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Forested watersheds provide the highest water quality among all land cover types, but the benefit of this ecosystem service depends on landscape context

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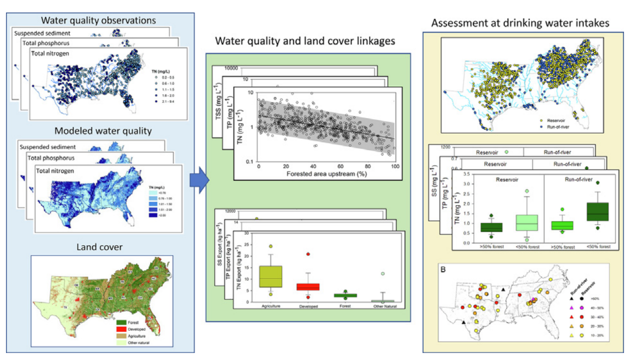
HIGHLIGHTS

- Land cover and water quality were linked regionally and at public water intakes.
- Nutrient and sediment concentrations decreased with increasing forest land cover.
- Both intake setting and land cover were important determinants of water quality.
- Small watersheds may experience the largest losses of natural land cover by 2070.

GRAPHICAL ABSTRACT



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ABSTRACT

Conversion of natural land cover can degrade water quality in water supply watersheds and increase treatment costs for Public Water Systems (PWSs), but there are few studies that have fully evaluated land cover and water quality relationships in mixed use watersheds across broad hydroclimatic settings. We related upstream land cover (forest, other natural land covers, development, and agriculture) to observed and modeled water quality across the southeastern US and specifically at 1746 PWS drinking water intake facilities. While there was considerable complexity and variability in the relationship between land cover and water quality, results suggest that Total Nitrogen (TN), Total Phosphorus (TP) and Suspended Sediment (SS) concentrations decrease significantly with increasing forest cover, and increase with increasing developed or agricultural cover. Catchments with dominant (>90 %) agricultural land cover had the greatest export rates for TN, TP, and SS based on SPARROW model estimates, followed by developed-dominant, then forest- and other-natural-dominant catchments. Variability in modeled TN, TP, and SS export rates by land cover type was driven by variability in natural background sources and catchment characteristics that affected water quality even in forest-dominated catchments. Both intake setting (i.e., run-of-river or reservoir) and upstream land cover were important determinants of water quality at PWS intakes. Of all PWS intakes, 15 % had high raw water quality, and 85 % of those were on reservoirs. Of the run-of-river intakes with high raw water quality, 75 % had at least 50 % forest land cover upstream. In addition, PWS intakes obtaining surface water supply from smaller upstream catchments may experience the largest losses of natural land cover based on projections of land cover in

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2070. These results illustrate the complexity and variability in the relationship between land cover and water quality at broad scales, but also suggest that forest conservation can enhance the resilience of drinking water supplies.

1. Introduction

Forests and water are inextricably linked (Jackson et al., 2004; Lockaby et al., 2013), and millions of people depend on forests for clean and reliable drinking water supplies (Liu et al., 2022; Millennium Ecosystem Assessment, 2005). However, land cover change is threatening the ability of forested lands to provision this ecosystem service (NRC, 2008; Sun and Vose, 2016; Vose, 2019; Vose et al., 2016; Vose et al., 2011). Policy makers, water utilities, and land managers need data and tools that link forests, water quantity and quality, and Public Water Systems (PWSs) so that they can make informed decisions regarding water treatment infrastructure investments as well as land cover, forest conservation programs, and forest management in critical water supply watersheds under increasing development pressure and climate change.

The assertion that forests support higher water quality than agriculture or urban development land cover is well established in the literature (Bolstad and Swank, 1997; Mehaffey et al., 2005; Piaggio and Siikamaki, 2021; Tong and Chen, 2002; Tu, 2013; Westling et al., 2020). Forests mitigate stormflows and reduce overland runoff (Bolstad and Swank, 1997; Shi et al., 2017) due to higher evapotranspiration rates (Boggs and Sun, 2011; Li et al., 2020) that provide water storage capacity in the soil, greater soil porosity, and higher soil infiltration rates compared to developed or agricultural watersheds (Price, 2011; Price et al., 2010). As a result, overland flow and stream channel erosion rates are lower in forested watersheds (Neary et al., 2009), resulting in lower sediment concentrations in streams and lower concentrations of other pollutants associated with developed or agricultural lands (Lockaby et al., 2013). Land cover is one of several important controls on water quality, and some have found forests are particularly beneficial at smaller scales (Lei et al., 2021) or in smaller watersheds (Piaggio and Siikamaki, 2021). Multiple factors can influence the forest-water quality relationship, including forest type and management (Shah et al., 2022), landscape complexity (Shi et al., 2017), and the presence of additional pollutant sources including wastewater treatment plants (Tasdighi et al., 2017).

Sustainable forest management and conservation has been shown to provide economic benefits through improved water quality and hydrologic function (Gartner et al., 2014). Declining water quality affects water treatment plant operations through temporary shutdowns, drinking water advisories and development of alternate resources, which can result in higher drinking water prices (Hanson et al., 2016; Henry, 2013; Jones et al., 2007; Snider, 2014). The literature focuses on two important ways forests reduce drinking water costs. First, vegetation in forests provides regulatory ecosystem services that stabilize flows and clean the water flowing through them, leading to cleaner and more predictable raw water at drinking water intakes (Piaggio and Siikamaki, 2021; Piper, 2003; Warziniack et al., 2017). Second, forests serve as buffers and protected lands, regardless of actual protected status, limiting higher-polluting activities in the watershed such as agriculture and development (Abildtrup et al., 2013; Brown and Froemke, 2012).

Investigating the link between forests and stable, clean surface water supplies has been the focus of numerous but geographically dispersed case studies at relatively small scales and/or over small sample sizes. Some studies analyzed the linkage between forest and other land cover types to water quality (Brogna et al., 2018; Tsegaye et al., 2006) and some of these also included effects on municipal water treatment facilities (Abildtrup et al., 2013; Cunha et al., 2016; Fiquepron et al., 2013; Lopes et al., 2019; Warziniack et al., 2017). At the U.S. national scale, there have been assessments linking forests and other land covers to water quantity (e.g., Brown et al., 2008), including efforts to connect the benefits of water supply originating on forested lands to downstream PWS intakes (Liu et al., 2021; Liu et al., 2022). However, syntheses of large-scale, high-resolution data and tools that use a consistent framework to quantify the linkage between forests, land cover, and water quality at drinking water supply intakes are lacking.

Here we examined the relationships between water quality, forests, and other land cover types across the southeastern US (hereafter, "South") and at drinking water intakes within the region. The extensive forest cover in the region (Oswalt et al., 2019), widespread private forest ownership (Hewes et al., 2017), forest vulnerability due to development (Wear and Greis, 2013), and PWS dependence on surface water originating on forested land for municipal water supplies (Liu et al., 2020) make the region an ideal study area to gain insights on the relationship between forested land and water quality. Our specific objectives included: (1) Link historical upstream forests and other land cover types to downstream water quality using water quality observations where available and spatially continuous published model outputs across the region; (2) Characterize historical water quality and upstream watersheds for PWS intakes across the South; and (3) Link future projections of upstream land cover to PWS intakes to identify vulnerabilities to forest loss due to land cover change. The overall motivation of this study is to provide information that could be used to prioritize forested watersheds for conservation, thereby enhancing the resilience of drinking water supplies and minimizing drinking water treatment costs.

2. Methods

2.1. Study region

Forest land cover comprises nearly half of all land cover in the South (Oswalt et al., 2019) (Fig. 1) and is an important yet threatened source of water for millions in the region (Liu et al., 2020). Approximately 56.6 million people in the South obtained their drinking water supply from surface water in 2017 (approximately 50 % of the total population in the region), and 14 million of these obtained more than half of their water from State and privately owned forest land (Liu et al., 2020). The South has experienced more loss of forest land to development than any other region in the U.S., accounting for over 60 % of all land developed from forest between 2000 and 2015 (USDA, 2018). Wear and Greis (2013) projected that forest land area across the South could decrease by 44,515–89,030 km^2 (6.5–13.1 %) between 1997 and 2060 depending on socioeconomic and timber pricing assumptions. Developed land rarely reverts to its natural state of forest cover so these threats, once realized, are essentially irreversible (Homer et al., 2020). Where it remains, forest land in the South is also highly dynamic. Timber harvest is the most common form of forest disturbance in the region and harvest rates are greater than other regions of the U.S. (Oswalt et al., 2019; Schleeweis et al., 2020). Privately owned forest land accounts for nearly 87 % of all forest area in the South (Hewes et al., 2017) and the region is under significant pressure from the expansion of developed land (Wear and Greis, 2013).

2.2. Water quality data

It is challenging to assess relationships between land cover and water quality across broad regions due to a paucity of water quality observations across time and space (Jiang et al., 2020). Among the reasons for limited water quality observations is that considerable effort and cost is required to gather water quality monitoring data (Kirschke et al., 2020), and to standardize them across multiple collection entities and analytical methodologies for a given parameter (Jiang et al., 2020). Therefore, we used both observed water quality data where available and published spatially continuous model output across the region. Use of water quality model outputs

