UNCERTAINTY IN PHOSPHOROUS LOAD ESTIMATION FROM A LARGE WATERSHED IN THE GREAT LAKES BASIN

Incertitude en l'Estimation de la Charge du Phosphore d'un Grand Bassin Versant dans le Bassin des Grands Lacs

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KEY WORDS

Saginaw Bay, Saginaw River, Regression model, Nutrient load, Monte Carlo analysis.

ABSTRACT

Saginaw Bay is a large and shallow embayment in western Lake Huron used for drinking water supply, recreation fishing, tourism, and navigation. Over time, high nutrient loading from agricultural runoff, industrial pollution, and public wastewater systems in its watershed caused eutrophication of the bay. To improve this situation, a target Total Phosphorus (TP) load of 440 metric tons/yr was established for Saginaw Bay and the resulting reduction of phosphorus output from point sources lead to diminishing eutrophication. However, eutrophication symptoms have recently returned to Saginaw Bay. In this paper we present a regression model developed to evaluate the current nutrient loads using the relatively few water quality measurements and daily discharge data available for the basin. The regression model accounts for the effect of discharge on TP concentration, including rising and receding flood phases and previous storms, as well as seasonality and long-term trends in pollution generation. The model tracks TP dynamics well (correlation with observed 1998-2008 daily concentrations and loads at the outlet of Saginaw River is 0.84 and 0.96 respectively) and indicates that the target load of 440 metric tons has been met only during dry years. The ability to closely replicate the observed TP concentrations results in a model uncertainty of annual TP loads of less than 6%. However, a Monte Carlo analysis of the propagation of the errors in the observed concentrations and discharges used for calibrating and driving the model shows that the uncertainty in annual load estimates due to these factors is above 10%.

RESUME

Incertitude en l'Estimation de la Charge du Phosphore d'un Grand Bassin Versant dans le Bassin des Grands Lacs
La Baie de Saginaw est un enfoncement grand et peu profond dans l'Ouest du lac Huron, utilisé pour l'approvisionnement en eau potable, la pêche de loisirs, tourisme et la navigation. Au fil des années, la haute charge de nutriments de ruissellement agricole, la pollution industrielle et le traitement inadequate des eaux usées dans le bassin hydrographique a causé l'eutrophisation de la baie. Pour améliorer cette situation, il a été établie l'objectif de limiter la charge de phosphore total (TP)à 440 tonnes/an pour la baie de Saginaw et les efforts qui ont résulté pour contrôler la

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sortie de phosphore provenant de sources ponctuelles conduisent à diminuer l'eutrophisation. Cependant, les symptômes de l'eutrophisation ont récemment resurgi dans la baie de Saginaw. Dans ce document, nous présentons un modèle de régression développé pour évaluer les charges en éléments nutritifs basé sur les données disponibles dans les mesures de la qualité de l'eau et la décharge quotidienne dans quelques points dans le bassin. Ce modèle de régression représente l'effet de la concentration de TP de décharge, montée et le recul des inondations, tempêtes précédentes, caractère saisonnier et tendances à long terme dans la génération de la pollution. La dynamique de TP est bien modelée (corrélation avec concentrations observé entre 1998-2008 et charges quotidiennes à la sortie de la Rivière Saginaw 0,84 et 0,96 respectivement) et indique que la charge cible de 440 tonnes métriques a été remplie uniquement pendant les années sèches. La capacité de répliquer les concentrations de TP observées limite le modèle d'incertitude des charges annuelles de TP à moins de 6 %. Toutefois, une analyse de Monte-Carlo de la propagation des erreurs dans les concentrations observées et les rejets utilisés pour l'étalonnage et l'opération du modèle montre que l'incertitude dans les estimations annuelles de charge en raison de ces facteurs est supérieure à 10 %.

1. INTRODUCTION

Phosphorous loading from human activities in the drainage basin is the major cause of eutrophication in fresh waterbodies (rivers, lakes, and swamps). Consequently, estimating phosphorous (TP) loads from watersheds at temporal scales varying from annual and seasonal, for policy analysis, to daily, for driving detailed water quality models of the recipient water bodies, is a major component of several water resources management schemes. Yet, water quality monitoring frequency is often insufficient for reliably assessing annual pollutants loads, let alone for estimating daily watershed outputs. Building full nutrient generation and transport models is the best response to this challenge, but it is a complex and time consuming endeavor. Simple regression models, on the other hand, can provide accurate TP loading quantification, even at fine temporal scales and in absence of frequent measurements, without the costs of developing a full transport model.

Theoretically, estimating nutrient outputs from watersheds should be relatively easy, since load is the product of concentration and discharge, two easily measurable quantities. However, while discharge data are frequently provided by river gages at daily or sub-daily frequency, water quality data are normally much less frequent, except when they are the product of ad-hoc campaigns. Thus, concentration measurements are often insufficient to represent the full range of concentration variability, causing uncertainty in load estimates. Methods for estimating watershed loads can be divided into two categories, including; A) methods employing simple relations between discharge and load, such as Averaging methods [1-4], Ratio estimators [2-6], and Regression methods [2, 3, 7-10], and B) methods employing complex nutrient transport models such as the Soil and Water Assessment Tool [11] or Agricultural Nonpoint Source Pollution Model [12].

