ASSESSING THE EFFECTIVENESS OF RESIDENT WATER QUALITY IMPROVEMENT PRACTICE ADOPTION ON NON-POINT SOURCE POLLUTION ACROSS URBAN-TO-RURAL LANDSCAPES IN NW INDIANA

by

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Soli Deo Gloria.

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ABSTRACT

Effective control of nonpoint source (NPS) pollution is critical for the long-term health of freshwater ecosystems. Previous research has focused primarily on the implementation of best management practices (BMPs) to reduce NPS pollution from agricultural or urban land uses. However, there is a critical need to incorporate landowner willingness to adopt BMPs to more accurately quantify the cumulative water quality improvement potential at the watershed scale. This project sent out 2866 surveys to ascertain the background knowledge and likely adoption levels of various BMP types by residents within the East Branch—Little Calumet River and Trail Creek watersheds in Northwest Indiana. The survey divided the population into 5 resident groups including urban, suburban, rural residential, row crop agricultural, and pastural. Loads of nitrogen (N), phosphorus (P), and sediment generated from these resident groups were quantified with the Generalized Watershed Loading Function – Enhanced (GWLF-E) hydrologic model under BMP implementation scenarios guided by the survey responses. Results show that row crop agriculture and urban land uses generated the greatest amount of N (54-75%) and sediment (37-62%) in these watersheds, respectively. Cover crops were the greatest reducer of watershed N (14.4-20.6%) and TP (6.0-15.9%) under full implementation. However, application to the likely adoption level (27.8%) of cover crops generated only 6.5-9.3% of N and 2.7-7.1% P reduction. Porous pavement was the most effective sediment reducing practice (12.0-12.7%), but the low level of likely adoption (3.7%) allowed only 0.4-0.5% reduction of watershed sediment. Resident group area, loading rates, background knowledge levels, and location within the watershed are shown to be important considerations for BMP selection and education efforts by watershed managers to improve water quality.

1. INTRODUCTION

The ways that humans interact with the natural and constructed landscapes around them has a pronounced effect on the quality of our water resources (USEPA, 2001a). Regions surrounding the United States-Canadian Great Lakes, especially the Corn-Belt states, have large metropolitan areas adjacent to major water bodies and a high density of surrounding row crop agriculture and pastureland. Although the implementation of the Clean Water Act (CWA) and the Great Lakes Water Quality Agreement (GLWQA) in 1972 have both effectively combatted point source pollution (Botts et al., 2018; Charlton et al., 1993; De Pinto et al., 1986), NPS pollution still remains the major driver of water quality problems to rivers, lakes, and coastal regions in the U.S. (Baker, 1992; Humenik et al., 1987). Of particular concern with NPS pollution is excess nutrient (nitrogen & phosphorus) inputs which fuel eutrophication and can lead to toxic algal blooms, oxygen depletion, loss of aquatic biodiversity, degradation of water quality for human use and consumption, and various other ecosystem services losses (Carpenter et al., 1998; Scavia et al., 2014). Approximately 21% of the lakes, ponds, and reservoirs are listed as hypereutrophic while 18% of the coastal waters (including the Great Lakes) are listed as having poor biological conditions (USEPA, 2017). What makes NPS pollution so difficult to treat is the diffuse nature of nutrient source locations and the diverse forms of nutrient loading that occur in a watershed. For mixed land-usage watersheds in particular, the heterogeneity of land cover throughout the watershed makes the tracking of nutrient sources even more difficult (USEPA, 1993, 2001b). however, the ability to accurately predict the nutrient and sediment loading from mixed land usage watersheds is crucial for effective water resource management.

The use of watershed models to predict the generation, transport, and loading of NPS pollution has been an increasingly common for watershed managers. Previous research with these models has focused on the effects of land use (Chiang et al., 2010; Liu et al., 2015c; Soranno et al., 1996) and climate change (Bosch et al., 2018; Chang et al., 2001; Liu et al., 2016b) on water quality. To combat future NPS pollution, methods for the identification of critical source areas that produce disproportional loads have been created for these models (Niraula et al., 2013; Tim et al., 1992) to direct the use of stormwater best management practices (BMPs) or agricultural conservation practices.

The incorporation of BMPs into watershed models has allowed researchers in the Great Lakes regions to estimate NPS pollutant mitigation through implementation of these practices (Bosch et al., 2013; Scavia et al., 2017). Methods of determining the most effective treatment approach in these studies has involved scenario testing of singular or multiple BMPs in different combinations or intensity. Optimization tools for determining the most cost-effective treatment strategy have also been developed for use in modeling studies (Gitau et al., 2006; J. G. Lee et al., 2012; Maringanti et al., 2009; Veith et al., 2003). Determination of BMP implementation scenarios in these studies were based on physical site characteristics or estimated adoption potential from local conservation officials. However, these approaches have failed to account for the landowner perspective. While there have been multiple studies into the values or concerns of residents with regards to BMP adoption (Brown et al., 2016; Gao et al., 2018; Greiner et al., 2009; Smith et al., 2007), as well as investigation into the perceived barriers or concerns with the institutions directing environmental conservation (Dhakal & Chevalier, 2017; Kalcic et al., 2014; Palm-Forster et al., 2016a; Roy et al., 2008)there has been limited translation of these factors into watershed modeling approaches. Studies that have included resident adoption of BMPs have used conservation workshops or conservation (i.e. reverse) auctions to inform implementation scenarios and incorporate resident suggestions to more accurately reflect current conditions and guide future modeling efforts (Hassanzadeh et al., 2019; Kalcic et al., 2016; Palm-Forster et al., 2016b). The results from these studies showed that stakeholder levels of BMP adoption are insufficient to meet water quality goals and funding should be directed towards projects that maximize the cost-effective reduction of NPS pollutants. Determination of the most cost-effective practices needs to be made at the field-scale and applied to a high extent to achieve the greatest load reduction for the watershed. It is important to allow stakeholders to engage with the model so that current practices and field conditions are most accurately reflected in the model. Bidding methods need to be conducted in a simple, straightforward manner that prevents landowners from deeming themselves ineligible. Once the most cost-effective approaches to NPS mitigation are determined, incentives should be given to residents in a manner that has the lowest transaction costs and a well-defined order of goals is needed to avoid trade-offs from trying to meet multiple objectives. In these studies, stakeholder participation was limited and only included farm owners and rural residents.

Incorporating the willingness of a greater population of residents to adopt conservation practices and quantifying the water quality improvements is needed at the watershed scale. There is also a need to understand how NPS loads vary amongst different resident groups and how familiar different resident groups are with various BMPs. To fill this gap, my research used survey and modeling approaches to analyze the effect of land use and best-management practice adoption on water quality in two mixed land use watersheds in northwest Indiana. The first goal of this research was to identify the current levels of nutrient (N and P) and sediment loads generated amongst different resident groups. These resident groups included farmers, rural residents, and homeowners living in different types of communities. Secondly, I determined which BMPs generated the greatest NPS pollutant reduction for each resident group. Third, I quantified the effect that resident willingness to adopt BMPs had on watershed scale reduction and compared it to the maximum potential BMP application rate in each resident group to the reduction if BMP would only be applied to the level that residents were willing to adopt. Lastly, I utilized the results goals to recommend which BMP-resident group relationships should be of focus of education and outreach by watershed planners to achieve greater levels of NPS pollutant reduction.

2. REVIEW OF THE LITERATURE

2.1 Background

Since the enactment of the Clean Water Act (CWA) in 1972, greater emphasis has been placed on the prediction of contaminant transport and delivery into receiving waters. Engineers and scientists have increasingly used computer models to predict contaminant fate and transport through erosion-deposition processes, rainfall-runoff dynamics, open-channel flow, groundwater flow, nutrient sorption/desorption, and biological decay. With increasing anthropogenic impact through modification and deterioration of the natural environment, these models have been used to help environmental managers and planners predict changes in contaminant generation, transport, and accumulation as well as understanding the effects of management practices on contaminant mitigation. The motivating factor behind this research project is compliance with Section 303(d) of the CWA which requires designation of impaired water bodies and development of Total Maximum Daily Loads (TMDLs) with the goal of reducing contamination in these water bodies below acceptable conditions. This review will examine research into modelling efforts to target NPS pollution sources, identify the scope of BMP treatment scenarios within hydrologic models, the societal acceptance of BMP adoption, and modelling efforts to incorporate resident willingness to adopt BMPs.

2.2 Predicting Watershed Pollutant Loads

There is a need for modern day water quality modelling methods to direct watershed stakeholders and planners with present and future resource allocation. Many recent modeling studies have focused on analyzing the effects of humans on the natural environment so that stormwater management projects can be focused on the proper types and placement of BMPs. With a growing population and migration towards urban environments (Grimm et al., 2008), there has been increased efforts to quantify the effects of future land-use change on watershed loading (Chiang et al., 2010; Liu et al., 2015c; Soranno et al., 1996; Xu et al., 2013). These studies have shown that conversion of forested lands into agricultural or urbanized environments are generating greater runoff, sediment, and nutrient loads with impervious features replacing vegetation. The effects of greenhouse gas emissions leading to changes in the climate are also prompting experts to predict the effects of changing temperature and rainfall events into watershed loads (Bosch et al., 2018; Chang et al., 2001; Liu et al., 2016b). Elevated temperatures, greater precipitation, and higher storm intensity are predicted to increase the financial resources required to combatting NPS pollution. The need for more effective stormwater management has promoted research into identifying critical source areas (CSAs) of NPS pollution. Modelling studies have used various tools to divide watersheds into smaller hydrologic response units (HRUs) that have similar site characteristics. Calculating the HRUs that have the highest load rates and greatest level of hydrologic connectivity have allowed modelers to pinpoint CSAs throughout full watersheds (Giri et al., 2016; Niraula et al., 2013; Tim et al., 1992).

2.3 Quantifying Pollutant Reduction through BMP Implementation

Several hydrologic and/or water quality models such as SWMM (Rossman, 2015), L-THIA-LID (Liu et al., 2016a), GWLF-E (Evans and Corradini, 2016; Haith et al., 1992), STEPL (Tetra Tech, 2018) and SWAT (Arnold et al., 2012) have included the capability of quantifying the effects of stormwater BMPs and agricultural conservation practices on reducing contaminant loads. Water quality and contaminant loading studies using these models have varied in scale from induvial sites or fields (Gao et al., 2015; Gitau et al., 2004; Jia et al., 2012; Merriman et al., 2019) up to entire watersheds (Bosch et al., 2013; Chaubey et al., 2010; Liu et al., 2015b; Scavia et al., 2017) for individual or multiple contaminants of concern. The majority of these watershed-scale studies quantify the reduction of either urban or agricultural practices but will typically not model both categories outright or to the same level of specificity. For example, some of studies that focus on agricultural BMPs will include an assortment of structural or cultural management practices that individually or jointly treat cropland regions, but only have a generic point source reduction that would include urban areas (Bosch et al., 2013; Scavia et al., 2017).

Water quality models that can simulate BMP application are commonly used in scenario-testing studies where current loading rates and already implemented management practices are compared to future scenarios with increased BMP presence. Obtaining information about currently implemented practices can be difficult, so many studies have limited practices or assume no current application (Her et al., 2016; Scavia et al., 2017). Scenario testing in agricultural regions typically include various individual or combined BMP trials that have multiple implementation levels up to the full expanse of cropland. Without known BMP locations, studies have tested scenarios with random implementation and targeted implementation into the regions of the watershed that generate disproportionally high contaminant loads (Bosch et al., 2013; Scavia et al., 2017; Teshager et al., 2017). These targeting approaches show more potential reduction than randomized testing and shows the need for careful consideration amongst stormwater managers in funding BMP projects throughout their watersheds. Considerations of limited resources and site-specific criteria to obtain maximum contaminant reduction has also led to the development of optimization tools and procedures for BMP placement (Gitau et al., 2006; J. G. Lee et al., 2012; Maringanti et al., 2009; Veith et al., 2003). These optimal implementation scenarios directed to more efficiently reduce watershed contamination are limited to factors such as existing NPS load, BMP reduction potential, cost of practice, and physical site characteristics.

2.4 Societal Willingness to Adopt BMPs

Engaging stakeholders with the goal of managing NPS pollution requires and understanding of their current knowledge of BMPs and the factors that motivate or dissuade them from adopting the practices. The desire to adopt BMPs stems from a growing sense of environmental stewardship and recognition of the benefits of these practices (Gao et al., 2018; Greiner et al., 2009; Kalcic et al., 2014; Smith et al., 2007). Although a desire to protect the environment is a shared concern, stakeholders in urban and agricultural landscapes can have different factors preventing adoption.

A major factor opposing the adoption of BMPs in agricultural regions is the monetary risk associated with implementation. Replacing or preserving viable cropland or pastureland with a conservation practice comes with capital losses (i.e. opportunity costs). Funding conservation practices through programs such as EQIP or the CRP are designed to help offset these opportunity costs but are not always obtainable to farmers applying for funding. While it has been shown that financial assistance is not the decisive factor in the adoption of BMPs, it is viewed an important promoter of adoption (Kalcic et al., 2014). Several major risks faced by farmers are concerns with improving or maximizing productivity, reducing farm debt, maximizing profitability, intensifying production systems in the face of rising input costs, changing environmental regulation, growing fear of drought or reduced access to water, and increasing competition (Greiner et al., 2009). In such instances the adoption of BMP’s will include a variety of factors including farm size, crop type(s), tenure, net income, and level of debt (Clearfield & Osgood, 1986).

Concerns about practice implementation in urban areas centers around a lack of familiarity with the different types of available BMPs. In the study performed by Gao et al. (2018), urban residents were participated in a social survey aimed at understanding the various concerns and motivating factors when considering implementation of rain gardens and rain barrels. This research found that amongst those with moderate levels of familiarity the top three concerns about these practices were their capacity to install and maintain the practice as well as possessing adequate amounts of time to maintain the practice. Along with various aesthetic concerns about these BMPs, increased levels of knowledge and familiarity with these practices reduced the level of concern and had higher levels of promotion that these practices should be required in new construction projects and areas of higher imperviousness. Disruption of property for construction and concerns of the suitability of their property have also prevented homeowners from applying for BMP adoption (Brown et al., 2016; Gao et al., 2018).

The concerns about BMP adoption surrounding individual capacity to properly implement these practices is further backed by a concern or distrust of the institutional goals and framework for stormwater management. Farmers have expressed concerns over government control and their objectives for conservation (Kalcic et al., 2014; Smith et al., 2007). At the institutional level, the multiplicity of actors within the realm of stormwater management make the translation of conservation knowledge and objectives difficult. Conservation with fragmented responsibilities being placed amongst various actors within a single watershed, complex policy and governance barriers, and limited extension or outreach hinders integration of conservation knowledge and successful implementation (Chaffin et al., 2016; Dhakal & Chevalier, 2017; Roy et al., 2008). Supplementing this with overly complicated methods of funding applications and unclarity with the selection criteria of governing bodies hinders residents from submitting requests for BMP financing (Brown et al., 2016; Palm-Forster et al., 2016a; Palm-Forster et al., 2016b).

2.5 Current Efforts to Incorporate Resident BMP Adoption in Modeling Studies

Multiple efforts have been made to incorporate the willingness of stakeholders to adopt BMPs into water quality modeling (Hassanzadeh et al., 2019; Kalcic et al., 2016; Palm-Forster et al., 2016b). The methods of gathering information about potential BMP adoption from stakeholders varied in these studies and comprised of mailing surveys to the public, interviewing landowners, meeting with conservation staff, operating conservation workshops, and performing conservation auctions. Each of these tools were then used to generate water quality model implementation scenarios in diverse ways. In the research performed by Palm-Forster et al. (2016b), conservation (reverse) auctions were used to direct BMP funding and application to bids from farmers that had the highest ratio of phosphorus reduction to cost of implementation. The practices funded by winning bids were the only modeled management practices in tandem with known, existing BMPs. This method received very low participation (around 1%) due the perceived complexity of the bid submission, ineligibility due to existing BMPs or rental agreements, or incapability of submitting a winning bid.

The most common method of engaging with the community was to host workshops where communication of conservation goals and identification of potential levels of BMP implementation would be discussed amongst various stakeholders. The research performed by Kalcic et al. (2016) included two sets of workshops with stakeholders to identify the most critical management practices, develop implementation scenarios, and alter initial BMP performance before the final modeling exercise. The stakeholders engaged in this study included mostly government officials or non-government organization officials with a few, presumably large-scale farmers. The expert opinion of these stakeholders was used in the designation of desired BMP practices and level of implementation, along with practice-implementation combinations that they deemed “feasible”. Application of BMPs to these projected feasible degrees never achieved enough water quality improvement to meet target levels. Hassanzadeh et al. (2019) built upon this work by focusing on engagement with local farmers and rural residents on their perceptions of BMP implementation. This research also included a post-model survey in which the stakeholders could identify desired manners in which the results BMP modeling studies can be presented to them as well as identifying other types of information they would like to see from these studies. In both studies the number of participants were limited.