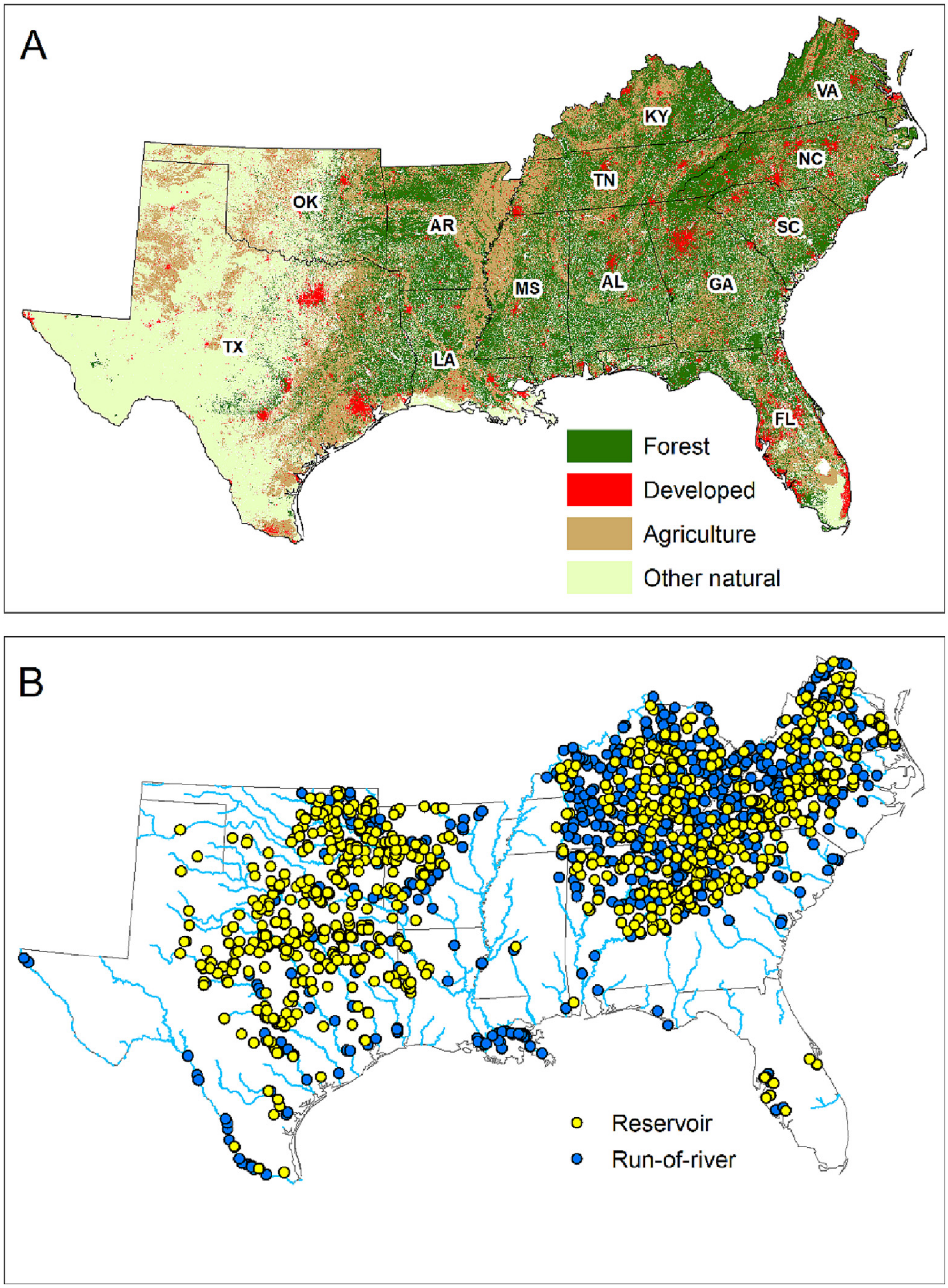

Fig. 1. Aggregated land cover (A), and the 1746 water utility facilities (B) across the South. land cover in (A) based on the 2011 NLCD. Utilities in (B) were designated as surface water source, community water systems, and an intake or reservoir in the EPA SDWIS database and are colored according to whether they occur on a reservoir/lake/impoundment or are located on a run-of-river based on visual inspection. State abbreviations in (A) are: AL = Alabama, AR = Arkansas, FL = Florida, GA = Georgia, KY = Kentucky, LA = Louisiana, MS = Mississippi, NC = North Carolina, OK = Oklahoma, SC = South Carolina, TN = Tennessee, and VA = Virginia.

that leverage observations to extrapolate more broadly across and within regions can help distinguish the relative contribution of different sources to constituent loads and overcome some of the limitations imposed by available observed data. The temporal resolution of all water quality data was the long-term mean annual scale based on water quality observations collected between 1999 and 2014 and model predictions representing ca. 2012. All water quality parameters were expressed in terms of concentration except where noted because concentration information is more meaningful for and familiar to water utilities, and concentration is the basis of most drinking water regulations (Title 40 Code of Federal Regulations Part 141, 2022).

2.2.1. Observed water quality

We used observed mean Total Nitrogen (TN), Total Phosphorus (TP), and Total Suspended Solids (TSS) loading estimates based on monitoring stations across the region in Saad et al. (2019). Details on the compilation of these data may be found in Saad et al. (2019) but are briefly summarized here. Streamflow, TN, TP, and TSS measurements from 1999 to 2014 were obtained from Federal, State, Tribal, and regional agencies, universities, and nongovernmental organizations across the U.S. Criteria for data inclusion were 1) flow measurements must have 10 or more years of daily observations with no gaps and must include the year 2012, and 2) water quality measurements must have three or more years of data, at least 24 samples, at least three samples per season, and must be within two years of 2012. Flow sites were matched to water quality sampling sites based on proximity and upstream/downstream relationships. Across the study region, loading estimates from Saad et al. (2019) drew from data collected by 139 entities at sites that were either within or in areas draining to the study region (Table S1). In total there were 1304, 1311, and 999 total monitoring sites in the South for TN, TP, and TSS, respectively (Fig. 2). We converted the ca. 2012 annual load estimates to equivalent concentrations by dividing constituent loads by the mean flow at each site.

2.2.2. Modeled water quality

We used published predictions of ca. 2012 mean annual TN, TP, and Suspended Sediment (SS) loads using the SPAtially Referenced Regression On Watershed attributes (SPARROW) model outputs developed by the U.S. Geological Survey (USGS) to provide estimates of water quality within all catchments across the South. SPARROW is a hybrid empirical and process-based mass-balance model that relates water quality observations to predictor variables such as constituent sources and watershed or channel features that affect the rate of constituent delivery to receiving waters

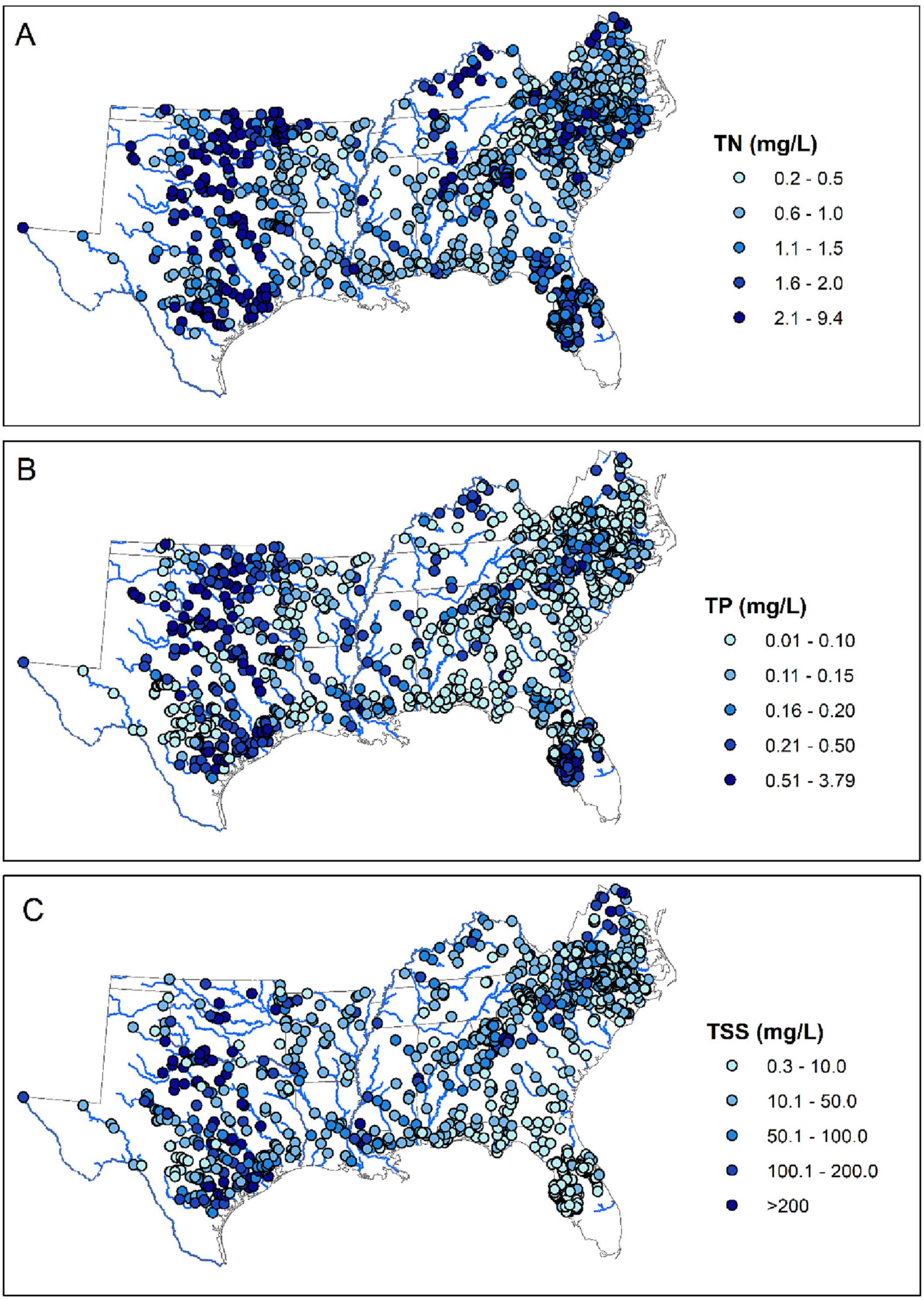

Fig. 2. Observed TN (A), TP (B), and TSS (C) monitoring sites across the South, colored according to observed equivalent concentration for base year 2012.

(Hoos and Roland, 2019; Schwarz et al., 2006). The variables representing land-to-water transport and delivery processes are generally physical characteristics of the watershed (e.g., land cover, soil properties, topography, climate variables) while aquatic-loss processes include loss or decay during transport through the stream network (e.g., reservoirs) (Hoos and Roland, 2019). The benefit of SPARROW in relation to other water quality models (e.g. SWAT (Arnold et al., 2012) or HSPF (Bicknell et al., 2005)) is that it can be more easily implemented at a large scale to answer broad research questions such as the relationship between land cover and water quality across multiple river basins. It would be extremely resource intensive to develop SWAT or other process-based models for these water quality parameters across a large region. One limitation of the SPARROW approach compared to others is that it is largely empirical, and thus could be limited in making predictions under conditions beyond those under which the model was developed. Another is that SPARROW predicts water quality under long-term steady-state conditions and does not capture fine-scale temporal dynamics. While additional information could be generated from other modeling approaches (e.g., temporal variation in water quality by season and associated with precipitation events at a finer temporal scale), SPARROW is a framework that provides reasonable estimates of the sensitivity of water quality to land cover at the regional scale.

