Final Report

Section A. Summary.

- **Title of Project**

Adaptive Management Framework Approach to Watershed Implementation of Nutrient Reduction Strategies

- **Completion Date** (If no-cost extension was approved, use the extension end date.)

8/31/16

- **Principal Investigator***

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- **Abstract**

Summarize project, accomplishments and/or results (250 words). Parts of this may be taken from your 90-2 project summary form.

Various computer models, ranging from simple to complex, have been developed to simulate hydrology and water quality from field to watershed scales. However, many users are uncertain about which model to choose when estimating water quantity and quality conditions in a watershed. This study compared hydrologic/water quality models including Spreadsheet Tool for the Estimation of Pollutant Load (STEPL)-Purdue, Soil and Water Assessment Tool (SWAT), High Impact Targeting (HIT), Long-Term Hydrologic Impact Assessment (L-THIA), Pollutant Load (PLOAD), Spatially and Temporally Distributed Model for Phosphorus Management (STEM-P), Region 5, and ensemble modeling (using STEPL-Purdue, SWAT, L-THIA, PLOAD, and STEM-P). Model capabilities, inputs, and underlying methods to estimate streamflow, surface runoff, baseflow, total nitrogen (TN), total phosphorous (TP), and sediment were examined. Uncalibrated, calibrated, and validated outputs of these models and uncalibrated ensemble modeling in estimating water quantity and quality for a 41.5 km^2 agricultural

watershed in Northeastern Indiana were explored, and suggestions were provided on the selection and use of models. Models need to be selected carefully based on the simulation objectives, data availability, model characteristics, time constraints, and project budgets.

- **Keywords**

Include a list of five keywords for indexing.
Hydrology, water quality, computer model, comparison, agricultural watershed.

- **Lay Summary**

Write a brief, 1-2 paragraph summary of your research project and important findings, using language that is understandable by a lay person (i.e., with very limited scientific background).

Various hydrologic/water quality models, which are useful for natural resources protection and mitigation of concerns, have been developed. However, which model(s) are the most useful in specific cases are not well defined. Hydrologic and water quality models (including STEPL-Purdue, SWAT, HIT, L-THIA, PLOAD, STEM-P, Region 5, and results of ensemble modeling), with varying data requirements, simulation methods, and complexity levels, were compared to identify situations in which the models are the most useful. Some of the models will be used in the web-based decision support system called Tipping Points and Indicators program, which helps decision makers identify impacts of land-based activities that threaten the sustainability of ecosystems in their watershed. Within Tipping Points, L-THIA will be used for estimating the impacts of urbanization on runoff and water quality, while STEPL-Purdue and SWAT will be used to estimate runoff and water quality from agricultural watersheds.

Key findings for the models explored are briefly summarized below. The modified STEPL-Purdue model is recommended for use in agricultural watersheds based on performance in the study watershed, its simplicity, and its ability to estimate the impacts of agricultural management practices. The L-THIA model is recommended for use in urbanized watersheds because it can estimate the impacts of urban management practices. SWAT, which simulates watershed processes more completely, is the most time consuming and difficult to apply model and therefore would be useful when more comprehensive analyses are required. Simpler models, including STEPL-Purdue, HIT, L-THIA, PLOAD, and STEM-P, are less time consuming and easier to set up than SWAT, and require minimum input data but may misrepresent watershed processes and provide inaccurate results in some cases. Among these simpler models, STEM-P provides more spatial and temporal details but at the expense of computational time. The Region 5 model can only be applied at field levels. The PLOAD model should be used with caution due to the likely need to update pollutant export coefficients based on local conditions. An ensemble modeling approach could be used to increase the reliability of predictions when no or limited monitored data are available.

The variability of the models for estimating hydrology and water quality is high. Models need to be selected carefully based on the simulation purposes, data availability, model characteristics, time limits, and project budgets.

Section B. Accomplishments

- **Introduction**

Include project goals and objectives.

(1) summarize model capabilities, model inputs, and simulation methods of hydrologic and water quality models including STEPL-Purdue, SWAT, HIT, L-THIA, PLOAD, STEM-P, and Region 5; (2) explore uncalibrated, calibrated, and validated outputs of these models and uncalibrated ensemble modeling (using STEPL-Purdue, SWAT, L-THIA, PLOAD, and STEM-P) in estimating average annual water quantity and quality for a 41.5 km2 agricultural watershed in Northeastern Indiana; and (3) provide suggestions on the selection and use of these models based on the results in this study.

- **Project Narrative**

Maximum length of 20 double spaced pages or 20,000 characters. Include methods, results, conclusions, recommendations, outreach accomplishments and other pertinent information. Focus on the project activities and accomplishments in context of the overall project goals.

1. Materials and methods

1.1 Model description

Table 1 provides descriptions of the models including STEPL-Purdue, SWAT, HIT, L-THIA, PLOAD, STEM-P, and Region 5. The detailed descriptions include model capabilities; model inputs to estimate hydrology, TN, TP, and sediment from the watershed without BMPs, and additional inputs to simulate BMPs; and methods to simulate hydrology, TN, TP, sediment, and BMPs. The section labeled "Optional inputs" in Table 1 identifies model inputs for which default values are used unless values are provided by users.

1.2 Study area

The AXL watershed, with a total area of 41.5 km^2, is located in DeKalb County, Northeastern Indiana. The land uses of the AXL watershed in 2006 show that 12% of the watershed is forest, 64% is cropland, 17% is pasture land, 1% is water, and 6% is urban (Figure 1). The average slope of the watershed is 0.97%, and the average annual precipitation is 948 mm.

