Water Quality Monitoring – Evaluating Agricultural Best Management Practices in two Huron County Watersheds - DRAFT

A report prepared for the Ontario Soil and Crop Improvement Association, Great Lakes Agricultural Stewardship Initiative Priority Subwatershed Project

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1.0 Introduction

The near-shore area of the Great Lakes provides many residents of Ontario with drinking water and recreational opportunities (*e.g.*, swimming and fishing). However, nutrient, sediment, and bacterial impacts can sometimes limit both the human uses and the ecological integrity of these near-shore waters. Agricultural activities contribute non-point sources of nutrients, sediment, and bacteria to the near-shore waters of the Great Lakes, but these contributions have been difficult to quantify due to the temporal and spatial variability of their sources. Reducing non-point source pollution is an important goal for federal and provincial agencies and local communities.

Agricultural Best Management Practices (BMPs) can help to reduce non-point sources of nutrients, sediment, and bacteria and improve surface water quality. There are many different practices that could be considered BMPs, including:

- nutrient and manure management practices (*e.g.*, following nutrient management guidelines and building adequate manure storage);
- field soil erosion reduction strategies (*e.g.*, conservation tillage and cover crops);
- structural practices (*e.g.*, Water and Sediment Control Basins – WASCoBs);
- fragile land retirement; and
- tile drain management approaches.

Kroger *et al.* (2012) outlined a framework that puts nutrient and sediment management practices into three tiers, with first-tier practices avoiding the introduction of nutrients and sediment into the aquatic system and additional tiers controlling their distribution. The first tier, input management (*i.e.*, nutrient management), avoids the introduction of the pollutant. The second tier controls the movement of the pollutant through field management (*i.e.*, conservation tillage). A third management strategy is to treat or trap the pollutant in primary aquatic systems (*i.e.*, swales, grassed waterways, WASCoBs, and ditch BMPs).

Beginning in 2010, the Watershed Based BMP Evaluation (WBBE), Huron, looked at the effectiveness of Avoid, Control, and Trap/Treat (ACT) BMPs by assessing the BMPs for their environmental effectiveness at the field and watershed scales (see Simmons *et al.* 2013 for a review of the broader study). Monitoring and evaluation of the BMPs continued in 2015 with the Great Lakes Agricultural Stewardship Initiative (GLASI) project. The purpose of this document is to summarize the ongoing water quality monitoring completed to verify the environmental efficacy of agricultural BMPs at the watershed and field scales. The BMPs evaluated included: vegetative cover and WASCoBs. This report in part, helps to meet the deliverable of BMP monitoring for the GLASI project.

Furthermore, the water monitoring program described herein addressed some of the requirements of environmental models that are further described by Guelph University's Watershed Evaluation Group (WEG 2017a, WEG 2017b).

2.0 Watershed Monitoring

2.1 Study Area

Two watersheds, Gully Creek and Garvey-Glenn Drain, were monitored for water quality and quantity since 2010 and 2012, respectively. The Gully Creek watershed, within the watershed jurisdiction of the Ausable Bayfield Conservation Authority (ABCA), is a representative lakeshore watershed of the Lake Huron Basin (Figure 1).

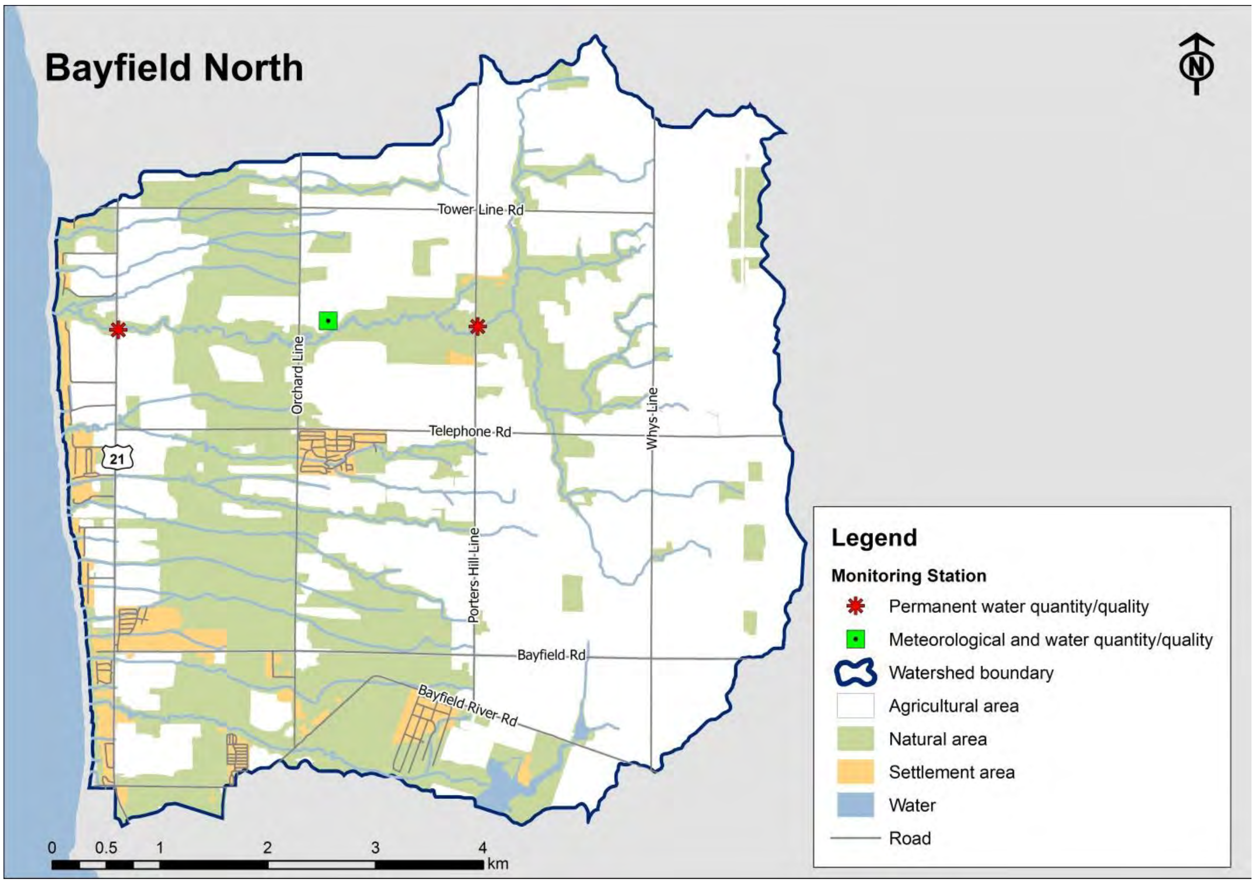

Figure 1: Study area and monitoring locations in the Gully Creek watershed.

The Gully Creek watershed is 14 square kilometres, while the area draining up to the primary gauging station is 10 square kilometres and mostly agricultural (Table 1).

The Garvey-Glenn Drain watershed is located north of Goderich within the watershed jurisdiction of the Maitland Valley Conservation Authority (MCVA) (Figure 2).

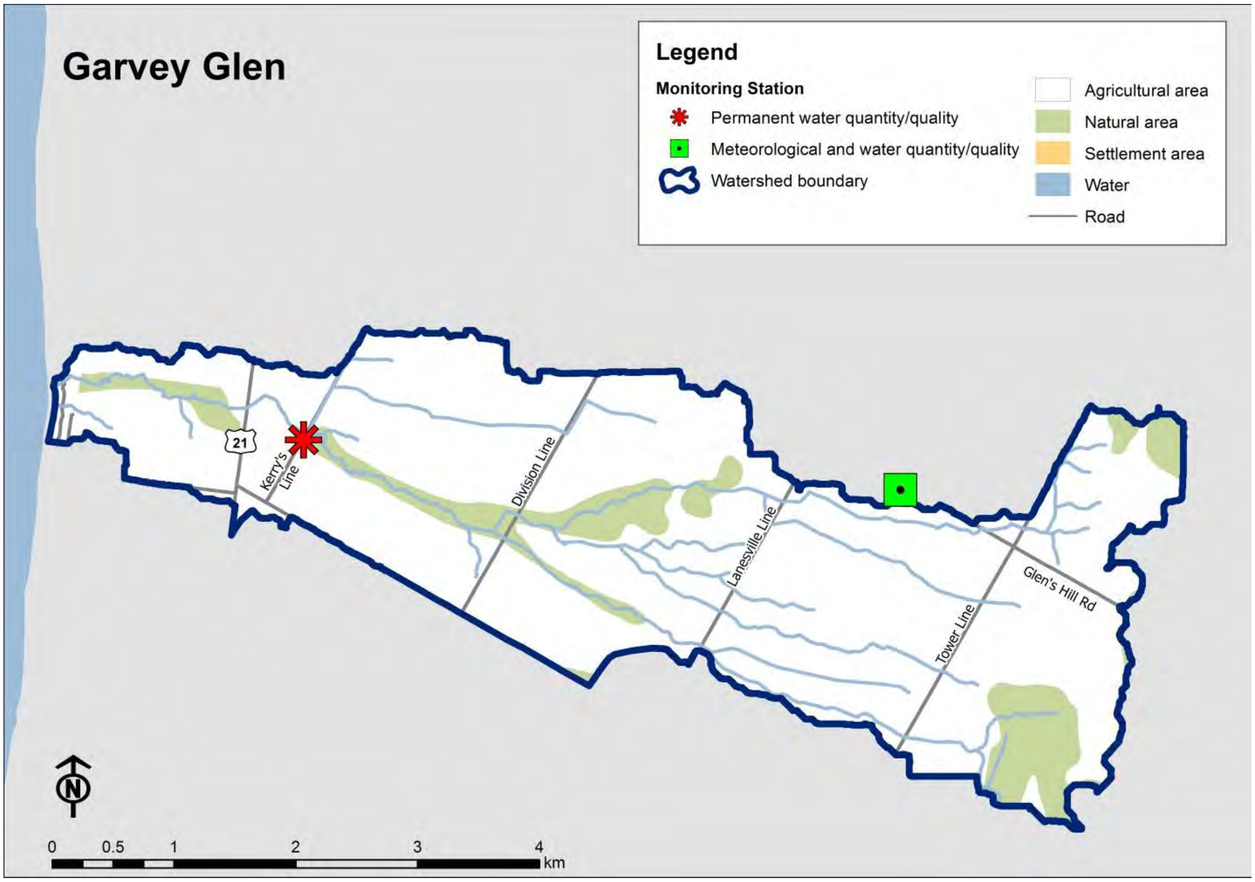

Figure 2: Study area and monitoring location in the Garvey-Glenn Drain watershed.

The Garvey-Glenn watershed is 16 square kilometres, while the area draining up to the gauging station is 13 square kilometres of primarily agricultural land (Table 1).

Table 1: Summary of Gully Creek and Garvey-Glenn Drain watershed size and land use (based on 2013 cropping year) upstream of main sampling location.

