A Methodological Framework for Assessing Sea Level Rise Impacts on Nitrate Loading in Coastal Agricultural Watersheds Using SWAT+: A Case Study of the Tar-Pamlico River Basin, North Carolina, USA

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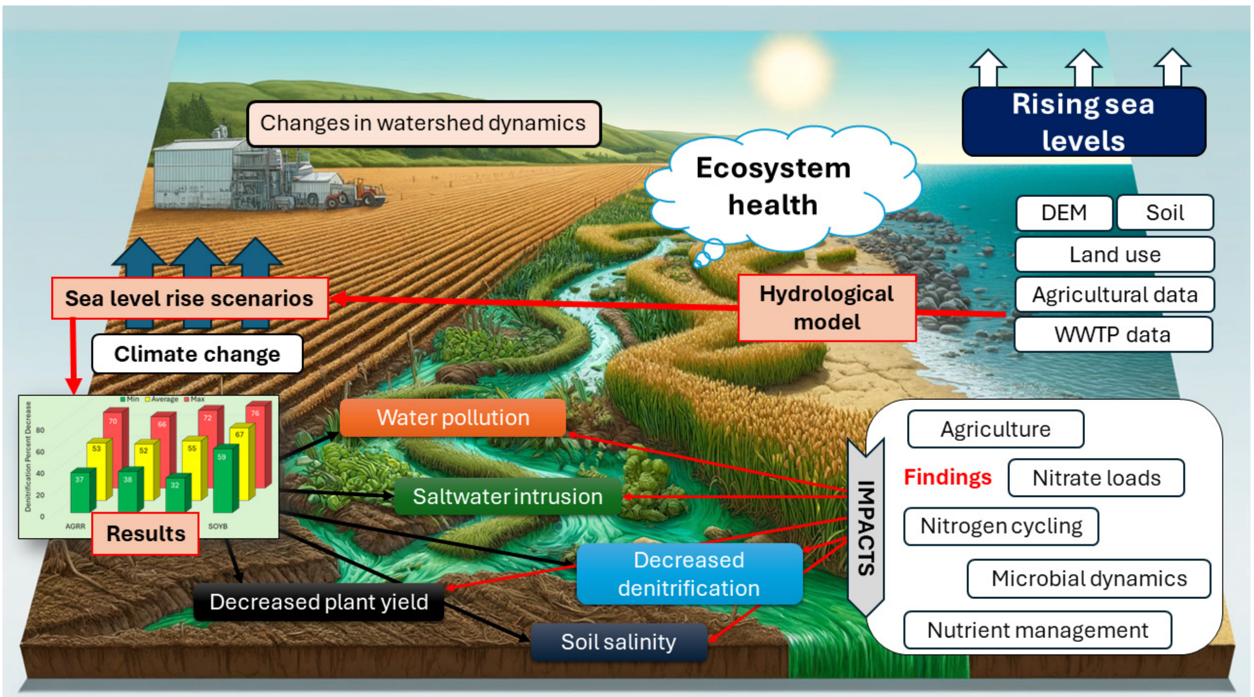
Abstract

This study addresses the urgent need to understand the impacts of climate change on coastal ecosystems by demonstrating how to use the SWAT+ model to assess the effects of sea level rise (SLR) on agricultural nitrate export in a coastal watershed. Our framework for incorporating SLR in the SWAT+ model includes: (1) reclassifying current land uses to water for areas with elevations below 0.3 meters based on SLR projections for mid-century; (2) creating new SLR-influenced land uses, SLR-influenced crop database, and hydrological response units for areas with elevations below 2.4 meters; and (3) adjusting SWAT+ parameters for the SLR-influenced areas to simulate the effects of saltwater intrusion on processes such as plant yield and denitrification. We demonstrate this approach in the Tar-Pamlico River basin, a coastal watershed in eastern North Carolina, USA. We calibrated the model for monthly nitrate load at Washington, NC, achieving a Nash-Sutcliffe Efficiency (NSE) of 0.61. Our findings show that SLR substantially alters nitrate delivery to the estuary, with increased nitrate loads observed in all seasons. Higher load increases were noted in winter and spring due to elevated flows, while higher percentage increases occurred in summer and fall, attributed to reduced plant uptake and disrupted nitrogen cycle transformations. Overall, we observed an increase in mean annual nitrate loads from 155,000 kg NO_3-N under baseline conditions to 157,000 kg NO_3-N under SLR scenarios, confirmed by a statistically significant paired t-test ($p = 2.16 \times 10^{-10}$). This pioneering framework sets the stage for more sophisticated and accurate modeling of SLR impacts in diverse hydrological scenarios, offering a vital tool for hydrological modelers.



Keywords

SWAT+; Water Quality; Nitrate; Coastal Watershed; Sea Level Rise; Ecosystem Health.

1. Introduction

Water quality is an important aspect of water resources management (Abbaspour et al., 2007). Since the 20th century, elevated nitrate levels in water bodies have posed significant threats to coastal watersheds (Pringle, 2001; Vilmin et al., 2018). While nitrogen-based fertilizers boost agricultural production, they risk coastal ecosystems (Galloway et al., 2013; Fixen & West, 2002). High nitrate levels fuel algal blooms, hindering sunlight and benthic plant growth (Wurtsbaugh et al., 2019). Decomposition of dead algae depletes oxygen, creating low-oxygen zones lethal to organisms that respire aerobically (Cui et al., 2021; Gerloff & Krombholz, 1966; Jewell & McCarty, 1971; Seibel, 2011).

Addressing elevated nitrate levels in coastal watersheds—a global issue—costs billions annually, particularly straining low and middle-income countries and threatening economic stability and aquatic ecosystem health (Sekhon, 1995; Bernhardt et al., 2005; Craswell, 2021; Rasiah et al., 2005; Mathewson et al., 2020). Here, we define ecosystem health as the ability of a coastal watershed to sustain biological productivity (Sherman, 1994), maintain ecological processes (O'Brien et al., 2016), support biodiversity (Qian et al., 2023), and meet societal needs (Christensen et al., 1996), specifically in the context of managing and mitigating excessive nitrate loading. Nitrate loading is a critical indicator of ecosystem health (Bobbink & Roelofs, 1995) because elevated nitrate levels can lead to eutrophication, harmful algal blooms, and hypoxia, which severely disrupt aquatic ecosystems and impair their ability to support diverse biological communities and provide ecosystem services (Addiscott, 2005; Paerl, 2006). By focusing on nitrate loading, we address a key factor that influences the overall health and functionality of coastal watersheds. Addressing nitrate pollution is of global concern and should be a major part of a country's plan for conserving or restoring healthy aquatic ecosystems. Climate change and anthropogenic activities greatly affect the nitrogen cycle (Aryal et al., 2022; Bennett et al., 2014; Vitousek et al., 1997), altering the rates of nitrogen fixation (Galloway, 1998), mineralization, and denitrification (Zhu et al., 2015). Nitrogen gas (N2) makes up most of Earth's atmosphere, 78 percent of its total composition (Hart 1978). Although nitrogen gas is abundant in the atmosphere, it needs to be converted to ammonia/ammonium (NH_3/NH_4^+) through fixation by microorganisms before plants and animals can use it (Postgate 1998). Animals obtain nitrogen through eating plants (Temperton et al., 2007), integrating it into the broader food web (Meunier et al., 2016). When plants and animals die, the organic nitrogen they contain is broken down by microbes, turning it back into NH_4^+ (mineralization) and eventually nitrate (NO_3^-) via nitrification (Abatenh et al., 2018; Gupta et al., 2017). In addition, denitrifying microbes transorm nitrate tonitrous oxide (N_2O) or N_2 gas (Vilar-Sanz et al., 2013).The alterations in the nitrogen cycle and nutrient availability impact coastal watersheds, especially where nitrogen is the primary limiting nutrient, leading to challenges for the health of aquatic ecosystems (Rabalais, 2002).

Human activities greatly modify the nitrogen cycle, carbon cycle, and climate (Bernal et al., 2012). Sea levels are rising due to rising temperatures causing thermal expansion of seawater and melting glaciers and ice sheets (Karl et al., 2009; Cazenave & Cozannet, 2014). Sea level rise (SLR) can cause flooding in low-lying areas, saltwater intrusion, and pose significant threats to aquatic ecosystems (Knighton et al., 1991; Moftakhari et al., 2015). Increased salinity due to SLR enhances ammonium bioavailability and affects nitrification and denitrification processes, altering plant-microbe interactions, the nitrogen cycle, and nitrogen dynamics in watersheds (Ardón et al., 2013; Kirwan & Megonigal, 2013; Waldron et al., 1997).