2.6 Conclusions

It is apparent that a greater level of inclusion with stakeholders is needed to properly allocate stormwater management resources. A management approach where governing bodies identify and try to impose management approaches can lead to a high level of resistance from landowners. Although local conservation experts may have a general sense of what level of management is possible, landowners have a higher level of specific knowledge and dominion with regards to their own property. A bottom-up societal approach where the knowledge and concerns of individual stakeholders about BMP implementation would give local officials a better since of the required outreach and education needed to mitigate NPS pollution. Combining this with a top-down modeling approach where the CSAs with watersheds are identified can direct local officials of the specific region-BMP combinations that should be promoted. This modeling approach will need the capability to simulate the mitigation potential of BMPs over multiple land uses. Not all watersheds are solely comprised of agricultural lands and with increasing urbanization, stormwater planners will need to be prepared to manage a variety of concerns and understand the differing dynamics of urban and rural NPS pollution.

3. MATERIALS AND METHODS

3.1 Study Areas

This study was conducted in the East Branch – Little Calumet (HUC 0404000104) and Trail Creek (HUC 0404000101) watersheds in northwest Indiana. Both the East Branch-Little Calumet (EBLC) River and Trail Creek (TC) watersheds are composed of multiple land uses, have agricultural and forested headwaters, and drain into developed regions before ultimately reaching the southeastern portion of Lake Michigan (Figure 1). Both watersheds are very similar in size and land use distribution (Table 1). In 2004, the TC watershed was issued a TMDL for E. Coli, which was soon replicated in 2005 in the Portage-Burns Waterway that lies in the northeastern portion of the EBLC watershed. The primary contaminants of concern in both watersheds include E. Coli, sediment, and nutrients (N & P).

Table 1. Modified land use distribution of EBLC and TC Watersheds from the 2011 NLCD dataset.

Land Uses	EBLC		TC	
	Area (ha)	Distribution (%)	Area (ha)	Distribution (%)
Water	118.7	0.6	49.7	0.3
Forest/Wetland	8,334.9	43.5	7,554.5	49.2
Pasture	883.1	4.6	710.0	4.6
Cropland	3,843.6	20.1	2,182.0	14.2
Suburban	2,470.1	12.9	1,751.6	11.4
Urban	749.3	3.9	682.2	4.4
Rural Residential	2,445.3	12.8	2,144.1	14.0
Industrial	104.0	0.5	154.0	1.0
Commercial	189.9	1.0	112.6	0.7
Total	19,138.9	100.0	15,340.6	100.0

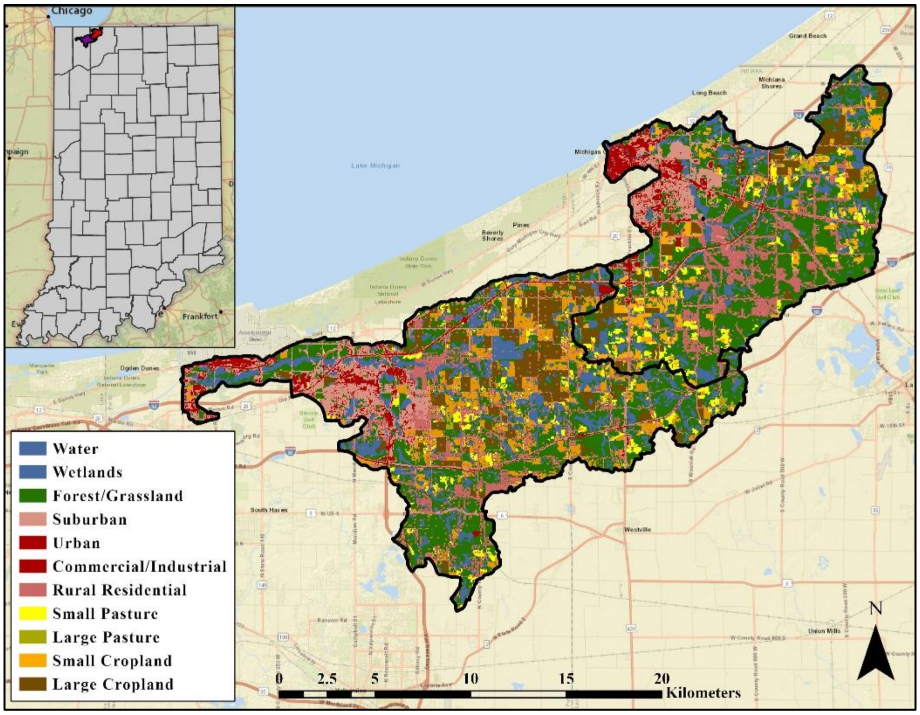

Figure 1. Location of Trail Creek and East-Branch Little Calumet Watersheds.

3.2 Model Description

The Generalized Watershed Loading Function (GWLF) is a continuously-simulating, combined distributed and lumped parameter watershed model used to quantify runoff, nutrient (N and P), and sediment loads from mixed-land use watersheds. The model is considered distributed due to the ability to simulate loads generated from multiple land uses, but also lumped as these land uses are considered homogenous units with the same biophysical attributes. There is no spatial discretization (i.e. no water or mass routing) within the watershed. GWLF operates on a daily time-step in which precipitation and temperature are used to calculate water balance. The daily water-balance consists of precipitation, snowmelt, runoff, evapotranspiration, and both current and maximum unsaturated zone storage. The standard SCS-CN approach to calculate runoff generation and infiltration (Cronshey, 1986). Accumulation of the daily water balance to the monthly scale is used to compute monthly runoff and loads of nitrogen, phosphorus, sediment. Surface nutrient (N and P) losses in non-urban areas are calculated with the use of export coefficients for dissolved nitrogen and phosphorus as well as a sediment coefficient for calculating particulate N and P. Surface nutrient losses in urban areas are assumed to be in the solid-phase and use an exponential nutrient accumulation and wash-off function similar to the SWMM model. Sediment loads are calculated using monthly erosion and delivery. Erosion is calculated using the USLE algorithm. Sediment yield is determined with a sediment delivery ratio that uses the daily transport capacity and available mass of eroded sediment. Subsurface loads are modeled with a lumped parameter approach where infiltrating water is multiplied by a groundwater nutrient coefficient. (Haith et al., 1992).

The GWLF-E model is an enhanced version of the GWLF model that was used in this study. The enhancements to the GWLF model included the ability to calculate loads from streambank erosion, agricultural tile drainage, and farm animals (including pathogen loads) as well as the effects of BMPs on load mitigation. It is also housed in the MapShed tool (Evans and Corradini, 2012) which allows the user to quickly import watershed boundary, land use, elevation, soils, hydrography, and weather data to build an input file and operate the model. Load reductions through the use of cropland and pastureland BMPs are calculated using nitrogen, phosphorus, and sediment reduction coefficients for the proportion of the area treated. Vegetated buffer strips (i.e. grass strips) and other stream practices also use nutrient and sediment reduction coefficients to the proportion of stream length treated. Animal waste management reduces nutrient and pathogen loads through the use of reduction coefficients applied to the percent of the animal population treated. Load reductions through the use of urban BMPs are calculated from the depth of rainfall captured (i.e. runoff reduction) per each acre of impervious cover and a dynamic pollutant reduction coefficient. The GWLF-E model has also been incorporated into the Stroud Water Research Center's WikiWatershed initiative (https://wikiwatershed.org/model/).

3.3 Input Data

3.3.1 Data Collection

The WikiWatershed's *Model My Watershed* web application that contains GWLF-E was used to generate the inputs for the visual-basic GWLF-E model from MapShed. The USGS HUC-10 boundaries for the TC and EBLC watersheds were created from the IndianaMap Layer Gallery (https://maps.indiana.edu/layerGallery.html). The *Model My Watershed* application collected data for all of the necessary inputs (e.g. weather, soil, hydrography, land cover, elevation, etc.) and additional inputs such as animal populations and point-source discharge from multiple government datasets. Once the *Watershed Multi-Year Model* (i.e. GWLF-E) was run, the GWLF-E input file was generated and exported for use in the visual-basic model.

Multiple datasets were modified and/or replaced with site-specific information, such as loads generated from different resident groups or data on land use practices. Daily local weather data including precipitation, maximum temperature, and minimum temperature were taken from the NOAA National Climatic Data Center (www.ncdc.noaa.gov); 24 years of data (1995-2018) were collected from 13 stations in Laporte and Porter counties (reference Appendix A). Hydrologic soil group and soil erosivity data for the state of Indiana were from the Soil Survey Geographic (SSURGO) database. The National Land Cover Dataset (NLCD) 2011 and a 1:24,000-resolution NHD Hydrography dataset were collected from the NRCS Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/GDGOrder.aspx). Measured daily streamflow data came from the United States Geological Survey (https://waterdata.usgs.gov/nwis) for the Little Calumet at Porter gage (Gage #4094000, 1995-2018), Trail Creek at Michigan City Harbor (Gage #4095380, 1995-2018), Trail Creek at Michigan City (Gage #4095300, 2007-2018). Parcel data for the watersheds were from the LaPorte and Porter County GIS departments and orthoimagery was from the Indiana Spatial Data Portal (http://gis.iu.edu/). Other GIS data including address points, street centerlines, incorporated area boundaries, and the National Agricultural Statistical Service (NASS) cropland data layer (CDL) were collected from the IndianaMap Layer Gallery. The monthly evapotranspiration cover coefficients, monthly daylight hours, and groundwater recession and seepage coefficients were set to match the GWLF model used in the 2003 Trail Creek Escherichia Coli TMDL report (TEI, 2003).

3.3.2 Classification of Resident Groups and Land Uses

The 2011 NLCD dataset was used to categorize land uses within the two watersheds. The land use classes in the NLCD dataset were reclassified in a manner similar to (Liu et al., 2015b) for input into the GWLF-E model. Deciduous forest, evergreen forest, mixed forest, and shrub/scrub were reclassified as forest. Woody wetlands and emergent herbaceous wetlands were reclassified as wetlands. Developed open space and developed low intensity were reclassified as low density residential. Developed medium intensity, developed high intensity, and barren land were reclassified as high density residential. Grassland/herbaceous was reclassified as open land.

Aerial photographs and OpenStreetMap (https://www.openstreetmap.org) were used to identify and demarcate industrial and commercial areas.

A rural residential land use class was created to model nutrient and water processing in this unique land use. This was accomplished by removing all address points from the 2015 Indiana Department of Homeland Security GIS address dataset that were within incorporated municipal areas (i.e. cities or towns). Address points without an owner record or current address were removed. Within each watershed, 60 rural households were selected at random to measure the area of human influence (i.e. area that is mowed, enclosed by fence or tree line, house, driveway, etc.) (Figure 2). The average over the 60 households in the TC watershed was 1.61 acres and 2.37 acres in the EBLC watershed. For consistent classification of rural residential properties, a 2-acre buffer was generated around each household in ArcGIS to delineate the area of human influence. The undisturbed portion of the property kept its original NLCD classification while the area of human influence was reclassified as rural residential. After the model scenarios were run, these land use classes were then grouped into 5 resident groups including urban (high-density residential), suburban (low density residential), rural residential, cropland, and pastureland to quantify the differences in load mitigation from resident knowledge and likely adoption of BMPs. The remaining land uses were grouped as forest/wetland (includes open land), water, industrial, or commercial (Reference Appendix A).

Figure 2. Example delineation of rural residential property

3.4 Calibration and Validation

Model calibration was performed using two interior gages, the Little Calumet River at Porter, IN (USGS #4094000) gage for the EBLC watershed and Trail Creek at Michigan City (USGS #4095300) gage for the TC watershed. Calibration the TC and EBLC watersheds was not performed using the gages at the watershed outlets because of inconsistencies at each. The Trail Creek at Michigan City Harbor (USGS #4095380) gage had recorded multiple periods of reverse flow from Lake Michigan each year on record which lasted for several months. The Portage-Burns Waterway at Portage Indiana (USGS #04095090) gage was within a canal that connected the EBLC watershed with the adjacent Salt Creek and thereby collected the combined streamflow from both watersheds. Calibration was implemented at the interior watersheds before performing a parameter transfer to the full watersheds. Due to an insufficient number of water quality samples, calibration was performed based only on streamflow.

The EBLC watershed was calibrated from 1995-2018 including 2 years of model spin-up (1995-1996), 12 years for calibration (1997-2008), and 10 years for validation (2009-2018). The Trail Creek watershed gage had a shorter period of record and was run from 2007-2018 including 1 year of model spin-up (2007), 6 years of calibration (2008-2013), and 5 years of validation (2014-2018). First a sensitivity analysis was performed on the hydrologic parameters in the GWLF-E model. These parameters included the percent impervious cover of urban land uses (% Imp), curve number of urban pervious surfaces (CNP), curve number of rural land uses (CNR), the potential evapotranspiration cover coefficient (Ket), soil available water capacity (AWC), and groundwater recession coefficient (GWR). Sensitivity analysis revealed that Ket and AWC were the most sensitive parameters for matching streamflow. Both watersheds were calibrated on an average monthly timescale for streamflow by altering the most sensitive parameters in the sensitivity analysis (reference Appendix B) to maximize both the coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE). Calibration and validation results of both the EBLC and TC watersheds were determined to be of satisfactory ($0.60 < R^2 < 0.75$; $0.50 < NSE < 0.70$) to good ($0.75 < R^2 < 0.85$; $0.70 < NSE < 0.80$) performance (Moriasi et al., 2015) for both the R^2 and NSE performance measures as shown in Table 2.

Table 2. Calibration performance measures for the TC and EBLC watersheds.

Watershed	Statistic	Aim	Calibration	Validation
TC	R^2	>0.6	0.83	0.69
	NSE	>0.5	0.78	0.61
EBLC	R^2	>0.6	0.73	0.70
	NSE	>0.5	0.71	0.54

3.5 LaPorte and Porter County Resident Surveys

In spring 2018, a survey assessing the awareness and likeliness to adopt stormwater BMPs was sent to 2,866 residents living within the census block groups of the TC and EBLC watersheds. Residents were asked to self-identify which of the resident groups (e.g. Urban, Suburban, Agricultural, or Rural Residential) they belong to and then specify the degree of familiarity ("knowledge") as well as how likely ("likely") they are to adopt each of the 20 management practices listed within the next calendar year (reference Appendix C for the survey instrument). The 20 BMPs that were mentioned in the resident surveys included practices for the household, community, and agricultural (farm and animals) landscapes within both watersheds. Both the knowledge and likeliness portions of the survey were constructed with a 4-point Likert Scale response. Residents who were deemed knowledgeable or likely to adopt are those who choose the responses in green in Figure 3. Those who suggested some familiarity with the BMP were considered unknowledgeable they are assumed to have heard of the BMP but have little knowledge of the functioning of the practice or the needed considerations for adoption.

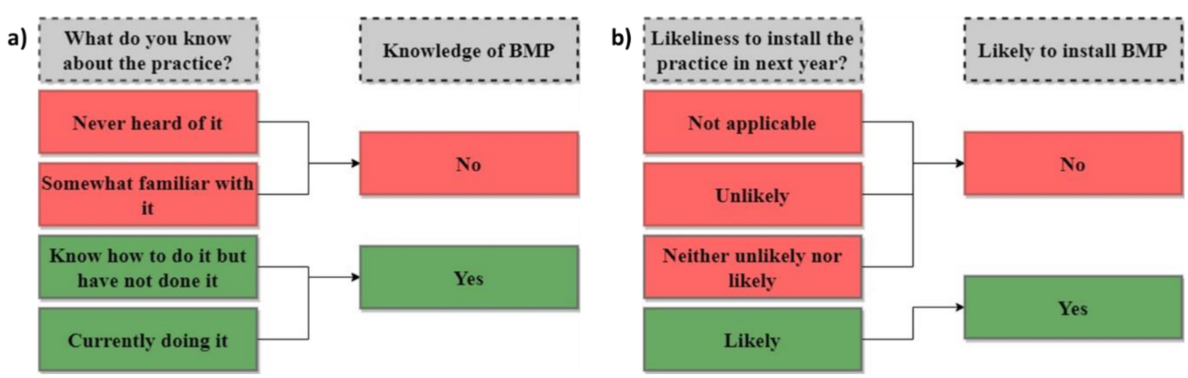

Figure 3. Survey response options and identification framework of residents who a) have knowledge of or are b) likely to adopt a BMP.

