Water Resources Research

RESEARCH ARTICLE

10.1029/2022WR033088

Key Points:

- Bayesian watershed modeling provides a data-driven, probabilistic characterization of phosphorus loading and retention across different sources and seasons
- We explore interannual drivers of phosphorus loading by incorporating changes in precipitation, land use, livestock, and point sources
- Contrasting annual and summer modeling results shows lower phosphorus export rates and higher stream retention during summer

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Karimi, K., Miller, J. W., Sankarasubramanian, A., & Obenour, D. R. (2023). Contrasting annual and summer phosphorus export using a hybrid Bayesian watershed model. *Water Resources Research*, *59*, e2022WR033088. https://doi.org/10.1029/2022WR033088

Received 20 JUN 2022
Accepted 5 DEC 2022

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Contrasting Annual and Summer Phosphorus Export Using a Hybrid Bayesian Watershed Model

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Abstract

Nutrient pollution is a widespread environmental problem that degrades water quality worldwide. Addressing this issue calls for characterizing nutrient sources and retention rates, especially in seasons when water quality problems are most severe. Hybrid (statistical-mechanistic) watershed models have been used to quantify nutrient loading from various source categories. However, these models are generally developed for long-term average conditions, limiting their ability to assess temporal drivers of nutrient loading. They also have not been calibrated for season-specific estimates of loading and retention rates. To address these issues, we developed a hybrid watershed model that incorporates interannual variability in land use and precipitation as temporal drivers of phosphorus loading and transport. We calibrate the hybrid watershed model within a Bayesian hierarchical framework on both an annual and summer basis over a multi-decadal period (1982–2017). For our study area in the North Carolina Piedmont region (USA), we find that urban lands developed before 1980 are the largest contributor of phosphorus (per unit area), especially under dry conditions. Seasonally, summer phosphorus export rates are generally found to be lower than corresponding annual rates (kg/ha/mo), while in-stream retention is found to be elevated in summer. In addition, we find that precipitation has a substantially larger influence on phosphorus export from agricultural lands than other source types, especially in summer, and that antecedent (May) precipitation significantly influences summer phosphorus export. Overall, our approach provides a data-driven and probabilistic line of evidence to support watershed phosphorus management across different sources and seasons.

Plain Language Summary

Excessive nutrients (nitrogen and phosphorus) can cause algal blooms, low dissolved oxygen, and other water quality problems for lakes, streams, and coastal waters. Thus, models that quantify the anthropogenic sources of nutrients are needed for managing water quality. Most modeling efforts focus on relatively short periods, but changes in land use and climate typically occur over decadal time scales. Here, we develop models to account for how annual and summer phosphorus loads are changing from year to year. We use a statistical (Bayesian) framework to combine prior knowledge of phosphorus loading rates with data from our study area to estimate contributions from different sources. We find that export from older urban development is the largest contributor (per unit area), compared to agriculture, undeveloped land, and newer development. We also find less phosphorus export (per month) in summer compared to other seasons. In addition, our models show higher phosphorus removal rates in streams in summer in comparison to other times of the year. These results can help inform where and when watershed nutrient management is most needed.

1. Introduction

Nutrient pollution is a major threat to water quality in the United States (Whitall et al., 2007) and worldwide (Woodward et al., 2012). It can result in algal blooms, hypoxia, and undesirable ecosystem shifts, jeopardizing economies dependent on affected natural resources (Brooks et al., 2016; Conley et al., 2009). Phosphorus is recognized to be the primary limiting nutrient of eutrophication for many lakes and reservoirs (Carpenter, 2008; Schindler et al., 2016), though nitrogen may also be important in some freshwater systems (Paerl et al., 2016). Nutrient sources typically include wastewater effluent from point sources, plus urban and agricultural nonpoint sources (Davidson et al., 2014; Howarth et al., 2002). While there has been considerable success in regulating point sources, less progress has been made toward reducing diffuse nonpoint fluxes (Howarth et al., 2000; Rissman & Carpenter, 2015). Management initiatives sometimes target nonpoint sources (Shen et al., 2015; Whitall et al., 2007), but these initiatives tend to have limited scope, especially regarding agricultural sources (Dowd et al., 2008; Howarth et al., 2002).

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Nutrient source apportionment studies aim to determine the contributions of various point and nonpoint sources in a watershed. Loads from point sources are often monitored based on regulatory requirements, but nonpoint loading estimates are often unavailable or associated with high uncertainties (Rissman & Carpenter, 2015). Nonpoint nutrient contributions can be further complicated by diverse sources and management practices (Kaushal et al., 2011; Line et al., 2002) as well as hydroclimatological variability (Sinha & Michalak, 2016; Strickling & Obenour, 2018). Export coefficients (ECs), which are widely used to characterize loadings from nonpoint sources, are often developed from small watershed studies of limited temporal scope (Beaulac & Reckhow, 1982; Hanrahan et al., 2001; Johnes, 1996). Using such ECs in large-scale watershed models may introduce inaccuracies and uncertainties that propagate to model predictions. Mechanistic models, such as the Hydrologic Simulation Program Fortran (Bicknell et al., 1997) and Soil and Water Assessment Tool (Arnold et al., 1998) have also been used to model nonpoint sources. These models use physically based governing equations to simulate nutrient fate and transport at fine spatial and temporal scales, but they can be expensive to construct and calibrate (Beven, 2006; Jackson-Blake et al., 2017; Johnes, 1996).

Hybrid watershed modeling combines process-based formulations with rigorous statistical inference on relevant rates, such as ECs (Alexander et al., 2004; Miller et al., 2021). The SPARROW (SPAtially Referenced Regressions On Watershed attributes) model uses mass-balance constraints and nonlinear regression to relate instream nutrient loading estimates to sources, watershed characteristics, and stream network losses (Smith et al., 1997). Hybrid models typically include a parsimonious mechanistic parameterization that helps to avoid equifinality issues (Beven, 2006) and readily allows for uncertainty quantification (Kim et al., 2017; Strickling & Obenour, 2018). SPARROW has been used in numerous studies, including across the southeast United States (García et al., 2011). However, SPARROW is based on static (long-term average) hydrologic and development conditions (Smith et al., 1997), which limits its application to understanding and predicting temporal variability. Incorporating time series data in hybrid watershed models can lead to a more robust estimation of nutrient loading, accounting for land use changes and hydrologic variations (H. Han et al., 2009). Wellen et al. (2012) considered multiple approaches to account for temporal variability within a hybrid watershed model, and results suggested that stream retention is inversely related to annual flows. Recent studies have incorporated precipitation-driven interannual variability directly into the nitrogen export and retention formulations of the hybrid model (Miller et al., 2021; Strickling and Obenour, 2018). In addition, a Bayesian hierarchical framework (used by some of these studies) allowed incorporation of prior knowledge and rigorous uncertainty quantification, which can provide more robust management decision support (Reichert, 2020).

Nutrient export is also expected to have substantial intra-annual (e.g., seasonal) variability. May et al. (2001) and Hanrahan et al. (2001) showed the dominance of winter phosphorus loading and much lower phosphorus export in summer. These studies used an EC model to calculate phosphorus export and adjusted it based on monthly relative runoff (monthly runoff divided by annual runoff) to determine monthly loads. However, uncertainties were not quantified, and seasonal variability may be affected by additional factors, beyond hydrology, such as the timing of fertilizer applications (Baker & Richards, 2002). Also, in summer, nutrient export and transport can be affected by higher rates of plant uptake and nutrient cycling (Lin et al., 2019; Reddy et al., 1999). To our knowledge, there are no studies that have considered seasonal loadings within the hybrid (statistical-mechanistic) watershed modeling framework, though such modeling could support developing management strategies at relevant time scales (i.e., seasonal vs. annual). Challenges for developing a seasonal model include greater variability in loading rates (when compared to annual averages), and the potential importance of antecedent watershed conditions.