Watershed	Size (ha)	Corn (%)	Soy (%)[A]	Winter wheat (%)	Other crops (%)[B]	Hay/ pasture (%)	Natural areas/ roughland (%)[C]	Other (%)[D]
Garvey-Glenn Drain, at Kerry's Line gauge	1286.1	28.0	39.3	10.7	4.7	2.2	11.4	3.7
Gully Creek, at Porter's Hill Line gauge	1040.4	20.7	31.4	19	0.0	3.7	20.7	4.4

[A] Included soy and edible beans
[B] Included agricultural fields where the crop type was listed as unknown or was another crop including spring cereals, canola, and vegetables
[C] Included riparian corridors, ditches, scrub land, woodlands and wetlands
[D] Included urban, roads, pits, farmsteads, farm access roads, ponds

2.2 Methods

2.2.1 Field Monitoring Methods

Water quality monitoring stations were selected to be as far downstream as possible in both watersheds, but remaining outside of the lake-effect zone. Stations were co-located with reliable flow gauging stations so that water quality results could be combined with stream discharge measurements for the computation of loads (Figures 1 and 2). Water level (also referred to as water stage) data were collected every five minutes at both stream gauges. A WaterLOG H-3553 Compact Combo Bubbler System was used to measure water stage, with a twelve-volt, 100-amp-hour valve-regulated lead acid battery and solar panel providing power, and an FTS Axiom H2 Datalogger logging and transmitting data through a Geostationary Operational Environmental Satellite (GOES) antenna. This continuous record of stage was translated to stream discharge by applying a stage-discharge relationship (also called a rating curve). A stage-discharge relationship was developed for each stream gauge by measuring the flow of the stream with a flow meter (Marsh-McBirney Flo-Mate™ Model 2000). For each measurement of discharge there is a corresponding measurement of stage. High and low stages and flows are particularly important for the development of the rating curve; however, it was unsafe to obtain manual measurements of flow in the streams when they were in peak-flow conditions. Instead, a theoretical equation related to the shape, size, slope, and roughness of the channel at the stream gauge was used to iteratively determine the stage-discharge relationship at higher stages and flows. This relationship differs between stream gauging stations and can also change over time at a specific station. More details on the water quantity monitoring methods can be found in Upsdell Wright *et al.* 2015.

Many water quality monitoring programs involve a random sampling strategy, whereby samples are collected on pre-determined days of the month. However, rain, rain-on-snow, and snowmelt events (herein referred to as events) are important because high concentrations of some pollutants, particularly sediment and phosphorus, are transported during these events. The monitoring and modelling results in the Watershed Based Best Management Practices Evaluation study found that intermittent channels that form across the land contribute to poor water quality during storm events (Simmons *et al.* 2013). Further, practices to address rural water quality nutrient enrichment issues are undertaken to reduce the formation and/or the effects of these intermittent channels on the landscape. To understand the effectiveness of rural best management practices (BMPs) on water quality, it is imperative to collect *event data* prior to and after the establishment of the BMPs. Therefore, water quality monitoring for this study included sample collection when water was running across the landscape in order to improve the accuracy of pollutant load estimates.

For the purposes of this study, water samples were collected year-round under both low-flow and high-flow conditions. Richards (1998) has shown that the 80th percentile of flow is an appropriate division for separating runoff events from low-flow periods for Lake Erie tributaries in Northwest Ohio. This study used the same approach. Continuous flow data from October 2010 to September 2017 were used to establish the low-flow conditions. A threshold was set at the 80th percentile of the continuous flow record for each of the sites to separate low flow from event flow. Low-flow grab samples were collected monthly between October 1, 2010, and September 30, 2017. High-flow events were sampled with an ISCO 6712 automated sampler at both stations. The ISCO samplers were set to trigger with a rise in water level and to collect samples throughout the hydrograph, attempting to capture samples at the onset of the event, mid-way up the rising limb of the hydrograph, at the peak, mid-way down the falling limb, and at the end of the event.

Water samples were primarily analyzed for nutrients and suspended solids by the Ministry of the Environment and Climate Change (MOECC) laboratory in Etobicoke; however, on occasion, samples were submitted for analysis to ALS Laboratory in Waterloo. There are different analytical approaches to estimating the bioavailable forms of phosphorus. In this study, phosphate-phosphorus was measured. It is important to note that a change in laboratory analysis method for total phosphorus occurred at MOECC in November 2012.

Approximately 1,000 tributary water quality samples were collected in Gully Creek between October 1, 2010, and September 30, 2017, while more than 400 water quality samples were collected in Garvey-Glenn Drain between October 1, 2012, and September 30, 2017.

In the eight-year period (2010 to 2017), Gully Creek experienced roughly 155 runoff events, while 81 events were documented in the Garvey-Glenn watershed between 2012 and 2017. Not all events were sampled. Some events were missed due to decisions made *a priori* about the size of the event, equipment malfunctions, and staffing issues.

2.2.2 Mass Loads and Flow-Weighted Mean Concentrations

For this report, both flow-weighted mean concentrations and the loads have been summarized. Dickinson (in Upsdell Wright *et al.* 2015) suggested that, if the focus of the study is on concentration targets or standards, then concentration values are needed. However, if the focus of the study is on land use management or Great Lakes impacts, then load estimates are needed. Calculating loads is important for comparing the contributions over time and eventually from different watersheds to Lake Huron.

Water quality indicator concentrations (nitrate-nitrogen, phosphate-phosphorus, total phosphorus , and total suspended solids) from the grab and ISCO samples collected during the study period were converted to loads (mass per time), flow-weighted mean concentrations (FWMC) (mass per volume), and export coefficients (mass per watershed area). These computations help to remove the variability associated with event discharge and watershed size.

Loads are the product of stream flow (volume per time) and concentration (mass per volume). A mass load (Equation 1) is a calculation of the total mass of a substance, usually expressed in kilograms, that is transported past a particular point on a stream or river over a given time period, often annually (Cooke 2000). For this section, annual loads were calculated (including events and low-flow periods).

Equation 1

Mass Load (kilograms) = $\sum_{i=1}^{n} \frac{c_i + c_{int}}{2} q_j$

Where,

n = total number of samples
i = number of a particular sample
c_i = concentration measured at the day and time of the ith sample
q_j = inter-sample mean flow
c_{int} = linearly interpolated concentration value between samples

In a flow-proportionate sampling program, an individual water sample does not characterize the event or low-flow period. To estimate the average concentration, each sample must be weighted to represent a particular portion of the hydrograph (Equation 2) (Cooke 2000). Flow-weighted mean concentrations are concentrations that are adjusted for stream flow over a given period – in this study, the length of the water year. This computation allows for comparisons between streams with different flows or the same stream at different times.

Equation 2

Flow-Weighted Mean Concentration (milligrams per litre) =
$$\frac{Mass\ Load\ (kilograms)}{Total\ Stream\ Flow\ Volume\ (litres)} \times 1000$$

The total mass export coefficient or unit-area load (Equation 3) is an estimate of the amount of the constituent that is lost per hectare of watershed for the given time period.

Equation 3

Mass Export (kilograms per hectare) = $\frac{Mass\ Load\ (kilograms)}{Watershed\ Area\ (hectares)}$

Continuous records of both stream flow and concentrations are needed to calculate loads. Since the concentrations of pollutants are not typically monitored continuously, load-estimation methods are used to calculate loads. Generally, there are five types of load-estimation methods: averaging, numeric integration, ratio, regression, and interpolation (Richards 1998). Bittman *et al.* (2017) evaluated the most appropriate approach to calculate loads with Gully Creek and Garvey-Glenn Drain water quality data and found that a linear interpolation method gave the best estimate of load for these datasets.

2.2.3 Trends in Monthly Water Quality Data

Regression analyses were performed to evaluate trends in water quality data for both watersheds during the current study period. A parametric approach (log-linear trend test) was used to evaluate the trends in monthly log-transformed flow-weighted mean concentrations (*i.e.,* improving trend, no trend, declining trend) for normally distributed datasets. However, if the water quality datasets were non-normally distributed, a non-parametric approach (Mann-Kendall trend test) was used instead. A Shapiro-Wilk test was completed to determine normality of the datasets. A trend was found to be statistically significant when the magnitude of the change was large relative to the variation of the data around the trend line (*i.e.,* $p<0.05$). Monthly concentrations were used instead of annual concentrations to limit the effect of outliers and to retain inter-annual variability. The average rate of change (%) in monthly flow-weighted mean concentrations was determined using Equation 4.

Equation 4

Monthly rate of change (%) = $(10^{\beta} – 1) \times 100$

Where,

β = log-linear slope coefficient

2.3 Best Management Practice Adoption

The outreach to landowners in the Gully Creek watershed was initiated in the fall of 2007 and has continued under the GLASI project (2015 to 2018). Between 2007 and 2015, at least 85 agricultural BMPs were implemented (Table 2), affecting most properties in the watershed (Figure 3). Since 2015, a total of 45 agricultural BMPs have been implemented through the GLASI project across both Gully Creek and Garvey-Glenn Drain watersheds (Gutteridge *et al.* 2017).

Table 2: Agricultural Best Management Practice Implementation in the Gully Creek watershed.

BMP Type	Number of Projects	Area Affected (if applicable)
Streamside Restoration	1	50 m
Riparian Tree Planting	1	300 m
Water and Sediment Control Basins (WASCoBs) – includes upgrades	31	
Wetland	1	0.46 ac
Grassed Waterway	2	167 m
Fragile Land Retirement	4	4.1 ac
Fragile Land Retirement – Windbreaks	2	460 m
Fragile Land Retirement – Vegetative Cover	1	5.4 ac
Manure Storage Upgrade	2	
Manure Amendments	4	241 ac
No Till Implemented	5	908 ac
Conservation Tillage Implemented	3	130 ac
Cover Crops Implemented	11	351 ac
Precision Agriculture Implemented[A]	11	670.5 ac
Nutrient Management Implemented	5	89 ac
Residue Management	1	141 ac
Total BMPs	85	

[A] Includes GPS systems, yield monitors, auto-steer equipment and variable rate applicators.

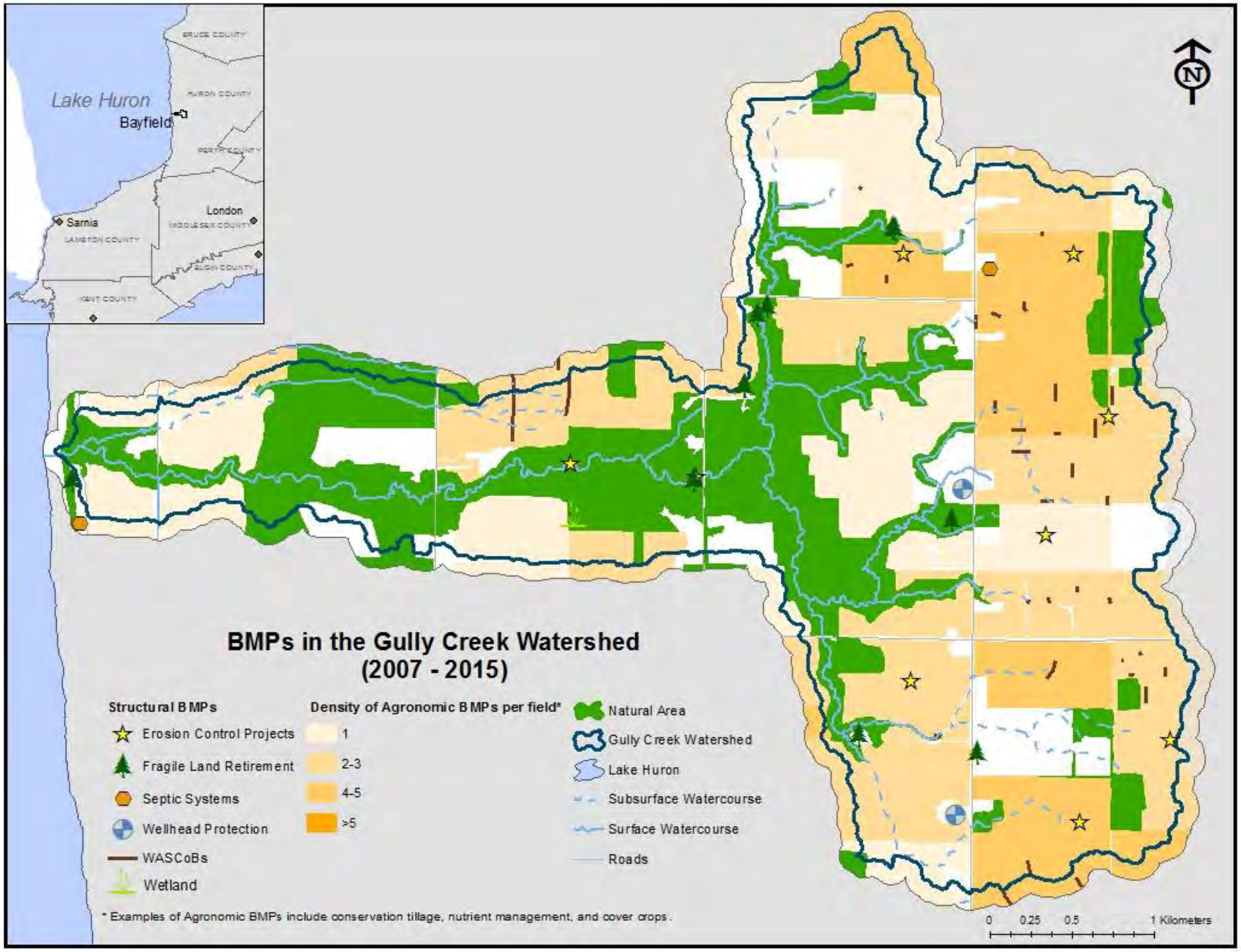

Figure 3: Implementation of agricultural best management practices in Gully Creek watershed (2007 to 2015).