3.6 BMP Implementation Scenarios

3.6.1 Overview

The implementation of BMP scenarios within the GWLF-E model was aimed to capture potential levels of sediment, pathogen, and nutrient reductions based on local landowner knowledge and willingness to adopt BMPs. Only practices that can adopted by individual landowners were used in the model. The adoption of community scale practices (e.g. wet ponds, wetland basins, etc.) were left out of the model due to the anonymity of the survey preventing us from determining if there were enough landowners willing to adopt multi-property within the same neighborhood. BMPs applicable to the model were separated into urban practices (rain barrels, rain gardens, and permeable pavement) and agricultural practices (composting manure, no-till, cover crops, grass strips, and rotational grazing). The model was calibrated by matching observed streamflow (i.e. gage records) and modeled discharge at the gage. This calibrated, baseline model was generated without currently implemented BMPs. While there are BMPs installed, the majority of them are on private property and not easily identifiable. Also, by assuming a baseline with no BMPs, I was able to assess relative reductions.

Records of no-till and cover crops were available from the 2014-2018 Indiana State Department of Agriculture tillage transects (https://www.in.gov/isda/2383.htm). The records from these transects were used as an additional implementation scenario for cover crops and no-till for comparison to potential BMP adoption as noted in the survey. Model scenarios were designed to test the benefit of multiple levels of BMP implementation for both a traditional modeling approach (i.e. ascending tiers of implementation) and a survey approach (i.e. knowledge and likely adoption of BMPs). Each of the practices were then applied to treat 25%, 50%, 75%, and 100% of the applicable land area, streambank mileage, or animal population (Bosch et al., 2013). Knowledge and likely adoption of BMPs were included as scenarios by applying each practice to a percent of land coverage based on the proportion of survey respondents who identified themselves as knowledgeable or likely to adopt that BMP. The limitation of this approach is that the proportion of respondents is not equal to land area, however the proportional increase is representative of landowner preferences. The survey results for both watersheds were aggregated to create a larger sample size for BMP adoption.

3.6.2 BMP Implementation & Isolated Routine Modification

Rural BMPs including no-till, cover crop, and rotational grazing practices were implemented by recording the percent of cropland or pastureland to which the practice was applied. Manure composting was applied to a percent of both the non-poultry and poultry animal populations in the watershed. Vegetated (grass) buffer strips were applied to a specific length of streams in agricultural land. The efficiency of agricultural BMPs was set to the default value from the MapShed (Evans and Corradini, 2016) or Model My Watershed (https://wikiwatershed.org/model/) versions of GWLF-E. Urban BMPs were implemented as a retrofit BMP capable of capturing 1 inch of rainfall. For each of the urban BMPs, the reduction coefficient was adjusted to match the average recorded contaminant reduction of that practice within the International Stormwater BMP Database (Liu et al., 2016b). Rain barrels were applied to ¼ (1 downspout) of the rooftop area within the watershed based on an idealized low-density or high-density residential unit (Yaoze Liu, Ahiablame, et al., 2015). Rain gardens were designated to treat runoff generated from ¾ of rooftop area. Although these practices were not modeled in series, rain gardens and rain barrels were designated in a manner in which any resident could adopt both practices. Porous pavement was modeled to include impervious areas of the idealized low-density residential or high-density residential unit.

The GWLF-E model has multiple routines to simulate loading mechanisms that don't distribute pollutant loads to the individual land uses. These routines include loads from farm animals, tile drainage, streambank erosion, groundwater, point sources, and septic systems. To understand the full effect of BMP adoption by the resident groups, these routines were attributed to the land use classes. Farm animal load was attributed to cropland and pastureland by area-weighting the load. Tile drainage was assumed to exist only in cropland regions and load reductions from no-till and cover crop practices were assumed to reduce tile-drainage loads. Streambank erosion loading was weighted among all land uses by the proportion of flow generated. Groundwater loads were area-weighted among all land uses. Point source loads were area-weighted among the developed land use classes (i.e., urban, suburban, industrial, and commercial). Septic systems were assigned to rural residential households.

4. RESULTS

4.1 Influence of Land Uses and BMPs on Nonpoint Source Loads

Cropland regions in the TC and EBLC watersheds generate around 67 kg/ha of nitrogen, over 4 times greater than any other land use (Table 3). With cropland comprising ~15-20% of total watershed area, farming practices are generating 75% and 54% of the total nitrogen load in the EBLC and TC watersheds, respectively (Figure 4). Phosphorus within both watersheds is more evenly distributed between non-rural residents (20.2% TC; 29.0% EBLC), rural residents (21.0% TC; 18.7% EBLC), pasturelands (31.4% TC; 18.6% EBLC) and cropland (14.2% TC; and 36.1% EBLC). Pastureland has the highest total phosphorus (TP) loading rate at 3.7 kg/ha in the EBLC and 9.7 kg/ha in the TC watersheds annually, over 2 times and 4 times that of any other land use in each watershed, respectively. The primary source of sediment loads varies amongst the two watersheds. Cropland regions in the EBLC watershed generate 39.2% of the load and have the highest loading rate (1,200 kg/ha). The TC watershed has most of its sediment load (42.2%) originating from urban and suburban residents, which generates 2,100 kg/ha/y.

Adoption of stormwater BMPs had varying levels of effect on reducing the contaminant loads based on different BMP-contaminant combinations. With the majority of watershed TN loads originating from cropland regions, cover crops (14.4% TC; 20.6% EBLC) and no-till (5.5% TC; 7.8% EBLC) showed the greatest TN reduction levels when then were implemented at 100% (Figure 4; Table 5). The use of grass filter strips near agricultural streams showed slight (~3%) reductions in watershed TN. Urban practices including rain barrels, rain gardens, and porous pavement showed almost no watershed TN improvement (< 0.3% reduction).

Agricultural BMPs also show the greatest potential for TP mitigation. Grass filter strips show the greatest TP reduction potential in the TC watershed (8.4%) and second greatest reduction in the EBLC watershed (9.6%). Cover crops and no-till are amongst the most effective practices for TP mitigation in the EBLC watershed (15.9% & 9.2%, respectively), but were less effective in the TC watershed (6.0% & 3.5%, respectively). The remaining practices show <3% reductions of watershed TP.

Urban BMPs were shown to have the greatest sediment reduction potential, especially in the TC watershed. Porous pavement (12.0% TC; 12.7% EBLC) and rain gardens (8.2% TC; 8.5%

EBLC) are the greatest sediment load reducers. No-till is the most effective agricultural practice for sediment mitigation (3.4% TC; 8.3% EBLC). No-till, cover crops, and grass strips have half the reduction potential in the TC as compared to the EBLC watershed. Rain barrels are seen to have slight (2.7-2.8%) watershed sediment reduction capabilities.

Table 3. Baseline annual sediment and nutrient loads from the Trail Creek and East Branch Little Calumet River watersheds.

Land Uses	EBLC				TC			
	Area (ha)	TN (kg)	TP (kg)	Sediment (x10^3 kg)	Area (ha)	TN (kg)	TP (kg)	Sediment (x10^3 kg)
Water	118.7	0.0	0.0	0.0	49.7	0.0	0.0	0.0
Forest/Wetland	8,334.9	27,170.9	1,124.5	2,329.7	7,554.5	37,029.7	968.4	1,969.6
Developed	3,513.3	19,403.8	3,572.8	3,282.4	2,700.3	26,604.6	6,350.1	5,613.6
Rural Residential	2,445.3	27,635.7	3,299.5	1,104.0	2,144.1	36,688.9	4,597.8	2,594.1
Pasture	883.1	13,047.8	3,275.1	579.7	710.0	24,563.3	6,876.3	516.8
Cropland	3,843.6	257,972.4	6,372.6	4,709.0	2,182.0	145,864.3	3,110.4	2,593.3
Total	19,138.9	345,230.6	17,644.5	12,004.8	15,340.6	270,750.6	21,903.1	13,287.4

Land Uses	EBLC				TC			
	Area (ha)	TN (kg/ha)	TP (kg/ha)	Sediment (x10^3 kg/ha)	Area (ha)	TN (kg/ha)	TP (kg/ha)	Sediment (x10^3 kg/ha)
Water	118.7	0.0	0.0	0.0	49.7	0.0	0.0	0.0
Forest/Wetland	8,334.9	3.3	0.1	0.3	7,554.5	4.9	0.1	0.3
Developed	3,513.3	5.5	1.0	0.9	2,700.3	9.9	2.4	2.1
Rural Residential	2,445.3	11.3	1.3	0.5	2,144.1	17.1	2.1	1.2
Pasture	883.1	14.8	3.7	0.7	710.0	34.6	9.7	0.7
Cropland	3,843.6	67.1	1.7	1.2	2,182.0	66.9	1.4	1.2
Total	19,138.9	18.0	0.9	0.6	15,340.6	17.6	1.4	0.9

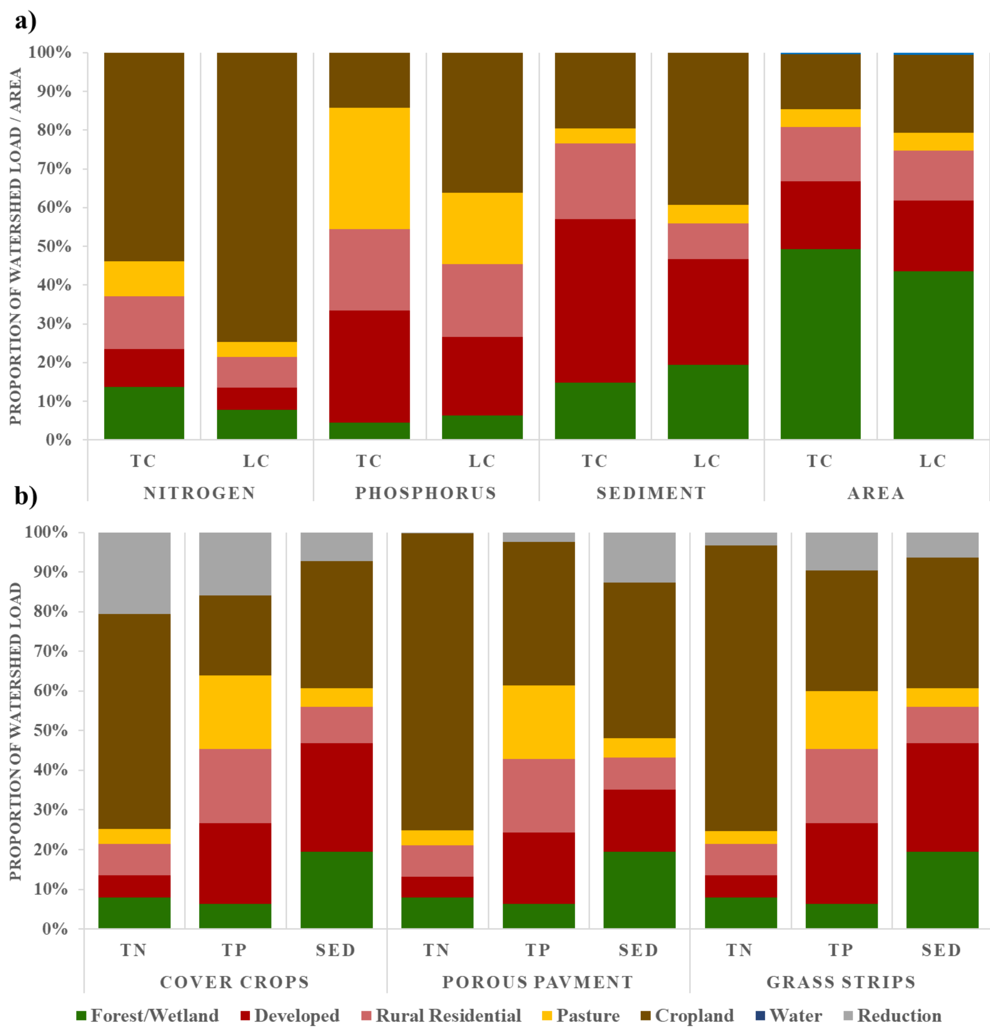

Figure 4. Quantification of a) the proportion of loads from each land use and b) the reduction capacity of the most effective cropland BMP (cover crops), urban BMP (porous pavement), and streambank BMP (grass strips).

Table 4. Applicable treatment area for each BMP within the Trail Creek and East Branch Little Calumet River watersheds.

BMP Type	EBLC			TC		
	Land use Area (ha)	Treatment Area (ha)	Fraction of Land use	Land use Area (ha)	Treatment Area (ha)	Fraction of Land use
Rain Barrel	5664.7	268.9	0.05	4577.9	220.5	0.05
Rain Garden	5664.7	806.6	0.14	4577.9	661.4	0.14
Porous Pavement	5664.7	1301.1	0.23	4577.9	1059.2	0.23
No-Till	3843.6	3843.6	1.0	2182.0	2182.0	1.0
Cover Crops	3843.6	3843.6	1.0	2182.0	2182.0	1.0
Grass Strips	186.1	186.1	1.0	130.7	130.7	1.0
Rotational Grazing	883.2	883.2	1.0	710.0	710.0	1.0
Manure Compost	883.2	883.2	1.0	710.0	710.0	1.0

4.2 Survey Responses

From the 2,866 surveys that were mailed to residents within the two watersheds, minus the 386 invalid addresses, there were 1,066 valid responses received (43% response rate). The results show that residents within the two watersheds have a higher knowledge level and likely adoption rate for agricultural practices (40-47% knowledge; 18-28% likely) as compared to the individual household practices (13-17% knowledge; 4-8% likely) typically seen in urban or suburban areas (Figure 5). Urban residents had considerably higher knowledge levels (62.9%) and likely adoption rates (26.1%) for rain barrels than for other urban BMPs. Likely adoption of agricultural BMPs had two distinguishable groups. Cover crops, no-till and manure composting were more likely (27.8-29.7%) to be implemented than grass strips or rotational grazing (15.1-17.7%)

Several of the BMPs in the survey were excluded from the model scenarios as they either required joint adoption amongst multiple residents (community scale), had no discernable input method in the GWLF-E model, or had relatively low levels of likely adoption (Figure 6). Community scale BMPs such as wet ponds, wetland basins and swale systems had similar levels of knowledge (16.8-17.6%) and likely adoption (6.2-10.4%) as rain gardens. Windbreaks were another community practice of which residents were highly knowledgeable (46%) and somewhat likely to adopt (16%).

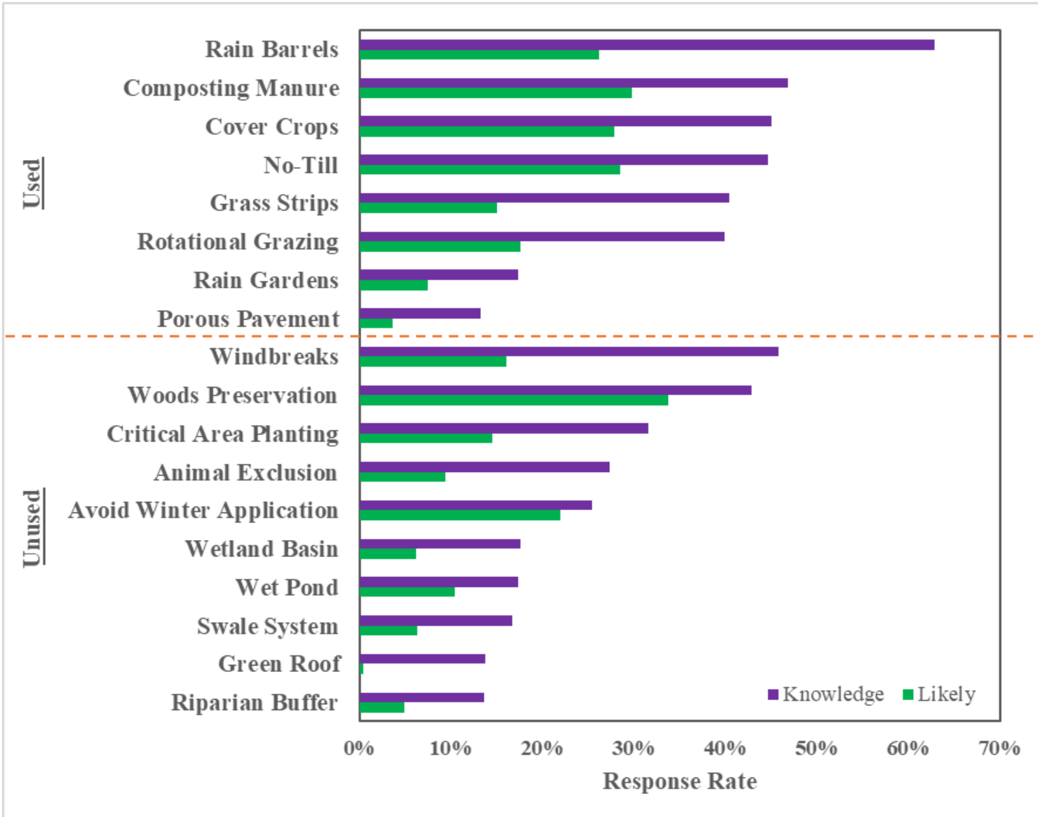

Figure 5. Survey results showing the resident knowledge and likely adoption level of 18 different BMP types. The red line highlights the boundary between those practices in the survey that were used (top) and not used (bottom) in the modeling scenarios.