In this study, we develop for the first time, a season-specific hybrid watershed model and compare the resulting loading and retention rates to a more conventional annual model. We focus on the summer season (June–August), as it is the critical period for harmful algal bloom development in our region (Y. Han et al., 2021; Wiltsie et al., 2018). We build on the hybrid watershed modeling approach developed by Strickling and Obenour (2018) and Miller et al. (2021), which is similar to SPARROW, but (unlike SPARROW) allows us to model interannual variability in loading and retention as a function of precipitation and land use change. Also, while these previous studies focused on total nitrogen (TN), here we explore total phosphorus (TP). We use a Bayesian hierarchical model to incorporate and update prior knowledge on TP export and retention rates with quantified uncertainty. Thus, the model allows us to compare export rates from different sources (i.e., various land uses, livestock, and point sources), seasons, and hydrologic conditions within a probabilistic framework. Within the summer model, we also consider the potential influence of antecedent (spring) precipitation on summer loading rates.

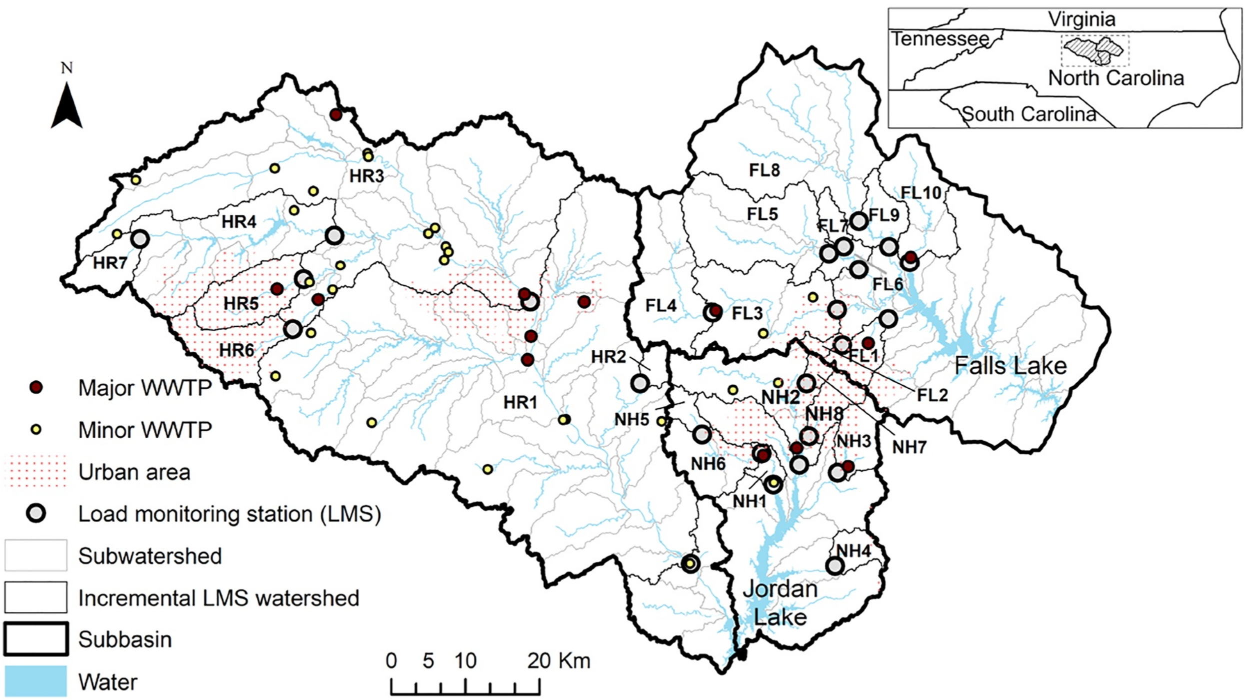

Figure 1. New Hope Creek (NH), Haw River (HR), and Falls Lake (FL) subbasins are shown along with the incremental load monitoring sites watersheds (labeled) and subwatersheds. Note that the Jordan Lake basin includes the NH and HR subbasins. Major and minor point sources along with major urban areas are also shown.

2. Materials and Methods

2.1. Study Area

Located in the Piedmont region of North Carolina (NC), Jordan Lake and Fall Lake (FL) are major water supply reservoirs within the Cape Fear and Neuse River Basins, respectively (Figure 1). Eutrophic conditions have been common in both reservoirs, and portions of both have been classified as impaired waters due to high chlorophyll-a levels (NCDEQ, 2007, 2009). The land use composition in 2012 in the Falls Lake basin was 66% undeveloped (mostly forest), 18% agriculture, and 12% urban; while for the Jordan Lake basin, it was 56%, 24%, and 18%, respectively (Falcone, 2015). The larger Jordan Lake basin was divided into two major subbasins for the purposes of this study: the New Hope Creek (NH) and Haw River (HR) subbasins. Substantial portions of the NH subbasin have been subject to relatively intense urbanization. The HR, NH, and FL subbasins drain 3,480, 890, and 2,022 km^2, respectively.

2.2. Monitoring Locations and Loading Estimates

Our model requires estimates of instream TP loading, which is the product of streamflow and concentration. Streamflow data were obtained from the United States Geological Survey (USGS, 2019; https://waterdata.usgs.gov/nwis) gaging stations, and water quality data were obtained from the national Water Quality Portal (WQP; National Water Quality Monitoring Council, 2019) and local monitoring programs of city of Durham (http://www.durhamwaterquality.org/) and Upper Cape Fear River Basin Association (http://monitor.unrba.org/). WQP data mainly consisted of USGS and NC Department of Environmental Quality (NCDEQ) sampling data. Because TP concentrations were infrequently sampled (roughly monthly), the Weighted Regressions on Time, Discharge, and Season (WRTDS; Hirsch et al., 2010) approach was used to impute concentrations and loadings across time. We estimated the uncertainty in these loads through subsampling of stations with intensive data collection (Strickling & Obenour, 2018), as described in Text S1 in Supporting Information S1.

We identified 25 load monitoring sites (LMSs) based on having at least 5 years of flow data and a minimum of 50 TP concentration samples (Figure 1). There were 7, 8, and 10 LMSs in the HR, NH, and FL subbasins, respectively. We delineated the watersheds for each LMS using ESRI ArcGIS 10.6.1. Incremental LMS watersheds were

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defined by subtracting any upstream LMS watersheds (Miller et al., 2021). Similarly, we calculated "incremental loads" as the load passing through each LMS's downstream monitoring site less the load from any upstream LMSs. To improve modeling of TP transport and retention, incremental watersheds were further divided into subwatersheds that largely followed USGS 12-digit hydraulic unit code (HUC 12) delineations, with additional delineations at LMSs and large impoundments (Figure 1).

2.3. Watershed and Precipitation Data

Model inputs were obtained from the sources described below and processed using the methods of Miller et al. (2021). Land use data were obtained from the U.S. Conterminous Wall-to-wall Anthropogenic Land Use Trends (NWALT) data set (Falcone, 2015) at the subwatershed level. Specifically, land uses were compiled as urban (low, medium, and high-density residential areas, transportation, industrial, and commercial development), agriculture (pasture and crop), and undeveloped (forest, semi-developed, low use, and wetlands). Urbanization was further separated into lands constructed before and after 1980 since pre-1980 urban lands have been found to have higher nitrogen export (Miller et al., 2021). Subwatershed estimates of cows, chickens, and swine were calculated from county-level US Department of Agriculture (USDA) census and survey reports (USDA National Agricultural Statistics Service, 2019). Point source discharger data, including major (>3,785 m^3/day) and minor wastewater treatment plants (WWTPs), were obtained from NCDEQ (Text S2 in Supporting Information S1). WWTP loads were determined as the product of the median yearly concentration and flow, based on reported values for the appropriate modeling interval (annual or summer). WWTP data were only available for 1994–2017, which limited modeling of watersheds with major WWTPs (i.e., HR1,3,5, NH1,2,3, and FL1,3,10) to these years. Minor WWTP loads were projected backward from 1994, as described in Miller et al. (2021).

Streams and waterbodies are expected to retain TP through biological uptake, settling, and burial. Here, estimates of stream residence time (d) and waterbody hydraulic loading rate (m/year) were obtained from the National Hydrography Data set Plus (NHD+; U. S. Geological Survey, 2021). NHD+ includes monthly stream velocities to estimate mean (summer and annual) stream residence time, as well as monthly flows to calculate mean waterbody hydraulic loading rates (flow/area). Reservoirs missing from the NHD+ (Little River Reservoir, Lake Mackintosh, and Lake Reidsville) were added manually for routing purposes.