2.4 Results

2.4.1 Mass Loads and Flow-Weighted Mean Concentrations

In both watersheds, annual flow-weighted mean total phosphorus and nitrate-N concentrations exceeded concentrations that are considered to minimize eutrophication (Figure 4): the Provincial Water Quality Objective for TP (0.03 mg/L; OMOEE 1994) and a concentration identified by the Canadian Council of Ministers of the Environment for nitrate-N (0.9 mg/L; CCME 2012). In Gully Creek, TP flow-weighted mean concentrations ranged from 0.15 to 0.67 milligrams per litre during the eight-year period, while TP concentrations in Garvey-Glenn ranged from 0.09 to 0.21 milligrams per litre during the five-year period. Flow-weighted mean nitrate-N concentrations ranged from 3.59 to 6.37 milligrams per litre in Gully Creek and 5.60 to 7.89 milligrams per litre in Garvey-Glenn. Sediment concentrations were highest in Gully Creek ranging from 138 to 618 milligrams per litre, but only 28 to 77 milligrams per litre in Garvey-Glenn.

Annual mass export coefficients were also calculated for Gully Creek and Garvey-Glenn Drain to compare load values per unit area. In Gully Creek, export coefficients for TP ranged from 0.83 to 4.40 kilograms per hectare, while export coefficients for TP ranged from 0.57 to 1.72 kilograms per hectare in Garvey-Glenn (Figure 5). Mass export coefficients for nitrate-N ranged from 23 to 52 kilograms per hectare in Gully Creek and 30 to 60 kilograms per hectare in Garvey-Glenn. Sediment loads were highest in Gully Creek ranging from 769 to 4,038 kilograms per hectare, but only 172 to 635 kilograms per hectare in Garvey-Glenn.

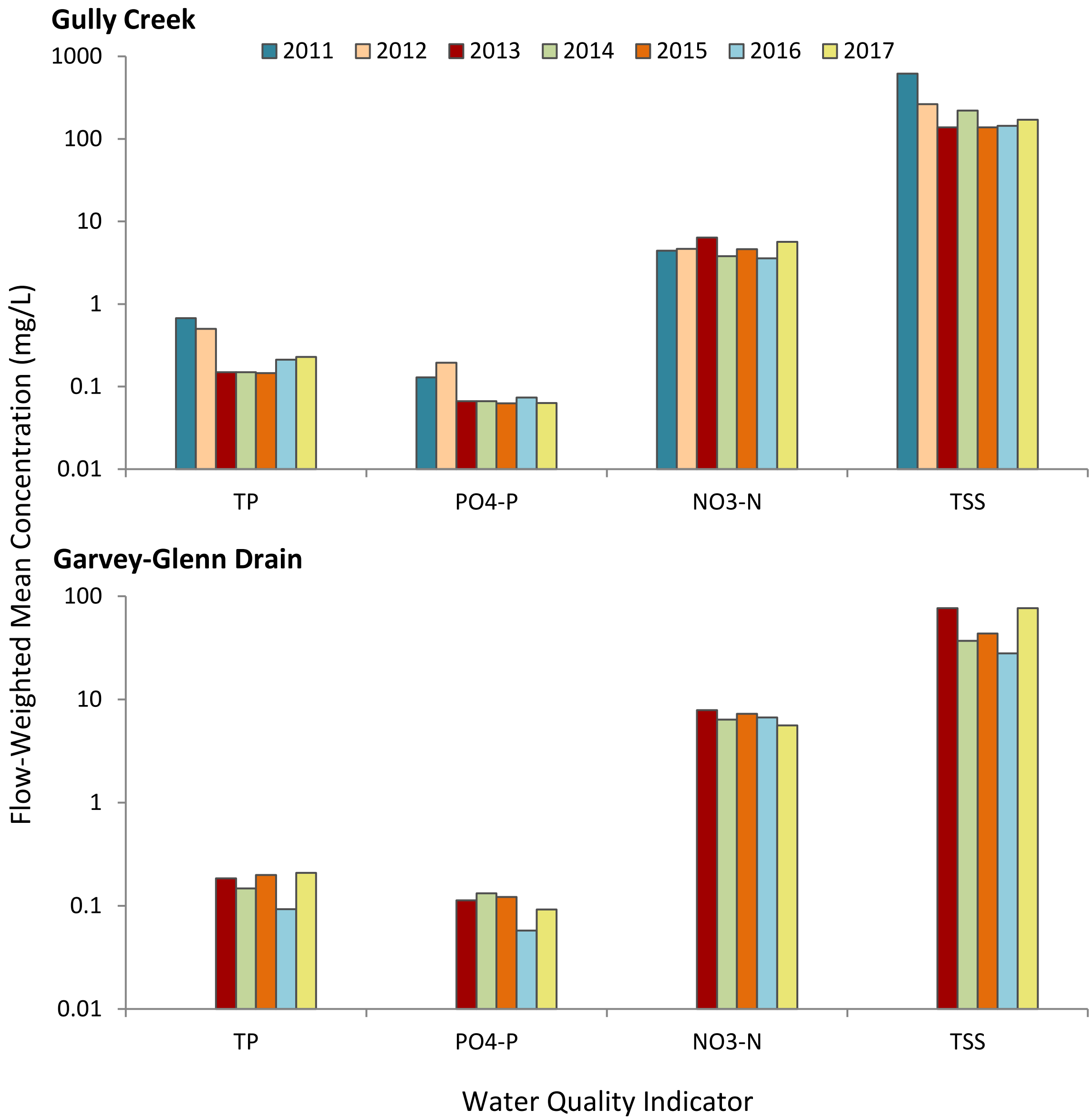

Figure 4: Water quality trends in annual flow-weighted mean concentrations for Gully Creek and Garvey-Glenn Drain. Note: A change of laboratory analysis method for total phosphorus occurred in November 2012 at the Ministry of the Environment and Climate Change.

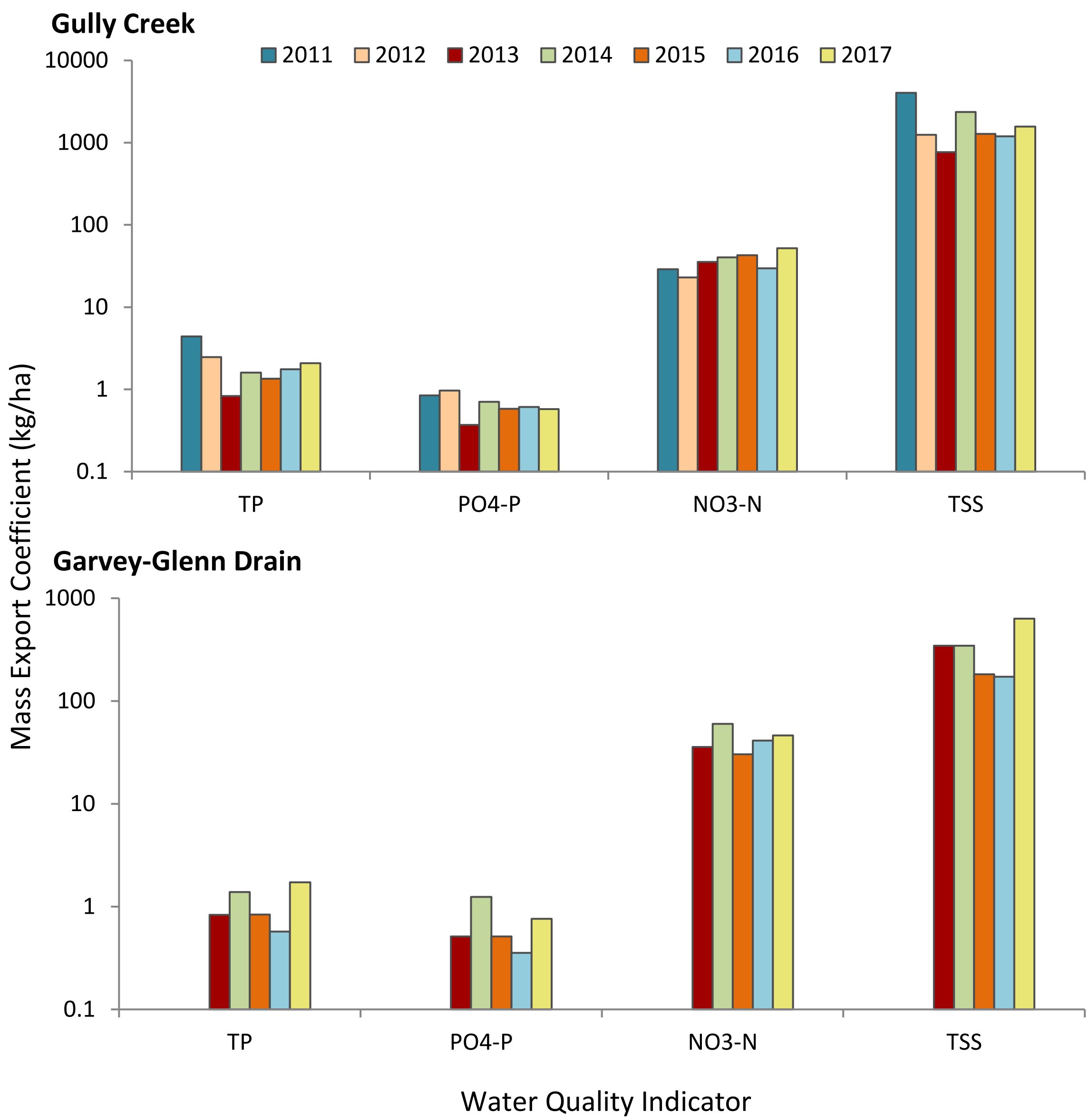

Figure 5: Water quality trends in annual mass export coefficients for Gully Creek and Garvey-Glenn Drain. Note: A change of laboratory analysis method for total phosphorus occurred in November 2012 at the Ministry of the Environment and Climate Change.

2.4.2 Trends in Monthly Water Quality Data

Monthly flow-weighted mean concentrations were determined for Gully Creek and Garvey-Glenn Drain over the study period with the expectation that patterns in water quality may be detected (Figures 6 and 7).

No statistically significant trends in water quality were determined for Gully Creek between October 2010 and September 2017 (*i.e.,* all *p*-values were greater than 0.05). By contrast, significant declines in flow-weighted mean concentrations of TP, TSS, and nitrate-N were observed between October 2010 and September 2016 (see Bittman *et* *al.* 2017). A possible reason for this discrepancy is that the 2017 water year had a number of very large rainfall events throughout the year (including one event that exceeded 100 millimetres of rain) which resulted in elevated pollutant concentrations. These differences exemplify the volatility of shorter-term monitoring trends and highlights the need collect longer term data sets (*e.g.,* >15 years) to reduce the impact of extreme data. An alternative method for analyzing trends using flow-adjusted concentrations (*e.g.,* Stammler et al. 2017) could be performed to remove completely the effect of discharge on pollutant concentrations and then compare the results to the current study.

