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Attenuation Coefficients for Water Quality Trading

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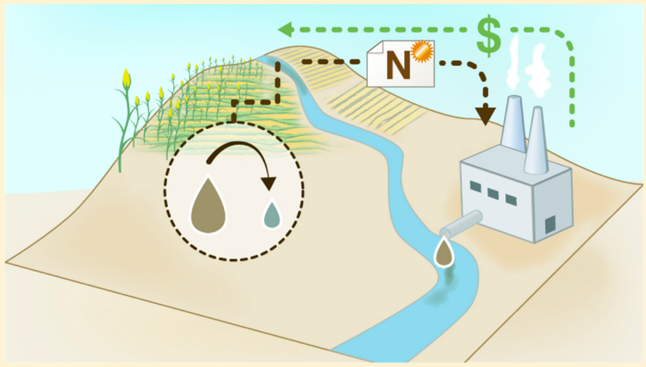
Supporting Information

ABSTRACT: Water quality trading has been proposed as a cost-effective approach for reducing nutrient loads through credit generation from agricultural or point source reductions sold to buyers facing costly options. We present a systematic approach to determine attenuation coefficients and their uncertainty. Using a process-based model, we determine attenuation with safety margins at many watersheds for total nitrogen (TN) and total phosphorus (TP) loads as they transport from point of load reduction to the credit buyer. TN and TP in-stream attenuation generally increases with decreasing mean river flow; smaller rivers in the modeled region of the Ohio River Basin had TN attenuation factors per km, including safety margins, of 0.19−1.6%, medium rivers of 0.14−1.2%, large rivers of 0.13−1.1%, and very large rivers of 0.04−0.42%. Attenuation in ditches transporting nutrients from farms to receiving rivers is 0.4%/km for TN, while for TP attenuation in ditches can be up to 2%/km. A 95 percentile safety margin of 30−40% for TN and 6−10% for TP, applied to the attenuation per km factors, was determined from the in-stream sensitivity of load reductions to watershed model parameters. For perspective, over 50 km a 1% per km factor would result in 50% attenuation = 2:1 trading ratio.



■ INTRODUCTION

Water quality trading allows for the cost-effective reduction of nutrient loading to water bodies through the generation of "credits" from agricultural conservation practices or point source reductions that are sold to buyers facing costly technological options for meeting clean water act permit limits. With growing interest in this watershed management approach, it is critical to ensure that credits represent the accounting unit for which they are sold, most commonly load reductions of total nitrogen (TN) or total phosphorus (TP). Since market participants generally seek to maximize financial returns,[1] program designs ideally imbed rules that will ensure environmental integrity. A fundamental issue is the appropriate estimation of credits both at the point of generation and the point of use, with appropriate safety margins. Here we develop a systematic methodology for determining the attenuation factor and safety margins for credit calculations, which is key for determining overall trading ratios. The methodology itself can be applied to any water quality trading program and may have broader application to Total Maximum Daily Loads and other programs.

Efforts to trade discharge loads to improve water quality have been around for over a decade,[2] with varying degrees of success; in many cases high trading ratios to address the various sources of uncertainty have hindered water quality markets, and low ratios may not protect water quality. A market system with a cap on discharges and freely tradable permits has been studied as an appropriate way to achieve water quality goals cost-effectively.[3] Allowing markets to allocate financial resources to the most cost-effective pollutant load reduction approaches[4−10] may be a viable method for providing incentives to others who can reduced their loading at a lower cost[11−14] The majority of the studies on water quality trading have focused on the economics and to some extent the social aspects of the programs.[2,11,15−23]

Although there are a number of programs in several countries,[24−26] the US leads the efforts in establishing water quality trading programs.[27] One pilot project led by the Electric Power Research Institute has established a trading program involving three states in the Ohio River Basin (http://wqt.epri.com). While the scale of this project presents unique social, economic, and watershed management opportunities, the challenge is to ensure that reductions comparable to those a point source might otherwise achieve are realized through credit trading, accounting for the attenuation of the load

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reduction. While many projects are being built and implemented, there are concerns regarding ad-hoc trading ratios that stress economic and social factors and that do not adequately account for scientific uncertainty. This research attempts to inform this gap.