Monthly precipitation estimates were retrieved from the PRISM climate group (PRISM Climate Group, 2020). Precipitation data were averaged across the incremental watersheds. We note there is great interannual variation in precipitation on both an annual (725–1842 mm) and summer (114–669 mm) scale (Figure S2C in Supporting Information S1).

2.4. Model Construction

In this study, we produce (for the first time) both annual and summer versions of the hybrid model. The deterministic formulation is the same for both, except where noted below. In general, the model relates the inferred incremental loading ($z_{i,t}$) of watershed i in year t to a combination of deterministic and stochastic components:

$$z_{i,t} \sim \mathrm{N}(\hat{z}_{i,t} + \eta_i, \sigma_{\mathrm{res}}) \quad (1)$$

where $\hat{z}_{i,t}$ is the deterministic prediction of incremental load, which is determined by the summation of source-specific loading contributions (from point and nonpoint sources) and subtraction of retention losses (see Text S3 in Supporting Information S1 for more details):

$$\hat{z}_{i,t} = L_{i,t,ur1} + L_{i,t,ur2} + L_{i,t,ag} + L_{i,t,und} + L_{i,t,ps} + L_{i,t,ch} + L_{i,t,h} + L_{i,t,cw} - U_{i,t}{}^{*}\, r_{i,z} \quad (2)$$

the first eight terms of Equation 2 are source-specific nutrient loading contributions from urban lands constructed before 1980, after 1980, agricultural lands, undeveloped lands, point sources, chickens, swine, and cows, respectively. In addition, $U_{i,t}$ and $r_{i,z}$ are upstream incremental watershed loadings and their associated retention within the main-stem stream of incremental watershed i, respectively.

Each loading contribution ($L_{i,t,x}$; kg/mo) from source x is determined as:

$$L_{i,t,x} = \beta_x \left(\tilde{p}_{i,t}^{\gamma_x}\right)^{*} \boldsymbol{a}_{i,t,x}^{\mathbf{T}}{}^{*}\, (\mathbf{1} - \mathbf{r}_{i,t}) \quad (3)$$

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where parameter β_x is the source EC or delivery coefficient (DC). ECs are used for land (kg/ha/mo) and livestock (kg/animal/mo) loadings, while a DC is used for point sources (unitless). The livestock export terms reflect potential excess export due to inefficient capture and use of animal waste (while manure applied to cropland, replacing other fertilizers, is expected to be reflected in the agricultural term). ECs represent nutrient export under mean precipitation. Variable $\tilde{p}_{i,t}$ is the scaled precipitation (unitless), defined by dividing summer or annual precipitation of year t by the long-term mean precipitation of the incremental watershed i. Parameter γ_x is the source-specific precipitation impact coefficient (PIC, unitless), which controls the influence of precipitation on nutrient export (for point sources, the PIC is set to zero because interannual variation is already accounted for in their historical data sets). Transposed vector $\mathbf{a}_{\mathbf{i,t,x}}^{\mathbf{T}}$ includes the source magnitudes (i.e., ha of land, counts of livestock, or loads from WWTPs) for all source locations (i.e., subwatersheds). These exports are multiplied by a vector of (one minus) retention losses ($\boldsymbol{r}_{i,t}$). Retention losses from streams are calculated assuming first-order decay with residence time (τ, days) and loss rate (κ, 1/d), while retention losses from waterbodies are calculated using a first-order mass transfer coefficient (ω, m/year) and areal hydraulic loading rates (q, m/year). Average stream residence times and hydraulic loading rates (from NHD+) were linearly adjusted across years based on precipitation and a retention PIC (unitless). Additional details on the retention formulations (Miller et al., 2021) can be found in Text S3 in Supporting Information S1.

Given that seasonal loadings could be significantly influenced by the antecedent watershed conditions, antecedent precipitation was incorporated in the summer model. We used a temporal framework adapted from Obenour et al. (2014), as follows:

$$P_{i,t} = \sum\nolimits_{m=1}^{8} p_{i,t,m}\psi_m$$

$$\psi_m = \begin{cases} 0, & m \le (\beta_\psi - 1) \\ m + 1 - \beta_\psi, & (\beta_\psi - 1) < m < \beta_\psi \\ 1, & m \ge \beta_\psi \end{cases} \tag{4}$$

where $P_{i,t}$ is the aggregated precipitation of incremental watershed i in year t, $p_{i,t,m}$ is precipitation in month m, and ψ_m is the weight for month m. Parameter β_ψ is the antecedent threshold coefficient, which determines the weights for January to August (m from 1 to 8). For example, if $\beta_\psi = 5.6$, then January to April receive zero weight, May receives a weight of 0.4, and June to August receive weights of one.

The remaining two components of Equation 1 are stochastic. Here, η_i is a normally distributed (incremental) watershed-level random effect (Gelman et al., 2014). It accounts for spatial variability not explained by the deterministic component, $\hat{z}_{i,t}$. It is centered on zero, with standard deviation (SD) σ_{LMS}. Residuals are normally distributed (with SD σ_{res}) and largely account for unexplained temporal variability. This error formulation differs from Miller et al. (2021), where residuals were assumed to follow a log-normal distribution. Here, residuals were represented with a normal distribution due to the prevalence of negative incremental loadings (10% and 4% of the 455 WRTDS-derived incremental loadings were negative on a summer and annual basis, respectively). Negative incremental loadings occur when the stream and waterbody retention of upstream LMS loads is greater than the source loading contributions within the incremental watershed. Finally, the inferred load, $z_{i,t}$, is probabilistically related to the WRTDS-derived incremental loading estimate ($\tilde{z}_{i,t}$) and its associated uncertainty $\tilde{\sigma}_{i,t}$ (Text S1 in Supporting Information S1):

$$\tilde{z}_{i,t} \sim \mathrm{N}(z_{i,t}, \tilde{\sigma}_{i,t}) \tag{5}$$

here, $z_{i,t}$ is a latent variable that is determined through Bayesian inference along with the model parameters. Note that $z_{i,t}$ also appears in Equation 1 and can be thought of as an estimate of the "true" incremental load, considering both the WRTDS-derived loading estimate and the watershed model prediction (based on loading sources, precipitation, etc.).

2.5. Bayesian Inference and Model Assessment

Model parameters were estimated through data-driven Bayesian inference (for both the annual and summer versions of the model). For some parameters, informative prior distributions were assigned based on literature review (Table S4A in Supporting Information S1). EC priors were obtained from Dodd et al. (1992), and retention rate priors were derived from a SPARROW model of the southeastern United States (García et al., 2011). Priors for livestock excess ECs were adapted from Strickling and Obenour (2018) based on a 3:1 ratio of TN:TP, typical of chicken and swine manure (NCSU, 2021). The source-specific PICs were related to each other hierarchically as members of a common hyperdistribution. For parameters without relevant prior information, wide uniform priors were used.

Bayesian posterior parameter distributions were determined using Hamiltonian Monte Carlo sampling (Neal, 2011) in RStan (Stan Development Team, 2020). Three parallel chains were run for 20,000 iterations, and the first 5,000 were discarded as burn-in. Then, by selecting every fifth posterior sample (to reduce autocorrelation), 9,000 samples characterize the joint posterior parameter distribution. Chain convergence was considered achieved when the scale reduction coefficient ($\hat{R}$) was below 1.1 (Gelman et al., 2014).

Model performance was evaluated by comparing predicted loads with WRTDS-estimated loads. Performance metrics include the coefficient of determination (R^2), as well as the SDs of the residual error and random effect distributions (σ_{res} and σ_{LMS}). For R^2, predicted incremental loadings were calculated using the mean posterior parameter estimates (for computational efficiency), both with and without the watershed-level random effect. Predictive skill was further evaluated through a 3-fold cross-validation (Elsner & Schmertmann, 1994), in which we split the data by major subbasin (HR, NH, and FL). Each model was trained on the data for two subbasins, and predictions were made for the excluded subbasin. This process was repeated for each possible combination of two subbasins (i.e., three times). The complete set of out-of-sample predictions was then used to determine performance (e.g., R^2).

