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Nonpoint Source Pollution Control Using a Multi-Objective Optimization Tool for Best Management Practices Selection and Spatial Placement in the Lower Bear River Watershed, Utah

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NONPOINT SOURCE POLLUTION CONTROL USING A MULTI-OBJECTIVE OPTIMIZATION TOOL FOR BEST MANAGEMENT PRACTICES SELECTION AND SPATIAL PLACEMENT IN THE LOWER BEAR RIVER WATERSHED, UTAH

by

Ali A. Salha

A dissertation submitted in partial fulfillment
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ABSTRACT

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Agricultural best management practices (BMPs) are effective in reducing the transport of nonpoint source pollutants to receiving water bodies. However, selection of BMPs for placement in a watershed requires optimization of the available resources, associated costs and regulation end-points to obtain maximum possible pollution reduction. Optimization methodologies are needed to select and place BMPs in a watershed to provide solutions that are both economically and environmentally effective. The approaches developed here utilize a watershed simulation tool (Soil Water and Assessment Tool (SWAT)) to reproduce the movement of flows and to simulate the sediments and total phosphorus loads for identifying the nonpoint source areas. The approaches use agricultural BMP databases to provide information on their types, pollution reduction efficiencies, and cost information of implementation. Two optimization frameworks were developed to help watershed managers evaluate optimal solutions generated from combining certain BMPs in selected NPS areas. Total phosphorus load from the watershed, and cost of implementing the required agricultural BMPs were the two objective functions during the optimization process. The first optimization approach consisted of a combination tool developed in Python to combine given agricultural BMPs with selected NPS areas identified by SWAT. The approach was tested and provided multiple solutions for conservation programs that can maximize load reduction set under specified budgets in the Lower Bear River (LBR) watershed located in Box Elder County in northern Utah. The other optimization approach, using a multiobjective genetic algorithm (AMALGAM) in combination with the output of the SWAT and the available agricultural BMPs data, was developed and tested for nonpoint source pollution control in the LBR watershed. The optimal solutions provided a trade-off between the two objective functions for phosphorus reduction. The results indicated that the proposed combination control plans of combining agricultural BMP (such as cover strips, tillage management, and different buffer strips) with the identified NPS areas resulted in effective reduction of the nonpoint source pollutants under budget constraints across the LBR watershed.

(162 pages)

PUBLIC ABSTRACT

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This dissertation presents a set of approaches to help address water quality problems related to total phosphorus loads in water bodies. Water quality degradation is caused by many nonpoint sources such as agricultural runoff, fertilizers applications, and bank erosion. Three studies present methodologies for water quality protection from degradation in watersheds. The first study demonstrates the application of a watershed simulation tool that can quantify flows in the watershed, the amount of released pollutants and identify the areas contributing to the pollutants' release in the watershed. The second study presents a simple combination tool that can pair potential management practices with the identified nonpoint sources areas to generate cost-effective combinations of management practices for reducing excess phosphorus loading to water bodies. The last study develops an optimization framework that recommends the area optimum sizes that are available for implementing management practices. These studies were applied to real-case problems to reduce excess nutrients within the Lower Bear River Watershed in northern Utah and expected to improve the management of nutrient control plans under the allocated funds.

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INTRODUCTION

The U.S. Environmental Protection Agency (USEPA) 2006 – 2011 Strategic Plan maintains the five goals that were described in the 2003 - 2008 Strategic Plan: (i) clean air and global climate change; (ii) clean and safe water; (iii) land preservation and restoration; (iv) healthy communities and ecosystems; and (v) compliance and environmental stewardship [1]. Within that context, water quality management is a critical component of overall integrated water resources management (IWRM). Most users of water depend on adequate levels of water quality. Water bodies that do not meet water quality standards are required to have loading limits to restore the water body to a healthy state. These are called Total Maximum Daily Loads (TMDLs) and are defined after intensive study of watershed characteristics as some are done with detailed modeling. States will often use models to determine the potential effect of policy mechanisms on pollutant loadings to the watershed, making them an important component to setting TMDLs and aiding decision-making [2].

Agricultural sources are responsible for 46% of the sediment, 47% of total P (TP) and 52% of total nitrogen (N) discharged into US waterways, making agricultural runoff a major contributor of pollutants to aquatic systems [3, 4]. That said, nonpoint source (NPS) pollution of streams and lakes has created a critical concern throughout the United States as a main water pollution contributor. Agricultural activities have been identified as the primary non-point source (NPS) in our research case study in the Lower Bear River (LBR) watershed of Northern Utah, USA [5]. Point source loads (e.g., wastewater treatment plants (WWTPs)) are monitored and regulated through Utah Pollutant

Discharge Elimination System (UPDES) permits set by the Utah Department of Environmental Quality (UDEQ). It is relatively easy to quantify and to evaluate the impact permitted point discharges because their effluent re-enters the hydrologic cycle at a single identifiable location that can be sampled. In addition, the Clean Water Act (CWA) has been successful at reducing pollution discharges from industries and municipalities (point sources) such that the single largest source of water contamination today comes from NPS pollution. NPS pollution can damage aquatic habitat, harm aquatic life, and reduce the capacity of rivers, streams, lakes, and wetlands to be used for drinking water and recreation. NPS pollution (surface runoff, grazing, agricultural return flows, and others) is not regulated through a permitting procedure. Regulation requires participatory and voluntary implementation of management activities, the impacts of which are difficult to identify, measure, and estimate. What characterizes NPS pollution is that there is no identifiable point where all discharge takes place, so pollution sources generally cannot be directly controlled. The CWA proposed and implemented precautionary measures, called best management practices (BMPs) to protect water bodies from NPS pollution. The use of BMPs was introduced by the U.S. government through many incentive programs in the 1980s to reduce agricultural runoff and erosion. More than 40 percent of Section 319 CWA grants have been used to control NPS pollution from farms and ranches.

Once a TMDL study is released for a specific watershed, several management practices are proposed to reduce the sources of pollution within the watershed. In agricultural watersheds TMDLs target NPS pollution from agricultural activities and propose watershed nutrient control plans to reduce the N, TP and TSS loads to protect water quality. Implementing such agricultural management practices cannot achieve the load reduction immediately after implementation due to resident nutrients in the system. This poses a challenge for the proposed watershed nutrient control plans in terms of setting a timeframe needed to achieve the pollution management goals.

An additional challenge is that these practices cannot be monitored on a regular basis because of cost and time concerns. This poses a question with regard to the impact of these practices through time in terms of their performance and effectiveness, and whether they were the right practice to be used to achieve water quality goals. There is an increasing interest to further evaluate implemented BMPs and their effectiveness in reducing NPS pollution and to investigate proper BMP selection and location arrangement at a watershed scale in a cost-effective solution to provide a means for adaptively managing water resources and mitigating key sources of pollution. In the end, questions remain with respect to the accurate location and quantification of the key nonpoint sources to watershed quality degradation. In most cases, the spatial interactions among BMPs are not considered when establishing a targeting strategy and pollutant control plan; a BMP that is selected based on given targeting conditions could, or might not, be the most cost-effective BMP at a watershed scale. Few studies have evaluated the impact of BMPs implementation impact over temporal and spatial sediment and nutrient loads at the watershed scale in the Intermountain West region. Such studies shall help track BMPs implementation in reducing NPS pollution and in developing approaches for quantifying the links between BMPs implementation and water quality improvements.

Water quality assessment at the watershed scale is accomplished using watershed monitoring and modeling techniques. Watershed modeling has emerged as an important scientific research and management tool, particularly in efforts to understand and control water pollution [6]. Watershed characteristics represented in a model are stream flows, seasonal variations in precipitation with wet winters and dry summers, land use and land cover, soil characteristics, topography, and point and nonpoint sources of pollution. Watershed models can be a tool for quantifying sediment and nutrient loads that originate from point and nonpoint sources during the period of pre- and post-BMP implementation. Such models that capture the variability in soils, climatic conditions, land use/cover and management conditions over extended periods of time are a primary means for estimating pollutant loads at watershed scales. On the other hand, continuous water quality monitoring at many locations within a watershed to evaluate the effectiveness of BMP implementation is in many cases time consuming, costly, and spatially infeasible at the watershed level, in particular when dealing with nonpoint source pollution to collect continuous data within a watershed [6, 7].

The watershed model applied in this research is the Soil and Water Assessment Tool (SWAT). It was used to estimate the changes in water quantity and quality within an agricultural watershed located in the Intermountain West region of the U.S. Climatic conditions and agricultural activities can be simulated and their impacts on water quality can be assessed using SWAT as a process model. SWAT is one of the most capable models to simulate the effects agricultural activities since it involves a large number of simulated components that can be used to predict over long periods of time the impact of management practices in watersheds with variations in soil type, land use, agricultural practices, and application of fertilizers and pesticides [8-11]. SWAT has been adopted as part of USEPA's Better Assessment Science Integrating Point & Nonpoint Sources

(BASINS) software package and is being applied by the U.S. Department of Agriculture (USDA) researchers for the Conservation Effects Assessment Project (CEAP) [12-14].

Official program records (i.e., 319(h) sections) are sources of BMPs information at the landscape scale. The records use spreadsheets to determine BMP load reduction at the site (i.e., Spreadsheet Tool for Estimating Pollutant Loads (STEPL) model). After a year of implementing BMPs, monitoring whether the conservative practice established at the site did reduce the pollutant loads or not is neither consistent nor continued. Thus, a watershed modeling approach can be used to: quantify NPS contamination (which allows for continuous/long-term simulation); locate optimal sites for BMPs; identify areas of high pollution risk; and evaluate the long-term impact of implemented and the proposed BMPs on nutrient and sediment loads. This approach supports validating official documents and reports regarding implemented BMPs in any given watershed.

The success of the implementation of BMPs and any conservation programs in protecting watersheds from NPS pollution depends on available planning tools (e.g., decision support systems) that can assist in identifying the most cost-effective watershed management processes. Selection of the most effective BMPs for placement in a watershed requires identification of critical areas, optimization of available resources, and minimization of associated costs in obtaining the maximum possible pollution reduction in efforts to meet water quality end-point requirements. Therefore, this research answers the question of “how can we optimize the placement of BMPs in an agriculturally dominated watershed to achieve maximum pollutant reduction at lowest cost?” The answer is to apply new optimization methods for deriving watershed-scale nutrient control plans for NPS pollution that can generate the suitable combination of BMPs that are both environmentally and economically effective.

The methods combine the use of a calibrated and validated process watershed model (SWAT) to define the critical NPS areas (i.e., areas of the watershed contributing significant NPS contaminants/constituents of concern), representation of agricultural BMPs (databases regarding types, reduction rates, and cost information), a combination tool written in Python [15], and a multi-objective genetic algorithm called A Multi-Algorithm Genetically Adaptive Multi-objective Method (AMALGAM) [16, 17] using MATLAB software [18]. The methods are unique because they do not only simulate the effects of combining agricultural BMPs in selected NPS areas on water quality targets, but help to determine the most feasible combination that watershed managers or users can choose to decide based on their budget constraints at a watershed scale. The combination tool proposes numerous solutions of pairing both the agricultural BMPs and the NPS areas along with their total phosphorus reduction and implementation cost. The AMALGAM algorithm ensures an effective, fast, dependable, and computationally efficient solution to multi-objective optimization problems compared to other algorithms such as Strength Pareto Evolutionary Algorithm (SPEA2) [18] and Non-dominated Sorted Genetic Algorithm-II (NSGA-II) [19].

The LBR watershed was used as the case study area where data such as Digital Elevation Model (DEM), land use/land cover (LULC), soil profiles and climate data for 10 years (2000-2010) were available as inputs to quantify streamflow, nutrient and sediment yields. Pollutant loading rates coming out of the hydrological response units from the SWAT simulation were spatially projected to a parcel map to ensure that the field scale is well represented for effective implementation of agricultural BMPs.

Optimization methods utilize SWAT model outputs to provide tools for watershed managers to optimize the cost and placement of BMPs within agricultural watersheds.

Research Objective

The overall objective of this research was to propose different approaches for managing, evaluating and optimizing the effectiveness of agricultural BMPs implemented for sediment and nutrient reduction within an agricultural watershed with a snowmelt-driven hydrology in the Intermountain West region. The research aimed to increase the knowledge of how to achieve the optimal selection and location of agricultural BMPs, and to quantify the impact of agricultural BMPs on the budget available for implementation and the water quality at a watershed scale. This would support better decision making on the feasibility and sustainability of agricultural BMPs, including the financial resources allocated for agricultural BMPs implementation. The following specific objectives in this research were used to address the challenges associated with the approach described above:

Objective 1: Apply a spatially distributed version of the SWAT model in a mountainous, agricultural watershed with snowmelt-driven hydrology using publicly available input data (e.g., DEM, land use, soil map, and weather and climate data): Assess the performance of using the SWAT model to simulate streamflow along with nutrients and sediments loads in an agricultural watershed under semi-arid conditions such as in the Intermountain West region. Examine using the SWAT model in the LBR watershed in the period from 2000 to 2010 as a case study to characterize watershed hydrology and to assess TP and TSS loads. Apply the SWAT model to identify the critical areas contributing to watershed quality pollution to simulate appropriate management scenarios targeting these critical areas.

Objective 2: Build a Combination Tool for selecting Agricultural Best Management Practices Package (BMPs) and Nonpoint Sources Areas under specific budget constraints. Find applicable agricultural BMPs that can be implemented within an agricultural watershed in the Intermountain West region. To provide knowledge regarding a comprehensive BMP database (e.g., type, cost, reduction rate, life span). Simulate high phosphorus loading rates NPS areas using calibrated and validated SWAT model (as selected in objective one). The combination tool works as an iteration process to join multiple BMPs in the proposed NPS areas to allocate the combination of BMPs that provide the maximum reduction solution under given budget.

Objective 3: Development of an optimization approach to implement multi-objective genetic algorithm (AMALGAM) for optimization and incorporate: 1) output from SWAT model (e.g., critical areas for NPS loading) under Objective 1 and 2) BMPs database under Objective 2 to find optimum feasible areas for BMPs implementation to control TP loads under different scenarios. Under this objective, different constraints such as TMDL water quality regularities, available budget, identified critical areas and areas where BMPs can be implemented are studied and analyzed. The hypothesis to identify most cost-effective combination of BMPs to populated sizes areas of NPS is tested to achieve the required phosphorus load reduction target.

Research Significance

It is expected that the research and its outcomes will contribute to the watershed and engineering community regarding the modeling of SWAT, implementation, and evaluation of agricultural BMPs in an agricultural watershed in the Intermountain West region.

This research is compatible with the National Water Quality concerns that agricultural nonpoint source (NPS) pollution is the leading source of water quality impacts on streams, rivers and lakes. This new research approach leverages optimization approaches to create a better understanding of the links between environmental variables and the selection and placement of BMPs within agricultural watersheds for better water quality management under implementation budget constraints. Further, using this optimization approach along with reported documentation will help close the feedback loop between the field level and watershed level. Documentation is for watershed managers and federal agencies to help validate results, redirect programs, provide progress to decision makers, assist with economic evaluations and obtain program funds.

Local consultation and data collection were carried out with local watershed and land managers who are responsible for meeting water quality goals and implementing water quality programs on agricultural land. The feedback and recommendation enhanced the evaluation process of BMPs' effectiveness and identified the proper location for each agricultural BMP based on their experience. This will advance the understanding of the relation between Land Use and selected BMPs. Others who can benefit from the research work include conservation districts; the agricultural services community; and the environmental and community organizations.

The research can be beneficial to farmers and local and federal agencies. It can assist watershed managers and planners through using calibrated and validated parameters in evaluating of proposed watershed nutrient control projects, quantifying potential impacts on watershed quality, providing a guide to where to apply conservation practices, and optimizing public investments in improving water quality in agricultural watersheds driven by snowmelt and climatic conditions existing in the Intermountain West region of the U.S.

Dissertation Organization

Seven chapters are contained in this dissertation. The main body of the dissertation consists of three separate but inter-related chapters (Chapter 2-4). The first chapter presents a general introductory description about the main body of the dissertation. The second chapter describes the application of Soil and Water Assessment Tool (SWAT) model in LBR Watershed. The third chapter demonstrates the combination tool used for generating best management practices for reducing phosphorus load reduction in LBR watershed. The fourth chapter addresses optimization of NPS control practices in LBR Watershed. Finally, the last chapter of this dissertation (Chapter 5) summarizes what was done and accomplished in the dissertation. Moreover, further research directions are suggested in Chapter 6.

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APPLICATION OF THE SOIL AND WATER ASSESSMENT TOOL (SWAT) MODEL IN THE LOWER BEAR RIVER (LBR) WATERSHED

Abstract

This chapter describes the hydrological assessment of an agricultural watershed in Northern Utah as part of Intermountain West region of the United States through the use of a watershed scale hydrologic model. The Soil and Water Assessment Tool (SWAT) model was applied to the Lower Bear River watershed, located in Box Elder County. The inputs to the model were obtained from several sources such as Utah Division of Water Quality and USGS database systems, meteorological input (precipitation and temperature from generated weather engine), and measured streamflow data at the watershed outlet (USGS 10126000 near Corrine), were used in the simulation. Model calibration, facilitated by SWAT-Calibration and Uncertainty Programs (SWAT-CUP) that offered the sensitivity analysis for list of calibrated parameters that are sensitive to stream flow, sediments and total phosphorus, was performed for the period 2002 through 2005, and validation was performed for 2006 through 2010. The model was found to reproduce the movement of water, sediments and total phosphorus across the watershed. It performed well with statistical measures of goodness-of-fit R^2 = 0.83, N_{SE} = 0.67 and RMSE = 0.36 m^3/sec for flow simulation. Total phosphorus simulation showed good prediction ability with the observations at R^2 = 0.59, N_{SE} = 0.54 and RMSE = 0.01 mg/L, while sediment simulation was reasonably represented with R^2 = 0.74, N_{SE} = 0.44 and RMSE = 1.61 mg/L. This hydrologic modeling will facilitate future applications using SWAT in the Lower Bear River watershed for various watershed analyses, including defining the

critical areas diffusing sediments and nutrient loads to the receiving water bodies in the watershed and proposing proper location and types of management practices to conserve the watershed water quality.

Introduction

Watershed models are essential for quantifying sediment and nutrient loads that originate from nonpoint sources (NPS). Such models are primary means towards generating pollutant estimates in gaged and ungauged watersheds and respond well at watershed scales by capturing the variability in soils, climatic conditions, and the land use/cover situation and management conditions over extended periods of time [1-3]. At present, agricultural activities in the Lower Bear River (LBR) pose a threat to the water quality in LBR waterways as the main NPS of nutrients and sediments. Physically-based, distributed hydrological models have been widely used for water resources management and planning. They have been extensively applied to study the impact of land use change on water quality and quantity, water related activities, and adaptation measures, among others [4, 5]. The dynamic development of GIS techniques, coupled with digital information on topography, soil and land use, has led to creation of complex modeling systems combining GIS with hydrologic/water quality models, where the GIS interface helps in preparation of input data required for the model. One of the most suitable models used worldwide to study hydrologic, biogeochemical and ecological processes at the watershed scale is the Soil and Water Assessment Tool (SWAT) [6-11], which integrates both hydrologic and water quality components combined within a GIS interface environment. Based on that, SWAT watershed model is applied in the research for estimating where the critical sediment and nutrient source areas.

SWAT is a physically based, semi-distributed and process-oriented hydrological model that has been developed by USDA - Agricultural Research Service (USDA-ARS) to predict the impact of land management practices on water, sediment, and agricultural chemical yields (including nutrients) in complex catchments with varying soils, land use, and management conditions over long periods of time [12, 13]. SWAT involves a large number of simulated components that can be used to predict over long periods of time, the impact of soil management practices in aquatic environments (surface and underground) in watersheds with variations in soil type, land use, application of fertilizers, and pesticides [14-16]. Since the LBR watershed is dominated by agriculture and has several miles of impaired streams, SWAT can be applied to capture these features. SWAT has been successfully applied in numerous studies for simulations of discharge and nutrient transport in watersheds with varying climatic, geologic and hydrologic conditions [17-19]. The SWAT model has been recently applied to assess watershed conditions, to develop and evaluate TMDL studies, and to investigate the effectiveness of best management and conservation practices in different regions of the U.S. Although it was originally developed for application in the United States, the expansion of its simulation capabilities has allowed it to become a globally used model [20-27].

The objectives of this study are: assess if the SWAT model could be successfully calibrated and validated for discharge, sediments, and total phosphorus loads from the LBR watershed of Box Elder County in State of Utah watershed that is dominated by agricultural use. The output discussion and results knowledge are useful for decision makers in order to manage water resources and to implement the most effective measures to limit diffuse pollutions from arable land to surface waters.

Literature Review

The development of SWAT is a continuation of USDA-ARS modeling experience that spans a period of roughly 30 years [28-32]. SWAT is a basin-scale, continuous-time model that operates on a daily time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in ungauged watersheds. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. It combines simulated hydrology, sediment and nutrient transport in one model. Full documentation about the applications, studies and research that has been carried out using SWAT can be seen in Gassman et al. 2007 paper [24].

In terms of sediment studies using SWAT, Saleh et al. [33] used the SWAT model in a study in North Bosque River watershed in north Texas for evaluating sediment load and observed that SWAT simulated sediment load matched well with the observed sediment load at monthly basis. Further, Santhi et al. [31] applied successfully SWAT in simulating sediment loads at different time scale in two sub watersheds in Bosque River in Texas. Arnold et al. [34], utilized SWAT for five major Texas river basins and observed that sediment yields predicted by SWAT were within reasonable range of sediment yields derived from rating curves in the watersheds.

There are many studies around the world that show the robustness of SWAT for modeling nutrient losses. Saleh et al. [33], Santhi et al. [31] used SWAT to evaluate nitrogen losses in watersheds in Texas. They found that SWAT was able to predict nitrogen losses within reasonable limits with the Nash–Sutcliffe model efficiency (N_{SE}), a widely-used statistic to evaluate efficiency of hydrologic predictions, value greater than 0.60 and phosphorus losses was also simulated within reasonable limit of N_{SE} ranging from 0.39 to 0.93. In a similar study in Iowa at Walnut Creek watershed, Chaplot et al. [35] applied SWAT with nine years of data to calibrate nitrate load and found that predicted loads were close to the observed loads at the Creek site. Hanratty and Stefan [36] used data collected from the Cottonwood River, Minnesota to calibrate the SWAT model and concluded that SWAT was suitable for simulating water quality variability under climate change. They simulated both nitrate-nitrogen and phosphorus for their study. Arabi et al. [22] studied the effect of best management practices (BMPs) on nitrogen and phosphorus losses in two small watersheds in Indiana and found SWAT an effective tool to do so. But they also noticed that SWAT underpredicted phosphorus yield in those months when measured phosphorus losses were higher and over predicted it for the months with low phosphorus losses.

In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the subwatershed area and are not identified spatially within a SWAT simulation. The ArcGIS extension ArcSWAT allows for the SWAT model to be executed within a geographic information system (GIS) to use its spatial analysis advantages. Such integration provides tools for developing and running the model and the aggregation of required input data for simulating watersheds [24, 37, 38].

SWAT vs other watershed models

Many studies and researches have examined the capabilities of several hydrological and water quality models [2, 39]. Table 1 summarizes watershed models and their main characters and features related to the nature of the study area.

Table 1. Watershed models main characters and features

Model	Suited Application	Main components	chemical simulation	temporal scale	watershed representation
Annualized Agricultural Non-Point Source (AnnAGNP)	Suited for agriculture watersheds; widely used for evaluating a wide variety of conservation practices and other BMPs No GIS interface	Hydrology, sediment, nutrients and pesticide transport, DEM used to generate grid and stream network	N, P, pesticides, organic carbon & nutrients	Continuous (daily or Sub-daily steps)	Homogeneous land areas, reaches, & impoundments
Hydrological Simulation Program-Fortran (HSPF)	Suited for both agriculture or urban watersheds; diverse water quality and sediment transport at any point on the watershed No GIS interface	Runoff /water quality constituents, simulation of pervious/impervious areas, stream channels & mixed reservoirs	Soil/water temp., DO, CO2, N, NH3, organic N/P, N/P, pesticides	Continuous	Pervious /impervious land areas, stream channels, & mixed reservoirs; 1-D simulations
Soil and Water Assessment Tool (SWAT)	Best suited for agriculture watersheds; and for calculating TMDLs and simulating a wide variety of conservation practices and other BMPs; successfully applied across watersheds in several countries GIS interface	Hydrology, weather, sedimentation, soil temperature and properties, crop growth, nutrients, pesticides, agricultural management and channel & reservoir outing	N, P, pesticides	Continuous (daily steps)	Sub-basins based on climate, HRU, ponds, groundwater, & main channel

Data Collection and Analysis Methods

Study Area

The research was conducted in the LBR watershed located in Box Elder County, Northern Utah as shown below in Figure 1. The LBR watershed includes the Lower Bear River from Cutler Dam to its confluence with the Great Salt Lake, the Malad River from the Utah-Idaho state line to its confluence with the Bear River, Box Elder Creek from its headwaters to its confluence with Black Slough and the Bear River, along with numerous springs and other small tributaries [40]. The LBR Watershed is a sub-basin of Lower Bear Malad River (LBMR) watershed (USGS HUC 16010204) that is part of Great Basin Region (HUC 1601) where LBR is much larger river than the Malad. The LBR watershed under study drains about 1052 km^2 from below Cutler Dam to the Bear River Migratory Bird Refuge. Flows leaving Cutler Reservoir increase at the lowest gaging station on the Bear River near Corinne, Utah (USGS 10126000). Discharge in the LBR below Cutler is affected by spring runoff, irrigation diversion, irrigation returns and regulated releases from upstream reservoirs. Daily flows from July through October can be very low, averaging 0.7 m^3/s. Baseline flows in the watershed range from 3.0 - 23.0 m^3/s over the year. Land use is dominated by irrigated crop lands, dry-farmed crop lands, livestock feed production, and grazing. As compiled by the Utah Agricultural Statistics Service, Box Elder County ranks as number one in the state for total winter and spring wheat production, oats, barley, corn for grain, and cattle and calves' inventory [41]. In Box Elder County, 100 irrigation companies and private users are delivering water from the LBR to irrigate over 428 Km^2 of agricultural land [40].

The flows in the LBR represent three types of sources: 1) water applied to crops in excess that is returned to the river or canal via overland flow; 2) water that remains in the canal system and is never used for irrigation; and 3) water that percolates through the soil, is collected in drains and returned to the river [41, 43].

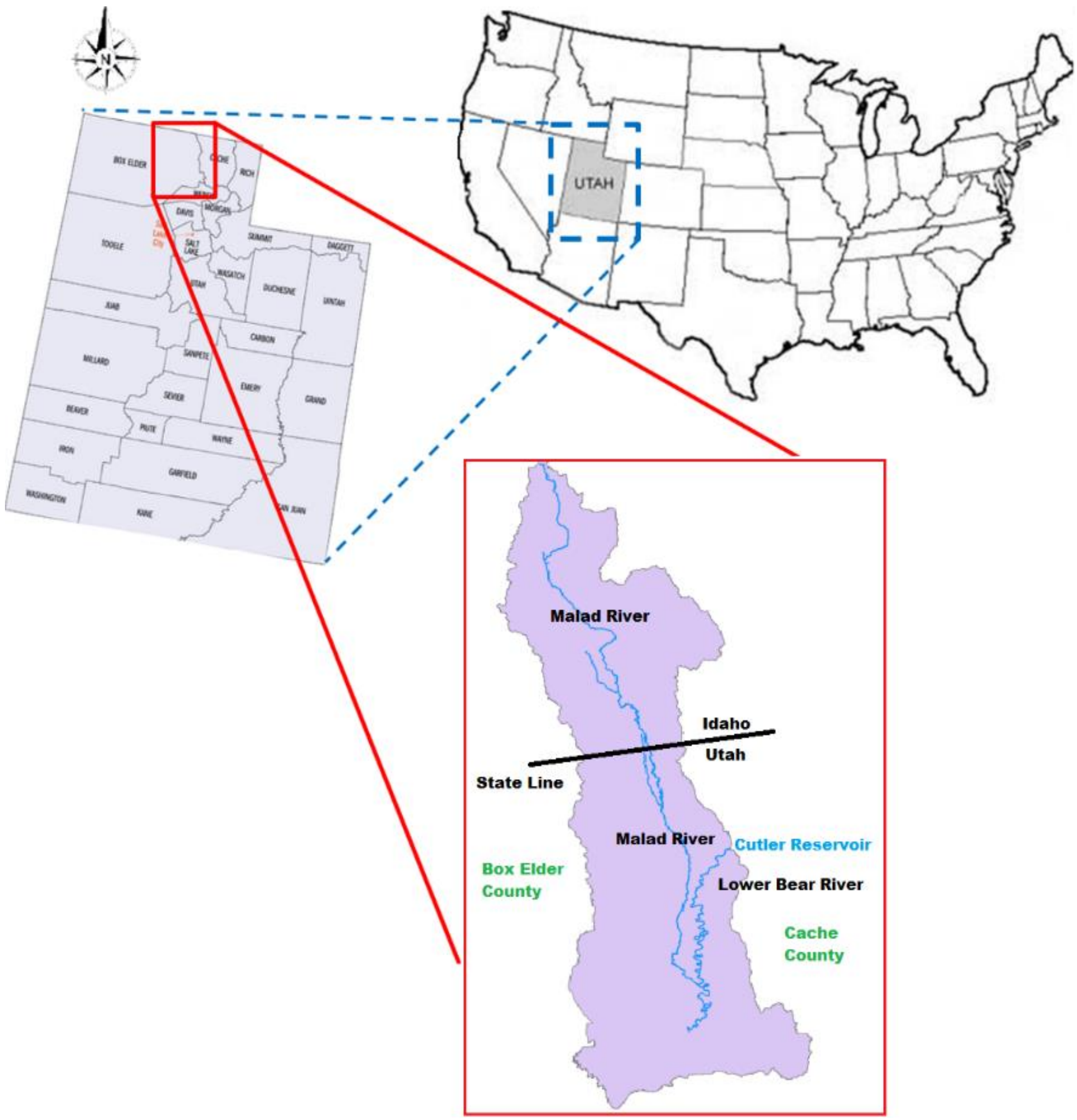


Figure 1. Location of Lower Bear River and Malad River in Northern Utah

The LBR travels 105 km southwest through a small, narrow canyon at the northern end of the Wellsville Mountains into the Great Salt Lake valley as it leaves Cutler Reservoir. The highest point in the watershed is Box Elder Peak (2,900 meters) in the Wellsville Mountains, while the lowest point is the Great Salt Lake (1280 meters) [42]. The entire water yield within the confines of the LBR Valley, including the inflow of the Malad River, adds less than 10 percent of the Bear River flow.