1.3 Simulation scenarios in this study

Watershed hydrologic/water quality models are typically used for watershed planning. For the purpose of accomplishing project goals with the lowest consumption of time and money, the user should select the correct model. Table 2 shows the simulation scenarios used to evaluate models in this study. STEPL-Purdue was applied in four ways, including typical use with observed rainfall data (STEPL-Purdue_1), modified use with observed rainfall data (STEPL-Purdue_2), typical use with CLIGEN rainfall data (STEPL-Purdue_3), and modified use with CLIGEN rainfall data (STEPL-Purdue_4) (for more details of typical and modified use, refer to 2.3.1 STEPL-Purdue simulation). Uncalibrated, calibrated, and validated average annual results of STEPL-Purdue_1, STEPL-Purdue_2, SWAT, L-THIA, and STEM-P were estimated. Uncalibrated average annual results of STEPL-Purdue_3, STEPL-Purdue_4, HIT, and PLOAD were computed. The Region 5 model was not included in this part of the study because it does not provide pollutant load outputs for all land uses. For example, the model provides outputs from agricultural, feedlot, and urban land uses, but it does not report outputs from other land uses. Further, the model is a field level model, and does not estimate watershed scale results. Detailed descriptions of simulation scenarios are discussed in the following sections.

The simulated results were compared with observed data. Observed data (2006 to 2013), including streamflow, TP concentration and TN concentration, were obtained from Agricultural

Research Service (ARS) Conservation Effects Assessment Project (CEAP) Water Quality Assessment Program. Observed runoff volume and baseflow volume were computed based on streamflow data using Baseflow Filter Program (BFLOW) (Arnold and Allen 1999). Missing TP and TN concentrations were filled using the LOAD ESTIMATOR (LOADEST) model (Runkel et al. 2004). Observed TP and TN concentrations were multiplied with flow to generate observed TP and TN loads for model calibration and validation.

2. Results and discussion

2.1 Uncalibrated results comparison

Table 3 shows the uncalibrated average annual results (2006-2013) using various models, including four applications of STEPL-Purdue (STEPL-Purdue_1, STEPL-Purdue_2, STEPL-Purdue_3, and STEPL-Purdue_4), SWAT, HIT, L-THIA, PLOAD, and STEM-P models. Table 3 indicates that the four ways to apply uncalibrated STEPL-Purdue model resulted in underestimating average annual streamflow volume by 36%, 29%, 39%, and 32%, respectively. Uncalibrated STEPL-Purdue applications underestimated average annual runoff volume by 39%, 49%, 42%, and 51%, respectively. Uncalibrated STEPL-Purdue applications underestimated baseflow volume by 34%, 14%, 37%, and 17%, respectively. The differences between observed and simulated flow were due to default CN values in the model that were not suitable for flow estimation in the AXL watershed. The differences between flow volumes estimated by typical and modified use of uncalibrated STEPL-Purdue model were obvious; this was due to typical use of STEPL-Purdue that only considered the study area as a single watershed with one soil group, while modified use of STEPL-Purdue model used all soil groups present and multiple subwatersheds. This demonstrated that to better represent the actual land uses and soil groups of a watershed, users should specify all soil groups in the watershed using multiple subwatersheds instead of using a single watershed with one dominant soil group. For both typical and modified use of STEPL-Purdue model, the differences of estimated average annual results using observed rainfall data and CLIGEN rainfall data were small; this indicates that users may be able to use either observed or GLIGEN rainfall data as the weather inputs for STEPL-Purdue model to estimate average annual results.

Uncalibrated STEPL-Purdue model applications underestimated TN load by 49%, 80%, 50%, and 81%, respectively. Uncalibrated typical use of STEPL-Purdue model with observed rainfall data and CLIGEN rainfall data overestimated average annual TP load by 153% and 150%, respectively. However, uncalibrated modified use of STEPL-Purdue model with observed rainfall data and CLIGEN rainfall data underestimated average annual TP load by 62% and 64%, respectively. The average annual sediment load estimated by typical use of uncalibrated STEPL-Purdue was also much higher than that assessed by modified use of uncalibrated STEPL-Purdue. The higher estimated results of nutrients and sediment loads by typical use of STEPL-Purdue model compared to that of modified use of STEPL-Purdue were mainly due to different USLE parameters used when computing sediment loads. For typical use of STEPL-Purdue model, the default values of USLE parameters for DeKalb County, Indiana from the model were used, including 180 for rainfall erosivity factor R, 0.34 for soil erodibility factor K, 1.47 for topographic factors LS, 0.2 for cropland cropping factor C, 0.04 for pastureland factor C, 0.003 for forest factor C, and 1.00 for conservation practice factor P. However, based on methods in the SWAT model and Foster et al. (1981), the values of USLE parameters used in the modified use of STEPL-Purdue model were changed to 140 for rainfall erosivity factor R, 0.30 for soil erodibility factor K, 0.11 for topographic factors LS, 0.2 for cropland cropping factor C, 0.003 for pastureland factor C, 0.001 for forest factor C, and 1.00 for conservation practice factor P. With the changed values of parameters in the USLE method, the modified use of STEPL-Purdue model resulted in significantly lower sediment loads compared to that of typical use of STEPL-Purdue. As a result, nutrient loads delivered with sediment, as well as the total nutrient loads at the outlet of the watershed estimated by modified use of STEPL-Purdue model, were much lower. This indicates that users should be careful about using the default values in STEPL and may want to generate their own USLE parameters for their watersheds of interest.

The uncalibrated SWAT model overestimated average annual streamflow, runoff, baseflow, TN, and TP by 58%, 109%, 19%, 21%, and 292%, respectively. This suggests the default values of parameters in SWAT to represent hydrological processes and nutrient cycles were not applicable for this watershed, and parameters needed to be calibrated. The simulation of different flows allows SWAT to consider the different pathways that will respond differently for different time scales, and quality of water from these different pathways will also be different.

