JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

AMERICAN WATER RESOURCES ASSOCIATION

CLIMATE SENSITIVITY OF PHOSPHORUS LOADINGS TO AN URBAN STREAM[1]

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ABSTRACT: We investigate the sensitivity of phosphorus loading (mass/time) in an urban stream to variations in climate using nondimensional sensitivity, known as elasticity, methods commonly used by economists and hydrologists. Previous analyses have used bivariate elasticity methods to represent the general relationship between nutrient loading and a variable of interest, but such bivariate relations cannot reflect the complex multivariate nonlinear relationships inherent among nutrients, precipitation, temperature, and streamflow. Using fixed-effect multivariate regression methods, we obtain two phosphorus models (nonparametric and parametric) for an urban stream with high explanatory power that can both estimate phosphorus loads and the elasticity of phosphorus loading to changes in precipitation, temperature, and streamflow. A case study demonstrates total phosphorus loading depends significantly on season, rainfall, combined sewer overflow events, and flow rate, yet the elasticity of total phosphorus to all these factors remains relatively constant throughout the year. The elasticity estimates reported here can be used to examine how nutrient loads may change under future climate conditions.

(KEY TERMS: climate elasticity; multivariate; nutrients; nutrient loading; nonpoint source pollution; streamflow; phosphorus; water quality.)

Munson, Kate M., Richard M. Vogel, and John L. Durant, 2018. Climate Sensitivity of Phosphorus Loadings to an Urban Stream. *Journal of the American Water Resources Association* (JAWRA) 1–16. https://doi.org/10.1111/1752-1688.12621.

INTRODUCTION

Watersheds are dynamic systems, changing over both short (hours, days, months, seasons) and long (years, decades) time scales. One particularly dynamic feature of watersheds is water quality. In addition to changes in infrastructure, population, and land use, changing weather patterns may greatly influence water quality (Wilby 1993; Mimikou et al. 2000; Whitehead et al. 2009). Over the past few decades, the impacts of a changing climate on water quantity have been studied at length (Frederick and Major 1997; Kundzewicz et al. 2007; Milly et al. 2008; Yang et al. 2013); however, the influence of climate variability and change on water quality has only recently been considered (Kundzewicz et al. 2007; Delpla et al. 2009; Whitehead et al. 2009; Loecke et al. 2017).

Water quality within hydrologic systems evolves due to a variety of influences such as changes in precipitation intensity, temperature, storm frequency, wind speed, atmospheric deposition, groundwater recharge, and streambed erosion. Nutrient pollution

[1]Paper No. JAWRA-17-0018-P of the *Journal of the American Water Resources Association* (JAWRA). Received February 27, 2017; accepted December 1, 2017. **Discussions are open until six months from issue publication**.

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is one of the most widespread environmental problems in the United States (U.S.) (Gilinsky et al. 2009; USEPA 2009b) and often supports the rapid growth of algal blooms that are potentially harmful to ecosystems and human health (Anderson et al. 2002; Conley et al. 2009). The presence of excess nitrogen and phosphorus can lead to eutrophication, which the U.S. Environmental Protection Agency (EPA) and U.S. Geological Survey (USGS) agree is one of the leading causes of water-body impairment in the U.S. (USEPA 2009a). Anticipated climate variability will likely pose significant impacts on water and nutrient dynamics (Bouraoui et al. 2004; Delpla et al. 2009).

Changes in temperature, along with changes in seasonality, will likely pose significant impacts to nutrient patterns within water bodies (Zhu et al. 2008; Kundzewicz and Krysanova 2010; Labeau et al. 2015; Tang et al. 2015). Climate scientists report with high confidence that the U.S. will experience a significant increase in the number of hot days by the end of the 21st Century (Gleason et al. 2008). Increases in the number of warm days per year may lead to changes in land use management, such as rates and timing of lawn and agricultural fertilization (Howden et al. 2007; Mueller et al. 2012). Warmer temperatures combined with land use management alterations may also result in changes to the microbial processes that dictate crop yield, phosphate activity, and nutrient mobilization in soils (Delpla et al. 2009; Jangid et al. 2008; Sardans et al. 2008; Rosenzweig et al. 2013; Tang et al. 2015). As a consequence, rainfall-induced runoff could potentially carry a larger annual quantity of nutrients into rivers. As weather extremes become more frequent and severe, intense precipitation may overload sewer systems, introducing yet another source of pollution into waters. Additionally, flooding as a result of increased severity of storms has the potential to increase erosion of nutrient-laden soil, which adds to degradation of water quality (Loecke et al. 2017).

The potential for climate-induced changes in water quality motivates the need for an investigation into the sensitivity of the water quality of individual watersheds to changes in climate variables. Johnson et al. (2015) performed a large-scale modeling study of 20 large U.S. watersheds using North American Regional Climate Change Assessment Program projected climate scenarios and found that statistically significant changes in total phosphorus and total nitrogen loads as a result of changes in climate are possible in about 60% of the watersheds studied. Analogous to the literature on the climate sensitivity of streamflow, there are two general approaches to evaluating the climate sensitivity of water quality: (1) running a water quality simulation model to explore the impacts of changes in climate inputs on simulation model output, as performed by Bouraoui et al. (2004), Johnson et al. (2015), and Tang et al. (2015); and (2) developing statistical relationships between climate variables and water quality and inferring expected sensitivities from those relationships. We were interested in the latter approach and focus our effort on developing a simple, data-driven nonlinear approach to assessing the sensitivity of phosphorus loading to changes in climate variables.

Climate–streamflow relationships have been used to determine precipitation and temperature elasticity of streamflow, providing a nonparametric (not involving any assumptions as to the form or parameters of a distribution) and nondimensional measure of the sensitivity of streamflow to changes in climate (Schaake 1990; Sankarasubramanian et al. 2001; Chiew 2006). Elasticity is a term that represents a form of nondimensional sensitivity analysis that can be generally defined as the proportional change in one variable, x, divided by the proportional change in another variable, y, where $\varepsilon_x(x, y) = \frac{\mathrm{d}y/y}{\mathrm{d}x/x} = \frac{\mathrm{d}y}{\mathrm{d}x}\frac{x}{y}$. The interpretation of this definition of elasticity is simple. If elasticity, $\varepsilon_x(x, y)$, is equal to 2%, then a 1% increase in x will yield a 2% increase in y. Discussion concerning the interpretation and estimation of elasticity dates back to the early 1900s in economic literature, and is now quite commonly used in hydrology since its introduction by Schaake (1990) and Sankarasubramanian et al. (2001). Evidence of the widespread usage of the concept of climate elasticity of streamflow is provided by hundreds of citations to the study by Sankarasubramanian et al. (2001).

Xia et al. (2014) noted that climate elasticities are often used to analyze changes in water quantity and called for the development and improvement of climate elasticity models in the water quality realm. Jiang et al. (2014) extended the climate–streamflow sensitivity methodology introduced by Schaake (1990) and Sankarasubramanian et al. (2001) to develop climate–water quality relationships using extensive sampling records and described the magnitude of stream water quality responses to climate change. Jiang et al. (2014) only considered the bivariate sensitivity of water quality to temperature separate from its sensitivity to precipitation. Saltelli and Annoni (2010) emphasized the shortcomings of such an approach to sensitivity analyses, presenting a generalized proof that demonstrates the inefficiency of one-at-a-time (OAT) sensitivity methods. Xia et al. (2014) also noted the importance of considering all possible contributors to changing water quality in climate modeling.

