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Improvement of simulating BMPs and LID practices in L-THIA-LID model

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IN L-THIA-LID MODEL

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To My Family, Teachers, and Friends

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ABSTRACT

Liu, Yaoze. Ph.D., Purdue University, May 2015. Improvement of simulating BMPs and LID practices in L-THIA-LID model. Major Professors: Bernard A. Engel and Vincent F. Bralts.

Best management practices (BMPs) and low impact development (LID) practices are popular approaches used to reduce the negative impacts of urbanization on hydrology and water quality. To assist planners and decision-makers in urban development projects, user-friendly tools are needed to assess the effectiveness of BMPs and LID practices on water quantity and quality.

To address this need, the Long-Term Hydrologic Impact Assessment-LID (L-THIA-LID) model was enhanced with additional commonly used BMPs and LID practices represented in the model, improved approaches to estimate hydrology and water quality, and representation of practices in series. The tool was used to evaluate the performance of BMPs and LID practices individually and in series in four types of idealized land use units and watersheds (low density residential area, high density residential area, industrial area, and commercial area). Simulation results were comparable with the observed impacts of these practices in other published studies.

Then, the model was enhanced further by creating L-THIA-LID 2.1 for modelling BMPs/LID practices at watershed scales and adding cost estimates of practices. The sensitivity and uncertainty of the enhanced model were analyzed using Sobol''s global sensitivity analysis method and the bootstrap method, respectively. CN (Curve Number) and Ratio_r (Practice outflow runoff volume/inflow runoff volume) were the most sensitive variables before and after BMPs/LID practices were implemented, respectively. The limited observed data in the same study area and results from other urban watersheds in scientific literature were either well within or close to the uncertainty ranges found in this study, indicating the model has good precision. Sixteen implementation scenarios of BMPs and LID practices were evaluated with the model at the watershed scale. The implementation of grass strips in 25% of the watershed where this practice could be applied was the most cost-efficient scenario. The scenario with very high levels of BMP and LID practice adoption provided the greatest reduction in runoff volume and pollutant loads among all scenarios. However, this scenario was not as cost-efficient as most other scenarios. The L-THIA-LID 2.1 model is a valid tool that can be applied to various locations to help identify cost effective BMP/LID practice plans at watershed scales.

Finally, a decision support tool, which linked L-THIA-LID 2.1 with the A Multi-ALgorithm Genetically Adaptive Multiobjective (AMALGAM) method using the multilevel spatial optimization (MLSOPT) framework, was developed to optimally select and place BMPs/LID practices. The decision support tool was applied to an urban watershed near Indianapolis, Indiana. Optimization results at the hydrologic response unit scale indicated that for sites with different features, the optimal BMP/LID practice solutions to attain the same environmental goals differed. For sites with the same characteristics, the optimal implementation of practices could vary significantly for different environmental goals. For higher expenditures, the implementation levels and types of favored practices tended to increase relative to those for lower expenditures. Watershed scale results showed that for initial expenditures of practices, the environmental benefits increased rapidly as expenditures increased. However, beyond certain expenditure levels, additional spending did not result in noticeable additional environmental impacts. Compared to random placement of practices, the optimization strategy provided 3.9 to 7.7 times the level of runoff/pollutant load reductions for the same expenditures. To obtain the same environmental benefits, costs of random practices placement were 4.2 to 14.5 times the optimized practice placement cost. Results indicate that the decision support tool is capable of supporting decision makers in optimally selecting and placing BMPs and LID practices at watershed scales.

CHAPTER 1. INTRODUCTION

1.1 Problem statement

Urbanization has become a global trend due to significantly increased population in urban areas (Grimm et al., 2008). Urban development changes land uses from pervious surfaces (such as grass and forest cover) to impervious surfaces (for instance, roof tops, parking lots, and roads) (Carter, 1961; Leopold, 1968). The increased imperviousness of the area generally leads to increased surface runoff volume and runoff velocities; decreased hydrologic recession time, groundwater recharge, baseflow recharge, and lag time between precipitation and runoff (Lerch et al., 1982; Ferguson, 1990; Shaw, 1994; Arnold and Gibbons, 1996; Bhaduri et al., 2000; Burns et al., 2005). Urban sprawl enhances the possibility of accumulating and delivering urban nonpoint source (NPS) pollution with runoff, which results in an adverse influence on water quality if the runoff is discharged untreated (Schueler, 1995; Grove et al., 2001; Ying and Sansalone, 2010). Although polluted water can be collected and delivered by combined sewer systems and then treated by treatment plants, combined sewer overflows (CSOs) may occur when capacities of sewer systems are overloaded due to intense rainfall events. CSOs may cause severe water pollution problems in streams, rivers, lakes, and even oceans (Gunderson et al. 2011; Hata et al., 2014).

To reduce the negative influence of urbanization on water resources, best management practices (BMPs) and low impact development (LID) practices are often applied to reduce stormwater runoff and control the movement of pollutants (Urbonas, 1994; USDBLM, 2005; Dietz, 2007; Gilroy, 2009). However, BMPs and LID practices differ in functionality. BMPs (such as wetland basin) control the peak discharge and NPS pollutants by collecting, storing, and treating the large stormwater runoff volume with facilities at the end of drainage areas (Gilroy, 2009). The implementation of BMPs usually requires large, contiguous areas of land; and involves constructing hard infrastructure (for instance, pipes, gutters, and curbs) to convey runoff off-site (USEPA, 2008). LID practices, such as bioretention systems and porous pavement, control storm runoff as near to its source as possible with processes such as infiltration, filtration, evaporation and storage (Prince George's County, Maryland, 1999; Damodaram et al., 2010). LID practices are small-scale, localized and decentralized source control approaches, which improve environmental conditions with possible reduced development costs compared to BMPs (The LIDC et al., 2006; USEPA, 2008).

Many field, laboratory, and modeling studies have reported the performances of BMPs and LID practices, both individually and in series, in treating water quantity and water quality at various scales and geographic locations (e.g., Hunt et al., 2006, 2008; Scholes et al., 2008; Stagge et al., 2012; Ahiablame et al., 2012b, 2013; Newcomer et al., 2014). However, because of the enormous time and costs to accomplish the experiments, spatial-temporal data are limited. In addition, results from these studies cannot be directly used to estimate the effectiveness of the practices in development projects for the reason that the performances of BMPs and LID practices are influenced by local conditions. Therefore, computer models need to be developed. However, complex computer models, such as the Storm Water Management Model (SWMM) and System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN) Model (Huber and Dickenson, 1988; Shoemaker et al., 2009), which use complicated algorithms, require numerous input variables and parameters, making them difficult to use. Thus, user-friendly models are needed for planners and decision makers to evaluate the influences of BMPs and LID practices on hydrology and water quality in development projects.

Both simple and complex computer based models, which are developed to model hydrology and water quality, are based on mathematical simplification of natural processes. Natural processes are complicated, making the measurements of spatial-temporal sensitive model inputs and parameters (together called variables) expensive. Therefore, spatial-temporal sensitive variables of the model must be specified when applying the model in each watershed (Duan et al., 2003). Model parameters are usually estimated by altering model parameters to match estimated results with observed results, which is called model calibration (Abbott et al., 1986; Gupta et al., 1998). After model calibration, a different time period of input data from the same study watershed are usually used to validate the model. After calibration, model uncertainty remains due to quantity and quality of input data, complicated natural processes, and parameter estimation (Beck, 1987; Tyagi and Haan, 2001; Muleta and Nicklow, 2005).

Sensitivity analysis of a model, which is conducted by estimating how much a variable contributes to model outputs, is a beneficial process to find the key variables impacting outputs of simulation models (Freer et al., 1996; Muleta and Nicklow, 2005). Commonly used sensitivity analysis methods (Tang et al., 2006; Yang, 2010) include regional sensitivity analysis (RSA), non-parametric smoothing, Sobol′'s global sensitivity analysis method, Analysis of Variance (ANOVA), Jacobean-based local method (parameter estimation software PEST), Morris method, and Linear Regression (LR). Uncertainty of model output indicates model precision (Jakeman and Hornberger, 1993). Uncertainty analysis methods (Li et al., 2010; Yang, 2011), such as the Generalized Likelihood Uncertainty Estimation (GLUE), first-order approximation method, contour plots method, Monte Carlo Simulation (MCS) techniques, bootstrap method, Bayesian method, are usually used to estimate the precision of a model.

To attain maximum hydrological and water quality benefits with minimum cost, spatial optimization can be used to select and place BMPs and LID practices at watershed scales by combining hydrology/water quality models with optimization algorithms (e.g. Bekele and Nicklow, 2005; Maringanti et al. 2009, 2011). Objective functions are defined first; then the optimization algorithms create sample populations for potential placement scenarios; finally, the hydrology/water quality model calculates the objective functions with the sample populations created by optimization algorithms to obtain optimum placement scenarios.

The Long-Term Hydrologic Impact Assessment-Low Impact Development (L-THIA-LID) model (Ahiablame et al., 2012b) is a user friendly tool designed to evaluate runoff and water quality influences of land use changes and LID practices resulting from past or proposed developments. The L-THIA-LID model uses readily available data (precipitation, land cover, and hydrologic soil groups) to assist land use planners and decision makers in making their decisions (Hunter et al., 2010; Engel and Ahiablame, 2011; Ahiablame et al., 2012b). To continue addressing user concerns and needs, eight improvements are needed to the existing L-THIA-LID model (Ahiablame et al., 2012a, b). (1) The latest L-THIA-LID supports rain barrel/cistern, bioretention systems, green roof, porous pavement, open wooded space, and permeable patio. Additional commonly applied BMPs and LID practices should be represented in the model. (2) L-THIA-LID model computes runoff with the Curve Number (CN) method. For BMPs and LID practices without documented curve number values, another method to calculate runoff volume needs to be used. (3) The current L-THIA-LID model only evaluates water quality based on the event mean concentration (EMC) from each land use and runoff volume reduction. The reduction of pollutant concentrations by practices and irreducible concentration should be included in the model. (4) The current L-THIA-LID model does not represent LID practices in series, and this should be modified in the enhanced L-THIA-LID model. (5) The cost of implementing BMPs and LID practices needs to be included in the model. (6) A framework of simulating BMPs and LID practices at watershed scales is needed. (7) The characteristics of the model should be evaluated at the watershed scale (with calibration/validation and sensitivity/uncertainty analysis). (8) The selection and placement of BMPs and LID practices need to be optimized.

1.2 Research objectives

The overall goal of this study is to enhance the Long-Term Hydrologic Impact Assessment-low impact development (L-THIA-LID) model to better simulate BMPs and LID practices. The enhanced L-THIA-LID model will be able to better assist planners and decision-makers in development projects to protect the environment. The specific objectives of the study are to:

1. Enhance the L-THIA-LID model and demonstrate its use with four types of idealized land use units and watersheds (low density residential area, high density residential area, industrial area, and commercial area).
2. Enhance the L-THIA-LID model in simulating BMPs and LID practices at watershed scales, and then apply the model to an actual watershed with calibration, validation, sensitivity analysis and uncertainty analysis.
3. Improve the ability of the enhanced L-THIA-LID model to optimally select and place BMPs and LID practices at watershed scales.

1.3 Thesis organization

There are six chapters in this dissertation. Chapter 1 is the introduction of the thesis, which focuses on problem statement and research objectives. Chapter 2 describes enhancements to the L-THIA-LID model and demonstrates its use on four types of idealized land use units and watersheds. Chapter 3 analyzes the sensitivity and uncertainty of the L-THIA-LID 2.1 model. Chapter 4 evaluates the effectiveness of BMPs and LID practices on hydrology and water quality at watershed scale with the L-

THIA-LID 2.1 model. Chapter 5 demonstrates optimal selection and placement of BMPs and LID practices with the L-THIA-LID 2.1 model. Chapter 6 summarizes the main research findings and gives recommendations for future studies. Chapters 2 to 5 are written in journal manuscript format.

1.4 References

Abbott, M.B., Bathurst, J.C., Cunge, J.A., O'Connell, P.E., Ramussen, J., 1986. An introduction to the European Hydrological System – Systeme Hydrologique Europpen, ''SHE''. 2: Structure of a physically based, distributed modeling system. Journal of Hydrology. 87, 61–77.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012a. Effectiveness of low impact development practices: literature review and suggestions for future research. Water Air Soil Pollution. 223, 4253-4273.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012b. Representation and evaluation of low impact development practices with L-THIA-LID: An example for site planning. Environment and Pollution, 1(2). doi:10.5539/ep.v1n2p1.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement. Journal of environmental management, 119, 151-161.

Arnold, C.L., Gibbons, C.J., 1996. "Impervious surface coverage: The emergence of a key environmental indicator." Journal of the American Planning Association, 62(2), 243–258.

Beck, M.B., 1987. Water quality modeling: a review of the analysis of uncertainty. Water Resources Research, 23, 1393-1442.

Bekele, E.G., Nicklow J.W., 2005. Multiobjective management of ecosystem services by integrative watershed modeling and evolutionary algorithms, Water Resources Research, 41, W10406, doi:10.1029/2005WR004090.

Bhaduri, B., Harbor, J., Engel, B., Grove, M., 2000. Assessing watershed-scale, long-term hydrologic impacts of land-use change using a GIS-NPS model. Environmental Management. 26 (6), 643-658.

Burns, D., Vitvar, T., McDonnell, J., Hassett, J., Duncan, J., Kendall. C., 2005. Effects of suburban development on runoff generation in the Croton River basin, New York, USA. Journal of Hydrology, 311, 266-281. http://dx.doi.org/10.1016/j.jhydrol.2005.01.022

Carter R., 1961. Magnitude and frequency of floods in suburban areas. U.S. geological survey. Paper 424-B, B9-B11. U.S. Geological Survey, Washington, DC.

Damodaram, C., Giacomoni, M.H., Prakash Khedun, C., Holmes, H., Ryan, A., Saour, W., Zechman, E.M., 2010. Simulation of combined best management practices and low impact development for sustainable stormwater management1. JAWRA Journal of the American Water Resources Association, 46(5), 907-918.

Dietz, M.E., 2007. Low impact development practices: A review of current research and recommendations for future directions. Water, air, and soil pollution, 186(1-4), 351-363.

Duan, Q., Gupta, H.V., Sorooshian, S., Rousseau, A.N., Turcotte, R., 2003. Calibration of watershed models. American Geophysical Union. Vol. 6, pp. 1-345

Engel, B. Ahiablame, L., 2011. L-THIA-LID Long-Term Hydrologic Impact Assessment-Low Impact Development model, sv_version1.1. Purdue University.

Ferguson, B.K., 1990. “Role of the long-term water balance in management of storm-water infiltration.” Journal of Environmental Management, 30(3), 221-233.

Freer, J., Beven, K.J., Ambroise, B., 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: An application of the glue approach, Water Resour. Res., 32, 2161–2173.

Gilroy, K.L., McCuen, R.H., 2009. Spatio-temporal effects of low impact development practices. Journal of Hydrology, 367(3), 228-236.

Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008. Global change and the ecology of cities. Science, 319, 756-760.

Grove, M., Harbor, J., Engel, B. A., Muthukrishnan, S., 2001. Impacts of urbanization on surface hydrology, Little Eagle Creek, Indiana, and analysis of L-THIA model sensitivity to data resolution. Physical Geography, 22, 135–153.

Gunderson, J., Roseen, R., Janeski, T., Houle, J., Simpson, M., 2011. Economical CSO Management. Stormwater, 12 (3): 10-25.

Gupta, H.V., Sorooshian, S., Yapo, P.O., 1998. Toward improved calibration of hydrological models: Multiple and noncommensurable measures of information, Water Resources Research, 34, 751– 763.

Jakeman, A.J., Hornberger, G.M., 1993. How much complexity is warranted in a rainfall-runoff model? Water Resources Research, 29(8), 2637-2649.

Hata, A., Katayama, H., Kojima, K., Sano, S., Kasuga, I., Kitajima, M., Furumai, H., 2014. Effects of rainfall events on the occurrence and detection efficiency of viruses in river water impacted by combined sewer overflows. Science of The Total Environment, 468, 757-763.

Huber, W.C., Dickinson, R.E., 1988. Storm water management model, version 4, user's manual. EPA 600/388/001a (NTIS PB88-236641/AS).USEPA, Athens, GA.

Hunt, W.F., Jarrett, A.R., Smith, J.T., Sharkey, L.J., 2006. Evaluating bioretention hydrology and nutrient removal at three field sites in North Carolina. Journal of Irrigation and Drainage Engineering, 132(6), 600-608.

Hunt, W.F., Smith, J.T., Jadlocki, S.J., Hathaway, J.M., Eubanks, P.R., 2008. Pollutant removal and peak flow mitigation by a bioretention cell in urban Charlotte, NC. Journal of Environmental Engineering, 134(5), 403-408.

Hunter, J.G., Engel, B.A., Quansah, J.E., 2010. Web-based low impact development decision support tool for watershed planning. Proceedings of Low Impact Development 2010: Redefining Water in the City. April 11–14. San Francisco, CA, USA.

Leopold L., 1968. Hydrology for urban planning, a guide book on the hydrologic effects of urban land use. U.S. Geological Survey Circular 554. U.S. Department of the Interior, Washington, DC.

Lerch, N.K., Hale, W.F., and Lemaster, D.D., 1982. Soil survey of Hamilton County, Ohio, U.S., Dept. of Agriculture and Ohio Dept. of Natural Resources, Ohio.

Li, Z., Shao, Q., Xu, Z., Cai, X., 2010. Analysis of parameter uncertainty in semi-distributed hydrological models using bootstrap method: A case study of SWAT model applied to Yingluoxia watershed in northwest China. Journal of Hydrology, 385(1), 76-83.

Maringanti, C., Chaubey I., Popp J., 2009. Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control, Water Resources Research, 45, W06406, doi:10.1029/2008WR007094.

Maringanti, C., Chaubey I., Arabi M., Engel B., 2011. Application of a multi-objective optimization method to provide least cost alternatives for NPS pollution control. Environmental Management, DOI:10.1007/s00267-011-9696-2

Muleta, M. K., Nicklow, J.W., 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. Journal of Hydrology, 306(1-4), 127-145.

Newcomer, M.E., Gurdak, J.J., Sklar, L.S., Nanus, L., 2014. Urban recharge beneath low impact development and effects of climate variability and change. Water Resources Research, 50(2), 1716-1734.

Prince George's County, Maryland (PGCo), 1999. Low impact development: an integrated design approach. Department of Environmental Resources, Largo, MD.

Scholes, L., Revitt, D.M., Ellis, J.B., 2008. A systematic approach for the comparative assessment of stormwater pollutant removal potentials. Journal of environmental management, 88(3), 467-478.

Schueler, T., 1995. Environmental land planning series: site planning for urban streams Protection. Washington, DC: Center for Watershed Protection Publication No. 95708. Metropolitan Washington Council of Governments.

Shaw E.M., 1994. Hydrology in practice, 3rd edition. Chapman & Hall: London: 569.

Shoemaker. L., Riverson Jr, J., Alvi, K., Zhen, J.X., Paul, S., Rafi, T., 2009. SUSTAIN—A framework for placement of best management practices in urban watersheds to protect water quality. Fairfax, VA.

Stagge, J.H., Davis, A.P., Jamil, E., Kim, H., 2012. Performance of grass swales for improving water quality from highway runoff. Water research.

Tang, T., Reed, P., Wagener, T., Van Werkhoven, K., 2006. Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. Hydrology and Earth System Sciences Discussions, 3(6), 3333-3395.

The LIDC (Low Impact Development Center, Inc.), GeoSyntec Consultants, University of Florida, Oregon State University. (2006). Evaluation of best management practices for highway runoff control. Transportation Research Board, National Research Council.

Tyagi, A., Haan, C.T., 2001. Uncertainty analysis using corrected first-order approximation method. Water Resources Research, 37(6), 1847-1858.

Urbonas, B., 1994. Assessment of storm water BMPs and their technology. Water Science & Technology, 29(1-2), 347-353.

USDBLM (United States Department of the Interior Bureau of Land Management), 2005. Land Use Planning Handbook. 55.

USEPA (US Environmental Protection Agency), 2008. Reducing stormwater costs through low impact development (LID) strategies and practices. EPA 841-F-07-006, Nonpoint Source Control Branch, Washington, D.C.

Yang, J., 2011. Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. Environmental Modelling & Software, 26(4), 444-457.

Ying, G., Sansalone, J., 2010. Transport and solubility of hetero-disperse dry deposition particulate matter subject to urban source area rainfall-runoff processes. Journal of Hydrology, 383(3-4), 156-166. http://dx.doi.org/10.1016/j.jhydrol.2009.12.030

CHAPTER 2. ENHANCING A RAINFALL-RUNOFF MODEL TO ASSESS THE IMPACTS OF BMPS AND LID PRACTICES ON STORM RUNOFF

2.1 Abstract

Best management practices (BMPs) and low impact development (LID) practices are increasingly being used as stormwater management techniques to reduce the impacts of urban development on hydrology and water quality. To assist planners and decision-makers at various stages of development projects (planning, implementation, and evaluation), user-friendly tools are needed to assess the effectiveness of BMPs and LID practices. This study describes a simple tool, the Long-Term Hydrologic Impact Assessment-LID (L-THIA-LID), which is enhanced with additional BMPs and LID practices, improved approaches to estimate hydrology and water quality, and representation of practices in series (meaning combined implementation). The tool was used to evaluate the performance of BMPs and LID practices individually and in series with 30 years of daily rainfall data in four types of idealized land use units and watersheds (low density residential, high density residential, industrial, and commercial). Simulation results were compared with the results of other published studies. The simulated results showed that reductions in runoff volume and pollutant loads after implementing BMPs and LID practices, both individually and in series, were comparable with the reported impacts of these practices. The L-THIA-LID 2.0 model is capable of

assisting decision makers in evaluating environmental impacts of BMPs and LID practices, thereby improving the effectiveness of stormwater management decisions.

2.2 Introduction

The growing urban population increases the conversion of undeveloped lands into urban use (US Census Bureau, 1999; McGee, 2001; Demographia, 2010). Urban development generally leads to increase in impervious surface, a major factor that affects variations in urban hydrology through increased runoff, decreased recession time, decreased groundwater recharge and decreased base flow (Arnold and Gibbons, 1996; Bhaduri et al., 2000; Burns et al., 2005). Urban activities have also been shown to adversely influence water quality in downstream waters (Grove et al., 2001; Davis, 2005; Ying & Sansalone, 2010), making urban stormwater runoff one of the most important causes of water quality damages in streams, bays, and estuaries (USEPA, 2007). Combined sewer systems can be used to collect and deliver storm runoff and domestic sewage. Then, the polluted water would be treated by treatment plants. However, when capacities of sewer systems are overloaded due to heavy storms, combined sewer overflows (CSOs) occur, potentially polluting receiving water (Hatt et al., 2004).

Best management practices (BMPs) and low impact development (LID) practices are two approaches frequently used to reduce the impacts of urban development and redevelopment activities on water quantity and quality (Urbonas, 1994; USDIBLM, 2005; Dietz, 2007; USEPA, 2008). The implementation of BMPs and LID practices reduces stormwater runoff and can result in fewer CSO events with significant savings on infrastructure expenditures (Banting et al., 2005). Although used for the same purpose (i.e. stormwater management), BMPs and LID practices have differences in functionality (Prince George's County, Maryland, 1999; Gilroy, 2009; Damodaram et al., 2010). BMPs are used to collect, store, and treat stormwater runoff with facilities at the end of drainage areas (The LIDC et al., 2006; Gilroy, 2009). They are designed to transfer stormwater runoff off-site rapidly (Davis, 2005; USEPA, 2008). LID practices are small-scale and localized source control measures, designed to replicate a location's natural features with processes such as infiltration, evaporation, and filtration (Prince George's County, Maryland, 1999; Damodaram et al., 2010). LID practices enhance post-development environmental conditions with possible reduced costs compared to those of BMPs (Davis, 2005; The LIDC et al., 2006; USEPA, 2008).

A substantial number of field and laboratory studies have documented the performance of BMPs and LID practices at various scales and geographic locations (e.g., Legret et al., 1996; NJDEP, 2004; NPRPD, 2007; Hunt et al., 2008; Stagge et al., 2012). For example, bioretention systems (e.g. with 3.8 cm/hr infiltration soil, 15 cm of 2.54 cm round stone) were used in Haddam, CT during a 56-week study period to capture shingled-roof runoff (Dietz et al., 2005), and were found to reduce runoff volume by 0.4%, and nutrient loads (Total Nitrogen and Total Kjeldahl Nitrogen) between 31% and 32%. Field experiments conducted in Charlotte, NC from 2004 to 2006 (Hunt et al., 2008) to evaluate the performance of a bioretention cell (with 1.08 cm/hr infiltration soil, soil media depth of 120 cm) showed 31% to 60% reduction for sediment (Total Suspended Solids) and nutrient loads (Total Phosphorous, Total Nitrogen, and Total Kjeldahl Nitrogen), 31% to

77% for metal loads (Copper, Lead, and Zinc), and reduction in fecal coliform (FC) colonies by 69%. Modeled bioretention systems with sand bed (30.5 cm) and planting substrate (91.4 cm) columns were found to reduce sediment loads (Total Suspended Solids) between 81% and 99% and fecal coliform (FC) colonies between 55% and 99.8% (Rusciano et al., 2007).

Comings et al. (2000) reported reductions of 19% to 81% for sediment (Total Suspended Solids) and nutrient (Total Phosphorus) loads, 37% to 76% for metal (Cadmium, Copper, Lead, and Zinc) loads with a wet pond evaluated in Bellevue, WA. Wet ponds with permanent pool volume of 15,300 to 47,300 m^3 were evaluated in Piedmont, NC over a period of 13 months (Wu et. al. 1996). The authors reported that reductions of sediment (Total Suspended Solids) and nutrient (Total Phosphorous and Total Kjeldahl Nitrogen) loads were between 21% and 93%, and between 32% and 80% for Zinc.

Although the performance of BMPs and LID practices was reported in numerous studies, spatial-temporal data are limited due to constraints of resources and measurement techniques. In addition, results from these studies cannot be directly used in the analysis of planning scenarios to demonstrate the effectiveness of the practices. Therefore, computer models should be developed to provide such capabilities.

However, most computer models use complicated algorithms and require a large amount of input data, which makes it difficult for users to run the models. Storm Water Management Model (SWMM) is a rainfall-runoff simulation model that can model effectiveness of both long-term and single storm events on hydrology and water quality in urbanized areas (Huber and Dickenson, 1988). SWMM simulates runoff volume and pollutant loads from a collection of subcatchment areas; the runoff is routed by pipes, storage/treatment devices, channels, regulators, and pumps; and LID practices are simulated based on processes and simulated as various vertical layers. The System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN) Model (Shoemaker et al., 2009) is a decision support tool for the selection and placement of BMPs and LID practices in urban areas. SUSTAIN simulates BMPs and LID practices through processes such as flow routing, infiltration, evapotranspiration, pollutant routing, and pollutant removal.

User-friendly tools are needed for planners and decision makers to assess the effectiveness of BMPs and LID practices on hydrology and water quality during planning, implementation, and evaluation stages of development projects. This article discusses the enhancement of an easy-to-use tool, L-THIA-LID, and demonstrates its use with four types of idealized land use units and watersheds (low density residential area, high density residential area, industrial area, and commercial area) to evaluate how BMPs and LID practices may impact hydrology and nonpoint source pollution in urban watersheds.

2.3 L-THIA model background

The Long-Term Hydrologic Impact Assessment (L-THIA) model is Curve Number (CN) method (NRCS, 1986) based and uses readily available data including land uses data, hydrologic soil groups data, and daily rainfall data (typically 30 years and more) to calculate average annual runoff; nonpoint source pollutant loads are simulated by runoff volume and pollutant coefficients associated with specific land uses (Harbor, 1994; Engel, 2001). The L-THIA model has been successfully used in a wide range of studies to assess the impact of land use changes on hydrology and water quality (Bhaduri et al., 1997; Bhaduri et al., 2000; Pandey et al., 2000; Grove et al., 2001; Kim et al., 2002; Tang et al., 2005; Lim et al., 2006; Muthukrishnan et al., 2006; Choi, 2007; Davis et al., 2010; Lim et al., 2010; Wilson and Weng, 2010; Gunn et al., 2012). The L-THIA model has also been combined with or incorporated in other models and Decision Support Systems (Web-based and GIS-based) (Choi and Engel, 2003a; Choi et al., 2003b; Engel et al., 2003; Tang et al., 2004; Shi et al., 2004; Choi et al., 2005a, b; Tang et al., 2005).

The Long-Term Hydrologic Impact Assessment-Low Impact Development (L-THIA-LID) model (Ahiablame et al., 2012b) is a user friendly standalone tool based on the L-THIA-LID model developed by Engel and Hunter (2009), which was developed from the L-THIA model to estimate the effects of land use changes and LID practices on runoff and water quality (Engel and Hunter, 2009; Hunter et al., 2010; Engel and Ahiablame, 2011). The latest L-THIA-LID model (Ahiablame et al., 2012b) uses curve numbers to represent LID practices (including bioretention systems, green roof, rain barrel/cistern, open wooded space, permeable patio, and porous pavement) when estimating runoff volume. The changes in water quality after implementing LID practices are estimated by runoff volume changes and pollutant coefficients of specific land uses. For more details on the L-THIA-LID model, readers should consult Ahiablame et al. (2012a, b). The L-THIA-LID model has been successfully applied from single lot scale to watershed scale

(Ahiablame et al., 2012b, 2013). Ahiablame et al. (2012b) applied the model on a residential subdivision, which showed the adverse impact of development on runoff volume and pollutant loads could be significantly reduced by implementing LID practices. Ahiablame et al. (2013) simulated the application of rain barrel/cistern and porous pavement with different scenarios in two urbanized watersheds around Indianapolis, and the results indicated that the L-THIA-LID model can be used to simulate LID practices at watershed scales.

2.4 Enhancement of the L-THIA-LID model

To continue addressing user concerns and needs, four improvements should be added to the existing L-THIA-LID model developed by Ahiablame et al. (2012a, b): (1) The latest L-THIA-LID supports bioretention systems, green roofs, rain barrels/cisterns, open wooded spaces, permeable patios, and porous pavements. Additional commonly applied BMPs and LID practices should be represented in the model, including detention basins, retention ponds, wetland basins, biofilter-grass swales, wetland channels, and biofilter-grass strips; (2) L-THIA-LID model computes runoff with the Curve Number (CN) method (NRCS, 1986; Sample et al., 2001). For BMPs and LID practices (newly added practices) without documented curve number values, another method to calculate runoff volume needs to be developed; (3) The current L-THIA-LID model evaluates water quality based only on the event mean concentration from each land use and runoff volume reduction. The reduction of pollutant concentrations by practices should be included in the model; (4) The current L-THIA-LID model does not represent LID practices in series, and this should be modified in the L-THIA-LID 2.0 model.

Data from the International Stormwater BMP database (www.bmpdatabase.org) were used to enhance the L-THIA-LID model. The database contains designs and related performance of BMPs and LID practices. In 2012, the database contained data for over 500 BMPs and LID practices from different areas of the world, with most of the data collected in the United States.

2.4.1 Impacts of BMP/LID Practices on Runoff

For BMPs and LID practices without documented CN values that are newly represented in the model (including detention basin, retention pond, wetland basin, biofilter-grass swale, wetland channel, and biofilter-grass strip), the runoff volume after the implementation of BMPs and LID practices is estimated as a percentage of runoff volume generated from the drainage area. As shown in Figure 2.1, after runoff generated from the drainage area flows into BMPs and LID practices, the effluent volume will be reduced by the percent runoff reduction. The percent reductions of runoff volume after implementing BMPs and LID practices are discussed below and the results are summarized in Table 2.1. BMPs and LID practices are designed with certain sizes to obtain the runoff volume reductions in Table 2.1.

2.4.1.1 Detention basin (dry, grass-lined)

A detention basin (dry), which is adapted for flood control, is designed to be completely empty during a period between storm runoff events. Pollutant removal is facilitated for the reason that the detention basin uses a small outlet that extends the detention time

(WWE and GC, 2010b). According to the International Stormwater BMP Database (GC and WWE, 2011), the runoff volume reduction after implementation of detention basins is 33% (median value).

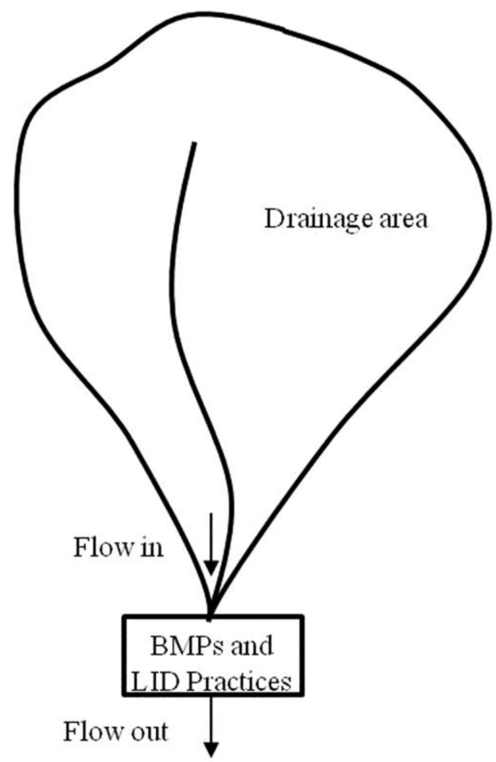


Figure 2.1 Representation of BMP/LID practice without documented CN Values.

2.4.1.2 Retention pond (wet pond)

Different from detention basins, which temporarily store water after a rainfall event and are dry during a period between storm runoff events, retention ponds never dry and the water in ponds is replaced to a degree or completely by stormwater for the period of storm events (WWE and GC, 2010b). According to the International Stormwater BMP Database, wet ponds have the ability to reduce annual runoff volume by 7% (Strecker et al., 2004). This value was determined based on the data of inflow storms greater than or equal to 0.2 watershed inches (0.508 cm). The percentage of runoff reduction would be bigger with smaller storms. However, because of limited data, we assumed that when the inflow storms are smaller than 0.2 watershed inches (0.508 cm), the percentage of runoff reduction is still the same (7%).

2.4.1.3 Wetland basin

A wetland basin, which is similar to a retention pond or detention pond, is an area filled with water (either permanently or periodically) and covered with wetland vegetation (WWE and GC, 2010b). According to the International Stormwater BMP Database, wetland basins have the ability to reduce annual runoff volume by 5% (Strecker et al., 2004). Similar to wet ponds, the data were summarized based on the data of inflow storms greater than or equal to 0.2 watershed inches (0.508 cm). We also assumed that when the inflow storms are smaller than 0.2 watershed inches (0.508 cm), the percentage of runoff reduction is still the same.

2.4.1.4 Biofilter-grass swale

A grass swale, with zero or small base width, is a shallow grass-lined waterway used for conveying storm flow close to the starting point of storm runoff (WWE and GC, 2010b). According to the International Stormwater BMP Database (GC and WWE, 2011), the runoff volume reduction after implementation of grass swales is 42% (median value). The size of drainage area is limited to small areas (e.g. approximately 1 ha).

2.4.1.5 Biofilter-grass strip

Grass filter strips, also called buffer strips, are areas with permanent vegetation built to treat flow from an upstream area. Grasses, meadows, and forests may be planted between fields and water bodies to filter, infiltrate, and settle pollutants (WWE and GC, 2010b). According to the International Stormwater BMP Database (GC and WWE, 2011), the runoff volume reduction after implementation of grass strips is 34% (median value). Similar to biofilter-grass swales, the size of drainage area is limited to small areas (e.g. approximately 1 ha).

2.4.1.6 Wetland channel

A wetland channel (also called a wet swale), which has wetland vegetation planted at the bottom, is built to convey flow at a very low speed (usually less than 0.3 m/sec for 2-year design storm) (WWE and GC, 2010b). The only two literature sources found, Strecker et al. (2004) and CWP and CSN (2008), reported that wetland channels do not reduce annual runoff volume. Therefore, we assumed that annual runoff volume reduction of wetland channels is 0%. Despite providing no reduction in runoff, wetland channels were included because they reduce pollutant constituents.

Table 2.1 Percent reduction of runoff volume after implementing BMPs and LID practices

(Strecker et al., 2004; CWP and CSN, 2008; GC and WWE, 2011)

BMPs and LID practices	Volume reduction (%)
Detention basin (dry, grass-lined)	33
Retention pond (wet pond)	7
Wetland basin	5
Biofilter-grass swale	42
Biofilter-grass strip	34
Wetland channel	0

2.4.2 BMP/LID Practice Impacts on Water Quality

When estimating the impacts of BMPs and LID practices on water quality, the concentration of effluent cannot be smaller than a certain threshold because of the treatment abilities of BMPs and LID practices. This threshold is called irreducible concentration (Schueler, 1996; Strecker and Quigley, 1999). For example, when input concentrations of pollutants are very low, BMPs and LID practices may actually release some pollutants over a short period. This will result in negative efficiency ratios—calculated as Eq. (2.1), using either pollutant concentrations or loads as a basis.

$$ER = \frac{Inflow - Outflow}{Inflow} \tag{2.1}$$

where *ER* is efficiency ratio, *Inflow* is inflow pollutant concentrations (or loads), and *Outflow* is outflow pollutant concentrations (or loads).

Schueler (1996) used the mean value of effluent concentration as the irreducible concentration for various pollutants. However, based on analyzing data from the International Stormwater BMP database (www.bmpdatabase.org) and related reports (WWE and GC, 2010a, b, 2011, 2012a, b, c, d, e), almost all of the mean values of the effluent concentrations were found to be greater than the median values. This suggests using mean values as irreducible concentration will result in overestimating the effluent concentration. More specifically, it suggests that the distribution of effluent concentrations is skewed so the mean is no longer a good estimator of central tendency of the data. As a result, median values of effluent concentration will be used as irreducible concentration values.

The ratio of median effluent concentration to median influent concentration for each pollutant and each BMP or LID practice based on the International Stormwater BMP database is calculated as:

$$Ratio = \frac{C_{out}}{C_{in}} \tag{2.2}$$

where C_{out} is median effluent concentration, C_{in} is median influent concentration.

Then, the pollutant concentration after implementing BMPs/LID practices (outflow concentration) will be calculated based on the irreducible concentration method. There are three conditions in the irreducible concentration method:

1) $EMC'_{HRU} < Irreducible\ Concentration$

When inflow concentration (EMC'_{HRU}) is smaller than irreducible concentration, the concentration of the effluent cannot be reduced further by implementing the BMPs or LID practices. Lenhart (2007), which used a similar approach, adopted the irreducible concentration as the effluent concentration for this situation. However, the L-THIA-LID 2.0 model is used to simulate long-term period water quality, and additional pollutants cannot be generated from the system which makes the effluent concentration bigger than the influent concentration in the long run. Thus, the effluent concentration in the L-THIA-LID 2.0 model when $EMC'_{HRU} < Irreducible\ Concentration$ is calculated as:

$$EMC_{HRU} = EMC'_{HRU} \tag{2.3}$$

2) $EMC'_{HRU} \geq Irreducible\ Concentration$ and

$EMC'_{HRU} \times Ratio < Irreducible\ Concentration$

For the situation when inflow concentration is equal to or greater than irreducible concentration and inflow concentration multiplied by ratio is smaller than irreducible concentration, although the pollutant concentration can be reduced, it cannot be reduced to values smaller than irreducible concentration. So the effluent concentration in this case is calculated as:

$$EMC_{HRU} = Irreducible\ concentration \tag{2.4}$$

3) $EMC'_{HRU} \times Ratio \geq Irreducible\ Concentration$

When inflow concentration multiplied by ratio is equal to or bigger than irreducible concentration, effluent pollutant concentrations can be calculated as the product of the concentration of a pollutant from an HRU and the Ratio:

$$EMC_{HRU} = EMC'_{HRU} \times Ratio \tag{2.5}$$

Where EMC'_{HRU} is a pollutant concentration from an HRU; EMC_{HRU} is the pollutant concentration from an HRU after implementation of BMPs or LID practices; *Irreducible concentration* is the median value of effluent concentration from the International Stormwater BMP database (www.bmpdatabase.org); and *Ratio* is obtained by analyzing data from the International Stormwater BMP database (www.bmpdatabase.org).

Water quality from the watershed is computed as (Ahiablame et al., 2012b):

$$WQ_m = \sum_i^N Q_{HRU} \times A_i \times EMC_{HRU} \tag{2.6}$$

Where WQ_m is the mass of a pollutant from the entire watershed (colonies for Fecal Coliform and Fecal Strep, MPN for E-coli, and g for all other pollutants in the model); N is the number of HRUs in the watershed; Q_{HRU} is the runoff depth of an HRU in the watershed (mm); A_i is the area of an HRU in the watershed (m^2); and EMC_{HRU} is the pollutant concentration from an HRU after implementation of BMPs and LID practices (colonies/L for Fecal Coliform and Fecal Strep, MPN/L for E-coli, and g/L for all other pollutants in the model).

