Landscape pollution source dynamics highlight priority locations for basin-scale interventions to protect water quality under extreme events

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Abstract

Extreme weather conditions are associated with a variety of water quality issues that can pose harm to humans and aquatic ecosystems. Under dry extremes, contaminants become more concentrated in streams with a greater potential for harmful algal blooms, while wet extremes can cause flooding and broadcast pollution. Developing appropriate interventions to improve water quality in a changing climate requires a better understanding of how extremes affect watershed processes, and which places are most vulnerable. We developed a Soil and Water Assessment Tool model of the Cape Fear River Basin (CFRB) in North Carolina, USA, representing contemporary land use, point and non-point sources, and weather conditions from 1979 to 2019. The CFRB is a large and complex river basin undergoing urbanization and agricultural intensification, with a history of extreme droughts and floods, making it an excellent case study. To identify intervention priorities, we developed a Water Quality Risk Index (WQRI) using the load average and load variability across normal conditions, dry extremes, and wet extremes. We found that the landscape generated the majority of contaminants, including 90.1% of sediment, 85.4% of total nitrogen, and 52.6% of total phosphorus at the City of Wilmington's drinking water intake. Approximately 16% of the watershed contributed most of the pollutants across conditions—these represent high priority locations for interventions. The WQRI approach considering risks to water quality across different weather conditions can help identify locations where interventions are more likely to improve water quality under climate change.

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Index terms: hydrologic modeling, SWAT, non-point source pollution, nature-based solutions, watershed management

Key Points:

- We developed a water quality risk index (WQRI) that highlights places where watershed-scale interventions can improve water quality across extremes.
- Using the WQRI we found that the highest priority areas for interventions in the Cape Fear River Basin comprise 16% of the watershed.
- Our approach can easily be adapted for locally specific water quality concerns and tailored to unique event thresholds.

Abstract

Extreme weather conditions are associated with a variety of water quality issues that can pose harm to humans and aquatic ecosystems. Under dry extremes, contaminants become more concentrated in streams with a greater potential for harmful algal blooms, while wet extremes can cause flooding and broadcast pollution. Developing appropriate interventions to improve water quality in a changing climate requires a better understanding of how extremes affect watershed processes, and which places are most vulnerable. We developed a Soil and Water Assessment Tool model of the Cape Fear River Basin (CFRB) in North Carolina, USA, representing contemporary land use, point and non-point sources, and weather conditions from 1979 to 2019. The CFRB is a large and complex river basin undergoing urbanization and agricultural intensification, with a history of extreme droughts and floods, making it an excellent case study. To identify intervention priorities, we developed a Water Quality Risk Index (WQRI) using the load average and load variability across normal conditions, dry extremes, and wet extremes. We found that the landscape generated the majority of contaminants, including 90.1% of sediment, 85.4% of total nitrogen, and 52.6% of total phosphorus at the City of Wilmington's drinking water intake. Approximately 16% of the watershed contributed most of the pollutants across conditions—these represent high priority locations for interventions. The WQRI approach considering risks to water quality across different weather conditions can help identify locations where interventions are more likely to improve water quality under climate change.

Plain Language Summary

Extreme weather is associated with water quality problems that harm humans and aquatic life. Dry conditions can cause higher pollution concentrations and harmful algal blooms, while wet conditions can cause flooding and increase pollution from urban and agricultural land. Developing appropriate interventions to improve water quality requires a better understanding of how extreme weather affects watersheds. We developed a water quantity and quality model for the Cape Fear River Basin in North Carolina, USA, representing current land use, pollution sources, and weather conditions from 1979 to 2019. This large and complex river basin has extensive agriculture and growing urban centers, and has a history of both droughts and floods. To identify intervention priorities, we developed a Water Quality Risk Index based on pollution amounts and variability under normal, dry, and wet conditions. We found that the landscape generated most pollution in waterways, including 90.1% of sediment, 85.4% of nitrogen, and 52.6% of phosphorus at the City of Wilmington's drinking water intake. Approximately 16% of the watershed contributed most pollution--these represent high priorities for further investigation. Considering pollution risks across weather conditions can help identify the best places to implement strategies to improve water quality in a changing climate.

1. Introduction

A high-quality supply of water is critical to the well-being of both human and natural systems, yet these resources face a number of threats. Freshwater makes up <1% of the surface water on the planet, yet supports 7-12% of all species, including one third of all vertebrates; many more species not restricted exclusively to freshwater habitats depend on these resources for at least some part of their life cycle (Abramovitz & Peterson, 1996; Dudgeon et al., 2006; Balian et al., 2010). Billions of people rely directly on freshwater, not only for their basic needs, but also for fisheries, agriculture, energy production, industry and other uses (Lynch et al., 2016; Pascual et al., 2017; Royal C. Gardner & Max Finlayson, 2018). Wetlands are being lost at three times the rate of forests (Gardner & Finlayson, 2018) and freshwater biota are declining more rapidly than taxa across other environments (Reid et al., 2018). The number of stressors on freshwater environments has increased and some threats have intensified, including not only direct loss and hydrologic alteration, but also invasive species, infectious diseases, salinization, emerging contaminants, and climate change (Reid et al., 2018). Climate change has already altered 23 of 31 ecological processes that support key freshwater functions, with perturbations from the level of genes, to communities, to the environment as a whole (Scheffers et al., 2016).

Extreme events are associated with a variety of risks related to both water quantity and water quality. Extremely wet weather conditions (i.e., flood events) can release pollutants over very large areas, posing concern for contamination of surface water and shallow groundwater (Du et al., 2020; Schaffer-Smith, 2020). Under extremely dry conditions (i.e., seasonal low flow periods or extended droughts), contaminants can become more concentrated in streams with a greater potential for harmful algal blooms to occur (Mosley, 2015). These distinct water quality issues can both cause harm to aquatic systems, including low dissolved oxygen levels, fish kills, and more (Ascott et al., 2016; Blaszczak et al., 2018; Golladay & Battle, 2002; Lake, 2003; Mallin et al., 2006; Mosley, 2015). Some watersheds also have persistent water quality issues under normal conditions—while these long-term ‘press’ disturbances may not always represent acute problems, their effect on environmental degradation and public health cannot be discounted (Frei et al., 2021; Lake, 2003).

Extreme events are becoming more frequent and severe under climate change (IPCC, 2018). Among recent natural disasters, 74% have been related to water, with at least 1 billion people impacted by droughts and floods from 2001 – 2018 (UNESCO & UN-Water, 2020). Droughts have become more frequent and intense, impacting larger areas for longer durations due to human activities (Chiang et al., 2021). Tropical cyclone driven precipitation events over the U.S. East Coast have increased by 2 to 4 mm/decade over the last three centuries, with most of the increase taking place over just the past 60 years (Maxwell et al., 2021). Climate change is expected to worsen the accelerating prevalence of harmful algal blooms (Chapra et al., 2017; Paerl & Paul, 2012). These climate-induced impacts to freshwater wetland systems will disproportionately impact the lives and livelihoods of vulnerable communities, particularly in coastal zones (IPCC, 2018).

Land use, land management, and appropriation of water resources can exacerbate the impacts of extreme events on people and ecosystems even further. Land use changes associated with ongoing urban and agricultural expansion, as well as intensification of these land uses, have had profound impacts on water and nutrient cycling (Shi et al., 2017; Tong & Chen, 2002). Loss of floodplains and coastal wetlands to urbanization and other land uses reduces the capacity of the landscape to buffer extreme conditions (Kris A. Johnson et al., n.d.; Narayan et al., 2017). Dams and water extraction activities are associated with increased hydrologic drought (Wada et al. 2013). Urbanization and population growth drive an increase in water use, as well as loadings of contaminants to streams (Foley, 2005; McDonald et al., 2011; Paul & Meyer, 2001). Despite the growing footprint of urban land use, agriculture is often the dominant water consumer, accounting for as much as 92% of the human water footprint (Foley, 2005; Hoekstra & Mekonnen, 2012; Power, 2010). Nutrients, sediment, bacteria, heavy metals and other contaminants in runoff from agricultural land uses can substantially reduce water quality (Foley, 2005; Gordon et al., 2010; Koneswaran & Nierenberg, 2008; Power, 2010). These compounding modifications to the water cycle may impose greater stress on water resources in the future (Haddeland et al. 2014).

How more frequent extreme events will impact water quality into the future is not well understood. Some previous studies have found that increasing extreme precipitation is intensifying erosion, and the delivery of nitrogen and phosphorus (Sinha et al., 2017; Z. Tan et al., 2021). More frequent hurricane events are heightening the risks of pollutant transport from vulnerable infrastructure and non-point sources, with consequences for both inland and estuarine water quality (Paerl et al., 2018; Schaffer-Smith, 2020). Formulating appropriate interventions that will deliver durable benefits requires understanding how both extreme dry and wet extreme events can affect water quality.

Strategies that rely on technical solutions or hardened infrastructure alone may not reduce vulnerability to droughts (Walker et al., 2022) or floods (Haghighatafshar et al., 2020). For example, reliance on built infrastructure for flood protection can cause a 'levee effect' where development in perceived 'safe' areas of floodplains produces a bigger catastrophe when a storm exceeds the defense capabilities of protective infrastructure (Di Baldassarre et al., 2009). Most current water distribution and treatment infrastructure, sewage, and stormwater management systems in the U.S. were designed using event intensity, duration, frequency information that did not consider climate and land use change (Wright et al., 2019). For rural areas, hardened infrastructure solutions may be less desirable given the high costs of engineering and design, permitting, implementation over large land areas, and long-term maintenance (Alves et al., 2018; Browder et al., 2019; Hovis et al., 2021; Suttles et al., 2021).

Nature-based solutions, such as wetland and forest conservation, restoration, agricultural field measures, and managed retreat can play an important role for improving the resilience of watersheds to extreme events (Antolini et al., 2020; Johnson et al., 2020; Keesstra et al., 2018; Suttles et al., 2021). These solutions may not only be less costly and faster to implement than hardened infrastructure solutions, but also may provide additional co-benefits for improved access to greenspace and recreation, opportunities for improving economies, as well as benefits for fish and wildlife habitat and biodiversity (A.M. Bassi et al., 2021; Chausson et al., 2020; DeLong et al., 2021; Keesstra et al., 2018). Among nature-based solutions, floodplain restoration is expected to have the greatest benefits for both water quality and flood-risk reduction (Suttles et al., 2021).

Watershed models, such as the Soil and Water Assessment Tool (SWAT), can provide insight into how interactions between, landform, soils, land use and climate interact and predict in-stream flow and water quality across watersheds (Gassman et al., 2014; J. G. Arnold et al., 2012). SWAT is one of the most widely used watershed models, and it has been previously applied to examine future changes in watershed processes by incorporating climate projections to evaluate resulting impacts on water quantity (Tan et al., 2021; Xu et al., 2019), with fewer studies examining water quality (e.g., Ouyang et al., 2018). A number of studies have explored contemporary extreme events with SWAT, including a sub-daily model of flash flooding for ungaged watersheds in Spain (Jodar-Abellan et al., 2019), examinations of streamflow response to climate variability and land use (Li & DeLiberty, 2020; Zhang et al., 2017), exploration of how more extreme rainfall has affected erosion and nutrient runoff into the Gulf of Mexico (Z. Tan et al., 2021), and assessment of impacts from frequent hurricane activity on water quality (Ouyang et al., 2022). While it is a well-established tool to guide placement of BMPs (e.g., Abimbola et al., 2020; Admas et al., 2022; Chiang et al., 2021), SWAT has not been used previously to identify priority locations for interventions to improve watershed resilience with explicit consideration of both extreme dry and wet conditions.

As many watersheds are already experiencing more frequent extreme events, retrospective analysis of extreme events can help to highlight places where additional attention and mitigation strategies may be warranted. The Cape Fear River Basin (CFRB) in North Carolina (NC), USA, represents an ideal study location given its dynamic hydrology, with a history of both droughts and floods, including 5 distinct 500-year flood events since 2016. A variety of interventions have been proposed to help manage water quantity and quality in the watershed, including both human-managed infrastructure and nature-based solutions. To evaluate the distribution of water quality risks across the basin, we developed a SWAT water quantity and quality model for the CFRB, representing contemporary land use and management under weather conditions spanning 1979-2019. We created a Water Quality Risk Index (WQRI) quantifying hotspot dynamics across conditions, and used the WQRI to identify strategic locations where landscape-based interventions could improve water quality and enhance the resilience of freshwater systems.

2. Methods

2.1 Study area

The CFRB is the largest river basin fully contained within NC, at >9,100 mi^2 (Fig. 1). The CFRB is divided into two major physiographic regions. The upper basin is in the Piedmont plateau east of the Southern Appalachian Mountains, with rolling topography from 450 – 100 m elevation. Below the confluence of the Deep and the Haw Rivers, the Piedmont drops into the lower basin on the Atlantic Coastal Plain, with sandy soils that slope gently to meet the Atlantic Ocean. The region is characterized by a humid subtropical climate, with average temperatures ranging from −1 °C during the winter to 31.7 °C in the summer. Snow is rare below the mountains, with most precipitation falling as rain in the Piedmont (112-122 cm/year) and Coastal Plain (112-142 cm/year). The CFRB is the most populous watershed in NC, home to growing cities such as Greensboro, Durham, Chapel Hill, Fayetteville and Wilmington, with millions of people directly dependent on the river for drinking water. Approximately 26% of NC residents, mainly rural communities, rely on privately owned shallow groundwater wells which are vulnerable to contamination (MacDonald Gibson & Pieper, 2017; Naman & Gibson, 2015). The watershed also features outstanding aquatic biodiversity (NatureServe, 2022; NC Wildlife Resources Commission, 2015).

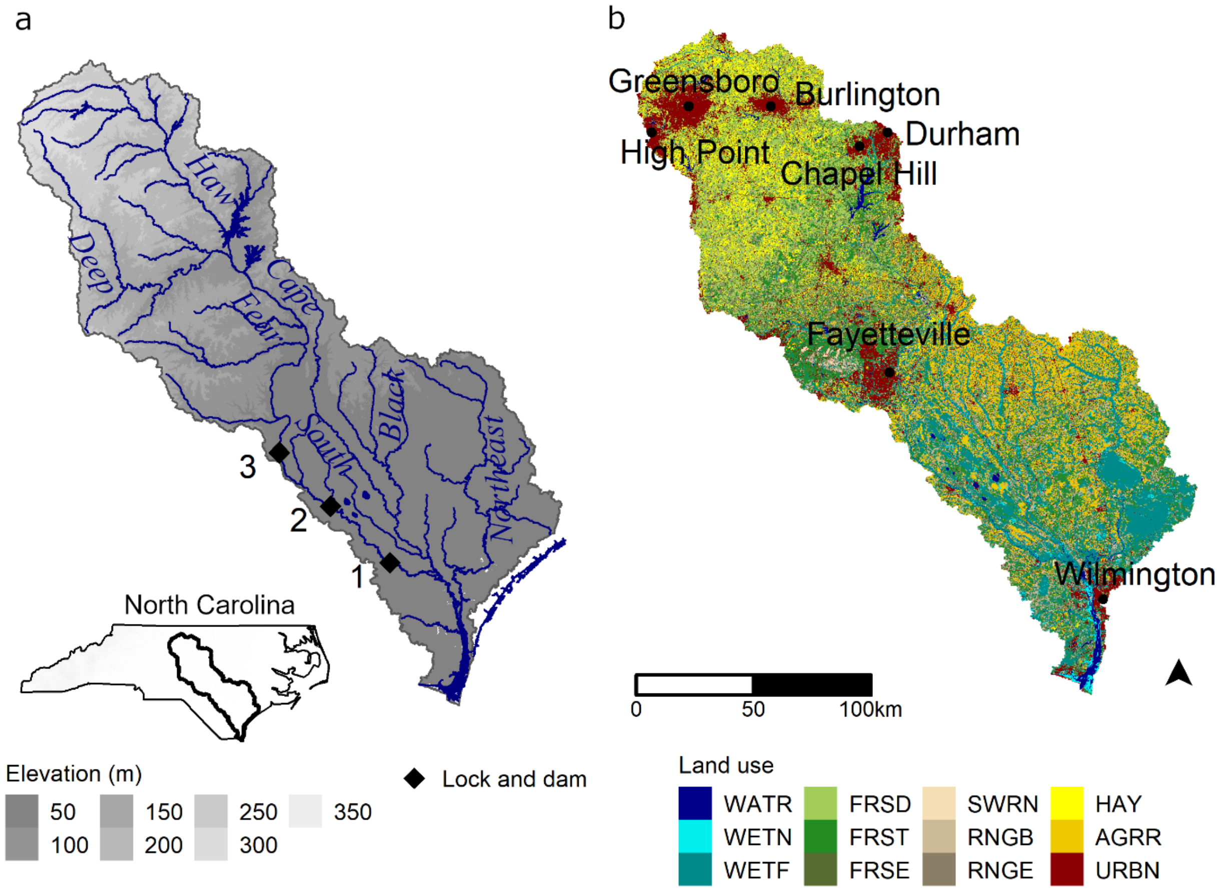

Figure 1. Landscape hydrography (a) and land use from the National Land Cover Database for 2019 (b) within the Cape Fear River Basin, North Carolina, USA. Abbreviations: water (WATR), non-forested wetland (WETN), forested wetland (WETF), deciduous forest (FRSD), mixed forest (FRST), evergreen forest (FRSE), range arid (SWRN), range grassland (RNGE), range shrubland (RNGB), hay (HAY), row crops (AGRR), urban (URBN).

Water quality and quantity are highly variable in the CFRB. Severe drought in 2007 resulted in widespread water supply concerns across the state – 79% of water customers faced restrictions and ~600 wildfires occurred in August alone (Davis, 2015). Yet more recently NC has experienced 5 distinct 500-year storms between 2016 and 2020, with additional extreme rainfall events impacting the CFRB (Davis, 2020). The basin has a long history of water quality issues, due in part to excessive nutrient pollution from both point and non-point sources (DeMeester et al., 2019; NC Department of Environment & Natural Resources, 2005), including the largest concentrations of concentrated animal feeding operations (CAFOs) in the entire U.S (Brown et al., 2020).

2.2 Watershed Modeling

2.2.1 Model Setup

To better understand the dynamics of hydrology and water quality of the CFRB, we developed a SWAT model representing contemporary land use, soil and slope, and historical weather conditions from 1979-2019 (SWAT version 2012, revision 681). SWAT is a semi-distributed hydrologic model that simulates a variety of watershed processes including the water balance, plant growth, and sediment and nutrient transport across the landscape and in-stream (Arnold et al., 2012). SWAT has been widely used in hydrologic studies and is well-suited to studies of agricultural landscapes (Gassman et al., 2014). We modified a SWAT model (SWAT version 2012, revision 664) originally developed by the U.S. Geological Survey (USGS) South Atlantic Water Science Center as part of a study of water availability and water use under population growth, land use change and climate change (U.S. Geological Survey, 2018). USGS delineated 2,928 subbasins comprised by 13,596 hydrologic response units (HRUs) and calibrated the model to represent unimpaired flow from 2000-2014.

Building on this prior work by USGS, we developed a new water quantity and quality model incorporating additional elements to capture water storage capacity and water quality in the basin. We updated the climate record using 1-km gridded weather data 1979-2019, spanning multiple drought periods and large storm events (Thornton et al., 2017). We included reservoirs, lakes, ponds and wetlands which store water and process nutrients based on the National Wetland Inventory (U.S. Geological Survey, National Geospatial Program, 2018). Contributions of flow, sediment, nitrogen and phosphorus from wastewater treatment plants, and other permitted emitters, were incorporated in the model using measured data 1994 – 2019 (NC Department of Environmental Quality, Division of Water Resources, 2019), and monthly averages for the period preceding recordkeeping. We also incorporated annual average atmospheric nitrogen deposition (National Atmospheric Deposition Program (NRSP-3), 2020). Nutrient and sediment loads from non-point sources were represented principally through land management practices, including cropping patterns and rotations, tillage, fertilizer and manure applications on crops, pastures, pine plantations, and lawns. We used a mass balance approach to parameterize fertilizer and manure applications considering fertilizer sales data (John & Gronberg, 2017), manure generated by grazing livestock (USDA-NASS, 2018), and by animals in concentrated animal feeding operations (College of Agriculture and Life Sciences, NC State University, 2019; Environmental Working Group & Waterkeeper Alliance, 2016; NC Department of Environmental Quality, 2019). Given differences in the physiography and land use in the Piedmont and Coastal Plain, we parameterized these regions separately. More detail regarding model development is provided in the Supporting Information.

2.2.2 Model Calibration and Validation

We calibrated and validated the model using observed streamflow and water quality monitoring records for the period 2000-2019 using a MATLAB routine integrated with SWAT; daily observations from 2010-2019 were used for calibration, while we retained observations from 2000-2009 for validation. The calibration and validation periods were chosen to represent a range of hydrologic flow conditions, as well as high and low loads of sediment and nutrients. Daily streamflow data spanning 2000-2019 were available at USGS gage #02105769 (Cape Fear River at Lock and Dam #1 near Kelly, NC). Loads of water quality parameters were calculated using streamflow measured at USGS gage #02105769 and in-stream concentrations measured at nearby state monitoring stations using available data through March 2020. Sediment data retrieved from the Water Quality Portal was provided from NC Division of Water Resources' monitoring station #B8349000, while total nitrogen and total phosphorus were collected from the NC Department of Water Quality's monitoring station #B8350000, both near Lock and Dam #1. Observations of total nitrogen in most cases were aggregated from individual measurements of total Kjeldahl nitrogen and inorganic nitrogen (nitrite and nitrate) recorded on the same day. For days with missing observations, we estimated daily constituent loads using the LOADEST model (regression model #0, Runkel et al., 2004); there were 256 true measurements of daily sediment (3.32%), 388 true measurements of daily total nitrogen (9.38%), and 308 true measurements of daily total phosphorus (5.13%) available. We used all available data to generate load estimates, and retained the load estimates 2000-2019 for calibration and validation of the model. Beginning with flow, followed by sediment, phosphorus, and nitrogen, calibration was performed iteratively, changing one parameter at a time. Sensitive parameters were altered in order to first achieve satisfactory hydrologic calibration, and then water quality calibration according to best practices for model evaluation (Moriasi et al., 2007; Arnold et al., 2012; Scavia et al., 2017). We relied on metric-based approaches for calibration and validation against streamflow and load estimates, including using the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) and percent bias (Moriasi et al., 2007; Arnold et al., 2012). We also employed graphical approaches to ensure that SWAT predictions generally captured the trends of true observations measured at in-stream gages. Additional details are included in the Supporting Information.

2.2.3 Simulations

To assess hydrology and water quality dynamics across many conditions, we ran a daily simulation with weather conditions from 1979-2019, with the first three years serving as a warmup period. To evaluate the relative importance of point vs. non-point sources of water quality contaminants, we also ran the model without point sources for 2010-2019.

2.3 Assessing the Importance of Point and Non-point sources

We examined the relative importance of point and non-point sources in terms of the average and standard deviation (sd) of the load from each source by month for 2010-2019. We also separately examined an extremely dry year (2011) and an extremely wet year (2016). These two extreme years were characterized by consistent departures from normal flows at both USGS gage #02102500 Cape Fear River at Lillington in the middle basin, and USGS gage #02105769 at Lock and Dam #1 relative to the entire period of record at these in-stream gages (National Water Quality Monitoring Council, 2021; Read et al., 2017).

2.4 Tracking Landscape Source Hotspots Across Conditions

Watershed-scale, nature-based solutions implemented on the landscape are expected to help improve water quality under both extreme dry and wet conditions, and also have benefits for moderating water quantity; therefore we focused the bulk of our analysis on landscape-derived sediment and nutrient source hotspots across conditions. Landscape sources include non-point source pollution, as well as applications of manure from permitted CAFOs, but do not include point-source dischargers like wastewater treatment plants and industrial emitters.

To better understand landscape source dynamics, we examined the spatial distribution of landscape-derived sediment and nutrient hotspots under dry, normal, and wet conditions, respectively. We defined climate extremes for each subbasin, respectively, based on runoff amounts generated over the full simulation period. We defined ‘dry’ conditions as the lower 25% of runoff volumes, ‘normal’ conditions as the middle 50%, and ‘wet’ conditions as the upper

25% of runoff. For each subbasin, we calculated the mean and sd of the load for each parameter under each climate condition. To facilitate comparisons across parameters and conditions, we standardized each measure, generating a *z*-score (eq. 1) with a mean at zero and sd equal to 1, capped at 3.5 sd to avoid undue influence from outliers. Z-scores are widely used to compare measurements with different scales to one another (Dixon, 1960), and can be used to create composite scores incorporating multiple factors (Song et al., 2013).

$$z = \frac{\mathrm{x} - \bar{x}}{\sigma} \tag{1}$$

Where:

z = z-score

x = observed value

$\bar{x}$ = population mean

σ = population standard deviation

By eq. 1 the average load z-score for sediment under dry conditions would be calculated as:

$$z_{avg}(sed)_{dry} = \frac{\mathrm{x(sed)}_{dry} - \bar{x}(sed)_{dry}}{\sigma(sed)_{dry}}$$

Where:

$z_{avg}(sed)_{dry}$= average load z-score under dry conditions

x = observed value of the average load under dry conditions

$\bar{x}$ = population mean of the average load under dry conditions

σ = population standard deviation of the average load under dry conditions

By eq. 1, the sd load z-score would be calculated as:

$$z_{sd}(sed)_{dry} = \frac{\mathrm{x(sed)}_{dry} - \bar{x}(sed)_{dry}}{\sigma(sed)_{dry}}$$

Where:

$z_{sd}(sed)_{dry}$= sd load z-score under dry conditions

x = observed value of the sd load under dry conditions

$\bar{x}$ = population mean of the sd load under dry conditions

σ = population standard deviation of the sd load under dry conditions

2.5 Identifying Intervention Priorities with a Water Quality Risk Index

Ideally, intervention strategies such as nature-based solutions, would be implemented at locations where they improve water quality under a range of conditions, representing no regrets investments of time, effort, and expense. Conservation of remaining high quality forests, floodplains, and wetlands is important for avoiding further loss of natural capacity to purify water and buffer communities downstream from droughts and floods. Restoration, either through landcover change or floodplain reconnection, can also add or enhance natural capacity.

To identify priority locations for interventions to enhance water quality and resilience under ongoing climate change, we developed a Water Quality Risk Index (WQRI) considering the relative amount, or 'intensity' and variability of sediment, total nitrogen, and total phosphorus loads under dry, normal, and wet conditions for all subbasins (Fig. 2). We considered the intensity (derived from the average load) and the variability (derived from the sd load) to be distinct aspects useful for characterizing the relative level of disturbance from contaminants across the watershed. Firstly, for each subbasin and each parameter we generated an intensity score by summing the average load z-scores across conditions (eq. 2). We generated a variability score for each subbasin and each parameter similarly using the sd load z-scores (eq. 3). Next, we generated a composite intensity score for each subbasin by summing the intensity z-scores across parameters (eq. 4), and a composite variability score in the same fashion based on variability z-scores (eq. 5). Finally, for each subbasin we calculated an overall WQRI as the simple average of the composite intensity z-score and the composite variability z-score (eq. 6). At each step where a z-score was calculated, the value was capped at 3.5 sd in order to limit undue influence from outliers.

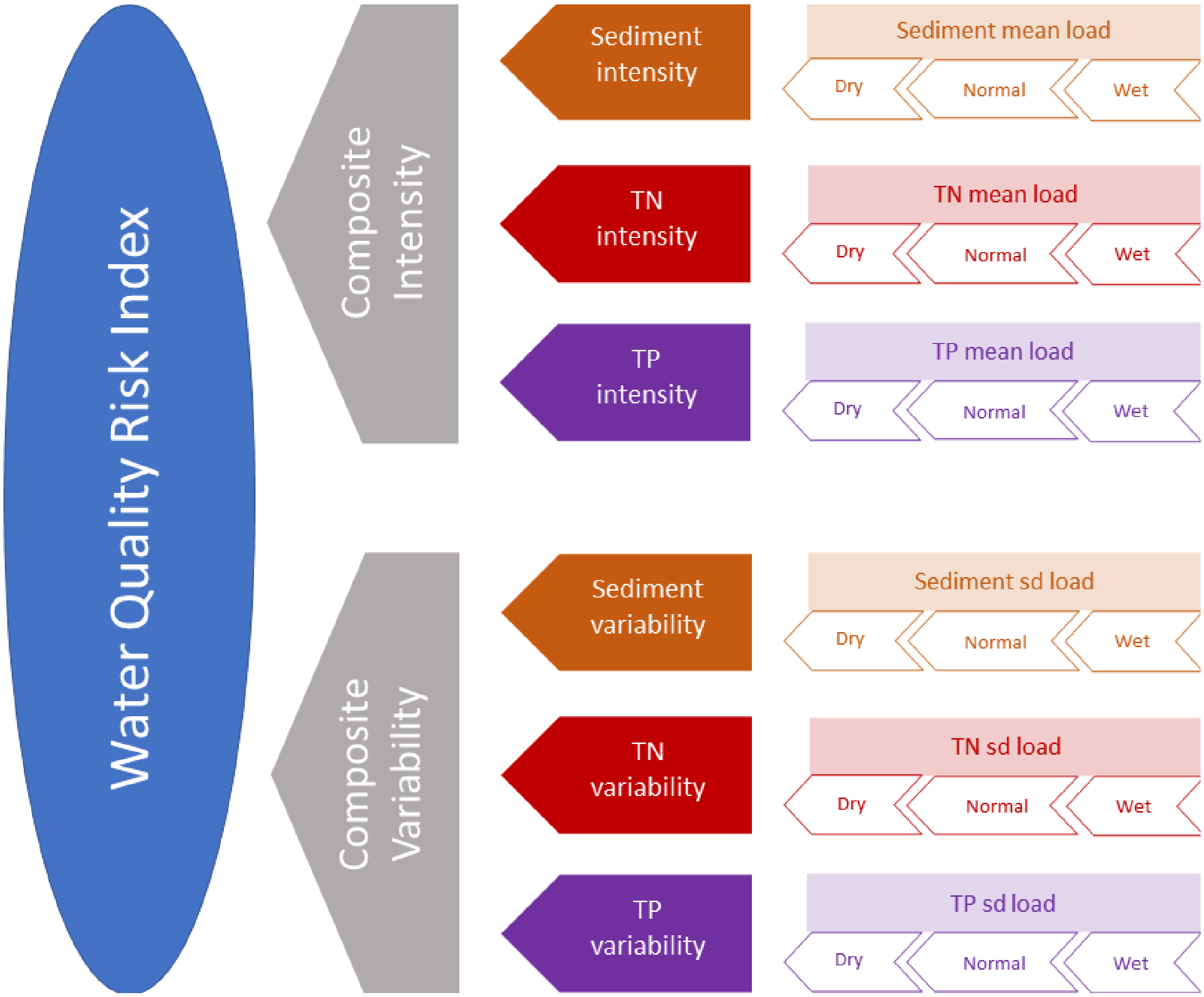

Figure 2. A water quality risk index (WQRI) was calculated for each subbasin in the Cape Fear River Basin using a series of z-score calculations and aggregations to account for distinct aspects of water quality risk for different parameters under different weather conditions (eq. 1-6). For each parameter, first a z-score (mean = 0, sd = 1, capped at 3.5 sd) was calculated for the load mean and standard deviation (sd) for each condition for each parameter. Intensity and variability for each parameter were calculated by summing z-scores across conditions. Composite intensity and variability scores were calculated by summing intensity and variability z-scores, respectively, across parameters. Finally, a WQRI was generated for each subbasin by taking a simple average of the composite intensity z-score and the variability z-score. 'Dry' conditions were defined as the lower 25% of runoff, while 'normal' constituted the middle 50%, and 'wet' conditions were represented by the upper 25% based on weather 1982-2019. Abbreviations: total nitrogen (TN), total phosphorus (TP).

$$I(p) = \sum_{c=1}^{3} z_{avg}\,(p)_c \tag{2}$$

Where:

I = intensity score

c = condition (1 = dry, 2 = normal, 3 = wet)

z_{avg}= average load z-score

p = parameter

By eq. 2, the intensity score for sediment would be calculated as:

$$I(Sed) = \sum_{c=1}^{3} z_{avg}(Sed)_c$$

Where:

I (Sed) = sediment intensity score

c = condition (1 = dry, 2 = normal, 3 = wet)

$z_{avg}(Sed)_c$= average sediment load z-score for a given condition

$$V(p) = \sum_{c=1}^{3} z_{sd}\,(p)_c \tag{3}$$

Where:

V = variability score

c = condition (1 = dry, 2 = normal, 3 = wet)

z_{sd}= sd load z-score

p = parameter

By eq. 3, the variability score for sediment would be calculated as follows:

$$V(Sed) = \sum_{c=1}^{3} z_{sd}(Sed)_c$$

Where:

V (Sed) = sediment variability score

c = condition (1 = dry, 2 = normal, 3 = wet)

$z_{sd}(Sed)_c$= sd sediment load z-score for a given condition

$$CI = zI(Sed) + zI(TN) + zI(TP) \quad (4)$$

Where:

CI = composite intensity score

zI(Sed) = z-score of sediment intensity

zI(TN) = z-score of total nitrogen intensity

zI(TP) = z-score of total phosphorus intensity

$$CV = zV(Sed) + zV(TN) + zV(TP) \quad (5)$$

Where:

CV = composite variability score

zV(Sed)= z-score of sediment variability

zV(TN)= z-score of total nitrogen variability

zI(TP)= z-score of total phosphorus variability

$$WQRI = \frac{zCI + zCV}{2} \quad (6)$$

Where:

WQRI = water quality risk index

zCI = z-score of composite intensity

zCV = z-score of composite variability

The approach we employed to generate the WQRI is similar to other assessments aimed at highlighting outliers and spatial priorities considering multiple factors. For example, The Nature Conservancy identified locations expected to be resilient to climate change that will support high biodiversity into the future based on a variety of biophysical and condition metrics using a z-score based approach (Anderson et al., 2014; Rebecca Benner et al., 2014). The Center for Disease Control's social vulnerability index (SVI) is another example aimed at measuring communities' ability to respond and recover after a natural disaster (Flanagan et al., 2018; Flanagan et al., 2011). The SVI uses percentile ranking to put 15 socioeconomic metrics on the same scale, and gives equal weighting to each when aggregating them into four themes, finally integrating the theme scores into an overall composite index (Flanagan et al., 2018; Flanagan et al., 2011).

3. Results

3.1 Model calibration and validation results

The final calibrated model demonstrated very good daily performance for hydrology and very good to excellent monthly performance for water quality parameters over the calibration period (Table 1; D. N. Moriasi et al., 2007). Weaker performance during the validation period is not surprising given that we set up the model with contemporary land use and management, and many changes have occurred in the watershed over 20 years. Within the U.S., the southeast has experienced the most rapid recent land use change, particularly forest loss to suburban sprawl (Gaines et al., 2022; Homer et al., 2020; Georgina M. Sanchez et al., 2020; Sleeter et al., 2018). NC, and particularly the Cape Fear Basin, has some of the highest urban and suburban growth rates in the country (U.S. Census Bureau, 2020) and is undergoing agricultural intensification, notably via expansion of swine CAFOs from the 1980s through the early 1990s and ongoing growth of poultry CAFOs (Environmental Working Group & Waterkeeper Alliance, 2016; Miralha et al., 2021; Montefiore et al., 2022).

We reported calibration statistics for the period January 2010 through December 2018 (Table 1, Figures S17-S20). After Hurricane Florence in September 2018, wet weather persisted through the spring of 2019 with extended high flow from Lillington down to the locks and dams. The locks and dams on the lower Cape Fear River may back water up behind them for extended periods of time—Lock and Dam #3 in particular is considered to be a dampening structure that causes backwater effects that may not be captured by SWAT (DeMeester et al., 2019). It is also possible that operations at the reservoir associated with the Shearon Harris nuclear facility affected flows. Additional calibration and validation details, including calibrated parameters and plots used in graphical model evaluation, are provided in the Supporting Information.

Table 1. Evaluation of the Cape Fear River Basin Water Quantity and Quality Model for the calibration period (2010-2018) and the validation period (2000-2009) against measurements collected at in-stream gages. Flow records were sourced from USGS gage 02105769 Cape Rear R at Lock #1 near Kelly, NC. Sediment records were gathered from the NC Division of Water Resources' monitoring station #B8349000, while total nitrogen and total phosphorus were collected from the NC Department of Water Quality's monitoring station #B8350000 Cape Fear River at Lock 1 Near Kelly. Loads for water quality parameters were estimated using LOADEST. Flow was evaluated at a daily timestep, while water quality parameters were evaluated at a monthly timestep.

	Calibration (Jan 2010 – Nov 2018)				Validation (Jan 2000 – Dec 2009)			
	Flow	Sediment	TN	TP	Flow	Sediment	TN	TP
R^2	0.78	0.86	0.74	0.71	0.57	0.48	0.59	0.42
NSE	0.76	0.79	0.74	0.69	0.53	-0.49	0.59	0.31
PBIAS	1.72	0.86	0.28	4.17	-0.17	69.41	3.5	15.21

3.2 Relative importance of point source discharge and landscape sources

Analysis of the sources of in-stream flow and contaminant loads at Lock and Dam #1 revealed that the landscape represented the major source of flow and contaminant contributions from 2010-2019 (Table 2). Over the long-term we did not observe notable seasonal variation in the contributions of landscape sources and permitted discharge into rivers, yet their relative importance did change under extreme wet or dry conditions. Effluent from permitted wastewater treatment plants and industrial dischargers accounted for an average of 9.7 % of the cumulative monthly flow at Lock and Dam #1; they accounted for as little as 0.7 % of flow during an extremely wet year and as much as 54.57 % in an extremely dry year. Non-point sources generally accounted for the vast majority of the cumulative monthly sediment and nutrient loads at Lock and Dam #1. During an extremely wet year, landscape sources contributed as much as 99.30 % of the monthly flow, 98.89 % of sediment, 97.69 % of total nitrogen, and 81.21 % of total phosphorus. During an extremely dry year in 2011, point sources contributed as much as 80.05 % of the monthly sediment, 84.50 % of total nitrogen, and 75.70 % of total phosphorus (Table 2).

Table 2. Average percentage of cumulative monthly flow, sediment, total nitrogen (TN) and total phosphorus (TP) contributions from permitted effluent and landscape sources measured at Lock and Dam #1 across conditions 2010-2019. Standard deviations are indicated by +/-.

	Point source discharges				Landscape sources			
	Flow	Sediment	TN	TP	Flow	Sediment	TN	TP
All data	9.66	9.94	16.77	47.57	90.34	90.06	83.23	52.43
	+/-2.55	+/-4.58	+/-6.14	+/-6.17	+/-2.55	+/-4.58	+/-6.14	+/-6.17
Dry year (2011)	38.05	61.85	51.09	67.67	61.95	38.15	48.91	32.33
	+/-11.23	+/-16.32	+/-20.32	+/-5.38	+/-11.23	+/-16.32	+/-20.32	+/-5.38
Wet year (2016)	6.70	10.59	24.91	46.10	93.30	89.41	75.09	53.90
	+/-4.82	+/-7.28	+/-15.83	+/-16.88	+/-4.82	+/-7.28	+/-15.83	+/-16.88

3.3 Landscape water quality hotspot dynamics

Landscape hotspots differed spatially by pollutant when examining long-term average loads generated under weather conditions from 1982-2019 (Fig. 3). Sediment was most often generated in urban areas, particularly in the Piedmont (upper basin), while nutrients were most often sourced from working lands, particularly in the Coastal Plain (mid-lower basin). Phosphorus loads were generally high both in cultivated crop areas and urban areas (Fig. 3).

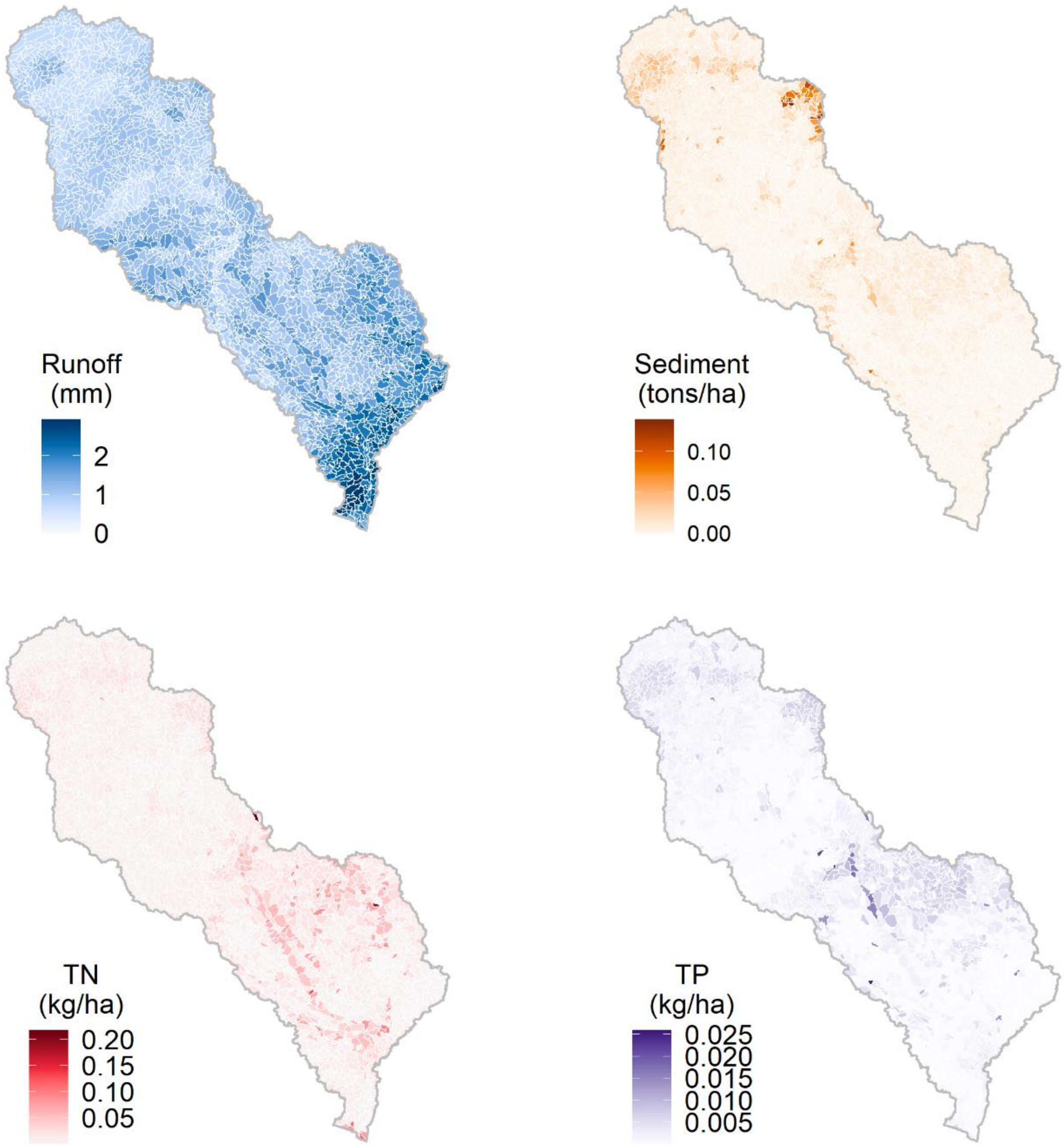

Figure 3. Long-term average daily runoff, sediment, total nitrogen (TN) and total phosphorus (TP) loads varied spatially across the Cape Fear River Basin based on contemporary land use and historical weather conditions from 1982-2019.

Examination of relative contributions under extremely dry, normal, and extremely wet conditions (Fig. 4, 5) revealed distinct patterns across pollutants compared to long-term average loads (Fig. 3). For example, important sediment source areas in terms of the relative average load were quite widespread under normal conditions, and more spatially concentrated around urban centers, and in the Northeast Cape Fear under extreme dry and wet conditions (Fig. 4). The patterns of importance in terms of relative sediment load variability were similar (Fig. 5). While the Piedmont generated relatively low nutrient loads overall (Fig. 3), relative contributions of nitrogen from the Piedmont were more important under extreme dry conditions (Fig. 4), though less variable than the contributions from the Coastal Plain (Fig. 5). Under normal conditions, the subbasins contributing relatively large amounts of phosphorus were broadly distributed throughout the basin, while a smaller number of localized hotspots emerged under extremes within urban areas, the lower Cape Fear River mainstem, and the Northeast Cape Fear (Fig. 4). Subbasins with high intensity based on average load typically also demonstrated greater variability based on load sd (Fig. 4, 5).

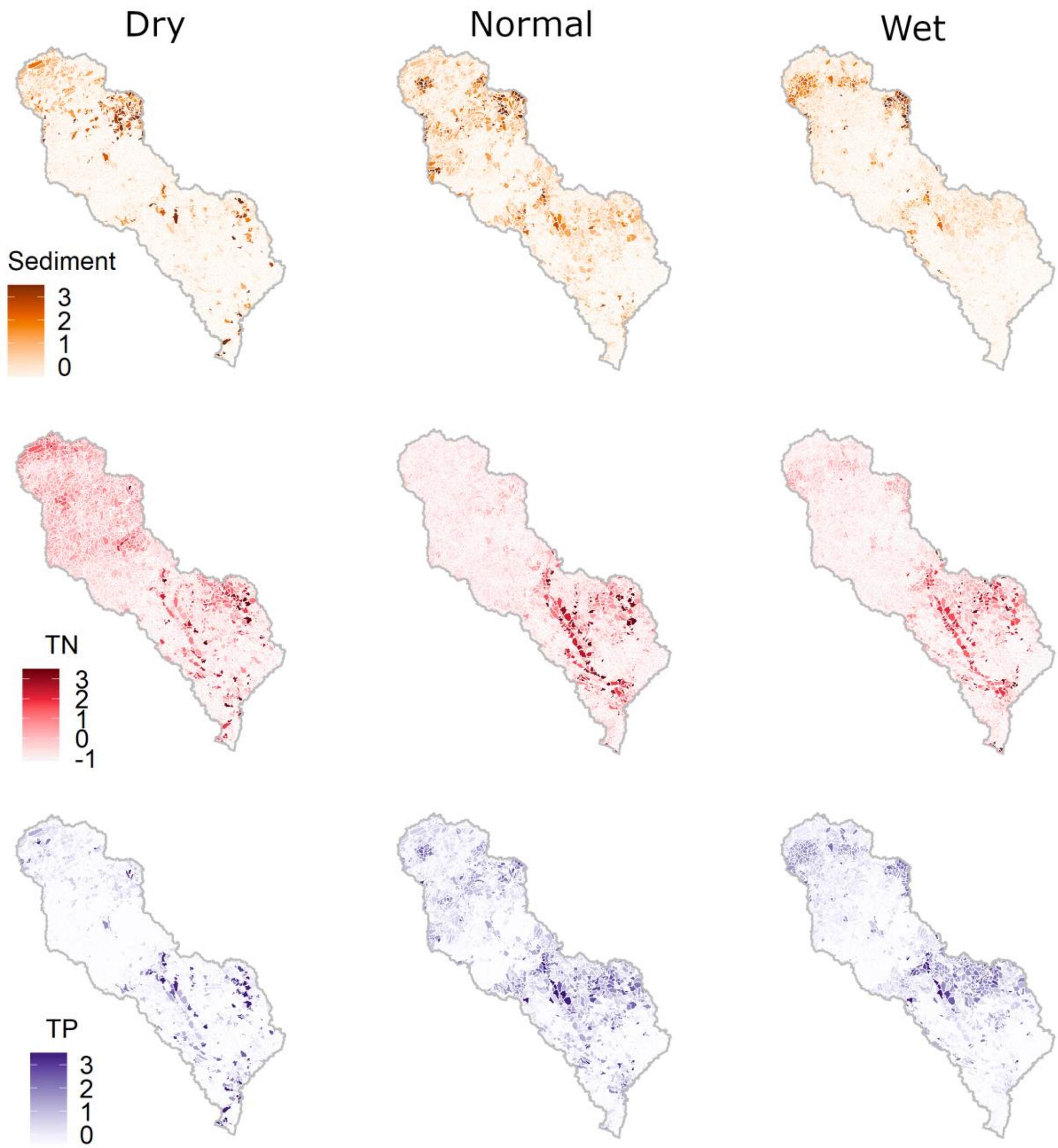

Figure 4. The relative intensity of contaminant loads across the Cape Fear River Basin varied by parameter across weather conditions 1982-2019, determined by calculating standardized z-scores of the average load for each, capped at 3.5 sd. Abbreviations: total nitrogen (TN), total phosphorus (TP).

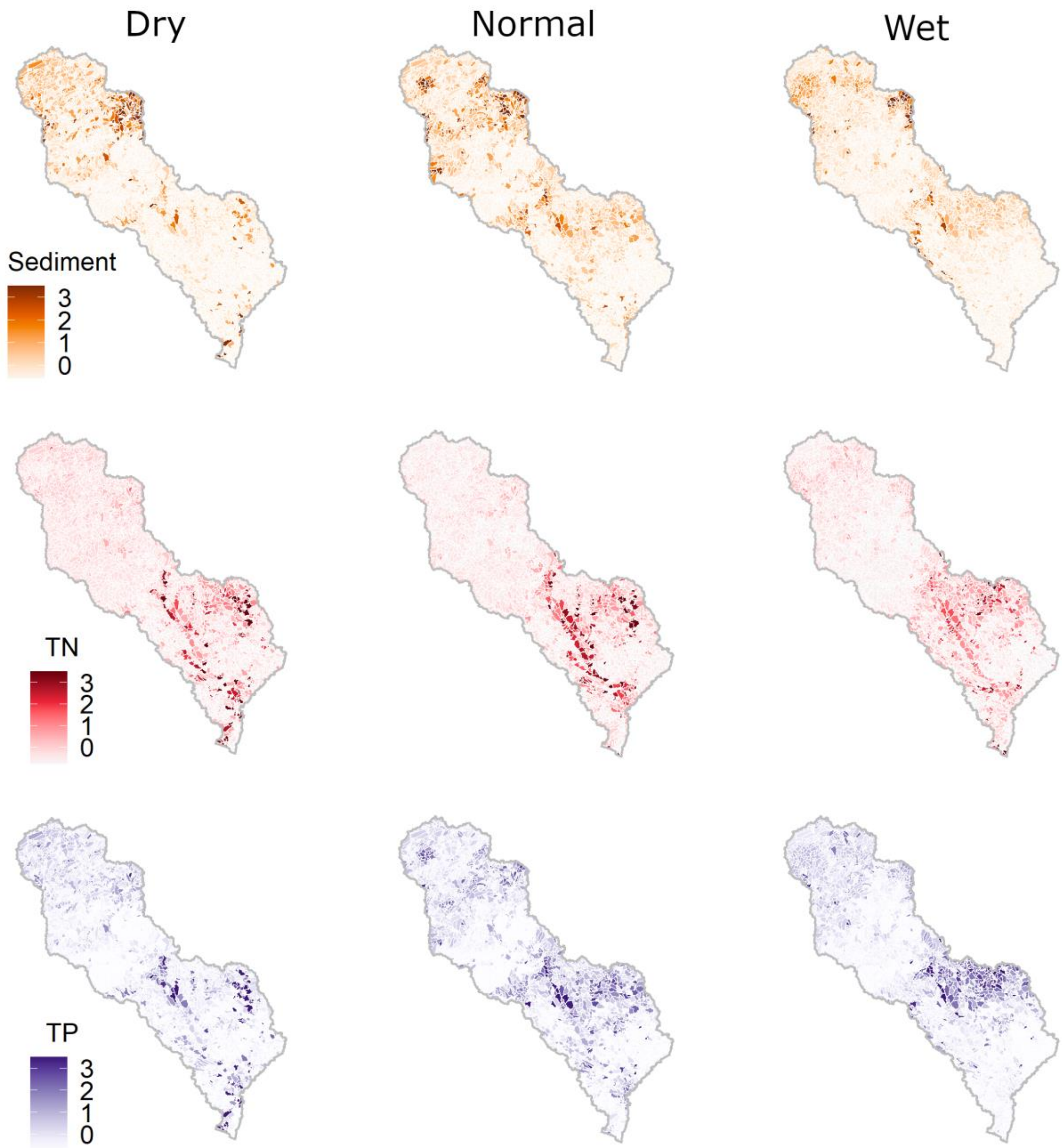

Figure 5. The relative variability of contaminant loads across the Cape Fear River Basin varied by parameter across weather conditions 1982-2019, determined by calculating standardized z-scores of the load standard deviation for each, capped at 3.5 sd. Abbreviations: total nitrogen (TN), total phosphorus (TP).

WQRI scores across the basin identified locations that merit attention based on their relatively high intensity and variability of sediment, nitrogen, and phosphorus contributions across conditions (Fig. 6). Subbasins with a low WQRI likely represent high priorities for land protection to maintain functioning floodplains, water purification, and habitat that supports biodiversity as well as high quality water community water supplies (e.g., Fig. 6a). Conversely, subbasins with a high WQRI represent high priorities for interventions, such as restoration, agricultural field measures, or urban green and grey infrastructure strategies to improve water quality, depending on local land use and management conditions (e.g., Fig. 6b). Many such strategies could also yield benefits for flood-risk reduction and water provisioning during droughts (Chausson et al., 2020; DeLong et al., 2021; Griscom et al., 2017; Kousky et al., 2013). We found that the highest risk regions (WQRI >1) comprised 16.4% of the watershed.

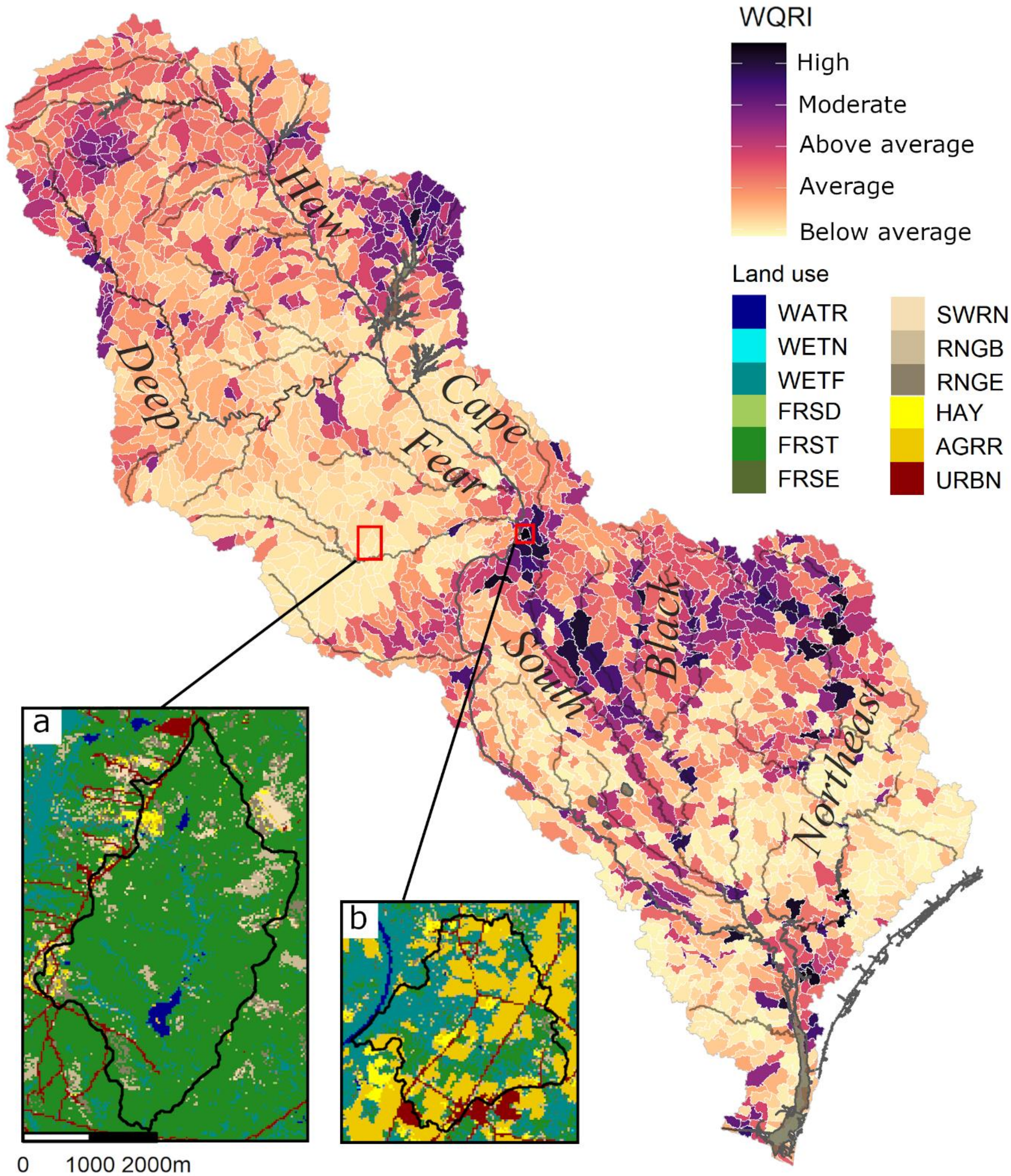

Figure 6. A water quality risk index (WQRI) summarizing landscape pollution hotspot dynamics across conditions highlighted locations in the Cape Fear River Basin that warrant further investigation. Subbasins with a low WQRI tend to have relatively in-tact natural land uses and represent priority conservation areas (a). Subbasins with a high WQRI tend to have a high degree of urban or agricultural land use, and represent candidates for interventions (b). Abbreviations: water (WATR), non-forested wetland (WETN), forested wetland (WETF), deciduous forest (FRSD), mixed forest (FRST), evergreen forest (FRSE), range arid (SWRN), range grassland (RNGE), range shrubland (RNGB), hay (HAY), row crops (AGRR), urban (URBN).

