Using the *Soil and Water Assessment Tool+* to

Simulate the Effects of Agriculture on Water Quality

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TABLE OF CONTENTS

Abstract

Despite the intense strain that various socioeconomic factors place on agriculture in the United States, few models can accurately depict the cross-system interactions occurring on and around farms. This research attempts to address the disconnect between policies, models, and the processes that they are representing and regulating by using the *Soil and Water Assessment Tool+ (SWAT+)* to simulate the coastal agricultural region of Eastern North Carolina. We used *SWAT+* to simulate farming practices and soil properties in this agriculturally productive, coastal watershed. Our research question was: How can we use *SWAT+* to simulate the effects of differing soil properties on crop yield and nitrate loss? To answer this question, we ran numerous trials within *SWAT+* model with varying soil properties and analyzed their effect on crop yield and nitrate loss. Our validation and calibration processes were primarily in formed by USDA North Carolina yield results.

We found that the model's output was most sensitive to changes in parameters relating to soil structure and partitioning of precipitated water (curve number and curve number soil water factor). The curve number parameters were the most effective in optimizing yield across the watershed's top three crops: corn, cotton, and soybean, as well as decreasing nitrate lost from each crop. Our model was more sensitive to the curve number parameters than the parameter relating to water availability (surface runoff lag). These results can be used to support land use management practices that address the utility of improved soil structure on crop yield and reduced nitrate loss. Therefore, our results suggest that land use management practices that increased soil health are at a confluence of interests between farmers, environmentalists, and consumers alike. These results can more accurately inform agricultural policies that reduce the strain that socio-economic and ecological processes currently place on agriculture.

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Introduction

The future of agriculture in the United States is facing escalating strains from the hydrological changes associated with climate change and various socioeconomic pressures (IPCC-AR6, 2023). Increases in atmospheric greenhouse gas concentrations associated with climate change result in drastic disruptions of ecological balances occurring on and around agricultural regions (IPCC-AR6, 2023). These disruptions include, but are not limited to, the following: increased intensity and frequency of damaging storms, ocean warming/rising, and rising temperatures (IPCC-AR6, 2023). Additionally, at the landscape level, human activities are impacting land cover dynamics, nutrient cycling and runoff, and other parameters key to the functioning of productive systems. Therefore, the hydrological changes associated with climate change directly threaten plant productivity, yield, soil structure, water quality and availability on farms.

Coastal agricultural regions are vulnerable to the physical disruptions associated with climate change due to three main reasons: (1) low elevation, (2) lack of shelter/ high rates of urbanization, and (3) proximity to saline water bodies (Oppenheimer, 2022). Increased intensity and frequency of storms lead to higher rates of flooding via precipitation in already low-lying, unprotected, coastal agricultural regions. Flooding events can quickly erupt in coastal regions as slight increases in precipitation can raise groundwater levels that then connect low-lying coastal regions to oceans (USDA, 2020). Compared to their in-land and higher elevation counterparts, coastal agricultural regions are not as easily drained due to their lack of slopes that would normally slow the flow of precipitated water. These flooding events can swiftly destroy crops and increase fertilizer runoff immediately after it is applied.

In addition to flooding from precipitation, coastal regions are also threatened by inundation from oceans. These regions are often popular tourist destinations that are highly urbanized. The urbanization process often includes the replacement of barrier islands and marshes – that would normally reduce the impact of incoming tides – with infrastructure such as cement. The replacement consequently increases the amount of highly saline water intruding urbanized areas as well as farmers' land. This process is known as saltwater intrusion. In addition to urbanization, ocean warming, acidification, and rising temperatures associated with climate change also increase saltwater intrusion from oceans (Stuz, 2005). Salt water intrusion greatly hinders crops' ability to grow in soil by dramatically changing its pH, killing useful bacteria, and changing its moisture content (Kantamaneni, 2020). As such, these hydrological changes threaten the productivity of coastal agricultural regions and the farmers, locals, and consumers alike who depend on their productivity.

Domestic and international markets, the structure of government subsidies, and societal pressure to produce plentiful inexpensive food are putting immense socio-economic pressure on farms to rapidly increase crop yield to keep their farms in business. Pressures to meet these demands often lead to overapplication of fertilizers (Osmond, 2015). The overapplication of fertilizers coincides with increased frequency and intensity of storms, flooding events, and diminished barrier structures along coasts. When fertilizers are applied faster than crops can take them up, the excessive nutrients from overapplication are transported into downstream bodies of water after rain events. This leads to a process called eutrophication to take place where excess nutrients eventually settle into a slowly moving water area and are consumed by algae (Howarth, 2006). During the day, algae photosynthesize and produce oxygen, however, at night, they primarily respirate and take up oxygen. The algae consume most of the available dissolved oxygen in the water and consequently, a significant portion of oxygen-dependent organisms such as fish, zooplankton, and crustaceans in the waterway die (Tong, 2007). Fish kills are not only ecologically destructive, but they also lead to decreased tourism in areas due to their undesirable sights and smells (Gatiboni, 2019).

The frequency and intensity of these eutrophic events, storms, and floods are only increasing alongside increasing greenhouse gas emissions/temperatures (IPCC-AR6, 2023). As such, there is a pressing need for models to quantify eutrophic events and the factors that are increasing their intensities (Rogers, 2021). These models can inform policies regarding global greenhouse gas emissions, the protection of coastal barrier islands, and fertilizer management within coastal agricultural watersheds. An increasingly popular way of informing environmental policies is using hydrological models (Gao, 2014). Hydrological models synthesize complex ecological processes into easily comprehensible numbers. These models are important because they can demonstrate the complex variables that crops, and farmland operate under. These include ecological cycles (hydrologic, nutrient, geologic, and plant growth) that are only further complicated by human behavior/interactions with the land and local climates. We can additionally use hydrological models to quantify the effects of differing practices on farms. Therefore, these models can simplify interconnected processes to inform policies that directly impact farms.

This research adds to the growing body of literature on hydrological models and their applications by using *Soil Water Assessment Tool*+ (SWAT+) , a hydrological model that can simulate ecological processes and interactions within a given watershed (Arnold et al., 1998). Our primary objective of this research was to identify how *SWAT*+ simulates the differing effects of different soil properties on crop yield and nitrate loss within the Tar-Pamlico region of North Carolina, United States.