Various models have been used to consider the fate and transport processes that occur from the moment fertilizers are applied on a farm or discharged at a point source, to the point where the credit will be needed. These processes include physical transport and abiotic chemical reactions as well as biological processing of the nutrients. Nitrogen and phosphorus compounds undergo complex biogeochemical processing on their journey through any given watershed. Thus, robust calculation methods and approaches are required to determine the underlying response of the various environmental factors and make predictions about the water quality impact of a proposed set of trades. Water quality models employed include annualized statistical relationships between land use, precipitation, broad soil types and residence time, used in SPARROW,[28−30] and mechanistic models such as SWAT,[31−35] WARMF,[36−45] and HSPF.[46] Bayesian networks[47] have also been applied to developing credit trading ratios. The statistically based models can be calibrated to reproduce region-specific results accurately, but since there is no explicit process representation it can be challenging to evaluate explicitly the effects of different types of load reductions. The mechanistic models generally require considerably more data, which presents a challenge, but can be used for forward predictions with projections about the changes in inputs (e.g., significant land use changes, modifications to point source discharges, changes in specific land management practices) which are not captured by the historical database used to generate the statistical relationships.

The scientific components of a crediting equation are

$$CR_{PoU} = (F_{farm\text{-}to\text{-}river} \times F_{in\text{-}stream} \times F_{equivalence} \times F_{safety})LR \tag{1}$$

where CR_{PoU} = credit at point of use (PoU); $F_{farm\text{-}to\text{-}river}$ = attenuation from point of credit generation (e.g., farm, stormwater BMP, point source) to edge of river; $F_{in\text{-}stream}$ = in-stream attenuation from entry point to PoU; $F_{equivalence}$ = accounts for load reduction in different N or P species than needed at PoU; F_{safety} = safety margin for uncertainties in attenuation calculation; and LR = load reduction at the point of credit generation, at the edge of farm.

Since watershed scale models use fairly coarse grids, the local farm load levels and effects of Best Management Practices (BMPs) are generally modeled using models such as Nutrient Tracking Tool and its variants[48−52] or the STEPL and USEPA Region V models.[53,54] For this study we assumed that LR would be estimated based on such models and did not consider the inherent uncertainty in the calculation of LR; uncertainty estimates from the LR will be addressed in a separate study. $F_{farm\text{-}to\text{-}river}$ considers the attenuation that may occur when LR is generated at a farm not directly on the edge of the stream segments modeled with the watershed model. The load may be carried overland as surface runoff in sheet flow, in drainage ditches, via shallow groundwater or even small tributaries to the larger segments. $F_{in\text{-}stream}$ accounts for nutrient assimilation or storage in sediments that may reduce LR as the nutrients are transported through the river network to the point of use or compliance. $F_{equivalence}$ takes into consideration that load reduction may be in the form of reduced application of ammonium, nitrate, or organic N, while the compliance at the PoU is in total nitrogen (TN); a similar consideration can be made for phosphate compounds and total phosphorus (TP). F_{safety} addresses the uncertainty in the fate and transport calculations, first by determining the sensitivity of the attenuation calculation to the watershed model parameters, and then evaluating the probability that the attenuation coefficients lie within a certain range.