4. Discussion

4.1 Utility of water quality risk index relying on watershed modeling

We developed the first SWAT water quantity and quality model for the entirety of the CFRB, with very good to excellent performance for flow and water quality parameters. We examined risks to water quality from landscape sources, taking into account the intensity and variability of pollution loads for multiple contaminants across extremely dry, normal, and extremely wet conditions 1979-2019, presenting a new application of SWAT model results. The WQRI revealed water quality risks that were not captured by long-term average estimated loads predicted by SWAT– notably in swaths of the upper and middle basin outside of urban centers (Fig. 3; Fig. 6). The overall WQRI and the underlying load intensity and variability scores for specific contaminants under dry, normal, and wet conditions shed light on the drivers of water quality issues, help avoid degradation of more resilient subbasins, and help select appropriate interventions to reduce water quality issues.

Our finding that the vast majority of contaminants in CFRB come from the landscape is consistent with previous SWAT-based assessments in the basin. A previous study of the lower CFRB found that while the upper basin contributed 50% of the total nutrient load at Lock and Dam #1, land applications of fertilizers and manures below Jordan Lake and the Deep River accounted for 70% of locally generated nutrients and 35% of the total load, while just 15% of the total load was derived from point sources (RESPEC, 2015). Similarly a previous analysis found that 70% of the total load of phosphorus load in the Northeast Cape Fear River was due to erosion (Narayan et al., 2017). A sub-daily model of the Jordan Lake Watershed in the upper basin found that overall nutrient loads decreased from 1997-2010 due to reductions in loads from point sources and rural land uses, yet urban landscape loads increased over the same period (Tetra Tech, 2014).

The spatial patterns of important landscape source areas we identified in CFRB also agree with other existing data. For example USGS SPARROW model identified sediment loads that were generally greater in the Piedmont, particularly urban areas and disturbed land, while nutrient loads were generally greater in the lower basin (Gurley, Garcia, Hopkins, et al., 2019; Gurley, Garcia, Terziotti, et al., 2019). The high risk hotspots that we identified with the WQRI overlap spatially with known surface water impairments, including surface waters near urban centers throughout the basin, the Jordan Lake Watershed, and a number of tributaries to the Northeast Cape Fear including Limstone Creek, Stocking Head Creek, Long Creek and Burgaw Creek (NC Department of Environmental Quality, Division of Water Resources, 2020). High risk hotspots also track with regions where groundwater nitrate likely exceeds the standard of 10 mg/L based on well monitoring data and modeling (Messier et al., 2014).

The CFRB SWAT model and our baseline model results provide vital information for ungaged, and poorly monitored areas of CFRB, with important insights for public health and ecosystem health. Given strong alignment between nitrate exceedances and high-risk landscape hotspots we identified, our model can provide information for communities that lack groundwater monitoring data. Groundwater nitrate levels as low as 2.5 mg/L may cause significant health impacts (De Roos et al., 2003; M. H. Ward et al., 1996; Mary H. Ward et al., 2005; Weyer et al., 2001). Our results also can provide new information regarding many reaches which currently have ‘insufficient information to make a determination’ about impairment status (NC Department of Environmental Quality, Division of Water Resources, 2020). In the upper basin, this includes sections of both the Haw and the Deep Rivers, in addition to Little Buffalo Creek and Carrs Creek near Sanford. In the mid-basin, the Little River north of Ft. Liberty (formerly known as Ft. Bragg), and Rockfish Creek have undetermined status. Relevant reaches in the lower basin include much of the upper Northeast Cape Fear, as well as tributaries to the Black River such as Colly Creek, Greater Coharie and Little Coharie Creeks. Reach specific outputs from the CFRB SWAT model may be useful in targeting future surface water monitoring efforts by state and federal agencies, as well as volunteer groups. Notably, stream gages and other surface water monitoring data tend to be sparse near more socioeconomically disadvantaged communities in the CFRB (Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program, 2016; National Water Quality Monitoring Council, 2021), which are more likely to be impacted by extreme events including flooding (Schaffer-Smith et al., 2020).

4.2 Limitations

Typically there are substantial uncertainties associated with watershed models and their predictions, which can be grouped into model uncertainty, input data uncertainty, and parameter uncertainty (Athira et al., 2018; Moges et al., 2020). We relied on the SWAT 2012 source code, without modifications, yet it is possible that the SWAT model does not capture all processes relevant to water quantity and quality in the CFRB, or that simplifications do not adequately represent how these processes function locally. We expect that input data uncertainty is the greatest source of uncertainty in our model, particularly for management decisions on private lands. We compiled the best available empirical data, literature, and guidance to establish our to initial parameter values, yet there is limited knowledge of actual management decisions by private landowners, which are influenced by many social and psychological factors in addition to regulations and best management practices (O'Connell & Osmond, 2022). While we did separately parameterize the Piedmont and Coastal Plain regions in the model to account for major biophysical differences, actual in-field management practices vary not only spatially but also year-to-year, given changing constraints and incentives for individual operators. Empirical data also may have substantial uncertainty; for example, errors in water quality observation data can occur during water sampling in the field, during analysis in the lab, and during recordkeeping and data cleaning and processing to produce a complete time series from sparse sampling events (McMillan et al., 2012; Rode & Suhr, 2007).

There are notable limitations relevant to simulating extreme events and climate change in watershed models. A recent assessment determined that underlying equations used by most hydrological models are pushed to their limits for contemporary extreme precipitation conditions (La Follette et al., 2021). Advances in watershed model development, calibration and validation methods are ongoing, offering refinements that could improve the use of SWAT for studying watershed resilience to climate change. For example, a recent study by Shen et al. (2022) provides strong evidence that split sample testing is not the most robust option for hydrologic model development, but rather found that using the full period of available data for calibration resulted in superior model performance. Wellen et al. (2014) implemented state-specific parameters in modeling of two watersheds near Lake Ontario and found that this improved predictions under extreme high flows. Dong et al. (2019) used a season-specific multi-site calibration to tailor a SWAT model of the Hamilton Harbour Watershed in southern Ontario, Canada. This study of the CFRB is part of a growing literature applying SWAT to explore the effect of extreme events on water quantity and quality. As interest in this topic grows, so too will guidance for appropriate model development and analysis methods.

4.3 Transferability

Our approach using watershed modeling and the WQRI can be applied in other watersheds to identify regions that present water quality issues across conditions, which may merit further study and interventions. The use of standardized z-scores to compare among distinct water quality risks and calculate an overall WQRI is transferrable to any watershed's local context and weather conditions. We used simple cutoffs for the lower and upper percentiles of runoff to separate dry and wet extremes from normal conditions, but identification of extreme conditions could be customized based on local knowledge and key thresholds relevant to basin-specific water management or ecological concerns. We weighted all contaminants and all climate conditions equally, but the WQRI could easily be adjusted to incorporate weights if specific conditions, or specific contaminants, are of greater concern in a given region. For example, The Nature Conservancy's resilient and connected network assessment assigned higher weights to some variables when creating composite scores (Anderson et al., 2014). To date a small number of studies have examined water quality under extremes with SWAT, but given the proliferation of watershed modeling, our analysis can be replicated for other basins with existing models.

4.4 Solutions to address water quality issues and improve resilience to extremes

Following on recent years of volatile weather conditions, including 5 distinct 500-year storm events within a 5-year period, NC is exploring a variety of options to improve resilience across the entire state. Large investments planned for modeling studies and increases in funding for conservation and restoration programs aimed at reducing flood-risk represent a golden opportunity to select interventions that also improve the health and resilience of watersheds more holistically. Nature-based solutions (e.g., wetland and forest restoration, field measures that improve soil quality) as demonstrated by Keesstra et al. (2018) could provide substantial benefits including buffering communities from flooding (Acreman & Holden, 2013; Antolini et al., 2020; Sutton-Grier et al., 2015), augmenting water supply during droughts (Acreman & Holden, 2013), carbon sequestration, providing plant and wildlife habitat (Fargione et al., 2018; Griscom et al., 2017), recreation opportunities (Chausson et al., 2020), and more.

The results of this study can inform policies and programs to implement nature-based solutions in the CFRB. Protections on riparian buffers are a widely used strategy to protect surface water quality (Cole et al., 2020; Lovell & Sullivan, 2006). Some basins in NC have regulations in place to protect riparian buffers from 50' – 200' around the margins of surface water features, but in the CFRB only the Jordan Lake watershed in the Research Triangle area (18.2% of the basin) is subject to a buffer rule (NC Conservation Network, 2016). Buffer protections could be an important strategy to avoid compromising remaining floodplains at-risk of development, particularly given high rates of population growth and land use change (Homer et al., 2020; Georgina M. Sanchez et al., 2020; U.S. Census Bureau, 2020). The WQRI that we developed could be included as part of the criteria for allocating funding towards conservation, restoration, and voluntary strategies available through a variety of state programs (e.g., the NC Land and Water Fund) and federal programs (e.g., the U.S. Department of Agriculture Conservation Reserve Program for privately owned agricultural lands and National Fish and Wildlife Foundation grants which apply to both public and private lands). Water quality issues in urban areas may be more successfully addressed with watershed-scale interventions rather than projects targeting individual stream segments or neighborhoods (Walsh et al., 2005). Our approach can support watershed planning and financing schemes for larger projects with cost-sharing and benefits for multiple jurisdictions. There is already precedent in the neighboring Neuse River Basin for nutrient trading schemes for permitted dischargers (Phthisic, 2018), creative partnerships between local governments and conservation groups such as the Upper Neuse River Basin Association (Upper Neuse River Basin Association, 2021) and the Upper Neuse Clean Water Initiative, which relied on a 'revenuesheds' approach to raise millions of dollars for upper basin conservation through a fee levied in the City of Raleigh (Patterson et al., 2012).

Additional landscape-based strategies can also be considered to improve water quality in the CFRB. Land applications of manure are subject to nutrient management plans, yet evidence suggests that these are not always followed in practice due to a variety of constraints (Cabot & Nowak, 2005; Osmond et al., 2015; Tao et al., 2014), and application above plant nutrient requirements can occur even while following nutrient management plan protocols (Long et al., 2018). Typically, agronomic rate limits are based on nitrogen, but some states have implemented nutrient limits based on phosphorus (Bradford et al., 2008; Sharpley et al., 2012). Phosphorus-based limits could be an appropriate intervention, given high existing legacy phosphorus concentrations (Wegmann et al., 2013); of statewide soil samples from 2016-2018, over 50 % had 'very high' phosphorus (Mehlich-3 soil test extractant) and additional phosphorus applications would not increase yields for 84% of the fields tested (Gatiboni et al., 2020). In the Neuse Basin, the implementation of a nutrient credit and trade system successfully reduced water quality issues and led to headwater protection that also provides flood storage, and other benefits (Phthisic et al., 2018; Walls & Kuwayama, 2019). Incentive programs can complement regulations to help reduce losses of sediment and nutrients. Reverse auctions are a popular approach that can more rapidly scale payment for services programs (Valcu-Lisman et al., 2017).

Our focus in this study was on landscape sources of contaminants, yet point sources are also an important source of phosphorus, and under very dry conditions they can be the dominant contaminant source at Lock and Dam #1, which provides drinking water to the City of

Wilmington. Nutrient management in NC is primarily managed through basin-wide water quality plans, in addition to a water quality standard specifying no more than 40 ug/L of chlorophyll-a for all surface waters (Fresh Surface Water Quality Standards for Class C Waters, 1976). Limits on point sources are recommended for specific waterbodies, including the Deep River from Randleman Reservoir to Carbonton Dam (NC Department of Environment & Natural Resources, 2005), the Cape Fear River between Jordan Dam and Buckhorn Dam as well as between Buckhorn Dam and Lock and Dam #3 (NC Department of Environment & Natural Resources, 2000), and for Jordan Lake within the Haw River Arm and the Upper and Lower New Hope River Arms of the reservoir (The Jordan Lake Nutrient Management Strategy, 2009). Updates to nutrient criteria and implementation of nutrient limits on point sources, especially during low flow periods, could help to improve water quality in the basin under anticipated population growth (U.S. Census Bureau, 2020).

4.5 Future work

To evaluate the effectiveness of possible strategies to improve water quality, and to determine how much intervention may be needed, additional scenario modeling can be performed with the CFRB SWAT water quantity and quality model. Scenarios simulating implementation of interventions will demonstrate how each type of strategy could alter flow and nutrient loads for each subbasin under a range of weather conditions. We expect this will highlight trade-offs among strategies and help to identify the places where the greatest potential exists to improve water quality, also offering quantitative estimates for moderation of floods and droughts. Furthermore, there is a need to consider the impacts of future changes in both climate and land-use. Urbanization will likely impact water availability in addition to altering contaminant loads in the CFRB (Sanchez et al., 2018). For the Neuse Basin, climate and land use change may result in a 30% increase in nitrogen loads by 2070 (Gabriel et al., 2018). The implications of future changes in the CFRB can be evaluated through additional land use change and climate change SWAT model scenarios.

5. Conclusion

Taking extreme climate conditions into account in watershed modeling can help highlight priority places to improve the resilience of watersheds in terms of both water quantity and quality. Conservation and restoration are key strategies that may help to ensure resilient, high quality water supplies into the future to support both human and natural communities. In the CFRB, the landscape consistently contributes a large amount of contaminants, but ~16% of subbasins are the most important contributors across extremely dry, normal and extremely wet conditions. These regions merit further attention for actions to improve water quality, and hopefully, other aspects of watershed condition. Regions with low WQRI scores that currently lack formal protection should be strongly considered for future conservation investment. Our straightforward WQRI approach to identify watershed-scale intervention priorities is directly translatable to any watershed seeking to increase the resilience of community water resources and aquatic ecosystems. The WQRI can easily be adapted based on locally specific concerns, including customized definitions of extreme climate conditions, and consideration of relevant contaminants of interest.

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Data Availability Statement

The SWAT 2012 revision 681 code is open source and available from https://swat.tamu.edu/. No modifications were made to the model source code. Model inputs, calibration and validation data are publicly available and included in the references cited. Detailed information regarding model setup, parameterization, calibration and validation is provided in the Supporting Information. Archiving of daily simulation outputs is in process at the HydroShare repository maintained by the Consortium of Universities for the Advancement of Hydrologic Science Inc. (CUAHSI; link to be updated once we have a manuscript ID to link the dataset to).

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AGU PUBLICATIONS

Earth's Future

Supporting Information

Landscape pollution source dynamics highlight priority locations for basin-scale interventions to protect water quality under extreme events

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Contents of this file

Introduction

The supporting information provides additional methodological details. It documents the development of the Cape Fear River Basin SWAT water quantity and quality model. Specifically, this document provides more details regarding literature review, input data sources, data processing, initial model parameterization, and model calibration and validation.

Text S1

Cape Fear River Basin Soil and Water Assessment Tool Water Quantity and Quality Model Documentation

Photo: Margaret Fields, The Nature Conservancy.

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Table of Contents

1 Original inputs

This SWAT model of the Cape Fear River Basin (CFRB), North Carolina (NC, Fig. 1) builds on a previous water quantity model developed by the U.S. Geological Survey (USGS) South Atlantic Water Science Center (SAWSC). As part of a Coastal Carolinas Focus Area Study on the estimated use of water, the USGS SAWSC developed a SWAT model to examine the potential effects of projected changes in population growth, land use change, and climate change on surface water availability in CFRB, particularly at ungaged locations.[1] Subbasin delineation and generation of the hydrologic response units (HRU) relied on slope, soil, and land use. Elevation and slope were derived from the National Elevation Dataset (Fig. 2).[2] Soil properties were derived from the U.S. General Soil Map (Fig. S3)[3]. The National Land Cover Dataset (NLCD) dataset for the year 2011 served as the source of land use and land cover represented in the model (Fig. 4)[4]. Based on these inputs, USGS defined 2,928 subbasins each approximately 2 $mi^{2,}$ comprised by a total of 13,596 HRUs with consistent slope, soil and landcover characteristics (Fig. 5). The flow network was determined based on the National Hydrography Dataset for NC (NHDPlus, Fig. 5).[5]

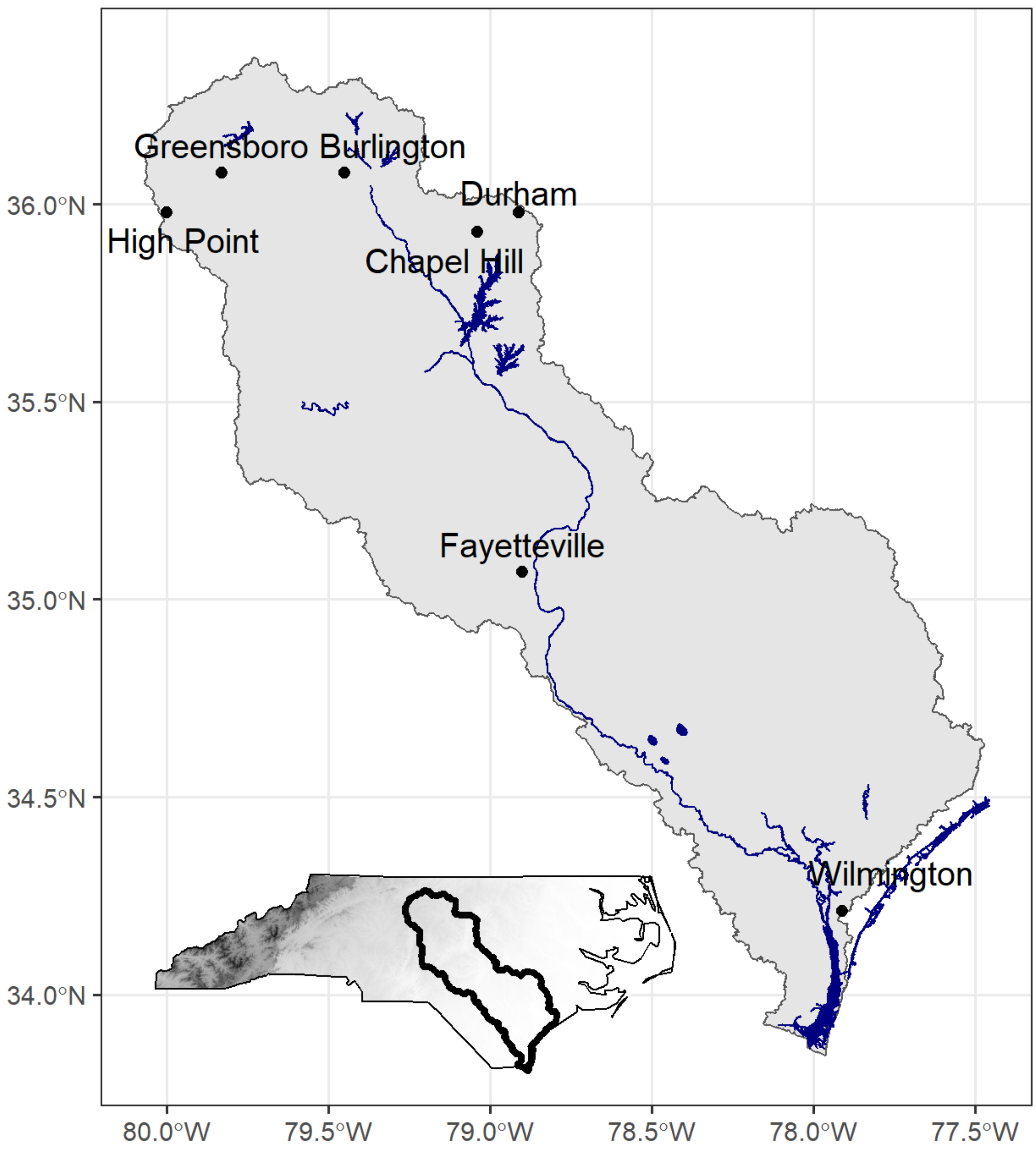

Figure 1. Study area in the Cape Fear River Basin, NC. Major hydrography and major cities within the basin are indicated.

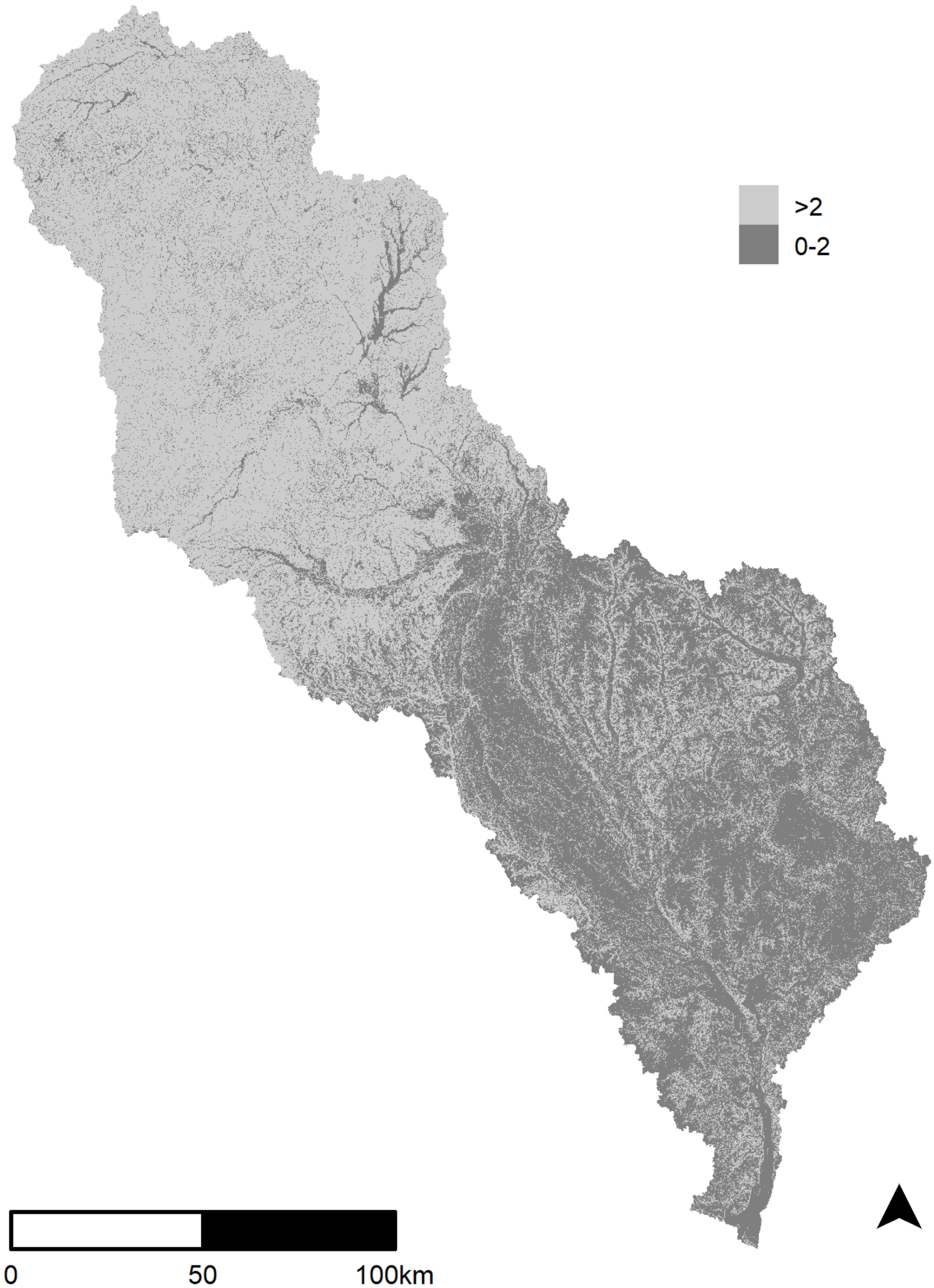

Figure 2. Slope classes (percent) incorporated in subbasin delineation by USGS. Source: National Elevation Dataset[2].

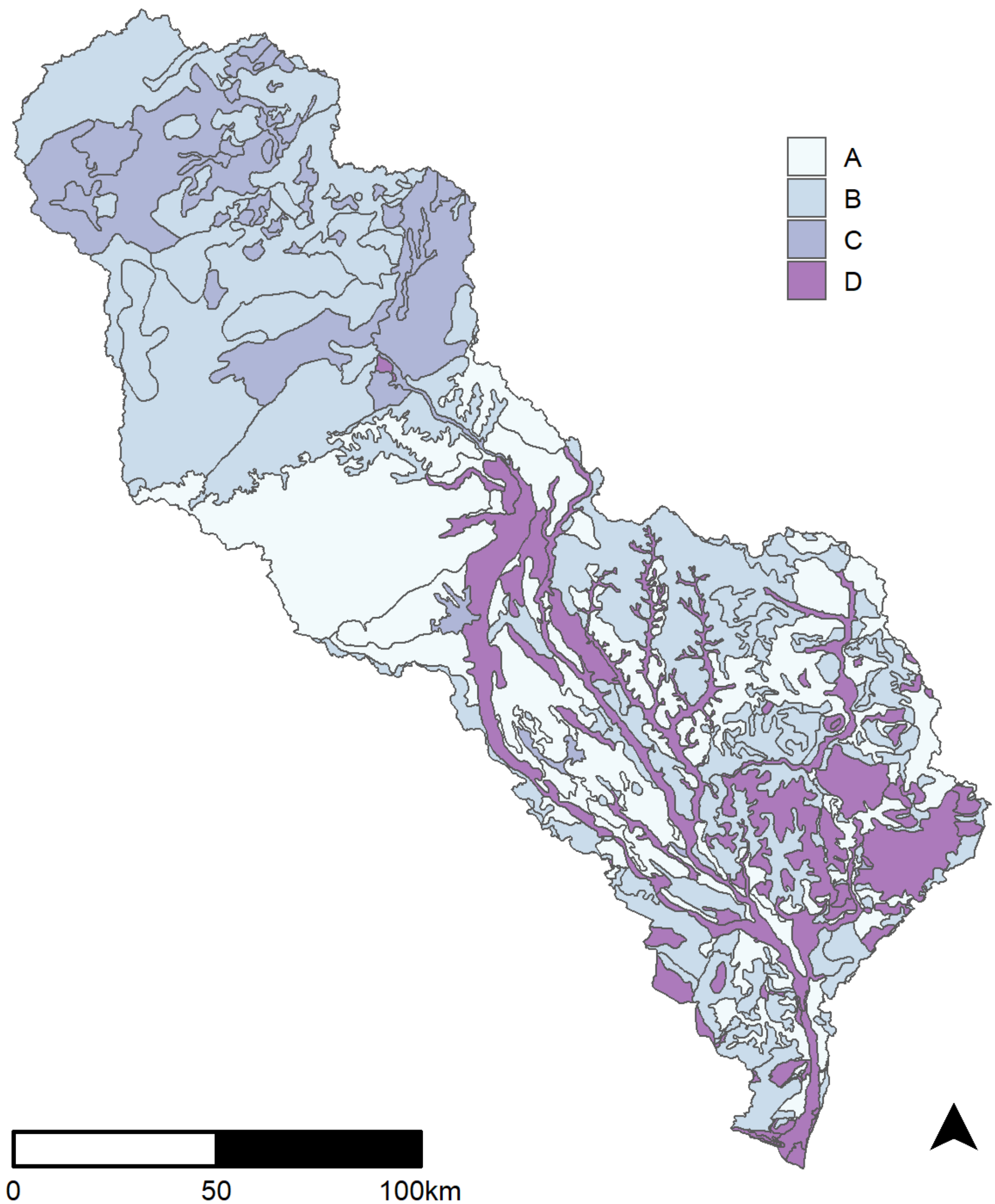

Figure 3. Soil hydrologic groups in the basin. Abbreviations: A = well to excessively drained with low runoff potential, B = moderately well to well drained, C = moderately high runoff potential, D = poorly drained with high runoff potential[6]. Source: STATSGO[3].

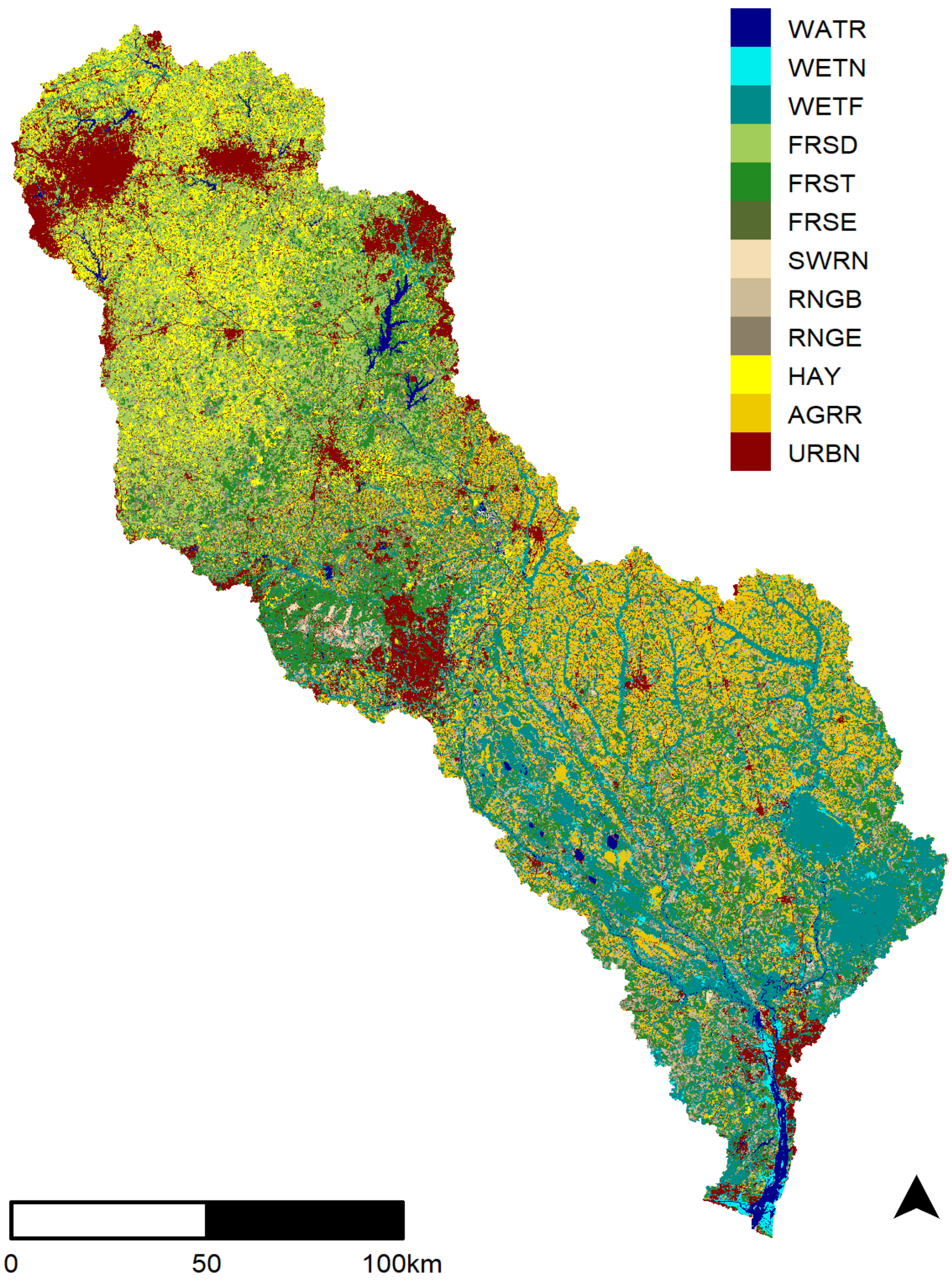

Figure 4. Land use and land cover in the study area. Abbreviations: water (WATR), non-forested wetland (WETN), forested wetland (WETF), deciduous forest (FRSD), mixed forest (FRST), evergreen forest (FRSE), range arid (SWRN), range grassland (RNGE), range shrubland (RNGB), hay (HAY), row crops (AGRR), urban (URBN). Source: NLCD[4].

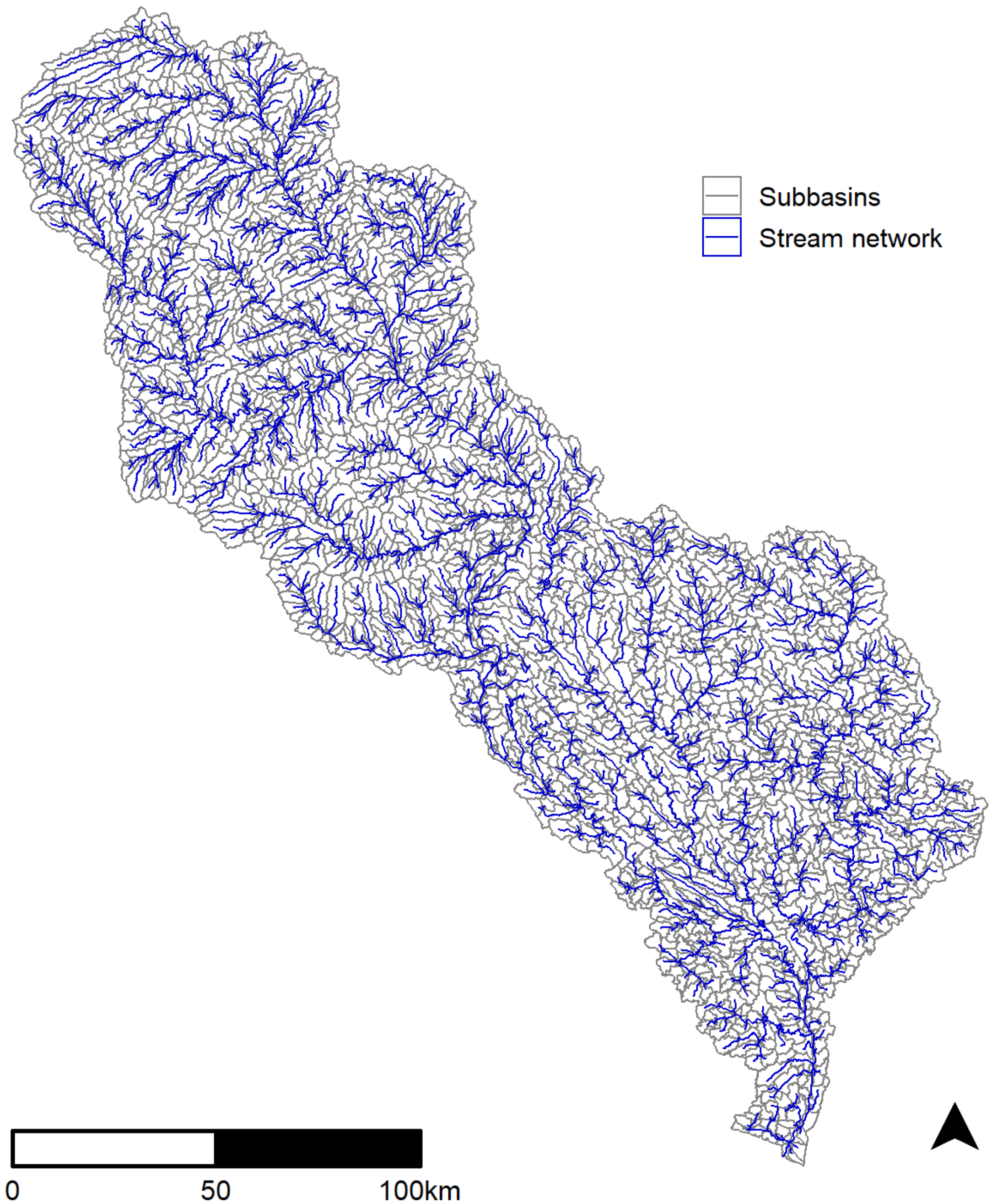

Figure 5. SWAT Subbasins and stream network delineated by USGS. Delineation of subbasins and smaller component hydrologic response units was based on slope, soil type, land use and land cover within the watershed.

2 Land use update

2.1 Land use

Subbasin delineation and HRU generation in the original SWAT model of water quantity relied on the National Land Cover Dataset (NLCD) to represent land use and land cover. Given the importance of rural landscapes in this study, we also examined the U.S. Department of Agriculture (USDA) Cropland Data Layer (CDL) from the past 10 years (2010–2019) to guide land use and management[7]. We found that the proportional cover of general land use categories was generally consistent over time (Fig. S6). High rates of year-to-year misclassification are known to occur between grasslands, hay, pasture, certain crop types, and fallow land[7,8]. Despite land cover changes, forests still comprise approximately ~25% of the basin and 10% of the basin consists of woody and emergent wetlands. Approximately 25% of the basin is cultivated land, with substantial grassland (22%) and shrubland (14%) areas that may be subject to grazing.

After analyzing the CDL, we determined that the existing model HRUs did not reflect the proportional extent of landcover and land use in the Piedmont and Coastal Plain regions based on the original NLCD-derived landcover used as an input for HRU generation (Table 1). In the Piedmont, deciduous forest and urban land uses were over-represented, while agriculture, hay and rangelands were under-represented. In the Coastal Plain, urban areas and row crops were over-represented while hay and rangelands were under-represented. Because land use is an important component of modeling land management and water quality outcomes, we decided to re-assign land uses for selected HRUs in the model in order to more accurately represent management operations that affect water quality. More detail is provided below in the Management section.

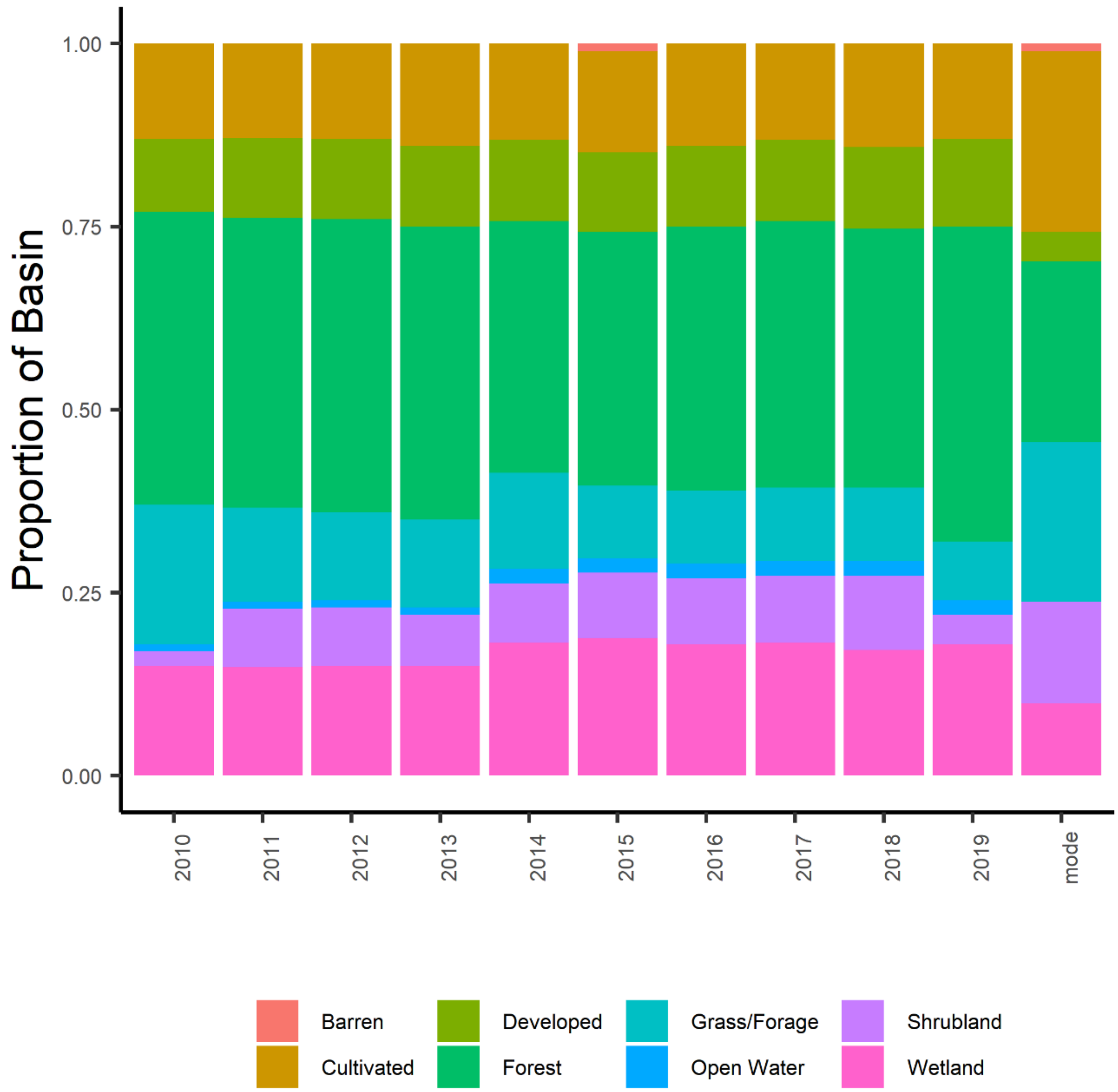

Figure 6. Generalized land use and land cover patterns remained consistent over the study period 2010-2019. Land uses from the CDL were simplified to approximate the categories in the NLCD. We considered cultivated land to include hay and fallow land, given potential for confusion between these land use categories. Due to high rates of misclassification between grass, hay, fallow land and some crops year-to-year, the mode may provide a more reliable representation of the dominant land uses across all 10 years.[7,8]

Table 1. Land use representation discrepancies by region in the CFRB SWAT Model. Abbreviations: deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), forested wetland (WETF), non-forested wetland (WETN), water (WATR), range grassland (RNGE), range shrubland (RNGB), range arid (SWRN), hay (HAY), row crops (AGRR), urban (URBN).

	Proportional land cover from the National Land Cover Dataset input to define HRUs											
	FRSD	**FRSE**	**FRST**	**WETF**	**WETN**	**WATR**	**RNGE**	**RNGB**	**SWRN**	**HAY**	**AGRR**	**URBN**
Coastal Plain	0.03	0.19	0.02	0.24	0.02	0.02	0.06	0.11	0.01	0.02	0.20	0.08
Piedmont	0.34	0.12	0.03	0.01	0.00	0.02	0.05	0.03	0.01	0.21	0.01	0.17
	Proportional land cover from the HRU assignments in the existing SWAT Model											
	FRSD	**FRSE**	**FRST**	**WETF**	**WETN**	**WATR**	**RNGE**	**RNGB**	**SWRN**	**HAY**	**AGRR**	**URBN**
Coastal Plain	0.03	0.17	0.00	0.26	0.01	0.01	0.02	0.03	0.00	0.00	0.24	0.21
Piedmont	0.45	0.07	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.19	0.00	0.26

3 Weather update

SWAT requires daily inputs of several meteorological variables used to simulate plant growth, water use, and export of water and nutrients from the landscape in response to precipitation. Daily precipitation and temperature data for each subbasin in the the Cape Fear SWAT model was assembled from the Gridded Surface Meteorological dataset (gridMET)[9]. The gridMET dataset provides daily temperature, precipitation, wind speed, relative humidity and solar radiation across the contiguous United States from 1979 to present at ~4-km resolution. The dataset aims to provide spatially and temporally continuous data that can be used for land surface modelling, by incorporating both the high-resolution spatial data from PRISM and the high temporal resolution data from the National Land Data Assimilation System (NLDAS). We assembled average daily precipitation, minimum and maximum temperature, minimum and maximum relative humidity, and solar radiation data for each subbasin, taking a spatial average of gridMET using Google Earth Engine (GEE)[10]. Precipitation measurements were shifted earlier by one day, as we found that this resulted in better model fit against observed in-stream data. Most precipitation occurs at night, yet gridMET considers a day to start at midnight.

We used R to further process and format daily gridMET data for input into ArcSWAT. Minimum and maximum temperature were converted from degrees Kelvin to degrees Celsius. Solar radiation was converted from Watts per square meter to Megajoules per square meter. We converted relative humidity from percentages to fractional values between 0 and 1. SWAT expects a single value representing relative humidity; we estimated this value using a simple average of the provided minimum and maximum relative humidity. True relative humidity values vary throughout the day based on ambient temperature[11], yet we found that the results of this approach spanned the expected range of daily values and we expect this daily observed data be superior to using the SWAT weather generator, which relies on a random number generator to select a daily value within the range of monthly observed relative humidity values[12]. We dropped 53 locations with missing precipitation and temperature information, incorporating a total of 2,875 stations representing precipitation, and temperature into ArcSWAT. To represent solar radiation and relative humidity, we generated 300 equally spaced points across the basin with a fishnet in ArcMap and retained the station locations and daily observed data for the 300 subbasins fully containing these points. To represent wind speed, we used simulated wind speed data provided by the SWAT Weather Generator; gridMET wind speed information are not suitable for representing mesoscale processes, given the 32-km spatial resolution of the original wind data integrated in the product.

4 Reservoirs, ponds, and wetlands

To represent wetlands, ponds, and other impoundments in the model, we used the National Hydrography Dataset (NHD) Waterbody features data[5]. Within CFRB there were 29,575 waterbody features mapped, including Lakes and Ponds, Reservoirs, and Swamp or Marsh, which fall more generally into two feature types 'Lakes and Ponds' (FType = 390) and 'Wetlands' (FType = 466). Incorporating both floodplain wetlands and isolated wetlands in hydrologic models can improve predictions of streamflow as well as modeling of pronounced droughts and floods.[13] SWAT requires detailed information for all of these features regarding the size, storage, spillway, and releases. SWAT also requires inputs that describe the nutrient cycling within these features. We gathered the best available information to inform these parameters from a statewide dam inventory[14], a lake and reservoir assessment of the basin[15], a surface water supply evaluation of the basin[16], other available literature regarding lake and wetland morphology, hydrology and nutrient processing[17–30], as well as values recommended by the SWAT developers[31] and the SWAT user community. Where possible, we separately parameterized the two distinct NHD feature types, waterbodies associated with known dams, and three major managed reservoirs in the upper basin.

By convention in SWAT any features that intersect the stream network are modeled as reservoirs, while features that do not intersect the stream network are modeled as ponds or wetlands. We retained 1,920 features at least 50ha in size (123.5ac) to model as reservoirs in 767 subbasins (Fig. 7). We also retained 142 features at least 50ha in size that were represented as ponds in 181 subbasins (Fig. 8). In each subbasin, only one pond or reservoir can be represented. Where multiple features occurred in one subbasin, we combined them into one feature representing the total extent and storage capacity, and compiled weighted parameters for the other characteristics (e.g., seepage rates, nutrient settling rates, Secchi clarity), weighting by the extent of each feature represented in the subbasin. Portions of wetlands and waterbodies that fell outside of the watershed were excluded.

There are three large managed reservoirs in CFRB. B. Everett Jordan Lake is owned and operated by The U.S. Army Corps of Engineers (USACE) with flood control as its primary purpose. Although the dam was authorized in 1963, impoundment of the Haw River and New Hope Creek was initiated in 1981, with the target pool elevation achieved in the spring of 1982[32]. Daily elevation, inflow and outflow data are available back to 1974[33]. Randleman Lake is managed by the Piedmont Triad Regional Water Authority with a primary purpose of providing drinking water[34]. Reservoir construction was completed in 2004 and the lake was opened in 2010. Stage and outflow information are only available from 2014 and the full record has not been consistently calibrated. Harris Lake is the source and outlet of cooling water for the single reactor at Shearon Harris nuclear power plant, which is owned and operated by Duke Energy[35]. Construction of the facility which included the impoundment of Buckhorn Creek began in 1978 and the facility began providing commercial power in 1987. Detailed release information was available for Jordan Lake, but not the other two managed reservoirs. We treated Randleman Lake and Shearon Harris Lake as run of river operations given the lack of consistent data available over the study period.

We established some assumptions for the hydrology and nutrient cycling for waterbodies in CFRB using available data and literature. We considered the entire year to be the ‘flood’ season, when any storage above the principal spillway volume of ponds and reservoirs would be released over a specified number of days required to reach target storage equivalent to the principal spillway volume. Many Coastal Plain riparian wetlands and swamps are adjacent to stream network and were therefore modeled as reservoirs. We chose to model these natural features to approximate run-of-river operations, initialized with a short-duration of days to return to target storage and seepage that returns to baseflow. Most reservoirs in the Piedmont region are managed impoundments and we modeled these with simulated releases initialized with SWAT’s default days to target storage (NDTARGR = 15) and no seepage (RES_K = 0mm/hr). Most ‘ponds’ are natural wetlands clustered in the Coastal Plain region. We initialized these similarly to Coastal Plain reservoirs with relatively short duration storage; in SWAT seepage from ponds does not return to baseflow. We considered April – September to be the mid-year nutrient settling season for all water bodies and we assumed the default median sediment particle size of 10µm. As described previously, if multiple wetland types mapped by the NHD occurred in a single subbasin, initial parameter values for those subbasins were developed as the mean value weighted by the extent of each type. Some storage parameters were later calibrated.

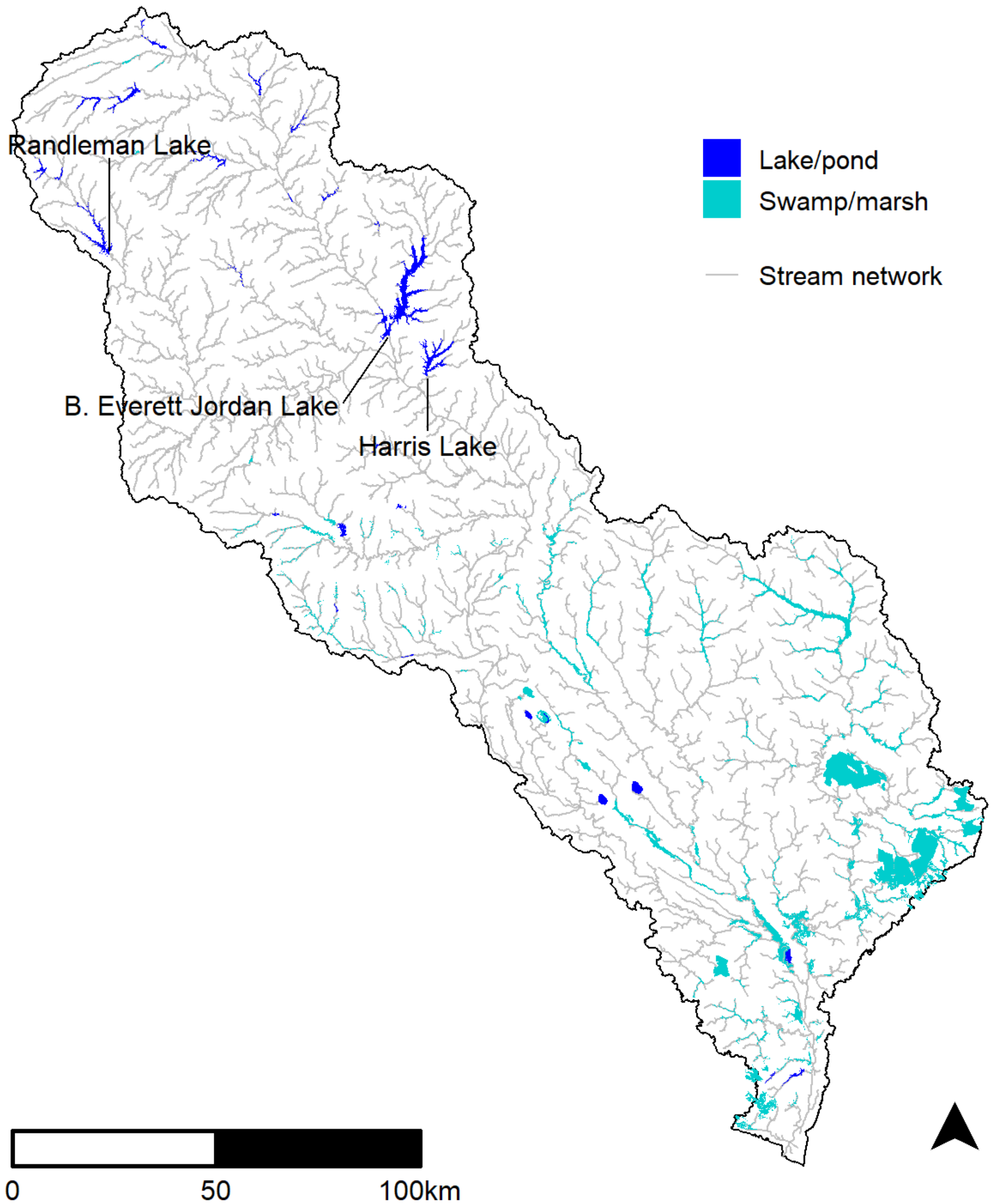

Figure 7. Adjacent wetlands and waterbodies represented as ‘reservoirs’ in the Cape Fear River Basin.

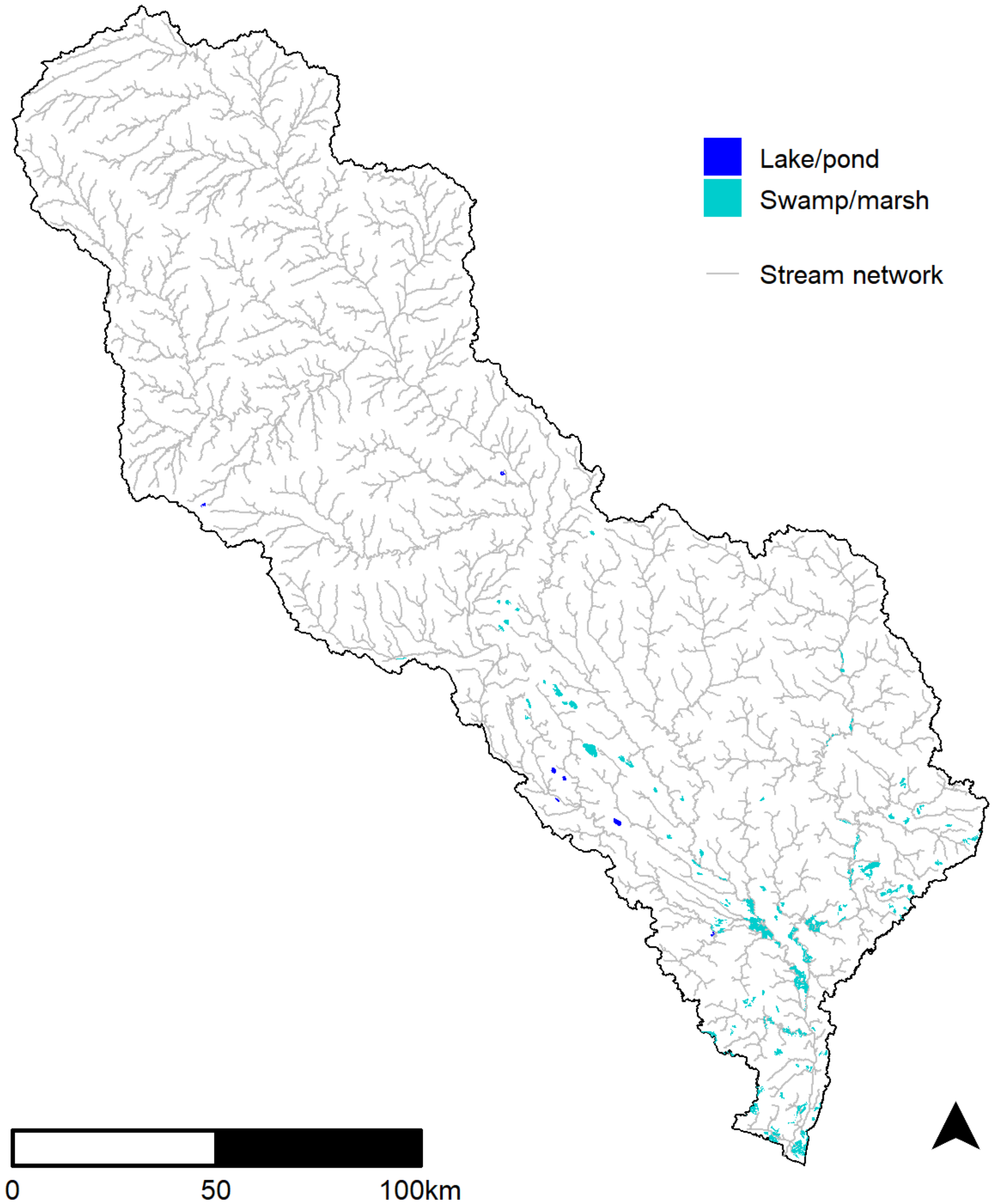

Figure 8. Isolated wetlands and waterbodies represented as ‘ponds’ in the Cape Fear River Basin.