Methods

Site Area

This study took place in the Tar-Pamlico River Basin of eastern North Carolina. The river-basin's area covers around 5,570 square miles and is composed of agricultural areas (~29%), forests (27%), wetlands (23%), shrub/grasslands (12%), developed areas (7%) and barren areas (2%) (NCDEQ, 2004, NCDWQ, 2010, and NCDWR, 2014; See Figure 1 in Appendix).

The River-Basin supplies water to around 470,000 people (NCDWR, 2014). In total, the River-Basin contains around 3,977 acres of freshwater reservoirs and lakes and 663,504 estuarine acres (NCDWR, 2014). Its population averages approximately 75 people per square mile, which is less than half of the state's average density of about 152 people per square mile (NCDEQ, 2004).

As of 2022, the Tar-Pamlico River Basin supports 45 thousand farms and 8.3 million acres of farms (NASS USDA, 2022). These farms are primarily corn and soybean, followed by cotton and small grain (wheat, oats, barely, rye) farms (NCDWQ, 2010). In this region, farmers frequently rotate crops year to year and partake in reduced tillage of crops. Farmers often double-crop (planting cotton and soybean at the same time) and switch to corn in order to reduce the threat of disease on monocrop fields. Since agriculture is North Carolina's leading industry, models that quantify the effects of farming corn, cotton, and soybean on water quality are incredibly important.

The River-Basin is divided up into two major parts: the northern Tar Basin range and the southeastern Pamlico River range (See Figure 2 in Appendix for division of basin). The basin is divided based on primary influence (freshwater or coastal water) and riverbed composition.

Tar-Basin Range

The Tar River originates from a freshwater spring in the central Northern region of North Carolina (NCDOT, 2018). This section of the river totals around 215 miles long until it reaches the city of Washington and its name changes to the Pamlico River (NCDOT, 2018). The elevation of the Tar Basin range averages about 700 feet at its origin and steadily decreases to around sea level when it transitions to the Pamlico Basin range. Streams within the Tar Basin range have low summer flows and are underlain with fractured rock formations and easily eroded soil. Riverbeds of this composition have limited water storage capacity (NCDEQ, 2014). There are no natural lakes in this basin range.

Pamlico-Basin Range

The Tar River Basin range ends when the river reaches the city of Washington, North Carolina and the Pamlico River Basin range begins. The Pamlico River spans south-east until it empties into the Albemarle-Estuarine system and eventually the Atlantic ocean. The entire Pamlico river is primarily coastally-influenced by saltwater from rising tides. The Albemarle-Estuarine system is enclosed by the barrier islands and popular tourist destination, the Outer Banks (Luchette, 2008). This estuary system is the second largest in the county, accounting for around 90% of all commercial seafood for North Carolina (NDEQ, 2013). In the Pamlico Basin range, streams are slow-moving black-water streams that will often stop flowing in the summer.

These streams are underlain with deep sands that have high groundwater storage capacity (NCDEQ, 2014). The Pamlico-River basin contains Lake Mattamuskeet, North Carolina's largest natural lake.

The collective Tar-Pamlico basin faces two main ecological challenges related to human interaction with the land: flooding and pollution. In their 2022 report, the U.S. Army Corps of Engineers reported that the Tar-Pamlico River Basin has experienced flooding that severely impacted life and property (Harris, 2022). In the past two decades, these floods have been caused by major rainfalls related to Hurricane Fran (1996), Floyd (1996), Matthew (2016) (Harris, 2022). Notably, these flooding events often cause woody debris build up from riverbank erosion, which only exacerbate flooding events. Flooding events related to hurricanes can also cause concentrated animal feeding operations (CAFOs) to leach increased wastewater into rivers when waste water retention ponds are overtaken with water (Luchette, 2008).

Accordingly, the river basin is heavily impacted by various types of pollution from agricultural runoff. The main contributors are nonpoint pollution sources from large CAFOs and fertilizer runoff from farms. Due to these two sources of pollution, in the early 1990s the North Carolina Environmental Management Commission designated the basin as "Nutrient Sensitive Waters (NSW)", calling for multifaceted strategies to reduce excessive nutrients in waterways. Between 1991 and 2003, the program was a large success– there was a 45% reduction in nitrogen loss largely because of less fertilizer runoff and implementation of best management practices (EPA, 2015). Additionally, a Tar-Pamlico River nutrient strategy was formalized in 2001 that implemented mandatory training for professionals that apply fertilizer as well as riparian buffer protections (NCDEQ, 2018).

Despite huge milestones reached in the early 2000s, excessive nitrate and phosphate entering waterways are still a prominent threat to wildlife and water quality in the region (Humphrey, 2014). The number of farms using fertilizer and CAFOs in the Tar-Pamlico area have increased since the NSW was last evaluated (Luchette, 2008). The Tar-Pamlico basin is particularly vulnerable to excessive nutrients in waterways due to the slow-moving streams and proximity to the Outer Banks (Luchette, 2008). In turn, this nutrient pollution can lead to the ecologically and economically harmful processes of eutrophication and fish kills.

SOIL AND WATER ASSESSMENT TOOL (SWAT+)

Our primary objective for this project was to use the Soil and Water Assessment Tool+ (*SWAT+*) to simulate the effects of varying soil properties on crop yield and nutrient runoff within the Tar-Pamlico River Basin. Furthermore, we wanted to explore how we could accurately represent real hydrological processes occurring in the Tar-Pamlico basin within the SWAT+ model. To do so, we varied our model’s inputs (parameters controlling soil properties) and examined how they affected our model's outputs (crop yield and water quality). We then evaluated how closely the model was able to represent real-world processes by comparing the model’s output to the USDA’s 2022 North Carolina crop year report. We specifically looked at the outputs for the region’s three most popular crops (corn, cotton, and soybean).

The SWAT+ model is a hydrological model designed to simulate the quality and quantity of water, sediment, and nutrient movement through a given watershed. Notably, in addition to inputting various spatial data, the model can also integrate various land use management practices. The model can simulate different land use management practices by allowing the user to define things like varying fertilizer management, tillage practices, and pesticide/insecticide applications. Then, the model runs through varying hydrological equations to determine how the basin will function. The model then outputs its results on nutrient runoff, water quality and movement, and crop yields that are informed by both spatial data and the prescribed land use management practices.