Average annual precipitation in the drainage ranges from 180-400 mm (11-16 in), with most of that falling as snow during the winter months. Mean annual air temperature is 8-11^{o}C (46-51 F) with a frost-free season of 100-150 days. Soils below the 1400-meter elevation level are formed in mixed lake sediments derived from many kinds of rocks. They are nearly level to gently sloping. Soils are mostly silt loam, silty clay loams, and are moderately well drained to poorly drained [42].

Water Quality Status in Lower Bear River Watershed

High levels of total dissolved solids (salts), sediment and phosphorus are the major water quality concerns in the LBR watershed [43]. Major sources of pollutants that have had a significant impact on water quality within the LBR watershed and its associated ecosystem come from agricultural runoff that carries sediments, fertilizers, and animal wastes from agricultural lands, streambank erosion caused by natural processes, changes in in-stream flows and grazing on streambanks, and large animal feeding operations along the watershed streams. Two waterbody segments (the LBR from Cutler Reservoir to the confluence with Great Salt Lake and the Malad River from the Utah-Idaho state line to the Bear River confluence) were declared impaired in Utah’s year 2000

303(d) list of water bodies needing TMDL analyses [41] based on Clean Water Act requirements of the state of Utah.

Point Sources

Within the LBR watershed, there are five permitted point source discharges. Four are waste water treatment plants (WWTPs) and one is an industrial source. As shown in Table 2, they included Corinne WWTP, Brigham City WWTP, Bear River City WWTP, Tremonton WWTP, and Nucor Steel [41]. The LBR TMDL [41] indicated that three main point sources (Corinne, Bear River and Tremonton cities) accounted for approximately 3% of the TP load to the Lower Bear River. The remaining 97% was attributed to NPS. Given that the NPS TP loads are more prominent than the point source contributions, the TP loads discharged from these point sources is considered insignificant in this research.

Nonpoint Sources

NPS pollution is usually associated with watershed impacts caused by diffuse land use activities. In the LBR, the most dominant nonpoint source pollutants are phosphorus and sediment. Sources include irrigated and non-irrigated croplands, rangelands, feedlots, and unstable streambanks.

Table 2. List of permitted point source in LBR Watershed

Point Source Name	Monitoring ID	Latitude	Longitude
Tremonton WWTP	4902710	41.6984034	-112.161616
Brigham City WWTP	4901200	41.5241527	-112.046225
Bear River City LAGOONS	4902030	41.5997351	-112.14331
Corrine LAGOONS	4901160	41.5368495	-112.11186
Nucor Steel	4902920	41.8863124	-112.204404

SWAT Model

The SWAT watershed model is able to predict daily runoff, sediment, and chemical yield. It generates runoff using the rational method. In-channel transport is simulated via simplified reach routing processes. Output consists of daily, monthly, annual, and average annual runoff values for subwatersheds and reaches [44]. The model is derived from several well known predecessors:

- SWRRB – Simulator for Water Resources in Rural Basins provides the basic hydrology [45, 46].
- CREAMS – Chemicals, Runoff and Erosion from Agricultural Management Systems for the nutrient and some sediment transport [47, 48].
- GLEAMS – Groundwater Loading Effects on Agricultural Management Systems for the groundwater quality component [49].
- EPIC – Erosion Productivity Impact Calculator for the link between erosion; Sediment transport and nutrient loss/gain [50, 51].

All of these are physically based models in their own right; SWAT combines them into a distributed framework that operates at the catchment/watershed scale. The hydrological cycle simulated in the SWAT model is based on the following water balance equation:

$$SW_t = SW_o + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{sw}\right)$$

Where SW_t and SW_o (final and initial soil water contents), R_{day} (precipitation), Q_{surf} (surface runoff), E_a (evapotranspiration), W_{seep} (water entering the unsaturated zone from the soil), Q_{sw} (return flow) and all units are in mm. The in-stream kinetics used in

SWAT for nutrient routing are adapted from the Enhanced Stream Water Quality Model (QUAL2E). QUAL2E is a receiving water model that analyzes water quantity and quality in a receiving water stream in response to loadings from its contributing watershed(s). It is a one-dimensional, steady-state and pseudo-dynamic, and non-uniform flow and water quality model [44]. A detailed description of the SWAT model can be found in a research report [32] and in theoretical documentation [52]. The SWAT model version selected for this study is ArcSWAT 2012.10.19 under ArcGIS 10.4.

Setup and Data

The required input data for SWAT are available from various sources as described below in Table 3. No field data were collected and as stated previously, the SWAT model was tested in the LBR watershed in the period from 2000 to 2010 as a case study to characterize the watershed hydrology and to assess phosphorus (TP) and sediment (TSS) loads.

Data on water quality parameters were obtained from the United States Geological Survey (USGS) monitoring stations. Utah Division of Water Quality (UDWQ) collects TSS/TP data using USGS streamflow-gaging stations as shown in Figure 2 (total of 112 sample for TSS and 64 samples for TP). Continuous average monthly and yearly loads for TP and TSS were estimated for the period of record from the grab samples using the USGS Load Estimator (LOADEST) regression model [53]. Provided a time series of discrete measured streamflow and constituent concentrations, LOADEST was be used to develop a regression model for estimating constituent loads in streams and rivers [53].

Table 3. Description of SWAT dataset and its sources

Dataset Name	Use / description	Source of Data
National Elevation Dataset (NED) Digital elevation map (DEM)	Watershed delineation (30 m resolution) Elevation, overland and channel slopes, lengths	http://ned.usgs.gov/ http://gis.utah.gov/data/elevation-terrain-data/
Soils data- State Soil Geographic (STATSGO and SSURGO)	HRU analysis Soil physical properties such as bulk density, texture, saturated conductivity)	http://soildatamart.nrcs.usda.gov/ http://bearriverinfo.org/htm/gis-mapping/
National Land Cover Dataset (NLCD)	HRU analysis Land Use/Land cover (2006 and 2011) Land use classification	http://www.mrlc.gov/
National Hydrography Dataset (NHD)	Subbasin delineation / Flow data & Stream networks	http://nhd.usgs.gov/ http://gis.utah.gov/data/water-data-services/
Climate data (Potential source: NOAA COOP stations for daily temperature, precipitation, solar radiation, and wind speed or any other measured data)	Weather data (Precipitation & Temperature) Climate conditions (readings from 2000 – 2010)	http://www.ncdc.noaa.gov/ http://uwrl.usu.edu/ http://climate.usurf.usu.edu
Monitoring Data (watershed quantity and quality data)	Calibration and Validation / (USGS/EPA readings from 2000 – 2010)	http://bearriverinfo.org http://waterdata.usgs.gov/nwis
Watershed (HUC8) and Sub-watershed (HUC12)	Watershed delineation	http://bearriverinfo.org http://gis.utah.gov/data/water-data-services/

Using the topography information as provided by the Digital Elevation Model (DEM), SWAT divides the basin into a number of subbasins as shown in Figure 3. Further division into Hydrologic Response Units (HRU) is based on the soil map, land use and slope information. Each HRU is a homogenous area in terms of soil and land use type as well as slope.

Water yield from each HRU is aggregated for subbasins and routed via the reach network to the watershed outlet (routing phase of hydrology). Then SWAT allows modelers to define the point sources and other watershed inlet discharges (e.g., inflows from Cutler Reservoir), including manually defining the outlet point of discharge for the sub-basin and for the whole watershed. After delineation, SWAT divided the study area into 126 subbasins with total area of 1998 Km^2 (Figure 4). With a threshold value of 20% for soil types, 10% for land use, 20% slope, and a 10-elevation bands (maximum number of elevations that can be represented in SWAT), the subbasins were further separated into 565 HRUs as shown in Figure 4.

Based on the given results, the dominant land use in the LBR watershed are pasture, sunflower and winter wheat (small grains). The climate inputs were generated internally within SWAT using monthly climatic data (sourced from Climate Forecast System Reanalysis (CFSR)) processed by SWAT's built-in weather generator. SWAT utilized the meteorological data (temperature, precipitation, solar radiation, relative humidity, and wind) to compute the required to simulate the potential evapotranspiration (PET) in the model. See Table A 1 in Appendix 1 for more details about the delineated subbasins.

Database files containing information needed to generate default input for SWAT are automatically set based on the watershed delineation and land use, soil and slope characterization. The SWAT model simulation was executed for conditions during the11 year period from 2000 until2010. The first two years were used as a warm-up period and were not used for model evaluation because, during early time periods for the simulation, model parameters such as soil–water content and residue cover are initially not in equilibrium with actual physical conditions as stated [54].

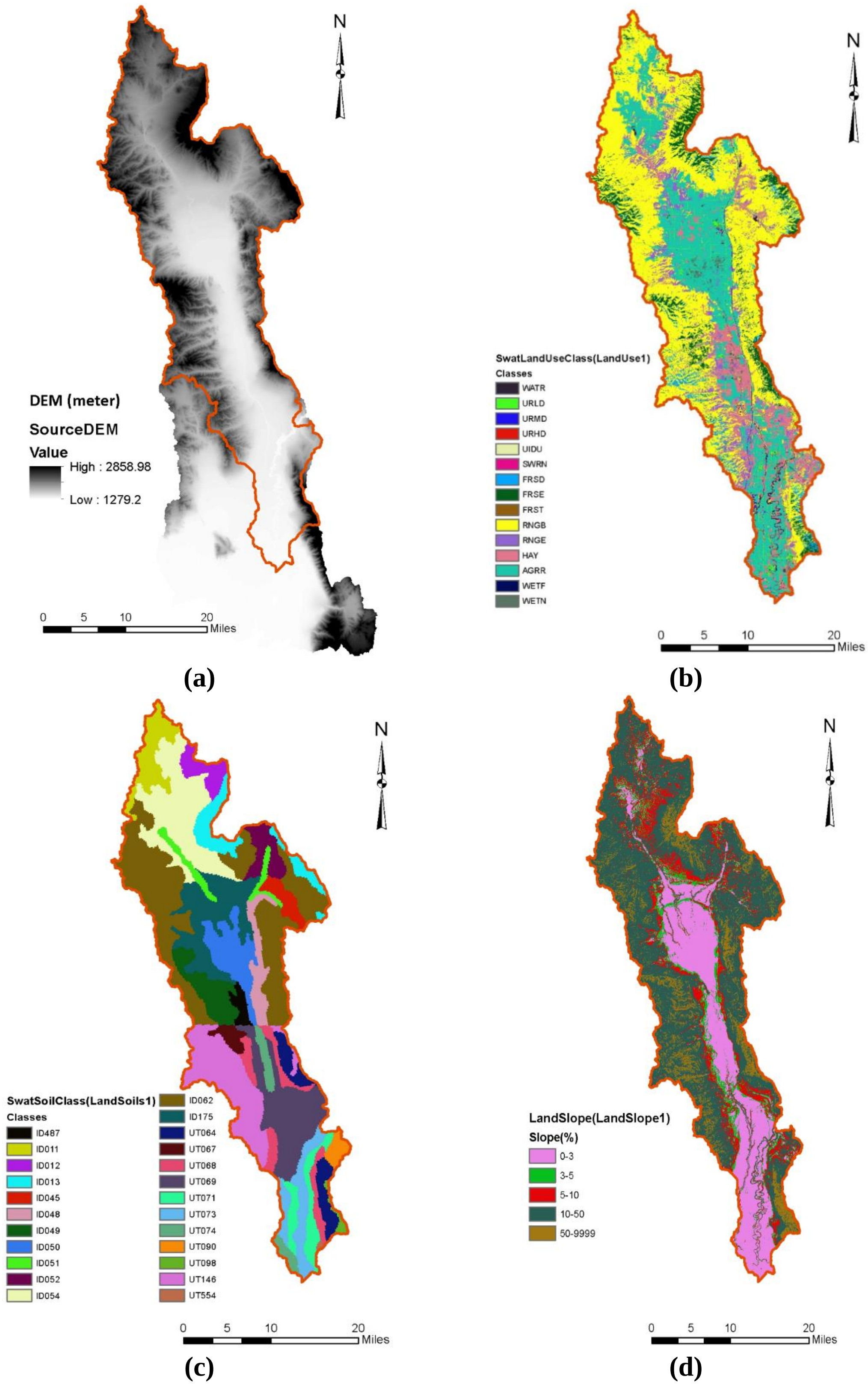
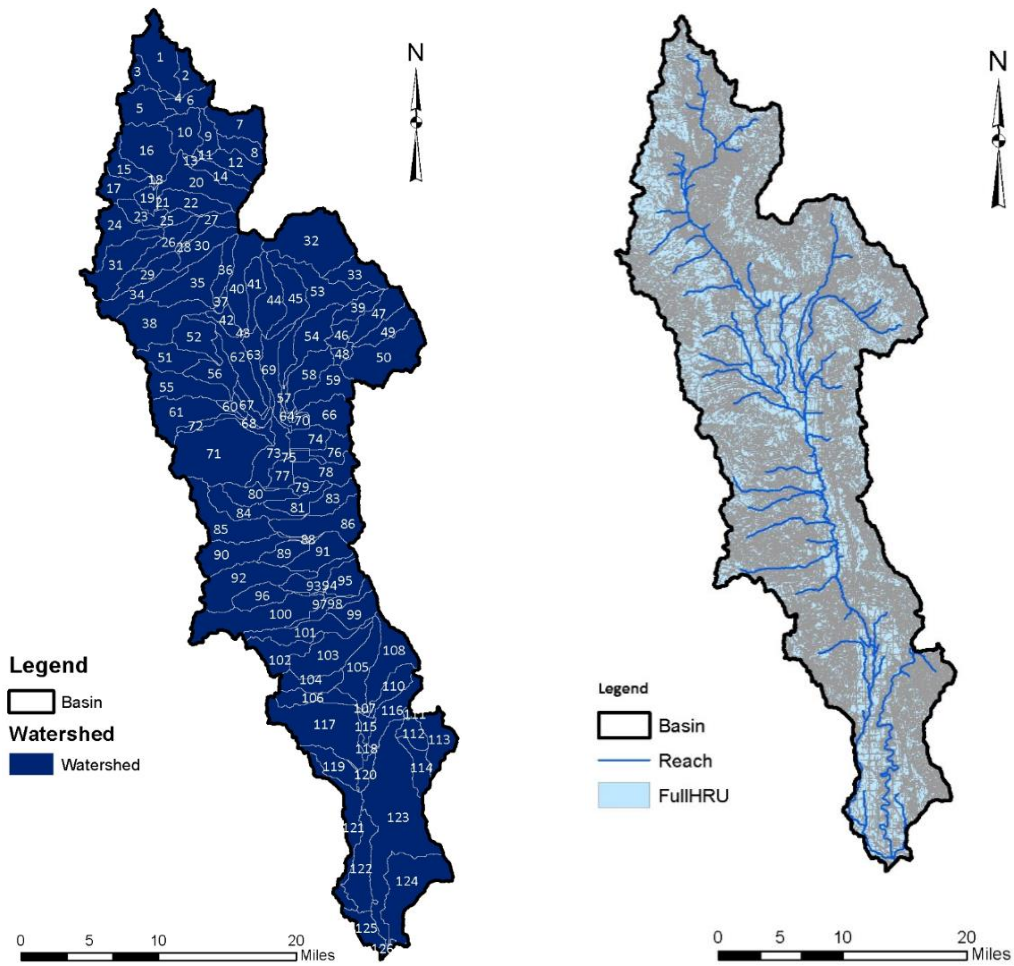


Figure 2. Study area GIS data provided in SWAT: a) digital elevation model, b) land use, c) soil map, and d) slope profile set for simulation



(a) **(b)**

Figure 3. The simulated watershed where a) is the Subbasins generated (126 Subbasins), and b) is the HRU map that represents 565 HRUs across the watershed

Model Calibration and Validation

The LBR watershed model was simulated on monthly time-step over the period 2000-2010. The years from January 2000 to December 2001 were used as a warm-up period for state variables to assume realistic initial values. The calibration was carried out at monthly time steps covering period from January 2002 to December 2005, while the validation process covered period from January 2006 till December 2010.

The initial simulations using default parameters were not able to correctly reproduce the discharge coming out of the LBR watershed because the actual discharge peaks (peak flows) were underestimated. The same was true for sediment and total phosphorus loads. Therefore, parameter calibration and identifying the most sensitive parameters for runoff, sediment, and total phosphorus were needed to improve the usability of the model in the beginning.

The Sequential Uncertainty Fitting version 2 (SUFI-2) optimization algorithm [55, 56] was applied within the SWAT Calibration and Uncertainty Program (SWAT-CUP) model 2012 and version 5.1.6.2 [57]. SUFI-2 is based on the concept of equifinality, which suggests that multiple models (i.e., multiple parameter sets) provide equally acceptable predictions and, as such, parameter values are treated as uncertain [58].

Model parameters selected for calibration were first assigned an initial global uncertainty range within SWAT-CUP based on the range of parameters values suggested by the SWAT technical documentation. Sensitivity analysis was then performed to identify those parameters that model outputs were sensitive to. Only the most sensitive parameters were included in model calibration at a monthly time-step against observations of discharge, sediments and total phosphorus loads recorded at the outlet. Using parameters that are sensitive for discharge, three iterations of 1000 simulations were performed to calibrate the model for discharge. The parameter ranges were updated after each iteration, as identified by the SUFI-2 optimization algorithm, until prediction uncertainty and model performance were considered satisfactory. Then, sediment calibration was carried out using parameters that are only sensitive to it with three iterations of 500 simulations. Finally, another calibration used parameters only sensitive to total phosphorus with three iterations of 500 simulations.

Tables 4, 5, and 6 illustrate the SWAT model parameters identified as significant by the sensitivity analysis and the final calibrated fitted values of each parameter for flow, sediments and phosphorus respectively. The most sensitive parameters during the calibration process are: CN2.mgt, SNOCOVMX.bsn, GWQMN.gw, SNO50COV.bsn, GW_DELAY.gw, GWQMN.gw, RCHRG_DP.gw, ALPHA_BF.gw, USLE_P.mgt, USLE_K.sol SMFMX.bsn, and SMFMN.bsn.

Table 4. Parameters that are sensitive to flow simulation

Parameter_Name	Description	Fitted_value	Min_value	Max_value
r_CN2.mgt	SCS runoff curve number	0.149	0.1	0.2
v_ALPHA_BF.gw	Baseflow alpha factor (days)	0.363	0	1
v_GW_DELAY.gw	Groundwater delay (days)	379.2	30	450
v_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	18.5	0	500
v_SNOCOVMX.bsn	Minimum snow water content that corresponds to 100% snow cover	182	100	500
r_SNOCOVMX.bsn	Snow water equivalent that corresponds to 50% snow cover	0.8	0	1
v_SFTMP.bsn	Snowfall Temperature	0.5	-1	1
r_SOL_AWC.sol	Available water capacity of the soil layer	-0.235	-0.3	0.1
r_SOL_K.sol	Saturated hydraulic conductivity	0.048	-0.25	0.2
r_SOL_BD.sol	Moist bulk density	-0.045	-0.25	0.2
v_SUB_SFTMP.sno	Snowfall temperature	10.765	-20	15
v_SUB_SMTMP.sno	Snow melt base temperature	-3.025	-20	15
v_SUB_SMFMX.sno	Maximum melt rate for snow during year (occurs on summer solstice)	10.815	0	15
v_SUB_SMFMN.sno	Minimum melt rate for snow during the year (occurs on winter solstice)	0.285	0	15
v_SUB_TIMP.sno	Snow pack temperature lag factor Subbasin snow	0.443	0	1
r_ESCO.bsn	Soil evaporation compensation factor	0.097	0	0.2
v_EPCO.bsn	Plant uptake compensation factor	0.793	0	1
r_ESCO.hru	Soil evaporation compensation factor	-0.044	-0.3	0.1
r_CH_N1.rte	Manning's "n" value for the tributary channels	0.156	-0.05	0.3
r_CH_N2.rte	Manning's "n" value for the main channel	0.058	0.01	0.3
v_TLAPS.sub	Temperature lapse rate	-4.46	-10	10
r_PLAPS.sub	Precipitation lapse rate	0.022	-0.25	0.25
r_SNOEB.sub	Initial snow water content in elevation band	0.067	-0.05	0.25

Table 5. Parameters that are sensitive to sediment simulation

Parameter_Name	Description	Fitted_value	Min_value	Max_value
v_CH_EROD.rte	Channel erodibility factor	0.425	0.1	0.6
v_CH_COV.rte	Channel cover factor	0.569	0.2	1.0
v__SPCON.bsn	Linear parameter to calculate maximum amount of sediment that can be retrained during channel sediment routing	0.004	0.001	0.01
v__SPEXP.bsn	Exponent parameter for calculating sediment retrained in channel sediment routing	1.243	1.0	1.5
v__PRF.bsn	Peak factor for Sediment routing factor in main channels	0.541	0.0	2.0
r__USLE_P.mgt	USLE equation Support practice factor	0.051	-0.15	0.15

Table 6. Parameters that are sensitive to total phosphorus simulation

Parameter_Name	Description	Fitted_value	Min_value	Max_value
v__PSP.bsn	Phosphorus availability index	0.621	0.5	0.7
r_ERORGP.hru	P enrichment ratio with sediment loading	3.148	2	4
r_SOL_SOLP	Initial soluble phosphorus concentration in the soil layer (ppm)	71.246	0	100
r_BC4.swq	Rate constant for mineralization of organic P	0.359	0.3	0.5
r_RS5.swq	Organic P settling rate	0.0941	0.08	0.1
v_BIOMIX.mgt	Biological mixing efficiency	0.156	0	1

The statistical analysis of calibration and validation of SWAT model outputs was carried out using the GNU R language (statistical computing and graphics environment, version R-3.3.3 [59]). The performance of the developed SWAT model was evaluated by examining measures of goodness of fit, coefficient of determination (R^2), root mean squared error (RMSE) and the Nash-Sutcliffe efficiency (N_{SE}). The larger the values of N_{SE} and R^2 and smaller the values of RMSE, the greater the precision and accuracy the SWAT model in predicting and simulating the movement of water, nutrient and sediments. Additional checks on the final parameter values to see if they are within physical limits were also conducted.

The statistical techniques are detailed as below:

- **Coefficient of determination (R^2)**: It describes the proportion of the variance in observations explained by the model. R^2 ranges from 0 to 1, with higher values indicating less error variance. In watershed water quality and hydrological modeling, a value greater than 0.5 are considered acceptable differences between model predictions and measured data [31, 60, 61]. R^2 allows us to determine how certain one can be in making predictions from a certain model/graph. R^2 is computed as Equation 1:

$$R^2 = \left[\frac{1}{n}\ \frac{\sum_{i=1}^{n}\left(x_i^{obs}-x_i^{obs\_mean}\right)\left(y_i^{sim}-x_i^{obs\_mean}\right)}{\left(\sigma_x\sigma_y\right)}\right]^2 \qquad (1)$$

where n is the number of observations used to fit the model, x_i^{obs} is the x value for observation i, $x_i^{obs\_mean}$ is the mean x value, y_i^{sim} is the y value for simulated i, $y_i^{obs\text{-}mean}$ is the mean y value, σ_x is the standard deviation of x, and σ_y is the standard deviation of y.

- **Root mean square error (RMSE):** RMSE indicates error in the units (the square root of the sum of squares) of the constituent of interest. Values of 0 indicate a perfect fit between the observations and simulation [62]. The square root of the average is taken. RMSE can be calculated by Equation 2:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i^{obs}-x_i^{sim}\right)^2}{n}} \qquad (2)$$

where n is the number of observations used to fit the model, x_i is the x value for observation *ith (obs= observed, sim = simulated).*

- **Nash-Sutcliffe efficiency (N_{SE}):** It is a normalized statistic that determines the relative magnitude of the residual variance (noise) compared to the observation variance [63]. N_{SE} values recommended for the research objective used values are shown in [22, 27] and Table 7. N_{SE} can be computed using the following Equation 3:

$$N_{SE} = 1 - \left[\frac{\sum_{i=1}^{n}\left(x_i^{obs} - x_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(x_i^{obs} - x_i^{obs\_mean}\right)^2}\right] \qquad (3)$$

where x_i^{obs} is the i^{th} observation for the constituent being evaluated, x_i sim is the i^{th} simulated value for the constituent being evaluated, x_i mean is the mean of the observations for the constituent being evaluated, and n is the total number of observations. N_{SE} ranges between ∞ and 1 (1 inclusive), with $N_{SE} = 1$ being the optimal value. Values between 0.35 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance [64, 65].

Table 7 summarizes the acceptable ratings for SWAT model performance based on several literature and studies used SWAT application in watershed simulation.

Table 7. Summary of SWAT model performance ratings

Performance ratings for N_{SE} [33]	
>0.65	Very good calibration and validation
0.54 to 0.65	Good calibration and validation
>0.4 to 0.5	Satisfactory calibration and validation
<0.35	Unsatisfactory calibration and validation

Results and Discussion

The present modeling effort was carried out with an objective to develop a reliable hydrologic model simulating stream flow discharge, sediments, and total phosphorus loads. SWAT, v. 2012, was used to simulate the stream flow, sediment, and total phosphorus of Lower Bear River located in Box Elder County, northern Utah for the period from 2000-2010. The SWAT model was calibrated and validated for flow against monthly measured discharge data at the outlet of the simulated LBR watershed (i.e., subbasin #126). In general, flow simulations at calibration stations compared well to measured flow records and simulated monthly flows (Fig. 4). Model calibration and validation were performed for monthly time periods using SUFI-2 algorithm within SWAT- CUP. 23 parameters for flow, 6 parameters for sediments and the same for total phosphorus simulation that were calibrated as shown in Tables 4, 5, and 6.

Flow Simulation

The calibration outputs for monthly-flow simulation for the period from 2002 to 2005 showed a good model performance with $R^2 = 0.87$, $N_{SE} = 0.71$ and RMSE = 0.43 as shown in Figure 4.

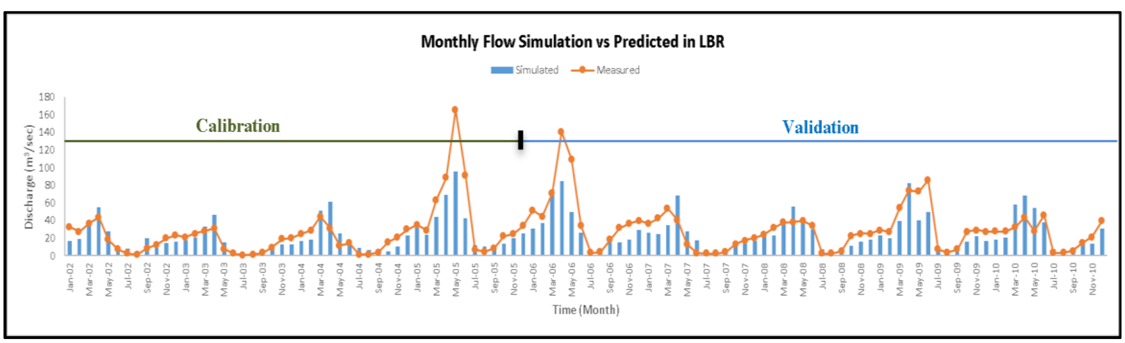


Figure 4.Measured vs. simulated monthly flow simulation (m3/sec) (2002-2010)

During the validation period (2006-2010), the flow simulation showed good performance with R^2 = 0.80, N_{SE} = 0.62 and RMSE = 0.58 (m^3/sec) meaning it mostly captured all hydrological characteristics of the LBR watershed as shown in Figure 4 and Table 8. See Table A4 in Appendix 1 for more details about flow data.

Further statistical analysis of between the measured and simulated flow data can be explored next through Table 9 and Figure 5.

