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A Monitoring and Modeling Approach to Quantifying the Effectiveness of Best Management Practices in a Small Agricultural Watershed

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Abstract

Conventional agricultural practices produce nonpoint source water pollution. The implementation of Best Management Practices (BMPs) in a watershed plays a vital role in improving water quality. Assessing the effectiveness of BMPs requires both monitoring and modelling. A nonpoint source management water policy change was introduced in Minnesota to monitor and model small watersheds for 16 years to determine the effectiveness of BMPs. Monitoring small watersheds alone has not shown water quality improvement; there has been a lack of observable improvement in water quality due to the fragmentation of landscape BMPs and lag time. Dobbins Creek was selected as a sentinel watershed to track water quality for a period longer than a few years to account for lag time. Dobbins Creek is a small agricultural watershed located in the headwaters of the Cedar River. This is an important large watershed that contributes to Gulf of Mexico hypoxia. A monitoring and modelling program were implemented in 2016 that included the analysis of sediment and nutrients at strategic locations in the watershed. We demonstrate how to show an exceedance of water quality standards primarily during stormflow before major BMP implementation. Over time we anticipate water quality changes with land use changes and financial incentives, but the proper approach must be designed and financially supported to be truly effective.

Keywords: Best management practices, Water quality, Watershed management

Introduction

Over usage of fertilizers and pesticides during agricultural practices can be a major contributor to nonpoint source pollution leading to the degradation of surface and groundwater quality.[1,2] Nonpoint source pollution generally results from precipitation. As runoff from precipitation moves from a higher elevation to an outlet, it interacts with the pollutants and transports pollutants into rivers, lakes, wetlands, and groundwater. Best Management Practices (BMPs), also popularly known as green infrastructure practices, gained global traction as a solution to address the water quality issues associated with agricultural land use practices.[3] BMPs have broad applicability, and each of the available BMPs can be categorized based on the complexity and expenses involved.[4] Contour farming, constructed wetland, vegetated buffer strips, crop rotation, and blind tile inlets are a few of the popular BMPs that can aid in dealing with the concern about water quality issues due to agricultural activities.[5] Although BMPs have been widely adopted, uncertainties persist regarding their performance and the optimal combination of practices to achieve desired goals. In view of the resources involved in empirical data collection, simulation models are also used to predict the impact of a chosen BMP before the implementation.[6] Evaluating the performance of BMP using simulation models is a major challenge since the dependency variables considered for simulation do not capture the involved physical processes.[7] This is why both monitoring and modelling are required to capture change over time.

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Efficiencies of BMPs in reducing runoff and pollutants are observed to be location specific and vary widely with changes in location.[5] A comprehensive review of 54 sites by Arora[8] demonstrated that the effectiveness of buffer strips measured in terms of reduction in runoff volume, sediment reduction, reduction in weakly sorting pesticide, strongly sorting pesticide, ranges between 0%-100%, 2%-100%, 0%-100%, and 53%-100% respectively.[8] Poultry litter treatment over six different agricultural lands reduced NH_3 content by a percentage varying between 28-75%.[9] Riparian zones created at eight different localities reduced runoff volume, Dissolved Reactive Phosphorous, and Total phosphorous by -71 to 84% -258 to 88%, -37 to 95%, respectively.[10] Vegetated filters implemented at 48 different sites resulted in the runoff volume and sediment reduction between 14.8 to 99.9% and 24-100%, respectively.[11] Grass strips, shrubs, and tree buffers, Basic and ponds resulted in the reduction of sediment by 24-97%, 45-100%, and 10-100%, respectively.[12] Streamside forest buffers at 37 different locations showed a wide variation in sediment reduction with a range between 21-97%.[13] The extent of improvement in the water quality due to the adoption of on-farm BMPs depends on the effective implementation of BMP in the appropriate location and the location where water quality is monitored.[14] Choosing a monitoring site far away from the agricultural land where BMP is implemented and observing the water quality for a shorter duration could result in an inaccurate assessment of a chosen BMP.[14,15] The prime reasons for these inaccurate results could be due to the discharge of pollutants from the agricultural farms lying downstream with no BMPs implemented – also referred to as BMP fragmentation or a change in geology.[16]

Despite the extensive implementation of BMPs in the watershed, most Nonpoint Source (NPS) projects in the past four decades have reported minimal or no improvement in water quality.[17-19] Several factors contribute to the inability of such projects to fulfil water quality objectives. These factors encompass inadequate engagement of landowners, unfavourable weather conditions, inappropriate selection of BMPs, misunderstandings regarding pollution sources, poor experimental design, insufficient or uneven distribution of BMPs, and lag time.[20,21]

From the literature, it is imperative that the implementation of BMPs at various locations do not yield similar results related to water quality. We propose an approach to the process of exploring the impact of BMPs implemented using data from Dobbins Creek watershed Figure 1. The Dobbin's Creek watershed is comprised of row crops, pasture, and some wooded areas, typical of most rural watersheds in the Cornbelt of the upper Midwestern USA. Many producers in the Dobbins Creek small watershed have exhibited a conservationist ethic and desire to see better water quality to demonstrate that farmers can manage the land for minimal NPS pollution. This observed behaviour and pre-existing attitude of the landowners presents a unique opportunity for water quality project success and sustainability. Dobbins Creek sub watershed is a state-targeted, and prioritized area in the Cedar River watershed that extends into Iowa. Within the sub watershed, the local Cedar River Watershed District has defined reaches and will target BMPs, with the final actions being tailored to specific landowner management objectives. The data presented in this work helps to illustrate the impact of BMPs implemented in a small watershed.