3. Results

3.1. Bayesian Parameter Estimates

The Bayesian posterior distribution provides a probabilistic characterization of model parameters (Figure 2) that can be summarized by means and credible intervals (Table S4B in Supporting Information S1). For most parameters, the marginal posterior distributions are much tighter than the prior distributions, indicating the efficacy of the model and data to reduce process uncertainties. Pre-1980 urban development has the highest EC, exceeding agricultural export with 96% and >99% probability in the annual and summer models, respectively (based on samples from the joint posterior distribution). Furthermore, the pre-1980 urban EC exceeds the post-1980 urban EC at 93% and >99% probabilities in the annual and summer models, respectively. Undeveloped lands show the lowest TP export among nonpoint sources (being less than post-1980 urban export at 93% and 90% probability for annual and summer models, respectively; and with >99% probability relative to other land types). Livestock ECs indicate that less than 2% of the phosphorus produced by each type of livestock (0.02, 0.37, and 1.61 kg/an/mo produced for chicken, swine, and cows, respectively; Ruddy et al., 2006) result in excess export to the stream network. Note that livestock waste used as fertilizer on agricultural land (replacing imported fertilizers) is expected to be reflected in the agricultural land EC.

Precipitation impact coefficients determine how TP export varies across the precipitation gradient based on an exponential relationship (Equation 3). Agriculture has the largest PIC (3.4 and 5.0 for the annual and summer models, respectively), while pre-1980 urban land has the lowest PIC (1.8 and 1.4, respectively). In fact, the agricultural PIC is greater than the pre-1980 urban PIC with >99% probability in both models. PICs for the other land uses and livestock classes have intermediate values with largely overlapping distributions (Figure 2). The antecedent threshold coefficient (summer model only) is estimated at 5.66, which indicates that precipitation from June-August receives a weight of 1, May receives a weight of 0.34, and January–April receive no weight. The 95% credible interval for this coefficient is relatively narrow (5.49–5.82), indicating a high likelihood of antecedent May rainfall contributing to summer (June–August) TP export.

Phosphorus retention is parameterized using a loss rate for streams and a mass transfer coefficient for waterbodies (Figure 2, Table S4B in Supporting Information S1). The stream loss rate in the annual model (0.06 days^{-1}) is lower than in the summer model (0.13 days^{-1}) at >99% probability. At the same time, the waterbody mass transfer coefficients are similar for the annual and summer models (both around 38 m/yr). Interannual variability in retention is regulated by a retention PIC using a linear relationship. PICs indicate that one SD change in precipitation

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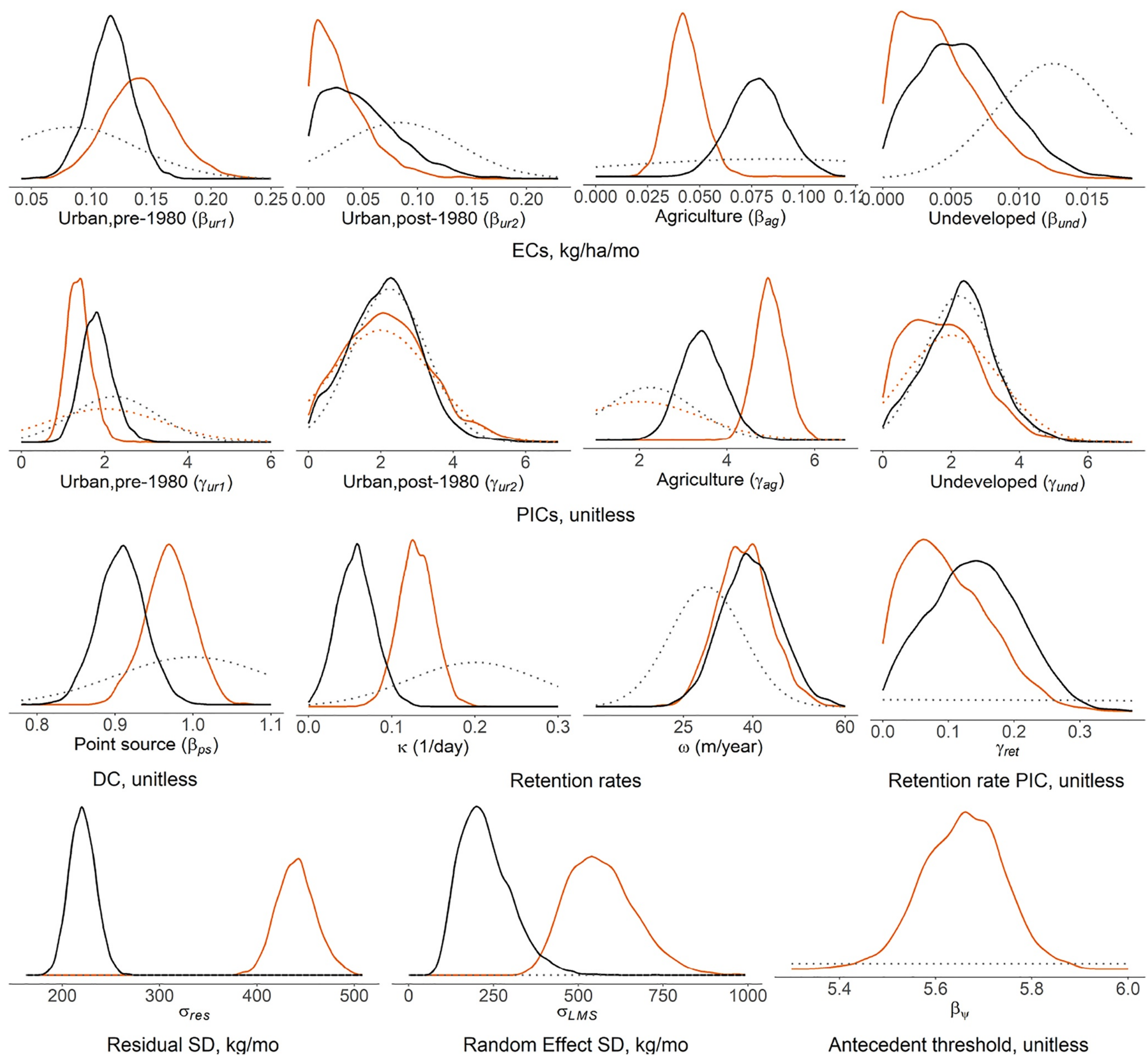

Figure 2. Posterior distribution of annual (black line) and summer (colored line) models with their priors (dashed line) for selected parameters. For land use precipitation impact coefficients (PICs), annual and summer hyper-distributions are provided (black and brown dashed lines, respectively) instead of priors. Prior and posterior mean and 95% credible interval for livestock excess Export coefficients and their PICs can be found in Text S4 in Supporting Information S1.

(14.3 and 33.3 mm/mo on an annual and summer basis, respectively) produces 14% and 10% changes in residence times (and hydraulic loading rate) in the annual and summer models, respectively.

The SDs for the residuals and random effects are also determined through Bayesian inference. The SD of the (incremental) watershed random effects is greater than the SD of the residuals (Figure 2), suggesting more unexplained spatial variability than temporal variability. Also, it is clear that the SDs of the summer model are much higher than those of the annual model, indicating summer instream loadings are more difficult to predict, at least based on the deterministic relationships included in this study.

