edit Subbasin Data* functionalities in ArcSWAT. When necessary, we also directly edited the project database to reflect calibrated parameter values. Most of our parameters were changed by a single value across the watershed (transformation = value in [S4 Table](#)), while four parameters, such as CN2, were changed by a proportion (transformation = relative).

2.6. Quantifying water quality responses to land use change

We analyzed water quality and water balance outputs for the BASE20 scenario and the four projected scenarios: LG-1, HG-1, LG-2, and HG-2. To determine the magnitude of water quality degradation or improvement from land use change, we evaluated mean annual concentration for TSS and TN to represent sediment and nutrient metrics at each subbasin, focusing our assessment at the drinking water intake locations. We also analyzed the change in extreme concentration events at each intake location. We first determined the value that marked the highest 10th percentile of TSS and TN concentration at each intake during the BASE20 period. Next, we calculated the number of days that surpassed this BASE20 threshold during the baseline period. Those days were considered extreme concentration events. We then calculated the number of days for each future scenario that surpassed the same BASE20 threshold and found the ratio between the baseline days and future days, or the exceedance day ratio.

3. Results

3.1. Model calibration and validation fit

We achieved acceptable fit between predicted and observed flow and water quality during calibration and validation at most gages according to Moriasi [63] metrics, suggesting the model was suitable for running projected scenarios (Table 2 and S1 Fig). For the calibration period, the model achieved satisfactory NSE, R², and PBIAS for streamflow, TSS, and TN at some, but not all gages across the watershed. For TN, lower NSE values, but satisfactory R² and PBIAS, indicate that the model struggles to capture high and low fluctuations but generally simulates the overall magnitude of the TN load. For example, at the outlet, monthly TN fit statistics during all periods suggest that while the model underpredicts some peaks and lows in the observed data, it still follows the overall trend (S1 Fig). During the validation period (January 1, 2017 – December 31, 2020), the overall model maintained performance that was consistent with the calibration period, indicating reliability over different hydro-climatic periods.

We anticipated that model performance would be generally better at the outlet, where calibration occurred, compared to upstream gages within the watershed, because we calibrated the model at the outlet and only assessed goodness of fit at the upstream gages. Since the observed sediment and nutrient time series were modeled using the WRTDS model, the “observed” data used for comparison with ArcSWAT simulated data were also derived from a modeled process with inherent uncertainty. Therefore, the goodness-of-fit of the SWAT model estimates of TSS and TN should be viewed in the context of the goodness-of-fit of the available observed sample data used as inputs to the WRTDS model (fit metrics in S1 Table). For example, the SWAT model underpredicted TSS load relative to WRTDS estimates and had negative NSE values at site ID 2 (Table 2); WRTDS TSS estimates for this site were overestimated by 32.5% and were based on relatively few observations (S1 Table). Further, nutrient calibration is challenging, as errors accumulate from streamflow to sediment, and finally to nutrient calibration [64]. Our challenges in capturing TN variability were consistent with findings from other SWAT studies, where limited observed data points may have constrained model TN performance [65].

3.2. Baseline 2020 results

We calculated the mean annual water balance, including precipitation, evapotranspiration (ET), and water yield (WY), as well as sediment and nutrient yields for the BASE20 scenario. These metrics were then compared with those of the future scenarios (S5 and S6 Tables). Across all subbasins, mean annual precipitation was 1,472 mm. BASE20 mean annual ET

Table 2. Monthly goodness-of-fit statistics for streamflow, total suspended sediment (TSS), and total nitrogen (TN) load at co-located gages and the watershed outlet. R^2 was calculated after the calibration process and indicates an overall satisfactory model performance at most gages. A negative PBIAS indicates that the model is underpredicting compared to observations, whereas a positive PBIAS indicates the model is overpredicting. The model was calibrated for site ID 5 at the watershed outlet; other sites were used to evaluate the spatial variability of model performance across the watershed. The superscripts indicate model performance according to Moriasi metrics [63].