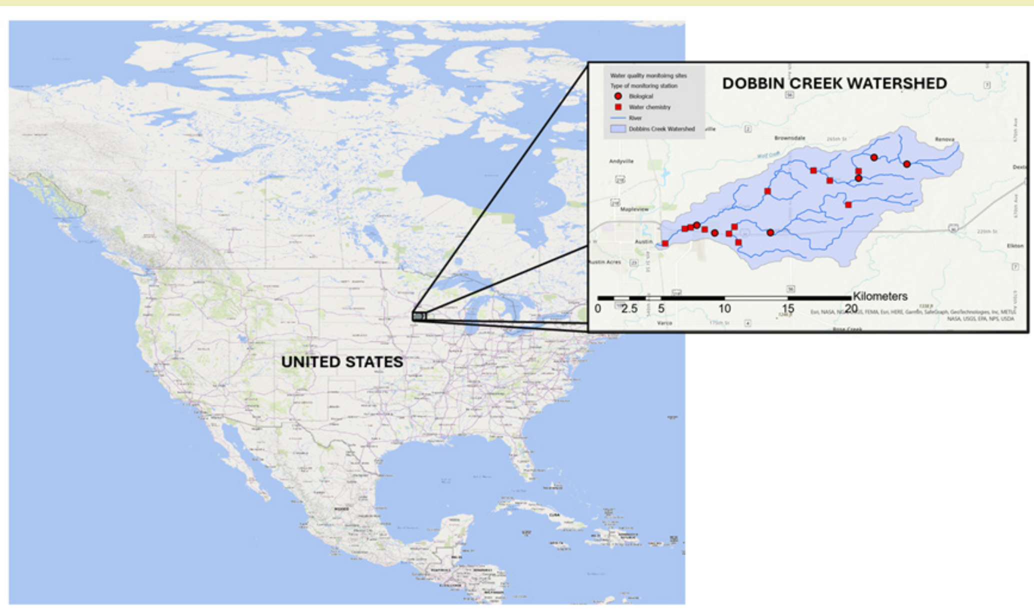

Figure 1: Spatial distribution of monitoring sites and the aerial extent of Dobbins creek watershed

Materials and Methods

Study area and the preliminary studies

Initial water quality monitoring and modelling in the Dobbins Creek Watershed took place from 2015 through 2018 to define “background” conditions. Effort is planned to continue until 2031 when the funding for the BMPs ends. Reconnaissance site identification and analysis during the growing season of 2015 suggested monitoring sites at discrete locations. Figure 1 presents the geographical extent of Dobbin creek watershed and the monitoring sites.

Temperature, pH, dissolved oxygen, specific conductivity, *E coli*, turbidity and nitrate-nitrogen concentrations were measured weekly throughout the summer. These datasets were analysed to determine if any significant difference existed between any of these sites and between branches as a whole. These results were used to inform the longer-term stream stormflow and baseflow monitoring that took place during the growing seasons of 2016-2018. It should be noted that concentrations, rather than loads, were compared within each site to identify outliers, and that median site concentrations were used to compare sites with one another. Therefore, any extreme concentration measures from a single event, such as a high concentration of E. coli or high turbidity readings, influenced results but were not used to identify exceedance of water quality standards. This is in contrast to storm sampling, where load duration curves were developed for comparison against the MN Rule Chapter 7050 water quality standard.

Monitoring sites and sample collection

Stormflow and baseflow sampling were conducted at four sites during 2016 and 2018 to capture the water quality in the northern and southern forks, as well as the creek outlet. Figure 2 presents the spatial distribution of these monitoring sites. Four parameters (total suspended sediment (TSS), total nitrate (NOx), total phosphorus (TP), and dissolved orthophosphate (PO4)) were measured using ISCO® automatic stream samplers installed at each site. on the rising and falling limbs of stormflows and by grab samples during baseflow conditions. Loads were estimated using FLUX32 load estimation software from flows calculated from measured stream stage data.