Coastal communities are more susceptible to the effects of climate change (Oliver-Smith, 2009; Tran & Lakshmi, 2024). For farmers in coastal regions, saltwater intrusion is a pronounced concern due to its threat to crop growth. The boundary between saltwater and freshwater shifts as inflow and outflow rates vary, with an increase in saltwater causing this interface to move further upstream (Michael et al., 2005). This progression leads to saltwater intrusion, resulting in elevated soil salinity, which disrupts crop growth. This increased salinity inhibits the activities of nitrogen-fixing microbes and interferes with the conversion of organic nitrogen compounds into forms that plants can easily assimilate (Etesami & Adl, 2021; Kirova & Kocheva, 2021). Consequently, this disruption in the nitrogen cycle ultimately decreases nutrient availability for crops (specifically for soybean, which is a major crop type in our study area), thereby affecting their overall yield. Additionally, high soil salinity can reduce growth or kill crops despite abundant nitrogen availability (Van et al., 1999), leading to an accumulation of unused nitrogen in soils where fertilizers are applied (Weissman & Tully, 2020). The effects of SLR are not limited to agriculture, as a higher SLR rate influences wetland composition and productivity, limiting nitrogen removal potential (Kirwan & Megonigal, 2013). In urban areas with high proportions of impervious surfaces, SLR can amplify flood frequency and increase anthropogenic nutrient runoff to waterways (Macías-Tapia et al., 2021).

Hydrological models are frequently used to assess the potential impacts of climate change and other anthropogenic influences on nitrogen transport and retention in watersheds (Hattermann et al., 2006). The Soil and Water Assessment Tool (SWAT) is one of the most widely used models for this purpose. Developed in the early 1990s, it is a semi-distributed hydrological model extensively used for water quality (Abbaspour et al., 2007; Arnold et al., 1998) and quantity analyses (Zhang et al., 2011). SWAT has proven effective in modeling nitrate loads in diverse watersheds, with applications in places such as the Vamanapuram River Basin, India (Saravanan et al., 2023), Brittany, France (Conan et al., 2023), the Lower Seyhan Plain, Turkey (Donmez et al., 2020), and the Des Moines River, United States (Schilling & Wolter, 2009). In recent years, the release of SWAT+, an enhanced version of SWAT, has gathered attention for its advancements in understanding interactions within watersheds and sub-watersheds, as well as its improved data management, analysis, and visualization capabilities (SWAT+, 2020). However, there is a gap in examining the integration of SLR in the SWAT+ model, likely due to the model's limited ability to manage the bidirectional flow (Bieger et al., 2017).

In this study, our primary goal was to use the SWAT+ model to demonstrate a method for simulating the effects of SLR on nitrogen processing within coastal watersheds, specifically using nitrate loading to the estuary as an indicator of ecosystem health. We achieved this by identifying key parameters and input changes in the model, which enabled the simulation of changes in nitrate transport and retention based on current literature. Additionally, we investigated how SLR influences nitrate loads in the downstream boundaries of a watershed. The Tar-Pamlico River Basin, located in eastern North Carolina, USA, is used as a case study, given its historical challenges with both SLR and elevated nitrate levels over recent decades (Helmers et al., 2022; NCDEQ, 2014; Ury et al., 2021).

Excessive nitrate loading from the Tar-Pamlico River Basin (Heffernan, 2015; Tapas, 2024), which discharges into the Pamlico Estuary, is causing algae blooms and economic losses (NCDEQ, 2014; McMahon & Woodside, 1997; Spruill, 1998; Woodside & Simerl, 1995). Previous studies have examined its hydrology (Phillips, 1989; Tapas, 2024; Tran et al., 2024), nitrate load (NCDEQ, 2014; Tapas, 2024), and climate change impacts (Hillman, 2019; Tran et al., 2024). Tran et al. (2024) highlight that low-lying coastal regions are prone to higher flood peaks and more frequent droughts, necessitating urgent action. Agriculture is the major source of nitrate pollution, compounded by urbanization (NCDEQ, 2014). Climate change intensifies these issues with increased rainfall variability, intensity (Tran et al., 2024), and SLR (Mazhar et al., 2022), complicating water resource management in a coastal watershed (Mazhar et al., 2022; Upadhyay et al., 2022). The uncertainty in nitrate dynamics with increasing saltwater (Murgulet & Tick, 2016), reduced agricultural productivity (Tarolli et al., 2023), and reduced denitrification rates (Neubauer et al., 2019) further complicates the management of water resources and ecosystem health in the basin (NCDEQ, 2014; Spruill, 1998; Tran et al., 2024). Through this work, we aim to improve the traditional coastal hydrological modeling framework by partially integrating the complex interactions and changes that arise from modifying nitrogen cycle processes due to SLR.

The primary objective of this study is to develop a methodology to incorporate the partial effects of sea level rise (SLR) on nitrate dynamics and apply it to a case study of the Tar-Pamlico River Basin. The specific objectives of this study were to: (1) Develop and optimize a nitrate model for the Tar-Pamlico watershed using the SWAT+ hydrological model; (2) Demonstrate a novel approach to incorporating SLR-influenced land use, plant database, and HRUs in SWAT+ based on the effects of salinity on nitrate processes found in literature, with a focus on agricultural land uses; and (3) Investigate the effects of SLR on changes in nitrate load to the Pamlico Estuary under baseline and SLR scenarios.

2. Materials and Methods

2.1. Study Area

This study focuses on the Tar-Pamlico River basin, a coastal watershed in North Carolina, USA (Figure 1). As the fourth-largest watershed in the state, the Tar-Pamlico River basin stands out as one of just four entirely contained within North Carolina, alongside the Cape Fear, Neuse, and White Oak River basins (NCDEQ, 2023). With its waters ultimately flowing into the Pamlico Sound, this watershed has a rich diversity of ecosystems and varied habitats (North Carolina Department of Environmental Quality (NCDEQ), 2023). The Tar-Pamlico covers an expansive 6,400 square miles (16,500 km^2) and spans 15 counties. It is home to a population exceeding

470,000 residents. The land use within this watershed is divided among agriculture (27.9%), forests (33.9%), wetlands (31.9%), pastureland (3.5%), rangeland (1.3%), and urban areas (1.4%) (Claggett et al., 2015). The freshwater streams and rivers within the basin originate in the Piedmont region in north-central North Carolina. These waterways flow southeastward and, upon nearing tidal zones, transform into the expansive (Figure 1), tidally influenced estuary (Keith, 2014), enhancing its ecological complexity and economic productivity (NC DEQ, 2009, 1994).

The mouth of the Tar-Pamlico River basin, where it flows into the Pamlico Sound, is characterized by significant agricultural land, wetlands, and forested areas (Heffernan, 2015; NCDEQ, 2014). This region has a low slope, facilitating hydrological connectivity and making it particularly susceptible to saltwater intrusion, which threatens agricultural productivity and water quality (Hillman, 2019; McMahon & Woodside, 1997; Spruill, 1998). This has raised concerns among farmers, prompting them to use additional fertilizers, which could further harm ecosystem health. Over the years, increased rainfall variability and intensity have further complicated nitrate dynamics in this area (Tran et al., 2024; Tapas, 2024), highlighting the critical need for effective strategies to mitigate the impacts of SLR.