2.4.3 Simulations of BMP/LID Practice in Series

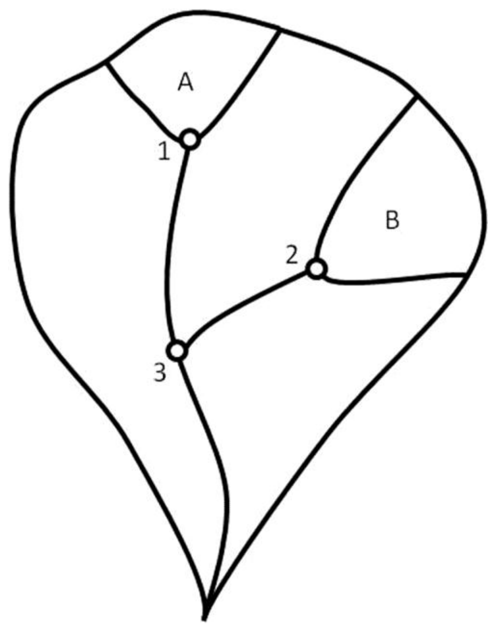


Figure 2.2 Conceptual watershed with subbasins for modeling BMP/LID practice in series with the L-THIA-LID 2.0 model.

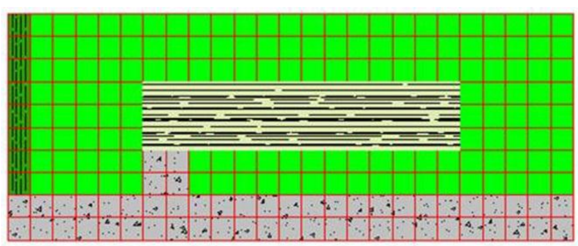
In real watersheds, multiple BMPs and LID practices are often combined, which makes it important to represent these practices in series for modeling purposes. As shown in Figure 2.2, BMPs and LID practices are represented in series. The outline is a watershed. A and B are two subbasins, and we assume the maximum number of subbasins that can be simulated in series is 10 to maintain the simplicity of the L-THIA-LID 2.0 model. Numbers 1, 2 and 3 are the BMPs and LID practices implemented in the watershed.

Based on Table 3-4 from Shoemaker et al. (2009), which shows the default criteria for BMP suitable locations used in the SUSTAIN model, suitable BMPs and LID practices will be implemented in the area. For example, the runoff that flows out of one BMP/LID practice (Number 1) will enter the next practice (Number 3) in the downstream, then runoff volume and water quality after implementing the practice (Number 3) will be estimated using the methods previously discussed (Section *3.1* and *3.2*).

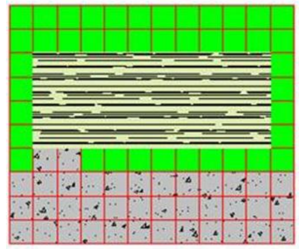
2.5 Materials and methods

2.5.1 Study area

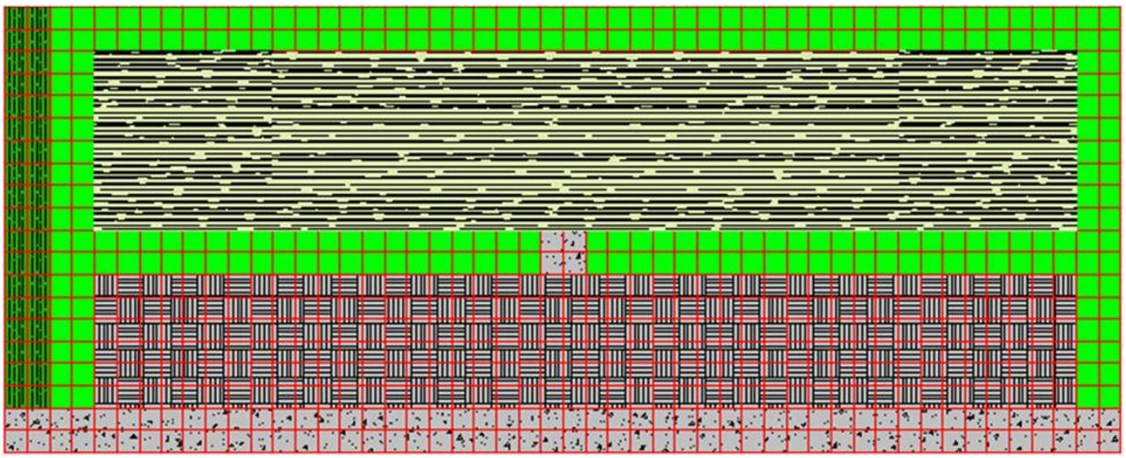
The modeling approaches discussed above were demonstrated with four types of idealized land use units and watersheds—low density residential area, high density residential area, industrial area, and commercial area. The approximate imperviousness of each watershed was obtained according to previous studies (NRCS, 1986; Homer et al., 2004). The layouts of the four types of land use units, which were designed based on the typical layouts and the imperviousness of different areas, are shown in Figure 2.3. Each area is separated into a grid of 2 m by 2 m cells. The idealized land use units are similar to “microwatersheds” described by Gilroy and McCuen (2009).



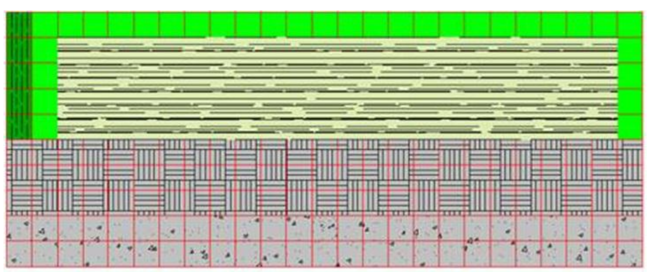
a. Low density residential area



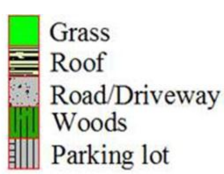
b. High density residential area



c. Industrial area



d. Commercial area



e. Legend

Figure 2.3 Layouts of the four types of idealized land use units used in the study.

The characteristics of each idealized land use unit are shown in Table 2.2. Each idealized watershed is the combination of multiple idealized units of the same land use type. The hydrologic soil group (HSG) of each area was also defined. The total areas of each type of idealized watershed are the same (121,406 m^2 or 30 acres). The number of land use units in each idealized watershed is 120, 250, 30, and 120 for low density residential, high density residential, industrial, and commercial, respectively.

Table 2.2 Characteristics of different land uses in each idealized land use unit

Types of areas		Low density residential area	High density residential area	Industrial area	Commercial area
Imperviousness (%)		38.4	65.0	72.0	85.2
HSG		B	D	D	D
Area(m^2)	Roof	170	162	1,424	356
	Road/driveway	219	154	421	202
	Grass	591	170	987	129
	Woods	32	0	146	20
	Parking lot	0	0	1,068	304
	Total	1,012	486	4,047	1,012

2.5.2 Methods

Daily rainfall data were adopted to estimate the long-term effects of BMPs and LID practices with the L-THIA-LID 2.0 model. Thirty (30) years (1983-2012) of daily rainfall data from weather station 129430 (WEST LAFAYETTE 6 NW IN US) were obtained from the National Climatic Data Center (http://www.ncdc.noaa.gov).

The runoff volume (RV) and pollutant loads of the four types of idealized land use units and watersheds—low density residential area, high density residential area, industrial area, and commercial area were calculated before implementing BMPs and LID practices. Event Mean Concentration (EMC) data (Table A.1) were used in the model to simulate pollutant concentrations in runoff from different land use areas. The simulated pollutants included Total Suspended Solids (TSS), Total Dissolved Solids (TDS), Total Phosphorus (TP), Dissolved Phosphorus (DP), Total Nitrogen (TN), Total Kjeldahl Nitrogen (TKN), Nitrate+Nitrite (NO_x), Total Cadmium (Cd), Total Chromium (Cr), Total Copper (Cu), Total Lead (Pb), Total Nickel (Ni), Total Zinc (Zn), Fecal Coliform (FC), Fecal Streptococcus (FS), Escherichia coli (E. coli), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Oil and Grease (O&G).

The performances of bioretention systems, biofilter-grass swale, porous pavement, biofilter-grass strip, detention basin (dry, grass-lined), retention pond (wet pond), wetland basin, and wetland channel were evaluated with the L-THIA-LID 2.0 model because there are adequate water quality data in the International Stormwater BMP database (www.bmpdatabase.org) to analyze those BMPs and LID practices. The distinction between BMPs and LID practices was made because the drainage areas of the two types of practices differ.

LID practices—including bioretention systems, biofilter-grass swale, and porous pavement, which are suitable for smaller areas based on the default criteria for BMP suitable locations used in the SUSTAIN model (Shoemaker et al., 2009), were implemented in each land use unit. There are no limitations for the drainage areas of implementing biofilter-grass strips and wetland channels in the default criteria for BMP suitable locations used in the SUSTAIN model (Shoemaker et al., 2009). However, drainage area for biofilter-grass strips is limited to small areas according to the discussion in runoff volume reduction. The drainage area of implementing wetland channel is also limited to small areas according to VDSDS (2011). As a result, biofilter-grass strip and wetland channel were applied in each land use unit.

According to criteria for BMP suitable locations in the SUSTAIN model (Shoemaker et al., 2009), detention basins (dry, grass-lined), retention ponds (wet pond), and wetland basins are implemented for capturing runoff from larger drainage areas. Therefore, these BMPs were applied in each idealized watershed to evaluate runoff volume and pollutants loads.

Two simulations were done to evaluate the performance of BMPs and LID practices in series. In the first simulation, runoff was treated by practices in the order of porous pavement and biofilter-grass swale—which means runoff was treated by porous pavement first and then treated by biofilter-grass swale; in the second simulation, runoff was treated by practices in the order of biofilter-grass strip and biofilter-grass swale. Both of the simulations were applied in each idealized land use unit.

2.6 Results and discussion

2.6.1 Performance of a single BMP

Reductions of runoff volume and pollutant loads after implementing BMPs individually are shown in Table 2.3. The column S showed simulated results and the column L showed the results from literature. All BMPs were represented with the percent runoff reduction method, and the range of reductions for each pollutant was due to differences in pollutant concentrations from different land uses.

There were two reasons why some pollutant load reductions were the same as the runoff volume reductions. First, there were no pollutant concentration reductions for these constituents because of a lack of data in the International Stormwater BMP database, such as Fecal Streptococcus (FS) treated by detention basins. As more data become available in the future, this could be changed. Second, the pollutant concentrations from some land use areas were smaller than the irreducible concentration of the BMPs or LID practices, such as NO_x and Cr treated by detention basins.

2.6.1.1 Performance of detention basin (dry, grass-lined)

As shown in Table 2.3, the reductions of TSS, TP, NO_x, Cd, Cr, Pb, Cu, Zn, and Ni after implementing a detention basin were similar to the findings of other authors (Stanley, 1996; NJDEP, 2004; NPRPD, 2007).

The percent reduction of FC after the implementation of a detention basin was 53%; while another author found reductions of 78% to 97% (NPRPD, 2007). However, the range of FC reductions from the literature was only based on two experiments.

The percent reductions of FS, E. coli, BOD, COD, O&G, TDS, DP, TN, and TKN after applying a detention basin were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction for these constituents because of a lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

Table 2.3 Reduction (%) of runoff volume and pollutant loads after implementing BMPs individually

(Hartigan, 1989; Oberts et al., 1989; Stanley, 1996; Wu et al. 1996; Carleton et al., 2000; Comings et al., 2000; Wossink et al., 2003; NJDEP, 2004; NPRPD, 2007; Scholes et al., 2008)

Runoff And pollutants	Reduction (%)					
	Detention basin (dry, grass-lined)		Retention pond (wet pond)		Wetland basin	
	S[a]	L[b]	S	L	S	L
RV	33	--	7	--	5	--
TSS	69 to 73	-1 to 90	76 to 79	50 to 93	58	46 to 92
TDS	33	--	7	--	5	--
TP	45 to 48	0 to 48	57 to 60	19 to 76	38	16 to 76
DP	33	--	34 to 55	41 to 74	46	6 to 53
TN	33	--	7 to 35	16 to 41	5	--
TKN	33	--	7 to 24	21 to 32	5	--
NOx	33 to 56	-10 to 79	32 to 62	24 to 67	67	22 to 80
Cd	46	54	56	52 to 68	46	50
Cr	33 to 60	49	40 to 69	--	5	--
Cu	64	10 to 73	51	37 to 74	40	18 to 63
Pb	66	55	70	73 to 76	43	--
Ni	33 to 60	43	7 to 54	--	5	--
Zn	72	-38 to 76	63	32 to 80	56	23 to 68
FC	53	78 to 97	66	52 to 94	15 to 55	67 to 88
FS	33	--	7	--	5	--
E. coli	33	--	7	--	5	--
BOD	33	--	7	--	5	--
COD	33	--	7	--	5	--
O&G	33	--	7	--	5	--

[a]S-simulated; [b]L-from literature

2.6.1.2 Performance of retention pond (wet pond)

As shown in Table 2.3, the reductions of TSS, TP, TN, TKN, DP, NO_x, FC, Cd, Cu, Zn, and Pb after implementing a retention pond were consistent with what other authors found (Hartigan, 1989; Wu et al. 1996; Comings et al., 2000; Wossink et al., 2003; NJDEP, 2004; NPRPD, 2007; Scholes et al., 2008).

The simulated reductions of Cr and Ni after applying a retention pond were 40% to 69% and 7% to 54%, respectively; no findings were reported in the literature.

The reductions of TDS, FS, E. coli, BOD, COD, and O&G after applying retention pond were the same as runoff volume reduction as there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data for these constituents in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.1.3 Performance of wetland basin

As shown in Table 2.3, the reductions of TSS, TP, DP, NO_x, FC, Cd, Cu, and Zn after the implementation of a wetland basin were similar to findings of other authors (Oberts et al., 1989; Carleton et al., 2000; Wossink et al., 2003; NJDEP, 2004; NPRPD, 2007; Scholes et al., 2008).

The reduction of Pb after implementing a wetland basin found in this study was 43%; no observed data was reported in the literature.

The reductions of TDS, TN, TKN, FS, E. coli, BOD, COD, O&G, Cr, and Ni after applying retention pond were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction due to lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.2 Performance of a single LID practice

The reductions of runoff volume and pollutant loads after implementing LID practices individually are shown in Table 2.4. The column S shows simulated results and the column L shows the results from literature. For LID practices represented with the Curve Number Method, such as porous pavement, the range of reductions for each pollutant was because the runoff and pollutant concentrations for different land uses varied. For LID practices represented with the percent runoff reduction method, such as wetland channel, the range of reductions for each pollutant was due to pollutant concentrations from different land uses varying.

2.6.2.1 Performance of bioretention systems

As shown in Table 2.4, the reductions of TSS, TP, DP, TN, TKN, NO_x, Cu, Pb, Zn, and RV after implementing bioretention systems suggested by the L-THIA-LID 2.0 model were consistent with the results other authors found (Wossink et al., 2003; NJDEP, 2004; Dietz et al., 2005; Glass and Bissouma, 2005; Hunt et al., 2006; NPRPD, 2007; Rusciano et al., 2007; Davis, 2008; Hunt et al., 2008; Lucas et al., 2010).

The reductions of TDS, FC, FS, E. coli, BOD, COD, O&G, Cd, Cr, and Ni after applying bioretention systems were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data for these constituents in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.2.2 Performance of porous pavement

As shown in Table 2.4, the reductions of TSS, TP, Cu, Pb, Zn, TKN and RV after implementing porous pavement found in this study were in accordance with other authors' findings (Legret et al., 1996; Rushton, 2001; Hunt et al., 2002; NJDEP, 2004; Bean et al., 2005; Dreelin et al., 2006; Gilbert et al., 2006; Seters, 2007; Tota-Maharaj et al., 2010).

The reduction of 40% to 78% of Ni after the implementation of porous pavement was found in this study, while no other findings were reported.

The reductions of TDS, DP, TN, NO_x, FC, FS, E. coli, BOD, COD, O&G, Cd, and Cr after applying porous pavement were the same as runoff volume reduction as there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data in the International Stormwater BMP database (www.bmpdatabase.org) for these pollutants.

Table 2.4 Reduction (%) of runoff volume and pollutant loads after implementing LID practices individually

(Whallen and Cullum, 1988; UD& FCD, 1992; Yu et al., 1993; Legret et al., 1996; Lee et al., 1998; Rushton, 2001; Yu et al., 2001; Hunt et al., 2002; Wossink et al., 2003; NJDEP, 2004; Bean et al., 2005; Dietz et al., 2005; Glass and Bissouma, 2005; Dreelin et al., 2006; Gilbert et al., 2006; Hunt et al., 2006; NPRPD, 2007; Rusciano et al., 2007; Seters, 2007; Davis, 2008; Hunt et al., 2008; Caltrans, 2010; Lucas et al., 2010; Tota-Maharaj et al., 2010; Winston et al., 2010; Stagge et al., 2012)

Runoff and pollutants	Reduction (%)									
	Bioretention systems		Porous pavement		Biofilter-grass swale		Wetland channel		Biofilter-grass strip	
	S[a]	L[b]	S	L	S	L	S	L	S	L
RV	15	0.4 to 93	40 to 55	50 to 93	42	30	0	--	34	23 to 37
TSS	81	15 to 99	85 to 89	64 to 91	63	20 to 97	28	-48 to -121	71	54 to 99.5
TDS	15	--	40 to 55	--	48	--	0	--	34	--
TP	33	-76 to 71	65 to 74	34 to 65	42	--	7	-70 to 1	34	--
DP	15 to 55	-9 to 92	40 to 55	--	42	--	0	--	34	--
TN	39	30 to 55	40 to 55	--	44	9 to 58	0 to 16	7 to 29	41 to 44	28 to 46
TKN	46	31 to 44	57 to 78	53	50	-47	0 to 15	-31 to 0	34 to 44	8 to 98
NOx	21 to 28	16 to 67	40 to 55	--	42 to 53	44 to 74	21 to 45	42 to 63	34 to 57	-27 to 20
Cd	15	66	40 to 55	--	64	72	2	--	77	58 to 99.9
Cr	15	53	40 to 55	--	42 to 70	--	19	--	34 to 67	78 to 99.6
Cu	55 to 57	37 to 99	64 to 73	13 to 67	65	23 to 81	0	--	67 to 68	82 to 99.7
Pb	43	31 to 81	74 to 81	67 to 79	70	37 to 87	15	--	85	47 to 99.8
Ni	15	--	40 to 78	--	42 to 78	--	0 to 22	--	34 to 64	67 to 99
Zn	79	37 to 98	84 to 88	71 to 88	63	46 to 79	32	--	80 to 84	50 to 99.8
FC	15	--	40 to 55	--	42	--	0	--	34	--
FS	15	--	40 to 55	--	42	--	0	--	34	--
E. coli	15	--	40 to 55	--	42	--	0	--	34	--

Table 2.4 Continued.

BOD	15	--	40 to 55	--	42	--	0	--	34	--
COD	15	--	40 to 55	--	42	--	0	--	34	--
O&G	15	--	40 to 55	--	42	--	0	--	34	--

[a]S-simulated; [b]L-from literature

2.6.2.3 Performance of biofilter-grass swale

As shown in Table 2.4, the reductions of TSS, TN, NO_x, Cu, Pb, Cd, and Zn after implementing grass swales were in accordance with other findings (Whallen and Cullum, 1988; UD& FCD, 1992; Rushton, 2001; Yu et al., 2001; Stagge et al., 2012).

The reductions of TDS, Cr, and Ni after the implementation of grass swale were 48%, 42% (no concentration reduction) to 70%, and 42% to 78%, while there were no findings found in the literature for these constituents. A 50% reduction of TKN after applying grass swales was found in this study, while another author (Stagge et al., 2012) found a reduction of -47%; however, the L-THIA-LID 2.0 model is a long-term simulation model—the system cannot produce TKN in the long run.

The reductions of TP, DP, FC, FS, E. coli, BOD, COD, and O&G after applying grass swales were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction because of lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.2.4 Performance of wetland channel

As shown in Table 2.4, the reductions of TP, TN, TKN, and NO_x after implementing wetland channels are similar to the findings of another author (Winston et al., 2010).

The reductions of Cd, Cr, Pb, Ni, and Zn after the implementation of wetland channels found in this study were 2%, 19%, 15%, 0% (no concentration reduction) to 22%, and

32%, respectively; while there were no values in the literature for these constituents. The reduction of TSS after implementing wetland channels was 28%; while Winston et al. (2010) found the reduction of -48% to -121%. However, the reduction should be in a positive range because of different experimental conditions and long-term simulation using L-THIA-LID 2.0 model. The reductions of TDS, DP, FC, FS, E. coli, BOD, COD, O&G, and Cu after applying wetland channels were the same as runoff volume reduction for the reason that there was only runoff volume reduction and no pollutant concentration reduction because of lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.2.5 Performance of biofilter-grass strip

As shown in Table 2.4, the reductions of TSS, TN, TKN, NO_x, Cd, Pb, Ni, Cr, Cu, and Zn after the implementation of grass strips were in the range of the results other authors found for this practice (Yu et al., 1993; Lee et al., 1998; NJDEP, 2004; Caltrans, 2010).

The percent reductions of TDS, TP, DP, FC, FS, E. coli, BOD, COD, and O&G after applying grass strips were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.3 Performance of BMPs and LID practices in series

The reductions of runoff volume and pollutant loads after implementing BMPs and LID practices in series are shown in Table 2.5. The column S showed simulated results and the column L showed the results from literature. The range of reductions for each pollutant varied because runoff volume or pollutant concentrations from land uses differed as did the methods used to represent practices.

Table 2.5 Reduction (%) of runoff volume and pollutant loads after implementing BMPs and LID practices in series

(Rushton, 2001; Stagge et al., 2012)

Runoff	Reduction (%)			
	Porous pavement +biofilter-grass swale		Biofilter-grass strip +biofilter-grass swale	
	S[a]	L[b]	S	L
RV	65 to 74	--	62	--
TSS	91 to 94	91 to 92	89	46
TDS	68 to 77	--	65	--
TP	80 to 85	3 to 76	62	--
DP	65 to 74	--	62	--
TN	66 to 75	42 to 71	67 to 69	-26
TKN	78 to 89	--	67 to 72	-50
NOx	71 to 79	66 to 79	62 to 79	--
Cd	78 to 84	--	86 to 92	44
Cr	65 to 86	--	62 to 90	--
Cu	85 to 89	81 to 94	83	46
Pb	92 to 94	85 to 93	92 to 95	27
Ni	65 to 88	--	62 to 85	--
Zn	91 to 95	75 to 89	89 to 94	18
FC	65 to 74	--	62	--
FS	65 to 74	--	62	--
E. coli	65 to 74	--	62	--
BOD	65 to 74	--	62	--
COD	65 to 74	--	62	--
O&G	65 to 74	--	62	--

[a]S-simulated; [b]L-from literature

2.6.3.1 Performance of porous pavement and biofilter-grass swales in series

As shown in Table 2.5, the reductions of RV, TSS, TP, TN, NO_x, Cu, Pb, and Zn after the implementation of porous pavement and biofilter-grass swales in series found in this study were consistent with what another author found (Rushton, 2001).

The reductions of TDS, TKN, Cd, Cr, and Ni after implementing porous pavement and biofilter-grass swales in series in this study were estimated as 68% to 77%, 78% to 89%, 78% to 84%, 65% (no concentration reduction) to 86%, and 65% to 88%, while no other findings were found in the literature.

The reductions of DP, FC, FS, E. coli, BOD, COD, and O&G were the same as runoff volume reduction since there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.6.3.2 Performance of biofilter-grass strips and biofilter-grass swales in series

As shown in Table 2.5, the reductions of TSS, TN, TKN, Cd, Cu, Pb, and Zn after the implementation of biofilter-grass strips and biofilter-grass swales in series found in this study were 89%, 67% to 69%, 67% to 72%, 86% to 92%, 83%, 92% to 95%, and 89% to 94%, while another author (Stagge et al., 2012) found results of 46%, -26%, -50%, 44%, 46%, 27%, and 18%. The negative reduction represented a short-term observation and thus does not represent conditions for the model because the system cannot produce pollutants in the long run; additional available data are needed from literatures to provide ranges of reduction instead of single values. The reductions of RV, TDS, NO_x, Cr, and Ni were 62%, 65%, 62% (no concentration reduction) to 79%, 62% (no concentration reduction) to 90%, and 62% (no concentration reduction) to 85%; however, no other findings were found in literature related to these pollutants.

The reductions of TP, DP, FC, FS, E. coli, BOD, COD, and O&G were the same as runoff volume reduction as there was only runoff volume reduction and no pollutant concentration reduction because of a lack of data in the International Stormwater BMP database (www.bmpdatabase.org).

2.7 Conclusions

The negative influences of urban development on hydrology and water quality can be mitigated by implementing BMPs and LID practices. User friendly models are needed for decision makers to assess the benefits of these practices on hydrology and water quality. Although this study emphasized modeling the hydrology and water quality impacts of BMPs and LID practices, there are other unquantified benefits. For instance, retention ponds not only reduce flooding and benefit water quality, but also improve site aesthetics; stormwater runoff collected by rain barrels and cisterns can be reused for various purposes, such as watering plants.

This study enhanced the capability of the L-THIA-LID model, an easy to use tool, to represent BMPs and LID practices in the following ways: (1) the diversity of BMPs and LID practices was increased from 6 types (bioretention systems, green roof, rain barrel/cistern, open wooded space, permeable patio, and porous pavement) to 12 types (added practices: detention basin, retention pond, wetland basin, biofilter-grass swale, wetland channel, and biofilter-grass strip); (2) the approach to calculate runoff volume reduction of BMPs and LID practices was enhanced based on both the Curve Number Method and percentage of runoff volume reduction method; (3) the method to determine water quality after the implementation of BMPs and LID practices was enhanced based on the International Stormwater Best Management Practices (BMP) Database and irreducible concentration method; and (4) impacts of BMPs and LID practices implemented in series can be simulated.

The performances of BMPs and LID practices, both separately and in series, were evaluated with the L-THIA-LID 2.0 model using 30 years of daily rainfall data (West Lafayette, Indiana) on four types of idealized land use units and watersheds—low density residential, high density residential, industrial, and commercial. To evaluate the performance of BMPs and LID practices in treating runoff volume and pollutant loads, bioretention systems, biofilter-grass swales, porous pavement, biofilter-grass strips and wetland channels were implemented in each idealized land use unit; detention basin (dry, grass-lined), retention pond (wet pond), and wetland basin were applied in each idealized watershed; porous pavement/biofilter-grass swale and biofilter-grass strip/biofilter-grass swale were implemented in series in each idealized land use unit. The L-THIA-LID results were compared to the findings of other researchers. The simulated reductions of runoff volume and pollutant loads after implementing BMPs and LID practices both separately and in series were comparable to observed reductions of runoff and pollutant loads in the scientific literature. Based on the analysis, one can conclude the L-THIA-LID 2.0 model can properly simulate BMPs and LID practices. L-THIA-LID 2.0 model, a user friendly tool, is able to support planners and decision makers in evaluating impacts of BMPs and LID practices on hydrology and water quality during planning, implementation, and evaluation stages of development projects.

After demonstrating the performances of the L-THIA-LID 2.0 model by implementing BMPs and LID practices in idealized land use units and watersheds, future research should be done to validate the performance of the model when there are more data available, evaluate the effectiveness of BMPs and LID practices by applying the model to actual watersheds, and to compare the L-THIA-LID 2.0 model with other commonly used tools.

2.8 References

Ahiablame, L., Engel, B.A., Chaubey, I., 2012a. Effectiveness of low impact development practices: literature review and suggestions for future research. Water Air Soil Pollution. 223, 4253-4273.

Ahiablame, L., Engel, B.A., Chaubey, I., 2012b. Representation and evaluation of low impact development practices with L-THIA-LID: An example for site planning. Environment and Pollution, 1(2). doi:10.5539/ep.v1n2p1.

Ahiablame, L., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement. Journal of environmental management, 119, 151-161.

Arnold Jr, C.L., Gibbons, C.J., 1996. Impervious surface coverage: the emergence of a key environmental indicator. Journal of the American Planning Association, 62(2), 243-258.

Baird, F.C., Dybala, T.J., Jennings, M.E., Okerman, D.J., 1996. Characterization of nonpoint sources and loadings to the Corpus Christi Bay National Estuary Program study area; Corpus Christi National Estuary Program, Corpus Christi, TX.

Banting, D., Doshi, H., Li, J., Missios, P., Au, A., Currie, B., Verrati, M., 2005. Report on the environmental benefits and costs of green roof technology for the city of Toronto. Available at http://www.toronto.ca/greenroofs/findings.htm. Accessed in August 2014.

Bean, E.Z., Hunt, W.F., Bidelspach, D.A., 2005. A monitoring field study of permeable pavement sites in North Carolina, in Proceedings of the 8th Biennial Conference on Stormwater Research & Watershed Management, Tampa, Florida, April 27-28, 2005, Southwest Florida Water Management District, Brooksville, Florida.

Bhaduri, B., Harbor, J., Engel, B.A., Grove, M., 2000. Assessing watershed-scale, long-term hydrologic impacts of land-use change using a GIS-NPS model. Environmental Management. 26 (6), 643-658.

Bhaduri, B., Grove, M., Lowry, C., Harbor, J., 1997. Assessing the long term hydrological impact of land-use change: Cuppy-McClure Watershed. Indiana. Journal of the American Water Works Association 89 (11): 94–106.

Burns, D., Vitvar, T., McDonnell, J., Hassett, J., Duncan, J., Kendall, C., 2005. Effects of suburban development on runoff generation in the Croton River basin, New York, USA. Journal of Hydrology, 311, 266-281.

Caltrans (California Department of Transportation), 2010. Final summary report, 2009-2010 summary report, Ornamental Roadside Vegetated Treatment Sites (ORVTS) Study CTSW-RT-10-208.18.1.

Camp Dresser & McKee Inc, 2004. Merrimack river watershed assessment study: Screening Level Model.

Carleton, J.N., Grizzard, T.J., Godrej, A.N., Post, H.E., Lampe, L., Kenel, P.P., 2000. Performance of a constructed wetlands in treating urban stormwater runoff. Water Environment Research, 295-304.

Choi, W., 2007. Estimating land-use change impacts on direct runoff and non-point source pollutant loads in the Richland Creek Basin (Illinois, USA) by applying the L-THIA model. Journal of Spatial Hydrology 7 (1): 47–65.

Choi, J.Y., Engel, B.A., 2003a. Real time watershed delineation system using web-GIS. Journal of Computing in Civil Engineering 17(3):189-196.

Choi, J.Y., Engel, B.A., Muthukrishnan, S., Harbor, J., 2003b. GIS based long-term hydrologic impact evaluation for watershed urbanization. Journal of American Water Resources Association 39(3):623-635.

Choi, J.Y, Engel, B.A., Farnsworth, R., 2005a. Web-based GIS and spatial decision support system for watershed management. Journal of Hydroinformatics 7(3):165-174.

Choi, J.Y, Engel, B.A., Theller, L., Harbor, J., 2005b. Utilizing web-based GIS and SDSS for hydrological land use change impact assessment. TRANS of ASAE 48(2):815-822.

Collins, S., Allen, R., Gill, E., 2004. The water framework directive: Integrating approaches to diffuse pollution, CIWEM Conference.

Comings, K.J., Booth, D.B., Horner, R.R., 2000. Storm water pollutant removal by two wet ponds in Bellevue, Washington. Journal of Environmental Engineering, 126(4), 321-330.

CWP and CSN (Center for Watershed Protection and Chesapeake Stormwater Network), 2008. Technical memorandum: The runoff reduction method. Ellicott City, MD www.chesapeakestormwater.net

Damodaram, C., Giacomoni, M.H., Khedun, C.P., Holmes, H., Ryan, A., Saour, W., Zechman, E.M., 2010. Simulation of combined best management practices and low impact development for sustainable stormwater management1. Journal of the American Water Resources Association, 46(5), 907-918.

Davis, A.P., 2005. Green engineering principles promote low impact development. Environmental Science and Technology, 39, 338A–344A.

Davis, A.P., 2008. Field performance of bioretention: hydrology impacts. Journal of Hydrologic Engineering, 13, 90–95.

Davis, A.Y., Pijanowski, B.C., Robinson, K., Engel, B.A., 2010. The environmental and economic costs of sprawling parking lots in the United States. Land use Policy 27 (2): 255–61.

Demographia, 2010. World Urban Areas: Populations and Projections. 6th Annual edn. http://www.demographia.com/db-wuaproject.pdf, accessed July, 2013.

Dietz, M.E., 2007. Low impact development practices: A review of current research and recommendations for future directions. Water, air, and soil pollution, 186(1-4), 351-363.

Dietz, M.E., Clausen, J.C., 2005. A field evaluation of rain garden flow and pollutant treatment. Water, Air, and Soil Pollution, 167(1-4), 123-138.

Dreelin, E.A., Fowler, L., Carroll, C.R., 2006. A test of porous pavement effectiveness on clay soils during natural storm events. Water Research, 40, 799–805.

Ellis, J.B., Revitt, D.M., 2008. Quantifying diffuse pollution sources and loads for environmental quality standards in urban catchments. Water, Air, & Soil Pollution: Focus, 8(5-6), 577-585.

Engel, B.A., 2001. L-THIA NPS Long-Term Hydrologic Impact Assessment and Non Point Source Pollutant Model, version 2.1. Purdue University and USEPA.

Engel, B.A., Hunter, J., 2009. L-THIA LID Long-term Hydrologic Impact Assessment Low Impact Development Model. Spreadsheet Version. West Lafayette, IN: Purdue University.

Engel, B.A., Choi, J.Y., Harbor, J., Pandey, S., 2003. Web-based DSS for hydrologic impact evaluation of small watershed land use changes. Computers and Electronics in Agriculture 39 2003:241-249.

Engel, B.A., Ahiablame, L., 2011. L-THIA-LID Long-Term Hydrologic Impact Assessment-Low Impact Development model, sv_version1.1. Purdue University.

GC and WWE (Geosyntec Consultants and Wright Water Engineers), 2011. International stormwater best management practices (BMP) database technical summary: volume reduction, 27. www.bmpdatabase.org, accessed November, 2012.

Gilbert, J.K., Clausen, J.C., 2006. Stormwater runoff quality and quantity from asphalt, paver, and crushed stone driveways in Connecticut. Water research, 40(4), 826-832.

Gilroy, K.L., McCuen, R.H., 2009. Spatio-temporal effects of low impact development practices. Journal of Hydrology, 367(3), 228-236.

Glass, C., Bissouma, S., 2005. Evaluation of a parking lot bioretention cell for removal of storm water pollutants. Ecosystems and sustainable development V, WIT, Southampton, U.K., 699–708.

Grove, M., Harbor, J., Engel, B.A., Muthukrishnan, S., 2001. Impacts of urbanization on surface hydrology, Little Eagle Creek, Indiana, and analysis of L-THIA model sensitivity to data resolution. Physical Geography, 22, 135–153.

Gunn, R., Martin, A., Engel, B.A., Ahiablame, L., 2012. Development of two Indices for determining hydrologic implications of land use changes in urban areas. Urban Water Journal 9 (4): 239–48.

Harbor, J., 1994. A practical method for estimating the impact of land use change on surface runoff, groundwater recharge and wetland hydrology. Journal of American Planning Association 60, 91–104.

Hartigan, J.P., 1989. Basis for design of wet detention basin BMPs. Design of Urban Runoff Quality Controls. American Society of Civil Engineers. New York, NY, p. 122- 144.

Hatt, B.E., Fletcher, T.D., Walsh, C.J., Taylor, S.L., 2004. The influence of urban density and drainage infrastructure on the concentrations and loads of pollutants in small streams. Environ. Manage. 34, 112–124.

Homer, C., Huang, C., Yang, L., Wylie, B., Coan, M., 2004. Development of a 2001 National Land Cover Database for the United States, Photogrammetric Engineering & Remote Sensing, 70(7):829-840.

Huber, W.C., Dickinson, R.E., 1988. Storm water management model, version 4, user's manual. EPA 600/388/001a (NTIS PB88-236641/AS).USEPA, Athens, GA.

Hunt, W.F., Jarrett, A.R., Smith, J.T., Sharkey, L.J., 2006. Evaluating bioretention hydrology and nutrient removal at three field sites in North Carolina. Journal of Irrigation and Drainage Engineering, 132(6), 600-608.

Hunt, W.F., Smith, J.T., Jadlocki, S.J., Hathaway, J.M., Eubanks, P.R., 2008. Pollutant removal and peak flow mitigation by a bioretention cell in urban Charlotte, NC. Journal of Environmental Engineering, 134(5), 403-408.

Hunt, W.F., Stephens, S., Mayes, D., 2002. Permeable pavement effectiveness in Eastern North Carolina. In Proceedings of 9th International Conference on Urban Drainage. ASCE. Portland, OR.

Hunter, J.G., Engel, B.A., Quansah, J.E., 2010. Web-based low impact development decision support tool for watershed planning. Proceedings of Low Impact Development 2010: Redefining Water in the City. April 11–14. San Francisco, CA, USA.

Kim, Y., Engel, B.A., Lim, K.J., Larson, V., Duncan, B., 2002. Runoff impacts of land-use change in Indian River Lagoon watershed. Journal of Hydrologic Engineering, 7(3), 245-251.

Lee, K.H., Isenhart, T.M., Schultz, R.C., Mickelson, S.K., 1998. Nutrient and sediment removal by switchgrass and cool-season grass filter strips in Central Iowa, USA. Agroforestry Systems, 44(2-3), 121-132.

Legret, M., Colandini, V., Marc, C.L., 1996. Effects of a porous pavement with reservoir structure on the quality of runoff water and soil. Science of the Total Environment, 189, 335-340.

Lenhart, J., 2007. BMP Performance Expectation functions–a simple method for evaluating stormwater treatment BMP performance data. In 9th Biennial Conference on Stormwater Research and Watershed Management, pp. 2-3.

Lim, K.J., Engel, B.A., Tang, Z., Muthukrishnan, S., Choi, J., Kim, K., 2006. Effects of calibration on L-THIA GIS runoff and pollutant estimation. Journal of Environmental Management 78 (1): 35–43.

Lim, K.J., Park, Y.S., Kim, J., Shin, Y., Kim, N.W., Kim, S.J., Jeon, J., Engel, B.A., 2010. Development of genetic algorithm-based optimization module in WHAT system for hydrograph analysis and model application. Computers & Geosciences, 36, 936-944.

Lucas, B., Greenway, M., 2010. Advanced bioretention experiments: Washington State University and the Science Museum of Virginia. In Stormwater'10: National Conference of the Stormwater Industry Association.

Maestre, A., Pitt, R., 2005. The National Stormwater Quality Database, Version 1.1. Center for Watershed Protection. U.S. EPA.

McCarthy, D.T., Deletic, A., Mitchell, V.G., Fletcher, T.D., Diaper, C., 2008. Uncertainties in stormwater E. coli levels. Water Research. 42, 1812-1824.

McGee, T., 2001. Urbanization takes on new dimensions in Asia’s population giants. Population Today 29, 1–2.

Miller, J., 2005. Clean Water Services DNA Fingerprinting of Bacteria Sources in the Tualatin Sub-basin. Bacteria DNA Fingerprinting – Final.

Muthukrishnan, S., Harbor, J., Lim, K.J., Engel, B.A., 2006. Calibration of a simple rainfall-runoff model for long-term hydrological impact evaluation. Journal of Urban and Regional Information Systems Association 18(2):35-42.

NPRPD (National pollutant removal performance database: version 3), 2007. Center for Watershed Protection. Ellicott City, Md.

NJDEP (New Jersey Department of Environmental Protection), 2004. New Jersey Stormwater Best Management Practices Manual.

NRCS (Natural Resources Conservation Services), 1986. Urban hydrology for small watersheds. Technical Release 55, USDA Natural Resources Conservation Services.

Oberts, G.L., Wotzka, P.J., Hartsoe, J.A., 1989. The water quality performance of select urban runoff treatment systems. Metropolitan Council of the Twin Cities Area. St. Paul, MN. June.

Pandey, S., Gunn, R., Lim, K.J., Engel, B.A., Harbor, J., 2000. Developing web-based tool to assess long-term hydrologic impacts of land use change: Information technology issues and a case study. Journal of Urban and Regional Information System Association (URISA). 12(4): 5-17.