In lieu of OAT approaches, a multivariate analysis to determine sensitivity of water quality to changes in climate is desired. Many multivariate models have been developed to describe the relationship between water quality and other factors (i.e., Driver and Tasker 1990; Cohn et al. 1992; Koklu et al. 2010; Nasir et al. 2011; Mustapha and Abdu 2012; Labeau et al. 2015; and many others). However, to our knowledge, these studies do not interpret the meaning of the coefficients of such models as elasticities. There are, however, numerous examples of the development of multivariate methods to determine elasticity of streamflow to changes in climate. Fu et al. (2007) extended the bivariate precipitation elasticity of streamflow introduced by Sankarasubramanian et al. (2001) to a multivariate climate elasticity considering both precipitation and temperature. The multivariate climate elasticity methodology was used by Ma et al. (2010) and compared to a geomorphology-based hydrological simulation model to estimate the impact of climate variability on the inflow into a reservoir responsible for domestic water supply in Beijing. The work of Ma et al. (2010) was extended to include a variable for interannual variability of soil moisture storage to represent the sensitivity of runoff to changes in soil moisture, precipitation, and temperature simultaneously (Xu et al. 2012). Gardner (2009) used multivariate elasticity techniques to estimate changes in mean annual runoff as a function of changes in precipitation, temperature, and potential evapotranspiration. Andréassian et al. (2016) compared five different methods to compute elasticity of streamflow to precipitation and potential evaporation. Allaire et al. (2015) compared two multivariate approaches for estimation of climate, land use, and water use elasticity of streamflow for a river in the vicinity of the brook considered in the present study. Wang et al. (2016) decomposed the potential evaporation elasticity of runoff into five evaporation-related elasticities to reflect the effects of temperature on runoff and to reduce the influence of correlations between radiation and relative humidity.

Yu et al. (2010), Saltelli and Annoni (2010), Allaire et al. (2015), and many others have shown that a complete and correct sensitivity analysis should consider a multivariate analysis which accounts for interaction effects among input explanatory variables to enable an evaluation of the effect of one input variable, while other input variables are allowed to vary at the same time. When estimating elasticities, economists have considered multivariate methods extensively in an attempt to reduce omitted variable bias (OVB), which occurs when a model incorrectly omits one or more important causal factors, thus overestimating or underestimating the effect of one of the other factors. However, the estimates of climate elasticity of water quality introduced by Jiang et al. (2014) did not account for OVB since they only considered estimation of the sensitivity of water quality variables to changes in precipitation and temperature, separately. Further information on the impact of OVB on multivariate models in water resources is provided by Farmer et al. (2015).

The primary goal of this study was to evaluate multivariate interactions among temperature, precipitation, streamflow, and nutrient loads in an urban watershed in an integrated fashion. We demonstrate the value of using multivariate approaches to estimate elasticity that result from models with high explanatory value and reduced OVB. One feature that distinguishes our approach from previous approaches (e.g., Fu et al. 2007; Ma et al. 2010; Mustapha and Abdu 2012) is that we offer a sensitivity analysis method that makes no model assumptions concerning the relationship between load and various independent variables. This is a critical issue with model sensitivity, because the form of the assumed model governs the form of the derivatives used to compute elasticities. The methodology introduced in this study is quite general and can be applied to a wide range of problems relating to water quality management in order to evaluate the evolution of water quality response of a watershed to many different climatic and other factors, such as land management and population growth. A case study is introduced to highlight the influence of precipitation, temperature, and surface water discharge on total phosphorus loading within Alewife Brook, a tributary to the Mystic River near Boston, Massachusetts.

METHODOLOGY

Climate Elasticity of Streamflow

Previous studies have examined the sensitivity of streamflow to changes in precipitation using the concept of precipitation elasticity (Schaake 1990; Sankarasubramanian et al. 2001; Chiew 2006). The precipitation elasticity of streamflow, ε_P, is defined as the relative change in streamflow, Q, divided by the relative change in precipitation, P:

$$\varepsilon_P = \frac{\mathrm{d}Q/Q}{\mathrm{d}P/P} = \frac{\mathrm{d}Q}{\mathrm{d}P}\frac{P}{Q} \tag{1}$$

Sankarasubramanian et al. (2001) presented a nonparametric form of ε_P in Equation (2)

$$\bar{\varepsilon}_P = \frac{\mathrm{d}Q}{\mathrm{d}P}\frac{\bar{P}}{\bar{Q}} \tag{2}$$

where $\bar{P}$ and $\bar{Q}$ denote the mean values of precipitation and streamflow, respectively.

Based upon the nonparametric elasticity estimator recommended by Sankarasubramanian et al. (2001), Jiang et al. (2014) developed the following elasticity estimator for several water quality parameters (e.g., nutrients, turbidity, dissolved oxygen) with respect to air temperature and precipitation at the monthly scale

$$\varepsilon_P = \text{median}\left(\frac{W_t - \bar{W}}{P_t - \bar{P}}\frac{\bar{P}}{\bar{W}}\right), \tag{3}$$

where W_t represents the water quality variable at time t, $\bar{W}$ represents the mean value of the water quality variable, P_t represents the monthly precipitation value at time t, and $\bar{P}$ represents the mean precipitation value for all the data assessed. The advantage of using the elasticity estimator in Equation (3) is that the use of the median minimizes the impacts from outliers, such as extreme events. However, we argue that certain water quality measurements, such as nutrient loads, are greatly influenced by weather extremes, and thus outliers are an integral component of the sensitivity of water quality to changes in climate.

One limitation of the Sankarasubramanian et al. (2001) and Jiang et al. (2014) OAT approaches is that they are only able to determine sensitivity of streamflow or water quality to changes in a single explanatory variable. However, water quality is influenced by simultaneous changes in precipitation, temperature, streamflow, seasonal cycling, and sometimes extreme events. Therefore, a multivariate approach is necessary to capture complex interactions among climate variables that influence nutrient concentrations. The following sections describe two general multivariate approaches to estimation of the elasticity of nutrient loads to various factors.

Multivariate Climate Elasticity of Nutrient Water Quality

Our initial approach to multivariate elasticity employs a nonparametric approach based on the chain rule introduced by Sathyamoorthy et al. (2014) and Allaire et al. (2015). To determine the generalized sensitivity of nutrient loading to changes in precipitation, temperature, streamflow, and number of combined sewer overflow (CSO) events per month, we consider the total differential of nutrient load (L) resulting from simultaneous changes in precipitation (P), temperature (T), flow rate (Q), and number of CSOs (CSO), as shown in Equation (4). CSOs may not exist in all urban stream environments, and so the CSO term may be removed if this model is applied to a stream that does not experience nutrient inputs resulting from CSO discharges. Though man-made, CSOs represent additional sources of phosphorus inputs (via storm discharge mixing with phosphorus-containing raw sewage from the sewer system) to an urban stream that are exacerbated during extreme storm events. Because CSO events may increase due to variability and extremes in climate, the CSO term was included as a climate variable:

$$\mathrm{d}L = \frac{\partial L}{\partial P}\mathrm{d}P + \frac{\partial L}{\partial T}\mathrm{d}T + \frac{\partial L}{\partial Q}\mathrm{d}Q + \frac{\partial L}{\partial CSO}\mathrm{d}CSO \tag{4}$$

