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

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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).

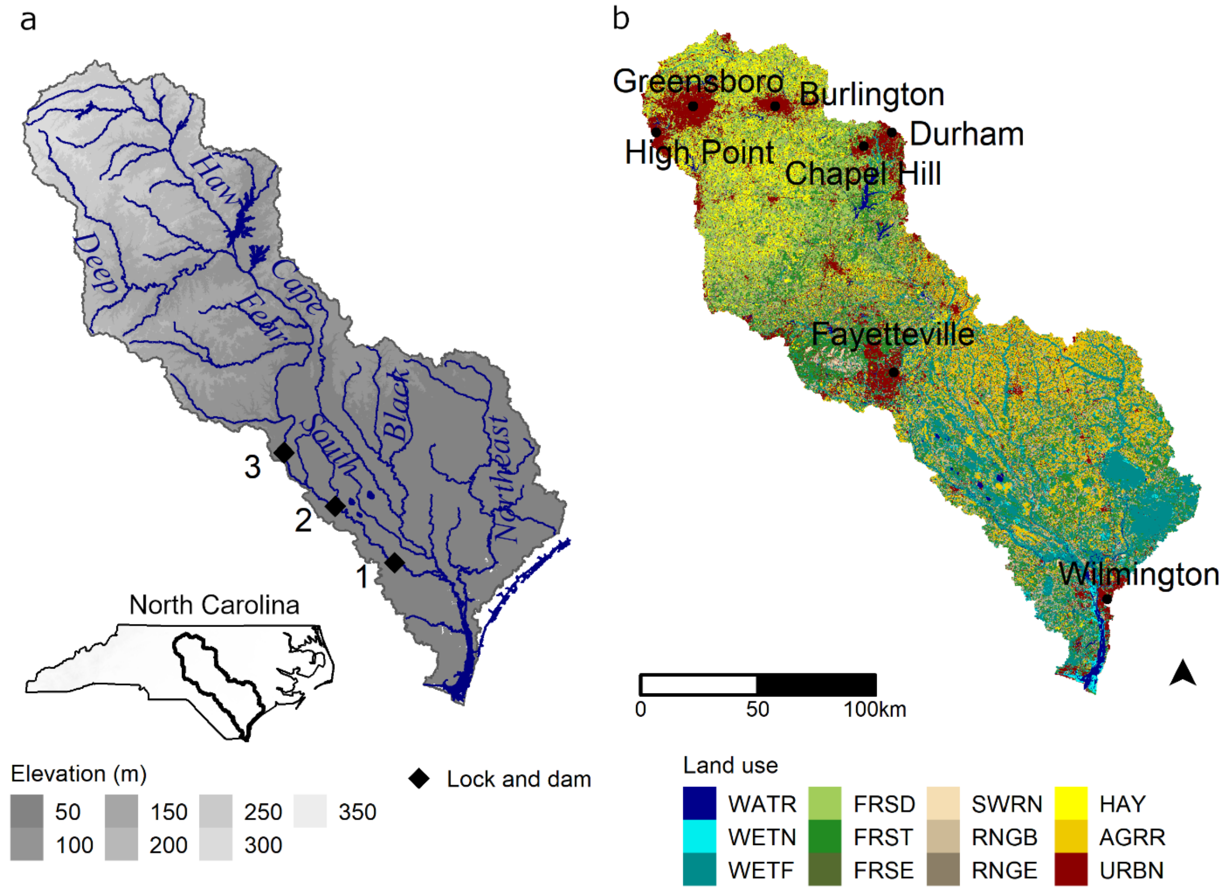

Figure 1. Landscape hydrography (a) and land use from the National Land Cover Database for 2019 (b) within the Cape Fear River Basin, North Carolina, USA. Abbreviations: water (WATR), non-forested wetland (WETN), forested wetland (WETF), deciduous forest (FRSD), mixed forest (FRST), evergreen forest (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.