Prince George's County, Maryland, 1999. Low impact development: An integrated design approach. Department of Environmental Resources, Largo, MD.

RRNWWDP (Rouge River National Wet Weather Demonstration Project), 1998. User's manual: Watershed Management Model. Version 4.1 Technical memorandum. Wayne County, Michigan. RPO-NPS-TM27.02. pp26

Rusciano, G.M., Obropta, C.C., 2007. Bioretention column study: Fecal coliform and total suspended solids reductions. Transactions of the ASABE, 50(4), 1261-1269.

Rushton, B.T., 2001. Low-impact parking lot design reduces runoff and pollutant loads. Journal of Water Resources Planning and Management, 127(3), 172-179.

Sample, D.J., Heaney, J.P., Wright, L.T., Koustas, R., 2001. Geographic information systems, decision support systems, and urban storm-water management. Journal of Water Resources Planning and Management, 127(3), 155-161.

Scholes, L., Revitt, D.M., Ellis, J.B., 2008. A systematic approach for the comparative assessment of stormwater pollutant removal potentials. Journal of environmental management, 88(3), 467-478.

Schueler, T., 1996. Irreducible pollutant concentrations discharged from stormwater practices. Technical Note 75. Watershed Protection Techniques 2:2 pp. 369-372.

Selvakumar, A., Borst, M., 2004. Land use and seasonal effect in urban stormwater runoff microorganism concentrations. World Water and Environmental Congress, 2004, Salt Lake City, UT

Shoemaker. L., Riverson Jr, J., Alvi, K., Zhen, J.X., Paul, S., Rafi, T., 2009. SUSTAIN—A framework for placement of best management practices in urban watersheds to protect water quality. Fairfax, VA.

Stagge, J.H., Davis, A.P., Jamil, E., Kim, H., 2012. Performance of grass swales for improving water quality from highway runoff. Water research, 46(20), 6731-6742.

Stanley, D.W., 1996. Pollutant removal by a stormwater dry detention pond. Water Environment Research, 1076-1083.

Stein, E.D., Tiefenthaler, L.L., Schiff, K.C., 2008. Comparison of stormwater pollutant loading by land use type. Southern California Coastal Water Research Project, AR08-015-027.

Strecker, E.W., Quigley, M.M., 1999. Determining urban stormwater best management practice (BMP) removal efficiencies. Prepared by URS Woodward Clyde and UWRRC of ASCE. USEPA, Washington, DC.

Strecker, E.W., Quigley, M.M., Urbonas, B., Jones, J., 2004. Analyses of the expanded EPA/ASCE International BMP Database and potential implications for BMP design. Proceedings of the World Water and Environmental Resources Congress 2004, Salt Lake City, Utah.

Tang, Z., Engel, B.A., Choi, J., Sullivan, K., Sharif, M., Lim, K.J., 2004. A web-based DSS for erosion control structure planning. Applied Engineering in Agriculture 20(5):707-714.

Tang, Z., Engel, B.A., Pijanowski, B.C., Lim, K.J., 2005. Forecasting land use change and its environmental impact at a watershed scale. Journal of Environmental Management 76 (1): 35–45.

The LIDC (Low Impact Development Center, Inc.), GeoSyntec Consultants, University of Florida, Oregon State University, 2006. Evaluation of best management practices for highway runoff control. Transportation Research Board, National Research Council.

Tota-Maharaj, K., Scholz, M., 2010. Efficiency of permeable pavement systems for the removal of urban runoff pollutants under varying environmental conditions. Environmental Progress & Sustainable Energy, 29(3), 358-369.

USDIBLM (United States Department of the Interior Bureau of Land Management), 2005. Land Use Planning Handbook. 55.

UD&FCD (Urban Drainage & Flood Control District), 1992. Urban Storm Drainage Criteria Manual: Volume 3 - Best Management Practices. Denver, CO.

Urbonas, B., 1994. Assessment of storm water BMPs and their technology. Water Science & Technology, 29(1-2), 347-353.

US Census Bureau, 1999. Population profile of the United States, Current Population Reports Series P23-205. US Government Printing Office, Washington, DC, USA, pp 89.

USEPA (US Environmental Protection Agency), 2007. National Water Quality Inventory: Report to Congress, 2002 Reporting Cycle. Report no. EPA 841-R-07-001. Washington, DC.

USEPA (US Environmental Protection Agency), 2008. Reducing stormwater costs through low impact development (LID) strategies and practices. EPA 841-F-07-006, Nonpoint Source Control Branch, Washington, D.C.

Seters, T.V., 2007. Performance evaluation of permeable pavement and a bioretention swale, Interim Report #3,Toronto and Region Conservation Authority, Downsview, Ontario, Canada.

Shi, Y., Asher, J., Bartholic, J., Choi, J., Engel, B.A., Farnsworth, R., 2004. An online webGIS-Based Hierarchical Watershed Decision Support System for United States. Environmental Informatics Archives, 2, 838-845.

VDSDS (Virginia DCR Stormwater Design Specification), 2011. Wet swales, Version 1.8. Richmond, VA. http://vwrrc.vt.edu/swc/april_22_2010_update/DCR_BMP_Spec_No_11_WET_SWALE%20_Final_Draft_v1-8_04132010.htm, accessed September, 2012.

Whallen, P.J., Cullum, M.G., 1988. An assessment of urban land use: stormwater runoff quality relationships and treatment efficiencies of selected stormwater management systems.

Wilson, C., Weng, Q., 2010. Assessing surface water quality and its relation with urban land cover changes in the Lake Calumet area, Greater Chicago. Environmental Management, 45(5), pp1096-1111.

Winston, R.J., Hunt, W.F., Wright, J.D., 2010. Evaluation of roadside filter strips, dry swales, wet swales, and porous friction course for stormwater treatment. American Society of Civil Engineers, pp. 1258-1269.

Wossink, G.A.A., Hunt, B., 2003. The economics of structural stormwater BMPs in North Carolina. Water Resources Research Institute of the University of North Carolina.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2010a. Categorical Summary of BMP Performance Data for Nutrients Contained in the International Stormwater BMP Database. 9-77. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2011. Categorical Summary of BMP Performance Data for Solids (TSS, TDS, and Turbidity) Contained in the International Stormwater BMP Database. 8-47. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2012a. Categorical Summary of BMP Performance for Stormwater Bacteria Data Contained in the International Stormwater BMP Database. 5-42. www.bmpdatabase.org, accessed November, 2012. , accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2012b. Categorical Summary of BMP Performance for Stormwater Metals Data Contained in the International Stormwater BMP Database. 5-296. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2012c. Categorical Summary of BMP Performance for Stormwater Nutrients Data Contained in the International Stormwater BMP Database. 5-224. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2012d. Categorical Summary of BMP Performance for Stormwater Total Suspended Solids Data Contained in the International Stormwater BMP Database. 5-28. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2012e. International Stormwater Best Management Practices (BMP) Database Pollutant Category Summary Statistical Addendum: TSS, Bacteria, Nutrients, and Metals. 9-30. www.bmpdatabase.org, accessed November, 2012.

WWE and GC (Wright Water Engineers and Geosyntec Consultants), 2010b. International Stormwater Best Management Practices (BMP) Database User's Guide for BMP Data Entry Spreadsheets, Release Version 3.2, 43-67. www.bmpdatabase.org, accessed November, 2012.

Wu, J.S., Holman, R.E., Dorney, J.R., 1996. Systematic evaluation of pollutant removal by urban wet detention ponds. Journal of Environmental Engineering. 122(11): 983-988.

Ying, G., Sansalone, J., 2010. Transport and solubility of hetero-disperse dry deposition particulate matter subject to urban source area rainfall-runoff processes. Journal of Hydrology, 383(3-4), 156-166.

Yu, S.L., Kuo, J.T., Fassman, E.A., Pan, H., 2001. Field test of grassed-swale performance in removing runoff pollution. Journal of Water Resources Planning and Management, 127(3), 168-171.

Yu, S., Barnes, S., Gerde, V., 1993. Testing of Best Management Practices for Controlling Highway Runoff. FHWA/VA 93-R16. Virginia Transportation Research Council, Charlottesville, VA.

CHAPTER 3. SENSITIVITY AND UNCERTAINTY ANALYSIS OF THE L-THIA-LID 2.1 MODEL

3.1 Abstract

Sensitivity analysis of a model can identify the key variables affecting the performance of the model. Uncertainty analysis is an essential indicator of the precision of the model. In this study, the sensitivity and uncertainty of the Long-Term Hydrologic Impact Assessment-Low Impact Development 2.1 (L-THIA-LID 2.1) model in estimating runoff and water quality were analyzed in an urbanized watershed in central Indiana, USA, using Sobol′'s global sensitivity analysis method and the bootstrap method, respectively. When estimating runoff volume and pollutant loads for the case in which no BMPs and LID practices were implemented, CN (Curve Number) was the most sensitive variable. When predicting water quantity and quality with varying levels of BMPs and LID practices implemented, Ratio_r (Practice outflow runoff volume/inflow runoff volume) was the most sensitive variable. The output uncertainty bounds before implementing BMPs and LID practices were relatively large, while the uncertainty ranges of model outputs with practices implemented were relatively small. The limited observed data in the same study area and results from other urban watersheds in scientific literature were either well within or very close to the uncertainty ranges determined in this study, indicating the L-THIA-LID 2.1 model has good precision.

3.2 Introduction

Computer based mathematical hydrologic/water quality models, from the simplest to the most complex, are based on simplified mathematical descriptions of natural watershed processes. In hydrologic and water quality simulation, the physical processes are complex and involve high costs for measuring model variables (inputs and parameters) which vary at spatial and temporal scales. As a result, to properly simulate hydrology and water quality at the watershed scale, model variables must be specified for each application of the model (Duan et al., 2003). Model calibration, which adjusts model parameters to match simulated results with observed data within a certain accuracy level, is commonly used to estimate model parameters (Abbott et al., 1986; Refsgaard et al., 1992). Before the calibration process, sensitivity analysis is often conducted.

Sensitivity analysis of a model is a useful screening tool developed to find the main parameters affecting performance of the model by estimating which contribute the most to output variability (Freer et al., 1996; Carpenter et al., 2001; Muleta and Nicklow, 2005). Commonly used sensitivity analysis methods (Tang et al., 2006; Yang, 2011) include Sobol′'s global sensitivity analysis method, Jacobean-based local method (parameter estimation software PEST), regional sensitivity analysis (RSA), Analysis of Variance (ANOVA), Morris method, non-parametric smoothing, and Linear Regression (LR). Sensitivity analysis methods can be divided into two groups: local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis, or one at a time sensitivity analysis, estimates sensitivity by varying each variable in a certain range while keeping other variables at their nominal values (Holvoet et al., 2005); although it is easy to operate, local sensitivity analysis has limitations due to assumptions of no interactions between variables and linear relationships between model outputs and variables (Helton, 1993; Muleta and Nicklow, 2005). In comparison to local sensitivity analysis, global sensitivity analysis is more reliable because of computing integrated sensitivity over the entire range of variables; the impacts of variable interactions on model outputs can also be investigated (Liburne et al., 2006). Sobol′'s global sensitivity analysis method (Sobol′, 1993) is a popular variance decomposition based method that can characterize single variable and multivariable interactions (Sobol′, 1993 and 2001; Tang et al., 2006 and 2007; Cloke et al., 2008; Cibin et al., 2010).

The calibrated model will have minimized propagation of variable uncertainties into the uncertainties of model outputs (Migliaccio and Chaubey, 2008). However, uncertainty remains because of the complicated stochastic features of environmental processes, quantity/quality of input data, and parameter evaluation (Beck, 1987; Tyagi and Haan, 2001; Muleta and Nicklow, 2005). Uncertainty analysis, which estimates overall uncertainty of the model results, is a vital indicator of the precision of a model (Jakeman and Hornberger, 1993). Commonly used uncertainty analysis methods (Li et al., 2010, Yang, 2011) include the bootstrap method, first-order approximation method, contour plots method, Generalized Likelihood Uncertainty Estimation (GLUE), Monte Carlo Simulation (MCS) techniques, Sequential Uncertainty Fitting 2 (SUFI-2), and Bayesian method. The bootstrap method, which is suitable for both simple and complicated models, is able to estimate confidence intervals for model outputs with the lowest time consumption (Archer et al., 1997).

The Long-Term Hydrologic Impact Assessment-Low Impact Development 2.1 (L-THIA-LID 2.1) model, which was developed from the L-THIA-LID model (Ahiablame, 2012b), is an easy to use tool that aims to estimate the impacts of best management practices (BMPs) and low impact development (LID) practices on runoff and water quality at watershed scales (Liu et al., 2015a and 2015b). Although studies analyzed the sensitivity of the L-THIA model (Wilson and Weng, 2010) and uncertainty of the L-THIA-LID model in estimating hydrology (Ahiablame, 2012a), studies about sensitivity analysis and uncertainty analysis of L-THIA-LID 2.1 model in estimating runoff and water quality have not been reported.

The objectives of this study were to 1) use Sobol′'s global sensitivity analysis method to analyze sensitivity of the L-THIA-LID 2.1 model in estimating runoff and water quality without and with BMPs and LID practices implemented; and 2) use the bootstrap method to analyze the output uncertainty of L-THIA-LID 2.1 model in predicting water quantity and quality without and with BMPs and LID practices implemented.

3.3 L-THIA-LID 2.1 model

3.3.1 Runoff volume and pollutant loads from drainage areas

Rainfall data, land use data, and hydrologic soil group (HSG) data are combined to estimate runoff volume generated from the development site before implementing BMPs and LID practices using the Curve Number (CN) method. CN, which is determined by the unique combinations of land use and hydrologic soil group (named hydrologic response unit or HRU), is an empirical parameter for predicting direct infiltration and runoff from rainfall excess. The initial abstraction S (mm) is the total losses of rainfall water before the happening of runoff (including infiltration, interception, evaporation, and surface storage), is estimated as (NRCS, 1986):

$$S = \frac{25400}{CN} - 254 \tag{3.1}$$

Stormwater runoff depth Q_h (mm) is calculated as:

$$Q_h = \frac{(P_h - 0.2S)^2}{(P_h + 0.8S)}, \text{ when } P_h > 0.2S \tag{3.2}$$

$$Q_h = 0, \text{ when } P_h \le 0.2S \tag{3.3}$$

Where P_h is daily rainfall depth (mm).

Then runoff volume from the HRU is determined by:

$$Q_v = 0.001 \times Q_h \times A \tag{3.4}$$

Where Q_v is the volume of runoff (m^3); and A is the size of HRU (m^2).

Pollutant loads from the HRU are estimated by:

$$WQ_{m1} = EMC \times Q_v \tag{3.5}$$

Where WQ_{m1} is the pollutant load from the HRU before implementing BMPs/LID practices (colonies for Fecal Coliform and Fecal Strep, MPN for E-coli, and g for all other pollutants in the model); and *EMC* is event mean concentration, which represents the pollutant concentration from each land use (colonies/m^3 for Fecal Coliform and Fecal Strep, MPN/m^3 for E-coli, and g/m^3 for all other pollutants in the model) (Liu et al., 2015a).

3.3.2 Influences of BMPs and LID practices on runoff volume

BMPs are large scale measures that treat runoff at the end of a drainage area, such as retention pond or detention basin. However, LID practices are small scale, localized practices that treat runoff on site, such as green roof and permeable pavement.

LID practices with documented Curve Numbers (CNs), including green roof, bioretention system, rain barrel, cistern, permeable patio, and porous pavement, are represented by adjusting CNs (Ahiablame et al., 2012). CNs used to represent those LID practices in the model are from previous research (Sample et al., 2001; Ahiablame et al., 2012).

BMPs and LID practices without documented CNs, including grass strip, wetland channel, grassed swale, retention pond, wetland basin, and detention basin, are represented with percent runoff volume reduction method to estimate their impacts on runoff volume (Liu et al., 2015a). Runoff volume after implementing each of those BMPs and LID practices is estimated as a percentage of runoff volume treated by the practice. The default percentage used for each practice in the model is the ratio of outflow runoff volume to inflow runoff volume (Ratio_r) for each BMP and LID practice from databases and literature (Strecker et al., 2004; CWP and CSN, 2008; GC and WWE, 2011).

3.3.3 Influences of BMPs and LID practices on water quality

Because of the limited treatment abilities of BMPs and LID practices, irreducible concentration (IC) is used as the lowest effluent concentration attainable from BMPs and LID practices. Based on the International Stormwater BMP database (www.bmpdatabase.org), median values of outflow concentration were used as the default irreducible concentration values (Liu et al., 2015a).

The default value of *Ratio_c* is the ratio of median outflow pollutant concentration to median inflow pollutant concentration for each BMP/LID practice based on the International Stormwater BMP database, and is calculated as (Liu et al., 2015a):

$$Ratio\_c = \frac{C_{out}}{C_{in}} \tag{3.6}$$

Where C_{out} is median outflow pollutant concentration, C_{in} is median inflow pollutant concentration.

Pollutant concentration after implementing BMPs/LID practices is calculated based on the irreducible concentration method with three conditions (Liu et al., 2015a):

1) When $EMC'_{HRU} < IC$:

$$EMC_{HRU} = EMC'_{HRU} \tag{3.7}$$

2) When $EMC'_{HRU} \geq IC$ and $EMC'_{HRU} \times Ratio\_c < IC$:

$$EMC_{HRU} = IC \tag{3.8}$$

3) When $EMC'_{HRU} \times Ratio\_c \geq IC$:

$$EMC_{HRU} = EMC'_{HRU} \times Ratio\_c \tag{3.9}$$

Where EMC'_{HRU} is the pollutant concentration before implementing BMPs/LID practices in each HRU; EMC_{HRU} is the pollutant concentration after implementing BMPs/LID practices in each HRU; IC is irreducible concentration; and $Ratio\_c$ is the ratio of median outflow pollutant concentration to median inflow pollutant concentration for each BMP/LID practice.

Water quality of the entire watershed is estimated as (Ahiablame et al., 2012):

$$WQ_{m2} = \sum_{i}^{N} Q_{HRU} \times A_i \times EMC_{HRU} \tag{3.10}$$

Where WQ_{m2} is pollutant load after implementing BMPs/LID practices (colonies for Fecal Coliform and Fecal Strep, MPN for E-coli, and g for all other pollutants in the model); N is the quantity of HRUs in the watershed; Q_{HRU} is the stormwater runoff depth (mm) from each HRU; A_i is the size of each HRU area (m^2); and EMC_{HRU} is the pollutant concentration after implementing BMPs/LID practices in each HRU (colonies/L for Fecal Coliform and Fecal Strep, MPN/L for E-coli, and g/L for all other pollutants in the model).

The simulated pollutants in the model include Total Nitrogen (TN), Total Kjeldahl Nitrogen (TKN), Nitrate+Nitrite (NO_x), Total Phosphorus (TP), Dissolved Phosphorus (DP), Total Suspended Solids (TSS), Total Dissolved Solids (TDS), Total Lead (Pb), Total Copper (Cu), Total Zinc (Zn), Total Cadmium (Cd), Total Chromium (Cr), Total Nickel (Ni), Fecal Coliform (FC), Fecal Streptococcus (FS), Escherichia coli (E. coli), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Oil and Grease (O&G).

3.4 Materials and methods

3.4.1 Study area

The study area is Crooked Creek Watershed in central Indiana, USA (Figure 3.1). The land uses in the watershed are shown in Table 3.1. The total area of the watershed is 5129 ha, and the watershed is highly urbanized with over 88% of its area covered by urban land uses (including low density residential, high density residential, industrial, and commercial areas), which makes it suitable to model the impacts of BMPs and LID practices.

Two groups of BMPs and LID practices, including lower level implementation and higher level implementation, were randomly selected in the watershed. The lower level random implementation of BMPs and LID practices in the study area included 19% green roof, 19% rain barrel/cistern, 6% green roof with rain barrel/cistern, 25% bioretention system, 25% porous pavement, 25% permeable patio, 25% grass strip, 12.5% grassed swale, 12.5% wetland channel, 18% retention pond, 4% detention basin, and 4% wetland basin. The higher level random implementation of BMPs and LID practices in the study area included 37.5% green roof, 37.5% rain barrel/cistern, 12.5% green roof with rain barrel/cistern, 50% bioretention system, 50% porous pavement, 50% permeable patio, 50% grass strip, 25% grassed swale, 25% wetland channel, 35% retention pond, 7.5% detention basin, and 7.5% wetland basin. The percentages mentioned above are percent implementation of each BMP/LID practice in areas where they are suitable to be implemented.

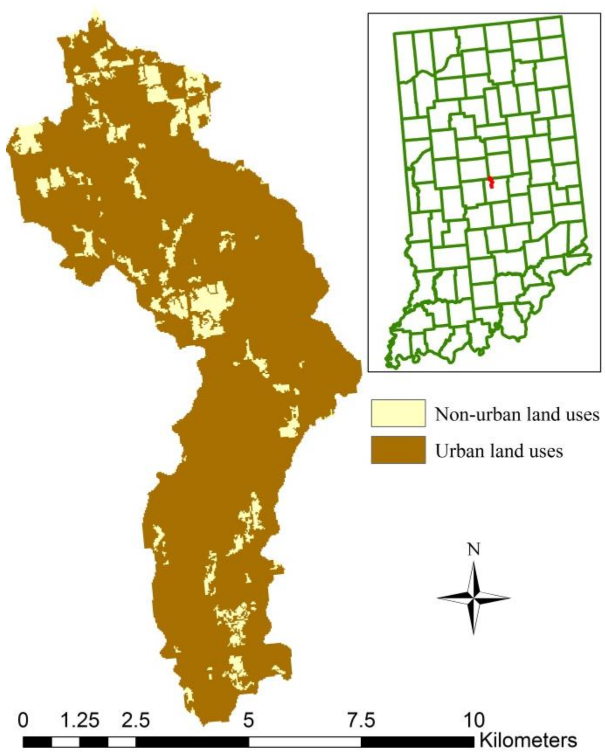


Figure 3.1 Location of Crooked Creek Watershed

Table 3.1 Land uses in Crooked Creek watershed

Land Uses	Area (ha)	Percent (%)
LD residential	3695	72.04
HD residential	355	6.92
Forest/Woods	315	6.14
Commercial	314	6.12
Agricultural	156	3.04
Industrial	135	2.63
Grass/Pasture	102	1.99
Water/Wetland	57	1.11
Total	5129	100.00

3.4.2 Input data

In L-THIA-LID 2.1 model, the basic input data include daily precipitation, land use, and hydrologic soil group data. Daily precipitation data (from 1993 to 2010) for stations near the study watershed were obtained from the National Climatic Data Center (http://www.ncdc.noaa.gov). The Thiessen method (Thiessen, 1911) was used to calculate areal average rainfall data. Hydrologic soil group (HSG) data were obtained from Soil Survey Geographic (SSURGO) database. All hydrologic soil groups of high density residential (HDR), commercial, and industrial areas were assumed to be D because of construction impacts (Lim et al., 2006). The National Land Cover Dataset 2001 (NLCD 2001) was applied to identify land use types in the study area. The land use classes in NLCD 2001 were reclassified by the method described in Liu et al. (2015b) using ArcGIS.

The GIS data for street centerlines, imperviousness, streams, lakes, and building footprints were downloaded from the IndianaMap Layer Gallery (http://maps.indiana.edu/layerGallery.html). Digital elevation model (DEM) data were obtained from the National Map (http://nationalmap.gov/). Based on methods described in Liu et al. (2015b), these data were combined to quantify surfaces of street, sidewalk, parking lot, driveway, roof tops, patio, streams, and lakes; and also estimate imperviousness of the area, drainage area, and drainage slope.

3.4.3 Variables and outputs for L-THIA-LID 2.1 model

The ranges and probability density function (pdf) of variables in L-THIA-LID 2.1 model are shown in Table 3.2. The inputs and parameters (together called variables) of L-THIA-LID 2.1 model, included curve number (CN), precipitation (P), event mean concentration (EMC), ratio of outflow runoff volume to inflow runoff volume (Ratio_r), irreducible concentration (IC), and ratio of outflow pollutant concentration to inflow pollutant concentration (Ratio_C). The ranges of variables were defined as percent changes from default values. The probability density functions (pdfs) of the percent changes were assumed to be uniform distributions based on the suggestions of previous studies (Haan et al., 1998; Helton, 1993; Muleta and Nicklow, 2005).

An upper limit of 2% changes from default CN values was used to keep the biggest CN lower than 100; and a lower limit of -20% changes from default CN values was adapted to keep the lowest CN of urban land uses reasonable. The lower and higher limits of changes (-10% to 10%) from measured P values were 25th and 75th percentiles of percent differences between the annual rainfalls of the two rainfall gauge stations used in the study. The lower and higher limits of percent changes from default EMC values were 25th and 75th percentiles of the percent differences between minimum and median, maximum and median values, respectively, using data from Baird et al. (1996). For Ratio_r, IC, and Ratio_c, based on data from the International Stormwater BMP database (www.bmpdatabase.org), the lower limits were median values of percent differences between 25th percentile and median values from the database; and higher limits were median values of percent differences between 75th percentile and median values from the database; for variables with insufficient data, the ranges were assumed to be the same as the ones with sufficient data.

Table 3.2 Ranges and probability density function (pdf) of variables

	Variables	Min (%)	Max (%)	pdf	symbol
1	Curve Number	-20	2	Uniform distribution	CN
2	Precipitation	-10	10	Uniform distribution	P
3	Event Mean Concentration	-59	64	Uniform distribution	EMC
4	Practice outflow runoff volume/ inflow runoff volume	-30	12	Uniform distribution	Ratio_r
5	Irreducible concentration	-47	63	Uniform distribution	IC
6	Practice outflow pollutant concentration/ inflow pollutant concentration	-14	17	Uniform distribution	Ratio_c

To calculate runoff volume before applying BMPs and LID practices, variables included CN and P. When estimating water quality before applying BMPs and LID practices, variables included CN, P, and EMC.

To compute runoff volume after implementing BMPs and LID practices, variables included CN, P, and Ratio_r. When predicting water quality after applying BMPs and LID practices, variables included CN, P, Ratio_r, EMC, IC, and Ratio_c. BMPs and LID practices were simulated based on the framework for simulating practices at watershed scales (Liu et al., 2015b), which considered the conditions of the watershed, suitable areas for implementing BMPs and LID practices, the rules of implementing practices in series, and percentages or levels of suitable areas with practices implemented.

Before implementing BMPs and LID practices, the outputs of the model tested included the runoff volume (m^3/ha/yr), and loads of TN (kg/ha/yr), TKN (kg/ha/yr), NO_x (kg/ha/yr), TP (kg/ha/yr), DP (kg/ha/yr), TSS (kg/ha/yr), TDS (kg/ha/yr), Pb (g/ha/yr), Cu (g/ha/yr), Zn (g/ha/yr), Cd (g/ha/yr), Cr (g/ha/yr), Ni (g/ha/yr), FC (colonies/ha/yr), FS (colonies/ha/yr), E.coli (MPN/ha/yr), BOD (kg/ha/yr), COD (kg/ha/yr), and O&G (kg/ha/yr).

After implementing BMPs and LID practices, the outputs of the model were cumulative runoff/pollutant value (CRPV) as shown in Equations 3.11 and 3.12.

$$runoff - CRPV = \frac{Runoff}{Runoff'} \tag{3.11}$$

$$\begin{aligned} pollutant - CRPV = \frac{1}{19}\Big(&\frac{TSS}{TSS'} + \frac{TDS}{TDS'} + \frac{TP}{TP'} + \frac{DP}{DP'} + \frac{TN}{TN'} + \frac{TKN}{TKN'} + \frac{NO_x}{NO_x'} \\ &+ \frac{Cd}{Cd'} + \frac{Cr}{Cr'} + \frac{Cu}{Cu'} + \frac{Pb}{Pb'} + \frac{Ni}{Ni'} + \frac{Zn}{Zn'} + \frac{FC}{FC'} + \frac{FS}{FS'} \\ &+ \frac{E.coli}{E.coli'} + \frac{BOD}{BOD'} + \frac{COD}{COD'} + \frac{O\ \&\ G}{O\ \&\ G'}\Big) \end{aligned} \tag{3.12}$$

Where, *runoff* and *pollutant names* are runoff volume and pollutant loads after implementing BMPs and LID practices. $runoff'$ and $pollutant\ names'$ (with right single quotation mark) are runoff volume and pollutant loads before implementing BMPs and LID practices.

3.4.4 Sobol′′s Sensitivity analysis method

To identify the key variables affecting the performance of the model, model sensitivity was analyzed using a variance-based technique named Sobol′′s global sensitivity analysis method (Sobol′, 1993). Although Sobol′′s global sensitivity analysis method requires a large number of model evaluations, it is the most useful method in characterizing single variable and multivariable interactions (Tang et al., 2006; Yang, 2011) compared to the Jacobean-based local method (parameter estimation software PEST), regional sensitivity analysis (RSA), Analysis of Variance (ANOVA), Morris method, non-parametric smoothing, and Linear Regression (LR). The Monte Carlo method was combined with Sobol′′s method to conduct sensitivity analysis (Sobol′, 1993 and 2001; Hall et al., 2005).

Sobol′′s method represents a model described by:

$$Y = f(\alpha) \tag{3.13}$$

Where Y is the outputs of the model; α represents the input variables.

The Sobol′′s method decomposes the total output variance (V) of model output Y into variance caused by single variables and variable interactions based on their percentage contributions:

$$V = \sum_{i} V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + \ldots + V_{12\cdots n} \tag{3.14}$$

Where V_i is the contribution of i^{th} variable to the variance of the model output Y, V_{ij} is the contribution of the interaction between i^{th} and j^{th} variables, V_{ijk} is the contribution of the interactions among i^{th}, j^{th}, and k^{th} variables, and n is the total number of variables.

Two Sobol′'s sensitivity indices are usually calculated:

First order Sobol′'s sensitivity index: $S_i = \frac{V_i}{V}$ (3.15)

Total order Sobol′'s sensitivity index: $S_{Ti} = 1 - \frac{V_{\sim i}}{V}$ (3.16)

Where S_i is the first order sensitivity index of i^{th} variable, which only takes into account the independent impacts of the i^{th} variable on model output; S_{Ti} is the total order sensitivity index of i^{th} variable, which considers both independent and interactive impacts of the i^{th} variable on model output; $V_{\sim i}$ is the average variance caused by all of the variables except for the i^{th} variable. The difference between S_{Ti} and S_i shows how much a variable impact the model output with variable interactions.

V_i, $V_{\sim i}$, and V are estimated using Monte Carlo numerical integration method (Sobol′, 1993 and 2001; Hall et al., 2005; Tang et al., 2007):

$$\hat{f}_0 = \frac{1}{n} \sum_{s=1}^{n} f(\alpha_s) \tag{3.17}$$

$$\hat{V} = \frac{1}{n} \sum_{s=1}^{n} f^2(\alpha_s) - \hat{f}_0^{\,2} \tag{3.18}$$

$$\hat{V}_i = \frac{1}{n} \sum_{s=1}^{n} f(\alpha_s^{(a)}) f(\alpha_{(\sim i)s}^{(b)}, \alpha_{is}^{(a)}) - \hat{f}_0^{\,2} \tag{3.19}$$

$$\hat{V}_{\sim i} = \frac{1}{n} \sum_{s=1}^{n} f(\alpha_s^{(a)}) f(\alpha_{(\sim i)s}^{(a)}, \alpha_{is}^{(b)}) - \hat{f}_0^{\,2} \tag{3.20}$$

Where n is the sample size of Monte Carlo approximation; α_s is the sampled from unit hypercube; and (a) and (b) are two dissimilar groups of samples. $\alpha_s^{(a)}$ are variables in sample (a); $\alpha_{is}^{(a)}$ and $\alpha_{is}^{(b)}$ are i^{th} variables from sample (a) and (b), respectively; $\alpha_{(\sim i)s}^{(a)}$ and $\alpha_{(\sim i)\ s}^{(b)}$ are all variables, expect the i^{th} variable, that draw values from samples (a) and (b), respectively. In this study, the number of samples for Monte Carlo approximation was set to be 2000 based on literature recommendations (Tang et al., 2007).

3.4.5 Uncertainty analysis with bootstrap method

After sensitivity analysis, the uncertainties of the model outputs were analyzed with the bootstrap method. The bootstrap method (Efron, 1979; Efron and Tibshirani, 1993) is a nonparametric estimation technique using a random mechanism to create bootstrap samples by direct resampling with replacement from empirical distribution functions of data. The bootstrap technique can be applied with minimum assumptions and with unknown sample distributions (Efron, 1979; Efron and Tibshirani, 1993).

The bootstrap approach is based on resampling with replacement. The K base samples (for all the sensitive variables) are resampled N times with replacements. The simulation model is run N times with outputs of runoff volume and water quality. A bootstrap estimate of sampling distributions of the outputs is obtained. Then, the 95% Confidence Intervals (CIs) of the outputs are estimated based on the sampling distributions. The 95% CIs are obtained by identifying the 2.5% and 97.5% threshold values. In this study, 2000 was used as the resample dimension N based on previous literature (Tang et al., 2006).

3.5 Results and discussion

3.5.1 Sensitivity analysis

The total order Sobol′'s sensitivity indices for estimating runoff volume without implementing BMPs/LID practices and for estimating runoff volume/pollutant loads with different levels of BMPs/LID practices implemented are shown in Table 3.3. The total order Sobol′'s sensitivity indices for estimating pollutant loads without implementing BMPs/LID practices are shown in Figure 3.2. Note that the total order Sobol′'s sensitivity indices measure contributions of both single variables and variable interactions to the L-THIA-LID 2.1 model output.

Table 3.3 shows that when estimating runoff volume without implementing BMPs and LID practices, CN, with total order index of 0.994, was more sensitive than P, which had a total order index of 0.035. Figure 3.2 shows that when estimating pollutant loads without implementing BMPs and LID practices, CN (total order index ranging from 0.738 to 0.832) was the most sensitive variable, and EMC (total order index ranging from 0.188 to 0.287) was more sensitive than P (total order index ranging from 0.030 to 0.093). The findings were in accordance with the results of Wilson and Weng (2010) for the L-THIA model, which showed CN was the most sensitive variable estimating runoff volume and pollutant loads. This was expected because CN is the main factor for estimating runoff volume from a hydrologic response unit. P was not as sensitive in this study when estimating runoff volume and pollutant loads before implementing BMPs and LID practices, which may be because the range (or uncertainty) of P was smaller than other variables due to using uncertainty of annual rainfall values. Pollutant load is the product of runoff volume and EMC, making EMC a sensitive variable when estimating pollutant loads.

Table 3.3 indicates that when estimating runoff volume with different levels of BMPs and LID practices implemented, Ratio_r, which had total order index of 0.989/0.997 (for lower level of practices implemented and higher level of practices implemented, respectively), was the most sensitive variable, and CN (with total order index of 0.040/0.037) was more sensitive than P (with total order index of 0.029/0.033). When estimating pollutant loads with different levels of BMPs and LID practices implemented (Table 3.3), Ratio_r, which had a total order index of 0.793/0.827, was the most sensitive variable. Other variables with less impact on estimating pollutant loads with BMPs and LID practices implemented were EMC, IC, CN, Ratio_c, and P, with total order index of 0.190/0.145, 0.137/0.128, 0.047/0.054, 0.038/0.050, and 0.031/0.039, respectively. High sensitivity of Ratio_r was expected because high level of BMPs/LID practice implementations were simulated in this study, and Ratio_r indicates the performances of BMPs and LID practices represented by percent runoff volume reduction method. IC was sensitive because it is the lowest pollutant concentration of effluent for BMPs and LID practices due to the treatment abilities of the practices. When estimating pollutant loads with BMPs and LID practices implemented, EMC was more sensitive than CN because EMC represents the original pollutant concentrations before treated by BMPs/LID practices, which is closely related to IC. P and Ratio_c were not as sensitive as other variables which may be because of the smaller ranges (or uncertainties) of P and Ratio_c in this study.

Table 3.3 Total order Sobol''s sensitivity indices for estimating runoff volume without implementing BMPs/LID practices, and for estimating runoff volume and pollutant loads with different levels of BMPs/LID practices implemented

Variable	Runoff w/o practices	Rank	Runoff w/ lower level practices	Runoff w/ higher level practices	Rank	Pollutants w/ lower level practices	Pollutants w/ higher level practices	Rank
CN	0.994	1	0.040	0.037	2	0.047	0.054	4
P	0.035	2	0.029	0.033	3	0.031	0.039	6
EMC	--	--	--	--	--	0.190	0.145	2
Ratio_r	--	--	0.989	0.997	1	0.793	0.827	1
IC	--	--	--	--	--	0.137	0.128	3
Ratio_c	--	--	--	--	--	0.038	0.050	5

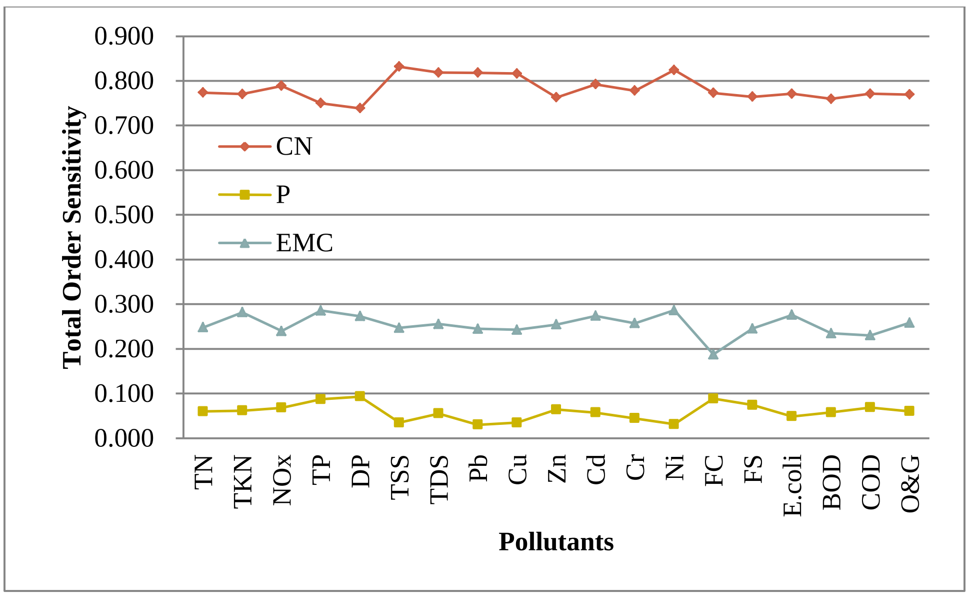


Figure 3.2 Total order Sobol''s sensitivity indices for estimating pollutant loads without implementing BMPs/LID practices

The first order Sobol''s sensitivity indices, which indicate the influence of single variables to the L-THIA-LID 2.1 model output, were also calculated; the results show the same sensitivity rankings comparing to results of total order Sobol''s sensitivity indices. The first order and total order Sobol''s sensitivity indices were computed when the ranges changing from default variables in Table 3.2 were set to similar values (-10% to 2% for CN and -10% to 10% for all of the other variables); results show that when estimating pollutant loads without implementing BMPs and LID practices, P was more sensitive than EMC; results indicate that when estimating pollutant loads with BMPs and LID practices, the sensitivity rankings of EMC and Ratio_c in Table 3.3 switched. All other sensitivity rankings were the same as using original ranges in Table 3.2 for variables.

3.5.2 Uncertainty analysis

Results of uncertainty analysis with 2.5% threshold values, 97.5% threshold values, width of 95% confidence interval (CI), and results observed or from literature are shown in Table 3.4. Distributions of samples for uncertainty analysis of the L-THIA-LID 2.1 model are shown in Figure 3.3. Figures 3.3(a) to 3.3(t) are results before implementing BMPs/LID practices. Figures 3.3(u) and 3.3(v) are results after implementing lower level of BMPs/LID practices. Figures 3.3(w) and 3.3(x) are results after implementing higher level of BMPs/LID practices.

Because of intensively simplifying natural processes, simple models, such as L-THIA-LID 2.1 model, are likely to generate more uncertain outputs compared to complex models (Patil and Deng, 2010). The ranges of variables used in Table 3.2 to estimate output uncertainty were relatively large, which could be one reason for the relatively large output uncertainty bounds before implementing BMPs and LID practices in Table 3.4. Figure 3.3(a) to 3.3(t) show that before implementing BMPs and LID practices, most model outputs were smaller than mean values. This could be caused by the -20% to 2%

change of CN from default values used in the uncertainty analysis, which increased the number of smaller CN values. The increased number of small CN values decreased the predicted runoff volume and in turn decreased the predicted pollutant load values. This could be another reason why uncertainty bounds before implementing BMPs and LID practices were relatively large.