		<i>Streamflow</i>								
		<i>Calibration</i>			<i>Validation</i>			<i>Full Period</i>		
<i>USGS Gage</i>	<i>ID</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>
02337410	1	0.85 ^{vg}	16 ^s	0.89 ^{vg}	0.84 ^{vg}	14.8 ^g	0.88 ^{vg}	0.85 ^{vg}	15 ^s	0.89 ^{vg}
02338500	2	0.97 ^{vg}	4.2 ^{vg}	0.98 ^{vg}	0.1 ^p	-1.9 ^{vg}	0.99 ^{vg}	0.98 ^{vg}	1.5 ^{vg}	0.98 ^{vg}
02338660	3	0.76 ^g	28.5 ^{us}	0.84 ^s	0.83 ^{vg}	19.8 ^s	0.88 ^{vg}	0.81 ^{vg}	24.3 ^{us}	0.86 ^{vg}
02338840	4	0.78 ^g	20.5 ^s	0.86 ^{vg}	0.83 ^{vg}	18.9 ^s	0.86 ^{vg}	0.81 ^{vg}	19.7 ^{us}	0.86 ^{vg}
02342881	5	0.87 ^{vg}	12 ^g	0.93 ^{vg}	0.87 ^{vg}	16.4 ^s	0.94 ^{vg}	0.87 ^{vg}	13.9 ^s	0.94 ^{vg}
		<i>TSS</i>								
		<i>Calibration</i>			<i>Validation</i>			<i>Full Period</i>		
<i>USGS Gage</i>	<i>ID</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>
02337410	1	-0.07 ^{us}	-94 ^{us}	0.32 ^{us}	-0.33 ^{us}	-93.7 ^{us}	0.51 ^s	-0.11 ^{us}	-94 ^{us}	0.35 ^{us}
02338500	2	-0.07 ^{us}	-83.4 ^{us}	0.89 ^{vg}	-0.08 ^{us}	-77 ^{us}	0.65 ^g	-0.07 ^{us}	-81 ^{us}	0.71 ^g
02338660	3	0.84 ^{vg}	20.7 ^s	0.93 ^{vg}	0.69 ^g	17.9 ^s	0.84 ^{vg}	0.77 ^g	19.3 ^s	0.88 ^{vg}
02338840	4	0.57 ^s	-17.3 ^s	0.59 ^s	0.64 ^s	2.9 ^{vg}	0.72 ^g	0.62 ^s	-8.1 ^{vg}	0.66 ^g
02342881	5	0.7 ^g	-0.35 ^{vg}	0.73 ^g	0.81 ^{vg}	7.3 ^{vg}	0.81 ^{vg}	0.74 ^g	3 ^{vg}	0.75 ^g
		<i>TN</i>								
		<i>Calibration</i>			<i>Validation</i>			<i>Full Period</i>		
<i>USGS Gage</i>	<i>ID</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>	<i>NSE</i>	<i>PBIAS</i>	<i>R²</i>
02337410	1	-0.22 ^{us}	5.7 ^{vg}	0.14 ^{us}	-1 ^{us}	-17.7 ^g	0.02 ^{us}	-0.5 ^{us}	-5.1 ^{vg}	0.08 ^{us}
02338500	2	-1.8 ^{us}	-59.3 ^{us}	0.27 ^{us}	-1.9 ^{us}	-59.7 ^{us}	0.36 ^s	-1.7 ^{us}	-59.5 ^{us}	0.31 ^s
02338660	3	-1.4 ^{us}	40.2 ^{us}	0.10 ^{us}	-0.53 ^{us}	-5.8 ^{vg}	0.17 ^{us}	-0.9 ^{us}	17.9 ^g	0.13 ^{us}
02338840	4	0.15 ^{us}	0.46 ^{vg}	0.31 ^s	0.4 ^s	-38.6 ^{us}	0.54 ^s	0.32 ^s	-18.9 ^g	0.35 ^s
02342881	5	0.18 ^{us}	4.4 ^{vg}	0.31 ^s	0.27 ^{us}	-11.4 ^{vg}	0.36 ^s	0.25 ^{us}	-2.4 ^{vg}	0.33 ^s

^pperfect fit.

^{vg}very good performance.

^ggood performance.

^ssatisfactory performance.

^{us}unsatisfactory performance

<https://doi.org/10.1371/journal.pwat.0000313.t002>

across all subbasins was 882 mm, varying from 707 mm to 1,312 mm depending on the location in the watershed. We observed high ET rates along the Chattahoochee River, especially near West Point Lake, because of the large amount of open water. The BASE20 mean annual WY across all subbasins was 505 mm, ranging from 398 mm to 770 mm. This is a generally expected pattern – elevated water yields in areas with higher precipitation and lower ET, and reduced water yields in areas with relatively less precipitation and higher ET (S2 Fig). We analyzed the sediment and nutrient yields from each subbasin, excluding point sources. Sediment yield (mt/ha) and nitrogen yield (kg/ha) were higher near the major cities of Atlanta, GA and Columbus, GA (S3 Fig).

3.3. Land use sensitivity analysis

We ran hypothetical fully forested and fully developed scenarios to assess model sensitivity to land use changes and confirm the model performed as expected when calibrated parameters were transferred to a new land use. Compared to BASE20, the fully developed scenario

showed substantial increases in mean annual TSS and TN loads. Conversely, the fully forested scenario resulted in the lowest loads relative to the other scenarios.

The mean annual TSS load in the fully developed scenario was one to two orders of magnitude greater at six DWI locations compared to the fully forested scenario (e.g., DWI 4: 126–8,225 m tons; Fig 2). Similarly, mean annual TN load during the fully developed scenario was one order of magnitude greater than the fully forested scenario at DWI locations 1–7 and 9–11. DWI location 9, serving as a public water system for West Point Lake, is the only intake on the mainstem of the Chattahoochee River with this large of a response in TN concentration (21,471 kg forested to 302,449 kg developed).