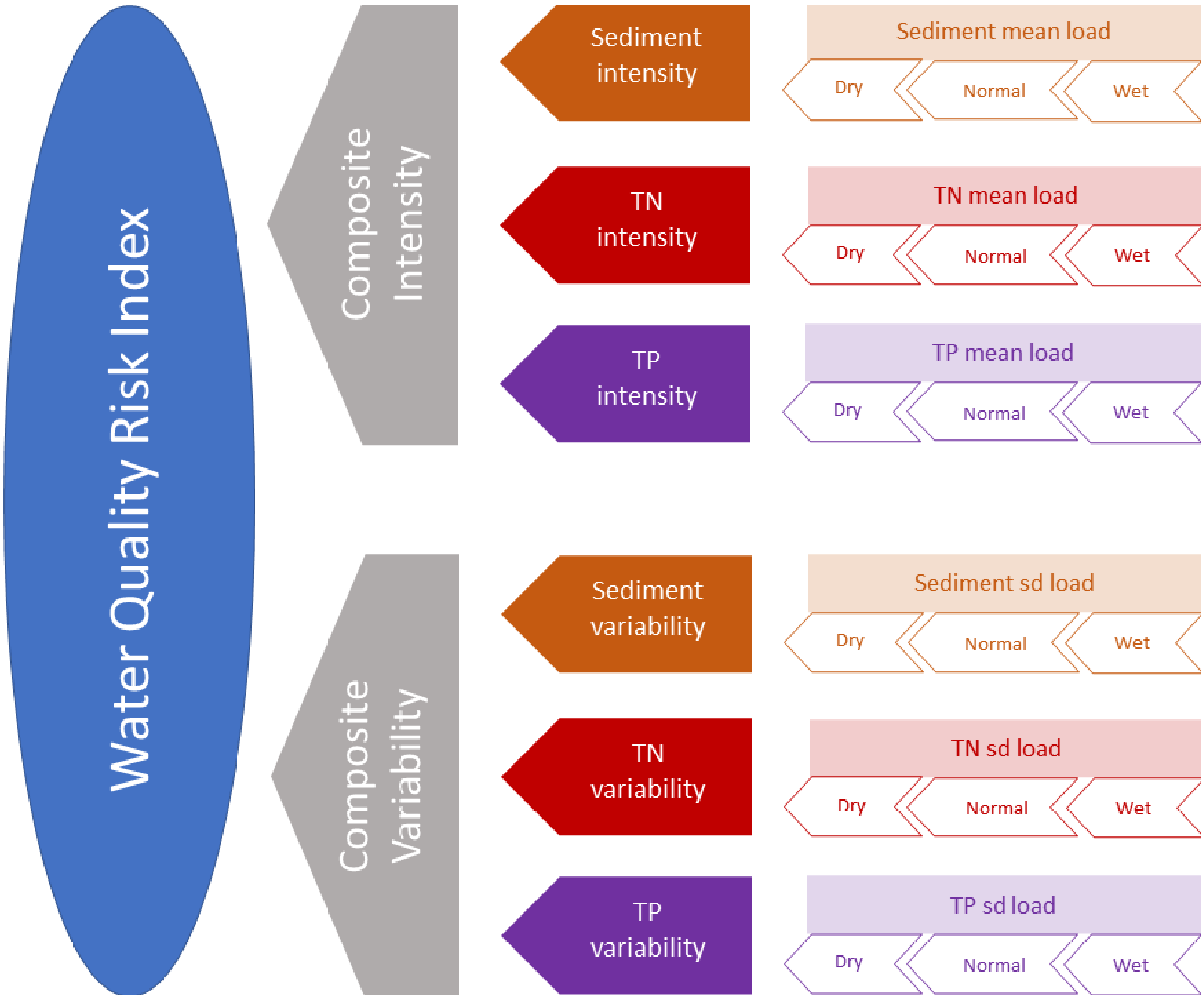

Figure 2. A water quality risk index (WQRI) was calculated for each subbasin in the Cape Fear River Basin using a series of z-score calculations and aggregations to account for distinct aspects of water quality risk for different parameters under different weather conditions (eq. 1-6). For each parameter, 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).