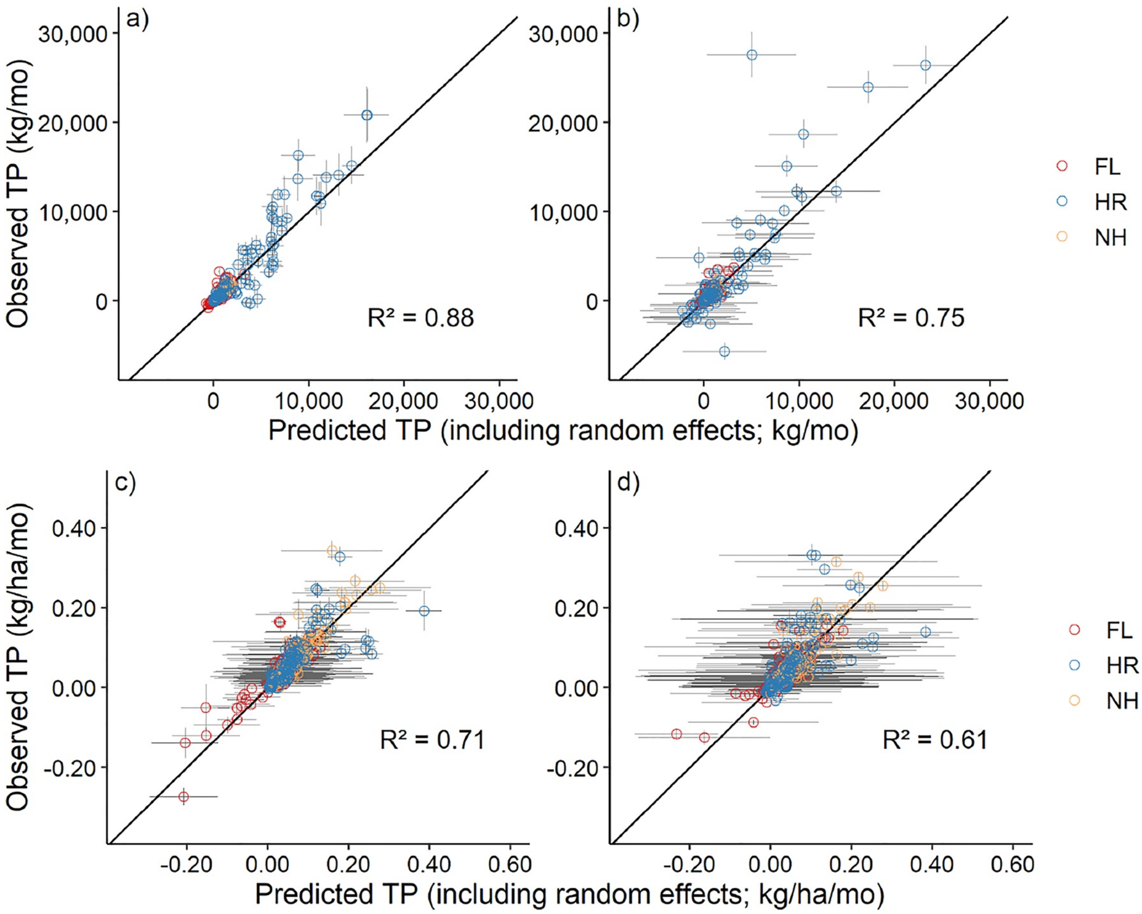

Figure 3. Observed (Weighted Regressions on Time, Discharge, and Season [WRTDS]) versus predicted (hybrid model with random effects) plots of incremental total phosphorus (TP) loads in annual (a) and summer (b) models, along with TP areal yields in annual (c) and summer (d) models. The bars show uncertainties (± one standard deviation) associated with WRTDS loading estimates (vertical bars) and with model parameters and residuals (horizontal bars).

3.2. Model Performance and Robustness

The calibrated models explain 88% and 75% of the variability in WRTDS-estimated annual and summer loads, respectively (Figure 3, top). If watershed random effects are not included in the predictions, the models still account for 86% and 70% of the variability in annual and summer loading, respectively (Figure S5A in Supporting Information S1, top). If TP loadings are normalized by their corresponding watershed areas (kg/ha/mo), the models explain 71% and 61% of the variability in annual and summer loads, respectively (Figure 3, bottom), which decreases to 60% and 45% if random effects are not included (Figure S5A in Supporting Information S1, bottom). In both models, uncertainties tend to increase with larger TP source loadings (reflecting export parameter uncertainties). However, this pattern is harder to discern in the summer model (based on Figure 3) due to greater residual errors and more frequent negative incremental loads resulting from substantial retention of upstream LMS loads. Temporal (interannual) autocorrelation in the residuals was assessed for each incremental watershed and found to be small (Figure S5B in Supporting Information S1). Average lag-1 autocorrelation coefficients were 0.14 and 0.08 for the annual and summer models, respectively.

In cross-validation, the variance explained (R^2) by the annual and summer models (without random effects) decreases from 86% to 83% and 70% to 63%, respectively, relative to the "full" model (i.e., model calibrated to all data). These modest reductions in R^2 indicate the predictive performance of the model is reasonably robust. Furthermore, the parameter estimates for the three subbasin-level folds of the cross-validation are mostly similar (Text S6 in Supporting Information S1) with largely overlapping posterior distributions. However, for the annual model, two of the cross-validation folds result in substantially higher ECs but lower PICs for agriculture. Higher ECs coupled with lower PICs somewhat compensate for each other in terms of long-term mean export, but they

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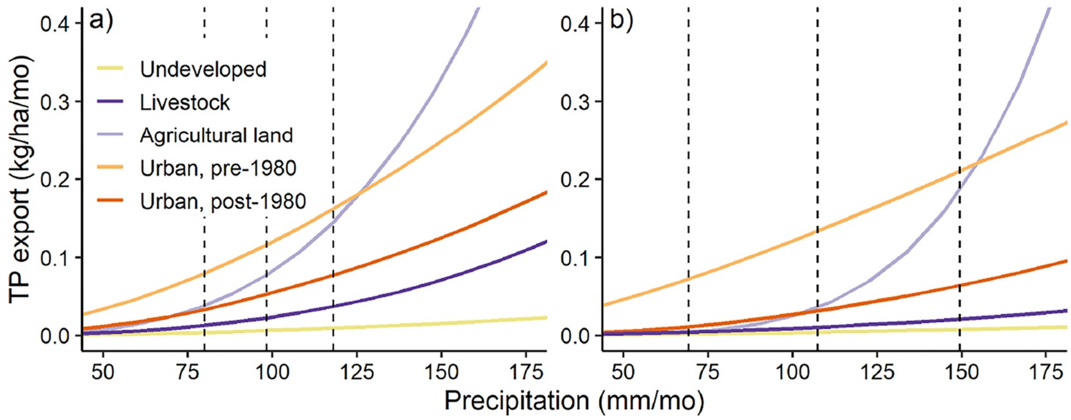

Figure 4. Source-specific export rate variability due to precipitation in annual (a) and summer (b) models. Dashed vertical lines represent the 10th, mean, and 90th percentiles of historical (1982–2017) precipitation.

suggest less interannual variability due to precipitation (see Section 3.3). In addition, for both models, we found considerable overlap between the two urban land classes in the fold without the HR subbasin (the pre-1980 estimate was lower than the post-1980 estimate in this fold, but at less than 90% credibility). Finally, for both models, there is a smaller random effect SD in the cross-validation fold without the HR (Text S6 in Supporting Information S1), likely due to the smaller average incremental watershed size in the other two basins. This could potentially be avoided by normalizing watershed random effects by watershed area. However, such an approach would be problematic for small watersheds with large point source discharges.

3.3. TP Export Versus Precipitation

Source-specific export rates can be compared across a range of historical precipitation (Figure 4). Urban lands constructed before 1980 export the highest load per unit area, except during years of extreme precipitation (>95th percentile precipitation) when agricultural export is likely to become more intense. Agricultural land export shows the greatest variability due to precipitation, consistent with its relatively high PIC. Livestock excess export (combining chicken, cows, and swine per unit of agricultural land) has less precipitation-related variability than baseline agricultural land (Figure 4). Total areal agricultural export (sum of the agricultural land and livestock excess export) remains below pre-1980 urban export across typical precipitation rates, especially in summer.

Summer export rates can be substantially different from annual export rates across the precipitation gradient. Here, we focus on comparing annual and summer export rates for agricultural and pre-1980 urban developments (considering parameter uncertainties, Figure 5) since they are the largest two contributors to TP loadings. For low-to-moderate precipitation rates (<130 mm/mo), the annual agriculture export rate is larger than the summer rate at >99% probability. As the precipitation rate increases, there is an increasing overlap between the summer and annual agricultural export rates (Figure 5a). However, even at a precipitation rate of 170 mm/mo, the annual agriculture export rate still exceeds the summer rate with an 83% probability.