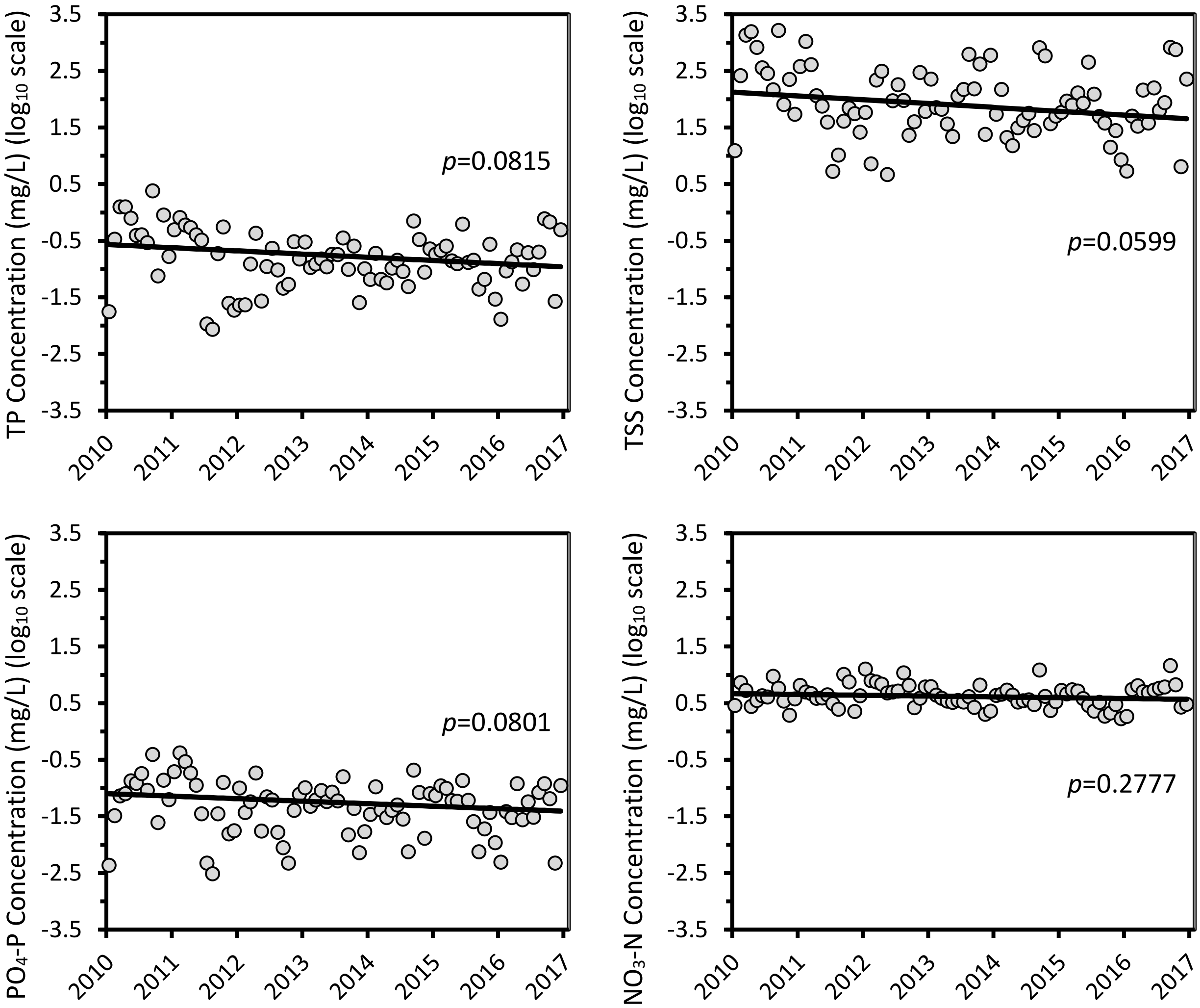

Figure 6: Water quality trends in monthly flow-weighted mean concentrations for Gully Creek (October 1, 2010 to September 30, 2017). Note: A change of laboratory analysis method for total phosphorus occurred in November 2012 at the Ministry of the Environment and Climate Change.

Additionally, no statistically significant trends in water quality were determined for Garvey-Glenn between October 2012 and September 2017 (*i.e.,* all *p*-values were greater than 0.05). However, between October 2012 and September 2016 monthly flow-weighted mean concentrations of TSS decreased significantly (see Bittman *et al.* 2017).

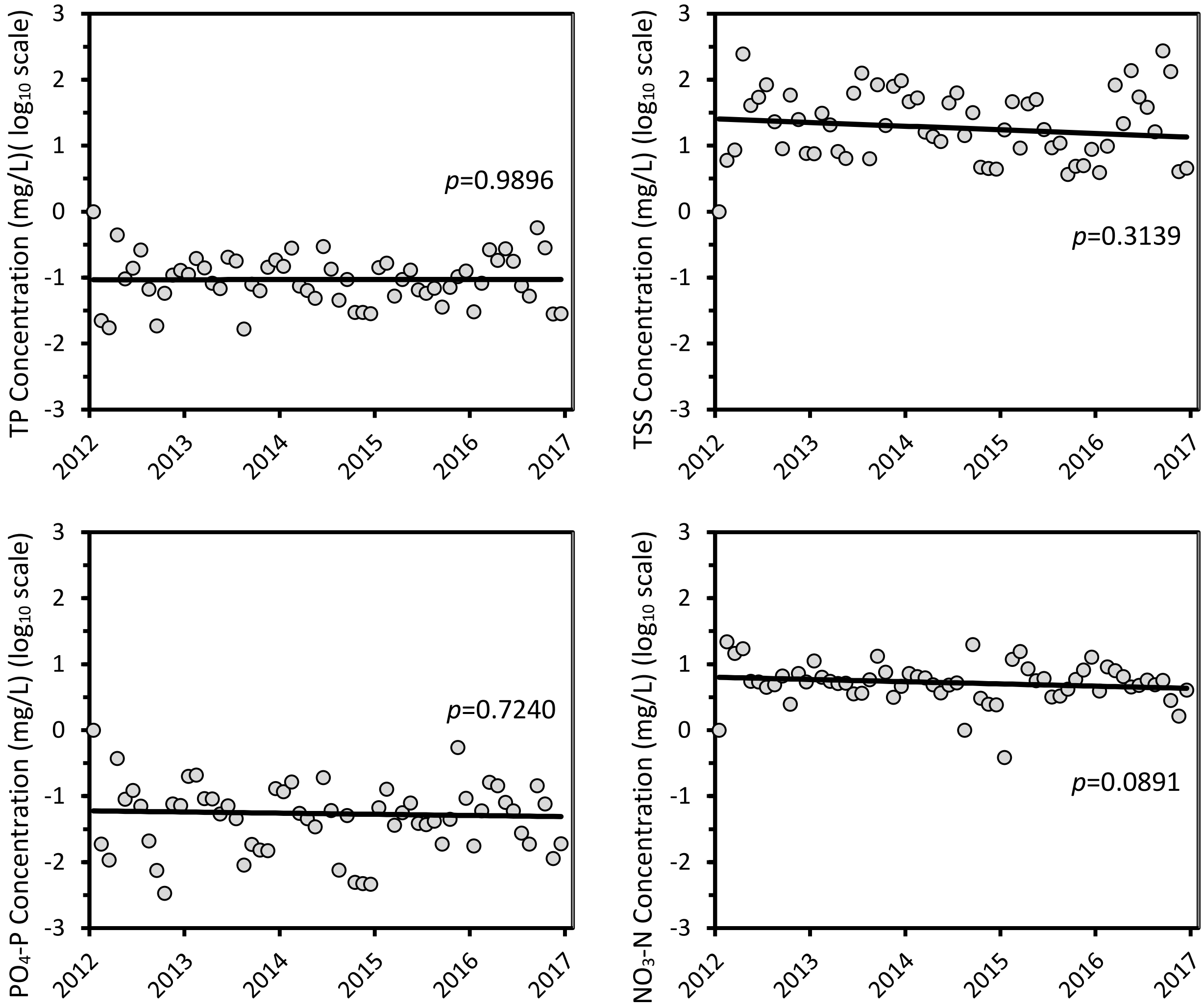

Figure 7: Water quality trends in monthly flow-weighted mean concentrations for Garvey-Glenn Drain (October 1, 2012 to September 30, 2017). Note: A change of laboratory analysis method for total phosphorus occurred in November 2012 at the Ministry of the Environment and Climate Change.

Although a relative decrease in some monthly nutrient and sediment concentrations was observed between 2010 and 2016, we cannot attribute the declines solely to the implementation of BMPs without the aid of computational modelling. For instance, the variability in concentrations or loads may be influenced by precipitation and/or total discharge volume, among other variables. Due to the complexity of climate and hydrologic conditions, a Soil and Water Assessment Tool (SWAT) was developed for Gully Creek and Garvey-Glenn to determine the effectiveness of BMP implementation. The University of Guelph's Watershed Evaluation Group (WEG) (2017b) documented that between 2002 and 2016, reductions in TP, TSS, and total nitrogen loads of up to

22%, 25%, and 18% per year, respectively, could be attributed to the current level of BMP adoption in Gully Creek. WEG (2017a) also documented that reductions in TP, TSS, and total nitrogen loads of up to 16%, 31%, and 13% per year, respectively, could be attributed to the existing level of BMP adoption in Garvey-Glenn.

3.0 Agricultural Best Management Practice Evaluation

Evaluating the effectiveness of agricultural BMPs with water quality samples is confounded by a number of factors, primarily precipitation (frequency and magnitude of events), soil conditions, and topography. However, a most important consideration is that the spatial scale that the field activity can influence is typically much smaller than the size of watershed that generates consistent flow. Thus, samples collected at “downstream” watershed stations will typically reflect a larger watershed area than the area that has had a BMP applied. It is important to remember that a single change in practice in a small area of a large watershed may not provide a large enough reduction in nutrients to produce demonstrable change in downstream nutrient conditions (Makarewicz *et al.* 2009).

The challenge is to collect a sample at the “edge of field” that reflects the effect of the applied BMP. It is also challenging to compare edge-of-field samples collected from fields with and without the BMPs under evaluation in practice. The water quality values will reflect not only the employed BMP but also the different slope, soil, and recent land management activities (*e.g.*, manure or fertilizer application, crop rotation). We have attempted to address these confounding issues by evaluating several edge-of-field locations over time to see what effect the land management practices have on the hydrology and water quality.

The following sections detail various BMPs that were evaluated including vegetation cover and Water and Sediment Control Basins.

3.1 Vegetative Cover

We endeavoured to document the effects of cover from 2012 to 2017 using several Water and Sediment Control Basins (WASCoBs) to evaluate the role that vegetative cover (*i.e.*, winter wheat, cover crops) has on hydrologic and water quality conditions.

Runoff (also referred to as flow) across agricultural lands is a function of temperature, soils, vegetation type, topography, antecedent moisture conditions, and the intensity, duration, and frequency of rainfall. Precipitation interacts with vegetation by three different methods: interception, stemflow, and throughfall. Interception occurs when precipitation remains on the surface of the plant, preventing water from reaching the soil surface due primarily to canopy storage and evaporation. Water that is not intercepted by the plant (*i.e.*, stemflow or throughfall) may be subsequently converted into runoff.

Interception of rainfall by agricultural crops has largely been overlooked in the soil-hydrologic cycle (Kozak *et al.* 2007). Crop canopy and residue layer interception is a function of crop density, row spacing, areal cover, and the intensity, duration, and frequency of rainfall. Past studies have shown canopy interception of 4 to 58 per cent and residue interception of 4 to 26 per cent (Table 3).