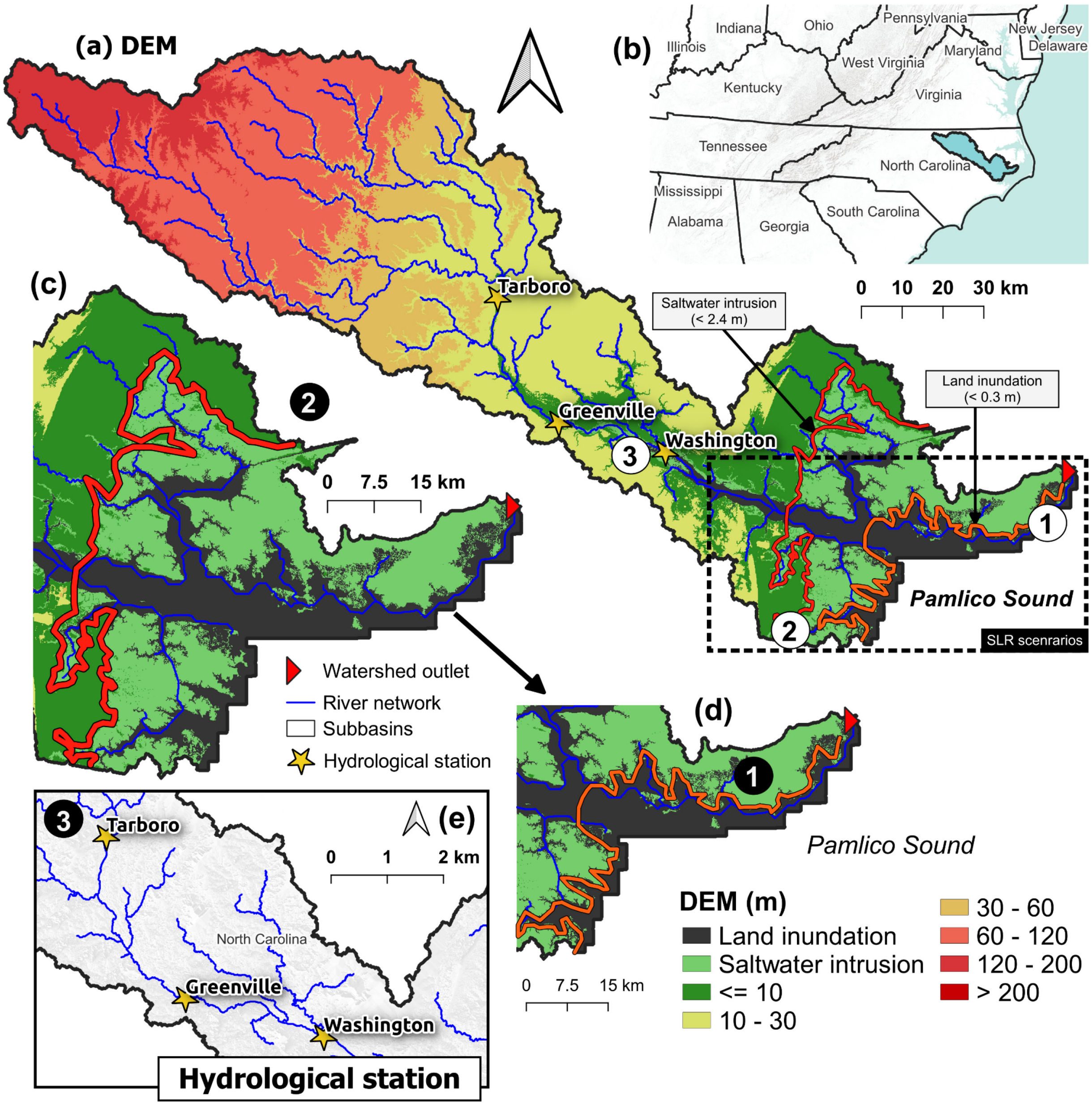


Figure 1. (a) Digital Elevation Model and geographical characteristics of the Tar-Pamlico watershed, (b) Location of Tar-Pamlico River Basin in the United States, (c-d) Tar-Pamlico's coastal region where we incorporated the effects of SLR [c: saltwater intrusion; d: land inundation], and (e) Hydrological monitoring stations used for model optimization and cross-validation.

2.2. SWAT+ Model Setup

In this study, we implemented the SWAT+ (version 2.3.3) model (SWAT+ IO Document, 2020) to simulate hydrological processes throughout the river basin (Figure 2). This tool excels at assessing dynamics within both watersheds and sub-watersheds. SWAT+ enables the evaluation of how various hydrological parameters influence watershed dynamics, affecting water quality, agricultural yields, and nitrogen cycle processes (SWAT+ IO Document, 2020). It allows for detailed simulation of environmental interactions, aiding the creation of policies and strategies aimed at mitigating ecosystem health issues (SWAT+ IO Document, 2020). The integration of SLR effects in the SWAT+ model presents challenges, particularly due to the model's inability to handle backflow (Bieger et al., 2017). The tides in the Pamlico River are primarily wind-driven, leading to less predictable and less consistent tidal effects compared to other tidal systems driven primarily by gravitational forces (Lagomasino et al., 2013; Xie & Pietrafesa, 1999). Observations at the Washington station indicate minimal occurrence of backflow in the data collected at 15-minute intervals (S2 Supplementary Information). Given these conditions, we believe that SWAT+ is appropriate for use in this study, as the occasional backflow that does occur is characterized by a low flow rate, which would have minimal impact on the overall nitrate load.

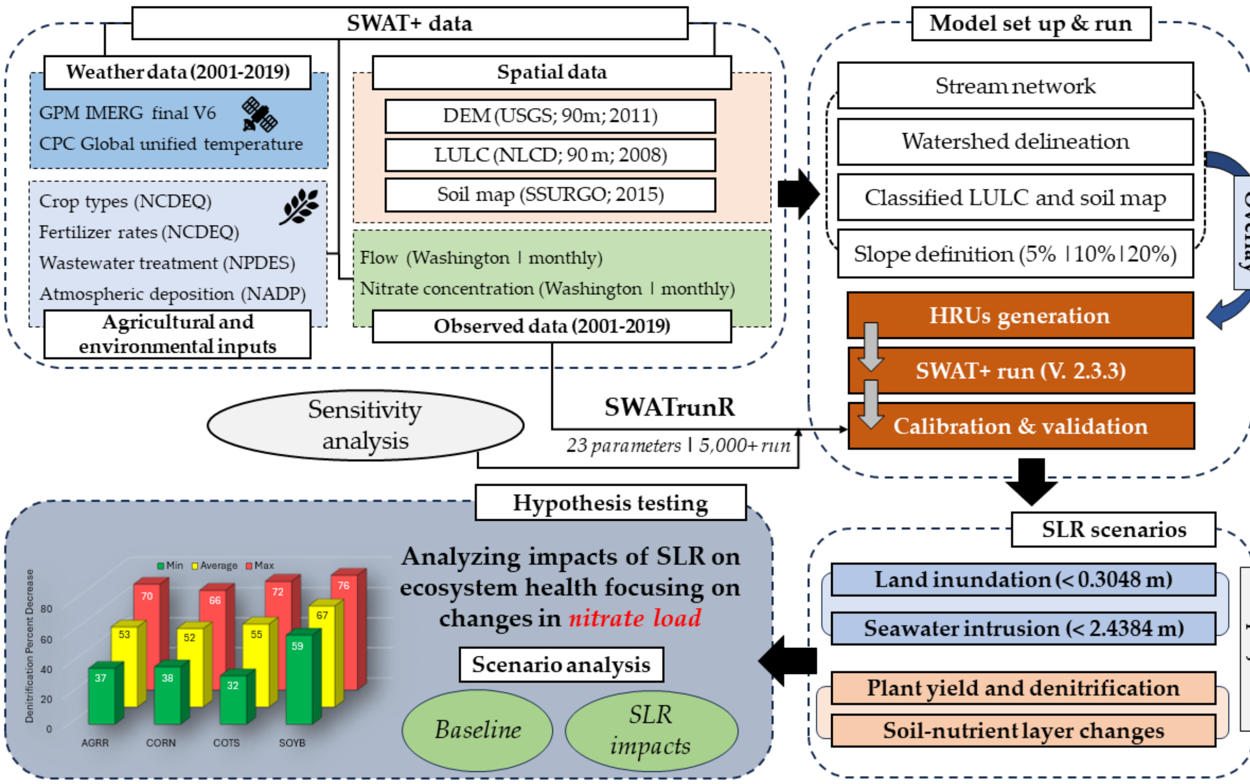


Figure 2. Framework for assessing the impacts of SLR on ecosystem health with a focus on nitrate load changes using SWAT+ model.

This study builds upon the foundational work of Tran et al. (2024) by further calibrating the SWAT+ model for nitrate dynamics. For setting up the SWAT+ model, a variety of data sources were used to accurately depict watershed characteristics. We obtained watershed boundary data from the United States Geological Survey (USGS) StreamStats service and incorporated elevation, land use, and soil type data from the USGS for 2011, the National Land Cover Database (NLCD) for 2008, and the Soil Survey Geographic Database (SSURGO) for 2015, all at a 90m resolution (Figure 2). These inputs were processed using QSWAT+ to delineate drainage networks, sub-basins, and Hydrological Response Units (HRUs), crucial for modeling the intricate hydrological behaviors within the watershed.

