Illinois-Indiana Sea Grant (IISG) Research Project Final Report

Section A. Summary

Title of Project: Combining societal acceptance and biophysical drivers of conservation practices to improve water quality in multi-use landscapes

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Abstract:

This research assessed the societal acceptance and biophysical potential of water quality improvement practices for reducing nutrient and sediment loading from urban and agricultural sources in the East Branch–Little Calumet River and Trail Creek watersheds in Northwest Indiana. Specifically, this research (1) characterized N, P, sediment and E. coli loading to Lake Michigan by resident groups within the watersheds (i.e., urban residential, suburban residential, rural residential, small agricultural, and medium/large agricultural); (2) determined different resident groups' willingness to adopt water quality improvement practices and the role of information in shaping their willingness to adopt; and, (3) aggregated potential nutrient and sediment removal at the watershed scale based upon resident groups' willingness to adopt. This research found that agricultural areas in the watershed, particularly cropland, produce higher N, P, sediment and E. coli loads than urban/suburban areas. Research results showed that watershed residents generally are aware of and have positive attitudes towards water quality improvement practices, although their likelihood of adoption is low. Watershed residents' perception of descriptive norm and value placed on being a good example to family, friends and neighbors both increase their likelihood of adoption. This research also showed that information alone is unlikely to change the willingness of adoption among watershed residents who already feel positive or negative about water quality problems; however, information about how to choose, install and maintain specific water quality improvement practices may play a role in promoting adoption among those who do not have strong feelings about water quality problems currently.

Keywords: best management practice, human dimensions, integrative modeling, non-point source, watershed

Lay Summary:
Our research aimed at understanding the societal acceptance and biophysical potential of conservation practices for reducing nutrient and sediment loading from urban and agricultural sources. We conducted our research in two watersheds in Northwest Indiana, the East Branch–Little Calumet River watershed and the Trail Creek watershed. Both watersheds are located within the larger Little Calumet-Galien (LCG) watershed, which is the only watershed in Indiana that drains to Lake Michigan. We conducted our research in three stages. First, we used an integrated modeling approach to help us quantify current water volume and pollutant loadings from different resident groups (e.g., urban and rural, agricultural and non-agricultural). Second, we used a mail survey to understand how residents in Porter and LaPorte Counties (where the East Branch–Little Calumet River watershed and the Trail Creek watershed are mostly located) perceive water quality problems and what they are doing to reduce water quality problems in terms of adopting best management practices (BMPs). Finally, we developed BMP implementation scenarios based on both biophysical characteristics of the watersheds and watershed residents' willingness to adopt BMPs. We are currently comparing the modeling results from a range of scenarios with results from the first stage of the project.

Through these three stages of conducting research, we found that watershed residents generally have high levels of awareness of and positive attitudes towards BMPs; however, they are not very likely to adopt any BMPs to improve water quality. We also found that resident groups differ in how they perceive social pressure from peers and others to adopt BMPs to improve water quality. Watershed residents generally value improved environmental quality and reduce flash flood risk as benefits of adopting BMPs, but they do not seem to know enough about specific conservation practices and have concerns about how to install and maintain the practices as main barriers to adoption. Generally, respondents who are younger, perceive more problems with various potential water pollution sources, are more aware of water quality improvement practices, have more positive attitudes, have a stronger sense of personal responsibility, have sought information in the past about water quality problems, or perceive stronger social pressure from peers are more likely to be interested in adopting BMPs to improve water quality in the next year. While information about how to choose, install and maintain specific water quality improvement practices may be useful for watershed residents, the effect may be different based on their initial perceptions about water quality problems. Information alone is unlikely to change the willingness to adopt BMPs among people who feel very positive or negative about water quality problems to begin with; however, information may play a role among people who do not have strong feelings about water quality problems.

Initial results from the watershed model showed that agricultural regions, in particular cropland, produce higher loads of N, P, sediment, and E. coli than urban and suburban regions. This trend remained when the loads were corrected for area of the watershed within each land use type. We also learned from our surveys that agricultural land owners were more knowledgeable and likely to implement BMPs than their urban counterparts. We used both biophysical and social information to develop several BMP implementation scenarios, including (1) implementation of urban/suburban BMPs in all available land, (2) implementation of agricultural BMPs in all

available land, and 3) implementation of both urban/suburban and agricultural BMPs at percentages in which the residents were both knowledgeable and willing to implement them. We are currently running these scenarios and will compare results to range of BMP adoption scenarios in both land uses to understand the complexities in pollutant reduction at the watershed scale. By doing so, we will be able to understand the realistic potential of using BMPs to reduce water pollution in our watersheds, and identify groups of residents within the watersheds who could be targeted for increased education, assistance, and incentives to promote adoption of conservation practices.

Section B. Accomplishments

Introduction

The overall goal of the proposed research was to assess the societal acceptance and biophysical potential of conservation practices for reducing nutrient (N, P), sediment, and pathogen (E. coli) loading from urban and agricultural sources in the East Branch–Little Calumet River watershed and the Trail Creek watershed in Northwest Indiana. The objectives of the proposed research were to: (1) characterize current N, P, sediment, and E. coli loading to Lake Michigan by resident groups within the watersheds (i.e., urban residential, suburban residential, rural residential, small agricultural, and medium/large agricultural) to develop baseline and optimized scenarios; (2) determine the willingness of different resident groups to adopt conservation practices that reduce N, P, sediment, and E. coli loading to Lake Michigan, and the role of information about attribution of responsibility in shaping their willingness to adopt; and (3) aggregate the potential N, P, sediment, and E. coli removal at the watershed scale based upon the willingness of different resident groups to adopt conservation practices.

Project Narrative

<u>Methods and Research Activities</u>

Objective 1:

We addressed both Objectives 1 and 3 with a modeling approach that used the Generalized Watershed Loading Function – enhanced (GWLF-E) watershed model to characterize water and pollutant export based on current land use and existing implementation of BMPs within the watershed. A robust model comparison was conducted to select the model that was well-suited to the scale of the research questions, particularly the ability to simulate all of the parameters of interest and implement both rural and urban conservation practices. We compared three models included in EPA's BASINS modeling framework: GWLF-E, the Soil and Water Assessment Tool (SWAT) and the Hydrologic Simulation Program – Fortran (HSPF). GWLF-E was chosen because the lower level of complexity was appropriate for annual comparisons of pollutant reductions at the watershed scale. GWLF-E is useful for mixed land-uses in our study since it is able to model the key nutrient, sediment (and pathogenic) processes in both urban and rural regions (U.S. EPA 1999). The GWLF model has been widely used for watershed planning and was applied in the Trail Creek Watershed in 2003 to support the watershed management plan that was completed in response to a Total Maximum Daily Load (TMDL) report for E. coli issued by the Indiana Department of Environmental Management. Since then, significant enhancements were made including the addition of tile drainage routines, point-source effluent, new pathogen and animal loading routines, and pollutant load and water volume reductions from multiple types of urban and agricultural BMPs.