In this study, the WARMF model was implemented for several major tributaries of the Ohio River (e.g., Allegheny, Muskingum, Scioto, and Great Miami) as well as the Upper and Middle Ohio River sections. Given the geographical scope of the Ohio River Basin Water Quality Trading Program, extending over several states, it was decided that watershed delineation would be at the USGS-defined Hydrologic Unit Code level 10 (HUC10) scale, with a watershed model for every HUC4 within the basin. Generally each river segment is around 5 to 50 km in length, with the majority around 20 km. Each HUC10 may contain hundreds or even a few thousand farms, mostly planting corn, soybean, and winter wheat, or supporting milk houses, typically with tens of point sources. After implementing and calibrating the WARMF model for the various watersheds, a sensitivity analysis was conducted to determine the parameters that affect calibration most significantly. Then the attenuation factors were determined for each HUC10 watershed modeled. This was followed by a sensitivity analysis for the attenuation factors. Using this information, we estimated a safety margin for attenuation from the edge of field to the point of credit purchase, and thereby creating the most robust scientifically informed water quality trading crediting equation to date. This study specifically focused on the attenuation aspect of crediting and did not consider policy, economic, or social factors that may influence an overall trading ratio.

METHODS

The WARMF models were implemented using the data and steps indicated in the Supporting Information. For reference, Figure 1 presents the watershed delineation for the modeled HUC4 of the Ohio River Basin (ORB). The delineations were done based on the USGS HUC10. The WARMF models for the various HUC 4s were calibrated[55,56] using observed water

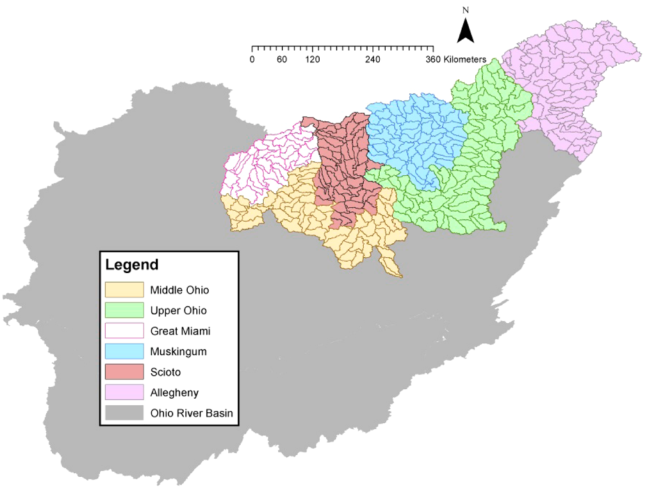

Figure 1. Modeled Ohio River Basin watersheds (HUC4) delineated based on HUC10.

quality to reduce variance between cumulative and observed flows and concentrations of ammonia, nitrate, Total Kjehldahl Nitrogen (TKN), TN, Total Suspended Solids (TSS), and TP. Hydrology was calibrated against USGS stream gages (>180 locations), and then sediment and nutrient parameters (e.g., adsorption coefficients, abiotic reaction rates, biotic assimilation, erosivity) were adjusted using USEPA STORET, Ohio EPA, and ORSANCO data for over 180 locations within these watersheds. Corn, winter wheat, and soybean fertilizer application rates were based on USDA Economic Research Service and regional information from the American Farmland Trust (cf. the Supporting Information).

Sensitivity Analyses. For the sensitivity and uncertainty analyses,[57] the Probability Collocation Method (PCM) was employed,[58,59] which is much more efficient computationally than Monte Carlo simulation which requires >10,000 model simulations. PCM is a stochastic response surface method developed in the late 1990s to address sensitivity and uncertainty in the implementation of geophysical models.[60,61] Recently it has been applied to determine watershed modeling uncertainty using variance decomposition.[62] By using a Polynomial Chaos Expansion (PCE) to approximate WARMF model output, PCM can capture the changes in output by using different orders of a single variable as well as their cross terms (cf. the Supporting Information).

Attenuation from Farm to Edge of River. While in some circumstances the edge of a farm coincides with the river bank, in many cases the distance between the edge of farm and a receiving HUC10 river segment may be considerable. To determine this portion of the attenuation, a WARMF model was set up with soil characteristics, crops (i.e., corn), and meteorology similar to that in the middle Ohio River basin. We considered five farms of 1,000 × 1,000 m^2 connected by an agricultural drainage ditch (or small shallow stream), with the first farm connected to a river segment and the others at various locations up to 5000 m from the river. The load carried via the ditch or shallow stream in surface runoff was evaluated over a 10 year period, noting also the load carried in shallow groundwater via lateral flow. BMPs such as riparian vegetation buffers and wetlands (natural or constructed) are considered within the farm load calculation and were thus not considered in this attenuation.