According to Quilbé et al. [3], averaging methods are accurate only when concentration measurements are frequent enough to cover the entire flow range and the ratio estimator is less sensitive to river and pollutant characteristics than regression methods, but requires more data to achieve the same level of precision. Furthermore, they conclude that regression methods can give the best results for sediments and TP if stream flow and concentration data are strongly correlated for a wide range of stream flow values. Complex nutrient transport models may supply more reliable high frequency estimates, have the capability of tracking the sources of pollutants, and of simulating alternative pollution prevention policies, but require a lot of effort and data to be deployed. In this paper we explore a regression model that takes advantage of infrequent, but long-term, water quality data to produce reliable daily TP load estimates and its application to the Saginaw River Basin, Michigan (Figure 1). We also quantify the uncertainty in daily and annual load estimates due to model error and that due to uncertainty in the water quality and discharge measurements used for calibrating the model and for driving the model.

The development of this model is the first step of a two-step effort to quantify the nutrient loads entering Saginaw Bay. As part of this step, we use the regression model to evaluate current nutrient loads from the relatively infrequent water quality samples and daily discharge data available at a few points in the basin. In a subsequent second step, we will adapt a distributed water quality model simulating pollution generation and transport to the watershed, using experimental data and the results of the models produced in the first steps for calibration and validation [13-15]. In Section 2, we describe the watershed, available data, and the model development. In Section 3 we compare the estimated load with the target load for the bay, analyze the uncertainty in the model estimates, and determine the contribution of each sub-watershed to the total load. Section 4 outlines the conclusions that can be drawn from this paper.

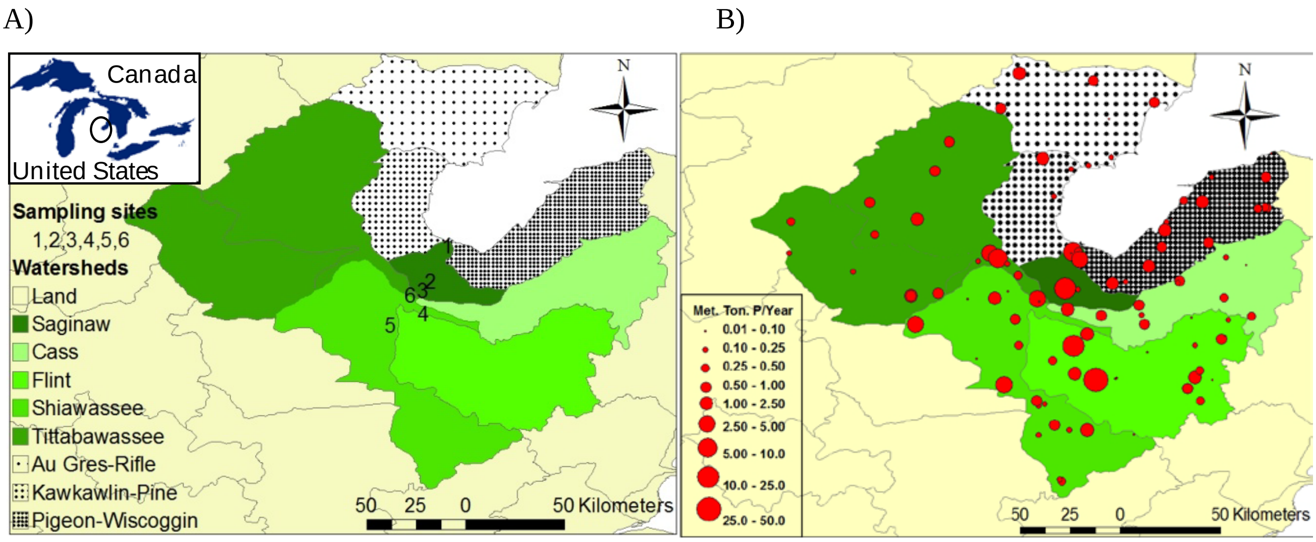

Figure 1: A) The Saginaw Bay basin and the sampling sites used for model calibration. B) Average 2004-2006 TP discharge from point sources.

2. METHODS

2.1 Study Area

The Saginaw River and its sub-basins (green shades in Figure 1) make the largest (16,680 km^2) tributary of Saginaw Bay, a large (2,770 km^2) and shallow (average depth 5.1 m) embayment in western Lake Huron, which is used for drinking water supply, fishing, tourism, and navigation. The basin is an important base for industrial supply and food production, with agriculture and forests being the two major land uses. Over the years, the extensive agricultural land use and associated runoff, improper manure management, industrial pollution, and inadequate sewage treatment systems have led to high nutrient runoff, eutrophication of the bay, loss of wildlife habitat, and beach closures. To improve this situation, the Great Lakes Water Quality Agreement between the United States and Canada [16] established in 1978 a target Total Phosphorus (TP) load of 440 metric tons/yr for Saginaw Bay. Consequently, efforts to control excessive phosphorus inputs, especially point sources (Figure 1.B), were implemented and early assessment indicated diminishing eutrophication symptoms in response to phosphorus load reductions. However, eutrophication symptoms, including algal blooms and nuisance algal beach deposits, have returned to Saginaw Bay underscoring the need for continued long-term phosphorus load evaluation [17].