The underlying model framework for GWLF-e is similar to the initially proposed combination of L-THIA-LID and STEPL model. It uses the SCS-CN approach to estimate runoff depth and volume. In rural regions, an event mean concentration (EMC) based on land use classification is applied to the runoff volume to quantify dissolved pollutant loads (Haith et al. 1992). Particulate loads are quantified by the product of sediment delivery and sediment nutrient concentrations. Nutrient loads in GWLF- E are based on the same exponential accumulation and wash off relationships used in many other models (Amy et al 1974, Sartor & Boyd 1972). We are running the model separately for each watershed using daily precipitation and temperature data collected from 13 weather stations in LaPorte and Porter Counties during the years 1995-2018 and creating a single time series for each via inverse distance weighting. Annual and monthly values are calculated as the aggregate of the daily direct runoff values. This approach also allows us to investigate climate effects by comparing loading and removal efficiency during wet, average, and dry years. In the GWLF-E model, pollutant removal for rural BMPs is accomplished by a BMP reduction coefficient based on the PRedICT model (Evans et al. 2008). Urban pollutant removal is accomplished using a BMP reduction coefficient that is determined from an adjustor curve in the U.S. EPA's Chesapeake Bay Watershed Model that includes the depth of runoff captured.

Current land use classifications were determined using the 2011 NLCD (Jin et al. 2013). We worked closely with our partner organizations, including Save the Dunes, Northwestern Indiana Regional Planning Commission (NIRPC), Porter and LaPorte County Soil and Water Conservation Districts, and NRCS, to determine existing BMPs in both urban and rural land uses based on their knowledge of the watersheds. We also contacted engineering companies (e.g., Christopher Burke Engineering, American Structurepoint, Inc.) who have developed and implemented watershed plans and stormwater management practices as part of the region's Municipal Separate Storm Sewer System (MS4) programs. We interviewed LaPorte County, Porter and Michigan City stormwater managers to ensure that the existing BMP implementation scenario accurately captures stormwater management strategies currently implemented in the urban/suburban areas. Though these efforts, we established proportions of BMP implementation by land use classification within each watershed and included those in the baseline (current conditions) model. While we recognize that this approach will not perfectly replicate existing conditions, our models are not spatially explicit and this approach allows for comparative analysis of future implementation scenarios.

The GWLF-E model was calibrated by adjusting several hydrologic parameters (e.g. CNs, ET cover coefficients, Available Water Capacity) to match observed streamflow data on an annual basis at the USGS gages (04095300, 04094000). We decided to not use the USGS gauge at the Michigan City Harbor in Trail Creek (04095380) for calibration since the streamflow record had frequent periods of upstream flow due to backwater effects from Lake Michigan. A sensitivity analysis for the hydrologic parameters in the GWLF-E model was performed by altering each parameter over its range of acceptable values to see how it affected streamflow, evapotranspiration, runoff, and subsurface flow.

We separated the existing periods of record for each gage t include 1 year of model spin up and approximately equal number of years for calibration and validation. Each model was calibrated by altering the hydrologic parameters from most sensitive to least sensitive to obtain the best match between predicted and observed runoff volumes with model performance based on R^2 and the Nash-Sutcliffe Efficiency (NSE). Because of limited time series water quality data, modeled nutrient loads were compared to the monitoring data from the Trail Creek Watershed Partnership to confirm that they fell within observed range.

Objective 2:
We first conducted a comprehensive literature review to identify conservation practices in urban and agricultural settings that reduce nutrient, sediment, and pathogen loading in watersheds. We generated a list of conservation practices that individuals/communities could potentially adopt with a focus on reducing urban and agricultural runoff, in consultation with our IISG and other stakeholder partners and additional water quality experts from Purdue Extension. We then developed and administered a human dimensions survey, targeting Porter and LaPorte Counties in Northwest Indiana.

Data for this study was collected through a household survey that was distributed to Porter County and LaPorte County residents from February to April 2018. Although watershed boundaries do not coincide with the county boundaries, the East Branch–Little Calumet River watershed is mostly located in northern Porter and LaPorte Counties and the Trail Creek watershed is mostly located in LaPorte County. Thus, we targeted residents in these two counties for our survey. To inform the development of the survey questionnaire, 12 face-to-face, semi-structured interviews were conducted with water quality professionals who had experience working in the East Branch-Little Calumet and Trail Creek watersheds from October to November 2017.

For the resident survey, because we are interested in understanding willingness to adopt water quality improvement behaviors and the associated role of personal and social norms across the rural to urban gradient, we needed to define and sample our resident types of interest. To do so, we overlayed block groups from the 2010 U.S. Census and land cover types from the 2011 National Land Cover Data (NLCD) in the software program ArcGIS Pro 2.2. For each block group in Porter and LaPorte counties, we determined the majority land cover type excluding open water, grassland, wetland, forest, industrial, and commercial coverage. Once the majority land cover type was determined through zonal statistics, an overlay of small-agriculture, large/medium agriculture, and rural residential shapefiles was added. We were then able to categorize block groups from the 2010 U.S. Census into five resident groups of interest: urban residential, suburban residential, rural residential, small agriculture, and large/medium agriculture. The urban residential group was defined as individuals residing in medium intensity or low intensity developed areas according to the 2011 NLCD data. The suburban residential group included residents living in open space developed land, low intensity developed land, or barren land classes according to the 2011 NLCD data. Adapting definitions from Perry-Hill and Prokopy (2014), we defined medium/large agricultural residents as individuals who are rural and have at least 50 acres of cultivated crops or pasture/hay; small agricultural residents as individuals who are rural and have less than 50 acres of cultivated crops or pasture/hay; and, rural, non-farming residents as individuals who are rural but do not have crops or hay/pasture. Both agricultural groups were designated by the cultivated crops classification in the 2011 NCLD and county parcel data taken from the Indiana Department of Homeland Security (IDHS).

To generate the rural residential group, the locations of houses outside of incorporated cities and towns were obtained from the 2015 IDHS County Address Points geodatabase for both LaPorte and Porter Counties. Each address point with a valid house number was considered a rural residential point and was given two-acre buffer around the residence. The two-acre buffer was determined by averaging the area of influence around the house as indicated by fencing, shrub lines, and mowed lawns across 120 houses over both watersheds. Based on the classification of each Census block and how we defined the five resident groups of interest, we were able to reclassify each Census block as part of the five resident groups.