We also evaluated mean annual water yield (mm) and ET (mm) rates to verify the water balance response to land use changes (S5 Table). Watershed-wide water yield increased 158 mm (31%) while ET decreased 80 mm (9%) in the fully developed scenario compared to the fully forested scenario. This response suggests the model behaves as expected where forest removal leads to reduced ET rates and alters other natural processes that enable forests to capture and moderate water flow (S5 Fig).

3.4. Projected land use change in 2070

RPA projections indicate an increase in new development across the watershed by 2070 compared to BASE20. Development comprised 14% of the watershed during BASE20 and increased to 18% (LG-1), 18.5% (HG-1), 18.6% (LG-2), and 19.2% (HG-2) in future scenarios. At drinking water intakes, the most substantial changes in upstream development occurred at tributary locations, partly because we did not simulate land use changes in the Upper Chattahoochee watershed. Development increased by at least 50% at 11 of the 15 DWI facilities during the HG-2 scenario.

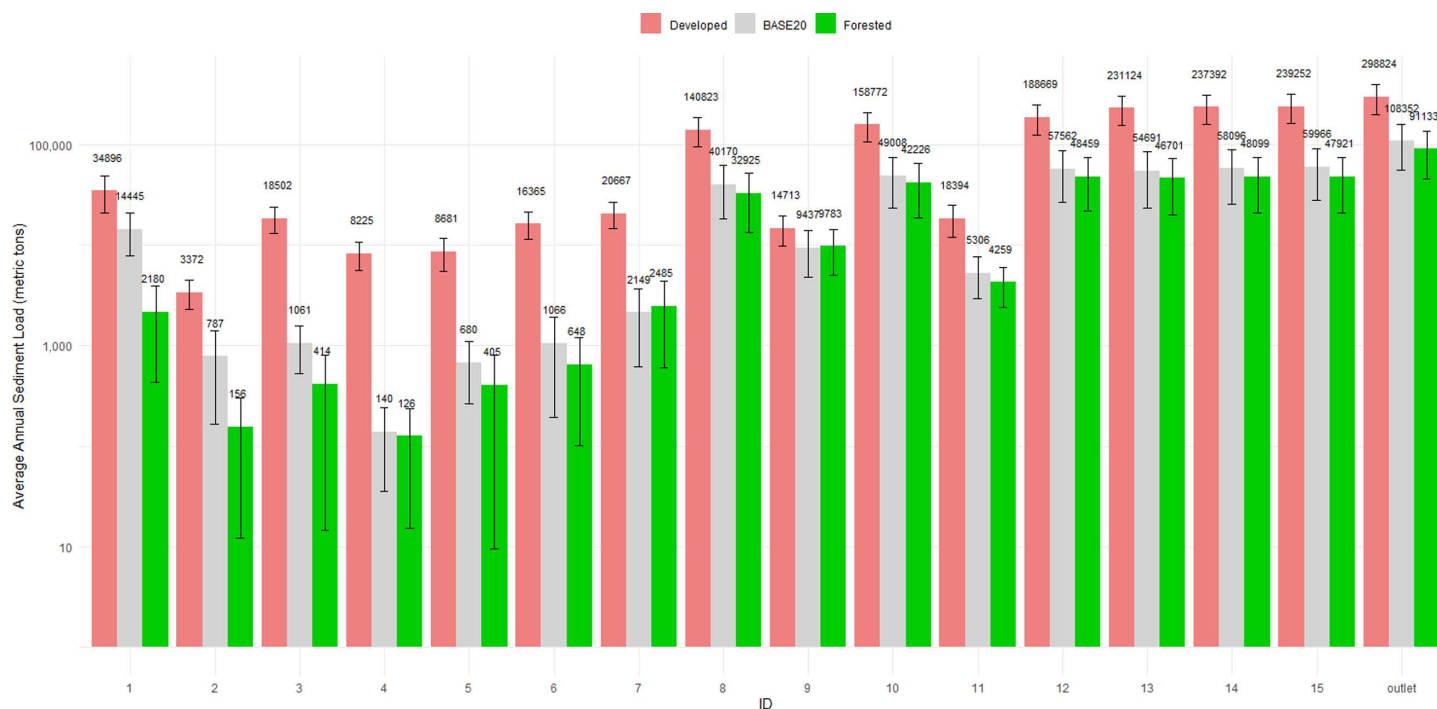


Fig 2. Mean annual TSS load (metric tons) across the BASE20 and hypothetical fully developed and fully forested scenarios. Error bars represent the standard deviation across all years.