We used weather data from the Global Precipitation Mission (GPM) Integrated Multi-satellitE Retrievals for Global Precipitation Measurement Final run Version 6 (GPM IMERGF V6) (Hou et al., 2014). Additionally, we assimilated agricultural data, including crop types and fertilizer application rates, from reports by the North Carolina Department of Environmental Quality

(NCDEQ) and the North Carolina Department of Agriculture & Consumer Services (NCDEQ, 2014; NCGAR, 2022), specifically pertaining to the Tar-Pamlico watershed. For detailing the Tar-Pamlico SWAT+ model, we simulated four different crop types—soybean (40%), corn (19%), cotton (19%), and a general agricultural crop (AGRR, 22%) (NCDEQ, 2014; NCGAR, 2022). The general agricultural crop type was used for all other crops (e.g., tobacco, sweet potatoes, etc.), and in SWAT+, we simulated that using the agricultural_land_row (agrr) crop type (SWAT+, 2020). This information proved essential for more accurate simulations of agricultural runoff and nutrient transport.

We also integrated wastewater treatment data for the 22 discharges (Supplementary Information) within the Tar-Pamlico watershed from the National Pollutant Discharge Elimination System (NPDES) and atmospheric deposition data from the National Atmospheric Deposition Program (NADP, 2023). We used observed flow and nitrate data in Washington, NC. Observed flow data was collected from the USGS monitoring station (station ID: 02084472) in Washington (Tran et al., 2024), as well as from USGS stations ID: 02083500 in Tarboro, NC, and 02084000 in Greenville, NC (Figure 1). Nitrate concentration data was obtained from NCDEQ (site 21NC01WQ) in Washington, NC.

To calculate the monthly nitrate load, we first calculated the average daily discharge in Washington for each month. Then, we calculated the average nitrate concentration for each month from the available nitrate concentration data. We multiplied the average discharge for a specific month by the average nitrate concentration for the same month and then multiplied it by the total number of days in that month (Preston et al., 1989). In 2003, there were 357 daily observations, indicating a high-frequency data collection effort at this location (site 21NC01WQ). However, this frequency declined sharply. By 2005, the frequency of data collection had decreased, with only 144 daily observations. This trend continued, and by 2010, only 40 observations were recorded. Eventually, the data collection frequency shifted to a monthly scale, with only about 10 to 13 observations per year from 2011 onwards. This reduction in data collection frequency over time introduces additional challenges in accurately estimating nitrate loads and concentrations, as fewer data points are available to capture the variability and trends (Birgand et al., 2011).

2.3. SWAT+ Model Optimization

In this study, we further modified the SWAT+ model for the Tar-Pamlico basin developed by Tran et al. (2024) to achieve combined accurate flow, nitrate dynamics, plant yield, denitrification, and HRU-level nitrate export. We simulated the period from January 2001 to December 2019 with a 2-year warm-up period. The calibration was conducted for the period from January 2003 to December 2011, and the validation was carried out from January 2012 to December 2019. We calibrated the model for the combined optimization of monthly nitrate load and monthly flow with observed data from Washington, NC (Figure 1), as described in section 2.2. For optimization, we maximized the performance index Nash-Sutcliffe Efficiency (NSE) with 5000+ simulations and additionally evaluated the model's performance using the Kling-Gupta Efficiency (KGE). We used the SWATrunR package (Schuerz, 2019) to assist with calibrating the model. Our calibration efforts targeted 23 parameters identified as crucial for accurately representing hydrological and nitrogen processes (Table 1), based on sensitivity analysis and literature.

For parameter adjustment, we employed three methods: absolute change (x' = x + y), percent change (x' = y * x / 100), and absolute value (x' = y), where x is the default value, x' the new value, and y the calibrated parameter value (SWAT+ IO Document, 2020). The choice of method was influenced by each parameter's resolution and initial range; for instance, basin-level parameters predominantly used absolute value adjustments. The decision between absolute and percentage changes depended on the magnitude of the parameter’s range—absolute changes were preferred for narrow ranges, while percentage changes were favored for wider ranges. This approach allowed for a broad range of parameter adjustments during model calibration, ensuring flexibility across varying resolutions and initial ranges.

To further ensure the robustness of our model, we also performed cross-validation (S3 Supplementary Information) for monthly flow at two additional locations: Tarboro, NC (USGS station ID: 02083500) and Greenville, NC (USGS station ID: 02084000) for the period from January 2003 to December 2019 (Figure 1; Figure S2 Supplementary Information; Figure S3 Supplementary Information). This additional validation helped verify the model's accuracy and reliability across different parts of the Tar-Pamlico River Basin.

We also soft-calibrated the model for yield, denitrification, and nitrate export for selected HRUs representing corn, cotton, soybeans, and general agricultural crops (Etheridge et al., 2014).

Soft calibration in this context involves selecting the top 5% of over 5000 simulations that yielded the highest combined NSE for monthly nitrate load and monthly flow. From these top 5% simulations, we chose the best simulation that provided optimal values for yield, denitrification, and nitrate export for the selected HRUs. The values for yield, denitrification, and nitrate export were ranges taken from literature relevant to the study area, but not at the selected HRUs during the simulation period. Soft calibration is the process of making sure the values for these outputs are within the expected range. For instance, we selected the simulation that produced yields for corn (8400-8500 kg ha^{-1}), cotton (1150-1200 kg ha^{-1}), soybeans (2500-2600 kg ha^{-1}), and general agricultural crops (4000-4100 kg ha^{-1}) in SWAT+ for the Tar-Pamlico watershed (NCDEQ, 2014; NCGAR, 2022). Detailed information regarding the soft calibration for denitrification and nitrate export is provided in the supplementary information (S4 Supplementary Information). The finalized parameter values, based on the initial maximization of NSE for monthly nitrate load and monthly flow simulation, followed by the soft calibration of yield, denitrification, and nitrate export, are shown in Table 1.

Table 1. SWAT+ model optimization parameters details. Note that bsn is Basin, sol is Soil, hru is Hydrological Response Unit, and plt is Plant.

Parameter	Parameter Range (Unit)	Resolution	Type of Change	Description	Initial calibration range (min, max)	Calibrated parameter value
surlag	0.05, 24.0 (days)	bsn	Absolute Value	Surlag controls delay in surface runoff release	0.05, 24	3.574
cmn	0.001, 0.003 (-)	bsn	Absolute Value	Rate factor for humus mineralization of organic nutrients	0.001, 0.003	0.0018
cdn	0.0, 3.0 (-)	bsn	Absolute Value	Denitrification rate control	0, 3	2.261
sdnco	0.0, 1.0 (-)	bsn	Absolute Value	Denitrification threshold water content	0, 1	0.559
nperco	0.0, 1.0 (-)	bsn	Absolute Value	Nitrate percolation coefficient	0.01, 1	0.080
n_updis	0.0, 100.0 (-)	bsn	Absolute Value	Nitrogen uptake distribution parameter controlling depth distribution of nitrogen uptake in soil	0, 100	49.233
awc	0.01, 1.0 (mm H2O mm^{-1})	sol	Absolute Change	The difference in soil water content between field capacity and permanent wilting point	-0.3, 0.3	0.081
bd	0.9, 2.5 (g cm^{-3})	sol	Absolute Change	Moist bulk density, representing soil's mass-to-volume ratio at or near field capacity.	-0.4, 0.8	0.271
k	0.0001, 2000.0 (mm hr^{-1})	sol	Percent Change	Saturated hydraulic conductivity, indicating the ease of water movement through soil	-30, 30	-4.024
z	0.0, 3500.0 (mm)	sol	Percent Change	Depth from soil surface to bottom of layer	-30, 30	1.469
esco	0.0, 1.0 (-)	hru	Absolute Change	Soil evaporation compensation factor which allows modification of depth distribution to meet soil evaporative demand, considering capillary action, crusting, and cracks.	-0.3, 0.3	-0.069
epco	0.0, 1.0 (-)	hru	Absolute Change	Plant uptake compensation factor which allows adjustment of water uptake depth distribution in response to plant transpiration demand and soil water availability.	-0.3, 0.3	-0.114
biomix	0.0, 1.0 (-)	hru	Absolute Change	Biological mixing efficiency, determining redistribution of soil constituents by biota activity.	-0.3, 0.3	-0.048