The Soil and Water Assessment Tool (SWAT) was created in a joint effort from the United States Department of Agricultural Research Service (USDA-ARS) and Texas A&M University AgriLife Research within Texas A&M University in the late 1980s (Arnold et al., 1998). In the early 2010s, SWAT's diverse applications and citations revealed how the model could be improved to make the model more user-friendly. This led to the transition from SWAT to SWAT+. While the model's underlying hydrological equations and basic algorithms remained the same, its structure, organization, and input have drastically changed. In general, compared to the old model, SWAT+ allows for greater flexibility in simulating their physical and spatial processes and interactions within a given watershed. The *SWAT+* model is still a physically based, deterministic, and spatially distributed model that can simulate complex hydrological systems and fertilizer schedules. It is a time-continuous model that computes at the hydrological response level and these results are routed through the entire watershed via stream connections. The scale on which computations are performed is much smaller in the SWAT+ model, providing for greater resolution within a watershed.

For this study, we used SWAT+ model version 60.5.7. The model inputs four main types of spatial data: (1) digital elevation models (from United States Geological Survey), (2) land use raster data (from USDA), (3) soil raster data (from STATSGO2), and (4) meteorological data (from the SWAT+ website). Using these inputs, the SWAT+ model then calculates how the watershed functions by using a variety of hydrological processes. The model uses equations relating to climate (energy, atmospheric water, weather), hydrology (surface runoff, evapotranspiration, soil water, ground water), nutrients/pesticides (nitrogen, phosphorus, pesticides/fertilizers), erosion (sediment, nutrient transport), land cover (uptake by plants/potential plant growth), management practices (tillage, harvesting, grazing, fertilizer application, pesticide application), water routing, and more (Neitsch, 2005). After computing these equations based on the given basin, SWAT will print output. The outputs from the model are primarily text file formats and provide results from the given watershed in terms on various spatial and temporal scales

Model Set-Up

Our first step towards running the SWAT+ model on the Tar-Pamlico River basin was to create a digital version of the river basin. We used a geographical information system program called Quantum Geographic Information System (QGIS) prior to using SWAT+. In QGIS software, there were four main steps that needed to be completed: (1) delineate the watershed, (2) create hydrological response units, (3) synthesize input, and (4) run the model.

We started with the delineation process to define the boundaries of the River-Basin (dividing the river basin into rivers, channels, and streams) based on given inlets and outlets. Here, we uploaded a digital elevation model (DEM) for the region with topographic information which informed the model on where there should be inlets and outlets of the watershed. For step two, to get hydrological response units, we had to create landscape units from the sub basin units. Landscape units can only be two types: flood plains or upslope. This process ensured that the model will correctly distinguish from flood plains and upland units (which have different slopes, storage, and sediment processes). The model can further increase the resolution of the River-Basin by dividing sub-river-basin units into hydrological response units (HRUs). These are unique combinations of landscape units' slope, soil, landscape unit, and landcover. Next, we then synthesized our input data by landscape and land use files as well as soil raster data in a QGIS file that could be used in the *SWAT+* interface.

Running the Model

Once the spatial data was synthesized in QGIS, we imported it into the SWAT+ editor. Here, there were five main steps: (1) edit inputs, (2) add weather data (3) set simulation period and warm-up period, (4) choose output options and where the model would send results, and (5) run the model. For step one, we edited our input results to include the weather generators and climate data that the SWAT+ model provides for the given region. We then could add them to the Tar-Pamlico River basin. The weather generators are specific to individual HRUs and are from the Climate Forecast System Reanalysis (CFSR). The observed weather data included precipitation, temperature, solar radiation, relative humidity, and wind speed for the given basin. The next step towards running the model was setting the simulation period. The simulation period included the start and end date, as well as the warm-up period for the model. The warm-up period is when the model runs but does not print output, allowing for “buckets” (reservoirs, soil moisture, and wetlands) to fill up (Kim, 2018). This is important because it allows for a basin to be set-up and equilibrated in terms of rates of water flow, crop yield, and nutrient and sediment runoff. We used a warm up period of three years, our simulation start date was January 1st, 2001 and our end date was December 31, 2019.

We performed an analysis at the scale of the HRU. We chose this spatial scale because it would allow for a more succinct calibration and validation process to take place as we could find data for this region in terms of corn, cotton, and soybean yield. As such, this is a small collection of farms located along the Pamlico River (Figure 2). The runoff from these farms output in the Albemarle-Pamlico sounds.

Calibration and Validation Process

After the model initially runs, we checked the results and decided whether we needed to calibrate the model to be more accurate for the study area. The calibration process is essentially an informed trial and error process. We could fine-tune model processes to be specific to the region, and then evaluate how those small adjustments affect their results. These adjustments are affecting the aforementioned equations that the SWAT+ model uses as building blocks. From there, we had to decide whether their calibrations need to be adjusted or kept the way they are. There are two methods for calibrations: hard data and soft data calibrations (Neitsch, 2002). While soft data calibrations focus on adjusting temporal processes within the model, hard data calibrations are more closely associated with specific events across time series. Soft calibrations can adjust parameters within the model relating to evapotranspiration, precipitation, surface runoff, percolation, and lateral flow.

Once we got our results from our first model run, we evaluated their accuracy by comparing them to 2022's agricultural data (USDA-NASS, 2022). Since our objective was to match crop yields in terms of corn and soybean, we only looked at matching these values. The specific numbers are in our results section. We focused primarily on soft calibrations for this project. Once we averaged out the expected results from the 2022 report, we found that the SWAT+ model was greatly underestimating yield for our given region. Once we knew this, we proceeded to step two of the calibration process in which we calibrated parameters within the model that would eventually impact the equations the model used.

Existing literature indicated that the following five parameters were the most efficient in optimizing crop yield: curve number (CN2), curve number conditions three soil water factor (CN3_SWF), percolation coefficient (PERCO), and nitrogen percolation coefficient (NPERCO), and surface runoff lag coefficient (SURLAG) (Arnold, 2012, Bailey 2015, and Musyoka, 2021). Curve number (CN2) is the proportion of precipitation that remains in/on top of the soil vs the amount that runs off. We chose to decrease this number from where it was originally because water was running off too quickly before it could be taken up by the plants. CN3_SWF refers to the initial saturation of the soil. This parameter can vary between the soil being at field capacity (least amount of water) and soil being fully saturated. Relatedly, PERCO, or percolation coefficient, impacts how much water from runoff the soil absorbs. NPERCO, or nitrate coefficient, controls how much nitrate is removed from the surface layer in runoff, relative to PERCO. SURLAG is defined as the surface runoff lag coefficient, which controls the amount of water available for the plant in proportion to the amount of water that is released into the nearest channel.