Table 3: Summary of interception rates for various crop types.

Canopy type	Rainfall interception (%) by study						
	Baver (1938)	Konstorshichikov and Eremina (1963)	Lull (1964)	Steiner *et al.* (1983)	Mohamoud and Ewing (1990)	Leuning *et al.* (1994)	Savabi and Stott (1994)
Corn	22		16	4 - 20			
Soybean	35		15				
Wheat		10 - 25	36			33	
Oat	58	16 - 23	7				
Corn residue					6		7 - 13
Soybean residue					4		14 - 26
Wheat residue							14 - 22

Savabi and Stott (1994) and Kozak *et al.* (2007) found that crop canopy and residue layer interception decreases runoff, or flow potential, during storm events.

3.1.1 Vegetative Cover over Time around a Water and Sediment Control Basin

We had anticipated that water quantity and water quality from within the WASCoBs over the study period would reflect the amount of vegetative or crop residue cover within small watershed boundaries (Figures 8 and 9).

Different runoff potential across the different field crops in various stages of development within the WASCoBs was expected. It is important to note that during the study period, March 2012 to September 2017, the crop rotation for one monitored field was corn, soybean, and wheat, while the other monitored field was soybean, soybean, wheat, and corn. Thus, there were potentially much more data for soybean compared to corn and wheat, but of course runoff data ultimately depended on how much rain there was. Both monitored fields were also planted in oat cover crop after wheat harvest; however, only for a limited amount of time (*e.g.,* 1-2 months)

A first-order, hydrologic response was to compare flow/no-flow conditions in the basin.

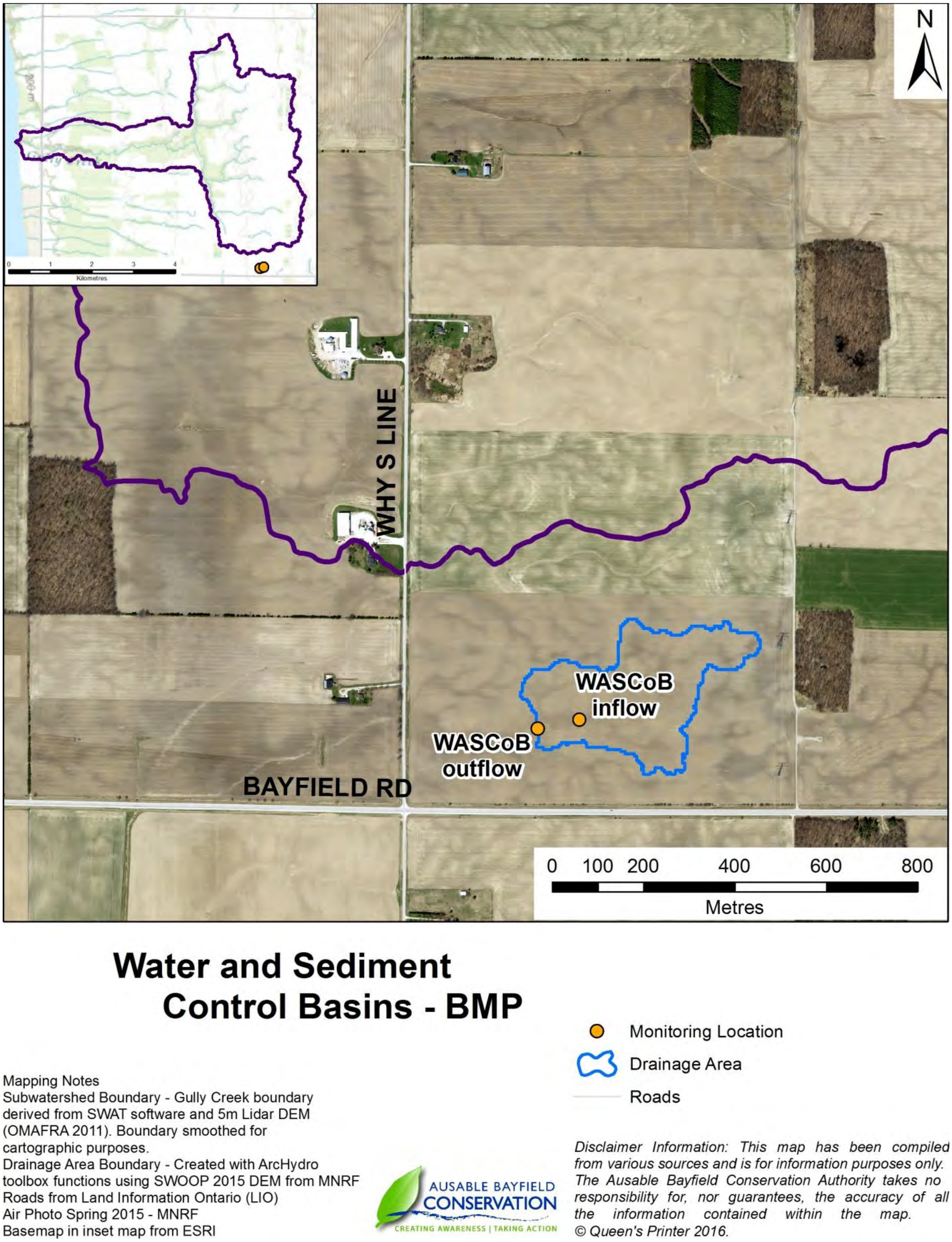

Figure 8: Map of monitoring stations for evaluating a Water and Sediment Control Basin just south of the Gully Creek watershed.

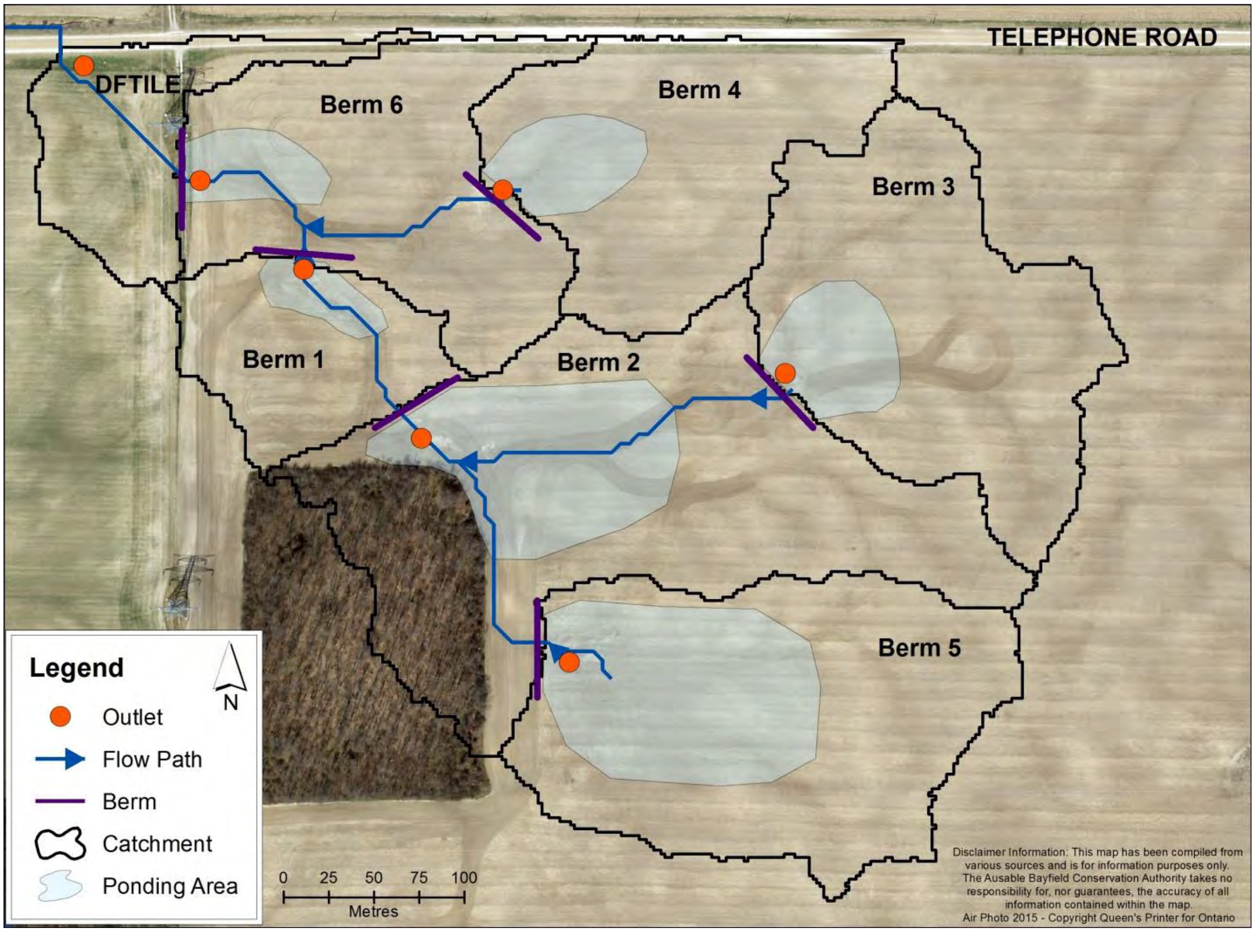

Figure 9: Map of a monitored field in the Gully Creek watershed. Only WASCoBs 2, 3, 5, and the tile (top left) are monitored for water quantity and quality. Flow direction is indicated by blue arrows.

3.2 Field Monitoring Methods

A Schlumberger ten-metre mini-Diver level logger (accurate to 0.025 metres) was installed in the ponding area behind the WASCoB south of Gully Creek on March 6, 2012, to record water depth (stage) at five-minute intervals. Three additional loggers were installed in the ponding areas behind the Gully Creek WASCoBs on June 26, 2013. Data included in this report extend to the end of the 2016/2017 water year, September 30, 2017. For the period of record from March 6, 2012 to September 30, 2017, there were 99 flow events recorded, while 89 flow events were recorded for the period June 26, 2013 to September 30, 2017. The stage (in metres) was converted to outflow (in cubic metres per second) following the methods documented by Wilson (2016).

Two meteorological stations were installed in close proximity to the study area to provide unfrozen precipitation data. The stations were leveled to allow for correct operation. A Davis Instruments Vantage Pro2 tipping bucket rain gauge (0.2 millimetres per tip) collected hourly rainfall data. The Davis unit was located within five kilometres of the WASCoBs and collected precipitation data for the period March 6, 2012, to January 10, 2013. An FTS RG-T Precision Tipping Bucket Rain Gauge was also used to collect unfrozen precipitation data on five-minute intervals. The FTS logger was located within four kilometres from the WASCoBs and collected precipitation data for the period January 11, 2013, to September 30, 2017.

3.3 Data Analysis Methods

In order to help explain the impact that vegetative cover has on flow, we used data from both monitored WASCoB fields to compare flow and no-flow conditions under different crop types. Predictive models were developed to estimate the occurrence of flow in the WASCoBs during a precipitation event.

3.3.1 Flow versus No-flow

Stage data from the WASCoBs were used to evaluate the effect of crop type on runoff during the growing and non-growing season. For simplicity, the response from precipitation events was divided into binary conditions: flow or no-flow. Events that generated flow were defined as having a water level greater than 0.025 metres; otherwise, an event was considered a no-flow event. No-flow events were characterized as those precipitation events that produced greater than 10 millimetres of rainfall within a 24-hour period, or had rainfall intensity greater than two millimetres per hour.

Flow/no-flow conditions were recognized to be highly constrained by the time of the year with different evapotranspiration rates and crop conditions. For simplicity, each year was divided into a growing season (May 1 to September 30) and non-growing season (October 1 to April 30).