Based on Sankarasubramanian et al. (2001), the mean values of each variable are used to estimate the differentials, leading to

$$L - \bar{L} = \frac{\partial L}{\partial P}(P - \bar{P}) + \frac{\partial L}{\partial T}(T - \bar{T}) + \frac{\partial L}{\partial Q}(Q - \bar{Q}) + \frac{\partial L}{\partial CSO}(CSO - \overline{CSO}) \tag{5}$$

Each term is then divided by the mean load, $\bar{L}$, and the three terms on the right are multiplied by unity in the form of $\frac{\bar{P}}{\bar{P}}, \frac{\bar{T}}{\bar{T}}, \frac{\bar{Q}}{\bar{Q}}$, and $\frac{\overline{CSO}}{\overline{CSO}}$, respectively, to result in

$$\left(\frac{L - \bar{L}}{\bar{L}}\right) = \frac{\partial L}{\partial P}\frac{\bar{P}}{\bar{L}}\left(\frac{P - \bar{P}}{\bar{P}}\right) + \frac{\partial L}{\partial T}\frac{\bar{T}}{\bar{L}}\left(\frac{T - \bar{T}}{\bar{T}}\right) + \frac{\partial L}{\partial Q}\frac{\bar{Q}}{\bar{L}}\left(\frac{Q - \bar{Q}}{\bar{Q}}\right) + \frac{\partial L}{\partial CSO}\frac{\overline{CSO}}{\bar{L}}\left(\frac{CSO - \overline{CSO}}{\overline{CSO}}\right) \tag{6}$$

The four terms in parentheses in Equation (6) represent the percentage change from the mean, and can be defined using lowercase variables l, p, t, q, and cso so that Equation (6) can be rewritten more compactly as

$$l = \bar{\varepsilon}_P \times p + \bar{\varepsilon}_T \times t + \bar{\varepsilon}_Q \times q + \bar{\varepsilon}_{CSO} \times cso \tag{7}$$

where

$$\bar{\varepsilon}_P = \frac{\partial L}{\partial P}\frac{\bar{P}}{\bar{L}},\ \bar{\varepsilon}_T = \frac{\partial L}{\partial T}\frac{\bar{T}}{\bar{L}},\ \bar{\varepsilon}_Q = \frac{\partial L}{\partial Q}\frac{\bar{Q}}{\bar{L}}, \text{and}$$
$$\bar{\varepsilon}_{CSO} = \frac{\partial L}{\partial CSO}\frac{\overline{CSO}}{\bar{L}}$$

are the precipitation, temperature, streamflow, and CSO elasticity, respectively. Given that Equation (7) is a linear model with no intercept term, we employ ordinary least squares (OLS) multivariate linear regression methods resulting in minimum variance and unbiased estimates of the four elasticity estimates. The model parameter estimates are then the elasticity estimates shown in Equation (7).

Nonparametric Model

Because the linear multivariate model in Equation (7) is based on the definition of the total differential given by the chain rule in Equation (4), we avoid uncertainty regarding the use of a correct model form. In other words, there are no model assumptions made in the above derivation concerning the relationship between the dependent variable of interest, L, and the various independent variables, P, T, Q, and CSO. Thus, our approach is nonparametric in the vicinity of the mean, where the differentials are estimated. Even if the relationship between the dependent variable L and the various explanatory variables is nonlinear, the linear relationship in Equation (7) in the vicinity of the mean values of the explanatory variables still holds. The primary assumption here is that the elasticity generated from this approach can only reveal sensitivity of the dependent variable to the various explanatory variables, around their mean values. Thus, the elasticities cannot represent the sensitivity of the dependent variable to changes in extreme values of the various explanatory variables.

The resulting model in Equation (7) is fit using multivariate OLS regression, which is attractive because resulting estimates of elasticities are unbiased and their standard errors, confidence intervals, and even hypothesis tests are easily obtained. This opens the possibility for corrections for heteroscedasticity (occurs when the variance of error terms differ across observations) (Stedinger and Tasker 1985; Kroll and Stedinger 1998), autocorrelated model errors (temporal correlation of residuals implies that OLS estimators are no longer the best linear unbiased estimator) (Draper and Smith 1981), and other violations of OLS model assumptions (Johnston 1984). The explanatory power of the overall regression (i.e., the value of R^2) is not preeminent for estimation of elasticity, which relies on unbiased model parameters with low standard errors, rather than high model explanatory value. Instead, OVB is a critical issue and such bias tends to decrease as R^2 increases. To enable proper statistical inference concerning elasticity estimates, residuals of the regression model must be approximately independent (in time) and normally distributed with a constant variance. Overall, we strive to build a multivariate model that provides unbiased elasticity estimates with minimum variance, while simultaneously exhibiting high explanatory value to enable the model to be used for other purposes such as load estimation.

Additional explanatory variables may be added to a multivariate model as long as they improve model explanatory power. Once additional explanatory variables are added, an analysis of the model sum of squared errors may be used to determine which explanatory variables have the greatest impact on nutrient loading. Here, either F-tests (tests overall fit of a regression model) or t-tests (tests statistical significance of individual parameters of a regression model) are suited to such analyses.

Parametric Model

Parametric modeling approaches are frequently used in economics and hydrology and make critical assumptions about the structure of the relationship between the independent and dependent variables. This approach leads to elasticity estimates that are not computed about the mean values of the variables, as shown in the form given in Equation (1).

In the field of economics, the concept of elasticity is widely used to determine the sensitivity of demand for a product to its price. This is termed price elasticity and is an approach that generally does not depend on mean values such as the elasticity in Equation (1), but usually assumes a log-linear model relating the independent and dependent variables

$$L = \theta \times P^{\varepsilon_P} \times T^{\varepsilon_T} \times Q^{\varepsilon_Q} \times CSO^{\varepsilon_{CSO}} \times v, \tag{8}$$

where L, P, T, Q, and CSO are defined as in Equations (3–7); θ, ε_P, ε_T, ε_Q, and ε_{CSO} are model coefficients; and v are lognormally distributed model errors. Note that log-linear models of the form given in Equation (8) are widely used in hydrology as evidenced by hundreds of such models available within the StreamStats water resources web application (Ries et al. 2004). Taking derivatives of the model coefficients in Equation (8) provides the elasticity estimates corresponding to Equation (8), such that

$$\varepsilon_P = \frac{dL}{dP}\frac{P}{L},\ \varepsilon_T = \frac{dL}{dT}\frac{T}{L},\ \varepsilon_Q = \frac{dL}{dQ}\frac{Q}{L}, \text{and}$$
$$\varepsilon_{CSO} = \frac{dL}{dCSO}\frac{CSO}{L}.$$

These elasticity definitions are more general than in Equation (7) because they are not defined strictly about the mean of the variables. However, estimation of multivariate elasticities using Equation (8) requires an assumption regarding the multivariate power law model structure in Equation (8), which was not a requirement for estimation of the elasticities about the mean values in Equation (7).

Model Interpretation

To highlight the importance of multivariate interactions, elasticity estimates were computed based on simple (bivariate) regressions between each explanatory variable separately. That is, the elasticity values were estimated from the following bivariate equations: $l = \bar{\varepsilon}_P \times p$, $l = \bar{\varepsilon}_T \times t$, $l = \bar{\varepsilon}_Q \times q$, and $l = \bar{\varepsilon}_{CSO} \times cso$, individually, instead of Equation (7), as well as $L = \theta \times P^{\varepsilon_P} \times v$, $L = \theta \times T^{\varepsilon_T} \times v$, $L = \theta \times Q^{\varepsilon_Q} \times v$, and $L = \theta \times CSO^{\varepsilon_{cso}} \times v$ instead of Equation (8). These bivariate values were also compared to the bivariate water quality estimators developed by Jiang et al. (2014), which were based on the median elasticity estimator given in Equation (3).