The sediment load estimated by the uncalibrated HIT model estimated from AXL watershed was 0.34 ton/ha/yr, but due to lack of monitored sediment load data, the performance of HIT was not compared with observed data. The uncalibrated L-THIA model underestimated average annual runoff volume, TN load, and TP load by 35%, 86%, and 75%, respectively; this indicates that the default values of curve numbers, and TN/TP EMC values in L-THIA model were too small to correctly estimate runoff volume and nutrient loads in the AXL watershed. The uncalibrated

STEM-P model, which had good estimation of baseflow, overestimated average annual streamflow volume and runoff by 19% and 38%, while underestimating average annual TP load by 14%. This suggests the default parameters in STEM-P model may also need to be calibrated to better estimate hydrology and water quality in the AXL watershed. The uncalibrated PLOAD model, which underestimated TN and TP loads by 10% and 3%, respectively, had good performance in estimating TN and TP loads in the AXL watershed (less than 10% difference from observed data), indicating that the default Export Coefficient values of TN and TP in PLOAD model were suitable for the AXL watershed. It should be mentioned that PLOAD uses annual pollutant load coefficients from each land use to estimate total pollutant loads, and therefore, if PLOAD was calibrated, results for the calibration and validation periods would be the same. Further, the model does not include an automated approach for calibration. Although pollutant estimation of the PLOAD model performed well in the AXL watershed, it uses a simple method of pollutant assessment and does not consider surface runoff, baseflow, or tile flow, which may not be the best way to simulate pollutants losses, especially when trying to identify best approaches to reduce pollutant loads.

Since STEPL-Purdue, SWAT, and HIT use similar methods (USLE, MUSLE, and RUSLE, respectively) to estimate soil erosion, the differences of average annual sediment load using modified use of STEPL-Purdue, SWAT, and HIT might be due to different methods to estimate sediment delivery ratio. STEPL-Purdue uses empirical sediment delivery ratio methods based on the size of drainage area without accounting for other characteristics of the watershed. In STEPL-Purdue, the larger the drainage area is, the smaller the sediment delivery ratio would be (Park 2014). The HIT model adopts a sediment delivery model (SEDMOD) based on surface roughness, soil texture, and distance to stream (Fraser 1999). The SWAT model estimates sediment routing based on a simplified Bagnold equation and physics based approach for channel erosion (Neitsch et al. 2011). The average annual sediment load estimated by the L-THIA model was much lower than results estimated by other models, which was due to the low sediment concentration from each land use (EMC values for TSS) in the model default inputs.

The above results show that other than the PLOAD model (good prediction of TN and TP loads) and HIT model (not compared to observed results), other models need to be calibrated to better predict hydrology and water quality in the AXL watershed. This was likely because to simulate hydrology and water quality at watershed scales, the complex physical processes need parameters that vary spatially and temporally, and model parameters must be identified for each study area (Duan et al. 2003). Model calibration is usually used to assess model parameters by adjusting model parameters to match predicted results with observed data (Abbott et al. 1986). Although SWAT is a complex, semi-distributed, and physically based hydrologic/water quality model that is more complicated to use, similar to the simpler models explored, the average annual results were not acceptable without calibration in the AXL watershed. This demonstrates that more complex models do not always provide better results, especially when the model parameters are not calibrated using measured watershed response.

Table 4 shows the performance of ensemble modeling. Ensemble means with 90% confidence intervals of uncalibrated STEPL-Purdue_2 (modified use with observed rainfall data), SWAT, L-THIA, PLOAD, and STEM-P models were estimated. All 90% confidence intervals for streamflow, runoff, baseflow, TN, and TP enveloped the corresponding measured data. The ensemble means overestimated streamflow, runoff, baseflow, and TP by 15.9%, 16.0%, 3.2% and 27.7%, respectively, while underestimating TN by 38.8%. Ensemble modeling performed better than STEPL-Purdue_2 and L-THIA in all estimations. Ensemble modeling had better performance than SWAT in all estimations except TN. Ensemble modeling had better results than STEM-P in all estimates except TP. Ensemble modeling did not perform as well as PLOAD in estimating TN and TP, due to the good performance of PLOAD in the AXL watershed. Overall, the ensemble modeling of uncalibrated models enhanced the hydrology and water quality predictions compared to most of the models alone. This approach could be used to increase the reliability of predictions when monitored data are not available.

2.2 Calibrated results comparison

Table 5 shows the calibrated results of two STEPL-Purdue applications (STEPL-Purdue_1 and STEPL-Purdue_2), SWAT, L-THIA, and STEM-P. STEPL-Purdue applications with observed rainfall data were calibrated for average annual runoff volume, baseflow volume, TN load, and TP load. Typical use of calibrated STEPL-Purdue with observed rainfall data resulted in good estimation of streamflow, runoff, baseflow, and TN. However, it overestimated TP load by 159%, which may due to the overly high TP coefficients in soil and associated with flow, and overestimation of sediment load. Modified use of calibrated STEPL-Purdue with observed rainfall data resulted in good estimation of streamflow, runoff, baseflow, and TP. However, it underestimated TN load by 16%. The modified use of the calibrated STEPL-Purdue model provided better estimation of streamflow, runoff, baseflow, and TP compared to that of typical use. However, modified use of calibrated STEPL-Purdue generated poorer estimation of TN compared to that of typical use. Overall, the modified use of the calibrated STEPL-Purdue model performed better than the typical use of the calibrated STEPL-Purdue model in predicting water quantity and quality.

The L-THIA model was calibrated for average annual runoff volume, TN load, and TP load. The calibrated L-THIA model resulted in good assessment of average annual runoff volume, TN load, and TP load. The nearly perfect performance of calibrated L-THIA model in estimating average annual results was mainly due to the way the L-THIA model was calibrated. The L-THIA model was calibrated for runoff first with an increase of all curve numbers by a percentage simultaneously. Then, EMCs from all land uses were changed by a certain percentage to match observed average annual TN and TP loads for the calibration period.

Monthly calibrations of SWAT (e.g. Spruill et al. 2000; White and Chaubey 2005) and STEM-P (Li et al. 2016b) are in line with standard modeling practices for these models, because the models were developed for simulating daily or monthly results, as well as annual results for long time periods. In many cases, the timing and pathways of pollutant losses are quite variable, therefore requiring daily or monthly results to facilitate understanding of the system and identification of the most appropriate mitigation practices. For example, P loss varies greatly daily and seasonally in the study watershed, and thus daily and monthly predictions are needed to accurately predict timing of P losses and identify strategies for its control.