Figure 6. List of BMPs included in resident survey. Practices in bold were used in the GWLF-E model.

4.3 Load Reduction Effects of BMP Adoption

When combined with the survey response rates, most BMPs experience a greater than 50% drop in pollutant reduction capacity at the current knowledge level and greater than 70% drop at the likely adoption level (reference Appendix F). The relatively higher knowledge and likely adoption levels for agricultural BMPs generates increased disparity of nutrient load reduction capacity. For example, full implementation of cover crops generates 63 times the TN reduction as porous pavement in the EBLC watershed. This number increases to 205 times the porous pavement reduction level at the current knowledge level and up to 304 times greater at likely adoption levels. Applying cover crops at the current knowledge level reduces more TN than no-till agriculture at full implementation. No-till practices have over double the TN mitigation as grass filter strips at the knowledge level. When the focus changes to how likely residents are to adopt the practice within the next year, the TN mitigation of no-till rises to 3.5-4.4 times the potential of grassland filter strips while the difference between cover crops and no-till remains relatively similar.

Agricultural practices remain more effective at reducing TP than household practices at current knowledge and likely adoption levels, but not to the same degree of disparity. The current knowledge of grass strips reduces TP to similar levels as no-till in the EBLC watershed but becomes the most effective TP mitigator in the TC watershed. As with TN, the lower level of likely adoption reduces the TP mitigation potential of grass strips. Manure composting in pastureland also shows noticeable benefit compared to urban BMPs when applied at the current knowledge level or likely adoption level in the EBLC. This same trend is noticed to a greater extent when analyzed for the TC watershed.

Urban BMPs have greater potential sediment reduction at current knowledge levels, but the lower level of likely adoption makes them less effective than agricultural practices (reference Appendix F). Model results show that in urban landscapes, rain barrels produce the greatest amount of TN, TP, and sediment reduction when applied at the level to which landowners are likely to implement. This level of reduction is reached despite having 1/3 the potential treatment area of rain gardens and roughly 1/5 that of porous pavement (Table 4). For sediment reduction in the EBLC watershed, likely adoption of rain barrels (86.47 x 10^3 kg reduction) reduces more than rain gardens (75.02 x10^3 kg) and porous pavement (54.30 x10^3 kg). The trend of rain barrel reduction > rain garden > porous pavement exists amongst TN, TP, and sediment where landowners are likely to adopt. The order of effectiveness for urban BMP at the knowledge level varies amongst TN (RB > RG > PP), TP (PP > RB > RG), and sediment (RB > PP > RG).

4.4 Improving Level of Adoption

Cover crops are the only practice to show over 5% reduction of any nutrient (5.7% TN in EBLC) when applied at the likely adoption level (Table 5). Higher levels of adoption are required to see notable reduction capacities. Raising the level of likely adoption for cover crops, no till, and grass strips (15.1-28.4%) to the current knowledge level (40.4-45.0%) would bring the reduction of these 3 practices up to 2.7-7.2% of annual TN and 1.7-4.5% of annual TP in the TC watershed. This additional 0.7-2.5% TN reduction and 0.6-2.2% of TP reduction would require 17-25% increase in the number of likely adopters. Urban BMPs such as porous pavement and rain gardens would reduce an additional 3.5-5.5% of sediment in the TC watershed with an increase in adoption from the likely level (3.7-7.5%) to the knowledge level (13.3-17.4%). This additional 10% of likely adoption would increase the sediment reduction up to only 4.1-6.0% of the annual watershed load.

Increasing likely BMP adoption to 50% for most agricultural practices would require doubling the number of adopters. Likely adoption of rain gardens and porous pavement would need to increase 6.7 and 13.5 times over, respectively. This level of adoption would reduce contaminants up to an additional 3-5% at the watershed scale for a select few BMP-contaminant relationships. These would include cover crops reducing TN (+4.57% EBLC; +3.2% TC), grass strips reducing TP (+3.37% EBLC; +3.21% TC), rain gardens reducing sediment (+3.6% EBLC: +3.5% TC) and porous pavement reducing sediment (+5.8% EBLC, +5.5% TC). Over 75% adoption would be needed for any BMP-contaminant relationship to add an additional 10% reduction at the watershed scale. Reduction of TN by cover crops would achieve this additional reduction (up to 15.5%) if another 47.2% of resident agreed to adopt the practice.

Table 5. Percent reduction of watershed nitrogen, phosphorus, and sediment loads across multiple treatment levels

EBLC															
	Full Implementation			75% Implementation			50% Implementation			Knowledge			Likely		
	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)
No-Till	7.8	9.2	8.3	5.9	6.9	6.2	3.9	4.6	4.1	3.5	4.1	3.7	2.2	2.6	2.4
Cover Crops	20.6	15.9	7.2	15.5	11.9	5.4	10.3	7.9	3.6	9.3	7.1	3.3	5.7	4.4	2.0
Grass Strips	3.3	9.6	6.4	2.5	7.2	4.8	1.7	4.8	3.2	1.4	3.9	2.6	0.5	1.4	1.0
Rotational Grazing	0.1	0.3	0.2	0.1	0.2	0.2	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.1	0.0
Manure Compost	0.4	1.6	0.0	0.3	1.2	0.0	0.2	0.8	0.0	0.2	0.7	0.0	0.1	0.5	0.0
Rain Barrel	0.1	0.5	2.8	0.1	0.4	2.1	0.0	0.2	1.4	0.0	0.3	1.7	0.0	0.1	0.7
Rain Garden	0.3	1.5	8.5	0.2	1.2	6.3	0.1	0.8	4.2	0.0	0.3	1.4	0.0	0.1	0.6
Porous Pavement	0.3	2.5	12.7	0.2	1.8	9.4	0.2	1.2	6.2	0.0	0.3	1.6	0.0	0.1	0.5
TC															
	Full Implementation			75% Implementation			50% Implementation			Knowledge			Likely		
	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)	TN(%)	TP (%)	Sed (%)
No-Till	5.5	3.5	3.4	4.1	2.6	2.5	2.7	1.7	1.7	2.4	1.6	1.5	1.6	1.0	1.0
Cover Crops	14.4	6.0	3.0	10.8	4.5	2.2	7.2	3.0	1.5	6.5	2.7	1.3	4.0	1.7	0.8
Grass Strips	2.9	8.4	2.1	2.2	6.5	1.6	1.5	4.5	1.1	1.2	3.5	0.9	0.4	1.3	0.3
Rotational Grazing	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Manure Compost	1.0	2.7	0.0	0.7	2.0	0.0	0.5	1.3	0.0	0.5	1.3	0.0	0.3	0.8	0.0
Rain Barrel	0.1	0.4	2.7	0.1	0.3	2.0	0.0	0.2	1.3	0.0	0.2	1.7	0.0	0.1	0.7
Rain Garden	0.3	1.2	8.2	0.2	0.9	6.1	0.1	0.6	4.1	0.1	0.2	1.4	0.0	0.1	0.6
Porous Pavement	0.3	2.0	12.0	0.3	1.5	9.0	0.2	1.0	6.0	0.0	0.3	1.6	0.0	0.1	0.4

5. DISCUSSION

5.1 Targeting of different land uses to reach mitigation goals

Limiting the watershed load of nitrogen will require a focus on agricultural BMP implementation. Annual nitrogen loads generated from cropland regions are more than half of the watershed load due to the high level of dissolved N transported through tile drains, which contribute 47% and 65% of the total nitrogen load in the TC and EBLC watersheds, respectively. The EBLC watershed generates higher tile nutrient loads because it has a higher proportion of flow redistributed to tile drains. Tile effluent in the GWLF-E has a consistent nutrient (N and P) concentration throughout the watershed and tile flow consists of 50% of the groundwater and runoff discharge in the fields in which they are installed (Evans and Corradini, 2012). With the majority of soils in the EBLC having moderate infiltration (34.3% hydrologic soil group B) and the majority of TC watershed soils having high infiltration (28.3% hydrologic soil group A), greater levels of runoff are seen in EBLC. Planting of non-legume cover crops would be one of the more effective approaches to reducing nitrogen loads as they scavenge excess soil nitrogen and absorb infiltrated water that would quickly transport dissolved nitrogen into tile drains (SAN, 2007). Although not included in this study, nutrient management could also be effective in concert with other BMPS to decrease excess tile TN loads and has been shown to considerably reduce nutrient loads in modeling studies in the Great Lakes region (Bosch et al., 2013; Scavia et al., 2017).

Mitigation of phosphorus will require similar, yet slightly varied approaches. Although both watersheds generate relatively equal levels of agricultural and urban TP, the EBLC watershed has a greater proportion of the load originating from row crop agriculture compared pasture in the TC. Animal waste is the greatest source of TP in the TC watershed (30.3% of annual TP load), but less of a source in the EBLC watershed (16.6% of annual TP load). With over twice the TP load coming from manure in the TC watershed (6,631 kg/yr.) as compared to the EBLC watershed (2,922 kg/yr.) despite having 20% less pastureland, manure management strategies are needed in the TC watershed. Manure composting proved relatively ineffective at mitigating these loads due to high levels of manure generated from non-grazing animals and manure applied to row crop agriculture. In the GWLF-E model, mitigation of loads from animal waste management systems (i.e. manure composting) is quantified through the use of a nutrient reduction coefficient to a percent of the grazing animal or poultry manure managed (Evans and Corradini, 2012). Quantifying the nutrient reduction effects and management of manure for composting is complex and would require significant alterations in the model. Manure from pigs, the predominant source of manure TP (74-82%) in both watersheds, is more difficult to properly compost as compared to other livestock (NRCS, 2009). As pigs are considered non-grazing animals in the model, composting isn't an applicable practice for their waste. Carbon-to-nitrogen ratios common in compost vary from different animals and compost is typically applied to meet crop N demands, without managing P levels (Augustin & Rahman, 2016). Manure also needs to be protected in compost piles and applied in a manner where nutrients won't leach to nearby waterbodies. With the high levels of animal manure in these watersheds, manure compost could be an effective way to manage nutrients, but limitations of the model may not of properly reflected their importance.

Urban landscapes and rural residential households within the TC and EBLC watersheds combined to generate relatively equal levels of phosphorus (39-50% of watershed TP) as cropland and pastureland combined (46-55% of TP). Management of urban pollutant sources thus requires equal levels of attention as agricultural practices. Point source loads from wastewater treatment facilities, industrial areas, and trailer parks generate 8.2-14.1% of watershed TP and is a greater contributor of phosphorus (3089 kg/yr.) than row crop agriculture (2632.29 kg/yr.) in the TC watershed. Other modeling studies that have quantified the benefits of BMP implementation at the watershed scale have typically focused on the use of only row crop agriculture or livestock management practices (Chiang et al., 2010; Merriman et al., 2019; Van Liew et al., 2013) including those in the Great Lakes region (Bosch et al., 2013; Scavia et al., 2017). In the research performed by Bosch et al. (2013), the Maumee River watershed had limited (11%) urban cover, but only a general level of point source reduction (25% of effluent rates) was considered. The Great Lakes region still has a high level of combined sanitary and stormwater sewerage (EPA 2004), so nutrients from stormwater runoff is a component of wastewater treatment point sources. The use of urban BMPs could further reduce point source discharge but are not applied in these studies. This phenomena couldn't be quantified in the GWLF-E model as urban BMP reductions didn't route through the stormwater network and point sources were considered a fixed load. Septic tanks in the TC and EBLC watersheds generated 10.8-16.6% of the total TP load. The effects of septic tanks, which we allocated to rural residents, on watershed scale nutrient loading has not been included in other BMP studies. While there are no BMPs to treat septic tanks effluent from faulty systems, it is an important factor for nutrient and pathogen loads. The Trail Creek Watershed Management Plan (ASI, 2007) included goals for maintenance and eventual replacement of septic tanks with sanitary sewers with an expected 55% TN reduction.

Reducing sediment loads within both watersheds will require a more integrated approach that primarily focuses on BMPs in urban, suburban, and rural residential landscapes as well as row crop agriculture. Porous pavement and rain gardens generating the greatest sediment reduction (8.2-12.7%) shows the importance of urban BMPs in watershed scale treatment. Most urban BMP modeling studies have focused site scale treatment (Gao et al., 2015; Jia et al., 2012). In the research performed by Liu et al. (2016b), quantification of the nutrient and sediment reduction from only the use of urban practices for the TC watershed was performed. This research suggesting that 41% of TKN, 36% of TP, and 57% of TSS loads could be mitigated from optimized practice implementation. Our research builds upon this previous work by modeling BMP treatment in both urban and agricultural land uses to determine the most effect treatment approaches.

The majority of sediment loads in the EBLC (76.6%) and TC (88.7%) watersheds come from streambank erosion. Because the quantification of streambank erosion in the GWLF-E model is generated from an isolated routine and not land use dependent (Evans et al., 2003), sediment loads were allocated to land uses based on runoff volume generation. The capacity of urban practices to capture runoff allows for greater sediment mitigation than cropland practices. Since the TC watershed has a greater proportion of developed landscapes and lower amount of cropland runoff than the EBLC watershed, urban BMPs were of greater importance in sediment mitigation at the watershed scale. Using runoff volume to allocate streambank erosion to individual land uses might not be reflective of actual watershed conditions. This approach assumes that runoff in each land use has the same streambank erosion potential. The lack of runoff reduction quantified in the GWLF-E model limits the ability of agricultural BMPs to limit streambank erosion. For example, cover crops can promote infiltration and absorb shallow groundwater, which would reduce the amount of runoff that would erode the stream (SAN, 2007). Streambank erosion is dependent on factors such as stream width, bank height, bank slope, soil bulk density, and bank cover (NRCS, 1996). Headwaters in the TC and EBLC watershed are primarily in forest or row crop agricultural land uses. Forested streams have high levels of vegetated riparian cover that would lower streambank erosion (Wynn et al., 2004). Agricultural streams in these watersheds are primarily drainage ditches that would receive flow from tile drains. With little vegetative cover and steep banks, rapid response to storms in these ditches can lead to bank failures (Little et al., 1982). Downstream reaches in these watersheds are primarily urban, so the streams are wider and armored. Urban development has covered natural streams with impervious material and replaced them with storm sewerage. High levels of runoff rapidly transported to streams through sewerage creates bank-full flow that can lead to large amounts of stream erosion (Walsh et al., 2005; Dunne and Leopold, 1978).

5.2 Effects of Resident Knowledge and Likely Adoption Levels on BMP Performance

The implementation of BMPs at current knowledge and likely adoption levels substantially decreased watershed scale nutrient and sediment loads as compared to full implementation. Rural BMPs reached 40% of their potential reduction while urban practices only reach 20% of their full implementation reduction potential when applied at knowledge levels. Likely adoption of BMPs reduced rural and urban BMPs to 30% and 8% of their reduction potential. Only rain barrels had high enough resident knowledge and likely adoption levels to reach 50% of its maximum reduction capacity.

Although rain barrels are a relatively inexpensive and easily available form of stormwater capture, limited treatment areas and high degree of user management have rendered this practice relatively ineffective (Jennings et al., 2013; Roy et al., 2014). The high level of acceptance for rain barrels made them more effective at reducing nutrient and sediment loads than rain gardens and porous pavement in most categories despite having only a fraction of their reduction potential. This shows that a critical need for educating residents about urban practices other than rain barrels. Several of the neighborhood practices such as wet ponds, wetland basins, and swale systems can treat larger areas of land and had more favorable feedback in our survey than rain gardens and porous pavement. Inclusion of these community practices should be the focus of future work in these watersheds.

The use of cover crops showed the greatest level of nutrient mitigation when both knowledge and likely adoption were considered. In their modeling study, Bosch et al. (2013) also showed that cover crops had the greatest nutrient reduction potential of any individual agricultural practice when implemented at feasible (25% implementation) and full adoption levels in the Western Lake Erie Basin. No-till practices were shown to have the greatest level of sediment reduction potential at both full implementation and resident adoption levels. While both cover crops and no-till both received around 28% levels of likely adoption and 45% knowledge levels, tillage transects from the Indiana State Department of Agriculture showed 67% and 58% no-till implementation and only 9% and 19% cover crop implementation in the EBLC and TC watersheds, respectively. The low levels of knowledge and likely adoption in the survey compared to estimated transect data may suggest that farmers who already employ no-till practices responded as unlikely to adopt or were unable to adopt the practice. Cover crops would experience this confliction differently as those likely to adopt would be in excess of those currently implementing the practice. If tillage transects hold true to field conditions, no-till would be much closer to its theoretical maximum adoption level and adoption of cover crops would be of increased importance in both watersheds. Although farm owners were able to identify the practices that they currently implement, or those that they will likely implement, there was no information collected pertaining to the acreage that the farmer operates, the fraction of cropland treated, or the type(s) of cover crops implemented. Without this information, all farmers were assumed to operate equal areas of cropland and the same composition of cover crops were used (Evans and Corradini, 2012). This data can be used to quantify the effects of BMP treatment in relation to disproportional contaminant loads seen across agricultural landscapes.