The published USGS SPARROW models were developed for five regions across the conterminous U.S. Four of the regional SPARROW models intersect with the South, including the Northeast (Ator, 2019), Southeast (Hoos and Roland, 2019), Midwest (Robertson and Saad, 2019; Robertson and Saad, 2021), and Southwest (Wise et al., 2019) regions (Fig. S1). It was not our goal to evaluate the uncertainty and assumptions associated with the published SPARROW models used in this study as those are described in these references. These studies and numerous others have used SPARROW to evaluate relations between sediment and nutrient sources and water quality (e.g., Ator and Garcia, 2016; Ator et al., 2022; Hoos and McMahon, 2009; Milstead et al., 2013; Preston et al., 2011). Collectively this body of literature suggests that SPARROW provides “a consistent set of information for identifying the major sources and environmental factors affecting nutrient fate and transport” in watersheds at regional and sub-regional scales (Preston et al., 2011) and uncertainty in SPARROW water quality estimates is comparable to other broad scale water quality modeling approaches (McCrackin et al., 2013; Montefiore and Nelson, 2022). Preston et al. (2011) and references therein provide a thorough review of SPARROW modeling applications for nutrient loading. Costa et al. (2019) reviewed water quality modeling applications globally and found 47 studies using SPARROW in the literature, and noted that it is among the seven most frequently used water quality models in the past 20 years. The USGS models are briefly summarized here, additional detail regarding SPARROW model assumptions, parameter estimates, and uncertainty can be found in these references and are summarized in Table S2.

The spatial resolution of the SPARROW models was the National Hydrography Dataset (NHD) NHDPlus Version 2.1 catchment (Moore and Dewald, 2016). There are >812,000 NHD catchments across the study region with a median area of 1.2 km^2. The regional models use a consistent methodology and databases but were developed independently. Only those predictor variables with statistically significant coefficients are included in the final model ($p < 0.10$ for southeast and northeast models, $p < 0.05$ for Southwest and Midwest models). The regional models generally included similar constituent sources, land-to-water delivery variables, and aquatic loss variables but varied in some instances to account for regional differences in sources and losses (Table S2). Sources in the final SPARROW models generally include natural and/or background sources (e.g., atmospheric N deposition, P mineral content of surficial geologic materials, sediment from stream channel erosion), and anthropogenic sources (e.g., wastewater treatment plants, fertilizer and manure application, mining operations, and surface runoff from different land cover types) (Table S2). Published standard error (SE) on the mean parametric bootstrapped SPARROW load estimates computed using methods of Schwarz et al. (2006) were used in this study to provide an estimate of the uncertainty in the TN, TP, and SS loading and concentration estimates.

Like the water quality observations, we computed equivalent concentrations of TN, TP, and SS by dividing the SPARROW predicted loads by the predicted flow for each NHD catchment.

The SPARROW model outputs for sediment were estimated as Suspended Sediment (SS), while the water quality observations were measured as Total Suspended Solids (TSS). These parameters differ in their analytical method; SS is the mass of all sediment in a volume of water collected directly from a water body whereas TSS is the mass of all sediment in a subsample of water collected from a waterbody (Guy, 1969). Despite differences in analytical methods, both TSS and SS represent the concentration of sediment in a volume of water collected from a water body as affected by the overland and channel erosion, deposition, and suspension processes of interest in this study. We treated these measures of observed (TSS) and modeled (SS) sediment separately but equivalent for the purposes of linking upstream land cover to downstream water quality.

The SPARROW predictions allowed us to attribute variability in water quality within land cover classes to both natural and anthropogenic factors. We selected comparison catchments across the region dominated by different land cover types to examine how these factors influence water quality.

2.3. Assessment of baseline water quality at Public Water System Facilities

The PWS intake information was derived from the U.S. Environmental Protection Agency (EPA) Safe Drinking Water Information System (SDWIS) database of public drinking water systems (USEPA, 2017a). This database contains information on those water systems such as intake locations, population served ca. 2017, and system type. PWS intake facilities in the EPA database were screened for obvious locational errors in the SDWIS, and only those designated as a community water system, having a surface water source, and having an intake or reservoir facility type were included. The facilities were indexed to the NHD catchments and each facility was visually inspected to determine whether it was located on a river or stream (hereafter run-of-river) or was on a reservoir. If the facility was on a reservoir, the NHD catchment associated with the facility was revised if necessary to account for potential mixing dynamics within the reservoir and inundated tributaries as in Caldwell et al. (2014). In total there were 1746 unique PWS intake facilities over 1361 PWS in the region (Fig. 1b).

We characterized the raw water quality and watershed characteristics for PWS intake facilities across the region and identified those where baseline raw water quality could be considered high. We used a similar approach to that implemented by the US EPA in the development of nutrient criteria for rivers and streams by aggregated Level III Ecoregion (USEPA, 2021a) (Fig. S2). In their approach, the US EPA used the 25th percentile of observed TN, TP, and turbidity by ecoregion to define conditions of surface waters that are minimally impacted by human activities and protective of aquatic life and recreational uses. In our approach we used the 25th percentile SPARROW predicted TN, TP, and SS concentrations across all NHD catchments in each ecoregion as the maximum threshold of high water quality for these parameters. We used the SPARROW predicted concentrations to estimate these criteria instead of observations because the observations are limited in their spatial distribution and therefore may not adequately represent conditions in some locations and under some watershed conditions upstream of the PWS facilities.

2.4. Linking water quality to baseline land cover

The observed water quality data was linked to historical baseline land cover across the region. The baseline land cover was based on the 2011 National Landcover Dataset (NLCD) (Homer et al., 2015). We used the Wieczorek et al. (2018) dataset that indexed the 2011 NLCD land cover along to the NHD catchments. We used the 2011 NLCD because it closely corresponds to the 2012 time period represented by observed and modeled water quality data and the Wieczorek et al. (2018) version of the 2011 NLCD was also used as an input for the SPARROW models. We aggregated the various land cover classes in the NLCD into four broad classes to simplify analysis, where Forest = deciduous forest, evergreen forest, mixed forest, and woody wetland; Developed = developed open space, low, medium, and high intensity development; Agriculture = Pasture/Hay and cultivated crops; and Other-natural = barren, scrub/shrub, grassland, and emergent wetland.

We then used two regression approaches to examine relationships between observed and modeled TN, TP, and TSS/SS concentrations and the baseline proportion of upstream area in forest, developed, agriculture, and other natural land cover. In both approaches we log-transformed the water quality data because they tended to be lognormally distributed and similar modeling approaches have found better model fits with log-transformed water quality parameters (Warziniack et al., 2017). We limited our analysis to include only observation sites and modeled catchments that were not nested within the watershed of another, thus it could be reasonably assumed that the remaining sites or catchments included in the analysis were independent. Observation sites from the full dataset were excluded beginning at the river basin outlets and moving upstream until there were no observation sites upstream of another. Modeled catchments were excluded when the catchment cumulative upstream area was greater than the catchment incremental area. The resulting dataset included 631 TN, 605 TP, and 495 TSS/SS observation sites, and 307,656 modeled catchments across the region. We first performed independent linear regressions of observed and modeled log-transformed TN, TP, and TSS/SS concentrations with the proportion of upstream area in each of forest, developed, agriculture, and other natural baseline land cover. The goal of this approach was to examine overall relationships between these water quality parameters and each land cover type to identify the significance and direction of change in water quality with increasing land cover percentage in each class. In our second approach we developed multiple regression models of observed and modeled log-transformed TN, TP, and TSS/SS concentrations with the proportion of upstream area in developed, agriculture, and other natural baseline land cover. The goal of this approach was to quantify the change in water quality for incremental changes in developed and agriculture land cover types. The model form was:

$$\log\left(Q_i\right) = \beta_0 + \beta_{dev}DEVELOPED + \beta_{ag}AGRICULTURE + \beta_{on}OTHERNAT + e_i \tag{1}$$

where Q_i is the water quality parameter (TN, TP, or TSS/SS concentration), *DEVELOPED*, *AGRICULTURE*, and *OTHERNAT* are the percentages of developed, agriculture, and other natural land cover classes upstream, respectively, β_x are regression terms, and e_i is an error term. The β_0 term represents the water quality parameter concentration when all of upstream developed, agriculture, and other natural land cover classes are zero, i.e., the water quality parameter concentration with only forest upstream. In conducting this regression analysis, we confirmed that 1) there was no multicollinearity among the land cover predictor variables (Variance Inflation Factor < 1.5), 2) samples could be considered independent (Durbin-Watson statistic ranged from 1.2 to 1.6), 3) standardized residuals centered on zero with no clear pattern in relation to predicted values, and 4) residuals were normally distributed as demonstrated by a linear relationship between residual quantiles and theoretical quantiles from a normal distribution in Normal Q-Q plots. If the estimated coefficient for a given non-forest land cover type is β_x, then a z percent change from forest cover to that land use will result in a $e^{z*\beta x} - 1$ % change in the water quality parameter (Warziniack et al., 2017). We used the β parameters of these water quality regressions to estimate the change in the mean TN, TP, and TSS/SS concentration for a one percentage point increase in developed and agriculture land cover using water quality observations, presented as the mean response ± 95 % confidence interval.

The SPARROW modeled TN, TP, and SS concentrations for some catchments across the region were zero or near zero. As a result, the log transformed concentrations for these catchments were either undefined or highly negative and thus were clearly outliers in the log-transformed modeled water quality data. These concentrations are well below typical Method Detection Limits (MDLs) for water quality analysis and thus cannot be meaningfully reported in practice. We assumed MDLs of 0.01 mg L^{-1} for TN and 0.002 mg L^{-1} for TP (USEPA, 2021b), and 1.0 mg L^{-1} for SS (USEPA, 2010), and replaced the modeled concentration with one-half of corresponding MDL when a modeled concentration was below the MDL. This affected 0.4 %, 1.1 %, and 2.5 % of the 811,002 total catchments in the region for TN, TP, and SS, respectively.

In addition to regressions between water quality and land cover, we compared modeled TN, TP, and SS incremental export rates (i.e., loads) among catchments dominated by each aggregated land cover type. We assumed that any land cover that encompassed >90 % of a catchment area was the dominant land cover for that catchment. This relatively high threshold of dominant land cover was used because developed and agricultural pollutant loads can easily overwhelm background sources in forested or other natural dominant catchments at lower thresholds, limiting our ability to isolate differences in incremental pollutant loads across land cover types. In total there were 16,139 catchments that were agriculture-dominant, 4785 developed-dominant, 94,446 forest-dominant, and 42,531 other-natural-dominant land covers. The distribution of catchments by dominant land cover type across States is shown in Fig. S3.