	Flint (4)	**Tittabawassee (6)**	**Shiawassee (5)**	**Cass (3)**	**Saginaw Upstream (2)**	**Saginaw River Basin Outlet (1)**
1997					4	
1998		13	13		4	8
1999					3	
2000	3	3	6	3	4	
2001	4	4	4	12	4	12
2002	4	12	4	4	4	12
2003	11	4	4	4	4	12
2004	4	4	4	4	4	12
2005	4	4	12	4	2	12
2006	4	4	4	12	2	12
2007	4	12	4	4		12
2008	8	8	8	8	32	31

Table 1: Available in-stream water quality data.

2.2 Data Sources

To estimate TP loads, TP concentration data for Saginaw River and sub-watersheds in 1997-2007 were obtained from the Michigan Department of Environmental Quality (MDEQ) [18], except for the Saginaw upstream site for which data was from the United States Geological Survey (USGS). Total Phosphorus concentration in 2008 was provided by the Cooperative Institute for Limnology and Ecosystem Research (Table 1). Flow data for Saginaw River and sub-watersheds at sample sites from 1997 to 2008 were obtained from U.S. Geological Survey (USGS) database.

2.3 Concentration Estimation

TP loading in most large watersheds is the result of point source discharges (such as municipal and industrial waste water treatment plants — WWTPs) and of nonpoint source discharges (such as agricultural and urban runoff). The discharge of some point sources is associated to precipitation (e.g., stormwater outlets or combined sewer overflows), while other point source loads are mostly independent from it (e.g., most WWTP effluents). On the other hand, nonpoint source loads are mostly carried by surface runoff. Therefore, it is not surprising that TP concentration has been frequently modeled as a function of the river discharge, especially at low temporal resolution ([7]-[10], [18]). Many of these applications (e.g., [18]) use the discharge and water quality measurements available for a given year to estimate the corresponding annual load and are thus often limited in their complexity by the few water quality measurements typically available in any given year (Table 1). The approach taken in this study, however, pulls together water quality data across a decade and takes advantage of the commonalities in watershed response to precipitation and seasonality to include multiple factors that can often make a direct relationship between TP concentration and discharge not straightforward ([9], Table 2).

2.3.1 Seasonality

Regression methods do not require extensive data, but the quality of the predictions depends on the correlation between flow and concentration. Quilbé et al. [3] proposed using the coefficient of determination (r^2) for selecting the best regression method, since the higher the r^2 is, the better streamflow explains concentration variability. Table 2 indicates that by splitting data into two seasons (April-September and October-March) the quality of predictions improves, especially for the Saginaw River basin outlet. The strong seasonality effect for this point is probably due to the impact that WWTP releases from the cities of Saginaw and Bay (Figure 1.B) have on the TP concentration during summer.

	Annual	Two seasons
Saginaw River Basin Outlet	0.446	0.510
Flint	0.005	0.111
Cass, Shiawassee, Tittabawassee	0.234	0.270
Saginaw Upstream	0.140	0.269

Table 2: Coefficient of determination (R^2) of TP concentration as function of discharge

2.3.2 Temporal trends

Because we pool together water quality data for a period spanning twelve years, we need to take into consideration the possibility that the watershed may have changed during this period. Indeed, all sampling points, with the exception of Saginaw Upstream, showed a temporal decrease in TP concentration on the order of 0.002 to 0.005 mg/year (Figure 2), probably due to long-term changes in watershed conditions (e.g., expansion of no-till agriculture, adoption of better wastewater treatment techniques, decrease in population and industrial activities, etc.). Because of seasonality, floods, and other events, the correlation between TP concentration and time is low, but the trend seems evident enough to merit the inclusion of time among the explanatory variables.

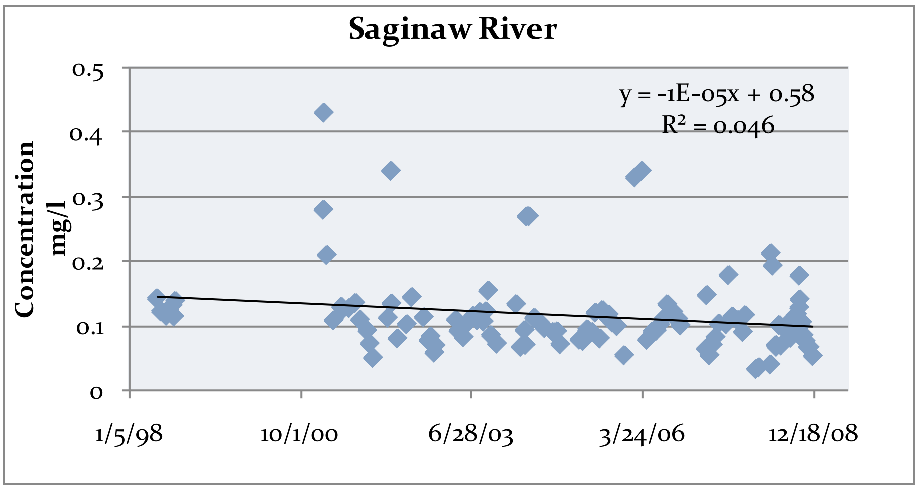

Figure 2: TP concentration at the Saginaw River outlet as function of time (x is the number of days since December 31, 1899).