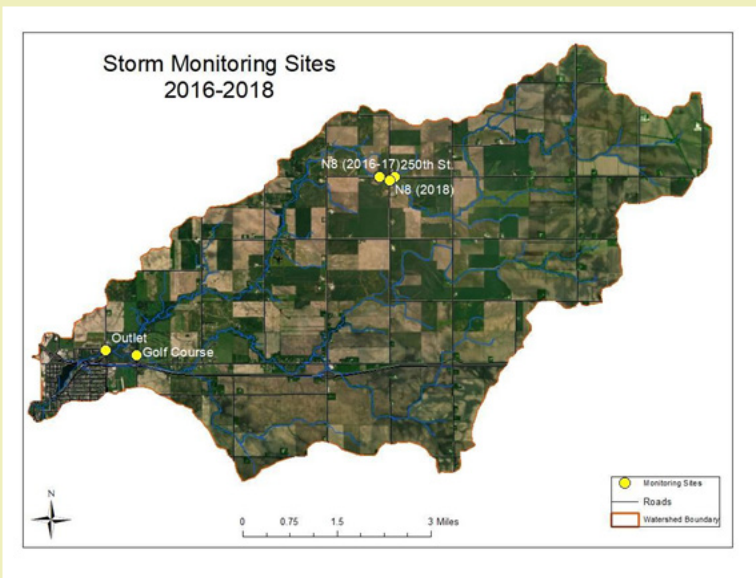

Figure 2: Watershed boundary and the monitoring sites for water sampling

The *Golf Course* and *250th* sites used pressure transducers to measure the stream stage; the *N8* site was equipped with a bubbler module that measured the stage. The 250th site also had an area velocity sensor that measured water velocity. Stage data were recorded and stored in the ISCO® device (models 6700 and 6712 at the N8 and 250th sites, respectively), or in a connected Campbell Scientific® CR10x module (ISCO® model 3700 at the Golf Course and Outlet sites). The samplers were programmed to begin filling sample bottles at one-hour intervals for 24 hours when the stream stage rose 0.3-feet above a pre-set trigger stage. When collected, samples at each site were combined into a composite rising limb and a composite falling limb sample based on the hydrograph and the recorded time each bottle was filled.

Composite samples were analysed for total suspended solids (TSS), total phosphorus (TP), total nitrogen (TN), and dissolved orthophosphate (PO4). Trigger stages were adjusted when samples were taken, or about every 4 days in the absence of an event. During the growing season (April through October in 2016 and 2017, May through August in 2018) samples were gathered following storm events. In the absence of an event for two weeks, baseflow grab samples were taken at each site and analysed for the same four constituents. Samples were analysed according to the grant Quality Assurance Program Plan at Minnesota Valley Testing Laboratories (MVTL) in New Ulm, MN for all samples taken from April 2016 through June of 2018. Samples were analysed by RMB Environmental Laboratories in Detroit Lakes, MN for July and August of 2018. This change was made to facilitate sample delivery and reduce project costs by having UMN students deliver samples to the RMB location in Bloomington, MN when returning to the Twin Cities campus. Samples were then delivered by RBM from Bloomington to Detroit Lakes. Both RMB and MVTL are MN certified water quality labs.

Method

Stage-to-flow relationships were established using a flow meter to create a rating curve at those sites where water velocity was not directly measured by the permanent equipment installed (N8 and Golf Course sites) to estimate the loads. Flow data for the outlet site came from the MN Dept. of Natural Resources (DNR) stream gage (site 48005001) at the creek outlet using an installed bubbler flow meter. Due to a bridge reconstruction on 250*th* Street scheduled for the summer of 2018, the N8 monitoring site was moved upstream to the next road crossing, 600th Ave. To account for the change of site, HOBO® U20 water level data loggers measuring absolute pressure (psi) were deployed in-stream at both the old and new sites, as well as a third to account for barometric pressure changes. This allowed for a stage relationship to be established between the two sites, as described in the HOBO® U20 manual.[22] Flow was then calculated based on the former stage-to-flow relationship at the earlier N8 site.

At the golf course site, a stage-to-flow relationship was developed in the same way, using flow measurements and corresponding stream stages. However, to account for the curve of the stream and the double-culvert through which water flows at that site, the following relationship was developed and expressed as Eq.1

$$Flow\ (cfs) = s^2 \times 8.1791 - 1.640 \times s \qquad (1)$$

Where s is equal to the stage in feet.

Finally, the 250th site, water velocity (ft/sec) and stage (ft) were measured with a pressure transducer in a circular culvert. The stream profile within the culvert was found using either Eq.2 or Eq.3 depending on the stage height.

Where stage, s (ft), was greater than half of the culvert diameter, d (ft),

$$A(ft^2) = \frac{d^2}{8\pi} \times \frac{(2-\pi)\theta}{180} + \sin\left(\theta \times \frac{2\pi}{360}\right) \qquad (2)$$

Where stage is less than half of the diameter:

$$A(ft^2) = \frac{d^2}{8\pi} \times \frac{\pi\theta}{180} + \sin\left(\theta \times \frac{2\pi}{360}\right) \qquad (3)$$

θ is the angle made by the radii at either side of the water surface, in degrees:

Flow was calculated as the product of the stream profile area and water velocity. Stage data taken every 15 minutes at the N8 and 250th sites and every hour at the Golf Course and Outlet sites were used to calculate flow values, which were averaged daily to establish a daily flow dataset at each site, aside from the Outlet, where the DNR gage-measured flow data were used. Sample flows were calculated using the average stage of each rising or falling limb composite sample and using the measured stage for grab samples. In the case of the N8 site, daily flows were substituted for sample flows, as the rating-curve derived sample flow values showed a poor fit to the scaled hydrograph. Stage data and hydrographs were downloaded using ISCO® Flow Link software from the 250th site, and from the CR10x modules with a Campbell Scientific® SC32B USB adapter and Campbell Scientific® Logger net software. A complete description of the sampling and data collection procedure used can be found in the appendix of the final section 319 report submitted to the MN Pollution Control Agency, entitled 'SOP Dobbins Creek All Sites'.