BMPs that show higher levels of load reduction when applied beyond likely adoption levels will be of more importance. With the level of likely adoption showing little reduction capability, it seems more apparent that increased education and assistance for adopting BMPs are needed to see tangible reductions. Raising the levels of likely adoption up to the knowledge level for any individual BMP was shown to have limited effect at the watershed scale. The additional TN reduction of 3.6% (cover crops), TP reduction of 2.7% (cover crops) and sediment reduction of 1.2% (porous pavement) resulting from the increase in likely adoption shows that improving beyond current knowledge levels is needed. Raising adoption of cover crops or porous pavement to the point where over 10% reduction of TN, TP, and sediment can be achieved would require implementation to 75% of the treatable area. An additional 47-71% of residents agreeing to adopt these practices for a 10% increase in contaminant reduction would be an unlikely and relatively inefficient course of action. Increasing the adoption of any BMP is expected to become more difficult as the practice, or practices with the same treatment area, become more prevalent.

Expanding the current level of adopters will require engagement with landowner to identify joint conservation goals and resolve concerns they have with BMP adoption. Farmers and landowners have shown more desire to protect the natural environment (i.e. stewardship) and more recognition of the benefits of BMPs, but limited amounts of adoption are still being seen (Smith et al. 2007; Greiner et al. 2009; Kalcic et al. 2014; Gao et al. 2018). Concerns have been shown to differ amongst rural and urban residents. Farmers are worried about maximizing the productivity and profitably of their farming practices while combating rising input costs, increasing environmental regulation, and increased competition (Greiner et al., 2009). Adopting practices such as cover crops will require input cost and practices such as grass strips or converting agricultural land to grassland requires capital losses (i.e. opportunity costs). Funding exist for these types of projects through programs such as EQIP or CRP and while they are not the primary motivating factor, it is an important way of promoting BMP adoption (Kalcic et al., 2014). Urban residents are concerned with being able to adopt and maintain practices. Homeowners in residential neighborhoods have shown concerns about practice adoption breaking homeowner association’s regulation and the suitability of their property for implementing the practice (Brown et al., 2016; Gao et al., 2018). Furthermore, the research performed by Gao et al. (2018) showed that landowners were unsure if they had the time and capacity to install and maintain the practice. Farmers and homeowners also both showed concern with government control and objectives of conservation programs as well as their ability to deal the complex barriers that limit BMP adoption and hinder integration of conservation knowledge (Chaffin et al., 2016; Dhakal & Chevalier, 2017; Roy et al., 2008). While the anonymity of the survey in this project was meant to encourage landowners in responding without fear of being isolated as a high contributor of contaminants, research has also shown that citizens are supportive in identifying and funding treatment of these disproportionally higher load generating properties if it means improving water quality regionally (Kalcic et al., 2014). Working with this information would better direct our stormwater modelling efforts in directing BMP implementation to obtain the greatest level of treatment with limited resources.

This research adds to the field of water quality modeling by incorporating the willing adoption of homeowners to implement BMPs to a large extent across a watershed scale. While we couldn’t delve to the levels of social norms and values due to the physical capacity of models to incorporate this field of research, identifying likely adoption and knowledge levels of the individual residents gives us a more practical sense of our current capacity and future limitations of meeting water quality goals. The results show that combinations of BMPs across multiple land uses that both target the primary contaminants of concern and are supported by the local community will be needed to meet watershed TMDL goals (Scavia et al., 2017). TMDL planners will need to consider the level of concern for each contaminant when it comes to BMP selection as well as the tradeoffs and likelihood of adoption for each BMP-contaminant combination. In the TC and EBLC watersheds, sediment pollution is more of a current concern than nutrient pollution, so prioritizing adoption of residential practices (e.g. porous pavement and rain gardens) as well as no-till agriculture will yield the most benefit. Although there would be a greater sediment reduction from choosing no-till agriculture over cover crops, this would come at the cost of reducing potential TN and TP mitigation by half if only one of the BMPs could be implemented in full. If nutrient mitigation became more of an issue, selecting BMPs such as cover crops and grass strips in agricultural areas and porous pavement and rain gardens for households would provide the most benefit at the watershed-scale, but may not for the individual resident group.

6. CONCLUSIONS

Meeting water quality goals will require a high level of BMP implementation that applies effective conservation practices to high pollutant source areas across the watershed. Landowners play a key role in meeting watershed goals through the implementation of BMPs. Incorporating resident willingness to adopt BMPs is thus a critical component in watershed modeling efforts to identify the water quality improvement potential of these practices. This project combined the results of a BMP adoption survey with the GWLF-E watershed model to quantify nutrient and sediment loads in Trail Creek and East-Branch Little Calumet River watersheds as well as the effectiveness of multiple practices in reducing NPS loads amongst different resident groups. Row crop agriculture was the primary source of watershed TN (53.9-74.7% of annual) while urban and rural residents generated the most sediment (36.5-61.8%). Phosphorous loads were more equally distributed amongst multiple land uses. Full implementation of individual BMPs showed only limited effectiveness in combatting NPS loads. Cover crops were shown to be the most effective practice at reducing watershed TN (14.4-20.6%) and TP (6.0-15.9%) loads. The greatest level of annual sediment load reduction was seen with porous pavement adoption (12.0-12.7%). Application of BMPs to current knowledge levels reduced the effectiveness of these practices down to 6.5-9.3% TN and 2.7-7.1% TP reduction for cover crops and 1.6% sediment reduction. Likely adoption of cover crops generated 4.0-5.7% TN and 1.7-4.4% TP reduction, while porous pavement showed only 0.4-0.5% watershed scale sediment reduction.

Improving resident knowledge and likely adoption of BMPs will be needed to meet water quality goals. Farmers had moderate levels of knowledge (40-47%) and with practice such a no-till, cover crops, manure composting or rotational grazing. Urban residents were less familiar with BMPs as only 13-18% identified having knowledge of porous pavement, rain gardens, or wet ponds. Likely adoption of these practices was low amongst farmers (15-30%) and extremely low for urban residents (4-8%). Watershed planners will need to understand the motivations and concerns that affect landowner decision-making process to apply these practices with the goal of increasing adoption to levels that generate needed water quality benefits. Clarity with the funding allocation process as well as presenting clear watershed goals to the community will yield increasing adoption. Rain barrels are a simple, low-cost BMP that are commonly used by local officials to present stormwater management to the community. With this outreach, urban residents were more knowledgeable (63%) and likely to adopt (26%) rain barrels than any other urban practice. This higher willingness to adopt made rain barrels more effective than porous pavement at knowledge and likely adoption levels, despite being a relatively ineffective practice. Educating the community about practices other than rain barrels will hopefully yield similar results with more effective practices.

Future work in this research should be directed at engaging with the local community to both inform citizens about sustainable stormwater management and approaches to improve current conditions. Collecting more information about the locations of current and potential BMP adoption is also important to quantify specific, field-scale benefits that can collectively reduce watershed scale NPS loads. With the quantification of field scale benefits, calculating the cost-effectiveness of BMPs will also help with allocating funds to help residents adopt these practice. This can help watershed planners to direct funds to the practices that would best improve water quality in Lake Michigan.

APPENDIX A. GWLF-E INPUT DATA

Land Use Reclassification

Small and large agricultural landscapes were aggregated by first identifying parcels owned by the same individual or company. If the sum of all their properties categorized as hay/pasture and cropland was less than 50 acres then those properties were labeled as small agricultural, and vice versa for large agricultural.

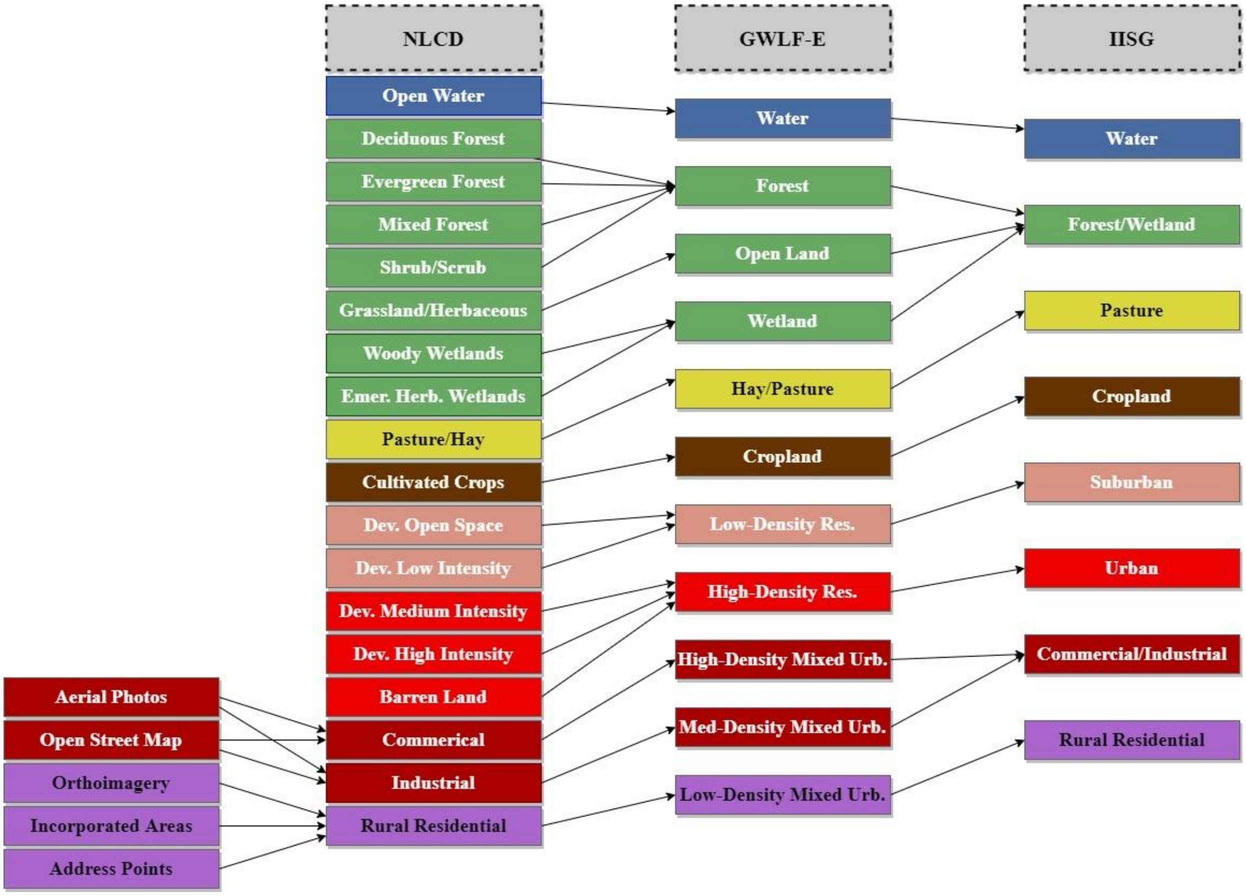

Figure 7. Reclassification of NLCD Land Uses for model input and quantification of resident group pollutant loads.

Landscape Imperviousness and Soil Properties

The Watershed Multi-Year Model (WMYM) in the Model My Watershed (MMW) is a web application that exists as part of the Stroud Water Research Center's WikiWatershed. The WMYM runs using the GWLF-E platform and generates all required inputs for the model from an array of data sources (https://modelmywatershed.org/) and was used to generate an initial input file for the TC and EBLC watersheds. The physical data required for determining water transport included soil hydrology, soil loss (USLE), curve number, soil water capacity, tile drainage and crop growing seasons were initially created from this dataset. The soil erosivity (K) factor for the USLE was modified by calculating an area-weighted K factor for each land use through the use of the SSURGO soil database layer and soil reports from the counties encompassing the watersheds and their adjacent counties (NRCS, 2004; SCS, 1972, 1981, 1982).

The available water capacity in the top 150 cm of the subsurface for each soil group was also calculated by taking a watershed area-weighted value from the SSURGO soil database. The curve number (CN) in GWLF-E is separated into 3 categories, the CN of impervious surfaces (CNI) in urban areas, the CN of pervious (CNP) surfaces in urban areas, and the CN of rural areas (CNR). The CNI and CNP were set to 98 and 79, respectively, as is standard for developed areas in the USDA's TR-55 Manual (Cronshey, 1986). An area-weighted CNR for each rural land use was calculated with the use a CN look-up table to generate a CN grid with the use of HEC-GeoHMS for ArcGIS v. 10.4. The hydrologic soil group (HSG) data for the lookup table use hydrologic soil group (HSG) data from the SSURGO soil database, with any unlabeled soil groups being reclassified (Table 6) based on the reports for adjacent counties. The percent of impervious cover was calculated from the 2011 NLCD impervious surfaces layer and area-weighted for the urban land-uses.

The potential evaporation cover coefficient (Ket) and growing season months were determined using the 2003 Trail Creek Escherichia Coli TMDL Report (TEI, 2003). The TMDL modelers had used the GWLF-E model in conjunction with the Water Quality Analysis Simulation Program (WASP) to determine E. Coli loads into Lake Michigan. The percent of agricultural land that is artificially drained by tiles was assumed to be 50% based on estimates from Purdue Extension (Lee et al., 2005).

Table 6. Classification of unidentified hydrologic soil groups in SSURGO database.

Initial Soil Type (muname)	Initial HSG	Reclassified HSG (GWLF-E)	Notes
Water	Null	D	No Infiltration
Udorthents, xxx	Null	A (Trail Creek) B (Little Calumet)	Match to most dominant soil HSG
Fluvaquents	Null	B/D	Matched to Fluvaquents, Loamy (B/D)
Urban Land-xxx	Null	D	Impervious Surfaces
Duneland	Null	A	High Sand Content, Nearby sandy soils are A
Pit	Null	D	Mining areas with compacted soil
Urban Area	Any	D	Impervious Surfaces

Rural Runoff and Tile Drainage Concentrations

The GWLF-E model uses the standard SCS-CN approach (Cronshey, 1986) for determining runoff from rural land uses along with an export coefficient for determining nutrient yield. Dissolved nitrogen (DN) and dissolved phosphorus (DP) runoff coefficients for hay/pasture and cropland were changed based on the literature from similar landscapes to northwest Indiana (Table 7). The nitrogen and phosphorus concentrations within agricultural tile drains were also changed to reflect conditions similar to northwest Indiana. All other dissolved runoff conditions were left as default from MMW.

Table 7. Runoff and Tile Drainage Export Coefficients.

Land Use	Nutrient	Concentration (mg/L)	Reference
Agricultural	DRP	0.15	(Gentry et al., 2007; King et al., 2016; King et al., 2015)
Agricultural	DN	2.79	(David et al., 1997; D. R. Smith et al., 2008)
Hay/Pasture	DN	0.8	(Yaoze Liu, Ahiablame, et al., 2015)
Tile	DRP	0.15	(Gentry et al., 2007; King et al., 2016; King et al., 2015)
Tile	DN	10.91	(King et al., 2016)

Septic System Populations and Failure Rates

The GWLF-E septic system routine consists of septic populations, a daily per capita production rate for nitrogen and phosphorus, and a daily per capita pathogen production rate (Evans and Corradini, 2012). Households with septic tanks were assumed to only be those classified as rural residential, as they lie outside incorporated regions and presumably stormwater sewerage. From the identified rural residential households, the rural residential population by multiplying the number of addresses by the average household size (2.5 ppl/household) based on the U.S. Census summary for Indiana (https://www.census.gov/quickfacts/IN). It is estimated that approximately a quarter of the septic systems in Indiana are failing or inadequate (Lee et al., 2005), so one quarter of the rural residential population were assumed to be living with failure in the model. Of the 25% of the population living with inadequate septic, half were assumed to have experienced "ponding" (surface failures) and the other half with "short-circuiting" (subsurface failure) (https://wikiwatershed.org/).

Urban Land Runoff and Wash Off

Urban land in GWLF-E is also modeled with the SCS-CN method but differs from rural landscapes with the addition of exponential accumulation and wash-off functions for nutrient loading. Nutrients are assumed to be in the solid phase and accumulate on the pervious or impervious surfaces until stormwater washes off the nutrients. The accumulated nitrogen and phosphorus export coefficients for pervious landscapes were modified to 0.1337 kg/Ha/day and 0.3334 kg/Ha/day respectively to account for urban lawn fertilization. Fertilization was assumed to be performed once per year with a 16:4:8 (N:P:K) ratio, applied at 1 lb. N/1000 ft (Polomski & Shaughnessy, 2019). All other MMW model inputs were left at the default values.