<https://doi.org/10.1371/journal.pwat.0000313.g002>

New development occurred primarily on forestland. The watershed was 67% forested in BASE20, with projected forest cover losses of 12.2% (LG-1), 13.5% (HG-1), 14.8% (LG-2), and 16% (HG-2) by 2070. Five DWI tributary locations experienced up to a 20% reduction in upstream forest cover, with DWI 6 and 11 experiencing the most substantial losses. DWI 6, serving 8,172 people in Franklin and Centralhatchee, experienced a land use change from 4% developed, 71% forested, and 24% agriculture (BASE20) to 12% developed, 62% forested, and 25% agriculture (HG-2). Similarly, DWI 11, located in Lake Harding and serving 38,943 people, experienced a shift from 9% developed, 68% forested, and 17% agriculture (BASE20) to 17% developed, 60% forested, and 18% agriculture (HG-2). Across the watershed, new development primarily replaced agricultural land, forests, and wetlands, while the expansion of agricultural land occurred on forests and wetlands.

DWI locations 4 and 7, both on tributaries, were the only intakes to experience minimal forest loss due to the projected conversion of agricultural land to forest or development. DWI 4, on Snake Creek, has a service population of 45,380. Total development in this area increased from 5% during BASE20–10% under HG-2, while forest cover increased from 75% to 77%, and agricultural land decreased 14% to 9%. DWI 7, on Hillabahatchee Creek with a service population of 8,172, experienced minimal change in forest cover from 86.3% (BASE20) to 86.4% (HG-2), with development increasing from 3% to 5%, and agricultural land decreasing from 9% to 7%.

The future land use scenarios indicate a shift in urban development patterns. While new development is projected to still occur outside the major urban cores of Atlanta and Columbus, GA, the projections also indicate dense, new development concentrated primarily around smaller towns. These towns include Centralhatchee, Waverly Hall, Richland, Hamilton, Pine Mountain, Grantville, Hogansville, West Point, Franklin, Newnan, and LaGrange, which have a median population of 3,041 [66]. These towns are in smaller subwatersheds, <1000 km², which are predominantly forested but may face water quality issues stemming from rapid development.

3.5. Water quality

3.5.1. Sediment concentration. The future scenarios projected increases in mean annual TSS concentration across the watershed, with the HG-2 scenario leading to the most substantial gains. At the watershed outlet, mean annual TSS concentration increased the most by 9.2% during HG-2, rising from a BASE20 value of 7.4 ± 8.5 mg/L to 8 ± 9.1 mg/L (Table 3). TSS concentrations were more sensitive to land use changes at the intake locations.

The DWI facilities on tributaries (2, 3, 4, 5, and 11) were projected to experience over a 50% increase in mean annual sediment concentration, with the greatest increase at DWI 3 (+318%: 3.1 ± 7.3 mg/L BASE20 to 13.1 ± 11.3 mg/L HG-1) (Fig 3). DWI 3, located on Dog River with a service population of 109,694, experienced increased development from 17% BASE20–20% HG-1 (33–40 km²), reduced forest cover from 65% to 61% (126–120 km²), and reduced agricultural cover from 16% to 15% (30–29 km²). The response at DWI 3 could indicate that TSS concentration is sensitive to new development in a small, forested upstream area. In contrast, intakes 4 and 7 were the only DWI locations with decreased mean annual TSS concentrations across the projected scenarios relative to BASE20. Reduced concentrations can be attributed to a combination of high forest cover and new development that occurs on agricultural lands.

Extreme sediment concentration events were defined as days exceeding the highest 10th percentile of concentration under the BASE20 land use. This threshold was determined for each DWI under baseline land use and subsequently utilized to quantify the number of days surpassing the threshold in the future period. DWI 4 and 7 were the only intake locations

Table 3. The mean annual TSS and TN load and concentration and area normalized (AN) load at the watershed outlet for the BASE20 and future scenarios. AN load includes the contribution of point sources. Load is expressed as metric tons for TSS and kg for TN. AN load is expressed as m tons/ha/year for TSS and kg/ha/yr for TN. Concentration is expressed as mg/L for both. The $\pm$ represents the standard deviation in annual values.

Scenario	TSS Load (m tons)	TSS AN Load (m tons/ha/yr)	TSS Conc (mg/L)	TN Load (kg)	TN AN Load (kg/ha/yr)	TN Conc (mg/L)
BASE20	108351.82 $\pm$ 52362.41	0.097 $\pm$ 0.047	7.39 $\pm$ 8.49	6.36 $\times$ 10 ⁶ $\pm$ 1.12 $\times$ 10 ⁶	5.71 $\pm$ 1	1.01 $\pm$ 0.61
HG-1	117097.07 $\pm$ 56649.76	0.105 $\pm$ 0.051	7.88 $\pm$ 8.95	7.37 $\times$ 10 ⁶ $\pm$ 1.27 $\times$ 10 ⁶	6.62 $\pm$ 1.14	1.13 $\pm$ 0.87
LG-1	117739.23 $\pm$ 56709.51	0.106 $\pm$ 0.051	7.93 $\pm$ 9.01	7.42 $\times$ 10 ⁶ $\pm$ 1.28 $\times$ 10 ⁶	6.67 $\pm$ 1.15	1.14 $\pm$ 0.89
HG-2	120308.61 $\pm$ 58002.18	0.108 $\pm$ 0.052	8.08 $\pm$ 9.15	7.58 $\times$ 10 ⁶ $\pm$ 1.33 $\times$ 10 ⁶	6.81 $\pm$ 1.19	1.16 $\pm$ 0.91
LG-2	120308.91 $\pm$ 57732.65	0.108 $\pm$ 0.052	8.07 $\pm$ 9.15	7.65 $\times$ 10 ⁶ $\pm$ 1.34 $\times$ 10 ⁶	6.87 $\pm$ 1.2	1.16 $\pm$ 0.94