Our calculated sample size was 2,600 across five groups based on power calculations for a small to medium effect size, so we decided to draw a stratified random sample of 560 individuals from each residential group containing all Census blocks classified as part of that resident group. To do so, we purchased mailing addresses of residents from SSI Global (https://www.surveysampling.com/) and Farm Market ID (http://www.farmmarketid.com/). SSI Global possesses an extensive list of residents in Porter and LaPorte counties. We provided SSI Global our classification of each Census block, and SSI Global made a complete list of addresses in all Census blocks that belong to each resident group and drew a random sample of 560 addresses from each list. Together, they drew a total sample of 2,800 individuals. To ensure sufficient representation of agricultural residents, an additional 816 individual records were purchased from FarmMarketID, which represents their available grower records for Porter and LaPorte counties. These addresses were added to the list of 2,800 addresses from SSI Global. We removed 750 addresses that were duplicates, invalid according to the U.S. Postal Service, or corporate farms for a final sample size of 2,866. Following a modified Tailored Design Method (Dillman et al., 2014), we sent five waves of mail (including three survey waves and two postcard waves) to all residents in our list, and included a $2 bill as a token of appreciation with our first survey packet. A total of 386 survey questionnaires were returned because of inaccurate addresses or deceased individuals, and 1,066 survey questionnaires were completed and returned, giving us a final response rate of 43%.

As previously mentioned, the development of the survey questionnaire was informed by our qualitative interview results and the Theory of Planned Behaviors sample questions (Ajzen & Fishbein, 1980; Ajzen, 2005; Ajzen, 1991). We also drew on a number of existing survey items from *The Social Indicator Planning and Evaluation System (SIPES) for Nonpoint Source Management* (Genskow & Prokopy, 2011). The final survey questionnaire consisted of 26 binary, Likert-scale, and multiple choice questions spanning seven sections: (1) residential classification questions, (2) general knowledge of and attitudes towards surface water resources, (3) conservation practices to improve water quality, (4) attitudes towards conservation practices to improve water quality, (5) social motivations to improve water quality, (6) water quality improvement program incentives and barriers, and (7) demographics. In the first section, we asked survey respondents a series of questions to self-determine their resident group which we used as the actual resident group variable for subsequent analyses.

In addition to the 26 survey questions, the survey instrument contained an experimental component in the form of an information page in the survey booklet. Individual residents in the final sample were randomly assigned into either a treatment or control group and were sent the corresponding survey questionnaire. The control information page was designed to mimic a type of commonly used flyer or information sheet about NPS pollution that would be given out by federal, state and local water resource professionals in the region. This page included general information organized in four sections: (1) a definition of NPS pollution, (2) what contributes to NPS pollution (i.e., general causes), (3) what issues are associated with NPS pollution (i.e., impacts), and (4) what I can do to help (i.e., suggested practices individuals can use to reduce NPS pollution. The treatment information page provided the exact same information in the aforementioned four sections as did the control information page, with the addition of a section that provided a short statement about a recent study conducted by Purdue University and five pie charts from this study. The short statement explained that a study in the East Branch-Little Calumet and Trail Creek watersheds found exactly how much each of the five major land uses (i.e., small agriculture, large agriculture, rural residential, suburban, urban) in the two watersheds contributes to each of four NPS pollutants (i.e., nitrogen, phosphorus, sediment, E. coli). This treatment information page also contained four pie charts each showing the percentage of each NPS pollutant coming from each land use, with an additional pie chart showing the percentage of land area in each land use across the two watersheds. The purpose of the information treatment was to determine if providing specific information to residents about their contribution to pollution would trigger a sense of personal responsibility that would ultimately lead to intention to adopt water quality improvement practices. The exact percentages used in the pie charts were drawn from the modelling results of NPS pollution produced by our collaborators from the Department of Agricultural and Biological Engineering at Purdue University. The treatment and control information pages were designed to be visually identical with the same layout, same background picture, and same font style and size. The only difference between the two was the aforementioned section about the Purdue study. An identical question about likelihood to adopt water improvement practices was asked before the information page in the survey booklet and immediately after the information page for both treatment and control groups.

To analyze the data, we first examined the potential non-response bias. As a proxy to detect differences between respondents and non-respondents, we compared responses from early first-wave survey respondents (n=63) and third-wave survey respondents (n=83) with respect to respondents' demographic characteristics, self-reported likelihood of adoption, attitudes toward conservation practices to improve water quality, and familiarity with such practices (Armstrong & Overton, 1977). No statistically significant differences ($p \leq 0.05$) were detected except for age; respondents in the third (last) wave were younger on average than those in the first wave. We also compared respondents' demographic characteristics with average characteristics of Porter and LaPorte county residents according to the 2010-2017 Census data. Our respondents on average were older, more often male, more often white, wealthier, and more educated. This suggests potential non-response biases and a need for using caution when interpreting the survey results. Missing data was also examined to explore any systematic non-response. For variables of interest, the number and percentage of missing responses were calculated. In addition, we explored which, if any, variables were consistently missing in combination with other variables of interest. No systematic non-response was found.

Univariate descriptive statistics were calculated to assess variable distributions and determine if any outliers existed; none were found. Bivariate relationships were explored using (1) Pearson chi-square test for associations between two categorical variables, (2) Fisher's exact test for associations between two categorical variables when chi-square assumptions were violated, and

(3) Kruskal-Wallis H test for associations between variables as a non-parametric alternative to one-way ANOVA. Where Kruskal-Wallis H test was conducted, a Bonferroni corrected p-value is also provided for more conservative inference (Armstrong, 2014). Responses from the large/medium agriculture group and those from the small agriculture group were combined for Kruskal-Wallis H tests due to the low response rate of farmers (Pennings et al., 2002; Ridolfo et al., 2013). Three social norm variables were constructed by using a number of survey items that were designed to capture the different types of norms. Specifically, each social norm variable was created by averaging a set of survey items for a given norm. High internal reliability was confirmed by the fact that calculated Cronbach alpha values were well above 0.7.

We also constructed an empirical model to assess factors influencing respondents' likelihood to adopt water quality improvement practices. The response variable (ADOPTBEFORE) was the self-reported likelihood of adoption before the information page. ADOPTBEFORE took value 1 if a respondent reported "likely" or "very likely" to adopt any conservation practice to improve water quality in the next year and 0 otherwise (on a five-point Likert scale with 1=very unlikely, 2=unlikely, 3=neither unlikely nor likely, 4=likely, 5=very likely). ADOPTBEFORE was modeled as a function of 20 explanatory variables informed by the literature and our specific interest in different types of social norms. Three of these explanatory variables were composite scores measuring three types of norms: descriptive norm, subjective norm, and normative social influence. In the survey, each type of norm was measured using a number of survey questions. Responses to each set of norm-focused survey questions were highly correlated according to the Cronbach alpha tests. Therefore, we generated a composite score for each type of norm by averaging responses across each set of survey questions. Four additional composite scores were calculated and used as explanatory variables, measuring perceptions of personal impact on water pollution, perceptions of humans' impact on water quality, perceived severity of potential water pollution sources, and self-reported importance of being a good example to others. They were also generated by averaging responses across each set of internally consistent survey questions.