2.5. Future land cover upstream of Public Water System Facilities

Future projections of land cover were overlaid on watersheds upstream of PWS intake facilities to identify those where raw water quality may be most vulnerable to land cover change in the future. The future land cover was based on the EPA Integrated Climate and Land-Use Scenarios (ICLUS) Version 2.1.1 projections for 2070 under the SSP5 RCP85 HadGEM2-ES scenario (USEPA, 2020), and was treated as a hypothetical land cover change scenario in the evaluation of potential water quality impacts to PWSs. This scenario represents a future of high dependence on fossil fuels to support robust economic growth and thus high global greenhouse gas emissions and high levels of population growth in the U.S. (IPCC, 2015; O'Neill et al., 2017), representing a potential upper bound (i.e., worst case) land use change scenario in the region. Although the ICLUS projections are based on land use rather than land cover, we apply the term land cover here to be consistent with the historical baseline land cover data from NLCD.

We examined projected changes in natural land cover by comparing the 2070 ICLUS land cover to the 2020 baseline ICLUS because direct comparisons to NLCD land cover were therefore not straightforward. ICLUS data assigns land use (hereafter land cover) to 20 different categories that do not precisely match NLCD land cover classes. We first aggregated ICLUS land cover classes into broad natural, agriculture, and developed classes. Natural land cover included ICLUS classes natural water, reservoirs/canals, wetlands, recreation/conservation, timber, grazing, and parks/open space. Agriculture land cover included ICLUS classes pasture and cropland. Developed land cover included ICLUS classes mining/barren, exurban, suburban, urban, commercial, industrial, institutional, and transportation. We then identified areas with natural land cover in 2020 that were projected to be converted to developed land cover in 2070. The ICLUS models project the conversion of natural and agricultural land covers to developed land cover and increases in development intensity among developed land cover classes. Thus conversion of natural to agricultural land cover, while plausible, was not an outcome considered in ICLUS (USEPA, 2017b). The gridded ICLUS data for 2020 and 2070 were scaled to the NHD catchment and the upstream baseline and future land cover was computed for each PWS intake watershed. We then identified those PWS intake facilities that were projected to have the largest proportion of natural land cover converted to developed land cover and therefore are most vulnerable to water quality degradation. In this way, we did not directly link future land cover to water quality at PWS intakes, rather the potential effects of projected land cover change for PWS intakes can be inferred based on relationships between baseline land cover and water quality we quantified in this study.

3. Results

3.1. Observed water quality linkages to upstream land cover at monitoring sites

Sites with more upstream forest land cover tended to have lower observed concentrations of TN, TP, and TSS than sites with more upstream developed, agricultural, and other natural land cover (Fig. 3, Table S3). Across all sites, the slope of the independent regressions between log-transformed TN, TP, and TSS and upstream forest land cover percentage were all significant ($\alpha = 0.05$) and negative, indicating decreasing concentrations with increasing upstream forest cover percentage. In contrast, slopes for regressions with upstream developed, agricultural, and other natural land cover percentage were generally significant and positive, indicating increases in TN, TP, and TSS with increasing developed or agricultural land cover upstream. The only exception was the slope of TSS with increasing upstream developed land cover was negative but was not significant ($p = 0.21$). The slope of TP with increasing upstream other-natural land cover was positive but was not significant ($p = 0.27$). While these relationships were generally significant when considering all sites, there was considerable variability in TN, TP, and TSS concentrations for any given percentage of forest, developed or agricultural land cover upstream (Fig. 3).

The multiple regression models corroborated the independent regression approach, and allowed an examination of the sensitivity of water quality to incremental changes in upstream developed and agricultural land cover types. The β_0 regression coefficient using the observed water quality suggested that TN, TP and TSS concentrations across observation sites, on average, could be 0.4 ± 0.04, 0.03 ± 0.01, and 12.2 ± 4.2 mg L^{-1}, respectively, if upstream developed, agriculture, and other natural land covers were zero (i.e., all upstream area was forested) (Table 1). The β_{DEV}, β_{AG}, and β_{ON} regression coefficients were all significant and positive, suggesting that changes in upstream land cover from forest to any of these land cover types would result in an increase in TN, TP, and TSS concentration. For TN and TP, the regression coefficients in order of magnitude were $\beta_{AG} > \beta_{DEV} > \beta_{ON}$, suggesting that upstream agricultural land cover increased TN and TP concentrations more so than developed, and developed more so than other natural land cover. In contrast, the TSS regression coefficients in order of magnitude were $\beta_{AG} > \beta_{ON} > \beta_{DEV}$ however β_{DEV} was not significant ($p = 0.13$). On average in our sample, these results suggest that a 1 % change from forest to developed land cover could result in an approximately 1.5 ± 0.2 % increase in TN concentration, a 1.9 ± 0.3 % increase in TP concentration, and a 0.4 ± 0.5 % increase in SS concentration. Similarly, these relationships suggest that a 1 % change from forest to agricultural land cover could result in an approximately 2.4 ± 0.3 % increase in TN concentration, a 3.2 ± 0.4 % increase in TP concentration, and a 1.4 ± 0.7 % increase in SS concentration.

3.2. Modeled water quality linkages to upstream land cover and other sources

Modeled concentrations of TN, TP, and SS exhibited spatial patterns consistent with those of observed concentrations (Fig. S4) and allow a more detailed analysis of the linkage between water quality and upstream land cover and other sources. Similar to the water quality observations, sites with more upstream forest land cover tended to have lower modeled concentrations of TN, TP, and SS than sites with more upstream developed, agricultural, and other natural land cover (Table S3). Multiple regression parameters relating modeled TN, TP, and SS concentrations to upstream developed, agriculture, and other natural land cover types were similar to those relating observed concentrations at observation sites (Table 1). Like the regression models using observed water quality data, the regression models using modeled water quality data had regression coefficients in order of magnitude of $\beta_{AG} > \beta_{DEV} > \beta_{ON}$ for TN and TP, whereas coefficients for modeled SS in order of magnitude were $\beta_{ON} > \beta_{AG} > \beta_{DEV}$ across the observation sites. These relationships suggest similar TN, TP, and SS concentration responses to increasing upstream developed and agricultural land cover from forested land across the observation sites.

Percent changes in modeled TN, TP, and SS concentration due to changes in developed and agricultural land cover varied somewhat across all independent catchments in the region compared to the observation sites. For example, the responses of modeled TN, TP, and SS to changes in upstream developed and agriculture for all independent catchments were lower than modeled responses for only the observation sites. In addition, the regression parameter estimates across all catchments in order of magnitude for SS were $\beta_{AG} > \beta_{DEV} > \beta_{ON}$ rather than $\beta_{ON} > \beta_{AG} > \beta_{DEV}$ for only the observation sites. Taken together, these results suggest that observed and modeled TN, TP, and SS concentrations have similar sensitivities to changes in land cover over the observation sites, and in some cases these sensitivities may differ from those across independent catchments in the region as a whole.

Catchments with dominant (>90 %) agricultural land cover upstream had the greatest export rates for all parameters, followed by developed, then forest and other-natural (Fig. 4). While differences in the central tendency of modeled TN, TP, and SS export among catchments with different dominant land covers were clear, there was considerable variability around these central values. For example, SPARROW estimates suggest the 90th percentile TN export from forest-dominant catchments (4.2 (1.7 SE) kg ha^{-1} yr^{-1}) may be greater than the 10th percentile TN export from developed-dominant catchments (3.2 (1.3) kg ha^{-1} yr^{-1}) and only slightly less than the 10th percentile TN export from agriculture-dominant catchments (4.7 (1.8) kg ha^{-1} yr^{-1}). Similar relationships between TP and SS export of forest-dominated and developed or agriculture-dominated catchments were also apparent (Fig. 4b and c). The relative modeled TN, TP, and SS export rates for the other-natural land cover type are seemingly at odds with the regression coefficient β_{ON} in the multiple regression models; export rates for the other-natural land cover type are lower than those of forested land cover, while the β_{ON} parameter is positive (Table 1). This reflects the fact that water yield in west Texas and Oklahoma where most of the other natural land cover type is located is typically low, resulting in low export in mass terms but could have higher concentration than other land cover types with greater water yield.

The SPARROW TN models estimate the contribution of atmospheric N deposition which varies considerably across the study area. This spatial variability, along with spatial variability in catchment properties (e.g., runoff rates, vegetation type, and density, etc.) is reflected in modeled TN export rates from forest or other-natural-dominant catchments. According to SPARROW model estimates, atmospheric deposition was the primary external N source in forest and other-natural dominant catchments across the region, contributing 90 % or more of the TN export for >90 % forest-dominant and 70 % or more for >90 % of other-natural-dominant catchments. For example, model estimates suggest that atmospheric N deposition was the only external N source contributing to the 1.9 (1.5) kg ha^{-1} yr^{-1} TN export of a 98 % forested catchment in the Hillside National Wildlife Refuge in western Mississippi (8.2 kg ha^{-1} yr^{-1} inorganic N deposition), as well as the only external N source of the 4.5 (1.8) kg ha^{-1} yr^{-1} TN export of a 100 % forested catchment in Sumpter National Forest, South Carolina (8.7 kg ha^{-1} yr^{-1} inorganic N deposition). Almost all of the other-natural-dominant catchments are located in western Texas and Oklahoma (Fig. 1a, S3), in predominantly grassland and shrubland land cover. Due to low atmospheric N deposition in this region, SPARROW estimated TN export for other-natural-dominant catchments was also low, even lower than forest-dominant catchments (Fig. 4a).