In-Stream Attenuation Matrix. In-stream attenuation was calculated by considering a load reduction with minimal flow (0.1 m^3/s, 100 kg/day TN or TP load) at an upstream location and determining the effect on river loads (in-stream concentration × flow) at all downstream reaches. The entire river network for a given HUC4 watershed was explored systematically using a script that generated the load reduction at an upstream location, and then ran the model and collected concentrations at all downstream river segments (i.e., HUC10s). Attenuation was determined over a long time period (e.g., several seasons or years) to reduce variability in the attenuation calculated on a day to day basis. The time-averaged attenuation, $\overline{A}_{i,j}$, is calculated using the sum over D days

$$\overline{A}_{i,j} = 1 - \frac{\sum_{k=1}^{D} Q_{j,k}^{L} * C_{j,k}^{L} - Q_{j,k} * C_{j,k}}{\sum_{k=1}^{D} Q_{i,k}^{L} * C_{i,k}^{L} - Q_{i,k} * C_{i,k}} \quad (2)$$

where $\overline{A}_{i,j}$ = attenuation in river segment j from load change in upstream river segment i, $Q_{j,k}$ = flow rate in river segment j on the k_{th} day (m^3/s), and C = concentration at j on the k_{th} day (mg/L). The superscript L refers to the condition where a load has been decreased at upstream location i to determine the effect downstream at j locations. Naturally, when $i = j$, $A = 1$.

A matrix of attenuation coefficients between every pair of connected locations (i,j) was determined for each HUC4 watershed. To determine the sensitivity of the attenuation coefficients, the PCE procedure (Figure S2) was followed. From previous work, 29 parameters were chosen for the TN attenuation sensitivity analysis (Table S3) and 20 parameters for the TP attenuation sensitivity analysis (Table S4).

Equivalence. Since models most commonly used for estimating edge of farm load reductions provide output as TN and TP, we considered $F_{equivalence}$ = 1, to be explored in a future study.

RESULTS

Attenuation from Edge of Farm to Edge of River. TN attenuation is a function of distance from the edge of the river, slope of the drainage channel, and level of flow rate (Figure 2).

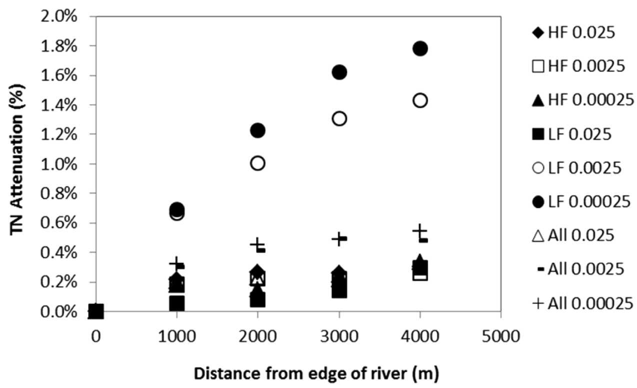

Figure 2. Attenuation of TN load from edge of farm to river as a function of flow rate (H = high, L = low, all) and slope (from 0.025 to 0.00025).

There are differences in attenuation between low flow rate (LF) days (i.e., small storms or days after a large storm) and high flow rate (HF) days (i.e., significant storm event days), while the average attenuation during all days (ALL) falls within these two conditions. Attenuation is also a strong function of slope, with very small gradients (0.00025) and thus more water retention time resulting in higher attenuation than high slope (0.025) channels where water flows rapidly to the river. Overall, edge of farm to river attenuation of TN is on the order of 0.2% to 2% ($F_{\text{farm-to-river,TN}}$ = 0.98 to 0.998) within a distance of 5,000 m, which is almost insignificant compared to the uncertainties in farm level reductions and in-stream attenuation.