An attempt was made to determine elasticity estimates for each of the four seasons by estimating separate seasonal sensitivities using fixed effects with interaction terms in both Equations (7 and 8). An interaction term is defined as the product of two independent variables that interact if the effect of one of the variables differs depending on the level of the other variable. In Equations (7 and 8), the binary seasonal fixed effects variables were multiplied by precipitation, temperature, and flow rate to determine whether or not the interactions between climate variables and seasons would produce differing elasticity estimates based on season.

According to economic price elasticity of demand principles, elasticity values <0.1 represent inelastic behavior, whereas values >1.0 represent elastic behavior. Thus, streamflow elasticity estimates >1.0 would imply that the response of total phosphorus loading to changes in flow rate is elastic with that elasticity increasing as values increase above unity.

The percentage of the model sum of squares corresponding to each variable (%SS) may be used to compare the importance of precipitation, temperature, streamflow, and CSO events in terms of how much of the variations in phosphorus load is explained by each term. The variance inflation factor (VIF) can be used to identify intercorrelation among the explanatory variables, with a VIF ≥ 10 denoting a severe multicollinearity problem (Helsel and Hirsch 1992) leading to suspect results that may not give valid information regarding individual predictors (i.e., predictors may be redundant with respect to other predictors).

CASE STUDY

In the following case study, we modeled the response of phosphorus loads in the Alewife Brook, a tributary to the Mystic River near Boston, Massachusetts, to changes in climate variables from 2007 to 2014. This temporal scale was chosen based on availability of streamflow data, which began when the USGS streamflow gage #01103025 was installed at the brook in 2007. We applied Equations (7 and 8) to estimate the generalized climate elasticity estimates of total phosphorus loads in the brook.

Background

Alewife Brook is located in an urbanized area (see Figure 1) and is a contributor of phosphorus to the main stem of the Mystic River, which is on the Massachusetts 303(d) List of Impaired Waters requiring calculation of a total maximum daily load (Massachusetts DEP 2014). Phosphorus originates from sources within the watershed, including fertilizer and animal waste runoff, erosion, and resuspension of phosphorus-rich soil and sediment, and leaking municipal sanitary systems. An additional source of phosphorus that is specific to Alewife Brook comes from the activation of CSOs during large rain events. When storm drains are at capacity due to a sizable rain storm, they direct stormwater to the sewer system, where stormwater and sewer water mix together and discharge into the brook through CSOs.

Since 2000, unfiltered baseflow water samples have been collected by the Mystic River Watershed Association in Alewife Brook at monthly intervals and analyzed for total phosphorus content (MyRWA 2015). In 2014, storm event sampling (samples taken at approximately hourly intervals throughout the duration of a storm) was performed to provide total phosphorus measurements during rain events. Monthly average temperature and monthly total precipitation data were acquired from the National Climatic Data Center and used for the analysis (Station at Logan Airport GHCND:USW00014739).

To develop long-term monthly estimates of total phosphorus loads for periods during which measured phosphorus concentrations were unavailable, a five-parameter lagged regression equation was developed, based on the seven-parameter LOAD ESTimator (LOADEST) model suggested by Cohn et al. (1992):

$$\ln[\text{Load}] = \beta_0 + \beta_1 \times \ln[Q] + \beta_2 \times \ln(Q_{t-1}) + \beta_3 \times \sin\left[\frac{2\pi T}{365}\right] + \beta_4 \times \cos\left[\frac{2\pi T}{365}\right] + \varepsilon, \tag{9}$$

where Q is the 15-min average discharge at the time of sample collection, Q_{t-1} represents the previous

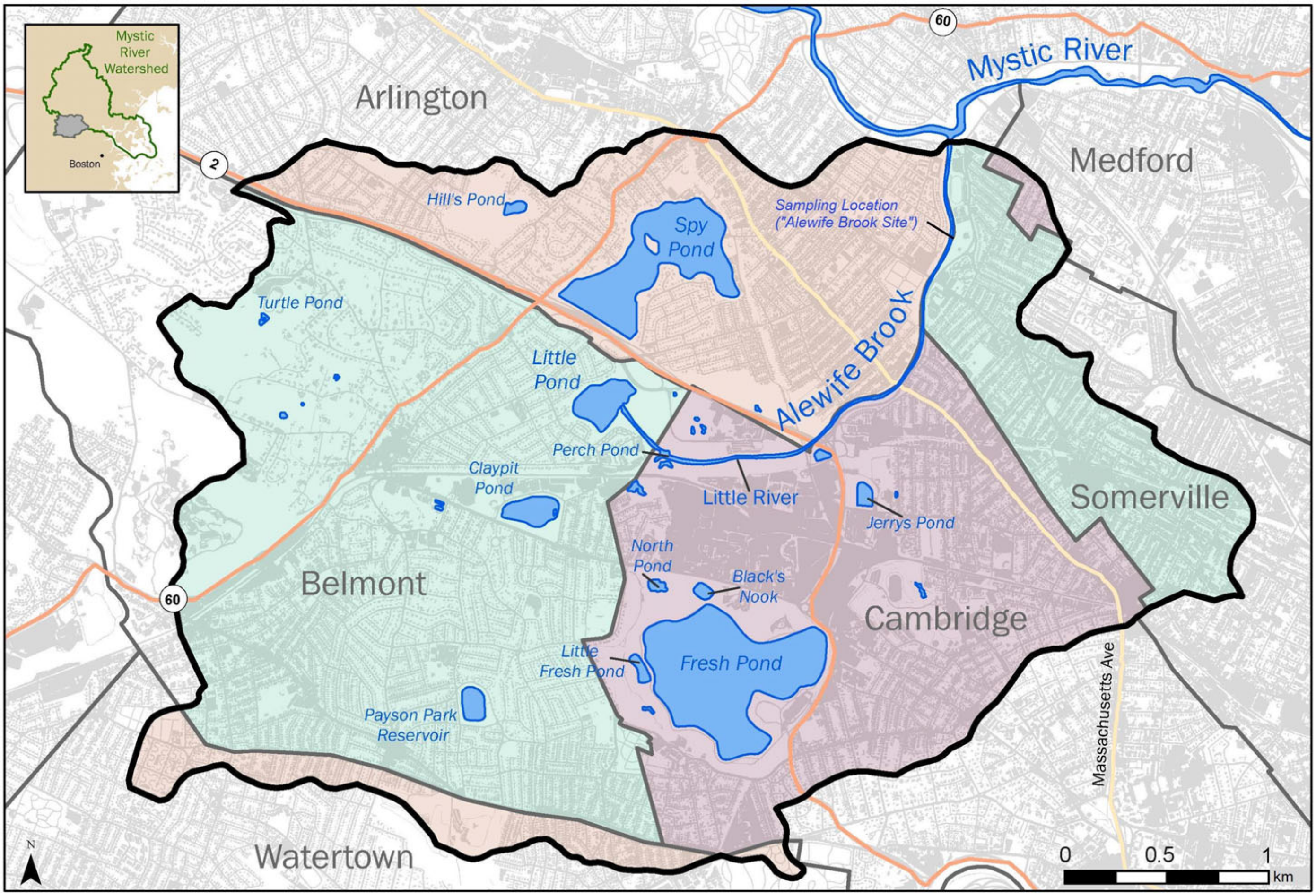

FIGURE 1. Alewife Brook watershed (source: mysticriver.org; accessed July 25, 2017).