5 Management

We assigned HRU management operations to approximate the extent of specific practices in each region of the watershed, including 132 unique HRU management configurations on terrestrial agricultural and urban lands (Appendix A). Typical management practices and timing for dominant crops, dominant crop rotations, pasture land, forest plantations and urban lawns in CFRB were compiled using the best available information from state agencies, NC State University Extension and peer-reviewed literature. We also reviewed animal operation waste management practices in the region, although actual practices implemented at individual operations may vary considerably[36]. Model results for a given HRU do not measure actual farm-level sediment and nutrient loads, but rather represent how typical management practices interact with the physical environment to affect water quality in CFRB.

5.1 Land use re-assignment

To better approximate true land use and land cover distributions in the Piedmont and Coastal Plain regions, respectively, HRU land uses were selectively re-assigned. Spatial data delineating the model HRUs were not generated by USGS with the original model; we therefore relied on a subbasin-level analysis of land cover to identify HRUs for re-assignment. Where a class was under-represented by the original model HRUs, we re-assigned HRUs from classes that were over-represented, prioritizing HRUs in those subbasins with a high proportion of our target land use as estimated by the original NLCD data. No forested wetlands (WETF), emergent wetlands (WETN), or water (WATR) HRUs were re-assigned, because these are not land uses which are intensively cultivated or treated with amendments.

In the Piedmont, AGRR, rangelands (RNGE, RNGB, SWRN), hay, evergreen forest (FRSE) and mixed forest (FRST) were under-represented. We re-assigned urban (URBN) and deciduous forest (FRSD) HRUs to crops, rangelands and hay in subbasins where the combined farm and rangeland cover exceeded the mapped forest or urban cover, prioritizing HRUs with a high proportion of that land use. To avoid unrealistic land use configurations (e.g., rangeland in the middle of an urban center), we excluded from consideration HRUs in subbasins with > 70% urban cover or > 70% forested cover according to the NLCD. We also re-assigned deciduous forest HRUs to evergreen and mixed forest, prioritizing HRUs in subbasins with a high proportion of true cover of the target forest type and a high proportion of mapped plantation extent.

In the Coastal Plain, evergreen forest, rangelands and hay were under-represented, while urban, row crop and deciduous forest were over-represented in the model HRUs. We followed a similar procedure as in the Piedmont to re-assign urban and row crop HRUs to evergreen forest and mixed forest; we selected HRUs from subbasins with < 70% urban cover and where forest cover exceeded the extent of urban and row crop according to the land cover analysis. We also converted urban and row crop HRUs to rangelands and hay in subbasins with < 70% urban cover where combined hay and rangeland cover exceeded urban or crop cover; we prioritized HRUs with a high proportion of the target land use.

We adjusted the curve number in the management file (CN2.mgt) for HRUs where land use was changed, and revised the values of Manning's "n" in the hru file (OV_N.hru) for all HRUs. Manning's "n" is a roughness coefficient used to calculate overland flow across the landscape, with larger values indicating higher roughness and slower movement of water. We examined the reported OV_N values used by a recent study within CFRB in addition to two other studies from other parts of the southeastern US, and elected to use an average across these previous studies to parameterize OV_N (Table 2).[37–39] The curve number specified in the management file is used by SWAT unless additional curve numbers are specified by management operations. The curve number is determined by the soil type, soil hydrologic group, and land use. Where the revised land use and soil combination did not already exist in the model, we used the average CN2 from other HRUs with the same land use and soil hydrologic group, weighted by the number of HRUs with distinct soil types. For revised FRST and SWRN land use and soil hydrologic group combinations that did not exist in the original model, we used recommended SCS II curve number values from the SWAT 2012 input output documentation (Table 20-2) for 'good' condition woodlands (for FRST) and 'fair' condition pasture (for SWRN).[31]

Table 2. Manning's "n" values for land use in the Cape Fear River Basin based on the National Land Cover Dataset (NLCD) was determined by evaluating parameters from a recent study within the basin [37], and two other recent studies within the southeastern US [38,39]. Abbreviations: deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), forested wetland (WETF), non-forested wetland (WETN), water (WATR), range grassland (RNGE), range shrubland (RNGB), range arid (SWRN), hay (HAY), row crops (AGRR), urban (URBN).

Land use		**Reported Manning's n values**			
NLCD	**SWAT**	**Lower Cape Fear River Basin**	**Southern Louisiana and Mississippi**	**Green's Bayou Texas**	**Average Manning's n value**
Open water	WATR	0.01	0.02		0.015
Developed	URBN	0.1	0.0855	0.0541	0.080
Barren	SWRN	0.15	0.07	0.0113	0.077
Deciduous forest	FRSD	0.4	0.16	0.36	0.307
Evergreen forest	FRSE	0.4	0.18	0.32	0.300
Mixed forest	FRST		0.17	0.4	0.285
Shrub/scrub	RNGB	0.4	0.07	0.4	0.290
Grassland/herbaceous	RNGE	0.4	0.035	0.368	0.268
Pasture/hay	HAY		0.033	0.325	0.179
Cultivated crops	AGRR	0.15	0.036		0.093
Woody wetlands	WETF	0.4	0.14	0.086	0.209
Emergent herbaceous wetlands	WETN		0.035	0.1825	0.109

5.2 Cultivated land

The aggregated 'AGRR' landcover category represents row crop cultivation. Management varies substantially by crop type in NC, therefore, we subdivided agricultural land cover types into dominant crops for the region based on an analysis of the CDL from the past 10 years (2010–2019). Note that there is potential for confusion between grass, pasture, and hay categories, and historically these categories have had higher uncertainty than other mapped land cover types in the CDL product[8,40] Fallow/Idle croplands mapped by this dataset are also subject to high error rates in NC[7].

Using GEE, we examined the proportion of land use types mapped by the CDL over time across cultivated crop types for the entire basin from 2010-2019. We excluded crop types that represented <1% of the total mapped cultivated area. We found that the proportional representation of cultivated land covers was generally consistent over time (Fig. S9). The most commonly mapped crop types making up at least 10% of the total crop area included: corn, cotton, soybeans, double crop winter wheat/soybeans, and fallow/idle cropland areas (Table 3).

To assign crop types to model HRUs, we further subdivided AGRR into five dominant crop types. We set targets based on the relative proportions of each dominant crop type in the Piedmont and Coastal Plain, respectively. We first assigned soy, the most common crop, prioritizing HRUs occurring in subbasins with a high proportion of mapped soy cultivation. We then proceeded with the remaining AGRR HRUs to assign corn, cotton, fallow/idle, and finally double crop winter wheat – soy, in order of relative extent. Fallow/idle land was the only crop type that was not in the existing SWAT plant growth database; we chose to model fallow/idle HRUs as sorghum, which is a commonly used summer cover crop.

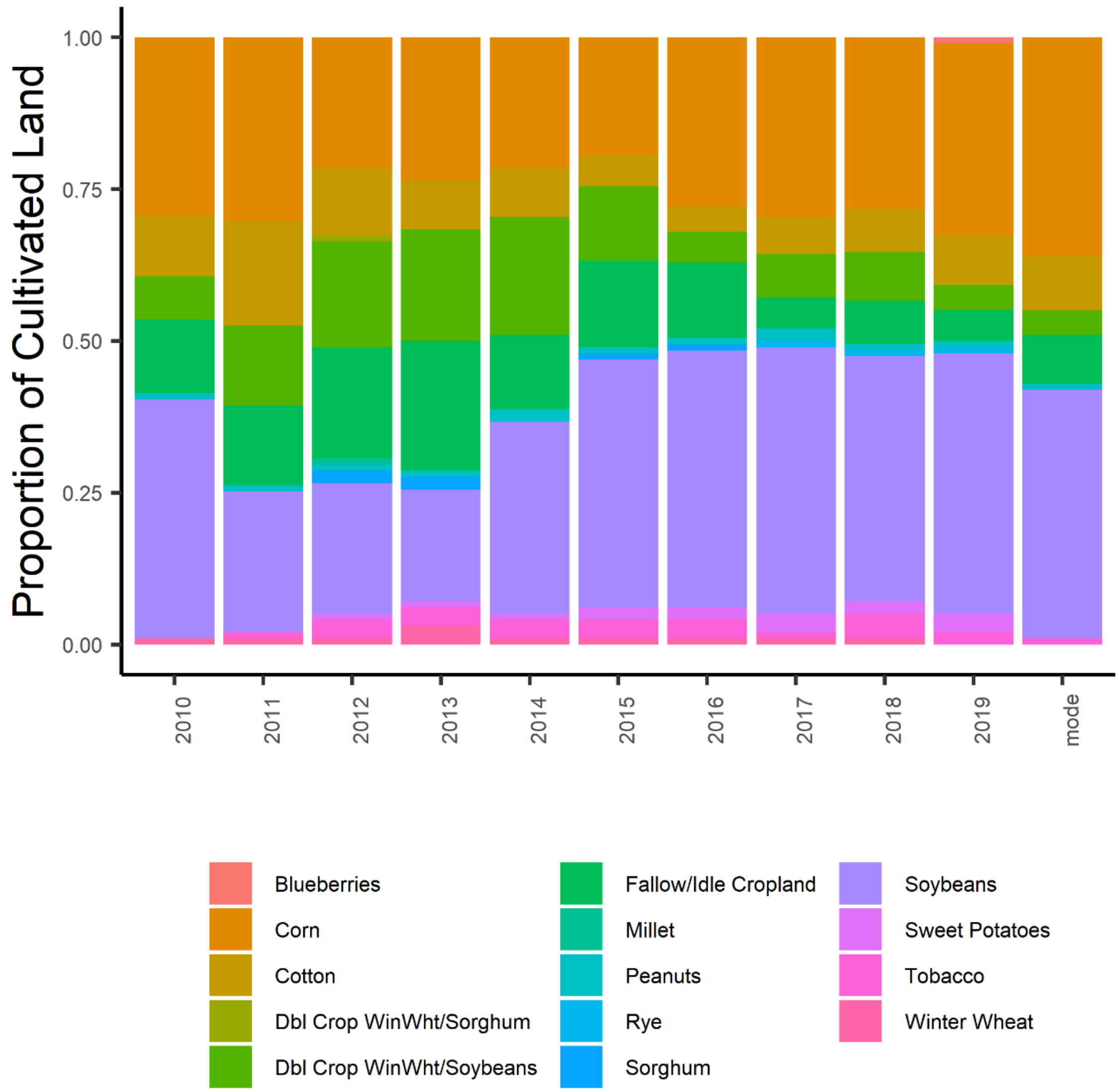

Figure 9. The extent of common agricultural land uses was generally consistent in the Cape Fear River Basin 2010-2019. The mode indicates the distribution of the land uses for the most frequently mapped crop type in each pixel.

Table 3. Extent of dominant row crops (>5% total cultivated area in the basin) by region in the Cape Fear River Basin in hectares. Numbers in parentheses indicate the proportion.

	All dominant crops	**Soy**	**Corn**	**Cotton**	**Idle/ Fallow**	**Double crop wheat - soybean**
Piedmont	38962.08	17212.38 (0.44)	12789.45 (0.33)	57.66 (0.00)	7855.87 (0.20)	1046.71 (0.03)
Coastal Plain	248499.19	103333.70 (0.42)	93194.42 (0.38)	26015.28 (0.10)	15920.26 (0.06)	10035.53 (0.04)

5.2.1 *Crop rotations*

We identified the extent of common crop rotations throughout the basin using GEE to analyze the CDL 2010-2019. We considered the mode for each pixel for 2010-2019 to be the dominant land use category. For each category making up at least five percent of the total agricultural land extent, we then examined the frequency of rotations to another crop type or to fallow land 2010-2019. Within rotation types, we also examined the slope, and soil type to inform management parameters.

We detected negligible fallowing of the dominant crops in the watershed 2010-2019. The most common rotations identified were: 'rotation 1', alternating corn / soybean, and 'rotation 2' alternating double crop winter wheat and soybean / corn (Table 4). Within the Piedmont region, we found that rotation 1 occurred on slopes <15% and rotation 2 occurred on slopes < 20%. Within the Coastal Plain, rotation 1 was most commonly practiced on slopes <12 % and rotation 2 was also normally on lower grade slopes <13%.

Table 4. Extent of crop rotations by region by within dominant crop types in the Cape Fear River Basin in hectares. Numbers in parentheses indicate the proportion. Rotation 1 = corn/soy. Rotation 2 = double crop winter wheat – soybean / corn.

		Rotation 1		**Rotation 2**	
	All rotations	**Corn**	**Soy**	**Corn**	**Double crop wheat - soybean**
Piedmont	2207.95	1174.13	389.50	539.59	104.73
		(0.09)	(0.02)	(0.04)	(0.10)
Coastal Plain	24804.35	11661.86	4787.46	7319.87	1035.17
		(0.13)	(0.05)	(0.08)	(0.10)

Following crop assignment, we assigned selected HRUs to the two most common crop rotations. Because rotation 1 was the most prevalent, we firstly assigned soy and corn HRUs to rotation 1 until we approximated the extent of this rotation in each region within appropriate slope ranges. We then assigned remaining corn HRUs and double crop winter wheat – soy HRUs to rotation 2 in a similar fashion.

5.3 Forestry

Although substantial land cover change has occurred in the basin, forested land still comprises ~25% of the land area. A substantial portion of remaining forests are managed plantations, most often dominated by loblolly pine, which may be subject to fertilizer and manure applications, controlled burns, and other intensive management[37,41–43]. Notably, pine plantations are a designated crop approved for applications of manure from CAFOs[44–46]. We identified plantations using an existing map of tree plantations across the southeastern US (Table 5)[47,48]. We analyzed slope conditions and determined that most plantations on slopes <10% in the Piedmont and <5% in the Coastal Plain.

Table 5. Extent of forested land and forest plantations by region in the Cape Fear River Basin in hectares. Numbers in parentheses indicate the proportion of forested land comprised by plantations.

	All forest	Forest plantations
Piedmont	368847.90	174309.20 (0.47)
Coastal Plain	327185.90	188041.20 (0.57)

In order to model forests as mature stands, we initiated forest HRUs with trees already growing and provided starting values for biomass, leaf area index (LAI) and plant heat units required to reach maturity. Deciduous forest (FRSD) and mixed forest (FRST) HRUs are modeled in SWAT as oak stands. Evergreen forest (FRSE) HRUs are modeled as pine stands. We incorporated the default plant heat units required to reach maturity for each forest type from the SWAT plant database. We specified an initial biomass of 1000 kg/ha (the maximum allowed by SWAT). Actual biomass measurements from southeastern forests are substantially higher than can be included in initial SWAT parameters; according to recent Forest Inventory Analysis data from NC, non-timberland biomass is >150,000 kg/ha and a previous assessment found that most piedmont and coastal plain forests measured from 66,000 – 110,000 kg/ha, while deciduous forests could reach ~291,000 kg/ha[49,50]. We sourced initial LAI values from field measurements of forests in the region, setting the initial LAI as 0.71 for FRSD, 1.22 for FRST, and 1.73 for FRSE[51–53]. When daylengths reach a threshold level specific to each forest type, by default SWAT considers trees to have gone dormant and converts a portion of biomass to leaf litter. We removed harvest and kill operations included in the default management parameters for forests.

We assigned forest plantation management to selected forest HRUs in the model. We first assigned plantations to FRSE HRUs, followed by FRST and FRSD, prioritizing subbasins with a high proportion of known plantation extent, until we approximated the mapped extent of plantation forests on appropriate slope ranges in each region. We did not include forestry practices such as harvesting, thinning, or burning operations, as these are not the focus of this study. We did, however, include manure applications on forest plantations in proximity to CAFOs, where applicable.

5.4 Application of fertilizers and manures

We used a mass balance approach for nutrient additions from both fertilizer and animal manure sources in the watershed.

5.4.1 Inorganic fertilizers

We determined county-level fertilizer applications using a database of fertilizer sales by county, using the average of the last five years of available data (2008-2012)[54]. We assumed that farm Nitrogen (N) and Phosphorus (P) would be applied as elemental N and P to crops and hay, while non-farm N and P would be applied to lawns in urban areas. The counties with higher non-farm fertilizer sales represent Raleigh, Durham, and Chapel Hill (Wake, Durham and Orange

Counties), the largest urban centers in the watershed. We determined the proportion of each county's extent represented in the entire watershed and scaled county-level data accordingly. The fertilizer amounts were then apportioned to subbasins based on the proportion of that county within the watershed that was contained in each subbasin.

5.4.2 Manure

5.4.2.1 Manure sources and quantities

The CFRB has a very high density of concentrated animal feeding operations (CAFOs), relative to other states in the U.S. and the rest of the world[55,56]. The NC Department of Environmental Quality provides a database of concentrated animal feeding operations (CAFOs) with at least 2,500 swine or 1,000 cattle using liquid waste management—a large portion of the swine and cattle production across the state[57]. The dataset provides geographic location information as well as counts of animals and the number of waste 'lagoons' storing liquid manure at each facility. Within CFRB, there were 2,039 swine CAFOs and 160 dairy CAFOs mapped. Most poultry facilities operate with dry waste management systems that do not require NPDES permits, and the locations of these CAFOs are not provided by the state. However, 1,120 poultry facility locations have been mapped by advocacy groups[58]. Livestock and poultry counts are reported at the county level by the USDA Census of Agriculture[59]. County-level livestock inventories were revised to reflect their proportional extent in the entire watershed and then apportioned to subbasins based on the proportion of that county within the watershed that was contained in each subbasin.

For swine and cattle, we assumed that the state's data most accurately reflected CAFO animal counts in the watershed. From USDA county livestock data, we excluded counts for the largest sized swine, beef cattle and dairy cattle operations (likely to be captured in state CAFO data) and assumed the remaining livestock represent grazing animals. We considered sheep, horses and other equine animals, and goats to be grazing animals which would distribute manure during grazing operations. USDA poultry inventories do not provide counts by facility size; we assumed any chicken or turkeys were CAFO animals while other types of poultry reported represented free-ranging animals; the majority of these were ducks. We estimated the annual production of manure from both CAFO animals and grazing animals based on animal counts and standard manure production rates.[58,60–63]

We chose not to directly model all possible routes of CAFO waste interaction with the environment. There are several routes of possible transport of liquid manure from CAFOs into the environment, including land applications of lagoon liquid and sludge, leaching from the lagoon into soil and groundwater, overtopping or breaching of lagoons during large storm events, and airborne transport of particulates.[56,64–69] There is limited data available to accurately model all of these processes. For example, predicting leaching would require understanding site-specific chemical composition of manure, as well as aspects of lagoon construction, local soil and groundwater characteristics. We represented CAFOs in SWAT through land application of wastes on HRUs with suitable land uses designated by state permits.[70–75]

5.4.2.2 Manure nutrient composition

Nutrient and solids composition of manures were gathered from the best available region-specific and animal-specific data and published literature values.[60,62,63,76–79,79–81] We updated the SWAT fertilizer database with customized CAFO manure nutrient fractions for swine lagoon liquid, swine sludge, cattle lagoon liquid and poultry litter (Table 6, Appendix B). For animals on rangelands, we used the SWAT defaults for fresh manures from beef and dairy cattle, horses, swine, goats, sheep, and ducks.

Table 6. CAFO-specific manure nutrient ratios added to fertilizer database

Code	**Manure**	**Min-N**	**Min-P**	**Org-N**	**Org-P**	**NH3-N Min-N Fraction**
55	Swine lagoon liquid	0.002	0.001	0.001	0.001	0.550
56	Swine sludge	0.006	0.012	0.015	0.001	0.550
57	Dairy slurry	0.007	0.003	0.010	0.001	0.500
58	Poultry litter	0.007	0.003	0.020	0.001	0.550

5.4.2.3 Determining which subbasins receive manure

CAFO manure applications can occur on row crops, hay, rangelands, and pine plantations.[44,73,82] We assumed that applications could be occurring on these land uses within 5 miles of a CAFO (Fig. 10-12, Table 7, Table 8). The best available information at the time we developed the model suggested that most liquid waste from swine and cattle operations stays within the same watershed, within 5 miles of where it is generated due to the cost associated with transporting waste.[83–85] A recent study within the basin indicates that most liquid manure is likely applied very close to the point of generation, mostly within 1 km.[86] We also assumed that poultry litter could be applied on land within 5 miles of a poultry CAFO location.

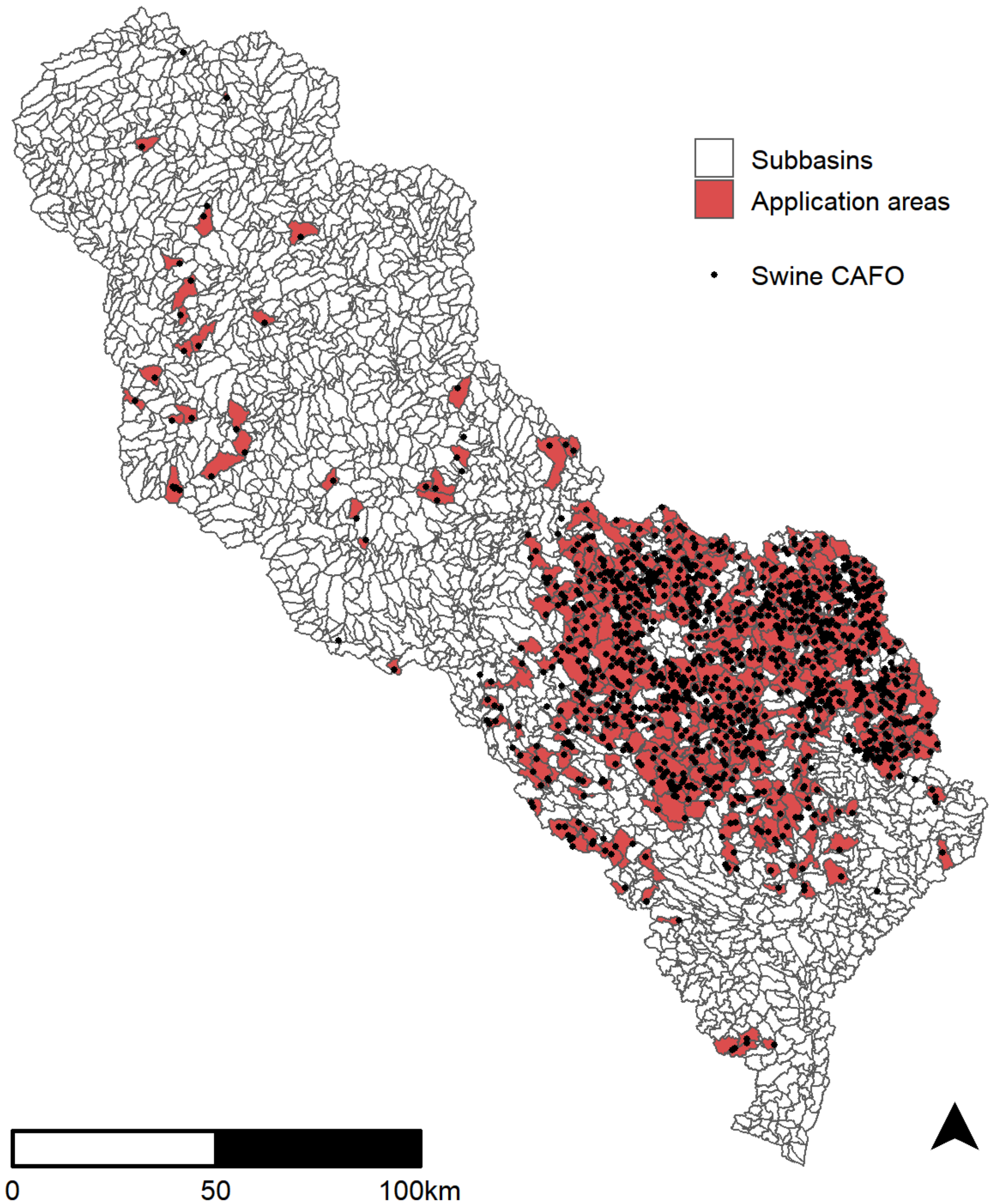

Figure 10. Swine CAFOs and subbasins receiving swine manure in the Cape Fear River Basin. Only HRUs with appropriate land use receive manure.

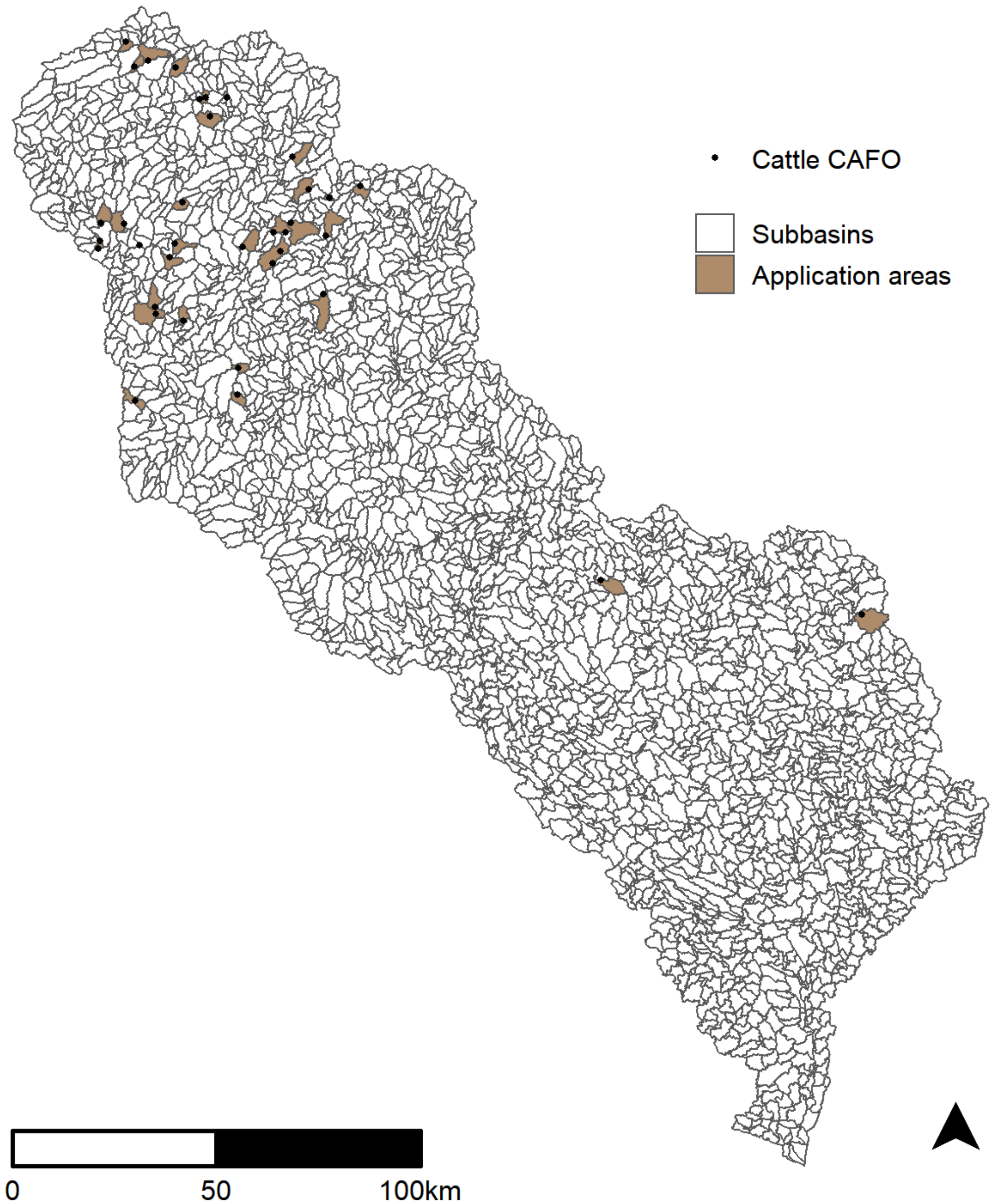

Figure 11. Cattle CAFOs and subbasins receiving manure in the Cape Fear River Basin . Only HRUs with appropriate land use receive manure.

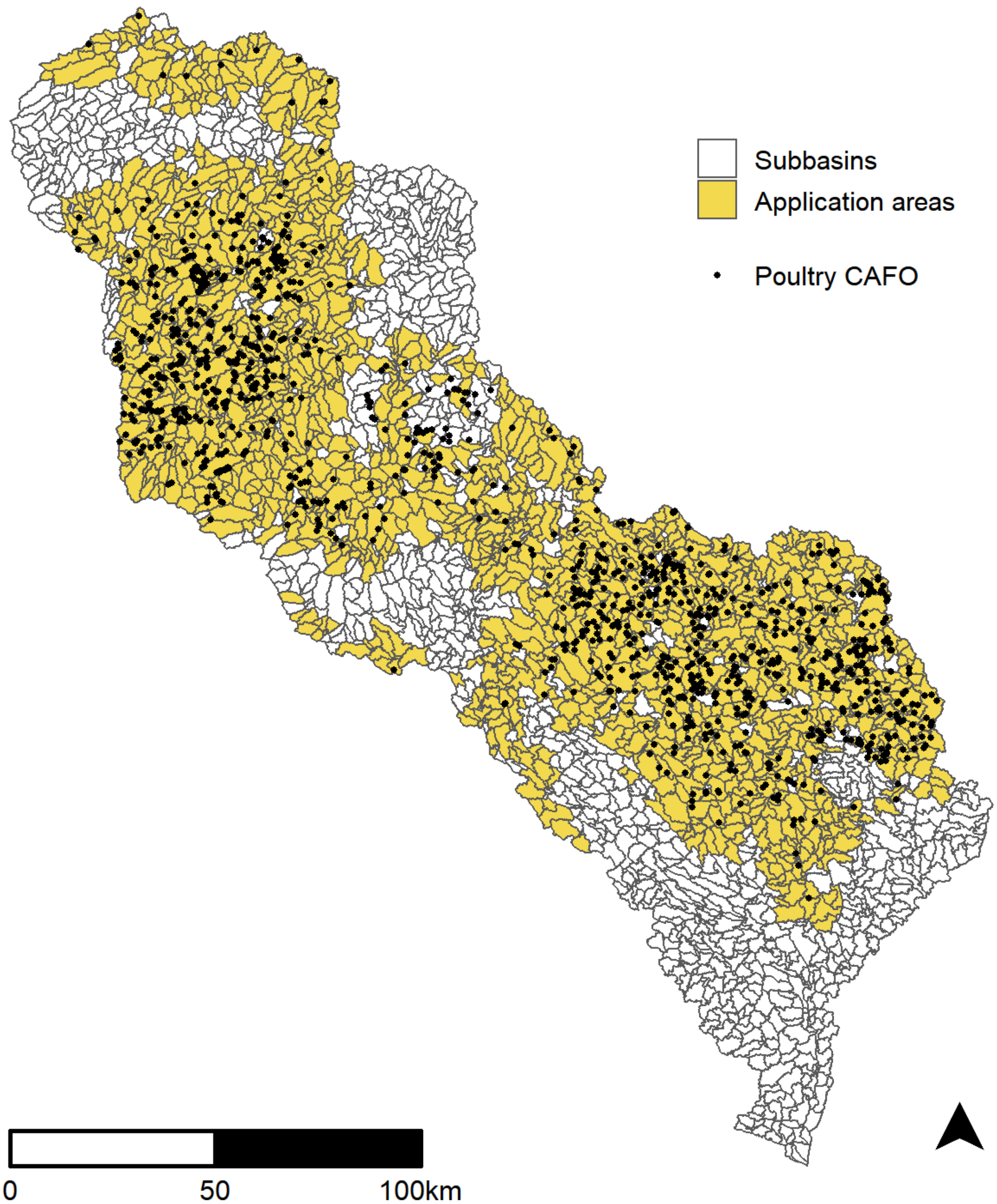

Figure 12. Poultry CAFOs and subbasins receiving manure in the Cape Fear River Basin. Only HRUs with appropriate land use receive manure.

Table 7. Extent of potential Piedmont manure application areas within five miles of CAFOs in hectares. Numbers in parentheses indicate the proportion of that landcover possibly subject to manure applications.

Land use	Swine	Dairy	Poultry
Forest plantation	43466.50	50334.86	136996.16
	(0.25)	(0.29)	(0.79)
Rangeland (SWRN)	2323.77	3296.36	5666.76
	(0.26)	(0.37)	(0.64)
Rangeland (RNGB)	9780.37	8225.74	18725.16
	(0.47)	(0.39)	(0.89)
Rangeland (RNGE)	14980.78	14806.41	32079.42
	(0.39)	(0.39)	(0.84)
Hay (HAY)	60154.20	88568.44	132135.00
	(0.39)	(0.57)	(0.85)
Row crops (AGRR)	2253.06	2326.05	5038.38
	(0.36)	(0.38)	(0.82)

Table 8. Extent of potential Coastal Plain manure application areas within five miles of CAFOs in hectares. Numbers in parentheses indicate the proportion of that landcover possibly subject to manure applications.

Land use	Swine	Dairy	Poultry
Forest plantation	120357.62	1113.23	123407.67
	(0.64)	(0.01)	(0.66)
Rangeland (SWRN)	4149.68	115.05	5037.31
	(0.40)	(0.01)	(0.49)
Rangeland (RNGB)	124817.89	3598.50	108329.85
	(0.80)	(0.02)	(0.69)
Rangeland (RNGE)	59530.35	689.27	64730.66
	(0.67)	(0.01)	(0.73)
Hay (HAY)	11676.10	130.35	20858.69
	(0.47)	(0.01)	(0.84)
Row crops (AGRR)	243558.82	13976.76	237700.22
	(0.91)	(0.05)	(0.89)

5.4.3 Determining nutrient application amounts

For simplification, we estimated uniform application rates for each fertilizer source within the Piedmont and Coastal Plain regions, respectively (Table 9, Table 10). We firstly summed the total amount of each distinct source, as well as total N and P by source across all subbasins in each region.

We determined region-specific weights for applying each nutrient source on applicable land uses. We compiled the best available information regarding nutrient requirements for land uses where fertilizers and manures could be applied from the NC Department of Agriculture and Consumer Services, NC State Extension, the NC Forest Service and crop-specific production guides [41,46,60,87–95]. We chose to treat fallow croplands as small grains, as there is potential for confusion between fallow land, hay and grain crops mapped by the CDL[8]. We also treated rangelands as small grains with a 25% reduction in the nutrient requirements given expected manure inputs from grazing animals. We computed a weight for each source, for each land use, based on the relative N and P needs over a 10 year period (Appendix C, Table C1; Table C2). For example, the weight for farm fertilizer applications on soy in the Coastal Plain would be calculated as follows:

*Corn N needs = Corn annual N needs (kg/ha) * Corn extent (ha)*

Corn N weight = Corn N needs / Total N need for crops and hay

*Corn P needs = Corn annual P needs (kg/ha) * Corn extent (ha)*

Corn P weight = Corn P needs / Total P needs of all row crops and hay

Corn weight = (Corn N weight + Corn P weight) / 2

We assumed uniform rates of non-farm fertilizer applications on urban lawns within each region. We also assumed uniform stocking rates of grazing animals within the Piedmont and Coastal Plain, respectively.

For each region, the application rate for each fertilizer source on each land use was determined as the total amount of the source multiplied by the weight divided by the total extent of that land use. For example, for corn, the total rate of farm fertilizer N would be calculated for each region as:

Farm N rate (kg/ha) = (Total farm N (kg) Corn weight) / Corn extent (ha)*

Table 9. Estimated nutrient rates in kilograms per hectare by fertilizer source for application areas in the Piedmont region. Abbreviations: N = Nitrogen, P = Phosphorus.

Source	Nutrient	Urban	Soy	Corn	Fallow	Cotton	Double crop wheat - soy	Rotation 1	Rotation 2	Hay	Rangeland	Forest plantation
Non-farm fertilizer	N	4.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Farm fertilizer	N	0.00	0.00	39.50	0.00	0.00	31.17	15.89	31.01	23.02	0.00	0.00
Grazing animals	N	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	37.77	0.00
Swine CAFO manure	N	0.00	0.00	0.00	0.00	0.00	0.00	5.90	0.00	7.58	6.66	5.98
Dairy CAFO manure	N	0.00	22.26	0.00	0.00	0.00	0.00	0.00	0.00	47.13	42.98	38.83
Poultry CAFO manure	N	0.00	3.70	11.24	8.46	0.00	9.64	6.74	9.81	8.05	7.32	6.58
Non-farm fertilizer	P	0.00	4.09	5.01	0.00	0.00	5.12	4.98	4.92	5.74	0.00	0.00
Farm fertilizer	P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.59	0.00
Grazing animals	P	0.00	0.00	0.00	0.00	0.00	0.00	1.46	0.00	1.88	1.65	1.48
Swine CAFO manure	P	0.00	5.34	0.00	0.00	0.00	0.00	0.00	0.00	11.30	10.31	9.31
Dairy CAFO manure	P	0.00	1.28	3.88	2.92	0.00	3.33	2.33	3.38	2.78	2.52	2.27
Poultry CAFO manure	P	0.00	4.09	5.01	0.00	0.00	5.12	4.98	4.92	5.74	0.00	0.00
	Total N	***4.85***	***25.96***	***50.74***	***8.46***	***0.00***	***40.82***	***28.54***	***40.82***	***85.77***	***94.36***	***51.40***
	Total P	***1.25***	***10.70***	***8.89***	***2.92***	***0.00***	***8.44***	***8.77***	***8.30***	***21.69***	***30.27***	***13.06***

Table 10. Estimated nutrient rates in kilograms per hectare by fertilizer source for application areas in the Coastal Plain region. Abbreviations: N = Nitrogen, P = Phosphorus.

Source	Nutrient	Urban	Soy	Corn	Fallow	Cotton	Double crop wheat - soy	Rotation 1	Rotation 2	Hay	Rangeland	Forest plantation
Non-farm fertilizer	N	3.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Farm fertilizer	N	0.00	0.00	127.94	0.00	45.40	101.10	50.99	101.58	74.31	0.00	0.00
Grazing animals	N	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.13	0.00
Swine CAFO manure	N	0.00	11.08	36.57	28.64	20.13	31.14	21.21	31.29	25.82	24.17	20.94
Dairy CAFO manure	N	0.00	11.52	28.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.18
Poultry CAFO manure	N	0.00	7.39	23.80	17.96	13.22	20.38	13.91	20.38	16.93	15.33	13.74
Non-farm fertilizer	P	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Farm fertilizer	P	0.00	14.37	15.52	0.00	14.24	14.44	14.66	15.06	14.42	0.00	0.00
Grazing animals	P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.61	0.00
Swine CAFO manure	P	0.00	2.77	9.16	7.17	5.04	7.80	5.31	7.84	6.47	6.05	5.24
Dairy CAFO manure	P	0.00	2.76	6.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.36
Poultry CAFO manure	P	0.00	2.51	8.07	6.09	4.48	6.91	4.72	6.91	5.74	5.20	4.66
	Total N	***3.79***	***29.98***	***217.05***	***46.60***	***78.75***	***152.61***	***86.11***	***153.26***	***117.06***	***45.62***	***52.86***
	Total P	***0.97***	***22.41***	***39.65***	***13.26***	***23.76***	***29.15***	***24.69***	***29.81***	***26.63***	***13.67***	***14.26***

5.4.4 Comparing nutrient application rates to published values

The upper limit for the nutrient application rates we calculated are on the order of crop needs according to state agencies and NC State University's Cooperative Extension. These rates are lower per unit area than a previous analysis of the lower CFRB, yet in our model the application areas may also be more extensive.[37]

5.4.5 Determining amounts applied for specific operations

We subdivided the annual application rates further for specific operations for each land use based on the best available information regarding timing and rates of application[41,45,60,87–95]. For many crops, farm fertilizer applications are concentrated at the time of planting, in early spring. Non-farm fertilizers applied on lawns are recommended as split applications throughout the growing season. We assumed that grazing and accompanying manure inputs could be occurring year-round. For land uses not receiving farm fertilizer or CAFO manure applications, we removed any automatic fertilization that might add additional nutrients into the system.

CAFO manure applications can occur year-round provided that there is active plant growth, and applications may occur on a weekly basis, weather permitting.[36,73,96] Based on available information regarding appropriate application windows, we assumed year round applications on hay, fallow/idle land and rangelands, and applications on croplands within 30 days of planting through 30 days before harvest (or the end of the growing season).[73,82,97] To maintain plant growth during the dormant season in hay, fallow/idle and rangeland HRUs receiving manure, we implemented fall planting of rye with a harvest and replanting of the default plants for these land covers in the spring. For plantation forests within five miles of a CAFO, we modeled manure applications every five years in accordance with recommended fertilization guidance, with applications from November through February.[41,84,85]

Liquid manure (mainly from swine and dairy CAFOs) is typically applied via irrigation.[36,98] Swine CAFO operators are advised to maintain lagoons at the minimum treatment volume in order to avoid overtopping due to rain events, particularly during hurricane season, and applications may occur weekly.[96,99] We modeled manure applications as continuous fertilization for a set number of allowed days with a set interval for applications of manure solids. The solid fraction of liquid manure was applied weekly during the allowed period with continuous fertilization on croplands and only once every five years on forest plantations. We did not model incorporation of the liquid fraction, as the amounts per application were quite small relative to rainfall.

There is very limited information regarding the storage, transport and application of dry-waste poultry manure in the watershed. Dry poultry manure is not to be stockpiled for more than a two-week period[82]. Therefore, we modeled land applications of solid manure bi-weekly during the appropriate date range.

5.5 Grazing

Grazing livestock reduce the biomass of pastures via daily forage consumption and trampling, and also supply nutrients via excretion. Grazing livestock may also receive supplemental feed. We assumed that all rangelands in the study area were grazed and assumed uniform stocking rates for each animal type within the Piedmont and Coastal Plain, respectively. There is limited information regarding differences in the relative grazing intensities and rotational grazing practices in the watershed. For each animal type for each region, we estimated the daily biomass consumption rate from the stocking rate, mature animal weight, proportion of body weight consumed daily, and the proportion of supplemental feed (Appendix D, Table D1; Table D2).[100,101,101–114] We assumed that forage plants have a digestibility of 60% and a dry matter content of 30%.[100–102] We assumed that the trampling rate was equivalent to the rate of biomass consumption.

5.6 Other agricultural practices considered, but not modeled

We analyzed the reported extent of other practices in these counties according to the USDA Census of Agriculture, including: irrigation, artificial ditch drainage, tile drainage, cover cropping, conservation tillage, no-till, and easements. These practices were rare in the counties contained within CFRB according to the census, and therefore we did not include them in the model. Where present, artificial drainage was clustered in the coastal plain ecoregion. Irrigation, though uncommon, was clustered in the same counties with high counts of swine animals. There is very little reported conservation tillage or no-till in the watershed; no till is unlikely to be continuous for extended periods of time so major differences in soil properties are not expected due to this practice[115]. Despite previous reports that statewide implementation of some form of soil conservation practice occurs across at least 43% of the harvested cropland area[116] in NC, the latest ag census indicates low adoption in CFRB.

6 Point sources discharges from municipal and industrial effluent

6.1 Discharge monitoring data collection

NC DEQ provided discharge monitoring records from January 1994 – September 2019 for the entire CFRB. These data summarize the average daily effluent by month for all facilities—not including CAFOs—permitted to discharge into waterways under the National Pollution Discharge Elimination System (NPDES). There were 329 unique facilities identified across the basin over this time period, some with multiple discharging outfalls (Appendix E, Table E1). We identified the correct subbasin to locate discharges based on the outfall latitude and longitude coordinates. In some cases, facilities located within the watershed had outfalls outside the watershed (e.g., the intracoastal waterway, the Atlantic Ocean), which were dropped. We retained a total of 320 facilities discharging to 258 subbasins (Figure 13).

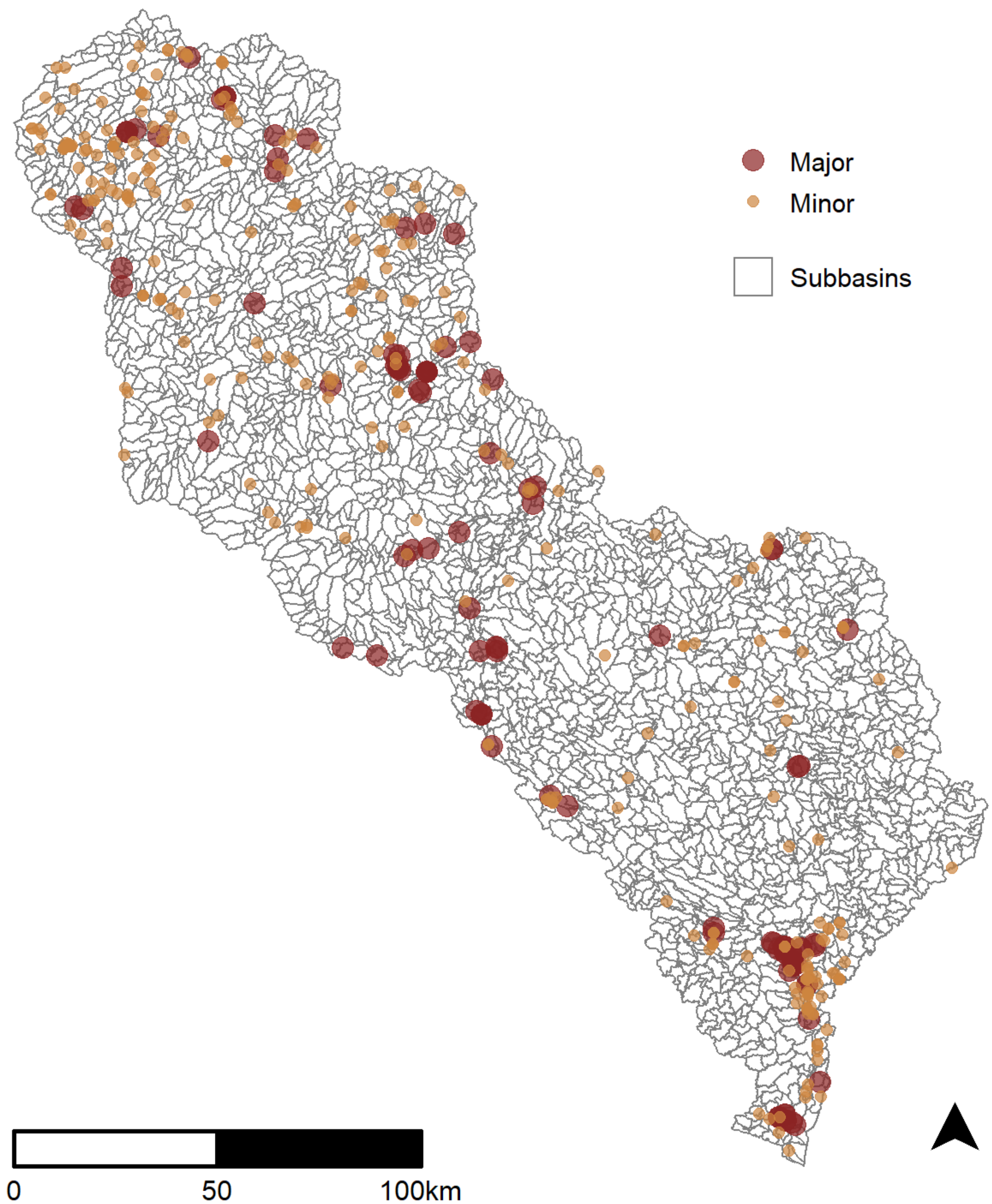

Figure 13. Point source discharges in the Cape Fear River Basin. Source: NC Department of Environmental Quality. Outfall geographic locations are shown. See Appendix E Table E1 for the complete list of facilities and outfalls discharging to SWAT subbasins.

6.2 Selecting parameters for SWAT input

We filtered the discharge monitoring data to select the appropriate inputs for SWAT. The model requires daily average point source discharges for each month, including water amount and loadings of sediment, nitrate, ammonia, organic nitrogen, organic phosphorus, and mineral phosphorus. In some cases, multiple parameter codes were recorded representing the same constituent of interest. In addition to these required constituents, we also retained records for total nitrogen, total phosphorus, nitrate plus nitrite and total Kjeldahl nitrogen to aid in calculating missing values for some nutrient loads. The complete list of parameter codes retained is included in Appendix E, Table E2.

6.3 Data cleaning

6.3.1 Measurement inconsistencies

The retained records included multiple parameter codes for some constituents, with a mix of quantity and concentrations measurements reported with various units of measure (Appendix E, Table E2). We converted all measurements into the units required for SWAT input. Daily average water discharges were converted to flow in cubic meters per day. Sediment loadings were converted to metric tons per day. Nutrient loadings were converted to kilograms per day. Values that were reported as concentrations were converted to quantities by multiplying the concentration by the flow.

6.3.2 Duplicate records

In some instances, multiple measurements representing the same parameter of interest were reported for a given year and month at the same outfall. For each constituent, we ranked parameter codes from the most frequently reported to the least frequently reported (Appendix E, Table E2). We opted to use measurements for the most frequently reported parameter codes where available, and then other parameter codes in order of rank. In some cases, multiple measurements for the same parameter code were reported for a given report year and month at a single outfall – in this case, we retained the mean of the reported values as a single daily average value for that month.

6.3.3 Outliers

After processing the data as described above, we further examined the discharge records for outliers. High nutrient loads in effluent can occur during extreme low flows, or during extreme high flow events caused by tropical storms or locally intense rainfall that may overwhelm the design capacity of water and waste treatment infrastructure. To identify potentially spurious high values, we defined outliers as any value at least 250 times greater than the median of all non-zero monthly values for flow, sediment and nutrients. For each outfall, we calculated the median of all the non-zero monthly values for each parameter and then identified candidate outliers from among the monthly records. For sediment and nutrient loads, we evaluated the individual candidate outliers to determine whether the high value was due to the flow record or the original parameter measurement. Across the entire period of record, of 243 candidate outliers, we confirmed that 47 flow values, 11 sediment values, and 12 nutrient values from 39 different facilities were outliers. NCDEQ verified that these outliers resulted from decimal errors (misplaced the decimal points of the number) or other reporting errors (incorrect units) (Charles Weaver, personal communication on March 15, 2021). In the case that corrected values were provided by NCDEQ, we substituted these corrected values. In cases where a corrected value was not supplied, we substituted the long-term daily average value for that month across the period of record for that outfall. NCDEQ did not evaluate the records for 8 facilities which do not have current permits and are no longer contributing to water quantity or quality in the basin, including 97 flow values, 1 sediment value, and 10 nutrient values. We replaced these values with the long-term daily average value for that month across the period of record for that outfall.

6.3.4 Handling missing records at each outfall

SWAT will not accept missing values for point source inputs, yet many discharge records do not include measurements for all of the parameters of interest, likely based on what reporting is required according to permit discharge limits on specific constituents. Where possible, we calculated missing values at each unique outfall location from the other recorded parameters. For example, missing organic nitrogen was calculated by subtracting available measures of ammonia from total Kjeldahl nitrogen. For remaining missing values, we used ratios calculated from other sites with available data to infer values; we considered municipal wastewater dischargers separately from other types of facilities when determining these ratios.

Many outfalls were missing reports for certain months and years within the monitoring period 1994-2019. We analyzed the patterns of missingness and determined that missing records occurred at random and not due to a systematic issue.[117] To produce a continuous record for each facility by subbasin, we performed multivariate imputation by chained equations with random forest models for 50 iterations, confirming that model results converged.[117] Given sparse observed records for organic phosphorus, and mineral phosphorus, we estimated parameter values using average ratios for the collective records from municipal wastewater or other dischargers, respectively, to infer missing values.

6.3.5 Generating a complete point source discharge time series by subbasin

SWAT permits one point source in each subbasin. Where multiple outfalls occurred in a subbasin, we combined the data to represent one point source. We summed the flow and mass loads of sediment and nutrients across all outfalls. If there were missing values for some parameters, we used ratios from other subbasins with complete information to infer missing data values. Where there were no records available for a subbasin for a given month/year within the period 1994-2019, we assumed that no discharge occurred. There were instances of dischargers active early in the monitoring period that ceased operations, and subsequent emergence of a new permitted point source in the same subbasin at a later date.

There was no significant seasonality or interannual variability in the observed discharge (Fig. 14.1 – 14.4). This is expected given that most of the point sources are wastewater treatment plants and therefore the major driver of discharges is human population. The spatial patterns of long-term average daily discharges show generally comparable flow, nutrient, and sediment contributions across the watershed (Fig. 15.1-15.4). Higher flow discharges are apparent in the vicinity of Jordan Lake (Fig. 15.1). Higher sediment discharges appear to be clustered in the lower basin (Fig. 15.2). Higher phosphorus discharges align with the locations of major urban centers in the watershed (Fig. 15.4).

SWAT requires a complete time series of discharge data matching the length of the observed weather data. For dates preceding the discharge monitoring records (1979-1993), we used the long-term daily average by month 1994-2019 as the input value for each subbasin.

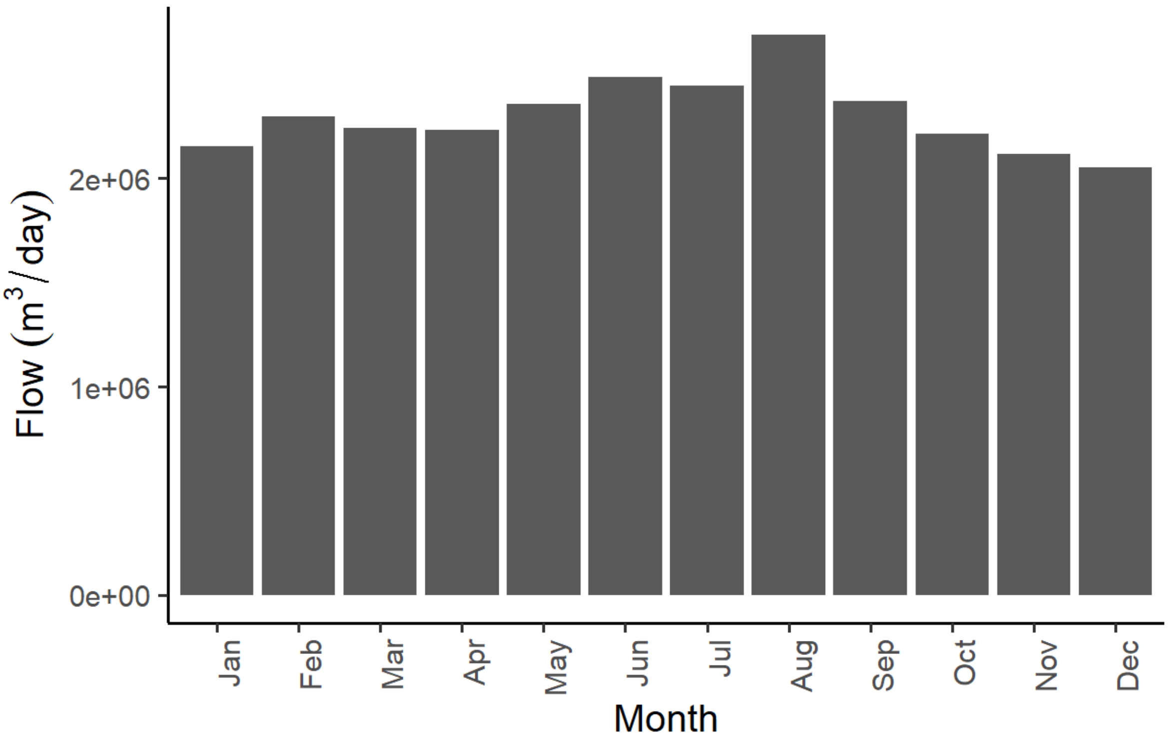

Figure 14.1. Daily point source contributions summed over the entire Cape Fear River Basin for flow.

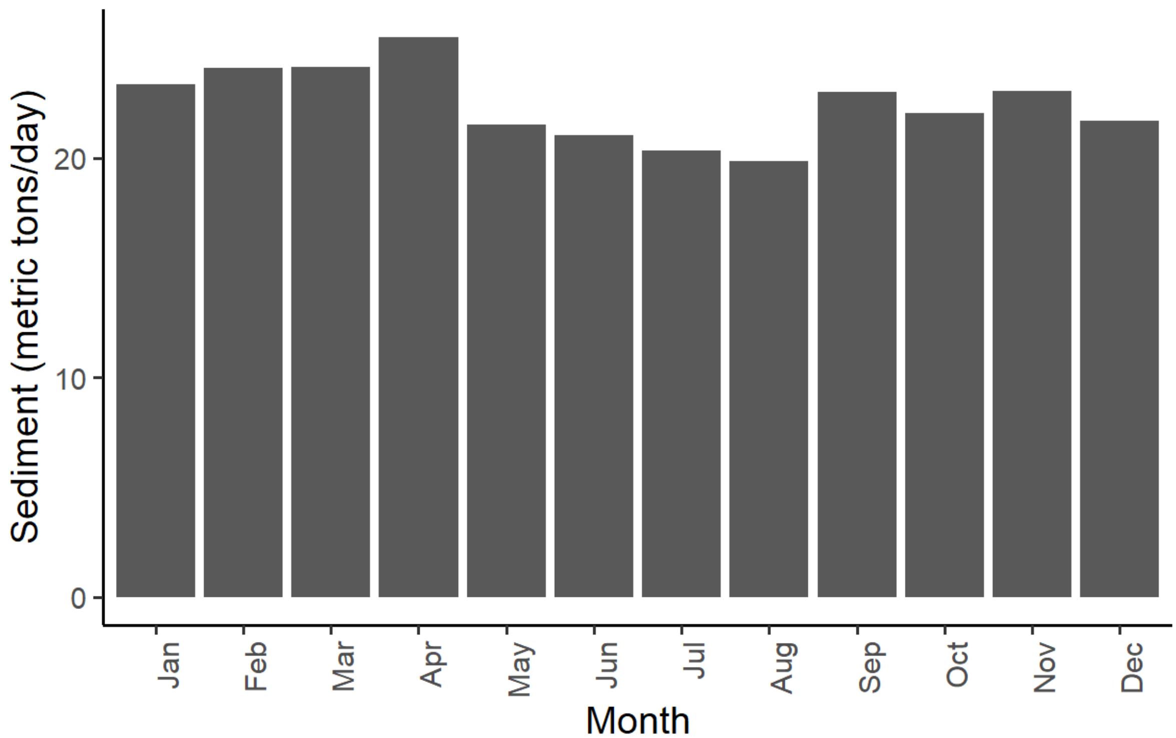

Figure 14.2. Daily point source contributions summed over the entire Cape Fear River Basin for sediment.