Parameter	Parameter Range (Unit)	Resolution	Type of Change	Description	Initial calibration range (min, max)	Calibrated parameter value
latq_co	0.0, 1.0 (-)	hru	Absolute Change	Coefficient for the Plant ET curve number	-0.3, 0.3	0.101
perco	0.0, 1.0 (fraction)	hru	Absolute Change	Percolation coefficient, adjusting soil moisture for percolation to occur.	-0.3, 0.3	-0.272
cn2	35.0, 95.0 (-)	hru	Percent Change	Curve number for Condition II runoff potential.	-30, 30	12.283
cn3_swf	0.0, 1.0 (-)	hru	Percent Change	Soil water factor for the curve number for condition III runoff potential	-30, 30	-24.729
ovn	0.01, 30.0 (-)	hru	Percent Change	Manning's "n" value for overland flow velocity estimation	-30, 30	14.865
canmx	0.0, 100.0 (mm H2O)	hru	Percent Change	Maximum canopy storage, representing the maximum amount of water held in the canopy when fully developed.	-30, 30	-0.189
lat_ttime	0.5, 180.0 (days)	hru	Percent Change	Lateral flow travel time allows the model to calculate travel time based on soil hydraulic properties.	-30, 30	-19.100
revap_min	0.0, 50.0 (m)	aqu	Percent Change	Threshold depth of water in shallow aquifer for percolation to deep aquifer	-30, 30	7.659
Lai_pot	0.5, 10 (m^2 m^{-2})	Plt	Absolute Value	Potential maximum leaf area index	NA	Corn: 5 Cotton: 2.5 Soyb: 2.027
Harv_idx	0.01, 1.25 (-)	plt	Absolute Value	Harvest index- crop yield/aboveground biomass	NA	Soyb: 0.418

2.4. SLR Incorporation

2.4.1. Framework Design:

We designed a framework to partially simulate the effects of SLR in the SWAT+ model with a focus on nitrogen cycle processes. We achieved this by systematically adjusting inputs and parameters to reflect the dynamic impacts of SLR. Although the SWAT+ model functions as a unidirectional rainfall-runoff model (SWAT+ IO Document, 2020), we focus on altering expected land uses, enhancing the model's capability to simulate critical land processes, such as altered denitrification rates and the reduction of crop yields under SLR conditions.

2.4.2 Land Use Adjustments:

Using mid-century SLR projections from the National Oceanic and Atmospheric Administration (NOAA, 2022), which forecasts an increase of approximately 0.3 m by 2050, we reclassified all landcover with elevations less than 0.3 m to water. To account for the effects of saltwater intrusion, we consider any areas with an elevation of less than 2.4 m to fall within the risk zone of saltwater intrusion (NOAA, 2022). For areas with elevations under 2.4 m, we used GIS to process the land use changes by developing a new category labeled as saltwater-intruded land use for each of the respective land uses.

2.4.3. SWAT+ Database Update:

After incorporating these new land use types, we added the saltwater-influenced crops to the SWAT+ plant database (Supplementary Information). Using the updated land cover map and the revised SWAT+ database, we generated new Hydrological Response Units (HRUs) for areas up to 2.4 m above the current mean sea level. For the baseline simulation, we retained the same parameters for the saltwater-intruded crops as their corresponding conventional crops. We confirmed that SWAT+ produced consistent outputs for these new crops, matching those of their parent crops when no parameters were altered. The creation of these new HRUs allowed us to modify SWAT+ parameters to simulate the impacts of SLR on the nitrogen cycle.

We changed multiple SWAT+ parameters in our initial efforts to simulate the effects of SLR. We conducted a literature review to identify processes and their corresponding SWAT+ parameters potentially affected by saltwater intrusion, such as soil pH (Al-Busaidi & Cookson,

2003) and electrical conductivity (Rhoades & Corwin, 1990). From our findings, we adjusted electrical conductivity (ec.sol) and pH (ph.sol) parameters in the model to account for SLR. However, despite significant alterations to these parameters, we observed no impact on the simulated denitrification rate and crop yields. This suggests that these parameters are not directly linked to the outputs we expected them to alter, and additional factors within the SWAT+ model would need to be considered to reflect the effects of SLR.

2.4.4 Indirect Approach to Incorporate SLR's Effects:

To address this challenge, we opted for an indirect approach to incorporating SLR effects. SLR can decrease denitrification rates by inhibiting the activity and abundance of denitrifying microorganisms that are adapted to freshwater or low-salinity environments. Salinity has been shown to lower soil heterotrophic respiration, including denitrification (Chen et al., 2022; Hu et al., 2014). Salinity can also induce oxidative stress, and interfere with DNA replication, transcription, and translation in heterotrophic denitrifiers (Chen et al., 2022). These general microbial stress responses to salinity may also be accompanied by decreases in the abundance and expression of denitrification genes (Chen et al., 2022; Pan et al., 2023; Wang et al., 2018). These changes are thought to be mediated through physiological (e.g., altered solute potential), and abiotic mechanisms (e.g., displacement of soil-bound NH_4^+) (Pan et al., 2023). Additionally, saltwater intrusion can change the composition of the microbial nitrogen cycling community, favoring dissimilatory nitrate reduction to ammonium (DNRA) over denitrification (Neubauer et al., 2019).

We introduced new soil nutrient layers in our model to better simulate denitrification rates and plant yield (SWAT+ IO Document, 2020) under SLR. The parameters altered were the coefficient for adjusting concentrations based on depth (exp_co) and the fraction of active soil humus (fr_hum_act). In the preliminary analysis, we found that increasing the exp_co parameter decreased denitrification, and decreasing fr_hum_act decreased denitrification. Increasing the exp_co parameter likely reduces denitrification by limiting the depth at which there are high concentrations of nitrate, meaning the high nitrate concentrations stay above the soil horizon where conditions are ideal for denitrification to occur. Decreasing fr_hum_act reduces denitrification by lowering the proportion of active humus that supports microbial activity essential for the denitrification process (SWAT+ IO Document, 2020).

We developed two new soil nutrient layers: one for saltwater-intruded agricultural crops and another for the rest of the saltwater-intruded land use. This distinction was necessary because, in general, simulated denitrification rates in wetland regions are lower than in agricultural regions, due to higher N availability in agricultural soils (Groffman et al., 2019). By creating specific soil nutrient layers for these distinct land uses, we aimed to capture the unique responses of each land type to saltwater intrusion, ensuring a more accurate simulation of denitrification processes and crop yield outcomes. The soil nutrient layers were applied at the HRU resolution for the respective land use (SWAT+ IO Document, 2020). The expected decrease in denitrification was simulated along with an excessive decrease in yield, thus we adopted a multiparameter approach to further fine-tune denitrification and plant yield by altering other HRU-specific parameters such as curve number (cn2), plant uptake compensation factor (epco), soil evaporation compensation factor (esco), available water capacity (awc), plant ET curve number coefficient (latq_co), and potential maximum leaf area index (lai_pot) (Table 1 and Section 3.2).

We selected these parameters based on our preliminary analysis of how they affected yield and denitrification under SLR conditions (Supplementary Information). We did not find significant literature on how much the parameters mentioned above should change under SLR conditions. For each parameter, the SLR calibration range was chosen based on the expected impact of increased salinity, aiming to simulate environmental changes realistically, which is further discussed in section 3.2. Increased salinity generally leads to reduced soil moisture retention, higher evaporation rates, altered plant water uptake, and modified runoff characteristics, all of which were considered in setting the calibration ranges. We then performed a soft calibration with 2000 simulations to adjust plant yield and denitrification for SLR conditions using the parameter changes described above. We used SWATrunR (Schuerz et al., 2022) to alter these parameters specifically for newly created saltwater-affected HRUs, aligning plant yield and denitrification rates with literature under SLR scenarios, which is further discussed in section 3.2. This innovative framework is intended to serve as a pioneering step for hydrological modelers, setting the stage for more sophisticated and accurate modeling of SLR impacts.

2.5. Hypothesis and Statistical Testing:

In the context of assessing the impacts of climate change on coastal ecosystems, understanding how sea level rise (SLR) affects nutrient dynamics is crucial. Elevated nitrate levels pose significant risks to water quality and ecosystem health, particularly in coastal agricultural watersheds. The hypothesis tested in this study was that there is no significant difference in the mean monthly nitrate loads between the baseline and SLR conditions in the Tar-Pamlico basin. This null hypothesis posits that the implementation of SLR scenarios would not lead to a statistically significant change in the amount of nitrate transported monthly from the watershed into the estuary, compared to the current baseline conditions. By testing this hypothesis, we aimed to determine whether the anticipated effects of SLR, such as reduced yield and denitrification, would have measurable impacts on nitrate load to the Pamlico estuary. To test this hypothesis, we conducted a paired t-test, a statistical method widely used in previous SWAT studies for hypothesis testing (Du et al., 2009; Pereira et al., 2016; Santos et al., 2018), comparing the mean monthly nitrate loads under baseline and SLR conditions to determine whether the observed differences between the two scenarios were statistically significant.