To estimate this empirical model, binary logistic regression was used and probabilities were assigned to each of the two possible outcomes of ADOPTBEFORE. For a binary response variable Y and a vector of explanatory variables X, these probabilities are:

$$P(Y\mathrm{i} = 1) = P\mathrm{i} = \frac{e^{\beta Xi}}{1 + e^{\beta Xi}}$$

$$P(Y\mathrm{i} = 0) = 1 - P\mathrm{i} = 1 - \frac{e^{\beta Xi}}{1 + e^{\beta Xi}} = \frac{1}{1 + e^{\beta Xi}}$$

where Pi represents the probability of a respondent reporting likely or very likely to adopt a water quality improvement practice in the next year, β is a vector of regression coefficients, and βXi is a standard notation representing the right-hand side of a regression model. Without transformation, binary logistic regression results are often reported in terms of odds ratios which is the relative odds of occurrence of an outcome given a variable of interest (Szumilas, 2010). As such, the coefficient estimates in a logistic regression do not carry the implication of per unit impact of individual explanatory variables as in the case of ordinary least squares regression (Mehmood & Zhang, 2005). To draw such implications, marginal effects for each explanatory variable were calculated and reported as follows: $dPi/dXi = Pi(1-Pi)\beta$. For the purpose of this study, the interpretation of the logistic regression results is mainly focused on the identification of significant explanatory variables and their associated signs.

To determine the role of information on respondents' self-reported likelihood to adopt water quality improvement practices, we constructed an empirical model that was similar to the one just described, but with a different response variable and two additional explanatory variables. The response variable for this model was the self-reported likelihood of adoption after the information page (ADOPTAFTER). Similar to ADOPTBEFORE, ADOPTAFTER also took value 1 if a respondent reported "likely" or "very likely" to adopt any conservation practice to improve water quality in the next year and 0 otherwise. The two additional explanatory variables were TREATMENT, indicating whether a respondent was in the treatment or control group, and ADOPTBEFORE, as previously defined. For both logistic regression models, variance inflation factor (VIF) was also calculated. The VIF for both the ADOPTBEFORE model and the ADOPTAFTER model was 1.34, which is well below 10, the standard for detecting multicollinearity in regressions.

We also explored changes in residents' self-reported likelihood of adoption before and after the information page (regardless of which information page). To do so, we created a new variable (ADOPTCHG) by subtracting the before-information self-reported likelihood of adoption from the after-information self-reported likelihood of adoption. As such, ADOPTCHG was an ordinal variable with an interval of 1, ranging from -4 to 4. Pearson chi-square tests were used to explore bivariate relationship between ADOPTCHG and other categorical variables. When assumptions for Pearson chi-square tests were violated, Fisher's exact tests were used instead. All analyses were conducted in software packages Stata 12.0 and R 3.5.1.

Objective 3:
The modeling approach described in detail under Objective 1 is currently being applied to aggregate the potential N, P, sediment, and E. coli removal at the watershed scale based upon the willingness of different resident groups to adopt conservation practices. We have developed BMP implementation scenarios based on both biophysical site suitability and watershed residents' willingness to adopt conservation practices determined through Objective 2. These BMP scenarios include: (1) implementation of urban/suburban BMPs in all available land, (2) implementation of agricultural BMPs in all available land, and 3) implementation of both urban/suburban and agricultural BMPs at percentages in which the residents were both knowledgeable and willing to implement them. We have also created multiple BMP implementation scenarios to maximize water quality improvements by mimicking scenarios developed by Liu et al. (2015). BMPs will be applied individually and in-series for a selected areal coverage (hectares) to identify the most effective practices for urban, agricultural, and mixed land usage. The areal coverage is then systematically increased to identify the relationship between treated area and level of mitigation. This is particularly important as we seek to identify thresholds in the response, which will likely be nonlinear as a function of BMP implementation. Results will be aggregated for all of these scenarios by each of the five groups (i.e., urban residential, suburban residential, rural residential, small agricultural, agricultural) at the sub-watershed (HUC-12) and watershed (HUC-10) scales to quantify nutrient loading reductions as compared to the baseline scenario (Objective 1). While we recognize that spatial arrangement of BMPs on the landscape can have important consequences for water quality, the focus on aggregated BMP implementation by agricultural and residential groups allows us to effectively address Objective 3 with a simplified modeling framework.

<u>Results</u>

The average age of respondents was 59 years old (SD=14, Min=21, Max=96) and over half of respondents (63%) were male. Of 1,042 respondents, 36% had obtained a Bachelor's or graduate degree. The majority of respondents (91%) owned their home. Over half (57%) of respondents shared responsibility for making decisions about their property or home with someone else, and approximately 8% indicated that someone else was entirely responsible for making decisions about their property or home. Thirty percent of respondents reported an annual income before tax of less than $50,000. For those respondents who were farmers, the average farm size was 95.4 acres (SD=222.6, Min=0.25 acres, Max=1,500 acres).

Across all resident groups, over half of respondents (55%) reported being somewhat aware or very aware of conservation practices to improve water quality on a four-point Likert scale (1=never heard of them, 2=slightly aware, 3=somewhat aware, 4=very aware). In general, large/medium-scale farmers reported the greatest awareness (somewhat or very aware: 84%) followed by small-scale farmers (somewhat or very aware: 64%) and rural residents (somewhat or very aware: 55%). No significant associations were found between respondents' self-reported awareness of water quality improvement practices and their education (χ^2=12.12, p =0.059) or income (χ^2=6.22, p =0.399). There was, however, a strong association between self-reported awareness and resident group (χ^2=25.272, $p < 0.05$) such that large/medium-scale farmers had greater self-reported awareness than did any other resident groups.

When asked about interest in learning more about conservation practices to improve water quality, 68% of respondents reported they were interested in receiving more information, with small-scale farmers reporting the greatest interest (73%). In general, a majority of respondents (82%) reported a somewhat or very positive attitude towards conservation practices to improve water quality on a five-point Likert scale (1=very negative, 2=somewhat negative, 3=neither negative nor positive, 4=somewhat positive, 5=very positive). This trend was observed across all resident groups, and there was no statistically significant difference across resident groups.
We asked respondents to indicate their agreement with two opposite statements about water quality in local waterbodies. Twenty percent of respondents agreed or strongly agreed with the statement "I think water quality in local waterbodies is excellent" (on a five-point Likert scale with 1=strongly disagree, 2=disagree, 3=neither disagree nor agree, 4=agree, 5=strongly agree), and the level of agreement was relatively consistent across all resident groups (Figure 8). Relatedly, 81% of respondents agreed or strongly agreed with the statement "I am concerned about water quality in local waterbodies" (also on a five-point Likert scale), with urban, suburban, and rural residents reporting greater levels of concern than farmer residents.