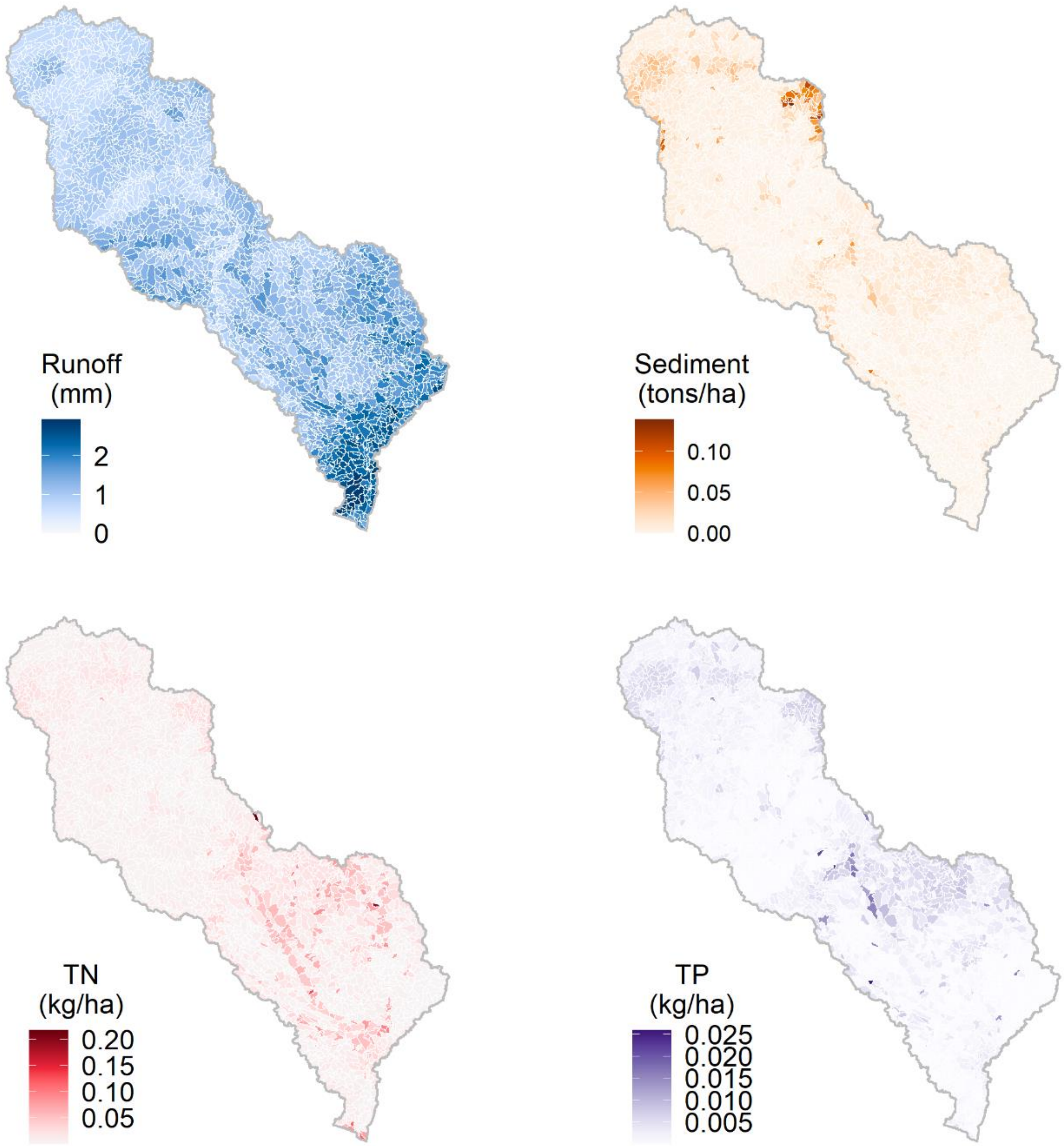

Figure 3. Long-term average daily runoff, sediment, total nitrogen (TN) and total phosphorus (TP) loads varied spatially across the Cape Fear River Basin based on contemporary land use and historical weather conditions from 1982-2019.

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).