A total of 205 precipitation events were observed at the monitoring station south of Gully Creek (KVBAY-HB) for the period March 2012 to September 2017, while 167 precipitation events were captured between June 2013 and September 2017 at the Gully Creek monitoring field (DFTEL-B2, DFTEL-B3, and DFTEL-B5). Combined, both locations experienced a total of 372 precipitation events, of which 188 events generated flow (or runoff) and 184 did not generate flow (*i.e.*, runoff was not observed) (Table 4).

Not surprisingly, flow occurred more often under non-growing season conditions (133 instances) compared to when flow was generated in the growing season (55 instances).

Table 4: Summary of runoff conditions during precipitation events at four Water and Sediment Control Basin monitoring locations under different growing conditions (March 2012 to September 2017).

Runoff Condition	Number of Events		
	Total	Growing Season[a]	Non-growing Season[b]
Flow	188	55	133
No-flow	184	117	67

[a] Growing season is defined as May 1 to September 30.

[b] Non-growing season is defined as October 1 to April 30.

In an attempt to relate crop conditions to flow and no-flow conditions (recognizing that growing season conditions were also relevant and potentially a confounding variable), the crop type was divided into eight (8) categories: corn, soybean, winter wheat, oat cover crop, corn residue, soybean residue, winter wheat stubble, and no cover (*i.e.*, bare soil).

A Fisher's exact test of independence was performed to evaluate the association between crop type and flow/no-flow conditions. A two-tailed Fisher's exact test is used to see whether the proportions of two or more categorical variables are statistically different from one another. The test is appropriate for contingency table analyses involving small sample sizes of less than 1,000 (McDonald 2014) as is the case in this study.

Two further tests, the odds ratio (OR) and one-tailed Fisher's exact test, were performed to evaluate the magnitude and directionality of association between crop types and flow/no-flow conditions. In this case, the OR explains how much more likely it is that flow will occur depending on crop type compared to when flow is not observed under similar conditions. The odds of an event occurring is the probability that the event will happen divided by the probability that the event will not happen. For instance, if the probability of flow occurring under corn residue is 75 percent and the probability that flow did not occur was 25 percent then the ratio would be 3:1 (*i.e.,* flow occurs three times more often than when flow is not generated). A *p*-value of less than 0.05 indicates that the association between crop type and flow condition is statistically significant. Conversely, a *p*-value greater than 0.05 suggests that there is not enough evidence to infer an association between crop type and flow condition (*i.e.,* flow is equally likely to occur as when flow is not generated).

3.3.2 Predicting Flow Occurrence

An added benefit of collecting flow/no-flow information, as well as meteorological data, is the ability to construct predictive models; however, it is not possible to conduct ordinary linear regression models when the response variable is binary and not continuous. A different approach is therefore necessary to accommodate this type of data. The purpose of this section is to present models for estimating the occurrence of flow in a WASCoB during a precipitation event under a variety of crop types. The following methods are adapted from Levin and Zarriello (2013) who developed models to predict irrigation water use in the eastern United States.

Logistic regression is a method for modelling the dependence of a binary response variable (denoted by either 1 or 0) on one or more explanatory variables, which can be a mix of continuous and categorical variables. Logistic regression equations were developed for each of the eight crop types to predict flow/no-flow conditions using data from the four WASCoB monitoring stations. Meteorological and hydrological data was used to investigate how flow (1) and no-flow (0) can be predicted by the amount of precipitation (0 to ∞) during the growing season (1) and non-growing season (0) in which antecedent moisture conditions were either wet (1) or dry (0). Antecedent moisture conditions were considered wet if the accumulated precipitation was greater than 2.5 millimetres within 72 hours of a precipitation event.

The model coefficients were determined using a bias-reducing logistic regression approach developed by Firth (1993). Firth's approach is appropriate to address the bias and small sample sizes of the parameter estimates in this study.

A general logistic regression equation for predicting the occurrence of flow in a WASCoB during a precipitation event is presented below in Equation 5.

Equation 5

$$P = \frac{1}{1 + e^{-(B_0 + B_1 \times PRCP + B_2 \times ANT\_CD + B_3 \times SESN)}}$$

Where,

P = probability of flow condition (ranges from 0 to 1)

e = base of the natural logarithm, equal to approximately 2.7183

B_0 = logistic regression intercept coefficient (log units)

B_1, B_2, B_3 = logistic regression independent variable coefficients (log units)

PRCP = total event precipitation (mm)

ANT_CD = antecedent moisture conditions (1 = wet, 0 = dry)

SESN = seasonal condition (1 = growing season, 0 = non-growing season)

In the event an independent variable is not appropriate for use in the model (e.g., seasonal condition) the term may be removed from the equation.

A variety of metrics were used to determine the fit and predictive accuracy of each logistic regression model. The model coefficients were tested for significance using Wald's test (p-values < 0.05 indicate that the explanatory variable is a good predictor of the response variable). A likelihood ratio chi-square test was used to determine the overall fit of the model compared to a simplified model without predictor variables (p-values < 0.05 indicate that the overall fit of the model is statistically significant). The strength of the model was evaluated using a pseudo R-square developed by McFadden (1974). McFadden's pseudo R-square is typically lower than traditional R-squared values. For instance, a value less than 0.2 indicates a weak relationship; 0.2 to 0.4 indicates a moderately strong relationship; and greater than 0.4 indicates an excellent relationship.

A probability cut-off (in this case the threshold for predicting the occurrence of flow) was determined for each model by plotting type I error (sensitivity) against type II error (specificity). Type I error occurs when an effect is detected that is not present, while type II error is failing to detect an effect that is present. The optimal cut-off value is found where the lines of sensitivity and specificity intersect (Figure 10). Computed probabilities equal to or greater than the cut-off represent events that generated flow and those less than the cut-off predict events that failed to generate flow. Overall accuracy of equations was determined by comparing the predictions of flow/no-flow occurrence and determining the percentage of correct predictions.

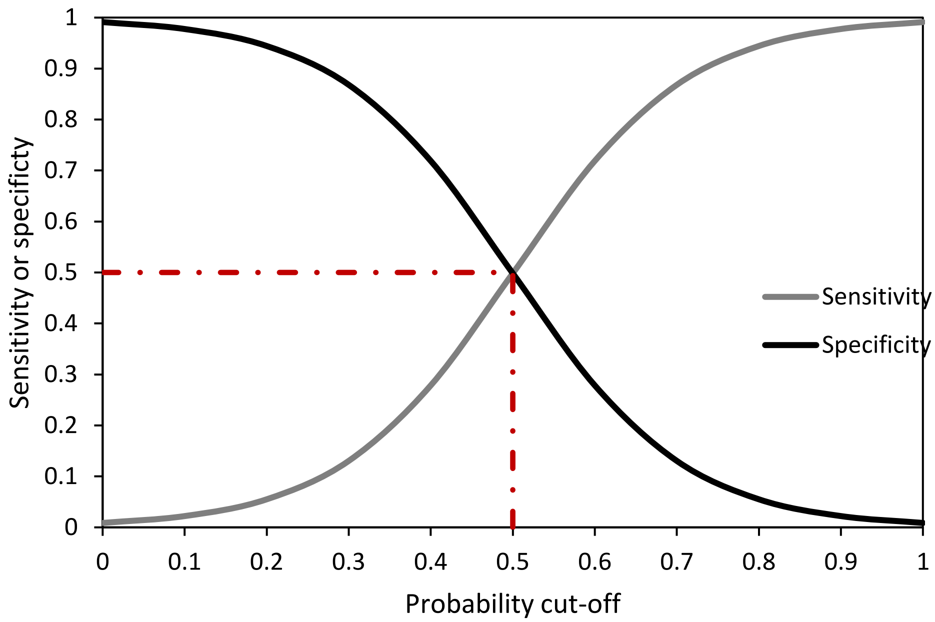

Figure 10: Sensitivity-specificity graph.

3.4 Results

3.4.1 Flow versus No-flow

Mean precipitation per event was 20.7 mm (range = 4.6 mm to 103.4 mm) during the growing season and 17.5 mm (range = 4.6 mm to 63.4 mm) during the non-growing season.

The two-tailed Fisher's exact test indicated that there was a strong association between crop type and the presence or absence of flow during precipitation events in the WASCoBs during the growing season (p<0.001) and non-growing season (p<0.001). Not surprisingly, flow was less likely to occur during the growing season when canopy cover is greatest and more likely to occur during the non-growing season when canopy cover is lowest (Figure 11).

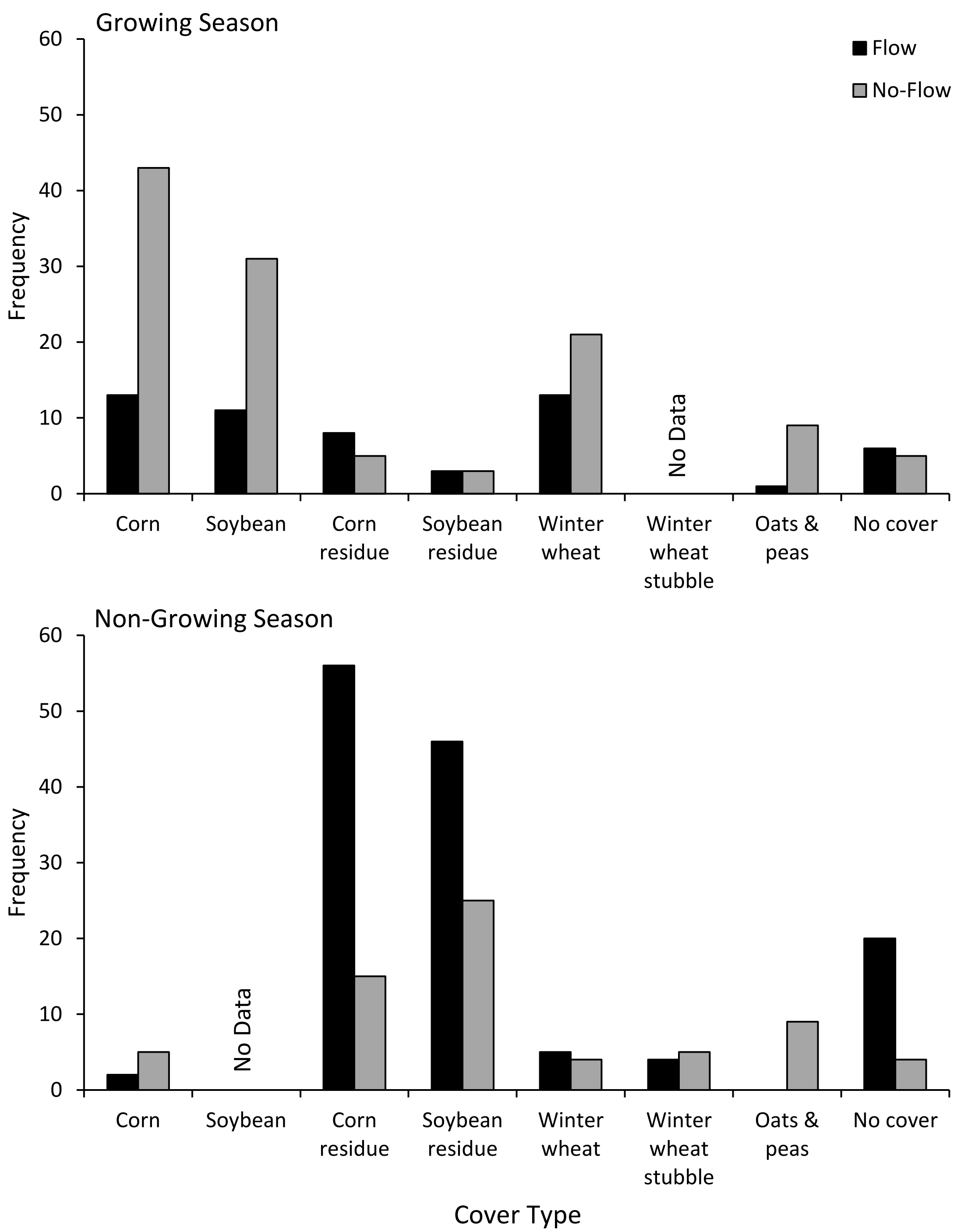

Figure 11: Frequency of flow/no-flow occurrences by cover type during the growing season versus the non-growing season at four Water and Sediment Control Basins (March 2012 to September 2017).