Usually, model performance deteriorates from average annual to annual to monthly to daily calibration due to calibration for smaller simulation time steps needing to match more complex observed data, which is more difficult to achieve, and thus decreasing the performance of the model when using the same quantitative statistics (Coffey et al. 2004; Moriasi et al. 2007). Thus, average annual predictions for a model calibrated at a monthly or daily scale will typically perform at least as good as the performance of the model at the monthly scale or daily scale calibration. SWAT was thus calibrated for monthly results to reflect its typical application, and STEM-P was also calibrated on a monthly scale to make the results comparable.

In the SWAT model, monthly streamflow volume (KGE = 0.88, R^2 = 0.96, NSE = 0.95), TN load (KGE = 0.83, R^2 = 0.81, NSE = 0.77), and TP load (KGE = 0.91, R^2 = 0.97, NSE = 0.97) were calibrated. The calibrated SWAT model performed well in estimating average annual streamflow. However, the calibrated SWAT model overestimated average annual runoff volume, TN and TP loads by 18%, 13%, and 50%, respectively, and it underestimated baseflow by 14%. The main reason SWAT did not perform well in estimating average annual flow and TN load was that SWAT was calibrated for monthly results instead of average annual results.

The STEM-P model was calibrated for monthly streamflow volume (R^2 = 0.70, NSE = 0.53, PBIAS = 3.4%) and TP load (with R^2 = 0.68, NSE = 0.65, PBIAS = 15.4%). The calibrated STEM-P model provided good estimates of streamflow and baseflow, overestimating average annual runoff and TP by 18% and 15%. STEM-P was developed to simulate the main processes governing hydrology and phosphorus transport with simple equations and few parameters.

STEM-P did not perform as well as models calibrated for average annual results for the reason that STEM-P was calibrated for monthly results.

Calibrated STEPL-Purdue and L-THIA performed better than calibrated SWAT and STEM-P in estimating average annual water quantity and water quality. This was likely because STEPL-Purdue and L-THIA were calibrated for average annual results, while SWAT and STEM-P were calibrated for monthly results. As noted above, monthly calibrations of SWAT and STEM-P are in line with standard modeling practices for these models. In many cases, monthly results are required to understand system and identify the best mitigation method due to variation of timing and paths of pollutant losses.

2.3 Validation results comparison

Table 6 shows the validation results of two STEPL-Purdue applications (STEPL-Purdue_1 and STEPL-Purdue_2), SWAT, L-THIA, and STEM-P. Parameters of calibrated models were used for model validation. STEPL-Purdue applications with observed rainfall data were validated for average annual runoff volume, baseflow volume, TN load, and TP load. Validation of typical use of STEPL-Purdue with observed rainfall data resulted in good estimation of average annual streamflow volume and TN load. However, it overestimated average annual baseflow volume and TP load by 12% and 102%, respectively, and it underestimated average annual runoff volume by 16%. Validation of modified use of STEPL-Purdue with observed rainfall data resulted in good prediction of average annual streamflow volume, runoff volume, baseflow volume, and TN load. However, it underestimated average annual TP load by 25%. The modified use of STEPL-Purdue model showed better validated results in estimating average annual runoff volume, baseflow volume, and TP load compared to that of typical use. However, modified use of STEPL-Purdue generated slightly poorer validated estimates of average annual streamflow volume and TN load. Overall, modified use of STEPL-Purdue performed better than typical use of STEPL-Purdue, indicating that users should provide more detailed land use and soil group information for the watershed and generate their own USLE parameters for the watershed. The performance of calibrated and validated STEPL-Purdue model in estimating average annual TN and TP loads was not always good. This might due to the model not being capable of accurately simulating crop management practices such as tillage operations, fertilizer and herbicide applications, crop rotation, planting time, and harvesting time.

The SWAT model was validated for monthly streamflow volume (KGE = 0.87, R^2 = 0.92, NSE = 0.91), TN load (KGE = 0.51, R^2 = 0.81, NSE = 0.49), and TP load (KGE = 0.91, R^2 = 0.97, NSE = 0.93). Validation of the SWAT model showed good estimation (less than 10% difference compared to observed data) of average annual streamflow volume, baseflow, TN load and TP load, and overestimation of runoff by 14%. Compared to the calibrated performance of the SWAT model, validation results for the model showed similar performance in estimating average annual streamflow, while better performance in assessing average annual runoff, baseflow, TN and TP.

The L-THIA model was validated for average annual runoff volume, TN load, and TP load. Validation of the L-THIA model indicated under prediction of average annual runoff volume, TN load, and TP load by 15%, 21%, and 47%, respectively. The validation performance of the L-THIA model was poorer than the calibration performance of L-THIA in estimating average annual runoff volume, TN load, and TP load. L-THIA may not be the best choice for estimating TN and TP loads in watersheds with mainly agricultural areas because the model does not consider physical processes of nutrients delivered by sediments, crop management and agricultural animals.

The STEM-P model was validated for monthly streamflow volume (R^2 = 0.77, NSE = 0.76, PBIAS = -10.5%) and TP load (with R^2 = 0.63, NSE = 0.50, PBIAS = -26.3%). The validation of STEM-P resulted in good estimation of runoff volume, and underestimation of average annual streamflow volume, baseflow volume, and TP load by 10%, 21%, and 26 %, respectively. Similar to the calibration results, the simulated TP of STEM-P was dependent on streamflow, and the error in streamflow was magnified in TP simulation. Overall, the accuracy of STEM-P was fair.

Validation of the SWAT model and modified use of STEPL-Purdue model generally showed better performance in estimating average annual water quantity and quality in the AXL watershed compared to that of typical use of STEPL-Purdue, L-THIA, and STEM-P. This indicates that the parameters for SWAT and modified use of STEPL-Purdue obtained for the calibration period were also suitable for the validation period. Due to the complexity of calibrating SWAT, the time, effort, and data required to obtain these improved results were much greater than in calibrating STEPL-Purdue model.