The effectiveness of BMPs and LID practices was evaluated using model output after implementing BMPs and LID practices, and the uncertainty ranges of model outputs were relatively small as shown in Table 3.4. Figures 3.3(u) to 3.3(x) showed that after implementing BMPs and LID practices, the distributions of outputs were more symmetric compared to results before implementing practices. This was consistent with other findings that uncertainty of model outputs estimating absolute results were found to be relatively large due to limitations of data availability and the model itself; that is to say, models are more accurate when comparing relative predictions instead of estimating absolute results (Osidele et al., 2003; Benaman and Shoemaker, 2004; Zhang and Yu, 2004; Arabi et al., 2007). The output uncertainty ranges of implementing higher levels of BMPs and LID practices were greater than those of implementing lower level practices; this was due to more uncertainties of simulating additional BMPs and LID practices in the model.

Before implementing BMPs and LID practices, the average observed runoff volume from the study area was 2000 m^3/ha/yr, which was included in the uncertainty ranges of 462 to 2183 m^3/ha/yr (Table 3.4) simulated by the L-THIA-LID 2.1 model; TP loads of 0.20 to

1.80 kg/ha/yr were found in other studies for urban areas (Beaulac and Reckhow, 1982; Weeks, 1982; Reinelt and Horner, 1995; Sinclair Knight Merz, 1999; Tang et al., 2005; Ellis and Mitchell, 2006; Dietz and Clausen, 2008; Bedan and Clausen, 2009; Li and Davis, 2009; Ahiablame et al., 2013), which fell within the uncertainty range of 0.19 to 1.81 kg/ha/yr (Table 3.4); O&G load of 1.80 to 6.43 kg/ha/yr was reported in other studies (Tang et al., 2005; Ellis and Mitchell, 2006), which fell well within the uncertainty ranges of 0.73 to 6.44 kg/ha/yr in this study (Table 3.4).

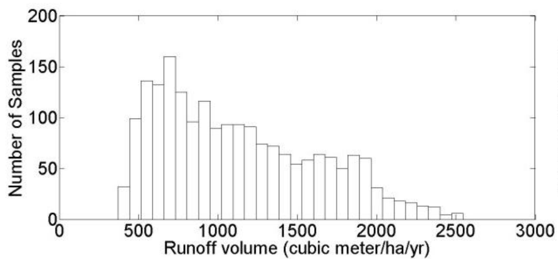
Before implementing BMPs and LID practices, TN loads of 1.70 to 10.00 kg/ha/yr were reported for other urban watersheds (Beaulac and Reckhow, 1982; Weeks, 1982; Sinclair Knight Merz, 1999; Tang et al., 2005; Ellis and Mitchell, 2006; Dietz and Clausen, 2008; Li and Davis, 2009; Ahiablame et al., 2013), while uncertainty bounds of 0.58 to 4.98 kg/ha/yr were found in this study (Table 3.4); TKN and NOx loads of 2.40-6.00 kg/ha/yr and 0.83-3.90 kg/ha/yr, respectively were found in other urban watersheds (Bedan and Clausen, 2009; Li and Davis, 2009), while the uncertainty ranges of 0.50-4.74 kg/ha/yr and 0.17-1.60 kg/ha/yr, respectively, were found in this study (Table 3.4); TSS loads of 65 to 570 kg/ha/yr were found in previous studies (Reinelt and Horner, 1995; Ellis and Mitchell, 2006; Bedan and Clausen, 2009; Li and Davis, 2009), while uncertainty bounds of 17 to 149 kg/ha/yr were found in this study (Table 3.4). Loads of Pb, Cu, Zn and Cr were found to be 2.0-30.0, 18.0-120.0, 17.0-360.0 and 9.8-20.0 g/ha/yr, respectively, in urban areas of other studies (Tang et al., 2005; Bedan and Clausen, 2009; Li and Davis, 2009), while uncertainty ranges of 3.3 to 29.3, 4.7 to 40.1, 34.4 to 349.9 and 1.2 to 12.0 g/ha/yr, respectively, were found in this study (Table 3.4); 4.20E+10 colonies/ha/yr of FC was found by Reinelt and Horner (1995), which was slightly lower than the uncertainty bounds of 4.95E+10 to 4.38E+11 colonies/ha/yr (Table 3.4); 59.0 kg/ha/yr of BOD was found by Ellis and Mitchell (2006), which was slightly above the uncertainty range of 6.4 to 57.0 kg/ha/yr (Table 3.4). No studies were found to directly compare other uncertainty results in Table 3.4. It should be noted that this work was conducted in a watershed with limited water quality data, and only the output uncertainty of runoff volume was compared to observed data from the same study area; all other output uncertainties in this study were compared to results of other study areas. More insight of the L-THIA-LID 2.1 model behavior could be obtained by analyzing model uncertainty using watersheds with more water quality data.

Table 3.4 Results of uncertainty analysis

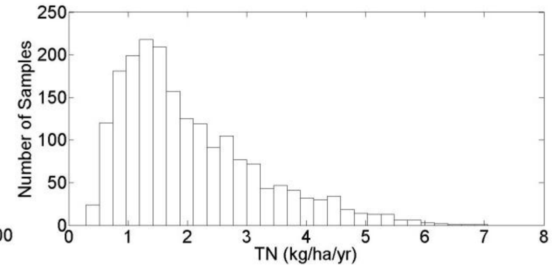
(Beaulac and Reckhow, 1982; Weeks, 1982; Reinelt and Horner, 1995; Sinclair Knight Merz, 1999; Tang et al., 2005; Ellis and Mitchell, 2006; Dietz and Clausen, 2008; Bedan and Clausen, 2009; Li and Davis, 2009; Ahiablame et al., 2013)

		95% confidence interval (CI)			Results Observed Or from literatures
		2.5% Threshold values	97.5% Threshold values	Width Of CI	
Before Implementing BMPs And LID practices	Runoff (m^3/ha/yr)	462	2183	1721	2000
	TN (kg/ha/yr)	0.58	4.98	4.39	1.70-10.00
	TKN (kg/ha/yr)	0.50	4.74	4.24	2.40-6.00
	NOx (kg/ha/yr)	0.17	1.60	1.43	0.83-3.90
	TP (kg/ha/yr)	0.19	1.81	1.62	0.20-1.80
	DP (kg/ha/yr)	0.14	1.16	1.01	N/A
	TSS (kg/ha/yr)	17	149	132	65-570
	TDS (kg/ha/yr)	49	461	412	N/A
	Pb (g/ha/yr)	3.3	29.3	26.0	2.0-30.0
	Cu (g/ha/yr)	4.7	40.1	35.4	18.0-120.0
	Zn (g/ha/yr)	34.4	349.9	315.5	17.0-360.0
	Cd (g/ha/yr)	0.3	3.2	2.9	N/A
	Cr (g/ha/yr)	1.2	12.0	10.8	9.8-20.0
	Ni (g/ha/yr)	0.7	8.2	7.5	N/A
	FC (colonies/ha/yr)	4.95E+10	4.38E+11	3.88E+11	4.20E+10
	FS (colonies/ha/yr)	1.15E+11	1.09E+12	9.77E+11	N/A

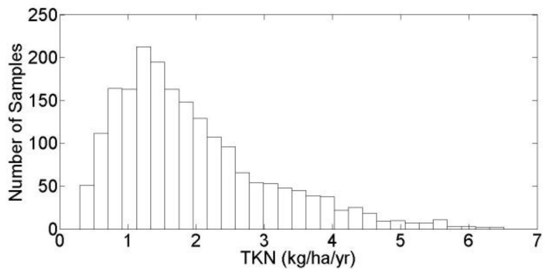
	E.coli (MPN/ha/yr)	2.69E+10	2.30E+11	2.03E+11	N/A
	BOD (kg/ha/yr)	6.4	57.0	50.6	59.0
	COD (kg/ha/yr)	11.0	109.1	98.1	N/A
	O&G (kg/ha/yr)	0.73	6.44	5.70	1.80-6.43
After implementing lower level practices	runoff -CRPV	0.69	0.81	0.11	N/A
	pollutant-CRPV	0.60	0.71	0.11	N/A
After implementing higher level practices	runoff -CRPV	0.50	0.68	0.18	N/A
	pollutant-CRPV	0.40	0.56	0.16	N/A



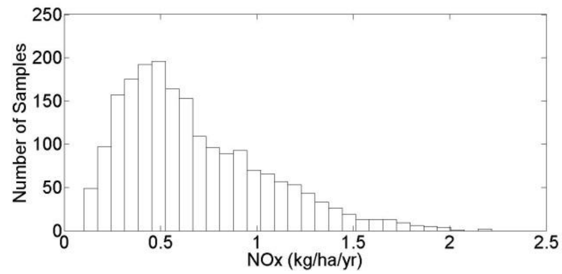
(a)



(b)



(c)



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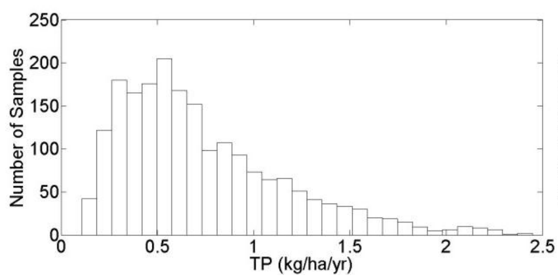
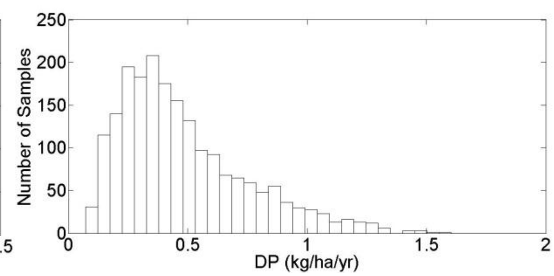
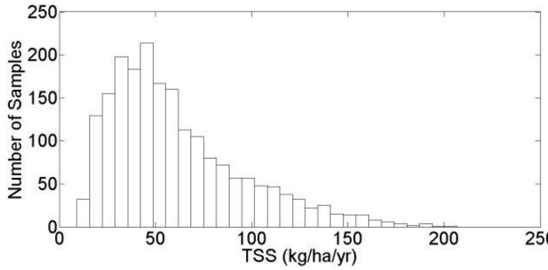


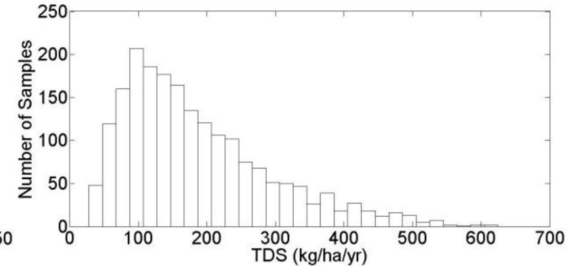
(e)



(f)


Number of Samples
250
200
150
100
50
0
0
50
100
150
200
250
TSS (kg/ha/yr)

(g)


Number of Samples
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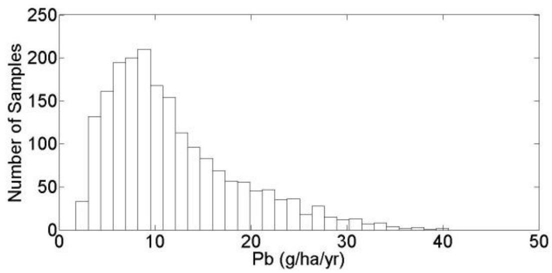
200
300
400
500
600
700
TDS (kg/ha/yr)

(h)


Number of Samples
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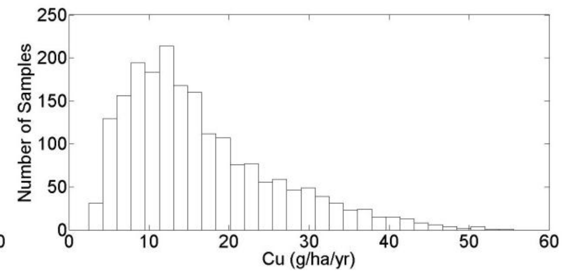
0
10
20
30
40
50
Pb (g/ha/yr)

(i)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10
20
30
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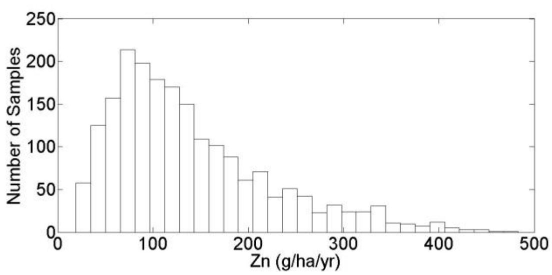
60
Cu (g/ha/yr)

(j)


Number of Samples
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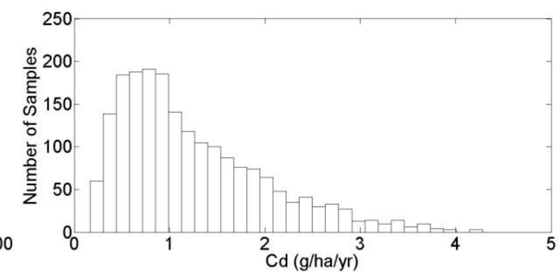
0
100
200
300
400
500
Zn (g/ha/yr)

(k)


Number of Samples
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200
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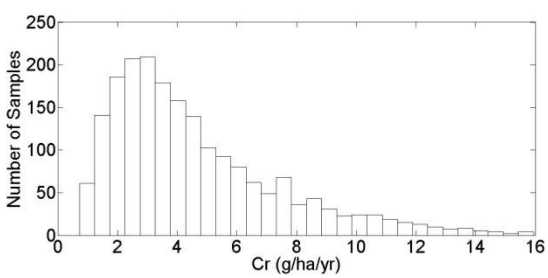
100
50
0
0
1
2
3
4
5
Cd (g/ha/yr)

(l)


Number of Samples
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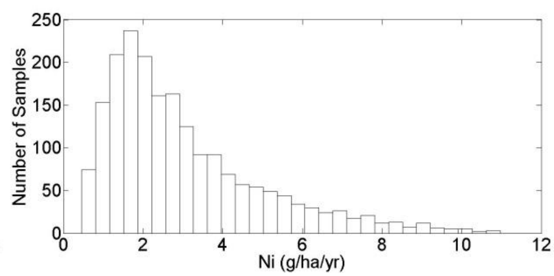
4
6
8
10
12
14
16
Cr (g/ha/yr)

(m)


Number of Samples
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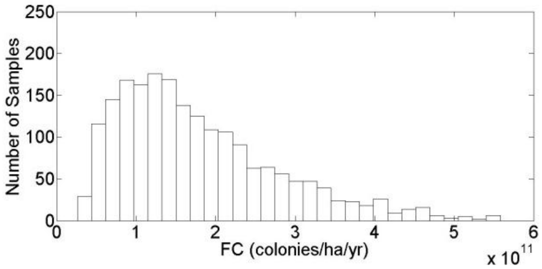
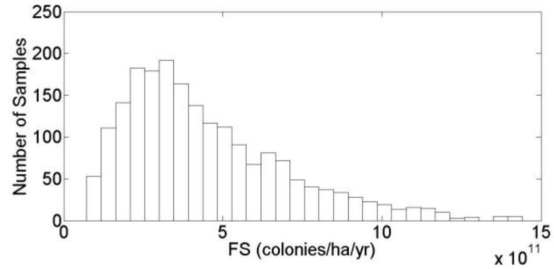
2
4
6
8
10
12
Ni (g/ha/yr)

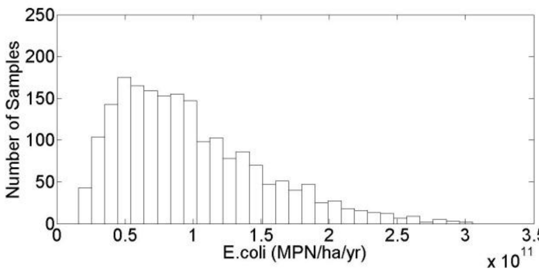
(n)


Number of Samples
FC (colonies/ha/yr)
x 10^11

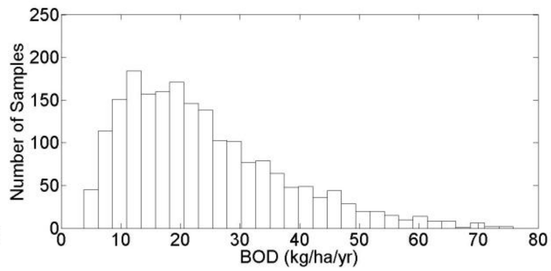
(o)


Number of Samples
FS (colonies/ha/yr)
x 10^11

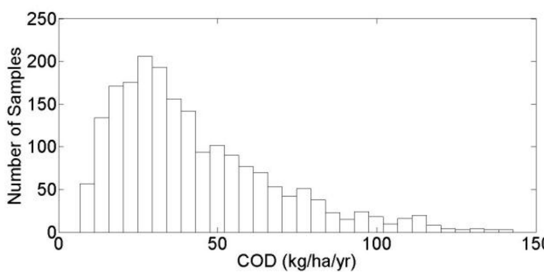
(p)


Number of Samples
E.coli (MPN/ha/yr)
x 10^11

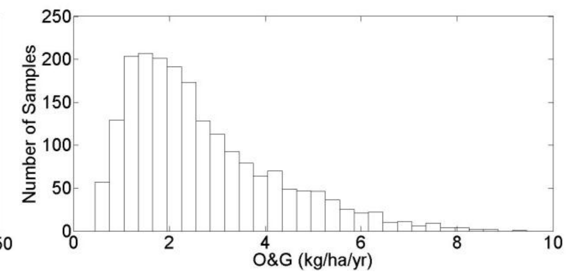
(q)


Number of Samples
BOD (kg/ha/yr)

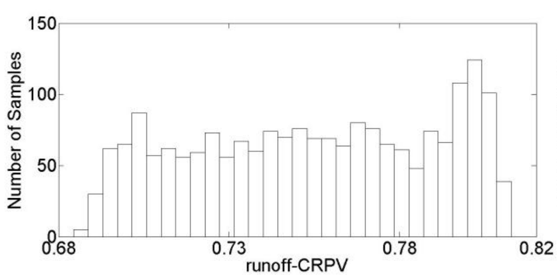
(r)


Number of Samples
COD (kg/ha/yr)

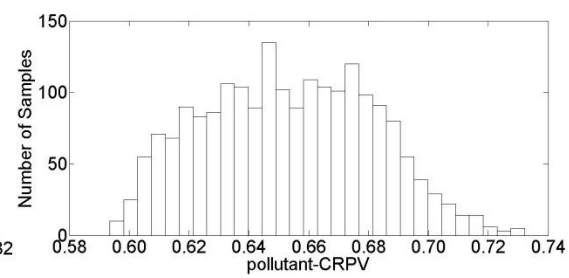
(s)


Number of Samples
O&G (kg/ha/yr)

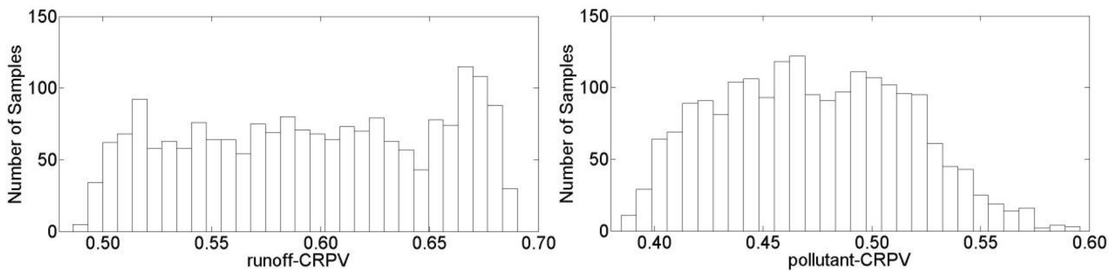
(t)


Number of Samples
runoff-CRPV

(u)


Number of Samples
pollutant-CRPV

(v)



(w) (x)

Figure 3.3 Distributions of samples for uncertainty analysis.
(a) to (t) are results before implementing BMPs/LID practices. (u) and (v) are results after implementing lower level of BMPs/LID practices. (w) and (x) are results after implementing higher level of BMPs/LID practices.

3.6 Conclusions

The sensitivity and uncertainty of the L-THIA-LID 2.1 model in estimating hydrology and water quality were analyzed in an urbanized watershed in central Indiana, USA using Sobol′'s global sensitivity analysis method and bootstrap method, respectively. When estimating runoff volume without implementing BMPs and LID practices, CN (Curve Number) was more sensitive than P (Precipitation). When computing pollutant loads without implementing BMPs and LID practices, the sensitivities were in the descending order of CN, EMC (Event Mean Concentration), and P. When predicting runoff volume with different levels of BMPs and LID practices implemented, the sensitivities were in the descending order of Ratio_r (Practice outflow runoff volume/inflow runoff volume), CN and P. When modeling nonpoint source pollutant loads with different levels of BMPs and LID practices implemented, the sensitivities were in the descending order of Ratio_r, EMC, IC (Irreducible Concentration), CN, Ratio_c (Practice outflow pollutant concentration/inflow pollutant concentration), and P.

The relatively large output uncertainty bounds before implementing BMPs and LID practices may be due to simplifying natural processes by the simple model, large ranges (or uncertainty) for variables, and unsymmetrical changes (-20% to 2%) of CNs from default values. The uncertainty ranges of model outputs after implementing BMPs and LID practices were relatively small, due to comparing relative predictions instead of absolute values. Before implementing BMPs and LID practices, the average observed runoff volume was well covered in the uncertainty ranges simulated by the L-THIA-LID 2.1 model; TP and O&G loads from other urban watersheds fell well within the uncertainty ranges in this study; TN, TKN, NOx, TSS, Pb, Cu, Zn, Cr, FC, and BOD loads from other study areas were similar to the uncertainty bounds found in this study; this indicates good precision of the model; however, no studies were found to directly compare other uncertainty results. It should be noted that only the output uncertainty of runoff volume was compared to observed data from the same study area; all other output uncertainties in this study were compared to results of other study areas due to lack of data. More insight of the L-THIA-LID 2.1 model behavior could be obtained by analyzing model uncertainty using watersheds with more water quality data.

3.7 References

Abbott, M.B., Bathurst, J.C., Cunge, J.A., O′Connell, P.E., Ramussen, J., 1986. An introduction to the European Hydrological System-Systeme Hydrologique Europpen, "SHE". 2: Structure of a physically based, distributed modeling system. Journal of Hydrology, 87, 61-77.

Ahiablame, L. M., 2012a. Development of methods for modeling and evaluation of low impact development practices at the watershed scale (Doctoral dissertation, PURDUE UNIVERSITY).

Ahiablame, L., Engel, B., Chaubey, I., 2012b. Representation and evaluation of low impact development practices with L-THIA LID: An example for site planning. Environment and Pollution, 1(2), doi:10.5539/ep.v1n2p1.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement. Journal of environmental management, 119, 151-161.

Arabi, M., Govindaraju, R.S., Hantush, M.M., 2007. A probabilistic approach for analysis of uncertainty in the evaluation of watershed management practices. Journal of Hydrology, 333(2), 459-471.

Archer, G.E.B., Saltelli, A., Sobol, I.M., 1997. Sensitivity measures, ANOVA-like techniques and the use of bootstrap. Journal of Statistical Computation and Simulation, 58(2), 99-120.

Baird, F.C., Dybala, T.J., Jennings, M.E., Okerman, D.J., 1996. Characterization of nonpoint sources and loadings to the Corpus Christi Bay National Estuary Program Study Area; Corpus Christi National Estuary Program, Corpus Christi, TX.

Beaulac, M.N., Reckhow, K.H., 1982. An examination of land use-nutrient export relationships1. Journal of the American Water Resources Association, 18(6), 1013-1024.

Bedan, E.S., Clausen, J.C., 2009. Stormwater runoff quality and quantity from traditional and low impact development watersheds. JAWRA Journal of the American Water Resources Association, 45: 998–1008. doi: 10.1111/j.1752-1688.2009.00342.x

Benaman, J., Shoemaker, C.A., 2004. Methodology for analyzing ranges of uncertain model parameters and their impact on total maximum daily load process. Journal of environmental engineering, 130(6), 648-656.

Beck, M.B., 1987. Water quality modeling: a review of the analysis of uncertainty. Water Resources Research, 23, 1393-1442.

Carpenter, T.M., Georgakakos, K.P., Sperfslagea, J.A., 2001. On the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model suitable for operational use. Journal of Hydrology, 253, 169–193.

Cibin, R., Sudheer, K.P., Chaubey, I., 2010. Sensitivity and identifiability of stream flow generation parameters of the SWAT model. Hydrological Processes, 24(9), 1133-1148.

Cloke, H.L., Pappenberger, F., Renaud, J.P., 2008. Multi-method global sensitivity analysis (MMGSA) for modelling floodplain hydrological processes. Hydrological processes, 22(11), 1660-1674.

CWP and CSN (Center for Watershed Protection and Chesapeake Stormwater Network), 2008. Technical memorandum: the runoff reduction method. Ellicott City, MD. www.chesapeakestormwater.net.

Dietz, M.E., Clausen, J.C., 2008. Stormwater runoff and export changes with development in a traditional and low impact subdivision. Journal of Environmental Management, 87(4), 560-566.

Duan, Q., Gupta, H.V., Sorooshian, S., Rousseau, A.N., Turcotte, R., 2003. Calibration of watershed models. American Geophysical Union. Vol. 6, pp. 1-345

Efron, B., 1979. Bootstrap methods: another look at the jackknife. The annals of Statistics. 7, 1–26.

Efron, B., Tibshirani, R.J., 1993. An introduction to the Bootstrap, Chapman & Hall, New York.

Ellis, J.B., Mitchell, G., 2006. Urban diffuse pollution: key data information approaches for the Water Framework Directive. Water and Environment Journal, 20(1), 19-26.

Freer, J., Beven, K.J., Ambroise, B., 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: An application of the glue approach, Water Resources Research, 32, 2161–2173.

GC and WWE (Geosyntec Consultants and Wright Water Engineers), 2011. International Stormwater Best Management Practices (BMP) Database Technical Summary: Volume Reduction, 27. www.bmpdatabase.org (accessed November, 2012).

Haan, C.T., Storm, D.E., Al-Issa, T., Prabhu, S., Sabbagh, G.J., Edwards, D.R., 1998. Effect of parameter distributions on uncertainty analysis of hydrologic models. Transactions of the ASAE, 41(1), 65-70.

Hall, J., Tarantola, S., Bates, P.D., Horritt, M.S., 2005. Distributed sensitivity analysis of flood inundation model calibration. Journal of Hydraulic Engineering, 131(2), 117– 126.

Helton, J.C., 1993. Uncertainty and sensitivity analysis techniques for use in performance assessment for radioactive waste disposal. Reliability Engineering & System Safety, 42(2), 327-367.

Holvoet, K., van Griensven, A., Seuntjens, P., Vanrolleghem, P.A., 2005. Sensitivity analysis for hydrology and pesticide supply towards the river in SWAT. Physics and Chemistry of the Earth, Parts A/B/C, 30(8), 518-526.

Jakeman, A.J., Hornberger, G.M., 1993. How much complexity is warranted in a rainfall-runoff model? Water Resources Research, 29(8), 2637-2649.

Li, H., Davis, A.P., 2009. Water quality improvement through reductions of pollutant loads using bioretention. Journal of Environmental Engineering, 135(8), 567-576.

Li, Z., Shao, Q., Xu, Z., Cai, X., 2010. Analysis of parameter uncertainty in semi-distributed hydrological models using bootstrap method: A case study of SWAT model applied to Yingluoxia watershed in northwest China. Journal of Hydrology, 385(1), 76-83.

Lilburne, L., Gatelli, D., Tarantola, S., 2006. Sensitivity analysis on spatial models: new approach. In Proceedings of the 7th international symposium on spatial accuracy assessment in natural resources and environmental sciences.

Lim, K.J., Engel, B.A., Muthukrishnan, S., Harbor, J., 2006. Effects of initial abstraction and urbanization on estimated runoff using CN technology1. Journal of the American Water Resources Association, 42(3), 629-643.

Liu, Y., Ahiablame, L.M., Bralts, V.F., Engel, B.A., 2015a. Enhancing a rainfall-runoff model to assess the impacts of BMPs and LID practices on storm runoff, Journal of Environmental Management, 147, 12-23.

Liu, Y., Bralts, V.F., Engel, B.A., 2015b. Evaluating the effectiveness of management practices on hydrology and water quality at watershed scale with a rainfall-runoff model. Science of The Total Environment, 511, 298-308.

Migliaccio, K.W., Chaubey, I., 2008. Spatial distributions and stochastic parameter influences on SWAT flow and sediment predictions. Journal of Hydrologic Engineering, 13(4), 258-269.

Muleta, M.K., Nicklow, J.W., 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. Journal of Hydrology, 306(1-4), 127-145.

NRCS (Natural Resources Conservation Services), 1986. Urban hydrology for small watersheds. Technical Release 55, USDA Natural Resources Conservation Services.

Osidele, O.O., Zeng, W., Beck, M.B., 2003. Coping with uncertainty: a case study in sediment transport and nutrient load analysis. Journal of Water Resources Planning and Management, 129(4), 345-355.

Patil, A., Deng, Z., 2010. Analysis of uncertainty propagation through model parameters and structure. Water Science and Technology, 62(6), 1230-1239.

Refsgaard, J.C., Seth, S.M., Bathurst, J.C., Erlich, M., Storm, B., Jorgensen, G.H., Chandra, S., 1992. Application of the SHE to catchments in India. Part 1. General results. Journal of Hydrology, 140, 1-23.

Reinelt, L.E., Horner, R.R., 1995. Pollutant removal from stormwater runoff by palustrine wetlands based on comprehensive budgets. Ecological Engineering, 4(2), 77-97.

Sample, D.J., Heaney, J.P., Wright, L.T., Koustas, R., 2001. Geographic information systems, decision support systems, and urban storm-water management. Journal of Water Resources Planning and Management, 127(3), 155-161. http://dx.doi.org/10.1061/(ASCE)0733-9496(2001)127:3(155)

Sinclair Knight Merz Pty. Ltd, 1999. Duck River stormwater management plan, Final, St Leonards, NSW.

Sobol′, I. M., 1993. Sensitivity estimates for nonlinear mathematical models, Math. Model. Comput. Exp., 1(4), 407–417.

Sobol′, I. M., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Mathematics and computers in simulation, 55, 271–280.

Strecker, E.W., Quigley, M.M., Urbonas, B., Jones, J., 2004. Analyses of the expanded EPA/ASCE International BMP Database and potential implications for BMP design. Proceedings of the World Water and Environmental Resources Congress 2004, Salt Lake City, Utah.

Tang, Y., Reed, P., Wagener, T., Van Werkhoven, K., 2006. Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. Hydrology and Earth System Sciences Discussions, 3, 3333– 3395.

Tang, Y., Reed, P., Van Werkhoven, K., Wagener, T., 2007. Advancing the identification and evaluation of distributed rainfall- runoff models using global sensitivity analysis. Water Resources Research, 43(6).

Tang, Z., Engel, B.A., Pijanowski, B.C., Lim, K.J., 2005. Forecasting land use change and its environmental impact at a watershed scale. Journal of environmental management, 76, 35-45.

Thiessen, A.H., 1911. Precipitation averages for large areas. Monthly weather review, 39 (7), 1082-1089.

Tyagi, A., Haan, C.T., 2001. Uncertainty analysis using corrected first-order approximation method. Water Resources Research, 37(6), 1847-1858.

Weeks, C.R., 1982. Pollution in urban runoff. In: Hart, B.T. (Ed.), Water quality management monitoring programs and diffuse runoff. Water Studies Centre, Chisholm Institute of Technology and Australian Society of Limnology, Melbourne, pp. 121–140.

Wilson, C., Weng, Q., 2010. Assessing surface water quality and its relation with urban land cover changes in the Lake Calumet area, Greater Chicago. Environmental management, 45(5), 1096-1111.

Yang, J., 2011. Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. Environmental Modelling & Software, 26(4), 444-457.

Zhang, H.X., Yu, S.L., 2004. Applying the first-order error analysis in determining the margin of safety for total maximum daily load computations. Journal of Environmental Engineering, 130(6), 664-673.

CHAPTER 4. EVALUATING THE EFFECTIVENESS OF MANAGEMENT PRACTICES ON HYDROLOGY AND WATER QUALITY AT WATERSHED SCALE WITH A RAINFALL-RUNOFF MODEL

4.1 Abstract

The adverse influence of urban development on hydrology and water quality can be reduced by applying best management practices (BMPs) and low impact development (LID) practices. This study evaluated the impact of several practices, including green roof, rain barrel/cistern, bioretention system, porous pavement, permeable patio, grass strip, grassed swale, wetland channel, retention pond, detention basin, and wetland basin on runoff and water quality in Crooked Creek watershed. The model was calibrated and validated for annual runoff volume. A framework for simulating BMPs and LID practices at watershed scales was created, and the impacts of BMPs and LID practices on water quantity and water quality were evaluated with the Long-Term Hydrologic Impact Assessment-Low Impact Development 2.1 (L-THIA-LID 2.1) model for 16 scenarios. The various levels and combinations of BMPs/LID practices reduced runoff volume by 0 to 26.47%, Total Nitrogen (TN) by 0.30 to 34.20%, Total Phosphorus (TP) by 0.27 to 47.41%, Total Suspended Solids (TSS) by 0.33 to 53.59%, Lead (Pb) by 0.30 to 60.98%, Biochemical Oxygen Demand (BOD) by 0 to 26.70%, and Chemical Oxygen Demand (COD) by 0 to 27.52%. The implementation of grass strips in 25% of the watershed where this practice could be applied was the most cost-efficient scenario,

with cost per unit reduction of \$1 m^3/yr for runoff, while cost for reductions of two pollutants of concern were \$445 kg/yr for Total Nitrogen (TN) and \$4,871 kg/yr for Total Phosphorous (TP). The scenario with very high levels of BMP and LID practice adoption (scenario 15) reduced runoff volume and pollutant loads from 26.47% to 60.98%, and provided the greatest reduction in runoff volume and pollutant loads among all scenarios. However, this scenario was not as cost-efficient as most other scenarios. The L-THIA-LID 2.1 model is a valid tool that can be applied to various locations to help identify cost effective BMP/LID practice plans at watershed scales.

4.2 Introduction

With more people shifting to live in urban areas (Paul and Meyer, 2001; Grimm et al., 2008), urbanization has become a global trend. Urbanization changes natural or agricultural land uses to residential, commercial, and industrial areas, which increases imperviousness. The increased imperviousness of the area and urban activities lead to increased stormwater runoff, decreased baseflow, reduced groundwater recharge, and water quality deterioration (Brun and Band, 2000; Rose and Peters, 2001; Lee and Heaney, 2003; Randhir, 2003; Tang et al., 2005; Olang and Furst, 2010; Newcomer et al., 2014). Although combined sewer systems are used in urban areas to treat polluted water, combined sewer overflows (CSOs) may occur during some rainfall periods. CSOs may discharge directly to lakes, streams, rivers, and even oceans, which result in severe water pollution problems (Hatt et al., 2004; Gunderson et al. 2011; Hata et al., 2014).

Best management practices (BMPs) and low impact development (LID) practices are two effective control measures to reduce runoff and control the movement of pollutants (Urbonas, 1994; USEPA, 2008). BMPs, including retention ponds, detention basins, and wetland basins, are large scaled, centralized approaches that treat stormwater runoff at the end of a drainage area (USEPA, 2008; Gilroy, 2009). LID practices, such as green roofs, rain barrels/cisterns, bioretention systems, porous pavements, permeable patios, grass strips, grassed swales, and wetland channels, are small-scale on-site practices to preserve pre-development site features or reduce the impact of development activities at the source (Prince George's County, 1999; Dietz, 2007).

Numerous studies have shown the capabilities of BMPs and LID practices in reducing water quantity and improving water quality (e.g. Barbosa and Hvitved-Jacobsen et al., 1999.Wright et al., 1999; Bhaduri et al., 2000; Pagotto et al. 2000; Brattebo and Booth 2003; Hunt et al., 2006; Bean et al., 2007; Dietz and Clausen, 2008; Damodaram et al., 2010; Zhang and Zhang, 2011; Vezzaro, 2011; Vijayaraghavan et al., 2012; Ahiablame et al., 2013; Kok et al., 2013; Autixier et al., 2014; Newcomer et al., 2014). For example, Dietz and Clausen (2008) studied runoff and pollutant concentrations for developments both with and without LID practices; the results showed that traditional development increased runoff and pollutant loads, while implementation of LID practices greatly reduced runoff and pollutants compared to traditional development conditions. Ahiablame et al. (2013) used the L-THIA-LID model to simulate six levels and combinations of porous pavement and rain barrel/cistern in two watersheds that were highly urbanized, which showed that the implementation of different LID scenarios resulted in 2% to 12% reductions in runoff and pollutant loads. Newcomer et al. (2014) conducted a field and model-based (HYDRUS-2D) study in San Francisco, CA, which demonstrated the benefits of BMPs/LID practices on groundwater recharge. Comings et al. (2000) studied two wet ponds at a commercial and residential area in Bellevue, WA, and found 61% to 81% reduction of TSS, 19% to 46% reduction of TP, and 37% to 76% reduction of metals.

Although there are numerous modeling, field, and laboratory studies evaluating the effectiveness of BMPs and LID practices on water quantity and quality, presently, there are few studies estimating the possible impacts of BMPs and LID practices at watershed scales when implementing various levels and combinations of these practices in series. Further, scientific papers evaluating the cost of implementing BMPs and LID practices at watershed scales are sparse. Research searching for cost-effective scenarios (levels and combinations) to implement BMPs and LID practices at watershed scales is also relatively rare.

The primary goal of the study was to evaluate the impacts of BMPs and LID practices on hydrology and water quality at a watershed scale with the L-THIA-LID 2.1 model. The model was calibrated and validated for runoff volume. A framework for simulating BMPs and LID practices at watershed scales was created. BMPs and LID practices, including green roof, rain barrel/cistern, bioretention system, porous pavement, permeable patio, grass strip, grassed swale, wetland channel, retention pond, detention basin, and wetland basin, were simulated for various levels of adoption and combinations.

The total cost of implementing BMPs and LID practices was estimated for each scenario, and the more cost-effective scenarios were identified.

4.3 Background and enhancement of L-THIA-LID model

4.3.1 Background of L-THIA-LID model

Based on the previous L-THIA-LID model (Ahiablame et al., 2012), the L-THIA-LID 2.0 model (Liu et al., 2015) was developed to better simulate the impacts of BMPs and LID practices on hydrology and water quality. Similar to other versions of the L-THIA model (Harbor, 1994; Engel et al., 2003; Ahiablame et al., 2012), input data for long term daily precipitation, hydrologic soil group, and land use types are needed. In the same way, the L-THIA-LID 2.0 model evaluates runoff volume based on the Curve Number (CN) method and estimates nonpoint source pollutant loads with runoff volume and event mean concentration (EMC) of specific land uses. To represent BMPs and LID practices, the L-THIA-LID 2.0 model computes runoff volume for land uses that include BMPs and LID practices based on both the CN method and percent runoff reduction method; estimates water quality changes with the runoff volume reduction method, pollutant concentration reduction method, and irreducible concentration method based on the International Stormwater Best Management Practices (BMP) Database; and simulates BMPs and LID practices in series (Ahiablame et al., 2012; Liu et al., 2015).

4.3.2 L-THIA-LID 2.1 model

In this study, to evaluate the performance of BMPs and LID practices at watershed scales, the L-THIA-LID 2.1 model was developed with the consideration of being applied in various locations.

4.3.2.1 Framework for simulating BMPs and LID practices at watershed scales

BMPs and LID practices were selected and implemented both individually and in series starting at the sub-hydrologic response unit (HRU) level based on the conditions of the area, suitable locations for LID practices, and percent implementation of BMPs and LID practices. Based on the site characteristics (Table A.2), which included drainage area (ha), drainage slope (%), imperviousness (%), hydrologic soil group (A-D), road buffer (m), stream buffer (m), and building buffer (m), together with other logistical concerns, suitable locations for implementing BMPs and LID practices were selected. After obtaining suitable locations for LID practices, the unique combinations of land use, soil type, and LID practices were obtained.