We calculated nitrate loss by using the SWAT+ output file called "annual average nutrient balance". We quantified nitrate loss by the summing of ground water nitrate loss, lateral nitrate loss, and surface nitrate loss. We then analyzed how each parameter impacted nitrate loss.

We ran multiple trials simultaneously using a loop coded in R. This method used a package called *SWATrunR* from a github repository (Schürz C, 2019). Here, we wrote a loop, using the "tibble" and "run-if" functions. These functions ran the SWAT+ model through five different parameter calibrations for each trial. As such, each trial had a different combination of calibrations to parameters. We were able to print the results of the R code in the same manner that SWAT+ allowed us to, with varying temporal and spatial scales and a simulation period with a defined warm up period. Once the trials ran, we identified which parameters were most influential to the nutrient run-off and crop yield values reported in existing literature. This allowed us to narrow down the original ranges and run trials again with alternative parameters (See parameter ranges in Figures 3,4,5 in Appendix).

Results

Prior to any calibration, we found that our model was greatly underproducing yield results for the Tar-Pamlico region (Table 1). After the calibrations, the model was eventually able to much more accurately represent the amount of yield that we expected for the region.

We were interested in identifying which parameters were the most influential in optimizing yield and nitrate loss than other parameters amongst all crops. These results were formulated from the output from 2500 simulation runs (for corn and cotton) and 500 simulations (for soybean) with the set-up, simulation period, and calibration changes to five different parameters (CN2, CN3_SWF, NPERCO, PERCO, and SURLAG) (Figure 1, 2, and 3). We chose to visualize the output of the model using correlation analysis on the effect of different inputs (parameters in this case) on outputs (yield and nitrate loss)

Corn

Curve number (CN2) was the most efficient parameter in increasing yield, showing a slightly positive correlation ($R^2 = 0.328$; Figure 3a). There appears to be a piecewise function-like pattern in the CN2 and yield graphs; it is possible that there was a threshold of CN2 increases that needed to be met (around 10 CN2) before yields dramatically increased. Curve number soil water factor (CN3_SWF) was the second most influential parameter in impacting yield and showed a slight negative correlation ($R^2= -0.3512$; Figure 3b). We saw a very slight positive correlation between nitrate percolation rates (NPERCO) and yield (R^2= 0.0197; Figure 3c) and groundwater (percolation rates) PERCO and yield (R^2=0.0248; Figure 3d). For NPERCO, yields did not increase beyond its maximum reached at the lowest amount of nitrate percolating the soil, exemplified in the strong upper boundary. The surface lag coefficient (SURLAG) had an insignificant impact on corn yield (R^2 = 0.00005; Figure 3e). The most influential parameter to yield, CN2, was also most impactful in decreasing nitrate loss. CN2 parameter is negatively correlated with nitrate loss (R^2= 0.183; Figure 3f). Bigger curve numbers resulted in less nitrate loss.

Cotton

We saw similar results for cotton yields as we did for corn. Curve number (CN2) was the most influential parameter and had a slightly positive correlation and piecewise like function (R^2= 0.3546; Figure 4a). There was a threshold CN2 calibration that needed to be met in order for yields to increase. The curve number three soil water factor parameter (CN3_SWF) was again the most influential parameter in impacting yields (R^2= -0.2263; Figure 4b). There was a weaker relationship between CN3_SWF in cotton compared to corn. For nitrate percolation coefficient (NPERCO; Figure 4c), we did not see as harsh of an upper boundary as exemplified in corn. However, there appears to be another piecewise like function in the percolation parameter (PERCO; Figure 3f). Additionally, there is a strong band of results around 5500 kg/ha of yield. Again, there was no relationship between SURLAG and yield (Figure 4e). There was an interesting relationship between CN2 and nitrate loss; there were two separate patterns; one piecewise function from ~350 to ~250 of kg/ha and an outward facing fan shape from around 10-40 CN2 calibrations (Figure 3f).

Soybean

We found CN2 to have a strongly positive correlation to soybean yield (R^2=0.834) compared to corn and cotton (See figure 5a). CN3_SWF had a far weaker relationship (R^2= 0.0002; Figure 5b). Similar to the previous two crops, NPERCO and PERCO had minimal effects on yields (Figures 5c and 5d, respectively). There was a slightly increased SURLAG correlation (R^2=0.0281; Figure 5e), however, still nothing as impactful as the curve number parameters. Similar to cotton results, there were two separate patterns present in the soybean results: one cluster of data between 120 kg/ha nitrate loss and around 20 kg/ha nitrate loss (Figure 5f).

Among corn, cotton, and soybean, we expected CN2 and CN3_SWF – parameters relating the amounts of runoff on the HRU scale – to be very influential in increasing yields. We believed this because, in drought conditions, corn responds by curling up its leaves and allocating less energy towards its kernel size and abundance, in turn decreasing its yield (McFadden, 2019). Similarly, in drought conditions, cotton decreases energy allocated to canopy growth and root development which in turn decrease leaf area indices and overall stomal conduction (Zafar, 2023) Soybean is relatively more drought resistant; their tap roots are able to grow deeper than other plants which is additionally useful for the plant to better uptake nutrients like nitrate and phosphate. This is because all three crops are not extremely drought resistant. Our results supported this hypothesis (Figures 3a, 4a, and 5a). We did, however, expect PERCO and NPERCO to be more impactful in increasing yields for the corn (Figures 3c, 3d, 4c, 4d, 5c, 5d). We expected PERCO to have an impact because if there is too much or too little water percolating the soil, it will of course have an impact on any crop's yield. Additionally, we expected SURLAG to have a greater impact on increasing crop yield since with higher SURLAG numbers, the model increases water storage capacity of the soil. These results signify that greater research needs to be done in how the PERCO, NPERCO, and SURLAG parameters function within the SWAT+ model. SURLAG had an insignificant effect on all crops. The reason for great discrepancies between corn/cotton and soybean plots is likely because of different crop characteristics and fewer soybean trials than cotton and corn trials.