3. Conclusions

Various hydrologic and water quality models (including STEPL-Purdue, SWAT, HIT, L-THIA, PLOAD, STEM-P, Region 5, and results of ensemble modeling), with varying data requirements, simulation methods, and complexity levels, were compared in this study. The details of models were described, including model capabilities; model inputs to estimate hydrology, TN, TP, and sediment from the watershed without BMPs; additional inputs to simulate BMPs; and methods to simulate hydrology, TN, TP, sediment, and BMPs. Uncalibrated, calibrated, and validated results of the models in estimating average annual water quantity and quality for a 41.5 km^2 agricultural watershed in Northeastern Indiana were explored.

The uncalibrated PLOAD model had good performance in estimating TN and TP loads in the AXL watershed; however, the PLOAD model should be used with caution in other watersheds due to the possible need to update the Export Coefficient table based on local conditions. The ensemble modeling with uncalibrated models enhanced the hydrology and water quality predictions compared to most of the models alone. This approach could be used to increase the reliability of predictions when no monitored data are available.

STEPL-Purdue, SWAT, L-THIA, and STEM-P were calibrated to explore performance of predicting hydrology and water quality after calibration in the AXL watershed. Then, the parameters of calibrated models were used in model validation. Overall, the modified use (detailed watershed level land use and soil group information and modified USLE parameters) of the STEPL-Purdue model (both calibrated and validated) performed better than the typical use (one subwatershed with land use information and single soil group, and default USLE parameters) of calibrated STEPL-Purdue model in predicting water quantity and quality. This indicates that users should provide more detailed watershed level land use and soil group information, and USLE parameters for the study watershed should be generated instead of using default values. Either observed or GLIGEN rainfall data could be used as the weather inputs for STEPL-Purdue model to estimate average annual results. The L-THIA model may not be the best choice for estimating TN and TP loads in watersheds with mainly agricultural areas, because the model does not consider processes associated with crop management, agricultural animals, and nutrients delivered by sediment in the study watershed. Compared to the performance of the calibrated SWAT model, validation results of SWAT provided similar performance in estimating average annual streamflow, while much better performance in assessing average annual runoff, baseflow, TN load and TP load. The calibrated STEM-P model resulted in overestimation of average annual runoff and TP, and good estimation of streamflow and baseflow. The validation of STEM-P model resulted in underestimation of average annual streamflow volume, baseflow volume and TP load, and good estimation of runoff volume.

Compared to other models in this study, the SWAT model comprehensively simulates watershed processes; at the same time, it is the most time consuming and difficult to apply model. STEPL-Purdue, HIT, L-THIA, PLOAD, and STEM-P are simpler models that need minimum input data and are less time consuming and easier to set up. However, simple models may misrepresent watershed processes and provide inaccurate results. Models need to be selected carefully based on the simulation purposes, data availability, model characteristics, time limits, and project budgets.

For future studies, the Region 5 model needs to be tested in an area with observed field level data. The performance of the HIT model needs to be further explored in future studies in watersheds with observed sediment data. The comparison of model performance in estimating impacts of BMPs could also be explored in the future.

Table 1. Description of capabilities, inputs and simulation methods of models

	STEPL-Purdue	SWAT	HIT
Model capabilities	Estimates average annual runoff, baseflow, streamflow, TN, TP, BOD, sediment. BMP simulations and identification of the most cost-effective BMP implementation plans.	Estimates daily, monthly, and yearly results of water, sediment, and agricultural pollutant yields (TN, NO_3, organic N, NH_4, NO_2, TP, soluble P, organic P, mineral P, PO_4, BOD, algal biomass, dissolved oxygen, pesticide, bacteria, metal, and fecal coliform). Simulation of BMPs.	For agricultural areas only. Estimates average annual erosion and sediment load, average annual rates of erosion and sediment loading, total reductions and percent reductions of average annual erosion and sediment load due to BMPs, BMP cost and BMP cost per erosion/sediment load reduced.
Model inputs to estimate hydrology, TN, TP, and sediment from the watershed without BMPs.	**Mandatory inputs:** Land use, daily precipitation data, Universal Soil Loss Equation (USLE) parameters, gully and streambank erosion parameters, and percent of pavement in feedlots, **Optional inputs:** Agricultural animals, number of months that manure is applied, septic system and illegal direct wastewater discharge data, Hydrologic Soil Groups (HSGs), runoff curve number, nutrient concentrations in runoff and shallow groundwater, soil nutrient concentrations, urban land use distribution, cropland irrigation, soil infiltration fraction for precipitation, wildlife density in cropland, standard animal weight, septic system nutrients, feedlot nutrients, dry density, correction factor for soil, lateral recession rate.	**Mandatory inputs:** Digital elevation model (DEM) data, soil data, land use data, hydrographic data, daily precipitation, maximum and minimum daily temperature, solar radiation, wind speed, relative humidity, crop management (tillage operations, fertilizer and herbicide applications, crop rotation, time of planting and harvesting).	**Mandatory inputs:** Selection of watershed results in automatically generating inputs, including surface roughness, soil texture, distance to stream, soil erodibility, rainfall intensity, slope length, slope steepness, and land cover management.
Additional inputs to simulate BMPs	**Mandatory inputs:** BMP type, percent of area with BMP applied, pollutant type, interest rate, required pollutant reduction. **Optional inputs:** Pollutant removal efficiency, practice establishment cost, annual maintenance cost, BMP life.	Complex input data for planting, harvest, irrigation applications, nutrient applications, pesticide applications, tile drains, tillage operations, and urban areas.	**Mandatory inputs:** BMP type **Optional inputs:** BMP costs per acre