The drainage area of each practice was based on features of the practices: (1) Rain barrel/cistern and green roof only treat runoff from roof tops (same as building footprints). It was assumed that rain barrels can only be implemented in residential areas, cisterns can only be implemented in commercial/industrial areas, and green roof can be applied in commercial and industrial areas only. (2) Porous pavement and permeable patio only treat runoff from the surface of the pavement or patio. (3) Bioretention system, represented with the Curve Number (CN) method, treat 15% of the remaining runoff after being treated by green roof, rain barrel/cistern, porous pavement, and permeable patio. (4) Biofilter-grass swale, biofilter-grass strip, and wetland channel, which were suitable for small drainage areas, only treated remaining runoff after being treated by green roof, rain barrel/cistern, porous pavement, permeable patio, and bioretention. Areas with different combinations of land use, soil type, and LID practices were assumed to be independent to each other when implementing LID practices. (5) A portion of runoff treated by the LID practices was then treated by BMPs (including detention basin, retention pond, and wetland basin).

To implement BMPs and LID practices in series, the following framework was followed. When there was more than one LID practice suitable to be implemented in an HRU: situation (1) (green roof and rain barrel/cistern, which can be implemented in series) and situation (2) (porous pavement and permeable patio) were parallel to each other; all other situations were applied in series. Grassed swale and wetland channel were parallel to each other. All LID practices can be applied in series with BMPs; however, BMPs were parallel to each other.

4.3.2.2 Cost of implementing BMPs and LID practices

Total cost (Tc) to implement BMPs and LID practices and cost per unit reduction per year were combined in the L-THIA-LID 2.1 model to evaluate the cost of implementing BMPs and LID practices. The total cost (Tc) to implement BMPs and LID practices was estimated by construction cost, maintenance cost, and opportunity cost (Arabi et al., 2006). Construction cost (Cc), ratio of annual maintenance cost to construction cost (Rmc), interest rate (s), and BMP/LID practice design life (dl) were used to calculate Tc:

$$Tc = Cc \times (1+s)^{dl} + Cc \times Rmc \times [\sum_{i=1}^{dl}(1+s)^{(i-1)}] \tag{4.1}$$

Construction costs and annual maintenance costs of BMPs and LID practices are shown in Table 4.1. All costs were converted to 2014 US dollars (http://www.usinflationcalculator.com/).

Table 4.1 Construction costs and annual maintenance costs of BMPs and LID practices (Schueler, 1992; Brown and Schueler, 1997; CWP, 1997; USEPA, 1999, 2006, 2012a, and 2012b; Arabi, et al., 2006; PSBMPM, 2006a and 2006b; EBRP, 2007; NCDENR, 2007; LIDMM, 2008; CNT, 2009; King and Hagan, 2011; TRC and CVC, 2011)

Practices	Construction Cost ($/m^2 drainage area) 2014 dollars	Annual Maintenance Cost (% of Construction Cost)
Wet Pond	1.22	4
Dry Pond	1.41	4
Wetland	1.55	4
Rain Barrel	6.71	1
Cistern	8.59	1
Permeable patio	121.68	1
Green Roof	168.34	6
Grassed Swale	0.90	6
Grass strip	0.34	3
Wetland Channel	0.90	6
Bioretention	15.12	6
Porous Pavement	59.20	1

Cost per unit reduction per year ($C_{ur,y}$) was used to estimate cost per m^3 of runoff volume reduction and cost per kg pollutant reduction based on an average year, calculated as:

$$C_{ur,y} = \frac{T_c}{nR} \tag{4.2}$$

Where R was the reduction of runoff volume (m^3) or pollutant loads (kg), Tc ($) was the total cost of implementing BMPs and LID practices, and n was the number of years simulated. The units of cost per unit reduction per year were $\$/m^3/yr$ for runoff volume and $/kg/yr for pollutants. The smaller the values of cost per unit reduction per year, the more cost-efficient the combination scenario of BMPs and LID practices would be.

4.4 Materials and methods

4.4.1 Study area

This study was conducted in Crooked Creek watershed (Figure 4.1), which is an urban watershed near Indianapolis, Indiana, USA. Crooked Creek watershed joins the White River about 4 miles northwest of downtown Indianapolis. The watershed, with a total area of 5129 ha, is highly urbanized with 88% of its area covered with low density residential, high density residential, industrial, and commercial land uses. The location of a streamflow gauge station, which is at the outlet of the watershed, together with the high urbanization level made the watershed suitable to simulate the impacts of BMPs and LID practices on hydrology and water quality.

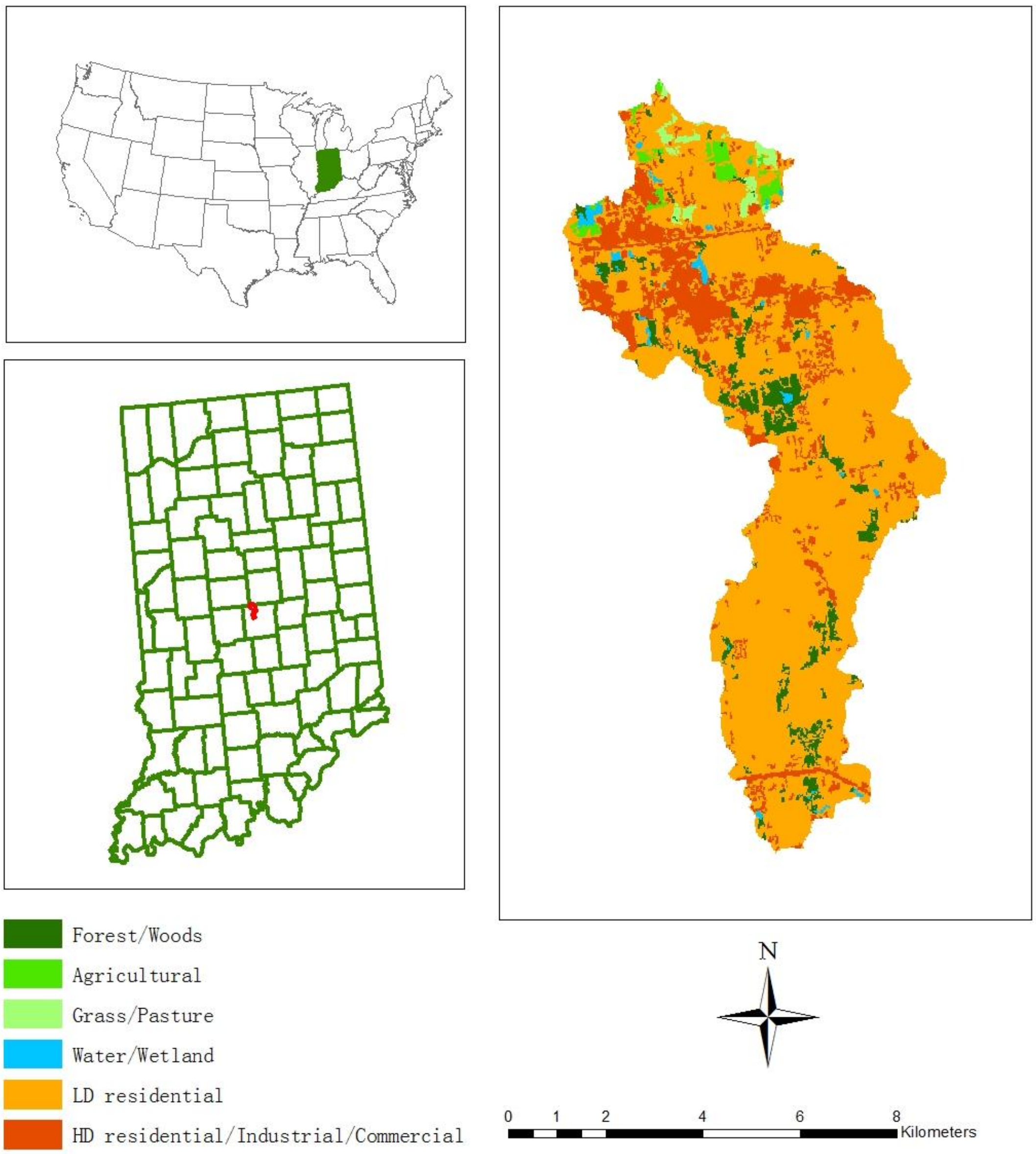


Figure 4.1 Location of Crooked Creek watershed in central Indiana USA (National Land Cover Database 2001)

4.4.2 Input Data

Precipitation data, land use data, hydrologic soil group data, and streamflow data were the basic input data for the L-THIA-LID 2.1 model. Eighteen years of daily rainfall data (from 1993 to 2010) measured by weather stations near the study area were obtained from the National Climatic Data Center (http://www.ncdc.noaa.gov). The Thiessen method (Thiessen, 1911), a popular method to calculate areal rainfall, was used to generate spatially varying rainfall data. Based on the area of the nearest part of the studied watershed to each rainfall station, relative weights were used to calculate areal average rainfall.

Measured daily streamflow data (1993-2010) from United States Geological Survey (http://www.usgs.gov/) streamflow gage station 03351310 were used to calibrate and validate runoff volume in the watershed.

Hydrologic soil group (HSG) data extracted from the Soil Survey Geographic (SSURGO) database were used in the model. The hydrologic soil groups B and C of high density residential (HDR), industrial, and commercial areas were considered disturbed after construction, and were shifted to hydrologic soil group D (Lim et al., 2006).

The National Land Cover Dataset 2001 (NLCD 2001) was used to quantify types of land uses in the watershed. Based on the imperviousness of each land use type in TR 55 (NRCS, 1986) and the description of NLCD 2001 dataset, the classes in NLCD 2001 were reclassified using ArcGIS. Developed low intensity and developed open space were reclassified as low density residential (LDR) land use. Developed medium intensity and developed high intensity were reclassified as high intensity, which included high density residential (HDR), industrial, and commercial areas. Aerial photographs were used to partition the land uses of HDR, industrial, and commercial. Deciduous forest, evergreen forest, mixed forest, and shrub/scrub were reclassified as forest/woods. Cultivated crops were reclassified as agricultural land use. Grassland/herbaceous and pasture/hay were reclassified as grass/pasture. Open water, emergent herbaceous wetlands, and woody wetlands were reclassified as water/wetland. Barren land was compared with aerial photos and reclassified as commercial area. The final categories for the model are LDR, HDR, industrial, commercial, forest/woods, agricultural, grass/pasture, and water land covers.

The GIS layers of building footprints, street centerlines, streams, lakes, and imperviousness were obtained from IndianaMap Layer Gallery (http://maps.indiana.edu/layerGallery.html). Digital elevation model (DEM) data were obtained from The National Map (http://nationalmap.gov/). The building footprints layer was used to define the area of roof tops. The street centerlines layer was used to define the street surfaces by using different widths for different types of road—4 m for small roads, 10 m for busy city roads, and 16 m for highways. Streams and lakes layers were used to identify the surface of streams and lakes. The imperviousness layer was used to represent the imperviousness of the area. DEM data were used to identify the drainage area and drainage slope.

Sidewalks were 1.83 m width on each side of roads (including roads with width of 4m, 10m; excluding highway, which had road width of 16 m). Driveways were assumed to be 1.6% of low density residential area. Parking lot was assumed to be a portion of residential area (8.63%), industrial area (7.70%), and commercial area (73.67%) (Davis et al., 2010). All houses in low density residential areas were assumed to have patios; and the suitable area for patios was assumed to be 12.5% of a certain area (4.57 m buffer around the houses) in low density residential area.

Pollutant loads from the watershed were estimated using event mean concentration (EMC) (Liu et al., 2015). According to the Upper White River Watershed Regional Watershed Assessment and Planning Report (Tedesco et al., 2011), the pollutants of concern, which can be simulated in the L-THIA-LID 2.1 model, included Total Nitrogen (TN), Total Phosphorus (TP), Total Suspended Solids (TSS), Lead (Pb), Biochemical Oxygen Demand (BOD), and Chemical Oxygen Demand (COD). Therefore, those pollutants were analyzed in this study.

4.4.3 Model calibration/validation

After simulating runoff volume and pollutant loads by running the L-THIA-LID 2.1 model with input data of land use data, hydrologic soil group data, and daily rainfall data, the model was calibrated and validated for runoff volume. The model was not calibrated and validated for water quality due to limited water quality data available for the watershed, and collection of sufficient water quality data was not possible within this project. The L-THIA-LID 2.1 model estimates pollutant loads based on the product of runoff volume and EMC (event mean concentration) values prior to implementing BMPs/LID practices. The model has been shown to perform well in estimating pollutant loads (e.g., Ahiablame et al., 2013; Tang et al., 2005). In this study, the calibrated and validated runoff volume values would be expected to contribute to reasonable water quality results.

The following process was followed to calibrate and validate the model for runoff volume.

4.4.3.1 Calibration

The simulated annual runoff was calibrated with data for the period of 1993 to 2001. First, the runoff from the area of roof tops, patio, road, driveway, sidewalk, and parking lot in each combination of land uses and hydrologic soil groups was calculated. The non-impervious parts of low density residential (LDR), high density residential (HDR), industrial, and commercial land uses were reassigned, as follows. For the other parts of land uses, LDR land use was reassigned to 94.86% of grass and 5.14% of woods; HDR land use was reassigned to grass; industrial land use was reassigned to 87.11% of grass and 12.89% of woods; and commercial land use was reassigned to 86.58% of grass and 13.42% of woods. Then, the runoff from each specific land use (including roof tops, patio, road, driveway, sidewalk, parking lot, forest/woods, grass/pasture, agriculture, and water/wetland) was summed to obtain total runoff.

Second, the primary BMPs and LID practices currently implemented in the watershed were simulated. The primary BMPs and LID practices currently implemented in the watershed were retention ponds (wet ponds). To calibrate the model, retention ponds were simulated in the watershed. Based on aerial photos, water body layer, and land use layer of the watershed, the percentage of each land use area with retention ponds implemented was calculated. Based on the results, it was assumed that retention ponds were applied in 60% of high intensity areas (including high density residential, commercial, and industrial areas), 50% of low intensity areas (low density residential areas), 95% of water/wetland areas, and 40% of other areas (including forest/woods, agricultural, and grass/pasture areas).

Third, Curve Numbers were increased or decreased simultaneously if necessary by 1% per model run until the best match in predicted and observed runoff was obtained to maintain consistency among CN value relationships.

Fourth, the simulated annual runoff volume was compared with observed runoff volume, which was obtained by applying the Baseflow Filter Program (BFLOW) (Arnold and Allen, 1999) to streamflow data. The performance of the model was analyzed by computing Percent Bias (PBIAS), R^2 and Nash-Sutcliffe efficiency coefficient (NSE).

4.4.3.2 Validation

After calibration, the model was validated for annual runoff volume with 9 years (2002-2010) of daily rainfall data and streamflow data. Percent Bias (PBIAS), R^2 and NSE were also calculated.

4.4.4 Simulation of additional BMPs and LID practices starting from current situation

BMPs and LID practices, including green roof, rain barrel/cistern, bioretention system, porous pavement, permeable patio, grass strip, grassed swale, wetland channel, retention pond, detention basin, and wetland basin, were applied in the watershed using the framework for simulating BMPs and LID practices at watershed scales (section 2.2.1). In addition, the costs of implementing BMPs and LID practices were evaluated.

After determining whether an HRU was suitable to implement LID practices, the scenarios of implementing different percentages of BMPs and LID practices were simulated from 1993 to 2010, as shown in Table 4.2. The baseline of the simulation (baseline or scenario 0) was when there was only retention ponds implemented in the area. The other fifteen scenarios were to implement various combinations and levels of BMPs and LID practices starting from the baseline situation. S1 installed green roof in 25% of roof tops in commercial and industrial areas. S2 implemented rain barrel/cistern in 25% of all roof top areas. S3 installed 25% green roof in commercial and industrial areas and 25% rain barrel/cistern in other urban areas. S4 implemented green roof and rain barrel/cistern in series starting from S1, where it was suitable for applying green roof. This means that S4 implemented green roof and rain barrel/cistern in series to 25% roof tops in commercial and industrial areas. All other practices were implemented in various percentages of the suitable locations.

Table 4.2 Scenarios for implementing different percentages of BMPs and LID practices

	S0 (%)	S1 (%)	S2 (%)	S3 (%)	S4 (%)	S5 (%)	S6 (%)	S7 (%)	S8 (%)	S9 (%)	S10 (%)	S11 (%)	S12 (%)	S13 (%)	S14 (%)	S15 (%)
Green roof	0	25	0	25	0	0	0	0	0	0	0	0	0	0	0	0
Rain barrel/cistern	0	0	25	25	0	0	0	0	0	0	0	0	0	0	0	0
Green roof with rain barrel/cistern	0	0	0	0	25	0	0	0	0	0	0	0	0	0	25	50
Bioretention system	0	0	0	0	0	25	0	0	0	0	0	0	0	0	25	50
porous pavement	0	0	0	0	0	0	25	0	0	0	0	0	0	0	25	50
permeable patio	0	0	0	0	0	0	0	25	0	0	0	0	0	0	25	50
Grass strip	0	0	0	0	0	0	0	0	25	0	0	0	0	0	25	50
Grassed swale	0	0	0	0	0	0	0	0	0	25	0	0	0	0	25	50
Wetland channel	0	0	0	0	0	0	0	0	0	0	25	0	0	0	25	50
Retention pond	b	b	b	b	b	b	b	b	b	b	b	70	b	b	70	80
Detention basin	0	0	0	0	0	0	0	0	0	0	0	0	5	0	5	10
Wetland basin	0	0	0	0	0	0	0	0	0	0	0	0	0	5	5	10

The total cost (Tc) to implement BMPs and LID practices was estimated for each scenario to find the total cost of each scenario. Design life of BMPs and LID practices used in the computation was 20 years based on previous studies (Schueler, 1992; Brown and Schueler, 1997; CWP, 1997; USEPA, 1999, 2006, 2012a, and 2012b; PSBMPM, 2006a and 2006b; EBRP, 2007; NCDENR, 2007; LIDMM, 2008; CNT, 2009; King and Hagan, 2011; TRC and CVC, 2011), and the interest rate used was 4.5% in the computation. Cost per unit reduction per year was estimated to find the more cost effective scenarios.

4.5 Results and discussion

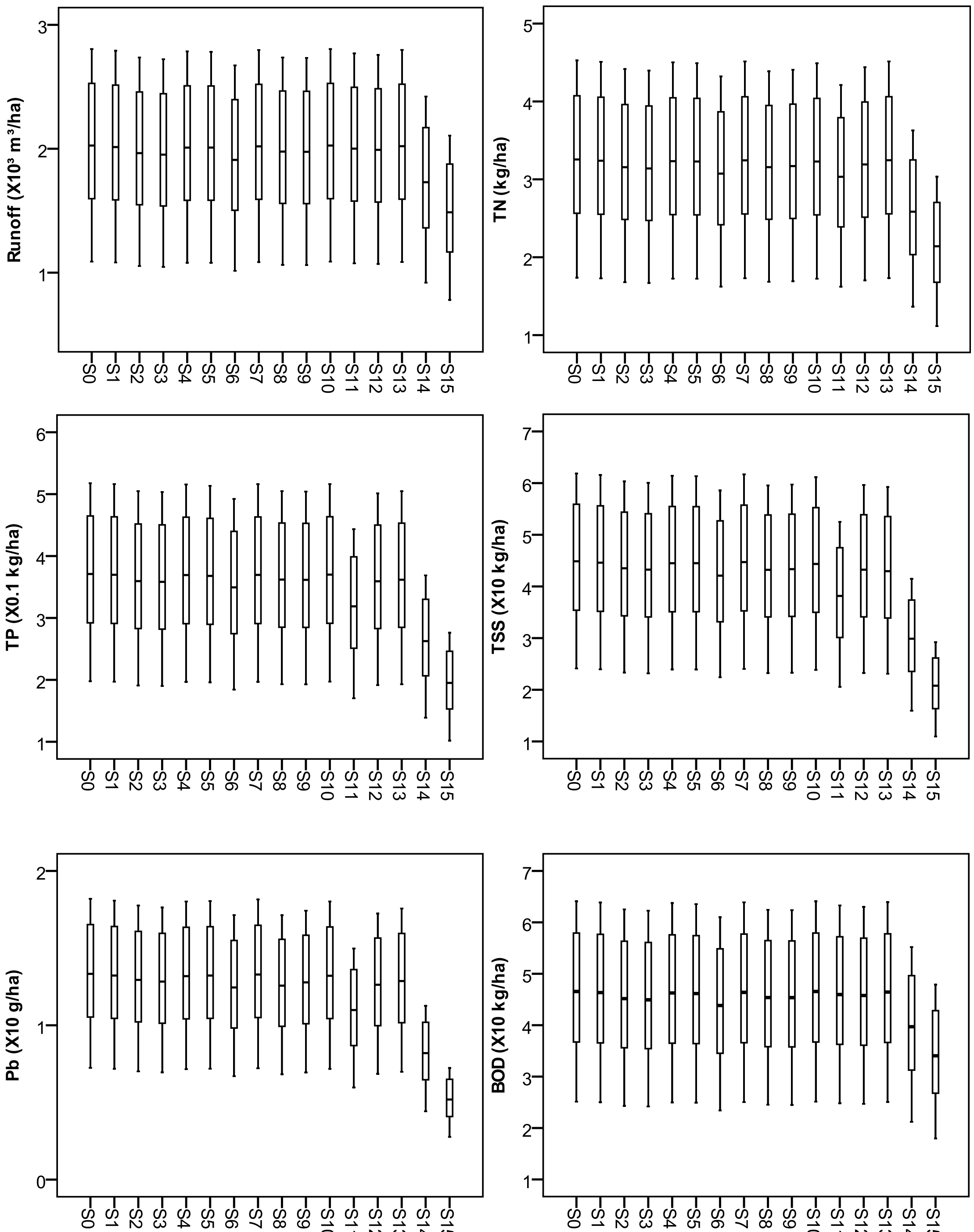
4.5.1 Calibration and validation

The L-THIA-LID 2.1 model was calibrated for the period 1993 to 2001. A decrease of CN values by 1% provided the best match in modeled and observed runoff. Then, the model was validated with data from years 2002 to 2010. With values of $R^2 \geq 0.5$ and $0 \leq NSE \leq 1$, model performance has been generally regarded to indicate acceptable level (Santhi et al., 2001; Moriasi et al., 2007). Values of $R^2 \geq 0.6$ and $NSE \geq 0.5$ were indicated as a good model performance (Engel et al., 2007). The values of R^2 for annual runoff after calibration and validation were 0.63 and 0.61, respectively. The NSE values for calibration and validation were 0.56 and 0.58, respectively. Results indicate that R^2 values were over 0.6, and NSE values were over 0.5. PBIAS values for calibration and validation were 9.9% and -4.6%, respectively. The PBIAS value for annual runoff volume from 1993 to 2010 was 1.6%. Based on the results, one can conclude that the L-THIA-LID 2.1 model can satisfactorily predict annual runoff for this watershed.

4.5.2 Performance of BMPs and LID practices

The estimated and observed annual runoff for the baseline scenario (S0) was shown in Table A.3. The simulated annual runoff fluctuated between 1089 and 2805 m^3/ha/yr for the watershed. The simulated annual runoff was consistent with Ahiablame et al.'s (2013) modeling results in two urbanized watersheds (near the study watershed in this paper), which showed a variation between 1000 and 4000 m^3/ha/yr for runoff from 1991 to 2010. No significant difference was found between average simulated annual runoff (2032 m^3/ha) and average observed annual runoff (2000 m^3/ha). The simulated annual runoff values for 2003 and 2008 were larger than those of other years. This can be explained as the result of abundant rainfall in those two years.

Annual nutrient loads (Table A.3) varied between 1.74 and 4.53 kg/ha for TN, and between 0.20 and 0.52 kg/ha for TP. Annual TSS loads (Table A.3) ranged from 24.12 to 61.87 kg/ha. Annual Pb loads (Table A.3) ranged between 7.24 and 18.20 g/ha. Annual organic compound loads ranged between 25.14 and 64.10 kg/ha for BOD, and between 42.77 and 106.61 kg/ha for COD. The simulated TP and TN loads in this study were consistent with the results of other studies conducted in nearby urbanized watersheds (Bhaduri et al., 2000; Ahiablame et al., 2013), which found annual TN loads of 3.0 to 12.0 kg/ha, and annual TP loads of 0.36 to 2.0 kg/ha. However, no directly applicable studies were found to compare the results of other pollutants.


Runoff (X10³ m³/ha)
TN (kg/ha)
TP (X0.1 kg/ha)
TSS (X10 kg/ha)
Pb (X10 g/ha)
BOD (X10 kg/ha)
S0
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
S15

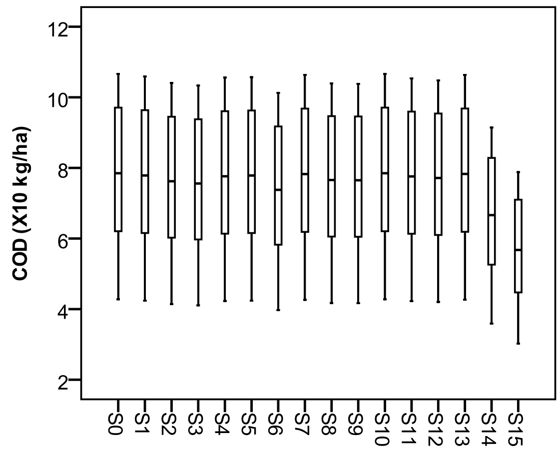


Figure 4.2 Boxplots of annual runoff and pollutant loads for all scenarios.

The low end and upper end of whiskers in boxplots represent the minimum and maximum of datasets when no outliers exist. When there are outliers, the low and upper ends of whiskers show 1.5IQR (interquartile range) beyond lower and upper quartiles. From the boxplots in Figure 4.2, which showed no outliers, the ends of whiskers represented the minimum and maximum values of annual runoff volume and pollutant loads in each scenario.

Table 4.3 Percent reduction of runoff volume and pollutant loads after simulating scenarios compared to baseline scenario (S0)

	Runoff (%)	TN (%)	TP (%)	TSS (%)	Pb (%)	BOD (%)	COD (%)
S1	0.59	0.48	0.32	0.58	0.79	0.45	0.78
S2	2.92	2.95	2.98	2.91	2.84	2.91	2.81
S3	3.50	3.43	3.30	3.49	3.63	3.35	3.59
S4	0.80	0.66	0.44	0.80	1.08	0.61	1.07
S5	0.82	0.81	0.83	0.82	0.82	0.85	0.83
S6	5.62	5.49	5.74	6.10	6.55	5.72	5.91
S7	0.33	0.34	0.38	0.33	0.30	0.36	0.30
S8	2.41	3.05	2.44	3.69	5.75	2.51	2.46
S9	2.51	2.62	2.55	3.41	4.14	2.61	2.56
S10	0	0.82	0.27	1.16	0.92	0	0
S11	1.24	6.86	14.11	14.97	17.60	1.25	1.15
S12	1.71	1.96	3.17	3.62	5.29	1.71	1.71
S13	0.26	0.30	2.50	4.25	3.48	0.26	0.26
S14	14.51	20.53	29.18	33.36	38.48	14.65	15.03
S15	26.47	34.20	47.41	53.59	60.98	26.70	27.52

Figure 4.2 presents the boxplots of annual runoff volume and pollutant loads for all scenarios. The variations of annual runoff volume and pollutant loads in each scenario were due to different precipitation amounts each year. The range of annual runoff volume and pollutant loads for scenarios 14 and 15 were the smallest compared to those of other scenarios because the high level of implementation of BMPs and LID practices reduced runoff and pollutant loads more in wet years than they did in dry years. The mean values of annual runoff volume and pollutant loads for each scenario were slightly larger than the median values, which meant the distributions were positively skewed. Tukey tests with significance level of 0.05 showed that for estimated mean runoff volume, BOD, and COD, S14 and S15 were not significantly different from other scenarios; while predicted mean TN, TP, TSS, and Pb, for S14 and S15 were significantly different from other scenarios. The mean values of annual runoff volume and pollutant loads varied because of implementing different combinations of BMPs and LID practices.

The impacts of implementing BMPs and LID practices on hydrology and water quality are shown in Table 4.3, represented as the percent reduction of runoff volume and pollutant loads after simulating different planning scenarios compared to the baseline scenario (S0).

The implementation of 25% green roof (S1 in Table 4.3) resulted in the reduction of runoff volume and pollutant loads between 0.32% and 0.79%. The implementation of 25% rain barrel/cistern (S2 in Table 4.3) resulted in reduction of runoff volume and pollutant loads between 2.81% and 2.98%. It was assumed that all of the roof tops were suitable to implement rain barrel/cistern, while only roof tops in commercial and industrial areas were able to apply green roof. This made the area of suitable roof top to apply green roof much smaller than that of rain barrel/cistern. Together with the fact that curve numbers representing green roof and rain barrel/cistern in the L-THIA-LID 2.1 model were the same, this resulted in S2 performing better than S1. The implementation of 25% rain barrel/cistern and 25% green roof (S3 in Table 4.3) led to the reduction of runoff volume and pollutant loads between 3.30% and 3.63%. Each percent reduction in S3 was equal to the sum of corresponding reductions in S1 and S2. This was because it was assumed that green roof and rain barrel/cistern were implemented in parallel, which meant there was no green roof combined with rain barrel/cistern. The implementation of 25% green roof with rain barrel/cistern (S4 in Table 4.3) reduced runoff volume and pollutant loads between 0.44% and 1.08%. Green roof with rain barrel/cistern only covered roof tops in commercial and industrial areas. Compared to the reductions of runoff volume and pollutant loads in S1, the reductions in S4 were more obvious because of applying green roof and cisterns in series. A modeling study conducted in a watershed located in Texas also found that green roof and rain barrel/cistern can significantly control stormwater for small rainfall events; the implementation of LID practices by combining them together performed better than applying them alone (Damodaram et al., 2010). In field studies, green roof was found to be efficient in reducing runoff volume, nutrients, heavy metals, and total suspended solids (VanWoert et al., 2005; Berndtsson et al., 2009; Vijayaraghavan et al., 2012; Kok et al., 2013; Speak et al., 2013). Rain barrel/cistern was also found helpful in reducing runoff and pollutant loads in field studies (Jones and Hunt, 2010; Jennings et al., 2012).

The implementation of 25% porous pavement (S6 in Table 4.3) and 25% permeable patio (S7 in Table 4.3) resulted in reduction of runoff volume and pollutant loads from 5.49% to 6.55%, and from 0.30% to 0.38%, respectively. Porous pavement was found to be able to reduce a variety of pollutants, such as total suspended solids, metals, and nutrients (Pagotto et al. 2000; Brattebo and Booth 2003; Bean et al., 2007). Wright et al. (1999) found that permeable patios and porous pavements (including parking lots, streets, and driveways) were attractive choices to mimic the area's pre-development conditions. Considering the curve numbers representing porous pavement and permeable patio were the same, the reductions in S6 were much bigger than the reductions in S7 because the suitable area to implement porous pavement was much bigger compared to the suitable area for permeable patio, and also because only porous pavement was able to reduce pollutant concentration based on the current dataset used in the L-THIA-LID 2.1 model that was generated from data in International Stormwater BMP Database (http://www.bmpdatabase.org/).

Runoff volume and pollutant loads were decreased between 0.81% and 0.85% when implementing 25% of eligible areas with bioretention systems (S5 in Table 4.3). Hunt et al. (2006) found that bioretention system was effective in reducing runoff and nutrients in North Carolina. Bioretention was also shown to be able to reduce heavy metals and total suspended solids (Davis et al., 2001; Fach and Geiger, 2005; Glass and Bissouma, 2005; Davis, 2007; Hunt et al., 2008; Mclntyre et al., 2014). The implementation of 25% grass strip (S8 in Table 4.3) led to the reduction of runoff volume and pollutant loads between

2.41% and 5.75%. Munoz-Carpena et al. (1999) demonstrated the performance of grass strip and found grass strip was efficient in reducing runoff and sediment. Lee et al. (1998) studied the effectiveness of grass strips on water quality, the results showed the effects of grass strips on removing sediments and nutrients were significant.

The implementation of 25% grassed swale (S9 in Table 4.3) and 25% wetland channel (S10 in Table 4.3) resulted in reduction of runoff volume and pollutant loads from 2.51% to 4.14%, and from 0% to 1.16%, respectively. Stagge et al. (2012) demonstrated the performance of grass swales with experimental methods to measure pollutant concentrations in inflow and outflow, which found that grass swales significantly reduced TSS and metals. Wetland channel was able to use natural vegetation growth to treat stormwater quality (Prince George's County, 1999). Winston et al. (2010) studied the effects of roadside wetland channel on stormwater treatment, which indicated significant reductions of nutrients and sediments. The results in this study (S9 and S10 in Table 4.3) indicated that grassed swale performed better than wetland channels, which meant grassed swale was a better choice to convey runoff compared to wetland channel without considering the cost of implementation.

The implementation of 70% retention pond (S11 in Table 4.3) resulted in the reduction of runoff volume and pollutant loads between 1.15% and 17.60%. The implementation of 5% detention basin (S12 in Table 4.3) and 5% wetland basin (S13 in Table 4.3) led to the reduction of runoff volume and pollutant loads from 1.71% to 5.29%, and from 0.26% to 4.25%, respectively. Retention pond, detention basin, and wetland basin were useful to treat stormwater runoff at the end of drainage areas (Revitt et al., 2004; The LIDC et al., 2006; Reinoso et al., 2008; Gilroy, 2009; Wang et al., 2014). Comings et al. (2000) evaluated the performance of two retention ponds in Bellevue, WA, finding significant reductions of sediments, nutrients, and metals. Stanley (1996) studied a detention pond in Greenville, NC, and found that the detention pond was useful to reduce runoff, TSS, nitrogen, phosphorus, and metals. The performance of wetland basin in removing pollutants (Carleton et al., 2000) was studied in northern Virginia, which showed that wetland basin was capable of reducing TSS, nutrients, and metals. Some reductions in S12 were bigger than that of S13 (such as runoff volume), while other reductions in S12 were smaller than that of S13 (for example TSS). This meant that choice of detention basin or wetland basin depended on the specific pollutants of concern and the cost of implementing practices.

The implementation of S14 (Table 4.3) and S15 (Table 4.3) resulted in the reduction of runoff volume and pollutant loads from 14.51% to 38.48%, and from 26.47% to 60.98%, respectively. This was expected because with more BMPs and LID practices implemented in the watershed, more runoff was collected, stored, infiltrated, filtrated, evaporated, or treated, resulting in a more significant environmental impacts.

Although the percent reductions of runoff volume and pollutant loads in scenarios from S1 to S13 were small, they were significant considering the percentage of area implementing BMPs and LID practices in the planning scenarios. BMPs and LID practices in these scenarios only treated runoff from a relatively small percentage of the overall area. Zimmerman et al. (2010) found that the decrease of impervious area due to implementing LID practices was not high enough to greatly affect runoff for large watersheds, while small area simulation indicated that LID practices had a substantial effect on runoff. In S14 and S15, by implementing a large numbers of BMPs and LID practices in series at a watershed scale, the effectiveness of BMPs and LID practices on hydrology and water quality became discernible.

4.5.3 Cost-efficient scenario of implementing BMPs and LID practices

The total cost of implementing BMPs and LID practices for 20 years in each scenario, and the results of cost per unit reduction per year for each scenario are shown in Table 4.4. Although BMP/LID practices provided reductions of runoff volume and multiple pollutants, all costs presented in Table 4.4 were attributed only to runoff volume or one pollutant when estimating cost per unit reduction per year.

From Table 4.4, the total cost of S15 was the most among all scenarios because more BMPs and LID practices were implemented in S15. Although rain barrel/cistern (S2) treated much more area of roof tops than that of green roof (S1), the total cost of S2 was lower than S1 because rain barrel/cistern was less costly to implement. The total cost of S3 was the sum of the total cost of S1 and S2. The total cost of S4 was lower than that of S3 because the total area suitable to implement green roof and rain barrel/cistern in series was smaller than the total area suitable to implement green roof and rain barrel/cistern separately. Grassed swale (S9) and wetland channel (S10) cost the same, but grassed swale performed better than wetland channel in reducing runoff volume and pollutant loads, which meant grassed swale was a better choice considering cost. Wetland basin (S13) cost more than detention basin (S12). However, the performance of S13 in reducing runoff volume and pollutant loads was not always better than that of S12. Therefore, to evaluate the cost-effectiveness of different scenarios, cost per unit reduction per year values needed to be compared.

The implementation of grass strips in 25% of the watershed where this practice could be applied (S8) had the lowest cost per unit reduction per year values (Table 4.4) of $1 per m^3/yr for runoff, $23 per kg/yr for COD, $38 per kg/yr for BOD, $27 per kg/yr for TSS, $445 per kg/yr for TN, $4,871 per kg/yr for TP, and $57,690 per kg/yr for Pb, and was the most cost-efficient scenario. By applying green roof and cisterns in series, S4 reduced more runoff volume and pollutant loads than S1 (only green roof applied) did (Table 4.3). At the same time, implementing green roof and cisterns in series (S4) increased the cost-effectiveness (Table 4.4) compared to S1. Although permeable patio (S7) cost less than porous pavement (S6), S6 was more cost-efficient in reducing runoff volume and pollutant loads. The better performance of S9 in reducing runoff volume and pollutant loads compared to that of S10 (Table 4.3), together with the lower values of cost per unit reduction per year for S9, indicated that grassed swale was a more favorable practice than wetland channel in this watershed. In comparison to S12, S13 was more cost-efficient in reducing TSS. However, S12 was more cost-effective in reducing runoff volume and other pollutant loads.

Table 4.3 shows that S15 reduced runoff volume and pollutant loads the most among all scenarios. However, cost per unit reduction per year values of S15 in reducing runoff volume and pollutant loads (Table 4.4) were higher than cost per unit reduction per year values of most other scenarios. This indicated that S15 was not as cost-efficient as most other scenarios because the high level implementation of BMPs and LID practices in series would not reduce runoff volume or pollutant loads as much as the sum of each practice alone; this meant that after runoff volume and pollutant concentrations were reduced to a certain level by one BMP/LID practice, runoff quantity and quality cannot be reduced as much or at all when flowing into the next BMP/LID practice. In comparison to S14, which was a scenario similar to S15, S15 reduced runoff volume and pollutant loads more but had bigger values of cost per unit reduction per year, indicating that although the higher implementation percentage of BMPs and LID practices in S15 reduced runoff volume and pollutant loads more than S14, S15 was not as cost-efficient.

In this study, the benefits of implementing BMPs and LID practices only estimated reductions in runoff volume and certain pollutants; however, there were other benefits that were not quantified. For example, the benefits of BMPs/LID practices in enhancing infiltration and groundwater recharge, and reducing peak runoff and other pollutants were not considered in this paper. Some practices, such as bioretention systems, retention ponds, wetland basins, and wetland channels, can enhance site aesthetics and provide habitat for wildlife. Rain barrel/cistern and retention pond not only reduced runoff volume and pollutants, they also collected water that can be used for landscaping and other purposes.

It was assumed that the implementation of each BMP/LID practice was a replacement or addition. For practices such as patios and pavement (roads, sidewalks, parking lots, and driveways), which would be implemented in an area no matter whether they were traditional or permeable, the cost of runoff and pollutant reductions computed for implementing permeable patio and porous pavement would be less than the findings in this study as costs would be based on cost difference between the conventional and LID version of the practice.

Table 4.4 Total cost of implementing BMPs and LID practices and cost per unit reduction per year for each scenario

	Total Cost (1000 $)	Runoff ($/m^3/yr)	TN ($/kg/yr)	TP ($/kg/yr)	TSS ($/kg/yr)	Pb ($/kg/yr)	BOD ($/kg/yr)	COD ($/kg/yr)
S1	167769	137	104331	1374778	6231	15515134	7868	2658
S2	22228	4	2249	19490	166	571686	160	98
S3	189997	26	16534	150488	1179	3823234	1184	656
S4	173199	104	78867	1039239	4710	11728399	5948	2010
S5	29842	18	10982	94130	789	2652407	733	446
S6	193536	17	10524	88210	688	2158679	707	406
S7	48387	71	42483	335993	3162	11732108	2793	2006
S8	4543	1	445	4871	27	57690	38	23
S9	12975	2	1477	13327	82	228584	104	63
S10	12975	N/A	4729	127169	243	1027929	N/A	N/A
S11	43497	17	1893	8066	63	180459	728	467
S12	13195	4	2005	10906	79	182148	161	95
S13	14506	27	14547	15199	74	304358	1167	693
S14	546654	18	7946	49038	355	1037132	779	451
S15	1072646	19	9357	59219	434	1284134	839	484

4.6 Conclusions

Implementation of BMPs and LID practices, including green roof, rain barrel/cistern, bioretention system, porous pavement, permeable patio, grass strip, grassed swale, wetland channel, retention pond, detention basin, and wetland basin, were simulated in series for Crooked Creek watershed from 1993 to 2010 using the L-THIA-LID 2.1 model. The L-THIA-LID 2.1 model was calibrated and validated for runoff volume. A framework for simulating BMPs and LID practices at watershed scales was created, and the impacts of BMPs and LID practices on water quantity and water quality were evaluated for 16 scenarios. The total cost to implement BMPs and LID practices was estimated for each scenario. Cost per unit reduction per year was estimated to find the more cost effective scenarios.