Figure 3 presents the attenuation from edge of farm to river for TP, nitrate (NO_3^-) and TSS, for all flow rates. Nitrate attenuation is insignificant, typically around 0.1% at a distance of up to 5,000 m, with a weak dependence on slope or flow rate. TP attenuation ranges from 5 to 10% ($F_{\text{farm-to-river,TP}}$ = 0.90 to 0.95) after 5,000 m, depending on the slope of the channel, with higher attenuation at lower gradients. TP attenuation from farm to river can be estimated using

$$\text{TP attenuation} = [2.22\text{E-05} \exp(-24.8S)]*D \quad (3)$$

where S = slope (−) and D = distance from edge of farm to the river (m). The attenuation of TP is driven in part by the significant attenuation of TSS loads under all conditions, which

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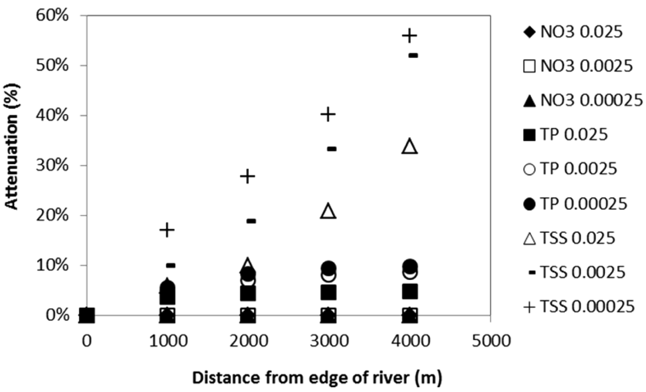

Figure 3. Attenuation of TP, NO_3^-, and TSS load from edge of farm to river as a function of slope, for all flow rates.

ranges from 34 to 55% after 4,000 m. TSS includes sands, silts, and clays, while TP is mostly associated with the clay fraction. Since TSS attenuation is strictly a physical process that does not depend on the concentration of TSS, it increases linearly with distance from the edge of the river. Not captured explicitly in this analysis is the potential flushing effect of a very large storm that completely displaces the deposited sediments from the drainage channel to the river; it is averaged out over the 10 year simulation.

Nutrient loads transported via shallow groundwater were generally very small (<1% of total load) during the 10-year simulation. Attenuation of such shallow groundwater loads will depend on local soil conditions (i.e., hydraulic conductivity, redox conditions, nutrient concentrations, and speciation). For a nutrient credit of less than 10 years, the load reduction contribution to the river from shallow groundwater can be considered insignificant in most cases. These results are generic for conditions around the Ohio River Basin and may be valid for watersheds with similar soils, climates and land uses.

In-Stream Attenuation. Patterns became apparent when comparing attenuation coefficients for the various watersheds modeled, normalized by length. The river segments were first classified according to mean flow rate (Table 1). Lakes and

Table 1. Classification of River Segments by Mean Flow Rate in the Various Watersheds Modeled

	small <10 m^3/s	medium 10−100 m^3/s	large 100−1000 m^3/s	very large >1000 m^3/s
Allegheny (Al)	12	14	2	0
Great Miami (GM)	6	15	3	0
Muskingum (Mu)	20	11	3	0
Scioto (Sc)	7	14	6	0
Northern Upper Ohio (NUO)	5	12	1	3
Southern Upper Ohio (SUO)	5	8	0	5
Middle Ohio (MO)	7	15	0	12

reservoirs were excluded from this analysis, since each one has a distinct impact on attenuation, and they represent a very small fraction of the water bodies (<1%) in the modeled ORB.