2.3.3 Flood phases and antecedent storms

Sediment and TP concentration changes between the rising and receding phases of floods, with the rising phase featuring higher concentrations than the receding phase, due to the transport of dissolved fractions, already detached particles, and debris. On the other hand, floods taking place after wet periods carry less debris and sediments than floods occurring after long dry periods. We modeled these two effects by including the average discharge in the previous five days (Q_5) and the average discharge in the previous ten days (Q_{10}) among the explanatory variables used in the regression. As shown in [19], the inclusion of these variables was critical to improve model performances, which were substantially better than those of simpler models.

2.3.4 Overall model

The final form of the regression model we considered is shown in Equation (1):

$$C(t) = a + b \cdot Q + c \cdot Q_5 + d \cdot Q_{10} + e \cdot t \tag{1}$$

where *a*, *b*, *c*, *d*, and *e* are the regression coefficients, Q is the areal discharge (in cm day^{-1}), Q_5 is the average discharge in the previous five days, Q_{10} is the average discharge in the previous ten days, and t is the date expressed as number of days since 12/31/1899.

2.3.5 Uncertainty quantification

The prediction interval (PI) for a linear regression model is given by ([20]):

$$PI(\text{individual Y at } X_1^*, X_2^*, \ldots, X_p^*) = \hat{Y} \pm t\left(S^2 + Var\hat{Y}\right)^{1/2} \tag{2}$$

where $X_1^*, X_2^*, \ldots, X_p^*$ is a given set of values for the explanatory variables, Y is the corresponding true value of the dependent variable(TP concentration, in this case), $\hat{Y}$ is the corresponding predicted value, *t* is 100(1-α/2) percentile of the Student's *t* distribution with *n-p-1* degrees of freedom (where *n* is the sample size, and *p* is the number of explanatory variables), S^2 is the regression residual mean square, and $Var\hat{Y}$ is the variance of $\hat{Y}$.

The prediction interval computed in this way accounts for the uncertainty due to model errors. We used the statistical package Minitab® 15, version 1.0.0 (Minitab Inc.) to compute the 95% prediction intervals for the TP concentration at the Saginaw River outlet on each day of 1997-2008 separately for the summer and winter models. Then, we multiplied the PIs by the corresponding observed daily Q to determine the prediction intervals for the daily TP loads. Assuming that daily load errors are independent from each other, then the annual load is the result of summing 365 (or 366) independent random variables, each distributed as a Student's *t* of known mean (the predicted daily load) and variance.

Model errors are not the only source of uncertainty affecting the TP concentration estimates and consequently the predicted TP loads. The random errors in the TP concentration and water discharge measurements used for calibrating the regression model also affects the uncertainty in model predictions, since a model trained to reproduce data with a relevant random component data will make predictions also affected by a relevant uncertainty, especially if the number of samples used to compute the regression model is low. Further uncertainty in the predicted TP is caused by the measurement errors in the discharge used as input of the model during prediction.

Analytically quantifying the effect of such uncertainties on the predicted TP loads is quite difficult due to the interactions between the different variables. Therefore, we used a Monte Carlo numerical simulation [21] to assess the overall effect on the predicted TP load. First, we evaluated the discharge and TP concentration error distributions and modeled them analytically. Then, we generated an ensemble of 10,000 alternative estimates for each TP concentration and discharge used in the model calibration and as model input. For each element of this ensemble, we computed an alternative regression model and we used it to compute the loads corresponding to that ensemble element.

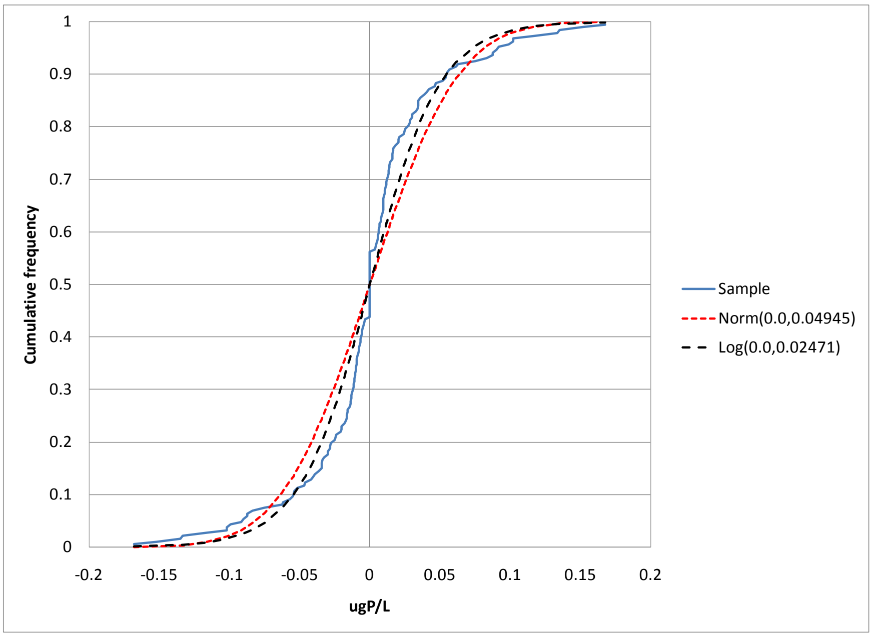

Figure 3: TP concentration error distribution and analytical fits.