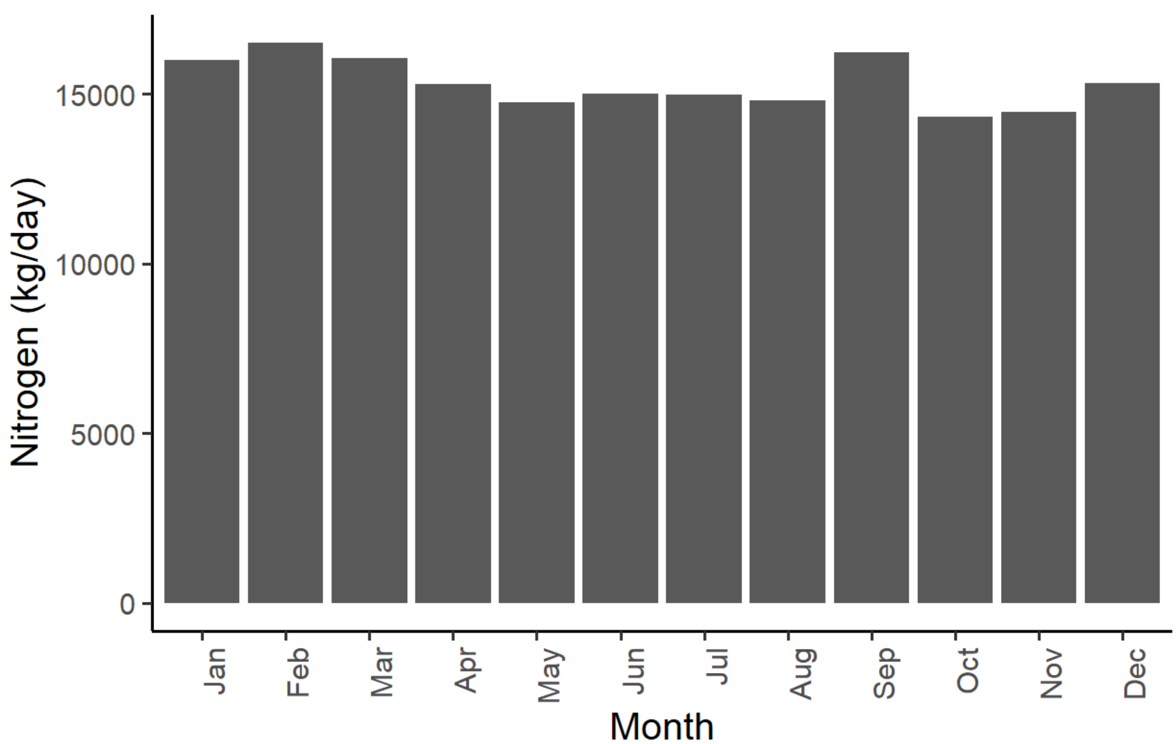

Figure 14.3. Daily point source contributions summed over the entire Cape Fear River Basin for total nitrogen.

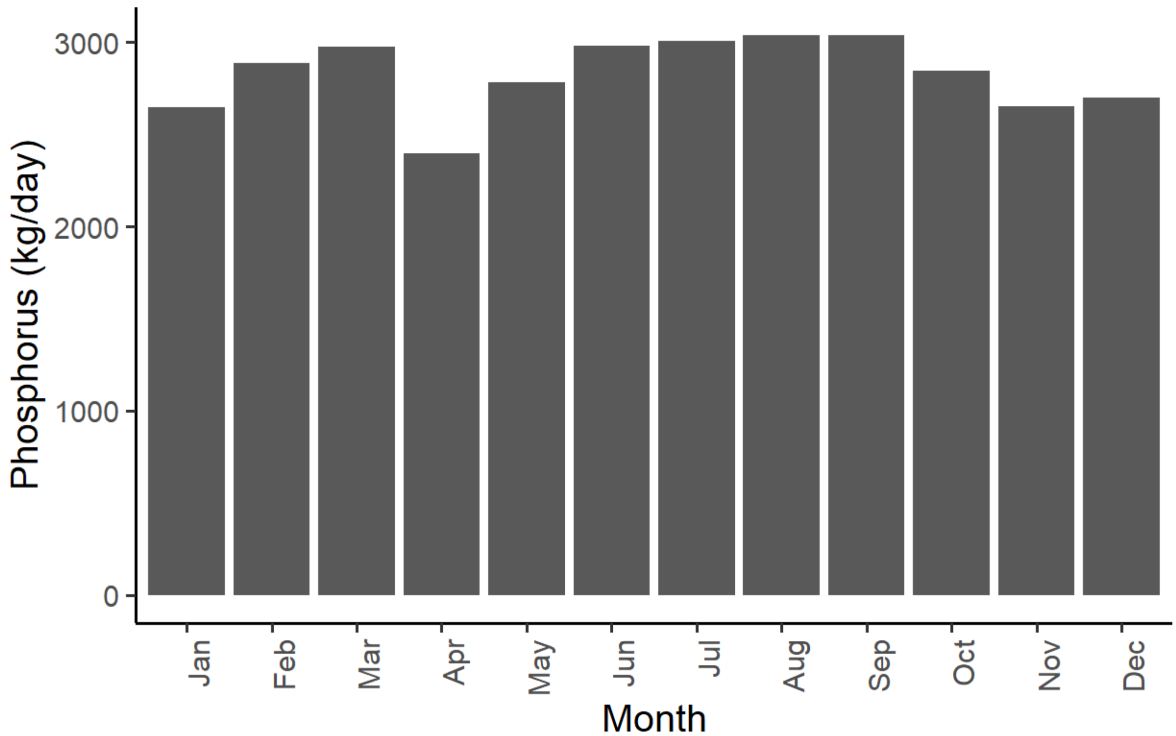

Figure 14.4. Daily point source contributions summed over the entire Cape Fear River Basin for total phosphorus.

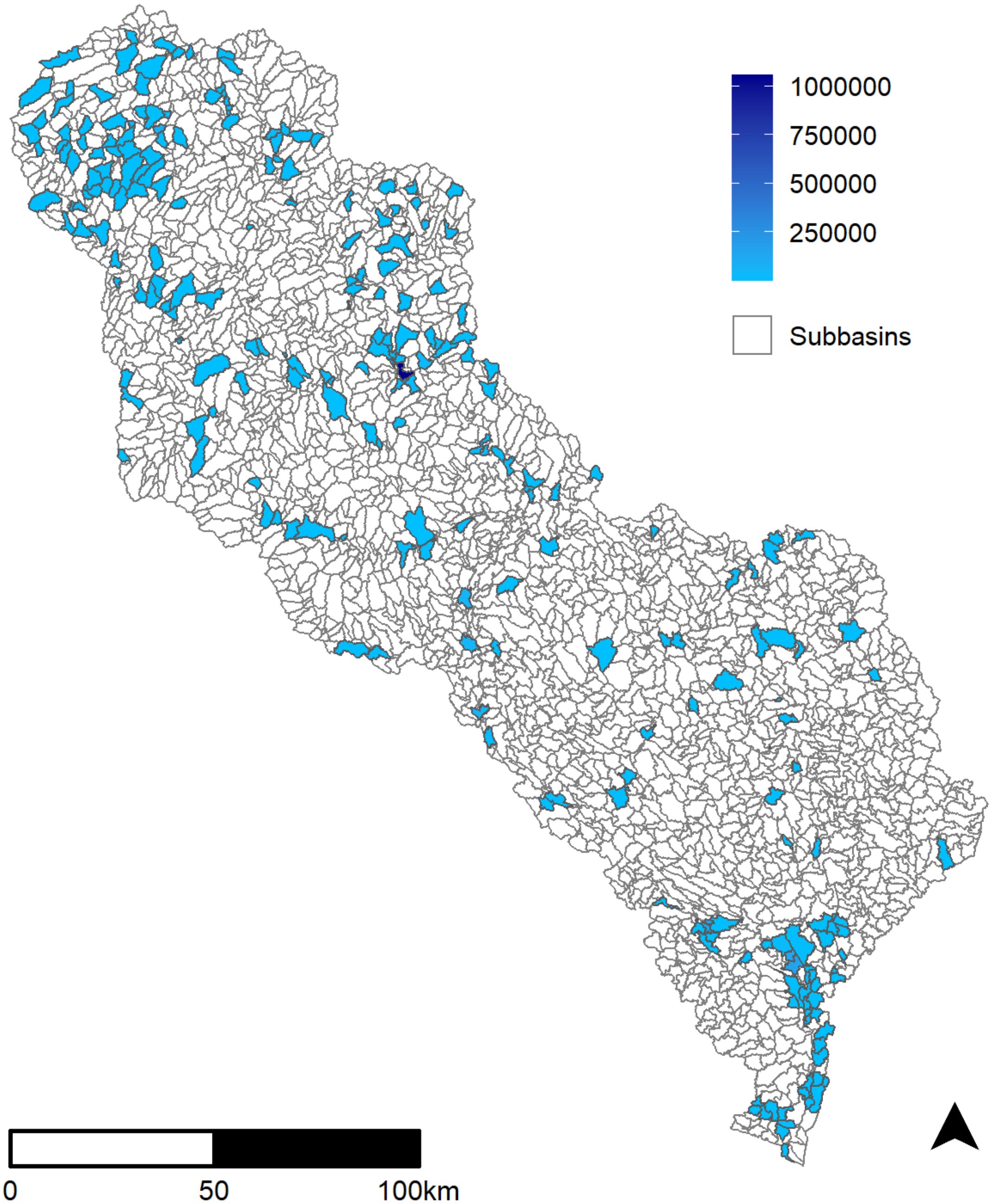

Figure 15.1. Long-term daily average flow discharge (cubic meters/second/day) from Cape Fear River Basin point sources by subbasin. Sources contributing more flow are shown with darker blue.

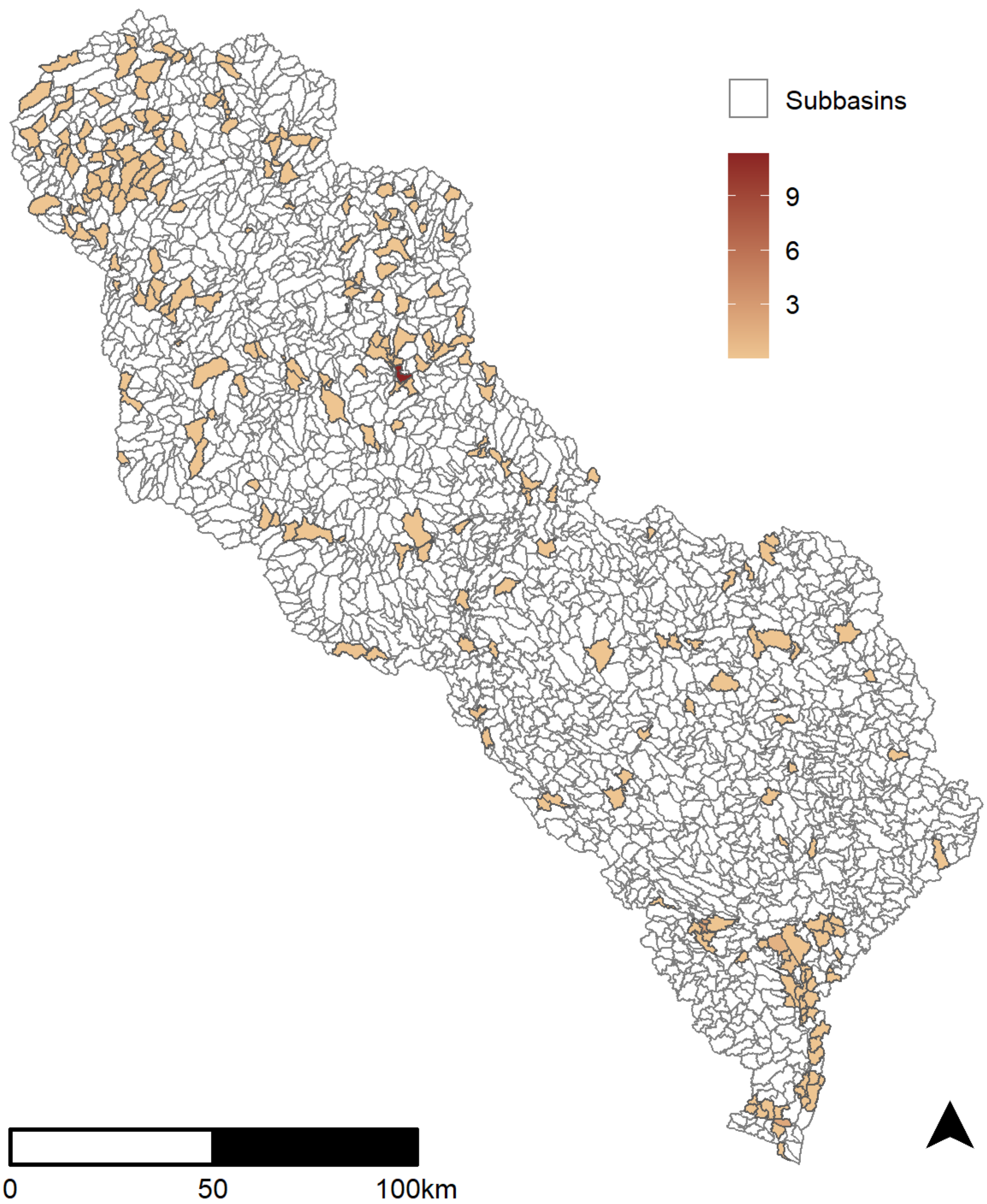

Figure 15.2. Long-term daily average sediment discharge (metrics tons/day) from Cape Fear River Basin point sources by subbasin. Sources contributing more sediment are shown with darker tan.

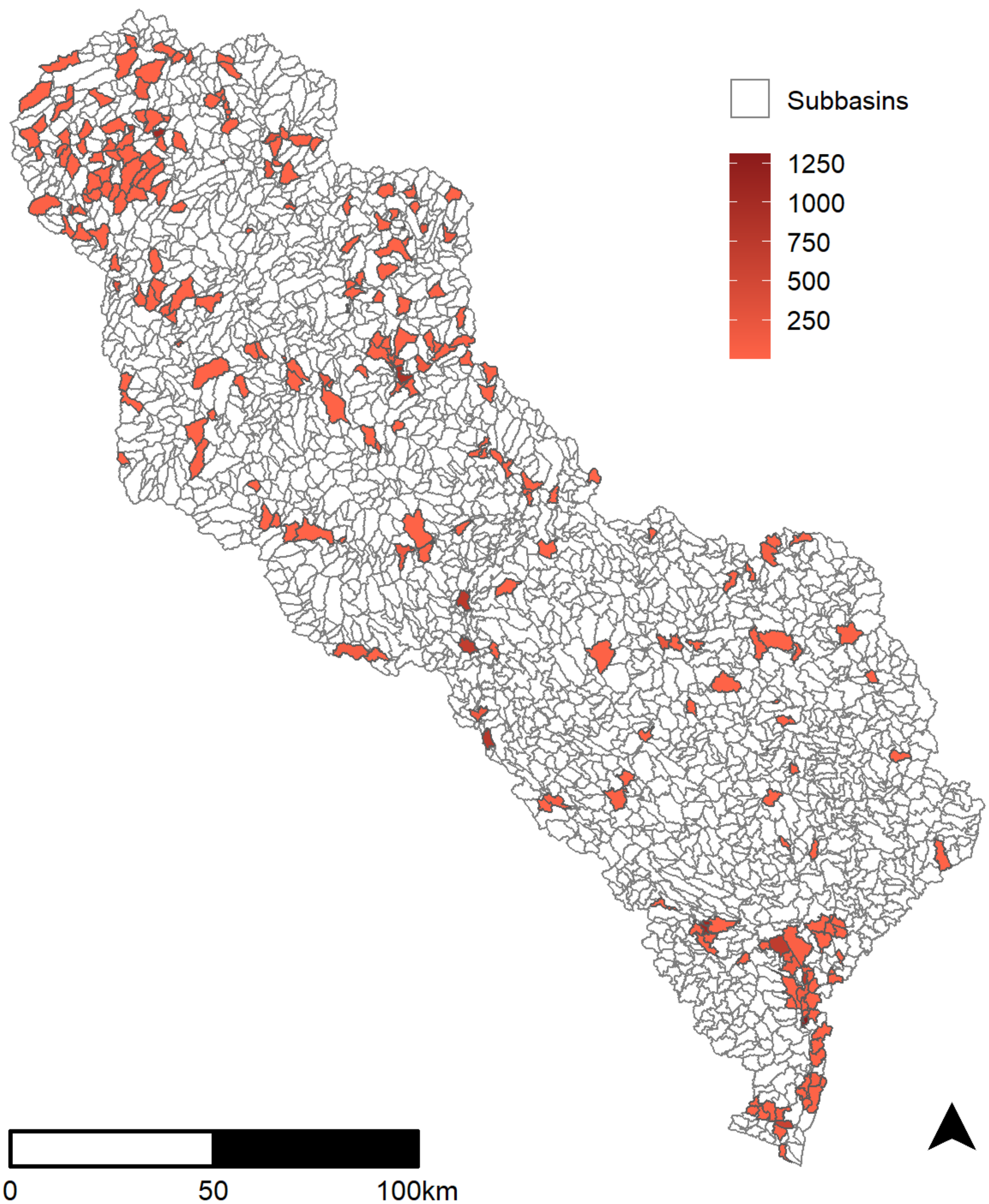

Figure 15.3. Long-term daily average total nitrogen discharge (kg/day) from Cape Fear River Basin point sources by subbasin. Higher contributions are shown with darker orange.

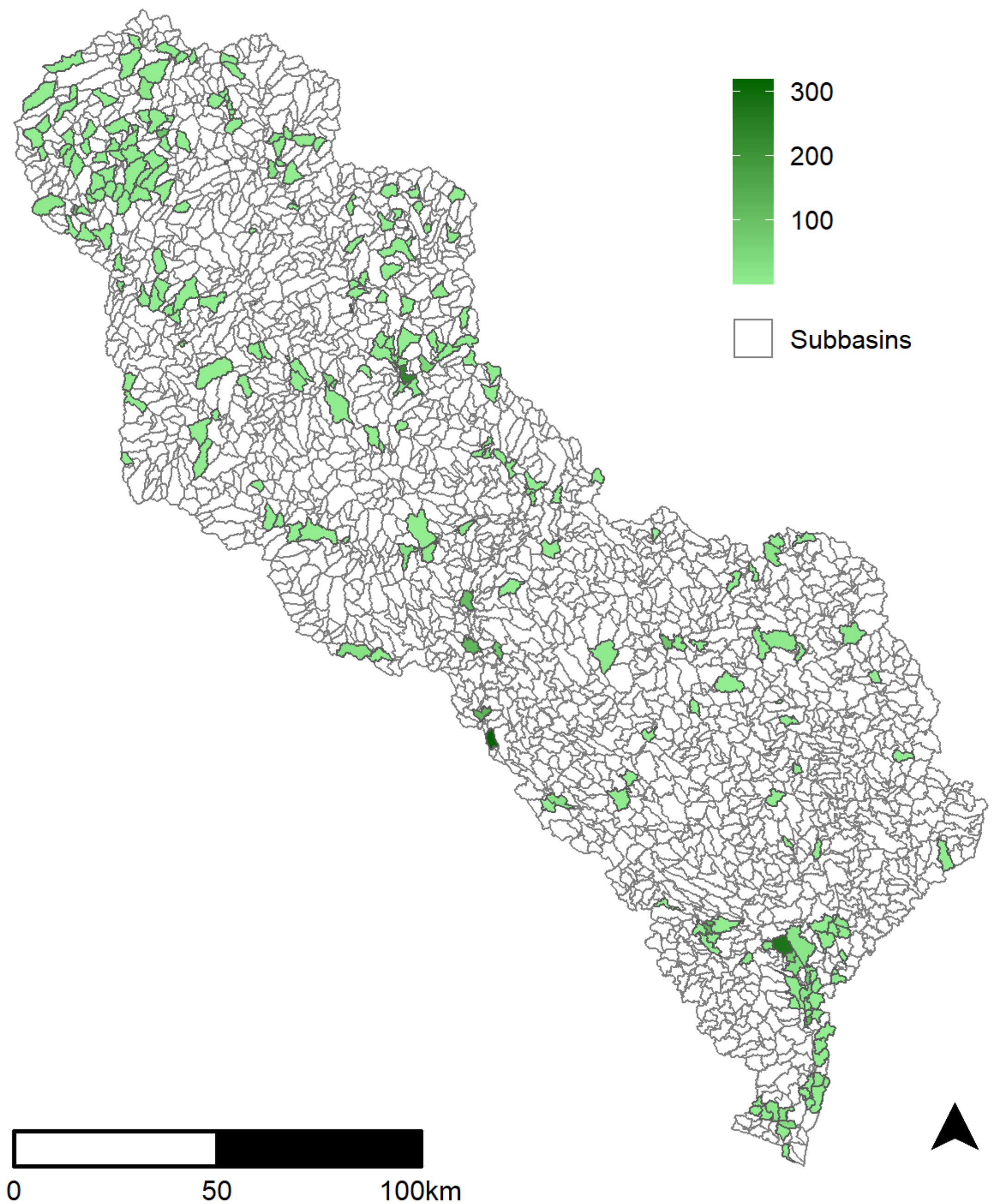

Figure 15.4. Long-term daily average total phosphorus discharge (kg/day) from Cape Fear River Basin point sources by subbasin. Higher contributions are shown with darker green.

Our revisions to point source discharges altered the values represented in the CFRB Water Quantity Model. In the original model, USGS incorporated estimated extractive water use activities (e.g., municipal use, irrigation, golf courses) in SWAT point source files with monthly averages of point source effluent and extractions estimated for the years 2000-2014[118], resulting in negative discharges in some subbasins. We chose not to include this information as data are not available with the same precision and temporal frequency as the discharge monitoring records, which we represent as average daily values for the month from 1979-2019 in this model.

7 Atmospheric deposition

Atmospheric deposition of nitrogen can be represented in the model as wet and dry deposition of ammonium and nitrate. The National Atmospheric Deposition Program produces annual gradient maps of precipitation-weighted mean concentrations and deposition rates across the continental United States at ~2-km resolution[119]. We gathered the most recent 10 years of data available (2009-2018) and computed the annual average wet and dry deposition of ammonium and nitrate across the entire basin. We then calculated the average rates across the 10-yr period to include in the model (Table 11).

Table 11. Annual average rates of atmospheric Nitrogen deposition for entire watershed based on National Atmospheric Deposition Program data 2009-2018[119].

Concentration in precipitation (mg/L)		Dry deposition (kg/ha)	
NH4	No3	NH4	No3
0.298	0.533	3.785	6.654

8 Observed flow and water quality data

Ideally, monitoring data at one or more in-stream gage stations in the watershed are used to calibrate and validate SWAT predictions for both, flow and water quality parameters. Within the CFRB , 50 USGS gage locations provide continuous streamflow records accompanied by sparse measurements tracking the concentration of water quality parameters. Flow and water quality data were accessed from the Water Quality Portal (WQP), a web based query combining records from USGS and STORET.[120,121] In addition, to WQP records, we considered alternative data sources, including information collected by the CFRB Monitoring Coalitions. Ultimately only water quality measurements from the WQP were included in this study given that ordered, non-continuous flow measurements from other data sources prevented accurate determinations of the load for water quality constituents.

Candidate calibration gages were determined by assessing monitoring locations based on their spatial location along the main stem of the stream network as well as the temporal distribution of records across the study period. Any locations within waterbodies were not considered, given the complexity of nutrient-impoundment mixing. hose Further, any gages located at the periphery of the watershed capturing very little upstream drainage, or those that were positioned far from the outlet of a subbasin were not considered. Remaining gages were ranked based on length of streamflow records and total count of nitrogen, phosphorus and sediment records. Given our interest in contemporary nutrient loadings in the watershed, we evaluated water quality parameter data quality over the period 2000-2019. Within the basin, we identified 32 gages with suitable flow data, 7 of which also had suitable co-located water quality data (Appendix F, Table F1). The principal gage selected for model calibration and validation was USGS gage #02105769, Lock and Dam #1 near Kelly, NC (Fig. 18). Although not directly included in calibration, we retained 13 additional gage stations (6 with co-located water quality and quantity information, and 7 with flow information only) to assess model performance spatially (Fig. 16, Table 12, Appendix H).

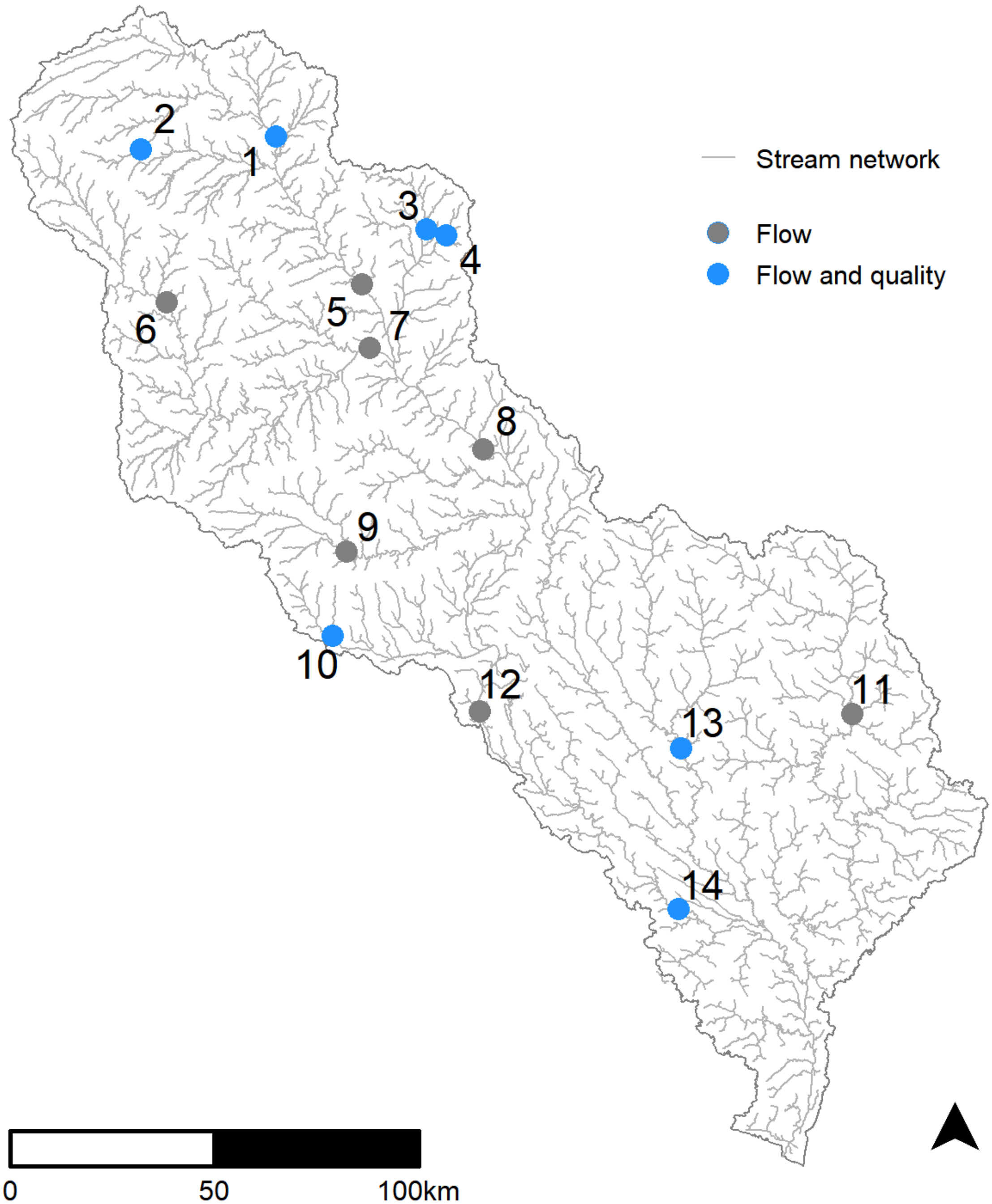

Fig. 16. Selected in-stream gage stations used to evaluate model performance for flow and water quality spatially across the Cape Fear River Basin. Source: Water Quality Portal.[121]

For model calibration and validation, complete time series of daily flow and estimated water quality data were used at the selected stations. Long term daily flow records were available at Lock & Dam #1 for the calibration and validation periods. Given the sparse measurement of observed water quality parameters, long-term daily loads for calibration and validation were estimated using streamflow measured at the USGS gage #02105769 as a predictor. All available in-stream concentrations measured at state monitoring stations nearby Lock and Dam #1 were used to calibrate the LOADEST, the USGS's constituent load estimator tool. Sediment data retrieved from the Water Quality Portal (WQP) was provided from NC Division of Water Resources' monitoring station #B8349000 (Cape Fear River above Lock & Dam 1 near East Arcadia), while total nitrogen and total phosphorus were collected from the NC Department of Water Quality's monitoring station #B8350000 (Cape Fear River at Lock 1 Near Kelly). Observations of total nitrogen in most cases were aggregated from individual measurements of total Kjeldahl nitrogen and inorganic nitrogen (nitrite and nitrate) recorded on the same day. For days with missing observations, we estimated constituent loads using the LOADEST model (regression model #0).[122] Performance of LOADEST was satisfactory for all parameters at the evaluated stations (Appendix F, Table F2; Table F3).

Table 12. Stations selected to evaluate model performance based on in-stream gage spatial distribution and data quality 2000-2019. Calibration and validation focused on the outlet of the Cape Fear River, near Kelly, NC (Subbasin 2667).

					Count of water quality records		
Station #	Subbasin	Nearest municipality	Waterbody	Daily flow record quality (% complete)	Sediment	Total Nitrogen	Total Phosphorus
1	213	Graham	Haw River	99.93%	58	159	159
2	265	Greensboro	South Buffalo Creek	100.00%	163	166	164
3	509	Blands	New Hope Creek	100.00%	390	424	423
4	528	Genlee	Northeast Creek	100.00%	246	281	281
5	663	Bynum	Haw River	100.00%			
6	717	Ramseur	Deep River	100.00%			
7	848	Moncure	Deep River	100.00%			
8	1144	Lillington	Cape Fear River	100.00%			
9	1575	Inverness	Flat Creek	100.00%			
10	1842	Raeford	Rockfish Creek	100.00%	123	124	120
11	2099	Chinquapin	Northeast Cape Fear	99.97%			
12	2125	Tarheel	Cape Fear River	100.00%			
13	2224	Tomahawk	Black River	100.00%	58	122	123
14	2667	Kelly	Cape Fear River	99.97%	254	385	305

9 Calibration and validation

We calibrated and validated the SWAT model with observed streamflow and water quality monitoring records collected at Lock and Dam #1 at Kelly for the period 2000-2019 using MATLAB; data from 2010-2019 was used for calibration while data from 2000-2009 was used for validation. This split sample of periods represented a mix of hydrologic conditions, as well as nutrient loads (Appendix G, Figures G1-G4). The two periods both featured pronounced droughts and extreme precipitation events with accompanying, low and high load events for water quality parameters. Annual flow trends were comparable between the periods, but the calibration period showed higher averages and standard deviations of nutrient loads when compared to the validation period (Appendix G, Table G1). This is unsurprising given ongoing land use change and population growth in the region.

We relied on both statistical and graphical approaches for calibration and validation. For each parameter of interest beginning with flow, followed by sediment, phosphorus, and nitrogen, we performed a one-at-a-time calibration for sensitive parameters. We considered the same flow parameters that were calibrated in the USGS Cape Fear Water Quantity Model, in addition to other parameters that strongly affect hydrology.[123,124] For water quality constituents, we considered parameters known to strongly affect sediment and nutrient loads across previous SWAT models.[123–125] We examined the long-term trends, seasonality, and fit under baseflow and high flow conditions. Best parameter values were chosen by comparing SWAT estimates to the long-term estimates from LOADEST but also based on how well SWAT predictions captured sparse true observations for water quality parameters. We evaluated three commonly used statistical measures of model performance against streamflow and load estimates, including the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) and percent bias.[123,124]

The final calibrated parameter values are provided in Table 13. The p-factor (USLE_P) is a parameter in the Modified Universal Soil Loss Equation (MUSLE) with high uncertainty, which remains challenging to quantify.[126,127] Erosion rates have been estimated for the Piedmont at 0.05-0.126 t/ha/yr at the low end and 0.60-0.75 t/ha/yr at the high end, while for the Coastal Plain the rate may approach as much as 9.3t/ha/yr.[128,129] There is limited documentation of erosion control practices in CFRB. We did test modification of USLE_P, but ultimately left this parameter at the default value of 1, assuming no practices have been implemented.
The final calibrated model demonstrated good performance for hydrology and good to very good performance for water quality parameters over the calibration period (Figures 17-20, Table 14).[123] Weaker performance during the validation period (Table 14) is not surprising given that we set up the model with contemporary land use and management, and many changes have occurred in the watershed over 20 years including population growth and urbanization, conversion of natural habitats, agricultural intensification, and expansion of poultry CAFOs in particular [58,130–133] A recent study by Shen et al. (2022) provides strong evidence that split sample testing is not the most robust option for hydrologic model development, but rather found that using the full period of available data for calibration resulted in superior model performance.[134] We reported calibration statistics for the period January 2010 through December 2018; following Hurricane Florence in Fall 2018 extended high flow persisted from Lillington down to the Locks and Dams during the extremely wet winter and spring of 2019. The lock and dams may back

water up behind them for extended periods of time; Lock and Dam #3 in particular is considered to be a dampening structure that can alter flow in ways that may not be captured by SWAT.[135] It is also possible that operations at the Shearon Harris nuclear facility affected flows during this period. Although we relied primarily on data from Lock and Dam #1, upstream from Wilmington, we also performed additional spatial evaluation of performance across the watershed (Appendix H).

Table 13. Calibrated parameters.

Calibration step	Parameter	File	Parameter definition[1]	Default	Modified
Flow	ESCO	.bsn, .hru	Soil evaporation compensation factor	0.95	0.7[2]
Flow	GWQMN	.gw	Threshold depth in the shallow aquifer required for return flow to occur, in mm H2O	1000.0	750.0[2]
Flow	REVAPMN	.gw	Threshold depth in the shallow aquifer required for 'revap' or percolation to the deep aquifer to occur, in mm H2O	750.0	0.0
Flow	GW_DELAY	.gw	Groundwater delay time (days)	31	5
Flow	ALPHA_BF	.gw	Baseflow alpha factor, in 1/days	0.048	0.90
Flow	GW_REVAP	.gw	Groundwater 'revap' coefficient	0.02	0.2
Flow	SURLAG	.bsn, .hru	Surface runoff lag coefficient	4.0	4.0[2]
Flow	CN2	.mgt	Initial SCS curve number	Varies	↓10%
Flow	SOL_AWC	.sol	Available water capacity of the soil layer, in mm H2O/mm soil	Varies	↑20%
Flow	CH_N1	.sub	Manning's 'n' value for tributary channels	0.014	0.035
Flow	CH_N2	.rte	Manning's 'n' value for the main channel	0.014	0.035
Flow	RES_EVOL	.res	Reservoir emergency spillway volume	Varies	↑100%
Flow	RES_K	.res	Seepage from the bottom of the reservoir (mm/hr)	0.5	Varies, 0 - 0.5.
Flow	NDTARGR	.res	Number of days over which the volume above the principal spillway will be discharged. E.g., NDTARGR = 3 will discharge 1/3 of the excess volume per day.	15	Piedmont = 15, Coastal Plain = 5
Flow	NDTARGR	.pnd	Number of days over which the volume above the principal spillway will be discharged. E.g., NDTARGR = 3 will discharge 1/3 of the excess volume per day.	15	5
Sediment	CH_EQN	.rte	Sediment routing method.	0	1
Sediment	SPEXP	.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	1	1.5

Table 13. Calibrated parameters.

Calibration step	Parameter	File	Parameter definition[1]	Default	Modified
Sediment	SPCON	.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing.	0.0001	0.00011
Sediment	CH_COV1	.rte	Channel erodibility factor (bank)	0	1
Sediment	CH_COV2	.rte	Channel cover factor (bed)	0	1
TN & TP	BIOMIX	.mgt	Biological mixing efficiency	0.2	0.4
TN & TP	ADJ_PKR	.bsn	Peak rate adjustment factor for sediment routing in the subbasin tributary channels.	1	0.1
TP	SOL_MINP	.chm	Initial concentration of SOLP.	5	3
TP	SOL_ORGP	.chm	Initial concentration of ORGP in soil.	0	3
TP	PHOSKD	.bsn	Phosphorus soil partitioning coefficient (m3/Mg)	175	200
TP	PSETLR1	.lwq	Phosphorus settling rate in reservoir for the mid-year nutrient settling season (IRES1 - IRES2) (m/year)	Varies	↑50%
TP	PSETLR2	.lwq	Phosphorus settling rate in reservoir for months other than IRES1 through IRES2 (m/year)	Varies	↑50%
TP	PSETLP1	.pnd	Phosphorus settling rate in pond for the nutrient settling season (IPND1 through IPND2) (m/year)	Varies	↑50%
TP	PSETLP2	.pnd	Phosphorus settling rate in pond for months other than IPND1 through IPND2 (m/year)	Varies	↑50%
TP	RS5	.swq	Local settling rate for organic phosphorus mineralization at 20° C (day-1)	0.05	0.1
TP	BC4	.swq	Rate constant for decay of organic P to mineral P	0.35	0.1
TP	AI2	.wwq	Fraction of algal biomass that is phosphorus (mg P/mg algae)	0.015	0.01
TN	SDNCO	.bsn	Fraction of field capacity water content above which denitrification takes place.	1.1	1
TN	NPERCO	.bsn	Nitrogen percolation coefficient	0.2	0.1
TN	HLIFE_NGW_BSN	.bsn	Half life of nitrate in groundwater in the basin (days). Optional.	5	25

Table 13. Calibrated parameters.

Calibration step	Parameter	File	Parameter definition[1]	Default	Modified
TN	NSETLR1	.res	Nitrogen settling rate in reservoir for the mid-year nutrient settling season (IRES1 - IRES2) (m/year)	Varies	↓90%
TN	NSETLR2	.res	Nitrogen settling rate in reservoir for months other than IRES1 through IRES2 (m/year)	Varies	↓90%
TN	NSETLP1	.pnd	Nitrogen settling rate in pond for the nutrient settling season (IPND1 through IPND2) (m/year)	Varies	↓90%
TN	NSETLP2	.pnd	Nitrogen settling rate in pond for months other than IPND1 through IPND2 (m/year)	Varies	↓90%

[1] Arnold et al. 2012.

[2] Modified from USGS calibrated value.

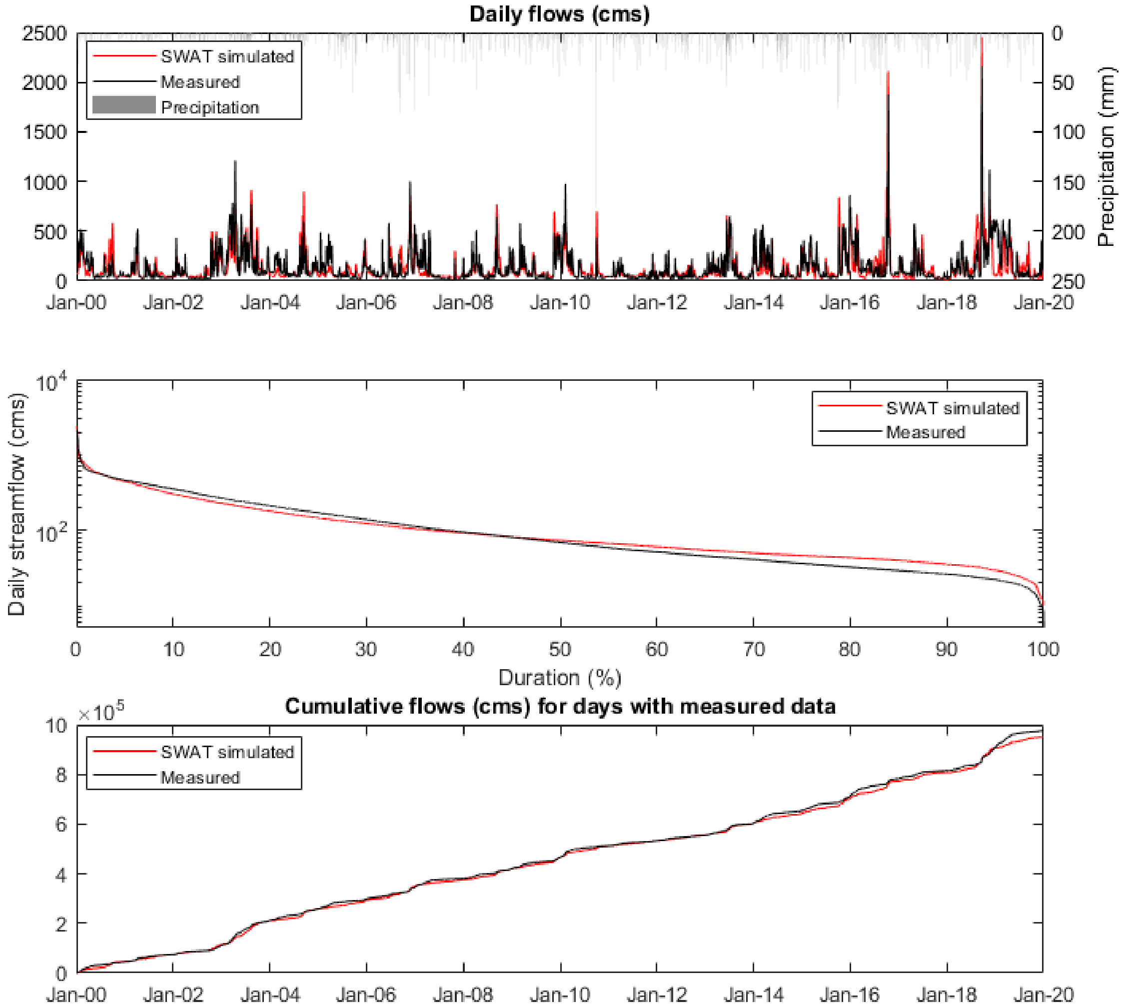

Figure 17. Flow time series plot for the calibration and validation periods at Lock and Dam #1.

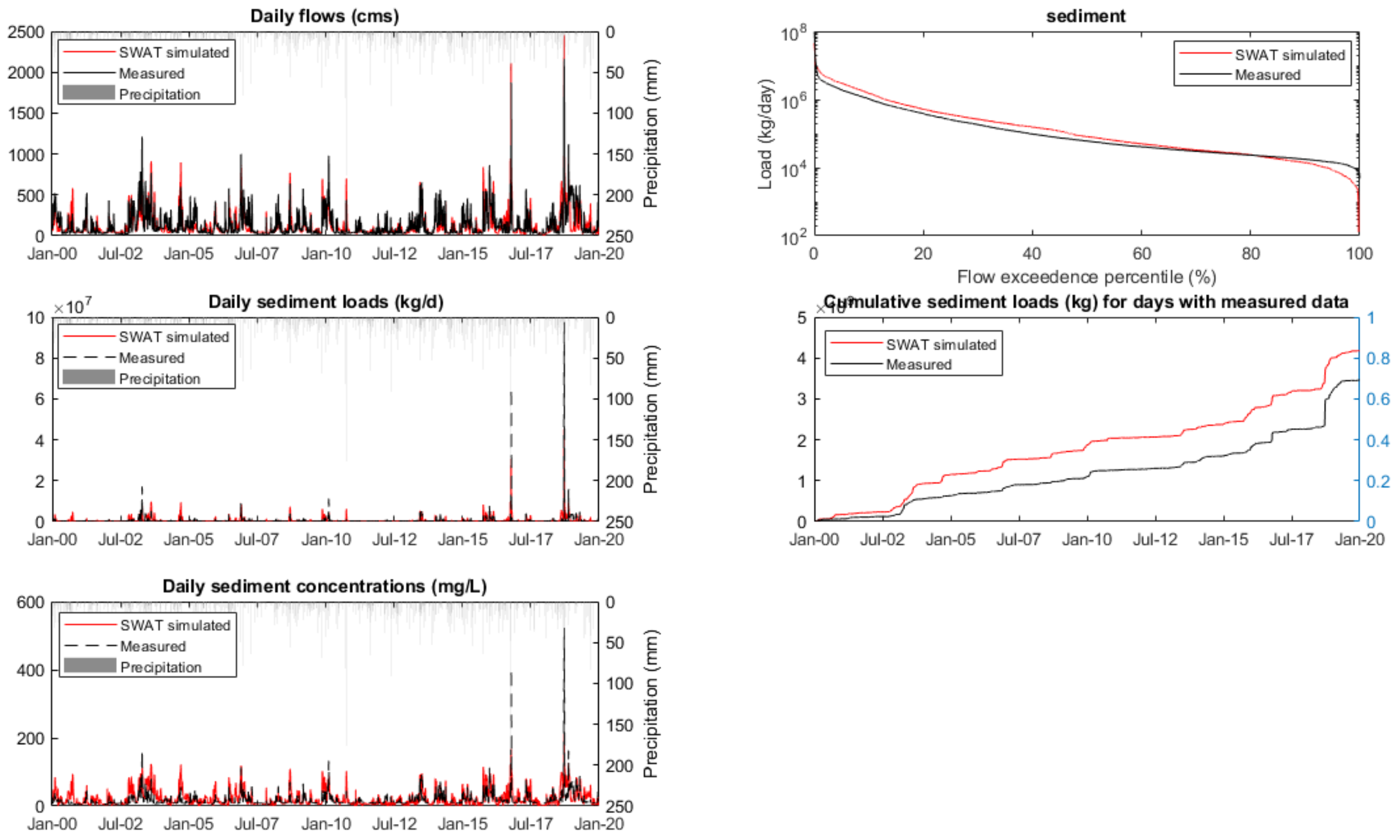

Figure 18. Sediment load estimation (LOADEST) time series for the calibration and validation periods at Lock and Dam #1.

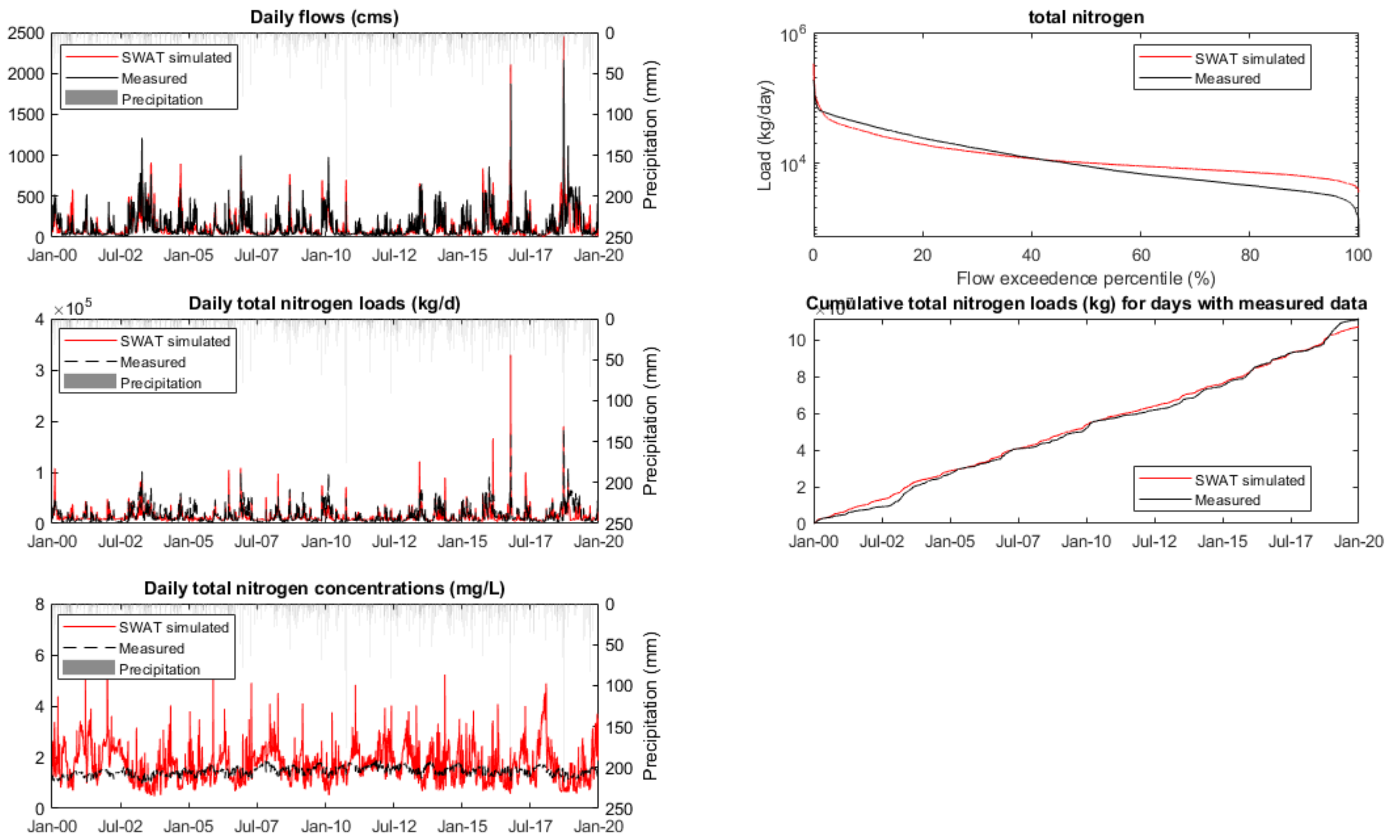

Figure 19. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at Lock and Dam #1.

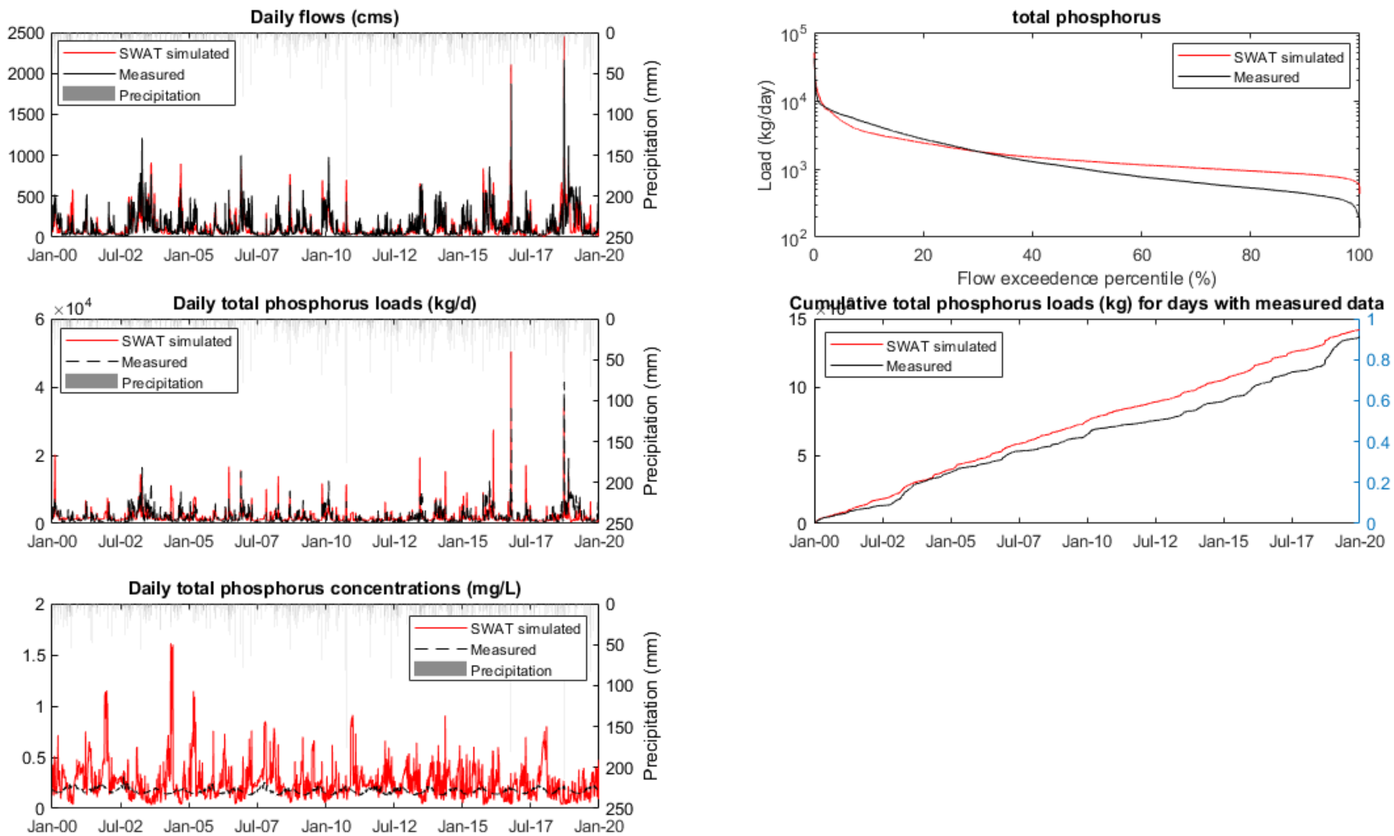

Figure 20. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at Lock and Dam #1.

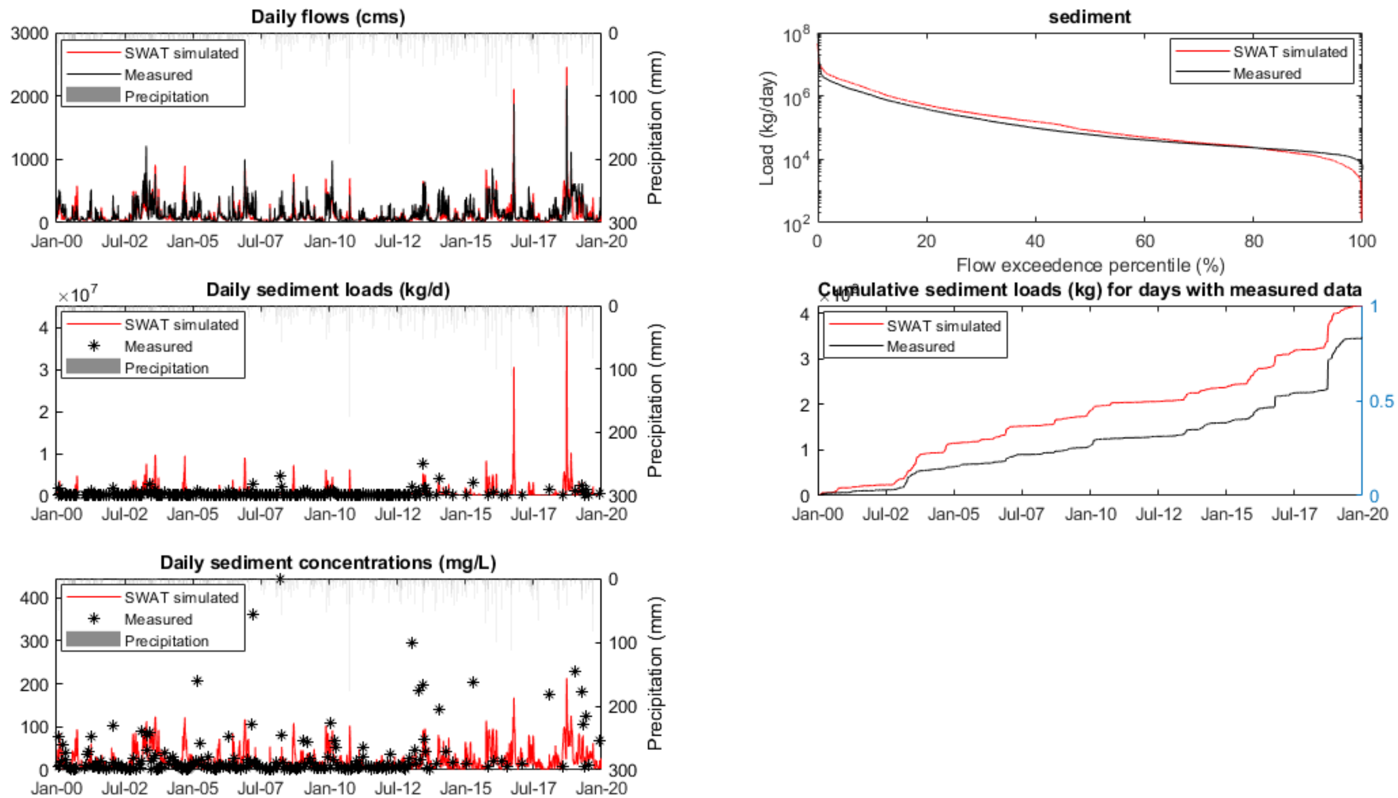

Figure 21. Sediment true observation time series for the calibration and validation periods at Lock and Dam #1.