day's average discharge, T is Julian day of the year, and ε accounts for model error. β_1 through β_4 are coefficients corresponding to each explanatory variable, Q, Q_{t-1}, and T. This model was chosen because it is one of the many possible forms of the LOADEST model developed and commonly used by the USGS (i.e., see table 7 in Runkel et al. 2004; USGS 2013) to estimate water quality loads from discharge measurements, it provides a good fit to the observations, and it is useful for computing phosphorus loads from easily acquired data, such as flow rate and day of year. Total phosphorus concentration data from both storm event samples and monthly baseflow samples during 2007–2014 were used to model monthly average phosphorus loads (Munson 2015). The measured concentration data were converted into loads (mg/s) by multiplying the measured phosphorus concentrations by the corresponding 15-min average discharge in the Alewife Brook (USGS gage #01103025; data approved for use after processing and review) prior to input in model Equation (9). Results of model Equation (9) in comparison to measured data are provided in the Supporting Information.

Multivariate Elasticity Methods

A time series of monthly total phosphorus loads was obtained from Equation (9) and used as inputs in Equations (7 and 8), with an additional term to represent the monthly number of CSO events at Alewife Brook. Although CSOs could be considered an anthropogenic source of phosphorus loading to the river, they are included because CSO activation is exacerbated when storms are high intensity and variable. Equations (7 and 8) were used to relate the time series of monthly total phosphorus loads (estimated using Equation 9) to precipitation, temperature, streamflow, and the number of CSO events. Additionally, given the results of Labeau et al. (2015) and others, seasonal fixed effects were added to the models in Equations (7 and 8) to account for seasonal fluctuations of phosphorus unaccounted for by the temperature variable. Fixed effects are easily accounted for within regression analyses by simply including binary (0,1) variables that control for unobserved heterogeneity associated with each season. These seasonal fixed effects are taken into account by including four additional input binary variables corresponding to the four seasons: spring (any day in the months April, May, or June), summer (any day in the months July, August, or September), fall (any day in the months October, November, or December), and winter (any day in the months January, February, or March). The seasonal binary variables were assigned a value of either 1 or 0 depending on the season during which the total phosphorus measurement was taken. For instance, the spring binary variable was given a value of 1 if the corresponding total phosphorus value was observed during spring (April, May, or June) or 0 otherwise. These seasonal fixed effects may account for seasonal changes in phosphorus (Figure 2) not accounted for in sampling or modeling procedures.

Estimates of elasticity in Equations (7 and 8) were obtained using OLS regression, where model residuals were tested to ensure that they were approximately uncorrelated in time, homoscedastic, and well approximated by a normal distribution. Helsel and Hirsch (1992) outlined that residuals must follow these patterns in order to obtain unbiased estimators of the dependent variable, test hypotheses, and estimate confidence intervals for regression coefficients. The addition of fixed effects, as well as an event-based CSO variable, assisted in removing potential OVB, ensuring that the majority of the primary factors contributing to phosphorus loading were taken into account. Concerns over possible serial correlation were addressed using the Durbin Watson test, which examines whether the regression model residuals exhibit significant serial correlation.

RESULTS AND DISCUSSION

Climate Elasticity of Total Phosphorus

Two approaches (parametric and nonparametric) to estimating the multivariate sensitivities of total phosphorus to changes in precipitation, temperature, streamflow, and number of CSOs were developed using Equations (7 and 8), and the results are reported in Table 1. Each elasticity estimate has a corresponding t-value defined as the ratio of each elasticity estimator to its standard deviation. Since such t-values follow a Student's t distribution, we also provide P-values corresponding to each elasticity estimate, defined as the probability that the estimated elasticity value is equal to zero, under the null hypothesis that is actually equal to zero. The P-values reported in Table 1 are all <0.03, which indicates that it would be extremely unlikely that these elasticity values are actually zero. In addition, Table 1 outlines the percentage of the model sum of squares corresponding to each explanatory variable

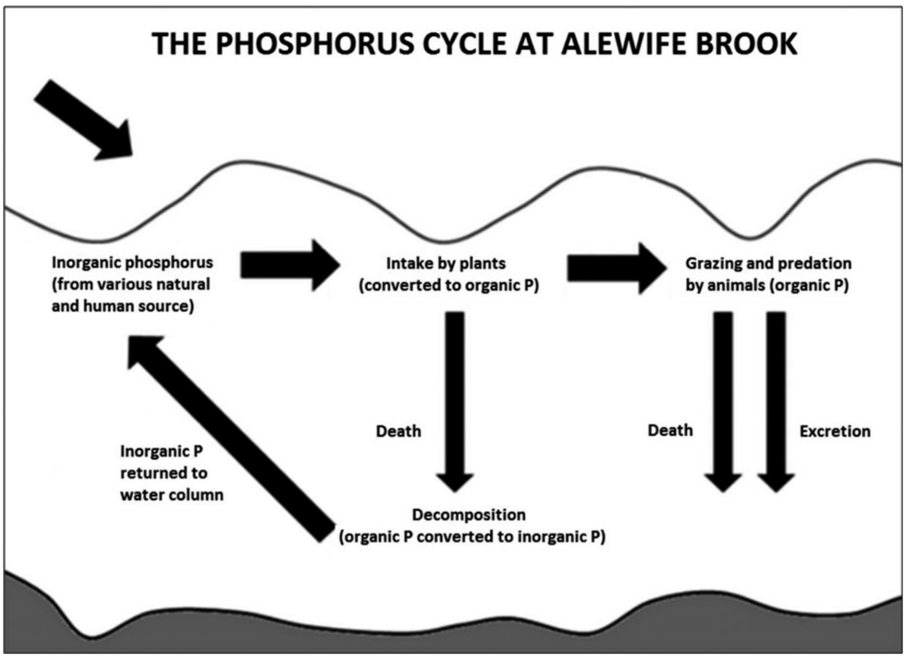

FIGURE 2. Simplified conceptual model of seasonal phosphorus cycling in Alewife Brook (based on Boman et al. 2002).

TABLE 1. Comparison of climate elasticity estimations in relation to monthly average total phosphorus loads.

Result	Precipitation	Temperature	CSO	Flow rate
Equation 7				
$\varepsilon_{P,T,CSO,Q}$	0.272	0.556	0.0473	1.12
t	5.34	3.91	2.85	19.86
P	0.00	0.00	0.01	0.00
%SS	67.12	1.19	7.14	19.28
VIF	2.52	5.34	1.91	3.15
R^2		96.2%		
R^2 (adj)		95.8%		
R^2 (pred)		95.1%		
Equation 8				
$\varepsilon_{P,T,CSO,Q}$	0.100	0.570	0.0155	1.23
t	2.18	4.29	2.42	19.28
P	0.03	0.00	0.01	0.00
%SS	47.42	4.32	4.36	35.64
VIF	1.78	4.68	1.48	2.05
R^2		92.1%		
R^2 (adj)		91.3%		
R^2 (pred)		90.2%		

Notes: CSO, combined sewer overflow; VIF, variance inflation factor. (1) Although Equation (7) requires that each model be fit without an intercept term, R^2 values are reported for Equation (7) fit with an intercept term only to help identify presence or absence of omitted variable bias. (2) ε refers to the elasticity estimate, not an error term. (3) Variables P, T, CSO, and Q refer to precipitation, temperature, CSO events, and flow rate, respectively. (4) Variables t and P in this table refer to t-values (ratio of each elasticity estimator to its standard deviation) and P-values (probability that the estimated elasticity value is equal to zero), respectively. (5) %SS refers to the percent sum of squares, and demonstrates the contribution of a particular variable to overall R^2. (6) R^2 (adj) is the percentage of response variable variation explained by its relationship with one or more predictor variables, adjusted for the number of predictors in the model. (7) R^2 (pred) shows how well the model will predict responses for new observations, with larger values of R^2 (pred) indicating models of greater predictive ability.