TN and TP attenuation per km of river length was distinctly different for the various rivers in the seven watersheds (Figure 4). Very large flow rate segments, on the main stem of the Ohio River, have some of the smallest attenuation rates for TN (around 0.0005 to 0.003 per km, or 0.05−0.3% per km) and TP (around 0.03−0.7% per km) (Figure 5). For a 100 km segment along the main stem of the Ohio River, in-stream TN attenuation would be 5 to 30% ($F_{\text{in-stream,TN}}$ = 0.70 to 0.95) . Adding in the edge of farm to river of 2% ($F_{\text{farm-to-river}}$ = 0.98) and a safety margin still results in an in-stream TN attenuation of around 10−50%, which is a trading ratio <2:1. However, this does not take into account policy or implementation risk into account. The lowest attenuation occurs in the Middle Ohio River and the highest in the southern Upper Ohio River. In general, there is increasing attenuation with decreasing stream magnitude (Figure 5), in part because smaller streams have much longer residence times during dry periods which leads to more TN assimilation and TP storage in sediments.

The Great Miami, Muskingum, and Scioto watersheds have substantial agricultural areas, while the Allegheny, Upper Ohio (northern and southern), and Middle Ohio are dominated by forested and wetland areas. Further analysis indicates that on average rivers in agricultural areas indeed exhibit greater TN attenuation per unit length compared to forested watersheds (Figure 6), since higher in-stream concentrations result in faster assimilation and transformation processes, due to higher overall rates of biotic and abiotic transformation and assimilation at higher concentrations, given assumed first-order processes. The pattern is less clear for TP mostly because smaller rivers in agricultural watersheds exhibit less attenuation than small rivers in forested watersheds, but the observations for TN hold well for medium, large, and very large rivers.

Safety Margin. Sensitivity of TN and TP in-stream attenuation coefficients to changes in WARMF model parameters is shown in Figure 7 for three typical river segments: a small stream near the headwaters, medium, and large river segments. TN attenuation coefficients are much more sensitive to changes in WARMF model parameters compared to TP. The 95 percentile attenuation factors per km are 29 to 40% larger than the median for TN, but only 6 to 10% for TP, given the much lower sensitivity of TP to the variation in model parameters. A protective (i.e., greater discounting of the credit) TN attenuation per km for the small river would be 0.59% instead of 0.46%, for the medium river 0.21% instead of 0.16%, and for the large river 0.15% instead of 0.11%. The most sensitive parameters in the TN attenuation calculation are related to denitrification, Manning's n (river channel roughness), initial sediment depth, and precipitation weighting factor (i.e., distribution of rainfall among catchments). For TP, the most sensitive parameters are all related to sediment transport (e.g., soil erosivity, sediment bank erosion factors, initial sediment depth) and precipitation weighting factor. The adsorption parameters for phosphate play a very minor role, since adsorption is quite significant and varying the value has little impact on the outcome. Tables S9 and S10 in the Supporting Information present a detailed analysis of the most sensitive parameters. Similar sensitivity was observed for the attenuation from edge of farm to the edge of river as for in-stream attenuation in small streams (25−30% for TN, 5−6% for TP). For the overall credit calculation (eq 1), it is operationally easier to use the 95 percentile attenuation factors per km to derive $F^*_{\text{farm-to-river}}$ and $F^*_{\text{in-stream}}$ factors which already incorporate a safety margin.