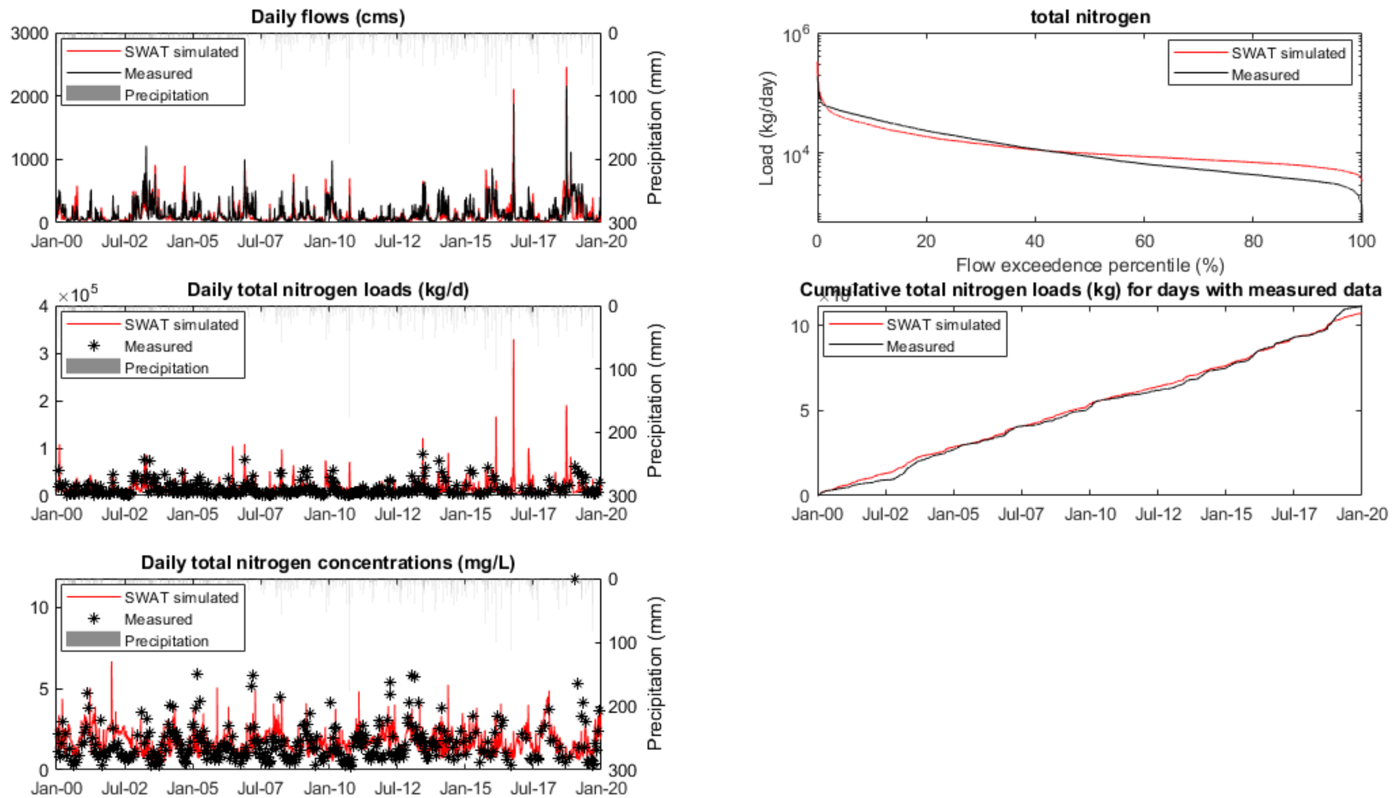

Figure 22. Total nitrogen true observation time series for the calibration and validation periods at Lock and Dam #1.

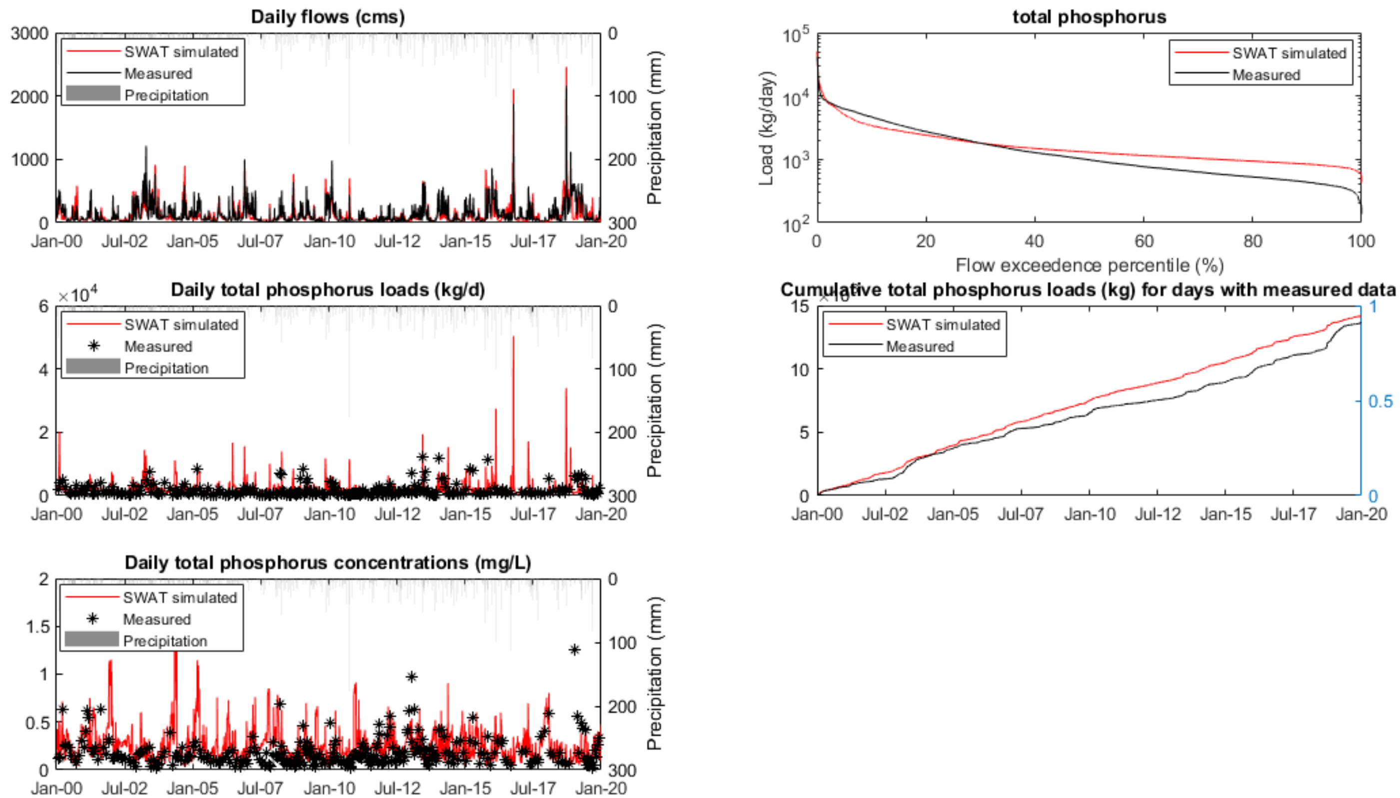

Figure 23. Total phosphorus true observation time series for the calibration and validation periods at Lock and Dam #1.

Table 14. Model performance metrics[a] for calibration (2010-2019) and validation (2000-2009) at Lock and Dam #1, Kelly, NC.

	Calibration (2010-2019)				Validation (2000-2009)			
	Daily	Monthly						
Metric	**Flow**	**Sediment**	**TN**	**TP**	**Flow**	**Sediment**	**TN**	**TP**
R	0.78	0.86	0.74	0.71	0.57	0.48	0.59	0.42
NSE	0.76	0.79	0.74	0.69	0.53	-0.49	0.59	0.31
PBIAS (%)	0.29	0.86	0.28	4.17	-0.17	69.41	3.5	15.21

[a]Monthly NSE and R from 0.65 - 0.75 indicate good performance for water quality parameters, while measures of NSE and R > 0.75 and PBIAS <15 indicate very good performance (Moriasi et al. 2007).

10 Baseline model results

Analysis of the sources of in-stream flow and contaminant loads at Lock and Dam #1 revealed that the landscape represented the major source of flow and contaminant contributions from 2010-2019 (Table 15). Over the long-term we did not observe notable seasonal variation in the contributions of landscape sources and permitted discharge into rivers, yet their relative importance did change under extreme wet or dry conditions. Effluent from permitted wastewater treatment plants and industrial dischargers accounted for an average of 9.70% of the cumulative monthly flow at Lock and Dam #1; they accounted for as little as 0.70% of flow during an extreme wet year and as much as 54.57% in an extreme dry year. Non-point sources generally accounted for the majority of the cumulative monthly sediment and nutrient loads at Lock and Dam #1. During an extreme wet year, the landscape sources contributed as much as 99.30% of the monthly flow, 98.89% of sediment, 97.69% of total nitrogen, and 81.21% of total phosphorus. During an extreme dry year in 2011, effluent from wastewater treatment plants and industrial dischargers contributed as much as 80.05% of the monthly sediment, 84.50% of total nitrogen, and 75.70% of total phosphorus.

Landscape hotspots differed spatially by pollutant when examining long-term average loads generated under weather conditions from 1982-2019 (Fig. 24). Sediment was most often generated in urban areas, particularly in the Piedmont (upper basin), while nutrients were most often sourced from working lands, particularly in the Coastal Plain (mid-lower basin). Phosphorus loads were generally high both in cultivated crop areas and urban areas (Fig. 24).

Table 15. Average percentage of cumulative monthly flow and contaminant contributions from permitted point source effluent and landscape sources measured at Lock and Dam #1 across conditions 2010-2019. Standard deviations are indicated by +/-.

	Point source discharges				Landscape sources			
	Flow	Sediment	Total N	Total P	Flow	Sediment	Total N	Total P
All data	9.66	9.94	16.77	47.57	90.34	90.06	83.23	52.43
	+/-2.55	+/-4.58	+/-6.14	+/-6.17	+/-2.55	+/-4.58	+/-6.14	+/-6.17
Dry year (2011)	38.05	61.85	51.09	67.67	61.95	38.15	48.91	32.33
	+/-11.23	+/-16.32	+/-20.32	+/-5.38	+/-11.23	+/-16.32	+/-20.32	+/-5.38
Wet year (2016)	6.70	10.59	24.91	46.10	93.30	89.41	75.09	53.90
	+/-4.82	+/-7.28	+/-15.83	+/-16.88	+/-4.82	+/-7.28	+/-15.83	+/-16.88

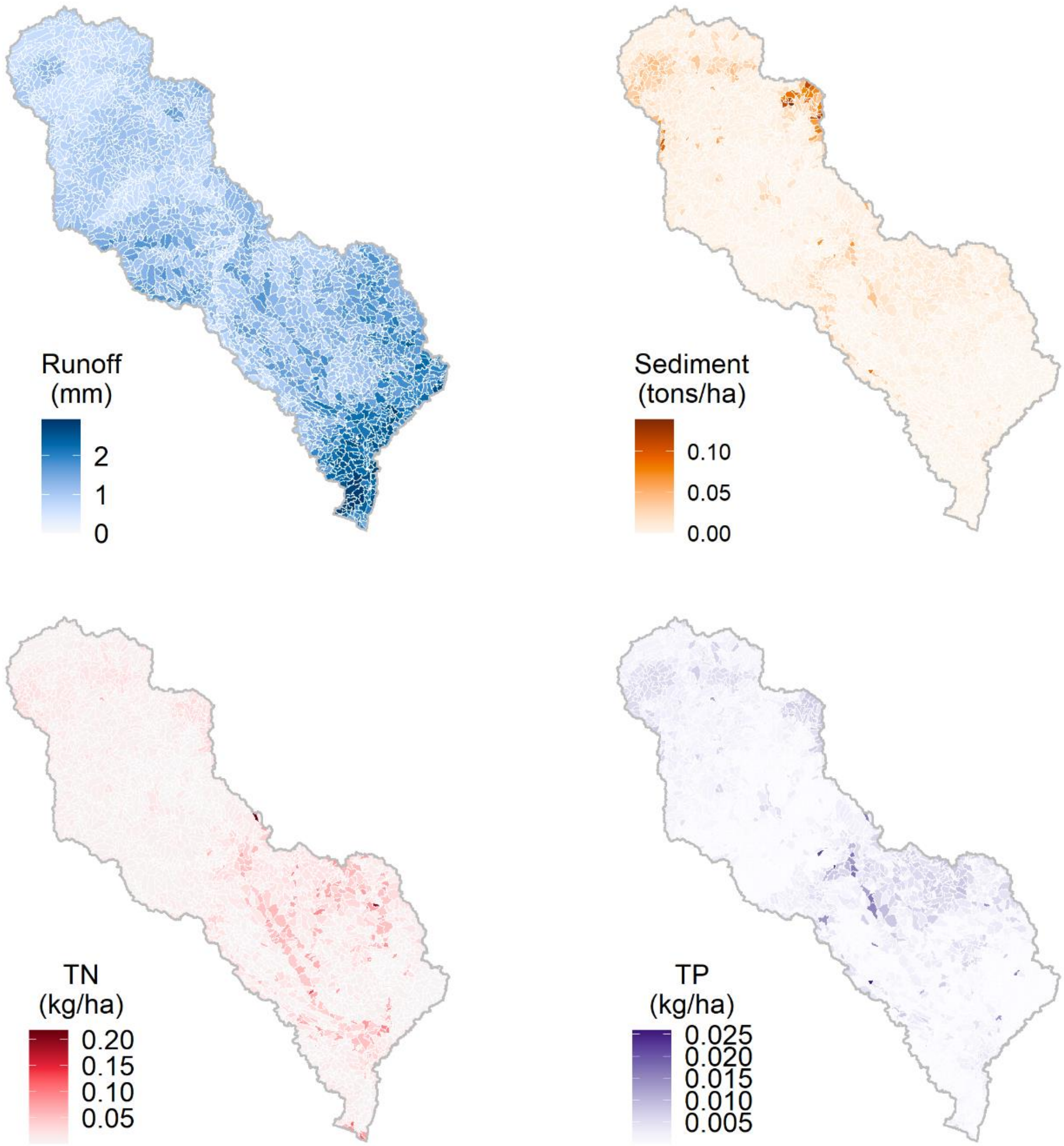

Figure 24. Long-term average daily runoff, sediment, total nitrogen (TN) and total phosphorus (TP) loads varied spatially across the Cape Fear River Basin based on contemporary land use and historical weather conditions from 1982-2019.

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Appendices

Appendix A.Upland land use and management schemes

Table A1. Revised upland land use management schemes represented in the Cape Fear River Basin SWAT Water Quality Model. Abbreviations: deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), range grassland (RNGE), range shrubland (RNGB), range arid (SWRN), hay (HAY), row crops (AGRR), urban (URBN). Rotation 1a rotates between corn and soy in alternate years, beginning with corn. Rotation 1b rotates between corn and soy in alternate years, beginning with soy. Rotation 2a rotates between corn and double crop winter wheat – soybean in alternate years, beginning with corn Rotation 2b rotates between corn and double crop winter wheat – soybean in alternate years, beginning with double crop winter wheat – soybean.

				CAFO manure applied				
Base .mgt file	**Region**	**Land use**	**Specialized management**	**Swine**	**Dairy**	**Poultry**	**Year manure is applied**	**Number of HRUs**
1	Piedmont	AGRR	Corn			X		5
2	Piedmont	AGRR	Double wheat - soybean			X		1
3	Piedmont	AGRR	Fallow			X		28
4	Piedmont	AGRR	Rotation 1a			X		8
5	Piedmont	AGRR	Rotation 1b			X		2
6	Piedmont	AGRR	Rotation 1b	X		X		1
7	Piedmont	AGRR	Rotation 2a			X		7
8	Piedmont	AGRR	Soybean					11
9	Piedmont	AGRR	Soybean			X		14
10	Piedmont	AGRR	Soybean		X	X		5
11	Piedmont	FRSD	Plantation					8
12	Piedmont	FRSD	Plantation			X	1	27
13	Piedmont	FRSD	Plantation			X	2	17
14	Piedmont	FRSD	Plantation			X	3	26
15	Piedmont	FRSD	Plantation			X	4	18
16	Piedmont	FRSD	Plantation			X	5	23
17	Piedmont	FRSD	Plantation		X	X	1	1
18	Piedmont	FRSD	Plantation		X	X	3	1
19	Piedmont	FRSD	Plantation	X		X	2	1
20	Piedmont	FRSD	Plantation	X		X	5	2
21	Piedmont	FRSD						497
22	Piedmont	FRSE	Plantation					54
23	Piedmont	FRSE	Plantation			X	1	26
24	Piedmont	FRSE	Plantation			X	2	17
25	Piedmont	FRSE	Plantation			X	3	19

26	Piedmont	FRSE	Plantation			X	4	21
27	Piedmont	FRSE	Plantation			X	5	36
28	Piedmont	FRSE	Plantation		X	X	1	2
29	Piedmont	FRSE	Plantation		X	X	2	3
30	Piedmont	FRSE	Plantation		X	X	3	2
31	Piedmont	FRSE	Plantation	X		X	1	1
32	Piedmont	FRSE	Plantation	X		X	2	1
33	Piedmont	FRSE	Plantation	X		X	3	2
34	Piedmont	FRSE	Plantation	X		X	4	1
35	Piedmont	FRSE	Plantation	X		X	5	3
36	Piedmont	FRSE						18
37	Piedmont	FRST	Plantation			X	1	8
38	Piedmont	FRST	Plantation			X	2	3
39	Piedmont	FRST	Plantation			X	3	5
40	Piedmont	FRST	Plantation			X	4	4
41	Piedmont	FRST	Plantation			X	5	6
42	Piedmont	FRST	Plantation	X		X	5	1
43	Piedmont	FRST						22
44	Piedmont	HAY						32
45	Piedmont	HAY				X		284
46	Piedmont	HAY			X			2
47	Piedmont	HAY			X	X		22
48	Piedmont	HAY		X				1
49	Piedmont	HAY		X		X		11
50	Piedmont	HAY		X	X	X		4
51	Piedmont	RNGB	Grazing					52
52	Piedmont	RNGB	Grazing			X		618
53	Piedmont	RNGB	Grazing		X			3
54	Piedmont	RNGB	Grazing		X	X		20
55	Piedmont	RNGB	Grazing	X		X		17
56	Piedmont	RNGB	Grazing	X	X	X		4
57	Piedmont	RNGE	Grazing					93
58	Piedmont	RNGE	Grazing			X		890
59	Piedmont	RNGE	Grazing		X	X		27
60	Piedmont	RNGE	Grazing	X		X		24
61	Piedmont	RNGE	Grazing	X	X	X		10
62	Piedmont	SWRN	Grazing					43
63	Piedmont	SWRN	Grazing			X		76
64	Piedmont	SWRN	Grazing		X	X		6
65	Piedmont	SWRN	Grazing	X	X	X		4
66	Piedmont	URBN						1491
67	Coastal Plain	AGRR	Corn					13
68	Coastal Plain	AGRR	Corn			X		36
69	Coastal Plain	AGRR	Corn	X				1
70	Coastal Plain	AGRR	Corn	X		X		101

71	Coastal Plain	AGRR	Corn	X	X	X		4
72	Coastal Plain	AGRR	Cotton					3
73	Coastal Plain	AGRR	Cotton			X		37
74	Coastal Plain	AGRR	Cotton	X		X		22
75	Coastal Plain	AGRR	Double wheat - soybean			X		8
76	Coastal Plain	AGRR	Double wheat - soybean	X		X		12
77	Coastal Plain	AGRR	Fallow					7
78	Coastal Plain	AGRR	Fallow			X		21
79	Coastal Plain	AGRR	Fallow	X				1
80	Coastal Plain	AGRR	Fallow	X		X		12
81	Coastal Plain	AGRR	Rotation 1a					2
82	Coastal Plain	AGRR	Rotation 1a			X		10
83	Coastal Plain	AGRR	Rotation 1a	X		X		16
84	Coastal Plain	AGRR	Rotation 1b			X		2
85	Coastal Plain	AGRR	Rotation 1b	X		X		8
86	Coastal Plain	AGRR	Rotation 2a					1
87	Coastal Plain	AGRR	Rotation 2a			X		4
88	Coastal Plain	AGRR	Rotation 2a	X		X		11
89	Coastal Plain	AGRR	Rotation 2b			X		2
90	Coastal Plain	AGRR	Rotation 2b	X		X		2
91	Coastal Plain	AGRR	Soybean					1
92	Coastal Plain	AGRR	Soybean			X		35
93	Coastal Plain	AGRR	Soybean	X				1
94	Coastal Plain	AGRR	Soybean	X		X		111
95	Coastal Plain	AGRR	Soybean	X	X	X		1
96	Coastal Plain	FRSD						80
97	Coastal Plain	FRSE	Plantation					264
98	Coastal Plain	FRSE	Plantation			X	1	57
99	Coastal Plain	FRSE	Plantation			X	2	65
100	Coastal Plain	FRSE	Plantation			X	3	70
101	Coastal Plain	FRSE	Plantation			X	4	55
102	Coastal Plain	FRSE	Plantation			X	5	59
103	Coastal Plain	FRSE	Plantation	X			1	7
104	Coastal Plain	FRSE	Plantation	X			2	5
105	Coastal Plain	FRSE	Plantation	X			3	3
106	Coastal Plain	FRSE	Plantation	X			4	5
107	Coastal Plain	FRSE	Plantation	X			5	8
108	Coastal Plain	FRSE	Plantation	X		X	1	41
109	Coastal Plain	FRSE	Plantation	X		X	2	41
110	Coastal Plain	FRSE	Plantation	X		X	3	28
111	Coastal Plain	FRSE	Plantation	X		X	4	45
112	Coastal Plain	FRSE	Plantation	X		X	5	43
113	Coastal Plain	FRSE	Plantation	X	X	X	4	1
114	Coastal Plain	FRSE						287
115	Coastal Plain	FRST						552

116	Coastal Plain	HAY			X	30
117	Coastal Plain	HAY		X	X	20
118	Coastal Plain	RNGB	Grazing			570
119	Coastal Plain	RNGB	Grazing		X	724
120	Coastal Plain	RNGB	Grazing	X		51
121	Coastal Plain	RNGB	Grazing	X	X	996
122	Coastal Plain	RNGE	Grazing			126
123	Coastal Plain	RNGE	Grazing		X	521
124	Coastal Plain	RNGE	Grazing	X		18
125	Coastal Plain	RNGE	Grazing	X	X	120
126	Coastal Plain	SWRN	Grazing			193
127	Coastal Plain	SWRN	Grazing		X	120
128	Coastal Plain	SWRN	Grazing	X		9
129	Coastal Plain	SWRN	Grazing	X	X	115
130	Coastal Plain	URBN				2228

Appendix B. CAFO manure nutrient fractions

For liquid manures (swine and cattle), I assumed a volume of 1000 gallons for calculations. For poultry dry litter, I used a volume of 1 ton.

Nutrient composition information was assembled from various sources. NC State Extension provided the total nitrogen and Phosphorus as P2O5 from CAFO manures[76–78]. Mineral and organic N and P fractions were sourced from the state's nutrient management planning software and from Clemson University's College of Agriculture training manuals for animal production, and peer-reviewed literature[62,79,79–81]. We assumed that inorganic nutrient fractions (and NH4-N) were equivalent to mineral and that organic was equivalent to organic in SWAT. We assumed that organic N is the difference between Total N and NH3-N, and vice-versa. When values were 0.000 we rounded up to 0.001 (if not naturally rounded) so SWAT would not default to an incorrect value

For simplicity, we defined single manure compositions for each type of confined animal. For swine facilities, we computed weighted averages according to the prevalence of different operation types in the study area[57,136]. The majority of swine facilities in CFRB are feeder to finish operations (62%), but 21% are farrow to wean animals. We also used a weighted average for poultry based on the production of distinct of types of poultry in the study area according to USDA Agricultural Census data[59]. Rooster manure was assumed to have the same composition as layers and pullets. Broiler manure represented 64% of the total poultry manure volume, with layers, pullets and roosters making up 13% and turkeys accounting for 22% of the litter.

Conversions are shown below:

Swine lagoon liquid

Code	Units	Total N	NH3-N	Organic N
55	lbs/1000 gallons	3.35	2.37	0.98
In one gallon of this manure there is…		0.00	0.00	0.00
The fraction of NH3-N to Organic N is…			2.43	
0.71				
	Units	P2O5		
	lbs/1000 gallons	1.30		
In one gallon of this manure there is…		0.00	lbs P2O5	
In one gallon of this manure there is…		0.00	lbs P	
Inorganic fraction of P in swine slurry		P	Inorganic P	Organic P
0.91		0.00	0.00	0.00

Swine lagoon sludge

Code	Units	Total N	NH3-N	Organic N
56	lbs/1000 gallons	20.40	5.76	14.64
In one gallon of this manure there is…		0.02	0.01	0.01
The fraction of NH4-N to Organic N is…			0.39	
0.28				
	Units	P2O5		
	lbs/1000 gallons	30.6		
In one gallon of this manure there is…		0.03	lbs P2O5	
In one gallon of this manure there is…		0.01	lbs P	
Inorganic fraction of P in dairy manure		P	Inorganic P	Organic P
0.91		0.01	0.01	0.00

Dairy slurry

Code	Units	Total N	NH3-N	Organic N
57	lbs/1000 gallons	16.70	6.83	9.87
In one gallon of this manure there is…		0.02	0.01	0.01
The fraction of NH4-N to Organic N is…			0.69	
0.41				
Code	Units	P2O5		
57	lbs/1000 gallons	9.1		
In one gallon of this manure there is…		0.0091	lbs P2O5	
In one gallon of this manure there is…		0.004004	lbs P	
Inorganic fraction of P in dairy manure		P	Inorganic P	Organic P
0.75		0.00	0.00	0.00

Poultry dry litter

0.2237	Units	Total N		NH3-N	Organic N
	lbs/ton		55.59	14.85	40.74
In one ton of this manure there is…			55.59	14.85	40.74
In one lb of this manure there is…			0.028	0.01	0.02
The fraction of NH4-N to Organic N is…				0.36	
0.267174304					
	Units	P2O5			
	lbs/ton		40.63		
In one ton of this manure there is…			40.63	lbs P2O5	
In one lb of this manure there is…			0.02	lbs P2O5	
In one lb of this manure there is…			0.01	lbs P	
Inorganic fraction of P in poultry litter		P		Inorganic P	Organic P
0.4			0.01	0.00	0.01

Appendix C. Annual Nitrogen and Phosphorus needs by land use

Table C1. Annual nitrogen needs by land use (lbs/acre). Abbreviations: deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), forested wetland (WETF), non-forested wetland (WETN), water (WATR), range grassland (RNGE), range shrubland (RNGB), range arid (SWRN), hay (HAY), row crops (AGRR), urban (URBN). Rotation 1 rotates between corn and soy in alternate years. Rotation 2 rotates between double crop winter wheat – soybean and corn in alternate years. Nutrient needs for fallow/idle lands and hay were estimated based on small grains. Nutrient needs for rangelands were estimated based on small grains, with a 25% reduction to account for manure inputs from grazing livestock.

		Year										
Land use	**Description**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**
AGRR	Corn	120-190	120-190	120-190	120-190	120-190	120-190	120-190	120-190	120-190	120-190	155
AGRR	Soybean	0	0	0	0	0	0	0	0	0	0	0
AGRR	Double crop winter wheat soybean	95-150	95-150	95-150	95-150	95-150	95-150	95-150	95-150	95-150	95-150	122.5
AGRR	Cotton	30-80	30-80	30-80	30-80	30-80	30-80	30-80	30-80	30-80	30-80	55
AGRR	Fallow/Idle	80-120	80-120	80-120	80-120	80-120	80-120	80-120	80-120	80-120	80-120	100
AGRR	Rotation 1	88-159	0	88-159	0	88-159	0	88-159	0	88-159	0	61.75
AGRR	Rotation 2	88-159	95-150	88-159	95-150	88-159	95-150	88-159	95-150	88-159	95-150	123
FRSE, FRST	Pine plantation	0	0	0	0	300	0	0	0	0	300	60
SWRN	Rangeland	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	75
RNGB	Rangeland	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	75
RNGE	Rangeland	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	60-90	75
HAY	Hay	80-100	80-100	80-100	80-100	80-100	80-100	80-100	80-100	80-100	80-100	90
URBN	Urban lawns	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9

Table C2. Annual Phosphorus needs by land use (lbs/acre). Abbreviations: deciduous forest (FRSD), evergreen forest (FRSE), mixed forest (FRST), forested wetland (WETF), non-forested wetland (WETN), water (WATR), range grassland (RNGE), range shrubland (RNGB), range arid (SWRN), hay (HAY), row crops (AGRR), urban (URBN). Rotation 1 rotates between corn and soy in alternate years. Rotation 2 rotates between double crop winter wheat – soybean and corn in alternate years. Nutrient needs for fallow/idle lands and hay were estimated based on small grains. Nutrient needs for rangelands were estimated based on small grains, with a 25% reduction to account for manure inputs from grazing livestock.

		Year										
Land use	**Description**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**
AGRR	Corn	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	13.10-21.83	17.47
AGRR	Soybean	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	6.55
AGRR	Double crop winter wheat soybean	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	4.37-30.57	17.47
AGRR	Cotton	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	4.37-8.73	6.55
AGRR	Fallow/Idle	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11
AGRR	Rotation 1	13.10-21.83	4.37-8.73	13.10-21.83	4.37-8.73	13.10-21.83	4.37-8.73	13.10-21.83	4.37-8.73	13.10-21.83	4.37-8.73	27.5
AGRR	Rotation 2	13.10-21.83	4.37-30.57	13.10-21.83	4.37-30.57	13.10-21.83	4.37-30.57	13.10-21.83	4.37-30.57	13.10-21.83	4.37-30.57	40
FRSE	Pine plantation	0	0	0	0	50	0	0	0	0	50	2.5
SWRN	Rangeland	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83
RNGB	Rangeland	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83
RNGE	Rangeland	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83	21.83
HAY	Hay	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11	29.11
URBN	Urban lawns	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9	108.9

Appendix D. Estimating daily biomass consumption by grazing livestock

Table D1. Daily biomass consumption by livestock in the Piedmont region. Biomass consumption was estimated using percent animal weight dry matter demand, proportion of supplemental feed, digestibility and dry matter content of pasture.

Animal Type	Stocking rate (animals per ha)	Animal mature weight (kg)	Predicted dry matter demand as a proportion of body weight	Proportion of diet that is forage	Total predicted dry matter consumption (kg)	Pasture dry matter proportion	Pasture digestibility	Fresh pasture consumed per animal (kg)	Estimated total fresh pasture consumed (kg/ha)
Beef cattle	0.93	453.59	0.02	1.00	9.07	0.30	0.60	50.40	47.11
Dairy cattle	0.06	453.59	0.02	0.50	4.54	0.30	0.60	25.20	1.39
Horse	0.07	498.95	0.02	1.00	9.98	0.30	0.60	55.44	3.94
Swine	0.06	90.72	0.02	0.20	0.36	0.30	0.60	2.02	0.12
Goat	0.09	70.31	0.04	1.00	2.64	0.30	0.60	14.65	1.27
Sheep	0.04	88.45	0.02	1.00	1.77	0.30	0.60	9.83	0.44
Duck	0.28	3.10	0.04	1.00	0.11	0.30	0.60	0.60	0.17

Table D2. Daily biomass consumption by livestock in the Coastal Plain region. Biomass consumption was estimated using percent animal weight dry matter demand, proportion of supplemental feed, digestibility and dry matter content of pasture.

Animal Type	Stocking rate (animals per ha)	Animal mature weight (kg)	Predicted dry matter demand as a proportion of body weight	Proportion of diet that is forage	Total predicted dry matter consumption (kg)	Pasture dry matter proportion	Pasture digestibility	Fresh pasture consumed per animal (kg)	Estimated total fresh pasture consumed (kg/ha)
Beef cattle	0.18	453.59	0.02	1.00	9.07	0.30	0.60	50.40	9.14
Dairy cattle	0.00	453.59	0.02	0.50	4.54	0.30	0.60	25.20	0.01
Horse	0.01	498.95	0.02	1.00	9.98	0.30	0.60	55.44	0.83
Swine	0.05	90.72	0.02	0.20	0.36	0.30	0.60	2.02	0.11
Goat	0.02	70.31	0.04	1.00	2.64	0.30	0.60	14.65	0.25
Sheep	0.01	88.45	0.02	1.00	1.77	0.30	0.60	9.83	0.06
Duck	0.01	3.10	0.04	1.00	0.11	0.30	0.60	0.60	0.01

Appendix E. Point source discharges within the Cape Fear River Basin

Table D1 indicates the complete list of outfalls by facility discharging to subbasins that represented in the model. Permit numbers and versions may change over time. The most recent permit information for each location is shown. Note that many of these facilities are no longer active.

Table E2 provides the complete set of parameter codes, units and conversions used to convert flow, sediment and nutrient records to the units required by SWAT.

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
A.B. Uzzle WTP	NC0078955	Minor	1	35.325	-78.6972	Juniper Branch	1279
AA Greensboro terminal	NC0074241	Minor	1	36.07472	-79.9217	East Fork Deep River	249
Acme Delco Elementary School WWTP	NC0043796	Minor	1	34.34861	-78.2544	Pretty Creek	2704
Acme Delco Middle School WWTP	NC0043788	Minor	1	34.31833	-78.2147	Lindscomb Branch	2743
Adams Products Co - Colfax	NC0084492	Minor	1	36.10111	-79.9975	West Fork Deep River	228
Alamance Rest & Retirement	NC0055000	Minor	1	36.02111	-79.3431	Haw Creek	341
Altamahaw/Ossipee Elementary School	NC0045161	Minor	1	36.18194	-79.5103	Haw River	90
American Crane Corporation	NC0065111	Minor	1	34.1775	-77.9403	Barnards Creek	2847
Angier WWTP	NC0082597	Minor	1	35.39833	-78.7708	Cape Fear River	1187
Aquasource, Inc.-Quarry Hil	NC0022446	Minor	1	36.03361	-79.3661	Haw River	292
Arauco NA Moncure Facility	NC0040711	Minor	1	35.59778	-79.0511	Haw River	892
Arclin USA, Inc	NC0000892	Major	1	35.6025	-79.0503	Haw River	886
Arrowhead Motor Lodge	NC0029351	Minor	1	36.07056	-79.2647	Haw Creek	237
Asheboro WWTP	NC0026123	Major	1	35.76667	-79.785	Haskett Creek	670
Asphalt Testing Site #6-48	NC0087629	Minor	1	35.74667	-79.0897	Haw River	713
Autumn Forest MHC WWTP	NC0022691	Minor	1	36.18528	-79.7214	Reedy Fork (Hardys Mill Pond)	100
Avocet f/k/a Buckhorn Ridge	NC0055051	Minor	1	35.6	-78.8708	Buckhorn Creek	891
B F Goodrich Tire Co	NC0072796	Minor	1	34.265	-77.8799	Smith Creek	2787
B&B Produce	NC0083135	Minor	1	35.36361	-78.5125	Mingo Swamp	1242
Bald Head Island WTP	NC0085553	Minor	1	33.87694	-78.0011	Bald Head Island Marina Basin	2928
Bay Tree Lakes WWTP	NC0036404	Minor	1	34.69167	-78.4306	Lake Creek	2311

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Bay Valley Foods Faison Processing Facility	NC0001970	Minor	1	35.1225	-78.1411	Panther Creek	1609
Beau Rivage Plantation WWTP	NC0065480	Minor	1	34.11056	-77.9261	Cape Fear River	2873
Beaverdam Creek WTP	NC0040061	Minor	1	33.95806	-78.0822	Beaverdam Creek	2899
Belville WWTP	NC0075540	Minor	1	34.22139	-77.9817	Brunswick River	2826
Bennett Elementary School WWTP	NC0039471	Minor	1	35.56306	-79.5489	Flat Creek	955
Beulaville WWTP	NC0026018	Minor	1	34.90861	-77.7614	Persimmon Branch	2002
Big Buffalo WWTP	NC0024147	Major	1	35.55083	-79.2247	Deep River	950
Birchwood Mobile Home Park	NC0042803	Minor	1	35.98472	-78.9992	New Hope Creek	391
Birmingham Place WWTP	NC0022675	Minor	1	36.05472	-79.6981	Little Alamance Creek (Guilford County)	295
Bladen Bluffs Regional Surface WTP	NC0088781	Minor	1	34.76472	-78.8044	Cape Fear River	2223
Bladen Bluffs Regional Surface WTP	NCG590020	Minor	1	34.76472	-78.8044	Cape Fear River	2223
Bonlee Elementary School	NC0039331	Minor	1	35.64333	-79.4236	Bear Creek	876
Brenntag / Durham remediation	NC0086827	Minor	1	35.97639	-78.8828	Third Fork Creek	385
Brenntag / Greensboro remediation	NC0078000	Minor	1	36.06444	-79.8769	South Buffalo Creek	244
Broadway WWTP	NC0059242	Minor	1	35.45944	-79.0286	Daniels Creek	1082
Brookside Housing Developme	NC0061045	Minor	1	36.02083	-79.7147	Little Alamance Creek (Guilford County)	317
Brunswick Steam Electric Plant	NC0007064	Major	10	33.95131	-78.0279	Atlantic Ocean	2905
Brunswick Steam Electric Plant	NC0007064	Major	11	33.95131	-78.0279	Atlantic Ocean	2905
Brunswick Steam Electric Plant	NC0007064	Major	3	33.95131	-78.0279	Atlantic Ocean	2905
Brunswick Steam Electric Plant	NC0007064	Major	4	33.9572	-78.0125	Atlantic Ocean	2898
Brunswick Steam Electric Plant	NC0007064	Major	5	33.9572	-78.0125	Atlantic Ocean	2898
Buies Creek WWTP	NC0030091	Minor	1	35.38056	-78.7528	Cape Fear River	1222
Burgaw WWTP	NC0021113	Minor	1	34.55694	-77.9247	Burgaw Creek	2521
Bynum WWTP	NC0035866	Minor	1	35.77056	-79.1403	Haw River	661
Calypso WTP	NC0002933	Minor	1	35.15111	-78.0978	Dicks Branch	1607
Campbell Oil/Azalea Plaza S	NC0072681	Minor	1	34.21556	-77.9156	Mill Creek	2822
Cape Fear Manufacturing Facility	NC0000663	Major	1	34.31806	-78.0278	Cape Fear River	2753

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Cape Fear Manufacturing Facility	NC0000663	Major	2	34.33056	-78.0431	Cape Fear River	2753
Cape Fear Manufacturing Facility	NC0000663	Major	3	34.3325	-78.0478	Cape Fear River	2736
Cape Fear Steam Electric Power Plant	NC0003433	Major	8	35.59389	-79.0514	Cape Fear River	908
Cape Fear Steam Electric Power Plant	NC0003433	Major	1	35.58778	-79.0444	Cape Fear River	948
Cape Fear Steam Electric Power Plant	NC0003433	Major	2	35.54083	-78.9897	Cape Fear River	978
Cape Fear Steam Electric Power Plant	NC0003433	Major	3	35.58778	-79.0444	Cape Fear River	948
Cape Fear Steam Electric Power Plant	NC0003433	Major	5	35.58778	-79.0444	Cape Fear River	948
Cape Fear Steam Electric Power Plant	NC0003433	Major	7	35.58417	-79.0408	Cape Fear River	948
Cape Fear Terminal	NC0028568	Minor	1	34.22583	-77.9519	Cape Fear River	2820
Carolina Beach WWTP	NC0023256	Major	1	34.02833	-77.9189	Cape Fear River	2886
Carolina Trace WWTP	NC0038831	Minor	1	35.41667	-79.0875	Upper Little River	1130
Carter's Pharamcy	NC0074179	Minor	1	34.2425	-77.9258	Mill Creek	2813
Carthage WWTP, Town Of	NC0025551	Minor	1	35.33444	-79.4417	Killets Creek	1252
Cary & Apex WTP	NC0081591	Minor	1	35.75417	-78.9208	White Oak Creek	686
Castle Creek Memory Care WWTP	NC0051969	Minor	1	34.33667	-77.9078	Prince George Creek	2731
Castle Creek Memory Care WWTP	NC0051969	Minor	2	34.34028	-77.915	Prince George Creek	2731
Castle Hayne Plant	NC0003875	Minor	1	34.37611	-77.8653	Northeast Cape Fear River	2699
Castle Hayne Plant	NC0003875	Minor	2	34.3505	-77.8592	Northeast Cape Fear River	2719
Castle Hayne Plant	NC0003875	Minor	3	34.37611	-77.8653	Northeast Cape Fear River	2699
Cedar Creek Site	NC0003719	Major	1	34.96889	-78.7828	Cape Fear River	1948
Cedar Creek Site	NC0003719	Major	2	34.97833	-78.7833	Cape Fear River	1948
Cedar Creek Site	NC0003719	Major	3	34.97778	-78.7822	Cape Fear River	1948
Cedar Village Apartments	NC0048429	Minor	1	35.84389	-79.0947	Cub Creek	591
Central Chatham High School	NC0039381	Minor	1	35.61278	-79.3925	Bear Creek	873
Chapel Hill West/ Tower Ap	NC0051331	Minor	1	35.86778	-79.1611	Meadow Branch	570
Chatham Co Sch-Northwoods H	NC0039357	Minor	1	35.75778	-79.1692	Haw River	688
Chatham Water Reclamation Facility	NC0056413	Minor	1	35.86111	-79.0117	Morgan Creek (including the Morgan Creek Arm of New Hope River Arm of B. Everett Jordan Lake)	549
Chemours Company-Fayetteville Works	NC0003573	Major	3	34.83167	-78.8233	Cape Fear River	2125

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Chemours Company-Fayetteville Works	NC0003573	Major	6	34.83111	-78.8236	Cape Fear River	2125
Chemours Company-Fayetteville Works	NC0003573	Major	1	34.83111	-78.8236	Cape Fear River	2125
Chemours Company-Fayetteville Works	NC0003573	Major	2	34.83889	-78.8367	Cape Fear River	2125
Churchill Estates WWTP	NC0061271	Minor	1	34.26528	-77.8842	Smith Creek	2787
Clairmont Shopping Center WWTP	NC0058599	Minor	1	34.23278	-77.9861	Brunswick River	2826
Coe-Jordan Manager Office	NC0052418	Minor	1	35.65278	-79.0675	Haw River	842
Cole Park Plaza Shopping Center WWTP	NC0051314	Minor	1	35.84472	-79.0842	Cub Creek	591
Coleridge Elementary School	NC0040975	Minor	1	35.64583	-79.6169	Deep River	829
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	1	36.07	-79.9353	East Fork Deep River	249
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	2	36.06861	-79.9364	East Fork Deep River	249
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	3	36.07056	-79.9358	East Fork Deep River	249
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	4	36.07	-79.9381	East Fork Deep River	249
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	5	36.06722	-79.9394	East Fork Deep River	249
Colonial Pipeline - Greensboro Junction WWTF	NC0031046	Minor	6	36.07139	-79.9347	East Fork Deep River	249
Columbus County WWTP	NC0087947	Minor	1	34.32944	-78.2056	Livingston Creek (Broadwater Lake)	2743
Cooper's Ranch WWTP	NC0031470	Minor	1	35.25556	-78.9978	Jumping Run Creek	1436
Cornerstone Conference and Resource Center WWTP	NC0046809	Minor	1	36.22917	-79.6914	Benaja Creek	60
Countryside Manor WWTP	NC0073571	Minor	1	36.24472	-79.9583	Troublesome Creek	54
Cp&L Bioassay-New Hill	NC0059323	Minor	1	35.63611	-78.9444	Buckhorn Creek (Harris Lake)	851
Cp&L Shearon Harris Env Ctr	NC0026735	Minor	1	35.6425	-78.9283	Buckhorn Creek (Harris Lake)	852
Cranbrook Village Community	NC0022098	Minor	1	36.00278	-79.7522	Little Alamance Creek (Guilford County)	339

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Creekside Townhomes II	NC0064700	Minor	1	34.19944	-77.9806	Jackeys Creek	2827
Cross Creek WWTP	NC0023957	Major	1	35.0625	-78.8561	Cape Fear River	1732
Crown Mobile Home Park	NC0055255	Minor	1	35.955	-79.8733	Hickory Creek	402
Crystal Lake WWTP	NC0057525	Minor	1	35.24028	-79.3058	Mill Creek	1386
Danaher Sensors and Controls	NC0001121	Minor	1	34.6382	-78.6328	Cape Fear River	2410
Danaher Sensors and Controls	NC0001121	Minor	2	34.6382	-78.6328	Cape Fear River	2410
Danaher Sensors and Controls	NC0001121	Minor	3	34.6382	-78.6328	Cape Fear River	2410
Danaher Sensors and Controls	NC0001121	Minor	4	34.64861	-78.625	Cape Fear River	2410
Days Inn- Fayetteville	NC0024481	Minor	1	35.12333	-78.7528	Bakers Swamp	1682
Deep River Seafood/E.L. Smi	NC0085987	Minor	1	35.56778	-79.4639	Tysons Creek	988
Devil's Woodyard WTP	NC0086941	Minor	1	35.21722	-77.9575	Horsepen Branch	1447
Dow Silicones Corporation- Greensboro	NC0088773	Minor	1	36.05389	-79.8511	South Buffalo Creek	273
Duke Energy Progress Visitor/Media Center	NC0061379	Minor	1	33.95083	-78.0258	Atlantic Ocean	2898
Dunn WWTP	NC0043176	Major	1	35.29194	-78.6858	Cape Fear River	1319
Duplin Bioenergy	NC0058271	Minor	1	35.02139	-77.8561	Northeast Cape Fear River	1855
Duplin Bioenergy	NC0058271	Minor	2	35.02083	-77.8569	Northeast Cape Fear River	1855
Duplin Bioenergy	NC0058271	Minor	3	35.02139	-77.8561	Northeast Cape Fear River	1855
East Arcadia Elementary School WWTP	NC0032913	Minor	1	34.42278	-78.3289	Cape Fear River	2667
East Coast Limestone Inc	NC0076864	Minor	1	34.74851	-77.7115	Angola Creek	2243
East Side WWTP	NC0024210	Major	2	35.93639	-79.8894	Deep River	443
East Side WWTP	NC0024210	Major	1	35.94083	-79.9069	Richland Creek	423
Eastside WWTP	NC0023868	Major	1	36.09667	-79.3736	Haw River	213
Elizabethtown WWTP	NC0026671	Major	1	34.63056	-78.5944	Cape Fear River	2410
Erwin WTP	NC0080560	Minor	1	35.32222	-78.6889	Cape Fear River	1295
Erwin WWTP	NC0064521	Major	1	35.32389	-78.6953	Cape Fear River	1295
Erwin WWTP #2	NC0001406	Major	2	35.32889	-78.6789	Cape Fear River	1280
Erwin WWTP #2	NC0001406	Minor	1	35.31722	-78.7	Cape Fear River	1295
Exxon Company, USA -Greensb	NC0084522	Minor	1	35.99583	-79.8639	Jenny Branch	374
Exxon Station No. 4-0779	NC0084018	Minor	1	35.91306	-79.0581	Bolin Creek	451

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Faith Christian School	NC0042030	Minor	1	35.70806	-79.6331	Deep River (Randleman Lake)	771
Fearrington Village WWTP	NC0043559	Minor	1	35.80722	-79.0772	Bush Creek	622
Forest Oaks Country Club	NC0050024	Minor	1	35.99222	-79.7083	Beaver Creek	321
Fort Bragg WWTP & WTP	NC0003964	Major	1	35.19111	-79.0081	Little River (Lower Little River)	1516
Fort Bragg WWTP & WTP	NC0003964	Major	2	35.17778	-79.0292	Little River (Lower Little River)	1516
Fortron Industries	NC0082295	Major	1	34.31583	-78.0131	Cape Fear River	2753
Frank L. Ward WTP	NC0081256	Minor	2	35.96722	-79.9739	Richland Creek	435
Frank L. Ward WTP	NC0081256	Minor	1	35.96722	-79.9739	Richland Creek	435
Franklinville WWTP	NC0007820	Minor	1	35.73694	-79.6856	Deep River	706
Garland WWTP	NC0025569	Minor	1	34.79056	-78.3792	Great Coharie Creek (Blackmans Pond)	2170
Glen Touch Yarn Company	NC0003913	Major	1	36.18194	-79.5061	Haw River	119
Glen Touch Yarn Company	NC0003913	Major	3	36.18194	-79.5061	Haw River	119
Glen Touch Yarn Company	NC0003913	Major	5	36.18194	-79.5061	Haw River	119
GNF-A Wilmington-Castle Hayne WWTP	NC0001228	Major	1	34.32861	-77.9358	Northeast Cape Fear River	2769
GNF-A Wilmington-Castle Hayne WWTP	NC0001228	Major	2	34.32583	-77.9319	Northeast Cape Fear River	2769
Golden Years Nursing Home	NC0058793	Minor	1	35.195	-78.6489	South River	1532
Goldston-Gulf WTP	NC0081795	Minor	1	35.55333	-79.2922	Deep River	958
Gordon Street WTP	NC0086801	Minor	1	35.18944	-78.0633	Northeast Cape Fear River	1502
Graham / Mebane WTP	NC0045292	Minor	1	36.09861	-79.3319	Back Creek	212
Graham WWTP	NC0021211	Major	1	36.04556	-79.3683	Haw River	292
Greensboro Petroleum Breakout Facility	NC0051161	Minor	1	36.07278	-79.9278	East Fork Deep River	249
Greensboro Petroleum Breakout Facility	NC0051161	Minor	2	36.07333	-79.9244	East Fork Deep River	249
Greensboro Piedmont Terminal	NC0069256	Minor	1	36.07528	-79.9294	East Fork Deep River	249
Greensboro Terminal	NC0022209	Minor	1	36.07417	-79.9175	Long Branch	282
Greensboro Terminal	NC0065803	Minor	1	36.07222	-79.9258	East Fork Deep River	249
Greensboro Terminal	NC0071463	Minor	1	36.07861	-79.9267	Horsepen Creek	249
Greensboro Terminal I	NC0000795	Minor	1	36.07667	-79.9283	East Fork Deep River	249

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Greensboro Terminal I	NC0074578	Minor	1	36.07222	-79.9186	Long Branch	282
Greensboro Terminal I	NC0074578	Minor	2	36.07194	-79.9183	Long Branch	282
Greensboro Terminal II	NC0003671	Minor	1	36.08083	-79.9319	Horsepen Creek	207
Guilford Co Sch- Alamance E	NC0038181	Minor	1	36.025	-79.7089	Little Alamance Creek (Guilford County)	317
Guilford Co Sch-Colfax Elem	NC0038261	Minor	1	36.10972	-80.0069	Reedy Fork	165
Guilford Co Sch-E Guilford	NC0038105	Minor	1	36.09194	-79.6186	Little Alamance Creek (Guilford County)	231
Guilford Co Sch-Northwest J	NC0038130	Minor	1	36.15583	-79.9494	Moores Creek	125
Guilford Co Sch-Ple'snt Gar	NC0043362	Minor	1	35.95194	-79.7608	Little Alamance Creek (Guilford County)	397
Guilford Co Sch-Southeast H	NC0044385	Minor	1	35.97417	-79.695	Big Alamance Creek (Alamance Creek)	381
Guilford Co Sch-Summerfield	NC0038245	Minor	1	36.19889	-79.9111	Reedy Fork	98
Guilford Correctional Center WWTP	NC0029726	Minor	1	36.11667	-79.7	North Buffalo Creek	174
Guilford CountyTerminal	NC0042501	Minor	1	36.07417	-79.9339	East Fork Deep River	249
Hanson Brick - Pleasant Garden WWTP	NC0085201	Minor	1	35.96778	-79.7675	Polecat Creek	444
Harnett County Regional WTP	NC0007684	Minor	1	35.40833	-78.8167	Cape Fear River	1140
Harvin Reaction Technology	NC0084778	Minor	1	36.06333	-79.8831	North Buffalo Creek	244
HeatCraft Groundwater Remediation Site	NC0083658	Minor	1	34.17583	-77.9372	Barnards Creek	2847
Hexion Acme Facility	NC0003395	Minor	1	34.32917	-78.2044	Livingston Creek (Broadwater Lake)	2740
Hexion Acme Facility	NC0003395	Minor	2	34.32917	-78.2044	Livingston Creek (Broadwater Lake)	2740
Hidden Forest Estates WWTP	NC0065358	Minor	1	35.89806	-79.8228	Deep River (Randleman Lake)	563
High Falls Elementary School	NC0032948	Minor	1	35.485	-79.5264	Deep River	1051
Hill Forest Rest Home	NC0038849	Minor	1	35.61222	-79.3419	Bear Creek	872
Hilltop Mobile Home Park WWTP	NC0074446	Minor	1	35.97722	-79.0672	Old Field Creek	366
Hoffer WTP	NC0076783	Minor	1	35.07778	-78.8656	Cape Fear River	1732

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Hoke County WWTP	NC0089176	Major	1	34.96111	-79.1017	Rockfish Creek [(Upchurches Pond, Old Brower Mill Pond (Number Two Lake)]	1946
Holiday Inn Express	NC0040703	Minor	1	36.055	-79.7425	South Buffalo Creek	265
Holly Springs WWTP	NC0063096	Major	1	35.645	-78.8519	Utley Creek	838
Holtrachem Mfg Co LLC	NC0023639	Minor	1	34.35306	-78.2028	Cape Fear River	2725
Holtrachem Mfg Co LLC	NC0023639	Minor	2	34.35306	-78.2028	Cape Fear River	2725
Hood Creek WTP	NC0057533	Minor	1	34.30222	-78.1133	Hood Creek	2771
Hooker Furniture plant	NC0084816	Minor	1	35.96333	-79.7672	Polecat Creek	444
House of Raeford - Rose Hill WWTF	NC0066320	Minor	1	34.85944	-78.0319	Beaverdam Branch	2064
Huntington Properties, LLC	NC0041505	Minor	1	36.025	-79.8994	Bull Run	314
IBP Foods	NC0007757	Minor	1	34.49583	-77.5664	Juniper Swamp	2560
Invista Wilmington Facility	NC0001112	Major	1	34.31889	-77.9694	Northeast Cape Fear River	2769
Invista Wilmington Facility	NC0001112	Major	2	34.31	-78.0131	Cape Fear River	2753
ITG Brands Operations	NC0003638	Minor	1	36.08194	-79.7528	Muddy Creek	211
J.D. Mackintosh, Jr. WTP	NC0083828	Minor	1	36.04083	-79.5039	Big Alamance Creek (Alamance Creek)	278
J.D. Mackintosh, Jr. WTP	NCG590013	Minor	1	36.04083	-79.5039	Big Alamance Creek (Alamance Creek)	278
James Rest Home WWTF	NC0059196	Minor	1	35.7	-78.88	Big Branch	792
John F. Kime WTP	NC0087866	Minor	1	35.86194	-79.8239	Deep River (Randleman Lake)	563
Jones Ferry Road WTP	NC0082210	Minor	1	35.90833	-79.08	Morgan Creek	498
Jordan Elementary School	NC0045152	Minor	1	35.94472	-79.3222	Haw River	431
Jordan Lake WTP	NC0084093	Minor	1	35.73444	-79.0056	New Hope River Arm of B. Everett Jordan Lake	751
Jordan Lake WTP	NCG590014	Minor	1	35.73611	-79.0206	New Hope River Arm of B. Everett Jordan Lake	751
Kenansville WWTP	NC0036668	Minor	1	34.96833	-77.965	Grove Creek	1896
Kenneth Creek WWTP	NC0028118	Major	1	35.56333	-78.7942	Kenneth Creek	945
Kure Beach WWTP	NC0025763	Minor	1	33.99667	-77.9178	Cape Fear River	2897