The L-THIA-LID 2.1 model was calibrated for annual runoff from 1993 to 2001 and validated from year 2002 to 2010. R^2 values were over 0.6 and NSE values were over 0.5 for annual runoff after calibration and validation. The results showed that various levels and combinations of BMPs and LID practices had different levels of effectiveness on water quantity and quality at the watershed scale. The variations of annual runoff volume and pollutant loads for scenarios 14 (high level of BMP and LID practice adoption) and 15 (very high level of BMP and LID practice adoption) were the smallest compared to those of other scenarios. The various levels and combinations of BMPs and LID practices reduced runoff volume by 0 to 26.47%, Total Nitrogen (TN) by 0.30 to 34.20%, Total Phosphorus (TP) by 0.27 to 47.41%, Total Suspended Solids (TSS) by 0.33 to 53.59%, Lead (Pb) by 0.30 to 60.98%, Biochemical Oxygen Demand (BOD) by 0 to 26.70%, and

Chemical Oxygen Demand (COD) by 0 to 27.52%. Although the percent reductions of runoff volume and pollutant loads in scenarios from S1 to S13 were small, they were significant considering the percentage of area affected by BMPs and LID practices. With more BMPs and LID practices implemented in scenarios 14 (high level of BMP and LID practice adoption) and 15 (very high level of BMP and LID practice adoption), the effectiveness became more discernible. The implementation of grass strips in 25% of the watershed where this practice could be applied, with the lowest cost per unit reduction per year values of \$1 per m^3/yr for runoff, \$23 per kg/yr for COD, \$38 per kg/yr for BOD, \$27 per kg/yr for TSS, \$445 per kg/yr for TN, \$4,871 per kg/yr for TP, and \$57,690 per kg/yr for Pb, was the most cost-efficient scenario. Scenario 15 reduced runoff volume and pollutant loads the most (26.47% to 60.98% reduction), but S15 was not as cost-efficient compared to most other scenarios. Model results presented in this study would apply to other similar watersheds. The L-THIA-LID 2.1 model, which can be applied to other locations, is a valid tool to help obtain cost effective BMP and LID practice plans at watershed scales.

Additional calibration and validation of the model, including for water quality, should be pursued to further demonstrate its utility. Additional exploration of the effectiveness of BMPs and LID practices on hydrology and water quality in a watershed is needed. In addition, opportunities to select and place various levels and combinations of BMPs and LID practices to obtain the maximum environmental benefits with minimum cost at watershed scales should be explored.

4.7 References

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012. Representation and evaluation of low impact development practices with L-THIA-LID: An example for site planning. Environment and Pollution, 1(2). doi:10.5539/ep.v1n2p1.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement. Journal of environmental management, 119, 151-161.

Arnold, J.G., Allen, P.M., 1999. Automated methods for estimating baseflow and ground water recharge from streamflow records1. Journal of the American Water Resources Association, 35(2), 411-424.

Arabi, M., Govindaraju, R.S., Hantush, M.M., 2006. Cost-effective allocation of watershed management practices using a genetic algorithm. Water Resources Research, 42(10).

Autixier, L., Mailhot, A., Bolduc, S., Madoux-Humery, A. S., Galarneau, M., Prévost, M., Dorner, S., 2014. Evaluating rain gardens as a method to reduce the impact of sewer overflows in sources of drinking water. Science of The Total Environment, 499, 238-247.

Barbosa, A. E., & Hvitved-Jacobsen, T., 1999. Highway runoff and potential for removal of heavy metals in an infiltration pond in Portugal. Science of the Total Environment, 235(1), 151-159.

Bean, E.Z., Hunt, W.F., Bidelspach, D.A., 2007. Evaluation of four permeable pavement sites in Eastern North Carolina for runoff reduction and water quality impacts. Journal of Irrigation and Drainage Engineering, 133 (6): 583-92.

Berndtsson, C.J., Bengtsson, L., Jinno, K., 2009. Runoff water quality from intensive and extensive vegetated roofs. Ecological Engineering, 30, 271-277.

Bhaduri, B., Harbor, J., Engel, A.B., Grove, M., 2000. Assessing watershed-scale, long-term hydrologic impacts of land-use change using a GIS-NPS model. Environmental Management, 26(6), 643-658.

Brattebo, B.O., Derek, B.B., 2003. Long-term stormwater quantity and quality performance of permeable pavement systems. Water Research, 37 (18): 4369-76.

Brown, W., Schueler, T., 1997. The economics of stormwater BMPs in the Mid-Atlantic Region. Prepared for Chesapeake Research Consortium, Edgewater, MD by Center for Watershed Protection, Ellicott City, MD.

Brun, S.E., Band, L.E., 2000. Simulating runoff behavior in an urbanizing watershed. Computers, Environment and Urban Systems. 24 (1), 5-22.

Carleton, J.N., Grizzard, T.J., Godrej, A.N., Post, H.E., Lampe, L., Kenel, P.P., 2000. Performance of a constructed wetlands in treating urban stormwater runoff. Water Environment Research, 295-304.

CNT (The Center for Neighborhood Technology), 2009. National green values calculator methodology.

Comings, K.J., Booth, D.B., Horner, R.R., 2000. Storm water pollutant removal by two wet ponds in Bellevue, Washington. Journal of Environmental Engineering. 126(4): 321-330.

CWP (Center for Watershed Protection), 1997. Stormwater BMP design supplement for cold climates. Prepared for U.S. Environmental Protection Agency Office of Wetlands, Oceans, and Watersheds, Washington, DC.

Damodaram, C., Giacomoni, M.H., Prakash Khedun, C., Holmes, H., Ryan, A., Saour, W., Zechman, E. M., 2010. Simulation of combined best management practices and low impact development for sustainable stormwater management1. Journal of the American Water Resources Association, 46(5), 907-918.

Davis, A.P., 2007. Field performance of bioretention: Water quality. Environmental Engineering Science, 24 (8): 1048-64.

Davis, A.P., Shokouhian, M., Sharma, H., Minami, C., 2001. Laboratory study of biological retention for urban stormwater management. Water Environment Research, 73 (1): 5-14.

Davis, A.Y., Pijanowski, B.C., Robinson, K., Engel, A.B., 2010. The environmental and economic costs of sprawling parking lots in the United States. Land Use Policy, 27(2), 255-261.

Dietz, M.E., 2007. Low impact development practices: A review of current research and recommendations for future directions. Water, air, and soil pollution, 186(1-4), 351-363.

Dietz, M.E., Clausen, J.C., 2008. Stormwater runoff and export changes with development in a traditional and low impact subdivision. Journal of Environmental Management, 87(4), 560-566.

EBRP (East Baton Rouge Parish), 2007. Stormwater BMPs. http://www.brgov.com/dept/planning/WWS/pdf/bmp5.pdf, accessed May, 2014.

Engel, B.A., Storm, D., White, M., Arnold, J., Arabi, M., 2007. A hydrologic/water quality model application protocol. Journal of the American Water Resources Association, 43(5), 1223-1236.

Engel, B.A., Choi, J.Y., Harbor, J., Pandey, S., 2003. Web-based DSS for hydrologic impact evaluation of small watershed land use changes. Computers and Electronics in Agriculture, 39 (2003):241-249.

Fach, S., Geiger, W.F., 2005. Effective pollutant retention capacity of permeable pavements for infiltrated road runoffs determined by laboratory tests. Water Science and Technology, 51 (2): 37-45.

Gilroy, K.L., McCuen, R.H., 2009. Spatio-temporal effects of low impact development practices. Journal of Hydrology, 367(3), 228-236.

Glass, C., Bissouma, S., 2005. Evaluation of a parking lot bioretention cell for removal of stormwater pollutants. WIT Transactions on Ecology and the Environment, 81: 699.

Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008. Global change and the ecology of cities. Science, 319, 756-760.

Gunderson, J., Roseen, R., Janeski, T., Houle, J., Simpson, M., 2011. Economical CSO management. Stormwater, 12 (3): 10-25.

Harbor, J., 1994. A practical method for estimating the impact of land use change on surface runoff, groundwater recharge and wetland hydrology. Journal of American Planning Association, 60, 91-104.

Hata, A., Katayama, H., Kojima, K., Sano, S., Kasuga, I., Kitajima, M., Furumai, H., 2014. Effects of rainfall events on the occurrence and detection efficiency of viruses in river water impacted by combined sewer overflows. Science of The Total Environment, 468, 757-763.

Hatt, B.E., Fletcher, T.D., Walsh, C.J., Taylor, S.L., 2004. The influence of urban density and drainage infrastructure on the concentrations and loads of pollutants in small streams. Environmental Management, 34, 112-124.

Hunt, W.F., Jarrett, A.R., Smith, J.T., Sharkey, L.J., 2006. Evaluating bioretention hydrology and nutrient removal at three field sites in North Carolina. Journal of Irrigation and Drainage Engineering, 132(6), 600-608.

Hunt, W.F., Smith, J.T., Jadlocki, S.J., Hathaway, J.M., Eubanks, P.R., 2008. Pollutant removal and peak flow mitigation by a bioretention cell in urban Charlotte, NC. Journal of Environmental Engineering, 134 (5): 403-408.

Jennings, A.A., Adeel, A.A., Hopkins, A., Litofsky, A.L., Wellstead, S.W., 2012. Rain barrel–urban garden stormwater management performance. Journal of Environmental Engineering, 139(5), 757-765.

Jones, M.P., Hunt, W.F., 2010. Performance of rainwater harvesting systems in the southeastern United States. Resources, Conservation and recycling, 54(10), 623-629.

King, D., Hagan, P., 2011. Costs of stormwater management practices in Maryland Counties. University of Maryland Center for Environmental Science.

Kok, K.H., Sidek, L.M., Abidin, M.R.Z., Basri, H., Muda, Z.C., Beddu, S., 2013. Evaluation of green roof as green technology for urban stormwater quantity and quality controls. Earth and Environmental Science, 16 (1). IOP Conference Series: 5.

Lee, J.G., Heaney, J.P., 2003. Estimation of urban imperviousness and its impacts on storm water systems. Journal of Water Resources Planning and Management, 129 (5), 419-426.

Lee, K.H., Isenhart, T. M., Schultz, R.C., Mickelson, S.K., 1998. Nutrient and sediment removal by switchgrass and cool-season grass filter strips in Central Iowa, USA. Agroforestry Systems, 44(2-3), 121-132.

LIDMM (Low Impact Development Manual for Michigan), 2008. Southeast Michigan Council of Governments Information Center. http://library.semcog.org/InmagicGenie/DocumentFolder/LIDManualWeb.pdf, accessed May, 2014.

Lim, K.J., Engel, B.A., Muthukrishnan, S., Harbor, J., 2006. Effects of initial abstraction and urbanization on estimated runoff using CN technology1. Journal of the American Water Resources Association, 42(3), 629-643.

Liu, Y., Ahiablame, L.M., Bralts, V.F., Engel, B.A., 2015. Enhancing a rainfall-runoff model to assess the impacts of BMPs and LID practices on storm runoff. Journal of environmental management. 147, 12-23. DOI: 10.1016/j.jenvman.2014.09.005.

McIntyre, J. K., Davis, J. W., Incardona, J. P., Stark, J. D., Anulacion, B. F., Scholz, N. L., 2014. Zebrafish and clean water technology: Assessing soil bioretention as a protective treatment for toxic urban runoff. Science of the Total Environment, 500, 173-180.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the American Society of Agricultural and Biological Engineers, 50 (3), 885-900.

Munoz-Carpena, R., Parsons, J. E., Gilliam, J.W., 1999. Modeling hydrology and sediment transport in vegetative filter strips. Journal of Hydrology, 214(1), 111-129.

NCDENR (North Carolina Department of Environment and Natural Resources), 2007. Stormwater BMP costs. Division of Soil & Water Conservation Community Conservation Assistance Program.

Newcomer, M.E., Gurdak, J.J., Sklar, L.S., Nanus, L., 2014. Urban recharge beneath low impact development and effects of climate variability and change. Water Resources Research, 50(2), 1716-1734.

NPRPD (National pollutant removal performance database), 2007. National pollutant removal performance database: version 3. Center for Watershed Protection. Ellicott City, Md.

NRCS (Natural Resources Conservation Services), 1986. Urban hydrology for small watersheds. Technical Release 55, USDA Natural Resources Conservation Services.

Olang, L.O., Furst, J., 2010. Effects of land cover change on flood peak discharges and runoff volumes: model estimates for the Nyando River Basin, Kenya. Hydrological Processes, 25, 80-89.

Pagotto, C., Legret, M., Le Cloirec, P., 2000. Comparison of the hydraulic behavior and the quality of highway runoff water according to the type of pavement. Water Research, 34 (18): 4446-4454.

Paul, M.J., Meyer, J.L., 2001. Streams in the urban landscape. Annual Review of Ecology and Systematics, 32, 333-365.

Prince George's County, Maryland, 1999. Low-impact development design strategies: An integrated design approach. Department of Environmental Resources, Programs and Planning Division, Largo, MD.

PSBMPM (Pennsylvania Stormwater Best Management Practices Manual), 2006a. BMP 6.4.9: Vegetated Filter Strip. http://www.elibrary.dep.state.pa.us/dsweb/Get/Document-67997/6.4.9%20BMP%20Vegetated%20Filter%20Strip.pdf, accessed May, 2014.

PSBMPM (Pennsylvania Stormwater Best Management Practices Manual), 2006b. BMP 6.6.2: Wet Pond/Retention Basin. http://www.elibrary.dep.state.pa.us/dsweb/Get/Document-68004/6.6.2%20BMP%20Wet%20Pond%20Retention%20Basin.pdf, accessed May, 2014.

Randhir, T., 2003. Watershed-scale effects of urbanization on sediment export: assessment and policy. Water Resources Research, 39 (6), 1-13.

Reinoso, R., Torres, L. A., Becares, E., 2008. Efficiency of natural systems for removal of bacteria and pathogenic parasites from wastewater. Science of the total environment, 395(2), 80-86.

Revitt, D. M., Shutes, R. B. E., Jones, R. H., Forshaw, M., Winter, B., 2004. The performances of vegetative treatment systems for highway runoff during dry and wet conditions. Science of the total environment, 334, 261-270.

Rose, S., Peters, N.E., 2001. Effects of urbanization on streamflow in the Atlanta area (Georgia, USA): a comparative hydrological approach. Hydrological Processes, 15, 1441-1457.

Santhi, C., Arnold, J.G., Williams, J.R., Hauck, L.M., Dugas, W.A., 2001. Application of a watershed model to evaluate management effects on point and nonpoint source pollution. Transactions of the American Society of Agricultural and Biological Engineers, 44 (6), 1559-1570.

Schueler, T.R., 1992. A current assessment of urban best management practices. Metropolitan Washington Council of Governments.

Shoemaker, L., Riverson Jr., J., Alvi, K., Zhen, J.X., Paul, S., Rafi, T., 2009. SUSTAIN—A framework for placement of best management practices in urban watersheds to protect water quality. Fairfax, VA. 3-29, 3-51~3-63.

Speak, A. F., Rothwell, J. J., Lindley, S. J., Smith, C. L., 2013. Rainwater runoff retention on an aged intensive green roof. The Science of the total environment, 461, 28-38.

Stagge, J.H., Davis, A.P., Jamil, E., Kim, H., 2012. Performance of grass swales for improving water quality from highway runoff. Water research, 46(20), 6731-6742.

Stanley, D.W., 1996. Pollutant removal by a stormwater dry detention pond. Water Environment Research, 1076-1083.

Tang, Z., Engel, B.A., Pijanowski, B.C., Lim, K.J., 2005. Forecasting land use change and its environmental impact at a watershed scale. Journal of environmental management, 76, 35-45.

Tedesco, L.P., Hoffmann, J., Bihl, L., Hall, B.E., Barr, R.C., Stouder, M., 2011. Upper White River Watershed regional watershed assessment and planning report.

TRC and CVC (Toronto and Region Conservation Authority and Credit Valley Conservation Authority), 2011. Low impact development stormwater management planning and design guide, Version 1.0.

The LIDC (Low Impact Development Center, Inc.), GeoSyntec Consultants, University of Florida, Oregon State University, 2006. Evaluation of best management practices for highway runoff control. Transportation Research Board, National Research Council.

Thiessen, A.H., 1911. Precipitation averages for large areas. Monthly weather review, 39 (7), 1082-1089.

Urbonas, B., 1994. Assessment of storm water BMPs and their technology. Water Science & Technology, 29(1-2), 347-353.

USEPA (U.S. Environmental Protection Agency), 1999. Preliminary data summary of urban stormwater best management practices. EPA-821-R-99-012, Washington, D.C.

USEPA (U.S. Environmental Protection Agency), 2004. Stormwater Best Management Practice Design Guide: Volume 2. EPA/600/R-04/121A. U.S. Environmental Protection Agency, Office of Research and Development, Washington, DC.

USEPA (U.S. Environmental Protection Agency), 2006. National Pollutant Discharge Elimination System, Dry Detention Ponds. http://cfpub.epa.gov/npdes/stormwater/menuofbmps/index.cfm?action=factsheet_results&view=specific&bmp=67&minmeasure=5, accessed May, 2014.

USEPA (US Environmental Protection Agency), 2008. Reducing Stormwater Costs through Low Impact Development (LID) Strategies and Practices. EPA 841-F-07-006, Nonpoint Source Control Branch, Washington, D.C.

USEPA (U.S. Environmental Protection Agency), 2012a. National Pollutant Discharge Elimination System, stormwater wetland. http://cfpub.epa.gov/npdes/stormwater/menuofbmps/index.cfm?action=factsheet_results&view=specific&bmp=74, accessed May, 2014.

USEPA (U.S. Environmental Protection Agency), 2012b. National Pollutant Discharge Elimination System, wet ponds. http://cfpub.epa.gov/npdes/stormwater/menuofbmps/index.cfm?action=factsheet_results&view=specific&bmp=68&minmeasure=5, accessed May, 2014.

VanWoert, N.D., Rowe, D.B., Andresen, J.A., Rugh, C.L., Fernandez, R.T., Xiao, L., 2005. Green roofs stormwater retention: effects of roof surface, slope, and media depth. Journal of environmental quality, 34, 1036-1044.

Vezzaro, L., Eriksson, E., Ledin, A., Mikkelsen, P. S., 2011. Modelling the fate of organic micropollutants in stormwater ponds. Science of the Total Environment, 409(13), 2597-2606.

Vijayaraghavan, K., Joshi, U.M., Balasubramanian, R., 2012. A field study to evaluate runoff quality from green roofs. Water Research, 46 (4): 1337-1345.

Wang, C. Y., Sample, D. J., & Bell, C., 2014. Vegetation effects on floating treatment wetland nutrient removal and harvesting strategies in urban stormwater ponds. Science of The Total Environment, 499, 384-393.

Winston, R.J., Hunt, W.F., Wright, J.D., 2010. Evaluation of roadside filter strips, dry swales, wet swales, and porous friction course for stormwater treatment. American Society of Civil Engineers, 1258-1269.

Wright, L.T., Heaney, J.P., Sample, D.J., 1999. Integrating functional landscapes with stormwater management systems. Planning Ahead, 1, 101.

Zhang, X., Zhang, M., 2011. Modeling effectiveness of agricultural BMPs to reduce sediment load and organophosphate pesticides in surface runoff. Science of the Total Environment, 409(10), 1949-1958.

Zimmerman, M.J., Waldron, M.C., Barbaro, J.R., Sorenson, J.R., 2010. Effects of low-impact-development (LID) practices on streamflow, runoff quantity, and runoff quality in the Ipswich River Basin, Massachusetts: A summary of field and modeling studies. US Department of the Interior, US Geological Survey.

CHAPTER 5. OPTIMAL SELECTION AND PLACEMENT OF BMPS AND LID PRACTICES WITH L-THIA-LID 2.1 MODEL

5.1 Abstract

Best management practices (BMPs) and low impact development (LID) practices are used to reduce the negative impacts of urbanization on hydrology and water quality. To obtain maximum environmental benefits with minimum cost, a decision support tool, which linked the Long-Term Hydrologic Impact Assessment-Low Impact Development 2.1 (L-THIA-LID 2.1) model with A Multi-ALgorithm Genetically Adaptive Multiobjective (AMALGAM) method using the multilevel spatial optimization (MLSOPT) framework, was developed to optimally select and place BMPs/LID practices. The decision support tool was applied in Crooked Creek watershed, Indiana, USA. Optimization results of hydrologic response unit scale indicated that for sites with different features, the optimal BMP/LID practice solutions to attain the same environmental goals would be different. For sites with the same characteristics, the optimal implementation of practices could vary significantly for different environmental goals. For higher expenditures, the implementation levels and types of favored practices tended to increase relative to those for lower expenditures. Results showed that for initial expenditures of practices, the environmental benefits increased rapidly as expenditures increased. However, beyond certain expenditure levels, additional spending did not result in noticeable additional environmental impacts. Compared to random placement of

practices, the optimization strategy provided 3.9 to 7.7 times the level of runoff/pollutant load reductions for the same expenditures. To obtain the same environmental benefits, costs of random practices placement were 4.2 to 14.5 times the optimized practice placement cost. The decision support tool is capable of supporting decision makers in optimally selecting and placing BMPs and LID practices at watershed scales.

5.2 Introduction

Best management practices (BMPs) and low impact development (LID) practices are two effective measures used to reduce the adverse impacts of urbanization on hydrology and water quality. BMPs and LID practices can treat and control runoff and pollutants generated by stormwater. In comparison to BMPs (such as wetland basins and retention ponds), which are large scale treatment facilities with big drainage areas, LID practices (such as green roof and rain barrel/cistern) are localized measures that treat stormwater runoff close to the source with relatively small drainage areas (Prince George's County, 1999; The LIDC et al., 2006; Dietz, 2007; USEPA, 2008; Gilroy, 2009; Damodaram et al., 2010; Ando and Freitas, 2011; Newcomer et al., 2014).

The planning strategies for implementing BMPs and LID practices at watershed scales incorporate conflicts among environmental concerns and economic considerations. The possible types, locations, and levels at which to apply BMPs/LID practices at a watershed scale are numerous because of the complexity of land uses, soil properties, and site characteristics of the watershed. Therefore, it is not feasible to identify the performances of all potential combinations of BMP and LID practice scenarios at watershed scales. The conflict among environmental considerations and economic concerns make it complex to solve the problem. For example, implementing additional practices in a given area would likely have increased environmental benefits; however, the cost to construct and maintain BMPs and LID practices would increase at the same time. Since watershed management projects usually have limited budgets or an explicit environmental impact goal, an efficient systematic approach is needed for decision makers to optimally select and place BMPs and LID practices by comparing tradeoffs among environmental impacts and economic considerations.

To obtain maximum environmental benefits at minimum cost, spatial optimization has become a popular multi-objective method that has tradeoff solutions to select and place BMPs and LID practices at watershed scales (e.g. Srivastava et al., 2002; Gitau et al., 2004; Bekele and Nicklow, 2005; Maringanti et al., 2009, 2011; Rodriguez et al., 2011). Spatial optimization solves optimization problems by combining simulation models with optimization algorithms. The optimization algorithms generate sample populations of possible placement scenarios, while the hydrology/water quality model computes the objective functions with the sample populations created to obtain optimal results. However, most spatial optimization methods require significant computational time to complete the model simulations due to the complexity of optimization problems (Arabi et al., 2006).

The multilevel spatial optimization (MLSOPT) framework (Cibin, 2013), which has two levels to be completed in sequence, was developed to reduce computational complexity of optimization with parallel computing. The MLSOPT framework was found to have good performance in optimal front convergence and computing time at watershed scales (Cibin, 2013). The selection of optimization algorithms is vital in spatial optimization to ensure convergence of the objective functions. Single or multi-optimization algorithms can be run repeatedly to compare results and find the best solution. A Multi-ALgorithm Genetically Adaptive Multiobjective (AMALGAM) method (Vrugt and Robinson, 2007) is a multi-algorithm method and has been found to be more efficient than single algorithm methods (Zhang et al., 2010). AMALGAM uses self-adaptive offspring creation to combine the strengths of multiple optimization algorithms (Vrugt and Robinson, 2007).

The Long-Term Hydrologic Impact Assessment-Low Impact Development 2.1 (L-THIA-LID 2.1) model has been created to evaluate the impacts of BMPs and LID practices on hydrology and water quality at watershed scales with the ability to estimate the total expenditure (Liu et al., 2015b), but optimal selection and placement of practices considering environmental and economic concerns using L-THIA-LID 2.1 model has not been studied. The MLSOPT framework and AMALGAM were combined to optimize stover removal rates with minimum environmental influences (Cibin, 2013), but they have never been combined to optimally select and place BMPs and LID practices. A decision support tool, which can help decision makers determine the most cost efficient implementations of BMPs and LID practices in reducing runoff volume and pollutant loads by linking the L-THIA-LID 2.1 model with AMALGAM using the MLSOPT framework needs to be explored. While other researchers have optimized the selection and placement of a small number of practices (e.g. Srivastava et al., 2002; Gitau et al., 2004; Bekele and Nicklow, 2005; Maringanti et al., 2009, 2011; Rodriguez et al., 2011), the implementation of the following group of BMPs/LID practices, including permeable patio, grassed swale, green roof, bioretention system, rain barrel, cistern, porous pavement, grass strip, wetland channel, wetland basin, retention pond, and detention basin, has not been optimized at watershed scales in urban areas.

The objectives of this study were to: (1) develop a decision support tool to optimally select and place BMPs and LID practices by linking the L-THIA-LID 2.1 model with AMALGAM using the MLSOPT framework; (2) demonstrate the use of the tool to optimize watershed scale implementation of BMPs and LID practices; and (3) compare optimization results with the findings of random BMP and LID practice implementation scenarios in the same watershed.

5.3 Materials and methods

5.3.1 Study area

The study area was Crooked Creek watershed, which is a highly urbanized watershed in central Indiana, USA with a 5,129 ha drainage area. The locations of Crooked Creek Watershed and hydrologic response units (HRUs) are shown in Figure 5.1. HRUs are areas with the same land uses and hydrologic soil groups. The characteristics of HRUs in the watershed are shown in Table 5.1. The watershed, which has about 72.04% low density (LD) residential area, 6.92% high density (HD) residential area, 6.12% commercial area, and 2.63% industrial area, is an urban watershed. The current water quality threats to the watershed, as reported in Upper White River Watershed Regional Watershed Assessment and Planning Report (Tedesco et al., 2011), include Total Nitrogen (TN), Total Phosphorus (TP), Total Suspended Solids (TSS), Lead (Pb), Biochemical Oxygen Demand (BOD), and Chemical Oxygen Demand (COD).

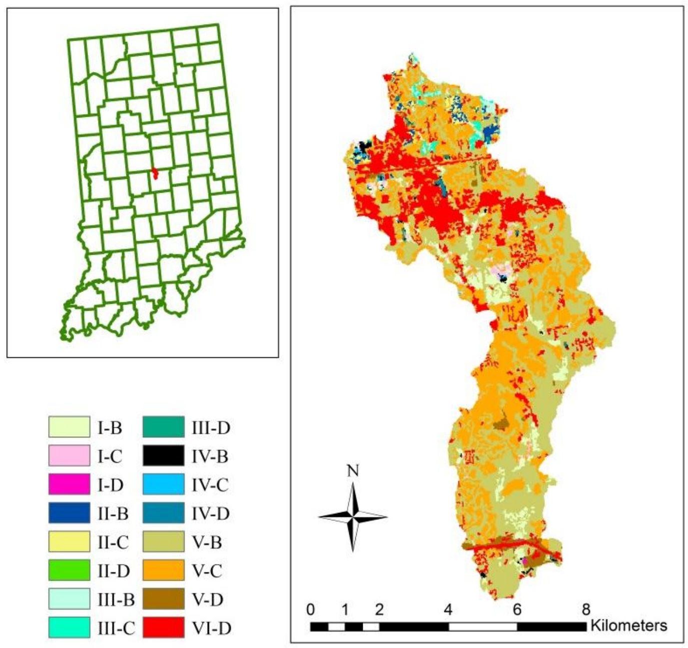


Figure 5.1 Locations of Crooked Creek Watershed and HRUs.

I, II, III, IV, V, and VI are Forest/Woods, Agricultural, Grass/Pasture, Water/Wetland, LD residential, and HD residential/Industrial/Commercial land uses, respectively. B, C, and D are hydrologic soil groups B, C, and D, respectively.

Table 5.1 Characteristics of HRUs (National Land Cover Database 2001)

Land use	Hydrological Soil group	Area (ha)	Code
	B	257.4	I-B
Forest/Woods	C	53.7	I-C
	D	3.9	I-D
	B	81.3	II-B
Agricultural	C	74.1	II-C
	D	0.7	II-D
Grass/Pasture	B	50.2	III-B
	C	51.4	III-C

	D	0.4	III-D
	B	28.5	IV-B
Water/Wetland	C	12.2	IV-C
	D	16.4	IV-D
	B	2045.1	V-B
LD residential	C	1550.6	V-C
	D	99.3	V-D
HD residential/Industrial/Commercial	D	804.0	VI-D

5.3.2 Simulation model—L-THIA-LID 2.1 model

The L-THIA-LID 2.1 model (Liu et al., 2015b) was developed from the L-THIA-LID 2.0 model (Liu et al., 2015a) to simulate the impacts of BMPs and LID practices on hydrology and water quality at watershed scales. As in previous versions of L-THIA models that have been applied in various studies (e.g. Harbor, 1994; Bhaduri et al., 1997; Pandey et al., 2000; Engel et al., 2003; Tang et al., 2005; Choi, 2007; Davis et al., 2010; Ahiablame et al., 2012, 2013), the L-THIA-LID 2.1 model estimates runoff volume using the curve number method and computes pollutant loads by multiplying runoff volume with pollutant concentration from each specific land use.

Currently, there are nine LID practices (permeable patio, grassed swale, green roof, bioretention system, rain barrel, cistern, porous pavement, grass strip, and wetland channel) and three BMPs (wetland basin, retention pond, and detention basin) represented in the L-THIA-LID 2.1 model (Liu et al., 2015a, 2015b). Using data from the International Stormwater Best Management Practices (BMP) Database, the impacts of BMPs and LID practices on runoff volume are calculated using curve number (CN) and percent runoff reduction methods. The influence of BMPs and LID practices on pollutant loads is estimated using runoff volume reduction, irreducible concentration, and pollutant concentration reduction methods (Liu et al., 2015a).

The model simulates BMPs and LID practices starting at the hydrologic response unit (HRU) scale. HRUs are areas with the same land uses and hydrologic soil groups. Based on the site characteristics and other logistical concerns, such as drainage area, imperviousness, drainage slope, hydrologic soil group, stream buffer, road buffer, and building buffer, suitable locations to implement BMPs and LID practices are selected. The suitable practices are combined with HRUs to generate the unique combinations of suitable BMPs/LID practices and HRUs. The drainage areas of LID practices and BMPs are based on the characteristics of the practices; for example, porous pavement/patio treats runoff from the surface of pavement/patio; grass swale, grass strip, and wetland channel treat runoff from the same unique combinations of BMPs/LID practices and HRUs; and BMPs treat part of the runoff that was treated by LID practices. Depending on the features of the practices, some LID practices can be implemented in series with each other in the same HRU; LID practices can be in series with BMPs; and BMPs are independent of each other, meaning they could not be in series. The L-THIA-LID 2.1 model can also estimate the total cost to implement BMPs and LID practices, which makes it possible to consider economics in the optimization problem. The total cost considered in the model includes construction cost, maintenance cost, and opportunity cost. More detailed information of the L-THIA-LID 2.1 model can be obtained from Liu et al. (2015a, 2015b).

5.3.3 Optimization scenarios

The optimal selection and placement of BMPs and LID practices requires consideration of the suitability of locations to implement practices, the percentages or levels of suitable locations with BMPs/LID practices implemented, the environmental impacts of practices, and the cost of applying practices.

Multi-objective optimization can compute multiple objective functions with tradeoff solutions to maximize the positive impacts on environment (hydrology and water quality) and minimize the cost of implementing BMPs and LID practices. This study conducted multi-objective optimization using two objective functions because of the complicated multi-dimensional decision vector generated by scenarios of more than two objective functions. For example, the results of using two objective functions can be plotted with a 2-dimensional coordinate system, which is easy to explain. However, the results of using three or more objective functions needs to be plotted using multi-dimensional coordinate systems, which greatly increases the complexity of explanations.

In this study, the objective function (Equation 5.1) was defined to: (1) minimize the cumulative runoff/pollutant value (CRPV) (Equations 5.2 to 5.7) generated from the watershed after implementing BMPs/LID practices, and (2) minimize the cost of implementing BMPs/LID practices. Constraints were considered in the optimization problem to identify suitable locations to implement practices. The entire area of the watershed was the potential area to implement practices, and the percentages or levels of suitable locations with BMPs/LID practices implemented were the variables used to search for optimal solutions.

$$Objective\ \ function = \min(CRPV \wedge Cost) \tag{5.1}$$

Constraints: Constraints of suitable locations to implement BMPs/LID practices from Liu et al. (2015b) include: drainage area, drainage slope, imperviousness, hydrologic soil group, road buffer, stream buffer, building buffer.

Variables: Different percentages or levels of suitable locations with BMPs/LID practices implemented.

Six optimization scenarios were created with tradeoffs to minimize runoff volume (RV) (Scenario 1, Eq. 5.2), minimize sediment loads (TSS) (Scenario 2, Eq. 5.3), minimize nutrient loads (TP, TN) (Scenario 3, Eq. 5.4), minimize metal loads (Pb) (Scenario 4, Eq. 5.5), minimize organic compounds (BOD and COD) (Scenario 5, Eq. 5.6), and minimize all pollutant amounts mentioned above (Scenario 6, Eq. 5.7).

$$Runoff - CRPV = \frac{Runoff}{Runoff'} \tag{5.2}$$

$$Sediment - CRPV = \frac{TSS}{TSS'} \tag{5.3}$$

$$Nutrient - CRPV = \frac{TP}{TP'} + \frac{TN}{TN'} \tag{5.4}$$

$$Metal - CRPV = \frac{Pb}{Pb'} \tag{5.5}$$

$$Organic\ Compounds - CRPV = \frac{BOD}{BOD'} + \frac{COD}{COD'} \tag{5.6}$$

$$All \;\; pollutants - CRPV = \frac{TSS}{TSS^{'}} + \frac{TP}{TP^{'}} + \frac{TN}{TN^{'}} + \frac{Pb}{Pb^{'}} + \frac{BOD}{BOD^{'}} + \frac{COD}{COD^{'}} \tag{5.7}$$

Where, $runoff$ and $pollutant\ names$ are the runoff volume and pollutant loads, respectively, after implementing BMPs and LID practices. $runoff^{'}$ and $pollutant\ names^{'}$ are the runoff volume and pollutant loads, respectively, before implementing BMPs and LID practices. All pollutant loads are given equal weights in these equations. If the reduction of a certain pollutant load is more or less important, the weights can be changed. Instead of minimizing runoff volume and pollutant loads at the outlet of the watershed, all of these scenarios considered the reductions at the HRU level, and minimize average runoff volume and pollutant loads from all HRUs. In this study, there would be no difference between optimization for all HRUs and for the watershed outlet, because there are no routing losses in the current L-THIA-LID model.

5.3.4 Multilevel spatial optimization (MLSOPT) framework and optimization algorithms (AMALGAM)

The MLSOPT framework (Cibin, 2013) contains two levels to reduce the computational complexity of optimization problems. The first level divides the watershed into smaller areas, and the optimization for each area is conducted individually. A lookup table of optimal results of objective functions is created for the first level single sub-areas. By satisfying the objective functions at the watershed scale, the second level conducts watershed scale optimization by linking optimization algorithms with the lookup table created based on the results of the first level. With one model run, the L-THIA-LID 2.1 model can provide results of objective functions for all sub-areas, which enables parallel computing in the first level optimization. For more details on the MLSOPT framework, readers should consult Cibin (2013).

To obtain faster and more dependable results for multi-objective optimization problems, AMALGAM combines the strengths of multiple optimization algorithms by running different algorithms at the same time using self-adaptive offspring creation (Vrugt and Robinson, 2007). The method adapts search procedures that adapt population sizes from optimization algorithms based on their performances in the guiding search to obtain well distributed Pareto-optimal front solutions. The fast non-dominated sorting algorithm (Deb et al., 2002) is used by AMALGAM for population ranking. There are four mutually consistent and complementary evolutionary optimization algorithms in the default AMALGAM (Vrugt and Robinson, 2007), including differential evolution (DE) (Storn and Price, 1997), adaptive metropolis search (AMS) (Haario et al., 2001), particle swarm optimization (PSO) (Kennedy and Eberhart, 2001), and Non-dominated Sorted Genetic Algorithm II (NSGAII) (Deb et al., 2002). Matlab source code for AMALGAM can be found at http://faculty.sites.uci.edu/jasper/sample.

5.3.5 Development of a decision support tool

To find the best selections and placements of BMPs and LID practices with tradeoffs among costs and environmental benefits, a decision support tool was developed by linking the L-THIA-LID 2.1 model with AMALGAM (Vrugt and Robinson, 2007) using the MLSOPT framework (Cibin, 2013). The L-THIA-LID 2.1 model was used to quantify the environmental impacts and costs of implementing BMPs/LID practices. The calibrated and validated L-THIA-LID 2.1 model from Liu et al. (2015b), which studied the same watershed from year 1993 to 2010, was used in this study. The optimal selection and placement of practices started from the current watershed situation with only retention ponds implemented in the watershed. Design life of all BMPs/LID practices was assumed as 20 years, and the interest rate was 4.5% when computing total cost using the L-THIA-LID 2.1 model. The performance of AMALGAM was improved by changing population size and number of generations, while other parameters of the optimization algorithms in AMALGAM were set as recommended.

The schematic of the decision support tool is shown in Figure 5.2. Alternative options of BMPs and LID practices with unique integer codes in this study are shown in Table 5.2. Proposed BMPs included wetland basin, retention pond, and detention basin; and proposed LID practices included permeable patio, grassed swale, green roof, bioretention system, rain barrel, cistern, porous pavement, grass strip, and wetland channel. The L-THIA-LID 2.1 model divided the watershed into hydrological response units (HRUs), which had the same land use types and hydrologic soil groups. When simulating LID practices, HRUs were in parallel and assumed not to affect each other. By definition, LID practices are localized techniques that make this assumption valid. A portion of runoff and NPS pollutants treated by LID practices could be treated by BMPs. This meant that after runoff and pollutant loads were treated by LID practices, a portion of the remaining runoff and pollutants could be treated by BMPs. This portion represented the percentage or level of suitable locations with BMPs implemented. Possible BMP and LID practice options for each HRU were identified based on site characteristics and other logistical concerns, such as drainage area, imperviousness, drainage slope, hydrologic soil group, stream buffer, road buffer, and building buffer (Liu et al., 2015b). In this study, 123 unique combinations of HRUs and suitable BMPs/LID practices were created, and referred to as sub-areas. Runoff and pollutants were routed from HRUs to the watershed outlet by additive routing, which meant that the values were simply added together.

Table 5.2 Alternative options of BMPs and LID practices in this study

Categories of practices	Names of practices	Integer Codes
BMPs	Retention pond	1
	Detention basin	2
	Wetland basin	3
LID practices	Rain Barrel/Cistern	4
	Permeable patio	5
	Green Roof	6
	Grassed Swale	7
	Grass strip	8
	Wetland Channel	9
	Bioretention system	10
	Porous Pavement	11

In the first level optimization, sample populations 1, which were various percentages or levels of BMP and LID practice implementation in each sub-area, were created by AMALGAM until termination criteria were satisfied. Sample populations were inputs for the L-THIA-LID 2.1 model. After model simulations were completed for all sample populations, lookup tables were created with optimum results for implementing practices in all sub-areas. The sub-areas, which were HRU scale areas, were the unique combinations of HRUs and suitable BMPs/LID practices.

The second level optimization was conducted at the watershed level based on the optimum results for the sub-area level. Since all optimization scenarios in this study only considered the impacts of BMPs and LID practices at the source level, the best solutions in each sub-area of the first level were used to estimate watershed level objective functions using an additive approach. Sample populations 2, which were various combinations of first level Pareto solutions, were created by picking one Pareto solution from each sub-area using AMALGAM until satisfying the termination criteria. The corresponding results of objective functions from each sub-area were added together to obtain watershed scale Pareto solutions.