For pre-1980 urban development, the annual and summer export rates tend to be similar, especially for low to moderate precipitation (Figure 5b). There is increasing probability that annual export exceeds summer export at higher precipitation rates (but never with >90% credibility). Comparisons between annual and summer export rates for other land uses and livestock excess generally exhibit wide uncertainties and substantial overlap (Text S7 in Supporting Information S1). However, there is a clear tendency for annual export rates to exceed summer export rates across all nonpoint source types and precipitation levels, with the exception of pre-1980 urban development noted above.

Since export rates vary interannually due to precipitation, the mean export from each nonpoint source can be determined by averaging yearly exports across the study period. These mean export rates may differ from the ECs due to the exponential relationship between TP export and precipitation. The ECs can be thought of as median export rates, while the mean export is more heavily influenced by the large loadings during years (or summers) of extreme precipitation. For summer agriculture, which has the highest PIC, the mean export is 0.08 kg/ha/mo

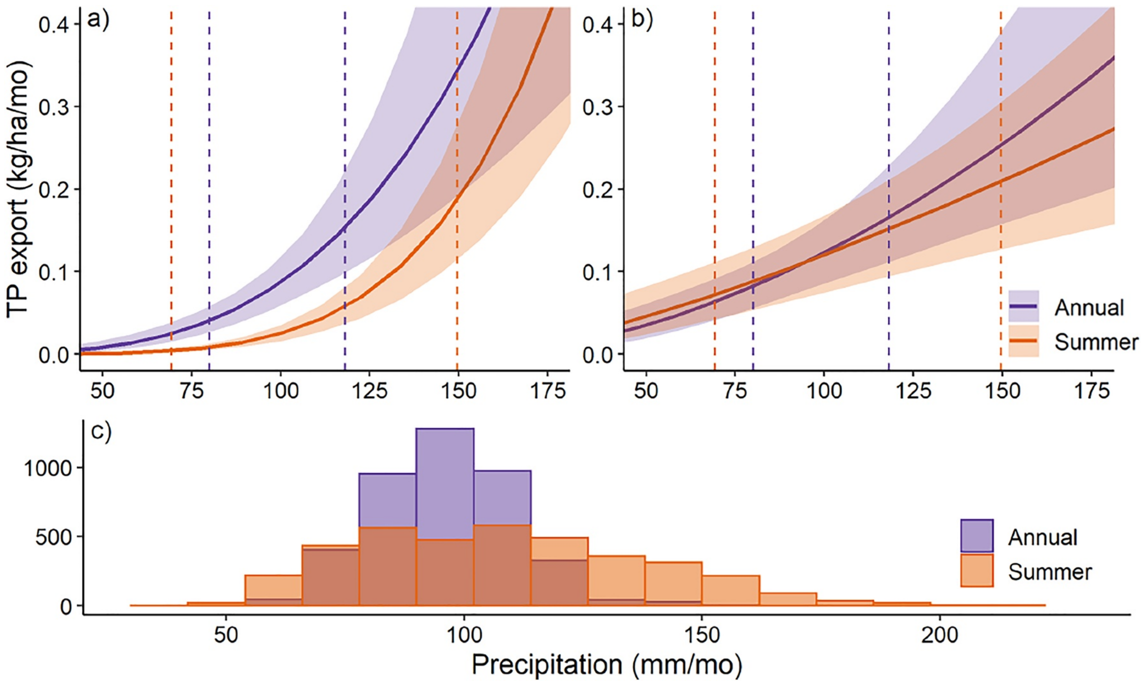

Figure 5. Annual and summer agriculture (a) and pre-1980 urban development (b) total phosphorus export rates along with their 95% credible interval versus precipitation. Dashed vertical lines represent the 10th and 90th percentiles of historical (1982–2017) annual and summer precipitation. Also shown (c) are annual and summer precipitation histograms.

across years, considerably higher than the EC of 0.04 kg/ha/mo. Interestingly, the mean annual agricultural export is the same as for summer (0.08 kg/ha/mo for both models) despite the difference in ECs (Figure 2). This is because summer is subject to more intense precipitation (Figure 5c) and has a larger PIC. In contrast, the mean export from pre-1980 urban development is approximately equal to the EC (for both annual and summer models) because of the relatively low PIC for this land use type (Figure 2). Finally, undeveloped lands have annual and summer mean exports of 0.007 and 0.004 kg/ha/mo, respectively, over an order of magnitude less than agricultural and pre-1980 urban lands.

3.4. TP Source Allocations and Retention Over Time

Temporal patterns in TP loadings vary substantially across the different subbasins (Figure 6). For the total load (sum of all sources), variability was greater in the HR and FL subbasins compared to the NH subbasin. For the annual model, the coefficients of variation (across years) were 38%, 32%, and 23% for the HR, FL, and NH subbasins, respectively. Even greater interannual variability is indicated by the summer model, with coefficients of variation of 81%, 63%, and 35%, respectively. From the lowest (2007) to the highest (2003) precipitation years, summer TP loadings increased more than fivefold in the HR and FL subbasins, while in the NH subbasin, they hardly doubled. We also note that annual and summer total point source loading (across the entire study area) decreased by 62% and 46%, respectively from 1994 to 2017, likely due to WWTP improvements. Spatially, TP export is typically highest in the major urban cores with substantial pre-1980 urban development (Figure S8A in Supporting Information S1).

TP retention also varies interannually and seasonally (Figure 7). On an annual basis, much more retention occurs in reservoirs than in streams; while in summer, reservoir and stream retention are approximately equal. Under mean precipitation conditions, 27% of the TP that enters streams is retained in summer, while only 8% is retained in streams annually. In reservoirs, the summer and annual TP retention rates are 30% and 24%, respectively. Overall, summer TP retention (49%) under mean precipitation conditions is substantially higher than annual TP retention (30%). Temporal variability in retention is controlled by the retention PIC, such that years with higher precipitation (e.g., 2003) have lower retention rates. Spatially, maximum TP removal occurs in large impoundments in the upstream portions of the HR subbasin (Figure S8B in Supporting Information S1).

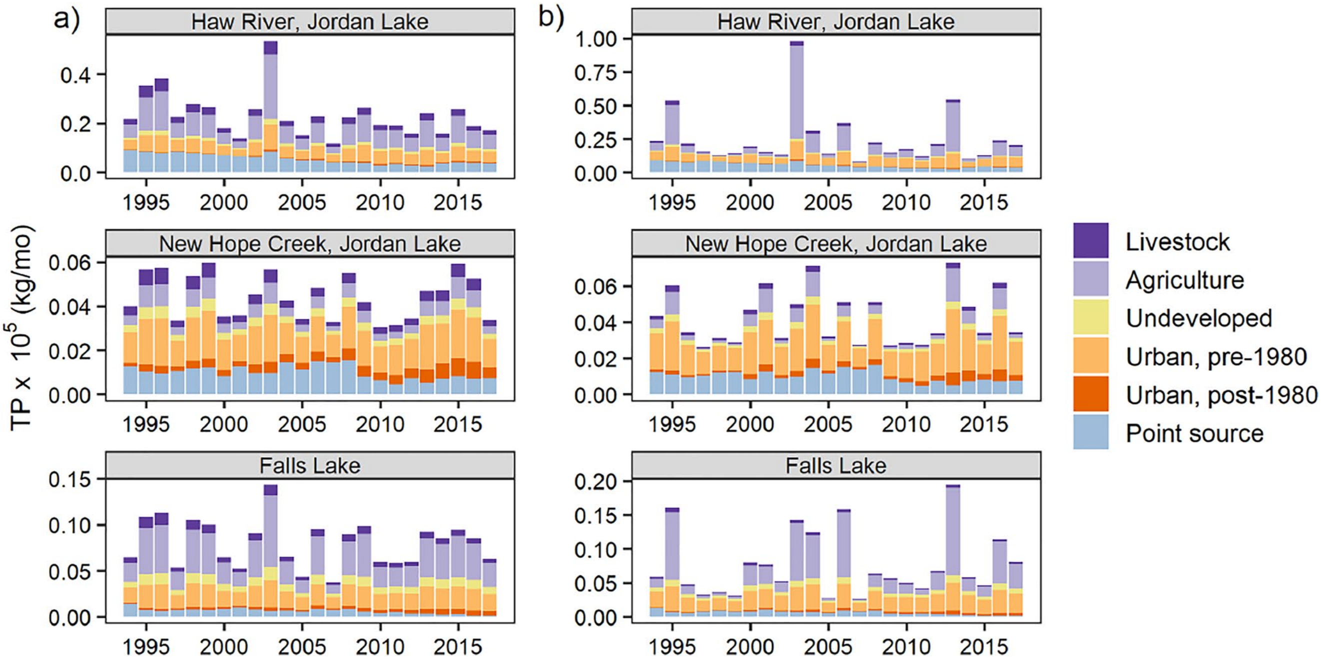

Figure 6. Annual (a) and summer (b) source-specific total phosphorus export (per month) entering stream network from 1994 to 2017 by subbasin. The period shown here is limited due to a lack of point source data before 1994.