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Lake Brandt DAF Pilot	NCG590007	Minor	1	36.17056	-79.8367	Reedy Fork (including Lake Brandt and Lake Townsend)	108
Lake Townsend WTP	NC0081671	Minor	1	36.19056	-79.7311	Reedy Fork	100
Lake Townsend WTP	NCG590017	Minor	1	36.19056	-79.7308	Reedy Fork (Hardys Mill Pond)	100
Landfill Leachate WWTP	NC0049743	Minor	1	34.33222	-77.9811	Northeast Cape Fear River	2769
Lear Corporation WWTP	NC0002305	Major	1	35.01667	-77.8464	Northeast Cape Fear River	1855
Lee Co. Sch.-Deep River Ele	NC0049115	Minor	1	35.59167	-79.1458	Copper Mine Creek	927
Leland Industrial Park	NC0065676	Minor	1	34.27139	-78.0019	Cape Fear River	2789
Lucks Inc-Seagrove	NC0000850	Minor	1	35.53444	-79.7678	Bear Creek	1020
Magnolia WWTP	NC0020346	Minor	1	34.90222	-78.1472	Stewarts Creek	2008
Magnolia WWTP	NC0020346	Minor	1A	34.90222	-78.1472	Stewarts Creek	2008
Mam Water & Sewer Corporati	NC0022861	Minor	1	35.93917	-78.9861	New Hope Creek	425
Mason Farm WWTP	NC0025241	Major	1	35.89528	-79.0239	Morgan Creek	496
McLeansville Middle School WWTP	NC0038172	Minor	1	36.1075	-79.6647	South Buffalo Creek	208
Mebane WWTP	NC0021474	Major	1	36.08889	-79.2875	Moadams Creek (Latham Lake)	216
Melbille Heights WWTP	NC0050792	Minor	1	35.8825	-79.8947	Muddy Creek	536
Melinda B Knoerzer Adaptive Ecosystem WWTP	NC0081736	Major	1	34.32389	-78.0139	Cape Fear River	2753
Military Ocean Terminal / Sunny Point	NC0029122	Minor	1	34.02139	-77.9503	Cape Fear River	2891
Military Ocean Terminal / Sunny Point	NC0029122	Minor	2	34.0075	-77.9556	Cape Fear River	2890
Military Ocean Terminal / Sunny Point	NC0029122	Minor	3	33.99389	-77.9578	Cape Fear River	2896
Moltonville Feed Mill	NC0081523	Minor	1	34.98587	-78.2536	Six Runs Creek	1875
Monarch Hosiery Mills Incorporated	NC0001210	Major	1	36.17556	-79.5158	Reedy Fork	109
Moncure Community Health Center	NC0030384	Minor	1	35.62556	-79.1003	Deep River	889
Moncure Holdings West WWTP	NC0001899	Major	1	35.61694	-79.0569	Haw River	860
Moncure Holdings West WWTP	NC0001899	Major	2	35.61667	-79.0433	Shaddox Creek	870
Moncure Plywood	NC0023442	Minor	1	35.61056	-79.0525	Haw River	886
Monroe's Mobile Home Park WWTP	NC0055913	Minor	1	35.97694	-79.8094	Polecat Creek	382
Monroeton Elementary School	NC0036994	Minor	1	36.29139	-79.7367	Troublesome Creek	10
Monterey Heights WWTP	NC0029173	Minor	1	34.10889	-77.9253	Cape Fear River	2873

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Moore Co Sch/Sandhills Elem	NC0032956	Minor	1	35.27278	-79.3933	Little River (Lower Little River)	1351
Mount Olive Pickle Company	NC0001074	Minor	2	35.19806	-78.0597	Barlow Branch	1502
Mount Olive Pickle Company	NC0001074	Minor	1	35.19806	-78.0597	Barlow Branch	1502
Mount Olive WTP #3	NC0003051	Minor	1	35.21667	-78.0542	Northeast Cape Fear River	1455
Mount Olive WWTP	NC0020575	Major	1	35.19167	-78.0472	Northeast Cape Fear River	1502
N.L. Mitchell WTP	NC0081426	Minor	1	36.08139	-79.8033	North Buffalo Creek	220
Nathanael Greene Elementary School WWTP	NC0038164	Minor	1	35.94472	-79.6089	North Prong Stinking Quarter Creek	428
National Mechanical Carbon	NC0060747	Minor	1	35.31944	-78.6172	Juniper Creek	1314
National Pipe And Plastics	NC0036366	Minor	1	36.11194	-80.0217	West Fork Deep River	228
National Pipe And Plastics	NC0036366	Minor	2	36.11139	-80.0233	West Fork Deep River	228
Nature Trails Mobile Home Park WWTP	NC0043257	Minor	1	35.85833	-79.0306	Cub Creek	591
NC DOC-Sandy Rdge Corr 4435	NC0027758	Minor	1	36.06639	-80.0025	West Fork Deep River	268
NC Renewable Power-Elizabethtown plant	NC0058297	Minor	3	34.65	-78.6372	Cape Fear River	2410
NC Renewable Power-Elizabethtown plant	NC0058297	Minor	1	34.64556	-78.6483	Cape Fear River	2420
NC Renewable Power-Elizabethtown plant	NC0058297	Minor	2	34.64556	-78.6483	Cape Fear River	2420
New Hanover Terminal	NC0076732	Minor	1	34.18861	-77.9544	Cape Fear River	2830
Newton Grove WWTP	NC0072877	Minor	1	35.225	-78.3589	Beaverdam Swamp	1433
Norman H. Larkins WPCF	NC0020117	Major	1	35.00417	-78.3458	Williams Old Mill Branch (Mill Branch)	1843
North Buffalo Creek WWTP	NC0024325	Major	1	36.10944	-79.7481	North Buffalo Creek	188
North Harnett Regional WWTP	NC0021636	Major	1	35.40139	-78.8003	Cape Fear River	1157
North Moore High School	NC0032964	Minor	1	35.46972	-79.5503	Bear Creek	1108
Northchase WWTP	NC0062804	Minor	1	34.36361	-77.8967	Northeast Cape Fear River	2713
Northchase WWTP	NC0062804	Minor	2	34.36361	-77.8967	Northeast Cape Fear River	2713
Northeast Brunswick Regional WWTP	NC0086819	Major	1	34.27083	-78.0011	Cape Fear River	2789
Northeast Middle & Senior High WWTP	NC0038156	Minor	1	36.08722	-79.6756	Reedy Fork	226

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Northside WWTP	NC0023965	Major	1	34.24083	-77.9528	Cape Fear River	2810
Oak Ridge Military Academy WWTP	NC0046043	Minor	1	36.17917	-79.9869	Haw River	94
Ocean Forest WWTP	NC0059978	Minor	1	34.09417	-77.9258	Cape Fear River	2873
Parson-Anders WTP	NC0086649	Minor	1	34.98056	-78.2822	Rowans Branch (Chestnut Pond)	1889
Parson-Anders WTP	NCG590015	Minor	1	34.98056	-78.2822	Rowans Branch (Chestnut Pond)	1889
PCS Nitrogen Fertilizer	NC0003727	Minor	1	34.27611	-77.9519	Northeast Cape Fear River	2784
Pender County WTP	NC0088820	Minor	1	34.32361	-78.0139	Cape Fear River	2753
Pender County WTP	NCG590022	Minor	1	34.32361	-78.0139	Cape Fear River	2753
Pender High School WWTP	NC0042251	Minor	1	34.54194	-78.0008	Long Creek	2531
Penderlea Elementary School WWTP	NC0085481	Minor	1	34.65139	-78.0431	Crooked Run	2369
Penman Heights WWTP	NC0055191	Minor	1	35.9	-79.9225	Muddy Creek	507
Piedmont Concrete Company	NC0078221	Minor	1	36.0575	-79.7908	Mile Run Creek	264
Pittsboro WTP	NC0080896	Minor	1	35.77444	-79.1497	Haw River	659
Pittsboro WWTP	NC0020354	Minor	1	35.71333	-79.1706	Robeson Creek	737
Pleasant Garden Enterprises	NC0001171	Minor	1	35.96083	-79.7681	Polecat Creek	444
Pleasant Garden Enterprises	NC0001171	Minor	2	35.96083	-79.7681	Polecat Creek	444
Pleasant Ridge	NC0065412	Minor	1	36.26972	-79.6083	Little Troublesome Creek	38
Pleasant Ridge WWTP	NC0065412	Minor	1	36.26972	-79.6083	Little Troublesome Creek	38
Poe's Ridge WWTP	NC0060909	Minor	1	35.6546	-79.0703	Haw River	818
Quarterstone Farm WWTP	NC0066966	Minor	1	36.13778	-79.6519	Buffalo Creek	156
Raeford WWTP	NC0026514	Major	1	34.97778	-79.1931	Rockfish Creek	1898
Ramseur WTP	NC0074454	Minor	1	35.73972	-79.6786	Sandy Creek	707
Ramseur WTP	NCG590019	Minor	1	35.73972	-79.6786	Sandy Creek	707
Ramseur WWTP	NC0026565	Minor	1	35.71861	-79.6519	Deep River	743
Randleman WWTP	NC0025445	Major	1	35.80639	-79.7833	Deep River	616
Randolph Co Boe-E Randolph	NC0040967	Minor	1	35.75472	-79.615	Reed Creek	744
Randolph Co Boe-Grays Chape	NC0040941	Minor	1	35.82111	-79.6967	Sandy Creek	625
Reedy Fork Mobile Home Park	NC0077968	Minor	1	36.175	-79.52	Reedy Fork (Hardys Mill Pond)	109
Reidsville WTP	NC0046345	Minor	2	36.2825	-79.6597	Troublesome Creek	30
Reidsville WTP	NC0046345	Minor	1	36.28444	-79.6617	Troublesome Creek (Lake Reidsville)	30

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Reidsville WWTP	NC0024881	Major	1	36.26722	-79.6039	Haw River	40
Riegelwood Mill	NC0003298	Major	1	34.35278	-78.2028	Cape Fear River	2725
Riegelwood Mill	NC0003298	Major	2	34.36417	-78.2028	Cape Fear River	2714
River Run Util-Shopping Ctr	NC0060291	Minor	1	33.94667	-78.0544	Jump and Run Creek	2901
Robbins WWTP	NC0062855	Major	1	35.42917	-79.5533	Deep River	1190
Rockfish Creek WWTP	NC0050105	Major	1	34.96889	-78.8275	Cape Fear River	1901
Rocky Point Ventures	NC0088277	Minor	1	34.37694	-77.9194	Northeast Cape Fear River	2718
Rose Hill WWTP	NC0056863	Minor	1	34.81722	-78.0072	Reedy Branch	2123
Roseboro WWTP	NC0026816	Minor	1	34.95972	-78.4925	Little Coharie Creek (Sinclair Lake)	1956
Royal Palms Mhp, LLC	NC0040860	Minor	1	34.1425	-77.9003	Mott Creek (Todds Creek)	2862
S&W Ready Mix Concrete Co.,	NC0077691	Minor	1	34.25667	-77.9494	Northeast Cape Fear River	2810
S.S. Mobile Home Park	NC0038300	Minor	1	35.73833	-79.5356	Brush Creek	740
Sampson County Rest Area	NC0024791	Minor	1	34.84722	-78.2639	Six Runs Creek	2084
Sanford plant	NC0023434	Minor	1	35.45778	-79.115	Carrs Creek	1129
Sanford Processing Plant	NC0072575	Minor	1	35.56389	-79.2197	Deep River	949
Sanford WTP	NC0002861	Minor	1	35.53611	-79.0475	Cape Fear River	960
Sanford WTP	NC0002861	Minor	2	35.53667	-79.0475	Cape Fear River	960
Sanford WTP	NC0083852	Minor	1	35.56806	-79.2322	Deep River	949
Sanford WTP	NCG590023	Minor	1	35.55472	-79.2267	Deep River	949
Sapona Manufacturing Company	NC0000639	Minor	1	35.7475	-79.7258	Deep River	694
Sapona Manufacturing Company	NC0000639	Minor	2	35.74722	-79.7261	Deep River	694
Sapona Manufacturing Company	NC0000639	Minor	3	35.74722	-79.7261	Deep River (Randleman Lake)	694
Saramar LLC	NC0084328	Minor	1	36.08333	-79.35	Haw River	255
Saxapahaw Plant WWTP	NC0042528	Minor	1	35.94639	-79.3194	Haw River	418
Scotchman 3303	NC0065307	Minor	3	34.25278	-77.9528	Northeast Cape Fear River	2810
Scotchman 3303	NC0065307	Minor	1	34.25278	-77.9528	Northeast Cape Fear River	2810
Scotchman 3303	NC0065307	Minor	1A	34.25278	-77.9553	Northeast Cape Fear River	2810
Scotchman 3303	NC0065307	Minor	2	34.25278	-77.9553	Northeast Cape Fear River	2810
Scottish Inn- Greensboro	NC0079928	Minor	1	36.02319	-79.8136	Hickory Creek	301
Seagrove Elementary School	NC0040924	Minor	1	35.54444	-79.775	Fork Creek	921

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Sears Logistics Services Inc	NC0086860	Minor	1	36.10806	-79.8242	Philadephia Lake, Buffalo Lake, and White Oak Lake)	189
Senters Rest Home	NC0048101	Minor	1	35.54028	-78.8139	Kenneth Creek	999
Shearon Harris Nuclear Power Plant	NC0039586	Major	1	35.57972	-78.9686	Buckhorn Creek (Harris Lake)	913
Shearon Harris Nuclear Power Plant	NC0039586	Major	2	35.57972	-78.9686	Buckhorn Creek (Harris Lake)	913
Shearon Harris Nuclear Power Plant	NC0039586	Major	4	35.57972	-78.9686	Buckhorn Creek (Harris Lake)	913
Shearon Harris Nuclear Power Plant	NC0039586	Major	5	35.57972	-78.9686	Buckhorn Creek (Harris Lake)	913
Shearon Harris Nuclear Power Plant	NC0039586	Major	6	35.57972	-78.9686	Buckhorn Creek (Harris Lake)	913
Shearon Harris Nuclear Power Plant	NC0039586	Major	7	35.63472	-78.9181	Buckhorn Creek (Harris Lake)	867
Shell Oil Co. Dist. Termina	NC0073938	Minor	2	36.07694	-79.9267	East Fork Deep River	249
Shields Mobile Home Park	NC0055271	Minor	1	36.14222	-79.4967	Travis Creek	145
Siler City WWTP	NC0026441	Major	1	35.72917	-79.4283	Loves Creek	714
Smith Creek WWTP	NC0000817	Minor	1	34.25861	-77.9311	Smith Creek	2795
Smith Crk Estates	NC0046299	Minor	1	34.29056	-77.8533	Smith Creek	2763
South Durham WRF	NC0047597	Major	1	35.90472	-78.9733	New Hope Creek	509
South Harnett Regional WWTP	NC0088366	Major	1	35.23028	-78.8833	Little River (Lower Little River)	1393
South Saxapahaw WTP	NC0059625	Minor	1	35.94222	-79.3267	Haw River	431
Southeast terminal	NC0026247	Minor	1	36.075	-79.9228	East Fork Deep River	249
Southern Elementary School	NC0038091	Minor	1	35.95444	-79.8567	Hickory Creek	402
Southern Guilford High School	NC0038229	Minor	1	35.95444	-79.8567	Hickory Creek	402
Southport Manufacturing Facility	NC0027065	Major	2	33.9389	-77.9956	Cape Fear River	2907
Southport Manufacturing Facility	NC0027065	Major	1	33.93417	-77.9861	Southport Restricted Area	2907
Southport Power Plant	NC0065099	Major	1	33.9436	-78.0108	Atlantic Ocean	2898
Southport Power Plant	NC0065099	Major	2	33.9436	-78.0108	Atlantic Ocean	2898
Southport WWTP	NC0021334	Minor	1	33.91667	-78.0278	Intracoastal Waterway	2920
Southside WWTP	NC0023876	Major	1	36.01806	-79.3739	Big Alamance Creek (Alamance Creek)	305
Spring Lake WWTP	NC0030970	Major	1	35.19417	-78.9644	Little River (Lower Little River)	1483
Springer Eubank Co, Inc.	NC0077682	Minor	1	34.19219	-77.9449	Cape Fear River	2830

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Staley Hosiery Mills	NC0048241	Minor	1	36.12722	-79.4744	Big Alamance Creek (Alamance Creek)	167
Star WWTP	NC0058548	Minor	1	35.39917	-79.7764	Cotton Creek	1192
Station 24154 remediation site	NC0086380	Minor	1	36.09278	-79.8833	Horsepen Creek	172
Stepan Company - Wilmington Facility	NC0001112	Major	1	34.31889	-77.9694	Northeast Cape Fear River	2769
Stepan Company - Wilmington Facility	NC0001112	Major	2	34.31	-78.0131	Cape Fear River	2753
Sumner Elementary School	NC0037117	Minor	1	35.99194	-79.8325	Hickory Creek	374
Sunrise Park	NC0041483	Minor	1	35.97278	-79.8386	Hickory Creek	379
Sutton Steam Electric Plant	NC0001422	Major	2	34.2825	-77.9889	Cape Fear River	2789
Sutton Steam Electric Plant	NC0001422	Major	4	34.30028	-77.9925	Catfish Creek (Sutton Lake)	2754
Sutton Steam Electric Plant	NC0001422	Major	1	34.2825	-77.9889	Cape Fear River	2789
Sutton Steam Electric Plant	NC0001422	Major	10	34.30778	-77.995	Catfish Creek (Sutton Lake)	2754
Sutton Steam Electric Plant	NC0001422	Major	11	34.28778	-77.9844	Catfish Creek (Sutton Lake)	2789
Sutton Steam Electric Plant	NC0001422	Major	1A	34.2825	-77.9889	Cape Fear River	2789
Sutton Steam Electric Plant	NC0001422	Major	8	34.29139	-77.9933	Catfish Creek (Sutton Lake)	2754
Sweeney WTP	NC0002879	Minor	1	34.25667	-77.9475	Northeast Cape Fear River	2810
Sylvan Elementary School	NC0045128	Minor	1	35.88528	-79.4392	Cane Creek (South side of Haw River)	512
T.Z. Osborne WWTP	NC0047384	Major	1	36.09583	-79.6861	South Buffalo Creek	208
Tar Heel Plant	NC0078344	Major	1	34.76111	-78.7958	Cape Fear River	2223
The Cape WWTP	NC0057703	Minor	1	34.07611	-77.9267	Cape Fear River	2879
The Summit at Haw River State Park WWTP	NC0046019	Minor	1	36.24889	-79.7542	Haw River	51
Town of Mount Olive WWTP	NC0020575	Major	1	35.19167	-78.0472	Northeast Cape Fear River	1502
Town of Pittsboro WWTP	NC0020354	Minor	1	35.71333	-79.1706	Robeson Creek	737
Trails WWTP	NC0042285	Minor	1	35.94167	-79.1722	Collins Creek	437
Triangle WWTP	NC0026051	Major	1	35.88083	-78.8972	Northeast Creek	528
UNC Cogeneration Facility	NC0025305	Minor	1	35.90556	-79.0617	Morgan Creek	498
UNC Greensboro	NC0082082	Minor	1	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	10	36.07361	-79.8069	North Buffalo Creek	220

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
UNC Greensboro	NC0082082	Minor	11	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	12	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	13	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	14	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	15	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	16	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	17	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	18	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	19	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	2	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	20	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	21	36.07361	-79.8069	South Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	3	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	4	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	5	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	6	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	7	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	8	36.07361	-79.8069	North Buffalo Creek	220
UNC Greensboro	NC0082082	Minor	9	36.07361	-79.8069	North Buffalo Creek	220
United Holy Church/America-	NC0070769	Minor	1	36.14931	-79.7311	North Buffalo Creek	168
Vass WTP	NC0007838	Minor	1	35.24583	-79.2903	Little River (Lower Little River)	1443
Vass WWTP	NC0074373	Minor	1	35.23889	-79.2889	Little River (Lower Little River)	1443
Violet Sanford Holdings	NC0081493	Minor	1	35.52472	-79.2328	Purgatory Branch	1057
Vulcan Materials-Stokesdale	NC0078051	Minor	1	36.24448	-79.9361	Troublesome Creek	54
Wallace Chicken Processing Plant	NC0003344	Minor	1	34.75194	-78.0511	Rock Fish Creek (New Kirk Pond)	2226
Wallace Regional WWTP	NC0003450	Major	1	34.71694	-77.9794	Rock Fish Creek (New Kirk Pond)	2284
Wallace WWTP	NC0020702	Major	1	34.71917	-77.975	Rock Fish Creek (New Kirk Pond)	2284
Walnut Hills WWTP	NC0039527	Minor	1	34.30583	-77.9514	Northeast Cape Fear River	2769
Warsaw Mill	NC0002763	Minor	1	35.01167	-78.0136	Grove Creek	1878
Warsaw Mill	NC0002763	Minor	2	35.01167	-78.0136	Grove Creek	1878

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Warsaw WWTP	NC0021903	Minor	1	34.99306	-78.08	Stewarts Creek	1921
WASTEC Incinerator WWTP	NC0058971	Minor	1	34.2825	-77.9522	Northeast Cape Fear River	2775
Waters Elementary School WWTP	NC0039349	Minor	1	35.60194	-79.3269	Cedar Creek	928
Well #5 WTP	NC0086100	Minor	1	35.32333	-79.2786	Little Crane Creek (White Oak Creek)	1310
West Point Place WWTP	NC0003522	Major	1	34.65278	-78.6389	Cape Fear River	2410
Western Alamance High School	NC0045144	Minor	1	36.15194	-79.49	Haw River	141
Western Alamance Middle School	NC0031607	Minor	1	36.15861	-79.4939	Haw River	129
Western Wake Regional WRF	NC0088846	Major	1	35.53611	-78.9847	Cape Fear River	978
Wheels Estates of Spring Lake	NC0022489	Minor	1	35.18167	-79.0228	Little River (Lower Little River)	1516
Whispering Pines WTP	NC0077101	Minor	1	35.25	-79.3742	Whispering Pines Lake	1357
White Lake WWTP	NC0023353	Minor	1	34.62778	-78.4581	Colly Creek	2422
White Oak Plant	NC0000876	Major	1	36.10389	-79.7694	North Buffalo Creek	193
White Oak Plant	NC0000876	Major	5	36.10389	-79.7694	North Buffalo Creek	193
White Oak Plant	NC0000876	Major	6	36.10389	-79.7694	North Buffalo Creek	193
Williamsburg Elementary School	NC0066010	Minor	1	36.27806	-79.6233	Haw River	38
Williamsburg Plant	NC0001384	Minor	1	36.25528	-79.5147	Laughin Creek	64
Williamsburg Plant	NC0001384	Minor	3	36.2575	-79.5161	Grays Branch	41
Williamsburg Plant	NC0001384	Minor	2	36.25556	-79.5158	Laughin Creek	64
Willow Oak MHP WWTP	NC0060259	Minor	1	36.27389	-79.6092	Little Troublesome Creek	38
Willow Oaks	NC0060259	Minor	1	36.27389	-79.6092	Little Troublesome Creek	38
Wilmington Acid Plant formerly EDC Mixed Acid Facility	NC0023477	Minor	1	34.27306	-77.9522	Northeast Cape Fear River	2784
Wilmington Facility WWTP	NC0059234	Major	1	34.32389	-78.0144	Cape Fear River	2753
Wilmington Facility WWTP	NC0059234	Major	2	34.32389	-78.0139	Cape Fear River	2753
Wilmington Fiber Optic Facility	NC0003794	Minor	1	34.25278	-77.8689	Spring Branch	2793
Wilmington Fiber Optic Facility	NC0003794	Minor	2	34.25306	-77.8675	Spring Branch	2793
Wilmington Northside WWTP	NC0023965	Major	1	34.24083	-77.9528	Cape Fear River	2810
Wilmington Processing Plant	NC0003794	Minor	1	34.25278	-77.8689	Spring Branch	2793
Wilmington Processing Plant	NC0003794	Minor	2	34.25306	-77.8675	Spring Branch	2793
Wilmington River Road Terminal	NC0073181	Minor	1	34.17833	-77.9506	Cape Fear River	2840

Table E1. Point sources represented in the SWAT model.

Facility	Permit	Size	Outfall	Latitude	Longitude	Water body	Subbasin
Wilmington Southside WWTP	NC0023973	Major	1	34.16556	-77.9489	Cape Fear River	2852
Wilmington Terminal	NC0089753	Minor	2	34.18861	-77.9539	Cape Fear River	2830
Wilmington Terminal	NC0089753	Minor	3	34.1875	-77.9536	Cape Fear River	2830
Wilmington Terminal	NC0089753	Minor	4	34.1875	-77.9539	Cape Fear River	2830
Wilmington Terminal - South Front St	NC0066711	Minor	1	34.21917	-77.9506	Cape Fear River	2820
Wilmington Terminal Facility	NC0082970	Minor	1	34.22111	-77.9508	Cape Fear River	2820
Wilmington Terminal Facility	NC0082970	Minor	2	34.22111	-77.9508	Cape Fear River	2820
Wilmington Terminal Facility	NC0082970	Minor	3	34.22222	-77.9511	Cape Fear River	2820
Wilmington Woodbine Street Terminal	NC0073172	Minor	1	34.21111	-77.9542	Cape Fear River	2822
Woodlake Country Club WWTP	NC0061719	Minor	1	35.2175	-79.1858	Crane Creek (Lake Surf)	1441
Woodlake MHC WWTP	NC0023299	Minor	1	35.97	-79.7953	Polecat Creek	395

Table E2. Point source discharge parameters, measurements, and conversion factors.

Parameter	Rank	Number of values	Parameter code	Parameter description	Measure type	Units
Flow	1	72985	50050	Flow, in conduit or thru treatment plant	Total	Million Gallons per Day
Flow	1	284	50050	Flow, in conduit or thru treatment plant	Total	Cubic Feet per Second
Flow	1	142	50050	Flow, in conduit or thru treatment plant	Total	Gallons per Day
Flow	1	22	50050	Flow, in conduit or thru treatment plant	Total	Milligrams per Liter
Flow	1	5	50050	Flow, in conduit or thru treatment plant	Total	Gallons
Sediment	1	36100	530	Solids, Total Suspended	Concentration	Milligrams per Liter
Sediment	1	4016	530	Solids, Total Suspended	Total	Pounds per Day
Sediment	1	1	530	Solids, Total Suspended	Concentration	Parts per Billion
Sediment	1	1	530	Solids, Total Suspended	Concentration	Parts per Million
Sediment	2	21242	CO530	Solids, Total Suspended - Concentration	Concentration	Milligrams per Liter
Sediment	3	1681	QD530	Solids, Total Suspended - Quantity Daily	Total	Pounds per Day
Sediment	3	2	QD530	Solids, Total Suspended - Quantity Daily	Concentration	Milligrams per Liter
Nh3	1	26648	610	Nitrogen, Ammonia Total (as N)	Concentration	Milligrams per Liter
Nh3	1	1124	610	Nitrogen, Ammonia Total (as N)	Total	Pounds per Day
Nh3	1	1	610	Nitrogen, Ammonia Total (as N)	Concentration	Micrograms per Liter
Nh3	2	16171	CO610	Nitrogen, Ammonia Total (as N) - Concentration	Concentration	Milligrams per Liter
Nh3	3	391	QD610	Nitrogen, Ammonia Total (as N) – Quantity Daily	Total	Pounds per Day
No2	1	20	615	Nitrogen, Nitrite Total (as N)	Total	Pounds per Day
No2	1	9	615	Nitrogen, Nitrite Total (as N)	Concentration	Milligrams per Liter
No3	1	55	620	Nitrogen, Nitrate Total (as N)	Concentration	Milligrams per Liter
No3	1	20	620	Nitrogen, Nitrate Total (as N)	Total	Pounds per Day
Organic N	1	158	605	Nitrogen, Organic Total (as N)	Concentration	Milligrams per Liter
Kjeldahl N	1	3922	625	Nitrogen, Kjeldahl, Total (as N)	Concentration	Milligrams per Liter
Kjeldahl N	1	35	625	Nitrogen, Kjeldahl, Total (as N)	Total	Pounds per Day
Kjeldahl N	1	17	625	Nitrogen, Kjeldahl, Total (as N)	Concentration	Micrograms per Liter
Kjeldahl N	1	5	625	Nitrogen, Kjeldahl, Total (as N)	Concentration	Parts per Million
No2+No3	1	3755	630	Nitrite plus Nitrate Total (as N)	Concentration	Milligrams per Liter
No2+No3	1	5	630	Nitrite plus Nitrate Total (as N)	Concentration	Parts per Million
No2+No3	1	4	630	Nitrite plus Nitrate Total (as N)	Total	Pounds per Day

Table E2. Point source discharge parameters, measurements, and conversion factors.

Parameter	Rank	Number of values	Parameter code	Parameter description	Measure type	Units
Total N	1	13204	600	Nitrogen, Total (as N)	Concentration	Milligrams per Liter
Total N	1	784	600	Nitrogen, Total (as N)	Total	Pounds per Day
Total N	1	56	600	Nitrogen, Total (as N)	Total	Pounds per Year
Total N	1	6	600	Nitrogen, Total (as N)	Total	Pounds Per Month
Total N	1	1	600	Nitrogen, Total (as N)	Concentration	Parts per Billion
Total N	2	10589	CO600	Nitrogen, Total - Concentration	Concentration	Milligrams per Liter
Total N	2	29	CO600	Nitrogen, Total - Concentration	Concentration	Micrograms per Liter
Total N	2	20	CO600	Nitrogen, Total - Concentration	Concentration	Parts per Million
Total N	2	1	CO600	Nitrogen, Total - Concentration	Concentration	Parts per Billion
Total N	3	430	QD600	Nitrogen, Total - Quantity (Daily)	Total	Pounds per Day
Total N	4	8	600	Nitrogen, Total (as N)	Concentration	Milligrams per Liter
Organic P	1	1	670	Phosphorous, Total Organic (as P)	Total	Pounds per Day
Mineral P	1	41	70507	Phosphorous, in Total Orthophosphate	Concentration	Milligrams per Liter
Mineral P	2	3	660	Phosphate, Ortho (as PO4)	Concentration	Milligrams per Liter
Total P	1	15105	665	Phosphorus, Total (as P)	Concentration	Milligrams per Liter
Total P	1	356	665	Phosphorus, Total (as P)	Total	Pounds per Day
Total P	1	19	665	Phosphorus, Total (as P)	Total	Pounds per Year
Total P	1	4	665	Phosphorus, Total (as P)	Concentration	Micrograms per Liter
Total P	1	4	665	Phosphorus, Total (as P)	Total	Pounds Per Month
Total P	1	1	665	Phosphorus, Total (as P)	Concentration	Parts per Million
Total P	2	11007	CO665	Phosphorus, Total (as P) - Concentration	Concentration	Milligrams per Liter
Total P	2	32	CO665	Phosphorus, Total (as P) - Concentration	Concentration	Micrograms per Liter
Total P	2	1	CO665	Phosphorus, Total (as P) - Concentration	Concentration	Milliliters per Liter
Total P	3	155	QD665	Phosphorus, Total (as P) - Quantity Daily	Total	Pounds per Day

Appendix F. Flow and water quality records in CFRB

Table F1. In-stream gage stations in the Cape Fear River Basin with high-quality daily flow observations 2000-2019. Source: Water Quality Portal.

Subbasin	USGS station id	Name	Data quality (% complete)	Evaluated stations
113	USGS-02094500	REEDY FORK NEAR GIBSONVILLE, NC	99.95%	
114	USGS-02093800	REEDY FORK NEAR OAK RIDGE, NC	98.85%	
146	USGS-0209399200	HORSEPEN CREEK AT US 220 NR GREENSBORO, NC	100.00%	
158	USGS-0209553650	BUFFALO CREEK AT SR2819 NR MCLEANSVILLE, NC	100.00%	
171	USGS-02095500	NORTH BUFFALO CREEK NEAR GREENSBORO, NC	99.99%	
213	USGS-02096500	HAW RIVER AT HAW RIVER, NC	99.93%	1
215	USGS-02095271	NORTH BUFFALO CREEK AT CHURCH ST AT GREENSBORO, NC	99.99%	
219	USGS-02095181	N BUFFALO CR AT WESTOVER TERRACE AT GREENSBORO, NC	99.92%	
265	USGS-02095000	SOUTH BUFFALO CR NEAR GREENSBORO, NC	100.00%	2
272	USGS-02099000	EAST FORK DEEP RIVER NEAR HIGH POINT, NC	99.95%	
250	USGS-02094659	SOUTH BUFFALO CREEK NR POMONA, NC	100.00%	
286	USGS-02094770	SOUTH BUFFALO CREEK AT US 220 AT GREENSBORO, NC	100.00%	
301	USGS-02094775	RYAN CREEK BELOW US 220 AT GREENSBORO, NC	99.84%	
352	USGS-02096846	CANE CREEK NEAR ORANGE GROVE, NC	92.69%	
450	USGS-02097464	MORGAN CREEK NEAR WHITE CROSS, NC	95.14%	
496	USGS-02097517	MORGAN CREEK NEAR CHAPEL HILL, NC	100.00%	

Table F1. In-stream gage stations in the Cape Fear River Basin with high-quality daily flow observations 2000-2019. Source: Water Quality Portal.

509	USGS-02097314	NEW HOPE CREEK NEAR BLANDS, NC	100.00%	3
528	USGS-0209741955	NORTHEAST CREEK AT SR1100 NR GENLEE, NC	100.00%	4
615	USGS-0210166029	ROCKY R AT SR1300 NR CRUTCHFIELD CROSSROADS, NC	99.45%	
663	USGS-02096960	HAW RIVER NEAR BYNUM, NC	100.00%	5
677	USGS-0209782609	WHITE OAK CR AT MOUTH NEAR GREEN LEVEL, NC	90.72%	
717	USGS-02100500	DEEP RIVER AT RAMSEUR, NC	100.00%	6
808	USGS-02101800	TICK CREEK NEAR MOUNT VERNON SPRINGS, NC	89.87%	
848	USGS-02102000	DEEP RIVER AT MONCURE, NC	100.00%	7
937	USGS-02102192	BUCKHORN CREEK NR CORINTH, NC	98.63%	
1144	USGS-02102500	CAPE FEAR RIVER AT LILLINGTON, NC	100.00%	8
1575	USGS-02102908	FLAT CREEK NEAR INVERNESS, NC	100.00%	9
1842	USGS-02104220	ROCKFISH CREEK AT RAEFORD, NC	100.00%	10
2125	USGS-02105500	CAPE FEAR R AT WILM O HUSKE LOCK NR TARHEEL, NC	100.00%	11
2099	USGS-02108000	NORTHEAST CAPE FEAR RIVER NEAR CHINQUAPIN, NC	99.97%	12
2224	USGS-02106500	BLACK RIVER NEAR TOMAHAWK, NC	100.00%	13
2667	USGS-02105769	CAPE FEAR R AT LOCK #1 NR KELLY, NC	99.97%	14

Table F2. Sediment data availability and LOADEST performance for evaluated Cape Fear River Basin gage stations. Source: Water Quality Portal.

					LOADEST performance for sediment (kg/day)			
Station #	Subbasin	Station id	Name	Sediment observations 2000-2020	rho^2	NSE	Obs. Mean	Est. Mean
1	213	ncB1140000	HAW RIV AT HWY 49N AT HAW RIVER	58	0.87	0.87	20182.22	20018.83
2	265	ncB0670000	S Buffalo Crk at SR 3000 McConnell Rd nr Greensboro	163	0.44	-1.78	3821.41	2639.29
3	509	ncB3040000	New Hope Crk at SR 1107 Stagecoach Rd nr Blands	390	0.5	0.33	5563.74	5456.16
4	528	ncB3660000	NORTHEAST CRK AT SR 1100 NR NELSON	246	0.25	0.23	2351.73	3223.37
10	1842	ncB7679300	Rockfish Creek at US 401 bypass near Raeford	123	0.35	0.32	1109.18	1091.6
13	2224	ncB8750000	BLACK RIV AT NC 411 NR TOMAHAWK	58	0.37	0.36	10814.34	11517.21
14	2667	comb600_8834930	CAPE FEAR RIV AT LOCK 1 NR KELLY	256*	0.56	0.55	328471.36	338677.90

*Two observations from 2020 were included in LOADEST load estimation for sediment.

Table F3. Total nitrogen data availability and LOADEST performance for evaluated Cape Fear River Basin gage stations. Source: Water Quality Portal.

					LOADEST performance for total nitrogen (kg/day)			
Station #	Subbasin	Station id	Name	TN observations 2000-2020	rho^2	NSE	Obs. Mean	Est. Mean
1	213	ncB1140000	HAW RIV AT HWY 49N AT HAW RIVER	159	0.83	0.83	2607.94	2623.68
2	265	ncB0670000	S Buffalo Crk at SR 3000 McConnell Rd nr Greensboro	166	0.88	0.57	81.05	69.99
3	509	ncB3040000	New Hope Crk at SR 1107 Stagecoach Rd nr Blands	424	0.68	0.68	403.98	400.19
4	528	ncB3660000	NORTHEAST CRK AT SR 1100 NR NELSON	281	0.47	0.39	168.53	160.09
10	1842	ncB7679300	Rockfish Creek at US 401 bypass near Raeford	124	0.47	0.46	101.19	106.86
13	2224	ncB8750000	BLACK RIV AT NC 411 NR TOMAHAWK	122	0.88	0.88	2472.37	2504.12
14	2667	comb600_8834930	CAPE FEAR RIV AT LOCK 1 NR KELLY	388*	0.93	0.93	14487.94	14481.00

*Three observations from 2020 were included in LOADEST load estimation for total nitrogen.

Table F4. Total phosphorus data availability and LOADEST performance for evaluated Cape Fear River Basin gage stations. Source: Water Quality Portal.

					LOADEST Performance for total phosphorus			
Station #	Subbasin	Station id	Name	TP observations	rho^2	NSE	Obs. Mean	Est. Mean
1	213	ncB1140000	HAW RIV AT HWY 49N AT HAW RIVER	159	0.81	0.81	305.4	301.73
2	265	ncB0670000	S Buffalo Crk at SR 3000 McConnell Rd nr Greensboro	164	0.86	0.85	5.78	6.11
3	509	ncB3040000	New Hope Crk at SR 1107 Stagecoach Rd nr Blands	423	0.65	0.63	41.79	39.99
4	528	ncB3660000	NORTHEAST CRK AT SR 1100 NR NELSON	281	0.64	0.55	17.88	16.55
10	1842	ncB7679300	Rockfish Creek at US 401 bypass near Raeford	120	0.06	0.05	6.9	8.49
13	2224	ncB8750000	BLACK RIV AT NC 411 NR TOMAHAWK	123	0.87	0.87	172.48	167.89
14	2667	comb600_8834930	CAPE FEAR RIV AT LOCK 1 NR KELLY	310*	0.72	0.71	1700.09	1696.42

*Three observations from 2020 were included in LOADEST load estimation for total phosphorus.

Appendix G. Recent flow and water quality observations at Lock and Dam #1

This SWAT model was developed to evaluate the effectiveness of various solutions to improve water quality under a range of hydrologic conditions. Based on the availability of both flow and water quality data, we decided to use the most recent 20 years for our calibration (January 1, 2010 – December 31, 2019) and validation (January 1, 2000 – December 31, 2009). We examined water availability and water quality parameters over time at the outlet of the watershed to ensure that the calibration and validation periods each represented dry, normal, and wet states, as well as low and high loads for water quality parameters (Fig. G1 – G4).

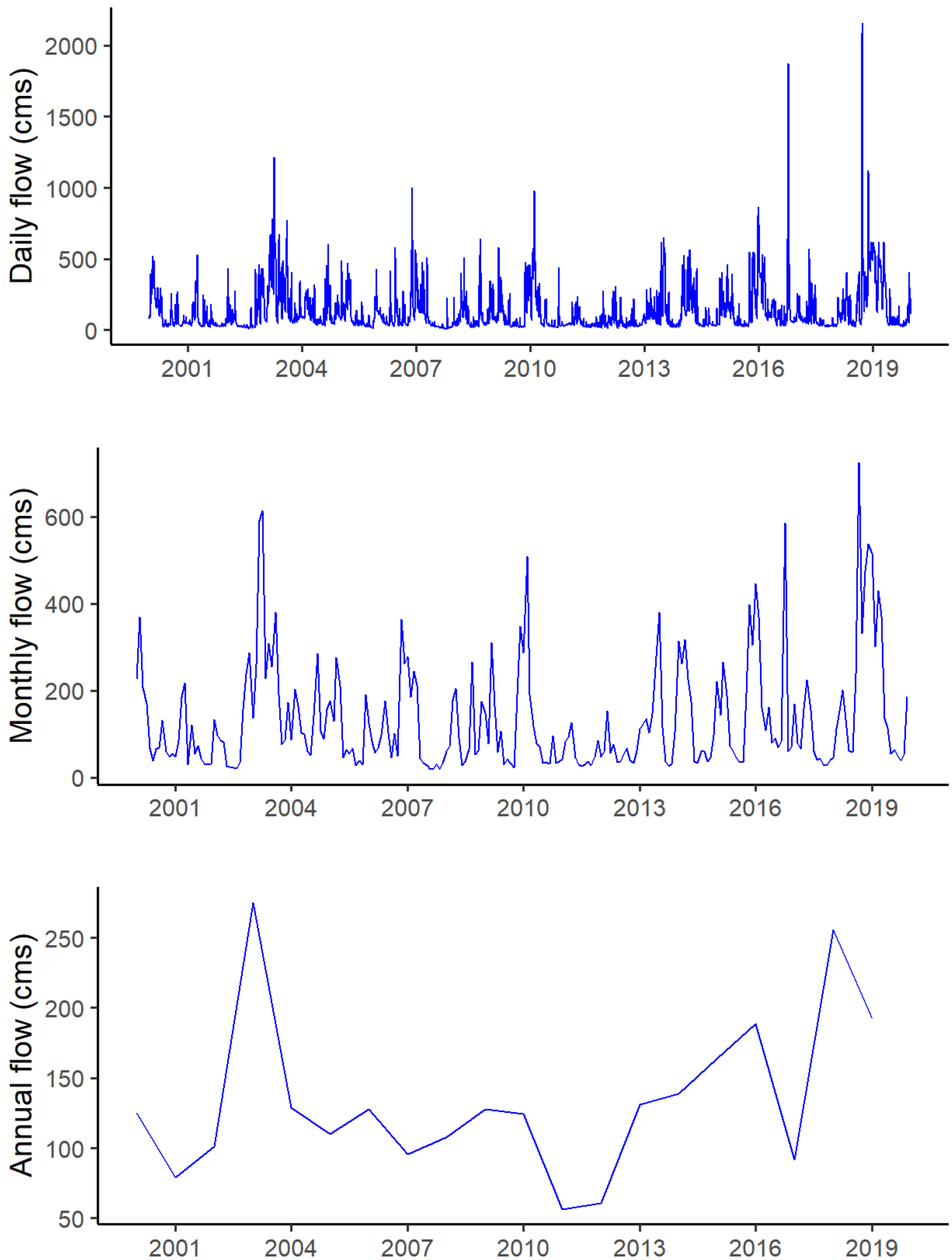


Figure G1. Observed average in-stream flow rate at Lock and Dam #1 near Kelly, NC, at daily, monthly, and annual scales 2000-2019. Source: Water Quality Portal.[120,121]

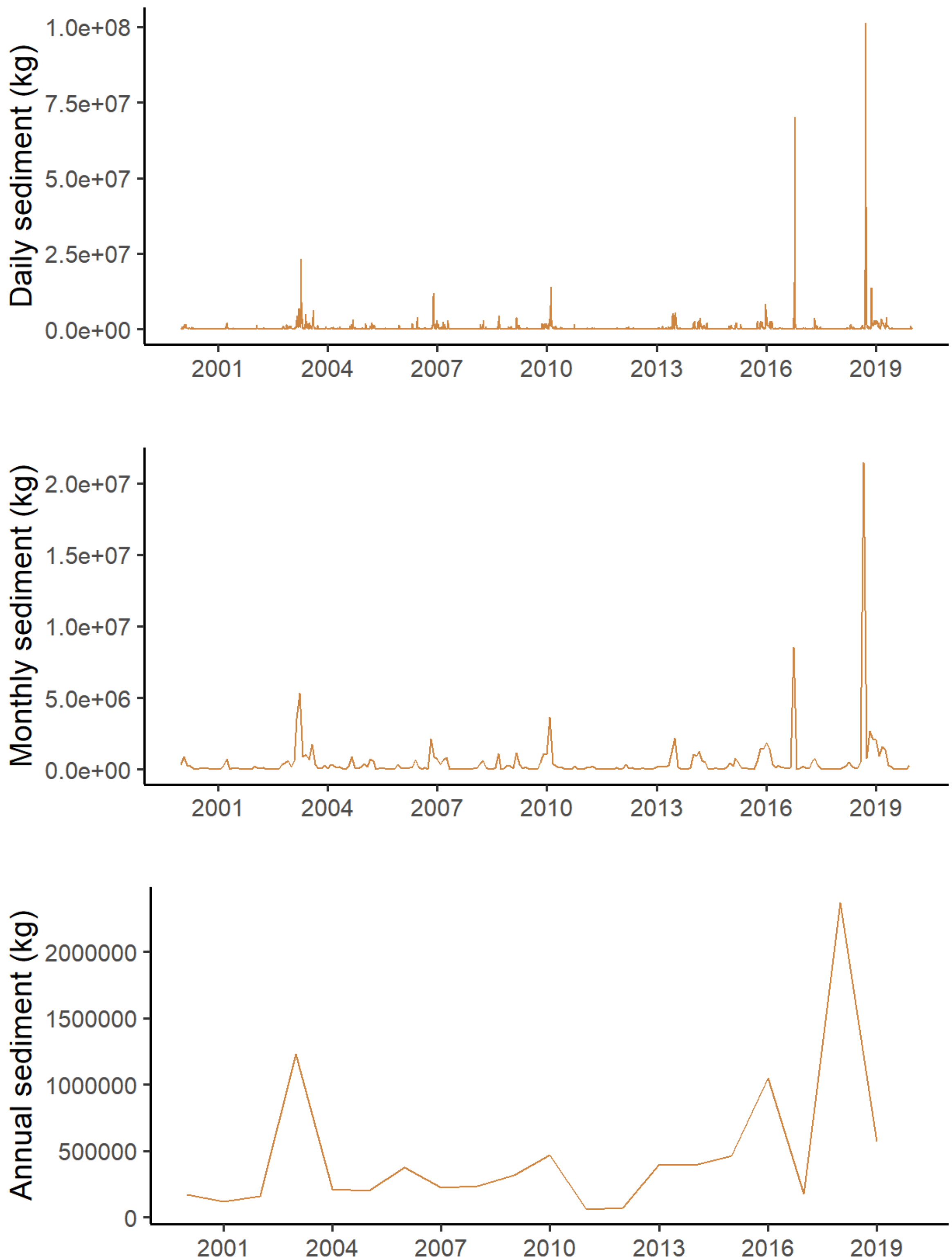


Figure G2. Mean sediment load at Lock and Dam #1 near Kelly, NC, at daily, monthly, and annual scales 2000-2019, estimated with LOADEST based on observed data. Source: Water Quality Portal.[120,121]

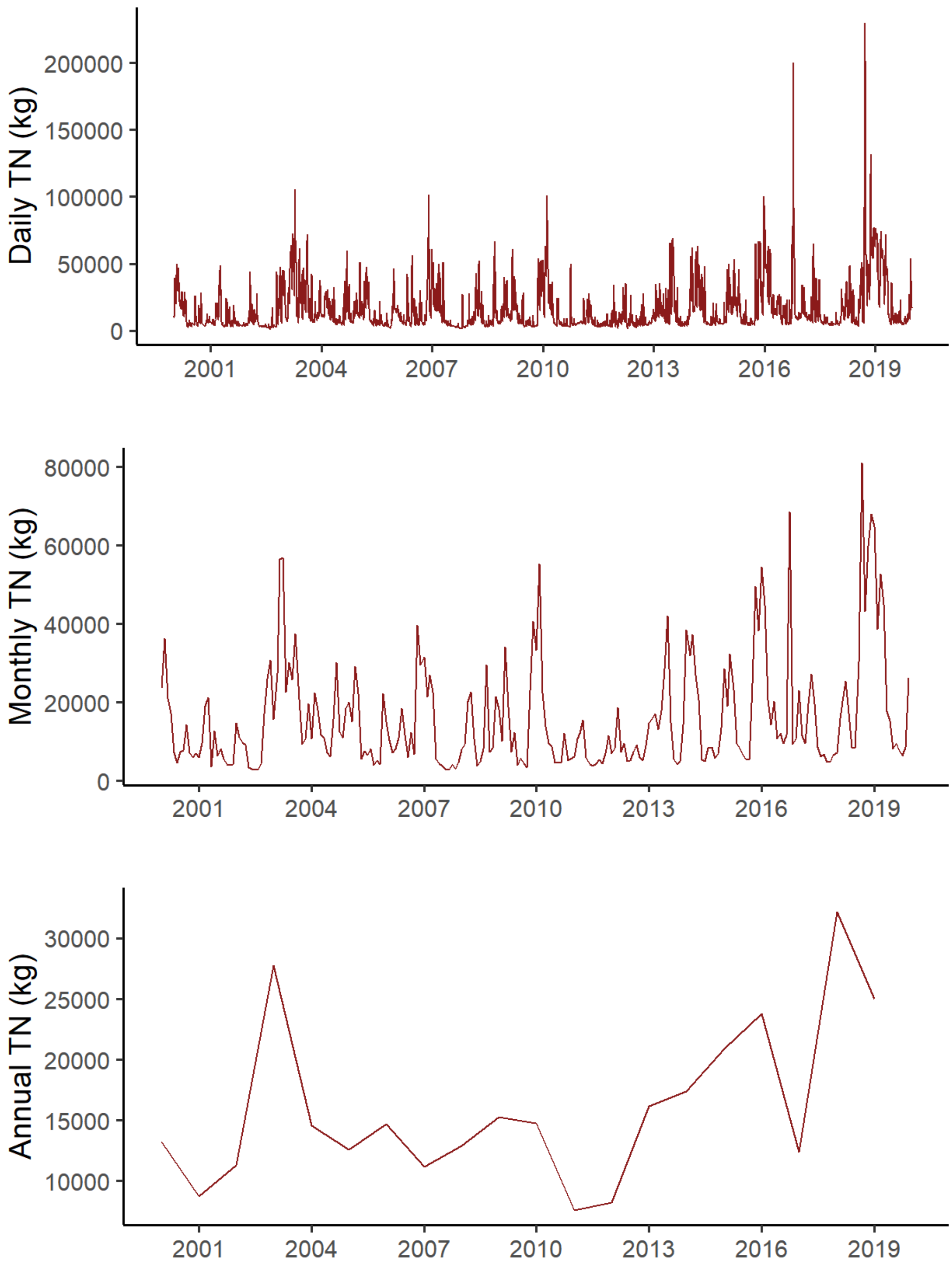


Figure G3. Mean total nitrogen load at Lock and Dam #1 near Kelly, NC, at daily, monthly, and annual scales 2000-2019, estimated with LOADEST based on observed data. Source: Water Quality Portal.[120,121]

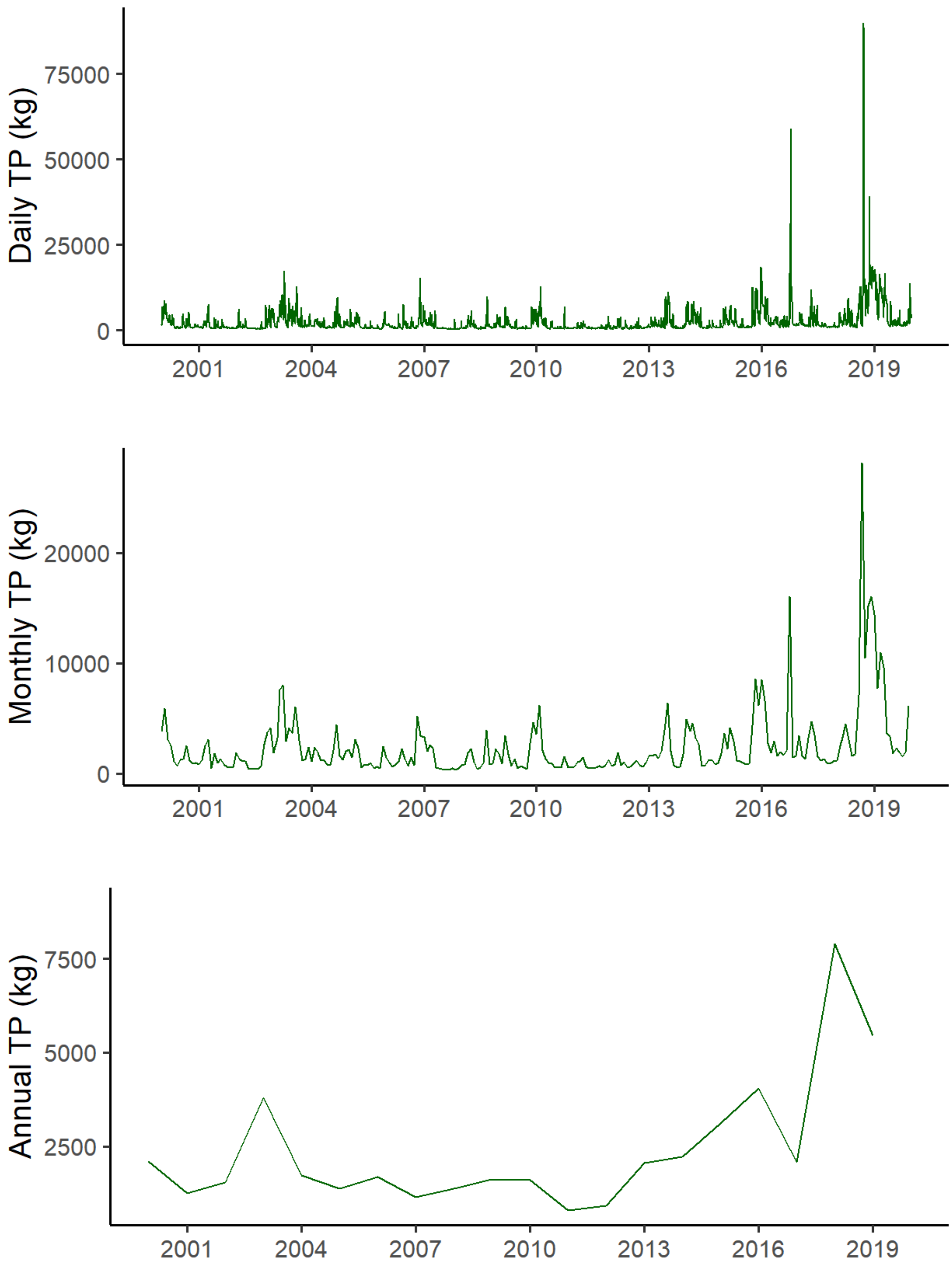


Figure G4. Mean total phosphorus load at Lock and Dam #1 near Kelly, NC, at daily, monthly, and annual scales 2000-2019, estimated with LOADEST based on observed data. Source: Water Quality Portal.[120,121]

Table G1. Daily in-stream observations of flow (cms), sediment (kg), total nitrogen (kg) and total phosphorus (kg) at Lock and Dam #1, Kelly, NC.

	Calibration (2010-2019)		Validation (2000-2009)	
	Mean	Sd	Mean	Sd
Flow	140.33	181.24	148.89	168.33
Sediment	604415.96	4094016.67	333779.71	1019575.97
Total Nitrogen	17828.21	20673.79	14416.33	14267.43
Total Phosphorus	3011.77	5401.49	1896.45	2285.91

Appendix H. Spatial evaluation of model performance

Although we relied primarily on measurements on the mainstem Cape Fear River near Kelly, NC for calibration, spatial performance was also evaluated at 13 additional stations (Table 11, Fig. 18, Fig. H.1.1-H.13.4). Six of these stations had sufficient water quality data available to perform LOADEST load estimation, and seven additional stations were retained to evaluate spatial performance for flow only.