Table 8. Correlation summary of simulated and measured monthly flow

Statistical Measure	Flow (2002-2005) Calibrated	Flow (2006-2010) Validated	Flow (2002-2010) Calib. - Valid.
Coefficient of determination (R^2)	0.87	0.80	0.83
Nush-Suttcliffe Efficiency (N_{SE})	0.71	0.62	0.67
Root Mean Square Error (RMSE)	0.43	0.58	0.36

Table 9. Statistical summary of simulated and measured monthly flow (2002-2010)

Statistical Summary	Measured (m^3/sec)	Simulated (m^3/sec)
Minimum	1.145	1.18
1st Quartile	7.80	10.20
Median	24.99	18.36
Mean	28.44	24.61
3rd Quartile	36.76	31.79
Maximum	166.03	96.12

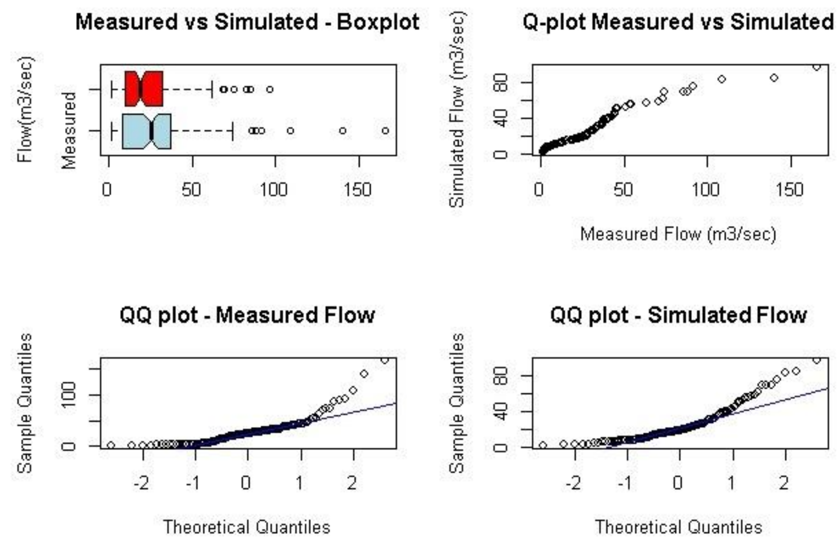


Figure 5. Statistical plots show histogram, scatter, and QQ plots for measured vs. simulated monthly flow in the period between 2002 and 2010

As shown in Figure 6, the residual between the measured and simulated monthly flow simulation shows random dispersion around the horizontal axis, which implies the suitability of the model with close normal distribution of the data on the histogram plot. The residual plot shows cyclic pattern suggesting some autocorrelation.

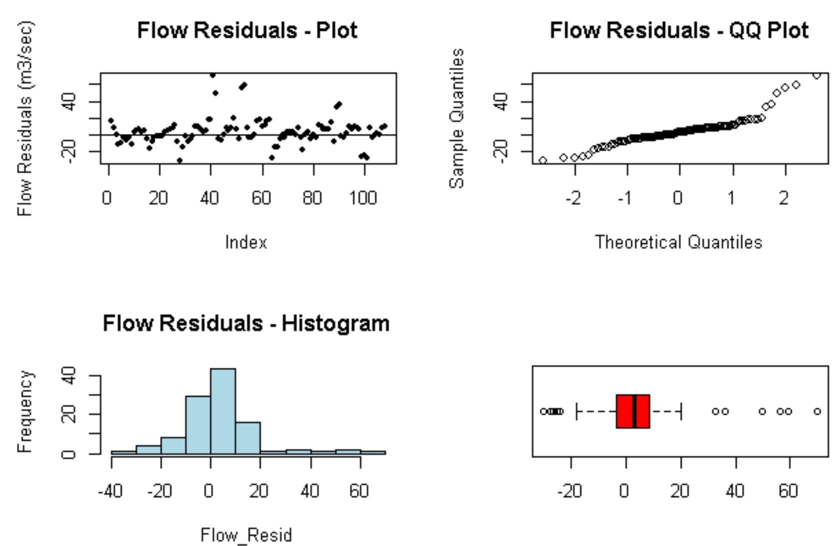


Figure 6. Residual analysis plots for monthly flow (2002-2010)

Total Suspended Solids Simulation

The calibration outputs for monthly TSS simulation for the period from 2002 to 2005 showed a reasonable model performance with correlation of $R^2 = 0.83$, $N_{SE} = 0.67$, and RMSE = 0.85. However, during validation period (2006-2010), the TSS simulation showed good correlation but poor prediction ability with values of $R^2 = 0.76$, $N_{SE} = 0.36$ and RMSE = 3.27 (mg/L) as shown in Figure 7 and Table 10. See Table A 5 in Appendix 1 for more details about total suspended solids data. Further statistical analysis of between the measured and simulated TSS data can be explored next through Table 11 and Figure 8.

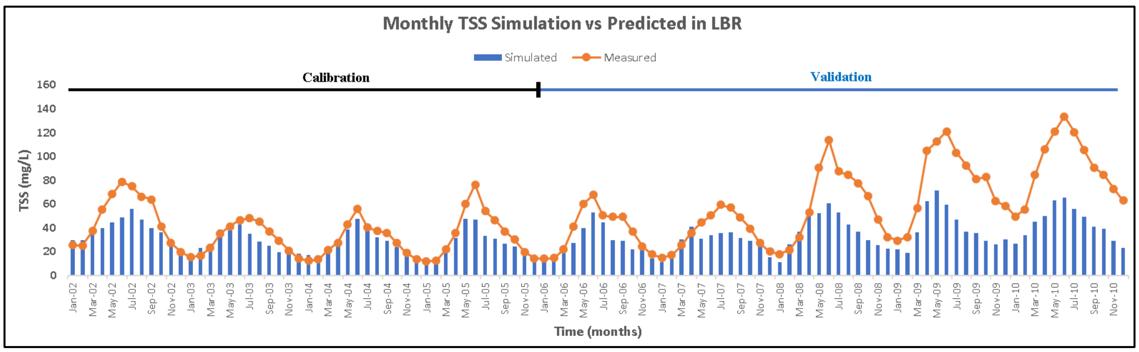


Figure 7. Measured vs. simulated monthly TSS simulation (mg/L) (2002-2010)

Table 10. Correlation summary of measured and simulated monthly TSS

Statistical Measure	TSS (2002-2005) Calibrated	TSS (2006-2010) Validated	TSS (2002-2010) Calib. – Valid.
Coefficient of Determination (R^2)	0.83	0.76	0.74
Nush-Suttcliffe Efficiency (N_{SE})	0.67	0.36	0.44
Root Mean Square Error (RMSE)	0.85	3.27	1.61

Table 11. Statistical summary of simulated vs. measured monthly TSS (2002-2010)

Statistical Summary	Measured TSS (mg/L)	Simulated TSS (mg/L)
Minimum	11.96	10.62
1st Quartile	25.14	23.30
Median	43.64	30.19
Mean	49.53	31.83
3rd Quartile	66.35	41.01
Maximum	133.55	71.16

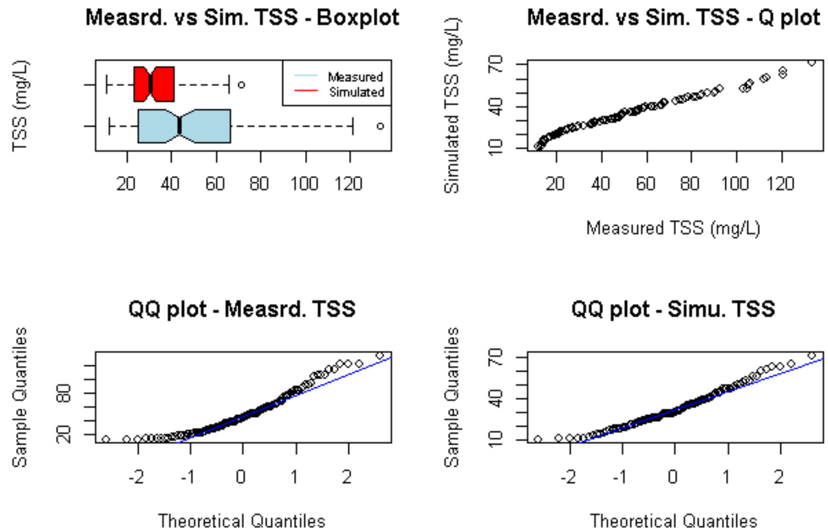


Figure 8. Statistical plots show histogram, scatter, and QQ plots for measured vs. simulated monthly TSS in the period between 2002 and 2010

As shown in Figure 9 next, the residual between the measured and simulated monthly TSS simulation shows poor random dispersion around the horizontal axis which affects the suitability of the model to accurately predict TSS values considering the uncertainties in the input data (land use/cover, snowmelt timing, etc.) and the yearly estimation for TP load data.

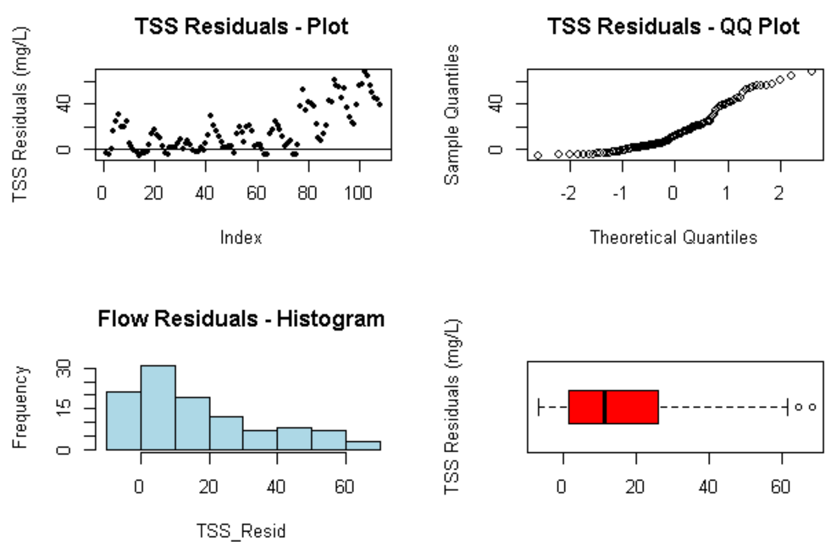


Figure 9. Residual analysis plots for monthly TSS (2002-2010)

Total Phosphorus Simulation

The calibration outputs for monthly TP simulation for the period from 2002 to 2005 showed a reasonable model performance with correlation of R^2=0.50, N_{SE} = 0.46, and RMSE = 0.002. However, during validation period (2006-2010), the TP simulation showed good correlation and prediction with values of R^2 = 0.67, N_{SE} = 0.62 and RMSE = 0.0015 (mg/L) as shown in Figure 10 and Table 12. See Table A 6 in Appendix 1 for more details about total phosphorus data. Further statistical analysis of between the measured and simulated TSS data can be explored next through Table 13 and Figure 11.

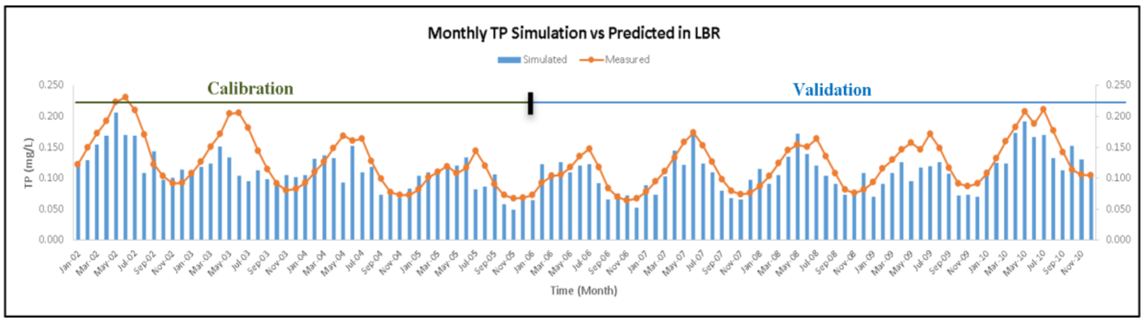


Figure 10. Measured vs. simulated monthly TP simulation (mg/L) (2002-2010)

Table 12. Correlation summary of simulated and measured TP (mg/L) (2002-2010)

Statistical Measure	**TP (2002-2005) Calibrated**	**TP (2006-2010) Validated**	**TP (2002-2010) Calib. - Valid.**
Coefficient of determination (R^2)	0.50	0.67	0.59
Nush-Suttcliffe Efficiency (N_{SE})	0.46	0.62	0.54
Root Mean Square Error (RMSE)	0.002	0.0015	0.0012

Table 13. Statistical summary of simulated and measured monthly TP (2002-2010)

Statistical Summary	**Measured TP (mg/L)**	**Simulated TP (mg/L)**
Minimum	0.067	0.049
1st Quartile	0.092	0.091
Median	0.119	0.109
Mean	0.128	0.112
3rd Quartile	0.161	0.126
Maximum	0.231	0.206

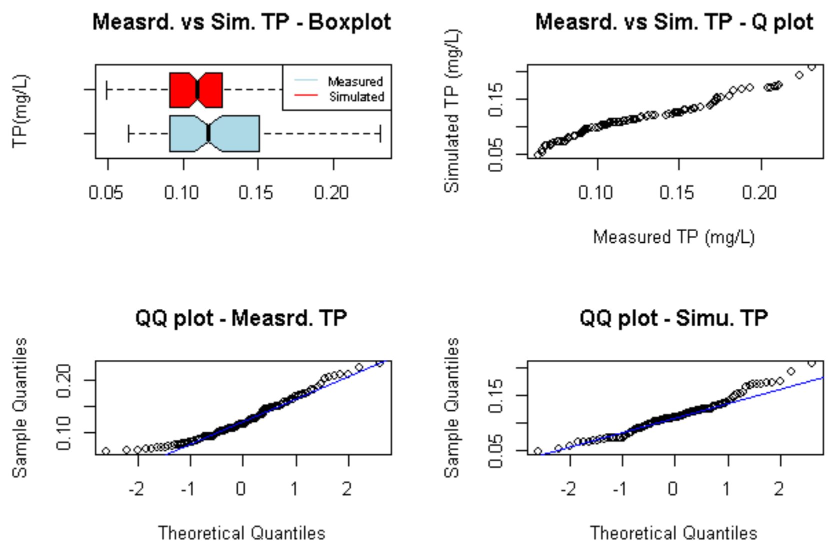


Figure 11. Statistical plots show histogram, scatter, and QQ plots for measured vs. simulated TP in the period between 2002 and 2010

As shown in Figure 12, the residual between the measured and simulated monthly TP simulation shows a reasonable random dispersion around the horizontal axis, which suggests the suitability of the model to predict TP values considering the uncertainties in the input data (land use/cover, snowmelt timing, etc.) and the yearly estimation for TP load data.

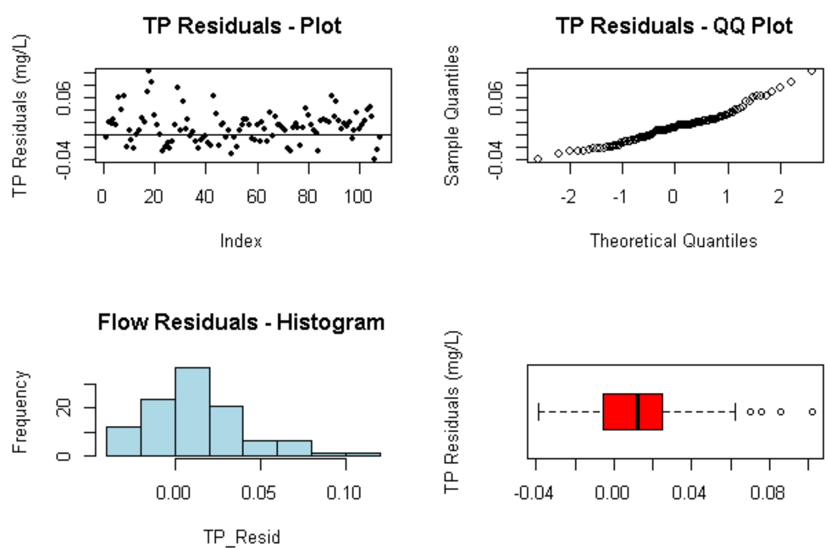


Figure 12. Residual analysis plots for monthly TP (2002-2010)

Conclusion

The SWAT model was applied under GIS environment to simulate monthly flow, sediment and total phosphorus loads in Lower Bear River watershed, Box Elder County in northern Utah. The comparisons between observed and simulated monthly flow data showed that the simulation results are acceptable with the R^2 value as 0.83, 0.74 and 0.59 for flow, TSS, and TP respectively. SWAT model proved to perform well and provide good results for calibration but not the case for validation. While the prediction power supported by NSE was acceptable for flow, TSS and TP simulations with values of 0.67, 0.44, and 0.54 respectively, SWAT underestimated flow, sediment and total phosphorus loads for some high-flow events.

The inability of SWAT to simulate high-flow events could be attributed to its dependence on many empirical and semi-empirical models, such as SCS-CN and MUSLE, which caused SWAT to track specific peak flow and sediment load less accurately. One thing that can be added is the effect of the estimated TSS and TP loads using LOADEST model and the lacking of continuous measured water quality data (especially in the period between 2004 and 2007) that could enhance the calibration of SWAT parameters and eventually improve its performance. In general, the methodology presented in this paper of calibrating the most sensitive parameters for flow, sediments and total phosphorus using SWAT-CUP can be used in other agricultural watersheds in the Intermountain regions. The results are instructive for future use of SWAT in evaluating different management practices in the northern part of Utah.

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COMBINATION TOOL TO GENERATE MANAGEMENT PRACTICE STRATEGIES FOR PHOSPHORUS LOAD REDUCTION IN THE LBR WATERSHED

Abstract

Significant federal investment in the last three decades in technical and financial assistance has been provided to implement agricultural best management practices (BMPs) that can help reduce nutrient loads leaving agricultural lands and farm fields, which in turn can reduce negative environmental impacts on receiving water systems. Watershed managers in that regard have limited budgets to propose conservation projects that are deemed feasible and will achieve the required water quality goals at watershed scale. Often, they don't possess the tools to prioritize these conservation projects or to find the optimal combination of these projects within a specified budget. This chapter provides an overall combination approach to agricultural BMPs' solution in selected non-point source (NPS) areas within specified budget for implementation at a watershed scale within the Lower Bear River (LBR) Watershed, an area with a large delivery of phosphorus (P) to the Great Salt Lake. An agricultural BMP database provides information on reduction efficiency and cost per area for implementation. Identified sources areas are obtained spatially from applying the SWAT model that uses a geospatial processing methodology to transform loading rates in the HRUs from the parcel map of the study area. The combination tool is a code written in Python script that runs the available agricultural BMPs and NPS areas to provide a series of combinations based on two constraints: available budget and required reduction. Three water quality

constraints were assigned as a total phosphorus reduction limit: 150, 200 and 250 kg/yr. The combination tool generated 671870 solutions (a solution is a conservation practice implemented on certain NPS area) from which the minimum cost implementation for meeting the three reduction targets were: a combination of six conservation practices with an approximate cost of US$12,400 for a 150 kg/yr total phosphorus reduction load. For a 200 kg/yr of total phosphorus load reduction limit, a minimum budget of US$18,800 for implementing eight (8) combined management practices achieved that limit. The 250 kg/yr of phosphorus load reduction limit was achieved through the lowest budget of US$24,500 with ten management projects to implement.

The simplicity of the proposed combination approach to generate alternatives for management practices can have significant feedback to conducting studies and research on the LBR watershed to provide the most reliable selection and placement of suites of BMPs across the watershed which will help program and policy development and analysis of water quality and conversation programs.

Introduction

A Best Management Practice (BMP) can be defined as a practice or combination of practices that is the most effective, technologically, and economically feasible means of preventing or reducing the pollutant load generated by NPS to a level that meets water quality goals [1, 2]. The use of BMPs was introduced by the U.S. government through many incentive programs in the 1980s to encourage agricultural producers to reduce agricultural runoff and erosion. BMPs’ impacts on watershed quality were evaluated and documented using site specific details obtained from grant reporting and monitoring that often lack the long-term impact of implementing such practices at watershed scale. When implementing BMPs, it is critical that the most appropriate BMP, or suite of BMPs, be selected, targeted, and implemented in a watershed within an allocated budget. Also, since many BMPs involve costs and management changes, which will most likely have negative impacts on landowners, fair and equitable financial support and technical assistance through cost-share programs will improve BMP adoption. Additionally, watershed managers face real challenges in identifying and differentiating the effects of BMPs from other landscape factors. It is difficult due to the variable hydrological, physiographic, land cover, and soil conditions that can affect the amount and composition of pollutants entering streams, especially in the Intermountain West region that is categorized by spatial variability in climate, a high frequency of fires, and, often, highly erodible soils.

This challenge can be faced with tools that aid watershed managers in deciding the type, and the number of BMPs based on the identified critical areas that are major contributors of pollutants into the receiving water. These tools may involve watershed simulations tools, spreadsheets for load calculations, BMPs database, and some optimization codes if the technical and the financial sources are adequate. When it comes to applying for funds, watershed managers and related extension personnel are asked for proposing conservation projects based on the Total Maximum Daily Load (TMDL) recommendations and their field observation within a specific budget. Finding a suite of conservation projects that can protect the watershed quality, within the specified budget, and to adequately have a positive impact at watershed scale requires time and effort in analyzing the NPS areas, their sediments and nutrient loads, and finally the implementation of the appropriate BMPs.

This chapter describes a combination tool that can help watershed managers determine the best combination among areas that are selected for BMPs implementation under specified budget to achieve the maximum quality benefits. The tool was written using Python and was tested for selected areas that were identified using a widely adopted watershed modeling tool (Soil and Water Analysis Tool – SWAT) and different BMPs related to the Lower Bear River (LBR) watershed in northern Utah.

Within the LBR watershed, high levels of phosphorus, sediments, and total dissolved solids (salts) are the major water quality concerns [3]. Major sources of pollutants that have had a significant impact on water quality within the LBR watershed and its associated ecosystem often come from agricultural runoff that carries sediment, fertilizers and animal wastes from agricultural lands. Two waterbody segments (the LBR from Cutler Reservoir to the confluence with Great Salt Lake and the Malad River from the Utah-Idaho state line to the Bear River confluence) were declared impaired in Utah’s year 2000 303(d) list of water bodies needing TMDL analyses [3] based on Clean Water Act requirements of the state of Utah. Several conservation projects have been implemented across the LBR watershed to protect water quality with an approximate expenditure of US$500,000 in the period between 2000 and 2010. The impact of these conservation practices was not sufficient to meet the required reduction in loads that set by the LBR TMDL. This chapter addresses the implementation of BMPs over a ten-year period (2000-2010) and their impact on reducing sediment and total phosphorus loads at a watershed scale.

For this chapter, the calibrated and validated Soil and Water Assessment Tool (SWAT) model for the LBR watershed developed in Chapter 2 was utilized to estimate total phosphorus-loadings across the LBR watershed and to identify the potential NPS areas that would be selected for agricultural BMP implementation under specific criteria. Different types of agricultural BMPs can be implemented to reduce total phosphorus. They include no-till management, filter strips, cover crops and vegetation. Pollutant load reductions can be calculated based on yield rate (kg/year/size of area) of each NPS area, and the ability of an installed BMP to reduce the targeted pollutant. The cost was associated with the size of implementation (that includes the management and the operation of the BMP in the implemented area). Once the NPS areas and the BMPs were verified, the modeling tool was utilized to generate a collection of solutions from different scenarios regarding the selection and placement of different types of BMPs in the identified NPS areas under available budget and load reduction constraints.

Literature Review

Increased sediment loads, increased nutrient levels (nitrogen and phosphorus), and the presence of pesticides/fertilizers are persistent water quality issues attributed to agricultural runoff in the United States [4, 5]. NPS pollution can include surface runoff of excess precipitation that flows over the landscape, tile drainage runoff that includes the excess water infiltrated through the soil that moves to the drainage ditches through the underground tile system [6, 7]. As defined in the Clean Water Act (CWA), BMPs are precautionary measures designed to protect water bodies. BMPs are one of the most effective and practicable means to control NPS pollution at desired levels and improve surface water quality [8].

The United States Department of Agriculture's National Resources Conservation Service (USDA-NRCS) is the well-known source for design, installation, and maintenance standards for agricultural BMPs. The NRCS has published over 155 agricultural BMP standards. The three-digit NRCS identification code is a recognized standard that has been incorporated into most of the databases reviewed as part of this literature review [9]. The most commonly studied BMPs were various tillage techniques followed by filter strips, vegetated buffers, and cover crops. Approximately 35 papers studied watershed scale implementation of multiple BMPs. NRCS Conservation Effects Assessment Project (NRCS-CEAP) Web based [10] resources are also accessible for specific USDA programs involving monitoring and research. In particular, the NRCS-CEAP was initiated in 2003 and has several small watershed investigation programs for studying BMP effectiveness.

To implement such conservation programs, the United States Environmental Protection Agency (EPA) 319 program [11] supports non-point source control projects across the nation. The Clean Water Act (CWA) established the Section 319 Nonpoint Source Management Program in 1987. Section 319 addresses the need for federal support to help state and local nonpoint source efforts by a grant program that supports a wide variety of activities including technical assistance, financial assistance, education, training, technology transfer, demonstration projects and monitoring to assess the success of specific nonpoint source implementation projects. In addition, the EPA 319 Grants Reporting and Tracking System (GRTS) [12] database contains details of thousands of projects supported by Section 319 of the Clean Water Act. Data are searchable by location. While most of the focus of this database is for tracking grants, over 1,500 studies have pollutant data available of varying types (measured and/or modeled). The Division of Water Quality in State of Utah is responsible for the funding and management of Section 319 under Utah Nonpoint Source Management Program [13].

Agricultural BMPs are general methods that reduce the transport of P with water and sediments [14, 15]. Yet, pollutant losses vary from field to field on the ground where some fields being much greater to sources of pollutants than others. It is noted that some pollutants, such as phosphorus, come from land surfaces that are more susceptible to pollutant loss than others and need to be managed with practices that prevent these losses. Usually, multiple BMPs in a watershed will be required to meet water quality goals. Some BMPs are cost-wise appropriate for relatively little of the land, while others are expensive and require more space. Thus, cost-effective implementation of BMPs requires identifying these most sensitive NPS areas and adopting BMPs that are most effective relative the cost of implementation. Targeting locations with proper type of conservation is a technical, economic and social challenge.

Recently, the available tools designed to get the optimum solution of targeting the NPS locations, and then selecting and placing BMPs under different conditions are consisting of application of mathematical programming involving genetic algorithms in combination with the watershed simulation tool. Most of these optimization methods have used either gradient-based or heuristic techniques to trade off with one objective or two. The sophistication of such techniques and their high-performance computer requirements leave little room for some of the watershed managers and extension personnel on field to apply such methods because of inadequate financial resources, technical assistance, or motivation, especially if they were restricted by a budget and deadline to submit their proposed conservation method to the concerned agencies.

There have been several attempts to target and/or optimize placement of BMPs within agricultural watersheds [16-20]. These studies have used models that were highly specific and research-oriented and not directed toward watershed planning with multiple objectives including socially acceptable BMPs and input from local stakeholders with the objective of developing watershed plans for implementation. In an effort to engage the concerned watershed managers who are aware of the stakeholders’ input and the social acceptance of BMPs that can be implemented, Mamo et al. [21] released an interactive computer-based tool for selecting BMPs for major cropping systems in Nebraska. Managers can set up current farm input and output factors, current prices, and management information.

Based on the users’ tolerance of economic loss and the soil erosion targets for a landscape, output from this tool provides stakeholders with several BMP alternatives that can be implemented across the watershed. William et al. [22] developed a spreadsheet-based model (Watershed Manager) that is used in extension education programs for learning about and selecting cost-effective watershed management practices to reduce soil, nitrogen, and phosphorus losses from cropland. The tool was developed to educate stakeholders about alternative best management practices (BMPs) that result in improvements in water quality and to select the combination of BMPs that yield the largest improvement in water quality per dollar spent. These were very useful approaches to be adopted by the watershed managers and related stakeholders for implementing BMPs.

The aim of this chapter is to provide a simplification process through using a combination tool that can offer optimal solutions for selected NPS areas with different types of BMPs under specified budgets. The tool comprises preprocessing procedures in R Language and a code written in Python that deals with spreadsheets developed by the watershed managers as inputs and outputs. The overall approach uses a protocol-written code with budget objectives to search for the optimum alternative(s) among many possible Area-BMP scenarios. The significance the tool is helping watershed managers identify low cost solutions based on the available budget for improving water quality under known NPS areas and the BMPs to be implemented, and the conditions of the watershed. Watershed managers can also provide and update estimates of annualized costs and effectiveness for individual BMPs.

Best management Practices History in the LBR

NPS pollution is diffuse, originating from a wide range of small sources dispersed across the landscape. In Utah, the most common agents of NPS pollution are sediments, nutrients, heavy metals, salts, and pathogens [23]. Since 1990, the state of Utah NPS programs has spent almost $30 million to address water quality problems [24]. In the LBR watershed, conservation projects were funded and implemented in the early 2000s. The total 319(h) award for LBR TMDL [25] implementation was approximately US$500,000.

The primary goals of these 319(h) projects are to:

i) Reduce nutrient and sediment loading to the LBR from animal feeding operations and other agricultural inputs such as field drains,

ii) Improve vegetation to enhance streambank stability, and

iii) Provide cover to control erosion.

The main BMPs implemented in the LBR watershed can be summarized as: fencing off riparian areas; stream bank stabilization and riparian buffer projects; rerouting agricultural field drains to reduce pollutant input to waterways; relocating an animal feeding operation; constructing dikes to prevent animal waste from entering waterways; providing off-stream watering facilities for livestock; and constructing animal waste storage facilities and waste transfer pipelines. Table 14 summarizes the BMPs projects implemented under Utah NPS 319(h) grants in the LBR watershed. The projects were selected by a Water Quality Task Force made up of a team of resource professionals from federal, state and local agencies [26].