Similarly, natural geological sources of P vary across the study area resulting in highly variable TP export from forested or other-natural-dominant catchments. According to SPARROW models, geological sources of P contributed 50 % or more of the TP export for >90 % of forest-dominant and 23 % or more for >90 % of the other-natural-dominant catchments. The estimated contributions of geological sources to TP export for these catchments was lower than the contribution of atmospheric deposition to TN export because geological sources of P are very low compared to sources from other land covers (e.g., urban, fertilizer, manure) in the remaining 10 % land area of these forest or other-natural-dominant catchments. Geological sources of P accounted for all of the estimated total

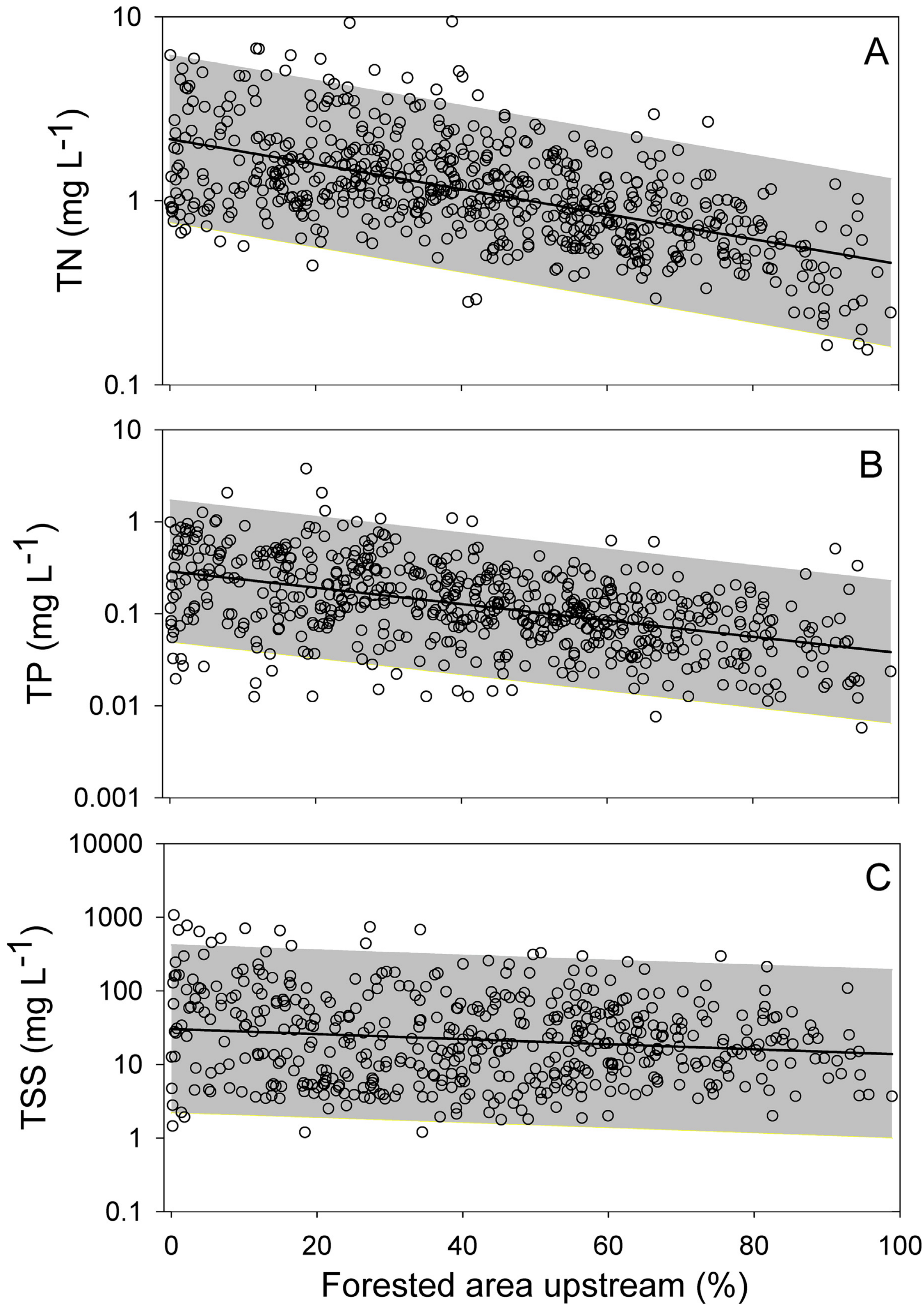

Fig. 3. Fit of observed TN (A), TP (B), and TSS (C) equivalent 1999–2014 mean concentration across the South as a function of upstream forested area based on the 2011 NLCD. The shaded grey region represents the 95 % prediction interval.

Table 1
Coefficient values (standard error) and fit statistics for multiple regression models relating log-transformed TN, TP, and TSS/SS concentration to upstream developed, agriculture, and other natural land cover types.

Water quality parameter	Coefficient	Observed	Modeled at observation sites	Modeled across all catchments
TN	β_0	−0.860 (5.15 × 10^{-2})	−0.608 (4.05 × 10^{-2})	−0.482 (2.60 × 10^{-3})
TN	β_{DEV}	0.015 (9.28 × 10^{-4})	0.012 (7.29 × 10^{-4})	0.006 (9.54 × 10^{-5})
TN	β_{AG}	0.023 (1.22 × 10^{-3})	0.020 (9.60 × 10^{-4})	0.015 (5.41 × 10^{-5})
TN	β_{ON}	0.013 (1.21 × 10^{-3})	0.009 (9.54 × 10^{-4})	0.001 (5.46 × 10^{-5})
TN	n	631	631	307,656
TN	R^2	0.41	0.45	0.20
TP	β_0	−3.358 (8.96 × 10^{-2})	−3.317 (6.83 × 10^{-2})	−3.015 (4.11 × 10^{-3})
TP	β_{DEV}	0.019 (1.63 × 10^{-3})	0.021 (1.25 × 10^{-3})	0.015 (1.51 × 10^{-4})
TP	β_{AG}	0.032 (2.09 × 10^{-3})	0.038 (1.59 × 10^{-3})	0.027 (8.57 × 10^{-5})
TP	β_{ON}	0.014 (2.02 × 10^{-3})	0.016 (1.54 × 10^{-3})	0.001 (8.66 × 10^{-5})
TP	n	605	605	307,656
TP	R^2	0.31	0.51	0.27
TSS/SS	β_0	2.498 (1.51 × 10^{-1})	3.612 (1.43 × 10^{-1})	3.895 (5.97 × 10^{-3})
TSS/SS	β_{DEV}	0.004 (2.79 × 10^{-3})*	0.009 (2.64 × 10^{-3})	0.010 (2.19 × 10^{-4})
TSS/SS	β_{AG}	0.014 (3.55 × 10^{-3})	0.025 (3.37 × 10^{-3})	0.022 (1.24 × 10^{-4})
TSS/SS	β_{ON}	0.012 (3.27 × 10^{-3})	0.030 (3.09 × 10^{-3})	0.008 (1.26 × 10^{-4})
TSS/SS	n	495	495	307,656
TSS/SS	R^2	0.05	0.20	0.10

* Not significant (p = 0.13).

export for 90 % of catchments that are 100 % forested (n = 30,575); model estimates suggest that the interquartile TP export among these catchments could range from 0.13 (0.10) to 0.34 (0.26) kg ha^{-1} yr^{-1}, a 2.6-fold difference. For example, geological P was the only source of the 0.06 (0.10) kg ha^{-1} yr^{-1} estimated TP export of a 100 % forested catchment in the Ouachita National Forest in eastern Oklahoma, as well as the only source of the 0.39 (0.30) kg ha^{-1} yr^{-1} estimated TP export of a 100 % forested catchment in the Chattahoochee National Forest in north Georgia. Like TN export, catchments with other-natural-dominant land cover in western Texas and Oklahoma were generally predicted to have much lower geological P contributions to TP export than that of forest-dominant catchments and thus had lower export (Fig. 4b).

SS export was also highly variable among forest and other-natural-dominant catchments across the region. Sources of SS in the SPARROW models were either overland erosion in catchment uplands or erosion of sediment in stream channels (Table S2). SPARROW models estimated that channel sediment sources were 25 %–100 % of the total SS loading for 29 % of the forest-dominant catchments, adding variability to SS export estimates for forest-dominant catchments. Among those with no channel SS contribution, the estimated interquartile SS export among forest-dominant catchments ranged from 127.2 (343.9) to 469.7 (1277.6) kg ha^{-1} yr^{-1} (a 3.7-fold difference) although these estimates should be considered in the context of the relatively large standard errors in the model predictions. These differences in SS export were largely related to differences in underlying soil types as well as land-to-water delivery variables in the SPARROW model (e.g., soil erodibility factor, annual runoff values, etc.). For example, estimated SS export of a 100 % forested catchment in the Sumter National Forest in northwestern South Carolina (annual runoff = 1292 mm) could be 590.3 (420.3) kg ha^{-1} yr^{-1}, while SS export could be 22.8 (15.8) kg ha^{-1} yr^{-1} for a 99 % forested catchment in Mount Hope Swamp near Lake Marion in South Carolina (annual runoff = 214 mm).

3.3. Water quality assessment and linkages to upstream land cover at PWS intake facilities

Across the South, there were a total of 1746 surface water supply intake facilities in 1361 Public Water Systems (PWS) and serving a total of 47 million people (Fig. 1b). 59 % of all surface water intakes were on reservoirs, and 46 % of those intakes on reservoirs were in Texas (29 %) and Oklahoma (17 %). In contrast, 53 % of all run-of-river surface water intakes were located in Virginia (14.6 %), North Carolina (13.2 %), Kentucky (12.9 %), and Tennessee (12.8 %). The median upstream land cover across all intakes was 50 % forested, 7 % developed, 18 % agriculture, and 10 % other-natural land cover. Run-of-river intakes tended to have greater upstream forest cover (median 58 %) than intakes on reservoirs (median 43 %), while upstream developed, agriculture, and other-natural land cover were similar for intakes on reservoirs and run-of-river (median 7.4 % and 7.2 % developed, respectively; median 17.1 % and 18.6 % agriculture, respectively; and median 12.8 % and 7.1 % other-natural, respectively).