Some crop canopies were found to reduce flow potential. For instance, precipitation events during the non-growing season were about five times more likely to result in no-flow under corn (p=0.043) and more than nine times for oat cover crop (p<0.001) compared to when flow did occur (Table 5).

A significant relationship between flow occurrence and corn residue and no cover was evident. For instance, precipitation events were about three times more likely to generate flow under corn residue (p=0.004) and no cover (p= 0.047) compared to when flow was not observed during the non-growing season and four times more likely to generate flow under corn residue (p=0.022) during the growing season.

Table 5: Likelihood of flow by cover type during the growing and non-growing seasons at four Water and Sediment Control Basins (March 2012 to September 2017).

Growing conditions	Crop type	Ratio of flow to no-flow: Flow		Ratio of flow to no-flow: No-flow	One-tailed *p*-value	Implication
Growing[a]	Corn	1	:	1.9	*p*=0.061	Equally likely to generate flow
	Soybean	1	:	1.4	*p*=0.233	Equally likely to generate flow
	Winter wheat	1.4	:	1	*p*=0.274	Equally likely to generate flow
	Oat cover crop	1	:	4.5	*p*=0.114	Equally likely to generate flow
	Corn residue	3.8	:	1	***p*=0.022***	More likely to generate flow
	Soybean residue	2.2	:	1	*p*=0.291	Equally likely to generate flow
	Winter wheat stubble	1	:	2.6	*p*=0.142	Equally likely to generate flow
	No cover	2.7	:	1	*p*=0.096	Equally likely to generate flow
Non-Growing[b]	Corn	1	:	5.3	***p*=0.043***	Less likely to generate flow
	Soybean	-	:	-	-----	--
	Winter wheat	1	:	1.6	*p*=0.344	Equally likely to generate flow
	Oat cover crop	1	:	>9	***p*<0.001***	Less likely to generate flow
	Corn residue	2.5	:	1	***p*=0.004***	More likely to generate flow
	Soybean residue	1.1	:	1	*p*=0.461	Equally likely to generate flow
	Winter wheat stubble	-	:	-	-----	--
	No cover	2.8	:	1	***p*=0.047***	More likely to generate flow

[a] Growing season is defined as May 1 to September 30
[b] Non-growing season is defined as October 1 to April 30
* Statistically significant at α=0.05
--- No data available

3.4.2 Predicting Flow Occurrence

The logistic regression equations for corn, soybean, winter wheat, oat cover crop, corn residue, soybean residue, winter wheat stubble, and no cover were determined as follows:

Equation 6

$$P_{Corn} = \frac{1}{1+\ e^{-(-4.430+0.122\times PRCP+2.333\times ANT\_CD-0.624\times SESN)}}$$

Equation 7

$$P_{Soybean} = \frac{1}{1+\ e^{-(-2.753+0.060\times PRCP+1.281\times ANT\_CD)}}$$

Equation 8

$$P_{Winter\ wheat} = \frac{1}{1+\ e^{-(-0.607+0.032\times PRCP+0.666\times ANT\_CD-0.850\times SESN)}}$$

Equation 9

$$P_{Oat\ cover\ crop} = \frac{1}{1+\ e^{-(-2.916+0.049\times PRCP-0.622\times ANT\_CD+0.500\times SESN)}}$$

Equation 10

$$P_{Corn\ residue} = \frac{1}{1+\ e^{-(-2.776+0.215\times PRCP+2.651\times ANT\_CD-1.440\times SESN)}}$$

Equation 11

$$P_{Soybean\ residue} = \frac{1}{1+\ e^{-(-2.338+0.118\times PRCP+2.031\times ANT\_CD-2.470\times SESN)}}$$

Equation 12

$$P_{Winter\ wheat\ stubble} = \frac{1}{1+\ e^{-(-4.320+0.101\times PRCP+2.536\times ANT\_CD)}}$$

Equation 13

$$P_{No\ cover} = \frac{1}{1+\ e^{-(-0.515+0.091\times PRCP+2.007\times ANT\_CD-2.378\times SESN)}}$$

Goodness-of-fit statistics and predictive power were statistically significant for corn, soybean, corn residue, soybean residue, winter wheat stubble, and no cover (Tables A-1 to A-4). Fit and predictive power was not appropriate for winter wheat and oat cover crop likely due to small sample size and nature of the data (*e.g.,* only one runoff event occurred under oat cover crop during both seasons).

In general, the logistic regression equations predicted the occurrence of flow/no-flow reasonably well for statistically significant models. When precipitation, soil moisture conditions, and season were known, regression equation accuracies were greater than 85 percent for corn, corn residue, winter wheat stubble, and no cover. Regression accuracies were 81 percent for soybean and 78 percent for soybean residue. Refer to Tables A-1 to A-4 for additional model metrics.

In the future we intend to evaluate the models by comparing the probability of flow occurrence between different cover types under similar precipitation, soil moisture, and seasonal conditions. For instance, we could determine the likelihood that flow will occur for corn residue versus for soybean residue if 20 millimetres of rain falls in the non-growing season when antecedent moisture conditions are wet. For this purpose, we may be able to distinguish which crop types are more or less likely to generating flow compared to other crop types. Additionally, pollutant loads should be related to the different types of cover to begin to appreciate the association of water quality with cover conditions.

4.0 Water and Sediment Control Basin Evaluation

Water and Sediment Control Basins (WASCoBs) hold back surface water runoff in headwater areas. This has been demonstrated to reduce sediment and nutrient loading into watercourses (Harmel *et al.*, 2008, Makarewicz *et al.*, 2009, Stuart *et al.*, 2010). Water quantity and quality was monitored at a WASCoB location near the Gully Creek watershed, as well as three berms and a tile station in Gully Creek, to determine the influence on the magnitude of peak flows and nutrient and sediment loads during runoff events.

4.1 Field Monitoring Methods

In addition to the level loggers installed in the four berms (see Section 3.2), a level logger was also installed in the tile located on the north-west side of the monitored field and recorded stage data from November 1, 2012 to September 30, 2017. All stage data was converted to outflow using a series of pipe flow and stage-storage equations (see Wilson 2016).

4.2 Data Analysis Methods

4.2.1 Peak Flow Analysis

Peak flow characteristics were evaluated for monitored runoff events at a WASCoB in Gully Creek (DFTEL-B2). The outlet tile was 200 millimetres in diameter with a slope of approximately 1 percent. As a result, the outflow rate was limited to a maximum drainage capacity of 24 litres per second. Reductions in peak flow between inflow and outflow were calculated by finding the difference in the peak inflow rate and the peak outflow rate of each runoff event. Inflow and outflow rates were determined by following the methods described by Wilson (2016). A total of 74 events were captured at the WASCoB for the period June 2013 to September 2017. Differences between inflow and outflow rates were tested with a Wilcoxon Signed Rank Test (the non-parametric equivalent of a paired t-test).

4.2.2 Mass Loads and Flow-Weighted Mean Concentrations

Water samples were collected from the hickenbottom outlet in each of the ponding areas with an ISCO sampler and were analyzed for nutrient and sediment concentrations. Water samples were also collected in the tile monitoring station. Water quality data were captured for 26 of the 99 events that had a measurable stage response in the WASCoB outside of Gully Creek, while water quality data were collected for up to 16 of the 89 events in the Gully Creek WASCoBs (Table 6). For comparison, 16 flow events at the tile station were captured that match the same events measured in the three Gully Creek WASCoBs. Some events were missed because equipment had to be removed to accommodate farm field work. At other times, there were equipment malfunctions, especially during the winter months.

Table 6: Summary of water quality monitoring efforts at four WASCoBs and a tile monitoring station.

Monitoring Station ID	Drainage Area (ha)	No. of Samples	No. of Sampled Events	Monitoring Period
DFTELB2	4.64	64	16	July 2014 - Sept 2017
DFTELB3	3.14	58	13	July 2014 - Sept 2017
DFTELB5	3.62	49	10	June 2015 - Sept 2017
DFTILE1	18.81	77	16	July 2014 - Sept 2017
KVBAY-HB	12.14	130	26	March 2012 - Sept 2017

Loads and flow-weighted mean concentrations were calculated for all monitored events at the four berms as well as the tile station using a linear interpolation method (see Equations 1–3).

4.3 Results

4.3.1 Peak Flow Analysis

Reductions in the peak flow rate into and out of the basin occurred on all 74 occasions, with a mean of 56 percent and ranging between 1 and 97 percent (Figure 12). The peak outflow rate is largely driven by the size of the outlet tile. As a result, the median inflow rate was significantly higher than the median outflow rate (p<0.001). Reductions in peak flow appear to be related to the amount of runoff generated during an event. Minor reductions in peak flow (*e.g.*, less than 20 per cent) tended to coincide with small runoff events, while the largest reductions occurred when water in the basin was at full capacity. These results align closely with those from a peak flow analysis of KVBAY-HB in which the range of peak flow reduction was also between 1 and 97 percent over 59 runoff events (see Bittman *et al.* 2016).

By holding back surface water runoff we would expect to see a decrease in erosion potential and removal of suspended solids and nutrients from the runoff waters. Evidence of decreases in sediment loads and some nutrient loads due in part to peak flow reductions in a WASCoB (KVBAY-HB) are presented in the Loads Results section of Bittman *et al.* (2016). Significant improvements in the quality of surface runoff were observed as it entered the WASCoB before exiting the field through a hickenbottom outlet in the basin. For instance, phosphate-P, TP, and suspended solids loads declined between the WASCoB inflow and outflow by an average of 35, 24, and 65 percent, respectively, over 14 runoff events. The differences between the inflow and outflow were statistically significant for phosphate-P (p=0.023) and for each of TP and suspended solids (p<0.01). By contrast, nitrate-N loads more often increased between the inflow and outflow, although the differences for nitrate-N were not statistically significant (p=0.347).

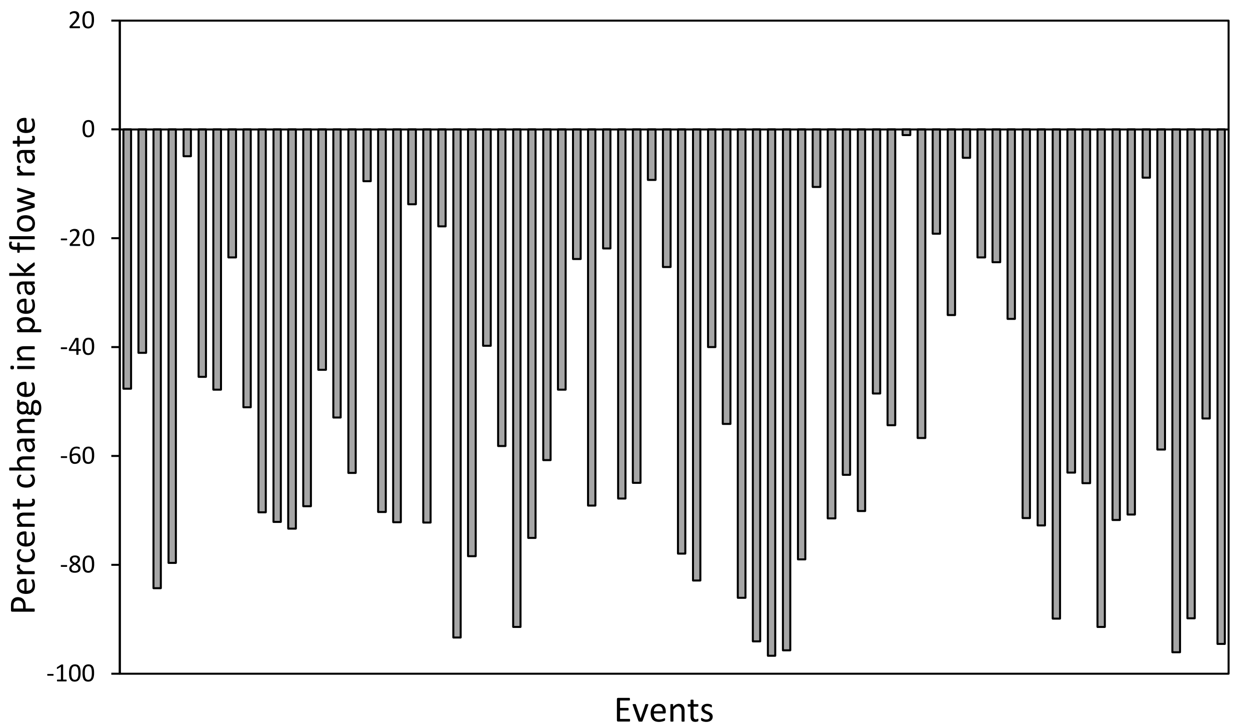

Figure 12: Percentage change in peak flow rates between inflow and outflow runoff from a Water and Sediment Control Basin (June 2013 to September 2017).