Loads were estimated using Flux 32 load estimation software.[23] Concentration data were stratified into groups based on flows, and then loads were estimated using a flow-weighted average (Method 2 in Flux32). In this estimation algorithm, the annual load within each stratum, W, is calculated using Eq.4

$$W = A_L \times (A_D / A_S) \qquad (4)$$

Where,

A_L = Average Load Within Stratum

A_D = Average Daily flow within stratum

A_s = Average sample flow within stream

As stated in the Data Stratification overview in Flux 32, this flow-based stratification improves the estimation of loads by grouping similar subsets of the data together, based on their flow-to-concentration relationship, to achieve a better 'fit' of the estimation model to the data.[23] These strata were adjusted to achieve as close of a convergence of the loading estimates by the different calculation methods used in Flux 32 and to decrease the Coefficient of Variance (C.V.) values of these estimates as much as possible.

Analysis, Results, and Discussion

Table 1 presents the estimated loads and the associated C.V. Loads calculated using a scaled hydrograph from the Outlet site, due to unrealistically high flow estimates made with the rating curve developed during this study. C.V. is a measure of the uncertainty of the loading estimate. It is defined as the ratio of the standard deviation of a dataset, σ, to its mean, μ: C.V. = σ/μ,[24] Higher C.V. values (> 0.2) indicate more estimated uncertainty. It can be difficult to achieve lower C.V. values in smaller, flashy stream systems, such as Dobbins Creek.[23] This is evident in the results at the 250th site – the drainage area is relatively small, and the vast majority of the flows recorded were low flow conditions as shown in Figure 3. Given that storm flows can rise and fall in a matter of minutes to hours, the daily average flow used in this software can miss these high flows, introducing more variation in the concentration to flow relationship.

These estimated annual loads as shown in Table 1 are meant to give baseline values at monitoring points in the stream network allowing for the possible changes over time. As stated earlier, the initial N8 loads appeared to be greater than they should be, given the relative size of that drainage area compared to the entire watershed. These values were likely the result of an overestimation of flows – the C.V.'s was not excessive, yet the load values for all constituents are unrealistically high. This is where a model is required! For comparison, daily flow estimates using the N8 rating curve were compared with a Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model output at the same site from a model run by Jim Solstad of the MN DNR for Dobbins Creek, and the outlet hydrograph scaled for drainage area for the same dates in 2016 (this was the only year that monitoring results overlapped the GSSHA outputs). The GSSHA model estimates overland and subsurface flow and transport within a defined watershed. A copy of the model outputs provided by Salam Murtada of the MN DNR (GSSHA Output, results, 'SOP Dobbins Creek All Sites' Section 319 Final Report to MPCA). The three datasets are shown in Figure 4.

It is clear that the daily flow values estimated by the rating curve developed in this study are significantly higher than the model outputs. The scaled hydrograph was used for these load estimates. Future work in the watershed should include the refinement of the rating curve used to calculate flows at this site. Full Flux32 load outputs, with strata definitions and load estimates by each of the seven estimation methods, can be found in USCOE (2017).

Table 1: Estimated annual loads

Site	Drainage Area (acres)	TSS (tons/yr)	C.V.	NOx (lb/yr)	C.V.	TP (lb/yr)	C.V.	P04 (lb/yr)	C.V.
Outlet	25,700	4,654.51	0.21	8,01,406	0.078	25,732.50	0.14	7,454.33	0.122
Golf Course	10,872	1,291.23	0.46	1,30,160	0.087	3,903.93	0.23	850.716	0.21
N8*	6,350	2,077.32	0.22	3,20,383	0.073	7,483.94	0.17	1,829.35	0.18
250th	464	351.09	0.87	21,047.20	0.14	1,289.90	0.35	333.17	0.25