When asked about sources of water pollution, the top three problem sources were (1) use of fertilizers, manure, and/or pesticides for crop production with 70% of respondents who considered it a moderate or severe problem on a four-point Likert scale (1=not a problem, 2=minor problem, 3=moderate problem, 4=severe problem), (2) excessive use of lawn fertilizer and/or pesticides with 68% who considered it a moderate or severe problem, and (3) use of salt and sand on paved roads with 61% who considered it a moderate or severe problem. Perceptions of water pollution sources differed by resident group. For example, urban, suburban, and rural residents viewed the use of fertilizers, manure, and/or pesticides from crop production as the most problematic source of water pollution whereas small- and large/medium-scale farmers were less concerned about this source. Urban and suburban residents tended to consider improperly maintained septic tanks as a more problematic source of water pollution than rural residents. Residents did not significantly differ in terms of their personal norms (χ^2=6.731, p=0.081; with Bonferroni correction, p=0.162). In terms of social norms, farmers perceived stronger descriptive norms than other resident groups (χ^2=19.761, p<0.05; with Bonferroni correction, p<0.05). Farmers also generally reported stronger subjective norms than other resident groups (χ^2=7.932, p=0.05; with Bonferroni correction, p=0.20). However, the significant association between being a farmer and perceiving subjective norms disappears when using a Bonferroni correction. There was also no statistically significant difference among resident groups in terms of their perceived normative social influence (χ^2=6.07, p=0.11; with Bonferroni correction, p=0.37).

There was no statistically significant associations between gender and normative social influence (χ^2=0.363, p=0.55). However, male respondents tended to perceive stronger subjective norms than female respondents (χ^2=7.487, p<0.05; with Bonferroni correction, p=0.0372). Male respondents also reported higher perceived descriptive norms (χ^2=29.558, p<0.05; with Bonferroni correction, p<0.05). Personal norms also differed by gender when utilizing raw p-value, but this difference disappeared when applying the Bonferroni correction (Fisher's exact=0.063; with Bonferroni correction, p=0.378). In terms of education, there was no statistically significant associations between level of education and personal norms (Fisher's exact=0.758), normative social influence (χ^2=1.735, p=0.8845), or subjective norms (χ^2=2.265, p=0.8115). Respondents with at least a high school degree or GED tended to perceive stronger descriptive norms than those who had less education (χ^2=27.925, p<0.05; with Bonferroni correction, p<0.05). With respect to income, no statistically significant associations were found between income and personal norms (Fisher's exact=0.082; with Bonferroni correction, Fisher's exact=0.492) or subjective norms (χ^2=7.479, p=0.1874). Respondents with lower income tended to perceive stronger normative social influence, but this significant relationship disappeared when applying the Bonferroni correction (χ^2=13.159, p<0.05; with Bonferroni correction, p=0.1314). Respondents with higher income tended to perceive stronger descriptive norms (χ^2=27.7128, p<0.05; with Bonferroni correction, p=0.005).

We found no statistically significant associations between respondents' self-reported awareness of water quality improvement practices and normative social influence (χ^2=2.173, p=0.5374). However, respondents who were more aware of water quality improvement practices were more likely to perceive stronger subjective norms (χ^2=12.911, p<0.05; with Bonferroni correction, p=0.0288), perceive stronger descriptive norms (χ^2=111.341, p<0.05; with Bonferroni correction, p<0.05), and possess stronger personal norms (χ^2=13.097, p<0.05; with Bonferroni correction, p=0.0264) than those who were less aware. Similarly, we found no statistically significant associations between respondents' attitudes towards water quality improvement practices and normative social influence (χ^2=7.039, p=0.1338). However, respondents with more favorable attitudes tended to report stronger subjective norms (χ^2=48.129, p<0.05; with Bonferroni correction, p=0.0006), stronger descriptive norms (χ^2=31.551, p<0.05; with Bonferroni correction, p<0.05), and stronger personal norms (χ^2=112.816, p<0.05; with Bonferroni correction, p=0.0006).

Despite the generally positive attitudes, less than half (41%) of respondents indicated that they were either likely or very likely to install any water quality improvement practice in the next year. By resident group, small- and large/medium-scale farmers reported greater likelihood of adopting any practice in the next year than other resident groups (53% and 54% likely and very likely, respectively; on a five-point Likert-scale with 1=very unlikely, 2=unlikely, 3=neither unlikely nor likely, 4=likely, 5=very likely; Figure 7). Rural residents and suburban residents reported similar likelihood (41% and 40% reported likely or very likely, respectively). Urban residents reported the lowest likelihood (38% reported likely or very likely). However, this difference was not statistically significant. In terms of demographics, a negative association existed between respondents' likelihood and age (χ^2=117.53, $p < 0.05$). Positive associations existed between respondents' likelihood of adoption and their education (χ^2=38.97, $p < 0.05$), income (χ^2=40.67, $p < 0.05$), and owning their home (χ^2=11.466, $p < 0.05$). Respondents' likelihood of adoption was also positively associated with their self-reported awareness of water quality improvement practices (χ^2=88.10, $p < 0.05$), although there was no statistically significant association between likelihood to adopt and general attitudes towards conservation practices.

The logistic regression model for assessing factors influencing residents' likelihood of adoption (ADOPTBEFORE) was significant overall (χ^2=234.94, p<0.001) (Table 8). Among all the demographic variables, age was the only significant one (p<0.001). Older respondents tended to report lower likelihood to adopt conservation practices to improve water quality than did younger respondents. When controlling for all the other factors, respondents' resident group had no effect on their self-reported likelihood of adoption. Generally, respondents who perceived more problems with water pollution in their area, who were more aware of water quality improvement practices, and who had more positive attitudes towards these practices were more likely to report intention to adopt a practice in the next year (p=0.013, p=0.004, and p=0.023, respectively). Likewise, respondents who felt a sense of responsibility to adopt conservation practices to improve water quality tended to report greater likelihood of adoption (p<0.001). Additionally, respondents who had noticed more of their family, friends, neighbors, or others in their community adopting water quality improvement practices (i.e., perception of descriptive norm) were more likely to report intention to adopt themselves (p=0.067). Those who perceived stronger subjective norm associated with the adoption of water quality improvement practices (i.e., perceived expectation from family, friends, neighbors, and others in community to adopt) also reported higher likelihood of adoption (p<0.001). Finally, respondents who had previously looked for information about water quality problems in their local waterbodies were also more likely to report intention to adoption (p=0.012).