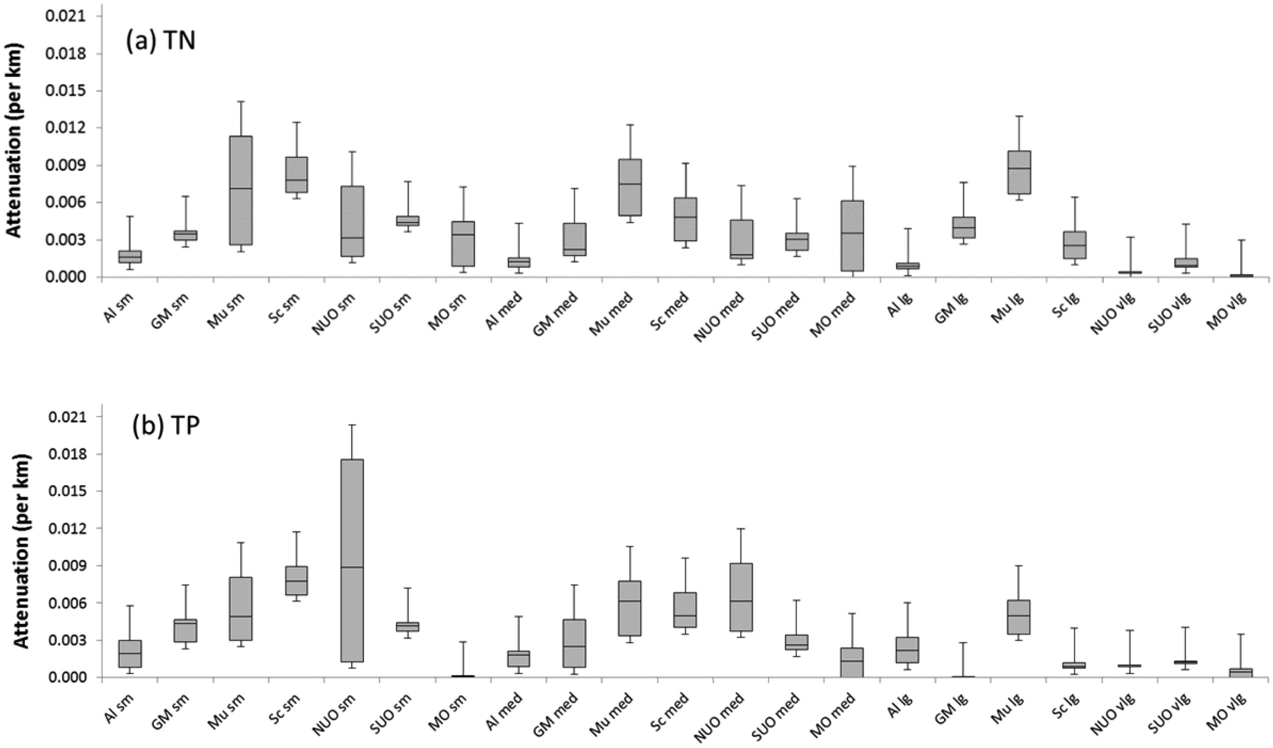

Figure 4. Attenuation coefficients for (a) TN and (b) TP in seven ORB watersheds. Watershed codes are presented in Table 1. For river size, sm = small, med = medium, lg = large, and vlg = very large.

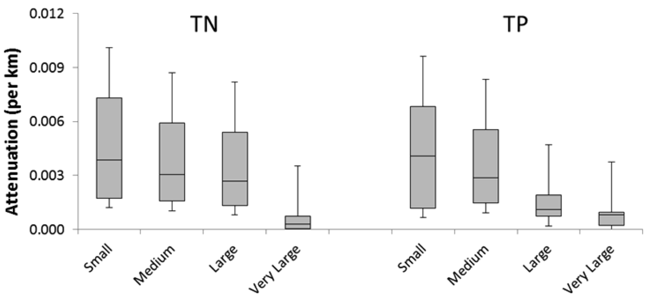

Figure 5. Attenuation coefficients sorted by river flow rate (per Table 1) for TN and TP.

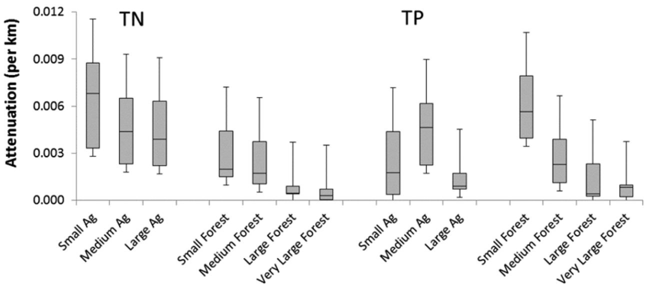

Figure 6. Attenuation coefficients sorted by river flow rate and land use for TN and TP.