USGS qualifies its streamflow gages as "excellent", "good", "fair", or "poor", indicating that measurements are respectively within 5%, 10%, 15%, or more than 15% from the real discharge 95% of times ([22]). The gage we used for determining the discharge at the Saginaw River Outlet (USGS gage 04157000 in Saginaw) is qualified as "poor" because heavy backwater effect and wind-induced seiches make estimating daily discharge there very difficult, especially below 10,000 cfs (283 m^3s^{-1}). The characteristics of the USGS "poor" gage definition are a bit ambiguous, since it specifies the minimum error bounds (15%), but not the maximum ones. Given the serious problems affecting gage 04157000, we modeled its relative measurement error as a logistically distributed random variable with 95% probability of occurrence within ±30% (that is a logistic of parameters 0.0 and 0.081887). The choice of using the logistic distribution instead of the more common normal distribution stems from the fact that relative error distribution for river discharge estimates normally features heavier tails than the Gaussian distribution ([23]).

TP concentration data used in this study were obtained by averaging the laboratory analysis of two individual water samples taken in the same occasion. Therefore, the distribution of differences between the individual samples and their mean should yield a good representation of the uncertainty in water quality measurements. In this case the absolute differences had a more stable distribution than the relative differences and were better represented by a logistic distribution fitted than by a Gaussian distribution (Figure 3).

3. RESULTS AND DISCUSSION

3.1 Model performance

Table 3 shows that model performances are very good, with correlation between modeled and observed daily concentration in 1998-2008 reaches 0.84 for the entire Saginaw River watershed, 0.63 for the combined Cass, Shiawassee, and Tittabawassee Rivers, and 0.62 for the Flint River, while correlation in daily load is above 0.96 for all watersheds. Overall bias is minimal both for concentration and load and it is relatively well distributed among the sub-periods considered. RMSE is also small, hovering around 30% of the average for concentration and around 30-60% for load.

		(1)		(4)		(3,5,6)		(2)	
		C	L	C	L	C	L	C	L
Correlation (R)	T1	0.84	0.96	0.62	0.98	0.63	0.97	0.76	0.96
	T2	0.84	0.95	0.61	0.99	0.56	0.99	0.63	0.99
	T3	0.87	0.99	0.30	0.91	0.72	0.95		
	T4	0.72	0.98	0.47	0.69	0.31	0.94	0.87	0.99
Bias	T1	0.04	0.07	0.00	0.00	0.00	0.05	0.00	0.00
	T2	0.05	0.07	0.01	0.03	0.02	0.03	0.01	0.13
	T3	-0.05	0.04	-0.12	-0.15	-0.08	0.10		
	T4	0.07	0.10	0.14	0.09	0.08	-0.11	-0.01	-0.08
RMSE/Average	T1	0.29	0.53	0.29	0.28	0.41	0.61	0.34	0.55
	T2	0.28	0.61	0.27	0.18	0.39	0.37	0.39	0.75
	T3	0.31	0.35	0.35	0.53	0.46	0.63		
	T4	0.29	0.31	0.30	0.34	0.48	1.01	0.29	0.38

C: concentration; L: load; T1:98-08; T2:98-05;T3:06-07;T4:08

Table 3: Model performances at the sampling sites for different periods (the number in parenthesis indicate the sampling site locations in Figure 1).A.

The model also does not seem to be affected by substantial biases or errors at the upper extreme of the observed concentration and load range (Figure 4), making it relatively robust.

3.2 Estimated load

Figure 2 and the values of ***e*** coefficient in (1) show that a reduction of the TP loading of Saginaw Bay as slightly decreased. However, Figure 5 indicates that the TP load from the Saginaw River has still been higher than the target TP load to the bay most of the years between 1997 and 2008. Considering that Saginaw River carries around 80-90% of the TP load to the Bay with the rest contributed by the AuGres-Rifle, Kawkawlin-Pine, Pigeon-Wiscoggin Rivers, and atmospheric deposition, it is clear that the target TP load has been met only during the driest years and that the average TP load is well above 500 metric tons P per year.