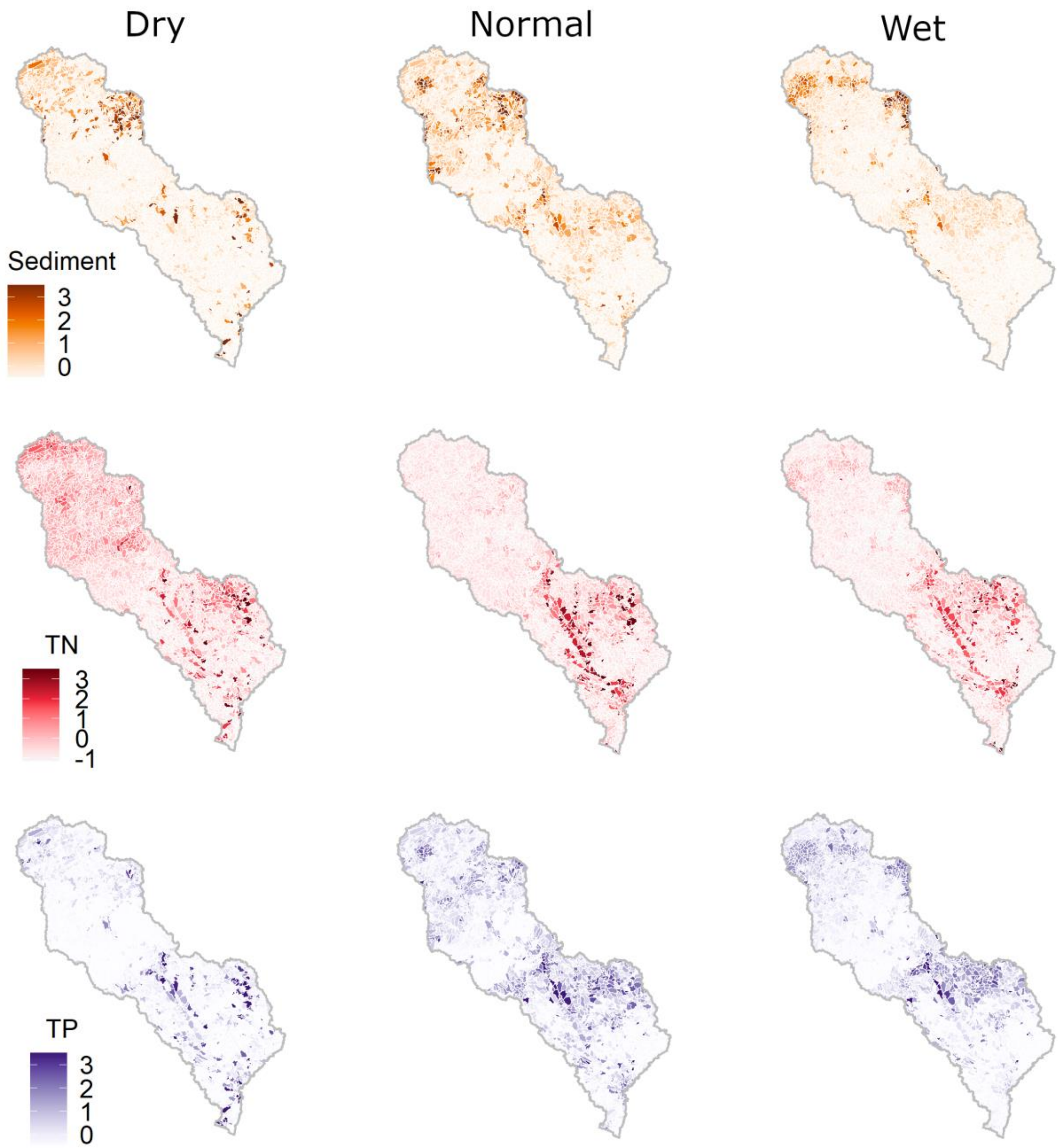

Figure 4. The relative intensity of contaminant loads across the Cape Fear River Basin varied by parameter across weather conditions 1982-2019, determined by calculating standardized z-scores of the average load for each, capped at 3.5 sd. Abbreviations: total nitrogen (TN), total phosphorus (TP).