Table 14. List of 319 projects implemented in the LBR Watershed [26]

Project Type	**Project #**	**Estimated Size**	**Location**
Riparian Fencing	1	3,593 feet	41°45'36.59"N 112°07'10.53"W
Storm Drain Piping	2	300 feet	41°40'22.44"N 112°07'36.96"W
Feedlot	3	155,600 Sq. ft.	41°36'29.00" N 112°06'54.35"W
Dairy	4	solid/Liquid Pits	41°38'11.29" N 112°06'30.83"W
Dairy	5	solid/Liquid Pits	41°33'39.21" N 112°05'13.67"W
Feedlot	6	48,840 Sq. ft.	41°33'56.73" N 112°07'20.80"W
Dairy	7	solid/Liquid Pits	41°36'02.85" N 112°08'37.66"W
Feedlot	8	73,080 Sq. ft.	41°37'26.61" N 112°10'00.11"W
Feedlot	9	300,591 Sq. ft.	41°37'40.03" N 112°10'15.93"W
Two feedlots	10	37,250 Sq. ft.	41°39'15.51" N 112°09'45.52"W
Compost facility	11	38,512 Sq. ft.	41°39'18.90" N 112°09'33.48"W
Feedlot	12	3,510 Sq. ft.	41°42'46.66" N 112°09'36.73"W
Feedlot	13	1,445,400 Sq. ft.	41°53'34.92" N 112°10'05.41"W
Runoff Pond	14	3,650 Sq. ft.	41°49'32.45" N 112°07'38.07"W
Dairy	15	solid/Liquid Pits	41°42'05.21" N 112°05'29.42"W

The selection is based on criteria reflect the priorities of the Nonpoint Source program, including protecting public health, restoring impaired waters, and preventing surface and ground water pollution. Figure 13 shows the spatial placement of these projects. The partners supporting the implementation of BMPs programs are the Utah Division of Water Quality (monitoring and lab analysis), Natural Resources Conservation Service (NRCS) and USU Extension (provide technical support and outreach education).

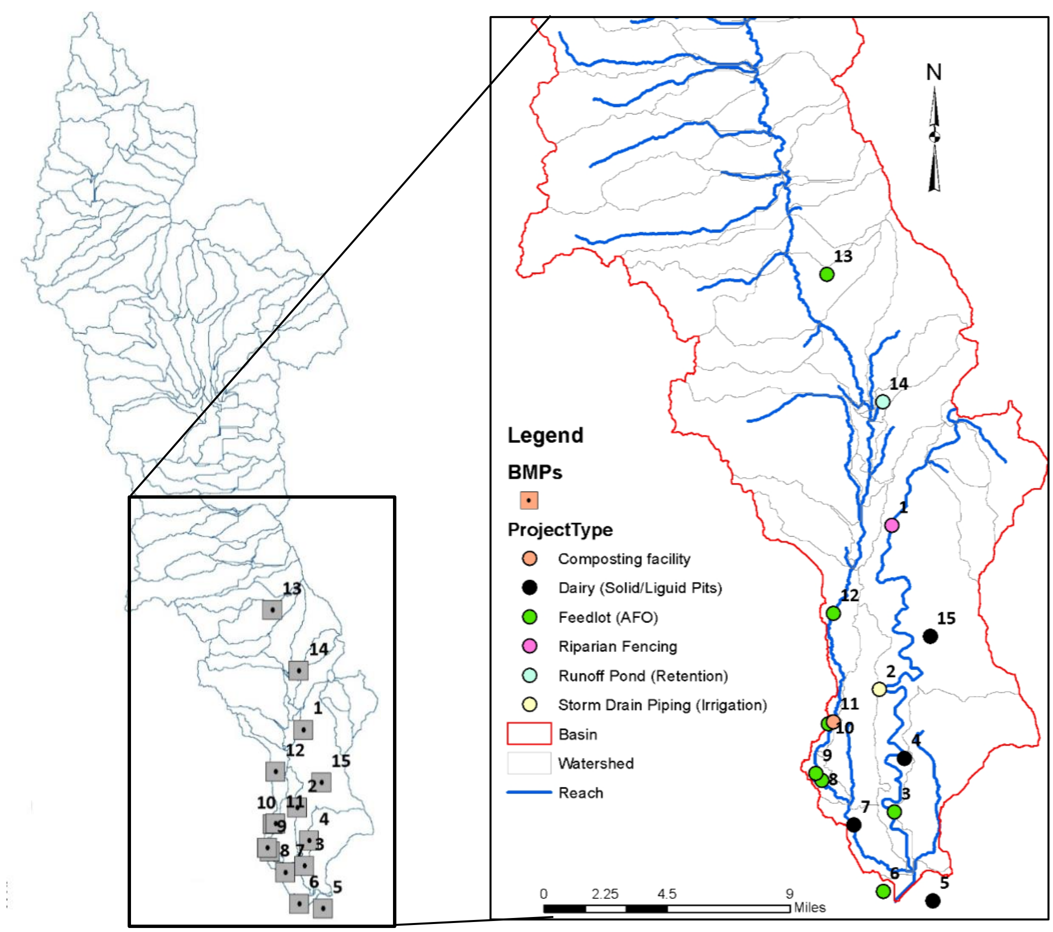


Figure 13. Spatial distribution of different implemented BMPs across LBR watershed

Data Collection and Analysis Methods

Study Area

The research was conducted in the LBR watershed located in Box Elder County, Northern Utah (Figure 14). The LBR watershed is unique because it is almost completely dominated by agriculture (76%) and very little urban (4%) (Table 15); therefore, the research focused on the effects of changes in agricultural practices and their related BMPs [3].

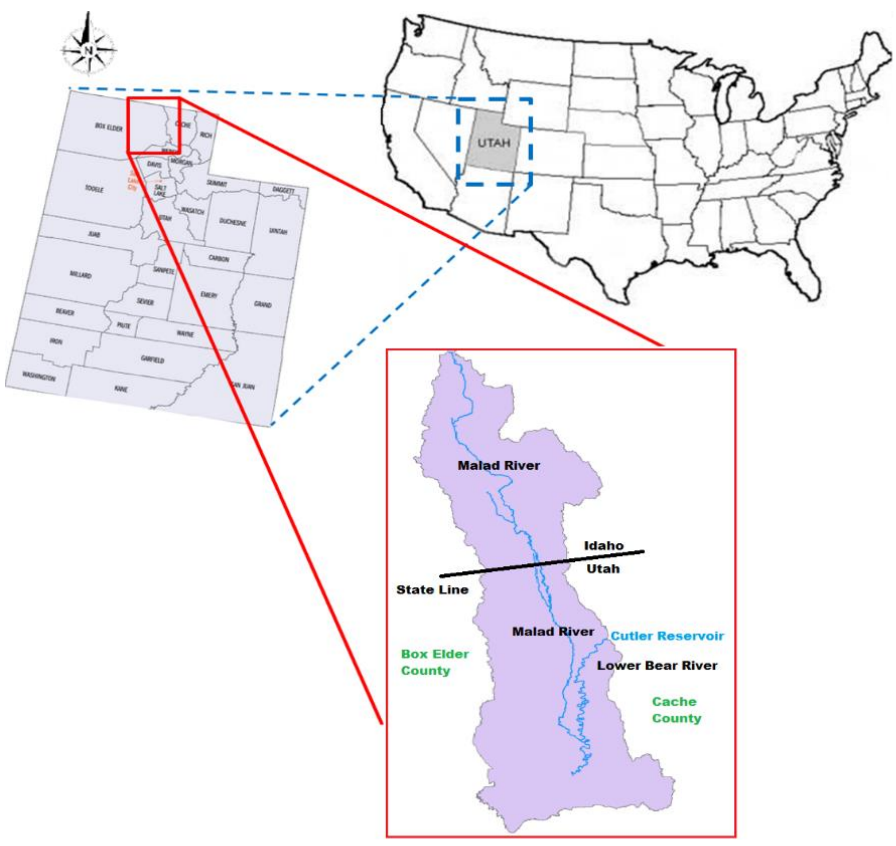


Figure 14. Location of Lower Bear River and Malad River in Northern Utah

Table 15. Landuse Distribution in LBR Watershed

Name	**Code**	**Area (Km^2)**	**%**
Water	WATR	4.10	0.21
Residential-Low Density	URLD	51.62	2.58
Residential-Medium Density	URMD	8.66	0.43
Residential-High Density	URHD	2.72	0.14
Industrial	UIDU	0.88	0.04
(Arid) Range	SWRN	0.45	0.02
Forest-Deciduous	FRSD	56.00	2.80
Forest-Evergreen	FRSE	136.79	6.85
Forest-Mixed	FRST	0.37	0.02
Range-Brush	RNGB	921.87	46.14
Range-Grasses	RNGE	157.51	7.88
Hay	HAY	179.46	8.98
Agricultural Land-Row Crops	AGRR	449.61	22.50
Wetlands-Forested	WETF	7.68	0.38
Wetlands-Non-Forested	WETN	20.13	1.01
Watershed Simulated Area		1,997.85	100

Two waterbody segments (the LBR from Cutler Reservoir to the confluence with Great Salt Lake and the Malad River from the Utah-Idaho state line to the Bear River confluence) were declared impaired in Utah's year 2000 303(d) list of water bodies needing TMDL analyses [27] based on Clean Water Act requirements of the state of Utah.

Water quality data sampling and collection from the LBR watershed was not consistent in the recent years. Samples were intensively taken in the period from 2000 till 2002 and again between 2008 and 2009 as shown in Figure 15.

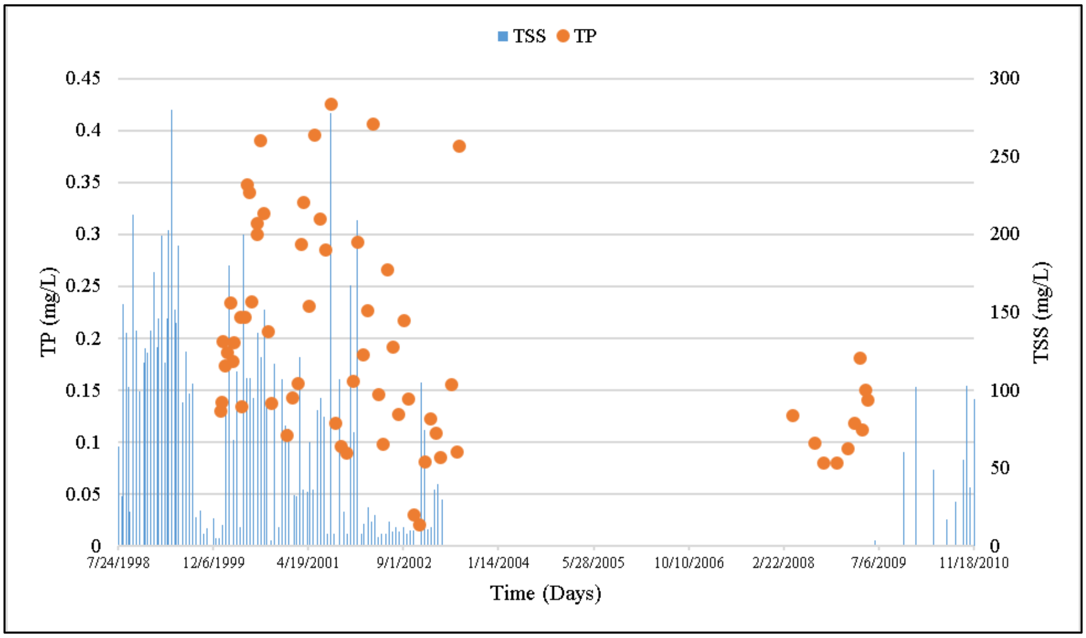


Figure 15. Distribution of water quality samples collected at the outlet of the study area (USGS 10126000 Bear River near Corinne, UT)

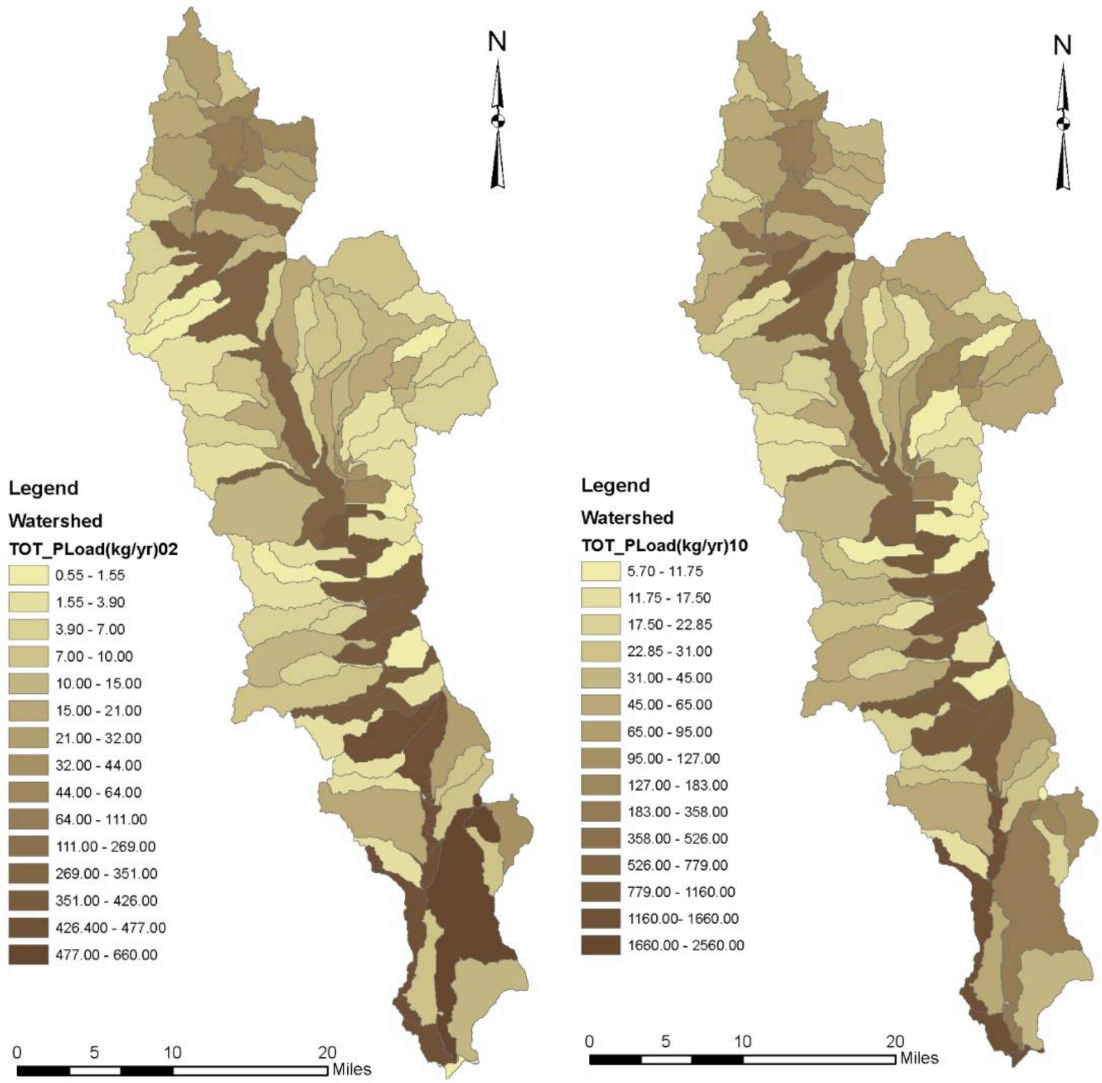
Pollutants Loads using LBR SWAT Watershed Model

The loadings map produced by the SWAT model showed high sediments and total phosphorus loads from subbasins around Malad River in particular subbasin 118, 121, and 125). This is attributed to the large number of agricultural fields acting as nonpoint sources to the Malad River, but, lower sediment and total phosporus loading from the subbasins/tributaries adjacent to Lower Bear River. This is likely due to the fact that Cutler Reservoir is trapping sediments and total phosphorus from being transported to the LBR and a majority of the loading is sourced from the LBR water rather than the larger Bear River drainage.

Spatial visualization of SWAT average annual sediment yield and phosphorus losses output are important tools to target and place the right BMP at the right subbasin modeled in the LBR watershed for the total hydrological period. Table 16 summarizes these yearly loads at the outlet of the simulated LBR watershed. Figures 16 and 17 demonstrate the spatial loads of sediments and total phosphorus across the watershed in years 2002 and 2010 where it shows that largest TP sources are the same as the largest TSS sources.

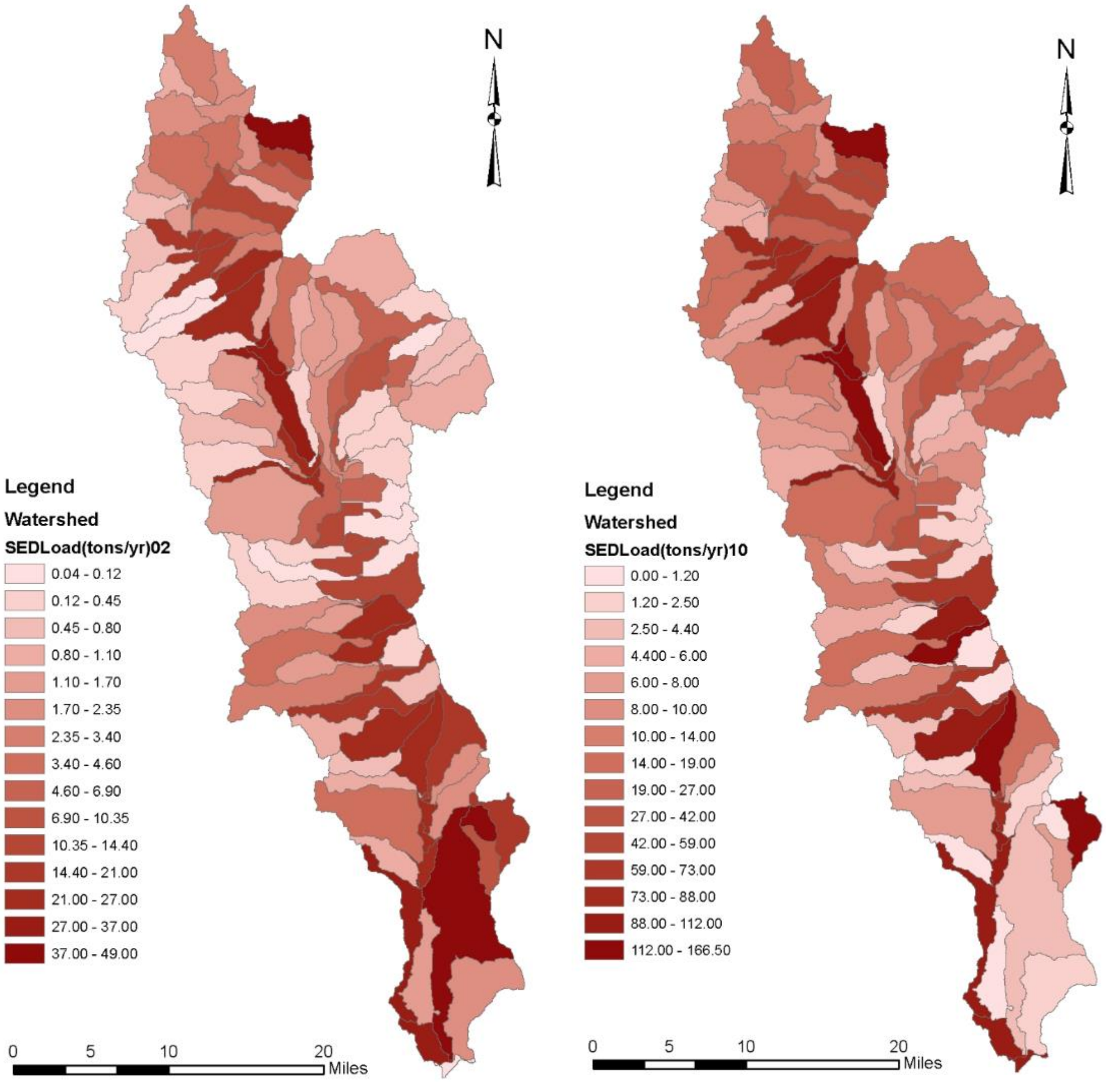
Table 16. Yearly loads of Sediments and total phosphorus from LBR watershed

Year	**SED (ton/yr)**	**TOT_P (kg/yr)**
2002	63.79	1109.90
2003	37.93	687.18
2004	45.41	902.34
2005	89.23	1317.72
2006	76.01	1341.35
2007	53.50	887.15
2008	79.61	1036.48
2009	112.68	1051.57
2010	112.01	1538.57
Avg (2002-2010)	74.46	1096.92



2002 2010

Figure 16. Total phosphorus loads (kg/year) in years 2002 and 2010 from Subbasins across the LBR watershed (LBR SWAT model output)



2002 **2010**

Figure 17. Sediment loads (ton/year) in years 2002 and 2010 from Subbasins across the LBR watershed (LBR SWAT model output)

Targeting Critical Areas

Many models exist to aid in modeling targeted areas and the BMP spatial placement and its effectiveness. SWAT is the most robust one [2, 28]. SWAT can offer a wide array of detailed outputs (i.e., daily weather, surface runoff, return flow, percolation, evapotranspiration, transmission losses, pond and reservoir storage, crop growth and irrigation, groundwater flow, reach routing, nutrient and pesticide loads) [29]. The outputs are quite detailed as well, as they provide the variability throughout the watershed via the hydrologic response units (HRUs). The majority of the pollutant load is transported and observed at the watershed outlet. The SWAT simulation results identified critical areas where the potential contribution of pollutants (sediments and phosphorus load critical areas) to the receiving waters is significantly higher than other areas in the watershed.

Map HRU output to Parcel Boundaries

To identify specific fields for implementation of BMPs, the SWAT HRU output needed to be mapped to the actual field boundaries, derived from the tax parcel coverage, that provide geospatial information, zip codes, ownership type, and the size of that field (parcel area). Converting SWAT HRU output to field-level results and identifying the fields that produced the highest total phosphorus and sediment yields involved several steps after running SWAT successfully. The approach was calculating the average annual total phosphorus for HRUs from the SWAT output tables and creating a new database file (csv format). Then, the new csv database file was joined with the FullHRU shapefile, which was converted from shapefile to grid (raster), so it could be used with the parcel map with the help of zonal statistics to get total phosphorus yields for each parcel. The parcel map, as shown in Figure 18, was obtained from the Box Elder County Geographic

Information System (GIS) website [30]. The resulting total phosphorus and total sediment loading maps are shown below in Figure 19, with the resulted parcels along with their loading rates.

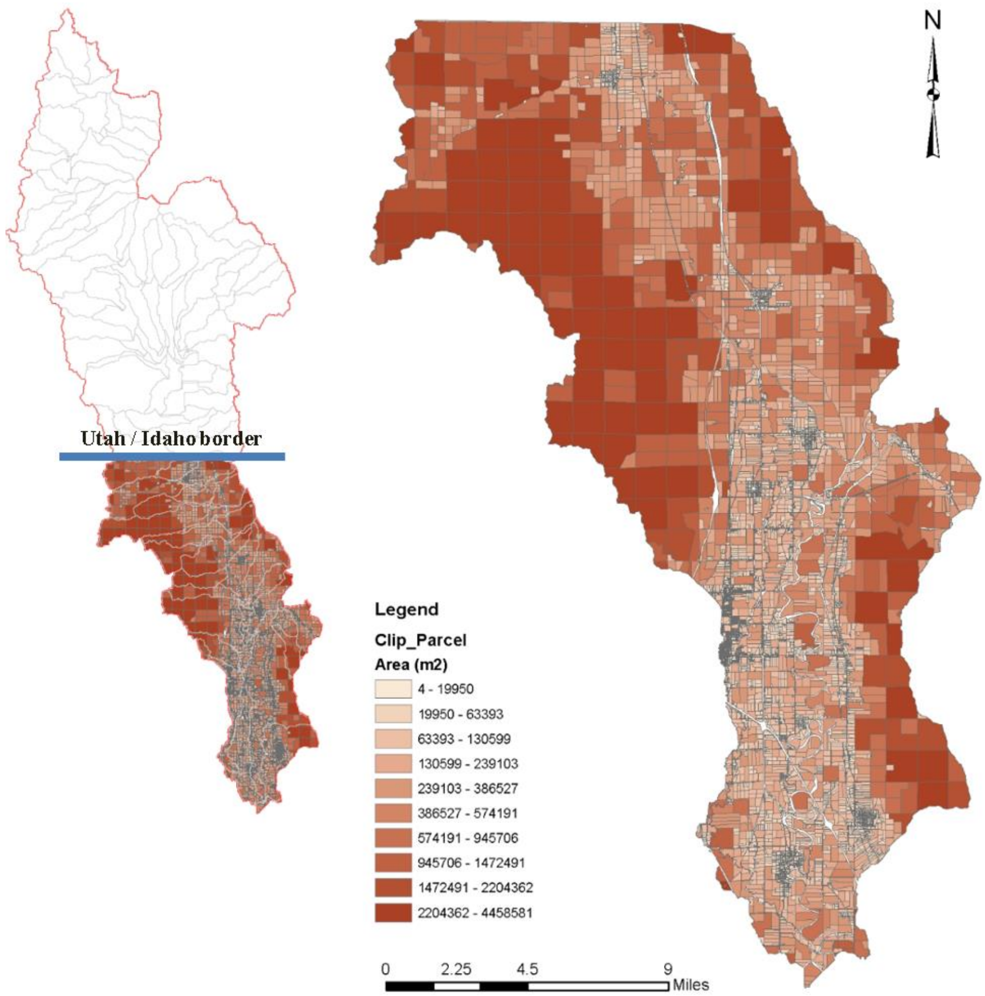


Figure 18. Parcel map of Box Elder County, Utah for the year 2016

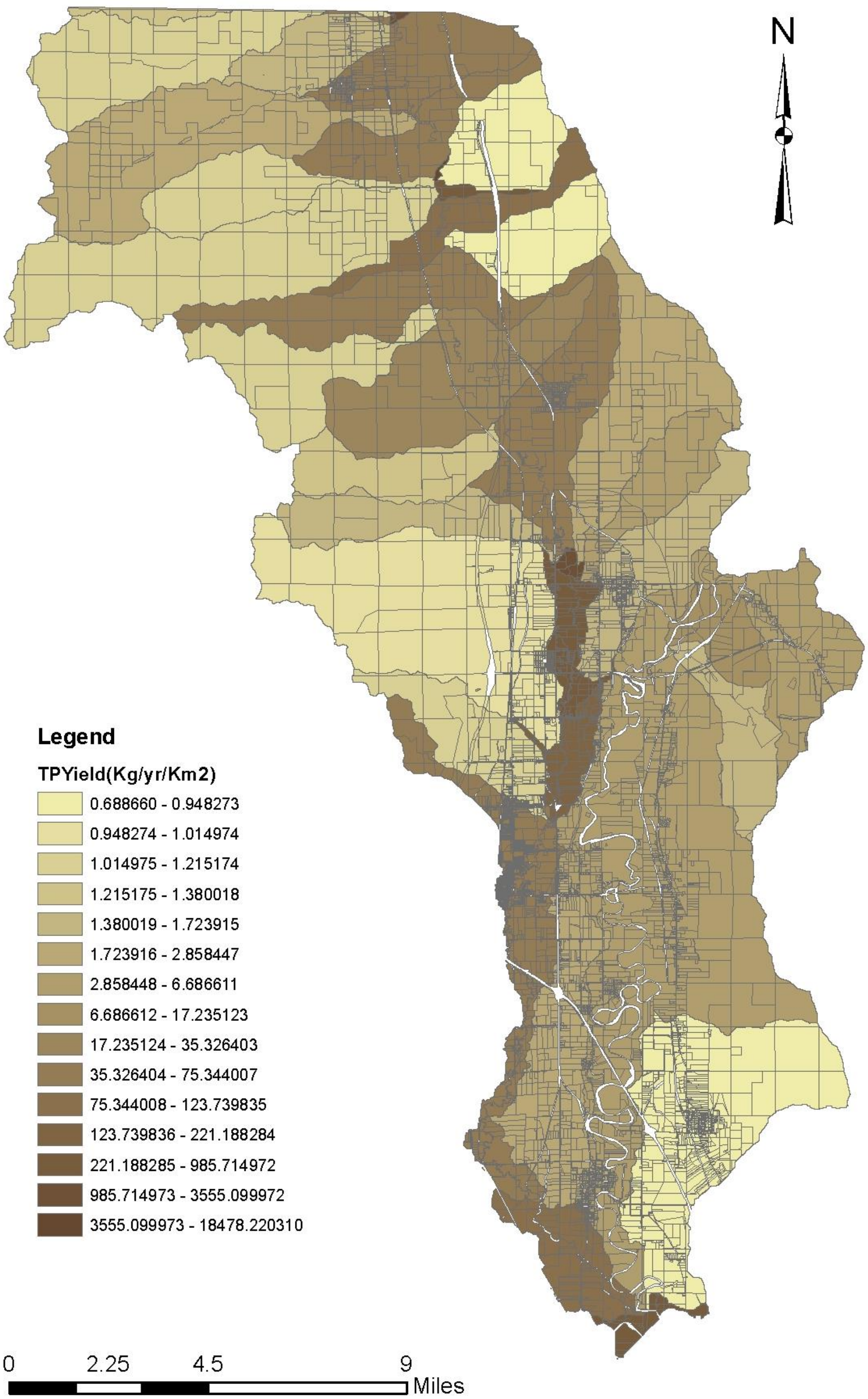


Figure 19. Generated parcel map with total phosphorus loads

Based on the resulting Parcel map with loads, the possible NPS locations were identified and selected as shown in Table 17. Depending on the nature of the receiving water, some BMPs may be promoted, restricted or prohibited, or special design or sizing criteria may apply. Thus, assumptions behind selecting the NPS sites and the BMPs are:

- Sites with high phosphorus yield amount based on SWAT watershed simulation.
- Physical feasibility of the site to implement BMPs and no restrictions to do so.
- Adjacent to waterways to have direct impact.
- Close to areas where previous BMPs were implemented.
- Community (landowners and farmers) accepting the implementation of such BMPs to prevent pollution and earn economic and environmental benefits.
- Only agricultural BMPs to be applied to reduce the size of structural BMPs.