Discussion

Our primary objective was to simulate how different agricultural practices affect yield and water quality within the Tar-Pamlico River Basin. We sought to fulfill this objective by using the *SWAT*+ model to represent the real-life agricultural activity occurring within North Carolina. We fine-tuned the SWAT+ model to match previously recorded yields for the state of North Carolina. We then looked at how the different calibrations impacted yields through the lens of corn, cotton, and soybean in the river basin. The various trials of the model revealed that the curve number parameters relating to soil structure and the partitioning of run-off and (CN2 and CN3_SWF) were the most effective in increasing crop yield. We analyzed how changes to initial soil structures impacted yield and nitrate loss results and primarily found that parameters relating to the partitioning of runoff and water percolation were most impactful in optimizing yield and nutrient loss.

Our simulated results support that curve number (CN2) and soil water factors (CN3_SWF) are most influential to yield and nitrate loss for corn, cotton, and soybean crops. This relationship agrees with previous studies completed in coastal watersheds (Lam, 2015; Osmond, 2015; Gopalakrishnan, 2019, Bailey, 2015). These studies support that improved soil health can improve overall yields and reduce nitrate loss. Soil health is determined by many factors: organic matter, structure of macroaggregates, presence of macro and microorganisms, aeration, vegetation cover, pH, and moisture content (infiltration/retention capacity), and temperature.

There are various steps that farmers can take towards increasing the overall health of the soil on their farm; the USDA Natural Resources Conservation Service (USDA-NRCS) set forth recommended practices to increase farm productivity and decrease related environmental damage (USDA-NRCS, 2019). These practices are often referred to as Best Management Practices (BMPs), an indirect result of USDA-NRCS's "avoid, control, and trap" (ACT) nutrient runoff reduction program (USDA-NRCS, 2019). BMPs include but are not limited to improved fertilizer management, attention to organic matter application, reduced frequency of conventional plowing, increased usage of cover crops, increased fallow/rest periods, and crop rotation (Prokopy, 2008 and Magdoff, 1993). BMPs can in turn impact soil structure in terms of curve number, percolation, and nitrate percolation within the soil to better increase yield and reduce nitrate loss. This relates back to our findings about the curve number (CN2) and curve number soil water factor (CN3_SWF) parameters being most influential in increasing yield as well as decreasing nitrate loss.

Precise fertilizer management can tangentially save farmers money, increase yields, and improve downstream water quality. Nitrogen and phosphorus are the most essential nutrients for plant growth and often the nutrients in deficiency (Magdoff, 1993). As a result, farmers turn towards application of fertilizers to address the deficiency and in turn increase their land's productivity. However, the rate at which plants take up nitrate from the soil is dependent on transient factors including precipitation, temperature, relative humidity, season, and plant fertility. This uncertainty makes it very difficult for farmers to know exactly how much fertilizer they need to apply for their land, so they often apply too much. This can lead to leaching of soil nitrate to groundwater and the excess nitrogen to flow into rivers (Magdoff, 1993). In coastal watersheds, nitrogen is the limiting nutrient in eutrophic events– when nitrate is in excess, it can lead to these cascading events to occur (Howarth, 2006). Implementation of BMPs for nutrient management include the awareness of the aforementioned factors that influence how fertilizer will be up taken by the plant can reduce nitrate loss and save farmers money on wasted fertilizer.

Application of organic matter can be a cost-efficient way to increase the health, aeration, and prevent compaction/crusting of soil. Organic matter (OM) can be composed of a variety of different things including crop residues, leaves, woodchips, manure, earthworms, beetles, microbes, fungi, and bacteria (Magdoff, 1993). The presence of organic matter (OM) is vital to the plant's ability to uptake nitrogen and phosphorus from fertilizer application. This is because, in well aggregated soils, the living organisms within the OM help to stabilize the macroaggregate structures via their fungi and digging to create infiltration channels. These structures facilitate the transfer of nutrients, water, air, and the exchange of gasses from the soil to the plant roots. In well aerated and healthy soil, there are pockets of space between the macroaggregates that allow plant roots to uptake the ingredients vital to its growth. Additionally, the decomposition of OM by legumes and fungi (nitrogen fixation) allows for nitrogen to become available to the plants in the form of nitrate (Magdoff, 1993). Within the SWAT+ model, organic matter can facilitate healthy soil structure and in turn increase curve number values.

Conventional plowing practices often destroy macroaggregate structure. Tillage practices have historically been used to flatten seed beds, improve seed germination, manage weeds, and loosen soil for eventual roots. These destructive systems include moldboard plows, chisel plows, and disc harrows. Tillage done too often leads to the destruction of soil structure when macro aggregates are upturned and exposed to sunlight and oxygen (Hoorman, 2011). The upturning and exposure to sunlight of macroaggregates then forms detrimental structures called “clods” to form (USDA, 2022). These make the soil very hard to penetrate by roots and can further inhibit plant growth. BMPs include suggestions for conservation tillage systems such as no-till, zone-till, and ridge-tills that disturb the soil far less.

Lastly, cover crops can be used to maintain soil infiltration, while reducing organic matter erosion and the impact of raindrops on the soil surface. Cover crops are used when a farmer’s target crop is not in use. The roots of cover crops allow for increased soil infiltration and decreased runoff water and nutrients. The cover crops effectively prevent rain drops from compacting the soil when there is no crop there. This compaction process can be detrimental because it can lead to a crust on the soil surface to form which again is very hard for plant roots to penetrate (USDA-ARS, 2006)

Despite extensive research on best management practices and their net benefits, they are not equally received and adopted by farmers. Prokopy (2008) synthesized 25 years of literature on the factors that determine farmers’ perception of BMPs. These factors include age, relative education level, awareness of BMPs, disposable income, and social networks. In summary, Prokopy (2008) found that, often, farmers who are younger, more educated on BMPs, with higher socioeconomic status, and more acres were more likely to adopt BMPs. North Carolina farmers that did not want to adopt BMPs cited distrust in government suggestions due to past discriminatory actions inhibiting farmers, fear of financial risks involved, and lack of equipment (Chin, 2012; Osmond, 2015, and Mair, 2023). Another factor contributing to farmers’ distrust in government, is that historically, federal policies surrounding agricultural management have benefited farms that were already prospering and inhibited smaller farms’ success (Cotnoir, 2016). For farmers that are already struggling financially, trying to implement new BMPs is a risk that puts their farms' future in jeopardy. While many BMPs have long-term payouts, they can have high up-front costs and risks. This research calls for a stronger connection between farmers and the scientists that are performing simulations of their farms. The U.S. government needs to adopt a more holistic approach to tangentially improve farmer quality of life, agricultural sustainability, farmland, and water quality, to further reduce the frequency and intensity of the impacts of farming on water quality.