(%SS) and the VIF. Durbin Watson test values were between 1.5 and 2.5; therefore, model residuals did not exhibit significant serial correlation.

A number of inferences may be drawn from the results in Table 1 based on the economic price elasticity of demand principles discussed in the Methodology (Parametric Model) section. The precipitation elasticity of total phosphorus loads, ε_P, is 0.272 for Equation (7) and 0.100 for Equation (8), indicating elastic or relatively elastic behavior. Table 1 also demonstrates that of all the explanatory variables, total phosphorus loads are most sensitive to changes in monthly streamflow. This may signify that the dynamic streamflow conditions that dictate erosion and sediment recycling within the river exacerbate phosphorus conditions more so than the impacts of precipitation alone. It is important to realize that temperature elasticities will depend on the units of temperature used, and comparison can only be made between temperature elasticities when the same temperature units are used in such comparisons, which is the case in this study. Elasticities are generally invariant to the units used, an advantage of using elasticity; however, this is only true for variables with homogeneous unit conversions, as is the case for nearly all variables other than temperature.

CSO had considerable explanatory value, as evidenced by its associated high t-values and very low P-values. However, Table 1 shows that the CSO elasticity of total phosphorus was only 0.0473 for Equation (7) and 0.0155 for Equation (8), indicating that monthly total phosphorus loads appear to be relatively insensitive to increases in the number of CSO events per month when compared to other variables. The influence of seasonal fixed effects combined with this CSO term improved the model explanatory value while correcting for OVB. These results indicate that even though total phosphorus loads are not highly sensitive to changes in the number of CSOs, the occurrence of CSOs is extremely important for predicting the actual magnitude of total phosphorus loads.

The attempt to determine elasticity estimates for each of the four seasons by estimating separate seasonal sensitivities using fixed effects and interaction terms in Equations (7 and 8) resulted in P-values corresponding to the interaction effects that were $\gg$0.05 in both models. Thus, even though the magnitude of phosphorus loading changes from season to season, multivariate sensitivities (or elasticity estimates) appear to remain constant.

Elasticity estimates from Equations (7 and 8) are not expected to agree exactly because each has a different interpretation: Equation (7) assumes no model form and can only represent sensitivity around the mean values of the various variables, whereas Equation (8) assumes log-linear model form and results in a more generalized interpretation of elasticity which is constant over the complete range of variability of all the variables, and is thus not limited to sensitivity about the mean. Both Equations (7 and 8) do, however, lead to the important conclusion that phosphorus loading is sensitive to changes in precipitation, temperature, discharge, and CSO events, which must all be considered simultaneously to fully understand the effects of climate change on a watershed.

Our elasticity estimates indicate similar results for streamflow elasticity using both multivariate and bivariate methods. However, bivariate methods show increased precipitation and CSO elasticity as well as decreased temperature elasticity, compared to multivariate methods, as indicated in Figure 3. In general, the bivariate results should not be trusted due to the now well-known caveats associated with OAT sensitivity analyses. Table 2 compares the coefficients of determination (R^2 and R^2 predicted) corresponding to bivariate vs. multivariate elasticity estimation

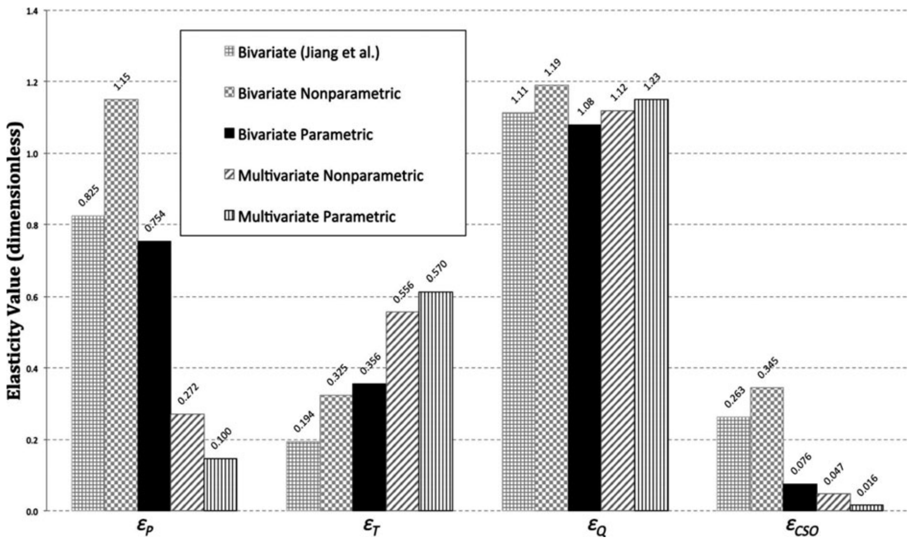

FIGURE 3. Comparison of bivariate and multivariate elasticity estimation methods (ε_P = precipitation elasticity, ε_T = temperature elasticity, ε_Q = flow elasticity, and ε_{CSO} = CSO elasticity).

TABLE 2. Comparison of coefficients of determination (R^2) for bivariate and multivariate elasticity estimation methods.

	R^2 (R^2 predicted) (%) for Bivariate and Multivariate Elasticity Methods			
	Bivariate Elasticity		**Multivariate Elasticity**	
	Nonparametric (Equation 7)	**Parametric (Equation 8)**	**Nonparametric (Equation 7)**	**Parametric (Equation 8)**
P	67.1 (58.9)	40.6 (37.2)	96.2 (95.1)	92.1 (90.2)
T	1.30 (0.00)	3.40 (0.00)		
Q	82.2 (81.2)	70.2 (68.9)		
CSO	46.2 (32.0)	23.7 (19.7)		

Note: (1) Variables *P*, *T*, *CSO*, and *Q* refer to precipitation, temperature, CSO events, and flow rate, respectively. (2) R^2 (adj) is the percentage of response variable variation explained by its relationship with one or more predictor variables, adjusted for the number of predictors in the model. (3) R^2 (pred) shows how well the model will predict responses for new observations, with larger values of R^2 (pred) indicating models of greater predictive ability.

methods. The multivariate nonparametric and parametric methods exhibit R^2 values closer to 100% than corresponding bivariate methods, indicating that the multivariate elasticity models more accurately reflect the properties of the load data and would be expected to yield models with lower OVB than corresponding bivariate models. We conclude that it is necessary to account for the multivariate interactions among precipitation, temperature, and streamflow to fully understand and explain their impacts on nutrient loading in this watershed. Elasticities estimated from bivariate models may represent the general relationship between nutrient loading and a variable of interest in some cases, but these methods cannot reflect the complex nonlinear multivariate relationships inherent among nutrients, precipitation, temperature, and streamflow. Additionally, it is important to include event-based factors that contribute to nutrient loading and seasonal fixed effects in models that estimate elasticity to reduce OVB and confidence intervals while increasing model explanatory value.