Hydrology	Runoff volume: Soil Conservation Service (SCS) curve number (CN) method. Baseflow volume: soil infiltration fraction as part of precipitation. Streamflow volume: sum of runoff and baseflow.	Runoff volume: SCS-CN method or Green and Ampt infiltration method. Baseflow volume: empirical relationships. Lateral subsurface flow: kinematic storage model. Tile flow: Hooghoudt and Kirkham tile drain equations Streamflow volume: sum of surface runoff, baseflow, and lateral subsurface flow.	N/A
Total Nitrogen	From runoff of each land use (runoff volume × concentration), feedlots (based on animal types, weight, and average rainfall), failing septic systems and illegal direct discharges (based on number of septic systems, failure rates, the ratio of persons per septic system, and calculated direct wastewater discharge), groundwater (groundwater × concentration), sediment (sediment load × concentration × nutrient enrichment).	Nitrogen cycle is modeled. Estimates total nitrogen in runoff, lateral subsurface flow, percolation, top soil, tile flow, sediment. Considers plant uptake of nitrogen.	N/A
Total Phosphorous		Phosphorus cycle is modeled. Estimates total phosphorus in top soil, runoff, tile flow, and sediment. Considers plant uptake of phosphorous.	
Sediment	Universal Soil Loss Equation (USLE), gully erosion (based on volume loss, soil dry density, years to form, correction factor), and streambank erosion (based on length, height, lateral recession rate, soil dry density, correction factor), sediment delivery ratio (based on size of drainage area).	Overland sediment estimated by Modified Universal Soil Loss Equation (MUSLE), snow cover effects, sediment lag in surface runoff. Sediment associated with groundwater and lateral flow based on sediment concentration. Sediment routing based on simplified Bagnold equation, physics based approach for channel erosion.	Uses RUSLE to estimate soil erosion. Uses Spatially Explicit Delivery Model (SEDMOD) to estimate delivery ratio based on flow path slope gradient, flow path slope shape, flow path hydraulic roughness, stream proximity, soil texture, and overland flow.
Representation of BMPs and BMP Cost Estimation	Estimate water quality impacts: pollutant removal efficiency. Estimate cost based on interest rate, establishment cost, annual maintenance cost, and BMP life.	Change parameters in SWAT model to represent BMPs. Cost estimates not included in model.	Change land cover management factor and support practice factor in RUSLE. BMP costs per acre (based on Environmental Quality

			Incentives Program payments).
Key References	Tetra Tech (2011); Park (2014); Park et al. (2014); STEPL-PURDUE (https://engineering.purdue.edu/~ldc/STEPL/)	Neitsch et al. (2011)	Renard et al. (1996); Fraser (1999); Ouyang et al. (2005); http://www.iwr.msu.edu/hit2/

	L-THIA	**Region 5**	**PLOAD**	**STEM-P**
Model capabilities	Estimates annual runoff, TN, TP, BOD, TSS, TDS, DP, TKN, NO_x, Cd, Cr, Cu, Pb, Ni, Zn, FC, FS, E. coli, COD, and O&G. Simulation of BMPs and LID practices.	Gully stabilization, Bank Stabilization, Agricultural Fields: estimates average annual reductions of sediment, phosphorus, and nitrogen load due to BMPs. Feedlots: estimates average annual BOD, TN, TP loads before and after BMPs. Urban: estimates average annual BOD, COD, TSS, Pb, Cu, Zn, TDS, TN, TKN, DP TP, Cd loads before and after BMPs.	Estimates average annual pathogens, BOD, COD, TSS, TDS, TN, TP, NOx, NO_3, TKN, NH_4, ORGN, PO_4, Zn, Cu, Pb, Cd, Cr, Ni, and Hg. Simulation of BMPs.	Estimates daily, monthly, and yearly results of surface runoff, base flow, tile flow, stream flow, TP
Model inputs to estimate hydrology, TN, TP, and sediment from the watershed without BMPs.	**Mandatory inputs:** Daily precipitation, HSGs, and land use types. **Optional inputs:** Curve numbers, pollutant concentrations from each land use.	**Mandatory inputs:** Gully Stabilization: soil textural class, top width, bottom width, depth, length, years to form, soil weight. Bank Stabilization: soil textural class, length, height, lateral recession rate, soil weight. Agricultural Fields: State, County, contributing area, soil texture. Feedlots: contributing area, percent area paved, State, County, nearest weather station, animal numbers. Urban: sewered and unsewered urban land use areas. **Optional inputs:**	**Mandatory inputs:** Export coefficient method: Subbasins layer, land use type. Simple (EMC) method: Subbasins layer, land use type, annual precipitation. **Optional inputs:** Export coefficient method: Export coefficients, point sources, bank erosion.	**Mandatory inputs:** Daily precipitation, temperature, land cover map, DEM, soil map and properties, map of water courses. Tile drain properties if tiles present. Zero-order mobilization rate and first-order retention rate for each land cover.

		Gully Stabilization, Bank Stabilization: soil TP, TN concentrations. Agricultural Fields: USLE factors. Feedlots, Urban: N/A	Simple (EMC) method: event mean concentrations (EMC), imperviousness, point sources, bank erosion.	
Additional inputs to simulate BMPs	**Mandatory inputs:** GIS data included lakes, street centerlines, streams, imperviousness, digital elevation model (DEM) data. **Optional inputs:** curve numbers, percent runoff volume reduction, percent pollutant concentration reduction, irreducible concentration, interests rates, BMP life, construction cost, maintenance cost.	**Mandatory inputs:** Gully Stabilization, Bank Stabilization: BMP efficiency. Agricultural Fields: cover management factor, support practice factor. Feed lots, urban: BMP type.	**Mandatory inputs:** Pollutant removal efficiency, BMP layer, subbasin ID field.	N/A
Hydrology	Runoff volume: SCS-CN method.	N/A	N/A	Distributed Hydrological Model for Watershed Management (DHM-WM). Surface runoff: Mishra and Singh modified long-term NRCS CN method incorporated with TOPMODEL concept. Base flow: Mishra and Singh modified long-term NRCS CN method. Tile flow: Empirical equation similar to the routine of SWAT
Total Nitrogen	Pollutant concentration × runoff volume from each land use	Gully Stabilization, Bank Stabilization, Agricultural Fields: based on sediment loads, nutrient concentration in sediment, and correction factor. Feedlots: based on animal types, weight, and average rainfall.	Export Coefficient Method: based on pollutant loading rate for each land use type and area of each land use type.	N/A
Total Phosphorous				Empirical equations based on zero-order mobilization and first-order retention