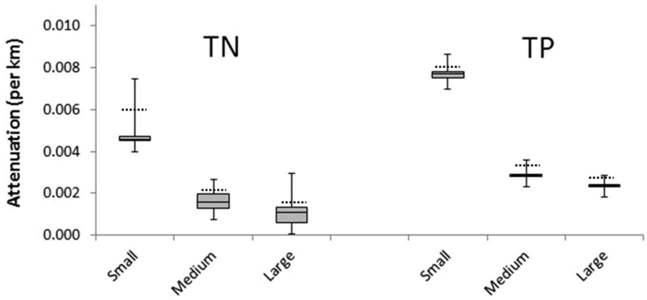

Figure 7. Sensitivity of TN and TP attenuation coefficients at three river segments. Whiskers represent the minimum and maximum; the dashed line is the 95 percentile.

■ ENVIRONMENTAL SIGNIFICANCE

A systematic framework for developing attenuation factors for a water quality trading program was developed, including a rigorous approach for determining the appropriate safety margin. The framework is independent of the model/method used to represent the watershed processes or the characteristics of the watershed(s). However, the results do indicate that the attenuation coefficients for TN and TP are watershed-specific, and thus it is recommended that each watershed be modeled to appropriately represent local conditions. Ideally, a specific trading ratio should be calculated considering the location of seller and buyer within a given watershed. Attenuation and uncertainty are different for TP and TN and need to be considered separately. In cases where data or resources are very limited, it may be possible to use the range of attenuation values presented here for similar watersheds elsewhere. Attenuation coefficients can also be estimated from observed data, but quantification of uncertainty would be challenging without a process-based approach.

Attenuation in small streams or drainage ditches transporting nutrients from farms to receiving rivers is relatively small for TN, up to 2% even for low channel slopes. For TP, attenuation can be up to around 10% and is a much stronger function of slope. In-stream attenuation factors for TN and TP generally increase with decreasing mean river flow rate; smaller rivers in the modeled region of the Ohio River Basin had TN attenuation factors per km, including safety margin, of 0.19−1.6%, medium rivers of 0.14−1.2%, large rivers of 0.13−1.1%, and very large rivers of 0.04−0.42%. For perspective, over 50 km a 1% per km factor would result in 50% attenuation = 2:1 trading ratio. Watersheds with substantial agricultural presence had higher TN attenuation for all river sizes than forested watersheds; the same was true for TP attenuation, except for small rivers in agricultural watersheds which had lower TP attenuation than forested watersheds. In this study, equivalence issues were not explored. These results should hold in general for the broader Ohio River Basin and other regions with similar characteristics, but it is important to note that other watershed characteristics can play an important role in determining the attenuation of TN and TP and the corresponding safety margins. The safety margin can be reduced as more monitoring data becomes available, which would constrain model parameters. The sensitivity analysis of the attenuation coefficients informs us as to the parameters that should be given particular attention during model calibration and for addressing attenuation uncertainty. With Monte Carlo simulation varying parameters that most influence the attenuation coefficients, we can determine the probability distribution of the attenuation coefficients and then select a protective safety margin. The safety margin is a function of distance traveled, which favors trading nearby.

This effort informs the determination of scientifically appropriate and protective trading ratios that account for attenuation between buyers and sellers in water quality trading. The methodology itself can be applied to other water quality trading programs and may have broader application for determining safety margins for other modeling efforts, such as determination of Total Maximum Daily Loads. This is an important step for ensuring that credits represent the offsets toward which they are applied at the point of compliance and, if the methods are enforced through program design, adds to the integrity and defensibility of water quality trading. Policy makers and program managers may need to apply other factors to a trading ratio to consider economics and address implementation risk and other issues beyond attenuation.

■ ASSOCIATED CONTENT

Supporting Information

Figures S1−S8 and Tables S1−S12. This material is available free of charge via the Internet at http://pubs.acs.org.

■ AUTHOR INFORMATION

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Notes

The authors declare no competing financial interest.

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