4.3.2 Mass Loads and Flow-Weighted Mean Concentrations

Loads and flow-weighted mean concentrations (FWMC) were calculated for only 11 to 29 percent of the events that generated measureable stage at all monitored berms and the tile station. It is important to note that because these are working agricultural fields, we often have to remove water sampling equipment to accommodate planting, harvesting and other field crop activities.

Across all monitored berms and the tile station, nitrate-nitrogen mass export coefficients ranged from less than 0.01 to 21 kilograms per hectare (Table 7). Phosphate-phosphorus mass export coefficients ranged from less than 0.01 to 0.70 kilograms per hectare. Total phosphorus mass export coefficients ranged from less than 0.01 to 1.03 kilograms per hectare. Suspended solids mass export coefficients ranged between 0.14 and 1,370 kilograms per hectare.

Station DFTEL-B5 appeared to have the highest mean loads for most water quality indicators; however, statistical analyses were not performed to determine if these differences were significant.

Table 7: **Mean (and range) mass export coefficients in three Gully Creek WASCoBs and a tile station (July 2014 to September 2017) and one WASCoB outside of Gully Creek (March 2012 to September 2017).**

Monitoring Station ID	Water Quality Indicator			
	Total Phosphorus (kg/ha)	Phosphate-Phosphorus (kg/ha)	Total Suspended Solids (kg/ha)	Nitrate-Nitrogen (kg/ha)
DFTEL-B2	**0.15** (0.01–0.48)	**0.04** (<0.01–0.48)	**42** (3–120)	**1.77** (<0.01–15.80)
DFTEL-B3	**0.14** (0.01–0.36)	**0.03** (<0.01–0.06)	**124** (4–491)	**0.60** (0.01–6.37)
DFTEL-B5	**0.30** (0.02–0.75)	**0.04** (<0.01–0.10)	**233** (5–1,127)	**2.38** (0.01–20.77)
DFTILE1	**0.05** (<0.01–0.13)	**0.01** (<0.01–0.03)	**25** (1–113)	**1.10** (0.12–10.15)
KVBAY-HB	**0.13** (<0.01–1.03)	**0.06** (<0.01–0.70)	**111** (<0.2–1,370)	**0.91** (<0.01–5.88)

Across all monitored berms and the tile station, nitrate-nitrogen FWMC ranged between 0.14 and 83 milligrams per litre (Table 8). Phosphate-phosphorus FWMC ranged from 0.02 to 2.13 milligrams per litre. Total phosphorus FWMC ranged between 0.08 and 20.24 milligrams per litre. Suspended solids FWMC ranged between 17 and 26,894 milligrams per litre.

Station KVBAY-HB appeared to have the highest mean FWMC for all water quality indicators; however, statistical analyses were not performed to determine if these differences were significant.

Table 8: **Mean (and range) flow-weighted mean concentrations in three Gully Creek WASCoBs and a tile station (July 2014 to September 2017) and one WASCoB outside of Gully Creek (March 2012 to September 2017).**

Monitoring Station ID	Water Quality Indicator			
	Total Phosphorus (mg/L)	Phosphate-Phosphorus (mg/L)	Total Suspended Solids (mg/L)	Nitrate-Nitrogen (mg/L)
DFTEL-B2	**0.56** (0.12–1.18)	**0.15** (0.02–0.79)	**188** (18–493)	**5.52** (0.32–39.67)
DFTEL-B3	**1.53** (0.30–5.75)	**0.32** (0.06–1.29)	**1,855** (109–15,096)	**4.30** (0.14–32.84)
DFTEL-B5	**0.83** (0.21–1.31)	**0.12** (0.03–0.25)	**516** (92–1,931)	**4.98** (0.17–35.60)
DFTILE1	**0.31** (0.08–0.60)	**0.11** (0.05–0.31)	**159** (17–535)	**7.53** (0.93–42.60)
KVBAY-HB	**2.25** (0.11–20.24)	**0.49** (0.03–2.13)	**2,348** (42–26,894)	**12.96** (0.20–83.33)

5.0 Conclusions

Overall, watershed-scale monitoring showed that it is difficult to link changes in stream water quality to the implementation of BMPs. Long-term monitoring of high-flow water quality – with concurrent collection of climate, slope, soil, and land use and management information – will be necessary to evaluate the range of BMP effectiveness. However, it may be that the effectiveness of the different BMPs are overwhelmed by precipitation events and that other landscape factors (e.g., soil antecedent conditions, land management activities in other areas of the watershed) may overwhelm the improvements at the watershed scale.

A helpful framework for thinking about the role of the agronomic BMPs was proposed by Tomer *et al*. (2013). Implementing a hierarchy of BMPs has been the suggested approach to reduce sediment and nutrient loss. Practices that cover the soil and build soil health are a most important first step to reduce sediment and nutrient loss. Through our continued watershed and field scale evaluations, we challenged to have equipment in place to measure before and after agronomic BMP implementation (*e.g.,* converting a cropped field to a hay field). The implications of the change in land management, in this case from a cropped field to a hay field extend to the downstream channel. Without the excess water, there is potential for there to be reduced downstream channel erosion. Changes in water flow over multiple fields throughout a watershed are difficult to capture with traditional monitoring techniques.

We continue to find it difficult to measure the effectiveness of the management practices such as cover crops, nutrient management, and conservation tillage at the field-edge. Although, we have made some understanding about the type of response we might be able to expect at the field edge. We think that the collection of flow/ no-flow information over different precipitation regimes with different crops and management practices should help to explain some background variability that should make the effectiveness of the BMPs more understandable. We have found that large runoff volumes and/or pollutant loads tend to occur during extreme events that result from a combination of contributing factors (*i.e.*, precipitation, soil moisture conditions, and recent land management practices). However, the particular combinations of conditions that result in extreme events are not predictable. We need more data from our WASCoB monitoring locations over time (with rotating crop conditions) and comparable data from other locations over time. Building a more comprehensive dataset may help to identify patterns in the conditions that generate higher runoff volumes and practices that ameliorate the flow generating conditions.

Measuring the effectiveness of the structural BMPs, particularly WASCoBs has been more easily accomplished. In this current study and in Bittman *et al.* (2016), we have documented decreases in peak flows in the basins. There has also been some suggestion of reduced loads of phosphorus and sediments within the basin.

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7.0 Appendix

Table A-1: Summary statistics for logistic regression equations developed to predict flow/no-flow for two *canopy types* at four Water and Sediment Control Basins (March 2012 to September 2017).

	Corn				Soybean		
	Intercept	**PRCP**	**ANT_CD**	**SESN**	**Intercept**	**PRCP**	**ANT_CD**
Model variables, coefficient values, and statistical significance							
Model coefficients (log units)	-4.430	0.122	2.333	-0.624	-2.753	0.060	1.281
Standard error	1.45	0.04	0.98	0.97	0.86	0.03	0.81
Wald's test *p*-value	0.003	0.002	0.020	0.522	0.003	0.044	0.120
Goodness-of-fit metrics of the model							
Likelihood ratio test *p*-value	<0.001				0.012		
McFadden's pseudo R-square	0.41				0.18		
Predictive accuracy of the model							
Sample size	63				42		
Optimal probability cut-off	0.4				0.3		
Percent of correct predictions	89				81		

PRCP = precipitation
ANT_CD = antecedent moisture conditions
SESN = seasonal condition

Table A-2: Summary statistics for logistic regression equations developed to predict flow/no-flow for two *canopy types* at four Water and Sediment Control Basins (March 2012 to September 2017).

	Winter wheat				Oat cover crop			
	Intercept	**PRCP**	**ANT_CD**	**SESN**	**Intercept**	**PRCP**	**ANT_CD**	**SESN**
Model variables, coefficient values, and statistical significance								
Model coefficients (log units)	-0.607	0.032	0.666	-0.850	-2.916	0.049	-0.622	0.500
Standard error	0.96	0.03	0.67	0.79	1.53	0.07	1.99	1.61
Wald's test *p*-value	0.528	0.325	0.326	0.291	0.077	0.518	0.758	0.761
Goodness-of-fit metrics of the model								
Likelihood ratio test *p*-value	0.358				0.988			
McFadden's pseudo R-square	0.06				0.02			
Predictive accuracy of the model								
Sample size	43				19			
Optimal probability cut-off	0.4				0.2			
Percent of correct predictions	67				95			

PRCP = precipitation
ANT_CD = antecedent moisture conditions
SESN = seasonal condition

Table A-3: Summary statistics for logistic regression equations developed to predict flow/no-flow for two *residue types* at four Water and Sediment Control Basins (March 2012 to September 2017).

	Corn residue				Winter wheat stubble		
	Intercept	**PRCP**	**ANT_CD**	**SESN**	**Intercept**	**PRCP**	**ANT_CD**
Model variables, coefficient values, and statistical significance							
Model coefficients (log units)	-2.776	0.215	2.651	-1.464	-4.320	0.101	2.536
Standard error	1.05	0.07	0.74	0.88	2.93	0.07	2.314
Wald's test *p*-value	0.010	0.003	0.001	0.098	0.191	0.183	0.315
Goodness-of-fit metrics of the model							
Likelihood ratio test *p*-value	<0.001				0.016		
McFadden's pseudo R-square	0.40				0.67		
Predictive accuracy of the model							
Sample size	84				9		
Optimal probability cut-off	0.6				0.5		
Percent of correct predictions	87				100		

PRCP = precipitation
ANT_CD = antecedent moisture conditions
SESN = seasonal condition

Table A-4: Summary statistics for logistic regression equations developed to predict flow/no-flow for two *residue types* at four Water and Sediment Control Basins (March 2012 to September 2017).

	Soybean residue				No cover			
	Intercept	**PRCP**	**ANT_CD**	**SESN**	**Intercept**	**PRCP**	**ANT_CD**	**SESN**
	Model variables, coefficient values, and statistical significance							
Model coefficients (log units)	-2.337	0.118	2.031	-2.470	-0.515	0.091	2.007	-2.378
Standard error	0.80	0.04	0.61	1.37	1.25	0.07	1.13	1.10
Wald's test *p*-value	0.005	0.002	0.001	0.075	0.682	0.190	0.086	0.038
	Goodness-of-fit metrics of the model							
Likelihood ratio test *p*-value	<0.001				0.007			
McFadden's pseudo R-square	0.25				0.31			
	Predictive accuracy of the model							
Sample size	77				35			
Optimal probability cut-off	0.55				0.6			
Percent of correct predictions	78				86			

PRCP = precipitation
ANT_CD = antecedent moisture conditions
SESN = seasonal condition