3. Results and Discussion

3.1. Model Optimization

We modified the Tar-Pamlico coastal watershed's SWAT+ model used in Tran et al., 2024. First, we improved it for combined optimization of monthly flow and monthly nitrate load at Washington, NC (Figure S1 Supplementary Information; Figure 3). We had to make some trade-offs to achieve a higher combined performance index (NSE) for monthly flow and nitrate load rather than optimizing each individually to its highest possible values. For monthly flow optimization (Figure S1 Supplementary Information), we achieved good performance indices, considering the coastal watershed (Upadhyay et al., 2022), with an NSE of 0.49 and a KGE of 0.66 during calibration, and an NSE of 0.55 and a KGE of 0.7 during validation (S2 Supplementary Information). For monthly nitrate load calibration (Figure 3), the model demonstrated a good level of accuracy within the coastal Tar-Pamlico watershed, achieving an NSE of 0.61 and a KGE of 0.77 (Figure 3). These metrics suggest a strong agreement between observed and simulated data, indicating that the model is well-calibrated (Upadhyay et al., 2022) and capable of simulating the dynamics governing nitrate transport and retention.

We found lower performance indices for the validation period for nitrate load (Figure 3); the model's performance metrics declined to an NSE of 0.33 and a KGE of 0.39, indicating moderate accuracy considering a coastal watershed (Upadhyay et al., 2022). This decline likely resulted from increased uncertainty in observed nitrate loads associated with the change in nitrate sampling frequency post-2010 (Birgand et al., 2011), as well as variations in hydrology and rain events that were not fully captured by the model. It is important to consider that model evaluation guidelines should be adjusted based on factors such as the quality and quantity of measured data, model calibration procedure, simulation time step, and project scope and magnitude (Moriasi et al., 2007). Additionally, we had to compromise higher performance index simulations with those of lower performance index to achieve better simulations for plant yield, denitrification, and nitrate export from agricultural lands, which played a significant role in this paper (S4 Supplementary Information). Therefore, despite the lower metrics, the model still demonstrated its capacity to provide reasonable nitrate load predictions under varying conditions (Moriasi et al., 2007; Upadhyay et al., 2022).

To further ensure the robustness of our model, we conducted cross-validation (S3 Supplementary Information) at two additional locations within the Tar-Pamlico River Basin: Tarboro, NC (USGS station ID: 02083500) and Greenville, NC (USGS station ID: 02084000). This cross-validation was performed for monthly flow for the period from January 2003 to December 2019 (Figure S2 Supplementary Information; Figure S3 Supplementary Information). The model showed a strong performance at these additional sites, achieving an NSE of 0.69 at Tarboro, NC (Figure S2 Supplementary Information), and 0.7 at Greenville, NC (Figure S3 Supplementary Information). By including these additional sites, we were able to evaluate the model's performance across different areas within the watershed, providing a more comprehensive assessment of its accuracy and reliability. The inclusion of multiple validation points allowed us to verify that the model is well set up for running multiple scenarios (Arsenault et al., 2018).

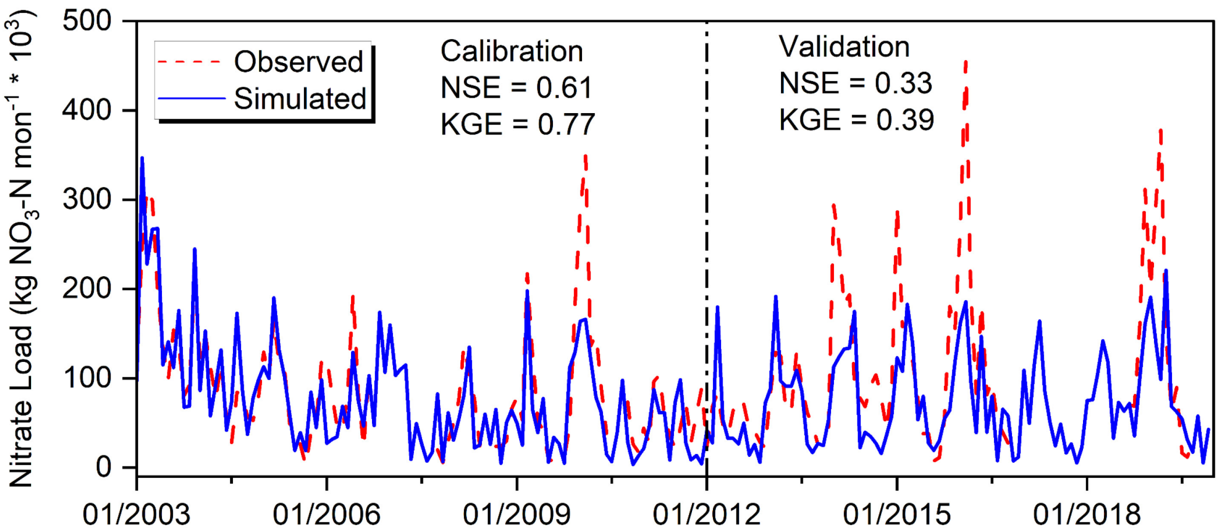


Figure 3. Monthly nitrate load optimization results.

3.2. Modeling the Effects of SLR on Nitrogen Processes

As mentioned in Section 2.5, simulating the ramifications of SLR on watershed processes, with a particular focus on the adjustment of plant yield and denitrification were not as straightforward as expected. Saltwater intrusion disrupts normal plant physiological processes, impeding nutrient uptake and causing osmotic stress in plants, which is reflected in the reduced yields observed (Okon, 2019; Safdar et al., 2019).

SLR reduces potential leaf area (by around 30%) by flooding coastal areas, increasing soil salinity, and altering vegetation, leading to sparse foliage (Bond-Lamberty et al., 2023), which we adjusted using the potential maximum leaf area index (lai_pot) parameter in SWAT+. Additionally, we modified several other key parameters through soft calibration to fine-tune plant yield and denitrification at HRU levels (Table 2). These parameters include Available Water Capacity (awc), which was reduced (Table 2) to reflect changes in soil water retention capacity due to increased salinity. Salinity can decrease AWC by decreasing the soil's ability to retain water due to the osmotic effect, which makes it harder for plants to extract water from the soil (Cousin et al., 2022; Safadoust et al., 2024). Additionally, high salt concentrations can lead to soil structure degradation, further limiting water availability (Bronick & Lal, 2005).

The Soil Evaporation Compensation Factor (esco) was increased (Table 2) to account for elevated evaporation rates in salt-affected soils, influencing soil moisture dynamics and nitrate transport (Hosseini & Bailey, 2022; Tirabadi et al., 2022). Salinity increases the soil evaporation compensation factor (esco) by enhancing capillary action, which draws water closer to the soil surface, and by promoting crusting, which reduces infiltration and increases surface evaporation (Nachshon, 2018). The Plant Uptake Compensation Factor (epco) was modified from -0.114 to -0.042 to reflect changes in plant root water uptake under saline conditions, impacting the overall water balance and nitrate uptake by plants. The Plant ET Curve Number Coefficient (latq_co) was adjusted from 0.101 to 0.279 to capture changes in evapotranspiration rates due to altered vegetation structure and water availability under SLR scenarios (Yang et al., 2022). The Curve Number (cn2) was increased to reflect changes in surface runoff potential under different land cover conditions influenced by SLR. Salinity increases the cn2 by decreasing soil infiltration rates and increasing surface runoff (Hosseini & Bailey, 2022; Sorando et al., 2019). Saline soils often have poorer structure, leading to crusting and reduced permeability, which results in higher runoff potential (Bronick & Lal, 2005).

Even though SWAT+ is not capable of simulating backflow, the hydrological parameter changes discussed in this section should enable the model to more accurately simulate processes in response to SLR when viewed at the monthly or annual scale. It is highly unlikely to be accurate at the daily time scale. This SLR-calibrated SWAT+ model offers valuable insights into the intricate interplay between SLR and watershed processes governing nitrate export.

Table 2. Parameters altered to simulate plant yield and denitrification changes under SLR. [a: corn, b: cotton, c: soybean, d: general agricultural crop].