The logistic regression model for understanding the role of information on respondents' self-reported likelihood to adopt water quality improvement practices was also significant overall (χ^2=389.17, p<0.001) (Table 9). Similar to the ADOPTBEFORE model, significant explanatory variables in the ADOPTAFTER model included respondent's age (p<0.001), attitude towards water quality improvement practices (p=0.001), a sense of responsibility for adopting these practices (p=0.065), and perception of descriptive norm (p=0.020). Valuing being a good example to family, friends, neighbors, and others in their community was also a significant variable in the ADOPTAFTER model (p<0.001). Perceiving more problems with water pollution in their area and being aware of water quality improvement practices were no longer significant, nor was having previously looked for information about water quality problems in their local waterbodies. While perception of subjective norm also became insignificant, having a stronger personal norm for keeping water clean became negatively associated with reporting a higher likelihood of adoption after reading the information page (p=0.017). Importantly, TREATMENT was not a statistically significant predictor in the model whereas ADOPTBEFORE (i.e., respondents' self-reported likelihood of adoption prior to reading the information page) was a statistically significant predictor of ADOPTAFTER (i.e., respondents' self-reported likelihood of adoption after reading the information page; p<0.001).

We further explored the change of self-reported likelihood of adoption before and after respondents read the information page. Overall, ADOPTCHG ranged from -4 to 4, with a mean of -0.03 (SD=0.88; Figure 19a). Using a Fisher's Exact Test, we found that ADOPTCHG was not associated with respondents reading either the treatment or control information page (Fisher's exact=0.911; Figure 19b). Further, ADOPTCHG did not differ based on respondents' income (χ^2=13.5383, p=0.195), education (χ^2=9.1279, p=0.520), or whether they rented or owned their home (Fisher's exact=0.509). ADOPTCHG did, however, differ between male and female respondents (Fisher's exact=0.034). Although the difference was small, male respondents were slightly more likely to report decreased likelihood of adoption (mean=-0.04; SD=0.81) than were female respondents (mean=-0.01; SD=0.98). Additionally, there was a statistically significant association between ADOPTCHG and respondents' self-reported likelihood of adoption before they read the information page (χ^2=123.6263, p<0.001). Specifically, for respondents who reported being very unlikely or unlikely to adopt water quality improvement practices before the information page, 51% reported the same likelihood after the information page while 40% reported higher likelihood of adoption; for those who reported being likely or very likely to adopt before the information page, 64% reported the same likelihood after the information page while 30% reported lower likelihood of adoption; and for those who reported being neither unlikely nor likely to adopt before the information page, 62% remained the same while 18% reported less likely and 20% reported more likely (Table 10).

The GWLF-E model for the Trail Creek and East Branch – Little Calumet River Watersheds was generated with the use of the "Model My Watershed" tool that is a part of the Stroud Water Research Center's WikiWatershed initiative. This tool is meant to help with TMDL planning as an all-in-one application that allows you to import all required inputs needed for the GWLF-E program from widely accepted national datasets. While the generalizability is advantageous, several of the calculated parameters were modified based on higher resolution data including available water capacity (AWC), animal populations, total stream length, total agricultural stream length, percent impervious cover, CN, soil erodibility (K), evapotranspiration cover coefficient, and percent of area with tile drainage. By exporting the "Model My Watershed" tool results and running GWLF-E separately, we also were able to use more detailed local weather data.

This approach also allowed us to modify the NLCD land cover classifications to match those identified in Objective 2 (Table 1). Rural residential households are not included in publicly available land use data products so were created as part of this project through the use of aerial photography and county address records. Rural residential households were defined to include all residential address points that didn't lie within incorporated townships or cities. We designated an individual rural residential area to include the area of human influence around the home (e.g. area of property mowed, area within fencing/shrub-boundary, etc.). The size of the rural residential plot was measured at 60 houses in each watershed by digitizing aerial photographs. Each homestead area was recorded and the average was 2 acres. This layer was incorporated into the NLCD and effectively transitioned households from low-density residential in the unincorporated regions to rural residential. Making this land use classification separate and explicit allowed these areas to be modeled as a separate class with representative impervious cover and contaminant loading. This transformation was substantial and accounted for 43% of the Trail Creek and 40% of the Little Calumet low density residential land use by area (combined developed open space and low intensity developed) being modeled as rural residential. This process also elucidates rural households that are not recognized by the NLCD and listed as forest or grassland.

Table 1: Area by land use classification for each watershed

Land use Classification	Little Calumet	Trail Creek
Urban	749.3	682.2
Suburban	2,470.1	1,751.6
Rural Residential	2,445.3	2,144.0
Large Ag	1,850.7	1,014.6
Small Ag	2,876.1	1,877.4
Commercial/Industrial	293.9	266.5
Forest/Wetland	8,334.9	7,554.5
Total	19,020.3	15,290.8

The sensitivity analysis for these watersheds revealed available water capacity (AWC) and the evaporation cover coefficient (Ket) to be the most sensitive parameters, which was also noted by the model developers for the 2003 Trail Creek TMDL. We used this information to guide the calibration procedure, focusing on these two parameters to determine the input parameter set that best matched observed data. We are currently analyzing these results to identify differences between land uses.

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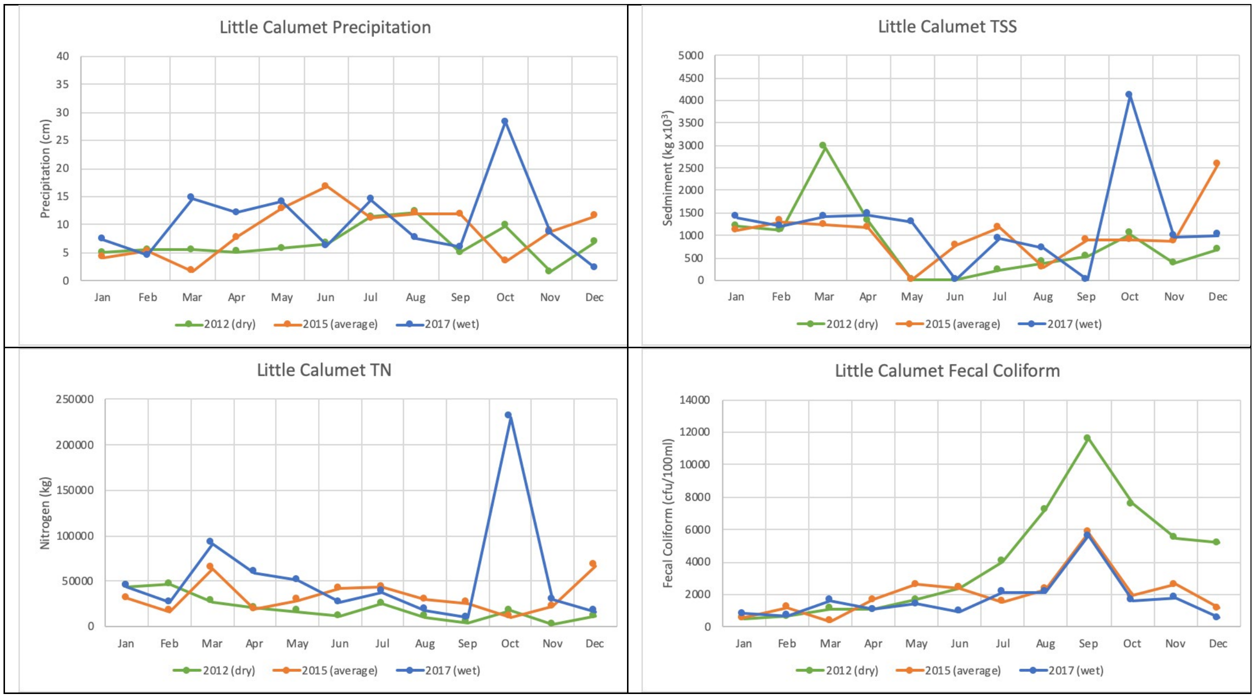

Figure 1: Monthly precipitation, total suspended sediment (TSS), total nitrogen (TN), and fecal coliform from representative dry (2012), average (2015), and wet (1017) years in the Little Calumet Watershed.