In summary, the results of this model provide support to suggest that agricultural practices intended to improve soil health tangentially improve crop yield and water quality. Notably, there is a confluence of interests between farmers, environmentalists, and additional stakeholders within agriculturally productive watersheds to act upon best land use management practices. Best land use management practices (such as reduced tillage, use of cover crops, applications of organic matter) can decrease the amount of excess nitrate running off soil and into watersheds. This decreases the likelihood of future ecologically harmful eutrophic events occurring in downstream areas. Since best land use management practices are not equally received by farmers, future research needs to address this disconnect between farms and the evidence presented to them. Agricultural policies need to be informed by synthesis of past climatic events and projections of future events, quantitative and qualitative inputs from farmers, environmental protectors, and climate scientists alike.

Appendix

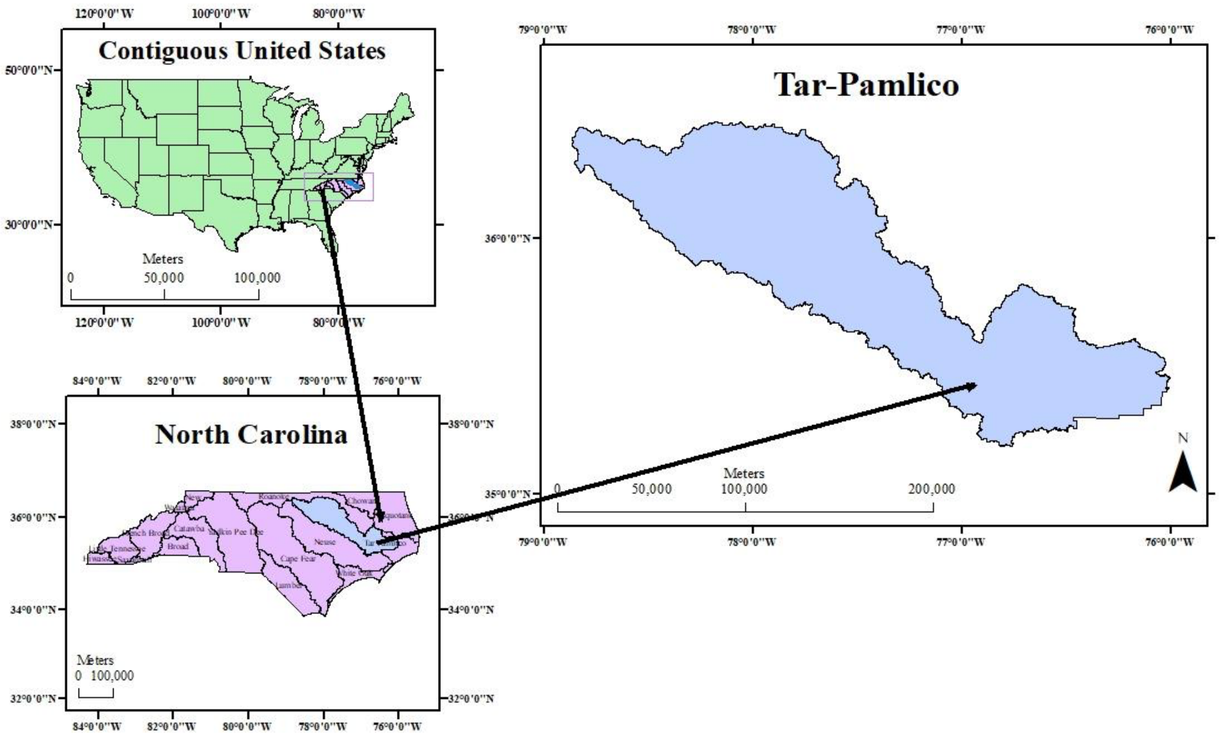

Figure 1 | **Tar-Pamlico River Basin Map** in North Carolina, U.S.A.

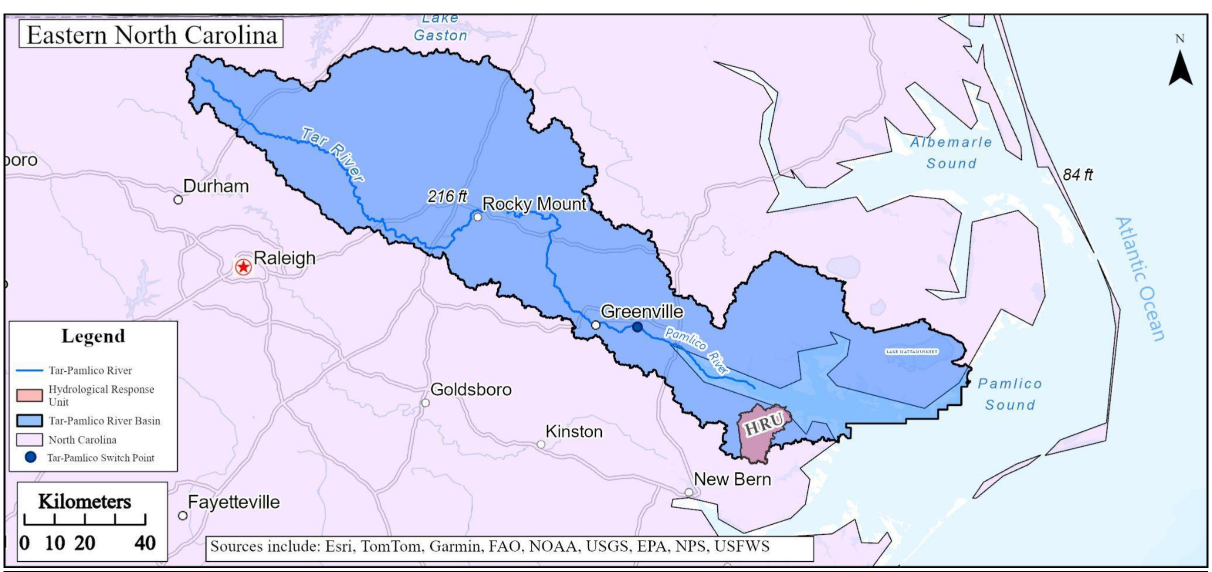

Figure 2 | Map of Tar-Pamlico River Basin including Tar-Pamlico river, its switch point, Albemarle-Pamlico

Sound, and the hydrological response unit's (HRU's) location.