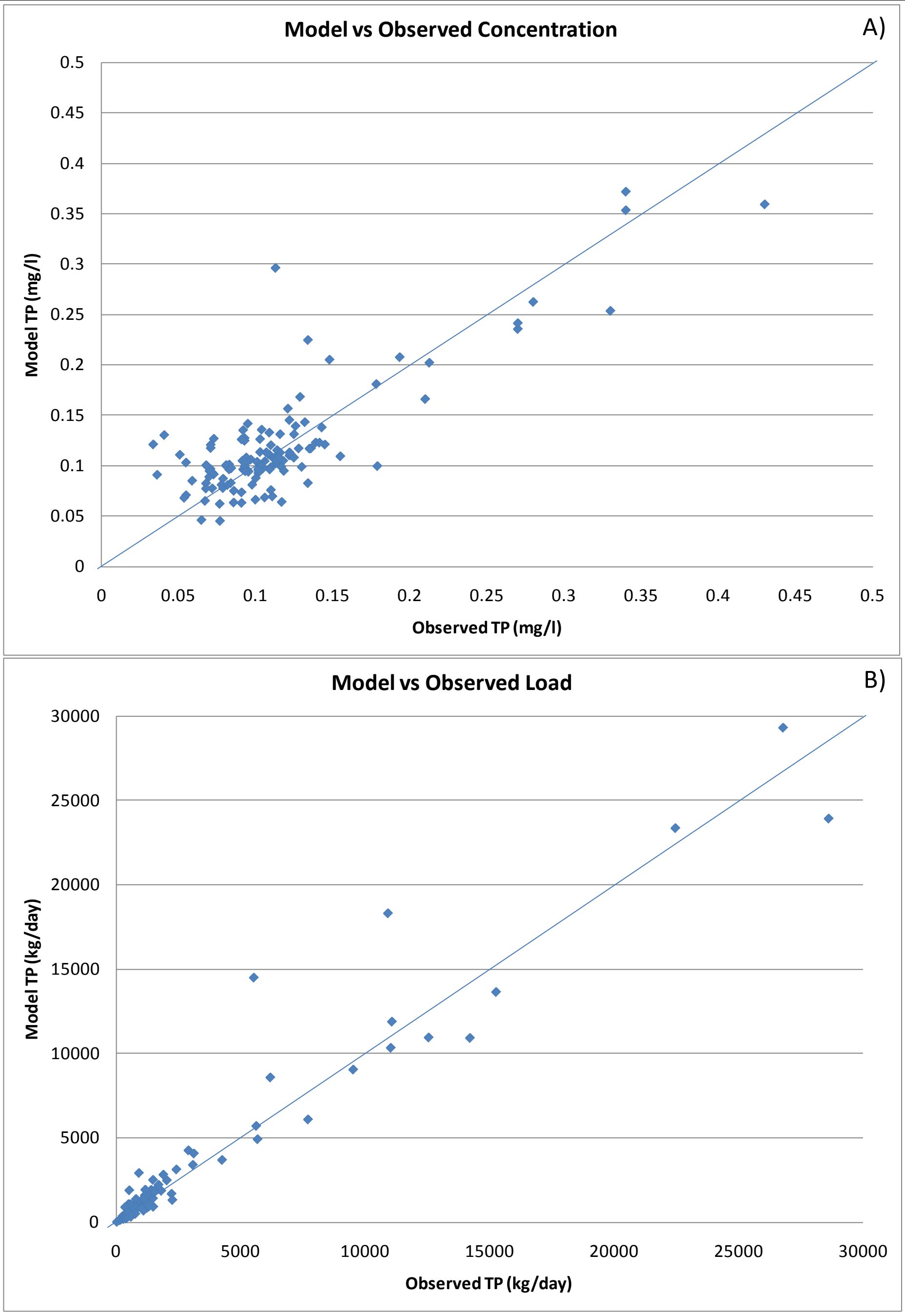

Figure 4: Model and observed TP concentrations (A) and loads (B) at the Saginaw River's outlet.

3.3 Load uncertainty

Assessing the reliability of the load estimates produced by a model at various temporal resolutions is important for policy analysis. Figure 6 shows the uncertainty in the daily TP concentration predictions due to model errors (Figure 6.A) and due to measurement errors in TP concentrations and river discharges used for model calibration and as input for TP predictions (Figure 6.B). At this temporal resolution, the uncertainty caused by model imperfection is substantially higher than that due to the measurement errors, especially during low flow. On the other hand, Figure 7 shows that at the annual resolution, the situation is reversed with the uncertainty due to model errors being lower than that due to measurement errors. This is a consequence of assuming that the model errors at consecutive days are independent from each other, thus allowing an averaging effect and a reduction of the uncertainty. On the other hand, errors in data used for model calibration data lead to the generation of completely different calibration coefficients, which cause persistent prediction errors, thus preserving a larger part of the uncertainty even over long time intervals.