H.1 Haw River, near Graham, NC (Subbasin 213)

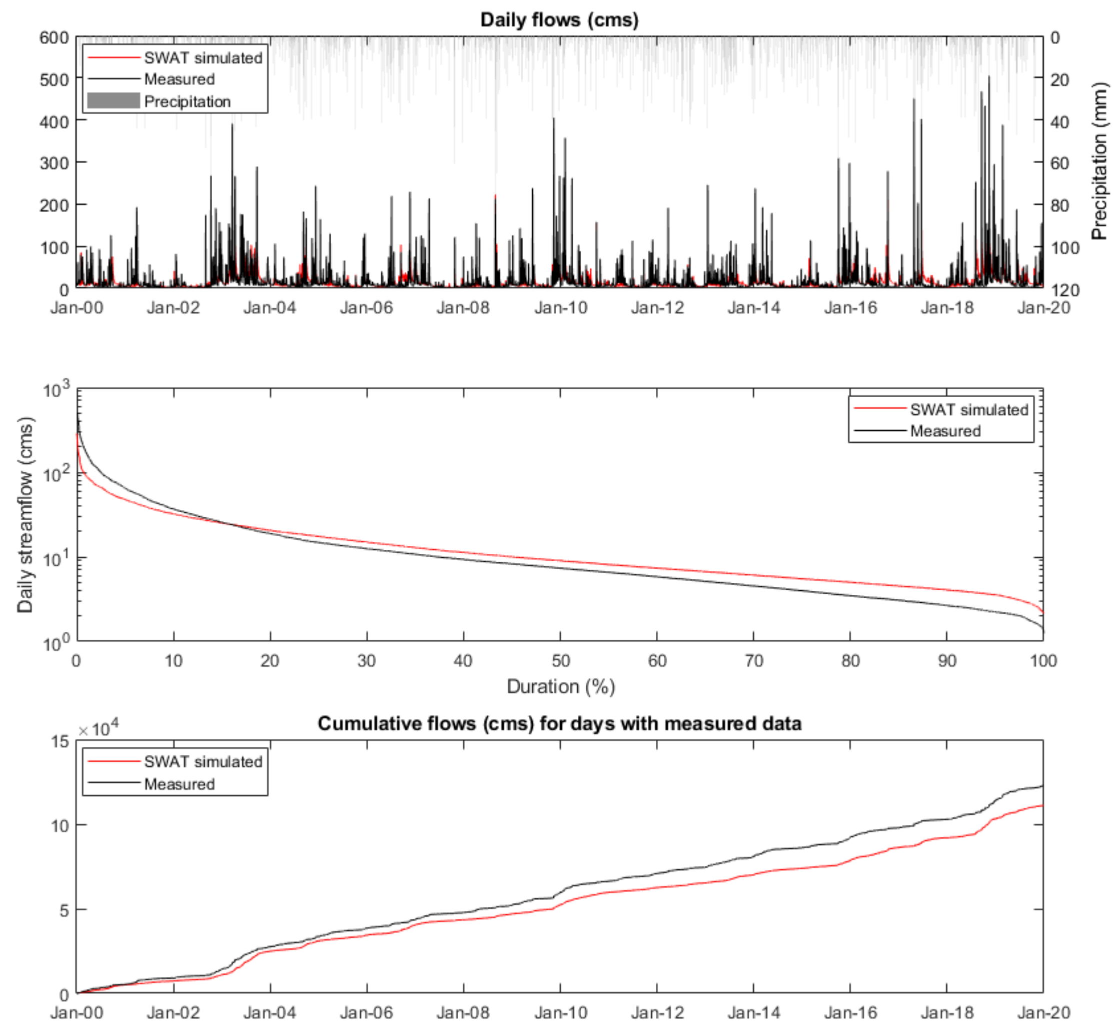


Figure H.1.1 Flow time series plot for the calibration and validation periods at the Haw River, near Graham, NC (Subbasin 213).

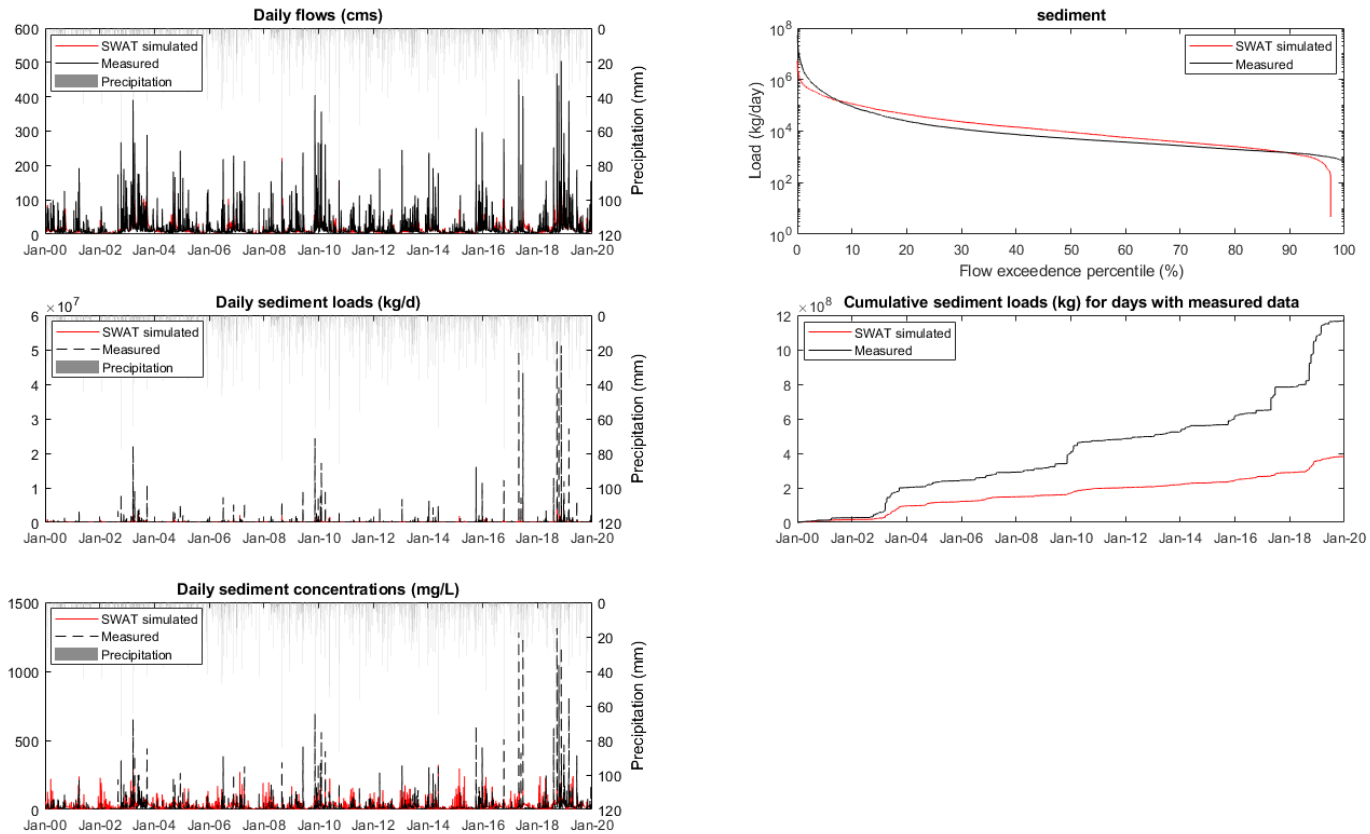


Figure H.1.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at the Haw River, near Graham, NC (Subbasin 213).

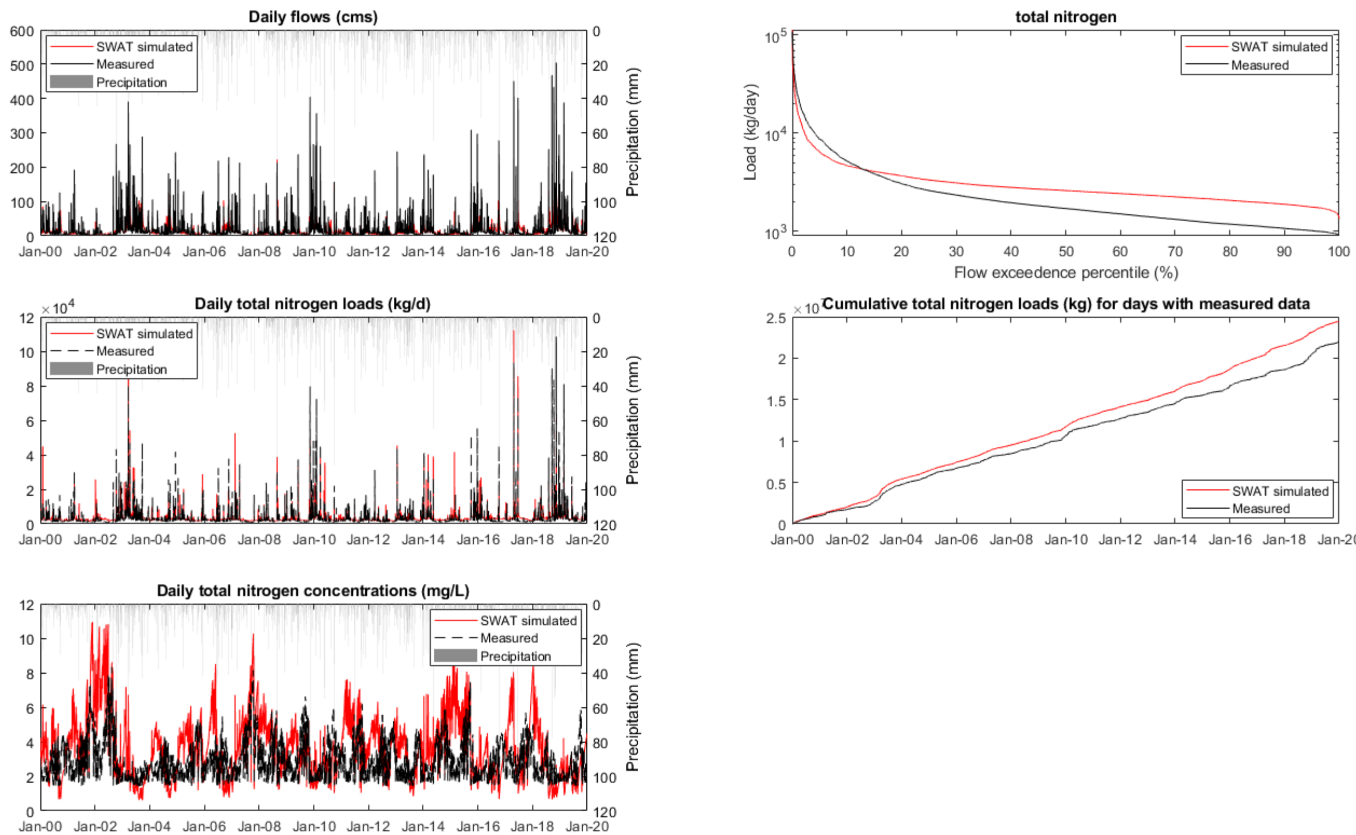


Figure H.1.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at the Haw River, near Graham, NC (Subbasin 213).

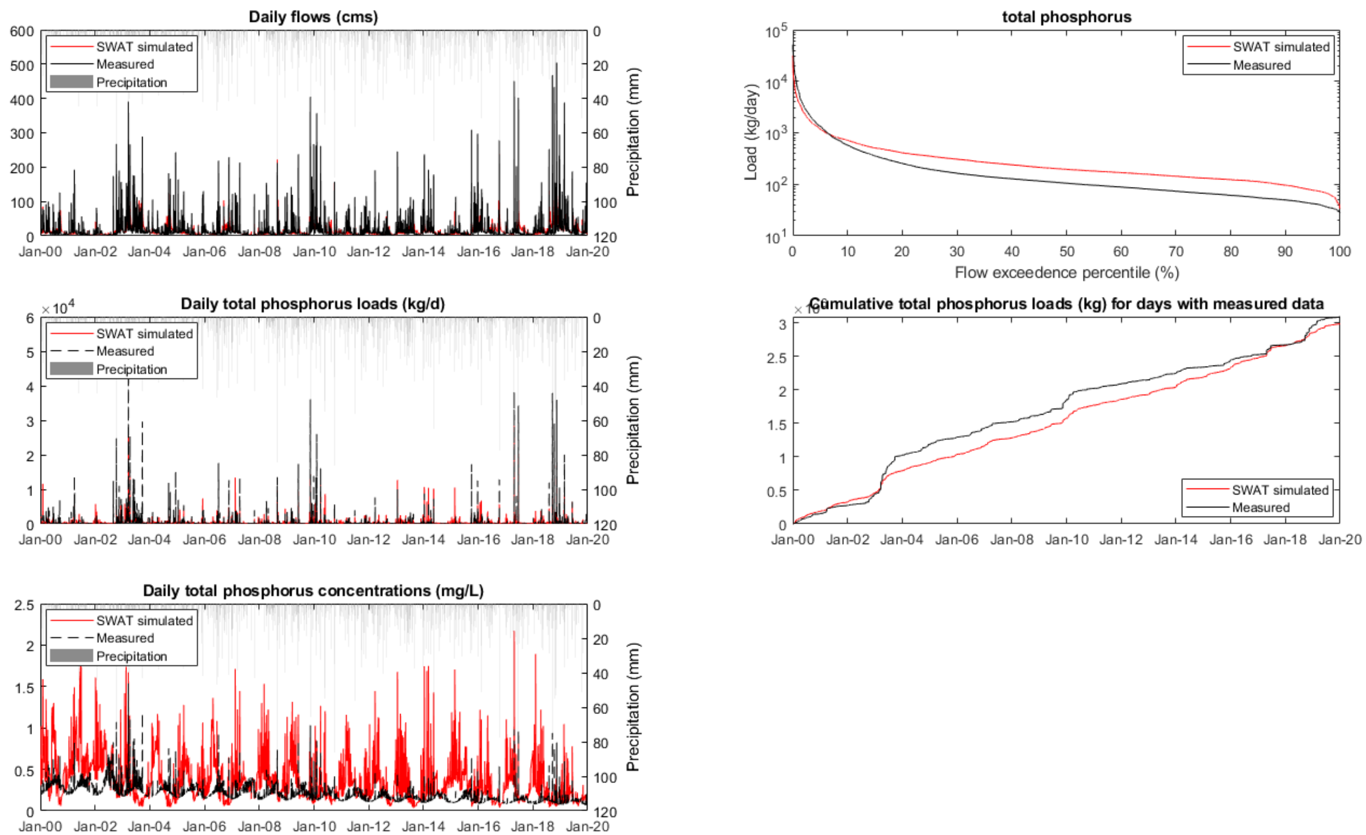


Figure H.1.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at the Haw River, near Graham, NC (Subbasin 213).
Station 2: Haw River, near Graham, NC (Subbasin 213).

H.2 South Buffalo Creek, near Greensboro, NC (Subbasin 265)

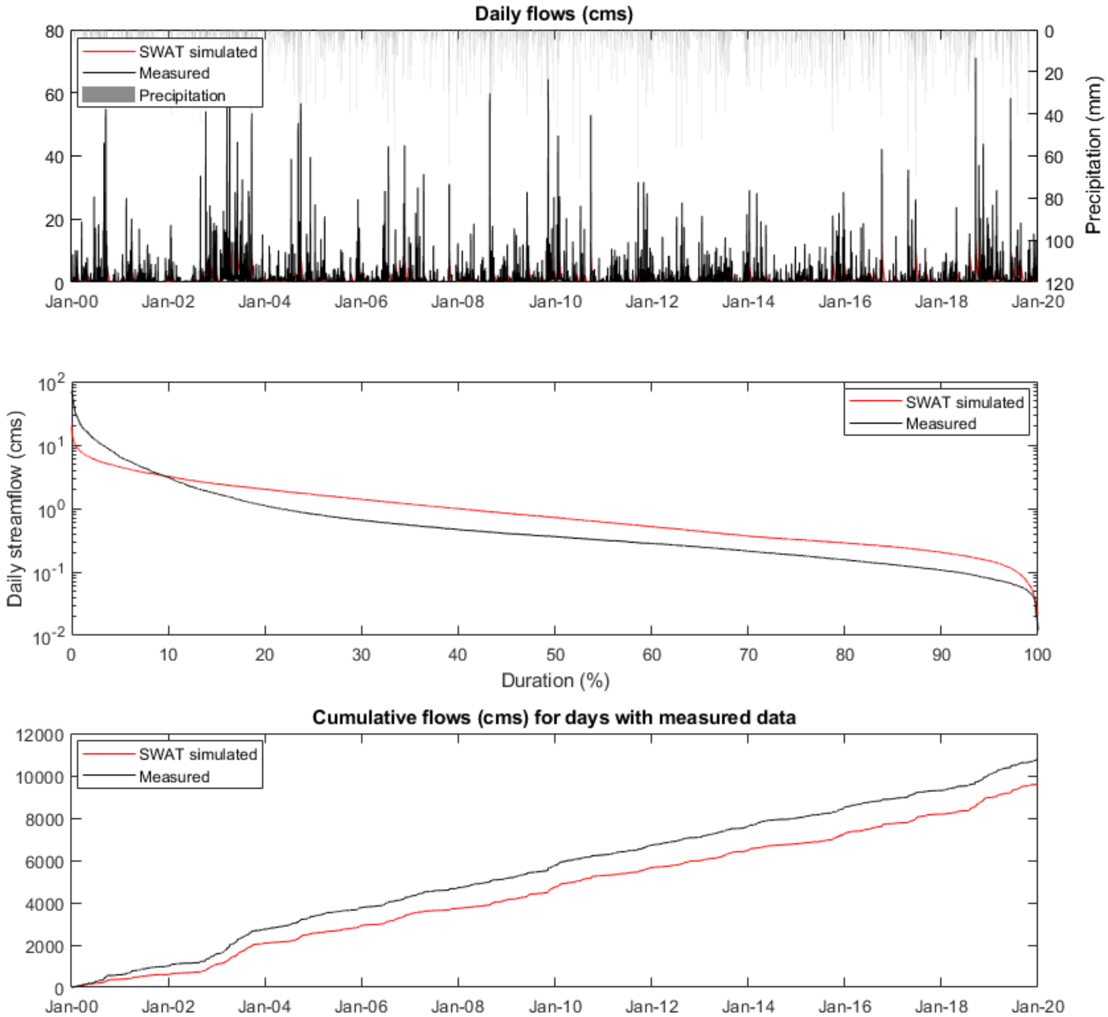


Figure H.2.1. Flow time series plot for the calibration and validation periods at South Buffalo Creek, near Greensboro, NC (Subbasin 265). There is a reservoir within Subbasin 265 that may have affected simulations at this location given that it was added after subbasin delineation. Simulated data shown is from Subbasin 233, the neighboring downstream subbasin.

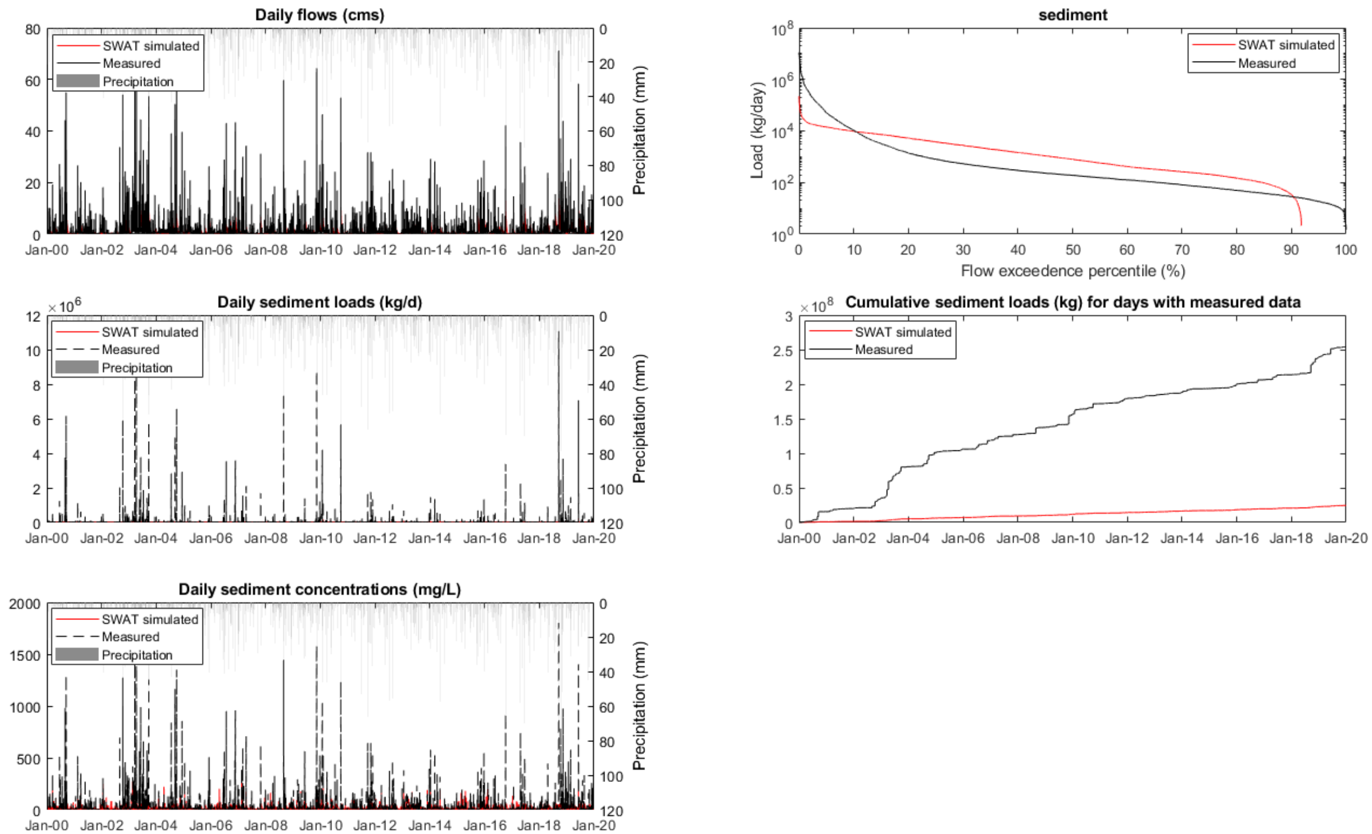


Figure H.2.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at South Buffalo Creek, near Greensboro, NC (Subbasin 265). There is a reservoir within Subbasin 265 that may have affected simulations at this location given that it was added after subbasin delineation. Simulated data shown is from Subbasin 233, the neighboring downstream subbasin.

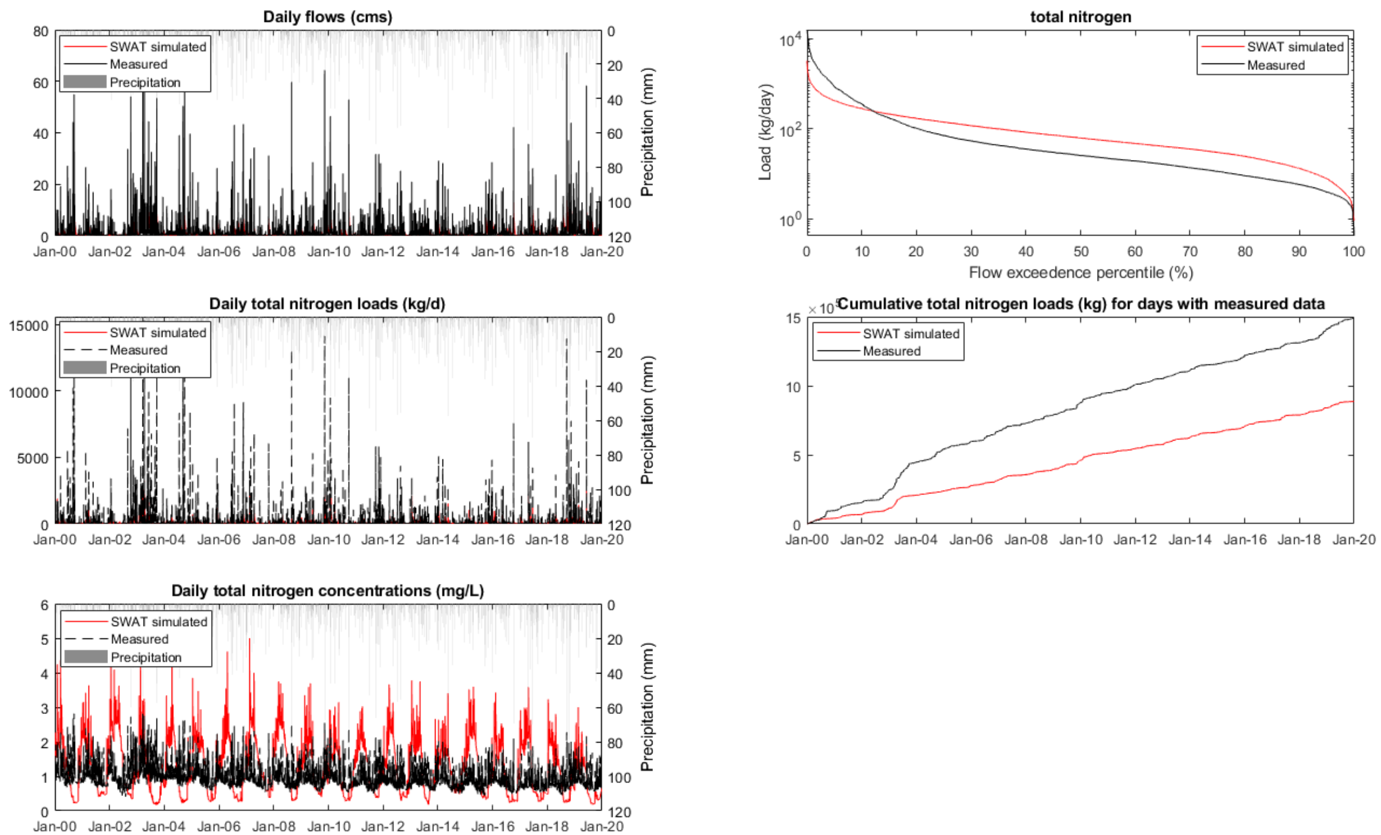


Figure H.2.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at South Buffalo Creek, near Greensboro, NC (Subbasin 265). There is a reservoir within Subbasin 265 that may have affected simulations at this location given that it was added after subbasin delineation. Simulated data shown is from Subbasin 233, the neighboring downstream subbasin.

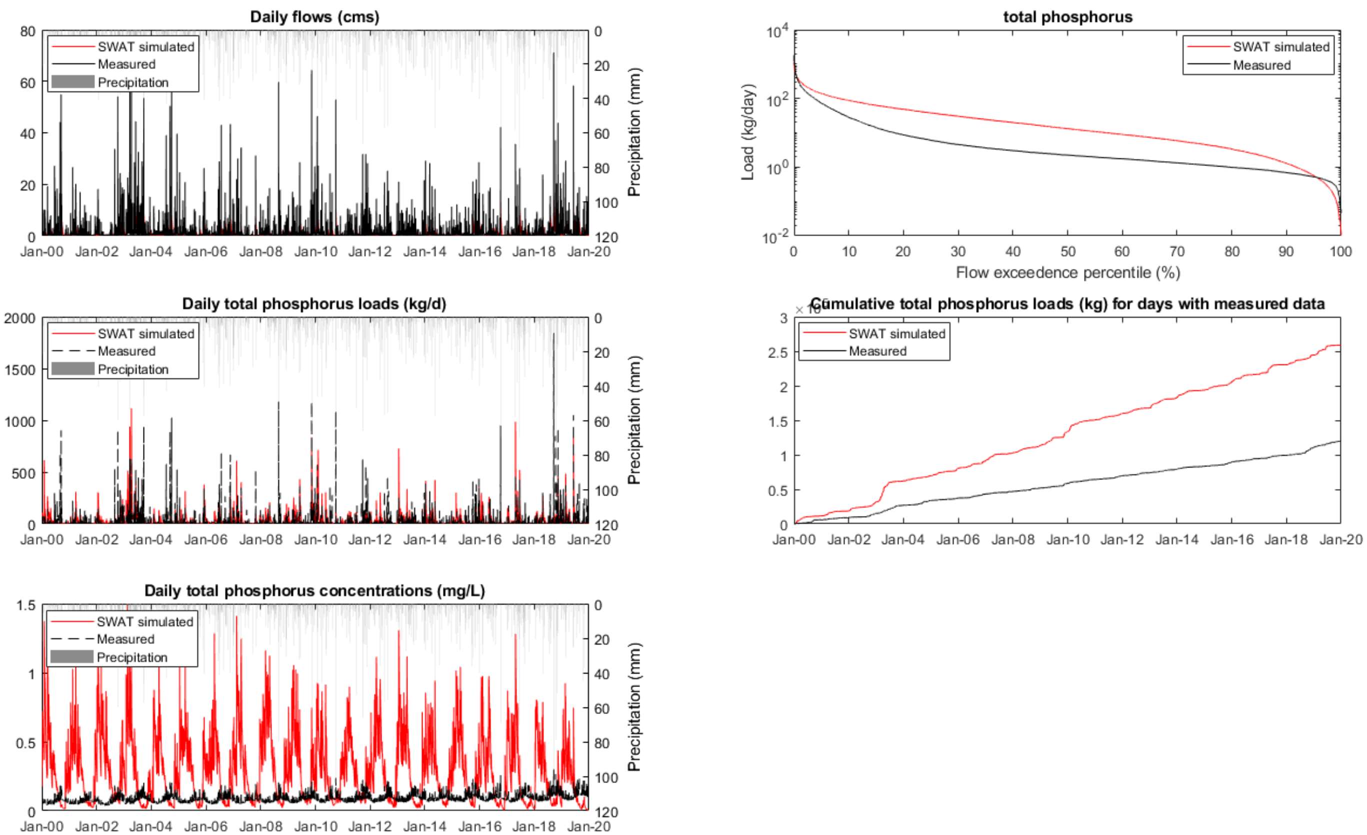


Figure H.2.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at South Buffalo Creek, near Greensboro, NC (Subbasin 265). There is a reservoir within Subbasin 265 that may have affected simulations at this location given that it was added after subbasin delineation. Simulated data shown is from Subbasin 233, the neighboring downstream subbasin.

H.3 New Hope Creek, near Blands, NC (Subbasin 509)

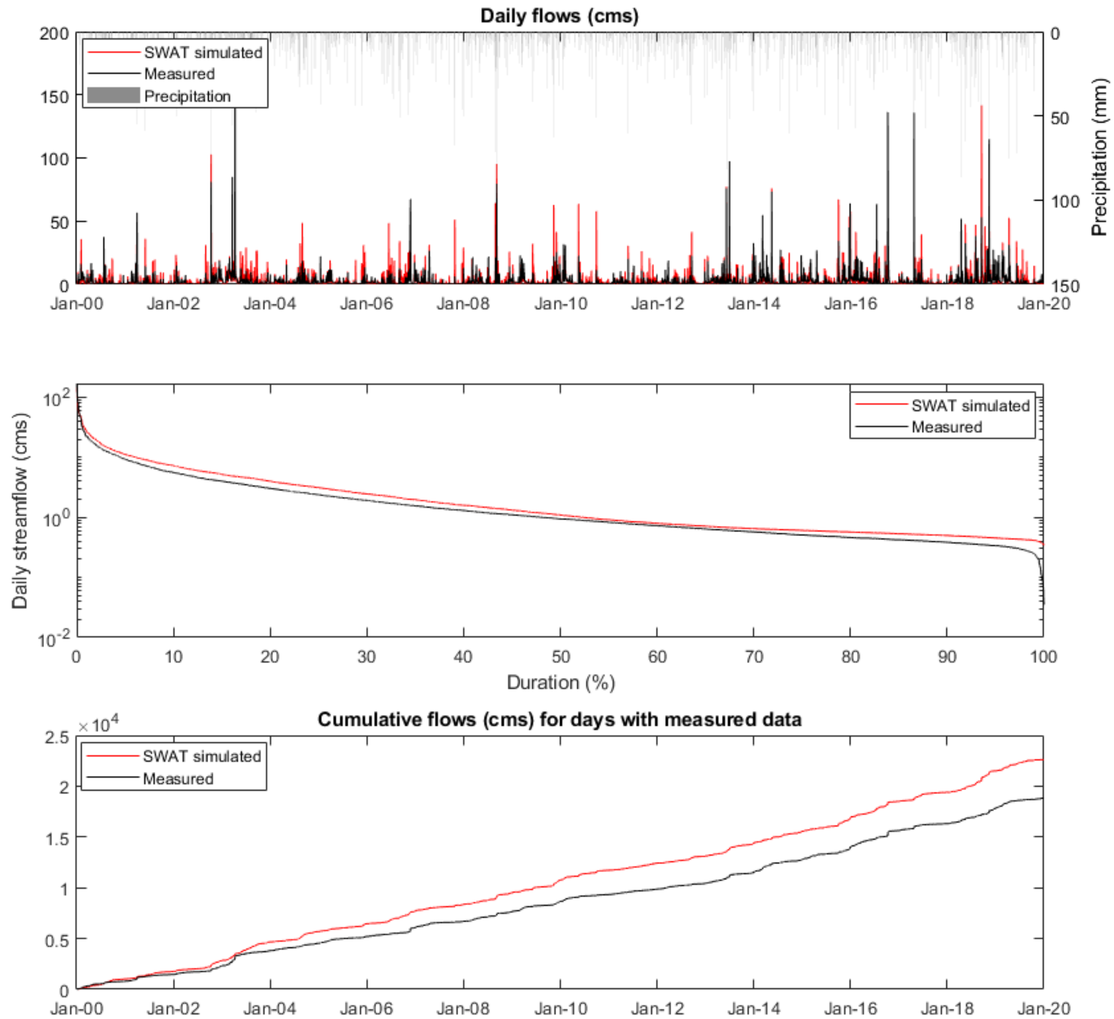


Figure H.3.1. Flow time series plot for the calibration and validation periods at New Hope Creek, near Blands, NC (Subbasin 509).

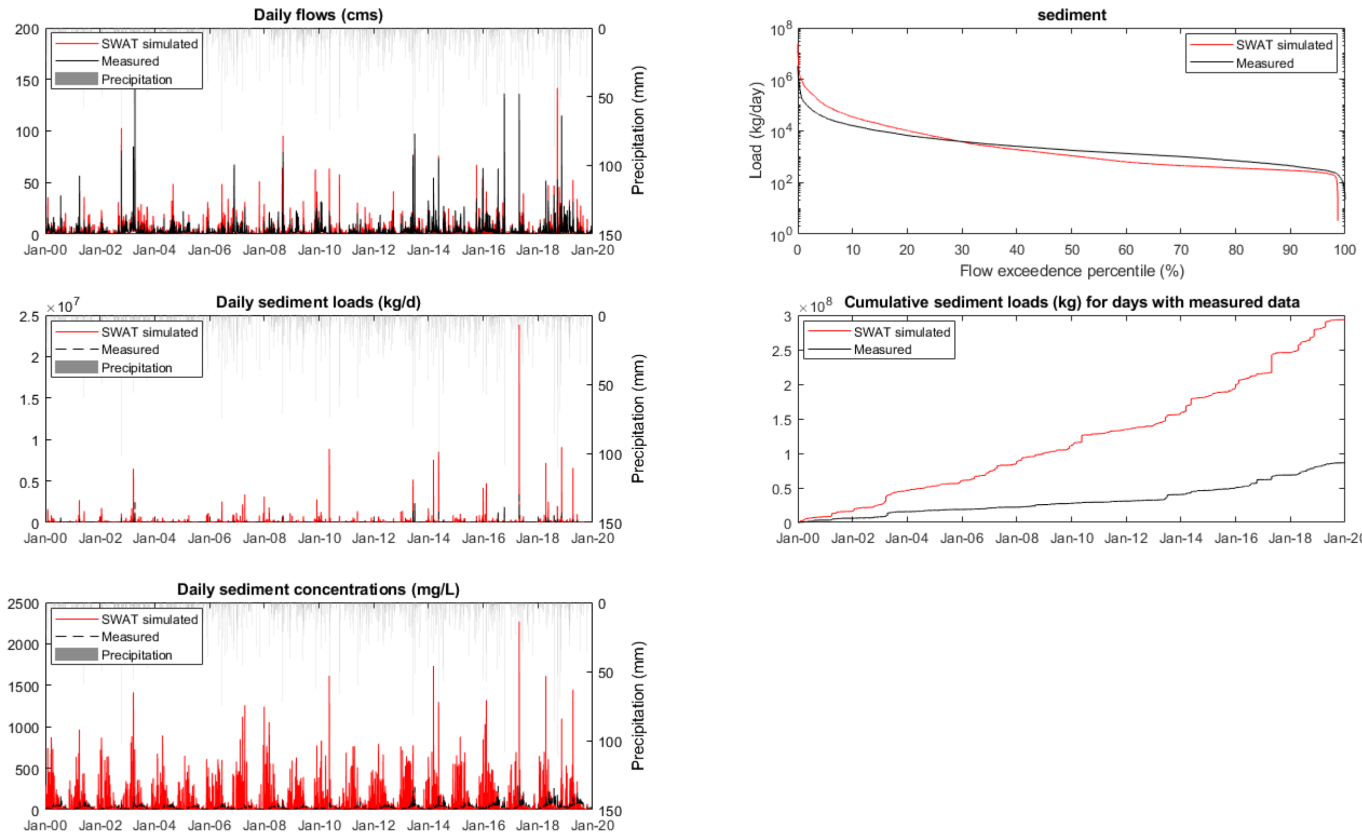
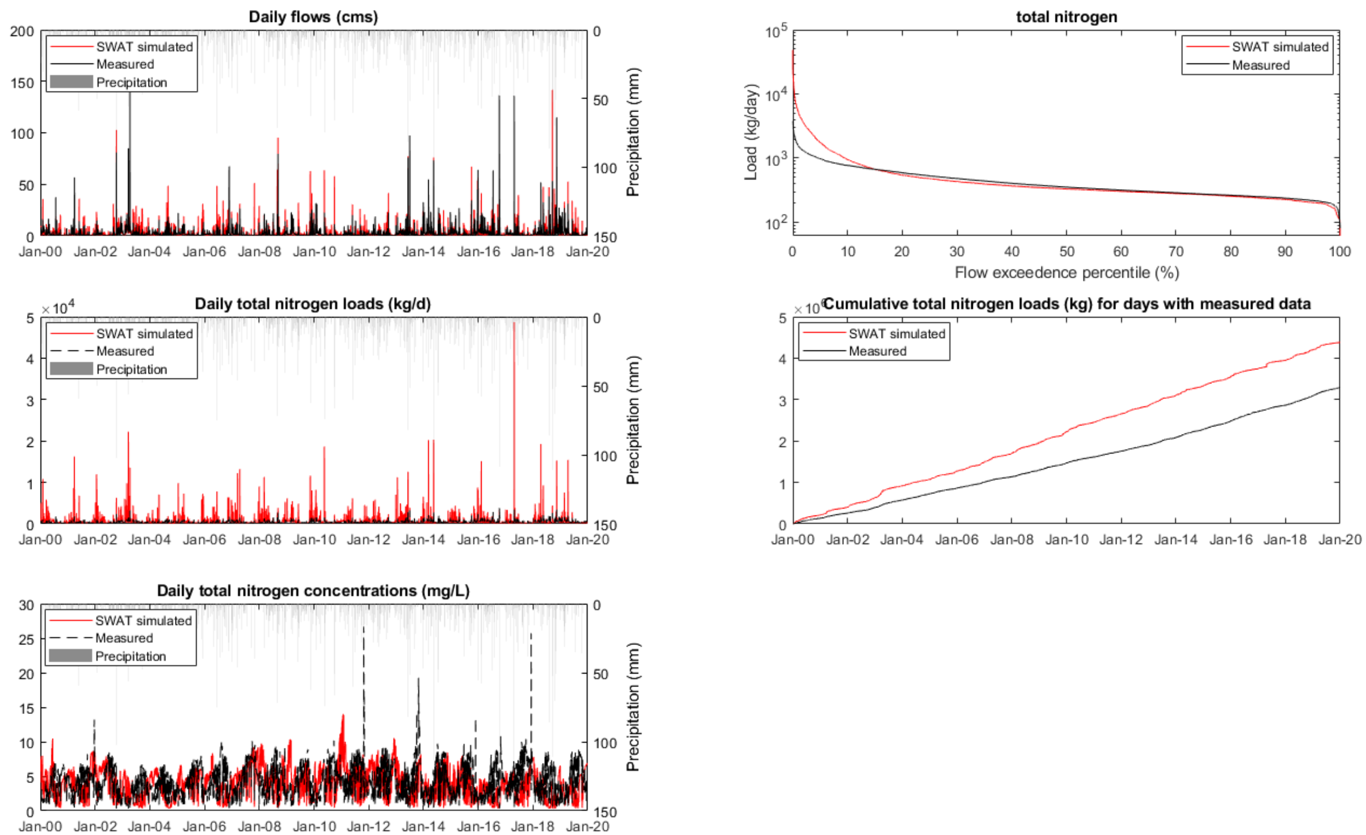


Figure H.3.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at New Hope Creek, near Blands, NC (Subbasin 509).



H.3.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at New Hope Creek, near Blands, NC (Subbasin 509).

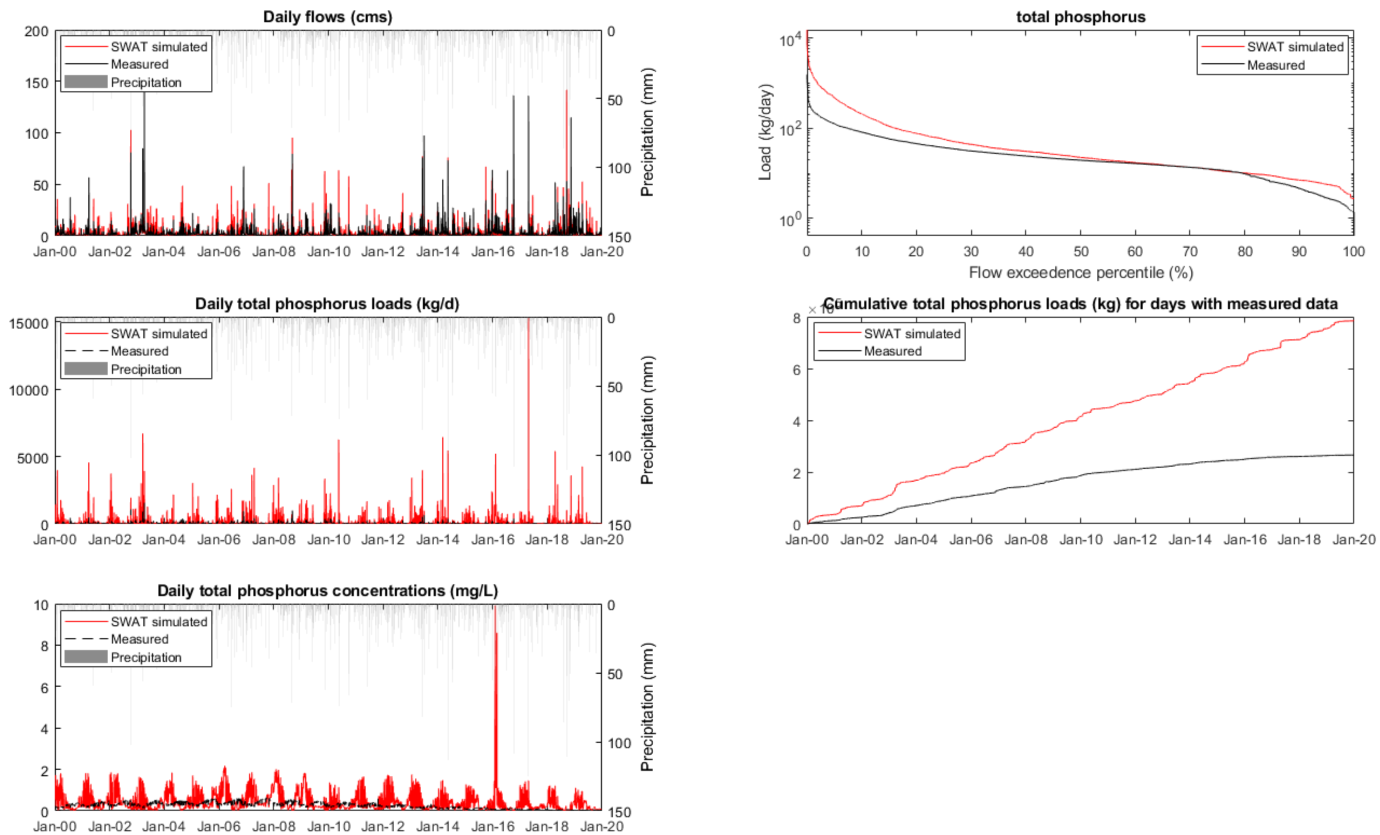


Figure H.3.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at New Hope Creek, near Blands, NC (Subbasin 509).

H.4 Northeast Creek, near Genlee, NC (Subbasin 528)

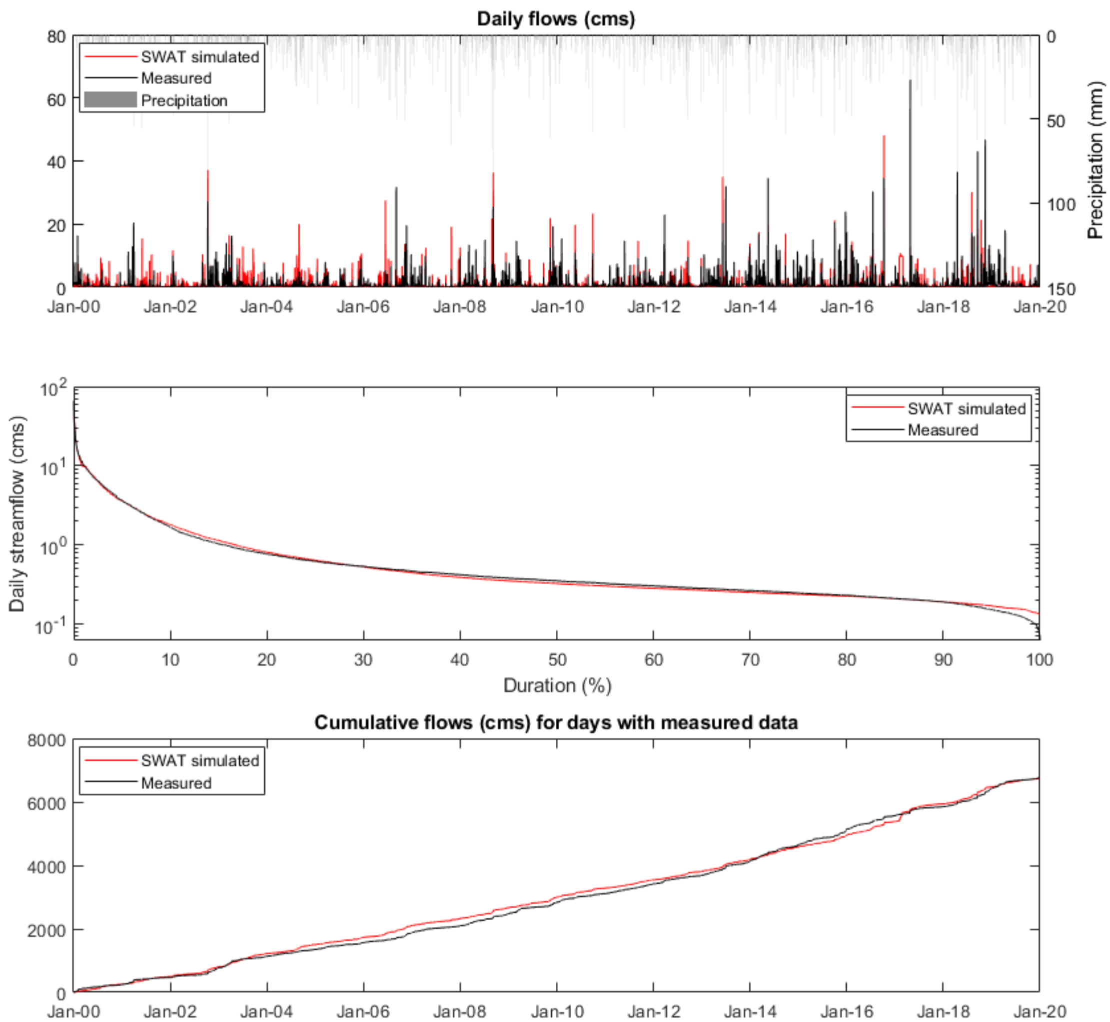


Figure H.4.1. Flow time series plot for the calibration and validation periods at Northeast Creek, near Genlee, NC (Subbasin 528).

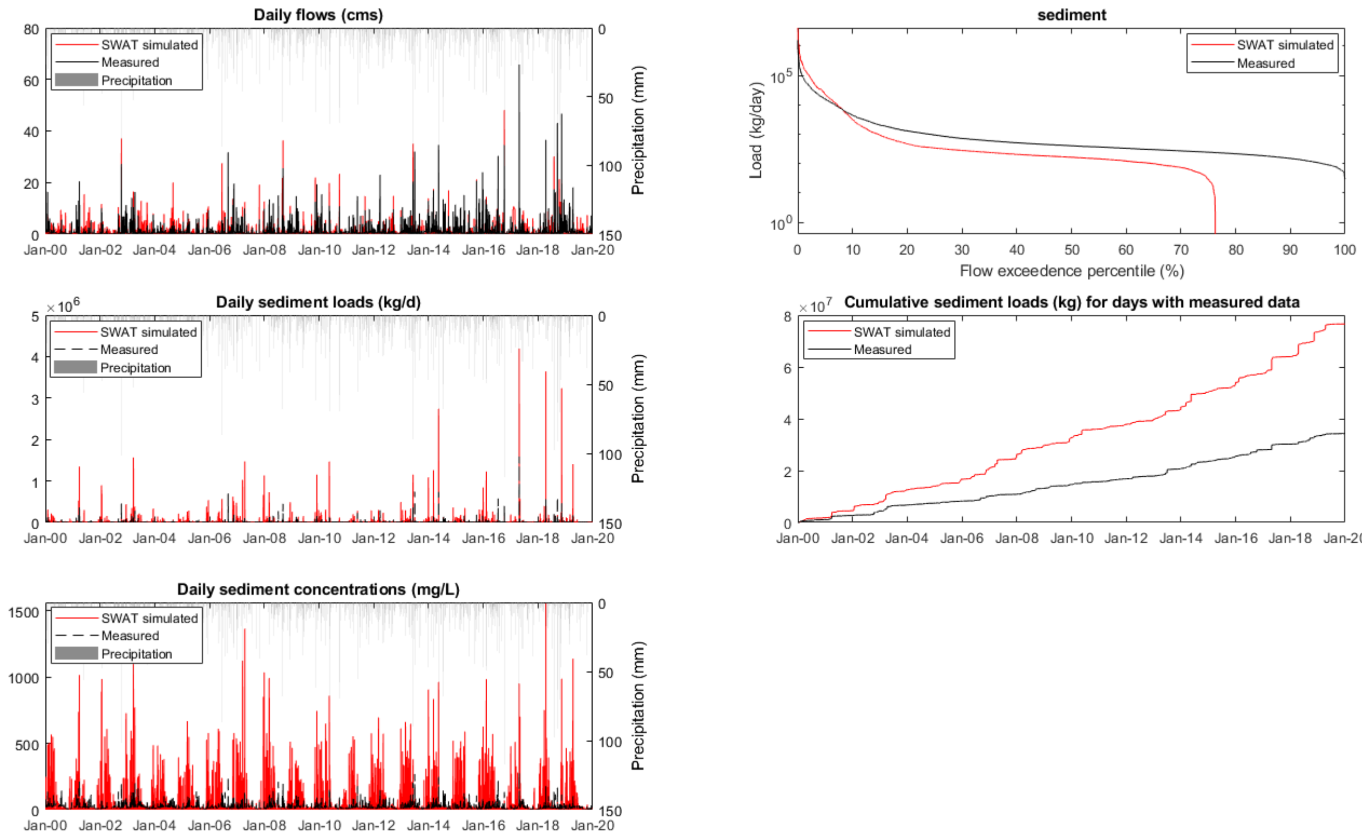


Figure H.4.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at Northeast Creek, near Genlee, NC (Subbasin 528).

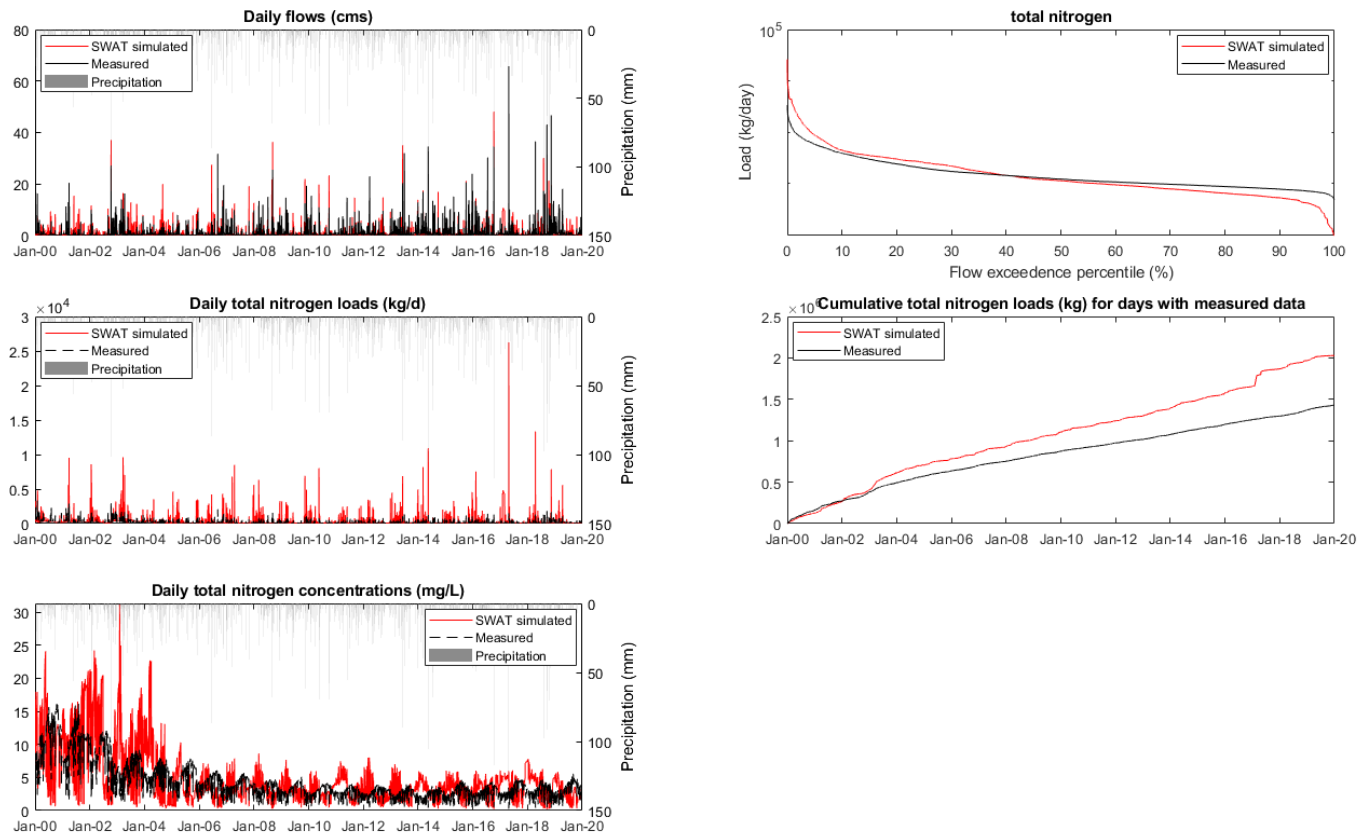


Figure H.4.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at Northeast Creek, near Genlee, NC (Subbasin 528).

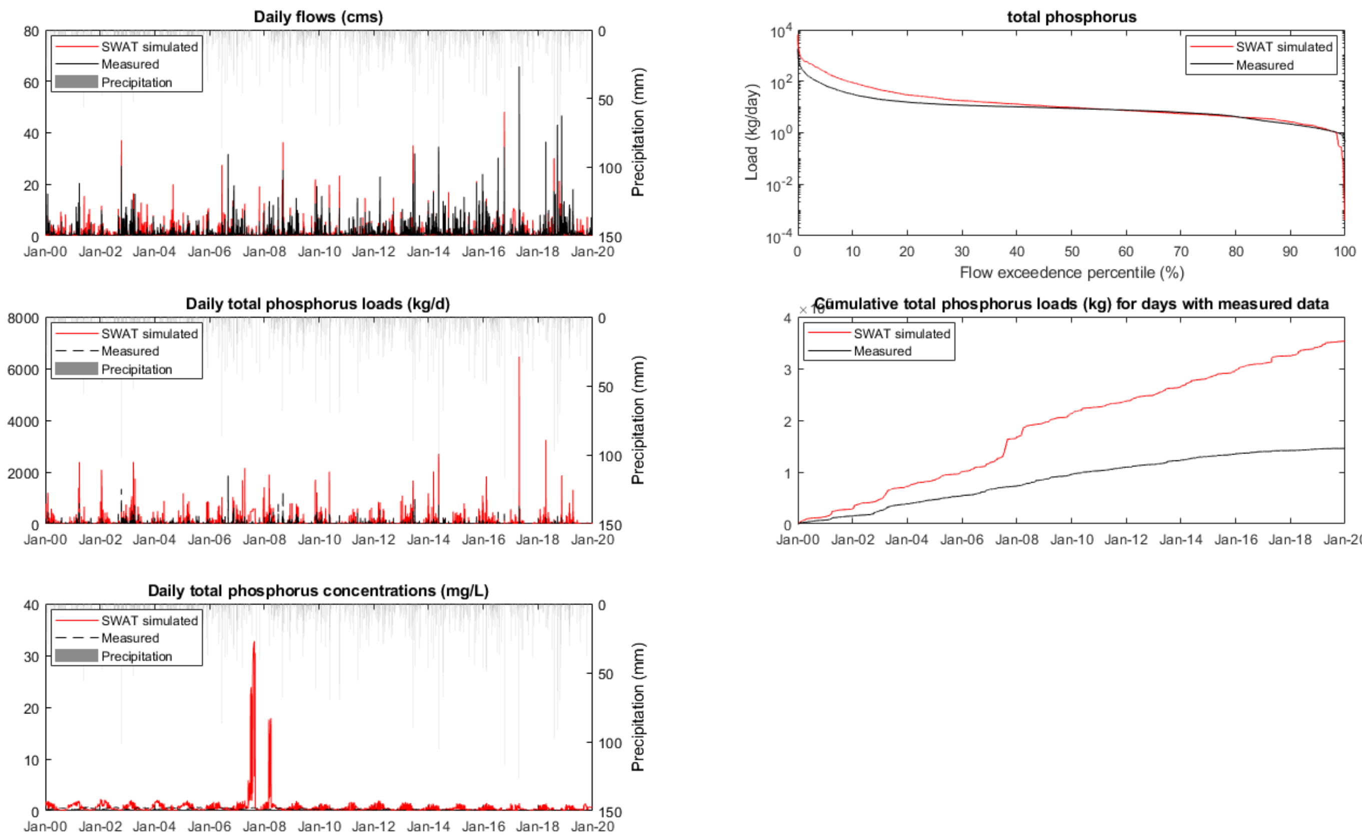


Figure H.4.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at Northeast Creek, near Genlee, NC (Subbasin 528).