4. Discussion

4.1. Phosphorus Sources

Phosphorus export under mean precipitation conditions (represented by ECs) varies substantially across different land use categories. We find pre-1980 urban development has substantially higher TP export than more recent urban development. This pre/post-1980 categorization of urban lands outperformed other categorizations, such as pre/post-2000 and high/low-density categorizations (not shown), as described in Miller et al. (2021) for TN. Potential reasons for higher phosphorus export from older development include higher impervious cover connectivity (Walsh et al., 2005), fewer stormwater control measures (Howells, 1990; NCDEMLR, 2013), more canopy and leaf litter over impervious surfaces (Janke et al., 2017), and older, leakier sewer infrastructure (Kaushal et al., 2011; Pennino et al., 2016). Of course, mitigation of these issues did not occur precisely in 1980, and we hope this study will motivate a more refined representation of changes to the urban landscape in the future. In the context of hybrid watershed modeling (García et al., 2011; Wellen et al., 2012), this is the first study to differentiate phosphorus export rates among different types of urban development.

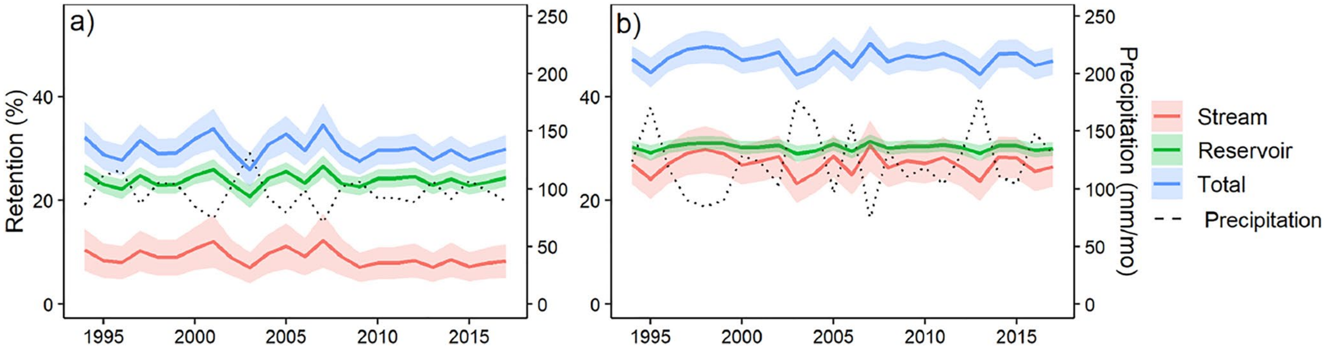

Figure 7. Annual (a) and summer (b) phosphorus retention in streams and reservoirs from 1994 to 2017 along with 95% credible intervals. The dashed black line shows annual/summer precipitation (mm/month).

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Our model also characterizes various rural phosphorus sources (i.e., agricultural land, undeveloped land, and three types of livestock). Results indicate lower levels of TP export from agriculture than the national average reported by Dodd et al. (1992) and Alexander et al. (2004) but similar to the regional study of García et al. (2011). This is likely due to the majority of agricultural area in our study being pastureland, where lower amounts of fertilizers are applied relative to croplands (Osmond et al., 2015). The overall livestock excess contribution is relatively low (<10% of total load). At the same time, our annual estimates of export per animal are about 2–3 times larger than the export suggested by García et al. (2011), which were approximately 0.0001, 0.001, and 0.016 kg/an/mo for chickens, swine, and cows, respectively. These estimates were derived from the manure DC calibrated by García et al. (2011) and the TP content of each livestock type (Ruddy et al., 2006).

Our annual undeveloped land EC (0.08 kg/ha/yr; 0.01–0.16 95% credible interval) is approximately consistent with measurements of 0.05–0.32 kg/ha/yr of TP export from small (<30 ha) forested watersheds in the NC Piedmont (Boggs et al., 2013). The higher values measured by Boggs et al. (2013) were from a relatively wet year, consistent with the substantial precipitation effects indicated by this study (Figure S7 in Supporting Information S1). At the same time, our undeveloped EC is at the lower end of the range suggested by Dodd et al. (1992) and only about 40% of the annual forest export in the national SPARROW model (Alexander et al., 2004). Several factors, such as geology, climate, vegetation type, and ecological succession can influence the export from forested land cover (Beaulac & Reckhow, 1982). Geology has been shown to explain substantial variability in TP export across the southeast US, and our study area is in a region with relatively low geologic yields (García et al., 2011). Atmospheric deposition may also be a relatively important source of TP for undeveloped land. A recent estimate of TP deposition for our study area is approximately 0.08 kg/ha/yr (Sabo et al., 2021), which is similar to our annual undeveloped export rate. This similarity indicates that the atmospheric TP input is in approximate equilibrium with TP export.

Comparing annual and summer ECs (Figure 2, top) shows higher annual export rates from most source types (agriculture, undeveloped, livestock, and post-1980 urban). Higher rates of evapotranspiration and lower groundwater recharge can reduce the hydrologic delivery of TP in summer months (Duncan et al., 2017). Seasonality of fertilizer application may also explain the difference between summer and annual agriculture export (Lin et al., 2019; Royer et al., 2006). Most of the pasture crop fertilization, which is the dominant type of crop in our study area, occurs during spring or fall (NCDA & CS, 2021). Only pre-1980 urban lands are likely to have summer export rates that are similar to annual rates, perhaps due to frequent summer lawn maintenance and convective summer storms that can regularly wash TP from impervious surfaces into streams (Keim, 1996; Shields et al., 2008).

4.2. Interannual Variability in TP Export and Retention

In this study, we model the interannual effects of precipitation variability on source-specific TP export. For both annual and summer models, results show that agricultural land export is most responsive to changing precipitation. This suggests that agricultural land needs higher levels of precipitation to mobilize phosphorus, which is generally consistent with Royer et al. (2006) and Banner et al. (2009), who found that the majority of agricultural phosphorus export occurred during periods of extreme discharge. On the other hand, the impervious surfaces and compacted soils associated with urban development may generate nutrient-laden runoff even with small precipitation events. This is consistent with the regression analysis of Tasdighi et al. (2017) indicating that urbanization has a greater impact on water quality during dry periods. As a result, watersheds with high agricultural land percentages (e.g., HR, Figure 6) show the greatest year-to-year variability in phosphorus loading.

Stream and reservoir retention also vary in response to precipitation and seasonality. Our estimated annual stream loss rate (κ; Figure 2) is lower than previous studies, including Wellen et al. (2012) and García et al. (2011). At the same time, we found a higher stream retention rate in summer, likely due to higher temperatures that favor biological uptake, consistent with Hanrahan et al. (2001) and Ator et al. (2011). In addition, stream velocities (from NHD+) are much lower in the summer (0.004 m/s) than annually (0.335 m/s), allowing more time for nutrient processing (e.g., uptake, adsorption, and settling). Empirical studies of phosphorus uptake in rivers also indicate significant interannual variability (Doyle et al., 2003; Mulholland et al., 1985; Simon et al., 2005). However, the interannual variability in retention rates (Figure 7) is generally much lower than the variability in phosphorus export (Figure 6). The fraction of annual load occurring in summer varies substantially from year to year in response to precipitation. Due to the combination of lower export from all sources (except pre-1980 urban lands) and higher stream and reservoir retention, the summer season typically contributed less than a quarter of the annual load (to Falls and Jordan Lakes). Summers with high precipitation rates tend to have the largest contributions. For example, in 2013, which had a very wet summer (160.8 mm/mo) and moderately wet overall year (108.9 mm/mo), nearly 39% of the annual load is estimated to have occurred in summer. In contrast, in 1998, which had a dry summer (76.1 mm/mo) and moderately wet overall year (108.3 mm/mo), only about 10% of the annual export occurred in summer.