Table 1 | Crop Yield for the Tar Pamlico Region in kilograms per hectare.

Crop Type	Expected Results (kg/ha) Per USDA-ARS, 2022 Report	Model Results (kg/ha) - Pre Calibration	Model Results (kg/ha) - Post Calibration
Corn	7843	473	7400
Cotton	1175	178	1750
Soybean	2588	201	1180

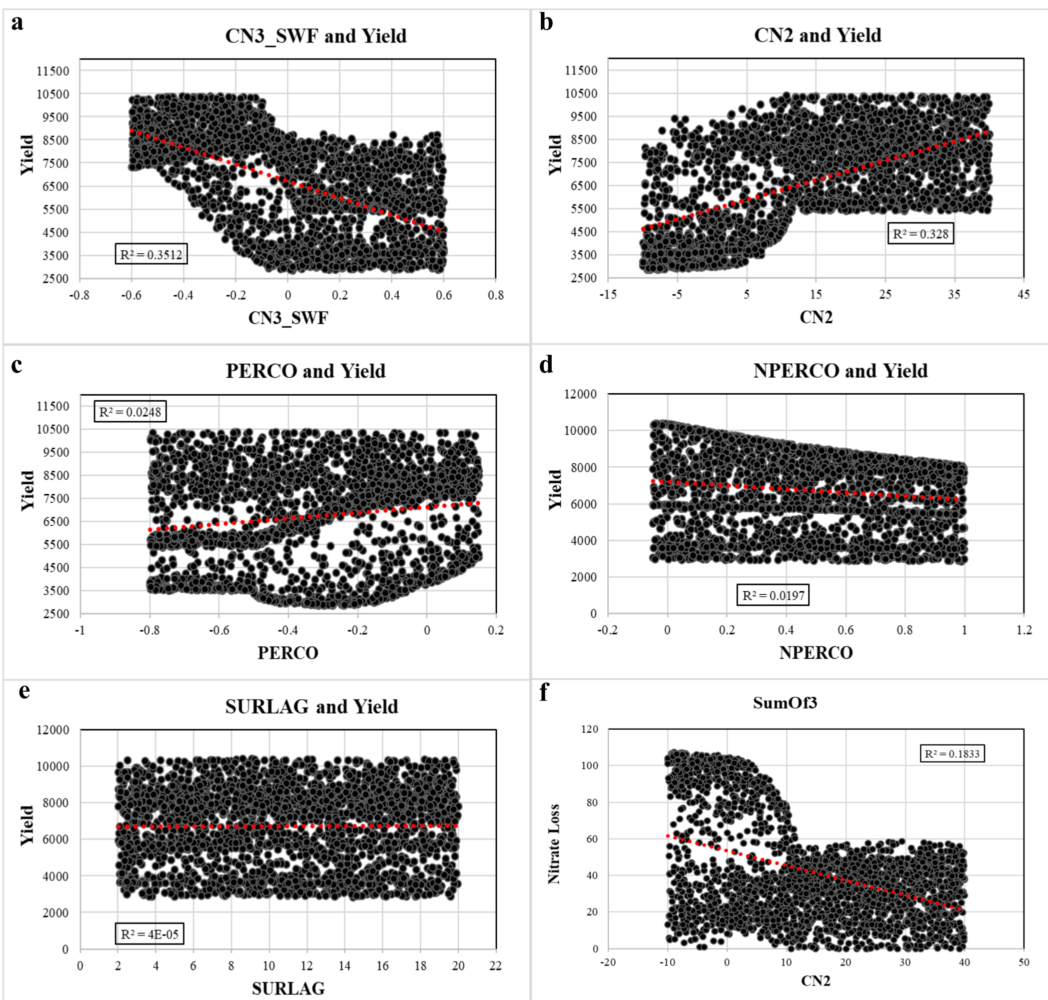

Figure 3 | Corn yield (kg/ha) and nitrate loss (kg/ha) as a function of model parameters (3a-e) Parameter calibrations' – curve number (CN2), curve number three soil water factor (CN3_SWF), nitrate percolation

(NPERCO), percolation rate (PERCO), and surface runoff lag coefficient (SURLAG) – effects on corn yield of kg/ha. **(3f)** Corn nitrate loss (kg/ha) in terms of surface, groundwater, and lateral flow nitrate.