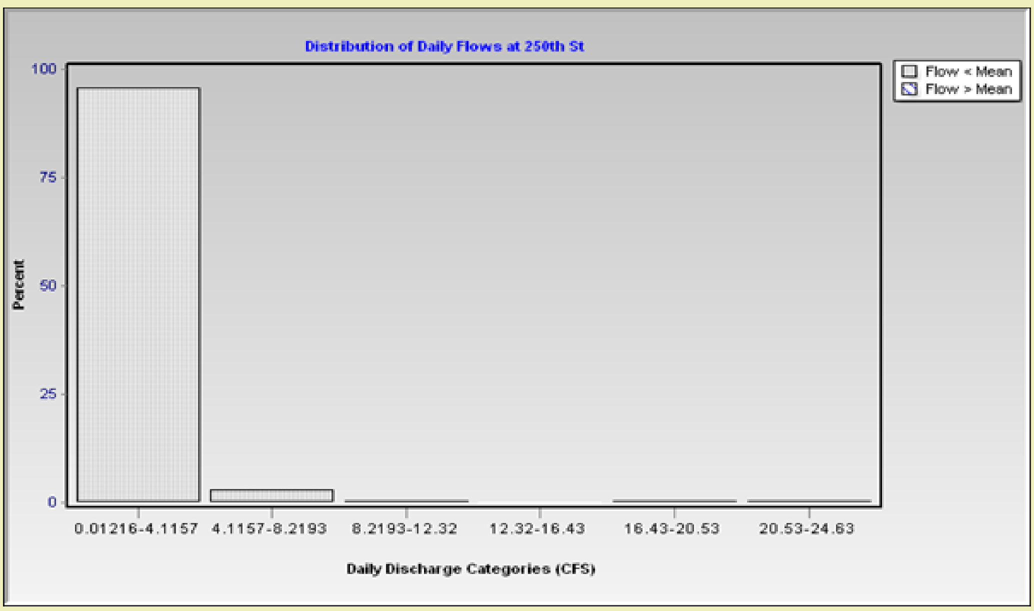

Figure 3: Histogram of flows at 250th St. site using the flux model

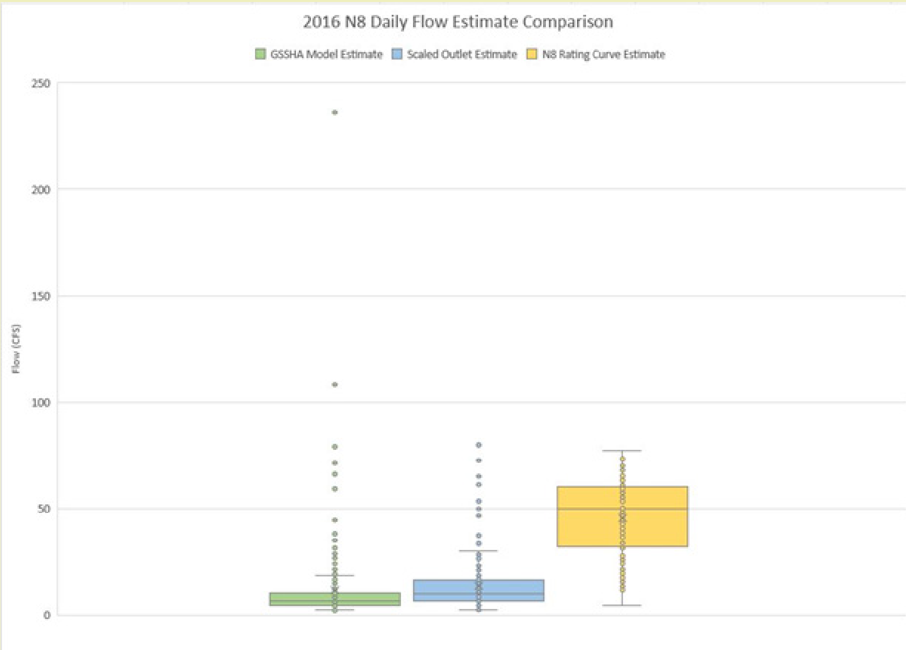

Figure 4: Box plot of N8 flow estimates using both modeled and measured methods

Analysis of load duration curves

Figures 5-8 will show on the X-axis the Percent of Days that the Load was Exceeded; the Y-axis will show TSS in Tons/year. Figure 9 is the same as Figure 5, but for Nitrate + Nitrite in Pounds/year. Figure 10 is similar to Figure 9, but for Total Phosphorus in Pounds/ year.

The outlet curve is shown in Figure 5 shows an exceedance of the standard at high and medium flows. This is as expected, given that higher flows have more stream power to move sediment, either from upland areas or from in-channel sources. The measured lower flow loads are below the standard as shown in the load duration curve.

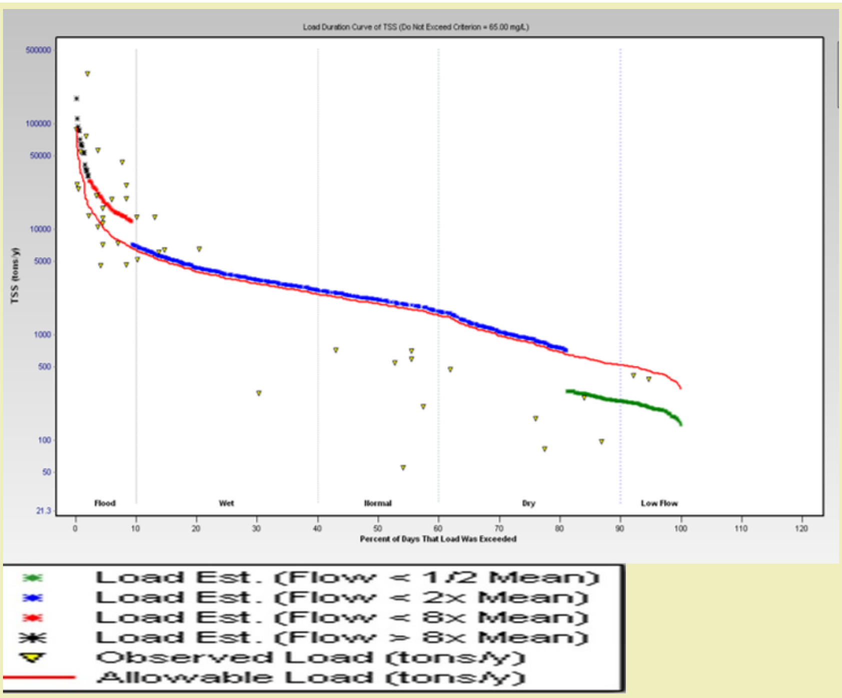

Figure 5: TSS load duration curve at outlet

The measured loads at the golf course monitoring site as shown in Figure 6 exhibited more variability, as apparent from the magnitude of C.V. for the overall annual load estimate.