Parameter	Potential Parameter Range (Unit)	Resolution	Type of Change	Default value	Freshwater landuse calibration	SLR calibration range	SLR-incorporated parameter
awc	0.01, 1.0 (mm H_2O mm^{-1})	sol	Absolute Change	0.14	0.081	-0.3, 0.08	-0.021
esco	0.0, 1.0 (-)	hru	Absolute Change	0.95	-0.069	-0.3, 0.3	0.038
epco	0.0, 1.0 (-)	hru	Absolute Change	0.5	-0.114	-0.3, 0.3	-0.042
latq_co	0.0, 1.0 (-)	hru	Absolute Change	0.01	0.101	-0.3, 0.3	0.279
cn2	35.0, 95.0 (-)	hru	Percent Change		12.283	13, 20	17.834
Lai_pot	0.5, 10 (m^2 m^{-2})	Plt	Absolute Value	6 (a) 4 (b) 5 (c) 3 (d)	5 (a) 2.5 (b) 2.027 (c) 3 (d)		3.5 (a) 1.75 (b) 1.419 (c) 2.1 (d)

3.2.1 Modeling the Effects of SLR on Crop Yield

In this study, we simulated the impacts of SLR on the yields of four distinct crop types (Figure 4)—general agricultural, corn, cotton, and soybean—quantified in kilograms per hectare (kg ha^{-1}). Our simulation used SLR projections for midcentury (NOAA, 2022), but the model was run for the period from Jan 2001 to Dec 2019 using SWAT+. This modeling approach provides a snapshot of potential impacts based on historical climate and hydrological data while incorporating future SLR scenarios.

In our simulation, crop yields under SLR conditions exhibited significant reductions across various land uses within the HRUs compared to baseline scenarios based on the literature. It is important to note that our calibration process focused on a few representative HRUs of each crop type (Figure S9 Supplementary Information), while Figure 4 captures the results from all HRUs. The average reductions in yields were 36% for general agricultural crops, 23% for corn, 36% for cotton, and 33% for soybeans going from freshwater conditions to saltwater conditions. This variability reflects the significant impact of SLR on crop productivity across different HRUs. As expected, due to calibration, these findings are consistent with previous literature on the impacts of salinization on crop yields (Gibson et al., 2021)

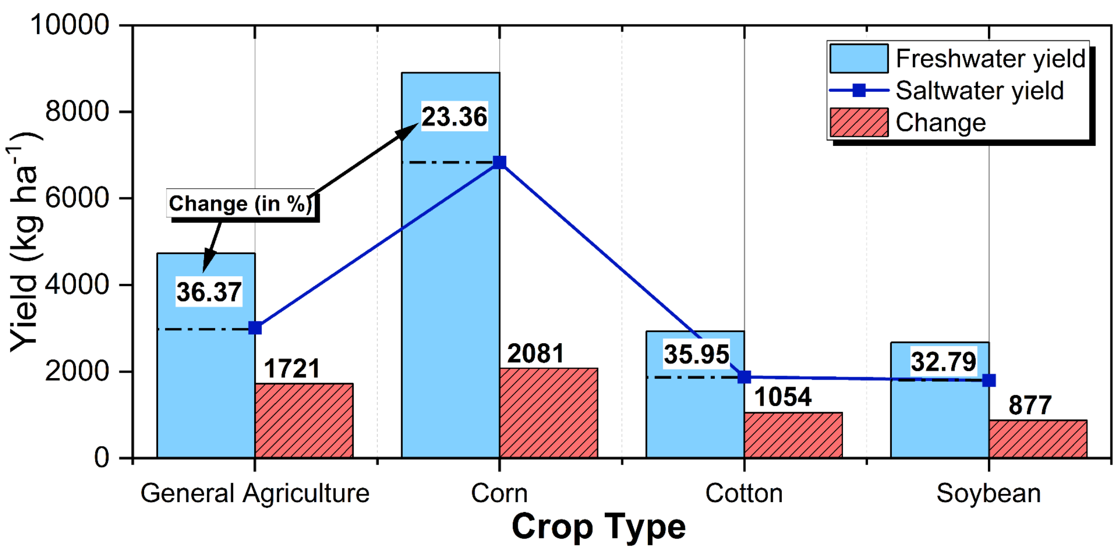


Figure 4. Simulated effects of SLR on annual average crop yields.

3.2.2 Simulated Effects on Denitrification Rate

Adjustments to model parameters for SLR-influenced land uses were specifically designed to simulate the impacts of increased salinity on denitrification. For general agricultural crops, denitrification rates showed significant decreases, ranging from about 37% to nearly 70%, with an average decrease of around 53% (Figure 5). In corn, the reductions were slightly less variable, ranging from approximately 38% to 66%. Cotton demonstrated a broader range of decreases, from 32% to over 72%, with an average reduction of 55%. Soybeans experienced the most substantial impacts, with denitrification rate declines ranging from about 59% to 76%, and an average decrease of 67% (Figure 5). This variability in denitrification changes across different crops and HRUs can be attributed to the fact that the model was not uniformly calibrated for denitrification changes in all HRUs, resulting in diverse responses under the simulated conditions of SLR. Additionally, local conditions such as soil type, moisture content, and microbial activity levels also influence denitrification rates, leading to further variability in the simulated changes.

The parameter modifications led to reductions consistent with earlier findings in the literature (Hofstra & Bouwman, 2005; Qian et al., 1997). The observed decrease in soil nitrate processing capabilities under SLR conditions, linked to increased soil salinity inhibiting microbial activity essential for nitrogen cycling, could further complicate microbial community structures and potentially reduce denitrification efficiency (Mazhar et al., 2022; Spivak et al., 2019). This underscores the complexity of interactions between environmental changes and biological processes, highlighting the need for detailed modeling and management strategies to mitigate the adverse effects on agricultural productivity and ecosystem health.

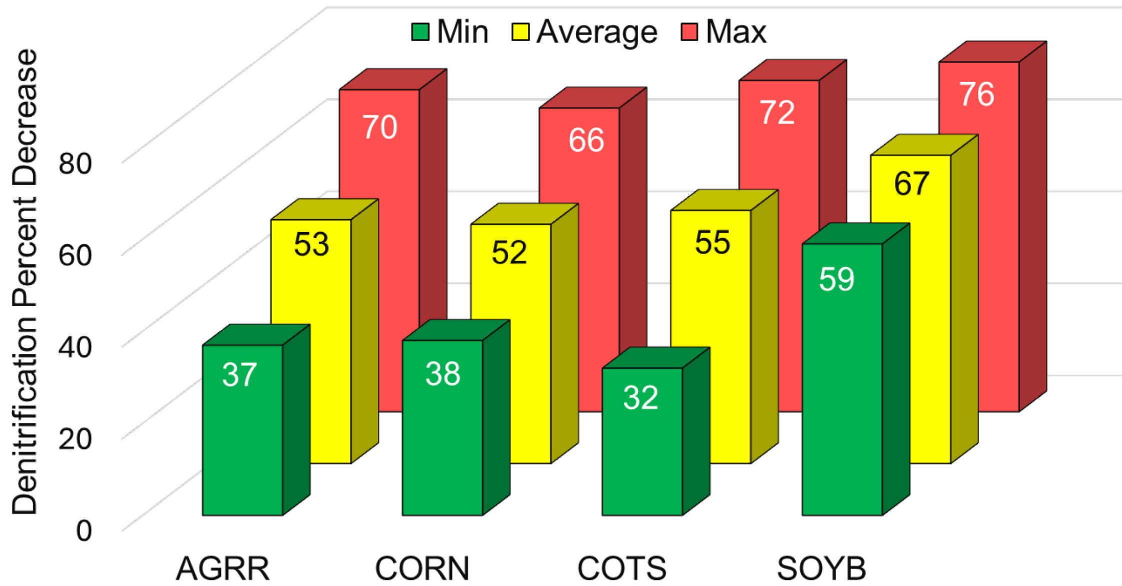


Figure 5. Impacts of SLR on annual average denitrification across different agricultural crops, in which AGRR is general agricultural crop, COTS is cotton, and SOYB is soybean.

3.3. Nitrate Load to the Pamlico Estuary

We conducted a comparison of the monthly nitrate load at the Pamlico Estuary under the baseline and SLR scenarios. We compared the model results for both scenarios from January 2003 to December 2019. This analysis aimed to quantify the variations in nitrate loads across different months, providing a clearer understanding of how rising sea levels could affect nutrient export to this coastal environment. Both datasets exhibit significant variability and peaks over time.

The results reveal notable variations in the seasonal nitrate loads when comparing the baseline with the SLR scenarios (Figure 6). Winter and spring exhibited higher nitrate loads compared to summer and fall. This pattern is likely influenced by increased precipitation during the colder months (Sayemuzzaman & Jha, 2014), which enhances runoff (Moraglia et al., 2022) and nitrate leaching (Oh & Sankarasubramanian, 2012), whereas the growing vegetation in warmer months can assimilate more nutrients (Tian et al., 2014), thereby reducing nitrate available for export.