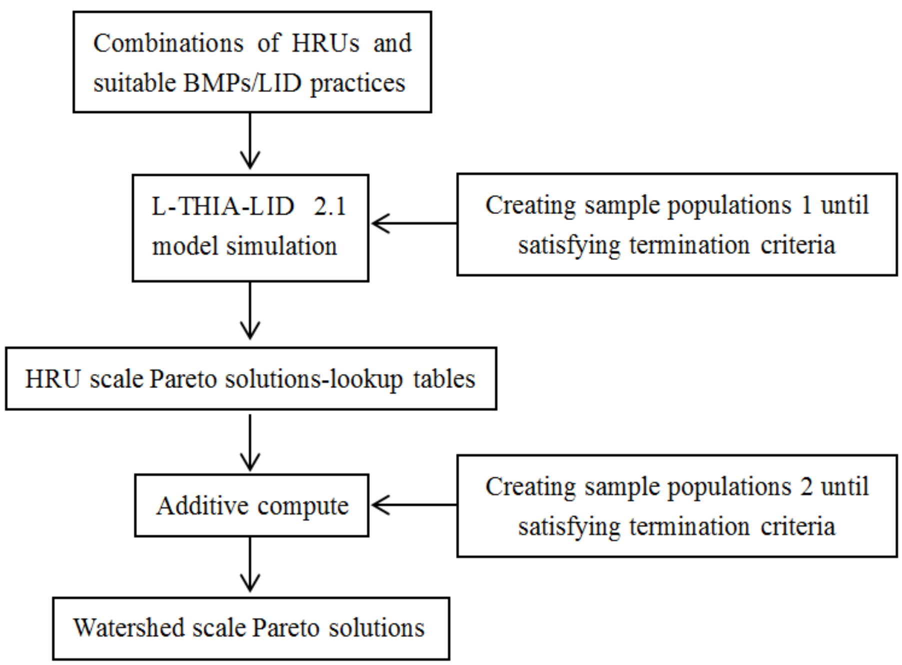


Figure 5.2 Schematic of decision making tool to optimally select and place BMPs and LID practices.

Sample populations 1 were various percentages or levels of BMP and LID practice implementation in each sub-area (e.g. a combination of 1% green roof, 2.5% rain barrel/cistern, 5% retention pond, 3% detention basin, and 4% wetland basin). Sample populations 2 were various combinations of first level Pareto solutions.

5.4 Results and discussion

The decision support tool was applied in the Crooked Creek watershed to optimally select and place BMPs and LID practices. For the specific application of the decision support tool, population sizes and number of generations were changed to find the most suitable parameters in AMALGAM. Based on the results of changing population sizes and number of generations, sizes of the population and generation used in the first level MLSOPT optimization were 100 and 400, respectively, for all optimization scenarios; in the second level MLSOPT optimization, all optimization scenarios were calculated using population size of 100 and generation size of 10000. The first level optimizations were finished on Intel Xeon-E5 processors with 12 parallel Matlab workers, which took about 5.25 days for each scenario. The second level optimizations were completed on a 3.40 GHz Intel Core i7-3770 CPU with 1 Matlab worker, which took about 4 hours for each scenario.

5.4.1 Possible locations of BMPs and LID practices

All BMPs selected in the study were assumed to be suitable in all areas in the watershed due to the fact that stormwater runoff from any HRU can be directed to any of the selected BMPs with pipes and channels. Possible locations of the selected LID practices in Crooked Creek watershed were identified as shown in Figure 5.3. The combinations of numbers shown in Figure 5.3 were the unique combinations of LID practices that were suitable to be implemented in that area. Over 41% of the total area was suitable only to implement BMPs, including retention pond, detention basin, and wetland basin. About 14%

of the whole watershed was suitable for BMPs and porous pavement. Approximately 11% of the study area was suitable to implement BMPs, grassed swale, grass strip, wetland channel, bioretention system, and porous pavement. The rest of the watershed was suitable for other various combinations of BMPs and LID practices. The optimal implementation of BMPs and LID practices at HRU and watershed scales were analyzed, and the results are discussed in the following sections.

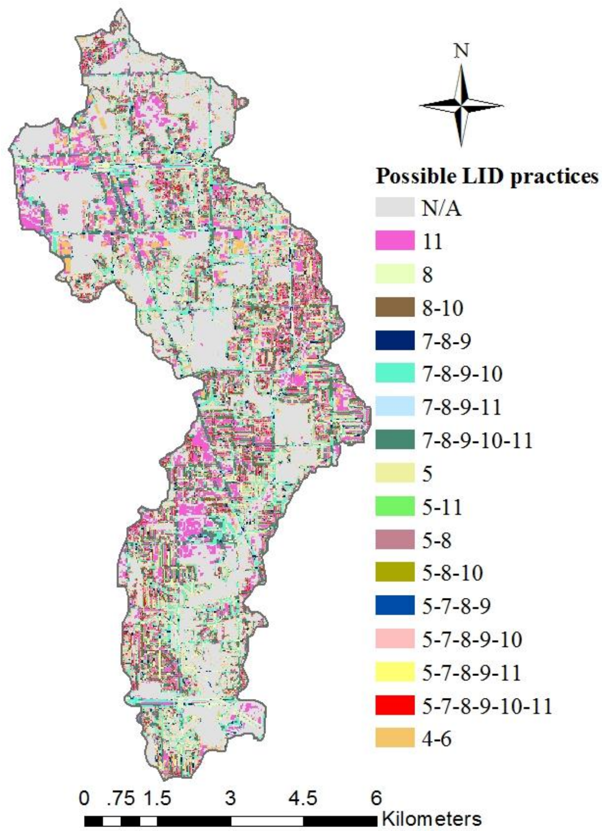


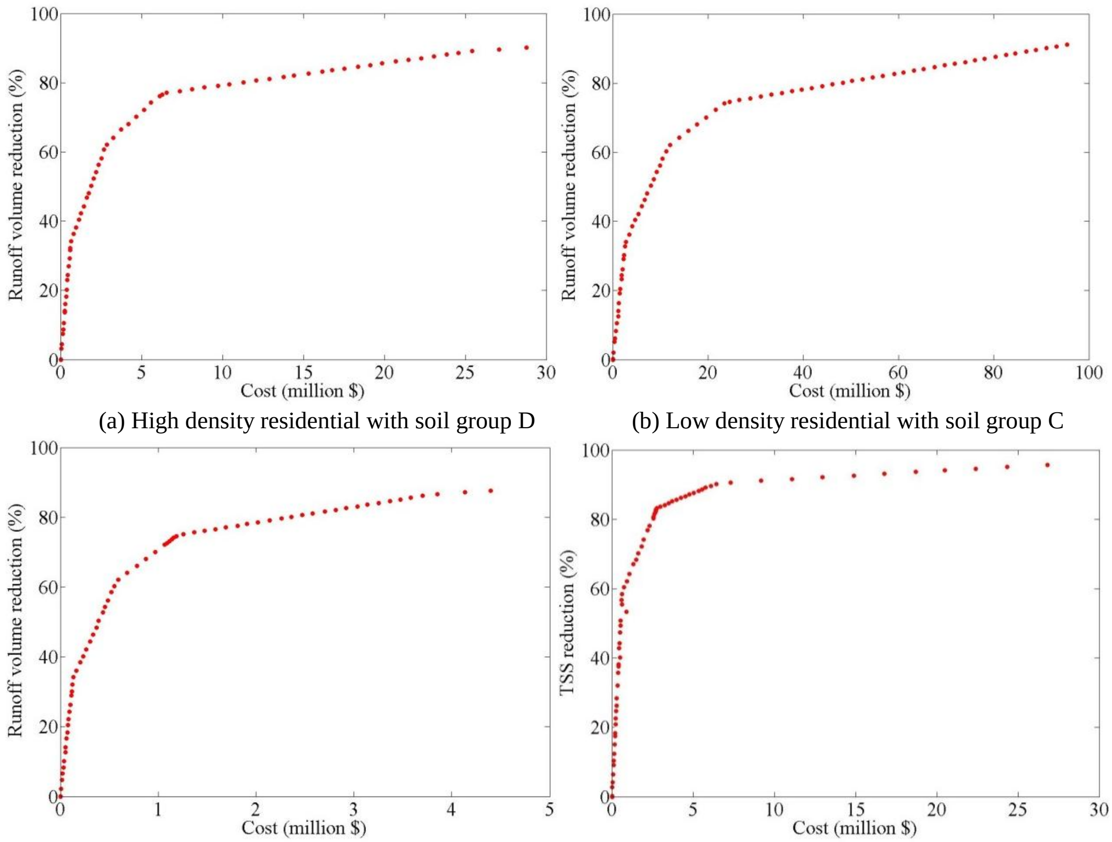
Figure 5.3 Possible locations of LID practices in Crooked Creek watershed

5.4.2 HRU scale optimization results

Figure 5.4 shows four examples of HRU scale optimization results for four sub-areas with objective functions to minimize runoff volume (Figure 5.4a-c) and minimize TSS load (Figure 5.4d) at minimum cost. In Figure 5.4, red circles are Pareto solutions; X-axis and Y-axis shows the costs to implement BMPs/LID practices and corresponding percent runoff volume or TSS loads reductions, respectively. The X-axis and Y-axis in Figure 5.4 were switched and shown in Figure A.1. Detailed Pareto solutions for various levels of implementing BMPs and LID practices in the selected HRU areas to reduce runoff volume or TSS loads are shown in Figure 5.5. Table 5.3 shows annual cost per unit of runoff volume/pollutant load reduction for suitable BMPs and LID practices corresponding to sub-areas selected in Figure 5.4. Lower annual cost per unit of runoff volume/pollutant load reduction indicates a higher cost efficiency of the BMP/LID practice in reducing runoff volume/pollutant load.

Table 5.3 Annual cost per unit of runoff volume/pollutant load reduction for suitable BMPs and LID practices corresponding to sub-areas selected in Figure 5.4

Names of practices	Annual cost per unit runoff volume reduction ($\$/m^3/yr$)			Annual cost per TSS load reduction($/kg/yr)
	Fig.5.3(a)	Fig.5.3(b)	Fig.5.3(c)	Fig.5.3(d)
Retention pond	14.6	20.8	21.1	75.7
Detention basin	3.6	5.1	5.2	80.5
Wetland basin	26.0	37.0	37.4	73.0
Grassed Swale	2.1	3.0	3.0	45.0
Grass strip	0.8	1.1	1.1	14.2
Wetland Channel	N/A	N/A	N/A	102.1
Bioretention system	14.9	21.1	21.4	480.5
Porous Pavement	16.8	15.4	16.4	465.6
Porous Pavement+ Bioretention system	18.4	18.8	19.9	531.3



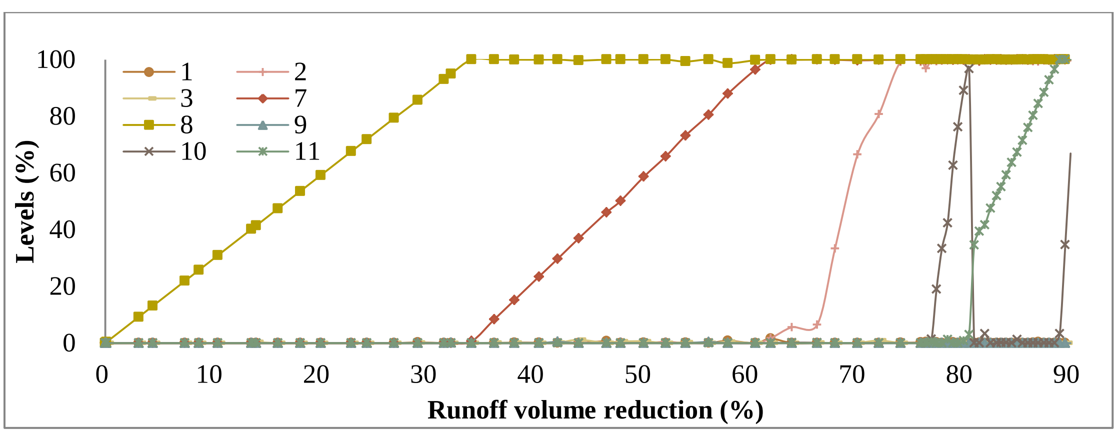
(a) High density residential with soil group D

(b) Low density residential with soil group C

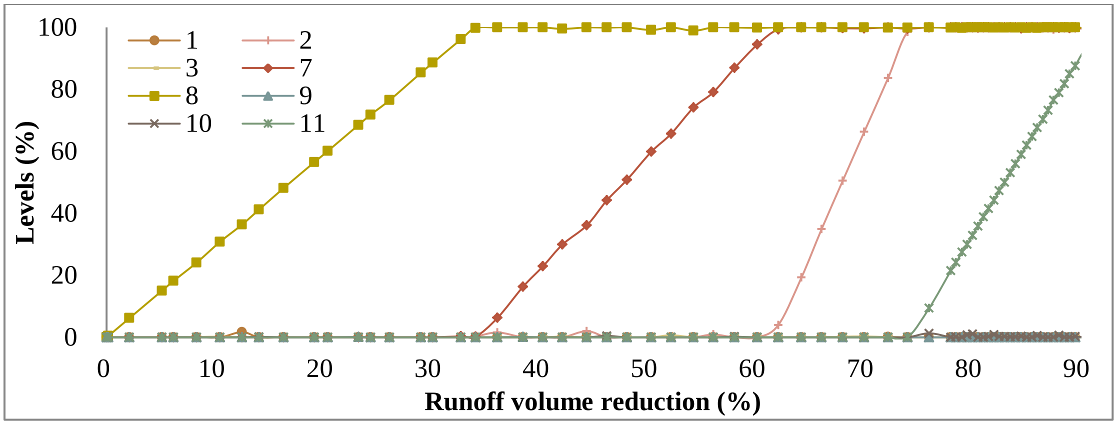
(c) Industrial with soil group D

(d) High density residential with soil group D

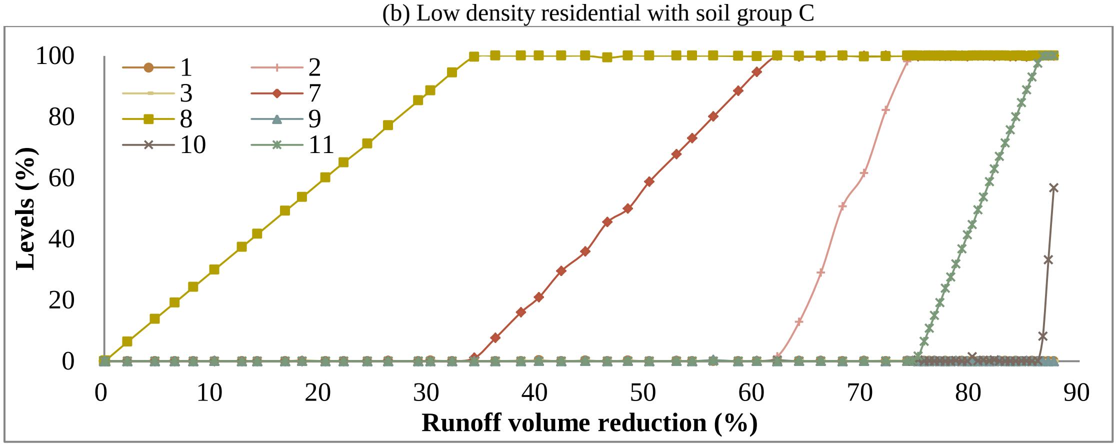
Figure 5.4 Examples of optimization results for HRU scale areas, which were suitable for retention pond, detention basin, wetland basin, grassed swale, grass strip, wetland channel, bioretention system, and porous pavement. Costs presented were totals for 20 years. Selected areas were 55 ha, 232 ha, 11 ha, and 55 ha, respectively.



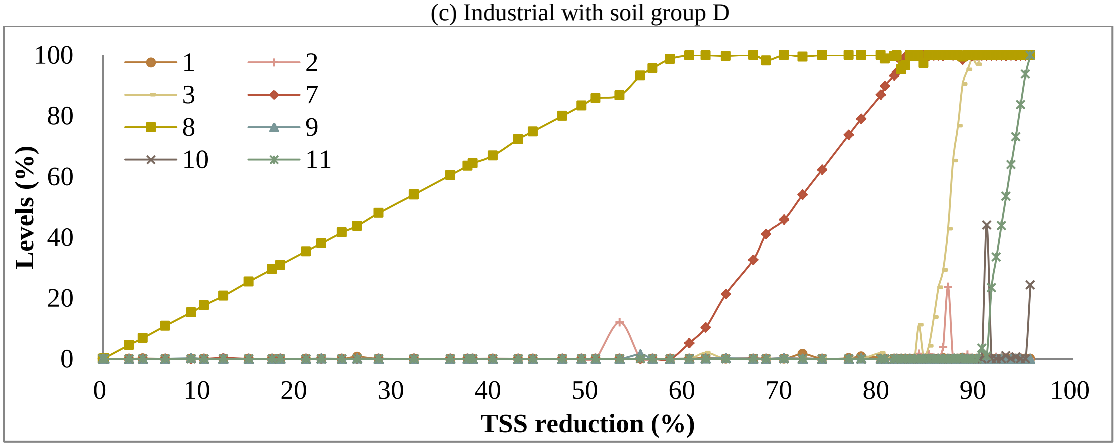
(a) High density residential with soil group D



(b) Low density residential with soil group C



(c) Industrial with soil group D



(d) High density residential with soil group D

Figure 5.5 Examples of detailed Pareto solutions for various levels of implementing BMPs and LID practices in HRU scale areas. Practices represented were 1-retention pond, 2-detention basin, 3-wetland basin, 7-grassed swale, 8-grass strip, 9-wetland channel, 10-bioretention system, and 11-porous pavement. The most cost-efficient BMPs/LID practices were picked up one by one during the optimization process.

The selected area in Figure 5.4(a), with an area of 55 ha, was high density residential land use with hydrologic soil group D, which was suitable for implementing retention pond, detention basin, wetland basin, grassed swale, grass strip, wetland channel, bioretention system, and porous pavement. Figure 5.4(a) indicates the maximum potential runoff volume reduction in this selected HRU scale area was 90% with the cost of 29 million dollars for a period of 20 years. Figure 5.5(a) shows that to reduce runoff volume in the selected HRU scale area, grass strip was the only favorable practice until a level of approximately 34% runoff volume reduction. At that level of reduction, grass strip implementation reached 100%, requiring implementation of other practices for further reductions. In this particular case, grassed swale implementation increased from that point, and remained at 100% implementation after runoff volume reduction reached 62%. Then, detention basin became favorable, and remained at 100% implementation level after runoff volume reduction reached 77%. Bioretention systems became favorable until reaching a level of 81% reduction of runoff volume. At 81% runoff volume reduction, porous pavement became favorable. Once the level of implementing porous pavement reached 100%, bioretention system became favorable again. Wetland basin and wetland channel were not favorable during the whole search process because they were not as cost efficient as the favorable practices (as shown in Table 5.3). Although retention pond (14.6 $\$/m^3/yr$) was more cost efficient than bioretention system and porous pavement (Table 5.3), retention pond did not become favorable because it was assumed that BMPs are independent to each other and with 100% implementation level of detention basin, no other BMPs could be implemented in the same sub-area.

The selected areas in Figure 5.4(b) and Figure 5.4(c), with areas of 232 ha and 11 ha, respectively, were low density residential land use with hydrologic soil group C and industrial land use with hydrologic soil group D, respectively. These areas were suitable for the same BMPs and LID practices as in Figure 5.4(a), including retention pond, detention basin, wetland basin, grassed swale, grass strip, wetland channel, bioretention system, and porous pavement. Figure 5.4(b) shows the maximum potential runoff volume reduction in the selected HRU scale area was 91% by spending 95 million dollars over a period of 20 years. Figure 5.4(c) shows the potential of reducing runoff volume by 87% in the selected HRU area with a cost of 4.4 million dollars for a period of 20 years. Figures 5.5(b) and 5.5(c) show similar behavior for changes of favorable BMPs and LID practices compared to Figure 5.5(a), except that bioretention system was not favorable during any of the search process for the HRU with results presented in Figure 5.5(b), and bioretention system only became favorable following high levels of porous pavement implementation as depicted in Figure 5.5(c).

The differences among the optimal solutions to reduce runoff volume by implementing BMPs/LID practices were due to different features of the HRUs. In the selected area of Figure 5.5(a), because of the land uses and soil properties, the cost per unit runoff volume reduction (Table 5.3) of bioretention system (14.9 $\$/m^3/yr$) was slightly lower than that of porous pavement (16.8 $\$/m^3/yr$). Therefore, bioretention system was favorable first; however, when the runoff volume reduction reached the maximum implementation level, implementing bioretention systems would not reduce runoff volume further due to the limited suitable areas. Thus, to reduce runoff volume further, implementation level of bioretention system dropped while porous pavement became favorable, since the combined implementation of porous pavement and bioretention system in series (18.4 $/m^3/yr) was not as cost efficient as implementing porous pavement alone (16.8 $/m^3/yr), and implementing porous pavement alone had the potential to reduce more runoff volume than implementing bioretention system alone. After the implementation level of porous pavement reached and remained at 100%, bioretention system became favorable again to further reduce runoff volume. For the selected areas in 4(b) and 4(c), the cost per unit runoff volume reduction of porous pavement (15.4 $/m^3/yr and 16.4 $/m^3/yr, respectively) was lower than that of bioretention system (21.1 $/m^3/yr and 21.4 $/m^3/yr, respectively) because of land use and soil type features; as a result, porous pavement became favorable first. In Figure 5.5(a) and 5.5(c), when bioretention system became favorable at about 90% reduction of runoff volume, the level of implementing porous pavement remained high; this is because implementing only bioretention system was unable to reduce runoff volume more than 100% implementation of porous pavement did, leading to the need to implement both practices.

The selected area in Figure 5.4(d) was the same as in Figure 5.4(a). Figure 5.4(d) shows the potential of reducing TSS by 96% at a cost of 27 million dollars for a period of 20 years. Figure 5.5(d) shows similar changes of favorable BMPs and LID practices as in Figure 5.5(a), except that at 84% reduction in TSS loads, instead of detention basin, wetland basin became favorable for the area associated with Figure 5.5(d). This was because wetland basin (73.0 $/kg/yr) was more favorable in reducing TSS than reducing runoff volume compared to detention basin (80.5 $/kg/yr). Although wetland channel

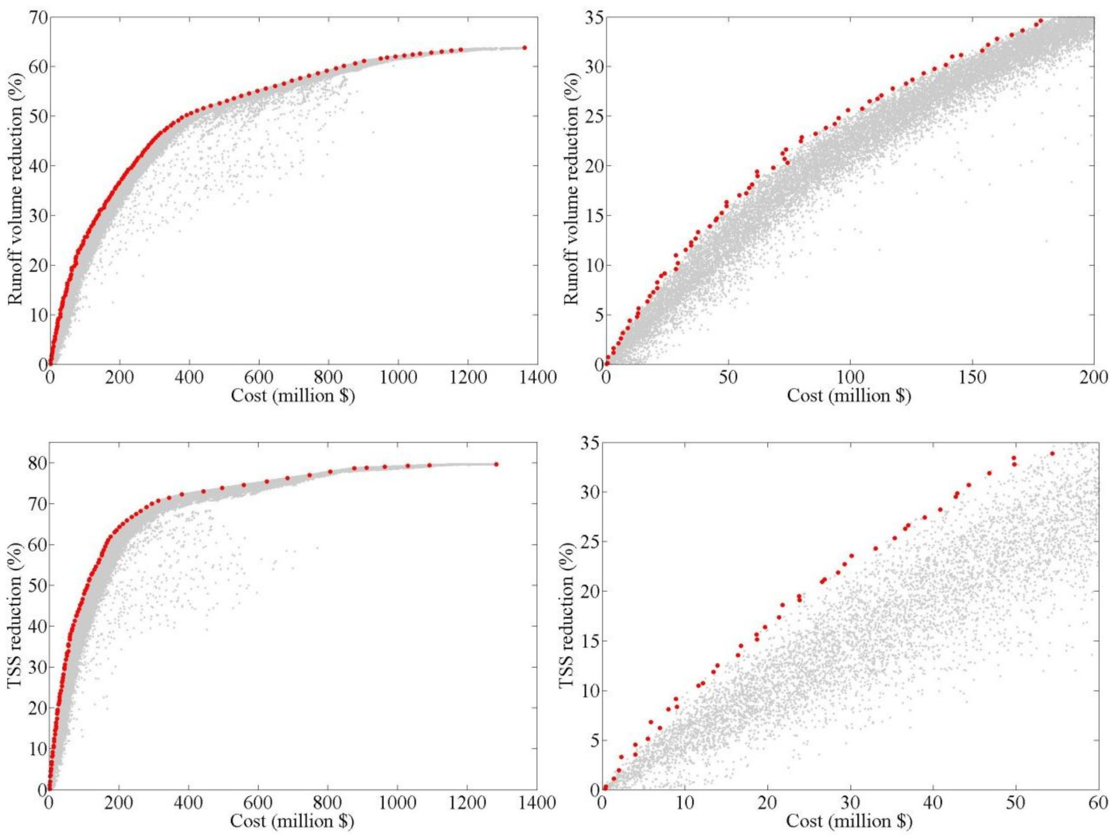
(102.1 \$/kg/yr), retention pond (75.7 \$/kg/yr), and detention basin (80.5 \$/kg/yr) were more cost efficient than some of the favorable practices (Table 5.3), they did not become favorable because it was assumed that BMPs are independent of each other and wetland channel is independent of grassed swale; with 100% implementation level of wetland basin, no other BMPs could be implemented for the same sub-area; with 100% implementation level of grassed swale, wetland channel could not be implemented for the same sub-area. The occasional relative high levels of detention basin and bioretention system for the area associated with Figure 5.5(d) were because there were various ways to reduce TSS at the same cost. This indicates that for the same combination of HRU and suitable BMPs/LID practices, favorable levels and combinations of BMPs and LID practices could vary significantly for different environmental goals.

The change points of favorable BMPs and LID practices depicted in Figure 5.5 correspond to the sharp turning points of Pareto fronts in Figure 5.4. The sharp turning points of Pareto fronts occurred when new BMPs/LID practices became favorable. This was expected because with different favorable BMPs and LID practices in the same HRU, the abilities of BMPs/LID practices to reduce runoff volume/pollutant loads were different for the same cost. Note that optimal selection and placement of BMPs and LID practices was based on tradeoffs of cost and runoff volume/pollutant load reduction. This meant that the higher priority of selecting and placing a BMP/LID practice during optimization was due to the lower cost per unit runoff volume/pollutant load reduction. From Figure 5.5, we can see that with the increase of runoff volume/TSS reductions (consistent with cost increments in Figure 5.4), most types of the BMPs/LID practices selected in the Pareto solutions were already selected with lower implementation levels for lower expenditures; the types of favored practices increased with expenditure. These features in Figure 5.5 demonstrated the need to optimally select and place BMPs and LID practices that give higher priorities to practices with lower cost in reducing per unit runoff volume/pollutant load.

For presentation purposes, four examples of optimization results for unique combinations of HRUs and suitable BMPs/LID practices, and only runoff volume reduction and TSS reduction were presented. The study examined all 123 combinations of HRUs and suitable BMPs/LID practices, and for runoff volume/various pollutant yields. Similar results could be plotted for runoff volume/pollutants yields for any combinations of HRUs and suitable BMPs/LID practices.

5.4.3 Watershed scale optimization results

Watershed scale optimization results for all scenarios are shown in Figure 5.6, in which grey circles are all results during optimization and red circles constitute the Pareto optimal fronts. The x-axis shows the costs in million dollars over a 20 year period, while the y-axis presents the effectiveness in percent reductions. The upper left fronts of optimization results are Pareto solutions that show the maximum environmental impacts with minimum cost of implementing BMPs and LID practices. A portion of left side plots were zoomed in and shown on the right side. Since plots were zoomed in at different scales to compare findings, the density of solution points differs among objective functions. All these Pareto solutions were the best solutions, and the objectives were conflicting—the improvement in hydrology/water quality would only be achieved with more expense to implement BMPs and LID practices. Each Pareto solution in Figure 5.6 was the optimal result for the whole watershed by combining 123 HRU scale allocations of BMPs and LID practices. The detailed optimal solution (in the format of Figure 5.5 in section 5.4.2) for implementing BMPs and LID practices at the watershed scale was not presented in the paper because of the complexity of each Pareto solution, which included 123 HRU scale optimal results. The X-axis and Y-axis in Figure 5.6 were switched and shown in Figure A.2.



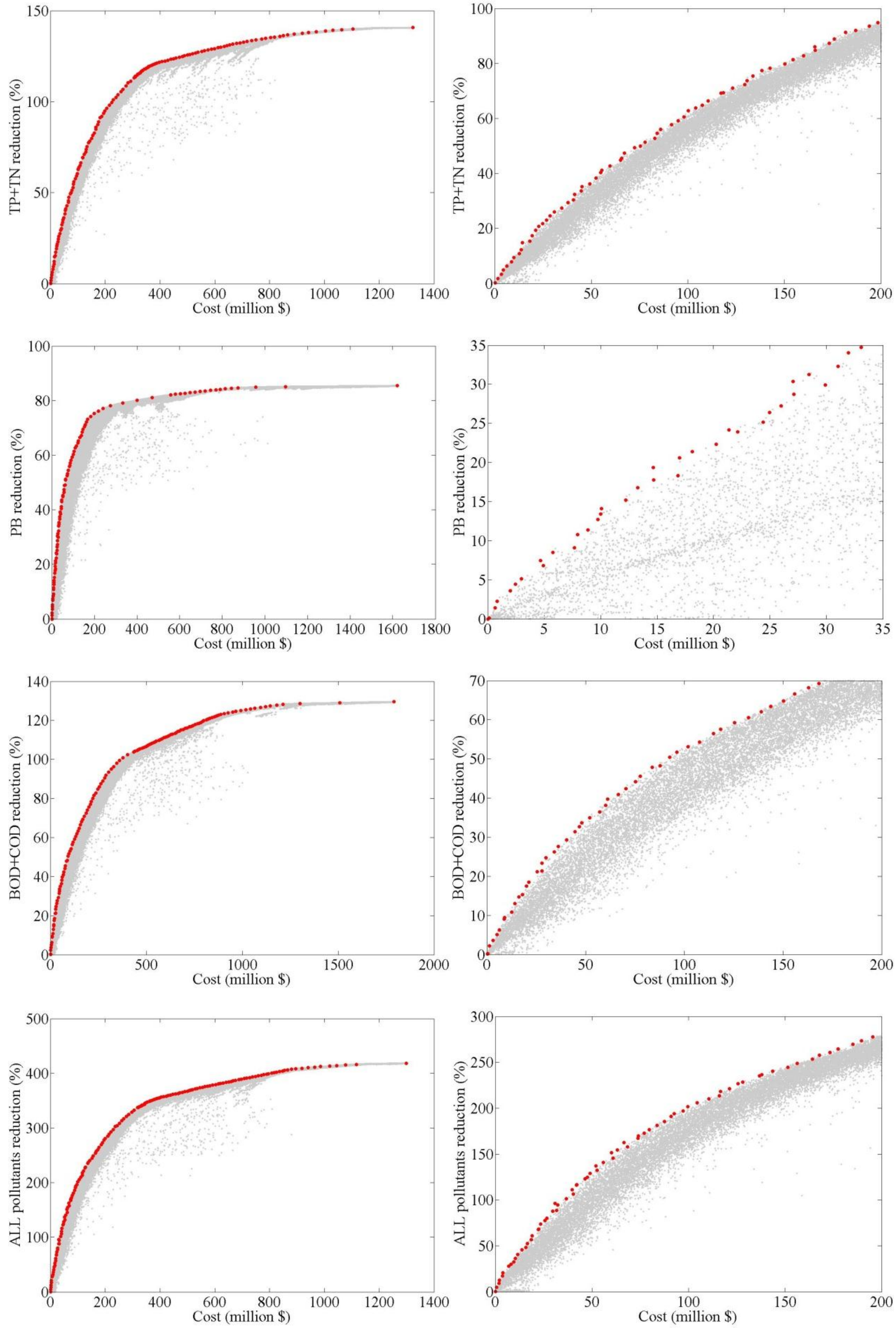

TP+TN reduction (%)
Cost (million $)
PB reduction (%)
Cost (million $)
BOD+COD reduction (%)
Cost (million $)
ALL pollutants reduction (%)
Cost (million $)

Figure 5.6 Watershed scale optimization results for all scenarios. Plots on the left side were zoomed in and shown as plots on the right side. Costs are total implementation and maintenance cost for a period of 20 years.

Pareto optimal fronts for all scenarios in Figure 5.6 indicate that by implementing more BMPs and LID practices, runoff volume and pollutant loads can be reduced further. For small total expenditures, additional expenditures to implement BMPs/LID practices greatly increased environmental impacts. However, beyond a given expenditure, spending more money did not result in substantial reductions of runoff volume and pollutant loads. Due to the treatment abilities of BMPs and LID practices, implementing more practices in series at the watershed scale would not necessarily result in significant further reductions in runoff volume and pollutant loads (Liu et al., 2015b). This resulted in less significant environmental impacts by spending more money beyond a certain level of expenditure.

For the same cost (Figure 5.6), reductions in runoff volume were smaller than reductions in pollutant loads. For example, by spending 60 million dollars for a period of 20 years, runoff volume was reduced by 18%, while TSS loads, average TP/TN loads, Pb loads, average BOD/COD loads, and the average of six pollutants loads were reduced by 38%, 22%, 49%, 19%, and 25%, respectively. This was expected because reduction of pollutant loads by implementing BMPs and LID practices was not only caused by reducing runoff volume, but also by decreasing pollutant concentrations.

5.4.4 Comparison of optimization and random scenarios

Two random BMP and LID practice implementation scenarios were compared with the optimization results. One way was to compare environmental benefits of the optimized and random strategies for the same budget. The other way was to compare the total cost of optimization and random scenarios with the same environmental impacts.

The random scenarios, which were applied starting from the current situation with only retention ponds implemented (Liu et al., 2015b), included: Random Scenario 1 (RS1) with a combination of 1% green roof, 2.5% rain barrel/cistern, 0.5% green roof with rain barrel/cistern, 2.5% bioretention system, 1% porous pavement, 1% permeable patio, 2.5% grass strip, 2.5% grassed swale, 2.5% wetland channel, 2.5% retention pond, 2.5% detention basin, and 2.5% wetland basin; and Random Scenario 2 (RS2) with a combination of 1% rain barrel/cistern, 1% bioretention system, 0.5% porous pavement, 0.5% permeable patio, 1% grass strip, 1% grassed swale, 1% wetland channel, 1% retention pond, 1% detention basin, and 1% wetland basin.

Table 5.4 shows the comparison of hydrology and water quality impacts of optimization and random scenarios for the same BMP and LID practice expenditure. For the same expenditure, optimized implementation of BMPs and LID practices had 3.9 to 7.7 times as much reduction in runoff and pollutant loads as the random scenario. For example, by spending 47.7 million dollars for a period of 20 years, the random scenario only reduced runoff volume by 2.3%, while the optimized scenario reduced runoff volume by 15.4%.

Table 5.5 shows the comparison of total cost of optimization and random scenarios to achieve the same hydrology and water quality impacts. To achieve the same runoff and pollutant load reductions, random scenarios cost 4.2 to 14.5 times as much as the optimized scenarios. For instance, to reduce runoff volume by 0.9%, the optimized scenario only cost 1.8 million dollars over 20 years, while the random scenario cost 16.0 million dollars for a period of 20 years.

Figure 5.7 shows a map of optimization and random scenarios for an approximately 7 ha area in the study watershed as depicted. The optimization scenario was to reduce the maximum runoff volume with expenditure of 16.0 million dollars in the watershed over 20 years, while the random scenario was RS2 in Table 5.4. Both the optimization and random scenarios had the same expenditure. However, the optimization scenario reduced runoff volume more than the random scenario. The map shows the types and levels of practices implemented in optimization and random scenarios were significantly different.

To optimally select and place BMPs and LID practices, the decision support tool can satisfy objectives of maximizing runoff volume/pollutant load reduction for a given budget or minimizing cost given a goal of runoff volume/pollutant load reduction. These results indicate the capability of the decision support tool to estimate tradeoffs among environmental impacts and economic considerations. The decision support tool is able to identify optimal solutions from a sizeable group of BMPs and LID practices with various cost efficiencies and levels of effectiveness in reducing runoff volume and pollutants for complex watersheds with intricate land use, soil, and other features.

For practical uses, the decision support tool could help decision makers optimally select and place BMPs and LID practices at watershed scales to attain maximum environmental impacts with minimum costs. Decision makers can choose the best solution from the alternative Pareto solutions by considering constraints in optimization problems based on additional criteria, such as limited budget resources and specific environmental goals.

Table 5.4 Environmental impacts of optimization and random scenarios with the same budget (total cost for 20 years) for implementing BMPs and LID practices

		RS1	RS2	RS1 Optimized/Random	RS2 Optimized/Random
Budget	(million $)	47.7	16.0	--	--
Runoff	Random reduction (%)	2.3	0.9	6.7	6.4
	Optimized reduction (%)	15.4	5.8		
TN+TP	Random reduction (%)	9.1	3.7	3.9	4.1
	Optimized reduction (%)	35.8	15.1		
TSS	Random reduction (%)	7.5	3.1	4.3	4.7
	Optimized reduction (%)	32.2	14.6		
Pb	Random reduction (%)	8.8	3.6	5.0	5.5
	Optimized reduction (%)	43.9	19.7		
BOD+COD	Random reduction (%)	4.6	1.9	7.2	7.7
	Optimized reduction (%)	33.1	14.7		
All pollutants	Random reduction (%)	30.1	12.2	4.1	4.0
	Optimized reduction (%)	124.6	48.3		

Table 5.5 Total cost for 20 years of optimization and random scenarios with the same environmental impacts

		RS1 (million $)	RS2 (million $)	RS1 Random/ Optimized	RS2 Random/ Optimized
Random Cost		47.7	16.0	--	--
Optimized cost	Runoff	5.9	1.8	8.1	8.9
	TN+TP	9.5	3.8	5.0	4.2
	TSS	5.7	2.3	8.4	7.0
	Pb	6.6	2.0	7.2	8.0
	BOD+COD	4.2	1.1	11.4	14.5
	All pollutants	8.3	2.1	5.7	7.6

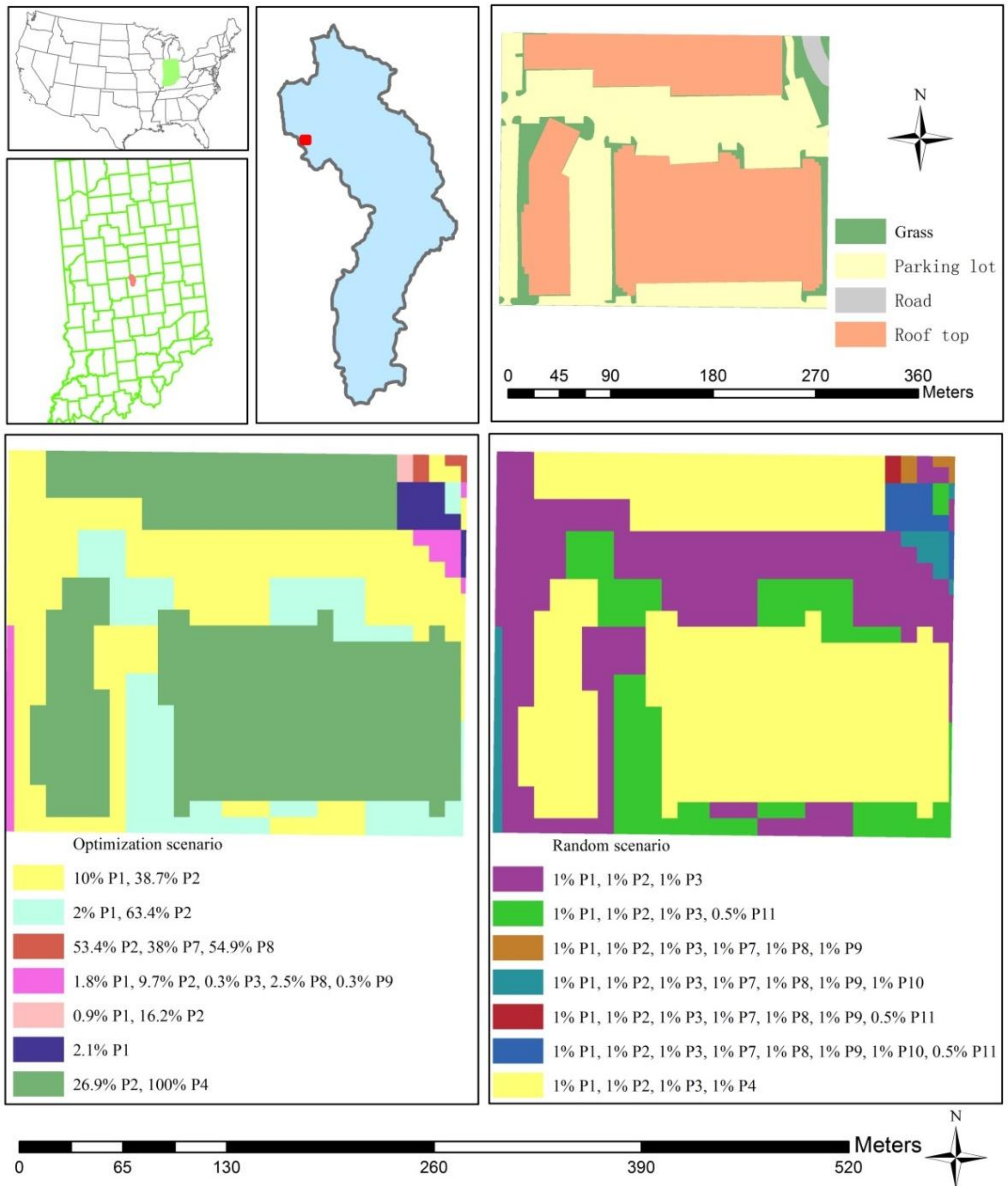


Figure 5.7 Map of optimization and random scenarios for an approximately 7 ha portion of study watershed results. Optimization scenario was to reduce the maximum runoff volume with expenditure of 16.0 million dollars over 20 years in the watershed. Random scenario was RS2 in Table 5.4. P1-retention pond, P2-detention basin, P3-wetland basin, P4-rain barrel/cistern, P7-grassed swale, P8-grass strip, P9-wetland channel, P10-bioretention system, and P11-porous pavement.