Table 17. Selected NPS sites of total phosphorus yield annually in the LBR watershed

Subbasin	**FID_Parcel**	**Parcel_Area (Km^2)**	**TP_Yeild(kg/yr/Km^2)**
123	5115	0.790	3.70
123	6473	0.374	3.70
125	1142	0.334	123.74
11	1146	0.320	123.74
125	1069	0.318	123.74
121	2946	0.314	52.36
123	1677	0.275	3.70
125	5	0.252	123.74
120	5706	0.250	221.19
125	1252	0.248	123.74
121	930	0.222	52.36
125	1189	0.222	123.74
123	1552	0.212	3.70
123	3318	0.211	3.70
123	574	0.207	3.70
123	1665	0.203	3.70
123	3249	0.191	3.70
121	936	0.178	52.36
121	939	0.158	52.36
121	920	0.157	52.36

Agricultural BMPs scenarios in the LBR

An Agricultural BMPs database was developed to provide information on costs and pollution removal efficiency estimates for each BMP to be implemented in the LBR watershed. Data and information were collected from several relevant standards, studies and literature. In addition, records from Environmental Protection Agency's Grants Reporting and Tracking System (GRTS) [31] can give historical NPS projects and the implemented BMPs in the LBR watershed. Table 18 is a summary of collected agricultural BMPs data and their characteristics. For this work, the BMP reductions obtained were assumed to not vary temporally, i.e. the BMP effectiveness performance remains the same throughout pre- or post-BMP periods in the study area. These BMPs are applicable in land uses of cropland, rangeland pasture, and forests.

The database in Table 18 was compiled from several resources [32-38]. As with all of these types of financial assessments, the costs presented here are simply baseline numbers and are meant to be informative rather than prescriptive. Other costs such as design, engineering, insurance was not included due to insufficient data from literature. The BMPs that were selected for this chapter/study are based on lieterature review and research recommendation: herbaceous riparian buffer, cover crops, residue tillage, filter strip and riparian forest buffer. Table 19 shows the selected BMPs that will be implemented in this chapter. The selection was based on BMPs history, relevance and its implementation in the area.

Table 18. Summary of proposed Agricultural BMPs database in the LBR watershed

BMP Type/Practices	NRCS Practice Code	Units (Based on Parcel Area)	Life Span (yr)	Cost Per Unit (US $)	TSS % Reduction Efficiency	TP% Reduction Efficiency
Filter Strips Are strips or areas of herbaceous vegetation that remove contaminants from overland flow. They are adjacent to water resources that protect water from nonpoint source pollution	393	Km^2	10	54363.0	60	50
Riparian Forest Buffer They are adjacent to water resources that protect water from nonpoint source	391	Km^2	15	81545.0	65	55
Terraces Earthen embankment, ridge or ridge-and-channel, to reduce erosion by reducing slope length	600	Linear m.	10	4.90	65	50
Stream bank Stabilization Streambank protection refers to both biological and structural method of stabilizing streambanks and/or shorelines on rivers, streams and ditches	580	Linear m.	20	26.3	65	55
Fencing A constructed barrier to livestock, wildlife, or people	382	Linear m.	20	30.0	70	55
Residue and Tillage Management, No till Conservation (Planting Systems)	329	Km^2	1	7413.15	65	50
Herbaceous Riparian Buffer Grasses, grass-like plants and forbs that are tolerant of intermittent flooding or saturated soils and established or managed in the transitional zone between terrestrial and aquatic habitats	390	Km^2	5	3707.0	60	55
Contour buffer strips narrow strips of permanent, herbaceous vegetative cover established around the hill slope, and alternated down the slope with wider cropped strips that are farmed on the contour	332	Km^2	5	12355	65	55
Cover Crops Cover crops are plants that are used to protect soils during the period between the harvest and establishment of crops such as corn and soybeans	340	Km^2	1	14826.0	25	25

Table 19. Selected BMPs for the study area

BMP type	BMP(#)	Cost per Km^2	TP_Eff %*
Herbaceous Riparian Buffer	(1)	741.4	65
Cover Crops	(2)	2965.2	25
Residue Tillage	(3)	7413.15	50
Filter Strip	(4)	10872.6	50
Riparian Forest Buffer	(5)	16309.0	55

* TP_Eff is the total phosphorus reduction effeciency as illustrated in Table 18.

3.3.1 Optimal Solutions Framework

The proposed framework is a combination tool that generates multiple solutions for watershed managers or others to select their best options based on a given budget. Implementing BMPs within a watershed based on selected NPS areas is beneficial for decision makers to evaluate such plans. The Optimal Solution framework developed here will aid the watershed managers to propose the practices they deem acceptable and applicable at selected NPS areas (feasible locations), provide them with generated scenarios with the help of the combination code, and prioritize the solutions based on their given budget to achieve the maximum environmental benefits (i.e., maximizing the nutrient and sediments reductions). The Optimal Solution framework consists of the following:

- Data preparation: Spreadsheets for the users (watershed manager/stakeholders) to assign the applicable and feasible BMPs to the identified NPS areas with known loading rates and hydrological conditions.
- Preprocessing of the data: Spreadsheets prepared by the users are

processed in the R Language [39] environment with a script for joining and merging the proposed BMPs with the selected NPS areas. The preprocessing involves calculating the cost of each BMP implemented in each Area, as well as to the total phosphorus load reduction amount based on the removal efficiency for each BMP implemented in each Area. At the end, a csv file is created that lists all scenarios associated with their costs and phosphorus reduction. Please see Table A 7 in Appendix 2 for more details about the R code.

- Combination of Scenarios: The created csv file is then used by a script written in Python to generate multiple solutions based on a given budget as a constraint for the combination model. The generated solutions are then filtered in spreadsheets upon preferences of the user that can be related to the maximum reduction a budget limit can provide.

Combination Tool

The combination script was written in Python [40]. The combination tool script has commands and packages that read the database variables, start the combinations based on budget criteria, and export the results. The combination module in Python "itertools" are iterators for efficient looping. The iterator is "combination ( )" where it can run the iteration based on the length of the data in sorted order and no repeated elements because they are unique. There will be no repeat values in each combination.

The combination tool uses a "functional components approach" (R Language and

Python Script) wherein basic Area and BMP components are selected and pieced together to achieve a desired outcome. This approach limits the inclusion of numerous individual BMPs or implementing in different areas that could not meet the required budget or the watershed quality goals. While the code runs the combination, it will automatically calculate the cost of that combination as well as the total phosphorus reduction associated for each proposed scenario. See Table A 8 for Python script in Appendix 2.

Results and Discussion

The selected NPS areas in Table 17 and the BMPs detailed in Table 18 were prepared in spreadsheets. Preprocessing of the information compiled in the spreadsheets is carried out using the R language and has generated fifty (50) scenarios. The top twenty scenarios with high phosphorus reduction amounts were selected as shown in Table 20 for combination processing. The scenarios are described as each BMP was implemented in each Area.

The output file was then used in the combination tool in Python. The code set two budget criteria: Max = US$ 50,000 and Min = US$ 10,000, and for phosphorus load reduction limits of 150, 200, and 250 kg/yr as suggested by the TMDL study. All combinations that falls within budget and quality limits should be considered and returned in the results. Combination tool results showed 671870 possible combination generated from the provided scenarios in Table 20. The data frame of the results is 671870 observations of two variables (Cost and TP reduction).

Table 20. Generated Area vs BMP scenarios for the study area.

Area*	BMP	Tot_Cost**	Tot_TP_Reduct.***	Combination Solutions (CS#) reference in Python
Area9	BMP (1)	185.35	35.94	CS1
Area9	BMP (5)	4077.25	30.41	CS2
Area9	BMP (3)	1853.28	27.64	CS3
Area9	BMP (4)	2718.15	27.64	CS4
Area3	BMP (1)	244.66	26.54	CS5
Area4	BMP (1)	237.25	25.74	CS6
Area5	BMP (1)	237.25	25.74	CS7
Area3	BMP (5)	5381.97	22.46	CS8
Area4	BMP (5)	5218.88	21.78	CS9
Area5	BMP (5)	5218.88	21.78	CS10
Area3	BMP (3)	2446.34	20.41	CS11
Area3	BMP (4)	3587.96	20.41	CS12
Area8	BMP (1)	185.35	20.11	CS13
Area10	BMP (1)	185.35	20.11	CS14
Area4	BMP (3)	2372.22	19.79	CS15
Area5	BMP (3)	2372.22	19.79	CS16
Area4	BMP (4)	3479.23	19.79	CS17
Area5	BMP (4)	3479.23	19.79	CS18
Area8	BMP (5)	4077.25	17.00	CS19
Area10	BMP (5)	4077.25	17.00	CS20

* Area as defined in Figure 19 (Parcel map)
** Tot_Cost is the total cost of implementing combination
*** Tot_TP_Reduct is the total reduction of total phosphorus when implementing the BMPs combination

For a **150 kg/yr** of phosphorus load reduction, the top combination solutions (refer to Table 20 to look for the CSs) that met the conditions are shown in Figure 20. For each solution provided, there are number of combinations (BMPs and Areas) that can be considered for implementation to meet the desired reduction. As per the results, the cost ranges from US$ 12,388 to US$ 24,268 for management scenarios of combination conservation practices that would achieve the 150 kg/yr load reduction as the lowest total cost shows a combination of six: CS_2, CS_5, CS_6, CS_7, CS_9 and CS_15 as shown in Table 21.

Table 21. Generated combination solutions (CS) and their implementation cost to target Phosphorus reduction by 150 kg/yr

1	2	3	4	5	6	7	Cost ($)
CS_2	CS_5	CS_6	CS_7	CS_9	CS_15	-	12,388
CS_2	CS_5	CS_6	CS_7	CS_9	CS_17	-	13,495
CS_2	CS_8	CS_11	CS_13	CS_15	CS_16	CS_19	20,913
CS_2	CS_8	CS_11	CS_13	CS_15	CS_17	CS_19	22,020
CS_2	CS_8	CS_11	CS_14	CS_15	CS_16	CS_20	20,910
CS_2	CS_8	CS_11	CS_14	CS_17	CS_18	CS_19	23,127
CS_2	CS_8	CS_12	CS_13	CS_16	CS_18	CS_20	23,160
CS_2	CS_8	CS_12	CS_13	CS_17	CS_18	CS_19	24,268
CS_2	CS_8	CS_12	CS_14	CS_15	CS_16	CS_19	22,054

For a **200 kg/yr** of phosphorus load reduction limit, the budget of implementing the management scenarios to achieve the required water quality reduction ranges from US$ 18,775 to US$ 34,765 (refer to Table 20 to look for the CSs). This is beneficial for the watershed managers, since they have the ability to select among different alternatives not only based on the budget and water quality reduction limits, but also on the management and maintenance associated with the number of management practices that need to be implemented. As shown in Table 22, the lowest cost shows a combination of CS_1, CS_3, CS_4, CS_5, CS_6, CS_8, CS_19 and CS_20.

For a **250 kg/yr** of phosphorus load reduction limit, interestingly, the budget ranges from US$24,485 to US$36,238 as shown in Table 23 (refer to Table 20 to look for the CSs). Again, this is helpful for the watershed managers to have feasible alternatives and, at the same time, room for decisions based on their preferences, available technical support, willingness of the landowners to cooperate, and the associated efforts in managing and monitoring these management practices. As shown in Table 23, the lowest total cost shows a combination of eleven: CS_2, CS_3, CS_5, CS_5, CS_6, CS_9, CS_11, CS_12, CS_13, CS_14, CS_16 and CS_20.

Table 22. Generated combination solutions (CS) and their implementation cost to target Phosphorus reduction by 200 kg/yr

1	2	3	4	5	6	7	8	9	Cost ($)
CS_1	CS_3	CS_4	CS_5	CS_6	CS_8	CS_19	CS_20	-	18,775
CS_1	CS_3	CS_4	CS_6	CS_8	CS_9	CS_10	CS_19	-	24,890
CS_2	CS_5	CS_8	CS_9	CS_10	CS_11	CS_15	CS_17	CS_19	32,517
CS_2	CS_5	CS_8	CS_9	CS_10	CS_12	CS_16	CS_18	CS_20	33,658
CS_2	CS_5	CS_8	CS_9	CS_10	CS_12	CS_17	CS_18	CS_19	34,765
CS_2	CS_5	CS_8	CS_9	CS_10	CS_13	CS_14	CS_17	CS_19	28,070
CS_2	CS_6	CS_7	CS_9	CS_10	CS_11	CS_13	CS_19	CS_20	27,776
CS_2	CS_6	CS_7	CS_9	CS_10	CS_12	CS_13	CS_19	CS_20	26,917
CS_2	CS_6	CS_8	CS_9	CS_11	CS_15	CS_16	CS_17	CS_18	29,065

Table 23. Generated combination solutions (CS) and their implementation cost to target Phosphorus reduction by 250 kg/yr

1	2	3	4	5	6	7	8	9	10	11	Cost ($)
CS_1	CS_2	CS_5	CS_6	CS_7	CS_8	CS_9	CS_10	CS_15	CS_16	-	25,546
CS_1	CS_2	CS_5	CS_6	CS_7	CS_8	CS_9	CS_10	CS_15	CS_18	-	26,653
CS_1	CS_2	CS_5	CS_6	CS_7	CS_8	CS_9	CS_10	CS_17	CS_18	-	27,760
CS_1	CS_2	CS_5	CS_9	CS_10	CS_13	CS_15	CS_16	CS_17	CS_19	CS_20	31510
CS_1	CS_2	CS_5	CS_9	CS_10	CS_13	CS_15	CS_17	CS_18	CS_19	CS_20	32,615
CS_2	CS_3	CS_5	CS_6	CS_8	CS_9	CS_10	CS_15	CS_16	CS_19	CS_20	35,130
CS_2	CS_3	CS_5	CS_6	CS_8	CS_9	CS_10	CS_15	CS_18	CS_19	CS_20	36,238
CS_2	CS_3	CS_5	CS_6	CS_9	CS_11	CS_12	CS_13	CS_14	CS_16	CS_20	24,485
CS_2	CS_3	CS_5	CS_7	CS_8	CS_9	CS_10	CS_17	CS_18	CS_19	CS_20	37,345

Prioritizing conservation projects under a given budget constraint to achieve maximum nutrient removal (total phosphorus) is of paramount goal for the watershed managers and extension personnel. The optimal solution framework approach presented here using combination is simple with direct procedures to select the most feasible combinations of agricultural BMPs to be implemented in different NPS areas. At the end, the combination results provided the cost of implementation and the amount of total phosphorus reduction for suits of Areas and BMPs considering that BMP performance remains the same throughout pre- or post-BMP implementation in the study area and not to vary temporally.

Conclusions

For better placement and selection of agricultural BMPS, NPS should be identified and targeted with the proper BMP to attain the watershed quality goals in the most feasible way. The NPS areas were identified using SWAT (watershed simulation model). The output of SWAT is detailed in hydrological responses units (HRUs) that reflect land use, soil, and slope characteristics in a specific geospatial environment in ArcGIS. Most of the time, the size of the HRUs doesn't correspond with the size of the existing fields on ground. Therefore, simulating practices in ArcSWAT might not reflect the same operation or the extent of management in the field that will achieve the required sediment and nutrients reductions. The chapter proposed an approach to generate a spatial information of HRUs that can be projected on the parcel map of the study area. The approach transforms the sediments and the nutrients loads to the parcel areas using zonal statistical and geometry applications within the ArcGIS environment.

Thus, NPS areas were identified based on the parcel size (field size) and its loading rates of sediments and phosphorus. As agricultural BMPs have multiple sources and references, the chapter collated the most relevant agricultural BMPs that can be applied within the LBR watershed (study area). The collected data reflects the type of BMPs, its life span, associated cost and removal efficiencies of both total phosphorus losses and sediments loads. For the purpose of the chapter, lists of NPS areas and BMPs were selected as a case study to perform a prioritization process using a combination tool that will help watershed managers make decisions for the feasible allocation of budget to implement the conservation projects. Watershed managers often have to propose conservation projects based on restricted budgets and time. These conservation projects depend on the location, size and the type of practices to implement. The approach in this chapter can help managers base their decision through the examination of multiple alternatives rather than single solutions to achieve the most environmentally-sound scenario among all those theoretically possible. In addition, instead of reviewing options as discrete alternatives, scenarios can provide multiple alternatives for making decisions. This is especially valuable when dealing with budget and BMPs that can be implemented in different areas.

A combination tool was written in the R language and Python in order to generate combination solutions of different scenarios of the selected agricultural BMPs and identified NPS areas under a specified budget. Three water quality constraints were used 150, 200 and 250 kg/yr based on the given conditions of the case studies (NPS areas and BMPs). The combination tool generated 671870 solutions with minimum budget to implement these water quality criteria of US$12,387, US$18,775, and US$24,485 respectively for three different total phosphorus removal requirements. The tool is aimed at helping watershed managers to base their decision through the examination of multiple alternatives rather than single solutions to achieve the most environmentally-sound scenarios of feasible combinations among all those theoretically possible. The ability to consider many NPS reduction scenarios when dealing budget and multiple BMPs that can be implemented in different areas is valuable.

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OPTIMIZATION OF NONPOINT SOURCE POLLUTION CONTROL PRACTICES IN THE LBR WATERSHED

Abstract

Best management practices (BMPs) are implemented to reduce nonpoint source (NPS) pollutants from agricultural areas in a watershed. Prior to implementation of agricultural BMPs in the watershed, it is important first to select a suite of BMPs that can be both economically and environmentally efficient. Simultaneous implementation of BMPs in specified NPS areas could affect their reduction benefits across the watershed. Therefore, several methods have been developed to identify cost-effective BMP combinations for improving water quality using plan- (e.g., targeting method) or performance- (e.g., optimization) based methods with only specified sizes of NPS areas for implementation. The research aimed to assess the selection and placement of agricultural BMPs in reducing pollutant losses in a watershed using multi-objective optimization that can populate different sizes of areas for BMPs implementation to target the water quality requirements under given budget constraints. Two objective functions were used in the optimization process; maximizing phosphorus load reduction and minimizing cost of BMP implementation. The optimization framework utilized a multi-objective genetic algorithm (AMALGAM), agricultural BMPs database, and a watershed model (Soil and Water Assessment Tool, SWAT). BMPs scenarios, which consist of Herbaceous Riparian Buffer, Cover Crops, Residue Tillage, Filter Strip, and Riparian Forest Buffer were considered in this study. Three scenarios of optimum BMP options were implemented in critical NPS areas identified in the LBR Watershed. The optimal

solutions produced as a Pareto front for scenarios 1, 2 and 3 generated a total phosphorus load reduction of 155, 160 and 150 kg/yr respectively. The cost associated with each reduction for each scenario was US$35,000, US$26,000 and US$25,000 respectively. This optimization approach achieved different target load reductions under different implementation costs for different sizes of NPS areas. This allows watershed managers to be informed about planning the different alternatives for implementing BMPs within a watershed.

Introduction

Best management practices (BMPs) are widely considered as effective control measures for agricultural nonpoint sources of sediments and nutrients. The 2014 Farm Bill (2014 Farm Act) was signed on February 7, 2014, and remained in force through 2018. It provided up to $2 billion funds for conservation programs aimed at protecting water quality from agricultural nonpoint source (NPS) pollution [1]. Clean Water Act Section 319 Nonpoint Source National Monitoring Program and the Natural Resources Conservation Service (NRCS) provides hundreds of millions of dollars in federal funds to support agricultural best management practices (BMPs) in an effort to reduce pollutants driven into waterways. Success of such programs, however, depends upon availability of efficient watershed-scale planning tools.

Implementation of agricultural BMPs is challenged by difficulties in incorporation of conflicting environmental, economic, and institutional concerns. Under the EPA’s Total Maximum Daily Load (TMDL) program, the environmental assessment centers around resolving social benefits such as achieving the goal of protecting water bodies from pollution. While BMPs facilitate achievement such targets, their establishment bears additional cost for watershed management and/or agricultural producers. Usually, management practices are implemented under a limited budget; costs associated with unnecessary/redundant management actions that may affect the attainability of designated water quality goals. Additionally, in a watershed with multiple NPS areas and multiple BMPs feasible for implementation, it becomes a daunting task to choose a right combination of BMPs that provide maximum pollution reduction for the least implementation costs. Identifying optimal combinations of watershed management practices requires systematic methods that allow decision makers to assess their goals of implementing management actions under environmental and economic criteria.

Optimization of cost-effective distribution of watershed management practices (mainly agricultural BMPs in this chapter) is a promising trial and error strategy that requires no linearity, continuity, or differentiability either for objective/constraint functions or for input parameters (e.g. the size of area of implementation) [2, 3]. Such a strategy can help accommodating certain economic and environmental criteria for deciding on implementation of watershed management plans with specified target values for pollutant loads, and total cost.

The main goal of this chapter is to develop an optimization framework that enhances watershed decision makers' capacity to evaluate a range of agricultural management alternatives implemented under different range of available area sizes of the identified NPS areas using a watershed simulation model. The method combines the use of: a watershed model [4] to identify the NPS areas; agricultural best management practices (using the database on implementation cost and removal efficiencies in Tables

18 and 19); development of different scenarios of implementing agricultural BMPs in different NPS areas (three different combination of areas and BMPs); and a genetic algorithm-based optimizer that can produce multiple solutions along a Pareto front. This method was designed to identify near optimal watershed conservation practices that reduce pollutant loads at a watershed outlet to target quality values with available or minimum budget allocated.

Literature Review

Several methods have been developed to select and place cost-effective BMPs in a watershed. Those methods can be categorized into either plan- or performance-based methods [2, 5-6]. Plan-based methods are mainly used to assign BMPs based on the identification of critical areas in a watershed. However, interactions among BMPs on pollutant reduction are typically not considered in plan-based methods, thus a BMP that is selected based on a certain targeting strategy may or may not be the most cost-effective BMP for the watershed. In contrast, optimization is a performance-based method that considers the effectiveness and cost of various BMPs, evaluates numerous BMP scenarios and incorporates the impacts of BMP interactions in assessing the cost-effectiveness of BMP scenarios [7].

Genetic Algorithms (GAs) are a subset of evolutionary algorithms that mimic biological processes to optimize an objective function [8]. Developed by Holland (1975) [9], a GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes/minimizes the cost. GAs do not require derivative or gradient information to evaluate optimal solutions [10]. After defining optimization parameters and the objective function, potential solutions are randomly generated in the initial generation. Selection, crossover and mutation are the GA operations which generate new solutions. While crossover selects properties from parent solutions to the offspring solutions, mutation ensures that the search will not converge in local maxima/minima. The search is stopped based on selected convergence criteria.

Many studies have combined the GA and NPS prediction models to optimize the BMP selection and placement in a watershed [11, 12]. Most of the previous work has focused on using a single objective function which combines both BMP effectiveness and cost [12], sequentially optimizing two objective functions separately [13] or optimizing two objective functions of BMP effectiveness and cost simultaneously [22]. These methods include a multiobjective genetic algorithm (GA) and a watershed simulation model to select and place BMPs [14], where the GA to search the combination of BMPs that minimize cost to meet pollution reduction requirements [2], and an optimization model based on discrete differential dynamic programming to locate BMPs in a watershed considering economic analysis [15].

Multiobjective optimization problems have been evaluated in the hydrology/water quality field, where optimal decisions need to be taken between two or more conflicting objectives. Single-objective optimization yields a single optimal solution, while a multiobjective optimization produces a family of near-optimal solutions known as Pareto-optimal set. Deb et al. 2002 [16] concluded that the nondominated sorted genetic algorithm (NSGA-II) can search a larger number of variables and better spread of solutions than the Strength Pareto Evolutionary Algorithm (SPEA-2) [17]. Another optimization procedure developed by Vrugt and Robinson in 2007 [18] called “A Multi

Algorithm Genetically Adaptive Method (AMALGAM)". AMALGAM was developed to be more efficient than a single algorithm optimization in watershed simulations since it blends four widely used optimization algorithms, including (NSGAII) [16], (SPEA-2), Particle Swarm Optimization (PSO) [19], and Differential Evolution (DE) [20]. The use of AMALGAM in identifying the Pareto front (feasible solutions) found to be useful in comparing effective combination of control scenarios by providing a trade-off (Pareto-optimal front) for the near optimal solution, between the two objective functions which aids decision makers to choose from a range of solutions [21].

The Lower Bear River watershed in Box Elder County, northern Utah, is an important agricultural producer with high phosphorus loading to the receiving waterbodies. Since the development of the LBR TMDL in 2002 the LBR Watershed managers have depended on field inspection and the TMDL recommendations to define where to implement the BMPs along with spreadsheets that calculate the NPS loading. The lack of a decision-making tool to propose conservation projects under a fixed budget, made it difficult for the managers to achieve environmental goals and reduce the impact of NPS. These tools can support watershed improvement by locating NPS areas, allocating BMPs, and optimizing their implementation within the watershed. Accordingly, a multi-objective genetic algorithm (MoGA) using Pareto ordering optimization can help in comparing effective combination of control scenarios by identifying optimum values of the design parameters. The method in this research offered optimization scenarios generated by AMALGAM code with additional statistical analyses, to compare the most feasible implementation size of each selected NPS area to implement the BMP allocated specifically for that NPS area.

Optimization Method and Data Collection

The optimization approach in this objective considers finding the most feasible size of NPS area to implement the effective agricultural BMPs in a cost-efficient manner. This will help the watershed managers to effectively implement and evaluate scenario managements under different phosphorus loads reduction targets (i.e., TMDL quality regulations), BMP characteristics (type, costs, reduction effectiveness), and identified critical NPS areas (simulated by SWAT as NPS model), with the use of multi-objective optimization genetic algorithm (e.g., AMALGAM) in MATLAB [22].

Multiobjective Optimization Framework

The water quality optimization problem for the watershed involves two, contrasting goals. The first aims to maximize phosphorus load reduction to surface waters. The second aims to minimize costs for BMPs implemented to reduce phosphorus load. The genetic algorithm was used in managing different scenarios of watershed control plans where multi-objective optimization can be formulated as a decision-making problem of simultaneous optimization of two or more design objectives that are conflicting in nature, [23, 24]. Further, the watershed managers will have the ability to compare the selection and placement of individual and combination of BMPs on watershed water quality at watershed scale under specific NPS areas for implementation. This approach can significantly minimize the time and cost associated with proposing conservation programs that include BMPs at field scale. AMALGAM optimization produces a family of near-optimal points known as Pareto-optimal set, which provides decision makers with insight into different characteristics of the proposed scenarios before a final solution can be determined for which they additionally can choose to weight criteria to emphasize their preferences and any constraints can be placed on design variables.

The optimization concept that was addressed this study is to minimize the cost of applicable combinations of BMPs targeting NPS critical areas of phosphorus sources through feasible selected NPS areas in order to meet the required water quality ends. Mathematically, this can be expressed as Objective function (C) as follows:

$$Minimize\ (C) = BMPsC = \sum_{i}\sum_{j} BMPsC_{ij}$$

The cost objective was compared with the other objective to maximize total phosphorus reduction loads from the selected NPS critical areas. Mathematically, Phosphorus loads reduced by each implemented BMP_i in each optimized critical NPS area $(A)_j$ can be represented by:

$$Maximize\ (TP_R) = Max. Total\ P\ Load\ Reduction = P\_L_T = \sum_{i}\sum_{j} P\_L_{ij}$$

Where,

$$P_{L_{ij}} = P_k \times e_i \times A_{kij}$$

Subject to

$$A_{max} \leq A_k \geq A_{min}$$

$$P\_L_T \leq P\_L_{max}$$
$$P_k \geq 0 \mid A_k \geq 0$$
$$BMPsC \leq BMPsBudg$$

Here,

- BMPsC is the total cost to implement the BMPs in the LBR watershed subbasins
- The BMPsC should not exceed the allocated budget constraint (BMPsBudg)
- $BMPsC_{ij}$ is the implementation cost of the BMP type *i* implemented in the critical area *j*.
- Potential BMP(s) implementation/placement are identified by the Parcels map (available from SWAT analysis). The types of BMP *i* to be implemented in the optimized critical area (A) *j*) is identified in different scenarios.
- P_k is the Phosphorus load produced/contributed by the optimized Critical Area A_k (values were obtained from SWAT load analysis).
- A_k is the size of the optimized area (km^2) of the critical area *k* value that lies within the HRU (optimization-defined), A_{max} is the maximum size of area of the critical areas assigned to the watershed (obtained from SWAT-Parcel analysis) and A_{min} is the minimum size of area of the critical areas assigned to the watershed (obtained from SWAT-Parcel analysis)
- P_L_T is the total annual phosphorus load (kg/yr) reduced by implementing the BMPs in the watershed subbasins (it is based on total potential load from a critical area multiplied by BMP reduction database), and the P_L_{max} is the user defined (constraint) maximum limit of annual phosphorus load

- The phosphorus loads allowed in the watershed were obtained from LBR TMDL.
- e_i = estimated unit sediment and phosphorus removal efficiencies for each BMP i (obtained from the BMPs literature)
- Non-negative decision variables: A_k, and $P_k \geq 0$

Environmental and Economic Criteria

The environmental component t for the optimization model is related to the Lower Bear River TMDL report [25]. The LBR TMDL stated that the watershed outlet had a load averaging of 980 kg/day annually of total phosphorus (TP) and the allowable load after the NPS controls are implemented is 458.8 kg/day annually based on 0.075 mg/l instream concentration of TP. As a result, the LBR TMDL report suggested several goals to be implemented to reduce non-point source pollution to meet the state indicator standards by reducing the amount of pollutants entering the watershed by improving riparian areas, fencing and other intensive grazing croplands throughout the watershed. Based on this, the environmental criteria for the optimization model is to achieve maximum reduction of 100 kg/day and a minimum of 25 kg/day on an annual basis over the next five to ten years needed by increment to achieve the remaining TMDL target which is 520 kg/day per year. The amount of reduction depends on the removal efficiency of the proposed agricultural BMPs that were implemented in the optimized NPS areas. These removal efficiencies are estimated based on relative sources and studies. The economic component of the optimization system depends simply on the available budget of the watershed managers responsible for proposing the LBR conservation projects. Yet, it is also associated with the cost of implementation, operation, and maintenance of proposed management practices.