4.3. Implications for Hybrid Watershed Modeling

Two important aspects of this work, relative to previous hybrid watershed modeling studies, are the formulation of a season-specific model and the representation of antecedent precipitation as a predictor of TP loading. In principle, the presented seasonal model can be extended to other seasons and to other temperate/humid watersheds, and could be used in conjunction with future seasonal precipitation projections from climate change scenarios. Furthermore, model parameter estimates show that antecedent (1 month ahead) precipitation is a significant driver of seasonal loading, at least for the summer season. It is likely that higher precipitation in May results in more saturated soils in June, enhancing mobilization and washoff of TP (Cavagnaro, 2016). At the same time, the summer model has lower predictive skill than the annual model, suggesting that further enhancements to the model structure may be beneficial for modeling summer-specific TP fate and transport. One possible enhancement to better explain summer TP loading and retention is developing a more complex PIC formulation by accounting for rainfall intensity or extreme precipitation (Sinha & Michalak, 2016). Also, given the high summer retention rates, a more detailed representation of retention may be beneficial. Retention could potentially decline as reservoirs gradually fill in with sediment, or as streams undergo urbanization or restoration (McMillan et al., 2014). At the same time, increases in model complexity must be balanced against the limited information content of the available data (e.g., WRTDS loading estimates).

Predictive performance and parameter estimates were found to be reasonably robust in both annual and summer models across the 3-fold cross validation (Section 3.2). At the same time, we found there is substantial overlap between EC estimates for pre- and post-1980 urban export in one cross-validation fold (i.e., the subsample without the HR), emphasizing the need for sufficient data to robustly characterize differences among a large number of source types, especially when prior knowledge (e.g., the Bayesian prior distributions) is relatively weak. Future gains in model robustness could likely be achieved by refining prior knowledge through additional literature review or field-scale mechanistic modeling, or by expanding the observational data set over time. In addition, a modification of WRTDS where a Kalman filter is applied to account for the serial autocorrelation in loading residuals (i.e., WRTDS_K) could potentially result in more accurate loading estimates (Zhang & Hirsch, 2019).

While the deterministic model formulation (e.g., Equation 3) and calibrated parameters provide a process-based expectation of TP loading for each watershed, the random effects identify watersheds that deviate from these expectations. For example, there were large positive random effects in small watersheds located directly downstream of point sources (HR5, NH1, FL10; Text S9 in Supporting Information S1), suggesting these point sources may be delivering more TP than expected. On the other hand, three highly urban watersheds (NH7, NH8, and FL2) had negative random effects, indicating that they export somewhat less TP than expected. Consistent with most hybrid watershed modeling studies, we did not model spatial correlation across LMS watersheds. Results suggest relatively little spatial correlation (Text S9 in Supporting Information S1), likely due to our relatively small study area. However, the spatial structure of random effects could be considered in future model enhancements, especially if applying the model across a larger region (Qian et al., 2005).

4.4. Implications for Watershed Management

In this study, the hybrid watershed modeling approach is applied to study seasonal nutrient loading dynamics. The summer season may be particularly relevant to watershed management, since it is often subject to the most severe water quality problems in our region (e.g., hypoxia and algal blooms, see Section 1). Results suggest substantially higher TP retention in streams in summer when compared to annual retention rates, which emphasizes maintaining the integrity of streams and vegetated buffers (Allan et al., 1997; Dosskey et al., 2010). In addition, the TP export from urban developments constructed prior to 1980 was found to be particularly high in summer (relative

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to other land use types), highlighting the need for further evaluation of contributing sources, such as those related to older sewer infrastructure and lawn maintenance (e.g., mowing and fertilizer application).

Understanding interannual variability in TP export may also help guide watershed management. The substantial and varying precipitation impacts across different source types, as shown in our results (e.g., Figure 4), indicate that average export rates (e.g., conventional SPARROW) may not be informative for addressing water quality problems that manifest in dry or wet years (or summers). In addition, attributing interannual variability to only stream and waterbody retention (e.g., Wellen et al., 2012) or only source export (e.g., Strickling and Obenour, 2018) may not be realistic. The importance of understanding temporal variability in nutrient export and retention is further highlighted by the potential for climate change to increase precipitation intensity, potentially leading to more severe eutrophication (Sinha et al., 2017). Results indicate that older urban developments need to be managed (along with point sources) if water quality problems are most prevalent under low-flow conditions, as is sometimes the case for harmful algal blooms (Katin et al., 2021; Michalak et al., 2013). On the other hand, agricultural export becomes a large TP contributor in high flow years, particularly for the HR and FL subbasins (Figure 6), which remain predominantly rural despite considerable urban development (Text S2 in Supporting Information S1). High riverine flows are often associated with severe hypoxia in downstream systems (Hagy et al., 2004; Katin et al., 2019).

The proposed hybrid modeling approach can also be used to assess the geographic distribution of TP export, which may be relevant to localized watershed management and eutrophication issues. Watershed random effects (Section 4.3) may motivate additional monitoring or site investigation to identify the unique factors (i.e., specific nutrient sources and management practices) driving TP loading within each incremental watershed. More generally, the spatial loading distribution varies across seasons and under different hydrologic regimes. TP export is most confined to urban centers under dry summer conditions (Figure S8C in Supporting Information S1), but elevated loadings are more evenly spread throughout the study area under wet weather, on both an annual and summer basis (Figure S8D in Supporting Information S1). Finally, areas with high forest coverage (e.g., around Falls and Jordan Lakes) typically have the lowest export under both wet and dry conditions.

Miller et al. (2021) developed a similar hybrid model for annual (only) TN loading in this study area, allowing for a comparison of TN to TP export and retention rates. While nonpoint TN loading rates are seven times higher than TP loading rates on average, we find similar patterns in export across different source types. Both the TN and TP models indicate that pre-1980 urban lands have the highest areal export rate, and both show the highest precipitation-driven temporal variability in agricultural export. However, while (annual) stream loss rates were similar across these models, the waterbody loss rate for TP (39.5 m/yr) was more than three times higher than for TN (11.2 m/yr). Because a substantial portion of TP is typically in the particulate form (Heathwaite & Dils, 2000; Johnson et al., 1976), there is greater potential for in-lake sedimentation and burial when compared to TN. While nitrate can be removed through denitrification under anaerobic conditions, these modeling results suggest that it is of lesser importance, at least in the waterbodies of our study area. If the primary management goal is to reduce TP loads reaching the major downstream reservoirs (Falls and Jordan Lakes), targeting sources located near these reservoirs (with less opportunity for stream and waterbody retention, Text S8 in Supporting Information S1) will likely be most effective.

5. Conclusion

We extended a hybrid watershed model to understand and contrast annual and summer phosphorus loading dynamics, particularly in response to precipitation variability and watershed development. Data-driven inference and uncertainty quantification were achieved through Bayesian methods. By leveraging multi-decadal loading estimates over a large area, results demonstrate a substantial reduction in phosphorus export and retention rate uncertainties. Results also show which sources have the highest contribution rate (i.e., older urbanized areas) and which are most responsive to precipitation (i.e., agriculture). Also, for the first time, the hybrid watershed modeling approach is applied to study seasonal nutrient loading dynamics. We find that summer TP export rates are relatively low while summer stream retention is relatively high (compared to annual rates). We also find that antecedent (May) precipitation has a significant influence on summer export. These season-specific results can inform more targeted watershed management strategies, especially for water quality problems that manifest in particular seasons.

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Data Availability Statement

The input data sets and codes for the annual and summer models are available at https://doi.org/10.5281/zenodo.7108999 (Karimi et al., 2022).

Acknowledgments
This research was primarily funded by the NC Policy Collaboratory (NCPC). We are also thankful for support from NC Water Resources Research Institute (WRRI, Project 20-07-W), and from the Science and Technologies for Phosphorus Sustainability (STEPS) Center, a National Science Foundation Science and Technology Center (CBET-2019435).

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