Animal Data

Daily loads of nitrogen, phosphorus, and fecal coliform bacteria from farm animals are modeled in GWLF-E with the current animal population of 8 different animal species and their average weight. Loads are then calculated by a coefficient relating the proportion of N, P, or F. Coliform bacteria per 1000 pounds of each species (Evans and Corradini, 2012). The current animal population was calculated with the use of the 2012 Census of Agriculture for the state of Indiana (USDA, 2019). For each animal species, the current population for each watershed was determined by proportioning the animal population to the portion of each county's hay/pastureland existing within the watersheds. The average weight, daily loading rates, and manure spreading rates and nutrient loss rates for grazing and non-grazing animals were left as default.

BMP Data

Due to low adoption and high percent of privately-owned BMPs within the two watersheds, only cover crops and no-till practices were included in the current conditions of the model before scenario-testing. The percent of cropland applied to these practices was estimated from the mean of the 2014-2018 Indiana State Department of Agriculture tillage transect data (https://www.in.gov/isda/2383.htm). The amount of cropland with active cover crops and no-till are recorded for corn, soybeans, specialty crops and small grains, individually. The amount of cropland falling into the four crop types within each watershed was calculated using the 2011 NASS CDL and proportioned from the county to obtain watershed treatment levels. The length of streams within the watershed was also updated to improve upon the NHDplus v2 medium resolution stream network used in WMYM. A 1:24,000-resolution NHD Hydrography dataset was used for finer resolution in calculating streambank management practice effectiveness.

GWLF-E calculates the effectiveness of BMPs applied to rural land uses through a pollution reduction coefficient for nitrogen, phosphorus, sediment, and fecal coliform bacteria. The pollutant reduction coefficients for rural BMPs were left as default with the exception of conservation tillage. The conservation tillage reduction coefficient was changed to reflect the WMYM default for no-till practices since the ISDA tillage transect data was recorded for no-till. Urban BMP's in GWLF-E also reduce loads through a pollution reduction coefficient, but also includes a runoff capture component unlike its rural counterpart. The default urban reduction coefficients were based on the "Performance Standard" approach used by Chesapeake Bay Watershed Program, which lumps all urban BMPs into two categories and assigns the same reduction coefficient for all BMPs within each category based on the amount of runoff treated. However, since these BMPs don't normally provide the same level of pollutant reduction, individualized nitrogen, phosphorus, and sediment reduction coefficients were selected from the literature (Table 8).

Table 8. Nutrient, Sediment, and Pathogen Reduction Coefficients for selected BMPs.

BMP	N	P	Sed	F. Coli	Source
Cover Crops	0.29	0.50	0.35	n/a	(Evans and Corradini, 2012)
No-Till	0.11	0.29	0.40	n/a	https://wikiwatershed.org/model/
Grass Strips	0.41	0.4	0.53	0.70	(Evans and Corradini, 2012)
Rotational Grazing	0.30	0.30	0.38	n/a	(Evans and Corradini, 2012)
Composting Manure (Livestock)	0.75	0.75	n/a	0.85	(Evans and Corradini, 2012)
Composting Manure (Poultry)	0.14	0.14	n/a	0.14	(Evans and Corradini, 2012)
Rain Barrels	0.00	0.00	0.00	n/a	(Liu et al., 2016a)
Rain Garden	0.28	0.21	0.78	n/a	(Liu et al., 2016a)
Porous Pavement	0.00	0.43	0.80	n/a	(Liu et al., 2016a)

Weather Data

Daily weather data was prepared to match MapShed 1.5.1 formatting. MapShed 1.5.1 is designed to create a weather input for GWLF-E as the average of all the weather stations located with the watershed or the average of the two stations nearest to the centroid of the watershed if no stations are located within the watershed. Of the stations listed in Table 9, only 4 lie within the boundaries of the two watersheds (US1INPT0091, US1INLP0050, USC00124244, USC00128992) and of these 4, only the latter two have a record of more than 10 years. To generate a full weather record spanning from 1995-2018, a geometric centroid of each watershed was generated in ArcGIS with this “gage” being composed of an inverse-distance weighted (IDW) record of all 13 stations. The equation for the IDW was applied to precipitation, maximum temperature, and minimum precipitation;

$$z_p = \frac{\sum_{i=1}^{n}\left(\frac{z_i}{d_i{}^p}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i{}^p}\right)}$$

Where z_p is the IDW calculated precipitation or temperature, n is the number of weather stations, z_i is the measured value at each station, dip is the distance of each station to the centroid. To make the centroid more representative of closer stations, a power of p=2 was used in the IDW formula. The IDW calculation was setup so that any stations with a gap in record were excluded from the daily calculation for the missing days, which means an altered number of stations (n) were used each day. The IDW values were then converted from imperial units (inches, °F) to metric (centimeters, °C) and the average daily temperature was then calculated from the maximum and minimum daily temperature and placed into the model input.

Table 9. List of weather stations used for constructing precipitation and temperature record used in GWLF-E.

GHCND Station ID	Begin Date	End Date	Precipitation(Y/N)	Temperature (Y/N)
US1INLP0028	2008-05-01	2019-04-03	Y	N
US1INLP0007	2006-12-02	2019-04-02	Y	N
USC00124613	1998-11-01	2018-01-12	Y	N
US1INLP0050	2012-01-15	2019-01-08	Y	N
USC00124837	1897-04-01	2019-04-02	Y	Y
USC00124244	1989-06-01	2019-04-02	Y	Y
USC00129222	1961-01-01	2019-04-03	Y	Y
US1INPT0032	2006-09-06	2018-12-10	Y	N
US1INPT0063	2007-09-26	2019-04-01	Y	N
USC00128999	1893-03-01	2005-03-31	Y	Y
USC00128992	2003-08-01	2014-05-14	Y	Y
US1INPT0091	2009-11-22	2019-04-03	Y	N
USW00004846	1997-12-01	2019-04-01	Y	Y

APPENDIX B. SENSITIVITY ANALYSIS & CALIBRATION/VALIDATION

The watershed areas draining to the gages were delineated for the two selected USGS gages with the use of ArcHydro Tools for ArcGIS v. 10.4. The 1:24,000-resolution NHD Hydrography dataset was "burned" into a 10-meter resolution digital elevation model (DEM) of the landscape, and then the DEM was used for delineation from the stream gages (Figure 8).

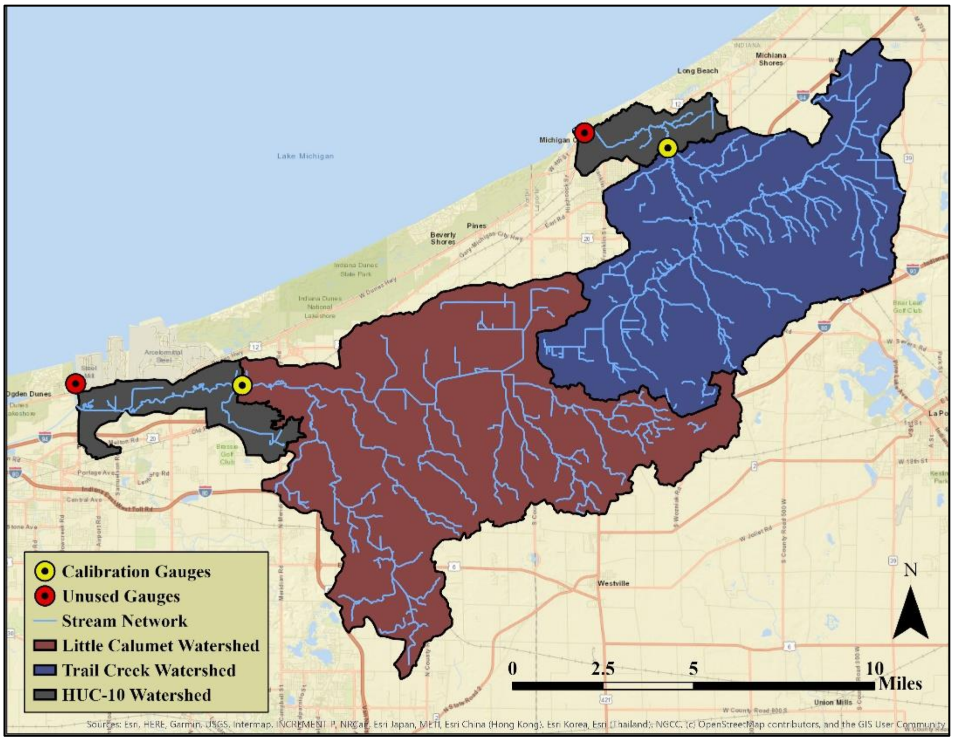

Figure 8. Map of gages used (USGS Gages #4095300 and #4094000) and unused (USGS Gages #4095380 and #04095090) for watershed calibration.

The identified hydrologic parameters in GWLF-E included the percent of urban impervious cover (% Imp), urban pervious curve number (CNP), rural curve number (CNR), potential evapotranspiration cover coefficient (Ket), available water capacity (AWC), and groundwater recession coefficient (GWR). Sensitivity analysis revealed that Ket and AWC were the most sensitive parameters for calibrating streamflow (Figure 9).

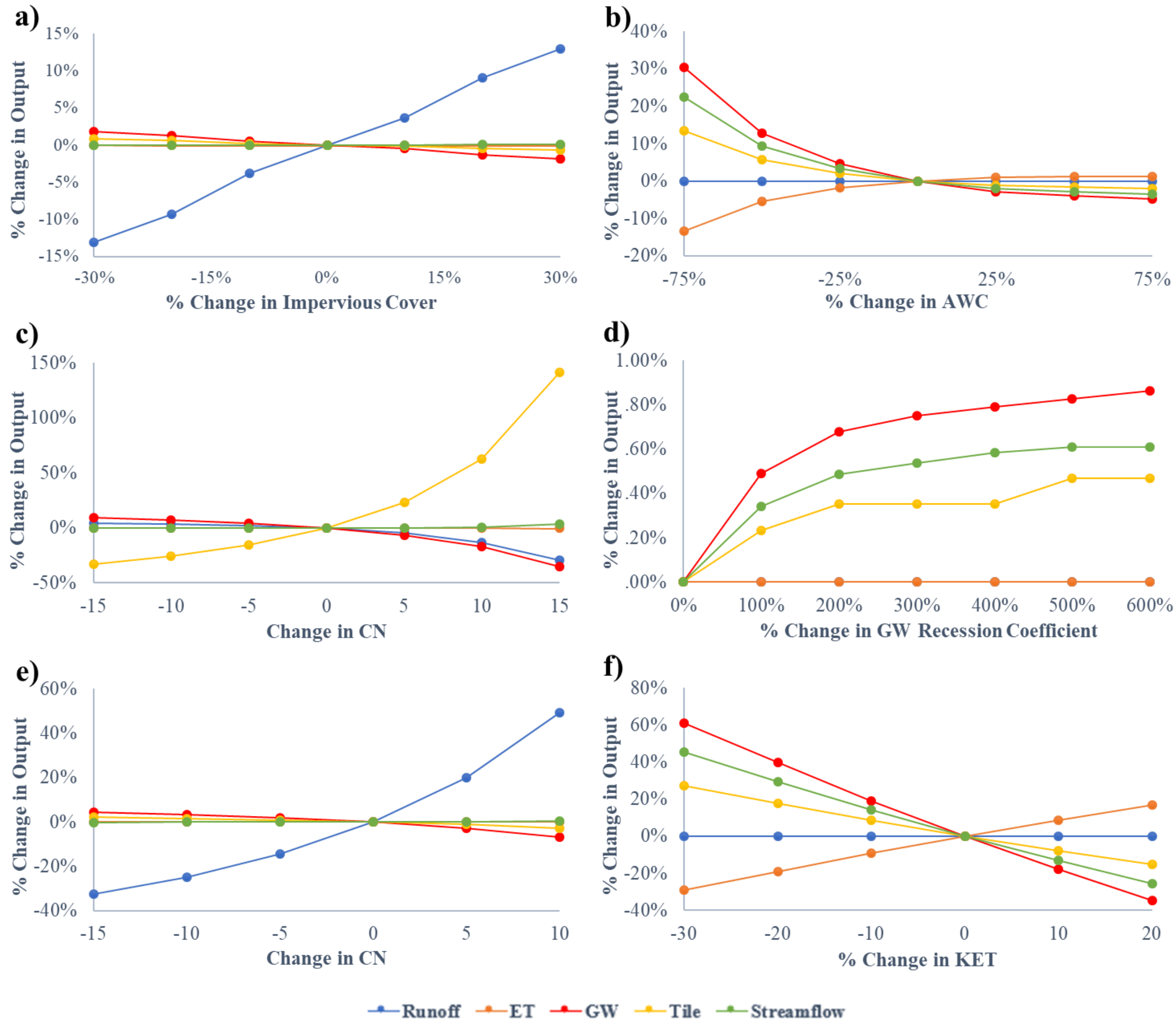

Figure 9. Sensitivity of GWLF-E parameters including a) percent impervious cover, b) available water capacity, c) rural land use curve numbers, d) groundwater recession coefficient, e) urban pervious land use curve number, and f) potential evapotranspiration cover coefficient.

The goodness of fit for the calibrated GWLF-E models can be seen with the simulated hydrographs for the EBLC and TC watersheds. The EBLC watershed had a 2-year spin-up (1995-1996), a 12-year calibration period (1997-2008), and a 10-year validation period (2009-2018). The TC watershed had a 1-year spin-up (2007), a 6-year calibration period (2008-2013), and a 5-year validation period (2014-2018). The calibration was performed on an average monthly timescale for streamflow by altering the most sensitive parameters to maximize both the R2 and NSE parameters (Figure 10; Table 10). The results for the calibration and validation periods in both watersheds were determined to be of satisfactory to good performance (Moriasi et al., 2015) for both the R2 and NSE performance measures.

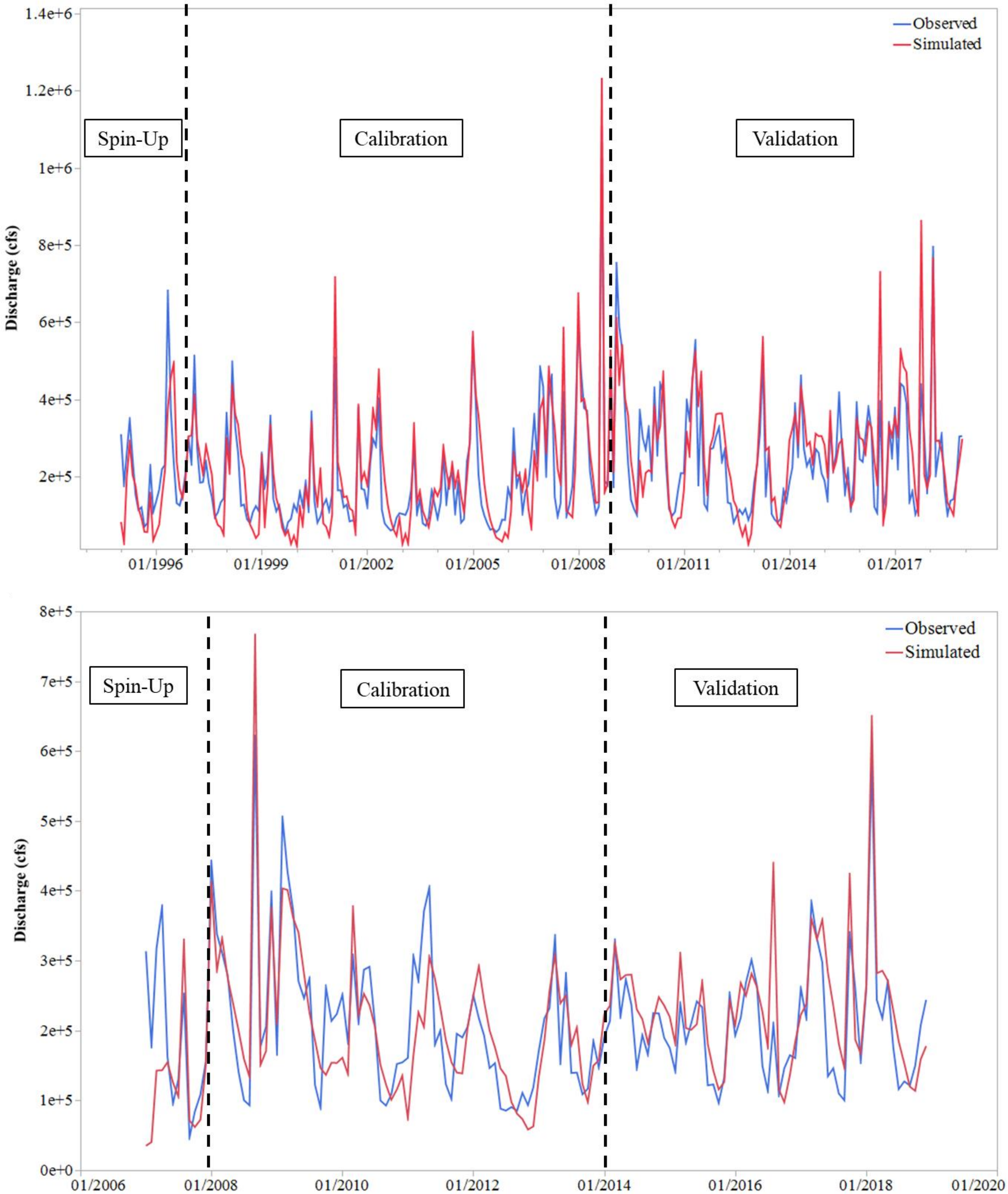

Figure 10. Hydrographs showing goodness-of-fit between observed and simulated streamflow.