There are incidences of both high and low loads (during low flow conditions), making conclusions more difficult to draw about expected water quality exceedances based on flow regime. Based on these results, the measured loads exceed the standard at all flows.

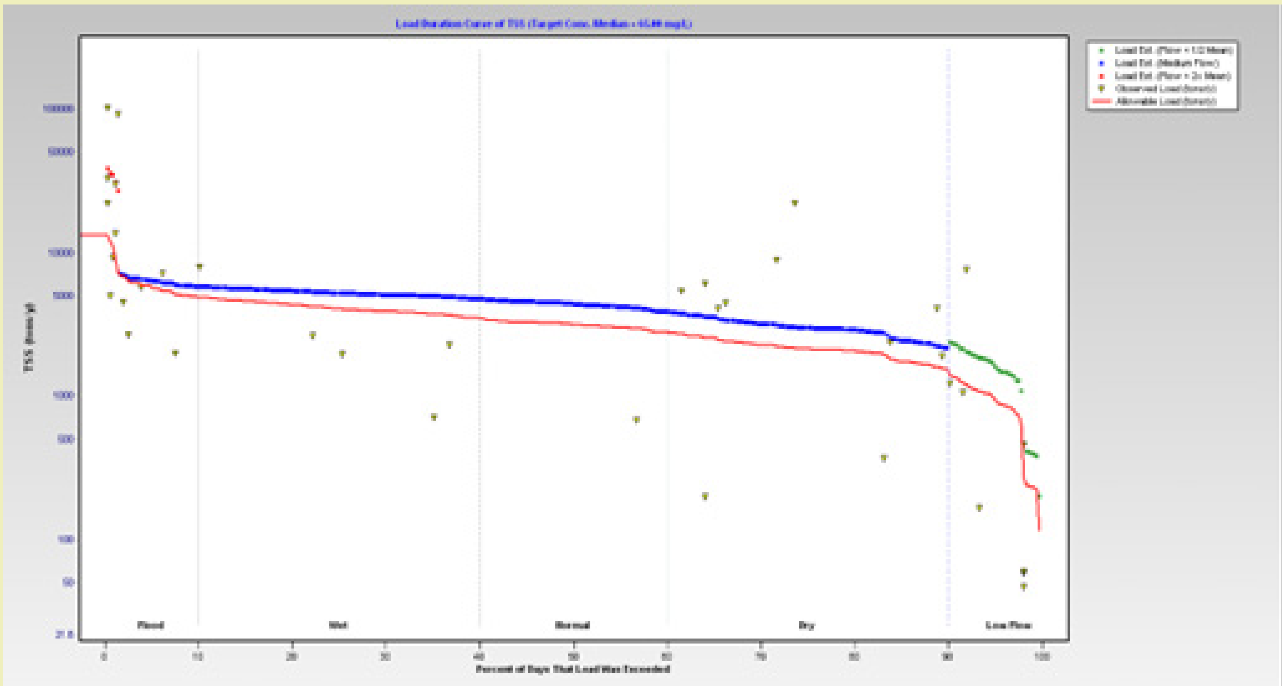

Figure 6: TSS load duration curve at the golf course monitoring site

The N8 load duration curve as shown in Figure 7 appears similar to the outlet curve in terms of an expected load exceedance at high and medium flows.

The load duration curve at 250th monitoring site as shown in Figure 8 shows exceedances at all flows. However, given the small and flashy nature of this stream segment and the corresponding uncertainty in the load estimate indicated by the 0.87 C.V. value, these load values are not constrained which makes it difficult to define a beginning, pre-BMP load for future comparison. Stream flashiness presents a monitoring challenge that requires modelling support. Flux 32 software only allows for a single flow value per day to be input as a daily flow. When hydrographs rise and fall within hours of an event, flow variation will not be entirely captured. It is possible that analysis of such a small catchment requires a smaller time interval of flow data to be considered. Yes, but this work is best performed by a model with solid GIS information. We plan to discuss the value of hydro-conditioned GIS models in a future follow up paper.