From the survey results, the 20 BMPs in the questionnaire were broken into 3 types, Individual Scale, Community Scale, and Agricultural. The individual scale included BMPs that are typically implemented on only one property parcel whereas the community scale included those BMPs that would take multiple landowner approval to implement. Since we do not know the location of individual landowners and their combined approval of community scale BMPs, we elected to not include these in the willingness scenarios. Residents were questioned on both Knowledge of BMPs and Likelihood to install BMPs (within the next year). Based on the response categories, we created 3 groups of BMP implementation measure including 1) Knowledge of BMP, 2) Likely to Implement BMP, 3) Not Unlikely to Implement. We are currently finalizing the implementation scenarios based on the knowledge and likeliness to implement BMPs. The targeted BMPs include rain barrels, rain gardens, permeable pavement and green roofs in urban and suburban areas as well as conservation tillage, cover crops, rotational grazing, composting manure, and grass strips in agricultural regions. We are also creating multiple BMP implementation scenarios to maximize water quality improvements (Liu et al. 2015). BMPs will be applied individually and in-series for a selected areal coverage. The areal coverage is then systematically increased to identify the relationship between treated area and level of mitigation. We will then complete multiple model runs to identify the relationship between treated area and level of mitigation in each watershed.

Conclusion and Recommendations

The adoption of BMPs and LID strategies by watershed residents is important for reducing NPS pollution in the United States. Extensive research has explored factors influencing farmers' adoption of BMPs, while considerably less research has focused on urban and suburban residents. This research encompassed the urban-to-rural gradient of two counties in northwestern

Indiana with mixed land uses. Through a household survey of residents in Porter and LaPorte counties, this research assessed watershed residents' awareness of, attitudes towards, and likelihood of adopting water quality improvement practices, as well as factors influencing their likelihood of adoption, particularly the role of norms and the role of information about responsibility. We used an integrated approach using watershed models combined with survey information to better inform both aspects: the survey included an information treatment based on modeling results of the current conditions in the watershed and the future scenarios in the model will be based on landowners willingness and knowledge. While the last component is not yet complete, we will follow up with an addendum when it is finalized. Nevertheless, this research offers the following three considerations for water quality professionals and researchers.

First, sometimes watershed residents may exhibit a general awareness of and positive attitude towards water quality improvement practices; however, many may not have an immediate plan to adopt any practices, and not all those who express an interest in adoption would end up adopting any practices. Thus, it important for water quality programs to be aware of various external constraints that may ultimately deter watershed residents from transitioning from a favorable intention to actual adoption (e.g., Ajzen, 2005; Blackstock, Ingram, Burton, Brown, & Slee, 2010; Dutcher, Finley, Luloff, & Johnson, 2004; Quimby & Angelique, 2011; Rogers, 2003; Steg & Vlek, 2008; Wall, 1995). Several important barriers were identified in this research, including watershed residents' not knowing enough about specific practices they could adopt for their own home or property, concerns about difficulties in installing a practice, and concerns about maintaining the practice. Reducing these barriers to adoption will be essential for water quality programs. Generally speaking, education and outreach programs have demonstrated success when they are comprehensive, adaptive, representing key stakeholder inputs, and specific to stakeholder needs and concerns (Loomis, Bair, & Gonzalez-Caban, 2001; Marynowski & Jacobson, 1999). Similarly, water quality programs could benefit from highlighting benefits associated with water quality improvement, such as improved general environmental quality and reduced flash flood risk, at least in the context of this research.

Second, this research expanded understanding of personal and social (descriptive and subjective) norms in motivating watershed residents' adoption of water quality improvement practices. Specifically, this research suggests that urban, suburban, rural non-agricultural, and rural agricultural residents may differ in their perceived descriptive and subjective norms. Because descriptive and subjective norms are important for watershed residents in terms of their interest in water quality improvements, more research is needed to understand why such difference in social norms exists across resident group. So far, few studies have examined and compared personal and social norms across segments of population in the context of water quality management. However, this research generated some evidence to suggest that rather than focusing on increasing people's personal norms about water quality protection, water quality programs could benefit greatly from developing and implementing outreach and communication strategies that utilize social norms to catalyze behavioral change in the context of water quality improvement.

Finally, traditional outreach and education programs tend to assume that people do not adopt sustainable resource management and conservation practices because they lack information or have insufficient knowledge, and that if they were provided with information, they would adopt desired practices (e.g., Burgess & Harrison, 1998). While this research showed that residents may benefit from information about installation and maintenance of water quality improvement practices, it also provided evidence suggesting a limited role that information could play in shaping water quality improvement behaviors when holding other factors constant. Particularly, this research showed no difference in residents' self-reported likelihood of adopting water quality improvement practices whether they were provided with specific information about the responsibility of different resident groups for NPS pollution or generic information about NPS pollution—in fact, neither seemed to have motivated change in self-reported likelihood of adoption. Several reasons have been posited for why specific information about the responsibility of different resident groups for NPS pollution may be ineffective in changing willingness to engage in resource management and conservation behaviors, including but not limited to: the strength of contextual forces (Stern, 1999), barriers to action such as cost or inconvenience (Steg & Vlek, 2008; Stern, 1999), lack of emotional response (Kollmuss & Agyeman, 2002), and cognitive dissonance (Festinger, 1957; Kollmuss & Agyeman, 2002). More research is needed to investigate when and why information works (or not) in the context of water quality management. Moreover, this research found that watershed residents responded to information about NPS pollution differently based on their initial intention to adopt water quality improvement practices prior to receiving any information. As such, understanding how and why information may have different effects on different segments of population would be important. One practical consideration for water quality programs is to tailor their outreach to target favorable and less favorable watershed residents using different information content, types, formats, and/or sources as a way to maximize positive effects of information while minimizing potential negative effects. Given the complex role of information, it is important to keep in mind that not all water quality improvement information is equally effective or ineffective. However, this research provides important preliminary evidence suggesting that water quality programs may want to consider moving away from providing generic information about NPS pollution and water quality improvement practices to focusing on actionable behaviors that are specific to different resident types and how they manage and live on their properties.