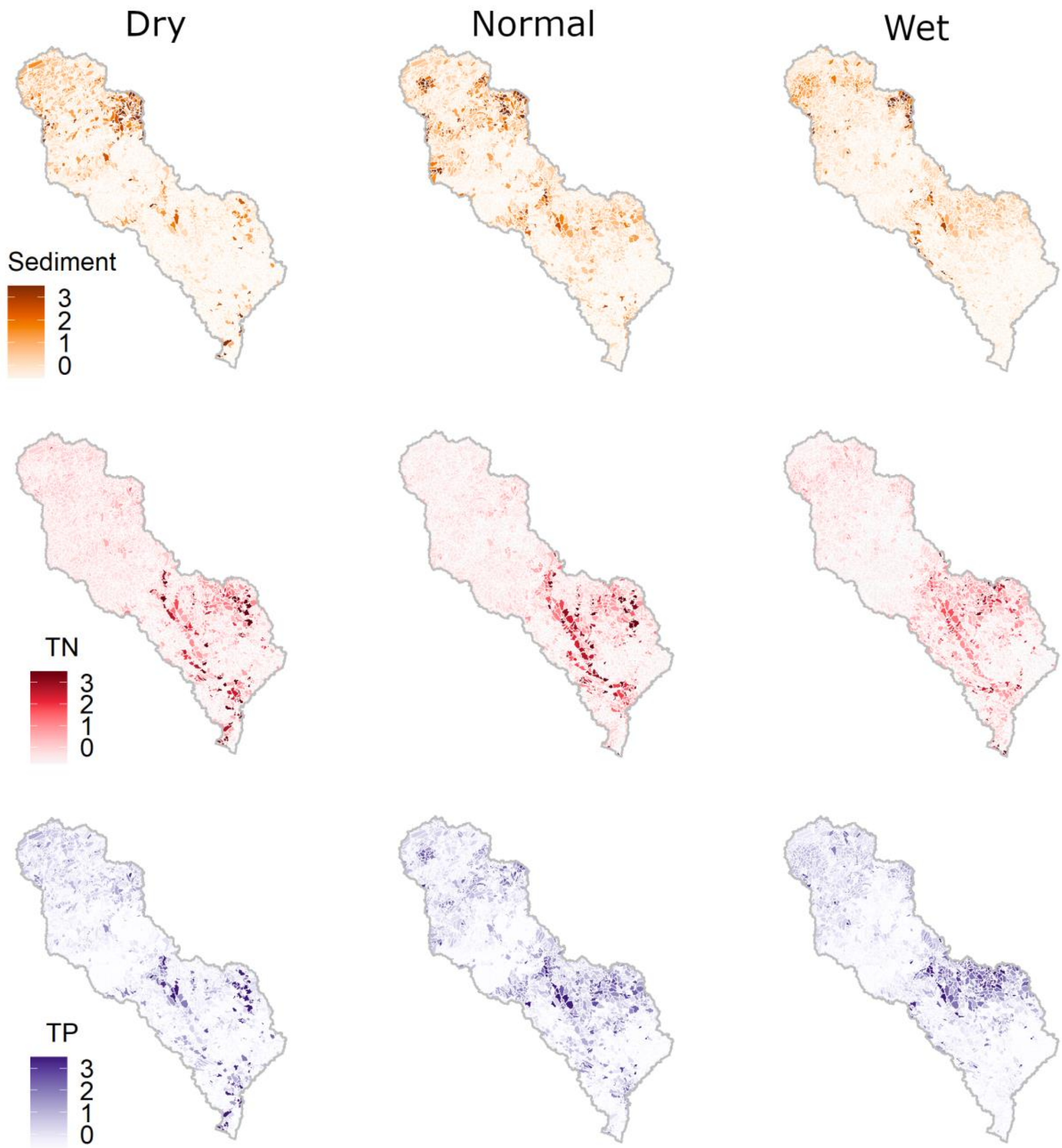

Figure 5. The relative variability of contaminant loads across the Cape Fear River Basin varied by parameter across weather conditions 1982-2019, determined by calculating standardized z-scores of the load standard deviation for each, capped at 3.5 sd. Abbreviations: total nitrogen (TN), total phosphorus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