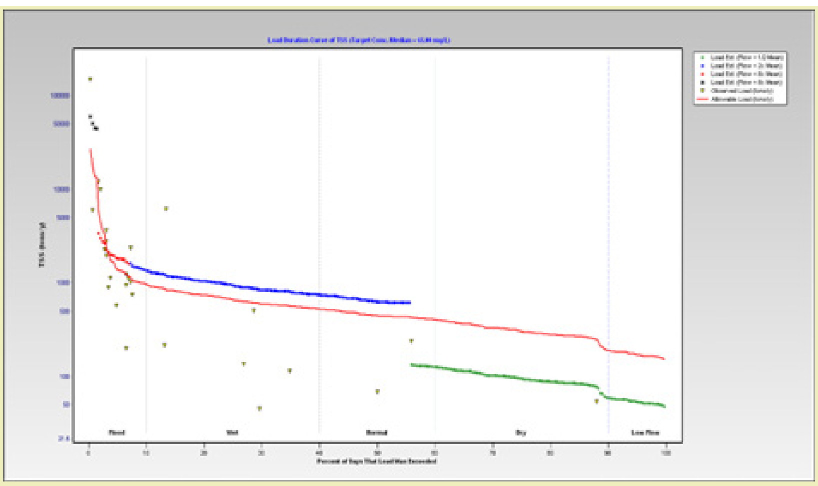

Figure 7: TSS load duration curve at N8 monitoring site

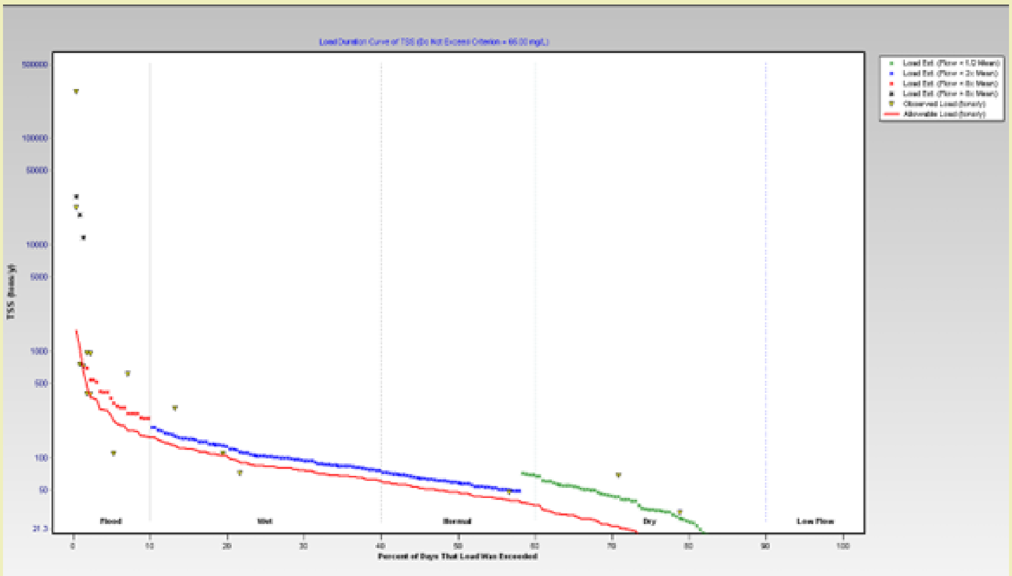

Figure 8: Load duration curve at 250th monitoring site

Analysis of Nitrate + Nitrite (NOx) load duration curves

In general, the C.V. values for the NOx load estimates as shown in Figure 9 exhibit much less uncertainty than the TSS estimates – estimates at all sites had C.V. values below 0.2. Again, this is a factor of the relationship of the flow-to-concentration relationship – the more closely related the two factors are, the better the model will fit to the data and the lower the C.V. value will be. The outlet NOx curve estimates show that loads at all flow regimes are below the 10 mg/L water quality standard. While there are load data points above the standard curve, the stratified estimates all fall below the standard. Equivalent load distribution curves are plotted for other monitoring sites such as golf course, N8, and 250th sites. The N8 load duration curve shows exceedances at normal to high flows. In contrast, NOx loads at 250th Street site is observed to be below 10 mg/L standard at all flow regimes.

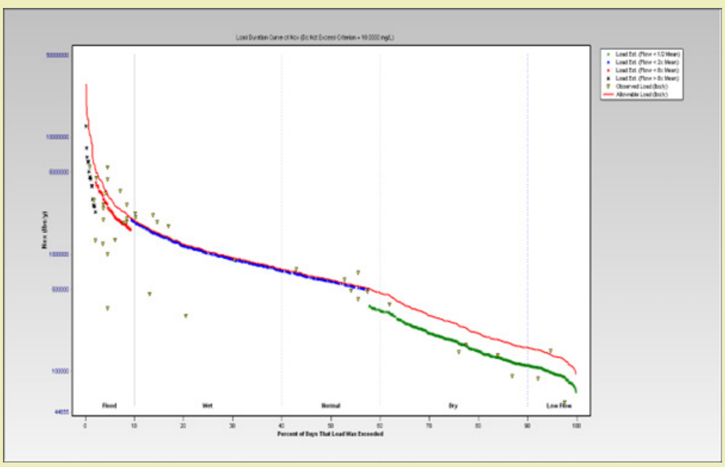

Figure 9: Load duration curves of Nitrate + Nitrite (NOx) at outlet

Analysis of total phosphorus load duration curves

Similar analysis is performed to create total phosphorus load duration curves at all the monitoring sites. The load duration curve corresponding to the outlet is shown in Figure 10 from which an exceedance of the 150µg/L total phosphorus standard in high flows is apparent. Given that phosphorus is often found bound to sediment in water, this result matches well with the TSS curve for this site.