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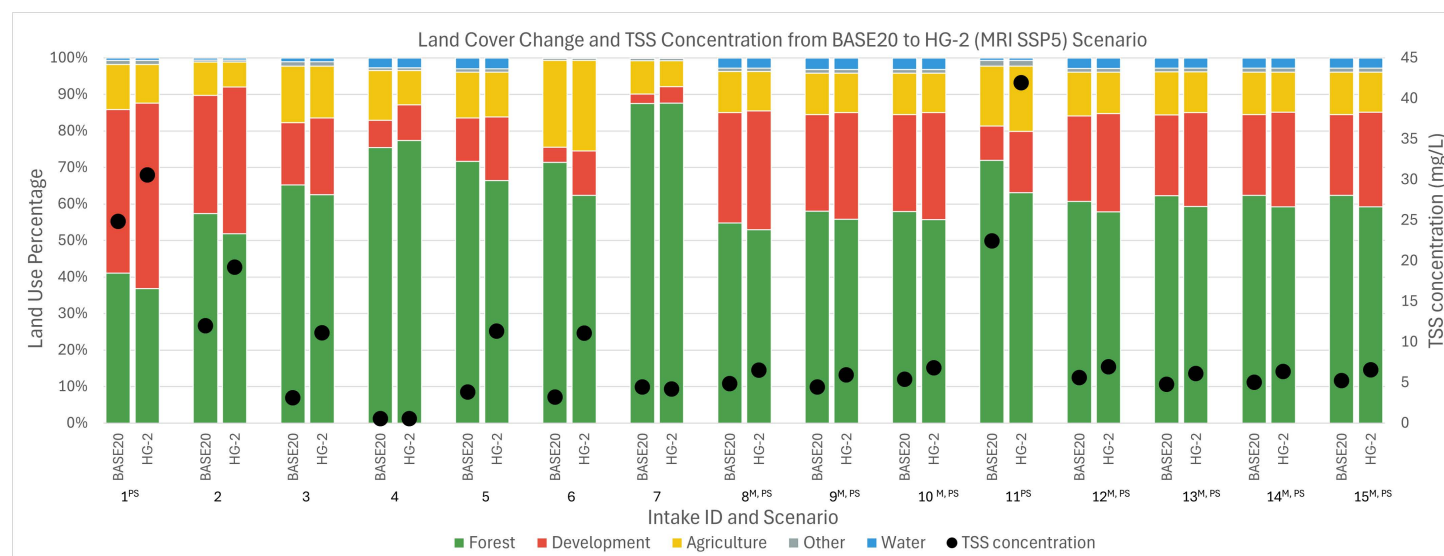


Fig 3. Percent of land use during the BASE20 and HG-2 (MRI SSP5) scenario along with corresponding mean annual TSS concentration values (mg/L) across all intake locations. The intake superscripts indicate M = mainstem and PS = point sources upstream. The black dots show the TSS concentrations with values on the secondary y-axis.

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that experienced a decrease in the frequency of extreme concentration events while DWI 3 exhibited the greatest increase in events from baseline to future scenarios. At DWI 3, extreme events were up to 6.6 times more frequent under the HG-1 and LG-2 scenarios compared to the baseline, escalating from 402 extreme days during the baseline up to 2,667 days during HG-1 (S6 Table).

3.5.2. Nitrogen concentration. The spatial pattern of mean annual TN concentration across the watershed was similar to TSS concentration. Mean annual TN concentration at the outlet increased up to 15% HG-2 (1.16 $\pm$ 0.94 mg/L) from a BASE20 value of 1.01 $\pm$ 0.61 mg/L (Table 3). DWI facilities in smaller subwatersheds were most sensitive to land use changes affecting mean annual TN concentrations. For example, DWI 11 experienced over a 100% increase in mean annual TN concentration across all future scenarios, rising from 0.36 $\pm$ 0.44 mg/L BASE20 to 1.2 $\pm$ 2.3 mg/L LG-2 (Fig 4). The area upstream of DWI 11, which drains into Lake Harding shifted from 9% to 16% developed, 68% to 60% forested, and 16% to 18% agriculture from BASE20 to all future scenarios, indicating a concurrent rise in development and agriculture on forestland. DWI 11 also exhibited the greatest increase in extreme TN events, with the frequency of extreme days rising to 3.6 times, from 402 extreme