		Urban: average pollutant loading rates by land use types, land use area.		
Sediment		Gully Stabilization: Gully Erosion Equation based on volume loss, soil dry density, years to form. Bank Stabilization: Channel Erosion Equation based on length, height, lateral recession rate, soil dry density. Agricultural Fields: USLE, sediment delivery Ratio (based on size of drainage area) Feedlots: N/A Urban: average pollutant loading rates by land use types, land use area.	Simple (EMC) Method: based on percent imperviousness, annual precipitation, ratio of storms producing runoff, runoff coefficient, EMC, area of land use.	N/A
Representation of BMPs and BMP Cost Estimation	L-THIA-LID 2.1 version. Estimate runoff and water quality: curve numbers, percent runoff volume reduction, percent pollutant concentration reduction, irreducible concentration, pollutant concentrations from each land use. Estimate cost: construction, maintenance, and opportunity costs.	Estimate water quality impacts: pollutant removal efficiency. Cost estimates not included in model.	Estimate water quality impacts: pollutant removal efficiency. Cost estimates not included in model.	N/A
Key References	Harbor (1994); Engel et al. (2003); Ahiablame et al. (2012); Liu et al. (2015a and 2015b).	MDEQ (1999)	USEPA (2001)	Li et al. (2016a and 2016b).

Table 2. Simulation scenarios to evaluate models (Y—Yes, N—No)

	STEPL-Purdue_1	STEPL-Purdue_2	STEPL-Purdue_3	STEPL-Purdue_4	SWAT	HIT	L-THIA	PLOAD	STEM-P
Streamflow	Y	Y	Y	Y	Y	N	N	N	Y
Runoff	Y	Y	Y	Y	Y	N	Y	N	Y
Baseflow	Y	Y	Y	Y	Y	N	N	N	Y
TN	Y	Y	Y	Y	Y	N	Y	Y	N
TP	Y	Y	Y	Y	Y	N	Y	Y	Y
Sediment	Y	Y	Y	Y	Y	Y	Y	Y	N
Uncalibrated results	Y	Y	Y	Y	Y	Y	Y	Y	Y
Calibrated results	Y	Y	N	N	Y	N	Y	N	Y
Validated results	Y	Y	N	N	Y	N	Y	N	Y

Table 3. Uncalibrated results of models in simulating average annual flow, nutrients, and sediment (2006-2013)

	Monitored	STEPL-Purdue_ 1	STEPL-Purdue_2	STEPL-Purdue_3	STEPL-Purdue_4	SWAT	HIT	L-THIA	PLOAD	STEM-P
Streamflow (m^3/ha/yr)	3469	2209	2465	2106	2368	5469	N/A	N/A	N/A	4130
Runoff (m^3/ha/yr)	1492	911	761	868	728	3117	N/A	977	N/A	2065
Baseflow (m^3/ha/yr)	1977	1298	1703	1237	1640	2352	N/A	N/A	N/A	2065
TN (kg/ha/yr)	20.60	10.52	4.06	10.28	3.91	24.90	N/A	2.88	18.61	N/A
TP (kg/ha/yr)	1.20	3.05	0.45	3.00	0.44	4.72	N/A	0.30	1.16	1.03
Sediment (ton/ha/yr)	N/A	4.37	0.22	4.33	0.22	3.45	0.34	0.03	2.32	N/A

Table 4. Ensemble modeling performance

	Observed	90% Confidence Interval		Ensemble mean	% difference between ensemble mean and observed
		Lower bound	Upper Bound		
Streamflow (m^3/ha/yr)	3469	1484	6558	4021	15.9
Runoff (m^3/ha/yr)	1492	451	3009	1730	16.0
Baseflow (m^3/ha/yr)	1977	1492	2588	2040	3.2
TN (kg/ha/yr)	20.60	0	25.41	12.61	-38.8
TP (kg/ha/yr)	1.20	0	3.27	1.53	27.7

Table 5. Calibrated results of models in simulating average annual flow, nutrients, and sediment

	Monitored	STEPL-Purdue_1	STEPL-Purdue_2	SWAT	L-THIA	STEM-P
Streamflow (m^3/ha/yr)	3799	3779	3799	3789	N/A	3929
Runoff (m^3/ha/yr)	1633	1634	1633	1932	1648	1925
Baseflow (m^3/ha/yr)	2165	2145	2165	1857	N/A	2004
TN (kg/ha/yr)	21.98	22.02	18.41	24.90	21.98	N/A
TP (kg/ha/yr)	1.04	2.70	1.01	1.56	1.01	1.20
Sediment (ton/ha/yr)	N/A	4.32	0.21	2.27	0.05	N/A

Table 6. Validation results of models in simulating average annual flow, nutrients, and sediment

	Monitored	STEPL-Purdue_1	STEPL-Purdue_2	SWAT	L-THIA	STEM-P
Streamflow (m^3/ha/yr)	3140	3142	3151	3199	N/A	2811
Runoff (m^3/ha/yr)	1350	1129	1238	1535	1144	1406
Baseflow (m^3/ha/yr)	1790	2013	1913	1663	N/A	1406
TN (kg/ha/yr)	19.23	19.05	18.08	21.00	15.25	N/A
TP (kg/ha/yr)	1.33	2.69	1.00	1.34	0.70	0.98
Sediment (ton/ha/yr)	N/A	4.32	0.21	2.39	0.03	N/A