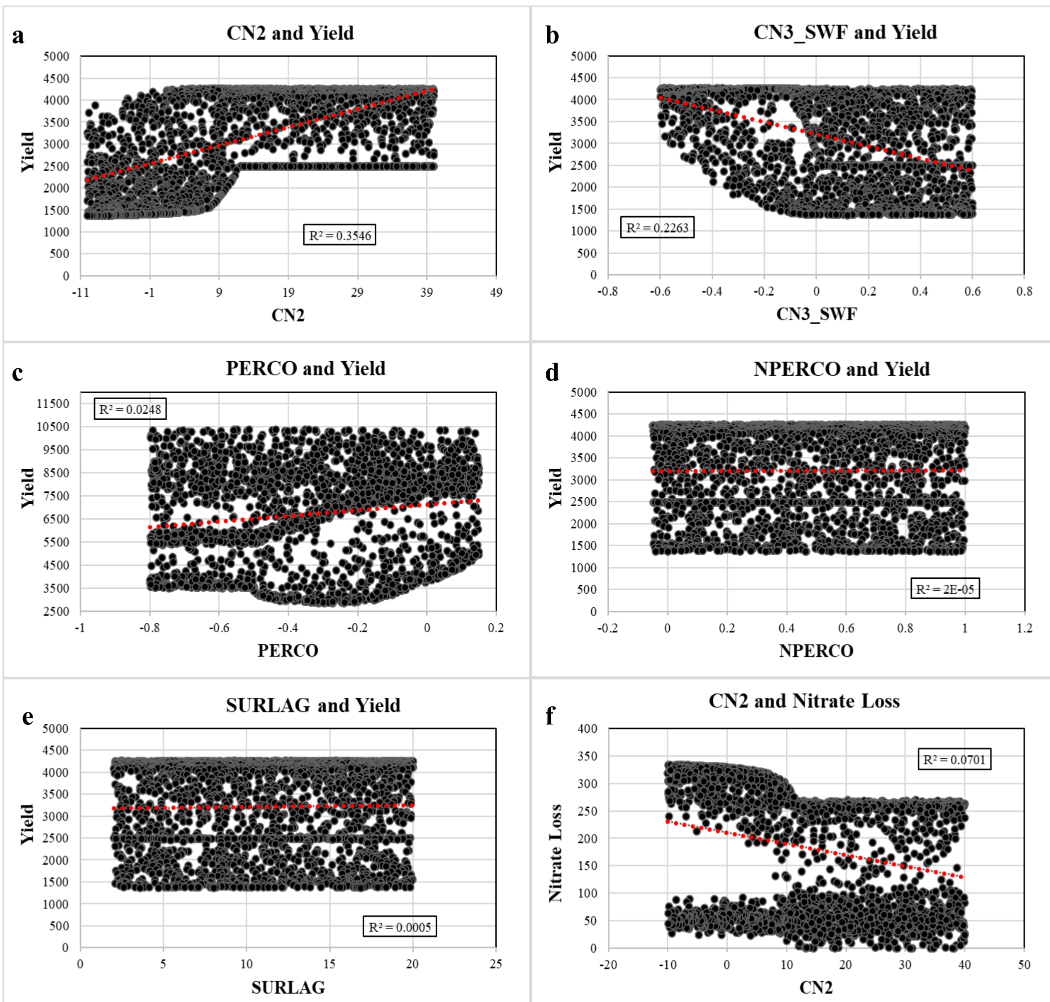

Figure 4 | Cotton yield (kg/ha) and nitrate loss (kg/ha) as a function of model parameters ((4a-e) Parameter calibrations' – curve number (CN2), curve number three soil water factor (CN3_SWF), nitrate percolation (NPERCO), percolation rate (PERCO), and surface runoff lag coefficient (SURLAG) – effects on cotton yield of kg/ha. **(4f)** Cotton nitrate loss (kg/ha) in terms of surface, groundwater, and lateral flow nitrate.

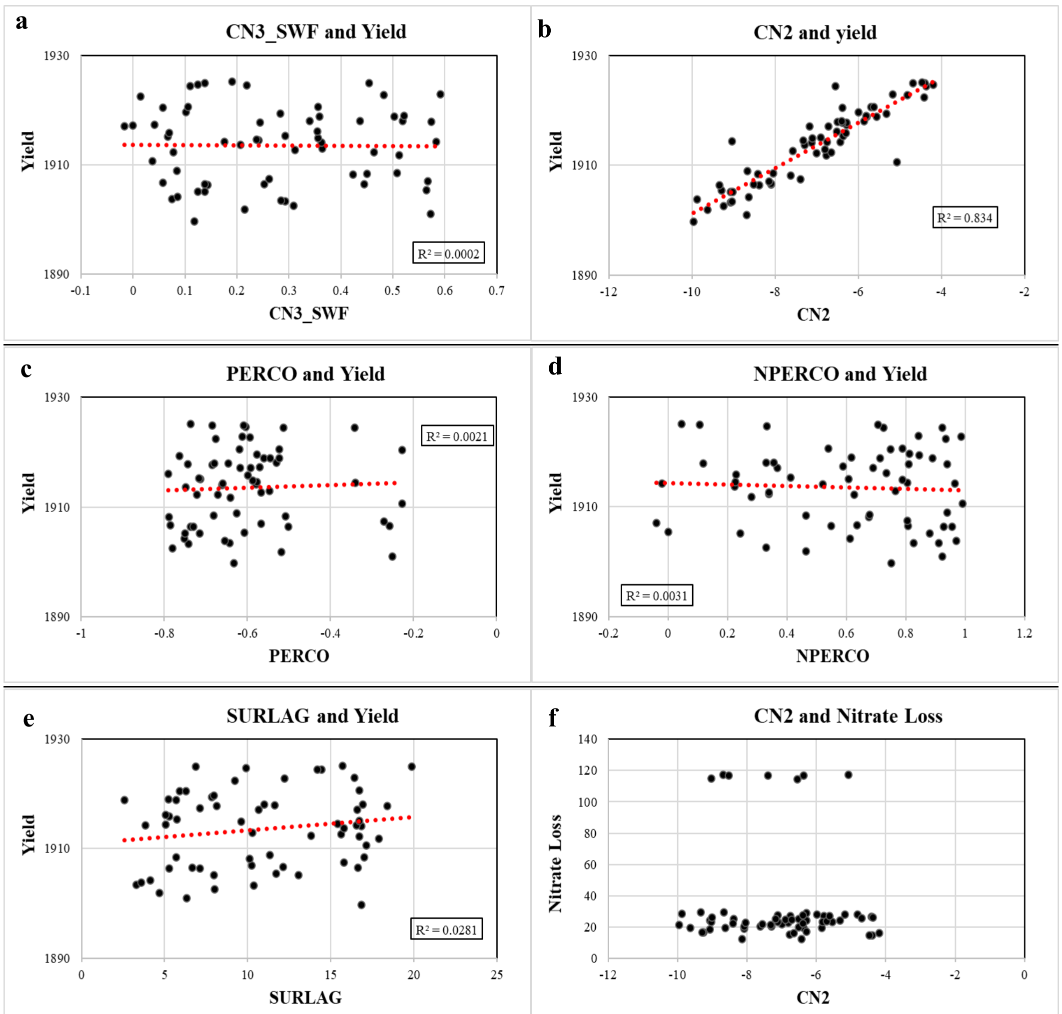

Figure 5 | Soybean yield (kg/ha) and nitrate loss (kg/ha) as a function of model parameters ((5a-e) Parameter calibrations' – curve number (CN2), curve number three soil water factor (CN3_SWF), nitrate percolation (NPERCO), percolation rate (PERCO), and surface runoff lag coefficient (SURLAG) – effects on soybean yield of kg/ha. **(5f)** Soybean nitrate loss (kg/ha) in terms of surface, groundwater, and lateral flow nitrate.

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