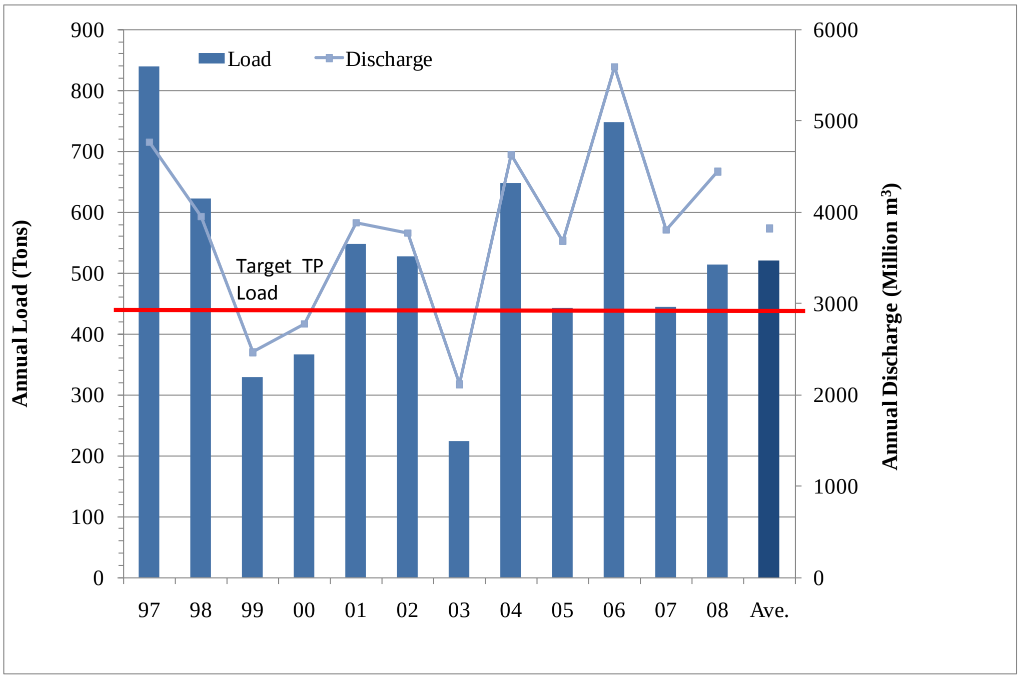

Figure 5: Saginaw River's Annual TP Load Estimates

Annual load estimates agree well with estimates produced by MDEQ using the Stratified Beale's Ratio ([18], [24]) for four years out of five. Estimates in 2005 are substantially different, however, with the MDEQ estimates very close to its estimates for 2003, a much dryer year (Figure 5), and quite certain despite being based on just 12 samples. Note that MDEQ's 2005 uncertainty range is comparable to our regression model uncertainty range, which is based on 123 sample points. It is also interesting to note the generally larger uncertainty affecting MDEQ's estimates caused by using just 12 water quality samples per estimate and a simpler model.

3.3 Contribution of sub-watersheds

By considering the difference between the TP loads carried by the tributaries and the load at the Saginaw River outlet is possible to determine the contribution of the different portions of the basin to the TP load entering the Bay (Figure 8). The largest source of TP in the watershed is the Tittabawasse River, that with an area of 6,550 km^2 is the largest sub-watershed, followed by the Saginaw/Bay subwatershed, which despite being the smallest subwatershed (990 km^2), hosts the cities of Saginaw and Bay. Notably, the Shiawassee National Wildlife Refuge (NWR), a large area of swamps and wetlands between the outlet of the Shiawassee River, Flint River, and minor tributaries (Bad River, Marsh Creek, Birch Run, and Bear Creek) and the city of Saginaw, acts as a sink of phosphorous, showing the important role of riparian vegetation in controlling nutrients.

When the effect of the NWR on the nutrient loads coming from the three upstream watersheds is taken into account, the more rural Tittabawasse River, Cass River, and Shiawassee River contributed about 31 percent, 12 percent, and 7 percent of the TP load entering the bay respectively, with agriculture being the largest emitter. The Saginaw-Bay urban area, which is at the mouth of the river, contributed 23 percent of the TP load ([19]). On a per square kilometer basis, both the Saginaw and Flint Rivers showed higher TP load than the average level of all other sub-watersheds, indicating significant contributions from urban sources as cities of Saginaw and Bay City, and Flint are located in the two watersheds respectively ([19]).