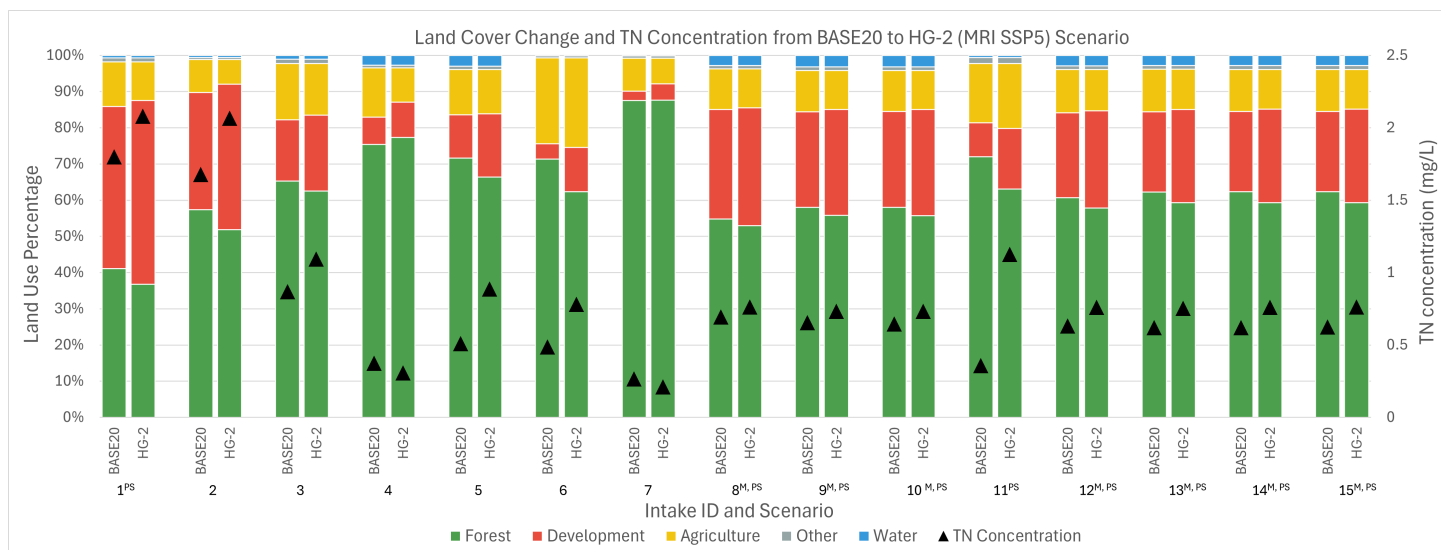


Fig 4. Percent of land use during the BASE20 and HG-2 (MRISSP5) scenario along with corresponding mean annual TN concentration values (mg/L) across all intake locations. The intake superscripts indicate M = mainstem and PS = point sources upstream. The black triangles show the TN concentrations with values on the secondary y-axis.

<https://doi.org/10.1371/journal.pwat.0000313.g004>

days in BASE20–1,443 days LG-2 (S7 Table). Like with TSS concentration, DWI 4 and 7 were the only intake locations that experienced a decrease of extreme TN days and mean annual concentrations due to the reforestation and development of agricultural land.

4. Discussion

In our study of future conditions across the Middle Chattahoochee watershed, we found that TSS and TN concentrations are generally projected to increase at the watershed outlet and at drinking water intake facilities under multiple land use change scenarios. However, concentrations decreased when upstream land cover was primarily forested and agricultural land was converted to either forest or low-intensity development, suggesting that certain types of new development can sometimes improve water quality compared to maintaining agricultural land. These findings align with previous studies which also found that forest conversion elevated TSS and TN concentrations, but forest loss to agriculture often had a greater impact on water quality than loss to development [2,67,68]. The most substantial increases in TSS and TN concentrations at the DWI were projected at facilities within smaller subwatersheds, typically less than 1,000 km², which tend to serve smaller towns and rural areas that may have fewer resources to manage water quality challenges. These results emphasize the importance of forest protection for water quality, equipping water resource managers with actionable information to support source water protection initiatives while also identifying key areas for future research applications.

4.1. Implications for water resource managers

The RPA land use scenarios projected development near larger cities and small towns in the MC watershed. This projected development exhibits urban sprawl, spreading outwards from urban cores. In Atlanta, this pattern aligns with historical trends and future projections, indicating the greatest increases in development will occur in outer portions of the city [69]. The notable development in smaller towns reflects the ongoing trend of rapid growth in rural

areas [70,71]. Although Atlanta has been central in ACF water allocation discussions [72,73], projected development around smaller towns in the MC watershed may compound those water quantity concerns with water quality issues for their respective water intake facilities and others downstream [74,75].