SPARROW estimated concentrations of TN, TP, and SS were lower for intakes with primarily forested upstream watersheds (i.e., >50 % forested), and estimated concentrations were lower for intakes located on reservoirs than those that were run-of-river intakes (Fig. 5). For example, the median estimated SS concentration was two times greater for run-of-river intakes (130 (109) mg L^{-1}) than for intakes on reservoirs (63.3 (54.7) mg L^{-1}). Among intakes on reservoirs, the median estimated SS concentration for those with <50 % forest land cover upstream (99.3 (85.8) mg L^{-1}) was two times greater than those with >50 % forest land cover upstream (49.5 (41.8) mg L^{-1}). Similarly, the median estimated SS concentration for run-of-river intakes with <50 % forest land cover upstream (226.8 (739.0) mg L^{-1}) was two times greater than those with >50 % forest land cover upstream (108.6 (101.2) mg L^{-1}). In contrast, while the median estimated TP concentration for intakes on reservoirs with <50 % forest land cover upstream (0.072 (0.069) mg L^{-1}) was virtually the same as those with >50 % forest land cover upstream (0.070 (0.064) mg L^{-1}), the median estimated TP concentration for run-of-river intakes with <50 % forest land cover upstream (0.206 (0.197) mg L^{-1}) was 2.1 times those with >50 % forest land cover upstream (0.099 (0.094) mg L^{-1}). Similarly, the median estimated TN concentration was 1.7 times greater for run-of-river intakes with <50 % forest upstream but was 1.3 times greater for intakes on reservoirs with <50 % forest upstream. Despite the variability in TN, TP, and SS concentration for a given upstream land cover and intake setting, these results suggest that both intake setting and upstream land cover are important determinants of water quality and surface water intakes. Run-of-river intakes may be more sensitive to upstream land cover in the context of future land cover change than those on reservoirs as illustrated by the larger differences in TN, TP, and SS concentrations between watersheds with greater or <50 % forest cover for run-of-river intakes than the differences in concentrations for intakes on reservoirs.

Using estimates of TN, TP, and SS criteria for high raw water quality by aggregated EPA Level III ecoregion using SPARROW model outputs (Table S4), 15 % (n = 268) of the intake facilities across 207 PWS met criteria for all three parameters (Fig. 6a). Twenty-four percent of these facilities were in Texas, followed by Oklahoma (24 %), Virginia (14 %), and North Carolina (13 %), and in total serve more than eight million people. Of the facilities with high water quality, 51 % had >50 % forest land cover upstream and 90 % had <16 % and 30 % developed and agricultural land cover upstream, respectively. Eighty-five percent of those facilities

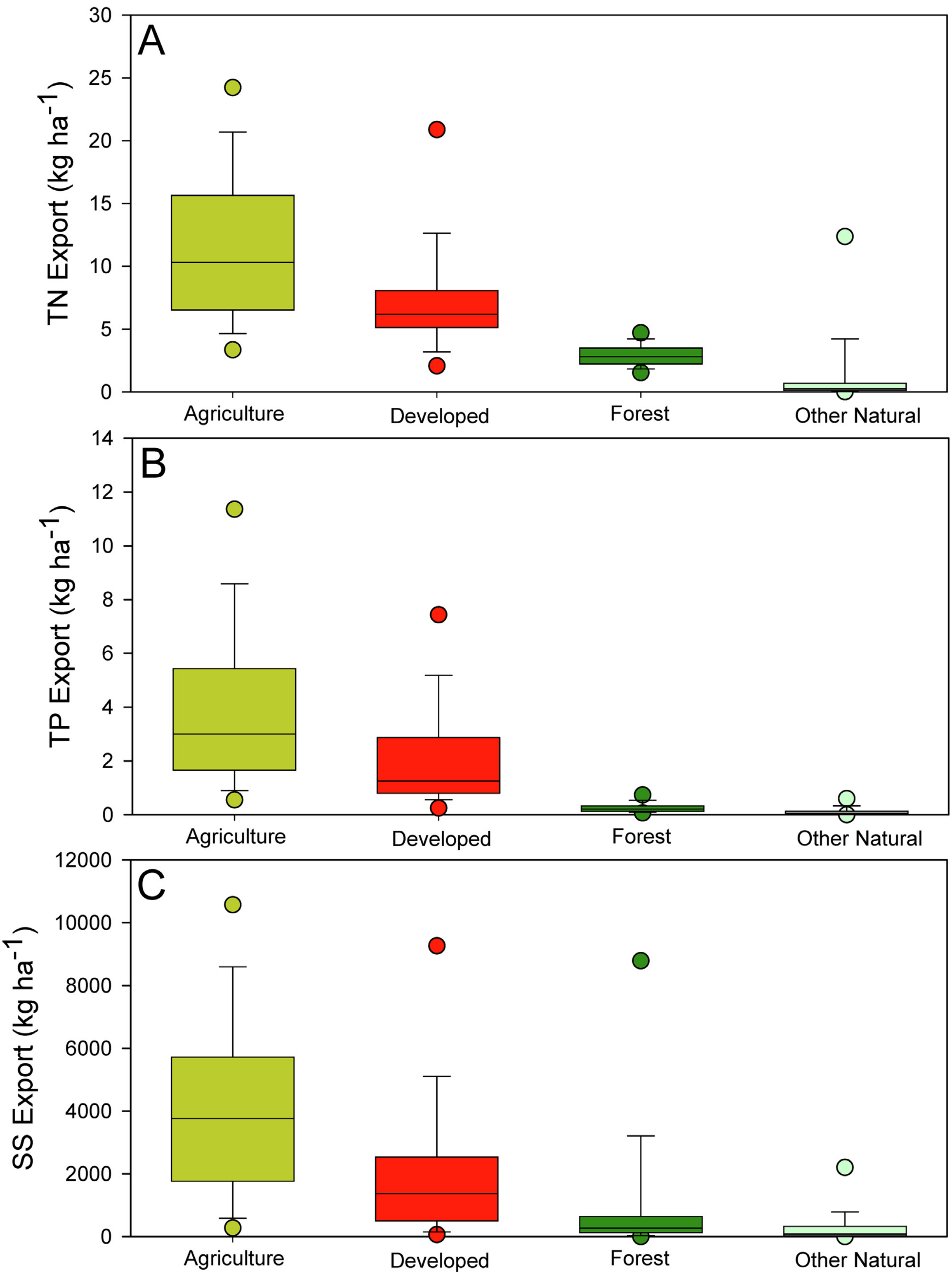

Fig. 4. Distribution of ca. 2012 annual TN (A), TP (B), and SS (C) export rates across all catchments in the South by catchment dominant land cover computed from SPARROW predicted incremental loads. A given land cover was assumed by be dominant in a catchment if it occupied >90 % of the catchment land area. Circles are the 5th and 95th percentile, whiskers the 10th and 90th percentile, boxes the 25th and 75th percentile, and line is the median export rate across all catchments with a given dominant land cover.

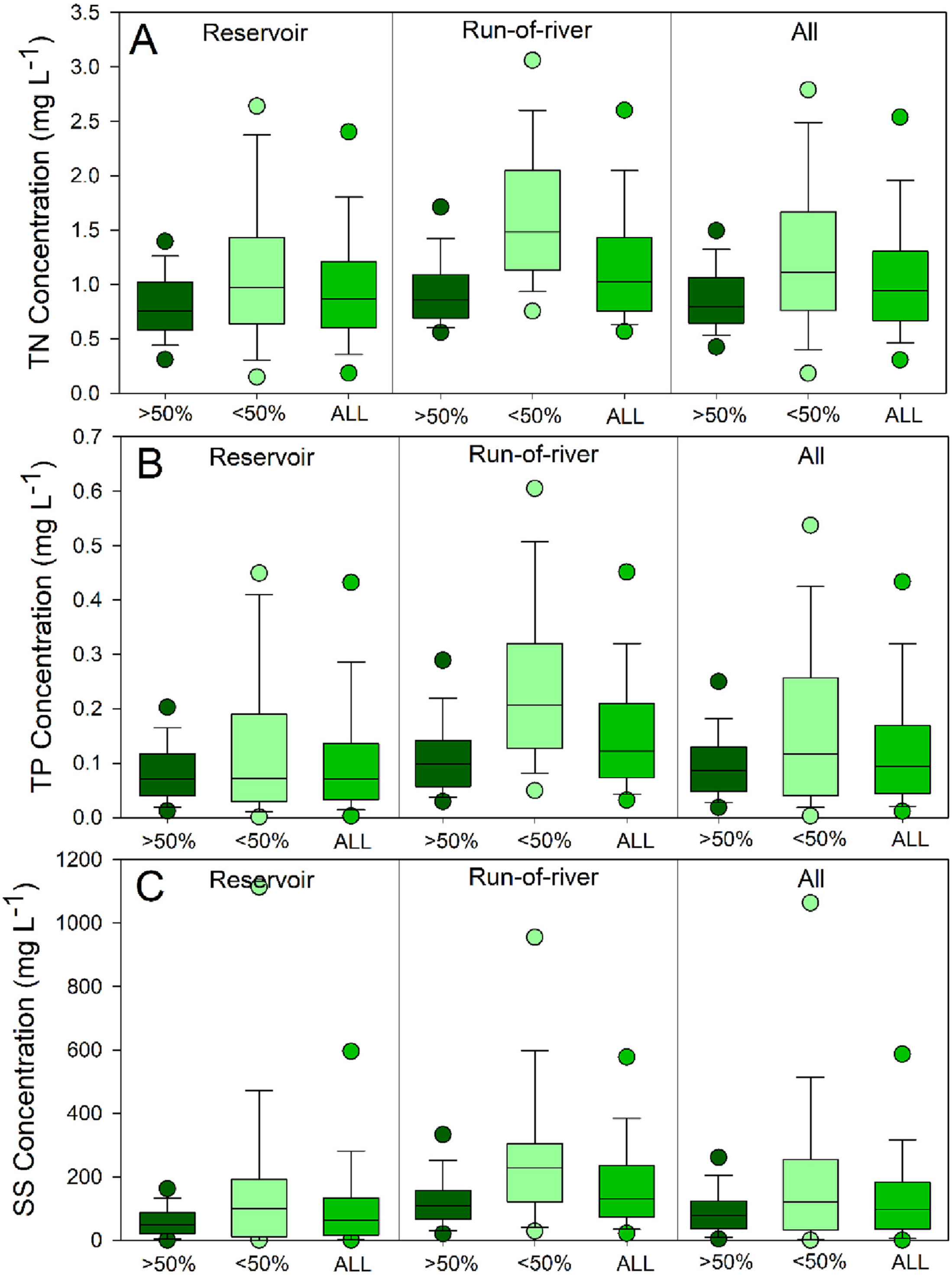

Fig. 5. Distribution of ca. 2012 TN (A), TP (B), and SS (C) concentration across intakes by setting (reservoir, run-of-river, all) and by upstream forest area (>50 %, <50 %, all).

with <50 % upstream forest land cover were located in Texas and Oklahoma, where the median percentage of other-natural land cover was 57 % and 93 % of facilities were on reservoirs. The generally lower upstream forest land cover for these PWS intakes is reflective of the lower forest land cover in Texas and Oklahoma, while the generally drier climate and more limited water availability in these states dictates the need for reservoirs to insure reliable water supplies. Of the facilities in the other 11 states, 87 % had >50 % forest land cover upstream. Eighty-five percent of facilities with high water quality were on a reservoir overall, while the remainder were run-of-river intakes. Forty-six percent of those on reservoirs had >50 % forest land cover upstream, while 75 % of the run-of-river intakes had >50 % forest land cover.