Equivalent load distribution graphs are plotted for the golf course monitoring point showing a slight exceedance of the standard in normal and wet flows, and definite exceedance in flood flows. The lower 50% of flows are shown to have loads under the standard. The N8 load duration curve shows exceedances at the upper 40% of flows while 250th Street site shows exceedances at normal to flood flows, with loads in the lower 40% of flows falling below the standard.

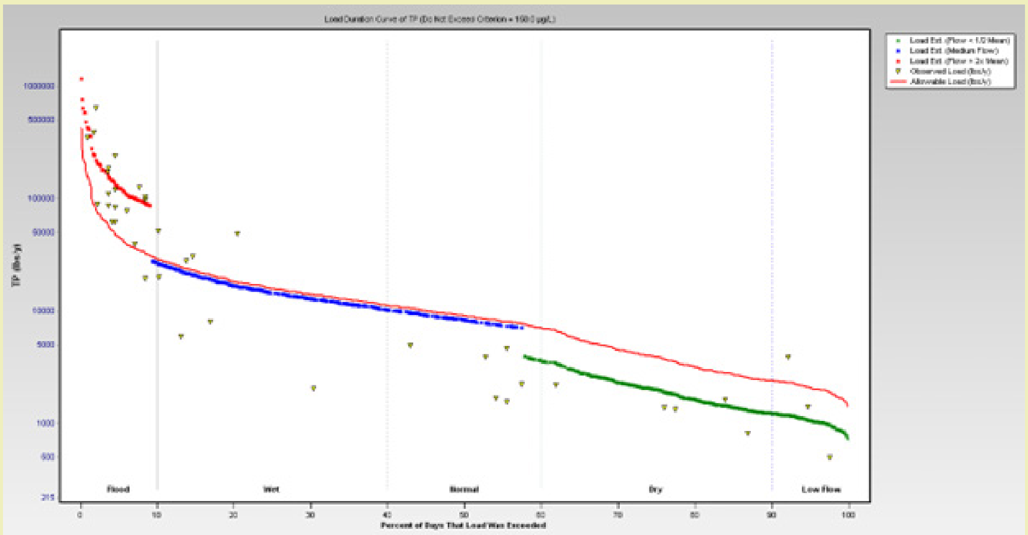

Figure 10: Load duration curves of total phosphorus at outlet

Analysis of dissolved orthophosphate (PO_4-P) load duration curves

There is no specific MN Rule Chapter 7050 water quality standard for dissolved orthophosphate, also described as bioavailable phosphorus, nevertheless, this is the portion of total phosphorus that is immediately available for uptake by organisms such as plants or bacteria.[25] The standard curve shown is the total phosphorus standard (150µg/L). All sites had loads below this total phosphorus standard at all flow regimes with the exception of 250th Street, which saw PO_4-P loads exceed the total phosphorus standard during the highest (<5% exceedance) flows.

Conclusion

Loads of TSS, and TP are intrinsically linked based on fine sediment detachment and transport with associated bound TP. This land use must have erosion reduction actions. However, NOx and PO_4-P are more soluble and will not be controlled by erosion reduction practices designed to reduce fine sediment transport. Land use practices that decrease overland runoff and encourage more water infiltration can lead to higher NOx values in groundwater that may discharge to the creek under baseflow. PO_4-P has been shown to be more bioavailable and mobile where grasses are used as part of the BMP.[26] The diversity of pollutant hydrologic pathways can create a land use management dilemma. It is critical that monitored data is gathered about these pollutants before and after BMP implementation. The load estimates made in this study showed varying degrees of uncertainty, however, the errors must be constrained over time with focused field measurement. In particular, the TSS loads at all sites had relatively higher C.V. values, but TSS data over time can sufficiently be linked back to land use. The load estimates for all constituents at the N8 site were likely unreliable, despite the relatively low C.V. values; this is based on the inflated flow values calculated using the stage-to-flow relationship developed in 2016. It takes a very concerted effort to constrain uncertainty at smaller watershed scales. Nevertheless, with a decade of time to further develop the rating curve, back calculation of initial flow estimates can be constrained. More data points taken over a wider range of flows will improve the rating curve and the accuracy of future load estimates. The method used during this study for measuring flow, standing in the stream with a wading rod and a Hach FH950 portable velocity meter cannot be used at a stream stage above 4 feet, as entering the stream in waders during such flows would be dangerous. We suggest the use of a floating acoustic doppler current profiler to provide better accuracy and user safety. Given the expected lag time between the implementation of BMPs and measured water quality changes, the load estimates presented in this work illustrate how benchmarking with duration curves, over time, can lead to understanding of the performance of BMPS. The field data can be used in the future to better calibrate and validate model estimates. Models without measured field data are useless, therefore, monitoring and modelling are required to answer questions about the effectiveness of BMP implementation in an agricultural dominated landscape.

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Conflicts of Interest

Regarding the publication of this article, the authors declare that they have no conflicts of interest.

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