Potential Applications, Benefits and Impacts

Although our project does not have direct benefits and impacts to stormwater management organizations in Indiana, learning from our project can be insightful to help these organizations understand the human dimensions of the adoption of water quality improvement practices and integrate human dimensions insights into their water quality management programs. Specifically, our aforementioned three learnings/recommendations can be helpful for these organizations. First, we found that watershed residents may exhibit a general awareness of and positive attitude towards water quality improvement practices; however, many do not know enough about specific practices they could adopt for their own home or property, have concerns about difficulties in installing a practice, and have concerns about maintaining the practice. Second, we found that descriptive and subjective norms are important for watershed residents in terms of their interest in water quality improvements, and we suggest that rather than focusing on increasing people's personal norms about water quality protection, water quality programs could benefit greatly from developing and implementing outreach and communication strategies that utilize social norms to catalyze behavioral change in the context of water quality improvement. Third, we found that although residents may benefit from information about installation and maintenance of water quality improvement practices, information may only play a limited role in shaping water quality improvement behaviors; instead, water quality programs may want to consider moving away from providing generic information about NPS pollution and water quality improvement practices to focusing on actionable behaviors that are specific to different resident types and how they manage and live on their properties. These potential applications of our research results could be carried out in both short and long terms.

International Implications

Although our project does not have direct international implication, learning from our project can be insightful to help international scholars to use similar approaches to understand the human dimensions of the adoption of water quality improvement practices and to integrate human dimensions insights into water quality modeling.

Data Management Plan

We generated human dimensions data and biophysical data through this proposed research. We recorded the human dimensions data in accordance with Purdue University's Institutional Review Board human subject requirements. We are storing interview and survey data in password-protected computers only accessible to co-PIs and graduate research assistant in this research. The biophysical data included synthesis of publicly available time series values of river discharge and water chemistry, as well as model results at the watershed outlets. In addition to the data themselves, all data sets contained metadata sufficient to explain methods used to collect and analyze results. In the next two years, we will store de-identified human dimensions data and biophysical data through its lifecycle in Purdue University Research Repository (PUUR). Links to data stored in PURR and to peer-reviewed publications from this research will be posted on co-PI's university faculty websites. We will direct all requests for data to these websites as well.

Section C. Outputs

Media Coverage: None

Publications, Theses, Dissertations

- Domenech, J. 2018. Assessing the role of norms and information in shaping residents' intentions to adopt water quality improvement practices across urban-to-rural landscapes. Master of Science Thesis. West Lafayette, In: Purdue University.
- Mills, J. 2019. Evaluating the effectiveness of landowner adoption of water quality improvement practices in mixed land-usage watersheds. Master of Science Thesis. West Lafayette, In: Purdue University. *Expected August 2019.*

Undergraduate/Graduate Names and Degrees

- Jennifer Domenech; M.S.; Natural Resource Social Science (2017-2018); Purdue University
- Jonathan Mills; M.S.; Agricultural and Biological Engineering; Purdue University (2018-present)
- Rachel Scarlett; Ph.D.; Interdisciplinary Ecological Science & Engineering (and Agricultural and Biological Engineering); Purdue University (2018-present)

- Priyanka Shankar; B.S. in Sustainable Biomaterial —Process and Product Designing; Undergraduate Research Assistant on the project; Purdue University (January 2017-May 2018)
- Kasha Halbleib; B.S. in Natural Resources and Environmental Science; Undergraduate Research Assistant on the project; Purdue University (January 2017-May 2018)

Other Outputs

- Wabash River Enhancement Corporation. 2018. *What You Can Do at Home for the Wabash River* [Brochure]. Lafayette, IN: Wabash River Enhancement Corporation.
- Wabash River Enhancement Corporation. 2018. *Wabash River Friendly Home* [Brochure]. Lafayette, IN: Wabash River Enhancement Corporation.

Patents/Licenses:

Not applicable

Project Partnerships:

We work with our partner organizations such as Purdue Extension and Northwestern Indiana Regional Planning Commission (NIRPC), to determine the existing BMP implementation in both urban and rural land uses based on their knowledge of the watersheds. Various partners also helped us identify potential stormwater management professionals with whom we conducted semi-structured interviews. In addition, these partners helped us pilot test our survey questionnaire before it was launched. Finally, all partners were invited to Jenn Domenech's MS thesis defense, and we will share additional publications from this project with these partners.

Related Projects:

- Purdue University, Engineering Faculty Conversations (EFC) on Smart Cities Program. 2019. Sara McMillan (PI), Zhao Ma (co-PI), Brady Hardiman (co-PI), Roshanak Nateghi (co-PI). *Socio-ecological resilience of urban ecosystems to extreme climate events*. $66,680 (funded).

Awards and Honors:

- Faculty Fellow, Faculty Leadership Academy for Interdisciplinary Research (FLAIR) Fellows Program, Office of the Executive Vice President for Research and Partnerships, Purdue University, 2019 (Z. Ma)
- Nominee for the Outstanding Graduate Mentor/Teacher Award, College of Agriculture, Purdue University, 2018 (Z. Ma)
- Seed for Success Award, Purdue University, 2018 (Z. Ma)
- William L. Hoover Exemplary Faculty Service Award, Department of Forestry and Natural Resources, Purdue University, 2017 (Z. Ma)
- The Bravo Award, College of Agriculture, Purdue University, 2017 (Z. Ma)
- Faculty Policy Fellow, Purdue Policy Research Institute, Purdue University, 2017-2018 (Z. Ma)
- D. Woods Thomas Memorial International Support Fund Award, Purdue University, 2018 (J. Domenech)
- International Symposium on Society and Resource Management (ISSRM) Student Subsidy Award, International Association for Society and Natural Resources, 2018 (J. Domenech)

- Purdue Graduate Student Government/Purdue Graduate School Travel Grant Award, Purdue University, 2018 (J. Domenech)
- Purdue Graduate Student Government Professional Grant Award, Purdue University, 2018 (J. Domenech)
- Purdue University Service-Learning Student Grant Program, Purdue University, 2018 (J. Domenech)
- Indiana Watershed Leadership Academy Scholarship, 2017 (J. Domenech)
- Teaching for Tomorrow Fellow, Purdue University, 2016-17 (S. McMillan)
- Seed for Success Award, Purdue University, 2018 (S. McMillan)
- George Washington Carver Fellow, 2015-present (R. Scarlett)
- Purdue Climate Change Research Center Travel Grant, 2017 (R. Scarlett)
- TU Dresden International Synthesis Workshop Travel Grant, 2017 (R. Scarlett)
- Heterotrophic Regimes Workshop Travel Grant, 2018, (R. Scarlett)
- ABE Departmental Travel Grant (3 awards), 2015-2019 (R. Scarlett)
- Purdue Graduate Student Government Travel Grant, 2018 (R. Scarlett)
- ASABE Global Water Security Conference Travel Grant, 2018 (R. Scarlett)