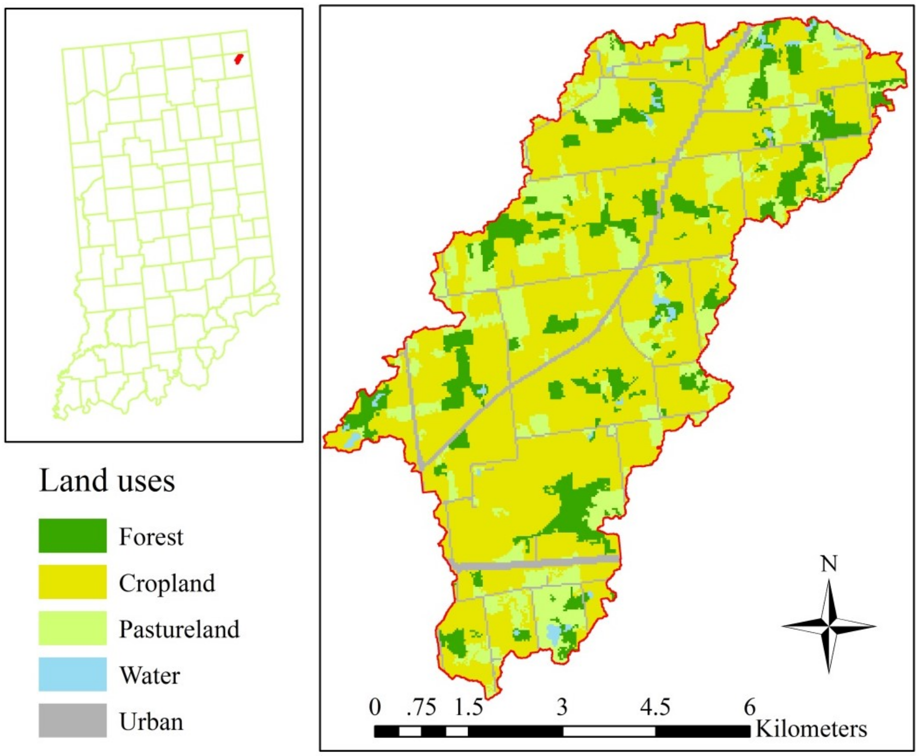

Figure 1. Location and land uses of AXL watershed in northeast, Indiana.

- **Potential Applications, Benefits and Impacts**

Include ways this project has affected industry development and productivity, resource management (e.g., acres of land restored, tools for use by managers created), behavior of target group of end users, and/or scientific advancement. Quantify these effects whenever possible. Include what you see as potential future applications of this project to these areas, considering both short (2-5 year) and long (>10 year) outcomes.

For short-term outcomes, the results of this project can help users select appropriate models to use for various situations. The models examined include Spreadsheet Tool for the Estimation of Pollutant Load (STEPL)-Purdue, Soil and Water Assessment Tool (SWAT), High Impact Targeting (HIT) (Ouyang et al. 2005), Long-Term Hydrologic Impact Assessment (L-THIA), Pollutant Load (PLOAD), Spatially and Temporally Distributed Model for Phosphorus Management (STEM-P) (Li et al. 2016a, b), and Region 5 (MDEQ 1999). Most of these models are widely used by watershed groups and states in the Midwest US and also are of interest to the Great Lakes Restoration Initiative. U.S. Environmental Protection Agency recommends using most of these models for evaluating water quantity/quality, total maximum daily loads (TMDLs), and/or effects of various conservation practices. For long-term outcomes, the results of the project demonstrate the significance of ensemble modeling, which can be a direction for future hydrologic/water quality model development.

- **International Implications** If applicable to your report.

The outcomes of the projects have international implications that are similar to the above potential applications, benefits and impacts. These implications include helping users select an appropriate model to use for various situations, and providing direction for future hydrologic/water quality model development.

Section C. Outputs

- **Media Coverage**

Include radio, TV, newspaper, and magazine coverage by universities, local interest groups, news outlets, etc. Please include URLs and/or send hardcopies of stories if possible.

N/A

- **Publications**

Include journal publications (submit full reference and copy of publication, where possible – we will respect all copyright laws), reports, papers presented at conferences, poster presentations specifically resulting from Sea Grant-funded research. Please submit a reprint of all publications to IISG as they become available. IISG support should be acknowledged in all resulting publications and presentations.

Comparison of computer models for estimating hydrology and water quality in an agricultural watershed. July 17-20, 2016, Orlando, Florida. 2016 American Society of Agricultural and Biological Engineers Annual International Meeting.

Liu, Y., Li, S., Wallace, C.W., Chaubey, I., Flanagan, D.C., Theller, L.O. and Engel, B.A., 2016. Comparison of computer models for estimating hydrology and water quality in an agricultural watershed. Water Resources Management. In review.

- **Undergraduate/Graduate Names and Degrees**

Include names of all undergraduate and graduate students supported by this grant and the degree pursued or earned. Theses or dissertations should be clearly identified as such, with author, title, degree, campus, date, and URL (if applicable).

N/A

- **Project Partnerships**

Include related projects with other institutions or individuals initiated or continued due to this Sea Grant-sponsored research.

N/A

- **Related Projects**

Include grants from other funding agencies that resulted, at least in part, from this SeaGrant sponsored research. Please include the title of the project, funding agency, amount of new funding, and funding decision (if known) and/or years of award. This piece is often necessary for **Discovery Grants.**

N/A

- **Awards and Honors**

List all awards and honors received within the time period covered by this annual report.

N/A

- **Patents/Licenses**

List any patents or patent licenses that have resulted from this project.

N/A

Graphs, figures and/or photos should be embedded in your text. Please recognize that we may wish to include these items in IISG publications with the appropriate credits. Similarly, we will post final reports on the IISG website within 2 months of receipt **UNLESS PIs REQUEST THAT REPORTS BE HELD BACK PENDING PUBLICATION**.

PLEASE NOTE: Final project invoices will NOT be paid until a final report has been received and approved by IISG.