Table 10. List of calibrated parameters in GWLF-E model.

Parameter	Note	Initial-LC	Initial-TC	Step	Lower Limit	Upper Limit	Final-LC	Final-TC
% Impervious Cover	LD-Mixed	0.04	0.09	10%	0.01	0.15	0.06	0.11
% Impervious Cover	MD-Mixed	0.63	0.75	10%	0.40	0.98	0.88	0.90
% Impervious Cover	HD-Mixed	0.62	0.75	10%	0.40	0.98	0.87	0.90
% Impervious Cover	LD-Residential	0.23	0.23	10%	0.15	0.35	0.32	0.28
% Impervious Cover	HD-Residential	0.51	0.57	10%	0.35	0.75	0.71	0.68
CN-Rural	Hay/Pasture	69	65	5(CN)	50	84	74	63
CN-Rural	Cropland	80	78	5(CN)	61	91	85	76
CN-Rural	Forest	64	55	5(CN)	30	77	69	53
CN-Rural	Wetland	73	69	5(CN)	54	88	78	67
CN-Rural	Open Land	72	65	5(CN)	50	87	77	63
Ket	Jan	0.5	0.5	10%	0.35	0.55	0.49	0.52
Ket	Feb	0.5	0.5	10%	0.35	0.55	0.49	0.52
Ket	Mar	0.5	0.5	10%	0.35	0.55	0.49	0.52
Ket	Apr	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	May	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Jun	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Jul	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Aug	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Sep	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Oct	0.9	0.9	10%	0.63	0.99	0.88	0.94
Ket	Nov	0.5	0.5	10%	0.35	0.55	0.49	0.52
Ket	Dec	0.5	0.5	10%	0.35	0.55	0.49	0.52
Groundwater Recession	n/a	0.024	0.016	100%	0.004	0.072	0.013	0.008
Available Water Capacity	n/a	22.02	16.67	25%	4.17	38.54	15.20	20.83

APPENDIX C. LAPORTE AND PORTER COUNTY RESIDENT SURVEYS

Section 3: Conservation Practices to Improve Water Quality

PRACTICES FOR YOUR HOME AND NEIGHBORHOOD	
Rain Garden, *a planted depression that captures runoff and allows water to soak into the ground slowly*	
a. What do you know about rain gardens?	**b. What is your likelihood to install a rain garden in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ________________
Vegetated or Green Roof, *a plant layer on roofs that reduces runoff and cooling costs*	
a. What do you know about green roofs?	**b. What is your likelihood to install a green roof in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ________________
Permeable Pavement, *pavement that allows runoff to soak into the ground and filter naturally through soil*	
a. What do you know about permeable pavement?	**b. What is your likelihood to install permeable pavement in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ________________
Swale System (Grassed Swale), *an open channel with grass or shrubs along the base and side to slow rain water*	
a. What do you know about swale systems?	**b. What is your likelihood to install a swale system in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ________________
Rain Barrel, *a barrel to collect rain water to reuse for watering plants and reduce stormwater runoff*	
a. What do you know about rain barrels?	**b. What is your likelihood to install a rain barrel in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently using it	☐ Not applicable ________________
Wet pond, *a pond designed to store and filter water from an entire neighborhood*	
a. What do you know about wet ponds?	**b. What is your likelihood to support the installation of a local wet pond in the next year?**
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ________________

4

Figure 11. Copy of the resident survey used in this study

Figure 11. Continued

If your property is **SMALLER** than one acre, skip to **Section 4** on page 8

GO If your property is **LARGER** than one acre, please **CONTINUE**

PRACTICES FOR YOUR LAND

Open wooded area, *a woodlot for small-scale production of forests as well as recreation uses*

a. What do you know about preserving wooded areas?
- ☐ Never heard of it
- ☐ Somewhat familiar with it
- ☐ Know how to do it but have not done it
- ☐ Currently doing it

b. What is your likelihood to preserve an open wooded area in the next year?
- ☐ Unlikely
- ☐ Neither unlikely nor likely
- ☐ Likely
- ☐ Not applicable ___________________________

Porous Pavement, ***pavement that allows runoff to soak into the ground and filter naturally through soil***

a. What do you know about porous pavement?
- ☐ Never heard of it
- ☐ Somewhat familiar with it
- ☐ Know how to do it but have not done it
- ☐ Currently doing it

b. What is your likelihood to install porous pavement for your driveway, sidewalk, or parking lot in the next year?
- ☐ Unlikely
- ☐ Neither unlikely nor likely
- ☐ Likely
- ☐ Not applicable ___________________________

Riparian Buffer/Vegetated Filter Strip, ***a strip of planted vegetation located along waterways and waterbodies***

a. What do you know about riparian buffers?
- ☐ Never heard of it
- ☐ Somewhat familiar with it
- ☐ Know how to do it but have not done it
- ☐ Currently doing it

b. What is your likelihood to install a riparian buffer in the next year?
- ☐ Unlikely
- ☐ Neither unlikely nor likely
- ☐ Likely
- ☐ Not applicable ___________________________

Wetland Basin, ***a shallow depression planted with vegetation designed to treat runoff***

a. What do you know about wetland basins?
- ☐ Never heard of it
- ☐ Somewhat familiar with it
- ☐ Know how to do it but have not done it
- ☐ Currently doing it

b. What is your likelihood to install a wetland basin in the next year?
- ☐ Unlikely
- ☐ Neither unlikely nor likely
- ☐ Likely
- ☐ Not applicable ___________________________

Windbreak, ***trees or shrubs planted in a line to reduce wind speed over bare soil, preventing soil erosion***

a. What do you know about windbreaks?
- ☐ Never heard of it
- ☐ Somewhat familiar with it
- ☐ Know how to do it but have not done it
- ☐ Currently doing it

b. What is your likelihood to install a windbreak in the next year?
- ☐ Unlikely
- ☐ Neither unlikely nor likely
- ☐ Likely
- ☐ Not applicable ___________________________

5

Figure 11. Continued

If you **DO NOT** operate farmland or have farm animals, skip to **Section 4** on page 8

GO If you **DO** operate farmland or have farm animals, please **CONTINUE**

PRACTICES FOR YOUR FARM

Cover Crops, *a crop grown during the winter to protect and enrich the soil*

a. What do you know about cover crops?	b. What is your likelihood to use cover crops in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________

Conservation Tillage, *soil cultivation that leaves crop residue on fields to reduce soil erosion and runoff*

a. What do you know about conservation tillage?	b. What is your likelihood to use conservation tillage in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________

Grass Strip or Filter Strip, *a strip of planted vegetation located along roads, ditches, or between crop fields*

a. What do you know about grass strips?	b. What is your likelihood to install grass strips in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________

Critical Area Planting, *permanent vegetation grown on sites expected to have high erosion*

a. What do you know about critical area planting?	b. What is your likelihood to use critical area planting in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________

No-till Farming, *growing crops year to year without disturbing the soil through tillage*

a. What do you know about no-till farming?	b. What is your likelihood to use no-till farming in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________

6

Figure 11. Continued

If you **DO NOT** have farm animals, skip to **Section 4** on page 8

GO If you **DO** have farm animals, please **CONTINUE**

PRACTICES FOR FARM ANIMALS

Animal Exclusion, *exclusion of farm animals from streams and critical areas not intended for grazing by fencing*

a. What do you know about animal exclusion?	b. What is your likelihood to install animal exclusions in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________________

Rotational Grazing, *farm animals are regularly rotated to fresh paddocks to prevent overgrazing and optimize grass growth*

a. What do you know about rotational grazing?	b. What is your likelihood to implement rotational grazing in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________________

Compost manure, *manure management to reduce volume and density and kill pathogen*

a. What do you know about composting manure?	b. What is your likelihood to compost manure in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________________

Avoid application of manure on frozen ground, *frozen manure is not absorbed into the soil when the ground is frozen and is often carried off the land with snowmelt*

a. What do you know about avoiding the application of manure on frozen ground?	b. What is your likelihood to avoid applying manure on frozen ground in the next year?
☐ Never heard of it	☐ Unlikely
☐ Somewhat familiar with it	☐ Neither unlikely nor likely
☐ Know how to do it but have not done it	☐ Likely
☐ Currently doing it	☐ Not applicable ______________________

GO Please **CONTINUE** to **Section 4** on the next page

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APPENDIX D. SURVEY RESPONSE SIMPLIFICATION

All responses where a resident group was not identified were excluded from the results. Blank responses for individual practices were treated as unanswered for that specific BMP but allowing room for a response to other BMP types open, so not all BMPs have the same number of respondents. Any respondent who self-identified as an urban or suburban resident but responded the rural residential BMP portions of the survey, were left as unanswered responses for only the rural BMPs. To simplify the modeling scenarios, the permeable pavement (individual property scale) and porous pavement (community scale) were combined into one porous pavement BMP. Similarly, due to the difficulty in distinguishing the level of treatment observed between conservation tillage and no-till practices for cropland, the two were combined and treated as no-till for the modeling scenarios. Once these changes were made, the likeliness or adoption of BMPs for the landowners were aggregated based on the BMP, not by resident class. This was done to better represent watershed-scale effectiveness of BMPs and prevent misidentification of resident classes from affecting modeled contaminant mitigation. Several of the BMP types had to be excluded from the modeled adoption scenarios as they cannot be properly represented within the GWLF-E model (i.e. windbreaks, woods preservation) or the level of potential adoption was deemed too low to be adopted at a large scale (i.e. green roofs, riparian buffers). Neighborhood BMPs were removed from the analysis due to the anonymity of the survey preventing our team from being able to determine if there were enough positive responses in any particular community to warrant adopting such a BMP.

APPENDIX E. LOAD DISTRIBUTION IN WATERSHED

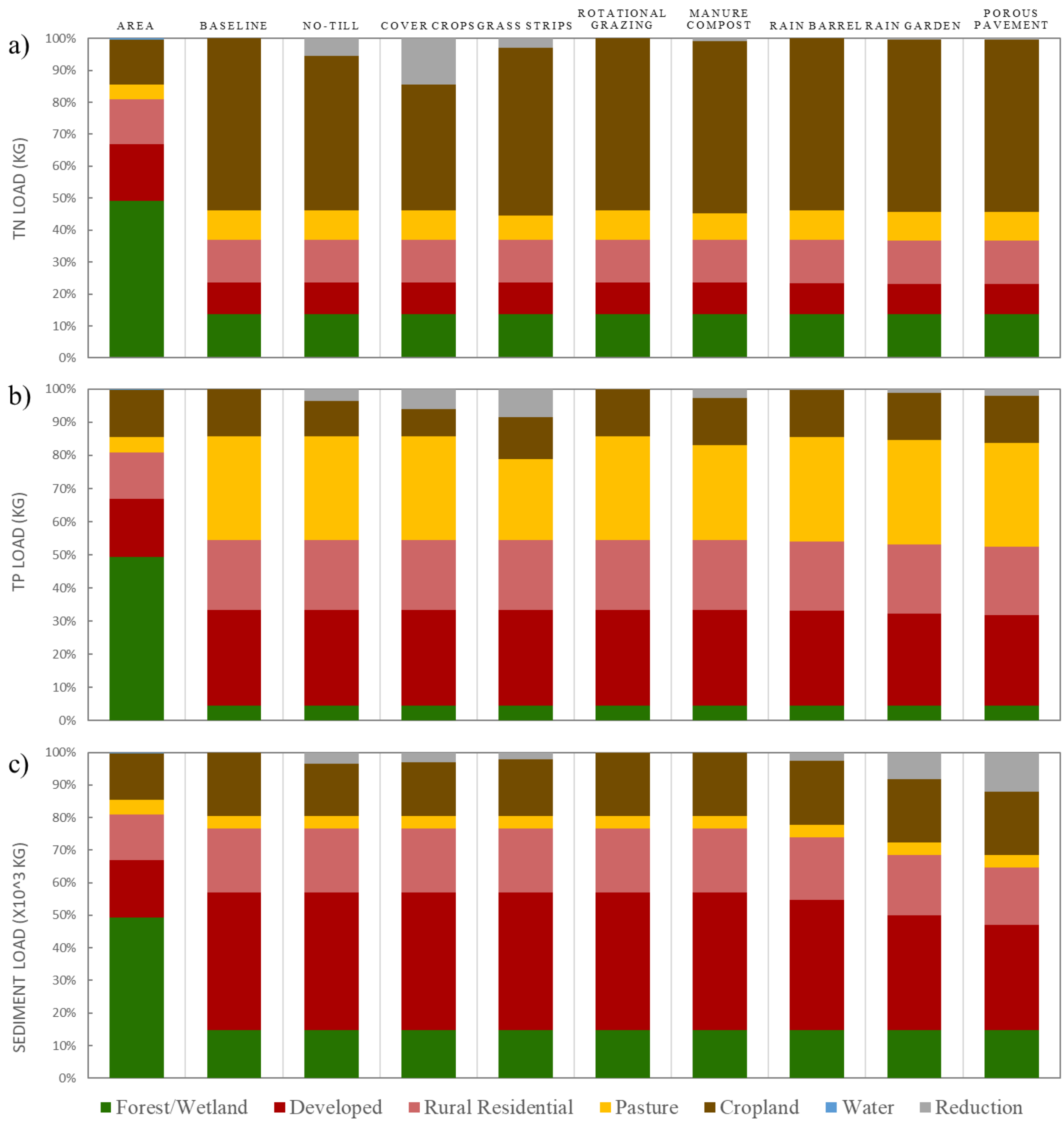
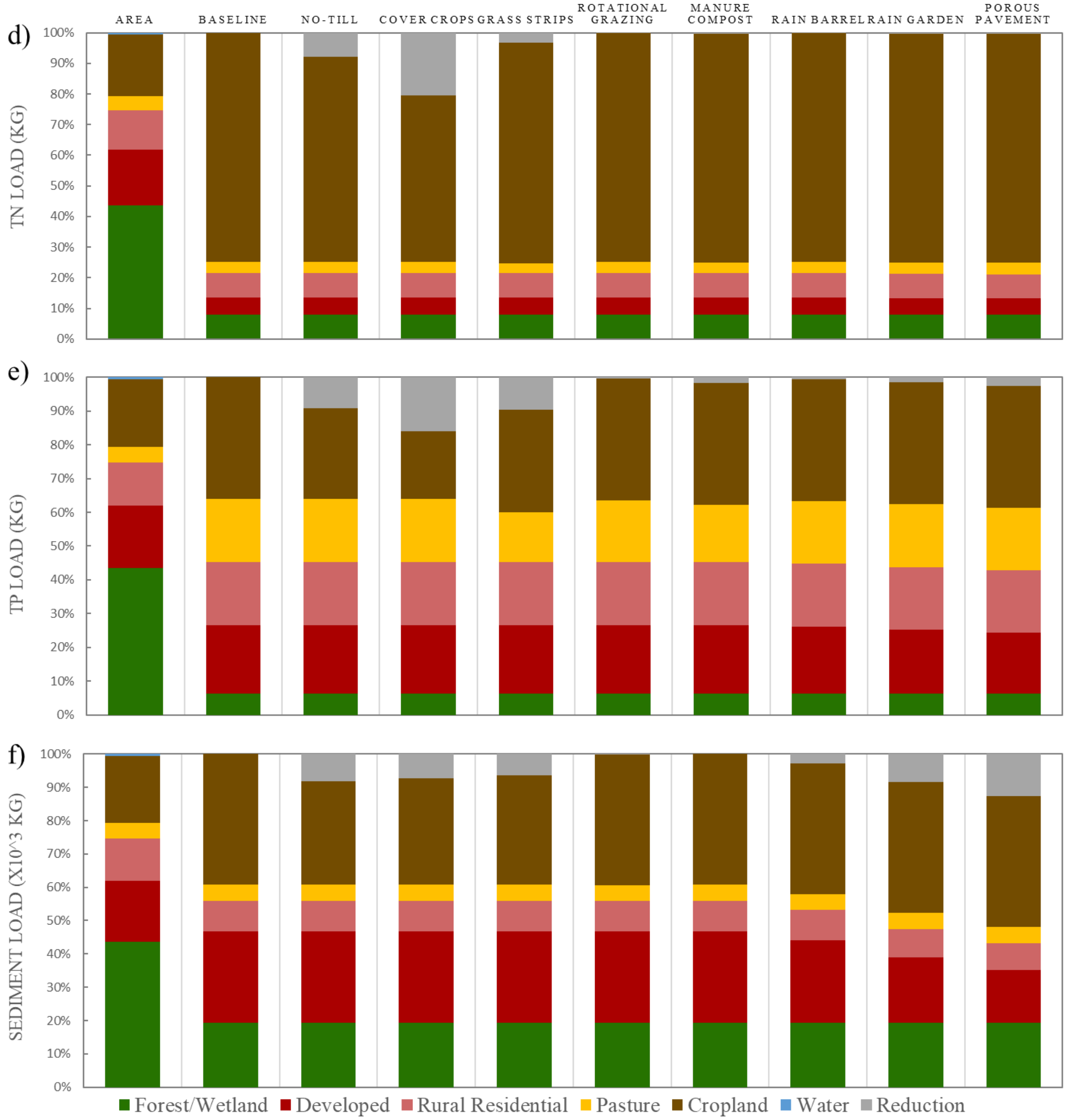


Figure 12. a) Nitrogen, b) phosphorus and c) sediment reduction from full implementation of BMPs within the Trail Creek watershed. d) Nitrogen, e) phosphorus and f) sediment reduction from full implementation of BMPs within the East Branch Little Calumet River watershed.