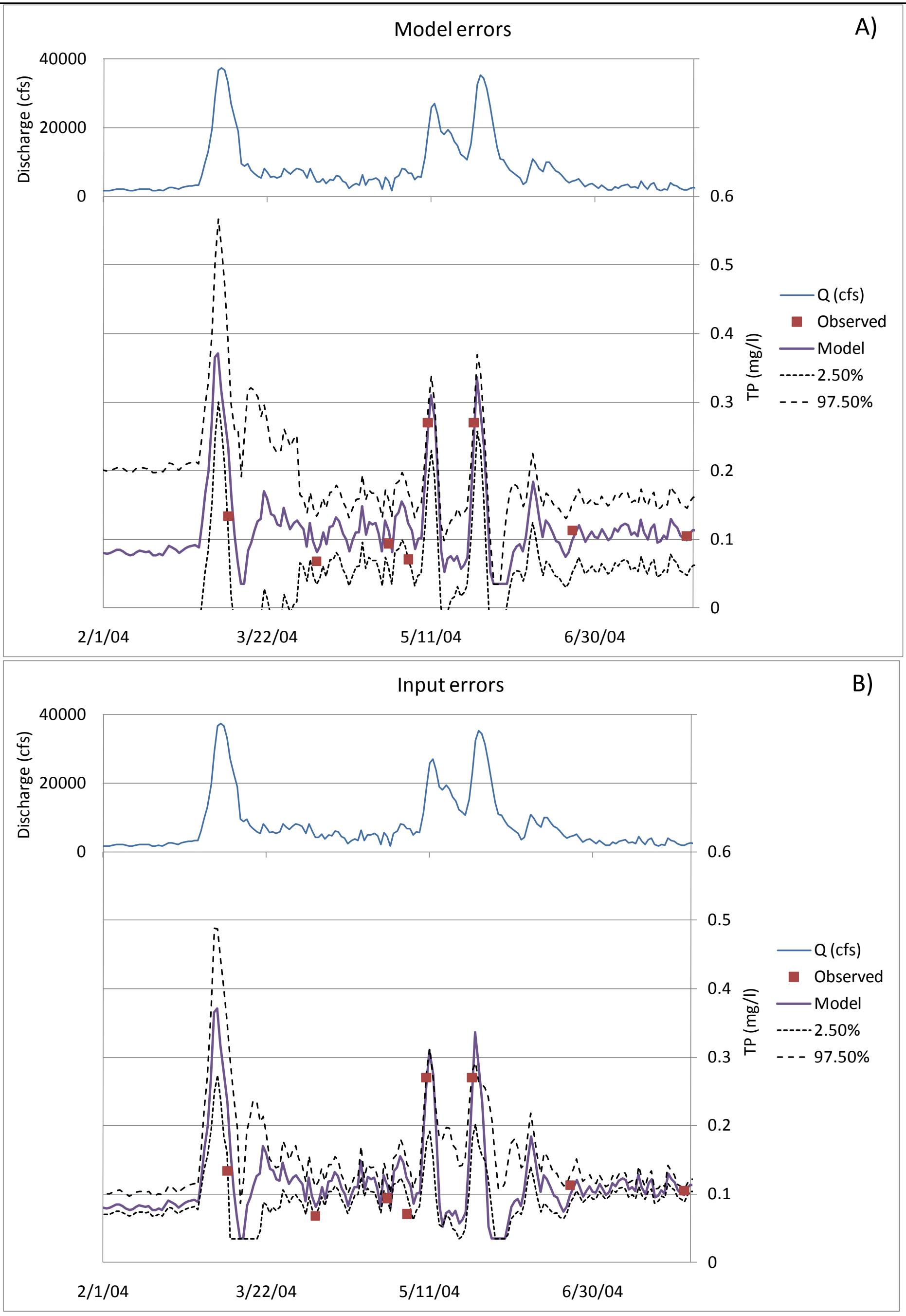

Figure 6: Uncertainty in average daily TP concentration estimates for the Saginaw River outlet. A) Model errors; B) Input errors.

4. CONCLUSIONS

Estimating total phosphorus loads from the drainage basin is fundamental for preventing eutrophication of lakes, rivers, and wetlands. The challenge in load estimation consists in making the best use of available information, which often includes daily or sub-daily stream flow data, but only infrequent water quality data. Although the relation between discharge and TP concentration is not very accurate, the approach shown here takes advantage of infrequent, but long-term, water quality samples to produce reliable estimates at high temporal resolution. The large number of samples used for model calibration, although distributed over twelve years, allows the model to include the effect of temporal trends, seasonality, difference between the rising and receding phases of floods, and previous storms' flushing. We also showed that such models can provide the answer to several policy questions concerning nutrients load generation in the watershed as well as supply reliable inputs to models simulating the water quality in the recipient water bodies with a minimal effort (no detailed land use surveys are required).

Figure 7: Uncertainty in Saginaw River TP annual load.

A) B)

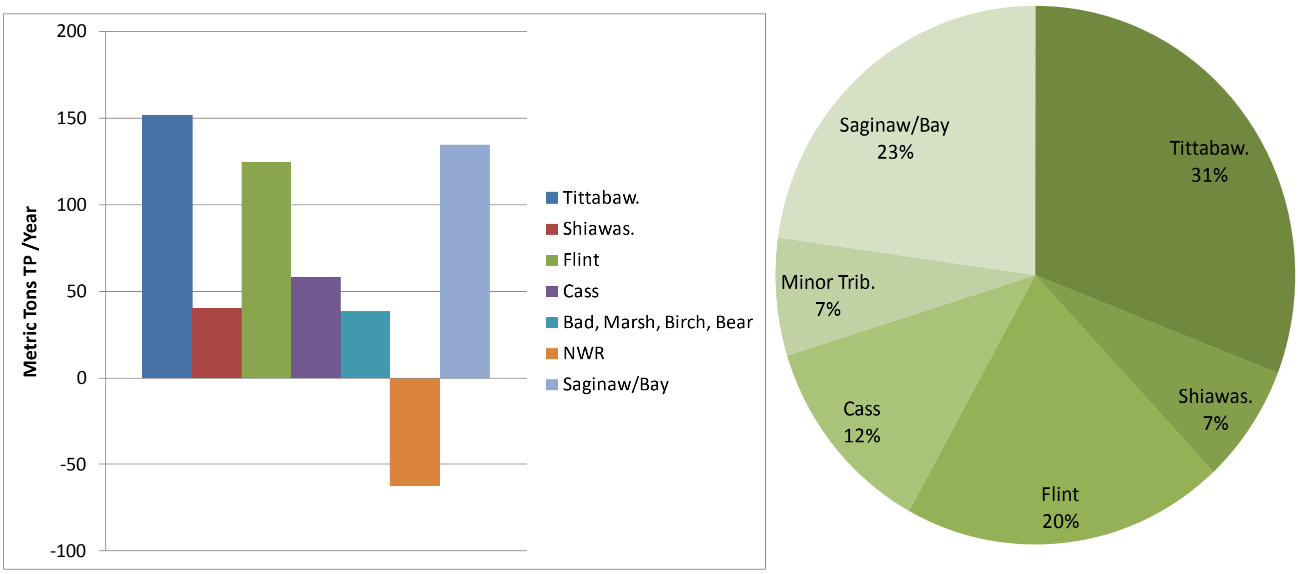

Figure 8: A) Average load of the Saginaw River sub-watersheds in 1997-2008; B) Average contribution of sub-watersheds to the total TP load of Saginaw River in 1997-2008.

The large number of samples used for model calibration allows the model error to be relatively small. While its impact at the daily resolution is still larger than the uncertainty caused by TP and Q measurement uncertainty, its impact over longer periods is smaller due to the model error independence. On the other hand, our results show the importance of considering the uncertainty in the data used for model calibration and as input for prediction, at least for cases in which such uncertainty is high (discharge measurements at Saginaw), since such uncertainty is persistent and has an impact even at coarse temporal resolutions.

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