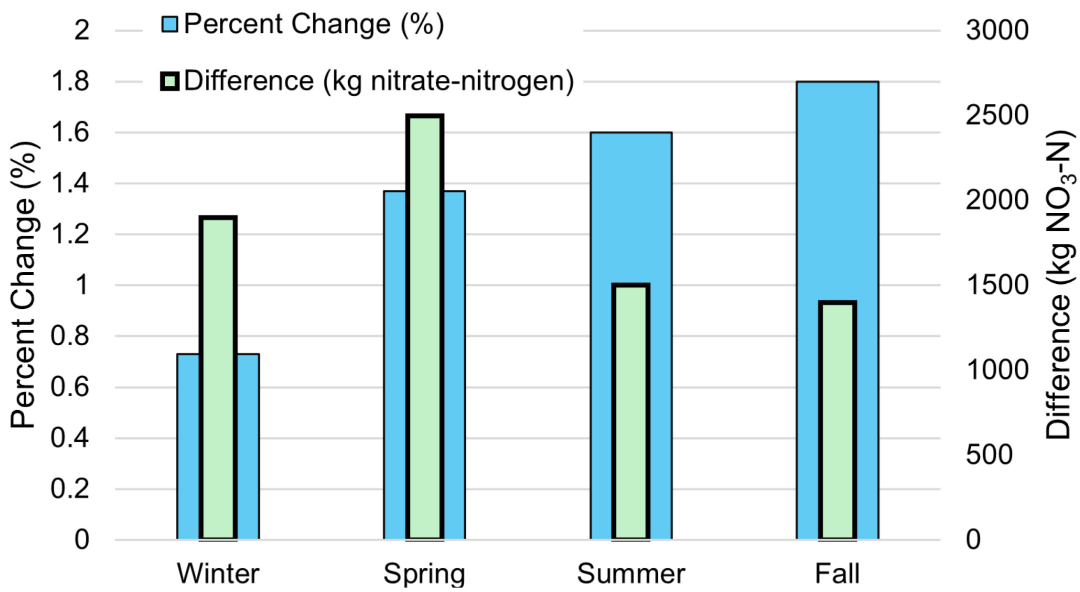


Figure 6. Seasonal variation in nitrate load (kg NO3-N) differences between SLR and baseline scenarios. The percent changes and differences are all positive, indicating an increase under SLR conditions.

The data showed that nitrate loads consistently increase across all seasons under SLR conditions, with the most substantial increases during winter and spring (Figure 6). SLR modifies nitrate availability and transport, especially during peak precipitation periods, which typically occur during the winter and spring seasons in the study region. These periods are characterized by increased precipitation, resulting in elevated surface runoff and higher flows (Stuart et al., 2011). SLR alters the water table (Hay et al., 1990) and inundates low-lying coastal areas (Mohd et al., 2018), exacerbating surface runoff (Wang et al., 2011) and leading to higher flows during heavy rains (Rotzoll & Fletcher, 2013). Historical data indicates that precipitation patterns in the Tar-Pamlico River Basin have shown increased variability and intensity over the years, further influencing nitrate dynamics (Tang et al., 2012; Tran et al., 2024).

These changes facilitate rapid nitrate movement from terrestrial sources to estuarine and marine environments, underscoring SLR's impact on nitrate loss (Munksgaard et al., 2019; Voss et al., 2015; Wang et al., 2017). The percent change in nitrate loads indicates higher increases during fall (1.8%) and summer (1.6%) compared to spring (1.4%) and winter (0.73%) under SLR scenarios (Figure 6). This increase during summer and fall can be attributed to saltwater intrusion increasing soil salinity (Bayabil et al., 2021), disrupting nitrogen cycling (Nelson & Zavaleta, 2012), and reducing nitrate uptake by crops (He et al., 2018), while altering hydrological dynamics to increase nitrate mobility (Donner & Kucharik, 2003). Increased salinity can disrupt microbial denitrification processes and can result in more residual nitrates leaching into waterways (Arce et al., 2013). Additionally, seasonal agricultural practices misaligned with changing environmental conditions may further contribute to nitrate export. Salinity impacts can alter plant growth cycles by inhibiting germination and slowing development, leading to misalignment with farmers' fertilizer application timings for specific crops. When fertilizers are applied based on the expected growth cycle of the crop, but plants develop slower or unevenly due to salinity stress, nutrients may not be effectively absorbed, resulting in increased nutrient runoff and nitrate load to the estuary (Conrad & Marinos, 2024; Shainberg & Shalhevet, 2012).

3.4. Statistical Analysis of Nitrate Load Under Baseline and SLR Conditions

To assess the impact of sea level rise (SLR) on nitrate loads in the Pamlico estuary, we tested the hypothesis that there is no significant difference in the mean monthly nitrate loads between baseline and SLR conditions. To test this hypothesis, we conducted a paired t-test comparing the mean monthly nitrate loads under baseline and SLR conditions. The baseline condition had a mean monthly nitrate load of 155,200 kg N, while the SLR condition had a mean nitrate load of 157,100 kg N, with each set comprising 204 observations. The Pearson Correlation coefficient of 0.99 indicated a very high degree of linear correlation between the paired samples, which is expected since the measurements under both scenarios pertain to the same time points (Cohen et al., 2009).

The paired t-test yielded a t-statistic of -6.6869, reflecting a significant difference between the means. The negative t-statistic suggests that the nitrate load under SLR conditions is higher than under baseline conditions. The two-tailed p-value of approximately 2.16×10^{-10} indicates that this difference is highly statistically significant, far below the conventional alpha level of 0.05.

Based on these results, we reject the null hypothesis that there is no significant difference in the mean monthly nitrate loads between the baseline and SLR conditions. This outcome provides strong evidence that SLR significantly increases nitrate loads in the Pamlico estuary from the Tar-Pamlico basin. These findings highlight the impact of SLR on nitrate availability and transport, particularly the increase during fall and summer seasons. Understanding these interactions is crucial for developing effective management strategies to mitigate the impacts of nutrient loading and protect aquatic ecosystems in the context of ongoing climate change (Hamilton et al., 2016).

4. Limitations and future works

This study acknowledges the limitations of SWAT+, particularly its inability to simulate backflow and the complexity of the nitrogen cycle, which has conflicting literature on the impacts of SLR on denitrification. Tidal influence has not been explicitly accounted for in this study. We recognize that our approach to modeling land processes under SLR conditions may not be definitive. However, this research represents an important first step towards integrating SLR impacts into the SWAT+ framework, providing a foundation for further refinement and development by hydrological modelers. Future research should focus on using the SLR-incorporated SWAT+ model to simulate how changes in climate precipitation and temperature would alter nitrate dynamics and to evaluate the performance of agricultural best management practices under SLR conditions.

5. Conclusions

This study presents a novel methodology to incorporate SLR into the SWAT+ model and simulate its impacts on ecosystem health. To simulate SLR effects in SWAT+, we reclassified low-lying land uses to water and adjusted parameters for low-elevation areas to model increased soil salinity's impact on crop yield and denitrification rates. We compared the nitrate export to the Pamlico estuary from the Tar-Pamlico River basin under both SLR and baseline conditions. These adjustments for the effects of SLR on hydrological parameters and inputs significantly enhance the model's ability to project changes in nitrate loads due to SLR.

The findings reveal that SLR significantly influences nitrate loads at the monthly scale, leading to increased nitrate transport to the Pamlico Estuary in all seasons. We observed higher nitrate load increases in spring and winter, attributed to elevated flows. In contrast, the highest percentage increases in nitrate loads were found in summer and fall, likely due to reduced plant uptake and altered nitrogen cycles. Incorporating SLR into the SWAT+ model enabled analysis of how altered hydrological dynamics and increased salinity affect agricultural productivity and ecosystem health.

Supplementary Information

The authors have provided supplementary information.

CRediT authorship contribution statement

Mahesh R Tapas: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing—Original draft preparation, Visualization, Funding acquisition; **Randall Etheridge**: Conceptualization, Methodology, Validation, Resources, Writing—Review and editing, Supervision, Project administration, Funding acquisition; **Thanh-Nhan-Duc Tran**: Writing—Review and editing, Visualization; **Colin Finlay**: Validation, Writing—Review and editing; **Ariane Peralta**: Writing—Review and editing, Funding acquisition; **Natasha Bell**: Writing—Review and editing; **Yicheng Xu**: Data curation, Writing—Review and editing; **Venkataraman Lakshmi**: Writing—Review and editing.

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Data availability

The data that support the findings of this study are available upon reasonable request from the corresponding author. Most of the data used in this study is open source.

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LLM Statement

During the preparation of this work, the authors used ChatGPT to improve grammar, enhance the flow of the manuscript, and create the graphical abstract. Additionally, the background for the graphical abstract was created using DALL.E, an advanced AI tool developed by OpenAI for generating visualizations. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

Conflicts of Interest

The authors declare no conflicts of interest.

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