The development patterns in our study project that forest loss in smaller subwatersheds (generally less than 1000 km²) has an outsized effect on water quality relative to the whole watershed scale. DWI locations in small subwatersheds showed substantial increases in mean annual sediment and nutrient concentrations and the frequency of extreme concentration events, compared to intakes on the Chattahoochee River that had a much larger upstream area. Specific areas in these subwatersheds that could benefit from source water protection include the Dog River Reservoir (DWI 3), Lake Harding (DWI 11), and towns like Whitesburg and Centralhatchee (DWI 6). Our finding that small subwatersheds are most vulnerable to forest conversion aligns with [2] and underscores the importance of protecting source water for smaller communities that may have limited resources for water treatment.

Smaller public water systems may be more susceptible to water quality challenges stemming from their limited customer base and financial capacity relative to large facilities [74,76]. Small facilities, especially in rural areas, often experience more monitoring and reporting violations [77]. Rural drinking water concerns are often not prioritized in state water resource planning [78], necessitating greater collaboration between municipalities and water governance institutions [79]. Therefore, water resource managers can prioritize forest conservation and best management practices in smaller subwatersheds to help mitigate the impact of future development on water quality at these facilities.

4.2. Future research applications

Our findings could be utilized in future research that advances the science and management of source water protection. The results from the land use change scenarios could be used alongside economic models to evaluate drinking water treatment costs linked to forest cover loss. Additionally, they could be combined with participatory management to locate areas where landowners are receptive to conservation measures like easements or payments for ecosystem services. The SWAT model could be utilized to assess the effectiveness of natural infrastructure, such as riparian buffers, in mitigating development impacts on water quality and quantity amid forest cover loss. Lastly, model results underscore the need to establish thresholds of forest and impervious cover at which water quality degrades within the watershed.

Integrating SWAT land use change results with economic models could one day support payments for ecosystem services strategies, compensating private forest landowners for the source water protection benefits their forests provide. Engaging and garnering support from private landowners might be a critical factor for water protection on private forestlands. Private forestlands in the SE represent the most important water source [3] and are also the most vulnerable to forest conversion to development [58]. Despite growing support in the SE to manage private forestlands for ecosystem services, government programs and policies to help landowners meet this demand are limited and landowners prefer assistance programs over regulatory policies [80]. Therefore, a participatory management approach, successful in areas like the Chesapeake Bay [81], could be adapted for the MC watershed, targeting specific parcels for source water protection and engaging minority landowners with generational ties to the land who may lack economic returns [82].

Our SWAT model can be tailored to evaluate the effectiveness of natural infrastructure on both water quality and quantity. In instances where the cost of forest restoration or conservation outweighs the savings in drinking water treatment [83,84], opting for nature-based solutions could be a more feasible and cost-effective alternative while still safeguarding water

resources. SWAT has been successfully employed to analyze the influence of riparian buffers [85,86], restored wetlands [87], and various management practices [88] on water resources. Therefore, our model can be used to assess the optimal nature-based solution(s) for protecting water resources when large-scale forest retention is not feasible or cost-effective.

The water quality response due to forest conversion to development in our study might be attributed to the amount of impervious surface cover associated with the projected new development. Impervious surfaces become sources of many pollutants that are collected, stored, and flushed to surface waters during storms [89,90]. Existing literature indicates that upstream watershed impervious cover between 5–20% is the common threshold at which water quality and quantity degrade [91,92], although this threshold can depend on watershed characteristics [93]. Therefore, while we found that increased sediment and nutrient concentrations can be linked to new development, we need to further analyze the amount of associated impervious surface cover to identify potential thresholds.

Lastly, coupled climate and development change are driving hydrologic extremes in the SE. Some water-rich watersheds in the region are becoming drier because of shifting precipitation patterns [94] while others are experiencing an increase in the frequency and intensity of flash flooding [95]. While the scope of our work here focused on the effects of land use change only, future work could couple the land use change scenarios with climate scenarios to identify how shifting precipitation and temperature patterns drive changes in water quality and quantity.

4.3. Limitations

Like all modeling studies, there were uncertainties and limitations associated with this approach that should be considered when interpreting our results. We held inlet data from the Upper Chattahoochee watershed constant for all scenarios, which corresponds to also holding land use in the Upper Chattahoochee constant. In addition, we had to make some assumptions about the projected land use. We rescaled the future projections from 90 m to 30 m and reclassified RPA classes to NLCD classes by overlaying the RPA projections on the 2016 NLCD. As a result, there may be minor differences between the 2011 NLCD used for model calibration and the 2020 basemap used as the baseline scenario in future projections. For future projections, we categorized all new development as “low intensity” (NLCD code 22), which may be a conservative estimate, whereas development in the “fully developed” hypothetical scenario was classified as medium-intensity development (NLCD code 23). Low-intensity development (NLCD code 22) corresponds to the SWAT classification URMD, which has 38% impervious cover. Comparatively, medium-intensity development (NLCD code 23) corresponds to SWAT classification URHD, which has 60% impervious cover. The amount of sediment and nitrogen that gets washed over impervious cover therefore differs between these two scenarios. We classified new forest cover as “mixed forest” (NLCD code 43), potentially impacting results due to how SWAT models mixed forest, deciduous, and evergreen forest types. Lastly, HRUs within a subbasin are not spatially connected in SWAT, as processes are modeled within HRUs and then aggregated to the subbasin level. Therefore, SWAT does not consider the spatial location of forest cover within a subbasin.