3.4. Public Water System intake facilities vulnerable to land cover change

Using the ICLUS projections of land cover change between 2020 and 2070, 98,658 km^2 (7.3 %) of land in natural land cover in 2020 (including forest) was predicted to be converted to developed land cover by 2070 across the South (Fig. 6b). Across the 1746 intake facilities, 10.4 % were projected to have a reduction in upstream natural land cover percentage

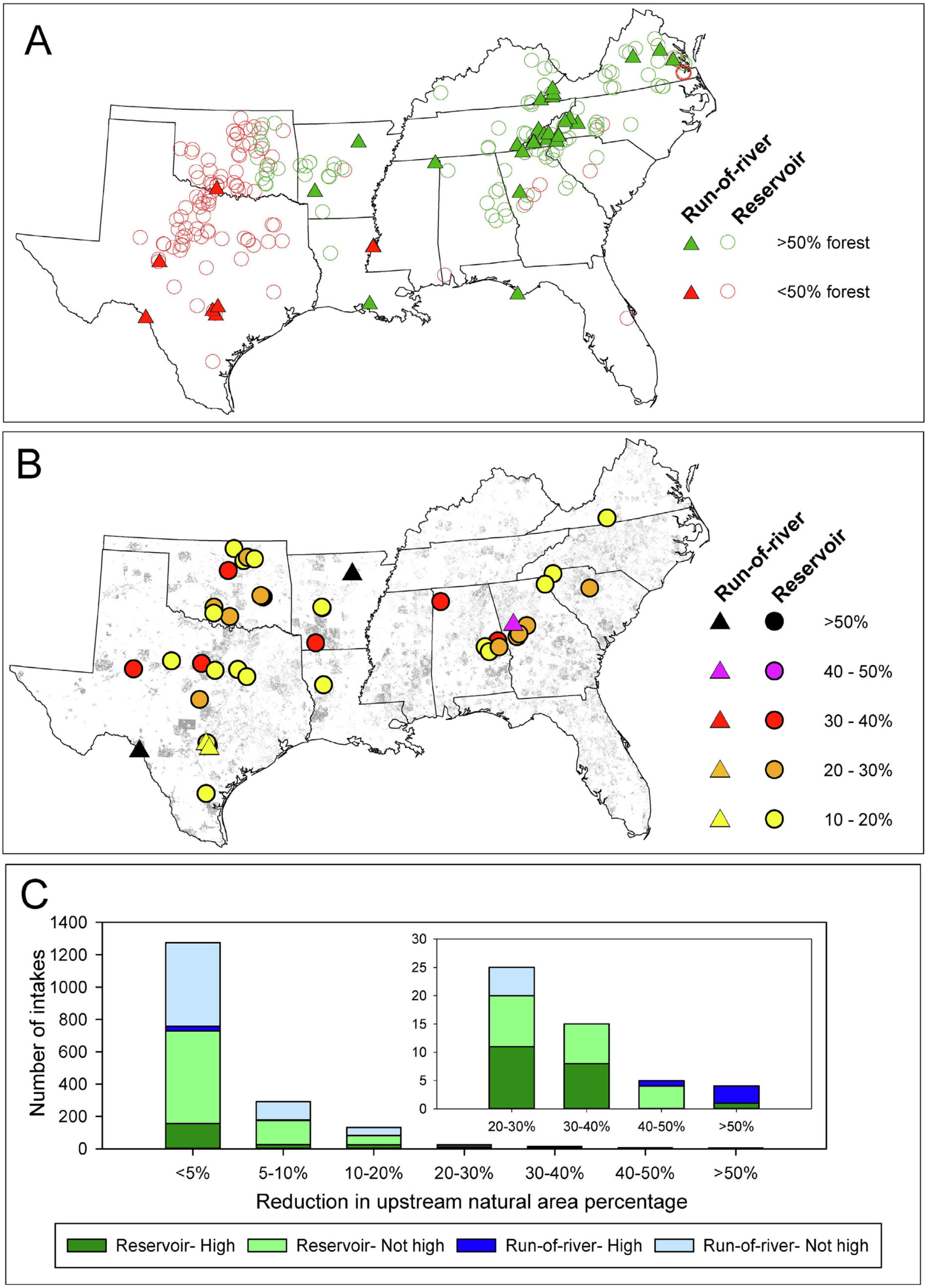

Fig. 6. Public Water System surface water facilities with high raw water quality ca. 2012 for all water quality parameters (A), areas where natural land cover in 2020 was predicted to be converted to developed land cover by 2070 (grey shading), and PWS intakes with high water quality and greater than a 10 % reduction in upstream natural land cover percentage (B), and the number of intakes with varying projected loss of upstream natural land cover by intake setting and raw water quality classification (C). The inset bar graph in (C) presents the same data as the main figure but with a magnified y-axis.

>10 % (Fig. 6c). The 2020 natural land cover percentage among these intake facilities ranged from 12.2 % to 100 % (median 58.7 %). By 2070, the natural land cover percentage among these intakes ranged from 1.3 % to 86.1 % (median 39.8 %) with reductions in upstream natural land cover of 11 % to 89 % compared to 2020. For example, natural land cover in the 107 km^2 Cherryville, NC water system Indian Creek intake watershed was projected to decrease from 12.2 % of the watershed in 2020 to 1.3 % by 2070, while natural land cover in the 6.0 km^2 Griffin, GA water system Still Branch Reservoir intake watershed was projected to decrease from 99.3 % to 73.1 %.

Intake facilities with smaller upstream watersheds tended to have larger projected reductions in upstream natural land cover than those with larger upstream watersheds. Of the 181 intake facilities with greater than a 10 % reduction in upstream natural land cover percentage, 90 % had watershed areas <5077 km^2 and the top 10 intake facilities in terms of projected upstream natural land cover loss had watershed areas <102 km^2. Among those facilities with greater than a 10 % reduction in upstream natural land cover, 51 were classified as having high raw water quality, with 44 on reservoirs and seven run-of-rivers (Fig. 6b). All four facilities with >50 % projected upstream natural land cover loss (one reservoir, three run-of-river) were classified has having high raw water quality (Fig. 6c). For example, upstream natural land cover was projected to decrease from 71.4 % to 10.1 % across the 101.6 km^2 watershed for the run-of-river intake facilities associated with the Del Rio Utilities Commission serving 36,662 people in Texas, where raw water quality is currently considered high. Similarly, upstream natural land cover for a run-of-river intake with high water quality associated with the Summerville, Georgia PWS serving 11,651 people was projected to decrease from 48.0 % to 20.8 % across the 65.5 km^2 watershed.

4. Discussion

We used observed and modeled water quality data to evaluate the linkage between water quality and land cover across the South, with emphasis on these relations at PWS intake facilities. Our results suggest that forests provide the highest water quality in terms of TN, TP, and SS concentrations relative to other land uses across the region. Further, PWS intake facilities with high water quality tended to have more upstream forest or other-natural cover, particularly for run-of-river intakes. Intakes on reservoirs generally had lower concentrations of TN, TP, and SS than run-of-river intakes. While these broad generalizations were identified, there was substantial variability in land cover and water quality relationships that were related to the influence of other factors including point sources, reservoir characteristics, and background natural sources. We found that many intake facilities could be at risk of water quality degradation due to loss of upstream natural land cover by 2070, especially those with relatively small upstream watersheds and those that were run-of-river intakes. To our knowledge, this is the first study to combine observed and modeled water quality data with information about PWSs and future land cover projections across a broad, heterogenous region, providing new insights into the relative influence of land cover on surface water supplies.

4.1. Land cover water quality linkages

Both observed and modeled TN, TP, and SS decreased with increasing upstream forest land cover and increased with increasing developed and agricultural land cover across water quality monitoring sites and all independent catchments in the region. For example, on average in our sample, these results suggest that a 1 % change from forest to developed land cover could result in an approximately 1.5 $\pm$ 0.2 % increase in TN concentration, a 1.9 $\pm$ 0.3 % increase in TP concentration, and a 0.4 $\pm$ 0.5 % increase in SS concentration based on multiple regression models using water quality observations. Warziniack et al. (2017) reported similar relationships between forest cover and raw water quality across a smaller sample size and over a larger region that included 37 Public Water Systems in the US, where a 1 % increase in forest land cover could result in a 3 % decrease in turbidity; whereas a 1 % increase in developed land cover could result in a 3 % increase in turbidity. Other studies have also found that forested watersheds tend to provide higher water quality by various measures albeit over generally smaller regions and sample sizes than those of this study (Abildtrup et al., 2013; Brogna et al., 2018; Cunha et al., 2016; Fiquepron et al., 2013; Lopes et al., 2019; Tsegaye et al., 2006).

While the broad generalization that forested watersheds tend to provide higher water quality has been well established, this study showed that numerous confounding factors can affect the benefit of this ecosystem service for drinking water supply and can complicate our ability to quantify forest benefits across large scales in mixed-use watersheds. Modeled TN, TP, and SS export rates at the catchment level show generally lower export of these pollutants in forest-dominant than developed- or agricultural-dominant land covers, but the variability in these export rates was considerable. Atmospheric deposition of N, geological sources of P, underlying soil types, and channel erosion all contributed to the variability in TN, TP, and SS export from forested watersheds, and some cases resulted in higher export rates from forested catchments than developed or agricultural catchments across the region. Despite the variability in export across land cover types, changing land cover from forest to developed or agricultural land cover under the same natural background pollutant sources would likely result in increases in TN, TP, and SS export depending on the intensity of the developed land cover (i.e., open space, low, medium, high) or type of agricultural land cover (i.e., pasture, row crop). This can partly be explained by uptake of nutrients and settling of sediment in forests (particularly riparian forests) (Lockaby et al., 2013) and also the general lack of additional sources of these pollutants associated with developed or agricultural land covers including fertilizers, manure, and surface erosion (Abildtrup et al., 2013; Brown and Froemke, 2012).

In addition to land cover and associated non-point sources of TN, TP, and SS, point sources (e.g., wastewater treatment plants) and reservoirs add to the variability and complexity in linking land cover to water quality at large scales. Wastewater effluent typically increases nutrient loads and other constituents in receiving waters (Hamdhani et al., 2020); the extent of these effects depend on the level of treatment and the relative flow volumes of effluent discharge and receiving waters. Reservoirs can act as sediment retention and nutrient cycling basins, typically resulting in decreases in nutrient and sediment concentrations downstream (Ignatius and Rasmussen, 2016).