H.5 Haw River, near Bynum, NC (Subbasin 663)

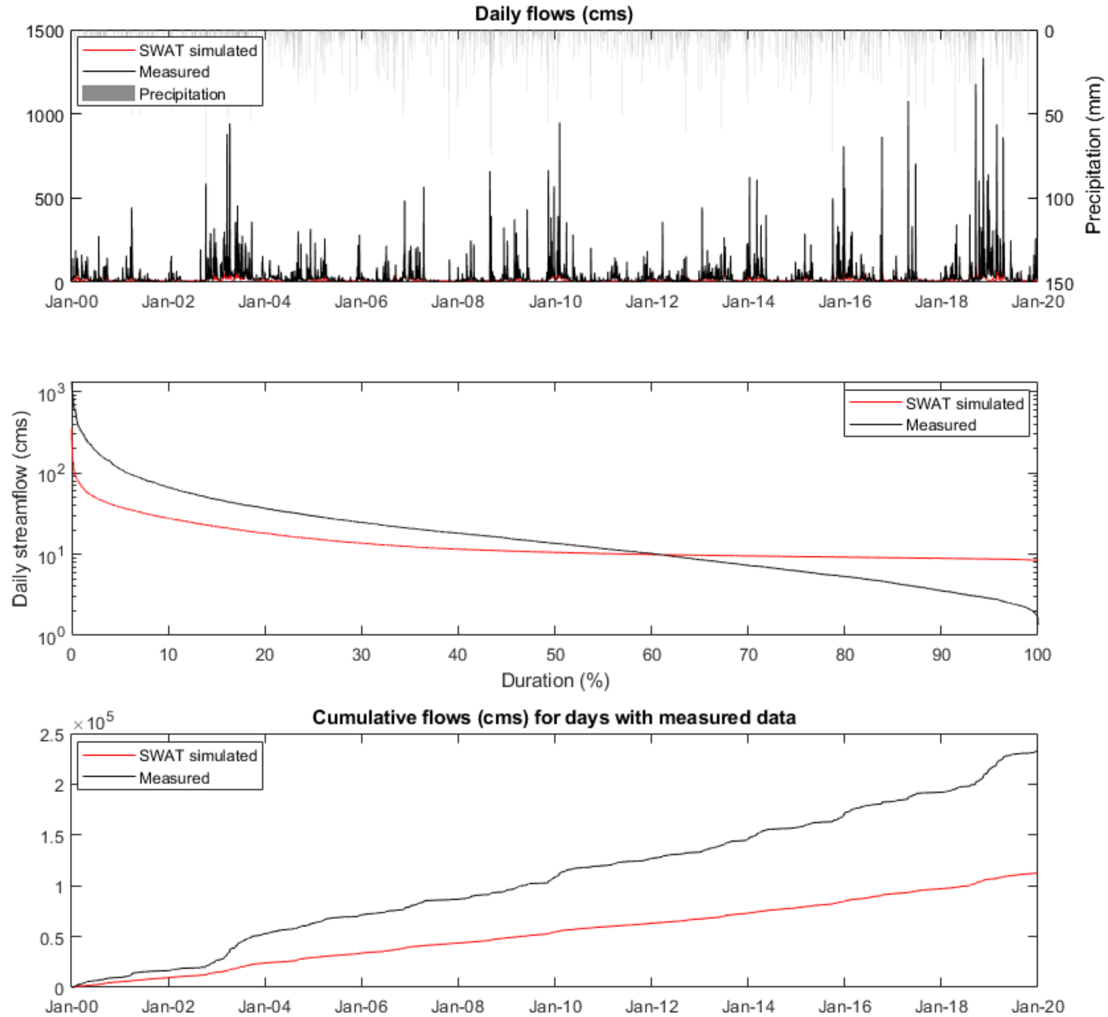


Figure H.5.1. Flow time series plot for the calibration and validation periods at the Haw River, near Bynum, NC (Subbasin 663).

H.6 Deep River, near Ramseur, NC (Subbasin 717)

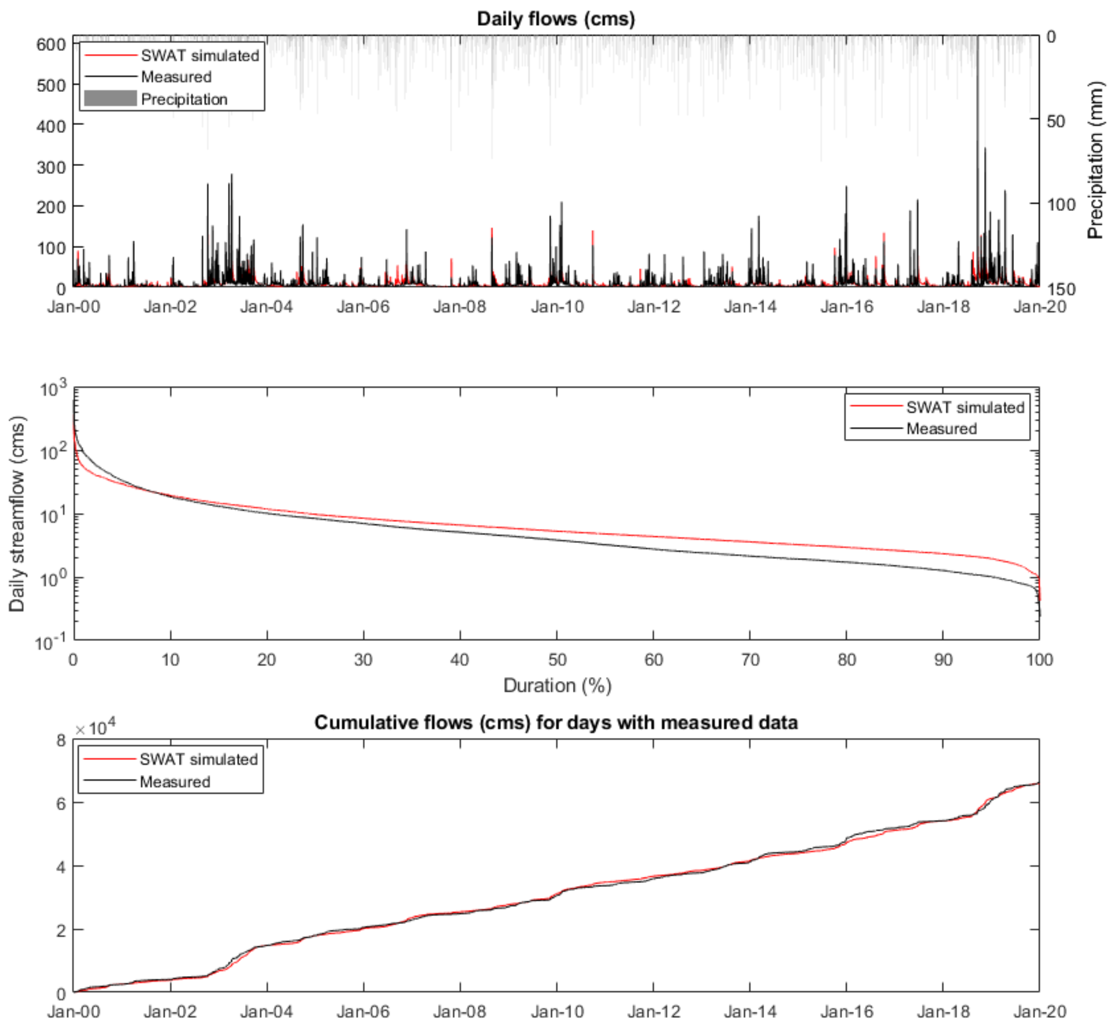


Figure H.6.1. Flow time series plot for the calibration and validation periods at the Haw River, near Bynum, NC (Subbasin 717).

H.7 Deep River, near Moncure, NC (Subbasin 848)

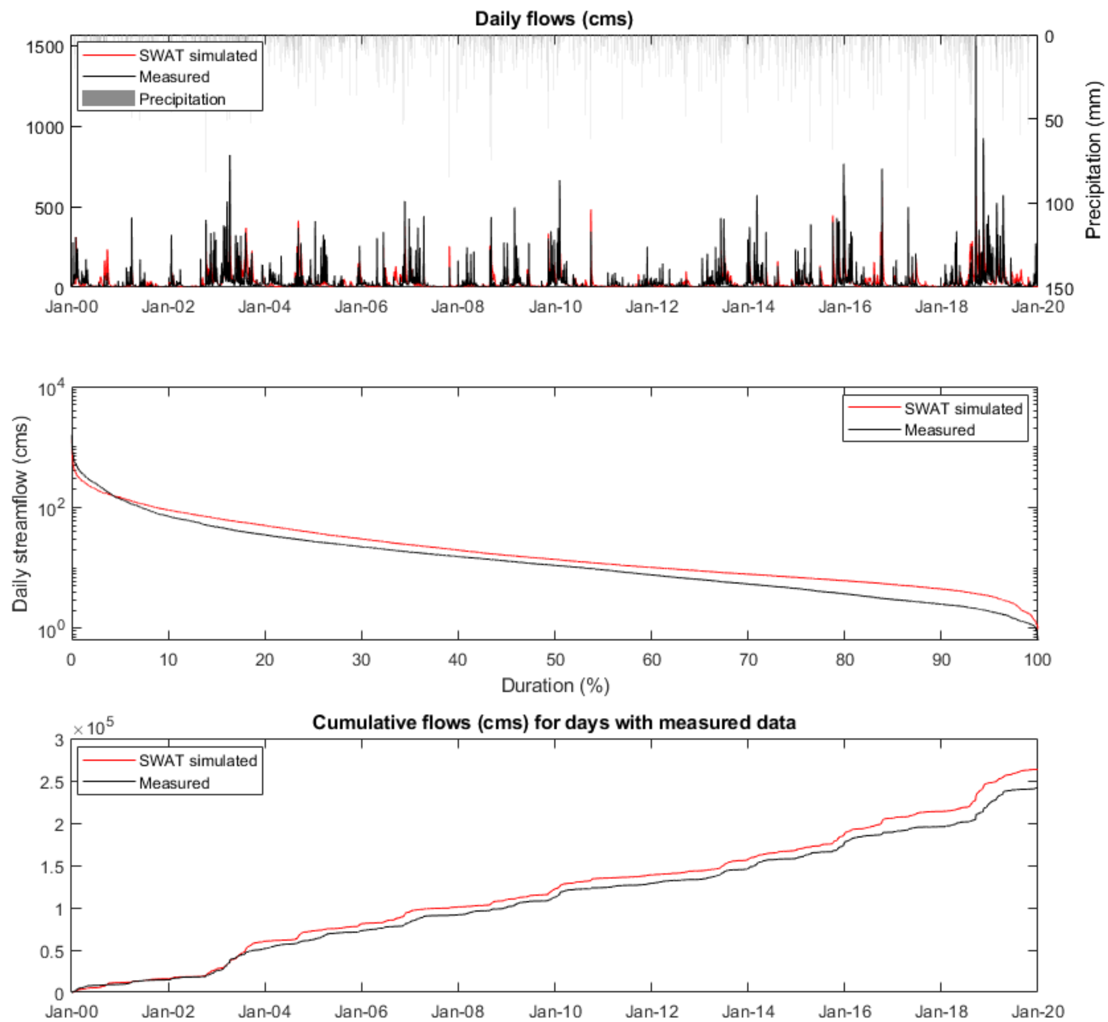


Figure H.7.1. Flow time series plot for the calibration and validation periods at the Deep River, near Moncure, NC (Subbasin 848).

H.8 Cape Fear River, near Lillington, NC (Subbasin 1144)

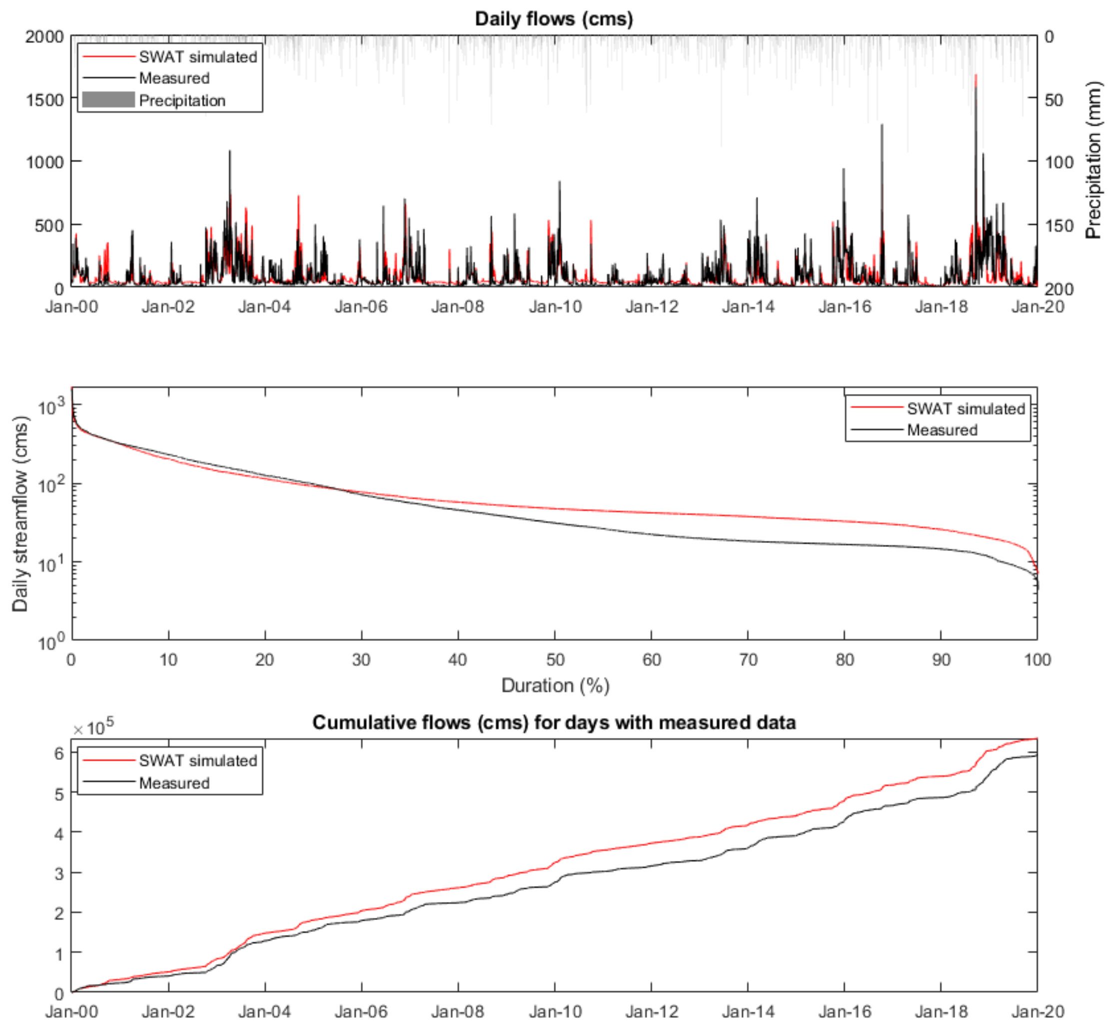


Figure H.8.1. Flow time series plot for the calibration and validation periods at the Cape Fear River, near Lillington, NC (Subbasin 1144).

H.9 Flat Creek, near Inverness, NC (Subbasin 1575)

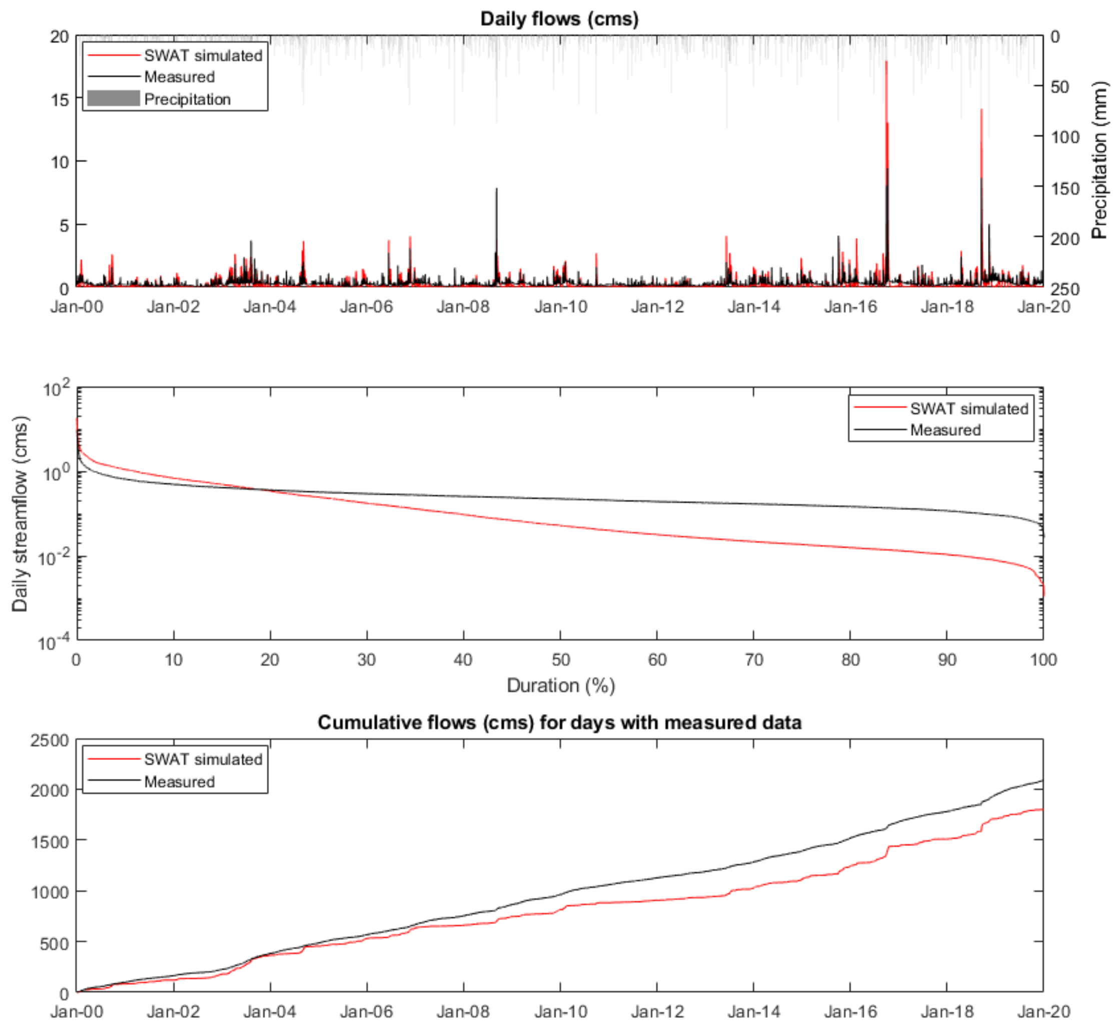


Figure H.9.1. Flow time series plot for the calibration and validation periods at Flat Creek, near Inverness, NC (Subbasin 1575).

H.10 Rockfish Creek, near Raeford, NC (Subbasin 1842)

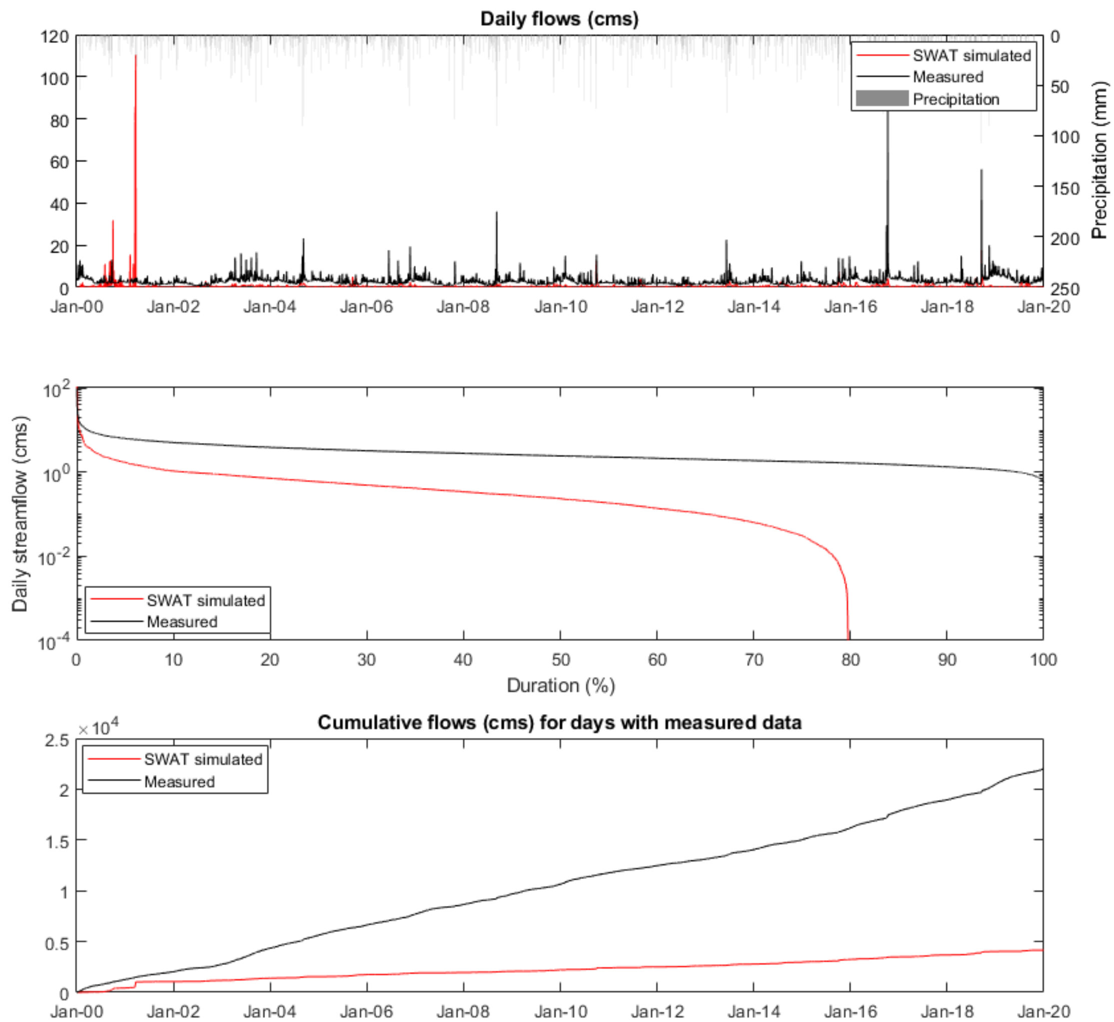


Figure H.10.1. Flow time series plot for the calibration and validation periods at Rockfish Creek, near Raeford, NC (Subbasin 1842).

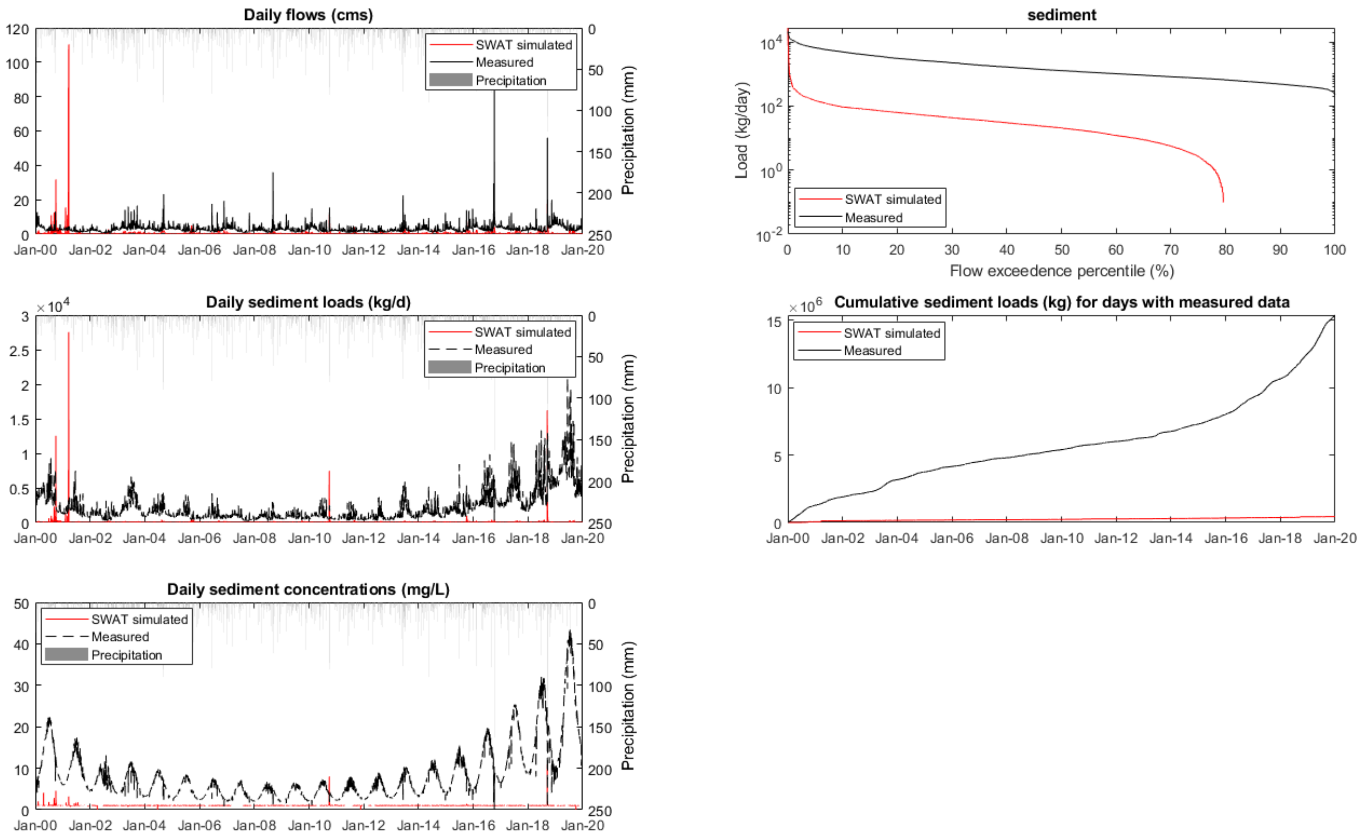


Figure H.10.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at Rockfish Creek, near Raeford, NC (Subbasin 1842).

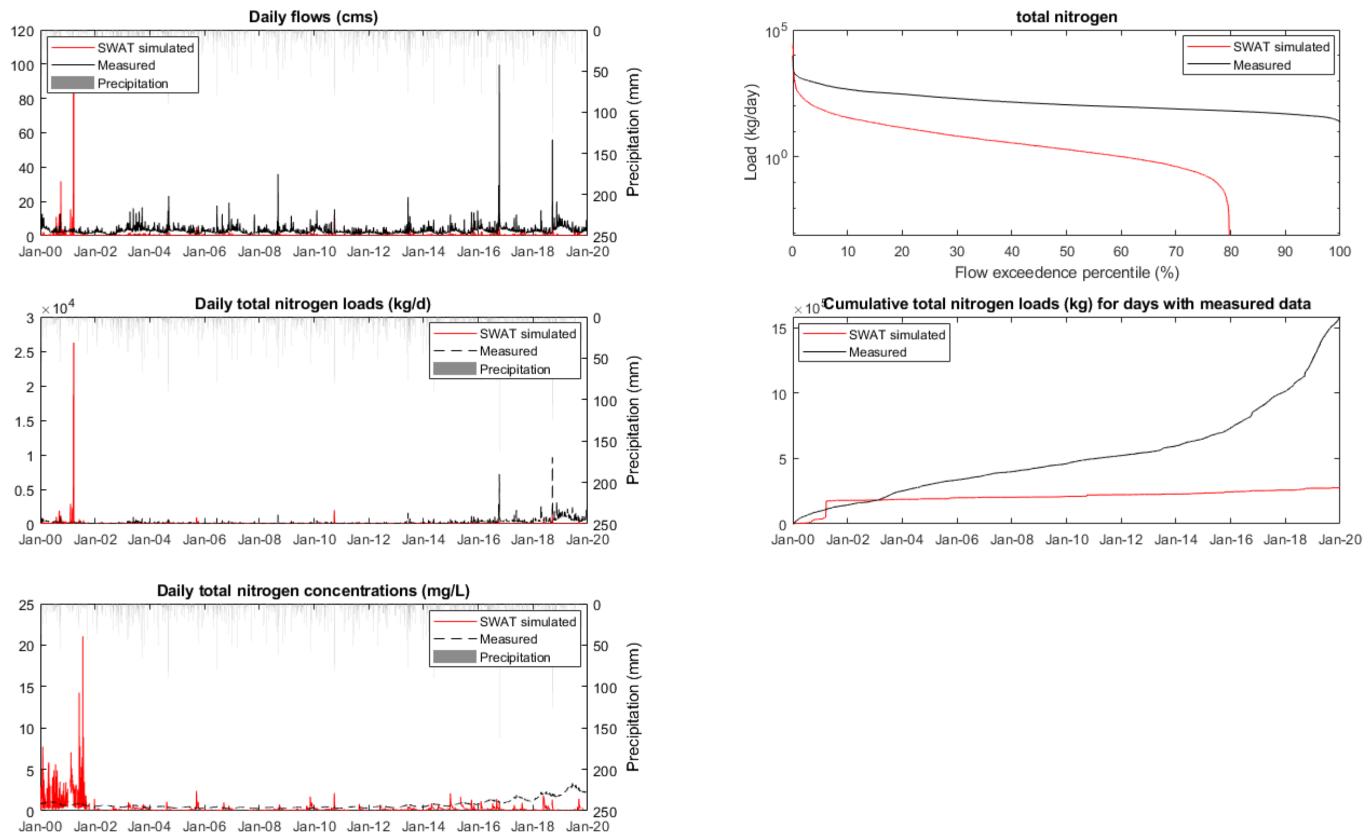


Figure H.10.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at Rockfish Creek, near Raeford, NC (Subbasin 1842).

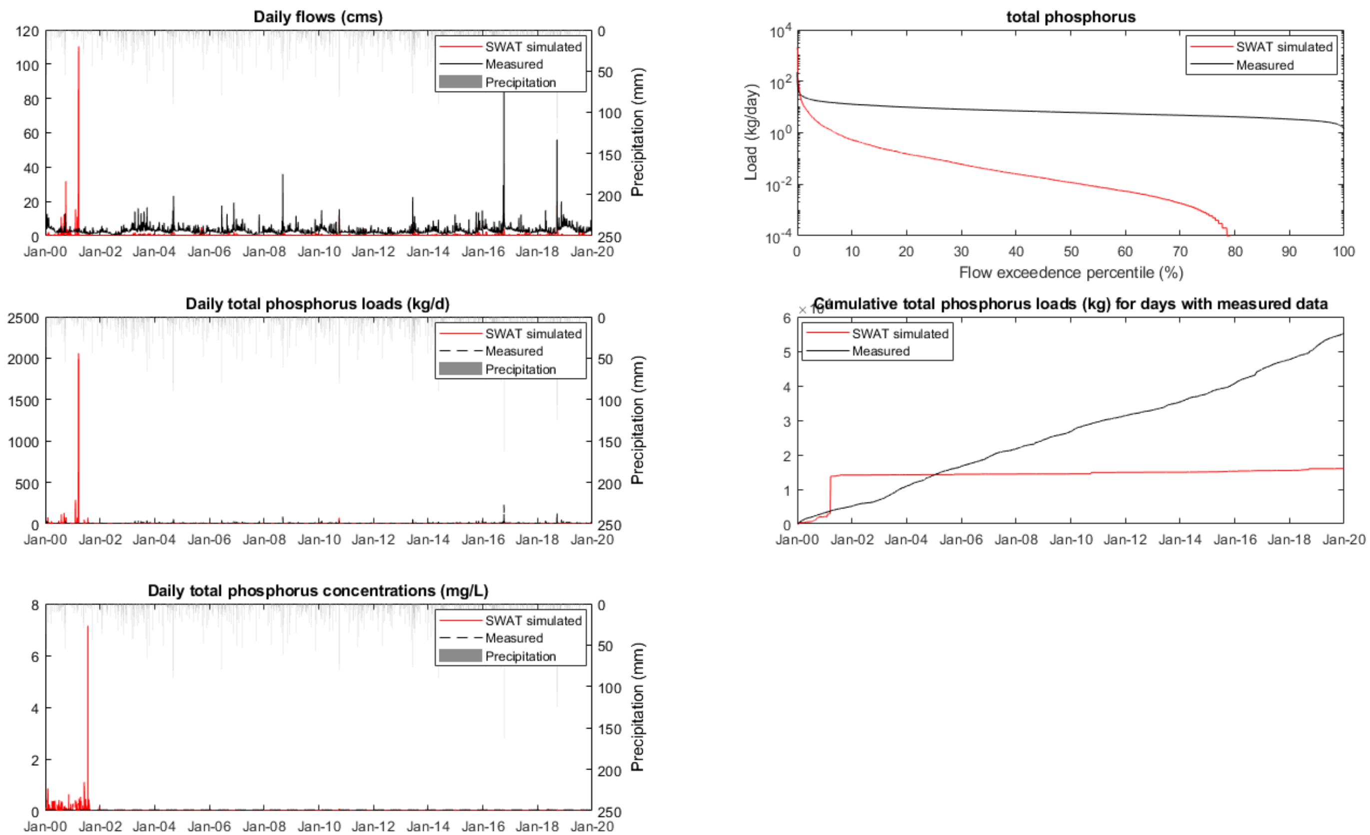


Figure H.10.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at Rockfish Creek, near Raeford, NC (Subbasin 1842).

H.11 Northeast Cape Fear, near Chinquapin, NC (Subbasin 2099)

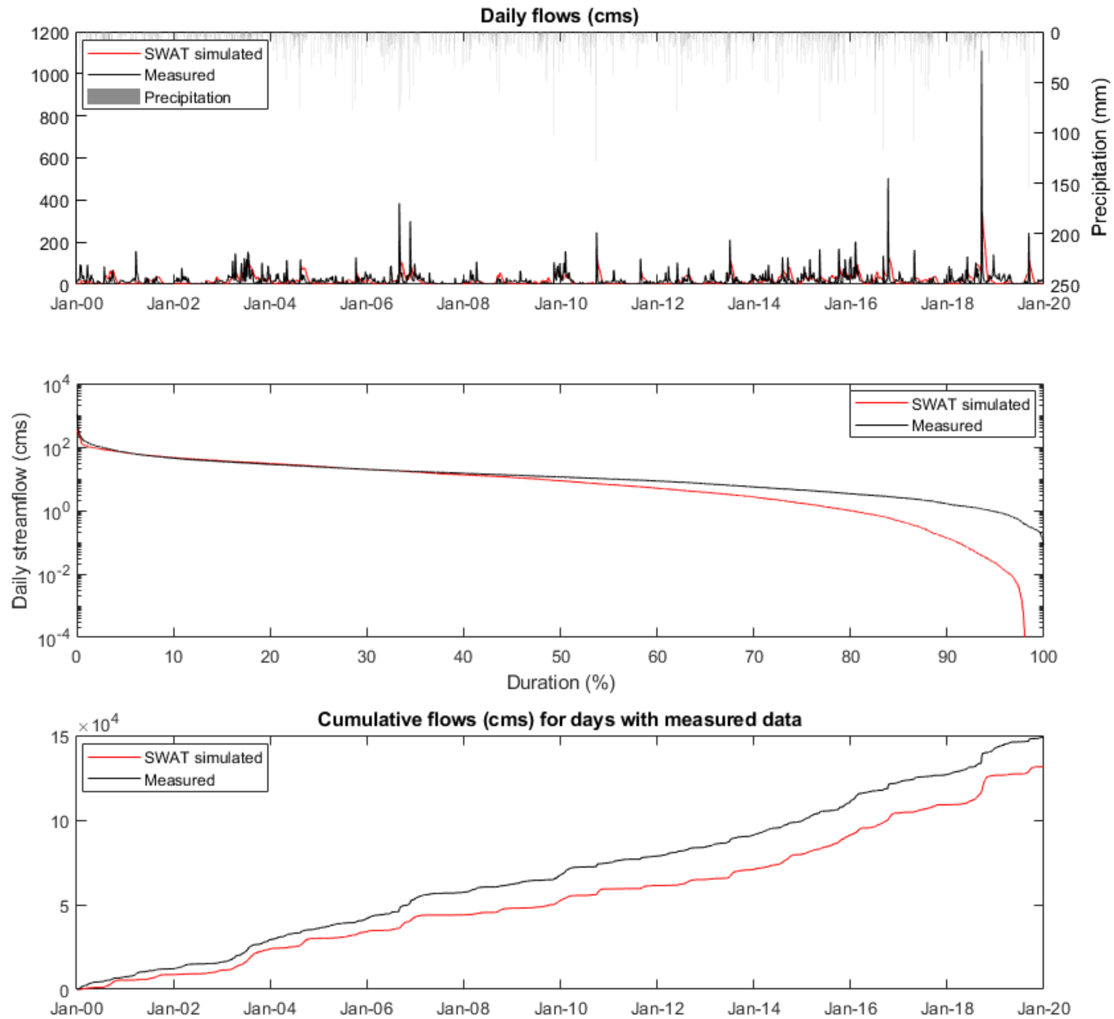


Figure H.11.1. Flow time series plot for the calibration and validation periods at the Northeast Cape Fear, near Chinquapin, NC (Subbasin 2099).

H.12 Cape Fear River, near Tarheel, NC (Subbasin 2125)

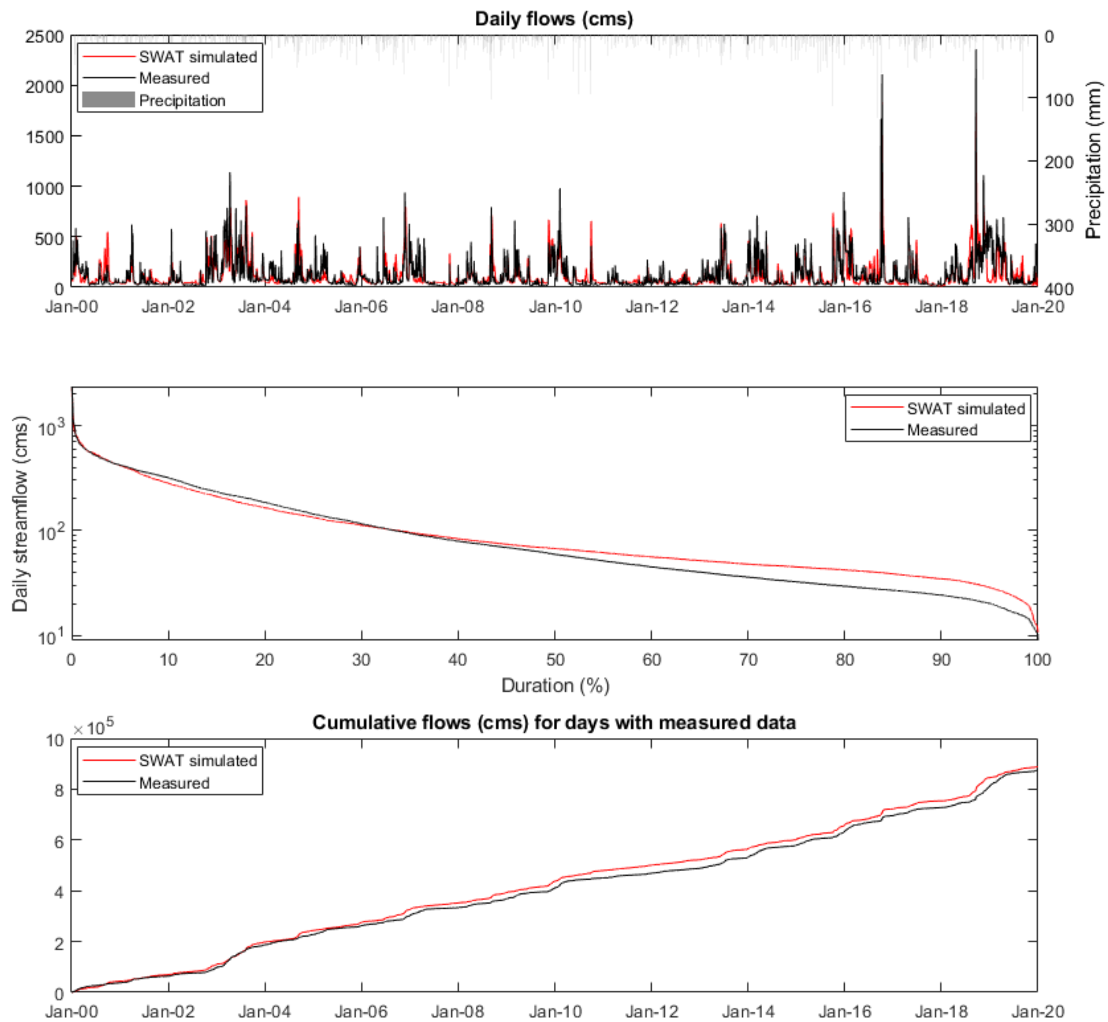


Figure H.12.1. Flow time series plot for the calibration and validation periods at the Cape Fear River, near Tarheel, NC (Subbasin 2125).

H.13 Black River, near Tomahawk, NC (Subbasin 2224)

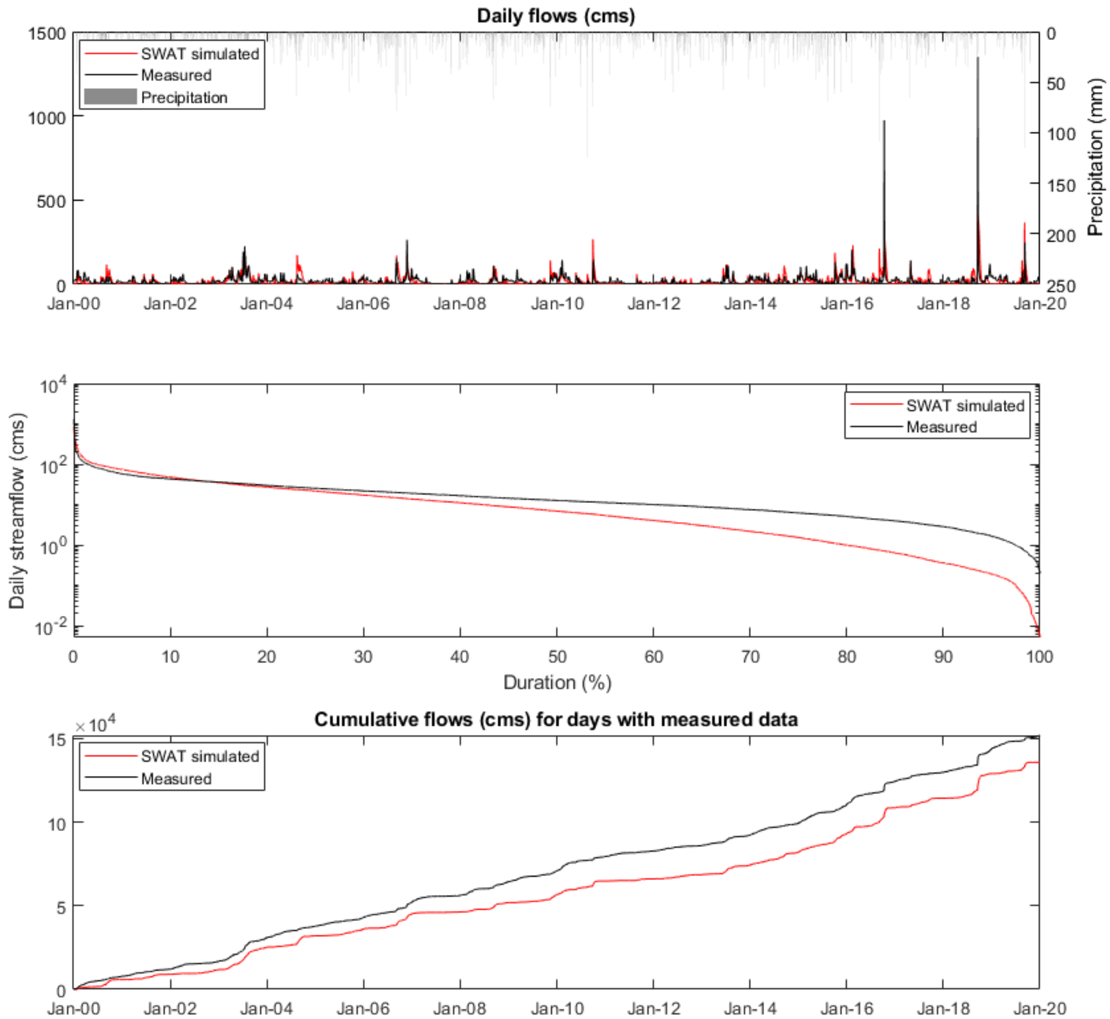


Figure H.13.1. Flow time series plot for the calibration and validation periods at the Black River, near Tomahawk, NC (Subbasin 2224).

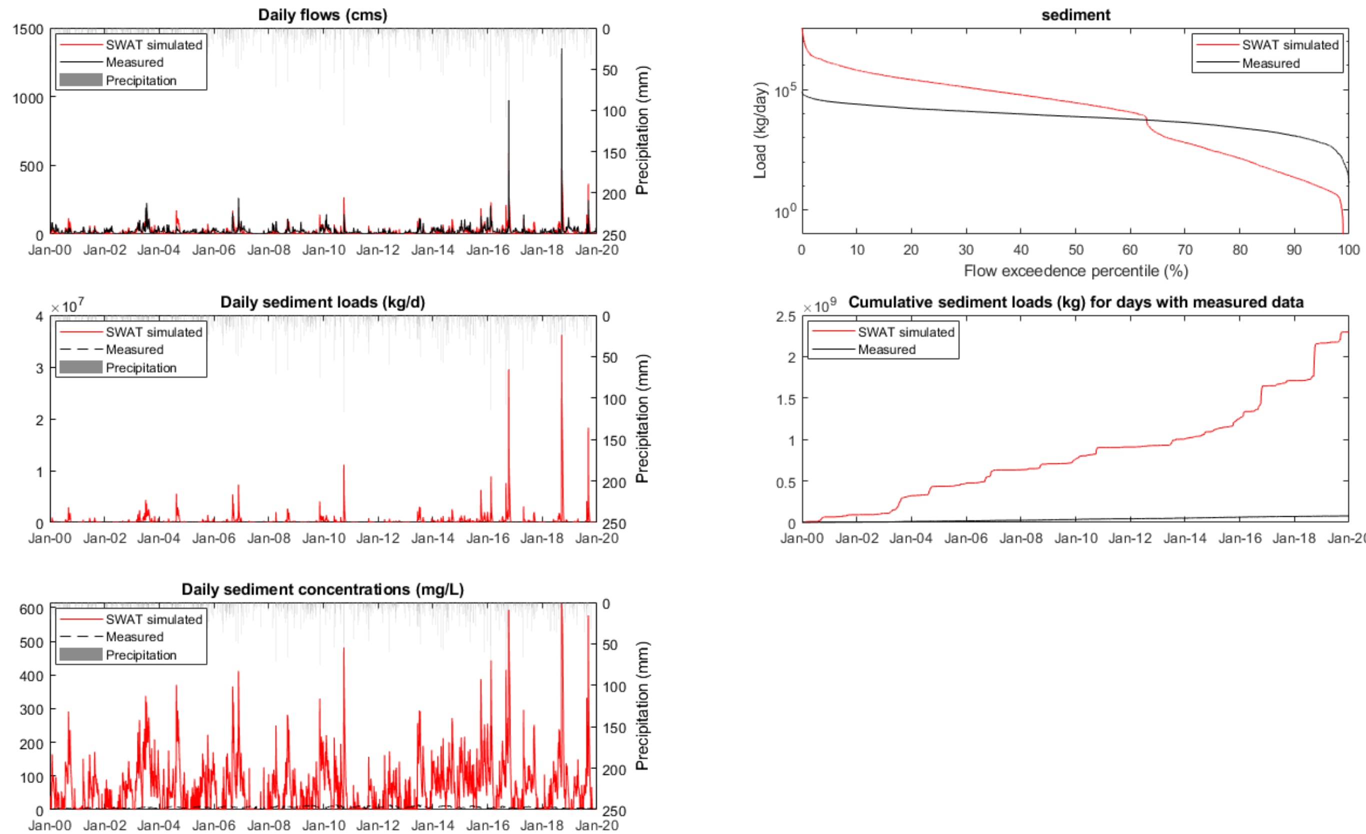


Figure H.13.2. Sediment load estimation (LOADEST) time series for the calibration and validation periods at the Black River, near Tomahawk, NC (Subbasin 2224).

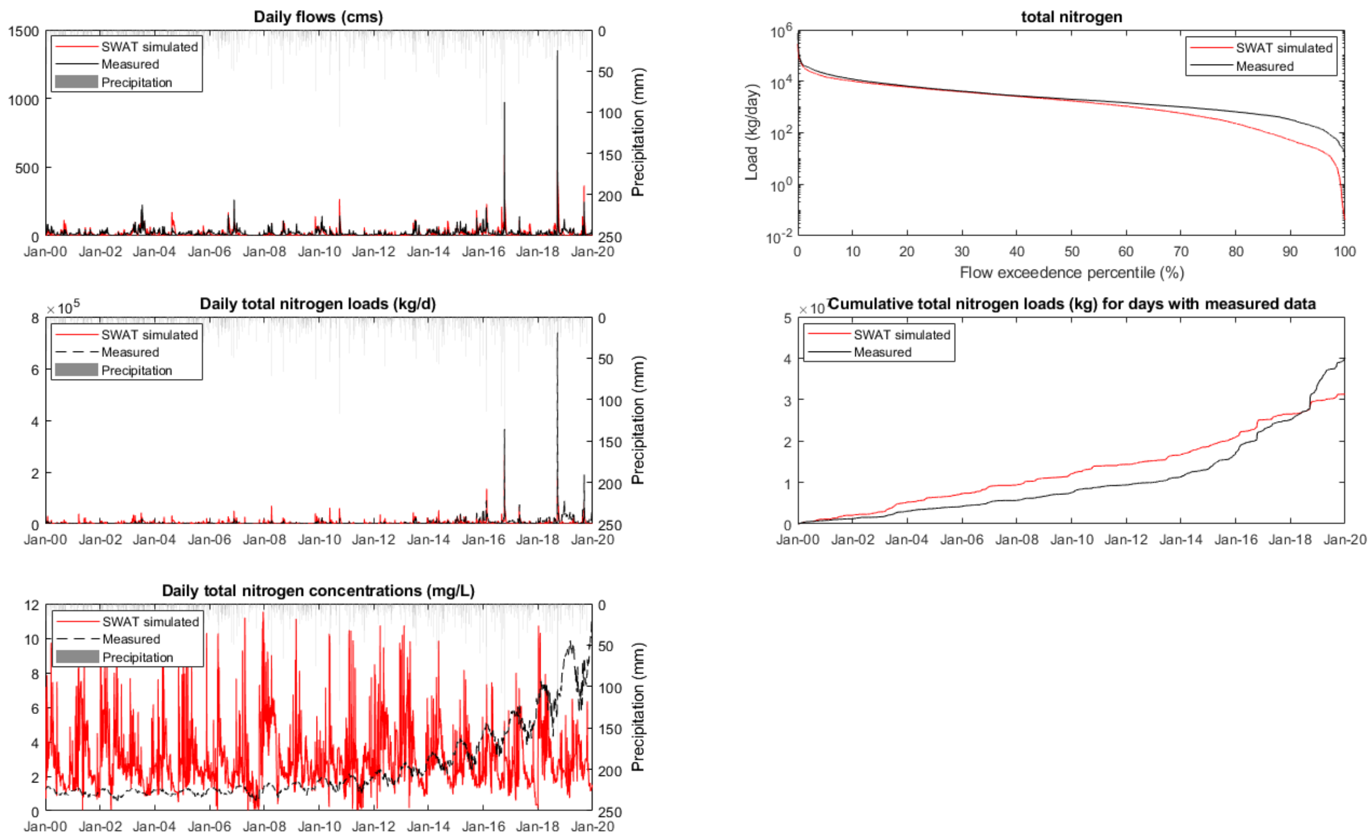


Figure H.13.3. Total nitrogen load estimation (LOADEST) time series for the calibration and validation periods at the Black River, near Tomahawk, NC (Subbasin 2224).

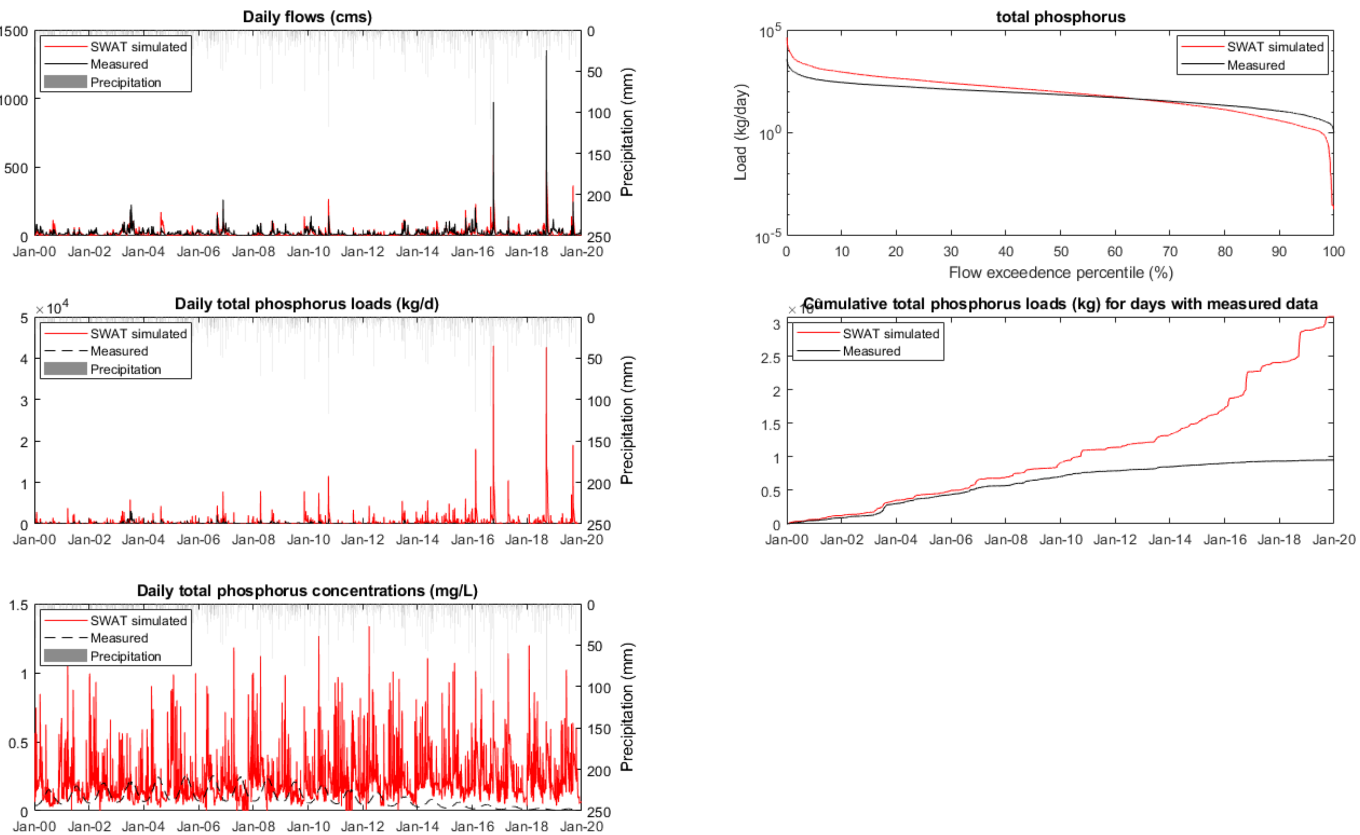


Figure H.13.4. Total phosphorus load estimation (LOADEST) time series for the calibration and validation periods at the Black River, near Tomahawk, NC (Subbasin 2224).