The maximum and the minimum budget was specified US$20,000 and US$5,000 respectively, taking into consideration the nature of the watershed and the number of selected NPS areas for BMPs implementation that was set in this study. The total cost of implementation of agricultural BMPs was estimated based on relative sources and literature as shown in Table 18. The BMPs cost proposed includes the installation, maintenance, and management costs.

Pareto Optimal Solution

In the presence of conflicting objectives in many engineering disciplines situations, solutions are chosen such that there are reasonable trade-offs among these objectives. Pareto search is an approach for handling such situations. As a replacement for providing a single optimal solution, many solutions are generated that satisfy Pareto Optimality Criterion forming a set of Pareto front surface of optimal solutions. Each Pareto optimal solution is good in some respects and depends on the preferences and constraints set by the decision maker [26]. The Pareto front helps engineers and managers to visualize the trade-offs that need to be made under different objectives.

Further, estimating the goodness of solutions in the Pareto optimal front is subjective. As the front moves, it is ensured that the magnitudes of the objective functions (high total P reduction and low cost is desired) for the solutions get reduced in the direction of both objectives. Therefore, the Pareto-optimal front as far from the origin (e.g., the ideal is to have 0 cost and 0 remaining TP) as possible is desired. In this case study, the Pareto front presents the tradeoff between the two objective functions with the x-axis representing the pollutant load reduction and y-axis representing the implementation costs. Each solution on this tradeoff curve represents a BMP implemented in an optimized NPS area as demonstrated in Figure 20.

AMALGAM Algorithm Code Development

The multi-objective genetic algorithm considered for optimization in the research is A Multi Algorithm Genetically Adaptive Method (AMALGAM) that was developed by Vrugt and Robinson in 2007 [18]. AMALGAM was selected because of its efficiency in locating the optimum solutions in a variety of applications [27-30]. In AMALGAM, four different sampling-based heuristic optimization algorithms are used: genetic algorithm (NSGA-II), particle swarm optimizer, adaptive Metropolis search, and differential evolution [18, 20, 31-32].

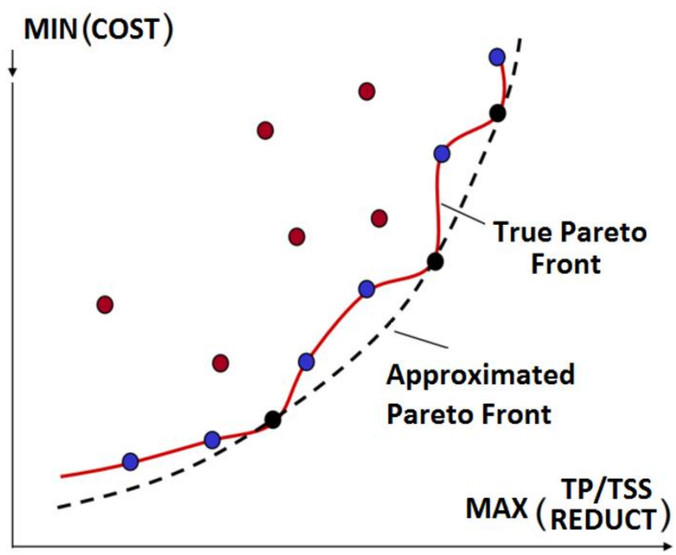


Figure 20. Demonstration of Pareto Optimal Front for maximizing the TP/TSS load reduction vs minimizing the Cost associated with BMPs implementation

The AMALGAM optimization script and its functions were written in AMALGAM files as detailed in Appendix 1. All statistical analysis for optimization results was performed in the R language [33]. AMALGAM optimization produces a family of near-optimal points known as the Pareto-optimal set within a single optimization run which provides set of solutions that can be compared.

Optimization Application

The AMALGAM optimization application for selecting agricultural BMPs uses the steps below:

- Identify critical areas using SWAT as an NPS watershed model;
- Identify sediment and phosphorus sources and reduction targets as set in the TMDL;
- Identify potential BMP types, unit cost, and reduction efficiency from the selected Agricultural BMPs dataset that are applicable for each NPS area.
- Developing different scenarios for implementing selected Agricultural BMPs in selected NPS areas
- Writing the functional code (MATLAB) for producing management scenarios that incorporates each BMPs implementation and their cost in the optimized NPS area.
- Implement the multi-objective optimization program that produces set of Pareto solution of optimal solution using the optimized NPS areas.

Study Area

The research was conducted in the LBR watershed located in Box Elder County, Northern Utah, USA as shown below in Figure 21. The LBR watershed is unique because it is almost completely dominated by agriculture (76%) and range, with very little urban development (4%); therefore, the research can focus on the effects of changes in agricultural practices and their related BMPs [34].

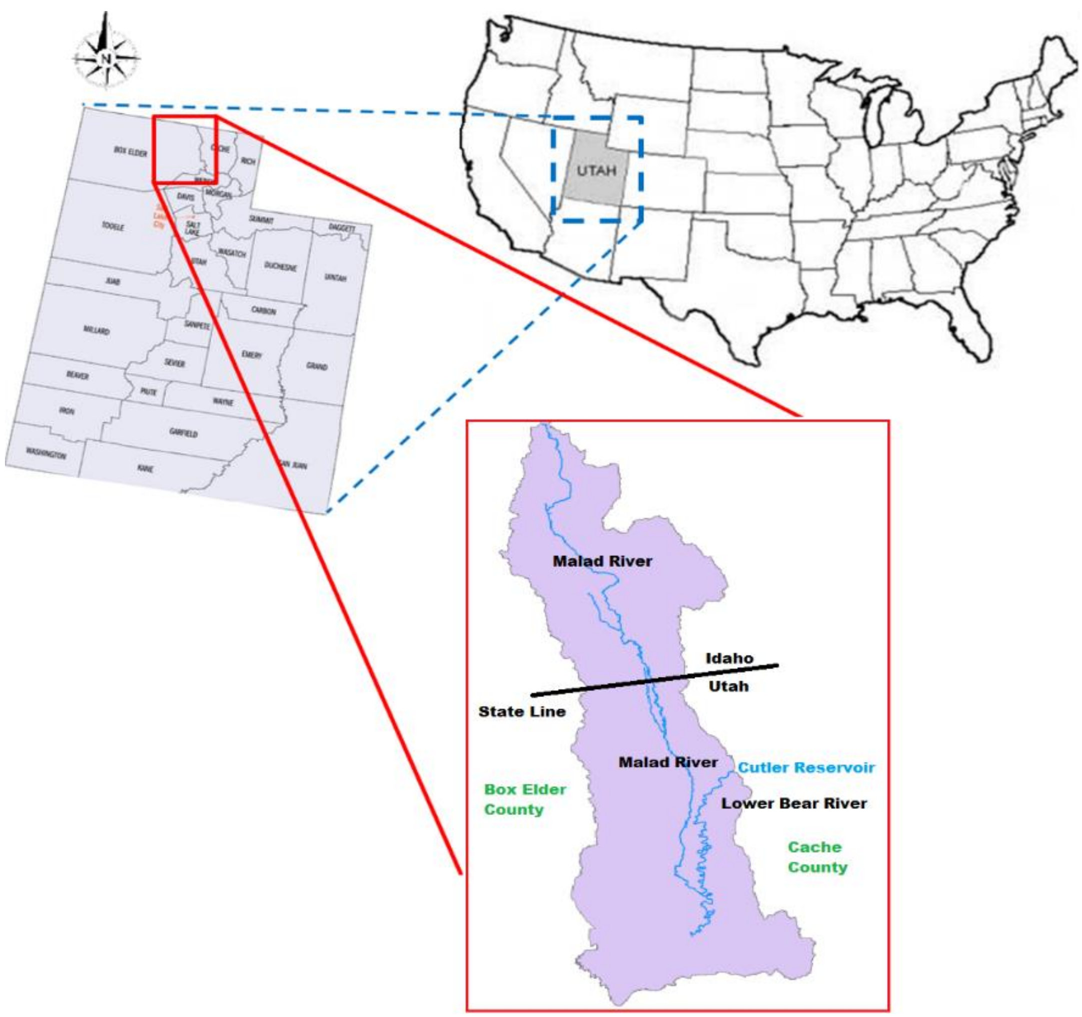


Figure 21. Location of Lower Bear River and Malad River in Northern Utah

Two waterbody segments (the LBR from Cutler Reservoir to the confluence with Great Salt Lake and the Malad River from the Utah-Idaho state line to the Bear River confluence) were declared impaired in Utah's year 2000 303(d) list of water bodies needing TMDL analyses [27] based on Clean Water Act requirements of the state of Utah.

Water quality data sampling and collection from the LBR watershed was inconsistent in the past 20 years. Samples obtained from USGS water information system were more intensively taken in the period between from 2000 - 2003 and again between 2008 and 2009 (Figure 22).

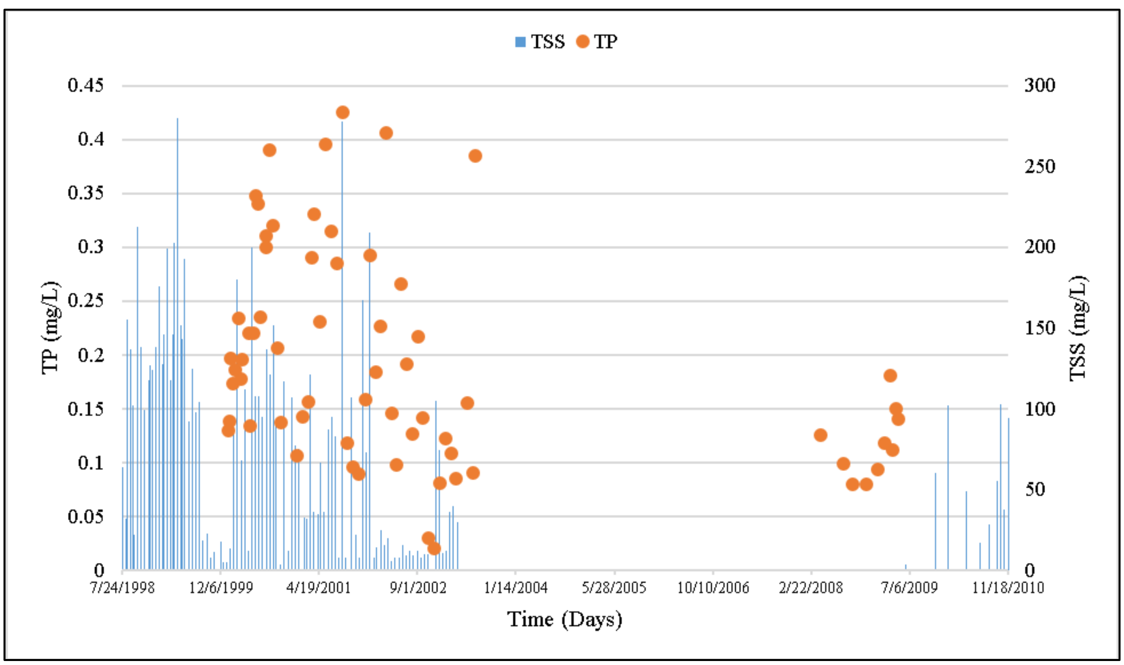


Figure 22. Distribution of water quality samples collected at the outlet of the study area (USGS 10126000 Bear River near Corinne, UT).

NPS areas using the SWAT watershed model

Based on the resulting Parcel map with loads from the calibrated and validated SWAT watershed model over the period from 2000 till 2010 in Chapter 2 and 3, the possible NPS locations were identified and selected as shown in Table 24 as a case study considered in this chapter.

Table 24. List of selected NPS areas of high total phosphorus yield annually in the LBR watershed.

Subbasin ID	**FID_Parcel**	**Parcel_Area (Km^2)**	**TP_Yield ($kg/yr/Km^2$)***
123	5115	0.790	3.70
123	6473	0.374	3.70
125	1142	0.334	123.74
11	1146	0.320	123.74
125	1069	0.318	123.74
121	2946	0.314	52.36
123	1677	0.275	3.70
125	5	0.252	123.74
120	5706	0.250	221.19
125	1252	0.248	123.74
121	930	0.222	52.36
125	1189	0.222	123.74
123	1552	0.212	3.70
123	3318	0.211	3.70
123	574	0.207	3.70
123	1665	0.203	3.70
123	3249	0.191	3.70
121	936	0.178	52.36
121	939	0.158	52.36
121	920	0.157	52.36

* TP_Yield: total phosphorus yield ($kg/yr/Km^2$) from the corresponding subbasin

Agricultural BMPS

The Agricultural BMPs database (Agricultural BMP Database Portal project website: http://www.bmpdatabase.org/agBMP.htm) provides information for the costs and pollution removal efficiency estimates for each BMP to be implemented in the LBR watershed. Data and information were collected from several relevant standards, studies and literature. In addition, records from Environmental Protection Agency's Grants Reporting and Tracking System (GRTS) [31] can give historical NPS projects and the implemented BMPs in the LBR watershed. Table 25 is a summary of collected BMPs data and its characteristics that were implemented in this case study.

Table 25. Summary of proposed Agricultural BMPs database in the LBR watershed

BMP Type/Practices	NRCS Practice Code	Units (Based on Parcel Area)	Cost Per Unit (US $)	TSS % Reduction Efficiency	TP% Reduction Efficiency
Filter Strips Strips or areas of herbaceous vegetation that remove contaminants from runoff flow	393	Km^2	54,363.0	60	50
Riparian Forest Buffer They are adjacent to water resources that protect water from nonpoint source	391	Km^2	81,545.0	65	55
Residue and Tillage Management, No till Conservation (Planting Systems)	329	Km^2	7,413.15	65	50
Herbaceous Riparian Buffer Grasses, like plants & forbs that are tolerant of intermittent flooding that are in between terrestrial & aquatic habitats	390	Km^2	3,707.0	60	55
Contour buffer strips Strips of herbaceous vegetative cover around hill slope, & alternated down slope with wider cropped strips that are farmed on contour	332	Km^2	12,355.0	65	55
Cover Crops Plants that are used to protect soils during the period between harvest & establishment of crops	340	Km^2	14,826.0	25	25

Table 26. Selected BMPs for the study area (refer to Table 18 for more information)

BMP type	**BMP(#)**	**Cost (US$) per Km^2**	**TP_Eff %**
Herbaceous Riparian Buffer	(1)	741.4	65
Cover Crops	(2)	2,965.2	25
Residue Tillage	(3)	7,413.2	50
Filter Strip	(4)	10,872.6	50
Riparian Forest Buffer	(5)	16,309.0	55
Contour Buffer Strips	(6)	2,471.0	55

The final selected agricultural BMPs for the case study in the LBR watershed are identified in detail of their cost and total phosphorus removal efficiency in Table 26.

Practices Management Scenarios

To implement the optimization procedures, possible three scenarios were developed to be included in the optimization process. These scenarios include implementing different agricultural BMPs in different NPS areas as shown in Table 27. The range of implementation size for each BMP was determined based on the Parcel areas provided by Box Elder County GIS portal (Box Elder County Geographic Information Systems (GIS) - http://www.boxeldercounty.org/gismaps.htm).

The scenarios that were developed considered the fact that BMPs selected are applicable and adaptable to any situation in the study area based on the history of past BMPs implemented in the watershed. BMPs selected proved through literature its efficiency in reducing total phosphorus loads as well to its cost of implementation and maintenance which can help the farmers/watershed managers to get funds under different state and federal programs (Section 319 Nonpoint Source Competitive Grants Program, for example) that could install BMPs to mitigate or prevent impacts on water quality. Lastly, the developed optimization process took into consideration selecting critical agricultural NPS areas that contribute greatest phosphorus losses in the watershed.

Optimization Code Application

The optimization model was run using an AMALGAM algorithm developed for MATLAB. The optimization run for each scenario was performed using the following files (full details about these files can be found in Appendix 3):

- **Data.dat** file to create and edit the variables.
- **Amalgam-zed** file to record the optimization functions for cost and load reduction.
- **optimization.m** file to set up the run (number of iterations along with generation of the data).
- **runAmalgam.m** file to run the code and to check the results along with the Pareto solution front.

Table 27. Scenarios of different combinations of agricultural BMPs and selected NPS areas in the LBR watershed.

Subbasin	**FID Parcel**	**P_k P load (kg/yr/Km^2)**	**$A_{max.}$ NPS area (Km^2)**	**$A_{min.}$ NPS areas (Km^2)**	**Scenario 1 BMP (#)**	**Scenario 2 BMP (#)**	**Scenario 3 BMP (#)**
123	5115	3.70	0.790	0.395	(3)	(6)	(4)
123	6473	3.70	0.374	0.187	(4)	(2)	(3)
125	1142	123.74	0.334	0.167	(6)	(6)	(6)
11	1146	123.74	0.320	0.160	(5)	(5)	(2)
125	1069	123.74	0.318	0.159	(3)	(3)	(1)
121	2946	52.36	0.314	0.157	(5)	(3)	(4)
123	1677	3.70	0.275	0.137	(3)	(3)	(3)
125	5	123.74	0.252	0.126	(5)	(5)	(6)
120	5706	221.19	0.250	0.125	(4)	(6)	(5)
125	1252	123.74	0.248	0.124	(2)	(2)	(2)
121	930	52.36	0.222	0.111	(5)	(1)	(3)
125	1189	123.74	0.222	0.111	(3)	(6)	(4)
123	1552	3.70	0.212	0.106	(4)	(4)	(2)
123	3318	3.70	0.211	0.105	(1)	(1)	(3)
123	574	3.70	0.207	0.103	(2)	(2)	(4)
123	1665	3.70	0.203	0.102	(6)	(4)	(5)
123	3249	3.70	0.191	0.095	(5)	(5)	(5)
121	936	52.36	0.178	0.089	(3)	(3)	(2)
121	939	52.36	0.158	0.079	(1)	(5)	(1)
121	920	52.36	0.157	0.078	(4)	(4)	(3)

Results and Discussion

The NPS areas with phosphorus loading rates were selected from the output of the calibrated and validated SWAT watershed model. The agricultural BMPs information was collected from relevant studies and literature as shown in Table 18. Both the selected agricultural BMPs and the NPS areas at parcel scale were combined through a targeting method shown in Chapter 3 to develop three scenarios for implementation across the LBR watershed. The three scenarios were applied in the AMALGAM optimization model to generate sets of solutions formed as in Pareto front corresponding to two objective functions. The two objective functions in the optimization model calculate the total phosphorus reduction and the associated cost of that reduction out of implementing its BMP.

The solutions generated to form the Pareto front surface were combinations of BMPs implemented in the proposed NPS areas. Each combination provided a value of the total phosphorus reduction and the total cost of implementing the scenarios. Initially, scenario 1 was applied to test the sensitivity of GA parameters and their impact on the optimization results. The GA parameters (population size, generations, mutation, and cross over) were changed, one at a time, to evaluate the effects of each parameter on the Pareto-front as shown in Table 28.

As referred in AMALGAM manual in Appendix 3, the default value for crossover probability rate is 0.9 and the mutation rate equals 1/d (number of variables), i.e. = (1/ #NPS areas) = 1/20 = 0.05. Two statistical analyses showed that these runs have the same mean and homogenous variance as shown in Appendix 3. We can conclude that the number of generations, crossover probability rate and the mutation rate have no significant impact on the optimization model. In this study, a 1000 population with 100 generations besides the default values for crossover and mutation was considered for each scenario.

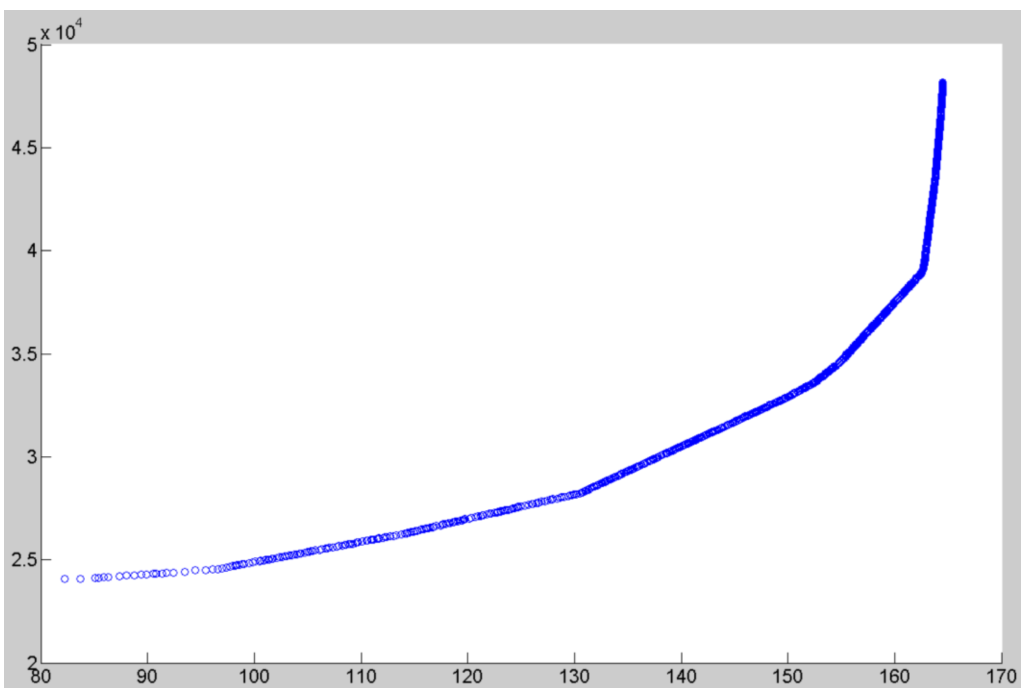
Table 28. GA parameters tested for sensitivity analysis

GA Parameter	1st Run	2nd Run	3rd Run	4th Run	5th Run	6th Run
Population	1000	1000	1000	1000	500	2000
Generation	100	100	200	100	100	100
Cross over	0.5	0.9	0.9	0.9	0.9	0.9
Mutation	0.05	0.05	0.05	0.5	0.05	0.05

Scenarios

The Pareto distribution of solutions for Scenario 1 is shown in Figure 23. We can infer that there are set of solutions that can give a max reduction of 165 kg/yr for maximum cost of almost US$47,500, while a minimum annual phosphorus reduction can go down to 85 kg/yr for a budget of US$ 24,000 and still meet water quality criteria. The optimal solutions generated by the populated sizes of the NPS areas are centered around 155 kg/yr of total phosphorus load reduction that can cost around US$35,000 to implement the proposed agricultural BMPs. The trade-off between the two objective functions (total cost and total reduction) was generated by populating the sizes of NPS areas and implementing BMPs in these areas.

Cost (US$)



TP load reduction (kg/yr)

Figure 23. Pareto front solutions generated in MATLAB for Scenario 1

We can also see the mean value of the populated sizes of each NPS area proposed in Scenario 1 (denoted as x variable) in Figure 26 in Appendix 3. See Table 27 for the list of selected agricultural BMPs and the NPS areas as parcels.

For Scenario 2, the Pareto front distribution of the generated solutions combining the selected agricultural BMPs with the populated sizes of area can be visualized in Figure 24. The Pareto solutions gave a maximum reduction of 168 kg/yr for almost maximum US$36,000, while a minimum phosphorus reduction was 85 kg/yr for a budget of US$ 17,500. The optimal solutions are centered around 160 kg/yr of total phosphorus load reduction that cost around US$26,000 to implement the proposed agricultural BMPs. The convergence of the Pareto front towards the center of the two axis is not as smooth as in Scenario 1 due to given scenario's parameters, constraint functions, available NPS areas, proposed BMPs and their costs. The mean values of the optimized sizes of NPS areas in Scenario 2, is listed in Figure 27 in Appendix 3. See Table 27 for the list of selected NPS areas as parcels.

The Pareto solutions for Scenario 3 provided alternatives to reduce the total phosphorus loads from 80 to 155 kg/yr under a cost range of US$20,000 to US$42,000, centered around 150 kg/yr for a budget of US$25,000 as shown in Figure 29. These optimized solutions are related to the sizes of the NPS areas that were optimized in the model for implementing the targeted agricultural BMPs. The mean values of the optimized NPS areas in Scenario 3 can be seen in Figure 28 in Appendix 3.

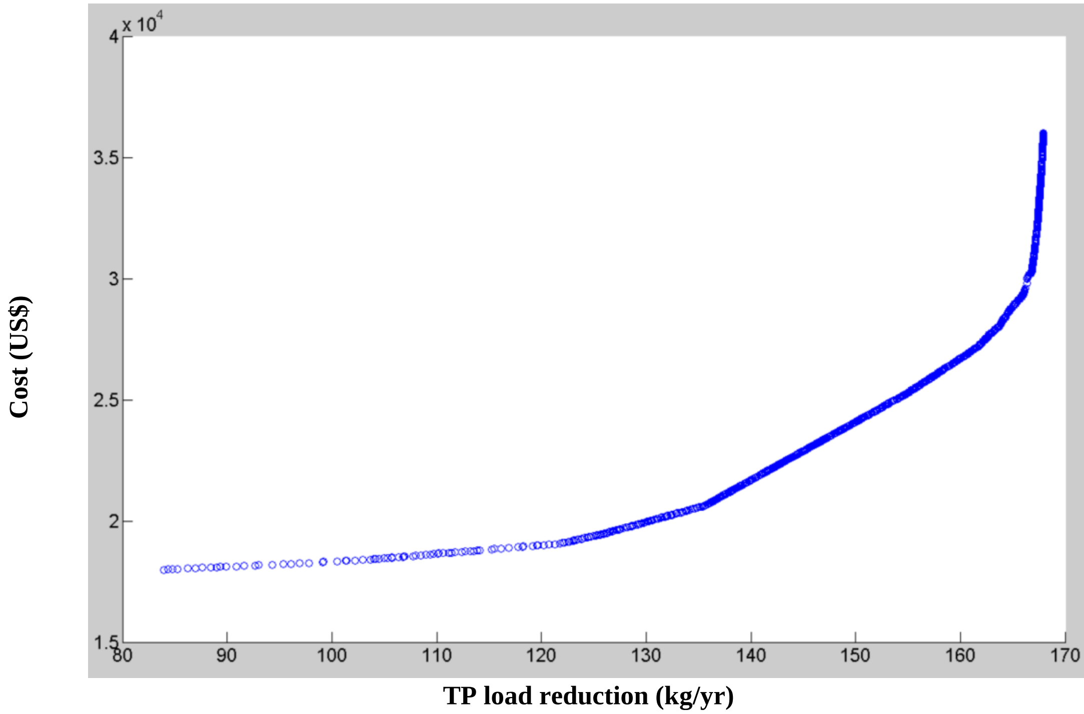


Figure 24. Pareto front solutions generated in MATLAB for Scenario 2

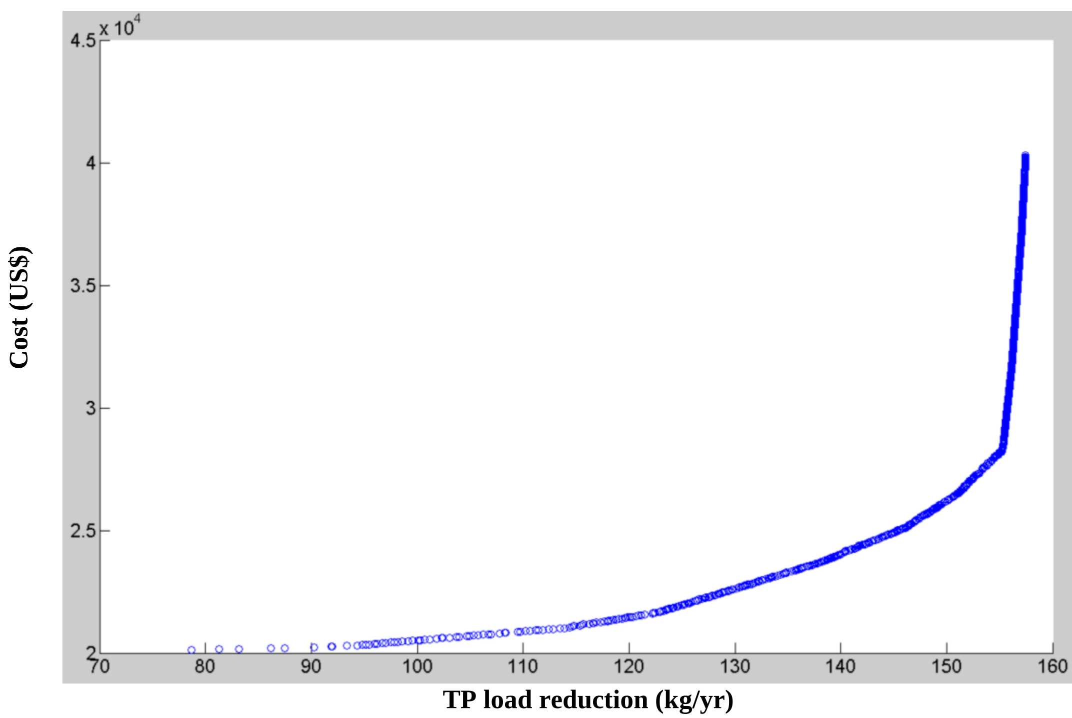


Figure 25. Pareto front solutions generated in MATLAB for Scenario 3

Table 29. Pareto solution for the proposed three scenarios

Description	**Scenario 1**	**Scenario 2**	**Scenario 3**
Reduction of TP loads	155 kg/yr	160 kg/yr	150 kg/yr
Cost of associated BMPs	US$35,000	US$26,000	US$25,000

Each scenario produced a set of Pareto solutions that converged towards the center of the two objective functions (total cost and total load reduction) as shown in Table 29 where scenario 3 demonstrated the optimal solution for the study area. This implies the feasibility of the optimization model and its parameters to provide Pareto front solutions.