Sediment and nutrient yields can also be impacted by point sources, atmospheric deposition, and other management activities. Nutrient loads from the 23 point sources we added are directly discharged into the channel network, bypassing any land-based processes that may otherwise mitigate their effects. We included TN load in the point source files as nitrate, which has high mobility and could accumulate downstream, resulting in elevated nitrogen loads and concentrations. However, the percent bias from calibration suggests that nitrogen might be underestimated within the model. There could be many reasons for this response, such as the atmospheric deposition of N and fertilizer applications. We did include both wet and dry

deposition of N. However, we left fertilizer application at model default settings, which applies nitrogen to 1% of a developed or agricultural HRU when nitrogen stress is reached. Future research could investigate typical fertilizer types and application rates on developed lands to provide a more realistic approximation for the impacts of developed land on nutrient loading.

5. Conclusions

This study aimed to enhance our understanding of the contribution of current forest cover to source water protection at drinking water intake facilities and evaluate the impacts of future forest loss on water quality in a rapidly developing watershed with water allocation challenges. We found that substantial increases in sediment and nitrogen concentrations could occur for intake facilities with smaller upstream watersheds that are projected to lose forestland. Additionally, the conversion of agricultural land to new, low-intensity development could lower sediment and nitrogen concentrations. These findings underscore the importance of focusing on land use change upstream of smaller drinking water intake facilities and provide actionable insights for water resource managers to advance forest protection initiatives. Our results contribute to the understanding of water-related ecosystem services provided by forest cover and highlight priority areas for source water protection. These efforts could bolster the resilience of drinking water supplies in a region experiencing substantial shifts in water resources.

Supporting information

S1 Table. Water quality monitoring sites in the Middle Chattahoochee Watershed SWAT model. The location of these sites was added as subbasin outlets. The inlet site was the only location where measured records were included to capture water, sediment, and nutrient inputs from the upstream Upper Chattahoochee Watershed.
(DOCX)

S2 Table. Point sources in the Middle Chattahoochee Watershed. The point sources are all wastewater treatment facilities. We held monthly point source data static across all scenarios to isolate the effects of land cover change on water quality. Point source data was derived from the Point-Source Nutrient Loads to Streams of the Conterminous United States dataset [42]. Q represents the mean annual flow rate in million gallons per day. TN represents mean annual nitrogen loading in kg and TP represents mean annual phosphorus loading in kg.
(DOCX)

S3 Table. Atmospheric deposition values for the Middle Chattahoochee Watershed SWAT Model. We held these annual values static across all scenarios. Values were derived from the National Atmospheric Deposition Program National Trends Network site GA41 (nadp.slh.wisc.edu/).
(DOCX)

S4 Table. Final parameter set used to calibrate the MC SWAT model.
(DOCX)

S1 Fig. Monthly simulated vs observed time series at the outlet for a) streamflow (m³/s), b) TSS (metric tons), and c) TN (kg). The calibration and validation periods are separated by the dotted line.
(DOCX)

S2 Fig. Mean annual precipitation, ET, and water yield (mm) across the MC watershed during the BASE20 period.
(DOCX)

S3 Fig. TSS yield (mt/ha) and TN yield (kg/ha) for each subbasin across the MC watershed during the BASE20 period.

(DOCX)

S4 Fig. Mean annual TN load (kg) across the BASE20 and hypothetical fully developed and fully forested scenarios. Error bars represent the standard deviation across all years.

(DOCX)

S5 Table. Mean annual water balance components across the watershed for all scenarios.

Runoff ratio represents the proportion of precipitation that was not taken up by ET and therefore contributed as WY. The percent change in ET and WY represents the percent change from the BASE20 scenario.

(DOCX)

S5 Fig. a) Mean annual water yield and b) mean annual ET percent change from the fully forested to fully developed scenarios.

(DOCX)

S6 Table. Exceedance day ratio of TSS extreme events under future scenarios compared to BASE20. The exceedance day ratio indicates the number of future days surpassing the 90th percentile threshold, relative to the baseline period.

(DOCX)

S7 Table. Exceedance day ratio of TN extreme events under future scenarios compared to BASE20. The exceedance day ratio indicates the number of future days surpassing the 90th percentile threshold, relative to the baseline period.

(DOCX)

Author contributions

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Investigation: Elly T. Gay.

Methodology: Elly T. Gay, Katherine L. Martin, Peter V. Caldwell.

Supervision: Katherine L. Martin.

Writing – original draft: Elly T. Gay.

Writing – review & editing: Katherine L. Martin, Peter V. Caldwell.

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