5.5 Conclusions

A decision support tool, which linked the L-THIA-LID 2.1 model with AMALGAM using the MLSOPT framework, was developed to optimally select and place BMPs and LID practices. The decision support tool was applied in Crooked Creek watershed, an urbanized watershed in Indiana, USA, to optimally implement BMPs and LID practices.

HRU scale optimization results indicated that for sites with different features, the optimal BMPs/LID practice solutions to attain the same environmental goals would differ; for the same combination of HRU and suitable practices, the favorable levels and combinations of practices could be significantly different for various runoff volume/pollutant load reduction objectives. For higher expenditures, the implementation levels and types of favored practices tended to increase relative to those for lower expenditures. These results demonstrated the need to optimally select and place practices with lower cost per unit runoff volume/pollutant load reduction.

The watershed scale selection and placement of BMPs and LID practices were optimized for the study watershed. When few practices were implemented in the watershed, increased practice expenditures greatly reduced runoff volume and pollutant loads. However, beyond a certain level of expenditure, spending more money did not always result in obvious reductions of runoff volume and pollutant loads. For the same BMP and LID practice expenditure, percent reductions in runoff volume were smaller than percent reductions in pollutant loads.

Optimization results were compared with the findings for random placement of BMPs and LID practices. The results showed that for the same BMP and LID practice expenditure, optimized implementation of BMPs/LID practices had 3.9 to 7.7 times as much reduction in runoff and pollutant loads as the random scenario. To achieve the same level of runoff and pollutant load reduction, random scenarios cost 4.2 to 14.5 times as much as the optimized scenarios.

To optimally select and place BMPs and LID practices at watershed scales, the decision support tool was capable of maximizing the reduction of runoff volume/pollutant loads for a given budget or minimizing cost given a runoff or pollutant load reduction goal. The decision support tool can support decision makers in optimally selecting and placing BMPs and LID practices to obtain maximum environmental benefits with minimum costs.

Future studies could be done to compare the differences of solutions to minimize one pollutant and multiple pollutants, and compare the decision support tool results with those of other tools that can optimally select and place BMPs and LID practices at watershed scales in urban areas, such as the Stormwater Treatment and Analysis Integration (SUSTAIN) Model (Shoemaker et al., 2009).

5.6 References

Ahiablame, L.M., Engel, B.A. Chaubey, I., 2012. Representation and evaluation of low impact development practices with L-THIA-LID: An example for site planning, Environment and Pollution, 1(2), doi:10.5539/ep.v1n2p1.

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2013. Effectiveness of low impact development practices in two urbanized watersheds: Retrofitting with rain barrel/cistern and porous pavement, Journal of Environmental Management, 119, 151-161, doi: 10.1016/j.jenvman.2013.01.019

Ando, A.W., Freitas, L.P., 2011. Consumer demand for green stormwater management technology in an urban setting: The case of Chicago rain barrels, Water Resources Research, 47, W12501, doi:10.1029/2011WR011070.

Arabi, M., Govindaraju, R.S., Hantush, M.M., 2006. Cost-effective allocation of watershed management practices using a genetic algorithm, Water Resources Research, 42, W10429, doi:10.1029/2006WR004931.

Bekele, E.G., Nicklow, J.W., 2005. Multiobjective management of ecosystem services by integrative watershed modeling and evolutionary algorithms, Water Resources Research, 41, W10406, doi:10.1029/2005WR004090.

Bhaduri, B., Grove, M., Lowry, C., Harbor, J., 1997. Assessing the long term hydrological impact of land-use change: Cuppy-McClure Watershed. Indiana, Journal - American Water Works Association, 89 (11): 94-106.

Choi, W., 2007. Estimating land-use change impacts on direct runoff and non-point source pollutant loads in the Richland Creek Basin (Illinois, USA) by applying the L-THIA model, Journal of spatial hydrology, 7 (1): 47-65.

Cibin, R., 2013. Optimal land use planning on selection and placement of energy crops for sustainable biofuel production, Doctoral dissertation, Purdue Univ., West Lafayette, Indiana, USA.

Damodaram, C., Giacomoni, M.H., Khedun, C.P., Holmes, H., Ryan, A., Saour, W., Zechman, E.M., 2010. Simulation of combined best management practices and low impact development for sustainable stormwater management1, Journal of the American Water Resources Association, 46(5), 907-918.

Davis, A.Y., Pijanowski, B.C., Robinson, K., Engel, B.A., 2010. The environmental and economic costs of sprawling parking lots in the United States, Land use Policy, 27 (2): 255-61.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation, 6(2): 182-197.

Dietz, M.E., 2007. Low impact development practices: A review of current research and recommendations for future directions, Water Air and Soil Pollution., 186(1-4), 351-363.

Engel, B.A., Choi, J.Y., Harbor, J., Pandey, S., 2003. Web-based DSS for hydrologic impact evaluation of small watershed land use changes, Computers and Electronics in Agriculture, 39:241-249.

Gilroy, K.L., McCuen, R.H., 2009. Spatio-temporal effects of low impact development practices, Journal of Hydrology, 367(3), 228-236.

Gitau, M.W., Veith, T.L., Gburek, W.J., 2004. Farm-level optimization of BMP placement for cost-effective pollution reduction, Transactions of the American Society of Agricultural Engineers, 47(6), 1923-1931.

Haario H., Saksman, E., Tamminen, J., 2001. An adaptive metropolis algorithm, Bernoulli, 7(2): 223-242.

Harbor, J., 1994. A practical method for estimating the impact of land use change on surface runoff, groundwater recharge and wetland hydrology, Journal of the American Planning Association, 60, 91-104, doi:10.1080/01944369408975555.

Kennedy J., Eberhart, R.C., 2001. Swarm Intelligence, Morgan Kaufmann: San Mateo.

Liu, Y., Ahiablame, L.M., Bralts, V.F., Engel, B.A., 2015a. Enhancing a rainfall-runoff model to assess the impacts of BMPs and LID practices on storm runoff, Journal of Environmental Management, 147, 12-23.

Liu, Y., Bralts, V.F., Engel, B.A., 2015b. Evaluating the effectiveness of management practices on hydrology and water quality at watershed scale with a rainfall-runoff model. Science of The Total Environment, 511, 298-308.

Maringanti, C., Chaubey, I., Popp, J., 2009. Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control, Water Resources Research, 45, W06406, doi:10.1029/2008WR007094.

Maringanti, C., Chaubey, I., Arabi, M., Engel, B.A., 2011. Application of a multi-objective optimization method to provide least cost alternatives for NPS pollution control, Environmental Management, DOI:10.1007/s00267-011-9696-2.

Newcomer, M.E., Gurdak, J.J., Sklar, L.S., Nanus, L., 2014. Urban recharge beneath low impact development and effects of climate variability and change, Water Resources Research, 50, 1716-1734, doi:10.1002/2013WR014282.

Pandey, S., Gunn, R., Lim, K.J., Engel, B.A., Harbor, J., 2000. Developing a web-enabled tool to assess long-term hydrologic impacts of land use change: information technology issues and a case study. URISA-WASHINGTON DC, 12(4), 5-22.

Prince George's County, Department of Environmental Resources, 1999. Low-impact development design strategies: An integrated design approach, Department of Environmental Resources, Programs and Planning Division.

Rodriguez, H.G., Popp, J., Maringanti, C., Chaubey, I., 2011. Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed, Water Resources Research, 47, W01507, doi: 10.1029/2009WR008549.

Shoemaker. L., Riverson Jr., J., Alvi, K., Zhen, J.X., Paul, S., Rafi, T., 2009. SUSTAIN—A framework for placement of best management practices in urban watersheds to protect water quality, Fairfax, VA.

Srivastava, P., Hamlett, J.M., Robillard, P.D., Day, R.L., 2002. Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm, Water Resources Research, 38(3), doi:10.1029/2001WR000365.

Storn R., Price, K., 1997. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces, Journal of global optimization, 11: 341-359.

Tang, Z., Engel, B.A., Pijanowski, B.C., Lim, K.J., 2005. Forecasting land use change and its environmental impact at a watershed scale, Journal of Environmental Management, 76 (1): 35-45.

Tedesco, L.P., Hoffmann, J., Bihl, L., Hall, B.E., Barr, R.C., Stouder, M., 2011. Upper White River Watershed regional watershed assessment and planning report.

The LIDC (Low Impact Development Center, Inc.), GeoSyntec Consultants, University of Florida, and Oregon State University, 2006. Evaluation of best management practices for highway runoff control, Transportation Research Board, National Research Council.

USEPA (U.S. Environmental Protection Agency), 2004. Stormwater best management practice design guide: volume 2. EPA/600/R-04/121A, U.S. Environmental Protection Agency, Office of Research and Development, Washington, DC.

USEPA (US Environmental Protection Agency), 2008. Reducing stormwater costs through low impact development (LID) strategies and practices, EPA 841-F-07-006, Nonpoint Source Control Branch, Washington, D.C.

Vrugt, J.A., Robinson, B.A., 2007. Improved evolutionary optimization from genetically adaptive multi-method search, Proceedings of the National Academy of Sciences, 104: 708-711.

Zhang, X., Izaurralde, R.C., Manowitz, D., West, T.O., Post, W.M., Thomson, A.M., Williams, J.R., 2010. An integrative modeling framework to evaluate the productivity and sustainability of biofuel crop production systems, Global Change Biology Bioenergy, 2(5), 258-277.

CHAPTER 6. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

6.1 Research overview

This study was conducted to enhance the Long-Term Hydrologic Impact Assessment-low impact development (L-THIA-LID) model in simulating best management practices (BMPs) and low impact development (LID) practices at watershed scales in order to better assist planners and decision-makers in development projects. The specific objectives were to:

1. Enhance the L-THIA-LID model and demonstrate its use with four types of idealized land use units and watersheds (low density residential area, high density residential area, industrial area, and commercial area).
2. Enhance the L-THIA-LID model in simulating BMPs and LID practices at watershed scales, and then apply the model to an actual watershed with calibration, validation, sensitivity analysis and uncertainty analysis.
3. Improve the ability of the enhanced L-THIA-LID model to optimally select and place BMPs and LID practices at watershed scales.

In the first objective, the capability of the L-THIA-LID model to represent BMPs and LID practices was enhanced (named L-THIA-LID 2.0 model) by increasing the practices from 6 types (bioretention systems, rain barrel/cistern, green roof, open wooded space, porous pavement, and permeable patio) to 12 types (added practices: detention basin, retention pond, wetland basin, biofilter-grass swale, wetland channel, and biofilter-grass strip); improving the approach to calculate runoff volume reduction of practices based on both the Curve Number Method and percentage runoff volume reduction method; enhancing the method to determine water quality after the implementation of practices based on runoff volume reduction, pollutant concentration reduction, and irreducible concentration reduction methods using data from International Stormwater Best Management Practices (BMP) Database; and simulating impacts of practices implemented in series.

The performances of BMPs and LID practices in treating runoff volume and pollutant loads, both separately and in series, were evaluated with the L-THIA-LID 2.0 model on four types of idealized land use units and watersheds—low density residential, high density residential, industrial, and commercial. Bioretention systems, biofilter-grass swales, porous pavement, biofilter-grass strips and wetland channels were implemented in each idealized land use unit; detention basin (dry, grass-lined), retention pond (wet pond), and wetland basin were applied in each idealized watershed; porous pavement/biofilter-grass swale and biofilter-grass strip/biofilter-grass swale were implemented in series in each idealized land use unit. Finally, the results of L-THIA-LID 2.0 model were compared to the findings of other researchers.

In the second objective, the L-THIA-LID 2.0 model was enhanced to create the L-THIA-LID 2.1 model for simulating BMPs and LID practices at watershed scales, and cost estimation of practices was added. The impacts of BMPs and LID practices, including green roof, rain barrel/cistern, bioretention system, porous pavement, permeable patio, grass strip, grassed swale, wetland channel, retention pond, detention basin, and wetland basin, on water quantity and quality were simulated with 16 scenarios in the Crooked Creek watershed near Indianapolis, Indiana from 1993 to 2010 using the L-THIA-LID 2.1 model. The sensitivity and uncertainty of the model in estimating hydrology and water quality for both before and after implementing BMPs and LID practices were analyzed using Sobol′'s global sensitivity analysis method and bootstrap method, respectively, to obtain the sensitive variables in the model and the precision of the model. The L-THIA-LID 2.1 model was calibrated for annual runoff from 1993 to 2001 and validated from 2002 to 2010. The total cost to implement BMPs and LID practices was estimated for each scenario. Cost per unit reduction per year was estimated to find the more cost effective scenarios.

In the third objective, a decision support tool, which linked the L-THIA-LID 2.1 model with A Multi-ALgorithm Genetically Adaptive Multiobjective (AMALGAM) method using the multilevel spatial optimization (MLSOPT) framework, was developed to optimally select and place BMPs and LID practices. The decision support tool was applied in Crooked Creek watershed, an urbanized watershed in Indiana, USA, to optimally implement BMPs and LID practices. Optimization results from both hydrological response unit (HRU) scale and watershed scale were tested. Optimization results were compared with the findings for random placement of BMPs and LID practices.

6.2 Major research findings

Major findings of this research are:

- The L-THIA-LID model was enhanced to create the L-THIA-LID 2.0 model to better represent BMPs and LID practices. By applying the model on four types of idealized land use units and watersheds, the simulated reductions of runoff volume and pollutant loads after implementing BMPs and LID practices both separately and in series, were comparable to observed reductions of runoff and pollutant loads in the scientific literature. Based on the analysis, one can conclude that the L-THIA-LID 2.0 model can properly simulate BMPs and LID practices.

- The L-THIA-LID 2.0 model was enhanced to create the L-THIA-LID 2.1 model to simulate BMPs and LID practices at watershed scales. The sensitivity and uncertainty analysis of the L-THIA-LID 2.1 model showed that:

    - When estimating runoff volume without implementing BMP and LID practice, CN (Curve Number) was more sensitive than P (Precipitation). When computing pollutant loads without implementing BMPs and LID practices, the sensitivities were in the descending order of CN, EMC (Event Mean Concentration), and P. When predicting runoff volume with varying levels of BMP and LID practice implementation, the sensitivities were in the descending order of Ratio_r (Practice outflow runoff volume/inflow runoff volume), CN and P. When modeling nonpoint source pollutant loads with varying levels of BMPs and LID practice implementation, the sensitivities were in the descending order of Ratio_r, EMC, IC (Irreducible Concentration), CN, Ratio_c (Practice outflow pollutant concentration/inflow pollutant concentration), and P.

  - The relatively large output uncertainty bounds prior to BMPs and LID practice implementation may be due to simplifying natural processes by the simple model, large ranges (or uncertainty) for variables, and unsymmetrical changes (-20% to 2%) of CNs from default values. The uncertainty ranges of model outputs after BMP and LID practice implementation were relatively small, due to comparing relative predictions instead of absolute values.
  - Prior to BMP and LID practice implementation, the average observed runoff volume was well covered in the uncertainty ranges simulated by the L-THIA-LID 2.1 model; TP and O&G loads from other urban watersheds fell well within the uncertainty ranges in this study; TN, TKN, NOx, TSS, Pb, Cu, Zn, Cr, FC, and BOD loads from other study areas were similar to the uncertainty bounds found in this study; this indicates good precision of the model; however, no studies were found to directly compare other uncertainty results.

- Sixteen BMP and LID practice scenarios were simulated with L-THIA-LID 2.1 at a watershed scale. Results showed that:

  - Although the percent reductions of runoff volume and pollutant loads in scenarios from lower levels of BMPs and LID practices adoption were small, they were significant considering the percentage of area affected by BMPs and LID practices. With high and very high levels of BMPs and LID practices implemented, the effectiveness became more discernible.
  - The implementation of grass strips in 25% of the watershed where this practice could be applied, with the lowest cost per unit reduction per year values, was the most cost-efficient scenario. Scenario with very high level of BMP/LID practice adoption reduced runoff volume and pollutant loads the most, but this scenario was not as cost-efficient as most other scenarios.
  - The L-THIA-LID 2.1 model is a valid tool to help obtain cost effective BMP and LID practice plans at watershed scales.

- A decision support tool was developed to optimally select and place BMPs and LID practices with the L-THIA-LID 2.1 model. The decision support tool was applied in Crooked Creek watershed near Indianapolis, Indiana, and the results indicated that:

  - Hydrological response unit scale optimization results indicated that for sites with different features, the optimal BMPs/LID practice solutions to attain the same environmental goals would differ; for the same combination of HRU and suitable practices, the favorable levels and combinations of practices could be significantly different for various runoff volume/pollutant load reduction objectives. For higher expenditures, the implementation levels and types of favored practices tended to increase relative to those for lower expenditures. These results demonstrated the need to optimally select and place practices with lower cost per unit runoff volume/pollutant load reduction.

- The watershed scale selection and placement of BMPs and LID practices were optimized for the study watershed. When few practices were implemented in the watershed, increased practice expenditures greatly reduced runoff volume and pollutant loads. However, beyond a certain level of expenditure, further expenditures did not always result in obvious reductions of runoff volume and pollutant loads. For the same BMP and LID practice expenditure, percent reductions in runoff volume were smaller than percent reductions in pollutant loads.
- Optimization results were compared with the findings for random placement of BMPs and LID practices. The results showed that for the same BMP and LID practice expenditure, optimized implementation of BMPs/LID practices had 3.9 to 7.7 times as much reduction in runoff and pollutant loads as the random scenario. To achieve the same level of runoff and pollutant load reduction, random scenarios cost 4.2 to 14.5 times as much as the optimized scenarios.
- To optimally select and place BMPs and LID practices at watershed scales, the decision support tool was capable of maximizing the reduction of runoff volume/pollutant loads for a given budget or minimizing cost given a runoff or pollutant load reduction goal. The decision support tool can assist decision makers in optimally selecting and placing BMPs and LID practices.

6.3 Recommendations for future research

Although baseflow volume was estimated in the previous L-THIA-LID model, the L-THIA-LID 2.1 model does not include baseflow since the method to calculate baseflow volume in the previous model is an empirical method with curve number as a parameter that is only suitable for areas in Indiana and the newly added BMPs/LID practices in L-THIA-LID 2.1 model are represented using percent runoff volume reduction method instead of using curve numbers. Future research is needed to develop an easy to use method to compute baseflow volume that is suitable for general areas and BMPs/LID practices represented by the percent runoff volume reduction method. In order to estimate the water quality changes after implementing BMPs/LID practices, the influence of BMPs/LID practices on pollutant concentration in baseflow needs to be studied and added to the model as well.

In the L-THIA-LID 2.1 model, runoff and pollutants were routed from HRUs to the watershed outlet by simply summing values. A method of routing runoff and pollutants needs to be added in the model.

In L-THIA-LID 2.1, the newly added BMPs and LID practices are assumed to be sized to obtain the default percent runoff volume reductions in the model. Future studies are needed to add size limitations to BMPs and LID practices based on more detailed data analysis of the International Stormwater BMP Database and other databases. Potentially the size of practices can be represented as a factor of stormwater runoff source area to surface area of each practice.

The default values of percent runoff volume reduction, percent pollutant concentration reduction, and irreducible concentration reduction for each BMP/LID practice were obtained based on data in International Stormwater BMP Database collected through 2012. Future research is needed to update the default values in L-THIA-LID 2.1 when additional data are released by the International Stormwater BMP Database or other databases.

This study analyzed the sensitivity of the L-THIA-LID 2.1 model in estimating hydrology and water quality without and with BMPs and LID practices implemented. Future studies are needed to estimate the sensitivity of L-THIA-LID 2.1 in estimating expenses of implementing BMPs and LID practices.

This study was conducted in a watershed with limited water quality data, and only the output uncertainty of runoff volume was compared to the observed data from the same study area; all other output uncertainties in this study were compared to results of other study areas. More insight into the L-THIA-LID 2.1 model behavior could be obtained by analyzing model uncertainty using watersheds with more water quality data, and even data before and after implementation of BMPs and LID practices.

In the current research, 30 m resolution of Digital Elevation Data (DEM) data were used to estimate the drainage areas and drainage slopes of the watershed. Future study is needed to compare 30 m resolution and other obtainable resolutions (such as 1 m resolution) of DEM data to determine the advantages and disadvantages.

The performance of AMALGAM was improved by changing population size and number of generations, while other parameters of the optimization algorithms in AMALGAM were set as recommended. Future studies could be conducted to analyze the parameters in AMALGAM in order to find the best parameters for the decision support tool. The decision support tool could be used to evaluate the optimum results of selecting and placing BMPs and LID practices in other watersheds.

After the development and demonstration of the decision support tool to optimally select and place BMPs and LID practices, future studies could be done to compare the decision support tool results with those of other tools that can optimally select and place BMPs and LID practices at watershed scales in urban areas, such as the Stormwater Treatment and Analysis Integration (SUSTAIN) Model.

APPENDIX

Table A.1 Values of event mean concentration used in the L-THIA-LID 2.0 model

(Baird et al,, 1996; RRNWWDP, 1998; Camp Dresser & McKee Inc., 2004; Collins et al., 2004; Selvakumar and Borst, 2004; Maestre and Pitt, 2005; Miller, 2005; Ellis and Revitt, 2008; McCarthy et al., 2008; Stein et al., 2008; Wilson and Weng, 2010)

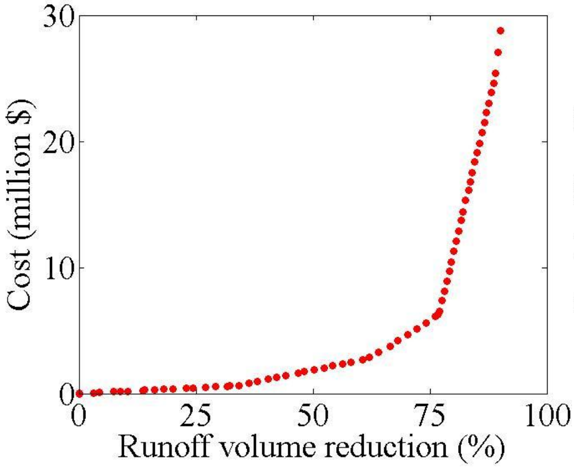
compound	Commercial	Agricultural	HD Residential	LD Residential	Grass/ Pasture	Forest	Industrial
Total Nitrogen (mg/L)	1.41	4.14	1.96	1.96	0.9	0.5	1.26
Total Kjeldahl Nitrogen (mg/L as N)	1.2	1.23	2.1	2.1	0.2	0.4	0.99
Nitrate+Nitrite (mg/L)	0.24	1.48	0.67	0.67	0.8	0.32	0.3
Total Phosphorus (mg/L)	0.27	1.3	0.83	0.83	0.11	0.01	0.28
Dissolved Phosphorus (mg/L)	0.09	0	0.57	0.57	0	0	0.22
Suspended Solids (mg/L)	56.27	75	52	52	1.4	0.8	60.5
Dissolved Solids (mg/L)	185	1225	134	134	245	245	116
Total Lead (µg/L)	14.5	0.93	9	9	5	2.2	15
Total Copper (µg/L)	14.5	1.5	15	15	10	10	15
Total Zinc (µg/L)	180	16	80	80	6	6	245
Total Cadmium (µg/L)	1.23	0.8	0.73	0.73	0.9	0.18	2
Total Chromium (µg/L)	10	10	2.1	2.1	7.5	7.5	7
Total Nickel (µg/L)	4.03	0	0.69	0.69	0	0	8.3
Fecal Coliform (colonies/100 ml)	6900	0	20000	20000	37	37	9700
Fecal Strep. (colonies/100 ml)	18000	0	56000	56000	0	0	6100
E-coli (MPN/100 ml)	5373	21813	11466	11466	3750	188	1281
BOD (mg/L)	18.47	3.2	25.5	25.5	0.53	0.46	14
COD (mg/L)	53.5	0	35.5	35.5	0	0	45.5
Oil and Grease (mg/L)	4.59	0	2.1	2.1	0	0	3

Table A.2 Site characteristics for BMP/LID practice suitable locations (Shoemaker et al., 2009; USEPA, 2004)

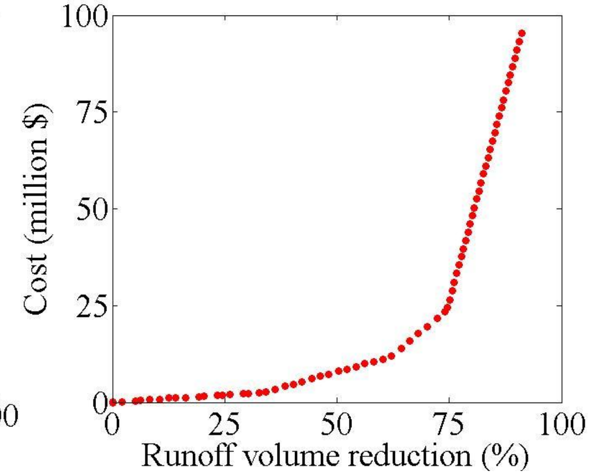
BMP	Site Suitability Criteria						
	Drainage Area (ha)	Drainage Slope (%)	Imperviousness (%)	Hydrologic Soil Group	Road Buffer (m)	Stream Buffer (m)	Building Buffer (m)
Wet Pond	> 10.12	< 15	> 0	A–D	/	>30.48	/
Dry Pond	> 4.05	< 15	> 0	A–D	/	>30.48	/
Wetland	> 10.12	< 15	> 0	A–D	/	>30.48	/
Rain Barrel/ Cistern	/	/	/	/	/	/	On building
Permeable patio	/	/	/	A-D	/	/	<4.57
Green Roof	/	/	/	/	/	/	On building
Grassed Swale	< 2.02	< 4	> 0	A–D	<30.48	/	/
Grass strip	/	< 10	> 0	A–D	<30.48	/	/
Wetland Channel	<2.02	<4	> 0	A–D	<30.48	/	/
Bioretention	< 0.81	< 5	> 0	A–D	<30.48	>30.48	/
Porous Pavement	< 1.21	< 1	> 0	A–D	/	/	/

Table A.3 Annual runoff volume and pollutant loads for the baseline scenario (S0)

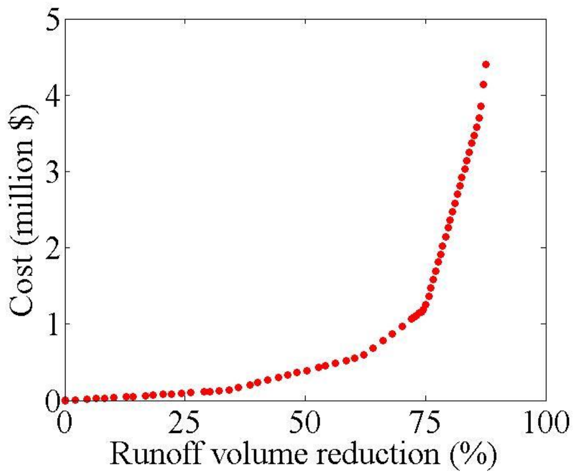
Year	Simulated Annual Runoff (m^3/ha)	Observed Annual Runoff (m^3/ha)	TN (kg/ha)	TP (kg/ha)	TSS (kg/ha)	Pb (g/ha)	BOD (kg/ha)	COD (kg/ha)
1993	2554	3253	4.11	0.47	56.50	16.74	58.60	98.40
1994	1385	1140	2.22	0.25	30.69	9.17	31.91	54.14
1995	1089	994	1.74	0.20	24.12	7.24	25.14	42.77
1996	2623	2822	4.22	0.48	58.05	17.18	60.15	101.00
1997	1484	1583	2.38	0.27	32.89	9.81	34.18	57.85
1998	2210	2011	3.55	0.40	48.97	14.57	50.81	85.86
1999	1597	1368	2.56	0.29	35.39	10.53	36.73	62.07
2000	2068	957	3.33	0.38	45.76	13.56	47.46	79.76
2001	1984	1331	3.18	0.36	43.98	13.10	45.65	77.23
2002	2096	1853	3.37	0.38	46.41	13.79	48.16	81.17
2003	2764	2525	4.47	0.51	61.08	17.96	63.19	105.30
2004	1690	1348	2.70	0.31	37.45	11.20	38.95	66.13
2005	1974	2606	3.17	0.36	43.75	12.99	45.36	76.52
2006	2504	2895	4.03	0.46	55.46	16.47	57.53	96.93
2007	1873	2526	3.01	0.34	41.50	12.35	43.09	72.80
2008	2805	3085	4.53	0.52	61.87	18.20	64.10	106.61
2009	2527	2341	4.07	0.46	55.90	16.52	57.92	97.08
2010	1355	1354	2.17	0.25	30.01	8.95	31.18	52.75



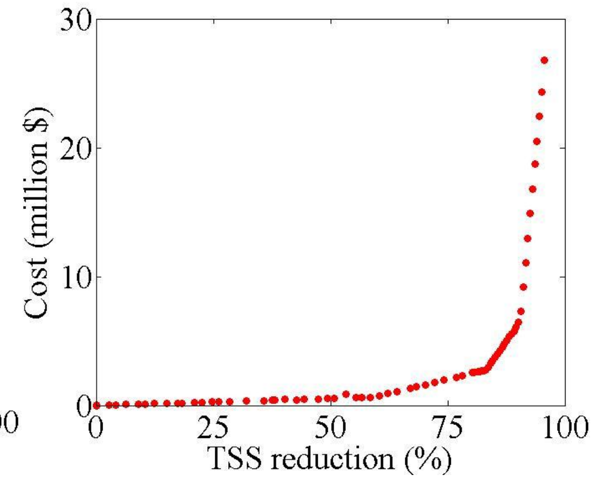
(a) High density residential with soil group D



(b) Low density residential with soil group C

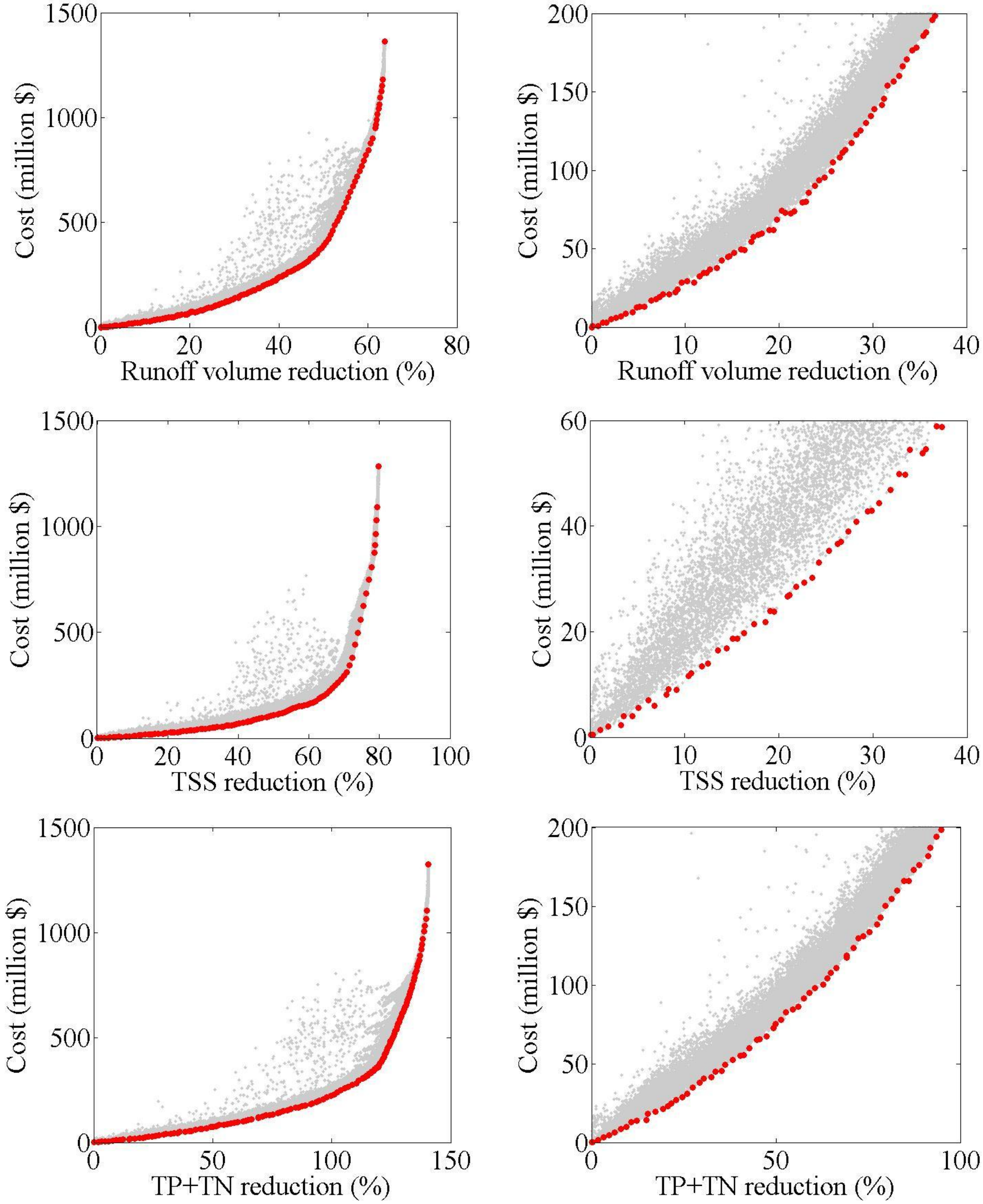


(c) Industrial with soil group D



(d) High density residential with soil group D

Figure A.1 Examples of optimization results for HRU scale areas, which were suitable for retention pond, detention basin, wetland basin, grassed swale, grass strip, wetland channel, bioretention system, and porous pavement. Costs presented were totals for 20 years. Selected areas were 55 ha, 232 ha, 11 ha, and 55 ha, respectively.


1500
1000
500
0
Cost (million $)
0 20 40 60 80
Runoff volume reduction (%)
200
150
100
50
0
Cost (million $)
0 10 20 30 40
Runoff volume reduction (%)
1500
1000
500
0
Cost (million $)
0 20 40 60 80 100
TSS reduction (%)
60
40
20
0
Cost (million $)
0 10 20 30 40
TSS reduction (%)
1500
1000
500
0
Cost (million $)
0 50 100 150
TP+TN reduction (%)
200
150
100
50
0
Cost (million $)
0 50 100
TP+TN reduction (%)

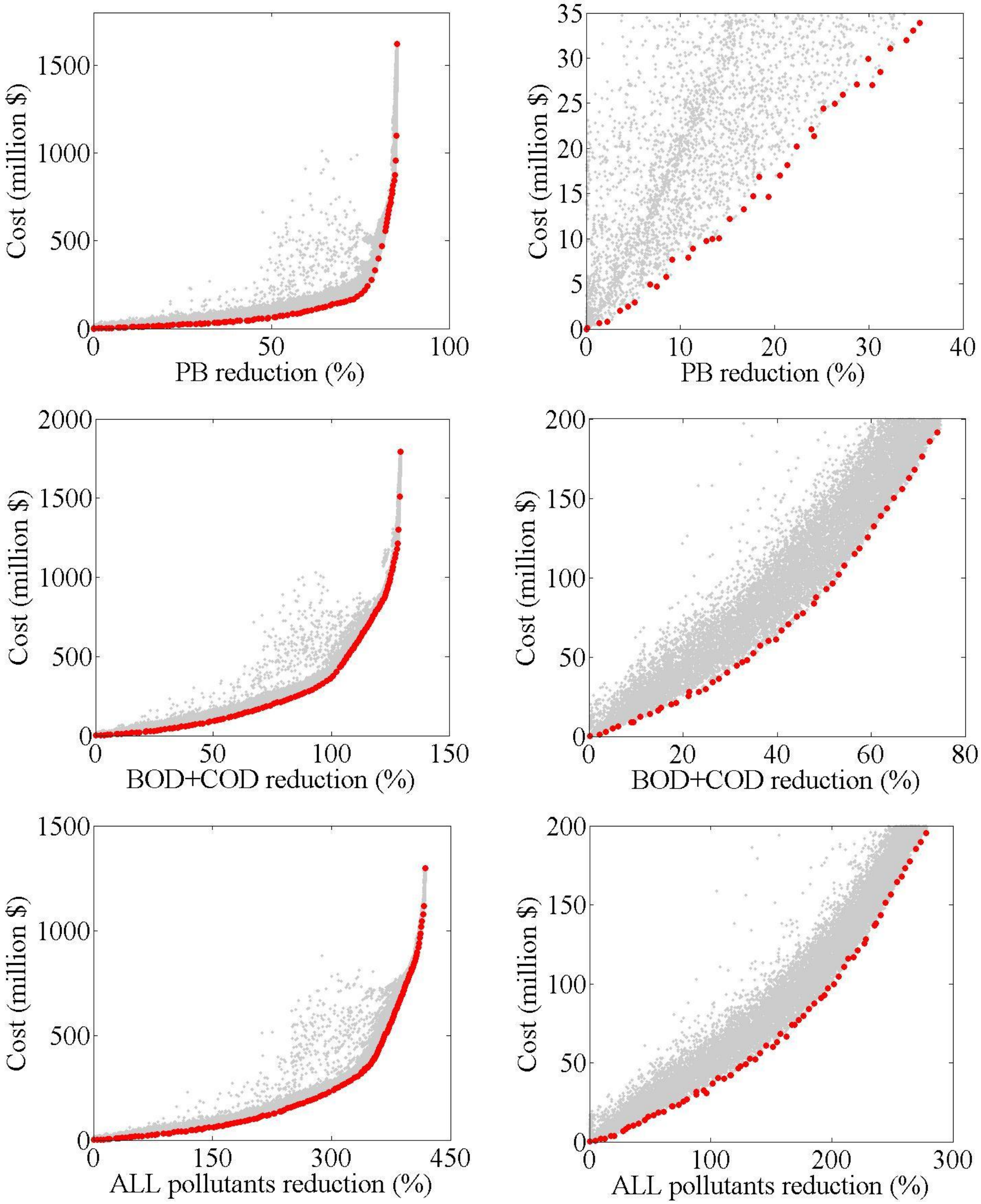


Figure A.2 Watershed scale optimization results for all scenarios.

Plots on the left side were zoomed in and shown as plots on the right side. Costs are total implementation and maintenance cost for a period of 20 years.

VITA

VITA

Yaoze Liu was born in Jiangsu Province, China. In July, 2009, he received his Bachelor of Engineering degree in Irrigation and Drainage Engineering, and Bachelor of Art degree in English as a double major from China Agricultural University, Beijing, China. He graduated with a Master of Engineering degree in Hydraulic Engineering from China Agricultural University, Beijing, China in July, 2011. He joined Agricultural and Biological Engineering Department’s Ph.D. program at Purdue University in August 2011, majoring in Environmental and Natural Resources Engineering.