The optimization approach proposed in this chapter using Pareto Optimal solution provided alternative options to for locating BMPs through assessing their impact on water quality while keeping in mind the availability of budget. The approach allows the watershed managers to apply different BMPs across different NPS critical areas taking into consideration availability of budget, landowners' willingness to implement BMPs, lifespan of BMPs, environmental benefits, monitoring and evaluation, BMPs maintenance, duration of the projects (e.g., five to ten years) and their knowledge about the watershed conditions. The approach can guide the manager to select a particular BMP for each NPS area and then the optimizer shall determine a portion of the NPS area to apply the BMP. The cost of implementation is then the size of area (Km^2) times the cost of that BMP/area with the idea to maximize Total P removal while minimizing costs.

For this analysis, it was assumed that all the aforementioned factors were taken into consideration during the selection of the agricultural BMPs as well as the identified NPS areas, however, it may not be the case when the BMPs are implemented. Most of the research was optimizing the cost against the nutrient load reduction to get the optimal BMP set, while we state here the importance of addressing the size of NPS areas to have the BMPs implemented. As such, this would give the watershed managers and the owners the opportunity to discuss and negotiate the benefits of such implementation.

Conclusion

In an agricultural watershed with multiple NPS areas and multiple agricultural BMPs feasible for implementation, it is an exhausting and expensive task to choose a right combination of BMPs that provide maximum pollution reduction for least implementation costs. Identifying optimal solutions of watershed management practices requires systematic approaches that allow decision makers to assess their goals of implementing management actions under environmental and economic criteria.

In this chapter, the optimization framework utilized the calibrated and validated SWAT model simulated over the period 2000-2010 in the Lower Bear River watershed to identify the nonpoint source areas, literature information about the types, costs, and phosphorus removal efficiencies regarding selected Agricultural BMPs, economic and environmental criteria, and finally a GA (AMALGAM algorithm) optimization technique to find the best combinations. The main variable to be optimized is the size of the available NPS area for BMPs' implementation. The optimization model was tested for its GA parameters by running scenario (1) six times, and in each run a GA parameter is changed. The GA parameters examined were: population, generation, crossover probability and mutation probability. Statistical analysis showed no significant difference among the six runs, implying that the GA parameters have no effect on the optimization model results. Other runs for the other scenarios were completed using a population of 1000 and a generation of 100, plus the default values of crossover and mutation. Three different scenarios of with different suite of agricultural BMPs selected for implementation in different NPS areas identified by the SWAT model for this study.

A MATLAB computer program was used to run the AMALGAM code in addition to the defined variables and the two objective functions for total phosphorus reduction and total implementation costs in different MATLAB files within the AMALGAM code. The optimization model was tested for optimizing the sizes of the selected NPS areas of high phosphorus loading rates using different agricultural BMPs of herbaceous riparian buffer, cover crops, residue tillage, filter strip, riparian forest buffer and contour buffer strips in the LBR watershed.

The optimization of the three scenarios were performed based on two different GA parameters: population (1000) and generation (500) in each run. Each run provided a different set of Pareto front solutions made of implementing the agricultural BMPs in the selected NPS areas. The optimal solutions produced by the Pareto front for Scenarios 1, 2 and 3 generated a total phosphorus load reduction of 155, 160 and 150 kg/yr respectively, and the cost associated with each reduction for each scenario was US$35,000, US$26,000 and US$25,000 respectively.

This study resulted in incorporating the sizes of populated NPS areas that will give much flexibility to the decision makers to select from to implement their agricultural

BMPs within a given budget and a water quality strategy. Previous studies determined the solutions based on given exact NPS areas with multiple choices of BMPs to be implemented. The study showed the implementation of a BMP per area in different scenarios using area factor as the variable to be populated and optimized based on given economic and environmental criteria. The results produced different set of optimum solutions for implementation at watershed scale. This approach can be further developed to be an interactive tool for the watershed managers or the decision-makers who plans to propose set of conservation projects where they can have an insight into different characteristics of the proposed management plans before a final solution is considered.

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SUMMARY AND CONCLUSIONS

In this dissertation, watershed models and decision approaches were developed to: (1) simulate the movement of water flows and to estimate the sediments and total phosphorus load releases to waterbodies in Lower Bear River watershed in northern Utah, (2) select a combination of best management practices (BMPs) to maintain water quality standards within a specified budget, and (3) generate the optimum areas of nonpoint sources that can be used for agricultural implementation to reduce total phosphorus load releases and to minimize the cost of implementation. These tools are presented in three independent studies in Chapters 2, 3 and 4.

Chapter 2 highlights the water quality issues in the Lower Bear River (LBR) watershed, Box Elder County in northern Utah. A watershed simulation model (SWAT) was developed in a GIS environment to simulate monthly flow, sediment and total phosphorus loads. Input data such as digital elevation model (DEM), land use, soil and climatic information were used for SWAT, using a watershed delineation that creating 126 Subbasins across the LBR watershed. SWAT was then used to simulate the period between 2000-2010, using a two-year warm up period. LOADEST was utilized to generate measured monthly concertation loads of sediments and phosphorus over the period of simulation due to lack of water quality parameters over several period of times at the outlet of the watershed. SWAT was calibrated using SWAT-CUP software to enable various calibration/uncertainty analyses for more than 20 different parameters related to flow, sediments and total phosphorus. The final set of calibrated parameters in SWAT provided good representation of monthly flow, sediments and total phosphorus loads covering the period 2002-2005. The validation of the model calibration used data from 2006 and 2010 and showed good prediction for both flow and total phosphorus, but poor prediction for the sediment load. SWAT was able to map out spatially the nonpoint source areas based on land cover/use and terrain features for further research and use in this dissertation.

Chapter 3 addresses the problem of total phosphorus loading in the LBR watershed in Utah. To tackle the field scale versus SWAT output, the total phosphorus loading rates from the 565 hydrological responses units (HRU) developed in SWAT were projected via ArcMap processing tools (zonal statistical and intersect spatial analysis) to a Parcel map of Box Elder County, Utah, where the watershed is located. This provided realistic sizes of NPS areas for management practices implementation. Further, the chapter provided information of agricultural BMPs that are applicable in the LBR watershed. Subsequently, a simple combination tool was developed to provide the cost-effective combination of BMPs and selected NPS areas to reduce phosphorus loading within LBR watershed. The written code pairs agricultural BMPs and NPS areas to maximize the total phosphorus reduction under a specified budget. Each budget may produce a set of different combination solutions to be implemented with different load reduction. Combination and post-processing results suggest that agricultural BMPs such as cover crops, filter strips, and buffers for private land grazing and diffuse runoff areas can feasibly reduce the phosphorus loads in the LBR watershed. This combination tool can help watershed managers to evaluate alternatives of management practices to reduce phosphorus load in watersheds under specific budgets.

In Chapter 4, an optimization framework was developed to utilize the output of SWAT model simulated over the period 2000-2010 in the Lower Bear River watershed to identify the nonpoint source areas, the literature information about the types, costs, and phosphorus the removal efficiencies of selected Agricultural BMPs, the economic and environmental criteria, and finally a GA (AMALGAM algorithm) optimization technique. Three scenarios of different agricultural BMPs selected to be implemented in different NPS areas were prepared for optimization. The optimization model was tested for optimizing the selected NPS areas of high phosphorus loading rates using different agricultural BMPs of herbaceous riparian buffer, Cover Crops, residue tillage, filter strip, riparian forest buffer, and contour buffer strips in the LBR watershed. The populated areas were considered variables in calculating the two objective functions: total reduction of phosphorus loads and the cost of implementation. This study concluded that incorporating the populated sizes of NPS areas will give much flexibility to the decision makers to select where to implement their agricultural BMPs within a specified budget for implementation and a water quality protection strategy to meet.

State regulators from the Utah Department of Environmental Quality and personnel from Utah State University-Bear River Watershed extension participated in chapter 3 by providing the current best management practices implemented so far along with their associated costs. They also provided feedback on the modeling the LBR watershed in Chapter 2. Pacificorp Co. was helpful in providing flow and water quality data regarding the discharge beyond cutler reservoir.

In conclusion SWAT was able to characterize the flow, sediments and total phosphorus loads in the LBR watershed, although it was a time-consuming process to calibrate and validate SWAT. However, SWAT, as a watershed model, is very comprehensive and powerful providing the ability to propose scenarios and management practices within a watershed. As with all models, its performance depends on the quality and the quantity of the input data available about the study area. There were many uncertainty factors that impacted the calibration-validation process of SWAT. Water quality sampling was inconsistent during the simulation period (2002-2010). Using LOADEST was helpful to generate monthly load concentration based many regression formulas, but it was also predicting the observations to predict other data. SWAT-CUP was very useful for calibrating and validation the model during the course of this work. It was found that calibration using SWAT-CUP requires longer computation time (because of the many iterations) than SWAT simulation itself. It is recommended to have supercomputer resources for such calibration and sensitivity analysis of SWAT parameters, to speed the calibration process.

Sediment and phosphorus pollutant loadings were estimated at Parcel map scale. The HRUs were processed to obtain their average weighting of loads, then using spatial analyst tools (zonal statistics and intersect), this process was very helpful in identifying the appropriate NPS areas with implementation area that represents the ground.

The optimization model developed is general and can be easily extended to other watersheds to develop the Pareto-optimal fronts. The model gives a range of options available for pollution reduction and their corresponding costs for the implementation of BMPs and the selection of a combination is subjective. This trade-off can aid the watershed modelers in TMDL development and to estimate the corresponding cost for the placement of BMPs to achieve TMDL goals.

The evaluation of the optimal BMPs combination in selected NPS areas using a simple optimization approach of combination, proved to be efficient with clear combination practices to be implemented to meet the water quality and budget constraints. The solutions obtained from the combination procedures were optimal for both reducing total phosphorus losses by placing agricultural BMPs in high phosphorus loading areas. Further, using the multiobjective GA optimization tool with selected BMPs targeting specific NPS areas showed promise. The optimization considers populating different sizes from the given area of NPS areas for the BMPs to be implemented This could result in less management burden, agreement and acceptance by the landowners and farmers, and more alternatives for the watershed managers to plan their water quality control efforts. After all, it is essential to differentiate the impacts of land use changes from the impacts of conservation practices in order realize a true picture of the conservation effectiveness. It is important to incorporate human factor in any optimization process which includes the wellness and adoption of farmers to implement BMPs and to incorporate social norms and uncertainty into decision-making. Some assumptions but to extent were made during the course of this study to facilitate the applying the optimization procedures and the results.

RECOMMENDATIONS/FUTURE WORK

Presently, there are thousands of impaired streams in the U.S. due to non-point sources (NPS) pollutants from agricultural watersheds. Therefore, understanding the responses of streams for various agricultural cropping systems, change in land use and land cover and agricultural BMPs is crucial for successful stream restoration towards providing the intended ecosystem services. The SWAT model can simulate the NPS sediment and nutrient loadings. Thus, applying SWAT in agricultural watersheds and having optimization tools can provide watershed managers and policy makers with the best location and most cost-efficient conservation practices to implement.

When applying SWAT to analyze agricultural watersheds, it is recommended to simulate watersheds using available and continuous flow and water quality data to minimize the uncertainties when it comes to calibration and validating the watershed model. SWAT-CUP is a very useful and powerful, but prior experience and the availability of supercomputers will facilitate the calibration and sensitivity process. It is also recommended when delineating the watershed and creating the subbasins, to assign their outlets at existing monitoring stations or similar Location. This can help in the calibration and validation procedures for a particular subbasin and then to generalize the parameters of the calibrated SWAT to nearby subbasins.

Though we use monitoring stations and US Geological Survey (USGS) flow and total phosphorus (TP) data to estimate phosphorus retained in soils, future work needs to better quantify P stored in the stream system. It is recommended to study floodplains, streambanks and stream sediment to quantify stored P. This could be done through multiple sampling of soil in each of these areas of storage and the spatial distribution of the TP to be analyzed. This will aid in both P modeling and to identify potential conservation practices.

In this study, two objective functions, maximizing the pollutant load reduction and minimizing the BMP-implemented cost, were used. With additional objective functions, a more optimal set of BMPs may be obtained using the optimization tool, which can easily be extended to more objectives. Other types of BMPs than the agricultural practices, could be applied in the study to assess their effectiveness and performance within the watershed using the optimization methods we have developed in this study. The combination tool can be further developed to be an interactive tool with stakeholders or watershed managers either through online or through an executable file with simple GUI interface. The same is true for the optimization model. The users can incorporate their knowledge and data about the BMPs, locations, watershed economic and environmental criteria to then evaluate their options.

The continuation of the land use/land cover change poses a challenge to the LBR watershed. In response, these changes should be monitored for their impact on the watershed management and operation. It is also useful to consider those changes for future studies such as TMDL, water quality studies and prevention measures.

The research could be further used for assessing the impacts of climate change. Different climate change scenarios on agricultural watershed water quantity and quality, and crop production can be applied using greenhouse gas emission scenarios. Greenhouse gas emissions are called representative concentration pathways (RCPs).

APPENDICES

APPENDIX 1

Table A 1. Simulated 126 subbasins using SWAT watershed model

SUB	AREAkm^2	SUB	AREAkm^2	SUB	AREAkm^2
1	29.38	43	0.18	85	31.62
2	10.68	44	20.07	86	28.58
3	10.20	45	19.69	87	0.11
4	0.01	46	7.93	88	0.48
5	21.17	47	16.53	89	10.64
6	10.93	48	4.15	90	26.49
7	20.14	49	13.00	91	19.65
8	10.54	50	41.08	92	34.66
9	8.63	51	18.36	93	13.20
10	17.56	52	18.22	94	0.14
11	0.89	53	38.06	95	14.03
12	13.50	54	21.55	96	14.73
13	1.40	55	24.46	97	1.04
14	10.11	56	16.87	98	10.36
15	11.30	57	1.85	99	13.85
16	32.43	58	18.10	100	42.97
17	13.68	59	18.50	101	21.42
18	0.26	60	4.39	102	18.66
19	6.29	61	28.64	103	30.09
20	27.27	62	22.70	104	13.24
21	0.23	63	12.64	105	23.55
22	16.72	64	0.98	106	13.60
23	10.20	65	0.96	107	0.42
24	20.81	66	18.15	108	27.46
25	8.38	67	6.53	109	0.33
26	14.02	68	1.32	110	11.68
27	10.52	69	17.05	111	1.13
28	0.97	70	4.32	112	8.48
29	14.33	71	63.58	113	18.49
30	16.01	72	8.97	114	11.57
31	27.28	73	18.80	115	3.97
32	50.26	74	11.29	116	17.41
33	17.02	75	0.09	117	52.41
34	19.11	76	10.71	118	2.74
35	28.64	77	12.39	119	14.69
36	11.06	78	17.57	120	5.73
37	2.28	79	5.78	121	25.08
38	35.45	80	14.25	122	23.74
39	10.75	81	11.34	123	96.72
40	25.19	82	0.04	124	43.43
41	11.92	83	12.91	125	11.34
42	6.83	84	17.12	126	2.50

Table A 2. Soil Profiles Distribution in the Simulated Watershed

Name	Code	Area (ha)	Area (Km^2)	%
VALMAR	ID011	8081.2084	80.81	4.04
REXBURG	ID012	4097.3875	40.97	2.05
PAVOHROO	ID013	7528.0324	75.28	3.77
COPENHAGEN	ID045	3070.7028	30.71	1.54
STERLING	ID048	4998.5466	49.99	2.50
HYMAS	ID049	7003.0906	70.03	3.51
LOGAN	ID050	8932.9126	89.33	4.47
GOOSE CREEK	ID051	3459.9582	34.60	1.73
YAGO	ID052	4619.6318	46.20	2.31
RIRIE	ID054	20437.7523	204.38	10.23
RIDGECREST	ID062	40487.3282	404.87	20.27
SAMARIA	ID175	15504.8459	155.05	7.76
KEARNS	ID487	1779.5689	17.80	0.89
AGASSIZ	UT064	6095.9969	60.96	3.05
MIDDLE	UT067	1967.6776	19.68	0.98
STERLING	UT068	6934.9326	69.35	3.47
KEARNS	UT069	16454.3809	164.54	8.24
FIELDING	UT071	6016.779	60.17	3.01
HONEYVILLE	UT073	7466.1687	74.66	3.74
LASIL	UT074	3521.7319	35.22	1.76
WHEELON	UT090	1948.525	19.49	0.98
	UT098	831.8322	8.32	0.42
RIDGECREST	UT146	18380.0667	183.80	9.20
	UT554	165.9888	1.66	0.08
Total			**1997.85**	**100**
Watershed Simulated Area			**1997.85**	

Figure A 3. Landuse Distribution Profiles

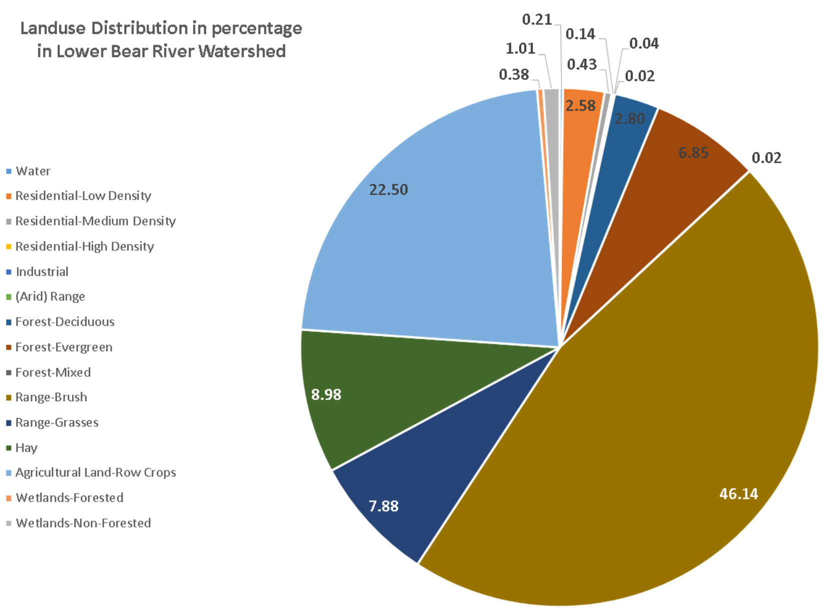

Table A 4. Measured vs. simulated monthly flow (m^3/sec) at the outlet of the LBR watershed

Time	Measured	Simulated
Jan-02	33.075	16.89
Feb-02	27.466	19.32
Mar-02	36.817	36.43
Apr-02	44.061	54.79
May-02	18.013	28.03
Jun-02	7.064	10.606
Jul-02	2.328	7.928
Aug-02	1.882	5.392
Sep-02	8.661	19.59
Oct-02	12.712	9.201
Nov-02	19.876	14.47
Dec-02	23.194	15.987
Jan-03	21.395	17.209
Feb-03	25.460	20.78
Mar-03	28.123	32.95
Apr-03	30.982	46.26
May-03	7.945	15.15
Jun-03	2.290	6.019
Jul-03	1.145	1.874
Aug-03	1.426	2.788
Sep-03	3.168	4.267
Oct-03	9.942	7.125
Nov-03	18.767	12.996
Dec-03	20.060	13.178
Jan-04	24.618	16.932
Feb-04	29.270	18.248
Mar-04	44.220	51.35
Apr-04	31.066	61.439
May-04	11.465	25.39
Jun-04	14.234	15.34
Jul-04	1.218	9.241
Aug-04	1.324	6.602
Sep-04	3.724	5.782
Oct-04	15.292	4.853
Nov-04	21.106	10.712
Dec-04	29.906	22.721
Jan-05	35.099	31.399
Feb-05	28.756	23.687
Mar-05	63.208	44.344
Apr-05	88.188	69.22
May-05	166.028	96.12
Jun-05	91.772	42.234
Jul-05	6.903	11.97
Aug-05	4.844	10.78
Sep-05	8.414	7.547
Oct-05	21.969	13.45
Nov-05	24.660	19.838
Dec-05	33.679	25.291
Jan-06	51.296	31.18
Feb-06	44.869	37.441
Mar-06	70.783	75.023
Apr-06	140.678	84.49
May-06	109.102	49.85
Jun-06	33.994	25.823
Jul-06	3.473	6.135
Aug-06	4.224	7.741
Sep-06	18.126	17.958
Oct-06	31.466	15.352
Nov-06	36.740	18.462
Dec-06	40.027	29.417
Jan-07	36.979	26.023
Feb-07	42.273	24.963
Mar-07	53.437	34.71
Apr-07	40.835	68.36
May-07	13.078	27.752
Jun-07	3.038	17.526
Jul-07	2.189	6.842
Aug-07	2.141	1.182
Sep-07	4.251	6.879
Oct-07	13.264	10.521
Nov-07	17.742	13.845
Dec-07	20.666	16.422
Jan-08	24.017	23.361
Feb-08	31.851	23.13
Mar-08	37.860	40.09
Apr-08	37.944	56.234

Time	Measured	Simulated
May-08	40.237	40.135
Jun-08	33.698	29.718
Jul-08	2.412	7.243
Aug-08	2.422	2.962
Sep-08	5.582	8.956
Oct-08	22.450	11.394
Nov-08	25.444	15.828
Dec-08	25.323	18.63
Jan-09	29.356	23.241
Feb-09	26.697	20.205
Mar-09	54.289	39.385
Apr-09	74.134	82.158
May-09	72.911	40.363
Jun-09	85.810	49.501
Jul-09	7.073	8.359
Aug-09	4.051	6.332

Time	Measured	Simulated
Sep-09	7.364	5.928
Oct-09	27.083	16.333
Nov-09	29.316	22.227
Dec-09	27.455	16.614
Jan-10	27.577	18.739
Feb-10	27.705	20.991
Mar-10	33.043	58.35
Apr-10	43.750	68.21
May-10	27.799	54.517
Jun-10	45.866	38.261
Jul-10	3.447	7.251
Aug-10	3.332	2.538
Sep-10	5.988	3.764
Oct-10	14.660	14.24
Nov-10	21.645	13.98
Dec-10	40.173	30.671

Table A 5. Measured vs. simulated monthly total suspended solids (mg/L) at the outlet of the LBR watershed

Time	Measured	Simulated
Jan-02	25.315	29.505
Feb-02	24.920	29.719
Mar-02	37.330	37.648
Apr-02	55.316	39.492
May-02	68.308	44.242
Jun-02	78.636	48.608
Jul-02	74.846	55.946
Aug-02	66.175	46.665
Sep-02	63.675	39.490
Oct-02	41.093	36.140
Nov-02	27.202	24.994
Dec-02	19.644	20.896
Jan-03	15.152	18.255
Feb-03	16.629	23.358
Mar-03	23.055	26.716
Apr-03	35.013	38.501
May-03	41.126	44.056
Jun-03	46.448	42.612
Jul-03	47.976	35.172
Aug-03	45.185	28.256
Sep-03	37.024	24.877
Oct-03	29.184	19.482
Nov-03	20.796	19.132
Dec-03	14.144	18.546
Jan-04	12.269	17.227
Feb-04	13.510	12.291
Mar-04	21.338	20.204
Apr-04	27.431	26.132
May-04	42.889	38.413
Jun-04	56.029	47.321
Jul-04	40.513	40.151
Aug-04	37.280	32.156
Sep-04	35.653	28.920
Oct-04	27.164	23.893
Nov-04	18.667	19.827
Dec-04	13.655	16.203
Jan-05	11.955	14.355
Feb-05	12.145	10.622
Mar-05	21.655	23.324

Time	Measured	Simulated
Apr-05	35.357	31.291
May-05	59.811	47.308
Jun-05	76.194	46.992
Jul-05	53.972	33.348
Aug-05	46.363	30.818
Sep-05	37.006	26.364
Oct-05	30.003	24.306
Nov-05	19.530	18.000
Dec-05	14.326	13.619
Jan-06	13.919	11.395
Feb-06	14.416	11.849
Mar-06	21.814	25.224
Apr-06	41.016	27.518
May-06	59.750	39.916
Jun-06	67.778	52.932
Jul-06	50.388	44.616
Aug-06	49.115	29.423
Sep-06	49.281	29.054
Oct-06	36.930	21.817
Nov-06	24.471	21.905
Dec-06	17.519	14.344
Jan-07	14.753	11.058
Feb-07	16.965	17.685
Mar-07	25.208	30.122
Apr-07	35.748	40.992
May-07	44.386	30.858
Jun-07	50.370	33.843
Jul-07	59.289	35.530
Aug-07	56.878	36.092
Sep-07	48.674	31.494
Oct-07	39.376	28.946
Nov-07	27.064	24.686
Dec-07	19.892	15.503
Jan-08	17.840	11.071
Feb-08	21.520	26.060
Mar-08	32.018	36.672
Apr-08	53.160	50.138
May-08	90.274	52.293
Jun-08	113.475	60.608

Time	Measured	Simulated
Jul-08	87.207	52.965
Aug-08	84.225	42.923
Sep-08	77.524	36.641
Oct-08	66.886	29.666
Nov-08	47.193	25.693
Dec-08	32.147	22.681
Jan-09	29.079	21.660
Feb-09	32.036	18.747
Mar-09	56.393	35.997
Apr-09	104.881	62.549
May-09	112.309	71.164
Jun-09	120.905	59.563
Jul-09	103.265	46.810
Aug-09	92.329	36.890
Sep-09	81.168	35.367

Time	Measured	Simulated
Oct-09	82.508	29.148
Nov-09	62.181	25.953
Dec-09	58.388	30.262
Jan-10	49.324	26.748
Feb-10	55.322	33.663
Mar-10	84.277	45.263
Apr-10	106.038	50.001
May-10	120.670	62.962
Jun-10	133.551	65.363
Jul-10	120.485	56.105
Aug-10	105.654	49.465
Sep-10	90.581	41.069
Oct-10	84.561	39.365
Nov-10	72.867	28.930
Dec-10	62.738	23.223

Table A 6. Measured vs. simulated monthly total phosphorus (mg/L) at the outlet of the LBR watershed.