Unlike common forms of sensitivity analyses, the nonparametric multivariate elasticity approach introduced in Equation (7) is standardized by normalizing each deviation by the mean, rather than the standard deviation. This model does not require any assumptions other than being restricted to estimation of sensitivity about the mean, because the derivation is based solely on the chain rule. That derivation resulted in a multivariate linear model without an intercept term, which is independent of the form of the original model that relates nutrient load to the explanatory variables. This is quite important because the form of that relationship dictates the value of the elasticity, and since that form is unknown, a nonparametric approach is attractive. Many sensitivity analyses differ from the approach presented in Equation (7) because they are based on a multivariate regression structural model form. Such a model assumption limits the analysis, especially when R^2 is low (<60%; indicating nonlinearity of the assumed linear model), because it is then questionable to use the values of the coefficients for ranking input factors (Saltelli et al. 2004; Saltelli and Annoni 2010). This study demonstrates that the discrepancy between bivariate and multivariate estimates of precipitation elasticity to phosphorus loading is caused in part by OVB present in bivariate elasticity estimation. The large estimates of precipitation and CSO-event elasticity shown in the bivariate analysis summarized in Figure 3 are likely compensating for omitted explanatory variables, thus overestimating the effect of precipitation and CSOs on nutrient loading.

An additional benefit of Equation (8) is that the model can provide both elasticity estimates and phosphorus loads, an advantage in practice. The final log-linear model is as follows:

$$L = \theta \times P^{0.1001} \times T^{0.5702} \times Q^{1.230} \times CSO^{0.0115}$$

$$\text{where} \begin{cases} \theta = 11.82 & \text{if spring} \\ \theta = 16.41 & \text{if summer} \\ \theta = 14.98 & \text{if fall} \\ \theta = 12.97 & \text{if winter} \end{cases}$$

The influence of seasonal fixed effects is represented in the model intercepts, θ, which demonstrate that phosphorus loads are higher in the summer and fall seasons, rather than in spring and winter. This is consistent with the total phosphorus load estimates provided by the LOADEST model (Figure 4). Possible explanations for higher phosphorus loading during the summer months include increased temperature mobilizing phosphorus from soils and sediments (Delpla et al. 2009; Sardans et al. 2008; Tang et al. 2016) and increased frequency of high-volume storms resulting in bank erosion, remobilization of sedimentary particulate phosphorus (Correll et al. 1999; Wetzel 2001), and more frequent CSO events. During autumnal senescence, organic phosphorus is released from plants and is thus an additional input of phosphorus to the water column (Carpenter et al. 1998; Keskitalo et al. 2005). As shown in Table 1, the parametric model has high explanatory value (R^2 = 92.1%), which is higher than many total phosphorus load models developed by other investigators (see Table 3). Our findings indicate that the use of fixed effects models combined with inclusion of the number of CSO events holds promise for improving regression models of nutrient loads, as evidenced by the much greater goodness of fit associated with the models developed here than in previous studies.

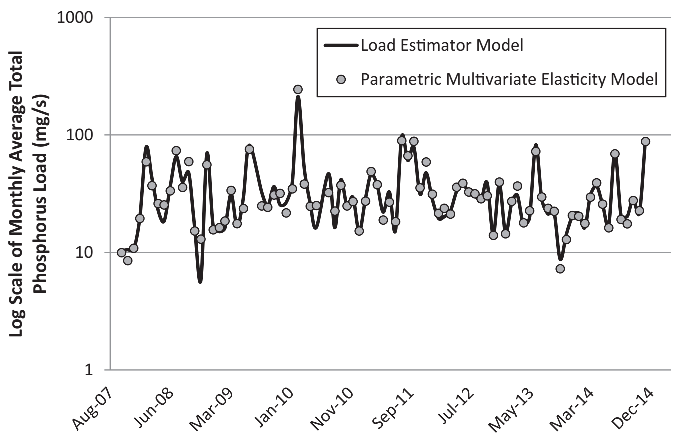

FIGURE 4. Comparison of modeled phosphorus data and multivariate parametric elasticity model.

Although our method for determining elasticity estimates in Equation (8) relies on an assumed log-linear model form, those estimates are not restricted to interpretation of sensitivity about mean values as is the case when using Equation (7). It is difficult to determine whether Equation (7) is preferred to Equation (8), or vice versa, because they produce elasticities with slightly different interpretations. Instead, this study presents two alternative methods for determining sensitivity of nutrients to changes in climate. It was found that the difference in elasticity estimates between the two methods was relatively small for each climate variable. Both methods have advantages over existing sensitivity analysis methods because they avoid the perfunctory complications associated with OAT sensitivity methods by considering several variables that may contribute to water quality changes simultaneously. By accounting for the interactions among precipitation, temperature, and streamflow on nutrient loading, both models avoid the negative effects of OVB so that one variable is not overcompensating for another omitted variable. Additional explanatory variables as well as fixed effects may be included in the analysis to strengthen explanatory power of the model while determining sensitivity of water quality to variables simultaneously.

Model Interpretation and Applications

Although it is often difficult to identify the many sources of phosphorus loading into a watershed, the impacts of these sources can be represented using the methodology outlined in this paper. Elasticity estimates enable us to understand how total phosphorus loading may respond to the simultaneous and interacting changes in precipitation, temperature, stream discharge, and number of CSO events. Our approach enables us to predict how phosphorus conditions may respond to various future climate scenarios. For example, a temperature elasticity of total phosphorus

TABLE 3. Coefficients of determination for multivariate total phosphorus load models that include climate-independent variables.

Reference	Regression Equation	R^2 (%)
Driver and Tasker (1990)	Ln[TP(lb)] = 262 + 0.828 × Ln(Total storm rainfall; inches) + 0.645 × Ln(Drainage area; sq. mi.) + 0.583 × Ln(Industrial land use; %) + 0.181 × Ln(Commercial land use; %) − 0.235 × Ln(Nonurban land use; %) − 1.376 × Ln(Mean annual rainfall; inches) + 1.548 × Ln(Bias correction factor)	72
Driver and Tasker (1990)	Ln[TP(lb)] = 0.153 + 0.986 × Ln(Total storm rainfall; inches) + 0.649 × Ln(Drainage area; sq. mi.) + 0.479 × Ln(Impervious area; %) + 1.543 × Ln(Max precipitation intensity; inches) + 1.486 × Ln(Bias correction factor)	64
Driver and Tasker (1990)	Ln[TP(lb)] = 53.2 + 1.019 × Ln(Total storm rainfall; inches) + 0.846 × Ln(Drainage area; sq. mi.) + 0.189 × Ln(Commercial land use; %) + 0.103 × Ln(Residential land use; %) − 0.16 × Ln(Nonurban land use; %) − 0.754 × Ln(Mean minimum January temperature; °F) + 2.059 × Ln(Bias correction factor)	54
Arheimer and Liden (2000)	Ln(TP; kg/m^2) = −1.25 − 0.078(Soil moisture; mm)^2 − 0.63sqrt(Flow rate; mm/day)	60
Brezonik and Stadelmann (2002)	TP(kg/event) = −1.205 + 0.801(Precipitation; cm) + 0.244(Precipitation intensity; cm/h) + 0.461 (Drainage area; acres)	40
Smith et al. (2003)	Log(TP; mol per km^2/yr) = 2.72 + 0.36 log(Population; people per km^2) + 0.78 log(Runoff; m/yr)	58

Note: TP, total phosphorus.

loads value of 0.57 implies that if temperature during a given month increases by 10%, Alewife Brook may see a 5.7% increase in total phosphorus loads for that month. In the context of the 2007 IPCC Special Report on Emissions Scenarios, which reports that the global average surface temperature will increase by 0.5°C (0.9°F; 255.9 K) by the 2020s (Solomon et al. 2007), this finding has relevance for characterizing potential nutrient loads in the future.