4.2. Future land cover and climate change impacts on water quality

Land cover and climate change can independently and collectively alter surface water quality with implications for aquatic ecosystems and Public Water Systems. Most projections of land cover in the South suggest that there will be continued conversion of agricultural and forested land cover to developed land over the 21st century (e.g., Wear and Greis, 2013). The results of this study suggest that these projected land cover changes, if realized, could have negative implications for water quality in the region. Climate change could magnify these land cover change driven effects on water quality through increases in the frequency and magnitude of extreme precipitation events (Gao et al., 2012; Zobel et al., 2018) as it is through precipitation events that a majority of nonpoint source pollutant loads from developed and agricultural land covers are delivered to surface water supplies (USEPA, 2003).

4.3. Implications for Public Water Systems

Our results showed that both intake setting and upstream land cover are important determinants of water quality and surface water intakes, and run-of-river intakes may be more sensitive to upstream land cover than those on reservoirs. Modeled concentrations of TN, TP, and SS were lower for intakes with primarily forested upstream watersheds (i.e., >50 % forested), and concentrations were lower for intakes located on reservoirs than those that were run-of-river intakes. Of the PWS intake facilities with high water quality by our definition, 90 % had <16 % and 30 %

developed and agricultural land cover upstream, respectively. Under the future land cover scenario, 181 intake facilities were predicted to have >10 % reduction in upstream natural land cover by 2070. Intake facilities with smaller upstream watersheds tended to have larger projected reductions in upstream natural land cover than those with larger upstream watersheds, and the top ten PWS intake facilities in terms of natural land cover loss served populations between 1385 and 36,662 (median 16,800). Among these facilities, 51 were classified as having high raw water quality based on modeled TN, TP, and SS concentrations and the water quality classification developed in this study, with 44 on reservoirs and seven run-of-rivers. These results suggest that smaller PWS (often with more limited resources) may be most vulnerable to future water quality impacts of land cover change.

These results could have implications for the costs and infrastructure needed to treat raw surface water for drinking water use. Cities like New York, Boston, Tokyo and São Paulo have implemented forest conservation policies to provide high quality drinking water (Gartner et al., 2014; McDonald and Shemie, 2014; Price and Heberling, 2018). Both surface water quality and drinking water prices are important components in U.S. EPA economic assessments of surface water quality regulations (Price and Heberling, 2018). With this in mind, organizations like the American Water Works Association (AWWA) and the U.S. Endowment for Forestry and Communities are furthering research on the relationship between drinking water treatment costs and forest cover and building partnerships with water utilities to protect the forested watersheds (Gartner et al., 2014). The federal government has contributed to water quality payments for forest conservation to landowners in the South via several programs including the Chesapeake Bay Watershed Initiative (CBWI) in Virginia and the Kentucky Soil and Water Conservation Cost Share Program with the goal of preventing soil erosion and protecting water quality. These government programs have been relatively small in dollar terms, averaging about $110,000 per year for forestry-related water quality projects in the region (Frey et al., 2021a; Frey et al., 2021b). By comparison, compliance markets for forested wetland mitigation, forested stream mitigation, and water quality trading credits from forested riparian buffers have averaged about $745 million per year for the region. The states of Florida and Louisiana were particularly active in forest wetland mitigation trading, averaging $450 million and $130 million per year, respectively (Frey et al., 2021a; Frey et al., 2021b). However, the benefits and costs of forest source water protection are highly varied, due in part due to spatial heterogeneity in how forest loss affects nutrient and sediment flow as well as variation in property values (the opportunity costs of forest preservation).

4.4. Implications for water resource management

Our results are timely from a management perspective given the global threats of forest loss to agriculture and development (FAO and UNEP, 2020), and potential implications for downstream water supplies. The linkages between land cover and water quality developed here could be coupled with information quantifying drinking water treatment costs and other benefits to estimate the economic value of forested lands for water quality (FAO IUFRO and USDA, 2021). Studies of this nature have been conducted in South Africa (Gelo and Turpie, 2022), Brazil (Cunha et al., 2016), France (Fiquepron et al., 2013), Portugal (Lopes et al., 2019), Costa Rica (Piaggio and Siikamaki, 2021), the United States (Warziniack et al., 2017), and globally (McDonald et al., 2016). Our results align with this larger body of literature linking land cover to water quality for Public Water Systems, and provide new information at a high resolution across a large, heterogenous region with clear dependence on water from forested lands (Liu et al., 2020) and threats to land cover change (Wear and Greis, 2013).

While a majority of the forested land in the western U.S. is publicly owned, most of the forested land in the eastern U.S. is privately owned (Hewes et al., 2017) and is therefore vulnerable to land use change and water quality impacts. Our results could inform a foundation for a payment for ecosystem services program in which private forest landowners in water supply watersheds in the eastern US could be compensated for the downstream benefits of keeping their land forested (McDonald et al., 2016). Such foundational efforts have been undertaken within some river basins in the South, including the Catawba river basin in North and South Carolina (Eddy et al., 2019) and riparian buffer credit trading in several other watersheds in North Carolina (NCDEQ, 2022), but the widespread PWS vulnerabilities across the South and eastern U.S. calls for a broader assessment of the value of forests for water supplies across the region.

4.5. Limitations and opportunities for future research

Regional assessments of water quality are challenging due to a lack of monitoring data at sufficient spatial and temporal scales (Jiang et al., 2020; Kirschke et al., 2020) and limitations of hydrological models used to predict water quality (Fu et al., 2020; Hallouin et al., 2018). Limitations of hydrological models are related to limitations of the monitoring data used to parameterize and test the models, as well as their ability to capture the complex and dynamic processes important for water quality in human-altered watersheds (Fu et al., 2020). Here we used published SPARROW model outputs to provide estimates of 1) the relative export rates of TN, TP, and SS among land cover types, 2) the relative contribution of various sources to TN, TP, and SS export, and 3) the concentration of TN, TP, and SS at public water system intake facilities across the region. Like other water quality modeling approaches, SPARROW is subject to uncertainty in input data and uncertainty in the manner in which hydrologic and water quality processes are simplified and represented. Uncertainty in the model-predicted pollutant loading and concentration can be substantial. For example, Moriasi et al. (2007) suggested that model bias of up to 70 % for N and P and up to 55 % for SS is indicative of "satisfactory" model performance. In light of this uncertainty, estimates of export, sources, and concentrations in this study should be considered in the context of this uncertainty as quantified with standard errors, summarized in Table S2, and detailed in cited SPARROW references. The contribution of forests to water quantity is simpler to quantify than the contribution to water quality and has been well studied (Brown et al., 2008; Liu et al., 2021; Liu et al., 2022). However even in these studies the human movement of water through withdrawals and interbasin transfers has added significant complexity to such analyses at large scales (Liu et al., 2022).

Our results suggest that there is considerable complexity in the relationship between land cover and water quality. These complexities are in part the result of sources and processes that are not directly related to land cover (e.g., point sources and reservoirs), gradients in the intensity of development and types of agriculture that were not captured in our aggregated land cover types, and others. Our goal was to examine broad land cover and water quality relationships across a large region, and thus it was beyond the scope of this work to analyze these relationships in fine detail with respect to these complexities. Further, present modeling tools are generally not sufficiently structured or parameterized, and model input data and water quality observations are generally not spatially and temporally distributed to make inferences at this level of detail at the regional scale. Despite these complexities and limitations, we identified significant relationships between land cover and water quality. Future research could seek to explicitly examine effects of these factors on water quality in greater detail.

Hydrologic model time-steps at the daily or hourly scale could provide an improved representation of land cover impacts on water quality compared to the long-term average time-steps such as that used in this study because land-cover related non-point source impacts on water quality are largely driven by precipitation events (USEPA, 2003). However, these models are difficult to parameterize and computationally expensive when applied at large regional scales. The ideal application of hydrologic models for regional land cover change impact studies would include relatively coarse regional water quality models (e.g., SPARROW) to identify "hot-spot" areas of concern, and then apply finer scale detailed river basin-scale water quality models in those areas (Caldwell et al., 2015). For example, Johnson et al. (2015) applied the SWAT (Neitsch et al., 2011) hydrologic model to predict streamflow, TN, TP, and SS loading in 20 river basins across the US, finding that the effects of future urbanization on water quality is small compared to the effects of climate change overall, but the effects could be greater in subbasins where development is concentrated. Future research could couple the regional results of this study with results of finer-temporal scale water quality model results in vulnerable water supply watersheds under climate and land cover change, and then link these products to economic models to assess the value of forests for a variety of ecosystem services including surface drinking water supply, aesthetics, improved recreation services, and mitigation of harmful algal blooms (Price and Heberling, 2018; Warziniack, 2014).

5. Conclusions

The objectives of this study were to examine relationships between land cover and water quality across a broad region in the southeastern US where future population growth is projected to result in development of natural land cover over the 21st century. We found considerable complexity and variability in this relationship that could be related to several confounding factors including catchment characteristics, background sources, point sources, reservoirs, and varying levels of development intensity and different agricultural activities. In addition, these results illustrate the challenges and uncertainty associated with modeling these relationships at broad scales. Despite these complexities, we identified significant relationships between land cover and TN, TP, and SS concentrations suggesting that forests support overall higher water quality in the region. We found that Public Water Supply intake setting (i.e., run-of-river or reservoir) and upstream land cover could be important determinants of water quality for these intakes. Further, run-of-river intakes with small accumulation areas may be most vulnerable to water quality degradation due to future loss of forest and other natural land cover in the future. This study provides new and timely broad-scale evidence that conserving or expanding forest land cover where possible could support overall higher water quality and enhance the resilience of drinking water supplies.

CRediT authorship contribution statement

Peter V. Caldwell: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Katherine L. Martin:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **James M. Vose:** Conceptualization, Writing – original draft, Writing – review & editing. **Justin S. Baker:** Conceptualization, Writing – original draft, Writing – review & editing. **Travis W. Warziniack:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Jennifer K. Costanza:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Gregory E. Frey:** Conceptualization, Writing – original draft, Writing – review & editing. **Arpita Nehra:** Writing – original draft, Writing – review & editing. **Christopher M. Mihiar:** Conceptualization, Writing – original draft.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.163550.

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