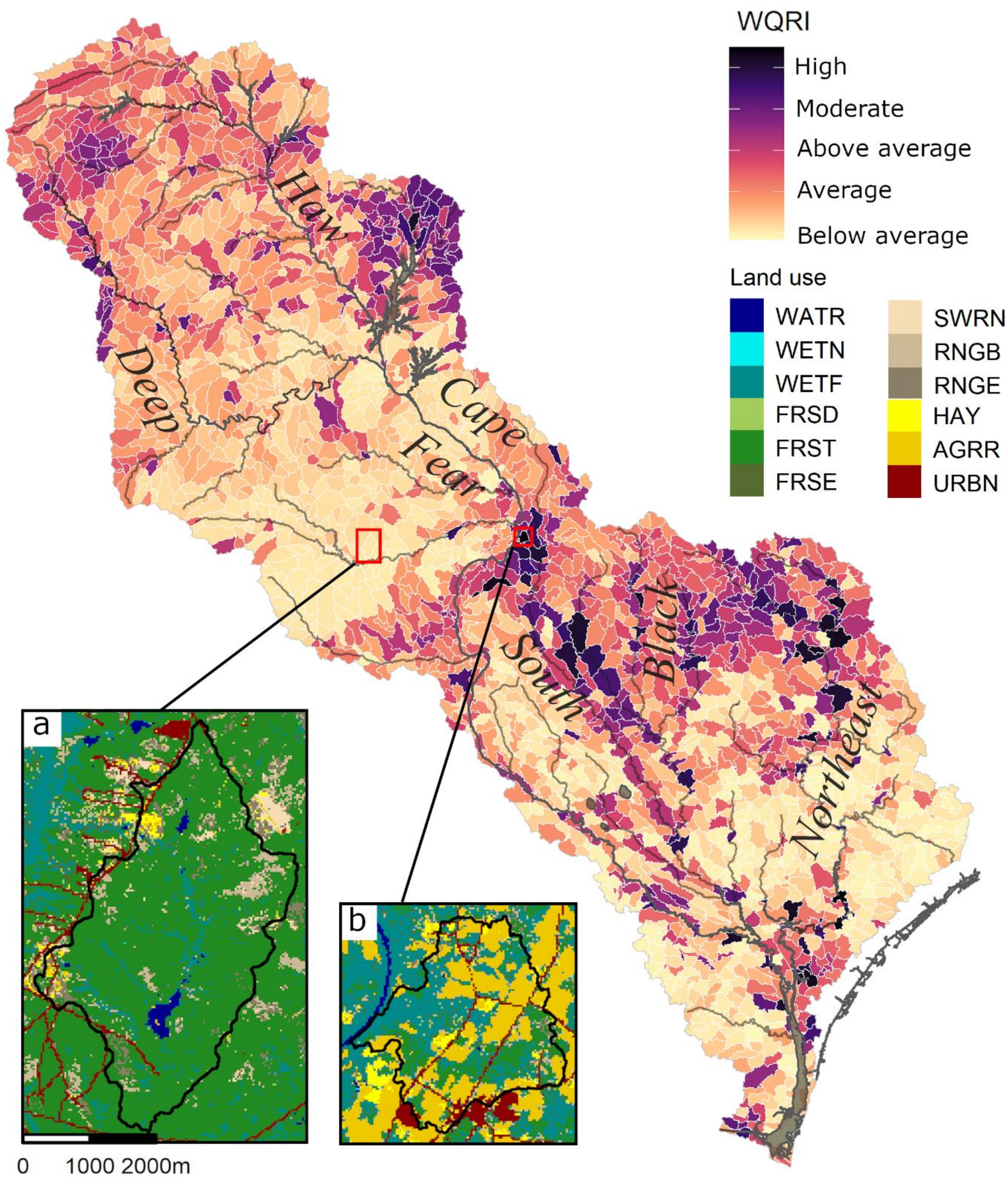

Figure 6. A water quality risk index (WQRI) summarizing landscape pollution hotspot dynamics across conditions highlighted locations in the Cape Fear River Basin that warrant further investigation. Subbasins with a low WQRI tend to have relatively in-tact natural land uses and represent priority conservation 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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