Because our elasticity estimates are based on a model that uses fixed effects to represent seasonal variation, this estimate of phosphorus sensitivity to a 10% temperature change is able to distinguish between actual changes in climate and normal seasonal variation. Pairing elasticity data with regional climate predictions can better inform future watershed planning. For instance, temperature scenarios specific to Cambridge, which is also part of the Alewife Brook watershed, project that annual temperature could increase by about 6% in 2030 and by as much as 18% in 2070 (Kleinfelder, 2015). Thus, if temperature increases by 6% during a given month in 2030, Alewife Brook may see a 3.4% increase in total phosphorus loads for that month. If temperature increases by 18% during a given month in the year 2070, phosphorus loads at Alewife Brook may increase by 10%. Although water managers do not have the ability to control future climate, they are capable of creating strategic plans to reduce the impacts of climate variability on phosphorus loading within a basin. Elasticity estimates draw attention to the climatic factors that will impact a water body with the greatest magnitude, potentially improving the organization of best management practices to implement for nutrient load reduction.

Limitations

There are numerous limitations to the multivariate statistical models and methods introduced here. In all modeling studies, OVB is always present to some extent, unless goodness of fit is perfect (i.e., $R^2 = 1$), which is never the case in practice. Some potential explanatory variables were not included here due to lack of monthly data over the study period, including changes in: impervious coverage, soil compaction, water imports and exports, water infrastructure, vegetation removal, population growth, lawn area, and fertilizer use. We emphasize, however, that the goal of this study was to elucidate the effects of changing climate variables on nutrient loads, including variables affected by a changing climate, such as CSO releases, rather than on the impacts of direct anthropogenic influences on nutrient loads.

The inclusion of fixed seasonal effects terms in the models may complicate the way in which the models are used with respect to anticipated shifts in seasonal climate patterns. Future research that explores the impacts of climate change on season length and distribution throughout the calendar year should be implemented in this model structure to improve climate elasticity estimates of total phosphorus loads. Although examining sensitivity of phosphorus loading to climate variables on a monthly scale will generally account for seasonal effects, it is possible that the monthly scale may obscure important intra-month event-based and seasonal relationships among the response and independent variables. Additional studies may consider evaluating the sensitivity of phosphorus loading to climate variables at a daily or event scale to further examine the effects of event-based factors and intra-month shifts in climate variables on the climate elasticity of phosphorus loading.

Another potential limitation of this study is that the nutrient data upon which the elasticity model Equations (7 and 8) rely are based on model estimates themselves from Equation (9). This is because, unlike streamflow, which is often monitored nearly continuously, most water quality constituents are measured only intermittently. Therefore, the data employed in nutrient loading studies, including the present study, tend to be based in part on models such as Equation (9), and this fact must be considered in any corresponding uncertainty analysis or application of model Equations (7 and 8). The sampling results used in Equation (9) were based on storm event sampling conducted in 2014 in combination with baseflow sampling performed from 2007 to 2014. Although Equation (9) is designed to yield unbiased estimates of annual load regardless of sample size, using only one year of storm sampling combined with seven years of baseflow sampling may lead to increased uncertainty. Nonetheless, it was important to include as much phosphorus loading and flow rate data as was available to better represent the responses of the brook to a range of conditions. In addition, the representativeness of climate data corresponding to the watershed defined by the river location of interest is always a concern because most long-term measured climate data are only available for point locations, whereas spatially representative watershed estimates, such as those modeled using PRISM (NACSE 2017), may improve the precision of the sensitivity analysis.

There are always concerns over scarcity of both sampled total phosphorus and flow rate data, and possible sampling errors (e.g., not taking enough samples to represent the full hydrograph of the storm). Further research on this topic should include development of models for multiple sites in multiple regions analogous to the work of Roman et al. (2012) for sediment loads, as well as consideration of biologically available forms of phosphorus as opposed to total phosphorus. Although water quality records are usually more sparse than streamflow records, improved sampling and modeling efforts over time will lead to improvements in our ability to detect long-term climate trends associated with nutrient loading.

CONCLUSIONS

There is now a relatively large literature that explores the nondimensional sensitivity, termed elasticity, of streamflow to numerous climatic and watershed factors, yet there is only a minimal corresponding literature concentrating on the sensitivity of nutrient loading to climate change. This study attempts to begin to bridge this gap by introducing two simple multivariate nondimensional sensitivity analysis techniques (nonparametric and parametric) for evaluating the impact of climatic and other watershed influences on phosphorus loads. A nonparametric multivariate regression method, Equation (7), for determining the sensitivity of nutrient loading to changes in climatic factors, such as precipitation, temperature, flow rate, and other possible explanatory variables, was introduced. Compared to other methods of sensitivity analysis, this approach is advantageous because it enables a multivariate analysis yet is not dependent on critical model form assumptions and is thus termed nonparametric. This model may also be used to estimate seasonal total phosphorus loads based on the input variables.

Overall, this study shows that nutrient loading in the study watershed is sensitive to changes in precipitation, temperature, streamflow, and event-based factors such as CSO. At Alewife Brook, total phosphorus loads appear to be more sensitive to changes in monthly flow rate than to monthly precipitation. Although increases in total monthly precipitation will likely have significant impacts on monthly phosphorus loads, an increase in the number of storms per month could produce the conditions necessary for erosion and sediment resuspension. Future changes in temperature, although less likely to affect total phosphorus loading than streamflow changes, may increase nutrient transport into the river through increased microbial activity in soil and sediments. The addition of seasonal fixed effects and a CSO variable did not alter sensitivity analysis results, but did improve the explanatory value of both models to the extent that our models appear to have greater goodness of fit than previous models of total phosphorus loads.

This study introduces a methodology that may improve our general understanding of the complex interactions among precipitation, temperature, streamflow, and nutrient loading using OAT sensitivity approaches and interpreting multivariate model coefficients in an elasticity context. The methodology introduced in this study can be applied to a broad array of water quality scenarios and may include additional climatic and other factors that were not considered in the case study, such as vegetation and runoff characteristics, changes in water infrastructure, land management, and population growth. Future studies might consider a multivariate model to describe the integrated impact of nitrogen and phosphorus loadings together when evaluating elastic response to climate variables. To improve meaningfulness of such analyses, more extensive records of nutrient loading are needed and the models should be extended to multiple sites and regions analogous to the regional models of sediment loads developed for the eastern U.S. by Roman et al. (2012).

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: Load estimator output and associated model statistics.

ACKNOWLEDGMENTS

This study was completed with the help of several individuals and institutions. We thank Ruhui Zhao, Patrick Herron, Andy Hrycyna, and the Mystic River Watershed Association for their sampling and analysis efforts. This work was funded by the Mystic River Watershed Association, the Tufts Community Research Center, and the Tufts Graduate Education and Research Program in: Water: Systems, Science, and Society.

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