Time	Measured	Simulated
Jan-02	0.122	0.126
Feb-02	0.149	0.129
Mar-02	0.173	0.154
Apr-02	0.193	0.168
May-02	0.223	0.206
Jun-02	0.231	0.170
Jul-02	0.210	0.169
Aug-02	0.170	0.108
Sep-02	0.123	0.143
Oct-02	0.103	0.097
Nov-02	0.092	0.100
Dec-02	0.093	0.114
Jan-03	0.108	0.107
Feb-03	0.126	0.118
Mar-03	0.151	0.123
Apr-03	0.171	0.151
May-03	0.204	0.134
Jun-03	0.206	0.104
Jul-03	0.181	0.095
Aug-03	0.144	0.113
Sep-03	0.114	0.099
Oct-03	0.091	0.091
Nov-03	0.080	0.106
Dec-03	0.083	0.102
Jan-04	0.092	0.105
Feb-04	0.110	0.131
Mar-04	0.127	0.137
Apr-04	0.148	0.133
May-04	0.169	0.093
Jun-04	0.160	0.153
Jul-04	0.163	0.109
Aug-04	0.127	0.118
Sep-04	0.099	0.073
Oct-04	0.077	0.079
Nov-04	0.072	0.067
Dec-04	0.072	0.083
Jan-05	0.081	0.103

Time	Measured	Simulated
Feb-05	0.101	0.110
Mar-05	0.109	0.112
Apr-05	0.119	0.121
May-05	0.108	0.120
Jun-05	0.116	0.133
Jul-05	0.144	0.082
Aug-05	0.120	0.087
Sep-05	0.090	0.107
Oct-05	0.073	0.058
Nov-05	0.067	0.049
Dec-05	0.068	0.072
Jan-06	0.072	0.065
Feb-06	0.092	0.123
Mar-06	0.104	0.109
Apr-06	0.106	0.126
May-06	0.117	0.110
Jun-06	0.135	0.120
Jul-06	0.147	0.123
Aug-06	0.117	0.092
Sep-06	0.083	0.066
Oct-06	0.069	0.075
Nov-06	0.064	0.072
Dec-06	0.067	0.052
Jan-07	0.078	0.089
Feb-07	0.094	0.073
Mar-07	0.111	0.102
Apr-07	0.134	0.144
May-07	0.159	0.122
Jun-07	0.173	0.175
Jul-07	0.153	0.124
Aug-07	0.126	0.110
Sep-07	0.097	0.080
Oct-07	0.080	0.068
Nov-07	0.073	0.066
Dec-07	0.076	0.098
Jan-08	0.087	0.114
Feb-08	0.103	0.091

Time	Measured	Simulated
Mar-08	0.124	0.105
Apr-08	0.146	0.134
May-08	0.154	0.172
Jun-08	0.150	0.139
Jul-08	0.163	0.120
Aug-08	0.135	0.104
Sep-08	0.107	0.091
Oct-08	0.082	0.074
Nov-08	0.076	0.073
Dec-08	0.081	0.108
Jan-09	0.093	0.070
Feb-09	0.115	0.090
Mar-09	0.130	0.108
Apr-09	0.146	0.125
May-09	0.157	0.095
Jun-09	0.147	0.118
Jul-09	0.172	0.119

Time	Measured	Simulated
Aug-09	0.149	0.126
Sep-09	0.116	0.107
Oct-09	0.091	0.072
Nov-09	0.086	0.073
Dec-09	0.091	0.070
Jan-10	0.107	0.113
Feb-10	0.131	0.125
Mar-10	0.159	0.124
Apr-10	0.183	0.173
May-10	0.208	0.192
Jun-10	0.188	0.166
Jul-10	0.211	0.170
Aug-10	0.176	0.132
Sep-10	0.142	0.112
Oct-10	0.113	0.152
Nov-10	0.105	0.130
Dec-10	0.104	0.107

APPENDIX 2

Table A 7. R Code Script for Data preprocessing and preparation along with the results

R version 3.3.2 (2016-10-31) -- "Sincere Pumpkin Patch"
Copyright (C) 2016 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

```
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Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[Workspace loaded from ~/.RData]
> #Setting the working directory WD
> setwd("C:/Users/Ali/Desktop/SWAT Results/BMP vs Area")
> #to get the working directory
> getwd()
>
> #reading the BMP data of the results
> BMPdata<-read.csv(file = "C:/Users/Ali/Desktop/SWAT Results/BMP vs Area/BMP.csv", header = TR
UE)
> str(BMPdata)
> summary(BMPdata)
> #reading the Area data of the results
> Areadata<-read.csv(file = "C:/Users/Ali/Desktop/SWAT Results/BMP vs Area/Area.csv", header = TRU
E)
> str(Areadata)
> summary(Areadata)
> #Creating a dataset of rows with Area (HRU numbers) names and BMP names
> Area_BMP=data.frame(merge(Areadata$Name, BMPdata$BMP))
> colnames(Area_BMP)<-c("Area#", "BMP#")
> Area_BMP
> ###############################################################
> #########          Total Cost per Area          ###########
> #Total Cost for implementing the BMP in each Area
> # Creating the loop for multiplication purposes by reading every cell
>
> Area_Cost=data.frame(merge(Areadata$Area,BMPdata$Cost, all=TRUE))
> colnames(Area_Cost)<-c("Area", "Cost_per_BMP")
> Area_Cost
> ## Calculating the total cost of each BMP in each Area
> Tot_Cost = Area_Cost$Area*Area_Cost$Cost_per_BMP
> Tot_Cost
> ###############################################################
> #########        Total TP Reduction          ###########
> ##creating new variable in the Area (Area * TP loads)
> Areadata$TP_Area<-c(Areadata$Area*Areadata$TP)
```

```
>
> ##reading the new output file for the Area to make sure it was added
> Areadata
> ## creating a matrix with the new outputs
> Area_TP_Reduct=data.frame(merge(Areadata$TP_Area, BMPdata$TP_Eff, all=TRUE))
> colnames(Area_TP_Reduct)<-c("Area", "TPReduct_per_BMP")
> Area_TP_Reduct
> ## Calculating the total reduction of TP from each BMP in each Area
> Tot_TP_Reduct = Area_TP_Reduct$Area*Area_TP_Reduct$TPReduct_per_BMP/100
> Tot_TP_Reduct
> Cost_Red
> ## Writing the output file for Python
> write.csv(Cost_Red, file="CostvsRed.csv")
```

Table A 8. Python Script for Combination tool

```
import pandas as pd
import itertools

def bmp(bmp_file,outfile=None):
    bmp_df = pd.read_csv(bmp_file, sep=',', header=None)
    print  bmp_df

    def read_other_col(combination_tuple):
        sum = 0.0
        for k in combination_tuple:
            sum = sum+ float( bmp_df.iat[int(k),2])
            # print  bmp_df.iat[int(k),1]
        return sum

    def add_tuple(combination_tuple):
        sum = 0.0
        for k in combination_tuple:
            sum = sum+ float( bmp_df.iat[int(k),1])
            # print  bmp_df.iat[int(k),1]
        return sum

    def tuple_string(combination_tuple):
        return ",".join(['CS_'+str(bmp_no) for bmp_no in combination_tuple])


    combo_list = []
    for t in range(1,len(bmp_df)):
        combo_list.append(t)
    with open(outfile, "a+") as f:
        for i in range(2,len(bmp_df)):
            print i,
            ith_combinations = list(itertools.combinations(combo_list,i))

            for a_tuple in ith_combinations:
                # print a_tuple,add_tuple(a_tuple),
                if (add_tuple(a_tuple) > 5000.0) and  (add_tuple(a_tuple) < 10000.0):

                    f.write(    str(tuple_string(a_tuple))+    "Cost="    +str(add_tuple(a_tuple))+    "Phosphorus"
+str(read_other_col(a_tuple))+   '\n'   )

    return f

bmp_file = 'CostvsRedpy.csv'
outfile= 'results.txt'
bmp(bmp_file, outfile=outfile)
```

Figure A 9. Python Script for Combination tool

```python
import pandas as pd
import itertools

def bmp(bmp_file,outfile=None):
    bmp_df = pd.read_csv(bmp_file, sep=',', header=None)
    print  bmp_df

    def read_other_col(combination_tuple):
        sum = 0.0
        for k in combination_tuple:
            sum = sum+ float( bmp_df.iat[int(k),2])
            # print  bmp_df.iat[int(k),1]
        return sum

    def add_tuple(combination_tuple):
        sum = 0.0
        for k in combination_tuple:
            sum = sum+ float( bmp_df.iat[int(k),1])
            # print  bmp_df.iat[int(k),1]
        return sum

    def tuple_string(combination_tuple):
        return ",".join(['CS_'+str(bmp_no) for bmp_no in combination_tuple])



    # combo_string = "".join(str(x) for x in  range(len(bmp_df)))
    combo_list = []
    for t in range(1,len(bmp_df)):
        combo_list.append(t)
    with open(outfile, "a+") as f:
        for i in range(2,len(bmp_df)):
            print i,
            ith_combinations = list(itertools.combinations(combo_list,i))

            for a_tuple in ith_combinations:
                # print a_tuple,add_tuple(a_tuple),
                if (add_tuple(a_tuple) > 15000.0) and  (add_tuple(a_tuple) < 15001.0):

                    f.write( str(tuple_string(a_tuple))+ "Cost=" +str(add_tuple(a_tuple))+ "Phosphorus" +str(read_other_col(a_tuple))+   '\n'   )

    return f

bmp_file = 'CostvsRedpy.csv'
outfile= 'results.txt'
bmp(bmp_file, outfile=outfile)
```

APPENDIX 3

AMALGAM files

The following is a description of the files used in the optimization frame:

Data.dat

It is a structured data file that represents the problem numbers. Each row represents a parameter while the columns represents a given data such as:

- e_i = percent of Phosphorus Removal efficiency
- BMPC = BMP implementation cost ($)
- P_k = load of either Phosphorus or Sediments from the area in kg/day (i.e., Parcel)
- A_{max} = maximum area for implementing BMP (in square kilometer)
- A_{min} = minimum area for implementing BMP (in square kilometer)
- Budget: constraint where the first cell represents the maximum ($) that can be utilized, while the second cell represents the minimum budget ($)
- Load Reduction: reduction constraint where the first cell represents the maximum and the second cell represents the minimum reduction

optimization.m

Defines the population size, which is the number populated of NPS area to implement the BMPs as combined solutions (Please see Table A11 in Appendix 3 for more details), where.

- **T** represents how many generations (i.e., how many iterations) to get the solution, which is can be modified according to result. If problem needs more time to reach to optimal set, then the number of iterations can be increased. Sometimes increasing the number of generations doesn’t affect the optimal solution.
- **d** defines the number of parameter (Area) used from the data file (number

of rows)

- **Par_Info** which focuses on variable area. The initial sample of Area is drawn using Latin hypercube sampling, and the boundary handling is activated to enforce the parameters to stay within their prior ranges (Par_info.min, Par_info.max) which represent Area max and Area min respectively.
- **Func_name** loads the objective functions from amalgam-zed file and send all of the data to amalgam to be processed.

Amalgam-zed

It contains the objective functions that was called **optmaztion.m**. The functions define both, the total cost (budget) and the total phosphorus load reduction. For more details see Table A 12 in Appendix 3. The mechanism:

- First step is to call Data.dat file that is filled into vectors and used in calculation.
- Second, it calculates the summation for both objective functions, according to the problem case (i.e., one parameter for each BMP's -in case of two BMP's).
- The final step is to check the budget and reduction boundary constraints). If it's within the given range, then it was considered, otherwise the solution was eliminated.

runAMALGAM.m file

This is a function to develop a problem file. Only used to pass file name to be executable. For more details, please see Table A10 in Appendix 3.

print.m file

This file does the multiply load reduction values and print the figure.

output.mat

This file contains the resulted structured data as vectors. Where,

- x > represents the solutions set of NPS areas per member of the population.
- F > two vectors. First one represents the total load reduction and the second one represents the total cost for implementing the selected BMPs in the selected Areas

Table A 10. RunAMLAGAM.m – MATLAB files

Main window:

```
%% ------------------------------------------------------------------------

% close all figures (progress bar if terminated early)

clc; close all hidden



%% ############################ DO NOT CHANGE ###############################
global AMALGAM_dir EXAMPLE_dir

%% Check whether running on PC or MAC/UNIX machine
if ispc, slash_dir = '\';
else
    slash_dir = '/';
end

%% Store working directory and subdirectory containing the files needed to run this example
AMALGAM_dir = pwd; EXAMPLE_dir = [pwd ,slash_dir,'optimiztion'];

%% Add subdirectory to search path
addpath(EXAMPLE_dir); addpath(AMALGAM_dir); addpath([pwd ,slash_dir,'postprocessing']);

%% NOW RUN EXAMPLE
eval('optimiztion');

% Now save to disk
save AMALGAM_output.mat output X F Z AMALGAMPar
%print result
Print();
```

```
% ------- The AMALGAM multiobjective optimization algorithm ---------- %
% This general-purpose MATLAB code is designed to find a set of parameter values that defines the Pareto trade-off surface corresponding to a vector of different objective functions. In principle, each Pareto solution is a different weighting of the objectives used. Therefore, one could use multiple trials with a single objective optimization algorithms using different values of the weights to find different Pareto solutions. However, various contributions to the optimization literature have demonstrated that this approach is rather inefficient. The AMALGAM code developed herein is designed to find an approximation of the Pareto solution set within a single optimization run. The AMALGAM method combines two new concepts, simultaneous multimethod search, and self-adaptive offspring creation, to ensure a fast, reliable, and computationally efficient solution to multiobjective optimization problems. This method is called a multi-algorithm, genetically adaptive multiobjective, or AMALGAM, method, to evoke the image of a procedure that blends the attributes of the best available individual optimization algorithms. %                                   %
% SYNOPSIS:
%
%[X,F,output,Z,sim]= AMALGAM(AMALGAMPar,Func_name,Par_info);
%[X,F,output,Z,sim]= AMALGAM(AMALGAMPar,Func_name,Par_info,options);
%[X,F,output,Z,sim]= AMALGAM(AMALGAMPar,Func_name,Par_info,options,func_in);
%[X,F,output,Z,sim]= AMALGAM(AMALGAMPar,Func_name,Par_info,options,func_in,Fpar);
%                                                                         %
% Input:
% AMALGAMPar = structure with AMALGAM settings/parameters
% Func_name = name of the function or model that returns objective functions
% Par_info = optional structure with parameter ranges
% Fpareto = optional vector with Pareto solution set (benchmark problems)
% options = optional structure with additional settings
% func_in = optional variable that user can pass to function
```

```
%
%
% Output:
% X = final population (matrix)
% F = final objective function values of "X" (matrix)
% output = structure with several output arguments computed by AMALGAM (structure)
% Z = archive of all past populations augmented with X (matrix)
% sim (optional) = Model simulations of Pareto solutions (see example 6 and 7)
%
% This algorithm has been described in
% Vrugt, J.A., and B.A. Robinson, Improved evolutionary optimization from genetically adaptive multimethod search,
Proceedings of the National Academy of Sciences of the United States of America, 104, 708 - 711,
doi:10.1073/pnas.0610471104, 2007.          %
% Vrugt, J.A., B.A. Robinson, and J.M. Hyman, Self-adaptive multimethod search for global optimization in real-
parameter spaces, IEEE Transactions on Evolutionary Computation, 13(2), 243-259, doi:10.1109/TEVC.2008.924428,
2009.
% For more information please read:%
% Vrugt, J.A., H.V. Gupta, L.A. Bastidas, W. Bouten, and S. Sorooshian, Effective and efficient algorithm for multi-
objective optimization of hydrologic models, Water Resources Research, 39(8), art. No. 1214,
doi:10.1029/2002WR001746, 2003.
% Schoups, G.H., J.W. Hopmans, C.A. Young, J.A. Vrugt, and W.W.Wallender, Multi-objective optimization of a
regional spatially-distributed subsurface water flow model, Journal of Hydrology, 20 - 48, 311(1-4),
doi:10.1016/j.jhydrol.2005.01.001, 2005.
% Vrugt, J.A., P.H. Stauffer, T. Wöhling, B.A. Robinson, and V.V. Vesselinov, Inverse modeling of subsurface flow
and transport properties: A review with new developments, Vadose Zone Journal, 7(2), 843 - 864,
doi:10.2136/vzj2007.0078, 2008.
% Wöhling, T., J.A. Vrugt, and G.F. Barkle, Comparison of three multiobjective optimization algorithms for inverse
modeling of vadose zone hydraulic properties, Soil Science Society of America Journal, 72, 305 - 319,
doi:10.2136/sssaj2007.0176, 2008.
% Wöhling, T., and J.A. Vrugt,. Combining multi-objective optimization and Bayesian model averaging to calibrate
forecast ensembles of soil hydraulic models, Water Resources Research, 44, W12432, doi:10.1029/2008WR007154,
2008.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%
%
% AMALGAM code developed by Jasper A. Vrugt, University of California Irvine: jasper@uci.edu %
% Version 0.5:   June 2006. %
% Version 1.0:   January 2009    Cleaned up source code and implemented 4 test problems
% Version 1.1:   January 2010    Flexible population size and no need divide by # algorithms %
% Version 1.2:   August 2010     Sampling from prior distribution%
% Version 1.3:   May 2014        Varous updates - cleaning and improved speed ranking%
% Version 1.4:   Januari 2014    Parallellization using parfor (done if CPU >1)
%      PLEASE CHECK MANUAL OF AMALGAM (ON MY WEBSITE)                    %
% Vrugt, J.A., Multi-criteria optimization using the AMALGAM software package: Theory concepts, and MATLAB
implementation, UCI, 2015
% NOTE: EXPLICIT PRIOR SAMPLING DISTRIBUTIONS CAN BE USED IN AMALGAM: CHECK DREAM
MANUAL
% Vrugt, J.A., Markov chain Monte Carlo simulation using the DREAM software package: Theory, concepts, and
MATLAB Implementation, Environmental Modelling & Software, 75, 273-316, doi:10.1016/j.envsoft.2015.08.013.
%% Check:  http://faculty.sites.uci.edu/jasper
%% Papers: http://faculty.sites.uci.edu/jasper/publications/
%% Google Scholar: https://scholar.google.com/citations?user=zkNXecUAAAAJ&hl=nl
%% ######################################################################
%%   Func_name: Name of the function script of the model/function
%% ######################################################################
%%                     CASE STUDY DEPENDENT
%% ----------------------------------------------------------------------
%% Func_name                % Name of the model function script (.m file)
%% ----------------------------------------------------------------------
%% ######################################################################
%%   AMALGAMPar: Computational setup AMALGAM and algorithmic parameters
%% ######################################################################
```

```
%%                     CASE STUDY DEPENDENT
%% -------------------------------------------------------------------------
%% AMALGAMPar.d             % Dimensionality Pareto distribution
%% AMALGAMPar.N             % Population size
%% AMALGAMPar.T             % Number of generations?
%% AMALGAMPar.m             % Number of objective functions?
%% -------------------------------------------------------------------------
%%                        DEFAULT VALUES
%% -------------------------------------------------------------------------
%% AMALGAMPar.rec_methods   % Recombination methods  : {'GA','PSO','AMS','DE'}
%% AMALGAMPar.beta_1        % DE scaling factor      : @(N) unifrnd(0.6,1.0,N,1)
%% AMALGAMPar.beta_2        % DE scaling factor      : @(N) unifrnd(0.2,0.6,N,1)
%% AMALGAMPar.c_1           % PSO social factor      : 1.5
%% AMALGAMPar.c_2           % PSO cognitive factor   : 1.5
%% AMALGAMPar.varphi        % PSO inertia factor     : @(N) unifrnd(0.5,1.0,N,1)
%% AMALGAMPar.p_CR          % NSGA-II crossover rate : 0.9
%% AMALGAMPar.p_M           % NSGA_II mutation rate  : 1/d
%% AMALGAMPar.eta_C         % NSGA-II mutation index : 10
%% AMALGAMPar.eta_M         % NSGA-II mutation index : 50
%% AMALGAMPar.gamma         % AMS jump rate          : (2.38/sqrt(d))^2
%% AMALGAMPar.K             % Thinning rate          : 1 (no thinning of Z)
%% AMALGAMPar.p_min         % Min. selection prob.   : 0.05
%% -------------------------------------------------------------------------
%% #########################################################################
%%   Par_info: All information about the parameter space and prior
%% #########################################################################
%%                     CASE STUDY DEPENDENT
%% -------------------------------------------------------------------------
%% Par_info.initial % Initial sampling distribution ('uniform'/'latin'/'normal'/'prior')
%% Par_info.min             % If 'latin', min parameter values
%% Par_info.max             % If 'latin', max parameter values
%% Par_info.prior           % Marginal prior distribution of each parameter
%% Par_info.mu              % If 'normal', mean of initial parameter values
%% Par_info.cov             % If 'normal', covariance matrix parameters
%% Par_info.boundhandling   % Boundary handling ('reflect','bound','fold')
%% -------------------------------------------------------------------------
%%                        DEFAULT VALUES
%% -------------------------------------------------------------------------
%% Par_info.boundhandling = 'none'   % no boundary handling (unbounded problem)
%% -------------------------------------------------------------------------
%% #########################################################################
%%   options: Structure with optional settings
%% #########################################################################
%%                          OPTIONAL
%% -------------------------------------------------------------------------
%% options.parallel  % Multi-core computation chains?
%% options.IO        % If parallel, IO writing model?
%% options.save      % Save DREAM output during the run?
%% options.ranking   % Pareto Ranking code, 'MATLAB' (default) or 'C' (faster)
%% options.density   % Which density of points 'crowding' (default) or 'strength'
%% options.modout    % Return model simulatons? 'no' (default) or 'yes'
%% options.restart   % Restart run ( continue previous run - options.save must be 'yes')
%% options.print     % Print to screen tables/figures (postprocessor)
%% -------------------------------------------------------------------------
%% #########################################################################
%%  Fpareto: Matrix ( Npar x d ) with Pareto solutions (synthetic problems)
%%  NOTE: Existing IGD.mexw64 in zip file compiled for 64 bit machine
%%  NOTE: If this gives error recompile IGD.cpp ("mex IGD.cpp")
%%  NOTE: If you do not have mex compiler and IGD gives errors just specify
%%  NOTE: Fpar = [];
%% #########################################################################
```

Table A 11. optimiztion.m - MATLAB files

Optimization file in the MATLAB

```
% ------------------------------------------------------------------------------------------ %
%                                                                                            %
%      AAA       MM        MM       AAA       LL        GGGGGGGGGGG      AAA      MM        MM   %
%     AA AA      MMM      MMM      AA AA      LL        GGG      GGG     AA AA     MMM      MMM   %
%     AA AA      MMMM    MMMM      AA AA      LL        GG        GG     AA AA     MMMM    MMMM   %
%    AA   AA     MM MM MM MM     AA   AA     LL        GGG      GGG    AA   AA    MM MM MM MM   %
%   AAAAAAAAA    MM  MMM  MM    AAAAAAAAA    LL        GGGGGGGGGGG   AAAAAAAAA   MM  MMM  MM   %
%   AA      AA   MM        MM   AA      AA   LL                 GG   AA      AA  MM        MM   %
%  AA        AA  MM        MM  AA        AA  LLLLLLLL           GG  AA        AA MM        MM   %
%  AA        AA  MM        MM  AA        AA  LLLLLLLL  GGGGGGGGGGG  AA        AA MM        MM   %
%                                                                                            %
% ------------------------------------------------------------------------------------------ %
%% Read Max of Area from Data.dat file
fid=fopen('Data.dat');
s=textscan(fid,'%s %s %s %s %s %s %s');
fclose(fid);
Amax = str2double(s{4}).';
Amin = str2double(s{5}).';

%% Define fields of AMALGAMPar
AMALGAMPar.N = 1000;                            % Define population size
AMALGAMPar.T = 100;                             % How many generations?
AMALGAMPar.d = 10;                      % How many parameters?
AMALGAMPar.m = 2;                              % How many objective functions?

%% Define fields of Par_info
Par_info.initial = 'latin';                    % Latin hypercube sampling
Par_info.boundhandling = 'bound';              % Explicit boundary handling
Par_info.min = Amin;
Par_info.max = Amax;
%% Define name of function (Zitzler et al., Evolutionary Computation, 8 (2), 183-195, 2000)
Func_name = 'AMALGAM_ZDT';


%% Define structure options
options.print = 'yes';                  % Print output to screen (tables and figures)


%% Run the AMALGAM code and obtain non-dominated solution set
[X,F,output,Z,sim ] = AMALGAM ( AMALGAMPar , Func_name , Par_info , options , []  );
```

Table A 12. amalgamZDT.m - MATLAB files

```
function F = AMALGAM_ZDT( x )

fid=fopen('Data.dat');           %read matrix of values from Data.dat file
s=textscan(fid,'%s %s %s %s %s %s %s');
fclose(fid);
Amax = str2double(s{4}).';
Amin = str2double(s{5}).';

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Getting data from file as vectors
e=str2double(s{1});               % vector of P removal efficiency (e)
c=str2double(s{2});               % vector of BMPC (cost)
p=str2double(s{3});               % vector of Pk (phosphorus)
Amax=str2double(s{4});            % vector of Area Max Values
Amin=str2double(s{5});            % vector of Area Min Values
CostBound=str2double(s{6});       % vector of CostBound Contain max,min
LoadBound=str2double(s{7});       % vector of LoadBound Contain max,min

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Putting the result in values
TotalCost =  sum(c(1:3).*x(1:3));                  % total cost formula
LoadReduct = sum(p(1:3).*(e(1:3)/100).*x(1:3));    % total Reduction formula

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Final objective functions
F(1) =(-LoadReduct);
F(2) =TotalCost;

% return objective functions

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Statistical Analysis

Statistical results:

Bartlett test of homogeneity of variances
data: dati and groups
Bartlett's K-squared = 0.023109, df = 5, p-value = 1
P> 0.05, meaning that the Null Hypothesis is true that all variances are equal.

ANOVA test
Response: dati

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
groups	5	0.00188	0.000377	0.0292	0.9996
Residuals	114	1.47060	0.012900		

Pr(>F) = p-value
Since p-value > 0.05, we accept the null hypothesis H_0: the six means are statistically equal.

Scenarios

Definitions:

Variable X represents BMP implemented.

Mean represents the average area (Km^2) of the populated NPS areas for BMPs implementation

```
--------------------------- AMALGAM output file
======================================
Variable          Mean        Std
--------------------------------------
  x_{1}          0.49898     0.16734
  x_{2}          0.21152     0.05753
  x_{3}          0.33184     0.01635
  x_{4}          0.27507     0.06778
  x_{5}          0.29497     0.05302
  x_{6}          0.22582     0.07345
  x_{7}          0.17302     0.05859
  x_{8}          0.21536     0.05307
  x_{9}          0.24205     0.02732
 x_{10}          0.24200     0.02292
 x_{11}          0.16330     0.05353
 x_{12}          0.20673     0.03678
 x_{13}          0.12099     0.03487
 x_{14}          0.16818     0.05013
 x_{15}          0.13702     0.04789
 x_{16}          0.13785     0.04744
 x_{17}          0.09874     0.01469
 x_{18}          0.14214     0.04311
 x_{19}          0.15771     0.00373
 x_{20}          0.12225     0.03866
======================================
```

Figure 26. Mean values of populated NPS areas for BMPs in Scenario 1

```
--------------------------- AMALGAM output file
======================================
Variable          Mean        Std
--------------------------------------
  x_{1}          0.50840     0.17668
  x_{2}          0.23349     0.07965
  x_{3}          0.32493     0.03569
  x_{4}          0.26546     0.06853
  x_{5}          0.29573     0.05194
  x_{6}          0.23098     0.07618
  x_{7}          0.16682     0.05593
  x_{8}          0.21233     0.05343
  x_{9}          0.24832     0.01217
 x_{10}          0.23693     0.03427
 x_{11}          0.21912     0.01712
 x_{12}          0.21625     0.02294
 x_{13}          0.12098     0.03413
 x_{14}          0.14909     0.04942
 x_{15}          0.12853     0.04359
 x_{16}          0.11484     0.03120
 x_{17}          0.09922     0.01604
 x_{18}          0.13077     0.04304
 x_{19}          0.10515     0.03639
 x_{20}          0.10840     0.03760
======================================
```

Figure 27. Mean values of populated NPS areas for BMPs in Scenario 2

```
--------------------------- AMALGAM output file
======================================
Variable          Mean        Std
--------------------------------------
  x_{1}          0.51048     0.16202
  x_{2}          0.28256     0.09090
  x_{3}          0.32795     0.02858
  x_{4}          0.30756     0.04145
  x_{5}          0.31714     0.01045
  x_{6}          0.25562     0.07397
  x_{7}          0.20551     0.06677
  x_{8}          0.24771     0.02012
  x_{9}          0.23208     0.04047
 x_{10}          0.23952     0.03007
 x_{11}          0.18878     0.05000
 x_{12}          0.19627     0.04540
 x_{13}          0.16815     0.05163
 x_{14}          0.16273     0.05136
 x_{15}          0.13662     0.04513
 x_{16}          0.10962     0.02137
 x_{17}          0.10398     0.02424
 x_{18}          0.15707     0.03651
 x_{19}          0.13280     0.03563
 x_{20}          0.15714     0.00786
======================================
```

Figure 28. Mean values of populated NPS areas for BMPs in Scenario 3

CURRICULUM VITAE

Ali Salha
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PROFESSIONAL SUMMARY

An experienced professional with +10 years of experience in management, planning and executing engineering and environmental projects and programs with public and private sectors. Proven ability to lead cross-functional teams to achieve results and meet deliverables.

EDUCATION

- Master of Science in Water Resources Engineering, IUG 2010
- Bachelor of Science in Civil Engineering, IUG 2000

AREA OF EXPERTISE

Programs/projects Management, Design and Modelling, Environmental Analysis, Utilities Management, Monitoring & Evaluation and Construction management

TECHNICAL SKILLS

- MS Office (Excel, Word, PowerPoint and Outlook), MS Project, Logframer
- R-language for Statistical Computing, MATLAB, ESRI-ArcGIS, QUAL2K, Soil and Water Analysis Tool (SWAT – watershed analysis), HEC-RAS, SWMM, Water-Sewer CAD, MODFLOW, Surfer (visualization), AutoCAD, GMS (Groundwater), WEAP, EPANET, and EPI Suite™

EXPERIENCE

Senior Infrastructure Advisor **2016 – present**
United Nations Office for Project Services (UNOPS) – Copenhagen, Denmark

Responsible for design review of water and wastewater projects.
Responsible for development of engineering manuals for Flood Control and Drainage Systems; Coastal Protection Systems; Water Resources Management Systems; and Irrigation Management & Practices

PhD Researcher
Utah Water Research Laboratory, Utah, U.S.A. 2010 –2018

- Researched and developed environmental management practices to protect watershed from nonpoint pollution sources. Work involves application of ArcGIS, hydrological modelling for surface water and groundwater quality (ArcSWAT QUAL2K, HEC-RAS and (GMS)), statistical analysis (R statistical and MATLAB for environmental database analysis), reviewing Total maximum daily loads (TMDL), investigating Water Treatment and Wastewater Treatment Plants (WWTPs) compliance.
- Awards: Dr. Robert W. Okey for Wastewater Treatment Plant scholarship in November 2014 & Water Environment Association of Utah (WEAU) Competition for WW treatment options in April 2015

Project Manager
WorldBank- Project Management Unit (PMU) 2007 – 2010

- Responsible for engineering and management of municipal water, wastewater and stormwater utilities projects with total budget US$ 70M
- Provided an environment of management and coordination among donors, local authorities, contractors and consultants to effective projects implementation
- Provided engineering, planning, management and procurement services of infrastructure projects in wastewater collection and stormwater drainage that served 25 local municipalities
- Prepared technical proposals, engineering reports, cost estimates, time schedule, project staffing, specification and detailed description of municipal works under local regulations and quality permits

Water Resources Specialist
Water Authority (PWA) 2005 – 2007

- Provided engineering, procurement, and management services for the delivery of watershed development plans (strategic plan for 20 years) considering surface and groundwater quantity and quality, demographic projection, available technical/financial resources, and climate change impact for 1.6 million residents
- Tasks included need assessment, design reports and plans, field visits, lab samplings, computer modelling, monitoring and evaluation, organization, and closing sessions with 25 local municipalities

Project Engineer
Technical Eng. Consulting Co. 2000 – 2005

- Responsible for designing and supervising the implementation of municipal project: water distribution, sewers collection systems and stormwater drainage (installations and rehabilitation projects)
- Managed local contractors and clients to coordinate work activities (engineering reports, design, drawings, BoQ) and effectively to meet deadlines
- Tasks included preparing tendering packages, cost estimates, project staffing, engineering design, construction oversight, site reconnaissance and safe & timely completion of projects

ADDITIONAL TRAINING / CERTIFICATION

- Project Management Institute, Inc. (PMI) May 2018 - present
- Project Management Certificate - Environmental Careers Organization of Canada (ECO Canada) December 2017
- PRINCE2® Foundation Certificate in Project Management (Project management method, its principles, themes & terminology) from AXELOS December 2016