Figure 12. Continued



APPENDIX F. BMP LOAD REDUCTION CAPACITY

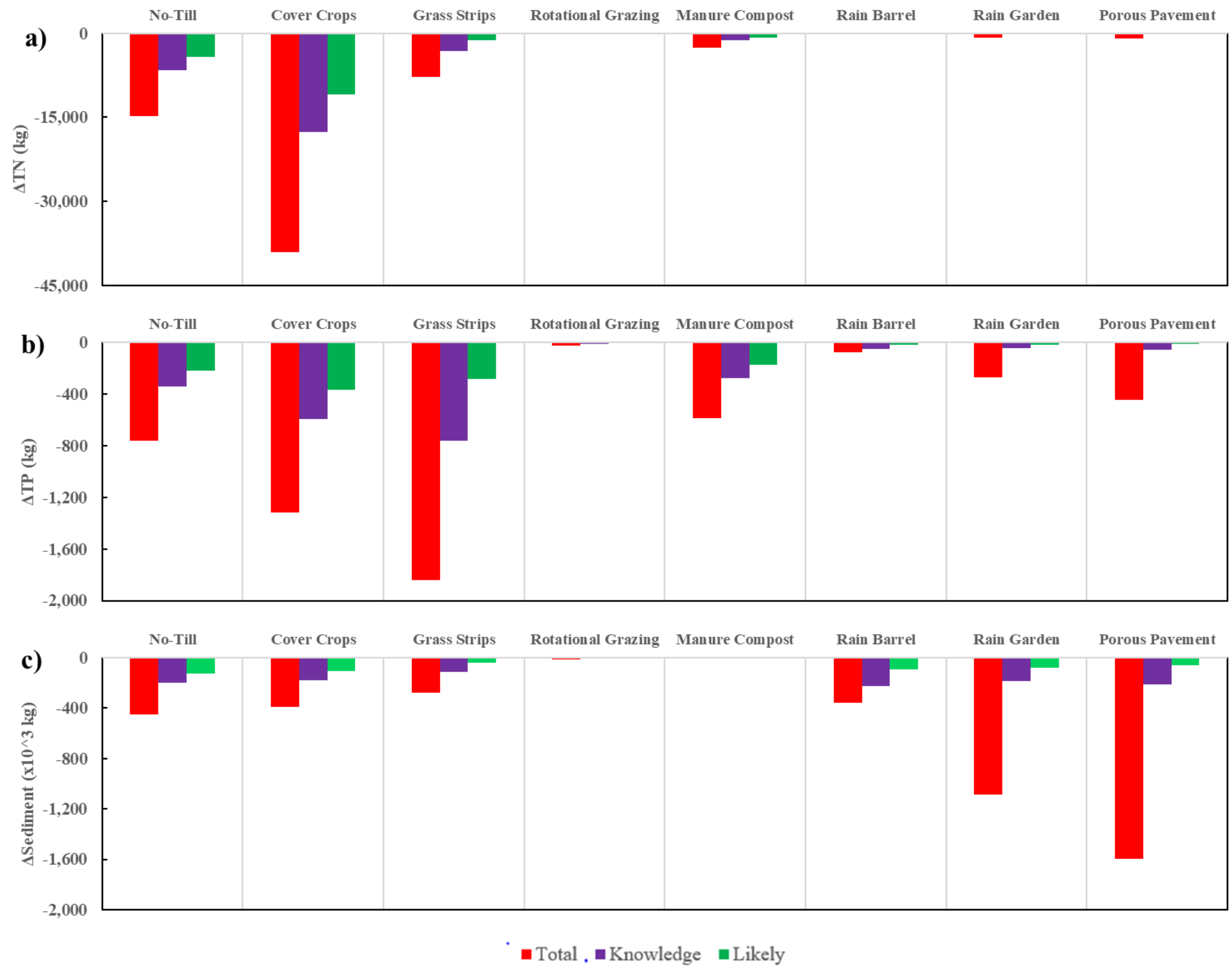
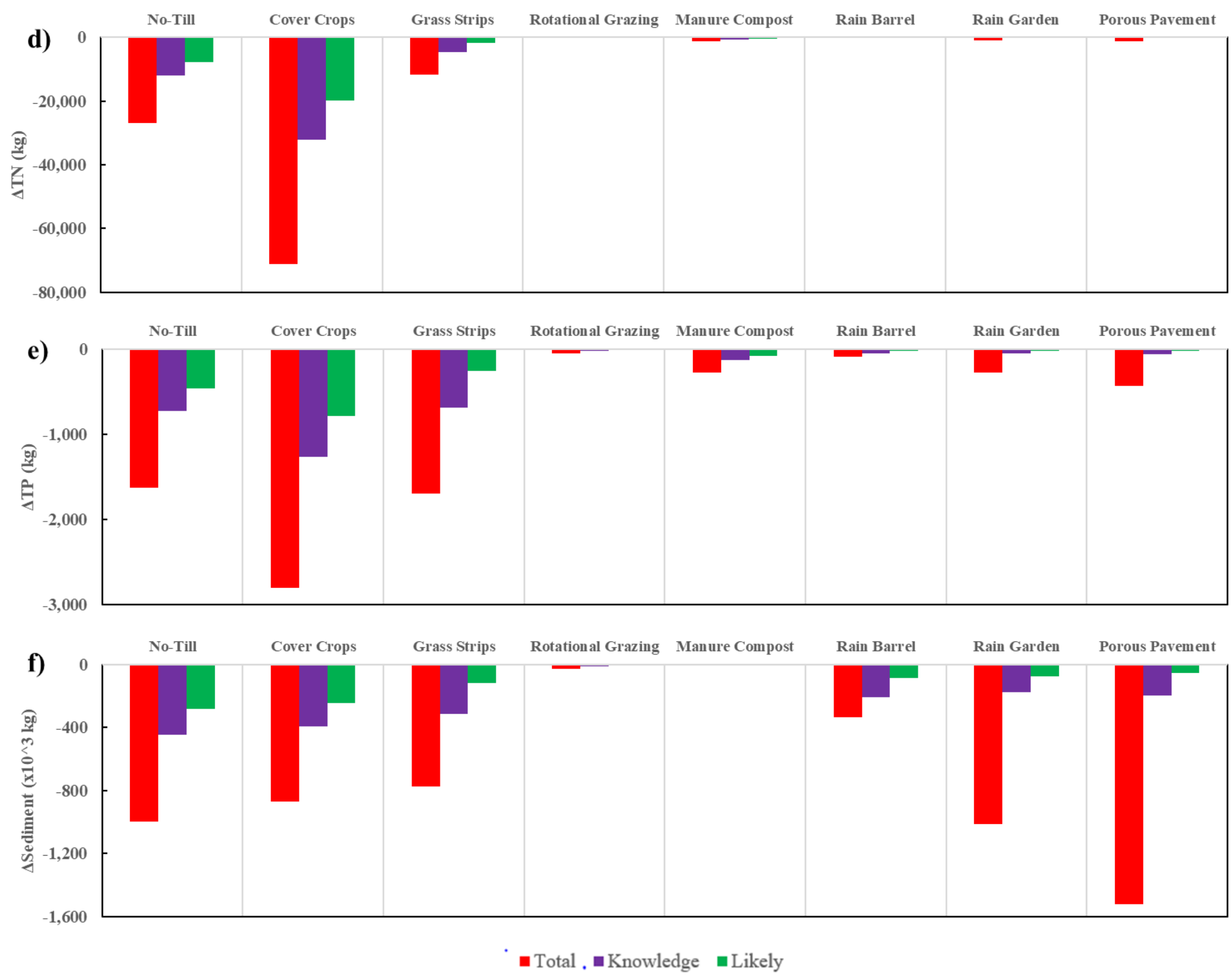


Figure 13. Load reduction of a) nitrogen, b) phosphorus, and c) sediment in the Trail Creek watershed as well as e) nitrogen, e) phosphorus, and f) sediment reduction in the East Branch-Little Calumet River Watershed.

Figure 13. Continued



APPENDIX G. LOAD REDUCTION SCATTER PLOTS

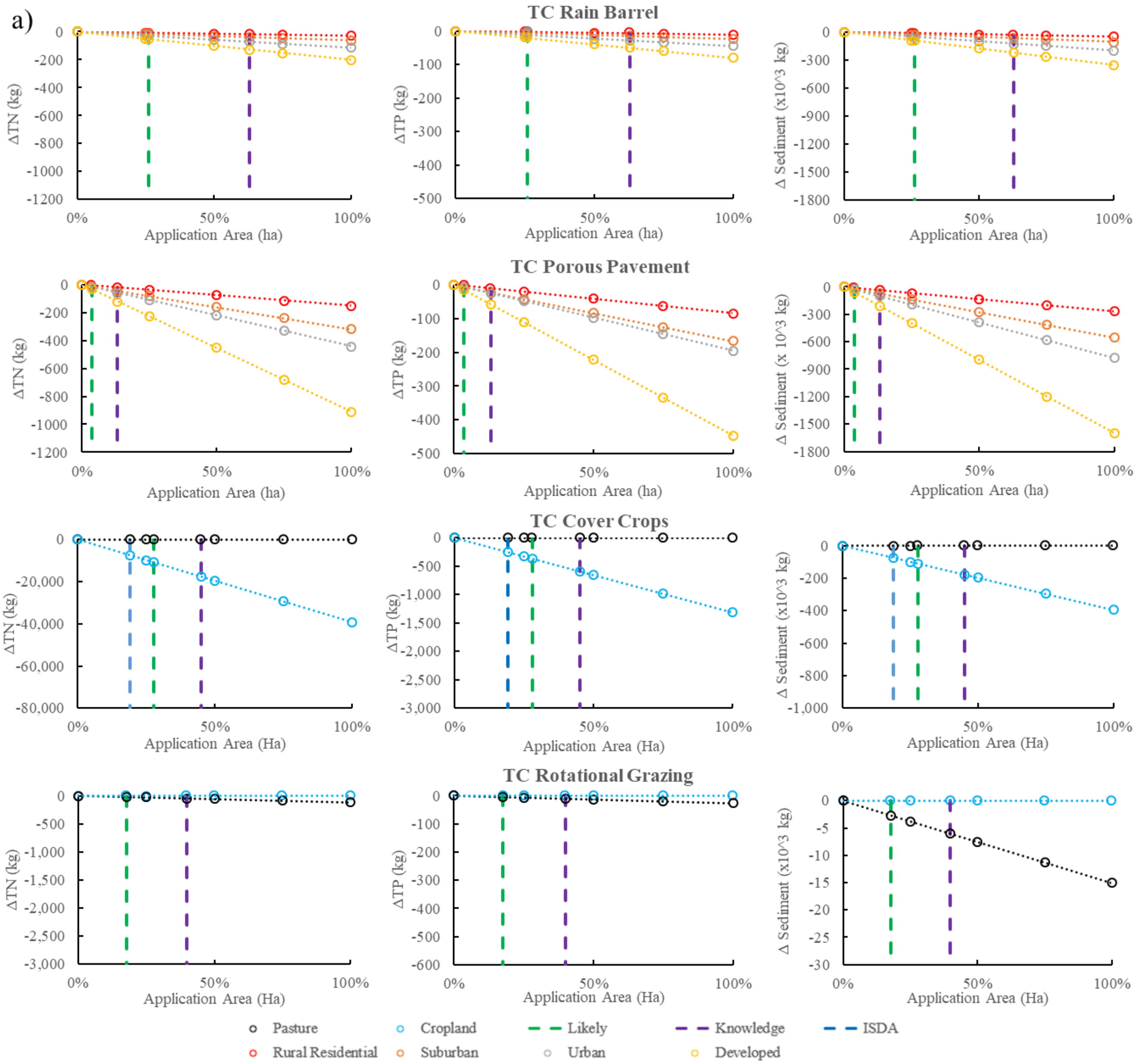
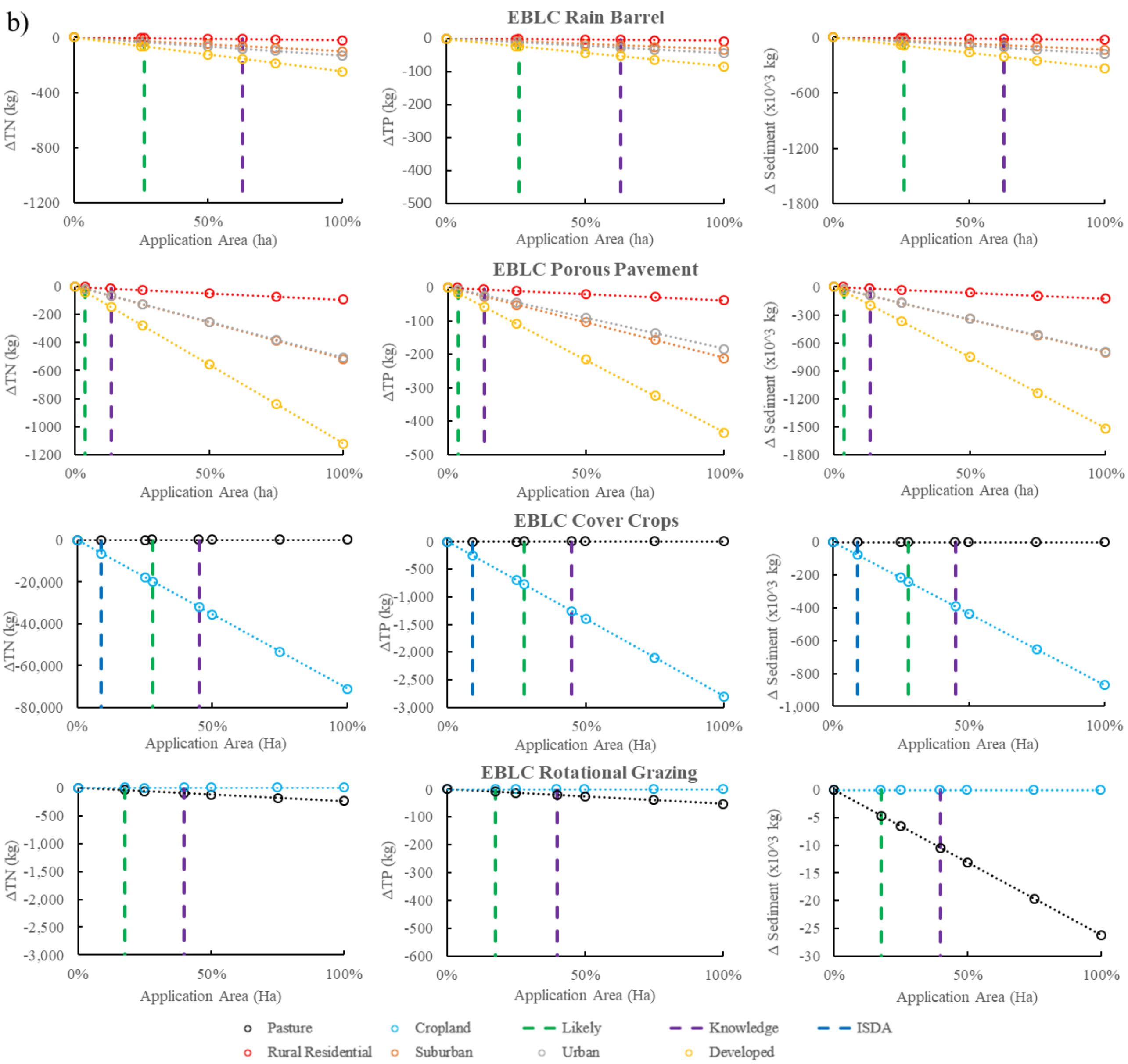


Figure 14. Load reductions for nitrogen (left), phosphorus (middle), and sediment (right) achieved by implementation of (from top to bottom) rain barrels, porous pavement, cover crops, and rotational grazing in the a) Trail Creek and b) East Branch -Little Calumet river watershed.

Figure 14. Continued



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